DEEP LEARNING BASED CLASSIFICATION USING BANGLADESHI MEDICINAL LEAVES

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Deep Learning Based Classification Using Bangladeshi Medicinal Leaves"**, submitted by Md. Asik Hossain, ID No: 193-15-13531 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13-07-2024.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Mr. Md. Ali Hossain, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Medicinal leaves are traditionally widely used in Bangladesh. Which plays a vital role in protecting the health of the human body. Bangladesh is a country where we find many plant species and each plant has its medicinal properties. The manual identity and classification process knowledge very difficult for human beings to remember all plant-specific names and uses. These medicinal leaves are very important and beneficial to many sectors such as the medical field, botanic research, and plant classification study. So, Medicinal leaves of Bangladesh can preserve this resource by researching the classification of medicinal leaves. Our research aims to accurately identify medicinal leaves by proposing an active classification system based on medicinal leaves. Our method is to first correctly preprocess the medicinal plant leaves then it will classify the leaves of the medicinal plant using DenseNet201, ResNet50V2, and InceptionV3 models. The models have been applied to 10 different classes their total 2094 original medicinal plant leaf images. Where DenseNet201 provides the highest 96.06% accuracy. The result indicates that it is feasible to automatically classify medicinal plants. The paper provides a valuable theoretical framework for the research and development of the medicinal plant classification system

Keywords: Medicinal leaves, DenseNet201, Prediction, Classification, Deep learning.

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CHAPTER 1

INTRODUCTION

1.1 Overview

In Bangladesh, the use of medicinal plants has a rich history and established tradition that is Intertwined with Bangladesh's cultural and social fabric. It has been used as Ayurvedic, Unani, and flock medicine. which tradition passed down through generations for centuries Medicinal plants play a crucial role in the ecosystem by providing a natural pharmacy for countless organisms, including humans [8]. Medicinal plants important class of plants, have been traditionally used to treat a variety of diseases. We must ensure the continuation and protection of this invaluable knowledge about medicinal plants passed down through generations. Accurately identifying medicinal plants with the desired properties is a complex and crucial task. Misidentification of medicinal plants can have life-threatening consequences. This underscores the urgent need for a fully automated and reliable system for accurate plant classification.

Deep learning leverages complex neural networks with many layers to analyze data and make increasingly accurate predictions. Deep learning algorithms learn from data through multiple processing stages. Medicinal leaf classification and identification is a challenging task that involves recognizing subtle differences in leaf shapes, colors, textures, and patterns. Where deep learning handles complex patterns and large data and also provides automated feature extraction, adaptability, and high accuracy.

Identification is the most commonly used method for the classification of medicinal plant leaves. Our paper aims to explore the application of deep learning techniques in the classification and identification of medicinal leaves, addressing current challenges and proposing solutions for more accurate and efficient identification. By leveraging modern technology, we can unlock new possibilities in the study and utilization of medicinal plants. Let us explore deeper into the rich history and promising future of this field.

1.2 Background and Present Stage

Bangladesh has a rich history of using medicinal plants for traditional medicine, with rural and remote communities relying heavily on these plants for healthcare due to limited access to modern medical facilities [13]. Identifying these plants accurately is crucial for their effective use, but traditional methods of identification take a long time and are easy to mess up. and prone to errors. With advancements in technology, deep learning algorithms are proving to be remarkably effective in tasks for image classification, offering a promising solution for the accurate identification of medicinal leaves.

Currently, the use of deep learning in botanical studies is gaining traction worldwide, but its application to Bangladeshi medicinal plants is still in its early stages [12]. Research in this area involves developing and training models such as DenseNet201, ResNet50V2, and InceptionV3 to classify various species of medicinal leaves. These models require large datasets of high-quality images for training, and the success of these models hinges on carefully chosen metrics like accuracy, precision, recall, and F1-score. The present state of the project involves the collection of data from online databases and local sources and the development of these deep-learning models. There is a growing interest in integrating these technologies into applications that can be used by healthcare practitioners, researchers, and farmers. This integration aims to enhance traditional medicine practices, support local economies, and contribute to scientific research and education. However, their performance can be hampered by challenges such as data quality, computational resources, and accessibility needed to fully realize the potential of deep learning-based classification of Bangladeshi medicinal leaves.

Overall, deep learning for the classification of Bangladeshi medicinal leaves represents a significant advancement in preserving traditional knowledge, supporting healthcare, and fostering economic benefits. However, ongoing research and development are essential to address the limitations and ensure the successful implementation and widespread adoption of these technologies.

1.3 Problem Statement

When we want to collect data online there are a lot of datasets about Bangladeshi medicinal plants but most of the data are segmented data, so it would have been difficult to do the desired research. Because I want to identify medicinal leaves directly from plant images. Also, when done with our collecting dataset and running in Google Collab facing lots of errors in our code.

1.4 Objectives

The project aims to develop and Implement advanced training techniques for deep learning models to accurately classify different species of Bangladeshi medicinal leaves. By leveraging advanced algorithms and techniques, the objective is to achieve high classification accuracy and reliability.

Another key objective is to gauge how well these models perform, we analyze them using metrics that capture different aspects of performance, including accuracy, precision, recall, and F1-score. This thorough assessment ensures that the models are effective and can be trusted for practical applications.

The project also seeks to enhance traditional medicine practices by providing reliable identification tools. These tools can significantly contribute to better healthcare outcomes, particularly in rural and isolated communities lacking modern medical facilities.

The project aims to promote research and education by offering a robust tool for the study and exploration of medicinal plants. This will facilitate academic and scientific research, enabling deeper insights into the properties and uses of these plants.

Furthermore, the project has an economic objective to support the local economy. Accurate identification and classification of medicinal plants can improve cultivation and harvesting practices, leading to better commercialization opportunities and economic benefits for local communities.

Lastly, the project aims to contribute to scientific discovery by enabling the identification of new medicinal properties and potential therapeutic uses of Bangladeshi medicinal plants. This detailed classification can open up new avenues for medical research and the development of novel treatments.

1.5 Scope and Limitations

The scope of the project includes collecting a comprehensive dataset of images of Bangladeshi medicinal leaves, building and rigorously evaluating deep learning models to ensure robust classification accuracy, and creating a user-friendly application for leaf identification. It aims to integrate with existing systems, support research and education, and enhance traditional medicine practices and local economies. However, the project faces limitations such as the dependency on high-quality data, the potential exclusion of less documented species, environmental variability affecting accuracy, and the computational intensity of deep learning models. Challenges also include ensuring accessibility, ethical considerations, regulatory compliance, and the need for ongoing maintenance, user training, and support.

1.6 Report Organization

To build upon existing knowledge, we first delve into the relevant investigations outlined in Chapter 2. This lays the groundwork for our inquiry, which we initiate by examining the proposed strategy detailed in the introduction and the projected outcomes outlined in the motivation section. Following the completion of the introductory part, we directed our attention to significant research and gathered internal data for our study.

In the methodology section, instead of utilizing deep algorithms. These deep learning algorithms were then applied to our dataset, and a comparative assessment was conducted to identify the most effective approach. Within the pre-processing step, we meticulously scrutinized the data, leading to the acquisition of our desired outcome, which we will now refer to as the comparison result. This outcome is comprehensively addressed in the concluding section of our work.

1.7 Summary

The project focuses on the deep learning-based classification of Bangladeshi medicinal leaves to support traditional medicine practices and enhance healthcare outcomes. Medicinal plants have a long-standing role in Bangladesh's healthcare, particularly in rural areas. The project aims to design and implement these models, support traditional medicine practices, promote research and education, and provide economic benefits

CHAPTER 2

LITERATUR REVIEW

2.1. Overview

Deep learning techniques are used to identify and classify medicinal leaves with high accuracy. This research investigates the classification of medicinal leaves using deep learning models. A literature review is a foundational element of a research paper that offers numerous benefits. It contextualizes your research, identifies gaps in existing knowledge, avoids duplication, helps develop a theoretical framework, provides methodological insights, establishes the significance of your study, supports your arguments, and enhances scholarly rigor. By conducting a comprehensive literature review, you ensure that your research is well-informed, original, and contributes meaningfully to the academic field.

2.2. Related works

For medicinal leaf image classification, the author [1] uses 12 different classes. They use two preprocessing grayscale processing and leaf image discretization after applying SP and GLCM Feature extraction techniques. Then applying the KNN, PNN, and SVM machine-learning models they get the highest accuracy 93.33% in SVM. The author [2] uses 10 different classes. He applied an augmentation preprocessing technique. Then use the Different Convolution Neural Network (CNN) architecture by trying different layers and some machine learning techniques. He gets the highest accuracy 71.3% using CNN 3 layer (with dropout + Gaussian noise + batch normalization). This work has some disadvantages because gets low accuracy in the future it is possible to increase its accuracy. The author [3] uses 2029 original medicinal leaf images of 10 classes. Then he augmented and resized the data. They use two different CNN architectures DenseNet201 and InceptionResNetV2 and get 92% accuracy. The author [4] focuses on texture-based classification. He uses 495 medicinal leaf images of 10 classes. At first, resize, median filter, and enhanced image preprocessing techniques were used. For feature extraction use 3 different techniques wavelet transforms, Gray Level Co-Occurrence Matrix, and Gray

Level Difference Method. There The wavelet transformation gives better (60%) accuracy compared to these three methods. The author [5] focused reviews on techniques for plant leaves classification. He finds grayscale, binary, and counter image preprocessing techniques better for image classification. Some classifier techniques showed ANN, CNN, PNN, SVM, and KNN which one best among them. The author [6] uses 1800 leaves to classify 32 kinds of medicinal plants. This paper applies most preprocessing and feature extraction techniques to compare other papers. After that 90% accuracy was obtained using Probabilistic Neural Network (PNN). In this paper author [7] comparative models performance analysis. Also, this paper uses various datasets. He uses 5872 images of 30 medicinal species distributed among 20 families. After that get the highest accuracy using DenseNet201. The author [8] proposed the classification of medicinal plants using deep learning. He used various deep-learning models in 2400 images in 40 classes and got 96% highest accuracy. The author [9] used various deep convolution neural network (CNN) to determine plant leaves. Researchers conducted a comparative study using popular CNN architectures like AlexNet, GoogLeNet, and VGGNet to identify the factors influencing their performance in plant part classification. VGGNet emerged as the most effective model, achieving an overall accuracy of 78% when trained on images of various plant components. The author of this paper [10] shows a comparison of machine learning algorithms for medicinal leaf detection. They use 650 images in 10 different classes. The GLCM matrix feature extraction is used and the two classifier techniques KNN and SVM are used here. They obtained the highest accuracy using KNN. The author of this paper [11] The study employs software that identifies the closest match to an input image of a leaf based on its textural features. This software analyzes each leaf individually and selects the most distinctive textural features for classification. This approach of feature selection is believed to improve the accuracy of medicinal leaf classification. The positive results of this method are documented in a table format.

2.3 Comparative Analysis and Summary

A comparison section in a research paper helps establish the novelty of your work by showing how it builds on or differs from previous research. This clarifies your contribution to the field and highlights the strengths and weaknesses of your approach relative to what's already been done. Table 2.1 presents a comparison of relevant research in this field.

Table 2.1: Comparative Analysis of Related Work

Ref.	Author and Year	Model	Highest Accuracy
[1]	Kan, H.X. et.al., 2017	KNN, PNN, SVM	SVM- 93.33%
[2]	Akter, R. et.al., 2020	CNN	CNN- 71.3%
[3]	Islam, S. et.al., 2023	DenseNet201, InceptionResNetV2	DenseNet201 -92%
[4]	Pushpa, B.R. et.al., 2020	Wavelet Transformation, GLCM, GLDM	Wavelet Transformation 60%
[5]	Azlah, M.A.F., et.al., 2019	ANN, CNN, PNN, SVM, and KNN	ANN- 88.34%
[6]	Wu, S.G., et.al., 2007	PNN	PNN- 90%
[7]	Dileep, M.R., et.al.,2019	DenseNet201, VGG16	DenseNet201 -93.48%
[8]	Ghazi, M.M., et.al., 2017	AlexNet, GoogLeNet, and VGGNet	VGGNet- 87%
[9]	Raghukumar, A.M., et.al., 2020	KNN, SVM	KNN- 84%
[10]	Sathwik, T., et.al., 2013	InceptionV3, VGG16	VGG16- 93%

Table 2.1 shows, that most of them in deep learning DenseNet201 and VGG16 perform higher accuracy.

2.4 Scope of the Problem

This research is broad and multifaceted, impacting various sectors. The challenges in traditional classification, the importance of biodiversity conservation, the efficacy and safety of herbal medicines, the need for technological advancements, and the potential for advancing scientific knowledge all underscore the significance of this research. By leveraging deep learning techniques for the classification and identification of medicinal leaves, this research aims to provide accurate, efficient, and reliable solutions that can benefit multiple fields and provide to the sustainable use of medicinal plant resources.

2.5 Summary

The literature review explores the use of deep learning techniques for classifying Bangladeshi medicinal leaves. It covers various algorithms and models, including convolutional neural networks and transfer learning, highlighting their accuracy and efficiency in image recognition tasks. The review also examines existing datasets and preprocessing methods, emphasizing the importance of accurate classification for medicinal applications and the potential benefits for healthcare in Bangladesh.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Overview

Research methodology is essential because it outlines the systematic approach used to conduct the study, ensuring its validity and reliability. It provides a clear framework for data collection, analysis, and interpretation, enabling other researchers to replicate the study and verify its findings. A well-defined methodology also helps in addressing research questions effectively and ensures the study adheres to scientific standards.

3.2 Proposed Methodology

In the pursuit of medicinal leaf classification, the design approach encompasses a series of structured steps. The workflow of our research design is illustrated in Figure 3.2.1.

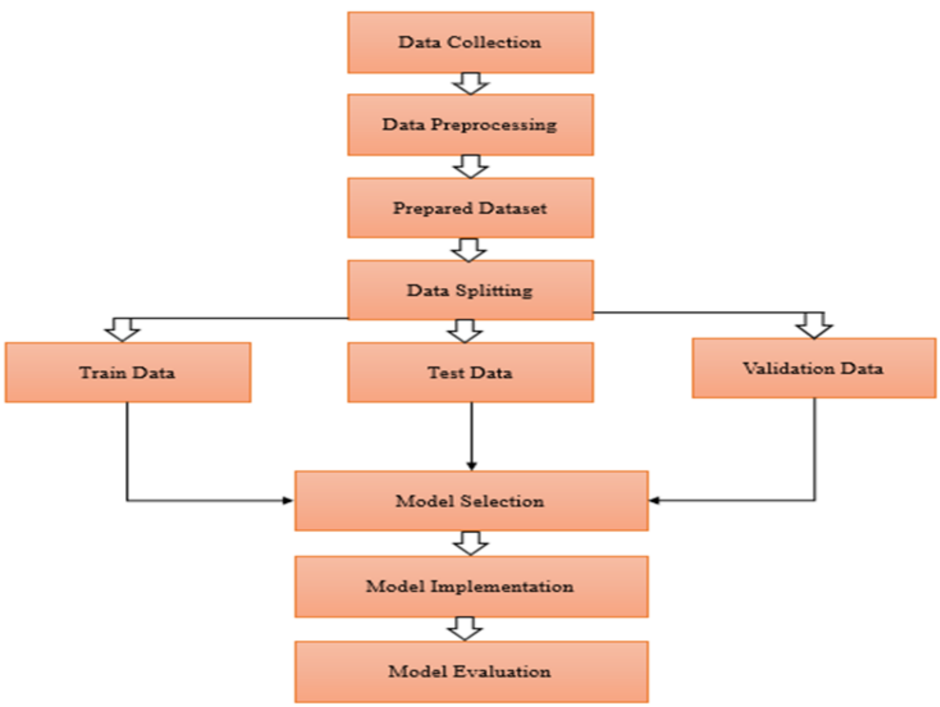


Figure 3.2.1**:** Workflow of research methodology

We show in Figure 3.2.1 that we initiated comprehensive data collection from Mendeley web platforms. Following this, data preprocessing is conducted to prepare the collected images by resizing, normalization, and augmentation to enhance model performance. These preprocessed images are then organized into a structured format, resulting in a prepared dataset suitable for deep learning models.

The next step is data splitting, where the dataset is separated into three subsections respectively, training data, testing data, and validation data. This division helps in model training, hyperparameter tuning, and evaluation. The training data subsection is used to train the deep learning model, while the test data subsection is employed to evaluate the model performance and ensure it generalizes well to unseen data. The validation data subsection is used during model training to tune hyperparameters and avoid overfitting. In the model selection part, use three different models respectively DenseNet201, Resnet50V2, and inceptionV3. Once the model is selected, model implementation takes place, involving the development and training model using the training data. Through this phase, model is optimized for accuracy and other performance metrics.

Finally, model evaluation is conducted to measure the model's performance using the test data. This evaluation involves authorizing the success of these models hinges on carefully chosen metrics like accuracy, precision, recall, and F1-score. Through this structured approach, a comprehensive and systematic process is established for effectively classifying medicinal leaves using advanced deep-learning techniques.

3.2.1 Data Collection Procedure

To create the "BDMediLeaves" dataset, we leveraged the Mendeley Data repository. This platform allows researchers to openly share their data, facilitating access to valuable resources. We specifically collected a dataset containing 2094 images belonging to 10 distinct medicinal leaf classes. Initially, this data's initial resolution is 4032 x 3024. Each image was carefully selected and ensuring accurate classification results.

3.2.2 Data Analysis

Data analysis for deep learning involves preprocessing data, splitting it into training, validation, and test sets, and feeding it into neural networks. Techniques include normalization, augmentation, and using frameworks like TensorFlow to train models, evaluate performance, and Now we show images in Fig 3.2.2 for each class in our dataset.

Figure 3.2.2: Sample image of each class dataset

Figure 3.2.2 shows, 10 different class data images that provide an idea about Bangladeshi medicinal leaves. For a breakdown of the image count per class, see Table 3.2 below.

Table 3.2: Details of the Dataset

Class name	**Train**	**Validation**	**Test**	**Total images**
Azadirachta indica	144	41	20	205
Centella asiatica	141	40	20	201
Phyllanthus emblica	140	40	20	200
Ocimum tenuiflorum	121	30	15	166
Kalanchoe pinnata	160	46	23	229
Terminalia arjuna	150	43	21	214

justicia adhatoda	140	40	20	210
Mikania micrantha	142	40	21	222
Hibiscus rosa-sinensis	151	43	21	214
Calotropis gigantea	169	43	21	233
Total Images	1458	406	202	2094

3.2.3 Data Preprocessing

Data preprocessing is a crucial step in preparing the dataset of Bangladeshi medicinal leaves for deep learning models. First, all images are resized to 224x224 pixels to ensure uniformity and compatibility with models like DenseNet201 and ResNet50V2. Image quality is enhanced through techniques such as histogram equalization and noise reduction, improving clarity and detail. Data augmentation techniques such as rotation, zooming, flipping, and brightness adjustments are employed to enhance the diversity of the dataset. These methods reduce overfitting and improve model generalization. These preprocessing steps help create a robust and high-quality dataset for effective model training and evaluation.

3.3 Hardware / Software Requirement

In this paper, some software and hardware that I have used for deep analysis and brief study of medicinal leaves classification.

Hardware:

1. Processor: Core i5
2. CPU

3. RAM 8 GB
4. 256 GB SSD

Software:

1. Windows 10
2. Microsoft Word
3. Google Drive
4. Google Colab

3.4 Project Management and Financial Analysis

This single-researcher thesis leverages focused project management to maximize efficiency and timely completion. Without external funding needs, the core objective is maintaining structured progress. Well-defined milestones and clear ownership ensure a systematic approach, while regular self-assessments allow for proactive adjustments. The streamlined decision-making facilitated by the solo nature of the project fosters successful thesis execution.

3.5 Summary

The research methodology encompasses several key components. The overview outlines the approach to leveraging deep learning for classifying Bangladeshi medicinal leaves. The proposed methodology details the system design, including data collection, preprocessing (resizing images to 224x224, enhancing quality, and augmenting data), and model development using DenseNet201 and ResNet50V2. The hardware and software requirements specify the computational resources and software tools needed, such as high-performance GPUs and deep learning frameworks like TensorFlow or PyTorch. Project management involves scheduling tasks, assigning responsibilities, and monitoring progress. Financial analysis covers without external funding for resources.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

Model implementation is crucial because it allows us to apply theoretical models to real-world problems, transforming abstract concepts into practical tools. This process lets us test and validate the models to ensure they work accurately with real data. The implementation also enables the optimization of models for better performance and efficiency, making them suitable for practical use. Additionally, implementing models automates complex tasks, such as identifying medicinal leaves, reducing manual effort and errors. It integrates these models into larger systems or applications, making them accessible to users. By using the models in real scenarios, we can gather feedback to improve and refine them continuously. Finally, implementation helps assess the impact and scalability of the models, ensuring they can handle large-scale applications effectively.

4.2 Train Model

DenseNet201: DenseNet201, belonging to the Densely Connected Convolutional Networks (DenseNet) family, is a powerful convolutional neural network architecture. It excels in various image analysis tasks, including image classification, object detection, and image segmentation. It has demonstrated excellent performance on benchmark datasets such as ImageNet. Many deep learning frameworks, like TensorFlow and PyTorch, offer pre-trained DenseNet201 models. This pre-training saves you time and effort, as you can fine-tune the model for your specific task without needing to train it from scratch. Each layer of DenseNet is connected to every other layer in a feed-forward manner.

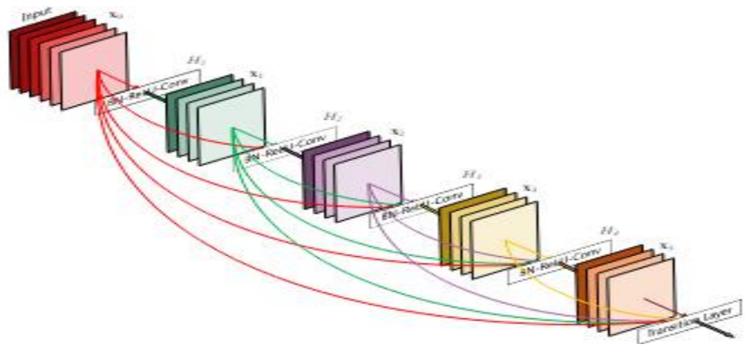


Figure 4.2.1: DenseNet201 Architecture [15]

The input layer takes an image as input, typically with dimensions of 224x224x3. DenseNet201 is characterized by its use of four dense blocks, each a self-contained unit. These dense blocks consist of consecutive convolutional layers interleaved with batch normalization layers for improved stability and ReLU (Rectified Linear Unit) activation functions for non-linearity. Transition layers are implanted between dense blocks. They compress the number of feature maps and reduce model complexity by applying 1x1 convolution to reduce the number of channels, followed by pooling to reduce the spatial dimensions. The final layer takes the output from the last dense block and classifies the image into a specific category.

DenseNet201 requires fewer parameters compared to traditional convolutional networks because they do not need to relearn redundant feature maps. The direct connections between layers ensure better gradient flow and more effective training. DenseNet201 is less prone to overfitting due to its efficient parameter usage and feature reuse.

ResNet50V2: ResNet50V2 is a convolutional neural network (CNN) architecture this is advanced variant of the original ResNet (Residual Network) architecture designed for image recognition and classification tasks. ResNet50V2 builds upon the original ResNet50 model with improvements in training stability and performance. ResNet50V2 is available in many deep learning frameworks such as TensorFlow, Keras, and PyTorch, often with pre-trained weights, making it easier to implement and fine-tune for specific use cases.

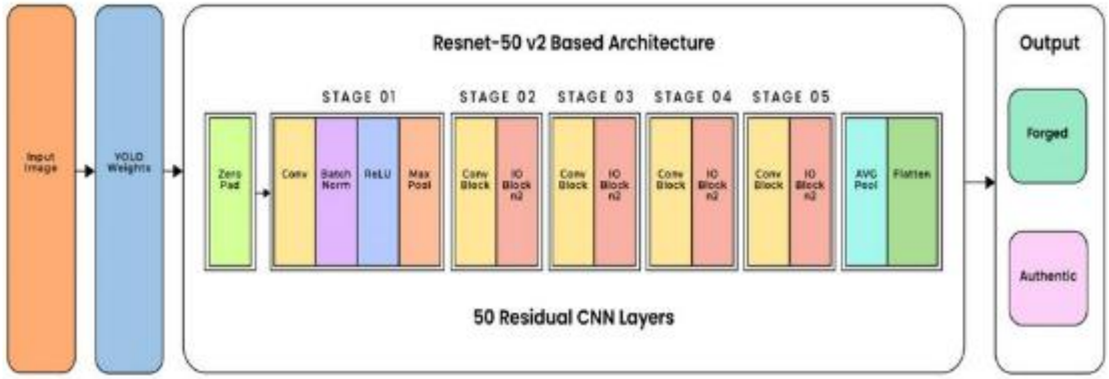


Figure 4.2.2: Resnet50V2 Architecture [16]

The ResNet50V2, pre-trained on the ImageNet dataset, provides powerful and robust feature extraction. This pre-training enables the model to leverage learned features, which can significantly improve performance on the target classification task. Despite the large number of parameters, the model's design balances trainable and non-trainable parameters effectively. Leveraging the pre-trained ResNet50V2 model allows for improved performance even on smaller datasets. The overall training time and computational resources required are reduced.

InceptionV3: InceptionV3 is another powerful architecture designed for image classification tasks. Inception modules are the heart of InceptionV3's architecture. These innovative building blocks excel at extracting features from images at various scales and resolutions. They achieve this by using a combination of convolutional filters with different kernel sizes (1x1, 3x3, 5x5). These filters capture a wider range of image information compared to a single filter size. For instance, small filters like 1x1 are useful for capturing local color variations, while larger filters like 5x5 can detect bigger patterns and shapes within the image.

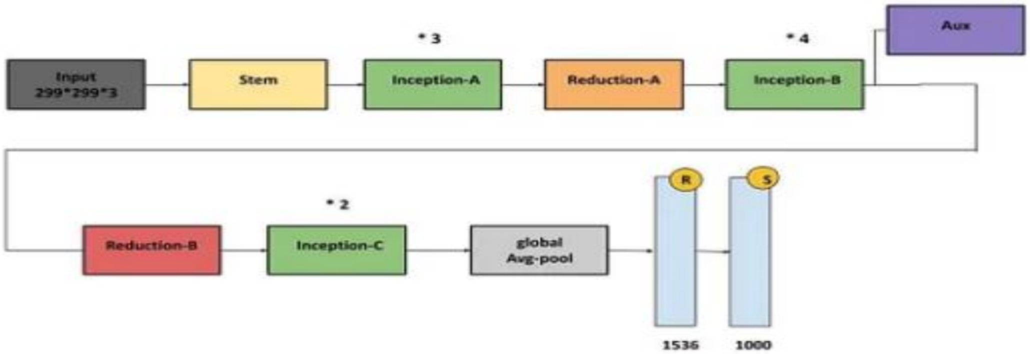


Figure 4.2.3: InceptionV3 Architecture [17]

It uses InceptionV3, a pre-trained expert at spotting image features, which saves time and improves accuracy. You can further customize it for your specific image problem. It can be slow to train because it's complex, and requires a lot of data to work well. It can also be fooled by unseen images if not adjusted carefully. Overall, it's a powerful tool, but you need to weigh the pros and cons for your specific use case

4.3 Model Evaluation

We assessed the suitability of our proposed dataset for deep learning applications by employing three established CNN-based models. Now, three CNN-based model are DenseNet201, ResNet50V2, and InceptionV3. Every model has powerful feature extraction capabilities with additional dense layers tailored to the specific. These evaluations help determine which model offers the best balance of accuracy, robustness, and computational efficiency for classifying Bangladeshi medicinal leaves. The insights gained guide further optimizations and practical implementations. Now describe the performance respectively of DenseNet201, ResNet50V2, and InceptionV3 models.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 densenet201 (Functional)    (None, 7, 7, 1920)        18321984

 flatten_1 (Flatten)         (None, 94080)             0

 dense_2 (Dense)             (None, 256)               24084736

 dropout_1 (Dropout)         (None, 256)               0

 dense_3 (Dense)             (None, 10)                2570

=================================================================
Total params: 42409290 (161.78 MB)
Trainable params: 24087306 (91.89 MB)
Non-trainable params: 18321984 (69.89 MB)
```

Figure 4.3.1: Pre-trained DenseNet201 architecture summary.

Figure 4.3.1 shows, that DenseNet201 (Functional) outputs a feature map of shape (7, 7, 1920). These are the feature maps extracted from the input images by the dense layers. Following the DenseNet201 layer is the Flatten layer, which transforms the 3D output of the DenseNet201 layer into a 1D vector with 94,080 elements, making it suitable for the dense layers. The next layer is a Dense layer, named dense_2, which reduces the dimensionality of the flattened feature vector from 94,080 to 512. This layer has 48,169,472 parameters This layer is used to learn higher-level features from the output of DenseNet201. Following the dense_2 layer is a Dropout layer, which maintains the output shape of (None, 512). The Dropout layer is crucial for regularization, as it helps prevent overfitting. The final dense-3 layer shrinks the data from 512 dimensions to 9, corresponding to the 10 output class probabilities. It has 4,617 parameters and performs the final classification task. The model has roughly 66,496,073 parameters (254 MB), with 48,174,089(184 MB) trainable and 18,321,984 (70 MB) frozen in the pre-trained DenseNet layer.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50v2 (Functional)     (None, 7, 7, 2048)        23564800

 flatten_2 (Flatten)         (None, 100352)            0

 dense_4 (Dense)             (None, 256)               25690368

 dropout_2 (Dropout)         (None, 256)               0

 dense_5 (Dense)             (None, 10)                2570

=================================================================
Total params: 49257738 (187.90 MB)
Trainable params: 25692938 (98.01 MB)
Non-trainable params: 23564800 (89.89 MB)
_________________________________________________________________
```

Figure 4.3.2: Pre-trained ResNet50V2 architecture summary.

Figure 4.3.2 shows, that the ResNet50V2 layer has an output shape of (None, 7, 7, 2048) and contains 23,564,800 parameters. These parameters are pre-trained on large datasets such as ImageNet, which allows the model to leverage learned features for effective image classification. Next, there is a Flatten layer that transforms the 3D tensor output from the ResNet50V2 into a 1D vector of 100,352 elements. This step is essential to transition from convolutional layers to fully connected layers, which require 1D inputs. The Flatten layer does not add any parameters to the model. After flattening, a Dense layer named "dense_4" shrinks the data from 100,352 units to 256. With 25.7 million parameters, "dense_4" refines the features extracted by ResNet50V2 into higher-level concepts. After the dense_4 layer, there is a Dropout layer that maintains the output shape of (None, 256). The Dropout layer helps prevent overfitting. The final "dense_5" layer condenses the 256-unit input to 10 class outputs. With just 2,570 parameters, it maps the learned features directly to the 10 classes. the model has a total of 49,257,738 parameters, Of these, 25,692,938 parameters are trainable, allowing the model to adapt to new tasks. The remaining 23.6 million (89 MB) come from the pre-trained ResNet50V2 layer, leveraging its knowledge from ImageNet.

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inception_v3 (Functional)   (None, 5, 5, 2048)        21802784

 flatten_3 (Flatten)         (None, 51200)             0

 dense_6 (Dense)             (None, 512)               26214912

 dropout_3 (Dropout)         (None, 512)               0

 dense_7 (Dense)             (None, 10)                5130

=================================================================
Total params: 48022826 (183.19 MB)
Trainable params: 26220042 (100.02 MB)
Non-trainable params: 21802784 (83.17 MB)
_________________________________________________________________
```

Figure 4.3.2: Pre-trained inceptionV3 architecture summary.

In our program**,** the model begins with the InceptionV3, which serves as the backbone and acts as a feature extractor. The InceptionV3 layer has an output shape of (None, 5, 5, 2048) and contains 21,802,784 parameters. InceptionV3's output goes through a flattening layer. This flattens the 3D data into a 1D vector of 51,200 elements, prepping it for fully connected layers. After flattening, "dense_6" shrinks the data from 51,200 units to 512, learning high-level features (26,214,912 parameters). A Dropout layer that maintains the output shape of (None, 512). The Dropout layer helps prevent overfitting. The final layer is another Dense layer, named dense_7, which reduces the 512-dimensional input to 10 output classes. This layer has 5,130 parameters and is responsible for producing the final classification output, mapping the learned features to the specific classes of the dataset. The total model size is 183 MB with 48,022,826 parameters. Of these, 26,220,042 (100 MB) are trainable for adapting to new tasks. The remaining 22,802,784 (83 MB) come from the pre-trained InceptionV3 layer, leveraging its knowledge from ImageNet.

4.4 Summary

DenseNet201, ResNet50V2, and InceptionV3 are advanced convolutional neural network architectures used for image classification tasks. DenseNet201 connects each layer to every other layer, optimizing parameter usage and gradient flow, and reducing overfitting. ResNet50V2, an improved version of ResNet50, leverages residual connections and pre-trained weights for robust feature extraction and enhanced performance. InceptionV3 uses inception modules with various filter sizes to capture multi-scale features, providing detailed image analysis. Each model benefits from pre-training on extensive datasets like ImageNet, making them adaptable to specific tasks through fine-tuning. They include Flatten, Dense, and Dropout layers to convert extracted features into class probabilities, ensuring high accuracy and preventing overfitting.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Overview

Experimental results and analysis are necessary to validate the models and methods developed, ensuring they work effectively in practical applications. They quantify performance through metrics like precision, recall, F1-score, and accuracy, enabling comparison between different approaches. The analysis uncovers strengths and weaknesses, guiding improvements and optimizations. Results confirm reliability, showing how well models handle new data. They enhance research transparency, allowing others to verify findings. This data-driven approach informs decisions on model deployment or further refinement. The analysis also identifies errors, aiding in refining data processing, model design, and training strategies for better performance. Experimental results and analysis are crucial for validating, improving, and understanding the capabilities of deep learning models.

5.2 Experimental Result

In this section, the performance of Densenet201, Resnet50V2, and InceptionV3 models for the identification of medicinal leaves based on leaves image. Here we focus on the accuracy rate, precision, recall, F1-score, confusion matrix, and ROC curves. The performance of ResNet50V2 exhibited notable accuracy rates of 93.10%. There InceptionV3 provides the lowest 83.74% accuracy. Of all of these models, DenseNet201 provides the highest 96.06% accuracy rate.

5.2.1. Performance Evaluation Metrics

(a) Accuracy*:* Accuracy is a performance evaluation metric used to measure the percentage of properly predicted observations out of the total observations in datasets. It discusses the percentage of predictions made using accurate testing data. It is among the easiest measuring techniques for any model. I must work to ensure the accuracy of my deep learning models.

$$\text{Accuracy} = \frac{TruePositive + TrueNagative}{TruePositive + FalsePositive + TrueNagative + FalseNagative} \qquad (1)$$

(b) Precision: Precision refers to measures of the accuracy of positive predictions made by a model. It's especially important when mistakes are high, like if a wrong positive has serious consequences. High precision means the model makes very few mistakes when classifying something as positive.

$$\text{Precision} = \frac{TruePositive}{TruePositive + FalsePositive} \qquad (2)$$

(c) Recall: Recall refers to measures of how good a model is at finding all the relevant cases. It looks at the completeness of the positive prediction. It evaluates how well the model represents true positive.

$$\text{Recall} = \frac{TruePositive}{TruePositive + FalseNagative} \qquad (3)$$

(d) F1-Score: The F1-score bridges the gap between precision and recall by offering a single, balanced metric. It takes into account both false positives and false negatives. This makes the F1-score particularly valuable in scenarios where achieving a balance between these two metrics is crucial.

$$\text{F1-Score} = 2 * \frac{Recall * Precision}{Recall + Precision} \qquad (4)$$

5.2.2. Model Performance Evaluation

Evaluating model performance is an integral step in the model development lifecycle. By testing the model on unseen data, we can assess its ability to generalize and confirm its reliability and accuracy before deployment. It helps in identifying overfitting (model performs well on training data but poorly on test data) or underfitting (model performs poorly on both training and test data). A thorough examination of each model's capacity for classification is provided by the matrix taken into account, which includes precision, recall, F1 score, and accuracy. Table 4.2.2 shows the performance evaluation with classification report for the three deep learning models applied in our study.

Classification Report (DenseNet201):

	precision	recall	f1-score	support
0	1.00	0.98	0.99	41
1	1.00	0.98	0.99	43
2	0.95	0.93	0.94	40
3	0.98	0.93	0.95	43
4	1.00	0.97	0.99	40
5	1.00	0.89	0.94	46
6	0.89	1.00	0.94	40
7	0.85	0.93	0.89	30
8	1.00	1.00	1.00	40
9	0.93	1.00	0.97	43
accuracy			0.96	406
macro avg	0.96	0.96	0.96	406
weighted avg	0.96	0.96	0.96	406

Classification Report (Resnet50V2):

	precision	recall	f1-score	support
0	0.95	0.98	0.96	41
1	0.95	0.98	0.97	43
2	0.88	0.93	0.90	40
3	0.89	0.91	0.90	43
4	1.00	0.95	0.97	40
5	0.93	0.93	0.93	46
6	0.90	0.90	0.90	40
7	0.87	0.67	0.75	30
8	1.00	1.00	1.00	40
9	0.91	1.00	0.96	43
accuracy			0.93	406
macro avg	0.93	0.92	0.92	406
weighted avg	0.93	0.93	0.93	406

Classification Report (InceptionV3):

	precision	recall	f1-score	support
0	0.95	1.00	0.98	41
1	0.91	0.98	0.94	43
2	0.88	0.57	0.70	40
3	0.56	0.93	0.70	43
4	0.94	0.75	0.83	40
5	0.80	0.87	0.83	46
6	0.89	0.82	0.86	40
7	1.00	0.30	0.46	30
8	1.00	1.00	1.00	40
9	0.81	0.98	0.88	43
accuracy			0.84	406
macro avg	0.88	0.82	0.82	406
weighted avg	0.87	0.84	0.83	406

Figure 5.2.1: Classification Report of DenseNet201, ResNet50V2, and InceptioV3

Figure 5.2.2 beautifully illustrates the comparison among the proposed pre-trained deep learning model considering their accuracy of classification. InceptionV3 attained an accuracy rate of 0.84%, In the differentiation of classes InceptionV3 precision macro average is 0.88 and the weighted average is 0.87. Where recall and F1-score macro average are the same as 0.82 the weighted average recall is 0.84 and the weighted average recall is 0.83. here class no 8 provides 1.00 for all of this section that better performance class of InceptionV3. Resnet50V2 demonstrated an accuracy of 93%. Here different classes' precision, macro, and weighted averages are the same as 0.93, and recall and F1-

score are the same as the 0.92 macro average and 0.93 weighted average. In Densenet201 shows a precision, recall, and F1-score of 0.96 the highest compared to other our deep-learning models. Now accuracy compassion bar chart is shown below.

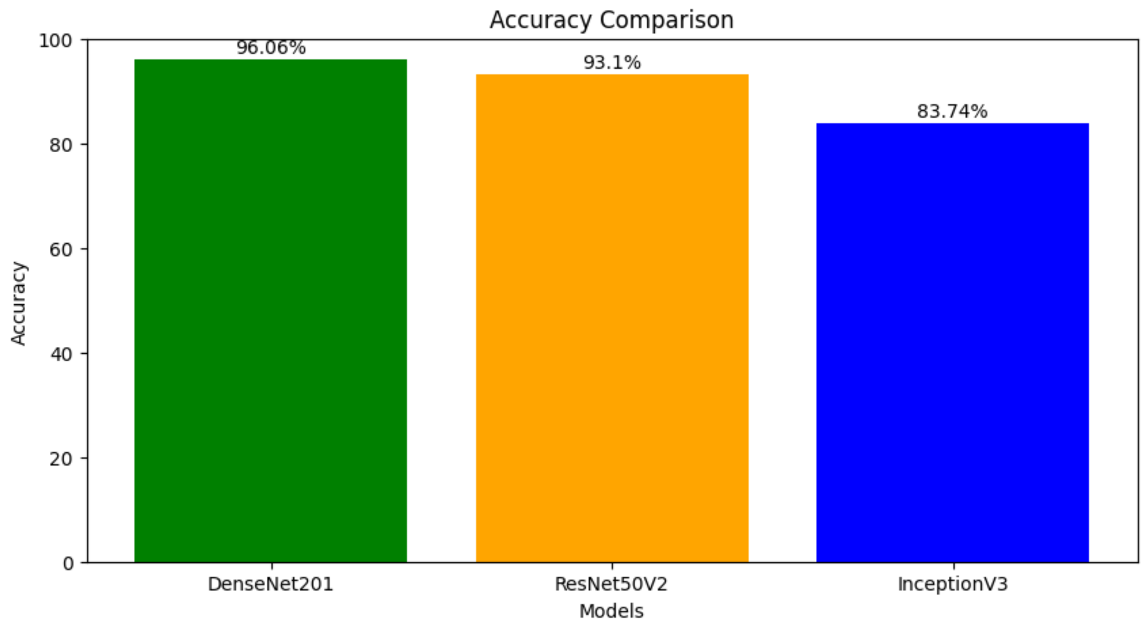


Figure 5.2.2: Accuracy comparison

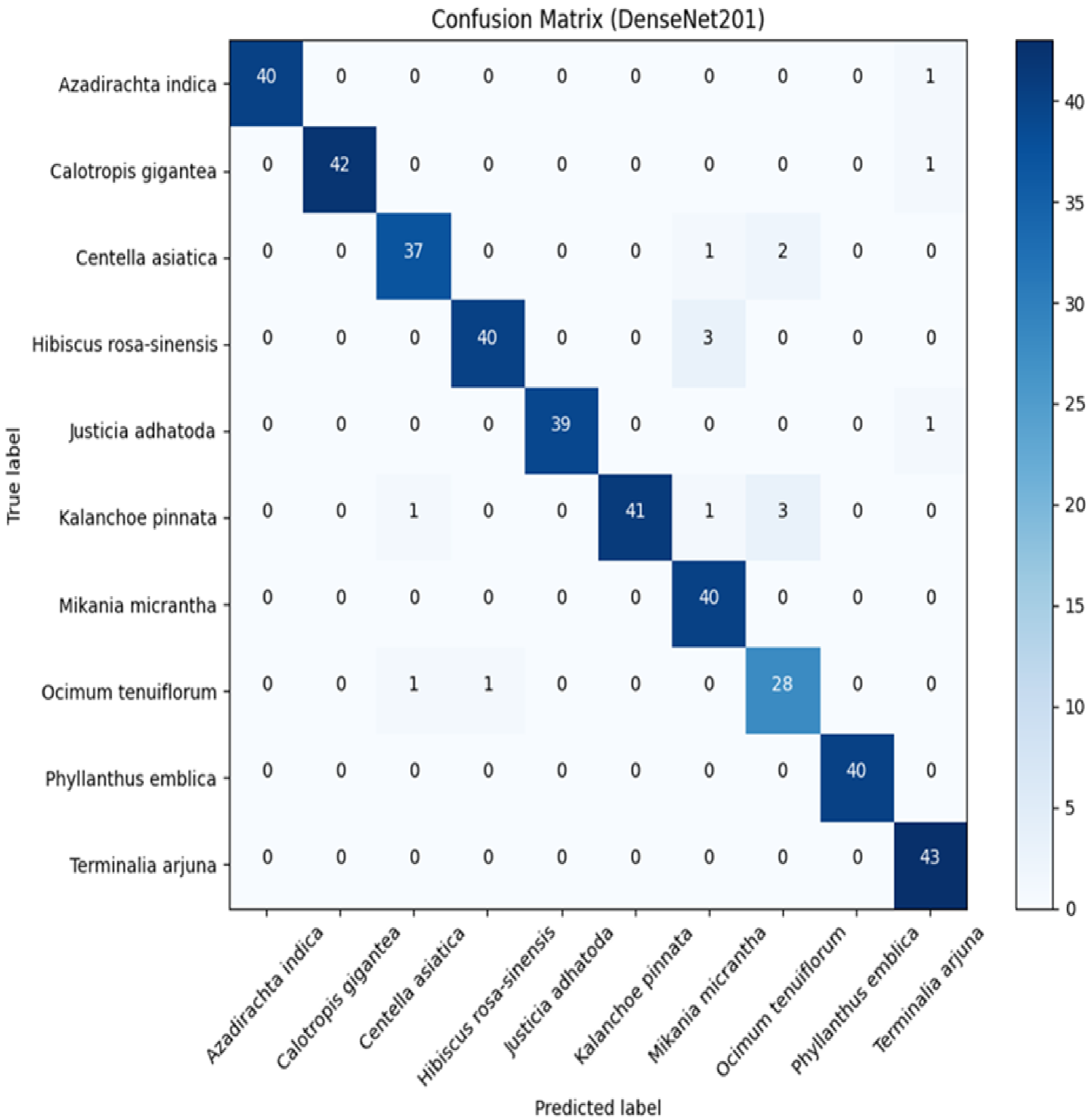
Figure 5.2.2 shows, The bar chart comparing the accuracy of three different image classification models: DenseNet201, ResNet50V2, and InceptionV3. DenseNet201 has the highest accuracy at 96.06%, followed by ResNet50V2 at 93.10% and InceptionV3 at 83.74%

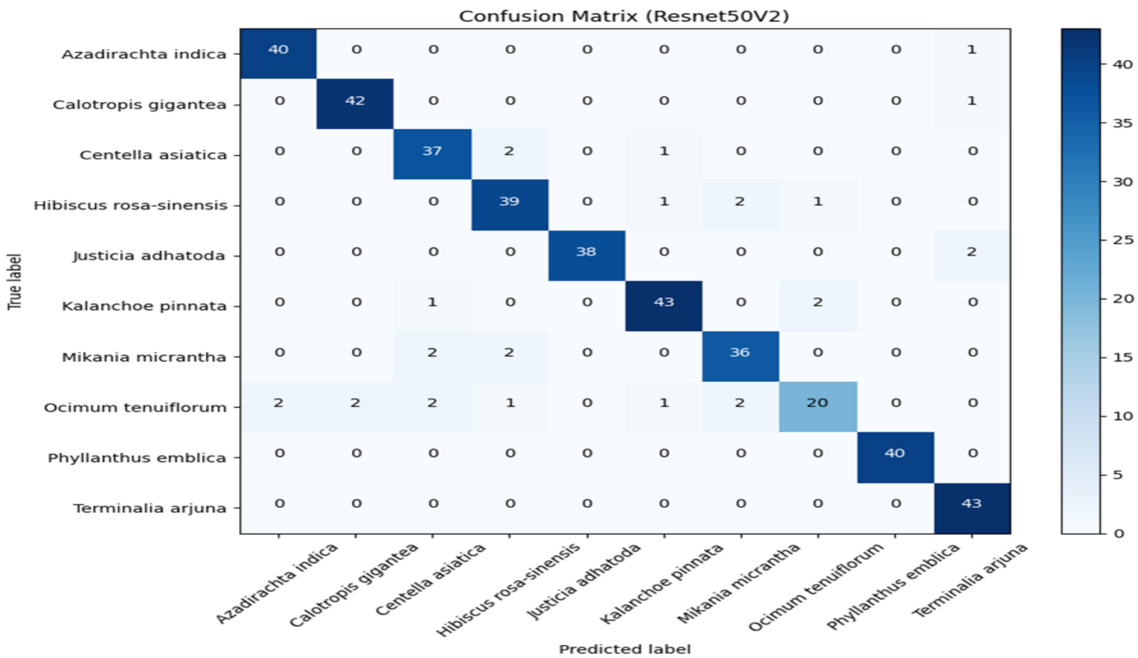
The performance evaluation metrics of all the transformers employed to assess these accuracy models revealed compelling insights into their capabilities.

4.2.3 Confusion matrix

In Deep learning, a confusion matrix uncovers how well your model classifies things. It's like a table showing all the ways your model nailed it or messed up, for each category. This helps you understand its strengths, weaknesses, and even biases. It's a cheat sheet for improving your model's performance. Beyond just accuracy, the confusion matrix reveals

hidden gems. It shows how your model trips up, whether it misses certain categories or confuses them. This lets you pinpoint its weaknesses and target improvements. Think of it as an X-ray for our model, showing its strengths and fracture points, guiding you towards a more robust and accurate system.





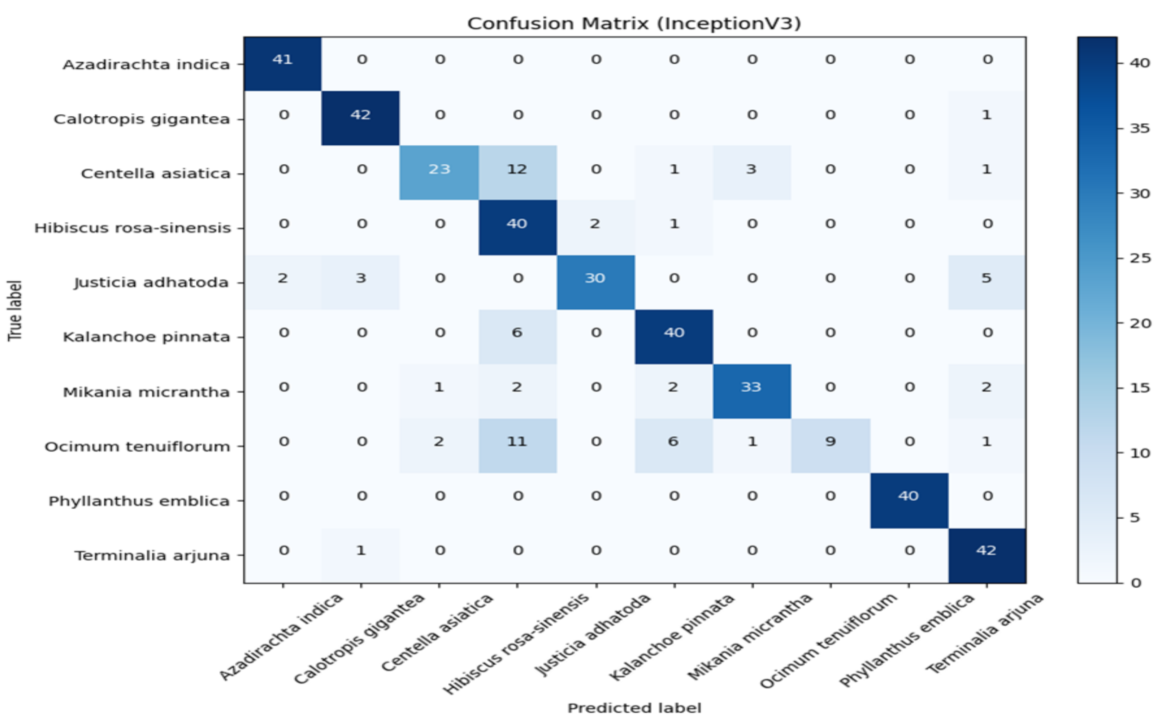
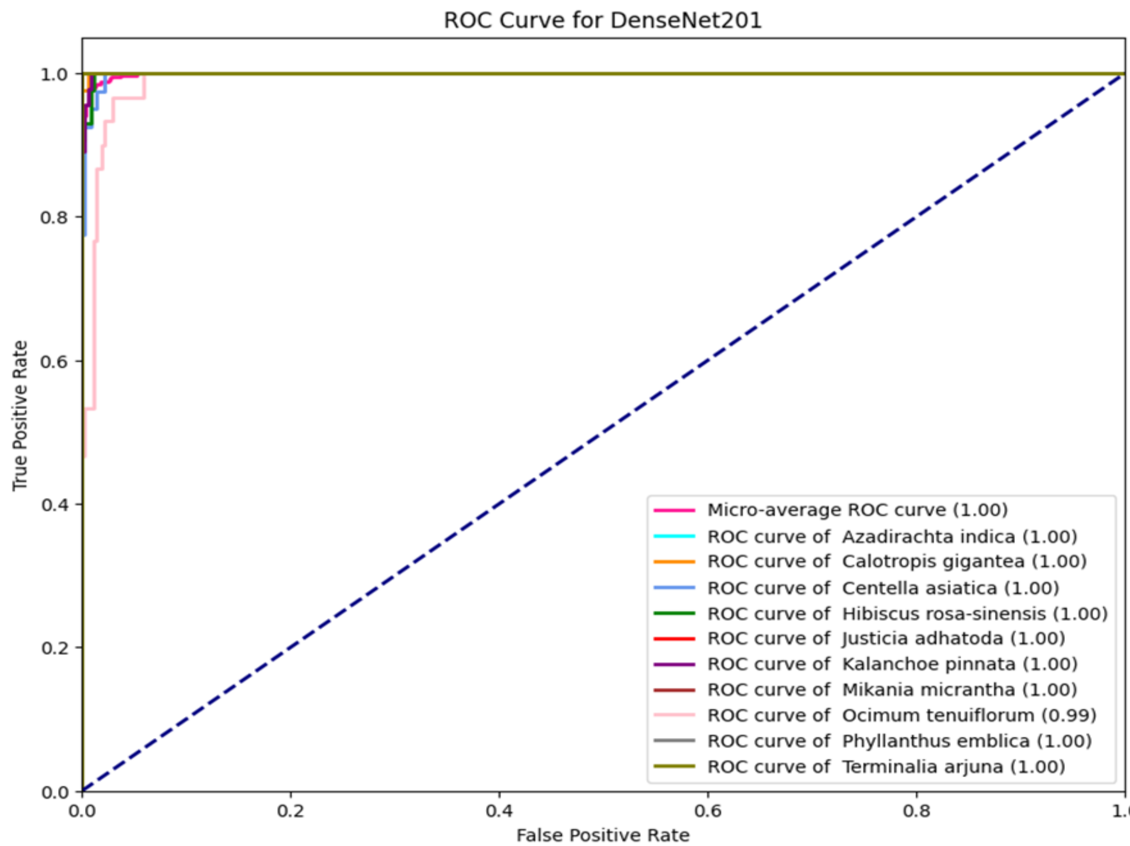


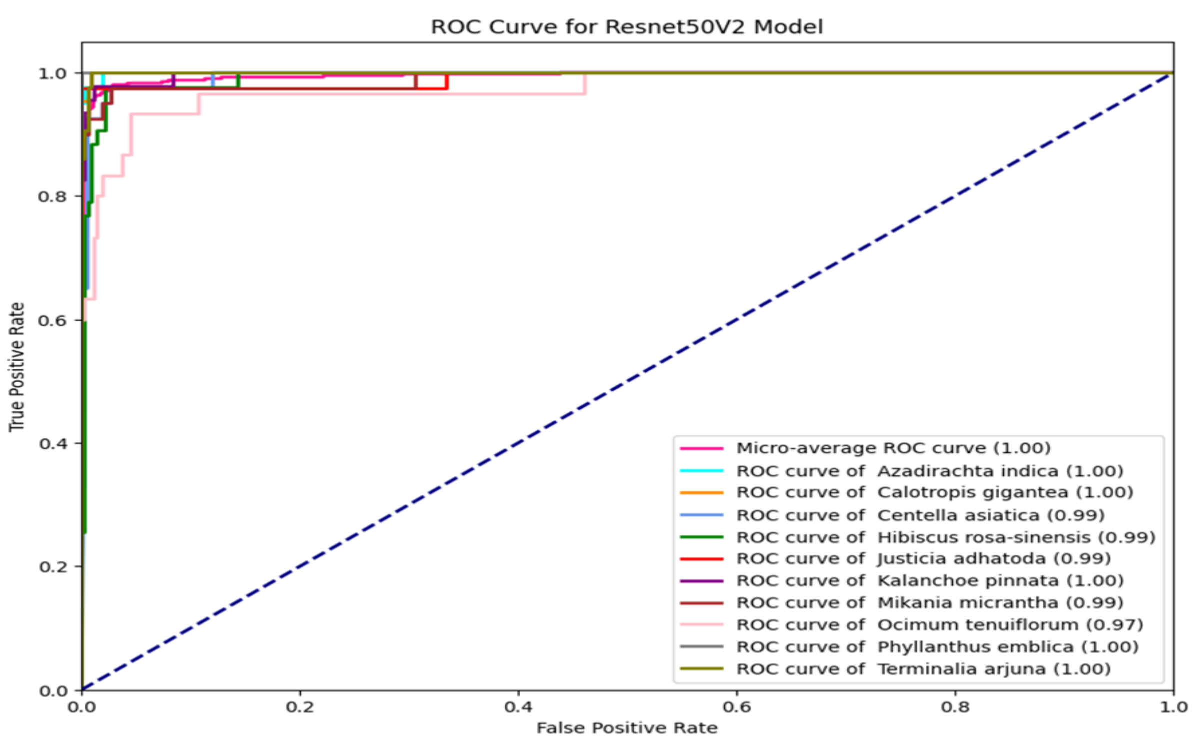
Figure 5.2.3: Confusion matrix of DenseNet201, ResNet50V2, and InceptionV3

We have shown this confusion matrix in Figure 5.2.3, Where three different models respectively, DenseNet201, ResNet50V2, and InceaptionV3 provide approximately good results. Here InceaptionV3 provides notable results there most of the classes' predictions are good and some classes have low predictions like class centile asiatica and ocimum tenuoflourm showing very poor performance. Then ResNet50V2 provides better results than InceptionV3. There most classes show better prediction except ocimum tenuoflourm. In DenseNet201 provides the best confusion matrix result compared to others in our model confusion matrix. So, DenseNet201 all classes provide the best results for the classification of medicinal plant leaves.

4.2.4 Roc curves

A ROC (Receiver Operating Characteristic) curve is a graphical representation used to evaluate the performance of a binary classification model. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. Understanding the ROC curve involves recognizing that a diagonal line from the bottom-left to the top-right represents the performance of a random classifier. Points above this line indicate a model performing better than random, while points below indicate worse performance. The Area Under the Curve (AUC) is a single metric that summarizes the performance of the model. AUC ranges from 0 to 1, where an AUC of 1 represents a perfect model, an AUC of 0.5 represents a model with no discriminative ability and an AUC less than 0.5 indicates a model performing worse than random guessing.


ROC Curve for DenseNet201
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Micro-average ROC curve (1.00)
ROC curve of Azadirachta indica (1.00)
ROC curve of Calotropis gigantea (1.00)
ROC curve of Centella asiatica (1.00)
ROC curve of Hibiscus rosa-sinensis (1.00)
ROC curve of Justicia adhatoda (1.00)
ROC curve of Kalanchoe pinnata (1.00)
ROC curve of Mikania micrantha (1.00)
ROC curve of Ocimum tenuiflorum (0.99)
ROC curve of Phyllanthus emblica (1.00)
ROC curve of Terminalia arjuna (1.00)


ROC Curve for Resnet50V2 Model
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Micro-average ROC curve (1.00)
ROC curve of Azadirachta indica (1.00)
ROC curve of Calotropis gigantea (1.00)
ROC curve of Centella asiatica (0.99)
ROC curve of Hibiscus rosa-sinensis (0.99)
ROC curve of Justicia adhatoda (0.99)
ROC curve of Kalanchoe pinnata (1.00)
ROC curve of Mikania micrantha (0.99)
ROC curve of Ocimum tenuiflorum (0.97)
ROC curve of Phyllanthus emblica (1.00)
ROC curve of Terminalia arjuna (1.00)

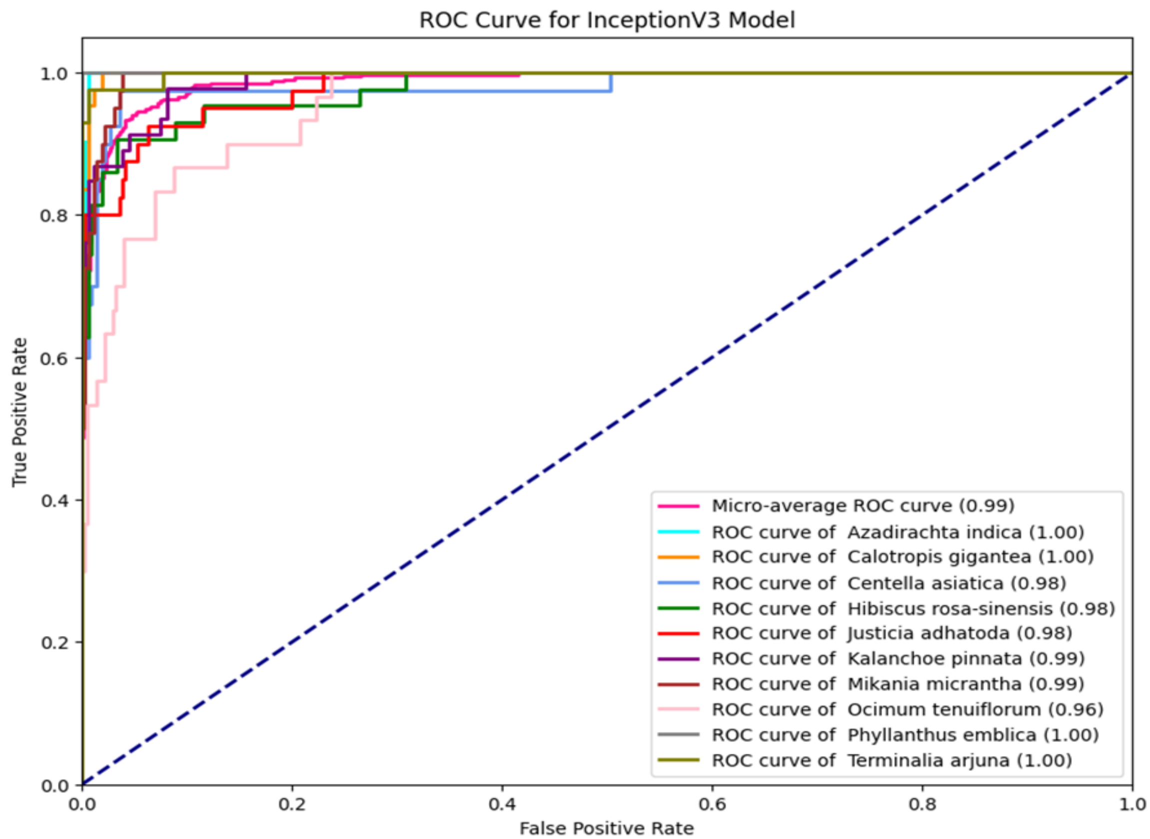


Figure 5.2.4: ROC curve for DeseNet201, ResNet50V2, and InceptionV3

Figure 5.2.4 shows that the ROC curve plot for DenseNet201 shows excellent model performance across multiple plant species, with AUC values close to 1.00 for each class, indicating high true positive rates and low false positive rates. Then the ROC curve plot for ResNet50V2 shows a better performance across multiple plant species, with AUCs between 0.97 and 1.00, which suggests good performance. After the ROC curve for an InceptionV3 mode evaluate models that predict how likely something is positive or negative. AUC score between 0.96 and 1.00 also suggests good performance.

5.3 Comparative Analysis

In the medicinal leaves classification using deep learning, choosing a suitable model architecture is critical for achieving high accuracy and efficiency. This comparative analysis examines three prominent deep learning architectures: DenseNet201, ResNet50V2, and InceptionV3. DenseNet201 has shown high accuracy in various image classification tasks due to its ability to capture intricate patterns through dense connections. it requires substantial computational resources. Then ResNet50V2 is known for its robustness and has consistently delivered high performance across various datasets. Its ability to handle deep architectures makes it a strong candidate for complex image classification tasks. At last, InceptionV3 has demonstrated high accuracy in various image classification challenges, benefiting from its ability to handle different spatial scales within the network. Its design optimizations help achieve a balance between performance and computational efficiency.

Table 5.4.1: Comparative analysis of DenseNet201, ResNet50V2, and InceptionV3

Feature	DenseNet201	ResNet50V2	InceptionV3
Depth	201 layers	50 layers	48 layers (including Inception modules)
Parameter Count	42,409,290	49,257,738	48,022,826
Training Time	High	Moderate	Moderate
Gradient Flow	Dense connections	Residual connections	Complex modules
Accuracy	96.06%	93.10%	83.74%
Memory Use	High	Moderate	Moderate

Table 5.4.1 shows the comparative analysis of models for medicinal leaves classification, DenseNet201 stands out as the most accurate model. ResNet50V2 offers a strong balance of performance and training efficiency, InceptionV3, despite its lower accuracy, remains a valuable model for applications where computational efficiency is critical.

5.4 Summary

Three deep learning architectures, DenseNet201, ResNet50V2, and InceptionV3, were evaluated for their performance in medicinal leaf classification. The models were assessed based on their classification accuracy, computational efficiency, and overall effectiveness in identifying various medicinal plant species. Where DenseNet201, with its high accuracy, stands out as the best performer, while ResNet50V2 and InceptionV3 offer viable alternatives based on computational efficiency and resource availability.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT, AND SUSTAINABILITY

6.1 Impact of Life

The impact of this research extends to improving quality of life by enhancing healthcare access through accurate plant identification, fostering environmental conservation through sustainable practices, and promoting ethical standards in technological advancements. These efforts collectively contribute to a healthier, more informed society with balanced ecological stewardship.

6.2 Impact on Society and Environment

The proposed deep learning-based classification of Bangladeshi medicinal leaves holds significant promise for both society and the environment. In society, accurate and efficient classification of medicinal plant images enhances healthcare by providing reliable tools for traditional medicine practitioners and improving treatment efficacy. This technology can empower communities by facilitating easier access to information about medicinal plants, their benefits, and uses. Mobile applications and educational platforms derived from this research can educate and raise awareness among the public, promoting healthier lifestyles and fostering a deeper understanding of local flora.

Furthermore, by supporting botanical research, this approach contributes to scientific knowledge and exploration of medicinal plants, potentially leading to discoveries in healthcare and pharmacology. Integration into traditional medicine practices preserves cultural heritage and promotes sustainable use of natural resources.

In terms of environmental impact, precise identification of medicinal plants aids conservation efforts by preventing overexploitation and promoting sustainable harvesting practices. This can safeguard biodiversity and ecosystems, ensuring the long-term availability of these valuable plant species. Identification of endangered or rare plants supports conservation initiatives, guiding conservationists in protecting vulnerable species and habitats.

6.3 Ethical Aspects

When it comes to a solution that combines information technology and computers, ethics is a very essential subject to consider. Our dataset and the models that we trained on it we constructed in methodologies. Ethical considerations are crucial in research as they ensure that the research is conducted in a manner that is respectful, fair, and safe for all parties involved. Ethical considerations help to protect the rights and dignity of research participants and ensure that they are not subjected to any harm or exploitation. Ethical research practices also help to maintain the integrity and credibility of the research by ensuring that the data is collected and analyzed in a fair and unbiased manner.

6.4 Sustainability Plan

Creating a sustainable plan for Bangladeshi medicinal leaf image classification research involves several key steps. Firstly, fostering local collaborations and involving community members throughout the research process ensures long-term engagement and support. Implementing open-source platforms and sharing the developed models can empower local stakeholders to continue and expand the project. Establishing educational programs to enhance local expertise in deep learning and image classification contributes to capacity building. Promoting ethical harvesting practices and biodiversity conservation through community outreach initiatives reinforces sustainability. Developing partnerships with governmental and non-governmental organizations facilitate the integration of research outcomes into broader policy frameworks. Encouraging the adoption of technology within local healthcare systems enhances the practical impact of the research on medicinal plant usage. Lastly, incorporating feedback loops and continuous monitoring allows for adaptive strategies, ensuring the sustainability and relevance of the research in the dynamic context of medicinal plant conservation in Bangladesh.

6.5 Summary

Ethical considerations in the research ensure that societal impact is positive, respecting participants and safeguarding their rights. Environmental sustainability is upheld through responsible data collection and model deployment, fostering long-term conservation efforts. This ethical foundation ensures that technological advancements benefit society while maintaining ecological balance and ethical standards.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

Bangladeshi medicinal leaves image classification is considered important for its knowledge utilization in future generations could easily forget the plant's benefits from this traditional treatment. In this paper, we propose an effective method for the classification of 10 kinds of Bangladeshi medicinal leaves images. Then basic image preprocessing techniques have been performed to prepare Bangladeshi medicinal plant leaf data. Serval classification techniques applied to the data like DenseNet2001, Resnet50V2, and InceptionV3. There DenseNet201 provides promising results of 96.06% to compare with other models.

7.2 Implication for Further Study

Investigate and experiment with more advanced deep learning architectures or custom model designs to further improve the accuracy and efficiency of Bangladeshi medicinal leaf classification. Increase plant variety by moving beyond 10 different kinds of leaf image data and include more diverse Bangladeshi medicinal plants, enriching your model and making it more applicable. Implement the proposed classification system in real-world scenarios, collaborating with healthcare professionals and botanists to validate the practical applicability of the model for medicinal plant recognition. Build a mobile app that is a user-friendly application for real-time medicinal plant identification in the field, empowering individuals and communities. Remember, the most fruitful future work will depend on your specific research goals and priorities. Carefully consider your resources, interests, and potential impact to choose the best path forward.

7.3 Limitation

While our research holds great promise, it's essential to acknowledge potential limitations. Because of limited plant diversity, there are only 10 different kinds of leaf image data, the model may struggle with broader applications encompassing more diverse medicinal plants. Environmental variations and lack of data from different regions, seasons, and growth stages could limit the model's accuracy in real-world scenarios. Complexity and resource requirements, DenseNet201, ResNet50V2, and InceptionV3 are powerful models but might be resource-intensive, limiting deployment on mobile devices or low-powered servers.

REFERENCE

1. Kan, H.X., Jin, L. and Zhou, F.L., 2017. Classification of medicinal plant leaf image based on multi feature extraction. Pattern recognition and image analysis, 27, pp.581-587.
2. Akter, R. and Hosen, M.I., 2020, December. CNN-based leaf image classification for Bangladeshi medicinal plant recognition. In 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE) (pp. 1-6). IEEE.
3. Islam, S., Ahmed, M.R., Islam, S., Rishad, M.M.A., Ahmed, S., Utshow, T.R. and Siam, M.I., 2023. BDMediLeaves: A leaf images dataset for Bangladeshi medicinal plants identification. Data in Brief, 50, p.109488.Venkatesh, S., & Raamesh, L. (2022). Predicting Lung Cancer Survivability: a Machine Learning Ensemble Method on Seer Data. doi:10.21203/rs.3.rs-1490914/v1.
4. Pushpa, B.R., Megha, N. and Amaljith, K.B., 2020, June. Comparision and classification of medicinal plant leaf based on texture feature. In 2020 international conference for emerging technology (INCET) (pp. 1-5). IEEE.
5. Azlah, M.A.F., Chua, L.S., Rahmad, F.R., Abdullah, F.I. and Wan Alwi, S.R., 2019. Review on techniques for plant leaf classification and recognition. Computers, 8(4), p.77.
6. Wu, S.G., Bao, F.S., Xu, E.Y., Wang, Y.X., Chang, Y.F. and Xiang, Q.L., 2007, December. 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). IEEE.
7. E. Dritsas and M. Trigka, “Lung Cancer Risk Prediction with Machine Learning Models,” Big Dataand Cognitive Computing, vol. 6, no. 4, p. 139, Nov. 2022, doi: 10.3390/bdcc6040139.
8. Dileep, M.R. and Pournami, P.N., 2019, October. AyurLeaf: a deep learning approach for classification of medicinal plants. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON) (pp. 321-325). IEEE.
9. Ghazi, M.M., Yanikoglu, B. and Aptoula, E., 2017. Plant identification using deep neural networks via optimization of transfer learning parameters.

Neurocomputing, 235, pp.228-235.

10. Raghukumar, A.M. and Narayanan, G., 2020, March. Comparison of machine learning algorithms for detection of medicinal plants. In 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC) (pp. 56-60). IEEE.

11. Sathwik, T., Yasaswini, R., Venkatesh, R. and Gopal, A., 2013, July. Classification of selected medicinal plant leaves using texture analysis. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)* (pp. 1-6). IEEE.

12. Babic, L., Jovanovic, L., Petrovic, A., Zivkovic, M., Zivkovic, T. and Bacanin, N., 2024, January. Leveraging Metaheuristic Optimized Machine Learning Classifiers to Determine Employee Satisfaction. In *International Conference on Multi-Strategy Learning Environment* (pp. 337-352). Singapore: Springer Nature Singapore.

13. Tanalgo, K., Plang, Y., Cruz, K.D., Rubio, M., Hilario-Husain, B.A., Respicio, J.M., Lidasan, A., Abdullah, S., Fabrero, G.V., Ele, R.J. and Murray, S., 2024. Patterns and Predictors of Medicinal Plant Use among Ethnolinguistic Groups in the 21st Century Philippines.

14. Karki, S., Basak, J.K., Tamrakar, N., Deb, N.C., Paudel, B., Kook, J.H., Kang, M.Y., Kang, D.Y. and Kim, H.T., 2024. Strawberry disease detection using transfer learning of deep convolutional neural networks. Scientia Horticulturae, 332, p.113241.

15. Adhinata, F.D., Rakhmadani, D.P., Wibowo, M. and Jayadi, A., 2021. A deep learning using DenseNet201 to detect masked or non-masked face. *JUITA: Jurnal Informatika*, *9*(1), pp.115-121.

16. Qazi, E.U.H., Zia, T. and Almorjan, A., 2022. Deep learning-based digital image forgery detection system. *Applied Sciences*, *12*(6), p.2851.

17. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z., 2016. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826).

18. Karki, S., Basak, J.K., Tamrakar, N., Deb, N.C., Paudel, B., Kook, J.H., Kang,

M.Y., Kang, D.Y. and Kim, H.T., 2024. Strawberry disease detection using transfer learning of deep convolutional neural networks. *Scientia Horticulturae*, *332*, p.113241.

Dataset link: [BDMediLeaves: A leaf images dataset for Bangladeshi medicinal plants identification - Mendeley Data]

Medicinal Leaf

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