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Qualifying scientific work on the rights of the manuscript

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DISSERTATION

ENVIRONMENTAL COUPLED MULTI-FACTOR PRECISE REGULATION AND OPTIMIZATION FOR THE ARTIFICIAL LIGHT PLANT FACTORY BASED ON A GROWTH MODEL

Specialty 133 - Mechanization and automation of agricultural production

Field of study 13 - Mechanical engineering

Submitted for a scientific degree of Doctor of philosophy

The dissertation contains the results of own research. The use of ideas, results and texts of other authors have references to the relevant source

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ANNOTATION

Wang Xinfa Environmental coupled multi-factor precise regulation and optimization for an artificial light plant factory based on a growth model. - Qualifying scientific work on the rights of the manuscript.

The dissertation for the degree of Doctor of Philosophy in the field of knowledge 13 - Mechanical Engineering, specialty 133 - Machines and means of mechanization and automation of agricultural production. - Sumy National Agrarian University, Sumy, 2023.

The dissertation is dedicated to solving an urgent scientific and technological problem in the field of Mechanization and automation of agricultural in modern agricultural production: innovating multi factor coupling precise regulation and optimization technology for the environment inside artificial light plant factories, in order to improve comprehensive resource utilization and reduce crop's industrial production costs. To meet the requirements of energy conservation and environmental protection and not be affected by external climate and land limitations, the construction of an artificial light plant factory in an enclosed and insulated chamber should be the best option. After research, we took the lead in proposing the concepts of modern building greenhouses and intelligent building greenhouses, and recommended building artificial light plant factories in urban areas and constructing larger scale intelligent building greenhouses plant factories to improve the building performance of plant factories, thereby ensuring permanent use and long-term production and operation. The urban intelligent plant factory is a highly intensive modern agricultural production system that can continuously provide the most suitable environment for plant growth and achieve high-quality and efficient production of plant products through precise environmental regulation techniques and mechanization, automation, digitization, intelligence, industrialization and factory technology. Moreover, this production method can adopt a "local production, local sales" operating model, continuously producing organic, green, clean, pollution-free, and fresh-eating plant products throughout the year, improving people's living standards, and ensuring the safety of the "vegetable basket" and food security. This is

very important for modern Ukraine, for China, and even for all countries in the world.

Object of research - theories and methods for constructing plant growth models based on deep learning algorithms; the overall composition, program architecture and development prospects of an artificial light plant factory; and the techniques and methods for mechanization, automation and intelligent regulation and optimization of the production environment.

The subject of research - is the design and development of mechanized, intelligent, industrialized, factorized, periodical and modern plant production systems that can be built in urban areas, and the analysis and study of their system composition and architecture; the studies of the theories and methods for building plant growth models based on IoT, big data technologies and deep learning algorithms, which are different from traditional mathematical algorithms; the studies of the machines, means and methods for the coupled multi-factor precise regulation and optimization of the environments in the artificial lighting factory based on a plant growth model.

Specifically, it includes three sub directions and subjects: firstly, investigate the construction form, system composition, development status, development trends and core technologies of the artificial light plant factory. The dissertation proposes recommendations for the construction of building greenhouses, intelligent building greenhouses, and intelligent building greenhouse plant factories. Second, research on methods and techniques for constructing plant growth models. The dissertation proposes a construction method and system architecture for plant growth models based on IoT and big data technologies. Furthermore, research on the relevant theories and core technologies of environmental regulation and optimization in artificial light plant factories. The dissertation proposes a multi-factor self-learning coupled precision regulation model, as well as research on the methods for constructing plant growth models based on deep learning models and the related studies on artificial lighting and nutrient solution regulation techniques.

The purpose of the work is to create and improve modern, intensive plant production complexes and systems that can be constructed in urban areas, independent of geo-climatic and land resource constraints, and to study the theory, law, methodology, and technology of mechanized, automated, intelligent, and precise control and optimization of plant growth and production environments of artificial light plant factories in buildings. The ultimate goal is to improve and optimize regulation strategies of the environment through intelligent and precise environmental regulation technologies, increase resource utilization efficiency, and reduce the cost of plant industrial production products.

To achieve this goal, the following **tasks** need to be solved:

1. To analyze the current development status, trends, obstacles and opportunities of the artificial light plant factory, and to clarify the importance and direction of research.

2. To analyze and improve the existing forms of greenhouses, explore the optimal bearing form of artificial light plant factories, propose development recommendations for building greenhouses, intelligent building greenhouses, and intelligent building greenhouse plant factories, and study their strategic significance and development strategies.

3. To analyze the system composition and core technologies of artificial light plant factories and intelligent building plant factories, and to identify research topics and directions.

4. To investigate the construction methods for plant growth models and plant factory big data, to propose and design a systematic framework for building plant growth models based on IoT and big data technologies, and to develop a plant factory big data management systems and plant growth model analysis platforms.

5. to systematically analyze the production environment factors of artificial light plant factories and their effect on plant growth, study the coupling effect of multiple factors on plant growth, to propose a multi factor self-learning coupling precise regulation model, and to develop a production management systems and environmental precise regulation platforms for artificial light plant factories.

6. To research on algorithms and implementation techniques for constructing plant growth models based on deep learning models. To research on object detection of tomato fruits for the artificial light plant factory using an improved YOLO deep

learning model and instance segmentation of plant seedlings for the artificial light plant factory using a modified Mask R-CNN and Transformer deep learning models, and to lay the theoretical and technical foundation for constructing plant growth models and environmental control models.

7. To experimental verify on the effects of different lighting conditions of LED artificial light and nutrient solution formulations on plant growth and quality, to improve to environmental regulation technology and means in artificial light plant factories, and to lay the foundation for theoretical research, model construction, and implementation technology of precise regulation of environmental multi factor coupling.

In the introduction, the choice of the topic of the dissertation and scientific tasks is substantiated, the purpose and tasks of research are formulated, the scientific novelty and practical value of the received results are defined, and also the information on approbation, structure and volume of work is resulted.

In the first Section, systematic literature analysis, social demand studies, and related theoretical research have been conducted on topics such as plant factories, intelligent building greenhouses, artificial light plant factories, plant growth model construction, and environmental regulation and optimization of plant factories. The necessity, importance and development prospects of the research topic of artificial light plant factories are clarified. A comprehensive analysis of the problems, obstacles and intelligent development needs encountered in their research and industrialization at the current stage has been carried out. Further research has been carried out on the core technologies for the development of artificial photoproduction plants, and a research topic based on growth models for the precise regulation and optimization of multi-factor couplings has been proposed. All this allowed the applicant to formulate the purpose, objectives and tasks of the dissertation.

In the second section, the laboratory situation, experimental conditions, experimental equipment, experimental materials, etc. of the scientific work are presented in a comprehensive and systematic manner. It also showcases image acquisition system platforms designed to successfully achieve scientific research goals and tasks, as well as the experimental design and research status of screening illumination formulations and nutrient solution formulations.

In the third section, basic research related to the construction of plant growth models is carried out to provide theoretical support for the construction of growth models and the precise regulation of the environment. collecting environmental data through the intelligent monitoring platform for plant factory environment and growth, constructing big data for plant factory environment, analysing plant growth parameters using different deep learning models and algorithms, and constructing big data for plant factory growth are studied. Then data mining techniques and deep learning models to construct a sub-model for plant growth is used, and a comprehensive model for plant growth is summarized and constructed.

In the fourth section, the effects of light environment, nutrient solution environment, and the comprehensive regulation of various environmental factors in plant factories on plant growth are studied, and the effectiveness of environmental regulation is experimentally verified.

In the fifth section, the full text is summarized, conclusions are drawn, recommendations for future research are made, and technical recommendations for implementing the results of the study into production are developed.

In accordance with the set goal and tasks, the following results were obtained in the work:

1. Ukraine is a vast, sparsely populated territory with a scattered rural population and densely populated urban areas. Moreover, most of the country has a temperate continental climate, with an average temperature of -7.4 ℃ in January and 19.6 ℃ in July. The mean annual temperature is relatively low. Planting vegetables in the open air, on the one hand, is difficult to meet the balanced supply of fresh vegetables throughout the year, and on the other hand, it is also difficult to meet the diverse supply of fresh vegetable varieties. The intelligent building greenhouse plant factory proposed by the applicant and the improved all artificial light plant factory can improve the situation in Ukraine, and develop micro or small artificial light plant factories in sparsely populated and dispersed rural areas to meet the perennial fresh

vegetable needs of the rural population; The construction of large-scale intelligent building greenhouses and plant factories in densely populated cities will enhance the demand of urban residents for the quality of fresh vegetables. The results of this work have been highly recognized by peer experts, government managers, and entrepreneurs, and have received government project funding. At the same time, it could serve as a reference for Ukraine.

2. According to a questionnaire survey from China, the main limiting factors for the development of plant factories at present are high construction costs (73.3%) and high operating costs (66.4%). Consumers are particularly concerned and anxious about the unbearable price (70.6%). Consumers prioritize cleanliness and pollution-free (39.3%), green and healthy (30.3%), high freshness (17.6%), product quality (8.8%), and nutritional index (3.7%) when making purchases. While the situation in Ukraine and China may not be exactly the same, the demand for vegetable quality should be consistent. The artificial light plant factory scheme proposed by the applicant and the precise control system architecture of environmental multi factor coupling can solve the following three problems: (1) the production environment of the artificial light plant factory is clean and pollution-free, and the vegetables produced are clean, pollution-free, and green and healthy. (2) Through precise environmental regulation and optimization, the production cost of vegetables will be greatly reduced, making it affordable for ordinary people to consume. (3) Although the construction cost of intelligent building greenhouse plant factories and artificial light plant factories is high, their materials are stable and their structure is firm, and they can be built for almost long-term use. The results of this work can address the balanced supply of fresh vegetables and hunger threats faced by Ukraine, China, and even the world, ensuring the "vegetable basket" and food security.

3. The dynamic and constantly changing growth environment of plants, with diverse growth characteristics and complex growth processes, makes the construction of plant growth models quite complex and difficult. It is almost impossible to construct a complete and perfect mathematical model. The applicant's proposal to build crop growth models based on IoT and big data technologies transforms the

intractable problem of simulating complex systems with mathematical formulas into the study of a divide and conquer relational correlation problem. Relational models of complex systems have been constructed using data mining algorithms and deep learning models. The applicants obtained a large amount of big data on growing environments and plant growth during their work, and extensive preparations were made to model the relationship between environmental factors and growth indicators.

4. Intelligent regulation and optimization of plant growth environments is the most complex and central scientific and technological problem in artificial light plant factories. Environmental regulation is not precise and accurate enough, and the most immediate results can affect plant growth, yield and quality. In addition, it may result in significant waste of production materials and integrated resources. The proposed system architecture of a multi-factor environmental regulation platform for an artificial light plant factory based on a growth model has been applied in the development of a comprehensive control system for the plant factories and has also been tried and tested by enterprises. The results of this work can improve the utilization rate of water resources by 10%, save water soluble fertilizer by 8%, and comprehensively reduce electricity by 18%, with huge market prospects.

5. The biomass accumulation of plants is closely related to water replenishment, lighting, fertilizers, CO_2, and even environmental temperature and humidity. Target detection of plant fruits and instance segmentation of seedlings can be used in intelligent monitoring systems for plant growth processes, obtaining real-time growth status information, perceiving growth trends, predicting biomass growth, intelligently and accurately controlling water and fertilizer replenishment, regulating environmental variables such as light, CO_2 concentration, temperature and humidity, providing the best environment for plant growth. The proposed improvements YOLOv5_MT algorithm is used for tomato fruit detection in artificial light plant factories, improving the detection accuracy of dense and obstructed tomatoes. The proposed CMRDF instance segmentation algorithm that integrates RGB-D multi-channel image data is used for the segmentation of plant seedling leaves in artificial light factories, with a PA of 93% and an IoU of 93.4%. These two research results

were both used in the control and management system of plant factories.

6. Three experimental studies were conducted in the laboratory of an artificial light plant factory, including the experimental study on illumination screening and uniformity simulation of hydroponic lettuce, the experimental study on the effect of light quality on the quality of hydroponic *Cichorium endivia* L., and the screening study on the formulation of nutrient solution for hydroponic green leaf lettuce. The control techniques for light and nutrient solutions have been improved and the effectiveness of environmental multi-factor control techniques has been demonstrated. The results of the work achievements have been applied in multiple government scientific research projects undertaken by the applicant and in the products of related enterprises, with broad market prospects and enormous economic benefits.

7. The technology of artificial light micro plant factories, such as LED supplementary light type planting cabinet (Chinese Patent NO. ZL 2023 2 0899208.6), a multispectral crop phenotype analysis platform for plant factories (Chinese Patent NO. ZL 2021 2 1596146.7), an assembled aerospace culture layer shelf with adjustable layer height for the plant factory with artificial light (Chinese Patent NO. ZL 2022 2 0821668.2), has been protected by Chinese utility model patents. The technology named "A general real-time detection and counting method for eggplant frost in plant factory (Chinese Patent NO. 202210152745.4)" is protected by Chinese invention patents. These patented technologies have been put into production, earning considerable economic benefits and generating enormous social value.

Scientific novelty of the obtained results:

1. For the first time, the concepts of intelligent building greenhouses and intelligent building greenhouses plant factories were proposed, with clear definitions. Extensive social demand research and literature analysis were conducted to systematically and scientifically demonstrate their strategic significance. The development strategy of "3-Positions and 1-Entity" was studied, providing an innovative model and systematic solution for the sustainable and clean plant production system in urban development.

2. For the first time, it is proposed to use the physiological mechanisms and

biological theories of plant light regulation as the theoretical basis for artificial light plant factory light environment regulation, improve the technical means of light environment regulation, and regulate the production process of plants through the role of light in photosynthesis, growth and development, morphological construction, material metabolism, gene expression, and nutritional quality, in order to adapt to market changes.

3. For the first time, a flat IoT solution using multiple sensors and controllable work units has been provided for artificial light plant factories. A system architecture for constructing scientific big data for plant factories has been proposed, and the process and methods of comprehensively utilizing IoT, big data, and deep learning technologies to construct plant growth models have been systematically studied. The plant factory big data platform and crop growth model service system constructed using this method can provide data and model services for plant factory industrial enterprises through cloud services.

4. For the first time, the architecture and framework of a multi-factor environmental regulation platform for artificial light plant factories based on growth models were proposed, and control system software was designed, developed, and tested. The system software can automatically obtain plant growth model files from the cloud, and intelligently and accurately regulate the environment of plant growth based on the plant growth model, to obtain high-quality and high-yield plant products with minimal cost.

5. An improved YOLOv3 deep learning model and algorithm have been proposed for target detection of hydroponic tomato fruits in artificial light plant factories, providing theoretical foundation and technical support for yield estimation, robotic picking, and precise regulation of growing environments. This method can classify and detect the growing tomato fruits, obtain the quantity of green fruits, color changing fruits, and red fruits, as a basis for precise regulation of light environment and nutrient solution concentration, thereby effectively reducing water, electricity, nutrient solution waste and sewage discharge, improving resource comprehensive utilization rate and yield.

6. For the first time, a CMRDF algorithm for plant seedling instance segmentation was proposed, which integrates RGB-D multi-channel image data to improve the accuracy of seedling instance segmentation. It is used to analyze plant phenotypic data in artificial light plant factories, to construct crop growth models, and to provide theoretical and technical support for plant intelligent growth monitoring, disease and pest detection, production management, yield estimation, robotic operations, and environmental regulation.

7. For the first time, experimental studies on illumination screening and uniformity simulation of hydroponic lettuce, experimental study on the effect of light quality on the quality of hydroponic *Cichorium endivia* L., and screening study on the formulation of nutrient solution for hydroponic green leaf lettuce are conducted in an artificial light plant factory, providing technical references for precise regulation of environmental multi-factor coupling.

The practical significance of the results obtained lies in providing a series of systematic theoretical achievements for the intelligent control and optimization of the artificial light plant factory environment, and proposing comprehensive technical suggestions. At the same time, it also provides a complete set of solutions and suggestions for sustainable and clean plant production systems for urban development. The use of these suggestions will improve the intelligence and intensification of plant factories, improve the utilization rate of comprehensive resources such as land, water, electricity, and fertilizers, reduce plant production costs, and generate considerable economic benefits and immeasurable social value. The theoretical achievements and technical solutions obtained in the work are protected by 4 patents and 7 computer software copyrights, and have been implemented by the high-tech enterprise "ZSP" Electronic Technology Co., Ltd. in Henan Province, China. After preliminary testing, it can improve the water resource utilization rate by 10%, save water soluble fertilizer by 8%, comprehensively reduce electricity by 18%, significantly reduce the production cost of plant, and bring huge economic benefits and social value.

The main results of the dissertation, generalizations, scientific prescriptions and conclusions that constitute the essence of the work were independently obtained and formulated by the applicant.

Keywords: plant factory, machine learning, spectrum, yielding capacity, productivity, agricultural technologies, wavelength, data structure, factor analysis, cherry, plant growth model, vertical agriculture, urban agriculture, precision agriculture, smart agriculture.

АНОТАЦІЯ

Ван Сіньфа Екологічно пов'язане багатофакторне точне регулювання та оптимізація для заводу штучного освітлення на основі моделі росту. - Кваліфікаційна наукова праця на правах рукопису.

Захищено дисертацію на здобуття наукового ступеня доктора філософії галузі знань 13 – Механічне машинобудування, спеціальність 133 – Машини і засоби механізації та автоматизації сільськогосподарського виробництва. – Сумський національний аграрний університет, м. Суми, 2023.

Дисертація присвячена вирішенню актуальної науково-технічної проблеми в галузі механізації та автоматизації сільськогосподарського виробництва в сучасному аграрному виробництві: розробці інноваційної багатофакторної технології точного регулювання та оптимізації мікроклімату в теплицях штучного освітлення з метою покращення комплексного використання ресурсів та зниження собівартості промислового виробництва сільськогосподарських культур. Щоб відповідати вимогам енергзбереження та охорони навколишнього середовища і не залежати від зовнішніх кліматичних та земельних обмежень, найкращим варіантом є будівництво заводу з виробництва рослин зі штучним освітленням у закритій та ізольованій камері. Після досліджень ми взяли на себе ініціативу запропонувати концепції сучасних будівельних теплиць та інтелектуальних будівельних теплиць, а також рекомендували будувати заводи зі штучним освітленням у міських районах та будувати більш масштабні заводи інтелектуальних будівельних теплиць для поліпшення будівельних характеристик рослинних заводів, забезпечуючи тим самим постійне використання та довгострокове виробництво та експлуатацію. Міська інтелектуальна фабрика рослин - це високоінтенсивна сучасна система сільськогосподарського виробництва, яка може постійно забезпечувати найбільш сприятливе середовище для росту рослин і досягати якісного та ефективного виробництва рослинної продукції за допомогою точних методів екологічного регулювання, а також механізації, автоматизації, оцифрування, інтелекту, індустріалізації та заводських технологій. Більше того, цей метод

виробництва може прийняти операційну модель "місцеве виробництво, місцеві продажі", безперервно виробляючи органічну, зелену, чисту, екологічно чисту та свіжу рослинну продукцію протягом усього року, покращуючи рівень життя людей, забезпечуючи безпеку "овочевого кошика" та продовольчу безпеку. Це дуже важливо і для сучасної України, і для Китаю, і навіть для всіх країн світу.

Об'єкт дослідження - теорії та методи побудови моделей росту рослин на основі алгоритмів глибокого навчання; загальний склад, програмна архітектура та перспективи розвитку фабрики штучного освітлення рослин; прийоми та методи механізації, автоматизації та інтелектуального регулювання і оптимізації середовища рослинництва.

Предмет дослідження - проектування та розробка механізованих, інтелектуальних, індустріалізованих, заводських, ювілейних та сучасних систем виробництва рослин, які можуть бути побудовані в міських умовах, а також аналіз та дослідження їх системного складу та архітектури; дослідження теорій та методів побудови моделей росту рослин на основі IoT, технологій великих даних та алгоритмів глибокого навчання, які відрізняються від традиційних математичних алгоритмів; дослідження прийомів і методів комбінованого багатофакторного прецизійного регулювання та оптимізації середовища заводу штучного освітлення на основі моделі росту рослин.

Зокрема, предмет дослідження включає три піднапрямки та теми: по-перше, дослідити будівельну форму, системний склад, стан розвитку, тенденції розвитку та основні технології заводу зі штучного освітлення. У дисертації запропоновано рекомендації щодо будівництва будівельних теплиць, інтелектуальних будівельних теплиць та інтелектуальних будівельних тепличних комбінатів. По-друге, дослідження методів та прийомів побудови моделей росту рослин. У дисертації запропоновано метод побудови та системну архітектуру моделей росту рослин на основі технологій IoT та великих даних. Крім того, дослідження відповідних теорій та основних технологій регулювання та оптимізації навколишнього середовища на фабриках зі штучним освітленням. У дисертації запропоновано багатофакторну модель точного регулювання, що самонавчається, а також дослідження методів побудови моделей росту рослин на основі моделей глибокого навчання та пов'язані з ними дослідження методів регулювання штучного освітлення та поживних розчинів.

Метою роботи є створення та вдосконалення сучасних інтенсивних рослинницьких комплексів та систем, які можуть бути побудовані в міських умовах, незалежно від геокліматичних та земельних обмежень, а також дослідження теорії, закономірностей, методології та технології механізованого, автоматизованого, інтелектуального та точного управління та оптимізації росту рослин і виробничих середовищ рослинних фабрик штучного освітлення в будівлях. Кінцевою метою є вдосконалення та оптимізація стратегій регулювання навколишнього середовища за допомогою інтелектуальних та точних технологій регулювання навколишнього середовища, підвищення ефективності використання ресурсів та зниження собівартості продукції рослинного промислового виробництва.

Для досягнення поставленої мети необхідно вирішити наступні **завдання**:

1. Проаналізувати сучасний стан розвитку, тенденції, перешкоди та можливості заводу штучного освітлення, а також з'ясувати важливість і напрямок досліджень.

2. Проаналізувати та вдосконалити існуючі форми теплиць, дослідити оптимальну несучу форму заводів штучного освітлення, запропонувати рекомендації щодо розробки теплиць, теплиць інтелектуального будівництва та фабрик тепличних рослин інтелектуального будівництва, вивчити їх стратегічне значення та стратегії розвитку.

3. Проаналізувати склад системи та основні технології заводів штучного освітлення та фабрик інтелектуальних будівельних заводів, а також визначити теми та напрямки досліджень.

4. Дослідити методи побудови моделей росту рослин та великих даних заводів рослин, запропонувати та розробити систематичну основу для побудови моделей росту рослин на основі технологій IoT та великих даних, а також розробити системи управління великими даними заводу та платформи аналізу

моделей росту рослин.

5. Систематично аналізувати фактори виробничого середовища заводів штучного освітлення та їх вплив на ріст рослин, вивчати вплив зв'язку багатьох факторів на ріст рослин, пропонувати багатофакторну модель точного регулювання зв'язку, що самонавчається, а також розробляти системи управління виробництвом та платформи екологічно точного регулювання для заводів штучного освітлення.

6. Дослідити алгоритми та методи реалізації побудови моделей росту рослин на основі моделей глибокого навчання. Дослідити виявлення об'єктів плодів томатів для заводу штучного освітлення рослин з використанням вдосконаленої моделі глибокого навчання YOLO та сегментації саджанців рослин для заводу штучного освітлення з використанням модифікованих моделей глибокого навчання Mask R-CNN та Transformer, а також закласти теоретичну та технічну основу для побудови моделей росту рослин та моделей контролю навколишнього середовища.

7. Експериментально перевірити вплив різних умов освітлення світлодіодного штучного світла та рецептур поживних розчинів на ріст та якість рослин, удосконалити технологію та засоби екологічного регулювання на заводах штучного освітлення, а також закласти основу для теоретичних досліджень, побудови моделей та технології впровадження точного регулювання екологічного багатофакторного зв'язку.

У вступі обґрунтовується вибір теми дисертації та наукові завдання, формулюються мета і задачі дослідження, визначаються наукова новизна і практична цінність отриманих результатів, а також наводяться відомості про апробацію, структуру та обсяг роботи.

У першому розділі систематичний аналіз літератури, дослідження соціального попиту та пов'язані з ними теоретичні дослідження були проведені на такі теми, як заводи рослин, теплиці інтелектуального будівництва, заводи штучного освітлення, будівництво моделей росту рослин, а також екологічне регулювання та оптимізація заводів. З'ясовано необхідність, важливість та перспективи розвитку теми дослідження рослинних фабрик зі штучним освітленням. Проведено комплексний аналіз проблем, перешкод та потреб інтелектуального розвитку, що виникають при їх дослідженні та індустріалізації на сучасному етапі. Проведено подальші дослідження основних технологій розробки установок штучного фотопродукування та запропоновано тему дослідження на основі моделей росту для точного регулювання та оптимізації багатофакторних зв'язків. Все це дозволило здобувачу сформулювати мету, цілі та завдання дисертаційної роботи.

У другому розділі всебічно і систематично представлені лабораторна ситуація, умови експерименту, експериментальне обладнання, експериментальні матеріали тощо наукової роботи. Він також демонструє платформи системи отримання зображень, призначені для успішного досягнення цілей і завдань наукових досліджень, а також експериментальний дизайн і стан досліджень скринінгових форм освітлення і рецептур поживних розчинів.

У третьому розділі проводяться фундаментальні дослідження, пов'язані з побудовою моделей росту рослин для теоретичного забезпечення побудови моделей росту і точного регулювання навколишнього середовища. Вивчається збір екологічних даних за допомогою інтелектуальної платформи моніторингу навколишнього середовища та зростання рослинних заводів, побудова big data для заводського середовища рослин, аналіз параметрів росту рослин за допомогою різних моделей та алгоритмів глибокого навчання та побудова великих даних для росту фабрики рослин. Потім використовуються методи інтелектуального аналізу даних та моделі глибокого навчання для побудови підмоделі росту рослин, а також узагальнюється та будується комплексна модель росту рослин.

У четвертому розділі досліджено вплив світлового середовища, середовища поживного розчину та комплексного регулювання різних факторів навколишнього середовища на рослинних фабриках на ріст рослин, а також експериментально перевірено ефективність екологічного регулювання.

У п'ятому розділі узагальнюється повний текст, робляться висновки, даються рекомендації щодо подальших досліджень, розробляються технічні рекомендації щодо впровадження результатів дослідження у виробництво.

Відповідно до поставленої мети і завданнями в роботі були отримані наступні результати:

1. Україна - це велика, малонаселена територія з розпорошеним сільським населенням і густонаселеними міськими районами. Крім того, більша частина країни має помірно-континентальний клімат із середньою температурою -7,4 °C у січні та 19,6 °C у липні. Середньорічна температура відносно низька. Висаджуючи овочі на відкритому повітрі, з одного боку, важко задовольнити збалансоване постачання свіжих овочів протягом року, а з іншого боку, також важко задовольнити різноманітну пропозицію свіжих сортів овочів. Запропонована заявником інтелектуальна будівля тепличного комбінату та вдосконалений комбінат зі штучним освітленням можуть покращити ситуацію в Україні, а також розвинути мікро- або малі комбінати зі штучним освітленням у малонаселених та розосереджених сільських районах для задоволення багаторічних потреб сільського населення у свіжих овочах; будівництво великомасштабних інтелектуальних будівельних теплиць та комбінатів у густонаселених містах підвищить попит міських мешканців на якісні свіжі овочі. Результати цієї роботи були високо оцінені колегами-експертами, державними управлінцями та підприємцями і отримали державне проектне фінансування. Водночас, вони можуть слугувати прикладом для України.

2. Згідно з анкетним опитуванням, проведеним у Китаї, основними обмежуючими факторами для розвитку фабрик з виробництва рослин на даний час є висока вартість будівництва (73,3%) та високі операційні витрати (66,4%). Споживачі особливо занепокоєні та стурбовані непідйомною ціною (70,6%). При здійсненні покупок споживачі надають пріоритет чистоті та відсутності забруднення (39,3%), екологічності та здоров'ю (30,3%), високій свіжості (17,6%), якості продукції (8,8%) та поживній цінності (3,7%). Хоча ситуація в Україні та Китаї може бути не зовсім однаковою, попит на якість овочів повинен

бути однаковим. Запропонована заявником схема заводу зі штучного освітлення та точна архітектура системи управління багатофакторним зв'язком з навколишнім середовищем можуть вирішити наступні три проблеми: (1) виробниче середовище заводу зі штучного освітлення є чистим та без забруднення, а вироблені овочі - чистими, без забруднення, зеленими та здоровими. (2) Завдяки точному екологічному регулюванню та оптимізації собівартість виробництва овочів буде значно знижена, що зробить їх доступними для споживання звичайними людьми. (3) Хоча вартість будівництва інтелектуальних будівельних тепличних заводів та заводів зі штучним освітленням висока, їх матеріали стабільні, а структура міцна, і вони можуть бути побудовані для майже довгострокового використання. Результати цієї роботи можуть вирішити проблему збалансованого постачання свіжих овочів та загрози голоду, з якою стикаються Україна, Китай і навіть світ, забезпечуючи "овочевий кошик" та продовольчу безпеку.

3. Динамічне середовище росту рослин, що постійно змінюється, з різноманітними характеристиками росту та складними ростовими процесами, робить побудову моделей росту рослин досить складним і важким завданням. Практично неможливо побудувати повну та досконалу математичну модель. Пропозиція здобувача щодо побудови моделей росту рослин на основі технологій IoT та великих даних трансформує нерозв'язну проблему моделювання складних систем за допомогою математичних формул у дослідження реляційної кореляційної задачі за принципом "розділяй і володарюй". Реляційні моделі складних систем були побудовані з використанням алгоритмів інтелектуального аналізу даних та моделей глибокого навчання. Під час роботи здобувачі отримали велику кількість великих даних про середовище вирощування та ріст рослин, а також провели велику підготовку до моделювання взаємозв'язку між факторами навколишнього середовища та показниками росту.

4. Інтелектуальне регулювання та оптимізація середовищ росту рослин є найскладнішою та центральною науково-технічною проблемою на фабриках

штучного освітлення. Регулювання навколишнього середовища недостатньо точне і точне, і його безпосередні результати можуть впливати на ріст, врожайність і якість рослин. Крім того, це може призвести до значних втрат виробничих матеріалів та інтегрованих ресурсів. Запропонована системна архітектура багатофакторної платформи екологічного регулювання для заводу з виробництва рослин штучного освітлення на основі моделі росту була застосована при розробці комплексної системи управління для заводів з виробництва рослин, а також була випробувана і протестована на підприємствах. Результати цієї роботи можуть покращити коефіцієнт використання водних ресурсів на 10%, заощадити водорозчинні добрива на 8% та комплексно зменшити споживання електроенергії на 18%, що має величезні ринкові перспективи.

5. Накопичення біомаси рослин тісно пов'язане з поповненням води, освітленням, добривами, CO_2 і навіть температурою та вологістю навколишнього середовища. Цільове виявлення плодів рослин і сегментація екземплярів розсади можуть бути використані в інтелектуальних системах моніторингу процесів росту рослин, отримання інформації про стан росту в реальному часі, сприйняття тенденцій росту, прогнозування зростання біомаси, інтелектуальне і точне управління поповненням запасів води і добрив, регулювання змінних навколишнього середовища, таких як світло, концентрація CO_2, температура і вологість, забезпечуючи найкраще середовище для росту рослин. Запропоновані вдосконалення алгоритму YOLOv5_MT використовуються для виявлення плодів томатів на фабриках зі штучним освітленням, покращуючи точність виявлення щільних і завалених томатів. Запропонований алгоритм сегментації екземплярів CMRDF, який інтегрує дані багатоканальних зображень RGB-D, використовується для сегментації листків розсади рослин у теплицях зі штучним освітленням, з показниками PA 93% та IoU 93,4%. Ці два результати дослідження були використані в системі контролю та управління рослинними фабриками.

6. Три експериментальні дослідження були проведені в лабораторії заводу

зі штучним освітленням, включаючи експериментальне дослідження скринінгу освітлення та моделювання однорідності гідропонного салату, експериментальне дослідження впливу якості світла на якість гідропонного *Cichorium endivia* L. та скринінгове дослідження формулювання поживного розчину для гідропонного салату з зеленим листям. Удосконалено методи контролю світла та поживних розчинів та продемонстровано ефективність методів екологічного багатофакторного контролю. Результати роботи були застосовані в декількох державних науково-дослідних проектах, виконаних заявником, а також у продукції споріднених підприємств, що має широкі ринкові перспективи та величезні економічні вигоди.

7. Технологія мікро рослинних фабрик зі штучним освітленням, таких як світлодіодна шафа для додаткового освітлення (Патент Китаю № ZL 2023 2 0899208.6), мультиспектральна платформа для аналізу фенотипу культур для рослинних фабрик (Патент Китаю № ZL 2021 2 1596146.7), зібрана полиця шару аерокосмічної культури з регульованою висотою шару для рослинної фабрики зі штучним освітленням (Патент Китаю № ZL 2022 2 0821668.2), була захищена китайськими патентами на корисні моделі. Технологія під назвою "Загальний метод виявлення та підрахунку заморозків баклажанів у реальному часі на теплиці (китайський патент № 202210152745.4)" захищена китайськими патентами на винаходи. Ці запатентовані технології були впроваджені у виробництво, приносячи значні економічні вигоди і створюючи величезну соціальну цінність.

Наукова новизна отриманих результатів:

1. Вперше були запропоновані поняття інтелектуальних будівельних теплиць і інтелектуальних будівельних теплиць заводів, з чіткими визначеннями. Проведено масштабні дослідження суспільного попиту та аналіз літератури, щоб систематично та науково продемонструвати їх стратегічну значимість. Досліджено стратегію розвитку «3 позиції та 1 суб'єкт господарювання», що забезпечує інноваційну модель та системне рішення для стійкої та чистої системи виробництва рослин у міському розвитку.

2. Вперше запропоновано використовувати фізіологічні механізми та біологічні теорії регуляції рослинного світла як теоретичну основу регуляції штучного освітлення заводського світлового середовища, удосконалювати технічні засоби регуляції світлового середовища, регулювати виробничий процес рослин через роль світла у фотосинтезі, рості та розвитку, морфологічна конструкція, матеріальний метаболізм, експресія генів та якість харчування, щоб адаптуватися до змін ринку.

3. Вперше просте рішення IoT з використанням декількох датчиків і керованих робочих блоків було надано для заводів зі штучного освітлення. Запропоновано системну архітектуру побудови наукових big data для заводів рослин, систематично вивчається процес і методи комплексного використання IoT, big data і технологій глибокого навчання для побудови моделей росту рослин. Платформа big data заводської фабрики та система обслуговування моделей росту сільськогосподарських культур, побудована з використанням цього методу, можуть надавати послуги даних та моделей для заводських промислових підприємств за допомогою хмарних сервісів.

4. Вперше була запропонована архітектура і структура багатофакторної платформи екологічного регулювання для заводів штучного освітлення на основі моделей зростання, а також спроектовано, розроблено і випробувано програмне забезпечення системи управління. Системне програмне забезпечення може автоматично отримувати файли моделей росту рослин з хмари, а також розумно і точно регулювати середовище росту рослин на основі моделі росту рослин, отримувати якісну і високоврожайну рослинну продукцію з мінімальними витратами.

5. Запропоновано вдосконалену модель та алгоритм глибокого навчання YOLOv3 для цілеспрямованого виявлення плодів гідропонних томатів на заводах штучного освітлення, що забезпечує теоретичну основу та технічну підтримку для оцінки врожайності, роботизованого збору та точного регулювання середовища вирощування. Цей метод дозволяє класифікувати та виявляти зростаючі плоди томатів, отримувати кількість зелених плодів, плодів,

що змінюють колір, та червоних плодів, як основу для точного регулювання світлового середовища та концентрації розчину поживних речовин, тим самим ефективно зменшуючи воду, електроенергію, відходи поживних розчинів та скидання стічних вод, покращуючи комплексну швидкість використання ресурсів та врожайність.

6. Вперше запропоновано алгоритм CMRDF сегментації екземплярів проростків рослин, який інтегрує дані багатоканального зображення RGB-D для підвищення точності сегментації екземплярів проростків. Він використовується для аналізу фенотипічних даних рослин на заводах штучного освітлення, для побудови моделей росту сільськогосподарських культур, а також для надання теоретичної та технічної підтримки інтелектуального моніторингу росту рослин, виявлення хвороб та шкідників, управління виробництвом, оцінки врожайності, роботизованих операцій та екологічного регулювання.

7. Вперше експериментальні дослідження з освітлювального скринінгу та моделювання однорідності гідропонного салату, експериментальні дослідження впливу якості світла на якість гідропоніки *Cichorium endivia* L. та скринінгові дослідження з рецептури поживного розчину для гідропонного зеленого листового салату проводяться на заводі штучного освітлення, що забезпечує технічні посилання для точного регулювання екологічного багатофакторного зв'язку.

Практичне значення отриманих результатів у полягає в наданні ряду системних теоретичних досягнень для інтелектуального управління та оптимізації заводського середовища заводу штучного освітлення і пропозиції комплексних технічних пропозицій. У той же час він також надає повний набір рішень та пропозицій щодо стійких та чистих систем виробництва рослин для міського розвитку. Використання цих пропозицій покращить інтелект та інтенсифікацію роботи заводів, покращить коефіцієнт використання комплексних ресурсів, таких як земля, вода, електроенергія та добрива, знизить витрати на виробництво рослин та створить значні економічні вигоди та незмірну соціальну цінність. Отримані в роботі теоретичні досягнення і технічні рішення захищені 4 патентами і 7 авторськими правами на комп'ютерні програми, реалізовані високотехнологічним підприємством «ZSP» Electronic Technology Co., Ltd. в провінції Хенань, Китай. Після попереднього тестування він може підвищити коефіцієнт використання водних ресурсів на 10%, заощадити водорозчинні добрива на 8%, всебічно скоротити електроенергію на 18%, значно знизити собівартість продукції заводу, принести величезні економічні вигоди та соціальну цінність.

Основні результати дисертації, узагальнення, наукові приписи і висновки, що становлять суть роботи, були самостійно отримані і сформульовані здобувачем.

Ключові слова: заводська фабрика, машинне навчання, спектр, врожайність потужність, продуктивність, сільськогосподарські технології, довжина хвилі, структура даних, факторний аналіз, вишня, модель росту рослин, вертикальне сільське господарство, міське сільське господарство, точне сільське господарство, розумне сільське господарство.

LIST OF PUBLICATIONS OF THE APPLICANT ON THE TOPIC OF THE DISSERTATION

SCOPUS / Web of Science publications

1. **Wang Xinfa**, Onychko Viktor, Zubko Vladislav, Zhenwei Wu & Mingfu Zhao. (2023). Sustainable production systems of urban agriculture in the future: A case study on the investigation and development countermeasures of the Plant Factory and Vertical Farm in China. Frontiers in Sustainable Food Systems, 2023,7. DOI: 10.3389/fsufs.2023.973341 **(Web of Science Core Collection, Q1, IF: 5.005)**

The applicant conducted a social survey on the research and industrialization status of plant factories among Chinese users, analyzed the cognitive levels and attitudes of different groups, and proposed development strategies.

2. **Xinfa Wang**, Zhenwei Wu, Meng Jia, Tao Xu, Canlin Pan, Xuebin Qi, Mingfu Zhao. (2023) Lightweight SM-YOLOv5 tomato fruit detection algorithm for Plant Factory. *Sensors,* 23(6),3336. DOI：10.3390/s23063336 **(Web of Science Core Collection, Q2, IF: 3.847)**

The applicant proposed a lightweight object detection algorithm based on YOLOV5's SM-YOLOv5 for tomato picking robots in plant factories.

3. **Wang Xinfa**, Zubko Vladislav, Onychko Viktor, Zhenwei Wu & Mingfu Zhao. (2022). Online recognition and yield estimation of tomato in plant factory based on YOLOv3. Scientific Reports, 12:8686. DOI: 10.1038/s41598-022-12732-1 **(Web of Science Core Collection, Q2, IF: 4.997)**

The applicant has proposed an improved YOLOv3 tomato target detection algorithm for online recognition, detection, and yield estimation of tomato in plant factories.

4. Zhenwei Wu, Minghao Liu, Chengxiu Sun, **Xinfa Wang (corresponding author)**. (2023). A dataset of tomato fruits images for object detection in the complex lighting environment of plant factories, Data in Brief, 5(48). DOI: 10.1016/j.dib.2023.109291 (Scopus and EI)

The applicant has disclosed the tomato fruit dataset in the complex environment of the artificial light plant factory for research on fruit classification, object detection, and instance segmentation.

5. Liu Qihang, **Wang Xinfa (Co-first author)**, Zhao Mingfu, Liu Tao. (2023). Synergistic influence of the capture effect of western flower thrips (*Frankliniella occidentalis*) induced by proportional yellow-green light in the greenhouse. International Journal of Agricultural and Biological Engineering (IJABE), 16(1):88-94. DOI: 10.25165/j.ijabe.20231601.7562 **(Co-first author, same as Liu's contribution, Web of Science Core Collection, Q2, IF:1.885)**

The applicant participated in research, result analysis, and paper writing, and conducted experiments to verify the phototaxis and capture effect of a certain proportion of yellow and green light on greenhouse western flower thrips.

6. **Wang Xinfa**, Vladislav Zubko, Onychko Viktor, Zhenwei Wu and Mingfu Zhao. (2022). Research on intelligent building greenhouse plant factory and “3-Positions and 1-Entity” development mode. Iop Conference Series: Earth and Environmental Science, 1087(1),012062. DOI: 10.1088/1755-1315/1087/1/012062 **(Scopus and EI)**

The applicant first proposed and systematically explained the concept of an intelligent building greenhouse plant factory, and also discussed its advantages and strategic importance.

7. Tao Xu, Weishuo Zhao, Lei Cai, Xiaoli Shi and **Xinfa Wang**. (2023). Lightweight saliency detection method for real-time localization of livestock meat bones. Scientific Reports, 2023,13(1). DOI: 10.1038/s41598-023-31551-6 **(Web of Science Core Collection, Q2, IF: 4.996)**

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

8. Lin Lu, Weirong Luo, Wenjin Yu, Junguo Zhou, **Xinfa Wang** & Yongdong Sun. (2022). Identification and Characterization of Csa-miR395s Reveal Their Involvements in Fruit Expansion and Abiotic Stresses in Cucumber. Frontiers in Plant Science, section Plant Bioinformatics, 13:907364. DOI: 10.3389/fpls. 2022.907364 **(Web of Science Core Collection, Q1, IF: 6.627)**

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

9. Hongxia Zhu, Linfeng Hu, Tetiana Rozhkova, **Xinfa Wang**, Chengwei Li. (2023). Spectrophotometric analysis of bioactive metabolites and fermentation optimization of *Streptomyces* sp. HU2014 with antifungal potential against *Rhizoctonia solan*. Biotechnology & Biotechnological Equipment, 2023,37(1):231-242. DOI: 10.1080/13102818.2023.2178822 **(Web of Science Core Collection, Q3, IF: 1.762)**

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

10. Jifei Zhao, Rolla Almodfer, Xiaoying Wu, **Xinfa Wang**. (2023). A dataset of pomegranate growth stages for machine learning-based monitoring and analysis, Data in Brief, 7(50). DOI: 10.1016/j.dib.2023.109468 **(Scopus and EI)**

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

11. Cao Zhishan, Cao Jinjun, Vlasenko Volodymyr, **Wang Xinfa**, & Weihai Li. (2022). Transcriptome analysis of Grapholitha molesta (Busk) (Lepidoptera: Tortricidae) larvae in response to entomopathogenic fungi Beauveria bassiana. Journal of Asia-Pacific Entomology, 101926. DOI: 10.1016/j.aspen.2022.101926 **(Web of Science Core Collection, Q3, IF:1.580)**

The applicant participated in research, analysis of the results and writing the article. This study can indirectly support the applicant's research topic.

12. Tengfei Yan, Yevheniia Kremenetska, Biyang Zhang, Songlin He, **Xinfa Wang**, Zelong Yu, Qiang Hu, Xiangpeng Liang, Manyi Fu, Zhen Wang. (2022). The Relationship between Soil Particle Size Fractions, Associated Carbon Distribution and Physicochemical Properties of Historical Land-Use Types in Newly Formed Reservoir Buffer Strips. Sustainability, 14(14):8448. DOI: 10.3390/su14148448 **(Web of Science Core Collection, Q2, IF:3.889)**

The applicant participated in research, analysis of the results and writing the article. This study can indirectly support the applicant's research topic.

Articles in scientific professional publications of Ukraine

13. **Wang Xinfa**, Zubko Vladislav, Onychko Viktor, Zhao Mingfu. (2022). Illumination screening and uniformity simulation of hydroponic lettuce in artificial light plant factory. Bulletin of Sumy National Agrarian University. The series “Mechanization and Automation of Production Processes”, 2022, Vol. 49 No. 3, p3-10. DOI: 10.32845/msnau.2022.3.1

The applicant simulated the uniformity of LED lighting, experimentally verified its effect on the growth of hydroponic lettuce, and screened a suitable lighting formula for hydroponic lettuce in plant factories, providing theoretical support for light environment regulation.

14. **Wang Xinfa**, Onychko Viktor, Zubko Vladislav, Zhao Mingfu. (2022). Screening study on the formulation of nutrient solution for hydroponic green leaf lettuce in plant factory with artificial light. Bulletin of Sumy National Agrarian University. The series “Agronomy and Biology”, 2022, Vol. 48 No. 2, p11-16. DOI: 10.32845/agrobio.2022.2.2

The applicant conducted experiments to verify the effects of different nutrient solution formulations on the growth of hydroponic green leafy lettuce, and selected nutrient solution formulations suitable for hydroponic green leafy lettuce in artificial light plant factories, providing a theoretical basis for nutrient solution regulation.

15. Li Fang, **Wang Xinfa**, Dubovyk Volodymyr, Liu Runqiang. (2021). Rapid electrochemical detection of carbendazim in vegetables based on carboxyl functionalized multi-walled carbon nanotubes. Bulletin of Sumy National Agrarian University. The series “Agronomy and Biology”, Vol. 46 No. 4, p76-82. DOI: 10.32845/agrobio.2021.4.11

The applicant participated in research, analysis of the results and writing the article. This study can indirectly support the applicant's research topic.

16. Han Yafeng, **Wang Xinfa**, Onychko Viktor, Zubko Vladislav, Li Guohou. (2020). Recognition and location of crop seedlings based on image processing. Vol. 42 No. 4: Bulletin of Sumy National Agrarian University. The series “Agronomy and Biology”. 2020, vol. 42 No.4, P33-39. DOI: 10.32845/agrobio.2020.4.5

The applicant participated in research, analysis of the results and writing the article. This study can indirectly support the applicant's research topic.

Articles in scientific journals of other countries

17. **Wang Xinfa**, Zubko Vladisla, Onychko Viktor, Mingfu Zhao & Zhenwei Wu. (2022). Experimental study on the effect of light quality on the quality of hydroponic *Cichorium endivia* L. in Plant Factory with Artificial Light. African Journal of Agricultural Research, Vol.18(6), pp. 455-463. DOI: 10.5897/ AJAR2022.16028

The applicant studied the effect of light quality on the growth of hydroponic *Cichorium endivia* L. and screened suitable light quality compositions to provide theoretical support for light regulation in artificial light plant factories.

18. **WANG Xinfa**, Vladislav ZUBKO, Viktor ONYCHKO, Mingfu ZHAO. (2022). Development status and trend of plant factory Intelligence in China. Scientific Bulletin. Series F. Biotechnologies (University of Agricultural Sciences and Veterinary Medicine Bucharest Romania), Vol. XXVI, Issue. 1, ISSN 2285-1364, 65-70. http://biotechnologyjournal.usamv.ro/pdf/2022/issue_1/Art8.pdf

The applicant reviewed the current status and trends of intelligent development in Chinese plant factories, further demonstrated the necessity of the research topic, and determined the research direction.

19. Shi Fang, Ma Yukun, **Wang Xinfa**, Zhao Mingfu. (2023). Research on potato pest identification based on RegNet network (In Chinese). Chinese Agricultural Mechanization, 44(09):8888. DOI：10.13733/j.jcam.issn.2095-5553.2022.09.026 **(Chinese core journals)**

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

20. ZHAO Zhenxiang, AO Wenhong, **WANG Xinfa**, LU Lin, LUO Weirong, SUN Yongdong. (2023). Genome-wide identification and transcriptional analysis of DME gene family in cucumber (In Chinese). Plant Physiology Journal, 59 (1): 209–218. DOI: 10.13592/j.cnki.ppj.100264. **(Chinese core journals)**

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

21. Zhang Wei, **Wang Xinfa,** Shang Junjuan, Wang Ling. (2022). Design and Implementation of Multifunctional Seed and Fertilizer Sowing UAV (In Chinese). Development & Innovation of Machinery & Electrical Products, 35(02), 47-49. DOI: 10.3969/j.issn.1002-6673.2022.02.014

The applicant participated in research, analysis of the results and writing the article. This study can directly support the applicant's research topic.

22. Sun Tingting, Zhao Songyu, **Wang Xinfa,** Qin Mingyi, Zhang Chao & Tian Xueliang. (2021). Screening for biocontrol bacteria against Alternaria porri from phyllosphere of welsh onion (In Chinese). Journal of Henan University of science and Technology (natural science edition) (Chinese), 2021,49(01):35-40. DOI: 10.3969/j.issn.2096-9473.2021.01.007

The applicant participated in research, analysis of the results and writing the article. This study can indirectly support the applicant's research topic.

Theses of the reports and Conference papers

23. Wu Zhenwei, Liu Minghao, Sun Chengxiu, **Wang Xinfa (Corresponding author)**. (2023). Real time detection and counting method of tomato fruit in an artificial light plant factory based on yolov5. The second International Workshop on Vertical Farming (VertiFarm2023), Chengdu, China, May 22-24, 2023, organized by the Institute of Urban Agriculture, Chinese Academy of Agricultural Sciences under the aegis of ISHS (International Society for Horticultural Science). https://vertifarm2023.scimeeting.cn/en/web/index/.

The applicant leads a graduate research team to an offline conference and presents a poster of the research results at the conference. The applicant led the study and was the principal contributor.

24. **Wang Xinfa,** Vladislav Zubko, Onychko Viktor, Zhenwei Wu and Mingfu Zhao. (2022). Research on intelligent building greenhouse plant factory and "3-Positions and 1-Entity" development mode. The Fifth International Workshop on Environment and Geoscience (IWEG2022), Qingdao, China, July 16-18, 2022. http://www.iwegconf.org/LAP.aspx.

The applicant participated in the online conference and presented a poster of the results of the research online. The applicant is the principal contributor and won the "OUTSTANDING POSTER PRESENTATION" award.

25. **WANG X.F.,** ONYCHKO V.I., ZUBKO V., ZHAO M.F. (2022). Development status and trend of plant factory with artificial lighting technology and industrialization. International Scientific and Practical Conference "HONCHAROV’S READINGS", Sumy, Ukraine, May 25, 2022,92-95.

The applicant participated in the online conference and presented a poster of the results of the research online and is the principal contributor.

26. **WANG Xinfa,** Vladislav ZUBKO, Viktor ONYCHKO, Mingfu ZHAO. (2021). Development status and trend of plant factory intelligence in China. One Health Student International Conference, Nov. 24th-27th, 2021, București, ROMANIA, P. 32. received a certificate. https://onehealth.usamv.ro/index/program/

The applicant participated in the online conference and verbally reported the results of the study at the conference and was the principal contributor.

27. Zhu Hongxia, **Wang Xinfa,** Rozhkova Tetiana. (2021). Preliminary study on antifungal activity of astreptomyces SP. strain hu2014 against phytopathogenic fungi. III International Scientific and Practical Conference “TOPICAL ISSUES OF MODERN SCIENCE, SOCIETY AND EDUCATION”, KHARKIV, Ukraine, 3-5 October 2021, received a certificate.

The applicant participated in research and online conferences. This study can directly support the applicant's research topic.

28. LI F., **WANG X.F.,** LIU D.M., DUBOVYK VOLODYMYR. (2022). A review of purified materials in quenchers pretreatment method for pesticide residue detection. International Scientific and Practical Conference "HONCHAROV’S READINGS", Sumy, Ukraine, May 25, 2022,157-158.

The applicant participated in research and online conferences. This study can directly support the applicant's research topic.

29. ZHU HONGXIA, ROZHKOVA T., **WANG XINFA**. (2022). Study the allelopathy of the fermentation extracts from streptomyces SP. HU2014 on cucumber. International Scientific and Practical Conference "HONCHAROV’S READINGS",

Sumy, Ukraine, May 25, 2022,165-166.

The applicant participated in research and online conferences. This study can directly support the applicant's research topic.

30. LIU D.M., IEVGEN KONOPLIANCHENKO, VIACHESLAV TARELNYK, **WANG X.F.**, LI F. (2022). Application research of agricultural mechanization based on genetic algorithm. International Scientific and Practical Conference "HONCHAROV'S READINGS", Sumy, Ukraine, May 25, 2022,231-233.

The applicant participated in research and online conferences. This study can indirectly support the applicant's research topic.

Patents

31. Zhao Mingfu, Wu Zhenwei, **Wang Xinfa** et al. (2023). LED supplementary light type planting cabinet, utility model patent, China, ZL-2023-2-0899208.6, July 04, 2023, **the third inventor**, has been authorized. https://s1.qizhidao.com/DZqawS

The applicant, as the main implementer, participated in the research, result analysis, and application of the patent.

32. **Wang Xinfa,** Qu Peixin, Wu Xiaoying et al. (2021). A multispectral crop phenotype analysis platform for plant factories, utility model patent, China, ZL-2021-2-1595146.7, November 19, 2021, **the first inventor**, has been authorized. https://s1.qizhidao.com/HMsvpq

The applicant, as the first contributor, completed the research, result analysis, and application of the patent.

33. **Wang Xinfa,** Qu Peixin, Wu Xiaoying et al. (2022). An assembled aeroponics culture layer frame with adjustable layer height for the plant factory with artificial light, utility model patent, China, ZL-2022-2-0821668.2, July 8, 2022, **the first inventor**, has been authorized. https://s1.qizhidao.com/Jchaxy

The applicant, as the first contributor, completed the research, result analysis, and application of the patent.

34. **Wang Xinfa,** Liu Qihang, Qu Peixin et al. (2022). A general real-time detection and counting method for eggplant fruit in plant factory, invention patent,

Application approval No.202210152745.4, February 19, 2022, **the first inventor**, Application accepted, Substantive review stage. https://s1.qizhidao.com/OHxtta

The applicant, as the first contributor, completed the research, result analysis, and application of the patent.

Computer software copyright

35. **Wang Xinfa**, Sun Chengxiu. (2023). Detection system for germination rates in plant factories - V1.0, Computer software copyright, China, 2023SR0557513, May 22, 2023, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

36. **Wang Xinfa**, Liu Minghao. (2023). Automatic monitoring system for cabbage diseases and pests - V1.0, Computer software copyright, China, 2023SR0557498, May 22, 2023, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

37. **Wang Xinfa**, Wu zhenwei. (2023). Water circulation control system of plant factory - V1.0, Computer software copyright, China, 2023SR0478585, April 18, 2023, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

38. **Wang Xinfa**, Wu zhenwei. (2023). Plant factory image acquisition system - V1.0, Computer software copyright, China, 2023SR0478584, April 18, 2023, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

39. **Wang Xinfa,** Wu zhenwei, Zhao Mingfu et al. (2022). Plant factory 3D image acquisition system - V1.0, Computer software copyright, China, 2022SR0665171, March 15, 2022, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

40. **Wang Xinfa**, Guo Dawei, Wu Xiaoying et al., (2022). National grain yield monitoring system (Abbreviated as the grain yield monitoring system) - V1.0, Computer software copyright, China, 2022SR0971135, March 16, 2022, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

41. **Wang Xinfa**, Zhao Jifei, Rolla Jamil Almodfer et al., (2022). Intelligent diagnosis system of pests and diseases in intelligent orchard based on knowledge map (Abbreviated as intelligent diagnosis system of pests and diseases in intelligent orchard) - V1.0, Computer software copyright, China, 2022SR0665174, March 24, 2022, **the first copyright owner**, has been authorized.

The applicant, as the first contributor, completed the design and implementation of the computer software.

Research projects approved and funded by the Chinese government

42. Intelligent building greenhouse plant factory key technology development and application, 212102110234, Henan Provincial Science and Technology Department, 2021 Henan Province Science and Technology Research Project, 2020.12, Approved.

The applicant is the principal and the primary participant in the project.

43. The development of aeroponics system of fully artificial light plant factory, 22A210013, Henan Provincial Department of Education, 2022 Annual Key Scientific Research Project of Henan Higher Education Institution, 2021.12, Approved and funded (CNY ¥30,000).

The applicant is the principal and the primary participant in the project.

44. Multi-factor coupling control and optimization of urban intelligent plant factory environment, 222102320080, Henan Provincial Science and Technology Department, 2022 Henan Provincial Science and Technology Research Project, 2021.12, Approved and funded (CNY ¥100,000).

The applicant is the principal and the primary participant in the project.

45. Research and industrialization of key technologies for precise management

and control of smart orchard, 21ZD003, major science and technology project of Xinxiang City, Henan Province, 2021.10, approved and funded (CNY ¥1,000,000).

The applicant is the primary participant in the project.

46. Research on intelligent management and control technology of the plant factory based on IoT and Big Data, 232102111124, Henan Provincial Science and Technology Department, 2023 Henan Provincial Science and Technology Research Project, 2023.3, Approved and funded (CNY ¥100,000).

The applicant is the principal and the primary participant in the project.

47. Study and Application of a Beneficial Streptomyces Strain for Disease Control and Growth Promotion in Wheat Planting, 232102111015, Henan Provincial Science and Technology Department, 2023 Henan Provincial Science and Technology Research Project, 2023.3, Approved and funded (CNY ¥100,000).

The applicant is the primary participant in the project.

48. Research on application technology of autonomous wall-climbing robot for large-scale ship cleaning task, 212102210161，Henan Provincial Science and Technology Department, 2021 Henan Province Science and Technology Research Project, 2020.12, approved and funded (CNY ¥100,000).

The applicant is the primary participant in the project.

49. Research and application of community intelligent security technology based on ghost module and morphological aggregation，222102210165，Henan Provincial Science and Technology Department, 2022 Henan Province Science and Technology Research Project, 2020.12, approved.

The applicant is the primary participant in the project.

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THE LIST OF SYMBOLS

English abbreviations	English full name
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
IoT	Internet of Things
YOLO	You Only Live Once
CNN	Convolutional Neural Network
R-CNN	Region-based Convolutional Neural Networks
mAP	Mean Average Precision
F1	F1-Score
SPP	Spatial Pyramid Pooling
XML	Extensible Markup Language
PF	Plant Factory
ALPF	Artificial Light Plant Factory
PFAL	Plant Factory with Artificial Lighting
PFALs	Plant Factories with Artificial Light
IBGPF	Intelligent Building Greenhouse Plant Factory
UIPF	Urban Intelligent Plant Factory
VF	Vertical Farm
TCI	Total Construction Investment
LED	Light-Emitting Diode
RGB	Red Green Blue
SfM	Tructure-from-Motion
FR	Far-Red light
UV	Ultraviolet Ray
PWM	Pulse Width Modulation
PPFD	Photosynthetic Photon Flux Density
PFD	Photon Flux Density
LUE	Light Energy Use Efficiency

BEGAN	Boundary Equilibrium Generative Adversarial Networks
PBMs	Process-based models
KDDM	Knowledge- and Data-Driven Modelling
CRY	Cryptochrome
PHOT	Phototropin
UVR8	UV Response Locus 8
cAMP	Cyclic Adenosine Monophosphate
cGMP	Cyclic Guanosine Monophosphate
IP3	Inositol Triphosphate
LOV1	Light-Oxygen-Voltage 1
COP1	Constitutively Photomorphogenic 1
HY5	Elongated Hypocotyl 5
RUP1	Repressor Of UV-B Photomorphogenesis 1
VC	Vitamin C
EC	Electrical Conductivity
DO	Dissolved Oxygen
PH	Pondus Hydrogenii

INTRODUCTION

Justification for choosing the research topic. The plant factory is an advanced stage in the development of modern agriculture, which is a high-investment, high-tech, and high-quality equipment production system. It is a factory farming system that allows agricultural production to be separated from natural ecological constraints and produces plant products on a scheduled annual basis without interruption, representing the future direction of agriculture. It is seen as an essential approach to addressing food security, population, resource and environmental issues in the 21st century, and as crucial to achieving future food self-sufficiency in metropolitan development, space engineering and planetary exploration.

Food is not only a crucial strategic substance for the economic stability and national prosperity of nations around the world, but it is also the lifeblood of the nation and a fundamental necessity for human survival. Food security is linked to social harmony, political stability and sustainable economic development, and is critical to national security. The use of science and technology to promote agriculture and develop modern agriculture is essential to ensure food production.

Global urbanization is accelerating, and by 2050 the world's population will exceed 9.1 billion, 34 percent more than now. More than 70 percent of the world's population will live in cities, 21 percent more than now. It is estimated that to sustainably feed this expanding population, at least a 70% increase in food production will be necessary to meet the increased demand for food and vegetables. Prior to the COVID-19 pandemic, 8.9 percent of the global population suffered food shortages, according to the most recent figures from the United Nations Food and Agriculture Organization. This suggests that the global food security crisis has not been resolved and is getting worse. Increasing food production, achieving dietary balance and eradicating hunger remain global challenges.

From the perspective of human development, on the one hand, with the development of society, the world faces numerous global problems, such as rapid population growth, accelerated urbanization, frequent climate extremes, severe environmental degradation, the spread of global coronaviruses, endless local wars, intensifying desertification, an increasing shortage of arable land resources, an inadequate food supply, and the loss of agricultural labor, etc. The conflict is getting worse and poses a grave threat to the survival and progress of mankind. On the other hand, with the advance of world civilization, economic development, and the accumulation of social wealth, the total annual income of the people is steadily rising, and prices will no longer be the first factor in their consumption of fruits and vegetables. It is possible that everyone will have access to high-quality agricultural goods, and the desire of the global population to achieve harmonious prosperity and high quality of life is growing. Improving the working environment for agriculture, increasing land utilization and improving the efficiency of food crop production are particularly important as humanity uses increasingly scarce arable land to feed an expanding population.

Agriculture is the primary sector that underpins the construction and development of the national economy and the survival and development of humanity. The uneven distribution of natural resources for agriculture, such as arable land, water, light and climate, has led to uneven distribution of traditional agricultural production and food supply, which has severely affected food security, regional security and quality of regional survival. In the future, it will be particularly important to study the development of new production-based agricultural systems that are efficient, intensive, resource efficient, self-sufficient and modern to meet the balance between inter-regional food supply, urbanization and the need for a growing population to eat well. Modern agriculture and smart agriculture are the most effective forms of technical engineering to address the scarcity of agricultural natural resources that are impeding sustainable development in the region, and are the primary means to transform the agricultural industry into one that is highly efficient and intensive. Modernization is the first step in developing agriculture. Digitalization and intelligence are crucial directions for agricultural modernization. As an advanced level of modern agriculture, plant factories are a crucial development direction for modern and intelligent agriculture. It not only enriches the regular intake of residents, ensures the balance of people’s diets, and raises the standard of living, but it is also on the verge of forming a fashionable and high-end new agricultural industry, which will become a crucial method for farmers to become wealthy and stimulate industrial revitalization. In 2021, our school's plant factory innovation research team conducted a China-wide survey on the development of plant factories and vertical farms, and the results showed that 93.55% of consumers believe that plant factories are a promising new form of urban agricultural production that can be vigorously developed in urban areas and is the most modern, high-tech, environmentally friendly, and resource-efficient. The primary reason customers are willing to purchase plant-based products is that they are clean and pollution-free (39.34%) and green and healthy (30.26%), followed by their high freshness (17.61%), high quality (8.80%), and high nutritional index (3.71%).

In recent years, 3D growing systems, plant factories and vertical farms have been developing rapidly worldwide and have emerged as the most promising urban agriculture and life-enhancing agricultural production systems in the world. An urban smart plant factory is a large indoor plant production system constructed in an urban area, using artificial light and hydroponics as primary production methods in a modern smart building greenhouse with a fully accurate and regulated environment.

Currently, urban smart plant factories are still in the stage of technological research and scientific demonstration, but are fast approaching the development process of commercialization, marketization and industrialization. Its system components, system architecture, environmental control, production technology, management standards, product standards and marketing must be researched, developed and optimized. There is significant room for growth in its intelligence, precision and modernisation.

In short, the artificial light plant factory is the fundamental form of urban intelligent plant factory and the best system for urban agricultural development. Moreover, environmental regulation is the core and key technology of artificial light plant factories. As a result, the technology for environmental multi-factor coupling precise regulation and optimization of the artificial light plant factory based on a growth model has become a research hotspot in the industrial engineering field of modern agriculture. On the basis of a questionnaire survey, field research, and literature review, this study has conducted a comprehensive summary and analysis of the current state of research on the development of urban intelligent plant factories, determined the research field and scope, clarified the research objectives, research directions, technical routes, experimental programs, and research contents, broken through a number of scientific and technical problems, attained diverse research results, and met the intended research expectations.

Relationship with academic programs, plans, topics. The dissertation title and research work are based on research area “Energy-saving technologies in the agricultural sector、Precision farming systems, Climate chamber with adaptive lighting for growing crops” of the scientific work program of the department of agricultural engineering, faculty of engineering technology, Sumy National Agrarian University, within the framework of scientific topics such as the research programs within the state budget of the Ministry of Education and Science of Ukraine “Scientific support of technologies for growing technical crops (corn for grain)” (State Budget Technical Work No. 0121U110453，executor Zubko V.M.，2021-2022) and “Scientific support of technologies for growing technical crops (sunflower for grain)” (State Budget Technical Work No. 0121U110454，executor Zubko V.M.，2021-2022), and Grant within the project “Interuniversity cooperation as a tool for enhancement of quality of selected universities in Ukraine" entitled "Climate chamber with lighting adapted for growing crops” (executor Zubko V.M. and Shelest M.S.，2019-2021); Key Research and Development and Promotion Special Project Plan of Henan Province “Research, development and application of key technologies for plant factories in intelligent building greenhouses” (No. 212102110234，executor Wang X.F.，2021-2022), “Environment multi-factor coupling regulation and optimization of urban intelligent plant factory” (No. 222102320080，executor Wang X.F.，2022-2023) and “Research on intelligent control technology of plant factories based on IoT and big data” (No. 232102111124， executor Zhao M.F. and Wang X.F., 2023-2024); and Key Research Project Plan of colleges and universities in Henan Province “Development of aeroponics system in full artificial lighting plant factories” (No. 22A210013, executor Wang X.F., 2022-2023). The research topic “Environmental multi-factor coupling precise regulation and optimization for an artificial light plant factory based on a growth model” was determined by the applicant in consultation with his supervisors, Prof. Zubko V.M. and Associate Prof. Onychko V.I. The research objectives, contents, and tasks are set by the applicant after comprehensive analysis and reporting to their supervisors through literature research, questionnaire surveys, and field surveys in several regions of China, combined with the existing laboratory experimental conditions, PhD training programs, and the requirements for scientific, technological, economic, and social development. The research aims to provide a new concept, new means, new methods, and innovative models for modern urban agriculture, as well as a scientific foundation and technical support for the development of sustainable urban production-based agricultural plant production systems.

The purpose and objectives of the study. to create and improve modern, intensive plant production complexes and systems that can be constructed in urban areas, independent of geo-climatic and land resource constraints, and to study the theory, law, methodology, and technology of mechanized, automated, intelligent, and precise control and optimization of plant growth and production environments of artificial light plant factories in buildings. The ultimate goal is to improve and optimize intelligent control strategies, increase resource utilization efficiency, and reduce the cost of industrial production plant products through precise environmental regulation technologies.

To achieve this goal, it is necessary to solve the following **tasks**:

1. To analyze the current development status, trends, obstacles and opportunities of the artificial light plant factory, and to clarify the importance and direction of research.

2. To analyze and improve the existing forms of greenhouses, explore the

optimal bearing form of artificial light plant factories, propose development recommendations for building greenhouses, intelligent building greenhouses, and intelligent building greenhouse plant factories, and study their strategic significance and development strategies.

3. To analyze the system composition and core technologies of artificial light plant factories and intelligent building plant factories, and to identify research topics and directions.

4. To investigate the construction methods for plant growth models and plant factory big data, to propose and design a systematic framework for building plant growth models based on IoT and big data technologies, and to develop a plant factory big data management systems and plant growth model analysis platforms.

5. to systematically analyze the production environment factors of artificial light plant factories and their effect on plant growth, study the coupling effect of multiple factors on plant growth, to propose a multi factor self-learning coupling precise regulation model, and to develop a production management systems and environmental precise regulation platforms for artificial light plant factories.

6. To research on algorithms and implementation techniques for constructing plant growth models based on deep learning models. To research on object detection of tomato fruits for the artificial light plant factory using an improved YOLO deep learning model and instance segmentation of plant seedlings for the artificial light plant factory using a modified Mask R-CNN and Transformer deep learning models, and to lay the theoretical and technical foundation for constructing plant growth models and environmental control models.

7. To experimental verify on the effects of different lighting conditions of LED artificial light and nutrient solution formulations on plant growth and quality, to improve to environmental regulation technology and means in artificial light plant factories, and to lay the foundation for theoretical research, model construction, and implementation technology of precise regulation of environmental multi factor coupling.

Object of research - theories and methods for constructing plant growth models based on deep learning algorithms; the overall composition, program architecture and development prospects of an artificial light plant factory; and the techniques and methods for mechanization, automation and intelligent regulation and optimization of the production environment.

The subjects of research - is the design and development of mechanized, intelligent, industrialized, factorized, periodical and modern plant production systems that can be built in urban areas, and the analysis and study of their system composition and architecture; the studies of theories and methods for building plant growth models based on IoT, big data technologies and deep learning algorithms, which are different from traditional mathematical algorithms; the studies of machines, means and methods for the precise regulation and optimization of environments using coupled multi-factors in the artificial lighting factory based on a plant growth model.

Specifically, it includes three sub directions and subjects: firstly, investigate the construction form, system composition, development status, development trends and core technologies of the artificial light plant factory. The dissertation proposes recommendations for the construction of building greenhouses, intelligent building greenhouses, and intelligent building greenhouse plant factories. Second, research on methods and techniques for constructing plant growth models. The dissertation proposes a construction method and system architecture for plant growth models based on IoT and big data technologies. Furthermore, research on the relevant theories and core technologies of environmental regulation and optimization in artificial light plant factories. The dissertation proposes a multi-factor self-learning coupled precision regulation model, as well as research on the methods for constructing plant growth models based on deep learning models and the related studies on artificial lighting and nutrient solution regulation techniques.

Research methods. In the scientific work, bibliometric methods, case study methods, questionnaire survey methods, comparative research methods, and statistical research methods were applied in a comprehensive manner to conduct a review of plant factories and smart building greenhouse plant factories related to the research topic. The necessity and importance of plant research has been identified, and the prospects for the development of techniques for the environmental regulation of artificial light plants have been clarified. A comprehensive application of data collection methods (such as manual surveys, traditional measurements, image analysis, machine vision, and data annotation methods), data analysis methods (such as traditional statistical methods, bioinformatics methods, machine learning methods, and deep learning methods), mathematical modelling, and other methods has been conducted to study the target detection and yield estimation of tomato fruits, as well as the segmentation of plant seedling leaf instances, This provides a theoretical basis for the construction of big data for plant factories and plant growth models. We comprehensively utilized computer simulation research methods, statistical research methods, experimental research methods, and hypothesis research methods to design multiple experiments for experimental research, verifying the effectiveness of plant factory light environment regulation technology and nutrient solution regulation technology, as well as the multi factor coupling regulation technology for plant factory environment.

The scientific novelty of the results obtained is that:

1. For the first time, the concepts of intelligent building greenhouses and intelligent building greenhouses plant factories were proposed, with clear definitions. Extensive social demand research and literature analysis were conducted to systematically and scientifically demonstrate their strategic significance. The development strategy of "3-Positions and 1-Entity" was studied, providing an innovative model and systematic solution for the sustainable and clean plant production system in urban development.

2. For the first time, it is proposed to use the physiological mechanisms and biological theories of plant light regulation as the theoretical basis for artificial light plant factory light environment regulation, improve the technical means of light environment regulation, and regulate the production process of plants through the role of light in photosynthesis, growth and development, morphological construction, material metabolism, gene expression, and nutritional quality, in order to adapt to market changes.

3. For the first time, a flat IoT solution using multiple sensors and controllable work units has been provided for artificial light plant factories. A system architecture for constructing scientific big data for plant factories has been proposed, and the process and methods of comprehensively utilizing IoT, big data, and deep learning technologies to construct plant growth models have been systematically studied. The plant factory big data platform and crop growth model service system constructed using this method can provide data and model services for plant factory industrial enterprises through cloud services.

4. For the first time, the architecture and framework of a multi-factor environmental regulation platform for artificial light plant factories based on growth models were proposed, and control system software was designed, developed, and tested. The system software can automatically obtain plant growth model files from the cloud, and intelligently and accurately regulate the environment of plant growth based on the plant growth model, to obtain high-quality and high-yield plant products with minimal cost.

5. An improved YOLOv3 deep learning model and algorithm have been proposed for target detection of hydroponic tomato fruits in artificial light plant factories, providing theoretical foundation and technical support for yield estimation, robotic picking, and precise regulation of growing environments. This method can classify and detect the growing tomato fruits, obtain the quantity of green fruits, color changing fruits, and red fruits, as a basis for precise regulation of light environment and nutrient solution concentration, thereby effectively reducing water, electricity, nutrient solution waste and sewage discharge, improving resource comprehensive utilization rate and yield.

6. For the first time, a CMRDF algorithm for plant seedling instance segmentation was proposed, which integrates RGB-D multi-channel image data to improve the accuracy of seedling instance segmentation. It is used to analyze plant phenotypic data in artificial light plant factories, to construct crop growth models, and to provide theoretical and technical support for plant intelligent growth monitoring, disease and pest detection, production management, yield estimation, robotic

operations, and environmental regulation.

7. For the first time, experimental studies on illumination screening and uniformity simulation of hydroponic lettuce, experimental study on the effect of light quality on the quality of hydroponic *Cichorium endivia* L., and screening study on the formulation of nutrient solution for hydroponic green leaf lettuce are conducted in an artificial light plant factory, providing technical references for precise regulation of environmental multi-factor coupling.

Practical significance of the obtained results. The practical significance of the experimental results lies in providing a series of systematic theoretical achievements for the intelligent control and optimization of the artificial light plant factory environment, and proposing comprehensive technical suggestions. At the same time, it also provides a complete set of solutions and suggestions for sustainable and clean plant production systems for urban development. The use of these suggestions will improve the intelligence and intensification of plant factories, improve the utilization rate of comprehensive resources such as land, water, electricity, and fertilizers, reduce plant production costs, and generate considerable economic benefits and immeasurable social value. The theoretical achievements and technical solutions obtained in the work are protected by 4 patents and 7 computer software copyrights, and have been implemented by the high-tech enterprise "ZSP" Electronic Technology Co., Ltd. in Henan Province, China. After preliminary testing, it can improve the water resource utilization rate by 10%, save water soluble fertilizer by 8%, comprehensively reduce electricity by 18%, significantly reduce the production cost of leafy vegetables, and bring huge economic benefits and social value.

Personal contribution of the applicant. The applicant together with the scientific supervisor set the purpose of the work and the tasks of the research, analysed and synthesised the results obtained. The statements and conclusions presented in the dissertation were obtained by the author independently. Among them: substantiation and development of research methods, planning of the experiments that were conducted, development of experimental programmes, as well as their implementation. The author's personal contribution is specified in the list of publications. The author's contribution to the works performed in co-authorship was the development of research methods and their implementation.

Approbation of the results of the dissertation. The main provisions and results of theoretical and experimental studies of the dissertation work were published and positively evaluated at international scientific and technical conferences. III International Scientific and Practical Conference “TOPICAL ISSUES OF MODERN SCIENCE, SOCIETY AND EDUCATION” (KHARKIV, Ukraine, 3-5 October 2021); one Health Student International Conference (București, ROMANIA, Nov. 24th-27th, 2021); International Scientific and Practical Conference “HONCHAROV’S READINGS” (Sumy, Ukraine, May 25, 2022,92-95); the Fifth International Workshop on Environment and Geoscience (IWEG2022), (Qingdao, China, July 16-18, 2022); the second International Workshop on Vertical Farming (VertiFarm2023), (Chengdu, China, May 22-24, 2023).

The applicant’s contribution is in planning an experiment, organizing, and conduct of analytical and experimental research in laboratory and production conditions, analysis, processing, and generalization results, formulating conclusions and recommendations, preparing materials for publication, and introducing of new technologies into production.

Publications and scientific research achievements. During the period of doctoral study, the author of the dissertation presented **30** scientific publications, 12 of which are in academic articles indexed by the Scopus/Web of Science scientometric database, 4 articles in scientific professional publications of Ukraine, 6 articles in scientific professional publications of other countries, 8 abstracts/papers in conference proceedings; obtained **11** other scientific research achievements, including 4 Chinese patents and 7 Chinese computer software copyrights; presided over or participated in **8** projects, including as the host, and applied for and are approved 4 projects at the provincial and departmental levels, 3 of which received the financial support of the provincial government and a total of 230000 yuan was approved, and as the main participant, participated in 5 projects and the indirectly available funds can reach 1.2 million yuan.

Structure and scope of the dissertation and scope of work. The dissertation consists of an introduction, five sections, a summary and prospect, a 393-item list of references, and six appendices. The full volume of the dissertation is presented in 293 pages of computer text, including 162 pages of the main part, 72 figures, and 16 tables.

SECTION 1. REVIEW AND RELATED RESEARCH ON A PLANT FACTORY WITH ARTIFICIAL LIGHTING

1.1 Research on intelligent building greenhouse plant factory and "3-Positions and 1-Entity" development mode

1.1.1 Greenhouses, soilless cultivation, and plant factories

Smart facility agriculture occupies a very important position in agriculture, is an important part of modern agriculture, and plays a very important role in the supply of agricultural products (Lia et al., 2016; Symeonaki et al., 2019; Han et al., 2020). Facility plant cultivation can get rid of the limitation of natural conditions and environment of traditional agriculture by comprehensively regulating the environmental factors of crop growth, and achieve high efficiency, high yield, high quality, diversification and anti-seasonal vegetable production (Hu & Jie, 2013). At present, from the early simple film mulching technology (Li et al., 2021; Zhao et al., 2021), solar greenhouse (Esmaeli & Roshandel, 2020) and its related supporting equipment are still the mainstream of facility agriculture, and its main idea is to make full use of solar conditions for heat storage and heat preservation. After years of development, the solar greenhouse has gradually developed into a comprehensive large-scale modern intelligent greenhouse with mechanization, automation, network and intelligence (Hemming et al., 2020; Liu et al., 2020). The development of intensive facility agriculture has become the trend of modern agriculture of China (Zheng, 2021).

In recent years, soilless cultivation technology (Zhu & Wang, 2013; Rathod et al., 2021) has developed rapidly and has been widely used in facility agriculture. Water cultivation, gravel cultivation, perlite plus peat cultivation and sawdust cultivation are commonly used in modern solar greenhouse production. Soilless cultivation is a trend of vegetable planting, which has the advantages of water-saving, fertilizer saving, labour saving, high-yield and optimal product quality (Savvas & Gruda, 2018). It has got rid of the limitation of soil, greatly expanded the agricultural production space, and made it possible to carry out plant production on barren land, with a very excellent development prospect. Almost all plant factories adopt soilless cultivation mode (Orsini et al., 2020).

With the research and practice of soilless cultivation, the development of LED energy-saving plant light source and the research of all artificial light plant factories are booming. In Japan, in recent years, the number of all artificial light source plant factories has increased rapidly, accounting for 44.2% of all Japanese plant factories. The proportion of combined solar and artificial light sources was 27.3%, and the proportion of sunlight was 28.6% (Kim & Lee, 2017; Wei & Wang, 2019). In June 2016, the Institute of Botany of Chinese Academy of Sciences and Fujian San'an group jointly built the artificial light plant factory in Fujian Province, which is the largest single plant factory with one hundred thousand class cleanliness in the world. It starts the landing and industrialization of the theory and technology of plant cultivation by using full artificial light in China. In September 2017, the Wafangdian plant factory of China Hualu Panasonic was completed and put into operation. On May 3, 2020, the special report of "labor is the most glorious, struggle is the happiest - don't use sunlight, don't use soil, intelligent production plant factory" of CCTV news channel entered the plant factory for live broadcast. The vegetables here are cultivated in an aseptic environment, no pesticides, zero residue and can be eaten immediately after picking, which is healthy and environmentally friendly. From sowing to marketing, the whole process is visual, traceable and remote monitoring and managing. The intelligent, industrial and modern plant production mode has entered the stage of industrialization, standardization and commercialization.

With the development of urban-rural integration (Yan et al., 2018; Zhao & Wan, 2021), the urban size is expanding, and the urban population is increasing rapidly, the agricultural population is decreasing, the land suitable for vegetable planting is decreasing due to the occupation of development and construction, the available resources, especially the water resources supply, are in short supply due to the vigorous consumption and waste, the climate environment is becoming fragile because of the green land occupied by construction and development and industrialization (Shrivastava et al., 2017). It is necessary to explore and develop more land-saving, labor-saving, energy-saving, environmental protection, and efficient agricultural planting mode. The emergence of all artificial light source plant factories is calling for the emergence of a more long-term, environmental protection, energy-saving intelligent building greenhouse. Although its investment in the early stage is large, its service life is very long, and the maintenance cost is relatively low in the later stage. The key point is zero pollution, zero emission and aseptic organic production. It can also break through the restrictions of geography, climate, space and other conditions. A "plant factory" of high-rise buildings can even be built in the downtown of a bustling commercial city, which provides a kind of high-quality fresh vegetables to citizens (Bon et al., 2010; Orsini et al., 2013; Dona et al.,2021).

1.1.2 Building greenhouse, intelligent building greenhouse and plant factory of intelligent building greenhouse

1.1.2.1 Development trend of greenhouse

The original idea of planting a greenhouse is to keep the earth's surface warm. From the early simple film mulching to the plastic greenhouse (Xu et al., 2011), arched shed (Wang, 2020), glass greenhouse (Jeong et al., 2020), ordinary solar greenhouse, sunshade momentum, single solar greenhouse (Cao et al., 2019), multi-span greenhouse (Rasheed et al., 2020), to large-scale intelligent solar greenhouse, although the form of greenhouse has changed a lot, its essence limited by land, sunlight and climate conditions has not changed. The stability and service life of greenhouse construction cannot meet modern building standards. With the development of soilless cultivation and full artificial plant lighting technology, the greenhouse gradually has the technical conditions to get rid of the constraints and restrictions of land and light conditions (Kozai, 2018). In order to achieve uninterrupted agricultural production no matter where and under what climatic conditions, the requirements for the stability, thermal insulation and durability of greenhouse building structure become more and more important. Therefore, the birth of architectural greenhouse is the call of the times, and once it appears, it will directly be the intelligent building greenhouse: the most advanced form of plant growth greenhouse. **Fig. 1** shows the development trend of the greenhouse form.

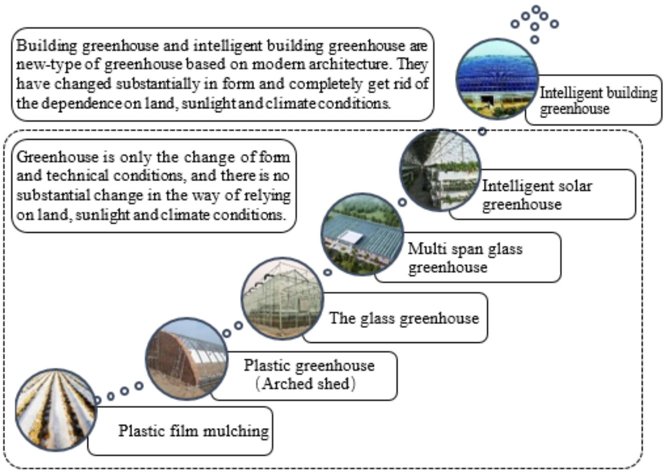


Fig. 1 Development trend of greenhouse form.

1.1.2.2 The definition of building greenhouse and intelligent building greenhouse

General buildings refer to permanent assets formed by manual construction which are engineering buildings for people to live in, work, study, produce, manage, entertain, store goods and carry out other social activities. The landscapes and gardens, in a broad sense, are also part of architecture. More broadly, the conscious nesting of animals can also be regarded as architecture. The building greenhouse to be discussed here refers to modern buildings designed and built to provide an artificial environment for plant growth. Therefore, the following definitions are given in this paper:

Building greenhouse is built through professional architectural function design, mechanical design, aesthetic design, structural design and other comprehensive architectural design, whose foundation is specially designed and treated and is a permanent building with brick, sand and concrete or steel and concrete as the main body. In order to improve land use efficiency, greenhouses are generally designed as multi-storey or high-rise buildings.

The building greenhouse, in short, is a professional building that provides plants with the most suitable growth according to the concepts, theories and methods of modern architectural engineering design. Therefore, the building greenhouse is very different from the existing greenhouse forms such as plastic greenhouse, arch greenhouse, glass solar greenhouse and intelligent solar greenhouse and it is a new greenhouse completely different from the existing greenhouse. Its structure is more stable and its service life is longer. High quality building greenhouses can be used permanently. Moreover, constructing a building greenhouse is inseparable from the development of high technology (Mofidi & Akbar, 2020). Therefore, this paper puts forward the following concepts:

Intelligent building greenhouse refers to the comprehensive use of modern information technologies such as the Internet, Internet of things, mobile communication and mobile Internet, wireless sensor, automatic control, cloud computing, big data, blockchain and artificial intelligence in the process of building greenhouse and plant production, combined with greenhouse engineering construction technology, soilless cultivation technology and all artificial light cultivation technology. According to the plant life characteristics and growth process model, the greenhouse environment is monitored in real time and dynamically, so as to maintain the most suitable growth environment for each growth stage of the whole plant life cycle, so as to realize the high-yield and high-quality production of plants.

1.1.2.3 Plant factory urgently needs intelligent building greenhouse

Plant factories are an efficient agricultural system that can realize the continuous production of crops every year through high-precision environmental control (Avgoustaki & Xydis, 2020; Huebbers & Buyel, 2020; Ares et al.,2021). The intelligent control system can automatically control the temperature, humidity, light, CO_2 concentration, nutrient solution, fertilizer and other elements of crop growth environment, so that plant growth is not or rarely constrained by natural conditions. It is a high-tech intensive industrial complex. Its production mode possesses outstanding advantages that other modes of production cannot be compared with (Sun et al., 2019). For a long time, the plant factory has been internationally recognized as the most advanced development stage of facility agriculture, and is one of the important indicators to measure the high-tech level of agriculture in a country (Yang, 2014). With the high concentration of urban population and the reduction of costs of construction and operation of plant factories, plant factories will be the most effective means to solve the problems of global resources, world population and environmental degradation in the future, and it must develop rapidly.

The intelligent building greenhouse will integrate high technology, enrich the wisdom of mankind, break the traditional fetters of crop planting, and realize the high intelligence and modernization in all aspects of plant production. After special design and technical treatment, the plant production has been greatly extended in space. Good fields are greatly saved. The growth time is shortened, and the efficiency of vegetable production is improved. Intelligent building greenhouse is not limited by land, region and climate. It can be built in areas with extremely hot or cold or rapid deterioration of weather. It can also be built on barren saline alkali land, sand beach, the Gobi Desert, polar area covered with ice and snow all year round. It can also be built in the downtown of the city to be urban landmark buildings, developing tourism and entertainment or becoming a picking garden, so as to extend and expand the function of plant factories. The plant factory based on intelligent building greenhouse can start planned production or realize order production. Just press a button to start a plant production mode. The artificial intelligence system based on plant growth process model can provide the most suitable production environment for different growth stages of the plant according to the model of the target plant, so as to achieve mass production, high yield and high quality production. The advantages of intelligent building greenhouse gases have outstanding advantages, which should be the best "production workshop" of plant factory in the future.

1.1.3 The strategic significance of developing intelligent greenhouse plant factory

1.1.3.1 Consolidating food security strategy

Currently, food security, energy security and financial security, known as the three major global economic security, are the important foundations of national security (Hlaing, 2006; Tikhomirov, 2019). Grain and vegetables are the most important necessities of life for people. Vegetables are essential for three meals a day. With the development of society, the growth of population, the improvement of people's quality of life and the enhancement of people's awareness of healthy diet, the demand for food and vegetables will increase rigidly. Along with urbanization, industrialization and modernization, problems such as climate deterioration, environmental pollution, poor quality of cultivated land, reduction of cultivated land, shortage of water resources, structural contradiction between food supply and demand, shortage of rural labor force and serious waste of grain have become increasingly prominent (Lee, 2009; Huang et al., 2019; Grubor et al., 2020; Wang et al., 2021). Food security is still affected by climate change, environmental pollution, natural disasters, turbulence, emergencies, land and water shortage, ecological damage and other factors. The novel coronavirus pneumonia has caused an emergency of food and vegetable supply, and food crisis occurs frequently. The development of intelligent greenhouse plant factories is one of the important measures of "storing grain in technology" (Carthy et al., 2018; Jim et al., 2019; Lakhiar et al., 2020). It can effectively overcome the influence of many adverse factors in the process of grain and vegetable production, storage, transportation and sales, so as to strengthen and consolidate food security. The intelligent building greenhouse plant factory is based on the intelligent building greenhouse. It adopts soilless cultivation and artificial light technology to plant in a highly intelligent, modern and precise controlled and clean artificial growth environment. It does not need sunlight and soil. It can effectively avoid the impact of adverse factors such as climate change, environmental pollution, natural disasters, ecological damage and so on. Therefore, it can completely change the supply of vegetables and plants. Not affected by the seasonal changes, the supply of vegetables can be stable all year round. Moreover, this kind of plant factory does not need soil at all, which can save a lot of land resources and strengthen the protection for "storing grain in the field" in arable land. According to the population distribution and the demand for vegetables, the intelligent building greenhouse plant factory can be built in cities, deserts, densely populated areas and any other places where it is needed. It can be directly produced and sold at any time, without long-term storage and long-distance transportation. Even if there is an epidemic or other emergency, it can ensure a timely and sufficient local supply of vegetables, thus consolidating the food security.

1.1.3.2 Intensive use of land and improvement of cultivated land planting structure

Arable land is the essence of land and the foundation of grain production. It is the material basis for human survival and is a scarce resource that is not renewable. On the earth's surface, the total land area of the world is 13.081 billion hectares, of which only 11.25% is cultivated land (data from Baidu wiki). According to the situation of land use in the world, the proportion of farmland is quite low. However, the arable land is facing various severe threats and challenges, such as rampant occupation, abandonment, disaster erosion, pollution deterioration, soil erosion, returning farmland to forest, the arable land area is decreasing and the quality is deteriorating (Nath et al., 2015; Wu et al., 2018; Prăvălie et al., 2021). Especially in the development of urbanization, the rapid expansion of cities occupies a large amount of the land, most of which is high-quality arable land. In the huge pressure of the reduction and degradation of arable land, it is particularly important to make intensive use of land, improve the utilization rate of land and improve the planting structure of cultivated land. Intelligent building greenhouse plant factories can highly intensively use land, greatly raise the land use efficiency. The intelligent building greenhouse can be built into multilayer or high-rise buildings. In each layer of production greenhouse, three-dimensional soilless cultivation can be adopted. According to relevant reports, the three-dimensional planting of single-layer solar greenhouse can increase the land use rate by three times (Despommier, 2013; Al-Kodmany, 2018). Moreover, under the increasing pressure of less farmland left, through reasonable layout, the intelligent building greenhouse plant factory was built on the land with poor quality or unsuitable for sowing, which not only improved the land utilization rate, but also improved and optimized the cultivated farmland planting structure, thus alleviating the pressure from the reduction of arable land resulted by social development to a certain extent.

1.1.3.3 Meet people's need for healthy diet

The ancients said: "we can have meals without meat for three days, but vegetables are needed every day." It was found that many vitamins, minerals, trace elements and related plant chemicals and enzymes are in vegetables and plants that are effective antioxidants. They are not only healthy food materials with low salt, low fat and low sugar, but also can effectively reduce the damage to the human body caused by environmental pollution and prevent many diseases (Volpe, 2019). It has been proved in a number of studies and dietary practices at home and abroad that dark green vegetables are good for preventing osteoporosis, obesity, diabetes, hypertension, cardiovascular disease, coronary heart disease and many kinds of cancer, and there are many benefits which have exceeded people's imagination (Griep et al., 2010). It is demonstrated that most vegetables can be eaten raw, and it would be better to eat raw, because raw vegetables can lock the vitamins, inorganic salts, anti-cancer factors and physiological active substances inside from being damaged, which can contact human mucosal cells more effectively to the maximum extent, so as to play a better role (Feng et al., 2022). The intelligent building greenhouse plant factory is the most suitable factory for vegetable planting. Vegetable production is carried out in a closed artificial environment. The growth environment can be strictly managed, highly sterilized. Chemical fertilizer is rarely used or no chemical fertilizer is used, and no pesticide is used. The vegetable itself is a clean vegetable that can be eaten directly. Clean vegetables will become the inherent label of intelligent building greenhouse plant factories, and will become a world famous brand to meet people's growing demand for high quality vegetables, so as to improve people's livelihood and living standards.

1.1.4 The development model of "3-Positions and 1-Entity"

1.1.4.1 The promotion of the "3-Positions and 1-Entity"

The intelligent building greenhouse plant factory has large investment, high-tech content and complex systems. In order to develop healthily and rapidly in the market environment, there must be a suitable development mode. **Fig. 2** shows the new development model of "3-Positions and 1-Entity" in intelligent building greenhouse plant factory. The "3-Positions and 1-Entity" mode refers to the "modern company plus intelligent building greenhouse" as the business entity and production entity of the intelligent building greenhouse plant factory, and integrates the production, operation and management of "factory production, corporate management, brand marketing" (Yuan et al., 2018; Hirsch, 2020). The modern company is the creator of the market subject, and the intelligent building greenhouse is the solid foundation of the plant production entity. The factory production, corporate management and brand marketing are the three directions of the plant factory facing the market, meeting the needs of high-grade life of consumers and leading the modern agricultural industry. The four are integrated and inseparable. Without the creativity of modern companies and the production "workshop" of plant factories with intelligent building greenhouse, there will be no foundation for the annual, large-scale, high-quality, intelligent, information-based and industrialization of vegetable production, and it will be difficult to fully realize the construction goal. Factory production, corporate management and brand marketing are useful tools for the rapid growth and development of plant factories, which, to a large extent, ensure the industrialization of production, the modernization of management, the high goal of enterprise development and the high quality of plant or vegetable products.

Fig. 2 New development mode of "3-Positions and 1-Entity".

1.1.4.2 Factory production

Factories, also known as "factories" and "production enterprises", are industrial buildings used to produce goods. Modern factories generally have production lines composed of large machines or equipment. In the past, the production of agricultural products mainly depended on natural conditions such as land, sunlight and climate. These conditions had their own movement rules, and the role of human intervention was very limited, so it was difficult to popularize industrialized plant production. The plant factory production of intelligent building greenhouse can realize plant planting, equipment mechanization, intelligent operation, process standardization, three-dimensional mode, capacity scale, production cycle and management system.

The plant production of intelligent building greenhouse plant factories will adopt the closed full artificial environment soilless cultivation. The temperature and humidity, light, water, air required for plant growth and fertilizer will be fully mechanized, fully automatic and multi factor precise control, so that the plant growth environment is always in the most suitable plant growth state in the whole plant growth process. The planting links including plant seedling, fixed planting, irrigation, fertilization, shaping, harvesting, sorting, packaging, inspection and others will be gradually realized mechanization, automation, information and intelligence. The plant factory eventually will develop into an unmanned factory, where production workers can produce at any time. With the in-depth application of artificial intelligence technology in the greenhouse plant factory of intelligent building, as long as press the start key, the expert system based on plant growth process model can realize the control from the growth environment to all planting operations, until the package is delivered to the warehouse for sale and shipment, and all operations are intelligent.

As the intelligent greenhouse building is a permanent building built by professional design to engage in efficient production of plants. In order to fully raise the utilization rate of land occupation, it is multi-storey buildings generally. Each floor has production greenhouses, which can be used for plant production. Each production greenhouse will adopt a multi-layer soilless cultivation bed or frame for stereoscopic plant production to ensure scale production and increase production capacity. Because plant production in the building greenhouse completely adopts artificial lighting which can be precisely controlled according to the needs of plant growth, thus it guarantees the plant production continuity and the periodicity, and ensure the fresh plant vegetable year-round supply.

When large-scale production is carried out in the intelligent building production greenhouse, the intelligent production control system will control the growth environment and standardize the operation according to the preliminary model of plant growth process constructed during the experimental planting. When the operation is not carried out according to the standard operation or lack of standardization, the system will send out intelligent prompting in time, so as to ensure that each operation is accurate and standard, to ensure the optimization of plant production to achieve energy saving, high yield and high quality.

1.1.4.3 Corporate management

The so-called corporate management is to take plant factories as a general production and operation enterprise, introduce the market mechanism and modern enterprise management mode, and construct the corporate management mode according to the form of corporatization, which includes organization optimization, system perfection, standardization and efficiency of production process, high professional quality of personnel, and large production capacity (Yekimov et al., 2021). The introduction of corporate management mode in plant factories will change the situation of agricultural development supported by the government and operated by agricultural science and technology leaders, stimulate the vitality of various production factors of agricultural industry, and make plant factories move towards the development path of market-oriented, professional, high-tech, and intensive.

Agricultural modernization must be realized by agricultural industrialization (Kremen et al., 2012). Agricultural industrialization is the inevitable choice of China's agricultural modernization process (Gu & Zhang, 2015). It is necessary to guarantee the production of a modern agricultural economy and fine modern enterprise management system. Farmers with decentralized management are the main body of traditional planting agriculture, whose economic capacity is limited and their professional quality is generally not high, so it is difficult to become the main body of modern agricultural industrialization. In the process of agricultural modernization with commodity economy as the mainstream, the important role of the government is to guide the adjustment and development direction of agricultural structure by formulating incentive policies, so as to attract more social forces to invest in intelligent greenhouse plant factories, and it is even possible to set up factories directly with state investment to engage in modern plant production and management. However, due to the special status of the government, it can’t be a part of its industrialization. Even if the government invested, the plant factory still needs to be operated in the form of corporation.

The fundamental problem of the development of modern agriculture lies in the contradiction between high investment and low investment level. The fundamental way to solve the problems and form sustainable development is to improve the input and management mechanism. We should increase agricultural input, raise investment level and improve input-output efficiency. Once the intelligent building greenhouse plant factory is born, it has the characteristics of modern agricultural industrialization, such as specialization, integration, science and technology, and intensification. Marketization, specialization, integration, intensification and standardization are the outstanding advantages of modern enterprise management system and the fixed attribute of corporatization (Arsenieva & Putyatina, 2021). The corporate management of intelligent building greenhouse plant factories is the specific embodiment of modern facility agriculture adapting to market demand. The corporate management mode of plant factory can attract companies with strong capital to join in, and the listed companies with outstanding performance can play a powerful role in financing, drive social capital investment, and build a larger plant factory. On the other hand, the company can efficiently combine high-quality resources in an organized and planned way, carry out product development, market expansion, industrial deepening and other development strategies, so as to rapidly promote the efficient industrialization of plant factories.

1.1.4.4 Brand marketing

Brand marketing strategy is one of the effective ways for product marketing to obtain a large market share (Li, 2019). Branding is the process of cultivating brands and improving their value. It can stabilize the consumer group and quickly occupy a larger market share. Through registered trademarks, it is convenient for consumers to identify, identify and purchase plant factory products, which is conducive to protecting the interests of consumers and promoting the consumption upgrading of plant products. Moreover, the registered trademark can protect the legitimate rights and interests, help to improve the product, standardize the production and sales behavior, and expand the product composition. The developed modern agricultural market needs the intelligent building greenhouse plant factory to establish the brand development strategy in construction planning, improve the market awareness and occupy the commanding height of the market. This requires the plant products of intelligent building greenhouse factories to meet the market demand. In the planning and construction stage, it is necessary to accurately locate position for the market and products, plan brand building from the long term, cultivate and register trademarks. and actively improve the new varieties of plants, enhance the quality of plants and perfect plant production technology and equipment, improve the service system, commit to innovation and creation, strengthen advantages, enhance corporate image, nurture corporate culture, enhance enterprise competitiveness in the activities of plant product planning, to achieve rapid prosperity and growth. The brand marketing of plant factory is market-oriented, aiming at meeting the diversified and high-quality consumption of vegetables and plants, guiding the production factors such as social capital, technical equipment and labour resources to concentrate on famous and excellent products, transferring the superior resources to superior enterprises, transforming resource advantages into quality advantages and efficiency advantages, and promoting, optimizing and upgrading the structural adjustment of modern facility agriculture industry , so as to promote the rapid development of intelligent building greenhouse plant factory.

1.1.5 Conclusion and Prospect

Due to its good sealing, the building greenhouse can effectively ensure high cleanliness and sterility indoors, prevent the invasion of diseases and pests, and become a "production workshop" for clean and pollution-free plant production. It also has good thermal insulation and heat preservation to cut down energy loss and reduce carbon emissions. When large-scale planting of vegetables and herbs is carried out in it, it can also clean the air to a certain extent, improve the amount of atmospheric eutrophication, and improve the surrounding microenvironment and microclimate. Moreover, the intelligent building greenhouse plant factory is built based on modern buildings, which can be built anywhere, even in the city center, and is not limited by climate conditions and geographical location. Therefore, it should be foreseen that the intelligent building greenhouse plant factory will open a new era of urban productive agriculture and become a beautiful landscape of the city.

1.2 The developmental status and social needs of plant factory intelligence in China

1.2.1 Intelligence and plant factories

With the rapid growth of population, large-scale expansion of cities, large-scale reduction of arable land, shortage of land resources, global spread of epidemic diseases, frequent occurrence of extreme weather, pesticide abuse, and serious biological pollution, green and clean crop production, food supply, and fruit and vegetable security are facing unprecedented enormous threats and challenges. On the other hand, with rising living standards, people are increasingly demanding food hygiene, nutrition, greenness, cleanliness, health and safety. Plant factories are one of the effective methods to solve the above-mentioned problems and contradictions. A plant factory refers to an efficient agricultural system that achieves annual planned crop production in a vertical three-dimensional space under fully enclosed or semi-enclosed conditions through high-precision environmental control (Yang, 2019). Artificial lighting plant factories refer to plant industrial production facilities with artificial lighting, insulation, and almost enclosed building structures (Kozai, 2013). Compared with open-air fields and greenhouse agriculture, protective planting with the same building area increased annual crop productivity by one order of magnitude (Mitchell, 2004), while indoor crop production in multi-layer greenhouses increased productivity by two orders of magnitude (Kozai et al., 2015). This type of environmentally controlled agriculture is known worldwide as indoor agriculture, urban agriculture, vertical agriculture, or plant factories. They have enormous potential for fresh and clean plant production, providing fresh and healthy agricultural products in a balanced manner throughout the year, without the need for long-distance transportation and multiple transfers, and can be built anywhere and under climatic conditions (Kozai et al., 2019). However, the initial construction investment of plant factories is high, the electricity consumption is high, and the operating costs are high. Moreover, planting management is mostly done manually, resulting in high labor demands, management difficulties, and high administrative costs. Therefore, how to increase the level of mechanization, digitization, automation and intelligence in the production process is the future research and development trend for the plant factory.

In recent years, plant factories have gradually become mechanized, digitalized, semi-automated and semi-intelligent in the production processes of sowing, seedling cultivation, transplanting, harvesting, transportation and logistics. The development of automated logistics systems and the successful application of some industrial production automation technologies have enabled automated handling of seedbeds during transplantation and harvesting processes, effectively reducing labor workloads, increasing production efficiency and reducing production costs. However, plant factories with weak AI are still unable to meet the requirements of intelligent and unmanned planting. Mechanization, digitization, automation, intelligence and unmanned systems will be important directions for the intelligent development of plant factories in order to reduce labor intensity, reduce human resource costs and damage the plant growth environment caused by frequent entry and exit of operators.

In addition, the lighting, temperature, humidity, carbon dioxide, and nutrient conditions required for the growth of different types of crops vary widely, and even the same variety of crops have different environmental requirements at each stage of growth. Therefore, it is not possible to regulate the environment for all plant growth processes based on a single plant growth model, and comprehensive regulation needs to be performed differently for different crops. However, so far, the production practices of plant factories still lack more accurate plant growth models, more refined production guidance and the necessary data support, resulting in poor crop growth, low quality, low resource utilization and low production efficiency. Therefore, the accuracy of production management metrics and production models is an important guarantee for improving the labour productivity of plant factories.

1.2.2 Development status

At present, in the field of plant factories, many countries such as the Netherlands, Japan, South Korea, the United States, Hungary and Israel are very advanced and have achieved a high level of mechanization, automation and intelligence to reduce the large amount of labor. Moreover, the rapid development of plant factories in the form of miniaturization, domestication, miniaturization and vertical agriculture is also moving in a more intelligent direction. In recent years, research progress and technological development in China's plant factories have been rapid, and the momentum of development is strong. By the end of 2020, more than 200 commercial plant factories, more than 600 individual lighting plant laboratories and more than 1,200 air-conditioned room laboratories have been built, gradually making progress in the path of industrializing plant production. (China Zhiyan Data Research Center, 2021). However, compared to the technical characteristics and intelligent requirements of plant factories themselves, there is still a significant gap (Zhang et al., 2021). Most of the existing equipment and systems come from other technologies in solar greenhouses and facility agriculture. There is still a lot of room for improvement in the hardware and software technologies needed for a plant factory application environment. Researchers predict that in the near future, technological research will make creative breakthroughs to improve the automation level of efficient operation of plant cultivation (Zhang et al., 2019). In terms of hardware, due to the complexity of crop growth processes, plant factory automation equipment needs to be further integrated with plant agronomy. In terms of software, due to the lack of a large amount of experimental data support, most plant factories in China mainly use computer programs to independently adjust single factors based on empirical parameters or expert systems, and their rationality and accuracy need to be further improved (Fang et al., 2021).

1.2.3 Existing problems

1.2.3.1 Passive perception of environmental information

The acquisition of growth environment and biological feature information in plant factories is the foundation of digitization, intelligence, and modernization of plant factories (Wang et al., 2021). Traditional data monitoring and information collection mainly relies on the deployment of various sensors or detection devices in a plant factory, their transmission via various wired or wireless buses or protocols, and their centralized collection via computers. This approach not only increases the initial investment cost of the plant factory, but also complicates the communication and wiring between systems, greatly limiting the movement of automated mechanical equipment within the plant factory (Xu, 2020). In addition, there are many metal material frames in the planting workshop of the plant factory, which have strong electromagnetic interference, poor wireless communication stability, low monitoring information transmission rate, and frequent information loss (Zhang et al., 2019).

1.2.3.2 Low positioning accuracy of indoor intelligent mobile equipment

Plant factories have high requirements for air tightness, walls and insulation materials may shield radio waves, and many indoor intelligent mobile devices that rely on global positioning system (GPS) or BeiDou Navigation Satellite System (BDS) and other satellite positioning systems cannot meet precise movement control due to reduced positioning accuracy (Liu & Huang, 2021). At present, indoor positioning mainly uses infrared, ultrasonic, Bluetooth, ultra-wideband, wireless LAN, RRFID and other wireless positioning technologies, but these technologies have electromagnetic interference, low accuracy, complex construction, limited scale, high equipment cost and many other problems (Zhang, 2021; Li et al., 2021; Cao et al., 2020). Therefore, a single indoor positioning technology is difficult to meet the needs of indoor positioning in plant factories.

1.2.3.3 Low automation of planting management

In a plant factory, in addition to plant management such as germination, sowing, seedling rearing, transplanting, inspection, replanting, pruning and harvesting, plant culture requires decontamination and cleaning of equipment such as planting trays, nutrient delivery equipment, reservoirs, filters and pipes. At present, these tasks are not automated and the level of intelligence is so low that they are mostly done by hand by operators (Liu et al., 2021; Ren et al., 2020). In addition, to fully utilize the 3D space and expand the growing area, a multilayer hydroponic 3D vertical culture mode is generally used. However, under this mode, the planting equipment is bulky, labor intensity is high, and climbing operations are required, which poses significant safety hazards (Zhang et al., 2019). In addition, due to the low level of overall automation in this mode, a large number of personnel and equipment are required to repeatedly enter and exit the cultivation workshop, which can easily bring pathogens and cause environmental pollution (Liu, 2020; Yu & Liu, 2014).

1.2.3.4 Inaccurate nutrient solution regulation and circulation

The growth of plants cannot be separated from sufficient nutrients. Insufficient nutrients can reduce the yield and quality of plants, while excessive nutrient supply can cause huge waste (Shao et al., 2021). In existing plant factories in China, the preparation of nutrient solutions is mostly based on expert experience to determine the mixing ratio of water and fertilizer. After being mixed and stirred, it is piped directly to the roots of the plant, where it is then recycled. The mixing and supplementation of nutrients lack scientific experimental data and crop growth model support, and precise regulation has not yet been achieved (Yang et al., 2021; Zhang, 2021; Sun et al., 2018). In addition, the dissolution and dilution of solid nutrients, the supplementation of nutrient solutions required for growth, and the control of waste liquid recovery and discharge all require a large amount of manpower (Guo et al., 2020; Xia, 2020).

1.2.4 Suggestions for the Development of Plant Factories

1.2.4.1 Research of information perception and acquisition

Agricultural ecological environment detection sensors and image sensors have been installed on drones and mobile devices to construct target self searching and active mobile unmanned monitoring system equipment, achieving fully automatic and all-weather non-destructive testing of the planting environment and plant growth situation in plant factories, and actively sensing comprehensive information. The detection system is flexible and intelligent, with strong adaptability to different crops. Moreover, they are connected to each other through Internet of Things technology, forming a network without the need to install communication equipment and additional wiring, thereby reducing system costs and improving communication efficiency. In addition, multi-sensor fusion technology is used to comprehensively process multi-sensor or multi-source information and data (Yang & Han, 2019), in order to obtain richer and actionable information, enhance the effectiveness and robustness of the sensor system, enhance the system's fault tolerance, and avoid the limitations of a single sensor.

1.2.4.2 Study of indoor high-precision positioning of intelligent devices

High-precision indoor positioning technology is one of the key technologies for intelligent and unmanned plant factories. Related research has found that the visible light emitted by LED lights used for plant growth lighting can not only be used for plant photosynthesis, but also for rapid and high-precision positioning and navigation of intelligent devices in plant factories (Wei et al., 2021). The dual function of lighting and positioning can be achieved without the need for additional installation of special positioning and navigation devices. It also overcomes the difficulties of weak indoor satellite signals and high complexity of RF positioning technology, with strong anti-interference and high positioning accuracy.

1.2.4.3 Research on precise regulation of environmental multi-factors

Various environmental factors affect plant growth and development in the canopy and in the root zone in different ways, mainly including temperature and humidity, light, moisture, CO_2 in the air, dissolved oxygen in the root zone, canopy air circulation, nutrients, and minerals. Plants are affected by a combination of factors, and a small change in one can cause a significant change in others. When combined with plant growth, it can have a significant impact on plant development. Therefore, it is a challenging task to promote rapid plant development while also improving the integrated utilization rate of resources. At present, the precise coupling regulation of multiple environmental factors has become one of the important contents of research on plant intelligent factories. Crop growth process models and agricultural expert systems are the foundation for intelligent plant factories to achieve multi-factor coupling and precise regulation (Xu et al., 2021). Crop growth models can quantitatively describe the dynamics of crop growth and development, fruit formation and yield, based on meteorological conditions, soil conditions and crop management measures. Agricultural expert systems can be applied in various areas of agriculture, such as crop cultivation, plant protection, formula fertilization, agricultural economic benefit analysis and marketing management. In China, research in these areas mainly focuses on four aspects: multi-source environmental information fusion monitoring (Yang et al., 2021), non-destructive monitoring of plant growth based on computer vision (Liu, 2020), construction of crop growth models based on deep learning (Cen et al., 2020), and coupling and precise regulation of environmental factors based on crop growth models (Zhu et al., 2020), mainly focusing on comprehensive intelligent regulation of plant canopy and root zone. A crop growth model and expert decision-making system for intelligent plant factories, including an expert decision-making model library, mainly used for precise collaborative management of crop growth, environmental changes, and intelligent facilities and equipment, predicting crop growth trends, comprehensively analyzing various real-time monitoring information, and developing a comprehensive dynamic management decision plan for nutrient solution management, LED light modulation, and environmental factor regulation. At the same time, the system also has functions such as agricultural material management, technical database and personnel management, which can help increase the efficiency of cultivation and reduce management costs.

1.2.4.4 Automatic precision logistics equipment research and development

By comprehensively utilizing technologies such as sensors, automatic control, model driving, and visible light communication, low-cost autonomous mobile seedbeds, three-dimensional multi-layer cultivation racks, and corresponding logistics control systems have been designed and developed (Tang, 2017). The system automatically transports the mobile seedbed or planting frame that needs to be irrigated and planted to the designated location in the planting area, and also transports the mobile seedbed or planting frame that needs to be harvested or processed to the operating workshop, facilitating workers to concentrate on efficient operations or other mechanical equipment for automatic processing.

1.2.5 Conclusions of this section

In recent years, with the rapid development of science and technology and the national economy, China's facility agriculture has developed rapidly. Plant factories are an important component of facility agriculture, and their scientific basic research, construction engineering techniques and production information management capabilities have been continuously improved. Mechanization, digitization, automation and the development of intelligence in plant factories are driving them to become the new industrial form of modern agriculture. In the future, plant factories could be built directly in urban centers as a sustainable form of urban productive agriculture.

1.3 Plant factory big data and plant growth model construction

1.3.1 Plant growth model and plant factory big data

With the growth of the global population and the acceleration of urbanization, the traditional agricultural production model has been unable to meet the diversified needs of people for clean, nutritious, pollution-free, multi-variety, high-quality, and stable-priced vegetables that can be eaten fresh without washing. Plant factories have gained widespread popularity as facilities that employ artificial light and regulate environmental factors such as temperature, humidity, and CO_2 concentration to simulate plant growth conditions. It enables the cultivation of crops with high quality and yield, irrespective of geographical and temporal constraints, while at the same time reducing water and soil consumption. The establishment of plant factories has emerged as a viable solution to address pressing societal issues, including but not limited to population expansion, decreasing arable land, climate deterioration, resource scarcity, regional instability, and sudden epidemics (Wang et al., 2023). Plant factories are highly efficient agricultural systems that produce crops in a vertical, three-dimensional space on an annual schedule under completely confined or semi-confined conditions and are an important part of Agriculture 4.0. It is recognized as the highest stage of development in protected agriculture because of its use of advanced technologies such as Internet of Things (IoT) technology, big data technology, and deep learning. The Internet of Things (IoT) technology facilitates the prompt collection of environmental data in plant factories. Big data technology analyzes this data. Deep learning technology learns the patterns and laws of plant growth from large amounts of data to build accurate plant models, which are used to predict plant growth, detect and diagnose plant diseases, and help project the optimal growth environment. Plant modeling is one of the key technologies of the plant factory, which is systematic, dynamic, mechanism-based, predictive, and universal, and is an important part of precision agriculture. It can assist plant factories in achieving intelligent control, optimizing the plant growth environment, producing more intelligently and efficiently, and real-time monitoring of plant growth.

Based on an overview of the types and status of plant models, this paper discusses the system framework and methods for constructing plant models based on IoT, big data, and deep learning technologies using environmental data such as temperature, humidity, light intensity, and various index parameters of nutrient solution and plant growth data in a plant factory production environment. In this paper, it is proposed to construct a plant growth model using multi-source heterogeneous data and multimodal neural networks. Furthermore, a general method based on plant models is proposed to achieve automatic and intelligent prediction of plant growth and efficient and stable production management. By building a cloud service platform, model sharing and data sharing can be realized, thus a providing theoretical basis and technical guidance for plant factories.

1.3.2 Research review of plant model

1.3.2.1 Development overview of plant model

In the 1960s, research on constructing plant models appeared in the field of protected agriculture and made rapid progress. The initial plant models were primarily concerned with morphological changes in the physical structure of the plant organism. Some classic plant models in the world are DSSAT in the United States (Jones et al., 2003), APSIM in Australia (Keating et al., 2003), STICS in France (Brisson et al., 2003), and GECROS in the Netherlands (Yin and Van, 2005). Each of these growth models can completely describe and predict the entire process of yield formation during the plant growing season and can be used to promote agricultural technology and provide advisory services. Since the 1990s, the University of Queensland in Australia and the University of Calgary in Canada have developed Virtual Plants and L-Studio systems based on the L-system, respectively. The system has been developed and improved for simulating crop growth processes, resulting in a series of morphological structure models that simulate the growth processes of cotton, soybeans, corn, barley, rice, and other crops. The French Agricultural Research for Development (CIRAD) has developed a series of AMAP software based on reference axis technology for simulating plant 3D structures, simulating “plant-environment” interactions, and analyzing and calculating organ sizes (Zhu et al., 2019). Badjonski and Ivanovi developed a genetic breeding multi-agent expert system (Barczi et al., 2007, de Reffye et al., 1997, Godin et al., 1997, Seleznyova et al., 2003), which was implemented to simulate breeding experts to select suitable varieties. Söffker et al. (2019) proposed a model based on state machines. The model can define growth behavior based on states and processes and has been applied to evaluate growth predictions under different irrigation treatments during the nutritional stage of corn, which can be used to evaluate growth predictions under different irrigation treatments (Söffker et al., 2019).

Research on greenhouse crop growth models began in the late 1970s and early 1980s. The prediction of plant growth and yield is increasingly becoming a significant area of research and holds a crucial position in crop breeding, seedling, and planting practices. Based on crop physiological processes, the plant model uses a series of mathematical formulas to synthetically simulate the dynamic processes of crop growth, development, and yield formation, expressing the principle that plants explore their growth environment to obtain efficient and optimal resources. Building plant models is particularly important for greenhouse production. Using plant growth models, Yang et al. (2013) conducted a growth and yield prediction study of tomatoes in greenhouses to explore the establishment and implementation of a greenhouse tomato fruit growth model (Yang et al., 2013). By studying greenhouse climate models and greenhouse crop growth models, Jin et al. (2022) proposed the use of mathematical models to simulate greenhouse microclimates, recognizing the need for indoor crop growth to quantify greenhouse systems and understand the complex responses of crops to environmental and artificial management practices. It is also recognized that the future trend in greenhouse crop production is an integrated system using digital and robotic technologies as well as artificial intelligence technologies (Jin et al., 2022). According to Luo et al. (2008), the growth of crops is significantly associated with the effective accumulation of temperature and radiation within their growing environment. The concept of photo-thermal product was introduced, and simulations were conducted to examine the correlation between growth indicators and photo-thermal product of various crops, including greenhouse cucumber, tomato, and melon. The results of the simulation were found to be satisfactory (Luo, 2008). Sun and Chen (2003) et al. monitored the photo-thermal product under the solar greenhouse and used it as a basis to derive the values of plant biomass accumulation, thus establishing a growth model of plant biomass and photo-thermal product (Sun and Chen, 2003). A simple two-stage crop model with a single state variable was developed by Seginer et al. (1998). The behavior of the model is very similar to that of the classic TOMGRO model. The optimal control strategy of this model can be used as a suboptimal control for TOMGRO (Seginer et al., 1998). Vegesana et al. (2013) explored the use of generic crop growth models that can be integrated into farmers' decision systems (Vegesana et al., 2013). Goodfellow et al. (2020) utilized Generative Adversarial Networks (GANs) to generate lifelike images for the purpose of predicting future frames. They also investigated the potential of incorporating both spatial and temporal features of plant growth to produce more practical and informative phenotypic data (Goodfellow et al., 2020). Sigalingging et al. (2023) used the Cobb-Douglas model, a general model for predicting farm yields, to develop a mathematical model using convolutional neural networks (CNN) for predicting energy productivity during green onion cultivation in the Utara Hutajulu area of Sumatra. The energy demand modeling and prediction system for green onion cultivation on agricultural land, which predicts the energy productivity during green onion production, can provide guidance to farmers in irrigation, fertilizer, and pesticide application during cultivation and develop environmental health strategies based on the energy domain for optimal yield (Sigalingging et al., 2023). Using greenhouse climate sensors that capture real-time information and crop images, Petropoulou et al. (2023) developed an autonomous artificial intelligence algorithm that enables AI algorithms to autonomously control the production of greenhouse lettuce crops (Petropoulou et al., 2023).

1.3.2.2 Classification and role of plant models

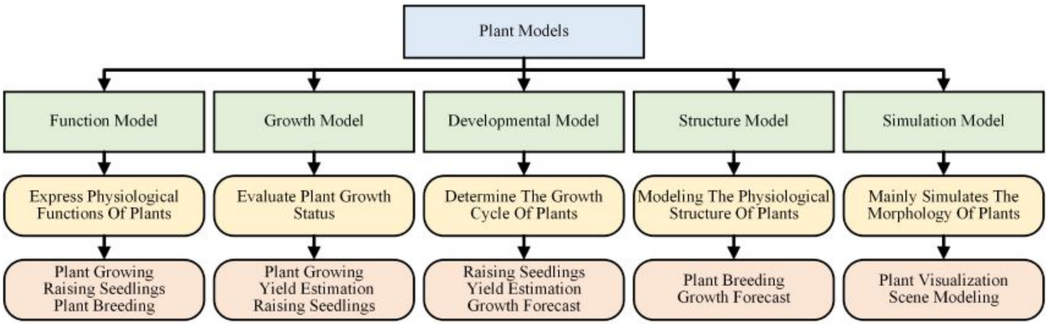


Fig. 3 Classification of plant growth models

The plant models are mainly divided into function models, fertility models, structure models and simulation models, as shown in **Fig. 3**. Using mathematical techniques, function models express various functions and operations in plant growth. It is a crucial model for researching the plant growth process and is used for plant breeding, seedling raising, and planting guidance. Depending on the content of concern, plant fertility models are divided into growth and developmental models. Developmental models focus on the growth characteristics of plants on a time series and predict the growth and development cycles of plants according to their different growth periods. The growth model concentrates on plant phenotypic analysis, such as plant height and leaf area, and aims to evaluate the growth status of plants and indicators of growth. Structure models segment and detect the structures of stems, leaves, flowers, and fruits of plants; build models of plants in different combinations; reconstruct the structures of plants; and simulate and predict the growth of plants. Simulation models use computers to simulate morphological changes during plant growth and development, and establish 3D morphological models of plants through visualization techniques, mostly for digital twin displays and scene modeling (Lin et al., 2003; Sun and Shen, 2019; Zhu et al., 2019; Zhu et al., 2020). Based on the growth process of plants, most of the general plant growth models do not consider the influence of the environment, which leads to poor universality of plant growth models. The ability to monitor and control the plant factory environment at any given time reduces the impact of environmental factors on model construction. This, in turn, decreases the complexity of plant model construction and enhances the accuracy of plant models in simulating the functional mechanisms of plant growth processes.

1.3.2.3 Plant model construction method

Traditional plant models are used for scientific research. Most of the construction methods are based on mathematical and empirical models to mathematically explain the processes of plant growth and development based on the physiological and ecological mechanisms of plants. Spitters et al. (1986) analyzed the distribution characteristics of light flux density within the plant canopy for photosynthesis within the crop canopy and proposed a mathematical model of daily crop plant assimilation by combining environmental factors such as temperature and factors of crop physiological characteristics such as leaf area index and leaf angle distribution. The instantaneous rate of photosynthesis was calculated from the plant balance analysis, and the total assimilation of the plant during the corresponding growth period was obtained by integral calculus. Some of them are used for the consumption of life-sustaining respiration, growth and development respiration, and the mathematical model of life-sustaining respiration and growth and development respiration (Spitters et al., 1986). Using the sine function, Cheng et al. (2019) calculated the trend of the temperature effect factor with temperature. Based on the experimental data, the varietal parameters for each developmental stage were determined, the growth and development process and key developmental periods of solar greenhouse cucumber were quantified, and the establishment of a developmental stage model, leaf area index model, and dry weight production model for greenhouse cucumber was studied (Cheng et al., 2019). The flow chart of a typical plant simulation model construction is shown in **Fig. 4**.

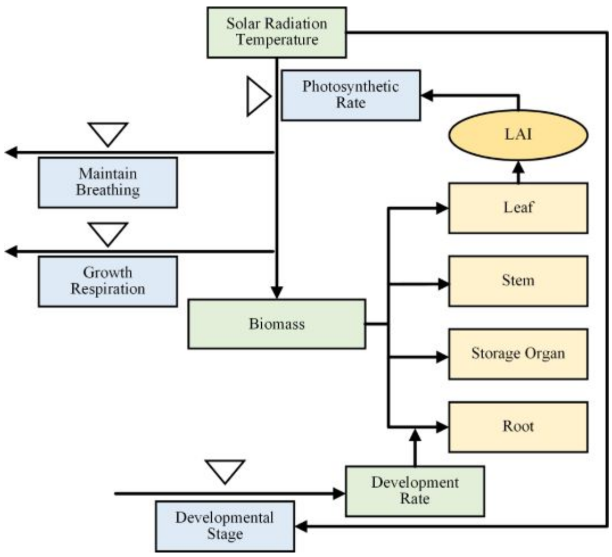


Fig. 4 Flow chart of typical plant simulation model construction

Traditional plant models are descriptive and empirical, a black box type of model. Based on the existing theoretical and practical experience, the relationships between the study factors were identified and obtained through the statistical analysis of a large amount of data. The acquisition of plant growth data, including leaf area, plant height, photosynthesis rate, and environmental data, presents a significant challenge due to the complexity of the process. The utilization of manual data collection methods has emerged as a significant impediment to the advancement of plant models. Furthermore, the limited state of computer technology results in significant constraints on the model's capacity for expansion and inference. Most of the models lack systematic elaboration of plant mechanisms, and each step requires multiple repetitions of the "build-manual correction-validation" process, which requires human monitoring and correction. Traditional plant model building methods have disadvantages such as complex structure, difficult implementation, and low universality. The main building method based on the traditional plant growth model is shown in **Fig. 5**.

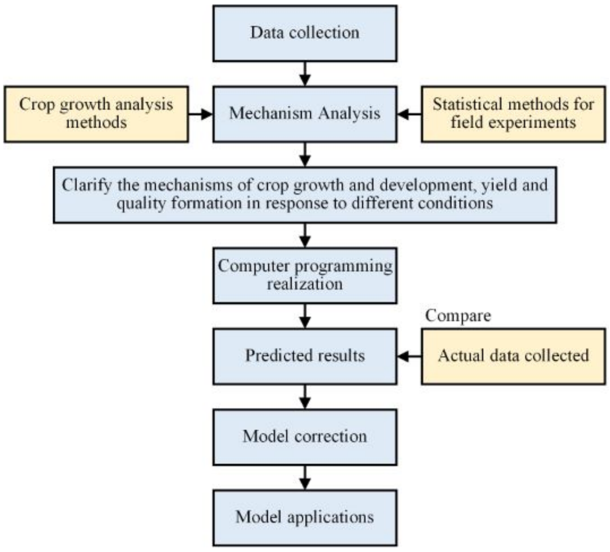


Fig. 5 Building method of traditional plant growth model

With the continuous development of information technology, deep learning methods have played an important role in the acquisition of plant phenotype data. By combining expert a priori knowledge and extracting high-level abstract features from raw data, it achieves automatic and precise identification of plant phenotypic traits and can formulate optimal environmental control strategies based on the response mechanisms of plants to the environment. Most plant modelling methods are based on this idea:

(1) Systematically analyze the structure of plant growth and development, determine the state variables, rate variables, driving variables, and interrelationships between the variables of the system according to the physiological-ecological principles of growth and development, map the correlations of the crop growth and development system, and establish the mathematical equations of their interrelationships and their changes over time;

(2) Using experimental observations to determine the parameters or coefficients in the equation, programming the model in a computer language to implement the computational process, and deriving the weight values for the different growth conditions of the plant through multi-network fusion;

(3) Verify whether the algorithm of the model and the selected parameters are reasonable according to the physiological-ecological principles of the plant; test the algorithm of the model using the trial-and-error method using the data obtained from several experiments so as to detect the sensitivity of the model; modify or reselect and determine the model parameters for the corrected model;

(4) Compare the simulated processes and results of the model with the actual observed data of the system and analyze the errors so as to verify whether the model can simulate or predict the behavior of the plant system and its change trend. A model can be applied if its simulation of the system or predicted trend is consistent with the observed reality and the error is within an acceptable range.

Based on the unique tropic movement of plants as a heuristic criterion, Li et al. (2020) proposed a parameter-free intelligent optimization algorithm, namely the plant growth simulational algorithm (PGSA). This strategy and model provide the perfect bionic prototype for the creation of algorithms to simulate plant growth. This original work has facilitated a large number of subsequent studies and algorithmic applications (Li and Wang, 2020). Hautala et al. (2011) proposed a crop growth model named C3. The model has a good consistency between simulated and measured values of biomass and leaf area, and the growth level of plants can be evaluated by collecting the amount of radiation used by the crop (Hautala et al., 2011). Gu et al. (2022) proposed a computer vision-based deep learning plant growth model analysis method and system (Gu et al., 2022). It extracts phenotypic features such as plant height and leaf area through deep learning models, and generates a relationship between the growing environment and the plant growth state by mapping with environmental data. Modeling based on regression algorithms and solution optimization solves a large number of optimization problems that cannot be solved by traditional methods, with high accuracy and reliability. Wang et al. (2022) used ST-LSTM to develop a plant growth and development prediction model that successfully predicted the growth state of Arabidopsis canopy leaf area, canopy width, and leaf number after a few days (Wang et al., 2022), and Shibata et al. (2020) proposed a semi-supervised depth state space model for plant growth modeling that estimated the change in sugar content of tomatoes over a time sequence (Shibata et al., 2020). Based on various algorithms, Sun et al. (2021) studied the fruit growth model of fruit trees. Through methods such as comparative statistics, machine learning, and deep learning, LSTM models showed greater accuracy and reliability in simulations of apple fruit diameters (Sun et al., 2021).

1.3.3 IoT, big data, deep learning and plant models in plant factories

The intelligent management system of a plant factory combines IoT, big data, and deep learning technologies. IoT plays a supporting role, providing a comprehensive perception of plant growth and environmental information. Quantitative analysis and statistics of information are carried out by big data technology, and the basis and data support for the subsequent construction of plant models are provided through data processing, analysis and decision-making. Deep learning is used to build models.

1.3.3.1 IoT, Big Data and Deep Learning

IoT, big data, and deep learning technology are the important directions of the development of computer technology at present. IoT integrates technologies such as intelligent devices, sensors, communication technologies, and cloud computing. Big data technology is a collection of a large number of data processing technologies and tools involving data storage, processing, analysis, mining, and visualization. Deep learning is based on multi-level neural network model to learn the complex nonlinear relationship between the input data to solve the regression problem, which cannot be solved by mathematical methods or is difficult to solve. The number of nodes in Wireless Sensor Networks (WSN) based on IoT can be increased, decreased, and moved as needed, improving the application of data technology in agriculture (Zhang, 2020; Lei and Zhang, 2017). A variety of sensors in the plant factory use radio frequency technology to independently network through the Wireless Sensor Network technology and realize the collection, transmission, storage, and application of the whole environmental data and plant growth data. The IoT three-layer model of the plant factory is shown in **Fig. 6**.

The plant factory IoT is composed of a perception layer, a transport layer, and an application layer. According to the communication protocol, the perception layer detects plant growth data and environmental data in real time; the transport layer transmits data to the application layer through WSN to realize information interaction; the application layer processes and analyzes the data, intelligently identifies plant phenotypes, precisely regulates the growth environment through terminal devices, realizes intelligent management of plant growth, and makes the plant growth environment optimal.

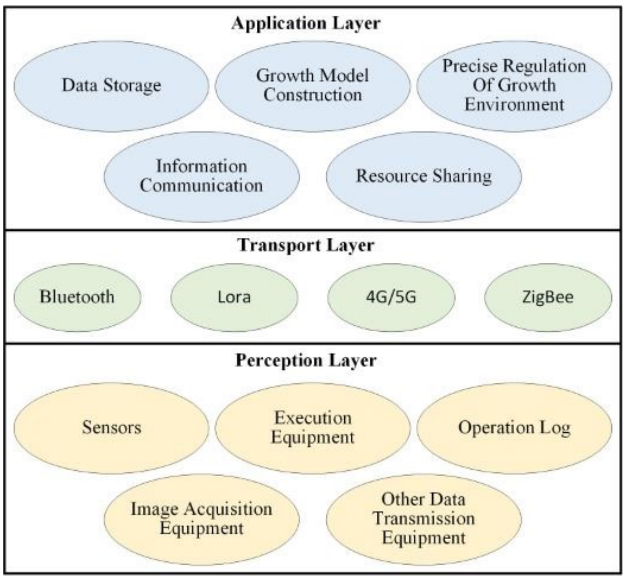


Fig. 6 IoT three-layer model of plant factory

The temperature, humidity, CO_2 concentration, nutrient solution liquid temperature, nutrient solution PH value, nutrient solution EC value, plant growth images, daily operation log, plant gene count, and market data of the plant factory come from sensors, image acquisition equipment, the Internet and manual input. In a highly automated and unified production environment, data of different types, structures, and dimensions from different data sources constitute multi-source heterogeneous data, such as time series data, structured data, unstructured data, etc. The storage, computation, analysis and visualization of massive multi-source heterogeneous data require technologies and methods from multiple fields, such as data mining, machine learning, artificial intelligence, and statistics, for comprehensive and integrated processing, as shown in **Fig. 7**.

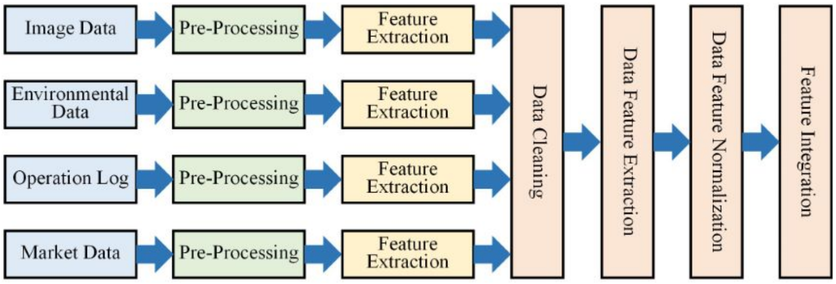


Fig. 7 Multi-source heterogeneous data processing method

According to the characteristics of data sources and data types, different analysis methods are used in this paper to integrate and analyze the data to support the construction of plant models. To ensure data consistency and effectiveness, data cleaning, normalization, and alignment are done on multi-source heterogeneous data. Feature fusion of data acquired from different data sources is performed by sequential fusion, parallel fusion, and deep fusion to obtain comprehensive and accurate information (Zhang et al., 2018; Yu et al., 2020; Feng et al., 2021; Petropoulou et al., 2023).

In recent years, deep learning has been widely used in the field of agriculture. Deep learning techniques can extract multi-scale and multi-level features from plant growth state image data and environmental change data on time series and then combine high-level features based on these features to build plant models. Based on computer vision support vector machines (SVM), random forests, artificial neural networks (ANN), convolutional neural networks (CNN), deep convolutional neural networks (DCNN) and other algorithms using multi-level neural networks, deep learning techniques can integrate expert a priori knowledge to extract high-level abstract features from raw data and achieve automatic and accurate recognition of phenotypic traits in massive big data. Convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory networks (LSTM), and generative adversarial networks (GAN) are among the classical deep learning models that have demonstrated promising outcomes in the modeling of plant growth.

Table 1 deep learning model

Target	Model	Model characteristics	Field of application
image data	CNN	Extract local or global features	Computer vision, image recognition, target detection, etc
	GAN	Learn to generate realistic samples, distinguish between real samples and generated samples, and thus generate high quality samples	Image generation, image editing, image enhancement, etc
Serial data	RNN	Process indeterminate long sequence data with memory capability, capture long-term dependencies in the data	Natural language processing, speech recognition, stock forecasting, etc
	LSTM	Use gating mechanisms to resolve long-term dependencies	Natural language processing, stock forecasting, video analysis, etc

As shown in **Table** 1, CNNs can process image data of plants and infer the growth status of plants from plant morphology and size. RNN can process time sequence data of plant growth, etc. LSTM is a special kind of RNN that effectively circumvents the shortcomings of RNN, such as gradient disappearance and gradient explosion during the training process, and can handle long-term plant growth data with changes in plant height, weight, and morphology during different growth cycles. GAN is trained to learn the features and distribution of plant images to generate new virtual plant images similar to real plant images for plant breeding and variety improvement.

1.3.3.2 Plant factory plant model significance

IoT networking technology connects the intelligent monitoring system of the whole plant factory, storing the two-dimensional or three-dimensional image data of plant growth status collected by image devices such as ordinary cameras, depth cameras, laser radar, and monitoring system of the plant factory, as well as environmental data such as air and rhizosphere collected by various sensors, into the database of the plant factory. The data generated by plant factories on a daily basis provides sufficient data sets for building robust and generalizable plant models, and the production data can be uploaded to the cloud service platform via the Internet. As shown in **Fig. 8**, the cloud platform performs data analysis and processing and provides data sharing and modeling services.

The plant model effectively manages the growth environment for plants during various stages of growth, ensuring real-time and precise regulation. Additionally, it optimizes energy consumption, resulting in a shortened growth cycle for plants. The utilization of the plant model can facilitate the estimation of vegetable yield and optimal timing for marketing, the assessment of vegetable growth status, the provision of scientific principles and directions for plant factory production, and referencing market data for sales management. Plant growth status information can be obtained by managers or consumers through the utilization of a 3D visualized sci-fi animated plant model, which can be interacted with by tapping various parts of the model.

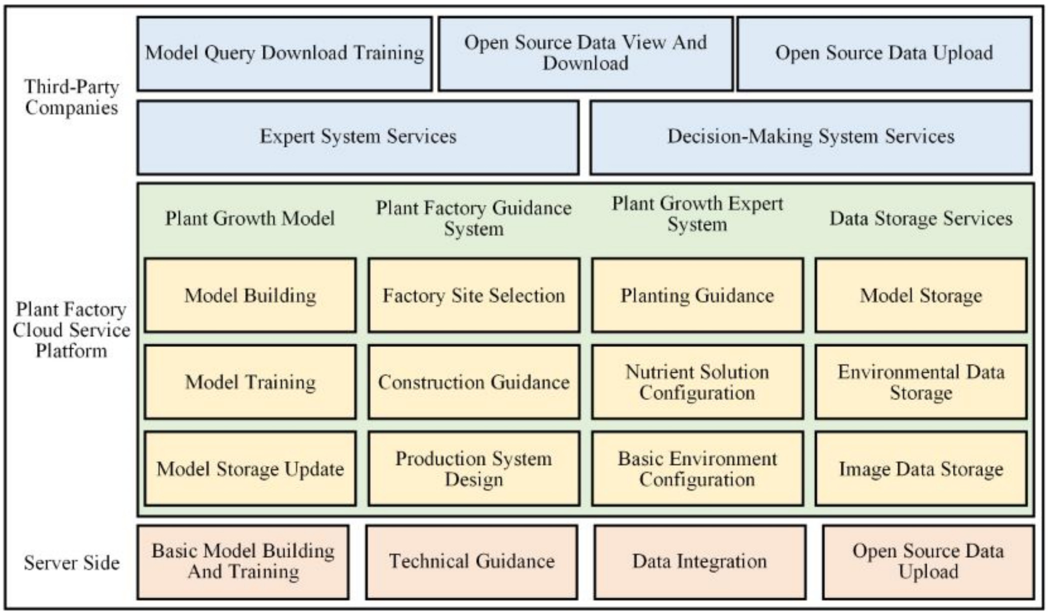


Fig. 8 Cloud service system framework of plant factory

1.3.4 Plant model construction

1.3.4.1 Plant model building framework and method

There is variability in the biological indicators across different plant species. During growth, the main concern needs to be the number of leaves, leaf area, and plant height of leafy vegetables. The biological indicators that are of interest to berry plants vary during different growth periods. In the initial stages, it is prudent to prioritize the examination of leaf quantity, leaf surface area, and plant height. In the later stages, the primary concern shifts to flowering number, fruit set, and fruit volume. As a means of building plant model, deep learning methods do not require too much attention to functional metrics during plant growth. It can calculate leaf surface area, count fruits, etc. by segmenting the leaves of the plant and using an image segmentation model. Based on specific networks, deep learning methods can predict biomass, solving the problem of difficult manual collection of plant growth data as well as environmental data and reducing a lot of tedious work compared to building mathematical models. The framework of the plant growth model is shown in **Fig. 9**.

The first step is the acquisition and processing of plant growth image data and environmental data. The training data comes from multiple sensor environmental parameter log sheets, growth stage log sheets, operation records, manager experience, and user feedback from different regions, which constitute multi-source heterogeneous data. Pre-process the collected environmental data and plant growth data, and annotate the growth image data. The morphological features of the plants in the images are extracted using convolutional neural network segmentation and stored in the cloud service system database after data pre-processing. The training set, validation set, and test set are continuously enriched by increasing the annotated image information, training classification models, and normalization operations.

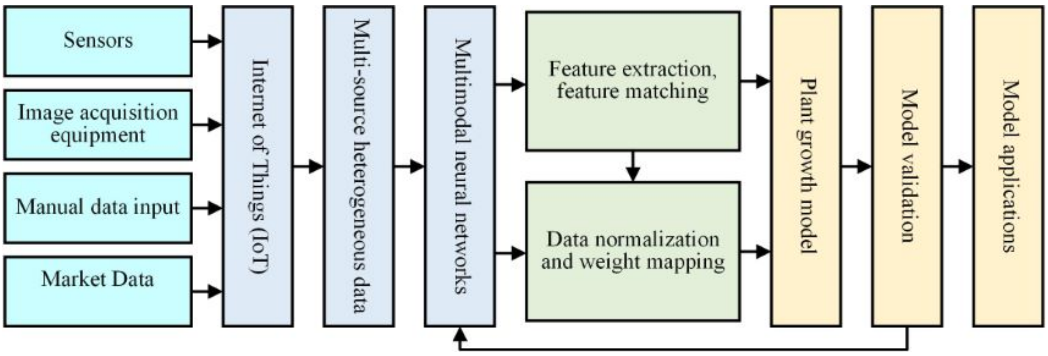


Fig. 9 Plant growth model construction in plant factory

The second step is to extract high-level abstract features from the raw data by training the plant model. Through multi-modal feature extraction, multi-modal data fusion, multi-modal learning integration, and training of multi-source data, CNN is used for image segmentation, and the growth characteristics of plants are extracted as image channel information. A multi-modal neural network trains multiple sub-models hierarchically, and the feature representation is input into the main model RNN for time sequence analysis and detection. Integrate multi-source environmental data, such as light intensity and temperature, and do model training. Mapping models with the best biological indicators and corresponding environmental information are sought through iterative training. In an end-to-end way, multiple sub-models are jointly trained in the same neural network, the multi-source data with mutual influence and coupling relationships is integrated and processed, and the plant growth data and environmental data in time series are mapped and regressed to establish the initial model of plant growth and environment.

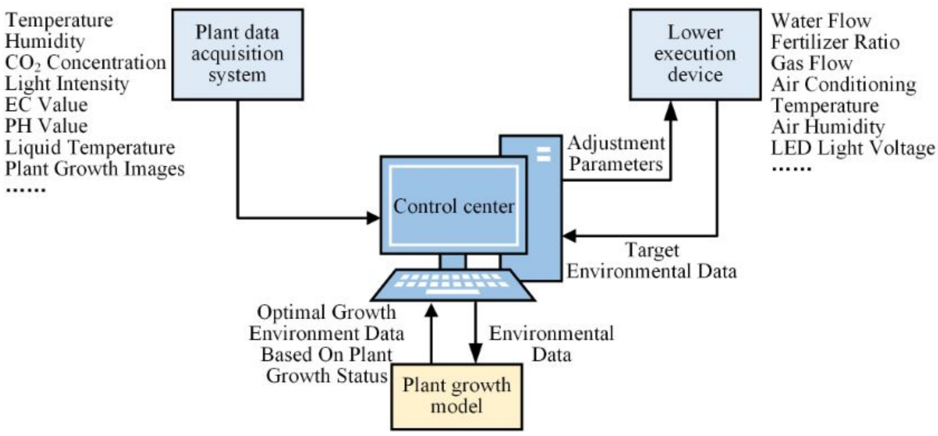


Fig. 10 Closed-loop feedback system of plant growth model

Finally, the model is corrected and validated by actual production of environmental data and plant image data, as shown in **Fig. 10**. In order to improve the regulation and prediction accuracy of the model, the initial model was applied to the environmental regulation and yield prediction of the plant factory decision system with fuzzy control of the environment. By collecting environmental data and plant growth data in real time, the actual production environmental data, plant image data, and prediction data are compared and fed back to the plant model to correct the model parameters in time. Thus, a closed-loop strategy of “data collection - model construction - actual production - environmental regulation - feedback - model correction” is formed. Notably, the cloud service platform can achieve self-correction of plant models by reducing manual intervention and inputting and matching growth data and environmental data of the same plant from other production sites, which contributes to the robustness of the model.

1.3.4.2 Application and prospect of plant models

Plant factory production involves a variety of fields such as protected horticulture, protected environment and engineering, and automation. It uses the powerful information processing and computing abilities of computers to systematically analyze the whole growth and development process of plants and its relationship with the influencing factors through a large amount of data training and establish the best environmental model under different growth periods by combining the relevant knowledge of plant growth and development. The introduction of generic plant models, such as model equations for respiration and photosynthesis rates, can be targeted and modified according to different application scenarios, and functional models can be established according to plant species and growth periods to study the functional changes in plants. The utilization of multi-source integrated real-time data and real-time images of plant growth has the potential to facilitate plant growth model prediction and simulation of plant growth status. Deep learning techniques for image processing neural networks can segment and store individual organs of plants to build a continuous library of plant organ models. Three-dimensional visualization technology and image processing technology can build a three-dimensional visualization simulation model of plants to evaluate plant height, leaf area, and other growth indicators. The plant factory connects various models to the decision system. Based on the image data of plant growth status and environmental change data on time series, vegetable varieties and corresponding growth periods can be selected according to actual needs. The phenotype information of plant growth is output by the decision system, which returns predicted images of plant growth, 3D visualization effects, etc., and detects the plant growth status and field environment. The regulation of the environment is achieved through the utilization of optimal conditions, which entail the lowest energy consumption and the highest quality of plants. This approach ensures that the regulation of the plant growth environment is carried out in a real-time and precise manner, as shown in **Fig. 11**.

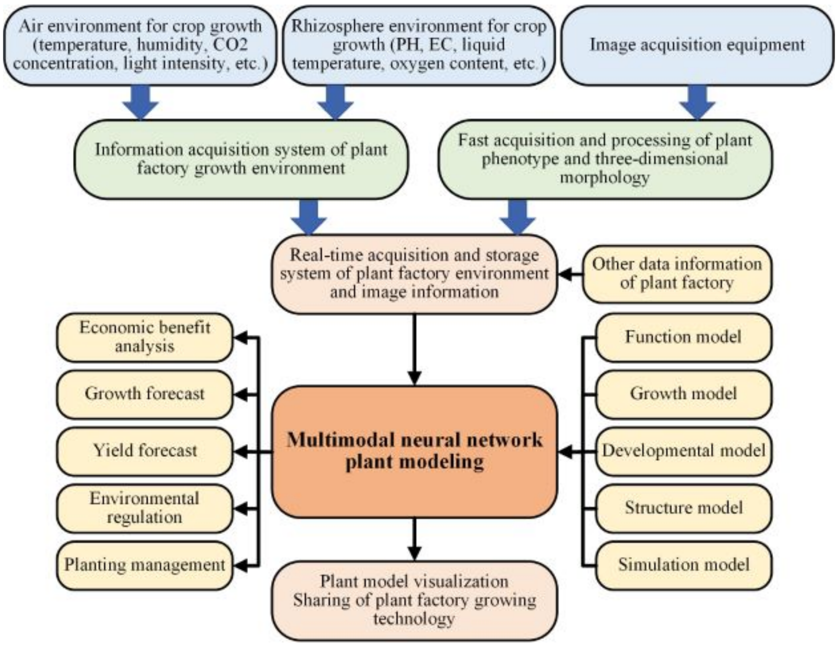


Fig. 11 Plant factory plant growth model application framework

According to Wang et al. (2022), plant factories need to rely on the rapid growth and development of plant models in order to achieve multi-factor precise control, industrial production, enterprise management, and brand marketing (Wang et al., 2022). This, in turn, can accelerate the maturation of Chinese plant factories to “go global” by enhancing the conditions and timing. The automation and precise control of plant factory production processes have been facilitated by information technology, particularly IoT, big data, and deep learning. Kolokotsa (2010) devised an intelligent system for managing the indoor environment and energy consumption of a greenhouse, thereby demonstrating the capacity of artificial intelligence to facilitate control and decision-making processes. The study also established the feasibility of automated environmental control. According to Hamon (2010), there is a need for further enhancement of the autonomy, robustness, and scalability of control systems (Kolokotsa et al., 2010). The employment of growth models to conduct quantitative analysis and dynamic simulation of plant growth, development, yield formation processes, and environmental impacts for the purpose of optimizing decision-making management has been a relatively recent research endeavor in China. Furthermore, the majority of studies conducted in this area have focused on a single model. Huang Jianxi suggested that future research efforts should be increased and multiple growth models should be integrated to achieve mutual complementarity among various models, which can improve the prediction and simulation accuracy of crop growth models under uncertain conditions and reduce labor demand (Huang et al., 2018). Cost issues and the development and implementation of more intelligent and expert systems are currently the most pressing issues in the development of plant factories. The plant factory industry is continuously enhancing plant growth models and exchanging data and plant models through cloud service platforms. The forthcoming path of plant factories is expected to prioritize cost-effectiveness, accessibility, and intelligence.

1.3.5 Conclusions of this section

Currently, the Internet of Things (IoT) facilitates the interconnection of all production units within the entire plant factory. Moreover, the plant model has evolved into the central component of the intelligent control system of the plant factory. The neural network can be utilized to facilitate the construction of plant models by incorporating real-time or periodic data on plant growth and environmental factors collected by various sensors. This approach enables the model to undergo self-training and self-correction through feedback from the data, thereby reducing the complexity of plant model construction and enhancing its precision over time. The cloud service platform provides model and data resource sharing services, which simplifies the plant model application method. However, the methods for constructing plant models using multimodal neural networks and multi-source heterogeneous data are procedurally intensive. The model training and data acquisition require a large amount of arithmetic power, and the accuracy of traditional methods to assist in verifying the model requires a large amount of manual measurement and testing. It is imperative to incorporate IoT networking and cloud service platforms during the initial stages of plant factory planning. Throughout the construction stage, it is essential to access various data interfaces of plant factories across the globe, which poses significant challenges to the security of the data network. The advancement of computer technology and the emergence of lightweight neural networks, coupled with the availability of plant factory production data from various regions globally, are expected to enhance the precision of plant models through training feedback. It will be applied to more applications and promote the advancement of plant factory technology.

1.4 Multi-factor environmental regulation platform structure of artificial light plant factory based on growth model

1.4.1 Plant growth model and plant factory environmental regulation

Where the dream can reach, so must the footsteps. Long has it been hoped that plant production may be conducted in urban downtowns, icy polar areas, scorching deserts, desolate territories, and even the wide expanse of space in the same manner as industrial commodities production (TSURU & FUJII, 2006; Kim, 2010; Shamshiri et al., 2018). Theoretically, plant factories are fully capable of optimizing the plant growth process and improving plant growth quality and production efficiency by creating an artificial plant growth environment and simulating the laws of movement of the natural environment.

In 1957, the first plant factory was constructed on a Danish farm. The phrase “plant factory” was coined by Japanese scholars and has since gained widespread acceptance, becoming a new type of agricultural production sought after by urban agriculture. Plant factories are horticultural facilities with a high degree of environmental regulation and plant growth prediction based on environmental data and plant growth monitoring, thereby producing a controlled environment for the annual planned production of vegetables and other plants (Goto, 2012). Plant factories are highly efficient agricultural systems that achieve crop production in vertical three-dimensional space and on an annual schedule through high-precision environmental control under completely enclosed or semi-enclosed conditions (TAKATSUJI, 2010; Kang et al., 2013). According to the different ways of using light energy, Toyoki Kozai et al. classified plant factories into three types: sunlight-utilizing, mixed sunlight and artificial light-utilizing, and artificial light-utilizing (Kozai, 2013). Chinese scholars Yang (2014), Liu & Yang (2014), and He (2018) divided plant factories into two categories: those that utilized sunlight and those that utilized artificial light (Yang, 2014; Liu & Yang, 2014; He, 2018). In contrast to the passive response of field and greenhouse plant production to environmental changes, artificial light plant factories have their own specific prerequisites and unique technological systems. It can transform an unfavourable environment into one that is optimal for plant growth based on the plant's physiological and biochemical, growth and development requirements, improve production efficiency, and reduce energy consumption; therefore, it is necessary to develop a novel theory of environmental regulation.

A plant growth model is a simulation model that quantitatively describes plant growth and development, output formation, and response to the environment using system analysis and computer simulation principles. It is a complex model that integrates plant, facility, environment, management measures, and their interactions and has been deeply promoted and widely used in protected horticulture crop production. In the midst of a severe energy crisis, crop models play a crucial role in balancing these parameters to create the optimal growth environment for protected crops with minimal inputs, hence attaining the production objectives of high quality, high yield, and ecological safety.

With the accelerated pace of global urbanization, the spurt of urban expansion, and the explosive growth of the urban population, modern metropolises are in urgent need of agricultural systems suitable for urban areas and sustainable annual production; consequently, artificial light plant factories have become the hope of urban residents to consume fresh, clean, healthy, and safe vegetables. This dissertation discusses the current research status of greenhouse microclimate dynamic simulation and plant growth model construction, analyses the adjustable environmental factors affecting plant growth and their precise coupling regulation technology, proposes the architecture of the multi-factor self-learning coupling precise regulation system platform for artificial light plant factory environments based on deep learning and growth model, and provides theoretical support and solutions for the design and development of a plant factory intelligent control platform.

1.4.2 Greenhouse microclimate dynamic simulation and plant growth model

The greenhouse is a hotbed for plant growth, a complex microenvironmental system that includes three subsystems: soil, crop, and microclimate, and their interrelated coupling systems. Agricultural models are an essential tool for the study of quantitative laws and the precise management of agricultural problems; the simulation of greenhouse microclimate using mathematical models is a major area of quantitative research in greenhouse systems; and crop growth models are an important component of optimal crop management (Katzin & Mourik, 2022). Based on the core elements of the greenhouse climate model and crop growth model, the Functional-Structural Plant Model (FSPM), which is currently in development, incorporates abiotic environmental modules, genetic modules, and biological modules, as well as 3D technologies, to show crop performance and the biological processes involved in its growth in 3D. The relationship among the climate model, crop model, and functional-structural plant model is shown in **Fig. 12**.

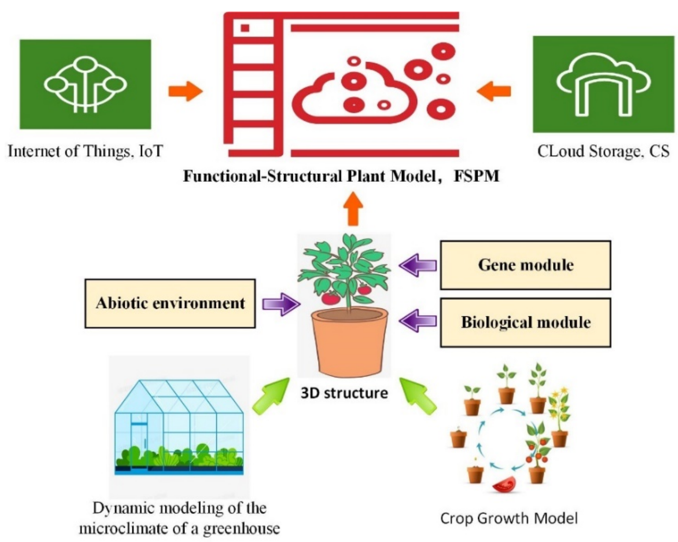


Fig. 12 Relationship diagram of climate model, crop model and functional-structural plant model.

1.4.2.1 Research status of greenhouse microclimate dynamic simulation models

Greenhouse climate dynamics models are divided into two categories: mechanical models and black box models. The mechanical model is built on physical principles in order to investigate quantitative algorithms that might be advised for optimal greenhouse system control. The black box model is an empirical model that is mainly used for greenhouse system control, optimization, and design. Bot (1983) developed the first chemodynamical greenhouse climate model, and Henten (1994) proposed the first greenhouse climate model with an optimal control objective. Taki et al. (2016) used a multilayer perception neural network (MLP) model to predict greenhouse temperature. These greenhouse climate models can be used to estimate changes in the internal environment of protected greenhouses and to achieve precise regulation of microclimate. Internationally, greenhouse simulation model research began in the 1970s, and Kimball (1973) analyzed and studied a double-roofed full-light greenhouse environment and performed dynamic simulations, which provided a theoretical basis for improving greenhouse structure and optimizing environmental regulation techniques. Dynamic simulation modeling of the greenhouse environment was started in the 1980s. Kindelan et al. (1980) used the energy balance method to simulate the indoor environment and divided the greenhouse environment into four units: soil, plants, indoor air, and mulch. Bot et al. (1983) developed a dynamic mechanics model of greenhouse climate by setting four levels of temperature variables: mulch, air, crop canopy, and soil, and using temperature, humidity, sunlight, and wind speed outside the greenhouse as input variables. In the 1990s, the study of modular component simulation models was started. Zwart (1996) conducted a modular study by dividing the greenhouse climate into physical modules for material and energy transfer in the greenhouse and a large number of modules that simulate conventional greenhouse climate controllers, using air temperature, CO_2 concentration, and humidity as state variables, and developed the greenhouse process

KASPRO model, which can be used to control heating, ventilation, dehumidification, humidification, shading, artificial lighting, and CO_2 supply. During the same period, Chinese scholars Cao et al. (1992) and Chen (1993) analyzed the relationship between light environment and structure of a solar greenhouse and started research on the simulation model of solar greenhouse microclimate dynamics in China. Subsequently, Chen & Wang (1996) established a mathematical model of the thermal environment based on heat transfer theory applicable to solar greenhouses to quantitatively reveal the change pattern of the thermal environment of solar greenhouses. Since the 21st century, conditional options have been added to greenhouse climate models from a structural perspective, and Vanthoor et al. (2011) developed a dynamic model of the effect of outdoor climate and greenhouse design on indoor greenhouse climate by setting up four types of greenhouse operation models under three climatic conditions: temperate maritime, Mediterranean, and semi-arid climate. In the past decade, quantitative studies of greenhouse climate prediction and estimation have expanded to include the complete spectrum of gas exchange, heat transfer, and energy balance. Joudi and Farhan (2015) conducted a dynamic modeling study that accurately predicts the indoor temperature by taking into account the heat exchange between the soil surface and greenhouse air. Salazar et al. (2019) studied a dynamic energy balance greenhouse climate model considering plant transpiration, ventilation, condensation, outdoor climatic conditions, crop leaf area index, stomatal and air resistance, mulching characteristics, and greenhouse characteristics in the greenhouse, and the model efficiency was improved to 33.84 percent. In recent years, there has also been a rapid development of greenhouse climate modeling research in China. Wei et al. (2021) studied the greenhouse dynamic prediction model with improved heat transfer theory and a mass-energy balance equation using internal and external environmental data of tomato greenhouse substrate cultivation for three consecutive months in a glass greenhouse as an experimental base. The results showed that the main influencing factors of indoor temperature were outdoor temperature and solar radiation, and the variation of indoor relative humidity was mainly affected by plant transpiration rate, indoor temperature, ventilation, and air exchange. Zhang et al.

(2020) studied the greenhouse mulch temperature prediction model and proposed a dynamic absorption rate calculation method for greenhouse mulch, which divided the solar radiation absorption rate of mulch into direct radiation absorption rate, scattered radiation absorption rate, and reflected radiation absorption rate at the surface for accurate calculation, respectively. Li (2021) optimized BP neural network parameters with a differential evolutionary algorithm and a grey wolf algorithm for correlation analysis affecting greenhouse temperature and humidity and established a short-term prediction model for greenhouse temperature and humidity.

1.4.2.2 Plant growth model research

The plant growth model is a numerical simulation system based on the mechanisms of crop physiological processes from the perspective of system science, which includes climate, soil, crop varieties, and management measures on factors affecting crop growth as an organic whole. Plant growth models can assess the different effects of climate, soil, moisture, and crop management factors on crop growth and development and are an important component of cultivation management optimization. In recent years, it has been applied in many fields, such as regionalization simulation, agricultural forecasting and risk analysis, climate change impact assessment, macro-agricultural decision making, and optimization of cultivation measures, and has become one of the most important tools for the quantitative evaluation of agricultural production. With the rapid development of intelligent technology in plant factories and the accelerated pace of marketization, the realization of precise control of environmental multi-factor coupling is more necessary for greenhouse plant growth model research. The current greenhouse crop model is optimized and upgraded from the field crop model with the development of protected agriculture. Compared with open-air and solar greenhouses' environments, artificial light plant factories are tightly enclosed, well insulated, and have a unique plant growth environment, which requires the construction of a model for plant growth in artificial light plant factory environments. Most modern solar greenhouses are mostly cultivated for tomatoes and cucumbers, and there are mostly greenhouse plant growth models with them as the main object of study. Some of the early well-known tomato plant simulation models are Tomsim-Susros87 (HEUVELINK, 1999), Tompousse (Abreu et al., 2000), and Tomgro (Jones et al., 1991) models. Typical cucumber models are the MarCeliS model, a simulation model of greenhouse cucumber dry matter distribution constructed based on the sink strength theory, and the KOSI model, which is based on the dry weight distribution and fruit growth model of cucumber. Common plant growth models are Tomgro and Hortisim models (Gijzen et al., 1997; Shamshiri et al., 2018), among which the Hortisim model can be implemented as a general-purpose system to simulate the growth and development processes of various horticultural crops such as tomatoes, cucumbers, and sweet peppers. For different greenhouse environmental conditions, researchers have conducted plant growth simulation model studies in terms of plant canopy structure, dry matter accumulation distribution, the critical fertility period, and crop output. Li et al. (2006) proposed the index of "photo-thermal product" and set the accumulated photo-thermal product as the independent variable to simulate photosynthesis of the leaf area index, thus establishing a simulation model of dry matter production and improving the simulation accuracy of dry matter production in cucumber. Qian (2014) extracted the dynamic and heterogeneous geometric parameters of the canopy structure of cucumber populations, used an integrated model describing organ dynamics and organ distribution heterogeneity to achieve the parametric construction of a three-dimensional cucumber colony canopy, and performed systematic validation using a multiscale approach. Chamont (1993) developed a model based on the Tomgro model to simulate the dry matter distribution in cucumber fruits and roots. Sun et al. (2005) developed a sub-model for dry matter production in greenhouse environments based on TOMSIMM and Susros87 models by simulating photosynthesis with the specific leaf area method and using temperature and solar radiation as environmental driving variables for cucumber leaf area index. Shi et al. (2008) established a model of aboveground growth and dry matter distribution of individual organs of cucumber plants based on the Richards growth function and the theory of plant dry matter distribution sink strength and simulated the distribution of plant dry matter before fruit set. Vanthoor et al. (2011) conducted a simulation model study of tomato yield under different light conditions and CO_2 concentrations in the Netherlands and southern Spain to establish a tomato yield model, and the experiment verified the effect of very low and average high temperatures on the yield and harvest time of the first spike of fruit. Zhou et al. (2018) verified that the LSTM recurrent neural network model could predict the target yield of tomato with high accuracy.

In recent years, a lot of research has been conducted on constructing plant growth models focusing on environmental management, crop response, and simulation accuracy improvement. Li et al. (2021) developed a greenhouse tomato Crop Water Stress Index (CWSI) prediction model based on Cuckoo Search optimization CatBoost (CS Cat-Boost) based on nine internal and external greenhouse parameters, including air temperature, humidity, and substrate moisture. Bao et al. (2021) compared and analyzed the variation of indoor air temperature, relative humidity, and light level in a 3-connected plastic greenhouse and a large-span film greenhouse to construct a crop growth model based on photo-thermal products. Based on the measured greenhouse tomato data, Niu et al. (2022) proposed a gradient boosting decision tree (CatBoost) algorithm based on support classification features to estimate the daily reference crop evapotranspiration in greenhouses. Li et al. (2021) studied the DSSAT-CROPGRO-Tomato growth model to simulate the growth and development and yield formation of tomato under straw return conditions in a northern solar greenhouse and used the GLUE parameter estimation module to obtain crop genetic parameters for different design scenarios.

1.4.2.3 Functional-Structural Plant Models

With the deep integration of mathematics, computer science, and botany, the study of functional-structural plant models (FSPM), which introduce the concept of plant architecture, has gained widespread attention, aiming to understand the complex interactions between plant structure and plant growth processes (Evers et al., 2018; Louarn & Song, 2020). Szanto (2016) designed a coupling module of steady-state photosynthesis and stomatal conductance to develop a functional-structural plant model of the greenhouse tomato. The model used the light tracing method for light environment simulation, and the study showed that the effect of border orientation on light interception was weaker at higher solar altitude angles. Using plant organs as the basic unit, Buck-Sorlin et al. (2022) performed multi-scale simulations of local light interception and photosynthesis within each leaf, using a virtual greenhouse environment with a functional-structural plant model (FSPM) with plants, light sources, and photosynthesis active radiation (PAR) sensors. The model was designed to reproduce PAR measurements for different light conditions at different times of the day for different canopy positions, better simulating the process of rose production in quality and quantity. Zhang (2019) conducted a cut flower plant experiment in a greenhouse using lilies and roses to study plant responses to changes in PAR, R: FR, water level, and nitrogen, and simulations validated that the FSP model could be combined with a leaf photosynthesis model and a leaf climate model.

1.4.2.4 Plant growth model construction based on Internet of Things and big data

Currently, with the development of greenhouse construction and artificial light plant factory technology, intelligent digital multi-span greenhouses have become the mainstream of greenhouses, with the possibility of moving to higher-end intelligent greenhouses in the future (Wang et al., 2022). Greenhouse plant growth models are evolving toward research that uses IoT sensors, climate models, and FSPM for integration. Based on the idea of functional-structural plant modeling, Chen et al. (2022) developed a 3D growth model for predicting tomato plants in an intelligent multi-span greenhouse. The model was used to simulate tomato yield, CO_2 absorption, nutrient, energy, and water use, as well as environmental impacts and benefits, while also measuring dynamic growth indicators of tomato plants in real time. Plant factory plant growth model construction can calculate and simulate environmental variables for plant growth and development to estimate plant traits and microclimate conditions using data generated from multiple sensors, such as multispectral 3D laser scanners, chlorophyll fluorescence cameras, thermal imaging cameras, and climate sensors. The model predictions allow adjustment of crop management strategies and identification of improved plant traits. The future trend of plant production is the use of digital technology, robotics, and artificial intelligence, the combination of plant growth models, the use of IoT sensors to collect greenhouse climate dynamic data, and the use of cloud storage and computing analysis of these data so as to achieve the plant factory environment's multi-factor coupling precise intelligent regulation, and optimization.

1.4.3 Environmental factors affecting plant growth in artificial light plant factories and their integrated regulation

1.4.3.1 Composition of environmental factors affecting plant growth

Detailed sorting and comprehensive analysis of environmental factors affecting plant growth are the basis for reducing production costs and conducting comprehensive, coupling precise regulation. Generally speaking, the environmental factors that have the greatest impact on plant growth include canopy environmental factors in the above-ground part and root zone environmental factors in the underground part. Environmental factors in the above-ground part include air temperature, air humidity, canopy light, canopy branch density, canopy spatial distribution, CO_2 concentration, airflow, gas composition, environmental cleanliness, etc. Environmental factors in the underground part include root zone temperature, water quality (cleanliness, water flow, and water velocity), fertilizer (nutrient and mineral content, EC value), acidity (pH value), dissolved oxygen content, etc. In summary, the factors affecting plant growth include the five basic elements of temperature, light, water, air, and fertilizer, as well as other elements such as airflow (wind circulation), dissolved oxygen, planting density, spatial distribution, and environmental cleanliness, as shown in **Fig. 13**.

Fig. 13 composition of environmental factors affecting plant growth.

1.4.3.2 Comprehensive environmental regulation

The biggest difference between an enclosed modern intelligent greenhouse and a solar greenhouse is that the intelligent greenhouse adopts permanent building materials, which completely eliminates the need for sunlight and occupies arable land resources. It has excellent sealing and thermal insulation, and all factors of the indoor environment offered for plant growth are highly adjustable. Therefore, the core and most critical task of an urban intelligent plant factory is to systematically and intelligently regulate various indoor environmental factors affecting the growth and development of vegetables and to combine a variety of environmental factors organically for comprehensive environmental regulation to meet the needs of the growth and development of protected vegetables. Theoretically, the process and results of indoor environmental regulation changes should be compatible with the growth and development of plants, their physiology and biochemistry, and other life laws inherent to plants themselves, in order to obtain the best regulation effect and improve the utilization of comprehensive resources. The relationship between greenhouse, greenhouse microclimate model, plant growth model, and environmental coupling precision regulation is shown in **Fig. 14**.

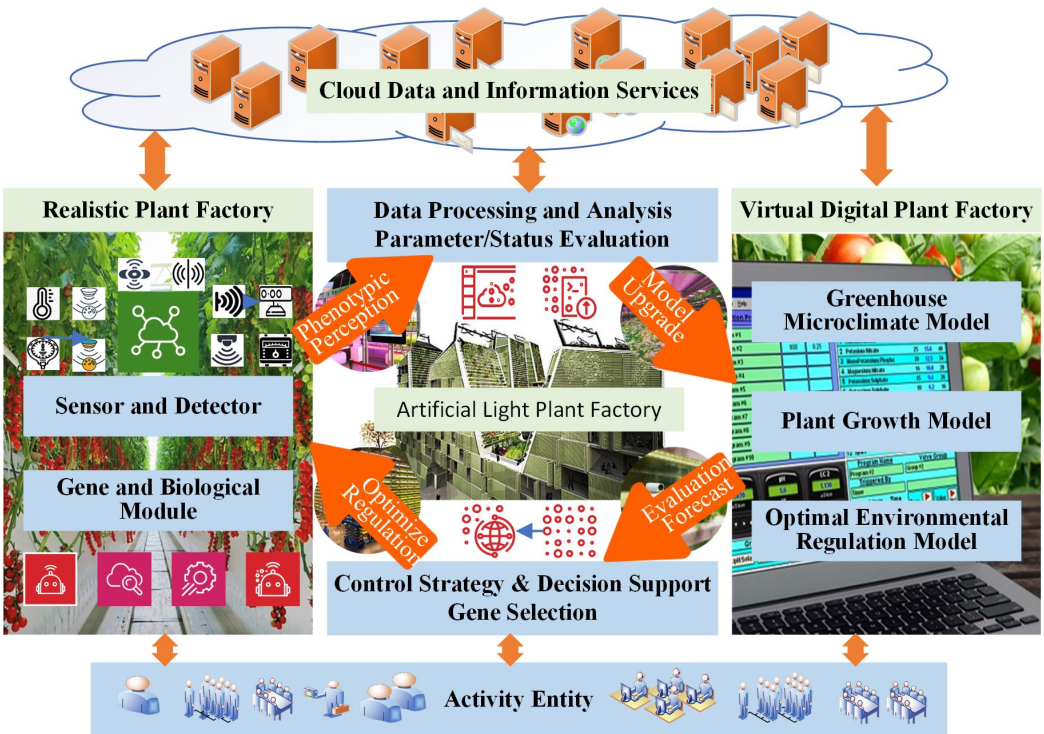
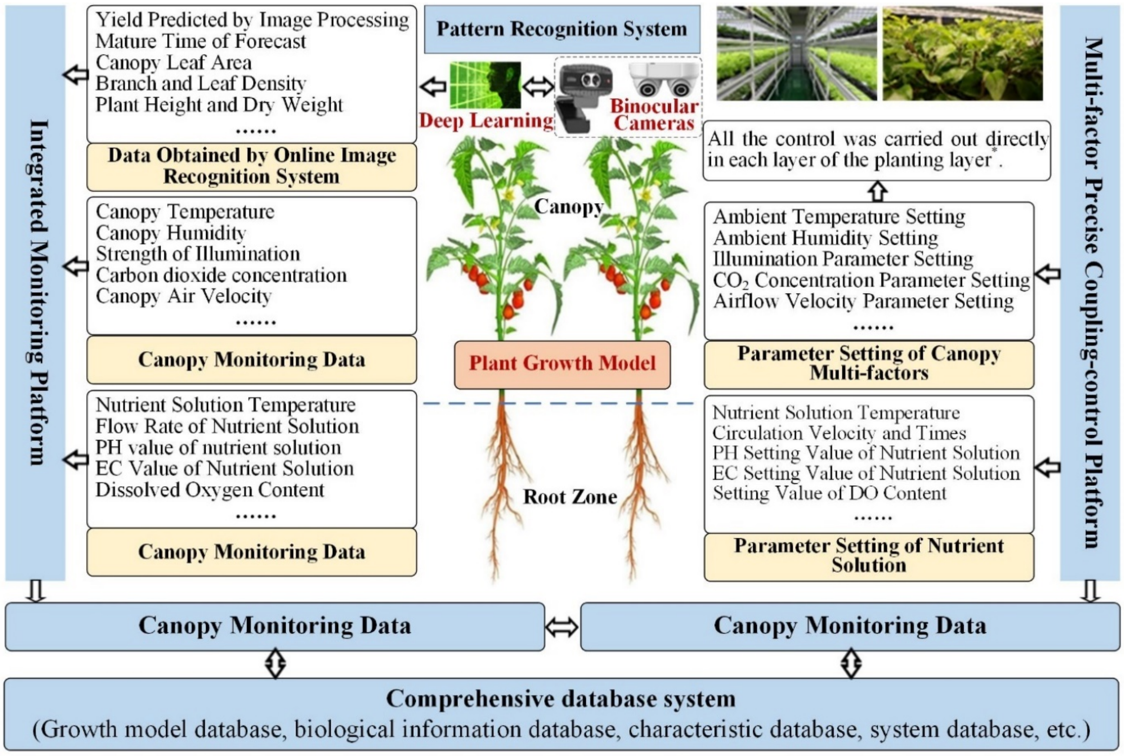


Fig. 14 Relationship between greenhouse, greenhouse microclimate model, plant growth model, and environmental coupling for precise regulation

1.4.4 Multi-factor self-learning coupling precision regulation model

The biggest challenge for intelligent plant factories based on artificial light plant factories is that it is quite difficult to couple and precisely regulate all the influencing factors to obtain the best environmental adaptation and the highest integrated resource utilization for growing crops.

The growth and development of plants are indirectly or directly influenced and constrained by various environmental factors, and the adaptability of different species of plants to environmental factors varies, as does the adaptability of the same plant to environmental factors at different growth stages. Therefore, in the process of plant cultivation, especially in the enclosed plant factory environment, it is necessary to take precise control measures according to the biological characteristics, habits, and different growth stages of plants to create the best growth environment for crop growth to meet their growth needs and obtain high quality and high yield.



*For example, CO2 gas is sent directly to the space of planting layer; fans are installed in each layer between planting layers to directly control air flow.

Fig. 15 Multi Factors Self Learning Coupling Precise Regulation Model Based on Machine Vision.

Inspired by the research on greenhouse climate model and plant growth model, combined with the analysis of environmental factors affecting plant growth in artificial light plant factories, we proposed a multi-factor self-learning coupling precision regulation model based on deep learning and a growth model. Our proposed model consists of a machine vision-based pattern recognition system, an integrated monitoring platform, a multi-factor precision regulation platform, a big data integrated analysis platform, a self-learning growth model analysis platform, and an integrated database system (growth model database, biological information database, growth characteristics database, and system database). **Fig. 15** hows the data and information processing and the working process of the model.

(1) Real-time acquisition of plant biological information and growth status information through an online image recognition system based on machine vision. Binocular cameras are set up at the top and side ends of a single layer of the planting shelf to take videos and images of plant growth at the right time. By converting, processing, and pattern recognition of the captured images through an online image recognition system, the biological information of the plants can be predicted, such as the number of leaves, branches, leaf area, branch density, plant height, fresh weight, dry weight, yield, and harvesting time. It can also predict the growth of plants, such as plant growth stages, health conditions, early warning if there is a poor growth state, giving the reasons for poor growth and preventive measures, etc. The prediction information and data obtained are sent to the integrated monitoring platform for processing.

(2) Monitoring data from the plant canopy and root zone are collected in real time by the integrated monitoring platform. Various sensors are installed in the production area to monitor the environmental conditions such as plant canopy temperature, humidity, strength of illumination, CO_2 concentration, air flow rate, etc., and parameters such as nutrient solution temperature, flow rate, pH value, EC value, and dissolved oxygen concentration in the root zone in real time. The integrated monitoring platform stores the collected data in the database system and presents it visually to the users.

(3) The monitoring data and system setting data are stored, managed, and analyzed by the big data and big data comprehensive analysis platform.

(4) The self-learning growth model analysis platform obtains the growth model and growth characteristics data of plants through specialized deep learning algorithms combined with the results of the big data analysis platform.

(5) According to the plant growth model and growth characteristics data, the multi-factor precise coupling control platform will analyze and calculate the precise control model, and the corresponding actuators will be precisely controlled by each sub-controller to complete the regulation of environmental factors. Environmental factors regulating devices are installed on each layer of the planting shelf to directly regulate the plant growth environment. For example, CO_2 is directly delivered to each shelf through the delivery pipe; airflow is directly regulated through the fan, etc.

(6) The integrated database system includes a crop growth model database, a crop biological information database, a crop growth characteristics database, and a system database.

1.4.5 Conclusions of this section

The intelligent greenhouse will become a modern "production workshop" for future plant production that can intelligently regulate the ambient temperature and humidity, simulate light, the concentration of carbon dioxide in the air and nutrients in the soil, accurately supply water, accurately apply fertilizer, etc. to create and maintain the optimal growth environment for plants. It can not only carry out real-time intelligent regulation according to the growth characteristics of plants to maintain a suitable and stable growth environment throughout the life cycle of plants but also create specific climatic conditions for specific plants to produce vegetables in a specific climate. The intelligent greenhouse is constructed in the countryside or city by maximizing the geographical advantage, and the structure is relatively enclosed and sealed, which allows it to overcome the limitations of climate and land as well as prevent the attack of pests and diseases, making it ideal for the "factory" production of clean vegetables and pollution-free vegetables. The proposed multi-factor self-learning coupling precision regulation model based on deep learning and growth model can improve the precision of plant factory environment regulation, achieve energy saving, reduce cost, and improve comprehensive resource utilization, which can be better integrated into the development of cities, thus promoting its landing construction and industrialization process in cities. It is imaginable and predicted that the exquisite and delicious meals served to urban families in the future will originate from local “plant factories.” The intelligent greenhouse will usher in the era of urban plant factories.

SECTION 2. EXPERIMENTAL PLATFORMS, MATERIALS AND METHODS

The majority of Ph.D.-related experiments were conducted in the artificial light plant factory laboratory of Henan Institute of Science and Technology, with a small number conducted in the university's solarium laboratory, the biological planting laboratory, and the collaborator's fruit tree base. This study's experiments were conducted between February 16, 2020 and February 20, 2023. The plant seeds for the experiments were partly cultivated by other research teams of the university and partly purchased from the market. The experimental environmental parameters were measured in our laboratory, while plant growth, biomass, nutrient content, and other parameters were measured in different laboratories with the assistance of faculty members from other university faculties.

2.1 Introduction of artificial light plant factory laboratory

In May 2020, the Artificial Light Plant Factory Laboratory was established as a comprehensive professional laboratory based on the discipline construction planning and the need for interdisciplinary integration development, applied by the School of Information Engineering and approved by the university, relying mainly on the strength of computer science and technology, data science and engineering, Internet of Things, agricultural engineering, control science and engineering, mechanical engineering, agronomy, biology, botany, plant protection, horticulture and landscape architecture, etc. The laboratory is currently the only fully artificial light plant factory laboratory in Henan Province research institutes.

The lab is oriented on the national major development strategies such as "Digital China" and "Rural Revitalization", and focuses on the technical needs of plant factory industrialization, with Internet of Things, big data analysis, artificial intelligence, edge computing, intelligent decision-making and control, deep learning-based plant growth model construction, agricultural engineering and environmental control, agricultural information technology and agricultural intelligent system as the core key technologies. The laboratory focuses on the research of plant production factors demand law, data analysis and crop quality control system development, LED energy-saving light source and its light environment intelligent control technology research, water and fertilizer precision drip irrigation system and equipment development, network management-based plant factory intelligent control equipment development, to carry out basic and forward-looking technology research in the field of intelligent plant factory. The laboratory transforms the traditional agricultural production system, builds a modern agricultural industrial technology innovation service system, undertakes scientific research and development and engineering research tasks assigned by localities and industries, implements the promotion and industrialization application of scientific and technological achievements, cultivates high-level innovative talents, and provides verification conditions for industries.

With the strong support of university and college administrators and the efforts of the entire laboratory staff, the laboratory has achieved rapid development in no more than two years and is now equipped to independently conduct both single and comprehensive experiments. Currently, relying on this laboratory, the plant factory research team I lead has applied for and established six projects and requested 1.33 million yuan in government support funds. Four projects hosted by me have received 230,000 RMB in government funding.

2.2 Experimental conditions

2.2.1 experimental facilities and systems

The laboratory is fully equipped with plant growth environment monitoring system equipment, plant growing frame, hydroponic tank, LED plant lighting and control system, nutrient solution circulation control system, CO_2 fertilization regulation system, water and fertilizer integration automatic circulation irrigation machine, water treatment and circulation system, greenhouse environment integrated control system, fresh air regulation system, airflow regulation fan system, dehumidifier, UV disinfection lamp, etc. Through secondary programming, these systems and equipment are able to conduct integrated intelligent control experiments of greenhouses and simultaneous comparative experiments on the cultivation of multiple groups of plants. In addition, the laboratory is equipped with specialized desktop computers, laptops, projectors, and other office, study, and seminar equipment, as well as a variety of research and study tools. Some of the laboratory equipment is shown in **Fig. 16**.

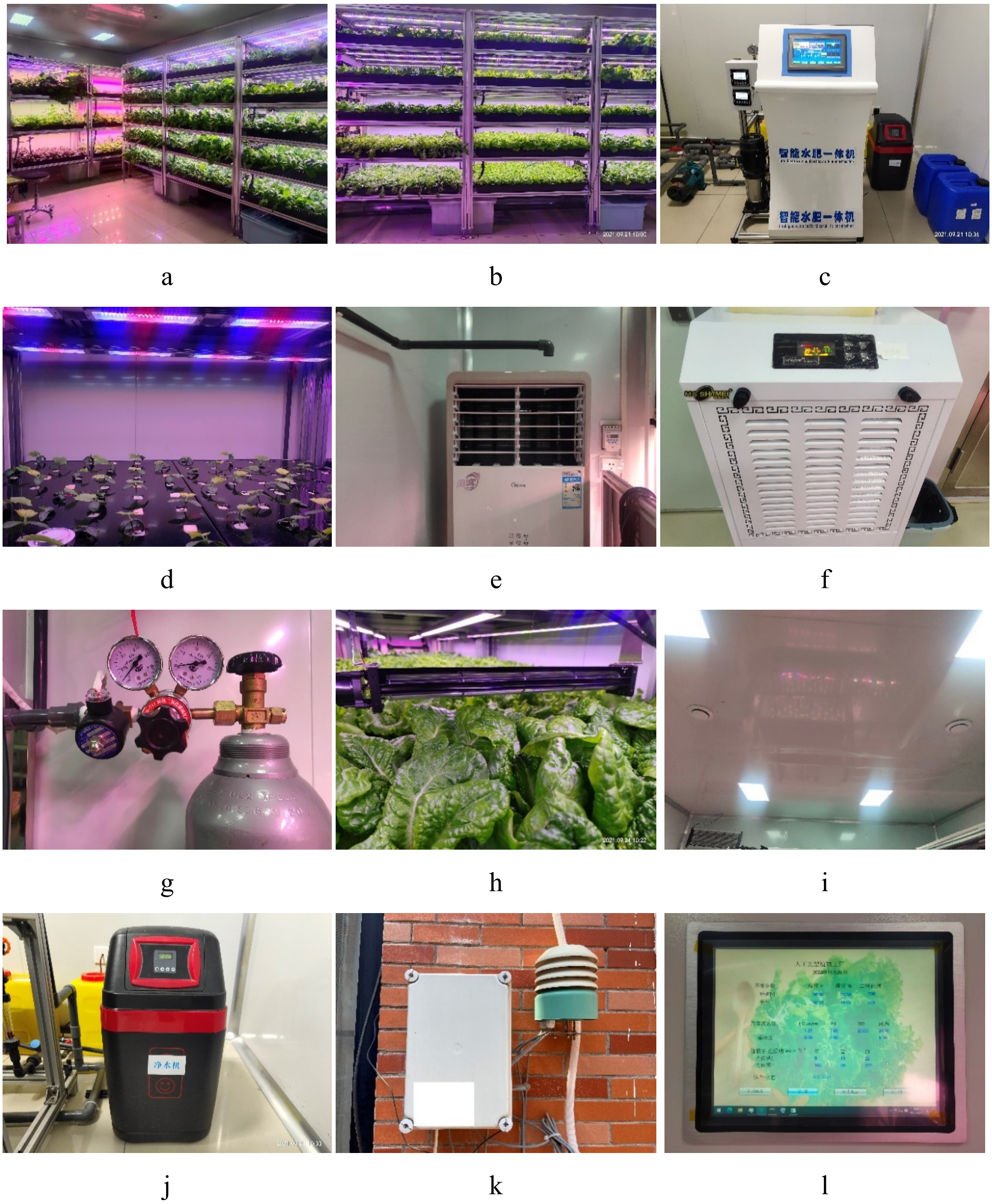


Fig. 16 Regulating means and experimental conditions of artificial light laboratory in school: (a) Laboratory planting room of plant factory; (b) a leaf vegetable trial planting shelf; (c) intelligent water fee integrated control equipment and system; (d) light regulation and control; (e) environmental temperature control (programmable); (f) environmental humidity control; (g) carbon dioxide concentration regulation; (h) airflow regulation of the planting rack; (I) fresh air

system regulation (air exchange); (j) source water purification equipment; (k) outdoor environmental monitoring wireless gateway; (l) plant factory integrated control system.

Monitoring equipment, sensors, remote controllable execution unit, intelligent equipment, and intelligent logic control unit for laboratory of artificial light plant factory are shown in **Fig. 17**.

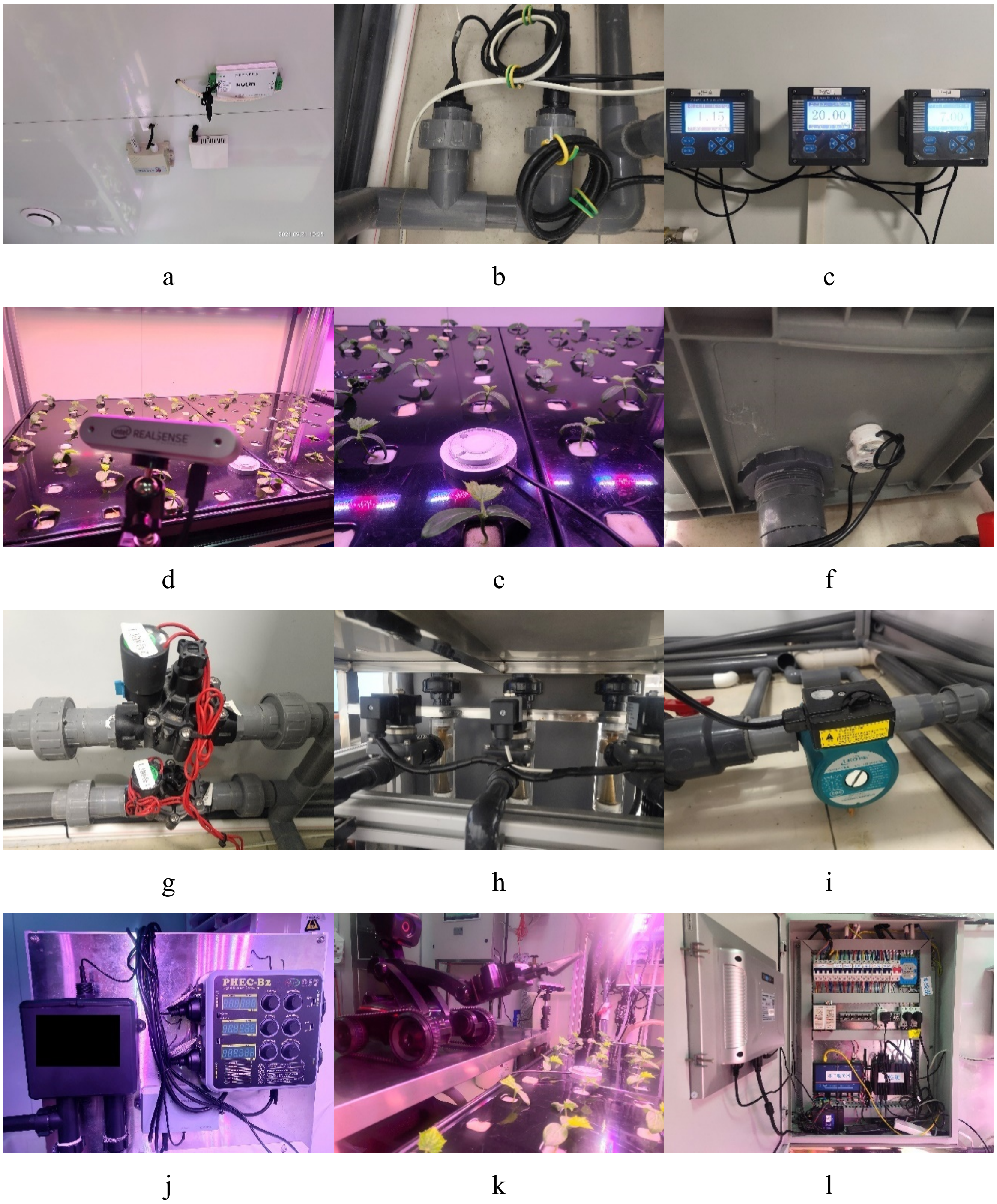


Fig. 17 Regulating means and experimental conditions of artificial light laboratory in school: (a) Integrated temperature, humidity and CO_2 sensors, (b) EC,

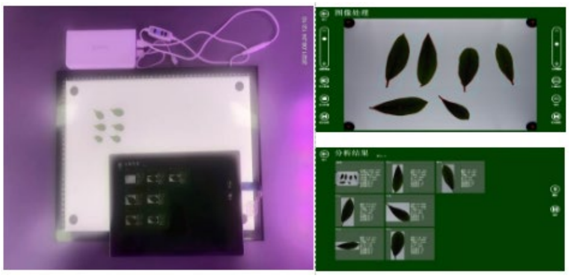
DO, PH sensor, (c) EC, DO, PH sensor, (d) RGB-D camera image sensor, (e) light quality and intensity sensors, (f) level sensor, (g) execution unit-solenoid valve, (h) execution unit-precision dispensing valve, (i) execution unit-return pump control, (j) nutrient solution automatic circulation control equipment, (k) intelligent work robot, (l) intelligent integrated front control system.

2.2.2 Experimental instruments

As shown in **Fig. 18** Intel RealSense D455 RGB-D high-definition camera, PLA-30 plant light analysis (Hangzhou Everfine Optoelectronics), Wseen LA-S panel touch-control Windows leaf area meter, temperature and humidity sensor and detection instrument, nutrient solution EC value detection instrument, PH value detection instrument, nutrient solution composition monitoring instrument, small automatic climate box, electronic scale, vernier caliper, ruler, etc.

a

b



c

d

Fig. 18 Experimental instrument: (a) PLA-30 plant illumination analysis (Hangzhou Everfine Optoelectronics), (b) Intel RealSense D455 depth camera, (c) A Wseen LA-S flat-panel touch-control leaf area meter, (d) Artificial climate chamber, EC and PH meter.

2.2.3 Development environment and software

Intel RealSense D400 series SDK2.0, Python+OpenCV+Pytorch comprehensive development environment software, device programmable interface software, simulation software, etc.

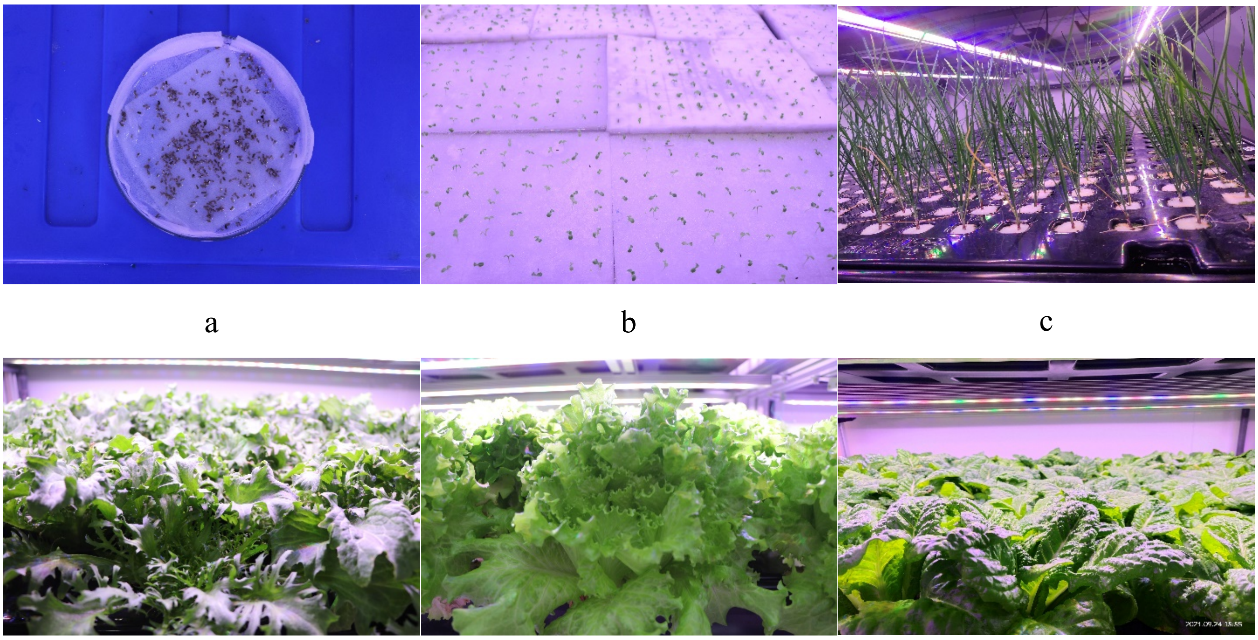
2.3 Experimental materials

2.3.1 Experimental consumables

A variety of experimental leaf vegetable and solanaceous plant seeds, plant nutrition solution, CO_2, planting cotton, clean water, etc.

2.3.2 Main experiments carried out continuously in the laboratory on a daily basis

The experimental planting and quality control of leaf vegetables are shown in **Fig. 19**.



a b c

d e f

Fig. 19 Trial planting test of leaf vegetables: (a) germination-breaking, (b) seedling production, (c) hydroponic leek in artificial light plant factory, (d) hydroponic endive in an artificial light plant factory, (e) hydroponic lettuce in an artificial light plant factory, (f) plant factory hydroponic sweet romaine lettuce.

The experiment of solanaceous fruit planting and quality control is shown in **Fig. 20**.

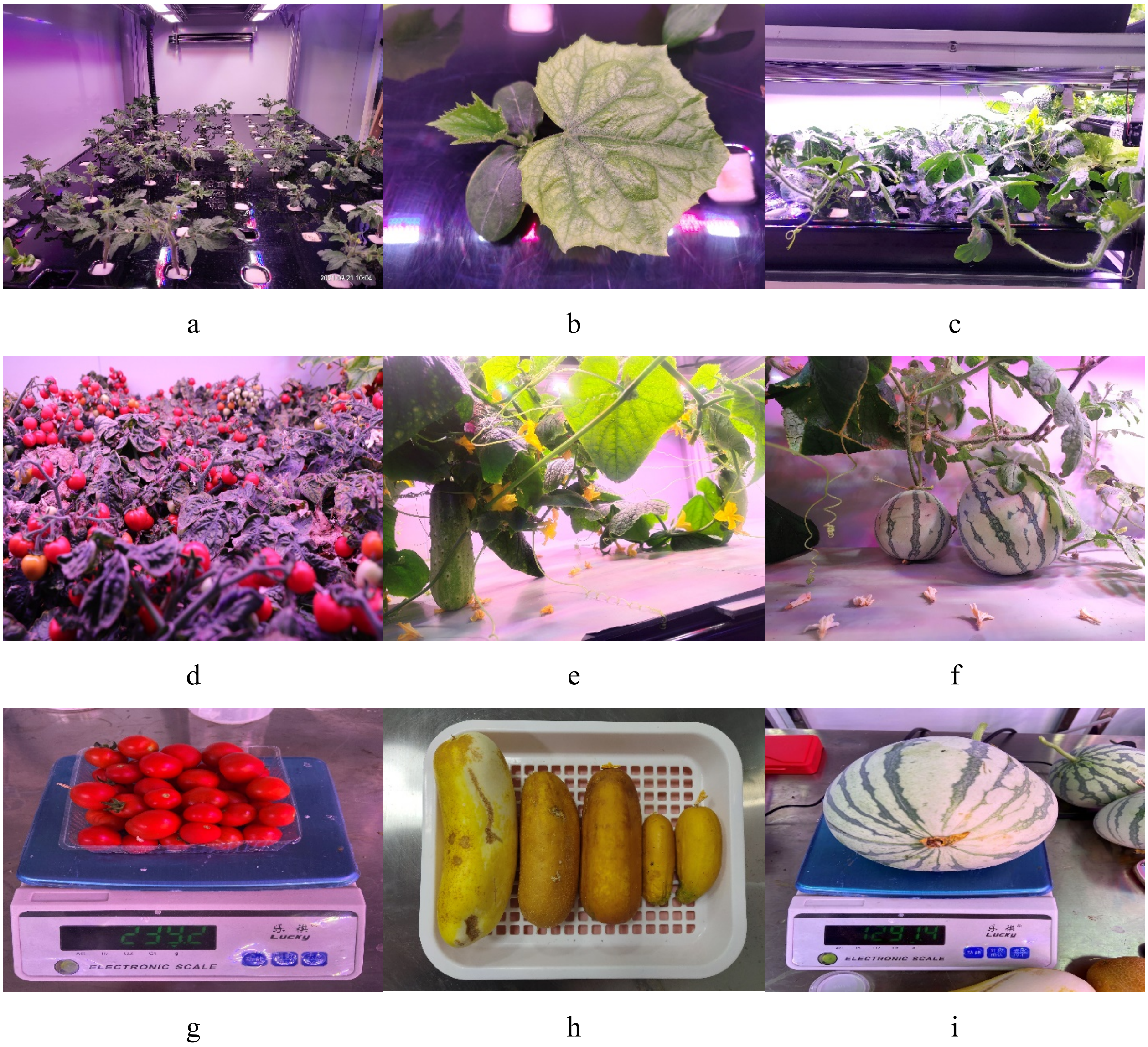


Fig. 20 Trial planting experiment of solanaceous plants in an artificial light factory: (a) hydroponic tomato seedlings in a plant factory, (b) hydroponic cucumber seedlings in a plant factory, (c) hydroponic watermelon seedlings in a plant factory, (d) hydroponic tomato in a plant factory, (e) hydroponic cucumber in a plant factory, (f) hydroponic watermelon seedlings in a plant factory, (g) harvested tomatoes reserved for planting, (h) harvested cucumber reserved for planting, (i) harvested watermelons.

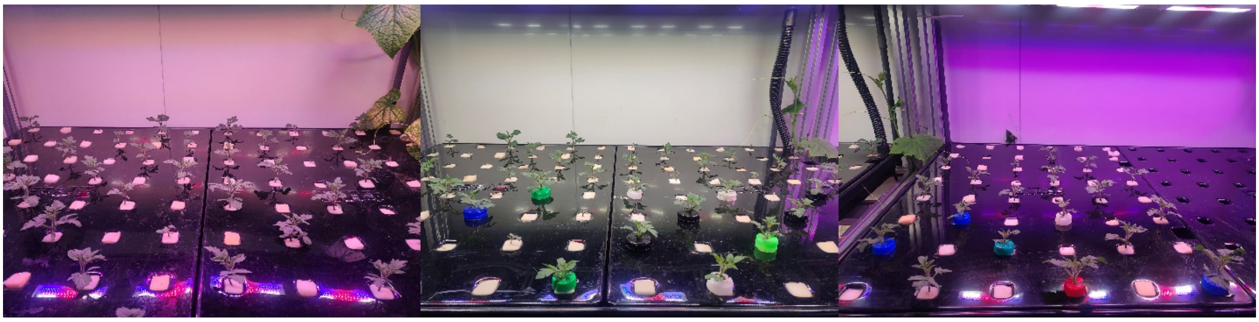
The crop growth monitoring experiment based on computer vision and RGB-D camera is shown in **Fig. 21**.

a b c

Fig. 21 Crop growth monitoring experiments: (a) RGB-D collection experiment site, (b) collected RGB images, (c) collected depth images.

The grouping experiments of intelligent environmental regulation and quality improvement of plant products were shown in **Fig. 22**.

The experiments are comprised of a multi-group grouping experiment and a comprehensive regulation experiment, for example, plant hydroponics experiments; fixed temperature and humidity, grouped to modify the light intensity, photoperiod, different spectral combinations and other environmental factors of the comparison experiments; plant growth quality control comparison experiments, etc.



a b c

Fig. 22 Comparison experiments of plant growth light formulations: (a) 3R:1B:2W weak light, (b) 1R:1B:3W weak light, (c) 1R:3B:1W weak light.

2.4 Experimental platform for plant growth monitoring and phenotypic analysis based on computer vision

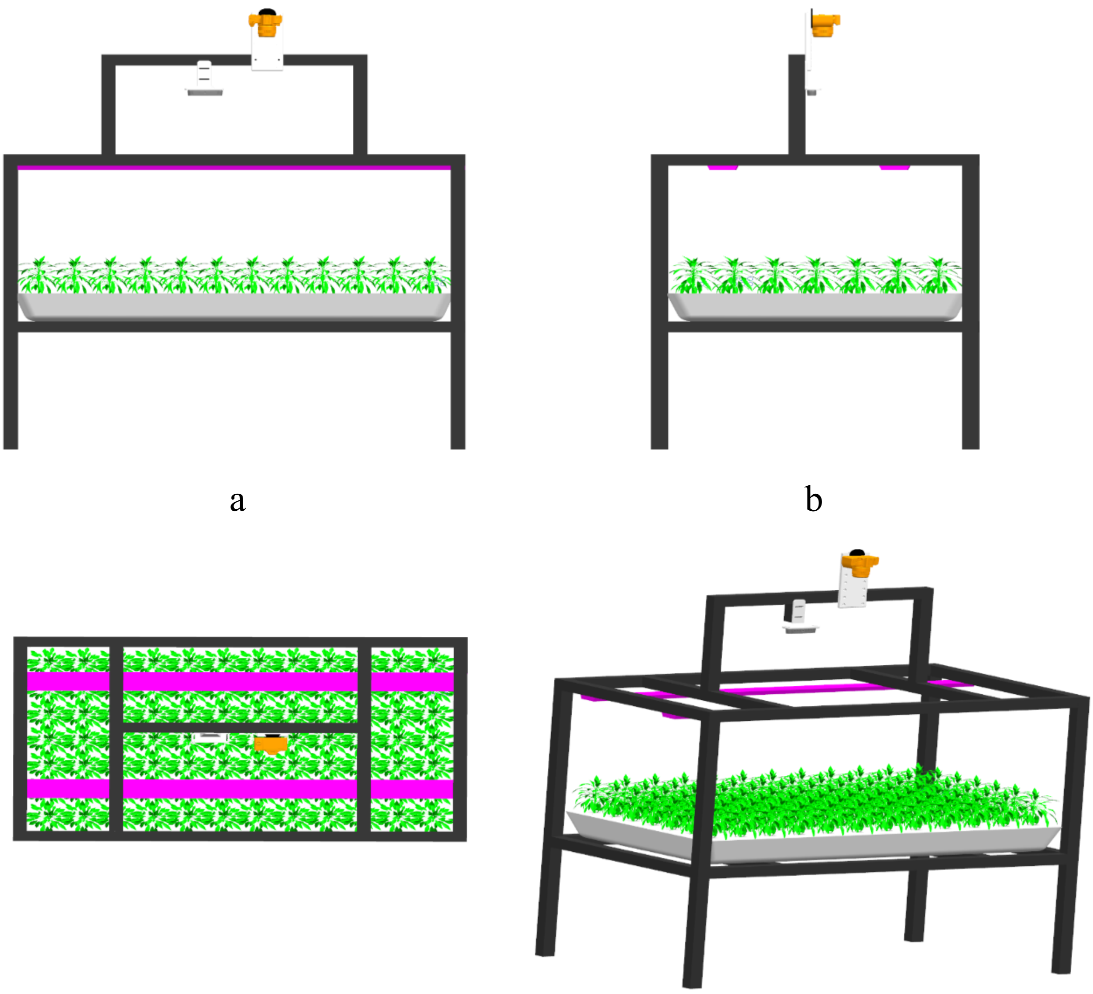
2.4.1 Introduction to the experimental platform

The experimental platform has been developed independently to cater to the research requirements of the project. It is a comprehensive platform that facilitates non-destructive monitoring of plant phenotypes, intelligent growth monitoring, and the creation of plant growth models. It is installed on the multi-layer, three-dimensional hydroponic planting frame in the artificial light plant factory laboratory of the Henan Institute of Science and Technology and consists of a computer, an RGB-D camera, a Canon 80D professional camera, light-adjustable LED lights, rails, and a gantry, among other components. The system is capable of achieving automated filming in order to gather image data pertaining to the growth of plants.

The experimental platform was utilized to conduct the studies presented in Sections 3.1 and 3.2 of this doctoral dissertation.

2.4.2 Platform structure and design

The structure and design diagram of the experimental platform are shown in **Fig. 23**.



a b c d

Fig. 23 Structure and design of the experimental platform for plant growth monitoring and phenotype analysis based on computer vision. (a) front view, (b) lateral view, (c) vertical view, (d) stereoscopic perspective view.

During the continuous research process, the experimental platform has been upgraded and improved multiple times, the structure and design diagram of the improved experimental platform are shown in **Fig. 24**.

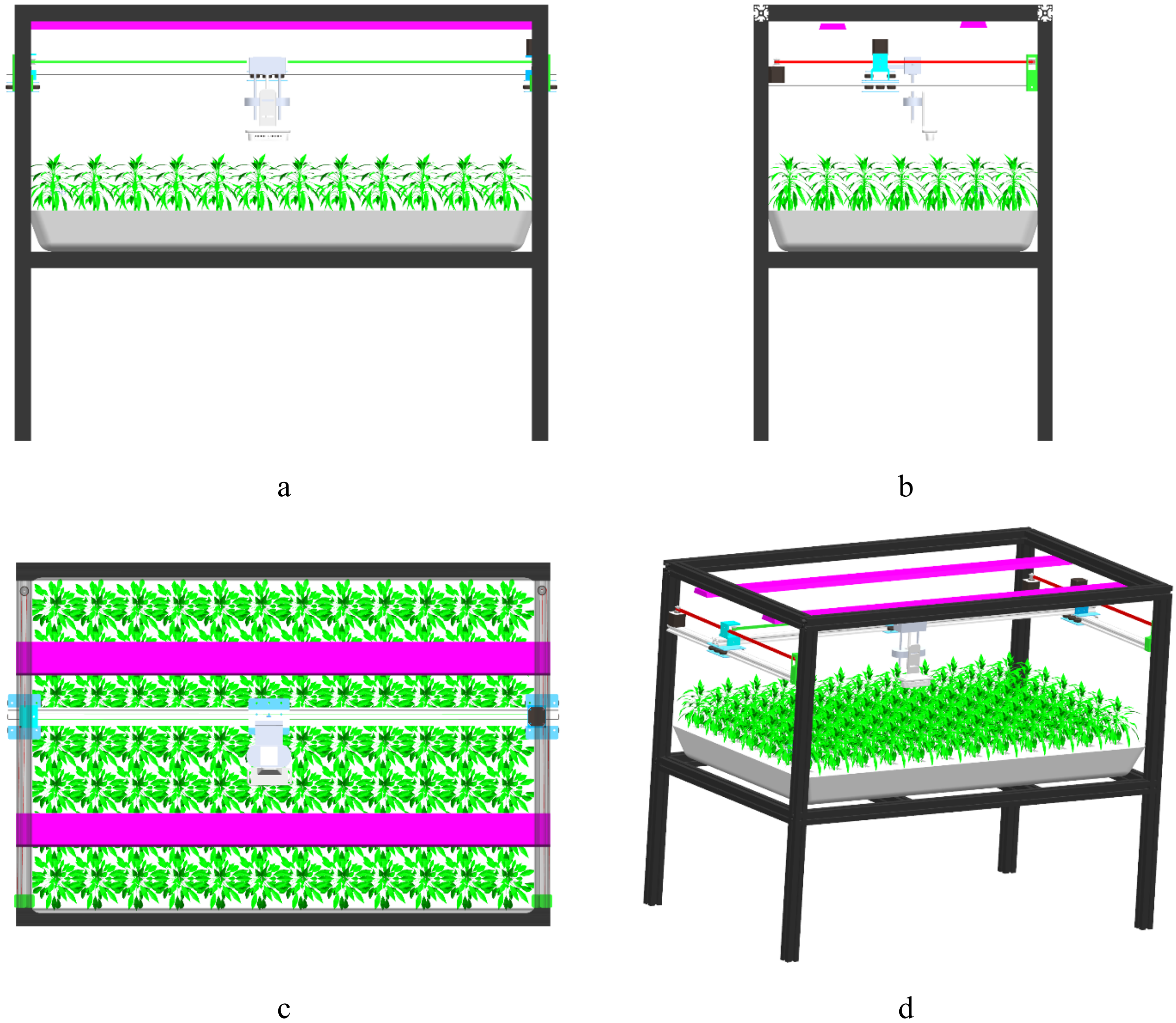
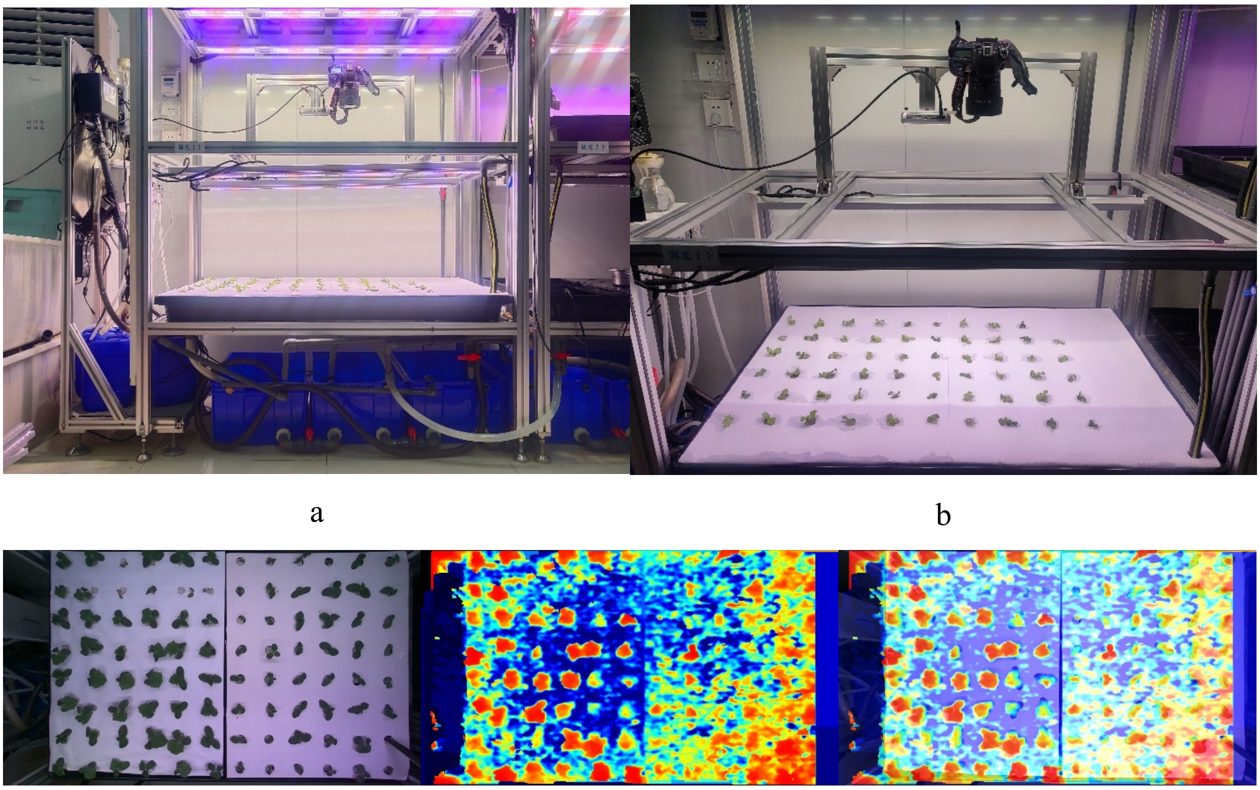


Fig. 24 Structure and design of the improved experimental platform for screening nutrient solution of hydroponic plants. (a) front view, (b) lateral view, (c) vertical view, (d) stereoscopic perspective view.

2.4.3 Work scenario

Fig. 25 shows the real working scene of the platform in the artificial light plant factory laboratory.



a b

c d e

Fig. 25 The real working scene of the experimental platform for plant growth monitoring and phenotype analysis based on computer vision in the artificial light plant factory laboratory. (a) Panorama of the experimental platform, (b) Overview of experimental platform, (c) Seedling RGB image, (d) Seedling depth image, (e) Mixed image of seedling RGB and depth.

2.5 Experimental platform for screening nutrient solution of hydroponic plants

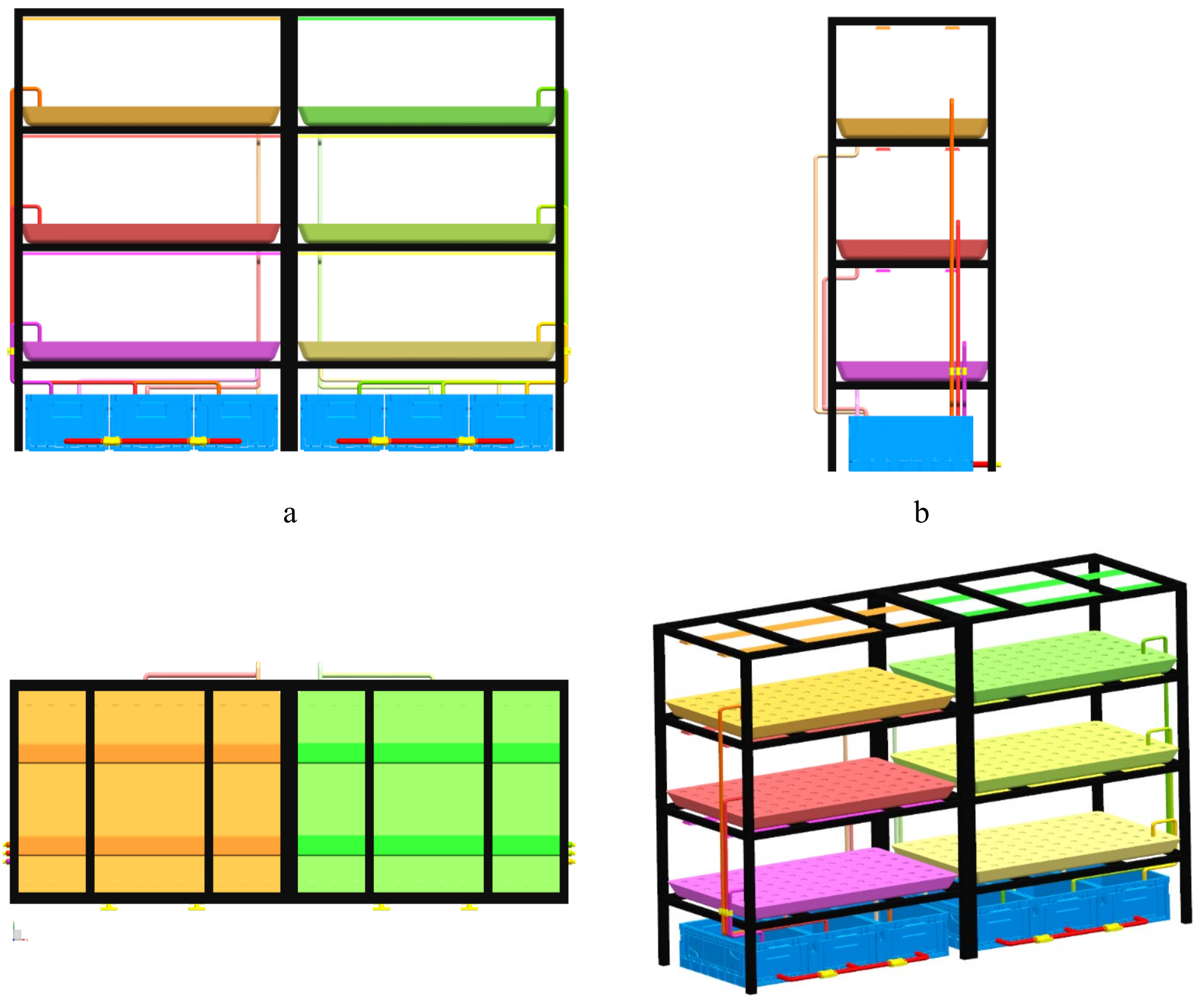
2.5.1 Introduction to the experimental platform

Plants exhibit varying requirements for light, nutrient solution, environmental temperature, and humidity during different stages of growth. The author independently created and developed the hydroponic plant nutrient solution screening test platform to satisfy the research and experimental requirements. The platform is a number of modifications to the two three-layer, three-dimensional hydroponic planting racks in the artificial light plant factory laboratory, with six additional water storage tanks and six submersible pumps, corresponding to the manual dispensing and refilling of each layer of planting tanks in the planting racks with independent circulation. The LED plant lights on each layer can be controlled independently in terms of light quality, light intensity, and photoperiod. Additionally, six sets of comparative tests can be conducted to evaluate plant growth under the combined influence of light, nutrient solution, and both light and nutrient solution.

The experimental platform was utilized to conduct the studies presented in Sections 4.1 and 4.2 of this doctoral dissertation.

2.5.2 Platform composition and structure

The structure and design diagram of the experimental platform are shown in **Fig. 26**.



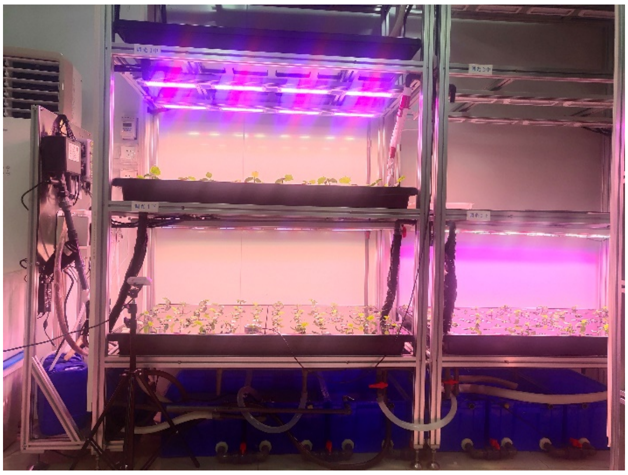
a b

c d

Fig. 26 Structure and design of the experimental platform for screening nutrient solution of hydroponic plants. (a) front view, (b) lateral view, (c) vertical view, (d) stereoscopic perspective view.

2.5.3 Work scenario

Fig. 27 shows the real working scene of the experimental platform for screening nutrient solution of hydroponic plants.



a

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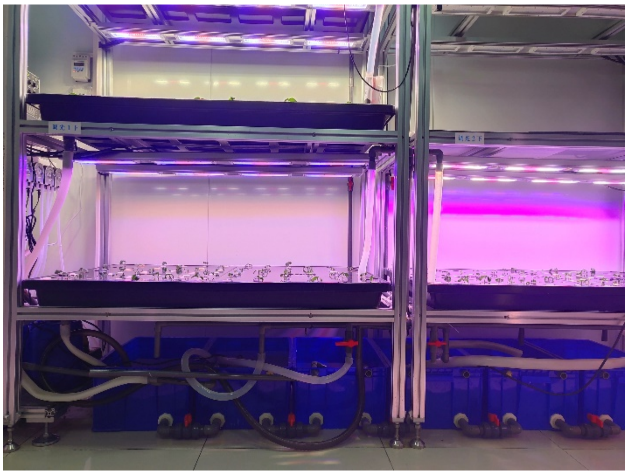
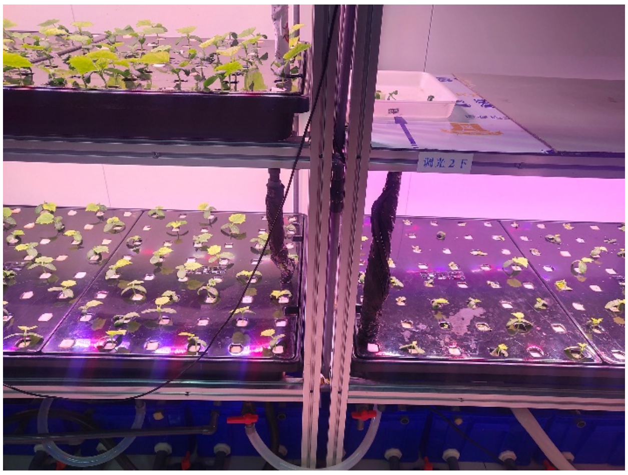


c



d

Fig. 27 The real working scene of the real working scene of the experimental platform for screening nutrient solution of hydroponic plants in the artificial light plant factory laboratory. (a) Panorama of the experimental platform, (b) Integrated irrigation machine for water and fertilizer, (c) 6 sets of nutrient solution independent circulation design, (d) Experiment on screening nutrient solution for hydroponic cucumber cultivation.

2.6 Experimental platform for precise regulation and control of environmental multi-factor coupling

2.6.1 Introduction to the experimental platform

With the assistance of the university, the author designed and constructed an artificial light plant factory laboratory to facilitate the comprehensive research on the multi-factor coupling and precise regulation of plant growth environments. The laboratory comprises a preparation room, operation room, and cultivation room, allowing a wide range of experimental research activities, including monitoring of the plant growth environment, non-destructive monitoring of multi-parameter growth states, integrated regulation of multi-factor coupling, planting tests, plant factory IoT tests, model verification, and system development.

The research for the doctoral dissertation was conducted in this laboratory.

2.6.2 Laboratory Design and Layout

The design and layout of artificial light plant factory laboratory for precise regulation and control of environmental multi-factor coupling are shown in **Fig. 28**.

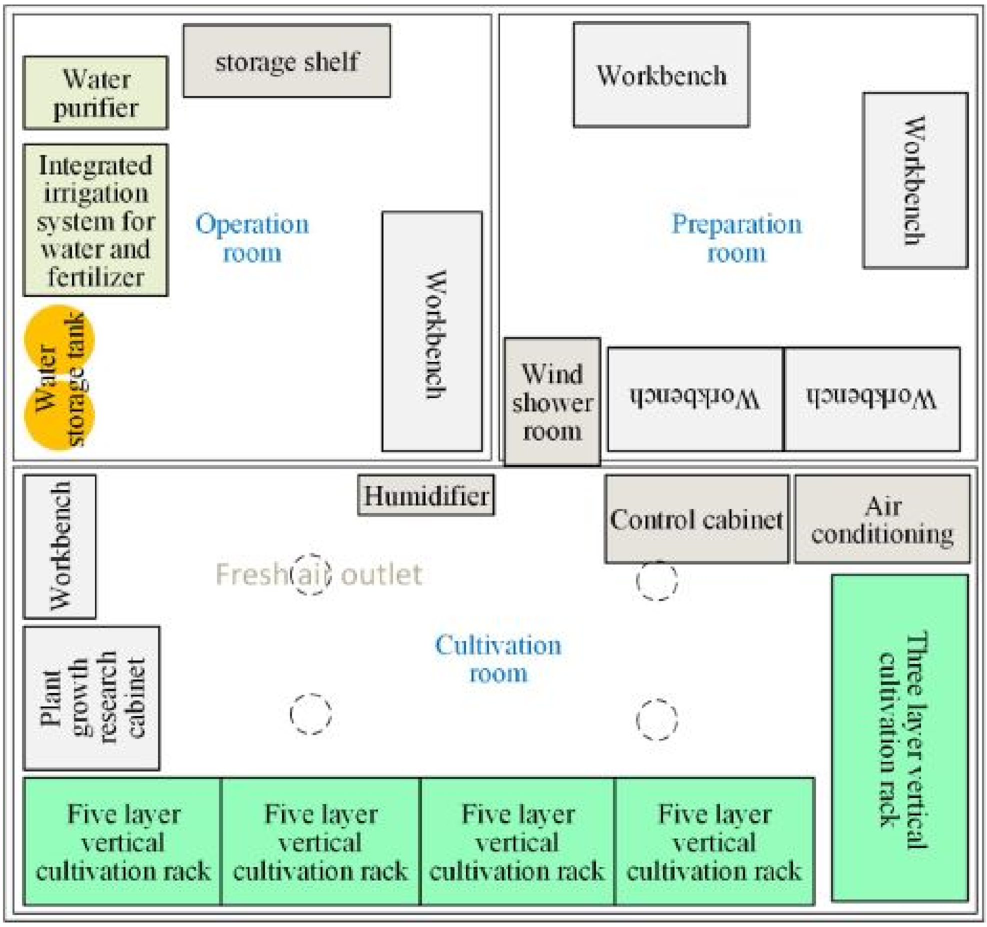


Fig. 28 Design and layout of artificial light plant factory laboratory for precise regulation and control of environmental multi-factor coupling.

2.6.3 Scientific research work scenario

The daily scientific research work scene of the artificial light plant factory laboratory for precise regulation and control of environmental multi-factor coupling is shown in **Fig. 29**.

a b c

d e f

Fig. 29 The artificial light plant factory laboratory for precise regulation and control of environmental multi-factor coupling: (a) Seeding; (b) Grow seedlings; (c) Transplantation and planting; (d) Planting management; (e) Growth observation; (f) Experiential education.

SECTION 3. BASIC RESEARCH RELATED TO BUILDING PLANT GROWTH MODEL BASED ON DEEP LEARNING

3.1 Real time detection and counting method of tomato fruit in artificial light plant factory based on yolov5

3.1.1 Deep Learning and Computer Vision in Agriculture

Artificial intelligence (AI) technology has penetrated the field of industrial and agricultural production, which has extensively promoted the rapid development of intelligence in various fields. The Plant Factory with Artificial Light (PFAL) (Kozai, 2019; Orsini, 2020; Ares, 2021) is widely regarded as the most advanced development stage of facility horticulture in the world. It is also an excellent model of productive urban agriculture that is most promising to effectively alleviate the great challenges brought to agriculture by population expansion, urbanization, extreme climate, sudden epidemic, regional production and supply imbalance, etc. The development of PFALs is inseparable from the high intelligence of equipment. Water supply and liquid supply for plant growth, light optimization and regulation, spatial environment regulation, CO_2 concentration regulation, and operation equipment robots need a high degree of automation and intelligence to achieve accurate control and reduce manual participation. Although this increases the capital investment of equipment, it will significantly reduce the amount of manual labor and labor investment cost.

The use of computer vision, deep learning and other artificial intelligence technology to achieve real-time detection, identification, counting and dynamic yield estimation of fruits and vegetables, its high accuracy, high degree of intelligence can be used to guide the production robot picking and marketing management accurately. The output estimation of fruits and vegetables in plant factories mainly depends on expert experience, which is highly subjective and has low accuracy, so it cannot be accurately used for production and marketing guidance. Picking mature fruits and vegetables also mainly depends on manual operation, which is time-consuming, laborious, high labor intensity and high cost. The trained fruit real-time detection model is implanted into the robot, the accurate position of the fruit is detected through the robot's machine vision system, and then the robot's manipulator accurately picks the fruit at the corresponding position, which will significantly reduce the damage of picking to the plant, decrease the labor cost of picking and greatly improve the picking efficiency. In order to obtain accurate dynamic yield estimation and accurate robot picking, fruit detection based on computer vision and deep learning is the most basic and essential task. Moreover, only when the fruit detection and recognition reach a certain accuracy, robot picking can surpass manual picking (Sparrow et al., 2020). Therefore, improving the accuracy of fruit detection is very important for robot picking.

Computer vision is the basic component of the real-time detection of fruits and vegetables. It is a rapidly developed technology based on target detection and image recognition algorithms and is widely used in many industries. The development of multi camera combined imaging system also makes computer vision technology meet the requirements of target accuracy and quality (Jian et al., 2014). The speed and accuracy of target detection based on computer vision provide an alternative to automated, non-destructive and cost-effective technologies to achieve increased production and quality requirements (Zhao et al., 2020). In recent years, great progress has been made in target detection and image recognition technology, which are increasingly widely used in agriculture, including the inspection and grading of fruits and vegetables. Fan et al. (2020), Gao et al. (2020), Gené-Mola et al. (2019) fused the deep learning model and computer vision technology, put forward the system method of apple fruit real-time detection, achieved high detection speed and accuracy, and realized the robot picking of apple. Sarabu et al. (2019), Nguyen et al. (2019), Tu et al. (2020), Fu et al. (2020) applied RGB-D cameras in real-time fruit detection and positioning to improve the positioning accuracy of robotic picking. Gené-Mola et al. (2020) merged instance segmentation neural networks with structure-from-motion (SfM) photography, proposed a new fruit detection and 3D location method, and the detection rate can reach 99.1% when there is less fruit occlusion. With the development of the target detection model and the wide application of picking robots, the requirements for the accuracy and processing time of non-destructive real-time fruit detection in agriculture are constantly improving.

Therefore, the research on fruit target detection using the latest deep learning network model is becoming more and more popular. Bargoti et al. (2017) generated a fruit detection model using Faster R-CNN to to increase the fruit recognition rate. Wan et al., (2019) Fu et al., (2020) Tu et al. (2020) applied the RGB-D camera to the picking robot and carried out relevant research and experiments on the Faster R-CNN target detection model. The results show that it greatly improves accuracy and can meet real-time requirements. However, the detection speed of the Faster R-CNN is still not fast enough, so it is not easy to be widely used in faster robot picking. Based on their research on Faster R-CNN, Redmon et al. (2016) invented the YOLO target detection model by computing target detection as a regression task, which greatly improves the speed of target detection without reducing the detection accuracy. The YOLO model has been continuously researched and rapidly developed in just a few years and has evolved from YOLOv1 to the latest YOLOv5. The YOLOv5 version includes four more versions with different depths and widths, YOLOv5S, YOLOv5M, YOLOv5L, and YOLOv5X, respectively, to meet application scenarios with different accuracy and real-time requirements (Redmon et al., 2017; Redmon et al., 2018; Alexey et al., 2020; Zhao et al., 2021). Luo et al. (2020) proposed an improved yolov3 pine cone detection method based on the Boundary Equilibrium Generative Adversarial Networks (BEGAN) and YOLOv3 model, for yield estimation of Korean pine forest. Kuznetsova et al. (2020) developed an apple inspection machine vision system for harvesting robots based on the YOLOv3 model. The system uses pre-processing and post-processing technology, with error rates and unrecognized rates of 7.8% and 9.2%, respectively, and an average detection time of 19ms, and it can also be used for an orange harvesting robot. Gao et al. (2021) used a deep learning development framework of Keras and Tensorflow to construct the YOLOv3 model for detecting and recognizing banana stems and banana bunches, with an average accuracy of 88.45% and 97.96%, respectively. Wang et al. (2021) adjusted the prediction scale and reduced the network layer based on YOLOv3, clustered the bounding boxes in the labeled data to determine the priori box size suitable for Litchi detection using the K-means algorithm, proposed an improved YOLOv3-Litchi model to detect densely distributed

Litchi fruits in large visual scenes, then trained and tested the model. The results show that the F1 value and average detection time are much better than YOLOv2, YOLOv3 and Faster R-CNN models. Liu et al., (2020) Lawal (2021) made various improvements to the YOLOv3 model, and put forward the corresponding improved YOLOv3 for the tomato fruit detection model that improved the detection speed of dense, blocked, and overlapping tomato fruits under different lighting conditions and enhanced the adaptability of harvesting robots for picking tomatoes. Chen et al. (2020) used Kinect V2 camera to collect RGB images of citrus trees and then used a canopy algorithm and K-means++ algorithm to automatically select the frame number and frame size of the previous frame from the captured RGB images, and proposed an improved yolov4 network structure. The model improves the detection ability of small citrus under complex background, and can be applied to citrus automatic harvesting robots and citrus yield estimation. Yan et al. (2021) improved the neck network, backbone network, and initial anchor frame size of the YOLOv5s model and proposed a lightweight apple target detection method for picking robots. The recall, accuracy, mAP, F1 and detection speed for apple detection and recognition are significantly improved over YOLOv3 and YOLOv4 models. Wang et al. (2022) constructed an image acquisition system based on fruit posture adjustment equipment, and studied the real-time detection and recognition of apple stem/calyx based on the YOLOv5 algorithm used for automatic loading and packaging of fruits after harvesting. Although the object detection based on YOLO can be applied in different directions such as robotic picking, grading and sorting, and yield estimation, compared with the research of applied YOLO to other fields, applying YOLOv5 model to the PFALs is less.

Dwarf eggplant fruit vegetable varieties are most suitable for soilless cultivation on the planting layer shelves, and will become the preferred species for PFALs (Kozai, 2013a; Yang et al., 2018; He, 2018; Kozai et al., 2019). Fruit real-time detection, counting and yield estimation are the important basis for mastering the dynamic production information of the plant factory, carrying out planting planning, formulating marketing strategies, and providing production data for the information service system that are also the key technologies for the plant factory to realize robot harvesting, intelligent grading sorting and automatic packaging (Häni and Isler, 2019; Bellocchio et al, 2019; Mekhalfi et al, 2020). Real-time statistics and prediction of tomato fruit temporal yield information and corresponding production control to achieve accurate response to supply orders are vital to solve the current problems of large fluctuations in tomato production capacity and discontinuous production processes (Jiang et al, 2019; Ohashi and Goto, 2020). Visual information acquisition of tomato fruits is crucial to support intelligent yield estimation. However, tomato plants in plant factories are overgrown and disorganized, and their stems, leaves, and fruits grow densely and overlap, making fruit image recognition an important factor limiting the accurate estimation of tomato yield. Moreover, the smaller fruit size of dwarf tomatoes in plant factories, complex light environment, and dense branches and leaves make accurate detection and identification more difficult. To this end, we planted and gathered a large number of tomato pictures in the PFAL laboratory of our university, in which the visible tomato fruits were precisely labeled to construct a standard dataset of Micro-Tom tomatoes for plant factories. In addition, the standard data set is extended through the data enhancement algorithm to construct the Micro-Tom tomatoes extended dataset.

The remainder of this paper is composed as follows. Section 2 describes the data acquisition, data annotation, and construction methods of Micro-Tom specific datasets for dwarf tomatoes in plant factories. Section 3 discusses the data enhancement methods and the improved YOLOv5s model. Section 4 provides an analysis of the experimental results. Section 5 summarizes and draws conclusions.

3.1.2 Materials and datasets

The experimental site of this study is the PFAL laboratory of our university, and the subjects of the study and detection are Micro-Tom dwarf tomatoes of hydroponic in PFAL and greenhouse potted. In the experiment, a total of 2023 RGB tomato images were obtained from multiple capture devices, including 1444 from PFAL-hydroponics, 503 from greenhouse-potted, and 76 background images without tomato (about 3.76% of the total dataset). A total of 40,500 tomato fruits were labeled using the Labelimg software, through a rectangular box, a combination of manual and automatic annotation methods, and the corresponding XML annotation files were generated and saved. First, a Micro-Tom dwarf tomato standard dataset was constructed with the original image files. Then, 40,460 images were acquired by geometric transformation and data enhancement algorithms to construct an extended dataset of PFAL Micro-Tom dwarf tomatoes.

3.1.2.1. Experimental materials

The experimental site is the PFAL laboratory of Henan Institute of Science and Technology (see **Fig. 30**. The research object is Micro-Tom dwarf tomato. The tomato fruit is tiny and the ripe tomatoes resemble cherries, so we call them Cherry-Tomato. Plant cultivation forms included PFAL-Shelvies-Hydroponics and Greenhouse-Potted. The filming equipment included Nikon D7500, iPad Air, Huawei M6 tablet, iPhone 13 Pro, vivo NEX, and so on. Data labeling software is the Labelimg v1.8.1. Hardware and software platforms for model training include Lenovo tower server ThinkSystem ST558 and Windows Server v2016 operating system, the hardware configuration is Intel Xeon 4310 processor, 64GB RAM, 1 Samsung pm9a1 1TB solid-state drive, 3 4TB15K high-speed hard drives, and ThinkSystem NVIDIA Quadro RTX 4000 8GB PCIe active graphics card. Test materials include Intel RealSense D455 camera, ordinary desktop or laptop computer, iPhone 13 Pro, Android smartphone, etc.

(a) (b)

Fig. 30 Experimental site, a. the PFAL laboratory of our school, b. hydroponic Micro-Tom tomatoes in our PFAL laboratory.

3.1.2.2. Image acquisition

From August 2020 to December 2021, we conducted hydroponic and potted Micro-Tom dwarf tomato experiments in 8 batches in the PFAL laboratory and greenhouse of our university, and took photographs of Micro-Tom tomato fruits at different growth stages with a minimum resolution of 3872*2592 pixels and a maximum resolution of 6000* 4000 pixels. In order to obtain better training models and higher robustness, robustness and generality of training models, we tried to acquire tomato images with different growth environments, growth periods and poses.

3.1.2.3. Data annotations

The fineness of data annotation directly affects the performance and effectiveness of deep learning model training. Moreover, Micro-Tom dwarf tomatoes have tiny fruits, dense branches and leaves, severe overlapping occlusions, and complex light environments in the PFAL where they grow. These factors overlap and affect each other posing great challenges for automatic detection, recognition and counting tomatoes. In the process of labeling tomatoes, we labeled all the tomatoes that the naked eye in the picture can identify and determine the size of the labeling box by exactly surrounding the exposed tomato. The software used for labeling was the Labelimg software (https://github.com/tzutalin/labelImg 2022) which we have improved, the VOC2007 was chosen as the data annotation standard, and the results were saved in the corresponding XML file format, as shown in **Fig. 31**. We also wrote a format conversion program that can flexibly convert XML format files to TXT format files needed by other YOLOv5 models. In order to solve the massive workload of accurate manual labeling, we have developed automatic labeling software, which adopts the method of automatic labeling plus manual correction and supplement labeling. The specific process is:

- first carry out a small amount of annotation,
- carry out model training, then
- carry out Micro-Tom fruit pre-detection,
- carry out automatic annotation and generate corresponding annotation files, then manually correct and supplement annotations,
- carry out model training again, and

- repeat the above process.

This cycle and repeated iteration greatly save the workload of manual annotation and improve the accuracy and efficiency of annotation.

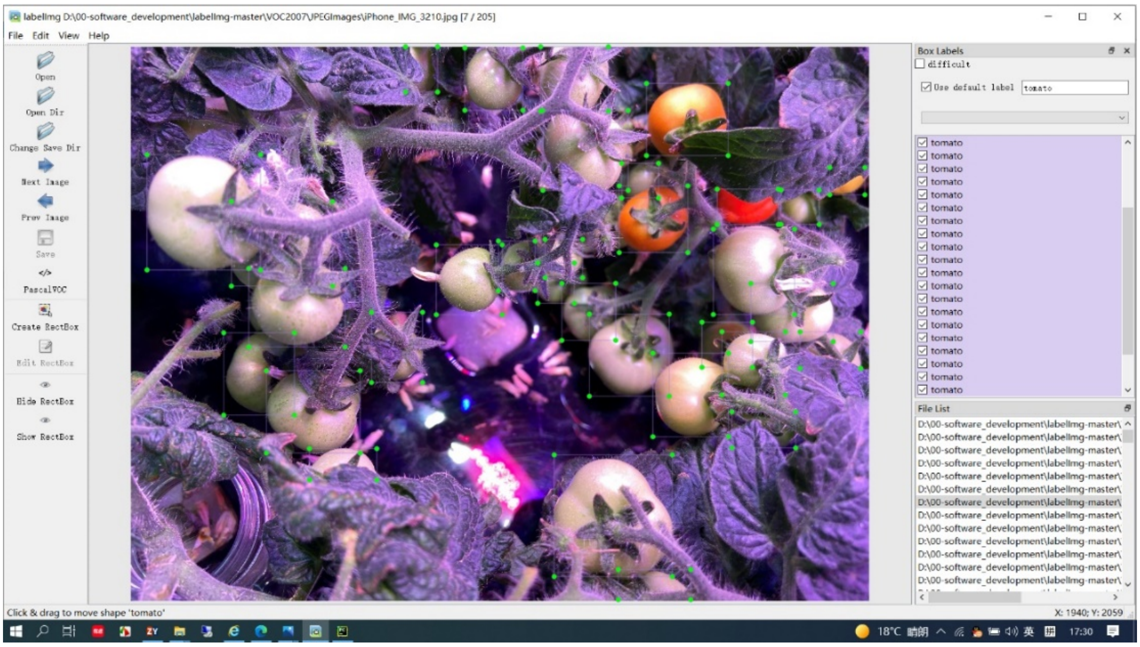


Fig. 31 The Labelimg software and labeling example, using the VOC2007 data standard.

3.1.2.4. Image data augmentation

Data enhancement is the most effective means to solve data sparsity and expand the data set. Fewer training images may lead to overfitting or non-convergence of depth learning algorithm, and using data augmentation to increase the number of training images may be an effective method to solve this problem (Huang et al., 2020). The translation, deformation and reflection of the image (Yann et al., 1998; Simard et al., 2003; Krizhevsky et al., 2017) have significantly improved image recognition performance (Zhang et al., 2020). In this study, different data augmentation methods are used in the process of datasets construction and model training. This study mainly uses 20 image data augmentation methods, such as flipping, rotation, RGB color transformation, hue transformation in HLS domain, saturation transformation, brightness transformation, Gaussian noise and Gaussian blur, which expand the datasets and improve the effect of model training and the generalization ability of target detection model, examples of image data augmentation is shown in **Fig. 32**.

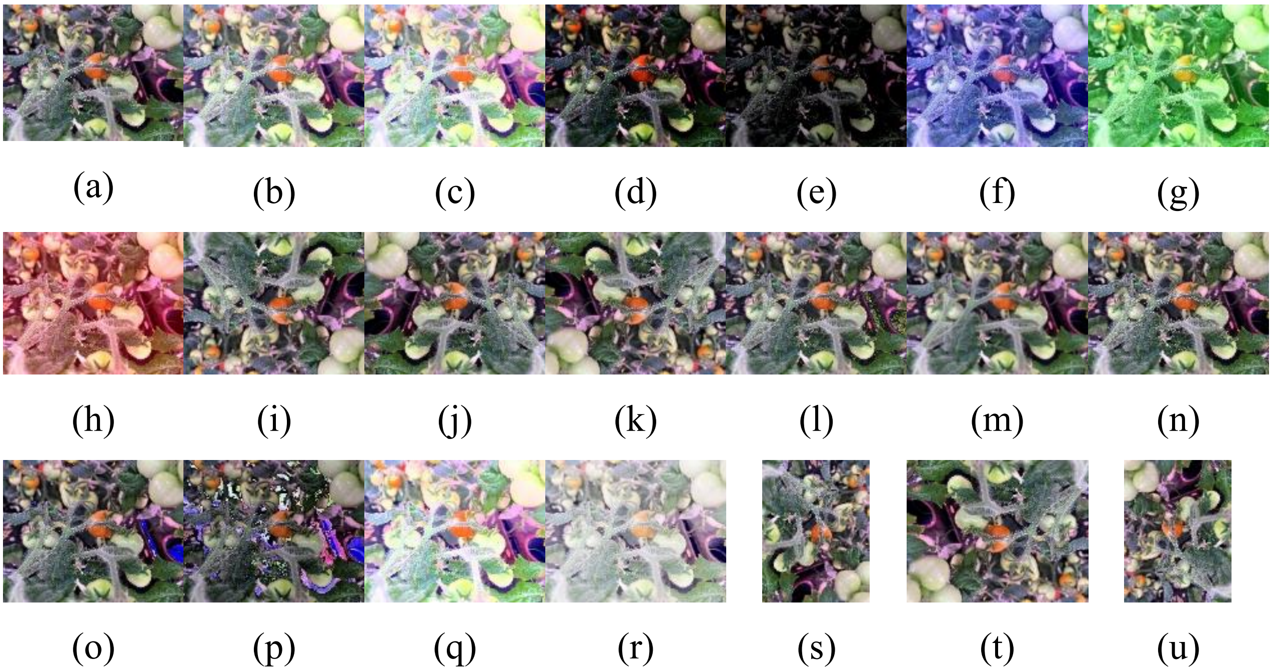


Fig. 32 The image enhancement examples, a. original image, b. brightened overall 1, c. brightened overall 2, d. darkened overall 1, e. darkened overall 2, f. blue enhanced, g. green enhanced, h. red enhanced, i. horizontal flipped, j. vertical flipped, k. vertical and horizontal flipped, l. Gaussian noise enhanced, m. Gaussian blur enhanced, n. sharpening enhanced, o. hue enhanced 1, p. hue enhanced 2, q. saturation enhanced, r. brightness enhanced, s. rotated 90°, t. rotated 180°, u. rotated 270°.

In the model training, the Mosaic data enhancement algorithm was added to the image data at the input side of the model. The Mosaic data enhancement used four images, which are spliced together in the way of random scaling, random clipping, and random arrangement, and the results are shown in **Fig. 33**. After this operation, it makes the originally larger targets become smaller after scaling down roughly twice, thus reducing the over-response to large objects and enhancing the ability of the model to detect small targets, which solves the problem of small target detection in the datasets to a certain extent and increases the robustness of the network. And it also reduces the use of GPU, making it possible to get good training results even with one GPU.

Fig. 33 An example of Mosaic data augmentation on the training set during model training. This algorithm used four images, which are spliced together in the way of random scaling, random clipping, and random arrangement.

3.1.2.5. Micro-Tom datasets construction

In this study, two Micro-Tom datasets, the standard and the expanding, were constructed. The Micro-Tom standard dataset is composed of captured original image files and corresponding annotation files in XML format that there are 2023 RGB image files in total, and each image file corresponds to one XML annotation file, which includes 1444 images taken from hydroponic culture in the PFAL laboratory, 503 images taken from pot planting in greenhouse and 76 background images without tomatoes. The data set is divided into training dataset, validation dataset and test dataset by the program. The Micro-Tom expanding datasets consist of 42483 image files (2023 original image files and 40460 enhanced image files) and corresponding XML annotation files. Similarly, it is also divided into training data set, verification data set and test data set by the program, and see **Table 2** for datasets division and composition.

Table 2 Micro-Tom datasets Division and Composition.

Dataset Type	Number of original image files	Number of enhanced image files	Number of tomatoes labeled	Number of validation dataset image files	Number of test dataset image files
Micro-Tom standard dataset	2023	0	40416	1821	202
Micro-Tom expanding dataset	2023	42483	848736	38235	4248

3.1.3 Methods and models

The YOLO series of deep learning network models is a very popular end-to-end target detection model in the world, which has been widely used in various fields. YOLOv5 (Liu et al., 2020) is the latest version of the current YOLO series of network models. In order to satisfy different real-time requirements, YOLOv5 has four versions, namely, YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x. Their kernel size, complexity, and the number of super parameters increase in turn, and the network depth and width gradually deepen and widen. As a result, they have high detection accuracy for objects of different sizes. Their reasoning speed is fast, and the fastest detection speed can reach 140 frames/s; their weight file is approximately 90% smaller than YOLOv4. YOLOv5 network has the advantages of high detection accuracy, lightweight, and fast detection speed (Ultralytics, 2021), and it is suitable for deployment to embedded terminals to complete real-time detection tasks. This research takes the YOLOv5s network as the benchmark model to improve, and puts forward YOLOv5s_ MT model, which is verified, and compared with the real-time detection performance of YOLOv3, YOLOv4 and YOLOv5 series.

3.1.3.1 Improved yolov5s network model

The framework of the YOLOv5s network model is shown in **Fig. 34** and **Fig. 35**, which is composed of four main modules: input side, backbone network, neck network and detection network. The input side preprocesses the input image that uniformly scales the image size to the input size of the network, such as 608 pixels * 608 pixels, performs normalization and other operations. The improved YOLOv5 network model utilizes Mosaic data enhancement operation in the network training phase to improve the training speed of the model and the prediction accuracy of the network and also proposes an adaptive anchor box calculation with an adaptive image scaling method. The backbone network generally consists of a classifier network used to extract some generic features of the detection target. YOLOv5 uses the CSPDarknet53 structure and the Focus structure as the baseline network to aggregate and form a convolutional neural network of image features at different image fine-grained. The neck network is located between the backbone and head network, consists of a series of network layers that mix and merge image features and transmit the image features to the prediction layer. The improved YOLOv5s mainly use SPP and FPN+PANET modules to improve the diversity and robustness of features further. The detection network, namely the head, predicts the image features, generally includes a classification branch and a regression branch, generates the boundary box and prediction category, and outputs the result of target detection.

The Focus component, which concatenates multiple slice results and feeds them into the CBL module, as shown in **Fig. 35a**. The CBL module consists of a convolution layer network, a normalization operation, and a Leaky_relu activation function, as shown in **Fig. 35b**. The Res_unit module, which draws lessons from the residual structure of the ResNet network, is used to build a deep network, where CBL is a sub-module of the Res_unit module, as shown in **Fig. 35c**. The CSP1_X module, which draws lessons from the CSPNet network structure, consists of CBL modules, x Res_unit modules, convolutional layers, Concate, Batch Normalization, Leaky_Relu and CBL modules, as shown in **Fig. 35d**. The CSP2_X module, which draws lessons from the CSPNet network structure, consists of 2*x CBL modules, convolutional layers, Concate, Batch Normalization, Leaky_Relu module and CBL modules, as shown in **Fig. 35e**. The SPP component used 1×1, 5×5, 9×9 and 13×13 maximum pooling for multi-scale feature fusion, as shown in **Fig. 35f**.

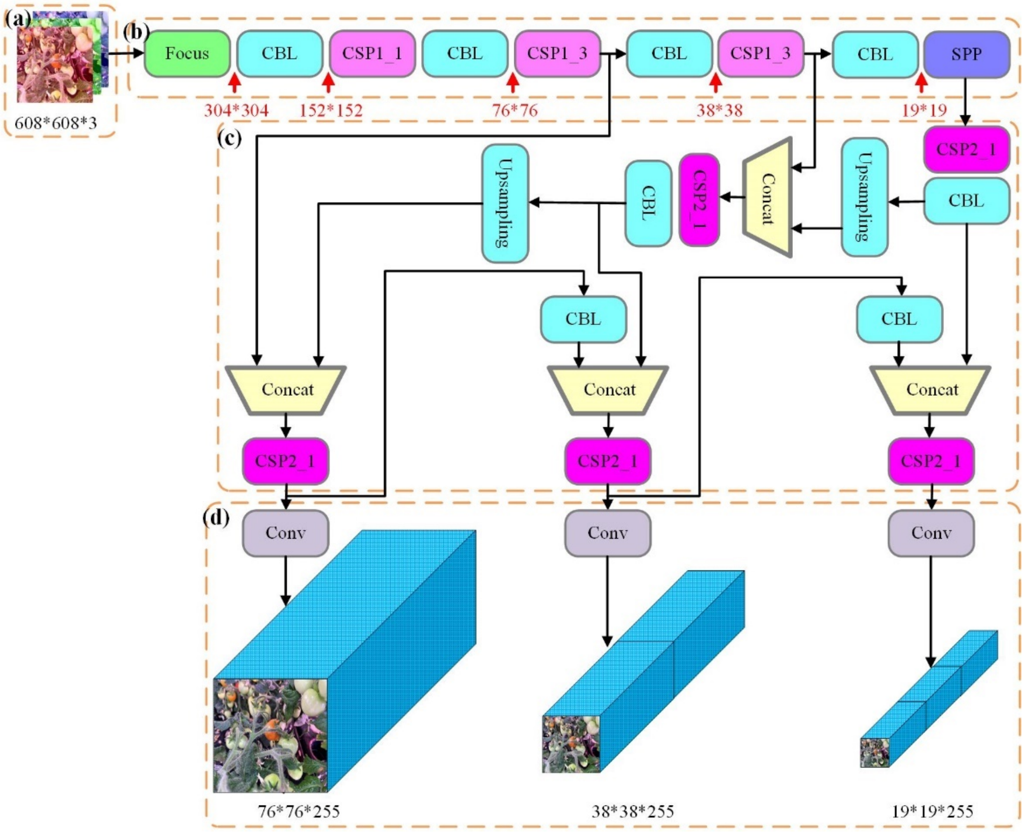


Fig. 34 Improved YOLOv5s network architecture, (a) Input side, (b) Backbone network, (c) neck network, and (d) detection network, i.e. head.

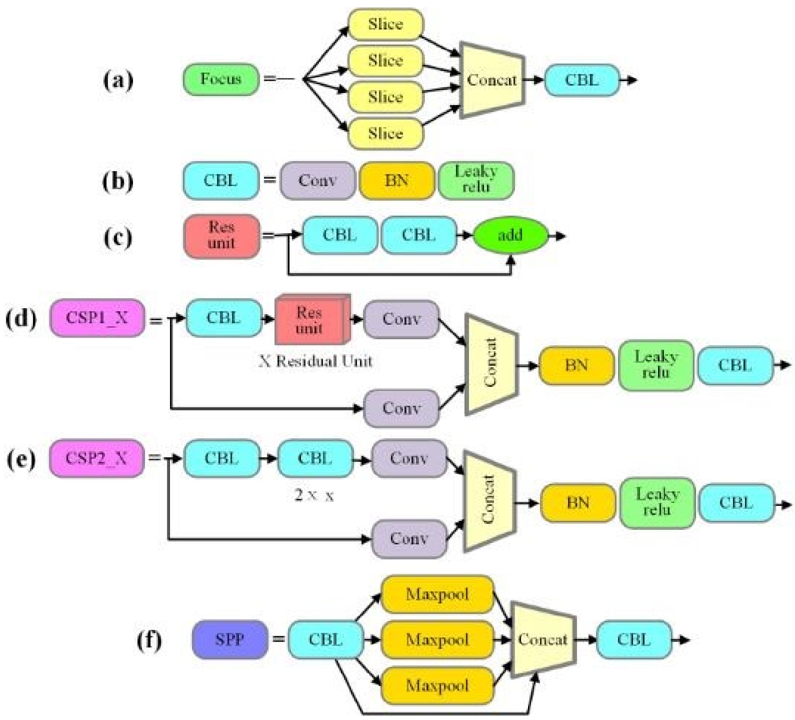


Fig. 35 Improved YOLOv5s components, (a) the focus component structure, (b) the CBL module, (c) the Res_unit module, (d) the CSP1_X module, (e) the CSP2_X module, (f) The SPP component.

3.1.3.2 YOLOv5s_MT improvements to YOLOv5s base network

In the backbone network of the YOLOv5s model, the feature information possessed by small targets decreases or disappears with the convolution operation, which increases the difficulty of detecting small target objects. To address this problem, this paper simplifies the feature extraction layer in the backbone network by changing the number of modules of BottleneckCSP in the original backbone network from (×3, ×9, ×9, ×3) to (×2, ×6, ×6, ×2) to extract more shallow feature information. In order to solve the problem that too many convolution kernels make the amount of parameters larger, the convolution layer on the branch of the original module is removed and the input feature map of the BottleneckCSP module is directly connected to the output feature map of another branch, effectively reducing the number of parameters in the module. The improved BottleneckCSP module is called BCSP_1, and its structure is shown in **Fig. 36**.

Fig. 36 BCSP_1 structure.

3.1.3.3 YOLOv5s_MT improvements to YOLOv5s base network

For the input image, the fruit of Micro-Tom tomato is small, the branches and leaves are lush, and the background occupies a large area of image. When performing the convolution operation, the iterative accumulation of the background will form a large amount of redundant information, which will overwhelm part of the target, resulting in a low detection accuracy. In order to highlight the target features, accurately locate and identify small tomatoes, and improve the detection accuracy, this paper adds a Cooperative Attention mechanism (Hao et al., 2020; Li et al., 2021) after the SPP structure of the backbone feature extraction network that embeds the location information into the channel attention to capture not only the cross-channel information but also the direction and location-aware information, so that the model can more accurately locate and identify the target of interest, and its structure is shown in **Fig. 37**.

CA encodes channel relationships and long-term dependencies with precise location information. First, given the input X, the global average pooling is used to decompose and encode along wth the horizontal and vertical directions, respectively, to obtain two one-dimensional direction-aware feature maps to realize the embedding of coordinate information. Then, the extracted feature information is stitched together. Next, the information is transformed using a 1×1 convolutional transform function, which in turn yields an intermediate feature map. It is decomposed into two separate tensors along the spatial dimension, and then transformed into a tensor with the same number of channels using two convolutions. Finally, the output results are expanded and used as the attentional weight assignment values, respectively, to generate the coordinate information feature map.

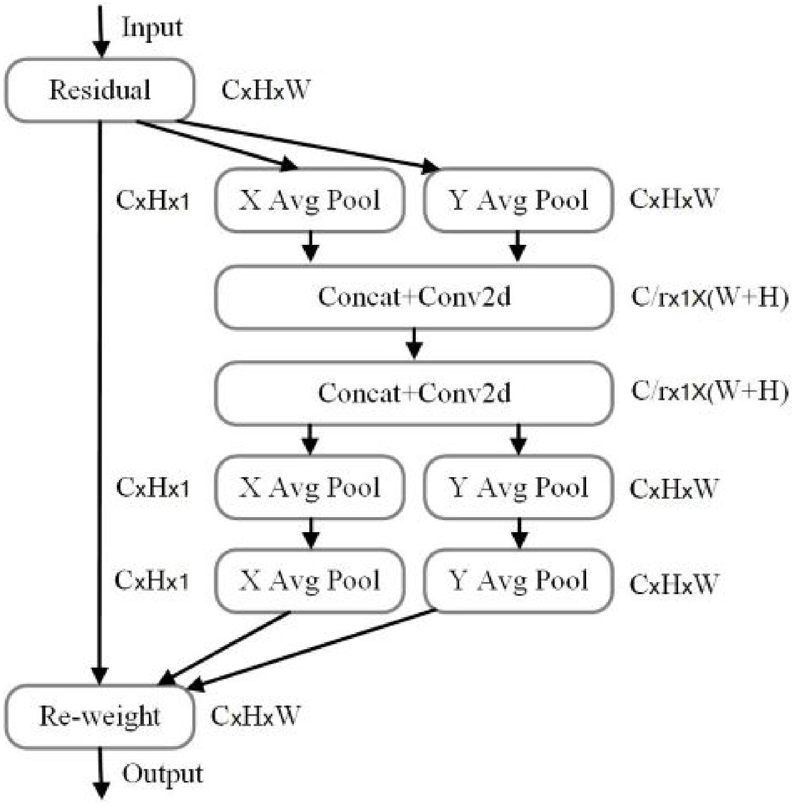


Fig. 37 Coordinate Attention.

3.1.3.4 Optimized anchor box setting

Nine anchor boxes are set according to the COCO dataset, which are: (10,13), (16,30), (33,23), (30,61), (62,45), (59,119), (116,90), (156,198), (373,326). In this paper, three anchor box sizes are added for the small target with an unclear boundary of Micro-Tom tomato, which is (5,6), (8,14), (15,11), respectively. The anchor boxes are allocated according to the scale of the detection layer to detect smaller tomatoes, and the anchor boxes distribution is shown in **Table 3**.

Table 3 Anchor box allocation table.

Feature maps	20×20	40×40	80×80	160×160
Receptive field	Large	Little Large	Medium	Small
	(116,90)	(30,61)	(10,13)	(5,6)
Anchor boxes	(156,198)	(62,45)	(16,30)	(8,14)
	(373,326)	(59,119)	(33,23)	(15,11)

3.1.3.5 Improved loss function calculation

The improved YOLOv5s_TM loss function defines three components of confidence loss denoted as l_{obj}, classification loss is denoted as l_{cls}, and prediction box location loss denoted as l_{box}, as shown in Formula 3-1-1.

$$Loss = l_{obj} + l_{cls} + l_{box} \quad (3\text{-}1\text{-}1)$$

Target confidence loss l_{obj} is defined as shown in Formula 3-1-2:

$$l_{obj} = -\sum_{i=0}^{S^2}\sum_{j=0}^{B} I_{ij}^{tomato}\left(\hat{C}_i log(C_i) + \left(1-\hat{C}_i\right)log\left(1-\hat{C}_i\right)\right) - \lambda_{notomato}\sum_{i=0}^{S^2}\sum_{j=0}^{B} I_{ij}^{tomato}\left(\hat{C}_i log(C_i) + \left(1-\hat{C}_i\right)log\left(1-\hat{C}_i\right)\right) \quad (3\text{-}1\text{-}2)$$

Target classification loss l_{cls}L is defined as shown in Formula 3-1-3:

$$l_{cls} = -\sum_{i=0}^{S^2} l_{ij}^{tomato}\sum_{C\in classes}\left(\hat{P}_i(c)log\left(P_i(c)\right) + \left(1-\hat{P}_i(c)\right)log\left(1-P_i(c)\right)\right) \quad (3\text{-}1\text{-}3)$$

The prediction box position loss l_{box} is defined using the $GIoU$ loss function as shown in Formula 3-1-4.

$$GIoU = IoU - \frac{|C-(A\cup B)|}{|C|} \quad (3\text{-}1\text{-}4)$$

In formula (4), A is the ground-truth bounding box, B is the bounding box, and C is the minimum circumscribed rectangle of A and B, as shown in **Fig. 38**.

In the original YOLOv5 model, $GIoU\_loss$ is used as the regression loss function of the bounding box, and the measurement of intersection scale is added to $GIoU\_loss$ to solve the problem that IoU_loss cannot optimize the situation when the prediction box and the target box do not intersect, i.e., the loss function is not derivable when $IoU = 0$. It also solves the problem that IoU_loss cannot distinguish the intersection of two prediction boxes when they have the same size and the same

IoU. However, $GIoU\_loss$ cannot solve the case where the prediction box is inside the target box and the prediction box is the same size, because the difference set of the prediction box and the target box is the same.

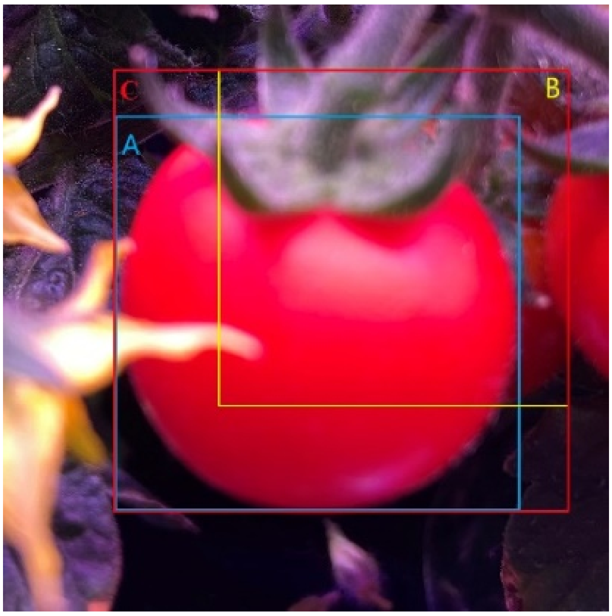


Fig. 38 The ground-truth bounding box, the bounding box and their relationships, A is the ground-truth bounding box, B is the bounding box, and C is the minimum circumscribed rectangle of A and B.

Therefore, this paper uses $CIoU\_loss$ as the regression loss function of the target detection task, and the calculation formula is shown in Formula 3-1-5. The overlap area and center point distance between the prediction box and the target box are considered in $CIoU\_loss$. When the target box wraps the prediction box, the distance between the two boxes is measured directly; thus, the information of the distance between the center point of the boundary box and the aspect ratio scale information of the boundary box is taken into account, and the aspect ratios of the prediction box to the target box are considered to make the boundary regression result better.

$$L_{CIoU} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v \qquad (3\text{-}1\text{-}5)$$

Where b represents the center point of the prediction box, b^{gt} represents the center point of the target box, ρ Indicates the Euclidean distance from the prediction frame to the target frame, c represents the diagonal distance of the outer minimum rectangle formed between the intersecting prediction box and the target box, α is a weight coefficient, and v is the parameter of consistency of aspect ratio, as shown in formulas 3-1-6 and 3-1-7:

$$v = \frac{4}{\pi^2}\left(arctan\frac{\overline{w}^{gt}}{h^{gt}} - arctan\frac{w}{h}\right)^2 \qquad (3\text{-}1\text{-}6)$$

$$\alpha = \frac{v}{(1=IoU)+v} \qquad (3\text{-}1\text{-}7)$$

Where w and h are the width and height of the ground-truth box and the bounding box, respectively.

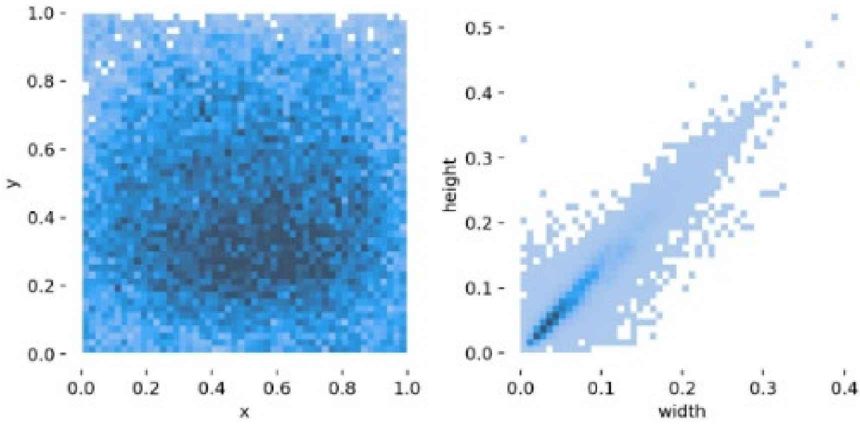
The CIoU_loss function solves the problem that the loss values of the prediction box and the target box are the same when they completely overlap at different positions, making the model more accurate in prediction box positioning and improving the detection performance of the model.

3.1.4 Results and Discussion

In this study, models of YOLOv3, YOLOv4, YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x are trained using the standard Micro-Tom dataset, respectively. The YOLOv5s_MT model is trained using the extended Micro-Tom dataset. The performance of each model was compared by using precision (P), recall rate (R), average precision (AP) and mean average precision (mAP) evaluation indexes, and the corresponding model files were used for pre-detection of image files and video files and to make real-time detection of tomatoes through smart terminals, and the test results showed that the detection performance of YOLOv5s_MT was significantly better than the detection performance of other models.

3.1.4.1. Tomato distribution in dataset

The visualization results of the target box size and location distribution of the tomato instances in the constructed Micro-Tom datasets are shown in **Fig. 39**. After image size regularization, the target box center point distribution is shown in **Fig. 39a**. The distribution of the length-width ratio of the target frame relative to the image is shown in **Fig. 39b**. The combined two figures show that the target box size is not uniform, the number of small tomatoes is high, and the tomatoes are mostly concentrated in the middle of the image.



(a) (b)

Fig. 39 Distribution of tomato instance target boxes in the Micro-Tom datasets, a. distribution of target boxes position and b. distribution of target boxes size.

3.1.4.2. Network model performance evaluation

This study mainly selects the mean average precision (mAP) and F1_score as the overall evaluation metrics of the network model performance. Precision (P) refers to the fraction of relevant instances among the retrieved instances, also called positive predictive value. Recall (R) refers to the fraction of retrieved relevant instances, also known as sensitivity. The precision-recall rate curve (P-R curve) can be drawn according to the relationship between precision and recall. The average precision (AP) of all categories refers to the area of the area surrounded by the curve and coordinate axes. If the AP of all categories is calculated and the mean value is taken, called mean average precision, all kinds of mAP can be obtained, as shown in the formula (7) ~ (11).

$$P = \frac{TP}{TP+FP} \qquad (7)$$

$$R = \frac{TP}{TP+FN} \qquad (8)$$

$$AP = \frac{\sum P(r)}{Num(TotalObjects)} \qquad (9)$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N(class)} \qquad (10)$$

$$F1 = \frac{2*P*R}{P+R} \qquad (11)$$

Where, TP is the number of positive samples correctly predicted. FN is the number of negative samples that is incorrectly predicted. FP is the number of positive samples that is incorrectly predicted. TN is the number of negative samples that is correctly predicted. $Num(TotalObjects)$ is the total number of target instances. $P(r)$ is the precision P corresponding to different recall r. AP_i is the detection precision of class i. $N(class)$ is the number of categories.

The Micro-Tom dataset was randomly split into a training and a test set according to a 9:1 ratio for model training. The input image size is 640 × 640, the amount of batch training data is 32, the training momentum is 0.9, the initial learning rate is set to 0.001, the weight attenuation is 0.0005, 300 batches (epochs) are trained, and the stochastic gradient descent (SGD) is used as the optimization function to train the model. The YOLOv3, YOLOv4, and Yolov5 series models are trained using the standard Micro-Tom dataset, and the YOLOv5s_MT model is trained using the extended Micro-Tom dataset, and the training results are shown in **Fig. 40** and **Fig. 41**. As can be seen from **Fig. 40**, the YOLOv5s_MT model has fast training convergence, the loss value is stable and tends to 0, and there is no phenomenon of underfitting and overfitting, and the convergence of the model is obviously better than other comparative models. The improved YOLOv5s_MT having the best detection performance can also be seen as from the PR and F1 curves **Fig. 41**.

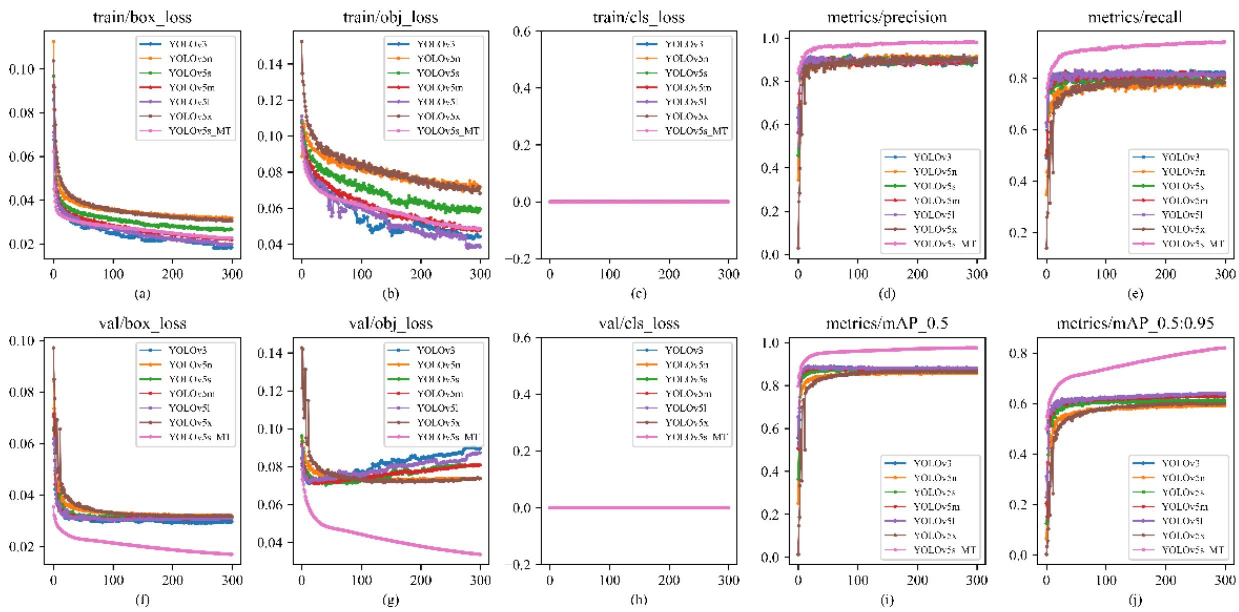


Fig. 40 Results of the loss function, accuracy and recall rate of the model training process.

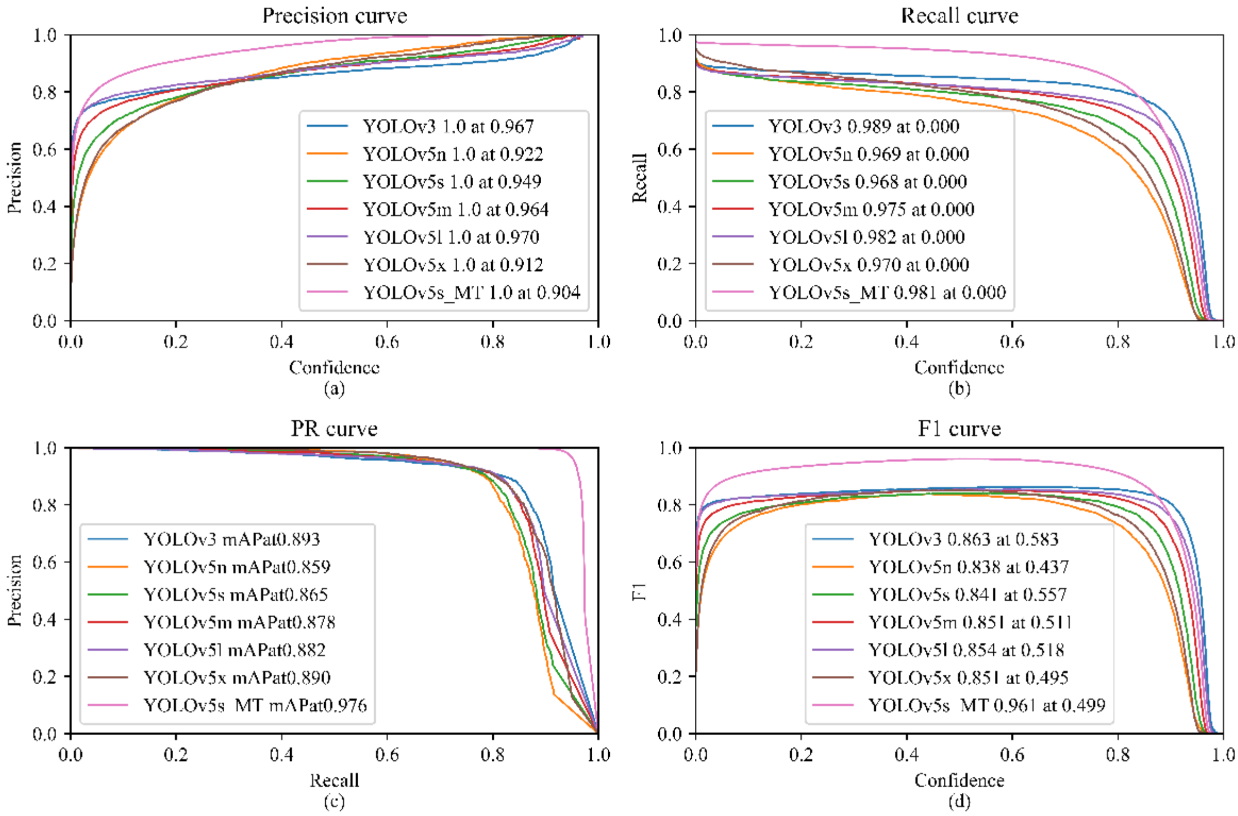


Fig. 41 Precision, Recall, P-R and F1_ score curves of model training.

The model training performance results are shown in **Table 4**. The precision, recall and mAP of the improved YOLOv5s_MT algorithm reached 92.9%, 96.0% and 95.9%, respectively. The results demonstrate that the enhanced YOLOv5s_MT algorithm proposed in this paper has better overall performance for Micro-Tom tomato image detection and recognition.

Table 4 Precision, Recall and mAP results of the improved model YOLOv5s_MT.

Model	Precision	Recall	mAP	mAP@0.5:0.95
YOLOv3	0.967	0.989	0.893	0.863@0.583
YOLOv5n	0.922	0.969	0.859	0.838@0.437
YOLOv5s	0.949	0.968	0.865	0.841@0.557
YOLOv5m	0.964	0.975	0.878	0.851@0.511
YOLOv5l	0.970	0.982	0.882	0.854@0.518
YOLOv5x	0.912	0.970	0.890	0.851@0.495
YOLOv5s_MT	0.904	0.981	0.976	0.961@0.499

3.1.4.3. Ablation experimental results

To analyze the contribution of the improvement method proposed in this paper to the performance of the YOLOv5s_MT algorithm, ablation experiments were designed and conducted. The experiments were conducted using YOLOv5s as the benchmark algorithm, with the optimized BottlenckCSP structure as improvement point 1, the addition of attention mechanism as improvement point 2, and the improvement of the border regression loss function as improvement point 3, and the improvement points were gradually increased, and the models were trained with a uniform Micro-Tom standard data set and the same training parameters, respectively, and the experimental results are shown in **Table 5**, "√" means the corresponding improvement strategy is used in the network model, "×" means the corresponding improvement strategy is not used in the network model. The analysis of **Table 2** shows that the optimization algorithm 1 uses the BCSP_1 structure to replace the original BottleneckCSP in the backbone network and adjusts the number of modules to ensure that the small target can make better use of shallow features and reduce the number of model parameters, so that the model has a small increase in mAP and a large increase in FPS. The optimization algorithm 2 adds the attention mechanism to the benchmark model, so that the model embeds the spatial information into the channel attention, and due to the addition of location information, it has a better prediction effect for the dense detection task relying on location information. Optimization algorithm 3 introduces CIoU as the loss function of boundary box regression to solve the problem that GIoU is reduced to IoU when the target box coincides with the prediction box in the original loss function, and improves the positioning accuracy of the model boundary box. The mAP value of the improved YOLOv5s_MT model is 0.959, which is 9.4% higher than that of the pre-improved YOLOv5s. The number of frames transmitted per second is 93.38, which is only 2.98 different from the benchmark model, and less video memory is required in training.

Table 5 Ablation experimental results

algorithm	improvement point 1	improvement point 2	improvement point 3	mAP	FPS (Frames/s)
YOLOv5s	×	×	×	0.865	96.36
optimization algorithm 1	✓	×	×	0.873	109.92
optimization algorithm 2	×	✓	×	0.876	108.76
optimization algorithm 3	×	×	✓	0.925	93.65
YOLOv5s_MT	✓	✓	✓	0.959	93.38

3.1.4.4. Experimental test results

The trained obtained model files were imported into the pre-detection program, and Micro-Tom tomato detection was performed on 200 image files and ten video files obtained from the PFAL laboratory, as well as real-time tomato detection, was carried out on video streams captured through the camera to verify the validity of the model. When the detection confidence is set to 0.5, the configuration of the computer terminal for the test is shown in **Table 6**, and the test results are shown in **Fig. 42** and **Table 7**.

Table 6 Composition and performance of Micro-Tom fruit detection and counting computer test terminal

component	Configuration and performance description
CPU	Intel i7-9700 @3.00G
RAM	16GB DRR4 2666MHz
GPU	Nvidia GTX 1650 4GB
SSD	256GB
DISK	1TB
operating system	Windows10 Home

As can be seen from **Fig. 42**, the YOLOv3, YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x, and the improved YOLOv5s_MT model, respectively, is used for the Micro-Tom tomato target detection of the same image file which is randomly selected. The number of correctly recognized tomatoes are 60, 67, 66, 70, 74, 75, and 77 and the average confidence is 0.8174, 0.8181, 0.8454, 0.8710, 0.7312, 0.7675 and 0.7275. Improved yolov5s_ MT compared with yolov5s model, although its average confidence is reduced, the accuracy of fruit detection is improved, which is 17% higher.

（a）The results of detection and counting with the trained YOLOv3 model in the actual scene target detection. The number of detected tomato fruits was 60, and the average confidence was 0.817, see the blue text in the figure.

（b）The results of detection and counting with the trained YOLOv5n model in the actual scene target detection. The number of detected tomato fruits was 67, and the average confidence was 0.818, see the blue text in the figure.

（c）The results of detection and counting with the trained YOLOv5s model in the actual scene target detection. The number of detected tomato fruits was 66, and the average confidence was 0.845, see the blue text in the figure.

（d）The results of detection and counting with the trained YOLOv5m model in the actual scene target detection. The number of detected tomato fruits was 70, and the average confidence was 0.871, see the blue text in the figure.

（e）The results of detection and counting with the trained YOLOv5l model in the actual scene target detection. The number of detected tomato fruits was 74, and the average confidence was 0.737, see the blue text in the figure.

（f）The results of detection and counting with the trained YOLOv5x model in the actual scene target detection. The number of detected tomato fruits was 75, and the average confidence was 0.767, see the blue text in the figure.

（g）The results of detection and counting with the trained improved YOLOv5s_MT model in the actual scene target detection. The number of detected tomato fruits was 77, and the average confidence was 0.727, see the blue text in the figure.

Fig. 42 Comparison of fruit detection results of Micro-Tom images.

From **Fig. 42** and **Table 7**, it can be shown that the yolov5s_ MT model does not accelerate its detection speed compared with the yolov5s model corresponding to the network scale, but its comprehensive performance has been significantly enhanced.

Table 7 Tomato target detection results.

Model	Size	Image	Video	FPS	GFLOPs @640(B)	Params (M)	Layers	Weight file size (MB)
YOLOv3	640	75.5	45.6	21.93	154.7	61.50	261	470
YOLOv5n	640	37.2	17.5	46.5	4.2	1.76	213	13.9
YOLOv5s	640	51.8	21.5	57.14	15.8	7.01	213	54
YOLOv5m	640	54.5	26.0	38.46	47.9	20.85	290	159
YOLOv5l	640	71.7	37.1	26.95	107.8	46.11	367	352
YOLOv5x	640	180.6	150.9	6.63	204.2	86.21	567	663
YOLOv5s_MT	640	52.9	22.1	45.24	15.8	7.01	213	54

3.1.4.5. Comparison of comprehensive detection performance using

different YOLO models

In this paper, the performance of different versions of the YOLO detection algorithm trained on the Micro-Tom datasets is compared, and **Table 8** shows the experimental results of the model input size, mAP, Speed, FPS, and Params for different algorithms, respectively. From this table, the following results can be obtained: (1) for the unified Micro-Tom datasets, under the same experimental conditions, input image resolution, and setting parameters, the detection speed of YOLOv5s_MT and YOLOv5s is faster, the model file is smaller, and a higher detection speed can be obtained on devices with low computing power, which is very suitable for real-time target detection on picking robots and mobile terminals. (2) the comprehensive real-time detection performance of the improved YOLOv5s_MT model is better, which can be directly transplanted to tomato robot picking and dynamic yield estimation and is widely used in plant factories. (3) all the YOLO series detection models can meet the real-time detection and tracking detection of targets, but each has its own advantages in terms of detection metrics, inference speed, and model weight file size that can be adapted according to the actual situation and needs. If you are more concerned about the speed, it is recommended to prefer the YOLOv5s and YOLOv5s_MT models. If accuracy is more important in some applications, the YOLOv5x model can be chosen. For the real-time detection of small targets, other corresponding YOLOv5 models can also be improved referring to the YOLOv5s-TM improvement method to meet the actual requirements.

Table 8 The detection performance of Yolo series models in the test process.

Model	Size	mAP	Speed	FPS	Weight file size
YOLOv3	640	0.893	75.5	21.93	470
YOLOv5n	640	0.859	37.2	46.5	13.9
YOLOv5s	640	0.865	51.8	57.14	54
YOLOv5m	640	0.878	54.5	38.46	159
YOLOv5l	640	0.882	71.7	26.95	352
YOLOv5x	640	0.890	180.6	6.63	663
YOLOv5s_MT	640	0.976	52.9	45.24	54

3.1.5 Conclusions of this section

Although the PFAL is still questioned because of its high construction and operation costs, and has not been widely recognized by people at present, it is also expected due to its high controllable environment, wash-free ready-to-eat, easy quality control and many others other advantages. Considering the utilization rate of resources and space, dwarf tomatoes are most likely to be the first to be widely planted in PFALs. However, because the dwarf tomato fruit is small, the light environment is complex, the growth is dense, and the overlap occlusion is severe. Therefore, it is challenging to detect tomato fruit in real-time and rapidly. Consequently, we take YOLOv5s as the reference network. By improving and optimizing the BottlenckCSP structure, adding attention mechanism, optimizing the anchor box setting algorithm and changing the boxes regression loss function, an improved real-time detection and counting method of dwarf tomato in PFALs is proposed, namely YOLOv5s_MT, that can provide technical support for harvesting robots and yield estimation in PFALs. Training and ablation experiments were conducted on the enhanced Micro-Tom dataset, and the performance was compared and analyzed with the six network models of the YOLOv3, YOLOv4, and YOLOv5 series. The experimental results show that the data-enhanced and improved YOLOv5s_MT algorithm can extract the feature information of the detection target more effectively, and the size of the input image is set to 640×640 scale, which reduces the loss of small target information during network down-sampling, and greatly improves in terms of speed and overall performance. Compared with the existing network structure, the method effectively improves the detection accuracy, speed and counting accuracy of small tomatoes that can meet the detection accuracy and speed requirements of future PFALs harvesting robots, as well as the counting accuracy requirements for dynamic yield prediction and real-time yield information display.

In this paper, we only study the detection and recognition of a single category of dwarf tomatoes in PFALs, which is the basis for the realization of robot picking and dynamic yield estimation. Nevertheless, in fact, the robot only needs to pick mature tomatoes, which requires the harvesting robot to have the ability to distinguish tomatoes in different growth periods and classify them in fine-grained. Accordingly, our future work goal will be based on this research: (1) to further expand and enhance data sets to provide the perfect Micro-Tom data sets for AI applications. (2) the algorithm is further enhanced to improve the detection accuracy of mature fruit, and the harvesting robot model in the PFAL will be studied more closely. Finally, (3) will deeply study to construct the yield dynamic estimation model, and to make production management more precise and marketing and decision-making information updating more time-sensitive.

3.2 CMRDF algorithm based on cucumber seedling and leaf segmentation in RGB-D plant factory

Nondestructive detection and analysis of plant phenotypes using computer vision technology is the basis for online dynamic plant monitoring, production guidance, disease early warning, yield prediction, and other related applications. Effective health management for cucumber seedlings is crucial for promoting their vigorous growth, which serves as the foundation for enhancing cucumber yield and associated economic gains. Therefore, computer vision-based seedling and leaf segmentation, plant height calculation, and leaf area calculation have become key technologies for seedling monitoring and management. This paper introduces a novel semantic segmentation algorithm, namely RGB-D Cross-Modal Fusion (RDCMF), for cucumber seedlings and leaves. The proposed algorithm is based on the cross-modal fusion of RGB-D images. The algorithm employs a cross-modal component to extract features from both RGB images and depth maps (D-modal) simultaneously while also executing reciprocal rectification of these features. By using an attention mechanism, the depth map and RGB image features are fused, thus maintaining the integrity of the channel features as much as possible. In addition, the paper proposes a depth image filtering algorithm that aims to improve the acquisition capability of depth maps under complex lighting conditions in artificial lighting factories. The results of the experiment indicate that the proposed model attains a mIoU (Mean Intersection over Union) value of 93.4% and a PA (Pixel Accuracy) value of 93% when trained and calibrated on the same dataset using the algorithm. In comparison to the model that does not utilize the depth map, there is a 15.5% improvement in the PA. Comparing to other prevalent RGB and RGBD segmentation algorithms, this model attains the highest level of segmentation accuracy for cucumber seedlings. The proposed model uses RGB-D sensors for segmentation of cucumber seedlings and leaves, and the segmentation results exhibit a remarkable degree of accuracy and performance. The model has promising applications in various areas, including plant modeling and accurate detection of agricultural robots.

3.2.1 Introduction of this section

Plant factories are considered one of the most promising forms of production in urban agriculture (Wang et al., 2023a) and are an advanced form of facility agriculture (Kozai et al., 2020; Saito and Goto, 2023; Wang et al., 2022b). It requires a high degree of mechanization, automation, informationization, and intelligence and represents the highest level of modern agriculture (Saranya et al., 2023). The application of robotics, artificial intelligence, and nondestructive detection technology in agriculture is expected to significantly enhance the intelligent development of plant factories (Karadağ and Kılıç, 2023; Milella et al., 2019; Wang et al., 2022a). Recent research has shifted its attention towards the utilization of deep learning models and algorithms for real-time detection and counting of tomato fruits in complex light environments [8], lightweight detection algorithms for robotic picking (Wang et al., 2023b), as well as plant phenotypic segmentation methods. This has become a popular topic and development direction for research on plant factory intelligence.

Semantic segmentation is one of the important techniques in the field of computer vision, aiming at classifying each pixel in an image and distinguishing the categories of different objects. This technology is currently widely applied in the fields of robot vision(Joki'c et al., 2021), autonomous driving(Feng et al., 2020), intelligent medical image analysis(Medley and Nascimento, 2021), geographic information analysis systems(Song et al., 2023), and plant growth monitoring(Grimm et al., 2019). The fundamental aspects of life and agricultural sciences involve the acquisition, identification, and analysis of various plant characteristics and phenotypes. Plant phenotypes are determined by the interaction of genes and the environment. However, conventional techniques for measuring plant phenotype manually are beset by several issues, including low efficacy, subjective evaluation, significant measurement inaccuracies, and potential interference with normal growth. Moreover, these methods are ill-suited for analyzing the complete growth cycle of plants. Hence, the segmentation of cucumber seedlings and detection of their phenotype hold significant importance in attaining growth monitoring and intelligent management of plant factories, thereby necessitating relevant research.

As a powerful deep learning model, convolutional neural networks (CNN) have been widely used in the field of computer vision and have been applied in various industries (Kromp et al., 2021; Pan et al., 2021; Shoshan et al., 2021) and achieved significant results (Akilan et al., 2020; Liao and Guo, 2021; Mao et al., 2021; Xiaolong Wang et al., 2021). The emergence of ViT(Dosovitskiy et al., 2020) has further improved the performance of tasks such as semantic segmentation. Adopting an encoder-decoder structure, it can process different sizes of input images adaptively and output the segmentation result with the same size as the input image. In the field of agricultural intelligence, a series of plant segmentation studies based on full-convolution neural networks (Marset et al., 2021; Ott and Lautenschlager, 2021; C. Wang et al., 2021) have significantly contributed to the development of this field. Meanwhile, the introduction of depth cameras has facilitated the acquisition of depth images that correspond to color images. Each pixel value in the depth image represents the distance from that pixel point to the camera plane, which can provide additional depth information for the semantic segmentation task to improve segmentation accuracy (Zhou et al., 2021). The utilization of depth information can aid in the improved differentiation of adjacent objects with comparable appearances in a color image.

Aiming at the problems of low accuracy of pure image detection, high application threshold due to the large network size of CNN convolutional networks, and neglect of spatial location information due to separate extraction of depth map and RGB image features, a new cucumber seedling segmentation algorithm is proposed in this paper. The algorithm employs the depth map and RGB image acquired based on the RGB-D sensor, uses the depth rectification algorithm to obtain a high-quality depth map in complex lighting environments, and utilizes cross-channel fusion technology to process the depth map and RGB image features. Tested on the constructed dataset, the proposed algorithm model in this paper achieves a PA of 93% and an IoU of 93.4%. The algorithm can be used for fine segmentation of cucumber seedlings, phenotypic measurement modeling, and precision agriculture applications.

Our contributions can be summarized as follows:

- A model and algorithm for segmenting cucumber seedlings and leaf instances based on RGB-D image cross-modal fusion (RDCMF, RGB-D Cross-Modal Fusion) are proposed. The algorithm improves the accuracy and robustness of the segmentation while ensuring the lightweightness of the model. We have applied the algorithm to an intelligent monitoring system for crop growth in artificial light plant factories and achieved remarkable results.

- A depth rectification algorithm is proposed. Through the fusion of multiple depth images and the integration of their gradient, the challenges posed by the complex lighting conditions in artificial light plant factories are effectively addressed, leading to the attainment of consistent and excellent depth image acquisition.

- A module named Cross-Depth Feature Rectification Module (CD-FRM) is designed and proposed. By combining the depth image to calibrate the RGB image features, a pair of rectified feature pairs are obtained, which can enhance the feature extraction capability and improve the precision and robustness of the model.

- Using the cross-attention mechanism, a Feature Fusion Module (FFM) is designed, which can realize long-distance context exchange and enhance the features in the two modes. The rectified feature pairs are mixed by deploying FFM to segment cucumber seedlings and leaves, which effectively improves the segmentation accuracy.

3.2.2 Methods and models

3.2.2.1 Image data acquisition

The cucumber seedling RGBD dataset used in this paper was collected from the Laboratory of Artificial Light Plant Factory, Henan University of Science and Technology, Xinxiang, China. Thanks to the plant factory ACE, cucumber plants will no longer be affected by the climate of the region. 6 batches of cucumber seedlings were grown between June 2022 and February 2023, with approximately 100 seedlings in each batch, and the data were collected during the seedling stage of the cucumber plants. Cucumber "Jin You No.1" was chosen for the experiment, and the planting experiment confirmed that this variety is suitable for planting under artificial light and hydroponic environment. Cucumber plants are planted on hydroponic seedling trays and grown using full artificial light hydroponics, where the ambient temperature, humidity, nutrient solution, and photoperiod are automatically adjusted as the plants grow.

The planting experimental platform used in this research is shown in **Fig. 43**, the platform was acquired by a camera and handheld camera fixed above the planter. The dataset consists of RGB images, depth map and GT, where the RGB images and depth map are used as input extraction features for network training, and GT is used to supervise the convergence of model weights. The RGB image and depth map are acquired by the program-controlled depth camera Intel RealSense D455 at regular intervals and saved as a 1280x720 pixel three-channel color and 8-bit depth map with depth filtering calibration correspondence. In addition, high-definition RGB images of up to 6,000x4,000 pixels can be acquired by shooting with a Canon 80D DSLR camera fixed directly above to improve the model's expressiveness. In addition, to increase the diversity of the dataset, RGB-D images and high-definition RGB images of the tilt angle were also acquired periodically above the diagonal of the nursery tray. The data from the raw data were processed to acquire a total of 500 raw RGB-D images and 300 RGB images.

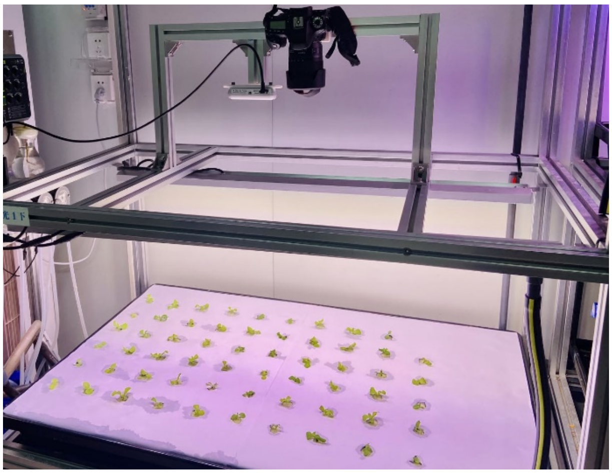


Fig. 43 Dataset augmentation.

3.2.2.2 Augmentation and Label

In order to increase the number of samples in the dataset and improve the generalization capability of the model, this paper uses image processing to augment the dataset in order to simulate the situations that may be encountered in real-life scenarios. Image processing is performed using OpenCV library functions, with one or more of the following methods chosen at random: 1) image rotation; 2) scale scaling; 3) brightness adjustment; 4) filter addition (red or blue); 5) blurring or sharpening; 6) adding noise. When RGB images are rotated, they are mapped to the depth map at the same time, but image brightness, filters, blurs, or noise do not correspond to the depth map. The data augmentation method for the depth map is to select a random portion of the image and perform the same zoom operation on the RGB image and the depth map. Also, the values are scaled down appropriately on the depth map to augment the number of close samples in the dataset. The principle of the data augmentation method is to crop the plants with a small area (crop area less than 30%) on both RGB images and depth maps, and discard the augmented images if the crop area is too large. A demonstration of the image enhancement algorithm used is shown in **Fig. 44**.

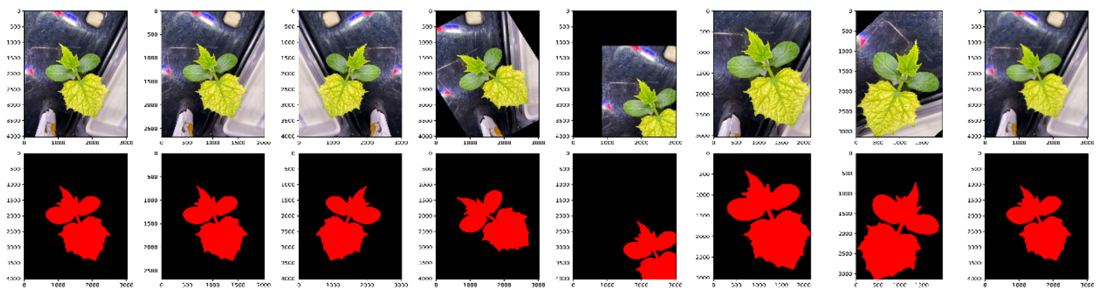


Fig. 44 Datasets augmentation. The three lines are the RGB image, depth map visualization, and GT; the first column is the original image, followed by reduction, mirroring, rotation, displacement, crop enlargement, rotation enlargement, blur, respectively.

Mark cucumber seedling instances with labelme software on RGB-D images acquired on RGB images, as shown in **Fig. 45**.

Fig. 45 Label result.

The labeled dataset consisted of 1260 sheets, which were randomly divided into a training set and a calibration set according to the ratio of 8:2, with 1008 sheets in the training set and 252 sheets in the calibration set, of which 3356 cucumber plant instances were labeled in the training set and 834 cucumber plant instances in the calibration set. The constructed dataset and the distribution of cucumber cotyledons and needle examples are shown in **Table 9**.

Table 9 The dataset used for segmentation model training.

Sets	Number of Images	Number of needles	Number of cotyledons
train	eight hundred	2563	2356
validation	200	434	2356
total	1000	2356	2356

3.2.2.3 Validation

In order to verify the effectiveness of the model, a general verification method is used to verify the training results. In addition to the Precision, Recall, AP, and F1 metrics used in target detection, a computational approach to validate IOU and PA (Pixel Accuracy) metrics was used to evaluate segmentation performance and accuracy. IOU is an important indicator for evaluating the segmentation accuracy, which can reflect the accuracy of the prediction result. Its calculation method is shown as Formula 3-2-1 to 3-2-5. PA is an important indicator of pixel-level accuracy, reflecting the proportion of correctly classified pixels to the total.

$$Precision = \frac{TP}{TP+FP} \quad (3\text{-}2\text{-}1)$$

$$Recall = \frac{TP}{TP+FN} \quad (3\text{-}2\text{-}2)$$

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3\text{-}2\text{-}3)$$

$$IOU = \frac{GT \wedge Prediction}{GT \cup Prediction} \quad (3\text{-}2\text{-}4)$$

$$PA = \frac{TP}{TP+FP} \quad (3\text{-}2\text{-}5)$$

Pixel indicate correctly predict the number of pixels to be segmented or the number of the entire image. TP, FP, FN represent true positive, false positive, and false negative, respectively; AP is the cucumber precision of pixels segmentation.

3.2.3 Related Work

3.2.3.1 2D Segmentation

D Deep learning models, such as the R-CNN series (Girshick et al., 2014), SSD (Liu et al., 2016), and YOLO (Redmon et al., 2016), have been widely used in the field of image detection based on CNN technology and have achieved outstanding results. Kaiming et al. (He et al., 2018) proposed the Mask RCNN model based on the Faster RCNN structure (Ren et al., 2017) by adding a target mask and successfully implementing instance segmentation, which laid the foundation for new developments in deep learning in the field of image target segmentation. Mask RCNN uses Region Proposal Net (RPN) to identify object candidates in the image and further expands the network by adding an FCN branch to predict the segmentation mask of each target object, as shown in the **Fig. 46**. Experimental results show that Mask RCNN has high efficiency and precision in instance segmentation, and has been applied in many fields.

In summary, Mask RCNN is a powerful and flexible object detection and instance segmentation network structure, but it needs high computational and storage resources and requires a large amount of image data for training to obtain high accuracy. In addition, the segmentation accuracy is affected when there is severe occlusion, overlap, or similar color and texture of the target. In applications that need higher segmentation speed, accuracy, and robustness, such as automatic driving, real-time robot operation, and high-precision modeling, the application of Mask RCNN will be greatly limited. In order to address these issues, this paper uses a 3D vision sensor, multi-modal image fusion, and a feature rectification algorithm, aiming to preserve the channel features as much as possible to improve the segmentation performance.

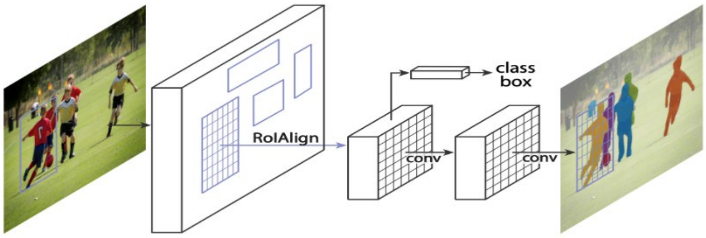


Fig. 46 Framwork of MaskRCNN.

3.2.3.2 RGB-D Segmentation

The RGBD vision sensor is a sensor that obtains both an RGB image and a depth image at the same time, in which the depth image contains spatial information and the overlapped targets in the RGB image can be distinguished by a three-dimensional point cloud, thereby improving the accuracy of image segmentation. In related research, Lafantasie (Lafantasie, 2016) fuses depth images into CNNs and extracts depth information and color information at the same time, which improves the accuracy of semantic segmentation. Lin et al. (Lin et al., 2019) used depth images in an SCN network to extract geometric relationships between objects to improve the accuracy of image segmentation. Chen et al. (Chen et al., 2021) proposed a spatial information-guided convolution network. The fusion of depth images does not increase the computational cost and greatly improves the ability to perceive geometric shapes. Zhang et al. (Zhang et al., 2021) proposed a Non-local Aggregation Network with multimodal non-local aggregation modules that can better segment images using the non-local context of RGB-D features. The RGB×D method proposed by Cao et al. (Cao et al., 2021) used the multiplication method to fuse the RGB information and the depth information in the early stages, and then the existing RGB segmentation network could be directly used to simply and effectively link the RGB and RGB-D semantic segmentation.

Compared with the 2D segmentation algorithm, the RGBD segmentation algorithm can provide additional spatial location information by adding depth map, so that the target segmentation on the image with depth information can increase the network expression ability and the degree of model convergence. 3DGNN proposed by Xiaojuan et al. (Xiaojuan et al., 2017) is an extension of Graph-based Neural Network (GNN) and can effectively process 3D data, such as 3D point cloud, 3D mesh, 3D voxel. The 3DGNN model is a segmentation and detection model that utilizes point cloud data. Its object detection and segmentation capabilities have demonstrated impressive performance. In contrast to conventional two-dimensional convolution, the 3DGNN employs node and edge information, while also considering the spatial arrangement of nodes in three-dimensional space, as depicted in **Fig. 47**. However, GNN-based networks necessitate the computation of 3D location relationships, which incurs a substantial computational burden, thereby constraining their broad applicability. Therefore, this paper presents a novel network structure that uses attention mechanisms and Transformer model to enhance network segmentation performance and reduce network size, thereby enabling more efficient target segmentation.

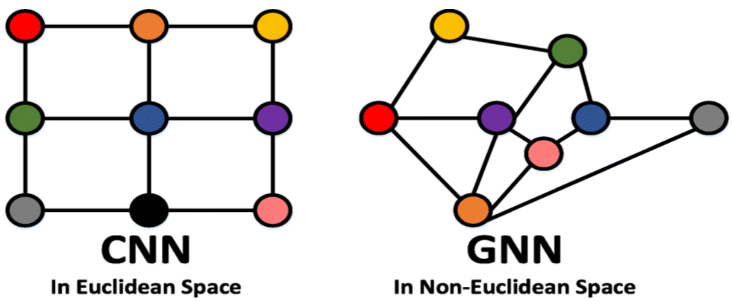


Fig. 47 Compare CNN with GNN.

3.2.3.3 Attention

With the successful implementation of the Encoder-Decoder model, the attention mechanism-based approach has been increasingly utilized in various fields, including Object Detection and Retrieval (ODR) (Sirmorya et al., 2022). In contrast to the process of coding and decoding words in the language model, image detection employs a spatial attention mechanism and a channel attention mechanism (Cirstea and Likforman-Sulem, 2016; Hu et al., 2018). The traditional attention mechanism model calculates the similarity of each element in the input sequence to the query element, and then uses these similarities as weights to weight and sum the input sequence to obtain a contextual representation associated with the query element. The multi-head attention mechanism further decomposes the attention mechanism calculation into a plurality of head, each of which learns a different weight matrix for calculating the similarity and the weighted sum. The results obtained from multiple heads are then stitched together, as shown in **Fig. 48**. This can increase the attention of the model to different features in the input sequence and improve its modeling ability for complex sequence data (Xiang Wang et al., 2021).

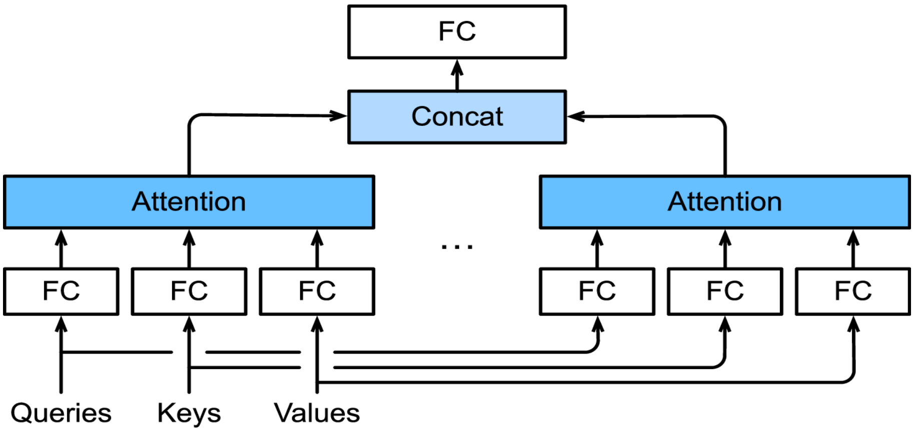


Fig. 48 Illustrate multiple head attention.

Attention-based models, particularly those utilizing multi-headed attention mechanisms as employed in this study, exhibit superior capacity for processing long sequence data, enhancing model generalization, enabling different feature space focus, and facilitating multi-task learning and application (W. Wang et al., 2021). The multi-head attention mechanism reduces the computation and storage cost by decomposing the input vector into multiple heads, so that each head pays attention to a different position. In addition, the multi-head attention mechanism can more easily capture important features in data and more easily adapt to new data distribution, further improving the generalization ability of the model. For the cucumber plant segmentation in this paper, the input image and depth map have more features, particularly the blade edge and texture, and the use of multi-head attention mechanism can make the model capture more features for detection and segmentation, thus improving the accuracy (Li et al., 2021).

3.2.3.4 ViT

Transformer is a widely used approach to modeling sequences that was initially employed in the field of natural language processing. Compared with traditional recurrent neural network (RNN) and long short term memory network (LSTM), Transformer model uses self-attention mechanism and full connection layer to process sequence data, thus avoiding the impact of sequence length and gradient disappearance. The model is mainly composed of encoder and decoder, as shown in **Fig. 49**. The encoder consists of multiple identical layers stacked on top of each other; each layer contains a multi-headed attention mechanism and a fully connected layer. The decoder consists of multiple identical layers stacked on top of each other, and each layer contains a multi-headed attention mechanism, a fully connected layer, and a multi-headed attention mechanism. Between the encoder and decoder, there is an embedding layer for converting the input and output sequences into a vector representation (Strudel et al., 2021).

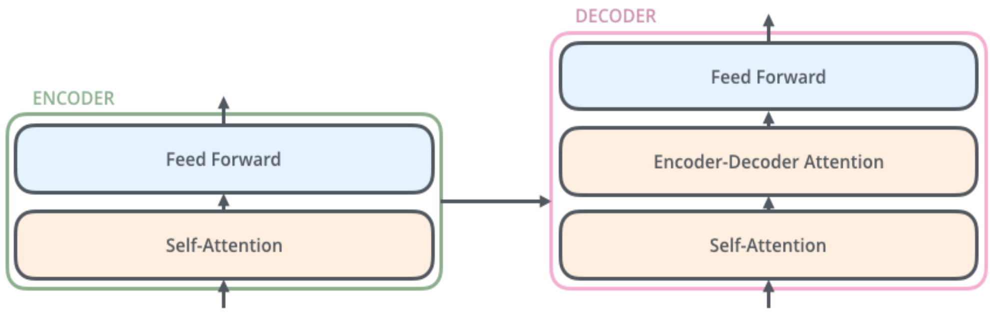


Fig. 49 Illustrate Vision in Transformer.

The Transformer model, based on a self-attention mechanism and fully connected layer, is not constrained by sequence length and gradient disappearance and thus has location- and context-specific awareness, which has made it successful in areas such as natural language processing. However, unlike text data, image data processed by computer vision can hardly find the division units of sequences (Dosovitskiy et al., 2020). Vision in Transformer (ViT) is a computer vision model based on Transformer that divides the image into a sequence of multiple small blocks and contains their position codes (Strudel et al., 2021), as shown in the **Fig. 50**. These blocks undergo feature transformation through the linear projection layer and are then input into multiple Transformer encoders. The encoder contains multiple self-attention heads and fully connected layers, which can capture the relationship between different positions and generate a vector. VIT passes the encoder output features into the decoding network together with the segmentation mask and transforms the decoder output feature map into the segmentation result through the output layer. Thus, VIT brings a new approach to the field of computer vision by dividing images into sequences and performing tasks such as detection and segmentation.

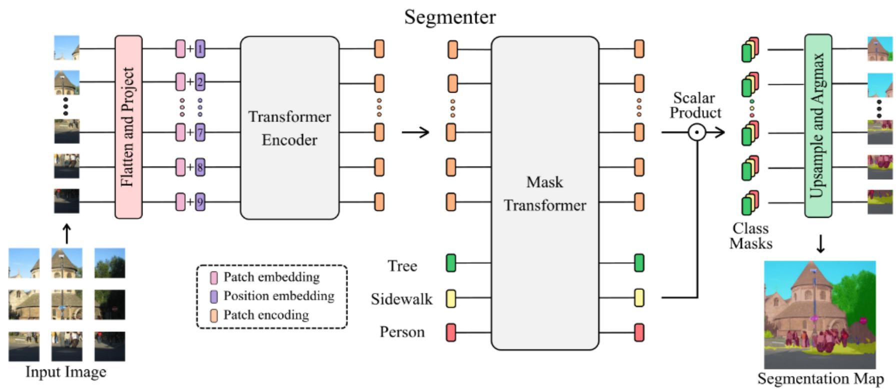


Fig. 50 Illustrate Vision in Transformer.

3.2.4 Improved Cross Model Depth Network

3.2.4.1 Framework Overview

This section introduces the RDCMF framework, a semantic segmentation model framework designed for the purpose of segmentation of cucumber seedlings. The framework mainly utilizes the encoder and decoder segmentation architecture of the ViT model, and is improved based on the CMX (Cross-Modal Fusion for RGB-X Semantic Segmentation with Transformers) model to adapt to the complex lighting environment of artificial light plant factories, as shown in **Fig. 51**. The model uses two parallel backbone networks to extract RGB and depth map features simultaneously, rectifies them by CD-FRM module and fuses the features by FFM, and finally outputs the fused features for segmentation (Liu et al., 2022).

The proposed network has two innovative points. On the one hand, it fully combines the structural advantages of CNN and transformer models. On the other hand, it supports two parallel backbone networks to mutually rectify and extract features by using depth maps and RGB. The backbone network adopts the MiT model for feature extraction and the CD-FRM module for cross-depth rectification feature processing (Xie et al., 2021). The backbone network was composed of four layers, with the input features of each layer being respectively (1/4, 1/8, 1/16, 1/32) of the original image resolution. The MiT block in each layer and the CD-FRM module jointly extract and rectify the features of the depth map and the RGB map and input the rectified features into the FFM module for feature fusion. The final output features are sent to the decoder for segmentation.

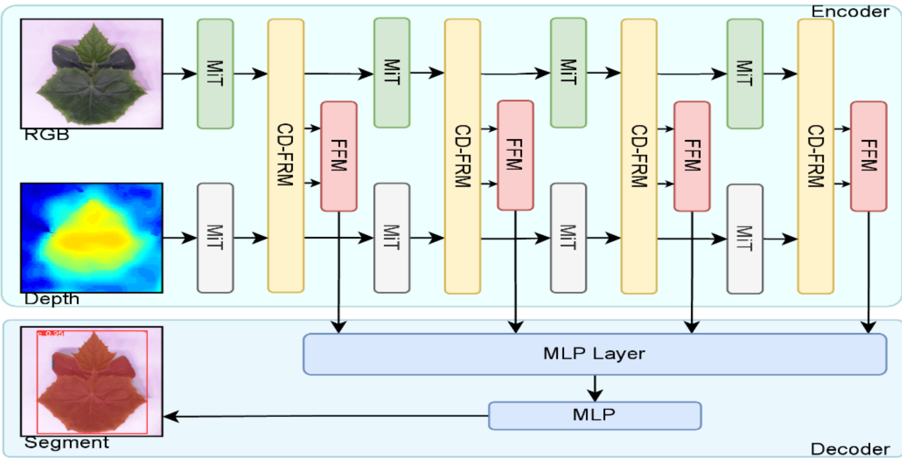


Fig. 51 Framework overview of RDCMF.

The MiT block is a visual Transformer structure, as shown in **Fig. 52**. It includes Efficient Self-Attention attention module for feature extraction, Mix-FFN for providing location information, N models connected and the number of N in each layer can be flexibly chosen according to the complexity of the task (Shen et al.2020; Xie et al., 2021). Finally, the Overlap Patch Merging module is used to complete the discontinuous features of the output so that the segmented cucumber plants are continuous (Patel et al., 2022). As shown in formula[formAttention], in the original multi-head self-attention module, Q, K, and V of each head have the same dimension N×C, where N=H×W is the length of the sequence. The MiT backbone network adopted a sequence reduction method to reduce the complexity of the model (W. Wang et al., 2021), where the self-attention estimation was performed based on these reduced sequence lengths.

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_{head}}}\right)V$$

Based on the design of the MiT backbone network, MiX-FFN is used as an alternative to position coding, using smaller convolutional operations to provide location information, thus improving the robustness of the model to the resolution of the input image. The operation can be represented as:

$$x_{out} = MLP\left(GELU\left(Conv_{3\times3}\left(MLP(x_{in})\right)\right)\right) + x_{in}$$

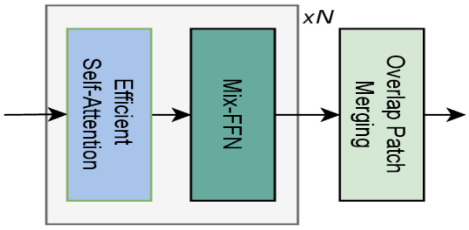


Fig. 52 MiT module schematic.

3.2.4.2 CD-FRM

The proposed CD-FRM (Cross-Depth Feature Rectification Module) is a modern cross-depth feature rectification module, as shown in **Fig. 53**. The module can be used to effectively rectify noise and uncertainty interference in depth maps and RGB images, thus improving performance in complex lighting environments of artificial light plant factories. This module is an improvement on CM-FRM and is optimized for the rectification of depth features. The proposed CD-FRM module contains feature rectification in two dimensions, channel-wise and spatial-wise, and the two interact to complete the rectification of the overall feature so as to achieve a better rectification effect.

First, depth feature Depth_inand RGB feature RGB_in∈R^(H×W×C)are obtained from two parallel backbone networks. Then, the average pooling and maximum pooling operations are used to extract features, and all result vectors are stitched into one vector Y∈R^4C. Next, a Multilayer Perceptron (MLP) layer with a sigmoid activation function is used to generate channel feature rectification weights W^C∈R^2C. These weights are divided into depth and RGB channel weights W_Depth^C and W_RGB^C. The channel rectification formula is as follows:

$$W_{RGB}^{C}, W_{Depth}^{C} = f_{split}\left(\sigma\left(f_{mlp}(Y)\right)\right)$$

$$RGB_{rec}^{C} = W_{Depth}^{C} \circledast Depth_{in}$$

$$Depth_{rec}^{C} = W_{RGB}^{C} \circledast RGB_{in}$$

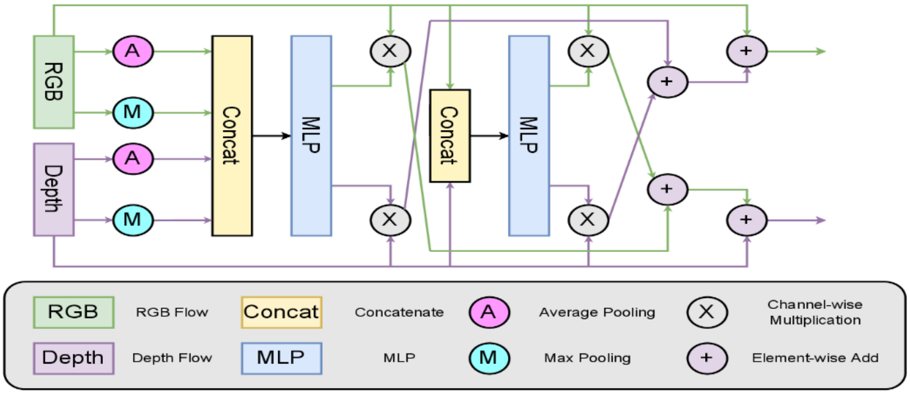


Fig. 53 Framework overview of CD-FRM .

3.2.4.3 FFM

A module used to fuse RGB and Depth features, as shown in **Fig. 54**. The features extracted by CD-FRM after rectification as FFM input in two synchronous backbone networks, and FFM outputs the fused features to the decoder for prediction. In FFM, two cross-channel attention mechanisms are added to the depth features and RGB features respectively in order to allow further fusion of the depth map and RGB features. This cross-channel attention mechanism decodes the input vector into Query Q, Key K, and Value V.

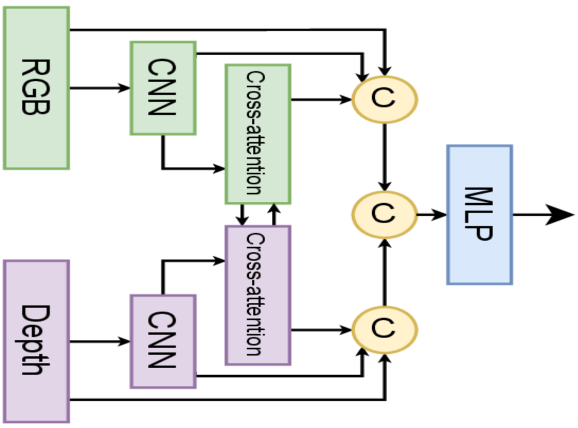


Fig. 54 Framework overview of FFM.

3.2.4.4 Depth map rectification algorithm

The depth Intel Realsense camera used in this article is similar to other commercially available depth sensors in that the imaging principle is modeling using infrared structured light. Due to the influence of ambient light, the camera will be affected by the ambient light in addition to its own infrared-excited structured light. In artificial light plant factories, red, blue, and white light are extensively used as the light source for plant growth in order to promote photosynthesis in the plants and are located close above the plants. In the factories, high-power LED light sources are used to obtain sufficient light intensity. However, the light source effects the data acquisition of the depth camera, resulting in a depth image with a high level of noise, which severely limits the model's ability to segment.

For complex artificial light plant factory environments, this paper proposes an algorithm for noise reduction and depth rectification. As shown in **Fig. 55**, three depth images are acquired alongside RGB images, and then our rectification algorithm calculates a depth image with less noise.

Since there are both characteristic plane and cucumber plants in the input image, they need to be processed separately. First, the plane is fitted, and then the plants located on the plane are separated. Then the features are extracted and matched from multiple input depth maps, and then the plane and the plants are filtered respectively. Finally, all the processed depth maps are fused into a rectified depth map.

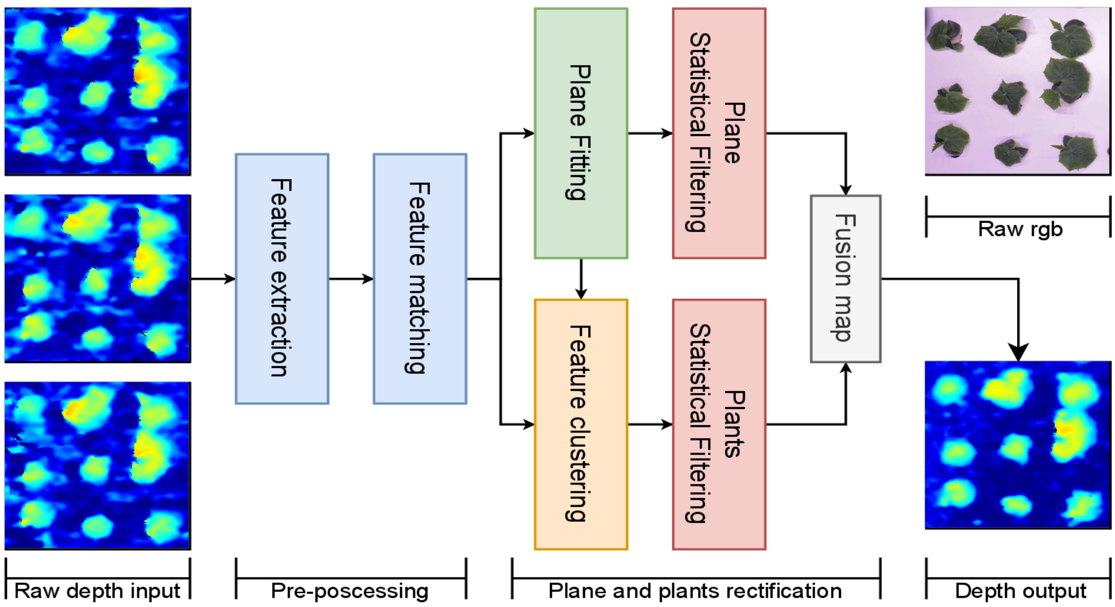


Fig. 55 Illustration of depth rectification algorithms. Three depth images are input, and their acquisition times are 1 second apart. By colorizing gray-scale images with a single depth value, these depth images are made convenient to view. In addition,

the original RGB image was taken against a white background and displayed in red under artificial light. In the preprocessing stage, the salient features in the three depth images are extracted and matched using a method similar to point cloud processing.

In the artificial light plant factory laboratory, depth measurements during plant growth are performed by fixing the plants on a flat planting disk. First, the planting plane of the plant is fitted to calculate the depth mean[formDepthS].

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

The standard deviation is s, is the number of samples is N, is the sample data is x_i, is the sample mean is $\bar{x}$

$$threshold = mean + k * std_d ev$$

mean is the mean of the heights of all points in a given voxel, std_d ev is the standard deviation of the heights of all points in a given voxel, and k is the standard deviation multiplier. If the difference between the height of a point and the mean value is greater than threshold, the point is considered an outlier. Usually, when k is taken as 2, most of the noise and outliers can be effectively removed; when k is taken as 3, the noise and outliers will be removed more strictly, but some useful information may be lost at the same time.

In point cloud data processing, fitting surface is an important step, whose purpose is to solve the mean and standard deviation of point cloud data in order to eliminate outliers. Fitting surfaces is usually performed using least squares plane fitting method. The method assumes that the point cloud data are distributed on a plane, and solves the parameters of the plane by minimizing the square of the distance from each point to the plane. Specifically, suppose the Formula 3-2-6 of the plane is:

$$ax + by + cz + d = 0 \qquad (3\text{-}2\text{-}6)$$

The parameters of the plane can be solved by minimizing the following Formula 3-2-7:

$$min\Sigma(ax_i + by_i + cz_i + d)^2 \qquad (3\text{-}2\text{-}7)$$

$(x_i, y_i, z_i)$is a point in the point cloud data.

Expanding the above equation, we can get the following linear equations 3-2-8:

$$\begin{aligned} x_i^2 a + x_i y_i b + x_i z_i c + x_i d &= -x_i z_i \\ x_i y_i a + y_i^2 b + y_i z_i c + y_i d &= -y_i z_i \\ x_i z_i a + y_i z_i b + z_i^2 c + z_i d &= -z_i^2 \\ x_i a + y_i b + z_i c + nd &= 0 \end{aligned} \qquad (3\text{-}2\text{-}8)$$

n is the number of points in the point cloud data.

3.2.5 Results and Analyse

To calibrate the segmentation performance of the model on cucumber seedlings, the same pre-assigned training and calibration sets were used to participate in training and calibration, and the model was evaluated using the same calibration method.

3.2.5.1 Experimental environment and Training Methods

All experiments were performed on the same workstation platform, which is equipped with hardware such as Intel i9-10920X CPU, NVIDIA RTX 3090 with 24G memory GPU, and 128G RAM, and uses software environments such as Ubunut18.04, CUDA11, CUDNN8.1, PyTorch1.11, and Python3.7. The dataset is randomly divided into training and calibration sets according to the scale, and trained on each model. In view of the differences between the models, three groups of experiments are designed, which are CMDFR, CNDFR without depth, and mainstream segmentation methods. Each model is trained to converge, that is, after 50 rounds of calibration, the results of the models did not improve. The trained model is evaluated on the test set.

Fig. 56 CMFDR model was used to train loss curve.

Experimental training CMFDR process is as shown in **Fig. 56**, where the loss curve gradually converges with the increase of the number of training rounds. Among them, the RGBD model achieves convergence at around 50 rounds and converges well. RGB did not achieve convergence until 100 rounds, and the degree of convergence was low.

3.2.5.2 Segmentation results

The cucumber seedling segmentation algorithm across model depth proposed in this experiment is based on depth map and RGB image extraction features. In order to verify the detection and segmentation capabilities of the model, the model CMFDR, which was trained and converged on the training set, was selected, and the backbone network SegFormer-B2 was selected. The model parameter quantity was 67.6GFLOPs, and the model file size was 94.3Mb. The environment and parameters of the test set were the same as those of the training set. There were 78 test set images and 234 plant instances. The test results were 93% PA, 93.4% IoU, and the mean time to predict images was 78 ms. As shown in **Table 10**, the plant detection and segmentation performance of the model proposed in this paper on the test set is demonstrated under the complex lighting environment of the plant factory.

Table 10 The plant detection and segmentation performance of the model proposed.

Model	Backbone	PA(%)	IoU(%)	FLOPs(%)	Weight Size(%)
CMFDR	SegFormer-B0	83.4	79.1	10.1G	14.1Mb
CMFDR	SegFormer-B1	85.2	83.7	37.5G	52.1Mb
CMFDR	SegFormer-B2	90.8	90.3	67.6G	94.3Mb
CMFDR	SegFormer-B4	89.5	92.3	122.3G	170Mb
CMFDR	SegFormer-B5	93.0	93.4	167.8G	234Mb

Through the observation of the experimental data, we can find that with the increase in the size of the Backbone, the detection and segmentation performance of the model are further enhanced. This suggests that the model exhibits a degree of generality and can be enhanced in scale to enhance its efficacy in handling a wider range of classification tasks or more refined classification tasks. In addition, it is observed from the IOU column of the detection box that the model has achieved good results on a small scale. The performance improvement is very limited as the network size increases, indicating that the majority of weight parameters of the network model contribute to the target segmentation, thereby enhancing the model's segmentation precision. Using CMFDR networks of different sizes to segment an example image can show that the segmentation results of larger networks are more accurate and can better fit the plants, as shown in the **Fig. 57**. Accurate plant segmentation is of great significance for precision agriculture, which can be used for seedling platforms, accurate modeling, plant genetic engineering experiments, etc. This suggests that the proposed network can be applied to more fine plant segmentation tasks now and in the future as the network size increases.

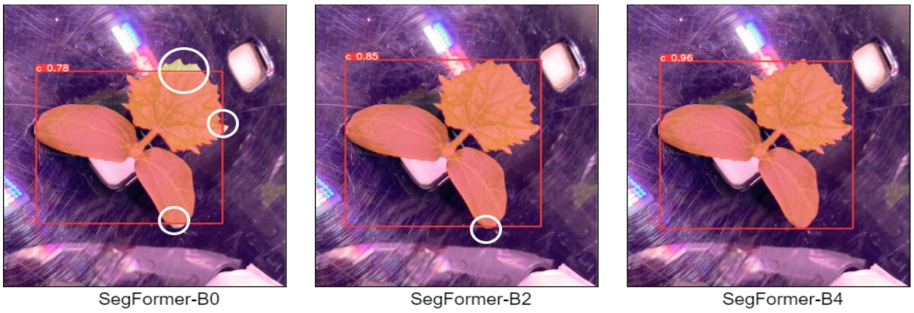


Fig. 57 Comparison of segmentation results. When CMFDR uses different size backbone networks, A, B, and C indicate that the CMFDR model is effective in predicting the same plant except when the SegFormer-B0, SegFormer-B2, and SegFormer-B4 backbone networks are used to visualize the same plant, respectively. The red and blue filters are the prediction results, and the white circle is added to emphasize the places with poor effect.

3.2.5.3 Effect of contrast depth map on results

In order to explore the impact of depth images on model detection and segmentation performance, this study further tested the model's performance in the absence of depth information, the results are shown in **Table 11**. Since the adopted cross-channel rectification algorithm needs to use the depth channel information to extract the features of the RGB images, if pure white or pure black is used to replace the depth image, the feature extraction process of the model may be misled, and thus the performance of the model is degraded. Therefore, in the test model, this study uses the gray image of the RGB image and the corresponding RGB image as the depth image input, where the gray image does not contain any additional features. In the experiment, SegFormer-B4 was selected as the backbone network, and its model scale was 78GFLOPs. The experimental results show that each test index using depth image is higher than that without depth image. In particular, the difference between the two is up to 20% in terms of segmentation indicators. Therefore, the depth image acquired based on the RGBD sensor has a large improvement potential for the plant segmentation task in complex scenes.

Table 11 The test results of improved models using and not using depth images.

Model	Input	PA(%)	IoU(%)
CMFDR-RGB	RGB	70.4	69.1
CMFDR-RGBD	RGBD	93.0	93.4

3.2.6 Conclusions of this section

In this paper, a CMFDR cucumber segmentation algorithm is proposed. The core idea is to use multimodal ideas to acquire depth maps and RGB images simultaneously and use two parallel backbone networks to rectify and extract these features. Specifically, this paper constructs a network using the idea of ViT segmentation and uses an efficient feature rectification and feature fusion module to introduce the fused features into the cross-scale decoder for segmentation and detection. In addition, a depth rectification algorithm is proposed to remedy the influence of the complex illumination environment on the depth sensor by rectifying the influence of complementary light on structured light. Finally, this paper also puts forward the backbone network of different scales to meet the needs of different tasks, so as to further guide agricultural production, and create economic and agricultural value.

The experimental results show that the CMFDR cucumber segmentation algorithm proposed in this paper performs better than the algorithm using only RGB segmentation, especially when dealing with plant segmentation in complex scenes. Therefore, the algorithm proposed in this paper can be used for cucumber plant phenotypic platforms, yield estimation, accurate modeling and other tasks and provides important technical support and economic value for agricultural production.

SECTION 4. BASIC RESEARCH RELATED TO THE COUPLING AND PRECISE REGULATION OF MULTIPLE ENVIRONMENTAL FACTORS IN A PLANT FACTORY WITH ARTIFICIAL LIGHTING

4.1 Illumination screening And uniformity simulation of hydroponic lettuce in artificial light plant factory

4.1.1 Illumination properties and artificial light plant factories

In recent years, the ALPF (Yang, 2014; Liu et al., 2014; He, 2018; Kozai, 2019; Kozai et al., 2020; Huebbers et al., 2020) have become the mainstream production mode of urban productive agriculture, as the plant growth environment is highly controllable and not limited by natural climate, geographical location, land resources, and other conditions (Lee, 2018). In addition, the agricultural products of plant factories have the advantages of pollution-free, pesticide residue free, washable and ready to eat, green, healthy and environmentally friendly, which are expected and loved by people (Huang, 2019; Ares, 2021). ALPF is the highest form of facility agriculture development and a new agricultural production method for the development of intensive and efficient modern agriculture. It is more suitable for the development of industrialization and commercial plant production in urban areas and has good development prospects (Orsini et al., 2020). Light is an essential energy substance for plant photosynthesis, growth and development, morphological construction, and material consumption. The light conditions required by different types of plants at different stages of growth vary greatly. Therefore, focusing on optimal lighting conditions for specific plants, including light quality, light intensity, light cycle, and light production form, has become a hot research topic in artificial light plant factories. Light emitting diodes (LEDs) have the advantages of low voltage, low power consumption, safety and energy conservation, easy control, long service life, small size, light weight, and wide working environment. They have become a common source of light for plant lighting in greenhouses, artificial climate rooms and other areas. With the rise and development of ALPF, they have also become the mainstream light source for ALPF applications (Tsuruyama et al., 2018; Prikupets et al., 2019; Wei et al., 2020; Paucek et al., 2020; Jiang et al., 2020).

Lettuce is widely grown in fields and greenhouses in China and many countries around the world. It is beloved for its crisp, thick leaves, good fresh taste, easy digestion, green health and high nutritional value. In addition, its low growing environment requirements, easy survival, rapid growth, lush foliage, compact growth, low plant height, and short growth cycle make it well suited for cultivation in PFALs. Philips pioneered the concept of plant lighting formulations and has played an important guiding role in the design, development and production of plant growth lamps due to the different lighting requirements of specific plants during a given growth phase. The lighting formula refers to the lighting conditions required by crops in a specific growth environment during a certain growth stage (Wang et al., 2015; Liu et al., 2017; Marondedze et al., 2018). A lighting formula usually consists of three aspects and eight parts: (1) The first aspect is the lighting characteristics, namely lighting quality, lighting intensity, light cycle, light source installation position, number of lamps and LED beads, and lighting uniformity. (2) Environmental factors, i.e. other environmental parameters based on the light formula, such as temperature, humidity, etc; (3) Light effects, such as energy-saving effects. All the above factors are interdependent, interacting, interwoven, and coupled to each other. In addition, coupled with the complex biological mechanisms of plants themselves, the study of plant illumination formulas has become extremely complex.

LEDs belong to cold light sources, and the closer they are to plants, the stronger the illumination and the higher the efficiency of light energy utilization (Wang et al., 2004; Massa et al., 2008; Yang et al., 2011). Illuminance (E) refers to the amount of light flux (φ) received by the illuminated surface of an object per unit area (S), and the calculation method for illuminance is shown in **equation** (1). The illuminance of LED lights varies with changes in power supply voltage and can be measured using a spectrophotometer.

$$E = \varphi / S \qquad (1)$$

It is necessary to choose different numbers of red and blue LEDs to match and combine for different plants, while taking into account the desired illumination and uniformity of illumination. Different types of plants require different levels of light uniformity (Wu et al., 2009; Zhu et al., 2015). The illumination uniformity (U_0) refers to the ratio of the minimum illuminance (E_min) of the light receiving surface to the average illuminance (E_ave) within a certain irradiation area, which is calculated as shown in **equation** (2). The value of illumination uniformity is $(0,1)$, and the closer the value is to 1, the more uniform the light the lettuce receives and the better its overall growth condition.

$$U\_0 = E\_min/E\_ave \qquad (2)$$

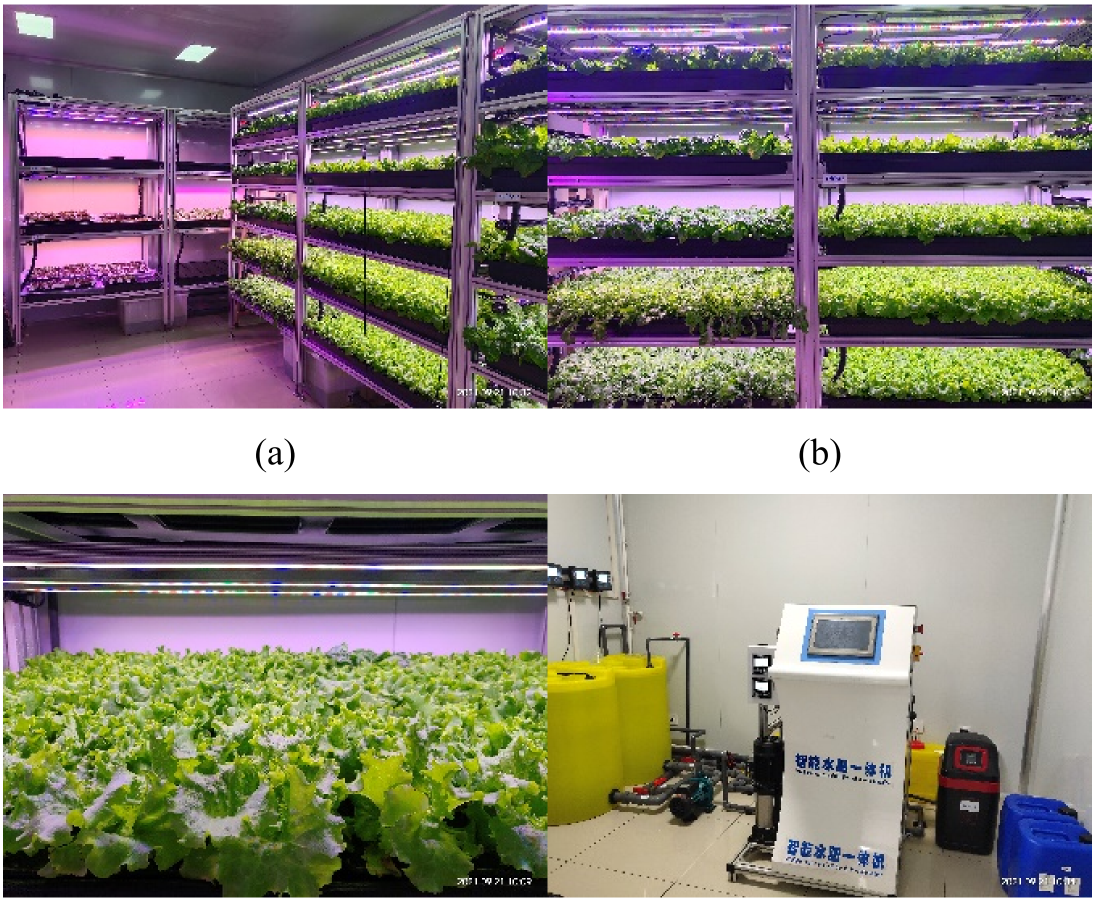
The growing process of ALPFs hydroponic lettuce is divided into three stages: germination, seedling, and growth, and its growing period is typically around 30 - 50 days. The requirement for light during the budding stage is not high, so light regulation is rarely carried out. The optimal composite ratio of red and blue light during the seedling stage is 7:1, and the optimal composite ratio during the growth stage is 6:1. The optimal lighting time for the seedling and growth stages is 16 hours. In general, LED light beads are arranged in equal intervals, and the uniformity of illumination varies greatly when different arrangements of light are used to illuminate lettuce, which can affect the overall growth of lettuce.

With the deepening of ALPF research and the advancement of its commercialization and industrialization, improving the automation and accuracy of light environment regulation under artificial lighting conditions, maximizing the promotion of high-quality and efficient plant growth, is an effective way to reduce energy consumption, improve resource utilization efficiency, and lower production costs (Saito et al., 2020; Yuan et al., 2021). In this study, different forms of LED illumination and distribution are used to design illumination gradient experiments and illumination uniformity computer simulation experiments. Experimental comparisons and computer simulation methods were used to investigate the effect of different illumination and LED arrangement forms on lettuce growth under ALPFs, with the aim of providing a standard lighting scheme for artificially illuminated plants.

4.1.2 Illumination gradient experiment

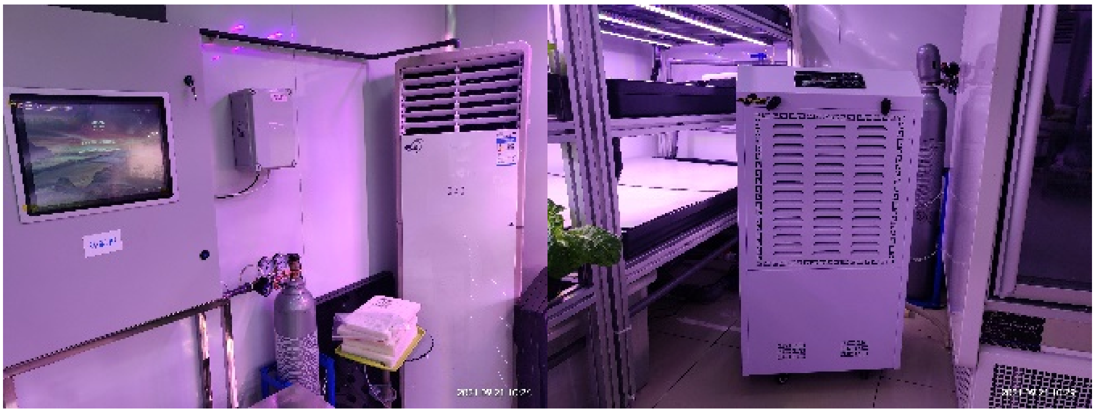
4.1.2.1. Experiment site and test material

The laboratory is decorated with fully enclosed insulation and is designed to have no light transmission. The plant growth is illuminated by controllable red, blue, and white LED lights. The growing room environment is controlled by a combination of cabinet air conditioners, fresh air systems, humidifiers and other equipment, intelligently controlled by centralized control software. The airflow and air volume of the planting layer frame are controlled by a DC axial fan. The nutrient solution that circulates in the hydroponic layer frame is intelligently regulated by a programmable integrated water and fertilizer system. Experiments were conducted alternately between early June 2021 and late December 2021. Multiple lettuce varieties were used in the experiments, and all lettuce seeds were purchased from legitimate seed companies with market licenses. All the experimental material was taken from hydroponic lettuce grown in the laboratory. The experimental site and some main experimental equipment are shown in **Fig. 58**.

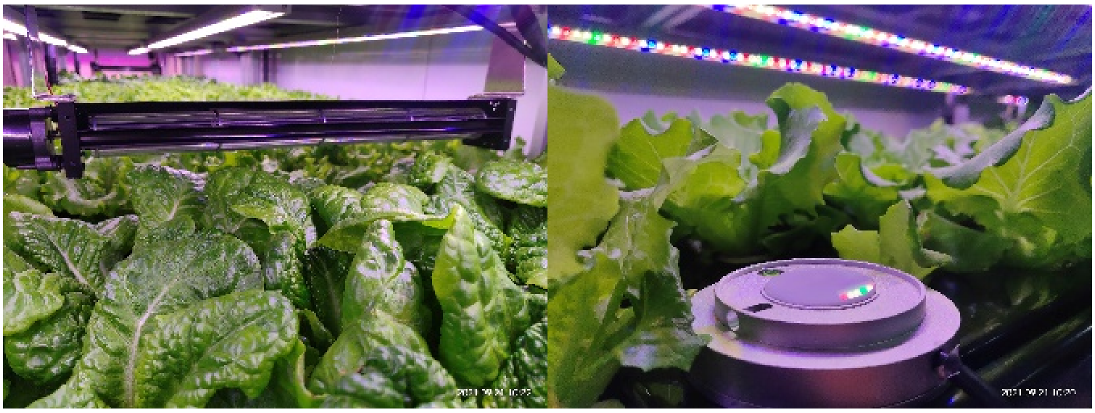


(a) (b)

(c) (d)



(e) (f)



(g) (h)

Fig. 58 The ALPF laboratory and main experimental devices. (a) The ALPF laboratory, (b) Hydroponic shelves, (c) Hydroponic Lettuce, (d) Integrated irrigation system (e) Environmental regulation system, (f) Dehumidifier, (g) DC fan, (h) Light sensor.

4.1.2.2. Experiment environment

The experimental LED plant growth light was custom-developed by ANCORGREEN, a specialist manufacturer from Anhui province. The light quality, intensity and duration of an LED lamp can be set according to experimental requirements and intelligently controlled by a program. The light quality is composed of red, blue and white lights according to the set ratio, and the ratio of the three lights can be precisely controlled by the program, as shown in **Fig. 59** for some of the LED lamps used in the experiment. When the plants are illuminated to simulate the daytime, the indoor temperature of the laboratory is set at about 23 ℃ and the CO_2 concentration is set at about 800ppm. Moreover, when the plants are not illuminated to simulate the night, the indoor temperature of the laboratory is set at about 18 ℃

and the CO_2 concentration is set at about 400ppm. The humidity in the laboratory setup was maintained between 70% and 80%. The DC fan, which regulates the flow of air through the growing shelf, operates for 2 minutes at 10-minute intervals. The nutrient solution in the planting layer shelves is continuously supplied for 5 minutes at 30-minute intervals, in which the EC value is always maintained at 800 $\mu s/cm$, and the pH value is maintained at about 6.8. LED lamps are installed at the top of each layer of the planting shelves, 28cm away from the lettuce growing canopy, and the plant light time is set to 16 $\hbar/d$.

(a) (b) (c)

Fig. 59 LED plant lighting lamps. (a) Matrix arrangement, (b) Triangular arrangement, (c) Circular arrangement.

4.1.2.3. Experimental design

To investigate the effect of different light conditions on lettuce growth, 60 healthy lettuce seedlings were randomly selected, and 15 seedlings were subjected to four sets of light conditions for the hydroponic experiment. Illumination levels are set to 200, 300, 400, and $500\mu mol/(m^2 \cdot s)$, respectively, denoted as T1, T2, T3, and T4. From the first day after transplantation, five plants were randomly selected at 5 p.m. each day to measure and record the height, length and width of the outermost leaves of the lettuce. When the lettuce is 50 days old, it is ripe and ready to be harvested. Eight good growing plants were selected from each control group, and the fresh weight of each plant was weighed and their average value calculated.

4.1.2.4. Results and analysis

After 50 days of hydroponic cultivation, the lettuce was harvested and the fresh weight of individual plants was weighed, the results of which are recorded in **Table 12**. The lettuce growth and growth curves for different experimental groups are shown in **Fig. 60** and **Fig. 61**, where **Fig. 61a** shows the average plant height growth curve, **Fig. 61b** shows the average leaf length growth curve, and **Fig. 61c** shows the average leaf width growth curve for lettuce.

Table 12 Average fresh weight of individual plant lettuces at harvest under different illumination conditions.

Illuminance	Fresh weight of individual plant*								Average fresh weight*
T1	112	126	115	109	128	117	119	120	118.25
T2	136	132	128	126	131	129	138	127	130.875
T3	168	163	162	169	158	160	159	153	161.5
T4	96	112	103	97	108	102	106	116	105

*illuminance unit: $\mu mol/(m^2 \cdot s)$, Fresh weight: grams.

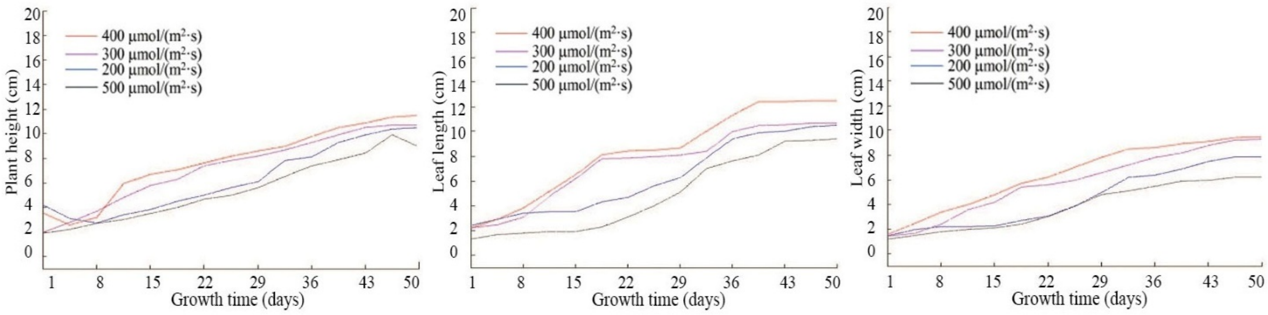
As can be seen from **Table 12** and **Fig. 60**, the growth of hydroponic lettuce under different illumination conditions is significantly different. For plant morphology, each experimental group of lettuce grew brittle green hypertrophy, but the number of lettuce leaves under 500 $\mu mol/(m^2 \cdot s)$ light was significantly less than that of the first three experimental groups. For biomass accumulation, compared with the average fresh weight of single lettuce after hydroponic culture to 50 days, the biological yield of single lettuce under 400 $\mu mol/(m^2 \cdot s)$ illumination is the highest, which is about 37% higher than that under 200 $\mu mol/(m^2 \cdot s)$ illumination, 23.4% higher than that under 300 $\mu mol/(m^2 \cdot s)$ illumination and 53.8% higher than that under 500 $\mu mol/(m^2 \cdot s)$ illumination. The results showed that the 400 $\mu mol/(m^2 \cdot s)$ illumination was more suitable.

(a) (b) (c) (d)

Fig. 60 Growth of lettuce in each experimental group at harvesting. (a) T1, (b)

T2, (c) T3, (d) T4.

As can be seen from **Fig. 61**, the plant height, leaf length and leaf width of hydroponic lettuce show an upward trend as the lettuce growth time increases, indicating that the illumination gradient setting is reasonable. For different growth indexes, the growth of lettuce in each experimental group was T3 > T2 > T1 > T4. The results showed that when the illuminance was set below 400 $\mu mol/(m^2 \cdot s)$, gradually increasing the illuminance could promote the growth of lettuce. When the illuminance reached 400 $\mu mol/(m^2 \cdot s)$, the growth of lettuce was inhibited by increasing the illuminance. The reason may be that the high-illumination LED lamps have high thermal power consumption and high heat, leading to water shortage in the plant. It is also possible that the high intensity of the light caused some damage to the plant's growing organs or some stress on physiological processes. The results also showed that the 400 $\mu mol/(m^2 \cdot s)$ illumination was more suitable for the growth of hydroponic Lettuce in PFALs.



(a) (b) (c)

Fig. 60 Growth of lettuce under different illumination. (a) Plant height growth curve, (b) Leaf length growth curve, (c) Leaf width growth curve.

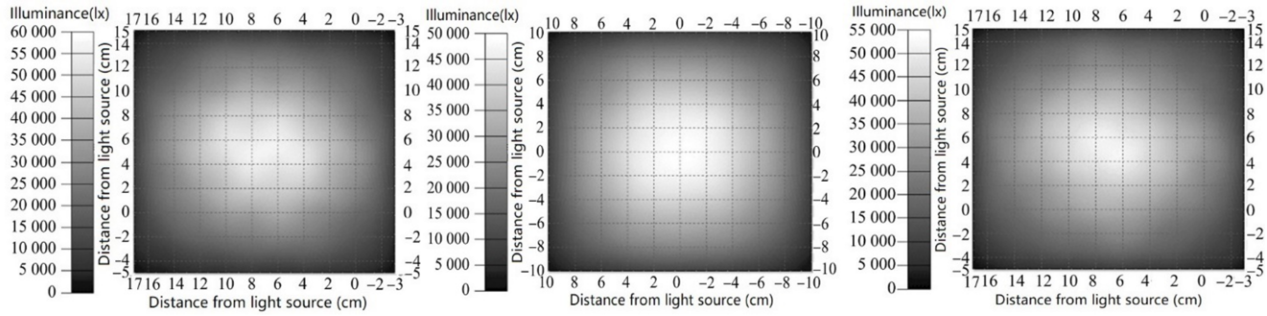
4.1.3 Simulation experiment of illumination uniformity

4.1.3.1 Experimental design

In general, led plant sources are arranged in arrays, triangles, and circles. In order to study the illumination uniformity characteristics of LED light sources with three arrangement modes, we use TracePro optical simulation system and three-dimensional composition method of MATLAB software to simulate the illumination uniformity, compare and analyze the advantages and disadvantages of the illumination uniformity of the three arrangement modes, and provide theoretical guidance for the design of plant light sources and plant production using artificial light sources.

(1) TracePro optical simulation experimental method

The TracePro optical simulation environment was systematically configured by selecting 25 identical LED beads and sequentially arranging them into matrix, triangular and circular forms, with the spacing set to 3 cm and the light source 28 cm away from the lettuce. The simulation plots were derived by running the Tracepro software after setting the remaining parameters, as seen **Fig. 62**.

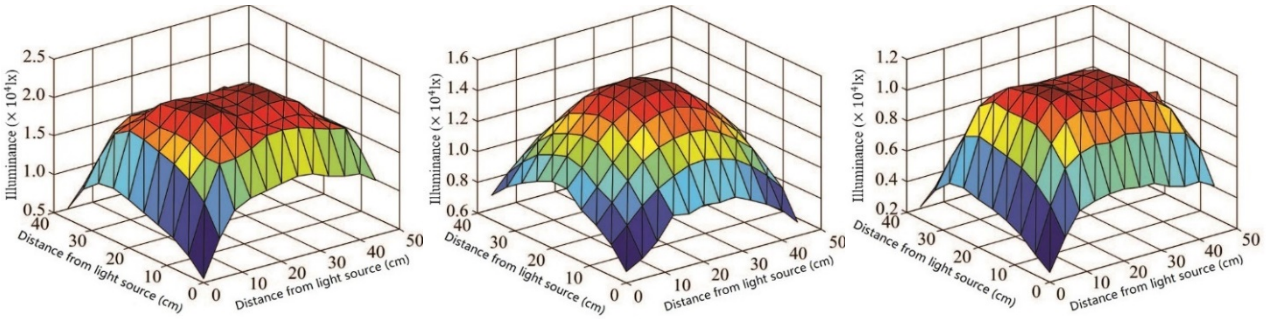


(a) (b) (c)

Fig. 61 Simulation results for the illumination distribution in different permutation patterns. (a) Simulation results of matrix illuminance distribution, (b) Simulation results of triangle illuminance distribution, (c) Simulation results of circular illuminance distribution.

(2) Matlab software simulation experimental method

Through the Matlab software system, a 3D map is constructed from the collected illumination data to visually display the distribution of illumination inhomogeneities. The test step was to attach LED light beads in the form of matrices, triangles and circles spaced 3 cm apart on top of the growing layer shelf, with the source 28 cm away from the coordinate paper. The specification of coordinate paper is 100cm × 100cm, composed of small squares of 1cm × 1cm. After preparation, the illumination at each small square was measured successively with the illuminant sensor, and the final summary data was constructed into a 3D map via Matlab software, as shown in **Fig. 63**.



(a) (b) (c)

Fig. 62 Matlab simulation of illuminance distribution in different arrangement forms. (a) simulation of matrix arrangement, (b) simulation of triangle arrangement, (c) simulation of circular arrangement.

4.1.3.2. Results and analysis

(1) Optical simulation results and analysis of TracePro software

As can be seen from **Fig. 62**, the three permutation modes all exhibit light distribution features where the middle region of the light receiving surface is brighter and the surrounding region gradually darkens. In particular, the overall illumination of the LED sources arranged in the matrix is significantly better than that of the triangular and circular arranged modes. The illumination uniformity index refers to the uniformity of the illumination distribution. According to the simulation results, the illumination uniformity of the matrix is 80%, as shown in **Fig. 62a**. The illumination uniformity of the triangular form is 71%, as shown in **Fig. 62b**. The circular pattern has a uniform illumination of 79%, as shown in **Fig. 62c**. Using TracePro computer simulations, it can be shown that the matrix LED source arrangement has the best illumination uniformity.

(2) Matlab 3D simulation results and analysis

In the stereo stereogram constructed by MATLAB, regions with different colors represent different illumination of the light receiving surface. If the adjacent regions are closer in color or the flat region at the crest position is larger, this indicates that the difference in the received illumination is smaller and the uniformity is larger. From **Fig. 63a**, **Fig. 63b** and **Fig. 63c**, it can be seen that the middle regions of all three figures show similar colors such as red, dark red, and orange, and the middle regions of **Fig. 63a** and **Fig. 63c** have more similar colors than **Fig. 63b**. Comparing **Fig. 63a** and **Fig. 63c**, all of them have a certain plane area at the wave peak position, and the plane area in **Fig. 63a** is significantly more than that in **Fig. 63c**, suggesting that the matrix arrangement represented in **Fig. 63a** has the best illumination uniformity. Therefore, the simulation method with Matlab software also proves that the matrix arrangement of the LED source has the best light uniformity.

4.1.4 Discussion and conclusion

The light environment parameters of plant culture consist mainly of light source, light quality, illumination, light duration, and light homogeneity. There are a number of scholars who have conducted related studies of some of these factors and have found some patterns in the effects of certain factors on plant growth. Yan et al. (2020) systematically studied the effects of white-red and red-blue LED lighting environment on the growth, quality and energy utilization efficiency of two kinds of lettuce, and found that white-red LED light quality can replace red-blue LED light quality and be used in lettuce hydroponic culture to improve resource utilization. Li et al. (2012) found that the growth trend of lettuce under 16h continuous light is generally better than that under 16h intermittent light. Kim et al. (2017) and Mu et al. (2020) studied the effects of different pulsed light on the growth, quality and photosynthesis of lettuce. They found that under the same conditions as the net photosynthetic rate of continuous light, pulsed light patterns not only did not affect lettuce growth but also improved quality. They also found that lettuce treated with pulsed light combined with low frequency and high duty cycle produced better quality. Therefore, they propose that in practical applications, an appropriate light source should be chosen in combination with the energy cost of pulsed light. Ding (2014) and Wang (2017) studied the effects of different duty ratios of LED on the growth, yield, quality, and photosynthesis of lettuce. They found that duty ratios affect lettuce growth in two ways: light and dark periods, and through the interaction of light and dark periods, lettuce photosynthesis, growth and development, morphogenesis, and yield formation. In this study, the illuminance gradient test found that 400 $\mu mol/(m^2 \cdot s)$ illuminance is the best illumination under artificial lighting conditions, and the simulation of TracePro and Matlab software found that matrix LED light source arrangement has the best illumination uniformity compared with triangle and circle arrangement. Through experimental research, we obtained the best light formula of hydroponic Lettuce in PFALs: the plant growth environment temperature is kept at about 22 ℃ and the humidity is kept between 70%~80%. The LED light source was positioned 28 cm away from the lettuce using a matrix arrangement. Compound light with a red-to-blue light ratio of 7:1 is used during the seedling stage and a 6:1 ratio is used during growth. The illumination was set to 400 $\mu mol/(m^2 \cdot s)$ and the photoionization period was set to $16h/d$. The light formula can be used as a general scheme for large-scale hydroponic lettuce in plant factories and also as a reference light formula for other leafy vegetable varieties. This research has some practical implications for promoting the industrialization and commercial production of artificial light vegetables.

4.2 Experimental study of the effect of light quality on the quality of hydroponic *Cichorium endivia* L. in ALPF

4.2.1 Light quality and plant factory planting

With the development of LED plant-lighting technology, LED plant growth lamp has become the mainstream light source for plant growth in the ALPFs, and the plant photosynthesis and light form construction under LED illumination has also become the heated research focus (Eva et al., 2014; Zakurin et al., 2020; Lee et al., 2021). Compared with traditional incandescent lamps, high-pressure sodium lamps and other artificial light sources, the new generation of LED artificial light sources has the advantages of small size, precise and controllable light quality and intensity, low heat energy consumption, energy saving and environmental protection (Yeh et al., 2009; Li et al., 2012; Sudthai et al., 2022). It is found that the red light and blue light with the wavelength of 400-700nm are closest to the efficiency curve of plant photosynthesis, and are the two main light sources for plant photosynthesis absorption (Niu et al., 2015; Miao et al., 2019; Paradiso et al., 2021). Some scholars have studied pea seedlings, lettuce seedlings and strawberries under illumination, and found that red light can increase leaf area of pea seedlings, inhibit internode elongation of plants, promote tillering and increase the accumulation of chlorophyll, carotenoids, soluble sugar and other substances (Chen et al., 2017; Li et al., 2017; Díaz-Galián et al., 2020). Blue light is an important influencing factor of photosynthetic system activity and photosynthetic electron transfer capacity of plants, which can obviously shorten the vegetable internode spacing, promote lateral extension and reduce leaf area, and at the same time, blue light can also promote the accumulation of secondary metabolites of plants (Hitz et al., 2020; Díaz-Rueda et al., 2021). There are clear species-specific differences in the requirements for plant light quality. Zhang et al. (2021) studied the effects of continuous lighting with LED red and blue light before harvest and lighting with different light quality on the growth and nutrient absorption of nitrogen form hydroponic Lettuce, and found that the aboveground fresh weight of lettuce increased significantly. Kim et al. (2018) studied the effects of different red and blue illumination time on the growth and development of ice plant, and analyzed its growth and development rules. It was found that when the ratio of red to blue light was 4:5 and the illumination time was 14 hours, it was more beneficial to the growth of ice plants and improved their nutritional quality. Shao et al. (2020) studied the effects of different red and blue LED illumination intensity on the growth and nutritional quality of purple leaf lettuce. Their research results showed that appropriate higher intensity lighting significantly promoted the accumulation of total ascorbic acid (TA) in lettuce leaves, but reduced the ratio of ascorbic acid/TA. Lee et al. (2013) studied the effects of white-red and red-blue LED lighting environment on the growth, quality and energy utilization efficiency of two kinds of lettuce. At present, the conditions under which the quality of the light affects the quality of the growth of various vegetables are mainly set by a mixture of light masses consisting of monochromatic light and light of different colours except white, or by different ratios of red and blue light. However, the lighting conditions of endivia L., a species of the genus Cichorium, have been poorly studied. In this paper, the PFAL is used as the experimental condition, the *Cichorium endivia* L. is used as the experimental material, the hydroponics is used as the cultivation method, the LED lamp is used to illuminate the plant growth, and the white light is added to the red, blue and white light, so as to study the influence of different proportions of LED red, blue and white light on the growth of *Cichorium* *endivia* L., and provide theoretical reference for the high-quality cultivation of *Cichorium endivia* L. in greenhouse and plant factory.

Cichorium endivia L., native to Asia, India, and southern Europe, is frequently used with its young leaves in fried, boiled, or cold foods. It is rich in nutrients such as VC, carotene, calcium and potassium, and has the functions of removing heat and relieving fever, inducing diuresis and relieving coughs, among other things, and is of extremely high nutritional and medicinal value. *Cichorium endivia* L. has the characteristics of strong stress resistance, readily cultivated and not easy to produce diseases and insect pests, thus, it is widely selected by farmers (AMIMOTO et al., 1997). It is also currently popular in China, where it has been planted in large areas. (Zhao, 2020) Nevertheless, with the continuous improvement of people's living standards, the requirements for the quality of vegetables are getting higher and higher, and products with higher nutritional content are more likely to be favoured. In order to meet the market demand for high-quality *Cichorium endivia* L., it is of great economic importance to study the growing illumination conditions that allow *Cichorium endivia* L. to produce better physiological indicators. The aim of this study is therefore to explore the most appropriate lighting formulation for industrial production of *Cichorium endivia* L. This will enable accurate regulation of the plant light environment, reduce the energy consumption of plant light, and facilitate the rapid development of the ALPF.

4.2.2 Materials and methods

4.2.2.1 Experimental materials

The material for the experiment was *Cichorium endivia* L., the seeds of which were procured in the market. Plant lighting uses red, blue and white long strip LED lights. The power is 200W and the quality, intensity and duration of the light can be changed remotely by a program. Experiments were conducted using a hydroponic approach, where the preparation and recovery of nutrient solutions is automatically controlled by smart integrated water and fertilizer equipment. The environment in the growing chamber, such as temperature, humidity, fresh air and plant canopy airflow, is centrally and regulated through an intelligent integrated control system.

4.2.2.2 Experimental design

According to the purpose of the experiment, the LED lamps with different proportion of red (R), blue (B) and white (W) were divided into three treatment groups and one control group, in which the red-light wavelength was 665 nm, the blue light wavelength was 445 nm and the white light wavelength was 330~770 nm. Treatment group 1 (T1) was 5R: 8B: 7W, treatment group 2 (T2) was 6R: 7B: 7W, treatment group 3 (T3) was 5.5R: 8B: 6.5W, and control group (CK) was white light, as shown in **Table 13**. The illumination intensity was $116 \pm 10 \mu mol/m^2 \cdot s$, the illumination period is set as the ratio of illumination time to non-illumination time of 16 hrs: 8 hrs, and the distance between LED lamp and cultivation board was 23cm. Under illumination, the growth environment temperature is constant at 22 ± 1℃ and humidity was constant at 76±2%; under no illumination, the environment temperature was constant at 18 ± 1℃ and humidity was constant at 76 ± 2%. Each process is repeated five times.

Table 13 Light quality composition of the experimental group

Experimental group	Combined LED light of red, blue and white	Illumination intensity ($\mu mol/m^2 \cdot s$)
CK	White	116±10
T1	5R: 8B: 7W	116±10
T2	6R: 7B: 7W	116±10
T3	5.5R: 8B: 6.5W	116±10

Note: CK is the control group and T1, T2 and T3 are the treatment groups.

4.2.2.3 Experimental procedure

Select high-quality seeds of *Cichorium endivia* L., soak them in warm boiled water at 50~60℃ for 3 hours, then wet them and put them in a ventilated shade for 20 hours, so as to relieve dormancy and promote the seeds to germinate, as shown in **Fig. 64** Select the seeds with strong germination and transplant them into the planting sponge, add clean water and place them under the LED lamp for cultivation as shown in **Fig. 65**. After about 7 to 10 days, when the seedlings have grown to 2 leaves and 1 heart, select the sturdy seedlings and transplant them to the planting tray for the growth and cultivation, as shown in **Fig. 66**. According to the requirements of the experimental design, keep the growth environment, indoor air and CO_2 concentration in line with the experimental requirements, ensure the air flow in the canopy and the supply and flow of nutrient solution in the root zone, and precisely control the LED light quality ratio and illumination intensity. After about 30 days, when *Cichorium endivia* L. grows to the level shown in **Fig. 67**. The five largest plants from each group were selected to measure the indices such as leaf number, dry weight (g) and fresh weight (g) above ground, dry weight (g) and fresh weight (g) below ground, chlorophyll (mg/g), carotene (mg/g), soluble sugar (mg/g) and so on.

Fig. 63 Seed germination of *Cichorium endivia L.*.

4.2.2.4 Index measurement and data processing

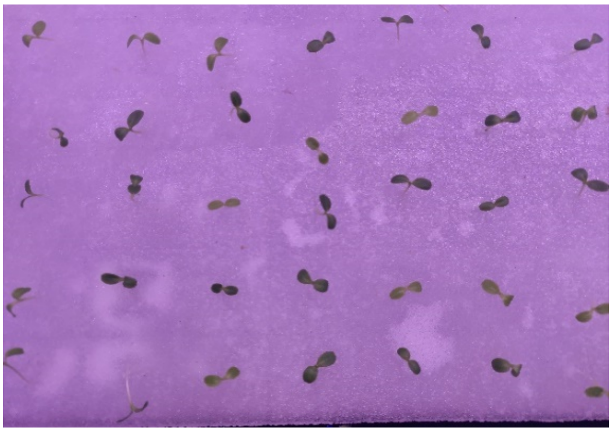


Fig. 64 Seeding of *Cichorium endivia L.*

The fresh and dried weight of *Cichorium endivia L.* in the ground and underground was measured by selecting the five largest plants from each treatment group, wiping the droplets on the leaves and roots, and letting them stand for 20 minutes. Accurately weigh the fresh weight of leaves and roots using an analytical balance, and then place them in an 80 ℃ oven. After drying to a constant weight, the corresponding dry weight is accurately weighed using an analytical balance.

Fig. 65 Hydroponic *Cichorium endivia L.* growth

Fig. 66 A sample of hydroponics *Cichorium endivia L.* after harvest.

The chlorophyll content, VC and carotene content of *Cichorium endivia* L. were measured by ultraviolet spectrophotometry, and the soluble sugar content was measured by enthrone colorimetry (Mu et al., 2010). Excel was used to collate the recorded data and SPSS 23 software was used to analyze the data variance ($P < 0.05$), and the S-N-K method was used to test the hypothetical variance (Larrinaga, 2010). GraphPad Prism v5 was used to create the graph. The results were shown in the form of mean ± standard deviation.

4.2.3 Results

4.2.3.1 Effects on the number of leaves and biomass

The statistical data for the number of leaves and biomass of Cichorium endivia

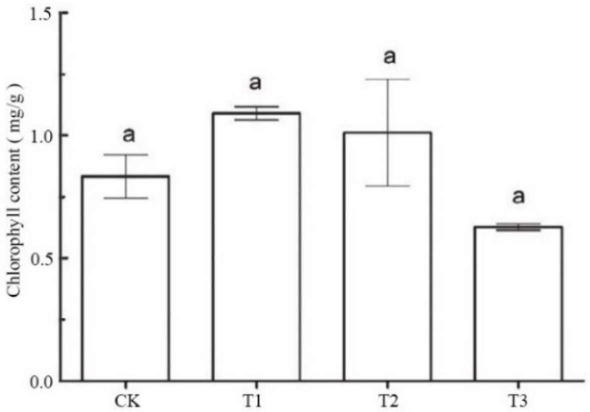
L. under different ratios of LED, blue and white light are shown in **Table 14**. For the number of leaves, T2(78±7.63) and T3 (80.62±3.85) are higher than CK (63±6.38) in the control group, but because of the large standard deviation in CK group, the data improvement is not obvious when the average number in T1 group is the same. T2 and T3 are significantly improved. For aboveground fresh weight and aboveground dry weight, there is little difference in CK between T2 and control group, but there is no improvement in CK between T2 and T3. For underground fresh weight and underground dry weight, there is no significant difference between T2 and CK in the control group, but CK in T2 is not improved compared with T3.

Table 14 Effects of different ratios of LED red, blue, and white light masses on leaf counts and biomass of *Cichorium endivia* L.

light treatment	number of leaves (pieces)	aboveground fresh weight (g)	aboveground dry weight (g)	underground fresh weight (g)	underground dry weight (g)
CK	63.00±6.38b	31.26±5.76a	2.39±0.72a	12.58±2.93a	1.06±0.29a
T1	63.00±3.26b	19.26±1.76b	1.36±0.16ab	9.76±1.65b	0.83±0.11ab
T2	78.00±7.63a	26.19±2.82a	1.91±0.23a	11.91±3.06a	0.91±0.09a
T3	80.62±3.85	18.96±2.69b	1.78±0.32ab	8.13±0.81b	0.63±0.12b

Note: CK is the control group and T1, T2 and T3 are the treatment groups.

4.2.3.2 Effect on Chlorophyll Content

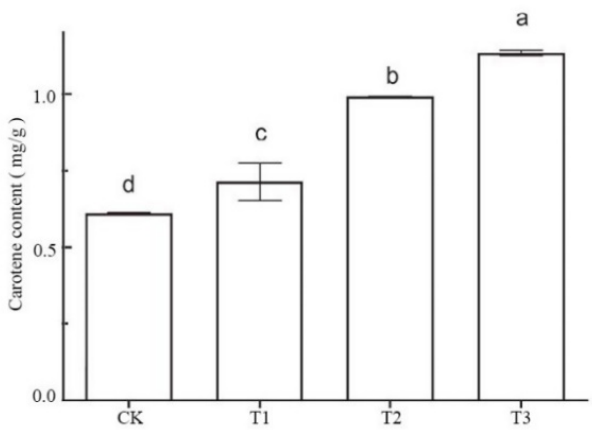


Note: CK is the control group and T1, T2 and T3 are the treatment groups. Different lowercase letters indicate significant differences at the level of P<0.05.

Fig. 67 Effects of different proportions of LED red, blue and white light quality on chlorophyll content of *Cichorium endivia* L..

Fig. 68 shows the effect of different ratios of LED, blue and white light quality on the chlorophyll content of *Cichorium endivia* L.. As can be seen from the figure, the T1 and T2 groups increases the chlorophyll content of *Cichorium endivia* L., while the T3 group decreases it. Compared with CK group (0.796), T1(5R:8B:7W) and T2(6R:7B:7W) had higher mean value (1.089) than T2 group (1.023). Overall, 6R:7B:7W light irradiation of Cichorium endivia L. had the most pronounced effect on increasing the soluble sugar content, and 5R:8B:7W light irradiation had the most pronounced effect on the chlorophyll content.

4.2.3.3 Effect on Carotene Content



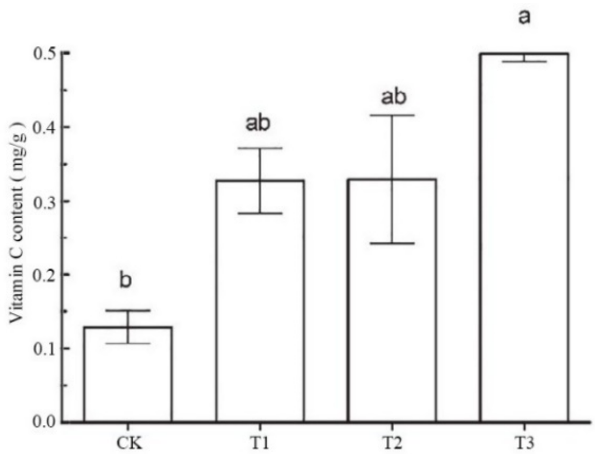
Note: CK is the control group and T1, T2 and T3 are the treatment groups. Different lowercase letters indicate significant differences at the level of $P<0.05$

Fig. 68 Effect of LED light with different ratios of red, blue and white on carotene content of *Cichorium endivia* L.

Fig. 69 shows the effect of different ratios of LED, blue and white light quality on the carotene content of *Cichorium endivia* L.. Variations in the carotene content of Cichorium endivia L. are similar to that of VC and show a ladder-like upward trend. The mean value of T1 group (0.071) was slightly higher than that of CK group (0.058), and the maximum value of T1 group was 0.091. The mean value of T2 group (0.096) and the data of three samples were all 0.096, which was significantly higher than CK group. The mean value of T3 group (0.108) and the maximum value of samples reached 0.116, which was close to twice the mean value of CK group, T1(5R: 8B: 7W), T2(6R: 7B: 7W) and T3 (5.5R: 7W) can obviously promote the synthesis of *Cichorium endivia* L., among which T3 group had the most significant effect.

4.2.3.4 Effect on vitamin C content

Fig. 70 shows the effect of light quality of different proportions of LED, blue and white on the vitamin C content of *Cichorium endivia* L.. Compared with the control group, the data of the three experimental groups were significantly improved. The mean value of group T1 (0.297) was about 2.6 times that of group CK (0.114), and the improvement was more significant. The mean value of T3 group reached (0.512), which was about 3.8 times that of CK group (0.131), greatly increasing the content of VC. The light combinations of T1(5R:8B:7W), T2(6R:7B:7W) and T3 (5.5R: 8B: 6.5W) can promote the synthesis of VC in *Cichorium endivia* L., among which T3 group had the most significant effect.

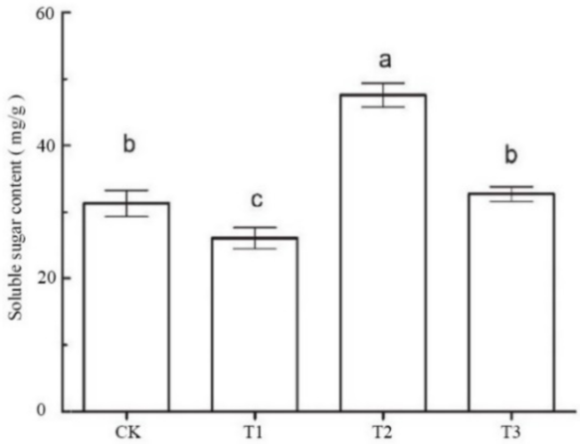


Note: CK is the control group and T1, T2 and T3 are the treatment groups. Different lowercase letters indicate significant differences at the level of P<0.05

Fig. 69 Effects of LED light with different ratios of red, blue and white on the vitamin C content of *Cichorium endivia* L.

4.2.3.5 Effect on soluble sugar content

Fig. 71 shows the effect of LED light consisting of different ratios of red, blue and white light as supplementary light on the soluble sugar content of *Cichorium endivia* L.. Significant differences were seen between the three treatment groups, with the T1 group having a lower mean content than the CK group. The difference between the T3 group and the CK group is not significant, with an average value (2.806) slightly higher than the control group (31.372). The T2 group had significantly higher levels of soluble sugar than the CK group. T2 (6R:7B:7W) significantly promoted the synthesis of soluble sugars in chicory, while T1 (5R:8B:7W) and T3 (5.5R:8B:6.5W) had no significant effect on the synthesis of soluble sugars in *Cichorium endivia* L.. Overall, irradiation with an composition of light quality of 5.5R:8B:6.5W had the most significant effect on increasing VC and carotenoid.



Note: CK is the control group and T1, T2 and T3 are the treatment groups. Different lowercase letters indicate significant differences at the level of P<0.05

Fig. 70 Effect of LED light with different ratios of red, blue and white on soluble sugar content of *Cichorium endivia L.*.

4.2.4 Discussion

In the process of plant growth and development, light is one of the indispensable factors affecting plant physiology and morphology. Among the influencing factors of light environment, light quality is closely related to plant growth and development, playing a crucial role in plant growth and development, light morphogenesis, photosynthetic pigment synthesis, and nutrient accumulation (Gao et al., 2021). LED lights composed of different light quality ratios have different effects on the growth and nutritional quality indicators of *Cichorium endivia L.* when supplementing plants with light. Experimentally, a light mass ratio of 5.5R:8B:6.5W promotes vitamin C and carotene synthesis in *Cichorium endivia L.*.

Young leaves of *Cichorium endivia L.* can be consumed, and the leaves contain mainly nutrients such as vitamins. The results show that increasing the number of chicory leaves is beneficial when the light-to-mass ratio is 6R:7B:7W and 5.5R:8B:6.5W. Increasing the chlorophyll content of *Cichorium endivia L.* is beneficial when the light-to-mass ratio is 6R:7B:7W and 5R:8B:7W. This suggests that increasing the proportion of blue light or decreasing the proportion of red light is more conducive to the synthesis of chlorophyll. Li et al. (2020) also confirmed this when studying the effect of different combinations of blue and red light LEDs on the growth of mung bean sprouts.

The soluble sugars in vegetables mainly include glucose, sucrose, trehalose, etc., which play a key role in maintaining the stability of plant proteins (Saldivar et al., 2010). The 6R:7B:7W light mass ratio significantly increases the soluble sugar content of *Cichorium endivia L.* compared to the 5R:8B:7W ratio. It is speculated that red light is more conducive to the synthesis of soluble sugars in plants, which is consistent with the research results of Liu et al. (2014).

VC is an antioxidant in plants, and its content can essentially reflect an active oxygen scavenging ability or antioxidant ability in the plant, which has a significant effect on the storage of vegetables. Experimental results show that an LED light quality of 5.5R:8B:6.5W is beneficial for increasing the VC content in *Cichorium endivia L.*. Ban et al. (2019) and Liu et al. (2021) found that under red and blue light conditions, VC content increases with an increase in red light ratio. In this experiment, compared with the light quality composition of 5.5R: 8B: 6.5W, the light quality composition of 6R: 7B: 7W increased the red light content and decreased the blue light content, while the increase in vitamin content was not significant.

4.2.5 Conclusions of this section

In summary, a mixture of red, blue and white light increased the number of leaves in the borage compared to pure white light, with a light quality of 5.5R:8B:6.5W being the most favourable for increasing the number of leaves, VC content and carotenoid content. The 6R:7B:7W optical quality is most favorable for increasing the soluble sugar content of *Cichorium endivia L.*, while the 5R:8B:7W optical quality is most favourable for increasing the chlorophyll content of *Cichorium endivia L.*. Choosing a certain proportion of mixed light quality for supplementary lighting can improve the quality of *Cichorium endivia L.*.

With this experimental study, we have further verified that the quality of plant products can be improved by precise regulation of the light environment. However, a comparison of the effects of artificial and natural light on plant quality and the need for light regulation in different varieties of plants requires a more in-depth and extensive study.

4.3 Screening study on the formulation of nutrient solution for hydroponic green leaf lettuce in plant factory with artificial light

4.3.1 Plant factory hydroponics and nutrient solution formula

Hydroponics is a soilless cultivation technique (Sambo et al., 2019; Son et al., 2021; Fussy et al., 2022) that has rapidly developed in recent years due to its promotion of clean and environmentally friendly plant production. It has been widely applied in plastic greenhouses, glass greenhouses (Khan, 2018; Koukounaras, 2020) , and ALPFs (Kozai et al., 2013a; Yang et al., 2019).This cultivation method involves growing plants directly in a nutrient solution without the use of soil or substrate (Wild, 1985; Peyvast et al., 2010; Khater et al., 2021). Hydroponics offers advantages such as shorter growth cycles, higher yields, superior quality, reduced susceptibility to pests and diseases, water and nutrient efficiency, and automated management (Hyunjin et al., 2021). However, the absence of soil buffering and microorganisms necessitates careful selection of nutrient solutions for optimal crop growth and development (Kilinc et al., 2007; Lele et al., 2020; Lu et al., 2022). In the production of hydroponic leafy vegetables, the formulation of nutrient solutions is closely associated with the source and quality of water (Vandam et al., 2017; Jakobsen et al., 2020). It can be said that the choice of water source, water quality, and water-soluble fertilizers determines the nutrient solution composition (Schwarz et al., 2005; Dias et al., 2018; Elisa et al., 2020). Selecting the optimal nutrient solution formulation based on water quality and leafy green specific requirements is a critical challenge in hydroponic leafy green production with the goal of achieving high yield and quality.

Lettuce, also known as leaf lettuce, is a year-round to biennial herbaceous plant in the family Asteraceae. It is crisp and tender, primarily consumed raw (Martínez-Sánchez et al., 2012), and is an indispensable leafy green ingredient in people's daily lives (Sirsat et al., 2018). Green leaf lettuce is highly suitable for hydroponic cultivation in ALPFs, characterized by its high germination rate, resistance to tip burn, downy mildew, and frost injury, as well as firm leaf bases (Saengtharatip et al., 2018;

Lee et al., 2019). It has a lush green appearance, resembling an open green rose. As such, it has both ornamental, culinary and commercial economic value.

4.3.2 Materials and methods

Experimental site and overview. The experiment was conducted at the ALPF laboratory of the Henan Institute of Science and Technology from July 2021 to March 2022. The laboratory is located on the first floor of Teaching Building 9 at the Henan Institute of Science and Technology in Xinxiang, Henan province. It has a total floor area of approximately 200 m^2 and a ceiling height of approximately 3.3 m. The laboratory is equipped with a range of equipment and systems, including air conditioning, dehumidifiers, integrated irrigation systems for water and nutrients, an intelligent LED plant lighting system, a ventilation system, an intelligent environmental monitoring system, water purification equipment, nutrient solution disinfection and recycling equipment, CO_2 automatic control systems, ultraviolet disinfection lamps, a wireless IoT system, and a comprehensive front-end control system. These devices and systems are primarily used to regulate environmental conditions, lighting, fertilization and irrigation needed for plant growth. During the illumination period, the laboratory maintained an ambient temperature of approximately 23°C and a carbon dioxide concentration of 800 mg/l. The ambient temperature was set to around 18°C during the non-luminous phase and the CO_2 concentration was 500 mg/l. Moisture control is around 70%. The illumination duration was set to 14 h/d. The combined use of these laboratory conditions and equipment helps to ensure optimal environmental and resource supplies for plants at different growth stages, providing strong support for experiments.

Experimental materials. Experiments were performed using the hydroponic method. Two three-tier culture racks were used. Each tier of the cultivation rack consists of a cultivation trough, an insulation board, a liquid reservoir, and a circulation and irrigation pump that circulates the nutrient solution automatically between the tiers. Each growing trough measures 120 cm in length, 80 cm in width and 8 cm in height and has a capacity of 46 litres, allowing simultaneous hydroponic cultivation of 96 leafy vegetable varieties. The top of each level of the growing rack is equipped with adjustable LED lights in red, blue and white. The light quality, intensity and illumination period of LED lights can be adjusted independently. Each treatment involved the planting of 48 lettuce seedlings and was repeated three times in a random arrangement. The hydroponic experiment of green leaf lettuce in PFAL laboratory is shown in **Fig. 72**.

Fig. 71 The hydroponic experiment of green leaf lettuce.

Nutrient formulation and management. In the experiment, Arnon and Hoagland general formula (Arnon), Huanong a formula (Hunong A), Yamazaki formula (Yamazaki) and Japanese garden experiment general formula (GE) (Petropoulos et al., 2018), which are most conducive to leaf vegetable cultivation, were used, and compared with the water-soluble chemical fertilizer produced by commercial enterprises. The general formula was used for the proportion of microelements (Laland et al., 1955), and the commercial water-soluble leaf vegetable fertilizer produced by Henan Xinlianxin enterprise was used as the control. The formula details are shown in **Table 15**. The water used for nutrient solution preparation is purified water treated by reverse osmosis purification equipment, with a pH of 7.1 to 7.3, no fluoride, arsenic, selenium, copper, lead, cadmium, or zinc detected in the water, chloride $< 0.25\,mg/L$ in the water, and an EC value of 0.25 to 0.4 mS/m^3. The nutrient solution is intelligently prepared by water and fertilizer integrated irrigation equipment, and is fed by an oxygen pump to maintain Dissolved Oxygen (DO) $DO \geq 10\,mg/L$, the EC value is set at 1.8～2.2 $mS \cdot m^{-3}$ and the pH value is set at 6.0-6.9. The nutrient solution is changed every 7 days.

Table 15 Specific formula of nutrient solution.

formula	macro-elements (mg/L) A solution	macro-elements (mg/L) B solution	micro-elements (mg/L)
Arnon and Hoagland (T1)	Calcium nitrate tetrahydrate 945 Potassium nitrate 506 Ammonium nitrate 80	Potassium dihydrogen phosphate 136 Magnesium sulfate 493 Iron salt solution 2.5	Disodium EDTA 30 boric acid 2.8 Manganese sulfate 2.2 zinc sulfate 0.22 copper sulphate 0.08 ammonium molybdate 0.02
Formula A of Leafy Vegetables in Agricultural Chemistry Room of South China Agricultural University (T2)	Calcium nitrate tetrahydrate 472 potassium nitrate 267 ammonium nitrate 53	Potassium dihydrogen phosphate 100 potassium sulfate 116 magnesium sulfate heptahydrate 264	
Japanese Yamazaki (lettuce) (T3)	Calcium nitrate tetrahydrate 472 potassium nitrate 267	Ammonium dihydrogen nitrate 77 magnesium sulfate heptahydrate 246	
Japanese Garden general formula (T4)	Calcium nitrate tetrahydrate 945 potassium nitrate 809	Ammonium dihydrogen nitrate 153 magnesium sulfate heptahydrate 493	

Determination items and methods. After 35 days of transplantation, leaf counts were manually recorded and measurements were taken using a ruler to determine root length, maximum leaf length, and maximum leaf width for green leaf lettuce. In addition, an electronic scale was used to measure the fresh weight and root fresh weight of individual plants. Data processing and analysis were performed using Excel 2021 and SPSS 20.0.

4.3.3 Results

Effect of different nutrient solution formulations on leaf growth in green leaf lettuce. From **Table 16**, it can be observed that T1 and T4 had higher leaf counts after 35 days of transplantation and there was no significant difference between them, but the T4 treatment had significantly higher leaf counts than the other formulations and control. T3 and CK had longer maximum leaf length and there was no significant difference between them, but the T3 treatment was significantly higher than the other formulations. The CK and T3 treatments had wider maximum leaf widths and there was no significant difference between them, but CK was significantly higher than the other treatment groups.

Table 16 Indexes of green leaf lettuce at harvest with different nutrient solutions.

Experimental group	Leaf number	leaf length /cm	leaf width /cm	root length /cm	Root weight /g	Fresh weight /g
T1	29ab	18.6d	12.3b	24.6c	6.2b	106.7c
T2	27c	19.5c	13.7b	32.7a	8.6a	137.3ab
T3	27c	21.6a	13.8ab	27.9b	6.7b	128.8b
T4	30a	20.1bc	13.6b	23.5c	6.3b	139.6a
CK	28bc	21.3ab	14.3a	23.6c	8.9a	138.1ab

Note: No identical lowercase letters after the data in the same column indicate significant differences between groups ($P < 0.05$).

Effect of different nutrient solution formulations on root growth of green leaf lettuce. From **Table 16**, it can be observed that after 35 days of transplantation, the maximum root length is significantly larger for the T2 treatment compared to the T3 treatment and significantly larger for the T3 treatment compared to the other treatments. The control group (CK) and the T2 treatment had the highest root weight, with no significant difference between them, but they were significantly higher than the other treatment groups.

Effect of different nutrient solution formulations on fresh weight of green leaf lettuce. From **Table 16**, it can be observed that after 35 days of transplantation, the highest fresh weight was found in the T4 treatment group, the CK control group, and the T2 treatment group, with no significant differences among them, but significantly higher than the T1 treatment group and the T3 treatment group. The T1 treatment group had significantly lower fresh weight compared to the T3 group.

4.3.4 Discussion

Producing vegetables using a hydroponic model requires the selection of the optimal nutrient solution formula for vegetable growth (Miller et al., 2020). In this experiment, four nutrient solution formulations were compared with a commercial leafy vegetable nutrient solution under the hydroponic model and the PFALs management method. Of these, T2 and T4 showed a significantly higher fresh weight of lettuce compared to the other formulations, but the difference from the commercial nutrient solution was not significant. The second best formulation, T3, has a slightly lower fresh weight compared to the three aforementioned formulations. Thus, in terms of yield factors, T2 and T4 can be used for hydroponic romaine in ALPFs, followed by T3. Maximum leaf length and maximum leaf width are essential factors in evaluating the appearance and quality of green leaf lettuce. Both the maximum leaf length and width of the T3 group exceed those of the other experimental groups. Since hydroponic romaine is sold primarily as individual plants, the T3 stands out as the best option in terms of aesthetic quality.

Zhang (2005) conducted experiments with 1/4 strength Hoglan-Anon formula, Yamamoto-Sasaki lettuce formula, and South China Agricultural University lettuce formula to cultivate American fast-growing lettuce with leaf ages ranging from 2 to 17. It turns out that the Hoglan-Anon formula at strength 1/4 yields the highest results. Li et al. (2019) used the Japanese Garden test formula and Hoagland formula to grow long-heading Italian lettuce. The results showed that the Japanese Garden test formula outperformed the Hoagland formula in terms of yield, plant height and leaf width. Ding et al. (2012) compared the effects of the Hogeland, Japanese Garden test, Japanese Yamazaki, and South China Agricultural University (SCCU) lettuce formulas in cultivating Italian lettuce with leaf ages below 8. The results demonstrate that the SCCU lettuce formulation achieves the highest yield.

Soilless cultivation of vegetables is a complex feedback system. Environmental factors, cultivation methods and nutrient supply are the primary factors influencing soilless cultivation (Balliu et al., 2021). In hydroponic management, nutrient solution temperature, dissolved oxygen (DO), pH, and EC value are all critical factors affecting root growth and nutrient absorption, and these influencing factors require further in-depth research (Suyantohadi et al., 2010). Therefore, in agricultural production, it is essential to screen a suitable nutrient solution formulation based on factors such as vegetable variety, growth stage, cultivation method and water quality.

4.3.5 Conclusions of this section

The experimental study concluded that, in terms of stem and leaf, fresh weight, root fresh weight, root-to-shoot ratio, plant height, stem diameter, and leaf count, the hydroponically grown green lettuce in the artificial light plant factory performed best when using the universal formula from Japanese horticultural trials and the Formula A from the South China Agricultural University's agricultural chemistry laboratory. The next best performer was the Yamasaki formula. In terms of visual appearance, however, the Yamasaki formula exhibits the most favourable results.

SECTION 5. SUMMARY AND PROSPECT

5.1 Summary of research work

Based on the analysis and study of artificial light plant factories, this dissertation proposes the construction vision and ideas for building greenhouse, intelligent building greenhouses and intelligent building greenhouse plant factories. As the research work progresses, this dissertation then proposes the concept of building and developing urban intelligent plant factories in urban areas and gives an overall framework and solution for the multi-factor coupling, precise regulation and optimization of an artificial light plant factory environment based on a growth model. The series of results and achievements achieved in the work have been used as a standard of industrial technology for modern agriculture in practical production for theoretical and technical guidance.

-The concepts and ideas of intelligent building greenhouses, intelligent building greenhouses, plant factories, and the "3-Positions and 1-Entity" development model proposed in the study have been recognized by some government management departments and enterprises. Several departments of the Henan provincial government have expressed great interest, and a company in Xinxiang and two in Zhengzhou have held multiple consultations and exchanges.

-The research results of "Sustainable production systems of urban agriculture in the future: A case study on the investigation and development countermeasures of the Plant Factory and Vertical Farm in China" have been widely cited by researchers, entrepreneurs, and government decision-makers as survey data to guide decision-making.

- Inspired by multiple research achievements, the college invested in the construction of an artificial light plant factory laboratory, conducted extensive related research, and taught graduate programs in agricultural engineering and information technology, crop cultivation, and agronomy. It has trained a large number of graduate and undergraduate students in more than a dozen of our school's specialties, including agricultural engineering, crop cultivation, botany, vegetable science, facility horticulture, and agricultural product processing. The lab has also become a popular science education base for multiple primary schools in Xinxiang City, where the clean and pollution-free leafy vegetables grown in the lab have been praised by 80 percent of the school's teachers and students.

-The system composition and structure proposed in the research on "Urban Intelligent Plant Factory Environmental Control and System Design" and "Plant Factory Big Data and Plant Growth Model" provide a complete product solution for enterprise design and development. It has been implemented and applied to the developed plant factory comprehensive management system platform.

- The proposed tomato fruit detection and CMRDF cucumber seedling instance segmentation algorithms have been implemented and applied in tomato yield estimation systems, smart orchard projects, plant growth model construction in plant factories, and are gradually being applied in robotic picking and post-harvest fruit grading and classification devices.

- Results of multiple experimental studies, including simulations of LED light distribution and uniformity, screening of lettuce light formulations, and screening of bitter chrysanthemum nutrient solutions, have been confirmed and applied in other laboratory studies. Also consider implementing some solar greenhouse facilities for cultivation and small plant factories in research and development. The results have been applied to Henan ZSP's intelligent plant lighting controller product, which has increased the level of intelligence in the product, generating huge economic benefits.

- Other research results are gradually being recognized and implemented as public awareness increases.

5.2 Shortcomings

Due to time constraints and the lack of experimental equipment and conditions for further research, the study has many shortcomings.

(1) At present, research on the construction methods of plant growth models based on big data and deep learning is relatively independent, scattered, and incomplete. Only a few deep learning models have been attempted for exploratory modeling studies, and substantial long-term research is still needed in the future.

(2) At present, relatively independent experimental studies have been

conducted on the effects of light environment, temperature and humidity environment, and nutrient solution environment factors on plant growth, and shallow research has been conducted on the coupling effect. Thereby, the precise intelligent regulation of multiple environmental factors is not comprehensive and deep enough.

(3) The current research on the architecture of the environment multi-factor precise regulation platform based on plant growth models is still in the development and testing stage of subsystems, subfunctions, and submodules, and has not yet been integrated into an integrated cloud platform. Further research and development is required to achieve multi-factor coupling precise regulation.

5.3 recommendations

For the government and social organizations: Using all available urban areas to develop urban agriculture is an unavoidable and essential step for the worldwide urbanization and modernization of agriculture. Environmental multi-factor coupling precise regulation, and optimization are the key core technologies of an urban intelligent plant factory, which must be planned as a priority to ensure its development direction of mechanization, automation, intelligence, and unmanned and promote its rapid development of commercialization, industrialization, and marketization.

For future research work: The study presented in the dissertation is only the beginning of this complex research topic, which requires further in-depth investigation and study of its theoretical foundations and key techniques. In future work, we should first conduct an in-depth theoretical exploration of the principles of plant photosynthesis, growth and development mechanisms, physiological and biochemical mechanisms, environmental signal transduction, gene expression and other aspects. We should then study the means and techniques of environmental regulation, verify the reliability and effectiveness of its regulatory techniques in the laboratory, and finally apply these to production practices to guide actual production.

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APPENDICES

APPENDIX A

List of publications on the topic of the dissertation and information on the approbation of the results of the dissertation

List of publications in which the main scientific results of the dissertation are published:

SCOPUS / Web of Science publications

1. Wang Xinfa, Onychko Viktor, Zubko Vladislav, Zhenwei Wu & Mingfu Zhao. (2023). Sustainable production systems of urban agriculture in the future: A case study on the investigation and development countermeasures of the Plant Factory and Vertical Farm in China. Frontiers in Sustainable Food Systems, 2023,7. DOI: 10.3389/fsufs.2023.973341 (Web of Science Core Collection, Q1, IF: 5.005)

2. Xinfa Wang, Zhenwei Wu, Meng Jia, Tao Xu, Canlin Pan, Xuebin Qi, Mingfu Zhao. (2023) Lightweight SM-YOLOv5 tomato fruit detection algorithm for Plant Factory. *Sensors,* 23(6),3336. DOI：10.3390/s23063336 (Web of Science Core Collection, Q2, IF: 3.847)

3. Wang Xinfa, Zubko Vladislav, Onychko Viktor, Zhenwei Wu & Mingfu Zhao. (2022). Online recognition and yield estimation of tomato in plant factory based on YOLOv3. Scientific Reports, 12:8686. DOI: 10.1038/s41598-022-12732-1 (Web of Science Core Collection, Q2, IF: 4.997)

4. Zhenwei Wu, Minghao Liu, Chengxiu Sun, Xinfa Wang (corresponding author). (2023). A dataset of tomato fruits images for object detection in the complex lighting environment of plant factories, Data in Brief, 5(48). DOI: 10.1016/j.dib.2023.109291 (Scopus and EI)

5. Liu Qihang, Wang Xinfa (Co-first author), Zhao Mingfu, Liu Tao. (2023). Synergistic influence of the capture effect of western flower thrips (*Frankliniella occidentalis*) induced by proportional yellow-green light in the greenhouse. International Journal of Agricultural and Biological Engineering (IJABE), 16(1):88-94. DOI: 10.25165/j.ijabe.20231601.7562 (Co-first author, same as Liu's contribution, Web of Science Core Collection, Q2, IF:1.885)

6. Wang Xinfa, Vladislav Zubko, Onychko Viktor, Zhenwei Wu and Mingfu Zhao. (2022). Research on intelligent building greenhouse plant factory and "3-Positions and 1-Entity" development mode. Iop Conference Series: Earth and Environmental Science, 1087(1),012062. DOI: 10.1088/1755-1315/1087/1/012062 (Scopus and EI)

7. Tao Xu, Weishuo Zhao, Lei Cai, Xiaoli Shi and Xinfa Wang. (2023). Lightweight saliency detection method for real-time localization of livestock meat bones. Scientific Reports, 2023,13(1). DOI: 10.1038/s41598-023-31551-6 (Web of Science Core Collection, Q2, IF: 4.996)

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9. Hongxia Zhu, Linfeng Hu, Tetiana Rozhkova, Xinfa Wang, Chengwei Li. (2023). Spectrophotometric analysis of bioactive metabolites and fermentation optimization of *Streptomyces* sp. HU2014 with antifungal potential against *Rhizoctonia solan*. Biotechnology & Biotechnological Equipment, 2023,37(1):231-242. DOI: 10.1080/13102818.2023.2178822 (Web of Science Core Collection, Q3, IF: 1.762)

10. Jifei Zhao, Rolla Almodfer, Xiaoying Wu, Xinfa Wang. (2023). A dataset of pomegranate growth stages for machine learning-based monitoring and analysis, Data in Brief, 7(50). DOI: 10.1016/j.dib.2023.109468 (Scopus and EI)

11. Cao Zhishan, Cao Jinjun, Vlasenko Volodymyr, Wang Xinfa, & Weihai Li. (2022). Transcriptome analysis of Grapholitha molesta (Busk) (Lepidoptera: Tortricidae) larvae in response to entomopathogenic fungi Beauveria bassiana. Journal of Asia-Pacific Entomology, 101926. DOI: 10.1016/j.aspen.2022.101926 (Web of Science Core Collection, Q3, IF:1.580)

12. Tengfei Yan, Yevheniia Kremenetska, Biyang Zhang, Songlin He, Xinfa Wang, Zelong Yu, Qiang Hu, Xiangpeng Liang, Manyi Fu, Zhen Wang. (2022). The

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Articles in scientific professional publications of Ukraine

13. Wang Xinfa, Zubko Vladislav, Onychko Viktor, Zhao Mingfu. (2022). Illumination screening and uniformity simulation of hydroponic lettuce in artificial light plant factory. Bulletin of Sumy National Agrarian University. The series "Mechanization and Automation of Production Processes", 2022, Vol. 49 No. 3, p3-10. DOI: 10.32845/msnau.2022.3.1

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16. Han Yafeng, Wang Xinfa, Onychko Viktor, Zubko Vladislav, Li Guohou. (2020). Recognition and location of crop seedlings based on image processing. Vol. 42 No. 4: Bulletin of Sumy National Agrarian University. The series "Agronomy and Biology". 2020, vol. 42 No.4, P33-39. DOI: 10.32845/agrobio.2020.4.5

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17. Wang Xinfa, Zubko Vladisla, Onychko Viktor, Mingfu Zhao & Zhenwei Wu. (2022). Experimental study on the effect of light quality on the quality of hydroponic *Cichorium endivia* L. in Plant Factory with Artificial Light. African Journal of Agricultural Research, Vol.18(6), pp. 455-463. DOI: 10.5897/ AJAR2022.16028

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20. ZHAO Zhenxiang, AO Wenhong, WANG Xinfa, LU Lin, LUO Weirong, SUN Yongdong. (2023). Genome-wide identification and transcriptional analysis of DME gene family in cucumber (In Chinese). Plant Physiology Journal, 59 (1): 209–218. DOI: 10.13592/j.cnki.ppj.100264. (Chinese core journals)

21. Zhang Wei, Wang Xinfa, Shang Junjuan, Wang Ling. (2022). Design and Implementation of Multifunctional Seed and Fertilizer Sowing UAV (In Chinese). Development & Innovation of Machinery & Electrical Products, 35(02), 47-49. DOI: 10.3969/j.issn.1002-6673.2022.02.014

22. Sun Tingting, Zhao Songyu, Wang Xinfa, Qin Mingyi, Zhang Chao & Tian Xueliang. (2021). Screening for biocontrol bacteria against Alternaria porri from phyllosphere of welsh onion (In Chinese). Journal of Henan University of science and Technology (natural science edition) (Chinese), 2021,49(01):35-40. DOI: 10.3969/j.issn.2096-9473.2021.01.007

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23. Wu Zhenwei, Liu Minghao, Sun Chengxiu, Wang Xinfa (Corresponding author). (2023). Real time detection and counting method of tomato fruit in an artificial light plant factory based on yolov5. The second International Workshop on Vertical Farming (VertiFarm2023), Chengdu, China, May 22-24, 2023, organized by the Institute of Urban Agriculture, Chinese Academy of Agricultural Sciences under the aegis of ISHS (International Society for Horticultural Science). https://vertifarm2023.scimeeting.cn/en/web/index/. (Participated in the meeting

offline and displayed posters.)

24. Wang Xinfa, Vladislav Zubko, Onychko Viktor, Zhenwei Wu and Mingfu Zhao. (2022). Research on intelligent building greenhouse plant factory and "3-Positions and 1-Entity" development mode. The Fifth International Workshop on Environment and Geoscience (IWEG2022), Qingdao, China, July 16-18, 2022. http://www.iwegconf.org/LAP.aspx. (Attended the meeting online, displayed posters and won the "OUTSTANDING POSTER PRESENTATION" award.)

25. WANG X.F., ONYCHKO V.I., ZUBKO V., ZHAO M.F. (2022). Development status and trend of plant factory with artificial lighting technology and industrialization. International Scientific and Practical Conference "HONCHAROV'S READINGS", Sumy, Ukraine, May 25, 2022,92-95.

26. WANG Xinfa, Vladislav ZUBKO, Viktor ONYCHKO, Mingfu ZHAO. (2021). Development status and trend of plant factory intelligence in China. One Health Student International Conference, Nov. 24th-27th, 2021, București, ROMANIA, P. 32. received a certificate. https://onehealth.usamv.ro/index/program/ (Attended the meeting and made an oral report.)

27. Zhu Hongxia, Wang Xinfa, Rozhkova Tetiana. (2021). Preliminary study on antifungal activity of astreptomyces SP. strain hu2014 against phytopathogenic fungi. III International Scientific and Practical Conference "TOPICAL ISSUES OF MODERN SCIENCE, SOCIETY AND EDUCATION", KHARKIV, Ukraine, 3-5 October 2021, received a certificate.

28. LI F., WANG X.F., LIU D.M., DUBOVYK VOLODYMYR. (2022). A review of purified materials in quenchers pretreatment method for pesticide residue detection. International Scientific and Practical Conference "HONCHAROV'S READINGS", Sumy, Ukraine, May 25, 2022,157-158.

29. ZHU HONGXIA, ROZHKOVA T., WANG XINFA. (2022). Study the allelopathy of the fermentation extracts from streptomyces SP. HU2014 on cucumber. International Scientific and Practical Conference "HONCHAROV'S READINGS", Sumy, Ukraine, May 25, 2022,165-166.

30. LIU D.M., IEVGEN KONOPLIANCHENKO, VIACHESLAV

TARELNYK, WANG X.F., LI F. (2022). Application research of agricultural mechanization based on genetic algorithm. International Scientific and Practical Conference "HONCHAROV'S READINGS", Sumy, Ukraine, May 25, 2022,231-233.

List of patents:

31. Zhao Mingfu, Wu Zhenwei, Wang Xinfa et al. (2023). LED supplementary light type planting cabinet, utility model patent, China, ZL-2023-2-0899208.6, July 04, 2023, the third inventor, has been authorized. https://s1.qizhidao.com/DZqawS

32. Wang Xinfa, Qu Peixin, Wu Xiaoying et al. (2021). A multispectral crop phenotype analysis platform for plant factories, utility model patent, China, ZL-2021-2-1595146.7, November 19, 2021, the first inventor, has been authorized. https://s1.qizhidao.com/HMsvpq

33. Wang Xinfa, Qu Peixin, Wu Xiaoying et al. (2022). An assembled aeroponics culture layer frame with adjustable layer height for the plant factory with artificial light, utility model patent, China, ZL-2022-2-0821668.2, July 8, 2022, the first inventor, has been authorized. https://s1.qizhidao.com/Jchaxy

34. Wang Xinfa, Liu Qihang, Qu Peixin et al. (2022). A general real-time detection and counting method for eggplant fruit in plant factory, invention patent, Application approval No.202210152745.4, February 19, 2022, the first inventor, Application accepted, Substantive review stage. https://s1.qizhidao.com/OHxtta

List of Computer software copyright:

35. Wang Xinfa, Sun Chengxiu. (2023). Detection system for germination rates in plant factories - V1.0, Computer software copyright, China, 2023SR0557513, May 22, 2023, the first copyright owner, has been authorized.

36. Wang Xinfa, Liu Minghao. (2023). Automatic monitoring system for cabbage diseases and pests - V1.0, Computer software copyright, China, 2023SR0557498, May 22, 2023, the first copyright owner, has been authorized.

37. Wang Xinfa, Wu zhenwei. (2023). Water circulation control system of plant factory - V1.0, Computer software copyright, China, 2023SR0478585, April 18, 2023, the first copyright owner, has been authorized.

38. Wang Xinfa, Wu zhenwei. (2023). Plant factory image acquisition system - V1.0, Computer software copyright, China, 2023SR0478584, April 18, 2023, the first copyright owner, has been authorized.

39. Wang Xinfa, Wu zhenwei, Zhao Mingfu et al. (2022). Plant factory 3D image acquisition system - V1.0, Computer software copyright, China, 2022SR0665171, March 15, 2022, the first copyright owner, has been authorized.

40. Wang Xinfa, Guo Dawei, Wu Xiaoying et al., (2022). National grain yield monitoring system (Abbreviated as the grain yield monitoring system) - V1.0, Computer software copyright, China, 2022SR0971135, March 16, 2022, the first copyright owner, has been authorized.

41. Wang Xinfa, Zhao Jifei, Rolla Jamil Almodfer et al., (2022). Intelligent diagnosis system of pests and diseases in intelligent orchard based on knowledge map (Abbreviated as intelligent diagnosis system of pests and diseases in intelligent orchard) - V1.0, Computer software copyright, China, 2022SR0665174, March 24, 2022, the first copyright owner, has been authorized.

List of research projects approved and funded by the Chinese government:

42. Intelligent building greenhouse plant factory key technology development and application, 212102110234, Henan Provincial Science and Technology Department, 2021 Henan Province Science and Technology Research Project, 2020.12, Principal and main participant of the project, Approved.

43. The development of aeroponics system of fully artificial light plant factory, 22A210013, Henan Provincial Department of Education, 2022 Annual Key Scientific Research Project of Henan Higher Education Institution, 2021.12, Principal and main participant of the project, Approved and funded (CNY ¥30,000).

44. Multi-factor coupling control and optimization of urban intelligent plant factory environment, 222102320080, Henan Provincial Science and Technology Department, 2022 Henan Provincial Science and Technology Research Project, 2021.12, Principal and main participant of the project, Approved and funded (CNY ¥100,000).

45. Research and industrialization of key technologies for precise management

and control of smart orchard, 21ZD003, major science and technology project of Xinxiang City, Henan Province, 2021.10, Main participant, approved and funded (CNY ¥1,000,000).

46. Research on intelligent management and control technology of the plant factory based on IoT and Big Data, 232102111124, Henan Provincial Science and Technology Department, 2023 Henan Provincial Science and Technology Research Project, 2023.3, Principal and main participant of the project, Approved and funded (CNY ¥100,000).

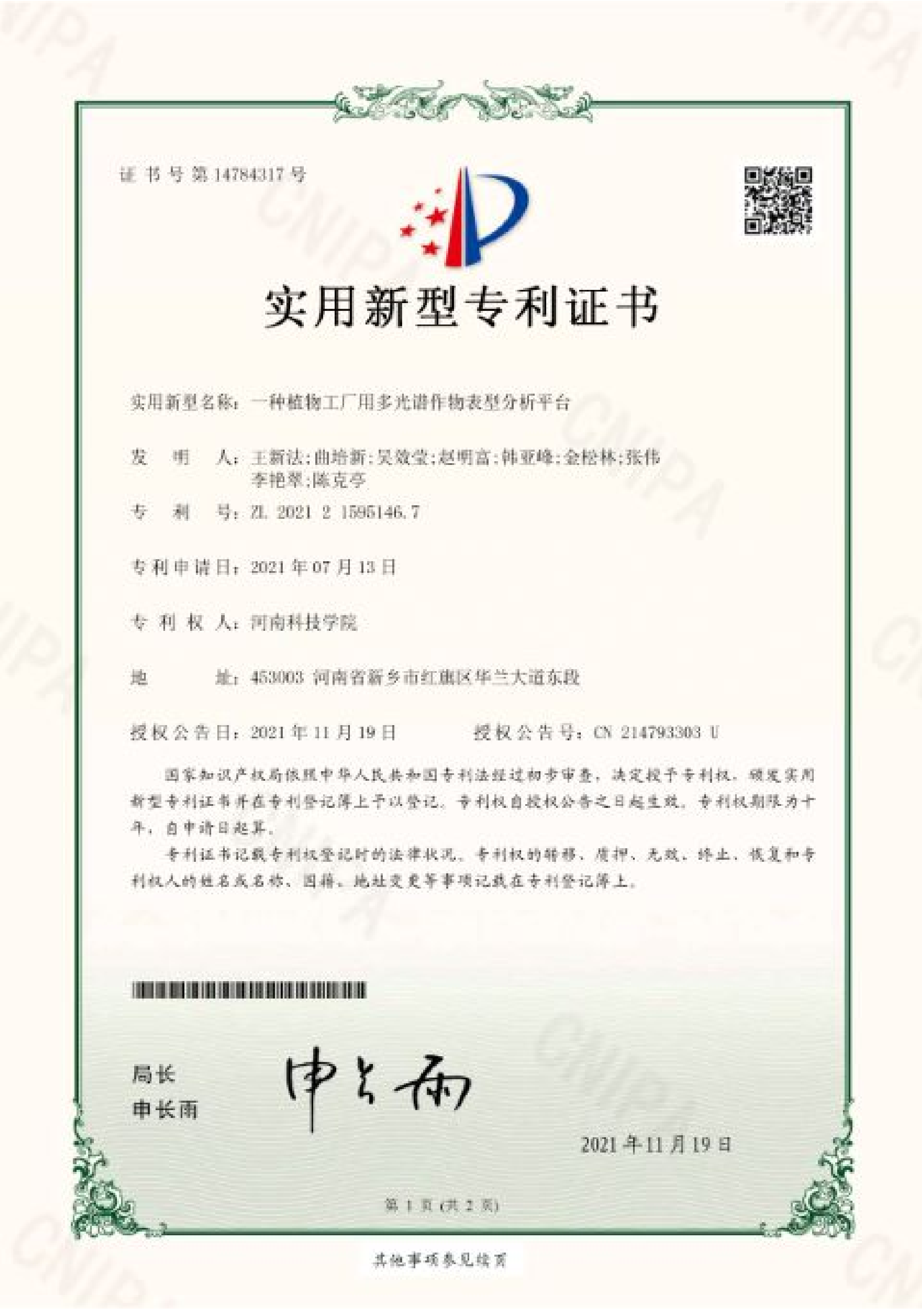
47. Study and Application of a Beneficial Streptomyces Strain for Disease Control and Growth Promotion in Wheat Planting, 232102111015, Henan Provincial Science and Technology Department, 2023 Henan Provincial Science and Technology Research Project, 2023.3, Main participant, Approved and funded (CNY ¥100,000).

48. Research on application technology of autonomous wall-climbing robot for large-scale ship cleaning task, 212102210161，Henan Provincial Science and Technology Department, 2021 Henan Province Science and Technology Research Project, 2020.12, Main participant, approved and funded (CNY ¥100,000).

49. Research and application of community intelligent security technology based on ghost module and morphological aggregation，222102210165，Henan Provincial Science and Technology Department, 2022 Henan Province Science and Technology Research Project, 2020.12, Main participant, approved.

APPENDIX B.1

Documents on the protection of rights to inventions and utility models on the topic of the dissertation



证书号第14784317号

实用新型专利证书

实用新型名称：一种植物工厂用多光谱作物表型分析平台

发 明 人：王新法;曲培新;吴效莹;赵明富;韩亚峰;金松林;张伟
李艳翠;陈克亭

专 利 号：ZL 2021 2 1595146.7

专利申请日：2021年07月13日

专 利 权 人：河南科技学院

地 址：453003 河南省新乡市红旗区华兰大道东段

授权公告日：2021年11月19日　　授权公告号：CN 214793303 U

国家知识产权局依照中华人民共和国专利法经过初步审查，决定授予专利权，颁发实用新型专利证书并在专利登记簿上予以登记。专利权自授权公告之日起生效。专利权期限为十年，自申请日起算。

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局长
申长雨

申长雨

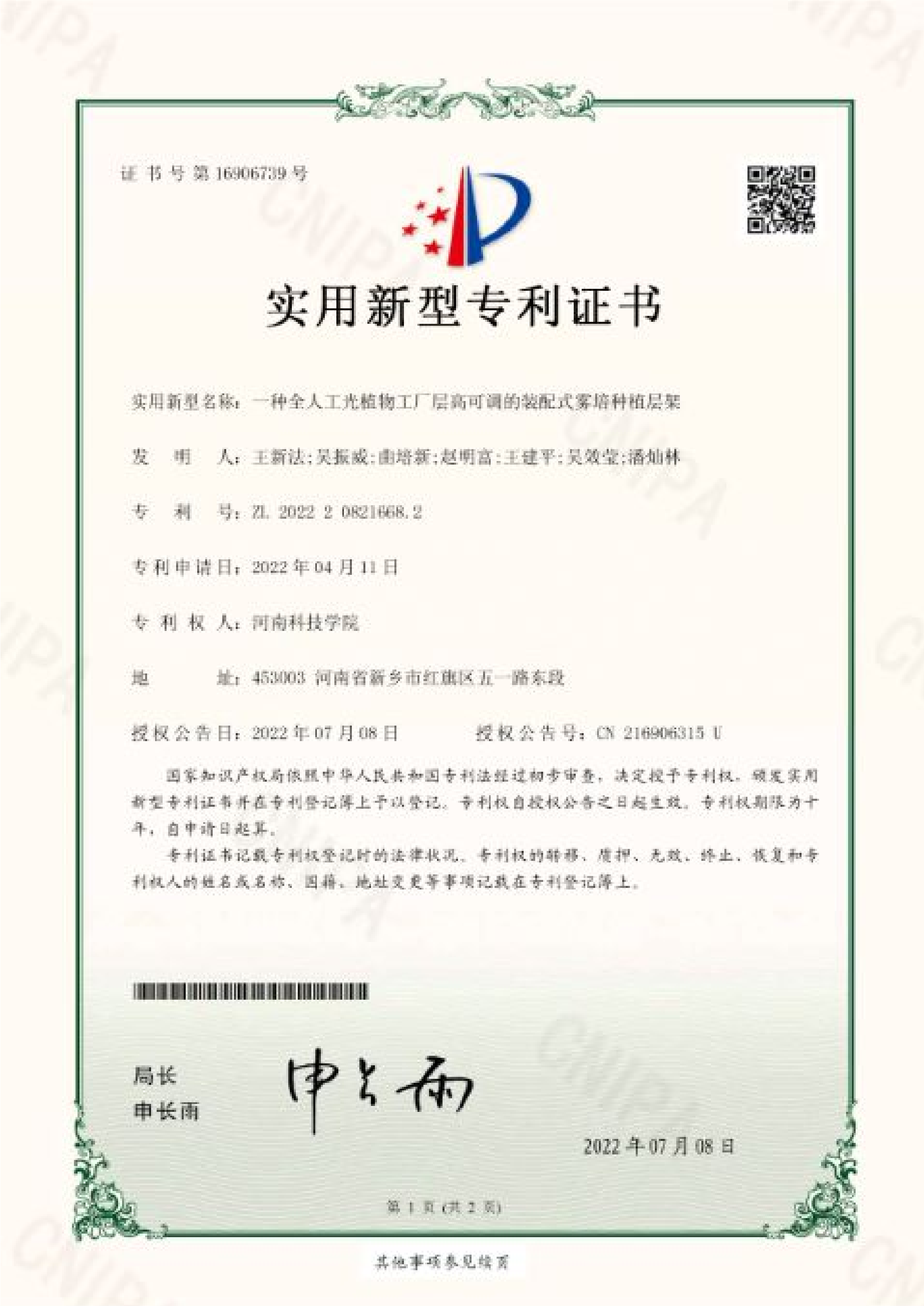
2021年11月19日

第1页(共2页)

其他事项参见续页

Utility Model Patent Certificate: A multispectral crop phenotypic analysis platform for plant factories. (In Chinese, Patent NO. ZL 2021 2 1596146.7)

APPENDIX B.2


证书号第16906739号

实用新型专利证书

实用新型名称：一种全人工光植物工厂层高可调的装配式雾培种植层架

发　明　人：王新法；吴振威；曲培新；赵明富；王建平；吴筱莹；潘灿林

专　利　号：ZL 2022 2 0821668.2

专利申请日：2022年04月11日

专利权人：河南科技学院

地　　址：453003 河南省新乡市红旗区五一路东段

授权公告日：2022年07月08日　　授权公告号：CN 216906315 U

国家知识产权局依照中华人民共和国专利法经过初步审查，决定授予专利权，颁发实用新型专利证书并在专利登记簿上予以登记。专利权自授权公告之日起生效。专利权期限为十年，自申请日起算。

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局长
申长雨

2022年07月08日

第1页（共2页）

其他事项参见续页

Utility Model Patent Certificate: A all-artificial-light plant factory layer height adjustable assembly type aeroponics culture planting layer shelf. (In Chinese, Patent NO. ZL 2022 2 0821668.2)

APPENDIX B.3

证书号第19284241号

实用新型专利证书

实用新型名称：LED补光型种植柜

发　明　人：赵明富;吴振威;王新法;吴效莹;刘明皓;孙承秀

专　利　号：ZL 2023 2 0899208.6

专利申请日：2023年04月20日

专利权人：河南科技学院

地　址：453000 河南省新乡市红旗区五一路东段

授权公告日：2023年07月04日　　授权公告号：CN 219288283 U

国家知识产权局依照中华人民共和国专利法经过初步审查，决定授予专利权，颁发实用新型专利证书并在专利登记簿上予以登记。专利权自授权公告之日起生效。专利权期限为十年，自申请日起算。

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局长
申长雨

国家知识产权局
2023年07月04日

第1页(共2页)

其他事项参见续页

Utility model patent certificate: LED supplemental light type planting cabinet. (In Chinese, Patent NO. ZL 2023 2 0899208.6)

APPENDIX B.4

国 家 知 识 产 权 局

453000
河南省新乡市新中大道与金穗大道交叉口嘉亿互联网大厦 1606 室
新乡市平原智汇知识产权代理事务所(普通合伙) 郝怀庆
(0373-3036134)

发文日：

2022年02月19日

申请号或专利号：202210152745.4 发文序号：2022021900352090

专 利 申 请 受 理 通 知 书

根据专利法第 28 条及其实施细则第 38 条、第 39 条的规定，申请人提出的专利申请已由国家知识产权局受理。现将确定的申请号、申请日、申请人和发明创造名称通知如下：

申请号：202210152745. 4
申请日：2022 年 02 月 18 日
申请人：河南科技学院
发明创造名称：一种植物工厂茄果类蔬菜果实通用实时检测计数方法

经核实，国家知识产权局确认收到文件如下：
权利要求书 每份页数:4 页 文件份数:1 份 权利要求项数： 4 项
说明书摘要 每份页数:1 页 文件份数:1 份
说明书 每份页数:12 页 文件份数:1 份
实质审查请求书 每份页数:1 页 文件份数:1 份
专利代理委托书 每份页数:2 页 文件份数:1 份
说明书附图 每份页数:7 页 文件份数:1 份
发明专利请求书 每份页数:5 页 文件份数:1 份

提示：
1. 申请人收到专利申请受理通知书之后，认为其记载的内容与申请人所提交的相应内容不一致时，可以向国家知识产权局请求更正。
2. 申请人收到专利申请受理通知书之后，再向国家知识产权局办理各种手续时，均应当准确、清晰地写明申请号。
3. 国家知识产权局收到向外国申请专利保密审查请求书后，依据专利法实施细则第 9 条予以审查。

审 查 员：自动受理 审查部门：专利局初审及流程管理部

国家知识产权局 专利审查业务章

200101 纸件申请，回函请寄：100088 北京市海淀区蓟门桥西土城路 6 号 国家知识产权局受理处收
2019. 11 电子申请，应当通过电子专利申请系统以电子文件形式提交相关文件。除另有规定外，以纸件等其他形式提交的文件视为未提交。

Notification of Acceptance of Invention Patent Application: A universal real-time detection and counting method for eggplant and fruit vegetables and fruits in plant factories. (In Chinese, Patent NO.202210152745.4)

APPENDIX B.5

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号： 软著登字第11065755号

软 件 名 称： 植物工厂图像采集系统
V0.1

著 作 权 人： 河南科技学院

开发完成日期： 2022年08月01日

首次发表日期： 未发表

权利取得方式： 原始取得

权 利 范 围： 全部权利

登 记 号： 2023SR0478584

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 12549216

2023年04月18日

Computer Software Copyright Registration Certificate: Plant factory image acquisition system V0.1. (In Chinese)

APPENDIX B.6

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第11065756号

软件名称：植物工厂水循环控制系统
V0.1

著作权人：河南科技学院

开发完成日期：2022年11月01日

首次发表日期：未发表

权利取得方式：原始取得

权利范围：全部权利

登记号：2023SR0478585

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中华人民共和国国家版权局
计算机软件著作权
登记专用章

No. 12549217

2023年04月18日

Computer Software Copyright Registration Certificate: Plant factory water circulation control system V0.1. (In Chinese)

APPENDIX B.7

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第9619370号

软 件 名 称：植物工厂3D图像采集系统
0.1

著 作 权 人：河南科技学院

开发完成日期：2022年03月15日

首次发表日期：未发表

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2022SR0665171

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No. 10808298

2022年05月30日

Computer Software Copyright Registration Certificate: Plant factory 3D image acquisition system V0.1. (In Chinese)

APPENDIX B.8

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第9925334号

软 件 名 称：全国粮食产量监测系统
[简称：粮食产量监测系统]
V1.0

著 作 权 人：河南科技学院

开发完成日期：2022年03月16日

首次发表日期：未发表

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2022SR0971135

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

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No. 11212052

2022年07月27日

Computer Software Copyright Registration Certificate: The national grain yield monitoring system (referred to as the grain yield monitoring system) V0.1. (In Chinese)

APPENDIX B.9

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第9619373号

软 件 名 称：基于知识图谱的智慧果园病虫害智能诊断系统
[简称：智慧果园虫害智能诊断系统]
V1.0

著 作 权 人：河南科技学院

开发完成日期：2022年03月24日

首次发表日期：未发表

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2022SR0665174

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No. 10808301

中华人民共和国国家版权局 计算机软件著作权登记专用章

2022年05月30日

Computer Software Copyright Registration Certificate: Intelligent diagnosis system for diseases and pests in orchards based on knowledge graph (referred to as intelligent diagnosis system for pests and diseases in orchards) V0.1. (In Chinese)

APPENDIX B.10

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第11144669号

软 件 名 称：白菜病虫害自动检测系统
[简称：白菜病虫害检测系统]
V1.0

著 作 权 人：河南科技学院

开发完成日期：2023年02月22日

首次发表日期：未发表

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2023SR0557498

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No. 12646928

2023年05月22日

Computer Software Copyright Registration Certificate: The automatic detection system for Chinese cabbage diseases and pests (abbreviated as the Chinese cabbage diseases and pests detection system) V0.1. (In Chinese)

APPENDIX B.11

中华人民共和国国家版权局

计算机软件著作权登记证书

证书号：软著登字第11144684号

软 件 名 称：植物工厂发芽率检测系统
V1.0

著 作 权 人：河南科技学院

开发完成日期：2022年11月21日

首次发表日期：未发表

权利取得方式：原始取得

权 利 范 围：全部权利

登 记 号：2023SR0557513

根据《计算机软件保护条例》和《计算机软件著作权登记办法》的规定，经中国版权保护中心审核，对以上事项予以登记。

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登记专用章

No. 12650519

2023年05月22日

Computer Software Copyright Registration Certificate: Plant factory germination rate detection system V0.1. (In Chinese)

APPENDIX C.1

International academic conferences attended during the work:

APPENDIX C.1

СНАУ
Університет, що вивчає життя

Факультет агротехнологій та природокористування СНАУ

CERTIFICATE

This certificate confirms participation

Xinfa Wang

in the work of the International Scientific and Practical Conference "HONCHAROV'S READING", devoted to the 93 th anniversary of the birth of the brider-potato, the laureate of the State Prize ohe USSR in science and technology, Honored Worker of Science and Technology of Ukraine, doctor of agricultural science, professor HONCHAROVA MYKOLY DEMIANOVICHA

Vice-rector for Scientific work
Doctor of Economics *Yu. Danko*

Sumy, May 25 th, 2022

APPENDIX C.1

CERTIFICATE AUTHORIZATION

The Fifth International Workshop on
Environment and Geoscience
(IWEG2022)

OUTSTANDING POSTER PRESENTATION

Paper ID: IWEG59173

Presenter: XinfaWang and Zhenwei Wu

Paper Title: Research on Intelligent Building Greenhouse Plant Factory and "3-Positions and 1-Entity" Development Mode

International Workshop on Environment and Geoscience
IWEG

IWEG2022 Organizing Committee   July 22, 2022   China | Virtual

APPENDIX C.2

Academic visits and exchanges for scientific work:

(a)

(b)

(c)

(d)

Photos of academic exchange activities with internationally renowned peer scholars: (a) Professor Toyoki Kozai, the most famous international plant factory expert (Japan); (b) Researcher Yang Qichang, the most famous expert in Chinese plant factories; (c) Researcher Tong Yuxin, a renowned expert in Chinese plant factories; (d) Professor He Dongxian, a renowned environmental control expert in Chinese plant factories.

APPENDIX C.3

(a)

(b)

(c)

(d)

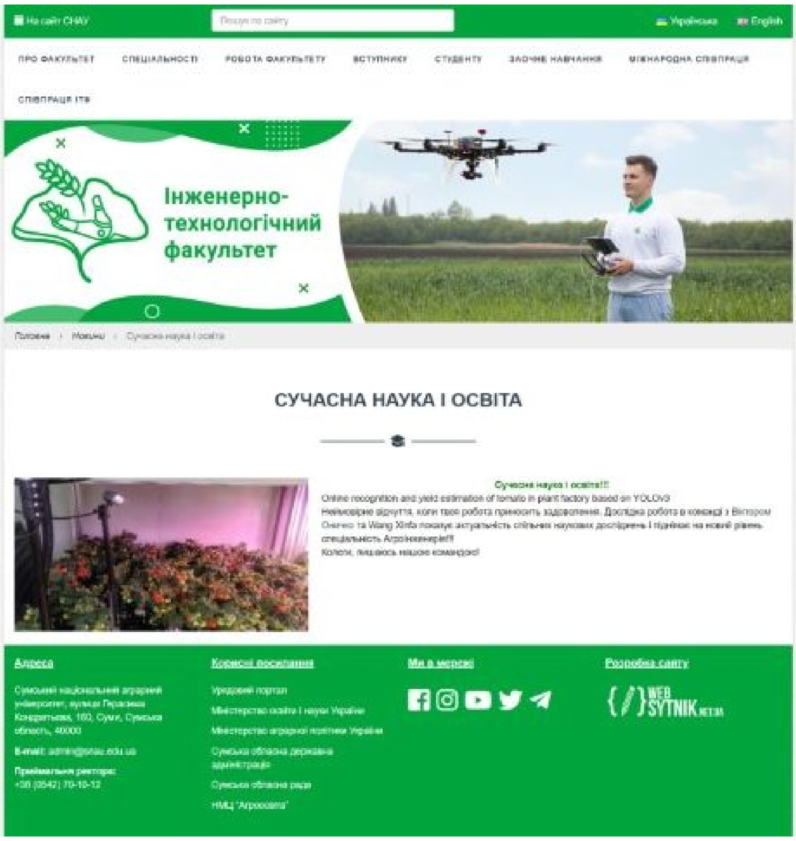
(e)

(f)

Photos of enterprise visits and research for scientific work: (a) Vegetable research center of Beijing academy of agricultural and forestry sciences (Beijing, China); (b) Yichuan Jianye green base development co., ltd. (Luoyang, China); (c) Shouguang vegetable high tech demonstration park (Shouguang, China); (d) Institute of urban agriculture, Chinese academy of agricultural sciences (Chengdu, China); (e) Intelligent horticultural equipment research center (Chengdu, China); (f) Future Zhinong technology co., ltd. (Beijing, China).

APPENDIX C.4

(a)



(b)

Photos of other scientific work: (a) Vice President Cao Guojie of Henan Institute of Science and Technology inspecting and guiding scientific work (Xinxiang, China); (b) News on the website of the School of Engineering and Technology at Sumy National Agricultural University (Sumy, Ukraine).

APPENDIX D.1

Experimental and research implementation sites and scenarios:

(a)

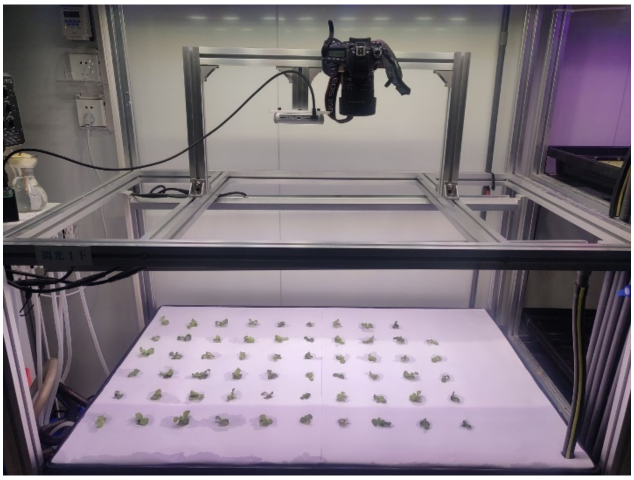
(b)

(c)

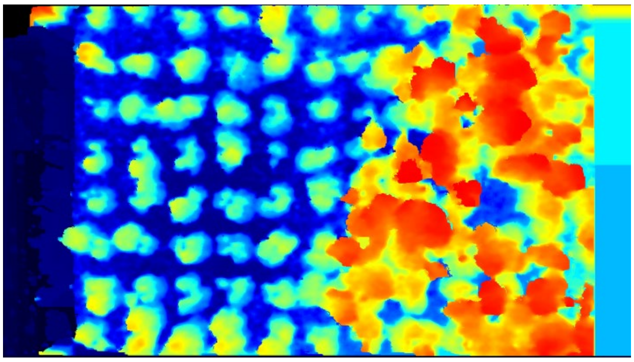
(d)

The photos of the all-artificial-light plant factory laboratory at Henan University of Science and Technology, Xinxiang, China (main experimental site): (a) panoramic view of the planting room; (b) hydroponic growing shelves; (c) one side of the planting room; (d) leaf vegetable planting experiments.

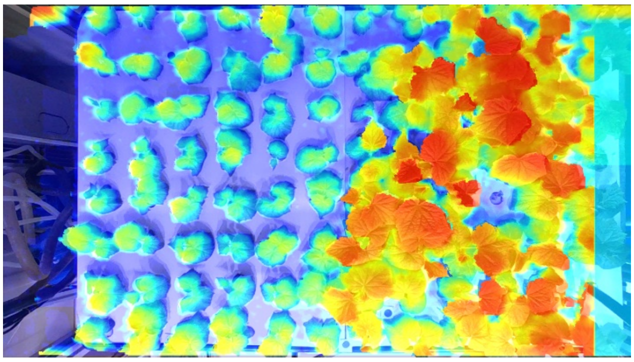
APPENDIX D.2

(a) (b)

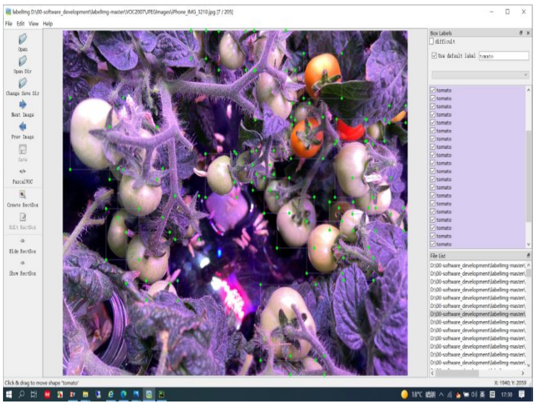
(c) (d)



(e)

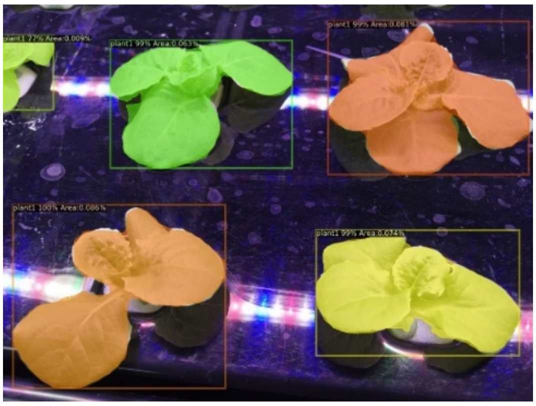
The photos of Image data acquisition equipment and platform (Experiment and Research 3.1, 3.2): (a) Tomato image data acquisition equipment; (b) Plant growth image data acquisition platform; (c) Collect RGB image data of cucumber seedlings; (d) Collected depth image data of cucumber seedlings; (e) The fused RGBD image data of cucumber seedlings.

APPENDIX D.3



(a)

(b)



(c)

(d)

(e)

(f)

The photos of laboratory research (section 3.1, 3.2, 4.1, 4.2, 4.3) at all-artificial-light plant factory of Henan Institute of Science and Technology, Xinxiang, China: (a) Data annotation results; (b) Real-time object detection results for tomato fruits (research 3.1); (c) instance segmentation results for green leafy vegetable seedlings (research 3.2); (d) experiments on the light uniformity of lettuce (research 4.1); (e) light quality screening experiments on the *Cichorium endivia* L. (research 4.2); (f) screening experiments on nutrient solutions for green-leafy vegetables (research 4.3).

APPENDIX D.4

(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

The photos of environmental single factor regulation methods and techniques: (a) Environmental temperature and humidity regulation techniques; (b) Environmental humidity regulation (using a dehumidifier); (c) Monitoring of environmental temperature, humidity, and CO_2 concentration; (d) Light regulation for plant growth (using LED lights); (e) Light monitoring (using light sensors); (f) Integrated irrigation system for water and fertilizer; (g) monitoring of EC, DO, and PH of nutrient solution; (h) environmental CO_2 concentration regulation; (i) Planting layer shelf airflow control.

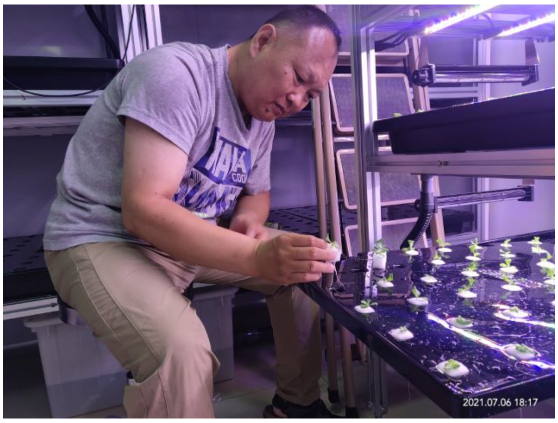
APPENDIX D.5

(a)

(b)

The photos of the central controller system with coupling regulation of multiple environmental factors: (a) the integrated central control system hardware; (b) the main interface of the control system software.

APPENDIX D.6



(a)

(b)

(c)

(d)

(e)

(f)

The photos of scientific work: (a) plant transplantation and planting; (b) planting management; (c) plant height measurement; (d) measurement of plant stem thickness; (e) academic exchange and guidance; (f) modern agricultural education and interest cultivation for primary school students.

APPENDIX E.1

Documents approving scientific research projects and obtaining funding from the government:

河南省科学技术厅文件

豫科〔2021〕1号

关于下达河南省二〇二一年科技发展计划的通知

各省辖市、省直管县（市）科技局，济源示范区管委会，郑州航空港经济综合实验区、国家高新区、国家郑州经济技术开发区管委会，省直有关部门，各有关单位：

按照“十四五”科技发展的总体思路，结合我省国民经济和社会发展的任务要求，现将《河南省二〇二一年科技发展计划》下达给你们，请按照计划项目目标，认真做好组织实施工作。

附件：河南省二〇二一年科技发展计划

河南省科学技术厅

2021年1月4日

APPENDIX E.1

项目编号	项目名称	承担单位	项目负责人	主管部门
212102110219	基于机器视觉的雾滴沉积特性检测系统设计及关键技术研究	河南农业大学	张开飞	河南省教育厅
212102110220	基于深度学习的玉米籽粒图像品种识别研究	河南省农业科学院农业经济与信息研究所	冯　晓	河南省农业科学院
212102110221	GNSS 辅助 MEMS-INS 的农机高精度导航定位技术研究	郑州轻工业大学	焦玉召	河南省教育厅
212102110222	秸秆类生物质复合菌兼氧预处理-厌氧发酵系统设计与工艺优化研究	河南农业大学	李攀攀	河南省教育厅
212102110223	节能型农机底盘自稳定关键技术及装置研发	河南科技大学	王焕昆	河南省教育厅
212102110224	铜绿假单胞菌@金属有机框架复合材料制备及其在水体污染物铬处理中的应用	河南牧业经济学院	闫花朵	河南省教育厅
212102110225	智能化花生小区播种机关键技术与装备研发	河南省农业科学院长垣分院	王东伟	长垣市科技和工业信息化局
212102110226	基于 NB-IoT 的草地贪夜蛾病虫害监测预警系统设计	安阳工学院	张天鹏	安阳市科学技术局
212102110227	基于多源信息融合的智能+规模化猪场典型疫病防控预警系统关键技术研究与应用	河南牧业经济学院	张俊逸	河南省教育厅
212102110228	秸秆活性炭复合吸附剂吸附式冷鲜配送箱的设计与性能实验	河南牧业经济学院	张　品	河南省教育厅
212102110229	水肥药一体化混合滴灌系统开发与应用	河南科技学院	赵明富	河南省教育厅
212102110230	纤维素乙醇生产菌株构建及发酵性能研究	河南农业大学	王　旭	河南省教育厅
212102110231	新型生物炭肥料研发及应用	河南应用技术职业学院	陈一岩	河南省教育厅
212102110232	花生种子真空射频保质干燥新技术研究	河南省农业科学院农副产品加工研究中心	谢永康	河南省农业科学院
212102110233	减氮对华北地区麦-玉轮作农田土壤 N2O 排放影响机理研究	中国农业科学院农田灌溉研究所	白芳芳	新乡市科学技术局
212102110234	智能建筑温室植物工厂关键技术研发与应用	河南科技学院	王新法	河南省教育厅
212102110235	基于种养结合模式的厌氧发酵尾液水肥一体化关键技术研究及应用	河南农业大学	李连豪	河南省教育厅
212102110236	基于精准扶贫的农业植保机智慧飞防模块研发	河南牧业经济学院	李红兰	河南省教育厅
212102110237	有机酸滴灌提高土壤 Cd 迁移和转化的机制研究	中国农业科学院农田灌溉研究所	陆红飞	新乡市科学技术局
212102110238	基于多源高光谱遥感数据的小麦条锈病监测关键技术与方法	河南理工大学	李长春	河南省教育厅
212102110239	SiSPMS 基因介导的多胺代谢途径在谷子籽粒灌浆中的功能研究	安阳工学院	王　涛	安阳市科学技术局

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Government project approval document: 2021 henan province key R&D and promotion special project, key technology R&D and application of intelligent building greenhouse plant factory (212102110234).

新乡市科学技术局文件

新科〔2021〕57号

新乡市科学技术局
关于下达2021年度新乡市科技专项项目的
通　知

各县（市）、区科技主管部门，各有关单位：

为解决一批制约新乡经济社会发展的关键共性技术，加快企业灾后尽快恢复研发活动，市科技局牢固树立“项目为王”理念，围绕我市产业链建链、强链、补链、延链重大需求，组织实施了一批科技专项、灾后重建项目。

按照《新乡市重大科技专项管理办法》（新科〔2018〕43号）、《关于印发新乡市灾后重建资金筹措工作方案的通知》（新政办〔2021〕36号）、《新乡市创新应用专项管理暂行办法》

（新科〔2021〕13号）、《新乡市揭榜制科技项目实施方案》（新科〔2021〕14号）文件规定，市科技局组织相关领域专家对2021年度新乡市科技专项开展了评审论证工作。

根据专家评审论证意见，经会议研究，确定2021年度新乡市重大科技专项28项、2021年度新乡市灾后重建科技专项7项、2020年度新乡市创新应用专项3项、2020年度新乡市揭榜制科技项目5项给予立项，现将立项的项目下达给你们。请按照管理办法，认真做好项目的组织实施工作。

附件：1.2021年度新乡市科技专项项目立项名单

2.2021年度新乡市灾后重建科技专项立项名单

2021年10月26日

新乡市科学技术局办公室　　2021年10月26日印发

APPENDIX E.2

附件 1

2021 年度新乡市科技专项项目立项名单

项目编号	项目名称	承担单位	项目类别	备注
21ZD001	氢燃料电池电极关键材料及核心技术研究	河南师范大学	重大科技专项	
21ZD002	肺纤维化新药 GC-1 研发	河南师范大学	重大科技专项	
21ZD003	智慧果园精准管控关键技术研究及产业化	河南科技学院	重大科技专项	
21ZD004	适宜机收籽粒玉米种质创新与新品种选育	河南科技学院	重大科技专项	
21ZD005	系列蜂产品精深加工及质量安全控制关键技术	河南科技学院	重大科技专项	
21ZD006	骨钛金属表面修饰关键技术开发与应用研究	新乡医学院	重大科技专项	
21ZD007	抗肿瘤新型工程 NK 细胞研发	新乡医学院	重大科技专项	
21ZD008	山楂高值化加工关键技术研究与应用	新乡学院	重大科技专项	
21ZD009	基于机器视觉的起重机防摇摆智能控制系统研究	新乡学院	重大科技专项	

Government project approval document: 2021 xinxiang city science and technology major special project, smart orchard precision control key technology research and industrialization (21zd003), with a funding of 1 million rmb.

APPENDIX E.3

河南省科学技术厅文件

豫科〔2022〕13号

关于下达河南省二〇二二年科技发展计划的通知

各省辖市科技局，济源示范区管委会科技管理部门，各县（市）科技管理部门，郑州航空港经济综合实验区、国家高新区、国家郑州经济技术开发区管委会，省直有关部门，各有关单位:

按照“十四五”科技发展的总体思路，结合我省国民经济和社会发展的任务要求，现将《河南省二〇二二年科技发展计划》下达给你们，请按照计划项目目标，认真做好组织实施工作。

附件：河南省二〇二二年科技发展计划

河南省科学技术厅

2022年1月26日

APPENDIX E.3

项目编号	项目名称	承担单位	项目负责人	主管部门
222102320067	石墨烯负载柱芳烃复合材料在电极表面的原位可控制备及在氯酚类污染物检测中的应用	河南工程学院	段群鹏	河南省教育厅
222102320068	切圆射流旋风辅助纳米颗粒流态化装置优化及关键技术研发	河南科技大学	王韶卫	河南省教育厅
222102320069	气-液-固三相耦合破碎煤体氧化动力机制研究	河南理工大学	韩学锋	河南省教育厅
222102320070	预应力装配式 UHPC 梁柱节点耗能减震关键技术研究	郑州航空工业管理学院	薛茹	河南省教育厅
222102320071	MnO2 基/电纺纤维复合材料的设计合成及其光驱动去除污染性气体甲醛的研究	河南科技学院	苏佳飞	河南省教育厅
222102320072	基于 RNA-seq 探讨小分子热休克蛋白 Hspb7、JAK/STAT 通路在电针干预肌肉损伤中的修复作用	河南中医药大学	栗俊伟	河南省教育厅
222102320073	用于环境污染物实时监测的先进植物传感器研究	郑州大学	周琪	河南省教育厅
222102320074	电动汽车用高能效混合励磁同步电机的关键技术研究与应用	郑州轻工业大学	贾宛英	河南省教育厅
222102320075	新型制冷剂 L20 在家用空调中应用的关键技术研究	郑州轻工业大学	金听祥	河南省教育厅
222102320076	基于流态智能识别的热泵高效运行控制系统关键技术研究	河南应用技术职业学院	范晓伟	河南省教育厅
222102320077	郏县红牛优良肉质性状关键分子标记的筛选及应用研究	河南城建学院	陈艳艳	河南省教育厅
222102320078	外源微生物缓解微塑料对小麦生长影响的机制与应用	河南农业大学	林迪	河南省教育厅
222102320079	Ag@AgCl/g-C3N4 复合光催化降解室内甲醛及其机理	郑州工业应用技术学院	马天	郑州市科学技术局
222102320080	都市智能植物工厂环境多因素耦合调控与优化	河南科技学院	王新法	河南省教育厅
222102320081	火灾环境下 GFRP 筋增强地聚物再生混凝土梁力学性能提升与应用关键技术研究	郑州大学	王自柯	河南省教育厅
222102320082	大别山森林植物叶片性状对大气氮沉降和增雨的响应及适应机制	河南大学	张晨露	河南省教育厅
222102320083	基于“源-流-汇”框架的黄河典型流域基流过程及其生态调控机制研究	华北水利水电大学	黄旭东	河南省教育厅
222102320084	南水北调中线工程渠道边坡除藻设备关键技术研究及其应用	华北水利水电大学	李冰	河南省教育厅
222102320085	黄河河南段湿地植被对土壤汞的活化及其调控技术	郑州大学	孙涛	河南省教育厅
222102320086	“双碳”目标下煤基复合高效封孔材料及综合配套关键集成技术开发	中原工学院	张钧祥	河南省教育厅
222102320087	基于 Topmetal 像素阵列芯片的极低本底氡探测器的研制	河南工业大学	邹曙光	河南省教育厅
222102320088	矿山废水中持久性有机污染物降解关键性技术研究	郑州大学	滕道光	河南省教育厅

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Government project approval document: 2022 henan province key r&d and promotion special project, multi factor coupling regulation and optimization of urban intelligent plant factory environment (222102320080), with a funding of 100000 rmb.

APPENDIX E.4

河　南　省　教　育　厅

河南省高等学校重点科研项目计划
立 项 通 知

河南科技学院：

你单位申报的下列研究课题，经专家评审、省教育厅审核，已列为河南省高等学校重点科研项目计划，并以 教科技〔2021〕383号 文件批准下达。现通知如下：

项目编号：22A210013

项目名称：全人工光植物工厂雾培系统研制

项目负责人：王新法

项目资助经费：3.0万元

项目研究期限：2022年01月01日--2023年12月31日

项目组成员：

排序	姓名	性别	单位
2	王新法	男	河南科技学院
3	卜瑞方	女	河南科技学院
4	韩亚峰	女	河南科技学院
5	赵明富	男	河南科技学院
6	黄勇	男	河南科技学院
7	张伟	男	河南农业大学
8	陈克亭	男	河南智圣普电子技术有限公司
-	-	-	-
-	-	-	-
-	-	-	-

（项目组共 8 人）

河南省教育厅
科研管理专用章

2021年10月22日

Government project approval document: 2022 key research project of higher education institutions in Henan province, research and development of an all-artificial-light plant factory aeroponics culture system (22a210013), with a funding of 30000 rmb.

APPENDIX E.5

河南省科学技术厅文件

豫科〔2023〕26号

关于下达河南省二〇二三年科技发展计划的通知

各省辖市科技局，济源示范区管委会科技管理部门，各县（市）科技管理部门，郑州航空港经济综合实验区、国家高新区、国家郑州经济技术开发区管委会，省直有关部门，各有关单位：

按照“十四五”科技发展的总体思路，结合我省国民经济和社会发展的任务要求，现将《河南省二〇二三年科技发展计划》下达给你们，请按照计划项目目标，认真做好组织实施工作。

附件：河南省二〇二三年科技发展计划

河南省科学技术厅

2023年3月13日

APPENDIX E.5

项目编号	项目名称	承担单位	项目负责人	主管部门
232102111115	无人机成像高光谱"时-空-谱"融合的冬小麦氮素早期亏缺诊断研究与应用示范	河南农业大学	付元元	河南省教育厅
232102111116	山药振动挖掘技术和装备优化设计研究	河南农业大学	刘晓潺	河南省教育厅
232102111117	华北平原冬小麦生产适应降水变化的过程和机制研究	华北水利水电大学	王冬林	河南省教育厅
232102111118	基于植物生长模型与Wide&Deep算法的草莓苗期旺长态势监测与预警技术研究	信阳农林学院	程浈浈	信阳市科学技术局
232102111119	多角度高光谱监测夏玉米全时域氮素垂直异质性分布模型构建与应用	河南农业大学	李岚涛	河南省教育厅
232102111120	联合收获机作业信息采集分析与智能化减损调控装备研发	河南科技大学	庞 靖	河南省教育厅
232102111121	基于多源遥感的河南省农作物长势生境智能监测方法研究	河南财经政法大学	刘 涛	河南省教育厅
232102111122	非规则扁平种子机械气力组合式精量排种器的研发	黄河水利委员会黄河水利科学研究院	余 幸	黄河水利委员会
232102111123	基于多光谱遥感“植-土”信息的冬小麦成熟期预测和收割监测研究	河南农业大学	岳继博	河南省教育厅
232102111124	基于 IoT 与大数据的植物工厂智慧管控技术研究	河南科技学院	赵明富	河南省教育厅
232102111125	基于多模态学习的小麦田间智能管理关键技术研究	河南科技学院	侯志松	河南省教育厅
232102111126	基于动态传热建模的粮仓主动隔热系统及其高效运行机制研发	河南工业大学	杨 柳	河南省教育厅
232102111127	基于无人机多光谱影像的果园水氮管理评估系统研发	河南科技学院	曲培新	河南省教育厅
232102111128	基于区块链的果品溯源平台及关键技术	河南科技学院	李 倩	河南省教育厅
232102111129	授粉多旋翼无人机协同作业航迹规划及控制方法研究	中原工学院	张利民	河南省教育厅
232102111130	光纤耦合 LED 原位在线土壤养分光学传感器研发	河南省农业科学院农业经济与信息研究所	杨张青	河南省农业科学院
232102111131	用于除草和施肥的芝麻田间管理自动驾驶作业车关键技术研究	华北水利水电大学	古冬冬	河南省教育厅
232102111132	联合无人机多光谱影像和机器学习的小麦全生育期叶绿素含量差异评估方法研究	安阳工学院	王 伟	安阳市科学技术局
232102521001	生物弹性体材料聚乳酸己内酯共聚物的关键合成与加工技术联合研究	郑州大学	王小峰	河南省教育厅

Government project approval document: 2022 henan province key r&d and promotion special project, research on intelligent control technology for plant factories based on IoT and Big Data (232102111124), with a funding of 100000 rmb.

APPENDIX E.5

项目编号	项目名称	承担单位	项目负责人	主管部门
232102111001	整合组学解析鸡生长性状遗传机制及其主效标记的开发与应用	河南农业大学	张彦华	河南省教育厅
232102111002	确山黑猪优质肉遗传机制解析及其产业化应用	河南农业大学	韩雪蕾	河南省教育厅
232102111003	基于 eQTL 定位鉴定影响奶牛酮病的分子标记及其在育种中的应用	河南农业大学	黄河天	河南省教育厅
232102111004	玉米交替灌溉土壤水氮耦合机制与节水增效关键技术	黄河水利职业技术学院	汪明霞	河南省教育厅
232102111005	钼污染土壤的植物共生丛枝菌根联合修复技术研发与应用	河南科技大学	石兆勇	河南省教育厅
232102111006	草地贪夜蛾的绿色防控复配药剂组合及纳米制剂开发	河南省对外科技交流中心	徐永贵	河南省科学技术厅
232102111007	河南省胡萝卜全程机械化优质高效栽培技术集成及应用研究	郑州市蔬菜研究所	郑军伟	郑州市科学技术局
232102111008	生物炭和 AM 真菌联合修复土壤镉污染关键技术研究	新乡学院	王晓冰	新乡市科学技术局
232102111009	旱地冬小麦—夏玉米适水改土绿色高产提质增效技术体系集成与应用	河南科技大学	吴金芝	河南省教育厅
232102111010	晚熟桃果锈发生机制与防控技术研究	中国农业科学院郑州果树研究所	段文宜	河南省科学技术厅
232102111011	包埋型介孔硅/环脂肽防治小麦赤霉病的研发与应用	河南工业大学	伊艳杰	河南省教育厅
232102111012	获草谷网蚜 L 型共生菌影响宿主抗药性的分子机制及应用	河南科技学院	李新安	河南省教育厅
232102111013	保幼激素调控马铃薯块茎蛾卵黄发生过程关键基因的筛选及其 dsRNA 喷雾剂研发	河南科技学院	吴建建	河南省教育厅
232102111014	基于高光谱成像的潮土剖面氮素含量预测及精细制图	华北水利水电大学	吴士文	河南省教育厅
232102111015	一株有益链霉菌在小麦种植中的防病促生研究及应用	河南科技学院	朱红霞	河南省教育厅
232102111016	解淀粉芽孢杆菌 PB-1 防治设施番茄灰霉病关键技术研究	河南科技学院	杨 蕊	河南省教育厅
232102111017	基于分子对接策略的桔小实蝇新型引诱剂开发与应用研究	河南科技大学	刘 欢	河南省教育厅
232102111018	外源褪黑素提高迷迭香耐涝性的关键技术体系构建与作用机制研究	河南农业大学	李明婉	河南省教育厅
232102111019	腐殖酸-钙-生物炭复合材料修复板结和重金属污染土壤的关键技术	黄淮学院	陈清泰	驻马店市科学技术局
232102111020	新型季铵盐类超铺展剂与芸苔素内酯组合物制剂研制及应用	河南农业大学	王 顺	河南省教育厅

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Government project approval document: 2023 Henan province key r&d and promotion project, research and application of a beneficial streptomyces strain in wheat planting prevention and growth promotion (232102111015), with a funding of 100000 rmb.

APPENDIX E.6

收录证书

证书编号：410--2023-000306

经审核，本报告已收录于河南省科技报告共享服务系统（http://kjbg.hnkjt.gov.cn）。

特颁此证。

报告名称：智能建筑温室植物工厂关键技术研发与应用

报告编号：212102110234/01

报告作者：王新法 韩亚峰;孙承秀;许园园;徐涛;赵明富;李国厚;吴振威;孙涌栋

收录时间：2023-05-18

支持渠道：河南省科技攻关计划

项目/课题名称：智能建筑温室植物工厂关键技术研发与应用

项目/课题编号：212102110234

河南省科学技术情报中心

2023 年 05 月 18 日

河南省科学技术情报中心 科技报告专用章

Technology Report Index Certificate: Research and application of key technologies for intelligent building greenhouse plant factory, Certificate no. 410-2023-000306.

APPENDIX E.7

Project completion certificate: Henan province science and technology research program project, key technology R&D and application of intelligent building greenhouse plant factory, project no. 212102110234.

APPENDIX E.7


河南省科技攻关计划项目

结项证书

该项目提交的研究资料完整，总结报告系统详实，经审查符合结项要求，准予结项。

河南省科学技术厅
科技计划专用章

2023年7月3日

项目名称：水肥药一体化混合滴灌系统开发与应用

立项年度：2021 年

项目编号：212102110229

承担单位：河南科技学院

项目负责人：赵明富

项目参加人（共 8 名）：

张利伟、曲培新、王新法、陈可可、王刘豪、张平川、白林锋、吴振威

Project completion certificate: Henan province science and technology research plan project, development and application of water fertilizer medicine integrated mixed drip irrigation system, project no. 212102110229.

APPENDIX E.8

河南省科技攻关计划项目

结项证书

该项目提交的研究资料完整，总结报告系统详实，经审查符合结项要求，准予结项。

项目名称：面向大型船舶清洁任务的自主作业爬壁机器人应用性技术研究

立项年度：2021 年

项目编号：212102210161

承担单位：河南科技学院

项目负责人：徐涛

项目参加人（共 8 名）：

蔡磊、柴豪杰、王新法、马玉琨、周纪勇、孔德川、付俊辉、孙乾坤

河南省科学技术厅 科技计划专用章

2023 年 7 月 3 日

Project completion certificate: Henan province science and technology research program project, applied technology research on autonomous operation wall climbing robot for large ship cleaning tasks, project no. 212102210161.

APPENDIX F

Acts of implementation of the results of dissertation work

Henan ZSP (ZhiShengpu) Electronic Technology Co., Ltd. has applied the new technology achievement certificate of "Multi factor Coupling Precision Control and Optimization of Artistic Light Plant Factory Environment Based on Growth Model".

Enterprise Application Certification

The new technology of "Multi factor Coupling Precision Control and Optimization of Artificial Light Plant Factory Environment Based on Growth Model" completed by **Wang Xinfa** has been successfully applied in our company's containerized artificial light plant factory equipment, implementing the annual, clean, and industrial production process of leafy vegetables, and conducting experimental verification and industry practical application testing. The test results and phased use prove that this new technology and invention has the advantages of high intelligence, high automation, and high control accuracy. It can increase water utilization rate by 10%, save water-soluble fertilizer by 8%, and comprehensively reduce electricity by 18%, significantly reducing the production cost of leafy vegetables. These scientific results and achievements have good commercial value and development prospects for the industrialization and commercialization of artificial light plant factories.

Hereby certify.

ZSP Technology Co., Ltd.

https://www.zsp-tech.com.cn/

河南智圣普电子技术有限公司

ZSP TECHNOLOGY CO.,LTD

Zhengzhou, China

December 16, 2022