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An Overview of Image Analysis-Based Plant Illness Recognition

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***Abstract*—Plants are very important source of energy supply to the mankind. Plant diseases will affect the leaf during the harvesting which will lead to decrement in the production and value in the market. Plant disease has a huge impact in the cultivation. These days computerized imagining is evolving rapidly. Image Processing techniques can help farmers to discover and identify the disease in the early stage. Advanced Image processing could be quicker and accurate technique of identifying the leaf plant diseases. Here we review plant disease identification and classification processing methods that may help the agriculturist in early detection and take required measures. Further, it gives a survey on various classification models with the analysis which would be used to which would be used to identify and group the plant leaf diseases. Techniques for extraction of features, segmentation, and classifying are also outlined.**

Keywords— Disease Analysis, acquisition, Preprocessing, Segmentation, Classification.

I. Introduction

India is a developing country with a predominantly agricultural economy. Approximately 70% of India's income comes from agriculture. Therefore, harm to the agricultural sector will lead to lower output, which will tangentially affect the country's economy. Food has come from the cultivated fields and agricultural areas. Consequently, an infection in the cultivation will cause a plant's yield to decline. From the beginning of the crop's life cycle until the point at which it is ready for harvesting, the crop must be watched for illnesses [1]. Initially, the unassisted eye was employed to visually evaluate the plants to maintain their health. It takes time and required expertise and experience in crop field monitoring . Some diseases are rather easy to contract and can be seen with the unaided eye. Some are so sophisticated that they require very powerful microscopes or specific electromagnetic spectrums. There are lots of illnesses, such as bacterial, viral, and fungal infections [2].

The ability to correctly process any kind of sickness, Image has made it very easy to recognize with the digital technology. Technology has also eliminated the need for medical specialists by enabling remote sickness diagnosis. The standard of the photos will increase with pre-processing. Analysis of this will produce a very good result. It employs segmentation, colour space modification, and image enhancement. Leaves, stem, and fruits are the most that suffer from the virus's negative effects.

Symptoms of an infection might appear on a plant leaf. Image processing is the technique of enhancing an image such that the outcomes are better suited for a specific goal. Photographs taken out of centre can be sharpened or de-blurred, edges can be refined, noise can be decreased, and brightness can be increased. The boundaries of the damaged leaf and stem, the character of the affected area, can be identified using the picture manipulation approach to distinguish between various leaf plant diseases. i) to determine the colour of the affected area ii) to separate the layers of an image iii) Image segmentation. Additionally, keeping an eye out for infections across such a big area is difficult. Therefore, techniques based on soft computing analysis and pattern recognition of the digital images may be applied to resolve the problem [3][4].

II. PLANT DISEASE ANALYSIS

There are various diseases found in plant caused due to various reasons like virus attack, bacterial attack, fungus attack, or nutrient deficiency. Plant related illness are categorized into two category called Biotic diseases and Abiotic diseases. Biotic diseases are furthermore categorized into three types that are Fungal diseases, Bacterial diseases and Viral diseases. Biotic disease is caused by micro-organism such as viruses, bacteria, amoeba and fungi in plants. Most commonly seen fungal diseases are Mildew, Rust, Wilts, Rot, Spots, Molds and Cankers. Few of the Viral diseases are Distortion, Dwarfing, Mottling. Most often, non-living things like chemicals, the environment, and so on have a huge impact on abiotic illnesses. Abiotic diseases are more avoidable, less dangerous, and not communicable. Abiotic diseases contains Nutrient Deficiency disease, disease caused by excess use of pesticide and the diseases caused due to soil quality [5].

Using image analysis, these objectives can be fulfilled:

1. Detection of leaf infections caused by fungal, bacterial and Virus attack.
2. Identification of the affected area.
3. Determine the root cause for the impacted region.

Viruses, fungi, and bacteria are the principal causes of leaf damage. These signs and symptoms are simple to identify. These might entail altering the plant's shape and colour. These are few signs that a plant can be infected as it is growing:

A. *Symptoms of a Bacterial Infection*

Bacterial infections in plants can cause warning signs that could be harmful to the overall health of a plant. Typical signs include spots on the leaves, withering, and necrosis, where the affected parts often turn dark or black. As with sunken lesions on stems or branches, infections caused by bacteria have the potential to cause cankers. The existences of bacterial ooze, a sticky substance that usually originates from wounded tissues, is one characteristic that sets the sickness apart. Stunted development and a general decrease in vigor are other indicators of bacterial infection, highlighting the importance of early detection and treatment to lessen the impact on crop yield [6] .

B. *Symptoms of a Viral Infection*

Plant viral infections have distinct symptoms and indicators. Typical symptoms include mottling or fading of the foliage, plant structure distortion, and mosaic patterns on the leaves. Some signs of a virus infection on a plant include necrotic lesions, bending or curling leaves, and an overall decline in vigor. Since the specific virus and the host plant can have a major impact on symptoms, accurate identification is essential for managing diseases. Minimizing crop output losses and lessening the consequence of viral infections need early detection and swift action.

C. *Symptoms of Fungal Infection*

Plant fungus infections can cause a variety of symptoms that could be detrimental to the health of the plant. Visual cues like wilting, discolored leaves, and the development of lesions or patches on the plant's surface can occasionally accompany these symptoms. Moreover, structural abnormalities caused by fungi may alter a plant's growth pattern. On the affected parts of the plant, spores or the mycelium of the fungus may be seen. Early detection of these symptoms is essential for putting disease control plans into action and stopping the illness's spread across the plant population.

III. GENERAL METHODLOGY

The image processing approach for plant illness identification consists of several general steps. Several tactics and algorithms may be utilized, depending on the approach and level of difficulty of the task. The following are the standard protocols for identifying plant illness using image processing techniques:

1. Acquisition of Image
2. Image Pre-processing
3. Segmentation of the image
4. Extracting features from the image
5. Classification of the extracted data
6. Post-processing of the data
7. Recognition of the disease in the image

A. *Acquisition of image*

Obtaining high-quality pictures is crucial for the diagnosis of plant illnesses. In well-lit environments, plants can be photographed in excellent condition during both healthy and unhealthy stages. Using cutting-edge imaging technologies for large-scale monitoring, such as RGB cameras, hyperspectral sensors, or even drones, is a component of this process. Accurate representation of plant health is guaranteed by proper photo capture, which also facilitates analysis. Better acquisition methods, such hyperspectral and multispectral imaging, help with more accurate illness diagnosis [7].

B. *Image Preprocessing*

For plant disease identification, image pre-processing is an essential step in improving raw data. To guarantee uniformity, methods including cropping, resizing, and normalizing photos are applied. Sophisticated pre-processing methods that aid in the best possible feature extraction include colour normalization, noise reduction, and contrast improvement. By lowering environmental unpredictability, these approaches reinforce the validity of later analyses .

C. *Segmentation of the image*

Image segmentation, or the procedure of dividing an image into segments or useable bits, is among the most popular procedures in the detection of plant diseases. Various technologies facilitate this process by aiding in the differentiation of distinct plant patches and the identification of hazardous areas from background clutter. Using pixel intensity levels, thresholding is a traditional segmentation technique that separates healthy plant components from damaged ones. More sophisticated techniques like watershed segmentation, employ gradient information to detect borders more precisely. Further homogeneous area identification is achieved by applying region-based techniques that follow predetermined criteria, such as region growth.

Deep learning models, particularly CNN, have revolutionized image segmentation in recent years for the identification of plant diseases. CNNs are better suited to capture the complex patterns and textures linked to various diseases since they can create hierarchical representations on their own. Semantic segmentation methods like U-Net and Mask R-CNN are highly accurate in drawing borders between regions of interest. Hyperspectral imaging aids in more precise segmentation by taking benfit's of the unique spectral fingerprints of both healthy and damaged plant tissues. Hyperspectral imaging records at different wavelengths. Combining information from many modalities, such RGB and hyperspectral, improves segmentation precision even further.

D. Extracting features from the image

Feature extraction in plant disease recognition involves extracting distinguishing information from images to distinguish between healthy and diseased plants. Texture analysis is used to identify surface patterns, while colour histograms are utilized in creating colour distributions. Shape descriptors characterize the geometric properties referred to as Hu moments. CNNs provide a more thorough representation in deep learning since they inherently collect hierarchical features. Feature extraction technologies are essential to increasing the precision and effectiveness of plant illness identification systems because they extract pertinent patterns and attributes from the images. These technologies could be anything from advanced deep learning algorithms to more traditional approaches [8].

IV. LITERATURE REVIEW

Development of a mobile application named iDahon for the identification of common diseases of vegetation utilizing a neural network trained with deep learning for image analysis. Results were trained using classification models that could identify the diseases at certain rate. In the training model of the Deep learning Neural Network Algorithm 1650 photos are used as datasets. Accuracy of this algorithm were tested using F1 score method and this Algorithm has an accuracy rate of 80 percentage, according to the results [9].

H. Sheik developed a system to predict the illness of corn leaf and peach leaf. This system uses a CNN (convolution neural network) algorithm, where the affected region of the foliage is segmented and analyzed and provides a user-friendly system. Nearly 8,000 photos of peach and maize leaves were gathered for the method from public repositories and field sources. After being enhanced and pre-processed, these photos are split into training and testing sets. According to the result training accuracy is 98.29% and accuracy of validation is 99.28% [10].

Ashqar and Abu-Naser used deep convolutional neural networks, or CNNs, the cutting-edge method for image identification problems. CNNs are perfect for this use case because of their capacity to automatically extract pertinent features from unprocessed visual data. CNN design utilizes max-pooling layers for down collection, convolutional layers for obtaining features, and thick layers for classification. And also examined two ways to comprehend how the model handles two different types of input grayscale and full-color photos. The full-color method produced an astounding 99.84% accuracy, demonstrating the model's tenacity in correctly identifying tomato leaf diseases. Simultaneously, the grayscale method achieves an accuracy of 95.54% and performs quite well. These high accuracies show how well the deep learning approach categorizes illnesses and suggest that it may have applications in the diagnosis of illnesses that impact agriculture [11].

Kerim Karadağ focuses on the crucial problem of spectral reflectance analysis in order to facilitate the prompt detection of Fusarium sickness in pepper plants. The spectral reflectance of pepper leaves was measured with a spectroradiometer over a broad wavelength range of 350–2500 nm. This non-destructive technique is used to obtain important data about the health of plants, allowing for the earlier detection of disease long before symptoms appear. Wavelet transformation is utilized to derive feature vectors from the spectrum reflectance data. By breaking down the reflectance spectra using wavelet functions Sym5, dB2, and Haar, the technique lowers the count of dimensions in the data while maintaining crucial details regarding disease marker's. KNN is employed to categorize data according to extracted feature vectors. For classification tasks, a two-layer feedforward neural network trained by backpropagation is employed. For classification, the Bayesian probability theory-based NB classifier is employed. Even with little training data, NB manages to produce strong output in a variety of classification tasks despite its simplicity. With a 90% success rate, KNN outperformed ANN (97.5%) and NB (90%) in the classification of healthy and sick peppers. CNN performed better than ANN and NB when all four groups-diseased, healthy, with and without mycorrhizal fungus were considered , with average success rates of 88.125% and 84%, respectively [12].

Bashir et al addresses the detection and categorization of illness in rice crops. To normalize leaf photos, reduce colour fluctuations, and improve analytical precision, grayscale conversion is used. Through the detection and characterization of local features even in the face of scale, rotation, and lighting variations, the Scale-Invariant Feature Transform (SIFT) technique provides robust feature extraction. The acquired features are converted into words using the Bag of Words (BoW) method for classification. K-means clustering facilitates the easier grouping of similar features together and generates visual terms for effective analysis. Because SVM performs well in both regression analysis and classification tasks, it is selected as the classification technique. Nu and gamma, two SVM parameters, are changed to increase the accuracy and efficiency. The proposed automated approach achieves promising results witch Accuracy of 94.16%, 5.83% Misclassification Rate , Recall Rate of 91.6%, 90.9% Precision. These results demonstrate that, in comparison to previous methods included in the literature review, the methodology is more successful in precisely identifying and categorizing disorders that impact rice. The gadget provides essential information for prompt crop management and intervention, namely identifying False Smut, Bacterial Leaf Blight, and Brown Spot [13].

Kusumo et al. focuses on the critical issue of identifying corn disease, which presents a major risk to Indonesia's crop production. Image processing characteristics such as RGB colour information, HOG object detector, SIFT, SURF, and ORB are all examined in this study. These characteristics are intended to document specifics related to disease-related colour changes, stains, or rotten areas in maize leaves. For categorization, several ML methods are employed, such as Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), and Support Vector Machines (SVM). According to the gathered characteristics, each corn disease diagnosis algorithm's performance is assessed. The experiments' findings demonstrate that RGB characteristics perform better than alternative machine learning techniques, suggesting that colour information could be useful in the identification of illnesses that affect maize. SVM and linear kernels typically produce the best results, especially when RGB features are used. But RF functions effectively, particularly when combined with SURF characteristics. Increasing the count of trees may improve RF's performance, suggesting a potential course of further research [14].

R.S.Tanksale and S.B.Mane used cutting-edge machine learning techniques to precisely identify and classify illnesses that impact different plant species in an effort to improve agricultural operations. Many deep learning architectures, such as Basic CNN, AlexNet, ResNet-50, and MobileNet, are utilized in this work. A dataset of images of plant leaves with several class labels denoting various illnesses is used to train these models. Accuracy, precision, and F1 score are only a few of the critical performance metrics that are computed in order to evaluate the effectiveness of deep learning models. These metrics offer a thorough assessment of the models effectiveness in multiclass and binary classification applications. Through the use of cross-validation techniques like k-fold cross-validation, the models are evaluated on a range of plant species and illnesses. The study's goal is to identify performance trends for various plant diseases and species. The study evaluates the latency of each model by tracking response times for different batch sizes of plant disease prediction requests. Throughput is a crucial metric for assessing the model's capacity to manage several requests at once. In order to determine the models' computational efficiency, a detailed analysis of CPU and RAM consumption is carried out. The relationship between resource utilization, power consumption, and system temperature is also examined in the study. Deep learning models have produced great accuracy in the diagnosis of plant diseases, with a training accuracy of 98.25% and a test accuracy of 96.72% for Basic CNN. The accuracy of training was 97.06% for ResNet-50, 95.05% for MobileNet, 92.72% for Testing, 98.25% for Training, and 96.22% for Testing for AlexNet. Since the F1 score accounts for both false positives and false negatives, it provides a meaningful evaluation of the model's performance [15].

Kerre and Muchiri developed a deep neural network model that employs a special method to differentiate between concurrent cases of strawberry foliage spot and foliage blight. Diagnosis gets more challenging when different illnesses under many classes manifest on the same leaf. So, the model must be capable of recognizing the overlapping qualities and draw conclusions from them. The model expanded as the deep neural network's intermediate layer activations got more consistent. The technique used has the benefits of shortening the training period and improving model accuracy. To do this, 1134 strawberry photos from a private dataset were assessed and trained. The model yielded a 95.9% F1-score, 89% precision, 98% accuracy, and 93.3% recall [16] 51].

Arnal Barbedo JG emphasizes the challenge of accurately identifying and categorizing illnesses that impact various plant species through the use of machine learning and computer vision techniques. CNNs are trained on large plant image datasets to recognize the visual traits associated with different diseases. The authors get around the issue of insufficient training data by using data augmentation techniques. This means employing tools like cropping, rotating, and other image editing techniques to take old photographs and turn them into new ones. Transfer learning enables the use of pre-trained CNN models, such as GoogLeNet, that were trained on large image datasets, such as ImageNet. The previously trained models are then modified using the knowledge of plant pathology. A novel approach is demonstrated, in which images are divided into smaller segments and regions containing diseased tissue are identified. Training accuracy increases as a result, and the model's ability to recognize subtle symptoms is improved. Comparing the study to earlier methods, classification accuracy has significantly improved. For instance, accuracy levels between 79% and 100% are attained in a variety of plant species, signifying a significant breakthrough in the diagnosis of diseases. When photos are manually divided into smaller groups, an enlarged dataset (XDB) is created. This improves performance, especially when the initial dataset was small. More number and variety of training samples lead to stronger and more dependable models [17] [51].

Pantazi et al focuses on differentiating between black rot, powdery mildew, downy mildew, and healthy leaves as four different plant leaf health problems. To distinguish the leaf area from the background in an image segmentation procedure, the GrabCut Algorithm is employed. Colour and texture information can be retrieved from segmented photos using the Hue Saturation Value (HSV) Transform. The segmented images texture information is extracted using Local Binary Patterns (LBPs). LBPs can record texture information and are resistant to changes in light. More specifically, leaf sample data is classified into groups that represent the healthy and the sick using One Class Support Vector Machines (OCSVMs) or One Class Classification (OCC). OCC is employed in anomaly detection assignments when a single class is of interest since it can represent data from a single class. The OCC model's effective generalization abilities were demonstrated by correctly classifying most leaf samples as either healthy or unwell. Since conflict resolution techniques enabled over 95% identification capacity and the resolution of disputes between rival classifiers, they were essential for accurate classification. With the model's ability to accurately diagnose a wide range of diseases in different plant species, crop management could benefit greatly from its use [18] [51].

Maniyath et al. employs Random Forests as a machine learning strategy's classification technique. Preprocessing include converting RGB images to grayscale and HSV colour spaces to facilitate feature extraction. During the feature extraction procedure, the Histogram of Oriented Gradients (HOG), Hu moments, Haralick texture, and colour histogram are utilized. These traits capture important aspects of leaves, such as shape, texture, and colour dispersion. A Random Forest classifier is trained using the features derived from a labelled dataset of leaves from both healthy and diseased plants. Random Forests are the recommended model because of their versatility in solving a wide range of classification issues and their ability to handle both category and numerical input. Using the Random Forest that has been trained. The study reports a 70% classification accuracy using a dataset including 160 photos of papaya leaves. This implies that the suggested method might be able to accurately identify between healthy and sick leaves. In addition to applying Bag Of Visual Word (BOVW) approaches, the authors propose that further improvements could be achieved by expanding the size of the training dataset and employing state-of-the-art feature descriptors like Scale Invariant Feature Transform (SIFT) and Speed Up Robust Features (SURF) [19] [51].

Harakannanavar et a developed a system that can accurately detect diseases in plant leaves, particularly focusing on tomato plants. Various image processing techniques are applied, including contrast enhancement, K-means clustering, contour tracing, and scaling. These techniques are necessary to separate diseased areas and enhance the quality of the pre-processed leaf photos. Convolutional neural networks (CNN), K-Nearest Neighbours (KNN), and support vector machines (SVM) are the three models used for classification. The two traditional supervised learning algorithms are SVM and KNN, CNN is a deep learning strategy that has shown promise in picture classification applications. Three processing techniques are utilized to extract pertinent information from the leaf images Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Gray Level Co-occurrence Matrix (GLCM). These methods aid in identifying pertinent trends and traits in the impacted areas. The results show that the model performs well in differentiating between healthy and unhealthy leaves, with an overall accuracy rate of 99.5%. With accuracy scores ranging from 95.3% to 100%, the model demonstrates remarkable accuracy in identifying a variety of tomato plant diseases, including mosaic virus, leaf Mold, yellow curl, spotted spider mite, and target spot. When compared to earlier techniques based on univariate statistical traits, K-means clustering with GLCM, and quick improved learning techniques, the suggested model performs better and attains higher accuracy [20][52][53].

Ahmed and Yadav focuses on the application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) methods in agriculture, particularly for the treatment and detection of plant diseases. Convolutional neural networks, or CNNs, are employed in the analysis of multidimensional data, primarily images of plant leaves. They are able to recognize sick plant leaves because of their skill in feature extraction, pattern analysis, and image classification. By mimicking biological processes, Artificial Neural Networks (ANNs) are utilized to extract patterns from complex agricultural data. They are necessary to understand and assess the various facets of plant diseases. Support vector machines are classifiers that work with linear data to categorize objects. They go by the name SVMs occasionally. They are employed in supervised learning techniques, namely in the diagnosis stage of the classification of plant diseases. This study also covers the integration of Industry 4.0 technologies, such as autonomous monitoring and real-time data processing, into plant healthcare systems. Sustainable farming practices are encouraged by these technologies, which help with the prompt and transparent decision-making process. CNNs diagnose plant diseases with an outstanding 97% accuracy rate, which surpasses previous methods. CNNs process information in parallel with amazing efficiency and require less training time due to their efficient topologies. ANNs show remarkable accuracy, with an average of 95% across multiple datasets related to plant diseases. With an average accuracy of 94%, VMs perform competitively when it comes to spotting sick plant leaves [21] [52][53].

Jangid developed an Automated plant disease detection, using convolutional neural networks (CNNs) and image processing methods, with a focus on rice plants. Pre-processing steps include data normalization and augmentation to prepare images of rice plants for input into the CNN model. To classify diseases, the deep CNN model VGG-16 is utilized, which was first trained on the ImageNet dataset. There are a total of 16 layers in this design, including convolutional layers stacked on top of one another like tiny 3x3 convolutional filters and completely linked layers. The trained VGG-16 model correctly classifies photos of rice plants into groups linked to health and illness at an outstanding 90% accuracy rate. This high accuracy indicates how well the device can identify different plant illnesses. The accuracy rate of the model is ascertained by contrasting its predictions with ground truth labels for a validation dataset, which consists of a group of pictures that were not utilized during training [24].

Reddy et al developed an automated method for early detection and classification of plant diseases. This technique uses a deep learning model called PDICNet to classify plant diseases using images of the leaves. Convolutional neural networks (CNNs) are mostly used for feature extraction and categorization. ResNet-50 architecture is employed to extract features from leaf images due to its deep design and history of success in numerous computer vision applications. bio-optimization method using the Modified Rao-Dutta Optimization Algorithm (MRDOA) and feature selection. By selecting the most relevant features from the gathered data, the goal is to decrease computer complexity and improve classification performance. A Deep Learning Convolutional Neural Network (DLCNN) classifier is used to categorize diseases based on the selected features. The model is trained on the dataset in order to enable it to recognize patterns associated with different plant diseases. Two datasets that are utilized and are available to the public are PlantVillage and Rice Plant Disease. The PlantVillage collection has 20,798 colour photographs of leaves, compared to 1600 images in the Rice Plant Disease dataset. On the PlantVillage dataset, the PDICNet model yielded values of 99.73% accuracy, 99.83% precision, 99.72% recall, and 99.78% F-measure. When tested on the Rice Plant Disease dataset, the PDICNet model yielded values of 99.68% accuracy, 99.72% precision, 99.70% recall, and 99.71% F-measure [22]][52][53].

Anim-Ayeko et al. created a ResNet9 model that can be used by farmers to identify the tomato and potato leaf blight disease. ResNet9's predictions took into account the morphology, the sick area of the leaf, and the total amount of green space. The 3990-piece PlantVillage dataset, which was later expanded for training and intense hyperparameter optimization techniques, was used by the suggested model.

After that, the model was evaluated on a test set of 1331 images after being trained using the hyperparameter settings. The model produced results with an F1-score of 99.33%, accuracy, precision, and recall of 99.25%, 99.67%, and 99.33%, respectively [23][54].

V. Conclusions

Various methods and tools—each with unique benefits and capabilities—that are utilized in the classification and diagnosis of plant diseases. Lots of studies have attempted to diagnose diseases affecting a count of plant species using a variety of algorithms, including image processing approaches, convolutional neural networks (CNNs), deep learning neural networks, and machine learning (ML) algorithms, with varied degrees of success. The results of these algorithms can be compared to determine which techniques perform better under specific circumstances. CNNs, for instance, have demonstrated remarkable accuracy rates; certain models can recognize illnesses with over 95% accuracy, such as tomato leaf blight and infections affecting rice plants. But machine learning methods such as Random Forests and Support Vector Machines (SVMs) have also shown some incredible results, particularly in the area of identifying healthy from damaged plant leaves often with an accuracy of over 90% .

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