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LEAF DISEASE DETECTION USING IMAGE PROCESSING

Ms. Ashwika V Shetty[*1], Ms. Ashika[*2], Ms. Amshitha R[*3], Ms. Deeksha[*4]

Dr. Laxmi Gulappagol[*5]

[*1,2,3,4]Student, Department Of Computer Science And Engineering, A J Institute Of Engineering And Technology, Mangalore, Karnataka, India.

[*5]Asst. Prof, Department Of Computer Science And Engineering, A J Institute Of Engineering And Technology, Mangalore, Karnataka, India.

ABSTRACT

Plant diseases are one of the main reasons for the decline in the quality and quantity of agricultural produce. Farmers have a lot of trouble recognizing and controlling plant diseases. As a result, it is critical to diagnose plant diseases at an early stage so that farmers may take accurate and timely action to avert future losses. The study focuses on a method for identifying plant diseases based on image processing and machine learning. We would create a device in this project that would assist farmers in identifying plant illness by capturing a leaf image. A set of algorithms in the system can detect leaf disease. The input image given by the user to the system undergoes various image processing steps to detect the disease.

Keywords: Plant Disease, Machine Learning, Algorithms, Image Processing.

I. INTRODUCTION

India is a cultivated country, with agriculture supporting roughly 70% of the population. Farmers have a wide range of options when it comes to choosing appropriate crops and insecticides for their plants. Plant disease causes a considerable decrease in the quality and quantity of agricultural goods. Plant disease research is concerned with the visual examination of patterns on plants. The monitoring of plant health and disease is critical to the effective development of farm crops. Leaf infections can be caused by changes in the environment, such as heavy rains, extreme temperature fluctuations, or incorrect maintenance, as well as insects and chemicals. Once disease-causing organisms such as bacteria and viruses have reached the leaf tissue, they grow, reducing the leaf's strength and causing degeneration. For example, illness outbreaks are common, resulting in large-scale death and starvation. In the beginning, plant disease monitoring and analysis were done manually by an expert in the field. This necessitates a great deal of effort as well as a long processing time. Plant disease detection can be done using image processing techniques. Disease symptoms are most commonly noticed on the leaves, stems, and fruits. The plant leaf is recommended for disease detection since it displays disease symptoms. This research introduces the image processing technology used to identify plant leaf disease.

TYPES OF LEAVES

Plant classification is critical in botany, medicine, and other plant-related businesses. Plants can be categorised based on a variety of characteristics such as stem bark, blooms, sizes, textures, and leaves, among others. The most essential aspect of the plant is its leaves, which come in a variety of shapes and sizes. In fact, most plants can be identified just by looking at their leaves. The texture, statistical, and geometrical characteristics of leaves can be used to distinguish them. Green leaves come in a variety of hues, textures, and sizes [2]. The following five characteristics are proposed in this research to analyse the form properties of leaves: Elongation, Rectangularity, Solidity, and Edge Regularity [3] are all terms used to describe the aspect ratio.

Simple leaf: The leaf is said to be simple when only one lamina is attached to the main stem by a petiole. A basic leaf can be carved to any depth except the midrib or petiole. Eg: Guava leaves

Compound leaf: A leaf with two or more leaflets is known as a compound leaf. The leaf's midrib is branched into different leaflets and joined by a single petiole in a complex leaf. For Eg: Pea, palm leaves [4].

The compound leaves are further classified into the categories of leaves listed below:

Palmately Compound Leaf: the leaflets are attached at the tip of the petiole. Eg., Silk cotton. These can be differentiated into:

- Unifoliate: There is only one leaflet on these leaves. Eg:Citrus

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- Bifoliate: There are two leaflets on these leaves.. Eg: Balanites
- Trifoliate: Three leaflets emerge from the same location on these leaves. Eg:Oxalis
- Quadrifoliate: Four leaflets sprout from the same spot on these leaves.. Eg: Marsilea
- Multifoliate: Many leaflets emerge from a single point on this form of leaf.. Eg: Bombax[4].

Pinnately Compound Leaf: The leaf's midrib is divided into several leaflets that are all connected by a single axis.. Eg: Neem. These can be further differentiated into:

- Pinnate: A pinnate leaf is a complex leaf with an axis on each side of the midrib.
- Unipinnate: On each side of the axis, there are leaflets. Eg:cassia
- Bipinnate: The centre axis creates a secondary axis that bears the leaflet. Eg: Acacia **Tripinnate:** A tertiary axis with leaflets arises from the secondary axis at this point. Eg: Moringa
- Decompound: More than three pinnate leaves. Eg: old leaves of coriander
- Parapinnate: A leaf without a leaflet at the end. Eg:Cassia
- Imparipinnate: A leaf with an unusually shaped terminal leaflet. Eg: Pea[5].

Needle like leaves: The needle-like leaves of coniferous trees. These are straightforward. They're scaled or pointed leaves with a point. [5].

TYPES OF LEAF DISEASE

One of the most common causes of plant growth reduction is leaf diseases. Plant diseases are investigated using the leaves of the plants[8]. Plant disease occurs when a virus or bacteria infects a plant and causes it to stop growing normally. Plant leaves can experience everything from discolouration to death. Fungi, bacteria, viruses, and nematodes are some of the causes of disease. [9] Plant diseases that originate from living organisms are known as biotic diseases. Different types of biotic diseases are caused by fungi, bacteria, and viruses. Non-living ecological circumstances, such as hail, spring frosts, meteorological conditions, chemical burns, and so on, cause abiotic conditions. Abiotic diseases are non-infectious, non- transmissible, and generally preventable. The top three varieties that are most usually regarded for identification and classification are spots (caused by fungi or bacteria), mildew, and rust. Furthermore, nutritional insufficiency is investigated for automation. [10].

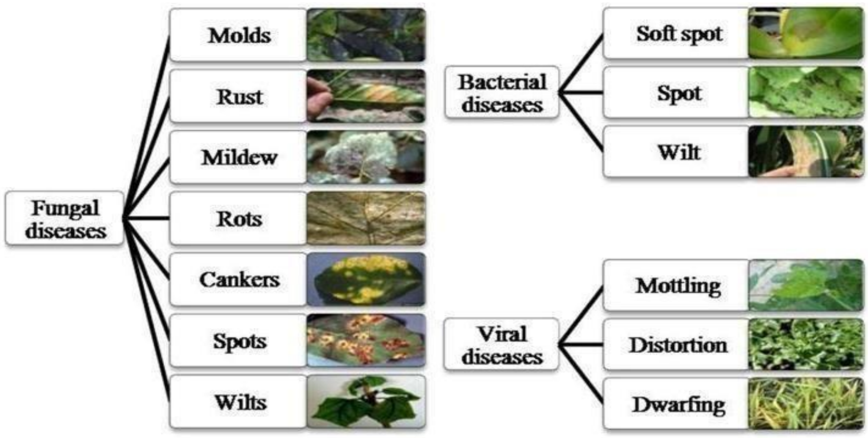

Figure 1: Different categories of plant biotic diseases and their types in various cultures[1].

- **Rust**: It lives on the lower surfaces of mature plant leaves. Raised dots on the undersides of leaves at first. These specks eventually turn into reddish orange spore masses. Leaf postules progressively turn yellow green and then black. Infestations that are severe will bend and yellow the leaves, resulting in leaf drop[9].
- **Rice Blast:** The most common rice disease in the world; it causes the most harm in regions where rice is grown intensively; disease onset favours high soil nitrogen concentration [7].
- **Yellow leaf disease:** The pathogen Phytoplasma causes this disease in arecanuts, causing the green leaves to become yellow and the yield to diminish [9].
- **Leaf rot:** It is caused in coconut tree. It is caused by fungi or bacteria. Leaf spot vary in size, shape and colors [9].

- **Leaf curl:** Leaf curl is a symptom of the disease. It can be caused by fungus, Taphrina genus, or virus. [7].
- **Angular leaf spot**: This disease kills the majority of cotton plants since it first develops on the leaves before becoming water drenched. Finally, the leaves become black and develop holes.
- **Leaf spot:** Xanthomonas campestris vesicatoria is a dangerous bacterial disease spread by Xanthomonas campestris. Small yellow green lesions and spots on leaves are symptoms. [6].
- **Late Blight:** Late Blight is a fast-spreading disease. The growth of the fungus as a result of cool and moist conditions. On the leaves, it leaves unevenly formed ashen dots. A ring of white mould will form around the spots. [1].
- **Bacterial wilt:** Brinjal yield decreases owing to bacterial wilt. The entire plant has collapsed owing to fading foliage. [8].
- **Brown spot:** Wherever rice is produced, the fungus overwinters on plant detritus, and disease development is aided by wetness on plant surfaces. grain with brown or black dots; decreased grain count; decreased kernel weight [7].

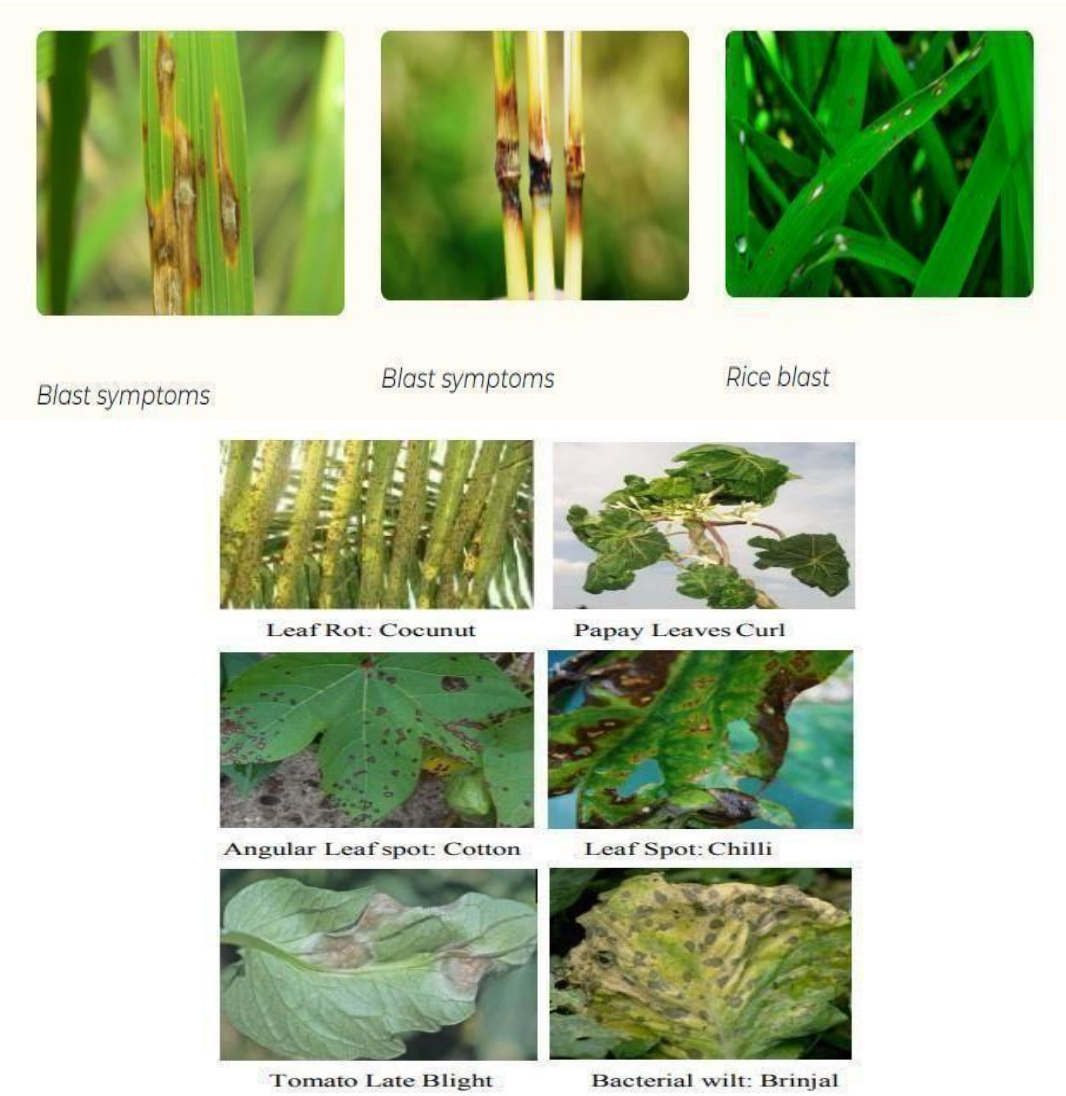

Fig 2: Plant Diseases in various plants [9].

II. LITERATURE REVIEW

Pallavi S. Marathe proposed the study "Plant Disease Detection Using Digital Image Processing and GSM." The proposed system employs digital image processing to identify plant illness and GSM to send the pesticide's name to the farmer's cell phone. Image acquisition, picture pre-processing, image segmentation, feature extraction and classification, and transmission are all processes in the disease identification process. [11].

"Plant Disease Detection Using Image Processing," suggested S. D. Khirade et al. This paper examined numerous strategies for segmenting the plant's diseased section. This research also examined feature extraction and classification strategies for extracting infected leaf features and plant disease categorization. Self-organizing feature map, back propagation algorithm, SVMs, and other ANN approaches for disease classification in plants can be employed effectively. Utilizing image processing techniques, we can accurately identify and classify numerous plant diseases using these methods. [12].

"Feasibility Study on Plant Chili Disease Detection Using Image Processing Techniques," proposed by Zulkifli Bin Husin et al., discusses chilli plant disease detection by leaf feature examination. Leaf pictures are taken and analysed in this system to determine the plant's health state. The image processing approach is utilised to perform the illness image. They had to undertake a variety of image processing operations. [13].

"Detection of Plant Leaf Disease Using Image Processing Approach," by Sushil R. Kamlapurkar, was proposed as a research paper. This research proposes a technique that can deliver more accurate disease identification and classification results based on a leaf image. They used several techniques such as preprocessing, training, and identification. They had to extract features from the photos, classify them, and then diagnose them. They discover sickness this way. [14].

"An Application of Image Processing Techniques for Detection of Diseases on Brinjal Leaves Using K-Means Clustering Method," by Anand R et al. The method for diagnosing brinjal plant leaf illnesses such as Bacterial Wilt, Cercospora Leaf Spot, Tobacco Mosaic Virus, and Collar Rot, as well as the method for careful disease detection, were presented in this study. They employed an artificial neural network for classification. The K-means clustering algorithm is utilised for segmentation, and Texture Features Identification is employed for feature identification. [15].

"Orchid Disease Detection Using Image Processing and Fuzzy Logic," by Muhammad Thaqif bin Mohamad Azmi et al. This research offered an image processing technique for recognising and detecting orchid illness. This framework has two parts: the first is image processing, and the second is fuzzy logic. They've done image grey scaling, noise removal, and segmentation. [16].

"Detection of leaf diseases and classification using digital image processing," according to G.P. Saraswathy. This study use digital image processing techniques to detect plant illness quickly and accurately. In this study, we used MATLAB software to create a k-means clustering technique with a multi SVM algorithm for disease diagnosis and classification. The K-Means segmentation method is used to segment the sick part [17].

"Plant Disease Detection and Classification by Deep Learning—A Review" was proposed by L. Li, S. Zhang, and B. Wang. They discussed the fundamentals of deep learning in this paper and provided a complete assessment of recent deep learning research in plant leaf disease recognition. The importance of large datasets with high variability, data augmentation, transfer learning, and visualisation of CNN activation maps in improving classification accuracy, as well as the importance of small sample plant leaf disease detection and hyper-spectral imaging for early plant disease detection, have all been discussed [18].

"Image Based Tomato Leaf Disease Detection" was explained by A Kumar and M. Vani. They built from the ground up multiple types of CNN architectures for the categorization of tomato leaf diseases, including LeNet, VGGNet, ResNet50, and Xception. "Image Based Tomato Leaf Disease Detection" was explained by A Kumar and M. Vani. They built from the ground up multiple types of CNN architectures for the categorization of tomato leaf diseases, including LeNet, VGGNet, ResNet50, and Xception. [19].

Other related papers on plant disease detection:

SL.No	Reference	Publication & Year	Contribution	Techniques Used	Results
1	Shivkumar Bagde et al.[27]	IJCSMC 2015	The main goal of the research work is to increase the efficiency of the disease detection technique	K-means clustering, SGDM Matrix Generation, Texture Statistics Computation, Color Co-occurrence Method, Otsu method, Artificial neural networks	An algorithm to detect whether a plant is healthy or unhealthy using the images of plant leaves and machine learning algorithms.
2	Aydin Kaya et al.[28]	ELSEVIER 2019	This paper proposes a method of classification of plant species using automated plant identification systems	End-to-end CNN, cross-dataset fine tuning, Deep Learning features	This method got average classification accuracy up to 95% on datasets Flavia Swedish Leaf UCI Leaves Plant village
3	Md. Nazrul Islam et al.[29]	ICECTE 2012	Develop a computer vision based recognition system automated disease detection and classification approach for plant leaf by analyzing the quality of GA and PNN.	Genetic Algorithm (GA) and Probabilistic Neural Network (PNN).	According to the model Genetic Algorithm achieved the highest overall classification performance, achieving an overall accuracy of 97 percent compared to PNN's 94.75 percent accuracy

4	Amandeep Singh et al.[30]	IEEE 2018	This paper proposes a method for the prediction of a paddy crop by using image processing technology, whichis simple androbust.	Histogram estimation and analysis.	100% accuracy
5	Alexander Johannes et al.[31]	ELSEVIER 2018	This paper proposes an algorithm for diagnosing plant disease using mobile devices for recording,	Image pre-processing	Results of classification on the K-fold evaluation dataset. Rust, 0.85, 0.82, 0.7, 0.95 (Septoria, 0.90, 0.85, 0.91, 0.79) (Tan place, 0.89, 0.73, 0.69, 0.78). Where (Disease Accuracy Sensitivity Specificity)
6	Siddhartha Singh Chauhan et al.[32]	IEEE 2018	This paper proposes a method of automatically using some artificial intelligence approach to recognise and classify plant leaf diseases.	Bacteria foraging algorithm, radial basis function neural network.	Average specificity of KMeans is 0.7914 Average specificity of Genetic-Algorithm is 0.8139 Average specificity of BRBFNN is 0.8558
7	Artzai Picon et al.[33]	IEEE 2018	This paper proposed an adapted Deep Residual Neural Network algorithm to detect multiple plant diseases under real conditions of acquisition.	Residual Neural Network	The algorithm results for an image of the leaf of a plant affected with Septoria shows the results Sensitivity– 0.94 Specification –

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					0.96 BAC – 0.96
8	Srdjan Sladojevic et al.[34]	Hindawi 2016	This paper proposes a method to recognize plant diseases using leaf image classification with Deep Neural Networks	Neural Network Training, Fine-Tuning	An accuracy of 96% was achieved after fine tuning
9	Chia-Lin Chung et al.[35]	ELSEVIER 2016	This paper proposed a method to create a model which detects whether the crop is healthy or not (i.e. Bakanae disease) using machine vision and by image processing and machine learning techniques	Support vector machine (SVM) classifiers	This method shows very high accuracy in detectingthe disease.
10	P. Revathi et al.[36]	IJCSIT 2018	Works in the world of agriculture on the importance of data mining techniques	Machine Learning Techniques, SVM	Highlights the significance of machine learning in plant disease detection

Convolution Neural Network [CNN]:

The common deep learning model is CNN, which is a multi-layer feed-forward neural network. CNN methods have been frequently used in picture classification issues in recent years [20]. It is a Deep Learning system that can take an input image, assign value to various characteristics or objects in the image using learnable weights and biases, and distinguish one from the other. In comparison to other classification algorithms, a CNN requires substantially less pre-processing.

Lee and colleagues [21] propose a hybrid model that combines CNN and Deconvolutional Networks to extract contextual information from leaf characteristics (DN). On a large dataset of open leaves, Konstantinos et al. [22] used many pre-trained CNN models. Their research shows that CNN is an excellent tool for detecting plant diseases automatically. To detect illnesses, Durmus et al. [23] employed AlexNet and Squeeze pre-trained CNN models on tomato leaves from an open dataset. To identify tomato leaf disease, Atabay et al. [24] fine-tuned a pre-trained model and created a new CNN model. According to their findings, the custom CNN model outperforms the pre-trained model. Setting a proper CNN model to yield improved accuracy values is a difficult task. To detect vegetable leaf illnesses, Zhang et al. [25] suggested a three-channel CNN model based on RGB colours. CNN consists of four main layers: convolutional layer, pooling layer, activation function layer and fully connected layer

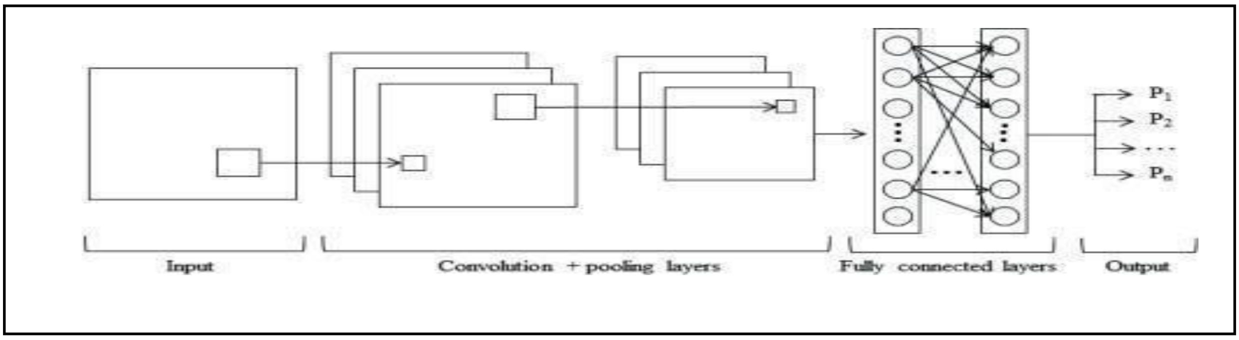

Fig 3: General architecture of CNN

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Convolution Layer: The feature map of the input image is extracted using a series of mathematical procedures in this layer [26]. The input image is then reduced in size using a filter. At each stage, the image's values are multiplied by the filter's values, and the result is added together. The supplied image is used to produce a new matrix with a reduced size. [20].

Pooling Layer: After the convolution layer, the pooling layer is frequently applied. This layer reduces the size of the convolution layer's output matrix. In this layer, you can utilise functions like max pooling, average pooling, and L2-norm pooling.

Activation Layer: Between the input and output layers, the activation function creates a curvilinear relationship. There are other activation functions available, including linear, sigmoid, and hyperbolic tangent, although CNN typically uses the nonlinear ReLU (Rectified Linear Unit) activation function.

Fully Connected Layer: After completing the convolution, pooling, and activation operations, the final generated matrix is fed into the fully connected layer as input. This layer is responsible for recognition and classification. [20]

Classification:

Training and testing with any classifier are the two stages of classification. The classifier is taught using feature values and target values in the training phase. This trained classifier is then used to determine whether or not a test image is contagious. It is categorized according to the parameters stated below:

No.	Feature	Formula
1	Contrast	$\Sigma_i \Sigma_j \lvert i-j \rvert^2 p(i, j, d, \theta)$
2	Uniformity (Energy)	$\Sigma_i \Sigma_j p(i, j, d, \theta)^2$
3	Maximum probability	$\text{Max}_{ij}\, p\, (i, j, d, \theta)$
4	Homogeneity	$\Sigma_i \Sigma_j p\, (i, j, d, \theta)/(1 + \lvert i-j \rvert)$
5	Inverse difference moment of order 2	$\Sigma_i \Sigma_j 1/(1 + (i-j)^2)\, p(i, j, d, \theta)$
6	Difference variation	Variance of $\Sigma_i \Sigma_j \lvert i-j \rvert\, p(i, j, d, \theta)$
7	Diagonal variance	Variance of $p(i, j, d, \theta)$
8	Entropy	$\Sigma_i \Sigma_j p(i, j, d, \theta) \log (p(i, j, d, \theta))$
9	Correlation	$\sum_{i,j} \frac{(i-\mu_i)(j-\mu_i)p(i,j)}{\sigma_i \sigma_j}$

Accuracy is another characteristic that refers to the measurement result. Its formula is as follows:

$$\text{Accuracy (\%)} = \frac{\text{Correctly Recognized Images}}{\text{Total Number of Test Images}} * 100$$

Precision refers to the degree of accuracy with which an operation or measurement is carried out. It is provided by

$$Precision = \frac{Number\ of\ TP}{(Number\ of\ TP + Number\ of\ FP)}$$

P. B. Padol and A. A. Yadav collaborated on 137 grape leaf photographs, 75 of which are Downy leaf images and 62 of Powderly leaf images. 60 Downy and 50 Powderly images are utilised in the training phase, and 15 Downy and 12 Powderly images are used in the testing phase. The accuracy attained is listed below. [37].

Dataset	Total test samples	Correctly Classified	% Accuracy
Downy	15	14	93.33%
Powderly	12	10	83.33%
Combined	27	24	**88.89%**

On data set samples of infected and healthy leaves, training and testing of the current approach were carried out. M. N. and K. J. Gowda looked at paddy leaves, which they found in the rice leaf disease repository's conserved samples. Color properties of the diseased leaf made segmentation problematic, hence training samples were obtained from 70% of particular data set photos. These results in more extensive framework training. The overall accuracy of the categorization was determined to be 89.47 percent when testing leaf samples were classified. [38]

The idea was proposed by V. Chaudhari and M. Patil and is based on a collection of 618 banana leaf disease photos obtained from diverse agricultural farms. Sigatoka disease, Cucumber Mosaic Virus, Bacterial Wilt, and Panama disease are four diseases that were considered for the experiment. During the experiment, two datasets are created: a training dataset and a testing dataset. There are 371 photos in the training dataset (60 percent) and 247 images in the testing dataset (40 percent). To forecast the disease, an SVM classifier is used in conjunction with K-means clustering segmentation. The overall accuracy of the SVM classifier is displayed below. [39].

$$Accuracy(\%) = \frac{No\ of\ accurate\ classified\ image}{Total\ image}$$

Disease	Testset	classified	Misclassified	Accuracy
sigatoka	80	65	15	84
CMV	120	103	17	86
Bacterial Wilt	20	17	3	85
Panama	27	23	4	85

The Maize Detection programme is written by D. J. M. Bonifacio, A. M. I. E. Pascual, M. V. C. Caya, and J. C. Fausto and runs on a Raspberry Pi. It displays two of the potential Maize statuses, indicating that they are the two closest Maize statuses according to the gadget. For this procedure, 30 out of 40 correct outcomes were recorded, giving it a 75 percent accuracy. The precision of image processing algorithms was determined using Equation(2) .[40]

S. Biswas, B. Jagyasi, B. P. Singh, and M. Lal developed an algorithm that was tested on a database of 300 photos of potato leaves from a publicly available dataset. Images of 100 healthy leaves and 200 sick leaves make up their experimental database. During the experiment, the database was divided into two sets: the training set, which contains 180 images with a 60% accuracy, and the testing set, which contains 120 images with a 40% accuracy. A multiclass SVM with a 'linear' Kernel was used for classification. Performance measures such as accuracy, sensitivity, recall, and F1-score were generated to evaluate the classification model's performance. The testing accuracy of the classification is 95% when the train-test split is 60%-40%. Furthermore, 5-fold cross validation was used to make the model more robust, and 93.7 percent accuracy was achieved[41].

C. U. Kumari, S. Jeevan Prasad, and G. Mounika used cotton and tomato samples to demonstrate how to detect leaf disease. Bacterial leaf spot, target spot septoria leaf spot, and leaf mould diseases are the four illnesses that are considered. Nine of the twenty cotton samples are appropriately categorized as bacterial leaf spot, whereas one sample is incorrectly classified as target spot. Two samples were misclassified as bacterial leaf spot and eight samples were classified as target spot. Ten of the twenty tomato samples were positive for septoria leaf spot disease and ten positive for leaf mould disease. The accuracy of four illnesses, bacterial leaf spot, target spot septoria leaf spot, and leaf mould, is 90%, 80%, and 100%, respectively, with an average classification accuracy of 92.5 percent [42].

The primary purpose of this endeavour is to determine whether or not the leaf is harmed. This task is difficult because we use various types of crop leaves and data collected from the crop field to determine the environmental condition. This dataset served as the foundation for all studies. When there are more than 20 classes, image processing becomes a major undertaking. With an accuracy of 90.38 percent, this model provides us with useful findings [43].

III. METHODOLGY

The goal of the research is to create a gadget that can detect leaf illness. It first uses a camera to take an image of an infected leaf, which is then translated into colour space. It detects the disease by comparing it to the database.

The plant disease detection system goes through four stages in total. The first phase entails capturing photographs using a cell phone or a web camera. For capturing photos, we use open CV. Image pre-processing is the second phase. For image contrast and background noise removal, we employ CLAHE(). The third phase uses the K-means clustering algorithm to divide the image into varying numbers of clusters. The next phase includes methods for extracting features.

We get the data for the training phase of the software from the Kaggle website. Image pre-processing, image segmentation, and image feature extraction are also performed on the dataset. All information is saved in a database. It is compared to a database that employs deep learning. We categorise using CNN classification, and the final phase involves diagnosing leaf disease.

IV. RESULTS

There are two types of training and testing environments. One is in a lab setting, which means the model is evaluated using photos from the same dataset that it was trained on. The other condition is the field condition, which implies the model has been tested using photographs captured in real-world scenarios (land). When we collect samples from the real world, the lighting circumstances and backdrop attributes of the photos are completely different, thus there's a potential that our model will yield very low accuracy when compared to the accuracy values obtained in the lab. So to overcome this impact, we have an idea of having a mixed variety of images during the training phase

V. CONCLUSION

The goal of this project is to create a device that uses image processing to detect plant leaf disease. One of the most important uses of image processing is image recognition, which is an important tool for early disease detection in crop production. This tool will assist in reducing the amount of time and money spent on manual forecasting. Based on the findings, we may conclude that our research has a high degree of accuracy in detecting disorders. This study could be expanded upon to create a real-time program that can detect further plant leaf illnesses.

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