EfficientNetB0-Based Deep Learning Framework for Automated Eggplant Leaf Disease Classification

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Abstract

Early and accurate detection of plant diseases is crucial for enhancing crop yield and sustainable agricultural practices. This work presents an automated classification of eggplant leaf diseases using the EfficientNetB0 deep learning architecture. The model is built to detect four different classes, namely Healthy Leaf, Insect Pest Disease, Leaf Spot Disease, and Mosaic Virus Disease. A publicly available dataset was used, and pre-processing all images in terms of resizing and normalization was done to match the input requirements of EfficientNetB0. Transfer learning using ImageNet pre-trained weights was used to improve feature extraction and decrease the training complexity. The dataset was split into train, validation, and test data using a stratified split strategy. Experimental results show that the accuracy of the overall classification is 88.5% with balanced precision, recall, and F1-scores in all classes. The confusion matrix analysis proves reliable class-wise performance with minimal misclassification. The results show that EfficientNetB0 is an effective and computationally efficient method for eggplant leaf disease detection, and has great potential to be used in real-world agriculture.

Keywords

Eggplant Leaf Disease, EfficientNetB0, Deep Learning, Transfer Learning, Image Classification, Precision Agriculture

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Introduction

Eggplant (Solanum melongena) is a widely grown vegetable crop with substantial economic and nutritional value, especially in Asia and other developing countries. However, the production of eggplant is seriously compromised by a range of foliar diseases that cause a reduction in crop yield and quality. Diseases such as leaf spot, infection by mosaic viruses, and damage caused by pests can spread very quickly under favorable environmental conditions, and the early and accurate detection of any disease can prove to be essential for effective crop management. Conventional methods of detecting disease involve a lot of manual visual inspection by agricultural experts, which is time-consuming, subjective, and often impractical in large-scale farming operations. To overcome these limitations, researchers have been searching for technology-driven methods to detect eggplant disease automatically. Early investigations were based on sensor-based and spectral analysis methods. Wu et al.[1] showed it is possible to use visible and near-infrared spectroscopy for early detection of Botrytis cinerea on eggplant leaves. Although such methods were found to be promising in terms of accuracy, the dependence of these methods on special equipment restricts their practical applicability in the agricultural field. As such, methods for detecting diseases based on images have received more and more attention because of their low cost and ease of implementation, as well as their compatibility with mobile and edge devices. The emergence of publicly available datasets has enabled research in this field to take a drastic turn forward. Matin et al.[2] proposed a large dataset for the accurate identification of eggplant diseases that can be utilized for the application of machine learning and deep learning algorithms for foliar disease classification. With the availability of these kinds of datasets, deep learning models, especially convolutional neural networks (CNNs), have proven to be much better than traditional forms of image processing. Nasution and Kartika[3] used the YOLO object detection framework for detecting eggplant disease and incorporated real-time notification via a telegram bot to demonstrate the viability of deep learning models for practical implementation in agricultural monitoring systems. Recent research has been focused more on lightweight and efficient deep learning architectures in order to support real-time and resource-constrained applications. Xie et al.[4] proposed YOLOv5s-BiPCNeXt, which is a lightweight detection model that enhances computational efficiency and accuracy while ensuring acceptable accuracy for eggplant leaf disease detection. Similarly, Liu and Wang[5] proposed EggplantDet, an optimized lightweight framework that considers detection accuracy and inference speed in balance, showing the importance of efficiency for applications in the field. While these detection-based models work well, there is still a need to have robust classification frameworks that can differentiate multiple disease categories with high reliability. Motivated by these problems, an EfficientNetB0-based deep learning framework for the multi-class classification of eggplant leaf diseases is proposed in this study. EfficientNetB0 provides a good balance of accuracy and computational cost using compound scaling of network depth, width, and resolution. By taking advantage of the transfer learning mechanism and the standard pre-processing, the proposed method is expected to achieve a reliable classification performance while keeping the efficiency suitable for the actual agricultural deployment.

Literature Review

Recent developments in deep learning have had a major impact on automated plant disease detection, especially of crops such as eggplant (Solanum melongena), which are highly susceptible to many diseases, both foliar and fruit. With the availability of labeled data sets and the ability of more powerful computers, researchers have been looking at different convolutional neural network (CNN)-based methods that would help improve the accuracy of disease recognition and lower the requirement for manual inspection. Transfer learning has been a dominant strategy in the disease classification of eggplant, especially when datasets are scarce. Saad et al.[6] came up with an automated eggplant disease recognition system based on three pre-trained deep learning models that were fine-tuned using leaf images of eggplant. Their approach showed enhanced levels of classification accuracy over traditional machine learning techniques, showing the power of using knowledge from large-scale data sets such as ImageNet. Similarly, Haque and Sohel[7] proposed a deep network with score-level fusion and inference-based transfer learning for detecting leaf blight and fruit rot diseases in eggplant. Their fusion-based approach enhanced robustness by combining several feature representations, which, however, increased computational complexity. Beyond standard RGB image analysis, researchers have explored multi-channel and multimodal techniques of data fusion to improve early detection of disease. Zhang et al.[8] proposed a deep learning method to detect Verticillium wilt in the early stage of eggplant leaves through fusing five channels of the image. Their results showed better sensitivity in identifying infection in its early stages; however, the need for multiple image channels adds extra complexity in data acquisition and restricts scalability under real-field conditions. These findings highlight the trade-off between accuracy at detection and practical deployability. Object detection frameworks have also been popularized in disease detection of eggplants, especially for real-time applications. Huang et al.[9] proposed YOLOv8-E, an eggplant disease detection model based on an improved version of YOLOv8. Their architecture improved the detection speed and accuracy of the results by optimizing feature extraction and anchor mechanisms. Likewise, Kaniyassery et al.[10] used a YOLOv8-based classification model in conjunction with meteorological data to analyse the incidence of leaf spot and fruit rot disease. Their study highlighted the importance of environmental factors like temperature and humidity in disease occurrence and suggested that the integration of climatic variables with image-based models can be used to enhance the predictive reliability. From a broader plant pathology perspective, knowledge of the biological context of eggplant diseases is still crucial. Kaniyassery et al.[11] reviewed all aspects of fungal diseases of eggplant and discussed the disease triangle of host, pathogen, and environmental factors. This review highlights the complexity of the manifestation of eggplant diseases and the necessity of intelligent systems with the ability to cope with different visual symptoms. In addition, Rao and Kumar[12] reviewed the global situation of the plant-parasitic diseases of eggplant caused by the corky psyllid, which also leads to eggplant epidemics and presents considerable difficulties in their diagnosis. Their findings illustrate the need for exact and automated detection systems to manage the spread of the disease effectively. While detection-based methods and fusion-based methods have shown promising results, several current methods are plagued by high computational requirements or low generalizability across multiple disease classes. Furthermore, some of the studies focus on binary or limited multi-class classification-related problems, which leaves room for efficient and scalable frameworks that can tackle several eggplant diseases at once. These gaps drive the development of lightweight yet accurate architectures, such as EfficientNet-based architectures, that can offer a good balance between performance and efficiency. Building on previous studies, the current research seeks to make a solid multi-class classification of eggplant leaf disease, which is consistent with requirements for practical deployment in agriculture.

Methodology

A. Dataset Compilation

The dataset used in this study was obtained from a publicly available Kaggle repository containing eggplant leaf images captured under real-field conditions[13]. It comprises four classes: Healthy Leaf (7,265 images), Insect Pest Disease (2,728 images), Leaf Spot Disease (3,010 images), and Mosaic Virus Disease (6,710 images). The images exhibit natural variations in illumination, background texture, leaf orientation, and disease severity, providing a realistic basis for evaluating deep learning–based classification models.

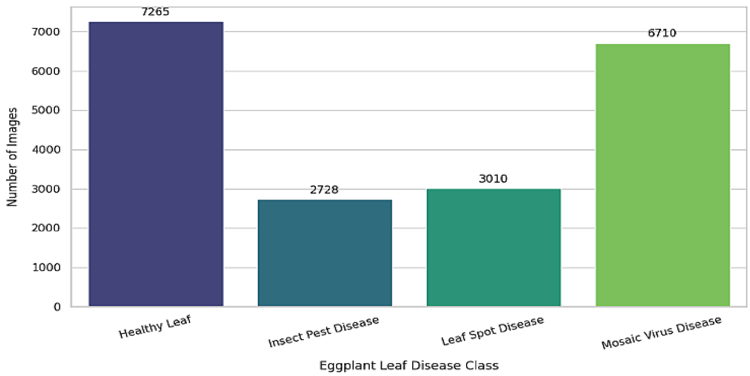

Figure 1. Class-wise Distribution of Eggplant Leaf Images in the Dataset

B. Preprocessing Framework

Prior to model training, all images underwent a standardized preprocessing pipeline to ensure compatibility with the EfficientNetB0 architecture, as illustrated in Fig. X. Each image was first converted to RGB format and resized to 224 × 224 pixels, which is the required input resolution for EfficientNetB0. Bilinear interpolation was applied during resizing to preserve spatial and structural information. Subsequently, pixel values were normalized using the EfficientNetB0 preprocessing scheme to align the input distribution with ImageNet pre-trained weights. This normalization enhances numerical stability and accelerates convergence during training.

Following preprocessing, the dataset was partitioned into training, validation, and testing subsets using a 70:20:10 split ratio, respectively. Stratified sampling was employed to preserve proportional class representation across all subsets. The training set was used to optimize model parameters, the validation set supported hyperparameter tuning and overfitting control, and the test set was reserved exclusively for final performance evaluation on unseen data.

C. Model Framework and Layer Configuration

In this study, EfficientNetB0 was used as the backbone deep learning model for eggplant leaf disease classification because of its good trade-off between accuracy and low computational cost. EfficientNetB0

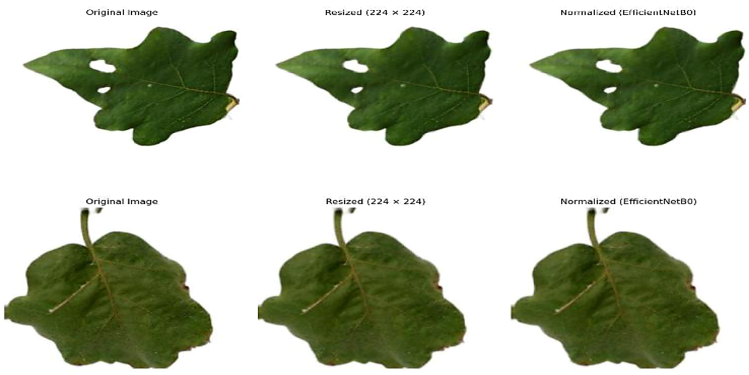

Figure 2. Preprocessing Pipeline Applied to Eggplant Leaf Images for EfficientNetB0

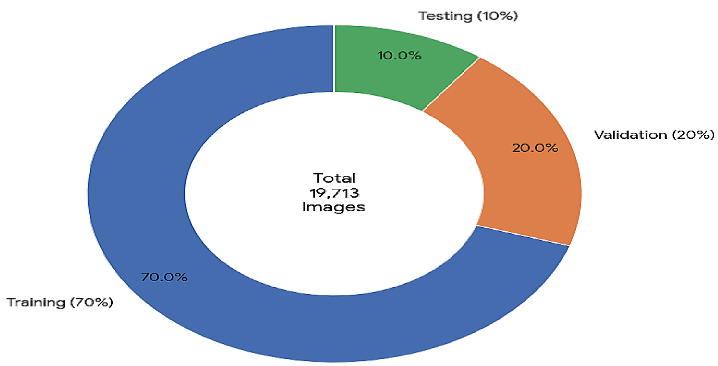

Figure 3. Dataset partitioning strategy (70:20:10 split)

makes use of a compound scaling strategy that scales network depth, width, and resolution in tandem, which allows for effective feature extraction with fewer parameters than traditional convolutional neural networks. The EfficientNetB0 model, which was pre-trained on ImageNet, was initialized with ImageNet pre-trained weights and used as a fixed feature extractor by removing the top classification layers. The base network takes input images of size $224 \times 224 \times 3$ and generates high-level feature representations. On top of the backbone, a custom classification head was added, which consists of a Global Average Pooling layer to decrease spatial dimension, followed by a fully connected dense layer with 256 neurons and ReLU activation to learn task-specific features. A dropout layer with a rate of 0.5 was included to reduce the overfitting effect. The last output layer is made up of 4 neurons with softmax activation corresponding to the four target classes: Healthy Leaf, Insect Pest Disease, Leaf Spot Disease, and Mosaic Virus Disease.

Table 1. Layer-Wise Architecture Summary of the Proposed EfficientNetB0 Model

Layer Type	Output Shape	Parameters	Description
Input Layer	(224, 224, 3)	0	RGB eggplant leaf image input
EfficientNetB0 (Base Model)	(7, 7, 1280)	4,049,571	Pre-trained backbone (ImageNet weights, top layers removed)
Global Average Pooling	(1280)	0	Reduces spatial dimensions and feature maps
Dense	(256)	327,936	Fully connected layer with ReLU activation
Dropout (0.5)	(256)	0	Regularization to prevent overfitting
Output Dense	(4)	1,028	Softmax layer for four-class classification
Total Parameters	—	4,378,535	—
Trainable Parameters	—	328,964	Custom classifier layers
Non-Trainable Parameters	—	4,049,571	Frozen EfficientNetB0 backbone

D. Optimization Process and Performance Evaluation

The EfficientNetB0-based model was trained using the Adam optimizer due to its adaptive learning capability and stable convergence. The categorical cross-entropy loss function was employed to handle the four-class classification task. Training was conducted for 30 epochs with a batch size of 32, using the training dataset, while performance was monitored on the validation set. To prevent overfitting and ensure optimal generalization, early stopping was applied by observing validation loss, and the model parameters corresponding to the best validation performance were retained. Model evaluation was performed on the unseen test dataset using accuracy, precision, recall, and F1-score. Additionally, a confusion matrix and classification report were generated to analyze class-wise performance and identify misclassification patterns among different eggplant leaf disease categories.

Results

A. Loss Curve Analysis Across Epochs

The training and validation loss curves show a steady and stable learning pattern over the 30 training epochs. At the beginning, the training loss was relatively large (1.2550 at epoch 1) because of random initialization of the weights, but the training loss reduced step by step as the model learned to extract discriminative features, reaching 0.0963 at epoch 30. Similarly, the validation loss had a significant decrease from 0.7710 to 0.2372, which indicates good generalization to the unseen data. Minor fluctuations in validation loss were observed after epoch 20, which is typical in deep learning models, suggesting sensitivity to complex class boundaries. The fact that the training and validation losses do not significantly differ means that the overfitting was well controlled. Overall, the reduction in losses trends shows the effectiveness of the optimized strategy and model convergence.

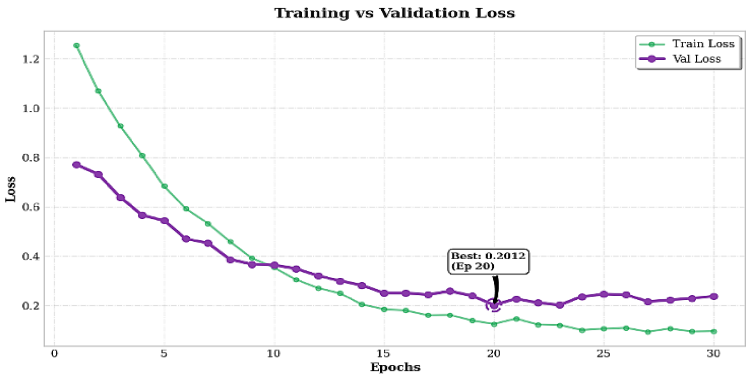

Figure 4. Training and Validation Loss Curves of the EfficientNetB0 Model

B. Accuracy Curve Analysis Across Epochs

The accuracy trends of training and the validation set show that the classification performance improves progressively. Training accuracy improved from 55.76% in the first epoch to 94.95% at 30 epochs, which indicates the model's ability to learn more discriminative feature representations. Validation accuracy showed a similar trend of improvement from 38.08% to 88.47%, showing good generalization ability. The rather small difference between the training and validation accuracy over the course of training implies little overfitting. Validation accuracy stabilized after about 22 epochs, which means the model had reached a near-optimal performance level. Occasional small differences in the validation accuracy are expected as a result of class imbalance and complex inter-class similarities. Overall, the trends in accuracy confirm the robustness and effectiveness of the EfficientNetB0-based classification framework.

C. Confusion Matrix-Based Performance Evaluation

The confusion matrix is a detailed evaluation of the classification performance of the EfficientNetB0 model in terms of four eggplant leaf categories. The Healthy Leaf class had the best performance values, with 675 samples correctly classified, meaning that the discrimination of healthy patterns was good. Insect Pest Disease had 224 true positives, and limited confusion (mostly with Healthy Leaf and Mosaic Virus Disease, as they share some visible characteristics). Leaf Spot Disease obtained 256 correct predictions, which showed reliable detection, but with slight misclassification with Mosaic Virus Disease. Mosaic Virus Disease demonstrated good performance with 590 correctly classified

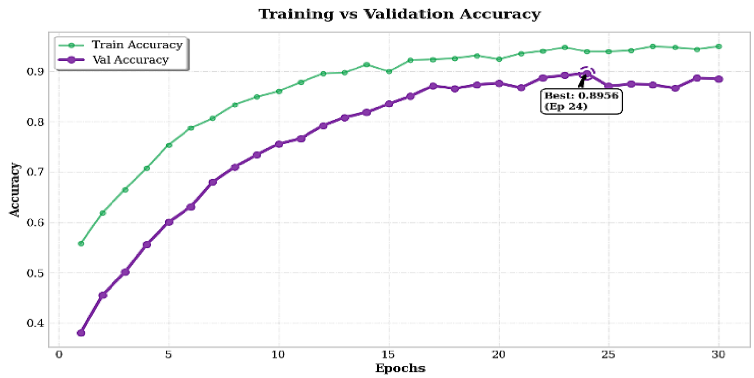

Figure 5. Training and Validation Accuracy Curves of the EfficientNetB0 Model

samples, confirming the model's ability to capture complex texture and discoloration patterns. Overall, the confusion matrix shows balanced performance and controlled misclassification, which validates the effectiveness of EfficientNetB0 for multi-class eggplant leaf disease diagnosis.

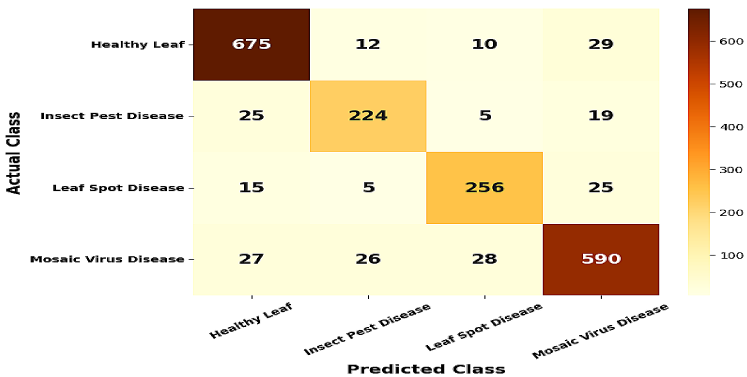

Figure 6. Confusion Matrix Showing Class-wise Classification Performance of EfficientNetB0

D. Classification Report Analysis

The classification report is a summary of the performance of the model, using precision, recall, F1-score, and support metrics. The Healthy Leaf class had high precision (0.91) and recall (0.93), which means that the class made correct predictions with very few false predictions. Insect Pest Disease was recalled relatively less (0.82), which suggests difficulty because of visual similarity with other classes of diseases. Leaf Spot Disease had a balanced precision (0.87) and recall (0.85), which proved to have a stable detection capability. Mosaic Virus Disease performed well with an F1-score value of 0.88, with a great amount of support from test samples. The overall accuracy of the model was found to be 88.5% with the macro and weighted F1 scores of 0.87 and 0.89, respectively. These results validate good generalization and stable multi-class classification performance.

Table 2. Classification Report of the EfficientNetB0 Model on the Test Dataset

Class	Precision	Recall	F1-Score	Support
Healthy Leaf	0.91	0.93	0.92	726
Insect Pest Disease	0.84	0.82	0.83	273
Leaf Spot Disease	0.87	0.85	0.86	301
Mosaic Virus Disease	0.89	0.88	0.88	671
Accuracy		0.885		1,971
Macro Avg	0.88	0.87	0.87	1,971
Weighted Avg	0.89	0.89	0.89	1,971

Conclusion

This research demonstrated an EfficientNetB0-based deep learning model to automatically classify eggplant leaf diseases. The proposed model was able to classify four classes, namely Healthy Leaf, Insect Pest Disease, Leaf Spot Disease, and Mosaic Virus Disease, using a common preprocessing pipeline and transfer learning based on ImageNet weights. Experimental results showed that it had good and stable performances, with an overall accuracy was 88.5%, and we achieved good and balanced performance of the precision, recall, and F1-score for all classes. The confusion matrix and classification report proved that the model successfully learned discriminative visual features but still maintained a good generalization, although visual similarities exist among the disease classes. The lack of data augmentation further shows the robustness of the EfficientNetB0 architecture in extracting meaningful features from raw leaf images. Future work can be done on better minority class recognition using advanced loss functions such as focal loss or class-weighted training. Incorporation of data augmentation and larger and more diverse datasets collected under different field conditions may further increase robustness. Additionally, hybrid architectures such as EfficientNet with attention mechanisms or transformer-based architectures could enhance fine-grained discrimination of the disease. Integration of environmental and temporal data may also allow more complete disease prediction systems, which could be practically implemented in precision agriculture and real-time applications in crop health monitoring.

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