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Deep transfer learning based disease detection and classification of tomato leaves - a comparative analysis

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ABSTRACT

A wide variety of diseases have a significant impact on tomato plants. To avoid crop quality issues, a prompt and precise diagnosis is crucial. Classifying plant diseases is one of the numerous applications where deep transfer learning models have recently produced remarkable results. This study dealt with fine-tuning by contrasting the most advanced architectures, including Inception V3, ResNet-18, ResNet-50, VGG-16, VGG-19, GoogLeNet, and AlexNet. In the end, a comparison evaluation is conducted. Nine distinct tomato disease classes and one healthy class from PlantVillage make up the dataset used in this study. Precision, recall, F1-score, and accuracy were the basis for a multiclass statistical analysis that assessed the models. The ResNet-50 approach yielded significant results with precision: 82%, recall: 81%, F1-score: 81%, and accuracy: 85%. With this high success rate, it is reasonable to say that mobile applications or IoT-compatible gadgets implemented with the ResNet-50 model can assist farmers in identifying and safeguarding tomatoes against the aforementioned diseases.

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1. INTRODUCTION

One of the most significant and widely consumed vegetables in Bangladesh is the tomato (*Solanum lycopersicum*). It has antioxidant components including lycopene, which protects cancer, and is a strong source of vitamins A and C [1]. It comes in third place in terms of area and fourth in terms of production [2]. Since diseases have a significant impact on healthy plants and cause significant losses in the agricultural sector, it is necessary to protect them from disease in order to ensure the quality and quantity of crops. Diseases caused about 12.45% of tomatoes to be lost at the farm level after harvest, with 8.86% of those losses being due to full destruction, according to a study was out in the districts of Jamalpur and Rangpur of Bangladesh [3]. This means that for every decimal of tomato cultivation, Bangladeshi Taka (BDT) 152.45 is lost. Therefore, it should be emphasized that early monitoring is crucial for selecting the best course of action and halting the spread of the diseases in both tomatoes and plants of the tomatoes. However, in order to control disease, farmers can hardly afford to keep a close eye on their tomato crops. Given the difficulty of acquiring agricultural knowledge in remote areas due to limited access to such expertise, manual monitoring is time-consuming and labor-intensive. For these reasons, individual farmers find it difficult to promptly diagnose and treat diseases in order to ensure the best possible quality. In the past, all diseases and problems were identified by visual examination by skilled people who might have aided their analysis with features like color, texture, and shape. But low efficiency and excessive expenses were the outcomes of this strategy. This study considers these problems as challenges and attempts to use deep transfer learning techniques to propose a technical solution.

The performance of various deep transfer learning architectures is compared in this study to help choose an automated system that allows its applications to be expanded in the agricultural domain. The main achievement of this study is a comprehensive summary of the workings of each deep transfer learning technique, in addition to applying each model in a database made up of a number of photos related to unhealthy and healthy tomato leaves. For possible future applications, this enables an unbiased comparison of the behavior of the several deep learning based transfer learning models. Finding the architecture that effectively captures the issue, successfully classifies tomato plant illnesses, and validates it using a range of statistical measures is the purpose. Agricultural technicians and specialists may find the deep transfer learning models useful as an automated system for identifying plant illnesses. Farmers can provide suited treatments, cut down on needless pesticide use, increase crop yields, and save production expenses by employing this architecture. The following are the study’s main contributions:

- To accurately identify and categorize diseases of tomato leaves.
- To compare deep transfer learning-based approaches for detecting and classifying tomato leaf diseases.
- To determine the most effective deep transfer learning model for identifying tomato leaf diseases.

To ensure a respectable crop output, numerous researchers have concentrated on deep transfer learning-based systems to automate tasks in the agriculture industry, including field monitoring, plant disease diagnostics, and prediction. Thangaraj *et al.* [4] investigated a deep convolutional neural network (CNN) model based on transfer learning to identify tomato leaf disease. The model detects illness in tomato plants by using both real-time and stored pictures. Furthermore, root mean square propagation (RMSprop) optimizers, stochastic gradient descent (SGD), and adaptive moment estimation (Adam) are employed to evaluate the performance of the proposed model. The experiment’s findings demonstrate that the proposed model, which makes use of the transfer learning technique, can successfully classify tomato leaf diseases automatically. The accuracy of the Adam optimizer is higher than that of SGD and RMSprop. Attallah [5] presented a method for the automatic detection of tomato diseases from leaf images using three different CNNs (ResNet-18, ShuffleNet, and MobileNet). Naive Bayes (NB), K-nearest neighbor (KNN), decision tree (DT), linear discriminant classifier (LDA), support vector machine (SVM), and quadratic discriminant analysis (QDA) are the six classifiers used in tomato leaf disease identification. The results demonstrate that the KNN and SVM obtained the highest accuracy of 99.92% and 99.90%, respectively, using only 22 and 24 features. Khasawneh *et al.* [6] conducted an update and retraining of eleven deep learning models to identify nine types of tomato diseases along with healthy plants. The resulting ten classes were characterized with mean values of 99.4%, 99.2%, 99.1%, and 99.3% for accuracy, F1-score, recall, and precision, respectively. Sanida *et al.* [7] suggested a VGGNet-based model that consists of two inception blocks and ImageNet pre-trained on it. Additionally, the model training process was extended to include the enhanced categorical cross-entropy loss function for the multi-attribute identification problem and two-stage transfer learning. Abbas *et al.* [8] demonstrated a deep learning–based method for diagnosing tomato diseases by generating synthetic images of tomato leaves using a conditional generative adversarial network (C-GAN). A DenseNet121 model, which has been trained on both generated and real images using transfer learning, is then used to classify the tomato leaf photographs into ten disease categories. Alzahrani *et al.* [9] investigated the effectiveness of three deep learning–based models DenseNet169, ResNet50V2, and the transformer model ViT for the classification of healthy and diseased tomato plants. The best-performing model was the DenseNet121, which achieved testing accuracy of 99.00% and training accuracy of 99.88%.

Pattnaik *et al.* [10] have developed a deep CNN-based system for tomato plant pest classification that uses transfer learning of previously learned data. The study’s dataset, which consists of 859 photos divided into 10 classifications, was gathered from internet sources. A thorough assessment of the classification performance of 15 pre-trained deep CNN models is also carried out in this work. The experimental results showed that the DenseNet169 outperformed with accuracy 88.83%. Diseased leaves of two crops (grapes and tomatoes) were gathered and produced into a dataset for the study [11]. The CNN-based VGG16 model is subjected to training, testing, dataset pre-processing, and data augmentation procedures. Saeed *et al.* [12] have classified images of healthy and diseased tomato leaves using two pre-trained CNNs, Inception V3 and Inception ResNet V2, in order to diagnose tomato leaf illnesses. The two models were trained using 5225 field-recorded images and an open-source database named PlantVillage. With an accuracy of 99.22% and a loss of 0.03, the most noteworthy outcomes Inception V3 and Inception ResNet V2 models performed the best with dropout rates of 50% and 15% respectively. Hassan *et al.* [13]

employed four deep learning models, namely InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, for the identification of plant illnesses using images of healthy and diseased leaves. They trained and assessed the model using the 53,407 images- all shot in a lab- from the standard PlantVillage dataset. This collection contains images of 14 different species in 38 different classes of both healthy and diseased leaves. Agarwal *et al.* [14] employed a CNN-based approach for the identification of tomato leaf disease. With varying numbers of filters, this model consists of three convolution and max pooling layers.

The novelty of our study is the integration of deep transfer learning and occlusion sensitivity. This framework's interpretability and robustness are improved by including occlusion sensitivity, particularly in intricate agricultural environments where illness signs tend to be obscured or subtle.

2. METHOD

2.1. Proposed system

The study consisted of five modules: image acquisition, image pre-processing, segmentation, contaminated leaf identification, and disease categorization. The evaluation and comparison of classifiers are also performed in this study. Figure 1 shows the categorization scheme for tomato leaf diseases.

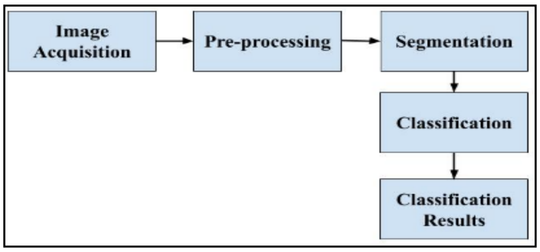


Figure 1. Categorization scheme for tomato leaf diseases

2.1.1. Image acquisition

Initially, tomato leaf images are obtained from the PlantVillage dataset for this study. In total, there are 18,160 tomato leaf images in this dataset [15]. This image dataset has ten classes and is separated into two parts: diseased (9 classes) and healthy (1 class). The sample images for each category are shown in Figures 2(a) to (j), where Figures 2(a) is healthy, (b) is bacterial spot, (c) is early blight, (d) is late blight, (e) is leaf mold, (f) is septoria leaf spot, (g) is spider mites (h) is target spot, (i) is tomato mosaic virus, and (j) is yellow leaf curl virus. The description of the dataset is shown in Table 1. The training dataset contains 80% of the acquired data, while the testing dataset for classification tasks contains the remaining 20%.

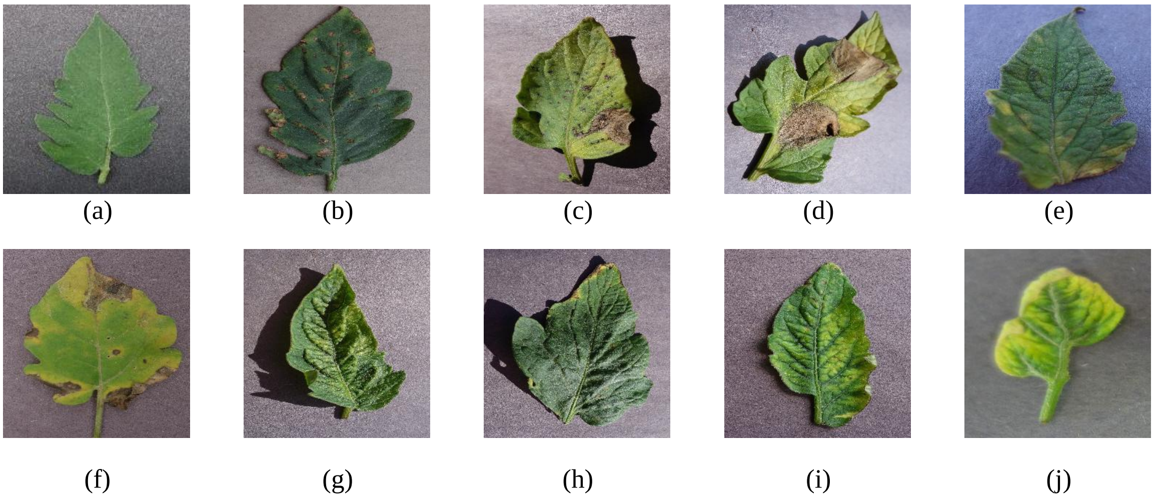


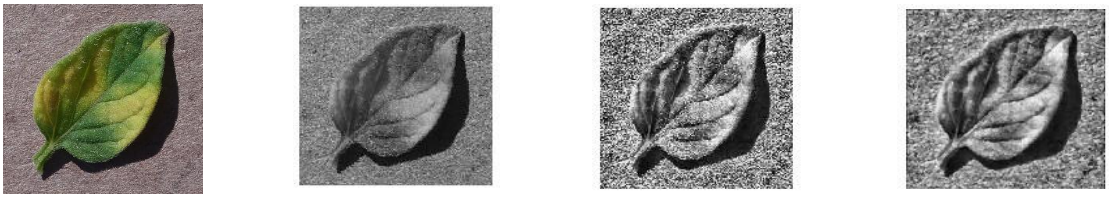
Figure 2. Sample images (upper row, from left to right); (a) healthy, (b) bacterial spot, (c) early blight, (d) late blight, (e) leaf mold, (f) septoria leaf spot, (g) spider mites (h) target spot, (i) tomato mosaic virus, and (j) yellow leaf curl virus

Table 1. Dataset description

Image type	Amount
Healthy	1,591
Bacterial spot	2,127
Early blight	1,000
Late blight	1,909
Leaf mold	952
Septoria leaf spot	1,771
Spider mites	1,676
Target spot	1,404
Tomato mosaic virus	373
Yellow leaf curl virus	5,357
Overall	**18,160**

2.1.2. Pre-processing

The input image is preprocessed by converting it from the red-green-blue (RGB) color space to a single-channel grayscale image in order to simplify calculation and make further analysis easier. In order to improve image contrast, this study uses adaptive histogram equalization (AHE) and median filtering. In image pre-processing, AHE and median filter can offer a number of advantages that improve image quality for subsequent analysis. When combined, they provide a potent method for local contrast enhancement and noise reduction, guaranteeing that the image is clear and contains distinct features, which makes it better suited for further processing tasks like segmentation and image classification. Figure 3 shows the original image and pre-processed images, where Figures 3(a) is original image, (b) is RGB to gray image, (c) is AHE image, and (d) is AHE + median filter image.



(a) (b) (c) (d)

Figure 3. The original image and pre-processed images; (a) original image, (b) RGB to gray image, (c) AHE image, and (d) AHE + median filter image

2.1.3. Segmentation

In this study, occlusion sensitivity is employed as a segmentation technique. A perturbation-based interpretability technique called occlusion sensitivity is used to determine which areas of an input image have the most impact on a deep neural network's classification decision. Using this method, various areas of the input image are covered with an occlusion mask, and the change in the model's output score is recorded. This approach produces a sensitivity map that shows which parts of the image are most important for classification. The definition of the occlusion sensitivity map is as (1):

$$\emptyset_i = C_s(z) - C_s\left(z_{[z_i=\bar{z}]}\right) \tag{1}$$

where, C_s is the unnormalized class score, z_i is the replacement of one feature with baseline $\bar{z}$ [16]. Figure 4 shows the sample occlusion sensitivity map.

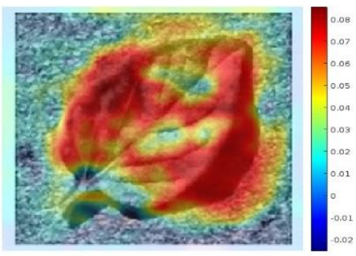


Figure 4. Sample occlusion sensitivity map

2.1.4. Deep transfer learning classification methods

The diseases of tomato leaves are categorized in this study using seven deep transfer learning classification techniques. These seven categorization techniques include Inception V3, ResNet-18, ResNet-50, VGG-16, VGG-19, GoogLeNet, and AlexNet. The fully connected layer and the final classification layer are adjusted to match the target task's class structure after the pre-trained models have been loaded. The input images are resized before classification to make sure it complied with the classifier model's input dimensionality requirements. Details of the input image size in accordance with the model's specifications are displayed in Table 2.

Table 2. Details of the input image size in accordance with the model's specifications

Model	Input image size
Inception V3	299*299
ResNet-18	224*224
ResNet-50	224*224
VGG-16	224*224
VGG-19	224*224
GoogLeNet	224*224
AlexNet	227*227

a. Inception V3: the ImageNet dataset contains more than a million images that have been used to train Inception V3 [17], a 48-layer CNN. The 1,000 object categories that this network can classify photographs into contain a wide variety of objects, including pencils, mouse, keyboards, and animals. Rich feature representations that may be applied to a broad range of images have thus been learned. In the first stage, the model architecture concentrates on extracting generic features from the input photos, and in the second stage, the features are used for image categorization. Inception V3 has 29.3 million parameters in total.
b. ResNet-18: sixteen convolutional layers and two fully connected layers make up the 18-layer CNN known as ResNet-18 [18]. The network was pre-trained using more than a million photos from the ImageNet dataset. Animals, keyboards, mice, pens, and a variety of other objects may all be classified into 1000 object categories by the pretrained model. The network has thus acquired extensive feature representations that may be used to a wide range of pictures.
c. ResNet-50: ResNet-50 [18] is a 50-layer deep CNN. The four main parts of the ResNet-50 architecture are the convolutional layers, identity block, convolutional block, and fully connected layers. The convolutional layers capture features from the input image, the identity block and convolutional block process and transform those features, and the fully connected layers classify the features. For a wide range of image classification tasks, such as object detection, medical image analysis, and facial recognition, ResNet-50 is a powerful model. It was trained on the extensive ImageNet dataset and achieved an error rate comparable to human performance. It has also been applied as a feature extractor for other applications, like semantic segmentation and object detection.
d. VGG-16: thirteen convolutional layers and three fully connected layers make up the 16-layer deep CNN known as VGG-16 [19]. It works well because of its remarkable depth. VGG-16 is renowned for its ease of use, effectiveness, and exceptional performance on a variety of computer vision applications, such as image categorization and object recognition. The model architecture is made up of max-pooling layers after a sequence of convolutional layers with gradually deeper layers. The network can learn intricate hierarchical representations of visual features because of this design, producing predictions that are precise and dependable.
e. VGG-19: the VGG-19 [19] is a deep CNN of 19 weight layers, 16 convolutional layers, and 3 fully connected layers. The VGG-19 model (also known as VGGNet-19) is similar to the VGG-16 model in its basic idea, except that it supports 19 layers.
f. GoogLeNet: with over seven million parameters GoogLeNet [20], has nine inception modules, four convolutional layers, four max-pooling layers, three average pooling layers, five fully connected layers, and three SoftMax layers for the principal and auxiliary classifiers. Each convolutional layer in the network uses ReLU activation functions, and the fully linked layers use dropout regularization. GoogLeNet's effective trade-off between computational cost and parameter count makes it ideal for real-time applications and deployment on devices with limited resources.
g. AlexNet: AlexNet [21] has eight layers in its design, the last three of which are fully connected, and the first five of which are convolutional layers. After the first two convolutional layers, overlapping max-pooling layers are applied to optimize feature extraction. The third, fourth, and fifth convolutional layers' outputs are directly connected to the fully connected layers. Every output transmitted through a ReLU non-linear activation function comes from the convolutional and fully connected layers. When

paired with a SoftMax activation function, the final output layer creates a probability distribution across 1000 class labels.

3. RESULTS AND DISCUSSION

This study evaluated the most advanced pre-trained transfer learning classification models for the task of classifying diseases from the images dataset of tomato crop. Four different assessment criteria are used to regulate the performance of these models: precision, recall, F1-score, and accuracy. These four metrics are determined by (2)-(5):

$$PS = \frac{TP}{FP + TP} \tag{2}$$

$$RCA = \frac{TP}{FN + TP} \tag{3}$$

$$F1 - S = 2 * \frac{PS * RCA}{PS + RCA} \tag{4}$$

$$ACC = \frac{TN + TP}{FP + TP + FN + TN} \tag{5}$$

where, the symbols for false positives, true positives, false negatives, and true negatives are viewed with the short terms false positive (FP), true positive (TP), false negative (FN), and true negative (TN), respectively.

The various classification outcomes of seven deep transfer learning classifiers are displayed in Table 3. We use the “round half up” rule to calculate the average precision, recall, F1-score, and accuracy.

Table 3. Findings for the evaluated deep transfer learning algorithms

Model	Precision	Recall	F1-score	Accuracy
Inception V3	0.70	0.71	0.70	0.77
ResNet-18	0.71	0.72	0.72	0.77
ResNet-50	**0.82**	**0.81**	**0.81**	**0.85**
VGG-16	0.76	0.77	0.76	0.81
VGG-19	0.75	0.78	0.76	0.81
GoogLeNet	0.67	0.68	0.61	0.74
AlexNet	0.76	0.77	0.76	0.81

ResNet-50 yields the highest average precision (PS), recall (RCA), F1-score (F1-S), and accuracy (ACC), with values of 0.82, 0.81, 0.81, and 0.85, respectively, while GoogLeNet yields the lowest average precision, recall, F1-score, and accuracy, with values of 0.67, 0.68, 0.61, and 0.74, respectively.

Table 4 displays the confusion matrix of ResNet-50, the model that produced the best results according to the performance metrics. Table 5 displays the results of the ResNet-50 model used to determine the performance metrics for each class. Figure 5 shows the precision recall (PR) curve of ResNet-50.

Table 4. Confusion matrix of ResNet-50 model

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**389**	6	0	2	2	9	0	0	0	24
2	8	**124**	0	29	9	10	6	4	0	7
3	0	2	**305**	1	2	3	3	10	0	0
4	7	28	0	**309**	13	15	1	8	1	10
5	1	10	1	9	**142**	8	3	7	4	5
6	9	4	3	15	7	**294**	8	19	4	4
7	2	3	4	0	4	5	**261**	31	2	8
8	0	4	5	8	2	10	39	**196**	0	8
9	0	0	0	1	3	0	3	1	**63**	2
10	9	19	0	8	6	0	11	5	1	**1003**

Note: (1) bacterial spot, (2) early blight, (3) healthy, (4) late blight, (5) leaf mold, (6) septoria leaf spot, (7) spider mites (8) target spot, (9) tomato mosaic virus, and (10) yellow leaf curl virus

Table 5. ResNet-50 model's performance

Image type	Precision	Recall	F1-score	Average accuracy
Bacterial spot	0.92	0.90	0.90	0.85
Early blight	0.62	0.63	0.62	
Healthy	0.96	0.94	0.95	
Late blight	0.81	0.79	0.80	
Leaf mold	0.75	0.75	0.75	
Septoria leaf spot	0.83	0.80	0.81	
Spider mites	0.78	0.82	0.80	
Target spot	0.70	0.72	0.71	
Tomato mosaic virus	0.84	0.86	0.85	
Yellow leaf curl virus	0.94	0.94	0.94	

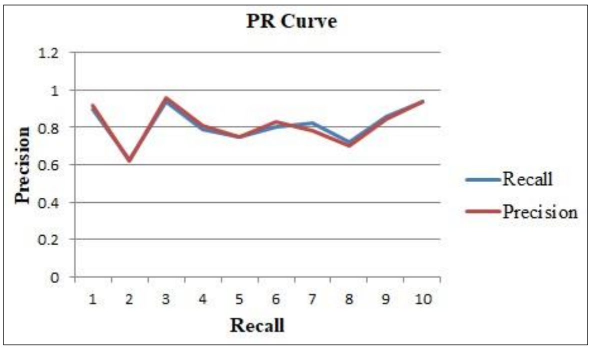


Figure 5. PR curve of ResNet-50

Several researchers have already advanced the field of plant disease identification through the use of image processing. To illustrate the effectiveness of our study, we conducted a comparative analysis with other pertinent research papers, as indicated in Table 6. Ayu *et al.* [22] used the MobileNetV2 approach to detect cassava leaf diseases with an accuracy rating of 65.6%. Gadade *et al.* [23] employed SVM, KNN, NB, and DT to identify tomato leaf diseases. With 73% accuracy, the Gabor features combined with SVM classification provide superior performance. Using a CNN, Ramcharan *et al.* [24] detected cassava leaf diseases with 80.6% classification accuracy on pictures and 70.4% accuracy on video. In order to detect pests in tomato leaves, Gutierrez *et al.* [25] employed KNN, multilayer perceptron (MLP), faster region-based convolutional neural network (R-CNN), and single shot detector (SSD). Among our applied models, ResNet-50 performed better than earlier studies, with the highest accuracy rate of 85%. In this work, the use of ResNet-50 for tomato leaf disease detection and classification results in high precision, recall, F1-score, and accuracy. These results suggest that the developed method may be used in agricultural settings to track and identify diseases early on.

Table 6. Comparison of various plant disease classification techniques

References	Applied technique (s)	Plant disease	Classification accuracy (%)
Ayu *et al.* [22]	MobileNetV2	Cassava	65.6
Gadade *et al.* [23]	SVM, KNN, Naive Bayes, and DT	Tomato	73 (SVM)
Ramcharan *et al.* [24]	CNN	Cassava	80.6 on images and 70.4 on video
Gutierrez *et al.* [25]	KNN, MLP, Faster R-CNN, and SSD	Tomato	82.51 (Faster R-CNN)
This study	Inception V3, ResNet-18, ResNet-50, VGG-16, VGG-19, GoogLeNet, and AlexNet	Tomato	85 (ResNet-50)

4. CONCLUSION

Disease assaults have an impact on tomato plant quality and amount. This study's objective is to identify the most effective deep transfer learning classification model for tomato leaf disease identification. Inception V3, ResNet-18, ResNet-50, VGG-16, VGG-19, GoogLeNet, and AlexNet are the seven deep learning transfer learning techniques that we assessed in this study. Given the dataset and classification job, the ResNet-50 outperformed the other tested algorithms with a precision of 82%, recall of 81%, F1-score of 81%, and accuracy of 85% meeting the accuracy requirements of disease classification. Nonetheless, GoogLeNet yielded the least efficient performance in comparison to the other layouts. ResNet-50 can be integrated into mobile applications or IoT-compatible devices to facilitate real-time illness identification for farmers. Additionally, the approach can be scaled to support other crops of same family and background variations by retraining the model with diverse agricultural datasets. Such implementations could play a vital role in precision agriculture and help reduce crop losses. However, the dataset used in this work is imbalanced, which may lead the classifier to perform poorly on rare diseases and favor the majority classifications. To verify categorization results, a cross-validation technique will be added to image processing in the future.

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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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Iffat Ara Badhan					✓	✓		✓	✓	✓	✓			
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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

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [MS], upon reasonable request.

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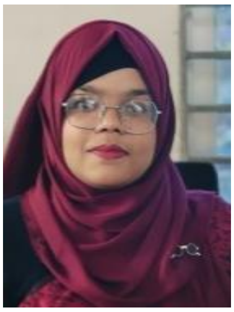

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