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Comprehensive Survey of Plant Disease Detection and Classification based on Machine Learning and Deep Learning Algorithms

Suresha S and Manimozhi
Department of Computer Science and Engineering
East Point College of Engineering and Technology Bangalore, India
suresh.radiance@gmail.com and srimanisen@gmail.com

Abstract: *Plant diseases are a major problem worldwide, affecting crop yield and quality and impacting food security. Early identification and accurate diagnosis of plant diseases is crucial to minimizing crop damage and maximizing eco-friendly farming practices. Traditional methods of plant disease detection include manual diagnosis by experts, which is time consuming to arrive at the final diagnosis and is prone to human errors. In recent years, Machine Learning (ML) and Deep Learning (DL) algorithms have been used for the automatic detect plant diseases, with no intervention needed by experts. These algorithms are used to detect diseases by analysing images of plant stems, leaves and other parts, differentiating between healthy and diseased plants. Step by step procedures are used to diagnose plant diseases by employing techniques such as image pre-processing, feature extraction, and classification to enhance image quality for accurate disease classification and prediction. This paper details the application of various existing ML and DL algorithms in the detection, classification and prediction of plant diseases, where image-based techniques are also adopted for accurate and swift diagnosis. Performance metrics such as sensitivity, accuracy, and specificity elaborate on the efficacy of ML and DL algorithms, acting as reliable tools for accurate plant disease detection. The outcomes of this study illustrate that these ML and DL models are well suited for the identification and classification of plant diseases.*

Keywords: deep learning, feature extraction, image processing, machine learning, plant disease

I. INTRODUCTION

Agriculture is a crucial sector that plays a vital role in the economic growth of every country. In India, agriculture contributes over 17% to the total GDP. However, decreasing agricultural land has become a significant issue, adversely affecting both the economy and the interests of farmers [1]. According to a global report, the world population is expected to reach 9.1 billion by 2050, which may lead to severe food shortages worldwide [2]. One of the most challenging tasks in agriculture is the timely identification of plant symptoms and diseases. Traditional methods are still used for the detection and classification of plant diseases. These approaches, commonly relied upon by farmers, are time-consuming as they require manual inspection through the human eye [3]. Early detection of plant diseases is essential to prevent the infection from spreading to other parts of the plant. The key advantage lies in identifying crop illnesses as soon as they manifest on the leaves, allowing for timely treatment [4]. Plant diseases can now be detected automatically using Artificial Intelligence algorithms, including ML and DL techniques. ML algorithms are applied to agricultural images to extract information related to the health of plants [5].

Both ML and DL algorithms have shown promising potential for accurate disease classification from digital images by employing techniques such as image processing, feature extraction, and classification, enabling rapid analysis of plant diseases. ML techniques have been effectively used across domains to detect plant diseases and classify them using methods such as Support Vector Machine (SVM), K- Nearest Neighbors (KNN) and Random Forest (RF). In addition, ML models often incorporate hyperparameter optimization and ensemble learning algorithms to enhance prediction accuracy [6]. DL techniques, particularly CNNs, have gained significant traction in computer vision applications, and recent research has focused on leveraging CNNs for plant disease detection [7]. These models efficiently identify various types of leaf diseases by extracting and combining relevant texture features [8]. CNN-based approaches have been reported on multiple datasets, including those for tomato, cotton, tobacco, and cassava, demonstrating strong performance in disease classification tasks [9]. The high accuracy achieved by these models offers a practical and scalable solution for early disease detection, facilitating timely intervention, reducing crop losses, and minimizing the economic impact on farmers [10].

The remaining part of this survey is structured as follows: Section 2 discusses the plant disease datasets. Section 3 covers the taxonomy of plant disease detection, including dataset descriptions and the literature review. Section 4 presents a comparative analysis. Section 5 outlines the problem statement, and Section 6 provides the summary.

II. PLANT DISEASE DATASET

Plant disease datasets consist of images of both healthy and diseased leaves, which are used to train ML and DL models for disease detection and classification. Several types of plant disease datasets are available, including the PlantVillage dataset, Cercospora Leaf Spot dataset, and Cassava Leaf Disease dataset.

• The plant village dataset [11]: This is a large collection of labeled plant leaf images categorized by crop species and disease types, used for accurate classification. The dataset contains 54,309 images from 38 different classes and includes 14 crop species such as apple, blueberry, corn, cherry, strawberry, tomato, potato, peach, bell pepper, grape, orange, raspberry, squash, and soybean. This diversity makes it an ideal resource for developing accurate and robust plant disease classification models using ML and DL techniques. The images were captured under controlled conditions to ensure consistency and reliability. This dataset is widely used to train CNNs for automated disease detection and precision agriculture applications.

• The cassava leaf dataset [15]: This dataset contains a collection of 21,367 labelled images of cassava plant leaves with healthy and diseased leaf images, which is widely used in deep learning models for classification of plant diseases.

• The cercospora leaf spot dataset [17]: This dataset consists of images of plant leaves infected with the Cercospora fungus, with labeled images indicating both healthy and diseased leaves. ML and DL algorithms are employed to enhance the accuracy of classification. Figure 1 represent the datasets of plant disease detection.

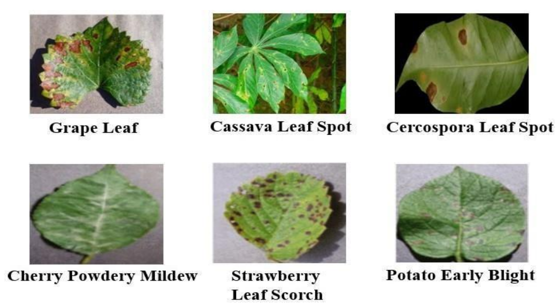

Fig. 1. Representation of plant disease detection datasets

III. TAXONOMY OF PLANT DISEASE DETECTION

The detection of plant diseases is crucial for preventing crop loss, ensuring food security, and protecting farmers' livelihoods. Various methods are employed for plant disease detection. In this section, Fig. 2 presents the taxonomy of ML and DL approaches for plant disease classification.

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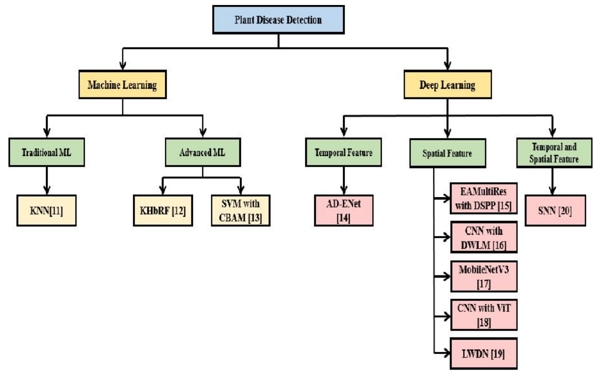

Fig. 2. Taxonomy of plant disease detection

A. Machine Learning (ML)

ML presents itself as a promising approach for automating and improving the detection of plant diseases in an effective manner. In general, ML techniques are categorized into supervised and unsupervised techniques. These techniques are often employed for plant disease detection using a dataset. The models that employ ML to detect plant diseases are discussed below.

1) Traditional ML: Traditional ML refers to classical algorithms like SVM, KNN, and Random Forest, which operate on structured, tabular data. These models require manual feature engineering, where domain knowledge is used to extract relevant features. They are typically efficient and perform well on smaller datasets. Traditional ML is widely used for tasks like classification, regression, and clustering in well-defined problem domains. Shafik et al. [11] introduced a method to effectively detect and classify plant diseases using ML algorithms. A normalization technique was employed to improve convergence during training. Pretrained CNN models, such as ResNet101, DenseNet201, ResNet50, AlexNet, EfficientNetB7, GoogleNet, ResNet18, NASNetMobile, and ConvNeXtSmall, were used to extract relevant features. Logistic Regression was applied in the final stage to analyze the performance of various CNN model combinations, while PDDNet-EA combines extracted features from multiple CNNs into a single feature. The KNN approach improved disease classification performance and enhanced generalization. However, these approaches were unsuitable for real-time agricultural system deployment, where images vary with natural-world backdrops. Fig. 3 represents an overview of PDDNet-EA.

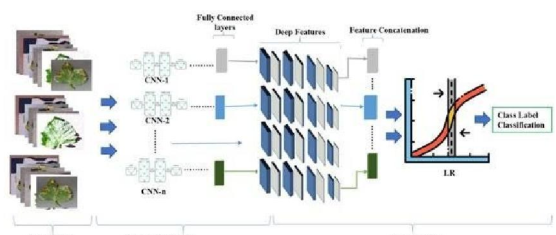

Fig. 3. General overview of PDDNet-EA

2) Advanced ML: Advanced ML includes modern techniques such as ensemble methods, DL, and hybrid models that automatically learn complex patterns in unstructured data. These approaches often combine feature extraction, optimization, and classification into an end-to-end pipeline. Advanced ML is well-suited for high-dimensional data like images, signals, and text, offering higher accuracy and adaptability. Srinivas et al. [12] utilized resizing and normalization techniques for plant disease prediction based on optimized ML algorithms. Resizing and normalization were used to standardize image sizes and pixel values to ensure the consistency of DL. K-means clustering was used for image segmentation, focusing on the affected areas. Statistical features such as mean, standard deviation, and skewness were employed to extract relevant features. The mean was used to measure the average color value of the image, providing an overall brightness. The standard deviation measured the pixel intensity values, while skewness helped differentiate between healthy and diseased regions. Krill Herd-based Random Forest (KHbRF) with an optimized fitness function was

used as the classification algorithm, which built multiple decision trees and merged them for better accuracy. However, relevant solutions were not achieved due to issues such as low accuracy, limited scalability, and the complexity of the algorithm structure. Fig. 4 represents the prediction process of RF.

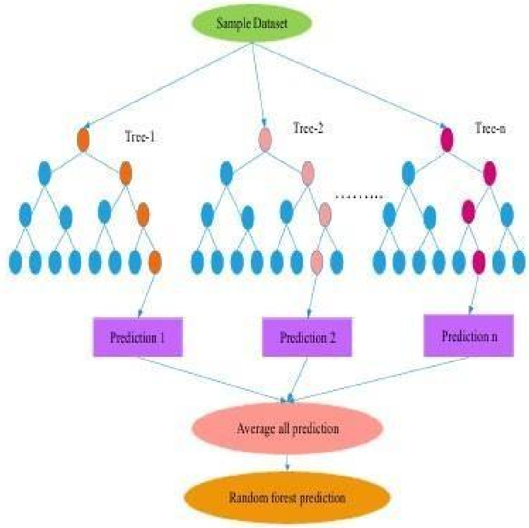

Fig. 4. Random forest prediction process

Kaur et al. [13] developed a method for detecting plant diseases and classification based on SVM. Image augmentation techniques were used to enhance the quality of images. The relevant features were extracted automatically using the CNN method, and the Convolutional Block Attention Module (CBAM) enhanced the features by focusing on essential spatial and channel-wise information. The extracted features were effectively classified based on the SVM method, which accurately classified the plant diseases. However, the combination of SVM, CNN, and CBAM made the model more complex than standalone deep learning models and highly dependent on training data.

B. Deep Learning (DL)

DL models automatically extract raw data without the need for manual human intervention. In image recognition, DL models learn to identify edges, textures, shapes, and even complex objects by training on large, labeled datasets, which enables accurate classification. DL models are highly effective in detecting and classifying plant diseases. Convolutional Neural Networks (CNNs), a type of DL model, are primarily used for processing grid-like data such as images. They automatically learn spatial hierarchies of features through layers of convolutions, pooling, and non- linear activations.

1) Temporal Feature Extractor: Temporal features capture patterns or changes over time in sequential data, such as ECG signals or time-series patient records, helping to identify durations and dependencies across different time steps. Kotwal et al. [14] utilized a technique for plant disease detection based on a DL model called Artificial Driving- EfficientNet (AD-ENet) for classification. Image resizing and a Gaussian filter were used to adjust the image dimensions and reduce noise. The Gray Level Co-occurrence Matrix (GLCM) was applied to extract texture-based features effectively, while the Gabor filter captured spatial frequency and orientation features for texture analysis. AD-ENet enhanced performance, achieving superior classification accuracy. However, the model still requires selecting the most discriminative features to further improve classification accuracy.

2) Spatial Feature Extractor: Spatial features capture the structure, arrangement, and patterns within data, such as images, by understanding local and global relationships like edges, textures, and shapes. Models like CNNs and attention- based architectures (e.g., CBAM) are commonly used to extract spatial features. Al-Gaashani et al. [15] employed a method for plant disease classification based on an Efficient Attention-based Multi-Residual Network (EAMultiRes) with Dilated Spatial Pyramid Pooling (DSPP). Image normalization was applied to scale pixel values to a standard range, and the MultiRes model extracted essential multi-scale features. Residual connections helped prevent the vanishing gradient problem, while CBAM enhanced the features by focusing on important spatial and channel-wise information. DSPP

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extracted multi-scale spatial features from the image, improving the recognition of different plant disease patterns. However, the model's performance was dependent on the characteristics of the training dataset and did not perform well on new datasets, leading to an overfitting issue. Fig. 5 represents the architecture of EAMultiRes.

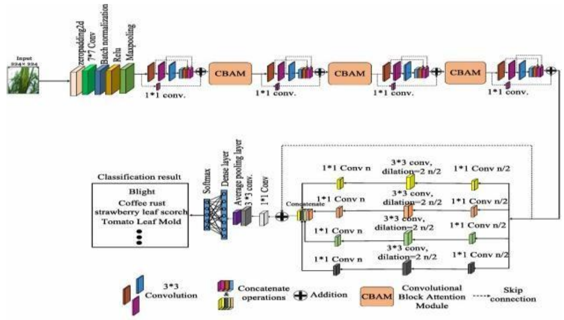

Fig. 5. Architecture of EAMultiRes

Nazeer et al. [16] introduced a method for plant disease classification based on DL algorithms. Image resizing, normalization, and image augmentation techniques were used to enhance image quality for better feature extraction. The CNN was used to extract spatial features such as edges, patterns, and textures automatically with a high classification accuracy. Dynamic Weighted Layering Model (DWLM) was an additional technique used for classification to improve and enhance feature learning in classification. However, the accuracy of CNN-based models heavily depended on the quality and diversity of the dataset. Fig. 6 demonstrates the architecture of CNN.

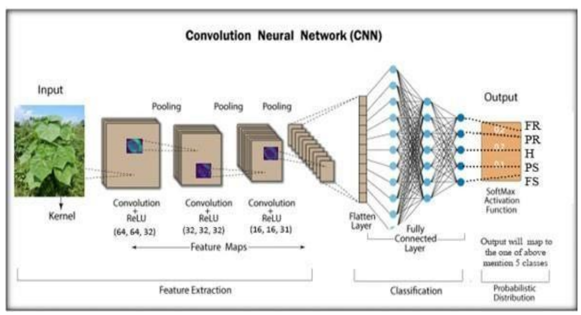

Fig. 6. Architecture of CNN

Joseph et al. [17] developed a method for real-time detection of plant disease based on DL models. Image resizing and image enhancement were used to improve the quality and dimension of the images. Convolutional layers were employed to extract spatial features such as textures, shapes, and edges through filters, while pooling layers were used to reduce dimensionality by preserving essential features. The pre- trained models helped to extract important features from images. Eight fine-tuned DL models, such as Xception, MobileNet, MobileNetV2, and InceptionV3 with softmax activation, were used for accurate classification. However, the limited dataset size and the fine-tuned pre-trained models required high-performance GPUs, which were not accessible in all environments. Fig. 7 represents the architecture of the proposed CNN model.

Kunduracioglu and Pacal [18] introduced a method to detect plant diseases based on CNN with vision transformer techniques. Normalization technique was used to scale the pixel values for faster functioning and data augmentation using techniques like flipping, rotation, and zooming to artificially increase the dataset’s size. Convolutional layers were used to extract spatial features automatically and vision transformer extracts features based on self-attention mechanisms, capturing long-range dependencies in image. Fine-tuned deep learning models were used to classify images into disease categories and softmax activation function was used to convert the model’s output into probability values for multi-class classification. However, CNNs extracted local features effectively and struggled with long-range dependencies as the CNN required large datasets for efficient processing. Fig. 8 represents the operating principle of the CNN model.

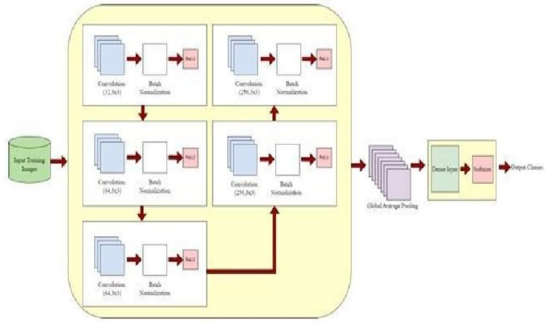

Fig. 7. Architecture of Proposed CNN Model

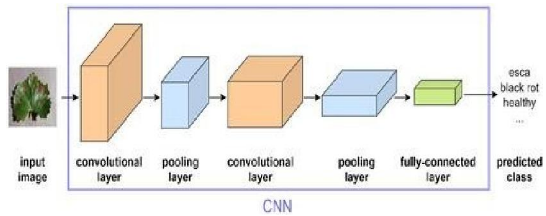

Fig. 8. The Operating principle of CNN Model

Dheeraj and Chand [19] developed a plant disease classification model based on the Light Weight DenseNet model (LWDN). A normalization technique was used to scale pixel values for faster processing, and partial layer freezing was applied to retain pre-trained knowledge in transfer learning. A feature fusion technique was employed to combine essential features extracted from different layers of the model, and DenseNet21 helped to extract deep features as well as improve accuracy. LWDN was a modified DL model based on DenseNet21, which improved disease classification on unseen data effectively. However, pruning layers in the DenseNet21 model removed some important features, which decreased the performance of plant disease classification. Fig. 9 demonstrates the architecture of the LWDN model.

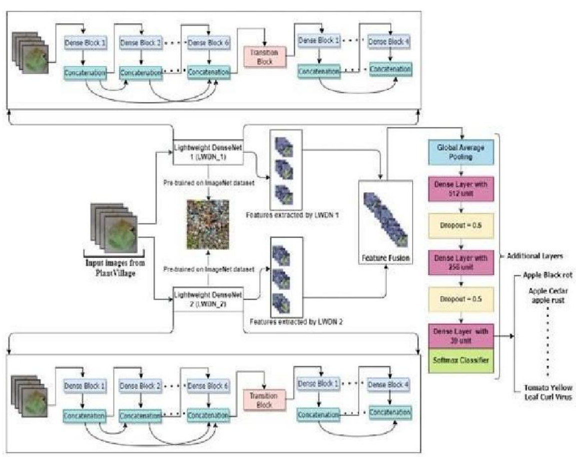

Fig. 9. Architecture of LWDN Model

3) Temporal and Spatial Feature Extractor: Combining temporal and spatial features enables a model to learn both structural patterns and time-based variations in complex data, which helps to improve overall accuracy. Saad and Salman [20] developed a method for plant disease classification based on One-Shot Learning (OSL) techniques with limited datasets, utilizing a Siamese Neural Network (SNN). Region- based segmentation was applied to divide an image into the most important regions for accurate feature extraction and classification. A data augmentation technique was used to enhance the size and dimension of the plant disease dataset. The relevant features were extracted from the image based on the SNN by learning the similarity metric, which effectively classifies plant diseases. The OSL technique helps

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minimize the distance between similar samples and maximize the distance between different samples. However, OSL struggles with generalization due to variations between classes, making it less reliable for highly diverse datasets. Fig. 10 represents the overall architecture of the proposed model.

Fig. 10. Overall Architecture of the Model

The overall analysis highlights the limitations in plant disease classification models, including issues like overfitting, poor interpretability, limited generalization, scalability challenges, and high reliance on large labeled datasets. While advanced ML methods enhance accuracy, they often increase model complexity and still depend significantly on pre-processing techniques. Deep learning models, such as CNNs and transformer-based architectures, are effective at automatically extracting features and achieving high accuracy, but they are prone to overfitting and lack robustness. To address these challenges, techniques such as data augmentation, lightweight model architectures, transfer learning, and attention mechanisms are being explored to enhance generalization and improve model transparency.

IV. COMPARATIVE ANALYSIS

Every method has specific advantages and limitations that make it more suitable for certain tasks. In this section, Table 1 summarizes the advantages and limitations of the various ML and DL approaches used for plant disease classification

Table 1: Comparative Analysis for Existing Methods

Author	Dataset	Advantage	Limitations	Performance Metrics
Shafik et al. [11] 2024	Wheat leaf disease dataset, Plant village dataset.	KNN approach improved disease classification performance and enhanced generalization.	The approaches were unsuitable for real-world smart-based agricultural system deployment that employed images that vary with natural-world backdrops.	Accuracy-96.74%
Srinivas et al. [12] 2024	Potato Leaf Disease Dataset	Krill Herd-based Random Forest (KHbRF) with optimized fitness function was used for the classification algorithm that built multiple decision trees and merged them for better accuracy.	Relevant solutions were not provided due to several problems, including a complex algorithm structure, limited scalability, and low accuracy.	Accuracy-99.55%, Precision-98.85%, Recall-98.98%, F1 score-99.12%.

Kaur et al. [13] 2024	Leaf dataset	Convolutional Block Attention Module (CBAM) enhanced the features by focussing on essential spatial and channel-wise information.	The combination of SVM, CNN, and CBAM made the model more complex than standalone deep learning models and highly dependent on training data.	Precision-0.97, Accuracy-0.987, Recall-0.93.
Kotwal et al. [14] & 2024	Tomato leaf disease dataset	The Gabor filter was enabled to capture spatial frequency and orientation features for texture analysis. AD-ENet enhanced the performance and achieved superior classification accuracy.	The model still required selecting the most discriminative features to further enhance classification accuracy.	Accuracy-99.91, Precision-99.87, Recall-99,81%, F1-score-99.84%.
Al-Gaashani et al. [15] 2024	ImageNet Dataset, Cassava leaf images dataset	DSPP was used to extract multi-scale spatial features from the image to enhance the recognition of different plant disease patterns.	The model's performance was dependent on the characteristics of the training dataset, performing well on new datasets.	Accuracy-99.35%, Precision-99.34%, Recall-99.35%, and F1 score-99.29%.
Nazeer et al. [16] 2024	Tea leaf disease dataset	Dynamic Weighted Layering Model (DWLM) technique was used for classification for accurate classification and enhanced feature learning in plant disease detection.	The accuracy of CNN-based models heavily relied on the quality and diversity of the dataset.	Average recognition accuracy-99%
Joseph et al. [17] & 2024	Rice, Maize, and wheat Datasets	Eight fine-tuned DL models such as Xception, MobileNet, MobileNetV2, and InceptionV3 with softmax activation were used for accurate classification.	Limited dataset size and fine-tuned pre-trained models required high- performance GPUs, which was not accessible to all environments.	Precision-0.9704, Recall-0.9706, and F1 score- 0.9808.
Kunduracioglu and Pacal [18] 2024	Plantvillage dataset	Fine-tuned DL models were used to classify images into plant disease categories, and softamax activation function converted the model's output into probability values for multi-class classification.	CNNs extracted local features effectively and struggled with long- range dependencies as the CNN required large datasets.	Precision, Classification Report, Recall, Confusion Matrix, and Accuracy- .
Dheeraj and Chand [19] 2024	Cold Chili Dataset	LWDN was a modified DL model based on DenseNet21, which improved disease classification on unseen data effectively.	Pruning layers in DenseNet21 model removed some important features, which decreased the performance of plant disease classification.	Precision-99.69%, Accuracy-99.69%, Recall-99.37%, and F1 score-99.36%.
Saad and Salman [20] 2024	Grape, wheat, cotton, cucumber and corn datasets	The OSL techniques helped reduce the distance between similar samples and increased distance between different samples.	The OSL struggled with generalization ability as different classes made the model less reliable for highly diverse datasets.	Accuracy, Precision, Recall, and F1 score.

Aboelenin et al. [21] 2025	Apple and corn datasets	Multi-class classification successfully detected multiple plant diseases across various datasets.	The model trained on a small dataset, which caused overfitting, leading to poor generalization to unseen data.	Accuracy for apple dataset – 99.24% and corn dataset – 98%

V. PROBLEM STATEMENT

In the plant disease classification process, several issues need to be addressed to improve the model's effectiveness. These issues stem from limitations in both ML and DL approaches. The problem statement and its potential solutions for ML and DL approaches are as follows:

• Misclassification occurs due to visually similar plant disease patterns, imbalanced datasets, overfitting, and noise in plant images, all of which reduce the model's accuracy.

• High-dimensional image data often contains noise and irrelevant features, making it challenging to extract meaningful patterns and consequently decreasing classification performance.

• The model may perform well on one dataset but struggle to generalize effectively on unseen datasets due to variations in image backgrounds, lighting, and environmental conditions, leading to overfitting.

VI. DISCUSSION

Plant disease poses a significant threat to global agriculture, affecting crop yields and the economic stability of farming communities. Traditional approaches to plant disease identification rely on manual inspection, which is often influenced by various imaging challenges such as lighting, leaf orientation, and background noise. Accurate disease diagnosis is essential to reduce crop damage, support sustainable farming practices, and maintain eco-friendly agricultural methods. This survey explores the application of advanced image processing techniques alongside machine learning (ML) and deep learning (DL) algorithms for accurate plant disease classification. These models demonstrate the ability to detect plant infections before visible symptoms appear, enabling proactive disease management within precision agriculture frameworks. Additionally, the performance of these approaches is evaluated using key metrics such as accuracy, precision, recall, and F1-score. These metrics validate the reliability and robustness of the techniques in real-world scenarios, making them essential tools for modern agricultural practices.

VII. SUMMARY

Plant disease is a critical issue globally, impacting overall crop yield and the economy of nations. Timely and accurate detection of plant diseases can reduce crop damage and promote sustainable, eco-friendly farming practices. However, traditional plant disease identification methods remain challenging due to variations in imaging quality, such as lighting, background noise, and leaf orientation. This survey presents highly reliable models that integrate image processing techniques with ML and DL algorithms to identify plant diseases before they are visually noticeable. The proposed techniques demonstrate a promising approach for plant disease detection and classification, enabling automated and accurate diagnosis even before visible symptoms appear. This makes them particularly valuable for precision agriculture. The performance of these models is evaluated using various metrics such as accuracy, precision, recall, and F1-score to ensure their reliability in real-world applications. The overall findings suggest that ML and DL methods provide a promising solution for enhancing plant health monitoring systems.

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