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Intelligent pest and disease control system for traditional Chinese medicine cultivation industry

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Abstract: *Aiming at the low efficiency of traditional Chinese herbal medicine pest control technology, an intelligent system for pest control of Chinese herbal medicine was proposed. The deep learning model was deployed to an intelligent UAV to realize real-time dynamic identification of diseases and pests, and the RTK module was used to connect the software end to realize data interconnection and real-time analysis of pest identification results, and then return to intelligent planning of management routes. To create a highly automated system for pest identification and management. The average pest identification accuracy of the system model reached 96.72%, covering 328 species of pests and diseases, and the software video stream return frame rate was no less than 30 frames, effectively improving the efficiency of pest and disease management.*

Keywords: *Chinese medicinal materials, Pests and diseases, Intelligent recognition, Prevention and cure*

1. Introduction

In the context of highly developed artificial intelligence, the SeeSpray system of BRT[1] in the United States uses UAV and machine vision technology to achieve targeted crop spraying. Tao Senhao et al. [2] improved the original YOLO model by using BIPFN, realized multi-scale fusion to make full use of the features of small targets, and solved the technical problems existing in the traditional methods of image recognition of Chinese medicinal materials. Nowadays, artificial intelligence technology is gradually applied in the field of pest management, but its prevention and control technology is still not mature and intelligent. Aiming at the problem of prevention and control of diseases and pests of Chinese medicinal materials, this paper proposes to build a disease and pest control system of Chinese medicinal materials based on UAV combined with AI. In the identification and management stage, the deep learning model is deployed in combination with UAV system to build an integrated and efficient governance system.

2. System overall architecture design

2.1. YOLOv7 Object Detection Algorithm

In view of the current disease and pest management problems facing the field of TCM planting, this paper proposes to design a TCM disease and pest control system based on the improved YOLOv8 algorithm [3] combined with UAV equipment. The system builds an integrated system of software and hardware, and the software side covers mobile app and web side. The hardware side uses the UAV as the carrier to deploy the deep learning model to realize the scanning and identification of pests and diseases, and realizes the automatic cruise flight spraying pesticide control according to the analysis results of the software side. This system is mainly divided into: user layer, network layer, presentation layer, business layer, data layer and infrastructure.

The user layer is divided into system manager and Chinese herbal medicine farmer. The network layer is responsible for connecting the user layer and the presentation layer through an interface with the http protocol to transmit data. The presentation layer is divided into the web side, the mobile side and the hardware side. The web side adopts the Vue framework to compile, and has functions such as flight operation lookup, user information management, governance data visualization, and pharmacopoeia data modification. The mobile terminal adopts the mixed programming of Java and

Kotlin, adopts the MVVM architecture, greatly reduces the coupling degree, and realizes the lightweight deployment of the disease and insect identification model through the ncnn model. Gamaya Agri-Technologies [4], based in Switzerland, uses drones and multi-spectral sensors to monitor crop conditions. Their system can detect pest and disease problems in crops and provide real-time reports on the health of the field to help farmers take timely measures to control them. In response to this demand, users of this system can identify diseases and pests of Chinese medicinal materials through app photos, and have functions such as data analysis, Chinese medicinal materials planting information, management log lookup, and UAV equipment binding. The main carrier of the hardware side is the intelligent pesticide spraying UAV, which realizes the deployment of the deep learning model on the edge device. The UAV is equipped with real-time dynamic identification of disease and pest information and sends the data back to the software side for data analysis, and realizes the independent route planning and management by integrating the location data of diseases and pests. The business layer is responsible for the data processing of pest image, the training and deployment of model, the control of software and hardware data sharing module, and the establishment of pest database. In the data layer, the system has designed four databases to store data, which are divided into Chinese herbal medicine database, user database, drone database and model data. In the UAV database, data such as the location of high incidence of diseases and pests, flight height, pesticide loading dose and treatment route are mainly stored. Infrastructure includes servers, operating systems, and network equipment.

3. Pest and disease recognition module design

3.1. Establishment of pest identification model

In the task of disease and insect detection of Chinese medicinal materials, the improved YOLOv8 has shown excellent advantages. First of all, its end-to-end detection framework enables the model to achieve target detection and location at the same time, thus improving the detection speed and accuracy. This real-time performance is crucial for the timeliness of the monitoring of diseases and pests of Chinese medicinal materials. The model takes YOLOv8 as the main backbone network. First, the backbone architecture is operated to increase the depth of the network [5], and additional residual blocks are added to the Darknet-53 backbone network to improve the feature extraction ability and better capture the complex features of diseases and pests of Chinese medicinal materials. Secondly, by adjusting the size of convolution nuclei to adapt to the changes of different sizes and textures of diseases and pests of Chinese medicinal materials, features can be captured more comprehensively by using convolution nuclei of different sizes. At the same time, the model introduced an attention mechanism to improve the model's attention to TCM diseases and pests by focusing on key areas. These improvements are designed to make YOLOv8 better adapt to the needs of the task of detecting pests and diseases in Chinese medicinal materials, so as to improve the accuracy and robustness of the model. The algorithm architecture diagram is shown in Figure 1.

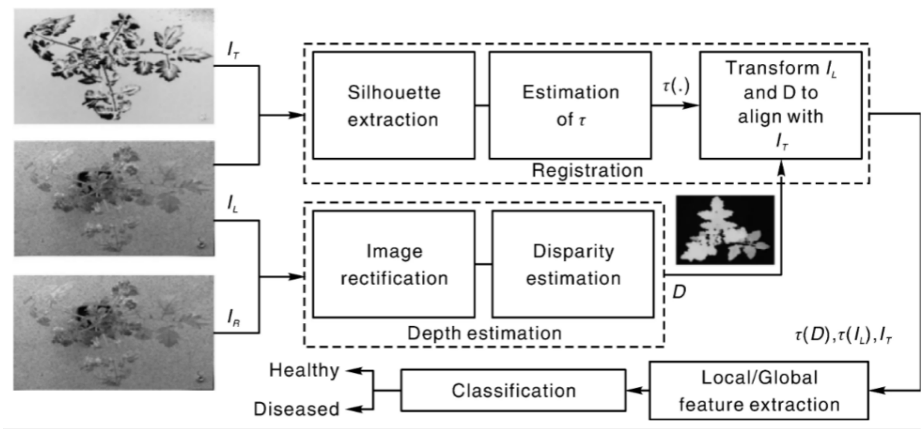

Figure 1: Classification algorithm architecture diagram

In order to keep the model lightweight, this paper selects MobileNet-V3 as an additional lightweight convolutional neural network, and improves the output layer of the network into 27 pest classification channels through Transfer Learning technology. Secondly, innovative research ideas such as multiple loss function were carried out in the training process to make the algorithm better fit the application field of disease and pest detection of Chinese medicinal materials. Combining Tansorflow

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and Pytorch deep learning framework, a scientific, efficient and real-time disease and pest detection system of Chinese medicinal materials was built. The algorithm construction process is shown in Figure 2.

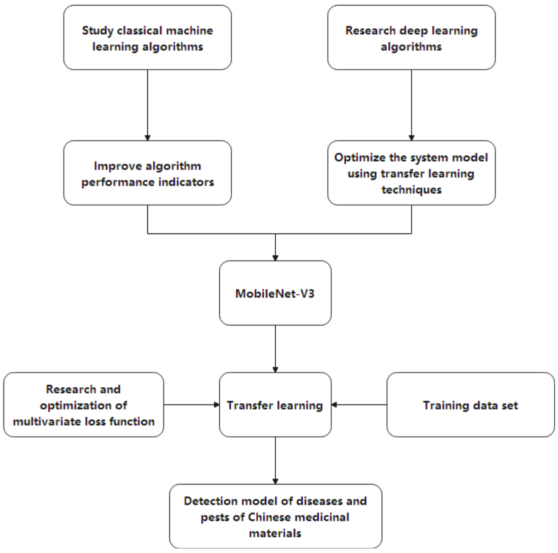

Figure 2: Chinese herbal medicine pest detection algorithm construction process

In order to achieve the fusion of YOLOv8 and MobileNet-V3 [6], this paper chose to insert the output of MobileNet-V3 before the last residual block of YOLOv8. The design was designed to retain the deep features of YOLOv8 and introduce the lightweight features of MobileNet-V3, thus taking full advantage of both in the model. In the specific fusion step, feature fusion is carried out first, and the output of the last residual block of YOLOv8 is combined with the output of MobileNet-V3 by adding elements one by one, and the feature level fusion is realized. This fusion strategy helps the model capture the information in the image more comprehensively, while maintaining YOLOv8's strong performance in object detection. Further, the fusion layer is designed with information transfer capabilities to effectively introduce the lightweight characteristics of MobileNet-V3 into YOLOv8. At the same time, adaptive adjustments are also made to ensure that the output of MobileNet-V3 has a similar size and number of channels to the features of YOLOv8 to maintain the overall network balance and collaborative work. Through this comprehensive fusion strategy, it is expected to realize the synergistic advantages of YOLOv8 and MobileNet-V3 in agricultural disease detection models, and fully leverage the potential of both in deep and lightweight networks.

3.2. Image set processing of pests and diseases

In view of the establishment of the data set used in the training module of the project, advanced web crawler framework (Scrapy, PySpider, etc.) has been adopted to obtain batch images of online Chinese medicinal plant diseases and insect pests, and a variety of pre-processing algorithms have been used to standardize and normalize the obtained images. Secondly, the image data set was manually annotated by using Fluid Annotation, a Google data annotation tool, and the training set was fused by combining the AI Challenge Chinese herbal medicine disease and insect pest data set to establish a complete and standardized Chinese herbal medicine disease and insect pest detection training data set. And ensure that the subsequent system model training module is more scientific and efficient. The data set processing flow chart is shown in Figure 3.

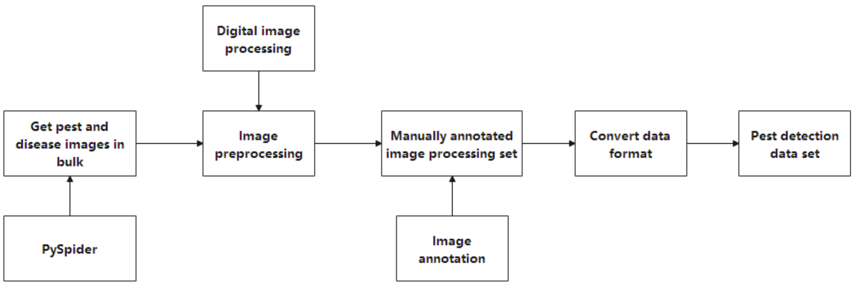

Figure 3: Flow chart of pest data set processing

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For the study of disease detection algorithms, in order to improve the accuracy of disease and insect recognition algorithms, it is also necessary to restore the initial images through Image Denoising and image enhancement operations such as pre-processing algorithms. Secondly, the processed image data is passed into the system model (lightweight neural network MobileNet-V3) for forward mapping, and the model output Label is retrieved through the system disease data information database, and the detection results and corresponding solutions are returned. The schematic diagram of the optimization layer is shown in Figure 4.

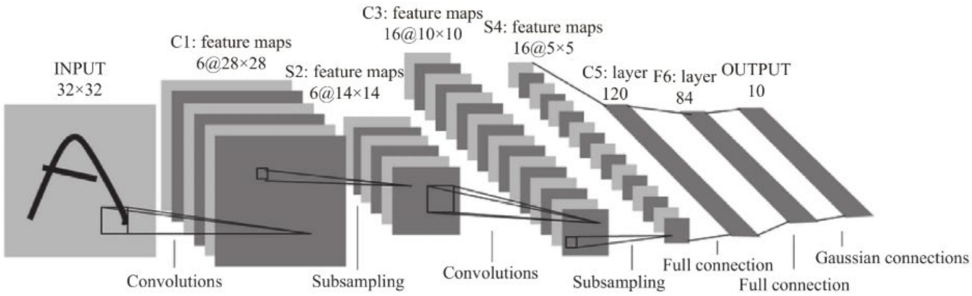

Figure 4: Multi convolutional layer neural network training optimization layer

4. Experimental verification

In this study, Pytorch deep learning framework was adopted, and experimental data were obtained through the Chinese medicinal plant database. A preliminary collection of 3 000 picture samples containing 30 kinds of diseases and pests of Chinese medicinal materials was used as the data set. To ensure the reliability and generalization of the verification results. In this paper, a cross-validation method was used to divide the labeled TCM pest and disease data set into k subsets of similar size, usually with a k value of 5 or 10. Each subset contains roughly the same proportion of samples of the dataset to ensure that each subset is representative. Then, the study takes one of the k subsets as the test set, and the rest K-1 subsets as the training set. In each round, the model was trained using the training set, using the adjusted network parameters and learning rate to maximize the diversity of TCM pests and diseases. The Batch Size of the model training was set to 20, and the training rounds were set to 400. The learning rate setting adopts piecewise constant attenuation learning rate, that is, the learning rate will gradually decrease with the increase of training rounds, so that the setting of model parameters can be optimized in the later stage of model training. Set the initial learning rate to 0.0001 and decay to a constant learning rate for each stage.

The training set is input to MobileNetV3 network for supervised training, and the detection effect of the model is evaluated. The nonlinear property of the activation function enables the neural network to approximate and fit the complex nonlinear relationship, which makes it have more powerful representation ability. Secondly, the activation function introduces nonlinear transformation, so that the neural network can better capture and learn the abstract features in the data. In this paper, two activation functions, Swish and ReLU, are selected for effect comparison, as shown in Table 1.

Table 1: Comparison table of activation functions

Activation function	Lost value	Accuracy rate /%
Swish	0.1764	97.743
ReLU	0.1532	98.681

It can be seen from the above that the accuracy of activation function ReLU is higher than that of Swish, and the loss value is 0.0232 lower than that of Swish activation function. The lower the loss value is, the better the experimental effect will be. Therefore, ReLU is selected as the activation function of the pest recognition model for training.

In order to verify the recognition algorithm of the intelligent pest control system of Chinese medicinal materials, a large number of images including normal plants and plants affected by pests and diseases were collected and accurately labeled during the data collection stage. Through data preprocessing, image enhancement technology is applied to rotate, scale and flip the data set to improve the adaptability of the model to diversity. The data set is divided into 80% training set and 20% validation set to ensure the effectiveness of training and evaluation. In the model selection and adjustment stage, the research adopted YOLOv8 as the basic model and set Eporch to 300 to avoid overfitting in the training of the model. Accuracy, precision, recall, and F1 scores on the validation set are monitored, the learning rate is attenuated by piecewise constants, and the lot size and number of layers are adjusted for optimal performance. After repeated training and verification, the model reached the expected high accuracy and robustness in identifying pests and diseases, and the accuracy rate exceeded 95% when the number of iterations reached 50 times. At the same time, transfer learning technology and Tansorflow2.0 deep learning framework are used to reconstruct and fine-turn the output layer of MobileNet-V3, ensuring that the Frames Per Second (FPS) of the model are not less than 50(detection time is 0.02s). At the same time, algorithm optimization was carried out to improve the accuracy of the system algorithm to more than 97%, as shown in Figure 5 and Figure 6.

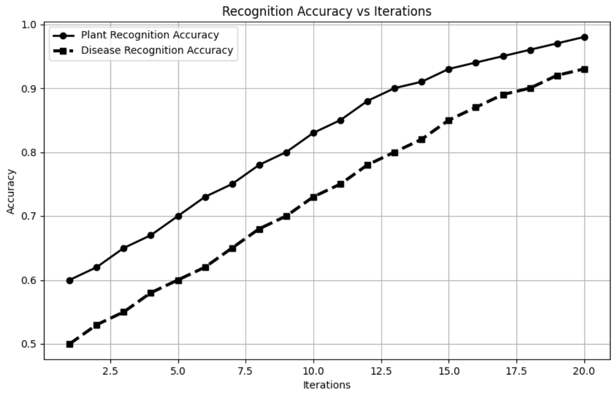

Figure 5: Accuracy curve of model disease identification

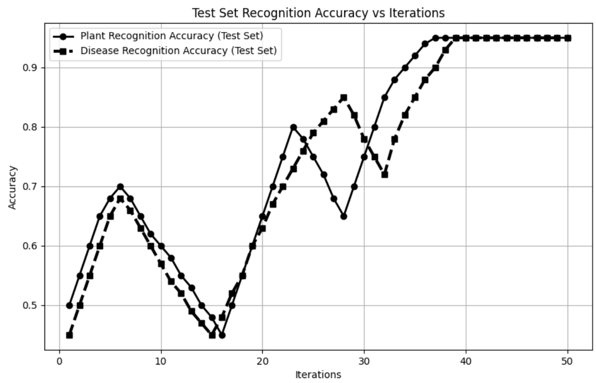

Figure 6: Accuracy curve of disease and pest identification in the test set

5. Conclusions

In view of the low efficiency and low application rate of AI technology in the current Chinese herbal medicine treatment industry, this paper proposes an intelligent disease and pest management system based on the combination of deep learning technology and unmanned aerial vehicle (UAV). The UAV scans diseases and pests to achieve automatic spray management and disease and pest data analysis, so as to achieve prevention effect. Through the comprehensive verification and performance evaluation of the detection system for diseases and pests of Chinese medicinal materials, the mobile terminal, the web terminal and the drone terminal all performed well in their respective performance indicators, the system's cooperative work stability reached 92%, the management efficiency was improved by about 95.14% compared with manual work, and the response ability and practicability of the system could meet the needs of more than 98% of growers. This provides a set of advanced and efficient pest control solutions for the Chinese herbal medicine planting industry, and provides strong support for further optimization of the system and expansion of application fields in the future.

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