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A Review Of Machine Learning Techniques For Detecting Plant Diseases

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Abstract -Agriculture holds immense importance in India due to its burgeoning population and escalating food demands, necessitating increased crop yields. However, low crop yields are often attributed to diseases caused by bacteria, fungi, and viruses. Detecting and managing these diseases is crucial, and one effective approach is utilizing plant disease detection methods. Machine learning techniques are particularly promising for disease identification in plants, leveraging data-driven insights for accurate detection. Moreover, deep learning has emerged as a powerful tool in computer vision, offering superior performance in disease detection. This comprehensive review explores various AI-based machine learning and deep learning techniques for plant dis-ease detection. Deep learning, in particular, has shown remarkable success in enhancing performance outcomes across diverse domains. By comparing machine learning and deep learning techniques, researchers have demonstrated the effectiveness of deep learning models in detecting plant diseases from images. Implementing deep learning techniques holds significant potential in mitigating major crop losses by promptly identifying leaf diseases from captured images.

I. INTRODUCTION

Agriculture is essential for the economic well-being of all nations. However, meeting current food demands is increasingly challenging due to factors such as population growth, weather variability, and resource limitations. Compounding these challenges is the worsening spread of crop diseases, which cause significant output losses. Yet, with continuous monitoring, these losses can be mitigated [1]. According to estimates from the Food and Agriculture Organization of the United Nations, plant diseases alone cost the global economy $220 billion annually. Developing innovative methods for early disease detection in plants or leaves holds immense potential for boosting yields.Precision agriculture is a fatly evolving field designed to tackle modern challenges in agricultural sustainability. It relies on cutting-edge technology known as machine learning (ML), allowing machines to learn without explicit programming. When integrated with Internet of Things (IoT) enabled farm equipment [2], ML becomes a cornerstone of future agricultural technology.

ML techniques have been widely explored in various research endeavours aimed at identifying and categorizing plant diseases. Many of these studies utilize plant or leaf images as input and determine the presence of disease through classification methods. This involves either multi-class classification, targeting different types of illnesses, or binary classification, distinguishing between healthy and diseased plants/leaves. Traditional ML techniques like Random Forest (RF) and Deep Learning (DL) have been commonly employed for this purpose [3].However, fewer studies have addressed the problem from the perspective of object detection, aiming to identify both the specific disease type and the affected regions within the input image.In scenarios where multiple plant diseases are present in an input image or when pinpointing the exact location of diseased plants within a larger crop area captured by Unmanned Aerial Vehicles (UAVs), the emphasis shifts towards object detection rather than classification. This becomes particularly crucial given the complexity of detecting objects compared to simply classifying them. Deep learning techniques, typically employed for object detection, face challenges in uncontrolled environments such as images containing objects amidst noisy backgrounds [4].

Image processing has emerged as a highly effective tool in various fields, including the medical field and weather forecasting. With advancements in technologies like drones, robots, and communication systems, gathering and processing information has become more efficient. Manual detection and treatment of diseased food crops are time-consuming processes. Therefore, leveraging image processing techniques offers a promising solution [5]. By analyzing crop properties and behaviors through image processing, researchers can streamline crop management processes and improve overall agricultural productivity.

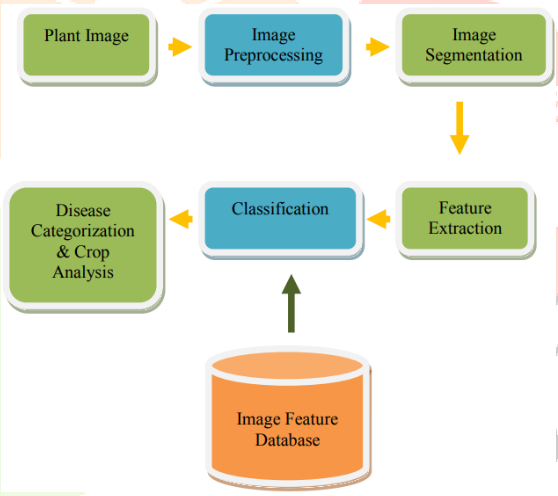

Fig. 1. Plant Disease Detection Stages

Figure 1 depicts the stages of plant disease detection, which are elaborated upon below:

i. Image Acquisition:The process begins with the acquisition of the image, which then undergoes preprocessing based on predefined specifications. Computational techniques are often employed in agricultural data to assess the robustness, length, and width of fruits or crops for analysis. If the obtained image is deemed unsuitable for processing, image enhancement techniques are applied to facilitate this stage [6].

ii. Image Preprocessing*:* Image preprocessing involves the initial processing of the raw image. This typically includes fine-tuning the image for clarity, removing unwanted noise, and enhancing specific features to facilitate further processing. In agricultural image processing, drone or satellite photos are commonly utilized to capture crop images for subsequent processing.

iii. Image Segmentation: Image Segmentation refers to the process of dividing a digital image into multiple segments or parts. The primary objective of image segmentation is to simplify the representation of an image, making it easier to analyze. It is commonly used to identify boundaries [7] and objects within an image, such as leaves, fruits, and vegetables. This process results in a set of segments that collectively cover the entire image. Image segmentation finds diverse applications in image processing, including object detection, traffic signal analysis, medical image analysis, and recognition tasks.

iv. Classification:Image classification is the process of taking an input, such as an image, and determining the class or the probability that the input belongs to a specific class [8]. In the context of identifying plant diseases, the primary objective of this step is to categorize the input plant image as either infected or healthy. If an image is identified as infected, further methods exist for classifying it into various diseases. Over time, numerous researchers have developed various classifiers for the classification of images. In image processing, classification often relies on a database of example images, which are compared to test data collected for evaluation.

v. Disease Categorization or analysis of crop: Once the data has been successfully processed and values obtained, the necessary step is considered complete. In the context of identifying plant diseases, most studies focus on recognizing different types of diseases and categorizing them accordingly [9].

A.Machine Learning algorithms for Plant Disease Detection

This section covers some popular machine learning techniques utilized for plant disease diagnosis:

i. Support Vector Machine (SVM): SVM is a binary classification framework. It aims to construct a hyperplane that separates positive and negative patterns in the best possible way based on the training data. The goal is to find a hyperplane that maximizes the margin between the positive and negative samples, ensuring accurate categorization. However, when dealing with a large number of patterns, SVM may transform the multidimensional pattern space into one that supports linear separation, leading to computational overhead and slower performance.

ii. Decision tree: The Decision Tree is a classification framework commonly used in supervised learning for image classification [10]. It employs a tree structure to consider all possible scenarios and provides the appropriate solution after evaluating all options. The decision tree comprises nodes and directed edges, where nodes can be internal (depicting characteristic features) or leaf (denoting a class). The edges of the decision tree represent the outcomes of feature tests. The accuracy of classification depends on the number of trees, making it effective for classifying small datasets. However, for extensive datasets, the classification accuracy decreases, and adjusting the decision tree structure to enhance performance becomes challenging.

iii. Random Forest: Random Forest (RF) is a machine learning algorithm known for its flexibility and user-friendliness [11]. It often delivers high-quality outcomes even without extensive hyper-parameter tuning. RF is widely recognized and utilized due to its simplicity and versatility. It operates as a supervised learning algorithm, creating a forest by integrating Decision Trees (DTs). This algorithm utilizes the bagging approach, which maximizes overall results through the combination of diverse learning models. RF can be effectively applied to both classification and regression tasks.

iv. KNN algorithm:The K-Nearest Neighbors (KNN) algorithm operates based on the principle of comparing the features of new input data with those of existing sample data in a dataset. Each sample data point in the dataset is associated with a classification label, indicating its category. When a new data point is inputted, KNN identifies the K data points in the dataset that are most similar to the new data based on their features [12]. The category assigned to the new data point is determined by the most common classification label among these K nearest neighbors. KNN is particularly suitable for classification of rare events and performs well for multi-classification problems, often outperforming Support Vector Machines (SVM).

However, its drawbacks include poor interpretability and inability to provide explicit rules like decision trees.

v. Artificial neural network: The Artificial Neural Network (ANN) method simulates the composition of the human brain's neural network structure into a mathematical framework. It comprises numerous interconnected neurons arranged to form a simulated neural network framework. Through dataset training, ANN learns the weight parameters of each neuron in the network. ANN can be divided into a training/learning phase and a recognition/classification phase [13], depending on the process used to establish the network model. To enhance the speed and accuracy of image recognition and classification, this algorithm optimizes and adjusts network metrics. Backpropagation (BP) networks and radial basis function (RBF) neural networks are currently the most widely used ANN models.

B.Challenges in Plant Disease Detection

A comprehensive review on machine learning to detect and classify plant diseases and the thorough computation study indictes that various challenges are occurred in practical applications to detect plant diseases. These challenges are defined as:

i. The frameworks used for handling non-image data are not available properly. The traditional method for classification and object detection (OD)methods are emphasized solely on image data, and neglected other applicable information like temperature and humidity. The fundamental task is to generate methods for incorporating non-image data to attain more optimal predictions.

ii. Only some datasets are available which are totally annotated open. Diverse studies are depending upon the PlantVillage dataset, that is gathered under a controlled laboratory situation. To create huge datasets under real-time scenarios, is essential. Collaborative efforts must be taken for producing representative datasets.

iii. Various works aimed to tackle the issue related to detect disease as a classification issue, either binary or multi-class classification. Whereas several studies focus on detecting diseases as a classification issue. So, the major intent is on object detection for recognizing disease kind and infected areas in the image.

iv. Several papers make the execution of an individual dataset for training and testing the frameworks. However, the accuracy of these frameworks isfound poor on diverse datasets. Thus, utilizing various datasets is required for making the model more robust.

v. Various images having numerous leaves are comprised in existing datasets. To annotate datasets for detecting disease at initial stage and recognize small leaf is required.

vi. Traditional algorithms have an issue related to images captured in varied lighting situations and constriction. These problems are tackled via more effective techniques.

vii. Different models are worked rigorously, that delay in real-time applications. To enhance the computational efficacy of their models is another significant task.

II. LITERATURE REVIEW

S. M, et.al (2023) discussed that the farmers were free to take the essential steps for discontinuing the spreadof diseases and ensuring healthy crop harvests after recognizing the plant disorders accurately and earlier [17]. A machine learning (ML)-based method was suggested to recognize plant diseases from digital images of plants. In this method, the images were pre-processed, crucial features were extracted, and the images were classified into 2 classes, namely healthy and infectious. For this,ML methods were employed to detect diseases. A public dataset in which plant images of diverse diseases comprised, was utilized to simulate and test the suggested method. The experimental results depicted that the suggested method offered superior accuracy up to 95%. Moreover, this method was capable of diagnosing plant diseases, and its applicability was proved in precision agriculture (PA)for improving crop health and harvests. Thus, a robust application was generated to distinguish the infected plants from healthy ones.

Y. Zhao, et.al (2022) introduced a Double Generative Adversarial Network (DoubleGAN) which produced images of diseased plant leaves for balancing large datasets [18]. This method was employed for creating infected images of higher resolution relied on fewer samples. This method was executed in 2 phases. Initially, theWasserstein generative adversarial network (WGAN) employed the healthy and diseased leaves as input for attaining the pretrained model. Subsequently, this model was fed with unhealthy leaves for producing 64*64pixel images of diseased leaves. The latter phase was aimed to implement a super-resolution generative adversarial network (SRGAN) for attaining corresponding 256*256pixel images so that the unbalanced dataset was extended. Eventually, the comparison of these images was done with the images of Deep convolution generative adversarial network (DCGAN). The generated images were found clearer. The experimental results demonstrated that the introduced method had offered an accuracy of 99.80% to detect plant species and 99.53% to detect diseases. Moreover, this method offered superior results in contrast to other methods on the original dataset.

S. M. N. Nobel, et.al (2024) presented a new technique in order to detect diseases of palm leaf based on a hybrid framework [19]. The central component of this framework aimed at integrating Efficient Channel Attention Network (ECA-Net) with reliable transfer learning (TL) methods. For this, ResNet50 and DenseNet201 were deployed. When the accuracy to detect disease was enhanced, this fusion was utilized for setting a novel performance bar in comparison with traditional methods. The presented framework was capable of maintaining accuracy up to 98.67% to validate data and 99.54% to train data to recognize diseases in an accurate way. Additionally, this framework had offered higher F1 score values to prove its potential in agricultural technology. An advance method was generated further to detect diseases palm leaves.

S. S. Harakannanavar, et.al (2022) recommended an approach to detect diseases occurred on plant leaves [20]. Furst of all, this approach was executed for resizing the samples of tomato leaves to 256 × 256 pixels and employing Histogram Equalization (HE)for enhancing quality of tomato samples. After that, the K-means clustering (KMC) method was presented to split dataspace into Voronoi cells. The contour tracing was executed to extract the boundary of leaf samples. Various descriptors called Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) and Grey Level Co-occurrence Matrix (GLCM)were adopted for extracting informative features of leaf samples. In the end, themachine learning (ML) methods, namely Support Vector Machine (SVM), Convolutional Neural Network (CNN) and K-Nearest Neighbor (K-NN) were exploited for classifying the extracted features. The testing results proved that the recommended approach yielded an accuracy of 88% with first method, 99.6% with second and 97% with last method. This approach was robust for diagnosing tomato diseases.

R. Maurya, et.al (2024) devised a meta-ensemble of lightweight Multi-Layer Perceptron-Mixer (MLPM) and faster Long Short-Term Memory (LSTM) algorithms to diagnose plant diseases on low-powered micro-controllers (MCUs) of IoT devices [21]. The initial algorithm was planned on the basis of a simple MLP network. In devised approach, the initial level was focused on attaining predictions based on trained models and fed them into next level for training the machine learning (ML) algorithm. Consequently, the accuracy to classify plant diseases was enhanced. Three datasets containing varied sizes and plant species, such as Maize, Cotton, and a dataset taken from the PlantVillage(PV) dataset, were employed to simulate the devised approach. The experimentation indicated that the devised approach had diagnosed plant disorders at an accuracy of 94.27% on first dataset, 98.43% on second and 97.45% on last dataset. Furthermore, this approach consumed least predictive time and utilized only few trainable metrics in contrast to other methods. Hence, the efficacy of devised approach was proved to detect plant diseasesusing restricted resources.

X. Zhang, et.al (2024) projected an image classification (IC) technique called SE-SK-CapResNet,to diagnose plant diseases in which capsule networks (CapsNet) was integrated with residual network (Resnet) [22]. At first, the existing algorithm was optimized and refined to improve the primary convolutional layer of second algorithm. For this, its kernel was replaced with a concatenation of 3×3 small convolutional kernels, for extracting features of plant leaf lesions. At second, a channel attention (CA) mechanism was incorporated into residual block for enlarging the focus on critical features. At last, the integration of both algorithms was utilized. The major task was of mitigating the loss of positional information after eliminating the initial pooling layer. The output of the 3rd residual module was related to CapsNet for making the technique more robust. The PlantVillage, AI Challenger 2018, and Tomato Leaf Disease datasets were employed for evaluating the projected technique. The projected technique attained an accuracy of 98.58% on primary dataset, 95.08% on next, and 97.19% on last dataset. The experiments confirmed the adaptability of projected technique to detect diseased leaves in agriculture domain.

S. Allaoua Chelloug, et.al (2023) designed a Multi-agent DRL and EfficientNet (MULTINET)-based model todetect 3D plant leaf disease and estimate severity [23]. Firstly, an Adaptable LoW Pass Weiner (AWW) filter was deployed to pre-process image which cleaned the data and EMbellished Manta-Ray Optimization Algorithm (EMMARO) based data augmentation (DA)for enhancing the image quality and balancing the classes. Secondly, Block Divider Model (BDM) was implemented to convert 2D image into 3D for navigating information from diverse perceptive. The Enhanced Deep Q-Network (EnDeep) was utilized to segment 3D image. In this algorithm, Haar-U-Net (HUNT) algorithm was employed to extract features and Convolution Feature Attention (CFA) method to reduce dimensionality. The designed model andDi-attention aided Bilinear-VGG (EBBI) algorithm was adopted for detecting species and disorders. Finally, the severity was estimated when lesions counts and its density was contemplated. The results revealed that the designed model was led to enhance the accuracy up to 29%, precision up to 19%-28%, sensitivity of 31%-38%, F1-score of 31%-38%, and ROC curve of 0.15–0.22.

V. Sharma, et.al (2023) intended a novel deeper lightweight convolutional neural network (DLMC-Net) modelfor detecting plant leaf disease over diverse crops for real-time agrarian applications [24]. A sequence of collective blocks was presented with the passage layer for extracting deep features. Hence, the vanishing gradient issue was handled. Additionally, the point-wise and separable convolution blocks were executed for alleviating the number of trainable metrics. Four datasets: citrus, cucumber, grapes, and tomato were exploited to simulate the intended model concerning accuracy, error, precision, recall, sensitivity, specificity, F1-score, and Matthews correlation coefficient (MCC). The experimentaloutcomes validated that the intended model was more effective to detect disorders under complicated background situations. The accuracy of this model was calculated 93.56% on first dataset, 92.34% on second, 99.50% on third, and 96.56% on last dataset. In addition, this model utilized only 6.4 million trainable metrics.

V. K. Vishnoi, et.al (2023) designed a convolutional neural network (CNN) to detect diseases of plantsin which smaller number of layers were utilized to mitigate computation burden [25]. Some augmentation methods, like shift, shear, scaling, zoom, and flipping were implemented for generatingmore samples to enlarge the training set for which no more images were required. The PlantVillage dataset was utilized for training the designed method so that diverse diseases, like scab, black rot, and cedar rust diseases were detected from apple leaves. The simulations depicted the suitability of designed model for detecting apple leaf diseases at an accuracy of 98%. This model consumed least storage and lower execution time as compared to other techniques. Furthermore, the designed model was applicable to implement handheld devices while detecting diseases.

S. Bhagat, et.al (2024) presented diverse lightweight and effective algorithms to detect plant diseases in resource-constrained devices [26]. A lightweight Lite-MDC model was suggested to detect diseases occurred in plants. The Multi-kernel Depthwise separable Convolutions (MDsConv) was utilized to extract multiscale feature of plant diseases. This module was helped in capturing spatial features across diverse scales when a lightweight design was maintained. This design was utilized for extracting multi-scale information so that the plant diseases were characterized at diverse scales. The suggested model was useful for alleviating the computation complexity up to 62% with only 2.2 million metrics in contrast to other methods. The experiments demonstrated the superiority of suggested model over the existing approaches to detect plant diseases. This model offered an accuracy of 94.14% on pigeon pea dataset, 99.78% on PlantVillage, 86.4% on Cassava, and 97.2% on apple leaf datasets. Moreover, the applicability of suggested model was proved on resource-constrained edge devices to detect plant disorders.

TABLE I
COMPARISON OF EXITING APPROACHES

Author/Year	Technique Used	Dataset	Parameters	Results	Advantages	Limitations
S. M, et.al (2023)	Machine learning (ML)-based method	PlantVillage dataset	Accuracy	The experimental results depicted that the suggested method offered superior accuracy up to 95%.	This method was capable of diagnosing plant diseases, and its applicability was proved in precision agriculture (PA)for improving crop health and harvests.	The dataset employed in this work was consisted of restricted amount of images.
Y. Zhao, et.al (2022)	DoubleGAN	PlantVillage dataset	Accuracy	The experimental results demonstrated that the introduced method had offered an accuracy of 99.80% to detect plant species and 99.53% to detect diseases.	This method offered superior results in contrast to other methods on the original dataset.	The issue of data imbalance was occurred in case the samples were maximized.
S. M. N. Nobel, et.al (2024)	A new technique of ECA-Net and TL	PlantVillage dataset	Accuracy and F1-score	The presented framework was capable of maintaining accuracy up to 98.67% to validate data and 99.54% to	This framework had offered higher F1 score values to prove its potential in agricultural	Higher training time and more computing needs led to make this technique

				train data to recognize diseases in an accurate way.	technology.	more complex in real-time applications.
S. S. Harakannanavar, et.al (2022)	An approach	PlantVillage dataset	Accuracy ,Precision, Recall and F1 score	The testing results proved that the recommended approach yielded an accuracy of 88% with first method, 99.6% with second and 97% with last method.	This approach was robust for diagnosing tomato diseases.	This approach was unable to detect other leaf samples.
R. Maurya, et.al (2024)	Meta-ensemble of lightweight Multi-Layer Perceptron-Mixer (MLPM) and faster Long Short-Term Memory (LSTM)	Maize, Cotton, and PlantVillage dataset	Accuracy and time	The experimentation indicated that the devised approach had diagnosed plant disorders at an accuracy of 94.27% on first dataset, 98.43% on second and 97.45% on last dataset.	This approach consumed least predictive time and utilized only few trainable metrics in contrast to other methods.	This approach was ineffective for precision agriculture (PA).
X. Zhang, et.al (2024)	SE-SK-CapResNet	PlantVillage, AI Challenger 2018, and Tomato Leaf Disease datasets	Accuracy	The projected technique attained an accuracy of 98.58% on primary dataset, 95.08% on next, and 97.19% on last dataset.	The experiments confirmed the adaptability of projected technique to detect diseased leaves in agriculture domain.	The computation complexity was not resolved.
S. Allaoua Chelloug, et.al	MULTINET-based model	PlantVillage	Accuracy, precision	The results revealed that the designed	The severity was estimated	This model had not recognized

(2023)			, sensitivity, F1-score and ROC curve	model was led to enhance the accuracy up to 29%, precision up to 19%-28%, sensitivity of 31%-38%, F1-score of 31%-38%, and ROC curve of 0.15–0.22.	when lesions counts and its density was contemplated effectively.	diseases at upper surface and under surface.
V. Sharma, et.al (2023)	DLMC-Net model	Citrus, cucumber, grapes, and tomato datasets	Accuracy, error, precision, recall, sensitivity, specificity, F1-score, and MCC	The accuracy of intended model was calculated 93.56% on first dataset, 92.34% on second, 99.50% on third, and 96.56% on last dataset.	The intended model was more effective to detect disorders under complicated background situations.	This model was not applicable on large datasets.
V. K. Vishnoi, et.al (2023)	Convolutional neural network (CNN)	PlantVillage dataset	Accuracy, execution time	The simulations depicted the suitability of designed model for detecting apple leaf diseases at an accuracy of 98%.	The designed model was applicable to implement handheld devices while detecting diseases.	This model was unsuitable on diverse geographic regions at which the image quality was varied.
S. Bhagat, et.al (2024)	Lite-MDC model	Pigeon pea, plant village, Cassava, and apple leaf datasets	Accuracy	The experiments demonstrated the superiority of suggested model over the existing approaches to detect plant diseases. This model offered an accuracy of 94.14% on pigeon pea dataset,	The applicability of suggested model was proved on resource-constrained edge devices to detect plant disorders.	This model was incapable of localizing disease accurately in an image.

				99.78% on PlantVillage, 86.4% on Cassava, and 97.2% on apple leaf datasets.		

III. CONCLUSION

Extensive research has been conducted on various machine and deep learning techniques for recognizing and classifying plant diseases. Following this, additional classification techniques in machine learning might be employed to aid in automatic disease detection across different crops, thereby benefiting farmers. This analysis delves into various approaches of machine learning/deep learning for detecting plant diseases. Additionally, several techniques and mappings have been summarized for identifying disease symptoms, showcasing the recent development of ML/DL technologies in identifying plant leaf diseases. We anticipate that this research will serve as a valuable tool for scientists investigating plant disease detection. Furthermore, a comparative study has been conducted between machine and deep learning techniques. Despite significant progress in recent years, there are still some research gaps that need addressing to implement effective techniques for plant disease detection.

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