Bachelor of Science in Computer Science & Engineering

Tree leaf identification system using CNN (Convolution Neural Network) model

by

Tahiat Mahabub Chowdhury
Md. Arafat Hossen
Md. Yeasin
ID:
1904073
1904096
1904097

Department of Computer Science & Engineering

Chittagong University of Engineering & Technology (CUET)

Chattogram-4349, Bangladesh.

16 January, 2024

Chittagong University of Engineering & Technology (CUET)

Department of Computer Science & Engineering

Chattogram-4349, Bangladesh.

Student Name	Tahiat Mahabub Chowdhury Md. Arafat Hossen Md. Yeasin
ID	1904073 1904096 1904097
Session	: 2021-2022
Supervisor Name	: Animesh Chandra Roy
Designation	: Assistant Professor Department of Computer Science & Engineering
Supervisor Name	: MD. Atiqul Islam Rizvi
Designation	: Assistant Professor Department of Computer Science & Engineering
Department	: Computer Science & Engineering
Program	: B.Sc. Engineering
Tentative Title	: **Tree leaf identification system using CNN (Convolution Neural Network) model**

Table of Contents

List of Figures

1 Introduction

Accurate identification of plant species through leaf images holds paramount importance in diverse agricultural applications, playing a pivotal role in effective pest and disease management, biodiversity monitoring, and precision agriculture strategies. The ability to discern between different plant species contributes swiftly and precisely significantly to informed decision-making and targeted interventions within the agricultural landscape.

In response to these imperatives, this project introduces a sophisticated solution in the form of a Convolution Neural Network (CNN) model. Leveraging the robust capabilities of the TensorFlow framework, this model is meticulously designed to address the challenges inherent in classifying leaf images. The primary objective is to accurately identify 10 distinct plant species, a task critical for optimizing agricultural practices and ensuring sustainable crop management.

The foundation of this endeavor rests on a comprehensive dataset, carefully curated to encapsulate the unique visual characteristics of each plant species. With approximately 200 images per species, the dataset encapsulates the inherent variability in leaf morphology, capturing the nuances essential for the model to discern minute differences between species. Through this meticulous dataset curation, the model is primed to recognize intricate patterns and features crucial for species-level identification.

1.1 Challenges

Several challenges were encountered during the leaf image classification project. These are discussed below:

Dataset Imbalance: The distribution of images among plant species may not be uniform, introducing difficulties in training the model to recognize less-represented classes.

Variability in Image Conditions: Environmental factors, lighting variations, and diverse image qualities contribute to the complexity of the dataset, demanding a resilient model capable of handling a wide range of scenarios.

Interclass Variability: Distinguishing between different plant species with subtle visual differences requires the model to capture intricate patterns and features.

Computational Cost: Training deep CNN models can be computationally expensive, requiring high-performance hardware and processing power. This can pose challenges for resource-constrained environments.

1.2 Applications

Convolution Neural Networks (CNNs) have revolutionized the field of plant leaf identification, offering a fast, accurate, and non-invasive approach compared to traditional methods. This technology has opened doors to various exciting applications across different sectors.

In different fields, it can be used in the following ways:

- Real-time identification of weeds and pest optimizing resource use and enhancing crop yields sustainably.
- Identifying plant species for effective land management, crop selection, and biodiversity monitoring.
- Early identification of invasive plants supports swift eradication, preserving native ecosystems.
- Identifying medicinal plants, supporting sustainable harvesting and preserving traditional herbal knowledge.
- Identifying and classifies seedlings, ensuring accurate plant labeling and supporting efficient nursery management.
- Development of mobile apps and user-friendly interfaces making these systems accessible to a wider audience, including non-experts for identfying plant species.

1.3 Objectives

The primary objective of this project is to develop a CNN-based model on the TensorFlow framework for accurate leaf image identification. Moreover, other objectives include:

- Investigating the influence of data augmentation and pre-processing techniques on model performance.
- Analyzing the computational efficiency of the model and exploring potential optimization strategies.

1.4 Background

Previous research underscores the prowess of Convolutional Neural Networks (CNNs) in automating image-based plant species identification, showcasing their adeptness in handling intricate visual patterns. Drawing inspiration from these successes, our project aims to contribute to this field by tailoring a specialized model for leaf image classification with a primary focus on accurate plant species identification. By delving into insights from related studies, we navigate potential challenges and optimize our model's architecture and training parameters. This approach ensures our project aligns with the latest advancements in botanical research, emphasizing practical applications in species identification, conservation, and agriculture. Ultimately, our research synthesizes collective wisdom, propelling us to the forefront of technological innovation in the intersection of computer vision and botanical sciences.

2 Literature Review

Leaf classification plays a pivotal role in the field of plant identification, aiding in biodiversity studies, precision agriculture, and ecological conservation. Over the years, various approaches and algorithms have been proposed to achieve accurate and efficient leaf classification.

Wu et al. introduced the Flavia dataset and applied probabilistic neural networks, achieving accuracies around 90%. Their approach utilized 12 simple geometric features, demonstrating the efficacy of probabilistic neural networks in leaf classification for plant species identification [**1**].

Kadir et al. extended the work on the Flavia dataset and their initially published Foliage dataset. They applied various features, including those derived from a leaf's shape, vein, color, and texture. Their best models, based on probabilistic neuronal networks, achieved accuracies of about 95% on the Flavia and 95.75% on the Foliage dataset. This study highlighted the importance of diverse features for accurate leaf classification [**2**].

Pavan et al. proposed a multiclass classification algorithm based on color, shape, volume, and cell features. Their approach involved three-stage comparisons, including features like redness, greenness, blueness index, shape, and cell features. While achieving a recognition rate of up to 85%, the semi-automatic nature of the approach was acknowledged as a limitation. This work emphasized on the significance of integrating various features for comprehensive leaf classification with more automation [**3**].

Arun Priya presented an algorithm consisting of preprocessing, feature extraction, and classification phases. The preprocessing involved transforming images to grayscale and enhancing boundaries. Feature extraction derived common DMF from five fundamental features, and Support Vector Machine (SVM) classification was employed for efficient leaf recognition. The study incorporated 12 leaf features orthogonalized into 5 principal variables, showcasing the effectiveness of SVM in leaf classification [**4**].

3 Methodology

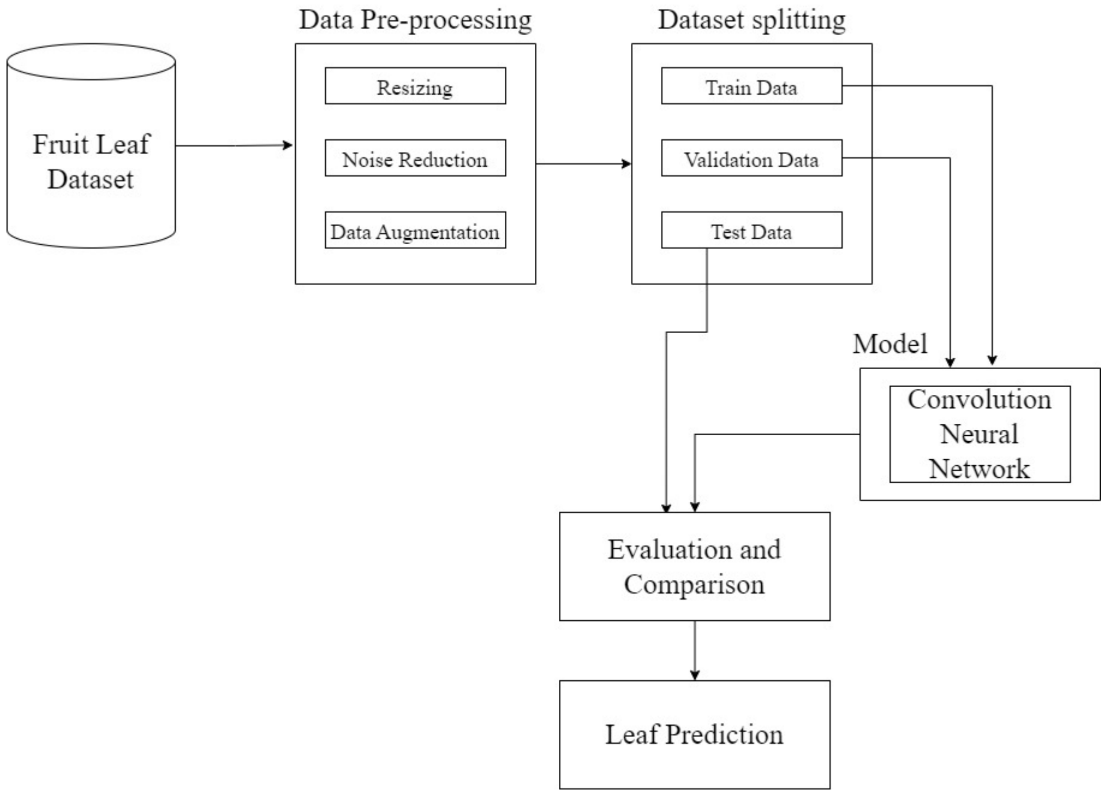

Figure 3.1: Methodology

The methodology is explained below:

- **Data pre-processing:** The first step is to collect a dataset of images of fruit leaves. The images has been pre-processed to ensure that they are all in the same format and size. This involved resizing the images, removing noise, and augmenting the dataset with additional images by performing transformations such as flipping, rotating, and cropping the images.

- **Dataset splitting:**The dataset is then split into three subsets: training, validation, and test sets. The training set is used to train the CNN model, the validation set is used to evaluate the performance of the model during training, and the test set is used to evaluate the performance of the model on unseen data.

- **Model Training:**The CNN model is trained on the training set. The model learned to extract features from the images that are relevant for fruit leaf detection.

- **Model evaluation:**The model is evaluated on the validation set to ensure that it is not over-fitting to the training data. If the model is over-fitting, the training procedure can be adjusted to reduce over-fitting.
- **Model prediction:**Once the model is trained and evaluated, it can be used to predict whether a given image contains a fruit leaf. The model outputs a probability score for each image, indicating the likelihood that the image contains a fruit leaf.

This methodology is used to develop a fruit leaf detection system that can be used to automate the process of fruit leaf detection. The system can be used to detect fruit leaves in different types of images, such as images of fruit leaves on the ground, and images of fruit leaves in the food supply chain.

4 Implementation Details

We implemented the model using CNN(Convolution Neural Network). In this model, we first pre-processed the data in different ways. We gray-scaled the image, filtered it for noise reduction, augmented the image by cropping and resizing. Some examples of the image are shown below:

Initially, the image we found in the training set is shown in Fig-4.1,

Figure 4.1: Initial image of Mango from dataset

We resized the image initially. We converted the image to 128*128 sized images. The image after resizing are shown in Fig-4.2,

Figure 4.2: Resized image of Mango

After greyscaling the image, the output we found is shown in Figure-4.3,

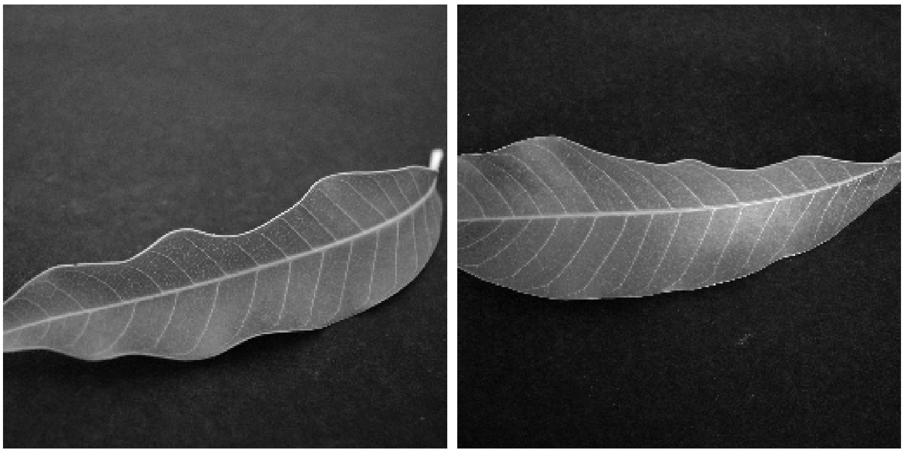

Figure 4.3: Grey-scale image of Mango

After applying some filters, we smoothened the image to reduce noise and we found the following output.

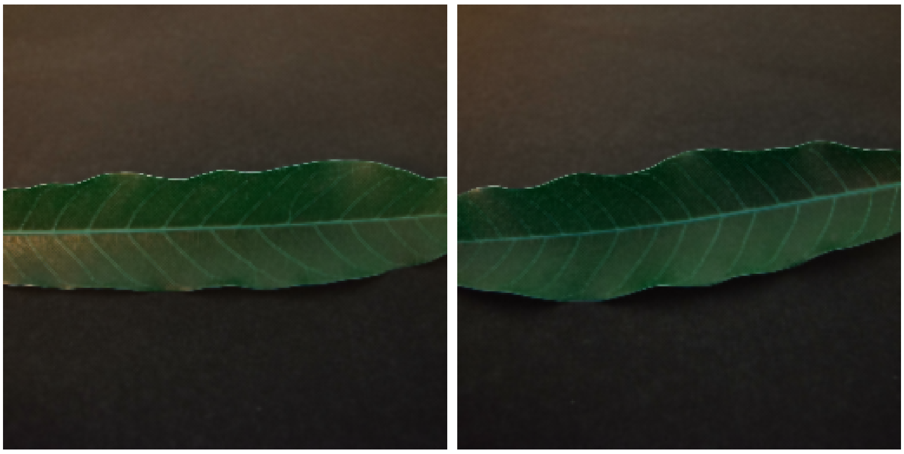

Figure 4.4: Smoothened image of Mango

After pre-processing the data, we then divided the model into 3 parts, that is, training set, validation set and testing set. We first trained the model with the training set. Then we further fine tuned the model using the validation dataset. We then built the model. Our model consisted of 2 hidden layers and 128 neurons. After that to avoid over-fitting, we used a function to dropout some values. While building the model, we used different activation functions. The activation functions we used were, ReLU and Softmax. ReLU is widely used as an activation function in hidden layers of neural network. Softmax is often used in the output layer of a neural network for multiclass classification.

Our model was then tested with test dataset. We checked if the model properly identified the images or not.

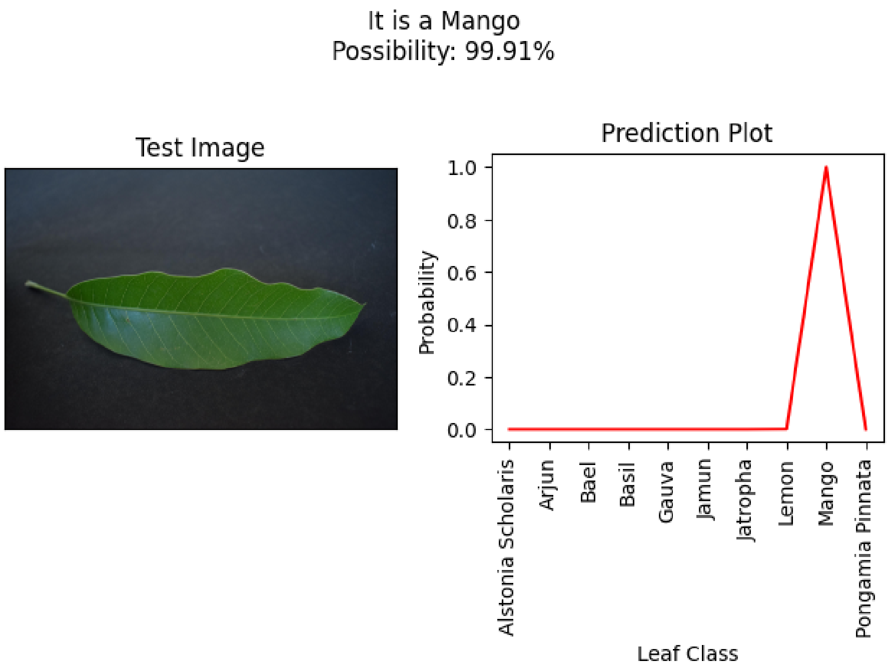

Figure 4.5: Prediction of Mango

5 Evaluation

We developed 3 different models by making some alterations in different parameters. In all the models, there were 10 classes of images.

In the initial model, labeled as 'Model 1', we encountered an imbalanced training dataset with varying image counts per class. The resizing of images to 64x64 pixels was applied during model development. Notably, certain classes contained over 600 images, while others had approximately 200 to 300 images. These considerations are crucial in understanding the challenges and characteristics of 'Model 1.'

For the second model, we opted for a reduced training dataset, ensuring each class was represented by approximately 200 images. In addition, the image size was adjusted to 128x128 pixels. This deliberate downsizing and uniform class representation in the dataset characterize key adjustments made in the development of the second model.

In the third model, our focus remained on maintaining a consistent image size of 128x128 pixels. However, we introduced a controlled level of imbalance in the training dataset, allocating approximately 250 to 400 images per class. This deliberate variation in class representation serves as a strategic departure from the balanced dataset approach, offering insights into model performance under different training conditions.

The Accuracy rate of the models are shown in Fig-5.1,

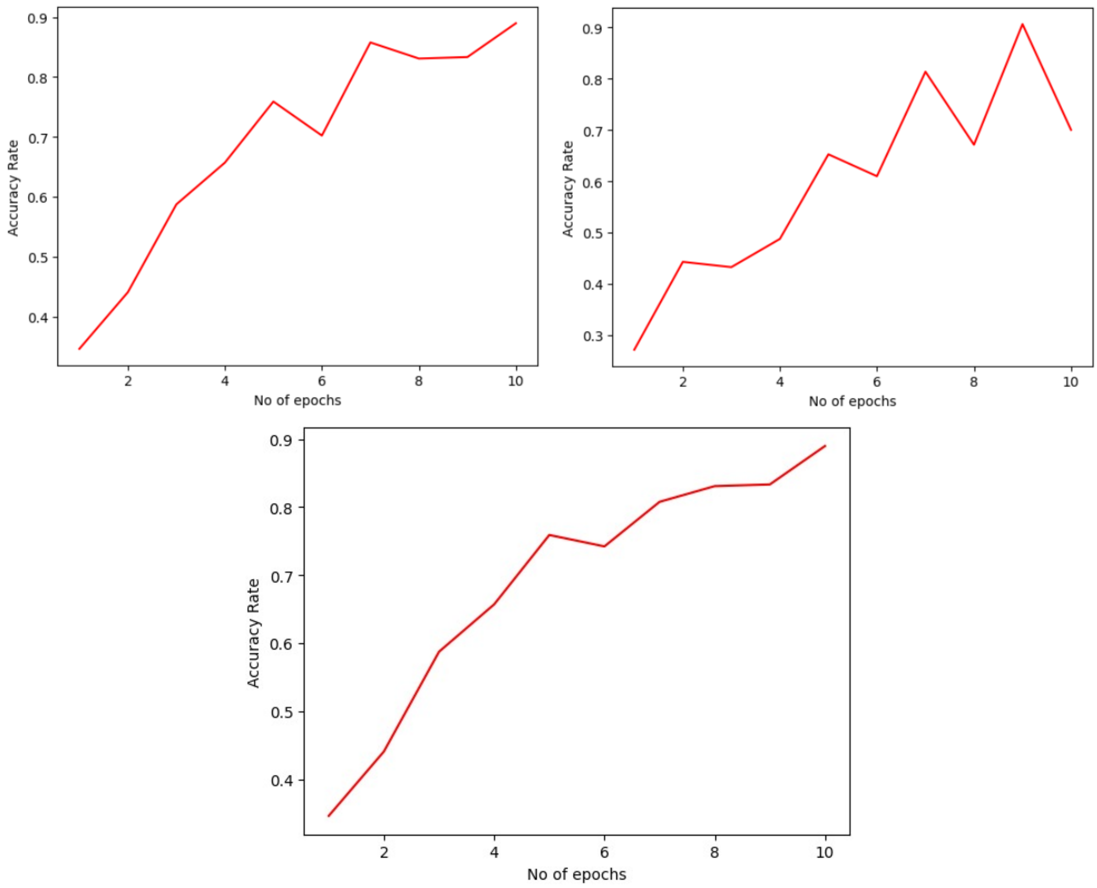

Figure 5.1: Accuracy rate of Model-1, Model-2 and Model-3

The Validation Accuracy of the models are shown in Fig-5.2,

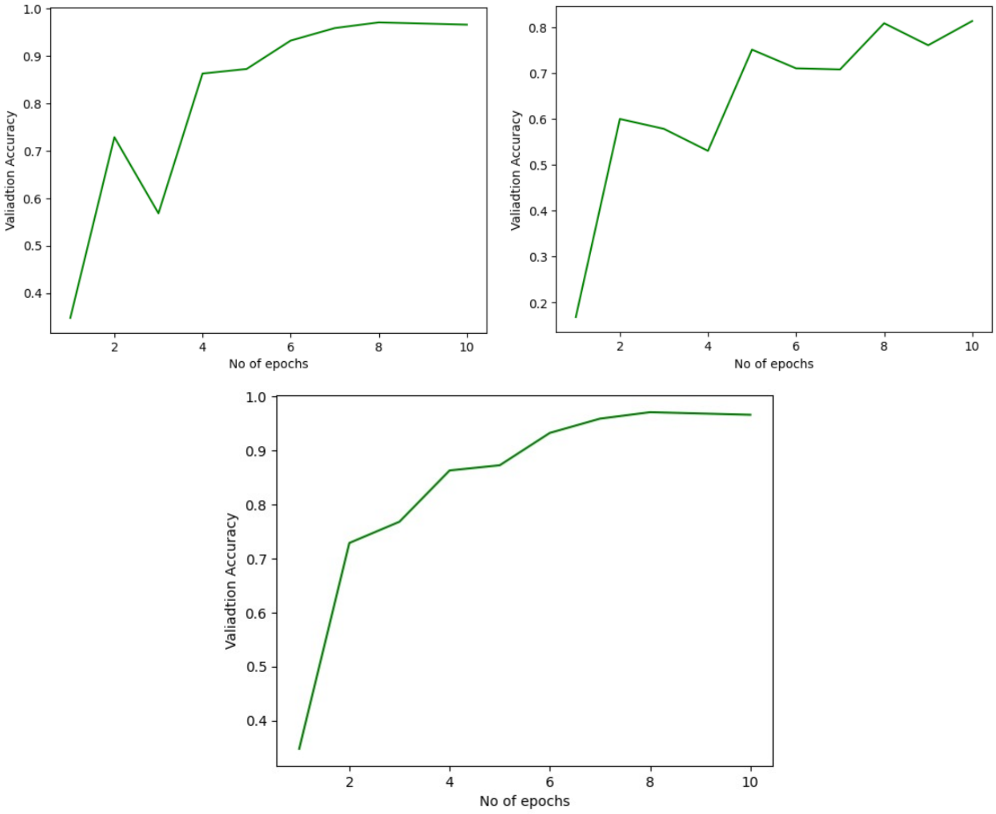

Figure 5.2: Validation Accuracy of Model-1, Model-2 and Model-3

The Data Loss of the models are shown in Fig-5.3,

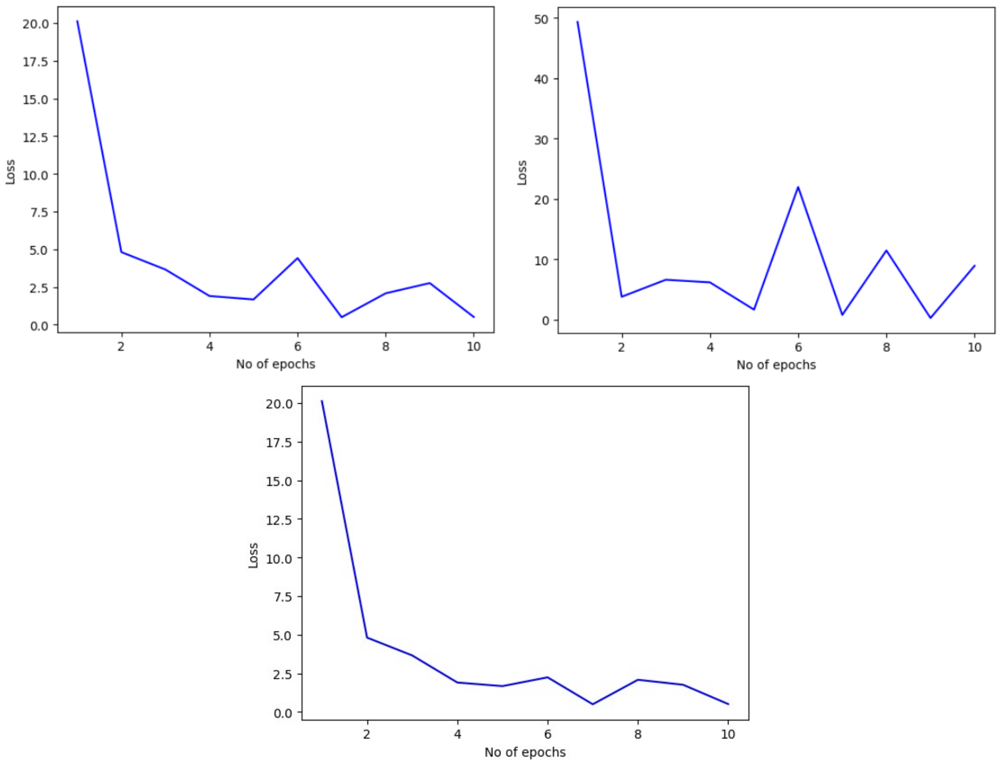

Figure 5.3: Data Loss of Model-1, Model-2 and Model-3

The Confusion Matrix of Model-1 is shown in Fig-5.4,

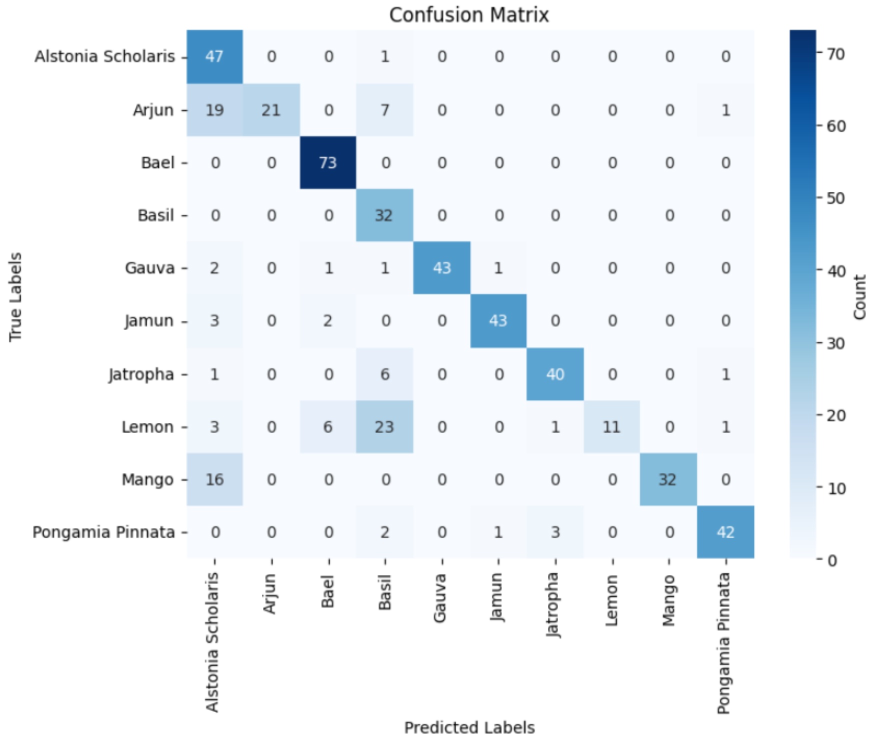

Figure 5.4: Confusion Matrix of Model-1

The Confusion Matrix of Model-2 is shown in Fig-5.5,

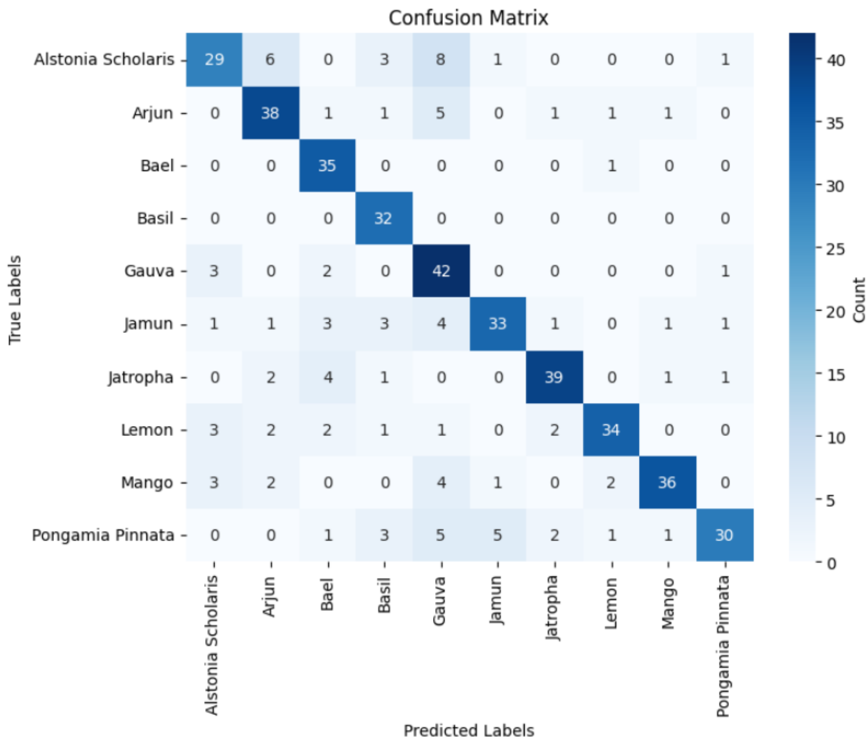

Figure 5.5: Confusion Matrix of Model-2

The Confusion Matrix of Model-3 is shown in Fig-5.6,

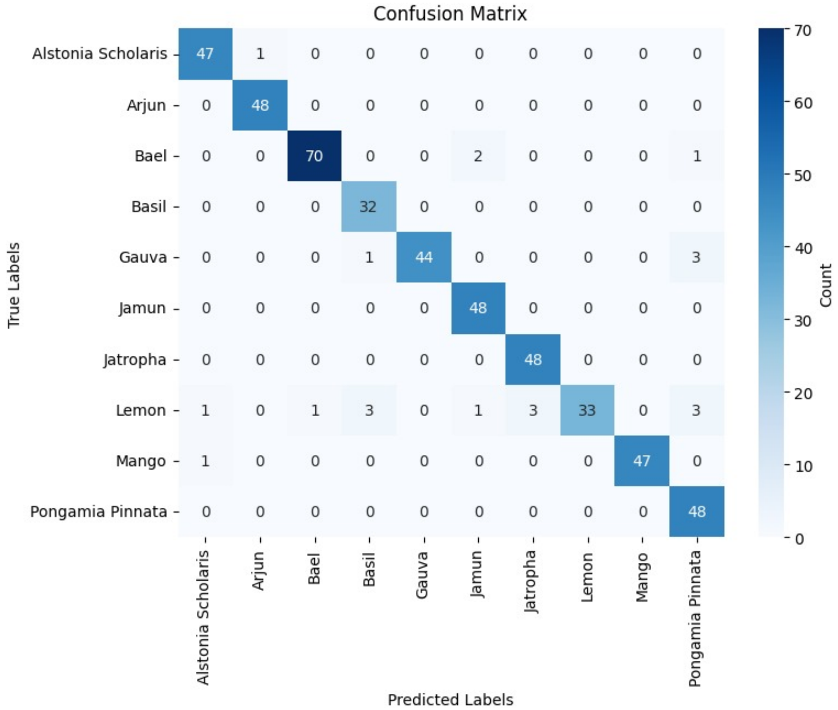

Figure 5.6: Confusion Matrix of Model-3

The Precision, Recall and F1-Score for each class identification of Model-1 is shown in Fig-5.7,

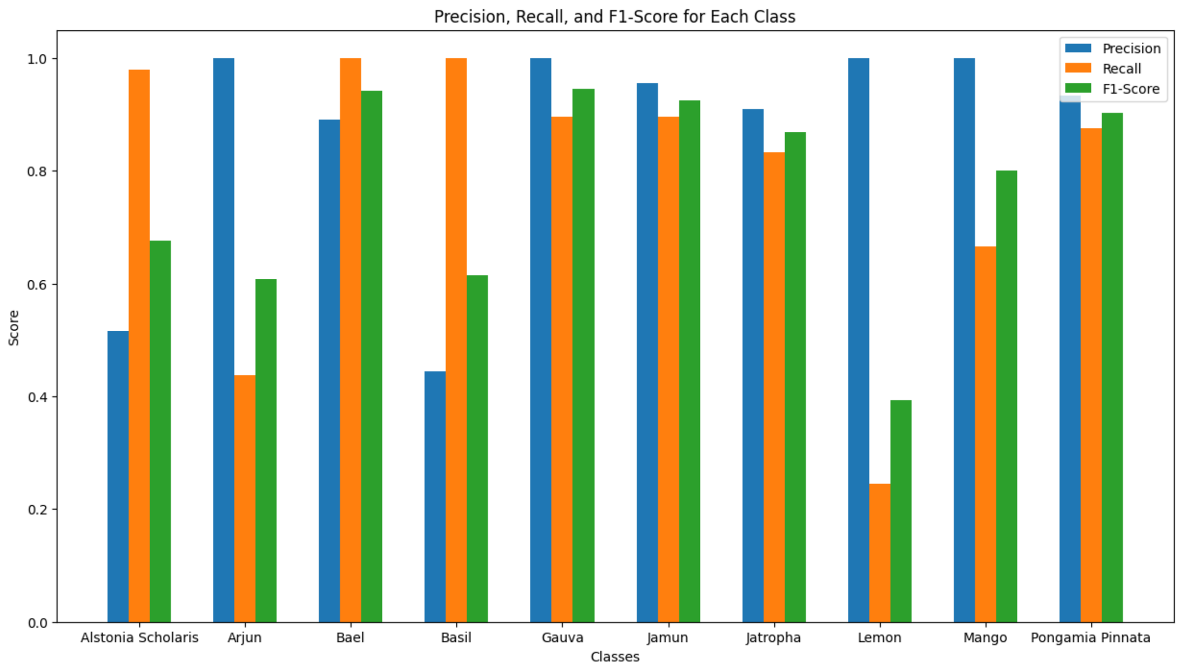

Figure 5.7: Precision, Recall and F1-Score of Model-1

The Precision, Recall and F1-Score for each class identification of Model-2 is shown in Fig-5.8,

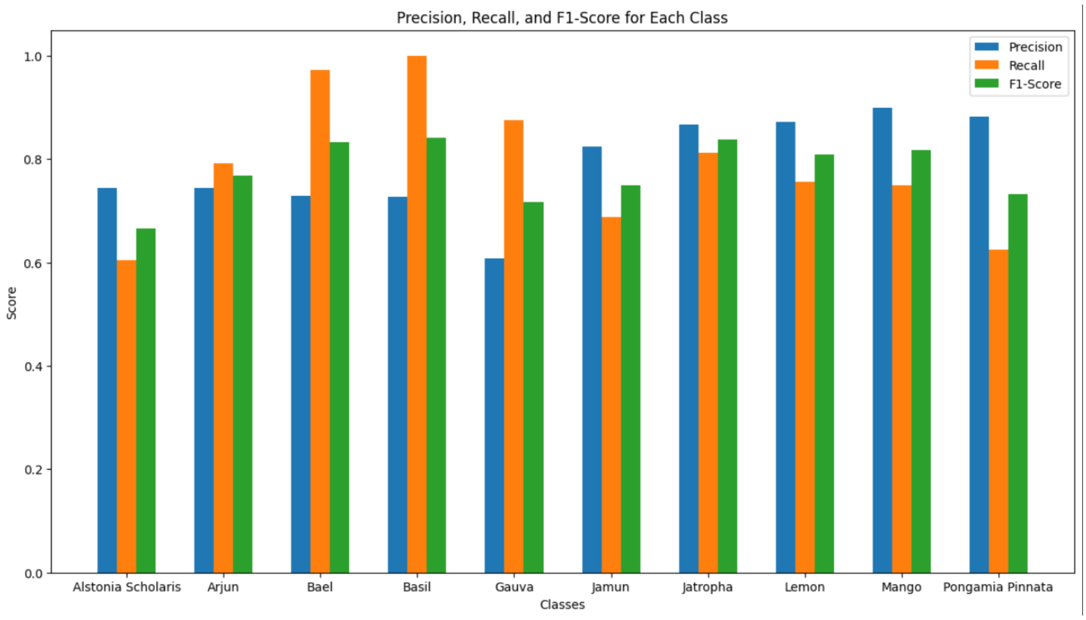

Figure 5.8: Precision, Recall and F1-Score of Model-2

The Precision, Recall and F1-Score for each class identification of Model-3 is shown in Fig-5.9,

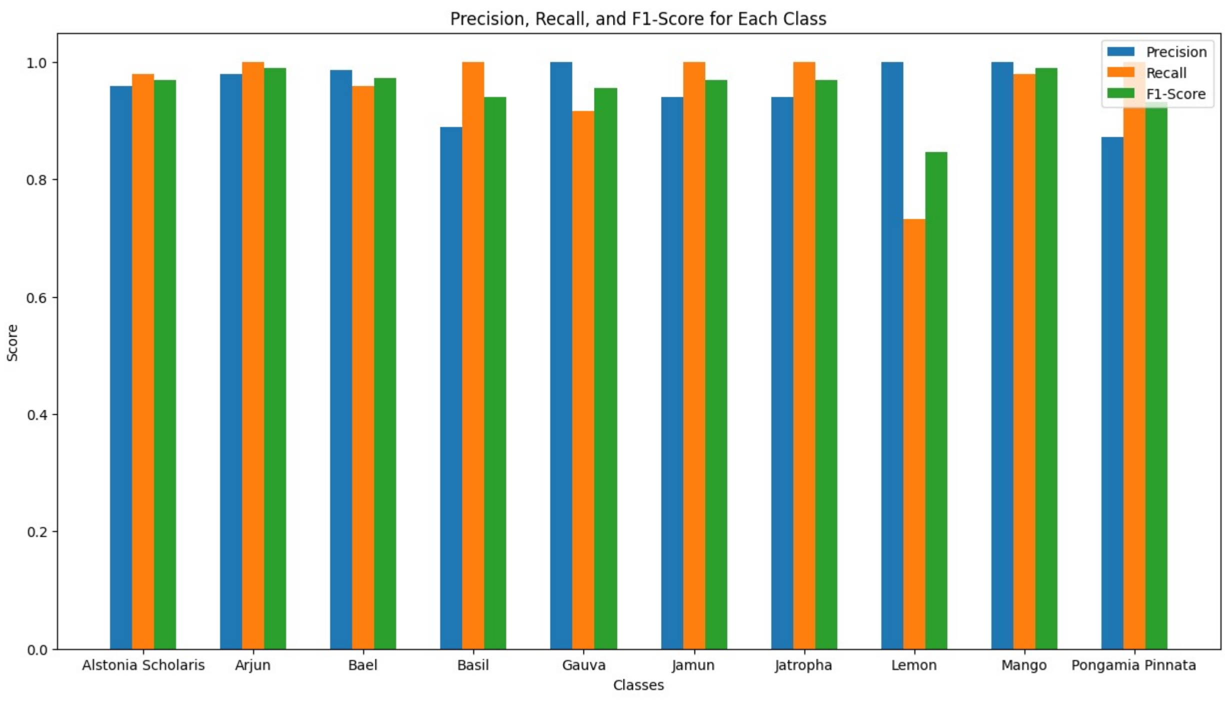

Figure 5.9: Precision, Recall and F1-Score of Model-3

Among the three models, Model-3 consistently outperforms Model-1 and Model-2 in terms of accuracy and overall classification metrics. Model-3 achieves the highest precision, recall, and F1-score across multiple classes, showcasing superior learning capabilities. Conversely, Model-1 exhibits lower performance, especially in recall and F1-score, indicating potential difficulties capturing relevant instances. While Model-2 performs comparably to Model-1, it falls short of achieving the accuracy and balanced metrics demonstrated by Model-3. In conclusion, Model-3 is the preferred choice, offering the highest accuracy and robustness in plant leaf identification, making it the most effective model for the given task.

6 Conclusion

In conclusion, our study focused on the development and evaluation of three distinct models for leaf detection, each designed with specific adjustments in parameters. The initial model, 'Model 1,' encountered challenges with an imbalanced training dataset, featuring varying image counts per class and resized image. In contrast, 'Model 2' addressed this imbalance by reducing the training dataset and resizing images, promoting more uniform class representation. 'Model 3' retained a consistent image size while introducing controlled imbalance.

The comprehensive evaluation of these models involved assessing accuracy, validation accuracy, data loss, confusion matrices, and precision, recall, and F1-scores for each class identification. Notably, 'Model 3' consistently outperformed the others, demonstrating superior accuracy and classification metrics across various classes. Its exceptional precision, recall, and F1-score underscore its robust learning capabilities and effectiveness in plant leaf identification.

While 'Model 1' faced challenges capturing relevant instances, and 'Model 2' exhibited comparable but inferior performance to 'Model 3,' the latter emerged as the preferred choice. The comprehensive assessment reveals that 'Model 3' offers the highest accuracy and robustness in fruit leaf detection, making it the most effective solution for our specified task. These findings emphasize the importance of careful parameter adjustments and dataset considerations in developing reliable and accurate machine learning models for image classification tasks

References

[1] Wu, S.G., Bao, F.S., Xu, E.Y., Wang, Y.X., Chang, Y.F., Xiang, Q.L.: A leaf recognition algorithm for plant classification using probabilistic neural network. In: 2007 IEEE International Symposium on Signal Processing and Information Technology. pp. 11–16 (Dec 2007)

[2] Kadir, A., Nugroho, L.E., Susanto, A., Santosa, P.I.: Foliage plant retrieval using polar fourier transform, color moments and vein features. Signal Image Processing: An International Journal (SIPIJ Journal) 2(3) (September 2011)

[3] Pavan Kumar Mishra, Sanjay Kumar Maurya, Ravindra Kumar Singh, Arun Kumar Misra, “A semi-automatic plant identification based on digital leaf and flower Images”, International Conference On Advances In Engineering, Science And Management (ICAESM), 2012, pp. 68-73

[4] ArunPriya C., Balasaravanan T., Antony Selvadoss Thanamani, “An Efficient Leaf Recognition Algorithm for Plant Classification Using Support Vector Machine”, Proceedings of the International Conference on Pattern Recognition, Informatics and Medical Engineering, 2012, pp. 428-432.