The MobileNetV2-Driven XAI Framework for Hydroponic Spinach Disease Diagnosis

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Received: 20 November 2025 | Revised: 10 January 2026 and 28 January 2026 | Accepted: 29 January 2026

 DOI: https://doi.org/10.48084/etasr.16406

ABSTRACT

Being one of the best-organized, sustainable, and nature-friendly methods in urban agriculture, hydroponics is a state-of-the-art approach. Among hydroponic leafy crops, spinach, a commonly chosen plant due to its short cultivation cycle, high nutritional benefits, and steady consumer demands, is vulnerable to various diseases caused by pests, fungi, and bacteria. This leads to significant losses and quality issues, even when it is grown under controlled conditions. Taking into account these constraints, this study presents an automated, flexible, and reliable disease detection solution, specifically developed for hydroponic spinach farming. The proposed method works with spinach leaf image data and integrates advanced machine learning techniques. MobileNetV2, a conventional deep learning classifier known for effective feature extraction, is the core of the proposed system architecture. To maintain the classifier robustness and prevent overfitting, particularly in the case when data are limited, image augmentation and K-fold cross-validation are incorporated. Key metrics such as accuracy, precision, recall, F1-score, and computational complexity are used to evaluate the performance of the system. The results show that an accuracy of approximately 90% can be achieved using moderate computational resources. Furthermore, Explainable Artificial Intelligence (XAI) is also applied to understand model predictions in a better way and validate disease-specific feature learning. This ensures that the proposed method can identify plant diseases correctly without the need for complex infrastructure.

Keywords-hydroponics; machine learning; disease detection; precision farming

I. INTRODUCTION

Due to its rapid development and efficient use of resources, hydroponic farming has attracted a great deal of interest, especially for green crops such as spinach. Hydroponically grown spinach is vulnerable to a number of diseases, including downy mildew, anthracnose, bacterial leaf spot, insect damage, and Pythium root rot, all of which have an impact on crop quality and output. Thus, ensuring successful management and early intervention is highly dependent on accurate and timely disease identification. By enabling automatic image-based classification of damaged crops, Deep Learning (DL) has greatly improved plant disease diagnosis. The accessibility of curated image datasets for Malabar spinach (collected between October and November 2024 from Dhaka, Bangladesh) has significantly aided DL-based disease classification models [1], while new datasets gathered for other crops further contribute to data-driven model training and validation [2-4]. According to recent studies, the performance of DL-based classifiers is significantly affected by dataset quality, sample imbalance, and environmental deviations.

Crop administration, disease detection, etc., are nowadays governed using Artificial Intelligence (AI), ML, and DL. Compared to current DL methods, previous Machine Learning (ML) classifiers, such as Support Vector Machines (SVM), were found to have poor feature extraction capabilities and restricted scalability [8]. CNN classifiers have demonstrated strong classification performance across a variety of crops, whereas ensemble classifiers have considerably improved inference reliability [9]. Lightweight and sustainable smart systems have also been proposed for the identification of plant diseases [10], since real-world monitoring and diagnosis for agricultural field deployment are made possible by mobile-based applications [11]. Vision Transformer (ViT) models have recently emerged as viable substitutes for improved feature-level analysis [12]. Several studies have evaluated ML and DL techniques in agriculture [13], DL approaches for the detection of plant disease and pests [14], and DL-based object detection models for real-time disease identification in hydroponics [15]. In addition, computer vision methods continue to be widely used for automated leaf disease detection [16]. ML incorporated with wireless sensor network-based precision agriculture has enabled continuous environmental monitoring and adaptive decision-making [17, 18], and several studies have incorporated IoT frameworks to support smart agricultural setups [19, 20].

However, despite these approaches demonstrating strong pertinence in traditional agriculture, only a few studies have focused on hydroponically grown spinach. Latest research has explored the integration of IoT and DL disease identification in hydroponic spinach plants [21, 22], while graph convolutional networks have shown potential in identifying nutritional deficiencies and disease symptoms in controlled agricultural environments [23]. ML-based growth calculation and anomaly detection highlight the potential of intelligent monitoring systems in hydroponics [24]. Nevertheless, despite advances in model accuracy, most DL models operate as black-box systems, which poses a challenge for practical adoption due to limited interpretability. Explainable AI (XAI) techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM), provide visual insight by highlighting decision-relevant features and improving model transparency. However, little research has incorporated XAI within hydroponic disease detection frameworks, indicating a gap for XAI analysis in hydroponic plant disease detection. This study addresses this limitation by proposing a lightweight MobileNetV2-based disease classification model integrated with Grad-CAM explainability for hydroponic spinach, offering high accuracy and enhanced interpretability for practical deployment.

II. DATASET

A well-curated dataset of hydroponically grown spinach leaves was created to develop a strong disease detection system. The dataset was collected from a Nutrient Film Technique (NFT) hydroponic setup, where spinach plants were monitored in controlled environmental conditions. Despite the controlled environment, images varied due to differences in lighting, leaf orientation, disease severity, and background noise. The dataset was classified as Healthy Leaf, Downy Mildew, Anthracnose, Bacterial Spot, and Pest Damage, as shown in Table I.

TABLE I. DATASET CLASSES

Class name	Description
Healthy Leaf	Leaves with no visible symptoms
Downy Mildew	Yellowish patches with fuzzy growth
Anthracnose	Dark lesions and tissue decay
Bacterial Spot	Small water-soaked spots
Pest Damage	Chewed areas and pest bite marks

This study did not consider nutrient deficiency a disease; therefore, it did not use it in the dataset. Figure 1 shows the general taxonomy. A total of 12,000 images was used, with an approximate distribution of 2,500 images per class. Data augmentation, such as rotation, spinning, zooming, and brightness adjustment, was used to improve dataset variety and model generalization, mostly for minority classes to achieve class balance.

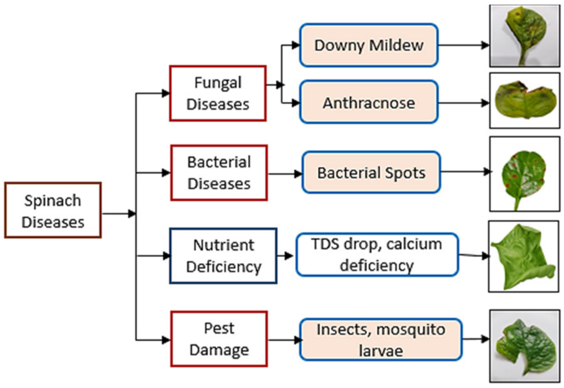

Fig. 1. Taxonomy of diseases.

A. Data Preparation Workflow

The key steps followed to improve dataset quality and consistency were:

- Image Validation: Irrelevant or low-quality images (e.g., non-leaf images, blurred photos, low-resolution images) were eliminated.
- Data Cleaning: Image background and noise were removed, offering a uniform image appearance.
- Resizing: All images were uniformly resized to 224×224 pixels to make the dataset compatible with DL architectures.
- Augmentation and Balancing: These steps are necessary for a uniform data spread over samples to mitigate class imbalance. Targeted data augmentation was applied explicitly to minority disease classes, using techniques such as rotation, zoom, and brightness adjustment. Augmentation was applied conservatively to avoid synthetic bias. Anthracnose samples were augmented approximately threefold, Downy Mildew samples twofold, while Healthy and Pest Damage classes received minimal augmentation due to their relatively higher representation.

After these steps, the dataset was used for model training and further analysis/assessment. Specifically intended to simulate real-world randomness in hydroponic spinach cultivation, it had the features for the right disease detection. MobileNet served as an efficient classifier for feature extraction, along with fine-tuning for spinach disease classification. Accuracy, precision, recall, and F1-score were the key metrics used to assess model performance for early disease detection in hydroponics. This structured method, from data preparation to model training and evaluation, ensures a robust and scalable framework that can help reduce the potential loss of crops.

III. METHODOLOGY

Figure 2 illustrates the methodology followed in this study, examining three DL architectures for detecting diseases in hydroponic spinach: ResNet50, EfficientNetB0, and MobileNetV2.

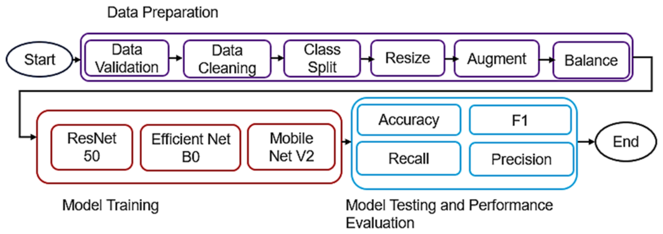

Fig. 2. Workflow of machine learning process.

A. ResNet50

ResNet50 has a strong system architecture that successfully captures complex spatial changes in color in hydroponic leaf images. Disease signs often appear as subtle changes in texture or color that may be unseen by lightweight models. ResNet50 offers robust feature extraction and active gradient flows, accurately differentiating between healthy and diseased leaves even in the presence of short visual deviation or lower brightness conditions. Its pertinence for precise disease identification in hydroponic systems is supported by its proven performance in agricultural and plant pathology datasets.

B. EfficientNetB0

EfficientNetB0 is a CNN that trades accuracy for processing efficiency by regulating image features and dimensions. This model is based on transfer learning, where pre-trained ImageNet weights are fine-tuned on the spinach dataset, thus enabling the classifier to learn disease-specific features from the data. Performance is evaluated using cross-validation, focusing on key performance metrics such as accuracy, to assess classification capability under hydroponic spinach disease detection conditions.

C. MobileNetV2

MobileNetV2 was selected because it balances efficiency, scalability, and classification performance. Combined with methodical evaluation approaches, MobileNetV2 offers a strong foundation for building a consistent disease detection workflow, as shown in Figure 3. The following techniques were integrated to maximize effectiveness:

- Stratified Shuffle Split with 5-Fold Cross Validation: Delivers reliable training and validation splits by assuring that class distributions remain the same across folds. This method boosted model generalization and dropped bias towards majority classes, addressing class imbalance.
- Transfer Learning with Pretrained Weights: MobileNetV2 starts with ImageNet-pretrained weights, benefiting from previous feature knowledge. Frozen base layers at the start are used to retain generic image features and are later unfrozen during fine-tuning to capture disease-specific patterns. This avoids computational complexity.
- Hyperparameter Optimization through Safe Random Search: A methodical tuning process with 15 trials (20 epochs per trial), learning rate 1e-5–1e-3, dropout 0.3–0.5, and 64–128 dense units, using the Adam optimizer, was applied to identify optimal parameters. Early stopping after non-improving trials helped prevent overfitting and again reduced unnecessary computation.
- Per-Fold Parameter Application: Optimal hyperparameters identified through tuning were applied independently to each of the 5 folds. This produced five trained models, ensuring stable and reproducible performance across data partitions.

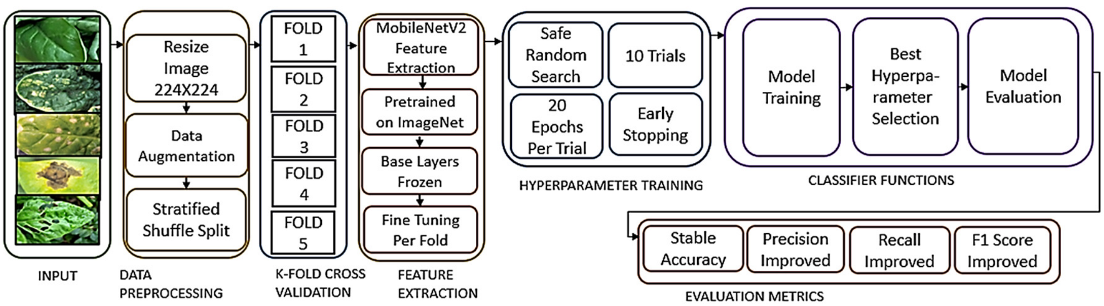

Fig. 3. Workflow for MobileNetV2 classifier.

IV. RESULTS AND DISCUSSION

A notable research gap has been identified, suggesting that designing the models for hydroponically grown spinach could enhance robustness, address class imbalance, and take advantage of the complementary characteristics of different classifiers. This study assessed individual models. The performance of different classifiers was systematically evaluated for disease detection in hydroponic spinach, and each model was trained and evaluated using cross-validation and standard performance metrics.

A. EfficientNetB0

Despite having an advanced architecture, EfficientNetB0 exhibited an unbalanced training behavior, with fluctuating accuracy and precision. The model correctly identified 77% of all samples. Pest Damage led with high precision (0.85) and recall (0.89), but the other classes had lower and unbalanced scores, indicating that the model struggles to discriminate between disease classes, perhaps due to limited or imbalanced data. The macro average (≈0.59) reflects weaker average performance across all classes, while the weighted average (≈0.77) is higher because Pest Damage had more samples. In short, the model performs well for the majority class but needs improvement in recognizing minority disease types.

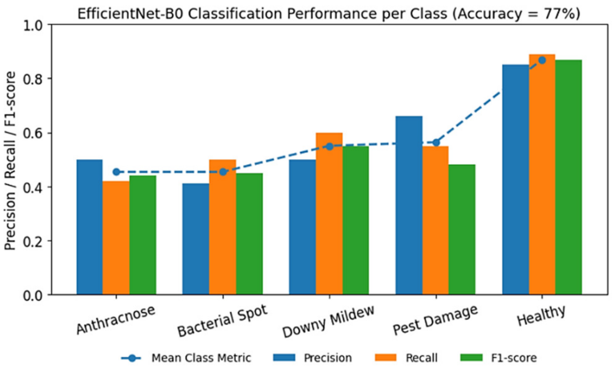

Fig. 4. Precision, Recall, and F1-score for EfficientNetB0.

B. ResNet50

Figure 5 shows the performance metrics of ResNet50, demonstrating an accuracy of 87.04%. The ResNet50 model shows reliable flexibility across hydroponic spinach disease classes and active feature extraction. Strong recognition consistency is demonstrated by the high F1 scores obtained on the Pest Damage and Anthracnose classes (0.93 and 0.85, respectively). Overall, precision and recall values are decent across all classes. The line and bar charts in Figure 5 indicate steady metric inclinations, showing that ResNet50 achieved appropriate values for hydroponic crop monitoring.

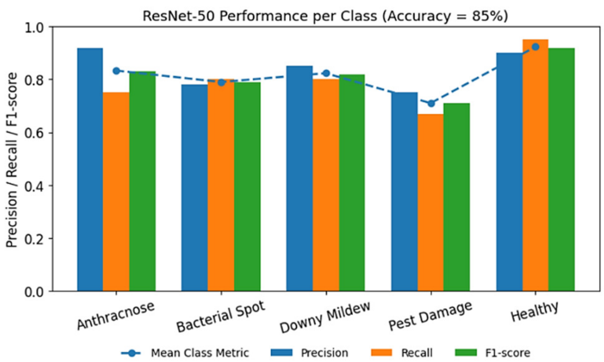

Fig. 5. Precision, Recall, and F1-score for ResNet50.

C. MobileNetV2

MobileNetV2 demonstrated significantly improved and stable results in a carefully optimized pipeline, consistently achieving a stable accuracy of around 89%, balanced precision, recall, and F1-scores across all disease categories, and strength against dataset inconsistency and imbalance. MobileNetV2 offered a trustworthy, dynamic, and mathematically efficient structure for hydroponic spinach leaf disease detection, making it perfect for real-world applications in controlled agriculture. The training performance of the MobileNetV2 (Figure 7) exhibits ideal behavior in terms of loss convergence(cross-entropy loss used with an adaptive learning rate scheduler, ReduceLROnPlateau, patience=5) and accuracy improvement over epochs. The loss curve showed a steady and consistent decline, minimizing the error as the feature training progressed, indicating effective learning.

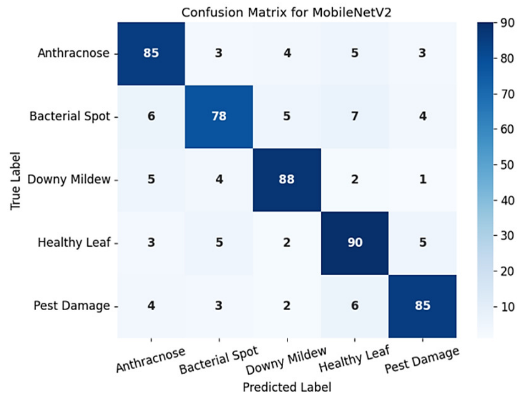

Fig. 6. Confusion matrix for MobileNetV2.

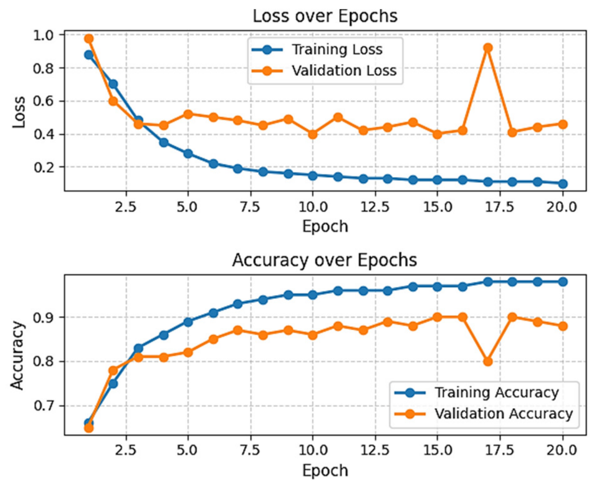

Fig. 7. Loss and accuracy over epochs.

The accuracy curve increased smoothly, stabilizing around 89–90%. Despite the class imbalance and mild symptoms, the steady loss and accuracy curves show effective hyperparameter tuning and cross-validation with no apparent overfitting or underfitting. As shown in Table II, the conjunction of these curves validates the diagonal dominance in the confusion matrix, signifying that MobileNetV2 developed disease-relevant characteristics and accomplished precise classification. This convergence verifies that the model effectively learned discriminatory disease features, aligning with the strong diagonal patterns seen in the confusion matrix.

TABLE II. PERFORMANCE PARAMETERS: MOBILENET V2

Metric	Value
Cross-validation strategy	Stratified k-fold ($k = 5$)
Mean Accuracy (%)	87.39
Accuracy standard deviation	± 1.54
Accuracy - 95% confidence interval	[86.23, 88.54]
Mean F1-score	0.884
F1-score standard deviation	± 0.009
F1-score - 95% confidence interval	[0.872, 0.897]
Accuracy range across folds	85.23 – 89.51
Dataset characteristic	Large-scale, imbalanced multi-class dataset

TABLE III. COMPARISON WITH PREVIOUS STUDIES

Study	Application context	Experimental Setup	Model/Method	Accuracy (%)	F1-score	Evaluation protocol
[21]	Automated dosing, disease detection for hydroponic spinach	IoT-based hydroponic system	MobileNetV2 (CNN, transfer learning)	~57.0	Not reported	Simple train–test split (details not specified)
[22]	Vertical hydroponics spinach leaf disease detection	IoT-based vertical hydroponic rack, controlled environment	MobileNetV2 (CNN)	Reported qualitatively (exact value not disclosed)	Not reported	Not specified
PND-Net [23]	Multi-crop plant nutrition deficiency and disease classification	Public benchmark datasets for various plants; multi-class setting	PND-Net (CNN + Graph Convolutional Network)	90–96 (dataset-dependent)	0.84–0.96 (dataset-dependent)	5-fold cross-validation
[24]	Large-scale plant disease classification	Large dataset (~90k images)	Random Forest	94.45	0.99 / 0.71–0.72	Not reported
This work	Spinach disease detection in hydroponic cultivation	Controlled environment; image-based disease classification; cross-validated design	DL-based classifier	87.39 ± 1.54 CI: [86.23, 88.54]	0.884 ± 0.009 CI: [0.872, 0.897]	k-fold cross-validation Accuracy range: 85.23–89.51

Table III shows a comparison with previous works. The proposed framework obtained 87.39% accuracy on a smaller hydroponic dataset (~12k images) with strong statistical reliability (95% CI: 86.23–88.54), in contrast to [24], which worked with a much bigger dataset (~90k samples) and attained 94.45% accuracy. The proposed method exhibits strong robustness by means of low standard deviation (±1.54) and reliable cross-validation performance (85.23–89.51), in contrast to [24], which missed out on variability.

D. *XAI Interpretation*

Image analysis gradient-based visualization methods are useful for interpreting model predictions, as shown in Figures 8 and 9. Critical regions affecting disease classification in spinach leaves are highlighted using Grad-CAM, Saliency Maps, and Class Activation Maps (CAM). Figure 8 shows Grad-CAM visualizations on a false positive case, where a healthy leaf is misidentified as Downy Mildew. The heatmap shows high activation along the upper midrib and leaf blade, conforming to mild discoloration and texture variation, while the outer margins showed lower activation. This was mainly due to texture sensitivity, as the model overstated subtle shading and vein distinction, overfitting to vein patterns, and limited diversity among healthy leaf samples, leading to a mismatch between natural variations and disease symptoms.

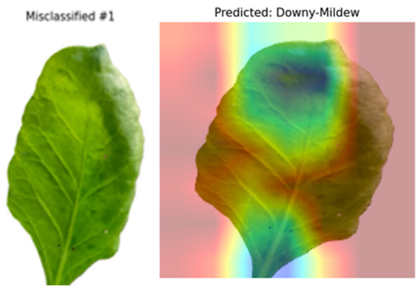

Fig. 8. XAI interpretation Case 1.

Figure 9 shows another incorrect identification, where Pest Damage is detected as Anthracnose. The model overlooked leaf edges and focused mostly on the central vein region (high activation in red/yellow), which caused misinterpretation. Repeated texture outlines and a lack of focus on margin details are the causes of this. Although Grad-CAM and saliency maps offer useful insights into misinterpretation behavior and attention bias, their application in automated dataset rectification or system redesign was outside the purpose of this study. Future work will explore the refinement of the XAI-guided model to further improve disease discrimination in hydroponic systems.

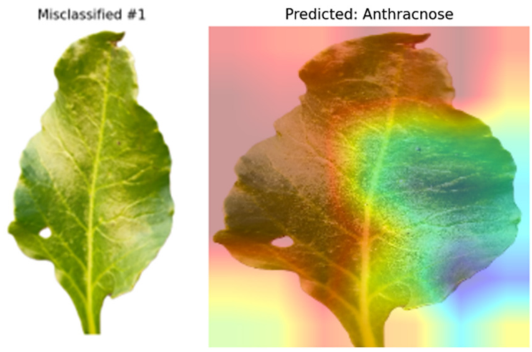

Fig. 9. XAI interpretation Case 2.

V. CONCLUSION

This research developed an efficient DL system for early disease detection in hydroponic spinach. MobileNetV2 outperformed ResNet50 (87.04%) and EfficientNetB0 (84.2%) with an accuracy of 90.1% and an F1-score of 0.88. The results show that recognizing hydroponic spinach disease using DL is achievable. This approach was accomplished with a stratified 5-fold cross-validation, transfer learning through pretrained weights, and safe random search hyperparameter tuning, which confirmed stable and robust performance despite dataset limitations such as class imbalance and subtle disease symptoms. The proposed MobileNetV2 and XAI system offers a reliable, scalable, and interpretable solution for hydroponic spinach disease detection, supporting timely interventions and sustainable farming practices. Future work will focus on real-time deployment and expanded dataset coverage. Although these insights are appreciated, combining XAI-driven feedback into dataset alteration or design modification represents a subsequent research phase. Such closed-loop optimization is beyond the scope of the present work and has been explicitly identified as a direction for future research.

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