

Jackfruit Leaf Disease Classification Using Computer Vision and CNN Models Integrated with a Gradio Web Interface

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DOI: <https://doi.org/10.51583/IJLTEMAS.2026.150900096>

Received: 25 September 2026; Accepted: 30 September 2026; Published: 16 October 2026

ABSTRACT

Jackfruit (*Artocarpus heterophyllus*) is one of the most important fruit crops in Bangladesh, but its productivity is often reduced due to leaf diseases such as black spot and chewing insect damage. Early and accurate detection of these diseases is crucial to prevent serious yield loss. However, traditional diagnosis mainly depends on expert visual inspection, which is time consuming, subjective, and often inaccessible to farmers in rural areas. To overcome this limitation, we propose a deep learning-based artificial neural system for jackfruit leaf disease detection using a field-collected dataset of approximately 4,500 images categorized into three classes: Healthy, Black Spot, and Chewing Insect Damage. Transfer learning is applied along with image preprocessing, data augmentation, and model tuning using DenseNet201, VGG19, and InceptionResNetV2 under varying real-world field conditions in Bangladesh. The final notebook uses ImageNet-pretrained bases, Adam optimization, categorical cross-entropy loss, and five epochs; the models were evaluated using accuracy and loss curves, confusion matrices, and classification reports. Experimental results show that DenseNet201 achieved the highest test accuracy of 94.52%, followed by VGG19 at 90.00% and InceptionResNetV2 at 87.33%. A Gradio interface allows the user to upload a jackfruit leaf image and receive class probabilities and a final prediction; inputs that do not pass the implemented validation gate are handled as undefined. This deep learning-based disease diagnosis system can support better crop management practices, timely decision-making, and long-term sustainable agriculture. The study is limited by its dataset scope, included classes, and lack of external multi-environment validation.

Keywords: Jackfruit leaf disease, computer vision, convolutional neural networks, transfer learning, Gradio web interface

INTRODUCTION

Background and Motivation

Jackfruit (*Artocarpus heterophyllus*) is one of the major fruit crops in Bangladesh and its contribution to the agriculture economy is considerable. However, its productivity is often reduced by leaf diseases like Black Spot and Chewing Insect Damage, since they directly impair photosynthesis and plant growth. If the diseases cannot be detected in time, treatment will be delayed and lower yield or more economic loss for farmers is expected [9]. In many rural areas, disease identification is still performed by visual inspection and relies on an observer's subjective judgment; traditional visual inspection may not be fully consistent since early stage symptoms can be subtle or environmental conditions may change [15]. Consequently, farmers frequently face difficulties in selecting the treatment and prevention of disease.

With the development of digital imaging technology and machine-learning methods, automatic plant disease detection has emerged as a feasible and effective substitute for manual observation. Deep learning systems can analyze leaf images and detect complex disease patterns with better performance than traditional machine-learning methods including SVM or classical image processing [17].

CNN has been used for discriminating diseases from a variety of strategies [4]. The motivation of this project is to fulfill the need for a reliable and computationally efficient approach to detect jackfruit leaf diseases at an early stage. Visual evaluation of symptoms is difficult as early symptoms may go unnoticed or are not distinguished easily, consequently delaying treatment and causing significant yield loss [8].

LITERATURE REVIEW AND RESEARCH GAP

Earlier studies on detecting plant leaf diseases predominantly relied on classical image-processing and machine-learning techniques, including K-means clustering and SVM, which were inconsistent in accuracy, especially from real field images due to image variations [13,17]. Deep-learning methods have been used for plant disease recognition across crops such as tomato, rice, and cucumber [9,10,11]. Research on agricultural leaf disease detection has also reported automatic and reliable disease recognition using deep-learning techniques [5,6]. Research on jackfruit biology and bronzing-related infection supports the need for improved crop-protection diagnostics [1,2,12,14]. A baseline study for jackfruit leaf disease classification is also included in the supplied literature [3].

While previous studies have extensively employed machine and deep learning methods for detecting leaf disease in plants, there are still several gaps that directly motivate this research. In real agricultural settings, lighting, background, and leaf orientation change a lot, so K-means, SVM, and other classical methods are not able to work reliably [9,17]. Although deep learning has performed well on other crop datasets, many approaches are based on controlled laboratory images and do not capture the challenges of the field environment [4,10].

Studies on jackfruit leaf diseases are extremely rare. Most available studies on jackfruit focus on biological characteristics or bronzing-related infections [1,7] and do not provide an image-based diagnostic framework. This work uses field-captured jackfruit leaf images to compare DenseNet201, VGG19, and InceptionResNetV2 for jackfruit leaf classification.

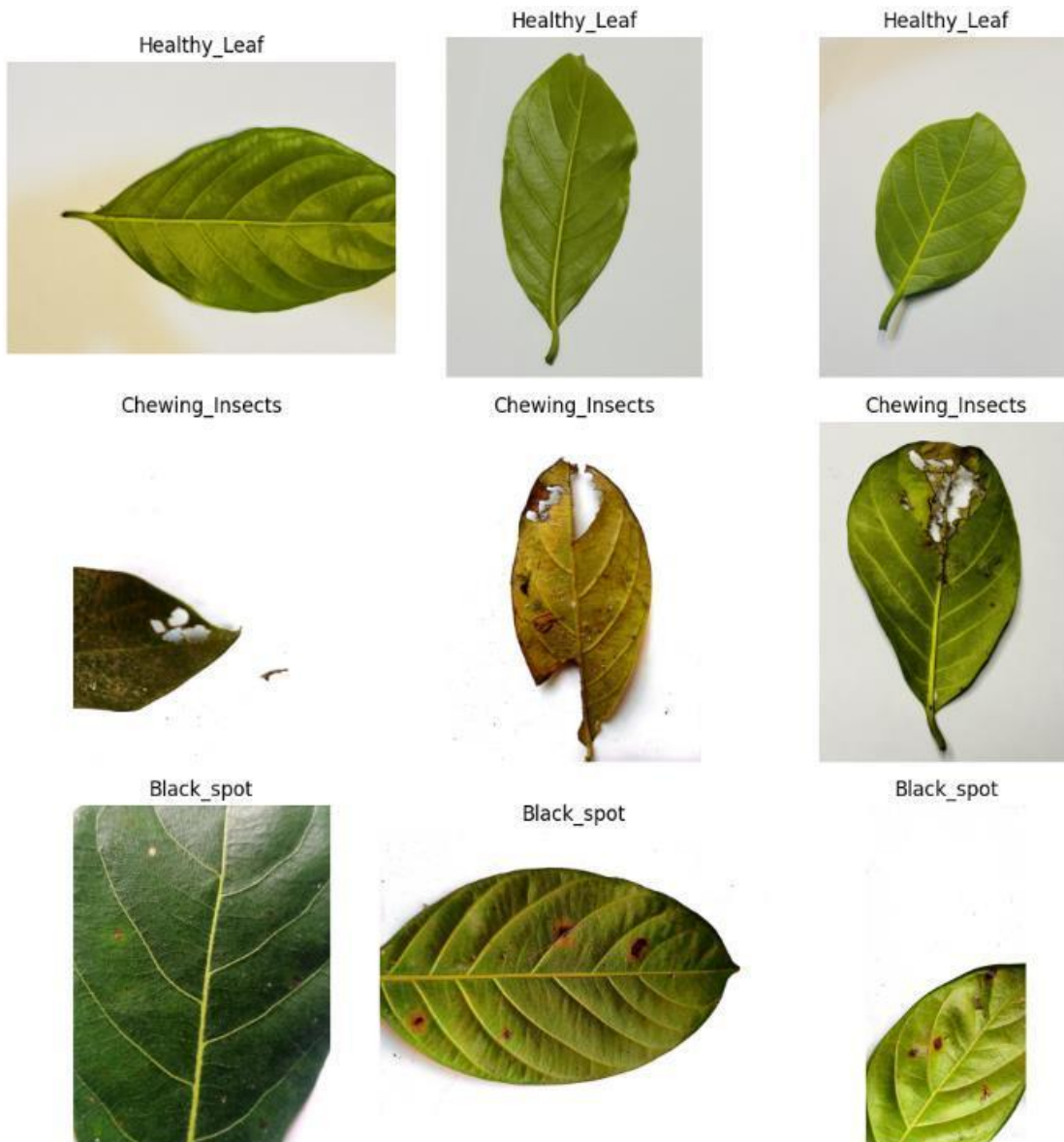
The objectives of this work are to create an automated deep learning system for precisely classifying jackfruit leaf diseases in real field conditions; to design and test DenseNet201, VGG19, and InceptionResNetV2 and improve prediction reliability using ensemble fusion; and to implement an easy-to-use Gradio web interface for diagnosis of jackfruit leaf diseases and decision support for farmers.

METHODOLOGY

Dataset Collection, Expert Verification, and Labeling

This work is based on a structured pipeline development methodology used to build a deep learning-based system for jackfruit leaf disease detection. It started with compilation of a database of around 4,500 jackfruit leaf images from real agro fields.

These images were visually inspected and classified into three classes: Healthy, Black Spot, and Chewing Insect Damage, to guarantee accurate ground-truth labeling for supervised learning. The Final Defense Report states that all images from the dataset and classes of disease were repeatedly validated by Md. Rezaul Karim, B.C.S (Agriculture), Upazila Agriculture Office, Senbag, Noakhali.



Field-collected jackfruit leaf images representing the three classes (source figure from the Final Defense Report).

Report-Described and Final Implemented Preparation

The Final Defense Report describes preprocessing and resizing, normalization, adjustment of non-uniform illumination or background noise, and data augmentation such as rotation, horizontal flip, zoom, and brightness to increase the diversity of training samples and alleviate model overfitting. It also describes ImageNet-pretrained weights, Adam optimization, categorical cross-entropy loss, early stopping, and checkpointing.

The final training notebook records the final implemented configuration separately. The data were stratified into 70% development and 30% test portions; the development portion was then split into 70% training and 30% validation portions, giving 2,205 training, 945 validation, and 1,350 test images. The notebook uses an input size of 224x224, batch size 32, and seed 42. Its training generator uses `tf.keras.applications.mobilenet_v2.preprocess_input`, horizontal flipping, and rotation up to 20 degrees. The validation and test generators use the same preprocessing function without augmentation. The notebook trains for five fixed epochs and saves each model after evaluation; it does not show zoom, brightness augmentation, early-stopping callbacks, or checkpoint callbacks.

Model Selection and Training

Various alternative methods were attempted in the development of the jackfruit leaf disease diagnosing system before this method was adopted. First, conventional image-processing methods including color thresholding, K-means clustering, edge detection, and handcrafted feature extraction [4,7] were investigated due to their computational efficiency and ease of implementation. However, these approaches showed inadequate accuracy in varied lighting conditions, shadowed conditions, cluttered backgrounds, and various leaf shapes. They failed to describe complicated disease textures such as diffuse black spots or irregular chewing insect scratches, and were not feasible for many datasets because of manual-parameter tuning. As a result, the traditional image-processing methods were eventually dropped.

Classical machine-learning classifiers such as SVM, Random Forest, and KNN were also tested as alternative solutions. These models are heavily reliant on hand-crafted features and cannot learn hierarchical visual patterns directly from image data. With the high variability of field-captured jackfruit leaf images, their average accuracy was consistently lower than that of modern CNN-based methods reported in related agricultural research. Therefore, classical machine-learning models were considered inappropriate for this work [16]. Another possibility was to train a custom CNN from scratch. Although this technique provides complete architectural freedom, it demands extremely large datasets to generalize well. The available dataset of around 4,500 images was not sufficient for this method, and custom networks were difficult to use for heterogeneous disease-relevant features in complex, noise-rich environments. Training a deep network from scratch could also be computationally demanding and time-consuming. Due to these reasons, training a custom CNN from scratch was not chosen as a viable approach [16].

Transfer learning on the basis of pretrained deep ConvNets was chosen for this study. The three architectures were DenseNet201, VGG19, and InceptionResNetV2. The final notebook uses ImageNet-pretrained bases with include_top=False; each base is frozen. The classification head consists of global average pooling, a 256-unit ReLU layer, dropout of 0.3, a 128-unit ReLU layer, and a three-unit softmax output layer. The models are compiled with Adam optimization and categorical cross-entropy loss. The use of pretrained ImageNet weights allowed the models to learn jackfruit-specific disease patterns from the available dataset while extracting texture, color, and structural features [11,16].

Table 1: Experimental setup from the Final Defense Report and final training notebook.

Category	Tools and configuration
Platform	Jupyter Notebook; GPU-accelerated environment
Programming language	Python 3.x
Deep-learning framework	TensorFlow 2.x and Keras
Supporting libraries	NumPy, Pandas, Matplotlib, Seaborn, Scikit-learn
Image processing	OpenCV and Pillow (PIL)
Pretrained weights	ImageNet weights for DenseNet201, VGG19, and InceptionResNetV2
Input and batch size	224x224 pixels; batch size 32
Training	Five epochs; Adam; categorical cross-entropy
Dataset storage and access	Google Drive integration

Evaluation, Ensemble Fusion, and Gradio Interface

Performance was evaluated through accuracy and loss curves, confusion matrices, classification reports, and test accuracy. During inference, the preprocessed image is passed through DenseNet201, VGG19, and InceptionResNetV2. Each model produces probability scores for the three classes. The Ensemble Fusion module integrates the probability scores generated by all three CNN models; by combining these independent predictions, the ensemble approach selects the disease class with the highest aggregated confidence.

The supplied Gradio implementation converts an uploaded image to RGB, resizes it to 224x224, converts it to an array, and normalizes the pixel values by dividing them by 255.0. Its model output probabilities are reordered from Black_spot, Chewing_Insects, Healthy_Leaf to the interface order Healthy_Leaf, Chewing_Insects, Black_spot. The implementation averages the three reordered probability vectors, $avg=(p_1+p_2+p_3)/3$, and reports the class with the largest averaged probability. The interface also uses green-pixel, texture, brightness, and ensemble-confidence checks. The confidence threshold is 0.70; an input that does not pass the implemented gate is shown as undefined rather than receiving a disease prediction.

Table 2: Sample probability outputs of CNN models for jackfruit leaf disease classification (source example from the Final Defense Report).

Model	Healthy	Black Spot	Chewing
DenseNet201	0.05	0.92	0.03
VGG19	0.10	0.80	0.10
InceptionResNetV2	0.15	0.70	0.15

RESULTS

Dataset distribution and model accuracy

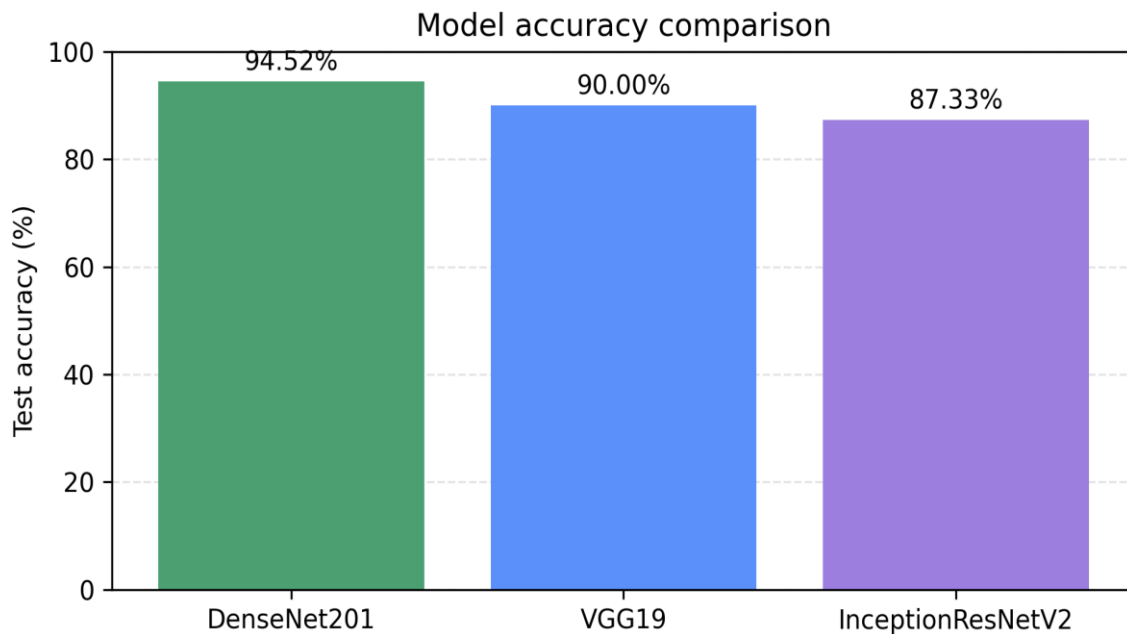
The dataset consists of approximately 4,500 jackfruit leaf images divided into three categories: Healthy (1,500 images), Black Spot (1,500 images), and Chewing Insect Damage (1,500 images). The final notebook establishes the following test-accuracy mapping: DenseNet201 94.52%, VGG19 90.00%, and InceptionResNetV2 87.33%.

Table 3: Dataset distribution.

Class	Images
Healthy	1,500
Black Spot	1,500
Chewing Insect Damage	1,500
Total	4,500

Table 4: Test accuracy comparison

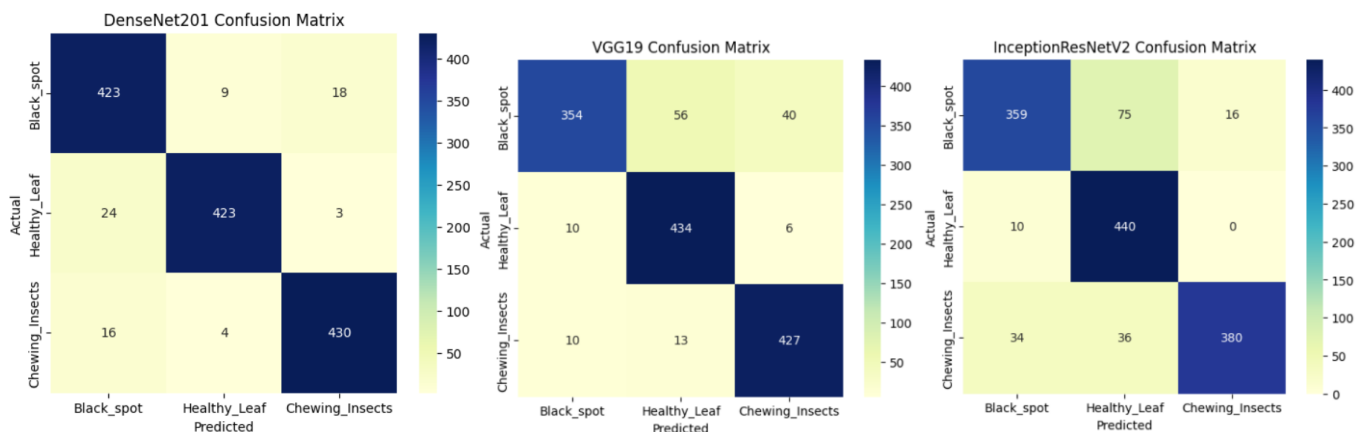
Model	Test accuracy (%)
DenseNet201	94.52
VGG19	90.00
InceptionResNetV2	87.33



Model accuracy comparison (source figure from the Final Defense Report).

Confusion matrices and classification reports

The final notebook classification reports used a test set of 1,350 images, with 450 images per class. The original confusion matrices are shown in Figure 3. Tables 5–7 preserve the available precision, recall, F1-score, support, macro-average, and weighted-average values.



Confusion matrices for DenseNet201, VGG19, and InceptionResNetV2, respectively (source figures from the Final Defense Report).

Table 5: DenseNet201 classification report.

Class	Precision	Recall	F1-score	Support
Black Spot	0.91	0.94	0.93	450
Healthy Leaf	0.95	0.96	0.95	450
Chewing Insects	0.97	0.94	0.95	450
Accuracy			0.95	1350
Macro average	0.95	0.95	0.95	1350
Weighted average	0.95	0.95	0.95	1350

Table 6: VGG19 classification report.

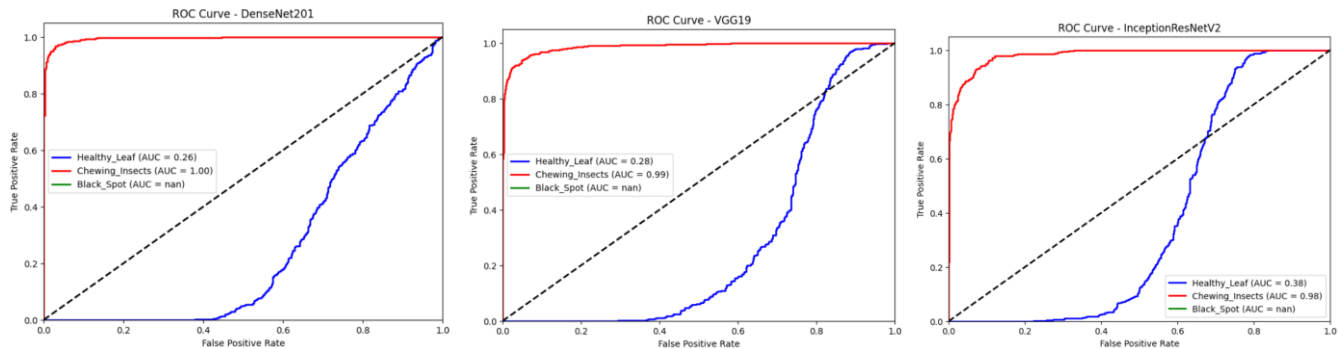
Class	Precision	Recall	F1-score	Support
Black Spot	0.95	0.79	0.86	450
Healthy Leaf	0.90	0.95	0.93	450
Chewing Insects	0.86	0.96	0.91	450
Accuracy			0.90	1350
Macro average	0.90	0.90	0.90	1350
Weighted average	0.90	0.90	0.90	1350

Table 7: InceptionResNetV2 classification report.

Class	Precision	Recall	F1-score	Support
Black Spot	0.89	0.80	0.84	450
Healthy Leaf	0.96	0.84	0.90	450
Chewing Insects	0.80	0.98	0.88	450
Accuracy			0.87	1350
Macro average	0.88	0.87	0.87	1350
Weighted average	0.88	0.87	0.87	1350

ROC/AUC figures

The Final Defense Report includes ROC curves and AUC-score figures for each evaluated model. The original figures are preserved in Figure 4. No numerical AUC values are added as a table because they were not verified as tabulated results in the supplied final notebook output.



ROC curves for DenseNet201, VGG19, and InceptionResNetV2, respectively (source figures from the Final Defense Report).

DISCUSSION

DenseNet201 outperformed the other models in terms of test accuracy at 94.52%. The source report describes the training and validation curves as showing stable convergence with little overfitting. The class-wise results for DenseNet201 are also high. There was slight misclassification between Black Spot and Chewing Insect Damage due to visual similarity in the initial period of the disease.

VGG19 achieved a test accuracy of 90.00%. It learned consistently, but was slower and less effective in fine-grained leaf texture features according to the source discussion. The confusion matrix showed occasional misclassification across the three classes. While still performing well, VGG19 showed good results and can be a model for leaf disease detection when a computationally limited environment is a requirement.

InceptionResNetV2 achieved a test accuracy of approximately 87.33%. The source discussion reports higher fluctuation in the loss curve and lower performance on complex texture patterns and varying lighting conditions in field images. While InceptionResNetV2 lagged behind compared with the other models, it still showed reasonable performance within the evaluated dataset.

DenseNet201 was selected as the best-performing model. The source discussion attributes this result to dense connections that help efficient feature propagation, reduce the vanishing-gradient problem in deep networks, and reuse features from earlier layers. The comparison also suggests that real-field datasets are more challenging for deep-learning models than laboratory or controlled datasets.

CONCLUSION

This work presented automated deep learning-based detection of jackfruit leaf diseases using a field-collected dataset of approximately 4,500 images. By performing systematic preprocessing and augmentation and using three transfer-learning models—DenseNet201, VGG19, and InceptionResNetV2—the project demonstrated classification of leaf images into Healthy, Black Spot, and Chewing Insect Damage categories. DenseNet201 achieved the highest test accuracy among the evaluated models. The project constructed a working classification pipeline, organized a structured dataset, and tested different model architectures against it. The Gradio interface implements image upload, ensemble prediction, probability visualization, and basic undefined-image handling.

LIMITATIONS AND FUTURE WORK

Although the proposed system showed promise in automatic detection of jackfruit leaf disease, the system has restrictions. The dataset consists of 4,500 field-captured images from a prescribed region and is limited by geographic location, season, and environmental variation. The three classes are limited to Healthy, Black Spot, and Chewing Insect Damage and omit other leaf ailments that may occur in realistic agricultural environments. Performance may be affected by poor image quality, low-resolution mobile cameras, and variable lighting during image acquisition. Robustness testing, external benchmarking, and multi-environment data validation remained outside the scope of this work.

Future work can use more diverse images across geographic areas, seasons, and environmental conditions; incorporate additional diseases, nutrient deficiencies, and pest-related conditions; use lightweight networks or model compression for mobile devices; conduct cross-region, low-resolution, and changing-light robustness tests; use Grad-CAM or heatmaps for interpretability; explore semi-supervised or weakly supervised annotation; and consider edge devices or budget-friendly hardware platforms such as Raspberry Pi.

ACKNOWLEDGEMENTS

The authors acknowledge Md. Rezaul Karim, B.C.S (Agriculture), Upazila Agriculture Office, Senbag, Noakhali, for the repeated validation of the dataset images and disease classes described in the Final Defense Report.

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