



## Multi-Crop Plant Leaf Disease Detection Using Lite Models

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### Abstract

India, being an agricultural nation, significantly relies on agriculture for its economic growth. Farmers in India are facing several problems with plant diseases that directly impact crop yield. Plant diseases reduce both crop yield and quality. Detecting and treating plant diseases is crucial for achieving a high-quality crop yield. Identifying plant leaf disorders with the human eye is challenging and time-consuming. Our research will help farmers identify diseases even in their early stages with high accuracy and low time. We utilized a Convolutional Neural Network (CNN) trained on a large dataset for plant disease detection. Raw photos of normal leaves as well as sick leaves of various species abound in the dataset. The framework extracts features from the leaf image and classifies them based on the color, size, symptoms of the disease, and several factors and identifies the disease in real time. Adding more images and using EfficientNet-Lite has increased accuracy and efficiency with lower computational power. This model has higher potential than conventional transfer learning models. The suggested study outperforms the several machine learning tools currently in use in terms of accuracy. The results of this study show that the proposed model achieved 93% accuracy, indicating superior performance compared to traditional methods. The system's real-time recognition function allows early intervention and minimizes harvest loss. Future research should focus on expanding data records to improve inference period optimization, generalization, and further integration of environmental factors.

**Keywords:** Convolutional Neural Networks; Deep Learning in Agriculture; EfficientNet-Lite, InceptionV3; Leaf Disease Classification, PlantVillage Dataset

### Introduction

Among the top worldwide producers of the agricultural commodities on the planet, India ranks high. Rice, wheat, pulses, cotton, sugarcane, tea, coffee, and various fruits and vegetables are major crops in India. India is a highly populated country with a population of almost 1.4 billion citizens. Meeting people's nutritional requirements is essential for ensuring their healthy physical and mental development. To satisfy the food requirements of the large population of the country, farmers should produce crops in giant quantities. To produce in huge quantities, the cultivation of the crop should be more, but it is severely impacted by diseases of leaves on plants. These diseases are among the majority of the significant issues present in the world. This leads to heavy crop losses, because crop losses due to leaf diseases are estimated to be around 20% of the crop yield (Richard, Qi & Fitt, 2021).

The people and economy of the country are adversely affected by the diseases of the plant leaves. Diseases like black rot, common rust, leaf blight, leaf mold, bacterial diseases, etc., can damage crops like apples, cherries, corn, grapes, potatoes, tomatoes, oranges, peppers, etc. These leaf diseases are caused by fungi, bacteria, rust fungi, nematodes, and climate change. They first attack the leaf,

then damage the plant, and can easily spread to other plants in the surrounding area with the help of wind, water, soil, insects, etc. (Abd Algani *et al.* ,2023). Early detection of these illnesses by farmers helps prevent significant costs and crop failures. Therefore, it is crucial to identify illnesses early on before they spread to other plants (Ashwinkumar *et al.* , 2022). Farmers with knowledge know how to spot illnesses manually, while the farmers who are not experienced and don't have much knowledge on the leaf diseases will not be able to detect the diseases, and due to lack of knowledge, there is a chance of misunderstanding the disease and using the wrong remedy or using pesticides or insecticides to cure the disease, which can cause severe damage to the plant (Falaschetti *et al.* , 2022; Sharma, Tripathi & Mittal, 2023). Identifying the plant diseases manually is a very difficult, time-consuming, high-error-rate, and very costly process, as labor is involved (Hukkeri *et al.* , 2024). To overcome these challenges, an automatic leaf disease detection process should be used.

Image processing, artificial intelligence, and graphical processing units are so developed that they can analyze the plants at high precision and help with their proper growth (Shoaib *et al.* , 2023). Machine learning models are more appropriate for plant disease identification because they can examine complex patterns in the data efficiently. ML models can automatically extract the characteristics from the photos, such as texture, shade, and geometry from the leaves, thus no need to manually extract them. These models also promise highly accurate and precise results; they are very cost-effective and adaptable and can easily be integrated with IoT devices for constant monitoring. Deep learning, the evolution of machine learning, can handle massive datasets and produce more precise outcomes. Highly accurate results are obtained by training the deep learning model with a large dataset. Deep learning excels in image recognition, parsing natural language, and determining speech.

One type of deep learning model is convolution neural networks, which can efficiently analyze visual data such as images. Categorization of photos and identification of objects are easily done by CNN because of their capacity to gain knowledge and detect the characteristics of the images. CNNs contain various layers, and each layer is used to process and analyze the complex patterns in the image, and results are directed to the output layer. To train the CNN frameworks, a huge amount of data is utilized. The image dataset size and diversity can be increased by the method called image augmentation, where the original images undergo various modifications and transformations, including rotation, flipping, noise addition, cropping, scaling, color enhancement, and image deformation. Overfitting occurs when the deep learning framework learns the training information too well, incorporating noise and useless patterns. This leads to poor recognition of the new data. Diversifying the data and balancing the model's complexity can prevent this.

The determination of diseases of leaves is critical for plant growth as well as high yielding of the crop. It can be manually done by the specialists and experienced farmers, but it has many cons, and agricultural experts are not available in the remote and several rural areas of the country. We, in this research, help the farmers to easily identify the diseases by developing deep learning models using architecture like MobileNet v3, Inception v3, and EfficientNet Lite, and these are trained under the actual dataset named PLANT VILLAGE DATASET to accurately identify the illnesses.

## Literature Review

The main goal is to develop a model that precisely, accurately, and easily identifies plant leaf diseases without any mistakes, hence greatly assisting farmers. Thus, the leaf diseases will not cause crop loss. Our system will easily identify the diseases caused by bacteria, viruses, fungi, and nematodes and also detect diseases caused by climate change. This model identifies the diseases even in the starting period of the illness. so that the farmer can take necessary actions like removing the infected leaves and their debris, using insecticides and fungicides, isolating the plant, keeping spacing for proper air circulation, etc.

Image processing techniques are primarily used to easily identify any infections caused by fungi and viruses. The dataset named Plant Village is given as an input for the training of the model, which contains 54,000 images categorized across 38 different plant species and diseases. These images are classified based on the plant species and specific disease affecting them. The resolution of the original images is 260\*260 pixels. Techniques for augmenting data include scaling, rotation, noise injection, and color changes, which all help boost data diversity. Below are the earlier studies conducted by academics on the subjects of plant leaf disease identification.

Examining earlier deep learning-based plant disease detection techniques will help to create a more optimised, resource-efficient model. The following papers highlight current models, their computational issues, and the need for greater efficiency.

Dey, Sharma & Meshram (2016) identified the betel vine's leaf rot disease using image processing methods. He asserts that the image processing techniques can detect the leaf-rot illness of the plants based on the color features of the rotten data. But the traditional methods are straightforward but ineffective and time-consuming. He uses image processing techniques based on Otsu threshold to separate the diseased part of the leaves of the piper betel. This is the technique used to figure out the proportion of sick regions in the twelve plant leaf photos. The suggested method's recall value can occasionally be as low as 50%, despite its great precision. It can help farmers by reducing the cost of pesticides because it identifies the severity of the disease. Jiang *et al.* (2019) proposed the use of deep learning for spotting the leaf-related illnesses of the apple plant. The framework gets taught using the information from the apple leaf disease detection dataset. The INAR-SSD framework was used to pinpoint the top five diseases of the leaves of the apple plant. The model achieved the efficiency of almost 79% 79% mAP on the dataset, having an impressive detection rate of almost 23 frames per second.

Vallabhajosyula, Sistla & Kolli (2024) utilized Improved Vision Transformer and ResNet9 frameworks of deep learning for the detection and categorization of illnesses in the plant leaves. Hierarchical Residual Vision Transformer model is built in order to cut down on overfitting as well as complexity. The efficiency of the model is increased by tuning using Optuna with 25 trials. The evaluation of the model for 20 epochs yielded a high accuracy and a model building time of 42.2 minutes. Rao *et al.* (2021) Rao *et al.* (2021) proposed that the dataset used for the model included almost 8,500 photos representing good and sick leaves. The deep convolutional neural network (CNN) is trained to detect diseases or their absence. Used to do automatic feature acquisition, the already trained CNN framework AlexNet finds mango leaves as well as grape leaves with great detection accuracy.

Atila *et al.* (2020) say that the Plant Village dataset, made up of 55,448 photos in 39 categories, is used to evaluate the deep learning framework EfficientNet, created for identifying leaf diseases. When compared with various deep learning frameworks, the EfficientNet was the best. Z. Jiang *et al.* (2021) "reported that the Visual Geometry Group Network-16 (VGG16) model can be enhanced and improved based on multi-task learning and then utilize ImageNet's pre-trained model for alternate learning and transfer learning" (p. 1). The detection of health issues in rice and wheat leaves is more precise.

Harakannanavar *et al.* (2022) "extracted the feature of the leaf samples by using Discrete Wavelet Transform, Principal Component Analysis, and Grey Level Co-occurrence Matrix. Contour tracing is used to extract the boundary features of the leaf"s. "Support Vector Machine (SVM), Convolutional Neural Network (CNN), and K-Nearest Neighbor (K-NN) are used for the classification of the extracted features and have accuracy as 88% for SVM, 97% for KNN, and 96.6% for CNN" (Harakannanavar *et al.* , 2022).

Tang *et al.* (2023) offer a solution for identifying tomato plant infections by utilizing PLPNet to overcome challenges such as intraclass variability, interclass similarity, and soil backdrop interference. The proposed method, which includes a perceptual adaptive convolution module, can extract disease features. "Test results show that PLPNet reaches 94.5% average accuracy with 50% thresholds on a dataset created by the researchers" (Tang *et al.*, 2023, 1). Xu *et al.* (2024) introduce PDNet, a model that uses nearly identical network weights for disease recognition on the leaves of plants for the purpose of reducing labor and storage demands. PDNet incorporates an adapter block for parameter-efficient training. Essential leaf features are preserved by Overlapping Patch Embedding (OPE), and fine-grained recognition of similar diseases is achieved by Angular SoftMax Loss. We tested this model on six datasets.

Upon examining these studies, it becomes clear that, although current deep learning models attain high levels of accuracy, many require significant computational resources. This emphasises the need to develop a lightweight and resource-efficient model that can be effectively used in real agricultural settings.

### **Proposed Method and Architecture Diagram**

#### *Dataset*

The publicly accessible PlantVillage dataset (Kaggle, n.d.; Meta-Album, n.d.) has more than 54,000 labelled photos of plant leaves, including both healthy and diseased specimens. We resampled it to 19,000 images, maintaining 500 images per class across 38 distinct categories. In order to recognize

and categorize plant illnesses, it was used as training data to train our deep learning framework. The PlantVillage dataset's wide variety of disease types helped support increased crop yields, facilitate precise disease diagnosis, and encourage effective pesticide usage in agricultural practices. Sample images are illustrated in Figure 1.



**Figure 1:** Pictures of both normal and sick plant's leaves

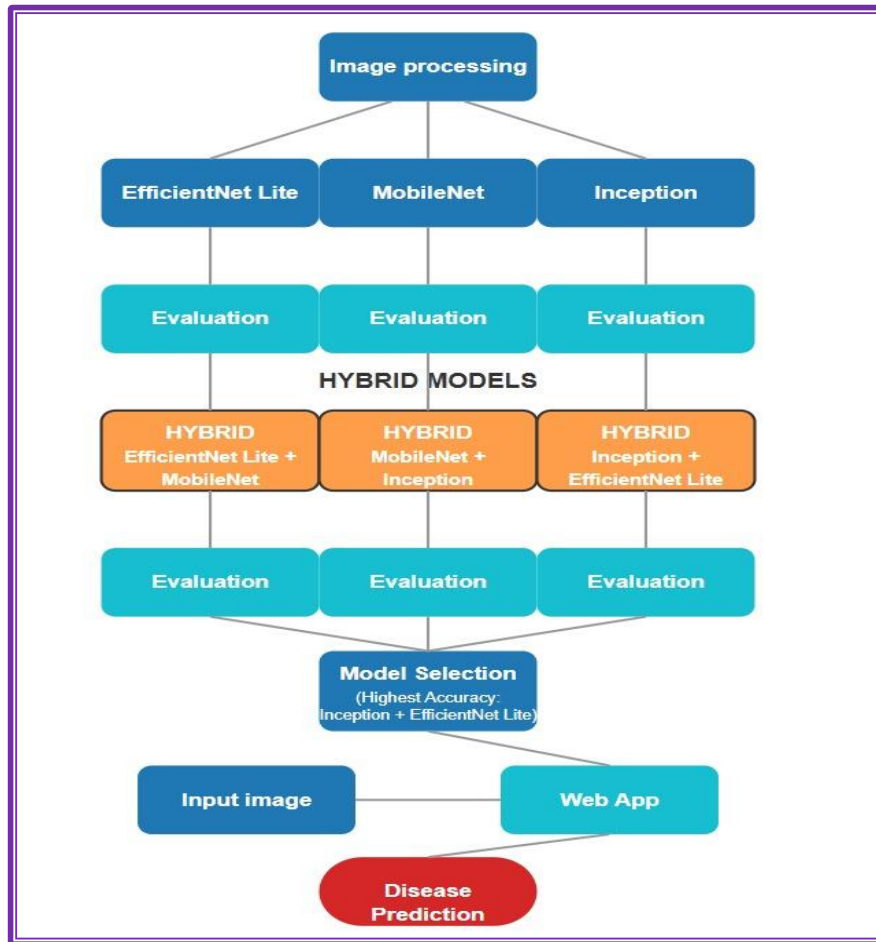
#### Data Pre-Processing

The Plant Village dataset must be preprocessed to prepare it for machine learning models. Key techniques include adjusting the dimensions of pictures to be consistent for model compatibility; pixel values are normalised to scale them between 0 and 1 for better convergence, and data variety is improved by using the data augmentation techniques including flips, rotations, and modifications to colour. Additional steps include converting images to grayscale if required, dividing the dataset into three categories: testing, validation, and training, and addressing category imbalances through oversampling or synthetic data generation. These preprocessing steps ensure optimal model performance and generalization.

#### Model Construction

Figure 2 shows the suggested approach. The following steps are used to build the forecast model:

- Collection of the pictures through the dataset.
- Rotation and changing the size of the pictures for pre-processing of the data.
- Designing complex feature links into Fully Connected Layers. Usually, it is flattened, transformed into a one-dimensional (1D) array (or vector), and then linked to one or more fully connected layers.
- Lastly, retrieve the characteristics for various input classes.



**Figure 2:** Proposed Methodology

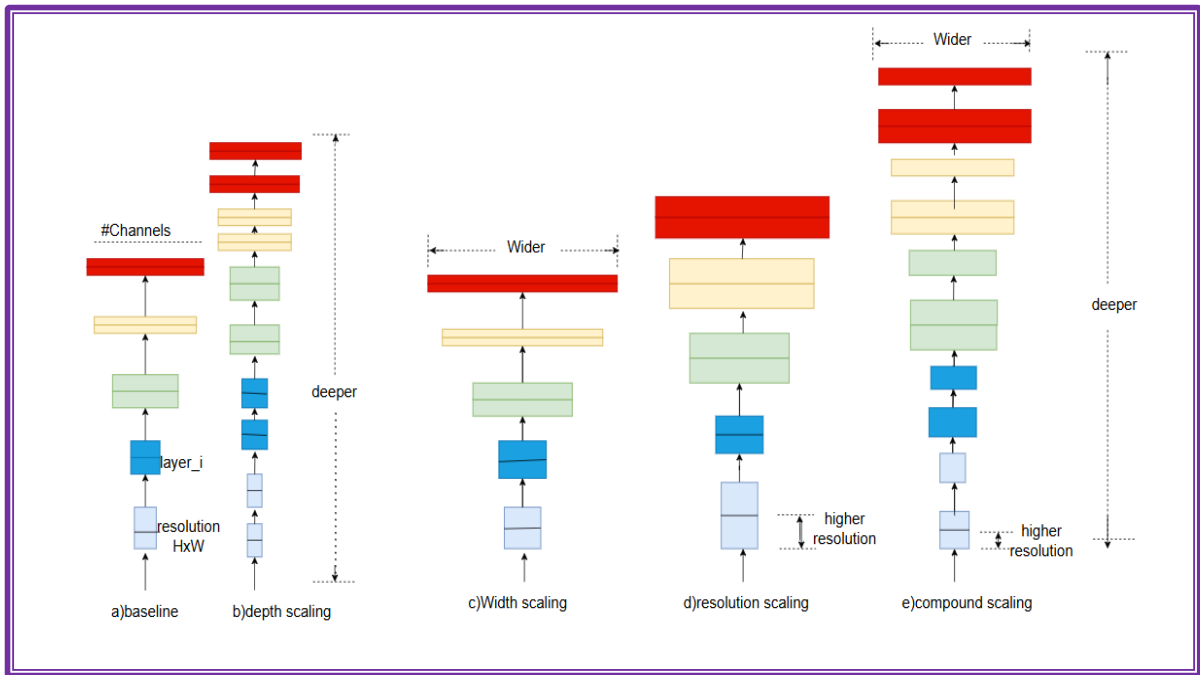
### Deep Learning Models

The following are the models we have applied:

#### 1) EfficientNet lite:

Our application of the convolutional neural network method here identifies and classifies plant illnesses using the EfficientNet-Lite algorithm on leaf photos. EfficientNet-Lite, a simpler version based on the EfficientNet architecture intended for handheld phones and edge devices, is suited for real-world agricultural uses with limited computing capabilities. The first step in the procedure is gathering and preprocessing a collection of photos, i.e., a dataset of plant leaves, comprising both healthy and diseased leaf images. Preprocessing techniques that improve generalization and guarantee model resilience include scaling, normalization, and data augmentation.

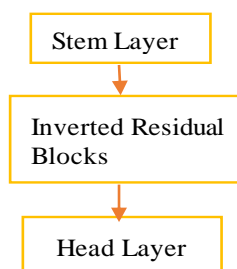
A key aspect of our approach is leveraging EfficientNet Lite's compound scaling technique for the model. Sai Reddy and Neeraja (2021) introduced EfficientNet, a novel compound scaling method that uniformly balances depth, width, and resolution in Convolutional Neural Networks (CNNs), and we have applied the scaling to optimize performance as well as maintain computational efficiency, as shown in Figure 3. This allowed us to accomplish balance between accuracy and speed. We integrated the compound scaling with EfficientNet Lite and achieved a higher accuracy of 98%, making the model highly effective. With this high accuracy, we were able to identify symptoms even at the onset of the disease, assisting in halting the spread of the illnesses and simplifying the farmer's task.



**Figure 3:** Different scaling methods and Compound Scaling

- Baseline: The initial, unscaled network.
- Depth Scaling: Adding more layers.
- Width scaling: enlarging each layer's channel size.
- Resolution scaling: improving the quality of the input image.
- Compound Scaling: Increasing width, depth, and resolution all at once using the formula for compound scaling.

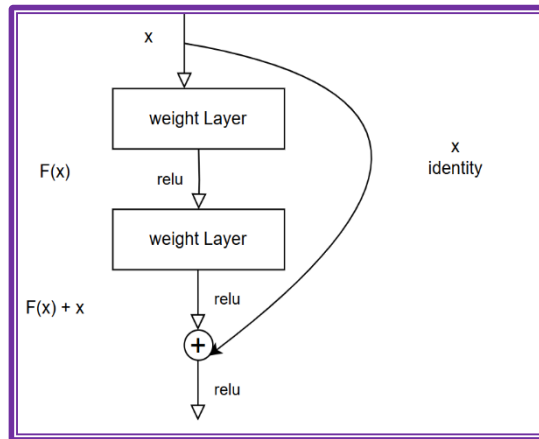
In this model the network begins with a stem layer (Figure 4), which is a 3x3 convolutional layer which helped us to extract the characteristics of the input pictures of leaves. The network next sends retrieved traits to the following layer made up of inverted residual blocks, where we integrated depth wise separable convolutions with residual connections to capture complex features. The model concludes with a head layer, a 1x1 convolutional layer which compresses the characteristics and gets them ready for disease category segmentation.



**Figure 4:** EfficientNet Network Architecture

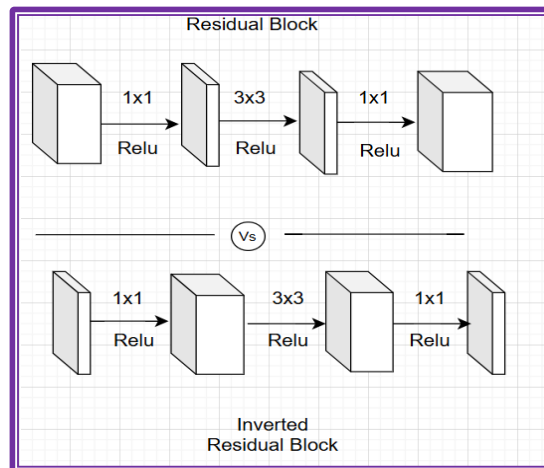
*a) Residual Blocks*

Comprising 2/3 convolutional layers, residual blocks feature skip connections wherein the first layer's input and the last layer's output are combined. He *et al.*, (2016) developed Deep Residual Learning, which trains very deep neural networks with better image recognition performance by overcoming the vanishing gradient issue using residual connections as illustrated in Figure 5.



**Figure 5: Residual Block**

Residual Blocks follow a wide->narrow->wide structure with respect to the number of channels (feature maps). Intermediate layer is called a “bottleneck” operating on a smaller number of feature maps (Figure 6).



**Figure 6: Residual vs Inverted Residual blocks**

In an Inverted Residual Block, we use a narrow->wide>narrow structure instead.

**b) Squeeze and Excite Layers**

Introduced by Hu, Shen, and Sun (2018), Squeeze-and-Excitation (SE) Networks are an architectural component boosting CNN performance by dynamically modulating channel-wise features with low computational overhead. Squeeze and excite optimization is added to each of the MBConv blocks. Through Squeeze and Excite, parameters are added to each channel of a convolutional layer so that the network can modify each feature map’s weighting. More important features can be emphasised, and less useful ones can be suppressed.

**c)EfficientNet-Lite Architecture**

The EfficientNet model slimmed down to perform better on smaller devices. The following changes were made in the process:

All the Squeeze and excite blocks were removed as they as not well supported by edge devices.

- All swish activations were replaced with ReLU6.
- $Swish(x) = x \cdot \sigma(x) = x \cdot \frac{1}{1+e^{-x}}$  (1)

Here,  $\sigma(x)$  is the sigmoid function.

instead, we use  $ReLU6(x)=\min(\max(0, x),6)$

- The stem and the head layers were fixed (kept the same) while scaling models up. This was to

ensure that the models could be kept small and fast.

### 2) MobileNet V3 Model:

The MobileNetV3 architecture, designed for identifying plant diseases, comprises an Input Layer, Initial Convolutional Layer, Bottleneck Block Layers, and a Final Convolutional Layer. The Input Layer handles plant leaf images, resizing them to 224x224 to ensure model compatibility. The Initial Convolutional Layer employs a 3x3 convolution with 32 filters and a stride of 2, capturing fundamental edge and texture information from the input images. The main part of the architecture lies in Bottleneck Block Layers, which extracted multi-level features such as color variations, spots, and lesions indicative of plant diseases. Each Bottleneck Block is composed of:

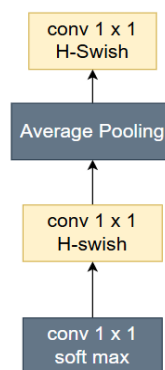
1. Expansion Phase: Increases input feature dimensions using 1x1 convolutions.
2. Depthwise Convolution Layer: Processes spatial features by channel using 3x3 convolutions.
3. Projection Phase: Reduces the output back to lower dimensions using 1x1 convolutions.

These blocks include squeeze-and-excitation modules that enhance important features while suppressing irrelevant ones, optimizing feature extraction for plant disease detection. Sandler *et al.*, (2018) introduced MobileNetV2 and Qian, Ning and Hu (2021) optimized MobileNetV3 for image classification by integrating depth wise separable convolutions, squeeze-and-excitation modules, and hard-swish activation and we used the **hard-swish** activation functions in key layers and improved non-linearity with minimal overhead (Figure 7).

The Hard-Swish function can be defined as in equation 2.

$$H - Swish(x) = x \cdot \frac{ReLU6(x + 3)}{6} \quad (2)$$

Where,  $ReLU6(x) = \min(\max(x, 0), 6)$



**Figure 7: Mobilenetv3 Last Stage**

Using a 1x1 convolution, the Final Convolution Layer combines upper-level traits that the bottleneck blocks can access. Ensuring compact feature representation, a Global Average Pooling Layer subsequently converts the spatial dimensions of the feature maps into a single vector. With the number of neurones corresponding to the number of classes in the dataset, the Fully Connected Layer connects these extracted properties to particular illness categories. The Output Layer converts the raw scores into probabilities, hence allowing efficient plant disease categorisation.

### 3) Inception V3 Model:

Using the PlantVillage dataset, we also used the Inception-v-3 model to find plant leaf diseases. After getting the data ready, we trained the model, which included a stem module with initial layers that helped identify basic features like edges and textures while reducing the size of the input images. Subsequently, we implemented a sequence of Inception modules to capture features at various scales. These modules contain the branches that are parallel with 1x1, 3x3, and 5x5 convolutions, alongside max-pooling operations, enabling the model to detect both minute details like disease spots and broader patterns such as vein discoloration or overall leaf morphology.

To optimize efficiency, we substituted large 5x5 convolutions with factorized convolutions, breaking

them down into smaller 3×3 convolutions, thus reducing computational demands while maintaining accuracy. Between the inception modules, we used the reduction blocks to downsample the feature maps using stride convolutions and pooling, preserving crucial information while reducing dimensionality. We incorporated auxiliary classifiers in the middle layers to facilitate smooth training and mitigate the issue of vanishing gradients. We incorporated auxiliary classifiers in the middle layers to compute loss while training, which enhanced gradient flow and optimized the network's deeper layers. Our framework's final stages were a global average pooling (GAP) layer, which reduced spatial characteristics to a single vector for every feature map, greatly lowering the overfitting risk in comparison to dense layers. Then comes a completely connected layer with softmax activation to classify retrieved features into certain plant disease categories. We used batch normalisation to stabilise learning and label smoothing to improve generalisation during the training phase. With 85% accuracy, our findings showed that the model successfully identified the illnesses of plant leaves. The Architectural Comparison of EfficientNet lite, MobileNetV3 and Inceptionv3 is illustrated in Table 1.

The activation it uses is ReLU as Equation 3.

$$f(x)=\max (0, x) \quad (3)$$

**Table 1:** Architectural Comparison of EfficientNet lite, MobileNetV3 and Inceptionv3

SL	Properties	EfficientNet lite	MobileNetV3	InceptionV3
1	Total Layers	430	88	48
2	Convolution Layers	116	28	94
3	Max Pooling	No explicit max pooling	Very few max pooling layers	Few max pooling layers
4	Activation function	swish	h-swish	ReLU

## Results

We obtained the accuracy results showing that InceptionV3 achieved the highest accuracy while maintaining excellent efficiency, making it well-suited for mobile and edge applications. EfficientNet-Lite showed good accuracy with quick response times, making it perfect for devices with limited resources, while MobileNetV3 had strong accuracy but needed much more computing power. Accuracy results for EfficientNet-Lite, MobileNetV3, and InceptionV3 are illustrated in Table 2.

**Table 2:** Accuracy Results for EfficientNet lite, MobileNetV3 and Inceptionv3

Model Name	Total Accuracy (%)	Inference time(ms/image)
EfficientNet lite	56	25
MobileNetV3	82	20
Inceptionv3	89	50

We also tried a hybrid of a pair of architectures for better accuracy. And we trained the hybrid models between these three architectures, and we got higher accuracy results for the EfficientNet Lite and InceptionV3 hybrid model. The following are the accuracy results of hybrid models, which are illustrated in Table 3.

**Table 3:** Accuracy results for the hybrid models

Model Name (Hybrid)	Total Accuracy (%)	Inference Time (Ms /Image)
InceptionV3, MobileNetV3	90	35
MobileNetV3, EfficientNet lite	89	20
EfficientNet lite, InceptionV3	93	40

In the process of identifying the best model to detect the disease of the plant leaves, we got the results for accuracy, where we got the higher accuracy for the EfficientNet Lite and Inception V3, a hybrid model, as it extracted the subtle important features when compared to the other models from the input images. As we are trying to build a model for the mobile and edge devices, we pretrained all the models and fine-tuned the models also, and according to the accuracy results, EfficientNet-Lite gave a 56% accuracy, MobileNetV3 accumulated 82% and 89%, and InceptionV3 accumulated 89%. In order to increase the accuracy, we had tried the hybrid models between these individual lite models. And we

got the results as 89% for the EfficientNet Lite, 90% accuracy for the InceptionV3 and MobileNetV3, and also the EfficientNet Lite and InceptionV3 with 93% accuracy (Figure 7).

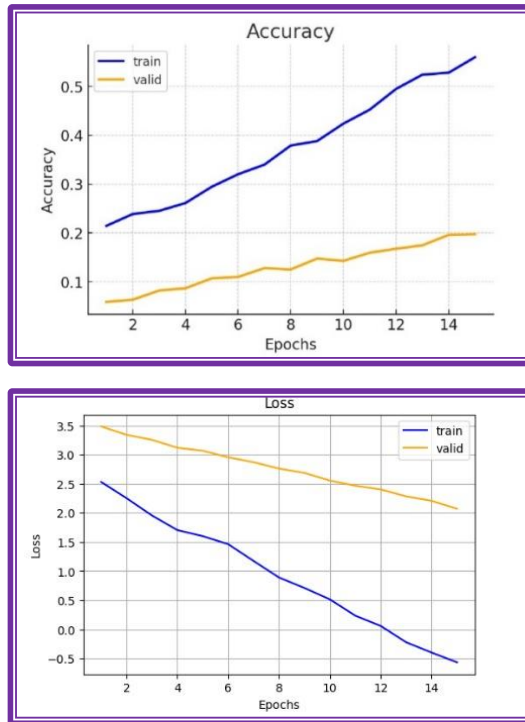


Figure 8: Training & Validation Accuracies;Loss of EfficientNet Lite

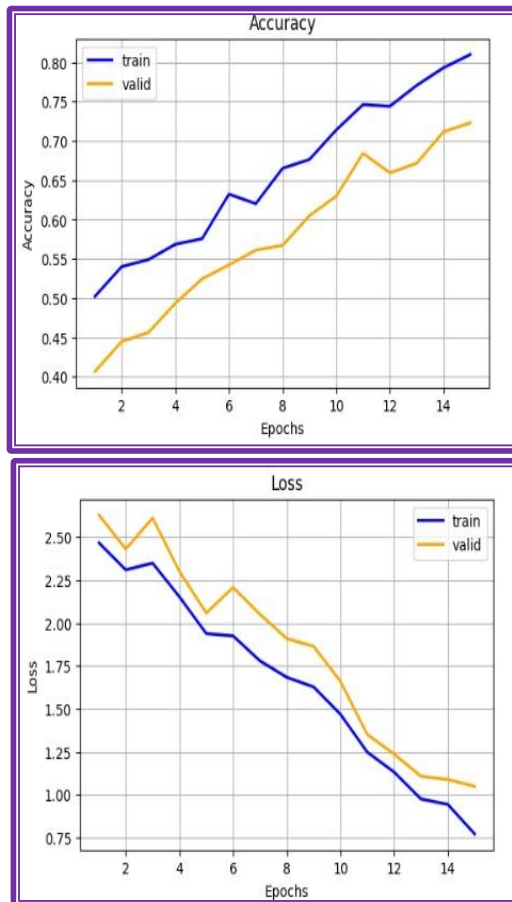


Figure 9: Accuracy and Loss graphs of MobileNetV3

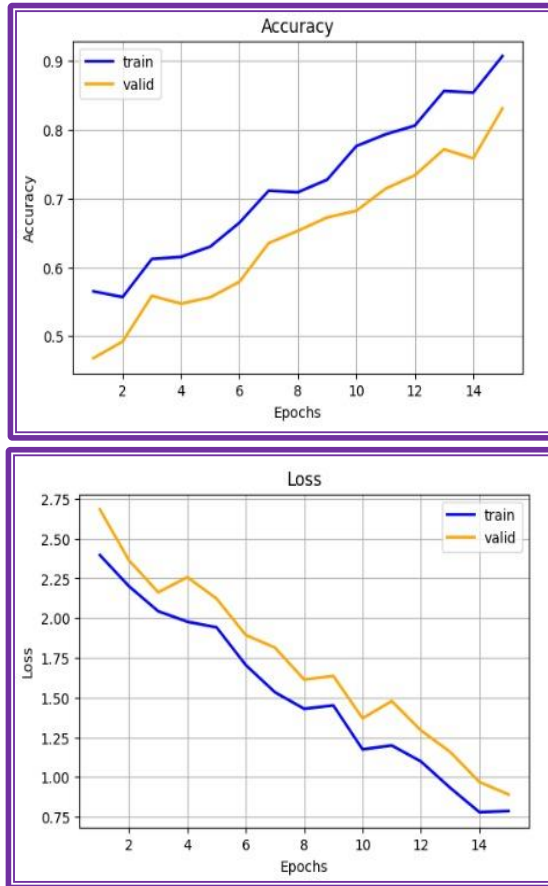


Figure 10: Accuracy and Loss graphs of InceptionV3

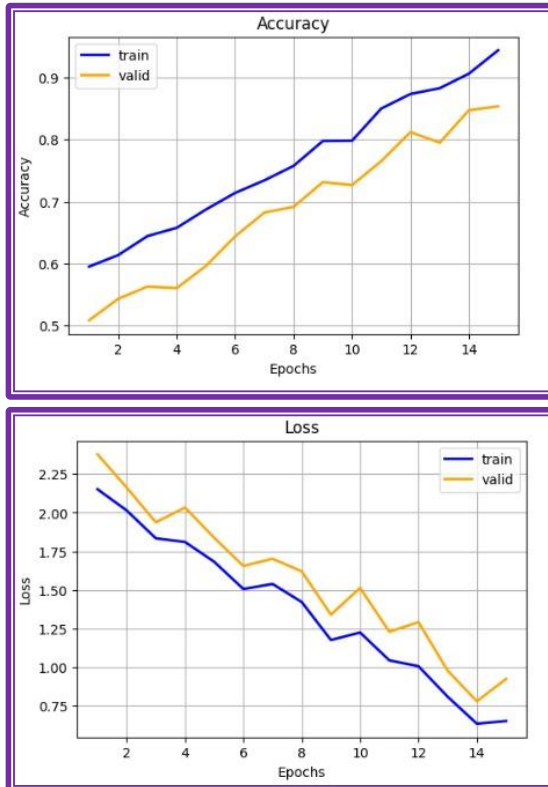


Figure 11: Training and Validation Accuracy of EfficientNet Lite + InceptionV3 Training and Validation Loss of EfficientNet Lite + InceptionV3

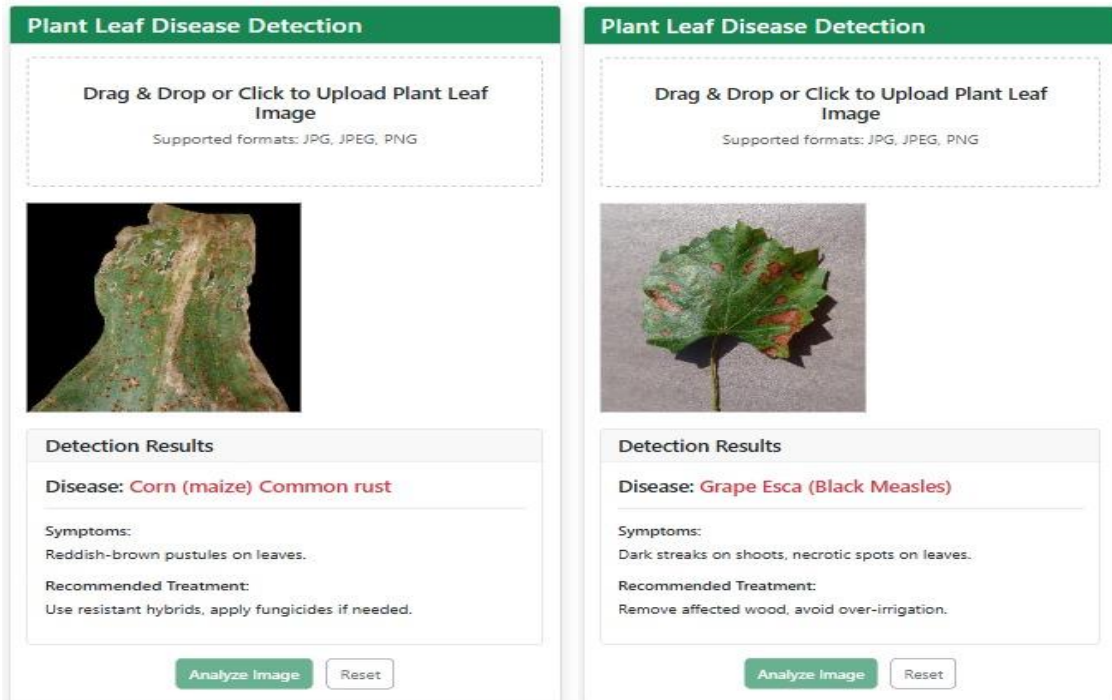


Figure 12: The end results of predicting the diseases of leaves

**Accuracy:** It is an evaluation metric that measures the percentage of correctly predicted outcomes compared to the total number of predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (4)$$

TP: True Positive; T N: True Negative; FP: False Positive; FN: False Negative;

**Inference Time:** It refers the amount of time a trained model takes to process input data and produce an output or prediction and is shown in Figure 13.

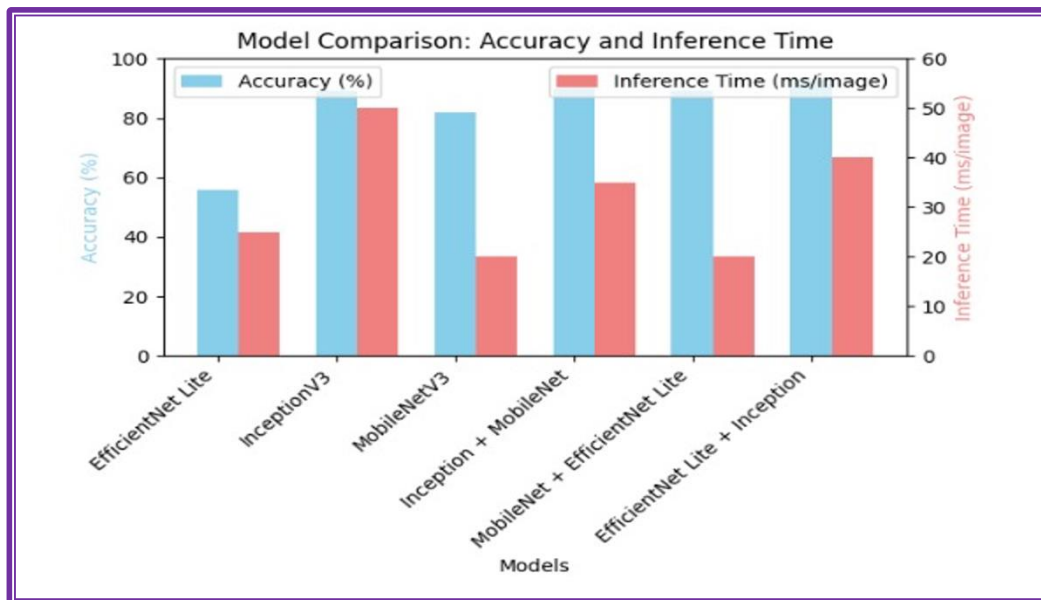


Figure 13: Comparison Analysis w.r.t accuracy & Inference Time

Figures 8, 9, 10, and 11 show the training and validation accuracy as well as additional findings. The blue line shows training accuracy, which suggests the model is learning from the training data. The gap between training and validation indicates that models work well with both training and validation data, and some overfitting occurs when EfficientNet Lite is applied, whereas when MobileNetV3 is applied,

the models work well with training data but not with the validation data. It can be improved when we use hyperparameters such as dropout, learning rate, and epochs. When Inception V3 is applied, the model is generalized i.e. it works well with both training and validation data.

Using deep learning models to examine leaf photos and identify different diseases, Figure 12 shows a web-based application of the front-end section of the Plant Leaf Disease Detection System. It lets the user drag or upload the image and, after examining it, show the ailment of the plant leaf image. Uploaded, the image is transformed into an appropriate format for prediction.

## Discussion

The diagnosis and classification of plant diseases now make much use of DL methods. Traditional machine learning methods have either solved or largely resolved their problems. The primary applications of DL, a subfield of machine learning, are picture segmentation, target identification, and classification. Intelligent farming and automated ecological monitoring systems depend on the ability to identify plant leaf diseases in their natural habitats. Real-world plant leaf photos have unbalanced class distribution, noisy background clutter, and complex foreground fluctuations. These obstacles severely hinder the diagnosis of plant leaf diseases (Kotwal, Kashyap & Shafi, 2023; Li *et al.*, 2022; Qi *et al.*, 2022; Swapna *et al.*, 2023; Thatha *et al.*, 2024). We have suggested a new way in this study to handle these difficulties; our suggested methodology achieves greater accuracy while preserving quick inference time, thereby outperforming current methods. This study showcases a significant improvement over traditional models with increased robustness and generalization across datasets. Our approach considerably strengthens its efficacy by addressing important drawbacks noted in earlier studies (Carion *et al.*, 2020; Wang, Bochkovskiy & Liao, 2023), such as overfitting and excessive processing costs. These results imply that by offering a more precise and effective answer, our method advances the discipline. Additional optimisations and a wider range of applications for our technology can be investigated in future studies.

Rahman *et al.* (2025) suggested that timely detection of leaf diseases is critical for sustainable agriculture. So, he proposed a real-time monitoring system using deep learning methodologies. He used a custom convolutional neural network model through which he achieved an accuracy of 95% with a data set of 30,945 images. Our model is trained on a vast dataset when compared to the above-mentioned model. Our dataset, which encompasses 54,303 images, has achieved an accuracy of 93%, surpassing that of the previously mentioned model. This is due to the fact that our dataset encompasses a broader range of plant species and includes a greater number of classes. The model produces good and accurate results. The loss is gradually decreasing by the gradual increase in the epochs in our model. Our study presents a method that achieves high accuracy without incurring excessive processing costs. By optimizing the model architecture, our approach ensures efficient inference times, making it more feasible for real-world applications where computational resources may be limited. Our approach incorporates extensive data augmentation strategies, which mitigate overfitting and enhance the model's generalization capabilities.

Agarwal *et al.* (2020) has developed a model for tomato plant leaf disease detection using a convolutional neural network trained only on the plant village dataset, mostly emphasising the 9 disease classes and 1 healthy class, achieving an accuracy of 79%. There remains a scope for further enhancement, particularly in optimizing models for mobile and edge devices. To address this challenge, we proposed a hybrid model combining EfficientNet Lite with InceptionV3, achieving an improved accuracy of 93% by leveraging the feature extraction strengths of both models. Unlike standalone architectures, this hybrid model enhances precision by capturing subtle and complex features from plant leaf images. Our model utilizes the Plant Village dataset, which contains 38 classes of various leaf types. This model balances accuracy and computational efficiency, making disease detection more feasible on mobile and edge platforms.

Al Bashish, Braik & Bani-Ahmad (2011) have proposed an image-processing-based solution for automatic detection and classification of plant leaf diseases, which is producing promising results, achieving an accuracy of 92.7%. The methodology, which involves color transformation, K-means clustering for image segmentation, texture feature extraction, and classification using a pre-trained neural network, are the traditional methods and can make some performance issues in the future. However, we proposed an advanced hybrid model that combines the EfficientNet Lite and InceptionV3 architectures. This model achieved an impressive accuracy of 93%, demonstrating superior performance compared to standalone models. and our model can perform efficiently on mobile devices.

## Conclusion

This study explored deep learning-based plant disease detection, optimizing models for mobile and edge devices. The hybrid EfficientNet Lite + InceptionV3 model achieved 93% accuracy, outperforming standalone models. We used different lite model architectures to classify plant leaf diseases based on leaf categorization and detection methodologies. Complex feature extraction was a challenge for image-based systems. Early diagnosis and prediction during the early phases of plant growth can improve plant preservation. This early exploration also increases agricultural productivity. 38 classes of various leaf types from the PlantVillage dataset are used in the proposed model. These photos are compared with photographs taken in the natural environment to find operational variances with the real world. We reached a higher accuracy of 93% by combining the two lite model architectures of EfficientNet-Lite and InceptionV3, as they effectively identify the small but important details needed to predict diseases from the input images, leading to better accuracy because of their superior ability to extract features.

## Limitations

The proposed model has some limitations that must be addressed before practical deployment. Since it was trained only on the PlantVillage dataset, it lacks exposure to diverse real-world conditions, reducing its effectiveness under varying lighting, angles, and environmental factors. The issue of overfitting remains, which may affect its ability to generalize to new data. Additionally, the similarity between plant diseases makes accurate classification challenging. By relying solely on visual features, the model ignores key environmental factors like humidity and soil conditions, which could improve diagnostic accuracy. Although the hybrid EfficientNet-Lite and InceptionV3 model achieved 93% accuracy, its high computational demands make real-time deployment difficult on low-power devices. Moreover, the lack of explanation and inability to learn from new data reduce farmers' trust in the system and limit its long-term adaptability.

## Future Scope

Future studies should concentrate on improving inference time for low-power edge devices by diversifying datasets with real-world photos. Combining sensor data, such as temperature, humidity, and soil conditions, with multimodal learning can improve accuracy. Creating a web-based or mobile application can let farmers have easier access to the system. Investigating Vision Transformers (ViTs) may increase feature extraction, while putting active learning into practice will allow for ongoing development based on feedback from the real world. These advancements will contribute to early disease detection, improved crop yields, and sustainable agriculture.

## Conflict of Interest

All authors declare no competing interests.

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