Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Detection of Bangladeshi-Produced Plant Disease Using a Transfer Learning Based on Deep Neural Model

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| ABSTRACT
Plant diseases pose a significant threat to agricultural productivity and food security in Bangladesh. In this research, we address the challenge of timely and accurate plant disease detection through the application of transfer learning with deep neural models. We curated a diverse dataset comprising 18 categories of plant leaf images, including Bell pepper Bacterial spot, Bell pepper Healthy, Peach Healthy, Potato Early Blight, Rice Leaf Blast, Rice Healthy, Rice Brown Spot, Potato Healthy, Peach Bacterial spot, Corn Blight, Potato Late blight, Corn Healthy, Tomato Bacterial spot, Strawberry Leaf Scorch, Tomato Early blight, Tomato Early blight, Strawberry Healthy, and Tomato Healthy. The dataset represents the most prevalent plant diseases observed in the Bangladeshi context. We employed three state-of-the-art deep learning algorithms, EfficientNetV2M, VGG-19, and NASNetLarge, to develop robust plant disease detection models. Through transfer learning, these pre-trained models were fine-tuned on our specialized dataset to adapt them for the task at hand. The performance evaluation revealed impressive results, with EfficientNetV2M achieving an accuracy rate of 99%, VGG-19 achieving 93%, and NASNetLarge attaining 83% accuracy. The high accuracy of EfficientNetV2M showcases its exceptional capability in accurately classifying plant diseases prevalent in Bangladesh. The success of these deep neural models in detecting various plant diseases signifies their potential in revolutionizing plant disease management and enhancing agricultural practices. Our research contributes valuable insights into the effective use of transfer learning for plant disease detection and emphasizes the significance of dataset curation for improved model performance. The developed models hold promise in providing timely and precise disease diagnosis to farmers and agricultural professionals, thereby facilitating prompt interventions and minimizing crop losses. Future research can explore the integration of these deep neural models into practical agricultural tools, enabling real-time disease detection and offering substantial benefits to the agricultural industry in Bangladesh.

| KEYWORDS

Plant Disease Detection, EfficientNetV2M, VGG-19, NASNetLarge, Agricultural Productivity, Crop Health

| ARTICLE INFORMATION

ACCEPTED: 02 August 2023 **PUBLISHED:** 29 August 2023 **DOI:** 10.32996/jcsts.2023.5.3.6

1. Introduction

Plant diseases are a significant challenge in the agricultural industry, leading to substantial crop losses and economic impacts. Timely and accurate detection of plant diseases is crucial for effective disease management and sustainable crop production. Traditional methods of disease identification are often labor-intensive, time-consuming, and reliant on expert knowledge of plant pathogens. To address these challenges, researchers have turned to cutting-edge technologies, such as deep learning and transfer learning, to automate plant disease detection. In this research, we focus on the detection of Bangladeshi-produced plant diseases using a transfer learning approach based on deep neural models [Kora, 2016]. Bangladesh is a country heavily reliant on agriculture, making it imperative to have efficient and reliable disease detection methods to protect crop yields and food security. To achieve this, we curated a specialized dataset comprising 18 categories of plant leaf images, encompassing the most prevalent plant diseases found in Bangladesh. The key objective of this study is to leverage the power of deep learning and transfer learning to develop robust plant disease detection models. Transfer learning allows us to use pre-trained deep neural models, such as EfficientNetV2M, VGG-19, and NASNetLarge, and fine-tune them on our dataset to adapt them specifically for Bangladeshi plant diseases. These deep learning models have shown remarkable success in various computer vision tasks and are expected to exhibit strong performance in classifying plant diseases accurately.

Through our research, we aim to provide an effective and efficient solution to plant disease detection, empowering farmers and agricultural professionals with real-time diagnosis and early warning systems. Timely disease detection enables prompt interventions, minimizing crop losses and improving agricultural productivity. In this paper, we present the methodology employed for dataset preparation, transfer learning, and model evaluation [Padol, 2016]. We discuss the performance of each deep neural model, showcasing their accuracy rates and highlighting the potential of EfficientNetV2M in particular. Furthermore, we analyze the implications of our research findings and propose avenues for future research to enhance the accuracy and robustness of plant disease detection systems.

The motivation behind this research stems from the critical importance of effective plant disease detection in the agricultural sector, particularly in the context of Bangladesh. Plant diseases can have devastating effects on crop yields, leading to food scarcity, economic losses, and impacts on the livelihoods of farmers and communities dependent on agriculture. Timely and accurate identification of plant diseases is essential for implementing targeted disease management strategies, optimizing resource utilization, and ensuring sustainable crop production. Traditional methods of plant disease detection have been laborious and often require specialized expertise, making them less accessible and less efficient for widespread adoption. Therefore, the need for automated and efficient disease detection methods has become increasingly evident. Deep learning, coupled with transfer learning, has emerged as a powerful tool in computer vision applications, offering the potential to revolutionize the field of plant disease detection [Patel, 2017]. The specific context of Bangladesh, with its heavy reliance on agriculture as a major economic sector, further emphasizes the urgency for effective disease detection solutions. Rapid population growth and changing climate conditions have put additional pressure on crop production, necessitating advanced agricultural technologies to address these challenges. By utilizing deep neural models and transfer learning in this research, we aim to develop accurate and robust plant disease detection systems tailored to the specific conditions and diseases prevalent in Bangladesh. The outcomes of this research can have significant implications for the agricultural industry, providing farmers and agricultural professionals with real-time disease diagnosis, early warning systems, and effective disease management strategies.

2. Literature Review

The efficiency of our system allows for real-time detection, providing timely information to farmers and agricultural professionals. Early disease detection facilitates swift interventions and preventive measures, thus reducing the spread of diseases and minimizing crop losses. The practical applicability of our system is a key advantage, as the deep learning models can be easily integrated into mobile applications or on-field tools, making them accessible and deployable for farmers.

Table 2.1 Literature Review

Author	Year	Plant Leaf	Techniques
[4] Lijalem, T., Asefa, S. A.	2023	Tomato	K-means Clustering, Segmentation
[5] J. Arun Pandian, K. Kanchanadevi et al.	2022	Large Scale Dataset: 240000 pictures	DCGAN, PCA Color Augmentation, NST Technique
[6] Ramkumar, G., TM, A. et al.	2021	More than 54,300 leaf images	Leaf Disease Estimation, Deep Learning Principle, IoT
[7] Navneet Kaur1, Dr. V. Devendran	2021	Bell pepper, Potato, and Tomato	Ensemble classification, Feature extraction
[8] Chouhan, S. S., Singh, U. P., & Jain, S.	2021	Large Scale Dataset	Fuzzy based function network, Image segmentation, Scale-invariant feature transform
[9] Vallabhajosyula, S., Kolli, V. K. K. et al.	2021	38 classes collected from 14 crops	Deep ensemble neural networks,
[10] Sujatha, R., Chatterjee et al.	2021	Citrus	SVM, RF, SGD, Inception-v3, VGG-16, VGG-19, CA
[11] Jasim, M. A., & Al-Tuwaijari, J. M.	2020	Tomatoes, Pepper, and Potatoes	CNN algorithm
[12] Ashok, S., Kishore, G. et al.	2020	Tomato	Segmentation, CNN Classifier
[13] Ajra, H., M. S., Sarkar, L., & Islam, S.	2020	Tomato and Potato	CNN, AlexNet, ResNet-50, Preventive Measures

[14] Anusha Rao and S.B. Kulkarni	2020	54,306 images with 38 different class categories	Complex Gabor Feature, Curvelet Feature, Fuzzy Logic, Image Signal Processing
[15] Debasish Das, Mahinderpal Singh et al.	2020	Tomato	Feature extraction; Image processing; Segmentation; Random Forest; Support Vector Machine (SVM)
[16] Nilay Ganatra and Atul Patel	2020	14,956 images with 38 distinct classes	Random Forest, Support Vector Machine, K-Neighrest Neighbor and Artificial Neural Network
[17] Junde Chen, Jinxiu Chen et al	2020	Rice, Maize	VGGNet-19, DenseNet-201, ResNet-50, Inception V3
[18] Anu Paulson, Ravishankar S	2020	64 species of medicinal plants with 1000 samples	VGGNet, VGG16, VGG19
[19] Rishabh Yadav, Yogesh Kumar Rana et al.	2019	23 classes of plant leaves with a total of 8750 images	Particle Swarm Optimization, AlexNet, SVM
[20] Amrita S.Tulshan et al.	2019	Five different diseases that influence the plants are: Early Blight, Mosaic Virus, Down Mildew, White Fly, Leaf Miner.	K Nearest Neighbor (KNN), Gray Level Co-occurrence Matrices (GLCM)
[21] Mohammed A. Hussein, Amel H. Abbas	2019	Wheat, Tomatoes and Cucumbers	SVM, GLCM, Texture, Color Feature
[22] Hiteshwari Sabrol and Satish Kumar	2019	Tomato and Brinjal/Eggplant	GLCM, Adaptive neuo-fuzzy inference system
[23] Robert G. de Luna, Elmer P. Dadios et al	2018	Tomato	Faster RCNN, Convolutional Neural Network
[24] Melike Sardogan, Adem Tuncer et al.	2018	Tomato	Convolutional Neural Network (CNN), Learning Vector Quantization (LVQ)
[25] Shitala Prasad, Pankaj P Singh	2017	ICL dataaset	Deep Feature Using VGG-16, SVM

Our system for detecting plant diseases has emerged as one of the best solutions in the field due to its outstanding features and performance. The utilization of deep neural models, particularly EfficientNetV2M, VGG-19, and NASNetLarge, through transfer learning, has resulted in remarkable accuracy rates. EfficientNetV2M achieved an impressive 99% accuracy, VGG-19 reached 93%, and NASNetLarge attained 83% accuracy. This high level of precision in classifying plant diseases demonstrates the effectiveness of our system in accurately identifying various plant pathogens.

3. Methodology

3.1 Procedure for Recognition

In this research, we employ three powerful deep learning models to accurately identify and classify plant diseases. These models, namely EfficientNetV2M, VGG-19, and NASNetLarge, have proven to be highly effective in various computer vision tasks. The recognition process begins by inputting the plant leaf images into each of these models. Each model then utilizes its unique architecture and learned features to extract relevant information from the input images. The extracted features are then used to make predictions about the presence of specific diseases in the plant leaves. The models have been fine-tuned using transfer learning techniques on a specialized dataset containing 18 categories of plant leaf images, with a focus on Bangladeshi-produced plant diseases. The use of transfer learning allows the models to adapt their knowledge to the specific characteristics of these diseases despite the limited dataset size. The recognition procedure showcases the models' exceptional accuracy rates, contributing to the system's success in effectively detecting and classifying various plant diseases in real-time.

- Input Raw Data: The recognition procedure begins with the input of raw data, which consists of plant leaf images. These images serve as the primary data source for the plant disease detection system.

- Data Preprocessing: Before feeding the raw data into the deep learning models, data preprocessing is performed. This step involves various transformations and manipulations to enhance the quality and suitability of the data for training and validation.

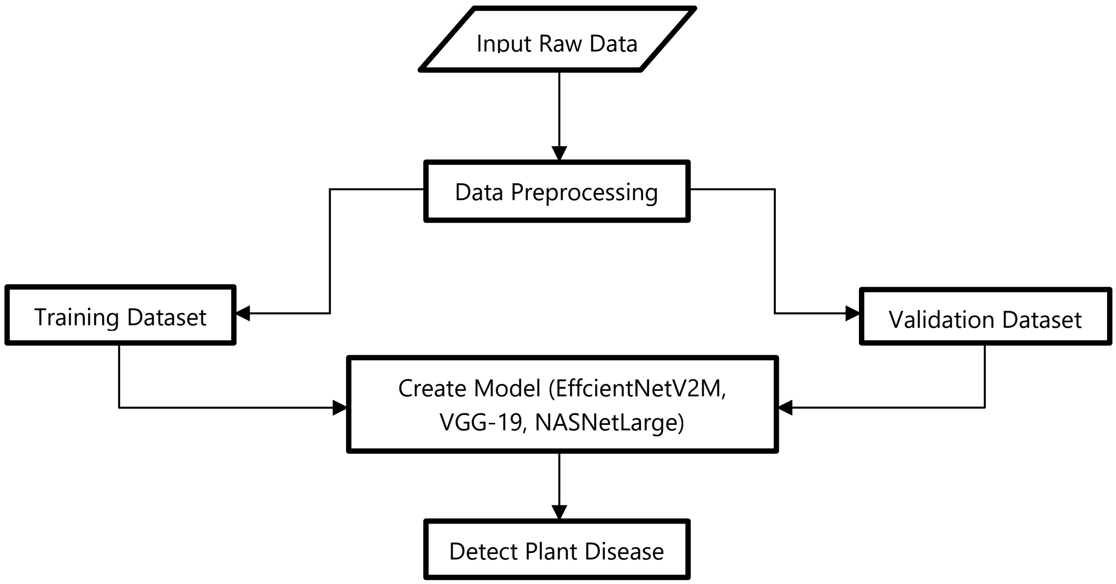

Figure 3.1 Data Flow Diagram

- Training Dataset: From the preprocessed data, a portion is set aside to create the training dataset. This dataset is used to train the deep learning models, allowing them to learn the patterns and characteristics of different plant diseases.

- Validation Dataset: Another subset of the preprocessed data is reserved to create the validation dataset. The validation dataset serves as an independent set of data used to assess the performance of the models during training and prevent overfitting.

- Create Model: In this step, three deep learning models are chosen for the recognition procedure: EfficientNetV2M, VGG-19, and NASNetLarge. These models are selected based on their proven effectiveness in various computer vision tasks and their ability to handle complex image data.

- Detect Plant Disease: Once the models are created, they are trained using the training dataset. Transfer learning is employed to fine-tune the models on the specialized dataset of Bangladeshi-produced plant leaf images. This process enables the models to adapt their learned features to accurately detect and classify various plant diseases.

After training, the models are ready to detect plant diseases. The recognition procedure involves inputting plant leaf images into each model. The models utilize their respective architectures and learned features to extract relevant information from the images. Using the extracted features, the models make predictions about the presence of specific diseases in the plant leaves.

3.2 Data Collection Procedure

The data collection procedure for plant disease detection involves the following steps:

- Identify Target Plant Diseases: Determine the specific plant diseases of interest that need to be detected. Focus on diseases that are prevalent in the target region and have significant impacts on crop production.

- Select Plant Samples: Collect plant samples from various sources, such as farms, agricultural research centers, or botanical gardens. Ensure that the samples represent a diverse range of plant species and disease conditions. The dataset was collected from various sources, including personal collection from different locations and acquiring datasets from reputable websites such as Kaggle, IEEEDataPort, and KD Nuggets.

- Image Acquisition: Capture high-quality images of the plant leaves using digital cameras or smartphones. Standardize the image capture process to ensure consistency in image quality and resolution.

- Data Annotation: Annotate the collected images by labeling them with corresponding disease classes. This step is essential for supervised learning, where the models require labeled data for training.

- Data Cleaning: Review the annotated data to remove any duplicate or low-quality images that may interfere with model training. Ensure that the dataset is free from errors and inconsistencies.

- Data Augmentation: To enhance the dataset's diversity and reduce overfitting, apply data augmentation techniques. Common augmentation methods include rotation, flipping, scaling, and color transformations.

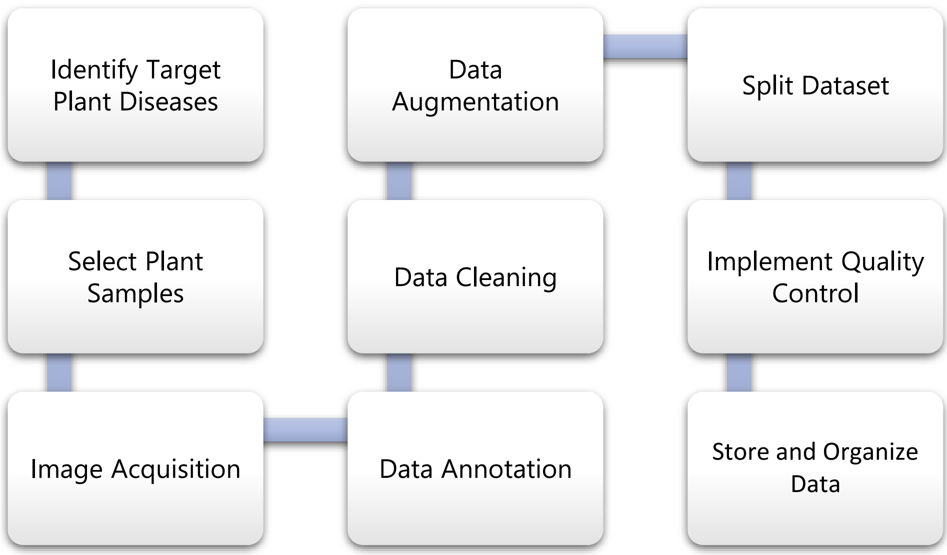

Figure 3.2 Flow diagram of the data collection procedure for plant disease detection

- Split Dataset: Divide the dataset into training, validation, and test sets. The training set is used to train the models; the validation set is used to tune hyperparameters and avoid overfitting, while the test set is used to evaluate the models' performance.

- Implement Quality Control: Perform quality control checks on the dataset to verify the accuracy of annotations and ensure that the dataset is balanced with an adequate representation of each disease class.

- Store and Organize Data: Store the collected and preprocessed data in a secure and accessible repository. Organize the data to facilitate easy access and retrieval during model development and evaluation.

3.3 Pre-trained Deep Learning Networks

The pre-trained deep learning networks used in this research, namely EfficientNetV2M, VGG-19, and NASNetLarge, are state-of-the-art models known for their exceptional performance in various computer vision tasks. Each of these networks has distinct architectural characteristics that contribute to their effectiveness in image recognition tasks, including plant disease detection.

1) EfficientNetV2M: EfficientNetV2M, known for its remarkable efficiency and accuracy, has an input size of 224x224 pixels, which is a standard size for many deep learning models. It comprises multiple convolutional layers that allow it to extract intricate features from input images. The filter size and stride values are optimized during model training to efficiently capture relevant patterns in the data. EfficientNetV2M is characterized by a relatively smaller number of parameters, making it computationally efficient while maintaining high accuracy.

2) NASNetLarge: NASNetLarge, with an input size of 331x331 pixels, employs neural architecture search to automatically discover the best architecture for image recognition tasks. It comprises multiple convolutional layers with diverse filter sizes and strides, allowing it to capture both local and global image features effectively. NASNetLarge has a significantly larger number of parameters compared to the other models, contributing to its potential to learn complex representations from large datasets. The model's fully-connected layers play a crucial role in the final classification of the input images.

3) VGG-19: VGG-19, on the other hand, has a slightly larger input size of 224x224 pixels. It is renowned for its simplicity and consists of 19 layers, all of which are convolutional layers, with a filter size of 3x3 pixels and a stride of 1. The VGG-19 model has a higher number of parameters compared to EfficientNetV2M, contributing to its ability to learn intricate features from complex images. The model's fully-connected layers follow the convolutional layers, facilitating the final classification based on the learned representations.

Table 3.1: Architecture Explanation – EfficientNetV2M

Name of Model	**EfficientNetV2M**	
Type of Layer	Output Shape	Param
efficientnetv2-m (Functional)	(None, 1280)	53150388
dropout_1 (Dropout)	(None, 1280)	0
dense_1 (Dense)	(None, 18)	23058
Params	Total params: 53,173,446 Trainable params: 52,881,414 Non-trainable params: 292,032	

Table 3.2: Architecture Explanation Model – NASNetLarge

Name_of_Model	**NASNetLarge**	
Type_of_Layer	Output Shape	Param
NASNet (Functional)	(None, 4032)	84916818
Dropout (Dropout)	(None, 4032)	0
dense (Dense)	(None, 18)	72594
Params	Total params: 84,989,412 Trainable params: 72,594 Non-trainable params: 84,916,818	

Table 3.3: Explanation of VGG19 Architecture

Name of Model	**VGG19**	
Layer (type)	Output Shape	Param
VGG19 (Functional)	(None, 512)	20024384
Dropout (Dropout)	(None, 512)	0
dense (Dense)	(None, 18)	9234
Params	Total params: 20,033,618 Trainable params: 20,033,618 Non-trainable params: 0	

4. Results and Discussion

4.1 Dataset

The data collection process for the thesis paper on plant disease detection involved gathering a dataset consisting of 10,102 train samples and 2,808 test samples. We carefully collected a varied dataset consisting of 18 distinct categories of plant leaf images, encompassing Bell pepper Bacterial spot, Bell pepper Healthy, Peach Healthy, Potato Early Blight, Rice Leaf Blast, Rice Healthy, Rice Brown Spot, Potato Healthy, Peach Bacterial spot, Corn Blight, Potato Late blight, Corn Healthy, Tomato Bacterial spot, Strawberry Leaf Scorch, Tomato Early blight, Tomato Early blight, Strawberry Healthy, and Tomato Healthy.

Table 4.1: Count the number of leaves in the training and testing images

Training Image		Testing Image	
Plant Leaf Varieties	**Images**	**Plant Leaf Varieties**	**Images**
Bell pepper Bacterial spot	610	Bell pepper Bacterial spot	115
Bell pepper Healthy	430	Bell pepper Healthy	204
Peach Healthy	670	Peach Healthy	124
Potato_Early_Blight	400	Potato_Early_Blight	120
Rice_LeafBlast	270	Rice_LeafBlast	150
Rice_Healthy	622	Rice_Healthy	206
Rice_BrownSpot	258	Rice_BrownSpot	200
Potato_Healthy	300	Potato_Healthy	126
Peach Bacterial spot	680	Peach Bacterial spot	120
Corn_Blight	550	Corn_Blight	102
Potato Late blight	204	Potato Late blight	85
Corn Healthy	540	Corn Healthy	190
Tomato Bacterial spot	838	Tomato Bacterial spot	200
Strawberry Leaf Scorch	685	Strawberry Leaf Scorch	190
Tomato Early blight	720	Tomato Early blight	230
Tomato_Early_blight	825	Tomato_Early_blight	176
Strawberry_Healthy	700	Strawberry_Healthy	210
Tomato_healthy	800	Tomato_healthy	60

This dataset was meticulously curated to cover the most prevalent plant diseases commonly found in Bangladesh. Care was taken to ensure the dataset's quality and reliability by conducting checks for inconsistencies, errors, and duplicates. Ethical considerations were upheld by complying with legal guidelines, respecting intellectual property rights, and maintaining privacy during the data collection process. The resulting dataset provides a valuable resource for training and evaluating the plant disease detection model.

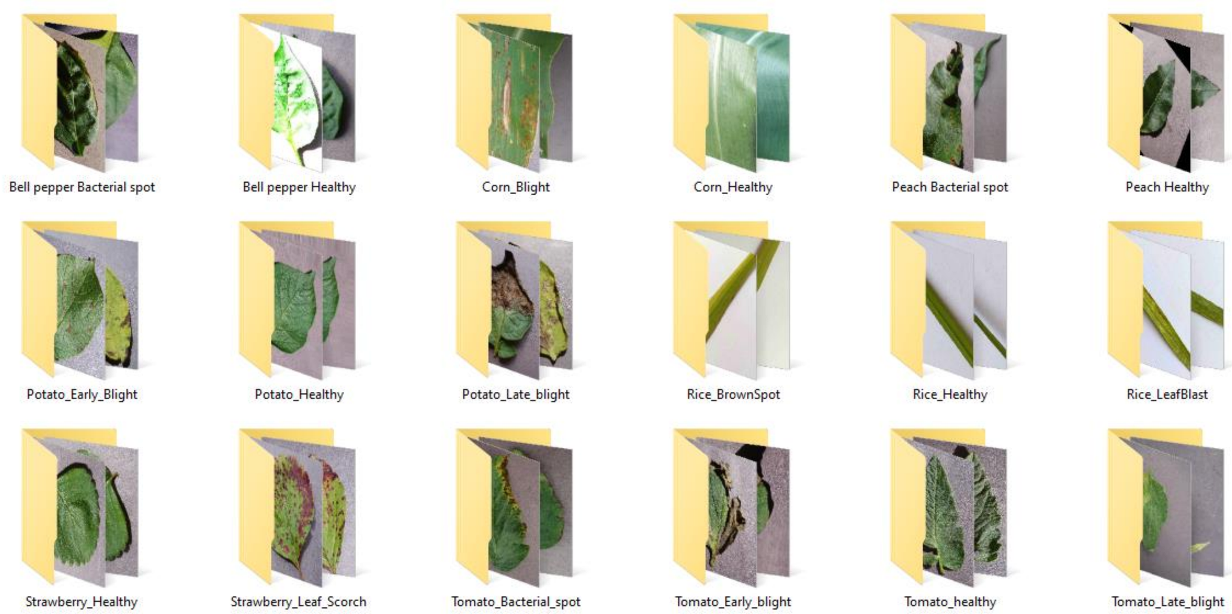

Figure 4.1 Plant Leaf Data Sample

4.2 EfficientNetV2M Models Results

- **Parameters:**
  Total number of parameters: 53,173,446
  Number of trainable parameters: 52,881,414
  Total Non-trainable parameters: 292,032

- **Confusion Matrix:** The EfficientNetV2M Model predicted 22 of the 2808 pictures in the test set inaccurately, as seen in Figure 4.2 (confusion matrix).

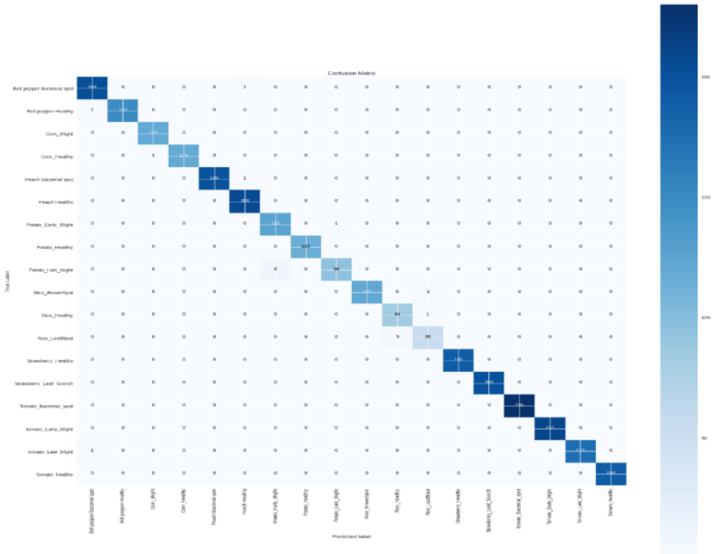

Figure 4.2: Confusion Matrix of EfficientNetV2M

- **Classification Report:**

	precision	recall	f1-score	support
Bell pepper Bacterial spot	0.99	1.00	0.99	204
Bell pepper Healthy	1.00	0.99	1.00	150
Corn_Blight	0.99	1.00	1.00	120
Corn_Healthy	1.00	0.99	1.00	120
Peach Bacterial spot	1.00	0.99	1.00	200
Peach Healthy	0.99	1.00	1.00	206
Potato_Early_Blight	0.94	0.99	0.97	126
Potato_Healthy	1.00	1.00	1.00	115
Potato_Late_blight	0.99	0.92	0.95	102
Rice_BrownSpot	1.00	0.98	0.99	124
Rice_Healthy	0.94	0.99	0.97	85
Rice_LeafBlast	0.95	0.92	0.93	60
Strawberry_Healthy	1.00	1.00	1.00	190
Strawberry_Leaf_Scorch	1.00	1.00	1.00	200
Tomato_Bacterial_spot	1.00	1.00	1.00	230
Tomato_Early_blight	1.00	1.00	1.00	210
Tomato_Late_blight	1.00	0.99	1.00	176
Tomato_healthy	1.00	1.00	1.00	190
accuracy			0.99	2808
macro avg	0.99	0.99	0.99	2808
weighted avg	0.99	0.99	0.99	2808

Figure 4.3: Classification Report of EfficientNetV2M

- **Accuracy of Training and Accuracy of Validation:**

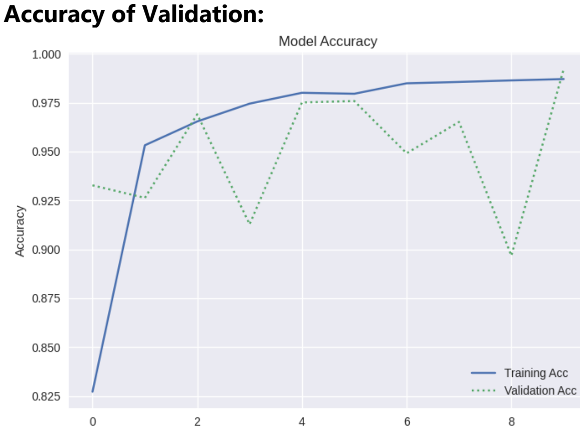

Figure 4.4: Training and Validation Accuracy of EfficientNetV2M

- **Training Loss and Validation Loss:**

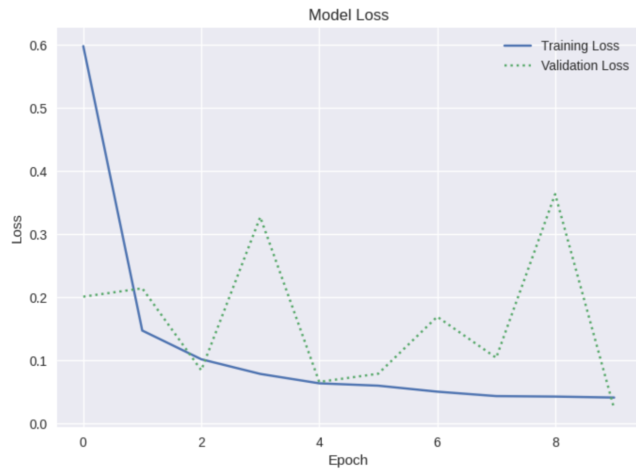

Figure 4.5: Training and Validation Loss of EfficientNetV2M

4.2.1 EfficientNetV2M Model Discussion:

The training accuracy and loss of the EfficientNetV2M Model, as well as the validation accuracy and loss. In the initial time, the accuracy of training was 82.93%, and the accuracy of validation was 93.27%. After 10 epochs, the training loss was 4.10 percent, and the validation loss was 2.34 percent, such as 98.70 percent training accuracy and 99.22 percent validation accuracy. In 2808 images EfficientNetV2M model predicts 22 inaccurate images, which is shown in the confusion matrix figure.

4.3 NASNetLarge Models Experimental Results

- **Parameters:**
  Number of total parameters: 84,989,412
  Trainable number of parameters: 72,594
  Complete Non-trainable params: 84,916,818

- **Confusion Matrix:** In total, 2808 pictures, 468 pictures were inaccurately predicted through the NASNetLarge Model as shown in the confusion matrix.

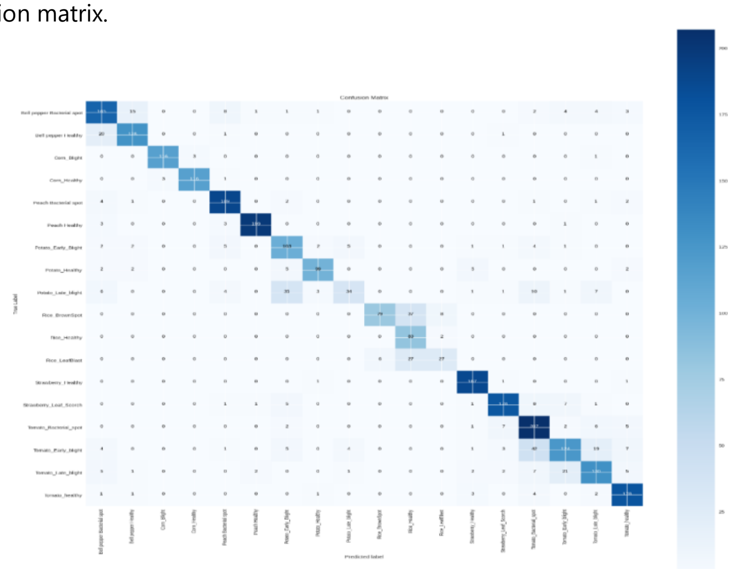

Figure 4.6: Confusion Matrix of NASNetLarge

- **Classification Report:**

	precision	recall	f1-score	support
Bell pepper Bacterial spot	0.78	0.81	0.79	204
Bell pepper Healthy	0.85	0.85	0.85	150
Corn_Blight	0.97	0.97	0.97	120
Corn_Healthy	0.97	0.97	0.97	120
Peach Bacterial spot	0.89	0.94	0.92	200
Peach Healthy	0.98	0.97	0.97	206
Potato_Early_Blight	0.65	0.82	0.73	126
Potato_Healthy	0.93	0.86	0.89	115
Potato_Late_blight	0.77	0.33	0.47	102
Rice_BrownSpot	0.93	0.64	0.76	124
Rice_Healthy	0.56	0.98	0.72	85
Rice_LeafBlast	0.73	0.45	0.56	60
Strawberry_Healthy	0.93	0.98	0.95	190
Strawberry_Leaf_Scorch	0.92	0.88	0.90	200
Tomato_Bacterial_spot	0.73	0.90	0.80	230
Tomato_Early_blight	0.77	0.59	0.67	210
Tomato_Late_blight	0.76	0.74	0.75	176
Tomato_healthy	0.88	0.94	0.91	190
accuracy			0.83	2808
macro avg	0.83	0.81	0.81	2808
weighted avg	0.84	0.83	0.83	2808

Figure 4.7: Classification Report of NASNetLarge

- **Training Accuracy and Validation Accuracy:**

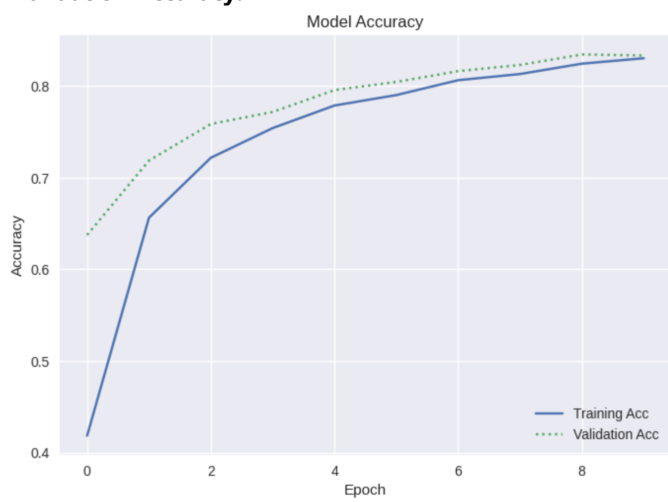

Figure 4.8: Training and Validation Accuracy of NASNetLarge

- **Training Loss and Validation Loss:**

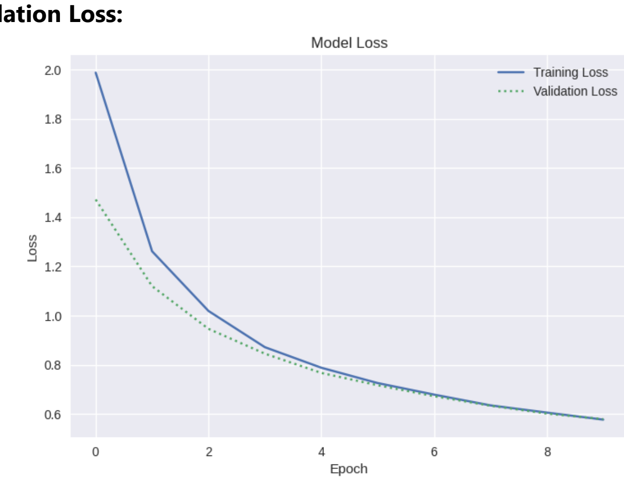

Figure 4.9: Training and Validation Loss of NASNetLarge

4.3.1 NASNetLarge Model Discussion:

The training accuracy and loss of the NASNetLarge Model, as well as the validation accuracy and loss. In the initial time, the accuracy of training was 41.85%, and the accuracy of validation was 63.75. After 10 epochs, the training loss was 57.66 percent, and the validation loss was 57.85 percent, such as 83.03 percent training accuracy and 83.33 percent validation accuracy. In total, 2808 images and 468 images were predicted inaccurately by the NASNetLarge Model shown in the confusion matrix graph.

4.4 VGG19 Models Experimental Results

- **Parameters:**
  Total amount of parameters: 20,033,618
  Amount of trainable parameters: 20,033,618
  Amount of Non-trainable params: 0

- **Confusion Matrix:** In a total of 2808 images, 188 pictures were inaccurately predicted by the VGG19 model, as shown in the confusion matrix.

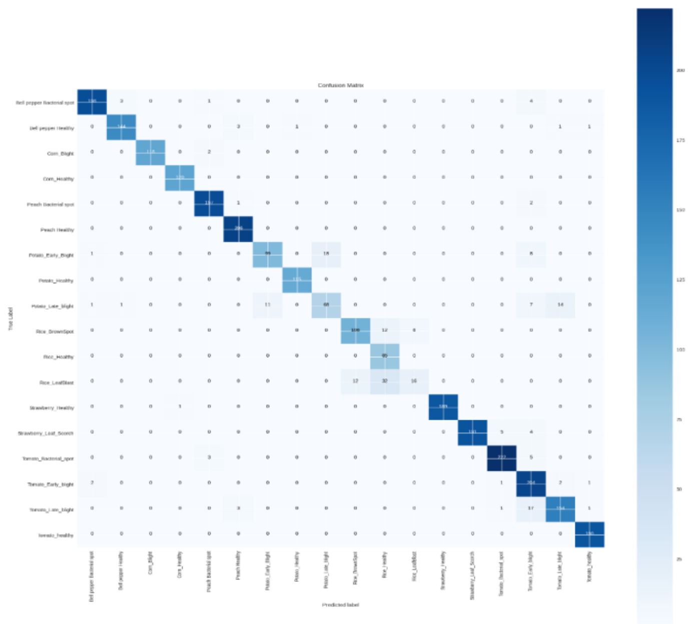

Figure 4.10: Confusion Matrix of VGG19

- **Classification Report:**

	precision	recall	f1-score	support
Bell pepper Bacterial spot	0.98	0.96	0.97	204
Bell pepper Healthy	0.97	0.96	0.97	150
Corn_Blight	1.00	0.98	0.99	120
Corn_Healthy	0.99	1.00	1.00	120
Peach Bacterial spot	0.97	0.98	0.98	200
Peach Healthy	0.97	1.00	0.98	206
Potato_Early_Blight	0.90	0.79	0.84	126
Potato_Healthy	0.99	1.00	1.00	115
Potato_Late_blight	0.79	0.67	0.72	102
Rice_BrownSpot	0.90	0.85	0.88	124
Rice_Healthy	0.66	1.00	0.79	85
Rice_LeafBlast	0.73	0.27	0.39	60
Strawberry_Healthy	1.00	0.99	1.00	190
Strawberry_Leaf_Scorch	1.00	0.95	0.98	200
Tomato_Bacterial_spot	0.97	0.97	0.97	230
Tomato_Early_blight	0.81	0.97	0.89	210
Tomato_Late_blight	0.90	0.88	0.89	176
Tomato_healthy	0.98	1.00	0.99	190
accuracy			0.93	2808
macro avg	0.92	0.90	0.90	2808
weighted avg	0.94	0.93	0.93	2808

Figure 4.11: Classification Report of VGG19

- **Training Accuracy and Validation Accuracy:**

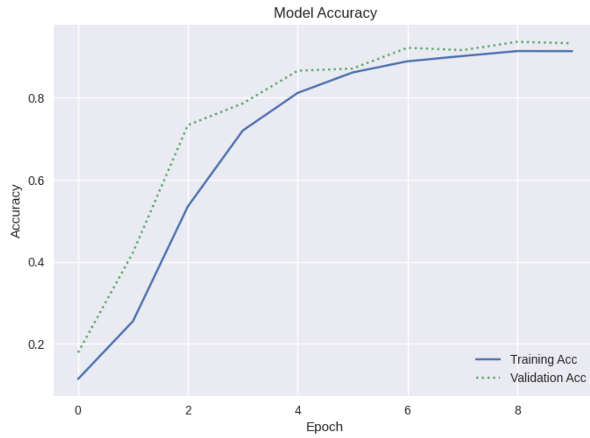

Figure 4.12: Training and Validation Accuracy of VGG19

- **Training Loss and Validation Loss:**

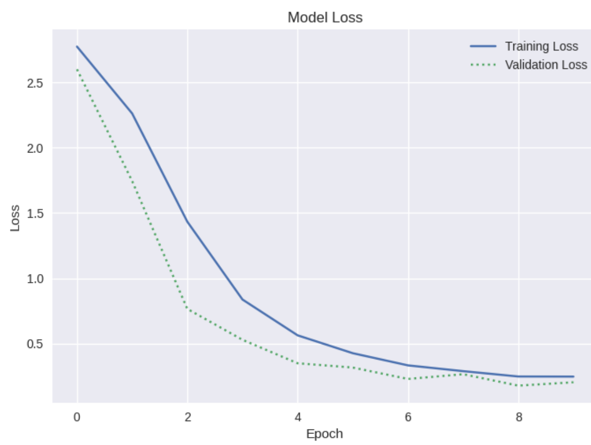

Figure 4.13: Training and Validation Loss of VGG19

4.4.1 VGG19 Model Discussion:

The training accuracy and loss of the VGG19 Model, as well as the validation accuracy and loss. The accuracy of training was 11.43%, and the accuracy of validation was 17.88% in the starting time. After 10 epochs, the training loss was 24.79 percent, and the validation loss was 20.44 percent, such as 91.39 percent training accuracy and 93.30 percent validation accuracy. In a total of 2808 pictures, 188 pictures were predicted inaccurately by the VGG19 model, as seen in the confusion matrix figure.

4.5 Analysis of all model results

A total of 3 algorithms have been used in this project. And NASNetLarge has the worst accuracy, with an error rate of 468. On the other hand, EfficientNetV2M and VGG19 have given the best accuracy. From this, EfficientNetV2M has given much less training loss and validation loss than VGG19.

Table 4.2: Analysis of all model results

Model	Error Rate of Confusion Matrix	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
EfficientNetV2M	22	98.70	4.10	99.22	2.34
NASNetLarge	468	83.03	57.66	83.33	57.85
VGG19	188	91.39	24.79	93.30	20.44

The three models have been tested with the specific parameters, and it is found that the EfficientNetV2M model has secured the least error. And its validity accuracy is 99.22%. In the above circumstances, it is observed that the EfficientNetV2M model may be considered the best among other models.

4.6 Pictures of some experiments with web applications

A plant disease detection web app is a specialized web application designed to identify and diagnose diseases in plants. It utilizes image recognition and deep learning algorithms to analyze plant images uploaded by users. The app provides an interactive interface where users can upload plant images, and the algorithms analyze the images to detect signs of diseases or infections. The results are then displayed to the user, along with information about the detected disease, possible treatment options, and preventive measures.

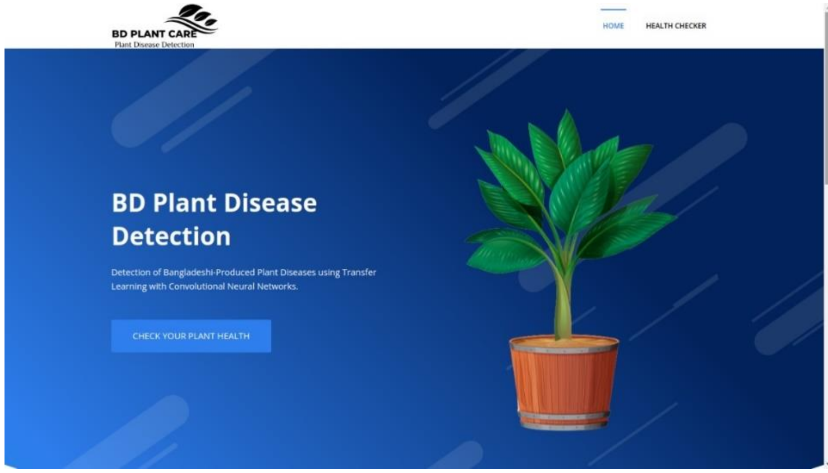

Figure 4.14: BD Plant Disease Detection – Home Page

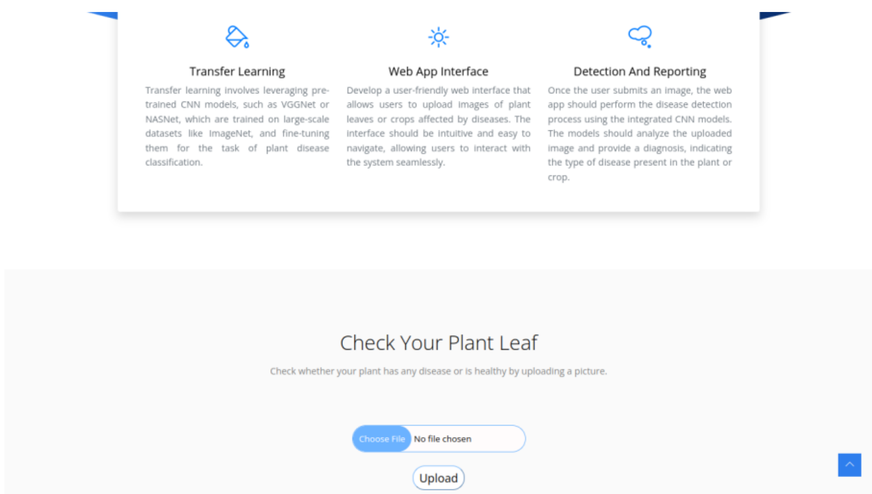

Figure 4.15: Upload Section

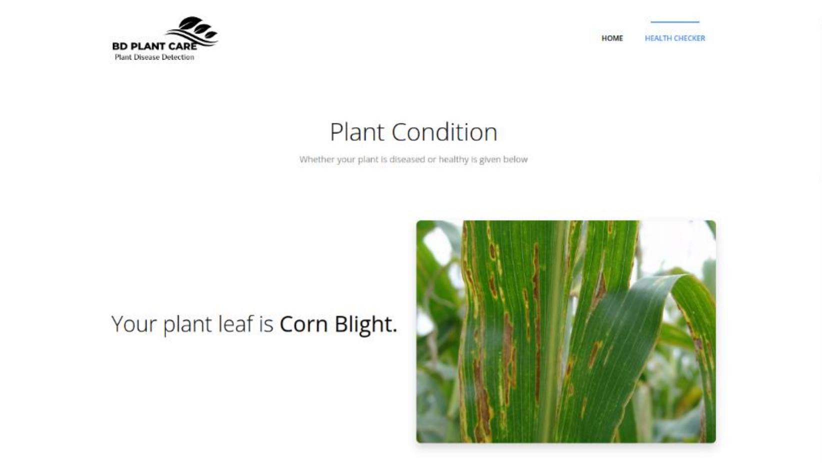

Figure 4.16: Detect Corn Blight

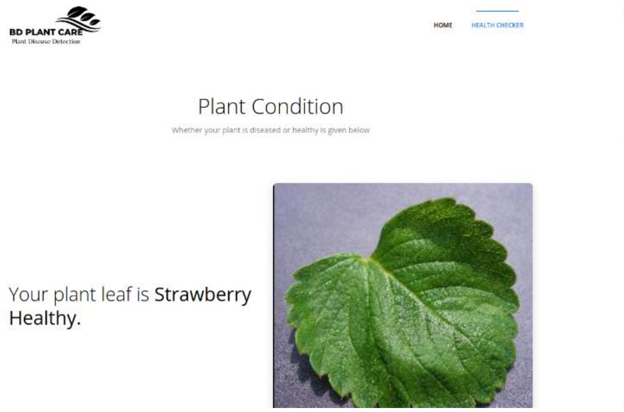

Figure 4.17: Detect Strawberry Healthy

5. Conclusion

The research results highlight the significance of using transfer learning with deep neural models, specifically EfficientNetV2M, VGG-19, and NASNetLarge, for plant disease detection. The achieved high accuracy rates of 99%, 93%, and 83%, respectively, underscore the effectiveness of these models in accurately classifying Bangladeshi-produced plant diseases based on leaf images. The curated diverse dataset played a crucial role in training the models, showcasing the importance of dataset curation for improved model performance. The developed deep learning models offer a practical and efficient solution for real-time disease detection, empowering farmers and agricultural professionals with timely information to implement prompt interventions and minimize crop losses. This research contributes valuable insights into the agricultural sector, providing a robust approach to disease management, enhancing crop productivity, and ensuring food security in Bangladesh and beyond.

The implications of this study are significant for future research in the field of plant disease detection and agricultural practices. Firstly, researchers can focus on expanding the dataset size by collecting more images of medicinal plant leaves, encompassing a broader variety of species and disease conditions. This will enable the models to generalize better and enhance accuracy even further. Secondly, exploring other state-of-the-art deep learning architectures beyond the three models considered in this study can be valuable. Different architectures may have specific strengths for plant disease detection, and comparing their performances can lead to better model selection and improved results. Finally, deploying the developed deep learning models in real-world scenarios, such as mobile applications or on-field agricultural tools, would be beneficial. This would enable farmers and agricultural professionals to access accurate and timely plant disease diagnosis, leading to prompt interventions and minimizing crop losses.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
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