Matrib leaf classification using Deep Neural Network: An Integrated Image Processing Technique

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***Abstract*—Healthy farm plant leaf classification and identification is a critical food security issue. In many places of the world, it remains tough as it needs appropriate infrastructure. Combining the rising worldwide prevalence of the smartphone with current progress in computer vision through deep learning, now it is possible to diagnose inconsistency of various farm plants. In this technology era, automation can help to replace manual prevention efforts in plants by employing image processing methods. This research deployed three pre-trained deep neural models: 3DCNN, ResNet50 and MobileNet, to classify the Matrib leaf into two categories: Good Matrib leaf and Bad Matrib leaf. We employed our own Matrib leaf customized dataset for this research. Experimental results demonstrate that MobileNet outperformed other models with an accuracy of 99.99% on test data, while ResNet50 and 3DCNN followed with an accuracy of 92.67% and 72.80%.**

Keywords—Matrib leaf, Deep learning, Convolution neural network, Image processing, MobileNet, Resnet50.

I. Introduction

Matrib leaf is one of several natural foods and drinks that can help people settle their stomachs without causing any adverse effects. After a meal, chewing a Matrib leaf (Paan) is an old culinary custom in South Asia. In Bangladesh, people thoroughly use Matrib leaf as a primitive food. Matrib leaf is a valuable and beneficial parthenogenetic popularised cash crop [1]. So, to enhance plantation, identification of healthy and quality matrib leaf is important.

The extent of superiority or a condition of being free of flaws, deficiencies, and significant variances is defined by the quality of leaves. Generally, the Matrib leaf vine endures for around 2-3 years [2]. Therefore, this crop may generate a good amount of money and thus can contribute to economic development. Sometimes, they are susceptible to a variety of fungal and bacterial infections during their brief lifetime. 'Leaf rot', 'leaf spot', and 'powdery mildew' are a few examples. When the betel vine garden is afflicted by Leaf rot, it suffers a significant yield loss. Leaf rot disease in betel vine has been linked to a 30-100% decrease in leaf production [3]. Therefore, early identification of good or bad matrib leaf is significantly important.

Growers and vegetation pathologists have traditionally used their visions to diagnose plant leaf and make judgments based on personal experiences, which is sometimes inaccurate and mostly prejudiced because many infections appear to be the same in the early stages. The human vision technique has many other disadvantages. The main disadvantage is that the procedure is time intensive and labour demand.

As a result, an intelligent computer vision technique is necessary to overcome the limitations of traditional methods. There are few recent breakthroughs in leaf classification and identification using a data acquisition method, especially for Matrib leaves, which are the rarest. Nowadays, Deep learning is employed for categorizing large data sets since it produces findings more quickly and efficiently [4]. In many models, the overall performance of deep learning is substantially higher than other machine learning models. Machine learning is also employed incomparable picture classification tasks; however, the input images need to be preprocessed, and they can be in monochromatic or a colour palette such as RGB.

However, in this paper, we present a Deep learning-based classification model to recognize the bad or good matrib leaf. We employed Convolution Neural Network (CNN) to improve model accuracy. The proposed approach uses three deep learning techniques: 3DCNN, ResNet50, and MobileNet, to train the model and improve the accuracy. The

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construction of CNN is distinct, and it contains several layers. The main feature of CNN is its convolution layer, and the surface help to scrape lines, corners, and colours. The experiment result depicts that the proposed model is effective in improving accuracy. The main contributions are:

- We developed a customized dataset of matrib leaf which contains 620 images.
- We proposed a novel method to detect good and bad matrib leaf.

The remaining part of the article has concluded through, Section II focuses on relevant studies, Section III concludes through methodology with data collection and preprocessing, input processing, training and model testing. The detail about implementation has described in section IV. In section V, we perform a comparison between the proposed model and other existing models and conclude through the conclusion in section VI.

II. Related Work

Nowadays, the importance of research in plant leaf classification and healthy leaf identification has grown faster. Especially in rice leaf, apple leaf, betel vine leaf, wheat leaf, tea leaf, and other crop leaf classification, computer vision and machine learning are more popular.

Dey et al. [2] proposed leaf rot detection technique using an image processing algorithm to identify the colour feature of the rotted leaf area of a betel vine leaf. By identifying the rotted areas, the image has segmented and deduced the rotted part of the leaf. They experimented on twelve leaf images and found a very high precision score.

Hasan et al. [5] proposed the Betel vine leaf classification method using the Machine Learning technique. They analyse 1275 images of Betel vine and classify into two categories: Bacterial Leaf Spot and Stem Leaf disease. To do pre-processing, they resize the image, and for feature extraction, they use the Gaussian mixture model (GMM). They trained the classification model through Support Vector Machine, Logistic Regression, K-nearest neighbor, and Random Forest. Among four classifiers, SVM achieve 83.69% accuracy.

Rothe et al. [6] proposed a solution for cotton leaf classification using the pattern recognition technique. They classify the cotton leaf into three diseases: Alternaria, Bacterial leaf blight, and Myrothecium diseases. They acquired images using a digital camera and performed pre-processing and segmentation to extract the features. To do pre-processing, such as removing the noise, they use a low pass filter, and for performing segmentation such as getting high frequency, they consider Gaussian filters. Finally, they use the Backpropagation network model for training the model and achieving 85.52% classification accuracy.

In recent days, several researchers implemented several deep learning models for plant leaf classification. Bansal et al. [7] proposed a model to analyse apple leaves and classify them into healthy, apple scab, apple cedar rust, and diseases/unhealthy using three deep learning models: DenseNet121, EfficientNetB7, and EfficientNet NoisyStudent. Furthermore, they use image augmentation techniques to improve the performance and consider accuracy, precision, recall, and F1 to validate the performance and achieve 96.25% accuracy.

Oyewola et al. [8] proposed a deep residual convolution neural network (DRNN) based Cassava Mosaic Disease (CMD) detection model for cassava leaf images. They use the cassava mosaic disease image dataset from Kaggle that contains 5,656 images. The proposed Neural Network model classifies leaf into five diseases: Healthy, CBB, CBSD, CGM, and CMD. They compare the proposed model and the plain convolutional neural network (PCNN) model to evaluate the effectiveness. The result shows that the proposed model outperforms the PCNN model by a significant margin of 9.25% for the Cassava Disease Dataset.

Swathi [9] proposed a Neural network-based leaf classification technique using seven deep convolutional models such as PNN, ENN, NARX, FNN, GRNN, PRNN, RBNN to classify sixty-five images. The author classified leaves into three categories: yellow-based leaves, brown-based leaves, and green-dominated leaves. For the performance measure of seven neural network models, confusion matrices have been considered and found that Regression Neural Network and Radial Bias Neural Network models have the better performance.

Sholihati [10] proposed a classification method of potato leaf using a deep learning model. They used VGG16 and VGG19 convolutional neural network architecture to classify potato plant leaves into three types: Phytophthora Infestans, Virus of Alternaria Solani, and Insect. This experiment has achieved an average accuracy of 91%, which demonstrates the effectiveness of the proposed model.

Gayathri et al. [11] proposed a convolution neural network (CNN) based LeNet deep learning model for tea leaf classification. They consider 80 images for analysing and classifying the selective tea leaf into blister blight, red scab, red leaf spot, and leaf blight. They use ROC (Receiver Operative Curve) for evaluating the CNN model. Among four categories, Blight leaf is common and higher than others with 90.23% average accuracy.

Waheed et al. [12] proposed dense convolutional neural network (CNN) architecture (DenseNet) for corn leaf classification. They classified leaves into three diseases: common rust, corn gray leaf spot, and northern corn leaf blight. They compared the DenseNet model with existing CNN architectures and found that the proposed DenseNet model has outperformed the traditional CNN models. The proposed optimized DenseNet model has achieved an accuracy of 98.06%.

By inspiring the past research, in this study, we implement three deep learning models, 3DCNN, ResNet50 and MobileNet to classify and identify the Matrib leaf into two categories: Good matrib and Bad matrib leaf.

III. METHODOLOGY

The proposed model works in three phases: Data collection and preprocessing, Input processing, and Training & model testing. A brief explanation of these three phases has given below.

A. Data collection and preprocessing

Data used in this study was collected from the matrib leaf field in Kholagachi, a village under Rajshahi division in Bangladesh. The images were captured manually/by hand through a mobile phone with 13MP camera in different positions such as different angles, different lighting conditions, etc. A total of 620 images were collected and made the matrib leaf dataset. The dataset has two classes: good matrib leaf (300) and bad matrib leaf (320). After obtaining good and bad matrib leaf images, we classified the dataset into two groups: processed data group and unprocessed data group. To obtain processed data, we did some preprocessing as preprocessing helps to utilize high-resolution images that help to get higher accuracy. At first, we perform de-noising to minimize the noise of the images by eliminating the part of the image that is not for analysis. Then we resize all the images to 3120x4120 pixels to standardize the images. The experiment was performed for both groups of data (process and unprocessed data).

B. Input processing

We require preprocessing before using this dataset for training and testing purposes. Using OpenCV, we split the frame from the image dataset and resize frame in a different dimension for our model training and testing purposes and then append it in an array. We transform this dataset to the NumPy array using Numpy [13] and split them into data and labels. We Use Keras np-utiles to transform the vector into binary class matrices label. Finally, we perform training and testing using the Scikit-learn [14] library.

C. Training and model testing

To implement the proposed model, we used the Jupyter Notebook [15], an open-source software application. To implement CNN model, we use TensorFlow platform through TFLearn pythone packages and Keras library.

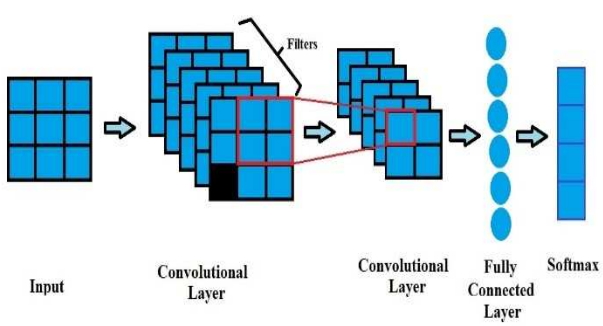

Figure 1: CNN Architecture.

We implement the proposed model through CNN architecture. It is effective in image analysis for its various layer. An input layer, convolution layer, hidden layer, polling layer, and output layer are the layers of CNN architecture. Figure 1 shows the CNN architecture with its multiple layers. Among several layers, convolution layer is the prime attribute of CNN architecture in image analysis for the scraping of lines, corners, and colours. And it also aids in understanding different shapes, digits, and unique parts. In the proposed model, we use 3D-convolution with 32 and 3X3 filter sizes on each layer. We employed several complex methods such as ReLU activation function. It helps to categorize the positive and negative results to improve the accuracy of the proposed model. Also, we consider activation functions such as Softmax to generate only two probabilistic values 0 or 1. Max-pooling [16] layer used to reduce the number of parameters resulting from image matrices and dropout layer for regularization. Furthermore, Adam optimizer [17] considers adjusting network widths in the training results.

IV. EXPERIMENTAL RESULT ANALYSIS

In this section we summarise the result of our findings. This section is divided into two subsections: Experimental dataset, and Experimental result & analysis.

A. Experimental data set

For training the proposed model, we used 620 Matrib leaf images including, processed data/images and unprocessed data/images. All the images were classified as either bad or good. Half of the considered images were good leaf, and the other half were bad leaf. Each image has a dimension is 3120 X 4120. Fig. 2 shows a sample of the processed good leaf, and Fig. 3 shows a sample of the processed bad leaf. Fig. 4 shows some of the Unprocessed good leaf data, and Fig. 5 shows a sample of unprocessed bad leaf data. We have utilized 80% of the data for model training and 20% for model testing. We use 496 (out of 620) images for training and 124 images for testing. Moreover, the proposed model achieves 99.99% testing accuracy that indicates the significance of the model.

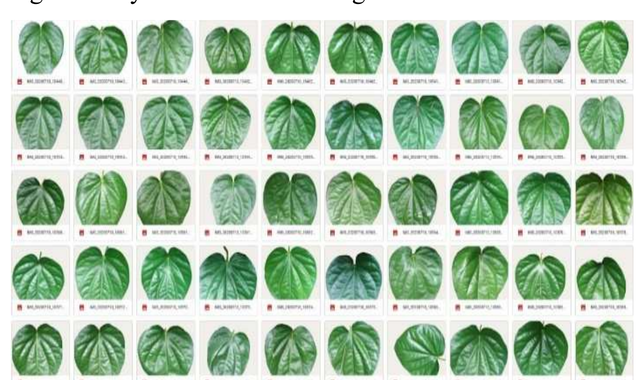

Figure 2: Process good matrib leaf sample.

Figure 3: Process bad matrib leaf sample.

Figure 4: Unprocessed good matrib leaf sample.

Figure 5: Unprocessed bad matrib leaf sample.

B. Experimental evaluation

We train the dataset into various epoch sizes to assess the model's performance. It aided in the improvement of the model's performance. However, increasing the epoch size to over 50 results in overfitting. Therefore, to minimize the overfitting problem, we limited the epoch number to 50. For the 3DCNN model, the maximum training and testing accuracy for 50 iterations is 88.12% and 72.80%. Fig. 6 depicts the training and testing accuracy graph after 50 cycles. The blue line represents training accuracy, whereas the green line represents testing accuracy. On the other hand, Fig.7 depicts the training and testing loss graph for the 3DCNN model after 50 iterations. The Blue line represents the training loss, and the Green line represents the testing loss based on each iteration.

For the Resnet50 model, we get maximum training, and testing accuracy for 50 iterations is 97.03% and 92.67%. Fig.8 depicts the training and testing accuracy graph. The blue line represents training accuracy, whereas the green line represents testing accuracy. On the other hand, the Resnet50 model training and testing loss curve has shown in Fig. 9. The Blue line represents the training loss, whereas the Green line represents the testing loss according to each iteration.

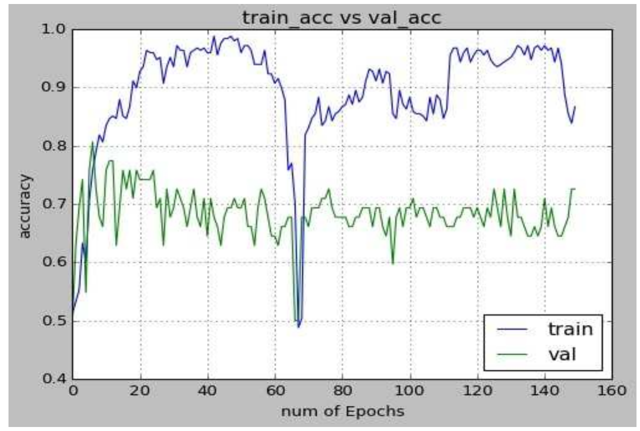

Figure 6: 3DCNN accuracy graph (50 iteration).

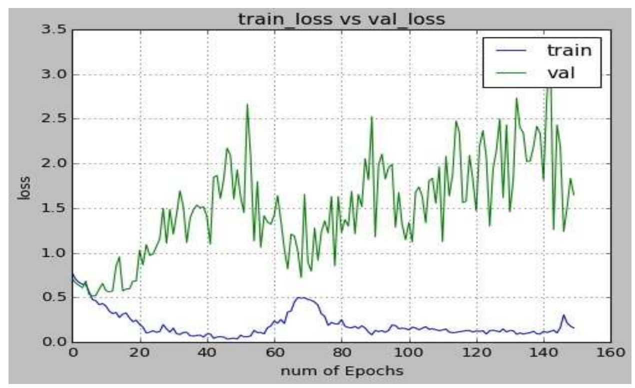

Figure 7: 3DCNN loss graph (50 iteration).

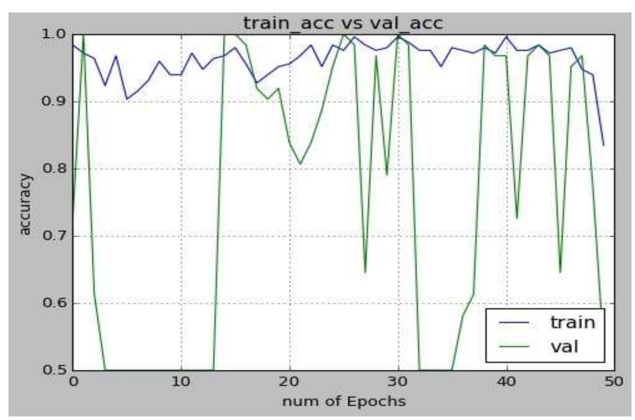

Figure 8: ResNet50 accuracy graph (50 iteration).

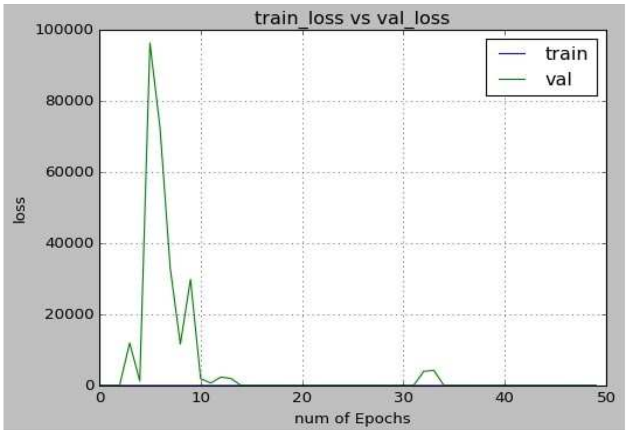

Figure 9: ResNet50 loss graph (50 iteration).

Table I displays the accuracy of the MobileNet model for various epoch sizes for both training and testing data. Fig. 10 depicts the training and testing accuracy graph for 30 iterations. The blue line represents training accuracy, whereas the green line represents testing accuracy based on each iteration. The training and testing loss graph has shown in Fig. 11. The Blue line represents the training loss, whereas the Green line represents the testing loss.

Table 1: ACCURACY OF THE MOBILENET MODEL (VARYING EPOCH SIZE)

No of Epoch	Accuracy (Train)	Accuracy (Test)
30	85.27%	80.79%
50	98.39%	99.99%

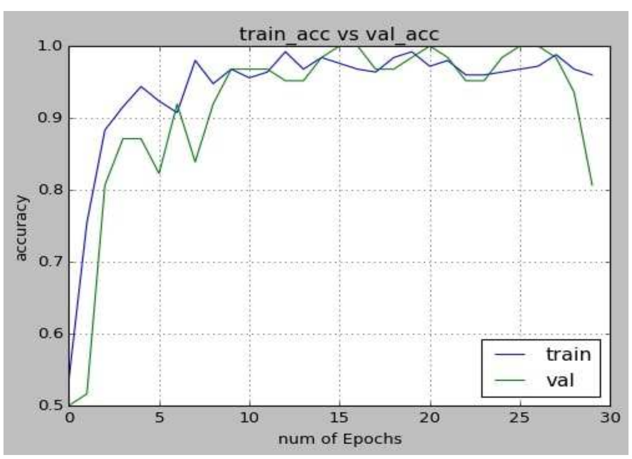

Figure 10: MobileNet accuracy graph (30 iteration).

Furthermore, Fig. 12 and Fig 13 have shown the training accuracy, testing accuracy, and the number of loss after 30 iterations of MobileNet model. These figures demonstrate that as the iteration number has increased, the testing and training accuracy has increased, and the testing and training loss has decreased, as shown in Table 1.

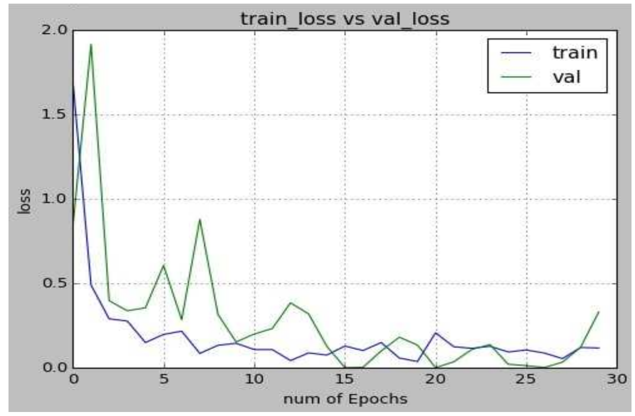

Figure 11: MobileNet loss graph (30 iteration).

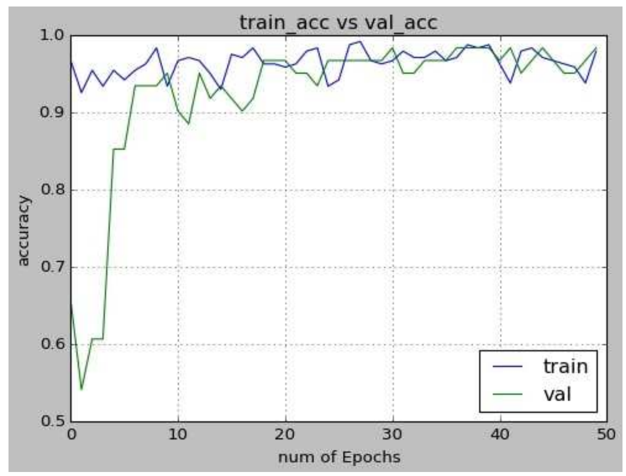

Figure 12: MobileNet accuracy graph (50 iteration).

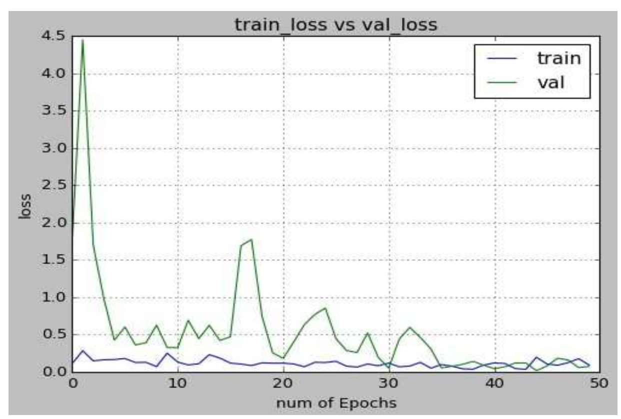

Figure 13: MobileNet loss graph (50 iteration).

Fig 14 shows the accuracy of 3DCNN, ResNet50, and MobileNet models. 3DCNN classifier obtains 72.8% accuracy, ResNet50 classifier obtains 92.67% accuracy, and MobileNet classifier achieves 99.99% accuracy. Among these three classifiers, MobileNet achieves the highest accuracy.

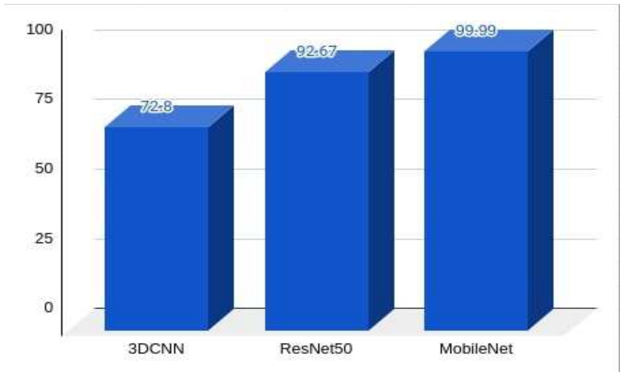

Figure 14: Testing accuracy of the proposed model.

V. COMPARISON

To evaluate the performance of the proposed model, we consider some other existing models: Support Vector Machine (SVM) classifier, Back Propagation Neural Network (BPNN), and Gaussian Mixture Model [1] [18] [19]. Fig. 15 shows the comparison result of the proposed model with other existing models. It depicts that the proposed model outperforms the other existing models.

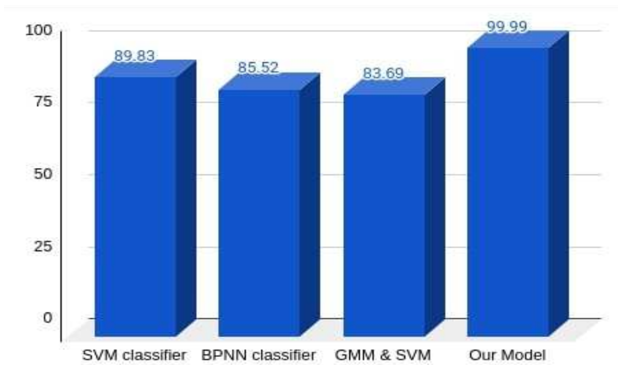

Figure 15: The comparison results of the proposed model and existing model.

VI. CONCLUSION

In this study, we propose a Deep neural-based Matrib leaf classification model to assure the quality of Matrib leaf. The proposed model has shown a competent result in detecting the good and bad Matrib leaf. The experiment result depicts that MobileNet exceeded other models with 99.99% accuracy on test data. However, we have few limitations as we have used only two categorical classifications. Therefore, the proposed model is limited to classifying bad and good matrib leaf only. In the future, we will look deeper into our dataset by making it more robust by increasing the number of categories for classification. We will utilize several pre-trained deep neural networks for further improvement. Furthermore, we will implement a disease monitoring system to deploy on several platforms.

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