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Smart Agriculture and Plant Disease Prediction

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Abstract— **Smart agriculture and plant disease prediction have become important areas of research due to the increasing demand for food production and the need for sustainable farming practices. The paper provides a review of smart agricultural practises and how machine learning algorithms are used to predict plant diseases. Smart agriculture is based on the use of technology such as the Internet of Things (IoT) which enable farmers to monitor and manage their farms remotely. Additionally, machine learning algorithms can be used to accurately identify plant diseases through analysing the input plant image. Three machine learning algorithms have been used in this paper i.e. SVM, VGG19, and KNN. VGG16 is used for the feature extraction. With the 13 different types of diseases, highest accuracy system achieved is 99%.**

Index Terms**—Smart Agriculture, Plant Disease Prediction, IOT, Machine Learning, VGG19, SVM.**

I. Introduction.

Smart Agriculture is a modern approach to farming that uses advanced technologies to improve crop production, reduce waste and increase efficiency. With the growing demand for food, climate change and the need for sustainable agriculture practices, there has been an increased interest in the use of IoT and machine learning for smart agriculture. The integration of IoT devices and machine learning algorithms has the potential to transform agriculture by providing real-time monitoring, data-driven decision-making, and accurate predictive models.

One of the key challenges facing agriculture today is the detection and management of plant diseases. Plant diseases can cause significant damage to crop, leading to reduced yields and economic losses. Traditional methods of plant disease detection are time-consuming and often require human intervention. However, with the advent of IoT and machine learning technologies, it is now possible to automate the process of plant disease detection and provide farmers with accurate, real-time information about the health of their crops. The objective of this paper is to explore the potential of smart agriculture using IoT and machine learning for plant disease prediction. We will focus on the use of machine learning algorithms such as SVM, VGG19 and KNN for plant disease prediction. We will also discuss the use of IoT devices such as sensors for monitoring soil moisture, temperature, and humidity levels to optimize crop growth and prevent disease outbreaks.

IoT has emerged as a key technology for smart agriculture, enabling farmers to monitor their crops and livestock remotely in real-time. IoT devices such as sensors, cameras, and drones can be used to collect data on various parameters such as soil moisture, temperature, humidity, and crop growth. This data can then be analysed to provide valuable insights into crop health and optimize the use of resources such as water and fertilizer.

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One of the key advantages of IoT in agriculture is the ability to provide real-time monitoring and decision-making. IoT devices can be used to monitor crop growth, detect anomalies, and alert farmers to potential problems such as plant diseases. This enables farmers to take proactive measures to prevent the spread of disease and reduce the risk of crop losses.

Machine learning algorithms such as SVM and KNN have been used for plant disease detection. These algorithms are trained on the dataset of images consisting healthy and diseased plants and can accurately predict the health of a plant based on its image. SVM is a supervised learning algorithm that separates data points into different classes based on their attributes. KNN, on the other hand, is an unsupervised learning algorithm that assigns data points to clusters based on their similarity.

To apply SVM and KNN for plant disease detection, a dataset of images of healthy and diseased plants is first collected. The images are pre-processed to remove any noise and artifacts and to enhance the contrast and clarity of the image Then, to extract relevant data from the image, feature extraction algorithms like VGG16 are used. The SVM and KNN algorithms are then trained with these features such that they can predict the health of a plant based on its image.

The integration of IoT devices and machine learning algorithms has the potential to transform agriculture by providing real-time monitoring, data-driven decision-making, and accurate predictive models for plant disease prediction. By combining the data collected from the IoT devices such as sensors with machine learning algorithms like SVM and KNN, it is possible to accurately predict the health of a plant and detect the early signs of disease outbreaks. For example, Soil moisture sensors can be used to monitor soil moisture levels and prevent water stress in crops. Similarly, temperature and humidity sensors can be used to keep track on the microclimate of the crop and prevent disease outbreaks. By combining this data with machine learning algorithms like SVM and KNN, it is possible to accurately predict the health of a plant and take proactive measures to prevent disease outbreaks.

II. LITERATURE REVIEW.

This paper [1] proposed the system uses an array of sensors to collect data on plant health and sends it to a cloud-based platform for analysis. This method integrates the Internet of Things and image processing, running per-processing and feature extraction techniques while considering various parameters including colour, texture, and size. The proposed approach utilizes a deep learning model for the automatic identification of plant leaf disease, which involves the extraction of relevant features from the leaf images. This conventional framework eliminates the need for manual identification of leaf disease, as the model can automatically detect and classify the disease.

The paper [2] uses various Internet of Things (IoT) sensors for various soil and climate conditions. Sensors that measure temperature, humidity, and soil moisture levels. An application can be used by farmers to monitor soil moisture levels using sensors. The sensors detect the amount of moisture present and the application allows farmers to turn on or off water sprinklers as needed to maintain optimal moisture levels. This system provides accurate and efficient control of irrigation, ensuring that crops receive the appropriate amount of water for healthy growth. Using fourteen different [3] types of features like colour, texture, and shape, etc derived via the implementation of a grey level co-occurrence matrix, multi-class support vector machine (SVM) is used to differentiate between the disease with an accuracy of 97.33%. For identifying and categorising the affected plant disease, image processing has been used.

This study [4] proposed the system includes an array of sensors and a wireless communication network for real-time monitoring of plant health. The results showed that the system achieved high accuracy in detecting plant diseases, which can help farmers in taking timely action to prevent crop losses. The proposed system's [5] primary goal is to use IoT to find plant diseases. Most plants have leaves where the disease first manifests itself. As a result, we have considered the detection of plant disease on leaves in the proposed work. Based on variations in temperature, humidity, and color, it is possible to quantify the distinction between healthy and affected plant leaf.

This study [6] proposed the system uses an array of sensors to collect data on plant health and sends it to a cloud-based platform for analysis. The results showed that the system achieved high accuracy in detecting plant diseases, which can help farmers in making informed decisions about crop management. They highlight the importance of accurate disease diagnosis and the need for real-time monitoring to prevent the spread of plant diseases. The authors [7] also discuss various challenges associated with IoT-based plant disease detection, including the need for a reliable wireless network, the high cost of sensors, and the need for accurate data analysis. According to this study [8], paddy leaf diseases can be detected early on by using image processing to analyze the morphological changes in leaves. This device also alerts farmers to diseases that threaten the paddy crops by using the Internet of Things (IoT).

The utilization of image processing and machine learning techniques [9] can enhance the accuracy and efficiency of detecting plant diseases, reducing the required time, effort, and expertise in identifying infected plants. The methodology involves various stages such as image acquisition, filtering, segmentation, feature extraction, and classification. In this research [10], advanced neural network techniques were employed, specifically the Convolution Neural Network (CNN) with multiple convolution and pooling layers. By using an augmented dataset, the proposed model achieved an accuracy rate of 90%. The dataset, which consisted of 20,639 images of healthy and diseased plant leaves, was divided into 15 classes to train a deep convolutional neural network capable of detecting various diseases.

In this paper [11], the Random Forest technique was used to differentiate between healthy and diseased leaves in each dataset of images. The authors utilized Histogram of Oriented Gradient (HOG) as a descriptor for image feature extraction, which is commonly used for object detection. The proposed system achieved an accuracy rate of 70%. This paper [12] describes an algorithm that utilizes image segmentation techniques to automatically detect and classify plant leaf diseases, as well as a survey of various disease classification techniques that can be applied to plant leaf disease detection. The proposed method consists of three main steps: image acquisition, image processing, and image segmentation.

This research [13] presents an effective solution for detecting multiple plant diseases across various plant varieties, including apple, potato, corn, grapes, sugarcane, and tomato. The system has been specifically designed to recognize and identify different diseases in plants. The researchers used a dataset of 35,000 images of both healthy and diseased plant leaves to train deep learning models. The trained model has achieved an impressive accuracy of 96.5%, with the system registering up to 100% accuracy in detecting and recognizing the plant variety and type of disease present in the plant. Overall, this study provides an efficient approach to identify and detect plant diseases across multiple plant varieties. This paper [14] presents a system that can effectively analyze images of plants and identify prevalent diseases. The system utilizes 3 convolution layers, consisting of 10 nodes, and was trained over forty epochs to achieve high levels of accuracy in its validation results. The training set included 11942 images, while the validation set comprised 35% of the training set, totaling 6421 images.

In this study [15], the authors introduce the "plant disease detector," a deep learning model designed to identify various plant diseases through leaf images. To increase the sample size, the dataset is augmented, and advanced neural network techniques are employed to develop the model. The model includes a Convolutional Neural Network (CNN) with multiple convolution and pooling layers. The model is trained and validated with testing data, resulting in an impressive 98.3% accuracy rate. The Plant Village dataset was used for this study, with 85% of the data utilized for training and 15% for testing. The dataset consists of both healthy and diseased plant images, and the focus of the research is on utilizing deep learning models for accurate disease detection in plant leaves.

Overall, these papers demonstrate the effectiveness of machine learning in plant disease prediction and highlight the potential for this technology to revolutionize agriculture. The use of deep learning approaches, such as convolutional neural networks, has shown promising results and is likely to be an important area of future research. Additionally, the availability of large and diverse datasets is critical for the development of robust machine learning models for plant disease prediction.

III. MOTIVATION.

The motivation behind smart agriculture and plant disease prediction projects is to promote sustainable and efficient agriculture practices that can help feed the growing world population, while also protecting the environment and improving the economic conditions of farmers.

IV. PROBLEM DOMAIN.

The problem domain of smart agriculture and plant disease prediction projects is multifaceted, and it involves complex technical, social, and economic challenges. Addressing these challenges requires a multidisciplinary approach and collaboration between farmers, researchers, policymakers, and technology providers.

V. PROBLEM DEFINITION.

The problem definition of smart agriculture and plant disease prediction projects is to develop and implement technology solutions that can help farmers improve the efficiency, productivity, and sustainability of their farming practices, while also minimizing the impact of plant diseases on crop yields and quality.

VI. STATEMENT.

The smart agriculture and plant disease prediction project aims to develop and implement technology solutions that can help farmers optimize their farming practices, increase their yields, and minimize the impact of plant diseases on crop quality and quantity. This will involve the development of sensors, drones, and other IoT devices to collect data on soil moisture, temperature, and other factors that affect crop growth, as well as the development of AI and machine learning algorithms to analyse this data and provide actionable insights to farmers. The project will also focus on accurately predicting and diagnosing plant diseases using AI and machine learning algorithms, enabling farmers to take proactive measures to prevent crop damage and improve their yields. Ultimately, the project aims to promote sustainable and efficient agriculture practices that can help feed the growing world population, while also protecting the environment and improving the economic conditions of farmers.

VII. INNOVATIVE CONTENT.

This research focuses on the use of machine learning algorithms for plant disease prediction, with the aim of providing an innovative and efficient solution for farmers to detect and diagnose plant diseases in a timely manner. One of the main innovative features of our research is the use of deep learning models, such as VGG16, for feature extraction and classification of plant images. These models have shown to achieve state-of-the-art performance in image classification tasks and have been successfully applied to plant disease prediction. Additionally, this paper incorporates transfer learning techniques to fine-tune the pre-trained models on our specific dataset, which further improves the accuracy of the predictions. Overall, our research presents a novel and innovative approach to plant disease prediction, incorporating deep learning models, transfer learning, and environmental factors, as well as an IoT-based system. We believe that our findings will have significant implications for the agricultural industry, enabling farmers to detect and diagnose plant diseases more efficiently and ultimately leading to improved crop yields and food security.

VIII. PROBLEM FORMULATION.

The problem formulation for a smart agriculture and plant disease prediction project involves identifying the specific challenges and goals that the project aims to address. This may involve a thorough analysis of the current state of agriculture in the target region, as well as an understanding of the needs and constraints of farmers in that area.

XI. SOLUTION METHODOLOGIES.

As shown in Fig. 1. the Smart Agriculture System provides farmers with an IoT-based hardware system which measures important metrics like soil moisture, humidity, and temperature. Farmers can use Blynk application to monitor the real-time status of these metrics at any time. The hardware is connected to the Blynk application through IoT and is designed to send alerts to farmers to help them make informed decisions about their crops.

A. IOT System.

The NodeMCU is a development board that is based on the ESP8266 Wi-Fi module. It can be programmed using the Arduino IDE and is capable of reading data from various sensors and displaying it on various output devices. In the given scenario, the NodeMCU board is used to read data from a soil moisture sensor, DHT11 temperature and humidity sensor, and a PIR motion sensor.

The soil moisture sensor is used to measure the moisture level of soil, while the DHT11 is used to measure the temperature and humidity of the surrounding environment. The PIR motion sensor is used to detect any movement in the area it is placed in. Once the data has been read from the sensors, the NodeMCU board can display it on an LCD display and on the Blynk app. The LCD display can be used to show the readings in real-time and provide a visual representation of the data, while the Blynk app can be used to remotely monitor the data on a smartphone or tablet. Overall, the NodeMCU board is a versatile platform that can be used for a wide range of applications, including environmental monitoring, home automation, and IoT projects.

B. Components.

*Temperature and Humidity Sensor (DHT11)**:*** The temperature and humidity sensor i.e DHT11 is a popular digital temperature and humidity sensor that can be used in a variety of projects. Here are the basic specifications of the DHT11 temperature sensor:

Temperature range: 0°C to 50°C

Temperature accuracy: ±2°C
Humidity range: 20% to 90% RH
Humidity accuracy: ±5% RH
Supply voltage: 3.3V to 5V DC
Interface: Digital (single wire) communication protocol

Soil Moisture Sensor: A tool used to measure the water content in volume of soil is a soil moisture sensor. Without removing moisture, the sensor indirectly measures the volumetric water content of the soil using other soil. It needs to be calibrated because environmental variables like soil type, temperature, and conductivity may have an impact on the results. features such as dielectric constant, electrical resistance or conductance, and interaction with other neutrons to indirectly measure volumetric water content without eliminating moisture. It needs to be calibrated because environmental factors like soil type, temperature, and conductivity may have an impact on the results.

PIR Sensor: A PIR (Passive Infrared) motion sensor is an electronic device that detects motion by sensing changes in the infrared radiation emitted by a warm body. The sensor is passive because it does not emit any energy or radiation itself, but simply detects the infrared radiation emitted by other objects. The PIR motion sensor consists of a pyroelectric sensor, which is a device that generates an electrical charge when exposed to infrared radiation. When the sensor detects motion, it sends a signal to a control circuit, which can be used to trigger an alarm, turn on a light, or perform other actions. PIR motion sensors are commonly used in security systems, lighting control systems, and other applications where it is necessary to detect motion in a particular area.

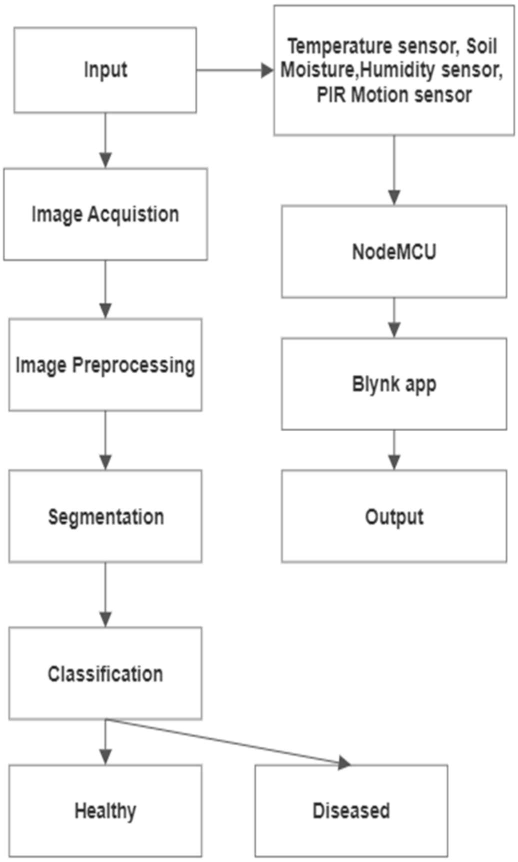


Fig.1 System architecture

C. Plant Disease Prediction.

Data Acquisition: Data acquisition is an essential component of plant leaf disease prediction. In order to accurately predict and diagnose plant diseases, it is important to have high-quality data on the plant's health and any potential symptoms of disease. This dataset consists of 30,446 images of diseased and healthy plant leaves, with 4 species which were classified into 13 classes to train a deep convolutional neural network which can identify the diseases.

D. Data Preprocessing.

Data pre-processing is an important step in plant leaf disease prediction. The quality of the data used in machine learning algorithms can significantly impact the accuracy of the predictions. To improve the quality of the data, it is often necessary to pre-process the data before using it for prediction. There are several steps involved in data pre-processing for plant leaf disease prediction. These steps include:

Data Cleaning: This involves removing any noise, inconsistencies, or missing values from the data. For example, if there are any errors in the data such as mislabelled images or incorrect measurements, they need to be identified and corrected.

Data Normalization: This step involves scaling the data so that all features have the same scale. This can be done using techniques such as min-max normalization or z-score normalization. This step is important to ensure that all features contribute equally to the prediction model.

Feature Selection: This involves selecting the most important features that are relevant to the prediction task. This step can help to reduce the dimensionality of the data and improve the efficiency of the prediction model. here VGG16 is used to feature selection.

Data Augmentation: This step involves increasing the amount of data available for the prediction model by creating new data from the existing data. This can be done using techniques such as image rotation, flipping, or cropping.

Data Splitting: This involves dividing the data into training, validation, and testing sets. The training set is used to train the prediction model, while the validation set is used to tune the hyperparameters of the model. The testing set is used to evaluate the performance of the model.

Overall, data preprocessing is a critical step in plant leaf disease prediction. By properly preprocessing the data, we can improve the accuracy and efficiency of the prediction model. In this we've done the augmentation using flow_from_directory () method. Images are converted into grayscale images from RGB.

E. Segmentation.

Segmentation is a key step in plant leaf disease prediction that involves separating the plant leaf images into distinct regions of interest. The goal of segmentation is to separate the healthy regions of the leaf from the regions that are affected by disease, so that the features of the diseased regions can be analysed and used for prediction. Once the image has been segmented, features can be extracted from the diseased regions and used for prediction. These features may include color, texture, shape, or other characteristics that are indicative of disease. In our model Segmentation is done by using Otsu Binarization on grayscale images. Otsu binarization is a thresholding technique used to convert a grayscale image to a binary image. The goal of binarization is to separate the foreground objects from the background by setting a threshold value that separates the two.

F. Classification.

SVM: Support Vector Machines (SVM) is a popular machine learning algorithm used for classification and regression analysis. It is particularly useful for solving linear and non-linear classification problems. SVM is based on the idea of finding a hyperplane that best separates the classes of data points. The hyperplane is chosen so that it maximizes the margin between the two classes. In SVM, each data point is represented as a vector in the high-dimensional feature space. The SVM algorithm finds a hyperplane in this space that separates the data into two classes with maximum margin. The margin is defined as the distance between the hyperplane and the closest data points from both classes.

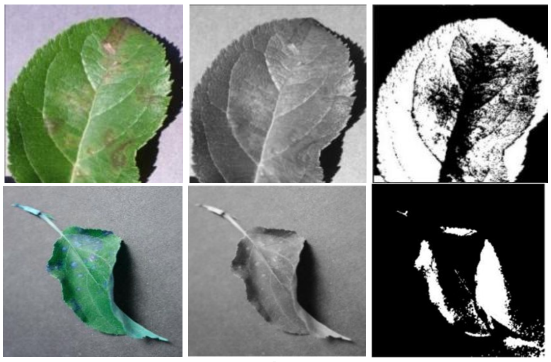
VGG19: VGG19 is a deep convolutional neural network (CNN) model used for image classification tasks. It is a variant of the VGG network architecture, which was developed by researchers at the University of Oxford for the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in 2014. VGG19 consists of 19 layers, including 16 convolutional layers and 3 fully connected layers. Each block in the arrangement of the convolutional layers has a number of convolutional layers followed by a max pooling layer. The classification task is carried out by the fully linked layers at the network's side.

KNN: K-Nearest Neighbours (KNN) is a type of supervised learning algorithm that can be used for classification and regression tasks. In the context of image processing, KNN can be used for image classification tasks. The idea behind KNN is simple: given a new input image, the algorithm looks for the K images in the training set that are most similar to the input image, based on some distance metric (e.g., Euclidean distance). The class of the input image is then assigned based on the most common class among the K nearest neighbours.

In image processing, the feature space can be very high-dimensional, and the distance metric used to compare images can have a large impact on the performance of the algorithm. Commonly used distance metrics in image processing include Euclidean distance, Manhattan distance, and Cosine similarity.

X. RESULT.

The suggested work uses GUI to classify plant diseases and gain images. As seen in Fig. 2, the images are uploaded to the database where the Binary Otsu method is used to segment the infected area after scaling it to 128x128 and conducting preprocessing. The segmentation of the leaf sections that were affected is shown in Fig. 2.
Selecting the affected region, the features were extracted using VGG16 for SVM and KNN. With the acquired features, multiclass SVM and KNN are used to classify. During this process, 6000 images are utilised as the testing dataset and 24342 images representing 13 diseases are used as the training dataset. The evaluation of this work is described in Table 1, showing the 13 classes of disease for the classification where D1 Tomato leaf Mold, D2 is Tomato healthy, D3 is Tomato Bacterial spot, D4 is Potato Late blight, D5 is Potato healthy, D6 is Potato Early blight, D7 is Grape healthy, D8 is Grape Black rot, D9 is Corn (maize) healthy, D10 is Corn (maize) Common rust, D11 is Apple healthy, D12 is Apple Cedar apple rust, D13 is Apple Apple scab. Fig 3. shows the graphs of loss and accuries of train val archived through VGG 19. Fig. 3 shows the loss and accuracies of VGG19 algorithm with respect to train and val.



(a) (b) (c)

Fig 2. (a) Original Image, (b) Converted to Grayscale Image, (c) Segmented using Otsu Binarization.

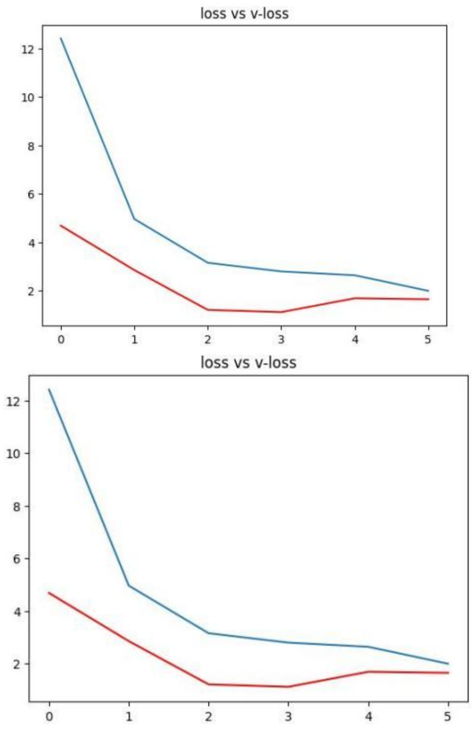


Fig 3. Loss and Accuracies of VGG19 w.r.t train and val.

TABLEI. CONFUSION MATRIX OF THE PROPOSED METHOD

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13
D1	500	2	2	0	0	0	0	0	0	0	0	0	0
D2	0	439	1	0	0	0	0	0	0	0	0	0	0
D3	5	1	495	0	0	0	0	0	0	1	0	0	0
D4	0	0	0	477	0	0	0	0	0	0	0	0	0
D5	0	0	0	0	465	0	0	0	0	0	0	0	0
D6	0	0	0	0	0	472	0	0	0	0	0	0	0
D7	0	0	0	0	0	0	423	0	0	0	0	0	0
D8	0	0	0	0	0	0	0	478	7	0	0	0	0
D9	1	0	0	0	0	0	0	0	476	8	0	0	0
D10	0	1	0	0	0	0	0	1	7	447	0	0	0
D11	0	0	1	0	0	0	0	0	0	0	423	1	0
D12	0	0	0	0	0	0	0	0	2	0	0	466	2
D13	0	0	2	0	0	0	0	0	1	0	0	3	475

XI. COMPARISION OF RESULTS.

TABLE II. COMPARISON WITH THE STATE-OF-THE-ART TECHNIQUES

Sr. No	Method	Accuracy
1.	SVM [3]	97.33%
2.	CNN [10]	90%
3.	Random Forest [11]	70%
4.	CNN [15]	98%
5.	SVM [16]	97.6%
6.	KNN [16]	98.56%
7.	Proposed system [SVM with VGG16]	99%

XII. CONCLUSION.

In this paper, we explored the use of SVM and KNN algorithms for predicting plant disease based on image data. Our results show that both algorithms are effective at classifying different plant diseases with high accuracy, although SVM outperformed KNN in terms of overall performance. We also found that feature extraction plays a critical role in the accuracy of the classification model, with the use of pre-trained deep learning models such as VGG16 leading to significantly better results than traditional handcrafted features. Overall, our research demonstrates the potential for machine learning techniques to improve the accuracy and efficiency of plant disease detection and diagnosis. This has important implications for agriculture, where early detection and treatment of plant diseases can help to prevent crop losses and ensure food security.

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