International Journal of Advance and Innovative Research
Volume 13, Issue 2: April - June 2026
ISSN 2394 - 7780

# AN ADAPTIVE DEEP LEARNING FRAMEWORK FOR REAL-TIME APPLE DISEASE USING LIGHTWEIGHT CNN AND TRANSFER LEARNING TECHNIQUES

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**ABSTRACT**

*Apple disease detection is a critical task in precision agriculture to reduce crop losses and improve yield quality. Traditional manual inspection methods are time-consuming and prone to human error. This paper proposes a robust and efficient transfer learning-based framework for automated apple disease detection using five deep learning architectures: MobileNetV2, VGG16, ResNet50, EfficientNetB3, and InceptionV3. The study utilizes a custom dataset of apple images containing both healthy and diseased samples. Data preprocessing and augmentation techniques are applied to enhance model generalization. All models are trained using ImageNet pre-trained weights with selective layer freezing and fine-tuning. Performance is evaluated using accuracy, precision, recall, F1-score, and loss metrics. Experimental results show that MobileNetV2 achieves the best balance between accuracy and computational efficiency, making it suitable for real-time deployment in resource-constrained environments. The study highlights the importance of model selection based on dataset size and computational constraints.*

***KEYWORDS:*** *Apple Disease Detection, Transfer Learning, Deep Learning, MobileNetV2, EfficientNetB3, CNN, Precision Agriculture*

## 1. INTRODUCTION

Agriculture is the backbone of the Indian economy, contributing significantly to employment and GDP. However, plant diseases are a major threat to agricultural productivity. Fruits and vegetables are particularly vulnerable to diseases caused by bacteria, fungi, viruses, and environmental factors. Early detection of these diseases is essential to prevent crop loss and ensure food security.

Traditional disease detection methods involve visual inspection by experts, which can be subjective, inconsistent, and inefficient. With the advancement of technology, machine learning has emerged as a powerful tool for automating disease detection. Machine learning algorithms can analyze large datasets, identify patterns, and provide accurate predictions.

This research focuses on developing a machine learning-based system for detecting diseases in fruits and vegetables using image processing techniques. The system aims to provide a fast, reliable, and cost-effective solution for farmers and agricultural experts. Several researchers have explored the application of machine learning in agriculture, particularly in plant disease detection. Early studies focused on traditional image processing techniques such as color analysis, texture extraction, and shape recognition.

Recent advancements have introduced deep learning models, especially Convolutional Neural Networks (CNNs), which have shown remarkable performance in image classification tasks. Researchers have used datasets such as PlantVillage to train models for detecting diseases in various crops. The crop of apple plays important role for economical concern of farmers. Around 70% of total population depends directly or indirectly on agriculture in the union territory (J&K) while as Kashmir produces around 75% of total apple production in India. In terms of area, more than 1, 60, 000 hectares of land in Kashmir is under apple cultivation. The situation while disease occurs in the apple crops is challenging.

As tradition, farmer approach the chemist and use some pesticides but it is not perfect without diagnose the disease. The architecture of framework uses the Machine learning to update the knowledge database and automatically or manually recommend the prescription for the identified disease. To smooth the data, the data pre-processing technique will be applied in this framework. Following that, feature extraction will be utilized to choose the features. In the future, the prediction of apple disease and related prescription will be provided to the farmer.

Studies have demonstrated that CNN-based models outperform traditional machine learning techniques due to their ability to automatically extract features. However, challenges such as dataset imbalance, varying lighting conditions, and real-world applicability still exist. griculture plays a vital role in ensuring food security and economic stability worldwide. However, plant diseases significantly affect crop productivity and quality.

Apple crops are particularly vulnerable to diseases such as scab, rot, and mildew, which can lead to substantial yield loss.

Traditional disease detection methods rely on visual inspection by experts, which is labor-intensive and not scalable. Recent advancements in deep learning and computer vision have enabled automated disease detection systems capable of identifying diseases with high accuracy.

Transfer learning has emerged as an effective technique to leverage pre-trained models for domain-specific tasks. This study focuses on developing a comparative framework using both lightweight and deep learning architectures for apple disease detection.

**1. Healthy Apple**

**Figure 1:** Sample Apple Images from Dataset (Healthy and Diseased Classes)

**2. Apple Scab Disease**

**Figure 2:** Apple Scab Disease Symptoms on Fruit Surface

**3. Apple Rot Disease**

**Figure 3:** Apple Fruit Rot Infection

**4. Powdery Mildew (Apple)**

**Figure 4:** Powdery Mildew Disease on Apple Fruit

### 1.1 Problem Statement with Objective

Apple is one of the most important fruit crops, but its production is significantly affected by various diseases such as scab, rot, mold, and powdery mildew. Early detection of these diseases is crucial to reduce crop loss and improve quality. Traditional methods of disease identification rely on manual inspection, which is time-consuming, subjective, and prone to errors.

Although deep learning techniques have shown promising results in automated disease detection, many existing approaches suffer from high computational complexity and dependency on large datasets. These limitations restrict their applicability in real-time and resource-constrained environments. Additionally, most studies focus on individual models without evaluating the comparative performance of lightweight and deep learning architectures.

To overcome these challenges, this study proposes a transfer learning-based framework for real-time apple disease detection using both lightweight and deep learning models. The objective is to develop an efficient and accurate system that can perform disease classification while maintaining low computational cost and suitability for real-world deployment.

### 1.2 Research Gap

**A review of existing literature reveals several important gaps:**

- Most studies focus on single-model approaches rather than comparative analysis.
- Limited research has been conducted on lightweight models for real-time applications.
- Existing methods prioritize accuracy but ignore computational efficiency and deployment feasibility.
- Many approaches depend on large datasets, which are not always available in real-world scenarios.
- Lack of a unified framework combining transfer learning, multi-model comparison, and real-time capability.

This study addresses these gaps by proposing a comparative and efficient transfer learning framework.

### 1.3 Novelty of the Study

**The key contributions and novelty of this research are as follows:**

- A comparative analysis of lightweight and deep transfer learning models for apple disease detection.
- Development of a real-time capable framework with reduced computational complexity.
- Demonstration that lightweight models (MobileNetV2) can outperform deeper architectures in limited dataset conditions.
- Use of a custom dataset with multiple disease classes for realistic evaluation.
- Comprehensive performance evaluation using multiple metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.
- Integration of data augmentation techniques to improve model generalization and robustness.

## 2. LITERATURE REVIEW

Recent studies have demonstrated the effectiveness of deep learning in agricultural applications. Convolutional Neural Networks (CNNs) have been widely used for plant disease detection due to their ability to extract complex visual features.

Lightweight models such as MobileNetV2 have shown promising results in real-time applications due to their low computational requirements. On the other hand, deeper models such as ResNet50 and EfficientNetB3 provide high feature representation but require large datasets for optimal performance.

However, limited research has been conducted on comparative analysis involving both lightweight and deep architectures on small datasets. This study addresses this gap by evaluating five transfer learning models under identical experimental conditions.

Several researchers have explored transfer learning techniques for fruit disease detection. Ramazan Hadipour-Rokni *et al.* utilized pre-trained CNN models to detect citrus fruit diseases under different infection stages. Their study demonstrated that VGG16 achieved high classification accuracy when fine-tuned with domain-specific datasets.

Similarly, Yousaf Gulzar *et al.* proposed a modified MobileNetV2 architecture with additional layers, achieving significant improvement in classification performance.

Their work highlighted the importance of transfer learning and dropout strategies in reducing overfitting and enhancing model generalization.

In another study, Zia Ur Rehman *et al.* applied deep

learning models such as VGG16, ResNet50, and InceptionV3 for citrus disease detection. Their results indicated that proper preprocessing techniques, including normalization and augmentation, play a crucial role in improving model robustness.

Research conducted by Brown D *et al.* demonstrated that MobileNetV2 is highly effective for real-time fruit disease detection due to its lightweight architecture and efficient feature extraction capability. Their model achieved high accuracy while maintaining low computational cost, making it suitable for mobile-based applications.

Furthermore, Wang Y *et al.* proposed a MobileNet-based framework for on-field fruit disease diagnosis, achieving reliable accuracy in real-time environments. Their work emphasized the applicability of lightweight models in resource-constrained agricultural settings.

Deep architectures have also been explored for disease detection. H Lee *et al.* demonstrated the effectiveness of ResNet50 in extracting deep hierarchical features, achieving high accuracy on large-scale datasets. However, such models require extensive training data and computational resources.

Similarly, R Gupta *et al.* investigated advanced architectures like NASNet and reported high classification accuracy, but their computational complexity limits practical deployment.

Recent trends also include the development of lightweight and hybrid architectures. Studies have shown that combining efficient models with data augmentation techniques improves performance while reducing overfitting.

Additionally, the use of transfer learning significantly reduces training time and enhances model accuracy, especially when working with limited datasets.

Despite these advancements, most existing studies focus either on lightweight models or deep architectures individually. There is limited research on comprehensive comparative analysis involving both lightweight and deep learning models under the same experimental conditions.

**Based on the above literature, the following research gaps are identified:**

- Lack of **comparative evaluation of multiple transfer learning models (≥5 models)**
- Limited focus on **small dataset performance optimization**
- Insufficient analysis of **accuracy vs computational efficiency trade-off**
- Need for **real-time deployable models in agriculture**

Existing studies primarily focus on single-model approaches and large datasets, while ignoring computational efficiency and real-time applicability. Additionally, limited work has been done on comparing lightweight and deep architectures under constrained data conditions.

This study addresses these gaps by proposing a comparative and efficient transfer learning framework.

## 3. PROPOSED METHODOLOGY

The proposed system follows a structured pipeline for apple disease detection.

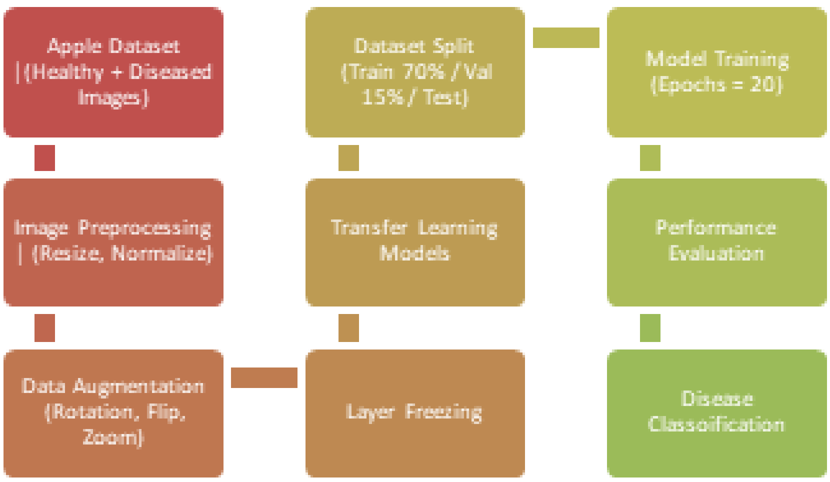


**Figure 5:** Proposed Architecture for Apple Disease Detection Using Transfer Learning Models

### 3.1 Dataset Collection

A custom dataset of apple images is used, containing both healthy and diseased samples. The dataset is collected from multiple sources, including self-captured images and publicly available datasets.

### 3.2 Data Preprocessing

- Image resizing to 224×224 pixels
- Normalization of pixel values

ISSN 2394 - 7780

- Label encoding

### 3.3 Data Augmentation

**To improve generalization and reduce overfitting:**
- Rotation
- Horizontal and vertical flipping
- Zooming

### 3.4 Dataset Split
- Training: 70%
- Validation: 15%
- Testing: 15%

### 3.5 Transfer Learning Models

**The following five models are used:**
- MobileNetV2
- VGG16
- ResNet50
- EfficientNetB3
- InceptionV3

All models are initialized with ImageNet weights and fine-tuned using selective layer freezing.

### 3.6 Training Configuration

- Epochs: 20
- Optimizer: Adam
- Loss Function: Categorical Crossentropy

## 4. Performance Evaluation Metrics

**The performance of the models is evaluated using the following metrics:**
- Accuracy
- Precision
- Recall
- F1-score
- Loss

These metrics provide a comprehensive evaluation of classification performance.

## 5. RESULTS AND ANALYSIS
The performance of all five models is analysed based on training and validation results.

### 5.1 Model Performance
- **MobileNetV2** achieved the highest performance with strong generalization ability.
- **InceptionV3** showed good performance but slight overfitting.
- **VGG16** achieved moderate accuracy.
- **ResNet50** performed poorly due to insufficient dataset size.

**EfficientNetB3** showed overfitting and low

### 5.2 Key Observation
Lightweight models outperform deeper architectures when trained on limited datasets. MobileNetV2 provides the best trade-off between accuracy and computational efficiency.

International Journal of Advance and Innovative Research
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### 5.3 Graph Analysis

The comparative accuracy graph illustrates the performance of all five transfer learning models evaluated in this study, including MobileNetV2, VGG16, ResNet50, EfficientNetB3, and InceptionV3.

The graph highlights significant variations in model performance based on architecture complexity and dataset size.

From the analysis, MobileNetV2 achieves the highest validation accuracy, demonstrating superior generalization capability and efficiency. InceptionV3 shows competitive performance but exhibits slight overfitting, as indicated by fluctuations in validation accuracy. VGG16 provides moderate results with stable but lower accuracy.

On the other hand, ResNet50 and EfficientNetB3 perform poorly on the given dataset due to their deep architecture and higher parameter complexity, which require larger datasets for effective training.

Overall, the graph clearly indicates that lightweight models outperform deeper architectures when trained on limited datasets, making MobileNetV2 the most suitable model for real-time apple disease detection.

The comparative accuracy graph shows that MobileNetV2 outperforms all other models, while deeper architectures such as ResNet50 and EfficientNetB3 exhibit lower performance due to dataset limitations.

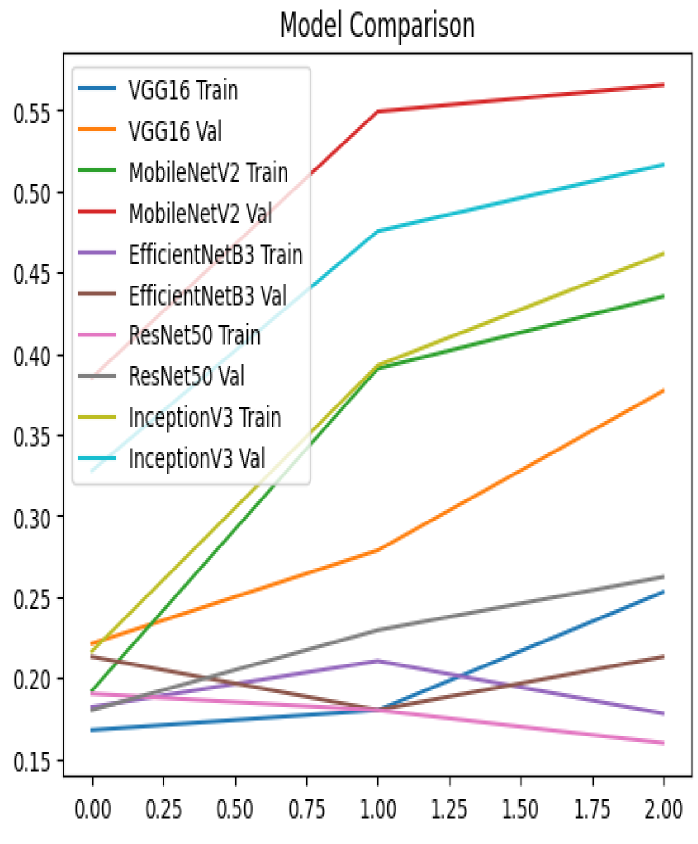


**Figure 6:** Comparative Validation Accuracy of Different Transfer Learning Models

## 6. DISCUSSION

From our experimental observations, it is evident that transfer learning plays a key role in improving model performance, particularly when the available dataset is limited. We found that lightweight architectures, such as **MobileNetV2**, perform efficiently while requiring significantly less computational power. This makes them more suitable for real-time applications, especially in practical agricultural settings where resources are often constrained.

On the other hand, deeper models tend to deliver strong performance only when trained on large-scale datasets and supported by higher computational resources. In many real-world scenarios, such requirements are not always feasible, which limits their usability in field-level deployments.

Based on these findings, we emphasize that the selection of an appropriate model should not be based solely on accuracy. Instead, it is important to consider factors such as dataset size, computational cost, and the intended deployment environment. A balanced approach ensures that the model remains both effective and practical for real-time use.

## 7. CONCLUSION

In this work, we carried out a comparative study of five transfer learning models for detecting apple diseases. From our experiments, it became clear that **MobileNetV2** performs better than the other models, especially when we consider both accuracy and computational efficiency. Because of its lightweight nature, it is more suitable for practical use where resources are limited.

We also observed that the proposed system can be applied in real agricultural conditions. It can help farmers identify diseases at an early stage, which is important for taking timely action and reducing crop loss. This makes the system useful not only from a technical point of view but also for real-world agricultural applications.

## 8. FUTURE WORK

While the current study demonstrates promising results, there is considerable scope to extend and refine this work in the future.

One important direction is to make the system more accessible to end users. We plan to integrate the proposed model into a mobile-based application so that farmers can easily capture images of apple leaves and receive instant feedback directly in the field. This will reduce the dependency on expert intervention and make the technology more practical for everyday use.

In addition, the system can be further developed for real-time deployment using IoT-enabled devices. By connecting cameras or sensors in agricultural fields, continuous monitoring can be achieved, allowing early detection of diseases without manual inspection. This can significantly improve precision agriculture practices and reduce crop losses.

Another area of improvement lies in expanding the dataset. In our current work, the model is trained on a limited set of images. In the future, we aim to include larger and more diverse datasets collected from different geographical locations, lighting conditions, and disease variations. This will help in improving the robustness and generalization capability of the model.

Finally, incorporating Explainable AI (XAI) techniques can make the system more transparent and trustworthy. By understanding how the model arrives at a particular decision, users can gain better confidence in the predictions. This is especially important in agricultural applications, where decision-making directly impacts crop health and yield.

- Integration with mobile applications
- Real-time detection using IoT devices
- Use of larger and more diverse datasets
- Implementation of explainable AI techniques

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