Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 6, December 2026, pp. 5265~5276
ISSN: 2302-9285, DOI: 10.11591/eei.v15i6.14038

CornLeaf-MIA Net: a novel deep learning architecture for corn leaf disease detection in precision agriculture

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Article Info

Article history:

Received Jul 21, 2026
Revised Sep 12, 2026
Accepted Oct 4, 2026

Keywords:

Computer vision
Convolutional neural network
Corn leaf disease detection
CornLeaf-MIA Net
Deep learning

ABSTRACT

Early detection of corn leaf diseases is important for maintaining crop productivity and supporting precision agriculture. This study proposes CornLeaf-multi-scale intelligent architecture network (CornLeaf-MIA Net), a lightweight convolutional neural network (CNN) for multiclass classification of blight, common rust, gray leaf spot, and healthy corn leaves. A dataset of 4,013 labeled images was preprocessed through resizing, normalization, and training-stage augmentation. The proposed model was evaluated against MobileNetV2, VGG16, and ResNet50 under identical experimental conditions. CornLeaf-MIA Net achieved 98.38% testing accuracy, with weighted precision, recall, and F1-score of 98.50%, 98.38%, and 98.40%, respectively. The model contains 2,982,052 trainable parameters and achieved a training-validation accuracy gap of 0.71%. It also outperformed MobileNetV2 (94.40%), VGG16 (94.89%), and ResNet50 (95.39%) in testing accuracy. The trained model was implemented in a Flask-based web application using OpenCV and TensorFlow for automated multi-leaf disease diagnosis. The results indicate that the proposed task-specific multi-scale CNN provides high classification performance with a relatively compact architecture and demonstrates practical applicability through web-based implementation.

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1. INTRODUCTION

Corn (*Zea mays L.*) is one of the world's most important cereal crops, serving as a source of food, livestock feed, and industrial raw materials [1]–[3]. However, its productivity is threatened by foliar diseases such as common rust, gray leaf spot, and northern corn leaf blight, which can reduce photosynthetic activity and crop yield. Early and accurate diagnosis is therefore essential for effective disease management [4]–[6]. Traditional disease identification relies on manual inspection and expert knowledge, making it labor-intensive, time-consuming, and potentially subjective, particularly when disease symptoms exhibit similar visual characteristics. These limitations have encouraged the application of artificial intelligence (AI) and computer vision for automated plant disease diagnosis [7], [8].

Deep learning, particularly convolutional neural networks (CNNs), has substantially improved image-based plant disease recognition by automatically learning hierarchical visual features [9]. Transfer learning models such as VGG16, ResNet50, and MobileNetV2 have achieved strong performance in agricultural image classification, while you only look once (YOLO)-based approaches support disease localization [10]–[13]. Nevertheless, challenges remain regarding task-specific architectural optimization, model complexity, and comprehensive evaluation of generalization and practical implementation [14]–[16]. To address these issues, this study proposes CornLeaf-multi-scale intelligent architecture network (CornLeaf-MIA Net), a task-specific CNN for classifying blight, common rust, gray leaf spot, and healthy corn leaves. The model was evaluated using 4,013 labeled images and compared with MobileNetV2, VGG16, and ResNet50 under identical experimental conditions using accuracy, precision, recall, F1-score, and confusion matrix analysis. Its practical applicability was further demonstrated through a web-based system for automated corn leaf disease diagnosis.

The main contributions of this study are:

- The development of CornLeaf-MIA Net, a task-specific CNN for multiclass corn leaf disease classification.
- A systematic comparison with MobileNetV2, VGG16, and ResNet50 under consistent experimental conditions.
- A comprehensive evaluation using multiple classification metrics, confusion matrix analysis, and comparative experiments.
- The implementation of the trained model in a web-based disease diagnosis system.

The novelty of CornLeaf-MIA Net lies in its task-specific architectural configuration rather than the invention of new CNN operators**.** Unlike approaches that directly adopt or modify established CNN architectures [17], [18], the proposed model organizes established components into a dedicated multi-scale feature-learning pipeline designed to capture diverse disease characteristics, including small spots, irregular lesions, and distributed discoloration, while maintaining a relatively compact architecture [14], [16]. Although established transfer learning architectures have demonstrated strong image-classification performance [19], [20], CornLeaf-MIA Net combines these established principles through a task-specific multi-scale feature extraction strategy. Its novelty is therefore associated with the proposed architectural configuration, feature-learning strategy, and empirical validation for corn leaf disease classification.

2. METHOD

This study proposes CornLeaf-MIA Net, a CNN architecture for automated multiclass corn leaf disease detection. Deep learning, particularly CNN, has been widely applied to image-based plant disease recognition because of its capability to automatically learn discriminative visual features from leaf images [21], [22]. The research framework consists of six stages: i) dataset acquisition, ii) image preprocessing, iii) development of CornLeaf-MIA Net, iv) model training, v) performance evaluation and comparison with transfer learning models, and vi) web-based implementation. Figure 1 illustrates the overall research workflow.

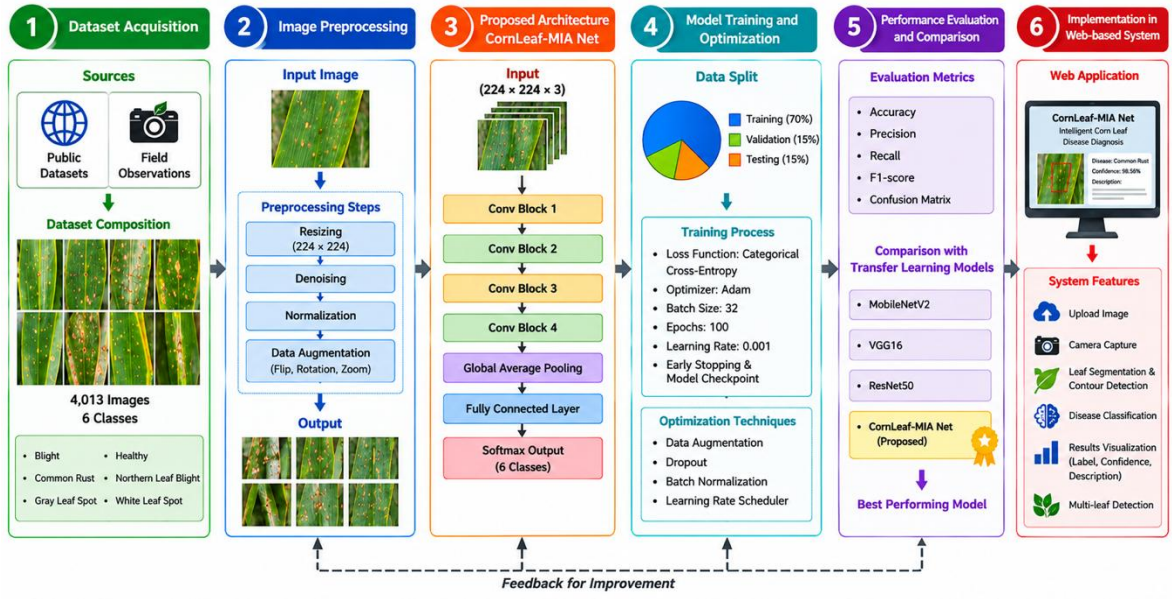


Figure 1. Overall workflow of the proposed research framework

2.1. Dataset description

Table 1 presents the dataset partitioning strategy adopted in this study to ensure a consistent basis for evaluating the proposed CornLeaf-MIA Net architecture and the comparative transfer learning models. The dataset was randomly divided once into training and testing subsets using an 80:20 ratio. This partition was maintained consistently across all experiments to ensure that each model was evaluated using the same testing data. Applying a fixed data split helps minimize variability arising from different dataset partitions and supports a fairer comparison of classification performance among the evaluated models. Therefore, the dataset partitioning strategy provides an important foundation for assessing the effectiveness of the proposed architecture relative to the baseline models.

Table 1. Dataset description

Parameter	Description
Dataset name	Corn leaf disease dataset
Total images	4,013
Number of classes	4
Disease classes	Blight, common rust, gray leaf spot, and healthy
Image sources	Publicly available plant disease datasets and field observations
Label verification	Manually verified for labeling consistency
Training set	3,210 images (80%)
Testing set	803 images (20%)
Data splitting method	Random sampling

Table 2 summarizes the preprocessing and augmentation steps used to prepare images for CornLeaf-MIA Net. These steps include resizing, normalization, data augmentation, and label encoding to ensure consistent inputs and increase training data diversity. The procedures aim to improve training stability and enhance the model's robustness in classifying corn leaf diseases.

Table 2. Image preprocessing and augmentation configuration

Step	Operation	Configuration	Purpose
1	Image resizing	156×156 pixels	Standardize input image dimensions for CNN processing
2	Pixel normalization	Rescaling pixel values from [0, 255] to [0, 1]	Standardize pixel intensity values and improve training stability
3	Random rotation	Random rotation applied during training	Improve robustness to variations in image orientation
4	Horizontal flipping	Random horizontal flipping applied during training	Increase training data diversity and orientation invariance
5	Zooming	Random zoom-in and zoom-out applied during training	Improve robustness to variations in leaf scale
6	Width shifting	Random horizontal translation applied during training	Improve robustness to variations in leaf position
7	Height shifting	Random vertical translation applied during training	Improve robustness to variations in leaf position
8	Label encoding	One-hot encoding	Convert categorical class labels into numerical representations for multiclass classification

Table 3 describes the input image configuration used in the proposed CornLeaf-MIA Net model. All images were standardized to a resolution of 156×156 pixels and represented in RGB format with three color channels. Pixel values were normalized to the range [0, 1] to ensure consistent input representation. These configurations provide uniform input dimensions and pixel values, supporting consistent model training and evaluation.

Table 3. Input image configuration

Parameter	Value	Description
Input resolution	156×156 pixels	Standardized spatial dimensions of all input images
Color mode	RGB	Three-channel color representation used for image input
Number of channels	3	Red, green, and blue color channels
Pixel value range	[0, 1]	Normalized pixel intensity after rescaling from [0, 255]

2.2. Proposed CornLeaf-MIA Net architecture

CornLeaf-MIA Net is a lightweight CNN specifically designed for multiclass corn leaf disease classification. The architecture was developed to address the visual characteristics of corn leaf diseases while

maintaining a relatively compact computational structure. Unlike conventional transfer learning approaches that employ deep pre-trained backbones originally developed for generic image recognition, CornLeaf-MIA Net learns task-specific representations directly from corn leaf images [23]. The design of CornLeaf-MIA Net is guided by three principles: i) multi-scale feature extraction to capture disease symptoms appearing at different spatial scales [24]; ii) feature aggregation to combine complementary information obtained from different receptive fields [24], [25]; and iii) lightweight computation to maintain a favorable balance between predictive performance and model complexity [25]. The proposed network consists of three main components: the feature extraction stage, the multi-scale intelligent architecture (MIA) blocks, and the classification head. The overall architecture is presented in Table 4.

Table 4. Overall architecture of CornLeaf-MIA Net

Stage	Layer	Kernel/operation	Output size
Input	RGB image	156×156×3	156×156×3
Stem	Conv batch normalization (BN)+rectified linear unit (ReLU)	3×3	156×156×32
MIA Block 1	Multi-scale conv	3×3, 5×5, dilated conv	78×78×64
MaxPool	2×2	—	78×78×64
MIA Block 2	Multi-scale conv	3×3, 5×5, dilated conv	39×39×128
MaxPool	2×2	—	39×39×128
MIA Block 3	Multi-scale conv	3×3, 5×5, dilated conv	19×19×256
Feature fusion	Concatenation+1×1 conv	—	19×19×256
Global average pooling	GAP	—	256
Dropout	P=0.5	—	256
Fully connected	Dense	512	512
Output	SoftMax	4 Classes	4

The principal contribution of CornLeaf-MIA Net lies in its task-specific MIA Block configuration and integration into the feature-learning pipeline, rather than in introducing new CNN operations. Each MIA Block employs parallel convolutional branches with different receptive fields, followed by feature concatenation and 1×1 convolution-based compression. This multi-scale configuration captures fine-grained textures, medium-scale lesions, and broader spatial context, distinguishing CornLeaf-MIA Net from conventional sequential CNNs that typically rely on a single convolutional scale at each stage. The architecture is therefore designed to accommodate the heterogeneous visual characteristics of corn leaf diseases, including spots, elongated lesions, necrotic regions, and distributed discoloration. Table 5 summarizes the network configuration of CornLeaf-MIA Net, including its input resolution, number of classes, parameter count, BN, dropout rate, and output activation. These specifications define the model's structure and complexity, providing insight into its design for multi-class corn leaf disease classification and supporting the evaluation of its predictive performance.

Table 5. Network configuration

Parameter	Value
Input resolution	156×156
Number of classes	4
Total parameters	2,982,052
Trainable parameters	2,982,052
BN	Yes
Dropout rate	0.5
Output activation	SoftMax

2.3. Multi-scale intelligent architecture block

The MIA Block is the core component of CornLeaf-MIA Net, designed to extract complementary features across multiple receptive-field scales [26]. It employs three parallel branches: 3×3 convolution for fine textures, 5×5 convolution for medium-scale lesions, and 3×3 dilated convolution (dilation rate=2) for broader contextual features. The outputs are concatenated, compressed using a 1×1 convolution, and followed by BN and ReLU activation for stable feature learning. This design integrates multi-scale feature extraction in a lightweight structure, consistent with recent lightweight CNN approaches for maize leaf disease recognition [27]. Table 6 describes the internal structure and main components of the MIA block in the proposed CornLeaf-MIA Net. It explains how multi-scale feature extraction supports the identification of discriminative patterns in corn leaf images, helping the model distinguish between disease classes with similar visual symptoms.

Table 6. Internal structure of the MIA block

Branch	Operation	Purpose
Branch 1	Conv 3×3	Fine texture extraction
Branch 2	Conv 5×5	Medium lesion representation
Branch 3	Dilated conv 3×3	Global contextual information
Fusion	Concatenate	Feature integration
Compression	Conv 1×1	Channel reduction
Normalization	BatchNorm	Stable learning
Activation	ReLU	Non-linearity

2.4. Design rationale

The design of CornLeaf-MIA Net was motivated by the heterogeneous appearance of corn leaf disease symptoms, which vary in size, shape, and spatial distribution. To capture these complementary characteristics, the architecture combines 3×3, 5×5, and dilated convolutions for multi-scale feature extraction. Their outputs are concatenated and compressed using a 1×1 convolution to integrate complementary features while controlling channel dimensionality. CornLeaf-MIA Net employs a task-specific architecture with approximately 2.98 million trainable parameters, avoiding the use of a large pre-trained backbone. This relatively compact structure indicates its potential suitability for resource-constrained applications; however, mobile or edge-device performance was not directly evaluated in this study. The effectiveness of the proposed architecture was subsequently assessed through comparison with established transfer learning models under identical experimental conditions. CornLeaf-MIA Net was trained using supervised learning for multiclass corn leaf disease classification. The same training configuration was applied to the proposed and comparative models to ensure a fair evaluation, as summarized in Table 7.

Table 7. Model training was performed using supervised learning

Parameter	Value
Training strategy	Supervised learning
Optimizer	Adam
Loss function	Categorical cross-entropy
Batch size	32
Maximum epochs	50
Learning rate	0.001
Activation function	ReLU
Output activation	SoftMax
Early stopping	Applied
Model checkpoint	Applied

2.5. Model training

CornLeaf-MIA Net was trained using a supervised learning approach for multiclass corn leaf disease classification. The training configuration was kept consistent across the proposed model and the comparative models to ensure a fair evaluation. The main training parameters are summarized in Table 7.

The Adam optimizer and categorical cross-entropy loss were used for model training, with a batch size of 32 and a maximum of 50 epochs. Early stopping and model checkpointing were applied to reduce overfitting and retain the model with the best validation performance. The same preprocessing, data partitioning, optimization settings, and evaluation protocol were applied to all comparative models to ensure a fair and unbiased performance comparison.

2.6. Performance evaluation

Model performance was evaluated using accuracy, precision, recall, and F1-score derived from the confusion matrix. Accuracy represents overall classification performance, whereas precision, recall, and F1-score provide complementary class-specific evaluations. The analysis was further supported by the confusion matrix, classification report, and training-validation accuracy and loss curves to assess classification performance and learning stability.

2.7. Comparative analysis

CornLeaf-MIA Net was compared with three established transfer learning models—MobileNetV2, VGG16, and ResNet50—using the same dataset, preprocessing, data partitioning, training configuration, and evaluation metrics. This consistent experimental protocol enables a fair comparison of the models by minimizing the influence of differences in data preparation and training conditions. The analysis considers both predictive performance and the number of trainable parameters to assess the balance between classification accuracy and model complexity.

2.8. Web-based deployment

To demonstrate its practical applicability, CornLeaf-MIA Net was deployed in a Flask-based web diagnosis system integrating OpenCV for image processing and leaf segmentation, contour detection for multiple-leaf identification, and TensorFlow for model inference. The interface supports image upload and real-time camera input. For images containing multiple leaves, each detected leaf is segmented and classified independently, with results displayed using bounding boxes, predicted labels, and confidence scores. This implementation demonstrates the potential integration of CornLeaf-MIA Net into an intelligent precision agriculture platform.

3. RESULTS AND DISCUSSION

This study proposes CornLeaf-MIA Net, a task-specific CNN for multiclass classification of blight, common rust, gray leaf spot, and healthy corn leaves. The dataset comprised 4,013 labeled images, including 3,912 public images (97.48%) and 101 field-observation images (2.52%). The limited field data may restrict real-world variability and model generalization, motivating broader field data in future studies. The dataset was randomly partitioned once into 3,210 training (80%) and 803 testing images (20%) and consistently maintained across experiments. Preliminary resolution tests selected 156×156 pixels for its highest classification performance with a relatively compact computational structure. CornLeaf-MIA Net contains 2,982,052 trainable parameters and uses convolutional layers with BN, max-pooling, dropout, and fully connected layers. Its MIA Block employs parallel 3×3, 5×5, and dilated 3×3 convolutions (dilation rate=2), followed by feature concatenation and 1×1 convolutional compression to capture complementary disease features while controlling feature dimensionality. The same data partition and experimental conditions were used for all models to ensure consistent evaluation.

Table 8 summarizes the training, validation, and testing performance of CornLeaf-MIA Net. The model achieved training, validation, and testing accuracies of 98.97%, 98.26%, and 98.38%, respectively. The training–validation accuracy gap was 0.71%, indicating a close agreement between training and validation performance. The testing accuracy was also comparable to the validation accuracy, suggesting consistent generalization under the experimental conditions.

Table 8. Training, validation, and testing performance of CornLeaf-MIA Net

Parameter	Value (%)
Training accuracy	98.97
Validation accuracy	98.26
Testing accuracy	98.38
Training–validation accuracy gap	0.71

As illustrated in Figure 2, the training and validation accuracy curves converged at approximately 98%, while both loss curves decreased and stabilized toward the end of training. The close agreement between the training and validation curves indicates stable learning without substantial overfitting. These results support the consistent performance of CornLeaf-MIA Net reported in Table 8.

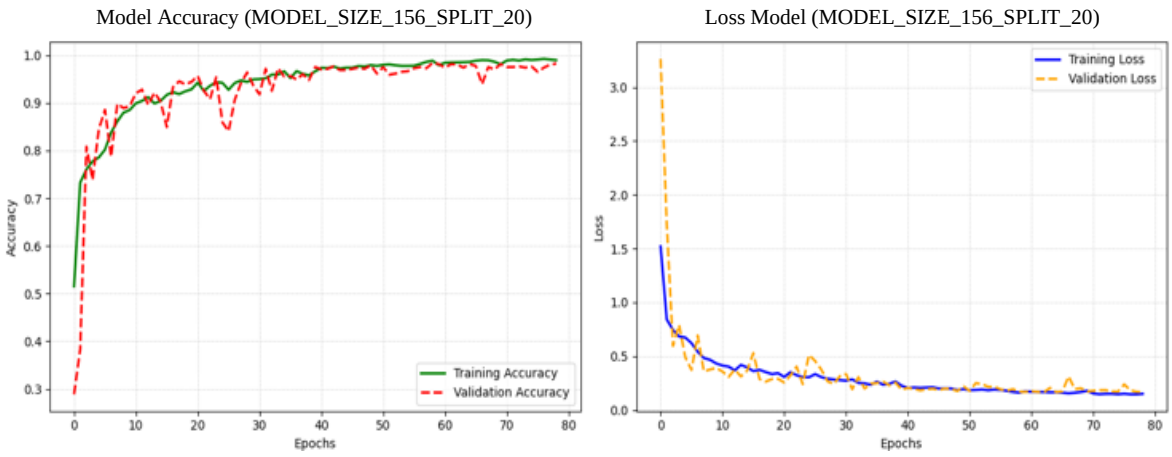


Figure 2. Training and validation accuracy and loss curves of CornLeaf-MIA Net

3.1. System workflow of CornLeaf-MIA Net

Figure 3 illustrates the CornLeaf-MIA Net disease identification workflow, from image acquisition to disease prediction. The system integrates OpenCV-based image processing with CornLeaf-MIA Net classification to enable automated diagnosis of one or multiple corn leaves within an image.

As illustrated in Figure 3, the system performs preprocessing, leaf segmentation, multi-leaf detection, disease classification, and result visualization. Input images are resized to 156×156 pixels and normalized before OpenCV-based segmentation and contour detection identify individual leaf regions. Each detected leaf is cropped and independently classified by CornLeaf-MIA Net as blight, common rust, gray leaf spot, or healthy. The predicted labels and confidence scores are then displayed on the original image through the web-based interface.

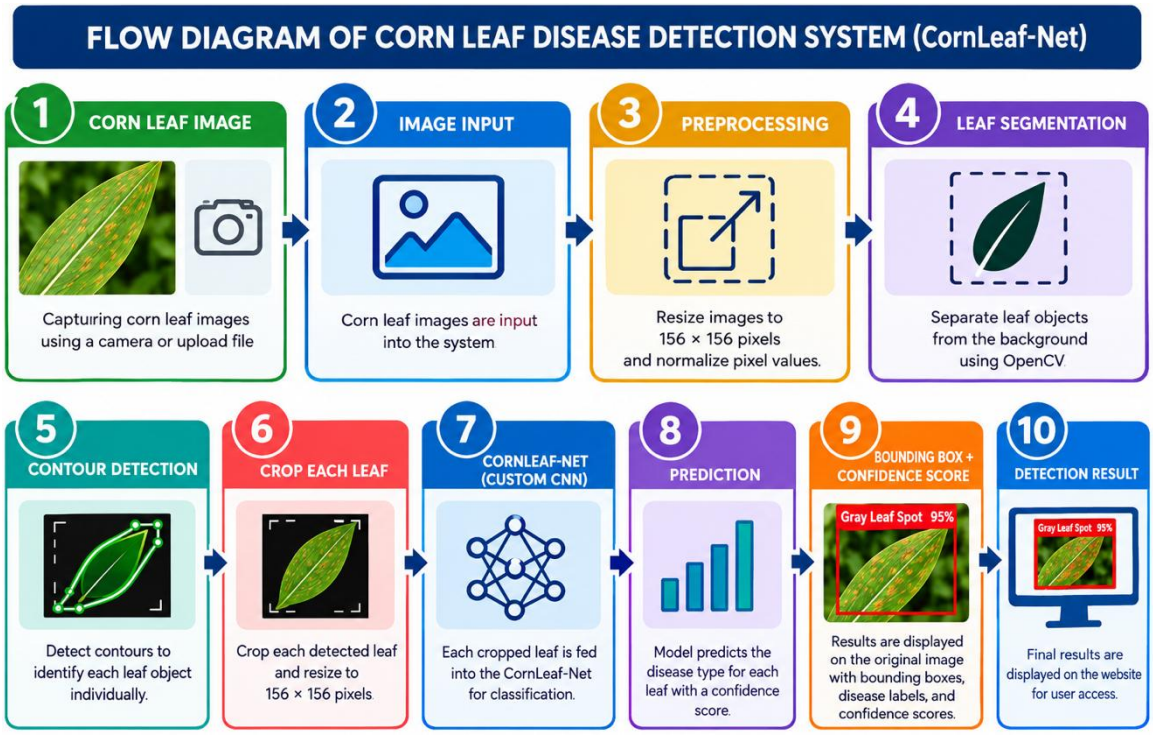


Figure 3. Overall workflow of the proposed CornLeaf-MIA Net system

3.2. Confusion matrix evaluation

The confusion matrix was used to evaluate the class-specific performance of CornLeaf-MIA Net by identifying correctly and incorrectly classified samples and revealing potential misclassification patterns among the disease categories.

As illustrated in Figure 4, most testing samples were correctly classified. Common rust showed no observable misclassification, while healthy also achieved strong recognition performance. The remaining errors primarily occurred between blight and gray leaf spot, possibly due to similarities in lesion and discoloration patterns. In practical applications, such confusion may affect disease-specific treatment decisions; therefore, confidence scores can help flag uncertain predictions for further verification before intervention. Nevertheless, the limited number of misclassifications indicates effective discrimination among the four categories under the testing conditions.

As shown in Table 9, CornLeaf-MIA Net achieved high classification performance across all four classes. Common rust achieved 100.00% precision, recall, and F1-score, while healthy obtained 99.57% precision, 100.00% recall, and 99.78% F1-score. Blight achieved 99.54% precision, 94.76% recall, and 97.09% F1-score, whereas gray leaf spot obtained 90.27% precision, 99.03% recall, and 94.44% F1-score. The relatively lower precision for gray leaf spot indicates that some samples predicted as gray leaf spot belonged to other classes, which is consistent with the confusion matrix and may be associated with similarities in lesion and discoloration patterns between gray leaf spot and blight. Overall, the model achieved weighted precision, recall, and F1-scores of 98.50%, 98.38%, and 98.40%, respectively, demonstrating strong and consistent classification performance under the testing conditions.

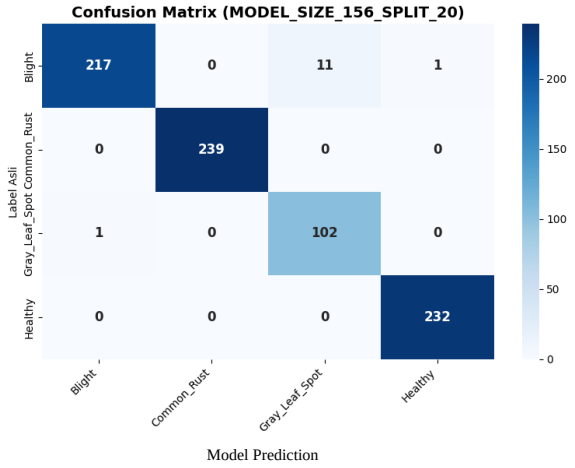


Figure 4. Confusion matrix of the proposed CornLeaf-MIA Net

Table 9. Classification performance of CornLeaf-MIA Net

Class	Precision (%)	Recall (%)	F1-score (%)
Blight	99.54	94.76	97.09
Common rust	100.00	100.00	100.00
Gray leaf spot	90.27	99.03	94.44
Healthy	99.57	100.00	99.78
Accuracy			98.38
Macro average	97.34	98.45	97.83
Weighted average	98.50	98.38	98.40

3.2.1. Comparative analysis of experimental configurations

To identify the optimal CornLeaf-MIA Net configuration, 14 experimental configurations varying input image resolution and model settings were evaluated. The results are summarized in Table 10.

Table 10. Performance comparison of experimental configurations

Model	Image resolution	Accuracy (%)
Model 1	156×156	85.00
Model 2	156×156	92.00
Model 3	156×156	93.00
Model 4 (CornLeaf-MIA Net)	156×156	98.38
Model 5	156×156	95.24
Model 6	256×256	90.04
Model 7	256×256	94.16
Model 8	256×256	94.76
Model 9	256×256	95.24
Model 10	256×256	95.00
Model 11	356×356	92.95
Model 12	356×356	94.22
Model 13	356×356	95.40
Model 14	356×356	95.12

3.2.2. Comparative performance of CornLeaf-MIA Net and transfer learning models

CornLeaf-MIA Net was compared with MobileNetV2, VGG16, and ResNet50, representing CNN-based transfer learning architectures with different network complexities. All models were trained and evaluated using the same four-class dataset, data partition, preprocessing procedures, and relevant experimental conditions to ensure a consistent comparison.

Table 11 shows that CornLeaf-MIA Net achieved the highest testing accuracy (98.38%), outperforming ResNet50 (95.39%), VGG16 (94.89%), and MobileNetV2 (94.40%) by 2.99–3.98 percentage points. This advantage may be attributed to task-specific multi-scale feature extraction through the MIA Block, although the results are limited to the dataset and experimental conditions evaluated. The model also maintained a relatively compact architecture, supporting its effectiveness for corn leaf disease classification. Since the evaluation used a single fixed train-test partition, confidence intervals and variance across multiple runs were not estimated; repeated runs or cross-validation are recommended to assess performance stability.

Table 11. Performance comparison between CornLeaf-MIA Net and transfer learning models

Model	Architecture	Testing accuracy (%)	Performance
MobileNetV2	Transfer learning	94.40	Highly stable
VGG16	Transfer learning	94.89	Highly stable
ResNet50	Transfer learning	95.39	Highly stable
CornLeaf-MIA Net (proposed)	Custom CNN	98.38	Highly stable

3.3. Web-based implementation of CornLeaf-MIA Net

CornLeaf-MIA Net was integrated into a Flask-based web diagnosis system using TensorFlow and OpenCV. The system supports image upload and camera input, performs leaf segmentation and contour detection, and independently classifies each detected leaf as blight, common rust, gray leaf spot, or healthy. Predictions and confidence scores are displayed on the original image using bounding boxes and labels. This implementation demonstrates the functional integration of CornLeaf-MIA Net into a web-based multi-leaf disease identification system. However, no formal usability, field-deployment, inference-time, or hardware resource evaluation was conducted.

3.4. System implementation results and evaluation

CornLeaf-MIA Net was successfully integrated into a Flask-based web application supporting image upload and camera input. Both acquisition methods follow the same preprocessing, leaf segmentation, contour detection, classification, and result visualization pipeline. The system can process multiple leaves within a single image and displays the predicted class, confidence score, bounding box, and detection summary for each detected leaf. These results demonstrate the functional integration of CornLeaf-MIA Net with the computer vision and web-based processing pipeline. However, the implementation was not evaluated through formal usability testing, field validation, or device-level performance benchmarking.

Figure 5 demonstrates the camera feature for corn leaf disease identification. After browser permission is granted, the captured image is processed using the same preprocessing and CornLeaf-MIA Net classification pipeline as uploaded images. The application displays the predicted disease class and corresponding confidence score. This implementation demonstrates the functional integration of camera-based image acquisition into the web-based disease classification system; however, no formal usability evaluation or quantitative comparison of inference performance between the two input methods was conducted.

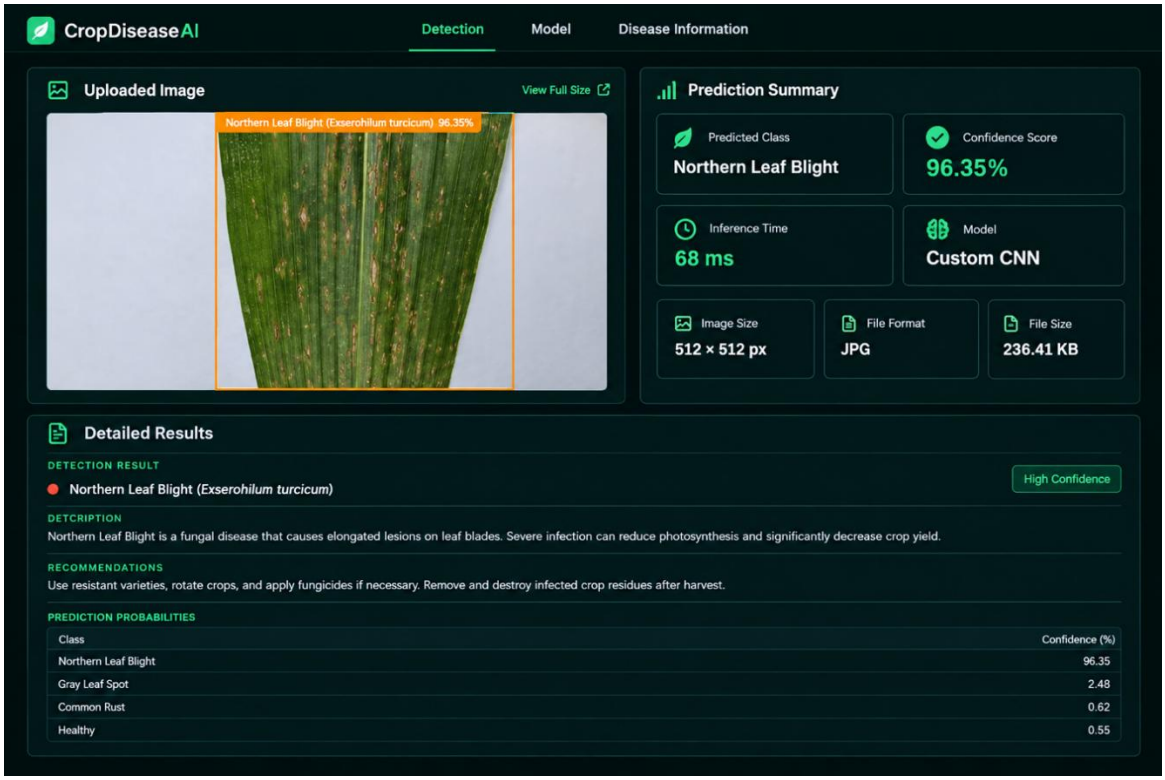


Figure 5. System implementation results using the upload image feature

4. CONCLUSION

This study proposed CornLeaf-MIA Net, a task-specific CNN for multiclass corn leaf disease classification. The model achieved a testing accuracy of 98.38%, with weighted precision, recall, and F1-score of 98.50%, 98.38%, and 98.40%, respectively. Most samples were correctly classified, with limited misclassification primarily occurring between blight and gray leaf spot. CornLeaf-MIA Net also outperformed MobileNetV2, VGG16, and ResNet50 under the experimental conditions. The model was successfully integrated into a Flask-based web application supporting image upload and camera-based disease identification. Future work should investigate the adaptability of the architecture to other crops, more diverse field data, additional disease categories, severity estimation, and computational performance, usability, and field applicability.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Universitas Muhammadiyah Gorontalo for providing academic and institutional support throughout this research. The authors also gratefully acknowledge the support and assistance of *Balai Besar Penerapan Modernisasi Pertanian* (BRMP) during the field activities and data collection process. Special appreciation is extended to the corn farmers in Gorontalo for their valuable cooperation, particularly in providing access to corn plants and leaf samples used in this study. The authors sincerely appreciate the contributions of all parties whose support facilitated the successful completion of this research. This research was supported through a research grant or contract under the program *Penelitian Fundamental Lanjutan* (PFL), funded through BIMA by the Ministry of Higher Education, Science, and Technology of the Republic of Indonesia.

FUNDING INFORMATION

This research was funded by the *Penelitian Fundamental Lanjutan* (PFL) program through the BIMA, Ministry of Higher Education, Science, and Technology (Kemdiktisaintek), Republic of Indonesia, under Decree Number 121/KPA/C3/KPT/2026 and Research Contract Numbers 143/C3/DT/05.00/PL-MULTITAHUN LANJUTAN/2026, 256/M/DST/LL16/AL.04/2026, and 009/PK-PFR/LPPM-UMGO/V/2026.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Mohamad Ilyas Abas	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
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Isminarti		✓				✓		✓	✓	✓		✓		
Asminar	✓		✓	✓			✓			✓	✓		✓	✓
Muh. Syahlan Natsir					✓		✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest associated with this study. The authors have no known competing financial interests, personal relationships, or professional affiliations that could have influenced the work reported in this paper.

INFORMED CONSENT

Informed consent was not applicable to this study because the research involved corn leaf images and agricultural field observations without the collection of personal or identifiable information from human subjects.

ETHICAL APPROVAL

This study did not involve human participants, animals, or clinical procedures. The research was conducted using corn leaf images obtained from publicly available datasets and field observations. No personal, sensitive, or identifiable information was collected or analyzed. Therefore, ethical approval was not required for this study in accordance with the applicable institutional and research regulations.

DATA AVAILABILITY

The dataset splits, preprocessing procedures, augmentation configurations, and source code used to develop and evaluate CornLeaf-MIA Net are available from the authors upon reasonable request. The availability of these materials is intended to support reproducibility and facilitate further evaluation of the proposed approach.

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