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Analysis of Plant Disease Detection and Classification Models: A Computer Vision Perspective

K. Jayaprakash[1,*] and S. P. Balamurugan[2]

[1] *Department of Education, Annamalai University*
[2] *Division of Computer and Information Science, Annamalai University*

Presently, rapid and precise disease identification process plays a vital role to increase agricultural productivity in a sustainable manner. Conventionally, human experts identify the existence of anomaly in plants occurred due to disease, pest, nutrient deficient, weather conditions. Since manual diagnosis process is a tedious and time consuming task, computer vision approaches have begun to automatically detect and classify the plant diseases. The general image processing tasks involved in plant disease detection are preprocessing, segmentation, feature extraction and classification. This paper performs a review of computer vision based plant disease detection and classification techniques. The existing plant disease detection approaches including segmentation and feature extraction techniques have been reviewed. Additionally, a brief survey of machine learning (ML) and deep learning (DL) models to identify plant diseases also takes place. Furthermore, a set of recently developed DL based tomato plant leaf disease detection and classification models are surveyed under diverse aspects. To further understand the reviewed methodologies, a detailed comparative study also takes place to recognize the unique characteristics of the reviewed models.

Keywords: Computer Vision, Plant Disease, Classification, Machine Learning, Deep Learning.

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1. INTRODUCTION

For every year, the Earth's population is enhanced around 1.6%, and it demands for all kinds of plants. Saving the plants from plant diseases is assumed as a significant operation to meet the progressive requirements of food quality as well as quantity. With respect to financial score, plant diseases have the expense of US$220 billion per year [1]. Based on the ICAR, around 30% of crop production ends in failure annually because of the bugs, pests and disease. Such diseases jeopardize food security and capture the extensive economic, social, as well as ecological factors. Regular prediction of plant disease is a challenging action for many farmers. They only consult the experienced farmers or the Kisan helpline and no other options can be applied. Well-experienced farmers would be able to find the type of diseases by seeing the affected leaves. Moreover, a laboratory is essential to find the plant disease.

While there is progressive growth in world's population, establishment of models for prediction and reduction of plant diseases acts as a dual services of maximizing plants cultivation and minimize the pesticide use. With the deployment of good plant varieties, disease prediction is a major aim to accomplish effective food security. Some of the classical models diagnose the disease manually by farmers or fellow farmers, which is time consuming and expensive, and it offers ineffective results. These limitations can be resolved by establishing computer vision approaches which is used for automated disease detection with the help of transparent symptoms of plants. Such modules are highly useful for the farmers to make a simple detection like fool proof as possible. In prior to identify the DL methods, studies have concentrated on applying image processing and feature extraction for developing models for predicting the disease with various final outcomes.

The greater challenging aspect of this model is that, the computers are not effective in finding the symptoms of plant disease, and it is resolved by applying DL technique where it does not require the features, however the features are learned by using optimization scheme. Recently, massive studies were developed and applied the abilities of DL approach for reaching diverse accuracy levels on laboratories. The effective classification models are applied and tested on data which is same as training data for obtaining better accuracy; however it fails unexpectedly while testing on diverse data [36–45]. Some of the samples are training models have reached best accuracy and confidence; hence it is sampled over images consumed from secured online resources, and the confidence is reduced.

*Author to whom correspondence should be addressed.

Barbedo [2] defined many number of factors which affects the function of DL approaches to plant leaf disease prediction and ended that in spite of achieving maximum success rate in newly deployed models, there are many other reasons which makes the process more challenging and it can be applied in real-time cases.

Transfer learning, tweaking the result of a trained neural network to novel dataset, is a well-known device for developers with tiny sized datasets which is available recently. The samples of applying this method and images from commonly accessible database like PlantVillage. Maximum efforts have applied DL method for predicting the place disease which are trained and tested under the application of PlantVillage dataset that is composed of images with lower difference and same backgrounds. In recent times, Barbedo [3] examined the function of DL approaches while trained models apply lesions and spots, by applying image segmentation as well as augmentation to enlarge the dataset size from relatively tiny count of images. Finally, the working principles of the models are enhanced in all plant types by examining the accuracies in many of the tedious cases with plant diseases.

This paper reviews a set of different computer vision based plant disease detection and classification techniques. The existing plant disease detection methodologies comprising segmentation and feature extraction techniques have been reviewed. Moreover, a brief survey of ML and DL models for plant disease detection is carried out. Furthermore, a set of recently developed DL based tomato plant leaf disease detection and classification models are surveyed under diverse aspects. To further understand the reviewed methodologies, a detailed comparative study also takes place to recognize the unique characteristics of the reviewed models.

2. PLANT LEAF DISEASE DIAGNOSIS USING HAND-CRAFTED FEATURE EXTRACTION

Previous studies regarding automated leaf disease prediction has applied the common workflow as showcased in Figure 1. Image capture is a process which collects the pictures and details with the application of a camera. Image pre-processing is performed in captured images for improving the image quality. In plant disease prediction system, segmentation is 2 fold. Initially, Segmentation is carried out for separating the leaf, fruit and flowers from the background. Moreover, segmentation is processed for isolating normal and affected tissues. Feature extraction mines the data from segmented image that acts as an accurate classifier. Some of the extracted features are texture, shape, size and colour.

In Ref. [4], it is stated to apply IPTs in analyzing 3 kinds of wheat diseases such as, Septoria, Rust and Tan-Spot at various phases of infection and several other environmental conditions. Numerous images have been captured from 2 pilot sites in Spain and Germany under the utilization of mobile tools. Area under Receiver Operating Curve (AuC) measures were addressed in the validation set and at the time of field trials correspondingly which depicts that the system is normalized. The 2 options are used for segmentation; automated segmentation but applying Simple Linear Iterative Clustering (SLIC) method depends upon the region of interest (ROI) and by mask refinement using Chan-Vese technology according to the saturation colour channel. Furthermore, segmentation is carried out to segregate malicious sub-regions (Hot-Spots) which depends upon colour features and Naïve Bayes classifier is applicable to predict the presence and absence of disease.

Developers of Ref. [5] applied a dataset with potato leaves collected from the PlantVillage dataset for developing a classification model which is applicable to examine the normal leaves and it is infected by late blight as well as early blight diseases. Multiclass SVM has been applied for classifying leaf images as 3 classes according to colour and texture features. The system has reached 5-fold cross-validation accuracy. Hence, the actual dataset is composed of normal potato images and late blight as well as primary blight images. It is highly advantageous to provide better function of the system on massive dataset. Tiwari and Tarum [6] presented a model according to the modified SVM classifier for examining the leaf diseases. Cuckoo Search (CS) optimization method is applied for finding the optimal classification attributes. The researchers have gained improved prediction accuracy while applying CS model when compared to SVM.

Ramesh and Vydeki [7] projected the Jaya optimization approach for optimizing the weights of a Deep Neural Network (DNN) that is used for analyzing paddy leaf diseases. K-means clustering method is utilized for eliminating background features and segregates the lesions. The 2 colour and 4 texture features have been employed for classification. Studies are processed in Ref. [8] and established the Genetic Algorithm (GA) which segments the affected leaves from normal portions. Additionally, GA has produced massive results which are compared to select the best one.

In Ref. [9], it has been presented Particle Swarm Optimization (PSO) for lesion segmentation of sunflower leaves. An MDC classification model was trained for examining the sunflower leaf diseases by applying colour as well as texture features. Chouhan et al. [10] deployed Bacterial Foraging Optimization (BFO) model for optimizing a Radial Basis Function NN (RBFNN) for finding and classifying the plant leaf diseases. Here, BFO was mainly applied for initializing the weights of RBFNN whereas affected regions are divided by applying Region Growing Algorithm (RGA).

Pantazi et al. [11] projected a grape leaf disease analyzing model which depends upon 1-class SVM classification approach. It is applied for disease prediction. Input

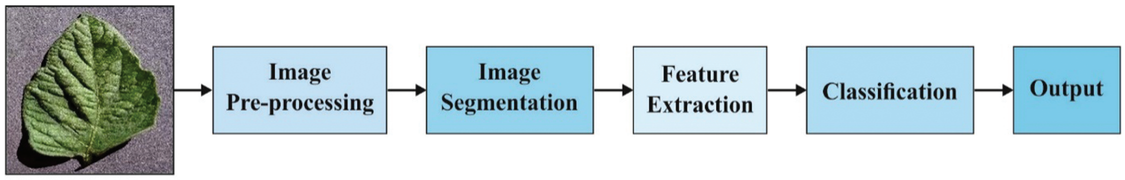

Fig. 1. General workflow of plant leaf disease diagnosis.

images are segmented by applying the GrabCut method to eliminate background components. Texture features are extracted by processing 32-bin LBP histogram from hue component. A lesion related with the disease has represented an exclusive histogram name. The 1-class SVM classifier undergoes training for examining the 6 LBP histogram patterns.

3. LEAF DISEASE RECOGNITION USING DEEP LEARNING TECHNIQUES

Recently, Convolutional Neural Networks (CNNs) acts as an optimal feature extractor and classifier in image analysis. It is evolved from the agricultural applications to proceed the operations like disease analysis, pest analysis, weed prediction, counting the fruits and flowers, and ranking. Specifically, many studies in leaf disease analysis by applying IPTs have leveraged DL. Lecun et al. [12] presented DL as a representation learning model where the method identifies optimized way to show data by optimizations. Using the learning principle, feature engineering is not essential as features are extracted automatically. Massive datasets have numerous images which are used for CNN training. But, in plant disease detection, larger and different datasets are not allocated and availed for usage. Presently, transfer learning is an efficient method used for training CNN classifiers and predict the plant disease. It activates the adaptation of pre-trained CNNs by sustaining tiny datasets where distribution is varied from massive dataset that has been applied for training the network from scratch. Then, literature have showcased that by applying CNN methods, ImageNet dataset was pre-trained and retraining them for leaf disease detection which provides best outcomes.

In Ref. [13], a dataset of leaf images were collected through internet. It is selected with Caffe DL approach and illustrated a pre-trained CaffeNet CNN structure is utilized for leaf disease analysis by transfer learning. Hence, researchers have addressed maximum prediction accuracy in prior to compute the fine tuning of model and better accuracy has been accomplished after fine tuning a method. In Ref. [14], is applied the PlantVillage dataset for computing leaf disease analysis processes by applying AlexNet and GoogLeNet CNN infrastructures. For every configuration, training is performed for 30 epochs with the help of standardized hyperparameters in the Caffe DL approach.

Amara et al. [15] developed a DL CNN method which depends upon the LeNet structure for banana leaf diseases classification. Developers have performed colour and grayscale images. It is addressed that methods are trained with the help of colour images with supreme function than the models trained by applying grayscale images; finally, the findings are reinforced. Atole and Park [16] has illustrated a pre-trained AlexNet CNN for examining the bugs and diseases of rice plants. A dataset is composed of field images that denotes normal, abnormal and golden apple snail infected conditions. The fine-tuned AlexNet model has gained maximum test accuracy.

Cheng et al. [17] developed a pest analysis scheme by applying deep CNNs (DCNN). Researchers have addressed that accurate performance of CNNs has outperformed SVM and BP classifiers by extensive margin. Wang et al. [18] applied the apple leaf images gathered from PlantVillage dataset and CNNs are employed for detecting the disease level. Especially, the dataset employed in this model is composed of normal leaves and black rot leaves. The images are classified into low, medium, severely affected. The developers have performed shallow CNN structures with 2, 4, 6, 8 and 10 convolutional layers.

Walleligh et al. [19] illustrated data augmentation, batch normalization (BN) and drop out function of a CNN method. It is presented that, the test set accuracy of LeNet style CNN has been maximized at the end of augmentation process. Zhang et al. [20] have depicted the shallow CNN structures which are capable predict the disease by enhancing the diversity of pooling actions and dropout dense layer of tiny CNN. The researchers have performed diverse integration of pooling actions in Cifar10 CNN methodologies and related the function of these systems to a GoogLeNet model.

Zhang et al. [21] have developed a 3-channel CNN (TCCNN) for tomato as well as cucumber leaf disease analysis. Here, the developers have executed 3 FC feature extraction systems in corresponding dense network. The FC networks have obtained 3 RGB colour channels. The tea leaf disease is predicted using DL model. A Cifar10-quick method is changed by executing 2 parallel convolution for multiscale feature extraction by replacing the series of connected convolution layers. The adjustable parameters can be reduced using remarkable convolution

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layers which are interchanged with depth-wise separable convolutions.

The process of DeChant et al. [22] have illustrated that integration of various CNN classifiers have resulted in best detection accuracy which is feasible for detecting the disease signs from high-dimension images. Here, 5 Stage-1 CNNs are trained for predicting the lesions present in Northern Leaf Blight (NLB) in maize plants. The detections of 3 optimally performing CNN methods are employed for producing heat map images. Ozguven and Adem [23] deployed an automated prediction models for detecting the leaf spot disease in sugar beet plants.

Barbedo [24] projected the images of lesions and spots and all leaves are classified with the application DL. The merits of this model are existence of several diseases on similar leaf can be predicted and it confirmed data augmentation by leveraging the leaf image as various sub-images. GoogLeNet structure was elected because of the supreme function. Background eliminations are enhanced the prediction accuracy accomplished by CNN.

Elhassouny and Smarandache [25] depicted that it is feasible to execute DCNNs for predicting the plant disease using mobile devices. The simulation outcomes have depicted that the choice of optimization model is mild accuracy. Castelao Tetila et al. [26] implied a model for detecting the disease of soybean leaf. Human professionals annotated the sub-images and classified into 6 classes. The developers have processed with diverse CNN structures such as, Inceptionv3, VGG19, ResNet-50, and Xception and related the performance by means of accuracy, training time as well as learning error.

4. REVIEW OF TOMATO LEAF DISEASE DETECTION MODELS

The Indian agriculture has massive number of crops and Tomato is one of the significant fruit or vegetable. India owns third place in tomato production which is planted in wider region and harvest maximum tomatoes. The cultivation ratio of tomato in India is significantly lower when compared to all other countries. The major reason for limited yielding is because of the plant diseases which exist prominently in plant leaves. Tomato plants are infected by diseases namely, bacterial spot, early blight, late blight, and leaf mold. Initially, blight is the common disease than others. The tomato crop is prone to blight and the disease is developed periodically. It is because of various factors like environmental conditions and parameters. By predicting the disease, the cultivation can be enhanced. Moreover, the final agricultural product is achieved by means of quality and quantity which has been maximized. Additionally, observing the plants in wider field needs many human interventions. Therefore, a diverse automation model for disease prediction is projected in last decades.

In Ref. [27], developers have analyzed the applications of defined regions and several prediction methods for exact classification, prediction, and quantification of plant diseases. The plant disease can be detected automatically by applying CNN model for image classification. Developers have stated that DL structures perform quote-well than Machine Learning (ML) tools significantly. Also, it has been examined that tomato leaf images are distributed in class labels. Once the performance is compared, ResNet50 have been an effective and accurate prediction model. It is applied for developing mobile application and identifies the tomato crop diseases in effective manner.

In this research [28], an effective solution was offered to the farmers with a model to be served as an appropriate plant management system. Here, 2 effective models were projected according to the DL for plant disease analysis. The initial model has established a real-time solution on the basis of deep meta-structure and a feature extractor for examining the plant diseases and the image position. Secondly, it reports the issues of class imbalance as well as false positives by developing the refinement function named as Filter Bank. The performance validation is carried out in tomato plant diseases as well as pest dataset. Here, the prediction of blight disease in tomato leaves is performed using microscope termed as Foldscope. Furthermore [29], a deep Residual Network101 (ResNet101) of CNN structure is applied for measuring the disease severity of blight disease. The dataset is trained by applying an open database named as PlantVillage dataset for lower, medium, and highly diseased leaves.

In Verma et al. [30], developers have applied 2 CNNs, such as, AlexNet and ResNet18, to learn the severity of disease in Grape plant. The photographs for Isariopsis Leaf Spot disease in Grape plant is also named as Leaf Blight, which are collected from the PlantVillage dataset, and classified as 3 classes of severity phases like mild, moderate and serious. It is mainly utilized for training CNN methods, by using transfer learning technology. The impacts of fine-tuning hyper-parameters like mini-batch size, epochs and data augmentation have been monitored and determined. In Zhang et al. [31], the impacts of diverse trace elements on plants has developed the identification models. In particular, it has been examined the 11 types of tomato nutritional infections. Afterwards, the training and prediction impacts the importance of super resolution of examination method. Followed by, a pre-trained model has improved deep super-resolution network (EDSR) method for pre-processing the dataset. At last, the implementation of diagnosing method depends upon DL.

This work [32] is mainly applied for examining the proficiency of methods like XGBoost, CNN and the structures namely, VGG16 and VGG19 in integration with data augmentation and transfer learning against traditional ML models like SVM, Random Forest (RF) and validate the efficiency in prediction and classification of tomato plant leaf diseases with respect to accuracy, precision, recall as well as training time. Model training is performed on commonly available PlantVillage dataset which is composed of 6500 images from normal and abnormal tomato plant leaves with 5 diverse classes. CNN's VGG19 structure with transfer learning has reached an optimal result with maximum accuracy than the former models with rapid training time. Here, a deep-learning-relied method has been presented [33] for predicting the plant diseases and bugs in tomato leaves with the help of images captured by cameras under different resolutions. The main aim of this model is to identify reliable DL structure in this approach. Moreover, the meta-architectures are combined with "deep feature extractors" like VGGNet and ResNet.

It is deployed [34] with a creative solution which offers proficient disease prediction in tomato plants. A motor-controlled image capturing box has been formalized for capturing 4 sides of tomato plants which helps in prediction and classification of leaf disease. A specific family of tomato like Diamante Max has been applied as test subject. In this approach [35], researchers have executed 3 familiar CNN methods such as AlexNet, SqueezeNet and Inception V3, for estimating the disease level in Tomato Late Blight disease. The images applied are taken from PlantVillage dataset and divided as 3 phases like low, medium and severe which is based on disease severity. The CNN structures are executed in 2 diverse modes, such as transfer learning and feature extraction.

5. PERFORMANCE VALIDATION

Table I and Figure 2 investigates the results analysis of the reviewed plant leaf disease diagnosis models in terms of accuracy. The figure denoted that the CNN model has exhibited ineffective classification performance with the minimum accuracy of 76%.

In line with, the Quadratic SVM model has demonstrated slightly higher accuracy of 83.50%. In addition, the SVM model has depicted even higher accuracy of 88.89%. At the same time, the VGG16 based CNN model has tried to exhibit somewhat higher accuracy of 89%. Followed by, the KNN and C5.0 models appeared to be superior to previous models by attaining an identical accuracy of 94.44%. Furthermore, the VGGNet based CNN model has shown reasonable performance with the high accuracy of 95.24%

Table I. Result analysis of existing methods on different performance measures.

Methods	Accuracy
CNN	76.00
Quadratic SVM	83.50
SVM classifier	88.89
VGG16 based CNN	89.00
VGGNet based CNN	95.24
GoogleNet based CNN	96.00
K-NN	94.44
C5.0	94.44

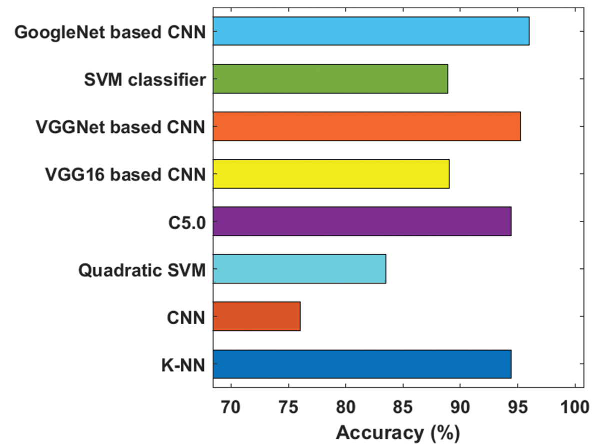

Fig. 2. Accuracy analysis of different plant leaf disease diagnosis.

whereas the GoogleNet model has appeared as an effective diagnosis tool with the maximum accuracy of 96%.

6. CONCLUSION

This paper has reviewed the recently presented computer vision based plant disease detection and classification techniques. The existing plant disease detection approaches including segmentation, feature extraction and classification models have been reviewed. Additionally, a brief survey of ML and DL models takes place to identify plant diseases also takes place. Furthermore, a set of recently developed DL based tomato plant leaf disease detection and classification models are surveyed under diverse aspects. To further understand the reviewed methodologies, a detailed comparative study also takes place to recognize the unique characteristics of the reviewed models. As a part of future scope, we plan to develop a novel DL based tomato plant disease detection and classification model.

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