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A Machine Learning Approach for Robust Plant Disease Prediction in Agriculture Fields

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Abstract
Plant diseases are becoming more prevalent, which poses a significant threat to global agricultural profitability and necessitates the development of reliable and effective disease detection technologies. This work employs machine learning (ML) techniques to provide a comprehensive evaluation of prior research on plant leaf disease identification, highlighting the benefits, drawbacks, and practical applications of the various approaches used in the last several studies. The study focuses on a variety of machine learning techniques, including Support Vector Machines (SVM), Decision Trees, Random Forest, K-Nearest Neighbors (KNN), and Naïve Bayes classifiers, which have been widely used for plant disease prediction and classification. Applying these ML algorithms to a range of crop categories, our research shows that plant leaf diseases can be reliably identified and categorized. The study also examines the difficulties and potential for the future in this area, emphasizing the significance of creating complex, real-time monitoring systems to increase the precision of disease detection and promote sustainable agricultural productivity.

Keywords: Support Vector Machine (SVM), Random Forest, Decision Tree, Naive Bayes, K- Nearest Neighbour (KNN), Classification algorithm and Convolutional Neural Network (CNN), Transfer Learning (TL).

INTRODUCTION

Agriculture is the main driver of India's economy. The majority of Indians are employed in agriculture. A significant factor in India's economic growth is the productivity of its agriculture. India's economy depends on agriculture to the tune of about 70–80%. Since agriculture is one of the primary sources of food, governments everywhere, wealthy or poor, place a high priority on it. The growth of fungi, bacteria, viruses, and non-biotics in agriculture is influenced by a variety of environmental factors, including water, atmosphere, and climate. Therefore, crop damage could result in a significant decrease in productivity, which could ultimately affect the financial structure [1]. The most important component for the early onset of symptoms in many plants is the leaves. Numerous plant diseases can result in large yield reductions, endangering human lives on a daily basis. Plant diseases pose a major threat to agricultural productivity, food availability, and global financial stability. Due to their critical role in photosynthesis, leaves are particularly vulnerable to a number of illnesses, including fungus, viruses, and bacteria. Early and accurate detection of leaf diseases is essential for managing them effectively, minimizing crop damage, and boosting agricultural productivity. In the past, knowledgeable experts have diagnosed plant diseases by eye inspection.

 **Fig 1– Apple leaf**	 **Fig 2– Potato Leaf**
 **Fig 3– Soyabean Leaf**	 **Fig 4 – Mango Leaf**
 **Fig 5– Egg Plant Leaf**	 **Fig 6– Blueberry Leaf**
 **Fig 7– Bitter gourd Leaf**	 **Fig 8 – Grapes Leaf**
 **Fig 9– Bottle Gourd Leaf**	 **Fig 10 – Tomato Leaf**

 **Fig 11- Corn (Maize) Leaf**	 **Fig 12– Orange Leaf**

Fig 13– Cucumber Leaf

Fig 14 - Bacterial Blight

Fig 15– Healthy Leaf

Fig 16- Spot Blight

Fig 17– Powdery Mildew

Fig 18– Downy Mildew

This method can be beneficial even though it is expensive, time-consuming, and subject to human error. Furthermore, because of their complex and variable symptoms, some diseases can be challenging to accurately diagnose, even for highly qualified personnel. The need for automated, reliable, and scalable systems for the precise diagnosis and early detection of plant leaf diseases is therefore growing. The creation of these autonomous systems is made feasible by recent advancements in machine learning (ML) technology. These technologies find patterns and traits that are frequently invisible to humans by using big data sets and strong algorithms. With the use of several machine learning algorithms, including Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbors (KNN) and Naïve Bayes Classifier, a complex plant leaf disease
prediction system can be developed.

These models accurately classify the disease type by analysing features like colour, texture, and shape that are extracted from leaf images. Datasets such as the PlantVillage dataset have shown that machine learning

techniques can accurately classify plant diseases [2][3]. These systems are crucial for enhancing food safety and agricultural productivity because they can effectively detect and identify a variety of crop diseases, especially those brought on by bacteria, fungi, and viruses [4]. ML-based systems can classify diseases using these algorithms and notify farmers beforehand so they can take the necessary safety measures to prevent financial loss. In this study, we look into how machine learning methods can be used to identify diseases of plant leaves.
In this study, we look into how machine learning methods can be used to identify diseases of plant leaves. We compare modern machine learning techniques with manual methods, and we analyze the current methods, highlighting their benefits and drawbacks. This study provides a comprehensive overview of the field in order to encourage the creation of efficient, self-sufficient plant disease control systems, which ultimately aim to guarantee food safety and environmental sustainability.
Bacterial Blight: This common plant leaf disease is more common in damp, cool environments. Seeds can spread the infection, and this disease is primarily found at low level.
Brown Spot: Inconsistent plant watering and a bacterial or fungal infection on the leaves are the causes of this disease.
Downy mildew: This foliar disease is brought on by an organism that resembles a fungus. Spores in the air carry it from one plant to another. Because the infection is facilitated by persistent leaf moisture, it is a wet-weather illness
Healthy: When a leaf is disease-free, it can be classified using this class's collection of healthy leaves.
Powdery Mildew: Lack of airflow and high humidity are the main causes of white mold. White mold can grow if you plant your plants too closely together, don't allow enough air to circulate, or water your garden or potting soil too much.

2. LITRETURE RIVIEW

Methods of Machine Learning for Identifying Plant Diseases Authors: Burhanuddin Babukhanwala and Divyanshu Varshney IEEE, August 2022 [5] Plant diseases may significantly reduce the production of agricultural products and have a significant effect on food safety. Digital images are the foundation of the vast majority of automated systems created to date, enabling the quick implementation of algorithms. Traditional machine learning techniques like support vector machines (SVM), multilayer perception neural networks, and decision trees have been used to overcome the challenge of autonomous disease identification in plants. This article's main focus was leaf plant disease. CNN is used as a feature extractor and SVM is used for classification in a new plant leaf disease detection method that is based on a transfer learning methodology like deep learning. The evaluation of the suggested model was conducted using the PlantVillage benchmark dataset. Examined and contrasted with existing approaches, the proposed model performed better than earlier research, attaining a training accuracy of 88.77 percent.
R. Nalawade et al. [2] proposed a system that provides whole field surveillance, leaf disease identification, and continuous tracking of field variables such as temperature, relative humidity, wetness, and so forth. An app can be used to monitor real-time data and regulate the water flow even when the user is not physically present at the device. While regularly monitoring the harvested field, the proposed method efficiently shows the produced application's current state. The water pump can be controlled by users thanks to the program. Application offers information about the plant, required fertilizers, soil types, and disease-treating chemicals. 98.07% is the model's overall precision. Leaf diseases are detected early on using a combination of edge detection and machine learning. The model that helps people make educated

decisions about diseases is trained using machine learning techniques. The application of the insecticide is advised as a remedy for contaminated illnesses.

Performance Evaluation of Best Feature Subsets for Crop Yield Prediction Using Machine Learning Algorithms. [7] Improving crop yield prediction accuracy in the ever-changing agriculture industry is the problem addressed. Using a dataset of 745 examples, the study assesses the effectiveness of several important machine learning algorithms, such as Random Forest, K-Nearest Neighbour, Support Vector Regression, and Artificial Neural Network. The Random Forest algorithm is the most accurate predictor across a variety of feature subsets, demonstrating its effectiveness in managing the complexity of agricultural data through a strong 70%-30% training-testing split. The study highlights how crucial feature selection is to maximizing predictive power and offers insightful information for accurate crop yield forecasting. However, significant limitations include the possible limited generalizability to other crop types and the absence of comprehensive information on the feature selection procedure. Furthermore, scalability issues for large-scale agricultural systems are not specifically addressed, and Random Forest's intrinsic complexity may make it more difficult to interpret. In spite of these drawbacks, the study emphasizes how useful Random Forest is for predicting crop yields with exceptional accuracy in a variety of agricultural scenarios.

Agriculture is the primary industry in many other countries, not just India. The latest technologies are being used by researchers worldwide to try and address a variety of problems that farmers are currently facing. Zhong and Zhao [8] have proposed three methods: regression, focus loss function, and multi-label classification. Their architecture is based on DenseNet121. There were 2462 images of apple leaves with six different apple leaf diseases. With a 93.5% accuracy rate, the suggested approach performed better than more well-known multi-classification algorithms.

S. Pawar et al. [10] proposed a CNN algorithm that recognizes diseases from leaf images and suggests pesticides based on disease-related findings. Finding the likely class of appearance on a plant leaf is the goal of this study. For this type of estimation, an uncontrolled technique known as a neural network is utilized. This study employs convolution neural networks (CNNs) to detect plant diseases. CNN's proposed strategy consists of fifteen layers. The proposed system will also provide additional information about the plant disease affecting the leaves in the affected area, such as the name of the disease, its full accuracy, timing, and weather prediction details, in addition to identifying the pesticide provider for each location. There are ten plant species in the dataset: pepper, tomato, corn, rice, cucumber, cucumber, apple, sugarcane, and soy. To pre-scan the image and separate the leaf area, the system uses Gaussian dimensions, restriction, and selection. Using a filtering technique, the proposed system can detect the type of leaf disease with an accuracy of up to 93%. When all of the contributing factors are taken into account, the Convolution Neural Network provides superior disease diagnosis accuracy. In order to help farmers make daily decisions, like deciding which fertilizer is best for a given weather condition, the proposed system provides them with access to weather prediction data.

3. PROBLEM STATEMENT

The project uses machine learning techniques to suggest the best crops to grow, fertilizers to use, and crop diseases. In order to make it simpler for farmers to expand and increase their yield, machine learning is being applied to agriculture. A brief history of the illness is given, along with some recommendations.

S. NO.	ALGORITHM /LEARNING TYPE	FUNCTIO-NALITIES	ADVANTAGES	LIMITATIONS	TYPICAL APPLICATION IN PLANT LEAF DISEASE PREDICATION
1	**Support Vector Machine (supervised)**	Finds optimal boundary between classes	Effective for high dimensional data	Needs careful parameter tuning	Disease classification from leaf images
2	**Convolutional Neural Network (Deep Learning)**	Image feature extraction & classification	High accuracy in image analysis	Requires large dataset and computation	Automatic leaf disease prediction
3	**K-Nearest Neighbors (supervised)**	Classifies based on neighbors	Simple and non–parametric	Slower with large datasets	Detection disease type based on leaf texture
4	**Decision Tree (supervised)**	Classification and Regression	Easy to visualize and interpret	Prone to overfitting	Identifying specific plant diseases
5	**Random Forest (supervised)**	Improves accuracy using multiple trees	High accuracy and reduces overfitting	Computationally expensive	Multi-disease classification
6	**Classification algorithm (supervised)**	General category of algorithms for mapping input data to class labels	Wide applicability, interpretable	May require extensive preprocessing	Classifying leaf images into different disease classes
7	**Naïve bayes (probabilistic)**	Uses Bayes` theorem assuming feature independence	Fast, works with small datasets	Assumes independent among features	Classifying disease presence using color histogram features
8	**Transfer learning (Pre – trained models)**	Utilizes pre trained networks for new but related image tasks	Reduced training time, improves accuracy with limited data	High memory requirement, domain adaptation challenges	Accurate plant disease detection using pre- trained CNN models

4. METHODOLOGY

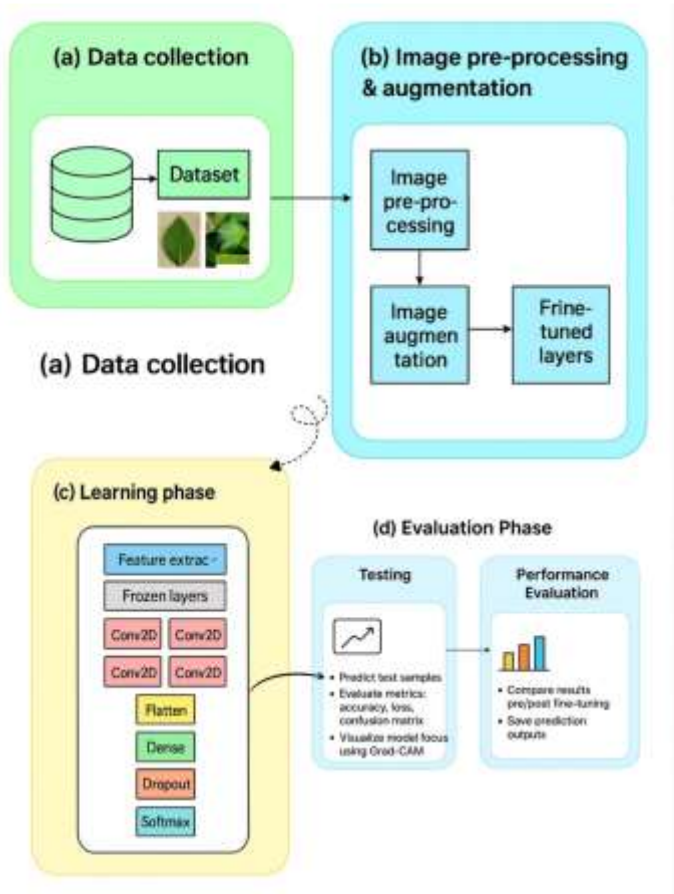


Fig 19 - Flow Chart

a) DATA COLLECTION

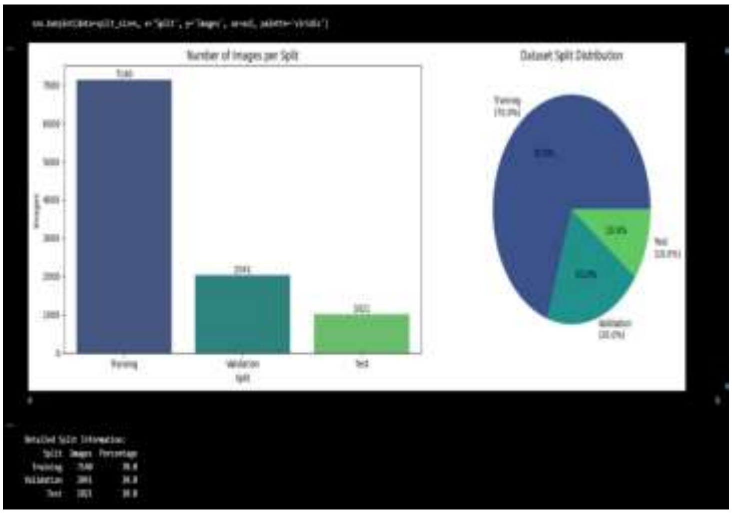
The initial and most crucial step in the development of any plant disease detection system is **data collection**. The foundation of this research work lies in the creation of a comprehensive and diverse dataset that encompasses multiple crop species and their corresponding diseased and healthy leaf images. The dataset used in this study was secondary collected from two reputable open-access sources **PlantVillage** and **Mendeley Data Repository** which are globally recognized databases for plant disease research and image-based agricultural studies. The **PlantVillage dataset** is an openly available, well-annotated collection of plant leaf images captured under controlled conditions with uniform backgrounds, lighting, and orientations. It includes thousands of high-resolution images for different plant species, each labeled according to the disease type or health status. On the other hand, **Mendeley Data Repository** provided an additional collection of plant leaf images captured under natural field conditions, containing variations in background, illumination, and leaf positioning, thereby improving the real-world robustness of the model. The dataset was organized into specific classes, and metadata such as date, location, and crop type were also maintained for future reference. The total dataset images were **27056** then divided into **training**, **validation**, and **testing** sets, maintaining an approximate ratio of **70:20:10**, respectively. This distribution helped the model to learn effectively while retaining unbiased samples for performance evaluation.

- **70%for Training**– used to train the model parameters,
- **20% for Validation** – used to tune hyperparameters and prevent overfitting
- **10% for Testing** – used to evaluate the model's performance on unseen data.

Plant Name	Number of classes	Class name
Apple	4	Apple Scab, Apple Black Rot, Apple Cedar Apple Rust, Apple Healthy
Bitter Gourd	3	Bitter Gourd Fusarium Wilt, Bitter Gourd Healthy, Bitter Gourd Mosaic Virus
Blueberry	1	Blueberry Healthy
Bottle Gourd	3	Bottle Gourd Anthracnose, Bottle Gourd Downy Mildew, Bottle Gourd Healthy
Corn (Maize)	4	Corn Cercospora Leaf Spot, Corn Gray Leaf Spot, Corn Northern Leaf Blight, Corn Healthy
Cucumber	3	Cucumber Anthracnose Lesions, Cucumber Healthy, Cucumber Downy Leaf
Eggplant	3	Eggplant Cercospora Leaf Spot, Eggplant Verticillium Wilt, Eggplant Healthy
Grape	4	Grape Black Rot, Grape Esca Black Measles, Grape Isariopsis Leaf Spot, Grape Healthy
Mango	6	Mango Anthracnose, Mango Bacterial Canker, Mango Die Back, Mango Gall Midge, Mango Powdery Mildew, Mango Sooty Mould
Orange	1	Orange Haunglongbing (Citrus Greening)
Potato	3	Potato Early Blight, Potato Late Blight, Potato Healthy
Soyabean	1	Soybean Healthy
Tomato	10	Tomato Bacterial Spot, Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, Tomato Septoria Leaf Spot, Tomato Spider Mites (Two-Spotted Spider Mite), Tomato Target Spot, Tomato Mosaic Virus, Tomato Yellow Leaf Curl Virus, Tomato Healthy

Table -1: Sample Table format

Table.2 - Dataset details with class names



b) IMAGE PRE-PROCESSING AND AUGUMENTATION

It was crucial to preprocess the images to ensure their consistency and quality before using them to train the deep learning model. A series of actions intended to increase image consistency and improve the model's capacity to extract significant features were included in the preprocessing phase.

Image Normalisation and Resizing, Noise Removal and Enhancement & Data Augmentation –

To meet the input requirements of the VGG16 architecture, all input images were resized to 224 × 224 × 3 pixels. After that, the pixel values were normalised to a range of 0 to 1 by dividing by 255. This ensures uniform input levels across all layers, stabilising and speeding up the training process.

Noise reduction techniques like Gaussian blur and median filtering were used to remove undesired disturbances without sacrificing crucial leaf texture features in order to increase clarity. Histogram equalization and other enhancement of contrast methods were also employed to increase feature visibility, particularly in outdoor photos in low light condition. Image methods for enhancement were used to improve model generalization and solve the overfitting issue. This required applying geometric modifications like these to create new images from preexisting ones:

Rotations at random (0°–40°) Zooming and cropping; flipping both horizontally and vertically; and adjusting brightness and contrast.

These modifications increased the model's variability and strengthened its resistance to unknown data. The additional dataset improved the depiction of environmental fluctuations and greatly expanded the number of training samples.

c) LEARNING PHASE

The **learning phase** is the core of the proposed framework, where the system learns to identify and classify potato leaf diseases using the **VGG16 transfer learning model**. Instead of building a CNN from scratch, transfer learning was utilized to leverage the pre-trained weights of VGG16, which was originally trained on the **ImageNet** dataset comprising over 50,000 images across 1000 categories. The convolutional base of VGG16 was used as a **feature extractor**.

The initial layers were frozen to preserve the general image feature knowledge, while the top layers were fine-tuned using the potato leaf dataset. The newly added dense layers were trained to adapt the pre-trained model's generalized feature space to the specific task of leaf disease classification.

the forward propagation in the network can be represented as:

$$\boldsymbol{f(x;\theta) = \mathrm{Softmax}(W_3 \cdot f_2(W_2 \cdot f_1(W_1 * x + b_1) + b_2) + b_3)}$$

where:

- x= input image tensor
- W_i, b_i= weights and biases for each layer
- $f_i(\cdot)$= non-linear transformation functions
- Softmax converts the output logits into class probabilities

Training Process - The model was trained using the **categorical cross-entropy** loss function, defined as:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where yi is the expected probability for each class and yi is the true label. Stochastic Gradient Descent (SGD) was used for the optimization, with a batch size of 32, a learning rate of 0.001, and a momentum of 0.9. When validation loss ceased improving, early stopping was used to prevent overfitting during the 50 periods of training.

d) EVALUTION PHASE

In order to evaluate the trained model's classification performance, the last step of the suggested methodology entails using test images that have not yet been seen. How well the model generalizes outside of the training set is shown by the evaluation.

Model Evolution and Forecasting -The trained VGG16 model is used to predict the disease category for each input image during testing.

Performance metrics are calculated by comparing the predicted class with the actual truth label. These are a few performance metrics:

- **Accuracy**: Measures the overall correctness of predictions.

$$\textbf{Accuracy} = \frac{\boldsymbol{TP + TN}}{\boldsymbol{TP + TN + FP + FN}}$$

- **Precision**: Indicates how many predicted diseased leaves are truly diseased.

$$\textbf{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

- **Recall (Sensitivity)**: Measures how many actual diseased leaves were correctly identified.

$$\textbf{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

- **F1-Score**: Harmonic mean of precision and recall.

$$\boldsymbol{F1} = \mathbf{2} \times \frac{\textbf{Precision} \times \textbf{Recall}}{\textbf{Precision} + \textbf{Recall}}$$

Classification Report:

	precision	recall	f1-score	support
Apple___Apple_scab	0.99	1.00	1.00	126
Apple___Black_rot	0.99	0.99	0.99	124
Apple___Cedar_apple_rust	1.00	1.00	1.00	55
Apple___healthy	0.98	1.00	0.99	128
Bitter_Gourd_Downey_mildew	0.79	0.13	0.23	114
Bitter_Gourd_Fusarium_wilt	0.88	0.99	0.93	100
Bitter_Gourd_Healthy	0.56	0.96	0.71	110
Bitter_Gourd_Mosaic_virus	0.96	1.00	0.98	120
Blueberry___healthy	0.99	0.99	0.99	129
Bottle_gourd_Anthracnose	1.00	0.99	1.00	120
Bottle_gourd_Downey_mildew	0.99	1.00	1.00	136
Bottle_gourd_Healthy	1.00	1.00	1.00	103
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	0.87	0.93	0.90	102
Corn_(maize)___Common_rust_	0.99	0.99	0.99	117
Corn_(maize)___Northern_Leaf_Blight	0.95	0.88	0.91	120
Corn_(maize)___healthy	1.00	1.00	1.00	131
Cucumber_Anthracnose_lesions	1.00	0.98	0.99	107
...				
accuracy			0.96	5402
macro avg	0.96	0.96	0.95	5402
weighted avg	0.96	0.96	0.95	5402

Fig .20 – Classification Report

To see classification performance across all classes, a confusion matrix was plotted. For every category, it offers comprehensive information about the proportion of samples that are correctly and incorrectly classified. Plotting accuracy/loss curves for training and validation was also done to track learning progress. A well-trained model with little overfitting is indicated by a steady and convergent loss curve.
Rembg is a tool that removes the background of an image automatically. It uses powerful AI models like U²Net or ISNet. When you give an image to Rembg, it studies the picture carefully — it looks at shapes, colors, edges, and the outline of the object. After that, the AI decides which part of the image is the main object and which part is the background. Then it removes the background or makes it transparent and gives you a clean PNG image. This process is very fast, accurate, and fully automatic, so you don't need to edit the image manually or use difficult image-processing methods.

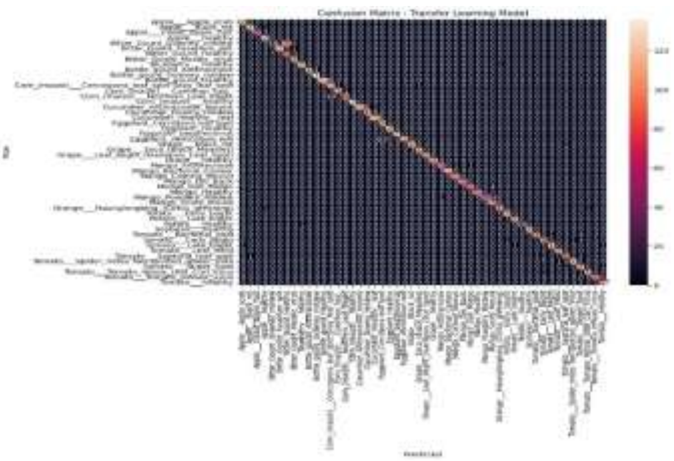


Fig .21 – Confusion matrix using Transfer Learning

5. RESULT & OUTCOMES

The results and discussion section of the crop project provides a testing accuracy **95.59 %** detailed evaluation of the effectiveness of key elements, including crop recommendation, fertilizer recommendation, and disease prediction modules. It assesses these modules' effectiveness using a variety of parameters, such as accuracy, recall, precision, and F1 score. While considering user feedback, model robustness, and data quality, the debate delves into the ramifications of the results. By performing comparative assessments with existing methods or literature, the benefits and drawbacks of the system can be better appreciated. It also looks for potential synergies between different modules to enhance system performance overall. Future research directions and improvements for each module are outlined with the aim of fixing problems and optimizing functionality. All things considered, this section provides critical analysis of the system's strengths, weaknesses, and potential directions for future development.

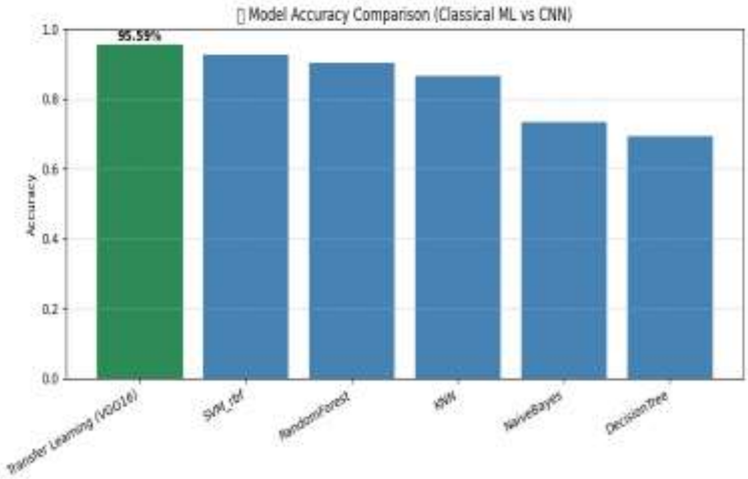


FIG .22 - Performance of plant leaf Prediction Model with different Datasets

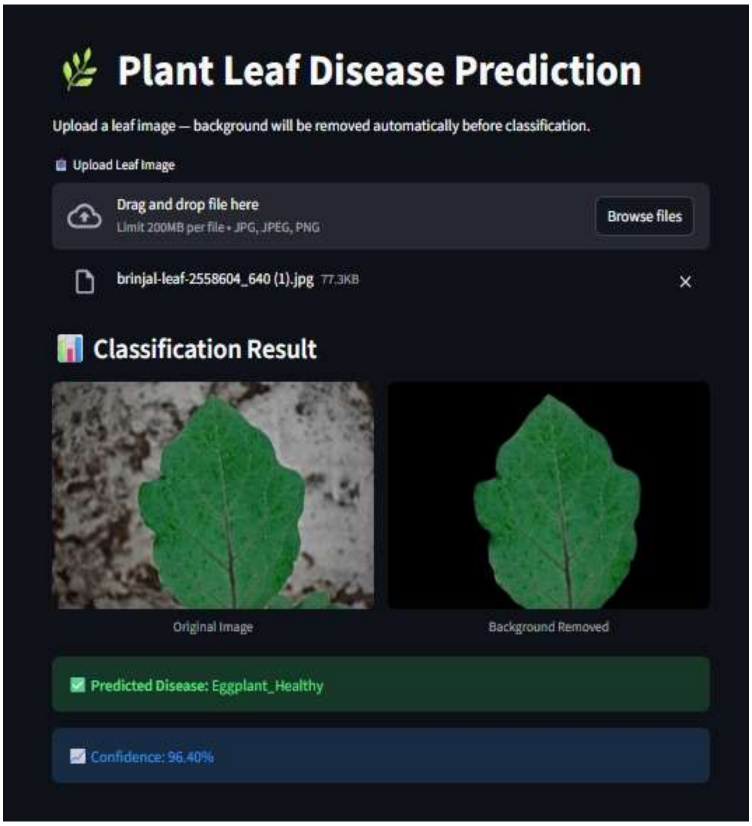


FIG .23 – Model interface and Prediction Result

6. FUTURE SCOPE

To increase its practical usability and accessibility for farmers, the suggested system for plant leaf disease prediction can be expanded and enhanced in a number of ways. The creation of a mobile application that enables farmers to simply take a picture of a plant leaf with their smartphones and receive immediate disease detection results is one of the main future goals. This will enable farmers to identify diseases directly in the field without the need for specialized equipment or professional intervention, making the technology more affordable, time-efficient, and accessible.

Additionally, multilingual support can be added to the system so that farmers with different linguistic backgrounds can use it in their native tongues with ease. The system can greatly improve adoption and usability in remote and rural areas by offering the interface and disease descriptions in local languages.

Furthermore, there is a lot of promise for integrating cutting-edge technologies like Internet of Things (IoT) devices and remote sensing. Furthermore, using artificial intelligence (AI) methods for purposes other than disease detection creates new opportunities to improve agricultural productivity and sustainability. To improve crop management techniques, resource allocation, and pest control tactics, researchers might investigate the application of AI-driven decision support systems.

7. CONCLUSION

In conclusion, automated plant leaf disease detection systems that make use of machine learning techniques present a revolutionary approach to contemporary agriculture. Researchers have shown that it is possible to accurately identify and categorise diseases affecting plant leaves through the development and application of robust **TRANSFER LEARNING**, allowing for prompt interventions to reduce crop losses and guarantee food security. Farmers and other agricultural professionals now have scalable,

effective, and easily accessible tools thanks to the application of sophisticated image processing techniques and machine learning algorithms. In order to solve lingering issues like model generalisation across various plant species and environmental conditions, as well as the integration of automated detection systems with precision agriculture technologies, further research and innovation in this area will be crucial. Plant leaf disease detection has the potential to transform crop
management techniques and advance sustainable agricultural development globally by utilising cutting-edge technologies and interdisciplinary collaboration.

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