

**IDENTIFICATION AND CLASSIFICATION OF MEDICINAL PLANTS
FOUND IN RURAL AREAS THROUGH LEAF IMAGE AND THEIR
BENEFIT ANALYSIS USING DEEP LEARNING.**

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This Report Presented in Partial Fulfillment of the Requirements for
the Degree of Bachelor of Science in Computer Science and
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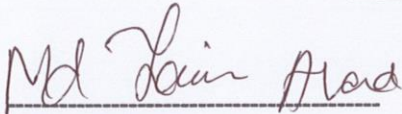
DHAKA, BANGLADESH

DECEMBER 2024

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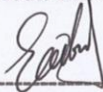
This Project titled “**Identification and Classification of Medicinal Plants Found in Rural Areas Through leaf Image and Their Benefit Analysis Using Deep Learning**”, submitted by Mir Shifat Mahmud, ID No: 221-15-4857 and Shamima Begum, ID No: 221-15-4769 to the Department of Computer Science and Engineering, 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 January, 2025.

BOARD OF EXAMINERS



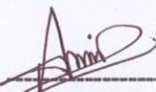
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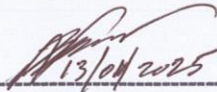
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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Md. Sazzadur Ahamed**, 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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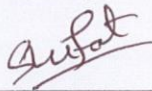
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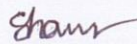


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ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty God for His divine blessing making us possible to complete the final year project/internship successfully.

We are really grateful and wish our profound indebtedness to **Md. Sazzadur Ahamed, Assistant Professor**, Department of CSE, Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of “*Deep Learning*” to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to **Professor Dr. Sheak Rashed Haider Noori, Professor & Head**, Department of CSE, for his kind help to finish our project and also to other faculty members and the staff of CSE Department of Daffodil International University.

We would like to thank our entire course mates in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

A medicinal plant identification system based on the EfficientNetB0 transfer learning model is suggested by the current study. People's trust in using medicinal plants and their ability to correctly identify them have a big impact on their utilization. Utilizing medicinal plants is crucial in the medical field to satisfy the demand for medication. Inappropriate usage of medicinal herbs can lower immunity and lead to a number of issues for humanity. To guarantee their effects, it is crucial to properly identify and utilize our medicinal plants. In this paper, we propose to use an automated deep-learning model to handle the problem of manually monitoring plants to identify and classify medicinal plants, which is initially quite difficult. In order to help people, recognize and utilize therapeutic plants, this study aims to identify and categorize them. We gathered a clean and high-quality dataset for the categorization and identification of medicinal plants. Finding medicinal plants in the village vicinity and taking pictures of their leaves was the first stage of the data collection process. We separated medicinal plant species into ten distinct classes using several transfer learning models in order to precisely identify and categorize medicinal plants. Nonetheless, the 99.87% reliability score of the medicinal plant dataset demonstrates how highly effective EfficientNetB0 is. Thus, this chapter's goal is to promote the use of medicinal plants, boost their dependability, and guarantee their usage by correctly recognizing them.

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CHAPTER 1

Introduction

1.1 Introduction

Although Bangladesh is a riverine country, it is surrounded by forest resources. All living things on earth need oxygen to survive, we get that oxygen from plants. Plants have been playing an important role in preserving biodiversity, so the importance of plants is immense. There are thousands of plants in the world, it is unknown to many that each plant has its own virtues. Not all plants in the world are beneficial to humans, some special classes of plants are beneficial to humans. There are four basic human needs namely food, clothing, shelter, and medical care. Plants play an important role in meeting these basic needs. There are thousands of species of plants in the world, one of them is the medicinal plant, which acts as a remedy for the diseases of the human body. People need to know which plant works as medicine for which disease, only then people can use medicinal plants properly. Acquiring knowledge to use, protect and conserve medicinal plants is important.

People have been using medicinal plants since ancient times. Early humans did not have modern medicine, they depended on medicinal plants to cure diseases and survive. In modern times, because of the system of good medicine, people do not use medicinal plants anymore, so medicinal plants are disappearing day by day. As people age, the immune system declines. Medicinal plants provide healing benefits.

There are thousands of different kinds of plants in the world; some are toxic to people, while others are utilized as medicines. Many of these plant species are currently in danger of going extinct. In addition to being essential to human and animal existence, plants are also crucial to the food chain. Ayurvedic medicine,

sometimes referred to as traditional medicine, is the primary application of medicinal plants. To treat illnesses organically, people still employ Ayurvedic medicine all around the world. The stems, roots, flowers, fruits, and leaves of medicinal plants have all been used by humans as therapeutic substances. Many kinds of medicinal plants are utilized to cure illnesses and conditions in people.

There is a huge demand for medicinal plants in Bangladesh and all other countries. Medicinal plants play a special role in the medical reputation of Bangladesh and are an important source of disease prevention. As Bangladesh is densely forested, there are many species of medicinal plants, accurate identification and classification of these medicinal plants is our main objective. Medicinal plants are identified and classified using deep learning algorithms based on leaf, flower, fruit, stem, plant size, shape, color and structure. Improper use of medicinal plants is dangerous for mankind. Manual identification of medicinal plants is very laborious and time consuming and requires extensive knowledge of medicinal plants.

It is very difficult for common people to identify medicinal plants. Hence a didactic technique for identification of medicinal plants has been used in our study. Deep learning, which is a form of machine learning. Deep learning algorithms have the power to uncover the complexities of our massive data sets. Medicinal plants are accurately and objectively identified and classified based on deep learning algorithms through medicinal plant leaves. Computerization of processes for identifying and classifying medicinal plants is achieved through deep learning and models capable of evaluating data.

Knowledge about medicinal plants should be collected for future generations. There are many types of medicinal plants in rural areas unknown to people. By identifying and analyzing medicinal plants through image processing, to inform the people of Bangladesh about the properties of natural medicinal plants. Our project

aims to inform the identification and classification of medicinal plants for future generations. People from all walks of life will get to know about medicinal plants and their properties and uses through our project. Many medicinal plants have been identified so far, yet many challenges and unsolved problems are encountered.

The rest of the paper is written as follows, Chapter-II: Describes and analyzes the work related to identification of plant species. Chapter-3: We describe the tools, techniques and methods used in identifying and classifying medicinal plants. Chapter-4: Provides Findings and Reports. Chapter-5: Analyzes our project impact on society, environment and sustainability. Finally, Chapter-6: concludes the project and gives directions for the future.

1.2 Motivation

Correct identification and classification of medicinal plants are strongly interrelated. Improper identification of medicinal plants increases susceptibility to damage, which reduces immunity through use. Accurate identification and use of medicinal plants provides opportunities for taxonomists and experts to determine how accurate medicinal plant identification and classification is, by researching and developing appropriate methods. The extent to which the use of medicinal plants will keep people healthy is related to the correct use of medicine. In order to ensure the production of medicinal plants and the good health of people, taxonomists and experts make rules for the correct use of medicine. Research on correct identification and classification of medicinal plants is conducted based on principles. Our strong efforts are aimed at making the proper use of medicinal plants by common people. Medicinal plants are on the way to extinction today due to lack of human knowledge. Through our project one can gain knowledge about medicinal plants and their properties and uses. Correct identification of medicinal

plants and their proper use helps to keep the human body healthy and prolong life. Scientists as well as experts work in the process of discovering new medicinal plants and evaluating their properties.

1.3 Rationale of the Study

The main aim of the article is to discuss and analyze the techniques and methods used to identify and classify medicinal plants. From identification of medicinal plants to use, advantages and disadvantages and objectives to be achieved for implementation and proper monitoring and investigation of medicinal plants. Medicinal plants can be studied using modern methods like image processing. The aim may be correct identification and classification and its proper use. The above-mentioned indicators and the quality of medicinal plant species are associated with evaluating the proper use of medicinal plants. In order to achieve the goal of educating people in rural areas about the use, advantages and disadvantages of medicinal plants, the problems need to be identified. Effective testing and proper use of medicinal plants can lead to the safety of human health. The beneficial properties of medicinal plants can give positive feedback to people, which influences people to use medicinal plants and the medicines prepared from medicinal plants can be used with confidence by people. Medicinal plant identification and classification is a critique and discussion of an emerging standard technology and an investigation of indicators, which increase user confidence. Identification and commercial development of medicinal plants and implementation of specific objectives. One of the objectives may be to increase knowledge among people about the use of medicinal plants. Our research works strongly in identifying and classifying medicinal plants and ascertaining the uses of plants.

1.4 Expected Output

The written part should give a proper analysis of the research part determining the properties of medicinal plants. A summary and analysis of research papers, techniques and technologies on medicinal plants should be presented. The effectiveness, precision and accuracy of each method are tested and used to evaluate the expected results of new medicinal plants. Deep learning helps to understand the best and most accurate techniques for identifying and classifying medicinal plants. Identification of medicinal plants and their use, promotion and interpretation will be expected results, if the paper includes data collection. Medicinal plant identification and classification evaluation results using deep learning algorithms or techniques are included.

1.5 Report Layout

The following characteristics set our efforts apart:

Chapter 1: The introduction contains the historical and contextual details of the research problem, the problem or issue of the inquiry, and the objectives and significance of the study. This part contains the paper's introduction (1.1), the motivation behind the study's topic (1.2), the rationale behind the study's methodology (1.3), the expected outcomes of the study (1.4), and the document's structure or summary (1.5).

Chapter 2: An summary of our work-related research is given in this chapter. Technology research is brought up here. The difficulties we encountered have demonstrated the scope of the issue. The areas we will look into for the paper in (2.1), the related works that demonstrate the scientist's earlier work in (2.2), the topic's comparative evaluation and summary in (2.3), the paper's overall goal in

(2.4), and the challenges we will face in (2.5) are all described in the terminologies subsection.

Chapter 3: The many forms of dataset management and model creation are thoroughly covered in this chapter. The research methodology is presented in (3.1), the dataset's assembly and sterilization are covered in (3.2) and (3.3), the dataset's initial processing strategy is covered in (3.4), and the suggested methodology and implementation al requirements are covered in (3.5) and (3.6), respectively.

Chapter 4: The assessment and results of our predictive approach are presented in this chapter. Included are every outcome from the pictorial depiction. The paper's evaluation and experimental findings are presented in this section. The introduction in section (4.1), the investigation of the findings in section (4.2), the classification report and confusion matrix similarity of the results in sections (4.3) and (4.4), the accuracy of the training and validation in section (4.5), and the results segment discussion in section (4.6).

Chapter 5: Sections 5.1, 5.2, 5.3, and 5.4 provide a brief overview of the identification and use of medicinal plants by the community, the environment, and the impact on the environment.

Chapter 6: This part presents a summary of the completed study, a conclusion, and possible future research in accordance with 6.1, 6.2, and 6.3.

CHAPTER 2

Background Study

2.1 Terminologies

Medicinal plant correct identification is the process of determining the identity and categorization of medicinal plants based on photos of their leaves. Only healthy medicinal plant leaves were used to identify the plants in our data collection. For precise identification and image processing, no study has used the leaves of the medicinal herbs Dronapushpi, Heliotropium-Indicum (Indian-Heliotrope), Moringa (Sahjan), Henna (Mehandi), Betel Leaf (Paan). In this instance, the identification and classification process of medicinal plants from photographs of medicinal plants is assessed using a unique deep learning classification algorithm.

Background data They are given the appropriate background information regarding the study when they register. Thus, the study's history piques the viewer's interest in the issue raised by the findings and clarifies their significance. The advantages of medicinal plants and the scientific concepts utilized for identification and classification evaluation are some of the crucial elements that may be significant when developing an academic registration about the identification of medicinal plant species. The advantages of medicinal plants' robust leaves, stems, flowers, fruits, and roots are considered, as are the traits of the leaves (size, form, color, texture, etc.). A pre-train model called transfer learning enables computers to learn from data. The identification and classification of medicinal plants is based on data from rural regions, which can be utilized to create models. In Bangladesh, accurately identifying medicinal plants is a crucial component of medical knowledge, which in turn contributes to medical knowledge. The importance of medicinal plant conservation in Bangladesh's local context might be better understood by identifying and categorizing the country's medicinal plants. The

advantages and applications of medicinal plants are becoming more well known in Bangladesh. People are learning about medicinal plants in the age of media and the internet. The identification of therapeutic plants can improve people's health.

2.2 Related Work

When composing a paper, related work is essential to portray its right environment, discover research differences, support arguments, guide procedures, and demonstrate scholarly engagement. It allows writers to situate their research within the corpus of knowledge, attesting to the fact that their work is current, original, compliant, and contributes to the advancement of scientific knowledge. Related work provides the background and context for the current study. It helps readers understand the current level of knowledge in the topic and the approaches already being used for similar projects. By analyzing related literature, authors can highlight the study's novelty or uniqueness and place its findings within the broader research environment. We can identify any gaps or areas that require more research by reviewing pertinent literature. We may use the limitations or shortcomings of previous studies as a reference for formulating research questions or the objectives that aid in filling in these gaps. This helps us to ensure that their research is worthwhile and advances the area. This topic was communicated using a variety of languages and forms. These are a few pertinent works that can support our efforts to improve the notion.

Dileep M.R. et al. [1] Proposes a standardized list for medicinal plants that are frequently found in different parts of Kerala, a state on India's southwest coast. This study makes use of a unique dataset that was gathered from her reference work; there are 40 classes, 60 images each class, and a total of 2400 images. Where RGB scaling is used for picture pre-processing, feature extraction has been used instead

of data augmentation. SVM and Softmax classifiers are used for the classification. 96.76% classification accuracy was attained by the model. The size of the dataset in this research will be increased in future work.

Abdollahi Jafar et al. [2] Finding therapeutic plants that grow in rural locations is the main goal of this study. This study makes use of a unique dataset that was gathered from her reference work; there are 30 classes, 100 images each class, and 3000 images in total. where normalization, cropping, rotation, and flipping both horizontally and vertically are used in image pre-processing. Rotation and Gaussian blur have been used to supplement data. Feature extraction has not been used. The MobileNetV2 pre-trained model used in this work had a 95.05% classification accuracy. This research on the identification of thousands of medicinal plants is planned to be expanded in future studies.

R. Upendar Rao et al. [3] The primary characteristics needed to recognize a medicinal plant are the color, texture, and form of its leaves. This study employs a custom dataset that was gathered from her reference work; there are 50 classes, 30 images each class, and a total of 1500 images. In image pre-processing, sizing is used. There has been no implementation of feature extraction or data augmentation. Using the CNN model, this paper's classification accuracy was 84.45%. A better machine learning classifier with some pre-processing and feature selection will be the focus of future research.

C.Amuthalingeswaran et al. [4] The identification of medicinal plants and their applications in both urban and rural areas. This study makes use of a unique dataset—four classes totaling 8,000 images—that was gathered for her reference work. where pre-processing of images is not used. Image transformation has been used to implement data augmentation. Feature extraction has not been used. This article uses a pre-trained model called MobileNet50.0, which achieved a

classification accuracy of 72%, and a bespoke model called MNN, which achieved a classification accuracy of 85.15%. Future research aims to expand the dataset's size by adding more types of medicinal plants and expanding the sample size.

Adams Begue, Venitha Kowlessur et al. [5] Using computer vision and machine learning approaches, an automated system for identifying medicinal plants has been demonstrated. This study makes use of a bespoke dataset that was gathered from her reference work; there are 24 classes, 30 images per class, and 720 images in total. where shadows and median blur are eliminated during image pre-processing. Both feature extraction and data augmentation have not been used. 90.1% classification accuracy was attained by the Random Forest classifier used in this work. In an effort to reach even greater accuracy, deep learning and probabilistic neural networks will be studied in future research.

S. Kavitha et al. [6] The goal of the study is to use a smartphone app to detect the therapeutic herb in real time. This study makes use of a Kaggle dataset that was gathered for her reference work; it has 3000 images total, divided into 6 classes with 500 images each. where resizing is used in image pre-processing. Rotate, Flip, and Color Manipulation have all been used to supplement data. Feature extraction has not been used. The pre-trained Mobile Net model used in this work had a 98.30% classification accuracy. Future research is By include more species of medicinal plants, future research will concentrate on improving or preserving the model's categorization ability.

Owais A. Malik et al. [7] An automatic real-time plant species identification system for medicinal plants found throughout the Borneo region was proposed in this study. A public and private dataset gathered for her reference paper is used in this work. In these cases, neither feature extraction nor data augmentation nor image pre-processing has been used. The CNN model used in this work produced

classification accuracy rates of 87% and 84%. Future research aims to enhance the training data sample gathering in order to further enhance the system's performance.

Nghia Duong-Trung et al. [8] The goal of this study is to take advantage of the concept of transfer learning, which is the enhancement of learning in a new prediction problem by the transferability of previously learned knowledge from a related prediction task. This study makes use of a bespoke dataset—in this case, 10 classes, totaling 2296 images—that was gathered for her reference work. In these cases, neither feature extraction nor data augmentation nor image pre-processing has been used. Mobile Net, a pre-trained model used in this work, had a 98.7% classification accuracy. A larger volume of data will be included in future projects.

Adibaru Kiflie Mulugeta et al. [9] The goal is to thoroughly evaluate previous studies on the use and applications of deep learning techniques in the classification and identification of medicinal plant species. This study makes use of a private dataset of medicinal plants from Bangladesh that was gathered for her reference paper; it consists of 10 classes with a total of 37,693 photos. where scaling and normalization are used in image pre-processing. Flip and Rotation have been used for data augmentation. An implementation of feature extraction has been made. Using the CNN model, this paper's classification accuracy was 71.3%. It is imperative that researchers prioritize filling important research gaps in their future work. Geographical differences and the paucity of datasets are two notable characteristics of these gaps that highlight the dearth of research in developing nations.

G. Kayhan, E. Ergun et al. [10] Using computer vision, the leaves of aromatic and medicinal plants are automatically categorized based on their color and shape. A unique dataset—in this case, five classes—was gathered for her reference work. In cases when data augmentation and picture pre-processing are not utilized, feature

extraction has been used. This study's classification accuracy of 98.39% was attained using the Naive Bayes Classifier (NBC) model. The future of this work is uncertain.

Banita Pukhrambam et al. [11] The field of image processing in the research region is lively when it comes to automatically identifying and classifying medicinal plants. An unidentified dataset gathered for her reference publication is used in this work. Data augmentation has not been used. An implementation of feature extraction has been made. Although the model is used in this paper, its information is not published, and its classification accuracy is unclear. Future research will need to identify specific therapeutic plants using a new method.

Stephen Opoku Oppong et al. [12] The researchers create a computer vision system that recognizes medicinal plants by their leaf textural characteristics using CNNs and custom filters made from Log-Gabor filters. This study makes use of a bespoke dataset that was gathered from her reference work; there are 49 classes, 50 images each class, and a total of 2450 images. when there is no need for image pre-processing. Data augmentation hasn't been used. A feature extraction system has been put into place. The pre-trained model used in this work, densenet201, had a 98% classification accuracy rate. The database of medicinal plants can be expanded in the future to include more species from across the country, their variations based on climatic conditions, and their uses.

Sameerchand Pudaruth et al. [13] The Republic of Mauritius has medicinal plants. This study makes use of a unique dataset that was gathered for her reference work; there are 70 classes, 100 photos each class, and 7000 images in total. where noise and resizing are used in image pre-processing. Neither feature extraction nor data augmentation have been used. Inception-v3, the pre-trained model used in this work, had a 95% classification accuracy. In the future, the dataset will be expanded

to include over 100 distinct medicinal plants, and thirdly, users will be able to access more details on each plant.

Gaurav Kumar et al. [14] In this paper, Deep Learning (DL) models are used to try to tackle the identification challenge of these herbal plants. A bespoke dataset, consisting of 25 classes and over 250 images per class, totaling 6628 images, was gathered for this paper from her reference publication. In image pre-processing, noise, blur, distortion, cropping, and resizing are used. Black and white, rotating, skewing, zooming, and flipping have all been used to supplement data. There has been no implementation of feature extraction. The pre-trained model used in this work, ResNeXt-50, attained a classification accuracy of 97.68%. Future efforts will focus on improving test accuracy and adding more classes of herbs to the collection.

Anchitaalagammai J V et al. [15] Have set out to develop a Deep Learning-based medicinal plant identification system. The custom dataset used in this paper was gathered from her reference paper; it includes five classes with roughly 10,000 images each, for a total of 58,280 images. Where picture pre-processing is not needed, feature extraction has been used instead of data augmentation. This study's classification accuracy of 96.67% was attained using the CNN model. The number of classes will be increased in the future.

Manjusha Deshmukh et al. [16] Propose a clever vision-based method for identifying herb plants that entails creating a deep learning (DL) model. This research makes use of a Kaggle dataset that was gathered for her reference work; it has 82,500 images total, divided into 15 classes with 5500 images each class. Feature extraction has been used in places where image pre-processing and data augmentation are not used. Multilayer Perceptrons, or MLPs, are the proprietary model used in this work. MLPs attained a classification accuracy of 99.01%, whereas CNN models reached an accuracy of 98.3%. Subsequent research can

focus on growing the dataset and testing the model in increasingly challenging real-world situations.

Nilesh S. Bhelkar et al. [17] Acquire a high level of precision in the recognition and classification processes that were conducted using computer vision algorithms. This study makes use of a unique dataset—45 classes, totaling 4682 images—that was gathered for her reference work. In these cases, neither feature extraction nor data augmentation nor image pre-processing has been used. The pre-trained model used in this work, Xception, had a classification accuracy of 97.65%. Future research will compare the performance of different models and create a tailored deep learning model to apply the classification for medicinal plant recognition.

Misganaw Aguate et al. [18] To use a sigmoid classifier as the final layer of a convolutional neural network (CNN) in order to identify the medicinal plant portion based on multi-label categories. 15,100 photos of medicinal plants were gathered for her reference document, which is used in this work. where scaling and normalization are used in image pre-processing. The implementation of feature extraction and data augmentation has not been done. Mobile Net, a pre-trained model used in this work, had a 92.6% classification accuracy. Future research aims to improve model performance by expanding the quantity of data sets.

Rahim Azadnia et al. [19] Proposes a clever vision-based method for automatically identifying herb plants using a Convolutional Neural Network (CNN). A bespoke dataset, consisting of five classes and 150 images per class, totaling 750 images, was gathered for this paper from her reference publication. where images are resized and backgrounds are removed during pre-processing. Color manipulation and rotations have been used to supplement data. There has been no implementation of feature extraction. The CNN model used in this work produced a 99.3% classification accuracy. Future work: To find less prevalent therapeutic plants, the

model created by the study will be tested in subsequent research, possibly with modifications.

Samreen Naeem et al. [20] Proposes classifying the leaves of medicinal plants using machine learning. This study makes use of a unique dataset that was gathered from her reference work; there are six classes, 100 images in each class, and 600 images in total. where noise is used in image pre-processing. The implementation of feature extraction and data augmentation has not been done. The classification accuracy of the multi-layer perceptron classifier used in this work was 95.87%. This suggested method can be enhanced with hyperspectral and three-dimensional digital image datasets and applied to more medicinal plant leaves in the future.

A. Hasib Uddin et al. [21] The findings of this study have important ramifications for correctly identifying and categorizing medicinal plants in Bangladesh. This study makes use of a unique dataset that was gathered from her reference work; there are 10 classes, 500 images each class, and 5000 images overall. where morphological gradient, Gaussian filter, blur, and background removal are used in image pre-processing. The implementation of feature extraction and data augmentation has not been done. DenseNet201, a pre-trained model used in this work, attained an 85% classification accuracy and a 99% soft ensemble accuracy. The capabilities and accuracy of the system would be improved by future efforts to expand the dataset to include a greater number of medicinal plant species.

Ms. Pooja Sharma et al. [22] Applications based on deep learning models are able to automatically classify plant diseases. This study makes use of a unique dataset—in this case, 21 classes—that was gathered for her reference work. where pre-processing of images is not used. In addition to feature extraction, data augmentation has been accomplished by translation, rotation, and transformation. The pre-trained model used in this work, VGG16, obtained a classification accuracy

of 98.52%, while VGG19 obtained an accuracy of 98.08%. In the future, datasets containing real-time conditions—like complicated photos with various backgrounds—will be utilized to test the accuracy and behavior of deep learning models.

Maibam Maikel Singh et al. [23] describes the image processing methods used to recognize leaves and extract important leaf characteristics. A custom dataset gathered from her reference material is used in this work. where edge detection, noise reduction, and enhancement are used in picture pre-processing. Both feature extraction and data augmentation have not been used. 84% classification accuracy was attained in this work using the LBP-SVM model. To address accuracy-related problems and increase performance, future studies in the field of plant identification will employ enhanced machine learning classifiers with preprocessing and feature selection models.

Sameer A Kyalkond et al. [24] One of the main objectives of the suggested system would be to identify plants from a user-uploaded snapshot. More than 20 leaves from 100 different plant species were gathered for her reference work, which includes 1050 medicinal and 550 non-medicinal leaves. where pre-processing of images is not used. The implementation of feature extraction and data augmentation has not been done. Alex Net, a pre-trained model used in this work, had a 90.01% classification accuracy. In the future, the CNN approach might be enhanced through model optimization, data reconfiguration, and hyper parameter adjustment.

Biplob Dey et al. [25] Using a variety of publicly available data sources and our own actual field photos of medicinal plants, this study attempts to analyze the performance of seven sophisticated deep learning algorithms (VGG16, VGG19, DenseNet201, InceptionV3, ResNet50V2, Xception, and InceptionResnetV2) in a family-wise manner. This study makes use of a public and private dataset—which

includes 30 classes and 5878 images—that was gathered for her reference publication. In these cases, neither feature extraction nor data augmentation nor image pre-processing has been used. This study used the pre-trained DenseNet201 model, which obtained a classification accuracy of 97.4% on private datasets and 99.6% on public datasets. Future research is uncertain. The robustness of our technique could be improved and refined by addressing these limitations through additional research.

A.D.A.D.S. Jayalath et al. [26] Visual morphological traits including the form, color, and texture of the leaves and flowers can be used to automatically identify plants. This study makes use of a unique dataset—ten classes, totaling 5000 images—that was gathered for her reference work. where pre-processing of images is not used. The implementation of feature extraction and data augmentation has not been done. Using the CNN model, this paper's classification accuracy was 90%. Future research is uncertain.

Shashank M Kadiwal et al. [27] Proposes a CNN model-based automated method for plant identification. This study makes use of a Kaggle dataset that was gathered for her reference paper; it has 1204 images in 10 classes. where resizing is used in image pre-processing. Rotate, flip, and zoom have been used to supplement data; feature extraction has not been used. The CNN model, which was used in this work, had a 93.75% classification accuracy. In the future, we will go beyond this barrier and investigate training with natural hand photographs, implementing a far more user-friendly method to identify the medicinal plants. Currently, we are limited to using just leaf images.

Silky Sachar et al. [28] Proposes using a leaf image and ensemble learning to quickly identify medicinal plants. This study makes use of a bespoke dataset that was gathered for her reference work; the medicinal leaf dataset has 1841 photos

altogether, divided into 30 groups. where resizing is used in image pre-processing. Neither feature extraction nor data augmentation have been used. The ResNet50 pre-trained model used in this work had a 99.66% classification accuracy. We plan to develop our own dataset in the future to benefit the scientific community.

Sukanta Ghosh et al. [29] Utilizing deep learning techniques for the identification and classification of medicinal plants. The dataset of thirty distinct kinds of medicinal plants gathered in her reference publication is used in this work. where segmented and cropped pictures are used in image pre-processing. The implementation of feature extraction and data augmentation has not been done. PCA is a pre-trained model used in this work. The model's classification accuracy, based on VGG16, was 95.25%. Future research could improve performance by include more photos and layers.

Saiful Islam et al. [30] The dataset's objective is to offer an extensive collection of leaf photos related to ten different species of medicinal plants that are often found in different parts of Bangladesh. The custom dataset used in this study was gathered from her reference paper and is divided into 10 classes. The dataset includes 2,029 original leaf photos and 38,606 enhanced images, with roughly 200 images in each class. Image pre-processing techniques include scaling and blur removal. Instead of using feature extraction, data augmentation techniques such as rotation, brightness, zooming, height and width shifting, shearing, vertical and horizontal flips, and shearing have been used. InceptionResNetV2, a pre-trained model, was used in this work. Its classification accuracy was 92.93%, 90.10%, and 90.09%. DenseNet201, a pre-trained model, obtained accuracy of 98.46%, 96.30%, and 80.69%. Future research is uncertain, and limitations do not apply.

2.3 Comparative Analysis and Summary

The benefits of medicinal herbs are impacted by their use. Only via human use are medicinal plants known to exist. A medicinal plant poses a risk to people if it is not directly fit for human consumption. The quality of medicinal herbs determines their use. It immediately affects a medicinal plant's suitability for human eating. People's immune systems weaken with age, therefore it's critical that they understand how to properly identify and use therapeutic plants. We have shown in this inquiry how to identify and categorize therapeutic plants. Every image in our dataset was personally captured with a smartphone. We create a method for recognizing and categorizing therapeutic herbs. We use the Keras application programming interface (API) to solve this challenge by constructing a deep learning-based neural network. We accomplish this by employing a cutting-edge detection method that is founded on deep learning techniques. To safeguard human safety and lower the risk of disease linked to medicinal plant abuse, accurate identification of medicinal plants is essential. To detect medicinal plants from photos, we employ various deep neural network techniques. The study offers a thorough explanation of each model's design, and based on the findings, it is possible to determine which specific model is the most effective and has the highest identification accuracy. The advanced learning topologies are compared using a dataset comprising pictures of 10 different kinds of plant leaves.

2.4 Scope of the Problem

Determine and research the variables that impact the identification and advantages of medical plants, including time, temperature, appropriate usage, insect response and remediation techniques, and the elements that influence the use of medicinal plants. Procedures for preparing medicinal plants for human consumption and preserving them under various circumstances. Assess medicinal plants, the efficacy

of tactics, and the degree to which medicinal plants benefit people. Examine the changes in a plant's leaves, roots, stems, blooms, fruits, and other advantages as it progresses through the many stages of medicinal plant conservation. Examine the relationship between human use and the therapeutic qualities of medicinal plants. Using medicinal plants increases the risk of sickness if they are not properly identified. It takes a combination of disciplines that integrate botany, biology, and human usage habits, including advantages, to completely comprehend and resolve the issues related to the accurate identification and classification of medicinal plants.

2.5 Challenges

There were several challenges in carrying out this research, as with nearly any undertaking. However, in order for this to be successful, we all work together to overcome the entire process.

- ✓ The primary, and most urgent, challenge is to collect or create a sufficient data set for our purposes.
- ✓ Utilizing the dataset is similarly relevant, but because it is in representational format, it is more challenging to perform initial image processing than with other collections.
- ✓ Photographing medical plant leaves from various areas was difficult and time-consuming because we needed medicinal plants to create the dataset and had to go throughout the countryside to do it.
- ✓ The process of developing a simulation that has a high level of consistency.
- ✓ Insufficient information for training and insufficient data to carry out the process.

CHAPTER 3

Research Methodology

3.1 Introduction

The research methodology section aims to provide an overview of medicinal plant identification and classification and proper use analysis and deep learning techniques. This section discusses the methods used to pre-process and enhance the data we collected. We include images of medicinal plant leaves found and collected from rural areas. We discuss the problem of classification of our data, which is addressed by the model we used. The proposed classification models have been selected, the different layers and functions of these models and the data sets we have added to make our work more accurate and reduce losses. Methods used in image data collection, data processing, graphical representation and classification model selection and design are specifically discussed and explained in this chapter. Establishing deep learning models for the problems we are working on in our research. Any model depends on data collection and data cleaning. We faced many problems while training the classification models, because it was not so easy to select the right model, still we managed to select the right model after many attempts.

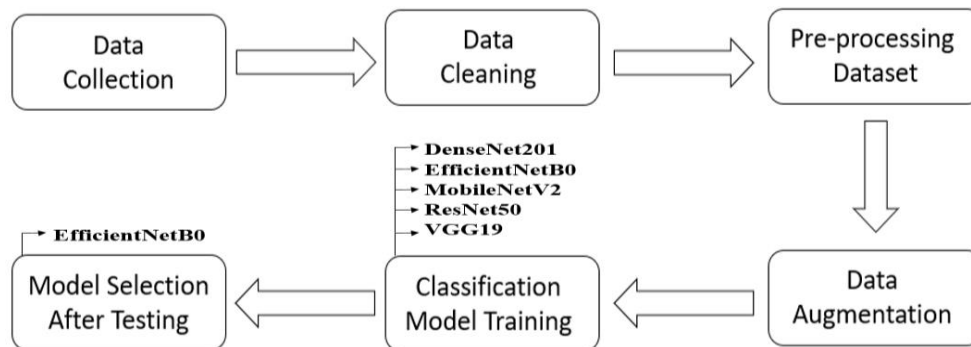


Figure 3.1: Proposed System Architecture

3.2 Data Collection Procedure

We have collected a high quality and clean dataset for medicinal plant identification and classification. The first step of data collection was to locate the medicinal plants in the village area and collect pictures of the leaves. To improve the quality of our dataset, the images were taken from different angles of each leaf.

Over 4000 images were taken throughout the data collection process. Divided into 10 categories, each category contains more than 375 images and the data is healthy data.

Below Table-3.2 shows some images of our data set:

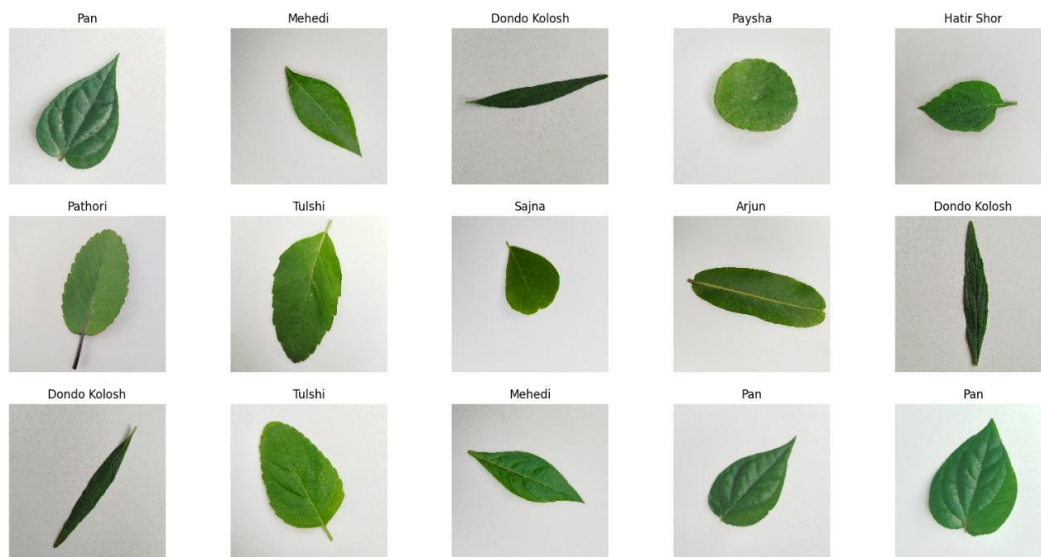


Figure 3.2: Sample Dataset

3.3 Dataset Cleaning

We collected the leaves of medicinal plants, then the leaves were not clean and the leaves were dusty and unhealthy leaves and many leaves were infested with insects. After cleaning all these leaves, I took pictures of healthy leaves. There was

background noise in some photos due to bright sunlight, clouds in the sky while taking photos. By removing those images, I created a complete dataset. The complete dataset table is shown in Table 3.3:

TABLE 3.3: THE FINAL DATASET TABLE

| Classes Name | Numbers of Images |
|--|--------------------------|
| Arjuna (Arjun Leaf) | 375 |
| Betel Leaf (Paan) | 375 |
| Dronapushpi Leaf | 375 |
| Heliotropium Indicum (Indian Heliotrope) | 375 |
| Henna (Mehandi Leaf) | 375 |
| Marsh Pennywort Leaf | 375 |
| Mint Leaf (Tulshi) | 375 |
| Moringa (Sahjan Leaf) | 375 |
| Neem Leaf | 375 |
| Rubble Leaf | 375 |
| Total Images | 3750 |

3.4 Dataset Preprocessing

Data preparation is an essential step in the data processing section. It contains cleaning, transforming, and organizing raw data in order to prepare it for evaluation and model training. The excellent 3000*3000-pixel photos that were taken in open conditions weren't suitable for our simulation models. We altered the pixels' dimensions from (0,255) to (0,1) to make rescaling the images less intimidating.

This will enable them to contribute equitably in the event of damage. The 224*224-pixel resolution of the converted images is maintained. There was no noise in our photos. The dataset should be divided in order to replicate the deep learning model. To maximize visual diversity, the dataset's 3000 and 750 photos are first divided into two distinct groups (train and test). To maximize the accuracy and diversity of the data, the training (that 80% of data) portrayals are again divided into training and validation stages, which are similarly divided in an 80-20 ratio. The train, test, and validation data sizes are shown in Table 3.4.

TABLE 3.4: THE NUMBER OF IMAGES IN EACH DATASET

| Dataset Splitting | Number of Images |
|--------------------------|-------------------------|
| Training 80% | 3000 |
| Validation 20% | 750 |
| Testing | 750 |

3.5 Proposed Methodology

The technique of applying prior designs to address a novel issue or challenge is known as transfer learning, and it is employed in deep learning. Propagate learning is an educational method or methodology used while training models; it is not a specific type of deep learning process. It is possible to complete a completely new assignment by reusing previously taught materials. The specific assignment will have some connection to the one that was practiced; for instance, it may include grouping items into a recognizable file type. To adjust to the new, invisible input, the old modeled system usually needs a significant amount of extrapolation. Using fewer components, this transfer mechanism for learning promises improved

precision from its created weights and has been used to develop three different deep neural network algorithms.

3.5.1 ResNet50

The majority of the 50 layers that make up ResNet50 are layers with block residuals, regularization by batch, and convolution. In order to gather features at various heights and laws, the network integrates 1x1, 3x3, and 1x1 convolutions with pooling layers. ResNet50, like other popular methods, has often been pre-trained on large picture categorization databases such as ImageNet. Pre-training allows the statistical framework to learn achievable features from a large number of images while being tailored for specific tasks or datasets. ResNet50 employs identity connections in residual code blocks, which append input directly to the output. Learning intricate abstractions is facilitated by this, which helps to preserve data and gradients throughout the network. ResNet50 can be used as a feature extraction tool for transfer learning. By removing the fully linked layers and using the activation signals from the previous layer, the model can be adjusted to do additional image-related tasks such as item identification, picture segmentation, or feature extraction. Much larger networks may now be trained because to relative connections, which have also spurred additional architectural advancements [31].

3.5.2 VGG19

The 19 layers that make up VGG19 are composed of 3 fully linked layers and 16 convolutional layers. The convolutional layers use max-pooling stages with a 2x2 window and a stride of 2 and tiny 3x3 filters with a stride of 1. With its many layered convolutional layer structures and straightforward architecture, the network

is comparatively easy to understand and use. There are 19 levels in all in the VGG19 deep structure. The depth of the system allows it to learn hierarchical qualities with increasing levels of complexity, allowing for better picture visualization and understanding. To keep the same design, VGG19 commonly deploys 3x3 filters and maximum pooling layers throughout the network. This uniformity facilitates the design and implementation of the network. Pre-training cases for VGG19 are often large picture classification databases such as ImageNet, which has millions of tagged visuals. The model may learn fundamental features from a large number of photos through pre-training, which can then be customized for usage on specific tasks or datasets. VGG19 can be utilized as a feature extractor for transfer learning, just like other pre-trained models. The model can be modified for various image-related tasks by eliminating the final completely connected layers and utilizing the activations from a previous layer [32].

3.5.3 DenseNet201

Further aesthetically pleasant advances and the ability to train far deeper networks have been spurred by relative connections. The advanced convolutional neural network architecture DenseNet201 is a member of the DenseNet family. Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger introduced it in their paper "Densely Connected Convolutional Networks" (CVPR 2017). Adding even more layers and characteristics to improve performance on image recognition tasks, DenseNet201 is an improvement on DenseNet121 and DenseNet169. The organizational principle of DenseNet201 is the concept of thick blocks. Every layer in a block of material uses the characteristic maps of every previous layer as input. This high level of connection facilitates direct information transfer across layers, which reduces the problem of diminishing gradients and

promotes feature reuse. DenseNet201 uses transitioning blocks between dense blocks to reduce the amount of maps with features and spatial dimensions. These transitional blocks consist of an average pooling 2x2 layer, a batch equalization layer, and a compression 1x1 convolution layer. In the bottleneck layer structure, a 3x3 convolution phase is followed by a 1x1 convolution layer [33].

3.5.4 EfficientNetB0

A CNN model called EfficientNetB0 was influenced by MobileNetV2. It is intended for large-scale, effective deep learning applications. This model, which belongs to the baseline family, efficiently balances the network's depth, width, and resolution by using a composite scaling technique. It combines the usage of activation functions like switches and works in detail to deliver great accuracy at minimal cost. The architecture of EfficientNetB0 uses a 224 x 224 pixel input picture network to process features at various scales and features an inverted residual block. With a pooling layer to maximize feature extraction, it uses 3 x 3 and 1 x 1 convolutional layers to process features at various sizes. Large datasets, such as image nets, are used to pre-train EfficientNetB0, which may then be adjusted for certain tasks. It is therefore beneficial for applications involving transfer learning. Among other image-related activities, it carries out object detection and image categorization. The EfficientNetB0 model achieves high dependability at cheap cost and low memory requirements by striking a balance between effectiveness and efficiency. [34].

3.5.5 MobileNetV2

The recently developed "Inverted Residual" is a construction element that MobileNetV2 promotes. This block includes a linear constriction layer and a separable depth-wise convolution. Because of the inverted residual, the simulation may increase the number of paths (width) while reducing the network's physical dimensions (i.e., width and height), resulting in a more efficient and lightweight network. The linear restriction layer in the inversion residual executes a 1x1 convolution with a low-dimensional bottleneck before carrying out the primary depth-wise separable convergence. The linear bottleneck prevents the loss of features and improves the depth-dependent separable convolution. In MobileNetV2, a new expansion factor dimension, denoted by "t," is introduced. The extension factor controls the capacity of the input channel of the depth-wise separable convolution. In accordance with hardware limitations, it allows the model to rapidly scale up or down and attain a balance between simulation dimension and performance. Furthermore, the width scaling argument with the designation " α " is added by MobileNetV2. The width converter $\alpha < 1$ is used to scale the number of channels in each layer. This feature makes it easier to deploy the model on devices with limited processing power, allowing the simulation to balance model complexity and accuracy [35].

3.6 Model Training

In each of the aforementioned CNN-based topologies, we have made advantage of the data that is accessible. However, EfficientNetB0 outperforms other CNN architectures in terms of efficiency. Therefore, we want to use the EfficientNetB0 architecture to further enhance our model. The following sentences will provide a detailed explanation of the EfficientNetB0 architecture.

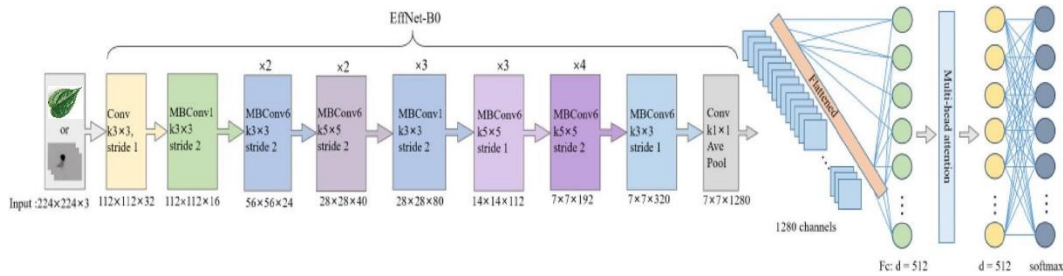


Figure 3.6: EfficientnetB0 Network Architecture

EfficientNetB0 can be used as a feature extractor for transfer learning, just as other pre-trained models. By removing the last classification layer and utilizing activation data from the preceding layer, the model can be altered to carry out a variety of scene-related tasks, such as object detection and image segmentation. EfficientNetB0 is frequently pre-trained using sizable image classification datasets like ImageNet, just as other deep neural network models. Pre-training allows the algorithm to learn common features from a large number of images before fine-tuning to particular tasks or datasets [34].

3.7 Implementation Requirements

- ✓ Tensorflow and other deep learning frameworks and libraries.
- ✓ Windows 11.
- ✓ HP XPS (Core i7 processor, 16GB RAM, 11th generation).
- ✓ Anaconda Navigator's Jupyter Notebook.
- ✓ Redmi Note 13 for Image Collection.

CHAPTER 4

Result Analysis and Discussion

4.1 Introduction

We are utilizing our custom-made dataset and five deep learning models (ResNet50, VGG19, DenseNet201, EfficientNetB0, and MobileNetV2) to get the best accuracy possible. We have developed distinct models (ResNet50, VGG19, DenseNet201, EfficientNetB0, and MobileNetV2) for our dataset using transfer learning. This allows us to build the model using our particular dataset by using the weights of the pre-trained model.

4.2 Experiment Results and Analysis

The process of using a range of evaluation criteria to gauge a deep learning algorithm's performance is known as experiment result analysis. A model's efficacy needs to be assessed early in the research process, and model evaluation also helps with model supervision. The accuracy of our model can only be assessed during the training and validation stages. In order to validate our model, we must analyze a wide variety of reports. To test our model, we need to create a confusion matrix and categorization report. The next sections will deal with the brief introductory paragraph. We can rapidly identify the method that has the best chance of detecting photos from situations by examining the comparison table between the simulators. The table below lists each model's results along with the corresponding assessment grades.

TABLE 4.2: THE EXPERIMENT RESULT OF THE EVALUATED MODEL

| Transfer Learning Model | Test Accuracy | Test Loss |
|--------------------------------|----------------------|------------------|
| ResNet50 | 99.60% | 0.0066 |
| VGG19 | 99.80% | 0.0017 |
| DenseNet201 | 93.47% | 0.2194 |
| EfficientNetB0 | 99.87% | 0.0015 |
| MobileNetV2 | 98.00% | 0.0597 |

4.3 Generating Confusion Matrix

The effectiveness of a classification model is evaluated using a table known as a matrix of disorientation. It provides a detailed summary of each prediction made by the framework by comparing the model's predictions with the actual values of the physical reality. The performance of the categorization system is described in a table known as the matrix of confusion. An inconsistency matrix displays and summarizes the results of a categorization system. A comprehensive assessment of the machine learning model's performance across multiple groups or divisions is made possible by the matrix. A model for an ambiguous matrix is a matrix of the same size that has the same number of rows and columns as types in the dataset. To determine how well the model works for each class, we can create a variety of assessment metrics, such as F1 score, precision, recollection (sensitivity), precisionness, and dependability. A matrix of squares that compares the expected and actual values of a collection of data points is commonly used as a confusion matrix. It consists of cells or regions that are True Positive, True Negative, False Positive, and False Negative [36].

Using our special dataset, EfficientNetB0 was able to accurately identify medicinal plant leaves in the following chronological order: 75, 75, 75, 74, 75, 75, 75, 75, 75, and 75.

The model's confusion matrix is illustrated in Figure 4.3.

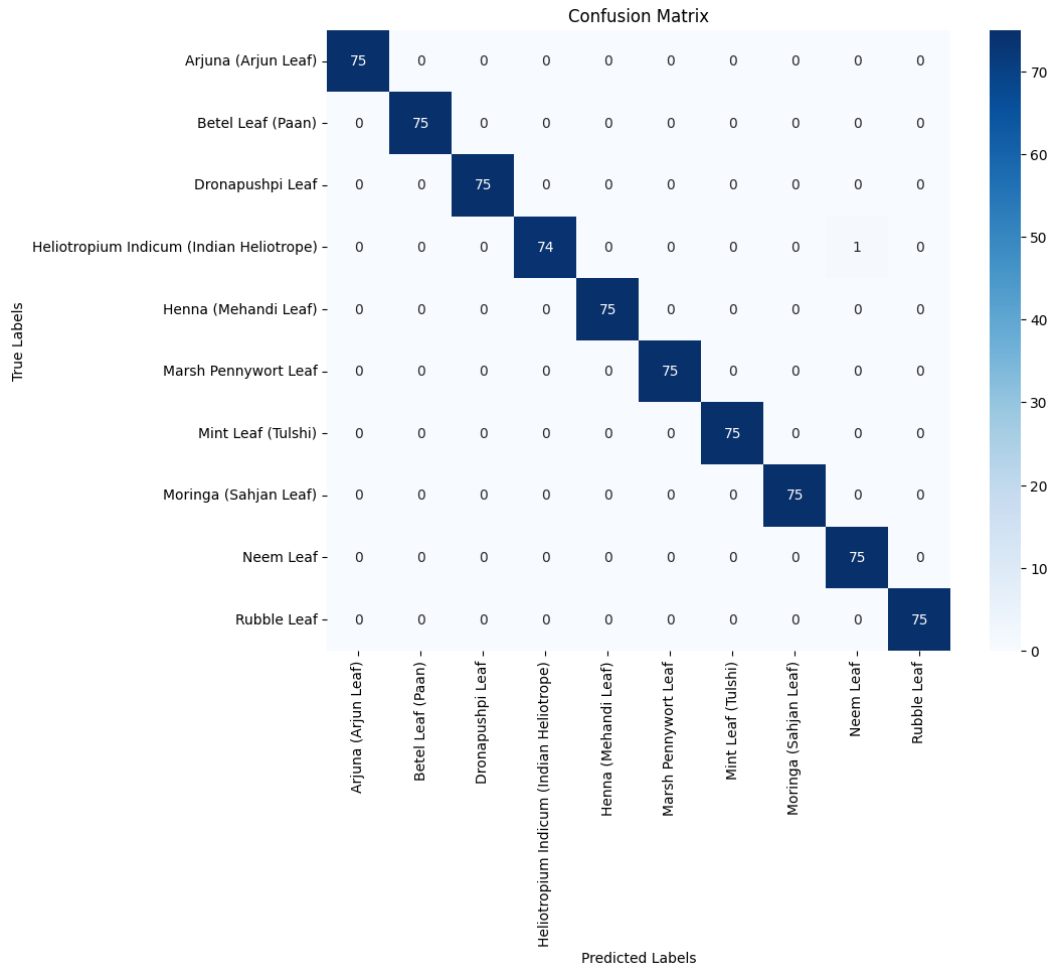


Figure 4.3: Heatmap of Confusion Matrix

4.4 Generating Classification Report

An oral presentation that provides a thorough analysis of the effectiveness of a classification strategy across multiple classes or types is called a categorization report. The overall percentages for accuracy, memory, F1 score, and support are among the noteworthy figures it presents for every class [37]. The sample average and general median are among the averages that are displayed. The categorization report offers information on how the model functions for particular demographics and helps assess the model's overall effectiveness. It is particularly useful when dealing with uneven datasets or when numerous classes have varying levels of importance.

TABLE 4.4: CLASSIFICATION REPORT OF EFFICIENTNETB0

| Class name | Precision | Recall | f-1 Score | Support |
|---|-----------|--------|-----------|---------|
| Arjuna (Arjun Leaf) | 1.00 | 1.00 | 1.00 | 75 |
| Betel Leaf (Paan) | 1.00 | 1.00 | 1.00 | 75 |
| Dronapushpi Leaf | 1.00 | 1.00 | 1.00 | 75 |
| Heliotropium Indicum (Indian Heliotrope) | 1.00 | 0.99 | 0.99 | 75 |
| Henna (Mehandi Leaf) | 1.00 | 1.00 | 1.00 | 75 |
| Marsh Pennywort Leaf (Pysha Pata) | 1.00 | 1.00 | 1.00 | 75 |
| Mint Leaf (Tulshi) | 1.00 | 1.00 | 1.00 | 75 |
| Moringa (Sahjan Leaf) | 1.00 | 1.00 | 1.00 | 75 |
| Neem Leaf | 0.99 | 1.00 | 0.99 | 75 |
| Rubble Leaf | 1.00 | 1.00 | 1.00 | 75 |

4.5 Training and Validation Accuracy and Loss Curve

Using the Keras Callback function, we initially executed 20 epochs of EfficientNetB0 with verbose set to 1, shuffle set to True, and validation steps set to none. The training and evaluation curves following 20 training epochs are displayed in Figure 4.5. Although the outcome was not considered very satisfactory, epoch 19 was identified as the best epoch, with almost perfect training and validation precision.

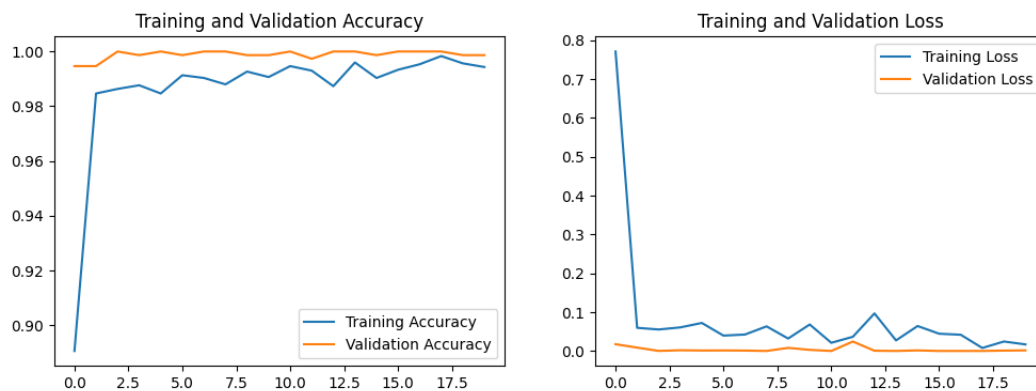


Figure 4.5: Training-Validation Curve with 20 Epochs

4.6 Discussion

Five deep learning models are employed in this work to identify and categorize medicinal plants. The accuracy of plant identification from medicinal plant leaves is determined by these models. Together with the detailed procedure of our work, we show that the research findings and analysis are accurate. After our studies were finished, the accuracy scores of the (ResNet50, VGG19, DenseNet201, EfficientNetB0, and MobileNetV2 models) were 99.60%, 99.80%, 93.47%, 99.87%, and 98.00%), respectively. The trial results showed that the EfficientNetB0 model performed better than other suggested simulations. When compared to other techniques, the model offers the highest identification accuracy.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

Our research has a significant influence on society and human existence. ensuring the health security of human welfare and the well-being of human existence. People can learn about health regulations and human health in order to properly identify medicinal plants for the diagnosis and maintenance of human health. People can enjoy therapeutic plants without sacrificing their immunity, and they lower the risk of contracting illnesses and infections. Research is necessary to understand the characteristics of medicinal plants and how to preserve them. Our project helps to ensure greater dependability among individuals by protecting and developing efficient ways to extend human life. It offers patients natural medications. Particularly in places where pharmacies and hospitals are inaccessible. Understanding medicinal plants is essential because they are significant to the local population. People profit economically from the increased use of medicinal plants, which also makes it possible to evaluate and preserve medicinal works. Medicinal plants are particularly beneficial to human well-being, biodiversity preservation, economic efficiency, and sustainable economic growth. Technology and Science The impact of medicinal plant research on society is substantial. By resolving the issues and accurately identifying medicinal plants, the research's findings improve human well-being and socioeconomic conditions.

5.2 Impact on Environment

The methods and environmentally sustainable use of medicinal plants can be supported by their identification and classification. People's economic costs are

decreased by the research. The ecology suffers when medicinal plants are used improperly. It promotes the use of medicinal herbs and has a moral impact on human safety. It raises the standard of medicinal plants that are useful for therapeutic purposes. People's issues with optimal processing, preservation, and appropriate use are shown by the study. It lowers the expenses associated with the environment. The utilization of medicinal plants will help people realize the value of trees. People's moral thinking will grow as a result. How we benefit from trees. People will be less likely to harm trees as a result of their increased environmental consciousness. Additionally, our project contributes to forest protection. It raises people's consciences, which encourages eco-friendly conduct. The study preserves environmental equilibrium and fosters an eco-friendly mentality.

5.3 Ethical Aspects

Effectively identifying and classifying medical plants, confirming and verifying their suitability for human use, and assessing the degree to which medicinal plants benefit humans are all necessary for human well-being, long-term efficacy, safety of use, and particularly the appropriate use of medicinal plants.

A list of some ethical factors is as follows:

- ✓ It is important to make sure that medicinal plants are properly identified and used.
- ✓ It is important to weigh the benefits and drawbacks of using therapeutic plants.
- ✓ It is important to develop sustainable infrastructure for both production and storage.
- ✓ Safety and human benefits should be prioritized.

5.4 Sustainability Plan

Sustainable deep-learning methods for medicinal plant identification and classification must be used in a way that promotes human health and physical and mental well-being over the long term, minimizes adverse environmental effects, and protects the use of medicinal plants for coming generations. The future use and well-being of medicinal plants depend heavily on preserving the quantity and use of medicinal plant species as well as integrating their productivity into a sustainable deep-learning method.

CHAPTER 6

Overview of the Study, Conclusion, and Future Work

6.1 Overview of the Study

One effective method that can identify something is deep learning. It is crucial and trustworthy for recognizing and categorizing therapeutic plants. We have shown how to recognize and categorize medicinal plants in this assessment. We are developing a prototype that can recognize, categorize, and advise on the appropriate usage of medicinal herbs. For instance, which diseases can be effectively treated by which plants. Deep learning techniques are used in the construction of our prototype. To recognize medicinal plants from photos of their leaves, we use deep learning techniques. Six chapters make up the entire endeavor. These consist of image collection, initial processing, training, updating, classification, and size reduction. We use descriptions of ten different kinds of medicinal plants to examine the deep learning topology.

6.2 Conclusions

To assess the quality of several medicinal plant classes and determine their potential benefits to human health. to use CNN and deep learning in computer vision to automate this classification process. Being able to classify correctly and in a way that humans can use is crucial. Using our custom dataset of 3000 pictures, the model with additional input layers of EfficientNetB0 achieves 99.87% accuracy. As a result, it demonstrates that our largest difficulty is preserving data availability.

6.3 Limitations

The dataset of medicinal plant leaves used in our current article is not sufficient. Only images of medicinal plant leaves that are available at hand have been collected. Rare species of medicinal plants have not been included in our dataset. Our model can identify only ten species of medicinal plants.

6.4 Future Work

In our current article, we have used CNN and deep learning models. In the future, we will include more medicinal plant species in our dataset. Develop a mobile app so that people can easily identify medicinal plants and learn about their uses.

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