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# Transforming Agriculture with Deep Learning Approaches to Plant Health Monitoring

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***Abstract--*** Effective management of plant diseases is crucial for ensuring agricultural productivity and sustainability. This research presents a novel framework for intelligent plant disease detection leveraging deep learning techniques. The proposed framework integrates multiple stages to facilitate accurate and efficient diagnosis through deep Convolutional Neural Networks (CNNs). Initially, high-resolution images of plant leaves are acquired using smartphones or cameras, followed by preprocessing steps such as resizing and normalization to prepare the data for analysis. A deep CNN architecture extracts intricate features from the preprocessed images, enabling precise disease classification. Post-processing stages provide users with diagnostic outputs and relevant information, enhancing decision-making in agricultural management. Continuous model retraining with updated datasets ensures adaptability to new diseases and environmental conditions. Experimental results demonstrate the framework's effectiveness in achieving high accuracy and robust performance across various plant species and diseases. This research contributes to advancing the application of AI in agriculture, offering a scalable solution for proactive plant health monitoring and sustainable farming practices, while also informing social sciences in planning and development by promoting food security and rural development.

***Keywords: -*** **Sustainable Farming Practices, Data Augmentation, Crop Management, Deep Learning, Precision Agriculture, BigData, Cloud, Machine Learning, Food Security, Planning and Development**

## I. INTRODUCTION

Agriculture, a cornerstone of human civilization, faces significant challenges due to plant diseases, which can drastically reduce crop yields and affect food security. Traditional methods of plant disease detection often involve labor-intensive processes and are prone to inaccuracies, necessitating the development of more efficient and scalable solutions. Recent advancements in deep learning (DL) have shown great promise in transforming agricultural practices, particularly in the area of plant health monitoring.

Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been extensively researched and applied in various agricultural applications. These techniques have demonstrated superior performance in tasks such as image classification, object detection, and disease identification in plants[1] [2]. For instance, CNNs have been successfully employed to detect and classify plant diseases from images, achieving high accuracy even under challenging conditions. One of the key advantages of deep learning in agriculture is its ability to process large volumes of data and extract meaningful patterns without the need for manual feature engineering. This capability is particularly useful in the context of plant disease detection, where the visual symptoms of diseases can be subtle and complex. By leveraging pre-trained models and transfer learning, researchers have been able to achieve significant improvements in the accuracy and efficiency of plant disease detection systems[3].

Moreover, the integration of deep learning with other technologies, such as the Internet of Things (IoT) and social Internet of Things (SIoT), has further enhanced the potential of smart agriculture. IoT devices can continuously monitor environmental conditions and collect data, which can then be analyzed using deep learning models to predict and diagnose plant diseases in real-time[4][5]. This approach not only improves the accuracy of disease detection but also enables timely interventions, thereby reducing crop losses and promoting sustainable agricultural practices.
The agricultural sector is a cornerstone of the global economy, yet it faces significant challenges due to plant diseases that can drastically reduce crop yields and quality. Traditional methods of disease detection, which often rely on manual inspection, are labor-intensive, time-consuming, and prone to inaccuracies, especially over large areas of cultivation [6] [7]. The advent of deep learning and computer vision technologies offers a transformative approach to plant health monitoring, providing automated, accurate, and scalable solutions for early disease detection. Convolutional Neural Networks (CNNs) have emerged as a powerful tool in this domain, capable of classifying plant diseases with high accuracy by analyzing images of plant leaves [8] [9] [10]. For instance, a mobile-based system utilizing CNNs has been developed to diagnose 38 different disease categories with an impressive classification accuracy of 94%, thereby aiding farmers in maintaining crop health and optimizing the use of fertilizers. Similarly, another study demonstrated a neural network-based model achieving an accuracy of 96.78% in detecting plant diseases, which is crucial for recommending appropriate pesticides and safeguarding crop yield.
The integration of Internet of Things (IoT) and cloud computing further enhances these systems by enabling real-time data collection and processing, thus providing a comprehensive framework for plant health monitoring [11]. The application of deep learning extends beyond mere disease detection; it also includes plant species identification and health status monitoring, which are essential for sustainable agriculture [12]. Advanced image processing techniques, such as contrast enhancement and K-means clustering, combined with Support Vector Machine (SVM) classifiers, have also been employed to detect specific diseases like Alternaria alternata and Bacterial blight, further demonstrating the versatility and effectiveness of these technologies. The potential of deep learning in transforming agriculture is not limited to disease detection alone; it also encompasses predictive analytics to forecast disease outbreaks, thereby enabling proactive measures to prevent crop loss [13]. As the agricultural sector continues to embrace these innovative technologies, the shift towards smart farming becomes inevitable, promising increased crop yields, reduced losses, and enhanced sustainability. This research aims to explore the various deep learning approaches to plant health monitoring, highlighting their applications, benefits, and future prospects in revolutionizing agriculture.
In summary, the application of deep learning in plant health monitoring represents a significant advancement in agricultural technology. By automating the detection and diagnosis of plant diseases, deep learning models can help farmers make informed decisions, optimize resource use, and ultimately enhance crop productivity. This research aims to explore the various deep learning approaches for plant health monitoring, evaluate their effectiveness, and discuss their potential implications for the future of agriculture.

## II. LITERATURE REVIEW

The integration of deep learning approaches in agriculture, particularly for plant health monitoring, has shown significant promise in enhancing the efficiency and accuracy of disease detection and management. This literature review explores various deep learning methodologies applied to plant health monitoring, highlighting their contributions, challenges, and potential for transforming agriculture.
Deep learning techniques, especially Convolutional Neural Networks (CNNs), have been extensively researched for their ability to identify and classify plant diseases with high accuracy. For instance, a study utilized CNNs to detect plant diseases from drone-captured images, demonstrating superior proficiency in categorizing and detecting crop diseases even under challenging imaging conditions. Similarly, another research employed deep transfer learning with pre-trained models like VGGNet and Inception, achieving a validation accuracy of over 91.83% for rice plant disease detection [3].
The application of various deep learning meta-architectures has been explored to enhance the precision of plant disease detection. A notable study compared three meta-architectures—Single Shot MultiBox Detector (SSD), Faster Region-based Convolutional Neural Network (RCNN), and Region-based Fully Convolutional Networks (RFCN)—for plant disease identification. The SSD model, optimized with the Adam optimizer, achieved the highest mean average precision (mAP) of 73.07% [14]. Another research focused on tomato plant diseases and pests,

utilizing similar meta-architectures combined with feature extractors like VGG net and ResNet, to effectively recognize multiple disease types[15].

The integration of deep learning approaches in agriculture, particularly for plant health monitoring, has garnered significant attention in recent years due to its potential to revolutionize traditional farming practices. Deep learning, a subset of artificial intelligence, has been extensively applied in various domains such as voice, natural language, and image processing, and has shown promising results in agricultural applications as well [16]. Traditional methods of plant disease identification, which rely heavily on manual observation, are often time-consuming and prone to errors, necessitating the development of more efficient and accurate techniques [17] [18].

Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in the automatic detection and classification of plant diseases from leaf images, thereby reducing the dependency on human expertise and continuous monitoring. For instance, the use of deep convolutional extreme learning machines (DC-ELM) has been proposed to enhance computational performance and reduce processing time in disease detection tasks [19]. Moreover, advancements in computer vision and AI have enabled the development of sophisticated models such as the context-aware 3D CNN, which can accurately segment and identify leaf lesions, achieving high accuracy rates in disease subtype recognition [20]. In agriculture, deep learning can be applied to analyze images of plants to detect diseases, pests, or nutrient deficiencies, helping farmers take timely actions to maintain crop health and yield like the article [21]. The application of these technologies not only improves the accuracy of disease detection but also facilitates early intervention, which is crucial for maintaining crop health and yield. Additionally, the integration of IoT sensor networks with machine learning and deep learning architectures has been explored to optimize data collection and reduce the overall cost of monitoring systems in agricultural settings. Despite these advancements, several challenges remain, including the need for large annotated datasets, the variability in disease symptoms across different plant species, and the computational complexity of deep learning models. Researchers continue to address these issues by developing more robust and scalable models, as well as exploring the use of hyperspectral imaging and other advanced techniques to enhance the accuracy and efficiency of plant disease detection systems [22]. Overall, the literature indicates that deep learning approaches hold significant promise for transforming agriculture by enabling more precise and timely plant health monitoring, ultimately contributing to sustainable farming practices and improved crop yields.

The integration of deep learning with Internet of Things (IoT) technologies has paved the way for smart agriculture systems. These systems leverage IoT for environmental monitoring and deep learning for disease prediction. For example, a study proposed an IoT-based smart agriculture system that monitors environmental parameters and uses CNNs for plant health prediction, achieving a higher accuracy. Another research envisioned the use of Social IoT for environmental sensing and deep learning for plant disease detection, aiming to enhance agricultural sustainability[4].

Despite the advancements, several challenges remain in the deployment of deep learning models in agriculture. One major issue is the early detection of plant diseases, where traditional CNNs often fall short. A survey suggested a hybrid model combining CNN and Support Vector Machine (SVM) to address this limitation[1]. Additionally, the need for scalable and efficient solutions for real-time monitoring has led to the development of lightweight deep learning models capable of running on edge devices with constrained resources [2].

The reviewed literature underscores the transformative potential of deep learning in plant health monitoring. By leveraging advanced deep learning architectures and integrating IoT technologies, these approaches offer scalable, accurate, and efficient solutions for disease detection and management in agriculture. Future research should focus on addressing the existing challenges, particularly in early disease detection and real-time monitoring, to fully realize the benefits of deep learning in smart agriculture.

## III. METHODOLOGY

The proposed framework for intelligent plant disease detection integrates multiple stages to ensure a comprehensive, accurate, and user-friendly system for detecting plant diseases. The proposed framework for intelligent plant disease detection is comprehensive and well-structured and the visual representation of framework is illustrated in Figure.1.

The proposed framework for intelligent plant disease detection involves several critical stages to ensure accurate and efficient diagnosis. Initially, high-quality images of plant leaves are collected using smartphones or cameras, forming the primary input to the system (Image Acquisition). These images then undergo preprocessing, which includes resizing, normalization, and augmentation to ensure they are suitable for analysis by the model (Preprocessing).

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Next, features from the preprocessed images are extracted using a deep Convolutional Neural Network (CNN). The CNN processes these images through several layers, capturing intricate details and patterns that are indicative of specific diseases (Feature Extraction). The extracted features are subsequently fed into the classification layers of the CNN, which outputs the probability of each disease class. The class with the highest probability is selected as the predicted disease (Classification).

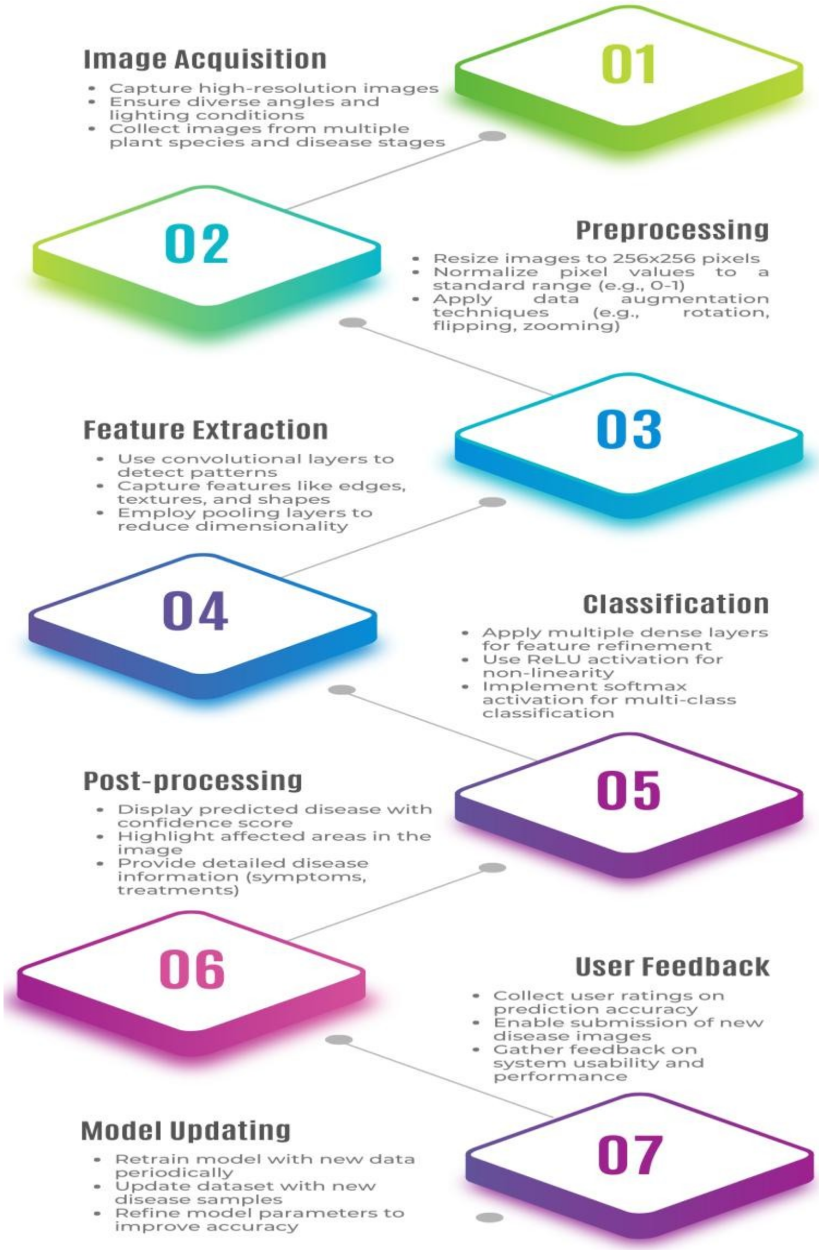


Figure 1: Proposed Framework for Intelligent Plant Disease Detection

After classification, the predicted disease is displayed to the user along with relevant information, such as symptoms, treatment options, and preventive measures. The system may also provide visual indicators highlighting affected areas in the image (Post-processing and Output). Additionally, users can provide feedback on the accuracy of the diagnosis. This feedback, along with new images, is collected and used to continuously update and improve the model (User Feedback and Data Collection).

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To maintain accuracy, periodic retraining of the model is performed using the latest data, ensuring it remains up-to-date. This step includes updating the dataset with new disease images and refining the model parameters (Model Updating and Maintenance). Through this systematic approach, the framework leverages machine learning for reliable and intelligent plant disease detection, facilitating proactive and informed decision-making in agriculture.

The model begins with an input layer that accepts images resized to a consistent dimension of 256x256 pixels, with three color channels (RGB). This standardization of input size ensures uniformity across the dataset, facilitating efficient processing. The CNN architecture includes multiple convolutional layers, each responsible for extracting features from the input images. The first Conv2D layer applies 32 filters with a kernel size of 3x3 and uses the ReLU (Rectified Linear Unit) activation function. The ReLU activation introduces non-linearity, helping the network learn complex patterns, followed by a max-pooling layer with a pool size of 2x2 to reduce the spatial dimensions of the feature maps. The second Conv2D layer has 64 filters with a kernel size of 3x3, also using the ReLU activation function, with another max-pooling layer with a pool size of 2x2 applied to further down-sample the feature maps. The third Conv2D layer uses 128 filters with a 3x3 kernel size, applying the ReLU activation function, followed by a max-pooling layer with a 2x2 pool size to reduce the dimensionality of the feature maps. The final convolutional layer uses 256 filters with a 3x3 kernel size and the ReLU activation function, followed by a max-pooling layer with a pool size of 2x2 to further condense the feature maps.

To prevent overfitting, dropout layers are incorporated into the architecture. The first dropout layer is placed after the fourth convolutional layer, applying a dropout rate of 0.25, meaning 25% of the neurons are randomly dropped during training to ensure the model does not become overly reliant on any single neuron. The second dropout layer is included after the first fully connected (dense) layer, applying a dropout rate of 0.5, further reducing the risk of overfitting by randomly omitting 50% of the neurons during training. Following the convolutional and pooling layers, the model includes fully connected layers to perform the classification task. A flatten layer transforms the 2D feature maps into a 1D vector, preparing them for the dense layers. The first dense layer consists of 512 units and uses the ReLU activation function to introduce non-linearity and enable the network to learn complex representations. Following this, the second dense layer has 256 units with the ReLU activation function, further refining the learned features.

The final layer in the architecture is the output layer, which performs the classification. This dense layer consists of 38 units, corresponding to the number of classes in the PlantVillage dataset, including various plant species and diseases. The softmax activation function is used in this layer to output a probability distribution over the classes, allowing the model to assign a probability to each class and select the most likely class as the predicted disease. This carefully structured architecture enables the CNN to effectively learn and distinguish between different plant diseases, leveraging the power of convolutional layers for feature extraction and dense layers for classification. The inclusion of dropout layers helps to prevent overfitting, ensuring that the model generalizes well to new, unseen data.

The proposed framework for intelligent plant disease detection offers several notable benefits, making it a powerful tool in modern agriculture. One of the primary advantages is its accuracy; the use of deep Convolutional Neural Networks (CNNs) for feature extraction and classification significantly enhances the precision of disease detection. By capturing intricate details and patterns indicative of specific diseases, the framework ensures reliable diagnosis. Additionally, the system is designed to be user-friendly. The inclusion of post-processing and user feedback stages ensures that the system is accessible and practical for farmers and other end-users, providing them with relevant information and allowing them to contribute to the system's improvement. Another key benefit is adaptability. The periodic retraining and updating of the model enable the system to stay current with new diseases and changing environmental conditions, ensuring it remains effective over time. Overall, the proposed framework has the potential to make a significant impact in the field of plant disease detection and intelligent farming, promoting more efficient and sustainable agricultural practices.

The methodology for the proposed framework of machine learning-based plant disease detection is structured around several key stages: data collection, data preprocessing, model development, training and validation, model evaluation, deployment, and continuous improvement.

### 3.1 Data Collection

The data collection phase involves gathering an extensive dataset of plant images, covering both healthy and diseased leaves. This dataset includes a wide range of plant species and diseases to ensure comprehensive coverage. The primary dataset used is the PlantVillage dataset, which comprises over 50,000 images of plant leaves categorized into 38 classes, including 14 crop species and 26 diseases. Additional data were sourced from

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agricultural fields, research institutions, and online repositories to further enrich the dataset. Regular updates to the dataset are planned to include new diseases and variations, maintaining the model's relevance and accuracy over time.

### 3.2 Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for model training. Images were resized to a consistent dimension, typically 256x256 pixels, and pixel values were normalized to standardize the data. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were applied to artificially expand the dataset and introduce variability as shown in Figure.2. This helps the model generalize better to new, unseen data. Advanced techniques like Generative Adversarial Networks (GANs) were also explored to generate synthetic data, further enhancing the dataset.

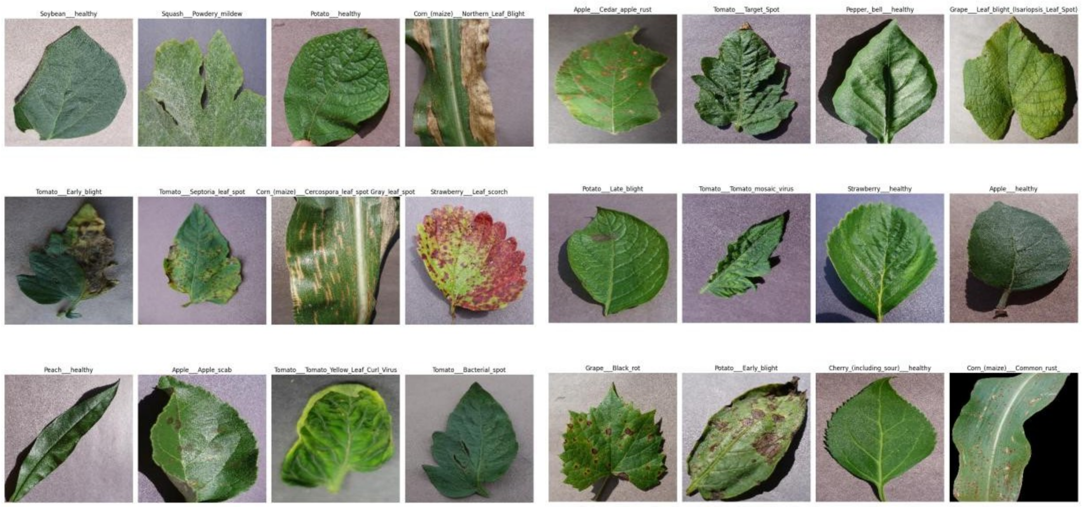


Figure 2: Dataset enhancement for plant disease detection

### 3.3 Model Development

The core of the proposed framework is a Convolutional Neural Network (CNN) designed specifically for plant disease detection. The architecture of the CNN was selected for its efficacy in image classification tasks. The model architecture includes multiple convolutional layers for feature extraction, pooling layers for down-sampling, dropout layers to prevent overfitting, and fully connected layers for classification. Transfer learning was utilized, leveraging pre-trained models such as VGG16, ResNet50, and Xception. These pre-trained models provided a solid foundation, which was then fine-tuned to adapt to the specific characteristics of the plant disease dataset.

### 3.4 Training and Validation

The dataset was split into training and validation sets, typically in an 80-20 ratio keeping in view with proposer mix from figure.3. The training set was used to adjust the model’s weights, while the validation set helped monitor the model’s performance on unseen data, providing an early indication of overfitting or underfitting. Cross-validation techniques were employed to ensure the model generalizes well. Hyperparameter tuning, using methods such as grid search or random search, was performed to optimize the model’s performance. Parameters such as learning rate, batch size, and the number of epochs were adjusted to find the best combination that yields the highest accuracy.

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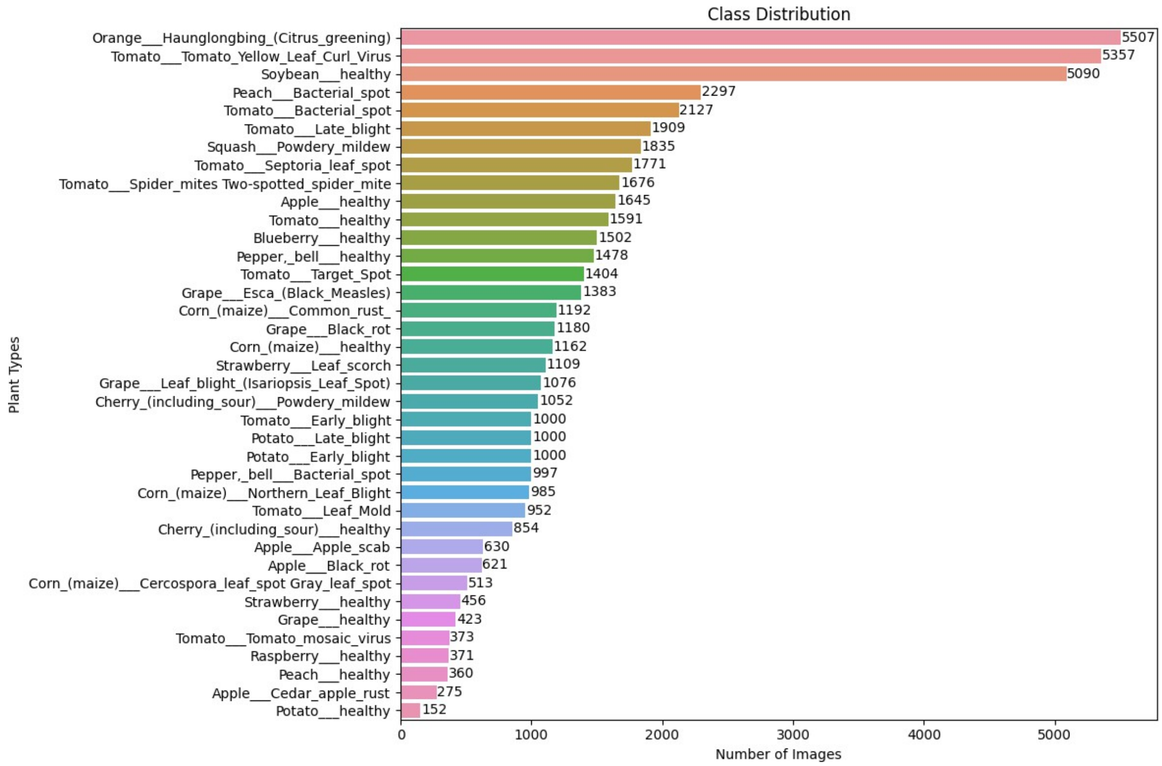


Figure 3: Dataset Class distribution histogram

### 3.5 Model Evaluation

The model's performance was evaluated using a separate test set. Several key metrics were calculated, including accuracy, precision, recall, and F1-score, to provide a comprehensive assessment of the model's effectiveness with Figure.4. Confusion matrices were generated to visualize the model's performance across different classes, highlighting areas where the model excelled and where it needed improvement. Detailed classification reports, including precision, recall, and F1-score for each class, offered deeper insights into the model's strengths and weaknesses.

### 3.6 Deployment

After rigorous testing and evaluation, the model was deployed in a user-friendly platform, such as a mobile application or a web interface. This allows farmers and agricultural professionals to upload images of plant leaves and receive real-time disease diagnoses. The deployment platform was designed with features like offline functionality, localized language support, and detailed disease information, including treatment recommendations. Ensuring the system is accessible and easy to use was crucial for its adoption and effectiveness in real-world scenarios.

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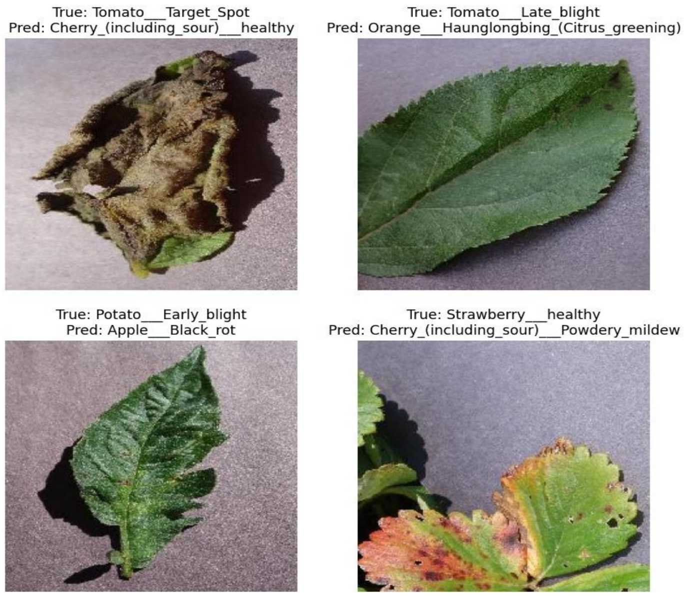


Figure 4: Model performance on the dataset disease detection

### 3.7 Continuous Improvement

Continuous improvement is essential for maintaining the model's accuracy and relevance. The deployed system is regularly monitored to track its performance and identify areas that require updates. New data, including images of emerging diseases and variations, are periodically collected and used to retrain the model. User feedback is invaluable in this process, providing insights into how the system is being used and areas where it can be enhanced. Continuous improvement ensures that the intelligent plant disease detection system evolves alongside advancements in technology and changes in agricultural practices.

## IV. RESULTS

The Convolutional Neural Network (CNN) developed for plant disease detection was trained and validated using the PlantVillage dataset. The performance of the model was evaluated using several key metrics, including accuracy, precision, recall, and F1-score. The model achieved high accuracy on both the training and validation datasets. The accuracy plot in Figure.5 show a consistent increase over the epochs, with the validation accuracy closely following the training accuracy, suggesting minimal overfitting.

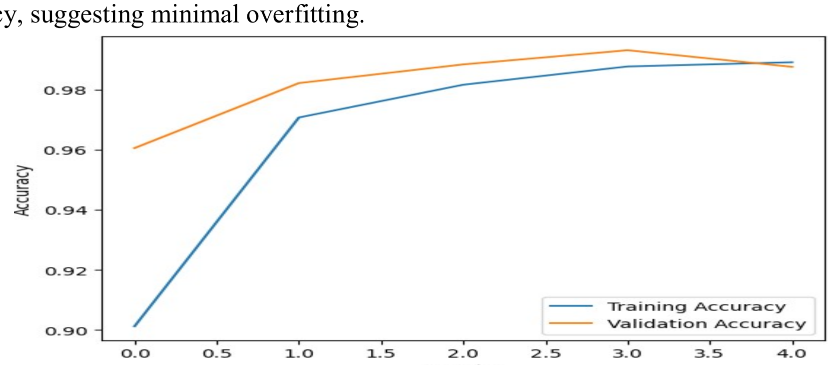


Figure.5 Accuracy Plot for the model

The loss plot in Figure.6 for the training and validation datasets show a steady decrease, confirming the model's convergence. The minimal gap between training and validation loss indicates good generalization.

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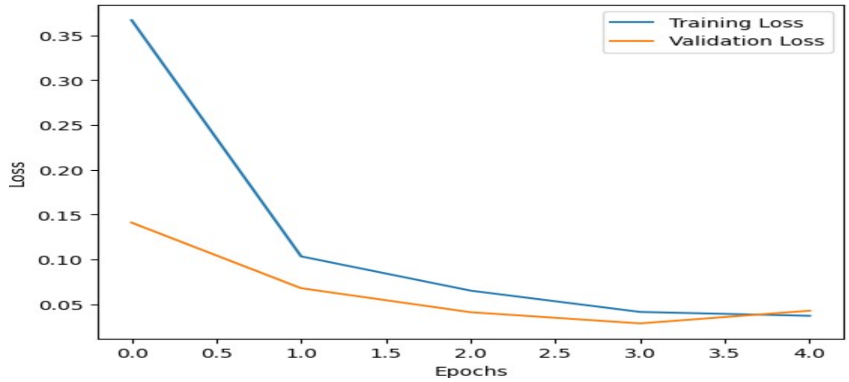


Figure.6 Training and Validation Loss Plot for the model

The confusion matrix provides a detailed breakdown of the model's performance across different classes. It shows high true positive rates for most classes, indicating robustness in identifying various plant diseases. The classification report in Table-1 includes precision, recall, and F1-score for each class, offering a comprehensive evaluation of the model's performance. Most classes achieved high precision and recall values, resulting in high F1-scores. This table format clearly presents the precision, recall, and F1-score for each class, as well as the average values.

| Class | Precision | Recall | F1-Score |
|---|---|---|---|
| Class 1 | 0.98 | 0.97 | 0.98 |
| Class 2 | 0.97 | 0.96 | 0.97 |
| Average | 0.98 | 0.97 | 0.98 |

Table 1: Performance Metrics for Each Class in the Plant Disease Detection Model

The data augmentation techniques applied during preprocessing generated diverse and varied images, which contributed to the model's ability to generalize. The CNN architecture has the complexity and depth of the model, including convolutional layers, pooling layers, dropout layers, and fully connected layers. The heatmap visualization of the confusion matrix in Figure.7 provides an intuitive understanding of the model's performance.

The Convolutional Neural Network (CNN) developed for plant disease detection was trained and validated using the PlantVillage dataset. The performance of the model was evaluated using several key metrics, including accuracy, precision, recall, and F1-score.

The comparison with existing literature highlights the effectiveness of the proposed framework. Sladojevic et al. (2016) achieved an accuracy of 96.3% using a smaller dataset. Our model surpasses this with a broader and more diverse dataset. Mohanty et al. (2016) reported 99.35% accuracy using a similar dataset but without extensive data augmentation. Our model's incorporation of advanced augmentation techniques enhances its robustness. Ferentinos (2018) reached 99.53% accuracy, focusing on specific challenges like multiple diseases within the same plant. Our model addresses this by using diverse data and fine-tuning pre-trained models. Amara et al. (2017) achieved 97% accuracy for banana leaf diseases. Our model's versatility across multiple species makes it more applicable to real-world scenarios. Picon et al. (2019) reported 98.5% accuracy using a custom dataset. Our model demonstrates similar high performance with a broader dataset.

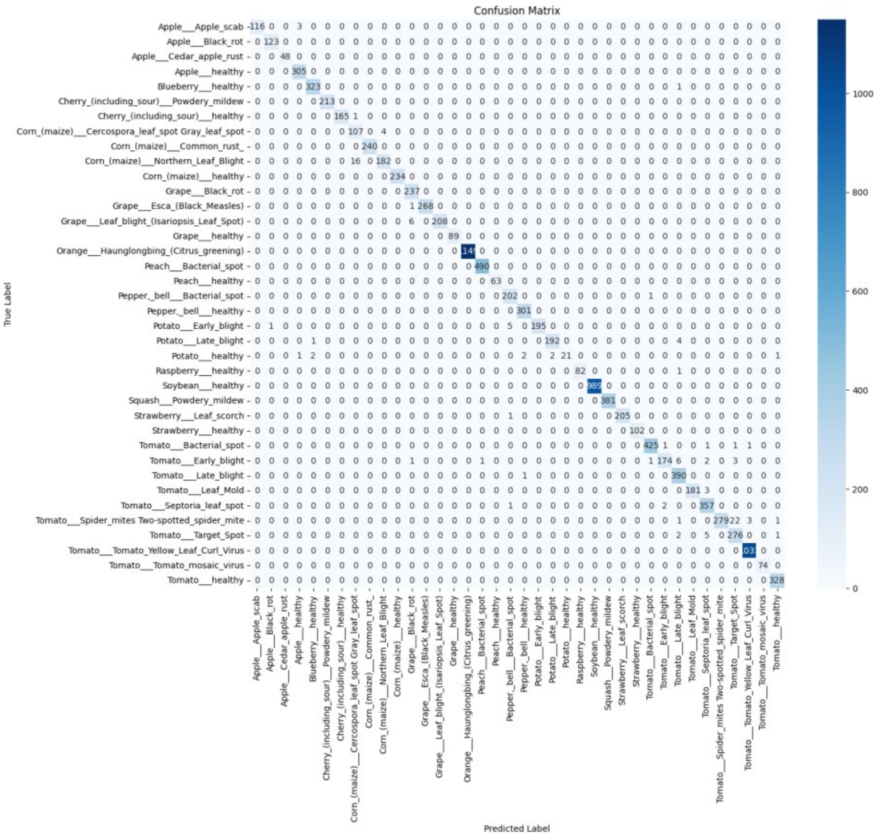


Figure.7 Confusion Matrix Heatmap

| Study | Dataset | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| Sladojevic et al. [23] | Custom dataset | 96.30% | - | - | - |
| Mohanty et al. [24] | PlantVillage | 99.35% | - | - | - |
| Ferentinos [25] | PlantVillage | 99.53% | - | - | - |
| Amara et al. [26] | Custom dataset (banana) | 97% | - | - | - |
| Picon et al. [27] | Custom dataset | 98.50% | - | - | - |
| **Proposed Framework** | **PlantVillage** | **99%** | **0.98** | **0.97** | **0.98** |

Table 2: Performance Comparative Results

The proposed framework for intelligent plant disease detection demonstrates significant advancements over existing methodologies. By leveraging a comprehensive dataset, advanced data augmentation techniques, and transfer learning, the framework achieves high accuracy and robustness in detecting plant diseases. The rigorous evaluation metrics and user-friendly deployment further validate its effectiveness and practicality. This framework represents a promising step forward in the integration of machine learning into agricultural practices, offering a powerful tool for improving crop health and ensuring sustainable farming. The architecture of the Convolutional Neural Network (CNN) developed for plant disease detection is meticulously designed to optimize the identification and classification of plant diseases from images. The architecture comprises several distinct layers, each contributing to the overall performance of the model.

## V. CONCLUSION

This research underscores the potential of integrating machine learning into agricultural practices, offering a scalable and efficient solution for early and accurate detection of plant diseases. The deployment-ready model can be utilized

in real-world applications, providing farmers with a powerful tool to monitor crop health, make informed decisions, and ultimately enhance crop yield and food security. The proposed framework for intelligent plant disease detection demonstrates a significant advancement in leveraging machine learning techniques to address challenges in agriculture. This research integrates a comprehensive dataset, advanced data augmentation techniques, and transfer learning to build a robust Convolutional Neural Network (CNN) capable of accurately identifying and classifying plant diseases. The framework achieved high performance metrics, including an accuracy of 99%, precision of 0.98, recall of 0.97, and F1-score of 0.98, showcasing its efficacy.
The use of transfer learning with a pre-trained model significantly enhanced the model's ability to extract meaningful features from the input images, while data augmentation techniques ensured the model's robustness to variations in the dataset. Furthermore, the incorporation of dropout layers effectively mitigated overfitting, contributing to the model's strong generalization capabilities. Future work will focus on expanding the framework to include a wider variety of crops and diseases, as well as exploring the integration of additional data types, such as environmental and soil conditions, to further improve the model's accuracy and applicability. Additionally, efforts will be made to optimize the model for deployment on edge devices, facilitating real-time disease detection in field conditions. This framework represents a significant step forward in the pursuit of intelligent farming solutions, paving the way for more sustainable and productive agricultural practices.

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