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Original Research Article

Intelligent diagnosis system for rice diseases and pests based on keras model and IoT

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Abstract: As a major rice-producing country, China's rice yield and quality are critical to food security and livelihood protection. Rice diseases and pests have become a key constraint on rice production, reducing both yield and quality and seriously affecting farmers' income and food supply stability. To realize accurate prevention, real-time monitoring and scientific management of rice diseases and pests, and overcome the low efficiency, poor accuracy and complex operation of traditional monitoring methods, this paper designs an intelligent diagnosis system for rice diseases and pests based on the Keras model and Internet of Things (IoT). The system integrates lightweight edge computing devices, UAV inspection terminals and environmental sensors, taking the lightweight Keras deep learning model as the core to achieve rapid identification and accurate diagnosis. With IoT and edge intelligence, it realizes real-time collection, monitoring and analysis of field environmental parameters such as temperature, humidity and light intensity, supporting intelligent monitoring, data recording and dynamic management throughout the rice growth cycle. The system forms a complete digital and intelligent monitoring and diagnosis scheme with standardized processes, providing efficient and scientific management support for farmers and effectively improving the prevention and control efficiency of rice diseases and pests.
Keywords: keras model; internet of things; rice diseases and pests; intelligent diagnosis system

1. Introduction

1.1. Research background and significance

In China, with its vast territory, abundant resources and large population, relies heavily on crop production to ensure people's well-being and food security. As a major food crop in China, rice yield and quality are closely related to national food security and agricultural sustainable development [1]. Rice diseases and pests are key factors restricting rice yield and quality, leading to yield reduction, income loss and even threatening food supply stability.

Effective monitoring and control of diseases and pests are crucial for improving crop production efficiency. However, traditional monitoring methods are inefficient, inaccurate, cumbersome and slow, failing to meet the needs of large-scale and refined agricultural production. Thus, developing scientific and efficient monitoring technologies is an urgent demand for agricultural intelligence [2].

To address these issues, this project constructs an intelligent diagnosis system for rice diseases and pests based on Keras model and IoT in rice planting scenarios. It adopts lightweight edge computing devices for real-time field monitoring, UAV inspection combined with lightweight Keras deep learning for rapid and accurate identification of diseases and pests [3], and integrates environmental sensors to realize real-time collection and analysis of farmland environmental parameters, achieving full-cycle intelligent management of rice [4].

Through multi-module integration, the system forms a digital and intelligent rice planting scheme, solving the pain points of difficult monitoring and prevention of rice diseases and pests, improving agricultural production quality and efficiency, and promoting the intelligent and refined upgrading of the rice planting industry, with important theoretical and practical significance. The system schematic diagram is shown in **Figure 1**.

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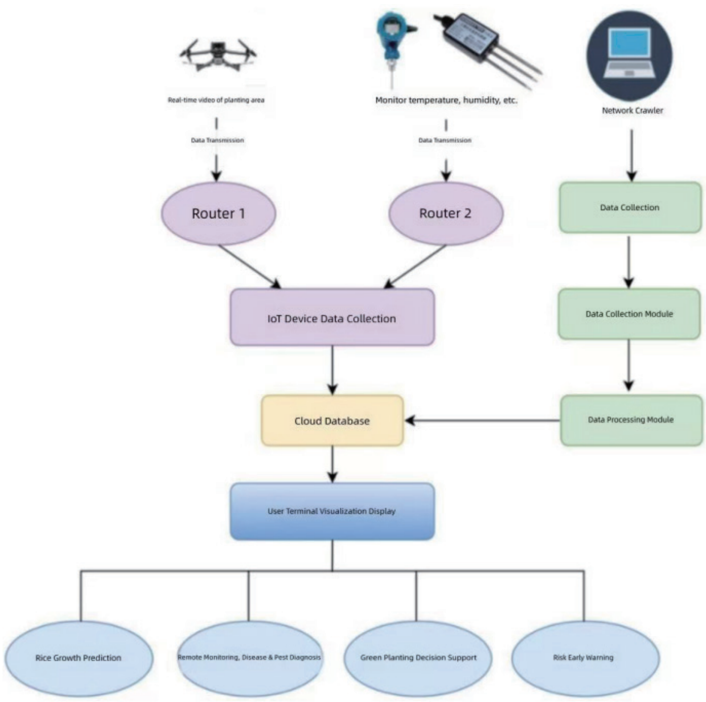

Figure1. Schematic diagram of the intelligent diagnosis system for rice diseases and pests.

1.2. Research status at home and abroad

With the rapid development of agricultural intelligence and information tec hnology, scholars at home and abroad have carried out a lot of research on ric e disease and pest monitoring and diagnosis technologies, forming a diversified technical path, which provides a solid theoretical and practical foundation for the research and development of this system, but there are still many problems to be solved urgently [5].

In China, the development of agricultural intelligence has been rapid in re cent years. Combined with the characteristics of rice planting in China, scholar s have made many achievements in the field of disease and pest diagnosis tec hnology [6]. At present, domestic research mainly focuses on two directions: on e is the optimization of disease and pest identification algorithms based on dee p learning models, which improves the accuracy and speed of rice disease and pest identification by improving the network structure and introducing transfer learning; the other is the application of IoT technology in farmland environment monitoring, which realizes the real-time collection and data transmission of farmland environmental parameters through sensor networking.

However, the existing research still has obvious shortcomings: most deep l earning models rely on high-performance computing equipment and are difficult to deploy on lightweight terminals; IoT monitoring and disease and pest diagnosis are mostly in an independent and separated state, without realizing technical integration and collaborative linkage; some systems are difficult to operate and have insufficient adaptability, which are difficult to meet the actual use needs of farmers, and a complete, efficient and convenient digital and intelligent d iagnosis and management system for rice diseases and pests has not yet been formed.

2. Introduction to related technologies of the system

2.1. IoT technology

IoT technology realizes the interconnection between the physical world and the digital world by deploying various terminal devices such as sensors and c ameras [6]. This system adopts wireless communication technologies such as Wi- Fi and LoRa to build a distributed monitoring network, collect key data such a s rice field soil humidity, air temperature and disease and pest images in real time, and complete data preprocessing through edge computing devices to redu ce data transmission pressure and ensure data real-time and reliability.

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2.2. Keras deep learning framework

Keras is a concise and efficient deep learning framework based on the Te nsorFlow backend, which supports the rapid construction of Convolutional Neur al Network (CNN) models and has good scalability and ease of use [4]. In this paper, a disease and pest identification model is built based on the Keras fra mework, and the model is lightweight through technologies such as data augme ntation, model pruning and knowledge distillation, which is adapted to low-conf iguration terminals such as mobile phones with 4GB RAM and meets the need s of rural offline use scenarios.

3. Rice pest and disease intelligent diagnosis system overall design

This system consists of four parts: UAV, image acquisition equipment, edge computing embedded equipment and system GUI interface. The image acquisition equipment mounted on the UAV collects rice field images through MJPG, and the collected data can be identified and calculated by the edge computing equipment on the UAV, and the results are transmitted and uploaded through 4G or 5G communication network. It can also carry out real-time monitoring through the rtsp image transmission of the camera and transmit the image data to the terminal.

The pre-deployed neural network model is used to identify crop diseases and pests for the input images, and the results are displayed on the interface by means of forwarding GUI. The data set selected in the experiment includes common diseases and pests such as rice sheath blight.

4. Rice pest and disease intelligent diagnosis system implementation

4.1. IoT data acquisition and transmission module

Sensor nodes are deployed in a cellular manner in rice fields with a spacing of 50-100 meters to achieve full coverage monitoring. IP cameras and USB high-definition cameras are selected as image acquisition equipment, which are installed on field poles and UAVs to take regular images of rice leaves and p lants; environmental sensors collect parameters such as soil humidity (measurem ent depth 0-50cm) and air temperature (range -40°C~+85°C) in real time, with a data sampling frequency of 1 time per minute [6].

A "wired + wireless" hybrid transmission scheme is adopted: short-distance sensor data is transmitted to edge nodes through LoRa/NB-IoT, and image dat a collected by UAVs is uploaded through 4G/5G networks; in the data preproc essing stage, the Kalman filter algorithm is used to remove noise, and wavelet transform is used to compress the data volume (compression rate 60%-70%) t o ensure transmission efficiency [1]. Edge nodes conduct preliminary verification of data, and mark abnormal data for re-collection to ensure data accuracy.

4.2. Research and development of lightweight keras identification model

4.2.1. Data set construction

1800 images of rice diseases and pests are obtained through web crawlers and field collection, covering common diseases and pests such as bacterial blight of rice, rice blast, brown spot of rice, rice weevil and rice leafhopper, as well as normal images of 3 growth stages: vegetative growth stage, filling stag e and mature stage [2]. The data set is uniformly adjusted to 224×224×3 pixe ls, and data augmentation is carried out by means of random flipping, brightne ss adjustment and Gaussian blur to improve the robustness of the model.

4.2.2. Model design and optimization

A Convolutional Neural Network (CNN) model is built based on Keras, w ith the input layer being 224×224×3 image data, including 5 convolutional la yers, 3 pooling layers and 2 fully connected layers, and the output layer being the probability distribution of disease and pest types [4]. To adapt to edge dev ices, lightweight optimization is carried out by adopting knowledge distillation and model pruning technologies: Pruning: Remove neuron connections with weights close to zero, reducing the number of model parameters by 30%; Quantization: Convert model parameters from FP32 to INT8 format, reduci ng storage occupation and computation; Knowledge distillation: Take ResNet50 as the teacher model to train the li ghtweight student model, which

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improves the reasoning speed by 3 times on t he premise of ensuring accuracy [2].

After optimization, the model size is compressed to 8MB, which supports offline operation on mobile phones with 4GB RAM, and the reasoning time is ≤ 500ms.

4.2.3. Model training and verification

The data set is divided into training set, verification set and test set at a ratio of 7:2:1. The Adam optimizer is adopted in the training process, the initi al learning rate is set to 0.001, and it is dynamically adjusted through the lear ning rate decay strategy; the cross-entropy loss function is selected as the loss function, and the number of iterations is 300 [4]. The training results show that the recognition accuracy of the model on the test set reaches 92.3%, and the recognition accuracy of various diseases and pests is shown in **Table 1**.

Table 1. Model recognition accuracy table.

Type of Diseases and Pests	Recognition Accuracy (%)
Bacterial blight of rice	94. 1%
Rice blast	93.5%
Brown spot of rice	91.8%
Rice weevil	92.7%
Rice leafhopper	90.9%
Average accuracy	92.3%

4.3. Cloud-edge collaboration and risk early warning module

Edge nodes Integrating environmental parameters (air temperature, soil humidity), crop growth stages and disease and pest identification results, a risk early warning model based on logistic regression is constructed [1]. The system presets environmental parameter thresholds and disease and pest occurrence probability thresholds: when the model predicts that the probability of disease and pest occurrence is ≥ 30% or parameters such as soil humidity and air temperature exceed t he thresholds, the system automatically triggers an early warning, pushes notifications and prevention and control suggestions through the APP .

4.4. Mobile APP and decision support module

The functions of the mobile APP include:(1) Real-time monitoring: Display environmental parameters such as soil humidity and air temperature and field images, and the data is visually presented in the form of line charts and bar c harts;(2) Diagnosis service: Farmers can upload images for manual diagnosis, a nd the system automatically returns the recognition results and confidence;(3) Early warning notification: Push risk early warnings in the form of pop-ups and short messages, with targeted prevention and control schemes (such as pesticid e selection, application amount, application time);(4) Market analysis: Integrate agricultural market data to provide rice price trends and sales channel recommendations [3].

Conclusion: The intelligent diagnosis system for rice diseases and pests ba sed on Keras model and IoT developed in this study effectively solves the pai n points of disease and pest monitoring and diagnosis in traditional rice plant in g. The system realizes real-time collection of multi-source data through the IoT sensor network, achieves accurate identification relying on the lightweight Keras model, and ensures efficient operation with the help of the cloud-edge collaborative architecture, providing convenient and scientific planting management schemes for farmers [6].The test results show that the system is advanced in technology and strong in practicability, which is of great significance in improving planting efficiency, ensuring food security and promoting the development of green agriculture, and has extensive promotion and application value. In the follow-up, the model performance will be further optimized, the coverage of crop types will be expanded.

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