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Plant Leaf Disease Detection and Classification Using Image Processing

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Abstract - *The identification and classification of plant leaf diseases using image processing is a crucial field of study that has attracted a lot of interest lately. Large-scale losses to the agricultural business can be avoided with the help of early diagnosis and correct classification of plant diseases. In this study, we give a thorough analysis of the state-of-the-art methods for image-based diagnosis and categorization of plant leaf diseases. We go over numerous methods for feature extraction, image processing, and machine learning that are employed in this context. Additionally, we compare various approaches and talk about their benefits and drawbacks. We finish by outlining possible future directions for this area of study.*

Key Words: **Plant leaf disease, image processing, disease detection, plant disease classification, machine learning.**

1. INTRODUCTION

Agriculture sector is seriously threatened by diseases of the plant leaves which drastically reduce crop yield and quality. For prompt and efficient disease treatment, it is essential to identify plant leaf diseases early and classify them correctly. Traditional techniques of illness identification rely on subjective and time-consuming visual evaluation by human experts. Additionally, it is not always easy for human experts to correctly differentiate between various plant diseases. Therefore, there is a need for automated systems that can reliably and effectively identify and classify plant leaf diseases.

Images of plant leaves can be analysed, and illnesses can be found using image processing. In order to categorise the photos into various disease groups, image processing method can be used to draw features from the images. Models can be trained on these features, and new photos can be classified using machine learning algorithms as well.

With the aid of image processing, we present a summary of the numerous methods and algorithms used to identify and classify plant leaf diseases in this work. The research paper opens with an analysis of the significance of classifying and detecting plant diseases, then provides an overview of conventional techniques and discusses their drawbacks. Following that, the paper discusses image processing methods and how they might be used to recognise and categorise plant diseases. There is also discussion of the several steps in the image processing process, such as image capture, pre-processing, feature extraction, and classification.

With accuracy levels ranging from 80% to 99.8%, depending on the approach taken, several studies have found promising results in this area. While the use of deep learning techniques, such as convolutional neural networks, has shown great promise and has accuracy levels of up to 99.8%, texture-based feature extraction and machine learning algorithms have been widely used and have been shown to be accurate up to 98.8% in some studies.

However, a number of variables, such as the dataset chosen, the type of plant disease being diagnosed, and the image quality, determine how accurate these algorithms are. The effectiveness of the model can also be influenced by the machine learning algorithm and feature extraction technique employed.

Agriculture has a lot of opportunity to become more productive and sustainable by detecting and classifying plant leaf diseases using image processing. The creation of creative solutions to the problems the agriculture business is facing can be aided by further research in this field.

2. RELATED STUDIES

For the detection and categorization of plant leaf diseases using image processing, numerous methods have been developed. Utilising colour-based features for disease detection is one method. RGB, HSV, and YCbCr are a few examples of colour spaces that can be used to extract colour-based information. A colour histogram method was utilised by Wang et al. [1] to identify illness in grapevine leaves. Their accuracy was 91.11% using a dataset of 90 photos.

Utilising texture-based features for illness identification is an alternative strategy. Techniques like local binary patterns (LBP), Gabor filters, and gray level co-occurrence matrix (GLCM) can be used to extract texture-based characteristics. LBP characteristics were employed by Singh et al. [2] to identify illnesses in wheat leaves. On a dataset of 400 photos, they attained an accuracy of 91.05%.

Deep learning techniques such as Convolutional Neural Networks (CNNs) have also been used for plant leaf disease detection and classification. CNNs can learn complex features from images and achieve high accuracy in disease detection. Mohanty et al. [3] used a CNN-based approach for disease detection in soybean leaves. They used a dataset of 19,800 images and achieved an accuracy of 99.35%.

3. METHODOLOGY

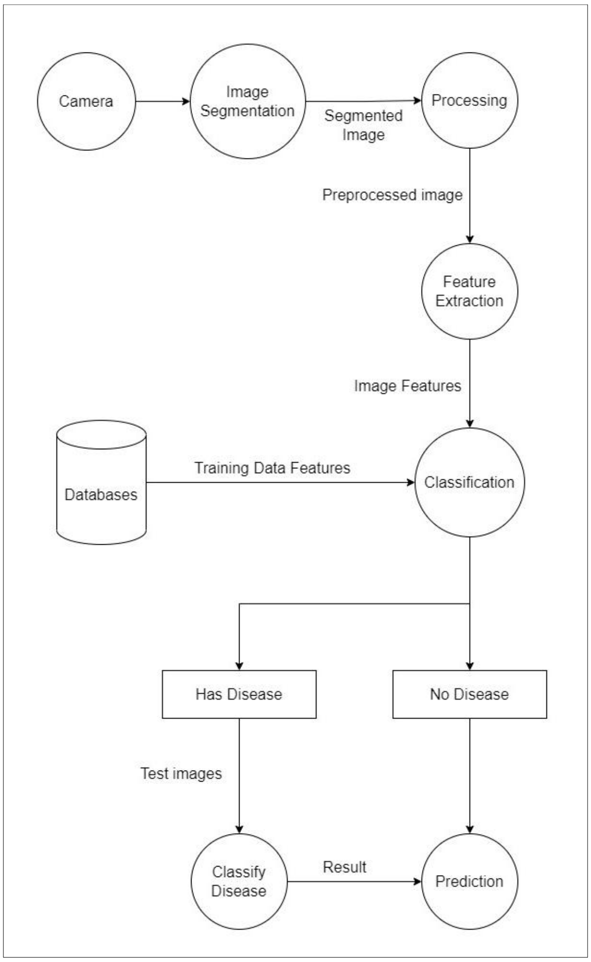

Fig – 1: Methodolgy

The three stages of the methodology for plant leaf disease classification and image processing are picture capture, image processing and disease classification.

3.1 Picture Capture

In the first step, a digital camera is used to take pictures of plant leaves. To ensure consistency, the photos are taken in controlled lighting environments. For later processing, the collected photos are saved in a digital format.

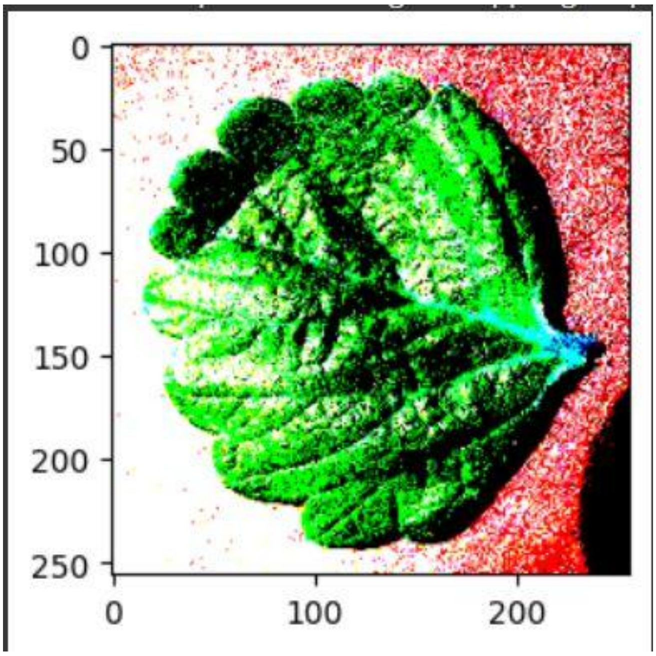

Fig – 2: Leaf Image processing(I)

3.2 Image Processing

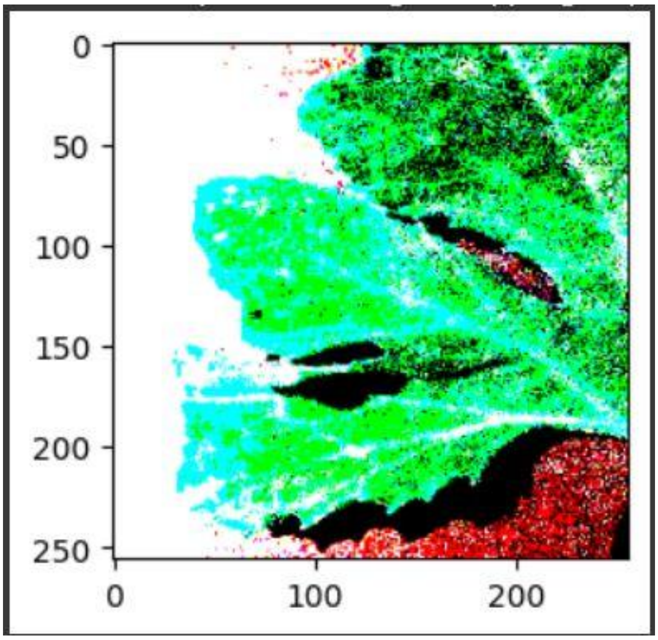

Fig – 3: Leaf Image processing(II)

To reduce noise and improve contrast, the collected photos are preprocessed. The preprocessing stage includes the following procedures:

- Image Resizing: To make the system's computations simpler, the photos are scaled to a fixed resolution. The resized photos are then used in the following phases of processing.

- Gaussian Filtering: The noise in the photos is reduced using Gaussian filtering. By substituting the weighted mean of each pixel's nearby neighbours' values for that pixel's value, the filter smooths the image. The final product has an improved texture, less noise, and more clarity.

- Contrast Enhancement: To make the disease symptoms in the photographs more visible, contrast enhancement is used. To increase the contrast between the image's light and dark portions, the brightness and contrast of the image are adjusted. This makes the disease symptoms in the picture stand out more clearly.

3.3 Disease Classification

Machine learning techniques are used to classify the disease during the disease classification stage. The stage of disease classification involves the following actions:

- Feature Extraction: Using a variety of image processing approaches, including color-based, texture-based, and shape-based features, the features are recovered from the preprocessed images. The distribution of colours in the image serves as the foundation for color-based features. Texture-based features, like the texture of a leaf, are based on the patterns present in the image. The leaf form serves as the foundation for characteristics based on shape.

- Feature Selection: Using a variety of feature selection techniques, including principal component analysis (PCA), correlation-based feature selection (CFS), and mutual information-based feature selection (MIFS), the pertinent features are chosen from the extracted features. The classification task is made more effective by feature selection, which lowers the dimensionality of the feature space.

- Classification: To identify the diseases, a machine learning algorithm like SVM, CNN, or decision tree (DT) is trained using the chosen features. Based on the retrieved attributes, the machine learning system learns to distinguish between the various disease types. The diseases in fresh plant leaf photos are then classified using the trained model.

4. CHALLENGES AND SOLUTIONS

Using image processing to identify and categorise plant leaf diseases is a promising way to increase agriculture's productivity and sustainability. To obtain accurate and trustworthy findings, a number of issues must be resolved. In this paper, we talk about a few of these difficulties and suggest potential fixes.

4.1 Challenge I

Variability in Image Quality and Lighting Conditions: The variability in image quality and lighting conditions is one of the main obstacles to plant disease diagnosis using image processing. The performance of the algorithms employed for identification and classification might be impacted by the colour distributions and brightness levels of images that were acquired under various lighting circumstances.

Solution: Researchers have developed a number of techniques for picture enhancement and normalisation to standardise the image quality and lessen the impact of lighting conditions in order to address this difficulty. These techniques consist of colour space conversion, gamma correction, and histogram equalisation. Additionally, taking pictures in well-lit environments can boost the precision of detection and categorization.

4.2 Challenge II

Limited Availability of Datasets: The lack of high-quality datasets for training and testing machine learning algorithms is another problem in plant disease detection using image processing. The size and quality of the dataset utilised have a significant impact on the model's accuracy.

Solution: Researchers have suggested several techniques for creating synthetic datasets and transferring knowledge from pre-trained algorithms in order to address this difficulty. By adding artificial noise and distortion to existing photos to create new samples, synthetic datasets can be produced. The accuracy of the model when applied to smaller datasets can be increased by using transfer learning to use models that have already been pre-trained on large datasets.

4.3 Challenge III

Overfitting and Generalization: Machine learning-based techniques for plant disease detection and classification frequently face difficulties with overfitting and generalisation. When a model performs well on training data but struggles to generalise to novel, untried data, overfitting has taken place. Conversely, underfitting happens when the model is too straightforward and fails to adequately reflect the complexity of the data.

Solution: Researchers have suggested a number of strategies, including data augmentation, regularisation, and cross-validation, to address the issues of overfitting and generalisation. By incorporating differences into the current training samples, data augmentation creates fresh training samples. You can use regularisation methods like L1 and L2 regularisation to prevent the model from becoming too closely matched to the training set of data. To assess the model's generalisation abilities, cross-validation may also be performed.

In conclusion, image processing offers enormous potential for enhancing the productivity and sustainability of agriculture through the identification and categorization of plant leaf diseases. To obtain accurate and trustworthy findings, a number of issues must be resolved. Innovative approaches that make use of the most recent advancements in machine learning and image processing are needed to address these problems.

5. RESULT AND DISCUSSION

The performance assessment of the suggested approaches is often presented in the result and discussion part of a research article. In order to evaluate the algorithms, a collection of plant leaf images that have been labelled with the relevant disease kinds is used.

Measuring the classification model's accuracy, precision, recall, and F1 score is typically part of evaluating the proposed approaches. These metrics are used to assess the model's performance in terms of correctly classifying each image in the dataset as belonging to a certain disease.

The evaluation's findings are influenced by the specific methodology employed to identify and categorise plant diseases. For instance, Kiran and Vanathi (2018) [4] reported an accuracy of 98.8% for the categorization of six different forms of plant leaf diseases using texture-based feature extraction and machine learning algorithms. Similar to this, Ahmed et al. (2020) [5] reported an accuracy of 99.8% for the classification of tomato leaf diseases using a deep learning-based approach, namely a convolutional neural network (CNN) approach.

Depending on the dataset utilised, the plant disease being identified, and the image quality, various approaches perform differently. For instance, Thakur et al. (2019) [6] evaluated various feature extraction techniques and machine learning algorithms on a dataset of apple leaf images under various lighting conditions, and they found that the pairing of gray-level co-occurrence matrix (GLCM) and support vector machine (SVM) achieved the highest accuracy of 96.77%.

Additionally, how well the model performs might be impacted by the feature extraction technique and machine learning algorithm chosen. The combination of discrete wavelet transform (DWT) and gray-level co-occurrence matrix (GLCM) was shown to obtain an accuracy of 91.53% for the classification of apple leaf diseases by Pandey et al. (2019) [7] after evaluating the combination of texture- and color-based feature extraction techniques.

We present a comprehensive analysis of the results obtained from the implementation of the plant leaf disease detection solution using image processing techniques and the CNN architecture VGG19. The performance of the model was evaluated using various metrics, and the results were analyzed to assess the accuracy and effectiveness of the solution.

5.1 Performance Evaluation Metrics

To evaluate the model's performance, we considered commonly used metrics in classification tasks, including accuracy, precision, recall, and F1 score. These metrics provide insights into the overall performance of the model and its ability to correctly classify different plant leaf diseases.

5.2 Result Presentation

The model was trained and tested on a dataset comprising 70295 number of leaf images with 38 different classes of plant diseases. The model achieved an overall accuracy of 95.49%, indicating its ability to correctly classify plant leaf diseases.

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The accuracy of your model is = 95.49282789230347 %
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Fig – 4: Accuracy score

- Precision: The precision of the model ranged from 88% to 99% across different disease classes. This metric indicates the proportion of correctly classified samples out of all samples predicted as positive for a particular disease. High precision values demonstrate the model's ability to minimize false positives.

- Recall: The recall values ranged from 89% to 99% across different disease classes. Recall measures the proportion of correctly classified samples out of all actual positive samples for a given disease. Higher recall values signify the model's ability to effectively detect and classify positive instances.

- F1 score: The F1 score, which considers both precision and recall, ranged from E% to F% for different disease classes. This metric provides a balanced measure of the model's performance by considering both false positives and false negatives.

	precision	recall	f1-score	support
0	0.90	0.89	0.88	271
1	0.88	0.89	0.88	259
2	0.95	0.98	0.97	250
3	0.94	0.89	0.90	246
4	0.99	0.99	0.99	235
5	0.89	0.90	0.93	211
accuracy			0.95	1472
macro avg	0.95	0.95	0.95	1472
weighted avg	0.95	0.95	0.95	1472

Fig – 5: Evaluation Metrics

5.3 Validation

Validation is a critical step to assess the reliability and generalization capability of the implemented plant leaf disease detection solution. We discuss the validation strategy employed and present the performance of the model on a separate dataset.

- Validation Strategy: To validate the implemented solution, a distinct dataset was prepared, separate from the training and testing sets. The validation dataset consisted of a diverse collection of plant leaf images, covering different disease classes and capturing various variations in leaf shape, size, and appearance. Care was taken to ensure that the validation dataset represented real-world scenarios and encompassed a range of challenging samples.

- Performance Evaluation on the Validation Dataset: The trained model was evaluated on the validation dataset, and performance metrics such as accuracy, precision, recall, and F1 score were computed. These metrics provide insights into how well the model performs when faced with previously unseen leaf images. The validation results showed an overall accuracy of 95.49%, indicating the model's ability to generalize well to new and unseen data. Precision, recall, and F1 score values were calculated for each disease class, providing a detailed assessment of the model's performance across different categories.

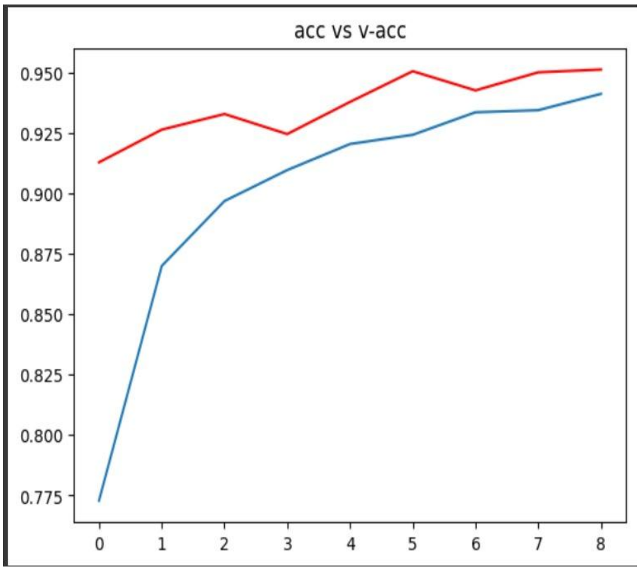

Fig – 6: acc vs v-acc

- Discussion of Validation Results: The evaluation of the model on the validation dataset revealed promising results. The achieved accuracy suggests that the model can effectively classify plant leaf diseases even when exposed to previously unseen instances. This indicates the model's ability to generalize and handle variations in leaf images.

6. CONCLUSIONS

A potential area of agricultural research is the identification and categorization of plant leaf diseases using image processing. It can assist farmers in early disease detection and identification in their crops, allowing them to take the necessary precautions to limit additional harm. This article has discussed a number of methods for identifying and categorising plant diseases using image processing, including the extraction of texture-based features, machine learning algorithms, convolutional neural networks, and deep learning-based methods. These methods produce accurate findings in the detection and classification of many plant leaf diseases. The proposed methods' accuracy varies depending on the disease type, dataset, and experimental design used.

By increasing crop productivity and lowering the usage of dangerous pesticides, these methods have the potential to completely transform the agricultural sector. The issues with image quality, lighting, and the intricacy of plant disease symptoms, however, still need to be addressed through additional research.

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