Transfer Learning Based Model for Plant Disease Detection with VGG16

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ABSTRACT : *In the evolving domain of digital image processing and multimedia systems, precision in plant disease detection has emerged as a critical component for enhancing agricultural productivity. Timely and accurate identification of plant infections remains a formidable challenge due to varying climatic conditions, which can significantly impact both the quality and quantity of horticultural outputs. Addressing this issue is vital to mitigate unnecessary wastage of financial resources and maximize crop yield. This research proposes an advanced plant disease detection model leveraging transfer learning by integrating VGG16 (Visual Geometry Group) and Convolutional Neural Networks (CNN). The model aims to diagnose plant ailments early and with high accuracy, thereby enabling proactive disease management. Implemented in Python, the model's performance is evaluated using key metrics such as accuracy, precision, and recall to ensure robust detection capabilities. The proposed model is tested using the Plant Village dataset, a comprehensive, publicly available resource containing high-quality images of various plant species and their corresponding diseases. Each image is meticulously labeled with the disease category, providing a solid foundation for training and validating the model's effectiveness in real-world scenarios. The proposed plant disease detection model, based on the integration of VGG16 and CNN, achieved impressive results across key performance metrics. The model demonstrated high accuracy, precision, and recall, indicating its effectiveness in accurately identifying and classifying various plant diseases. Using the Plant Village dataset, the model was able to diagnose infections early, significantly enhancing the potential for timely intervention in agricultural practices. The precision of the model minimizes false positives, ensuring reliable predictions for practical deployment. In conclusion, this model presents a viable solution for improving plant disease detection, contributing to sustainable agricultural management by reducing wastage and increasing crop productivity.*

Keywords: Transfer Learning,VGG16, Plant Disease Detection, Deep Learning, Image Classification

1. INTRODUCTION

Diseases in plants significantly impact both the quantity and quality of crops, making early and accurate forecasting and diagnosis crucial for minimizing crop losses and boosting production. In India, the agricultural sector contributes only 17% to the gross domestic product, with essential crops like pepper, potatoes, and tomatoes ranking among the top in terms of cultivation. The spread of plant diseases is influenced by various factors, such as cross-contamination, pests, and environmental conditions. Pests alone account for a 30-33% reduction in crop yield. Infectious diseases caused by bacterial, viral, and fungal species pose a significant threat to agriculture. With such diversity in pathogens and contributory factors, managing these diseases becomes a complex task for agricultural experts, who must adapt infection control strategies while minimizing damage to the crops. Despite the advancements in agricultural technology, many farmers continue to rely on traditional methods of visual inspection to identify crop diseases. These methods depend largely on a farmer's experience and intuition, which can be highly subjective and prone to error. Certain plant diseases exhibit subtle symptoms, making them difficult to diagnose through visual inspection alone, leading to undetected infections that can result in severe crop loss. Moreover, these traditional techniques limit the ability of agricultural research to evolve, as they provide no real-time data or scalable solutions for modern challenges. The worst-case scenario is that an undiagnosed infection can result in a complete failure of a crop, diminishing both quality and output, and ultimately harming the farmer's livelihood.

In contrast, modern technologies such as machine learning (ML) and deep learning (DL) offer significant potential to overcome these challenges. Computer-aided, automated systems can now provide precise, rapid, and early detection of plant diseases, addressing the key problems that arise in traditional farming practices. ML and DL algorithms can analyze vast datasets, recognize patterns, and identify plant diseases even in their early stages, leading to timely interventions. These technologies also enhance decision-making, offering real-time results that allow farmers to take immediate action. The use of such AI-driven methods is revolutionizing agricultural practices by reducing labor costs, eliminating unnecessary delays, and improving both the quality and yield of crops.

Furthermore, Artificial intelligence (AI) is being increasingly used in agriculture for the diagnosis and classification of plant diseases. The first stage of this sequence involves classifying data, with the main goal being to identify and categorize plant leaves, particularly between healthy and unhealthy specimens. Machine learning (ML) and deep learning (DL) are essential for this process. ML algorithms are primarily focused on problem- solving and decision-making, while machine learning is a branch of AI that learns progressively through a training process. Supervised learning involves providing input data and inferring goal values from it, while unsupervised learning involves introducing data without clear input-output guidelines. Semi-supervised learning results when one data is labeled and the other is unlabelled.

Classification tasks assign inputs to groups and find qualitative information, while regression tasks handle numerical outputs and predict values based on input data. Techniques commonly used include naive Bayes, decision trees, random forests, K nearest neighbors, support vector machines, artificial neural networks, linear regression, and linear discriminant analysis.

Deep learning (DL), a subfield of AI and machine learning, has significantly impacted fields such as natural language processing, object recognition, and picture classification. It uses neural networks to choose features independently, eliminating the need for labor-intensive artificial feature engineering. Deep learning architectures, including deep neural networks, back propagation (BP), and multilayer perceptrons (MLP), have been used in various tasks, including diagnosis of plant diseases, image detection, segmentation, and classification.

Thus, the integration of advanced technologies like ML and DL into plant disease management represents a significant shift from reactive to proactive agricultural practices. These technologies provide real-time insights and accurate diagnostics, enabling farmers to respond to diseases before they become widespread. The use of AI in farming not only improves crop yield but also ensures sustainability by reducing the need for excessive pesticide use, thereby promoting environmentally friendly farming practices. As the demand for food continues to rise globally, the adoption of AI- powered solutions will play a critical role in addressing the challenges faced by modern agriculture. By ensuring the health and productivity of crops, these innovations are set to transform the future of farming, contributing to food security and sustainable agricultural development on a global scale.

2. LITERATURE REVIEW

The utilization of early crop health data and disease location to implement timely management actions is a key strategy for controlling the spread of plant diseases. Automated systems for rapid disease detection have become a necessity in modern agriculture, as they help prevent common crop diseases and reduce associated losses. AI-powered automatic disease detection systems follow a set of well-defined processes. One of the initial steps is the acquisition, recording, and storage of plant images using various sensors. These images are processed and segmented to serve as inputs for training algorithms [7][8]. The machine learning (ML) models then predict whether a leaf is healthy or diseased. The framework for predicting plant diseases includes several stages such as image capture, pre-processing, feature extraction, segmentation, and classification.

The first step involves collecting and capturing relevant images of plants, which are then classified using automated methods. In this context, a picture is a representation of binary data that can be manipulated and analyzed using computers. High- resolution digital cameras are typically employed to capture the images, although smart phones have also proven useful by providing images in various formats. Numerous online datasets related to plant diseases, such as Plant Village, New Plant Diseases, IPM Images, APS Images, Plant Doc, and PLD, are available for training AI models [9][10].

Pre-processing is one of the most important steps in image collection. Acquired images often contain elements such as noise, blur, uneven lighting, or unwanted backgrounds. Therefore, it is essential to process this raw data to make it suitable for accurate disease classification by automated systems. The raw data is cleaned by removing distortion and noise, then converted into a specific format for further processing. At this point, the images move on to segmentation and feature extraction. In agricultural research, segmentation involves breaking the image into different components to enable a deeper analysis. This step helps to identify and differentiate between healthy and diseased areas. Segmentation techniques, such as thresholding, edge detection, region-based methods, and clustering, are commonly used to analyze the images.

Feature extraction is an essential phase in processing. This entails collecting fundamental attributes from raw pictures, including form, colour, and texture, which are crucial descriptors for categorising the input data [11][12]. Feature extraction is essential for assessing plant health. Feature engineering, a machine learning methodology, converts unstructured data into a collection of pertinent and significant properties, hence enhancing the precision of disease detection models. Utilising these innovative methodologies, automated systems can provide dependable and effective evaluations of plant health, assisting farmers in making educated choices and executing appropriate measures to safeguard their crops. J Omaye et al. (2024) conducted a comparative examination of machine learning techniques and their applications for the identification of plant diseases. The focus was mostly on four economically significant crops: apple, cassava, cotton, and potato. Following the application of the inclusion criteria to many research,113 articles were recognised as relevant, focussing on those that shown individual predictive accuracy for the illness categories associated with the chosen plants. They analysed contemporary methodologies, associated challenges, and prospective applications of machine learning for disease identification in the chosen plants based on these investigations. Deep learning and numerous algorithms have shown efficacy in detecting plant diseases, as evidenced by the review findings. Furthermore, they acknowledged further suggestions for plant disease management, including prohibition, analysis, resistance, and monitoring. Consequently, to address prevention, control, evaluation, and therapy, they initiated the development of machine learning-based solutions.

Tejaswini et al. (2024) highlighted the analytical challenges associated with the early detection of diseases using deep learning models, namely convolutional neural networks (CNNs) [18]. Various leaf disease detection technologies were used for different crop kinds. This study used a pre- trained deep learning model for the detection and categorisation of foliar diseases. This experiment used a collection of leaf images from tomato, potato, and bell pepper sourced from the Plant Village library. The created model is capable of identifying 12 plant diseases in healthy leaf tissue. The quantitative evaluation of their CNN-based approach indicated an accuracy of around 86.21%. This exceptional accuracy underscored the efficacy of their methodology in the challenging field of plant disease detection. The study concluded that it offered a significant approach for using AI-driven solutions to tackle the persistent challenges of plant disease identification. Consequently, it significantly improved the welfare of farmers and the sustainability of the Indian agricultural economy.

S. Amritraj et al. (2023) said that deep learning approaches may effectively extract features from extensive datasets, demonstrating considerable robustness against variations in brightness, occlusion, and perspective [19]. These approaches were used because to their efficient management of large datasets within a little timeframe. A plethora of research has shown efficient and automated illness detection techniques. The bulk of investigations were limited to one or two plant species and a narrow range of disease categories. This study created a computer vision solution using the latest YOLO algorithm, employing a proprietary dataset including eight unique types of plant leaf illnesses caused by fungus, bacteria, viruses and pests. Their technique effectively predicted illnesses by the use of bounding boxes and class probabilities, resulting in dependable conclusions. This research used YOLOv5 to develop a technique for identifying plant illnesses and improving automated farm management systems.

S. Ashwinkumar et al. (2022) created a model including many phases: preprocessing, segmentation, feature extraction, and classification, designated as OMNCNN [20]. Bilateral filtering (BF) preprocessing and Kapur's thresholding-based image segmentation were used to identify the damaged areas of the leaf image. The Emperor Penguin Optimiser (EPO) method was used to optimise the hyperparameters of the Mobile Net model, serving as a feature extraction technique to enhance the plant disease detection rate. An extreme learning machine (ELM) classifier was used to assign the appropriate class labels to the processed image of the plant leaf. A considerable quantity of replications was conducted to illustrate the exceptional effectiveness of the OMNCNN model. The latest methodologies reveal that the OMNCNN model achieved a peak accuracy of 0.985, are call of 0.9892, an accuracy of 0.987, an F-score of 0.985, and a kappa of 0.985.

K. Beena et al. (2022) discussed that agriculture is the cornerstone of the Indian economy [21]. The agricultural yield decreased due to several detrimental organisms affecting the plants. The identification of plant diseases significantly affected agricultural productivity in terms of both traits and yield. Infected plants exhibit abnormalities in several areas, including leaves, stems, buds, flowers, fruits, and roots. Prompt identification of the illness will save more crop loss. This research identified four separate stages. The first phase focused on several kinds of illnesses and their associated symptoms. The second section addressed several traditional methods for illness diagnosis. The concluding section demonstrated several techniques for identifying plant illnesses using image processing, deep learning, and convolutional neural networks. The fourth portion emphasised the challenges and prospective improvements in illness detection. This study conclusively illustrates that reliance only on expert knowledge for disease detection and classification may be both costly and time-intensive, particularly in distant regions and developing nations.

P.Bedi et al. (2021) presented a novel hybrid model for automated plant disease diagnosis, combining a Convolutional Auto encoder (CAE) network with a Convolutional Neural Network (CNN) [22].The most recent research has not introduced a hybrid system that combines CAE and CNN for the automated identification of plant diseases. This study used a proposed hybrid model to identify Bacterial Spot illnesses in peach plants using leaf pictures; nonetheless,it is suitable for detecting any plant disease. This study used leaf images of peach trees obtained from the publicly accessible Plant Village collection. The suggested approach may achieve around 99.35% training accuracy and 98.38% testing accuracy with just 9,914 training parameters. Compared to current methodologies in the literature, the devised hybrid model required a minimal number of training parameters. Consequently, time was crucial for detecting plant illnesses using the trained model, and the model's training for automated disease detection substantially reduced the required time.

R. Nalawade et al. (2020) developed a novel method for detecting leaf diseases while simultaneously tracking real-time environmental parameters, including temperature, humidity, and moisture levels. [23] The user may autonomously regulate water flow with an application that facilitates real- time data monitoring. This application proved beneficial for obtaining information on the requirements for plant fertilisers, soil conditions, and pesticides for disease control. The findings indicated that the implemented system achieved an average accuracy of 98.07%. This technology enabled users to see results, including the field report, and identify issues within the program.

H. Andrianto et al. (2020) developed a deep learning system using VGG16, applying machine learning on a cloud server and a mobile application. The smartphone application enables the acquisition of photographs of rice plant leaves, uploads them to a cloud server, and offers classification data pertaining to various plant illnesses. The findings demonstrated the system's efficacy in diagnosing rice plants. The results showed that the implemented system achieved an accuracy of 100% during training and 60% during testing. This approach improved productivity via the treatment of rice plant diseases.

J. Zhao et al. (2019) created a convolutional neural network (CNN) called YOLOv2 (You Only Look Once version 2) for the diagnosis of healthy and damaged tomato fruits [25]. This approach was developed using a regression framework, enabling speedy and precise diagnosis of the illness. The data augmentation methods used to enlarge the picture datasets were intended to alleviate the risk of overfitting, resulting in enhanced datasets of 1000 photos of tomato fruit. Subsequently, the picture data type was examined using the grey scale processing and foreground extraction modules. The K-means clustering(KMC) technique was developed to reduce model training time and improve detection efficacy. The constructed model achieved a mean Average Precision (mAP) of 97.24%. The experimental results confirmed the efficacy of the established model in identifying physiological problems in tomato plants.

3. RESEARCH METHODOLOGY

The main challenge in plant disease detection is the identification of disorders on foliage. This methodology has three phases: pre-processing, feature extraction, and classification. In the pre-processing phase, noise will be removed from the image. Machine learning and deep learning are methodologies within artificial intelligence often used for classification tasks. The Proposed Model is a transfer learning framework that combines VGG16 with a convolutional neural network (CNN). The many phases of the proposed model are delineated below:

Uploading Image and Preprocessing : The provided image will be subjected to pre-processing using a Gaussian filter. The Gaussian filter will reduce noise in the image. This filter improves visual clarity and is known as a smoothing operator. This filter removes fundamentally existing minute visual characteristics. The impulse response is defined by a Gaussian function that specifies the probability distribution of the noise. This filter efficiently removes Gaussian noise. A non-uniform, linear low-pass filter defined by a Gaussian function with a given standard deviation.

Segmentation: The snake segmentation method will be used to precisely outline the specific area of the image. The Snake segmentation method employs raster scanning, allowing it to include most of the image's edges. The Snake active contour model initialises a parameterised contour curve inside the image space and establishes an energy function that characterises the region's shape based on internal and external energy components. The internal energy is determined by the characteristics of the curve itself. The external energy is defined by attributes related to the picture, including curvature parameters and curve length. By minimising the energy functional, the starting contour curve C(s)=(x(s),y(s),s∈[0,1]) gradually converges to the boundary of the target area, dictated by the inner and outer energy parameters :

$$\boldsymbol{E(C)=\int_{0}^{1} \alpha E_{int}(C(s)) + E_{img}(C(s) + \gamma E_{con}(C(s)))ds} \qquad \text{……….(1)}$$

The energy function has three components: E_int denotes internal energy, which guarantees the continuity and uniformity of the curve; E_img signifies image energy, which is determined based on the characteristics of the desired target location, such as edges. E_con represents contained energy, often shown as a curve. The measurements and curvature have been determined. The principal advantage of the Snake active contour model is its comprehensive incorporation of geometric constraints. Regardless of image quality, smooth and closed boundaries may reliably be reconstructed; nonetheless, the method has several drawbacks, the most significant of which is its reliance on the original contour. The effectiveness of control points in terms of position, form and number is contingent upon the selection of a suitable initial contour.

Classification : A transfer learning model integrating VGG16 and CNN is used to predict the kind of disease. The VGG16 serves as the underlying model upon which the CNN model is developed.

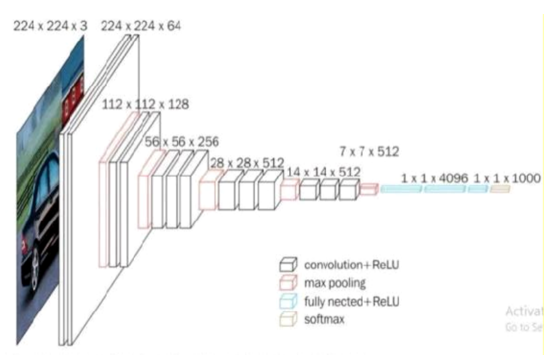

Figure 1 : VGG16 Model Architecture

The specifications of VGG16 Model are given below in the table :

Table 1 : Specifications of VGG16 Model

Specifications	Details
Number of Layers	16 layers with weights (13 convolutional layers, 5 max pooling layers, 3 dense layers). Total: 21 layers, but only 16 learnable parameters layers
Input Tensor Size	224x224 with 3 RGB channels
Filter Size	3x3 filter with stride 1, same padding

Layers)	& Conv-5: 512 filters
Fully Connected (FC) Layers	3 FC layers:1st & 2nd FC layers have 4096 channels each, 3rd FC layer performs 1000- way ILSVRC classification with 1000 channels (one for each class)
Final Layer	Softmax layer
Unique Feature	Focuses on using convolution layers with a consistent arrangement and avoids large hyper- parameters by using 3x3 convolution filters and 2x2 max pooling layers

3.1 Dataset Description

The experiment conducted on the developed model involves using the Plant Village dataset. This dataset is publicly available and provides comprehensive information about various plants and their associated contagions. Imagery in the dataset is labeled with the corresponding disease type it represents.

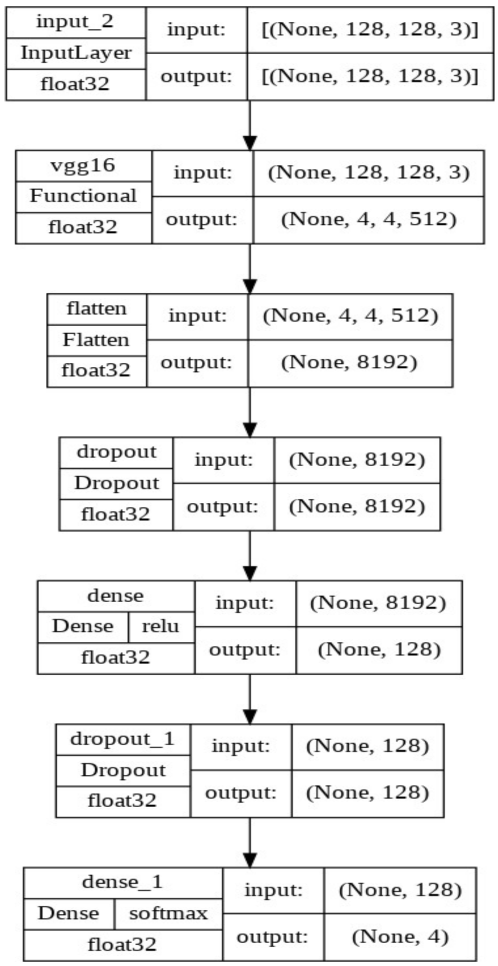

Figure 2: Proposed Transfer Learning Model

4. RESULTS AND DISCUSSION

The document emphasises readability, dynamic semantics, and object-oriented features. It is often used as a scripting language to integrate diverse components and facilitate rapid application development. The straight forward syntax of Python promotes code modularity and reusability by facilitating the usage of modules and packages, hence reducing program maintenance costs. On the majority of prominent systems, the Python interpreter and comprehensive standard library are available at no cost in either source or binary format. The Python API is used by apps such GIMP, Inkscape, Blender, and Autodesk Maya to augment its capabilities.

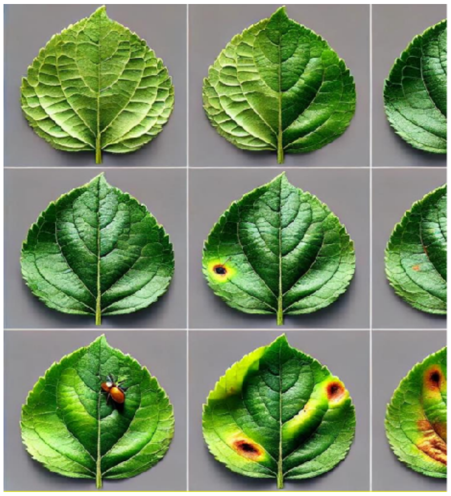

Figure 3 : Input Images

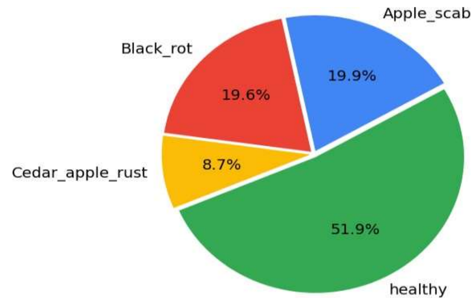

Figure 4: Class Distribution

As shown in Figure 4, the dataset has four classes which are cedar apple rust, black rot, apple scab and healthy. The dataset distribution in terms of percentage is shown in figure.

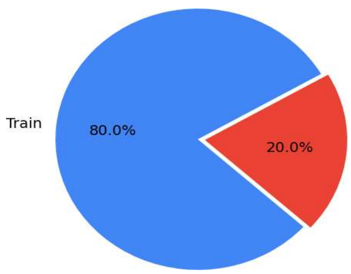

Figure 5 : Training and Test Data

Figure 6 : Model Training Information

As shown in Figure 5, percentage of training and test data is illustrated. The training data is 80 percent and test data is 20 percent and Figure 6 reveals the model training accuracy and loss information.

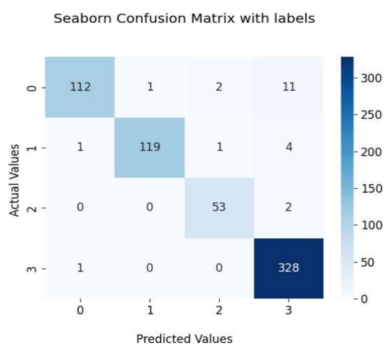

Figure 7 : Confusion Matrix

As shown in Figure 7, the proposed model is tested on the test data. The confusion matrix is plotted with the true positive, true negative, false positive and false negative values.

4.1 Result Analysis

Accuracy : Accuracy is a widely used metric for evaluating the performance of a program. It measures the proportion of correctly classified samples out of the total number of samples. Mathematically, it can be represented as:

t

In this equation, t denotes the count of samples that are correctly classified, while n represents the total number of samples.
.Precision : Precision is a performance metric that quantifies the ratio of accurately predicted positive cases to the total number of predicted positive cases. Precision= TP/TP+FP
Recall : Recall, also referred to as sensitivity in psychology, is a performance measure that evaluates the proportion of true positive cases that are accurately predicted as positives. It provides an indication of how well the positive prediction rule (+P) covers the true positive cases.

Table 2 illustrates a comparative analysis of the KNN (K-Nearest Neighbors) and voting classifier models based on their accuracy, precision, and recall. The metrics are presented as percentage values.

Table 2 : Performance Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)
Random Forest	66	56	66
SVM	77.59	78	78
KNN	69.88	70	70
Proposed Model	91	91.2	92

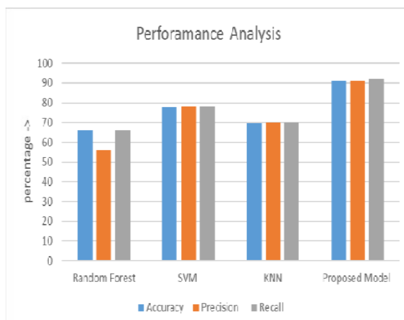

Figure 8 : Performance Analysis

The results of the contrast among the proposed methodology, the voting classification algorithm, and the current method, KNN classification, is shown in Figure 8. According to the analysis, the proposed method performed better for forecasting plant illnesses than the current method with respect to precision, recall, and accuracy.

5. CONCLUSION

The main goal of this activity is to diagnose illnesses in plant foliage. Historically, the diagnosis of plant diseases was performed manually using microscopes. This approach is labor-intensive and impractical for large-scale detection. Digital image processing techniques, along with machine learning algorithms, facilitate the identification of diseases in plant leaves using digital imagery by plant pathologists. This research utilizes digital image processing methods and a voting-based framework for disease detection. Digital cameras capture images, which are then subjected to image processing algorithms to extract essential features. This research utilizes a transfer learning model for the detection of plant diseases. The proposed model has an accuracy of 92 percent, about 8 percent higher than existing models.

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