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# An automated approach for eggplant disease recognition using transfer learning

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**ABSTRACT**

In Bangladesh, eggplant is a widely grown crop that is vital to the country's food security. The vegetable is consumed on a regular basis by the majority of people. Since Bangladesh's economy is heavily reliant on agriculture, eggplant growing might help the country's economy and productivity flourish more efficiently. It provides several health benefits, including reducing cancer risk, blood sugar control, heart health, eye health, and others. Although eggplant is a valuable crop, it is subject to severe diseases that reduce its productivity. It's hard to detect those diseases manually and needs a lot of time and hard work. So, we introduce an agricultural and medical expert system based on machine vision that analyzes a picture acquired with a smartphone or portable device and classifies diseases to assist farmers in resolving the issue. We studied and used a convolutional neural network (CNN)-based transfer learning approach for identifying eggplant diseases in this paper. We have used various transfer learning models such as DenseNet201, Xception, and ResNet152V2. DenseNet201 had the highest accuracy of these models with 99.06%.



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## 1. INTRODUCTION

Bangladesh is mainly an agricultural country. Varieties of crops grow abundantly in this country, thanks to its excellent soil and pleasant climate. In fiscal year (FY) 2019-2020, the agriculture sector contributes around 13.02 percent to the country's gross domestic product (GDP) and employs around 40.60% of the entire labor force [1]. Agriculture is a means of livelihood for 84 percent of Bangladesh's rural people, who rely on it either directly or indirectly [2]. Approximately 50% of Bangladesh's workforce is employed in agriculture, which occupies more than 70% of the nation's land. Among the most important crops produced are rice, jute, wheat, tea, legumes, oil seeds, vegetables, and fruits [3]. Since Bangladesh is a very populous country, ensuring long-term food security demands an agricultural system that is both sustainable, profitable, and ecologically friendly. As a result, the current government has placed the agricultural sector at the top of its priority list in order to ensure Bangladesh's food security. Agriculture production is falling, and its contribution to overall national GDP is falling even faster. Bangladesh's agricultural growth is declining due to a number of factors, including pressure on agricultural land, the rapid rate of population increase, and global warming. A decline in agricultural productivity and a rise in food insecurity have a positive relationship. Bangladesh had self-sufficiency in food production in FY 1999-2000 as compared to its population proportion. Agricultural productivity is dropping year after year as a result of climate change. As a result, it limits the amount of food available in the market to meet market demand. Since the last decade, the government has been importing food from other countries to meet demand. The government of Bangladesh is currently facing serious difficulty in securing food for all [4].

About 50,000 hectares of land in Bangladesh are used to grow eggplant, making it the third most important crop in the country [5]. And with a production of 341000 tons (Bangladesh Bureau of Statistics (BBS), 2010), providing for around 25.4% of the country's total vegetable area. It is grown all over the area in Bangladesh, in all climates and seasons [6]. It has numerous health benefits, including better heart health, digestion, cancer prevention, bone health, anemia prevention, and increased brain function [7]. Vitamins A and C, two antioxidants found in eggplant, which protect our cells health. Polyphenols, a naturally occurring plant component, are also abundant in it, and they may aid diabetic cells in processing sugar more effectively [8]. The physical method of identifying these diseases is slow and difficult. However, using an automated approach is simple and accurate. As a result, we are using an automated method to assist farmers in identifying diseases before their cultivation, which saves time and money.

This study explores the use of computer vision technology along with convolutional neural network (CNN)-based transfer learning to efficiently identify eggplant diseases-aphids, eggplant shoot and fruit borer, cercospora, flea beetle, fruit rot, leaf curl, leaf roller, leafhopper, mealybug, healthy fruit, healthy leaf, powdery mildew, spider mite, spotted beetle, thrips, whitefly. As technology has developed, some researchers have continued to focus on the identification and detection of crop diseases in the agricultural industry. This problem has been resolved by the CNN, artificial neural network (ANN), transfer learning (TL) and support vector machine (SVM) approaches. This article will go through the many detection methods used to find diseases in different crops like eggplant.

Aravind *et al.* [9] suggested utilizing AlexNet and VGG-16 to classify eggplant diseases. Five diseases and healthy plants are categorized using photographs taken from a smartphone. They were successful in achieving a 93.33% accuracy rate by modifying the VGG-16 model. In another research Aravind *et al.* [10] classified eggplant diseases using a pre-trained model. To classify eggplant diseases, they used modified support vector machine (MSVM) and pre-trained VGG16 as the feature extractor. They used different color spaces (RGB, HVS, YCbCr, and grayscale) to evaluate performance and get the highest classification accuracy of 99.4% using RGB images. C Xie *et al.* [11] research about early blight disease of eggplant leaves with the spectrum and texture features. They classified models using K-nearest neighbor (KNN) and AdaBoost and got 88.46% accuracy. In their work, they cover wavelengths to get hyperspectral pictures. Following that, they identified gray pictures based on the effective wavelengths. After that, they extracted texture characteristics from grayscale and hyperspectral pictures using gray level co-occurrence matrix (GLCM). Sabrol and Kumar [12] they have described different types of diseases of tomato and eggplant. In this study they have used neuro-fuzzy classifier for classification. This classifier combines fuzzy logic and neural networks. They used pure grayscale image for analysis and achieved overall accuracy 90.7% for tomato and 98% for brinjal which is quite excellent. Anand *et al.* [13] research about image processing technique with k-means clustering method for identifying Brinjal leaves disease. To improve image quality before clustering, the authors used histogram equalization. To extract the colors and texture features, the color co-occurrence method (CCM method) was implemented. The features have been trained using the k-means clustering technique, using three clusters: infected object, infected leaf and the black background of leaf. To detect eggplant disease Jake [14] used image processing techniques. He used feature extraction to get the prominent features of diseased leaves and fruits. Individual pixels of a color image were broken into RGB values. He performed the MobileNetV2 model to classify different diseases in leaves and fruits. Wu *et al.* [15] used a hyperspectral visible near-infrared (VNIR) spectroradiometer to investigate the reflectance intensities of both healthy and Botrytis Cinerea-infected leaves of eggplants. With the help of a principal component analysis and a back-propagating neural network (NN). trained on the collected data, the authors were able to detect fungal disease 85% of the time before symptoms occurred. Based on information gathered in a controlled setting with little ambient illumination, the findings were generated. It is possible to identify more early with these VNIR techniques, but they are difficult and expensive for automated imaging applications. With considerable success, the technique of spectral angle mapping (SAM), which compares reference and observed spectra by figuring out their angular differences when handled as n-dimensional vectors, has also been used to find disease spread in plants. For cucumber disease identification, Mia *et al.* [16] introduced two alternative approaches: CNN based transfer learning and traditional machine learning (ML). They applied k-means clustering to split the image by color and label each pixel, and they used GLCM to extract texture and statistical features for disease identification. Using a random forest classifier in machine learning, they were able to achieve an accuracy of 89.93%. They also proposed utilizing InceptionV3, MobileNetV2, and VGG16 to classify cucumber disease, with results of 89.69%, 93.23%, and 90.75%, respectively. Rahman *et al.* [17] proposed using CNN to identify pigeon breeds. The authors tested and analyzed classification performance using a baseline model. When testing and validation were conducted, the baseline model achieved an accuracy of 96.19 percent and 95.33 percent, respectively, despite only having four convolutional layers. Mia *et al.* [18] has classified five categories of herbs Betel, Mehndi, Basil, Aloe Vera and Mint. In this paper, the authors have used a NN model using YOLO for herb leaves classification and they got 95% accuracy which is impressive when compared to other similar studies. Maria *et al.* [19] has proposed many techniques for identifying diseases that affect cauliflower plants. The authors compare transfer learning with traditional machine learning in this paper. A segmentation called k-means clustering is utilized to find disease-affected regions of cauliflower pictures, as well as ten relevant features, which are extracted. They apply a variety of classification methods, including the random forest algorithm, to achieve an overall accuracy of 81.68 percent. They have also used different types of CNN-based models with transfer learning and they got 90.08 percent accuracy from InceptionV3 which is the highest accuracy among these two approaches. For an in-depth exploration of automated jackfruit disease recognition, Mia *et al.* [20] suggest a system. The disease-infected region was divided to extract the characteristics using a k-means clustering segmentation approach. With 480 jackfruit photos and nine important classifiers, random forest emerged as the top performer with an accuracy rate of 89.59%. Parul *et al.* [21] explored potential approaches for automated disease detection in plants using image segmentation. The authors analyzed two models, S-CNN and F-CNN for independent data. To do this, CNN models were trained using segmented visual data. The S-CNN and F-CNN models were compared on the basis of accuracy and data. When compared to the S-CNN model and F-CNN model, the S-CNN model gives the best accuracy of 98.6% when trained on segmental images. An automated system to detect cotton leaf spot diseases was described by Revathi *et al.* [22]. In this method, images of cotton leaves are captured and kept as image features in a database. The authors extracted characteristics including shape, color and texture using the skew divergence approach. The extracted feature should then be chosen using particle swarm optimization (PSO), an effective feature selection technique. In this study, they classify diseases using the cross information gain deep forward neural network (CIGDFNN) classifier. This approach improves the system's accuracy and mistake rate while assisting in the identification of cotton leaves with infected leaf spots. Jafari *et al.* [23] describe the ability of thermal imaging to detect pre-symptomatic rose powdery mildew and gray-mold diseases. The selection of superior thermal characteristics with linguistic hedge values was done for the purpose of classifying healthy and infected plants. Two neuro-fuzzy classifiers are used by them for classification. According to this study, the best detection rates for powdery mildew and gray mold illnesses were 69% and 80%, respectively, on the second day after vaccination. In sugar beet, Zhou *et al.* [24] proposed an automated system for detecting Cercospora Leaf spot. The author has suggested using a robust template matching approach to identify diseases. For disease identification, they used the orientation code matching (OCM) technique. For pixel-wise disease identification, an accuracy of 87% has been achieved using a two-dimensional color histogram and a SVM method.

## 2. RESEARCH METHOD

We have divided this part into three sub-items. In the beginning, data description and augmentation, system overview, and then CNN-based transfer learning. Details of these sub-items are enumerated below.

### 2.1. Data description and augmentation

Serious eggplant diseases are mainly caused by funguses, mites, and insects. Some of these diseases are in Figures 1(a) aphids, (b) eggplant shoot and fruit borer, (c) cercospora, (d) flea beetle, (e) fruit rot, (f) leaf curl, (g) leaf roller, (h) leafhopper, (i) mealybug, (j) powdery mildew, (k) spider mite, (l) spotted beetle, (m) thrips, (n) whitefly, healthy fruit, and healthy leaf. Figure 1 shows the example of image data for some common eggplant diseases.

Data augmentation helps machine learning models perform better and provide better outcomes by producing fresh, new data to add to training datasets. Large and varied datasets for machine learning models improve performance and accuracy. So, this happens with some slight modification to the existing train dataset. Some commonly used data augmentation is translations, rotations, scaling, shearing, flipping (vertical and horizontal), shifting, zooming, fill mode, etc. In our field of work, we used some of the data augmentations like scaling, shear, rotation, zooming, fill mode, and flipping. For rescaling, we used 1./255. We used 20% (0.2) in image datasets in the shear range. We used a random angle of 20 (0.2) degrees for rotation in image datasets. In zooming, we used 20% (0.2) in datasets. In fill mode, we set it to 'reflect.' Next, we used vertical and horizontal flipping in the image dataset. We have collected 2766 image data of eggplant. Among them, 80% of data was used for training purposes, and the rest of the 20% was used for test purposes.

### 2.2. System overview

Figure 2 shows the proposed approach for identifying eggplant diseases. The eggplant disease images must be sent to the expert system by the user to get the output result. After processing the given image, the system will apply CNN-based transfer learning techniques. The system will classify the name of the disease that will be delivered to the user device after evaluating the image with a validated and trained dataset.

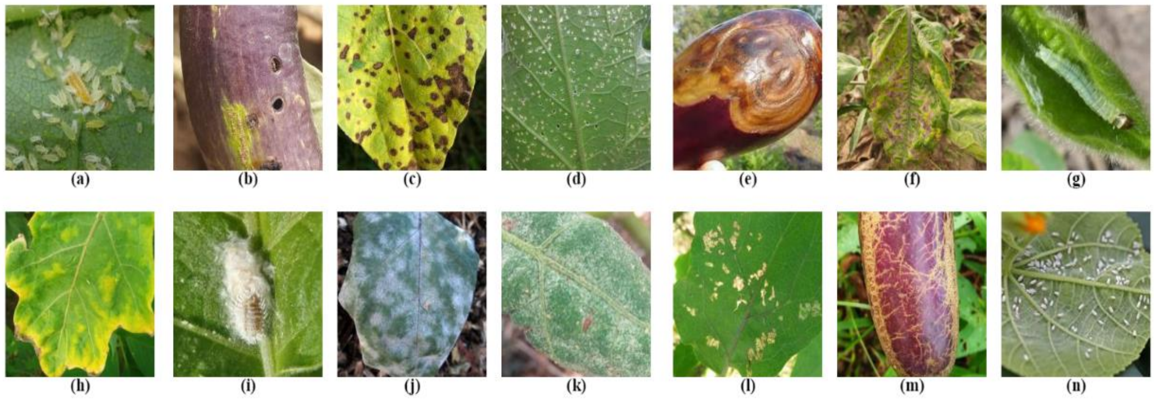


Figure 1. Common eggplant disease in Bangladesh, (a) aphids, (b) eggplant shoot and fruit borer, (c) cercospora, (d) flea beetle, (e) fruit rot, (f) leaf curl, (g) leaf roller, (h) leafhopper, (i) mealybug, (j) powdery mildew, (k) spider mite, (l) spotted beetle, (m) thrips, (n) whitefly

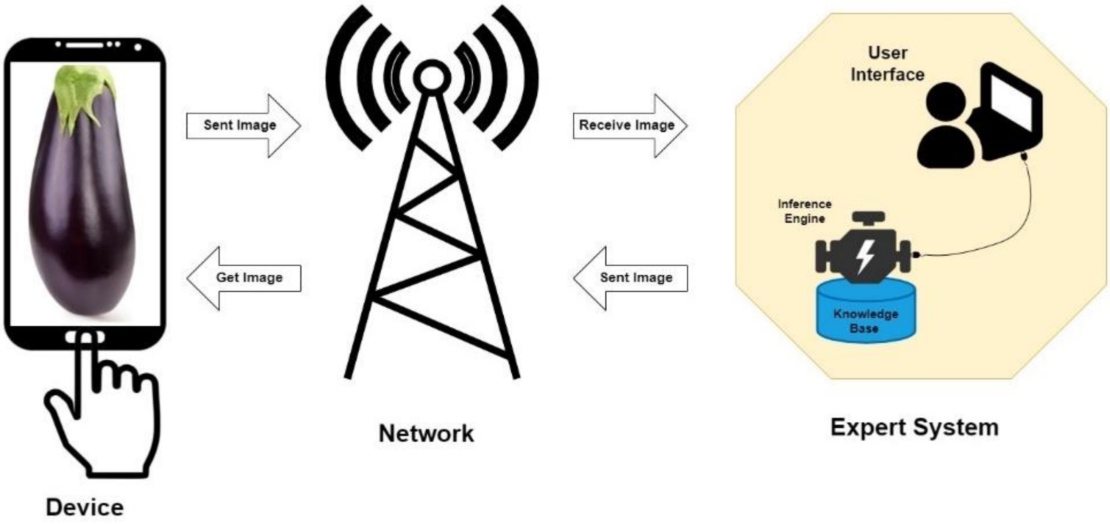


Figure 2. Proposed expert system to recognize eggplant disease

## 2.3. CNN based transfer learning

For disease identification in eggplant, we implemented transfer learning. Figure 3 represents a CNN-based transfer learning flow diagram for identifying eggplant disease. Transfer learning is the technique of reusing parts of a machine learning model that have already been trained in order to solve a new problem. In most cases, this is the model's core data, with optional elements added to address a particular issue [25]. Transfer learning has emerged as a revolutionary learning approach for plant disease identifications in recent years, demonstrating its efficiency in classification tasks. In transfer learning, there are many models to choose from, but for our research, we tested three pre-trained models and compared them. Our tested models are: DenseNet201, Xception, and ResNet152V2.

Our dataset was divided into two sets: testing dataset and training dataset. The training and testing datasets ratio was 80:20. We have worked with sixteen classes. Among these, fourteen classes consist of eggplant diseases, and two are healthy. As cross-entropy loss function works in the multi-class classification task, we also used this in our work for loss function.

In most cases, Adam is the best adaptive optimizer [26]. So, we used Adam optimizer with the default learning rate of 0.001. As an activation function, the softmax function is applied. Batch size of 16, epoch as 50, and pre-trained ImageNet weights are among the hyperparameters that have been configured to train. With an accuracy of 99.06%, DenseNet201 is the most accurate.

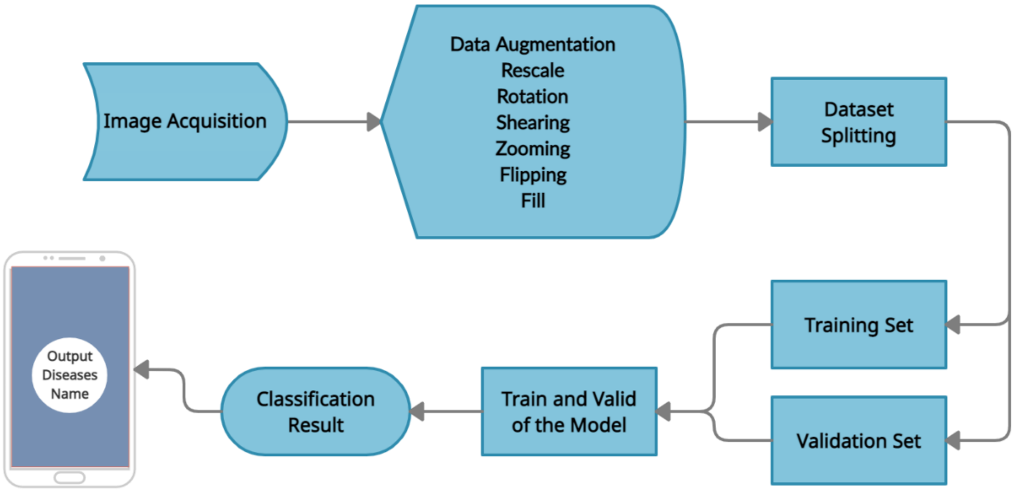


Figure 3. Flow chart of CNN-based transfer learning approach for eggplant disease recognition

## 3. RESULTS AND DISCUSSION

We divided the data into two groups called train and test with a specified ratio of 80:20 to start training our CNN-based transfer learning models. Data from the remaining 20% was utilized for testing, and the remaining 80% was used for training. After that, we utilized data augmentation for our train datasets. After data augmentation, we trained three of the chosen pre-trained models.

We compared the performance of different types of CNN-based transfer learning approaches using classification model performance metrics. Each of the models created a confusion matrix, which we analyzed. M, or the multiclass confusion matrix, an n×n square matrix with n columns and n rows and $n^2$ entries. Because we worked on sixteen classes, each model yields a 16×16 confusion matrix [27]. A multiclass confusion matrix performance evaluation matrix is shown. The following formula is used to figure out the percentages of accuracy, precision, specificity, sensitivity, false negative rate (FNR), and false positive rate (FPR).

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN} \times 100\%\right) \tag{1}$$

$$Precision = \left(\frac{TP}{FP + TP} \times 100\%\right) \tag{2}$$

$$Specificity = \left(\frac{TN}{FP + TN} \times 100\%\right) \tag{3}$$

$$Sensitivity = \left(\frac{TP}{TP + FN} \times 100\%\right) \tag{4}$$

$$FNR = \left(\frac{FN}{TP + FN} \times 100\%\right) \tag{5}$$

$$FPR = \left(\frac{FP}{FP + TN} \times 100\%\right) \tag{6}$$

For each of the models in Table 1, the resulting confusion matrix is provided below. Here, 'A' represents aphids, 'b' represents brinjal shoot and fruit borer, 'c' represents cercospora, 'd' represents flea beetle, 'e' represents fruit rot, 'f' represents leaf curl, 'g' represents leaf roller, 'h' represents leafhopper, 'i' represents mealybug, 'j' represents powdery mildew, 'm' represents spider mite, 'n' represents spotted beetle, 'o' represents thrips, and 'p' represents whitefly.

Using the confusion matrix from Table 1, we have done a calculation of several evaluation metrics. From Table 2, we can see that with the classification accuracy of 99.06%, DenseNet201 has achieved the highest accuracy compared to other models.

Table 1. Created 16*16 confusion matrix

| Model | Matrix | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Prediction | | | | | | | | | | | | | | | |
| | | | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
| | | A | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 2 | 3 |
| | | B | 0 | 46 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | C | 0 | 0 | 64 | 1 | 0 | 0 | 1 | 0 | 2 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| | | D | 1 | 0 | 0 | 28 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 |
| | | E | 0 | 0 | 0 | 0 | 19 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | F | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | G | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| DanseMet201 | Actual | H | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | I | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 59 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | J | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 52 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | K | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 48 | 0 | 0 | 0 | 1 | 0 |
| | | L | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 1 | 0 | 0 |
| | | M | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 61 | 0 | 0 | 0 |
| | | N | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 45 | 0 | 0 |
| | | O | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 14 | 2 |
| | | P | 2 | 0 | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 |
| | | | Prediction | | | | | | | | | | | | | | | |
| | | | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
| | | A | 12 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 3 |
| | | B | 0 | 47 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | C | 1 | 0 | 66 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 |
| | | D | 1 | 0 | 0 | 27 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| | | E | 0 | 2 | 0 | 0 | 19 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | F | 0 | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 |
| | | G | 0 | 0 | 0 | 0 | 0 | 0 | 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Xception | Actual | H | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 20 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| | | I | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 58 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| | | J | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 53 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | K | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 49 | 0 | 1 | 0 | 1 | 0 |
| | | L | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 2 | 0 | 0 | 0 | 0 |
| | | M | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 61 | 0 | 0 | 0 |
| | | N | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 42 | 0 | 0 |
| | | O | 2 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 14 | 1 |
| | | P | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 |
| | | | Prediction | | | | | | | | | | | | | | | |
| | | | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
| | | A | 15 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| | | B | 0 | 47 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | C | 0 | 0 | 69 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | D | 1 | 0 | 2 | 27 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 |
| | | E | 0 | 3 | 0 | 0 | 17 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | F | 0 | 0 | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | G | 0 | 0 | 0 | 0 | 0 | 0 | 29 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| ResNet152V2 | Actual | H | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | I | 0 | 0 | 1 | 0 | 0 | 2 | 0 | 1 | 52 | 0 | 0 | 0 | 0 | 4 | 1 | 1 |
| | | J | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 51 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | K | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 49 | 0 | 0 | 0 | 0 | 0 |
| | | L | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| | | M | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 57 | 1 | 0 | 0 |
| | | N | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 43 | 0 | 0 |
| | | O | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 | 1 |
| | | P | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 8 |

Table 2. Class wise performance evaluation metrics using three models

| Model Name | Accuracy (%) | Precision (%) | Sensitivity (%) | Specificity (%) | FPR (%) | FNR (%) |
|---|---|---|---|---|---|---|
| DenseNet201 | 99.06 | 99.45 | 87.30 | 99.49 | 0.51 | 12.70 |
| Xception | 99.04 | 88.86 | 85.61 | 99.48 | 0.52 | 14.39 |
| ResNet152V2 | 98.93 | 90.19 | 85.49 | 99.42 | 2.81 | 14.51 |

Table 3 shows the outcomes of DenseNet201's class-wise evaluation metrics for the particular class. During the classification of the Leaf Roller and Spider Mite classes, the model DenseNet201 achieved a 100% accuracy rate. Precision, sensitivity, specificity, FPR, and FNR, for the Leaf Roller and Spider Mite classes, are 100%, 100%, 100%, 0%, and 0%, respectively remarkable when compared to other classes.

Table 3. Class-wise evaluation metrics using DenseNet201

| Class name | Accuracy (%) | Precision (%) | Sensitivity (%) | Specificity (%) | FPR (%) | FNR (%) |
|---|---|---|---|---|---|---|
| Aphids | 97.85 | 70.59 | 63.16 | 99.07 | 0.93 | 36.84 |
| Brinjal Shoot and Fruit Borer | 99.64 | 100 | 95.83 | 100 | 0.0 | 4.17 |
| Cercospora | 98.75 | 96.97 | 92.75 | 99.59 | 0.41 | 7.25 |
| Flea Beetle | 98.39 | 84.85 | 87.5 | 99.05 | 0.95 | 12.5 |
| Fruit Rot | 99.11 | 95 | 82.61 | 99.81 | 0.19 | 17.39 |
| Leaf Roller | 100 | 100 | 100 | 100 | 0.0 | 0.0 |
| Leaf Curl | 99.82 | 96.77 | 100 | 99.81 | 0.19 | 0.0 |
| Leafhopper | 99.82 | 95.45 | 100 | 99.81 | 0.19 | 0.0 |
| Mealybug | 98.75 | 92.19 | 96.72 | 99 | 1 | 3.28 |
| Normal Fruit | 98.39 | 86.67 | 98.11 | 98.42 | 1.58 | 1.89 |
| Normal Leaf | 99.46 | 97.96 | 96 | 99.8 | 0.2 | 4 |
| Powdery Mildew | 99.64 | 100 | 60 | 100 | 0.0 | 40 |
| Spider Mite | 100 | 100 | 100 | 100 | 0.0 | 0.0 |
| Spotted Beetle | 98.75 | 90 | 95.74 | 99.02 | 0.98 | 4.26 |
| Thrips | 98.39 | 82.35 | 70 | 99.44 | 0.56 | 30 |
| Whitefly | 98.21 | 58.33 | 58.33 | 99.09 | 0.91 | 41.67 |

Table 4 shows the outcomes of Xception's class-wise evaluation metrics for the particular class. During the classification of the Leaf curl class, it was found that the model Xception had the highest accuracy of 100%. Precision, sensitivity, specificity, FPR, and FNR, for the Leaf curl class, are 100%, 100%, 100%, 0%, and 0%, respectively remarkable when compared to other classes.

Table 4. Class-wise evaluation metrics using Xception

| Class name | Accuracy (%) | Precision (%) | Sensitivity (%) | Specificity (%) | FPR (%) | FNR (%) |
|---|---|---|---|---|---|---|
| Aphids | 97.67 | 66.67 | 63.16 | 98.89 | 1.11 | 36.84 |
| Brinjal Shoot and Fruit Borer | 99.28 | 94 | 97.92 | 99.41 | 0.59 | 2.08 |
| Cercospora | 98.93 | 95.65 | 95.65 | 99.39 | 0.61 | 4.35 |
| Flea Beetle | 98.93 | 96.43 | 84.38 | 99.81 | 0.19 | 15.62 |
| Fruit Rot | 98.93 | 90.48 | 82.61 | 99.63 | 0.37 | 17.39 |
| Leaf Roller | 99.64 | 100 | 75 | 100 | 0.0 | 25 |
| Leaf Curl | 100 | 100 | 100 | 100 | 0.0 | 0.0 |
| Leafhopper | 99.46 | 90.91 | 95.24 | 99.63 | 0.37 | 4.76 |
| Mealybug | 98.03 | 87.88 | 95.08 | 98.39 | 1.61 | 4.92 |
| Normal Fruit | 99.64 | 96.36 | 100 | 99.6 | 0.4 | 0.0 |
| Normal Leaf | 99.64 | 98 | 98 | 99.8 | 0.2 | 2 |
| Powdery Mildew | 99.28 | 66.67 | 40 | 99.82 | 0.18 | 60 |
| Spider Mite | 99.46 | 95.31 | 100 | 99.4 | 0.6 | 0.0 |
| Spotted Beetle | 98.57 | 93.33 | 89.36 | 99.41 | 0.59 | 10.64 |
| Thrips | 98.57 | 87.5 | 70 | 99.63 | 0.37 | 30 |
| Whitefly | 98.57 | 62.5 | 83.33 | 98.9 | 1.1 | 16.67 |

Table 5 shows the outcomes of ResNet152V2's class-wise evaluation metrics for the particular class. During the classification of the Leafhopper class, it was found that the ResNet152V2 model had the maximum accuracy of 100%. Precision, sensitivity, specificity, FPR, and FNR, for the Leafhopper class, are 100%, 100%, 100%, 0%, and 0%, respectively remarkable when compared to other classes.

Table 5. Class-wise evaluation metrics using ResNet152V2

| Class name | Accuracy (%) | Precision (%) | Sensitivity (%) | Specificity (%) | FPR (%) | FNR (%) |
|---|---|---|---|---|---|---|
| Aphids | 98.57 | 78.95 | 78.95 | 99.26 | 0.74 | 21.05 |
| Brinjal Shoot and Fruit Borer | 99.28 | 94 | 97.92 | 99.41 | 0.59 | 2.08 |
| Cercospora | 97.67 | 84.15 | 100 | 97.35 | 2.65 | 0.0 |
| Flea Beetle | 98.75 | 93.1 | 84.38 | 99.62 | 0.38 | 15.62 |
| Fruit Rot | 98.21 | 80.95 | 73.91 | 99.25 | 0.75 | 26.09 |
| Leaf Roller | 99.64 | 80 | 100 | 99.64 | 0.36 | 0.0 |
| Leaf Curl | 99.82 | 100 | 96.67 | 100 | 0.0 | 3.33 |
| Leafhopper | 100 | 100 | 100 | 100 | 0.0 | 0.0 |
| Mealybug | 98.03 | 96.3 | 85.25 | 99.6 | 0.4 | 14.75 |
| Normal Fruit | 99.11 | 94.44 | 96.23 | 99.41 | 0.59 | 3.77 |
| Normal Leaf | 99.46 | 96.08 | 98 | 99.61 | 0.39 | 2 |
| Powdery Mildew | 99.28 | 100 | 20 | 100 | 0.0 | 80 |
| Spider Mite | 99.28 | 100 | 93.44 | 100 | 0.0 | 6.56 |
| Spotted Beetle | 98.21 | 87.76 | 91.49 | 98.83 | 1.17 | 8.51 |
| Thrips | 98.57 | 77.27 | 85 | 99.07 | 0.93 | 15 |
| Whitefly | 98.93 | 80 | 66.67 | 99.63 | 0.37 | 33.33 |

The use of image processing techniques for the detection of plant diseases has grown increasingly prominent in agricultural research. Researchers have come up with a variety of ways to detect disease. These strategies and algorithms have a unique set of restrictions and failures. However, due to their robustness, some of them are suitable to be applied in this sector. Table 6 compares the performance of all methods for identifying eggplant disease.

The performance of any approach is influenced by the size of the dataset, the technology used, and other factors. The majority of the techniques shown here achieved high accuracy. However, in some articles, the dataset size was insufficient, which can hamper the model's training and testing ability to classify accurate diseases. In various studies, they dealt with a few classes of eggplant diseases. Nevertheless, we have worked with fourteen different types of eggplant diseases. In comparison to previous works, we may state that our approaches produced a better outcome. Nonetheless, there is always room for improvement. We can expand our dataset and experiment with more eggplant disease classifications in the future.

Table 6. Comparative study of our work and existing work for eggplant disease recognition

| Research work | Crops | Number of class | Original dataset | Technique used | Classifier | Accuracy |
|---|---|---|---|---|---|---|
| This paper | Eggplant | 16 | 2766 | TL | DenseNet201 | 99.06% |
| Aravind *et al.* | Eggplant | 6 | 643 | Deep CNN | VGG-16 (Modified) | 93.33% |
| Aravind *et al.* | Eggplant | 5 | 1747 | Deep CNN | MSVM | 99.4% |
| C Xie *et al.* | Early blight disease of eggplant leaves | 2 | 235 | ML | KNN, AdaBoost | 88.46% |
| Sabrol and Kumar | Tomato and eggplant | 9 | 1170 | ML | Neuro-Fuzzy | 90.7%, 98% |
| Anand *et al.* | Brinjal leaves | NM | NM | ML | ANN | NM |
| Maggay | Eggplant | 5 | 2465 | Deep CNN | ANN | NM |
| Wu *et al.* | Eggplant leaves | 2 | NM | VNIR | BP-NN | 85% |

*NM: not mentioned

## 4. CONCLUSION

Our research is based on eggplant disease classification, where we introduced 14 kinds of diseases of eggplant. This is the first attempt to include so many classified diseases of eggplant in Bangladesh so far. Our main target is to accurately predict what disease is affecting an eggplant based on Asian subcontinent weather. That's why we have included as many diseases as possible. As a result, we have worked with the eggplant diseases named Aphids, Eggplant fruit and shoot borer, Cercospora, Flea Beetle, Fruit rot, Leaf curl, Leaf roller, Leafhopper, Mealybug, Powdery mildew, Spider mite, Spotted beetle, Thrips and Whitefly. After collecting the raw images, we implement augmentation techniques called Image resizing, Rescaling, Rotation, Shearing, Zooming, Flipping, and Fill Mode. After that, we use CNN based Transfer Learning models to fit our data into various models called DenseNet201, Xception, ResNetV2. For our proposed Eggplant Disease Classification, we obtained 99.06% accuracy for DenseNet201, 99.04% for Xception, and 98.93% for ResNet152V2. We found that the DenseNet201 transfer learning model achieved the highest accuracy with 99.06% among those three approaches.

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