Revolutionizing Agriculture: Advanced Methods for Plant Disease Detection and Management

[1]Priyanka D, [2]Anusha, [3]Kiran B M, [4]Rohan Raj M V, [5]Rohith Y

[1]Assistant Professor

[1]Department of Information Science and Engineering

[1]Vidya Vikas Institute of Engineering and Technology, Mysore, India.

Abstract - Plant leaf disease identification is critical for ensuring crop health and minimizing production losses. Image processing methods have drawn a lot of attention recently because of their potential to automate illness identification procedures. This research paper offers a thorough examination of the various image processing methods used to find plant leaf diseases. The main steps of the image processing pipeline—image acquisition, pre-processing, segmentation, feature extraction, and classification methods like SVM, ANN, CNN—are covered in this study. It emphasizes recent developments, including deep learning-based techniques. The research aids in the comprehension and development of effective and precise plant disease detection systems, assisting farmers and scientists in disease control.

Index Terms - Image Processing, Convolution Neural Networks, plant disease, Hyperspectral Imaging, Thermal Imaging, Segmentation, Extraction, classification techniques.

I. Introduction

Plant leaf diseases are a major concern in agriculture and horticulture. They may negatively impact plant health in general as well as crop yield and quality. Different pathogens, such as fungi, bacteria, viruses, and other microbes, are responsible for causing leaf diseases. These pathogens affect plant leaves, causing apparent signs as withering, lesions, malformations, and discoloration. To reduce crop losses and ensure food security, plant leaf diseases must be identified early and effectively managed. Farmers can put suitable management measures in place, such as targeted medicines, cultural practices, or resistant cultivars, by determining the exact disease that is affecting their plants. Plant diseases represent a serious danger to agricultural productivity, resulting in large financial losses and a shortage of food. For efficient crop security, plant diseases must be quickly identified and managed. Image processing methods have recently come to light as a viable strategy for the non-invasive, effective, and precise identification of plant leaf diseases. By enabling early disease identification, eliminating the need for human inspection, and permitting prompt action, image processing approaches for plant leaf disease detection have the potential to revolutionize agriculture. Farmers may save time and money, increase crop output and quality, and automate the disease diagnosis process. In order to improve the precision and dependability of disease detection systems and advance sustainable agricultural practices, more research and development is required in this area. Images of plant leaves are taken and analyzed to find disease symptoms as part of the process of detecting plant leaf disease using image processing techniques. These methods take advantage of the capabilities of computer vision algorithms to extract useful features from leaf images, classify them according to the presence of diseases, and give farmers useful information for effective disease management.

Plant leaf disease management requires a combination of preventive measures, cultural practices, and tailored treatments. Crop rotation, the use of disease-resistant cultivars, good hygiene, the pruning of affected plant portions, effective irrigation and nutrient management, and the selective use of fungicides, bactericides, or other control agents are a few examples. Automated illness detection systems are also being developed with the use of technological advancements including image processing, machine learning, and remote sensing. These devices can help farmers detect leaf diseases early, allowing for quick action and reducing crop losses. Continuous study and development in the field of plant pathology are required for understanding the biology of leaf diseases, establishing appropriate management measures, and improving disease resistance in crops. Farmers may safeguard their crops, increase output, and support sustainable agricultural practices by applying integrated disease management practices and utilizing technological advancements.

Infectious agents including fungi, bacteria and viruses can cause plant diseases. Plant disease signs are obvious indications of infection, whereas symptoms are the visible repercussions of the illness [19]. Bacterial infections are very dangerous to plants because they spread quickly, causing serious damage or even death. Bacteria frequently infiltrate plants via wounds, insect bites, or natural openings in leaves and stems. Bacteria grow and infiltrate plant tissue once inside the plant, causing cell and tissue damage. Bacterial infection can cause wilting, reduced growth, and a general reduction in overall health of plants. The severity of the symptoms varies according on the type of bacteria and plant species involved. Leaf and fruit spots are common symptoms of bacterial infection and are often contained by veins on the leaf. Symptoms of fungal infections include visible spores, mildew, or mold, as well as leaf stains and yellowing. Fungi can infect plants by consuming nutrients and causing tissue breakdown. They are the most prevalent cause of plant infections, with symptoms such as spots on plant leaves, leaf yellowing, and bird's-eye spots on fruit. In rare circumstances, the fungus can be observed as a growth or mold on the leaves. Symptoms of infection are direct observations of the disease-causing organism.

Viruses are infectious particles that are too small for a light microscope to detect. They infiltrate host cells and take over host machinery, forcing the host to produce millions of copies of the virus. Viral illnesses do not manifest in plants because viruses cannot be spotted under a light microscope. However, there are several indications that a skilled eye can detect. A mosaic leaf pattern, yellowed, or crinkled leaves are all signs of viral infection. Many plant viruses, such as the tobacco mosaic virus, receive their names from this typical pattern of discoloration [19].

II. Dataset details

A) Plant Village:

A collection of images of plant diseases and diagnostic tools are available on the internet platform PlantVillage, which offers a variety of materials pertinent to plant health. The platform supports more than 60 crop species, and the collection contains more than 54,000 images of healthy and diseased plants as well as details on the signs, causes, and treatment options for various plant diseases.

Fig 1. Sample Image of Plant-Village dataset

B) Fruits-360:

The A collection of images of plant diseases and diagnostic tools are available on the internet platform PlantVillage, which offers a variety of materials pertinent to plant health. The platform supports more than 60 crop species, and the collection contains more than 54,000 images of healthy and diseased plants as well as details on the signs, causes, and treatment options for various plant diseases.

C) Plant Pathology:

Dataset for the Plant Pathology Challenge was made available by the Kaggle community and the Plant Pathology Society. Images of leaves from several plant species, including apple, grape, peach, and strawberry, as well as leaves with various diseases, including rust, powdery mildew, and scab are included in the dataset. Over 18,000 images from the collection have been classified into several disease categories.

Fig 2: Sample image of Plant Pathology 2021 dataset

D) DeepWeeds:

This collection of weed images includes a number of weeds that compete with crops for resources and have the potential to transmit plant diseases. The dataset is helpful for creating machine learning models for weed detection and management because it contains over 17,000 images of nine different weed species.

Fig 3. Sample Image of DeepWeeds dataset

E) *Mango Leaf Dataset:*

Approximately 4,000 images make up the mango leaf dataset, most of which were taken with a mobile phone camera while mango leaves were still on the trees. Around 1,800 of these images are of distinct leaves, and the remaining images were made by rotating and zooming the original images as needed. Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mold are the seven specific diseases that affect mango trees that are the focus of the dataset. There are now eight classes in all as a result of the addition of a category for healthy mango leaves.

Fig 4: Sample Image Mango Leaf dataset

Sl No	Dataset name	Classes	Samples
1.	Plant-Village	39	54000
2.	Fruits-360	131	90380
3.	DeepWeeds	9	17509
4.	Plant pathology 2021	12	18701
5.	Mango leaf	8	4000

Table1: Dataset Details

III. LITERATURE SRUVEY

The first step in a research project on identifying plant leaf diseases is image acquisition. The images can be gathered using openly accessible datasets like Plant Village, or the researchers can build their own database using photos taken with smartphones or digital cameras. The damaged image will undergo preprocessing. This preprocessing can reduce the background influence. You can adjust the image's brightness and contrast by applying thresholds. The initial phases of the research will involve doing this.

A) *SEGMENTATION:*

Segmentation separates an image into sections that have a strong correlation to the area of interest. A properly segmented image's features can make it simple to distinguish between healthy and diseased leaf samples. In paper [10] For segmentation purposes, the authors selected a method based on creating masks using colour information, colour intensity, and HSV colour space brightness. The region of interest is separated from the images by thresholding an HSV image for the range of green and brown colours. In the image samples, green denotes health and brown denotes disease.

For an image of a healthy and diseased potato leaf in RGB color space, thresholding an HSV image generates a mask. In another approach [15] (Saradhambal.G et al (2018)) the authors suggested an improved k-mean clustering approach. The contaminated region is divided into segments and assigned to classes according to its relevance using the color-based segmentation approach. On sample images, experimental analysis was performed in terms of time complexity and the area of the infected region. In this study, the k-means clustering algorithm and the Otsu classifier are applied. In another paper [16] (S. Megha et al (2017)) the authors presented the FCM Clustering Technique for Segmentation. SVM is used to categorize plant diseases. With the use of this method, it is possible to accurately determine the severity of the illness, the amount of the damage, and whether or not the illness is contagious.

B) CLASSIFICATION:

The authors of the paper [4] used a support vector machine classifier to classify the images. The support vector machine classifier is a machine learning algorithm that can be used to classify images into two or more classes. The authors trained the classifier on a dataset of images of tomatoes that were labeled as either mature or diseased. The classifier was able to achieve an accuracy of 95%. We came across the paper [12] and observed that the features are extracted from both the diseased and healthy images. From these training features, classification models are created. The classification is done during testing. The authors employed the Convolutional Neural Networks (CNN) for the classification of leaf images and achieved the accuracy of 97.43%. they also mentioned that other machine learning algorithms like k-NN, Naive Bayes, SVM, and BPNN were compared to the system. The quantitative analysis unmistakably demonstrated how effective the proposed CNN system is compared to all other classifiers. The authors in [7] (M. S. Arya, K. Anjali and D. Unni) used a genetic algorithm to choose the optimum set of attributes from the preprocessed images for distinguishing healthy from diseased leaves. To classify the leaves, the authors trained a support vector machine (SVM) classifier on the selected features. The authors used an Arduino microcontroller board to acquire images and process them in real-time to achieve the proposed approach. The scientists tested their suggested method on a dataset of plant leaf images and found that it performed well and outperformed other current methods by achieving the accuracy of 95%. In the paper [27] (N Banupriya et.al) The k-means clustering algorithm was used to identify five pathogens, including early blight, late blight, and Alternaria, anthracnose, and bacterial blight in potato leaves, as well as Alternaria, anthracnose, and bacterial blight in pomegranate leaves. K-means was employed to group images of the sick leaf. Then, a classifier neural network received the clustered images. The result was that the Neural Network classifier was very accurate and strong. The overall accuracy for pomegranate leaf disease detection using the CNN and K-means clustering algorithm is about 89.8%, and for potato leaf disease detection it is about 91%, meaning that both plants have an accuracy of about 90% for disease detection.

C) USAGE OF NEURAL NETWORKS AND DEEP LEARNING:

The end-to-end pipeline for diagnosing the severity of plant disease is enabled by the deep learning approach proposed in the work [28] to automatically discover the discriminative features for fine-grained classification. Using only a few training samples, the authors trained four cutting-edge deep models—VGG16, VGG19, Inception-v3, and ResNet50—from scratch and trained small convolutional neural networks of various depths. According to a comparison of these networks, pretrained deep models can be fine-tuned to significantly increase performance with limited data. The optimized VGG16 model performs best, achieving a test set accuracy of 90.4%, proving that deep learning is a new and promising technology for fully automatic plant disease severity classification. The authors in the paper [6] used SVM, ANN, and fuzzy classification to classify leaf paddy disease based on lesion kind, border color, spot color, and paddy leaf color. SVM only detects defective leaves, while ANN and FUZZY can diagnose sickness. In paper[23] authors have used Back propagation neural network with three layers having one input, one hidden and one output layer, is considered in the proposed method to classify the ROIs. Input layer has seven nodes for seven texture features and hidden layer consists of 15 nodes. In paper [29] authors developed Convolutional neural network models to detect and diagnose plant disease using simple leaves images of healthy and diseased plants. Training was performed with an open database of 87,848 images, with the best performance reaching 99.53% success rate. In the paper [27] the CNN learns to automatically extract relevant features from the images and make predictions based on those features. This allows the CNN to classify new images as either healthy or diseased based on the patterns it has learned. The author explains the specific architecture of the CNN used, which involves multiple layers of convolutional and pooling operations to extract hierarchical features from the input images. These features are then fed into fully connected layers, followed by a final softmax layer for classification.

D) THEORITICAL CHALLENGES:

A correct Dataset availability and quality of images is a greatest challenge. In paper [20] Acquiring a sufficiently large and diverse dataset of plant images that includes a wide range of healthy and diseased plants was a challenge. Performance of the model may be impacted by a class imbalance, in which the proportion of healthy plant images significantly surpasses that of diseased plant images (or vice versa). In paper [27] it was observed that Plant images captured under different lighting conditions, angles, resolutions, and with various camera setups can introduce variations that can affect the model's performance. Therefore, ensuring the quality of images and balancing class and Ensuring accurate and consistent labeling of images is crucial for training an effective model. In paper [27][28] it was observed that it can take a lot of computing power to build and infer CNN models, which can be extremely computational. This problem can be solved by improving the model architecture, lowering the number of parameters, or using hardware accelerators. Given that they learn intricate representations, CNN models are frequently regarded as "black boxes". It can be difficult to interpret and explain the model's choices, particularly in crucial areas like agriculture. Creating interpretive and explanatory techniques for the model's predictions can boost confidence and speed adoption.

IV. Methodology

Images of diseased leaves from various plants are captured using digital cameras or mobile phones. On these images, image processing techniques are used to extract valuable information for analysis. Figure 5 depicts the various stages involved.

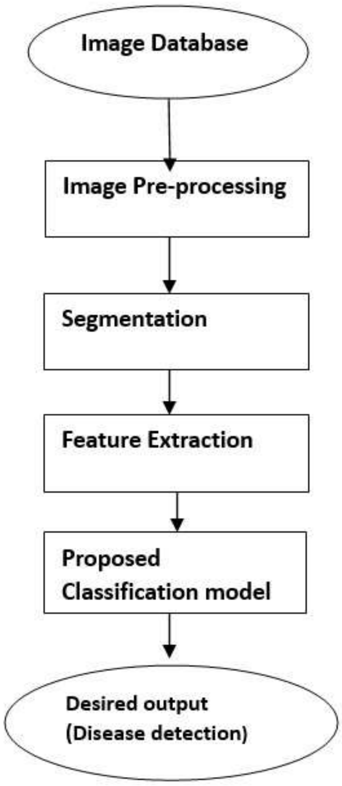

Fig 5: Stages involved in Classification of plant leaves

1) IMAGE ACQUISITION:

In order to detect minute variations in the reflectance or absorption of light by various portions of the plant, hyperspectral imaging involves taking images of crops at a variety of light wavelengths. This can be used to examine the water and nutritional status of plants as well as to look for early indicators of stress or disease. For instance, it is practicable to locate particular pigments that can represent the health and nutrient status of a plant by examining the reflectance spectra of leaves. On the other hand, thermal imaging monitors the temperature of the crops. This can be used to identify temperature changes between crop portions, which can indicate water stress, nutrient insufficiency, or pest infestation. Since different plant growth stages have different temperature signatures, thermal imaging can also be used to track plant metabolism.

2) IMAGE PRE-PROCESSING:

This image has to be pre-processed to remove unwanted distortions and boost certain aspects that are crucial for subsequent processing and analysis.

- *Image calibration:* To adjust for distortion, vignetting, and other optical problems, images may need to be calibrated depending on the camera used to capture them.
- *Image cropping and resizing:* Resize the images to a standard resolution and crop them to remove any undesired portions to make analysis easier.
- *Image normalization:* To account for changes in lighting and color balance, normalise the images. By doing this, it is possible to guarantee that all images will use the same image features for analysis.
- *Image enhancement:* Improve the visual appeal and analytical suitability of the images by using image enhancement. Sharpening, histogram equalisation, and contrast stretching are often used methods.
- *Noise reduction:* To eliminate any remaining noise from the image, use noise reduction techniques like median filtering or Gaussian smoothing.

3) IMAGE SEGMENTATION

To divide an image into distinct sections or segments based on its visual characteristics, such as color, texture, and form, is the basic purpose of image segmentation in computer vision. Image segmentation can be used to separate the diseased areas of the leaf from the healthy areas in the context of plant leaf detection and disease diagnosis. Rather of focusing on the leaf's natural green color, the hue estimation method in this instance is employed to locate and group the leaf sections that exhibit evidence of disease.

Thresholding is a popular method for image segmentation in plant disease diagnosis, where a threshold value is established to distinguish between the healthy and sick parts of the plant. Clustering is a different method in which groups of pixels with like characteristics are used to create unique regions. K-mean segmentation is a popular method for segmenting images, which divides pixels into clusters based on how similar they are. K-means clustering can be used to segment the image, and the resulting clusters can then be examined and processed further for feature extraction. The cluster image containing the diseased area is typically chosen for additional analysis since it includes the most pertinent data for disease diagnosis. The segmentation makes it possible to analyze the diseased areas with greater precision and focus, which can help with the early detection and prevention of plant diseases.

Convolutional neural networks (CNNs), a type of deep learning-based segmentation approach, have recently demonstrated promising outcomes in the detection of plant diseases. Without the need for human feature extraction, these algorithms can automatically extract features from the image data and segment the image depending on those characteristics. Overall, image segmentation is an important stage in the diagnosis of plant diseases since it enables us to precisely identify and separate the sick areas of the plant, which can aid in the early detection and efficient treatment of plant diseases.

4) FEATURE EXTRACTION:

The ability to select the most pertinent details from a image that may be used to categorize a disease is what makes feature extraction such an important stage in the identification of plant diseases. The capacity of texture features to capture minute variations in the visual appearance of diseased regions has made them increasingly popular among researchers. Features can be based on color, shape, or texture. A plant disease detection system can be created using a variety of feature extraction techniques. Three major categories—texture features, color features, and shape features—can be used to classify the features derived from plant leaf images. Texture characteristics are the patterns that appear repeatedly in an image at different scales and angles. Texture characteristics are particularly significant in plant leaves because they can indicate minute variations in the surface characteristics of the leaves that may be a sign of a disease. The GrayLevel Co-occurrence Matrix (GLCM) is one well-liked approach. GLCM is a statistical technique that determines the likelihood that a image will include pixel pairs with a particular combination of grey values. The color information in an image is referred to as its color features. Changes in the color of the leaves, which may be a sign of a disease, can be recognized using color features in plant disease detection. Different techniques, including the color histogram, color moments, and color co-occurrence matrix, can be used to extract color information. The morphological characteristics of the leaf, such as area and size, are referred to as shape features. Changes in a leaf's form that can be a sign of a disease can be recognized using shape features. Several techniques, including chain codes, Fourier descriptors, and moment invariants, can be used to extract shape characteristics.

5) CLASSIFICATION:

The plant's health or illness is determined using the attributes that were derived from the image. In the event that a diseased plant is discovered, the disease's type is determined. A classifier which has been taught to categorize features into several classes depending on their characteristics, is used to accomplish this.

a) Support Vector Machine (SVM):

The retrieved features from the image are used in the classification stage to identify the health or sickness of the plant. The type of illness is determined if the plant is proven to be ill. A classifier, that has been taught to categorize features into several classes depending on their characteristics, is used to accomplish this

b) Artificial Neural Networks (ANNs):

Due to its capacity to recognize intricate patterns and connections in data, artificial neural networks (ANNs) have been widely used in the diagnosis of plant diseases. ANNs can learn from enormous datasets through a process of trial and error and function by imitating the behavior of the neurons in the human brain. Utilizing features taken from images of both healthy and diseased plants, ANNs can be trained to detect plant diseases. These characteristics could include details about color, texture, and shape. The learnt patterns and correlations in the training data allow the ANN to categorize fresh images as either healthy or unhealthy once it has been trained.

c) Back Propagation Neural Networks (BPNNs):

Using methods like GLCM or texture-based analysis, the initial stage in plant disease diagnosis with BPNN is to extract relevant characteristics from the plant images. The BPNN model is then trained using these features, which entails initializing the weights and biases of the neurons randomly, sending training data through the network, determining the error, and then making the necessary weight and bias adjustments using the backpropagation technique. Until the error is minimized, the training process is continued. Using the recognized patterns and correlations in the features, the BPNN model may be trained to identify fresh plant images as healthy or unhealthy.

d) Convolution Neural Networks (CNNs):

The identification of plant diseases using image processing frequently makes use of convolutional neural networks (CNN). A deep neural network called a CNN is able to automatically recognize and extract key elements from images, making it a good choice for image classification tasks. An extensive collection of images with each image classified as either healthy or unhealthy can be used to train a CNN model for the purpose of detecting plant diseases. The algorithm can reliably classify new, unseen images as either healthy or unhealthy after learning to recognize the distinctive characteristics and patterns linked to each form of disease.

Convolutional layers, pooling layers, and fully linked layers are the main parts of a CNN. While pooling layers down-sample the feature maps to minimize dimensionality, convolutional layers apply a collection of filters to the input image to extract significant features. The final classification is carried out by the fully connected layers using the output that has been flattened by the preceding layers. With high accuracy rates and superior performance to conventional machine learning methods, CNNs have demonstrated promising outcomes in the diagnosis of plant diseases. Additionally, they may be applied to field real-time disease detection with drones or smartphone cameras [21].

Our goal is to create software capable of diagnosing and classifying plant diseases, as well as providing prevention and treatment recommendations. With the aid of machine learning and image processing, we can build an Android app and a web application to accomplish this. Using the CNN (Convolutional Neural Network) technique, the Python-programmed system will examine input images of plants and categorize any diseases that may be present. Additionally, using image recognition, our application will be able to identify pests and diseases in crops. It will also offer advice on natural and organic pest control techniques, details on crop rotation and sustainable farming methods, and a forum for farmers to exchange knowledge and ask questions with other farmers and experts. In order to help with crop management, we also hope to incorporate local weather and climatic data and also a platform to support regional agriculture and get in touch with thr neighborhood farmer's markets and cooperatives.

V. COMPARATIVE STUDY

PAPER	CULTURE	ALGORITHM	SAMPLES	ACCURACY
18	Rice	SVM, ANN	120	SVM – 92.4% ANN – 99.5%
19	Database of leaves infected with various disease	Feature extraction, CNN	150	96%
23	Potato	fuzzy C-means clustering and Back Propagation Neural Network	200	93%
27	PlantVillage (potato, Pomegranate)	CNN, K means clustering	<100	90%
28	PlantVillage (Apple)	VGG16 ,CNN	2086	90.4%

Table 2: Summary of disease plant detection using neural networks

In the paper [18] A machine learning model, such as an ANN or support vector machine (SVM), is trained using image samples of diseased rice plants that have been collected, pre-processed, and important features extracted. Decision assistance for disease identification is then provided by classifying new photos as healthy or sick using the trained model. The accuracy of the paper was 92.4% for SVM and 99.5% for ANN. The paper [19], consist 150 images of different crops containing various diseases. Feature extraction and convolution neural network (CNN) strategies were applied on the dataset providing the accuracy of 96%. The proposed system in paper [23] uses decorrelation stretching to improve color disparities in input images, fuzzy C-mean clustering to segment the disease affected area, and a neural network-based classification method to separate disease-affected patches from a background with similar color and texture features. The accuracy achieved is 93%. To accurately predict leaf disease, the paper [27] proposes using image processing, k-means clustering, and convolution neural networking algorithms. Image segregation, data preprocessing, image fragmentation, detection, and recognition of characteristics are all steps in the disease detection process. Pomegranate leaves had an overall accuracy of 89.8%, while potato leaves had an accuracy of 91%, or 90% disease detection for both plants. These results were obtained for both leaf disease analysis methods using image processing, CNN, and K-means clustering algorithm. In the paper [28] the Plant-Village dataset is used to train a series of deep convolutional neural networks to determine the severity of apple black rot. Systematically assessing the effectiveness of shallow networks and deep models that have undergone transfer learning. The deep VGG16 model with transfer learning training is the most accurate, with a total accuracy of 90.4% on the hold-out test set.

PAPER	CULTURE	ALGORITHM	SAMPLES	ACCURACY
3	Grape	SVM, GLCM	225	94.22
8	potato	K means clustering, GLCM, SVM	Not Specified.	95.99%
9	Alberseem Leaves	K-Means Clustering, KNN algorithm, and Local Binary Pattern (LBP)	120	95.83%
10	Potato	Random Forest	450	97%
22	Citrus	SVM, K-means Clustering, GLCM	200	96%
24	Vegetable crops	K-nearest neighbor	54300	99%
25	Pomegranate	K-means clustering, SVM	610	82%

Table 2: Summary of disease plant detection using neural networks

In paper [3] Segmentation by K-means clustering is used to first identify the sick area, after which texture and color features are extracted. In order to identify the type of leaf disease, SVM classification methodology is applied. The proposed system can correctly detect and classify the tested disease with an accuracy of 88.89%. The research paper [8] proposed a methodology for the detection and classification of diseases in potato plants. It used the Plant Village Dataset, K-means for image segmentation, gray level co-occurrence matrix for feature extraction, and multi-class support vector machine (SVM) for classification. The proposed methodology was able to achieve an accuracy of 95.99%. The paper [9] uses 120 images of alberseem leaves as dataset and image segmentation is done through k means clustering, KNN classifier and Local Binary Pattern (LBP) is used for the classification which provides the accuracy of 95.83%. In the research [10], image segmentation is performed on 450 photos of healthy and sick potato leaves obtained from the publicly available plant village database, and seven classifier techniques are utilized for diseased and healthy leaf recognition and classification. The Random Forest classifier is used which provides an accuracy of 97% for this group. The proposed framework in paper [22] is broken down into four sections: image pre-processing, which includes converting RGB to various color spaces, image enhancement, segmenting the region of interest using K-mean clustering, feature extraction, and classification. Statistical GLCM is used to extract texture features, while mean values are used to extract color features. SVM was used to finally achieve classification. The accuracy achieved was 96%. The paper [24] introduces a new Deep Learning methodology called Leaf Disease Estimation using Deep Learning Principle (LDEDLP). It adapts IoT technologies to identify the disease effectively from plants and provides alerts to users. It uses image segmentation and classification logic to estimate the category of disease. The accuracy is 99%. In another approach [25] A web-based tool was proposed to help farmers identify fruit disease by uploading an image to a trained dataset. Features such as color, morphology, CCV, k means clustering, SVM, and intent search were used to classify the image. Experimental evaluation was 82% accurate.

VI. Conclusion

In conclusion, this work presents a complete investigation on plant leaf disease identification utilizing image processing approaches. The suggested method employs image pre-processing, feature extraction, and classification techniques like SVM, ANN, CNN, BPNN and K-means clustering methods to precisely identify and diagnose diseases in plant leaves. This study has the potential to fundamentally alter plant disease management by facilitating early detection and prompt control methods. However, further study is required to address issues such as changing climatic conditions and the availability of various information. overall, this study advances automated disease detection technologies for better agricultural practices. Additionally, we intend to increase the system's functionality to enable the identification of pests and insects in crops and also increase the number of images in the preconfigured database and changing the architecture to match the dataset in order to improve accuracy. Future work on this topic may involve extending the study to cover a wider range of datasets, plant species, and illnesses. The accuracy and robustness of the disease detection system could also be improved by investigating cutting-edge deep learning architectures and transfer learning methods.

REFERENCES

[1] Kamlapurkar, S. R. (2016). Detection of Plant Leaf Disease using Image Processing Approach. *International Journal of Scientific and Research Publications, 6*(2), 73-77. ISSN 2250-3153.

[2] Mondal, Dhiman, Chakraborty, Aruna, Kole, Dipak, & Majumder, D. (2015). Detection and classification technique of Yellow Vein Mosaic Virus disease in okra leaf images using leaf vein extraction and Naive Bayesian classifier. *2015 International Conference on Signal Processing and Integrated Networks (SPIN)*, 166-171. DOI: 10.1109/ICSCTI.2015.7489626.

[3] Padol, P. B., & Yadav, A. A. (2016). SVM classifier based grape leaf disease detection. *2016 Conference on Advances in Signal Processing (CASP)*, 175-179. DOI: 10.1109/CASP.2016.7746160.

[4] Mehra, T., Kumar, V., & Gupta, P. (2016). Maturity and disease detection in tomato using computer vision. *2016 Fourth International Conference on Parallel, Distributed and Grid Computing (PDGC)*, 399-403. DOI: 10.1109/PDGC.2016.7913228.

[5] Tripathi, M. K., & Maktedar, D. D. (2016). Recent machine learning based approaches for disease detection and classification of agricultural products. *2016 International Conference on Computing Communication Control and automation (ICCUBEA)*, 1-6. DOI: 10.1109/ICCUBEA.2016.7860043.

[6] Narmadha, R. P., & Arulvadivu, G. (2017). Detection and measurement of paddy leaf disease symptoms using image processing. *2017 International Conference on Computer Communication and Informatics (ICCCI)*, 1-4. DOI: 10.1109/ICCCI.2017.8117730.

[7] Arya, M. S., Anjali, K., & Unni, D. (2018). Detection of unhealthy plant leaves using image processing and genetic algorithm with Arduino. *2018 International Conference on Power, Signals, Control and Computation (EPSCICON)*, 1-5. DOI: 10.1109/EPSCICON.2018.8379584.

[8] Singh, A., & Kaur, H. (2021). Potato Plant Leaves Disease Detection and Classification using Machine Learning Methodologies. *IOP Conf Ser Mater Sci Eng, 1022*(1), 012121. DOI: 10.1088/1757-899X/1022/1/012121.

[9] Abusham, E. A. (2021). Image Processing Technique for the Detection of Alberseem Leaves Diseases Based on Soft Computing. *Artificial Intelligence & Robotics Development Journal*, 103–115. DOI: 10.52098/airdj.202127.

[10] Iqbal, M. A., & Talukder, K. H. (2020). Detection of Potato Disease Using Image Segmentation and Machine Learning. *2020 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, 43–47. DOI: 10.1109/WiSPNET48689.2020.9198563.

[11] Fuentes, A., Yoon, S., & Park, D. S. (2020). Deep Learning-Based Techniques for Plant Diseases Recognition in Real-Field Scenarios. DOI: 10.1007/978-3-030-40605-9_1.

[12] Yogeshwari, M., & Thailambal, G. (2021). Automatic feature extraction and detection of plant leaf disease using GLCM features and convolutional neural networks. *Mater Today Proc*. DOI: 10.1016/j.matpr.2021.03.700.

[13] Jasim, M. A., & AL-Tuwaijari, J. M. (2020). Plant Leaf Diseases Detection and Classification Using Image Processing and Deep Learning Techniques. *2020 International Conference on Computer Science and Software Engineering (CSASE)*, 259–265. DOI: 10.1109/CSASE48920.2020.9142097.

[14] Wang, G., Sun, Y., & Wang, J. (2017). Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning. *Hindawi Computational Intelligence and Neuroscience*, 2917536. DOI: 10.1155/2017/2917536.

[15] Saradhambal, G., Dhivya, R., Latha, S., & Rajesh, R. (2018). Plant Disease Detection and Its Solution using Image Classification. *International Journal of Pure and Applied Mathematics, 119*(14), 879-884.

[16] Megha, S., Niveditha, R. C., SowmyaShree, N., & Vidhya, K. (2017). Image Processing System for Plant Disease Identification by Using FCM Clustering Technique. *International Journal of Advance Research, Ideas and Innovations in Technology*.

[17] Hasan, N., Mustavi, M., Jubaer, A., Shahriar, M., & Ahmed, T. (2022). Plant Leaf Disease Detection Using Image Processing: A Comprehensive Review. *Malaysian Journal of Science and Advanced Technology*, 174-182. DOI: 10.56532/mjsat.v2i4.80.

[18] Shrivastava, G., & Patidar, H. (2022). Rice Plant Disease Identification Decision Support Model Using Machine Learning. *ICTACT Journal on Soft Computing*. DOI: 10.21917/ijsc.2022.0365.

[19] Suresh, V., Krishnan, M., Hemavarthini, M., & Jayanthan, D. (2020). Plant Disease Detection using Image Processing. *International Journal of Engineering Research and*, V9. DOI: 10.17577/IJERTV9IS030114.

[20] Meyyappan, S., & Chandramouleeswaran, S. (2018). Plant Infection Detection Using Image Processing. *International Journal of Modern Engineering Research (IJMER)*, 8. DOI: 2249-6645.

[21] Saraswathi, K. (2014). Detection of plant leaf disease using image processing approach. *International Journal of Computer Science & Engineering Technology (IJCSET), 5*(5).

[22] Gavhale, K. R., Gawande, U., & Hajari, K. O. (2014). Unhealthy region of citrus leaf detection using image processing techniques. *International Conference for Convergence for Technology-2014*. DOI: 10.1109/I2CT.2014.7092035.

[23] Biswas, S., Jagyasi, B., Singh, B. P., & Lal, M. (2014). Severity identification of Potato Late Blight disease from crop images captured under uncontrolled environment. 2014 IEEE Canada International Humanitarian Technology Conference (IHTC), 1–5.

[24] Ramkumar, G., Prabu, R. T., & Sabarivani, A. (2021). An Effectual Plant Leaf Disease Detection using Deep Learning Network with IoT Strategies. Available: http://annalsofrscb.ro.

[25] Bhange, M., & Hingoliwala, H. A. (2015). Smart Farming: Pomegranate Disease Detection Using Image Processing. Procedia Computer Science, 58, 280–288. DOI: 10.1016/j.procs.2015.08.022.

[26] Afzal, M. Z., Khan, M. A., Rehman, A., Sharif, M., Lee, S., & Rho, S. (2019). A deep learning approach to plant disease detection. Computers and Electronics in Agriculture, 162, 219-232. DOI: 10.1016/j.compag.2019.04.017.

[27] Banupriya, N., Chowdry, R., Yogeshwari, & V, Varsha. (2022). PLANT DISEASE DETECTION USING IMAGE PROCESSING AND MACHINE LEARNING ALGORITHM. DOI: 10.37896/jxu14.7/012.

[28] Wang, G., Sun, Y., & Wang, J. (2017). Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning. Computational Intelligence and Neuroscience, 2017, 1-8. DOI: 10.1155/2017/2917536.

[29] Ferentinos, K. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318. DOI: 10.1016/j.compag.2018.01.009.