

Deep Learning Techniques for Plant Leaf Disease Identification: A Detailed Survey and Analysis

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Abstract—Plants provide a substantial contribution to the global food supply. Nevertheless, a multitude of plant leaf diseases can lead to economic loss. Hence, in order to enhance agricultural productivity, it is imperative to promptly and precisely detect plant leaf diseases. Farmers and professional agriculturists have always been manually predicting crop leaf conditions to identify diseases caused by pests, nutritional deficits, or atmospheric circumstances. This process is arduous, complex, and susceptible to errors. Artificial Intelligence (AI) frameworks, like those incorporating Machine Learning (ML) and Deep Learning (DL) models with computer vision, were employed create automated systems aimed at tackling these issues. These technologies play a crucial role towards timely identification of plant leaf diseases. Many efforts within past decades concentrated on building DL models that automatically segmenting plant leaf images and detecting diseases. This article discusses the background of plant leaf disease segmentation and detection methods in order to encourage more study in this field. At first, the review will examine DL models specifically designed for division and categorization of crop disease leaves. Subsequently, the strengths and weaknesses of each framework are assessed in order to evaluate their efficacy in terms of performance. Finally, some improvements to attain greater effectiveness in the recognition and segmentation of plant leaf diseases are proposed. Examining then analysing difficulties encountered in literature enables readers to clearly identify problems and provide novel solutions with DL-based frameworks for finding plant diseases

Keywords—Plant leaf diseases, Deep learning, Automated disease detection, Convolutional Neural Networks (CNNs), Data augmentation and Feature extraction, Agricultural productivity, Recurrent Neural Networks (RNNs).

I. INTRODUCTION

Agriculture essentially contributes to feeding both humans and animals worldwide. Over 90% of people on the planet are dependent on agriculture. Since 2014, the global population of hungry individuals has consistently increased, as reported by the United Nations Food and Agriculture Organization [1]. 80% from the food in the world is harvested by farmers, but plant diseases cause more than 50% of crop yields to be lost during

harvest [2]. Food scarcity, a major cause of crop diseases, is one of the most pressing global issues facing people today. Thus, it could seriously affect the agro-economic sector's sustainability, which could risk a particular zone's food security [3]. The rapid advancement of DL and ML methods became effective tools for revolutionizing disease detection in plants. Table 1 illustrates the sample images of plant diseases [4].

TABLE 1. Enumeration of common plant leaf diseases

S.no	Images	Disease name	Technical Name	Type
1.		Tomato Bacterial Spot	Xanthomonas campestris pv. vesicatoria	Bacteria
2.		Potato Late Blight	Phytophthora infestans	Oomycete
3.		Apple Black Rot	Botryosphaeria obtusa	Fungal

4.		Citrus Canker	Xanthomonas pv. citri	Bacterial
5.		Rice Bacterial Leaf Blight	Xanthomonas oryzae pv. oryzae	Bacterial
6.		Raspberry Gray Mould	Botrytis cinerea	Fungal
7.		Strawberry Leaf Scorch	Diplocarpon earlianum	Fungal
8.		Grape Mite Infection	Eriophyidae family (mites)	Mite / Pest
9.		Guava Algal Spots	Cephaleuros virescens	Algal
10.		Turmeric Bacterial Leaf Spots	Colletotrichum capsici	Bacterial

1.1 Steps included in Leaf Diseases Detection

In order to overcome such challenges in the traditional paradigm, computational imaging techniques was developed that assess disease kinds using plant images. The process of diagnosing diseases in plants by analysis of images encompasses the following stages [5], as enumerated below.

Image collection: The preliminary phase is acquiring images of plant leaves with a mobile or photographic device and subsequently saving it on internet. The saved images are extracted via the file system as recovered the memory for subsequent analysis [6].

Image pre-processing: The primary objective of image pre-processing to identify image features that are not impacted by the background, such as dimension, leaf pattern, lighting and camera setting, during disease identification. It is utilized to highlight specified characteristics and expose information in a

picture. It applied numerous methods, including noise removal, rescaling, masking, classification, topological operations among others. The images captured might include noise which is performed by different kinds of filtering schemes. Also, the images can be enriched using image enhancement methods like histogram normalization to discriminate between objects and backgrounds [7].

Image segmentation: Segmentation of images is employed to partition the infected areas and healthy areas in leaves. This task splits the digital image and processes the visuals to determine the item and Region of Interest (ROI). A frequently utilized the subdivision approach applied is K-means grouping, which is the simplest technique for partitioning images containing contaminated leaf areas. In grouping, the images can be divided under categories which might contain a few clusters in the affected area. [8].

Feature extraction: This process extracts the required information's from the images i.e., shade, appearance, and structure. Color attributes pertain to the spectral composition of the image, whereas consistency refers to intensity fluctuation within a pixel neighborhood. Texture characteristics in the segmented image derived from the mathematical distribution of luminance combinations at particular locations. Shape attributes like size, perimeter, circularity, and complexity were computed from the binary segmentation images. [9].

Classification: This main procedure in image processing is categorization. Once the features are extracted from the images, disease classes or levels can be detected. Once the extraction attributes from the images, disease categories or levels can be detected. Once the disease level is detected, agricultural experts can make a proper diagnosis decision to avoid the sickness from

spreading. There are two phases in the classifying process: training and testing. The training phase involves training the classifier using image processing steps which include picture acquisition, image pre-processing, feature extraction, and classification, applying a training image as input. The testing phase involves evaluating the uploaded image by according to the training procedure, which includes test image capture, preliminary analysis, and extraction of features, and classifications [10]. ML and DL are subsets of AI that autonomously diagnose numerous plant diseases, rendering them a compelling choice for optimizing agricultural strategies, enhancing crop output, and mitigating economic losses in agriculture [11]. The figure 1 depicts the organizational module of ML and DL utilizing image processing approaches for identification of leaf diseases.

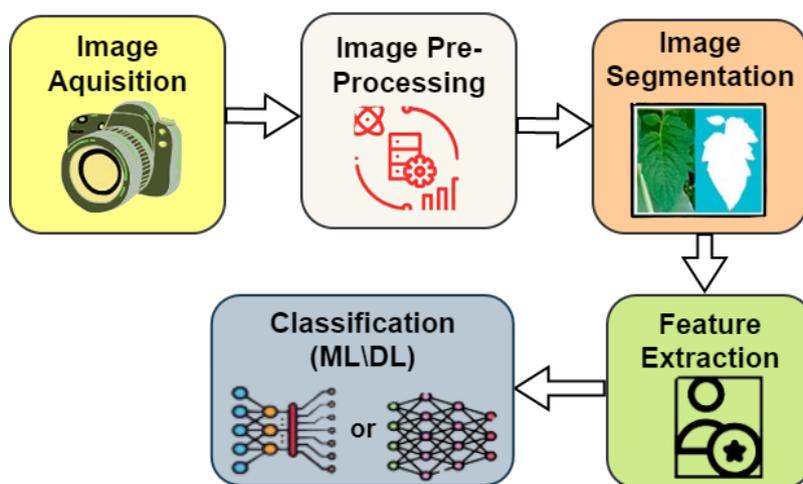


Figure 1. Fundamental Steps in Leaf Disease Detection

1.2 ML Method

ML methodologies are employed to forecast plant diseases using image analysis. ML seeks to discern associations within data through statistical algorithms, leveraging intricate patterns and advantages to facilitate automated operations for hypothesis development [12]. ML algorithms include:

KNN: The memory-based, supervised KNN classifies input based on similarity. It calculates neighbor distances, finds closest neighbors and votes for labels. Distance functions calculate data similarity. Most common distance functions are Euclidean, cosine, correlation, Manhattan and Murkowski. Its main benefit is no model or parameter tuning. It classifies unlabeled objects using nearby labels [13]. The algorithm slows down with more data and features and performs better with fewer features. The binary KNN classifier classifies new examples using different K values. If the K value changes for a problem, the classifier's performance may change. The K value identifies neighbor data, and the difference across neighbor data and new data is the most important labeling parameter.

Decision trees: Another simple and widely used supervised ML method is the decision tree, which shows decision characteristics as nodes, probable results as branches, and classes as leaves. Every decision tree parent node must have a child node. Decision tree algorithms solve classification and

regression problems [14]. Splitting the source dataset into successor children creates the decision tree. Classification rules split the dataset. Decision tree algorithms' drawbacks include data overfitting and node overlapping.

Logistic regression: It classifies example data into two classes using supervised ML [15]. It uses probability distributions to classify categorical outputs. Simple distribution functions determine input data probability, which elucidates the correlation among a single dependent binary value and one or more independent components that are arbitrary, numerical, range, or ratio in nature. Probability distribution values ranging from 0 to 1, which can be used to classify data.

SVM: It is a common statistical learning concept-based supervised ML technique that uses an optimal separating hyperplane for classification and regression. Support vectors are hyperplane-defining training data. Image, numerical and text classification and regression applications used SVM [16]. It uses various kernel mathematical functions to process data. Most kernel operations are classified as exponential, non-linear, polynomials, or sigmoid. SVM training using massive datasets takes longer than other ML algorithms. It efficiently handles non-linear data using kernel functions. However, Traditional ML-based methods often struggle to handle large data sets. Therefore, DL models were used to overcome these limitations,

which provide better scalability and accuracy for plant disease detection.

1.3 Deep Learning Model

DL models provides an efficient performance on plant diseases prediction and classification [17]. DL model can perform the feature extraction, delivering useful insights that assist farmers in making informed decisions, hence minimizing crop treatment expenses and enhancing output. It provides a prompt, objective, and economical alternative to manual techniques, alleviating computational demands and mitigating deficiencies in agricultural expertise in resource-limited environments. Among the DL mechanisms includes CNN [18], Recurrent Neural Network (RNN) [19], Long Short-Term Memory (LSTM) [20], Deep Belief Network (DBN) [21] etc. This types of DL frameworks, CNN models are extensively utilized for plant disease prediction because they effectively mitigate the challenges associated with subpar performance and inadequate image division inherent in traditional ML

algorithms, emphasizing pixel input processing and obviating the need for the extraction of features manually [22]. The CNN structure was utilized to extract attributes, generally involve traditional, max-pooling, and completely linked layers. A layer of convolutional was utilized to extract features from crop leaf images. The deep superficial level of convolution (low-level) tier can be utilized to acquire basic boundary and surface features, the mid-level portion serves to retrieve intricate texture and certain linguistic data, and the deep (high-level) layer has been utilized to obtain advanced lexical characteristics [23]. This layer of convolution is succeeded by a max-pooling layer to preserve relevant features in the image. Lastly, the classifier employs fully linked layers to sort high-level semantic data into distinct illness classifications. The advancement of CNNs has enhanced the efficacy and automation of agricultural leaf disease identification. The figure 2 provides the simplified representation of CNN approach for plant diseases classification.

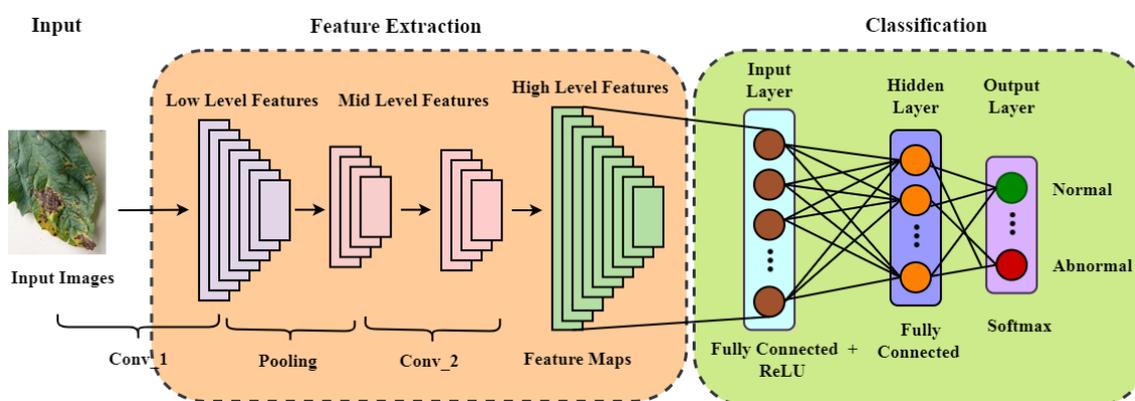


Figure 2. CNN Layout for Plant Disease Detection

However, simple CNNs, which concentrate on regional trends and characteristics, may have difficulties in grasping wider implications, especially in bigger, intricate images, owing they have restricted comprehension of geographic connections. preconditioned CNN models such as AlexNet, DenseNet201, EfficientNet, XceptionNet, InceptionV3, MobileNetV2, ResNet, and ShuffleNet address the limitations of fundamental techniques [24]. This trained CNN model excels in feature extraction and the classification of plant diseases at its earliest stages, thus facilitating prompt plant intervention. These approaches assist physicians in identifying diseased plants by analyzing distinctive characteristics from captured images, therefore ensuring resilience, improved crop yield, optimized disease control, and increased recognition precision. [25].

The major goal of this document is to present an in-depth review of diverse forecasting and categorizing schemes for plant leaf diseases utilizing images. A contrast is offered to examine the advantages and weaknesses of these structures, aiming at suggesting alternatives. The subsequent sections are organized as follows: Section II examines multiple DL techniques developed for the prediction and diagnosis of plant diseases. Section III presents a comparative examination of the

paradigms. Section IV encapsulates the comprehensive survey and offers the upcoming scope.

II. LITERATURE SURVEY

In recent decades, DL methods displayed efficacy in accurately recognizing and categorizing plant leaf diseases. Studies have explored using DL architectures like MobileNet, VGG16, and U-Net variants for this intent. This part covers recent DL procedures for finding and classifying leaf diseases.

Jasim et al. [26] suggested a CNN method for detect and diagnosis plant leaf diseases with a dataset of 20,636 images from the PlantVillage database. The system includes image acquisition, and then pre-processing where those images resized to 128x128 pixels, afterwards utilizes a CNN architecture that has convolutional layers, max-pooling, ReLU activation, batch normalization, and a Softmax output layer. This design allows the model to classify diseases in tomato, pepper, and potato plants with good accuracy. Although the system shows promising results for disease detection, it still faces issues like overfitting, particularly while working on enormous datasets, that may need more optimization for wider applications.

Sachdeva et al. [27] proposed a Deep CNN model employing a Bayes learning framework for plant disease categorization. A complete dataset of plant leaf images gathered by with both diseased and healthy foliage. Then, the DCNN strategy applied to organize the plant diseases depending on the extracted attributes. However, the model faced challenges with large-scale applications, particularly in handling diverse and complex dataset.

Xu et al. [28] introduced a lightweight CNN model for fast and accurate crop disease identification, combining Channel Attention (CA) and Spatial Attention (SA) mechanisms. At first, the model simplified the ShuffleNetV1 architecture to diminish computing demands and increase speed. Then, dilated convolutions was added to augment the simulator's perceptual field and enhance accuracy. Even with these improvements, the model's attention mechanism could still be optimized further to balance the computational depth and power consumption, making it more suitable for diverse crop disease identification task.

Xiao et al. [29] proposed a lightweight model, SE-VRNet, which integrate an sophisticated retained network and an attention mechanism to extract more precise area of curiosity and defects for leaf disease determination. This framework combines a deep Variant Residual Network (VRNet) alongside a Squeeze-and-Excitation (SE) component to deal with challenges caused by the dispersed leaf disease features. Experiment outcomes across several datasets, including PlantVillage, OriData, NewData, and SelfData, shows that SE-VRNet performs better than many existing methods for leaf disease identification on mobile devices. However, the model's efficiency and performance on large-scale or more diverse datasets still needs further investigation

Ma et al. [30] proposed a Binary neural network with dual attention (DABNN) for plant disease detection. Our network architecture consists of three stages: the base block, features remover, and grouping layer. Initially, stem block includes quantified convolutions, batch normalizing, 3x3 binary combination with duo emphasis, and 1x1 longitudinal binary convolution with double attention. In the subsequent phase, the parameter extraction uses six fundamental binary neural network nodes to extracts the elements. Finally, the feature maps are processed through adaptive averaging pooling, followed by PReLU activation, and then classified by using a quantized linear classifier. However, the model still faces some challenges with overfitting, especially when working with larger datasets

Abinaya et al. [31] developed the Cascading Autoencoder with Attention Residual U-Net (CAAR-UNet) model for segmenting and classifying plant leaf diseases. The model uses patch-based optimization and data supplementation to help improve the dataset. The Symmetric Autoencoder (SAE) was generating pixel-wise features, which then were refined by the Attention Residual U-Net (ARU-Net) to produce more accurate segmentation masks. These results were later cascaded to improve the performance on complex backgrounds and also overlapping objects. The final classification was done by using dense layers with Softmax activation. However, the model might face issues with high computational requirements and

can struggle while managing extensive datasets or real-time applications.

Panchal et al. [32] presented a DL approach for crop disease detection leveraging infected leaf images. In this method, pixel-based operations were applied to process the images, followed by feature extraction and image segmentation. CNN were then used for disease classification utilizing the trends collected by analyzing diseased leaves. This design can be demonstrated using a public dataset of approximately around 87K RGB images, including both healthy and diseased leaves. However, challenges related to the variation in disease patterns and image quality has affected the model's overall robustness

Saleem et al. [33] proposed the AgirLeafNet model, a DL system combining NASNetMobile for feature extraction and Few-Shot Learning (FSL) for classification. The model incorporates the Excess Green Index (ExG), a vegetation index that enhances its ability to identify vegetal traits, despite limited labeled data. AgirLeafNet outperformed existing models in detecting potato, tomato, and mango leaves, demonstrating significant improvements in accuracy. However, challenges with model generalization in complex agricultural environments remain.

Krishna et al. [34] established a DL system for the identification of plant diseases with a combined dataset of PlantDoc and web-sourced images. In this method, CNN architectures like EfficientNet-B3, ResNet50, and DenseNet201 was customized for leaf disease prediction. Advanced data supplementation methods, including the addition of Gaussian variability, were used to enhance the hypothesis's generalization. The model showed strong effectiveness among different plant diseases, but it still faces challenges in achieving consistent generalization across more diverse datasets.

Alhwaiti et al. [35] introduced a DL strategy utilizing the You Only Look Once (YOLO) mechanism for fruit plant disease recognition. This methods, YOLOv3 and YOLOv4 was trained to identify healthy and diseased apricot leaves and burn disease on strawberry foliage, including bacterial spots on peach foliage and scorch illness on strawberry stems. The models were trained on data from the publicly accessible Plant Rural dataset. However, challenges related to distinguishing very subtle disease symptoms in some plant varieties were faced, which has affected the model performance in certain cases

Sathya et al. [36] suggested a new plant disease detection algorithm that comprises the Attention Mechanisms with Residual Networks (AARN) and Generative Adversarial Networks (GANs) to augment the data. Conditional GAN (cGAN) was used to create artificial images of both ill and well-being plants to enhance variety of datasets. AARN provided a better feature detection by extraction by prioritizing important image locations and jointly with Faster Region-CNN (Faster-RCNN) detection features. The augmented dataset enhanced the generalization and precision of the methods in detecting of plant diseases. A comparative analysis reveals the approach surpasses current technologies in accuracy, precision, recall, and F1-score, which provides a solid approach for detecting plant disease.

Syed et al. [37] proposed an Efficient Labelled Feature Dimensionality Reduction utilizing CNN-BiLSTM (ELFDR-LDC-CNN-BiLSTM) model for leaf disease classification. At first, CNNs was used for feature extraction, while BiLSTM networks were added to determine the temporal dependencies within leaf image data. This technique effectively reduces the feature dimensionality, allowing early and accurate disease identification. The system was evaluated using datasets of peppers and corn leaf images, and it was outperforming many existing dimensionality reduction techniques. However, the integration of CNN and BiLSTM, even though being cost-effective, still need further evaluation for scalability when working with larger datasets.

Liu et al. [38] proposed a lightweight model for plant disease recognition, named the Lightweight Pyramidal Multi-scale Attention Residual Network (LPMA-ResNet). The strategy mainly focused on selecting relevant aspects from pyramid multi-scale data while mitigating unnecessary information by using an attention mechanism. A dual pyramid feature selection approach was used so it can capture more useful information effectively. Experimental results on the soybean diseases dataset and the PlantVillage dataset show that LPMA-ResNet outperformed several existing methods while using fewer parameters, rendering it suitable for implementation on resource-limited embedded systems. However, the model might still face challenges was applied to extremely big or highly heterogeneous datasets

Sultan et al. [39] devised an extensive training approach for plant disease identification in roses, mangoes, and tomatoes using an enhanced variant of the Xception design. First, a

extensive dataset of 5491 plant leaf images across four disease types were collected. Then the model used advanced preprocessing and augmentation techniques to try preventing overfitting. Even though the performance was strong, the model may still face challenges when managing massive amounts of data with higher variability, that can limit its scalability.

Prommakhot et al. [40] introduced a DL system for plant disease prediction utilizing two-stream convolutional operators combined with BiLSTM (TwoConv-BiLSTM) to efficiently capture and learn the important features. The model was further enhanced with TransNet, which incorporate sequential learning methods such as BiLSTM, LSTM, Sequence-to-Sequence (Seq2Seq), and Gated Recurrent Unit (GRU) to focus on identifying the key features in plant disease classification. The network was trained on 38 plant disease strains in the Planting Village dataset and was evaluated using accuracy, precision, and recall. However, the model may face some challenges with the computational cost and might not be ideal for execution on restricted resources gadgets.

III. COMPARATIVE ANALYSIS

This section, a contrasting review assesses the pros and limitations of several DL methodologies for plant leaf disease detection. The technical details and performance outcomes were presented in Table 2. From this assessment, the most effective approach is selected to tackle the challenges in disease detection, enhancing characterization accuracy and overall efficiency in plant health monitoring.

TABLE 2. Validation of Numerous Plant Disease Prediction Models Utilizing DL Techniques

Author name & Ref. No.	Algorithms	Advantages	Disadvantages	Dataset	Performance Evaluation
Jasim et al. [26]	CNN	Efficient classification of diseases in tomato, pepper and potato plants	May struggle with highly diverse datasets	Plant Village dataset	Accuracy = 98.02%
Sachdeva et al. [27]	DCNN	It utilizes Bayesian learning for efficient feature learning	Limited to specific plant types and diseases	PlantVillage dataset	Accuracy = 98.9%
Xu et al. [28]	CNN, CA and SA mechanisms	It uses dilated depth wise convolutions for better accuracy	Computational complexity with attention mechanism	PlantVillage dataset	Accuracy = 99.86%
Xiao et al. [29]	SE-VRNet	Accurate region extraction and lesion detection	Need further exploration for large scale datasets	PlantVillage dataset and self-built leaf disease dataset	For PlantVillage dataset Accuracy = 99.73% For SelfData Accuracy = 95.71%
Ma et al. [30]	DABNN	Dual attention mechanism enhances classification accuracy	Overfitting risk with smaller datasets	PlantVillage dataset	Precision = 99.40%, Accuracy = 99.40%, F1 Score = 99.39%, Recall = 99.39%
Abinaya et al. [31]	CAAR-UNet	High accuracy in disease segmentation and classification	Limited to four disease classes	PlantVillage Dataset and Coffee Leaf Dataset	Accuracy = 95.26%, Weighted mean intersection over union = 74.51%, Dice Coefficient = 61.76%, Mean boundary F1-Score = 55.54%
Panchal et al. [32]	CNN	Improves crop yield by minimizing disease spread	Requires high quality labeled image datasets	Plant Village dataset	Accuracy = 93.5%

Saleem et al. [33]	AgirLeafNet model	High detection accuracy for multiple crops	Limited by the quality of labeled data for training	Potato, tomato and mango leaf disease dataset	Accuracy = 98%, Recall = 97% and F1 score = 98%
Krishna et al. [34]	EfficientNet-B0, EfficientNet-B3, ResNet50, and DenseNet201	Incorporates multiple pre trained CNN models for improved results	Requires fine tuning for specific agricultural regions	PlantDoc dataset and Web-Sourced Dataset	For PlantDoc dataset Accuracy = 73.31%, For Web-Sourced Dataset Accuracy = 76.77%
Alhwaiti et al. [35]	YOLO model (YOLOv3, YOLOv4)	Fast and accurate disease detection	It struggles with subtle symptoms in some plant varieties	Plant Village dataset	Accuracy = 98%, Precision = 98%, Recall = 99%, F-measure = 99%
Sathya et al. [36]	AARN, cGAN	Improves detection speed with faster RCNN integration	Data augmentation might not cover all disease types	PlantVillage dataset	Precision = 98.56%, Accuracy = 98.78%, Recall = 98.92% and F1 score = 89.6%
Syed et al. [37]	ELFDR-LDC-CNN-BiLSTM	Efficient feature dimensionality reduction for early disease detection	Model performance may decrease with low quality images	Pepper Leaf Dataset and Maize Leaf Dataset	Accuracy = 99.37%, F1 score = 99.5% Precision = 98.4%, Recall = 97.8%
Liu et al. [38]	LPMAResNet	Lightweight and efficient with fewer parameters	Limited evaluation on real world noisy datasets	Soybean diseases dataset and plant village dataset	Accuracy = 95.80%
Sultan et al. [39]	Deep Transfer Learning method	Fast and efficient disease classification with low latency	Model interpretability may be challenging	FlowerNet, ISPGULDataset8C, Chinese Disease Datasets	Recall = 98%, Accuracy = 98%, and F1 score = 98% and Precision = 99%
Prommakhot et al. [40]	TwoConv-BiLSTM,	High accuracy ensures reliable disease classification	Dataset imbalance handling is not clearly addressed	PlantVillage dataset	Accuracy = 97.88%, Precision = 97.93% and Recall = 97.62%

IV. RESULTS AND DISCUSSION

The evaluation of the current DL algorithms presented. Table 2 demonstrates the accuracy of total forecast and detection of plant diseases. The majority among the papers utilized PlantVillage datasets [41] a image database including of 54,309 instances, wherein leaves illnesses were exposed along the ventral aspect of the leaf on a homogeneous

background (black or grey). The image collections includes 14 crop classes, such as tomato and images of 17 fungi, 4 bacteria, 2 mould, 2 viruses, and 1 caused by mite disease. This section examines the precision of various DL plant disease estimation techniques leveraging the PlantVillage dataset and additional standard datasets. The visual illustration demonstrates the efficacy that algorithms for identifying as well as categorizing plant diseases using contaminated images.

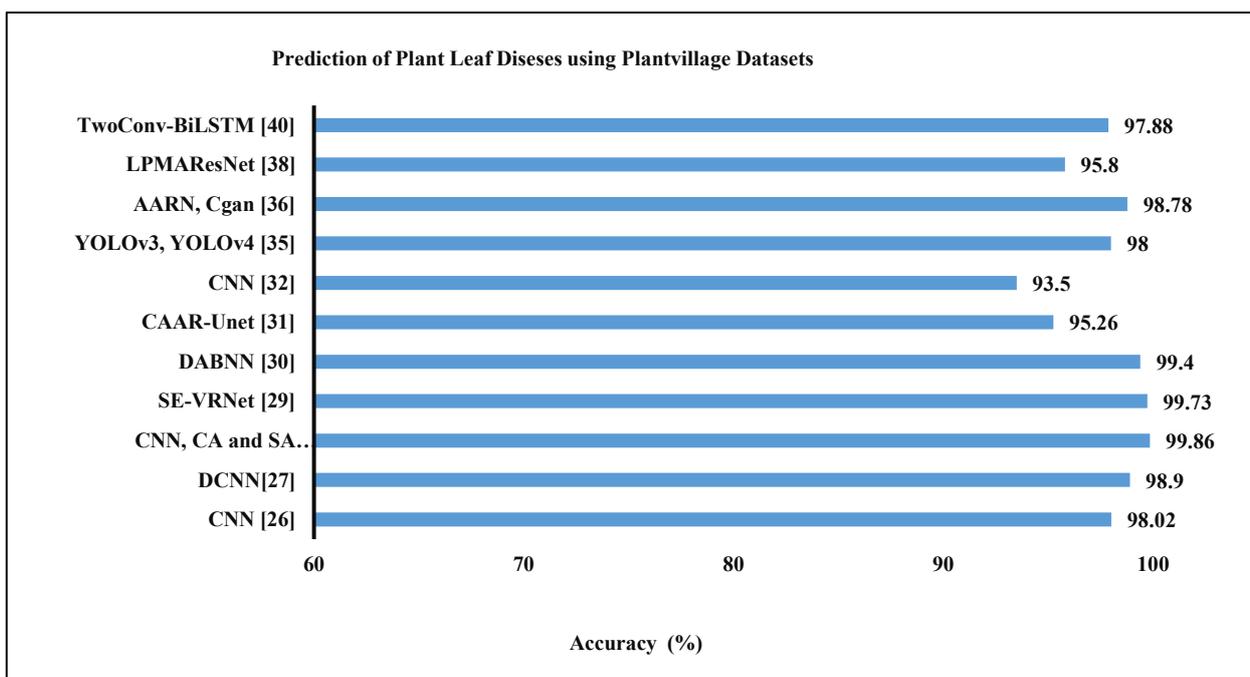


Figure 3. DL based Plant Diseases Forecasting on PlantVillage datasets

Figure 3 demonstrates the performance of various DL models in predicting plant leaf diseases applying the PlantVillage dataset. As it is observed in the figure, several models achieved high accuracy levels, with DABNN, SE-VRNet, and the combination of CNN with channel and spatial attention mechanisms surpassing 99% accuracy, which indicate their strong capability in disease classification. Models such as Two Conv-BiLSTM, AARN with cGAN, YOLOv3/YOLOv4, DCNN, and CNN also shows competitive performance, consistently achieving accuracy values above 97%. LPMA-ResNet and CAAR-UNet maintained accuracy levels above 95%, showing their effectiveness in handling multiclass disease prediction tasks. However, a standard CNN model recorded a comparatively lower accuracy of 93.5%, which suggest some limitations in capturing complex disease-related features without additional enhancements like attention modules or advanced preprocessing. Overall, the results highlight the advantages of attention mechanisms, bidirectional LSTM integration, generative modeling, and hybrid architectures for improving plant disease detection accuracy. Even though many models performed strongly, factors such as computational cost, preprocessing needs, and robustness across diverse datasets still remain important considerations for real-world agricultural adoption.

V. CONCLUSION

This study presents a detailed review was conducted to highlight how DL has transformed plant leaf disease detection by providing exceptional capabilities to learn more intricate patterns directly from raw images. With the progress in CNNs and other DL architectures, these models deliver improved accuracy, scalability, and reliability compared to the conventional ML approaches. By automating the feature extraction and using large datasets, not only boost the diagnostic performance but also supports timely and efficient identification of plant diseases, which greatly contributes to agricultural productivity and sustainability. As the field continue to advance, the emerging DL techniques are expected to bring even greater improvements to precision agriculture and crop management.

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