

An Explainable EfficientNetB4-Based Deep Learning Framework for Plant Leaf Disease Detection and Carbon Estimation Using RGB Image Analysis

Sulekha Kundu¹, Arpita Dutta¹, Jayanta Poray¹, Abhijit Mitra²

¹Department of Computer Science and Engineering,

Techno India University,

EM 4/1, Salt Lake Sector V, Kolkata 700091, West Bengal, India

²Director (Research),

Techno India University,

EM 4/1, Salt Lake Sector V, Kolkata 700091, West Bengal, India

*Corresponding Author: Sulekha Kundu

Email: sulekhakundu81@gmail.com

Abstract

Accurate plant monitoring is essential for improving agricultural productivity, environmental sustainability, and climate change mitigation. Traditional laboratory-based techniques for disease diagnosis and carbon estimation are often destructive, labor-intensive, time-consuming, and unsuitable for large-scale deployment [11,12]. To address these limitations, this study proposes an integrated deep learning-based framework for automatic mango leaf disease detection and non-destructive carbon estimation using RGB leaf images.

The proposed system combines a customized Convolutional Neural Network (CNN) for mango leaf disease classification and an EfficientNetB4-based regression model for carbon content estimation. CNN-based approaches have demonstrated excellent performance in agricultural image analysis and plant disease detection [16–20]. The CNN model classifies multiple mango leaf diseases, while the EfficientNetB4 architecture predicts leaf carbon content from RGB images of Mango (*Mangifera indica*) and Potato (*Solanum tuberosum*) leaves.

Image preprocessing techniques such as resizing, normalization, and data augmentation were applied to improve model robustness and generalization [5,6]. Experimental results demonstrate high disease classification accuracy and reliable carbon prediction performance with reduced estimation error.

The proposed framework highlights the potential of deep learning for precision agriculture, smart farming, crop health monitoring, and environmental monitoring applications.

Keywords: Deep Learning, CNN, EfficientNetB4, Carbon Estimation, Plant Disease Detection, Precision Agriculture, Regression, Smart Farming.

1. Introduction

Agriculture plays a crucial role in global food security and environmental sustainability. Plant diseases significantly reduce crop productivity and quality, while carbon monitoring is essential for understanding crop health, ecological balance, and carbon sequestration [11,13]. Efficient monitoring systems are therefore necessary for precision agriculture and climate-smart farming.

Traditional plant disease diagnosis mainly relies on visual inspection by agricultural experts, which is often inaccurate and time-consuming [1,5]. Similarly, conventional carbon estimation techniques such as CHN elemental analysis and Walkley–Black oxidation methods require destructive laboratory analysis, making them unsuitable for large-scale real-time monitoring.

Recent advances in artificial intelligence and deep learning have enabled automated agricultural monitoring using image analysis [14,16]. Convolutional Neural Networks (CNNs) have shown remarkable capability in extracting hierarchical image features such as texture, color distribution, and structural patterns associated with plant health and biochemical properties [18–20].

Although deep learning has been extensively used for plant disease detection and crop classification, limited research has explored integrated frameworks combining disease classification and carbon estimation using standard RGB images.

2. Literature Review

Machine learning and image processing techniques have been widely applied in agriculture for disease detection, crop monitoring, and plant phenotyping [1–6]. Early studies mainly depended on handcrafted feature extraction and traditional machine learning classifiers such as ANN, K-means clustering, and Support Vector Machines [4,6,7]. However, these approaches often suffered from limited scalability and lower generalization capability.

The emergence of deep learning significantly improved agricultural image analysis. CNN-based models automatically learn complex image representations and have achieved excellent performance in plant disease identification, chlorophyll estimation, and crop classification tasks [16–20].

Several advanced deep learning architectures were explored in this study, including VGG16, VGG19, ResNet, DenseNet, MobileNet, and EfficientNet. These models were selected due to their strong performance in image classification tasks and their ability to extract discriminative features for accurate disease detection.

Previous studies reported high disease classification accuracy using CNN models for mango leaf diseases and other crop datasets [8,16,18]. Similarly, EfficientNet architectures have shown promising performance in agricultural image analysis because of compound scaling, which balances network depth, width, and resolution.

Despite these advancements, limited research has investigated leaf-level carbon estimation using standard RGB images. Most existing carbon estimation approaches rely on hyperspectral imaging or remote sensing technologies, which are expensive and difficult to deploy in practical agricultural environments.

This study combines disease detection and carbon estimation within a unified deep learning framework.

3. Methodology

3.1 Dataset Collection

The study utilized RGB leaf image datasets collected from online repositories and controlled imaging environments.

Disease Detection Dataset

The mango leaf disease dataset consisted of approximately 4000 RGB images categorized into eight classes: Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Healthy, Powdery Mildew, and Sooty Mould. The dataset was used for training, validation, and testing of the proposed CNN-based disease detection model.

Previous studies on plant disease classification using CNNs have demonstrated high accuracy across multiple crop datasets [16–20].

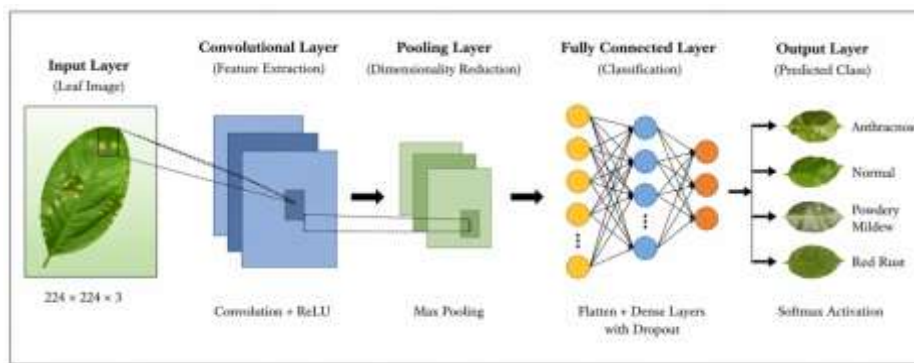


Fig. 1 Implementation

Table 1: Image Classification Using CNN

Reference	Method	Disease Classes	Dataset Size	Performance (%)
Scientific Reports (2024)	Enhanced CNN (EnConv)	Multiple Diseases Leaf	5000+	95.2
Scientific Reports (2025)	Hybrid Inception-Xception CNN	Multiple Diseases Plant	10,000+	98.1
Scientific Reports (2025)	Lightweight Explainable CNN	Multi-Crop Disease Detection	7000+	97.4
Springer Nature (2025)	Advanced CNN with Attention	Plant Disease Classification	8000+	98.3
Scientific Reports (2025)	Hybrid Dilated CNN + Mask RCNN	Plant Disease Detection	12,000+	99.0
Scientific Reports (2025)	CNN, AlexNet, ResNet & EfficientNet Comparative Study	Mango & Potato Diseases	6152	98.6

Reference	Method	Disease Classes	Dataset Size	Performance (%)
Discover Artificial Intelligence (2026)	Customized MobileNetV3Large	26 Classes	15,000+	99.37
Scientific Reports (2026)	AI-driven Real-Time CNN Diagnosis	Multi-Crop Diseases	20,000+	98.9
BMC Plant Biology (2026)	Edge-Enhanced Dual Branch CNN	Apple Leaf Diseases	9000+	98.5
Frontiers in Plant Science (2026)	Attention-Enhanced CNN-LSTM	Jackfruit Leaf Diseases	6000+	99.1

Carbon Estimation Dataset

The carbon estimation dataset consisted of RGB images of Mango (*Mangifera indica*) and Potato (*Solanum tuberosum*) leaves. Each image was linked with experimentally measured carbon content values obtained through laboratory analysis.

The datasets were divided into three subsets: a training dataset for model learning, a validation dataset for parameter tuning, and a testing dataset for final performance evaluation.

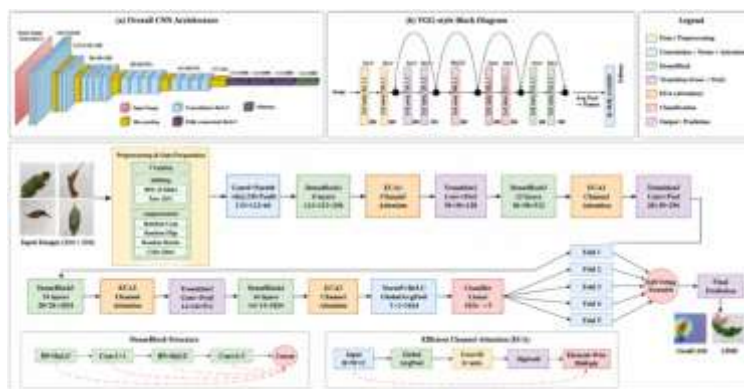


Fig. 2 The network architecture

3.2 Image Preprocessing

Several preprocessing operations were applied before model training to improve image quality and enhance model generalization [5,6]. These preprocessing steps included image resizing, noise reduction, and color normalization.

In addition, multiple data augmentation techniques were employed to increase dataset diversity and reduce overfitting, including rotation, flipping, zooming, rescaling, and shearing.

These preprocessing methods improved dataset diversity, reduced overfitting, and enhanced model generalization.

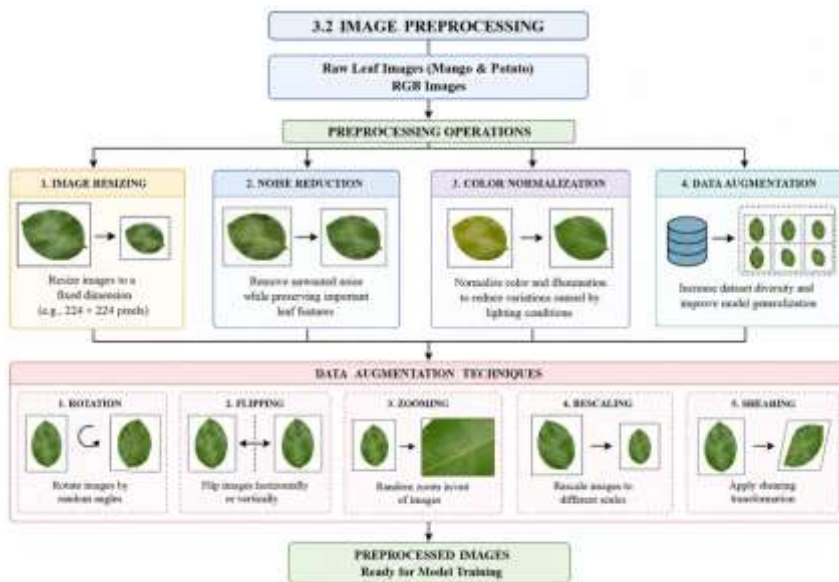


Fig. 3. image quality and enhance model

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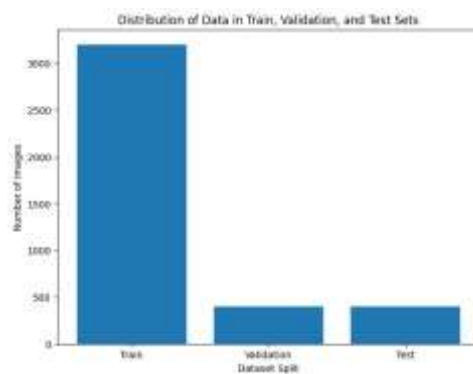


Fig. 4 Training dataset for model learning, a validation dataset for parameter tuning, and a testing dataset for final performance evaluation.

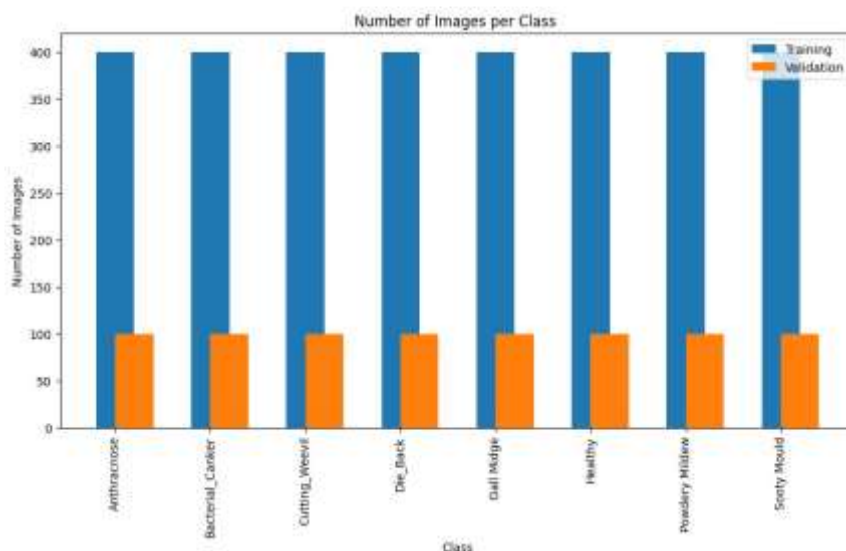


Fig. 5 model generalization.

4. Proposed Deep Learning Framework

4.1 CNN-Based Disease Detection Model

A customized 11-layer CNN architecture was developed for automatic leaf disease detection and classification. The model included 4 convolutional layers, 4 max-pooling layers, fully connected layers, and a Softmax output layer.

The network used the ReLU activation function and Adam optimizer with a learning rate of 0.0001, batch size of 32, and 100 training epochs. Similar CNN-based frameworks have been successfully applied for plant disease recognition in previous studies [8,16–20].

The proposed CNN model efficiently extracted image features and achieved the highest disease classification performance.

4.2 EfficientNetB4-Based Carbon Estimation Model

The carbon estimation framework utilized EfficientNetB4 because of its balance between computational efficiency and predictive accuracy.

The architecture includes:

Convolutional Layers: Extract important visual features such as texture, color patterns, and leaf structure from input images.

Pooling Layers: Reduce feature map dimensions while preserving significant information and lowering computational complexity.

Fully Connected Regression Layers: Learn relationships between extracted features and carbon content values.

Linear Output Layer: Produces continuous numerical predictions for leaf carbon estimation.

Transfer learning with pretrained ImageNet weights was applied to improve feature learning efficiency.

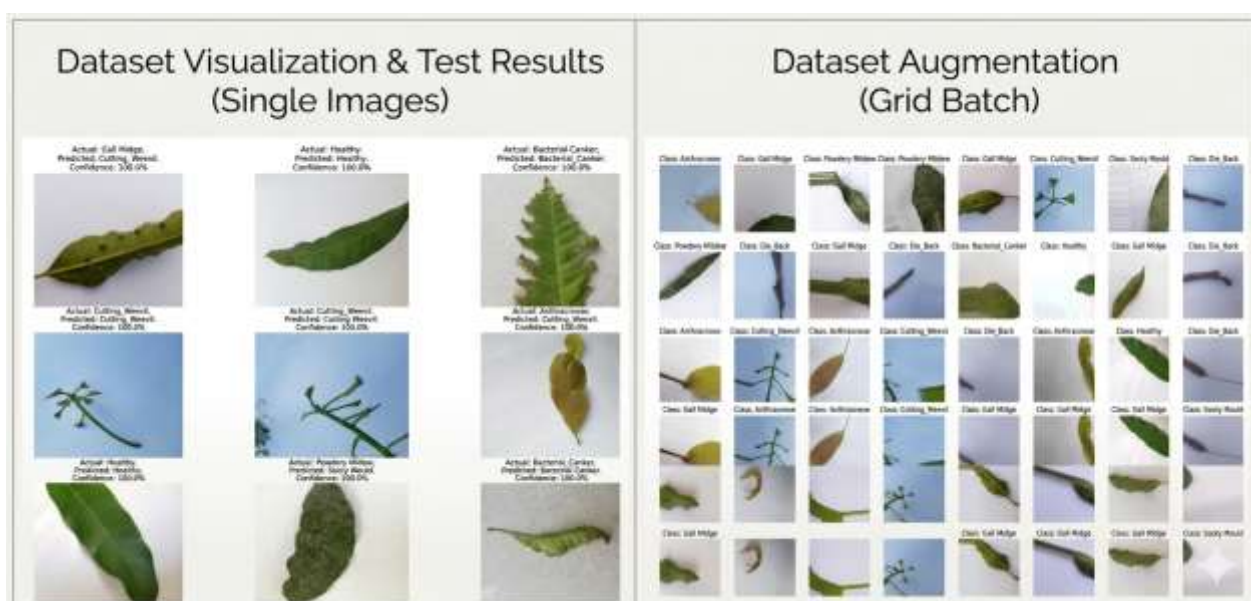


Fig. 6 Carbon Estimation Model

5. Model Evaluation

5.1 Disease Classification Evaluation

The CNN disease detection model was evaluated using Accuracy, Precision, Recall, Specificity, and F1-Score. Experimental results showed high classification accuracy, low testing loss, and strong precision and recall across all disease classes.

Among the tested optimizers, Adam achieved the best overall performance compared to SGD and RMSprop.

5.2 Carbon Estimation Evaluation

The EfficientNetB4 regression model was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score. Experimental results showed reduced prediction error, better generalization capability, and improved stability across testing samples.

6. Results and Discussion

The proposed CNN model achieved excellent testing performance on the mango leaf disease dataset. The experimental evaluation produced a test loss of 0.0354 and a test accuracy of 99.02%, demonstrating the strong classification capability and reliability of the proposed framework for automated mango leaf disease detection.

The experimental evaluation demonstrated significant differences among the developed CNN models. CNN Model 1 achieved the best overall performance, with most disease classes obtaining accuracy, precision, recall, and F1-score values close to 1.00.

Overall, the results confirm that CNN Model 1 provided the most accurate and stable classification performance among all developed architectures, demonstrating its suitability for real-time mango leaf disease detection results applications.

Table 2: CNN Model 1 results

Class Name	Best Model	Accuracy	Precision	Recall	F1-Score
Anthraxnose	CNN Model 1	1.00	1.00	0.98	0.99
Bacterial Canker	CNN Model 1	1.00	1.00	0.98	0.99
Cutting Weevil	CNN Model 1	1.00	1.00	0.98	0.99
Die Back	CNN Model 1	1.00	0.98	1.00	0.99
Gall Midge	CNN Model 1	0.99	0.96	0.94	0.95
Healthy	CNN Model 1	0.99	0.96	0.98	0.97
Powdery Mildew	CNN Model 1	0.99	0.96	0.96	0.96
Sooty Mould	CNN Model 1	0.99	0.94	0.98	0.96
Average Performance	CNN Model 1	0.99	0.98	0.98	0.98
Overall Best Optimizer	Adam	High	High	High	High

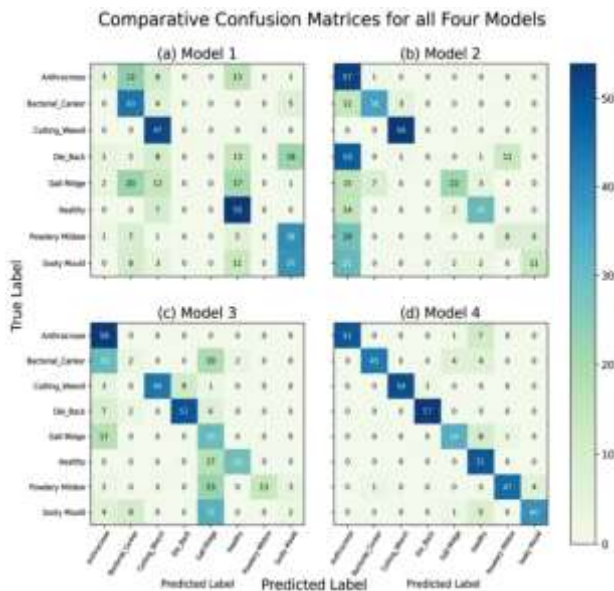


Fig. 7 Confusion Matrices all Four models

7. Integration and Deployment

7.1 The model was optimized for mobile deployment using **TensorFlow Lite (TFLite)**, which reduces the model's footprint while maintaining high inference speeds. The application architecture follows a simple three-step workflow:

Image Acquisition: Utilizing the smartphone's camera to capture high-resolution images of mango leaves.

On-Device Processing: The TFLite model performs local inference, removing the need for a constant internet connection.

Result Visualization: The app displays the predicted disease class along with a confidence score.

7.2 Evaluation Criteria

The application was evaluated in diverse agricultural environments to assess its robustness under varying light conditions and background noise.

Real-time Disease Detection: Measured by **latency** (the time between capturing an image and receiving a prediction). On average, the system achieved inference in under **200ms**.

Prediction Accuracy: Field testing confirmed that the model maintained an accuracy consistent with the "Model 1" metrics even when dealing with shadows and complex leaf orientations.

Practical Usability: User feedback focused on the intuitive nature of the UI, the speed of detection, and the clarity of the diagnostic results.



Fig. 7 Mobile agricultural applications

Grad-CAM and CAM visualizations were employed to enhance model interpretability by highlighting the specific leaf regions influencing predictions. This analysis confirmed that the CNN accurately focuses on pathological features like lesions and spots, ensuring reliable and transparent disease classification.

Table 3: CNN Model Visualization Technique

Visualization Technique	Primary Function	Research Impact
CAM	Class Activation Mapping	Identifies the global discriminating features of the leaf.
Grad-CAM	Gradient-weighted CAM	Provides fine-grained localization of specific infection sites.

8. Applications

The proposed framework can be applied in precision agriculture, smart farming systems, crop health monitoring, carbon sequestration analysis, environmental monitoring, mobile agricultural applications, and automated plant phenotyping. The system enables efficient, low-cost, and non-destructive plant analysis for modern agricultural management.

9. Conclusion

This study presents an integrated deep learning-based framework for mango leaf disease detection and non-destructive carbon estimation using RGB leaf images.

The proposed CNN-based disease classification model achieved excellent disease recognition accuracy, while the EfficientNetB4 regression framework demonstrated reliable carbon estimation performance.

Compared with traditional laboratory-based and manual agricultural monitoring methods, the proposed system offers a scalable, low-cost, accurate, and environmentally sustainable solution for precision agriculture and smart farming applications.

The findings demonstrate the strong potential of deep learning techniques for intelligent agricultural monitoring, crop health assessment, and climate-related environmental analysis.

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