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Review of Artificial Intelligence-Based Approaches for Plant Leaf Disease Detection in Agricultural Applications

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***Abstract*—Plant leaf diseases significantly affect crop productivity and quality, making early detection essential for effective crop management. Artificial Intelligence (AI), particularly machine learning and deep learning, offers efficient solutions for automated disease detection from leaf images. This review examines major AI-based approaches, including CNN, transfer learning, and other deep learning techniques, along with datasets, preprocessing, and classification methods. It highlights their benefits in improving detection accuracy and reducing manual inspection. Key challenges such as limited datasets, environmental variations, computational requirements, and real-field deployment are also discussed. Finally, future directions for developing accurate, lightweight, and real-time AI-based plant disease detection systems are presented.**

Keywords*— *Artificial Intelligence, Plant Disease, Leaf Detection, Deep Learning, CNN, Smart Agriculture.

I. INTRODUCTION

Plant diseases are among the major challenges affecting agricultural productivity, crop quality, and food security worldwide [1]. The occurrence of fungal, bacterial, viral, and other diseases can cause severe damage to crops when appropriate preventive measures are not taken at the right time [2]. Therefore, early and accurate identification of plant diseases is essential for effective crop protection, reduction of production losses, and sustainable agricultural practices [3]. Traditional disease identification generally depends on visual examination of plant leaves by farmers or agricultural experts. Although this approach is widely used, it can be time-consuming, subjective, and difficult to implement effectively over large agricultural areas [4].

The development of Artificial Intelligence (AI) has created new opportunities for automated plant disease detection and classification. AI-based systems can process plant leaf images and identify disease-related patterns with high speed and consistency [5]. Machine learning algorithms have been applied to extract and classify important visual characteristics such as color, texture, shape, and lesion patterns from diseased leaves. These techniques can assist farmers and agricultural professionals in making faster and more reliable disease management decisions [6].

Deep learning has further improved the performance of image-based plant disease detection. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in automatically learning discriminative features from plant leaf images without requiring extensive manual feature extraction [7]. Different CNN architectures have been investigated for identifying multiple diseases across various crop species. Their ability to learn complex image patterns makes them suitable for automated agricultural disease recognition systems.

Transfer learning is another important development in AI-based plant disease detection. Pretrained deep learning models can be adapted to agricultural datasets, reducing training requirements and improving classification performance when the available dataset is relatively small [8]. Models based on established architectures can therefore be customized for different crops and disease categories. This approach has contributed to the development of efficient disease recognition systems for crops such as tomato, potato, apple, grape, maize, and several other economically important plants.

The overall performance of AI-based disease detection systems depends strongly on the quality and characteristics of the image dataset. Common processing stages include image acquisition, preprocessing, segmentation, feature extraction, and classification [9].

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Image preprocessing techniques are generally used to improve image quality and reduce unwanted variations before classification. Proper dataset preparation is particularly important because differences in image resolution, background, illumination, leaf orientation, and disease severity can influence the accuracy and reliability of AI models.

Despite significant progress, several challenges remain in applying AI-based plant disease detection under real agricultural conditions. Models trained on laboratory or controlled datasets may not perform equally well on field images because of changing illumination, complex backgrounds, overlapping leaves, environmental conditions, and different stages of disease development [10]. In addition, insufficient training samples, class imbalance, high computational requirements, and limited model interpretability can restrict the practical implementation of AI-based systems. These challenges highlight the need for robust models that can perform reliably across different crops, locations, and field environments.

The integration of AI with smart farming and precision agriculture can further enhance the practical value of automated disease detection. AI-based systems can potentially be integrated with smartphones, drones, remote sensing platforms, and agricultural monitoring systems to provide rapid disease assessment [11]. Such integration can support timely intervention, reduce unnecessary application of pesticides, improve resource utilization, and contribute to more sustainable crop production.

Considering the rapid growth of research in this field, a systematic review of existing AI-based approaches is important for understanding their capabilities and limitations. This review focuses on Artificial Intelligence techniques used for plant leaf disease detection in agricultural applications, with particular emphasis on machine learning, deep learning, CNN, and transfer learning approaches [12]. It also discusses commonly used datasets, preprocessing and classification methods, major challenges, practical applications, and future research directions for developing accurate, efficient, and reliable plant disease detection systems.

II. LITERATURE SURVEY

Borey et al., [1] investigated deep learning-based multi-class classification of plant leaf diseases using Convolutional Neural Networks (CNN) and the VGG16 architecture. The study focused on automatically identifying different plant diseases from leaf images. The use of VGG16 enabled effective extraction of complex visual features associated with disease symptoms. The results demonstrated the potential of CNN-based deep learning for accurate multi-class plant disease classification.

Bhola and Kumar et al., [2] presented a hybrid deep feature-support vector machine (SVM) model for identifying diseases in multiple crops, including corn, rice, and wheat. The approach combined deep feature extraction with SVM-based classification to improve disease recognition. The study addressed the challenge of identifying diseases across different crop types using a common framework. The proposed hybrid model provided an effective solution for multi-crop leaf disease identification.

Kumar et al., [3] developed a hybrid approach for cotton disease detection with the objective of improving crop health and yield. The study integrated multiple computational techniques to identify disease symptoms from cotton plant images. The proposed approach aimed to provide timely and reliable disease information for agricultural management. The findings indicated that automated disease detection can support improved crop monitoring and contribute to better cotton production.

Mohammed et al., [4] presented an edge-cloud remote sensing framework for plant disease detection using deep neural networks and transfer learning. The study focused on combining remote sensing data with deep learning to support large-scale agricultural disease monitoring. Transfer learning was employed to improve the effectiveness of disease recognition while reducing model training requirements. The approach demonstrated the potential of edge-cloud computing for scalable and intelligent plant disease detection.

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Shafik et al., [5] conducted a systematic literature review of plant disease detection techniques, datasets, classification methods, and research challenges. The study examined the development of traditional machine learning and modern deep learning approaches for plant disease recognition. It also highlighted limitations related to dataset availability, environmental variations, and real-world implementation. The review identified important future trends for developing more robust and practical disease detection systems.

Tabbakh and Barpanda et al., [6] presented a deep feature extraction model based on transfer learning and Vision Transformer, referred to as TLMViT, for plant disease classification. The approach combined the feature-learning capability of transfer learning with the advanced representation capabilities of Vision Transformer models. The study aimed to improve the identification of disease-related visual patterns in plant leaves. The results demonstrated the potential of transformer-based architectures for improving automated plant disease classification.

Fan et al., [7] developed a leaf-image-based plant disease identification method using transfer learning and feature fusion. The approach utilized pretrained deep learning models and combined complementary features to improve disease recognition. Feature fusion helped capture more informative representations from plant leaf images. The study showed that combining transfer learning with feature fusion can provide an effective approach for automated plant disease identification.

Li et al., [8] presented a comprehensive review of plant disease detection and classification using deep learning techniques. The study analyzed the application of CNNs and other deep learning models for recognizing disease symptoms from plant images. It discussed different datasets, model architectures, and factors influencing classification performance. The review concluded that deep learning offers considerable potential for automated and efficient plant disease detection.

Liu et al., [9] introduced a large-scale benchmark dataset for plant disease recognition and proposed a visual region and loss reweighting approach. The study addressed the difficulty of training disease recognition models using large and diverse plant image datasets. The proposed method focused on emphasizing important visual regions and improving the learning process through loss reweighting. The work provided a useful benchmark and methodological foundation for improving large-scale plant disease recognition.

Ahmad et al., [10] investigated plant disease detection under imbalanced dataset conditions using efficient CNNs and stepwise transfer learning. The study focused on the problem of unequal numbers of images among different disease classes, which can negatively affect classification performance. Stepwise transfer learning was used to improve feature learning and classification efficiency. The results demonstrated the usefulness of transfer learning and efficient CNN architectures for disease detection with imbalanced agricultural datasets.

Das et al., [11] presented a Support Vector Machine (SVM)-based approach for leaf disease detection. The study focused on extracting useful characteristics from leaf images and using SVM for distinguishing diseased and healthy plants. The approach demonstrated the applicability of conventional machine learning techniques for automated plant disease classification. The work provides an important foundation for comparing traditional machine learning methods with later deep learning-based approaches.

Chen et al., [12] investigated deep transfer learning for image-based plant disease identification. The study utilized pretrained deep learning models to recognize disease symptoms from plant leaf images. Transfer learning reduced the dependence on training deep models from scratch and enabled effective utilization of available agricultural image datasets. The findings demonstrated that deep transfer learning can provide an efficient and accurate approach for automated plant disease identification.

Table 1: Literature Review Summary

Sr. No.	Author name	Work	Outcome
1	Borey et al.	Deep Learning-Based Multi-Class Classification of	CNN and VGG16 effectively classified multiple

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		Plant Leaf Diseases with CNN and VGG16	plant leaf diseases from images.
2	Bhola et al.	Deep Feature-Support Vector Machine Based Hybrid Model for Multi-Crop Leaf Disease Identification	The hybrid deep feature-SVM model provided effective multi-crop disease identification.
3	Kumar et al.	Hybrid Approach of Cotton Disease Detection for Enhanced Crop Health and Yield	The hybrid approach enabled automated cotton disease detection for improved crop monitoring.
4	Mohammed et al.	Edge-Cloud Remote Sensing Data-Based Plant Disease Detection Using Deep Neural Networks with Transfer Learning	The edge-cloud framework supported scalable plant disease detection using remote sensing and transfer learning.
5	Shafik et al.	Present the Plant Disease Detection: Classification Techniques, Datasets,	The review identified major techniques, datasets, challenges, and future directions in plant disease detection.
6	Tabbakh et al.	A Deep Features Extraction Model Based on Transfer Learning and Vision Transformer (TLMViT) for Plant Disease Classification	TLMViT demonstrated the potential of transfer learning and Vision Transformer for disease classification.
7	Fan et al.	Leaf Image Based Plant Disease Identification Using Transfer Learning and Feature Fusion	Transfer learning with feature fusion improved the representation and identification of plant diseases.
8	Li et al.	Plant Disease Detection and Classification by Deep Learning—A Review	The review highlighted deep learning, particularly CNNs, as effective for automated plant disease detection.
9	Liu et al.	Plant Disease Recognition: A Large-Scale Benchmark Dataset and a Visual Region and Loss Reweighting Approach	The proposed benchmark dataset and reweighting strategy improved large-scale plant disease recognition.
10	Ahmad et al.	Plant Disease Detection in Imbalanced Datasets Using Efficient CNNs with Stepwise Transfer Learning	Efficient CNN with stepwise transfer learning addressed class imbalance in plant disease datasets.
11	Das et al.	Leaf Disease Detection Using Support Vector Machine	The SVM-based method demonstrated the feasibility of machine learning for automated leaf disease detection.
12	Chen et al.	Using Deep Transfer Learning for Image-Based Plant Disease Identification	Deep transfer learning provided an effective approach for image-based plant disease identification.

III. MACHINE AND DEEP LEARNING BASED TECHNIQUES

1. Machine Learning-Based Techniques

Machine learning techniques are widely used for plant leaf disease detection by analyzing manually extracted features such as color, texture, shape, and infected regions. Among the commonly used methods, Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) are effective classification approaches. SVM provides reliable classification for high-dimensional feature data, RF combines multiple decision trees for robust prediction, while KNN classifies a new leaf based on its similarity to existing samples.

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However, the performance of these methods largely depends on the quality of feature extraction and image preprocessing.

(a) Support Vector Machine (SVM)

Support Vector Machine is a supervised ML technique widely used for plant leaf disease classification. It separates different disease classes by identifying an optimal decision boundary in the feature space. In plant disease detection, features such as color, texture, shape, and infected-region characteristics are generally extracted from leaf images and provided to the SVM classifier. SVM performs well with high-dimensional features and relatively small datasets. However, its performance depends strongly on the quality of manually selected features and appropriate parameter selection.

(b) Random Forest (RF)

Random Forest is an ensemble ML technique that combines multiple decision trees to perform classification. For plant disease detection, RF can utilize different leaf characteristics to distinguish healthy leaves from different disease categories. Its major advantage is its ability to handle multiple features and reduce the effect of overfitting compared with individual decision trees. RF can also provide useful feature-importance information, making it helpful for understanding which leaf characteristics contribute to classification. Nevertheless, its effectiveness depends on the quality of extracted features.

(c)K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a simple instance-based ML algorithm that classifies a new leaf image according to the classes of its nearest training samples. The similarity between samples can be determined using extracted image features such as color, texture, or shape. KNN is easy to implement and does not require a complex training process. However, its computational cost can increase with dataset size, and its performance can be affected by feature scaling and the selection of an appropriate value of K.

2. Deep Learning-Based Techniques

Deep learning techniques can automatically learn disease-related features directly from plant leaf images, making them highly suitable for automated disease detection. Convolutional Neural Networks (CNN), VGG16, and Vision Transformer (ViT) are important approaches used for this purpose. CNN models effectively learn spatial features such as lesions, spots, and discoloration, while VGG16 can utilize transfer learning for improved classification with limited datasets. ViT uses attention mechanisms to capture relationships between different image regions and provides strong potential for complex multi-class plant disease classification.

(a)**Convolutional Neural Network (CNN)**

CNN is one of the most widely used DL techniques for image-based plant disease detection. Unlike traditional ML methods, CNN automatically learns important features from raw leaf images through convolutional and pooling operations. It can recognize disease-related patterns such as spots, lesions, discoloration, and texture variations. CNN models can perform both feature extraction and classification within a single framework. Their effectiveness has made them highly suitable for automated plant disease recognition.

(b) VGG16

VGG16 is a deep CNN architecture containing multiple convolutional layers that can learn detailed visual representations from images. In plant disease detection, VGG16 is frequently used through transfer learning, where knowledge learned from large image datasets is adapted to agricultural disease datasets. This approach reduces the need for training a complete network from the beginning and can provide effective feature extraction and classification. However, VGG16 contains a relatively large number of parameters and therefore requires considerable computational resources.

(c)Vision Transformer (ViT)

Vision Transformer is an emerging DL architecture that applies transformer-based learning to image analysis. Instead of relying mainly on convolution operations, ViT divides an image into smaller patches and learns relationships between these patches using self-attention mechanisms. For plant leaf disease detection, this enables the model to capture both local disease symptoms and broader spatial relationships within the leaf image. ViT-based approaches have shown strong potential for complex and multi-class plant disease classification, although they may require substantial training data and computational resources.

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IV. CHALLENGES

Although AI-based plant leaf disease detection has achieved significant progress, several challenges still limit its accuracy, reliability, and practical agricultural deployment. Variations in leaf appearance, environmental conditions, image quality, disease severity, and crop varieties can affect model performance. In addition, limited and imbalanced datasets, high computational requirements, lack of model interpretability, and difficulties in real-time field deployment remain important concerns. Addressing these challenges is essential for developing robust, lightweight, and reliable AI-based disease detection systems suitable for real-world agricultural applications.

1. Limited and Diverse Datasets

The performance of AI models strongly depends on the availability of large and diverse datasets. Many existing datasets contain limited crop varieties, disease classes, or controlled laboratory images. Such datasets may not adequately represent real agricultural conditions, reducing model generalization.

2. Class Imbalance

Some plant diseases have significantly fewer images than others, creating an imbalanced dataset. AI models may become biased toward frequently occurring disease classes and perform poorly on minority classes. Data augmentation and suitable learning strategies are required to address this issue.

3. Environmental Variations

Changes in illumination, weather, background, shadows, and leaf orientation can significantly affect image-based disease detection. A model trained under controlled conditions may show reduced performance when applied to images captured in natural field environments.

4. Similar Disease Symptoms

Different diseases can produce visually similar symptoms on plant leaves. Similarly, a single disease may appear differently depending on its growth stage and severity. This makes accurate classification challenging, particularly for closely related disease categories.

5. High Computational Requirements

Advanced deep learning models often require substantial computational resources for training and inference. Large models may not be suitable for low-cost agricultural devices or mobile applications. Developing lightweight and computationally efficient models is therefore important.

6. Model Interpretability

Many deep learning models operate as black-box systems, making it difficult to understand why a particular disease prediction was generated. Lack of interpretability can reduce user confidence among farmers and agricultural experts. Explainable AI can help provide meaningful visual or feature-based explanations.

7. Real-Time Field Deployment

Deploying AI-based disease detection systems in real agricultural fields presents practical difficulties. Smartphone cameras, drones, and edge devices may capture images with different resolutions and environmental conditions. Real-time systems must therefore provide fast and reliable predictions with limited hardware resources.

8. Generalization and Scalability

A model developed for one crop, geographical region, or dataset may not perform equally well for other crops or locations. Differences in plant varieties, disease patterns, and cultivation environments affect model generalization. Future systems should therefore be designed to support multiple crops and disease categories with better scalability.

V. CONCLUSION

Artificial Intelligence has emerged as an effective approach for automated plant leaf disease detection and classification in agricultural applications. The reviewed studies show that machine learning, CNNs, deep learning, transfer learning, and Vision Transformer-based methods can improve the speed, accuracy, and reliability of disease identification from leaf images. AI-based systems can reduce dependence on manual inspection and support timely crop disease management. However, challenges related to dataset limitations, class imbalance, environmental variations, computational requirements, and real-field deployment still need to be addressed. Future research should focus on developing lightweight, explainable, robust, and real-time AI models that can operate effectively under diverse agricultural conditions and support smart and sustainable farming practices.

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