Implementation of a corn leaf disease classification system using EfficientNetV2-S and transfer learning

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Abstract. Manual detection of corn leaf diseases makes it difficult for farmers to recognize early symptoms, resulting in delayed treatment. Meanwhile, deep learning methods generally require high computing power that is not compatible with simple devices in the field. To overcome this, this study developed a corn leaf disease classification system using the lightweight and efficient *EfficientNetV2-S* architecture. The research data came from a public dataset with four classes, namely Healthy, Leaf Blight, Common Rust, and Leaf Spot. The model was trained with transfer learning from ImageNet for 30 epochs (±22 minutes on GPU). The evaluation showed an accuracy of 84% with an average precision of 83%, recall of 84%, and F1-score of 83%. Per class, the best performance was obtained for Common Rust (F1 = 0.98) and Healthy (F1 = 0.88), while the lowest was for Leaf Spot (F1 = 0.64). The best results were obtained in the scenario without data augmentation. The system was implemented as a Flask-based web application optimized for mobile devices. The results of this study show that *EfficientNetV2-S* is efficient and performs well and has the potential to be a practical solution for corn disease detection at the farmer level.

1 Introduction

Corn (Zea mays L.) is one of the most important cereal crops in Indonesia after rice and plays a vital role in food security, animal feed, and the agro-industry [1], [2]. However, its productivity is often constrained by foliar diseases such as Common Rust (Puccinia sorghi), Northern Leaf Blight (Exserohilum turcicum), and Gray Leaf Spot (Cercospora zeae-maydis), which can lead to yield losses exceeding 40% if not properly diagnosed and treated [3], [4], [5]. Early and accurate identification of these diseases is therefore essential for effective control and sustainable agricultural production [6]. Traditional disease diagnosis relies heavily on expert visual inspection, which is time-consuming, subjective, and error-prone; consequently, computer vision and deep learning are increasingly adopted for automatic crop disease detection and classification [6], [7].

Deep learning models, particularly Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in extracting spatial and color features from leaf images for plant disease classification [6], [8]. In previous studies, CNN-based approaches achieved high performance in recognizing corn leaf diseases; for example, Wahyuningrum et al. (2023) reported 94.15% accuracy with a Loss-Fused CNN for four corn-leaf classes [9]. Despite these promising results, conventional CNNs can be computationally heavy and prone to overfitting on limited datasets, constraining deployment on mobile/edge devices [7], [10].

Recent advances in transfer learning and lightweight architectures mitigate these challenges by reusing knowledge from large-scale pretrained models (e.g., ImageNet). EfficientNetV2 combines training-aware scaling and progressive learning to deliver higher accuracy with faster training and fewer parameters than traditional CNNs [11]. Empirical studies show EfficientNetV2 is competitive for plant-disease and pest recognition while maintaining compactness; on tomato leaf disease, pairing EfficientNetV2 with augmentation improved robustness and mobile inference efficiency [12], [13].

Further evidence in agriculture highlights the effectiveness of lightweight models for real-time field deployment [10], [14]. For maize specifically, improved MobileNet/Efficient backbones and classical pipelines have achieved strong accuracy under in-field conditions [15]. Moreover, explainable AI (e.g., Grad-CAM) has been shown to enhance interpretability and diagnostic confidence in corn leaf disease classification [16], [17].

Building upon these developments, this study proposes the development of a corn leaf disease classification system based on EfficientNetV2-S using transfer learning. The proposed approach aims to classify four categories of corn leaf images Common Rust, Northern Leaf Blight, Gray Leaf Spot, and Healthy Leaves using a fine tuned EfficientNetV2-S

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model pretrained on ImageNet. The objectives of this reseach are to implement and optimize the EfficientNetV2-S architecture for corn leaf disease classification and to evaluate accuracy, precision, and computational efficiency. Through this research, it is expected that the proposed system can deliver a fast, accurate, and lightweight solution for automated corn disease diagnosis, facilitating practical deployment in mobile and field-based smart agriculture systems. The objectives of this research are to implement and optimize the EfficientNetV2-S architecture for corn leaf disease classification and to evaluate accuracy, precision, and computational efficiency, aiming for a fast, accurate, and lightweight solution suitable for mobile/field deployment [12], [14].

2 Literature review

Corn leaf diseases as Common Rust (*Puccina sorghi*), Northern Leaf Blight (*Exserohilum turcicum*), and Gray Leaf Spot (*Cercospora zeae-maydis*) can severely reduce crop yield. Traditional diagnosis through manual observation is slow and prone to human error, prompting the use of deep learning and transfer learning for automated disease classification.

In 2023, Ang Gao et al. [18] proposed an improved MobileNet V3-Small network for the detection of maize leaf diseases using UAV-captured imagery in complex field conditions. Their study investigated the impact of data augmentation and transfer learning on recognition accuracy, obtaining an average accuracy of 79.52 %, recall of 77.91 %, and F1-score of 78.62 %, indicating that lightweight models can operate efficiently on embedded devices. Yahya Auliya et al. In 2025 [19] optimized a Convolutional Neural Network (CNN) architecture based on ResNet50 through Bayesian Optimization to classify four corn leaf diseases using a Kaggle dataset. Their unoptimized model achieved an accuracy of 82.82 %, while the optimized configuration increased to 87.79 %, demonstrating that fine-tuning hyperparameters could enhance performance.

Firmansyah and Nafi'iyah in 2024 [20] implemented a CNN model to identify four types of corn leaf diseases Blight, Common Rust, Gray Leaf Spot, and Healthy using 2,000 training and 120 testing images sourced from Kaggle. The classification process achieved an accuracy of 84.5 %, revealing the necessity for architectural modifications to improve prediction reliability. Gao J et al. In 2022 [21] developed a hyperspectral-based classification model for the identification of Southern Corn Rust severity at the leaf level under natural solar illumination, reporting an overall accuracy of 81.30 %, which highlights the potential of hyperspectral data yet also its limitations in noisy outdoor conditions. In 2025, Askale G et al. [22] proposed a mobile-based deep CNN model integrating VGG16, AlexNet, and ResNet50 architectures for real-time detection of maize leaf diseases. Among these, the ResNet50 architecture achieved the lowest performance, with 72 % accuracy, confirming that deeper networks may underperform on lightweight mobile platforms.

Overall, recent literature shows a clear evolution from standard CNNs to lightweight and scalable architectures such as EfficientNetV2-S, which balance accuracy and efficiency. Therefore, this research implements EfficientNetV2-S with transfer learning to classify four corn leaf categories, Common Rust, Northern Leaf Blight, Gray Leaf Spot, and Healthy Leaves, as a robust and efficient approach for smart agricultural systems.

3 Methodology

3.1 Methodology process

The research methodology process is shown in Figure 1. This study began with defining the problem and objectives, namely early detection of corn leaf disease. Next, a dataset was collected from public sources and field images. The data obtained then underwent preprocessing to ensure uniform image quality. The dataset was stratified into training, validation, and test data with a ratio of 80:10:10.

The next stage was model preparation using the EfficientNetV2-S architecture with a transfer learning approach. The model was trained using early stopping and fine-tuning techniques to optimize performance. The validation process and selection of the best model were carried out based on validation metrics. After that, testing was carried out using accuracy, precision, recall, F1-score, and confusion matrix metrics. The best model was then implemented in a Flask-based web application that is mobile-friendly. The final stage included monitoring and error analysis, particularly on the differences in detection between the Blight and Gray Leaf Spot classes.

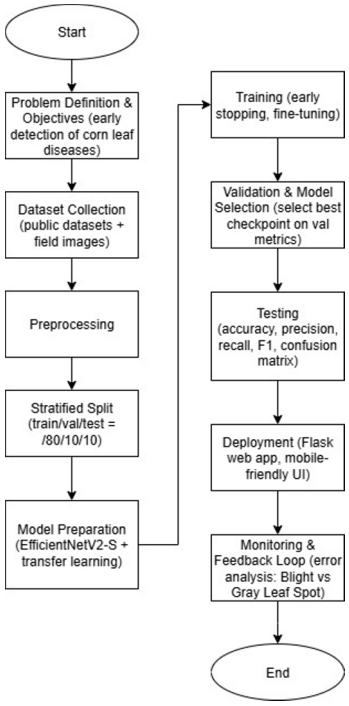


Fig. 1. Methodology flowchart.

3.2 Dataset

The dataset used in this study comes from the PlantVillage Dataset, which is publicly available on the Kaggle platform and managed by Abdalla Halidev (https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset). From the entire collection, this study uses a subset of images focusing on corn plants (Zea mays). The subset consists of 3,852 corn leaf images divided into four classes based on leaf health conditions, namely Common Rust, Healthy, Leaf Blight, and Gray Leaf Spot.

The distribution of the number of images in each class is as follows: Common Rust with 1,192 images, Healthy with 1,162 images, Leaf Blight with 985 images, and Gray Leaf Spot with 513 images. All images are in color (RGB) format with a resolution of 256×256 pixels, taken in various natural lighting conditions, and display variations in shape, size, and severity of symptoms on the leaf surface. Overall, this dataset represents corn leaf conditions at various levels of health, making it suitable for use in image-based leaf disease classification research [23].

3.3 Pre-processing data

The data augmentation process is performed on-the-fly using the ImageDataGenerator module from TensorFlow Keras. This augmentation aims to enrich the variety of training data without permanently increasing the size of the dataset. The transformations applied include random rotation up to 20°, width shift up to 10%, shear transformation of 10%, zoom up to 10%, and horizontal flip. All augmentations are performed using the nearest fill mode method to fill in the empty areas resulting from the transformation.

The next step is to divide the dataset into three subsets, namely training data (80%), validation data (10%), and test data (10%). The division is done randomly while maintaining the proportion of each class so that the data distribution remains balanced (stratified split). The results of the dataset division after the augmentation process can be seen in Table 1.

Table 1. Augmentation dataset division.

Set Data	Common Rust	Healthy	Leaf Blight	Leaf Spot	Total
Training	974	974	973	957	3878
Validation	122	122	122	122	488
Testing	96	96	96	96	384
Overall Total	1192	1192	1191	1175	4750

3.4 Model architecture

EfficientNetV2-S is a variant of the EfficientNetV2 architecture developed by Tan and Le (2021) as an improvement on the previous EfficientNet series. EfficientNetV2-S is ideal for scenarios that require faster inference and lower memory usage [24]. EfficientNetV2-S uses a compound scaling approach that optimizes the depth, width, and resolution of the network simultaneously, but with a faster and more adaptive training method than the previous version. EfficientNetV2-S was chosen because it is well-suited for various computer vision tasks, including image classification, object detection, and semantic segmentation. Its adaptive architecture allows for refinement for specific tasks with minimal computational overhead [25].

In this study, we applied the EfficientNetV2-S architecture described in detail by Tan et al. This architecture has 8 stages (Stages 0–7) and extensively uses MBConv and fused-MBConv. In Stage 0, there is a convolutional layer with a kernel size of 3 × 3. In Stages 1–3, these blocks apply fused-MBConv, and the number of layers ranges from 2 to 4. In Stage 1, the convolution operator has an expansion ratio of 1 and a kernel size of 3 × 3. In Stages 2 or 3, it has an expansion ratio of 4 and a kernel size of 3 × 3. In stages 4–6, these blocks use MBConv, and the number of layers ranges from 6 to 15. In Stage 4, the operator is with an expansion ratio of 4, a kernel size of 3 × 3, and an SE0.25 block. In Stage 5 or 6, with an expansion ratio of 6, a kernel size of 3 × 3, and an SE0.25 block. In Stage 7, the convolutional operators include a convolution layer with a kernel size of 1 × 1, a pooling layer, and a fully connected layer [26]. The architecture can be seen in Fig. 2.

EfficientNetV2-S is used as the main model (backbone) for classifying corn leaf diseases. The model is initialized using pre-trained weights from ImageNet through a transfer learning approach, then fine-tuned at the upper layer so that the model can adapt to the specific characteristics of corn leaf images.

3.5 Transfer learning

Transfer learning is a technique in deep learning that is used to train convolutional neural networks (CNNs) quickly and accurately without having to initialize the weights from scratch. Instead of starting training from scratch, the model utilizes weights that have been learned from other CNNs that were previously trained on much larger datasets. According to the literature [27], one of the most commonly used sources of pre-trained weights in transfer learning is the ImageNet dataset, which contains more than 14 million images with 1000 different classes.

In this study, the transfer learning method was applied to the EfficientNetV2-S architecture using pre-trained weights from ImageNet. The training process was carried out by freezing most of the model's initial layers, namely the layers that function to extract general features such as edges, colors, and textures. Meanwhile, the top layer (fully connected layer) was unlocked and retrained using a corn leaf disease dataset to adjust the model to the specific characteristics of each leaf class. After several epochs, the frozen layers were gradually unlocked again for comprehensive fine-tuning, so that the model could adjust the high-level feature representation without losing the generalization ability obtained from ImageNet.

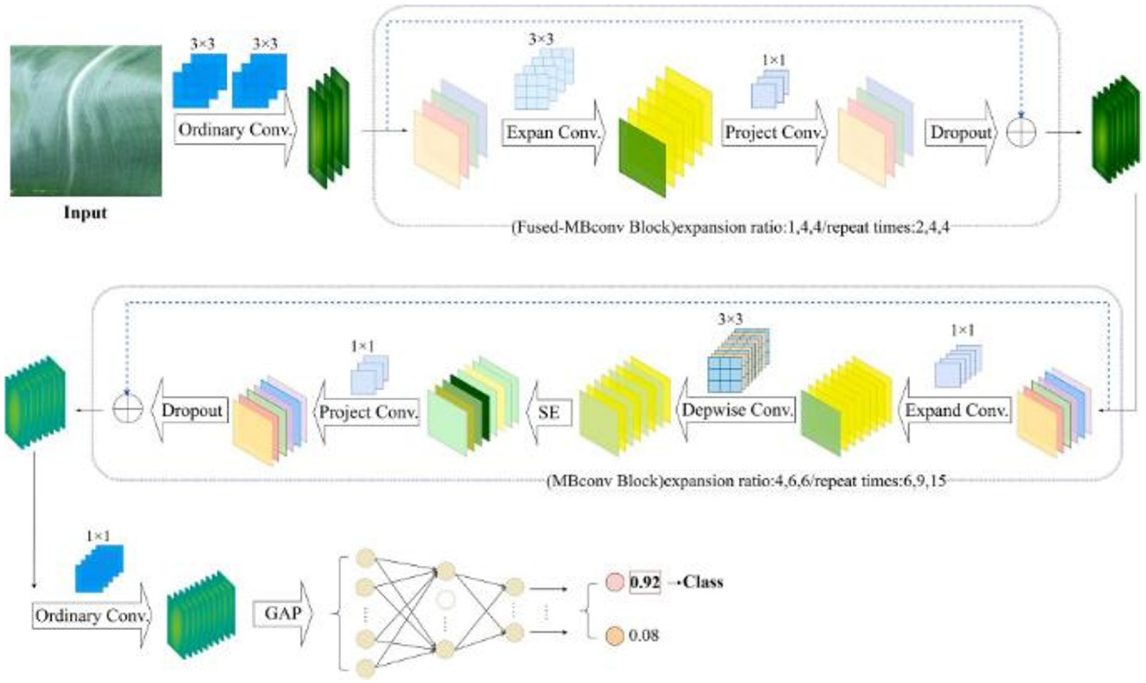


Fig. 2. EfficientNetV2-S architecture.

3.6 System implementation

The system implementation stage is the process of applying the trained model into an application that can be used by end users. In this study, the system implementation was carried out using the Flask framework, which is a lightweight and easy-to-use Python-based micro web framework for creating web-based applications.

The Flask framework was chosen because it has a simple and flexible structure, making it suitable for integrating the CNN EfficientNetV2-S-based deep learning model that has been developed. Through Flask, the corn leaf disease classification model can be deployed to a local server or online server (web hosting) and connected to a web-based user interface.

In this system, Flask acts as a link between the model and the user (interface). Users can access the application through the web page provided, then upload images of corn leaves to be analyzed. Once the images are uploaded, Flask will process the data by calling the previously trained model. The prediction results, in the form of corn leaf disease classes (e.g., Healthy, Common Rust, Leaf Blight, or Gray Leaf Spot), are then displayed interactively on the web page.

The general structure of the system consists of three main components:

1. CNN Model (EfficientNetV2-S) – A model that has been trained and saved in .h5 format is used to perform inference.
2. Flask Backend – Functions as application logic that receives user input, processes images, runs models, and sends prediction results to the web interface.
3. Frontend Interface – Built using HTML, CSS, and JavaScript to display a simple and interactive interface, allowing users to easily perform tests without having to run the code directly.

With this implementation, the corn leaf disease classification system not only functions as a computational model, but also as a web-based interactive application that can be accessed by anyone through a browser. This approach is expected to help farmers and researchers identify corn leaf diseases more quickly, efficiently, and easily on various devices.

4 Results and discussions

4.1 Model training results

The model training process was carried out using the EfficientNetV2-S architecture with a transfer learning approach. To evaluate the effect of augmentation on model performance, two training scenarios were carried out, namely: Scenario 1: Training without data augmentation. Scenario 2: Training with on-the-fly data augmentation using ImageDataGenerator.

Both scenarios used the same training parameter configuration, as shown in Table 2.

Table 2. Training parameter configuration.

Parameter	Score
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epoch	70
Early Stop	5

The dataset is divided into 80% training data, 10% validation data, and 10% test data. The training process is run using a GPU T4 form google collab for more efficient computing time. The training results for both scenarios are shown in Table 3.

Table 3. Training outcome scenario.

Scenario	Without Augmentation	With Augmentation
Training Accuracy	0.8295	0.8197
Validation Accuracy	0.8464	0.8424
Training Loss	0.4230	0.4495
Validation Loss	0.4011	0.3681
Training Time	22 minutes 41 seconds	28 minutes 42 seconds

Based on the results in Table 3., the scenario without augmentation performs better than the scenario using augmentation. This is indicated by higher validation accuracy and lower loss values.

This phenomenon may occur because the applied augmentations, such as rotation and geometric transformations, can alter the structure of leaf disease patterns, which are important features in classification. As a result, the model loses its ability to consistently recognize these specific patterns. The visualization of the training results for both scenarios can be seen in Fig. 3 and Fig. 4.

Overall, the EfficientNetV2-S model without augmentation showed more stable training performance and converged faster. Therefore, the model from the first scenario (without augmentation) was used as the main model in the subsequent evaluation and testing stages.

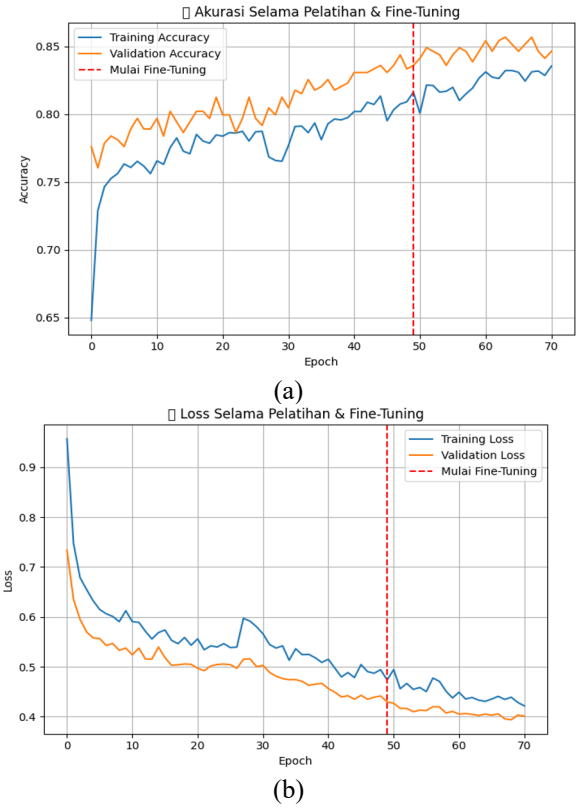


Fig. 3. Model performance without augmentation: (a) Training and validation accuracy, and (b) Training and validation loss.

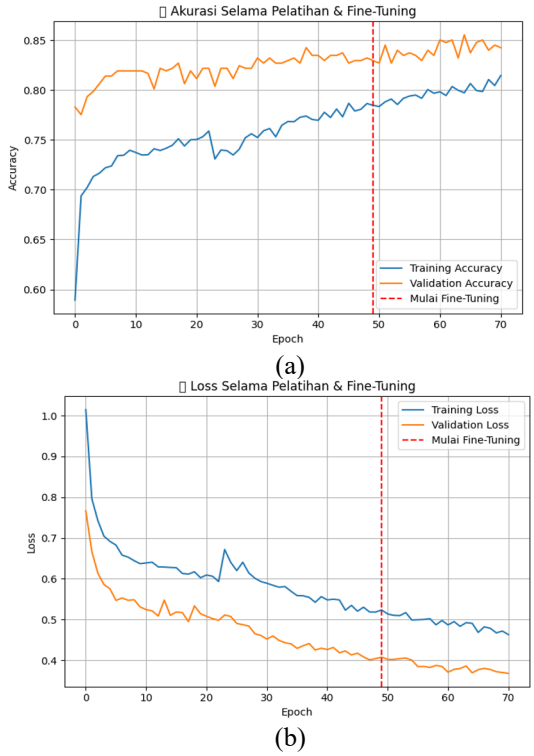


Fig. 4. Model performance with augmentation: (a) Training and validation accuracy, and (b) Training and validation loss.

4.2 Model evaluation

The model evaluation was conducted to measure the performance of the EfficientNetV2-S architecture in classifying corn leaf diseases in the test data. The model used was a model trained without data augmentation, as it showed higher validation performance compared to models with augmentation.

The test was conducted on 388 test images, divided into four classes, namely Common Rust, Healthy, Leaf Blight, and Leaf Spot. The evaluation was carried out using the accuracy, precision, recall, and F1-score metrics obtained from the confusion matrix.

Based on the results in Fig. 5, the EfficientNetV2-S model achieved an overall accuracy of 84% on the test data. The average precision, recall, and F1-score values also showed fairly balanced performance, each in the range of 80–84%.

	precision	recall	f1-score	support
Common_Rust	0.98	0.97	0.98	120
Healthy	0.84	0.91	0.88	117
Leaf_Blight	0.71	0.70	0.70	99
Leaf_Spot	0.69	0.60	0.64	52
accuracy			0.84	388
macro avg	0.81	0.80	0.80	388
weighted avg	0.83	0.84	0.83	388

Fig. 5. Evaluation results of the efficientnetv2-s model on test data.

The best performance was obtained in the Common Rust class with an F1-score of 99%, indicating that the model was able to recognize the typical patterns of leaf rust very well. Meanwhile, the lowest performance was obtained in the Leaf Spot class with an F1-score of 64%,

which was likely due to the relatively smaller number of samples and the visual similarity with the Leaf Blight class. The visualization of the test results is shown in the confusion matrix in Fig. 6.

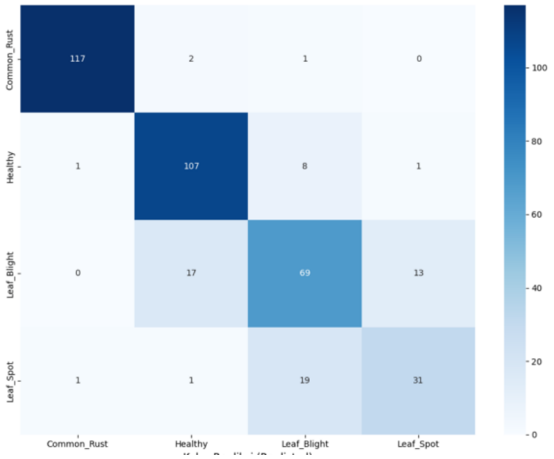


Fig. 6. Confusion matrix of EfficientNetV2-S model test results.

From the confusion matrix, it can be observed that most of the model predictions are on the main diagonal, which means that the model is able to classify most of the images correctly. The classification errors that still occur generally occur between Leaf Blight and Leaf Spot, which have similar color patterns and texture spots.

Overall, the evaluation results show that the EfficientNetV2-S architecture has good capabilities in recognizing corn leaf diseases, although there is still room for performance improvement, especially in classes with limited data. Furthermore, the results of this study were also compared with other similar studies, as shown in Table 4.

From the accuracy results shown in Table 4, it is stated that our proposed method (*EfficientNetV2-S* and *Transfer Learning*) obtained better accuracy results compared to other methods from previous studies of the same field.

Table 4. Comparison with other studies.

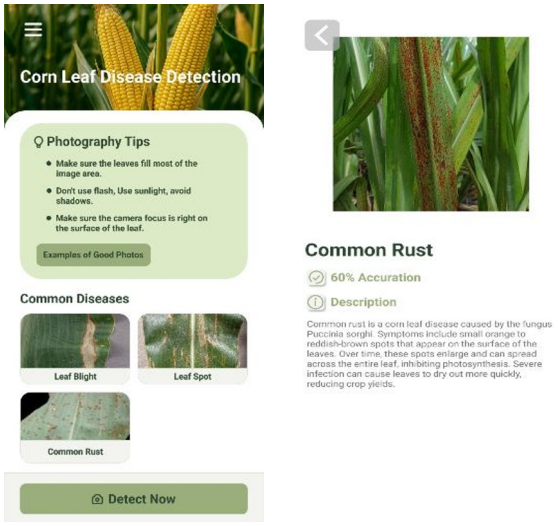
Author and year	Methods	Object	Accuracy (%)
Askale G et al. 2025 [12]	*ResNet50*	Maize leaf diseases	72%
Ang Gao et al. 2023 [8]	*MobileNet V3*	Maize leaf diseases	79.52%
Yahya Auliya et al. 2025 [9]	*Bayesian Optimization CNN*	Corn leaf diseases	82.82%
Gao J et al. 2022 [11]	*Hyperspectral-based CNN*	Southern Corn Rust severity at the leaf	81.30%
Proposed method	*EfficientNetV2-S* and *Transfer Learning*	Corn leaf diseases	84%

4.3 System implementation results

The developed corn leaf disease detection system is implemented as a Flask-based web application, designed with a simple interface to ensure user accessibility. As shown in Figure 7a, the main interface is the image upload page. This minimalist design focuses on the core functionality: allowing a user to easily select and upload a corn leaf image, after which the system automatically begins the analysis process.

Once the image is processed, the system displays the prediction results, as demonstrated in Figure 7b. This output provides the user with two key pieces of information: the predicted disease class name and the corresponding confidence score. This clear and immediate feedback loop validates the successful integration of the classification model into the web application and effectively delivers the analytical results to the end-user.

Strengths and limitations. This study demonstrates that EfficientNetV2-S fine-tuned via transfer learning provides an effective and lightweight solution for classifying corn leaf diseases into Common Rust, Northern Leaf Blight, Gray Leaf Spot, and Healthy. Using a stratified 80:10:10 split, the model achieved 84% test accuracy with balanced precision, recall, and F1-score, performing best on Common Rust and weakest on Gray Leaf Spot due to class imbalance and visual similarity with Leaf Blight. The research shows that a compact transfer-learned EfficientNetV2-S can effectively handle multi-class plant disease classification, highlighting the role of network architecture and transfer learning in agricultural image analysis. The trained model was deployed as a Flask web application optimized for mobile use, demonstrating practical applicability in resource-limited field settings. Despite these promising results, the study is limited by the relatively small and imbalanced dataset. Future work could expand the dataset, employ advanced augmentation techniques, explore ensemble or hybrid models, and implement real-time deployment in diverse agricultural environments, further supporting automated plant disease diagnosis and sustainable agriculture practices.



(a) (b)

Fig. 7. Display of the Flask-based corn leaf disease detection system: (a) Main Display and (b) classification results.

5 Conclusion

This study demonstrates that EfficientNetV2-S, fine-tuned through transfer learning, offers an effective and lightweight approach for classifying corn leaf disease into four categories, Common Rust, Northern Leaf Blight, Gray Leaf Spot, and Healthy. The best model, trained without augmentation, achieved 84% accuracy with balanced precision (83%), recall (84%), and F1-score (83%), confirming its reliability for practical field deployment. These results highlight the model's efficiency and potential for supporting farmers through mobile-based smart agriculture applications. Theoretically, this work contributes to the growing body of research on lightweight CNNs, showing that EfficientNetV2-S can achieve high accuracy while maintaining computational efficiency, thus bridging deep learning theory and real-world agricultural needs. However, the study is limited by dataset imbalance and the use of RGB imagery under controlled conditions, which may restrict generalization to broader environments. Future studies should explore larger and more diverse datasets, multimodal imaging (e.g., hyperspectral or thermal), and deployment on edge devices to enhance robustness. This research provides new insights into the development of accessible AI-driven plant disease detection systems and motivates further exploration into explainable AI, multi-crop disease detection, and offline mobile applications to advance sustainable smart farming solutions.

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