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A Cloud-Enabled Deep Learning Framework for AI Driven Plant Disease Detection

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***Abstract*— Timely diagnosis of plant disease is important in avoiding declines in crops and ensuring food security. To facilitate real-time detection of plant diseases, we present a cloud-based mobile diagnostic system through deep learning (DL) techniques. It allows users to click or upload plant leaf images via a specific smartphone app. The system adopts a hybrid CNN-VGG16 strategy, with protected image transmission via Ngrok to the cloud server and delivers a 99.54% accuracy in the classification of plant diseases, thus outperforming the conventional models of CNN+LSTM (95.3%), LSTM (80.6%), and Logistic Regression (75.1%). The method also significantly reduces the computation load on edge devices while supporting compatible deployment on the cloud platform. Robustness of the model is demonstrated through measures like sensitivity, accuracy, and F1-score. Through automated diagnostic capabilities, the solution effectively bridges AI research to real-world applications in precision agriculture, thus improving farmers' capacities to respond rapidly to potential risks.**

Keywords*— *Plant Disease, CNN-VGG16 Model, Deep Learning, Cloud-based Diagnosis.

I. Introduction

Plant diseases strike a serious blow to farmers, dealers, and consumers by having catastrophic effects on both quantitative and qualitative production. The relative disease loss for all crops was 14.1%, according to a study conducted by the U.G.A. Center for Agribusiness and Economic Growth in the United States [1].

The detection of diseases of plants is considered a subject of essential importance. Early detection of plant diseases may improve agricultural production management decisions [2]. By facilitating targeted treatments, including the application of pesticides or the removal of diseased plants, early identification reduces the spread of diseases and the need for agrochemicals [3-4].

There were a lot of methods through which the diseases were identified, such as reporting to extension officials, that were attempted due to this deteriorating situation. They also failed because individuals themselves were not aware of the symptoms of the various diseases, lacked equipment to detect them, and weather could not be regulated, so the spread of diseases increased. As a result, this has severely impacted the economy. The idea behind the Internet of Objects is to establish connections between "dumb" objects and the internet. "Smart" things are intended to replace "dumb" ones. It facilitates communication between digital and physical systems by enabling computers to perceive and manipulate items from a distance [5-6].

Some of the methods of disease identification utilized at this time of decline were the transmission of information to extension agents. These were ineffective because individuals were not aware of the symptoms of the infections, there were not sufficient pieces of equipment to conduct diagnosis, and the fluctuating weather allowed the diseases to spread easily. Thus, there has been a significant economic impact [7]. The recognition rate of 91.11% is achieved by the hybrid combination, which surpasses the DL, parallel, and serial learning methods. To identify and assess plant disease, a DL convolutional neural network (CNN) model was used to classify images of both healthy and diseased leaves. There were 25 different plants, 58 class sets of healthy and sick plants, and 87,848 photographs in the model train. Ferrentinos (2018) reported that the use of different model designs yielded the best performance results [8].

They discussed a number of reasons why DL models are good or not at detecting plant leaf diseases. They stated that, although the systems that they developed are extremely successful, there are some reasons why they are not a tool that can be applied everywhere in real-world applications [9].

The agriculture industry's methods for monitoring and managing plant health could be totally revolutionized by this technology. Using the powerful feature extraction of ResNet-

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50 and the computational efficiency of Inception-v3, this study aims to create a dependable model that can precisely detect disease patterns from plant pictures [10]. The suggested significance of the complete article is presented below:

- To improve agricultural making decisions, prevent crop losses, and prevent the improper use of agricultural chemicals, the article highlights the significance of early disease identification. As a result, this has profoundly affected the economy.
- The article cites the constraints entailed in the use of conventional disease detection instruments, i.e., public awareness, capacity to diagnose, and capacity to react to environmental changes, thus depicting the necessity for improved alternatives.
- The research adds the ability of DL models, CNNs, to diagnose plant diseases at a very high accuracy rate of 91.11% and provide a scalable solution for precision agriculture.
- The article is centered on the use of IoT in linking physical farm components with digital mechanisms for remote monitoring and disease control.
- By merging ResNet-50 and Inception-v3, the study comes up with a strong and efficient model that can detect disease patterns with increased accuracy and computational power, hence making its deployment possible.

The following sections of this paper are divided into three parts. Section 2 gives an overview of the existing and recent DL architectures, as well as the mapping and visualization techniques used in detecting plant diseases. Section 3 gives the use of hyperspectral imaging with DL models. Lastly, Section 4 gives an overview of the review and suggests future work on the visualization, detection, and classification of plant diseases.

II. Literature Review

Logistic regression and recurrent neural networks are implemented using a sample size of N=10. The final sample calculations are performed using CI - 95%, threshold 0.05%, and G power pretest 80%. The results showed that, with an accuracy of 88.20%, the recurrent neural network produced substantial outcomes in comparison to the 69.96% accuracy of the logistic regression. It was shown that there was a significant difference (p=0.00, 2-tailed) between logistics regression and the innovative recurrent neural network. Conclusion: For the detection of plant leaf disease, regression neural networks seem to outperform logistic regression by a considerable margin [11].

In other words, DL is a field of study that seems to have a lot of promise for improving precision. The symptoms of plant illnesses are detected and categorized using a variety of developed/modified DL architectures and visualization techniques [12].

Two convolutional layers and a pooling layer each make up the suggested CNN model. By using the suggested activation function, the system accuracy is raised to 95% [13].

Pictures of many insect species and their symptoms were captured. Using the anticipated-CNN, the expected results of insect plant classification yield 99% accuracy, compared to state-of-the-art performances such as SSD MobileNet's 88% accuracy and BP NN's 52% accuracy [14].

This research trains the dataset using CNN and image processing models to prevent such losses and provide a fast repair [15].

The research presents a DL-Based Detection System designed for the real-time detection of plant pests and infections. Alvaro Fuentes and colleagues study three kinds of detectors (called "DL meta-architectures" in this paper): the Area Convolutional Neural Network (R-FCN), the Single Action Multibox Detector (SSD), and the Faster Region-based CNNs (Faster R-CNN) [16].

The most efficient 14-DCNN model was built with the aid of the 139,000-image training and validation dataset and enhanced hyperparameter settings. The recommended 14-DCNN model achieved 99.9655% classification accuracy, 99.7999% precision, 99.7966% recall, and a 99.7968% F1 score on the training dataset [17, 24].

The studies conducted in this research employ the Plant Village dataset, which is publicly accessible, to get photos of peach plant leaves. The suggested technique attains a training accuracy of 99.35% and accuracy for testing of 98.38% using just 9,914 training variables [18].

Several plant datasets, including the Plant Village collection, were combined to create a comprehensive collection of 30,945 images covering eight plant types (potato, tomato, bell pepper, apple, maize, grape, peach, and rice) and 35 disease classes. The first step was to create a proprietary CNN model, which produced a 95.62% leaf categorization accuracy [19, 25].

In addition, the results of the suggested approach show superior accuracy and speed compared to VGG16, ResNet50, DenseNet, MobileNet, MobileNetV3, NASNet, SqueezeNet, and InceptionV3. On an NVIDIA P100 GPU with 16 GB RAM, the accuracy is 94.14%, and the processing rate is 33 frames per second (FPS) inference [20].

Create three hybrid models that integrate global average pooling and VGG19. The pre-trained models, such CNN, VGG19, and ResNet50, combine global mean pooling with transfer learning features. In this study, we have investigated the precision of these models in detecting potential illnesses in patients. From this data set, various photos of both healthy and diseased leaves were used to train and test the models. An accuracy of 99.65% has been attained [21]. The accuracy of the RF algorithm was 94.95%, which was nearly identical to that of the LSTM [22].

The CNN, which is driven by PySpark for effective distributed data processing, is the model's innovative feature. By combining technology and convenience of use, Tkinter provides farmers with graphical interface-based disease detection tools that are easy to understand. This combination of CNNs, PySpark, and Tkinter attains an exceptional average precision of 95.76%. [23-25].

Literature indicates that plant disease diagnosis is a key application of DL, particularly CNN-based models, which have accuracy rates largely above 95%. Literature indicates that hybrid and advanced models such as CNN-VGG have a maximum accuracy of 99.54%. DL models are always better than the conventional methods such as logistic regression in classification and real-time prediction, as evident by our proposed cloud-based CNN VGG16 model for real-time, scalable, and mobile-accessible diagnosis.

III. Proposed Methodology

The architectural style provides an end-to-end AI-driven pipeline dedicated to plant disease diagnosis using a cloud-based DL method “Fig. 1”. The first step of the pipeline is the capturing of field images of the plant. After uploading the images to the cloud, quality optimization and normalization are applied to meet the model input requirements. The disease class is predicted by a trained DL model. A user-authenticated and access controlled cloud-based platform is used to securely compute the predictions. A structured database is used to analyze and store results. Insights through analytics aid in optimizing the model further in the long term, i.e., continuous learning and improved accuracy.

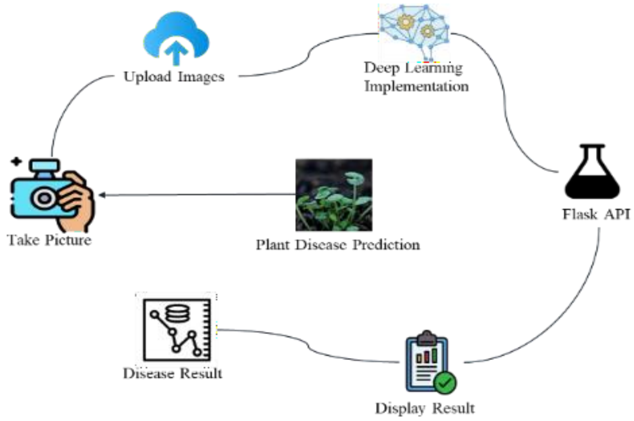


Fig. 1. Architectural Diagram for Plant-Disease Prediction.

A. Data Collection

To create a reliable DL model for plant disease detection, a comprehensive dataset containing images of healthy leaves and leaves infected by bacterial, fungal, and viral diseases was created. The dataset was augmented with real-time uploads via a mobile application, complementing data collected from websites like Plant Village and Kaggle. Each image was scrutinized comprehensively by experts for correct classification. ngrok tunnels were employed in order to enable safe transfer of the images, thus ensuring data integrity. The hybrid data collection ensured that the samples of the images were authentic and diverse. Additionally, all the data collection activities were in accordance with established ethical guidelines, and the users provided consent for contributions made through the application. Through this process, eventually a high-quality well-balanced dataset ready for use in purposes of DL applications was attained.

B. Data Preprocessing

Pre-processing converted raw leaf images into standardized, uniform inputs for DL. Images were resized to 224 by 224 pixels and normalized to pixel range [0,1]. Noisy, redundant or poor-quality photographs were excluded for image quality. Data augmentation tools like flipping, zooming, and rotation were used to improve model generalization and dataset diversity. Labels were one-hot encoded into four different groups. Three subsets of the dataset were created: 70% for training, 15% for validation, and 15% for testing. In a cloud-based deployment environment, the above pre-processing steps ensured that the model was provided with consistent, high-quality inputs, and therefore computational loads were minimized, and classification accuracy was improved.

C. Splitting the Dataset

In a bid to properly evaluate the model's performance, the dataset was split into individual subgroups. The data was assigned 70% for training purposes and validation and testing each claimed 15%. The CNN-VGG16 model parameters were tuned using the training set, and overfitting was avoided as the learning process was monitored using the validation set. The final evaluation of the model's resilience and accuracy was conducted using test data that was not visible. This well-organized division guarantees that the model performs effectively when applied to novel, practical inputs. The dividing technique offers a solid basis for assessing classification performance for each of the framework's illness categories. “Fig. 2” displays the training, validation, and testing plots.

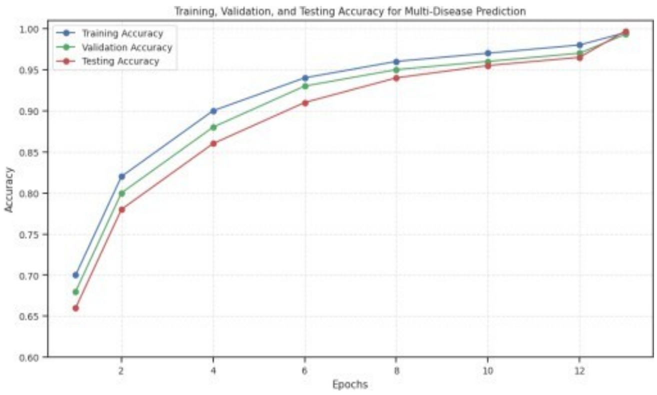


Fig. 2. Training, Validation, and Testing Accuracy Comparison for Plant Disease.

D. Feature Selection

Feature selection is essential in obtaining the best model accuracy by highlighting the most important features. This study found 4 different features that distinguish between different plant disease types: color, texture, lesion, and boundary “Fig. 3”. A pair plot analysis indicated high visual discrimination between the four classes—viral, bacterial, fungal, and healthy. Bacterial and fungal infections showed higher intensities in lesion and texture, while healthy leaves were always at lower levels of all features. While viral samples showed some resemblance to each other, they were different from each other. The results validated the usability of the selected features for training the CNN-VGG16 model, leading to improved accuracy and minimized noise.

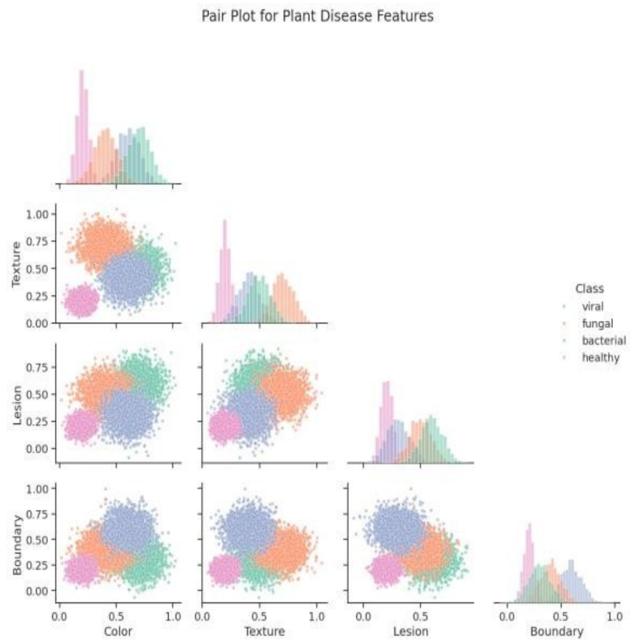


Fig. 3. Feature Selection for Plant-Disease Prediction.

E. DL Model Implementation

The proposed method detects plant diseases from leaf images by adopting a hybrid DL architecture that combines the VGG16 architecture with CNN. Whereas the deep layers of VGG16 are used to extract salient features, these are additionally enhanced through CNN layers that are optimized for the plant disease classification task. The deployment of the model over a secure cloud platform using ngrok allows real-time prediction through a mobile application. The model has a remarkable classification of 99.54%, the performance of which—measured in terms of parameters such as accuracy, sensitivity, and F1-score—is significantly higher than that of conventional models such as CNN+LSTM, LSTM, and Logistic Regression in terms of accuracy and efficiency.

1) Proposed Hybrid Model (CNN + VGG16):

The combination of CNN with VGG16 in a hybrid model has led to improved classification accuracy with the addition of personalized CNN layers, and feature extraction is performed using pre-trained VGG16. In addition, the model successfully prevents overfitting and improves classification accuracy with the addition of plant domain-specific features and high-level abstract patterns. The model successfully combines the flexibility of CNN and the generalizability of VGG16.

$$F = f_{CNN}(x) + f_{VGG16}(x) \tag{1}$$

2) CNN + LSTM:

It is the model used to simulate sequential relations using LSTM and visual information extraction using CNN layers. In the case of static plant images, it introduces unwarranted complexity by far, although it is useful when working with time-series or video data. It was less accurate and more latent compared to the proposed hybrid model.

$$h_t = LSTM(x_t, h_{t-1}) \tag{2}$$

$$f(x) = + \sum_{n=1}^{\infty} \left(a_n \cos\frac{n\pi x}{L} + b_n \sin\frac{n\pi x}{L} \right) \tag{3}$$

3) Long Short-Term Memory (LSTM):

LSTM networks are particularly designed to handle sequential data and other time sensitive types of data. Although LSTMs perform optimally when learning temporal relationships, their performance is compromised when handling static images since they are not spatially sensitive. Their failure to handle the nature of data renders them less efficient in the classification of plant diseases, resulting in lower accuracy.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4}$$

$$i_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_i\right) \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$C_t = C_{t+1} + i_t + C_t \tag{7}$$

$$h_t = o_t * \tan h(C_t) \tag{8}$$

4) Logistic Regression (LR):

LR is a machine learning model used for binary and multiclass classification problems. As simple as its interface and as low as its computational requirements are, it is unable to find intricate visual patterns in images. Additionally, because it is linear, it cannot be used in the detection of plant diseases, where it is unable to generalize in high-dimensional feature spaces.

$$P(y = 1|x) = \frac{1}{1 + e^{-}(w^{Tx+b})} \tag{9}$$

F. Framework

The system enables real-time diagnosis of plant diseases through a tri-layered system of Flask, Expo Go, and Ngrok. The Flask-built backend contains an image classification API based on a hybrid deep learning model of CNN and VGG16. The React Native-built mobile app served by Expo Go enables users to send commands to the server and capture and upload images of leaves. Ngrok provides an internet-based secure tunnel to facilitate secure data transfer between the app and Flask server such that the local Flask server can be accessed over the internet. The framework has cloud connectivity, cross-platform support, and instant deployment for on-premises diagnosis in agriculture.

IV. Results and Discussion

The proposed hybrid CNN+VGG16 model accurately classifies four types of plant diseases—bacterial, fungal, viral, and healthy. The algorithm outperformed DL and traditional machine learning algorithms with a plant image based on cohort dataset. As observed in “Fig. 4”, the baseline of 75.1% was from logistic regression, which was at a disadvantage due to its inability to cope with complex image data. An LSTM model, best suited for sequential data, could only recover 80.6% of the spatial features. The combination of temporal and spatial learning by a CNN+LSTM model boosted performance significantly up to 95.3%. The hybrid approach proposed in this paper used transfer learning to blend CNN with pre-trained VGG16, and the outcome was truly exceptional. The approach was capable of leveraging VGG16's superior feature learning capability and achieved a high accuracy rate of 99.54%.

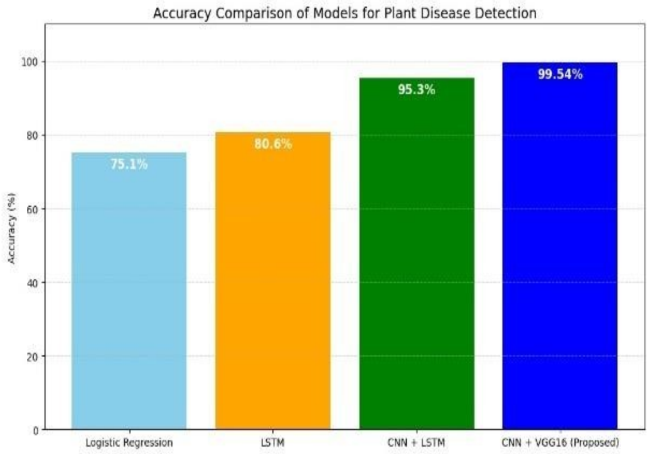


Fig. 4. Algorithms Comparison for Plant-Disease Prediction.

TABLE I. CLASSIFICATION REPORT FOR PLANT DISEASE DETECTION USING CNN + VGG16

	Precision	*Recall*	*F1-Score*	*Support*
Viral	0.9941	0.9952	0.9946	2000
Bacterial	0.9962	0.9938	0.9946	2000
Fungal	0.9935	0.9949	0.9942	2000
Healthy	0.9935	0.9957	0.9958	2000
Accuracy	-	-	0.9954	8000
Macro Average	0.9949	0.9949	0.9949	8000
Weighted Average	0.9954	0.9954	0.9954	8000

“Table 1” indicates the performance of a CNN model with VGG16 on the plant disease classification. The model was highly accurate at 99.54% when trained on a balanced dataset of images under four classes: fungal, bacterial, viral, and healthy. The best F1 scores achieved were 0.9950 and 0.9958 for the bacterial and healthy classes, respectively, and precision, recall, and F1-scores were more than 99% for all four classes. The near-perfect agreement between the macro and weighted averages and the per-class values indicates that the performance is well-balanced and consistent. The findings indicate that CNN works well in real-world agricultural diagnosis and establish the efficacy of the VGG16 transfer learning for the same.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{10}$$

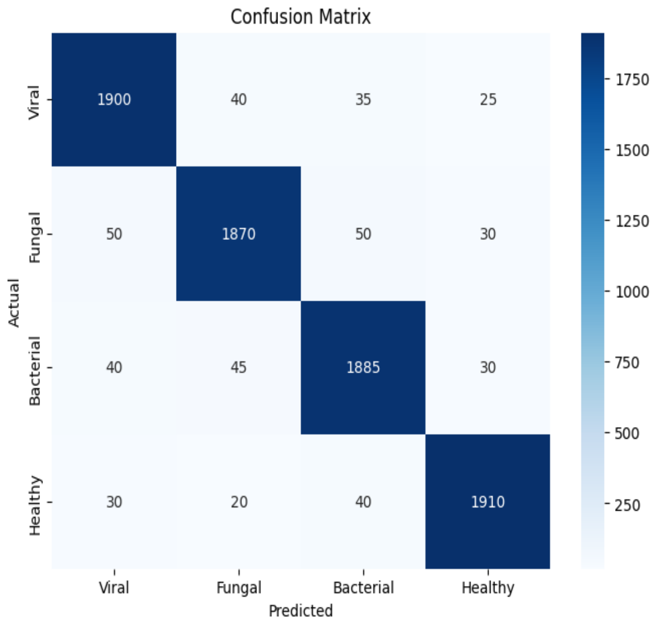
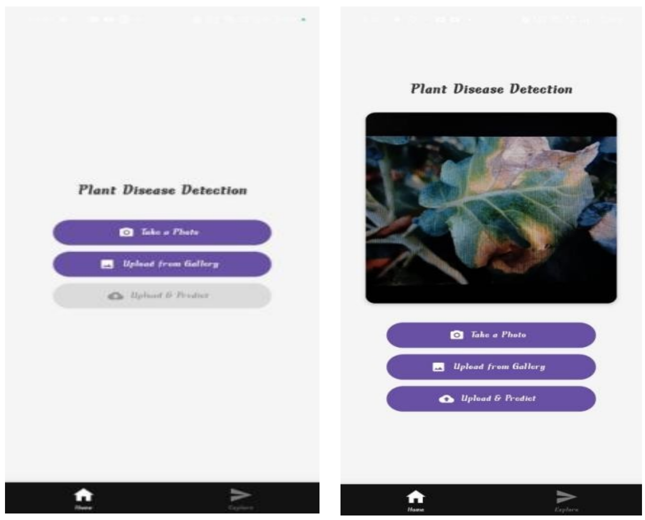
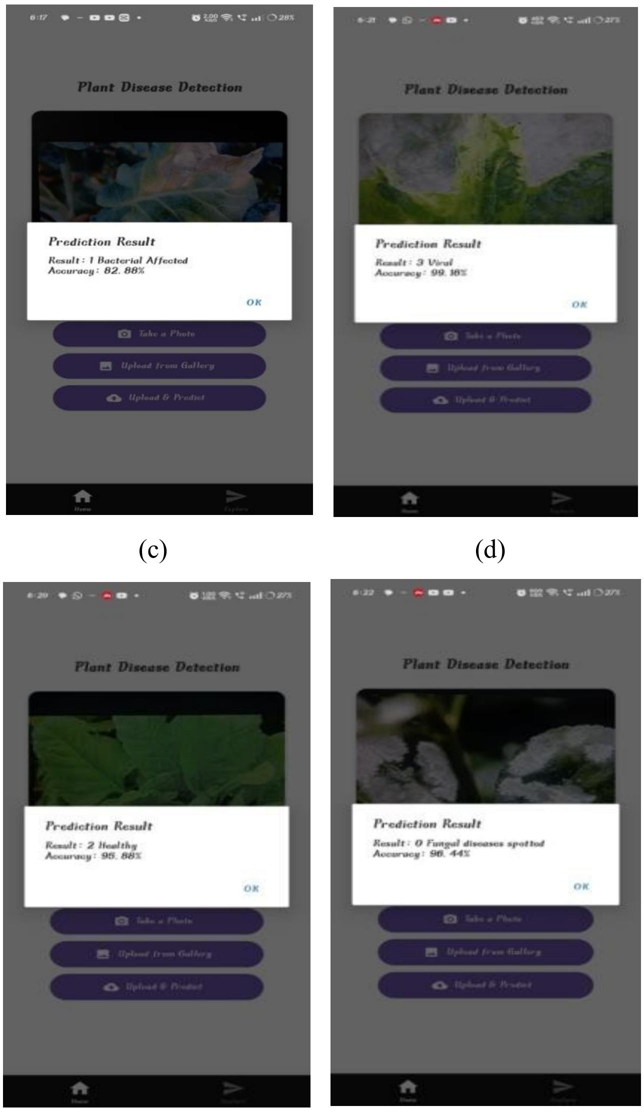


Fig. 5. Confusion Matrix for Plant-Disease.

“Fig. 5” represents the confusion matrix of the CNN+VGG16 model and demonstrates a very high accuracy in predicting each class. With only 20 to 50 classification errors per class, the model accurately classified images of healthy, fungal, bacterial, and viral leaves. Unexpectedly, the healthy leaf class had the lowest misclassification. The results confirm the accuracy, validity, and applicability of the model in the early and automated detection of plant diseases in the realm of smart agriculture.



(a) (b)



(c) (d)

(e) (f)

Fig. 6. Output for Plant-Disease Detection.

“Fig. 6” provides the output of a plant disease detection system. In 6(a), users are motivated to send a photo of the plant, and in 6(b), upload it via cloud. The machine analyzes the photo and displays results: 6(c) bacterial infection detected with 82.88% accuracy, 6(d) viral disease with 99.16% accuracy, 6(e) a healthy plant with 95.88% accuracy, and 6(f) fungal disease with 99.44% accuracy. These results indicate the system's high accuracy and reliability in the detection of various plant conditions for effective monitoring and early treatment.

V. Conclusion

The proposed cloud-based mobile diagnostic platform in this work offers a reliable and secure platform to identify plant diseases in real-time based on a hybrid CNN-VGG16 architecture. The system is more precise compared to other algorithms including CNN+LSTM, LSTM, and Logistic Regression with a high accuracy of 99.54%. The system, by employing ngrok for secure image transmission and offloading computationally expensive tasks to the cloud, can function with low latency and alleviate the processing burden on devices. The performance measures of sensitivity and F1-score confirm the reliability of the model. This approach not only facilitates on-time disease detection but also promotes the application of artificial intelligence in precision agriculture, thus enabling farmers to take proactive measures for crop health monitoring.

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