ITM Web of Conferences **54**, 01014 (2023) https://doi.org/10.1051/itmconf/20235401014
I3CS-2023

Applications of CNN in leaf diseases: a critical survey

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Abstract. Crop diseases can significantly impact crop yield and overall productivity, posing challenges for farmers in increasing output and market prices. Early detection of these diseases is crucial for preventing further spread and reducing their impact. To overcome this, researchers have utilized image processing technology, including deep learning techniques such as convolutional neural networks (CNNs), to detect crop diseases. In this critical survey, we provide a comprehensive review of recent studies and developments in the use of CNNs for identifying leaf diseases in agricultural plants. We discuss the benefits and drawbacks of different deep learning techniques and image processing methods for disease diagnosis and management in agriculture. Our research highlights the potential of CNNs and deep learning to significantly advance the field of agricultural research and development. We also analyze the factors affecting the outcomes of each technique, including the accuracy, precision. Our study emphasizes the need for further research and development to optimize the use of CNNs in agricultural applications, particularly for improving disease management and crop productivity.

1 Introduction

This paper aims to explore the use of deep learning and convolutional neural networks (CNNs) for the identification of leaf diseases in agricultural plants. The goal of this research is to provide a comprehensive review of the most recent findings and developments in the area, as well as to discuss the various methods and procedures employed for disease identification. By highlighting the potential of deep learning and CNNs to significantly advance the field of agricultural research and development, our tests also aim to identify the advantages and disadvantages of adopting these techniques.

2 How CNN is useful in solving leaf diseases

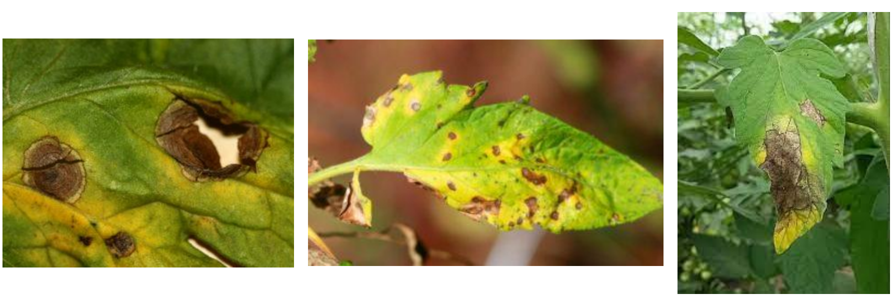
CNN have emerged as a potent approach for addressing the issue of leaf disease. These diseases often show unique symptoms that can be captured and CNN can be trained to accurately identify these patterns. Image classification is a primary application of CNNs in this domain. The network may be trained to distinguish between healthy and diseased leaves depending on how they appear, allowing early detection and effective treatment. This can enhance overall disease management efforts and contribute in preventing the disease's spread.

In comparison to more conventional techniques, CNNs provide several advantages for identifying leaf diseases. For instance, CNNs are particularly suited for real-time diagnosis because they can quickly and efficiently analyse massive amounts of data. CNNs may also be used to process images of various sizes, resolutions, and quality because they are very scalable. This enables analysis of a greater variety of images and a more precise diagnosis.

3 Different leaf diseases

3.1Tomato Leaf

The fungus Phytophthora infestans is the source of late blight, one of the most prevalent illnesses afflicting tomato plants. This disease results in leaf and stem lesions that are black and wet, which can quickly spread to the fruit and cause rot and plant death. Cool, humid weather is ideal for late blight, which can significantly affect tomato crops, especially in areas with high rainfall. Early blight, which is a frequent disease affecting tomato plants and is brought on by the fungus Alternaria solani. This infection results in cirrhotic, dark brown lesions on the stem and leaves that might grow and cause the plant to lose its leaves. Warm, humid weather is ideal for early blight, which can spread quickly in the field.



(a) Early blight (b) Septoria leaf spot (c) Late blight

Fig. 1: Sample images of Tomato leaf diseases

Kumar et al. (2019) proposes a method for the detection of tomato leaf diseases using image processing techniques. The authors utilized three different classifiers, including Support Vector Machine (SVM), Decision Tree, and Random Forest, to classify the images into different classes based on the presence of diseases. The authors reported an accuracy of up to 94% with the SVM classifier

Agarwal et al. (2020) propose a CNN architecture that can classify tomato leaves into six different classes of diseases, including early blight, late blight, and leaf mold. They then trained the CNN model using this dataset and evaluated its performance using metrics such as accuracy, precision, recall, and F1 score. The authors also compare their approach with other state-of-the-art deep learning models and show that their model is superior in terms of accuracy and computational efficiency.

3.2 Potato Leaf

Late blight, which is brought on by the fungus Phytophthora infestans, is one of the most prevalent diseases that harm potato leaves. This illness results in black, wet sores on the leaves and stems that can quickly spread to the tubers, causing rot and the eventual death of the plant. Cool and humid weather favours late blight, which can have a major influence on potato yields. Early blight, which is brought on by the fungus Alternaria solani, is another prevalent disease that affects potato leaves. This illness results in cirrhotic, dark brown lesions on the stems and leaves that might grow and cause the plant to lose its leaves. Warm and muggy weather favour early blight, which spreads quickly in the field.

(a) Alternaria (b) Black dot

Fig. 2: Sample images of Potato leaf diseases

Tiwari et al.(2020) used a pre-trained VGG16 model to extract features from the input images, followed by a custom-built classifier to classify the disease. The dataset used in the study consists of 400 images of healthy and diseased potato leaves, including early blight, late blight, and healthy leaves.

Rashid et al. (2021) proposed model consists of three levels, including the feature extraction level, feature fusion level, and classification level. The authors used transfer learning with pre-trained models such as VGG16, VGG19, ResNet50, and InceptionV3 to extract features from the input images. The proposed model was evaluated on a publicly available potato leaf disease dataset and achieved an accuracy of 98.1%, which outperforms several existing methods.

3.3 Tea Leaf

Tea plants are also vulnerable to a number of additional ailments, such as tea rust, tea stem rot, and tea wilt, which can manifest as leaf yellowing, decay in the stem and roots, and plant mortality. These diseases, which can be brought on by fungi, bacteria, or viruses, can significantly affect the production of tea. Tea anthracnose is one of the most prevalent ailments that infect tea leaves and is brought on by the fungus Colletotrichum theae. This disease results in tiny, dark brown spots on the leaves that can grow and cause the plant to become defoliated. Tea mosaic disease, which is a common ailment affecting tea leaves, is brought on by a virus. Along with stunted growth and lower yields, this disease results in the mottling and yellowing of the leaves.

(a) Red rust (b) Blister blight

Fig. 3: Sample images of Tea leaf diseases

Mukhopadhyay et al.(2021) developed a novel algorithm called Multi-objective Segmented Mean Shift (MOSMS) for segmentation of tea leaf images. This algorithm is based on the Mean Shift algorithm and uses multiple objectives such as color, texture, and shape to segment the image. They used Support Vector Machine (SVM) and Random Forest (RF) classifiers for this purpose and achieved an overall accuracy of 98.3% using the SVM classifier.

Gayathri et al. (2020) used a dataset consisting of 5000 tea leaf images, which includes healthy leaves and leaves infected with four different types of diseases. They have used the VGG16 architecture for feature extraction and classification, and the model is trained using the transfer learning technique. The authors have also discussed the limitations and future scope of their work, such as the need for a larger and diverse dataset, and the possibility of using other deep learning architectures.

3.4 Maize Leaf

Northern leaf blight, which is brought on by the fungus Exserohilum turcicum, is a disease that affects maize leaves. Long, oval, tan to brown lesions on the leaves caused by this disease can defoliate the leaves and impair yield. Warm, humid weather is ideal for northern leaf blight, which can seriously harm maize harvests in areas with considerable rainfall. Grey leaf spot, a disease brought on by the fungus

Cercospora zeae-maydis, is another prevalent condition that affects maize leaves. Small, circular, grey to brown spots appear on the leaves because of this disease. These spots might get larger and result in defoliation. Warm, humid weather is ideal for grey leaf spot, which can significantly reduce maize yield.

(a) leaf blight (b) Gray leaf spot

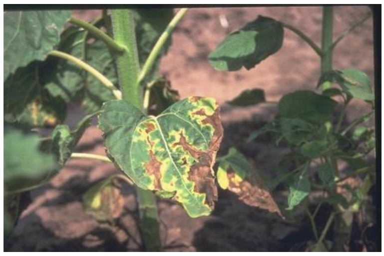
Fig. 4: Sample images of Maize leaf diseases

Panigrahi et al. (2020) proposed a machine learning-based approach for the detection and classification of maize leaf diseases. They extracted features from the images using pre-trained convolutional neural networks (CNNs) and trained machine learning classifiers, namely, support vector machine (SVM), random forest (RF), and k-nearest neighbor (KNN) classifiers. The authors compared the performance of these classifiers and found that SVM outperformed the other two classifiers in terms of accuracy. The proposed approach achieved an overall accuracy of 93.3% in detecting and classifying maize leaf diseases.

Akanksha et al. (2021) proposes a maize disease detection system based on optimized probabilistic neural network (OPNN). The system uses leaf images for disease identification and utilizes pre-processing techniques such as normalization, segmentation, and feature extraction to enhance image quality. The extracted features are used to train and test the OPNN model for classification of different maize plant diseases. The results showed that the proposed OPNN model achieved high accuracy in detecting and classifying different maize plant diseases.

3.5 Cotton Leaf

Verticillium wilt, which affects cotton leaves, is brought on by the fungus Verticillium dahliae and V. albo-atrum. This disease can result in decreased yields and plant death by causing the leaves to yellow, wilt, and die. Warm, humid weather is favourable for verticillium wilt. Fusarium wilt, which is also frequently found to harm cotton leaves, is brought on by the fungus Fusarium oxysporum. In addition to restricted development and lower yields, this disease causes the leaves to yellow and wilt. Warm, humid weather is ideal for fusarium wilt, which can significantly reduce cotton yield.



(a) Verticillium wilt

(b) Verticillium dahliae

Fig. 5: Sample images of Cotton leaf diseases

Manavalan et al. (2022) discusses the various types of cotton diseases and their symptoms.The paper then delves into the various intelligent approaches used for cotton disease detection, such as computer vision, machine learning, deep learning, and artificial intelligence. the author concludes by highlighting the need for further research to overcome the limitations and to develop accurate and efficient intelligent approaches for cotton disease detection.

Kumbhar et al. (2019) focuses on the four most common cotton leaf diseases, namely, Alternaria leaf spot, bacterial blight, leaf curl disease, and grey mildew. The pre-processing phase uses the VGG-16 model to extract features. The authors use transfer learning to retrain the last layer of the VGG-16 model with the cotton leaf dataset. The classification phase uses a CNN model to classify the cotton leaf images into the four disease categories.

Table 1: Summary of leaf diseases in various plants

S.No	Crop	Disease	Method	Advantages	Disadvantages
1	Tomato	Early blight	CNN	High accuracy, non-invasive	Requires large dataset, computationally expensive
2	Tomato	Late blight	SVM	Fast, simple	Limited accuracy, may require feature engineering
3	Potato	Late blight	Deep Belief Network (DBN)	High accuracy, robust to noise	Computationally expensive, requires large dataset
4	Potato	Early blight	Random Forest	Fast, simple	Limited accuracy, may require feature engineering

5	Rice	Rice blast	CNN	High accuracy, non-invasive	Requires large dataset, computationally expensive
6	Rice	Bacterial blight	Random Forest	Fast, simple	May require feature engineering
7	Rice	Sheath blight	SVM	Fast, simple	May require feature engineering
8	Rice	Brown spot	CNN	High accuracy, non-invasive	Requires large dataset, computationally expensive
9	Rice	Leaf folder	Decision Tree	Fast, simple	May require feature engineering
10	Maize	Gray leaf spot	CNN	High accuracy, non-invasive	Requires large dataset, computationally expensive
11	Apple	Apple scab	CNN	High accuracy, early detection and timely treatment	High computational power required
12	Apple	Fire blight	SVM	Good performance, less prone to overfitting	Requires more domain knowledge and feature engineering
13	Apple	Powdery mildew	CNN	Non-invasive, high accuracy, can detect the disease in advance	Requires large datasets and computational resources
14	Apple	Cedar apple rust	Random Forest	Handles missing data well, reduces overfitting	May not perform well on complex data
15	Grape	Black rot	CNN	High accuracy, early detection	High computational power required

16	Grape	Downy mildew	CNN	Non-invasive, high accuracy, can detect the disease in advance	Requires large datasets and computational resources
17	Grape	Powdery mildew	SVM	Good performance, less prone to overfitting	Requires more domain knowledge and feature engineering
18	Grape	Grapevine leafroll-associated virus 3	Decision Tree	Simple and easy to interpret, handles irrelevant features	May not perform well on complex data
19	Cotton	Fusarium wilt	CNN	High accuracy, early detection and timely treatment	High computational power required
20	Cotton	Verticillium wilt	Random Forest	Handles missing data well, reduces overfitting	May not perform well on complex data
21	Cotton	Bacterial blight	SVM	Good performance, less prone to overfitting	Requires more domain knowledge and feature engineering
22	Tea	Red blister	CNN	High accuracy, can detect at early stages	Requires large dataset

4 Conclusion

The main goal of this research is to examine various CNN approaches that are frequently used to predict plant diseases and to determine how these techniques could be improved in the future to provide disease prediction systems that are more accurate, resilient, and affordable. It is verified that CNN's classification accuracy was greatly improved by using a different training technique. This study helps to identity different models of CNN to predict the disease. Several studies have shown that CNNs have a high accuracy in detecting leaf diseases and classifying them into various categories. These results demonstrate the efficacy of CNNs in predicting plant leaf diseases and their superiority over other machine learning methods.

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