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A Review on Plant Leaf Disease Detection

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Abstract*— Diseases affecting plants contribute to declining crop yields and associated economic costs. The cost, duration, and precision of a plant disease diagnosis depend on the early detection methods. This study analyzes the many techniques for identifying plant diseases by examining available photos and using different processing algorithms. It does this by utilizing both traditional machine learning methods and deep learning methods to perform a careful analysis of the work that has been done in the literature about the datasets that were used, the various image processing techniques that were implemented, the models that were used, and the efficiency that was obtained. The paper explains each technique's potential pitfalls and advantages and the obstacles that need to be overcome for efficient plant disease diagnosis. The results suggest that deep learning is superior to other machine learning algorithms in identifying plant diseases, whereas visible-range photos are preferred over spectral ones.

***Index Terms*—Plant disease detection, visible range image, spectral image, traditional machine learning, deep learning.**

I. INTRODUCTION

For many people in rural areas of developing nations, agriculture is the primary means of subsistence. As much as 25% of GDP in certain low-income nations comes from farming [1]. Growing the crop's production is one way to keep up with the needs of a populace on the rise. However, the contribution given by agricultural goods is significantly impacted by losses due to crop diseases and pests. Diseases may spread quickly in unstable weather, further compounding the issue of food insecurity. The prevention of crop losses in the early stages is essential for the economy's growth and food provision for humans and animals. Maintaining ecological balance relies on this. The increased interest has been seen in implementing precision agriculture strategies to achieve a sustained boost in productivity and yields to overcome these hurdles and achieve success.

The early diagnosis of plant diseases is now being accomplished in several ways. A classic agronomic diagnosis relies on the expert's ability to evaluate the plants visually. This approach, however, is time-consuming, expensive, and inaccurate. There is a substantial danger of output losses owing to crop diseases, and many growers in rural extensions lack access to this expert guidance. Because of the time and effort involved, laboratory testing can only provide much information. Non-invasive procedures have received more attention in recent decades as an alternative to the limitations of laboratory-based approaches. The extensive research in this field aims to overcome the limitations of conventional approaches by creating an automated, rapid, and precise system. Employing different image processing techniques is a common approach to fulfilling the abovementioned conditions. Recent years have seen the development of several cameras with sensitive sensors explicitly designed for gathering this information from crops. Visual, spectral, thermal, and fluorescence imaging are examples of the many imaging technologies available. To train and evaluate machine learning algorithms, the pictures taken by the appropriate imaging instruments are processed using various image processing techniques. All previous work in disease detection relied only on traditional machine-learning methods. However, the automated systems based on conventional machine learning techniques have performance and crop/disease limitations due to their reliance on tiny datasets and a human-constructed feature extraction approach.

Deep learning is a practicable tool for increasing automated processes for extraordinary speed, a more significant crop and disease range, and real-time disease diagnosis due to recent breakthroughs in fields like computer vision and graphics processing units. The academic community has recently placed a greater emphasis on automated feature extraction and illness categorization. This research aims to evaluate the efficacy of employing RGB and spectral imaging to detect plant disease, emphasizing both conventional machine learning and deep learning architectures. Each technique's advantages and disadvantages are weighed, and the obstacles that must be overcome to achieve quick, accurate, real-time plant disease detection are outlined. Figure 1 depicts the several methods for diagnosing plant diseases included in this analysis.

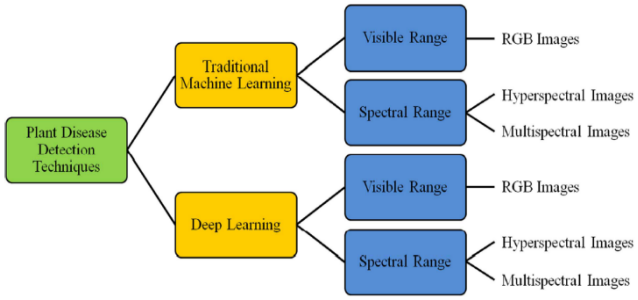

Figure 1. Various methods for detecting plant diseases

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The remaining sections of the research are organized as follows. Section 2 looks at relevant research on image processing algorithms to detect pests and diseases. The strengths and weaknesses of the approaches are discussed in Section 3, along with the obstacles that must be overcome to develop a reliable crop disease diagnostic system. The findings are presented in section 4.

II. SURVEY ON PLANT LEAF DISEASE DETECTION

Over several decades, scientists have developed various invasive and non-invasive approaches for early disease detection in plants. But new agricultural technologies need a non-invasive, automated approach to diagnosing plant diseases. Different image processing techniques are used to create a reliable and efficient system for the autonomous plant disease detection job. This is made possible by the proliferation of cameras equipped with susceptible sensors that can catch even the finest crop characteristics. Leaves, roots, fruits, flowers, and even the stem may all show signs of illness. Even though you can look at pictures of stems [2], fruits [3], and the whole plant [4], most of the work in the literature has mostly looked at pictures of leaves.

This article will examine the history of machine learning and deep learning concerning disease diagnosis. Classical machine-learning approaches for crop disease diagnosis using RGB and spectral pictures are reviewed in subsection A. In contrast, the work on deep learning architectures applied to visible light, and spectral images are reviewed in subsection B.

A. Conventional machine learning approaches for plant disease detection

We turn to machine learning techniques to uncover functional, general patterns in otherwise unstructured data. Traditional machine learning algorithms were first utilized for picture categorization in early work on an illness diagnosis. In Figure 2, we see the standard procedures for using conventional machine learning algorithms for plant disease identification and classification.

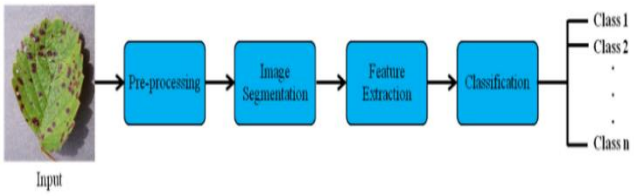

Figure 2. General steps in traditional machine learning

Whether starting from scratch or utilizing a publically accessible dataset, the initial step is to compile a database of photos. Preprocessing the image is a crucial first step that speeds up subsequent processing stages by improving picture quality. Image scaling, noise reduction, contrast improvement, color space conversion, etc., are all common preprocessing operations. We may extract the desired area from a larger picture by using image segmentation. Among the many segmentation methods available, thresholding and K-means clustering are two of the most used. Segmented photos are then processed to remove non-essential information and focus on the essentials, such as shape, size, texture, and color. After extracting feature vectors, they are used to teach machine learning algorithms how to classify pictures. Images may be categorized using a variety of classifiers, such as support vector machines (SVMs), naive Bayes classifiers (NBs), artificial neural networks (ANNs), and many more. The trained model is then applied to test data to assign the novel data to one of the predefined classes. Accuracy, precision, the F1-score, and the area under the curve are only a few assessment criteria used to calculate the model's potential.

B. Conventional machine learning with RGB images

There has been a lot of research in this area, and different illness detection systems have different recommendations for classifying and segmenting data. A system for the diagnosis and categorization of citrus diseases based on outward signs was given by Ali et al. [5]. Image-contaminated areas were separated based on the distance between colors. Color histogram and texture traits were used to classify citrus leaves as either healthy, diseased, downy, or infected. The technique was evaluated using an SVM, K-Nearest Neighbor (KNN), boosted tree, and bagged tree classifiers, as well as a Local Binary Pattern (LBP) and color features. The authors used illness-level and picture-level classification and found that color characteristics provided a substantial distinction for disease-level classification. It was stated that both the accuracy and sensitivity combined were 99.7%. Results from an experiment using a mixture of color and texture characteristics lagged behind those obtained using either feature alone. One hundred ninety-nine photos were all that was stored in the database.

Potato disease classification using photos from the plant village dataset [7] was suggested by Islam et al. [6]. For picture separation, the authors used the La*b* color model to generate masks. Results showed a 95% accuracy using a combination of 10 color and texture characteristics and multiclass SVM. However, only 300 photos were included in the study's experiments, but there are many photographs of potato leaves in the plant village collection. A more extensive dataset might have helped performance in these experiments [5, 6].

Zhang et al. [8] showed a technique for diagnosing citrus canker by combining global characteristics and zone-based local features retrieved from photographs of leaves obtained in the field. The canker lesions were separated from the background using an enhanced AdaBoost algorithm, and a descriptor for them was generated by combining color and the distribution of the local texture. Citrus canker lesions were identified using a two-tiered hierarchical structure that

achieved classification accuracy on par with human specialists.

Using three separate datasets, Sharif et al. [3] devised an algorithm for identifying lesions on citrus fruit and leaves. The preprocessed photos were then subjected to an optimized weighted segmentation approach. The color, texture, and geometric characteristics were used to create a codebook, from which the best features were chosen using a hybrid feature selection method. An average accuracy of 92.435% was achieved during classification using a multiclass SVM.

Hassanien et al. [9] developed a moth-flame approach based on rough sets to detect powdery mildew and early blight in tomato leaves. The SVM algorithm classified sick tomato leaves using a feature selection approach given in this work. Particle Swarm Optimization (PSO) and a Genetic Algorithm (GA) were compared to the suggested moth flame optimization method. The classification accuracy was enhanced by 6% using the suggested feature selection strategy.

This research [3,9] showed that classifiers' performance might improve with careful feature selection. To automatically detect and classify five types of leaf disease, Singh et al. [10] developed picture segmentation approaches based on GA. Bacteria cause infections on roses and beans, sunburn on lemon leaves, early scorch on banana leaves, and fungus on beans. A color co-occurrence matrix was used to determine four distinct features of the textures. We employed minimum distance criteria (MDC) and SVM during the separating procedure. The authors discovered that the accuracy of MDC with K-means was 86.54%, that of MDC with the suggested GA was 93.63%, and that of SVM with the proposed GA was 95.71%. This work demonstrates that using learning algorithms for lesion segmentation is possible and practical.

Barbedo et al. [11] advocated using digital image processing to detect several plant diseases in field circumstances simultaneously. They utilized data from a database that included 82 unique diseases seen in 12 distinct plant species. For this purpose, we used the guided active contour (GAC) method. The degree to which each pixel diverged from green for symptom segmentation was determined using a binary mask and two ratios. Different properties useful for symptom identification were obtained by color manipulation. Color histograms were used for training to reflect the disease's overall pattern of activity, and a reference histogram was used for paired categorization confusion matrix was used to show what was found. Challenges like the link between diseases and the different ways pictures were taken were also mentioned in the research as things that could lead to mistakes.

Alternaria, black spots, and leaf miner pests were identified in apples using image processing approaches by Omrani et al. [12]. K-means clustering was used to segment the photos after they were collected in a controlled laboratory setting. To do this, we employed the wavelet transform and a co-occurrence matrix of grey levels to extract color and texture information in the La*b* color space. SVMs using radial basis functions (RBFs), polynomial functions (polys), and ANN classifiers were used to classify apple leaf diseases. The algorithm was put through its paces using only well-lit, black-background photographs.

Fermi energy-based segmentation techniques were used by Phadikar et al. [13] to categorize brown leaf patches, leaf blasts, sheath rot, and bacterial blight. Rough set theory was used to choose salient characteristics, including the infection's color, shape, and location. This study employed a rule-based classifier to categorize rice diseases with 92.29% accuracy. The authors tested their proposed technique on the benchmark UCI dataset in addition to the state-of-the-art feature selection and classification methods, finding that it outperformed them with an overall accuracy of 80%. Selecting principal characteristics may simplify the classifier and limit the data lost. It is always important to balance feature dimension and information loss.

In his review, Barbedo [2] compared several techniques for diagnosing plant diseases and quantifying their impact. The author referred to digital photographs of leaves and stems captured in the visible spectrum. A method for automated identification and quantification of leaf disease signs was published by Barbedo [14], which uses image processing methods. Using just elementary morphological processes and the * channel in La*b* space, the author obtained a 96% overall classification accuracy in illness detection. However, the algorithm only worked if the photo was taken against a dark or white backdrop.

Camargo et al. [15] detailed a technique for observing leaf symptoms. After adjusting the color of the RGB photos, we used the histogram's intensity distribution to create segments and then used local maxima as thresholds. The performance of the automated segmentation method was compared to that of a manual segmentation method to see how well it works. The authors continue their analysis by applying the discovered target locations [16]. It was used to classify retrieved features from the target areas. When pictures lack distinct color and form, the scientists found that texture attributes provided the greatest discriminating. These analyses revealed the significance of using suitable hand-crafted features for enhancing classifier performance.

Johannes et al. [17] suggested an approach that uses the detection of a possible hot zone and statistical reasoning for the on-site diagnosis of Septoria, rust, and tan spot in wheat. According to the research results, two distinct approaches may be used for segmentation: manually generated masks, simple linear iterative clustering (SLIC), and visual characteristics. We were able to locate and evaluate potential disease hotspots by using the features of the surrounding neighborhoods. Using a meta classifier, the AUC was found to be more than 0.8. The authors say their algorithm is

effective across various crops and diseases and has been implemented in a mobile app. The authors demonstrated that color constancy might be utilized to correct light fluctuations by dealing with the illumination shifts that occur in field circumstances.

Johannes et al. [17] devised a way to determine if wheat has Septoria, rust, or tan spot on-site by looking for a possible hot zone and using statistical reasoning. Making this choice when using manually built features and shallow classifiers necessitates trial and error since performance might fluctuate with a little shift in any of these variables. The hand-crafted method bound both the crop and disease range and the number of training samples.

C. Classical machine learning with spectral images

Fluorescence, thermal, hyperspectral, and multispectral imaging are non-visual imaging techniques that have significantly impacted many areas of plant disease detection [18,19]. The most common imaging methods are multispectral and hyperspectral imaging. These imaging approaches may potentially provide spatial and spectral information on plants for assessment purposes. Within our investigation's scope, key concerns are the manual work required to carry out hyperspectral and multispectral imaging methods. Multispectral and hyperspectral methods acquire data across different wavebands. Hyperspectral data collection covers a more comprehensive spectral range than multispectral. The rich spectrum information in spectral imaging may be used to diagnose diseases before any outward symptoms arise.

Cucumber downy mildew was detected via hyperspectral imaging by Tian et al. [19]. Image fusion was the first step in the process, followed by picture enhancement, binarization, corrosion, etc. This allowed them to obtain an accuracy rate of 90%. Bauriegel et al. [20] and Barbedo et al. [21] researched how to detect wheat infected with fusarium head blight. Wheat was studied by Bauriegel et al. [20] utilizing hyperspectral pictures for early identification of fusarium under realistic settings. We could pinpoint four spectral regions that were useful in the classification process using principal component analysis (PCA). The authors' results show that stage 75, as determined by the Chemical Industry, the Biologische Bundesanstalt, and the Bundessortenamt, is the ideal stage for disease detection during the development period (BBCH). The illness index was analyzed using a spectral angle mapper (SAM). The research did find that SAM was a time-consuming procedure, which is why they developed the head blight index: for speedy diagnosis.

Hyperspectral imaging was used by Barbedo et al. [21] to detect fusarium head blight in wheat grains. The method returned an index representing the likelihood that the kernel was compromised. The system accurately classified the kernels and estimated the quantity of the mycotoxin deoxynivalenol inside them. In their study, Li et al. [22] used a hyperspectral imaging technique to identify common flaws in orange peels. This research used a straightforward thresholding approach with principal component analysis and band ratio to assess the hyperspectral pictures. However, only 270 samples were utilized in the experiments. Therefore, the research cannot be considered statistically significant.

Huang et al. [23] identified the rice leaf folder using hyperspectral reflectance. A linear regression model was developed to investigate the relationship between the leaf reflectance measurements obtained during the rice growth booting phase and the ensuing impacted canopy. The research determined which was most effective for spotting the rice leaf folder using the red, green, and near-infrared spectrums. This model used spectral indices to identify a leaf roll rate and an infection scale. The root means square error (RMSE) method was used to examine the data, and the authors proposed employing hyperspectral reflectance to detect the rice leaf folder. However, the scope of the research was too narrow to account for a wide range of variables, including crop type, growth stage, pest kind, and so on.

Zhang et al. [24] investigated Winter wheat's spectral reflectance to detect the presence of powdery mildew. The authors investigated the possible use of hyperspectral reflectance as a winter wheat powdery mildew diagnosis tool. When the reflectance of healthy and ill leaves was examined in controlled laboratory conditions, it was found that there were significant spectral changes in the visible and near-infrared areas. According to the severity of the patient's injuries, researchers divided the patients into three groups using Fisher's linear discriminant analysis (FLDA), multivariate linear regression (MLR), and partial least square regression (PLSR). The results showed that PLSR outperformed MLR in determining the degree of the illness, whereas FLDA excelled in a discriminatory analysis of highly damaged leaves.

According to studies by Rumpf et al. [25] and Mahlein et al. [26], sugar beet is vulnerable to Cercospora leaf spots, leaf rust, and powdery mildew. As an early warning system, Rumpf et al. [25] employed SVM to identify and categorize sugar beet diseases detected by hyperspectral reflectance before the onset of apparent symptoms. In addition to being able to tell the difference between healthy and sick leaves, the study was also able to tell the difference between different types of leaves with over 86 percent accuracy.

Particular disease spectral indices were developed by Mahlein et al. [26] to aid in diagnosing sugar beet diseases using hyperspectral signatures. This study used the RELIEF-F method to derive the optimal and normalized wavelength differences. With this technology, we were able to detect sugar beet diseases with an accuracy of 89%, including leaf spot (92%), powdery mildew (95%), and rust (87%).

Shi et al. used a kernel discriminant technique based on spectral vegetation indicators [27] to detect and categorize winter wheat pests and diseases. Discriminant analysis was

performed using a Gaussian kernel function, and redundant spectral vegetation indicators were eliminated using independent t-tests and correlation analysis. The system achieved an accuracy of over 87% when determining which leaves in the canopy were healthy and which were damaged. The total accuracy of the program at the leaf level was 82.9 (light), 89.2 (moderate), and 87.9 (very accurate) (severe). The first plant pathogen detection systems used hyperspectral and multispectral imaging methods.

Soybean rust was detected using multispectral pictures by Cui et al. The authors separated the diseased area using a threshold established following a hue-saturation-intensity (HSI) color model. The rust severity index was calculated with the help of two different disease diagnostic factors. In addition, a study of the leaflet's central color spread in polar coordinates was carried out to automate the rust identification process. Aleixos et al. [29] captured images of citrus faults using visible and near-infrared spectral ranges. The algorithm was built on a board with two DSPs to speed up calculations. The system also recognized citrus fruits like lemons and mandarins.

The effectiveness of multispectral and RGB systems in identifying winter wheat head illness was evaluated by Dammer et al. [30]. The RGB system required calibration for R, G, and B values in the grayscale channel and adjusting each type's threshold. On the other hand, the multispectral strategy only required a single calibration before the measurements, which led the authors to conclude that it was more effective than the RGB system. Only one calibration was necessary for the multispectral approach.

Oberti et al. [31] took multispectral images of grapevine leaves from five angles to test off-angle sensing calculations' effectiveness in boosting powdery mildew's detection sensitivity. A combination of two spectral indices was used to determine the detection sensitivity. The authors found that the optimal viewing angle was 60 degrees and that sensitivity increased from 0 to 75 degrees. The studies above show that pictures with a wide spectral range (multispectral or hyperspectral) might aid in an early diagnosis of illness. However, their use is limited by factors like their prohibitively high price, the need for specialized sensors and calibration, the need to operate in a tightly controlled environment, carefully picking an acceptable spectral band, and so on.

D. Classical machine learning with spectral images

Because of recent developments in artificial intelligence, processor technology, image processing, and the software that supports these processes, deep learning represents a significant advancement in computer vision technology. Supervised and unsupervised pattern recognition and classification methods have seen considerable use in this promising area of research. Similarly, it has been used to solve problems associated with food production in the agricultural sector [32]. Plant disease diagnostics is one area where deep learning may be used. During model training, convolutional neural networks (CNNs) in deep learning are famous for extracting characteristics from the input. Deep learning architecture for identifying plant diseases. Many computer vision tasks may now be completed without the requirement for feature engineering because of the success of deep learning as a feature extractor and classifier. Deep learning architectures need extensive datasets for proper training, which is necessary for effective feature extraction. However, extensive and diverse datasets are scarce in plant disease identification. Some of these challenges are being overcome by using transfer learning. An example of transfer learning is using a model trained on a large dataset to perform a similar but distinct task [33, 34].

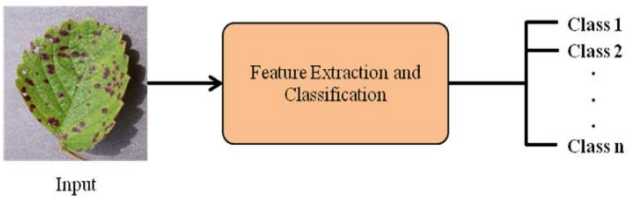

Figure 3. Classification steps in deep learning

In recent years, there have been several advances in identifying plant diseases using deep learning algorithms applied to visible band pictures. Single-shot multi-box detector (SSD) was used by Jiang et al. [35] to identify apple diseases. The improved VGGNet and rainbow concatenation method is reported in the paper. The model achieved a recognition speed of 23.13 frames per second (FPS) and a mAP of 78.80 %. In addition, it was shown that the model could identify many diseases in a single picture of the damage. DCNN was suggested by Selvaraj et al. [4] to identify pests and diseases in banana plants by their outward symptoms. The authors employed transfer learning to propose six models (one for each component of the banana plant) and 18 classifications. We employed the ResNet50, InceptionV2, and MobileNetV1 models to classify data. Rapid object identification was achieved by combining an SSD model with MobileNetV1. These results show that SSD's capabilities may be used for real-time applications like plant disease detection.

To identify plant diseases from leaf lesions and spots, Barbedo et al. [36] turned to a pre-trained network, GoogLeNet. Segmenting the original photos into discrete lesions and spots was required, with various symptoms (small, big, dispersed, solitary, extensive, and powdery) taken into account. The fidelity of the detected lesions and spots was higher than that of the source images. They've made the database freely available online. Because of this study, we can now accurately detect many illnesses on a single leaf. With DCNN, Geetharamani et al. [37] were able to categorize 13 types of plant leaves from the plant village dataset into 39 distinct groups. The authors state that the model's accuracy increased by augmenting the data by 91.43

% to 97.87 %. They experimented with different epochs, batch sizes, and dropouts when training their model. This study demonstrates that augmenting data improves recognition accuracy.

Transfer learning and visual geometry group-16 are both used in the method suggested by Coulibaly et al. [33] to identify mildew illness in millet crops at an early stage (VGG16). The model performed exceptionally well, with an F1-score of 91.75 %, 95 % accuracy, 90 % precision, 95 % recall, and 95 % F1-score. This was achieved even though the dataset was tiny. Too et al. [38] worked to improve the CNNs, now considered state-of-the-art. Utilizing a dataset consisting of photos from 38 different illness types, they compared the effectiveness of six distinct deep architectures. According to the results, DenseNets performed better regarding accuracy, necessary parameters, and computational time.

By comparing infected and healthy leaves, Mohanty et al. [34] were able to train a deep convolutional neural network (DCNN) to distinguish between 14 crop kinds and 26 diseases. Based on their examination of two prominent topologies, AlexNet and GoogleNet, the authors conclude that GoogleNet performs better on the dataset. These researches show that when there aren't enough publically accessible big datasets for plant disease diagnosis, transfer learning may still outperform models created from scratch.

To build on the work done by Johannes et al. [17] and tackle the problem of disease categorization in crops produced in the wild, Picon et al. [39] used DCNN. The system uses a deep residual neural network (ResNet), enhanced augmentation techniques, and tile cropping to classify real-world images of three wheat illnesses. It improved artificial background training, superpixel segmentation, and confidence estimation, among other things, to an average of 0.87 (ResNet) from 0.78. (Traditional technique). On the pilot test, the model likewise showed a balanced accuracy of 0.96. The investigation showed that putting random pictures in the backdrop of training photographs improved recognition performance in field situations.

Diseases in tea leaves might be identified using a low-shot learning method, as suggested by Hu et al. [40]. Tea leaf classification using VGG16's conditional deep convolutional generative adversarial networks achieved an average accuracy of 90%. (C-DCGAN). The spots were segmented using color and texture data using SVM.

The plant disease diagnosis work of Ferentinos [41] included training several CNN architectures (VGG, over feat, AlexNet, GoogLeNet, and AlexNetOWTBn) utilizing photos of infected leaves. 87,848 photos from controlled lab settings and natural environments were included in the data collection. The authors found that a success rate of 99.53 % was achieved by using the VGG model. However, the scientists noticed a significant decrease in identification accuracy when testing the model using field photos instead of laboratory images. This study shows that for the model to generalize to new images, especially those taken outdoors successfully, it must be trained on large datasets with high variability.

Ghazi et al. [42] assessed how various factors influenced the effectiveness of DCNN for plant identification using the LifeCLEF 2015 database. They examined three deep learning models (GoogLeNet, AlexNet, and VGGNet) via fine-tuning and discovered that combining several classifiers resulted in significant performance increases. There was an 80% success rate in validation using the suggested model, and an inverse rank score of 0.752 was obtained using the test data. A comprehensive performance analysis based on critical aspects that affect the honed performance of deep learning models was also highlighted in the research. This research showed that a better classifier might be achieved by combining results from many classifiers. It also showed how the recognition rate was affected by tweaking the data and the hyperparameters.

DCNN was suggested by Lu et al. [43] as a tool for identifying rice diseases. Plant life, namely leaves and stems, inspired their designs. This investigation attained an accuracy of 95.48% using a tenfold cross-validation technique. Using stochastic pooling, the authors improved classification accuracy. Using CNN for plant identification, Lee et al. [44] suggested using valuable discriminating characteristics extracted from photos of leaves. To quantify the traits that best distinguish the leaves, they used a deconvolutional network (DN) technique. According to the research, the vein structure is crucial for detection when the form characteristic is insufficient. The results showed that including both regional and international characteristics improved identification accuracy.

III. DISCUSSION

Several different early detection approaches are being developed to reduce the financial impact of pests and diseases on crops. Some of the most common methods used for this goal are those that are automated and use machine learning algorithms. These methods analyze the imaging hardware and software data to classify photos. Many different imaging methods have been documented in the literature, each with its advantages and disadvantages. However, many imaging methods exist, with RGB imaging being the most well-known and straightforward. Technology like digital cameras and sensors have allowed for widespread acceptance of this technique. However, certain illnesses have no apparent symptoms or don't present themselves until it's too late to treat. In such situations, the symptoms often only become apparent in the electromagnetic spectrum ranges beyond the typical human visual system's ability to detect them. Multispectral imaging, hyperspectral imaging, thermal imaging, etc., might all be valuable tools in these scenarios.

One benefit of using these photos is that they may spot diseases before symptoms appear. It has been shown in the literature that chlorophyll fluorescence and thermography are best at recognizing early stress in plants but are less effective at detecting particular diseases [18]. At the same time, multispectral and hyperspectral pictures are more effective at detecting these diseases. No doubt, many helpful studies have been accomplished using these imaging methods. However, the expense currently prevents such imaging technology's widespread use. Large sensors and unusual hardware are required, and choosing the right spectral band is a crucial step that may impact predictions' accuracy and the processing time required to make them. Even if several different imaging technologies are available, an appropriate application of the algorithms that analyze and classify the images plays a vital part in detecting agricultural diseases and pests. Due to the tiny datasets and need for feature engineering for manually constructed feature extraction, these techniques have limitations. Thus, this results in constrained crop and disease scope and performance. The early research on identifying pests and diseases was done using traditional machine-learning techniques. The number of experiments using deep learning architectures has increased during the last several years. The availability of more enormous datasets, the fast advancements in GPU processing capability, and the creation of auxiliary software libraries are some of the causes of this growth.

IV. CONCLUSION

This study provides a comprehensive overview of current methods for identifying plant diseases using various imaging modalities, classical machine learning, and deep learning frameworks. According to recent studies, convolutional neural network (CNN) models are superior to traditional machine learning models for diagnosing agricultural diseases in terms of accuracy and detection breadth across a wide range of plant species and diseases. However, to train the model effectively, vast datasets are required. In addition, the constraints caused by the absence of publicly accessible datasets and photographs recorded in natural situations are discussed. The research also discusses using many imaging modalities to collect as much data as feasible for early illness diagnosis. As one of several imaging methods available, RGB imaging is by far the most common. There is no way to diagnose diseases before they show symptoms. We may employ hyperspectral and multispectral pictures to accomplish this asymptomatic illness detection. However, the processing of high-dimensional data, the need for a significant amount of computer time, the handling of spectral band noise, the choice of the most valuable bands, and other difficulties must be overcome. Smartphones with sophisticated built-in sensors and small deep-learning architecture will be used for real-time, rapid, accurate, and early disease detection for many plants and illnesses to minimize financial and agricultural losses. This has been made possible by advancing technology, including image sensors, GPUs, and computer vision.

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