Survey of Deep CNN Models for Plant leaf Disease classification

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ABSTRACT

Crop disease diagnosis is an essential responsibility for farmers and individuals alike as it helps prevent numerous setbacks such as reduced productivity, compromised quality and quantity, and potentially defective yields. Consequently, the timely identification and detection of diseases can play a pivotal role in safeguarding crop yields, while appropriate treatment and solutions provided promptly can preserve both the quantity and quality of production. Conventional methods for disease detection in plant leaves have proven to be inadequate, resulting in slow detection rates. Early detection of diseases can yield superior outcomes. Therefore, the application of computer vision-based technology and deep learning techniques can be employed for more timely disease detection. The objective of this research is to give review on different types of Deep CNN Models like EfficientNetB0, DenseNet ,ResNet, Alexnet, GoogLeNet and VGG. This research paper presents a detail survey of the mentioned models.

***Keywords**: CNN, Image Processing, Leaf Diseases, Machine Learning, Segmentation.*

INTRODUCTION

In a country like India, where the economy heavily relies on agriculture, technology plays a crucial role in the production of food, significantly impacting the lives of its population. The escalating threat to food security posed by plant diseases is a global concern. Plant diseases play a critical role in the development of agriculture, impacting both the quality and quantity of plants. Consequently, the detection of plant diseases emerges as a pivotal step in ensuring optimal crop outcomes. However, classifying plants as either "with disease" or "without disease" presents a challenging task due to the vast diversity and similarities among plant species in nature. These diseases can encompass various types such as fungi, bacteria, viruses, and molds. Some of the most common plant diseases include Alternaria Alternata, Anthracnose, Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew, Black Mold, Downy Mildew, and Rust[19]. When a plant leaf is infected, it exhibits symptoms that can be observed through changes in texture, color, shape, and size. Typically, farmers or specialists rely on However, many of these symptoms are microscopic, making it challenging for human vision alone to accurately identify the diseases. This manual method of observation is time consuming and inefficient, typically relay on the credibility of observer and and majority of the time it gives incorrect diagnosis. The utilization of machine learning algorithms in computer vision has become increasingly popular in the field of automated plant pathology diagnosis. This integration has resulted in improved accuracy and speed in diagnosing plant diseases. By harnessing the power of machine learning and computer vision[3].These approaches involve several key steps, including data acquisition, pre-processing, model training, and utilizing the trained model for predictions or classifications. Supervised learning relies on labeled data. Traditional machine learning approaches have certain limitations when it comes to non-uniform backgrounds and accurate feature extraction. They may struggle to handle such scenarios effectively and often require an extensive pipeline of methods for data pre-processing before the model training phase. These limitations can hinder their performance and make them less suitable for certain complex tasks. Many researchers preferred CNN over traditional ML model. Benefit of preferring CNN over others is that the entire system is trained end-to-end. Convolutional neural networks (CNNs), a specific type of artificial neural networks (ANNs), have shown remarkable success in classifying different plant diseases in recent years [7]. This development has also made it possible for non-experts to identify diseased plants with greater accuracy. Although CNN have made significant strides in enhancing the detection rate of plant diseases, one persistent limitation is the large parameter size in the models used [1]. Additionally, efforts are focused on improving the final classification accuracy of plant disease identification models. These areas of research aim to enhance the performance and efficiency of CNN-based models for plant disease classification [6]. However, there is still a need for further research to address certain challenges. One such challenge is reducing the training time required for CNNs, enabling faster convergence rates Employing pre-trained models offers several advantages, with one notable benefit being the time efficiency of the feature extraction process. Since pre-trained models have already undergone extensive training on large datasets, the feature extraction step can be completed swiftly. This is because the images only need to pass through the network once, leveraging the learned representations from the pre-trained model. This saves computational time and resources compared to training a model from scratch, making pre-trained models a valuable asset in various applications [4]. The field of deep convolutional neural networks (CNNs) has witnessed substantial advancements, particularly with the introduction of new meta architectures such as VGGNet, LeNet, ResNet, and others[11].These state-of art models of deep learning gives high accuracy in image processing. For the implementation of DL models, several steps are required, from the collection of datasets to visualization mappings. These steps are Data/ Image Acquisition, Segmentation, Feature Extraction and classification. Pretrained DL model require large number of images as an input image. Augmentation techniques like, rotation, flipping, shearing, LGXP are used to increase the size of input dataset. For this review images from PlantVillage dataset from Kaggle has been used for the analysis purpose.

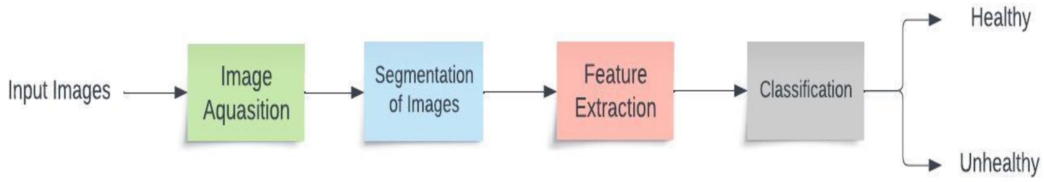

Fig1: Image processing Architecture.

RELATED WORK

In the agricultural field, researchers have made numerous attempts to classify, diagnose, and extract features related to plant diseases. Deep learning techniques, along with image processing and traditional machine learning approaches, have been extensively employed for this purpose. This section specifically highlights previous studies that have utilized deep learning techniques to classify diseases affecting corn leaves using digital images.

Hassan Amin et al[1] proposed an end-to-end deep learning model is developed to identify healthy and unhealthy corn plant leaves. In the proposed model, two pre-trained convolutional neural networks (CNNs), EfficientNetB0 and DenseNet121, are utilized to extract deep features from corn plant images. The deep features obtained from each CNN are combined using the concatenation technique, creating a more comprehensive feature set. This merged feature set enhances the model's ability to learn and gain deeper insights from the dataset, ultimately improving its performance in classifying and analyzing corn plant diseases. In this study, the obtained results of the proposed model are compared with the performance of other pre-trained CNN models, specifically ResNet152 and InceptionV3. It is noted that ResNet152 and InceptionV3 have a larger number of parameters and demand more processing power compared to the proposed model. Remarkably, the proposed model achieves an impressive classification accuracy of 98.56%. This outcome demonstrates the superiority of the proposed model over ResNet152 and InceptionV3, which achieved classification accuracies of 98.37% and 96.26% respectively. The higher accuracy achieved by the proposed model highlights its effectiveness and potential in accurately classifying corn plant diseases.

V V Srinidhi et al [3], proposed a work on Apple leaf disease classification. This paper uses Canny Edge Detection, Blurring, and Flipping were applied to augment the dataset. Subsequently, two models utilizing EfficientNetB7 and DenseNet were proposed and achieved impressive accuracies of 99.8% and 99.75% respectively.

Stefania Barburiceanu et al [4],proposed different layers of Pretrained Model like AlexNet, VGGNet, ResNet are used to extract texture features and classification done by a machine-learning classifier SVM.

T.Vijaykanth Reddy et al [5], Previous approaches using Convolutional Neural Networks (CNNs) have shown limitations in terms of adaptability and reusability of learned outcomes. To address this gap, this paper proposes a framework called Deep Leaf Disease Prediction Framework (DLDPF) that integrates CNN with pre-trained deep models using transfer learning. The specific algorithm employed is known as Cascade Inception based Deep CNN with Transfer Learning

Xulang Guan [6], carried the work over four CNN models, namely Inception, Resnet, Inception Resnet, and Densenet, were utilized. To further enhance the accuracy, the results of these CNN models were processed using a stacking method, which combines their predictions. The application of the stacking method resulted in an impressive accuracy rate of 87%, a substantial improvement compared to using a single CNN model. This high accuracy rate suggests that employing a combination of CNN models through the stacking method holds potential as an advanced plant disease warning tool that can be effectively extended to practical cultivation conditions.

Changjian Zhou et al[7], worked on GAN based leaf spot identification method was proposed. He suggested that the early stages of a disease or in the case of rare diseases, there are often limited training samples available, posing a challenge for machine learning models, particularly deep learning models, which typically require a large amount of training data to perform well due to their strong representative ability. To address this issue, a method called fine-grained GAN-based grape leaf spot identification was proposed. This approach effectively addresses the problem of limited training samples by leveraging the power of GANs to generate additional data, enabling deep learning models to perform better even with a smaller training dataset. This methodology contributes to enhancing the accuracy and reliability of disease prediction models for grape leaf spot identification.

Lili Li et al [10], surveyed that, collecting a large-scale dataset of plant diseases in real conditions can be challenging, as it requires extensive fieldwork and expert knowledge to accurately identify and label the diseases.

Hepzibah Elizabeth David et al [11], presented a Hybrid CNN CNN-RNN Classifier to detect a leaf disease on a tomato plant.This work uses a RNN mothd for object detection.

Changjian Zhou et al [12], proposes a restructured residual dense network (RDN) for tomato leaf disease identification. The RDN model combines the strengths of deep residual networks and dense networks, aiming to improve calculation accuracy, information flow, and gradient propagation by reducing the number of training parameters. The experimental results presented in the paper demonstrate the effectiveness of the restructured RDN model. It achieved a top-1 average identification accuracy of 95% on the Tomato test dataset from the AI Challenger 2018 datasets. This high accuracy indicates that the model performed well in accurately classifying tomato leaf diseases.

Pin Wang et al [13], this study concludes that traditional machine learning methods, such as SVM, tend to have better solution effects or higher recognition accuracy when applied to small sample datasets. On the other hand, deep learning frameworks, such as CNN, exhibit higher recognition accuracy on large sample datasets like MNIST. SVM model achieved an accuracy of 0.86, while the CNN model achieved a slightly lower accuracy of 0.83 when the dataset is small. These results suggest that in the case of small sample datasets, the traditional machine learning method (SVM) performed better in terms of solution effect or classification accuracy compared to the deep learning framework (CNN).

Sandeep Kumar et al [15], uses fusion of CNN and ML algorithms. The Gray Level Co-occurrence Matrix (GLCM) to capture texture information from the segmented leaf images. Finally, the Support Vector Machine (SVM) classifier to classify the different types of leaf diseases.

Below table mentioned the summarize version of all the deep learning model.

S.no	Deep Learning Models	Input Parameters	Classification Accuracy	Limitation of Model
1	VGG Net	138	99.53	This model is expensive and it is difficult to deploy on a system with less resources.
2	GoogLeNet	5	99.35	There may be loss of information while doing feature extraction
3	AlexNet	60	95.5	This model has overfitting Problem.
4	Inceptionv3	24	99.76	This is very complicated model to build.
5	ResNet	26	96	It has many layers which contribute to very little information.

Table1: Summery of Deep CNN Model

CONCLUSION

In the majority of studies, researchers utilized the PlantVillage dataset to assess the effectiveness of deep learning models. This dataset contains numerous images of various plant species afflicted with diseases, but it was collected within a laboratory setting. Consequently, there is a need to develop a comprehensive dataset of plant diseases captured under real-world conditions. This review presents a comparative analysis of various cutting-edge machine learning (ML) and deep learning (DL) algorithms for the identification and categorization of plant leaf diseases. Based on the findings, several potential areas for further investigation have been identified.

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