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A Survey Paper On Plant Disease Prediction

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Abstract *– Agriculture plays an important role in Indian economy and development. But due to unfamiliar weather conditions and attacks by different microorganisms, crops are getting infected. This causes a huge loss to the farmer and impacts the economy and food security. Therefore, determining crop diseases at an early stage is very important to prevent losses, maintain quality and increase crop productivity. However, due to a lack of knowledge and unavailability of resources, immediate identification of diseases through visual monitoring is difficult. To overcome this problem, we need a proper monitoring system that helps to predict the type of infection or disease present. This information can be valuable for farmers to take appropriate measures to prevent and control the spread of diseases.Many researchers have been working in this direction for decades. This survey paper provides a comprehensive overview of the current state of research in the field of plant disease prediction, focusing on various techniques, methodologies, and advancements. The survey paper begins by discussing existing plant disease prediction methods, different machine learning -based models, various technologies used in them, their performance, and challenges associated with plant disease prediction. Furthermore, the survey paper includes the future possibilities of the development in the domain of plant disease prediction. The paper concludes by highlighting why it is important to predict plant diseases accurately. If done well, accurate prediction can help farmers grow food in an environmentally friendly manner and ensure there is enough food for everyone around the world.*

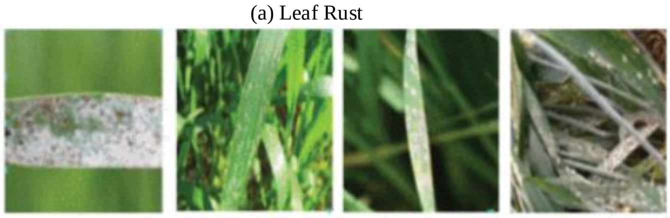
Keywords*: Image Processing, Plant Leaf, Feature Extraction, Image Classification.*

I. Introduction

Due to their ability to make more accurate predictions and provide greater reliability, the development of digitalized systems has gained significant traction in the implementation of applications within agricultural production areas and fields. These applications encompass a range of tasks including but not limited to the identification of different crop varieties [1,2], the detection of weeds [3], and the grading of crops. Furthermore, the expansion and enhancement of this technological domain also aim to delve into the realm of plant disease investigation and detection.

The rapid increase in plant diseases, exacerbated by unstable environmental conditions and climate change, poses a looming threat of food shortages in various parts of the world in the foreseeable future. Currently, the prevalent method for detecting plant diseases relies primarily on naked eye observation by trained experts. This approach necessitates the involvement of a sizable team of experts and requires continuous monitoring of plants, which can incur significant costs particularly when dealing with large-scale farms. Moreover, in certain regions, farmers lack access to adequate facilities or knowledge to seek assistance from experts, further compounding the challenges. In such circumstances, the proposed technique of automatic disease detection proves to be advantageous for monitoring extensive crop fields. By enabling the automatic detection of diseases based solely on observable symptoms on plant leaves, this approach offers a more convenient and cost-effective solution. Additionally, it leverages machine vision to facilitate image-based automatic process control, inspection, and robot guidance [4, 5].

(a) Leaf Rust



(b) Powdery Mildew

(c) Tan Spot

Fig. 1 Leaf disease types

The scientific community has extensively studied plant diseases, with a predominant focus on their biological properties. These diseases represent a formidable challenge as they are inevitable and can significantly impact crop production through pest infestations, fungal attacks, and adverse environmental conditions such as unexpected meteorological variations. To address these challenges, there is a growing emphasis on adopting cutting-edge techniques to preemptively manage diseases within specific regions and for various disease variants [6]. This proactive approach not only reduces labor-intensive tasks but also minimizes the reliance on conventional methods or the need to wait for expert intervention. Moreover, the occurrence and spread of plant diseases are intricately linked to specific environmental factors and soil conditions.

In recent years, numerous real-time computer vision systems have been developed utilizing machine learning algorithms and other computational methods. Among these, deep learning techniques have emerged as the preferred choice due to their efficacy in analyzing and extracting features from diverse datasets [7]. Deep learning has garnered considerable attention across various domains and has witnessed particularly widespread adoption in agriculture due to its ability to deliver precise results [8]. Many researchers are opting to train their data using artificial neural networks, particularly convolutional neural networks (CNNs) or ConvNets, which have demonstrated remarkable success in tasks such as image segmentation, feature extraction, and pattern recognition.

II. Related Work

In their study [9], Prajapati and colleagues embarked on collecting images of infected rice leaves, selecting a farm in India as their primary location. The complexity of the images necessitated preprocessing steps to isolate the leaves from the background, which was achieved through techniques like K-means clustering and Ostu's method for image segmentation. The resulting segmented images were then fed into a Support Vector Machine (SVM) classifier to assign appropriate labels to each image, ultimately forming the foundation for a rice disease classifier.

In [10], Honglei Li and their team proposed a diagnostic model incorporating a combination of classifiers from deep learning and ensemble learning. Their evaluation of five different models revealed that the stacking ensemble learning classifier outperformed the others, achieving remarkable accuracy rates. Notably, this stacking ensemble learning classifier demonstrated validation and test dataset accuracies of 98.05% and 97.34%, respectively, indicating its superiority in performance.

Md. Sakib Hossain Shovon et al. [11] introduced the PlantDet model, leveraging architectures like InceptionResNetV2, EfficientNetV2L, and Xception to address issues of underfitting and enhance robustness. Through techniques such as pre-processing, data augmentation, and incorporating various architectural components like global Average Pooling layer and Dropout mechanisms, the PlantDet model showcases improved performance and robustness, particularly in scenarios with limited data and diverse backgrounds.

Yousef Methkal et al. [12] proposed an innovative approach named ACO-CNN for disease detection and classification in plant leaves. By integrating ant colony optimization with CNN, the model effectively extracts features related to color, texture, and leaf arrangement, surpassing existing techniques in accuracy rates. Their meticulous analysis and performance evaluation underscore the effectiveness of the proposed method in disease diagnosis.

In their work [13], Sabbir Ahmed and team presented a lightweight transfer learning-based approach for disease detection in tomato leaves. Employing a pretrained MobileNetV2 architecture coupled with effective preprocessing methods, the system enhances leaf images for improved classification. Additionally, runtime augmentation is utilized to address data leakage and class imbalance issues, ensuring robust performance in disease detection tasks.

C. Madhurya et al. [14] devised an optimized framework based on YOLOv7, termed YR2S, for disease detection in leaves. Leveraging pre-processing and hybrid optimization techniques, the proposed framework incorporates PCFAN for feature map generation and ShuffleNet with ERSO for classification optimization. Through FCN-RFO, the framework facilitates segmentation of disease-prone areas, contributing to effective disease detection in plants.

Table I Comparison of Plant Leaf Disease Models

Year	Technique	Outcomes
Vimal Singha et. al. in [16], 2023	EfficientNetB6	Works for a Beans leaf dataset with variable leaf background.
Yun et. al. [17], 2022.	CBAM	The proposed model reduces the training parameters as well as shortens the training time.
Verma et. al [18], 2022	AlexNet SqueezeNet ResNet50 VGG16/19 InceptionV3	The proposed methodology improves the performance substantially as compared to standard CNN models.
Ahmed et. al. [19], 2021	CNN Model	A convolutional neural network (CNN) model designed for mobile platforms was suggested to streamline the process of identifying plant diseases.
Sahu et. al. [20], 2020	Transfer Learning	For a small dataset, fine-tuning hyper parameters on a

		retrained model is a preferable option.

III. Features for Image Classification

Color feature: The color feature of an image is derived from its matrix of light intensity values, with each value representing a different hue or shade. This feature is crucial for object identification, offering the advantage of low computational cost. Image files come in various color formats, such as RGB (red, green, blue), which represents a three-dimensional matrix where each two-dimensional matrix represents a single color channel. Grayscale format, on the other hand, simplifies intensity calculations with values ranging from 0 to 255, while binary format condenses colors to just black and white (0 or 1). Utilizing this color feature has facilitated efficient face detection in previous studies [8].

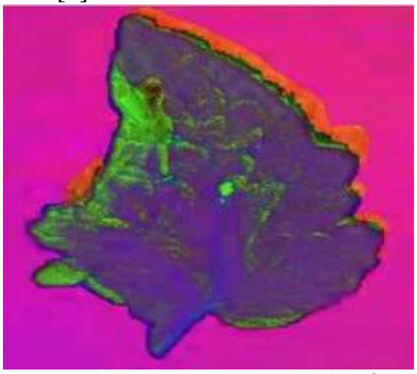


Fig. 2 Represent the HSV (Hue Saturation value) format of an image

Edge Feature: The edge feature arises from sudden intensity changes within an image and is instrumental in object detection tasks such as identifying buildings or roads within a scene.

Fig. 3 Leaf edge feature by Canny algorithm

Various algorithms, including Sobel, Prewitt, and Canny, have been developed for effective edge detection, with the Canny edge detection algorithm particularly renowned for its accuracy in delineating image boundaries.

Texture Feature: Texture, representing the degree of intensity variation across a surface, offers insights into properties like regularity and smoothness. While texture features require additional processing steps compared to color space models, they are less sensitive to illumination changes, similar to edge features.

Histogram Feature: The histogram feature involves quantifying the distribution of pixel values within an image. By generating histograms, one can analyze the frequency of pixel values across different intensity levels, providing valuable insights into the image's overall characteristics.

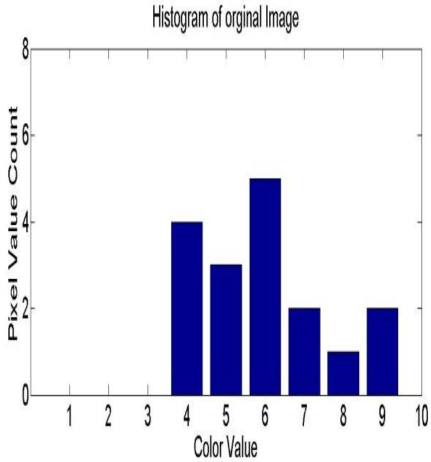


Fig. 4 Histogram of the original image

Corner Feature: Corner detection is utilized to stabilize leaf image frames in scenarios involving a moving camera, enabling tasks such as resizing windows to maintain the original view. Additionally, corner features aid in determining angles and measuring distances between objects across frames, facilitating target object tracking.

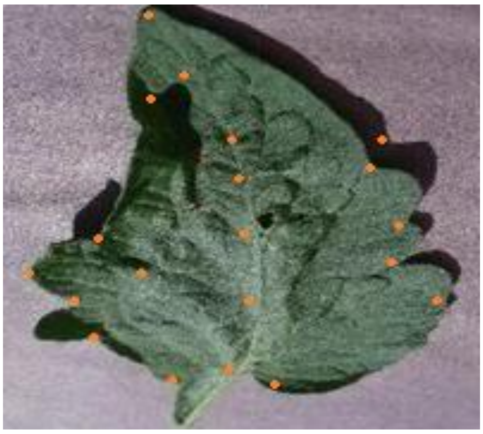


Fig. 5 Represent the corner feature of an image with green point

DWT (Discrete Wavelet Transform):
The Discrete Wavelet Transform (DWT) breaks down an image into its constituent frequency components, yielding sub-bands such as LL (approximate), HL (horizontal edge), LH (vertical edge), and HH (diagonal edge). Each sub-band captures specific information about the image, enabling detailed feature extraction for analysis and classification purposes.

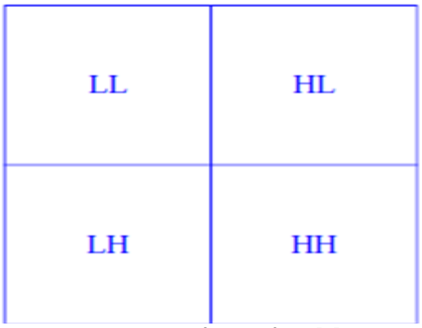


Fig. 6 DWT of image from [8]

IV. Attack on Image

In the realm of image classification, a variety of attacks are employed to assess the resilience of the system in extracting features from the source image. These measures are implemented prior to data delivery to digital media platforms, aiming to evaluate the robustness and security of image classification algorithms.

Noise Attack: When transmitting leaf images through secret channels, noise is intentionally introduced to test the integrity and security of the images. Various types of noise attacks, such as Gaussian noise, Salt and Pepper noise, and Speckle noise, are utilized to gauge the system's resistance to interference.

Filter Attack: In this type of attack, the received leaf images undergo filtration through different types of filters, challenging the resilience of the image classification process. Common filtering attacks include Median filtering, Sharpen filtering, and Motion filtering, among others.

Compression Attack: Leaf images are subjected to compression using various techniques after being received from the network. The classification and feature extraction algorithms must be robust to safeguard against compression attacks, which commonly involve techniques like MPEG compression and MP4 compression.

Detection-Disabling Attack: This attack aims to compromise the security of data by altering its correlation, thereby rendering it difficult to extract the intended message. Geometric distortions such as cropping, pixel permutation, temporal shifts, rotation, zooming, or insertion are often employed to thwart detection.

Ambiguity Attacks: Bogus messages are introduced alongside the genuine message to confuse the detector, leading to uncertainty in identifying the true message. Multiple watermarks may be embedded to cast doubt on the authority of the original secret message.

Third-Party Involvement: The involvement of a third party in producing a compressive sensing matrix enhances image privacy. Specific pixels are selected within this matrix and evaluated against hidden headers. If the pixels align with the message, it is selected for classification; otherwise, it is rejected. On the extraction side, the image undergoes analysis via calculations, with acceptance or rejection based on the results. However, no counter-attack measures have been implemented in this domain of the work.

V. Conclusions

Plant diseases pose a significant threat to the world's nutrition and can have severe consequences for smallholder farmers who rely on a crop for their livelihoods. Therefore, it is crucial to create an algorithm for early automated diagnosis of plant diseases. This paper has found that most of learning models are based on convolutional neural network but no steps were taken for attacked images. Further paper has summarized the features of image and in plant leaf disease detection color feature was commonly used. Most of dataset used by the researchers has constant background or static background hence real time variable dataset work need to be done in future for the application of research.

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