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A Survey on Plant Leaf Disease Detection Using Image Classification Techniques

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ABSTRACT

As the world's population grows, so does the need for food, which must be met while safeguarding crops from various deadly illnesses. Plant disease detection has traditionally been done by farmers and plant pathologists using experience-based research. The old approach is complicated, time-consuming, and erroneous at times, leading to major agricultural economic loss. Later, other research in the field of plant disease diagnosis used machine learning, but the results were not promising and the results were too sluggish for practical application. Convolution Neural Networks, as compared to machine learning, have lately made great strides in the field of computer vision thanks to features like automatic feature extraction and the capacity to quickly and effectively provide results with little datasets. This article discusses the challenges in identifying plant leaf diseases and makes an effort to address the problem of inaccurate and time-consuming disease detection and classification by reviewing numerous state-of-the-art approaches and algorithms that are being used to address the issue.

KEYWORDS: D L, Machine Learning ,CNN,PlantPathology, ANN, Classification, Detection, Image Processing.

1. INTRODUCTION

Every developing nation relies heavily on agriculture, and as the population increases, so must agricultural productivity. Optimizing output from current manufacturing is the least that can be done. On the other hand, plant diseases can injure any part of the plant, including the seed, stem, root, flowers, fruits, and leaves. As a result, they tend to reduce output quality and quantity. Two conventional methods for plant disease detection are now in use: manual diagnosis of plants by farmers or plant pathologists, who typically use their experience-based studies to identify plant disease. These methods are frequently time-consuming, inaccurate, and lead to the improper application of herbicides and fertilizers, which can worsen crop damage.

Image processing, Deep learning, and Machine learning are all current hot subjects with applications in almost every industry. And using them in agriculture has the potential to have a significant influence on the sector. These technologies have helped in pattern recognition, object identification, and categorization.Complex image processing techniques are required because features must be explicitly provided to the models in machine learning.[15]Deep learning is therefore becoming one of the most promising technologies that may be used for a range of image-based activities. Deep learning can extract features and learn features only from input, and it also imitates the neuronal structure of the human brain. CNN, a more sophisticated variant of ANN, takes leaf images as input. CNN can handle difficult computational and data preparation procedures. CNN generates impressive outcomes using images as the input data.

- Leaf diseases are categorized using a variety of classification technologies..
- Future work has been suggested to fill the research gap.

The structure of this essay is as follows:

2. CLASSIFICATIONOFPLANTDISEASES

Various diseases can damage plants at any moment during their lives, from seed planting to harvesting.
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offers several cutting-edge algorithms that may help us classify cropped photographs into various groups.A subset of machine learning called "deep learning"

A. Contribution

Clearly and systematically, this review summarizes the various studies and research that have been conducted in the field of plant pathology.

II is focused on the categorization of plant diseases.

The literature review in Section IV gives an overview of the numerous studies that have been done in this field. Section V outlines the different difficulties found in the publications under study as well as potential future research paths.

Pathogen proliferation is aided by a variety of biotic and abiotic causes. Fungi, bacteria, viruses, oomycetes, viroid's, nematodes, protozoa, and parasitic organisms are all examples of infectious organisms or pathogens

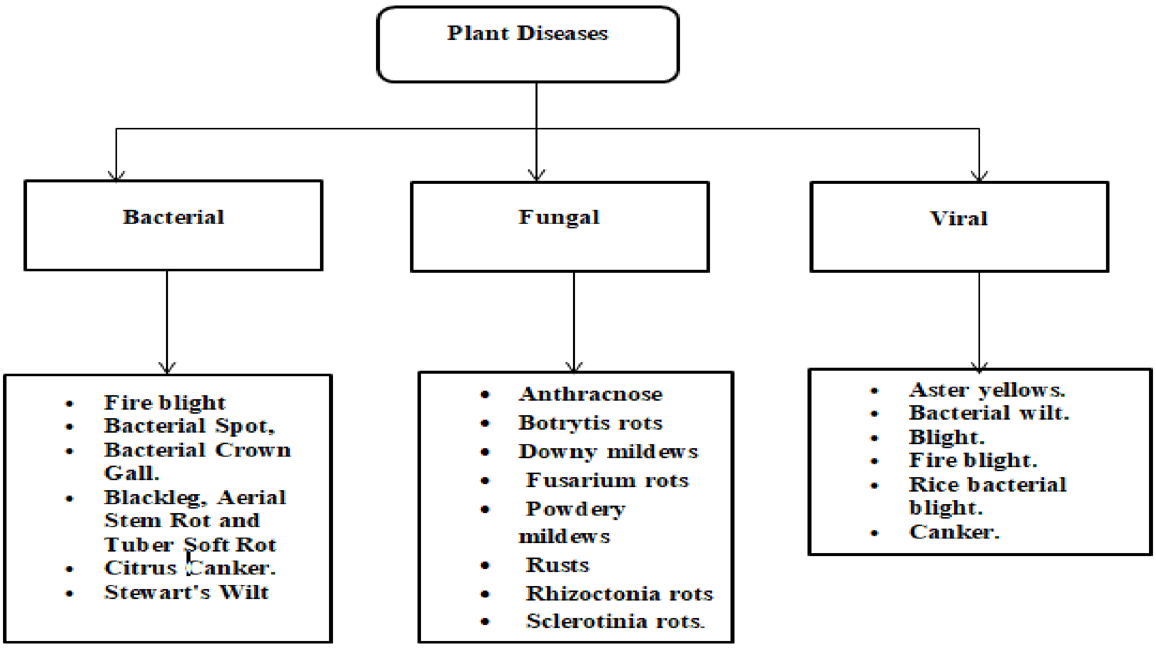

Fig.2:ClassificationofPlantDiseases

Bacterial, viral, and fungal illnesses are the most frequent, as seen in Fig.2. The study of plant diseases brought on by harmful microorganisms and aided by particular environmental variables is known as plant pathology. It also involves controlling plant diseases and identifying pathogens.

Fig.2 divides plant illnesses into three categories: bacterial, fungal, and viral diseases, as well as the numerous names of diseases that fall into each category. Some of these disorders are depicted in Fig.3 [25], along with their images, to aid us in visually distinguishing between them.

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Fig.3. Various types of plant diseases [25]

3. LITERATURE REVIEW:

In [1] an IoT-enabled leaf wetness sensor (LWS) and soil moisture sensor (SMS) are created in this research. In addition, the aforementioned sensors, as well as an in-house designed IoT-enabled system, have been deployed in the field for around four months. On the mango plant, we looked at Powdery mildew (D1), Anthracnose (D2), and Root rot (D3) diseases. Furthermore, researchers have created the Long Short Term Memory (LSTM) network, which outperforms the present plant disease control systems. The proposed network obtains a 96 percent accuracy, precision-recall, and F1 score of 97 percent, 98 percent, and 99 percent, respectively, for accuracy, precision-recall, and F1.

The author of [2] suggest a method for learning orchard geometry characteristics from UAV photos and using them to enhance plantation row recognition. To segment planting rows in RGB pictures, we first train a detection encoder-decoder network (DetED). We next use labeled data to train an encoder-decoder correction network (colored), which learns to convert binary masks with misleading row segmentation geometries into corrected ones. Finally, the CorrED network is used to correct geometric errors in DetED results. The suggested CorrED post-processing can recover missing portions of plantation rows and increase detection accuracy in testing data, according to our experiences with commercial orange tree plantations.

In [3] an integrated method is employed in this study to propose a convolutional neural networks (CNNs) model. The suggested CNN model aims to distinguish healthy fruits and leaves from those suffering from common citrus illnesses including black spot, canker, scab, greening, and Melanosis. By combining several layers, the proposed CNN model captures complementing discriminative characteristics. On the Citrus and PlantVillage datasets, the CNN model was compared to several state-of-the-art deep learning models. The CNN Model surpasses the competition in a range of measuring criteria, according to the findings of the experiments. The CNN Model has a test accuracy of 94.55 percent, making it a useful decision support tool for citrus fruit/leaf disease classification.

In [4] the categorization of illnesses (powdery mildew, anthracnose, rust, and root rot/leaf blight), a multi-layered perceptron model is utilized, which not only successfully identifies plant diseases but may also dramatically enhance productivity. The suggested method includes three key steps: dataset pre-processing, exploratory data analysis, and detection. To begin, the soil sensors system at Sardarkru Srinagar Dantiwada

Agricultural University in Gujarat, India, captures real-time data, as well as satellite data for other micro-meteorological parameters. The acquired data was then subjected to a thorough exploratory data analysis to get new insights. Plant diseases were predicted using a machine learning algorithm. The average accuracy in forecasting each illness was found to be over 98 percent in the testing findings.

The author of [5] suggested the gold-standard polymerase chain reaction technique used to evaluate leaves from 62 plants for viral infection in this study. Hypothesis testing was performed using a commercial E-Nose system, the Alpha MOS Fox 3000, which yielded a random forest classifier accuracy of 95.30 percent. These findings were utilized to determine the most significant sensors and their target gases in response to the CTV infection, and they served as a foundation for selecting sensors for a bespoke prototype. The prototype was created using simulations to achieve the best airflow in the sensor chamber. With 99.36 percent and 97.58 percent accuracy, the bootstrap ensemble of k-nearest neighbors and the adaptive boost ensemble of the decision tree classifier discriminated the data generated from the prototype, respectively.

The study of [6] suggested six different types of popular models were trained to detect the severity of citrus HLB, to determine which kind of models are best for detecting HLB severity under identical training conditions. Due to its great computational efficiency and a minimal number of parameters, the Inception v3 model with epochsD60 may reach a better accuracy of 74.38 percent in the experiments. We also used DCGANs (Deep Convolutional Generative Adversarial Networks) to supplement the original training dataset up to two times its original size to see if GANs-based data augmentation may help enhance model learning performance. Finally, the Inception v3 model was trained using a new training dataset with 14,056 leaf pictures comprising the original training photos and the enhanced ones. As a consequence, we achieved a model learning accuracy of 92.60 percent, which is nearly 20% higher than the Inception v3 model trained using the original training dataset, implying that GANs-based data augmentation is particularly effective in improving model learning performance.

The automated detection and image recognition of citrus illnesses is provided, and it can assist farmers in locating and identifying the ailment from the photographs they have been given [7]. This technique uses the YOLO (You Only Look Once) algorithm, an object detection model, to find and identify illnesses in photos of citrus leaves. The sickness can be circled on the picture and video in real-time via YOLO. Images of citrus leaves with the illnesses citrus canker and citrus greening are included in the dataset.

The classification of diseased citrus leaf pictures into four classes—Black spot, Cancer, Greening, and Healthy—is accomplished using a CNN recognition model for citrus plant illnesses [8]. The Kaggle website was used to collect these datasets. The generated model has an accuracy of 95,6 percent, according to an analysis utilizing the 5-fold cross-validation on datasets of 600 picture data of citrus leaves. With an accuracy of 90.4%, this study's accuracy findings are superior to those of earlier research employing the M-SVM model and weight segmentation.

In this study[9] experts create a picture dataset of six types of citrus ailments and implement an intelligent diagnosis system for citrus diseases using simplified densely connected convolutional networks (DenseNet). The system is implemented on a mobile device using the We Chat applet, which allows users to contribute photographs and get diagnostic findings and comments. The experimental findings demonstrate that by simplifying the DenseNet structure, the recognition accuracy of citrus illnesses has increased to almost 88 percent, and the predicted time consumption has been decreased.

In [10] provides a deep learning method for the real-time identification of apple leaf diseases that is based on enhanced convolutional neural networks (CNNs). The apple leaf disease dataset (ALDD), which consists of complex photos captured in the field and in laboratories, is initially created in this study using data augmentation and image annotation techniques. On the basis of this, the GoogLeNet Inception structure and Rainbow concatenation are introduced, along with a novel deep-CNN-based model for the diagnosis of apple leaf disease. In the hold-out testing dataset, the proposed INAR-SSD (SSD with Inception module and Rainbow concatenation) model is trained to identify these five widespread apple leaf illnesses using a dataset of 26,377 pictures of sick apple leaves. According to the testing findings, the INAR-SSD model achieves a high detection speed of 23.13 FPS and a detection performance of 78.80 percent mAP on ALDD. The findings show that the innovative INAR-SSD model offers a high-performance approach for the early diagnosis of apple leaf illnesses and can identify these problems more quickly and accurately in real-time than earlier techniques.

The CNN model that was employed in [12] has been dubbed MCNN (Multilayer Convolutional Neural Network), which is being suggested for the categorization of mango tree leaves. MCNN is nothing more than a standard CNN model with Anthracnose, a fungal illness inspired by AlexNet architecture. It claims to be 97.13 percent accurate.

Researchers have employed the K-means clustering technique to group the photos of tomato illnesses in addition to identifying tomato diseases and detecting tomato leaf positions [13]. Based on the results, the anchors have been improved. For feature extraction, ResNet101 is employed. The findings show that the approach presented in this study has a greater detection rate than the original Faster R-CNN (Regions with Convolutional Neural Networks). The data is laboratory-based, however, the drawback is that just one leaf disease can be found in the image.

Using two upgraded deep convolutional neural network models, GoogLeNet and Ci-far10, the authors of [14] study on maize leaves have classified the leaves into 9 groups, with classification rates of 98.9 percent and 98.8 percent, respectively.

Verticillium wilt is a strawberry disease, and in [15] SVWDN based on Faster R-CNN has been proposed for determining whether a strawberry has the illness based on the monitored sections (i.e., leaves and petioles). 99.95 percent accuracy was attained. Faster R-CNN has performed well in object identification when compared to R-CNN, particularly in terms of improving the speed and accuracy of identifying tiny objects. Faster R-CNN has been employed as a baseline detector for high detection accuracy with few items that are present in the dataset. The authors built a dataset for strawberry verticillium wilt and claimed that they were the first to apply the technique to identify verticillium wilt on strawberries based on the many identified components.

According to the research of Ma et al. [20], the four diseases that affect cucumber leaves are leaf spots, anthracnose, powdery mildew, and downy mildew. The photos that make up the data were taken in real-time. The Deep Convolutional Neural Network (DCNN) for illness categorization is the name given by the authors to the suggested CNN model. DCNN is nothing more than the CNN model, which was inspired by the Lenet5 model, and is employed because it is effective and quick to deploy in applications requiring recognition of small-scale pictures.

In [16], two CNN models, AlexNet and GoogLeNet, were trained using a transfer learning strategy in one example and from scratch in the other. Using publicly accessible data with a total of 54, 306 pictures, Mohanty et al. evaluate 26 illnesses and 14 crop species. The model has a 99.35 percent accuracy rate. The model's accuracy increased to 31.4% when it was applied to internet sources with photos other than those used for training. This occurs as a result of the dataset's inclusion of photographs shot under well-controlled laboratory circumstances.

In [17], Ferentinos trained several CNNs, including Google, AlexNet, and VGG, using a database with 58 distinct combinations of plants and illnesses. With an accuracy of 99.53 percent, the VGG convolution neural network emerged as the most effective CNN design.

In [21], the authors developed a variety of CNNs for illness detection and classification, including VGG 16, Inception V4, ResNet, and DenseNets. The PlantVillage picture collection, which included 38 classes of plant illnesses and 14 classes of healthy plant photos, is being used. The DenseNets network outperformed the other networks in terms of outcomes, attaining a greater classification success while requiring less time to do so.

To overcome this issue, suggest a deep convolutional network-based technique. The fundamental concept is to create a 7-layer network structure, with the main goal being to extract the rich characteristics of citrus [19]. These traits are more accurate in identifying many types of illnesses than standard features, which might increase the identification rate. With an input layer, three convolutional layers, two fully connected layers, and one output layer, we suggest a unique network. A convolutional operation and a pooling operation are both included in the convolutional layer. When it comes to identifying citrus illnesses, the suggested approach works well. We do three sets of tests to demonstrate that our results are more accurate than those of two other widely used machine learning techniques. The suggested approach is successful in recognizing citrus illnesses, according to experiments, which provides strong technological support for accurate diagnosis and citrus disease prevention.

4. CHALLENGESAND FUTURE RESEARCH DIRECTIONS

Some points that have been observed that have a significant impact on the outcomes are given below, based on an analysis that has been conducted by reading various study papers:

A.Model over fitting

It is recommended to utilize vast and diverse datasets for better deep learning model training and to prevent over fitting and data imbalance issues. Different picture augmentation approaches have been employed to handle this issue of insufficient symptom diversity and data scarcity, including rotating, cropping, gray-scaling, and changing images pixel-by-pixel to become blurry, distorted, or mirrored [18], [24]. When typical data augmentation approaches are failing to significantly improve the results, generative adversarial networks (GANs) [12], [9] can be employed to alleviate the problem of a lack of pictures in the training data.

B. Collecting the Data

In this area of study, certain limitations have been noted. One of them, which significantly affects the outcomes, is the collection of images. Many of the datasets that are now available are mostly made up of photos that were taken in a controlled setting, as opposed to photographs that were captured and annotated in real-life situations. As a result, the model's practical application is less trustworthy because results obtained during testing and testing in real fields have significant discrepancies..

C. Multiple occurrences of disease on a leaf

Another issue that has to be addressed is that the proposed approaches are insufficiently accurate when numerous illnesses are present on a leaf or when leaves have multiple instances of disease. The unsatisfactory outcomes in the aforementioned situations open up a lot of possibilities for further investigation. All of these issues, including issues like photos with numerous leaves from various plants or several categories with complicated backgrounds, are being resolved by researchers utilizing deep neural network-based object recognition techniques. These algorithms produce accurate detection results, but they might potentially be better.

D. AvailabilityofDatasets

The dataset is extremely important in the domains of machine learning and deep learning. However, there is a scarcity of publicly available datasets in the field of plant pathology. Many researchers have used the PlantVillagedataset, however, the difficulty is that they only supply laboratory photographs, not real-world images. Fellow researchers should be able to contribute their expertise to improving agribusiness by making the dataset on which the research is based publicly available.

5. CONCLUSION

This study summarizes and examines a variety of deep learning algorithms for sorting plant leaves into disease groups. When compared to prior machine learning-based technologies, deep learning methods produce excellent outcomes. Transfer learning has been frequently utilized to increase model speed and accuracy. The approaches presented above demonstrate how deep learning technology may be a game-changer in plant pathology by automating, fast, and accurate disease analysis and optimizing agricultural production profitability. However, this field hasn't been sufficiently investigated, even though it offers a lot of potential for future study. However, the absence of standard, high-quality datasets is a significant drawback. Many articles have dealt with data imbalance and over-fitting issues, which have been overcome to some extent with the use of various data augmentation and image processing techniques, but the subject still requires more attention and better approaches to fix. Object identification algorithms, as well as CNN models, have the potential to pave the way for future studies. A future study might focus on adapting the models stated above to smartphone-based sickness diagnosis for real-world use by regular people, as well as a variety of crops and ailments that haven't been examined before.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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