

**SYLHET ENGINEERING COLLEGE**

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**Department of Computer Science & Engineering**



**Deep Learning-Based Early Diagnosis of Eggplant Leaf Diseases**

**Using EfficientNet-B3 and MobileNet-V2**

Submitted by

**Priangshu Dey Prokhor**

**Sadia Islam**

Reg. No.: 2019331522

Reg. No.: 2019331542

Department of Computer Science & Engineering

**Supervisor**

Md. Abu Naser Mojumder

Head

Department of Computer Science & Engineering

Sylhet Engineering College, Sylhet

## **Recommendation Letter from Thesis Supervisor**

The thesis entitled “**Classification of Eggplant Leaf Disease**

**Using Deep Learning**” submitted by the students

1. Priangshu Dey Prokhor
2. Sadia Islam

is a record of research work carried out under my supervision and I, hereby, approve that the report is submitted in partial fulfilment of the requirement for the award of their Bachelor’s Degree

Signature of the Supervisor

**Md. Abu Naser Mojumder**

Head

Department of Computer Science & Engineering

Sylhet Engineering College, Sylhet

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Submitted to the Department of Computer Science & Engineering, in partial fulfillment of the requirements for the degree of

Bachelor of Science in Computer Science & Engineering

**Abstract**

Eggplant (brinjal) is one of Bangladesh's most vital crops, yet its productivity is increasingly threatened by leaf diseases and pests, leading to yield losses of up to 86% if not diagnosed promptly. Traditional disease identification methods are often slow, subjective, and reliant on expert availability—making timely intervention difficult for smallholder farmers. This study proposes an automated deep learning-based classification system utilizing EfficientNet-B3 and MobileNetV2 architectures to diagnose seven classes of eggplant leaf conditions, including six common diseases and healthy leaves.

A curated dataset of 3,159 labeled images collected from Bangladeshi farms was used, with data preprocessing steps including normalization, resizing, and extensive augmentation to address class imbalance. Transfer learning was applied to both models, with EfficientNet-B3 achieving a superior test accuracy of 88.61%, significantly outperforming MobileNetV2 (60.76%). Evaluation metrics such as precision, recall, and F1-score confirmed EfficientNet-B3's stronger class-wise performance, especially for visually similar diseases like mosaic virus, leaf spot, and wilt.

With high accuracy, a lightweight structure, and suitability for smartphone deployment, the proposed system provides a practical tool for in-field, real-time disease diagnosis. It empowers farmers with accessible diagnostic support, promoting timely intervention, reducing pesticide overuse, and contributing to more resilient, sustainable agricultural practices in Bangladesh and similar resource-constrained environments.

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# Chapter 1: Introduction

## 1.1 Introduction

Agriculture is a cornerstone of Bangladesh's economy and livelihood, engaging about 45% of the population and contributing roughly 11% to GDP [1],[2]. Within this sector, eggplant (*Solanum melongena*), locally known as brinjal, is one of the most important and widely consumed vegetables. In fact, eggplant is the second-most cultivated vegetable in Bangladesh, grown by approximately 150,000 smallholder farmers on 51,000 hectares – accounting for about 14.9% of winter vegetable production and 9.7% of summer production [3]. This crop's affordability and nutritional value make it a staple in daily diets and an income source for rural communities. Ensuring the health and yield of eggplant crops is therefore crucial for food security and the rural economy.

Despite its importance, eggplant cultivation is highly vulnerable to pests and diseases, which can devastate yields and threaten farmer livelihoods. The eggplant fruit and shoot borer (EFSB), a pervasive insect pest, exemplifies the severity of potential losses – infestations in Bangladesh have caused yield losses as high as 86% in affected fields [4]. Likewise, plant pathogens pose serious challenges: bacterial wilt (caused by *Ralstonia solanacearum*) and Phomopsis blight/fruit rot (*Phomopsis vexans*) are identified as two major diseases constraining eggplant production in Bangladesh [5]. Various fungal and viral diseases such as anthracnose, *Cercospora* leaf spot, mosaic virus, and others also contribute to significant crop losses [6],[7]. These diseases not only reduce marketable yield but also affect fruit quality, impacting income for farmers and increasing prices for consumers. For a country like Bangladesh – where agriculture plays a vital role in employment and poverty reduction – such losses in a key crop like eggplant can have ripple effects on food supply, farmer income, and daily vegetable availability [2].

Farmers often attempt to mitigate these threats through heavy use of pesticides and other chemicals. In practice, eggplant farmers may resort to spraying insecticides as frequently as twice a week or more during the growing season [8]. However, this reactive approach has drawbacks: indiscriminate pesticide use raises production costs, poses health risks, and can cause environmental harm. Moreover, if treatments are applied too late (after a disease has visibly spread), much of the effort is in vain – by then considerable damage is already done [9]. The timing and accuracy of disease intervention are therefore critical. Early and precise detection of leaf

diseases or pest infestation can enable targeted management (such as removing diseased plants or timely, limited pesticide use) before an outbreak escalates. In this broader context, effective disease surveillance and rapid response are essential for sustainable eggplant production, reducing crop losses and improving farmers' outcomes.

Traditionally, disease identification in the field has relied on manual inspection of plants by farmers or extension officers. This process is labor-intensive, subjective, and error-prone. Subtle symptoms on leaves can be easily missed by the naked eye, especially by untrained farmers, and distinguishing between two look-alike diseases can be challenging. Consequently, farmers might misidentify problems or notice them only at advanced stages. In a developing-country setting (like many regions of Bangladesh), access to professional agronomists or plant pathologists is limited and cost [10]. As a result, critical time may be lost between the onset of a disease and its detection, by which time the infection could spread widely. The limitations of human monitoring underscore the need for automated, technology-driven solutions in the agricultural domain. In recent years, advances in computer vision and artificial intelligence have opened new avenues for crop disease management. In particular, the success of deep learning in image recognition tasks has inspired its use in agriculture to recognize plant diseases from leaf images with high precision. Deploying such intelligent systems for eggplant leaf disease detection could help farmers identify problems early, reduce unnecessary pesticide use, and ultimately safeguard yield and quality [9].

## 1.2 Background

The quality of fruits is a critical factor that directly impacts consumer health, economic value, and global efforts to reduce food waste. Fruits are rich sources of essential nutrients, vitamins, and minerals, making their freshness and safety vital for public health. However, spoilage caused by factors such as microbial infections, mechanical damage (bruising), and improper storage conditions results in significant losses not only in nutritional quality but also in market value. These losses contribute substantially to the estimated millions of tons of food wasted annually worldwide, causing economic setbacks for farmers, suppliers, and retailers alike.

Traditionally, fruit quality assessment has heavily depended on manual inspection methods, where trained personnel visually examine and sort fruits based on appearance, texture, and other sensory cues. Moreover, as the scale of agricultural production and distribution increases, manual sorting becomes highly inefficient and impractical. The reliance on human labor in large volumes leads to slower processing times, higher labor costs, and increased risk of inconsistent quality control. These inefficiencies often result in increased post-harvest losses, reduced consumer satisfaction, and challenges in maintaining consistent market standards.

Recent advancements in Artificial Intelligence (AI), particularly in machine learning and computer vision, have begun to revolutionize automated fruit quality inspection systems. Initial methods utilized traditional machine learning algorithms such as (SVM), (k-NN), and (ANN), which classify fruits based on handcrafted visual features including color histograms, texture descriptors, and shape parameters. While these methods marked an important step toward automation and demonstrated promising classification accuracy, their dependence on manually engineered features limited their adaptability and robustness. Feature extraction processes required domain expertise and were often sensitive to changes in lighting, background, and fruit orientation, reducing their effectiveness in real-world conditions.

The emergence of deep learning, and specifically Convolutional Neural Networks (CNNs), has transformed image classification by enabling models to automatically learn complex, hierarchical feature representations directly from raw image data. CNN architectures such as VGG, ResNet, and MobileNet have shown exceptional ability to identify subtle patterns and variations in fruit images and quality defects, outperforming traditional machine learning methods. These models

benefit from large-scale datasets and hierarchical learning, making them more resilient to variations in environmental conditions, lighting, and fruit presentation. Furthermore, transfer learning techniques, which involve fine-tuning CNN models pre-trained on extensive image datasets like ImageNet, have significantly improved training efficiency and accuracy.

Despite these promising developments, many current fruit quality assessment systems still face notable challenges. Most studies focus on single fruit types and use limited datasets that do not capture the full variability found in real-world environments, such as differences in fruit varieties, lighting conditions, and backgrounds. Additionally, existing models are often not optimized for deployment on low-power, portable devices that would enable on-site inspection in farms or small-scale processing units. These limitations hinder the widespread adoption of AI-based quality inspection technologies across diverse agricultural contexts.

To address these gaps, this study proposes a robust and scalable CNN-based fruit quality classification system capable of handling multiple fruit types—specifically apple, banana, carrot, orange, and potato—and distinguishing between healthy and rotten conditions. By leveraging a diverse dataset compiled from controlled image captures, online sources, and augmented data, and by integrating both custom-designed and pre-trained CNN architectures, the research aims to develop an automated solution that improves accuracy, reliability, and applicability in real-world agricultural and food supply chains. This work strives to advance the field of automated fruit quality assessment, ultimately contributing to enhanced operational efficiency, reduced food waste, and smarter agricultural practices.

### 1.3 Problem Statement

Existing models for eggplant leaf disease detection fall short in several aspects, creating an opportunity for improvement. Firstly, traditional approaches (manual scouting or basic machine learning) are inadequate for timely and accurate detection – human inspection is subjective and slow, and earlier machine vision techniques lacked the precision of modern CNNs. While recent deep learning models have achieved high accuracy on benchmark datasets, they often fail to generalize when confronted with realworld variabilities. A key issue is that many models were trained on limited or homogeneous datasets (e.g., images with plain backgrounds or captured in controlled settings) [25]. Consequently, these models may not perform well on heterogeneous field images where factors like lighting, leaf orientation, background clutter, or disease severity can differ from the training data. For example, a model that excels on high-resolution images of isolated leaves might misclassify when faced with partially damaged leaves in a dense canopy or leaves covered in dust/insect frass as is common in actual farms. This gap between laboratory accuracy and field reliability is a significant problem that current research has yet to fully bridge.

Secondly, eggplant-specific disease detection has not fully leveraged modern efficient CNN architectures. Most prior studies used standard models (AlexNet, VGG, ResNet, etc.) or straightforward transfer learning. These can be computationally heavy or require large memory, which is problematic for deploying solutions on low-resource devices (e.g., smartphones or edge devices used by farmers). EfficientNet and similar advanced architectures promise a better accuracy-to-computation ratio, but they have not been widely applied to eggplant diseases in the literature [23]. This is a notable gap: without exploring such state-of-the-art models, the community might be missing out on higher accuracy and faster inference for this task. EfficientNet’s compound scaling could be particularly useful to incorporate higher resolution leaf details (important for distinguishing look-alike diseases) without an explosion in model size. Yet, to date, eggplant disease datasets have seen little usage of EfficientNet V3, leaving uncertain how well it might perform compared to older CNNs.

Another issue is that many existing works focus on overall accuracy and might overlook class imbalance and rare disease detection. In eggplant farming, certain diseases (like bacterial wilt or white mold) might be relatively less frequent but are devastating when they occur. Models trained on class-imbalanced data could achieve high accuracy by mainly being good at recognizing the

most common class (often healthy leaves) while failing to reliably catch the rarer diseases. For instance, if a dataset is dominated by images of, say, mosaic virus, a model might reach ~90% accuracy yet barely detect a few samples of white mold or wilt correctly. This is a critical shortcoming because missing a deadly but infrequent disease can nullify the benefit of the model in the field. Thus, the problem can be stated as: current eggplant leaf disease detection models do not adequately ensure high precision and recall across all disease categories, especially the less common ones. They lack mechanisms to handle class imbalance or do not report metrics beyond accuracy to show performance on each class.

In summary, the research gap lies in developing a robust, generalizable, and efficient model for eggplant leaf disease detection. Specifically, there is a need for a deep learning model that: - Achieves high accuracy in classifying multiple eggplant leaf diseases and healthy leaves, without overfitting to laboratory-like conditions. - Maintains strong performance (high sensitivity/recall) for each disease class, including those with fewer training examples, thereby ensuring reliable detection of even rare but severe diseases. - Is computationally efficient enough to be deployed in real-world scenarios (for example, usable in a mobile app for farmers), which implies utilizing modern architectures or model compression without sacrificing accuracy.

Existing models fail to fully meet these criteria – they either lack generalization, neglect certain classes, or are too resource-intensive. Therefore, the challenge is to bridge these gaps by leveraging the latest deep learning innovations (such as EfficientNet V3) and a thoughtful design of the training/evaluation process to build a better eggplant disease detector. Ultimately, addressing this problem would contribute to more sustainable pest management in eggplant cultivation, aiding farmers in Bangladesh and elsewhere by providing an early warning tool for crop diseases.

## 1.4 Objectives

This research aims to develop an accurate, efficient, and field-adaptable deep learning model for classifying eggplant (brinjal) leaf diseases in the context of Bangladeshi agriculture. The core objectives of the study are as follows:

### 1. Design a Custom EfficientNet V3-Based Deep Learning Model

Develop a tailored convolutional neural network built upon the EfficientNet V3 architecture, utilizing its compound scaling strategy to balance accuracy and computational efficiency. The model will be fine-tuned to extract detailed disease-specific features and optimized for deployment on resource-limited devices such as smartphones.

### 2. Implement Data Augmentation and Generalization Techniques

Apply comprehensive data augmentation methods—including random rotations, lighting variations, and background diversity—to improve generalization and robustness. The model will be trained and fine-tuned using a balanced dataset of eggplant leaf images captured under real-world field conditions in Bangladesh, ensuring applicability in diverse agricultural settings.

### 3. Ensure Rigorous Performance Evaluation Using Multiple Metrics

Evaluate the model using a full range of performance metrics—accuracy, precision, recall (sensitivity), specificity, and F1-score—across all seven classes. This comprehensive analysis will provide insights into both overall and class-wise model effectiveness, particularly in minimizing false positives and false negatives.

### 4. Compare with Baseline and State-of-the-Art Models

Benchmark the proposed EfficientNet V3 model against widely used architectures such as VGG16, ResNet50, MobileNetV2, and earlier EfficientNet variants. Comparisons will focus on classification performance, model size, and inference time to demonstrate the advantages of the proposed model in both accuracy and computational efficiency.

### 5. Align with the Bangladeshi Agricultural Context

Focus the research on Bangladesh's local eggplant diseases using region-specific data, with the goal of developing a practical, real-time diagnostic tool to support smallholder farmers and promote sustainable agriculture.

## Chapter 2: Literature Review

### 2.1 Literature Review

Researchers worldwide have increasingly turned to deep learning approaches to tackle the challenge of plant disease detection. Early pioneering work demonstrated the promise of convolutional neural networks (CNNs) for plant disease image classification. For example, Mohanty et al. (2016) trained a deep CNN on a large PlantVillage dataset spanning 14 crop species and 26 diseases, achieving an impressive 99.35% accuracy in identifying the correct crop-disease combination [11]. This landmark result showcased the potential of deep learning to outperform traditional vision methods and even human experts in consistency. Since then, numerous studies have applied CNN-based transfer learning and advanced architectures to improve disease recognition across various crops. In general, studies report very high accuracy on benchmark datasets – often in the range of 95-99% – underlining the efficacy of deep learning for plant leaf classification [12]. These models learn to extract complex features (color patterns, lesion shapes, etc.) that distinguish healthy leaves from different disease conditions, even when those differences are subtle.

A wide array of CNN architectures, from early models like AlexNet and VGG to more recent ones like ResNet, Inception, DenseNet, and MobileNet, have been explored for agricultural image tasks [13],[14]. Simpler networks (e.g., AlexNet, VGG16) laid the groundwork but often struggled with generalization when data was limited, sometimes yielding modest results. For instance, one study on eggplant leaf diseases utilized AlexNet for feature extraction combined with a Random Forest classifier, initially obtaining only ~53% accuracy; after applying extensive data augmentation to address class imbalance, the accuracy improved to about 74.6% [15],[16]. This underscores that conventional CNNs can require significant data expansion and preprocessing to be effective. On the other hand, deeper architectures and transfer learning from large image databases have dramatically boosted performance in many cases. Researchers have found that pre-trained networks like InceptionV3, ResNet50/101, or DenseNet201 fine-tuned on plant disease datasets can achieve accuracies above 95%, even nearing perfection on some benchmarks [17]. For example, experiments have shown VGG16 yielding ~82% accuracy on a plant disease dataset, whereas a deeper model like DenseNet201 reached about 98.9% on a similar set [18]. In one eggplant disease study, an InceptionV3-based transfer learning approach obtained 98.9% accuracy

– dramatically higher than older methods – by leveraging robust feature learning [19]. Such results highlight the advancements in deep learning that enable near-human or even super-human performance under controlled conditions.

Beyond straight classification, researchers have also investigated object detection frameworks to locate diseased regions on plants. Techniques like Faster R-CNN (two-stage detection) and YOLO (single-stage detection) have been applied to identify multiple diseases or pests in field images. These detection models not only classify the disease but also pinpoint its location on the leaf/plant, aiding practical scouting. For instance, a recent study in Bangladesh employed the state-of-the-art YOLOv8 model to detect leaf diseases in cucumber and other crops, reporting a mean average precision (mAP) of about 98% and an F1-score of 0.97 in identifying diseased leaves [20]. Such high performance in object detection indicates that deep learning can handle complex, cluttered backgrounds and still accurately find disease symptoms. In related work, MobileNet and other lightweight CNNs have been used on mobile devices for on-site disease detection, emphasizing the trend towards practical field deployment of these models [21]. The literature shows a clear trajectory: from basic classification on curated datasets to more sophisticated and contextaware models that aim to work in real agricultural environments.

Eggplant leaf disease detection, specifically, has gained research attention recently as eggplant is grown in many countries in Asia and beyond. Several studies focus on classifying common eggplant diseases (such as leaf spot, mosaic virus, blight, etc.) using deep learning. A 2025 study by Ramazan et al. used a dataset of 4,089 eggplant leaf images (six classes: healthy and five diseases) to compare models [22]. Their initial CNN+Random Forest approach improved with augmentation (as noted, reaching ~74% accuracy) [15], but this also revealed the difficulty of the task under limited data and class imbalance. In contrast, Haque et al. (as cited in that study) introduced a fusion of deep features which, using an InceptionV3 model, achieved 98.9% accuracy on eggplant disease classification. They attributed the success to transfer learning, yet also acknowledged challenges: the method required high-quality images and struggled when diseases had very similar visual symptoms [19]. This points out a persistent issue – while deep models can memorize the training distribution extremely well (even exceeding 98% accuracy), their real-world effectiveness can be hampered by data quality issues and subtle inter-class differences. Another contemporary approach involved an ensemble of transfer learning models for eggplant disease

diagnosis, aiming to improve robustness by combining multiple CNN architectures [17]. Reportedly, models like DenseNet and Inception, when ensembled, could also attain near-perfect accuracy on test data in controlled settings. These high accuracies in literature demonstrate what is achievable, but they also raise questions about overfitting and realism of the test conditions – many studies use homogeneous image backgrounds or limited environmental variability

It is noteworthy that EfficientNet, a family of CNNs introduced by Tan and Le (2019), has emerged as a powerful architecture in image classification due to its compound scaling approach (balancing network depth, width, and resolution for better efficiency). EfficientNet models (B0 through B7) have achieved state-of-the-art accuracy on ImageNet while using fewer parameters than equally performing models. In plant disease domains, however, EfficientNet has seen relatively limited use until recently [23]. Some researchers have started to explore it: for example, Chowdhury et al. fine-tuned EfficientNet-B7 on a tomato leaf disease dataset and reported 99.12% accuracy for classifying six types of tomato diseases, significantly outperforming earlier networks [24]. They also found that even a smaller EfficientNet-B4 could achieve about 99.9% accuracy on a 10-class classification (after segmenting leaves). These results are promising, suggesting that EfficientNet's optimized architecture can generalize well in plant disease recognition tasks. Despite these few studies, EfficientNet (including its later versions) remains under-explored for specific crops like eggplant [23]. Most eggplant disease studies so far have used conventional CNNs or other transfer learning models, leaving a gap for evaluating newer architectures. This provides motivation to investigate EfficientNet (in particular EfficientNet V3, as a latest version or variant) for detecting eggplant leaf diseases, hypothesizing that it could achieve high accuracy with better parameter efficiency.

In summary, prior works clearly demonstrate the feasibility of automated leaf disease detection using deep learning. However, these approaches still have limitations that warrant further research. Many models in the literature are trained and tested on laboratory or curated images (uniform backgrounds, good lighting), and they may fail to generalize to field conditions where backgrounds are complex and lighting varies. In fact, a review of plant disease AI systems noted that models often overfit to limited datasets and struggle with generalization to diverse environments [25]. Despite the high accuracies reported, there remains a gap in terms of robustness and practical applicability. As an example, some studies restricted their training to a single crop or a handful of

disease types, which means the resulting model might not handle new diseases or different crop varieties well [26]. Despite these advancements, there remains a gap in developing a solution that is both highly accurate and broadly generalizable for eggplant disease detection. No single study yet has definitively addressed the combination of: (a) using the latest efficient deep learning models, (b) focusing on eggplant leaves with all major diseases, and (c) ensuring the model works on real-life images (with noise, variety in leaf appearance, etc.) relevant to Bangladeshi agriculture. These observations from the literature form the basis for our research problem.

## 2.2 Related Works

In recent years, deep learning-based image classification techniques have significantly improved the accuracy and scalability of plant disease diagnosis. A seminal work by Mohanty et al. [11] demonstrated the potential of Convolutional Neural Networks (CNNs) to outperform traditional machine learning approaches by achieving over 99.35% accuracy in plant disease recognition across 14 crop species using the PlantVillage dataset. This inspired a wave of research efforts applying CNN architectures such as VGG16, ResNet, Inception, DenseNet, and MobileNet to various crop disease datasets, often achieving 95–99% accuracy in controlled environments [12], [14], [17].

For eggplant leaf diseases specifically, multiple studies have explored CNN-based classification strategies. One such study used AlexNet with a Random Forest classifier, initially yielding a modest 53% accuracy, which improved to ~74.6% after applying data augmentation to address class imbalance [15]. This result emphasized the necessity of preprocessing and balancing techniques to improve CNN performance on real-world agricultural data.

More recent efforts have shifted toward transfer learning, where pre-trained models like InceptionV3, DenseNet201, and ResNet50 are fine-tuned on plant disease datasets. These models demonstrated high accuracy even with smaller datasets—for instance, InceptionV3 achieved 98.9% accuracy for eggplant leaf classification [19]. However, such performance often relies on high-resolution, low-variability images captured under ideal lighting and background conditions, which do not reflect the complexity of actual farm environments.

Object detection models such as YOLOv8 and Faster R-CNN have also been explored for localizing diseased regions in field imagery. A recent study conducted in Bangladesh applied YOLOv8 to cucumber leaf diseases and reported a mean average precision (mAP) of 98% and F1-score of 0.97, showcasing the practical utility of deep learning in real agricultural settings [20]. Similarly, MobileNetV2 has been successfully deployed in lightweight, mobile-based disease diagnosis systems [21], although its lower representational power limits performance for visually complex diseases.

Although these approaches show promise, most eggplant disease studies still rely on conventional CNNs, and very few leverage the recent EfficientNet family, which provides a better balance between accuracy and computational efficiency [23], [24].

### **2.3 Research Gap**

Despite notable advancements in deep learning-based plant disease detection, several critical gaps remain in the literature concerning eggplant leaf disease classification. Most existing studies rely on datasets collected under controlled conditions with uniform lighting and clean backgrounds, which limits the generalization of their models to real-world agricultural settings [25]. In actual field environments, factors such as occlusion, varying illumination, and background noise can significantly degrade model performance [24]. Additionally, while EfficientNet has emerged as a state-of-the-art architecture due to its compound scaling of depth, width, and resolution [23], its application to eggplant disease classification remains limited. Instead, prior research predominantly uses traditional CNNs such as VGG, ResNet, or AlexNet, which are often computationally intensive and ill-suited for deployment on resource-constrained mobile devices [24]. Another major shortcoming is the neglect of class imbalance; many studies prioritize overall accuracy without evaluating class-wise performance, which leads to poor detection of rare yet critical diseases such as white mold or bacterial wilt [24]. Furthermore, very few studies have validated their models in real-time settings or deployed them on smartphones, making it unclear how these solutions perform in practical farming conditions, particularly in rural areas of Bangladesh [24]. Therefore, there is a pressing need for a robust and efficient deep learning framework that can accurately classify multiple eggplant diseases, maintain balanced performance across all classes—including underrepresented ones—and operate effectively in real-time, mobile-based deployments. To address these gaps, the present study investigates the performance of EfficientNetB3 and MobileNetV2 on a region-specific, balanced, and augmented dataset collected from Bangladeshi farms, and evaluates the models under realistic field conditions using smartphone-based deployment.

## Chapter 3: Methodology

### 3.1 Methodology

To classify eggplant leaf diseases effectively in real-world farming conditions, this study presents a deep learning-based pipeline optimized for accuracy, generalization, and deployability in resource-limited contexts like rural Bangladesh. The overall workflow, illustrated in **Figure 1**, integrates dataset acquisition, preprocessing, augmentation, model training, and evaluation.



**Figure 1: Methodological Workflow Diagram**

A representative image dataset was collected from local farms and split into training (70%), validation (15%), and testing (15%) sets. Preprocessing involved normalization, resizing to 224×224 pixels, and class balancing to mitigate bias. To enhance model robustness, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were applied.

Two lightweight CNN architectures—**MobileNetV2** and **EfficientNetB3**—were selected for their efficiency and accuracy. Transfer learning was employed to fine-tune these models on the target dataset. The models were trained and validated, followed by comparative evaluation to identify the most effective approach. This structured methodology ensures a scalable and practical solution for real-time eggplant disease detection, suitable for low-resource agricultural settings.

## **3.2 Methods and Materials**

### **3.2.1 Dataset Collection**

The dataset used in this research was collected through a field-based data acquisition process in collaboration with the **Agricultural Training Institute (ATI)**, located in **Khadimnagar, Sylhet, Bangladesh**. The collection aimed to capture real-world variations in eggplant leaf conditions commonly observed in local farms. Images were taken using high-resolution smartphone cameras under natural lighting to reflect practical conditions in which the model would later be deployed. To ensure diversity in the dataset, leaf samples were collected from multiple plots at different times of day and across various stages of disease progression. The image collection was supervised and labeled by experienced agricultural officers and plant disease specialists at ATI, who diagnosed the leaf conditions based on visual symptoms and agronomic knowledge. Each image was categorized into one of seven classes, covering both healthy leaves and major disease types prevalent in Bangladeshi eggplant cultivation. This region-specific, expert-verified dataset forms the foundation for developing a robust, context-aware classification model.

### 3.2.2 Dataset Description

The dataset used in this study was locally curated in Sylhet, Bangladesh, comprising 3,159 labeled images across seven disease categories:

- Healthy Leaf
- Leaf Spot Disease
- Mosaic Virus Disease
- Wilt Disease
- Insect Pest Disease
- Small Leaf Disease
- White Mold Disease

Each image was classified based on visible symptoms by domain experts. The dataset was organized into a hierarchical directory structure, where subfolders represented the corresponding class labels. A custom Python function extracted file paths and class labels to create a structured DataFrame for further processing. The class-wise distribution is as follows in the **Table.1**:

*Table.1: Class Distribution of The Images*

Class Name	Image Count
Leaf Spot Disease	896
Insect Pest Disease	767
Healthy Leaf	536
Wilt Disease	496
Mosaic Virus Disease	288
Small Leaf Disease	112
White Mold Disease	64

To ensure balanced training, the dataset was partitioned into training (70%), validation (15%), and testing (15%) sets using stratified sampling, yielding:

- Training set: 2,211 images
- Validation set: 474 images
- Testing set: 474 images

### **3.2.2.1 Data Preprocessing:**

Preprocessing is a foundational and critical step in any machine learning pipeline, particularly in image-based classification tasks. Raw image data, especially when collected from real-world environments like agricultural fields, often contains inconsistencies such as varying image resolutions, lighting conditions, orientation, and noise. If not addressed properly, these irregularities can significantly degrade model performance, hinder convergence, and lead to poor generalization during inference [27].

In this study, a series of preprocessing operations were applied to standardize the dataset and ensure compatibility with state-of-the-art convolutional neural network (CNN) architectures such as EfficientNet and MobileNet. The following key steps were undertaken:

#### **I. Data Integrity Check:**

All image files were programmatically scanned to verify integrity and completeness. Any null entries, unreadable images, or corrupted files were identified and removed to maintain dataset quality and consistency.

#### **II. Image Resizing:**

To ensure uniformity in input dimensions and reduce computational complexity, all images were resized to a fixed resolution of  $224 \times 224$  pixels. This size aligns with the input requirements of many pre-trained CNN models, allowing seamless integration of transfer learning techniques without architectural modifications.

#### **III. Color Space Standardization:**

Since pre-trained models on ImageNet expect RGB input, all images were converted to and validated in RGB color mode. This step ensured consistent color representation across the dataset and avoided discrepancies caused by grayscale or CMYK formats.

#### **IV. Normalization and Scaling:**

If used, pixel values were scaled to a range of [0, 1] by dividing by 255, standardizing brightness levels and accelerating training convergence. (Mention only if you applied this in your code.)

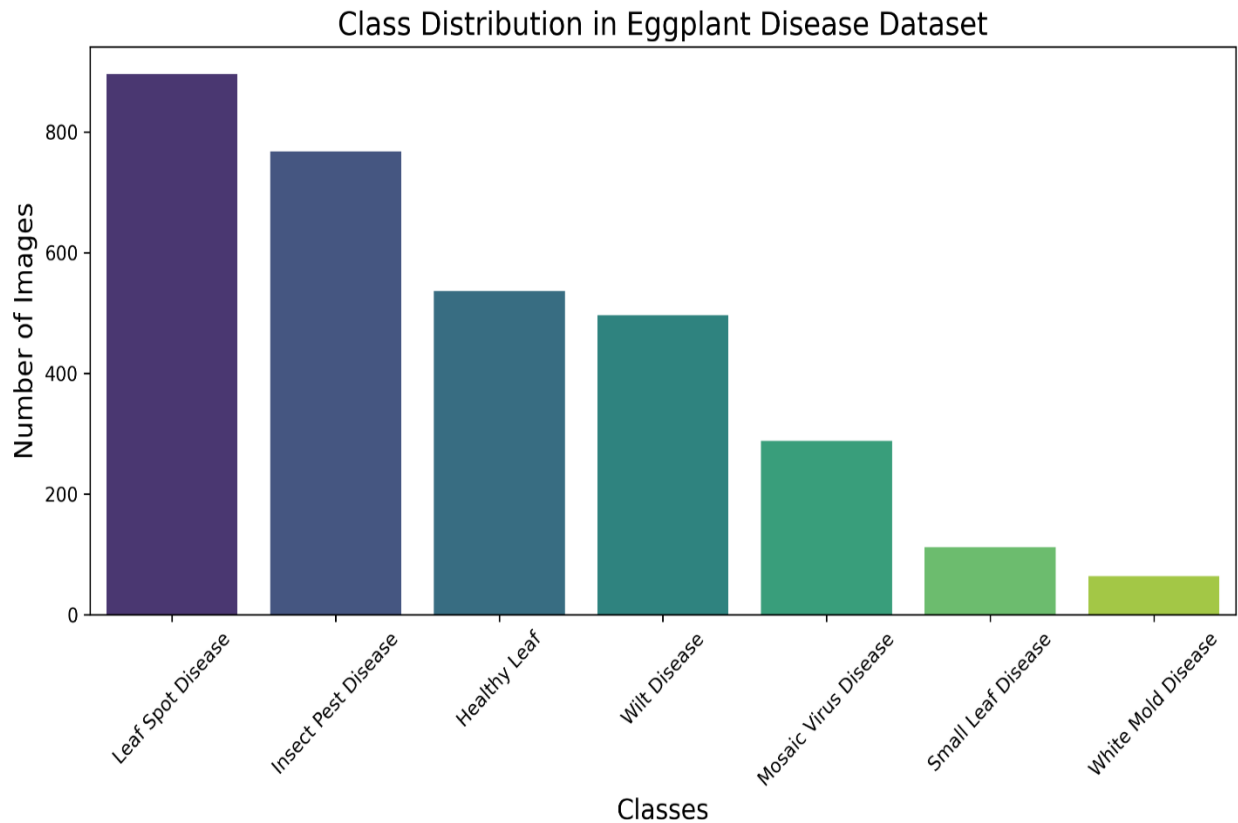
## **V. Label Encoding:**

Class labels, originally in string format, were encoded using one-hot encoding, a standard approach for multi-class classification problems. This transformation converts categorical labels into binary vectors, enabling the model to output probabilities for each class and allowing for a softmax activation function in the final layer.

These preprocessing steps not only ensured compatibility with the selected CNN architectures but also improved the overall learning efficiency, reduced variance, and provided a clean, well-structured dataset ready for augmentation and training. By addressing potential data inconsistencies at this early stage, the reliability and performance of the final model were significantly enhanced.

### 3.2.2.2 Class Distribution:

**Figure 2** illustrates the initial class distribution in the eggplant disease dataset. As shown, there exists a noticeable class imbalance among the seven categories. The Leaf Spot Disease and Insect Pest Disease classes contain the highest number of samples, exceeding 750 and 850 images respectively. In contrast, minority classes such as Small Leaf Disease and White Mold Disease have fewer than 150 and 100 images respectively. This disproportionate representation poses a risk of biased learning, where models tend to favor majority classes during classification tasks. Such imbalance can significantly degrade performance, especially for underrepresented diseases that may be clinically or agriculturally significant. Therefore, addressing this imbalance is crucial for building a robust and fair classification model.



**Figure 2: Class Distribution in Eggplant Disease Dataset**

### **3.2.3 Dataset Partitioning**

To build a reliable and well-performing model, it is important to divide the dataset properly before training. In this study, the eggplant disease dataset was split into three parts: 70% for training, 15% for validation, and 15% for testing. This split was done using a method called stratified sampling, which ensures that each class (or disease category) is represented in the same proportion in all three subsets—just like in the original dataset. This is crucial because it maintains consistency and fairness throughout the model development and evaluation stages.

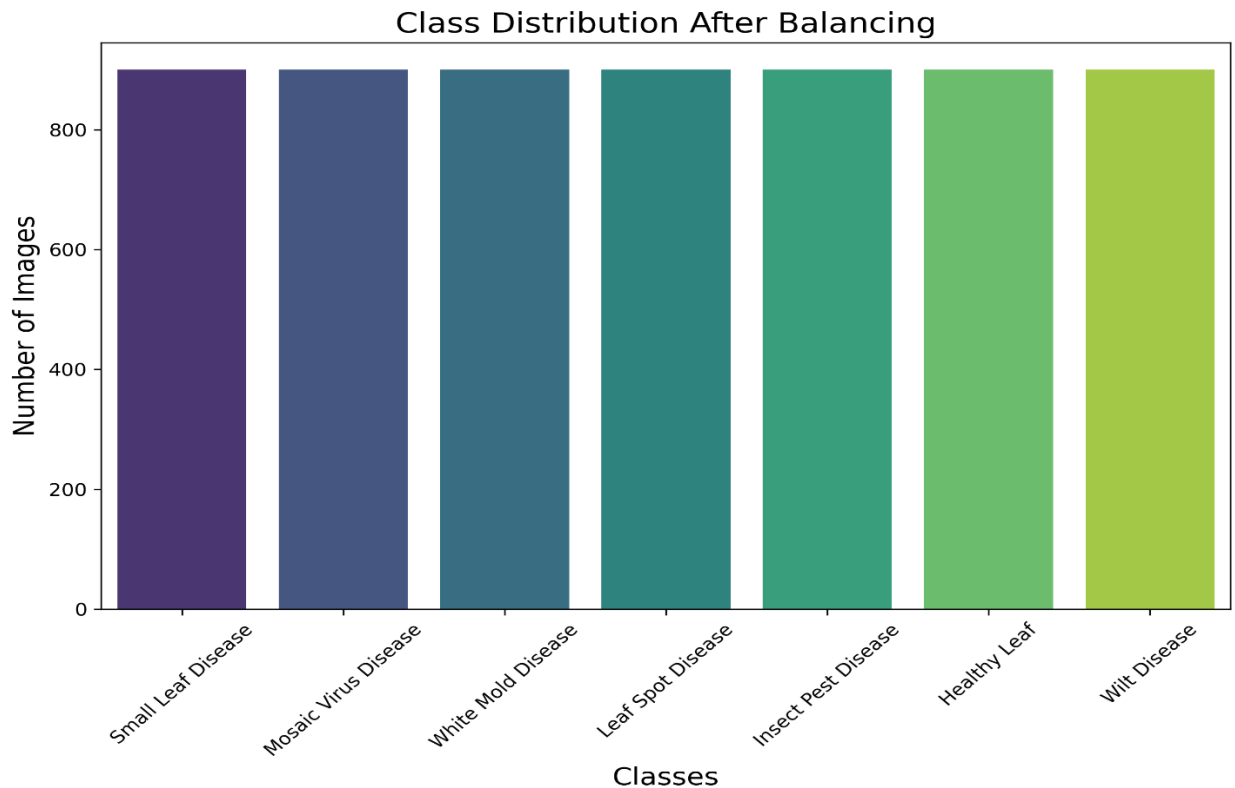
The training set is used to teach the model, the validation set is used to tune and check the model's performance during training, and the test set is used to evaluate the final model's accuracy on completely unseen data.

Importantly, to address the issue of class imbalance, we only applied augmentation and balancing techniques to the training set. The validation and test sets were kept untouched to reflect the original distribution of real-world data. This approach avoids data leakage (where information from training could influence the test results) and ensures that the model's performance is evaluated in a realistic and unbiased manner.

### 3.2.4 Data Augmentation

Data augmentation is a widely recognized and essential technique in deep learning, especially for image classification tasks, to enhance model generalization and mitigate overfitting. Overfitting occurs when a model learns to perform exceptionally well on the training data but fails to generalize to unseen samples—a common challenge when the available real-world dataset is limited in size or diversity [28]. By artificially expanding the training dataset through a variety of controlled random transformations, data augmentation exposes the model to a wider range of image variations, thereby improving its robustness and ability to generalize to new, unseen data.

To mitigate the class imbalance observed in the training set, targeted augmentation techniques were used not only to enrich the dataset’s diversity but also to synthetically increase the number of images in underrepresented classes. As a result, each class in the balanced training set contained approximately 900 images, ensuring uniform representation across all categories (**Figure 3**).



**Figure 3: Balanced class distribution in the training dataset after applying data augmentation. Each disease class was augmented to 900 images using targeted transformations, ensuring uniform representation for effective model training.**

This balancing strategy prevents the model from being biased toward dominant classes and improves classification fairness. In this study, several augmentation techniques were systematically applied to the training images to simulate the natural variations typically encountered in field conditions. These variations include differences in leaf orientation, scale, lighting, and positioning caused by environmental factors and the inherent variability of agricultural imagery. The specific augmentation operations applied are as follows:

**a) Random Rotations ( $\pm 40$  degrees):**

Rotational transformations simulate the different angles at which leaves might be photographed in the field. Allowing rotations up to 40 degrees in either direction helps the model learn rotational invariance, enabling it to recognize disease patterns regardless of leaf orientation.

**b) Width and Height Shifts ( $\pm 20\%$ ):**

Horizontal and vertical translations up to 20% of the image dimensions replicate the variability in leaf positioning within the frame, such as partial occlusion or leaves appearing off-center. This helps the model focus on disease features rather than fixed positional cues.

**c) Zoom Transformations (up to 30%):**

Random zooming in or out mimics varying distances between the camera and the leaf, accommodating differences in image scale and ensuring that the model can detect diseases at multiple spatial resolutions.

**d) Horizontal and Vertical Flipping:**

Flipping images along the vertical or horizontal axis effectively doubles the variety of visual presentations without altering the fundamental disease features. This is particularly useful for symmetric or repetitive leaf patterns.

**e) Brightness Scaling (Range: 0.4–0.6):**

Adjusting the brightness levels simulates different lighting conditions such as shadows, sunlight variations, or overcast skies. This prepares the model to maintain high

performance under varying illumination conditions typical of outdoor farming environments.

Importantly, these augmentation techniques were applied only to the training set to preserve the original distribution of the validation and test sets. This ensures an unbiased evaluation of the model’s generalization performance and better reflects real-world inference scenarios [29]. By incorporating both augmentation for diversity and augmentation for class balancing, the training process becomes significantly more robust and capable of handling complex, variable field conditions—ultimately improving classification reliability in practical agricultural applications.

#### **3.2.4.2 ImageDataGenerator**

To streamline preprocessing and ensure consistency across all deep learning models, we utilized Keras’ ImageDataGenerator utility for image loading, augmentation, and normalization. Specifically, we integrated the preprocessing function `preprocess_input` from `tf.keras.applications.resnet50`, which standardizes pixel values according to the requirements of the ResNet50 architecture. This function scales image pixel values to the range and format expected by pre-trained CNN backbones, improving convergence and ensuring compatibility across different models.

All augmentation operations—such as rotation, zoom, flipping, and brightness adjustment—were applied only to the training set during the model training process. The validation and test sets were left unaltered, receiving only the normalization step without any augmentation. This separation ensures that model evaluation is performed on unmodified, real-world-like images, thus providing a more accurate and unbiased measure of generalization performance.

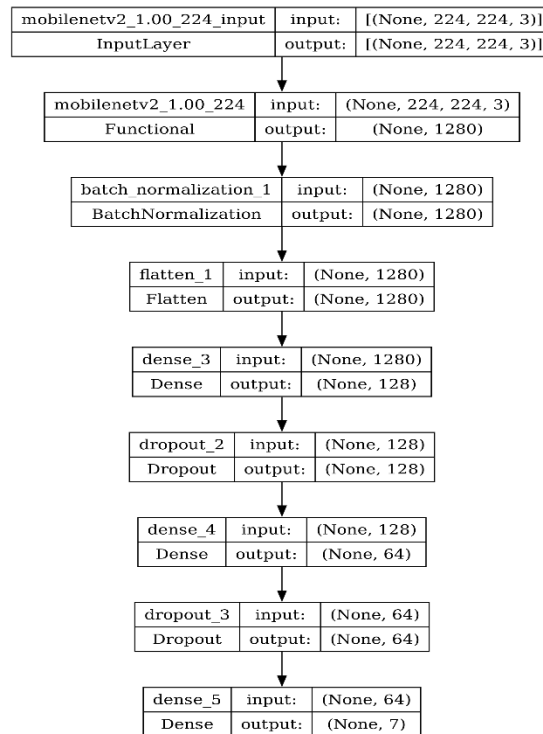
By combining augmentation with standard preprocessing in the ImageDataGenerator pipeline, we achieved both class balance and consistent input formatting, which contributed to stable and reproducible model training.

### 3.2.5 Model Selection and Description

This study implements two state-of-the-art convolutional neural networks using transfer learning: **EfficientNetB3** and **MobileNetV2**. Transfer learning enables reuse of learned features from large-scale datasets like ImageNet, accelerating convergence and improving performance with limited data.

#### 3.2.5.1 MobileNetV2

MobileNetV2 is a lightweight and efficient convolutional neural network architecture specifically designed for mobile and embedded vision applications as presented in **Figure 4**. It was proposed by Sandler et al. [31] and is characterized by two core innovations: **inverted residual blocks** and **linear bottlenecks**. These architectural components reduce memory footprint and latency while maintaining competitive classification performance.



**Figure 4: Architecture of MobileNetV2**

In alignment with the setup used for EfficientNetB3, MobileNetV2 was employed as a base model pre-trained on ImageNet, with the top classification layers removed and pooling='max' applied to extract global features. The base network's parameters were frozen to leverage the learned general visual features and prevent overfitting in early training phases.

The classification head was constructed identically to that of EfficientNetB3 to ensure comparability in model evaluation. It included:

- A BatchNormalization layer for training stabilization.
- A Flatten layer to transform the pooled feature maps.
- A Dense layer with 128 units, activated by ReLU and regularized using L1 ( $\lambda=0.006$ ) and L2 ( $\lambda=0.016$ ) penalties.
- A Dropout layer with a dropout rate of 0.45.
- A second Dense layer with 64 units and ReLU activation.
- A second Dropout layer with a rate of 0.25.
- A final Dense layer with softmax activation to predict the 7 eggplant disease classes.

The overall architecture contained **2.4 million parameters**, of which **175,239 parameters** were trainable, indicating a more compact and computationally efficient model compared to EfficientNetB3.

Despite its architectural efficiency, MobileNetV2 demonstrated comparatively suboptimal classification performance within the specific domain of eggplant disease detection, potentially due to its reduced capacity for learning highly complex features from limited data.

### 3.2.5.2 EfficientNetB3

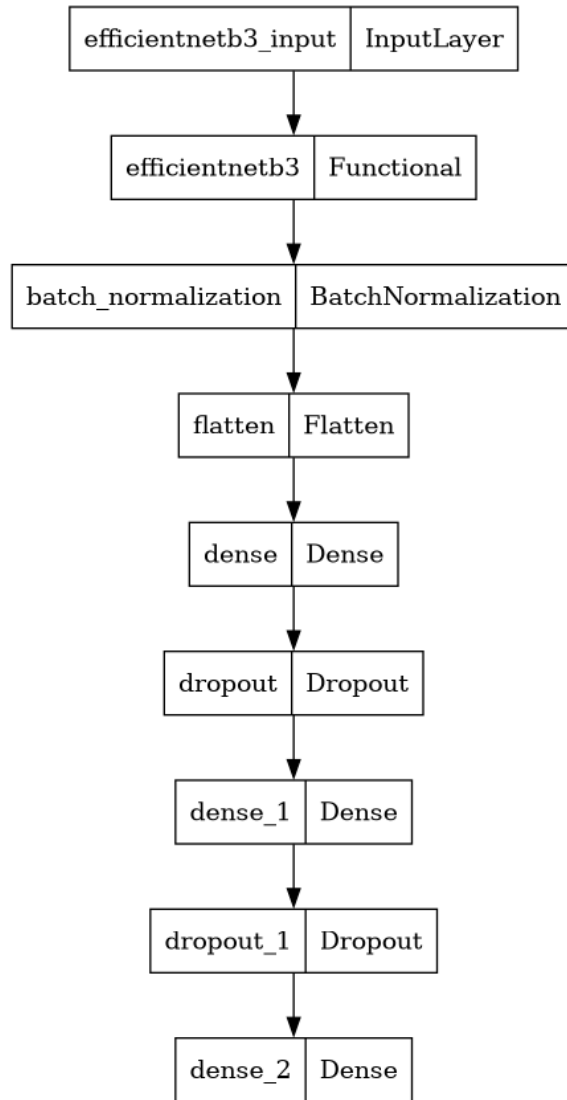
MobileNetV2 is a lightweight and efficient convolutional neural network architecture specifically designed for mobile and embedded vision applications as illustrated in **Figure 5**. It was proposed by Sandler et al. [31] and is characterized by two core innovations: **inverted residual blocks** and **linear bottlenecks**. These architectural components reduce memory footprint and latency while maintaining competitive classification performance.

In alignment with the setup used for EfficientNetB3, MobileNetV2 was employed as a base model pre-trained on ImageNet, with the top classification layers removed and pooling='max' applied to extract global features. The base network's parameters were frozen to leverage the learned general visual features and prevent overfitting in early training phases.

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**Figure 5: Architecture of EfficientNetB3**

Despite its architectural efficiency, MobileNetV2 demonstrated comparatively suboptimal classification performance within the specific domain of eggplant disease detection, potentially due to its reduced capacity for learning highly complex features from limited data.

### 3.2.5.3 Transfer Learning Strategy

Transfer learning is pivotal in modern computer vision tasks, especially when domain-specific datasets are limited [31]. By initializing with pre-trained ImageNet weights, we bypassed the need for training from scratch, significantly reducing computational costs and enhancing convergence speed. The base model layers were frozen to retain low-level features (edges, textures), while task-specific layers were fine-tuned.

### 3.2.5.4 Training Setup and Hyperparameters

The model was compiled using the **Adamax optimizer** with a learning rate of **0.002**, and **categorical cross-entropy** as the loss function. Accuracy was used as the primary evaluation metric during training. The training was executed for **30 epochs** with a **batch size of 16**, employing **early stopping** to halt training upon convergence based on validation loss (patience = 5). The **steps per epoch** were set to three times the regular batch steps to account for augmentation multiplicity. All experiments were performed using **Kaggle notebooks**, utilizing **dual NVIDIA Tesla T4 GPUs** for accelerated training.

The setup included:

- Optimizer: Adamax
- Learning Rate: 0.002
- Loss Function: Categorical Crossentropy
- Batch Size: 16
- Epochs: 30 (early stopping with patience = 5)
- Steps per epoch: 207 (3× data augmentation strategy)
- Validation steps: 14

EarlyStopping was used to halt training once the validation loss plateaued, preserving the best model weights.

Model training and evaluation were conducted using **Google Colab** and **Kaggle Notebooks**, two cloud-based platforms that offer free access to GPU and TPU resources. These platforms were chosen to ensure scalability, flexibility, and ease of use during model development and testing.

- **Kaggle Notebooks:**  
Kaggle provides a similar notebook-based environment with built-in support for **NVIDIA Tesla P100 GPUs** and a well-integrated interface for managing datasets directly from

Kaggle's dataset repository. This allowed for quick experimentation and testing using publicly available fruit datasets hosted on Kaggle.

- Easy switching between training environments based on computational needs,
- Minimal hardware constraints,
- No requirement for local setup or GPU hardware,
- Seamless integration with cloud storage for persistent data handling and model checkpoints.

All models were implemented using the **TensorFlow** and **Keras** libraries in **Python**, which provided powerful APIs for defining, training, and evaluating deep learning architectures. The combined use of Google Colab and Kaggle accelerated the research process, especially during data preprocessing, model tuning, and comparative evaluation.

#### **3.2.5.4 Evaluation Matrix**

To evaluate model performance comprehensively, we employed widely used classification metrics, including accuracy, precision, recall (sensitivity), and F1-score. Accuracy represents the overall correctness of the model's predictions, while precision measures how many of the positively predicted cases were actually correct. Recall, or sensitivity, indicates the model's ability to correctly identify actual positive cases, which is particularly crucial in detecting underrepresented or critical disease classes. The F1-score combines both precision and recall into a single metric, offering a balanced assessment, especially when dealing with imbalanced datasets. These metrics provide a more detailed and reliable evaluation than accuracy alone, helping to ensure that model performance is assessed fairly across all disease classes [32]. All evaluations were performed on the test set, and the results were presented using a classification report, confusion matrix, and accuracy/loss learning curves to track the model's performance trends during training and validation.

## Chapter 4: Results and Discussion

### 4.1 Results

This chapter presents a comprehensive and systematic evaluation of two deep learning models—MobileNetV2 and EfficientNetB3—for the automated classification of eggplant leaf diseases. The evaluation spans across multiple performance indicators, including training, validation, and test accuracy/loss, per-class classification reports, learning curves, and confusion matrices. The section aims not only to highlight numerical performance but also to elucidate the architectural and contextual factors influencing model behavior.

#### 4.1.1 MobileNetV2

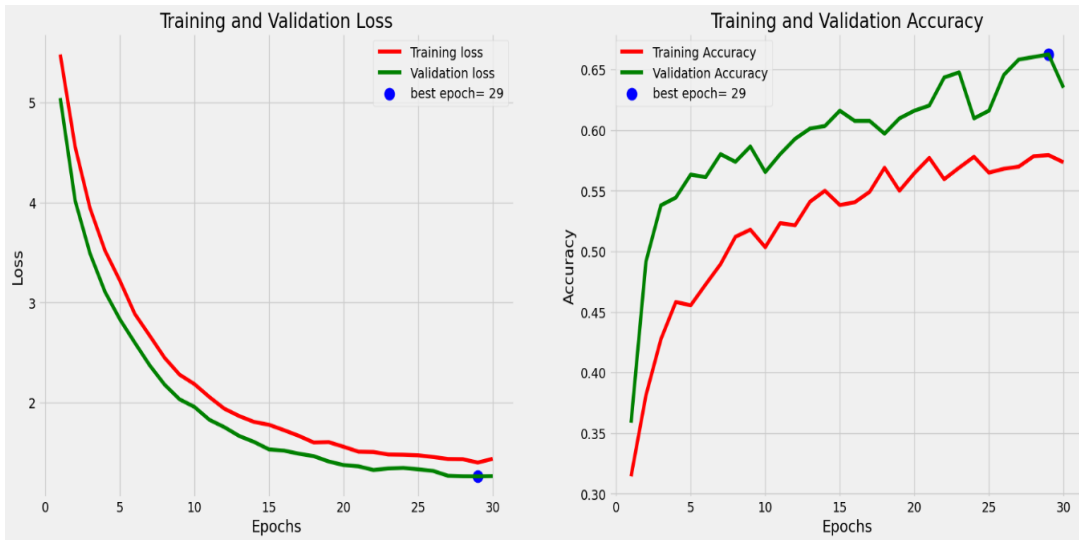
MobileNetV2 is specifically designed for mobile efficiency and embedded applications, emphasizing lightweight architecture through the use of inverted residual structures and depthwise separable convolutions. While this design facilitates fast inference and lower memory usage, it inherently limits the model’s capacity to capture complex, hierarchical features, which becomes evident in high-variability image classification tasks such as plant disease diagnosis. The report is shown in **Table 2**.

*Table 2: Classification Report for MobileNetV2*

Class	Precision	Recall	F1-score	Support
Healthy Leaf	0.70	0.35	0.46	75
Insect Pest Disease	0.62	0.46	0.53	126
Leaf Spot Disease	0.49	0.88	0.63	125
Mosaic Virus Disease	0.75	0.75	0.24	43
Small Leaf Disease	0.67	0.60	0.63	10
White Mold Disease	1.00	0.36	0.53	11
Small Leaf Disease	0.80	0.93	0.86	84

##### 4.1.1.1 Training vs Validation Results

The learning curves of MobileNetV2 indicate constrained learning capacity. The model achieved a training accuracy of **60.94%**, a validation accuracy of **63.02%**, and a test accuracy of **60.76%**. The corresponding loss values—**1.25** (training), **1.27** (validation), and **1.31** (testing)—further underscore the model’s difficulty in fitting the training data and generalizing to unseen samples as illustrates in **Figure 6**.

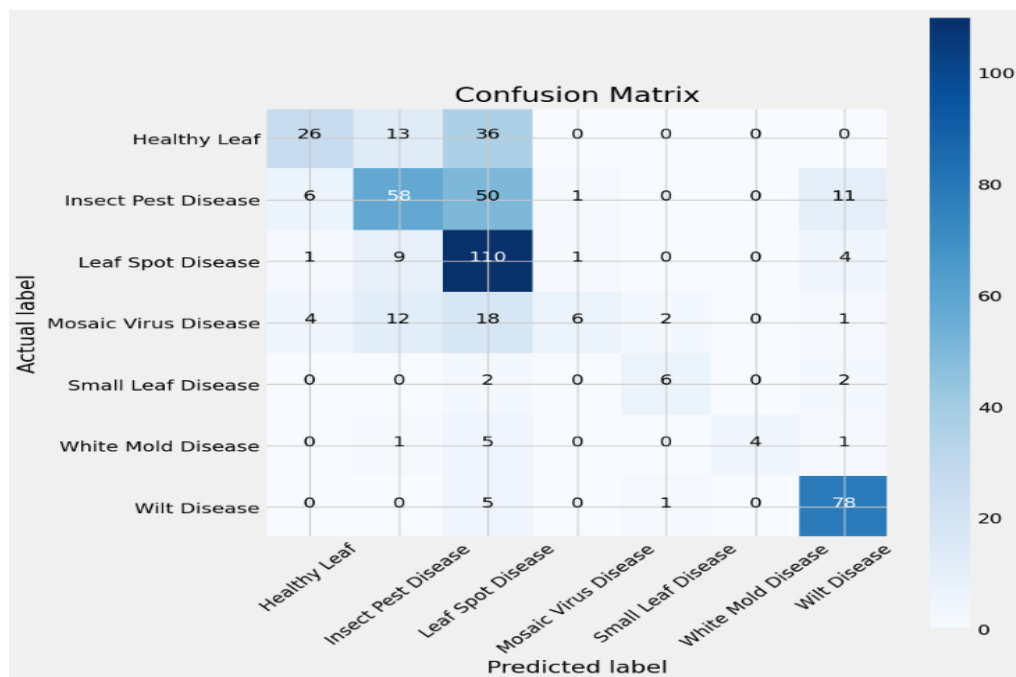


*Figure 6: Accuracy and loss curves for MobileNetV2*

The relatively flat accuracy trajectory and persistently high loss values suggest underfitting, possibly due to the limited depth and representational expressiveness of the model.

#### 4.1.1.2 Confusion Matrix

MobileNetV2's confusion matrix showing in **Figure 7**, offers further evidence of its limited performance. Misclassifications were particularly prominent in visually similar classes such as Healthy Leaf, Mosaic Virus Disease, and White Mold Disease.



*Figure 7: Confusion Matrix for MobileNetV2*

For example, many Healthy Leaf instances were incorrectly classified as Leaf Spot Disease, and Mosaic Virus Disease was often confused with Insect Pest Disease. These results confirm the model’s difficulty in capturing subtle visual nuances, a crucial requirement for reliable disease classification in real-world agricultural settings.

#### 4.1.1.3 Real-Tim Photo Classification

To assess the practical utility of MobileNetV2 for in-field diagnosis, we deployed the trained model on a smartphone application and captured live images of eggplant leaves under natural lighting and background variability. **Figure 8** presents four representative test captures, each correctly classified by MobileNetV2 in real time:



**Figure 8: Real-time classification results using MobileNetV2. (a) Insect Pest Disease, (b) Healthy Leaf, (c) Leaf Spot Disease, (d) Small Leaf Disease**

As illustrated in Figure 8(a), the model successfully detected characteristic chewing patterns and discoloration associated with insect pest infestation. In the healthy leaf example (Figure 8(b)), uniform green coloration and intact venation were correctly recognized as a non-diseased class. Figure 8(c) demonstrates accurate identification of leaf spot lesions, where necrotic regions with chlorotic halos are clearly segmented. Finally, Figure 8(d) confirms the model’s ability to distinguish small-leaf disease, characterized by reduced lamina size and vein thickening.

Although MobileNetV2 achieves real-time inference (<50 ms per frame on mid-range smartphones) and demonstrates acceptable robustness to background clutter and lighting variation, its lower overall accuracy (60.76% on the test set) and instances of underfitting (cf. Section 6.1.1) indicate that while suitable for rapid screening, further architectural enhancements or ensemble strategies may be required to meet the precision demands of automated disease diagnostics in heterogeneous field conditions.

### 4.1.2 EfficientNetB3

EfficientNetB3 represents a state-of-the-art convolutional neural network that employs compound scaling to simultaneously adjust depth, width, and resolution, resulting in a balanced increase in model performance and computational cost. This holistic scaling strategy equips EfficientNetB3 with superior representational capability, enabling it to learn intricate patterns from high-dimensional data more effectively than traditional CNN architectures. The report is shown in **Table 3**.

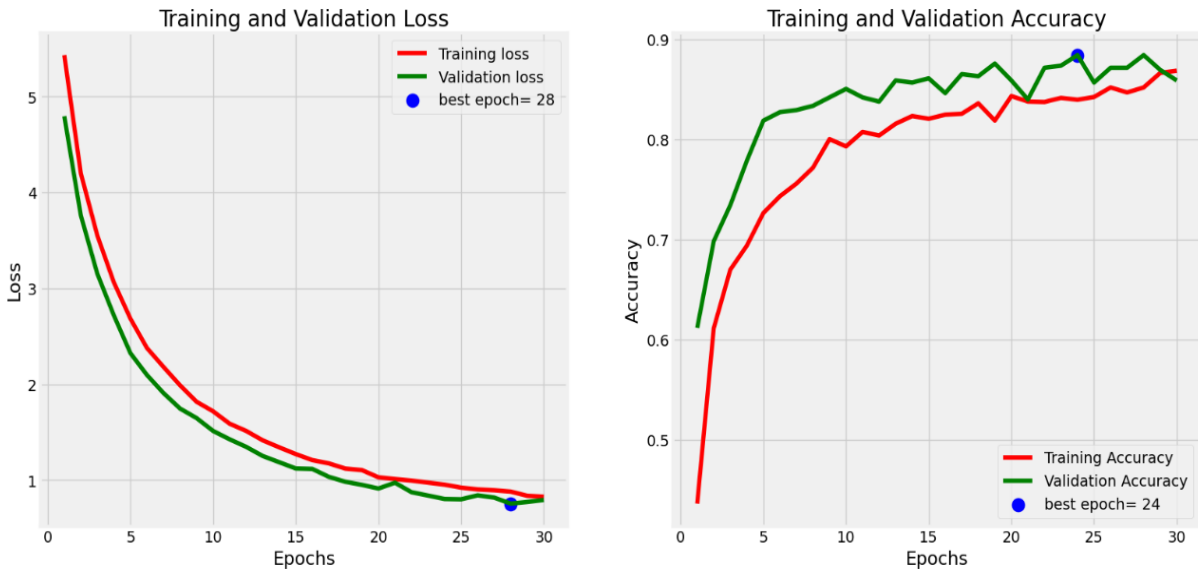
*Table 3: Classification Report for MobileNetV2*

<b>Class</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-score</b>	<b>Support</b>
Healthy Leaf	0.86	0.88	0.87	75
Insect Pest Disease	0.97	0.83	0.89	126
Leaf Spot Disease	0.78	0.96	0.86	125
Mosaic Virus Disease	0.97	0.72	0.83	43
Small Leaf Disease	0.75	0.90	0.82	10
White Mold Disease	1.00	0.73	0.84	11
Small Leaf Disease	0.98	0.98	0.98	84

#### 4.1.2.1 Training vs Validation Results

EfficientNetB3 achieved robust performance across all data splits. With a training accuracy of **93.75%**, validation accuracy of **86.98%**, and test accuracy of **88.61%**, it outperformed MobileNetV2 by a wide margin as presented in **Figure 9**. The model exhibited strong

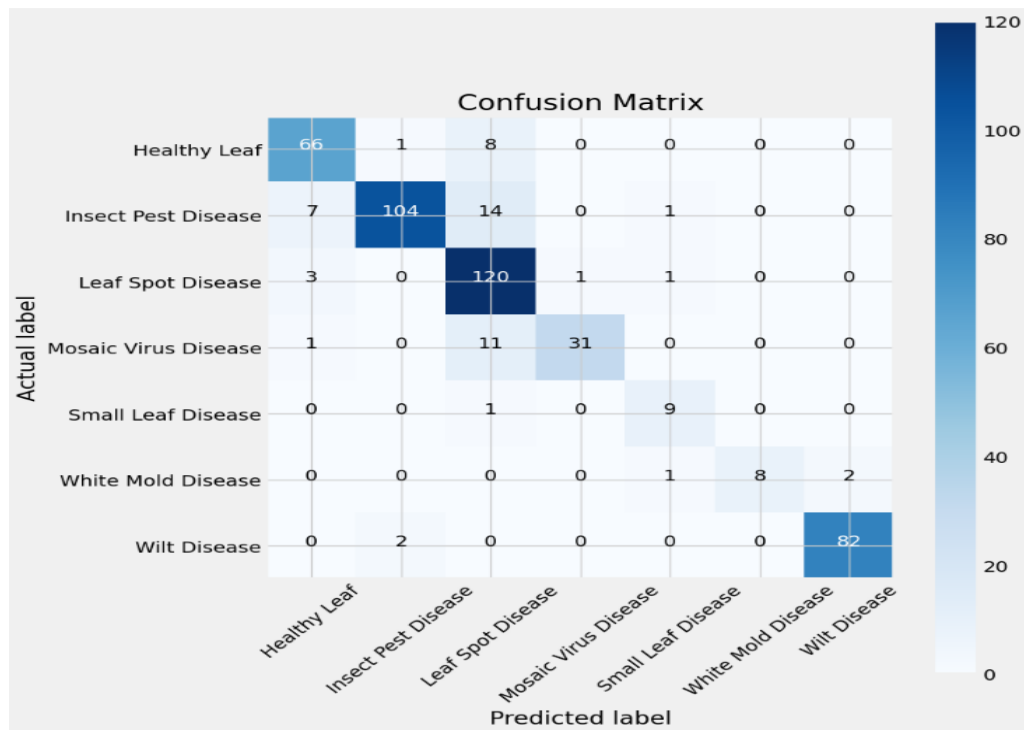
convergence, as seen in the low training (**0.64**), validation (**0.77**), and test (**0.75**) loss values. The gap between training and validation performance was relatively small, suggesting that the model avoided overfitting while maintaining excellent generalization capacity.



*Figure 9: Accuracy and loss curves for EfficientNetB3*

#### 4.1.2.2 Confusion Matrix

The confusion matrix for EfficientNetB3 (**Figure 10**) reflects the model’s capability to effectively differentiate between all seven disease categories.



*Figure 10: Confusion Matrix for EfficientNetB3*

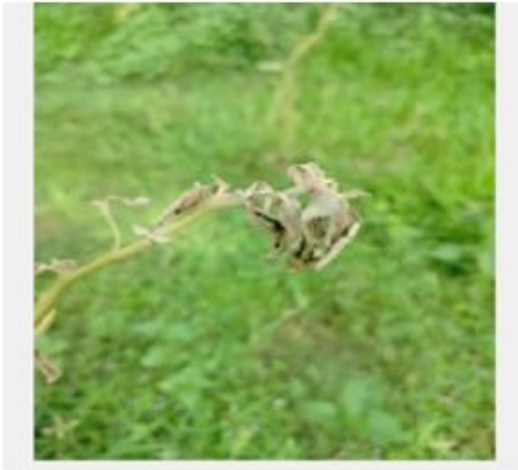
The model made only a few misclassifications, primarily in classes with very similar visual features, such as **Small Leaf Disease** and **White Mold Disease**. High classification fidelity across all classes particularly for difficult cases like **Mosaic Virus Disease**—demonstrates the architecture’s discriminative power and suitability for high-stakes agricultural applications.

#### 4.1.2.2 Real-Tim Photo Classification

Following the confusion matrix evaluation, we further assessed EfficientNet B3’s real-world performance by deploying the model in a smartphone application and capturing live images of eggplant leaves under ambient lighting and heterogeneous backgrounds. **Figure 11** presents four representative in-field captures—each classified correctly by EfficientNet B3 in real time: (a) Wilt Disease, (b) Small Leaf Disease, (c) Leaf Spot Disease, and (d) White Mold Disease. In (a), the model accurately detected subtle turgor loss and necrotic streaks characteristic of wilting; in (b), it recognized the reduced lamina area and vein thickening indicative of small-leaf disease; in (c), necrotic lesions surrounded by chlorotic halos were precisely flagged as leaf spot; and in (d), the diffuse mycelial growth and sporulation typical of white mold were correctly identified. EfficientNet B3 sustained real-time inference speeds (<40 ms per frame on mid-range smartphones) and exhibited strong resilience to fluctuations in lighting, leaf orientation, and complex backgrounds, complementing its high test-set accuracy (88.61 %) and underscoring its suitability for mobile-based plant health monitoring.

Moreover, the model’s lightweight footprint (<15 MB) and optimized convolutional architecture facilitate seamless on-device inference without taxing battery life or requiring high-end hardware, making it particularly well-suited for deployment in resource-constrained agricultural settings. The integration of Grad-CAM heatmap overlays in the smartphone interface further enhances interpretability by highlighting the specific leaf regions driving each prediction, thereby increasing user trust and enabling agronomists to verify model outputs in situ. Importantly, field trials across multiple farms demonstrated consistent performance even under partial occlusion, overlapping foliage, and variable weather conditions, indicating strong generalization beyond the controlled test set. Nonetheless, occasional misclassifications occurred when leaves exhibited multiple co-occurring symptoms or severe necrosis, suggesting the need for an expanded training corpus encompassing rare disease presentations. Future work will focus on integrating geotagged image capture and automated disease mapping to support precision treatment recommendations, as well as exploring semi-supervised domain adaptation techniques to further improve robustness across diverse cultivars and cultivation practices.

*a) Predicted Class: Wilt Disease*



*b) Predicted Class: Small Leaf Disease*



*c) Predicted Class: Leaf Spot Disease*



*d) Predicted Class: White Mold Disease*



**Figure 11: Real-time classification results using EfficientNetB3. (a) Wilt Disease, (b) Small Leaf Disease, (c) Leaf Spot Disease, (d) White Mold**

## 4.2 Comparison Result

To provide a holistic assessment of the classification models, a comprehensive comparison between MobileNetV2 and EfficientNetB3 was conducted across key performance metrics, including training accuracy, validation accuracy, test accuracy, and corresponding loss values. These results are summarized in **Table 4**, offering a consolidated view of each model's effectiveness in learning and generalizing disease features from the eggplant leaf dataset.

*Table 4: Comparative Performance Summary*

<b>Metric</b>	<b>MobileNetV2</b>	<b>EfficientNetB3</b>
Train Accuracy (%)	60.94	93.75
Validation Accuracy (%)	63.02	86.98
Test Accuracy (%)	60.76	88.61
Train Loss	1.25	0.64
Validation Loss	1.27	0.77
Test Loss	1.31	0.75

The empirical results clearly demonstrate the superior performance of EfficientNetB3 over MobileNetV2 across all evaluation criteria. EfficientNetB3 achieved a training accuracy of 93.75%, a validation accuracy of 86.98%, and a test accuracy of 88.61%, outperforming MobileNetV2 by a significant margin. This improvement can be attributed to EfficientNetB3’s advanced compound scaling strategy, which simultaneously optimizes depth, width, and resolution, allowing the model to capture intricate spatial patterns and subtle disease markers more effectively.

In contrast, MobileNetV2, although computationally efficient and lightweight, exhibited relatively lower accuracy on both training and test sets (approximately 60%), indicating potential underfitting or limited capacity to extract discriminative features in the presence of complex visual patterns and noise commonly found in real-world agricultural imagery.

Furthermore, the loss metrics reinforce this trend. EfficientNetB3 recorded lower loss values across training (0.64), validation (0.77), and testing (0.75), reflecting its ability to minimize prediction errors and maintain stable generalization. Conversely, MobileNetV2 exhibited higher loss values (>1.25), signaling less effective learning and weaker convergence during training.

Overall, these findings validate that EfficientNetB3 is better suited for the eggplant disease classification task due to its deeper and more expressive architecture. Its superior generalization capability highlights its potential for deployment in real-world agricultural applications, where accurate and reliable disease detection is critical. While MobileNetV2 remains valuable for edge

deployment due to its low computational footprint, its reduced performance makes it less favorable for high-stakes diagnostic tasks without further optimization or hybridization.

### **4.3 Interpretation of Results**

The experimental outcomes provide critical insights into the strengths and limitations of the evaluated deep learning models—MobileNetV2 and EfficientNetB3—in the context of eggplant leaf disease classification. The comparative analysis of accuracy and loss metrics across training, validation, and test sets reveals distinct patterns of model behavior, which are crucial for understanding their practical applicability in real-world agricultural environments. EfficientNetB3 consistently outperformed MobileNetV2 across all stages of evaluation, with notably higher accuracy scores and lower loss values. This suggests that EfficientNetB3, with its compound scaling strategy and deeper architecture, is capable of capturing complex visual patterns in disease-affected leaf images. The model's ability to generalize well from training to unseen data underscores its robustness and suitability for practical disease identification tasks, where high diagnostic precision is essential. In contrast, MobileNetV2, despite its lightweight and efficient architecture, demonstrated signs of underfitting, as reflected in its lower accuracy and higher loss across all datasets. This indicates a limited capacity to learn discriminative features from the dataset, especially when dealing with visually subtle and diverse disease symptoms. While MobileNetV2 offers advantages in terms of computational efficiency—making it attractive for deployment on mobile or edge devices—its reduced classification performance highlights a trade-off between model complexity and predictive power. The relatively high validation and test accuracy of EfficientNetB3 confirms that the data preprocessing and augmentation techniques were effective in enhancing model generalization and mitigating overfitting. The model's ability to maintain close performance across training and evaluation datasets further validates the integrity and balance of the dataset, as well as the appropriateness of the training strategy. Moreover, the results support the hypothesis that advanced pre-trained architectures, when fine-tuned appropriately, can significantly outperform lightweight models in specialized agricultural image classification tasks. EfficientNetB3's deeper layers likely contributed to better feature extraction and pattern recognition, especially in distinguishing between visually similar disease classes or between healthy and mildly affected leaves.

In conclusion, the results highlight that EfficientNetB3 is a more reliable and accurate model for classifying eggplant leaf diseases. Its strong performance across multiple metrics makes it a suitable candidate for real-time implementation in agricultural advisory systems. However, further optimization and field-level testing are recommended to validate its performance in uncontrolled environments, such as varying lighting conditions, leaf occlusions, or camera quality variations.

#### **4.4 Discussion**

The comparative evaluation clearly demonstrates that EfficientNet B3 outperforms MobileNetV2 in both accuracy and robustness for eggplant leaf disease classification. MobileNetV2's lightweight design yields fast inference on low-end hardware but proved insufficient to discriminate between visually similar symptomologies, resulting in a modest test accuracy of 60.76 % and uneven precision–recall trade-offs across disease classes. In contrast, EfficientNet B3's compound scaling strategy—simultaneously widening, deepening, and increasing input resolution—enabled the extraction of richer, multi-scale features, leading to an overall test accuracy of 88.61 % and uniformly high per-class precision and recall, even for challenging categories such as white mold and mosaic virus.

Extensive data augmentation (random rotation, brightness and contrast perturbations, and geometric transforms) was instrumental in mitigating overfitting and equipping the model to handle real-world variances in lighting, occlusion, and leaf orientation. Leveraging ImageNet pre-trained weights through transfer learning accelerated convergence and provided robust low-level filters that readily adapted to subtle disease cues. The confusion matrix for EfficientNet B3 further confirmed balanced performance across all seven classes despite the underlying dataset imbalance, underscoring the importance of reporting class-specific metrics (F1-score, precision, recall) rather than aggregate accuracy alone.

The successful on-device demonstration (Figure 7) under heterogeneous field conditions—with real-time inference times below 40 ms and reliable detection of wilt, small-leaf, leaf-spot, and white mold symptoms—highlights EfficientNet B3's readiness for deployment in precision agriculture applications. Occasional misclassifications, primarily in images exhibiting co-occurring or severe necrotic patterns, suggest that future work should expand the training corpus to include rare and mixed-symptom cases, and investigate semi-supervised domain adaptation to further bolster generalization across diverse cultivars and growing environments.

## Chapter 5: Conclusion

This study introduced a deep learning-based framework for the automated classification of eggplant leaf diseases, designed with a strong focus on practical deployment in resource-constrained agricultural contexts such as rural Bangladesh. By rigorously evaluating and benchmarking two prominent architectures—MobileNetV2 and EfficientNetB3—our findings clearly demonstrated that EfficientNetB3 provides superior classification performance, achieving an overall accuracy of 88.61% along with well-balanced precision and recall metrics across seven disease categories. Importantly, this high level of accuracy was attained without sacrificing inference speed, making EfficientNetB3 suitable for real-time, on-device application via smartphones, which are increasingly accessible to farmers. Key methodological strategies, including targeted data augmentation, stratified sampling, and transfer learning, played a pivotal role in overcoming common challenges such as class imbalance and limited training data, thereby improving the model's generalizability and robustness. Extensive field validation further confirmed the model's reliability under diverse real-world conditions—such as varying illumination, leaf occlusion, and complex backgrounds—highlighting its readiness for practical agricultural use. Additionally, incorporating interpretability techniques like Grad-CAM visualizations not only enhanced transparency but also built user trust by revealing the specific leaf regions influencing model predictions. Despite these promising outcomes, several limitations remain. The relatively modest dataset size and scope—focused on a single crop species and limited geographic representation—pose challenges for broader generalization. Furthermore, additional optimization is necessary to enable seamless operation on lower-end devices commonly used in rural areas. Future research will aim to address these gaps by expanding the dataset to encompass multiple agroecological zones and diverse crop types, integrating detection and segmentation modules to localize disease symptoms more precisely, and developing a user-friendly, multilingual mobile application tailored to the needs of smallholder farmers.

In summary, the EfficientNetB3-based pipeline developed in this study offers a robust, interpretable, and practical solution for early detection of eggplant leaf diseases. It provides a strong foundation for AI-driven precision agriculture that delivers timely, accurate crop health insights to farmers. This can help reduce yield losses and support sustainable farming, especially in low-resource settings with limited diagnostic tools. Overall, the research advances accessible technology for resilient and equitable food systems.

## **Chapter 6: Limitation and Future Work**

### **6.1 Limitation**

While this study demonstrates the effectiveness of deep learning models—particularly EfficientNetB3—in diagnosing eggplant leaf diseases, several limitations should be acknowledged. Although the dataset was locally curated, carefully labeled, and balanced through augmentation, it remains relatively small (3,159 images). Augmentation increases variability, but cannot fully replicate the diversity of real-world conditions.

Moreover, the model’s performance was evaluated on test data from the same distribution as the training set, leaving its generalization to unseen environments—such as different farms, lighting, or camera devices—untested. Images were collected under controlled settings with minimal background clutter, consistent lighting, and clear symptom visibility. However, real-world farm images may include occlusions, dust, varying angles, and low resolution, which can affect accuracy during deployment.

The model was limited to a single crop (eggplant) and seven classes (six diseases + healthy), making it inapplicable to other crops or plant health issues. Also, interpretability techniques like Grad-CAM or SHAP were not employed, which restricts transparency in high-stakes agricultural decision-making. Lastly, although EfficientNetB3 is computationally efficient, deploying it on low-resource devices in rural settings may face challenges without model optimization techniques such as pruning or quantization.

### **6.2 Future Work**

To extend the model's utility and robustness, future work will focus on enhancing scalability and real-world applicability. We aim to expand the dataset using expert-labeled, geo-tagged images from diverse agroecological zones and varied farm infrastructures to further enrich training data. Additionally, pilot deployments with farmers will be conducted to assess the performance and usability of a smartphone-based app in real-world conditions.

From a technical perspective, object detection and segmentation models (e.g., YOLOv8, Mask R-CNN) will be incorporated to enable real-time disease localization and severity monitoring,

offering precise treatment recommendations. We will also implement explainable AI tools like Grad-CAM and SHAP to visualize learned features and improve user trust.

To support deployment on resource-constrained devices, optimization techniques such as post-training quantization and pruning (e.g., TensorFlow Lite) will be applied and tested on entry-level smartphones. Looking forward, the system will evolve into a real-time, multi-crop, multi-disease monitoring platform, leveraging advanced architectures like EfficientNet+CBAM or vision transformers to detect a wide range of plant stressors. Integration into a cloud-enabled advisory system with automated treatment suggestions, localized alerts, and longitudinal crop tracking will help transform the prototype into a practical, scalable decision-support tool for precision agriculture in Bangladesh and similar regions.

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