DCNN Based Disease Prediction of Lychee Tree

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Abstract. Tree disease classification is needed to determine the affected leaves as it controls the economic importance of the trees and their products and decreases their eco-friendly eminence. The lychee tree is affected by some of the diseases named Leaf Necrosis, Stem Canker and leaf spots. Therefore, classifying the Lychee tree is essential to find the good and affected leaves. Our economic growth will be very high if we can adequately do the Lychee tree classification. In this paper, we tried to do a Lychee tree disease classification to make things easier for the farmers as they cannot correctly distinguish the good and bad leaves in an earlier stage. We have created a new data set for training the architectures. We have collected about 1400 images with three categories of pre-harvest diseases "Leaf Necrosis", "Leaf Spots", and "Stem Canker". There are 1400 images in total, and out of those, 80% of the data is for training and 20% is for testing, this dataset has fresh and affected leaves and stems. For Lychee tree disease classification, we have chosen pre-trained CNN and Transfer Learning based approach to classify the layer of the 2D image by layer. This method can classify images efficiently from the images of disease leaves and stems. It will address disease from the images of the leaves and trees and determine specific preharvest diseases.

Keywords: Lychee tree disease · Leaves · Stems · MobileNet · NASNetMobile · InceptionV3 · VGG16 · CNN

1 Introduction

Fruits are essential for our bodies. It provides many health benefits. The tropical fruits of Bangladesh are great sources of antioxidant vitamins and antioxidant minerals. One type of tropical fruit that can be found in Bangladesh is lychee. It is one of the fruits in the highest demand and has the best flavor in our nation. It is beneficial to one's health and it also offers nutritional value. Although somewhat pricey, it is one of the most sought-after and essential fruits for table use in Bangladesh. It is generally available in the market in May-June in every year.

Diseases of the lychee tree include Leaf Necrosis, Leaf Spots, Stem Cancer, Anthracnose, Root Rot, and Red Algae, among others. The pathogens that cause these diseases, such as bacteria, viruses, fungi, parasites, etc., as well as unfavorable environmental and mental factors, are to blame. Environmental stress is the root of the majority of

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plant issues, either directly or indirectly. The disease's type is determined by the signs and the areas of the leaves that are impacted. In the past, identifying plant diseases was often done by specialist farmers inspecting plants on a constant basis. Unfortunately, it necessitates a great deal of effort and money to produce a significant number of plants on large farms. Therefore, finding an automated, precise, quick, and less expensive system for identifying plant diseases is crucial. The most common and commonly used technologies are image processing and machine learning.

According to Bangladeshi tradition, these months are called "Madhu Mash". 46% of fruits harvested during this Madhu Mash. Although, despite the market's abundance of some of the other fruit varieties, unpreserved lychee is in high demand due to its special mouthful, flavorful, and its amazing color. The availability of lychee is sadly limited to 60 days due to insufficient supply. Lychee yields on average per acre are roughly 2.5 MT, which is quite low when compared to other nations. The courtyard (two to three plants) or a small fruit garden (15 to 20 plants) next to the house are where lychee is mostly grownIt is grown all over the country, but the most important places are the districts of Dinajpur, Khulna, Jessore, Rajshahi, Kushtia, Sylhet, Rangpur, Dhaka and Chittagong. Bangladesh is an agricultural country and this sector plays a vital role in our GDP. More than 47% of people's livelihood depends on the agriculture sector. The fruit sector is Bangladesh's agriculture's biggest and manifold economic area. After finishing our demands, litchi can also participate in Bangladeshi remission by exporting in several countries with the UN's Food and Agriculture Organization (FAO). Commercial assembly and business of litchi are increasing day by day at a very higher rate. A significant part of the GDP, around 13%, comes from agriculture. Not being able to manage our agriculture sector properly causes us unexpected losses in our economy. Therefore, we must properly guide our farmers and keep a friendly agricultural system to ensure the long-term security of the food processor. If we can make this happen then, our GDP will also grow and we can give more employment to people in our country. We demonstrate a technique for automatically classifying Lychee tree diseases using four pre-trained Convolution neural networks (CNN).

The structure of the paper is as follows: Sect. 2 clarifies the relevant work of several disease classification methods. The method and materials that were used are illustrated in Sect. 3. The experimental analysis, including performance and results, is depicted in Sect. 4. Section 5 discusses the article's conclusion.

2 Literature Review

In this section, we have tried to associate the related work. The research that was done in the past about plant disease classification and prediction and the methodology is shortly presented here:

Hossain et al. [1] have used a framework established considering two models: One is a suggested light model with six layers of CNN and another is a fine-tuned pre trained deep learning model for group-16 visual geometry. They used two datasets: the first contains clear fruit photos with an accuracy of 99.49%, while the second contains fruit ages with an accuracy of 96.75%. Dandavate et al. [2] have proposed a system for classifying four fruits into three stages by using Convolutional Neural Networks. For this study, they've put together a list of local fruits images. In 8 epochs, the accuracy was 97.74%, and the validation clarity was 0.9833. CNN and AlexNet architecture have been used by Arya et al. [3] to identify leaf diseases mango and potato. Then, the various architectures' performance metrics were compared with one another. AlexNet achieves greater accuracy than the CNN architecture. Using deep learning, Jayakumar et al. [4] were able to classify the diseases and make predictions after processing and segmenting images of leaf surfaces. The prediction and identification were made using image acquisition, processing, and segmentation. They got higher accuracy by predicting and classifying the leaf diseases and got computational precision compared to the other models. Lakshmanarao et al. [5] have predicted plant disease by applying the transfer learning technique. They have taken the plant village dataset, which was collected from Kaggle. They divided the real dataset into three parts for three different plants. They used three transfer learning techniques named VGG16, RESNET50, and Inception and got an accuracy of 98.7%, 98.6%, and 99% sequentially.

Their proposed model achieved good accuracy when compared to other models. Machine learning models were used by Qasrawi et al. [6] to cluster, predict, and classify tomato plant diseases. For clustering, they used image embedding and hierarchical clustering algorithms. The accuracy of the clustering model was measured at 70%, while the accuracy of the neural network model and the logistic regression model were measured at 70.3% and 68.9% respectively. Beikmohammadi et al. [7] have presented a transfer learning technique to identify plants leaf, which has first used a pre-trained deep CNN model and then takes the input data representation. Two familiar botanical datasets were used to classify the proposed method. Both Flavia, which has 32 classes, and Leaf snap, which has 184 categories, have achieved an accuracy of 99.6% and 90.54%, respectively. Gosai et al. [8] have made an effort to construct a model that categorizes the harvest leaves into healthy and unhealthy categories in order to better detect plant diseases. The researchers trained a model to recognize distinct harvests and 26 diseases using 54,306 images of unhealthy and healthy plant leaves taken under controlled conditions. A convolutional neural network with 13 layers was built by Zhang et al. [9]. Image rotation, Gamma correction, and noise injection were the three methods used for data augmentation. With an overall accuracy of 94.94%, their approach outperformed five state-of-the-art techniques approaches. A constructive machine vision framework is recommended for use in date fruit harvesting robots, according to Altaheri et al. [10]. They have utilized pre-trained DCNN through the process of fine-tuning and transfer learning. Wang et al. [11] established a dataset of 3743 samples grouped into three groups, namely mature, defects, and rot, and assessed the plausibility of automating the detection of defective surfaces for lychees. They use a transformer-based generative adversarial network (GAN) as a method of data augmentation to effectively enrich the initial training set with more diverse samples in order to rebalance the three categories in order to overcome this issue. Haque et al. [12] employed convolutional neural networks to construct a model for the detection of diseases in rice plants. K-Means clustering was utilized in their study because it can process photos by limiting the total number of colors in each image. A robust UAV DOM-based instance segmentation method for photos of litchi trees is provided by Mo et al. [13]. To alleviate the lack of diversity in the primary litchi dataset, citrus data are added to the training set. The model obtained the best Mask AP50 of 95.49% and the best Box AP50 of 96.25% on the test set with the aid of training on the litchi-citrus dataset.

3 Proposed Methodology

The role of methodology is one of diligence, as it meticulously follows agreeable steps and procedures in order to achieve its goal. In this section of our study, we have applied pre-trained Convolutional Neural Networks [14, 15] for identifying fresh and affected leaves and stems. Classical neural networks are very hard for image recognition. CNN is used to ease the complication and struggles. We are able to recognize the pattern in the input image, which is difficult for computer vision to do, by using CNN. CNN's key advantage is that it only needs a small number of parameters, allowing for a more compact model and faster results. Layers in a CNN are as follows: Convolution Layer, the first layer in a CNN. It works in 32 dimensions, utilizing two or three-dimensional input images and weights. Pooling layer: it preserves essential information, It does this by lowering the total amount of information contained in each convolutional layer's features. Typically, a pooling layer follows the activation layer and can reduce the number of map presented. In most cases, an activation layer is followed by a pooling layer, which has the ability to minimize the amount of feature maps that are presented. In addition to this, it assigns a label to each image.

3.1 Dataset

Data is an important aspect of the research research work. Given that our project is centered on the subject of the detection of fresh and affected leaves and stems, we have taken both fresh and affected leaves and stems of the Lychee tree. We have taken leaves from the garden and trees of the village. The whole dataset consists of 1400 images separated into five classes, including 1120 training and 280 testing images depicted in Table 1. The following are examples from the 5 categories shown in Fig. 1.

3.2 Data Pre-processing

Preprocessing data refers to the steps taken before using the data to improve the consistency of the information produced. The training procedure for CNN models was optimized by applying two standard pre-processing techniques. 1) Resizing: This dataset contains images with varying resolutions and dimensions. We rescaled the original size of each image to 224 by 224 pixels so that the dimensions of all of the images that were input would be the same. 2) Normalization: we used ImageNet mean subtraction to rescale the intensity values of the pixels as a pre-processing step for image normalization. By applying min-max normalization [16] to the intensity range [0, 1], we standardized the intensity values of all images within the range [0, 255] to the standard normal distribution.

Fig. 1. Sample images of five classes

Table 1. Dataset Description.

Classes	Train Set (80%)	Test Set (20%)	Total Image
Leaf Spots	160	40	200
Leaf Necrosis	240	60	300
Fresh Leaf	240	60	300
Stem Canker	240	60	300
Fresh Stem Canker	240	60	300

3.3 Model Evaluation

Its purpose is to determine, based on upcoming data, how well a model generalizes to those data. We utilized well-known assessment metrics such as recall, precision, accuracy, and f1-score in order to evaluate the prediction performance of the algorithms that were investigated in this study (Fig. 2).

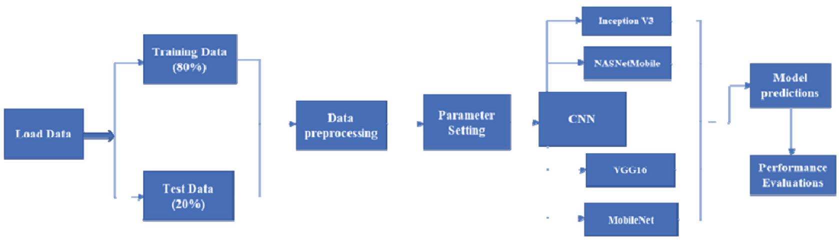

Fig. 2. Proposed method workflow.

3.4 InceptionV3

The Deep learning convolutional neural architectures sequence has reached its third part with this segment. The TensorFlow category of InceptionV3 [17] was trained using the actual ImageNet dataset, which included more than 1 million training images. Its initial debut was in the ImageNet Large Visual Recognition Challenge, where it placed second all in all. Transfer learning gives us the ability to retrain the final layer of an existing model, which results in a significant reduction in the amount of training time required as well as the size of the dataset. The InceptionV3 model is a well-known model that is used for transfer learning. This model was trained using more than a million photos from one thousand different classes on some exceptional dynamic machines, as was previously mentioned.

3.5 VGG16

It's another form of a convolutional neural network. The number that follows a network's name represents the number of architectural layers. The objective aimed to build a very deep convolutional neural network by stacking layers. A network that would do duties well. One of the awards in the ImageNet 2014 competition was won by the VGG16 [18] team. Five categories to watch evaluation following the output of the categorization vector. The ReLU serves as the activation mechanism for the entirety of the hidden layers.

3.6 MobileNet

The MobileNet [19] model uses depth-wise separable convolutions, a kind of factorized convolution, to convert a conventional convolution into a depth-wise and a pointwise convolution, respectively (11 convolutions). One filter is used for each input channel in Mobile Nets' depth-wise convolution. The results are then blended using an 11 convolution in terms of points. Convolution done in depth is called production. A modern convolution produces a fresh set of outputs by filtering and integrating inputs simultaneously. Using depthwise separable convolution, this is separated into two layers, one for filtering and one for mixing. With this factorization, compute time and model size are significantly reduced.

3.7 NASNetMobile

Reinforcement learning is used to optimize the simple building pieces that make up the scalable CNN architecture. Convolutions and pooling are the only two operations that make up a cell and they are repeated numerous times depending on the desired capability of the network. Within this version of NASNetMobile [20], there are 12 cells, 5.3 million parameters, and 564 million multiply-accumulates (MACs).

3.8 Parameter Setting

The training parameters for all convolutional neural networks are, learning rate $\eta = e-5$, $\beta 1 = 0.9$, $\beta 2 = 0.999$, $\varepsilon = e - 8$, and decay rate is set to 1e$-$5 for adaptive moment estimation (Adam) optimizer. Activation function Softmax is used and sets a dropout rate of 0.5 to prevent the model from becoming overfitting. All models are trained over the duration of 10 epochs, with a batch size of 32.

4 Result and Discussion

The consistency of the employed model is on the order of four. InceptionV3 outperforms the other three models in terms of accuracy, recall, precision, and FI scoring (88.21%, 0.88, 0.88, and 0.87 respectively). The VGG16 come in second with an 84.64% accuracy. Table 2 displays the confusion matrix results using four distinct evaluation criteria.

The values on the main diagonal represent all instances that were correctly classified. The rate of accuracy achieved for each predicted class and misclass prediction is indicated in the row under each confusion matrix in Fig 3. As it can be observed, the highest misclassified value is claimed by NASNetMobile which is 78. And InceptionV3 has the lowest misclassified value of 33 (Table 3).

Table 2. Classification report of the four CNNs.

Algorithms	Accuracy	Precision	Recall	F1-score
InceptionV3	88.21%	0.88	0.88	0.87
VGG16	84.64%	0.85	0.85	0.83
MobileNet	83.21%	0.86	0.81	0.82
NASNetMobile	72.14%	0.78	0.68	0.66

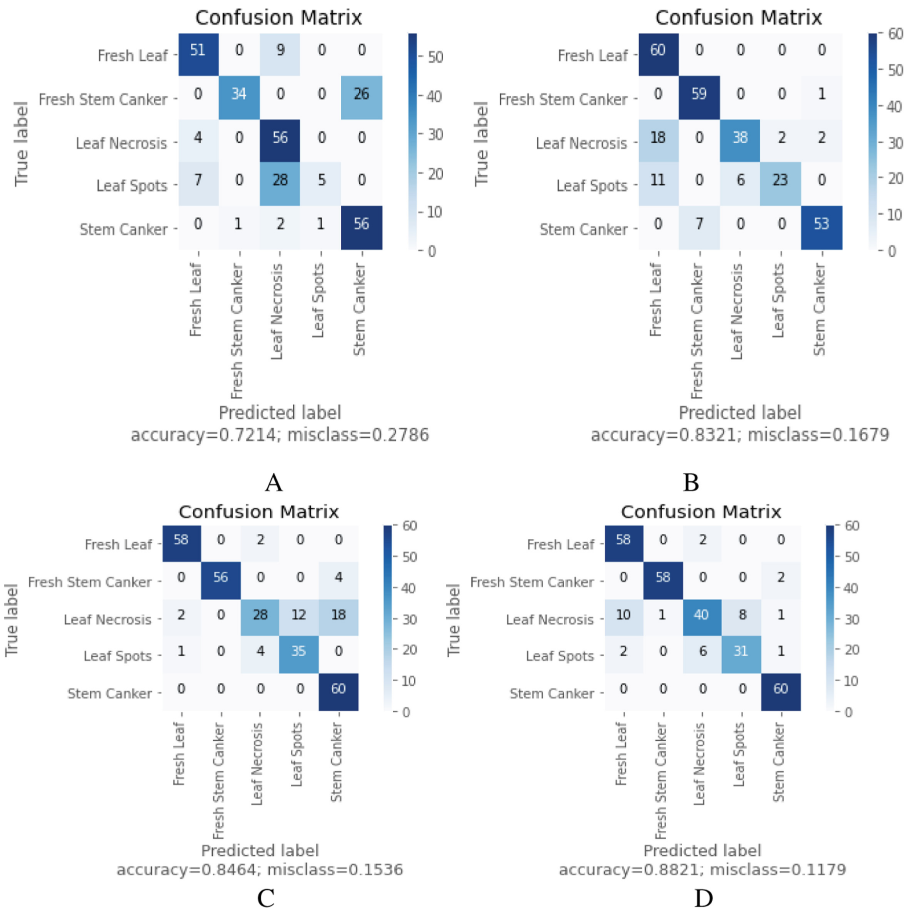

Fig. 3. Confusion matrix of four DCNN models. A) NASNetMobile, B) MobileNet, C) VGG16 and D) InceptionV3.

Table 3. Study comparison.

Paper	Method	Best Accuracy	Worst Accuracy
Yamparala et al. [21]	Convolution Neural Network(CNN) based classification method	CNN gives the highest accuracy of 90%	PNN gives the lowest accuracy 86%
Peng et al. [22]	Feature-extraction network model	Results show that the improved YOLOv3 Litchi model achieved better results The mean average precision (mAP) score was 97.07%	The YOLOv3_Tiny model has 94.48% mAP which is the lowest
Wang et al. [23]	YOLOv3-Litchi model	The average detection time of YOLOv3-Litchi is 29.44 ms	The test results show that the F1 of YOLOv3-Litchi is higher than that of Faster R-CNN algorithm 0.05
Miah et al. [15]	CNN	The InceptionV3 model has the highest accuracy, at 97.34%	NASNetMobile 75.29%
Our Study	CNN	The highest accuracy of 88.21%was achieved by the InceptionV3	NASNetMobile has given us the least accuracy of all

According to all of these metrics, the InceptionV3 model outperforms all others. This study showed that well-tuned deep learning algorithms perform better in terms of accuracy when compared to deep learning algorithms with automatically produced features for impacted leaf and stem diagnosis on images.

5 Conclusion

This is very important in agriculture to find the difference between fresh and affected leaves and stems. For the classification of fresh and affected leaves and stems, we have taken four CNN models, along with VGG16, InceptionV3, MobileNet, and NASNet-Mobile. In this study, we take into account a wide variety of variations, including hyper-parameter discrepancy, batch size, epoch number, optimizer, and learning rate. Used models' findings show that they can esteem between fresh and affected leaves and stems. Therefore, the help of the methodology will automatize the human brain's classifying operations, reducing human errors when classifying fresh and affected leaves and stems of the Lychee tree. The highest accuracy was 88.21% which we got from the InceptionV3 model. One caveat of our study is that our dataset is quite limited. Accuracy may decrease if there is much noise in the images. The capacity of this research work will enlarge in the coming future to embrace more leaf pictures that will be classified, giving every fruit farmer the opportunity to utilize the system. We will add more leaf images in the near future and focus on classifying more classes.

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