# Real-Time Leaf Disease Detection and Fertilizer Recommendation System

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Keywords: Leaf Disease Detection, Hybrid Model, Feature Extraction, Image-Based Disease Detection.

Abstract: This project highlights the importance of leaf disease detection in precision agriculture, enabling early identification and timely intervention to protect crops from various diseases. This project presents a novel approach to detecting leaf diseases using deep learning (DL) and machine learning (ML) techniques. The study employs four powerful convolutional neural network (CNN) architectures: VGG16, VGG19, Inception v3, and Inception v6 to train a comprehensive leaf image data set, enabling robust disease classification. VGG-based models are used to extract features, which are then input into a support vector machine (SVM) classifier for disease classification. This hybrid DL-ML framework improves both the accuracy and efficiency of the system in distinguishing between healthy and diseased leaves. An interactive interface was developed, allowing users to upload leaf images for real-time disease detection, while an IoT camera system was integrated for automated leaf disease analysis in the field. The proposed solution demonstrates significant potential to improve crop management practices and advance automated agricultural systems, offering an innovative tool for early-stage disease diagnosis and management.

## 1 INTRODUCTION

In recent years, global demand for food has increased significantly due to rapid population growth, placing greater pressure on agricultural systems to ensure optimal crop pro- duction. One of the primary challenges faced by farmers is the timely detection of leaf diseases, which can severely impact crop health and yield. The timely and precise detection of these diseases is essential for efficient pest management, reducing crop loss, and minimizing the use of pesticides, this ultimately results in more sustainable farming practices.

Traditional leaf disease detection methods often depend on manual inspection, which is time consuming, labor intensive, and susceptible to human error. With rapid progress in machine learning (ML) and deep learning (DL), there is great potential to automate and enhance the accuracy of disease detection processes. In this context, computer vision techniques powered by convolutional neural networks (CNN) have shown great promise in analyzing plant leaf images to identify disease patterns.

This study uses advanced CNN architectures, specifically VGG16, VGG19, Inception v3, and Inception v6., to train and evaluate a comprehensive data set of leaf images for disease detection. These deep learning models are used for feature extraction, where the VGG models play a pivotal role in identifying relevant features from leaf images. The extracted features are then fed into a support vector machine (SVM) classifier for further processing, a traditional machine learning algorithm, to classify whether the leaf is healthy or diseased. By combining the strengths of CNN for feature learning and SVM for classification, the proposed method seeks to improve both the accuracy and efficiency of disease detection.

In addition, an interactive user interface was developed that allows users to upload images of plant leaves and receive real-time feedback on whether the leaf is healthy or infected. To further extend the practical application, the system was integrated with an IoT camera device, allowing automated image capture and analysis directly in agricultural fields. This IoT-enabled camera provides real-time monitoring and disease detection, creating a seamless and efficient solution for farmers.

Integrating deep learning with IoT technology represents a significant step toward modernizing



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agricultural practices. By automating the leaf disease detection process, the proposed system can help farmers make informed decisions faster, improve crop management, and contribute to increased agricultural productivity.

# 2 LITERATURE SURVEY

The detection of leaf diseases using machine learning and deep learning models has been a key focus in modern agricultural research. The goal is to automate the process and enhance crop management. This section examines various studies on leaf disease detection and emphasizes the key distinctions in our approach.

## 2.1 Deep Learning Approaches for Leaf Disease Detection

Mohanty et al. (2016) developed a convolutional neural network (CNN) model to classify images of various crops, such as tomatoes, cucumbers, and peppers, achieving re- markable results in leaf disease detection. Their approach leverages CNNs to automatically extract features from images, significantly reducing the need for manual feature engineering. However, their model was trained on a small dataset, which reduced its ability to generalize between different plant species and environments.

## 2.2 Convolutional Neural Networks Diagnose Plant Disease

Toda and Okura (2019) developed a convolutional neural network (CNN) model to diagnose plant diseases by analyzing leaf images. Their approach aimed to improve the interpretability of CNN-based predictions by extracting learned features in an understandable way, enhancing the model re- liability. Using deep learning, their method reduced the dependence on manual feature extraction, making the diagnosis plant disease more efficient. However, their study focused mainly on interpretability rather than improving classification precision, and the ability of the model to generalize between different plant species and environmental conditions remained a challenge.

## 2.3 Deep Neural Networks-based Recognition of Plant Diseases

Sladojevic et al. (2016) developed a deep convolutional neural network (CNN) model to recognize plant disease using leaf image classification. Their model was developed to differentiate between healthy and diseased leaves, covering 13 different plant diseases. Using CNNs, their approach automates feature extraction, reducing the need for manual preprocessing. The study also utilized the Caffe deep learning framework to train the model on an extensive dataset, achieving an accuracy of 96.3%. However, the model's performance was influenced by dataset limitations, particularly in generalizing across diverse environmental conditions and plant species.

## 2.4 Convolutional Neural Networks for the Automatic Identification of Plant Diseases

Boulent et al. (2019) carried out an extensive review on the use of convolutional neural networks (CNNs) for the automatic identification of plant diseases. Their study analyzed 19 research papers that implemented CNNs for crop disease detection, highlighting key aspects such as dataset characteristics, model architectures, training strategies, and performance metrics. The review emphasized the potential of CNNs in precision agriculture, improving food security through automated disease diagnosis. However, challenges such as dataset limitations, model generalization, and interpretability were identified as critical areas for improvement. The authors also offered recommendations to improve the reliability of CNN-based plant disease identification systems for practical agricultural applications.

## 2.5 Fast and Accurate Detection and Classification of Plant Diseases. International Journal of Computer Applications

Al-Hiary et al. (2011) developed a machine learning-based approach for the rapid and accurate detection of plant diseases using image processing techniques. Their model used K- means clustering for segmentation and artificial neural net- works (ANNs) for classification, greatly enhancing efficiency compared to traditional expert-based disease identification methods. The proposed method successfully classified various plant diseases with a precision ranging between 83% and 94%, achieving a 20% speedup compared to previous approaches. However, the model's performance was affected by factors like dataset variability and environmental conditions, which presented challenges for its implementation in real-world applications.

### 2.6 Detection of Unhealthy Region of Plant Leaves and Classification of Plant Leaf Diseases Using Texture Features

Arivazhagan et al. (2013) developed a machine learning- based method for detecting and classifying plant leaf diseases by utilizing texture features. Their method involved transforming input images into the HSI color space, masking and removing green pixels, segmenting infected regions, and extracting texture statistics for classification. The study employed a SVM classifier, achieving an accuracy of 94% on a dataset of 500 plant leaves. The proposed approach improved efficiency in plant disease detection, reducing dependency on expert analysis. However, its performance was influenced by variations in leaf conditions and environmental factors.

### 2.7 Detection of Unhealthy Region of Plant Leaves and Classification of Plant Leaf Diseases Using Texture Features Using ANN

Kanjalkar and Lokhande (2013) developed an approach using artificial neural networks (ANN) to detect and classify plant leaf diseases through image processing techniques. Their method involved converting RGB images to the HSI color space, removing noise, segmenting infected regions using connected component labeling, and extracting key features such as size, color, proximity, and centroid distance. The ANN classifier was trained on four different plant diseases, achieving reliable classification results. However, the model's performance was affected by dataset limitations and variations in leaf appearance due to environmental factors.

### 2.8 Diseases Detection of Various Plant Leaf Using Image Processing Techniques: A Review

The paper" Diseases Detection of Various Plant Leaf Using Image Processing Techniques: A Review" explores the importance of detecting plant diseases to improve agricultural productivity. Given that over 70% of India's population depends on agriculture, early disease detection is crucial to prevent economic losses. The study reviews various plant diseases affecting crops like maize, are can't, coconut, papaya, cotton, chili, tomato, and brinjal. It discusses key challenges, such as image quality, background noise, and the need for large datasets. The paper highlights different image processing techniques, including K-Means clustering, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Deep Learning for disease classification. Various studies are reviewed, the use of color space transformations, wavelet transforms, and machine learning models for effective disease detection. The research emphasizes the importance of automation in agriculture to reduce manual monitoring and pesticide usage. Future improvements include enhancing classification accuracy and expanding the dataset for better detection of plant diseases. [8]

### 2.9 Recent Technologies of Leaf Disease Detection Using Image Processing Approach – A Review

The paper" Recent Technologies of Leaf Disease Detection using Image Processing Approach – A Review" presents a comprehensive study of advancements in image processing techniques for plant leaf disease detection. Given the critical role of agriculture in economic growth, early disease detection is essential to prevent yield loss. The paper reviews various methodologies, such as segmentation, feature extraction, and classification, and organizes them according to the technologies used and their applications. Techniques such as histogram equalization, median filtering, and machine learning classifiers like Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) are analyzed. The study also discusses challenges such as varying lighting conditions, image noise, and dataset limitations. Future research should aim at integrating hybrid algorithms, deep learning models, and mobile-based solutions to enable real-time disease detection and enhance precision agriculture.

### 2.10 A Review of Machine Learning Approaches in Plant Leaf Disease Detection and Classification

The paper" A Review of Machine Learning Approaches in Plant Leaf Disease Detection and Classification" offers a thorough analysis of recent advancements in the identification and classification of plant diseases using Machine Learning (ML) and Deep Learning (DL) models. The study reviews over 45 research papers from 2017 to 2020, highlighting techniques such as Support Vector Machine (SVM), Neural Networks, K- Nearest Neighbor (KNN), and advanced DL architectures like AlexNet, GoogLeNet, and VGGNet. Various image processing techniques, including segmentation and feature extraction, are employed, and classification, are discussed along with their accuracy and dataset details. The paper emphasizes the importance of mobile-based applications for real-time plant disease detection, improving agricultural productivity. It also addresses key challenges like dataset quality, segmentation precision, and the need for hybrid ML-DL models to enhance accuracy. Future research should focus on real-time image datasets, mixed lighting conditions, and automated severity estimation to improve detection performance.

### 2.11 Comparison with Our Work

While existing studies have contributed significantly to the field of leaf disease detection, they primarily focus on training deep learning models for classification or rely on traditional machine learning methods for disease identification. Our approach differentiates itself in the following key areas:

- **Integration of Advanced Deep Learning Models** – Unlike previous works, our study utilizes a combination of VGG16, VGG19, Inception v3, and Inception v6 models for feature extraction. These architectures are designed to handle complex patterns in image data, improving the accuracy of leaf disease detection across various plant species and environments.
- **Hybrid Deep Learning and Machine Learning Approach** –By combining VGG-based deep learning models with an SVM classifier, our approach leverages the strengths of both deep learning (for feature extraction) and machine learning (for classification). This hybrid framework improves the system's robustness and ac- curacy. compared to traditional deep learning models, which may struggle in some real-world conditions due to overfitting or lack of generalization.
- **User Interface for Practical Application** – We have developed an easy-to-use interface that allows farmers and users to upload leaf images for instant disease diagnosis. This interactive feature makes our system more practical and accessible to non-expert users, differentiating it from previous works that often do not focus on user-friendly implementations. Table 1 gives the overall literature survey.
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Table 1: Literature survey.

| Study | Focus Area | Key Findings |
|---|---|---|
| Shrada P.Mohanty(2016) | Deep learning for plant disease detection | High accuracy but real- world challenges. |
| Toda T.Okura(2019) | Deep learning for plant disease recognition. | Achieved 96.3% accuracy in classifying 13 plant diseases. |
| Boulent,J.; Foucher(2019) | CNN-based automatic plant disease identification. | CNNs achieve high accuracy but require diverse datasets for real-world ap- plication. |
| M.V.V.R.S.Varma and P.P.V.S.Reddy,(2019) | Advanced convolutional neural networks | Improved accuracy and efficiency in disease classification |
| Arivazhagan S.,Newlin Shebia R.(2019) | Texture-based plant dis- ease classification. | Achieved 94.74% accuracy using SVM classifier. |

# 3 METHODOLODY

## 3.1 Existing Model

- **Visual Inspection** - Visual inspection is the most traditional and commonly used method to detect plant leaf diseases, farmers and agronomists rely on their expertise to identify symptoms such as discoloration, necrotic spots, wilting, or abnormal growth patterns. This method is cost-effective and does not require specialized equipment, making it accessible to small-scale farmers. However, it is highly subjective, as accuracy depends on the observer's experience and knowledge. In addition, visual inspection is often limited to detecting diseases in advanced stages when symptoms become evident, reducing the chances of early intervention. Factors such as lighting conditions, environmental stress, and plant variety can also lead to misdiagnosis. Furthermore, the presence of multiple diseases with overlapping symptoms complicates the identification. Although visual inspection remains a valuable initial screening method, it is increasingly being supplemented by technology-driven solutions to improve accuracy and early detection capabilities.

- **Feature Extraction and Machine Learning:** Traditional methods involve segmenting leaf images to isolate dis- eased areas, followed by extracting characteristics such as color, texture, and shape. These features are then used to train classifiers like Support Vector Machines (SVM) for disease identification. For example, a study applied K-means clustering for segmentation and extracted color features to train an SVM, achieving significant accuracy in classifying different plant diseases.
- **Deep Learning Approaches:** The integration of Convolutional Neural Networks (CNNs) has revolutionized feature extraction by allowing models to learn directly from raw pixel data, thus improving classification accuracy. A notable study developed a CNN-based model capable of diagnosing 26 unique plant diseases in 14 plant species, achieving an accuracy of 98.14%. This model was also integrated into a mobile application, facilitating real-time on-field disease diagnosis for farmers.
- **Sensor based Technologies:** Innovations in sensor-based technologies have led to the development of wearable devices for plants, allowing early detection of stress signals such as elevated levels of hydrogen peroxide $H_2O_2$. These sensors, often designed as microneedle patches, attach to plant leaves and monitor H2 O, a signaling scaling the pixel values in the range of 0 and 1, thus improving training efficiency.

- **Feature Extraction Using Pretrained Deep Learning Models**
- **VGG16 and VGG19:** The Deep convolutional neural networks intended for image classification. These models include an increasing number of convolutional, pooled, and fully connected layers. They were fine-tuned with pre-trained weights using a data set of leaf diseases. The last few layers will be modified to support the binary classification, in which two classes (healthy versus diseased) will be treated.
- **Inception v3 and v6:** These models are more complicated and perform better at obtaining characteristics and generalizing models. Inception networks have applied different sizes of the convolutional kernel on all layers, thereby enabling the model to capture features at different ranges like VGG models, Inception v3 and Inception v6 are also fine-tuned on the leaf disease dataset to detect disease.
- **Feature Extraction and SVM Classification** With the help of the VGG-16 and 19 models, these molecule indicatives of environmental stressors such as dehydration, excessive heat, infections, or pest attacks. By detecting these biochemical changes before visible symp- toms manifest, such as wilting or discoloration, these devices provide real-time alerts to growers, facilitating timely intervention to mitigate potential crop damage. For example, researchers have developed a wearable patch that can detect stress signals in plants before visible symptoms appear, allowing early intervention. Furthermore, advances in Nano sensor technology have allowed the real-time monitoring of plant health by detecting $H_2O_2$ signaling waves, providing deeper insights into plant stress responses. These innovations represent a significant leap toward precision agriculture, improving crop management practices, and potentially improving agricultural productivity.

### 3.2 Proposed Model

- **Dataset Collection and Processing:**

A dataset is gathered consisting of images of healthy and diseased leaves of various species. Open datasets- like the Plant Village dataset- can be used for this purpose; they contain labeled images for the model to train on.

Data Augmentation: Data augmentation techniques such as rotation, flipping, cropping, and color changes increase the diversity of training data and diminish the chance of overfitting. This helps mimicking the actual world variance in leaf appearance.

Image preprocessing: The collected image data would first undergo resizing to account for model input requirements from a ground-truth perspective, for example, to 224x224 pixels. Normalization allows general patterns are extracted from images related to disease detection in leaves. These models primarily help to capture hierarchical patterns in the images, such as edges, textures, and shapes. The output of the last few aforementioned Conv-n layers is flattened and then used as input features for the SVA learning model.

After features are extracted from the VGG-16 and VGG- 19 models, these features are given to the Support Vector Machine SVM) classifier. SVM is a supervised learning method that works by identifying the hyperplane in the feature space that best separates healthy and diseased leaf images. The SVM model is fitted on the extracted features to classify the leaf images as either" healthy" or" diseased."

Training the SVM: The SVM is trained with the feature vectors extracted from the dataset. Hyperparameters such as the kernel function (linear, radial basis function, etc.), regularization parameters, and so on will be optimized to maximize the classification accuracy.

- **IoT Camera Integration for Real-Time Image Capture VGG Model for Feature Extraction**

The VGG16 and VGG19 models will be utilized to extract advanced features from the images. These models are built to detect different levels of features in the images, such as edges, textures, and shapes, that are crucial for the identification of diseases in leaves. The output of the last convolutional layers is flattened and used as input features for the machine learning model. Support Vector Machine (SVM): This extracted feature is fed into the SVM classifier. The SVM algorithm functions by identifying the optimal hyperplane that separates the two classes of healthy and diseased images in the feature space. The trained SVM is being trained on the extracted features to classify the two classes of the leaf image as healthy or diseased.
Training the SVM: The extracted feature vector is used to train the SVM, along with hyperparameters such as the kernel function (for example, linear, radial basis function, etc.) and also the regularization parameters.

IoT Camera Hardware: IoT-enabled cameras are developed to capture real-time leaf images in the agricultural field. The images are processed by connecting the IoT camera to a local server or a cloud platform.

- **User Interface for Image Upload and Diagnosis Web interface design**

To enable users (farmers, re- searchers, etc.) to upload leaf images for disease diagnosis, a user-friendly Web interface is created. The interface is made using web technologies (HTML, CSS, JavaScript) linked with a back-end server where the disease detection model is hosted.
Image upload: Users can upload leaf images in a variety of formats (JPEG, PNG, etc.) through the interface. The uploaded image will be passed through trained models to determine whether the leaf is healthy or diseased.

Real-time diagnosis feedback: After image processing is complete, the system will provide feedback about the condition of the leaf indicating that it is healthy or diseased along with possible disease names, and will be given in real time by the system. The system may also suggest actions or treatments to be performed based on the detected disease.

- **Deployment and Testing**

Model Evaluation: Standard performance metrics, such as accuracy, precision, recall, and F1 score, are used to evaluate the trained models (VGG16, VGG19, In- ception v3, and Inception v6). Through cross-validation, the trained models are proven to be robust enough to withstand validation on various datasets.

By enabling federation, users can join external com- munities, share resources, and maintain open lines of communication while still benefiting from end-to-end encryption and administrative control. This makes it an ideal choice for organizations with distributed teams or multiple branches that require secure internal and external collaboration.

System Testing: The whole system, including the user interface and the IoT camera, is operated in real-time conditions so that the hardware interacts with the users as required. These tests will include uploading images to the Web interface, retrieving feedback in real time, and examining the IoT camera for disease detection accuracy.

Using Arduino and IoT Hardware Camera Device to Capture Images for Leaf Disease Detection: Integrating an IoT camera system with an Arduino plat- form is a powerful way to capture images for leaf disease detection in real time. This setup allows for easy deployment in agricultural fields or greenhouses. An Arduino- based device can capture images of leaves and upload them to a server or cloud for processing. Below is an overview of the methodology for using Arduino with an IoT camera for leaf disease detection:

IoT Camera Module Camera Module: The camera module attached to Arduino is responsible for capturing images of leaves. Popular camera modules include

OV7670 Camera Module: A low-cost, simple-to-use camera that can be interfaced with Arduino to capture small images.

ESP32-CAM: An all-in-one solution with a built-in camera, Wi-Fi capabilities, and low power consumption, ideal for IoT applications.

Arducam Mini Module Camera: A high-resolution camera that can be used for more detailed image capture. The ESP32-CAM is an ideal choice for IoT applications due to its built-in camera and Wi-Fi capabilities, offering a compact and energy-efficient solution. Alternatively, the OV7670 and Arducam Mini provide options for different levels of image quality and complexity, depending on the application’s needs. So, we choose ESP32-CAM.

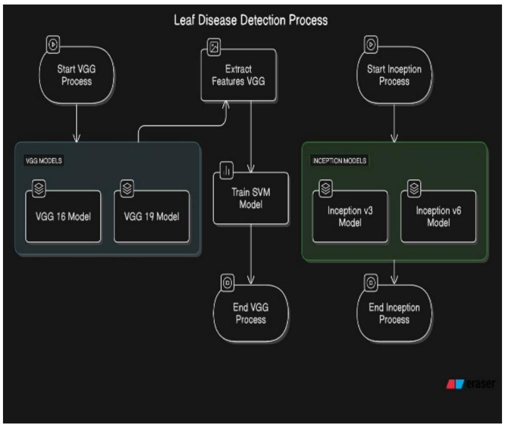


Figure 1: Block-Diagram.

Figure 1 illustrates a leaf disease detection process that uses deep learning models for the extraction and classification of characteristics. The process begins with two parallel approaches: VGG-based models VGG-16 and VGG-19 and Inception-based models Inception V3 and Inception V6. In the VGG pipeline, feature extraction is performed using VGG models, followed by training a Support Vector Machine (SVM) for classification. Inception models process images separately, but do not involve SVM training. Both approaches operate independently and terminate after their respective processes. This methodology leverages deep learning for feature extraction while integrating machine learning for classification, enhancing the accuracy of plant disease detection.

**Image Capture and Processing Flow Capturing Images:** The camera module captures images of the leaves by triggering the Arduino to capture the image using the camera. A button or sensor (such as a light or motion sensor) can be used to trigger image capture when a leaf enters the camera’s field of view.

**Sending Images to a Server:** Once an image is captured, it needs to be sent to a server or database for analysis. The ESP32 can use its built-in Wi-Fi capabilities to upload the image to a server, or it can send the image via HTTP POST requests.

**Image Processing and Leaf Disease Detection:** After the image is uploaded to the server, it is processed using machine learning models like VGG16, VGG19, or InceptionV3 to classify whether the leaf is healthy or diseased. This can be achieved by integrating a pre- trained model with a Flask API to receive images and return predictions.

**Secure Transmission via HTTPS:** To ensure privacy and prevent tampering, we implemented HTTPS using a self- signed SSL certificate. The Flask Web server was con- figured to encrypt image uploads and model predictions, securing communication between users and the server.

**ESP32-CAM with Arduino:** To integrate an ESP32-CAM with an Arduino to capture images via a web interface (providing an IP address and allowing image capture directly through the browser), you will need to set up the ESP32-CAM as a web server.

In this way, users can access the camera’s web page from a browser, where they can trigger image captures and send them to a server or save them locally.

**Hardware Software Requirements:**

- ESP32-CAM Module

- Arduino IDE
- ESP32 Camera Library

### 3.3 Install ESP32 Board in Arduino IDE

Open Arduino IDE.
Go to Tools > Boards > Boards Manager, search for ESP32, and install it.

### 3.4 Configure the Web Server Code

code to configure the ESP32-CAM as a web server that will give you an IP address and allow you to capture an image through a web interface.

### 3.5 Upload the Code to ESP32-CAM

On the ESP32-CAM while uploading the code (to enter programming mode).

- After uploading, restart the ESP32-CAM.

### 3.6 Monitor Output

Open the Serial Monitor (at 115200 baud) in the Arduino IDE. Once connected to Wi-Fi, the ESP32-CAM will print its IP address.

```
{
   css
Connecting to WiFi... Connected to
WiFi
IP Address: 192.168.1.100
}
```

### 3.7 Accessing the Web Interface

Open a web browser and enter the IP address displayed on the Serial Monitor. For example, http://192.168.1.100/. The ESP32-CAM will capture and serve a JPEG image of what the camera sees.

### 3.8 Capture Image

ESP32-CAM will capture images automatically and from different angles. Figure 2 shows the camera module.

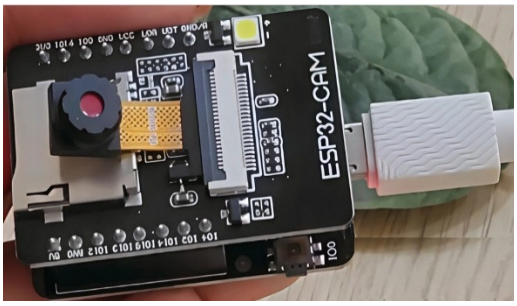


Figure 2: IOT based ESP-32 CAMERA MODULE.

## 4 RESULTS AND DISCUSSION

The table compares the performance of deep learning models (VGG-16, VGG-19, Inception V3, and Inception V6) for plant disease classification using different activation functions (ReLU, Sigmoid, and Tanh). The accuracy and loss values were obtained by training these models on various datasets, such as the Fruit Dataset, Vegetable Dataset, Healthy Dataset, and Diseased Dataset, while fine-tuning the activation functions to assess their impact.

In Table 2, VGG-16 and Inception V3 demonstrated superior performance, achieving peak accuracy of 96% with Tanh, while VGG-19 and Inception V6 showed relatively lower accuracy, ranging from 68% to 73%, with higher loss values. ReLU suffered from slightly higher loss, likely due to the" dying ReLU" issue, while Sigmoid and Tanh exhibited better gradient propagation, leading to lower loss values, particularly in VGG-16 and Inception V3.

Table 2: Fruit dataset- existing model.

| Model | Activation Function | ReLu | Sigmoid | Tanh |
|---|---|---|---|---|
| VGG 16 | Accuracy | 93 | 95 | 96 |
| VGG 16 | Loss | 18 | 4 | 4 |
| VGG 19 | Accuracy | 73 | 71 | 70 |
| VGG 19 | Loss | 57 | 58 | 62 |
| Inception V3 | Accuracy | 92 | 94 | 96 |
| Inception V3 | Loss | 17 | 4 | 4 |
| Inception V6 | Accuracy | 68 | 73 | 72 |
| Inception V6 | Loss | 55 | 57 | 56 |

Table 3: Vegetable dataset- existing model.

| Model | Activation Function | ReLu | Sigmoid | Tanh |
|---|---|---|---|---|
| VGG 16 | Accuracy | 80 | 100 | 91 |
| VGG 16 | Loss | 54 | 23 | 22 |
| VGG 19 | Accuracy | 94 | 87 | 100 |
| VGG 19 | Loss | 20 | 35 | 21 |
| Inception V3 | Accuracy | 93 | 93 | 93 |
| Inception V3 | Loss | 18 | 18 | 20 |
| Inception V6 | Accuracy | 93 | 92 | 92 |
| Inception V6 | Loss | 19 | 20 | 21 |

In Table 3, VGG-16 achieved a maximum accuracy of 100% with Sigmoid, although its loss remained slightly higher at 23 compared to Tanh's 22. VGG-19 performed best with Tanh, reaching 100% accuracy while maintaining a lower loss of 21. Inception V3 demonstrated consistent performance across all activation functions, with an accuracy of 93% and a minimal variation in loss values between 18 and 20. Similarly, Inception V6 exhibited stable accuracy, hovering around 92–93%, with slight fluctuations in loss values.

Table 4: Healthy dataset- proposed model.

| Model | Activation Function | ReLu | Sigmoid | Tanh |
|---|---|---|---|---|
| VGG 16 | Accuracy | 90 | 91 | 60 |
| VGG 16 | Loss | 34 | 21 | 29 |
| VGG 19 | Accuracy | 50 | 65 | 52 |
| VGG 19 | Loss | 70 | 78 | 82 |
| Inception V3 | Accuracy | 70 | 69 | 64 |
| Inception V3 | Loss | 60 | 67 | 83 |
| Inception V6 | Accuracy | 72 | 65 | 66 |
| Inception V6 | Loss | 59 | 64 | 74 |

In Table 4, VGG-16 demonstrated the highest accuracy with Sigmoid (91%) while maintaining a lower loss (21), whereas its performance dropped significantly with Tanh (60% accuracy and 29 loss). VGG-19 showed moderate accuracy, peaking at 65% with Sigmoid, but suffered from high loss values across all activation functions, with the highest loss (82) recorded for Tanh. Inception V3 exhibited balanced performance, with ReLU providing the highest accuracy (70%) and the lowest loss (60), while Tanh resulted in lower accuracy (64%) and the highest loss (83). Similarly, Inception V6 performed best with ReLU, achieving 72% accuracy with the lowest loss (59), whereas its performance declined with Sigmoid and Tanh.

Table 5: Diseased dataset- proposed model.

| Model | Activation Function | ReLu | Sigmoid | Tanh |
|---|---|---|---|---|
| VGG 16 | Accuracy | 93 | 70 | 95 |
| VGG 16 | Loss | 25 | 25 | 17 |
| VGG 19 | Accuracy | 68 | 75 | 71 |
| VGG 19 | Loss | 62 | 56 | 58 |
| Inception V3 | Accuracy | 69 | 61 | 68 |
| Inception V3 | Loss | 62 | 71 | 69 |
| Inception V6 | Accuracy | 64 | 72 | 64 |
| Inception V6 | Loss | 64 | 64 | 76 |

In Table 5, VGG-16 showed the highest accuracy with Tanh (95%), while ReLU also performed well (93%), while Sigmoid showed a significant drop (70%). The loss values for VGG-16 remained low across all activation functions, with Tanh achieving the lowest loss (17). VGG-19 exhibited moderate accuracy, peaking at 75% with Sigmoid, but struggled with higher loss values, particularly with ReLU (62).

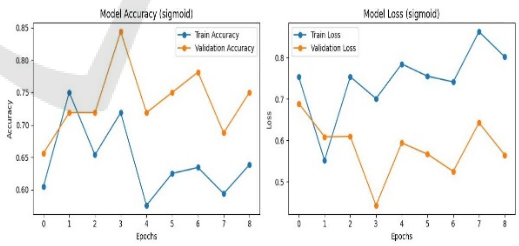


Figure 3: VGG-19 Healthy.

Inception V3 showed relatively lower accuracy, ranging from 61% (Sigmoid) to 69% (ReLU), and had consistently high loss values, with Sigmoid performing the worst (71). Inception V6 achieved its best accuracy with Sigmoid (72%) but showed similar accuracy with ReLU and Tanh (both 64%), while its loss values were higher, reaching 76 with Tanh. Figure 3 shows the healthy statics.

The performance analysis of VGG-16, VGG-19, Inception V3, and Inception V6 models across four datasets—fruit, veg- etable, healthy, and diseased—demonstrates variations in accu- racy and loss based on activation functions. In the fruit dataset, VGG-16 and Inception V3 achieved the highest accuracy with Tanh (96%), while VGG-19 and Inception V6 showed lower performance, with their best accuracy reaching 73%. The vegetable dataset exhibited strong performance, particularly with VGG-19 using Tanh (100%) and VGG-16 using Sigmoid (100%), indicating robust classification abilities. Loss values in this dataset were also relatively low, signifying stable training.

In contrast, the healthy dataset showed decreased accuracy, with VGG-19 performing the worst (50% with ReLU), and high loss values were observed, particularly for VGG-19 and Inception models, suggesting challenges in detecting healthy samples accurately.

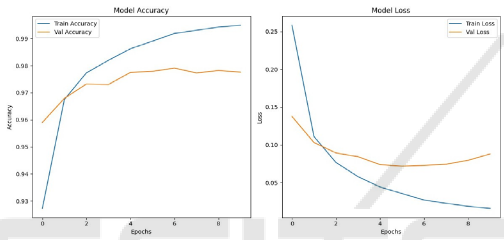


Figure 4: SVM Model for Healthy and Diseased Dataset.

The accuracy and loss curves in Figure 4 illustrate the training performance of the proposed model. The left plot shows a steady increase in training and validation accuracy, reaching above 98%, indicating effective learning. The right plot demonstrates a consistent decrease in training and validation loss, with a minor gap suggesting minimal overfitting. These results confirm the model's high generalization capability in plant disease classification.

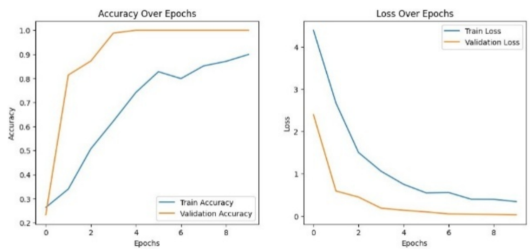


Figure 5: VGG 16 Healthy.

In Figure 5, the diseased dataset exhibited moderate performance, with VGG-16 achieving the highest accuracy of 95% using Tanh, while Inception models struggled to exceed 72%.

Figure 6 illustrates the accuracy and loss trends of the model across the training epochs. The left graph shows training and validation accuracy improving steadily, with validation accuracy reaching near-perfect levels early on.

The graph on the right shows a steady decrease in both training and validation loss, indicating effective learning and highlighting the accuracy and loss trends of the model across multiple epochs.

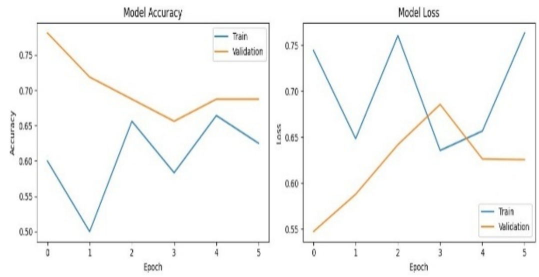


Figure 6: VGG 19 Diseased.

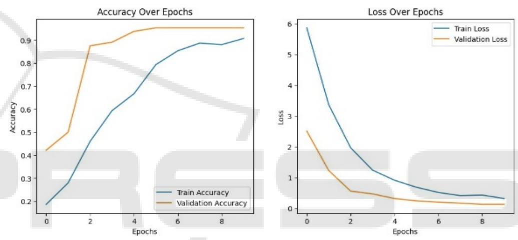


Figure 7: VGG 16 Diseased.

The accuracy graph in Figure 7, indicates fluctuating training accuracy, while validation accuracy declines, suggesting poor generalization. The loss graph shows instability in training loss.

The implementation of HTTPS using a self-signed certificate effectively encrypts communication, preventing interception. HTTPS conversion successfully encrypted data transmission, preventing snipping and MITM attacks. Self-signed SSL reduced costs, making it feasible for small-scale applications and internal tools. Figure 8 shows the user interface.

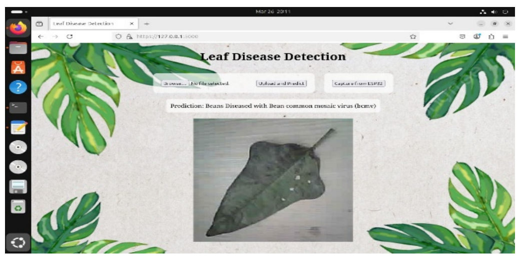


Figure 8: Secured Web interface detecting real-time leaves through ESP-32 camera module.

Once an image is uploaded or captured, it is processed and classified as" Healthy" if no disease symptoms are detected. The result is displayed on a user-friendly web interface, with an option for further analysis or expert consultation as shown in figure 9.

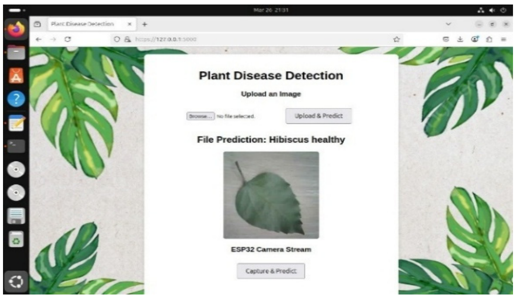


Figure 9: Secured Web interface detecting leaf images through Real-time Database.

In Table 6, it presents the classification performance of the Support Vector Machine (SVM) model on various plant dis- ease categories. The model achieves an overall accuracy of 91%, with macro and weighted F1-scores of 0.92, indicating strong classification capabilities. While most classes exhibit high precision and recall values, some, such as Bottleguard Diseased (F1-score: 0.73) and Tomato Diseased (F1-score: 0.75), show relatively lower performance, suggesting potential misclassification. The perfect scores (1.00 F1-score) in several classes indicate effective feature extraction and differentiation by the model.

Table 6: Classification Report on SVM.

| | Precision | Recall | F1-score | Support |
|---|---|---|---|---|
| Beans Diseased | 0.77 | 0.91 | 0.83 | 22 |
| Beans Healthy | 1.00 | 0.88 | 0.94 | 17 |
| Blackgram Diseased | 1.00 | 1.00 | 1.00 | 10 |
| Blackgram Healthy | 1.00 | 0.90 | 0.95 | 21 |
| Bottleguard Diseased | 0.57 | 1.00 | 0.73 | 16 |
| Bottleguard Healthy | 1.00 | 1.00 | 1.00 | 15 |
| Brinjal Healthy | 1.00 | 0.78 | 0.88 | 9 |
| Brinjal Diseased | 1.00 | 0.78 | 0.88 | 9 |
| Greengram Diseased | 1.00 | 1.00 | 1.00 | 12 |
| Guava Healthy | 1.00 | 1.00 | 1.00 | 15 |
| Guava Diseased | 1.00 | 1.00 | 1.00 | 8 |
| Hibiscus Healthy | 1.00 | 0.82 | 0.90 | 11 |
| Jungle flower Healthy | 1.00 | 1.00 | 1.00 | 17 |
| Jungle flower Diseased | 1.00 | 1.00 | 1.00 | 4 |
| Rose Healthy | 1.00 | 0.75 | 0.86 | 8 |
| Tomato Diseased | 1.00 | 0.60 | 0.75 | 10 |
| Accuracy | | | 0.91 | 204 |
| Macro avg | 0.96 | 0.90 | 0.92 | 204 |
| Weighted avg | 0.94 | 0.91 | 0.92 | 204 |



## 5 CONCLUSION AND FUTURESCOPE

In this project, an integrated and comprehensive system is developed for leaf disease detection using advanced deep learning models such as VGG16, VGG19, and Inception V3. This system aims to achieve very efficient and accurate diagnosis or detection of leaf disease based on the developed ground of pre-trained Convolutional Neural Networks (CNNs); this is done to classify healthy plant images against those with diseases. Through the integration IoT hardware (like the ESP32 camera), farmers and agricultural experts can shoot leaf images and upload them for instant observation. The model was trained with healthy and diseased leaves across various datasets so that it could generalize over several plant species. Transfer Learning was applied, where we harvested the power of the pre-trained layers from VGG and Inception models, significantly reducing training time and computation costs while ensuring desirable accuracy. Additionally, optimization was done based on performance, with machine learning classifiers like SVM being used for better prediction performance.

Additionally, the project considered the possible deployment of the system on the cloud, so as to leverage the platform's scalability and global accessibility, such that users from different parts of the world can ultimately take advantage of the leaf disease detection system available. An easy interface design was done for seamless interaction that would allow an easy image upload and feedback on prediction. Also, steps to make the model scalable are catered for with performance optimizations in place, and this would further enable the system to easily handle a large volume of concurrent users with no significant performance degradation at all.

Thus, this project has shown the possibility of using deep learning, IoT, and cloud technologies to radically change the methods of farm management practices. Systems have now been developed that provide automatic, accurate, organic, and efficient leaf disease detection systems that would allow for timely interventions and particular attention to crops growing. Future work may include creating comprehensive models encompassing multiple plant species, improving real-time detection/dynamic detection, and interfacing mobile platforms for more wide accessibility.

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