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Design of a Robot for Predicting Strawberry Growth Environments Based on AI and Visual Fusion

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Abstract. In view of the fact that strawberry cultivation is prone to diseases, and when detected, the diseases are often already severe, leading to reduced production. This work aims to design an intelligent robot capable of predicting strawberry diseases 7 days in advance, helping strawberry growers respond to diseases in a timely manner and reduce losses. This paper adopts the K230 vision module, which is installed on an intelligent trolley. The trolley visually identifies strawberry pests and diseases, takes timed photographs of strawberry plants, and detects environmental information. The vision module uploads the photos to a cloud platform, which communicates with a WeChat mini-program via HTTP. An AI model system is deployed on the mini-program side, and the system analyzes and processes the photos to achieve disease prediction. After extensive experiments and testing, the prediction success rate reaches as high as 98%, enabling relatively accurate advance prediction of strawberry diseases. This intelligent robot system is practical and effective, providing a reliable means for strawberry growers to detect diseases early, effectively solving the problem of untimely disease detection, and has high value for promotion and application.

Keywords: *AI; Machine Vision; K230; Strawberry Diseases; Intelligent Greenhouse*

1. Introduction

In recent years, agricultural robots in China have become increasingly intelligent, reflecting a significant shift towards smart agriculture as a prominent trend in modern agricultural development. Therefore, the development of advanced intelligent functions for agricultural robots is of great significance, as it plays a crucial role in creating an optimal environment for crop growth while simultaneously improving both the yield and quality of various crops.

Currently, many domestic institutions are conducting research on smart greenhouse scenarios. In agricultural planting, reference [1] proposed a flower greenhouse spray robot, effectively solving the problems of low manual spraying efficiency and the health impact of airborne residues. Reference [2] proposed a self-propelled greenhouse film-covering robot, effectively reducing labor input and improving cost-effectiveness. In crop management and monitoring, reference [3] proposed an agricultural inspection robot to monitor greenhouse crops and assist farmers in managing and inspecting greenhouse information. Reference [4] proposed a rail-guided robot to further improve efficiency and expand the application scenarios of robots in greenhouses. In visual recognition, for strawberry disease identification, reference [5] proposed a strawberry disease detection model based on YOLO-Strawberry, which improves detection efficiency based on an improved Yolov8 model. The above studies all focus on robots in greenhouse scenarios and have good practical effects, but most have some shortcomings in recognition functions, especially in visual detection and recognition. On this basis, this paper proposes a robot that integrates vision and AI for disease prediction and detection, which can help farmers monitor the basic conditions of crops in the greenhouse, improve inspection efficiency, and is of great significance for the management of greenhouse systems and the development of smart agriculture. This robot can not only accurately identify diseases but also predict them, providing scientific recommendations for farmers and reducing their losses.

2. Methodology

This paper takes a greenhouse planted with strawberries as the research object and designs an agricultural robot for internal inspection. The design principle of unity of function and form is adopted. According to the functional requirements of the greenhouse, the robot needs to realize visual recognition, wireless communication, motor drive operation, and other functions. The corresponding implementation modules are shown in Table 1.

Table 1. An example table.

Function	Module
Image collection & detection, real-time crop monitoring	Vision Module
Bluetooth remote-controlled car	Bluetooth Module
Control vertical rotation of the car	Servo Module
Drive the car forward/backward	Motor Driver Module
Control horizontal rotation of the car	Stepper Motor Module
Detect CO_2 concentration, light intensity, temperature & humidity	Environment Detection Module
Predict crop disease occurrence for the next 7 days	Mini Program Module

According to the correspondence between the various system functions and their respective modules detailed in Table 1, the overall layout of the entire system is illustrated in Figure 1.

This visual representation provides a clearer understanding of how each component interacts within the overall framework.

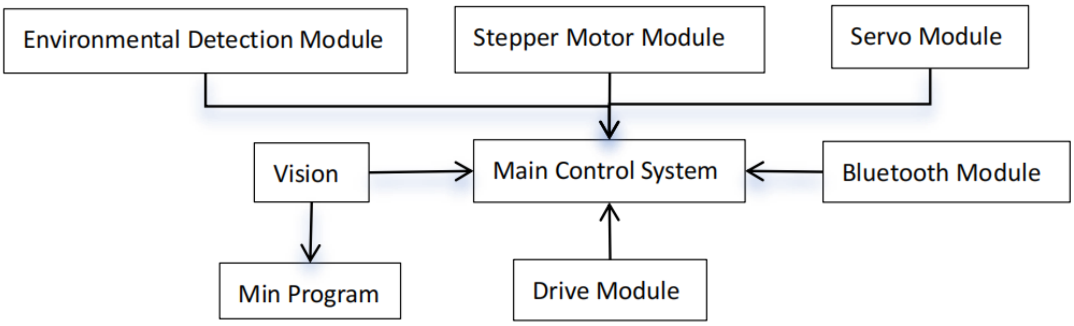

Figure 1. System layout diagram.

3. System Hardware Design

3.1. Construction of the robot's 3D model

Based on the system layout and corresponding modules, the first step in hardware design is to complete the construction of the robot's 3D model. The approach is parts design followed by whole assembly: first, the modules and mechanical structural components of the robot are designed, and then they are assembled into a whole according to the coordination relationships among the parts. Some main components are shown in Figures 2–7, and the assembled whole is shown in Figure 8.

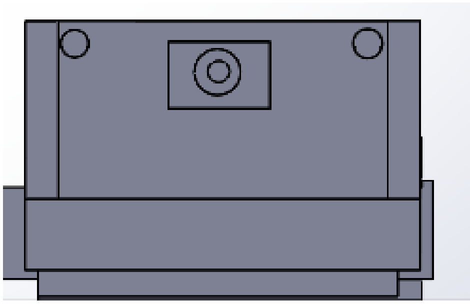

Figure 2. 3D Model of vision module.

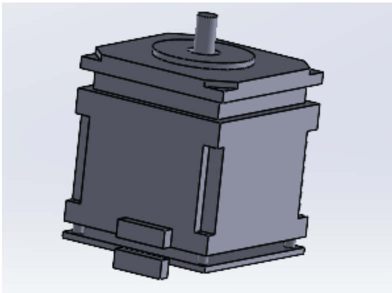

Figure 3. 3D Model of stepper motor.

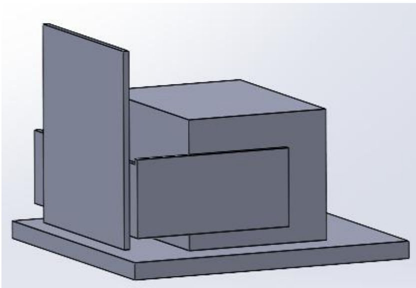

Figure 4. 3D Model of servo module.

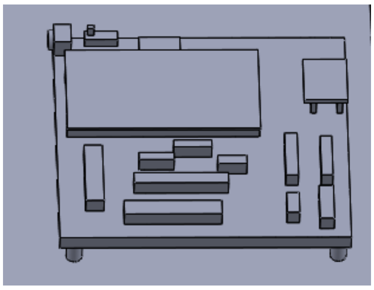

Figure 5. 3D Model of robot main control PCB.

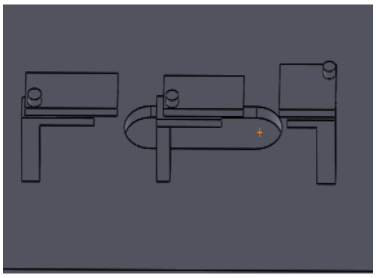

Figure 6. 3D Model of environmental detection module.

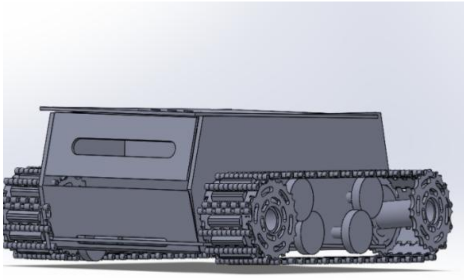

Figure 7. 3D Model of robot base board.

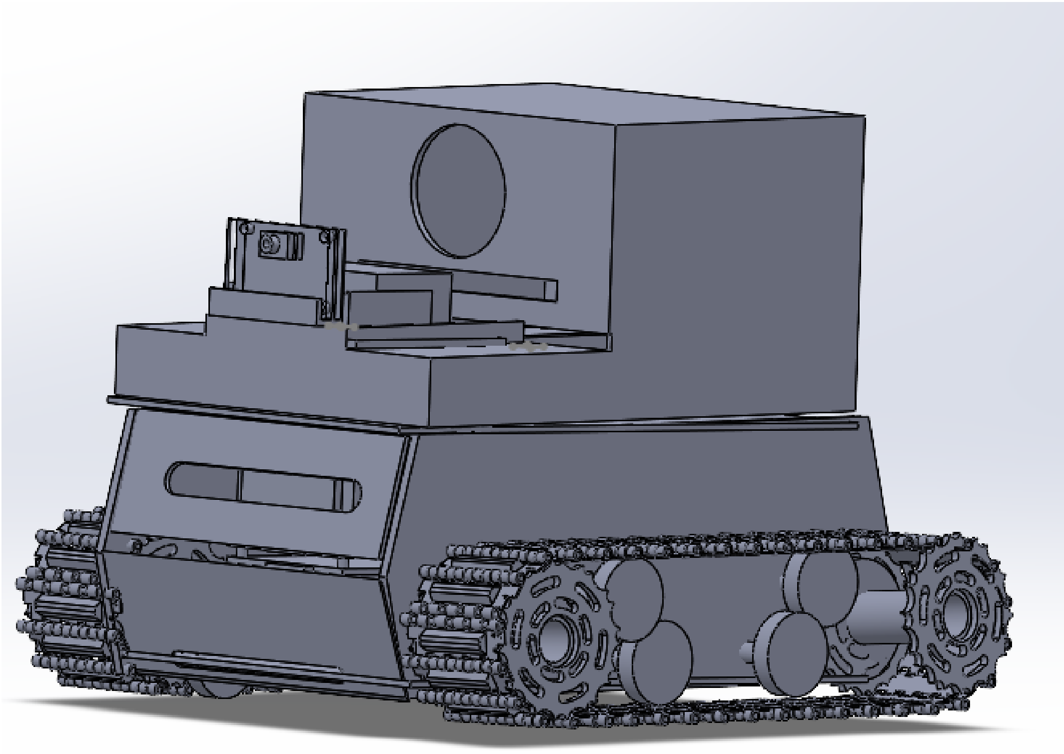

Figure 8. Integral 3D model of robot.

3.2. System control circuit design

3.2.1. Main control module design

To achieve control of servos and stepper motors, high-precision motor control, efficient and stable multi-channel serial communication, precise task processing in complex tasks, and convenient future expansion for connecting various external devices, after comprehensive consideration, this paper selects STM32F407ZGT6 as the main control unit. Its minimum system is shown in Figure 9.

This main control unit is based on the high-performance ARM Cortex-M4 core, with a main frequency of up to 168 MHz, enabling rapid processing of complex tasks and providing a solid guarantee for system real-time performance. Its peripheral interfaces are extremely rich, integrating UART, SPI, I2C, CAN, and other interfaces, easily meeting the needs of multi-channel motor PWM control and multi-channel serial communication, and creating convenience for system expansion and connection of various external devices. In addition, it has a mature ecosystem, with STM32CubeMX and HAL libraries greatly simplifying the development process and effectively improving development efficiency [6].

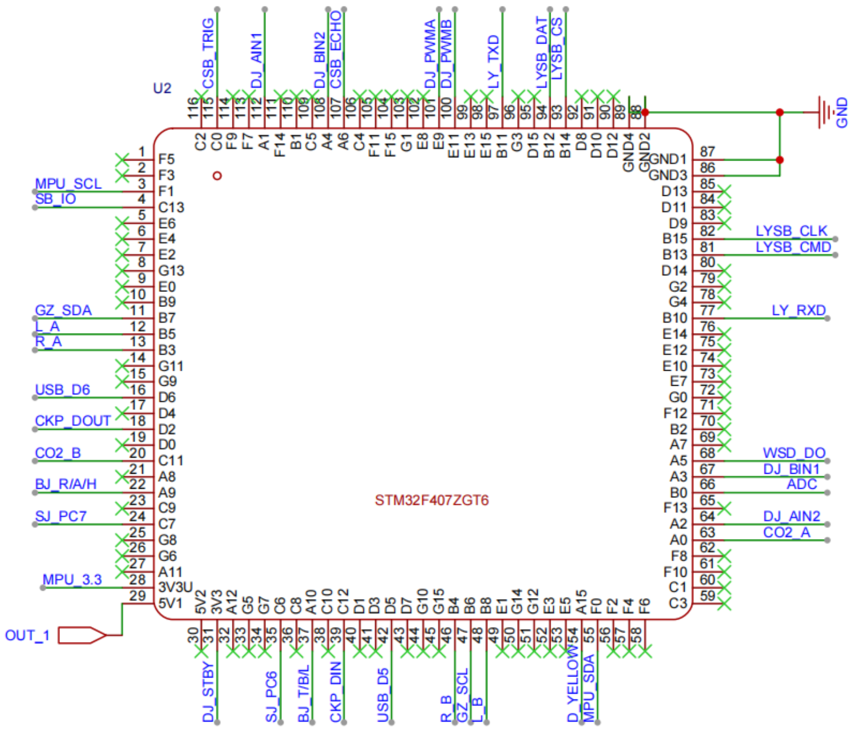

Figure 9. Minimum aystem diagram.

3.2.2. Vision module design

The vision module is designed to achieve three essential functions: facilitating seamless communication with the mini-program, enabling real-time collection of vital crop information that is uploaded to the cloud platform, and accurately identifying various diseases affecting the crops. Based on these critical requirements, this paper has chosen the K230 as the ideal vision module for implementation.

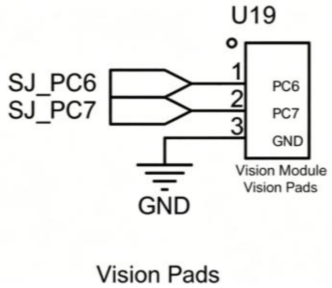

Figure 10. Vision hardware construction module.

The K230 has a built-in Wi-Fi module and is adapted for communication with the cloud platform, with a communication time of about 1 second. The 230 processor integrates dual RISC-V cores and a dedicated AI acceleration engine [7], supporting efficient inference of lightweight YOLOv8 models through hardware-level optimization, achieving a good balance between power consumption and computational power. The vision module is shown in Figure 10. A comparison of different vision modules is shown in Table 2.

Table 2. Comparison of vision modules.

Comparison Dimension	**Camera**	**On-board WiFi**	**Multi-channel Camera**	**Cost**
K230 (This Paper)	OV5640	Yes	3-channel parallel	219
K210	OV2640	No	1 channel	120
Raspberry Pi	IMX219	Yes	1 channel	398
OpenMV	OV7725	No	1 channel	150

3.2.3. Control module design

The control system is designed to seamlessly integrate servos and stepper motors, all managed through a Bluetooth module [8]. By utilizing specific Bluetooth commands, the main control outputs PWM pulse signals to effectively drive both types of motors. This advanced control system ensures a wide visual field for the vision module, enhancing overall functionality. The servo is responsible for the vertical adjustment of the vision field, offering a rotation range from 0 to 90 degrees. A powerful 180-degree, 20 kg servo has been selected for this purpose. The configuration and characteristics of the servo module are illustrated in Figure 11 for better understanding.

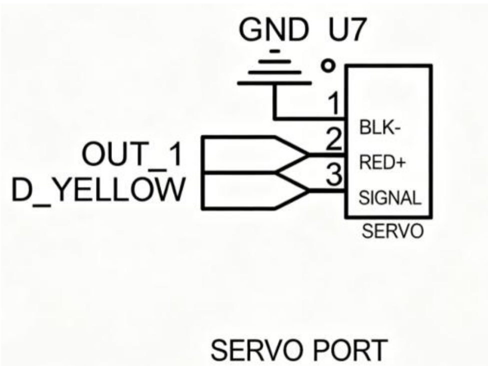

Figure 11. Servo hardware setup module.

The stepper motor controls horizontal rotation of the vision field, with a range of up to 360 degrees. A 42-stepper closed-loop driver is selected, as shown in Figure 12. The combination of the two enables comprehensive photographing of strawberry plants from root to top, providing clear and accurate image data support for K230 visual monitoring and prediction.

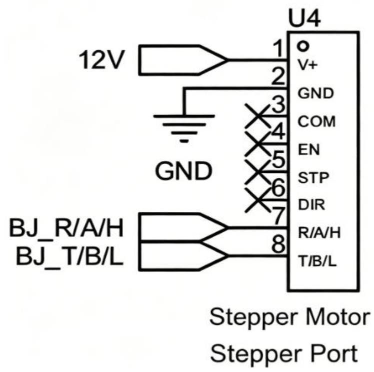

Figure 12. Stepper motor hardware construction module.

3.2.4. Drive module design

To ensure the trolley travels at a constant speed in the greenhouse, a tracked drive is adopted, which flexibly adapts to various complex terrains and provides a stable mobile foundation for the equipment. Given the relatively heavy weight of the trolley, a 12V DC motor is used, combined with a Hall encoder (390 pulses per revolution). The STM32 acquires pulse signals using the encoder interface mode of the advanced timer, providing a reliable guarantee for high-precision speed feedback. In motion control, a dual-loop PID architecture is employed [9]. The inner current loop is implemented by the motor driver hardware, ensuring precise and stable current control; the outer speed loop is implemented by the STM32 software, where the speed-loop PID output is cleverly converted to PWM duty cycle, and then the TB6612 driver precisely controls the motor speed, as shown in Figure 13. Through this design, independent, fast, and stable closed-loop regulation of the left and right wheels is achieved. Whether for straight-line driving or obstacle-avoidance steering, commands are executed accurately, effectively coping with various complex scenarios and laying a solid foundation for stable operation and precise manipulation of the equipment.

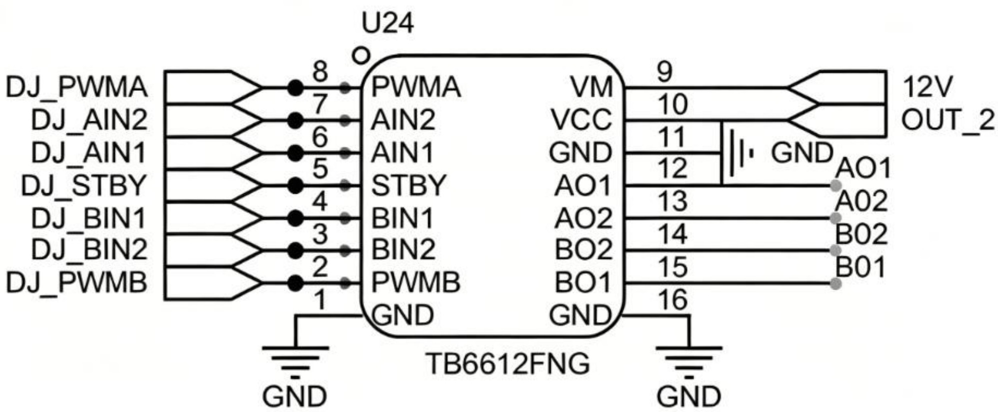

Figure 13. Motor hardware construction module.

3.2.5. Environment detection module design

The environment detection module consists of a CO_2 concentration monitoring module, a light intensity module, and a temperature and humidity module. The environment detection module assists visual prediction results to improve prediction accuracy. Data is transmitted to the main control via I2C communication, and then the main control sends it to the K230 via serial port, finally reaching the mini-program together with the photos and the cloud platform.

The Risym GY-302 BH1750 light intensity module, the DHT11 temperature and humidity detection module, and the JW01-CO2-V2.2 carbon dioxide concentration monitoring module are selected, as shown in Figure 14. All three feature high precision, ease of use, low power consumption, and low cost, making them suitable for detecting the strawberry greenhouse environment [10].

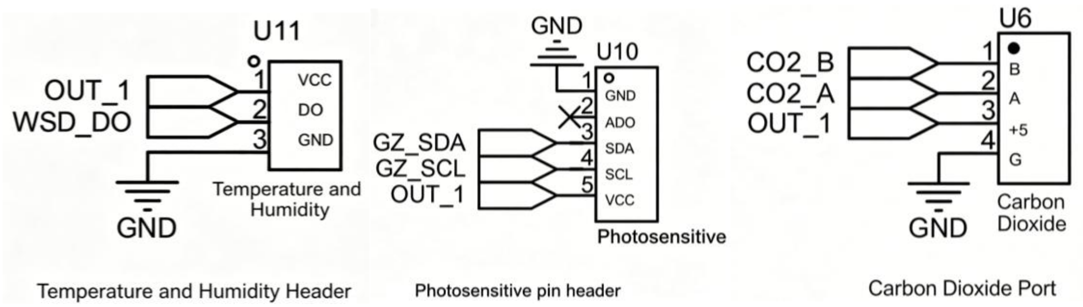

Figure 14. Environment detection hardware setup.

4. System Software Design

4.1. Underlying embedded design

The underlying embedded system uses STM32 as the core to build a closed-loop control chain of "Bluetooth remote control", "drive operation", "vision acquisition", and "cloud upload" [11]. The specific logic is:

(1) Commands are sent to the main control via the Bluetooth module. After receiving and parsing the commands, the main control drives the servo and stepper motor via PWM signals to adjust the K230 shooting angle.

(2) The vision module captures photos upon receiving information, processes and detects the photos, and simultaneously reads current environmental data.

(3) The collected photos and environmental information are synchronously transmitted to the cloud platform using the K230’s onboard Wi-Fi module.

The embedded design flow is shown in Figure 15.

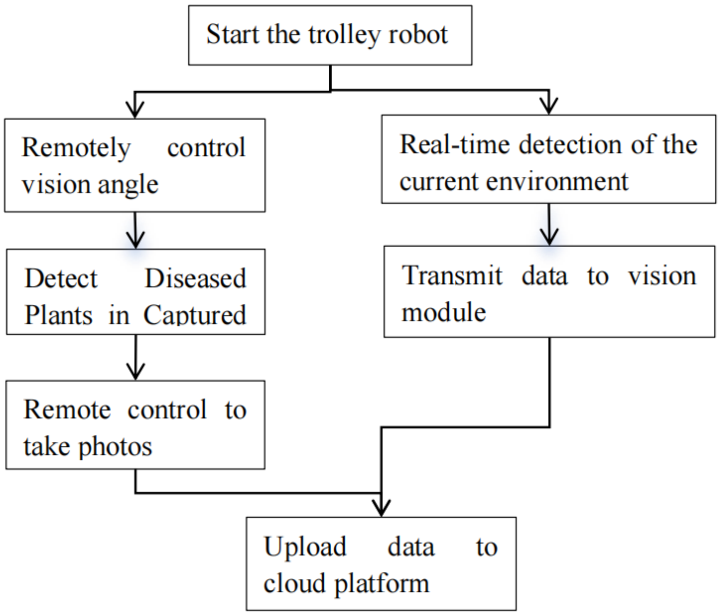

Figure 15. AI working principal diagram.

4.2. Mini-program design

This system is equipped with a WeChat mini-program specifically designed for the farmer side, as illustrated in Figure 16. The transmission process from the K230 side to the mini-program side is highly efficient, taking less than 2 seconds to complete. This rapid transmission facilitates timely updates and enhances overall user experience for farmers.

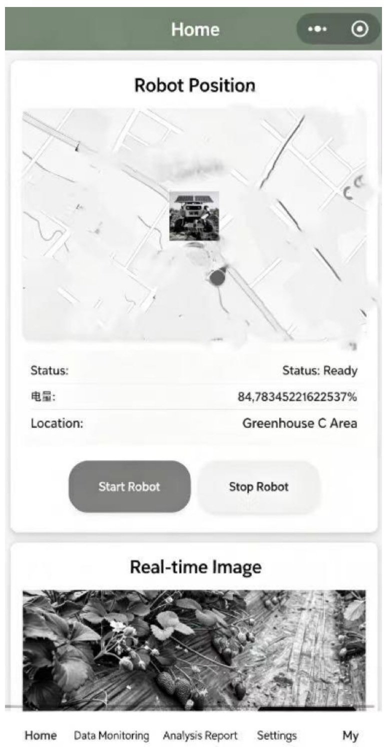

Figure 16. Mini-program home page interface display.

The mini-program has five functional pages. The first page, the home page, displays the latest status of greenhouse environment data, strawberry health index, and the VET-Net output of 7-day disease predictions and management suggestions. The second page provides real-time monitoring of current environmental information. The third page, analysis report, records historical detection data. The fourth page, settings, is responsible for cloud platform connection management and configuration. The fifth page, "My", records user login information. The mini-program provides a convenient platform for farmers to help manage their greenhouses [12].

4.3. Visual recognition algorithm and edge deployment

4.3.1. Subsubsection title

This paper is based on photos taken 7 days before disease occurrence from 500 diseased strawberry plants, totaling 3,500 photos, covering 5 periods and 6 types of diseases, as shown in Figure 17.

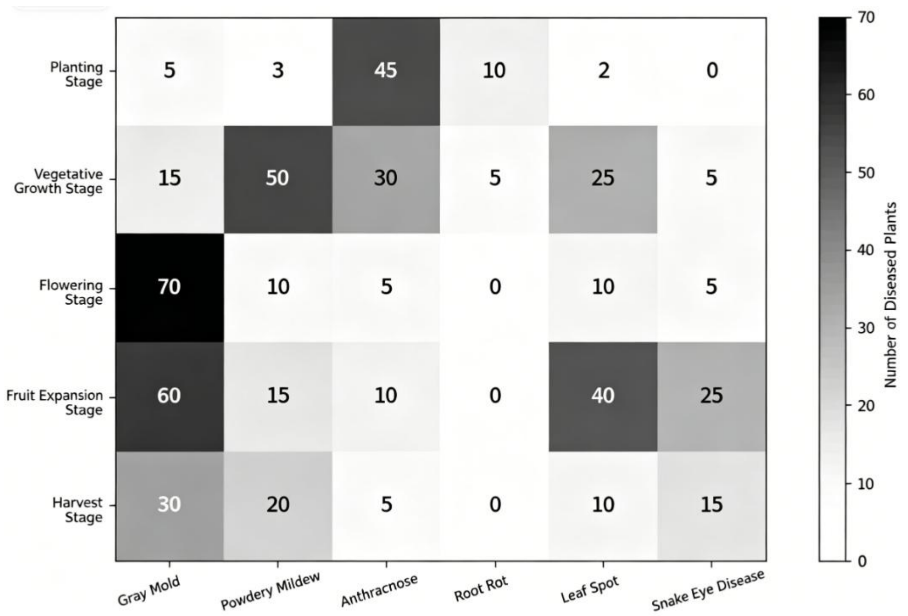

Figure 17. Heat map of distribution of 500 diseased plants.

Aiming at the multi-variable coupling characteristics of greenhouse crop growth, a CNN+LSTM prediction fusion algorithm plus K230 detection is proposed, trained on the Baidu PaddlePaddle platform [13] as shown in Figure 18.

Input layer: environmental sensor sequences (temperature, humidity, CO_2, light intensity) + image feature vectors;

Processing layer: dual-channel LSTM models temporal environmental impacts and spatial image features separately, weighted fusion via attention mechanism, and fixed sentence analysis of agricultural conditions;

Output layer: growth score for the next 7 days (0–10 points) + growth suggestions + future management measures.

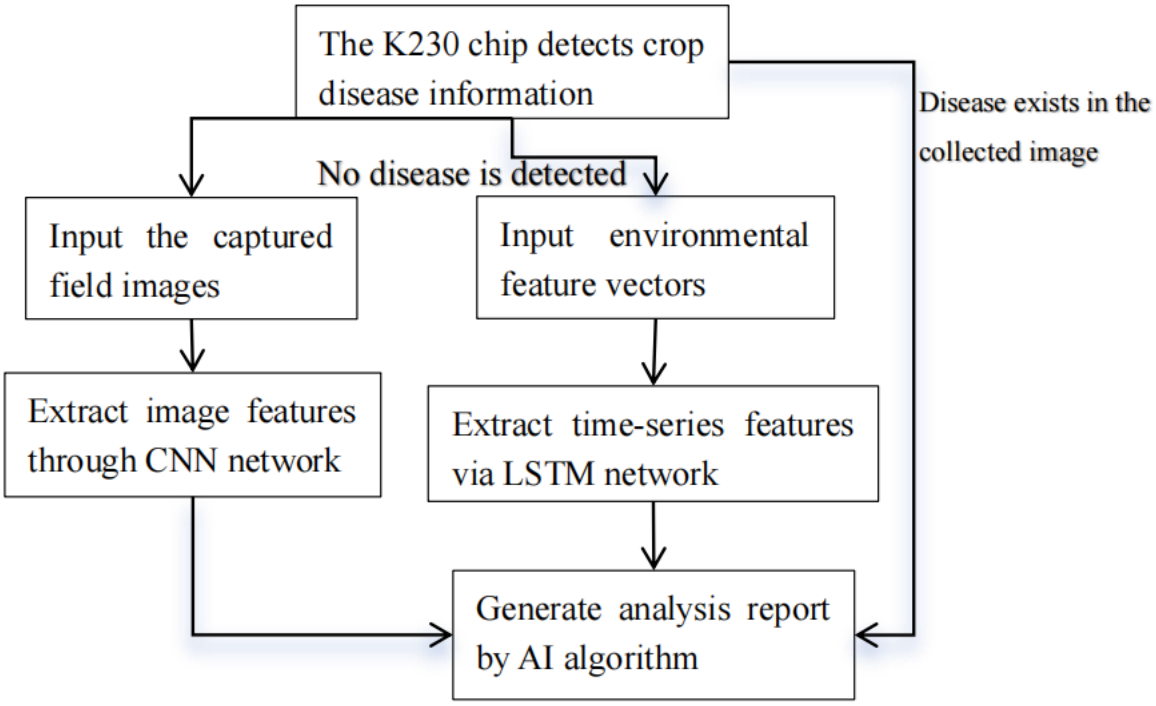

Figure 18. AI working principle diagram.

4.3.2. YOLOv8 model training for strawberry disease recognition

To improve the precision of strawberry planting management, this system introduces the YOLOv8 algorithm to achieve accurate identification of strawberry diseases, as shown in Figure 19. When processing strawberry images captured by vision, preprocessing operations such as denoising and enhancement are first performed to improve image quality [14]. Then, the YOLOv8 model, trained and optimized with a large number of annotated data, is used to analyze the images. The model can quickly and accurately identify disease spots on strawberry leaves and fruits, providing key information to growers in a timely manner, and facilitating fine management of strawberry cultivation.

Figure 19. Training experiment photos.

The collected 4,000 disease photos were divided into training set, test set, and validation set for training.

5. Experimental Verification

5.1. Visual recognition accuracy test

To thoroughly verify the effectiveness of the YOLOv8 model deployed on the K230 edge side [15], the experimenters meticulously collected a diverse set of 200 high-quality strawberry leaf images from the greenhouse to serve as a comprehensive test set. This dataset includes four distinct categories: powdery mildew, gray mold, anthracnose, and healthy leaves, which are clearly illustrated in Table 3. The careful selection of these categories aims to enhance the model's ability to accurately identify and classify various leaf conditions.

Table 3. Visual recognition disease accuracy experiment.

Disease Category	**Samples**	**Precision**	**Recall**	**mAP@0.5**
Powdery Mildew	50	95.0%	94.5%	0.95
Gray Mold	50	94.8%	93.0%	0.94
Anthracnose	50	92.5%	91.0%	0.92
Healthy Leaf	50	96.0%	97.5%	0.97

Experimental data show that the average precision of disease recognition reached 94.6%, the average recall was 94.0%, and the mAP@0.5 indicator reached 0.945. Among them, healthy leaves achieved the highest recognition rate of 96.0%, effectively reducing false positive rates and avoiding misjudgment of healthy crops. This proves that the YOLOv8 model has extremely high robustness in edge inference environments and can meet the real-time and accuracy requirements for early disease warning in strawberry cultivation.

5.2. AI prediction experiment for future strawberry diseases

The dataset consisting of 500 diseased strawberry plants was carefully divided, allocating 400 plants for training purposes and reserving 100 plants for testing. The testing phase involved a strict evaluation of these 100 plants, utilizing a total of 700 photos to ensure comprehensive analysis, as detailed in Table 4. This systematic approach facilitated a more accurate assessment of the model's performance on a per-plant basis.

Table 4. Division of the 500-plant dataset.

Dataset	**Plants**	**Images**
Training Set	400 plants	2800 images
Test Set	100 plants	700 images

The experimental results indicate that the AI successfully detected 98 diseased plants out of a total of 100, one day prior to the actual occurrence of the disease. Additionally, it recorded only 2 false detections during this process. This impressive performance led to an overall efficiency rate of 98%, as detailed in Table 5. These findings underscore the potential effectiveness of AI in early disease detection within agricultural settings.

Table 5. Test results.

Metric	Value
Test Samples	100 plants
Prediction Accuracy	98.0%
Miss Detection Rate	2.0%

5.3. Overall system experiment

To thoroughly verify the reliability and performance of the system in various real-world application scenarios, the robot was taken to a greenhouse for extensive field experiments. This hands-on testing aimed to comprehensively assess its capabilities and overall effectiveness in a practical environment, providing valuable insights into its operational efficiency and adaptability.

5.3.1 K230 data transmission test

The robot was taken to the greenhouse for field experiments, as illustrated in Figure 20. During this process, we tested the success rate of disease recognition results, collected environmental data, and uploaded photos to the mini-program at varying distances between the mobile phone and the robot. This examination aimed to assess the effectiveness of communication and data transmission under different spatial conditions, providing valuable insights into the system's performance.

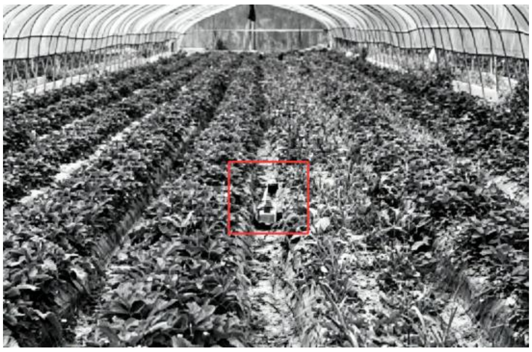

Figure 20. Field experiment.

Test indicator short distance (inside greenhouse) Medium distance (outside greenhouse) Long distance (10 km away) Experimental results: Within 10 meters, the data packet upload success rate reached 99%, and single upload took about 300 ms. Analysis: The system can effectively compress image data (uploading only recognition results rather than original images), greatly reducing data consumption and ensuring data integrity under weak network conditions.

Table 6. Experimental data.

Test Metric	**Short Distance (Inside Greenhouse)**	**Medium Distance (Outside Greenhouse)**	**Long Distance (10 km Away)**
Response Time	2s	2.2s	2.4s
Upload Success Rate	100%	100%	100%
Recognition Accuracy	98%	97%	97%

6. Conclusion

This paper designs and implements an intelligent strawberry disease monitoring trolley system based on the K230 vision module and STM32 microcontroller. This work innovatively proposes a dual-channel prediction and monitoring model combining a "CNN+LSTM" algorithm and "K230 information", which successfully solves the problems of high labor costs, poor real-time performance, and lack of environmental data in traditional agricultural disease monitoring. Future research will focus on optimizing the algorithm to adapt to extreme environments and exploring the application of this system to a wider range of smart agriculture scenarios.

References

[1] Chen Kefei, Wang Tieguang, Li Wenqin, et al. (2025). 花卉大棚喷药机器人远程控制系统设 [Design of a Remote Control System for Flower Greenhouse Spraying Robots]. *Agricultural Mechanization Research*, 61-67. [in Chinese]

[2] Zhang Ruibin. (2024). 面向新能源的大棚自走式覆膜机器人控制策略研究 [Research on the control strategy of autonomous film-covering robots for greenhouses oriented towards new energy]. *Electronic Components and Information Technology*, 5-78. [in Chinese]

[3] Wang Shaocong, Du Xiaopeng, Wang Huiqiang, et al. (2024). 温室巡检机器人关键技术研究进展与展望 [Research Progress and Prospects of Key Technologies for Greenhouse Inspection Robots]. *Jiangsu Agricultural Science*, 1-10. [in Chinese]

[4] Jin Huawei, Liu Zhiguo, Liu Qingqing, et al. (2026). 农业机械检测的挂轨式巡检机器人 [Track-mounted inspection robot for agricultural machinery testing]. *Agricultural Machinery*, 87-89. [in Chinese]

[5] Wu Qianru, Zheng Chenjun, Dai Minghan, et al. (2024). 基于形态分析的温室大棚农业机器人设计 [Design of Greenhouse Agricultural Robots Based on Morphological Analysis]. *Mechanical and Electrical Technology*, 59-62. [in Chinese]

[6] Zhao Chong. (2025). 基于 STM32 的智能环境检测系统设计与实现 [Design and

Implementation of an Intelligent Environmental Monitoring System Based on STM32]. *Consumer Electronics*, 17-19. [in Chinese]

[7] Liu Qin, Luo Qijian, Zeng Tao, et al. (2026). 基于 K230 芯片和 YOLOv11n 的蓝莓果实成熟度识别系统设计 [Design of a Blueberry Fruit Ripeness Recognition System Based on the K230 Chip and YOLOv11n]. *Agricultural Engineering*, 14-20. [in Chinese]

[8] Wang Liyu, Wu Xiaona, Lü Ensheng, et al. (2025). 复杂场景下移动机器人机载视觉云台稳定跟踪控制策略 [Control strategy for stable tracking of mobile robot airborne vision gimbal in complex scenarios]. *IoT Technology*, 135-138, 145. [in Chinese]

[9] Zhang Chenliang, Zhang Yazhou. (2024). 基于机器视觉的小车跟随行驶系统设计 [Design of a Car Following System Based on Machine Vision]. *IoT Technology*, 118-119, 122. [in Chinese]

[10] Li Chongwei. (2025). 基于 STM32 单片机的智能大棚环境检测控制系统 [Intelligent Greenhouse Environment Monitoring and Control System Based on STM32 Microcontroller]. *China Agricultural Machinery Equipment*, 41-44. [in Chinese]

[11] Wang Wei. (2024). 基于单片机和蓝牙遥控的智能小车设计与实现 [Design and Implementation of a Smart Car Based on Microcontroller and Bluetooth Remote Control]. *Computer Applications Digest*, 85-89. [in Chinese]

[12] Yin Zhiyong, Yin Zhangxuan, Yu Chuntao, et al. (2026). 蔬菜大棚智能控制系统设计 [Design of an Intelligent Control System for Vegetable Greenhouses]. *Mechanical Engineering and Automation*, 192-195. [in Chinese]

[13] Xie Zhaomin, Chen Yongming, Guo Jun. (2026). 基于 CNN+LSTM 混合神经模型的脑电情绪识别 [EEG Emotion Recognition Based on a CNN-LSTM Hybrid Neural Model]. *Journal of Chengdu University of Information Technology*, 147-153. [in Chinese]

[14] Li Yan, Dai Jiahao, Dai Qingyu. (2025). 基于 YOLO-Strawberry 的草莓病害检测模型 [Strawberry Disease Detection Model Based on YOLO-Strawberry (2026)]. *Jiangsu Agricultural Science*, 272-27. [in Chinese]

[15] Sun Jian. (2025). 基于 YOLOv8 的草莓多类病害图像识别与检测方法研究 [Research on Strawberry Multi-Disease Image Recognition and Detection Method Based on YOLOv8]. *Heilongjiang Science*, 115-117, 121. [in Chinese]