Research on Intelligent Diagnosis of Rice Diseases and Pests Based on IoT and Keras Model

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Abstract：As a core crop safeguarding global food security, rice production has long been threatened by diseases and pests. The traditional manual diagnosis model, limited by low efficiency and strong subjectivity, can hardly meet the needs of large-scale agricultural production. With the iteration of Internet of Things (IoT) sensing technology and deep learning algorithms, building an integrated intelligent system of "perception-analysis-diagnosis" has become a key path to break through the bottleneck. Focusing on technological collaborative innovation, this paper proposes an intelligent diagnosis scheme for rice diseases and pests based on IoT and Keras Model: IoT technology is used to realize real-time perception and data transmission of field crop status, and a lightweight deep learning model is constructed based on the Keras framework to complete the feature recognition and classification of diseases and pests, forming a full-process intelligent system from field data collection to diagnosis result output. The research focuses on the design of system collaborative architecture, the adaptation and optimization of perception modules, the logic of model feature extraction, and the construction of closed-loop diagnosis process. It provides a technical paradigm for crop disease and pest control in smart agricultural scenarios and promotes the transformation of agricultural production from "experience-driven" to "technology-driven".

Keywords：Internet of Things (IoT); Keras Model; Rice Diseases and Pests; Intelligent Diagnosis; Technology Synergy; Deep Learning

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1 Research Background and Significance

1.1 Research Background: From Traditional Dilemma to Technological Breakthrough

Rice production is crucial to global food security, but diseases and pests restrict the stability of its yield. Traditional manual inspection and diagnosis are costly and have limited scope. It is difficult to accurately identify diseases and pests in their early stages, and misjudgments or omissions are likely to lead to the expansion of disasters. With the development of smart agriculture, IoT technology can realize 24/7 monitoring of crops and the environment, while deep learning can extract subtle image features. The combination of the two to build an intelligent diagnosis system for rice diseases and pests has become an important direction to solve traditional dilemmas and improve agricultural intelligence.

1.2 Research Status at Home and Abroad: From Technological Exploration to Insufficient Collaboration

Internationally, countries such as those in Europe, America, and Japan have initially combined IoT with image recognition technology. However, these schemes can hardly adapt to China's rice scenarios, and the module collaboration is poor, resulting in the problem of "disconnection between perception and diagnosis". Domestically, although progress has been made in model optimization and the research and development of perception equipment, most studies focus on single technical links, lacking full-process design. Some systems have high hardware costs and are difficult to promote. Therefore, the development of an integrated system with "low cost, high synergy, and strong adaptability" has become an urgent need.

1.3 Research Objectives and Significance: From Technological Innovation to Industrial Value

This research aims to construct a diagnosis system based on IoT and Keras Model, realizing the closed-loop of "perception-transmission-diagnosis-feedback". It solves the data collection problem through low-cost IoT modules, balances accuracy and efficiency with a lightweight model, and integrates functions through a software platform. Its significance lies in the following aspects: technically, it optimizes the diagnosis architecture and enriches the smart agriculture system; in application, it reduces costs, improves efficiency, and reduces yield losses; industrially, it promotes the precision of rice production and facilitates the implementation of smart agriculture.

2 Architecture Design of Intelligent Diagnosis System Based on IoT and Keras Model

2.1 Overall System Architecture: A Four-Layer Collaborative Technical System

To realize the full-process intelligence of "perception-transmission-diagnosis-feedback", the system is divided into four layers: Perception Layer, Transmission Layer, Platform Layer, and Application Layer. Each layer interacts through standardized interfaces to ensure stability and scalability.

The Perception Layer is the data source, including image acquisition (adapted to paddy field lighting to obtain clear plant images), environment perception (collecting parameters such as temperature and humidity), and control units (coordinating equipment to ensure collection timing). The Transmission Layer adopts a "wireless + wired" mode: field equipment transmits data to the gateway via LoRa, and then transmits it to the Platform Layer through Ethernet or 4G/5G. The Platform Layer serves as the "core brain": cloud servers run the Keras Model to classify leaf features and optimize diagnosis by combining environmental data, and distributed databases store data. The Application Layer provides users with access to field status, diagnosis results, and pest control suggestions through Web/mobile terminals, and supports historical data query and regularity analysis.

2.2 Design of IoT Perception Module: A Low-Cost Scheme Adapted to Paddy Field Scenarios

The module needs to take into account the characteristics of paddy fields (such as high humidity and fluctuating light) and cost control, and optimizes three units:

The image acquisition unit is equipped with an adaptive fill light module and an adjustable bracket, and selects an industrial-grade high-definition camera to balance clarity and cost. The environment perception unit uses high-humidity-adapted sensors (moisture-resistant temperature sensors, anti-condensation humidity sensors, and light sensors suitable for strong/weak light) to collect and transmit data in real time. The control unit uses a low-power MCU, which triggers collection according to preset logic, compresses images to reduce data transmission volume, converts data formats, and adopts a "sleep-wake" mode to reduce power consumption.

2.3 Data Preprocessing Scheme: Laying the Foundation for Model Diagnosis

Data from the Perception Layer needs preprocessing:

Image preprocessing includes four steps: denoising (using Gaussian + median filtering to preserve details), segmentation (extracting pure leaves via the HSV threshold method), enhancement (using histogram equalization + CLAHE to highlight disease spots), and standardization (adjusting size + normalizing pixels). Environmental data preprocessing includes cleaning (removing outliers and supplementing missing values) and standardization (unifying parameter ranges) to support the fusion analysis with image data.

3 Construction of Rice Disease and Pest Diagnosis Model Based on Keras

3.1 Model Selection and Network Structure Design: Balancing Accuracy and Efficiency

The core of rice disease and pest diagnosis is to extract features from leaf images. Convolutional Neural Network (CNN) has become the preferred algorithm due to its advantages in image feature extraction. The Keras framework, with its modular and user-friendly features, supports lightweight adjustments of the model to adapt to different computing needs.

Considering that the original CNN model requires a large amount of data and computing power, and has insufficient pertinence to the features of rice diseases and pests, this study adopts transfer learning and improves based on VGG16: first, retain the first 13 convolutional layers as feature extractors, and remove the top fully connected layers and output layer to reduce parameters and computational complexity; second, add a custom classification layer: first set a global average pooling layer to convert feature maps, then set two fully connected layers to optimize features, and finally set a softmax output layer to match the categories of diseases and pests; third, optimize the activation function and inter-layer connection: use the ReLU activation function for fully connected layers, and add batch normalization layers between layers to improve model efficiency and fitting ability, thereby balancing accuracy and efficiency.

3.2 Model Training Strategy: Ensuring Accuracy and Generalization Ability

To ensure the accuracy and generalization ability of the model, a scientific training strategy is formulated: the training logic adopts "step-by-step training + progressive optimization"—first, freeze the parameters of the VGG16 convolutional layers to train the classification layer, then unfreeze some shallow convolutional layers for joint training. This avoids excessive parameter fluctuations and reduces data demand. For regularization optimization, multiple methods are used: add Dropout layers to fully connected layers, adopt L2 regularization, and expand data diversity through data augmentation (such as random image rotation) to alleviate overfitting. During the training process, monitoring is conducted through the validation set and training curves to record loss and accuracy. When signs of overfitting appear, parameters are adjusted, and an early stopping mechanism is set to avoid ineffective training, ensuring model performance.

3.3 Collaboration Logic Between Model and IoT System: Closed-Loop from Data to Diagnosis

The Keras Model and the IoT system collaborate in depth to form a closed-loop logic: in terms of data input, preprocessed images and environmental data are jointly input into the model — images serve as the core basis, and environmental data assist in optimizing the diagnosis logic (e.g., increasing the recognition weight of related diseases in high humidity). In terms of diagnostic computing, the model is deployed on the cloud server of the Platform Layer and is also adapted to edge computing. In areas with weak networks, a simplified model is deployed on the local gateway for preliminary diagnosis, and difficult samples are transmitted to the cloud for accurate analysis. In terms of result feedback, the diagnosis results are processed and fed back to users through the Application Layer, generating pest control suggestions. Meanwhile, data is stored in an associated manner to form a database, providing support for model optimization and regularity analysis.

4 System Function Implementation and Application Scenario Adaptation

4.1 Implementation of Core System Functions

The system realizes four core functions: first, real-time data collection and monitoring—the IoT perception module collects paddy field images and parameters (such as temperature, humidity, and light) at a preset frequency, and users can view and zoom in on images through the Application Layer to intuitively grasp the crop growth status. Second, automatic diagnosis of diseases and pests—preprocessed leaf images are input into the Keras Model to quickly complete feature extraction and classification, outputting diagnosis results and confidence levels. Third, feedback of diagnosis results and pest control suggestions—combining environmental parameters and the rice growth stage, it generates recommendations such as pesticide types and application methods. Fourth, historical data query and trend analysis—it stores data and diagnosis results, supports multi-dimensional queries, and generates trend charts of disease and pest occurrence to assist in formulating prevention and control plans.

4.2 Adaptation to Application Scenarios

Optimizations are made to adapt to different paddy field scenarios: for large-scale contiguous paddy fields, "multi-node distributed acquisition + cloud centralized diagnosis" is adopted—multiple nodes collect data, the cloud platform processes it efficiently, and the Web terminal provides batch plot management and data comparison. For scattered small-scale paddy fields, "lightweight perception nodes + mobile terminal diagnosis" is used—low-cost equipment is easy to deploy, and the mobile terminal supports local preliminary diagnosis and cloud accurate diagnosis. For hilly and mountainous paddy fields, the Transmission Layer is optimized: LoRa relay nodes are added to ensure data transmission, a simplified model is deployed on the local gateway, and equipment adopts a waterproof and anti-drop design to adapt to complex environments.

5 System Advantages and Technological Innovation Points

5.1 Core Advantages of the System

Compared with traditional diagnosis methods and similar systems, this intelligent diagnosis system for rice diseases and pests has three significant advantages:

First, it balances "low cost and high adaptability". In terms of hardware, the IoT perception module selects industrial-grade cost-effective equipment, simplifies unnecessary functions, and optimizes circuits to reduce costs. For different paddy field scenarios (contiguous, scattered, mountainous, etc.), differentiated deployment plans are designed to avoid high-cost "one-size-fits-all" and adapt to diverse planting scenarios.

Second, it constructs a "full-process and high-collaboration" closed-loop. It breaks the limitation of "disconnection between perception and diagnosis" and forms a collaborative system of "perception-transmission-diagnosis-feedback". After preprocessing, data from the Perception Layer is input into the Keras Model together with environmental parameters; diagnosis results are combined with environmental data to generate pest control suggestions, which are then fed back through the Application Layer. All modules are seamlessly connected through standardized interfaces, improving operational efficiency.

Third, it takes into account "high accuracy and high efficiency". Relying on the deep learning advantages of the Keras Model and the transfer learning strategy, it accurately extracts subtle features of diseases and pests, with higher accuracy than traditional manual diagnosis and simple image recognition. Through lightweight model design and step-by-step training, computational complexity is reduced to meet the needs of real-time field diagnosis.

5.2 Technological Innovation Points

The technological innovations of the research are reflected in three aspects:

First, scenario-based optimization of the IoT perception module. In response to the characteristics of paddy fields (high humidity, large light fluctuations), the image acquisition unit is equipped with an adaptive fill light and an adjustable bracket; environmental sensors are anti-condensation and moisture-resistant; the control unit adopts a "sleep-wake" low-power mode, breaking through the bottleneck of agricultural adaptation of general equipment.

Second, the Keras Model integrates environmental data for diagnosis. It innovatively incorporates temperature, humidity, and light data collected by IoT, analyzes the correlation between such data and diseases/pests, and dynamically adjusts the model's recognition weight. This reduces interference from similar features and realizes "image + environment" multi-dimensional diagnosis, improving accuracy.

Third, "cloud + edge" hybrid diagnosis deployment. According to the differences in paddy field network conditions, cloud centralized diagnosis is used for contiguous paddy fields; in mountainous areas or scattered paddy fields with weak signals, a simplified model is deployed on the local gateway for edge diagnosis, and difficult samples are transmitted to the cloud. This balances network dependence, accuracy, and efficiency.

6 Research Challenges and Future Outlook

6.1 Existing Research Challenges

Although the system has made breakthroughs in technical design and scenario adaptation, it still faces three challenges in practical operation:

First, the model has insufficient adaptability to complex scenarios. The current model is mostly used for single disease/pest diagnosis, and its accuracy needs to be improved for scenarios such as "mixed multiple diseases and pests" and "similar appearances between diseases/pests and physiological stress". In addition, the leaf morphology and disease/pest manifestations of rice vary in different growth stages, so the cross-stage recognition stability of the model needs to be enhanced.

Second, issues regarding the long-term operation reliability and maintenance cost of the system. The high temperature, high humidity, and large number of mosquitoes in paddy fields easily cause wear and tear to IoT equipment, requiring regular maintenance. Equipment battery life and data transmission stability are greatly affected by seasons. It is necessary to continuously optimize protection and transmission schemes to avoid excessive maintenance costs hindering promotion.

Third, issues of user acceptance and operation threshold. Some farmers (especially elderly farmers) are not familiar with the operation of intelligent equipment, resulting in an operation threshold. Farmers' trust in diagnosis results needs long-term verification, and initial misjudgments may reduce acceptance. Therefore, the promotion process needs supporting operation guides, training, and result feedback mechanisms.

6.2 Future Research Directions

Combined with the development trend of smart agriculture, future research can be deepened in three directions:

First, optimize the model's adaptability to multiple scenarios. Expand training samples to cover complex scenarios, and improve the diagnosis ability through data augmentation and network structure improvement. Explore multi-modal data fusion diagnosis to enrich data dimensions and improve accuracy and stability.

Second, iterate the system hardware and operation and maintenance mode. Develop high-durability and low-power perception equipment to reduce maintenance needs. Explore the "agricultural service company + farmer" operation and maintenance mechanism to reduce farmers' costs and thresholds and promote large-scale application.

Third, promote the in-depth integration of the system with agricultural production. Combine the system with links such as precision pesticide application and water-fertilizer management to build an integrated platform of "diagnosis-prevention-control-management", extending to full-cycle production management and enhancing industrial value.

7 Conclusion

Aiming at the demand for intelligent diagnosis of rice diseases and pests, this research constructs a system based on IoT and Keras Model. Through scenario-based IoT perception modules, lightweight Keras Model, and full-process collaborative architecture, it realizes real-time perception, accurate diagnosis, and timely feedback of diseases and pests.

With the advantages of "low cost and high adaptability", "full-process and high collaboration", and "high accuracy and high efficiency", the system solves the problems of low efficiency and strong subjectivity of traditional diagnosis, and breaks through the shortcomings of insufficient collaboration and limited adaptability of similar systems.

The research confirms that the integration of IoT and deep learning is an effective path to intelligent diagnosis. Scenario-based optimization, multi-dimensional data fusion, and flexible deployment can improve the practicality of the system. Although it faces challenges such as adaptation to complex scenarios, future deepening of model optimization, hardware iteration, and industrial integration is expected to improve the system. This will provide support for smart agriculture, promote the transformation of rice production to "technology-driven", and contribute to food security and agricultural economic development.

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