A High-Performance EfficientNetV2-M Model for Robust Corn Leaf Disease Classification

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Abstract

Corn leaf infections are highly yield-reducing and need to be diagnosed for effective field management. This study proposes a deep learning-based corn leaf disease detection framework based on EfficientNetV2-M, in a transfer learning setting. A structured preprocessing pipeline was used, which involved image resizing (480 $\times$ 480 pixels), contrast enhancement with CLAHE in LAB color space, and ImageNet-based normalization for matching inputs with pre-trained weights. The data set was successfully collected from the existing 4,226 field-acquired images of corn leaves categorized into Healthy and Infected classes and divided into training, validation, and testing data samples with stratified sampling. The model was trained for 22 epochs and had an overall test accuracy of 91%. Performance analysis revealed good class-wise metrics, with a precision/recall score of 0.92/0.87 for healthy leaves and 0.89/0.93 for infected leaves. The confusion matrix showed a low level of misclassification, which confirmed the effectiveness of generalization under realistic conditions. The results show that efficientNetV2-M offers an accurate and scalable approach for automated screening of corn leaf disease, enabling precision agriculture and early intervention strategies.

Keywords

Corn Leaf Disease Detection, EfficientNetV2-M, Deep Learning, Transfer Learning, CLAHE, Image Classification

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Introduction

Corn (maize) is one of the most widely grown cereal crops in the world and is used as a major food, feed, and industrial raw material. Its productivity is important for global food security and agricultural economies, especially in the developing world. However, corn crops are highly susceptible to a variety of leaf diseases, including northern leaf blight, gray leaf spot, common rust, and leaf streak. These diseases cause a serious reduction in the yield and quality of the crop if not detected and controlled at an early stage. Traditional methods of detecting diseases are based upon manual field inspection by farmers or agricultural experts, which is labor-intensive, time-consuming, and is often subject to subjective judgment. In wide expanses of farming, the detection is even harder, and treatment is delayed, resulting in more crop losses. Therefore, the automated and intelligent systems for classifying diseases are crucial for modern precision agriculture. With the rapid development of artificial intelligence and computer vision, deep learning-based approaches have become powerful tools for plant disease diagnosis. Amin et al.[1] suggested an end-to-end deep learning approach for corn leaf disease classification, which demonstrated high accuracy by directly automatically learning the features in the raw images. Their work demonstrated the superiority of deep neural networks, as opposed to traditional handcrafted feature-based methods. In contrast, some earlier research, including Rachmad et al.[2], implemented the local binary pattern (LBP) feature extraction along with conventional classifiers on corn leaves with disease classification. Although their approach was able to attain reasonable performance, it was based on extensive manual feature engineering, which reduces adaptability to different disease patterns. Machine learning techniques have been studied in this field, too. Noola and Basavaraju[3] used different machine learning algorithms to classify images of corn leaves, and the results were promising. However, what they found was that while machine learning models have challenges with complex visual variations on complex visual content, deep learning approaches to machine learning are better at this task. As a result, the recent research has moved towards deep neural networks for better classification robustness. Advanced deep learning architectures have also further improved the performance of disease detection. Mohanty et al.[4] have performed field research work in Bangladesh with the help of modern deep learning models for the classification of corn leaf diseases under real agricultural conditions. Their results showed a good generalization power, highlighting the practicality of deep learning systems for farming environments. Similarly, Maximilliano and Rachmat[5] conducted a comparative analysis of MobileNetV3-Large and MobileNetV3-Small architectures for corn leaf disease classification, demonstrating the importance of model efficiency in addition to model accuracy, especially for deployment on mobile devices and edge devices. Despite these improvements, many deep learning models that have been developed so far prioritize between high accuracy and high computational cost or simplified lightweight architectures that may compromise performance. Furthermore, differences in lighting, background complexity, orientation of leaves, and severity of disease continue to pose challenges for classification systems. There is a need for scalable and efficient deep learning architectures that are able to provide high accuracy while still having a reasonable computational cost. EfficientNetV2-M is a state-of-the-art convolutional neural network that optimizes training speed and classification results by implementing compound scaling, fused convolutions, and optimized architecture components. Compared to traditional CNNs, EfficientNetV2 models have better accuracy, fewer parameters, and faster convergence. The EfficientNetV2-M variant provides a good balance between model capacity and efficiency and can be used for complex image classification problems, such as plant disease recognition. This research is about the classification of corn leaf disease using EfficientNetV2-M Deep learning Architecture. By exploiting the transfer learning and the fine-tuning techniques, the proposed approach is able to precisely detect multiple corn leaf diseases under various environmental conditions. The study is a contribution to the advancement of smart agriculture by making an efficient, robust, and scalable system of automated disease detection. Such a solution can help farmers with early diagnosis of the disease, minimise crop losses, and encourage sustainable agricultural practices.

Literature Review

Recent research on corn leaf disease classification has made more use of deep learning techniques in order to improve the accuracy of detection and to make them applicable for real-time testing. Lightweight and optimized neural networks have attracted attention to strike a balance between performance and computational efficiency. Zeng et al.[6] have proposed a region classification for corn leaf disease identification as a Lightweight Dense-Scale Network (LDSNet). Their architecture was able to capture multi-scale features effectively whilst reducing model complexity, with high accuracy and faster inference time. This work has shown that deep learning models can be made efficient and deployed in agricultural environments with limited computational resources. Hybrid deep learning architectures have also been investigated in an effort to better represent features. Ashwini et al.[7] proposed a hybrid model of 3D-CNN and Long Short-Term Memory (LSTM) for classifying corn leaf diseases. By integrating spatial feature extraction with temporal dependency learning, their system was able to perform classification better than conventional CNN models. This brought into the spotlight the advantage of combining different deep learning paradigms and harvesting complex patterns of diseases. Transfer learning is still one of the most used approaches in the classification of corn diseases because of the scarcity of labeled datasets. Fraiwan et al.[8] developed pretrained deep learning models to classify diseases of corn leaves and showed significant improvement in accuracy and training efficiency. Their research proved that deep transfer learning allows us to achieve a strong feature extraction with small datasets. Similarly, Rajeena et al.[9] performed an analytical study using EfficientNet architectures for detecting leaf disease of corn, where EfficientNet models perform better than many traditional CNNs in terms of accuracy and the number of parameters. With the development of smart farming technologies, technologies related to disease detection systems with the Internet of Things (IoT) have arrived. Rashid et al.[10] proposed an early detection of disease using IoT sensors coupled with multiple deep learning models. Their system allowed for in-time monitoring and classification of corn leaf diseases and proved to be highly reliable in dynamic field conditions. This approach focused on the role of intelligent systems to support proactive crop management. Explainable artificial intelligence (XAI) has also been integrated to increase the trust in disease diagnosis using deep learning. Tariq et al.[11] used the VGG16 model enhanced with explainable AI for classifying corn leaf diseases. Their work offered visual interpretations of model predictions, which helped users understand which parts of the leaves contributed to classification decisions. Such interpretability is key to its practical adoption in agricultural decision support systems. Residual network architectures have been able to capture complex disease features with promising results. Prasetyo et al.[12] proposed the ResNet9-based model for corn leaf disease classification with good performance, with decreased network depth. Their findings showed that residual connections have a significant positive effect on feature learning and convergence stability. Complementing this, Firmansyah et al.[14] implemented deep learning-based classifiers for the classification of various diseases in the corn leaf disease and confirmed the effectiveness of CNN architectures in the agricultural image analysis setting. Standard CNN-based models still have a fundamental role in this field. Fadhilla et al.[15] proposed a convolutional neural network for the recognition of corn leaf disease and provided promising results for various classes of leaf diseases. Their study solidified the importance of deep feature extraction for the accurate diagnosis of plant disease. Comparative studies have been done further on the performance analysis of deep learning architectures. Nalli et al.[16] tested a number of pretrained deep learning models for corn leaf disease classification and concluded that deeper models with transfer learning are typically more accurate than shallow networks. However, they also pointed out the higher computational requirements of deeper models, which is why efficient yet powerful architectures are required. Overall, the literature proves an evident shift from the conventional machine learning algorithms towards sophisticated deep learning frameworks for classifying corn leaf diseases. Lightweight networks, hybrid architectures, transfer learning models, explainable AI, and IoT-integrated systems have all helped in driving better accuracy and real-world applicability. However, there are still challenges, such as environmental variability, background noise, and high computational cost. EfficientNet-based architectures have demonstrated great potential in addressing these challenges by achieving high performance with optimized resource usage. While some studies have been done with the EfficientNet variants, there is limited research work done with the advanced EfficientNetV2 family, especially the EfficientNetV2-M model, in the area of corn leaf disease classification. This offers an opportunity to harness the efficiency of EfficientNetV2-M's improved training capability and better feature extraction ability to build a robust and scalable system for disease detection. The adoption of EfficientNetV2-M can further serve the development of automated diagnosis of corn leaf diseases with improved accuracy and computational practicality for its real-world application in agriculture.

Methodology

Data Collection and Preprocessing Techniques

The Corn Leaf Infection Dataset used in this study was fetched from Kaggle[25] and consists of 4,226 high-resolution images of corn leaves, and is divided into two categories: Healthy Corn (2,000 images) and Infected Corn (2,226 images). The infected class comprises mostly leaves damaged by pests and symptoms of diseases, captured directly from the field environment. As a result, the dataset has high variability of real-world lighting, viewing angle, leaf orientation, and background conditions that help to establish robust deep learning models.

To achieve compatibility with the EfficientNetV2-M architecture and to improve the learning of discriminative features, a structured image preprocessing pipeline was applied for all the leaf images of corn. Initially, raw RGB images acquired under natural field conditions were kept without background removal in order to conserve contextual information of texture. Each image was then resized down to 480 x 480 pixels, which is the native input resolution of EfficientNetV2-M and which helps retain fine-grained spatial details critical for disease recognition. Afterwards, Contrast-Limited Adaptive Histogram Equalization (CLAHE) was applied on the luminance channel in the LAB color space. This step increased local contrast and highlighted subtle lesion boundaries, vein structures, and discoloration patterns commonly associated with corn leaf infections, but did not over-amplify noise. After enhancement, pixel intensities were normalized in the range [0, 1] and standardized with ImageNet mean and standard deviation values in order to make the input distribution the same as that of pre-trained weights.

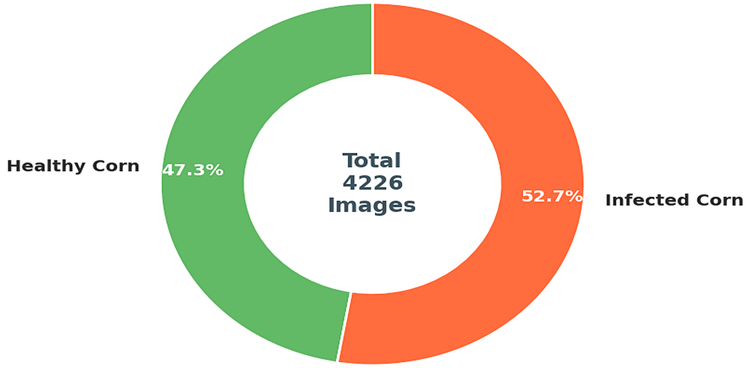

Figure 1. Distribution Of Corn Leaf Images

This preprocessing pipeline resulted in high-quality, standardized inputs, which increased convergence stability and overall classification performance.

Figure 2. Preprocessing Steps Applied to Corn Leaf Images

Dataset Allocation and Structure

The prepared corn leaf dataset with 4,226 images was divided after being stratified by a sampling method in order to keep the same distribution of the number of healthy and infected leaves in the original set. The dataset was split into 70% training (2,958 images), 15% validation (634 images), and 15% testing (634 images). The training set was used to learn the parameters of the EfficientNetV2-M model, and the validation set enabled hyperparameter tuning, monitoring of training convergence, and the control of overfitting during training. The independent test set was reserved only for the final performance evaluation to have an unbiased evaluation. A fixed random seed was used to ensure reproducibility of the data split across the experimental runs. This structured and balanced partitioning strategy of data ensured stable learning, fair evaluation, and strong generalization capability of the proposed disease detection model.

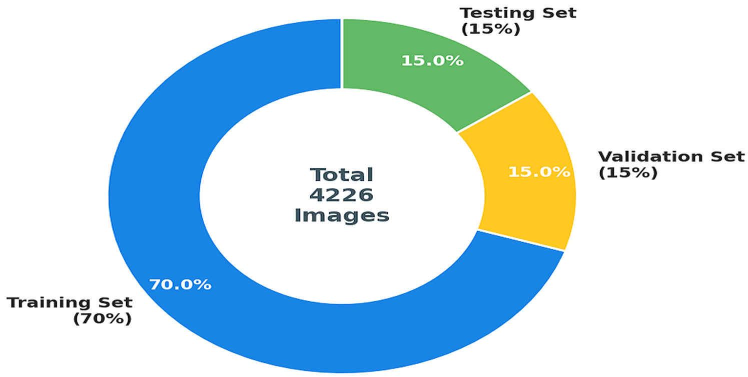

Figure 3. Distribution of Corn Leaf Images for Model Training and Evaluation

Model Selection and Architecture

EfficientNetV2-M was chosen for the detection of corn leaf diseases as the core model because of its good representational ability, faster training convergence, and better accuracy-efficiency trade-off than the traditional CNN architectures. The model was initialized with ImageNet pre-trained weights in a transfer learning framework to use rich generic visual features. All input images were resized to 480×480 pixels so that they correspond to the EfficientNetV2-M native resolution. The original classification head was removed, and the backbone was used as a feature extractor. The feature maps obtained through extraction were passed through a Global Average Pooling layer to decrease spatial dimensions while retaining salient activations. A fully connected dense layer of 512 neurons and ReLU activation was added, followed by dropout regularization (0.5) to reduce overfitting. The last output layer was a single neuron with sigmoid activation, and binary classification (healthy vs. infected leaves of corn) was performed with high reliability.

Model Fitting Process and Assessment

EfficientNetV2-M model trained with transfer learning using ImageNet initialized weights. Training was performed with 30 epochs using 32 batches and the Adam optimizer, which was chosen for its stable convergence properties. An initial learning rate of 0.0001 was employed so as to ensure smooth fine-tuning of the deep network. Since the problem was a binary classification problem, binary cross-entropy was used as the loss function. To mitigate the issue of over-fitting, dropout regularization has been used in the classification head, and early stopping with a patience of five epochs was used to track the validation loss during training. Model performance was tested on a separate test set using common evaluation metrics such as accuracy, precision, recall, and F1-score. Additionally, a confusion matrix was created to study the class-wise prediction behavior and misclassification pattern to obtain a complete evaluation of the effectiveness of the model for detecting corn leaf disease.

Table 1. Proposed EfficientNetV2-M Architecture for Corn Leaf Disease Classification

Block / Layer	Type / Configuration	Output Shape	Parameters
Input	RGB Image	(480, 480, 3)	0
Preprocessing	CLAHE $\rightarrow$ Normalize [0,1] $\rightarrow$ ImageNet Standardization	(480, 480, 3)	0
Feature Extractor	EfficientNetV2-M (ImageNet), include_top = False	(15, 15, 1280)	$\sim$54M
Pooling	GlobalAveragePooling2D	(1280)	0
Dense Head	Dense (512) + ReLU	(512)	1280$\times$512 + 512 = 655,872
Regularization	Dropout (p = 0.5)	(512)	0
Output Layer	Dense (1) + Sigmoid	(1)	512$\times$1 + 1 = 513
Total Parameters	Backbone + Head	—	$\sim$54.66M
Trainable Params	Head only (if backbone frozen)	—	656,385
Non-trainable Params	Backbone (if frozen)	—	$\sim$54M

Results

Epoch-Wise Variation in Training and Validation Loss

The trends of training and validation losses show a stable and effective learning behavior of the EfficientNetV2-M model for 22 epochs. Training loss continuously fell from 1.2050 in Epoch 1 to 0.1116 in Epoch 22, which shows the model could continuously decrease the classification error. Similarly, validation loss exhibited a continuous decreasing trend from 0.9510 to 0.2029 with slight fluctuations during the later epochs. These fluctuations are to be expected in deep models trained on real-world agricultural data and do not reflect severe overfitting. The relatively close alignment between training and validation loss in the last epochs is a good witness to good generalization capability. Overall, the loss curves confirm the success of the preprocessing pipeline, optimizer configuration, and EfficientNetV2-M architecture for corn leaf disease classification.

Epoch-Wise Variation in Training and Validation Accuracy

The accuracy curves show a good and steady increase in classification performance during training. Training accuracy went from 53.76% in the first epoch to 94.91% by Epoch 22, showing effective learning of features and convergence of the model. Validation accuracy showed a similar upward trend as it went from 46.08% to a peak of 89.18% in the final epoch. The reasonable difference between training and validation accuracy implies controlled overfitting and effective regularization. Validation accuracy stabilized after Epoch 16, which implies convergence of the learning process. These results show the good generalization ability of EfficientNetV2-M on unseen images of corn leaves and validate its application to the accurate and reliable detection of diseases for precision agriculture applications.

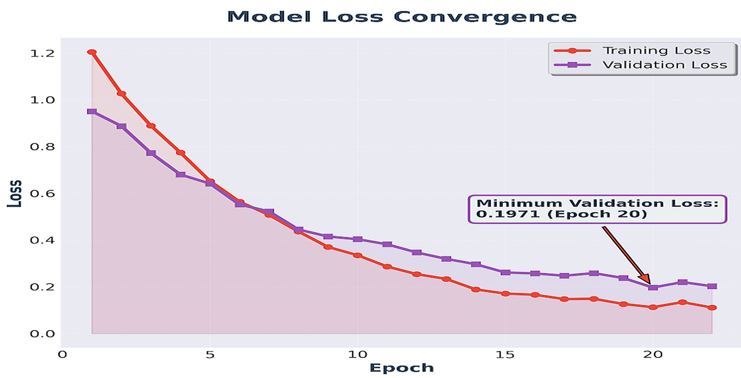

Figure 4. Training and Validation Loss During Model Training

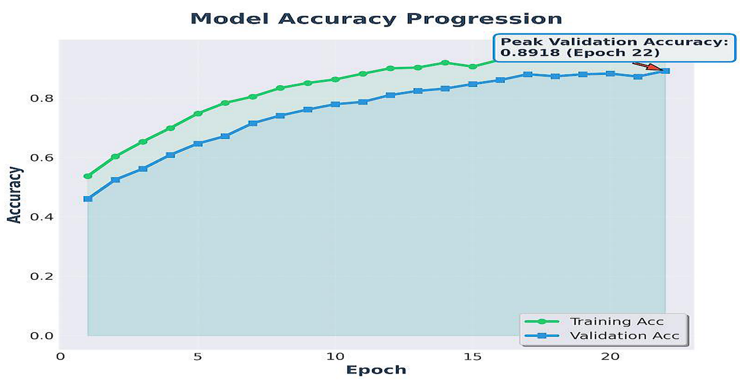

Figure 5. Training and Validation Accuracy During Model Training

Confusion Matrix Analysis

The confusion matrix gives a detailed understanding of the classification performance of the proposed EfficientNetV2-M-based classification framework on the test dataset of 634 corn leaf images. Out of 300 healthy corn samples, 262 were correctly classified, whereas 38 were misclassified as infected, meaning there was slight confusion because of visual similarities between early-stage infections and healthy leaf textures. For the infected class, 312 out of 334 samples were correctly classified, with only 22 being misclassified as healthy, showing good sensitivity to diseased leaves. The relatively small number of false negatives is of special interest in agricultural applications, because failure to detect an infection may result in uncontrolled spread of disease. Overall, the confusion matrix indicates a well-balanced model with high true positive rates for both classes, as well as confirming the reliability of the model for corn leaf disease detection in the wild.

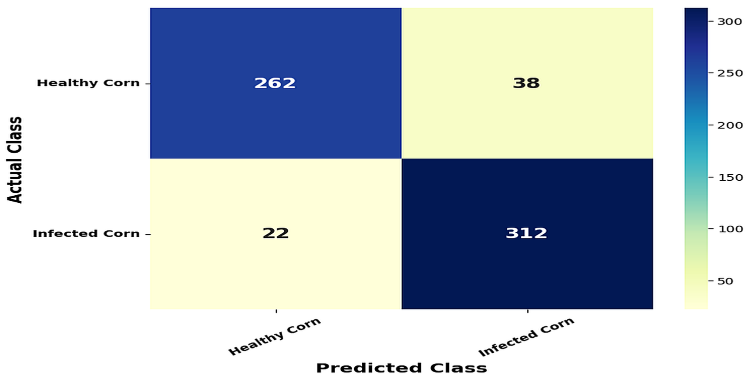

Figure 6. Confusion Matrix for Corn Leaf Disease Classification

Classification Report Analysis

The classification report also confirms the robustness of the proposed classification model by showing the precision, recall, and F1-score metrics for both classes. Healthy corn leaves had a precision of 0.92 and a recall of 0.87, which indicates reliable identification with few false positives. Infected corn leaves received a precision of 0.89 and a high recall of 0.93, indicating a good ability of the model to identify diseased samples effectively. The corresponding balanced performance of F1-scores, 0.90 and 0.91, is confirmed. The overall accuracy of the model was 91%, and both macro and weighted average F1-scores were near 0.91, which shows that the model is able to classify samples with consistent behavior, even though there is some class imbalance. These results validate the use of EfficientNetV2-M in accurate and reliable corn leaf disease diagnosis.

Table 2. Classification Report: Assessing Model Accuracy for Corn Leaf Health

Class	Precision	Recall	F1-Score	Support
Healthy Corn	0.92	0.87	0.90	300
Infected Corn	0.89	0.93	0.91	334
Accuracy		0.91		634
Macro Avg	0.91	0.90	0.90	634
Weighted Avg	0.91	0.91	0.91	634

Conclusion

This study proposed an EfficientNetV2-M-based deep learning model for automated detection of corn leaf disease with field-acquired imagery. A consistent preprocessing pipeline (resizing to 480X480, CLAHE-based contrast enhancement, and ImageNet-standardized normalization) allowed for stable model training and effective feature extraction. Experimental evaluation showed good results with 91% overall accuracy and reliable class-wise results. The confusion matrix showed that most of the healthy (262/300) and infected samples (312/334) were correctly classified, and the classification report showed that the precision, recall, and F1-scores were balanced for both classes. Importantly, the model had a high recall for infected leaves (0.93), which is important in agricultural diagnostics where missed infections can lead to severe crop loss. Future work can extend this binary framework to multi-class disease recognition for specific diseases and types of damage in corn (i.e., diseases in corn as well as pest damage). Additional improvements can be in the form of larger and more diverse datasets acquired during different seasons and illumination, advanced augmentation, or attention-based or hybrid CNN-Transformer architectures to be sensitive to early-stage symptoms. Finally, the model deployment on mobile or drone platforms, as well as saliency/Grad-CAM explainability, can enable real-time, interpretable decision-making for precision agriculture.

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