



A Study and Analysis of Plant Leaf Disease Prediction using Deep Learning Techniques

Tanisha Ranjan^{*1}, Onima Tigga² and J a y a P a l³

^{1, 2, 3} Department of Comp. Sc. & Engg, Birla Institute of Technology, Mesra, Ranchi, India.

*ranjantanisha9@gmail.com, otirkey@bitmesra.ac.in, jayapal@bitmesra.ac.in

Abstract. Contaminating crop diseases are serious issues affecting agricultural output. So, the dynamic identification of these problems accurately in a rapid manner is a potential. Traditional disease observation relies on hands-on visual inspection of plant tissue, an approach that is slow and relies heavily on expert advice. That puts it beyond the reach of small farmers. The revolution in deep learning has the potential to enable the automation of the diagnostic process using computational picture analysis. This paper presents the design, building and evaluation of a deep learning system to verify illnesses under investigation in plant leaf images. 87K RGB leaf images from 38 labelled classes with healthy and ill specimens during training. The input images are standardized to 240 X 240 pixels and pixel normalization is performed. In addition, augmentation operations including rotation, mirror flipping, random zoom and luminance modification are used to enhance diverse training in order to improve generalization and reduce overfitting. Initially, a baseline CNN is developed to set up a reference performance stage and then three pretrained architectures for allocation learning are integrated. EfficientNetB0, MobileNetV2, and ResNet50 are pretrained on large-scale ImageNet data and are efficient in the plant pathology field. All models are evaluated using accuracy, confusion matrix visualization, and the loss function. EfficientNetB0 generates the prospective disease classification of outcomes, whereas MobileNetV2 is distinguished for its incredibly low inference latency and moderate computing footprint. This research study covers a wide range of potential methods in which intelligent computational models might contribute to modernizing agricultural health monitoring and ensuring long-term food production security.

Keywords: Deep Learning, EfficientNetB0, ResNet50, MobileNetV2.

1 Introduction

All over the world, cultivated plants are the basis of food systems and village economies. They provide food, fiber, and jobs to billions of people. Polluting plants on a regular basis is one of many environmental pressures that might have an impact on crop production. If not studied, these pollutants spread through fields rapidly, reducing both yield volume and marketable quality. Therefore, early detection of this contamination is one of the highest-leverage treatments available to anyone trying to preserve agricultural productivity and stability of the food supply [1]. Recognition of crop diseases has been the task of experienced agronomists and expert farmers for decades that organize field walks and identify plant tissue by eye, watching for categorization signs consisting of necrotic lesions, yellowing, and the structure deformity of leaves. This method is largely exclusive, depends on trustworthy specialists, and is labor-intensive, requiring easy access to experts that are not universally available. In isolated geographic communities and smallholder farming areas, the absence of optimal plant health expertise sometimes results in delayed disease detection until the rot has gone far enough to be difficult to control. Large-scale digital image capability combined with rapid improvements in artificial intelligence (AI) has opened a pathway to automation [2]. Deep learning, which

uses multilayered neural networks to extract hierarchical properties of raw input, is highly effective in visual identification. Deep learning architectures such as convolutional neural networks (CNNs) can extract spatial properties from image arrays, without the requirement for human feature descriptors [3]. The use of CNNs for disease classification has continuously achieved high rates, above 95%, in balanced conditions, as shown in a large amount of research literature. However, there is always a constraint, i.e., suitable data size and financial resources are often required for designing such networks from random start. Transfer learning offers a practical alternative: a new model can be begun with weights learnt on a big general-purpose benchmark such as ImageNet [11]. This technique re-uses knowledge encoded in those weights, minimizing data conditioning and training time. EfficientNetB0, MobileNetV2, and ResNet50 are the models that were optimized for the classification of plant diseases [4-5].

The following areas are where this study makes significant progress: A comprehensive end-to-end automated system has been developed to accurately diagnose 38 distinct types of plant leaf diseases.

- EfficientNetB0, ResNet50, and MobileNetV2 are the three transfer learning architectures used in this system, which also includes a custom-built CNN baseline.
- The key distinction is that all three designs are evaluated in controlled comparison research using the same experimental conditions and dataset.
- The system includes a data preparation pipeline that utilizes a variety of stochastic augmentation methods along with systematic standardization. By training the models on a wider variety of visual situations than the raw dataset, this pipeline significantly improves their robustness to out-of-distribution inputs.

The workflow diagram of the research paper is depicted in Fig. 1 as follows:

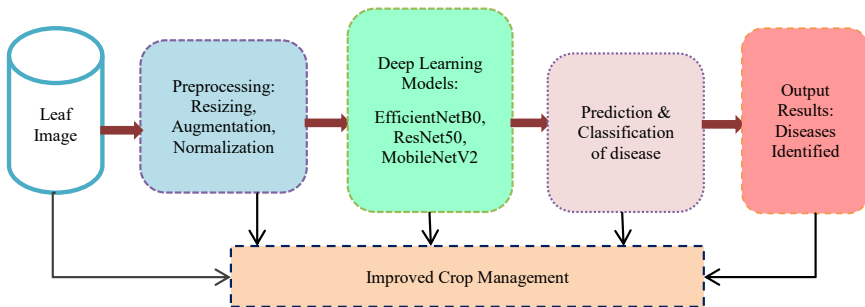


Fig. 1. Workflow diagram of this research paper

1.1 Problem Statement

Plant diseases are persistent and costly problems for agricultural systems because they lower crop yields and degrade crop output, which means less money for farmers and less food for people. Physical examination of leaf tissue by specialists is the dominant idea, but it is too slow, too subjective, and too dependent on the needs of contemporary large-scale farming to provide timely and definitive disease identification, the first and most important step towards effective outbreak control [6]. A theoretically feasible path to automation has emerged thanks to the rapid development of deep learning capabilities

and the rising availability of digital image sensors. This research looks into a technique that may accurately identify plant diseases from leaf photos while still surviving the usual challenges of field photography, such as variations in lighting, background clutter, and image quality [7]. To tackle this head-on, this study builds and evaluates a deep learning pipeline for automated plant disease classification. Subsequently, it assesses ResNet50, EfficientNet50, and MobileNetV2 to determine the architecture that optimizes computational efficiency and accuracy, thereby making it suitable for use in contemporary large-scale farming.

1.2 Objectives

This research has three key objectives as listed below:

- Designing a plant disease classification system based on a custom convolutional neural network (CNN) baseline and transfer learning models such as MobileNetV2, EfficientNetB0, and ResNet50.
- A robust data preparation technique is required to improve classification accuracy and assure broad generalization, encompassing uniform scaling, pixel normalization, and augmentation.
- To provide a prediction interface with several models that provides labels for the category of sickness, as well as confidence estimates per model and to evaluate all models according to accuracy and loss function criteria.

The outline of the research is as follows: Section 2 reviews the related work. Section 3 presents the methodologies. The experiment is described in detail in section 4, including the dataset and the assessment metrics. Results and analysis are presented in Section 5. The study concludes with section 6.

2 Related Work

In the study of Mohanty et al., the CNN models have potential for large-scale plant disease categorization. The authors observed the two architectures, Alex Net and Google Net with respect to number of experimental criteria using Plant Village dataset, which contains photos of 14 distinct crop types leaves and 38 different illness classifications. The major result showed that when the handicraft-feature approaches were prioritized, the CNN classifier had an accuracy rate of 99.35% with the background conditions tested in the lab. The job is a suitable research field for designing developed CNN based plant disease identification and a vital reference to the later studies [8].

Kumar et al. discuss the problems of putting illness identification into mobile devices that have limitations in memory and computing power. The authors selected EfficientNet as the optimal choice for balancing accuracy with resource usage after identifying a variety of lightweight architectures. The model was able to achieve an accuracy of approximately 94.7% on a large disease image corpus by utilizing a minimal amount of memory. The study demonstrates that high-quality diagnostic inference can be achieved within the constraints of mobile technology by reducing the gap between research photographs and operationally deployable solutions [9]. Using a dataset collected around different lighting and environmental requirements, Yasin and Fatima evaluated different pretrained CNN architectures, including Inception-V3, Dense Net, and Xception, on two commercially important crops that are susceptible to infections. The best results are produced by DenseNet, which achieves proof accuracy above 97%. The work examined the principle that allows fact model convergence and intensive classification accuracy even with moderately sized labeled benchmarked-domain data, thanks to transfer learning [10].

For the purpose of documenting diseases in several crops, Kanakala and Ningappa investigated a hybrid architecture that combines LSTM-based disease detection with CNN-based spatial characteristic removal. The CNN-only setup achieves 96.4% clarity, whereas the hybrid design offers small incremental improvements. No matter how much

organized modeling is applied later on, the CNN component's strength in extracting discriminative visual features from leaf imagery has been reaffirmed by the basic study [11]. Sun et al. derived with FL-EfficientNet, an improved version with advanced element scaling metrics augmented for plant disease images. Observation is completed on huge leaf image collections; the model produced 99.72% classification accurately. They discussed that marked architectural refinement which produces meaningful performance with no proportional gaining model complexity or training expenses [12].

Smitha et al. stated that the study sought the best configuration of hyperparameters, including learning ratio and filter dimensions, for a conventional convolutional neural network (CNN). The researchers employed Beluga Whale Optimization (BWO) to accomplish this search. Instead of replacing architectural innovation, the BWO-tuned model's remarkable performance on a typically constructed baseline demonstrates that arranged hyperparameter finding can deliver favorable performance enhancement [13]. Trivedi et al. developed a bespoke CNN model trained on photos of plant diseases by using a combination of pooling layers, frequent dropout and several convolutional layers. This bespoke design proved to be efficient, with an accuracy of 98-99% in the multi-class collection of leaf diseases. The study showed performance differentiation in large pretrained models, resulting from domain-informing architectural choices and proper data preparation [14].

Guo et al. observed that an effective convolutional neural network (CNN) with well-tuned convolutional and pooling parameters can obtain comparable accuracy in sickness classification. Task-specific design can successfully substitute complicated architecture in the scenarios with limited deployment resources. The model achieves an astonishing 92.23% accuracy with a comparatively simple architecture [15]. Kashyap et al. successfully fine-tuned VGG19, a deep architecture originally built for general object recognition, to plant disease classification using transfer learning, obtaining an accuracy of above 95%. This study shows that transfer learning should be the dominant technique for agricultural classification tasks, as pretrained models have good generalization across visually varied domains [16]. Pretrained architectures for leaf disease classification, including MobileNetV2, VGG variation, Efficient Net, and ResNet50, were empirically differentiated in detail by Hukkeri et al. The study discovered that Efficient Net achieved a high accuracy of 98.48%. This high accuracy was due to the success of its compound scaling technique, as measured by accuracy, loss, precision, and recall on a multi-class illness dataset [17].

3 Methodologies

3.1 Algorithms:

Three transfer learning architectures are adopted for comparative evaluation: EfficientNetB0, ResNet50, and MobileNetV2. All three were selected because they come with ImageNet-pretrained weights, have demonstrated leading performance on large-scale image classification benchmarks, and support rapid task-specific fine-tuning with reduced data and training time requirements.

3.1.1 EfficientNetB0:

EfficientNet was conceived as a principled response to the inefficiencies that arise when CNNs are scaled by independently adjusting network depth, width, or input resolution. The EfficientNet family achieves improved scaling through compound scaling — a strategy that simultaneously modulates all three dimensions according to a fixed coefficient — producing a series of architectures (B0 through B7) with progressively superior accuracy-efficiency profiles. The EfficientNetB0 maximizes accuracy per parameter; exhibits strong generalization; practical for real-time applications.

Algorithm 3.1.1 presents a pseudocode for EfficientNetB0.

Algorithm 3.1.1: The EfficientNetB0

Input: Leaf image dataset

Output: Predicted disease label

Step 1: Resize all images to 224×224 and Normalize pixel values to $[0,1]$

Step 2: Load EfficientNetB0 with ImageNet weights

Step 3: Replace classification head with 38-class output

Step 4: Per MBConv block:

expand channels $\rightarrow$ depthwise convolution $\rightarrow$ SE attention $\rightarrow$
pointwise projection

Step 5: Apply compound scaling across depth, width, resolution and
train on labeled training set

Step 6: Evaluate on validation partition and Classify test images.

3.1.2 ResNet50:

ResNet-50 comprises 50 parametric layers organized into residual blocks and has delivered consistently strong results for plant disease classification on both controlled and field-collected datasets: eliminates vanishing gradients; provides reliable training dynamics; produces powerful discriminative feature maps.

Algorithm 3.1.2 presents a pseudocode for ResNet-50.

Algorithm 3.1.2: The ResNet-50

Input: Plant leaf image dataset

Output: Disease classification result

Step 1: Resize images to 224×224 and normalize image data

Step 2: Load ResNet-50 with pretrained weights

Step 3: Per residual block:

convolution $\rightarrow$ batch normalization $\rightarrow$ ReLU activation $\rightarrow$ add
skip connection

Step 4: Stack blocks to required depth and Replace FC head with 38-
class output

Step 5: Optimize via backpropagation and Validate on held-out partition

Step 6: Test on unseen images.

3.1.3 MobileNetV2:

The architecture's distinctive structural element is the inverted residual block with a linear bottleneck: unlike classical residuals that operate in a compressed space, MobileNetV2 first expands channel dimensionality, applies depthwise convolution in that high-dimensional space, and then projects back through a linear activation to a compact output — preserving information while maintaining efficiency. Transfer learning enables MobileNetV2 to regularly exceed 95% accuracy on plant disease benchmarks.

Algorithm 3.1.3 presents a pseudocode for MobileNetV2.

Algorithm 3.1.3: The MobileNetV2

Input: Leaf image dataset

Output: Plant disease prediction

Step 1: Resize to required resolution and Normalize pixel intensities
and Load pretrained MobileNetV2

Step 2: Per inverted residual block:

expand channels $\rightarrow$ depthwise convolution $\rightarrow$ linear bottleneck
projection $\rightarrow$ optional skip $\rightarrow$ connection

Step 3: Replace output head with 38-class classifier

Step 4: Fine-tune on training set

Step 5: Evaluate on validation set and Run inference on test images.

3.2 Performance Evaluation:

All trained models are assessed using the following complementary metrics:

3.2.1 Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where, TP = correctly identified disease cases, TN = correctly identified healthy cases, FP = healthy samples misclassified as diseased, FN = diseased samples misclassified as healthy. While accuracy is the most widely reported metric, it may be misleading when class sizes are unequal.

3.2.2 Loss:

Loss represents the difference between the actual output and the predicted output. It is used during model training to optimize performance.

$$\text{Loss} = -\sum (\text{actual_target value} \times \log(\text{predicted_target value})) \quad (2)$$

A lower loss value indicates better model performance. During training, the objective is to minimize the loss function so that predictions become more accurate over time.

3.2.3 Model Comparison Metrics:

Three summary statistics are used for cross-architecture comparison: per-prediction confidence score distributions, training and validation loss trajectories, and final validation accuracy. Together, these statistics offer a thorough overview that may assist in choosing the most suitable architecture for deployment. Utilizing this multi-metric evaluation technique allows us to ensure that model selection is not influenced by a single metric and that all significant performance dimensions are duly considered.

3.3 Data Preprocessing:

Four operations are applied sequentially to all images before they enter the training or inference pipeline:

- **Image Resizing** — Each image is uniformly rescaled to 224×224 pixels to satisfy the input dimension requirement shared by all three architectures
- **Normalization** — Pixel intensities are remapped to the continuous interval [0,1] by dividing by 255, which stabilizes backpropagation dynamics
- **Data Cleaning** — Corrupted, truncated, or unreadable image files are identified and removed prior to training
- **Data Augmentation** — Stochastic geometric and photometric perturbations including random rotation, horizontal mirroring, zoom variation, and brightness modulation are applied during training batches to diversify the effective training distribution and reduce overfitting risk.

4 Experiment

4.1 Datasets

We used this Kaggle dataset in our study [18]. There are around 87,000 RGB images of both healthy and sick crop leaves, divided into 38 distinct classes, in the plant diseases dataset that is used for this study. In a ratio of 80:20, the dataset is split between the training set and the validation set. In order to make estimates, a set of 33 test photos is generated.

The statistics of dataset is presented in Table 1.

Table 1. Datasets Description

Datasets	Images	Classes
Plant Disease	87K rgb	38

To validate how well the deep learning algorithms perform for classification methods and a comparison with EfficientNetB0, ResNet50, and MobileNetV2 techniques for (100%) of data, for the plant diseases dataset.

5 Results and Analysis

In this research work, we have used four deep learning Techniques: Base CNN, EfficientNetB0, ResNet50, MobileNetV2 for Plant diseases dataset. The performance analysis of the above techniques are depicted in Table 2.

Table 2. Performance Measures

Models	Accuracy (%)
Base CNN	89.54
EfficientNet	2.88
ResNet50	13.35
MobileNetV2	91.17

In Table 2, Base CNN, EfficientNetB0, ResNet50, and MobileNetV2 give accuracy as 89.54%, 2.88%, 13.35%, and 91.17% respectively for dataset Plant disease. The pictorial representation of the accuracy and loss of four deep learning techniques Base CNN, EfficientNetB0, ResNet50, and MobileNetV2 for Plant diseases dataset is shown in Fig.2.

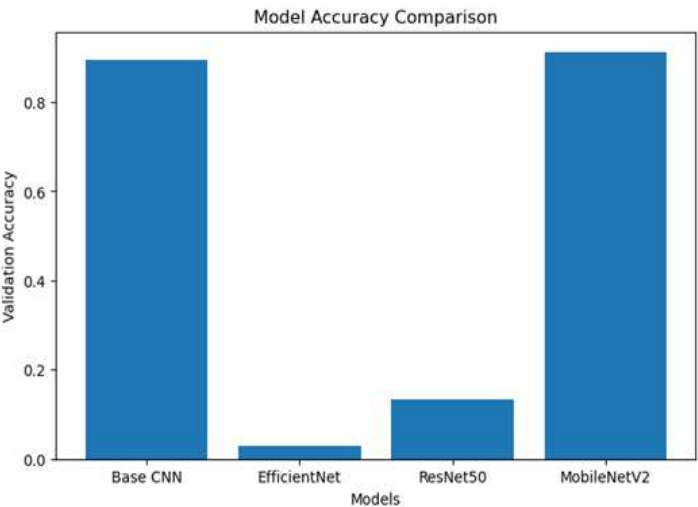


Fig. 2. Performance Measurements of Base CNN, EfficientNetB0, ResNet50, and MobileNetV2
Some examples of leaf images which are uploaded for finding prediction values are

shown in Fig.3.

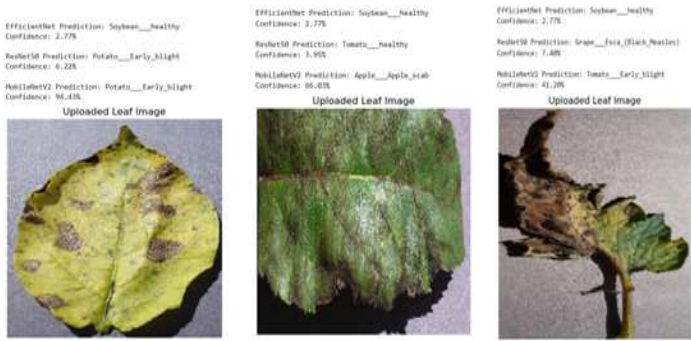


Fig. 3 Examples of uploaded images.

Table 3: Comparative prediction values with confidence(%) by Baseline CNN, EfficientNetB0, Resnet50, and MobileNetV2

Sl. No.	Class Name (Actual Value)	Prediction by Baseline CNN	Baseline CNN Confidence (%)	Prediction by EfficientNet	EfficientNet Confidence (%)	Prediction by ResNet50	ResNet50 Confidence (%)	Prediction by MobileNetV2	MobileNetV2 Confidence (%)
1.	Apple_Apple_scab	Apple_healthy	41.95	Soybean_healthy	2.77	Orange_Huanglongbing (Citrus_greening)	5.84	Apple_Cedar_apple_rust	52.38
2.	Apple_Black_rot	Apple_Black_rot	67.90	Soybean_healthy	2.77	Grape_Esca (Black_Measles)	4.98	Tomato_Septoria leaf spot	31.93
3.	Apple_Cedar_apple_rust	Apple_Cedar_apple_rust	97.79	Soybean_healthy	2.77	Orange_Huanglongbing (Citrus_greening)	7.09	Apple_Cedar_apple_rust	99.52
4.	Apple_healthy	Apple_healthy	99.66	Soybean_healthy	2.77	Grape_Esca (Black_Measles)	5.21	Apple_healthy	97.56
5.	Blueberry_healthy	Blueberry_healthy	92.97	Soybean_healthy	2.77	Pepper_bell_healthy	4.84	Blueberry_healthy	33.49
6.	Cherry (including_sour)_Powdery mildew	Cherry (including_sour)_Powdery mildew	99.84	Soybean_healthy	2.77	Orange_Huanglongbing (Citrus_greening)	6.23	Cherry (including_sour)_Powdery mildew	99.64
7.	Cherry (including_sour)_healthy	Cherry (including_sour)_healthy	82.05	Soybean_healthy	2.77	Potato_Early_blight	6.54	Cherry (including_sour)_healthy	99.69
8.	Corn (maize)_Cercospora leaf spot_Gray leaf blight	Corn (maize)_Cercospora leaf spot_Gray leaf blight	89.88	Soybean_healthy	2.77	Soybean_healthy	3.86	Corn (maize)_Cercospora leaf spot_Gray leaf blight	96.28
9.	Corn (maize)_Common rust	Corn (maize)_Common rust	100.00	Soybean_healthy	2.77	Corn (maize)_Common rust	7.85	Corn (maize)_Common rust	99.39
10.	Corn (maize)_Northern Leaf Blight	Corn (maize)_Northern Leaf Blight	89.51	Soybean_healthy	2.77	Orange_Huanglongbing (Citrus_greening)	5.84	Corn (maize)_Northern Leaf Blight	98.81

The Comparisons of the prediction values with confidence(%) by Baseline CNN, EfficientNetB0, Resnet50, and MobileNetV2 are depicted in Table 3. We found the results by analysis that the prediction output results shown in bold letters achieved by MobileNetV2 are better than the other techniques ResNet50 and efficientNetB0. In the last row, the actual image is Corn (maize) Northern Leaf Blight, for which the confidence results (89.50 %) achieved by Baeline CNN, whereas it is found the confidence (2.77%) by EfficientNetB0 which is very low, also, found confidence (5.84 %) by ResNet50 that is also low value, but the confidence value which is found (98.81%) by MobileNetV2 is outperformed. Also, accuracy and loss of models are shown in Fig. 3 as follows:

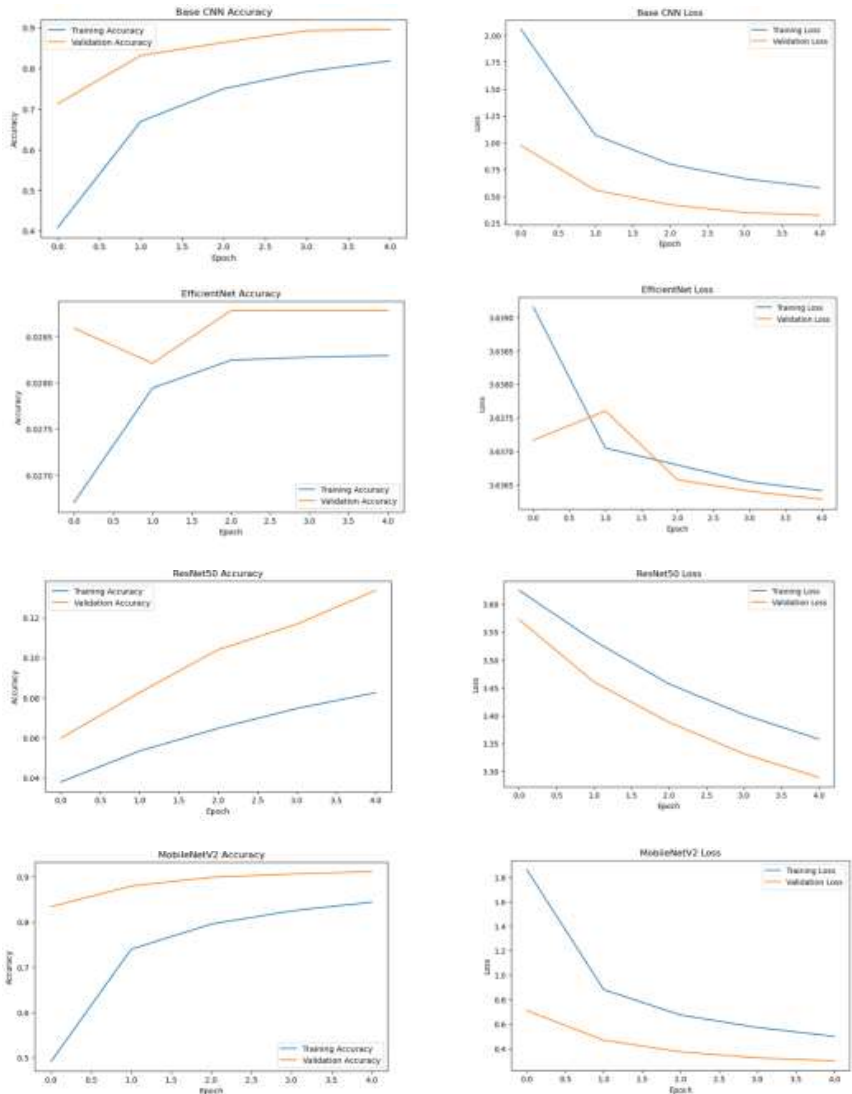


Fig. 3. Model Accuracy / loss for Base CNN, EfficientNetB0, ResNet50, and MobileNetV2

6 Conclusion and Future Enhancements

Visual inspection of plant tissue has long been the most reliable method for detecting diseases. For small-scale farmers, such an approach is just not feasible. Recent breakthroughs in deep learning have made it possible to automate the diagnosis process using computational picture analysis. The objective of this study is to authenticate the diseases examined in plant leaf photographs by the development, construction, and evaluation of a deep learning system. Pixel normalization was used to keep input images at 240 x 240 pixels, and augmentation operations like rotation, mirror flipping, random zoom, and luminance modification are used to enhance diversity training while reducing overfitting and strengthening generalization.

In this study, we compare three learning architectures that are effective in the field of plant pathology: EfficientNetB0, MobileNetV2, and ResNet50. All three of these architectures use a CNN base model, as shown in Table 2. The weights of these models are initialized using data from large-scale ImageNet training. The following metrics were used to assess each model: accuracy, loss function, and confusion matrix visualization: While MobileNetV2 stood out for its moderate computation of footprint and extremely minor inference latency, EfficientNetB0 produced results that may be used for disease categorization. Integrated probability is also constructed, making it advantageous for resource-limited or portable hardware. EfficientNetB0 (2.88%) and ResNet50 (13.35%) underperformed significantly due to a combination of three compounding factors: all pretrained convolutional layers were fully frozen, allowing only a small classifier head to learn; training is limited to 5 epochs, which was insufficient for convergence as evidenced by still-rising accuracy curves at the point of termination; and a low learning rate of 0.0001 further slowed the already constrained weight updates.

In contrast, the Base CNN (89.54%) trained all its layers freely with a higher learning rate of 0.001, allowing it to converge efficiently within 5 epochs despite having no pretrained knowledge. MobileNetV2 (91.17%) achieved the highest accuracy because its lightweight depth wise separable convolution architecture produces more compact and transferable feature representations, enabling even its frozen pretrained features to provide a rich and immediately useful basis for the trainable classification head — a characteristic not shared by the heavier and more task-specific architectures of EfficientNetB0 and ResNet50.

Any user can submit a leaf image and receive simultaneous outcome fulfillment with confidence percentages from all three designs. Based on our comparisons, MobileNetV2 outperforms the first three models shown in Table 2. Experimental relevant evidence reveals that deep learning is clearly superior to more conventional approaches to plant disease diagnosis.

Thus, our research points to the potential of smart automation to augment plant health research, reduce the demand on scarce expert resources, and develop a diagnostic tool accessible to farmers of all sizes.

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