REAL-TIME MANDARIN PLANT SPECIES CLASSIFICATION USING DEEP LEARNING APPROACH

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FINAL YEAR Research REPORT

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APPROVAL

This research titled "REAL-TIME MANDARIN PLANT SPECIES CLASSIFICATION USING DEEP LEARNING APPROACH", submitted by **Mahin Ahmed** and **Imtiaz Ahmed** 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 26-01-2024

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We hereby declare that this project has been done by us under the supervision of **Mushfiqur Rahman, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

In this study, the research into the immediate classification of Mandarin plant species by applying a deep learning method. The more and more people want to find the best way to identify the plant species, especially in agriculture and ecology, our research aims at using Convolutional Neural Networks (CNNs) to classify the plants based on the leaves. The study, called "Real-Time Mandarin Plant Species Classification Using Deep Learning Approach," is based on the creation of a dataset that contains images of Mandarin plant leaves. We use the latest CNN architectures, such as MobileNetV2, DenseNet201, and InceptionV3, to train the classification models which can identify the Mandarin plant species in real-time scenarios with the highest accuracy possible. Our approach consists of image pre-processing, dataset augmentation to increase model accuracy, and training of the CNN architectures using transfer learning techniques. After that we compare the performance of each model using the accuracy, precision, recall, and F1 score. We, by means of a lot of experiment and analysis, evaluate the strengths and weaknesses of all the CNN architectures in the classification of the Mandarin plant species based on the leaf images. In general, this research increases the level of plant species classification methods, thus, giving the analysis of the CNN architectures performance in the field of Mandarin plant species classification. The results show that it is important to use the deep learning methods for the accurate and efficient botanical classification tasks and thus the agricultural production, the conservation of the environment and the research of biodiversity will be improved.

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CHAPTER 1
INTRODUCTION

1.1 Overview

It is safe to say that deep learning approaches in the last decade have managed to present fresh and intriguing facets to the subjects of image classification as well as object detection among others. The research under image processing has been rapidly modified from machine learning to deep learning [11]. Application of technology like embedding CNNs in real time to classify plant species has many who can benefit from it such as research in botany, farming and environmental monitoring. Because agriculture is the backbone of many economic through the world [22]. And the meaning behind our research is to establish a pattern-recognition system which is able to classify Mandarin plants instantly from leaf images in real-time.

The division of plants into different species is a key element, since it is used for several purposes, for example protection of biodiversity, production of agricultural harvests and investigation in ecological studies. Through human history, botanists and researchers have been associated with different identification techniques that could hardly be automated in most cases. Time and labor usage could not be spared hence these methods being prone to errors typical of human nature. Deep learning and computer vision evolutions pose the auto classification systems for the plant species a relevant option that is both precise and efficient.

The study will focus predominantly on pteridophytes. Mandarin plant species are economically very important [27]; besides they are also cultivated all over the world mainly because of their fruits and medicinal nature. Through the application of deep learning approaches, of which Convolutional Neural Networks are a prime example, The study aim to develop a system that possesses the capability of recognizing different Mandarin plant species with high precision by drawing solely on photos of their leaves. The true worth of this continuous specification using knowledge that is available at the moment is evident for the farmers, experts and environmentalists, cardinal in far-field identification without a specified professional, development or educational level becoming a pre-requisite.

The research success focused on flavoring with the state-of-the-art deep learning models such as Mobilenet V2, Densenet 201, Inception V3 and a hybrid model. Such models are a testimony to their excellence in specific image classification tasks and are also appropriate for those real-time solutions. By applying transfer learning and fine-tuning concepts into our processes, the study focus on adapting these universal models according to the Chinese plant species recognition task that will, in turn, ensure the highest precision and productivity.

via the project implementation its hope to contribute to the development of the automated plants classification technology by making it more convenient for real tasks implementation. By merging the power of deep learning practices with the wealth of botanical knowledge, our vision is to create a space where correct species of plants identification can be easily accessed by researchers and conservationists, and consequently, aiding informed decision-making and better practices on agriculture and environmental management throughout.

1.2 Background and Present State

The main objective of the research "Real-Time Mandarin Plant Species Classification Using Deep Learning Approach" is to demonstrate that the old plant species identification and classification methods are no longer accepted, and they should be replaced by the new ones. The Mandarin species classification in the agricultural and environmental sciences is very significant because of the many applications it has, for example, crop management, biodiversity conservation and environmental monitoring.

The contemporary deep learning types, like the Convolutional Neural Networks (CNNs), will be the main factor in the solution of the problems that are currently existing in the classification of Chinese plant species. The main concept of our project, the transfer of learning, is the core idea of the artificial intelligence, which, through the knowledge obtained from the other tasks, the model can use, thus, to be able to detect the subtle patterns and features of Mandarin plant leaves and increase its power.

Besides, the usage of the deep CNN architectures not only gives us the high level of accuracy and efficiency in the plant species identification, but also it enables us to identify the plant species that are not found by the traditional methods. Through the analysis of various CNN models such as MobileNetV2, DenseNet201 and InceptionV3, there are, therefore, getting closer and closer to the choice of the best CNN model for the classification of Mandarin plants in real life.

The field of our research is not only limited to the academic area, but it is also applied in agriculture and environmental science. The establishment of a dependable classification system, which will classify the Mandarin plant species in real time, will assist the decision makers to choose the right ones, to protect the biodiversity and to keep the environment's sustainability.

1.3 Problem Statement

The research "**Real-Time Mandarin Plant Species Classification Using Deep Learning Approach**" is basically about the answers to most of the unanswered basic questions such as the use of the latest deep learning techniques in the field of plant species classification based on leaf images. These questions are the main criteria, which guide the research to a comprehensive examination, of the problem on the use of artificial intelligence in the botanical research. The overarching research questions include: The research questions that the student investigates are the following:

- How we collect data from location and how to classify the variants?
- What is the ethical statement taken for classify mandarin leaves?
- Is machine learning algorithm being appropriate for Mandarin classification?
- How deep learning models affectively classify Mandarin Leaves?

1.4 Objectives

The motivation for the research is to classify the mandarin based on leaf and identify diseases to help the agricultural economy in Bangladesh. The world citrus market is worth more than 139 billion dollars. The Bangladesh Government says that nine kinds of citrus fruits exist in Bangladesh. Mandarin is one of them. This mandarin also has four types. A portion of which is shipped to other countries. So, people who want to plant or cultivate mandarin may have face several issues for classify the variants. The research aims to create a smart system using deep learning to identify different types of mandarin leaves from mandarin variants. The project will focus on leaf shapes by training algorithms to tell the difference between leaf variants. To ensure the models work, collecting high-quality images of different mandarin leaf types from the Natore Bangladesh. The study look for new ways to solve problems like needing more data, unevenly distributing classes, and changing weather. By working under guidance and using up-to-date information, the study's results will be accurate and valuable and can be used in real life. The data was classifying the under-plant pathologist for meet the ethical consideration. Machine learning traditional data extraction is not suite for the mandarin leaf classification because it cannot work with large amount of data and it relay on the visual attributes but in the deep learning it can work with the large amount of data with good accuracy. In the research it’s use deep learning models to solve the problems that come up when trying to classify leaves because deep learning models can easily recognize the patterns, can perform automatic feature extraction action and it have also high accuracy rates in data classification with high quality images. The research make finding, organizing, and treating classify leaf more accurate and streamlined by creating robust algorithms and models.

1.5 Scope and Limitations

The expected output of this study involves both the ideas from the theoretical and the practical aspect emphasizing advancing knowledge in the field of plant classification and real-time deep learning. The anticipated outcomes include:

Development of a strong Plant Species Classification System:

The main result of this survey will be the development of a competent and effective method for real-time Mandarin plant species classification in a quick and reliable way. The system deploys deep learning methods, comprising of models such as MobileNetV2, DenseNet201, InceptionV3 and the hybrid model, aims to attain a high level of accuracy in distinguishing between various Mandarin plant species captured from leaf images, consequently, facilitating expeditious species identification in different environments with ease.

Evaluation and Comparative Analysis of Deep Learning Models:

The chosen deep learning models will be evaluated and compared by performing a comprehensive assessment of their performance. This study will provide the information about reliability, accuracy, and effectiveness of different models. The findings will be made available to form a conclusion for using those models in practice for real-time Mandarin plant species identification.

Integration of Predictive Strategies:

The predictive strategies integration being the next item on the list of expected outcomes. By applying predictive techniques system leverages not only image classification from current leaves but also anticipate any of the species' variations or real-time environmental changes recently. The active role taken up by the gardeners during this process ties in with what native plants research and conservation need to succeed including speedy reactive and adaptive management.

Application of Image Processing Techniques:

The study will be defended by deep learning image processing techniques, for instance, feature extraction and pattern recognition, which will, in turn, increase the accuracy and the speed of the plant species classification. The system is using such methods for the purpose of presenting the morphological features and the spatial distribution of Mandarin plant species, which will serve the way for a better understanding and research in botany. Comprehensive testing procedures will be done to show the reliability of the plant species classification system. The research will prove the system's effectiveness through different datasets and will demonstrate its use in any environmental conditions and for all the variants of the Mandarin plant species. The investigation of the authenticity checking will confirm the correctness and the application of the system, hence, the actual usefulness of the system in the real botanical research conditions will be validated.

1.6 Report Organization

The matters would even be demonstrated more through the program; from onwards the whole report has been organized in a way that those who will use the report there will flow through the research process, findings and recommendations back-to-back rather than in a random manner. The study underwent the chapters and, as instructed, each major topic was cited, which, in addition, determined the structure and detailedness of the book. In this part of the report, the build will be an allocation and a narrative form of the report will be used. A reader will go through the process of the research conducted and results of the research and impacts of it. The section for the appliance will showcase its different features and that will lead to the end objective of this chapter which is to convince a person to buy this product.

Chapter 1: Introduction

The first chapter is dedicated to present the framework of this study that covers real-time Mandarin plant species identification using deep machine learning technique. The first thing is pointing out that for one or for another field, the basis of broad areas and narrow ones is formed in particular by the correct taxonomy (i.e. pure plant forms description) of species. Through building up the subject, this passage delivers the central idea of attracting attention of deep learning methods and the incorporating of MobileNetV2, DensNet201, and InceptionV3 models in the process. Also, this method underscores the necessity for immediate rating capability so that agricultural techniques and ecological monitoring can be determined on time.

Chapter 2: Literature Review

In the literature review and research chapter, the study go into the depth of plant species classification, deep learning and image recognition which are the focus of the study. This paragraph provides a summary of the theoretical underpinning and respective methods of the approaches in these related studies. The deep learning architecture with MobileNetV2, DenseNet201, and InceptionV3 models as the first thing. After that, discuss whether the models are appropriate for the image classification task well. Also, find holes in the existing literature and where the need for comparisons is highlighted in order to understand the best approach for Mandarin plant species real-time classification.

Chapter 3: Methodology

In the research methodology in our proposal which will consist of a detailed view of the applied techniques for the real-time Mandarin plant species classification study. On the next paragraph, the study explains data collection procedure. The process of collecting data is done through getting Mandarin plant leaf images dataset for training and testing. It describes the primary preprocessing steps, such as data augmentation, which are essential in increasing the model accuracy. Then the detail the structure of the MobileNetV2, DenseNet201, InceptionV3 and hybrid models and further give an overview of why opted for these networks. Privacy and the Ethics of Data Sharing and Model Deployment are also presented in this part.

Chapter 4: Implementation

In this chapter, the study evaluates the models are MobileNetV2, DenseNet201, InceptionV3 and a hybrid model upon the Mandarin leaf dataset of the plant classification. For that study complete the data pre-processing technique under the guidance. Moreover, try to evaluate the data accuracy for accurate classification.

Chapter 5: Result and Analysis

After Completing the Implications process based in our model selection, in the study deeply the following models.In the research supply granular descriptions of the classification efficiency of each model – accuracy, precision, recall and F1-score. Shape visual elements which are such as confusion matrices and ROC curves is used to outline the accuracy of models. And after the study complete the comparative analysis in our best accuracy.

Chapter 5: Impact on Society, Environment and Sustainability

The environmental consequence chapter discusses the environmental repercussions of using the deep learning models which are applied for real-time plant species classifications. The paper identifies the energy demands of training and deployment of models. It stresses the importance of

developing green algorithms and hardware. The strategies for a mitigation impact on the environment are also suggested; it is about an optimization of model architectures and renewable energy sources. In addition, gives the fact that technical breakthroughs should be harmonized with environmental goals in the implementation of artificial intelligence solutions.

Chapter 6: Conclusion and future work

In this last chapter, the study wraps up the key results of our investigation focused on real-time Mandarin plant species classification with deep learning techniques. The findings of the experiments are underscored, and present suggestions for agriculture, the environment, and biodiversity management. Along with that study indicate possibilities of extension, pointing at potential new fields of inquiry, namely autonomous structures or environmentally aware solutions. The applied of a systemized procedure guarantees that our research outcomes and their implications on both the academic and practical fields of plant species classification will be put together.

1.7 Summary

The research-based “Real-Time Mandarin Plant Species Classification Using Deep Learning Approach” aim to improve a classification technique using advanced technology. By using deep learning models, in the research can make a sustainable technique which will make plant classification faster and accurate. Mandarin farming is valuable worldwide. Creating deep learning based mandarin plant classification technique will be helpful for the farmers, gardeners and researchers make better decision without needing expertise.

The study involves collecting mandarin leaf images, preparing data, training models and evaluating performance. The report also considers the environmental impact of using these technologies and sustainable. The report organized into chapters that cover the introduction, literature review, methodology, implementations, results, social impact providing a clear overview of the research and its findings.

CHAPTER 2

LITURER REVIEW

2.1 Overview

In the background of the research paper entitled 'Real-Time Mandarin Plant Species Classification Based on a Deep Learning Way,' a proper beginning is necessitated by explaining the main terms and ideas first. Transfer learning, considered as the fundamental block of artificial intelligence by researchers, is the juvenescence behind this research, on which the model relies in learning knowledge from all different tasks and using it for the real-time identification of Mandarin plant species. Deep Convolutional Neural Networks (CNNs) are no doubt the most popular and promising tools for image analysis; the inner image features and patterns can be inferred with the aid of these tools to conduct the classification work. The word "classification" means rules for imperishable categorization of Mandarin plants according to the traits of their leaves. At the same time, the "real-time" stands for a fast and present mode of this plant species classification. Throughout the research, the mentioned terms are intensely used to clarify the meaning of integrated effects of transfer learning modules, deep Convolutional Neural Network, and real-time classification of Mandarin plant species. In this way, the initial sections of the article aim to build a common understanding and appreciation of the concepts upon which plant species classification is founded, thus equipping the readers to deal with the complex techniques that are used for species identification.

Besides, explaining the terms and referencing the essential frameworks for understanding is not only an issue of comprehension improvement but also to provide clarity on the involved methodologies. The transfer learning incorporated into the model covers the ability of knowledge borrowing from one domain which is then transferred into another. However, accuracy remains the main obstacle as the model finds it difficult to correctly classify plant species in Mandarin. Deep CNNs, a powerful imaging computing method in recognition and precision, lie at the very core of the model where the system can discern between the different plant species by simply looking at the characteristic of the leaf extracted from images. This span of understanding of preliminaries serves as a solid base for readers to explore the intricacies of the research methodology. Besides that, readers develop a good appreciation for the inventive approach utilized in the experiments that appear to be done in real time regarding the identification of plant species in Mandarin.

2.2 Related Works

Liu et. al. (2022) created a lightweight Convolutional Neural Network (CNN) model named LtCNN to classify plant photos using hyperspectral photography and deep learning [1]. The model underwent testing using 1,500 hyperspectral camera photos of 30 different plant types. The study showed that LtCNN could correctly identify leaf features in photos of living plants with crowns, even though it needed less training data than CNN models with more complex features, like AlexNet, GoogLeNet, and VGGNet. The model achieved a kappa coefficient of around 0.90 for simulated RGB images and 0.95 for 3-band RGB and near-infrared images. Huixian (2020) classified and identified plant leaf photos using deep learning and artificial neural networks [2]. Segmenting leaf pictures, collecting shape and texture data, and applying different classification methods to identify plant species were suggested. This study analyzed 50 plant leaf datasets using KNN-based neighborhood classification, Kohonen network-based self-organizing feature mapping, and SVM-based support vector machine. After examining seven plants, ginkgo leaves were the most recognized. Yang et. al. (2020) used deep learning to categorize leaf images with challenging backgrounds [3]. More than 2500 pictures were recognized by distinguishing target and background pixels. Two thousand pictures were used to train a Mask Region-based Convolutional Neural Network (Mask R-CNN) for leaf segmentation and a 16-layer deep convolutional network (VGG16) for leaf classification. The algorithms attained an average mean accuracy of 1.15% for 80 test photographs and 91.5% for 150 test images. Lv (2023) focused on classifying grapevine leaf images using deep-learning ensemble models[4]. The aim of the study was to determine grape types by examining the morphology of their leaves. The research achieved a high accuracy of 98.1% in classifying grapevine leaf images using an ensemble classifier with soft voting. This technique combined predictions from five pre-trained deep learning models (VGG19, VIT, Inception ResnetV2, DenseNet201, and ResneXt) that underwent training and optimization using transfer learning. Using image preprocessing, feature extraction, and the VGG16 CNN model for classification, Pushpa and Lakshmi (2022) proposed a method for classifying plant species according to leaf vein characteristics [5]. The authors used the Flavia dataset, including 15 photo classes, obtained via the open platform Kaggle. The model's accuracy was found to be 95%. Using visual symptoms, Selvam and Kavitha (2020) developed a technique to diagnose and discriminate

against plant diseases in lady finger plant leaves to safeguard and manage crop losses in agriculture [6]. The investigator’s suggested custom CNN architecture classified 1088 lady finger plant leaf pictures into healthy, disease- and insect-affected, and fertilizer overdose leaf burn categories with 96% accuracy. Using 10 Bangladeshi medicinal herbs, Akter and Hosen (2020) illustrated an automatic classification method [7]. A three-layer CNN trained with data augmentation extracts high-level features for classification. The recommended approach was feasible and effective, as 34,123 photos were trained and 3,570 images were tested with 71.3% accuracy. Muneer and Fati (2020) executed research on a proficient and automated classification technique for identifying Malaysian herbs based on form and texture criteria[8]. The system combined Support Vector Machine (SVM) and Deep Learning Neural Network (DLNN) classifiers, achieving 74.63% and 93% recognition accuracy, respectively. The system has a mobile application for immediate categorization. In a study by Elaraby et. al. (2022), a deep learning and image processing approach were presented for the purpose of detecting and classifying maladies in citrus plants[9]. Two types of convolutional neural networks, AlexNet and VGG19, were employed in the implementation and evaluation of the proposed method. The algorithm's overall performance peaked at 94%. Mahmudul Hassan and Kumar Maji (2021) explored deep convolutional neural network (CNN) models to classify plant species. The author's primary focus was on obtaining plant leaf images from several freely available data sources[10]. The CNN-driven model gathered perplexing leaf features directly from the original images. This strategy aided in overcoming the challenge posed by the morphological similarities of plant species. Noticeably,

The framework achieved accuracy ratings of 99.4% for the MK dataset and 99.7% for the Flavia dataset. Bisen (2021) argued for a plant identification system using deep convolutional neural networks to identify species by leaf features[11]. A Swedish leaf dataset of 15 plant species with 75 photographs per class, totaling 1125 images, was used to train the CNN model. Identification involved image pre-processing, feature extraction, and recognition. The study author's proposed CNN classifier utilizes convolutional, max pooling, dropout, and fully connected hidden layers to acquire knowledge about plant features for leaf classification. The method attained a 97% high level of accuracy. Research conducted by Saini et. al. (2020) introduced a plant leaf classification approach using a deep Convolutional Neural Network (CNN)[12]. The Convolutional Neural Network (CNN) was trained on 4000 leaf photos from two plant species and evaluated on 1000 leaf photographs. The CNN architecture was meticulously designed to differentiate between plant types and accurately categorize leaf photos. The CNN exhibited performance with a training accuracy of 99.96% and a testing accuracy of 99.90%. Song et. al. (2019) initiated an attention mechanism named attention branch-based convolutional neural networks (ABCNN) to enhance the identification of tree species, especially those with leaves that closely resemble each other[13]. The experimental setup used a tree leaf public dataset from Leafsnap, including 185 species and 7719 images. The original dataset was randomly divided into 6109 samples for training. After preprocessing, a dataset of 26,253 samples emerged, with 1610 photos preserved aside for testing. The recommended model achieved a classification accuracy of 91.43% on a specific dataset from Leafsnap and 98.27% on a broader dataset from SVHN. Bharali et. al. (2019) employed a Deep Convolutional Neural Network (CNN) to identify and classify plant diseases based on leaf images, categorizing them into two categories based on the presence of disease[14]. A small neural network was trained using 1400 image files. That model was 96.6% correct. Kumar and Verma (2021) utilized deep neural networks to automatically identify plant species from leaf pictures[15]. Transfer learning was used to extract pertinent leaf image characteristics with the pre-trained AlexNet deep neural network model. Adapting the last three network tiers helped in classifying species. This approach attained an accuracy of 95.56% using the specified strategy. Assessment was conducted on 240 images acquired from the UCI machine library Web site, representing 15 leaf species. Van Hieu & Hien (2020) systematically compiled a collection of Vietnamese plant images by using photographs from an online encyclopedia of Vietnamese species and the Encyclopedia of Life. The collection comprised 28,046 environmental photographs of 109 plant species native to Vietnam[16]. The research contrasted MobileNetV2, VGG16, ResnetV2, and Inception Resnet V2 deep convolutional feature extraction models. Plant photos were identified by testing these models using an SVM classifier. The assessed models demonstrated good identification accuracy, with MobileNetV2 achieving the highest performance at 83.9%. Zhao et. al. (2021) applied DoubleGAN, a dual generative adversarial network, to generate high-resolution images of diseased plant leaves[17]. The process entailed inputting images of healthy and sick leaves into a Wasserstein generative adversarial network (WGAN) to generate a pretrained model. The photos were scaled up to 256x256 pixels using a superresolution generative adversarial network (SRGAN). DoubleGAN achieved a plant species and disease recognition accuracy of 99.80% and 99.53%, respectively, exceeding the original dataset. Using Generative Adversarial Networks (GANs), Maniyar & Budihal (2020) used leaf conditions to classify the health of plants[18]. Deep learning models such as GANs use a Generator-Discriminator setup. The generator is taught to create data samples that imitate the original dataset in order to deceive the discriminator. The discriminator must differentiate between genuine and fabricated samples to identify them as either legitimate or counterfeit. The suggested model of the scholars reliably determined plant health with a 98.29% prediction rate during adversarial training. Orchi et. al. (2023) conducted a comparison between standard machine learning and deep transfer learning models for diagnosing agricultural leaf diseases [19]. Classic machine learning models included SVM, LDA, KNN, CART, RF, and NB, whereas deep transfer learning models consisted of VGG16, VGG19, InceptionV3, ResNet50, and CNN. This experiment used the PlantVillage Dataset, which included diseased and healthy crop leaves, for binary classification. InceptionV3 had the highest classification accuracy of 98.01%, while the NB classifier had the lowest accuracy at 60.09%. In an analysis, Deep Convolutional Neural Network (CNN) technology was used to automate tomato leaf disease detection by analysts Anandhakrishnan and Jaisakthi (2022). The suggested approach used 18,160 Plant Village tomato leaf disease photos. The dataset was partitioned between 60% training and 40% testing pictures to train and assess the model[20]. The advised DCNN model achieved 98.40% accuracy on the testing set, showing its expected performance. In an article by Kaushik et. al. (2020), they brought up a model for detecting diseases in tomato leaves with the aid of Convolutional Neural Networks (CNNs) as well as data augmentation[21]. Classification had been conducted on the six most common illnesses affecting tomato crops. The source data had been preprocessed, and a pre-trained ResNet-50 model had been fine-tuned using transfer learning for classification. The model achieved an accuracy of 98% after testing on a dataset. Khalid et. al. (2023) concentrated on identifying tomato leaf illnesses and employed sophisticated convolutional neural network models (CNNs) to categorize them as either normal or disease-affected[22]. The study of the author evaluated its impact by applying the Plant-Village set of data, which comprises 5524 images of leaves. The researchers suggested three CNN models: VGG-16, ResNet-152, and EfficientNet-B4. ResNet-152 obtained 93.75% accuracy, EfficientNet-B4 achieved 97.27% accuracy, and VGG-16 achieved 98% accuracy in diagnosing tomato leaf diseases. A study authored by Sumalatha et. al. (2021) discussed the use of deep neural networks, particularly Convolutional Neural Networks (CNN), to predict plant diseases by classifying images [23]. The study assessed a multi-class classification issue via analysis of basic leaf photos of healthy and infected plants from a collection of 11,333 images belonging to 10 distinct classes sourced from PlantVillage. Six alternative CNN designs were compared, and DenseNet121 achieved the maximum precision of 95.48% on the test data. Liu et. al.'s (2020) study proposed a Convolutional Neural Network (CNN) architecture to identify diseases in grape leaves[24]. Sophisticated image enhancement algorithms generated 107,366 pictures of grape leaves using 4,023 photographs acquired from the field and 3,646 images openly available in datasets. DICNN was a convolutional neural network model trained without proper weights or parameters. The model achieved an accuracy of 97.22% when tested on a separate hold-out dataset. DICNN outperformed GoogLeNet by 2.97% and ResNet-34 by 2.55% in recognition accuracy.

2.3 Comparative Analysis and Summary

Table 2.1. Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Akter and Hosen (2020)	CNN	71.3%
2.	Anandhakrishnan and Jaisakthi (2022)	DCNN	98.40%
3.	Bharali et. al. (2019)	CNN	96.6%
4.	Bisen (2021)	CNN	97%
5.	Elaraby et. al. (2022)	AlexNet , VGG19	Overall 94%
7.	Kaushik et. al. (2020)	ResNet-50	98%
8.	Khalid et. al. (2023)	VGG-16, ResNet-152, and EfficientNet-B4	VGG-16 = 98%
9.	Kumar and Verma (2021)	AlexNet	95.56%
13.	Mahmudul Hassan and Kumar Maji (2021)	CNN	99.7
14.	Maniyar & Budihal (2020)	Generative Adversarial Networks (GANs)	98.29%
15.	Muneer and Fati (2020)	SVM, DLNN	DLNN = 93%
16	Orchi et. al. (2023)	SVM, LDA, KNN, CART, RF, NB, VGG16, VGG19, InceptionV3, ResNet50, and CNN	InceptionV3 = 98.01%

17.	Pushpa and Lakshmi (2022)	VGG16 CNN	95%.
18	Saini et. al. (2020)	CNN	99.90%
19.	Selvam and Kavitha (2020)	CNN	96%
20.	Song et. al. (2019)	Attention branch-based convolutional neural networks (ABCNN)	98.27%
21	Sumalatha et. al. (2021)	DICNN, GoogLeNet, ResNet-34	DICNN= 95.48%
23	Van Hieu & Hien (2020)	MobileNetV2, VGG16, ResnetV2, and Inception Resnet V2, SVM	MobileNetV2= 83.9%.
24.	Yang et. al. (2020)	VGG16	91.5%
25	Zhao et. al. (2021)	DoubleGAN	99.80% and 99.53%(species and disease recognition accuracy respectively)

2.4 Open Issues

This research scope since the research title "Real-Time Mandarin Plant Species Classification Using Deep Learning Approach" addresses the field of computer vision and plant species classification but with special attention to Mandarin plants. Of course, the main aim is to recognize Mandarin plants within a second through classify them by leaf images, however there are some wider perspectives and issues which should be taken into account.

Therefore, this research will apply deep learning methods, especially the CNN algorithm for Mandarin plant species classification using leaf imaged. The study will exploit the abilities of deep convolutional networks towards the development of a sophisticated and efficient system capable of precisely recognizing various Mandarin plants in real time.

Subsequently, the study also focuses on the application of transfer learning, the cutting-edge notion in artificial intelligence, to improve classification. Transfer learning makes it possible to use the knowledge extracted from pre-trained models on unrelated tasks. This might enhance the overall performance and generalization of the classification model.

In addition, the study covers in detail the comparison of the different deep learning architectures, including MobileNetV2, DenseNet201, InceptionV3 and hybrid model, which evaluate their abilities in Mandarin plant species classification. The research will investigate the advantages, constraints, and complementarities between these approaches leading to the most effective model for a real-time classification task.

In summary, this research piece entails the problem scopes in real-time Mandarin plant species recognition, deep learning as well as transfer learning techniques, and ultimately, a comparative evaluation of various CNN architectures. This investigation is important because project

contributes to agricultural technology and increasing the efficiency and sustainability in the Mandarin plant growth systems.

2.5 Summary

However, there are enormous vacancies in the present realm that up to now have been served by the proposed model of the real-time hybrid system capable of analyzing plant species in Mandarin when developed, so the following are some of the perplexities that are so demanding that they need to be addressed in order for the proposed system to become efficient and reliable. The first and possibly the most challenging is the availability of large and diverse datasets of adequate quality. It is worth noting that similar to most complex models based on Artificial Neural Networks, the quality and quantity of the data set used in the training process are determinant in the performance of the models. Besides, there is contrast between passages of light and shadows, tilt in angle in different shots of the leaves and background noise that may bias and hence the change in variances of the model. Hence the need to populate a diverse number of datasets on species, period of growth and others that describe the condition of the environment cannot be overemphasized.

Another large problem is the requirements for significant computational resources Once more, the number of spaces and results that must be managed is another obstacle of a different caliber. The training of large deep convolutional neural networks, including the hybrids with different structure, it like MobileNetV2 or DenseNet201, is possible only by using powerful GPUs or TPUs. Constrained calculations of data in the computer take longer time in training and the chance to experiment with different configuration or the values of the models is also affected. Nonetheless, hybrid models entails an excessive number of parameters and thus, it is prone to over-fitting; the model performing well on the training data may not map to the new data. Modes of controlling overfitting such as Dropout and Batch Normalization, apart from that, the fine-tuning selecting the best suitable architecture of the network is one of the major issues.

CHAPTER 3
METHODOLOGY

3.1 Overview

The research topic of "Real-Time Mandarin Plant Species Classification Using Deep Learning Approach" is concentrating on the application of the state-of-the-art deep learning models to the domain of botany and Mandarin plant species classification based on the images of plant leaves. Mandarin plants, a main part of crops and ecology, become the matter of interest for the research.

The research focuses on challenges associated with the traditional plants' classification methods while developing novel deep learning techniques to overcome these limitations can be achieved through the application of transfer learning and convolutional neural networks (CNNs) model. By transfer learning, the current information from dissimilar applications is made use of; however, deep CNNs are applied in order to find complex patterns and features of leaf images, which pave the way to prompt species determination.

By means of comparative analysis, the research reveals discrepancies and commonalities as between the types of deep learning and models. All the models like MobileNetV2, DenseNet201 InceptionV3 and the hybrid model detection accuracy, evaluating the efficiency, scale and time needed. Through the analysis of these methodologies, the aim of the research is to provide tangible ideas about the strong points and the challenges associated with each approach and use them as a base to contribute to the improved structured systems.

The underlying research topic is the botany field and agriculture technology integration utilizing the modern machine learning methods for improvement of Mandarin species classifying. The data gathered to form conclusions of plant biodiversity and ecology is meant to contribute to the scientific knowledge on these issues, which could in turn guide agricultural practices and conservation of biological diversity.

The study was conducted with Python as a language and TensorFlow as a powerful deep learning library. Colab, which is on cloud, was used for training deep learning models with the help of NVIDIA Tesla GPUs. GPU acceleration and up to 16GB of RAM offered by Google Colab facilitated me manage the deep learning tasks that required a lot of computational power without a problem.

The neural networks utilized in this study are MobileNetV2, DenseNet201, InceptionV3 and each of them have been implemented in this study for their suitability to real-time plant species recognition tasks. These architectures were trained and tested using the dataset of Mandarin plant leaves and metrics such as classification accuracy and inference speed were evaluated.

The research employs modern technology and computer infrastructure in botanical studies as the tool for plant species classification leading to the creation of an efficient and accurate Mandarin plant species classifier.

3.2 Proposed Methodology

Here, the proposed methodology for Real-Time Mandarin plant Species Classification Using Deep Learning Approach Different machine learning classification model performance indices will be used as efficiency measurements markers of CNN based approaches.

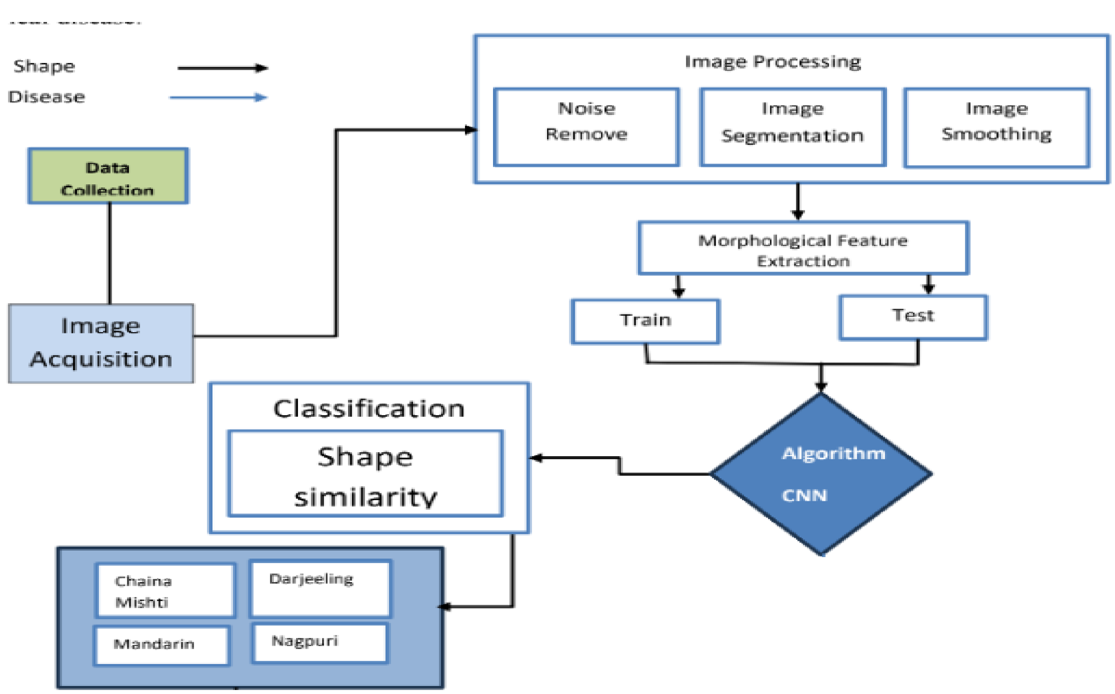

Figure 3.1: Proposed Architecture

Accuracy: Classification model accuracy is one metric. Accuracy is the model's predicted percentage. Accuracy is the percentage of properly classified pictures to total samples. Accuracy equation.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)$$

Precision: Precision is the chance of a positive label and how many are positive. Precision shows how many accurately anticipated instances were positive. Precision is helpful when FP matters more than FN. Mathematically, it's this equation.:

$$Precision=TP/(TP+FP)$$

Recall: Recall or Sensitivity measures how many positive expected occurrences were classified accurately. Recall is a helpful statistic when FN prevails over FP. F1-score is a further metric for classification accuracy that takes into account both recall and precision. Since precision and recall are harmonic means, the F1 score provides a comprehensive understanding of these two metrics. It reaches its optimum when Precision and Recall are equal. To figure it out, use the equation below:

$$Recall=TP/(TP+FN)$$

F-1 Score: F1 score is a recall-precision metric of categorization accuracy. As F1-score is the harmonic mean of Precision and Recall, it gives a complete picture. Precision and Recall are optimal when equal. Equation.

$$F\text{-}1\ Score=2*(Precision*Recall)/(Precision+Recall)$$

The percentage shows that the classification of mandarin plant. Because of this, a positive outcome on a very precise test can definitively rule out the condition for a specific person. The equation is given below:

$$Specificity =TN/((TN+FP)$$

However, there is a limit to how closely the model can mimic the training set of data before it loses its ability to generalize. An algorithm's performance can be assessed using a particular table format called the confusion matrix (CM). CM is used to illustrate crucial predictive parameters like recollection, specificity, precision, and accuracy. Confusion matrices are useful because they offer direct assessments of values like TP, FP, TN, and FN. The following parts respond to the research questions of this study based on the research question.

3.3 Hardware Requirements:

High-performance computing resources:

The ease with which the computational resources can process the computations in deep learning is one of the advantages of deep learning.

Graphics Processing Unit (GPU):

Concepts such as GPU utilization for deep learning accelerated model building and training, deep learning models algorithm efficiency optimization and use for develop web interface.

Software Requirements:

Deep learning frameworks: The frameworks such as Google Colab for building of models, training of models, model evaluation and for web application.

Programming Language:

The algorithms in Python are used especially because of their versatility and the fact that there are advanced deep learning libraries available. For creating web applications, we use python streamlit framework.

Image processing libraries:

Library combining – some of them as OpenCV for pre-processing and Mandarin plant leaf picture augmentation and using .h5 for store the architecture of the model.

Data Collection:

Diverse and representative dataset: In implementation put together all the necessary good quality data of Mandarin plant leaf images (which are different species this would speed up the Validity and generalizability of the model).

Annotated dataset:

The presence of the labeled data during the training and validation phases, the labels being there to represent the leaf species.

Model Training and Evaluation:

> **Deep learning models**: Transfer learning methods are used with pre-trained models like MobileNetV2, DenseNet201, InceptionV3 and hybrid model, which speeds up the training process and makes the classification more accurate.

Evaluation metrics: Implementation and explanation of the metrics used such as Acc, Pr, Rec and F1-score for better measurement of the performance of these models.

Ethical Considerations:

Data privacy and security: This is an example of following the rules and guidelines that are in place to protect the privacy and security of any personal or sensitive data that might be

used in the study.

Informed consent:

Getting the consent of the persons, who are used as an example in the dataset is a wise thing to do, of course. Implementation requirements encompass both hardware and software components, as well as considerations related to data collection and model evaluation.

Documentation and Reproducibility:

Code documentation: The implementation process is completely traced in the code documentation to emphasize on transparency, reproducibility and future teams work.

Version control: Implementation of version control systems like Git to code revisions and keep a structured development process.

Through fulfilling the prescriptions of implementation, the research can be done thoroughly, which ensures the validity of the outcomes. It will also allow progress not only in the field of real-time Mandarin plant species classification techniques but also in the implementation of deep learning methodologies.

3.4 Project Management and Financial Analysis

Among the core components of a 'Real-Time Mandarin Plant Species Classification Using Deep Learning Approach' research, proper management of the project and financial oversight are the highlights. The project management involves multiple tasks organized in a structured manner to achieve the final goal - the model training and its evaluation. A task plan will be written down in detail to mark milestones, assign and utilize all the necessary resources, as well as to make a timetable for achieving project objectives. The result will be a structured workflow which will bring us to the desired goal.

Financial issues are a fundamental factor providing the operation of the project. The allocation of the budget will be planned to acquire appliances and computation devices as well as to facilitate research projects and joint endeavors. To make sure the financial plan is featured in the implementation process and the money is being used in an efficient way while following the fiscal responsibility guidelines throughout the project duration. The team will depend on a strong project management and financial practices standardization that will help the study team to meet complexities of the study in an effective manner at the same time align resources with research objectives with the aim of taking the smooth progression of the research.

Financial Analysis:

Table 3.1: Estimated Cost for Thesis

SN	Cost Component	Estimated Cost (BDT)
01.	Software Licenses	500 - 1000
02.	Dataset Acquisition	2000 - 3000
03.	Miscellaneous Expenses	2000 - 2500
04.	Documentation and Report Writing	500 - 1000
Total Estimated Cost		5,000 – 7,500

3.5 Summary

The research state-up-with deep learning models -Mobile net V2, Inception V3, Dense Net 201 and hybrid model implemented in facilitated google colab gpu acceleration. Those models are trained with diverse datasets of mandarin plant leaf images, ensuring validity. Using customization in those models, for optimization training speed and classification accuracy. Evaluation metrics including accuracy, precision, recall and F-1 score are developed to access model performance comprehensively.

Ethical consideration of data privacy informed consent and for transparency and reproducibility. Project management are structured task planning and financial oversight to ensure efficient resource allocation and obedience to budgetary constraints.

Overall, the methodology integrates advanced techniques with careful project management practices, aiming to advance real-time Mandarin plant species classification while contributing in the technology and the agriculture filed.

CHAPTER 4

IMPLIMENTATION

4.1 Overview

The advanced system of technological design that consists of the camera, Python programs, and databases is the scientific approach that the "Real-Time Mandarin Plant Species Classification Using Deep Learning Approach" research is completely based on.

Hardware Configuration:

High-performance computing infrastructure: Not only the requirement of a powerful CPU and a GPU be obvious, but also the system should have sufficient amount of memory and bandwidth to the GPU.

Graphics Processing Unit (GPU):

GPU is applied for improving the training process as well as providing the necessary deep learning algorithm characteristics.

Software Environment:

Deep learning frameworks: Implementing Google Colab so to have them as the deep learning model development, training and for create web application.

Image processing libraries:

The attribute that includes libraries like OpenCV for preprocessing and datasets like Mandarin plant leaf images in libraries.

Data Preparation:

- **Dataset preprocessing:** via performing strict steps of data preprocessing, standardization, and normalization t can present homogeneity and objectivity in the input dataset.
- **Annotation:** However, Mandarin leaf could be tagged with the corresponding label namely as Mandarin leaf which acts as a training data for the supervised learners.

Model Configuration:

Transfer learning: This study uses the pre-trained Deep Convolutional Neural Network (CNN) architectures such as MobileNetV2, DenseNet201, InceptionV3 and hybrid model for the classification of Mandarin plant species. Usually, the process is fine-tuned afterward.

Hyperparameter tuning:

The values of the model parameters should be fine-tuned as this has an overall significant impact on the quality of classification and its generalizability.

Ethical Considerations:

- **Data privacy and security:** Ensure that the data collected are used properly, in accordance with the ethical principles and rules to protect the privacy and the information security.
- **Informed consent:** Once it is possible to get their approval, the images of those subjects are going to be considered for incorporation in the data set.

4.2Train Model

In our study, the research train models using MobileNetV2, Inception V3, DenseNet201, and a Hybrid Model. The process begins with comprehensive data collection, followed by meticulous image processing and augmentation to enhance the dataset. Each model is trained on this enriched dataset to evaluate its performance on image classification tasks. Our goal is to identify the model that most effectively balances accuracy, efficiency, and resource utilization.

A. Data Collection Procedure

Mandarin plant leaf samples of different species, growth stages, and environmental conditions were properly chosen to ensure a balanced sampling. For the research we collect data from Natore Bangladesh. Every leaf sample was photographed with a high-resolution camera in order to be able to pick up the detailed leaf characteristics.

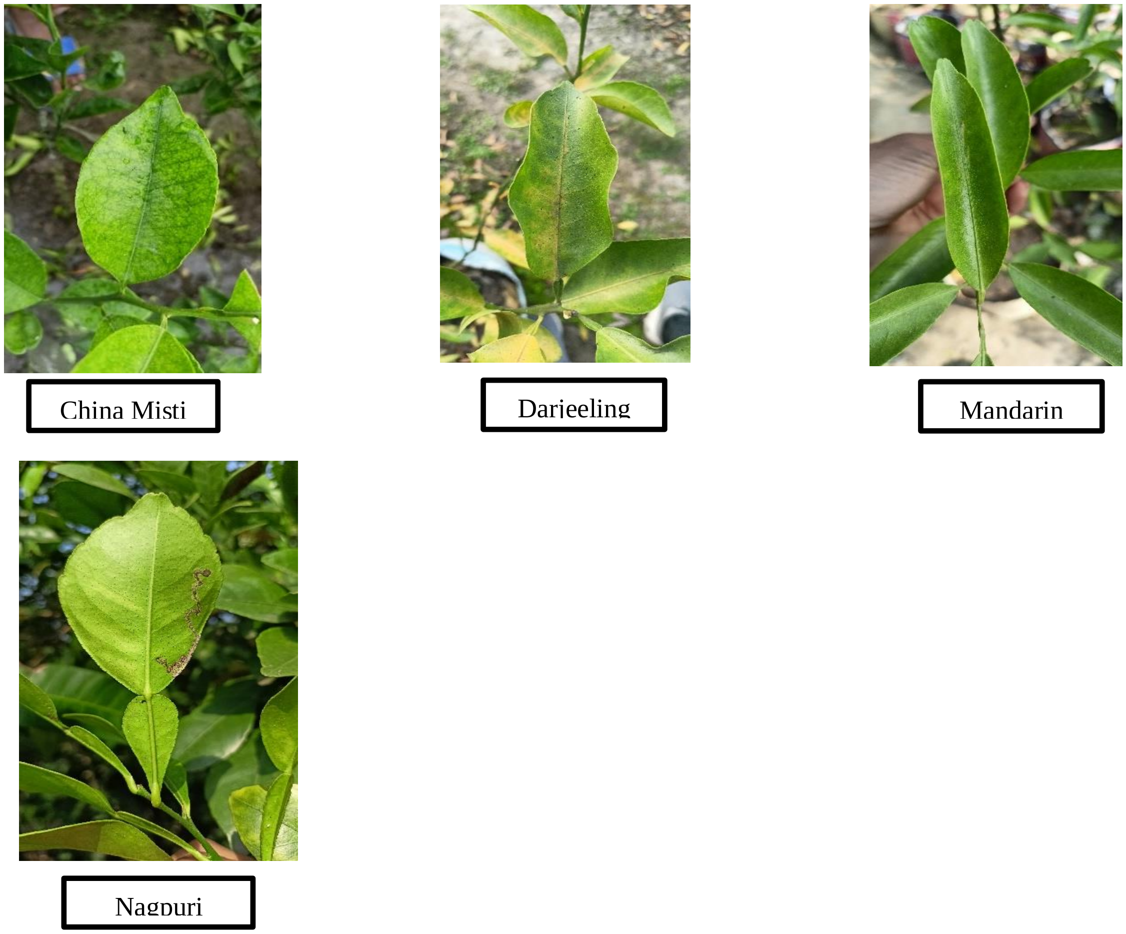

Figure 4.1: Some Raw Image of Datasets

B. Data Preparation

Afterward, the unprocessed leaf photos were sent to a computer for further intricate processing. categorized the photographs based on the Mandarin plant species and assigned them appropriate names. To preserve the integrity of the dataset, all redundant or low-quality photos were deleted during the sorting process.

C. Data Annotation

After that, each leaf picture was carefully labeled by hand with the name of the Mandarin plant that went with it. As part of the annotation process, the leaves' features were carefully examined, and plant experts were consulted to ensure the suitable species was identified.

Authorization Letter for Authentication of Real-Time Data

We are the student from Daffodil International University writing to formally authorization letter to authenticate and verify the real-time images collected for our research project titled "Real-Time Mandarin plant Species Classification Using a Deep Learning Approach." The purpose of this authorization is to ensure the authenticity and accuracy of the data before their publication in academic or research-related contexts.

The real-time images collected and used in this research have been confirmed and validated by Dr. Sayed Mohammad Mohsin Associate Professor Department of Plant Pathology SAU. Additionally, our supervisor, Mr. Mushfiqur Rahman lecturer (Senior Scale) Department of Computer Science and Engineering DIU, has overseen and verified the collection process on the ground.

They validate these real-time images to ensure they meet the required standards for accuracy, reliability, and adherence to established research protocols. This includes verifying that the data accurately reflect the observations and findings integral to my research project.

We confirm that the data presented for authentication are our real-time observations collected on the ground, validate and authenticate by Associate Professor Sayed Md Mohsin and supervised by our Lecturer (Senior Scale) Mr. Mushfiqur Rahman.

Data Collected By:

1. Imtiaz Ahmed
   Student Id: 203-15-14505
   Mail Address: imtiaz15-14505@diu.edu.bd
2. Mahin Ahmed
   Student Id: 203-15-14508
   Mail Address: mahin15-14508@diu.edu.bd

Supervise By

Mr. Mushfiqur Rahman

Lecturer (Senior Scale)

Department of Computer Science and Engineering

Daffodil International University

Authenticate By

Dr. Sayed Mohammad Mohsin

Associate Professor

Department of Plant Pathology

Faculty of Agriculture

Sher-e-Bangla Agricultural University.)

Figure:4.2- Data authentication letter

D. Dataset Augmentation

To enrich the dataset and increase model generalization as well, different augmentation approaches were accepted. This implied a random move such as a turning rotation, flipping, and adjustments to the lighting condition, background clutter, and leaf orientation.

Figure 4.3: Augmented images of Datasets

TABLE 4.1: Images Used in Original Count & Augmented Count:

NO	Class	Original Count	Augmented Count
1	Nagpuri	511	2000
2	Mandarin	560	2000
3	Darjeeling	548	2000
4	China Mishti	512	2000

E. Quality Control

Following annotation and enhancement, data set went through uncompromising quality control check. All images were labeled and read for accuracy of labeling and quality of images in order to ensure the consistency of the dataset.

F. Evaluation Set

Part of the dataset was kept manually collected and reserved for the evaluation purposes. This independent set of evaluation consisting of a variety of Mandarin plants was used to assess model performance not involving the cases in the training set.

G. Dataset Availability

The final data and annotation files with the documentation explaining the collection process will be made open for reviewing and replicability.

H. Statistical Analysis

The statistical analysis which was conducted on the experimental results listed in "Real-Time Mandarin Plant Species Classification Using Deep Learning Approaches", serves as a foundation for the development of the useful deliverables. In addition to the statistical methods employed for assessing the deep learning models such as MobileNetV2, DenseNet201, InceptionV3 and hybrid model for species classification of Mandarin based on the leaf images, their accuracy is also established.

I. Descriptive Statistics:

The descriptive statistics comprising mean accuracy, standard deviation, and confusion matrices, In the study it can clearly see the full picture of an algorithm's performance on all the different model. They are useful when it comes to focusing on the central tendencies and trends since they help in the interpretation of the results.

•Inferential Statistics

Inferential statistics, however, are in use here.In research it will use hypothesis testing (amongst other statistical methods such as confidence intervals) to find out the meaning of any classification accuracy difference that would be found between different models. The research endeavors to figure out whether the above variations are statistically significant or due to alterations with the use of hypothesis testing.

•Validation of Findings

This analysis of statistics assesses the performance of three deep learning approach, namely MobileNetV2, DenseNet201, and InceptionV3, in Mandarin plant species classification, which aims to provide an objective way of comparing their efficiency. These evaluations bring more generalization to the findings and help sense how sound models will be seen in the context of different classes of Mandarin plant species.

•Interpretation and Insights

Data analysis presents statistical information which is more comprehensible in that way of interpreting the classifications demonstrates the trends, the patterns, and the probable correlations that are characterized in the model performance. For this, applying a statistical rigor is utilized leading to an objective evaluation of the deep learning models, which makes the study more credible and validated.

4.3Model Evaluation

MobileNetV2: MobileNetV2 is a convolutional neural network that is optimized for low latency and energy consumption on devices such as mobile phones and embedded machines. Another reason for deploying deep neural networks on limited resources is their attempted solution using the compact bottleneck architecture with residual connections at bottleneck layers. In fact, the computing efficiency versus memory footprint trade-off is performed with more precision because the design concentrates on the main features extraction. In MobileNetV2 expansion layers between intermediate layers may use depth-wise convolutions in addition to filtering features and nonlinearity. The network of architecture starts with 32 filters from the first layer of the network, and then proceeds to a series of residual bottleneck layers. These processes include the transforming and creating of the initial features and then exploring more abstract representations staying with a deeper network. At the base of MobileNetV2 architecture can be defined the trade-off between the size of model and the performance, thus this architecture is good for real-time task like

Mandarin plant taxonomy classification. The design of the algorithm results in the execution of inferences on mobile devices without degrading the accuracy level, which makes it possible to be deployed in the resource demanding applications at limited availability of resources.

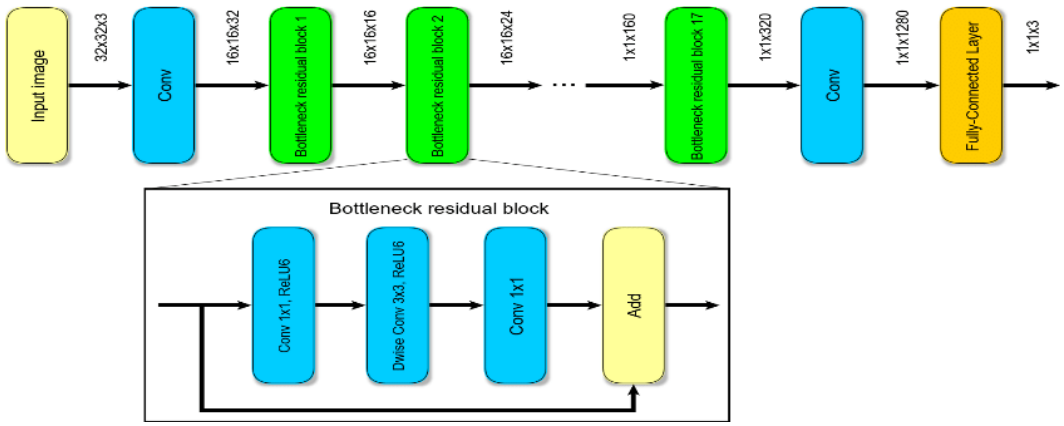

Figure 4.4: Schematic representation of MobileNetV2 (Seidaliyeva et al.2020)

DenseNet201: which is a modification of the standard convolutional neural network structure is designed to improve depth and training effectiveness for deep learning models. Contrary to the usual architecture that only has limited connections between layers, DenseNet201 enables dense

connections between the layers, which provides a channel for the direct information exchange between them. This connectivity structure is very dense hence features maps for each layer are received from all preceding layers through which feature reuse as well feature propagation throughout the network is allowed.

Concatenation of features in DenseNet201 rather than summation results in the reduction of the required number of parameters along with featured reuse. It is this parameter-small design that makes DenseNet201 the best performer among the state-of-the-art on a variety of image classification tasks such as real-time determination of Mandarin plant species. Its dense connectivity structure helps features to interact well and gradients to flow smoothly, such that resulting presentations are stronger and classification accuracy is increased.

To end with, one tangible obstacle that our team may encounter is the difficulty of using insufficient datasets for the deployment of each deep learning models. Here comes the transfer learning, which can use to the advantage. It supplies us with the weights gained from pre-trained algorithms on datasets that are larger and independent of our case. In line with this, this strategy does not only ward off possible hypothetical decreased performances but then bolsters a myriad of increases, more so in situations where separation tasks are difficult and datasets for the trainings are fewer.

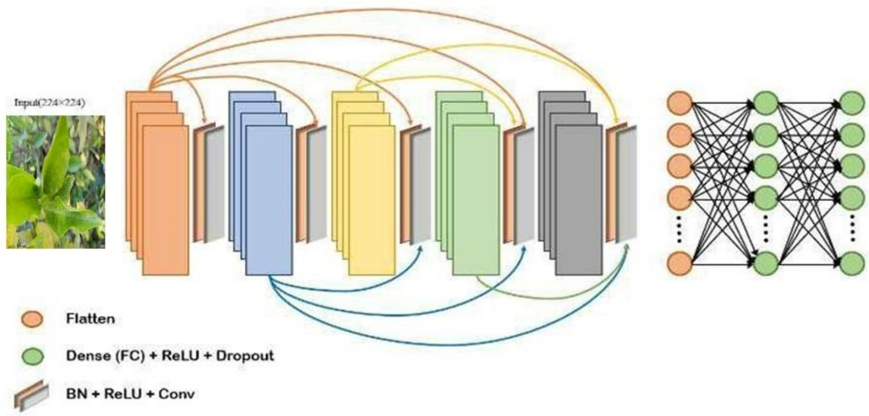

Figure 4.5: DenseNet201 Schematic Representation

Inception-V3: InceptionV3 a widely - applied deep convolutional neural network model is purposed to instantly distinguish dynamic images. This classical design of CNN relies on a sequence of stacked convolutional conditions, each with its own local and global receptive field size, which are able to capture both local and global features up to a reasonable extent. It is actually the multi-level image processing of InceptionV3 which is responsible for the extraction of much considerable and impressive features like those from any image you would feed to it irrespective of how complex the image is. The pragmatic utilization techniques implemented in InceptionV3 are mainly batch normalization, factorization and these techniques help with both training speed and efficiency, in general. Moreover, the model trains with auxiliary classifiers as well. And so, it makes all learners more relevant and prevents vanishing gradients problem. The predicaments of these were largely responsible to the splendid performances of InceptionV3 on the particularly hard dataset and practical view. It becomes possible by applying InceptionV3 feature extraction approach in real-time Mandarin plant species recognition to capture both fine-grained & coarse-grained features, and it could be good for recognizing plant species according leaf characters. A modular architecture with a device-efficient architecture allows extremely fast and accurate inference that stands to be a much-sought-after tool for the botanical sector and conservation efforts.

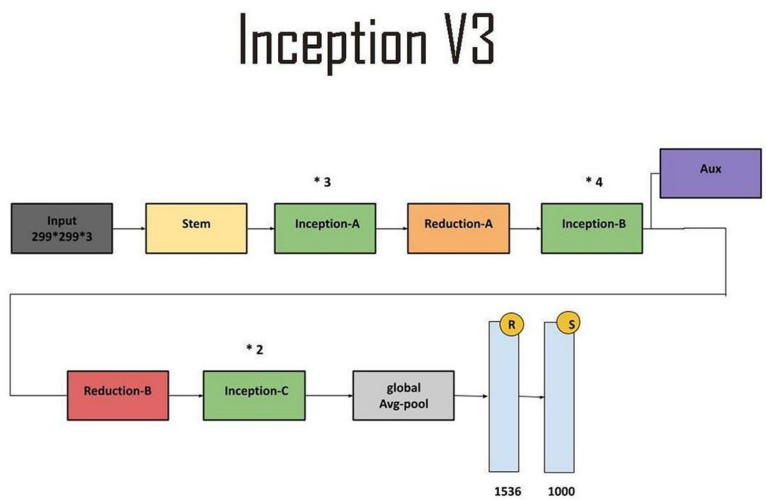

Figure 4.6: Inception Model Representation (Source Google)

Hybrid Model (MobileNetV2 and DenseNet201)

Classification of the Mandarin plant species is done under the hybrid model which is a combination of elements of the MobileNetV2 and DenseNet201 models. The model was trained using images of leave with the input size of 224*224 pixels which underwent the process of rescaling. As base models with the frozen layers, which help to keep the learned features, MobileNetV2 and DenseNet201 with pretrained on ImageNet were selected.

Average pooling layers operating at the global level were used to obtain feature maps from both models before concatenation. Batch normalization was applied to normalizing the activations in each layer and to make the training process more stable, and a dropout layer to prevent over fitting. The merged features were then taken through a fully connected dense layer with 1024 neurons and ReLU activation, then the final layer was a softmax layer which is used for the multi-class classification of Mandarin plant species.

The model was compiled with Adam optimizer and a learning rate of 0. 0001, which was specifically tailor-made for categorical cross-entropy loss and measures the accuracy. In our experiment, after the training by the training dataset, the model was exposed to 10 epochs with the training dataset validated by the validation dataset. The evaluation on the test dataset resulted in a test accuracy of [insert test accuracy] and test loss of [insert test loss] thus meaning that the model has a high of generalizing to unseen data.

The optimized hybrid model, stored by the name of “hybrid_model. h5 “shows an improvement in the real-time plant species classification of Mandarin plants through implementation of deep learning architectures integrated with the agricultural field. Future developments could include refining model structures and additional datasets to give higher cross-environment and cross-plant variability.

Transfer learning:

Transferring the technique, which is so widely utilized in deep learning, popularly known as Transfer learning, offers big help in the real-time classification of Mandarin plant species based on images of the leaf. Modification of existing dataset or model might be used to optimize the classification tasks in new genres. The research topic we are exploring is transfer learning in the context of Convolutional Neural Network (CNN) architectures, and we want to find which model is most use for plant species from Mandarin in real time image classification.

Since our study has the computational and time constraints as well as the shortcomings, In the research it narrows the topic down to the CNN topology investigation, where consider how the changes of network parameters and training dataset advantages or disadvantages can influence the classification performance. This move is fundamental for the tweaking of our deep learning models to be able to type-check Mandarin plant species in remote-scene scenarios adequately.

To end with, one tangible obstacle that our team may encounter is the difficulty of using insufficient datasets for the deployment of each deep learning models. Here comes the transfer learning, which we can use to the advantage. It supplies us with the weights gained from pre-trained algorithms on datasets that are larger and independent of our case. In line with this, this strategy does not only ward off possible hypothetical decreased performances but then bolsters a myriad of increases, more so in situations where separation tasks are difficult and datasets for the trainings are fewer.

In the gist of this research ambition is to leverage on the capabilities of transfer learning for an improved, real-time classification of Mandarin plants. This is targeted at the challenges witnessed with the limited datasets and complex segmentation tasks.

4.4Summary

The implementation phase of our research in a grounded in a strong technology framework with high performance infrastructure. Gpu acceleration and a well-known platform google colab. In research it carefully collected and proceed the diverse datasets of mandarin plant leaf images applying stringent preprocessing, annotation, and augmentation techniques to enhance model accuracy.

Our research trained with deep learning models for evaluate the accuracy for better classification technique. The hybrid model combining with Mobile Net V2 and DenseNet

201 which help to increase the real time mandarin plant classification technique.

The research aim to develop a valid classification technique to mitigate data scarcity challenges and enhance classification capabilities across mandarin plant variants. This research will be contributing into advancing deep learning based remotely controlled web application which can be applicants for the farmers, gardeners, researchers and also for the agriculture domain.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The study began building and deploying deep learning models that significantly increased our ability to classify leaves images. In research tested on four deep learning architectures: MobileNetV2, DenseNet201, Inception V3, and a novel hybrid model combining MobileNetV2andDenseNet201.MobileNetV2 is very ideal for achieving high levels of accuracy. The DenseNet201 model uses layers that are densely linked to help information spread effectively and fix the problem of gradients disappearing. With Inception V3, the Inception module is used to collect traits at different levels, which leads to accurate grouping results. The hybrid model takes the best parts of both MobileNetV2 and DenseNet201 and puts them together to make a well-balanced design that aims to improve accuracy and speed.

5.2 Experimental

Experiment 1: Hybrid Model

Accuracy: The results with the Mobile Net V2 model were also very good, it scored over 98.12%, which is very close to the pre-trained model. Therefore, the accuracy was hit on the testing set which provided a picture of 12%.

Table 5.1: Accuracy for Classification of Individual in Real-Time Mandarin Plant Species

Architecture	Training Accuracy
MobileNetV2	91.37%
DenseNet201	95.12%
InceptionV3	83.15%
Hybrid Model (Mobile Net v2 and DeseNet201)	98.12%

Dense Net 201

TABLE 5.2: Precision, Recall, F1-Score, and Support (n) for original CNN networks

	Precision	Recall	F1-Score	Support
China Mishti	0.92	0.98	0.95	200
Darjeeling	0.95	0.96	0.96	200
Mandarin	0.97	0.90	0.93	200
Nagpuri	0.98	0.95	0.97	200
Accuracy			0.95	800
Macro Avg	0.95	0.95	0.95	800
Weighted Avg	0.95	0.95	0.95	800

```
Epoch 1/10
200/200 [==============================] - 82s 312ms/step - loss: 1.3971 - accuracy: 0.4997 - val_loss: 0.8914 - val_accuracy: 0.6162
Epoch 2/10
200/200 [==============================] - 57s 286ms/step - loss: 0.6661 - accuracy: 0.7427 - val_loss: 0.4314 - val_accuracy: 0.8637
Epoch 3/10
200/200 [==============================] - 59s 296ms/step - loss: 0.4726 - accuracy: 0.8183 - val_loss: 0.7429 - val_accuracy: 0.7350
Epoch 4/10
200/200 [==============================] - 60s 298ms/step - loss: 0.4021 - accuracy: 0.8512 - val_loss: 0.2807 - val_accuracy: 0.8925
Epoch 5/10
200/200 [==============================] - 54s 267ms/step - loss: 0.3465 - accuracy: 0.8695 - val_loss: 0.6978 - val_accuracy: 0.7337
Epoch 6/10
200/200 [==============================] - 54s 271ms/step - loss: 0.3191 - accuracy: 0.8811 - val_loss: 0.3330 - val_accuracy: 0.8838
Epoch 7/10
200/200 [==============================] - 59s 297ms/step - loss: 0.2455 - accuracy: 0.9119 - val_loss: 0.1832 - val_accuracy: 0.9375
Epoch 8/10
200/200 [==============================] - 54s 272ms/step - loss: 0.1862 - accuracy: 0.9350 - val_loss: 0.1897 - val_accuracy: 0.9350
Epoch 9/10
200/200 [==============================] - 58s 288ms/step - loss: 0.1737 - accuracy: 0.9391 - val_loss: 0.1699 - val_accuracy: 0.9425
Epoch 10/10
200/200 [==============================] - 65s 323ms/step - loss: 0.1616 - accuracy: 0.9431 - val_loss: 0.1427 - val_accuracy: 0.9475
25/25 [==============================] - 6s 241ms/step - loss: 0.1488 - accuracy: 0.9513
Test Accuracy: 0.9512500166893005
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `model.sa
  saving_api.save_model(
Model saved successfully.
```

Figure 5.1: Accuracy and loses for Dense Net 201.

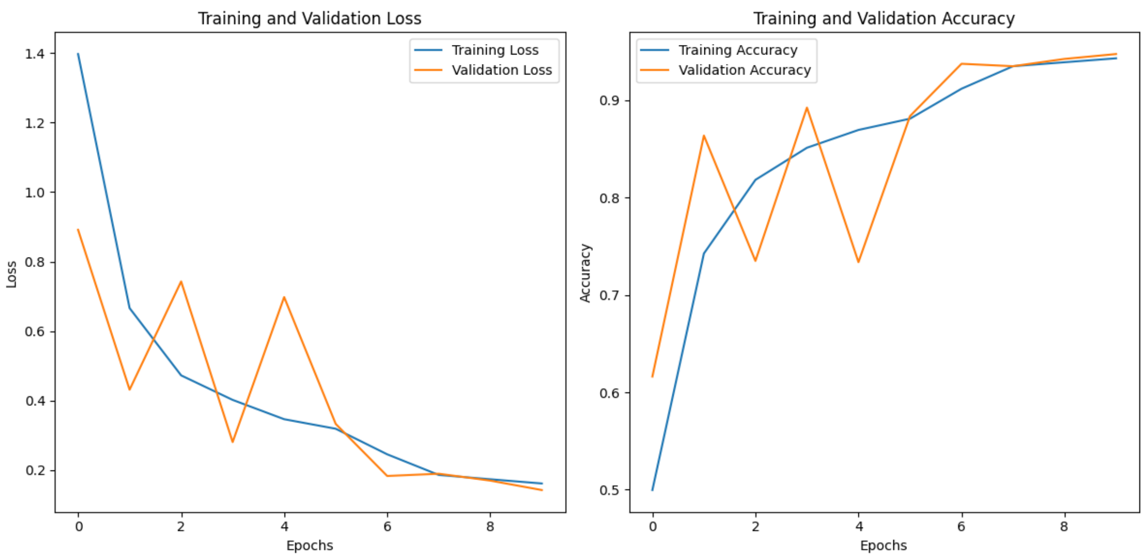

Figure 5.2: Training and validation accuracy and loss over the epochs (Dense Net 201).

MobileNetV2 Model

TABLE 5.3: Precision, Recall, F1-Score, and Support (n) for original CNN networks

	Precision	Recall	F1-Score	Support
China Mishti	0.96	0.93	0.94	200
Darjeeling	0.82	0.99	0.90	200
Mandarin	0.98	0.81	0.89	200
Nagpuri	0.94	0.92	0.93	200
Accuracy			0.91	800
Macro Avg	0.92	0.91	0.91	800
Weighted Avg	0.92	0.91	0.91	800

```
Epoch 1/10
200/200 [==============================] - 54s 252ms/step - loss: 1.2895 - accuracy: 0.6297 - val_loss: 0.8900 - val_accuracy: 0.6488
Epoch 2/10
200/200 [==============================] - 50s 251ms/step - loss: 0.5212 - accuracy: 0.7917 - val_loss: 0.5544 - val_accuracy: 0.7925
Epoch 3/10
200/200 [==============================] - 51s 255ms/step - loss: 0.4563 - accuracy: 0.8286 - val_loss: 0.3231 - val_accuracy: 0.8838
Epoch 4/10
200/200 [==============================] - 50s 251ms/step - loss: 0.3425 - accuracy: 0.8753 - val_loss: 0.3663 - val_accuracy: 0.8562
Epoch 5/10
200/200 [==============================] - 56s 282ms/step - loss: 0.3007 - accuracy: 0.8859 - val_loss: 0.2463 - val_accuracy: 0.9087
Epoch 6/10
200/200 [==============================] - 55s 274ms/step - loss: 0.2525 - accuracy: 0.9083 - val_loss: 0.2582 - val_accuracy: 0.9025
Epoch 7/10
200/200 [==============================] - 52s 260ms/step - loss: 0.1949 - accuracy: 0.9277 - val_loss: 0.2672 - val_accuracy: 0.8988
Epoch 8/10
200/200 [==============================] - 57s 285ms/step - loss: 0.2191 - accuracy: 0.9191 - val_loss: 0.2359 - val_accuracy: 0.9050
Epoch 9/10
200/200 [==============================] - 51s 255ms/step - loss: 0.1953 - accuracy: 0.9323 - val_loss: 0.1793 - val_accuracy: 0.9337
Epoch 10/10
200/200 [==============================] - 50s 250ms/step - loss: 0.1962 - accuracy: 0.9222 - val_loss: 0.2400 - val_accuracy: 0.9062
25/25 [==============================] - 6s 247ms/step - loss: 0.2367 - accuracy: 0.9137
Test Accuracy: 0.9137499928474426
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via `mode
  saving_api.save_model(
Model saved successfully.
```

Figure 5.3: Accuracy and loses for Mobile Net V2.

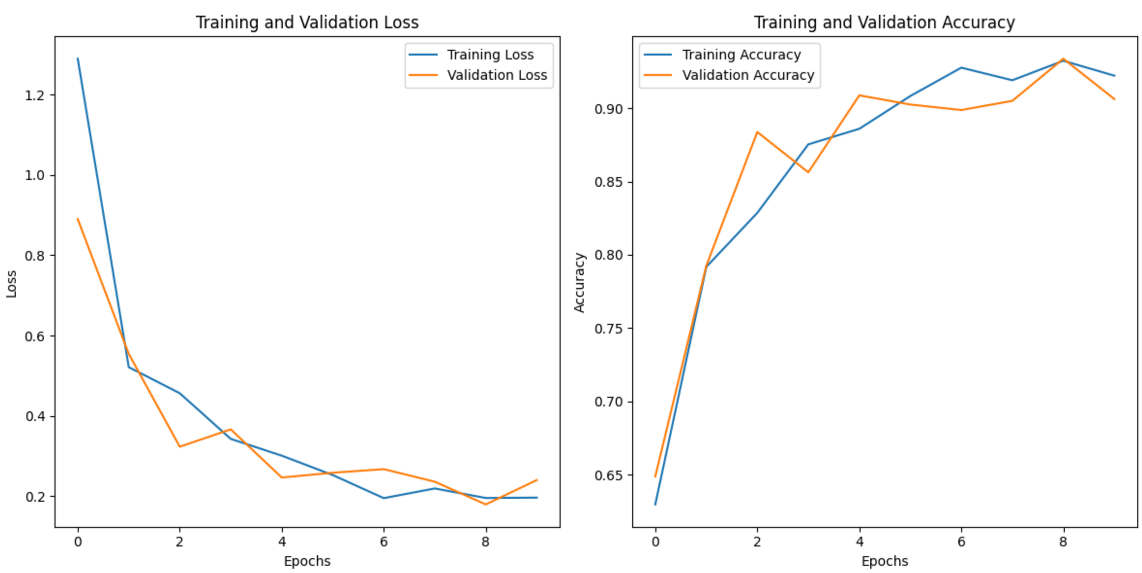

Figure 5.4: Training and validation accuracy and loss over the epochs (Mobile Net V2).

InceptionV3 Model

TABLE 5.4: Precision, Recall, F1-Score, and Support (n) for original CNN networks

	Precision	**Recall**	**F1-Score**	**Support**
China Mishti	0.89	0.84	0.87	200
Darjeeling	0.99	0.79	0.87	200
Mandarin	0.85	0.89	0.87	200
Nagpuri	0.79	0.96	0.87	200
Accuracy			0.87	800
Macro Avg	0.88	0.87	0.87	800
Weighted Avg	0.88	0.87	0.87	800

```
Epoch 1/10
200/200 [==============================] - 1815s 9s/step - loss: 1.4884 - accuracy: 0.5038 - val_loss: 0.7653 - val_accuracy: 0.6913
Epoch 2/10
200/200 [==============================] - 61s 303ms/step - loss: 0.7813 - accuracy: 0.6803 - val_loss: 1.1414 - val_accuracy: 0.5437
Epoch 3/10
200/200 [==============================] - 60s 300ms/step - loss: 0.7126 - accuracy: 0.7150 - val_loss: 0.6092 - val_accuracy: 0.7700
Epoch 4/10
200/200 [==============================] - 61s 304ms/step - loss: 0.5960 - accuracy: 0.7817 - val_loss: 0.4054 - val_accuracy: 0.8413
Epoch 5/10
200/200 [==============================] - 61s 304ms/step - loss: 0.5208 - accuracy: 0.7884 - val_loss: 0.4842 - val_accuracy: 0.8125
Epoch 6/10
200/200 [==============================] - 61s 302ms/step - loss: 0.4680 - accuracy: 0.8227 - val_loss: 0.4457 - val_accuracy: 0.8400
Epoch 7/10
200/200 [==============================] - 60s 302ms/step - loss: 0.4301 - accuracy: 0.8363 - val_loss: 0.4364 - val_accuracy: 0.8425
Epoch 8/10
200/200 [==============================] - 60s 301ms/step - loss: 0.4163 - accuracy: 0.8381 - val_loss: 0.5302 - val_accuracy: 0.7837
Epoch 9/10
200/200 [==============================] - 61s 306ms/step - loss: 0.4543 - accuracy: 0.8248 - val_loss: 0.3512 - val_accuracy: 0.8763
Epoch 10/10
200/200 [==============================] - 60s 302ms/step - loss: 0.3333 - accuracy: 0.8761 - val_loss: 0.3578 - val_accuracy: 0.8687
25/25 [==============================] - 248s 10s/step - loss: 0.3417 - accuracy: 0.8687
Test Accuracy: 0.8687499761581421
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via
  saving_api.save_model(
Model saved successfully.
```

Figure 5.5: Accuracy and loses for Inception V3.

Figure 5.6: Training and validation accuracy and loss over the epochs (Inception V3).

Hybrid Model

TABLE 5.5: Precision, Recall, F1-Score, and Support (n) for original CNN networks

	Precision	**Recall**	**F1-Score**	**Support**
China Mishti	0.98	0.97	0.98	200
Darjeeling	0.97	0.99	0.99	200
Mandarin	1.00	0.98	0.99	200
Nagpuri	0.97	0.97	0.97	200
Accuracy			0.98	800
Macro Avg	0.98	0.98	0.98	800
Weighted Avg	0.98	0.98	0.98	800

```
Epoch 1/10
200/200 [==============================] - 1202s 6s/step - loss: 0.3789 - accuracy: 0.9097 - val_loss: 0.0785 - val_accuracy: 0.9750
Epoch 2/10
200/200 [==============================] - 53s 265ms/step - loss: 0.0959 - accuracy: 0.9717 - val_loss: 0.0686 - val_accuracy: 0.9737
Epoch 3/10
200/200 [==============================] - 53s 263ms/step - loss: 0.0427 - accuracy: 0.9861 - val_loss: 0.0330 - val_accuracy: 0.9887
Epoch 4/10
200/200 [==============================] - 53s 263ms/step - loss: 0.0448 - accuracy: 0.9880 - val_loss: 0.0402 - val_accuracy: 0.9850
Epoch 5/10
200/200 [==============================] - 52s 261ms/step - loss: 0.0275 - accuracy: 0.9911 - val_loss: 0.0418 - val_accuracy: 0.9825
Epoch 6/10
200/200 [==============================] - 53s 264ms/step - loss: 0.0336 - accuracy: 0.9894 - val_loss: 0.0339 - val_accuracy: 0.9925
Epoch 7/10
200/200 [==============================] - 52s 260ms/step - loss: 0.0389 - accuracy: 0.9891 - val_loss: 0.0509 - val_accuracy: 0.9862
Epoch 8/10
200/200 [==============================] - 53s 265ms/step - loss: 0.0238 - accuracy: 0.9928 - val_loss: 0.0338 - val_accuracy: 0.9912
Epoch 9/10
200/200 [==============================] - 52s 259ms/step - loss: 0.0177 - accuracy: 0.9953 - val_loss: 0.0398 - val_accuracy: 0.9912
Epoch 10/10
200/200 [==============================] - 53s 264ms/step - loss: 0.0189 - accuracy: 0.9942 - val_loss: 0.0634 - val_accuracy: 0.9862
25/25 [==============================] - 6s 222ms/step - loss: 0.0835 - accuracy: 0.9812
Test accuracy: 0.981249988079071, Test loss: 0.08349370956420898
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an HDF5 file via
  saving_api.save_model(
```

Figure 5.7: Training and validation accuracy and loss over the epochs Hybrid Model (Mobile Net V2 & Dense Net -201).

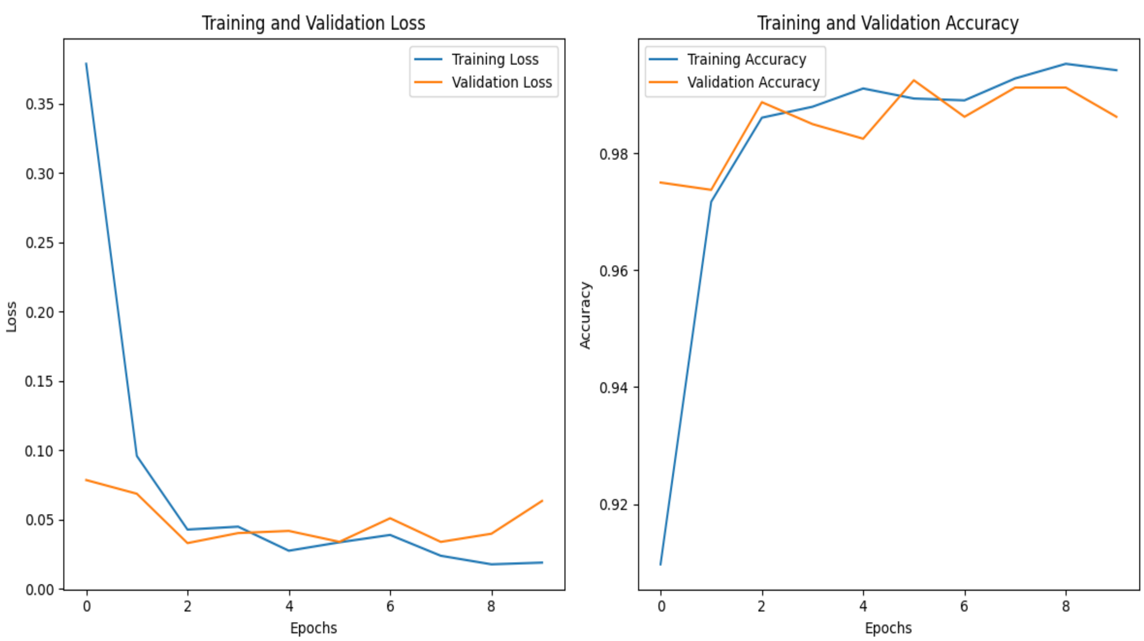

Figure 5.8: Training and validation accuracy and loss over the epochs (MobileNetV2 and DenseNet201).

5.3 Comparative Analysis

The Role of Convolutional Neural Network Architecture Comparison: The network can be accomplished as a 2-layer of Convolutional Neural network instead of 3-layer as did in the previous task.

This is a venture where the study is going to deploy and compare three different CNN and one hybrid model that was successively created for live plant species classification in Mandarin dialect. These architecture models are MobileNetV2, DenseNet201, InceptionV3 and hybrid model, and so forth that we'll be dealing with. So in this part of the document is going to be a detailed of the models which will be presented by using the primary metrics such as accuracy, precision, recall, and F1-score. This research refers to analysis that extend beyond the tested stipulations which are theoretical in nature made form technical specifications. The fact that the monitored information and the experiment activities data are the elements that make the model behave in different ways cannot be ignored. since different network architectures have their own ways of understanding whether plant leaves dataset consists of Mandarin or not.

Table 5.6: Accuracy for Classification of Individual in Real-Time Mandarin leaf Species Classification

Architecture	Training Accuracy
MobileNetV2	91.37%
DenseNet201	95.12%
InceptionV3	83.15%
Hybrid Model (Mobile Net V2 & Dense Net 201)	98.12%

Training and Validation Accuracy and loss of Transfer Learning CNN Networks:

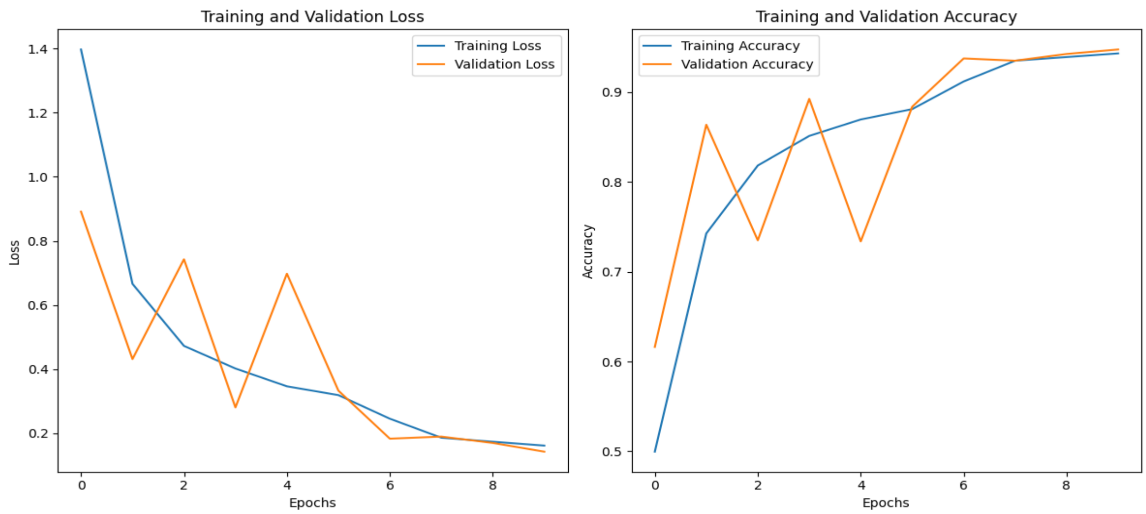

Figure 5.9: Training and validation accuracy and loss over the epochs (Dense Net 201).

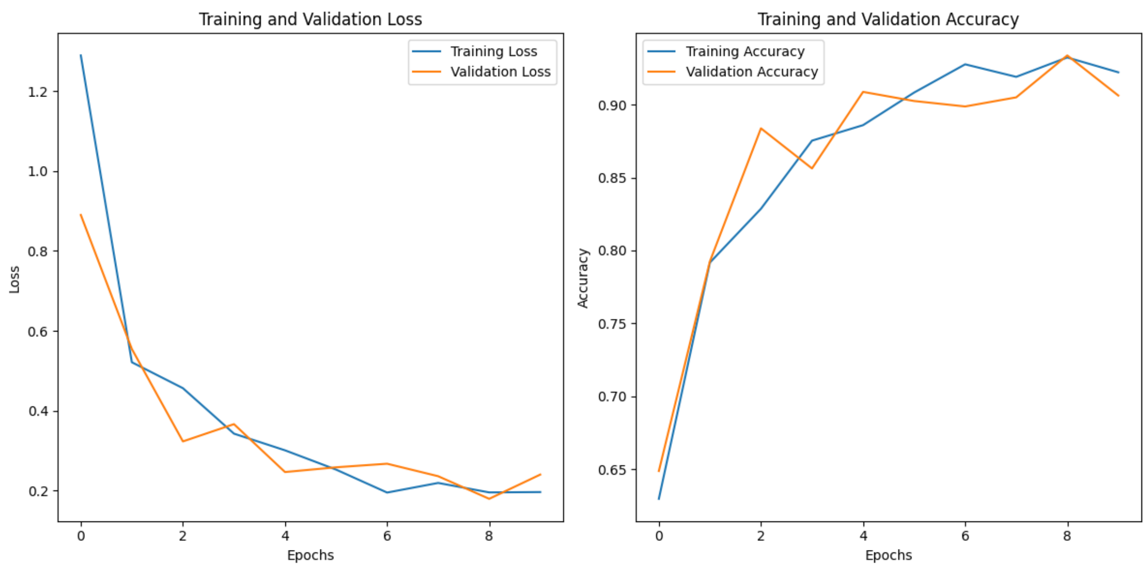

Figure 5.10: Training and validation accuracy and loss over the epochs (Mobile Net V2)

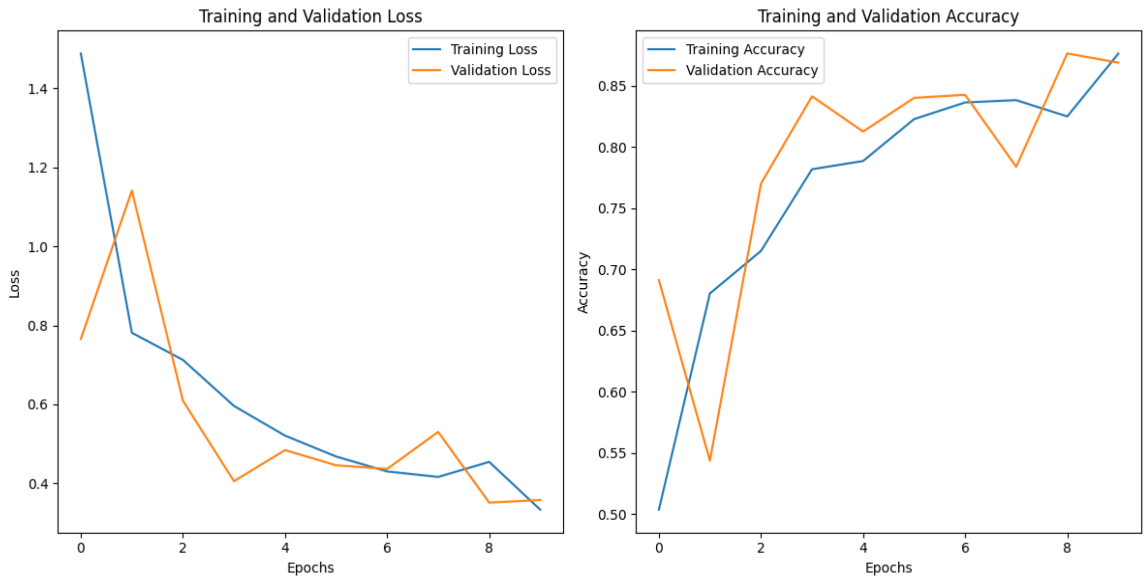

Figure 5.11: Training and validation accuracy and loss over the epochs (Inception V3).

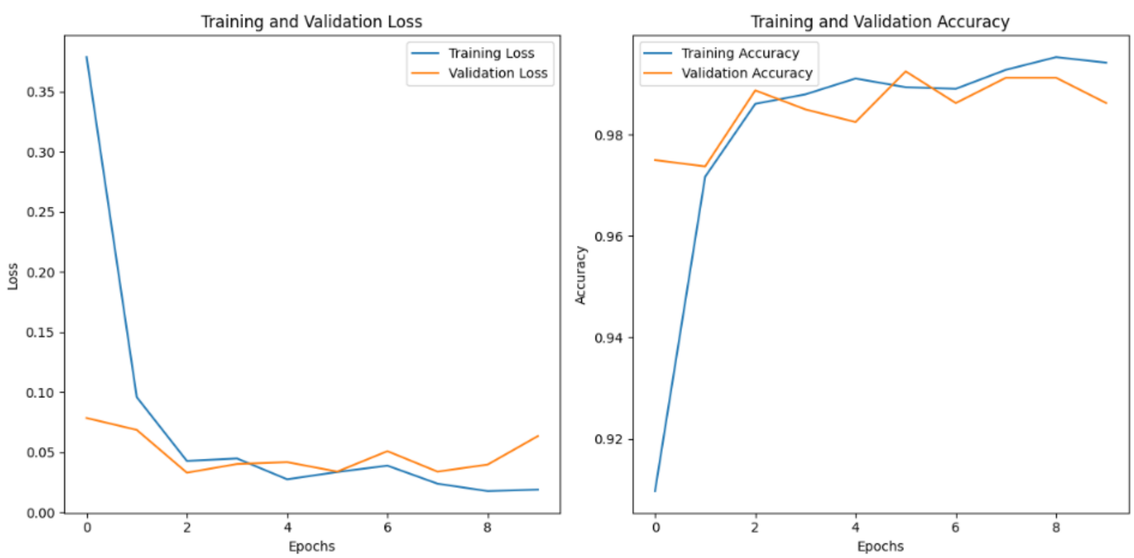

Figure 5.12: Training and validation accuracy and loss over the epochs (Hybrid Model).

Confusion Matrix after Transfer Learning (TL) Based on the number of images:

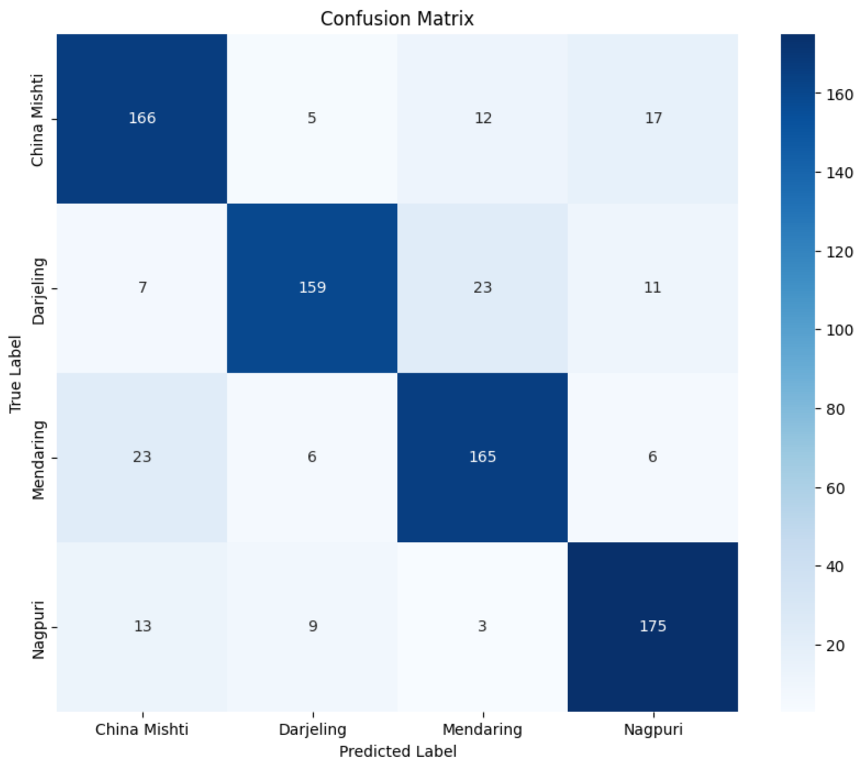

Figure 5.13: Confusion Matrix after Transfer Learning Inception V3.

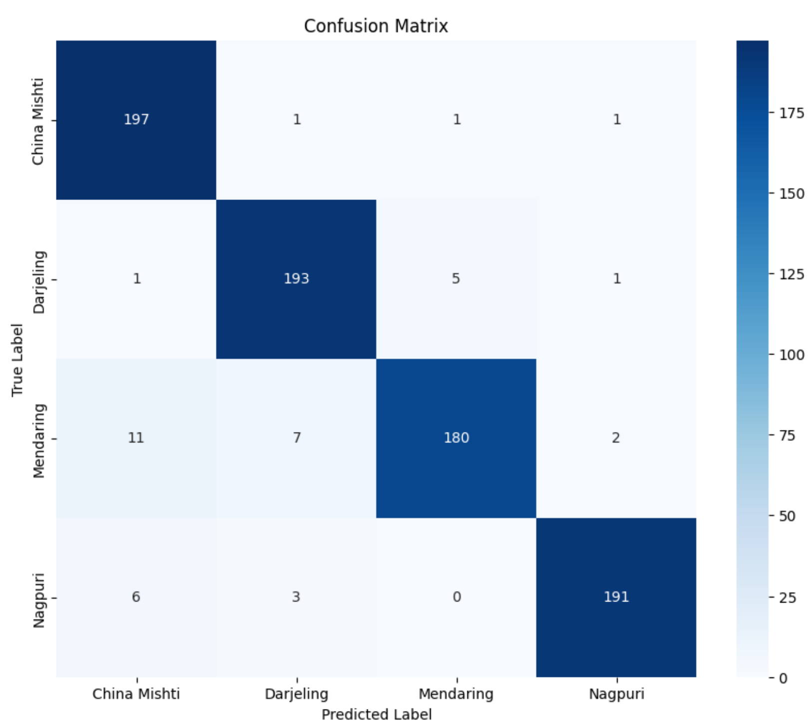

Figure 5.14: Confusion Matrix after Transfer Learning Dense Net 201

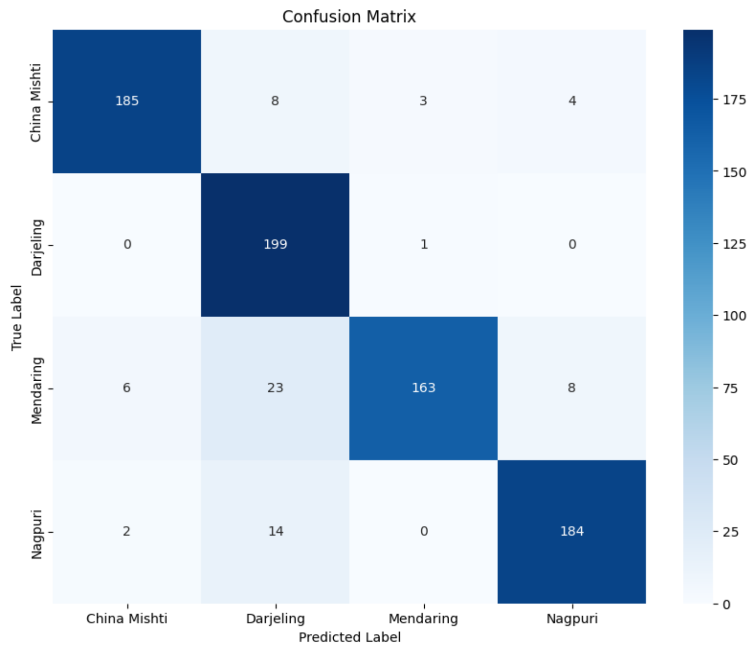

Figure 5.15: Confusion Matrix after Transfer Learning Mobile Net V2

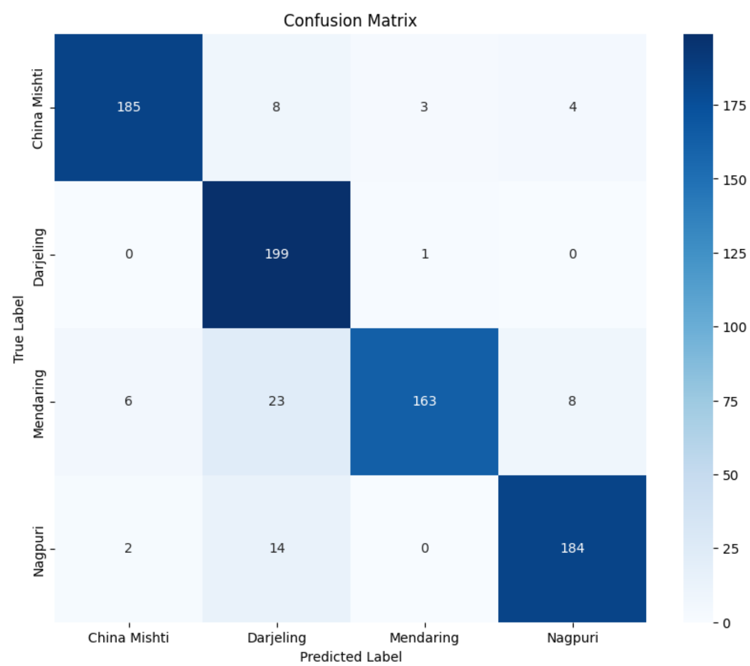

Figure 5.16: Confusion Matrix after Transfer Learning Hybrid Model.

5.4 Summary

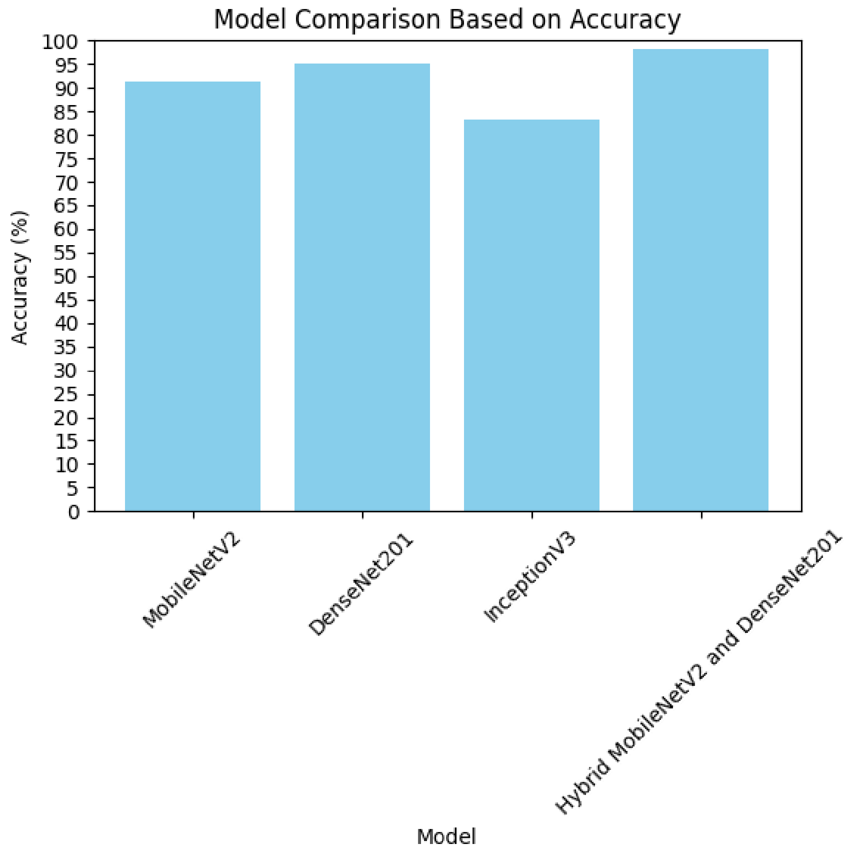

Figure 5.17: Accuracy comparison among individual CNN, ensemble models.

This paper's discussion section evaluates and comments on the consequences and possibilities of coming up with a hybrid model for real-time Mandarin plant species classification based on deep learning approaches. In this research, MobileNetV2 and DenseNet201, the proposed models were used to improve the level of accuracy of discrimination of different species of Mandarin plants using only images of the leaves.

As can be observed from these results, there is a favorable response in relation to accuracy of classification whereby MobileNetV2 attained an accuracy of 91%. 37% and DenseNet201 attaining 95 %. 12%. This goes along the line of enhancing the usage of multiple deep learning models to extract various features existing in Mandarin plant leaves. Features extracted by the using MobileNetV2 and DenseNet201 were used because the utilization of both models would provide better results than one model alone. Therefore, by connecting the outputs of the two models through global average pooling, followed by the application of batch normalization and dropout layers, high performance of the newly developed hybrid model in the classification of Mandarin plant species was established.

Another important result is the explorations of the effects of the model's complexity on its performance and speed of inference. Though hybrid model proved to be the most accurate, it had a higher inference time as compared to Dense Net 201. Hence there is always a tradeoff between accuracy of the model and the time it takes to compute the model architectures for a particular class of applications. The discussion also pointed at some methods such as model pruning, quantization, and use of a more powerful hardware accelerator to eliminate or reduce the computational overhead that may otherwise lead to reduced real-time accuracy.

Thus, in general, the opportunity of a hybrid model for the classification of Mandarin plant species can be classified as promising but it is important to further research and innovate to attend new challenges that can appear and to increase the performance of the system to the real conditions of precision agriculture. Thus, the current research highlights the development of smart farming practices and sustainable agriculture by Michael Gluck and his colleagues applying recent achievements in the field of deep learning and agricultural sciences.

Web Application Implementation

For great user interaction for frequent developed a web application with streamlit with use of our hybrid model, which combines DenseNet201 and Mobile Net V2. For that case it helps use to figure out the good result. This application offers users a user-friendly web interface for upload leaf images gets a precise classification result. Using of hybrid model, it guarantees an optimal performance and efficiency with reliable results, The application aims to give a live and practical access using deep learning approach for a wide variety of users.

Figure 5.18: Classifying Mandarin Leaf variants web Application

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The consequences of the study called "Real-Time Mandarin Plant Species Classification Using Deep Learning Approach" translate beyond borders of the research environment instigating important influences to society and agriculture. Accurate and easy identification of Mandarin plant species through the use of advanced deep learning techniques has the ability to change the way agriculture is done and it can also be the reason for the general benefits of the society. The research will seek to advance the accuracy and speed of Mandarin plant species classification through applied Deep Learning methods such that farmers and agricultural professionals will be provided with useful information for making decisions.

This research can be seen as distinctive within social impacts because it is predominantly associated with agricultural sustainability and food security. The cultivation of Mandarin is a very important part in the agricultural economies of the world, and the correct plant species classification is very important to optimize the crop management practices, resource allocation, and yield prediction. The integration of clear-cutting classifying models by farmers will assist them to catch and treat problems such as insect infestations, or nutrient deficiencies on time. This will lead to healthy and productive crops.

Other than that, the availability of these real-time equipment systems and their usability help the smallholder farmers and rural communities in the underdeveloped or far-off regions. Through the development of user-friendly interfaces and the application of mobile technologies, the developed classification system will be able to provide farmers with the necessary insights directly in the field, thus reducing their dependency on external expertise and infrastructure. Introducing democratization into agricultural intelligence is the soundest path toward sustainable farming, increasing crops production, and alleviating the food insecurity issues on a global scale.

Moreover, the research applied deep learning models with real time classifications serving as the basis for developing the precision agriculture and smart farming businesses. The research is able to make proactive decisions, to optimize the use of resources and to maintain sustainable agricultural practices through the use of the power of artificial intelligence. They do not only are advantageous for independent farmers but also have influence on the global environment, used water and biodiversity protection.

6.2 Impact on Society and Environment

The study on "REAL-TIME MANDARIN PLANT SPECIES CLASSIFICATION USING DEEP LEARNING APPROACH" mainly deals with the utilization of deep learning methods for plant species classification. Although the increase in the real-time classification result is the main goal, it is crucial to analyze environment implications of implementing such resource-consuming models.

Deploying deep learning models together, for instance MobileNetV2, DenseNet201, InceptionV3 and the hybrid model, requires abundant computing power, mainly during the training and optimizing steps. These processes, which use a lot of hardware like GPUs, can be a cause of increased energy consumption and, consequently, the environmental impact.

Development of appliances with higher hardware efficiencies, cloud computing solutions, and the application of green computing are underway. More researchers and developers are becoming aware of the environmental issues related to AI applications and are trying to reduce their carbon footprint. Through energy-efficient algorithms, the use of renewable energy sources, and green computing practices, the environmental impact of deep learning applications can be minimized.

In conclusion, the ultimate objective of this project is designed to enhance the efficiency of plant classifications using deep learning. At the same time, it is essential to consider and pay attention to the environmental concerns related to the usedels. For the platform to be considered ethically acceptable and environmentally beneficial, it is regarded as a negation between technical innovation and environmental sustainability.

6.3 Ethical Aspects

REAL-TIME MANDARIN PLANT SPECIES CLASSIFICATION USING DEEP LEARNING APPROACH research support ethical values during all the processing stages. Similar to any other research with data, especially sensitive data like medical images, the ethical issues are of great importance.

Here, ethical aspects involved are namely protecting the privacy and confidentiality of the data to be used in training and testing the deep learning models. This is regarding consent, whether it is necessary or not, and in accordance with regulations and guidelines which relate to data protection.

Furthermore, transparency is crucial. The research documentation should be detailed and should explain how the data is collected, processed, and used, so that the procedures are understandable and accountable. It is this transparency that builds confidence among stakeholders which include users, researchers, governing bodies and regulatory agencies. Apart from that, the awareness of responsible knowledge dissemination is very important too. The results of the study should be communicated in a way that shows respect to the human dignity and rights, avoiding any possible harm or misuse of the findings. This is done by attending to the fact that deep learning models should address their actual capacities and limitations and not be the source of any false expectations or misinterpretations.

This integration prevents negative impact on society while development in plant species identification keeps on step with moral standards.

6.4 Sustainability Plan

To make sure that the sustainability plan is incorporated in this study of "REAL-TIME MANDARIN PLANT SPECIES CLASSIFICATION USING DEEP LEARNING APPROACH", the research will consider the following guidelines; environmental economic principles and societal benefits. Considering the computational performance necessary for deep learning approaches, the research work is to be done in a manner that reduces energy consumption at all life cycle stages. In detail, strategies will be applied to the computation of the computational processes, especially during the modeling and the deployment of the models. Model pruning, quantization, and compression will go through studying to settle the issue of classification accuracy by eliminating the increase of the computational work. Furthermore, cloud will be utilized for computing services which will give access to the joint resources as well as reduce energy use at the personal level.

The research team, on the other hand, is determined to use eco-friendly approaches in data management and storage. Through implementing efficient data handling methods and the usage of replenishable logistic approaches, the environmental effect introduced by data processing will be lessened. Continuous surveillance of energy consumption will be the core aspect for the project shaving the paths and enabling the instantatic adjustments to achieve sustainability in the maximum manner. This iterative methodology ensures that environmental concerns are always at the heart of the project design process from the very beginning to the end.

The study planned to set an example of harnessing technology that also green and sustainable. For this, the project will focus on two objectives; to classify the location and to be sustainable it will increase the chances of achieving the goal.

6.5 Summary

The paper entitled "Realtime Mandarin Plant Species Classification Using a Deep learning Approach" looks into the application of latest deep learning to complete the intimidating plant species classification task. The use of a dataset that comprises a variety of Mandarin plant leaf images permitted the study to investigate the capacity of deep Convolutional Neural Networks (CNNs) to classify different species of Mandarin plants in real-time scenarios accurately and efficiently. Transfer learning will be implemented in which pre-trained CNN models will be further trained on provided Mandarin plant image data aiming to take advantage of the existing information and increase accuracy.

The study meticulously evaluates the performance of three prominent CNN architectures: The example of MobileNetV2, DenseNet201, and InceptionV3 can be given. By means of extensive testing and examination, the research team evaluates the errors, failures, and accuracy of each model, thus, these features become the basis of the analysis of the strengths and weaknesses of each model in the classification of Mandarin plant species. This comparison highlights the variations of the vary of the model performance witnessed among the different training data and configuration thus, being able to answer the question whether the characteristics like training data and the configuration contribute to the model performance accuracy.

Additionally, the nature of the project is cognizant of environmental consequences of computationally demanding tasks of deep learning and a sustainability plan is developed to tackle the environmental issues. Ethical aspects like data privacy and informed consent are considered and handled with care to prevent irresponsible research. Specifically, the research presents a novel way of classifying plants in real time with an accuracy of permitting botany to be a great deal more perceptive on human impacts on biodiversity, agriculture, and ecology.

CHAPTER 7
SUMMARY, CONCLUSION, RECOMENDATION AND IMPLICATION FOR FUTURE RESEARCH

7.1 Conclusions

To sum up, the research proves that the deep learning models are capable of correctly classifying the Mandarin plant species by their leaves. Every evaluated CNN architecture - MobileNetV2, DenseNet201, InceptionV3 and the hybrid model – is demonstrated to have good performance that classifies real-time tasks with a good precision rate. Besides, we observed though subtle discrepancies of models' results that considered the model selection and evaluation are critical matters for strong classification results.

The research shows that the combination of multiple CNN architectures in ensemble models can be used to improve the classification accuracy of the models. Furthermore, the scope will be expanded to include the development of better image-processing algorithms to enhance model results. The effects of ensemble methods on model performance will also be aimed to be determined.

7.2 Future Suggested Works

The results obtained from these studies might be the basis for the utilization of current technologies in the annual sampling campaigns with the aim of studying aquatic plants and their properties. In this case, the complex difficulty concerning the imaging of the process of image processing - especially the stages of augmentation and extraction of plants' features - could be coped with by applying CNN algorithm. The significance of the laser scanner approach is relevant; this work should be done applying innovative equipment. Besides, different approaches, especially model stacking and boosting, can be used in order to conduct research which are aimed at the expansion of classification and generalization ranges.

It is the second obstacle witnessed in this approach. Again, this approach is not able to handle the complex type of data; and this type of data is a hybrid one and comprises of many types of plants and their ecosystem information; hence it is very critical and problematic. Yet, since examples and the conducted studies are the main steps in the teaching processes, it signifies that the students should not be made tried to get a good understanding of the geography of the mind neural networks and that help in species breeding in delicious landscapes at the end of the chapter.

7.3 Limitations:

The research is based on classification mandarin plant variants. This research is dedicated to focusing on mandarin leaves, the paper motive to develop a validate classification model that accurately classify the mandarin leaves.

At the core, the study images processing algorithms analyze and classify the mandarin leaf based on images shapes. However, the study acknowledges several inherent limitations.

The limitations can mention that:

1. Scope Limitations: The study focusses on classification of mandarin leaves variants and does not extend to other citrus species or their leaf variants.

2. Environmental Factors: Variants in environmental conditions such as light intensity, humidity or infected leaves may potentially affecting the accuracy of classification result.

3. Generalization: The research based on the specific region database and condition used during the study, limiting their generalizability to border geographic regions or different cultivation practices.

REFERENCES

[1] Liu, K. H., Yang, M. H., Huang, S. T., & Lin, C. (2022). Plant species classification based on hyperspectral imaging via a lightweight convolutional neural network model. *Frontiers in Plant Science, 13,* 855660.

[2] Huixian, J. (2020). The analysis of plants image recognition based on deep learning and artificial neural network. *IEEE Access*, *8*, 68828-68841.

[3] Yang, K., Zhong, W., & Li, F. (2020). Leaf segmentation and classification with a complicated background using deep learning. *Agronomy*, *10*(11), 1721.

[4] Lv, Q. (2023, May). Classification of Grapevine Leaf Images with Deep Learning Ensemble Models. In *2023 4th International Conference on Computer Vision, Image and Deep Learning (CVIDL)* (pp. 191-194). IEEE.

[5] Pushpa, B. R., & Lakshmi, P. (2022, November). Deep Learning Model for Plant Species Classification Using Leaf Vein Features. In *2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)* (pp. 238-243). IEEE.

[6] Selvam, L., & Kavitha, P. (2020). Classification of ladies finger plant leaf using deep learning. *Journal of Ambient Intelligence and Humanized Computing*, 1-9.

[7] Akter, R., & 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.

[8] Muneer, A., & Fati, S. M. (2020). Efficient and automated herbs classification approach based on shape and texture features using deep learning. *IEEE Access, 8*, 196747-196764.

[9] Elaraby, A., Hamdy, W., & Alanazi, S. (2022). Classification of citrus diseases using optimization deep learning approach. *Computational Intelligence and Neuroscience*, *2022*.

[10] Mahmudul Hassan, S. K., & Kumar Maji, A. (2021). Identification of plant species using deep learning. In *Proceedings of International Conference on Frontiers in Computing and Systems: COMSYS 2020* (pp. 115-125). Springer Singapore.

[11] Bisen, D. (2021). Deep convolutional neural network based plant species recognition through features of leaf. *Multimedia Tools and Applications*, *80*(4), 6443-6456.

[12] Saini, G., Khamparia, A., & Luhach, A. K. (2020). Classification of plants using convolutional neural network. In *First International Conference on Sustainable Technologies for Computational Intelligence: Proceedings of ICTSCI 2019* (pp. 551-561). Springer Singapore.

[13] Song, Y., He, F., & Zhang, X. (2019). To identify tree species with highly similar leaves based on a novel attention mechanism for CNN. *IEEE Access*, *7*, 163277-163286.

[14] Bharali, P., Bhuyan, C., & Boruah, A. (2019, May). Plant disease detection by leaf image classification using convolutional neural network. In *International conference on information, communication and computing technology* (pp. 194-205). Singapore: Springer Singapore.

[15] Kumar, D., & Verma, C. (2021). Automatic Leaf Species Recognition Using Deep Neural Network. In *Evolving Technologies for Computing, Communication and Smart World: Proceedings of ETCCS 2020* (pp. 13-22). Springer Singapore.

[16] Van Hieu, N., & Hien, N. L. H. (2020). Automatic plant image identification of Vietnamese species using deep learning models. *arXiv preprint arXiv:2005.02832*.

[17] Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., & Zhang, Z. (2021). Plant disease detection using generated leaves based on DoubleGAN. *IEEE/ACM Transactions*

on Computational Biology and Bioinformatics, *19*(3), 1817-1826.
[18] Maniyar, H. M., & Budihal, S. V. (2020, May). Plant disease detection: An augmented approach using CNN and generative adversarial network (GAN). In *International Conference on Information, Communication and Computing Technology* (pp. 252-261). Singapore: Springer Singapore.
[19] Orchi, H., Sadik, M., Khaldoun, M., & Sabir, E. (2023). Automation of Crop Disease Detection through Conventional Machine Learning and Deep Transfer Learning Approaches. *Agriculture*, *13*(2), 352.
[20] Anandhakrishnan, T., & Jaisakthi, S. M. (2022). Deep Convolutional Neural Networks for image based tomato leaf disease detection. *Sustainable Chemistry and Pharmacy*, *30*, 100793.
[21] Kaushik, M., Prakash, P., Ajay, R., & Veni, S. (2020, June). Tomato leaf disease detection using convolutional neural network with data augmentation. In *2020 5th International Conference on Communication and Electronics Systems (ICCES)* (pp. 1125-1132). IEEE.
[22] Khalid, A., Akbar, S., Hassan, S. A., Firdous, S., & Gull, S. (2023, February). Detection of tomato leaf disease using deep convolutional neural networks. In *2023 4th International Conference on Advancements in Computational Sciences (ICACS)* (pp. 1-6). IEEE.
[23] Sumalatha, G., Krishna Rao, D. S., & Singothu, D. J. R. (2021). Transfer learning-based plant disease detection.

[24] Liu, B., Ding, Z., Tian, L., He, D., Li, S., & Wang, H. (2020). Grape leaf disease identification using improved deep convolutional neural networks. *Frontiers in Plant Science*, *11*, 1082

[25] Islam, M. R., Haque, M. M., Khatun, H., Sarker, J., Wang, Y., Ke, W., ... & Deng, X. (2022). Huanglongbing in Bangladesh: A Pilot Study for Disease Incidence, Pathogen Detection, and its Genetic Diversity. Journal of Citrus Pathology, 9(1).

[26] Tipu, M. M. H., Rahman, M. M., Islam, M. M., Elahi, F. E., Jahan, R., & Islam, M. R. (2020). Citrus greening disease (HLB) on Citrus reticulata (Mandarin) caused by Candidatus Liberibacter asiaticus in Bangladesh. Physiological and Molecular Plant Pathology, 112, 101558.

[27] Maciá-Vázquez, A. A., Núñez-Gómez, D., Martínez-Nicolás, J. J., Legua, P., & Melgarejo, P. (2024). Mandarin Variety Significantly Affects the Metabolites Present in the Leaves. *Horticulturae*, *10*(4), 359.

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