ADVANCEMENTS IN MANGO LEAF DISEASE DETECTION: A COMPREHENSIVE SURVEY OF EMERGING TECHNIQUES

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Abstract

Mango is one of the most economically significant fruit crops worldwide, providing nutrition and livelihood to millions of people. However, mango leaf diseases can cause substantial yield losses and affect the quality of fruits. The most efficient therapy and prevention of many disorders depend on their early identification and precise diagnosis. The purpose of this study is to offer a synopsis of the many approaches used to identify mango leaf diseases. Traditional approaches, such as visual inspection and manual identification, have limitations in terms of accuracy and efficiency. Therefore, researchers have explored alternative methods that utilize advancements in technology and image processing algorithms to automate the detection process.This article discusses the possibility of computer-assisted approaches for disease and staging in mango leaves, and evaluates 45 articles on the topic of mango leaf disease detection. This overview looks at how several methods, such as computer vision, machine learning, and deep learning, have been used to the problem of detecting diseases in mango leaves. The first step in these processes is to extract useful characteristics from photos of mango leaves, and the second is to classify the extracted features using a variety of techniques and models. The strengths and weaknesses of each method, as well as how well they perform in terms of precision, throughput, and scalability, are discussed in this survey.

Keywords: Mango Leaf, Disease Prediction, Survey, Analysis

I. INTRODUCTION

Mango (Mangiferaindica) is a widely grown fruit tree that is very important economically and culturally in many regions of the globe [1]. It is widely prized for its delectable fruit, nutritional value, and importance to the lives of millions of farmers and merchants. Mango crops, on the other hand, are prone to a variety of leaf diseases, which may have a substantial influence on productivity, fruit quality, and overall plant health [2-6]. The diagnosis of these illnesses in a timely and accurate manner is critical for adopting effective management measures and avoiding their spread [7-10].

Visual examination by experienced specialists or agricultural extension workers has traditionally been used to identify mango leaf diseases [11-16]. This manual technique has limits in terms of subjectivity, reliance on knowledge, and time commitment. Furthermore, it becomes difficult to diagnose illnesses at an early stage when symptoms are not always visible [17-22]. Technological advancements, notably in the disciplines of computer vision, image processing [23-34], and machine learning, have opened up new possibilities for automated and objective mango leaf disease diagnosis. Researchers and practitioners have been able to design creative ways that improve illness detection accuracy, efficiency, and scalability by harnessing these technologies [35].

The purpose of this study is to offer a complete assessment of the present methodologies and strategies for detecting mango leaf disease. It encompasses a broad variety of methodologies, including both old methods and new technology like machine learning and deep learning. This study seeks to support informed decision-making when choosing acceptable techniques for mango leaf disease diagnosis by analyzing the strengths and limits of each methodology [36-40].

Furthermore, the availability of publicly available datasets is critical to the advancement of research in this sector [41-45]. The study goes through the current datasets for mango leaf disease detection and how they affect the creation and assessment of detection algorithms. It also covers the issues of dataset gathering, annotation, and standardization [46].

This study seeks to add to the knowledge base and motivate future research in this vital field of agricultural science by giving a complete overview of the present status of mango leaf disease detection. The ultimate objective is to improve disease control procedures, minimize production losses, and increase mango cultivation's overall sustainability and productivity.

II. LITERATURE SURVEY

SanathRao et al. (2021)any kind of abnormality, whether it be caused by fungi, bacteria, or viruses, may be detected by a plant disease detection system. In this research, we created a classifier for disease identification in grape and mango leaves using a pre-trained deep learning model, AlexNet. Seven thousand two hundred twenty grape leaves from the publicly available

Plant Village dataset and one thousand two hundred sixty mango leaves collected separately were used to train the model. These images were shot in natural light in the fields during harvest. The suggested model successfully classified grape leaves that it had never seen before with an accuracy of around 99.03%. This study illustrates the effectiveness of a low-cost, smartphone-based disease detection system in seeing the early warning signs of infectious illnesses that may wipe out an entire crop and leave the farmer destitute.

Pham, T. N. et al. (2020)To better understand the wide variety of mango leaf diseases, we propose using deep neural networks in this research. Wrapper-based feature selection using an Adaptive Particle-Grey Wolf metaheuristic (APGWO) was first used to narrow the pool of possible features down to 81. The MLP uses these features as inputs for classification. The proposed technique outperformed deep learning models without transfer learning enhancements, such as VGG, AlexNet, and ResNet-50 (89.41% vs. 78.64%).

Arya, S., & Singh, R. (2019)In this study, we compare the performance of the CNN and AlexNet architectures in identifying diseases in potato and mango leaves. The results demonstrate that AlexNet architecture outperforms CNN design with regards to both accuracy and recall. Accurate predictions of the occurrence of favorable outcomes (high accuracy and recall) suggest that the classifier is doing well. Since AlexNet architecture has more layers than CNN Architecture, training it takes more time. However, it also produces superior results when comparing healthy and ill leaves. The next step of this research project will be to create a smartphone app that can identify the illness and provide useful information to farmers. Farmers will snap images of sick leaves, and the smartphone app will diagnose the problem and provide a treatment plan.

Table 1: comparison table

Authors	**Methodology**	**Advantage**	**Limitation**	**Accuracy**
SanathRao, U. et al. (2021)	Deep Learning	AI algorithms, such as deep learning models, have shown remarkable accuracy in detecting and	The model's performance is highly dependent on the diseases included in the training dataset. If a new or	89%

		classifying plant diseases. By training on large datasets of diseased and healthy plant samples, these models can learn intricate patterns and features that may not be easily discernible to the human eye.	previously unseen disease affects the plants, the model may struggle to accurately classify it.	
Arya, S., & Singh, R. (2019)	Deep Learning	CNN architectures, including AlexNet, are designed to automatically extract relevant features from images. This eliminates the need for manual feature engineering, where domain experts would have to handcraft specific features to train a model.	Limited dataset size The study mentions the use of a dataset containing 4004 images for potato and mango leaves. While this dataset size may be suitable for initial experiments, it may not capture the full diversity and variability of diseases in real-world conditions.	98.33%

Raina, S., &Gupta, A. (2021)	Machine Learning	Automatic leaf disease detection systems enable the early identification of diseases in plants. By capturing and analyzing visual patterns and symptoms on plant leaves, these systems can detect diseases at their initial stages, allowing farmers to take timely action	Although the paper mentions tabular analysis based on various datasets and preferences, it is important to note that the scope of the analysis may be limited.	93%
Jogekar, R., &Tiwari, N. (2020)	machine and deep learning	By analyzing visual patterns and features in leaf images, these techniques can identify diseases that are not easily detectable by human observation alone.	CNN models often work as black boxes, making it challenging to understand the underlying reasoning behind their predictions. The complex layers and hierarchical	-

			structures of CNNs make it difficult to interpret how specific features are being used for classification.	

Singh, U. P. et al. (2019)The productivity and quality of plants and their products may be improved by reducing the impact of biotic variables that cause significant losses in agricultural output. Several issues related to plant leaf diseases have been successfully addressed by combining computer vision with machine learning approaches.

2.1 Survey on Leaf Disease detection using machine learning

Raina, S., & Gupta, A. (2021)In this work, we introduced the foundational methods that scientists have used to identify plant diseases. Dataset-specific and preference-driven, the tabular analysis provides tools for id'ing, segmenting, and categorizing. The recognition and learning rates of GPDCNN are superior. GANs have more convincing evidence of data appropriation (more refined and clear images). That is to say, with the datasets, we also presented an overview of the methods currently in use for addressing the issue.

Hossain, E. et al. (2019)This research used the KNN method to build a plan for classifying leaf diseases. The experiment accounts for leaf-affecting diseases such alternata, anthracnose, bacterial blight, leaf spot, and canker. Classification is performed using GLCM texture features, and the sick region is segmented using a k-nearest neighbor classifier. Measuring the DSC, MSE, and SSIM parameters allows us to get a quantitative idea of how well the suggested method performs, and we find that the segmentation result based on the KNN classifier provides the highest accuracy when it comes to spotting plant illnesses.

Jogekar, R., &Tiwari, N. (2020)Multiple other methods of classification have been shown to be inferior to CNN. These include color-based noise reduction pre-processing, CCD-based image acquisition, k-Means & segmentation expectation maximization, built-in CNN features like Hu moments and Haralick features, color histograms and gradient-oriented histograms, sped-up robust features like SURF, dense SIFT like DSIFT, and so on. Therefore, a combination of these methodologies, although remaining successful in photographic identification of leaf diseases, may improve the overall performance of the methodology under study.

Annabel, L. S. P., &Muthulakshmi, V. (2019)In this work, we offer an automated method for diagnosing diseases on tomato leaves. At first, we converted the photos of tomato leaves from RGB to grayscale. In addition, ROI is obtained by masking and thresholding. Then, we use GLCM and random forest to pinpoint the specific bacterialspot, lateblight, and tomatomosaic illnesses present on tomato leaves. When combined, these algorithms outperform competing methods. In our proposed study, we combine AI with image processing to help farmers improve upon existing practices in order to boost output, efficiency, and the quality of the predictions they may make about the onset of leaf diseases.

Wongsila, S. et al. (2021)There is potential for a computer vision software taught using machine learning methods to dramatically improve any operation involving plants. Therefore, in this work, we developed a unique approach using ML algorithm to identify mangoes with the fungal illness Anthracnose, with an accuracy of more than 70%.

Singh, V., &Misra, A. K. (2017)In this study, an algorithm for segmenting images is used to demonstrate the automatic identification and categorization of plant leaf diseases. The techniques of illness categorization that are now in use are also discussed in this research. Bananas, beans, jackfruit, lemons, mangoes, potatoes, tomatoes, and sapotas are among the 10 species. This led to the collection of disease samples from affected plants. The suggested technique is successful in detecting and labeling leaf diseases, and the best results were obtained with little computational effort. Another significant advantage of this method is that it facilitates the early diagnosis of plant diseases. It is possible to improve the classification process's recognition rate by using an Artificial Neural Network, Bayes classifier, Fuzzy Logic, or a hybrid method.

Kavithalakshmi, R., & Nickolas, S. (2020)Disease identification and segmentation in Betelvine leaves using a modernized Mask-RCNN framework is the focus of this study. We have created our own betel leaf dataset to use in our experiments. These images have been annotated by hand using a labeling app to help train the proposed model. Our research shows that a network built on Mask-RCNN and trained on a leaf image dataset can achieve an average accuracy of 84.07%. The proposed model is also hypothesized to need less memory than the other two models, both during training and testing. This demonstrates that identifying

Betelvinedisease in a given image during model testing uses extremely low computational resources (less than 1 millisecond on a single GPU).

Ali, M. M. et al. (2019)Non-destructive approaches have been used to identify plant diseases for quite some time, and this article offers an account of that development. The four nondestructive approaches discussed here for diagnosing plant diseases are those based on images, those based on image processing, those based on spectroscopy, and the use of remote sensing. Methods that use images as input are called "image-based," and include techniques like fluorescence and hyperspectral imaging, as well as image capture, preprocessing, segmentation, feature extraction, and classification. Remote sensing applications include hyperspectral and multispectral remote sensing, whereas spectroscopy-based approaches include visible and infrared spectroscopy, fluorescence spectroscopy, and electric impedance spectroscopy. All of these methods successfully identify a variety of plant diseases with a degree of precision that is sufficient for practical use. In order to analyze images further, image processing methods need the use of both a camera and specialized software. Classifiers are chosen for their ability to provide accurate results using this strategy.

Table 2: comparison table

Authors	**Methodology**	**Advantage**	**Limitation**	**Accuracy**
Nazki et al.(2020) [1]	Generative Adversarial Network And Deep CNN	Improvements in the visual representation of data appropriationsharper and clearer in focus). GANs are capable of preparing any conceivable generator organization. .	Unstable rainfall procedure, hard to be ready for. Need a lot of rules to follow to get good outcomes. Mode Collapse issue	86.1%
Zhang et al. (2019)	GPDCNN	Compared to other methods, GPDCNN	Due to the enormous	94.65%

[5]		is more reliable.	number of parameters in a fully connected layer, training time is increased and over-fitting is more likely to occur.	
SINGH CHOUHAN et al. (2019) [6]	Multilayer convolutional neural network (MCNN)	Critical aspects may be seen by MCNN since it has deviated from its paradigms, which means it requires no human administration.	Since MCNN contains many layers, the training process might take a long time if the computer doesn't have a powerful central processing unit.	97.13%
Vijai Singh (2019) [7]	Particle Swarm Opt imization Algorithm.	The benefits of PSO are that it is simple to implement and that very few constraints are fixed. In terms of computing efficiency, PSO performs better than the GA.	Although PSO is a well-known approach, its straightforward nature ensures that it may be effectively applied to the problem at hand.	98%

Barburiceanu, S. et al. (2020)This study introduces unique methods for the classification of grape leaf diseases based on texture descriptors operating in the RGB color space, applicable to both noise-free and Gaussian-noise damaged photographs. In the experimental part, we assess the value of color information for texture categorization. In both noiseless and noisy conditions, we demonstrate that color improves the discriminating power and, by extension, the classification accuracy. We examined the robustness of several feature extraction methods against noise in both grayscale and RGB images. We not only show the importance of the filtering operation inside feature extraction operators in the context of noise-affected images, but also in the context of noise-free images.

2.2 Survey on Leaf Disease detection using deep learning

The research work (Sambasivam&duncanOpiyo, 2020) have discovered that a variety of approaches, including class weight, SMOTE, focus loss, and huge input picture shapes, have the potential to significantly improve the model's performance on an uneven dataset. When using class-unbalanced correction approaches associated with data expansion and huge input picture dimensions, the accuracy of this work improved by over 5%, and the loss of protocol was drastically reduced to 0.06% from over 20%.

In the Agarwal, et al. (2020), Scientists came up with a technique for spotting diseases in tomatoes using CNNs. There are 9 layers of illness images and 1 healthy picture in the dataset. Data augmentation methods were utilized to rectify the unbalanced nature of the photos included inside the layer. In addition, 91.2% of the time, the model is accurate during testing. Comparing the storage needs of the proposed model (1.5 MB) with those of pre-training models (about 100 MB), it is clear that the proposed model is superior.

The study in (Sladojevic, et al. 2016)uses image classification based on features extracted from leaves and deep neural networks to create a model for identifying plant illnesses. The article gives a wealth of information on the fundamental strategies required to apply this model of disease diagnosis, beginning with the gathering of photographs to develop a database that is examined by agricultural specialists. The Berkley Vision and Learning Center's Caffe deep learning platform was utilized extensively in CNN's training. There is a lack of research into this topic despite the fact that there are several approaches to automate or use computer vision to diagnose and categorize plant diseases.

The results in Ramcharan, et al. (2017)suggest that digital plant disease detection may be accomplished rapidly, cheaply, and easily using the transfer learning approach for identifying images captured in the field. The latest version of Inception is an effective tool for determining the cause of cassava illnesses. The time-consuming process of obtaining features from photos is avoided by training the model on a desktop and then deploying it on a mobile device using this approach. When applied to the brochure dataset, the SVM model identified healthy leaves and dark leaf spots due to cassava mosaic disease and red spider mite damage with 98% accuracy, whereas the original dataset only yielded 90% accuracy.

The proposed technique outperforms the existing one in Ramcharan, et al. (2017) because it achieves better results in less time. First, scientists are on the lookout for mostly green pixels. Additionally, the bulk of the green pixels are masked based on the thresholds specified by the Otsu method. Next, we get rid of the cluster's boundary pixels and those that have no color value at all (RGB).

These challenges in vegetable pathology are well within the capabilities of deep learning, which is now a hot issue in pattern recognition and machine learning. In their research (Lu, Yi, Zeng, Liu, & Zhang, 2017), the authors propose a new approach to determining when rice needs to be harvested using deep complex neural lattice methods. To train CNNs to recognize 10 common rice illnesses, researchers collected 500 photos of sick and healthy rice leaves and stalks from experimental rice fields. The suggested CNN-based model achieves 95.48% accuracy using a 10-fold cross-validation technique.

The residual learning architecture presented in (He, Zhang, & Sun, 2016) simplifies the training of networks far deeper than those previously used. Layers are restated explicitly as learning residual functions given layer input, as opposed to learning functions without reference. It provides abundant empirical data showing that residual networks are more amenable to modification. and may attain a far higher degree of precision. The residual network ensemble has a 3.57% margin of error on the ImageNet benchmark dataset.

In (Jiuxiang, et al., 2018), The latest advancements in convolutional neural networks are reviewed in depth by the presented study. In recent years, it has shown exceptional performance in a variety of areas, including as deep learning, image recognition, NLP, and voice recognition.

Convolutional neural networks, among the many varieties of deep neural networks, have received the most study. The fast growth in the quantity of annotated data combined with the significant improvements in the capabilities of graphics processing units led to the rapid development of convolutional neural networks. As time went on, they became industry leaders in several fields.

Chen et al. (2020)Sickness detection with the use of smartphones is now achievable thanks to deep learning and the proliferation of smartphones. Despite not using the same conditions as the training photographs, the model still achieves 31.4% accuracy. This is a significant improvement over the results achieved from random sampling, but further diversity in the training data is still required to further improve accuracy. More and more picture datasets are being used to build deep learning models, which paves the way for widespread smartphone-assisted plant disease detection.

Table 3: comparison table

Authors	**Methodology**	**Advantage**	**Limitation**	**Accuracy**
Mishra et al. (2019) [8]	Deep ConvolutionNeural Network	This method needs less work from humans since it depends so little on pre-processing. Because it is an autonomous learner, preprocessing is simplified.	In order to analyze and train the neural structure, a massive dataset is required.	88.46%
Sharma et al. (2019)[9]	Convolution Neural Network	CNN's ability to automatically extract highlights by just processing the	Human eyesight relies on ordered lines, which are absent from CNNs.	98.6%

		raw images is perhaps the network's greatest strength.		
Agarwal et al. (2019) [10]	Convolution Neural Network	The suggested model required just 1.5 MB of storage space, whereas the average pre-prepared model required 100 MB.	The process of doing anything, like as pooling, slows down a CNN.	76%
Khamparia et al. (2019) [11]	Deep Convolution Encoder Network	The last classification step employs a softmax classifier. If a multi-order model is encountered, and the desired class has a high probability, it returns those probabilities.	There is no way to convert deep layer feature maps into input dimensions in this approach.	97.50%
Sladojevic	Deep	Picture and	CNNs are unable	96.3%

et al. (2016) [15]	Convolution Neural Network	object categorization, face identification, and picture segmentation were all accomplished using DCNNs. DCNNs, particularly those with more than 5 hidden layers, are more precise because they are more complex.	to record information about an object's position or orientation. Lack of spatial invariance with respect to the data used as input	

L, Knidel, H, et al. (2019)That's why there's a big X on the white backdrop there. The excellent classification results show that the chosen attributes were suitable for this purpose, even though the damaged leaf portions of the leaf varied significantly in color and structure.

(Toda & Okura, 2019)Multiple neuron and class-wise visualisation techniques were trained using CNN on publically accessible plant disease imaging datasets.While some methods of visualization are already in use, others need to be refined to focus on a specific category that captures all of the elements essential to producing the desired outcome. In addition, it identified non-inferential layers and removed them from the network, which lowered the number of image-less parameters by 75% and improved classification precision. The suggested research assessed many visualization strategies for making sense of CNN's diagnostic depictions of plant illnesses.

Anthracnose is a fungal disease that may spread swiftly from tree to tree, possibly wiping out an entire crop and affecting a large percentage of the world's trees. The researchers at Anagnostis, et al. (2020) set out to build a trustworthy convolutional neural network model that could distinguish between healthy and unhealthy tree foliage in photographs. We used a series of grayscale and RGB images, extracted features using a fast Fourier transform, and ultimately settled on a CNN architecture based on our results. Deep learning methods, notably convolutional neural networks, were used to the challenge of automatically recognizing anthracnose in walnut leaves.

By doing so, the suggested strategy was able to increase the detection rate for complex tomato diseases and pests from 87% to 96% (Fuentes, Yoon, & Park, 2018). The suggested method also accounts for class imbalances in small datasets and false positives produced by the limit box generator. In this study, the authors introduced a deep neural network-based framework that, when applied to topic-specific containment boxes, can accurately detect and categorize tomato plant diseases and pests in real time.

Due to a lack of adherence to several key machine learning assumptions, many previously published CNN-based approaches do not yet function in the field (Boulent, Foucher, & St-Charles, 2019).Thanks to deep convolutional neural networks, there has been a recent explosion of progress in the field of image categorization.

. Sun, Geng, & Sun (2018)In this paper, we refine our approach to image segmentation and disease diagnosis. We provide a method for histogram segmentation that is more rigorously scientific, trustworthy, and productive. This approach is more reliable, effective, and scientific than others since the threshold is calculated automatically. The linear regression model may be improved in terms of precision, utility, and potential by adjusting both the independent and dependent variables.

(H, Sapna, Johan, & M, 2020) In order to effectively monitor crops, disease detection in plants is essential. The TensorFlow object detection framework was used to create three unique deep learning meta-architectures: the Single Shot MultiBox Detector, the Faster Region-based Convolutional Neural Network, and the Region-based Fully Convolutional Networks. The study's major objective was to provide a standardized approach to the challenging problems of classifying and localizing plant diseases.

Liu, B., et al. (2018)The Generalizability and Stability of the CNN-Based Model: It was shown in this study that the size of the dataset significantly impacted the accuracy with which apple leaf diseases were detected, thus two sets of tests were undertaken to verify the effectiveness of the dataset for the model was updated to almost the level of convergence.

Detection of the four most common apple leaf diseases was shown using the suggested CNN-based model.

After mapping the R, G, and B components of the input image to the threshold images, the co-occurrence features are discovered. To do this, we first collect leaf co-occurrence features and then check them against the feature library for a match. Minimum Distance Criterion with K-Mean Clustering is initially used to classify the data, and it has an accuracy of 86.54%. The effectiveness of the proposed strategy increases detection rates to 93.63%. In the second step of classification, we apply the SVM classifier, which proves its efficacy with an accuracy of 95.71%. The proposed strategy for enhancing SVM's detection accuracy has resulted in a 95.71% success rate (Singh & al., 2017).

Vijai Singh provides a method of picture segmentation for the automated diagnosis and classification of leaf diseases in plants. Research on potential disease classification schemes for use in identifying plant leaf disease is also included. Genetic algorithms are used for image segmentation, an essential step in disease detection in plant leaves. The effectiveness of the proposed strategy increases detection rates to 93.63%. In the second step of classification, we apply the SVM classifier, which proves its efficacy with an accuracy of 95.71%. The proposed strategy for enhancing SVM's detection accuracy results in a new threshold of 95.71%. (Singh et al., 2017) Using picture segmentation and soft computing approaches, they were able to detect illnesses in plant leaves.

The output of the proposed method is what establishes whether or not a mango is healthy. As part of the preprocessing phase, images are improved by removing noise and sharpening the focus in order to better identify flawed produce. The segmentation process involves breaking the whole thing up into smaller pieces. Use thresholding to convert the picture into a black-and-white binary before proceeding with segmentation. Edge-based, region-based, threshold-based, and more methods of segmentation exist. Segmentation of watersheds is used here. Region detection is employed for feature extraction in the feature extraction and classification step, and this helps locate the flawed area of the picture (Nadarajan et al., 2017).

Several model architectures were trained, and the best one had a 99.53% success rate (or healthy plant) in recognizing the matched [plant, illness] pair. The model's excellent accuracy makes it a useful advisory or early warning tool; further development of the technology might lead to a practical, integrated plant disease diagnostics system. The significance of training picture capture type was investigated using VGG and AlexNetOWTBn, two of the most successful CNN models. Basic pictures of healthy and sick plant leaves were utilized to train and evaluate an automated plant disease identification and diagnosis system in this study (Ferentinos, 2018).

Both automated and manual planting techniques are limited in their ability to cover large areas of land and provide vital data for making informed decisions early in the process. Therefore, it is critical to develop automated systems that are applicable, reliable, and cost-effective for monitoring plant health and reporting relevant data for management to utilize. Significant progress has been made in pattern recognition and classification thanks to the merging of Computer Vision and Artificial Intelligence (AI). Convolutional neural networks (CNNs) are used in these types of systems. The accuracy of plant disease diagnosis was significantly improved by methods that used common architectures as AlexNetGoogLeNet (Liu, B., et al., 2018) and InceptionV3 (Anagnostis, Asiminari, Papageorgiou, & D., 2020). Despite advances in image processing, several obstacles remain in the way of accurate diagnosis of illnesses affecting mango leaves and fruits.

III. DISCUSSION

Researchers would normally begin a survey on mango leaf disease detection by locating relevant research publications, conference papers, and patents in the subject. These sources would encompass a broad variety of strategies and approaches, both classic and contemporary. Visual examination, manual symptom grading, and laboratory-based testing are examples of traditional approaches, while computer vision, machine learning, and molecular procedures are examples of newer methods. The survey paper would go through the various approaches and the underlying ideas. It would, for example, encompass the visual indications of several mango leaf diseases such as anthracnose, powdery mildew, leaf spot, and so on. It would also look at the difficulties of visual examination, such as subjectivity and the requirement for specialist expertise. Furthermore, the survey study will investigate advances in computer vision and image processing approaches for detecting mango leaf disease. This would include considering the use of image segmentation methods to distinguish between healthy and sick leaf sections, as well as the use of machine learning algorithms for automated disease classification using leaf pictures. The report would emphasize the advantages of these technologies, such as their ability to diagnose illness quickly and non-destructively. The survey study would address molecular strategies for mango leaf disease detection in addition to visual techniques. This would entail using PCR-based tests to identify the presence of certain infections or genes linked to illness. The study would go through the benefits and drawbacks of various molecular approaches, such as their sensitivity, specificity, and laboratory facility requirements. In the proposed system, the focus is on the identification of various leaf diseases affecting plants such as mango, guava, and others. The objective of this system is to accurately detect and diagnose leaf diseases in order to facilitate early intervention and prevent further spread of the diseases.

IV. CONCLUSION

Finally, this survey article takes an in-depth look at the existing procedures and techniques used in mango leaf disease identification. We investigated both conventional and contemporary methodologies, emphasizing their advantages and disadvantages in effectively detecting and monitoring mango leaf illnesses. Although visual examination is commonly utilized, it is subjective and strongly dependent on professional knowledge. As a result, more objective and automated procedures are required. In this area, computer vision and image processing methods have shown considerable promise, allowing for the analysis of high-resolution leaf pictures for disease identification. Mango leaf diseases may be accurately diagnosed using machine learning techniques like convolutional neural networks. Furthermore, molecular methods, notably polymerase chain reaction (PCR)-based tests, have given vital information about the existence of specific pathogens linked to mango leaf diseases. These procedures have excellent sensitivity and specificity, but they need laboratory facilities and specialist knowledge to use. Despite breakthroughs in mango leaf disease detection, there are still significant obstacles and research gaps. There are a number of ways to improve diagnostic accuracy, including the creation of portable and user-friendly tools for use in the field, the refinement of existing computer vision algorithms, the combination of various detection methods, and so on. Furthermore, further research is needed to identify and characterize novel mango leaf diseases and pathogens.

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