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Application of image recognition technology based on deep learning in plants disease detection and diagnosis

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Abstract. With increasing demographic trends, the world will likely confront a looming food crisis in the coming decades. This paper points out the world's food crisis brought by the increasing population and the agricultural sector's challenges. Among them, the increase in plant diseases is considered one of the leading causes of agricultural inefficiency and food production problems. For example, in many countries, cash crops such as jute, pomegranate, and tomato have been severely affected by plant diseases, resulting in reduced yields and, thus, increased economic losses. Traditional disease detection methods, such as manual visual inspection and laboratory analysis, are inaccurate and time-consuming, requiring a lot of manpower and capital investment. In recent years, researchers have begun to apply deep learning-based image recognition technology to detect and diagnose plant diseases to improve accuracy and efficiency. This paper will lay the foundation for further research by summarizing the existing research and analyzing the advantages and applicability of different application methods.

Keywords: plants disease detection, image recognition technology, image recognition technology.

1. Introduction

The world will face the food crisis problem in the face of increasing demographic trends. It can be said that the agricultural sector is struggling to support the rapidly growing population. However, in many agricultural countries, the efficiency of agricultural production is still not high, and the problem of food production is still unresolved. One of the main reasons for this phenomenon is the increasing number of plant diseases [1-4]. To give some examples of what is happening worldwide, in the world's major jute producing countries, such as Bangladesh, Myanmar, India, etc., jute leaf Mosaic is widespread in these countries, in turn, has an impact on the production output of the key cash crop, thereby influencing its overall yield [2]. Pomegranate holds significant importance as a fruit crop in India, but in recent years, farmers have encountered huge problems in cultivating pomegranate. In the early stage of planting pomegranates, their plants are easily infected by plant pathogens, infecting the fruit and decreasing yield [3]. Many kinds of tomato diseases in China have seriously affected the yield and quality of tomatoes and caused great economic losses to China [5]. Of course, the same is true of "plentiful" plants that people often come into contact with daily, such as apple plants [6].

Plant diseases have caused huge economic losses to agriculture. At present, it is impossible to avoid plant diseases, and it is only possible to rely on plant disease detection and diagnosis to help farmers identify plant diseases early, which can reduce crop losses and thus reduce economic losses.

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In fact, at present, the identification of plant diseases is mostly done by manual visual inspection or laboratory sampling analysis. Manual visual methods tend to make wrong judgments and require more human resources, laboratory analysis takes too long, and there is no way to reflect its timeliness [1]. However, these techniques come at a high financial cost to farmers [4]. In order to recognize plant diseases, researchers have recently developed picture recognition software based on deep learning, which can detect plant diseases more accurately and reduce the workload of detection.

The following paper analyzes some application examples of image recognition technology based on deep learning in plants disease detection and diagnosis through examples. Analyze what their experiments did and what results they got. At present, there are few articles about this kind of review. This paper will summarize the experiments and analyze the excellence and universality of each application through the review study, to lay the foundation for further research in the future.

2. Applications in plant disease detection and diagnosis

The studies that follow in this article makes use of various image processing and machine learning techniques to identify and categorize diseases. Common methods include convolutional neural networks (CNN), YOLO (You Only Look Once), Fast RCNN, etc. Each approach has its specific advantages and applicability.

2.1. Former cases

Chau Chung Song et al. did a study on the automatic identification and visual recognition of citrus illnesses,the researchers utilized the YOLOv4 model to accurately identify and classify citrus leaf diseases by showing the The location of the disease is displayed on the image. YOLO v4 is characterized by using PANet to extract image features, which takes advantage of FPN's top-down advantages while adding a bottom-up path that helps shorten the path.The algorithm achieved an impressive accuracy of 95.4% on the test set, which consisted of 885 images . The PANet structure is shown in Figure 1 [1].

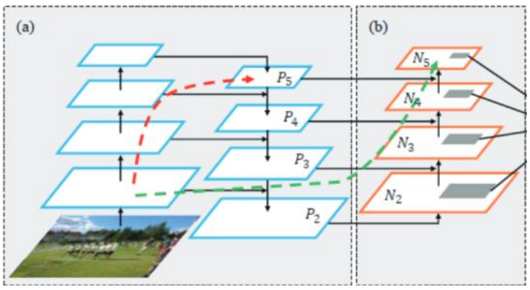

Figure 1. PANet structure [1].

In the study of image classification and recognition of jute diseases by Md. Zahid Hasan and his co-authors. They collected a dataset of 600 images and employed Convolutional Neural Network technology to train their model for disease recognition in jute plants. Their study considered 99 iterations to train the CNN model. This study used image flipping, rotation, and scaling techniques, and it was helpful to mention that if the rotation factor is plus or minus 0.5, the black background in the image will be visible. A maximum validation accuracy of 96% and a minimum validation loss of 4% were attained by the model [2].

The plant disease detection method involved in all the research in this paper has practical application value for farmers and plant management, which can help detect diseases in advance and take corresponding preventive measures to reduce losses and increase crop yield. For example, the experiments mentioned below focus on preventing plant diseases. In Sharath D M and his co-authors' study on detecting pomegranate leaf blight disease, in nearly 400 sample pictures, the researchers divided the pictures. Then they carried out edge detection by canny algorithm after segmentation to determine whether there was an infection in the images by comparing the processed pictures. The sensation is then rated by the percentage of the infection degree in the picture, and preventive measures

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can be taken against the plant when the infection is in an early stage [3]. These researchers plan to develop a user-friendly application allowing farmers to easily identify diseases.

In a study by Veni S and his co-authors on leaf recognition by retrieving content maps. The proposed work successfully developed a method for identifying and detecting leaf diseases efficiently. This approach offers a faster and more accurate solution for classifying leaf diseases. The researchers also conducted a comparative study on disease classification using SVM and KNN algorithms. The results showed that SVM outperformed KNN in accuracy and precision [4]. The accuracy and performance evaluation metrics used in the studies also varied. Some studies reported accuracy, detection accuracy, and validation loss, while others reported measures such as overall accuracy, sensitivity, or accuracy. In this study, CBIR processing process is adopted, Figure 2 depicts the process flow of the Content-Based Image Retrieval (CBIR) model [4].

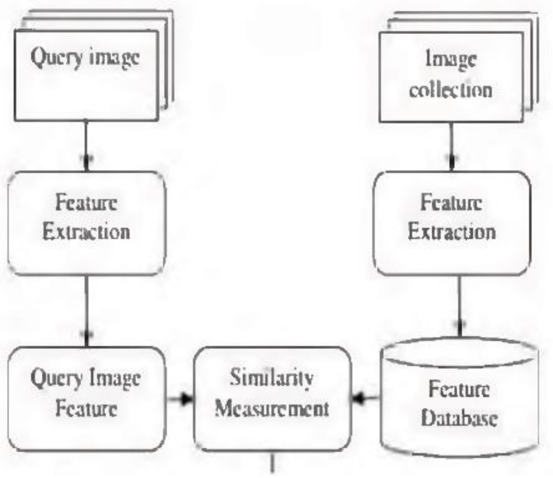

Figure 2. The process flow of CBIR model [4].

These studies used data sets of different sizes and sources. Some studies have used hundreds or thousands of real images, while others have used comparison experiments or images collected from the Internet.Qimei Wang and her co-authors' study on the identification of tomato diseases using the fast RCNN method collected 207 images of tomatoes on the Internet, divided them into seven kinds of tomato fruits, and then expanded to 1035 images by other means. The training times in the experiment were 70,000 times. Finally, they tried three models, and the comprehensive performance of resnet101 was the best, with a comprehensive accuracy of 90.87% [5].

2.2. The succeeding case

Combined with the above research, the target plants and disease types differed in these studies. Some studies focus on disease detection in specific plants such as citrus, eggplant, and pomegranate, while others involve the identification of multiple leaf diseases. Then moves on the next couple of case studies. In the study of improved segmentation method for plant disease detection by Md Arifur Rahman and his co-authors, the method based on deep learning neural network model they used has an accuracy of up to 99.25% in the experiment. At the same time, the common k-mean clustering segmentation method was set for data comparison, and their proposed method performed better in the same experimental environment [7]. This section wants to draw your attention to the deep learning neural network model depicted in Figure 3. It demonstrates the connectivity between a single neuron in each layer and all other neurons in the subsequent layer.

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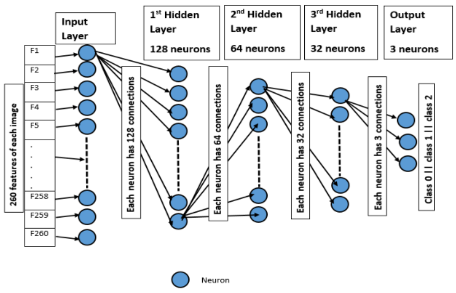

Figure 3. Deep learning neural network model [7].

Then, in the study of Nikhitha M and his co-authors, using Inception v3 model, image processing,and transfer learning, they proposed to find out what percentage of fruits were affected in a given image and identify fruits, mainly by using fruit confidence. It is helpful for fruit disease detection [8]. It is important to note that the Inception v3 model is a pre-trained convolutional neural network widely used for image recognition purposes. It consists of 28 layers or floors. In addition, researchers employed transfer learning by reusing a pre-trained Inception model and only modifying the last grouped layers. This technique allows adapting a model for a specific task without altering or replacing the initial model's lower layers. Consequently, only the outer layer requires modification in transfer learning [8].

In the study by Kirti et al., the researchers investigated the detection of grape black rot using Support Vector Machine (SVM). They analyzed the data using three kernel functions: linear, RBF (Radial Basis Function), and polynomial. The results demonstrated that their method successfully detected the disease. Interestingly, the data indicated that the RBF kernel function of SVM yielded the best system performance [9]. In their image dataset, there were a total of 400 images. Of these, 250 images were used for training, while 150 were used for testing. Afterward, the feature vectors generated from the images were subjected to processing during the classification stage. To analyze the data, the researchers employed Support Vector Machine (SVM) for classification. They utilized three different kernel functions of SVM: linear, RBF, and polynomial kernel functions [9].

In the study by Rahamathunnisa U et al., The researchers explored the application of K-means clustering and Support Vector Machine (SVM) algorithms for vegetable disease detection. During the experiment, the researchers utilized the k-means clustering algorithm for image segmentation of the preprocessed images. Subsequently, morphological features, including color, shape, and size, were extracted from the segmented images. These extracted features were then employed in conjunction with SVM for classification purposes. They focused on using SVM for supervised learning to classify images into two categories. The SVM training algorithm effectively assigns new examples to a class, showcasing its strong performance [10].

In the study conducted by Abirami Devaraj et al., they explored the application of image-processing technology in identifying plant diseases. Specifically, MATLAB image processing technology was employed to automatically detect four diseases: alternispora, anthracnose, white leaf blight, and tail leaf spot. The process involved image loading, preprocessing, segmentation, feature extraction, and classification. The development of automated detection systems utilizing advanced technologies like image processing greatly benefits farmers by enabling early identification and providing valuable data for disease management [citation needed][11].

2.3. Preliminary synopsis

Although these studies differ in target plants, disease types, methods, and data sets, the common denominator is that they apply advanced image processing and machine learning techniques, which have made significant progress in plant disease detection and identification. These methods provide farmers with faster and more accurate agricultural disease detection and important decision support.

3. Conclusion

This paper presents instances of recent use of deep learning-based image recognition technology to identify and diagnose plant diseases. It examines various application approaches' precision, contribution, benefits, and suitability, establishing a basis for future research.

Based on the main findings and derived conclusions of these studies, the application of image processing and machine learning in the detection of plant diseases holds significant potential for the advancement of agriculture. The findings of these studies provide farmers with new tools and methods to better manage plant diseases and help secure and improve crop yields and quality. In future studies, relevant researchers can further develop the following aspects:

1. Richness and diversity of data sets: In future studies, more plant disease images can be collected and a wide coverage and diversity of data sets can be ensured. Enhancing the model's generalization performance will not only facilitate the application of image processing and machine learning techniques to a broader range of plant and disease types but also contribute to the overall progress in this field.

2. Integration and optimization of methods: Future research could explore integrating and optimizing different image processing and machine learning methods. By using a combination of methods, the accuracy and robustness of disease detection can be further improved in response to different geographical and environmental conditions.

3. System usability and deployability: Researchers can place emphasis on converting image processing and machine learning techniques into practical and usable systems for disease detection. This requires consideration of various challenges in the actual field environment, including low light conditions, image quality issues, and computational resource constraints. Therefore, future research should focus on how these technologies can be applied to actual farms, taking into account farmer acceptability and sustainability.

Integration with agricultural management systems: Besides disease detection, future research may consider integrating these technologies with agricultural management systems. By combining disease detection results with other farm information, such as weather data and soil conditions, more comprehensive agricultural decision support can help farmers achieve precision farming and sustainable development.

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