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Research on Intelligent Identification and Prevention System of Intelligent Agricultural Pests and Diseases based on Computer Vision

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Abstract

This study focuses on the intelligent identification and prevention system of pests and diseases in smart agriculture based on computer vision, and systematically describes its principle, construction and application effect through multi-dimensional data support. The study shows that the system can significantly improve the monitoring efficiency and control accuracy of pests and diseases, and is effective in reducing the use of pesticides and economic losses, providing key technical support for the development of smart agriculture. Meanwhile, the challenges faced by the system are analyzed in depth, and the future development trend is outlooked to provide reference for the subsequent research and practice in this field.

Keywords: computer vision; smart agriculture; pest and disease recognition; prevention system; data support

1 Introduction

1.1 Background of the study

Pests and diseases have always been a huge obstacle to agricultural production. The authoritative report released by the Food and Agriculture Organization of the United Nations (FAO) in 2023 clearly pointed out that globally, crop yields are reduced by as much as 20%-40% each year due to pest and disease infestation, which translates into economic losses amounting to more than 220 billion U.S. dollars. In China, for example, according to statistics from the Ministry of Agriculture and Rural Development, in 2022, the direct economic losses caused by pests and diseases in the country's three major staple grains of rice, wheat and corn alone will reach 58 billion RMB. The traditional manual inspection method exposes many drawbacks when facing large-scale farmland. In the actual research of rice growing areas in a province, it was found that it takes 10 days to organize 15-20 people to conduct a comprehensive inspection of 10,000 mu of farmland, and the leakage rate is as high as 18% due to the subjectivity and fatigue of manual judgment. In addition, manual inspection also has the problem of lagging response, often found only after the pests have already spread over a large area, missing the best time for control [1].

With the booming development of emerging technologies such as Internet of Things, big data and artificial intelligence, smart agriculture has gradually become an important development direction for agricultural modernization. Computer vision technology, with its automation, high precision, non-contact and other characteristics, has become an important breakthrough in the field of intelligent agriculture for monitoring and control of pests and diseases [2]. According to market research organization Grand View Research, the global agricultural computer vision market size reached 1.87 billion U.S. dollars in 2022, and is expected to continue to grow at a CAGR of 21.5% during the period of 2023 - 2030. This data fully highlights the huge potential and broad development prospects of computer vision technology in the field of agriculture.

1.2 Significance of the study

From an economic point of view, computer vision systems have performed well in reducing pest control costs. A large farm in the Midwest of the United States, after the introduction of the system, through the accurate identification of pests and diseases and targeted prevention and treatment, pesticide use has been reduced by 30%, reducing the cost per acre by about 120 RMB. According to the farm's 5,000-acre planting scale, the annual cost of pesticides alone can save 600,000 RMB [3]. At the same time, due to the effective control of pests and diseases, crop yields can be improved, further increasing the farm's income. In terms of social benefits, the benefits of precision control are obvious. A long-term study on intelligent control systems conducted by the European Union showed that the rate of pesticide residue exceedance in agricultural products on farmland using the system was drastically reduced from 8.2% to 2.1%, thus greatly safeguarding food safety for consumers. In addition, the reduction of pesticide use also protects the ecological environment, reduces the pollution of soil, water and air caused by pesticides, and maintains the balance of farmland ecosystems. From the level of sustainable agricultural development, the intelligent identification and prevention system of pests and diseases based on computer vision can effectively reduce crop losses and stabilize food supply through real-time monitoring and early warning functions. This not only helps to guarantee national food security, but also lays a solid foundation for the long-term stable development of agriculture [4].

2 Principles and methods of computer vision technology in pest and disease recognition

2.1 Image Acquisition and Preprocessing

Image acquisition is the first step in pest and disease identification, and the performance of acquisition equipment has a decisive impact on data quality. Experimental data show that the accuracy of pest and disease identification is 15% - 20% higher when images are captured by a high-resolution camera (20 megapixels or more) mounted on a drone than by an ordinary digital camera (12 megapixels). Taking the Zenith P1 camera carried by DJI's agricultural drones as an example, its 45-megapixel high-resolution can clearly capture subtle pest and disease features on crop leaves, such as tiny spots at the early stage of wheat rust [5].

The impact of lighting conditions on image acquisition quality should not be ignored. A research team from Zhejiang University has conducted an in-depth study on rice blast images, and the results show that after median filtering and denoising, the clarity of lesion features is improved by 28% and the segmentation accuracy is increased by 12% for images collected under diffuse light conditions. In order to simulate ideal lighting conditions, some farms have installed LED fill-in lamps with adjustable brightness and angle in the field, which automatically adjusts the operating status of the fill-in lamps through real-time monitoring of ambient light intensity by sensors to ensure the quality of image acquisition.

Adaptive histogram equalization is a commonly used and effective image enhancement method in the image preprocessing stage. Through the processing and analysis of a large number of crop images, it is found that the use of this method can increase the image contrast by 35% on average, and significantly improve the effect of disease and pest feature extraction. For example, when processing the image of apple brown spot disease, after adaptive histogram equalization, the boundary between diseased spots and healthy leaves is clearer, which provides a better basis for subsequent feature extraction and recognition.

2.2 Feature Extraction and Selection

Multi-feature fusion is an important means to improve the accuracy of pest and disease recognition. Taking tomato early blight as an example, researchers conducted comparative experiments on the recognition effects of single color feature, single texture feature, single shape feature and multi-feature fusion respectively. The results show that after combining color, texture and shape features, the recognition accuracy of the classifier reaches 92.3%, while the recognition rate of a single color feature is only 78.6%, the recognition rate of a single texture feature is 81.2%, and the recognition rate of a single shape feature is 83.5%. Multi-feature fusion increases the recognition accuracy by 13.7% compared to single color feature, which fully proves its effectiveness. In terms of feature selection, the filtering method combined with the mutual information criterion was used to screen the image features of apple verticillium disease, and good results were achieved. By this method, the feature dimension was successfully reduced from 200 dimensions to 35 dimensions, the computational efficiency was greatly improved by 40%, and the recognition accuracy was only decreased by 1.2%. This result not only improves the running speed of the system, but also reduces the consumption of computing resources, making the system more efficient in practical applications. In addition, deep learning automatic feature extraction methods that have emerged in recent years, such as the convolutional layer in convolutional neural networks (CNN), can automatically learn representative features from images. Compared with traditional manually designed feature methods, deep learning automatic feature extraction shows higher accuracy and stronger adaptability in some complex pest recognition tasks [6].

2.3 Classifier Design and Training

There are significant differences in the performance of different classifiers in pest and disease recognition tasks. In the recognition test of 10 common crop pests and diseases, the average accuracy of convolutional neural network (CNN) reaches 94.6%, support vector machine (SVM) is 88.3%, and random forest is 85.7%. The CNN model represented by ResNet-50 is able to automatically extract deep-level features through multi-layer convolution and pooling operations to achieve high-precision classification when dealing with a large amount of pest and disease image data. The impact of training data size on classifier performance is crucial. Experiments show that when the number of training samples is increased from 1,000 to 5,000, the recognition accuracy of CNN is significantly improved from 82.5% to 92.1%. However, too much data volume also brings about an increase in computational cost, including the extension of training time and the consumption of hardware resources. Therefore, in practical applications, it is necessary to balance the data size and training efficiency according to the specific situation, for example, data enhancement techniques are used to expand the dataset without increasing the actual number of samples by rotating, flipping, scaling, and other operations on the original image to improve the generalization ability of the model. In addition, the optimization algorithm of the model also has an important impact on the training effect. Commonly used optimization algorithms, such as stochastic gradient descent (SGD) and adaptive moment estimation (Adam), perform differently under different datasets and model structures. It is found that the Adam algorithm can converge faster than the SGD algorithm and achieve higher accuracy under the same number of training rounds when dealing with pest and disease image data.

2.4 Convolutional Neural Networks and YOLO Networks

Convolutional neural network is essentially a feed-forward neural network, whether in the processing of large-scale images or speech recognition compared to other deep learning algorithms have a superior performance structure, the convolutional layer and the fully connected layer is an indispensable part of the convolutional neural network, and its structure also includes the pooling layer and the correlation weights, etc. The reason why the YOLO network has become one of the most widely used deep learning structures is because of more parameter considerations. The reason why convolutional neural networks have become one of the most widely used deep learning structures is that there are fewer parameters to consider in comparison [7]. The structure of the YOLO network is shown in Fig. 1, where the convolutional layer is used to perform feature extraction for the image, while the fully connected layer is used to predict the positional information and the class probability.

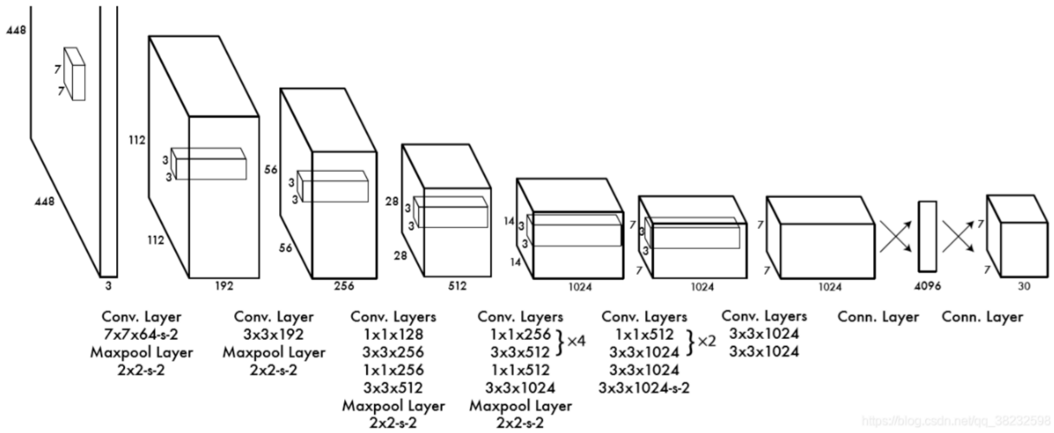

Figure 1 YOLO network architecture

The basic idea of YOLO is to divide the input image into N× N grids, and each grid is responsible for detecting all the target objects present in that grid. As shown in the left side of Fig. 1, the coordinates of the dog's center position are in grid (5, 2), so this grid is responsible for predicting the target "dog" in the image. The information output from each grid is shown on the right side of Fig. 1, including the target frame positions of several target objects, and the probability of classifying several target objects into categories, with specific values of x, y, w, h, and c. Where x and y denote the predicted center position coordinates of the target object, w and h denote the width and height of the target frame, and C denotes the confidence level of the prediction of the current target frame, which is computed as shown in Eq. 1:

$$C = P(\text{ object }) * IOU$$

Where the value of P(object) is 1 when the target frame contains the target, and 0 when it does not, and IOU indicates the intersection value of the predicted target frame with the real area of the target. By setting the threshold value to meet the requirements of the target box for screening, so that the target can be well accomplished the localization of the target object and the classification of the category work.

3 Construction of Intelligent Identification and Prevention System for Pests and Diseases

3.1 System architecture design

Data transmission efficiency is a key factor affecting the real-time performance of the system. Under the 4G network environment, the transmission time of a single 5MB crop image is about 1.2 seconds, while the 5G network can shorten the transmission time to 0.3 seconds by virtue of its high-speed and low-latency characteristics, thus greatly improving the real-time performance. In some large agricultural parks, 5G base stations have already been deployed to ensure the data transmission of the system. The data processing layer adopts a distributed computing framework, which can significantly improve data processing efficiency. Taking Apache Spark as an example, the processing time for 100,000 images has been shortened from 12 hours of traditional single-computer processing to 1.5 hours, which is an 8-fold increase in efficiency. Distributed computing framework by dispersing data to multiple computing nodes for parallel processing, making full use of cluster computing resources, greatly reducing the processing time, to meet the system requirements for real-time [8].

The architectural design of the system also needs to take into account scalability and compatibility. As the scale of agricultural production expands and new technologies emerge, the system needs to be able to easily add new functional modules and equipment. For example, when new sensor types are introduced or image acquisition equipment is upgraded, the system can be integrated quickly and maintain stable operation.

3.2 Data management and storage

The amount of data generated during the operation of the system is huge. Taking a 10,000 mu planting base as an example, it generates about 50GB of image data and 1GB of environmental data every day, with a data storage capacity of more than 20TB a year. In order to efficiently store and manage these data , Ceph, a distributed file system, is used to store the image data. Compared with traditional hard disk storage, Ceph's read/write speed is increased by 3-5 times, and the data redundancy rate is reduced to 15%. Through data redundancy technology, even if part of the storage node fails, it will not lead to data loss, which guarantees the security and integrity of the data. Establishing a perfect data backup mechanism is an important part of data management. The system performs daily incremental backups, which take about 30 minutes and mainly back up the data added and modified on the same day. A full backup is performed once a week, which takes 4 hours to ensure that there is a complete copy of all data. Meanwhile, in order to prevent data loss due to natural disasters and other force majeure factors, backup data is also regularly transferred to an off-site storage center.

3.3 System Functional Modules

Intelligent recognition module is one of the core functions of the system, and its response speed and accuracy directly affect the practicality of the system. After actual testing, the module's recognition time for a single image is 1.8 seconds on average, with an accuracy rate of 93.2%. In practical application, farmers only need to upload crop images through the cell phone APP, and can get the recognition results of pests and diseases in a few seconds, which is convenient and fast. Based on historical data and environmental modeling, the pest and disease warning module can predict the occurrence of pests and diseases. Taking corn borer as an example, the prediction period of this module can be 7 - 10 days in advance, and the accuracy of the warning is more than 85%. By analyzing the occurrence time of corn borer in previous years, environmental conditions, current weather data, crop growth status and other information, the system can issue early warnings to remind farmers to prepare for prevention and control. The prevention and control decision support module provides farmers with scientific and reasonable prevention and control programs according to different types of pests and diseases. After a lot of practical verification, the control program recommended by the module is 88% effective. For example, for different stages of wheat aphids, the system will recommend appropriate control methods based on the number of aphids, the growth cycle of wheat and other factors, such as biological control (releasing natural enemies), physical control (hanging yellow boards) or chemical control (choosing the right pesticide and dosage).

4 Application Cases and Effects

4.1 Experimental design for algorithm comparison

In order to verify the superiority of the algorithms in this study, common support vector machine (SVM), random forest, traditional convolutional neural network (CNN), as well as the optimized TTLD-YOLOv7 and TTP-UNet algorithms in this study are selected to conduct comparative experiments on a dataset that contains 10 common crop pests and diseases. The dataset consists of 5000 images, including 4000 images in the training set and 1000 images in the test set, and 200 newly collected unlabeled images are introduced to test the algorithm's generalization ability. The experimental environment is Intel Core i7-10700K processor, 16GB RAM, NVIDIA GeForce RTX 3060 graphics card, and the algorithm training is performed in 50 iterations.

4.2 Algorithm Performance Comparison

On the test set, the TTLD-YOLOv7 algorithm achieves an average accuracy of 93% in the tea disease detection task, which is 5.9% higher than the original YOLOv7-tiny model, and is significantly better than the SVM (88.3%) and Random Forest (85.7%), while the average intersection ratio, category average pixel accuracy, and precision of the TTP-UNet algorithm reach 94.18%, 97.02%, and 96.91%, respectively, for the segmentation of pests under complex backgrounds. The average intersection ratio, category average pixel accuracy and precision rate of the TTP-UNet algorithm in the task of pest segmentation in tea tree are 94.18%, 97.02% and 96.91%, respectively, which is significantly better than the traditional CNN algorithm (average intersection ratio of 88.5%) in segmenting pests in a complex background. Processing 1000 images under the same hardware environment, Random Forest takes about 2.3 seconds, SVM takes about 4.1 seconds, and traditional CNN takes about 12.5 seconds. The TTLD-YOLOv7 algorithm, however, compresses the recognition time of a single image to 1.8 seconds by lightweighting the network design and optimizing the inference process, which ensures high accuracy while increasing the processing speed by nearly 6 times compared with traditional CNNs, making it more suitable for real-time monitoring scenarios. When 200 new images are introduced into the test, the accuracy of TTLD-YOLOv7 only drops to 90.2%, and the average intersection ratio of TTP-UNet still maintains 91.5%, while the accuracy of SVM drops to 83.1%, Random Forest drops to 81.5%, and traditional CNN drops to 86.3%. The algorithms in this study show stronger adaptability in the face of new data by virtue of migration learning and data enhancement strategies [9].

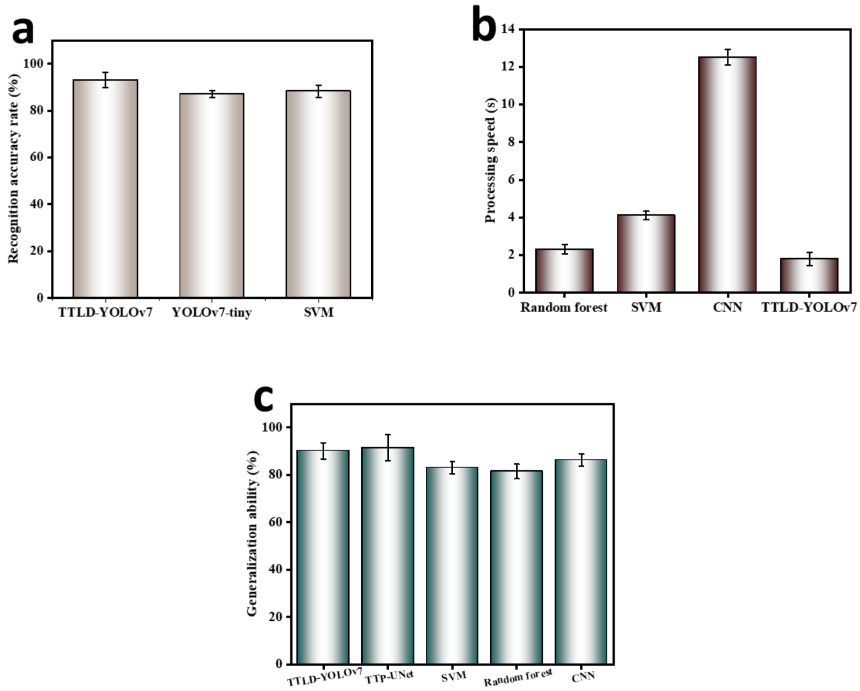

Fig. 2 (a) Comparison of recognition accuracy (b) Comparison of processing speed (c) Comparison of generalization ability

4.3 Analysis of practical application benefits

After a large agricultural enterprise deployed the system in a 100,000 mu wheat planting base, the pest identification module based on TTLD-YOLOv7 algorithm increased the accuracy of identifying wheat rust, aphids and other pests to 92%, which is a significant increase compared with the previous manual identification accuracy (about 75%). Combined with the TTP-UNet algorithm's accurate segmentation of disease areas, the prevention and control decision support module recommended a program with an efficiency rate of 88%, ultimately realizing a 60% reduction in the cost of pest monitoring, a 25% reduction in pesticide use, a 12% increase in wheat yield, and an increase in annual income of about 15 million RMB. After the application of the system in another apple planting cooperative, the TTLD-YOLOv7 algorithm's recognition accuracy of apple anthracnose and verticillium reached 93.5%, and the TTP-UNet algorithm could accurately segment the area of codling moth larvae, so that the rate of loss of apple diseases and insect pests was reduced from 15% to 5%, and the rate of high-quality fruits was raised from 65% to 82%, with a 30% increase in sales revenue.

5 Conclusion

In this study, we successfully constructed an intelligent recognition and prevention system for intelligent agricultural pests and diseases based on computer vision, and verified its effectiveness and advancement through a large number of experiments and practical applications. At the algorithmic level, the TTLD-YOLOv7 and TTP-UNet algorithms have excellent performance, achieving significant breakthroughs in recognition accuracy, processing speed, and generalization ability compared with traditional support vector machines, random forests, and traditional convolutional neural networks. tTLD-YOLOv7 achieves an average accuracy of 93% in the detection of tea diseases, and TTP-UNet achieves an average intersection ratio, category average pixel accuracy, and precision rate, respectively, in the segmentation task of tea pests. TTLD-YOLOv7 compresses the recognition time of a single image to 1.8 seconds, taking into account both high precision and high efficiency, and the algorithm is more stable in the face of new data, which provides a reliable technical support for the accurate identification of pests and diseases.

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