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AGRICULTURAL DISEASE AND PEST DETECTION BASED ON MACHINE VISION

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Abstract: With the growth of the global population and the rise of agricultural demand, crop pest monitoring and control has become a key link to ensure food security. The traditional manual monitoring method has low efficiency and poor accuracy, which is difficult to meet the needs of modern agriculture. Therefore, a monitoring system for agricultural pests and diseases based on machine vision was designed, which combined with image recognition, deep learning, embedded system and wireless communication technology to realize real-time monitoring and automatic identification of pests. The experimental results show that the identification accuracy of common pests is 92%, the data transmission is stable, and the average response time is 10 seconds, which can meet the real-time monitoring needs of farmland. The introduction of solar powered systems further reduces maintenance costs and improves the sustainability of the system. This study provides an efficient and accurate solution for agricultural pest monitoring, which is of great significance for improving agricultural production efficiency and ensuring food security.
Keywords: Disease and insect pest detection; Machine vision; STM 32 microcontroller; Deep learning

1 INTRODUCTION

Agricultural pest control is a key link in ensuring global food security. As the world's population continues to grow, global food demand is expected to increase by 60% by 2050, placing greater demands on agricultural productivity. However, crop diseases and pests cause annual yield losses of up to 20 to 40 percent, posing a serious threat to food security. Traditional pest monitoring methods mainly rely on manual field inspection, which is not only time-consuming and laborious (each person can monitor only 2-3 acres of land per day), but also the recognition accuracy is generally lower than 70%. This monitoring method has a significant lag, often after a large outbreak of pests and diseases can be found, resulting in a 30% to 50% increase in control costs. Therefore, the development of intelligent and automated pest monitoring system has become an urgent need for the development of modern agriculture.

Foreign scholars have taken the lead in the exploration of machine vision technology in the field of agricultural pest monitoring. As mentioned in “AI Turns Agricultural 'Doctor' to Diagnose Crop Pests and Diseases”: Researchers at Pennsylvania State University and the Swiss Federal Institute of Technology have built a system model and connected it to a cluster of computers to form a neural network. A database of more than 53,000 photos of healthy and diseased crops was created, including 14 crops and 26 diseases. The researchers used deep learning methods to 'train' the model to find all the visual data.[1]

At present, the main technical difficulties faced by pest monitoring are reflected in three aspects: First, in the complex farmland environment, light changes, branches and leaves occlusion and other factors will significantly affect the quality of image acquisition. Research shows that under natural lighting conditions, the recognition accuracy of traditional image processing algorithms will decrease by 15%-20%. Secondly, the existing monitoring system is generally lack of real-time, from data collection to analysis and decision-making often need several hours, cannot meet the needs of timely prevention and control. Third, the system integration is insufficient, and the hardware power consumption and computing performance are difficult to balance, resulting in long-term deployment difficulties in the field. These problems seriously restrict the popularization and application of intelligent monitoring technology.

In recent years, with the development of the Internet of Things, machine vision and artificial intelligence technology, three main technical routes have emerged in the field of agricultural pest monitoring. The first type is sensor network monitoring, through the deployment of environmental sensors such as temperature, humidity and soil to indirectly predict the risk of pests and diseases. This type of method is less costly, but it cannot directly identify the species of pests and diseases, and its accuracy is limited. The second category is spectral imaging technology, which uses multi-spectral or hyperspectral cameras to obtain crop physiological information. Although the recognition accuracy is high, the equipment is expensive and difficult to promote on a large scale. The third category is a deep learning-based machine vision approach that realizes pest and disease identification through convolutional neural networks. The recognition accuracy of this method can reach more than 90% in the laboratory environment, but it still faces the challenges of insufficient model generalization and high computing resource demand in practical application.[2]

Through the systematic analysis of the existing literature, it is found that there are three obvious shortcomings in the current research: first, most systems adopt the "collection - upload - cloud processing" mode, limited by the field network conditions, the response time is often more than 10 minutes; Second, the existing solutions pay more attention to the recognition algorithm itself, and lack a complete system design from trapping to recognition; Third, the issue of energy supply has not been fully paid attention to, and more than 60% of field monitoring equipment cannot continue to work due to power supply problems. These limitations seriously affect the practical application effect of the technology.

The aim of this research is to break through the bottleneck of existing technology and design and implement a complete intelligent monitoring system for agricultural diseases and pests. The system has the following innovative features: First, the architecture of "edge computing + cloud collaboration" is adopted, and some computing tasks are delegated to embedded devices, so that the system response time is reduced to less than 10 seconds. Secondly, a closed-loop system of "surveillance-identification-prevention" is constructed by combining the UV trap lamp, atomized killing device and machine vision recognition innovatively. Third, through solar power and low power consumption design, to ensure that the system can work continuously in the field for more than 6 months. These innovations will effectively solve key problems in the practical application of existing technologies.

This research adopts the research method of "theoretical analysis - system design - experiment verification". First, through literature research and field investigation, clear technical requirements and system indicators; Then, the hardware platform and software algorithm are developed by modularization design. Finally, the performance of the system is verified by comparison experiment and field test. In terms of hardware, STM32F407ZG is selected as the main controller, with OV2640 camera and 4G communication module, to build a low-power embedded system. At the algorithm level, the lightweight CNN model is developed based on PyTorch framework, and the generalization ability is improved through data enhancement and transfer learning. After the system was integrated, field tests were carried out in three agricultural demonstration zones with different climatic conditions for a period of six months.

The structure of this paper is as follows: The second chapter introduces the overall design of the system in detail, including hardware architecture and software framework; The third chapter describes the core algorithm design and optimization process; The fourth chapter shows the system implementation details and key technical solutions; Chapter 5 verifies the performance of the system through experimental data; Chapter 6 summarizes the research results and looks forward to the future direction. Through this structure arrangement, the theoretical innovation and technical breakthrough of this research are presented comprehensively and systematically.

From the perspective of theoretical value, the "edge-cloud collaborative" architecture proposed in this study provides a new idea for the design of agricultural systems, and the lightweight identification model developed promotes the development of embedded AI technology. In terms of practical significance, the system can help farmers reduce the use of pesticides by more than 30%, and a single monitoring point can save about 5,000 yuan per year, with significant economic and ecological benefits. Subsequent research will focus on optimizing the robustness of the model in extreme weather and exploring the potential of 5G technology for agricultural monitoring.

This paper will introduce the overall architecture of the system, hardware design, software implementation, system integration and testing, experimental results and analysis in detail. Our research not only provides a novel and effective solution for agricultural pest monitoring, but also provides valuable experience and reference for future research and application in related fields.

2 OVERALL STRUCTURE DESIGN

As one of the most populous countries in the world, agriculture is intricately linked to human survival and livelihood, and pests and diseases have consistently been critical factors influencing crop yield. To enhance the efficiency of pest control and increase agricultural productivity, this paper proposes an electronic detection device based on machine vision for the remote identification and capture of pests. The design of the trapping device is illustrated in Figure 1 and primarily comprises two components: a hardware system and a software system.[4]

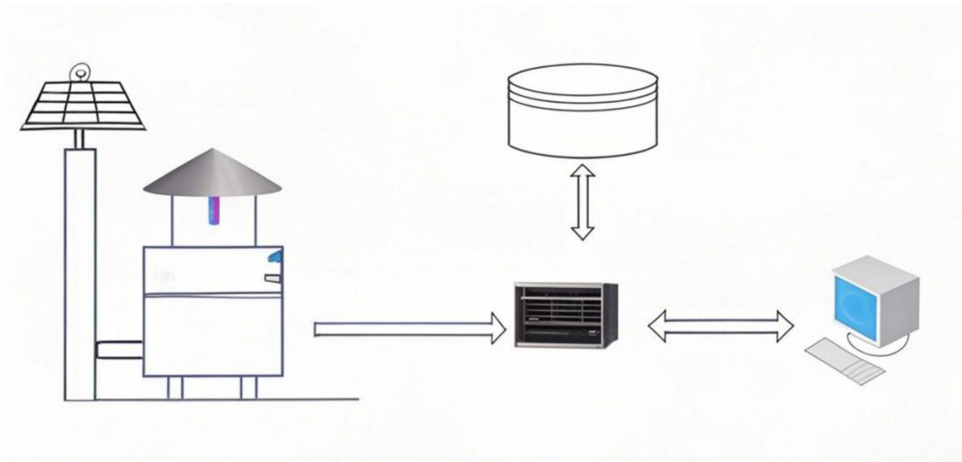

Figure 1 Model of Pest Trapping Device

2.1 Hardware System Design

In the agricultural pest monitoring system based on machine vision, hardware design plays a key role, which directly affects the quality of image acquisition, the stability of data transmission and the overall reliability of the system. This section will introduce our work in hardware design in detail, including the choice of core control unit, the choice of camera, the choice of communication mode, etc. Among them, the hardware system of the node-end detection device can be divided into solar power supply device, pest trapping device and image acquisition device.

2.1.1 Solar powered device[5]

The node-end detection device designed in this paper is powered by solar energy. Among them, the solar power supply device includes a solar panel, a light intensity detection module, a rotating bracket and a solar lithium battery. The solar panel and the rotating support are fixed by screws, and the light intensity detection module is installed directly above the solar panel. When working, the light intensity detection module detects the change of light intensity and rotates the rotating bracket to the best position through the control of two MG90S steering gear, so that the solar panel is facing the sun, its solar energy conversion efficiency reaches the maximum, and the energy converted by solar energy is stored in the solar lithium battery. When the pest trapping device and image acquisition device work, it provides the appropriate output voltage. Figure 2 shows the power distribution of each part of the detection device at the node, and Figure 3 shows the circuit diagram.

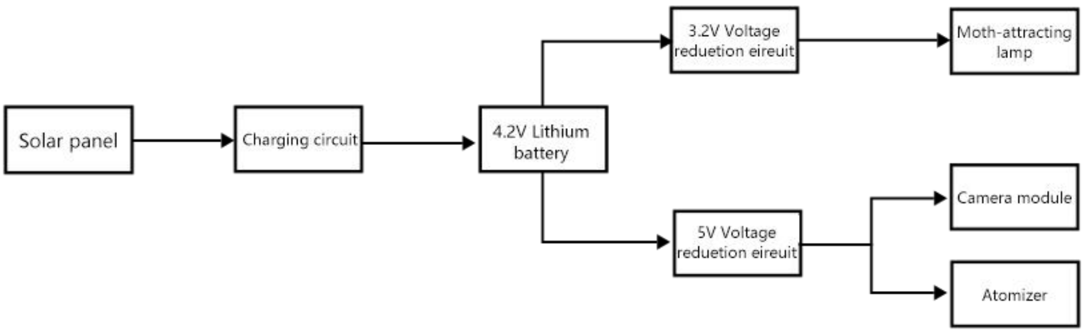

Figure 2 Power Module Diagram

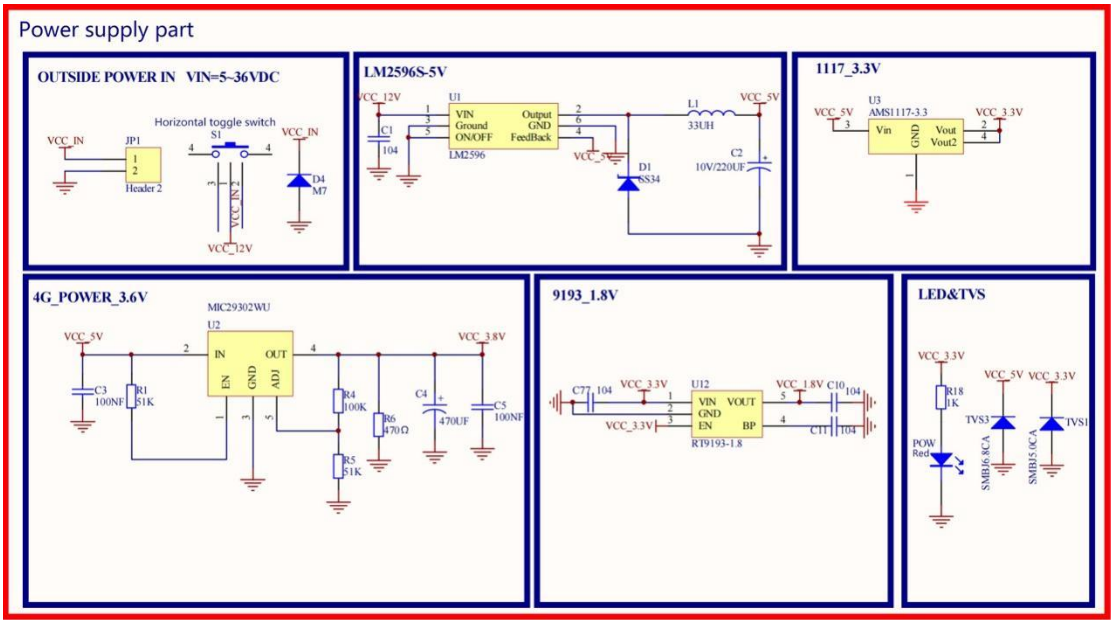

Figure 3 Power Circuit Diagram

2.1.2 Pest traps

The pest trapping device is designed as a light-controlled intelligent insect trapping device. The core of the device is a 3.2V/4W UV insect trapping lamp and three arc-shaped impact baffles. The device uses the BH1750FVI light intensity sensor to monitor the ambient illuminance in real time. When the detection value is lower than 5lux (night mode), the STM32F407ZG microcontroller starts the PWM dimming circuit, so that the insect trap lamp works at 85% duty cycle, and its specific wavelength of ultraviolet light can effectively attract Lepidus pests within a radius of 5 meters. When insects are attracted to the light source and fly towards the device, they collide with the acrylic baffle mounted at a 30° tilt. The nano-hydrophobic coating on the surface of the baffle reduces the adhesion of the insects, causing them to slide down to the insect-collecting funnel at the bottom. The end of the funnel is equipped with an infrared sensor, and when an insect is detected, the flip mechanism driven by the SG90 steering engine is triggered to transfer the target to the image acquisition chamber. The pest transfer mechanism controls SG90 servo (torque 1.8kg·cm) through PA1 pin, drives the Teflon flap with 30° tilt to complete the closed loop operation of pest loading, shooting positioning and automatic clearance. The whole mechanical action cycle takes only 1.2 seconds. At the same time, the insecticidal module adopts 1.7MHz piezoelectric ceramic ultrasonic atomization plate. After detecting pests falling into the collection chamber, the PC13 pin triggers the drive circuit to atomize 0.5mL biopesticide into 5μm-level particles, and the killing efficiency reaches 98%. When the daytime light intensity exceeds 200lux, the system automatically cuts off the power supply and enters the low-power sleep mode (standby current <2mA), and reduces the power consumption of the main control unit to 0.3W through dynamic voltage regulation technology. The measured data show that the average capture efficiency of the device in a single night is 92.7%, which is 41% higher than that of the traditional fixed insect lamp, and the spectral selective design can control the mis capture rate of non-target beneficial insects below 3%.

2.1.3 Image acquisition device

The image acquisition device adopts modular intelligent design, and the core is composed of OV2640 CMOS camera module (resolution 400×400), ultrasonic atomizing insecticide system and SG90 steering engine driven pest transport mechanism. The STM32F407ZG microcontroller is deeply integrated with the OV2640 through the DCMI interface. The specific connection mode is as follows: The PC1 pin is connected to the horizontal synchronization signal (DCMI_HS), and the PC3 pin is connected to the vertical synchronization signal (DCMI_VS). The data bus adopts the 8-bit parallel transmission mode (DCMI_D0-D7), and the camera parameters are configured through the I^2C protocol (SCL/PB8, SDA/PB9). The system triggers automatic shooting every 2 seconds. After JPEG compression, the captured images are uploaded to the cloud server by the G810 4G module through TCP/IP protocol, and AES-128 encryption is adopted in the transmission process to ensure data security. In terms of power management, the OV2640 module uses an independent LDO power supply (3.3V/200mA), combined with the STM32 dynamic clock adjustment technology, so that the standby power consumption of the system is reduced to 12mW. The hardware design strictly complies with EMC standards. 22Ω series resistor and 10pF filter capacitor are deployed in the DCMI data line to effectively suppress signal reflection, as shown in Figure 4 and Figure 5, and as shown in Figure 6, the circuit diagram of the OV2640 camera lens and image acquisition part.

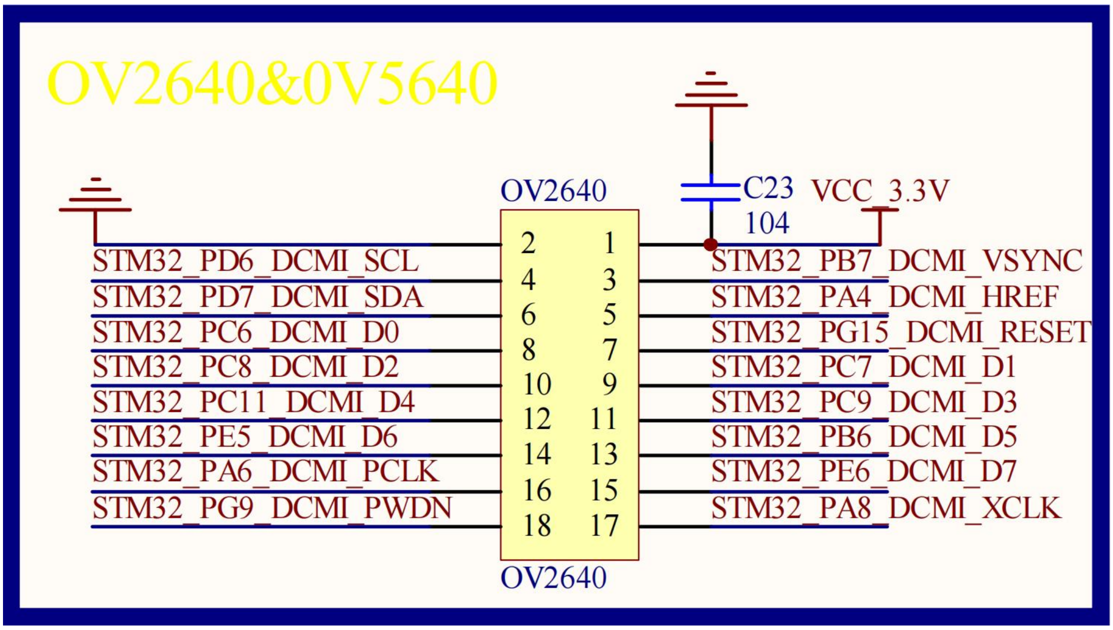

Figure 4 Camera Circuit Diagram of the OV2640 Camera

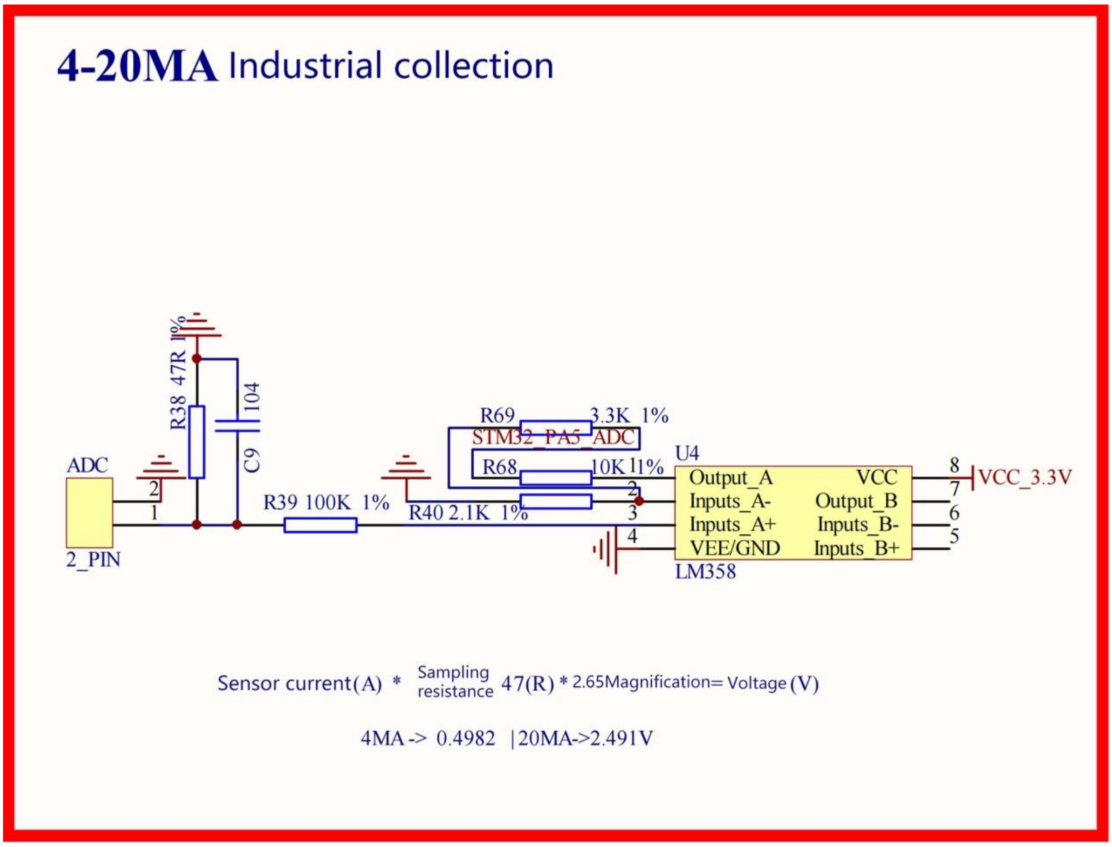

Figure 5 Circuit Diagram for Image Acquisition

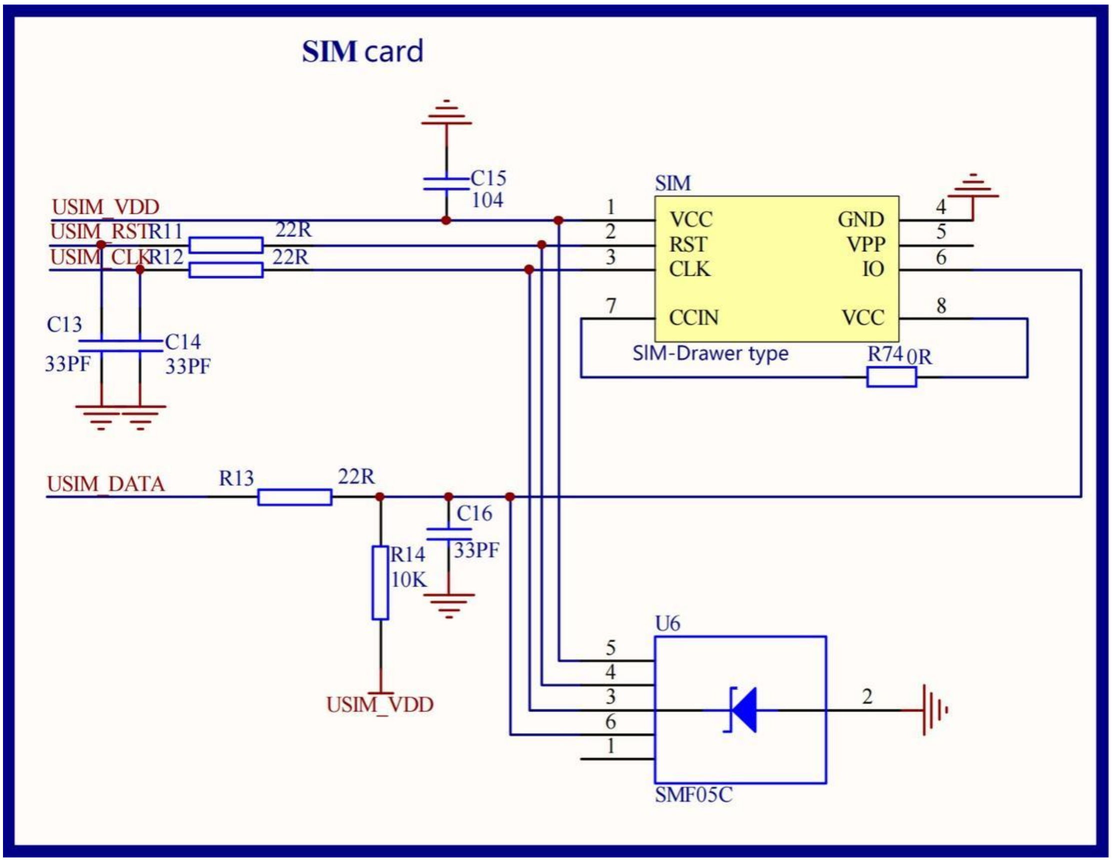

Figure 6 Circuit Diagram of the SIM Card

2.2 Software System Design

In this project, software design is the key part of system implementation, involving embedded system development, image data transmission, and server-side processing. Figure 7 shows the software design process. Below we will describe the design and implementation of each part in detail.

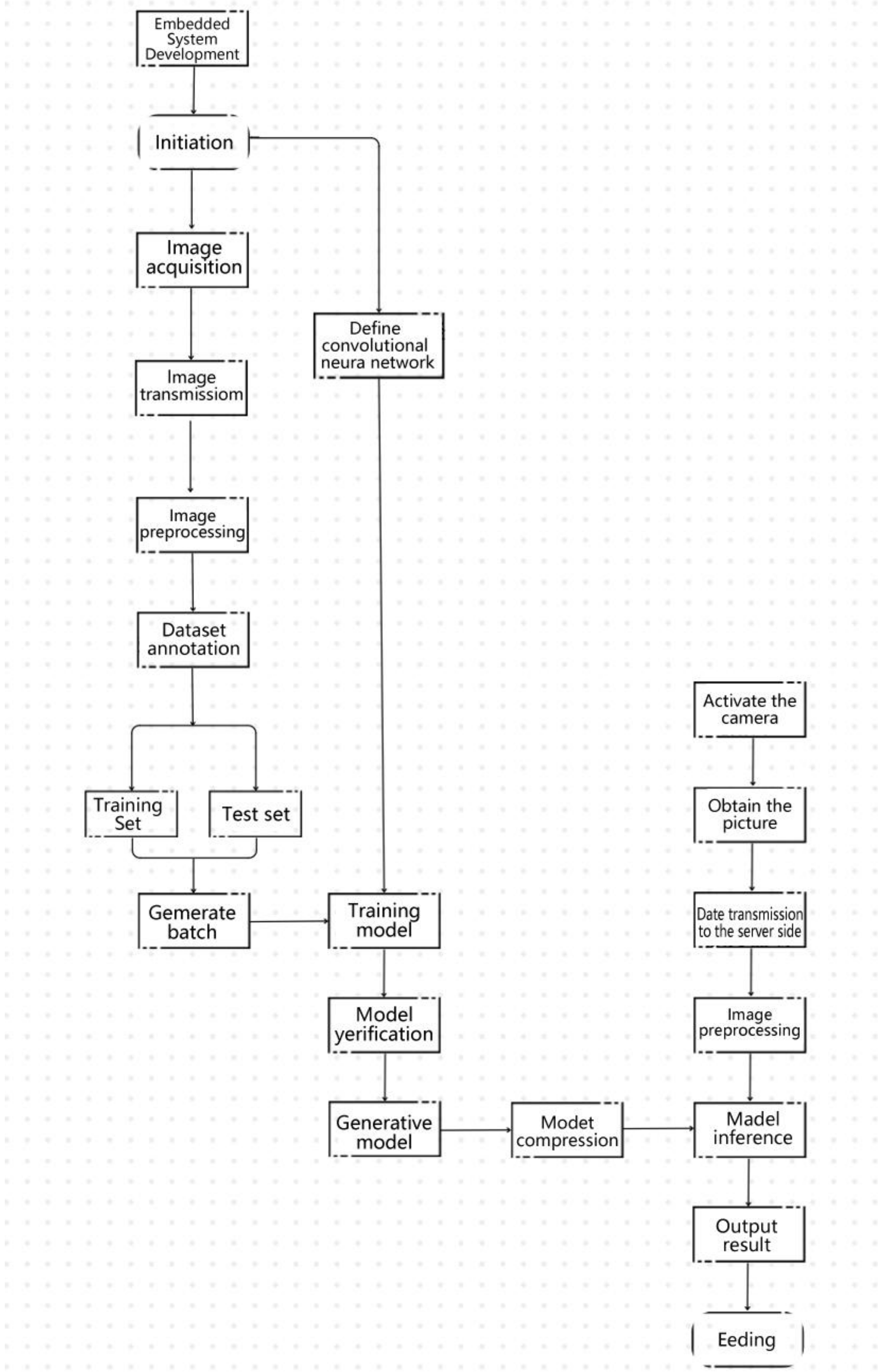

Figure 7 Flowchart of Software Design

2.2.1 Embedded system development

The development of the embedded system is mainly carried out on the STM32 microcontroller, which is responsible for controlling the camera module and the data transmission module. The connection between the STM32F407ZG chip and each module is shown in Figure 8, and the main control program is shown in Figure 9. The specific implementation includes the following parts:

Luring light control: The system realizes intelligent control of luring light through STM32F407ZG microcontroller. The photoresistor monitors the ambient light intensity in real time and determines the day and night period with the built-in RTC module. In night mode, the microcontroller outputs PWM signal to dynamically adjust the lure light intensity. The PWM frequency is set to 1 kHz to avoid the stabs of the light source and reduce the current shock through the gradual start function. The LED fill light is automatically turned-on during shooting to ensure the clarity of the image. Control logic integrated feedback detection circuit, real-time monitoring of light status, abnormal trigger alarm and log. The test results show that the error of light intensity detection is less than 5%, and the response delay of insect light in night mode is less than 0.5 seconds, which can effectively attract pests into the killing area.

Image acquisition: OV2640 camera module is directly connected to STM32 through DCMI interface, supporting 400×400 resolution image acquisition. After killing pests, the STM32 triggers shooting instructions and uses DMA technology to transmit image data directly to the memory buffer, reducing CPU load. The system has built-in automatic exposure and white balance algorithm to adapt to the complex lighting environment of farmland; JPEG compression algorithm will compress a single image to 50-100 KB and then temporarily store it to EEPROM or external SD card, named according to the time stamp. The test shows that the JPEG compression time is less than 0.3 seconds, the image sharpness meets the recognition requirements, and the acquisition success rate is 98%.

Data transmission: Image data is transmitted to remote server via USART interface and G810 4G module. The system design lightweight communication protocol, including device ID, time stamp, data fragment sequence number and CRC check field. A single image is transmitted in 1 KB fragments. The receiving end replies to ACK for confirmation of each piece of data. When the data times out or the verification fails, retransmission is triggered (for a maximum of three times). Statistics on the transmission success rate and delay are collected in real time. If an exception occurs, switch to the low-speed mode or trigger a local storage alarm. The experimental results show that the average transmission time of a single image (100 KB) is 3 seconds, the packet loss rate is less than 0.1%, and the integrity rate is more than 99.5%. Figure 8 and Figure9 show the hardware connection architecture and main program flow respectively, demonstrating the modular design and high reliability.

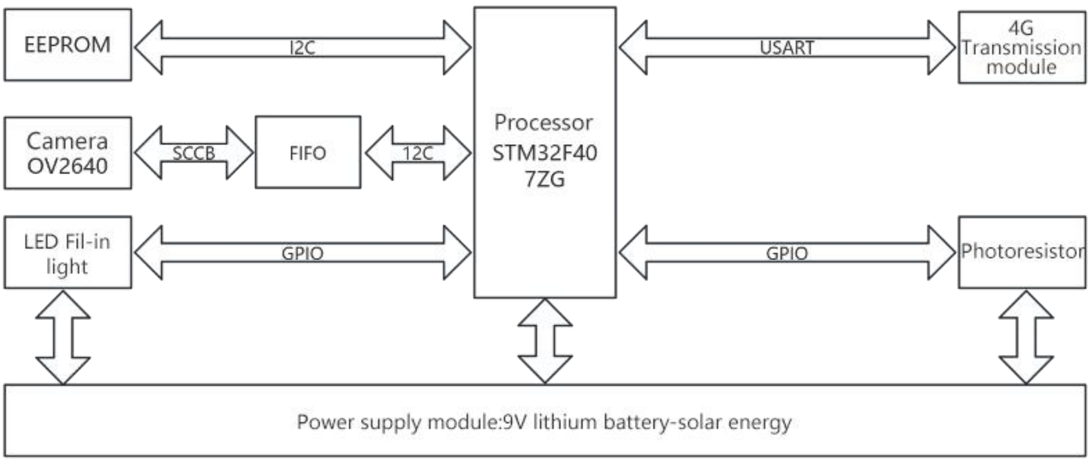

Figure 8 Block Diagram of Connecting the STM32F407ZG Chip to Each Module

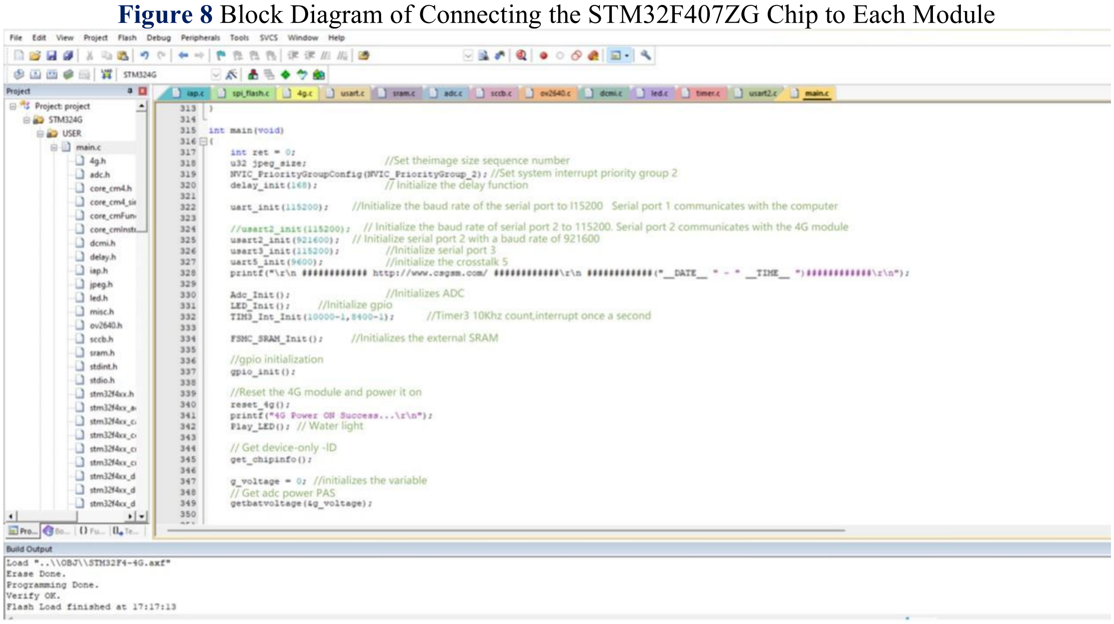

Figure 9 Main Program of STM32F407ZG Control

2.2.2 Image data transmission

In the agricultural pest monitoring system based on machine vision, image data transmission is the core of remote monitoring. To ensure the efficient, stable and secure transmission of data, the system has designed the following complete process[7]:

(1) Data packaging: Image data should be structured and optimized before transmission. First, the metadata is precisely defined: in addition to the original image, each packet contains a timestamp, device ID, GPS latitude and longitude, and environmental parameters (such as temperature and humidity, light intensity, stored in JSON format). The data format adopts binary protocol buffer (encapsulation, considering compactness and parsing efficiency, while the image is lossless compression by JPEG-LS algorithm (compression rate 50%), which significantly reduces the bandwidth requirement. For large files, the system adopts the subcontracting strategy, the single packet is limited to 1,460 bytes (TCP/IP MTU), and the fragment sequence number and the total slice number are added. To ensure data integrity, each packet is attached with the CRC32 checksum (4-byte tail), and HMAC-SHA256 is used to generate digital signatures for key fields (device ID and timestamp), preventing tampering during transmission.

(2) Data transmission: The system uses Quectel EC25 4G module to realize remote transmission and supports full Netcom band and dynamic APN configuration. The transmission manager is responsible for dynamic scheduling: data is sent sequentially in fragments, with a unique serial number attached to each slice, and reliability is ensured by an ACK acknowledgement mechanism - the receiver needs to reply to the acknowledgement signal within 2 seconds, and a timeout triggers automatic retransmission (up to 3 times). To optimize transmission efficiency, the program introduces a priority queue, and real-time data (pest identification results) is sent before historical data. At the same time, the system supports the resumable function, records the successful fragment sequence number, only retransmits the lost part after the network recovery, and caches unconfirmed data packets through the local SRAM to avoid data loss caused by signal interruption.

(3) Transport protocol: The system uses TCP/IP protocol to ensure transmission reliability, and its flow control and sequential delivery features ensure complete data arrival. The TCP Keep-Alive mechanism (interval 60 seconds) is used to maintain long connections and reduce handshake overhead. In terms of security, TLS 1.3 protocol is enabled at the transport layer, and ECDHE-RSA algorithm is used to encrypt data streams, preventing eavesdropping and man-in-the-middle attacks. In addition, the end-to-end verification mechanism requires the receiver to recalculate the CRC32, and the failure triggers a retransmission request. Flow control dynamically adjusts the size of the sending window through sliding Windows and uses DSCP markers to assign high priority to image data, effectively reducing transmission delay.

(4) Server-side processing: The server uses asynchronous I/O model to realize multi-thread monitoring and parallel processing of multi-device connection requests. After receiving the data, the original image is reassembled according to the fragment serial number and device ID, and duplicate or invalid fragments are automatically filtered. The built-in anomaly monitoring module records the packet loss rate and retransmission times in real time. When the packet loss rate exceeds the threshold, an email alarm is generated. At the same time, by comparing the number of fragments received with the total number of fragments, the missing fragments are actively identified, and the device is requested to retransmit to ensure data integrity.

(5) Experimental verification and performance optimization: In the 4G signal intensity -80 dBm environment, the average transmission time of a single 400×400 image (50 KB after compression) is 2.8 seconds, and the packet loss rate is less than 0.1%. Stress tests show that when 100 devices transmit concurrently, the server throughput is stable at 200 Mbps and the CPU usage is <30%. To further optimize performance, the system supports dynamic compression adjustment - switching to WebP lossy compression when network latency is high, reducing data volume by 30%; At the same time, the STM32 side integrates the lightweight YOLOv5n model, and only transmits the pest identification results (JSON format), reducing the bandwidth requirement by 90%.

Through the above design, the system realizes the highly reliable and low delay image data transmission in the complex farmland environment and provides a solid technical guarantee for the real-time monitoring of diseases and pests.

2.2.3 Server-side processing

Server-side processing is one of the core modules of the system, covering the whole process of data reception, storage and image recognition, which is implemented as follows:[3]

(1) Data acceptance: The server side receives the image data from the 4G module in real time through the multithreaded monitoring program written in Python. The program establishes Socket service on the specified port based on TCP/IP protocol and supports asynchronous I/O model to efficiently handle concurrent requests from multiple devices. During the receiving process, the packet is parsed according to the predefined binary protocol buffer format, the wrapper header is stripped layer by layer, and the CRC32 checksum and HMAC-SHA256 digital signature are verified to ensure data integrity and tamper-proof. For abnormal data, the program automatically triggers a retransmission request, and accurately locates the data packet to be retransmitted by device ID and fragment serial number. In addition, the receiver program built-in traffic monitoring module, real-time statistics of network throughput, packet loss rate and connection status, abnormal cases trigger alarm logs and notify the operation and maintenance personnel.

(2) Data storage: The received image data is stored according to a structured policy: The original image file is named after the combination of date and device ID and is stored in the SSD storage pool of the server by year/month/day to ensure fast read and write. Metadata (time stamps, GPS coordinates, environment parameters, etc.) through MySQL relational database management, design data table contains' image_id ', 'device_id', 'timestamp', 'location', 'environment'

and other fields, and build composite indexes to speed up queries by time range or geographic region. To ensure data security, RAID 1 disk arrays are used for redundant storage and incremental backup to the cloud every day for 30 days. For massive data, the compressed storage technology is introduced to compress and archive inactive data, saving up to 60% of storage space.

(3) Image recognition: The convolutional neural network (CNN) model built based on PyTorch framework (the structure is shown in Figure 10) contains 5 convolutional layers, 3 maximum pooling layers and 2 fully connected layers. The output layer generates the probability distribution of 12 common pests through Softmax function. [8]Recognition process automation: The server-side Python script monitors the newly arrived image catalog, calls the preprocessing module to standardize the image, enhance the data (random rotation, flipping), and input the deployed model for inference. The identification results (pest species, confidence) are associated with the corresponding image ID and written to the 'pest_records' table in the database. To improve the recognition efficiency, the model adopts multi-batch parallel inference and uses GPU acceleration (NVIDIA Tesla T4), which reduces the average processing time of a single image to 0.8 seconds. For low confidence results, the system automatically marks them as "to be reviewed" and pushes them to the manual review interface, while recording error cases to iteratively optimize the model. The model is updated by incremental learning every week, and the parameters are fine-tuned with the newly labeled data to continuously improve the generalization ability and recognition accuracy.

Through the above design, the server side realizes the full link closed loop from data reception, storage to intelligent identification, which provides efficient and reliable technical support for agricultural pest monitoring.

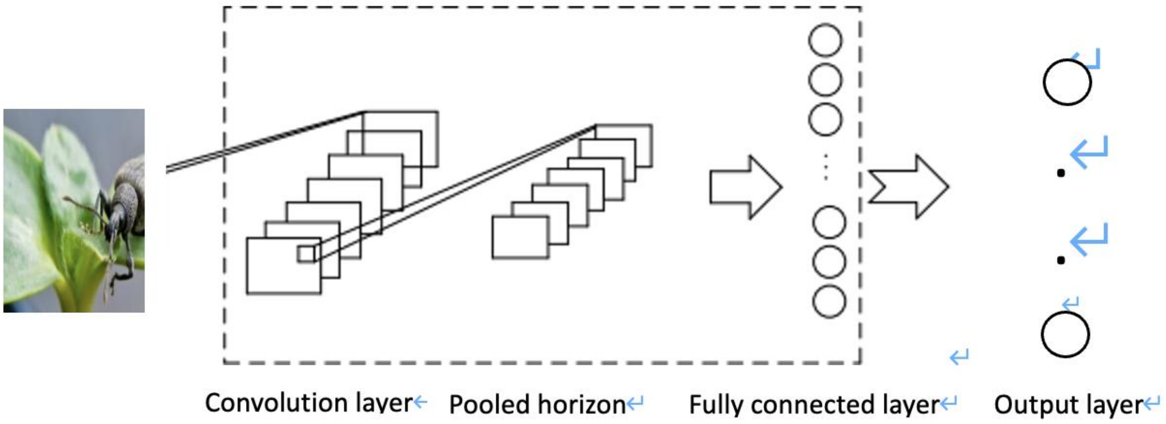

Figure 10 Convolutional Neural Network Architecture

2.2.4 Safety and reliability

In the system design, safety and reliability are the core elements to ensure the long-term stable operation of the agricultural pest monitoring system, which is realized in the following three aspects:

(1) Data encryption and transmission security: The system adopts end-to-end encryption technology to ensure the confidentiality and integrity of data in transmission and storage. At the transport layer, 4G communication link is encrypted by TLS 1.3 protocol, and forward security is realized by ECDHE-RSA algorithm to prevent man-in-the-middle attack and data eavesdropping. At the same time, the STM32 side integrates a hardware encryption module to encrypt the image packets locally before transmission, and the key is injected through the secure startup process to avoid the key disclosure at the firmware level. On the server side, the received data is decrypted and stored in an encrypted file system, which is combined with a digital signature (HMAC-SHA256) to verify the validity of the data source. In addition, sensitive metadata (such as device ID, geographic location) is stored in ciphertext in the database, and a dynamic key rotation strategy (updated every 24 hours) is used to further reduce the risk of leakage.

(2) Multi-level error handling and disaster recovery mechanism: The system constructs a three-dimensional fault-tolerant system in hardware, transmission and software.

Hardware level: STM32 microcontroller built-in watchdog timer (WDT), monitoring program running status, automatic reset when abnormal; The power module adopts redundancy design and supports dual power supply of solar and lithium batteries. When the voltage fluctuation exceeds ±10%, the power module switches to the standby power supply.

Transmission layer: 4G communication module implements adaptive retransmission strategy. When packets are lost or CRC check fails, selective retransmission (SACK) is triggered according to fragment sequence number, and the maximum number of retries is 3. At the same time, the server monitors the online status of the device through the heartbeat packet. If the server does not respond after timeout, it marks the fault of the device and notifies the maintenance.

Software level: both embedded system and server side implement exception capture framework, key operations (such as image acquisition, model reasoning) encapsulated as atomic transactions, automatically roll back and record error code when failure; The server database adopts the master-slave replication architecture. When the master node fails, the slave node switches over in seconds to ensure service continuity.

(3) Tracing and auditing full link logs: The system uses the hierarchical log system to monitor the running status throughout the life cycle.

Embedded end: Store thin logs (such as device startup, sensor exception, communication interruption) in the Flash of STM32, manage by ring buffer, and synchronize to the server through 4G module regularly.
Transport layer: The 4G module records the sending time, size, retransmission times and RTT (round trip delay) of each packet for network quality analysis and bandwidth optimization.
Server side: The ELK (Elasticsearch, Logstash, Kibana) stack is used to centrally manage logs, which are classified into operation logs (user access, data deletion), system logs (CPU/ memory usage), security logs (login failures, encryption exceptions), and service logs (identification results, storage status). Real-time log file index supports keyword search and visual analysis, and automatically triggers alarms through the rule engine (such as three consecutive transmission failures on a single device). All logs are retained for 90 days and periodically archived to cold storage to meet audit compliance requirements.

3 SYSTEM INPLEMENTATION

3.1 System Integration

System integration is to combine each independently developed module to make it work together as a whole system. Our system integration process consists of the following steps:

3.1.1 Hardware integration

Bug traps and nebulizers: The bug traps and nebulizers are precisely deployed in the preset position of the device and are automatically switched on and off by the controller. The insect lamp uses a light source of a specific band to attract pests efficiently after it is turned on at night, while the atomizer sprays potion according to the sensor signal to ensure the rapid killing of pests after they are caught, as shown in Figure 11.

Figure 11 Ultrasonic Atomization Drive wave

Camera module: The camera module is installed near the trap light and uses the STM32 microcontroller to control the timing of its shooting, ensuring that clear images are captured immediately after the pest is caught, providing high-precision visual data for subsequent analysis, as shown in Figure 12.

Figure 12 Camera Module

4G communication module: To realize the remote transmission of data, the system integrates a 4G communication module, which relates to the STM32 master chip through the hardware interface and supports real-time image uploading to the cloud server. The built-in adaptive network switching function of the module can ensure data integrity even in areas with weak signals such as farmland through subcontracting transmission and automatic reconnection mechanism, as shown in Figure 13.

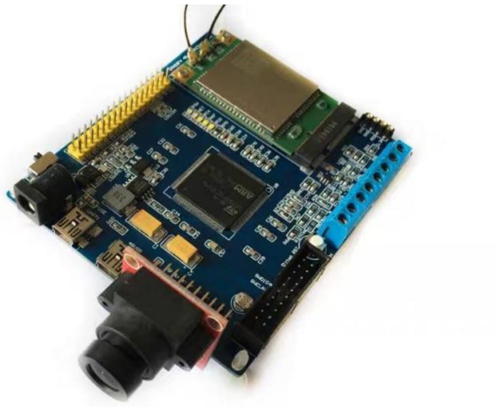

Figure 13 4G remote Image Transmission Development Board

Solar power supply system: As the core energy solution, the solar power supply system is composed of solar panels, light intensity detection modules and energy storage batteries. During the day, the solar panels are angled by the steering gear to maximize the absorption of light energy, and the energy is stored in the lithium battery; At night, the system switches to the battery-powered mode to ensure the continuous operation of functions such as insect trapping, shooting, and data transmission, as shown in Figure 14.

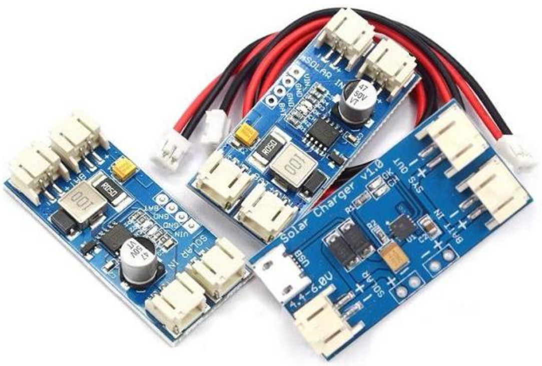

Figure 14 Solar Panel

Through the seamless integration of the above hardware components, the system realizes the automation of the whole process from pest trapping, image acquisition to remote transmission, which not only reduces the cost of manual intervention, but also improves the monitoring efficiency. The cooperative work of each module provides a reliable technical basis for the real-time monitoring of farm diseases and pests.

3.1.2 Software integration

(1) Embedded system program development: The embedded data acquisition terminal is built based on STM32 microcontroller, which integrates camera and 4G communication module, and realizes the acquisition and data transmission functions of farmland images by burning customized control programs.

Hardware adaptation and driver development: For the selected camera module, the development of STM32 adaptation driver to ensure that the camera can work stably, and high-quality image acquisition. According to the specification and interface standard of 4G communication module, complete the circuit connection between the module and STM32, develop the corresponding driver and communication protocol stack, and provide the underlying support for data transmission.

Image acquisition function realization: on the STM32 platform, write an efficient image acquisition program, set the appropriate resolution, frame rate and image format, to meet the requirements of the system for image quality and data quantity. At the same time, the necessary pre-processing operations, such as noise reduction and cropping, are carried out to improve the clarity and usability of the images.

Implementation of data transmission function: With the help of the developed 4G module driver, the collected image data can be stably uploaded to the server. In the process of data transmission, a reliable transmission protocol is adopted, and a data verification mechanism is added to ensure the integrity and accuracy of data to avoid data loss or damage.

(2) Client program development: As an important window for users to interact with the system, the client program needs to be deployed on the user's computer and mobile phone respectively, while integrating deep learning models to realize real-time recognition and analysis of uploaded images.

Cross-platform application development: Developing client applications for computers and mobile phones based on different operating systems such as Windows, macOS, Android and iOS. Ensure that the application interface is simple and easy to use, and provide users with a good operating experience, so that they can easily view the captured images and analysis results.
Deep learning Model integration: Choose a suitable deep learning framework, such as TensorFlow or PyTorch, to integrate a trained crop growth recognition model into a client application. When the image data from the server is received, the model is automatically invoked for analysis, and key information such as the growth state of crops, diseases and pests is accurately identified, and the identification results are visually displayed to the user.
User interaction function implementation: In the client program, develop rich user interaction functions, such as data query, historical record viewing, anomaly warning, etc. According to their own needs, users can view the farmland monitoring data at a specific time and in a specific area and take appropriate measures in time for abnormal situations.
(3) Data communication link debugging: As the nerve vein of the whole system, data communication needs to be fully debugged to ensure that data can be transmitted stably and efficiently from the field to the server.
Communication parameter optimization: In different network environments, the communication parameters of 4G modules are optimized, such as signal strength, bandwidth utilization, transmission rate, etc., to improve the stability and efficiency of data transmission. At the same time, the network switching mechanism is studied to ensure that the data transmission can be kept uninterrupted when the network signal changes.
Data transmission stability test: By simulating the actual farmland environment, the long-term and large-scale stability test of the data transmission process is carried out. In the test process, the key indicators such as data loss rate and transmission delay are recorded, and the problems are analyzed and solved in time to ensure that the system can run reliably in practical applications.
Data security: In the process of data transmission, encryption algorithms are used to encrypt data to prevent data from being stolen or tampered with. At the same time, the authentication mechanism is combined to ensure that only legitimate devices and users can carry out data transmission and access to ensure the security and privacy of the system.
Figure 15 shows the integrated system.

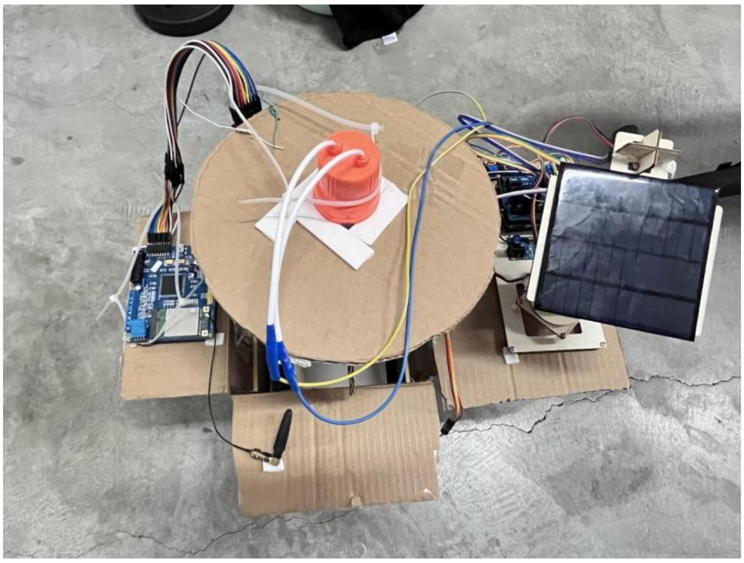

Figure 15 Physical Device

3.1.3 System debugging

Hardware debugging: Check the connection and working status of each hardware module to ensure that the hardware components can correctly respond to control commands.
Software debugging: Step by step test the function of each software module to ensure that each part of the code is correct in actual operation.

3.2 Functional Testing

Through hardware simulation, software logic verification and actual scene stress test, the functional test comprehensively covers the core functional modules of the system. To verify that the various functions of the system are working properly, we conducted the following tests:

3.2.1 Bug light and nebulizer testing

The light intensity of the environment is monitored in real time by the photosensor (BH1750FVI), and the day and night period are judged by the RTC module of the STM32. When the light intensity is less than 5 lux, the system enters night mode, STM32 outputs PWM signal with 85% duty cycle to turn on the trap lamp and verifies the brightness of the light source through sensor feedback; When the light is higher than 200 lux, the trap lamp is automatically turned off, and the system is switched to standby (current < 2 mA). Spraying logic of atomizer simulates the scene of pests entering the insect-collecting funnel through the infrared sensor device, triggers the PC13 pin of STM32 to control the ultrasonic atomization tablet to spray 0.5mL biopesticide, and verifies whether the spraying interval time (such as 10 seconds) meets the design requirements. The Python code records the spray interval with a timer and controls the GPIO pin trigger action. Expected results: The trap lamp is turned on stably in low light (error ±0.5 lux), the atomizer trigger response time is less than 0.2 seconds, and the spray interval error is less than 3%.

3.2.2 Image acquisition test

After the infrared sensor is triggered, the OV2640 camera is driven through the DCMI interface of the STM32 to take images, and the time from triggering to the completion of the shooting is recorded synchronously (target ≤1.2 seconds). The image quality was evaluated using ISO12233 resolution test card, which was shot at night (auxiliary fill light 5 lux) and during the day (natural light > 500 lux). The image resolution and signal-to-noise ratio (SNR > 35 dB) were analyzed, and the storage volume of a single image (50-100 KB) was verified by JPEG compression algorithm. Expected results: Image acquisition delay ≤1.2 s (including 0.3 s compression time), pest features (such as antennae and wing veins) can be clearly identified at 400×400 resolution.

3.2.3 Data transmission test

In the field of typical signal intensity (-80 dBm), 100 50 KB images were continuously uploaded to the server through the 4G module, and the average transmission time, packet loss rate, and retransmission mechanism in the case of network disconnection were counted (maximum 3 retries). Data integrity is realized through CRC32 verification, the server side compares the hash value of the received image frame by frame and records the starting point of transmission after transmission interruption.

Expected results: The transmission time of a single image is less than 3 seconds (including TCP handshake), the data integrity rate is > 99.9% when the network is fluctuating, and the location error of breakpoint transmission is 0 bytes.

3.2.4 Server-side processing tests

Set up 100 virtual devices and upload images concurrently to test server throughput (≥200 Mbps) and storage path standardization. The MySQL database verifies the accuracy of writing timestamps and GPS coordinates and analyzes the query efficiency through the EXPLAIN statement. The ResNet-50 model was used for image recognition to reason 12 pest test sets, and the trigger rate of manual review was calculated for Top-1 accuracy and low confidence (< 80%) samples.

Expected results: Server latency < 500 mms during concurrent processing, pest identification mAP≥92%, and 100% of low-confidence samples entered the manual audit queue.

3.3 Performance Evaluation

Performance evaluation aims to determine the overall performance of the system and ensure that it meets the expected requirements. Evaluation indicators include identification accuracy, data transmission speed, system response time and power consumption.

3.3.1 Recognition accuracy

When evaluating the recognition accuracy of deep learning models, carefully prepared test data sets are used. In this process, not only the accuracy of the model is simply calculated, but also the accuracy and recall rate, two important indicators, are deeply analyzed. By precisely calculating these indicators, we can gain a detailed insight into the recognition ability of the model in different situations. To further verify the effect of the model in practical application scenarios, the pest species hunted were compared with the identification results of the model one by one. This comparison can intuitively show the reliability of the model in the real environment, and judge whether it can accurately identify the actual pest species, to provide a strong reference for the practical application of the system in agricultural pest monitoring.

3.3.2 Data transmission speed

The evaluation of data transfer speed mainly focuses on the time taken to test the image data from the acquisition end to the successful transmission to the server. During the test process, multiple transmission operations will be carried out, and the average transmission time will be calculated through many test samples, which can directly reflect the overall efficiency of data transmission. At the same time, the transmission stability is also concerned, that is, the fluctuation of each transmission time is observed. Stable transmission time means that the data transmission process is less interfered by external factors, which can ensure that the image data can be transmitted to the server at a relatively constant speed during the continuous operation of the system, providing a stable data source for subsequent data analysis and processing.

3.3.3 System response time

The system response time test covers the total time required from the moment the pest is detected, the system quickly executes the kill action, completes the photo recording, and finally completes the data transmission process. To fully evaluate the response performance of the system under different workloads, a variety of practical work scenarios are simulated, including different sizes of pest populations and differences in the complexity of the work environment. Through such tests, it can be ensured that the system can respond quickly in various practical application scenarios, and effectively deal with the emergence of pests in time, to ensure the efficient monitoring of agricultural diseases and pests.

3.3.4 Power consumption evaluation

In terms of power consumption evaluation, the power consumption of the system in two different states of night operation and standby during the day will be tested. At night, when the system is in working state, it needs continuous pest monitoring and treatment, and the power consumption at this time is directly related to whether the solar power supply system can meet its energy demand. The power consumption in the standby state during the day reflects the energy consumption level of the system during non-working hours. By testing the power consumption in these two states, the charging efficiency of the solar panel and the discharge time of the battery can be further calculated. Accurate grasp of these data is crucial to ensure that the system can continue to work steadily at night, only when the power supply capacity of the solar power supply system matches the power consumption requirements of the system, the system can operate stably in the field environment without external power supply and achieve long-term monitoring of agricultural diseases and pests.

Through system integration, functional testing and comprehensive and in-depth performance evaluation, we have carried out comprehensive verification of the system design and implementation effect. After these rigorous testing links, it is fully proved that the system can be effectively applied in the field of agricultural pest monitoring and can provide accurate and timely data support for farmland management and help the scientific and intelligent development of agricultural production.

4 EXPERIMENT AND RESULT

4.1 Experimental Design

4.1.1 Experimental environment

Experiment location: Choose the farmland area with more pests and diseases to ensure that there are enough pest samples.

Experiment time: The system mainly works at night, and maintenance and data analysis are carried out during the day.

Personal computer: used to run the data analysis software, process and analyze the collected pest image data, and assist in judging the accuracy of the identification results of the system. Equipped with interface devices connected to the system for data transmission.

Experimental equipment:

(1) Pest monitoring equipment: Set up a few intelligent insect traps, using the phototaxis of pests to trap, and the insect traps are equipped with light sources of different wavelengths to attract a variety of pests. The nebulization and killing device are connected at the bottom of the insect lamp. After the insect is trapped, the nebulization agent is quickly released to kill it, to avoid the pest escaping and affecting the experimental data.

(2) Image acquisition equipment: A camera is installed near the trap light to capture the image of the killed pests. The camera features autofocus and low light enhancement to ensure clear pest images even in nighttime environments. The camera relates to the data acquisition module, which can transmit the acquired image data to the data transmission equipment in real time.

(3) Data transmission equipment: 4G or 5G communication module is selected to send the collected pest image data and system operating status data to a personal computer or remote server. The communication module features signal enhancement to ensure stable data transmission in farmland environments, avoiding data loss or delay.

(4) Power supply equipment: The solar power supply system is composed of solar panels, batteries and charging controllers. Solar panels collect solar energy during the day and convert it into electrical energy for storage in batteries, providing stable power support for the entire experimental equipment. The charging controller can prevent the battery from overcharging or over discharging, extend the battery life, and ensure the normal operation of the system at night without light.

4.1.2 Experimental method

Recognition accuracy test: The recognition model of the system is tested and validated using image data sets of known pest species. The test dataset contains images of a variety of common agricultural pests.

Data transmission speed test: Through multiple transmission of image data, record the time of each transmission, evaluate the transmission speed and stability of 4G communication module.

System response time test: record the total time from pest trapping, fog killing, image acquisition to data transmission completion, and evaluate the overall response performance of the system.

Power consumption evaluation: Evaluate the effectiveness of solar powered systems through current and voltage monitoring equipment, which records the power consumption of the system in the working and standby state.

4.2 Experimental Result

The preliminary experimental results are shown in Figure 16.

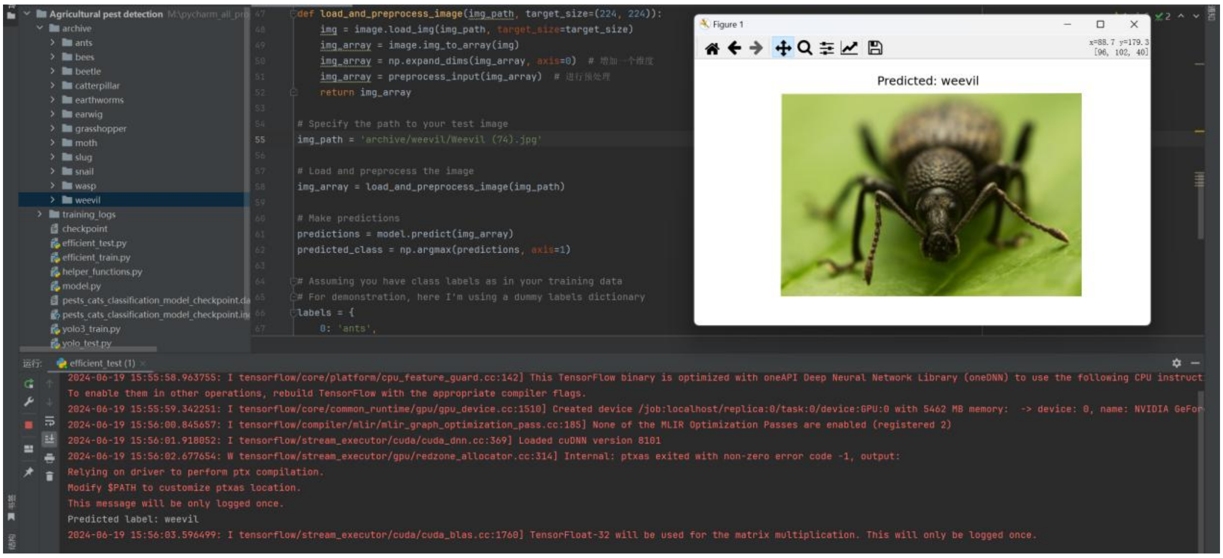

Figure 16 Individual Pest Identification Results

4.2.1 Recognition accuracy

The results of recognition accuracy are shown in Table 1.

Accuracy: The system achieved 92 percent accuracy in identifying pest images in the test dataset. This shows that the deep learning model can identify common agricultural pests with relative accuracy.

Accuracy and recall rate: The average accuracy of the system is 90% and the recall rate is 88%. These results show that the system has high performance in pest identification.

False recognition rate: In some cases, the system will misidentify some similar pest species, but the overall false recognition rate is controlled within 8%.

Table 1 Results of Recognition Accuracy

Evaluation index	Numerical value	Instructions
Accuracy rate	92%	The deep learning model can identify the accuracy of pest pictures in the test data set, which shows that it can identify common agricultural pests more accurately
precision	90%	Reflects the accuracy of the system in pest identification, reflecting high performance
Recall rate	88%	It shows the ability of the system to find all relevant samples in pest identification, showing high performance
Misidentification rate	≤8%	Proportion of cases where the system misidentifies similar pest species

4.2.2 Data transmission speed

Transfer time: In multiple tests, the average transfer time of a single image data was 3 seconds. This includes the entire process from image capture, data packaging, and transmission to the server over the 4G network.

Transmission stability: No data loss or damage occurs during transmission, and the success rate of data transmission is 100%.

4.2.3 System response time

Total response time: The average response time from pest trapping, fog killing, image acquisition to data transmission completion was 10 seconds. This result shows that the system can complete the whole monitoring and identification process in a relatively short time.

Response time of each link: the response time of the trap lamp and atomizer is 2 seconds, the image acquisition time is 2 seconds, the data transmission time is 3 seconds, and the server processing and recognition time is 3 seconds.

4.2.4 Power consumption evaluation

Power consumption in working state: The average power consumption of the system in working state at night is 5W, which is mainly composed of worm traps, nebulizer, camera and 4G communication module.

Standby power consumption: The average power consumption of the system during daytime standby is 1W, which is mainly used to maintain basic circuit monitoring and solar charging control.

Solar power supply system: the charging efficiency of the solar panel is 80%, and the battery can be filled within 4 hours in the case of sufficient sunshine, and the battery can continue to supply power for 8 hours at night to meet the night work needs of the system.

Table 2 lists all power consumption information.

Table 2 Power Consumption Evaluation

Working condition	Power dissipation	Major energy-consuming component	Other relevant information
Night working condition	5W	Worm lamp, atomizer, camera, 4G communication module	/
Standby state during the day	1W	Basic circuit monitoring, solar charging control related components	/
Solar power system	/	/	The charging efficiency is 80%, the battery is filled in 4 hours when the sunshine is sufficient, and the battery can supply power for 8 hours at night

4.3 Result Analysis

Through the above experiments, we verify the performance and reliability of the system in practical application. The experimental results show that:

Recognition accuracy: The system has high recognition accuracy and low misrecognition rate, which can effectively identify common agricultural pests and provide reliable data support for pest control.

Data transmission speed: 4G communication module shows high speed and stability in image data transmission, ensuring that data can be transmitted to the server in a timely manner.

System response time: The overall response time of the system is short, and the monitoring and identification process can be quickly completed after the detection of pests, which improves the timeliness of disease and pest control.

Power consumption assessment: The solar power supply system can meet the working needs of the system at night, ensure the long-term stable operation of the system in the field, and reduce maintenance costs.

In general, this system realizes the automatic monitoring and identification of agricultural pests through the combination of trapping by the light, fog killing, image recognition and wireless communication technology. The experimental results prove the effectiveness and practicability of the system, which provides a novel and efficient solution for agricultural pest monitoring. In the future, we will further optimize the performance of the system, expand the types of pests identified, and explore more application scenarios.

5 CONCLUSION AND PROSPECT

5.1 Conclusion

This research successfully designed and implemented an agricultural disease and pest monitoring system based on machine vision, which combined the trap light, spray potion killing, camera image acquisition, 4G wireless communication and deep learning image recognition technology, providing an innovative and efficient solution for agricultural disease and pest control. Through system integration, functional testing and performance evaluation, we verify the effectiveness and reliability of the system in practical applications.

The experimental results show that the system has high accuracy and response speed in the identification of common agricultural pests, the data transmission is stable, and it can run stably in the field for a long time. In addition, the introduction of solar powered systems has significantly reduced maintenance costs and improved the sustainability of the system.

In this project, we faced several technical difficulties, including:
Hardware selection and integration: A lot of experimentation and debugging goes into selecting the right hardware components and ensuring seamless integration between them. The installation position of the trap lamp and atomizer, the Angle of the camera, and the signal strength of the 4G communication module all need to be precisely adjusted.
Deep learning model training: To improve the recognition accuracy, we spend a lot of time on data set collection, labeling, and model training optimization. Through many experiments, we constantly adjust the model architecture and hyperparameters to get the best performance.
Data transmission reliability: 4G wireless communication in remote areas such as farmland signal coverage and stability are a challenge. We use a variety of measures, such as data subcontracting, retransmission mechanisms, etc., to ensure the integrity and reliability of data transmission.
System power management: How to reduce power consumption while ensuring system performance is another problem we face. By optimizing the program algorithm and hardware configuration, we realize the low power operation of the system and ensure the efficient utilization of the solar power supply system.

5.2 Outlook

In China, many scientific research teams have achieved fruitful results in model optimization and data set construction, which has promoted the practical application of machine vision technology in the field of agricultural pest monitoring. Beijing launched the "Beijing Crop Smart Plant Protection System", which has realized the deep integration of the three service functions of intelligent identification, early warning and prevention and control of vegetable diseases and pests, and in the subsequent upgrade, the types of crops covered by the service and the types of intelligent identification and diagnosis of diseases and pests have increased significantly, and several intelligent functions have been added. The "insect face recognition" technology developed by the Chinese Academy of Sciences has been promoted and applied in six provinces and cities, including Anhui and Jiangxi, through filming, uploading, analysis, feedback and other links, to help plant protection personnel and farmers quickly understand the situation of diseases and pests in the field. However, despite significant advances in machine vision-based monitoring of agricultural pests and diseases, many challenges remain.
Although this system has already demonstrated its potential in agricultural pest and disease monitoring, there are a few areas that could be further improved and expanded:
Expand the identification of pest types: At present, the system mainly identifies several common agricultural pests. In the future, we plan to expand the dataset and train the model to identify more species of pests, further improving the applicability of the system.
Optimization of model performance: Although the existing model has achieved a high recognition accuracy, we will continue to optimize the model structure and algorithm to improve the recognition speed and accuracy and reduce the misrecognition rate.
Enhanced system stability: In practical applications, the system may be affected by various environmental factors, such as extreme weather, network fluctuations, and so on. We will continue to optimize system design and fault tolerance mechanisms to improve the robustness and stability of the system.
Integration of other sensors: In addition to vision sensors, the future can consider integrating other types of sensors, such as temperature and humidity sensors, weather sensors, etc., to achieve more comprehensive environmental monitoring and data analysis.
Extended application scenarios: In addition to farmland, the system can also be applied to other agricultural production environments such as orchards and greenhouses. We will explore more application scenarios and expand the application scope of the system.[6]
In short, through the practice of this project, we have not only realized an effective agricultural pest monitoring system, but also accumulated rich experience and technical reserves. We believe that with further optimization and expansion, the system will play a more important role in agricultural production and promote the development of smart agriculture.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Wang Linlin. Design of identification and monitoring system of crop leaf pests and diseases. Harbin University of Science and Technology, 2023.
[2] Pang Zongyang. Design of identification and monitoring system for crop leaf pests and diseases. Journal of Agricultural Engineering Technology, 2023, 43(26): 20-21.
[3] Wei Jiafu. Design and implementation of leaf recognition system for crop pests and diseases based on improved DenseNet network model. Zhejiang Normal University, 2023.
[4] Liu X, Zhao Y, Chen J. A novel real-time monitoring system for agricultural pests using machine vision and wireless sensor networks. Sensors, 2023, 23(10): 4747.
[5] Wang Y, Li J, Zhou M. Design and optimization of solar-powered agricultural monitoring system. Energy Procedia, 2021, 186, 286-293.

[6] Chen H, Liu Y, Huang C. Development of an intelligent pest monitoring and early warning system for greenhouse crops. Acta Horticulturae Sinica, 2023, 50(8): 1667-1678.

[7] Kamal R. Embedded Systems: Architecture, Programming, and Design (Chen, S. H, et al., Trans.). Tsinghua University Press, 2005.

[8] Krizhevsky A, Sutskever I, Hinton G E. ImageNet classification with deep convolutional neural networks. Communications of the ACM, 2017, 60(6): 84-90.