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Classification of Multi-Crop Leaf Diseases in Rice, Wheat, and Bean Using a Deep Transfer Learning Approach

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Abstract: In Bangladesh, crop leaf diseases create a serious risk to food security and production from agriculture. Timely identification of leaf diseases in rice, wheat, and bean crops is considered crucial for the implementation of effective disease detection and classification strategies. To address this challenge, a MobilenetV2-based disease identification and classification system is proposed in this research. Previous studies focus on classifying diseases of a single species, leaving the need to train models separately for each species. This research focuses on forming a single standard model to perform leaf disease classification for multiple crop species including rice, wheat, and beans. The approach makes use of transfer learning with the MobilenetV2 model, which is fine-tuned using a dataset of annotated crop leaf images specific to Bangladesh. Following a comprehensive evaluation, an overall accuracy of 97.87% was achieved in the classification of crop leaf diseases, which surpasses the accuracy of a number of previous studies focusing on leaf disease detection of a single crop. The system demonstrates the capability to rapidly diagnose diseases in real time by enabling the users to prompt intervention to mitigate potential crop losses, ultimately leading to amplified crop yield and food security. Overall, the research highlights the promise of AI-powered solutions in tackling crop leaf disease detection, which in turn encourages greater research and technology adoption to support sustainable farming methods especially in the crop disease classification domain in Bangladesh and throughout the world.

Keywords: multi-crop leaf disease classification, deep transfer learning, MobileNetV2, plant disease detection, agricultural image analysis

1. Introduction

From a global perspective, agriculture plays a pivotal role in underpinning economies and world food security. In Bangladesh, this significance is particularly pronounced, contributing over 16% to the GDP and employing more than 45% of the workforce [1]. Moreover, around half of the global population solely eats rice as a basic meal. However, a significant challenge exists, notably in crop diseases, particularly leaf diseases, which are responsible for substantial yield losses of up to 30% in staple crops like rice (*Oryza sativa*), wheat (*Triticum aestivum* L.), and beans (*Phaseolus vulgaris* L.). This issue extends beyond Bangladesh's borders, encompassing the broader global imperative for sustainable agriculture and food production. Several key factors depicted in Figure 1 are generally considered for the most common leaf diseases. In this study, the leaf diseases caused by pathogens are taken into consideration, where the effects of the diseases are visible in the leaves as marks. Existing studies mostly focus on classifying diseases only for a single-crop leaf; for example, a study conducted by Ahmed et al. [2] and Mallick et al. [3] has effectively classified leaf diseases of beans or rice, although obtaining higher classification accuracy has been considered.

Only crop leaf diseases of a single species are detected by these models. This insight underscores the urgency of finding effective solutions that can identify more than one crop disease. This research employs the state-of-the-art MobilenetV2 model on a dataset containing images of affected leaves of rice, wheat, and beans, achieving an impressive accuracy for classifying the crop leaf diseases. The dataset is created by merging the images for rice and wheat crop types from a dataset publicly provided by Bangladesh Agricultural Research Institute (BARI) and the type of beans from a dataset provided by Bangladesh Agricultural University (BAU).

Additionally, the nature of disease classification accuracy of deep learning models in the case of combined datasets with multiple crop types has never been explored locally. Thus, examining the efficiency of the MobilenetV2 as a deep transfer learning model in a dataset containing multiple crop types preserving the classification accuracy is the main focus of this study. While existing disease classification systems can identify the disease of a single-crop type, the proposed classification system in this study

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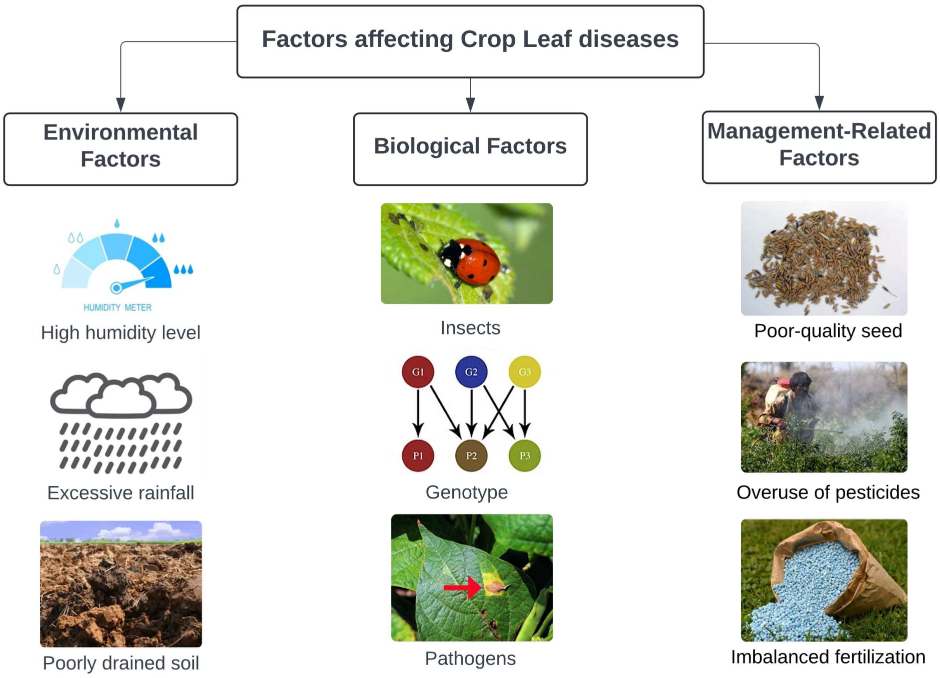
Figure 1
Key factors causing crop leaf diseases



would be advantageous for farmers or agriculturists with its ability to classify multiple crop disease types using a single system. In summary, this research's core mission is to develop an accessible, accurate, and reliable crop leaf disease identification system for Bangladeshi farmers. Image quality is crucial because the disease recognition algorithm's accuracy is affected by things like illumination and camera limitations. Subsequent investigations will concentrate on surmounting the limitations and augmenting the impact of the research.

The rest of this paper is organized into four sections. Section 2 provides a background study and related works. This section provides previous works on which improvements have been made. Section 3 introduces the methodology of this study. Section 4 contains the result analysis and comparisons. Section 5 denotes the conclusion of the study, limitations of the study, and some potential future work.

2. Literature Review

Crop leaf disease is one of the major issues in agricultural production worldwide. Researchers are working to solve this problem to reduce crop losses caused by leaf diseases. Manual visual inspection of the leaves by professionals or farmers is the traditional method for identifying crop leaf diseases. The identification of any obvious signs or anomalies on the leaves, such as discoloration, spots, lesions, or other odd patterns, depends on their experience and understanding. Although this conventional method has some merits, it may not be very precise or timely. Since then, new cutting-edge strategies have evolved to offer more accurate and effective methods for crop leaf disease identification, including the use of machine learning (ML) and computer vision techniques. Previous works of relevant research and studies involving ML approaches in the field of leaf disease recognition and classification have demonstrated a significant advancement. An ML-based system for automatically detecting rice leaf diseases is suggested to help Bangladesh's rice-dependent economy earlier. Several ML strategies were used, using crisp images of damaged rice leaves against a white background. After preprocessing, the dataset is trained using a variety of ML algorithms, including KNN, naive Bayes, Decision Tree (J48), and logistic regression. Ahmed et al. [2] applied the Decision Tree algorithm that delivers an effective tool for quick disease detection and treatment with an astounding accuracy of over 97.91% on the test dataset. Recent deep learning approaches using convolutional neural networks (CNNs) have demonstrated effective classification of rice leaf diseases. For example, Mannepalli et al. [4] applied VGG16, a CNN model that is employed to distinguish bacterial leaf blight, leaf smut, and brown spot in rice leaves with high classification performance, highlighting the potential of CNN-based methods in automated rice disease diagnosis. EfficientNetB6 with the Adam optimizer attained the maximum validation accuracy of 91.74%, according to the results of trials conducted in a separate research from Singh et al. [5]. Additionally, CNN models such as VGG-19, Inception-Resnet-V2, and ResNet-101 are used to achieve this. Islam et al. [6] presented that an Inception-ResNet-V2 achieves an accuracy of 92.68%, which is a significant improvement over manual detection and leads to a decrease in crop damage and farmer losses. An innovative strategy is also used to address the problem. With the help of deep learning models (ResNets, DenseNets) developed by Mathulaprangsan et al. [7], they generate an image collection of a rice illness and achieve an average accuracy of above 95%.

Gaikwad and Musande [8] proposed a method for detecting plant diseases. It involves several image processing phases, including image acquisition, preprocessing, feature extraction, and the use of a neural network classifier. Another study by Poovidha et al. [9] showed the initial application of image processing in identifying plant leaf diseases in association with k-means clustering, Probabilistic Neural Network (PNN), and Gray Level Co-occurrence Matrix (GLCM). In addition, Dixit and Nema

[10] reviewed the detection of wheat leaf disease, which is also discussed using ML methods, where the Support Vector Machine (SVM) classifier was used to detect wheat disease. Various algorithms efficiently detect prevalent viral, bacterial, fungal, and insect-related illnesses in wheat leaves. Farmers can keep an eye on extensive plantings with the use of leaf photographs and data processing. These studies examine ML methods for identifying and categorizing diseases while emphasizing significant difficulties. CNNs have produced impressive image categorization results recently. Earlier research presents a novel deep learning-based method for identifying mung bean pests and diseases. Due to the restricted number of training photos in the study of Mallick et al. [3], transfer learning is used, leading to the successful detection of six disease categories and four pest kinds with an average accuracy of 93.65% when utilizing a smartphone-based model [3]. The study aims to determine the best network architecture and optimization techniques for classifying bean leaf diseases. For quicker training, more accuracy, and simpler retraining, the MobileNetV2 architecture was explored in that research. The model from Elfatimi et al. [11] was tested on 1296 bean leaf images, and for the ill and healthy classes, it achieved an average accuracy of over 97% on the training dataset and over 92% on the test data. A recent research by Paithane and Wagh [12] proposed a modified kernel fuzzy c-means algorithm for cotton leaf spot detection. Another study by Paithane [13] has proposed a Hybrid-Net model for medical image segmentation. Although these papers have significant methodological contributions, they are either crop-specific or out of the scope of agricultural disease classification.

The early identification of bean leaf illnesses is addressed by a novel deep learning framework. Abed et al. [14] proposed a framework that shows good accuracy; on a dataset of 1295 images, the Densenet121 model obtained a classification accuracy rate of 98.31% in binary classification and 91.01% in multi-classification. In the case of binary classification of diseases, the accuracy often remains higher. For example, Dolatabadian et al. [15] introduced an image processing technique to detect crop disease using ML. Jiang et al. [16] developed a refined VGG16 model with multi-task transfer learning that can identify rice leaf sickness (97.22%) along with wheat disease of the leaves (98.75%) with excellent accuracy. That method provides a dependable solution for the simultaneous detection of leaf diseases in different plants, outperforming single-task models, ResNet50, reuse-model transfer learning, and DenseNet121. Fan et al. [17] proposed a deep learning model to detect plant diseases based on transfer learning, feature fusion, and center loss to increase the power of discrimination. It reached a maximum of 99.79% accuracy on three datasets.

To give a better understanding of how various approaches have addressed crop disease classification, Table 1 presents a thorough comparison of recent studies. The datasets, approaches, and classification accuracy attained by different researchers tackling related issues are represented in this comparison. The table shows that there is still a significant gap in the development of unified models that can handle multiple crop types at once, even though several studies have achieved high accuracy for single-crop disease classification.

Most of the research focuses on categorizing diseases for a single-crop type, as indicated in Table 1, which calls for creating distinct models for every crop species. Agriculture-related applications would benefit from a single system that could diagnose diseases in a variety of crops, even though these studies have seen significant success in their respective fields. In order to close this gap, the proposed method uses MobileNetV2 and transfer learning to accurately classify diseases in three major crops: rice, wheat, and beans. A useful development for practical agricultural applications is this multi-crop capability.

3. Methodology

In this section, the overall workflow, source, and description of the dataset along with the utilized deep transfer learning have been illustrated. Figure 2 shows the overall workflow of the study. The proposed model uses the MobileNetV2 model, which is a type of CNN especially optimized for resource-constrained environments, to classify leaf diseases across rice, wheat, and bean crops.

This research utilizes the MobileNetV2 model to classify crop leaf diseases, and this section briefly introduces the underlying mechanism and description of the process. The methodology consists of the following steps:

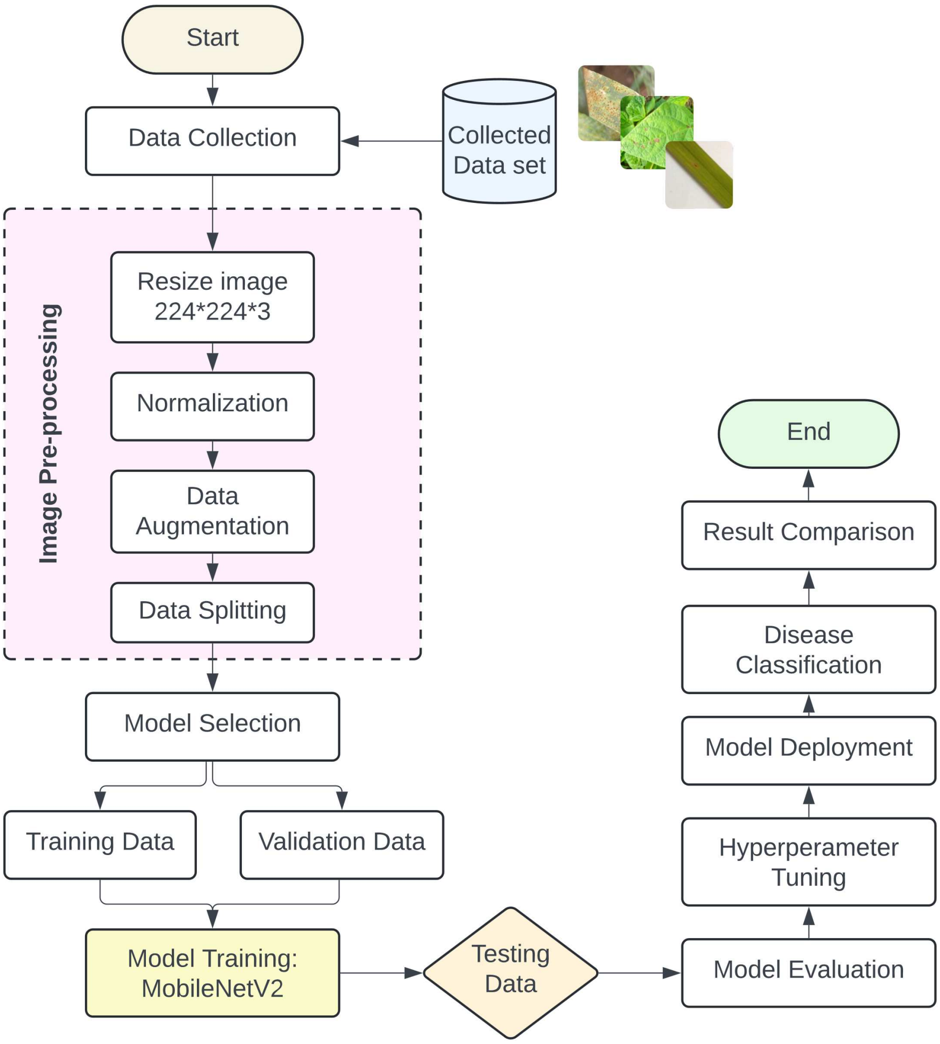
1) Dataset preparation

The datasets utilized in this study were collected from two organizations. The publicly available dataset provided by the BARI was utilized for the analysis of rice and wheat leaves displaying disease symptoms, and for the analysis of bean leaves exhibiting disease signs, the dataset supplied by BAU was taken

Table 1
Comparison of related studies on crop leaf disease classification

Study	Crop type(s)	Method/model	Accuracy (%)	Limitation
Ahmed et al. [2]	Rice only	Decision Tree (J48), KNN, naive Bayes	97.91	Single-crop focus, limited to rice diseases
Jiang et al. [16]	Rice and wheat	Multi-task deep transfer learning	Not specified	Limited to two crop types
Singh et al. [5]	Beans only	EfficientNetB6 with Adam optimizer	91.74	Limited to bean disease classification
Elfatimi et al. [11]	Beans only	MobileNet models	Not specified	Only addresses bean leaf diseases
Mallick et al. [3]	Mung bean only	Deep learning	Not specified	Specific to Indian mung bean diseases
Paithane et al. [12]	Cotton only	Modified kernel fuzzy c-means	Not specified	Focus on cotton leaf spot detection
Mannepalli et al. [4]	Rice only	VGG16	97.77%	Limited to rice crops only

Figure 2
Workflow diagram of the proposed model



into consideration. Figure 3 shows some sample images of infected crop leaf disease classes, three for each class. Rice, wheat, and beans are the three considered crops.

There are 7037 sample images of the crop leaves with the signs of 11 different disease categories. Bean Angular Leaf Spot, Bean Rust, Rice Bacterial Leaf Blight, Rice Healthy, Rice Brown Spot, Rice Hispa, Rice Leaf Smut, Rice Leaf Blast, Wheat Brown Rust, Wheat Healthy, and Wheat Yellow Rust are the disease groups that have been taken into consideration. A total of 7037 photos included in the mentioned datasets were used to fit the model. Within the dataset, the sample image count varies between classes. The statistics of the dataset are shown in Table 2.

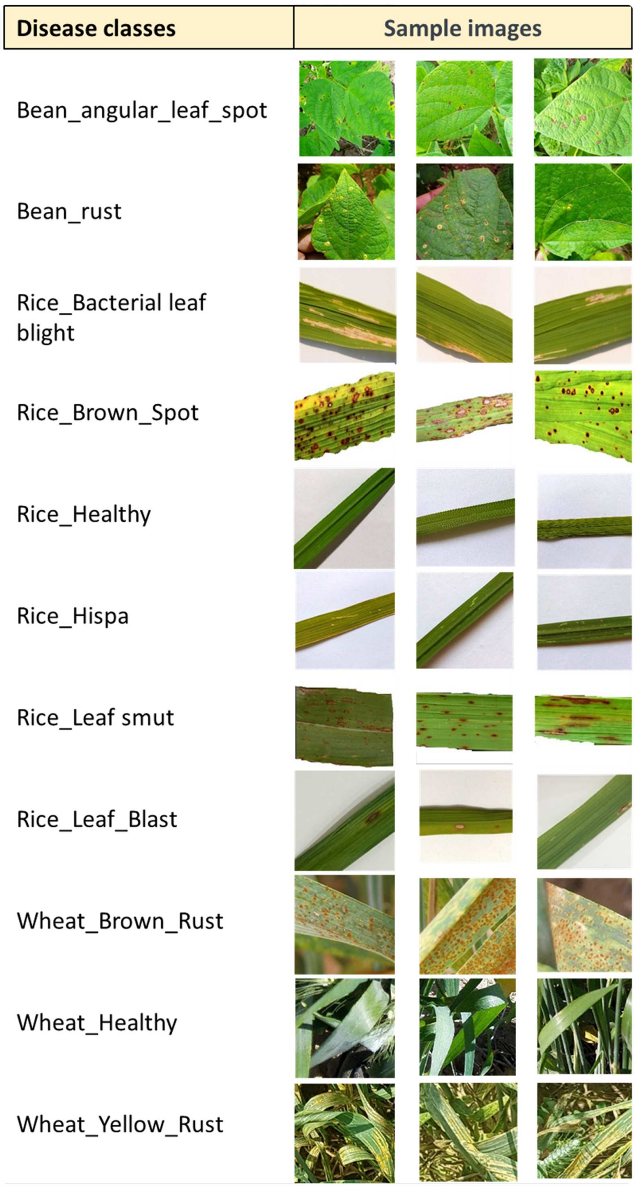
2) Data preprocessing

One of the important phases of every deep learning procedure is data preprocessing. The photos were preprocessed to make it simpler to extract features before being included in the model. The magnified image's pixel value is a single integer in the range of 0–255 that denotes the pixel's brightness. Black pixels are those with a value of 0, and white pixels are those with a value of 255. The dimensions of all input photos were changed to $224 \times 224 \times 3$. Scaling each image to a value between 0 and 1. The preprocessed images are then fitted into the MobileNetV2 model. Images were resized into 224×224 pixels, then normalized to [0, 1], and after that, augmented with rotation, flipping, and zooming to enhance robustness to lighting and resolution variations. To improve the generalization capability of the model and reduce the problem of overfitting, data augmentation techniques have been employed while training the model. The data augmentation techniques employed included random rotation, horizontal flip, and zooming of the data. These techniques are useful in extracting features from the data that are invariant to changes in illumination conditions, orientation, and resolution, which are common in real-world agricultural environments. The dataset was split into 70% training, 15% testing, and 15% validation sets.

3) Hyper parameter configuration

Transfer learning [18] is an approach that reduces the cost and effort of learning by using information from one area to solve problems in another area. When fine-tuning models' hyperparameters, this approach works particularly well because only the upper layers of the model need to be retrained, leaving the lower layers of the model unchanged. Thus, the model uses general features gathered by lower layers, while upper layers adapt and adjust more specific features relevant to the current dataset. The MobileNetV2 utilizes the transfer learning method. Pre-training was done using

Figure 3
Sample images from the dataset



the ImageNet dataset, which is a collection of 1000 classes and 1.4 million images. MobileNetV2, pre-trained on ImageNet, was used as the base model. The lower 15 layers were frozen to retain generic features, while the upper layers and a custom classification head (with a softmax layer for 11 classes) were fine-tuned. The Adam optimizer was used with a 0.001 learning rate and a 32-batch size.

4) Model architecture

In this study, the utilization of the MobileNetV2 model has been focused on for image classification. In 2017, the MobileNet architecture, a neural network that is lightweight and optimized for mobile applications, was first introduced [19]. Later in 2018, the concept of MobileNetV2 was introduced with linear bottleneck and inverted residual features.

The main advantage of MobileNetV2 is that it requires less memory, making it ideal for implementation in mobile contexts, and it is an improved version of MobileNetV1, which performs

Table 2
Dataset statistics

Crops	Disease	Number
Wheat	Yellow Rust	1156
	Healthy	1497
	Brown Rust	1128
Rice	Bacterial Leaf Blight	422
	Brown Spot	882
	Healthy	152
	Hispa	250
	Leaf Smut	432
	Leaf Blast	250
Bean	Angular Leaf Spot	432
	Leaf Blast	436
	Total	7037

better and uses fewer parameters, ensuring excellent accuracy [20]. The primary advantage of MobileNetV2 is that it requires less memory, making it ideal for implementation in mobile contexts. MobileNetV2 uses depthwise separable convolutions to improve portability, employs linear bottlenecks to deal with the problem of information loss in nonlinear layers inside convolutional blocks, and introduces inverted residuals, a framework that improves data retention [21, 22]. In Figure 4, the MobileNetV2 Model Architecture is illustrated.

Depthwise separable convolution in MobileNetV2 effectively reduces processing requirements, maintaining model performance. Hence, this is an important component for building efficient neural networks for mobile and embedded devices. The convolution process using this method is divided into two separate processes: depthwise convolution and pointwise convolution. In this stage, a convolutional filter is applied to each input channel. Computational cost and parameter calculation are greatly reduced by this method. The outputs of the depthwise convolution are concatenated by performing a 1 × 1 pointwise convolution. Depthwise convolution is used by MobileNetV2 to create a lightweight model suitable for embedded and mobile applications. Compared to conventional convolution, this method uses fewer multiplications, which reduces computing cost and memory consumption. In particular, for an input $DF \times DF \times M$ dimensions, a simple convolution with N filters of size $K \times K \times M$ would require operations:

$$K \times K \times M \times N \times D_F \times D_F \tag{1}$$

On the other hand, depthwise separable convolution leads to a significant reduction in the number of operations required. The required operation number is:

$$K \times K \times M \times N \times D_F \times D_F + M \times N \times D_F \times D_F \tag{2}$$

Following the first convolution layer with 32 filters, MobileNetV2 inserts 19 inverted residual bottleneck layers before finishing with a pointwise convolution that produces an output. A conventional residual block, represented by Figure 5(a), shows that the input image first undergoes a 1 × 1 convolution to reduce dimensions, and then a standard convolution consists of dwise 3 × 3 with rectified linear unit (ReLU) activation. The “Dwise 3 × 3” refers to the depthwise spatial filtering using

Figure 4
MobileNetV2 model architecture

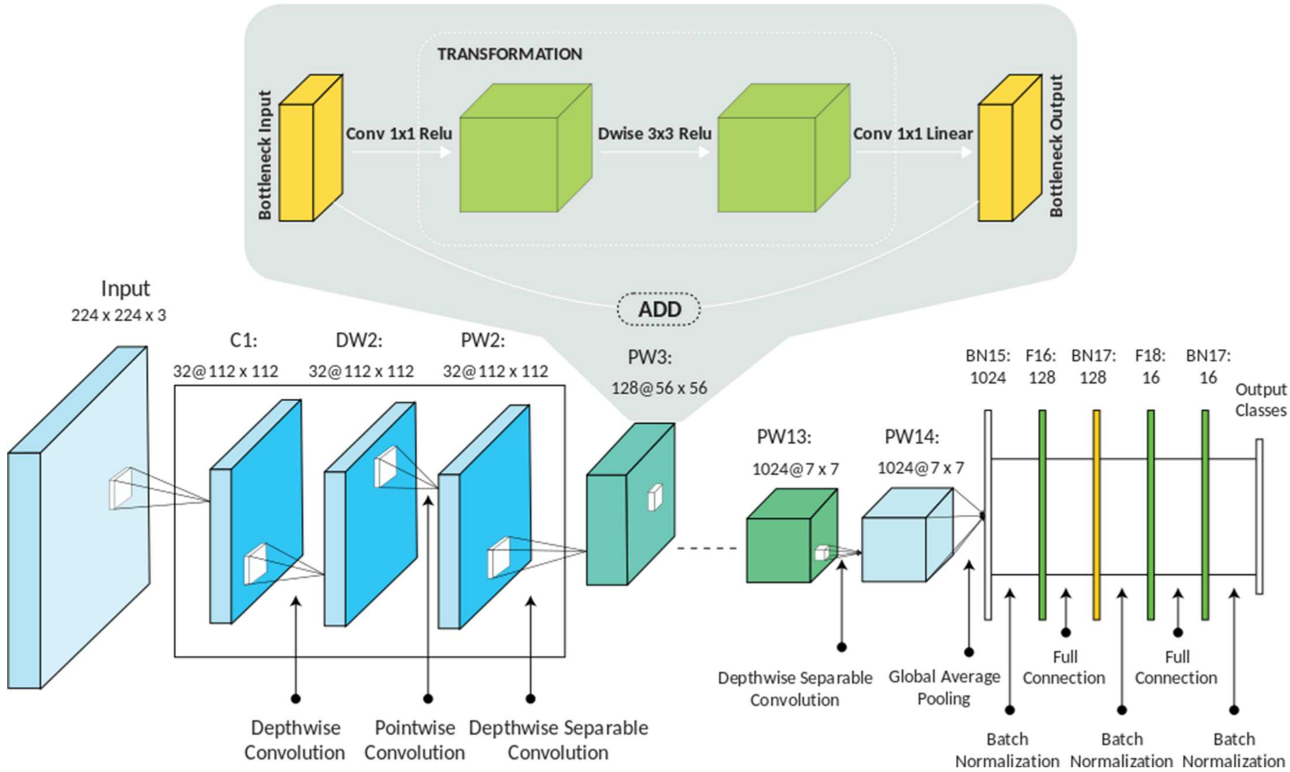
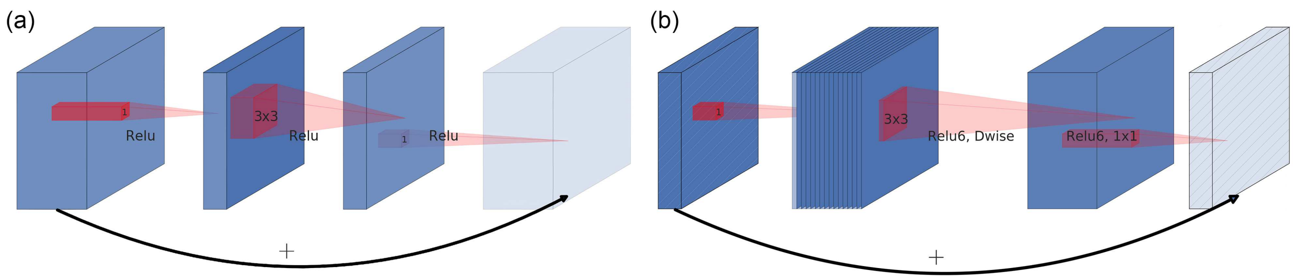


Figure 5
(a) Residual block and (b) inverted residual block



a 3 × 3 kernel, while "relu" indicates that the ReLU activation function is applied after the convolution to introduce nonlinearity. This separation dramatically reduces computational cost and the number of parameters compared to standard convolutions, making the model lightweight enough to run on mobile devices while maintaining strong feature extraction capabilities. At the end, a 1 × 1 convolution is used to increase dimensions. In Figure 5(b), the inverted residual block is presented, where the input image goes through a 1 × 1 convolution to increase dimension, then passes through a depthwise convolution, and finally a pointwise convolution to decrease dimension. The input data gets transformed into higher dimensions by the inverted residual blocks, which can then extract features using depthwise separable convolution. This is due to the fact that feature extraction on high-dimensional input often expects depthwise separable convolution, which might enhance the expressiveness of the model. The linear bottleneck model enhances MobileNetV2 after the depthwise convolution in the inverted residual block, which is achieved by eliminating nonlinear activation functions in the 1 × 1 pointwise convolution. This preserves the features retrieved during convolution and maintains the model's interpretation.

In high-dimensional regions, activation functions frequently promote nonlinearity, but they may also disrupt it in low-dimensional regions. The implementation structure shown in Table 3 describes the features' conversion from N to M channels with a stride of s and an expansion factor of t. This bottleneck structure uses a linear activation function after the pointwise convolutional layer rather than a nonlinear one and contains a 1 × 1 convolutional layer before the depthwise convolutional layer.

A summary of the MobileNetV2 architecture is shown in Table 4, where "conv2d" denotes standard convolution, "avgpool" denotes average pooling, "c" denotes the number of output channels, and "n" is the number of repeats. The network employs the intermediate levels for feature extraction, and the final layer, which consists of 19 layers, is saved for classification.

Table 3
Bottleneck of Mobilenetv2

Input	Operator	Output
H × W × N	1 × 1 conv2d, ReLU6	H × W × tN
H × W × tN	3 × 3 dwise s=s, ReLU6	H/s × W/s × tN
H/s × W/s × tN	linear 1 × 1 conv2d	H/s × W/s × M

Table 4
Network structure of MobilenetV2

Input shape	Operator	t	c	n	s
224 × 224 × 3	conv2d	–	32	1	2
112 × 112 × 32	bottleneck	1	16	1	1
112 × 112 × 16	bottleneck	6	24	2	2
56 × 56 × 24	bottleneck	6	32	3	2
28 × 28 × 32	bottleneck	6	64	4	2
14 × 14 × 64	bottleneck	6	96	3	1
14 × 14 × 96	bottleneck	6	160	3	2
7 × 7 × 160	bottleneck	6	320	1	1
7 × 7 × 320	conv2d 1 × 1	–	1280	1	1
7 × 7 × 1280	avgpool 7 × 7	–	–	1	–
1 × 1 × 1280	conv2d 1 × 1	–	k	–	–

5) Training

The model was trained for 100 epochs, minimizing categorical cross-entropy loss. Dropout (0.5) was applied to prevent overfitting.

6) Evaluation

Accuracy, loss, precision, recall, and F1-score were evaluated on the validation and test sets. A confusion matrix was utilized to analyze classification performance across classes.

7) Summary of the reason to use MobileNetV2

A new softmax classification layer for 11 disease classes was added to adapt the model to the multi-crop dataset.

a. Transfer learning strategy
b. Custom classification head
c. Multi-crop dataset integration

- MobileNetV2 pre-trained on ImageNet was used as the base model.
- The lower 15 layers were frozen to preserve general feature representations.
- Higher layers were fine-tuned to learn crop-specific disease features.
- Unlike most existing studies that focus on a single crop, our model was trained on a merged dataset containing 7037 images from rice, wheat, and bean crops.

4. Result and Discussion

A comprehensive set of performance metrics [23, 24], including precision, accuracy, F1-score, recall, and loss, was utilized to examine the performance of the suggested MobileNetV2 model on multi-crop leaf disease classification. In order to ascertain the efficacy and generalization capability of the model, the said metrics were calculated over the training, validation, and testing datasets. Training was done with the Adam optimizer for 100 epochs and categorical cross-entropy loss minimization.

Accuracy estimates the proportion of samples correctly classified out of the total number of samples. It can be represented as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

where TP (true positives) is the number of properly identified diseased samples, TN (true negatives) is the number of properly identified healthy samples, FP (false positives) is the number of misclassified healthy samples as diseased, and FN (false negatives) is the number of misclassified diseased samples as healthy.

Precision calculates the proportion of the properly identified positive predictions to all positive predictions:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Recall (or sensitivity) is the ratio of correctly predicted positive samples to all actual positive samples:

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

F1-score is the harmonic mean of recall and precision that gives a well-balanced estimate of the performance of the model:

$$F1 - Score = 2 \cdot \frac{Precission \cdot Recall}{Precission + Recall} \tag{6}$$

Loss was calculated using categorical cross-entropy, which measures the distance between the predicted probability distribution and the actual distribution in multi-class classification:

$$Loss = -\sum_{i=0}^{C} y_i \cdot \log\left(\bar{y}_i\right) \tag{7}$$

where the number of classes is denoted by C, the true label is denoted by y_i, and the predicted probability is $\overline{y_i}$ for class *i*.

The performance metrics are presented in Table 5. The model showed a training accuracy of 98.40%, validation accuracy of 97.59%, and testing accuracy of 97.87%, with very good generalization to new data. The training loss was 4.72%, the validation loss was 9.83%, and the testing loss was 8.07%, with minimal overfitting, as the validation and testing losses are very close to the training loss. Accuracy, recall, and F1-score were determined as

Table 5
Model performance metrics

Parameter	Crop disease (%)
Training accuracy	98.40
Training loss	4.72
Validation accuracy	97.59
Validation loss	9.83
Testing accuracy	97.87
Testing loss	8.07
Precision	97.50
Recall	97.60
F-1 score	97.55

97.50%, 97.60%, and 97.55%, respectively, for the high-reliability test set in classifying the diseases.

Accuracy and loss of train and validation data were considered while evaluating model performance. The classifications of the leaf diseases employed in this study were based on 100 epochs, and the Adam optimizer was utilized. After the training phase was finished, the validation phase's disease classification accuracy was 98.40%. However, during the testing phase, a disease classification accuracy of 97.87% was demonstrated. The model is less overfit since both the training and validation losses are minimal.

The training and validation accuracy curves are shown in Figure 6. The proposed model performs better as the number of epochs rises. It's crucial to remember that the training accuracy and the validation accuracy have converged, which means that the model's performance on the validation set and the training set are almost similar. This convergence suggests that there is less of a tendency to overfit in the suggested model. In other words, the model generalizes well to fresh, unknown data, as seen by the equivalent performance on the validation set, and does not simply memorize the training data. This shows that the model was picking up crucial traits and trends from the training set that apply to fresh data.

Figure 7 shows that, during the convergence phase, the suggested model exhibits a reduced degree of error and loss. This finding further emphasizes how well the model captures the fundamental patterns in the data. The decrease in error and loss shows how effective and efficient the model's learning process is. For the model's predictions to be as accurate as feasible, there must be little error and loss during convergence.

Together, the results from Figures 8 and 9 show conclusively that the suggested model not only performs brilliantly on new, untrained data but also learns well from the training data, highlighting its potential for use in real-world scenarios. In this section, we describe misclassification issues that have been seen in photos that have been exposed to sunlight. The MobileNetV2 model has trouble correctly classifying diseases in images with different lighting, which causes misclassification. Additionally, several of the photos in the suggested datasets have lower pixel values, which increases the possibility of misclassification.

Figure 8 displays instances of incorrectly categorized photos along with both their actual and predicted levels. In the observed circumstances, the model incorrectly forecasts the true label of the first image, which is "Bean Angular Leaf Spot" as being "Bean Rust." Similarly, the second image's real classification is "Bean Angular Leaf Spot" despite the model's prediction

Figure 6
Training accuracy and validation accuracy

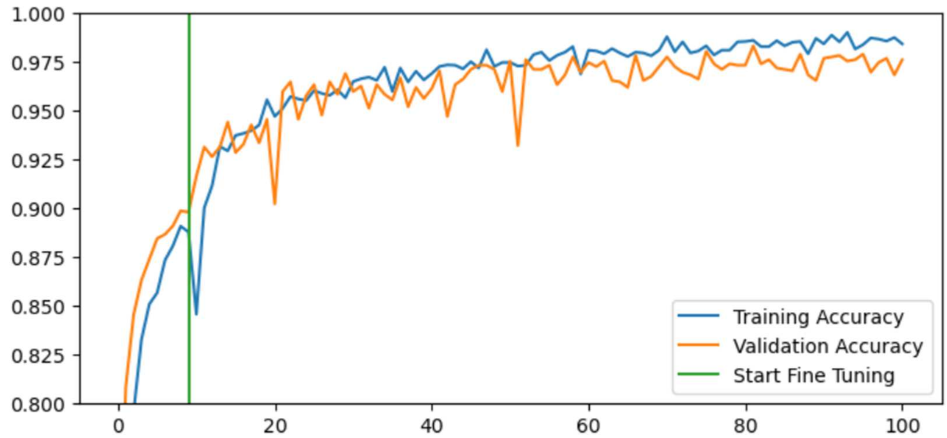
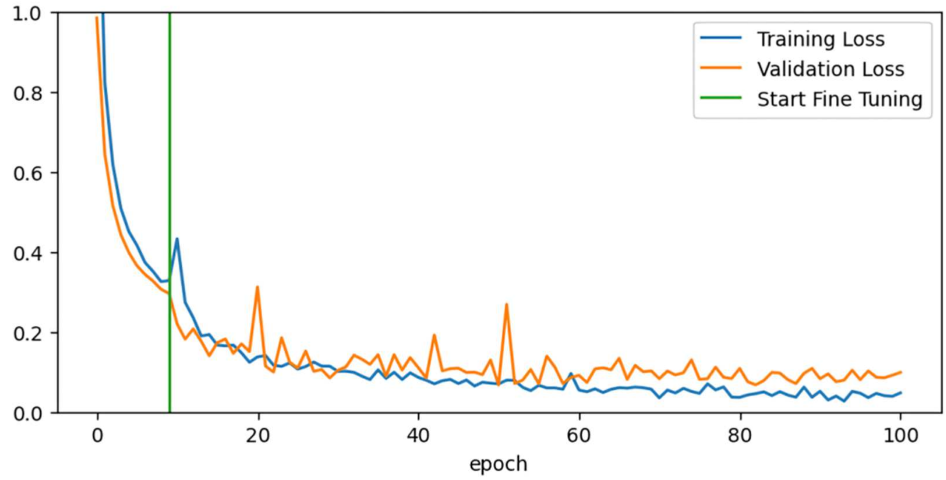


Figure 7
Training loss and validation loss



that it is “Bean Rust.” Furthermore, the model incorrectly forecasts the third image’s true class as “Rice Healthy” although it belongs to the category of “Rice Brown Spot.” These occurrences indicate that the model’s predictions were misclassified in several cases.

The confusion matrix shown in Figure 9 serves as a visual representation of the results attained by the leaf disease detection system. The matrix emphasizes the system’s strong performance by including a diagonal line of true positives, which denote precise predictions. The system continuously achieves a remarkable

Figure 8
Misclassified images

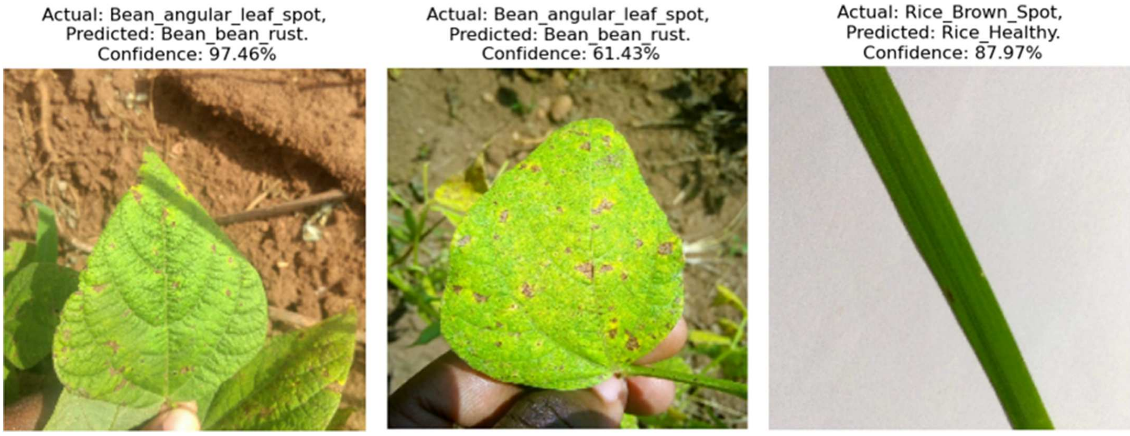


Figure 9
Confusion matrix

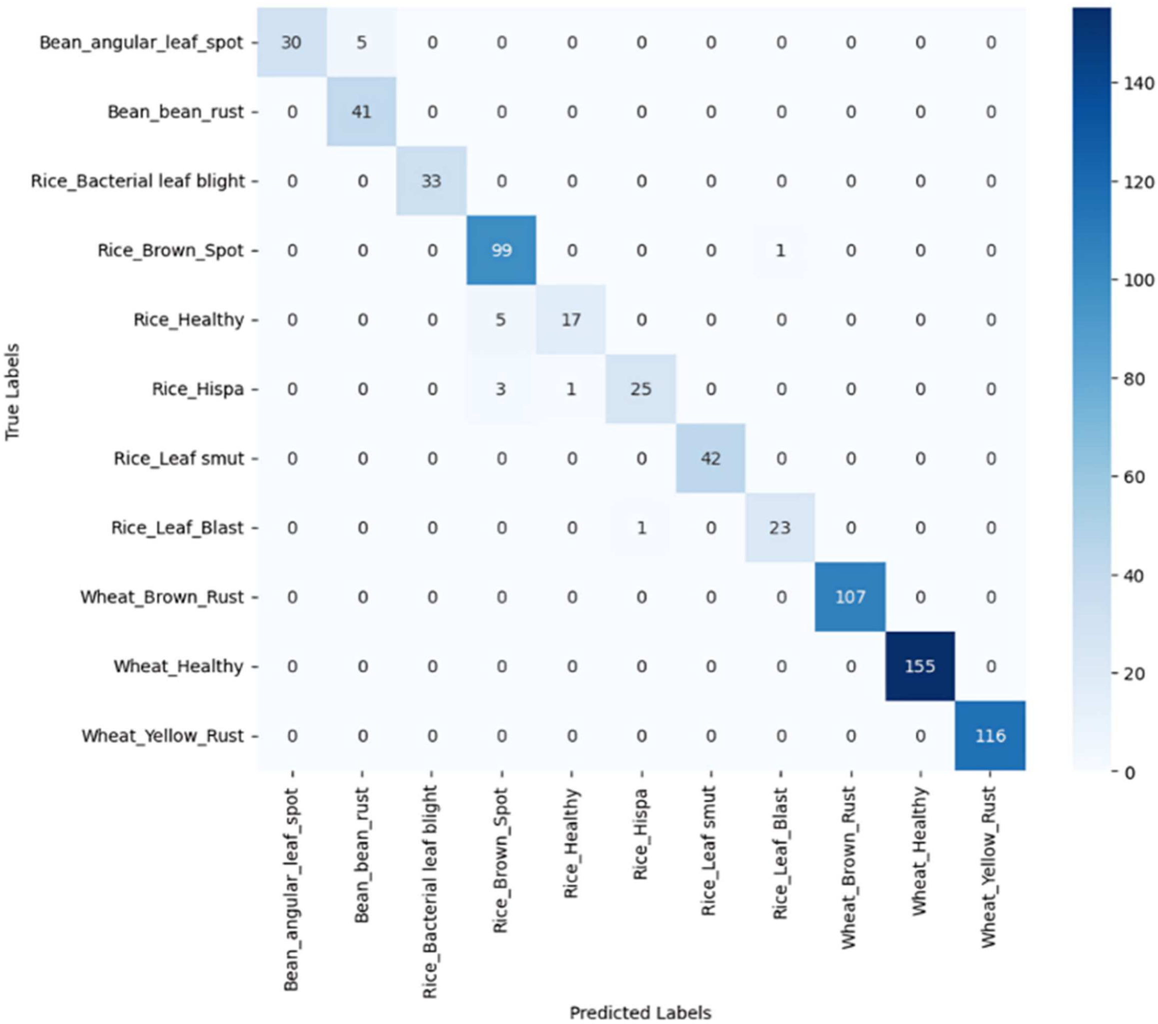


Table 6
Comparison with previous studies worked with a single crop

Refs.	Model/approach	Crop type	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Parameters (M)	Dataset size
Ahmed et al. [2]	Decision Tree	Rice	97.91	97.50	97.30	97.40	0.01	1000
Mallick et al. [3]	CNN (custom)	Mung Bean	93.65	93.50	93.70	93.60	2.0	1500
Islam et al. [6]	Inception-ResNet-V2	Rice	92.68	92.50	92.70	92.60	55.8	2500
Mathulaprangsan et al. [7]	DenseNet	Rice	95.00	94.80	95.20	95.00	8.0	3000
Poovidha et al. [9]	Image processing	Leaves	92.4	–	–	–	–	–
Elfatimi et al. [11]	MobileNetV2	Bean	92.00	91.80	92.10	91.95	3.5	1200
Zhang et al. [25]	EfficientNet-B4	Cucumber	97.0	–	–	–	~19M*	–
Chen et al. [26]	Improved MobileNetV2	Agriculture products	96.20	95.90	96.00	96.46	3.4	Fruit-360
Proposed	MobileNetV2	Multi-crop	97.87	97.50	97.60	97.55	3.5	7037

average accuracy rate of roughly 97.87% during the testing phase, following its training, across the spectrum of 11 separate categories, spanning multiple dataset partitions. This level of accuracy shows the model's capability to classify the mentioned plant leaf diseases, indicating the model's usability in real-world problems.

In Figure 9, there are some misclassifications in the confusion matrix. For example, in the first row, five occurrences of Bean_angular_leaf_spot were incorrectly shown as Bean_bean_rust. In the fourth row, one indication of Rice_Brown_Spot was incorrectly classified as Rice_Leaf_Blast. Similarly, false classifications have occurred in other disease classes. These misclassifications may be due to several factors including visual similarities between classes, poor lighting and image quality, and background noise in the images.

Using test datasets, the MobileNetV2 model achieves a high accuracy rate of 97.87% for disease classification, demonstrating impressive effectiveness in identifying crop illnesses. This accuracy performs better than the findings of several earlier research conducted to classify a single crop or plant disease detection. A thorough comparison between our study and other prior studies is given in Table 6, and the suggested MobileNetV2 model outperforms earlier single-crop studies with a testing accuracy of 97.87%. Because of its lightweight architecture (3.5M parameters vs. 55.8M for Inception-ResNet-V2), the proposed model outperforms Inception-ResNet-V2 (92.68%) and DenseNet (95.00%), making it appropriate for mobile deployment in resource-constrained environments such as rural Bangladesh. Furthermore, unlike single-crop models, the multi-crop approach generalizes to rice, wheat, and beans, increasing its usefulness for farmers.

MobileNetV2 was chosen due to its efficiency on mobile devices and low computational complexity (3.5M parameters), which is in line with the objective of implementing the model for farmers in Bangladesh to use in real time. Compared to MobileNetV2, EfficientNet-B4 is less practical for resource-constrained environments due to its ~19M parameters, despite its high accuracy of 97.0%. Thus, the experimental models outperformed the study that examined the detection of diseases for a single-crop disease classification. The model has the potential to be a useful tool for enhancing crop disease management, which would increase agricultural productivity.

5. Conclusions

In this study, a MobileNetV2 model utilizing transfer learning was successfully used to classify diseases of multiple crops rather than a single crop. The three important crops that were the subject of the study were rice, wheat, and beans. A 97.87% accuracy in classifying multiple crop leaf diseases was achieved, which outperforms most of the previous studies for single-crop disease classification. Due to the lightweight nature of MobileNetV2, it can be deployed on smartphones and tablets, allowing farmers access to real-time disease diagnosis through smartphone apps. In areas with limited resources, this scalability increases the model's potential to enhance crop management and food security. The real-life application of this study would be easier with its integration of multiple crop disease classification capabilities rather than a single-crop disease with higher accuracy. Despite research advancements, there are still limitations. The accuracy of the leaf disease recognition system is impacted by factors like lighting and camera-resolution constraints; therefore, image quality is essential. The study's narrow scope is due to its emphasis on particular crops (rice, wheat, and beans). There are issues with data collection, annotation, and model flexibility when adding more crops. Performance is impacted by data variety, including regional variances of leaves and other environmental influences. Future studies will focus on overcoming the constraints and increasing the research's extent.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in the Bangladeshi Crops Disease Dataset at https://www.kaggle.com/datasets/nafishamoin/bangladeshi-crops-disease-dataset and the Bean Disease Dataset at https://www.kaggle.com/datasets/therealoise/bean-disease-dataset.

Author Contribution Statement

Md. Mahmudul Hasan: Conceptualization, Methodology, Visualization, Supervision. **Md. Omar Faruq:** Software, Validation, Writing – original draft. **Mahadi Hasan Musa:** Formal analysis, Investigation. **Mohammad Mamunur Rashid:** Resources, Data curation, Writing – review & editing. **Khandaker Mohammad Mohi Uddin:** Writing – review & editing, Project administration, Supervision.

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