LEAFY VEGETABLES IDENTIFICATION THROUGH IMAGE PROCESSING WITH TRANSFER LEARNING METHODS.

BY

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

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DHAKA, BANGLADESH
15 JULY, 2024

APPROVAL

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I hereby declare that this project has been done by us under the supervision of **Ms. Tania Khatun, Assistant Professor, and Department of CSE** at Daffodil International University. I also declare that neither this project nor anypart of this project has been submitted elsewhere for the award of any degree.

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ACKNOWLEDGEMENT

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

I am grateful and wish to profound indebtedness to **Ms. Tania Khatun, Assistant Professor, Department of CSE** Daffodil International University, Dhaka. Her endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

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

I would like to thank my entire course mate at Daffodil International University, who took part in this discussion while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

Abstract

Maintaining a healthy and robust lifestyle necessitates the consumption of nutritious food, with vegetables playing a pivotal role. Among the different types of vegetables, leafy vegetables are one of them which provide a rich source of important nutrients, including vitamins, minerals, and antioxidants. However, it might be a difficult task to correctly identify and distinguish between various leafy vegetables, especially when they have a similar appearance. The challenges can be addressed by replacing the monitoring system with an automated system for leafy vegetable Identification. The aim of this study is to propose a leafy vegetable identifying system using a transfer learning model. A sophisticated machine learning method called transfer learning is used to improve the performance of recognition and classification utilizing image processing. The proposed model focuses on using a pre-trained CNN model to extract leaf attributes and Analysis different kinds of leafy vegetables and identify the actual name of leafy vegetables. In this study, a custom dataset is used for implementing the transfer learning model utilizing image processing which consists of six types of leafy vegetables, including Colocasia, Red Spinach, Malabar Spinach, Jute Spinach, Organic Spinach, and Stem Amarnath. Evaluating the models on the custom dataset, InceptionV3 achieved the highest accuracy which is 99.75% based on performance metrics such as precision, recall, and f1-score. Thus, this study reduces the eye dependency of humans and consumes the time of the general public.

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CHAPTER 1

Introduction

1.1 Introduction

Eating healthy and nutritious food is necessary to keep the body healthy and strong. Vegetables are nutritious and delicious. It contains enough vitamins, essential minerals, and antioxidants for the human body. Different types of vegetables are available in our country throughout the year. Among these vegetables, leafy vegetables stand out as an important source of essential nutrients. They are a great source of necessary nutrients, which are crucial for maintaining healthy human physiology. It strengthens our bones [1]. Several vital nutrients, such as vitamins A, C, and K, minerals such as calcium, iron, and magnesium, and dietary fiber are abundant in leafy vegetables. These nutrients are essential for supporting several biological processes, including digestion, bone health, blood coagulation, and immunological function. It significantly improves our capability to defend ourselves against illnesses. Some species are also crucial for the health of our skin, eyes, hearts, kidneys, and hair [1]. A wide variety of leafy vegetables are available in Bangladesh. There are different types of leafy vegetables. One of them is spinach. In Bangladesh, 107 types of spinach are available. But they all are found in different areas of Bangladesh [1]. Besides spinach, there are more types of leafyvegetables available in Bangladesh. But most of the leafy vegetables looks quite similar. So, sometimes it creates confusion among different leafy vegetables. Although a lot of leafy vegetables are available in Bangladesh, most people especially the youth generation and children cannot recognize the leafy vegetable properly. Even they do not know the name of those leafy vegetables. As each typeof leafy vegetable has unique nutritional advantages, it is crucial to know and distinguish them from one another. It can be difficult to precisely identify many leafy vegetables because of their comparable structural features and outward appearance. The food industry, agriculture, and the field of nutrition research are just a few of the areas where this identification problem presents challenges. Therefore, it is crucial for developing a system that can accurately and consistently identify leafy vegetables. Human visual perception is not enough to properly identify a leafy vegetable accurately. But Computers can do that. The computer-based system can analyze an image from pixel to pixel by using image processing so that it can be more effective and accurate for analyzing a leafy vegetable.

The primary objective of this study is to develop an automated system for the detection of a leafy vegetable based on computer vision. Fundamental elements of the subject of deep learning include deep learning models, more especially the Convolutional Neural Network (CNN) and the Artificial Neural Network (ANN). For tasks like image categorization, object localization, and object segmentation, these models are frequently employed [2]. Different Convolutional Neural Networks are being used to implement Machine learning and Deep Learning approaches. Time-consuming to train a model from scratch. As a consequence, the transfer learning model is the best choice for recognizing classifying. It allows a aspire-trained model, the lay layer layer-specific answer learning is a machine learning technique where knowledge obtained from solving one problem is applied to another that is unrelated but yet arises in the same domain. It is especially beneficial for activities like identifying and categorizing images. It enables the use of pre-existing information from large-scale labeled datasets, reduces time and resources on data labeling, aids in the generalization of learned features to new tasks improves effectiveness, and enhances performance by reusing lower-level features.

This research proposed a different transfer learning model using a pre-trained version of CNN to identify the various leafy vegetables to extract the features of leaves.

1.2 Motivation

Vegetables are one kind of palatable plant-based goods that stand out for providing a very high nutritional content. As a consequence, they are an excellent source of nutrients that are crucial to human physiology. One of the essential nutrients for the human body is found in leafy vegetables. Leafy vegetables supply the body with vital vitamins, minerals, dietary fiber, and antioxidants. In Bangladesh, a variety of leafy vegetables are available. Most of the leafy vegetables are pretty similar. As a result, most people, especially the young generation and new buyers who come to the market to buy vegetables, do not recognize leafy vegetables properly. Apparently, the names of these vegetables are unknown to them [1]. Different leafy vegetables provide different nutrients. So, it is very important to recognize proper leafy vegetables for proper nutrition. Leafy Vegetables contain a variety of nutrients. Therefore, it is crucial to determine the correct leafy vegetables for an appropriate diet. However, due to their variety of them and anatomical similarities, specifically recognizing various leafy vegetables can be a difficult undertaking. For several purposes, including agriculture, the food industry, and nutrition research, it is crucial to create an effective and trustworthy recognition system for leafy vegetables. By manual visual perception, it is quite challenging to recognize and differentiate between various leafy vegetables. This identification issue with leafy vegetables can be solved by a computer-based approach. Computers can analyze images pixel by pixel and identify a leaf of a leafy vegetable's color, size, form, and other characteristics, which is beyond the capacity of a human to do. An effective solution to these issues is the classification of leafy vegetables using transfer learning techniques.

1.3 Objective

The primary objective of this study is to build a system that is effective and trustworthy for identifying leafy vegetables using transfer learning techniques. The objectives of this study are as follows:

- Analysis and identify advanced transfer learning methods for image classification and recognition purposes.
- To develop a system utilizing image processing based on transfer learning techniques that can automatically analysis a leafy vegetable by observing the different features from images which can assist common people in distinguishing between different types of leafy vegetables.
- To accumulate a large, well-labeled collection of leafy vegetable's raw images for the dataset

1.4 Research Question

- How to collect datasets for research?
- How will the dataset be processed for research?
- Will deep learning models be able to correctly identify leafy vegetables?
- What is the impact of this research?

1.5 Expected Outcome

The main goal of this research is to correctly identify leafy vegetables using image processing based on transfer learning technique from leaf images. I expected that my built-up model would be able to reliably identify leafy vegetables from captured images of different types of leafy vegetables. It would allow appropriate nutrient-based selection, support numerous industries like agriculture and food processing, and ease the process of making well-informed decisions. It enables the reduction of eye dependency on human eyes. It also reduces the time of a human and assists to distinguish between various leafy vegetables.

1.6 Report Layout

This is stated in the format of the report, how this report format was created.
I worked on five chapters here and they are...

In “Chapter 1” Introduction, In the first chapter, which is mentioned, the introduction, goals, research question,and expected results of the study are covered. The report format is then covered. In “Chapter 2” Literature Review: The background Study for the research is discussed in Chapter two. In “Chapter 3” Methodology: My overall research technique, including data collecting, analysis, preprocessing, splitting, transfer learning model, and my proposed model for this study, is discussed in chapter three. In “Chapter 4” Transfer Learning and Image Processing in Depth Analysis forLeafy Vegetables Analysis: Deeply analysis all the images for model implementation. How image processing and transfer learning model improve the accuracy and efficiency of the system aredescribed in this section. In “Chapter 5” Evaluation and Result: The performance of every model I used for my research is discussed in Chapter four along with the results' confusing metrics, graphs, classification report, etc. In “Chapter 6” Conclusion and Future Work: The next work of my research and the study's conclusion are discussed in chapter number five.

1.7 Conclusion

The goal of this study is to create a system that can recognize various leafy vegetables accurately utilizing transfer learning and computer vision. The system's goals are to support many industries, including agriculture and food processing, and help consumers make educated decisions about their nutrition. The suggested system may efficiently differentiate between visually similar leafy vegetables and lessen human dependence on visual perception by utilizing deep learning models and transfer learning techniques. The desired result is a trustworthy and effective model that promotes sustainable agricultural growth and healthier eating habits. Overall, this study has the potential to progress the field of computer vision in agriculture and have an impact on a number of industries.

CHAPTER 2

Literature Review

2.1 Preliminaries

Literature Review is known as background study which provides a detailed understanding of the context and existing knowledge relevant to the research topic. The literature review examines prior works, approaches, and conclusions regarding leafy vegetable identification, computer vision, deep learning, and transfer learning in the context of leafy vegetable recognition using transfer learning techniques. The literature review creates the framework for the current research and emphasizes the importance and novelty of the study by looking at the body of existing information. With regard to leafy vegetable recognition and transfer learning, this literature review will concentrate on major issues and studies. The research on leafy vegetables' nutritional value, the difficulties in classifying and identifying them, and the promise of computer-based methods to address these difficulties will all be covered. This review seeks to advance knowledge of leafy vegetable recognition and the efficacy of transfer learning techniques in this field by synthesizing the existing material.

Understanding several fundamental terminologies and concepts related to deep learning and agricultural image classification is imperative before diving into the specific leafy vegetable identification approach employing leaf feature analysis and transfer learning techniques.

2.1.1 Deep Learning

In order to discover patterns and make decisions based on input data, deep learning includes training artificial neural networks with numerous layers. Convolutional neural networks (CNNs) are a popular deep learning architectural type for image classification tasks.

2.1.2 Transfer Learning

A deep learning technique called transfer learning uses a neural network model that has already been trained as the foundation for a new assignment. The knowledge acquired from learning one task is transferred to related work instead of training a model from scratch, reducing computation time and enhancing performance, especially when the new task contains limited data.

2.1.3. Analysis of Leaf Feature

To identify between various kinds of leafy vegetables, a procedure known as "leaf feature analysis" involves extracting pertinent information from leaf photographs. These characteristics could include the vein patterns, color, texture, and form of the leaves.

2.2 Related Works

The use of deep learning algorithms for image classification in agriculture has been an active research area in recent years. Several studies have explored the use of convolutional neural networks (CNNs) for classifying different crops, vegetables, and fruits based on images.

One such study [1] by researchers explored the classification of different species of spinach using CNNs. They used four different CNN models and trained them with data from a training set, then measured their accuracy on a test set. The results showed that VGG16 achieved the highest accuracy of 99.79%, indicating the effectiveness of CNNs in identifying plant species.

Similarly, in another study [2] a multi-class vegetable image classifier using CNN and DenseNet201 was proposed, achieving an accuracy of 98.58%. They preprocessed the dataset using different pre-processing operators and resized it to feed the proposed convolution model.

Another study [3] focused on fruit image classification using attention-based MobileNetV2, outperforming the four latest DL methods used in previous studies. The proposed method achieved the highest classification accuracy of 95.75%, 96.74%, and 96.23% on three different datasets. The authors suggested exploring the use of offline data augmentation techniques and combining features from other layers of MobileNetV2 to further improve the performance of fruit classifications.

Furthermore, another paper [4] discussed the use of automatic image annotation (AIA) to annotate images of oil palm fruit, which can be useful for crop monitoring and disease detection. They trained three versions of YOLO, a popular object detection algorithm, and evaluated their performance on a test set of 1000 images. The results showed that AIA can be an effective tool for annotating images of agricultural products.

Another study [5] developed several models that classify fruits and vegetables based on an image, achieving high accuracies with their plain dataset models and a customized transfer learning model based on VGG16. They explored the challenges of vegetable classification, such as the complexity of vegetable image backgrounds and the similarity between different species of vegetables.

Additionally, paper [6] presented a study on the diagnosis of tomato leaf diseases using pre-trained convolutional neural networks. They retrained two deep neural networks using transfer learning and different dropout rates and compared their performance in diagnosing healthy and unhealthy tomato leaves. The results showed that both models were very competitive and achieved a high degree of accuracy close to 99.22%.

Similarly, in paper [7], the authors developed a CNN-based model for multi-crop leaf disease image classification using transfer learning with the VGG architecture. They achieved high accuracy for grapes and tomatoes, highlighting the importance of accurate crop disease classification for agricultural development.

Another paper [8] proposed an automatic fruit and vegetable classification system using a CNN of the AlexNet type, transfer learning, and data augmentation techniques. The study demonstrated the effectiveness of transfer learning in improving classification accuracy and addressing the variability of data due to thousands of classes and subclasses of produce.

Additionally, a study [9] focused on the classification of visually similar tropical fruits, jackfruit, and cempedak. The authors proposed a deep CNN architecture and compared its performance with transfer learning algorithms such as Xception, VGG16, VGG19, ResNet, and InceptionV3. The study concluded that the proposed CNN architecture achieved an accuracy of 89% to 93.67% and highlighted the challenges of accurately classifying fruits and vegetables due to inconsistent features within cultivars.

In the context of pest classification in Sri Lanka, a paper [10] proposed a deep transfer learning approach using pre-trained CNN models, VGG16 and InceptionV3. The authors achieved a classification accuracy of 99.8% through an

8-fold cross-validation technique, demonstrating the effectiveness of transfer learning in capturing the information of pest classes with limited samples.

In another study [11], the authors proposed a methodology for identifying and classifying different types of fresh leafy vegetables using computer vision techniques. They tested the accuracy of the method on 1000 images of leafy vegetables, with a maximum identification rate of 100% observed for Coriander and Curry leaves. The paper presented a useful approach for automated leafy vegetable identification and classification.

Finally, a paper [12] proposed a pipeline for the automatic detection and classification of tomato leaf diseases using deep learning techniques. The pipeline included image preprocessing, training of three compact CNNs with transfer learning, feature concatenation and selection, and classification using machine learning algorithms. The study demonstrated the potential of deep learning in addressing the pressing issue of plant disease detection in agriculture.

In conclusion, these studies have provided valuable insights into the potential of deep learning algorithms in agriculture, showcasing their effectiveness in crop monitoring, disease detection, and classification of various crops, fruits, and vegetables. The use of data augmentation techniques, transfer learning, and pre-processing operations has proven to enhance the accuracy of deep learning models, making them a valuable tool for addressing the challenges faced by the agricultural industry. Further research in this area can lead to more advancements and solutions for sustainable agriculture.

2.3 Comparison Analysis

Several trends and methods are applied in the application of deep learning for agricultural image classification, including the identification of leafy vegetables, according to a comparative analysis of the related studies.

First of all, several studies have made use of CNN technology to categorize diverse fruits, vegetables, and crops with great accuracy. In the agricultural domain, CNNs like VGG16, DenseNet, and MobileNetV2 have been shown to be efficient architectures for categorization of images.

Secondly, transfer learning has become a useful method for enhancing deeplearning models' performance, particularly when utilizing limited data. The benefits of utilizing pre-trained models for agricultural image categorization tasks have been demonstrated in numerous researches.

In addition, by increasing the diversity of the training data and removing noise and irrelevant information, data augmentation techniques and image preprocessing have frequently been employed to improve model performance.

2.4 Scope of the Problem

The goal of developing an automated system that is capable of reliably classifying various varieties of leafy vegetables based on their leaf images is the scope of the leafy vegetable identification method employing leaf feature analysis and a transfer learning approach. The suggested approach will expand on the knowledge now available from deep learning research in agriculture, particularly in relation to the classification of crop and leaf diseases.

The technique seeks to handle differences in leaf appearances caused by elements including lighting conditions and growth stages, as well as the difficulties of effectively differentiating visually similar leafy vegetables.

2.5 Conclusion

An overview of the background and relevant research in the area of deep learning for agricultural image classification has been provided in this chapter. The proposed leafy vegetable identification method will be presented in the following chapter along with a discussion of the breadth of the issue and the difficulties that must be overcome. The objective is to create a precise and effective system to aid in the classification and identification of leafy vegetables, advancing sustainable agriculture.

CHAPTER 3

Research Methodology

3.1 Introduction

Research methodology is a crucial part of research work. It refers to the systematic method and technique devoted to research studies to collect, analyze, interpret, and recent data. It covers the general framework and processes utilized to address the study's goals, questions, and hypotheses. A highly defined research methodology ensures reliability, integrity, and validity. It offers researchers a clear road map for carrying out their research and enables them to acquire accurate and meaningful outcomes.

3.2 Research Methodology

The research methodology is followed by some key points:

3.2.1 Data Collection

Data collection is an important part of the research. The quality of the research depends on the data collection. Data can be collected through surveys, interviews, observation, experiments, photography, secondary data analysis, etc. When selecting the data for the leafy vegetables dataset it ensures that the selection is done properly.

3.2.2 Data analysis

Data analysis for research requires inspecting and clarifying the collected data to reveal the sample and perceptions of the dataset. In data analysis, it encompasses

Data cleaning, Data sorting, calculating descriptive and statistical data, applying statistical tests, and so on.

3.2.3 Data Preprocessing

Transforming raw data into fair data before performing a model is as known data preprocessing. In data preprocessing, removing any noisy or irrelevant data, and handling missing values and other inconsistencies. The purpose of data preprocessing is to improve the quality and usability of the data to prepare it for appropriate and efficient analysis.

3.2.4 Data Splitting

A key perspective in data science is data splitting. To guarantee a representative sample in each subset, stratify the dataset into training, validation, and test sets.

3.2.5 Transfer Learning Model Train

An appropriate pre-trained deep learning model is selected which is trained on a large-scale image dataset. The pre-trained model is customized by changing the layers to accommodate the specific vegetable detection task. A pre-trained model enables the last layers to learn task-specific features while retaining general features in the earlier layers. Analyze loss and accuracy data to track training progress and implement any necessary model parameter modifications.

3.2.6 Model Evaluation

To assess the trained model's effectiveness and pinpoint areas for advancement, evaluate it to the validation dataset. Calculate assessment measures like recall, accuracy, precision, and F1 score to assess the classification performance of the model.

3.2.7 Selecting the Best Model

Analyze the efficiency of various training models using their evaluation metrics. For additional study and development, the model with the highest accuracy and optimal metric balance is chosen. To ensure reliability and generalizability additional validation process performs on the selected model using an independent test set. The following figure illustrates the working architecture of our proposed model.

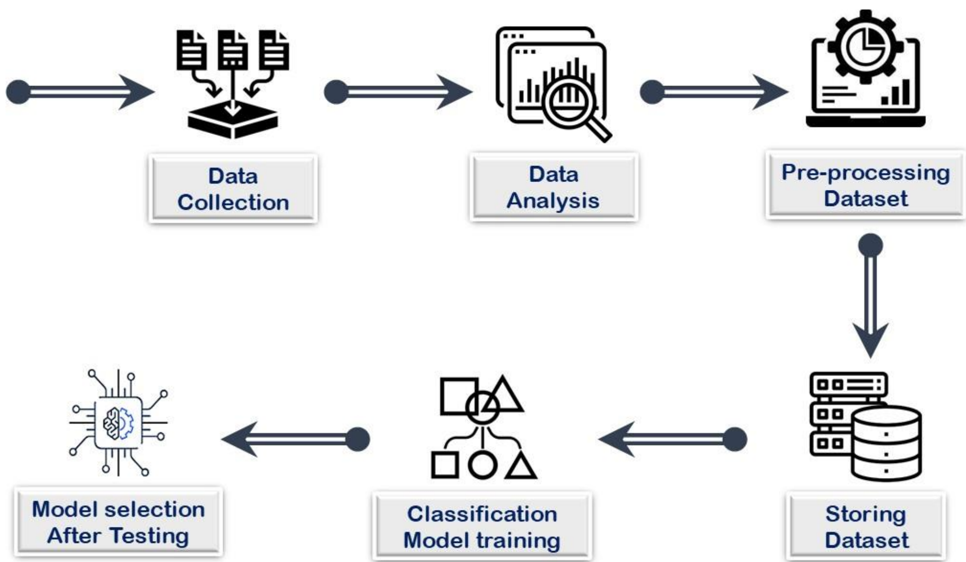

Fig 3.2: Working Architecture of Proposed Model

Throughout the study, the maintenance of comprehensive documentation, detailing the methods used to collect the data, data preprocessing techniques, hyperparameters, model architecture, configurations, and evaluation outcomes are kept. This documentation guarantees reproducibility and transparency and acts as a priceless resource for additional studies on leafy vegetables.

3.3 Data Collection

The challenging part of this research is to collect the dataset. A Custom dataset is made for recognizing leafy vegetables. To ensure diversity and representative samples, data collection of leafy vegetable images for this study is divided into several parts. Initially, six types of leafy vegetables are selected: Red Spinach, Colocasia, Organic Spinach, Stem Amaranth, and Jute Spinach. Six varieties of leafy vegetables are different in shape, color, and size. This selection process was carried out on seasonal leafy vegetables. Once the leafy vegetables are selected the next step is to purchase from different local markets or super shops. To ensure the quality and accuracy of the dataset, it is essential to ensure that the leafy vegetables being used are fresh and in good condition. Ensure that the leafy vegetables are free from any spoilage, blemishes, or signs of disease. Carefully selecting and testing leafy vegetables which can enhance the reliability and validity of datasets, thereby facilitating more accurate and meaningful analyses.

After purchasing the vegetables, six types of vegetables were photographed using the best camera configuration to ensure image quality. While taking pictures, make sure that the background is clean and use the same background for all pictures. The background can be a white surface, or lightbox, to reduce distractions and focus on the features of the leafy vegetables. Each vegetable is photographed multiple times from various angles and positions to capture all of its details, such as shape, color, texture, and size. It is important to avoid blurred and noisy images. Each image is labeled separately from the corresponding species name, date of capture, and other relevant details. Each image must be labeled carefully to ensure that the correct image is placed in the correct category. The total number of images is 4440 that are captured from different leafy vegetables. Table 1 shows the Total collected dataset and figure 2 displays the sample dataset of this study below:

TABLE 3.3: Collected Dataset

Class Name	**Number of Images**
Jute Spinach	750
Malabar Spinach	775
Colocasia / Taro	680
Organic Spinach	805
Stem Amaranth	660
Red Spinach	730
Total	**4400**

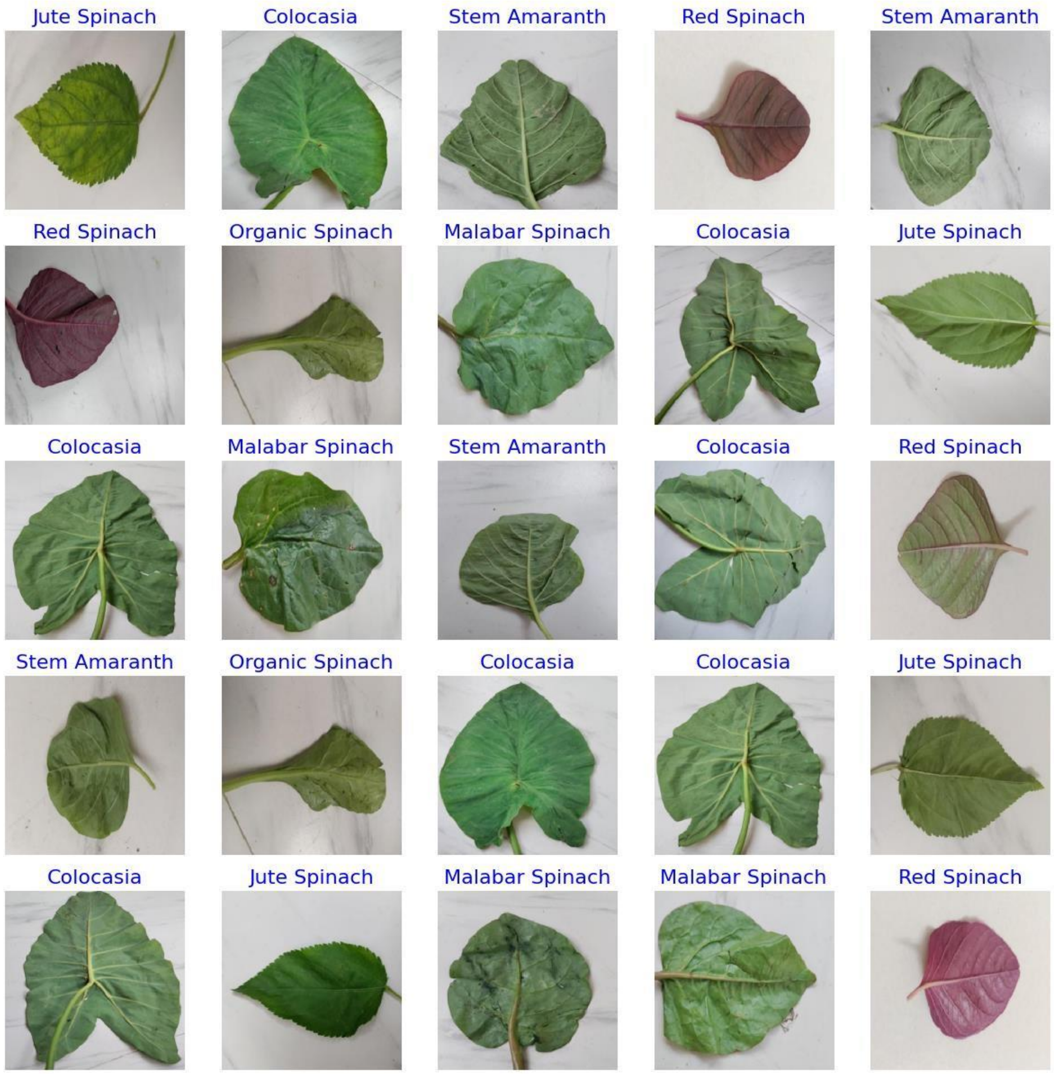

Fig 3.3: Sample Dataset

3.4 Data Analysis

After collecting the dataset, the next step is to analyze the dataset. While photographing each species of vegetable, the total number of photographs in each category was not the same. It is very important to balance the data in each class. In addition, some images are fuzzy and noisy which are considered inappropriate data for model implementation.

Data Preprocessing

Preprocessing is a crucial step in ensuring that the acquired images are ready for efficient training and categorization. To enhance the quality, consistency, and utility of the obtained dataset, various preprocessing approaches were performed. The primary step of preprocessing is to clean the dataset. Unnecessary and unsuitable data are removed which was considered as unfit for the model implementation from the previous step of data analysis. Making sure that the dataset only contains images of excellent quality and free of visual imperfections like distortion or variations in color is essential. By doing this, any disparities brought on by different lighting circumstances during image capture are reduced. Get more accurate and dependable outcomes from the study by making sure the dataset is consistent. 3960 images are obtained from 4440 images that are captured and recorded both locally and in the cloud for this study.

A manual procedure is used to make sure the data is accurate. Each image is closely inspected, and any that are deformed or blurry is manually found and eliminated from the collection. This method boosts the dataset's dependability and makes it ready for further analysis. The final custom dataset is shown in Table 2.

TABLE 3.5: Classification of Custom Dataset

Class Name	Number of Images
Jute Spinach	660
Malabar Spinach	660
Colocasia/ Taro	660
Organic Spinach	660
Stem Amaranth	660
Red Spinach	660
Total	**3960**

To enhance the performance and efficiency of the models, image resizing can be applied. The leafy vegetable images collected may be of various sizes. It is therefore possible to speed up processing and lower computational overhead by minimizing them to a consistent dimension.

Data Splitting

Data splitting is a significant step in machine learning, involving the partition of a dataset into two or more subsets. The data is often divided into two sets: a training set and a testing or validation set. Primarily, 80% of the data are designated for the training set, and the remaining 20% are utilized for testing and performance assessment of the model.

The steps involved in data splitting are as follows: To ensure that the data points are not organized in any particular sequence, the dataset is initially shuffled at random. Through randomization, any bias that might emerge from an ordered subsequent of data is eliminated. The partitioned dataset is then based on the predetermined ratio after being randomized. In this situation, 20% of the shuffled dataset is going to be utilized to assess the trained model's performance, and the remaining 80% will be allocated to the training set.

By splitting the data in this manner, we can use a substantial portion of it to train machine learning while keeping another section aside for independent evaluation. This technique makes it accessible to evaluate the model's generalization capabilities and offers insight into how well it performs on untested data. Data splitting also aids in identifying and resolving problems like overfitting.

A model overfits when it focuses exclusively on training data and fails to perform on untrained data. We can evaluate the model's performance on unidentified data by using a separate testing set, ensuring the model's capacity to generalize properly. Adjustments may be made throughout this phase to improve the model's accuracy and dependability. The dataset's 80/20 split provides a balanced approach to model training and evaluation, which aids in the development of effective and reliable machine-learning models. This partition makes sure that an adequate amount of the data (80%) is set aside for the model's training and that a different subset (20%) is set aside to evaluate the model's performance. The distribution of images by the class following the dataset's partition is displayed in Table 3 which is shown below.

TABLE 3.6: Data Splitting

Number of Train	**Number of Test**	**Number of Valid**
3168	369	369

Transfer Learning Model Train

Transfer learning is the process of applying a pre-trained model on one task and adjusting them to different related tasks. The process of adopting a pre-trained model which has normally been trained on a large dataset and adapting it to a new job that may have a smaller dataset available is known as transfer learning model training. The basic concept of a transfer learning model is to use the knowledge and representations gained from a model that has already been trained on one task as a source and apply them to a target task that is unrelated to the source task.

Transfer learning serves as relevant feature extraction, enhancing generalization, increasing data efficiency, and enabling domain adaptation from the input data. To benefit the target task and achieve higher performance with less data and computational resources, it makes use of the learned representations from a pre-trained model. Transfer learning is seen to have two primary benefits. One is performance improvement. Transfer learning gives a head start by utilizing a pre-trained model with rich feature representations from a source task. General patterns and features that can be used for the target task have already been learned by the pre-trained model. superior accuracy, quicker convergence, and overall superior performance result from this. The second is data and resource efficiency. It reduces the training time and enhances sustainable computational resources as it is not started from scratch.

Deep learning model training from the start frequently demands a significant amount of labeled data and computational resources. Transfer learning has been applied in different domains such as image classification, object recognition, natural language processing (NLP), healthcare and biomedical applications, and so on. These are just a few instances, but transfer learning may be used in several other fields and tasks. Its adaptability and efficiency make it a useful technique in a variety of disciplines where there may be a lack of data or when pre-trained models with the necessary expertise are available.

ConvNeXtSmall:

ConvNeXtSmall is a variant of the ConvNeXt architecture, which was introduced by Facebook AI Research in 2018. The ConvNeXt architecture aims to enhance the performance of Convolutional Neural Networks (CNNs) by employing a combination of grouped convolutions and concatenation. In particular, ConvNeXtSmall is a modified version of the ConvNeXt architecture. It broadens the model's depth and width, enhancing its ability to pick up complicated features and representations. The widely used ImageNet dataset and other image classification benchmarks demonstrate that this version performs at its finest. The use of grouped convolutions and concatenation is the main innovation of ConvNeXt. Grouped convolutions entail splitting the input channels into smaller groups and carrying out convolution operations separately inside each group. As a result, the model's efficiency and scalability are increased while using fewer parameters and calculations during training. The model can collect various and complementary data from various receptive fields owing to the concatenated outputs from the grouped convolutions. As a result, the network has greater representational power and can learn more robust and discriminative features.

As a ConvNeXtSmall variation, the model's effectiveness, scalability, and performance on image classification tasks are enhanced by the use of grouped convolutions and concatenation. Its cutting-edge performance on benchmark datasets demonstrates how well it can learn intricate visual patterns and achieve high accuracy in image categorization.

ResNet50:

ResNet50 is a Convolutional Neural Network (CNN) architecture that Microsoft Research introduced in 2015. It is a member of the ResNet (Residual Network) family of models, which is renowned for its capability to manage deep neural networks with hundreds of layers. In ResNet50, 50 layers are available. 48 layers for convolutional, one for MaxPool, and one is Average Pool layer. ResNet50 uses skip connections—also known as shortcut connections—to solve the problem of deep neural network training. It is made up of several convolutional layer-containing residual blocks. The network can bypass some layers and directly propagate information from one block to another to the shortcut connections. As the depth of the network increases, this reduces network performance deterioration and aids in learning residual functions. ResNet50 can successfully train and extract features from images by utilizing these skip connections, which leads to enhanced accuracy and better representation of complicated visual patterns. For several computer vision tasks, including image classification, object identification, and picture segmentation, ResNet50 has been heavily utilized. On benchmark datasets like ImageNet, it has achieved state-of-the-art performance, highlighting its capacity to extract and learn useful characteristics from images. It works as both a backbone network for diverse visual identification tasks and a potent tool for transfer learning.

Inception V3:

InceptionV3 is Convolutional Neural Network (CNN) architecture that was developed by Google Research in 2015. It belongs to the Inception model family, which is renowned for its enhanced performance and effective use of computational resources. The basic model Inception V1 was released as Google Net in 2014, and the Inception V3 is a modified version of that model. InceptionV3 has high efficiency and deep network compared to InceptionV1 and InceptionV2. It consists of 42 layers and has a lower error rate. To address the trade-off between depth and processing efficiency in CNNs, the InceptionV3 architecture was created. This is accomplished by combining 1x1, 3x3, and 5x5 convolutional filters in the same layer, which enables the model to effectively capture both local and global data. On a variety of computer vision tasks, such as image classification, object identification, and image segmentation, InceptionV3 has demonstrated excellent performance. It can learn complex and discriminative features because it is trained on massive datasets like ImageNet. The architecture is frequently employed in both academic and real-world applications because of its effective design and capacity for multi-scale feature collection.

3.5 Proposed Model

InceptionV3:

The InceptionV3 model is selected as the proposed model for this study. It is a 48-layer convolutional neural network (CNN), which includes convolutions, average pooling, maximum pooling, concatenations, dropouts, and fully connected layers. The model also uses symmetric and asymmetric building pieces to increase the strength of its representation. Batch normalization is often used throughout the model and is applied to the activation inputs to provide steady training. The Batch size for this study was 64. The loss is computed using the SoftMax activation function, which is a common method for multi-class classification tasks. The architecture of InceptionV3 is shown below in figure 3 [13]:

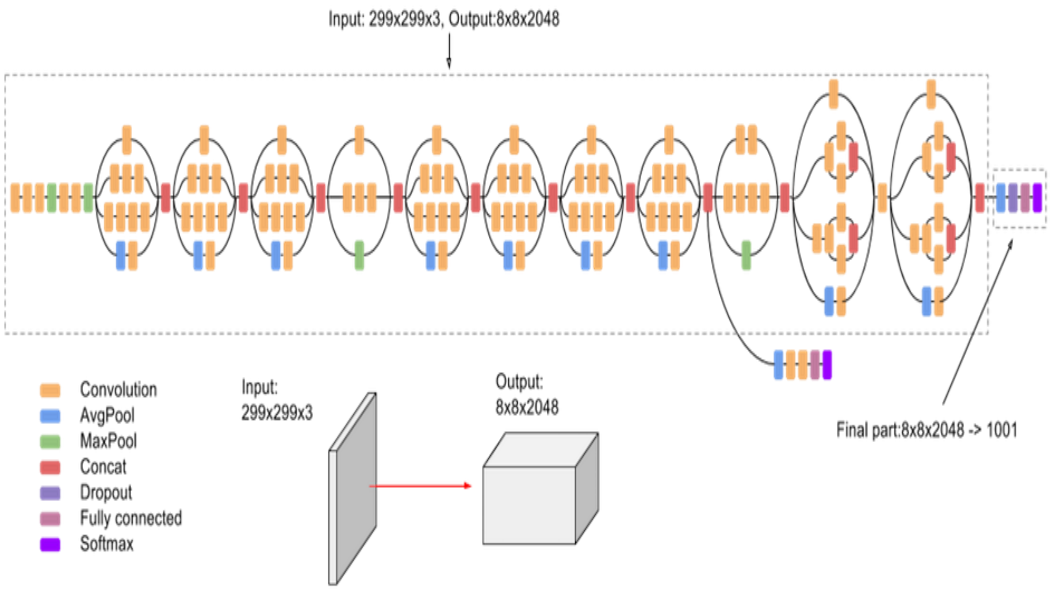

Fig 3.8: Proposed Model Architecture

3.6 Conclusion

This study used a structured research methodology to develop an automated system for recognizing various vegetable leaves. The procedure included meticulously gathering and curating a varied dataset of images of leafy vegetables. Techniques for data analysis and preparation were used to guarantee the accuracy and consistency of the data. InceptionV3 was chosen as the proposed model based on its high and effective performance of image identification tasks.

CHAPTER 4

Transfer Learning and Image Processing In-Depth Analysis for Leafy Vegetables Analysis

4.1 Introduction

In this chapter, we examine how image processing approaches and transfer learning enhance the accuracy of leaf vegetable analysis. Transfer learning permits us to utilize pre-trained models for preferable results. Examine all the images preciously in this section. In order to acquire the best results for leaf vegetable analysis, models must be carefully chosen, considering aspects like architecture, performance on related tasks, and dataset compatibility. Identify various leaf vegetable species more precisely by making use of existing knowledge, which will help the environment, the food and agriculture sectors, and the medical field.

4.2 Depth Analysis by Selecting Pre-Trained Models:

Selecting a proper model for implementation is a very important procedure. With the help of the complex machine learning technique known as transfer learning, I may use the knowledge learned from previously trained deep learning models for straightforward object identification tasks. For the transfer learning process in leaf vegetable analysis, selecting pre-trained models entails selecting the most appropriate model from the available possibilities, including InceptionV3, ResNet50, and ConvNeXtSmall.

Depth Analysis by ConvNeXtSmall

ConvNeXtSmall is a small convolutional neural network model made to recognize images effectively and precisely. ConvNeXtSmall is an appealing option for situations with constrained resources since it is a smaller model that may be favored in scenarios with constrained computational resources. When choosing the pre-trained model for leafy vegetable analysis, the compactness of the model could affect its capacity to capture fine-grained information. ConvNeXtSmall may be preferred over larger models like InceptionV3 or ResNet50 if the dataset is small or the available computing power is constrained.

Depth Analysis by ResNet50

The popular deep learning model ResNet50 is well renowned for its exceptional performance on image recognition challenges. By addressing the issue of vanishing or bursting gradients in deeper networks, its distinctive residual network design enables the development of more complicated models that can be trained successfully.

ResNet50 emerges as a desirable choice for the pre-trained model in the area of leafy vegetable analysis for a number of reasons. Because of its strength, it can manage a wide variety of leaf vegetable species, each with a unique visual appearance. This adaptability is essential for effectively identifying and categorizing different kinds of leafy vegetables.

Model complexity and performance are also balanced by ResNet50's architectural design. It is a good choice for transfer learning in leafy vegetable analysis since it can manage deeper networks while minimizing gradient-related problems. The model's excellent accuracy and reliability in classifying leafy vegetables are a result of its expertise in capturing complicated visual information.

Depth Analysis by InceptionV3

Based on its effective deep convolutional neural network architecture, which underwent pre-training on a sizable dataset for generic object recognition tasks, InceptionV3 was chosen as the pre-trained model for leafy vegetable analysis. InceptionV3 is now capable of extracting specific information and intricate features like color, shape, size from images, making it particularly appropriate for tasks requiring strong visual recognition, such leaf vegetable analysis.

The choice to use InceptionV3 is further supported by its outstanding results on a wide range of image recognition tasks. It can effectively build hierarchical models and recognize fine-grained relationships and features within visual data, enabling precise and trustworthy analysis of leaf vegetable images.

Additionally, InceptionV3's architecture demonstrates excellent generalization skills, enabling it to successfully handle a variety of leaf vegetable species with various distinctive features and perform well on a variety of datasets. Its accuracy in jobs requiring the classification of leaf vegetables is improved by its ability to recognize and detect a wide variety of visual indicators.

The model can considerably aid in the precise identification and categorization of leafy vegetable species because of its ability at capturing specific characteristics and capacity to learn complicated representations.

4.3 Leaf Feature Analysis:

This research concentrates on the analysis of six variety of leafy vegetables with every class represented by captured images at three type of different stages such as young, semi-matured and matured. As the leaves have varied appearances at various growth phases, choosing these three conditions for each type of leafy vegetable enables an in-depth analysis. The types of vegetable used in this study included Red spinach, Jute spinach, Malabar spinach, Colocasia, Organic spinach, and Stem Amaranth. Compared to their mature counterparts, the leaves in the early stage are smaller and exhibit various colors. Throughout its three growing stages, each leafy vegetable displays distinct traits that are useful for research.

Organic spinach:

- Young Age: Tiny, tender, compact leaves with bright green in color.
- Semi-Matured Age: Larger leaves with wide canopy, still tender.
- Mature Age: Deep green color, maximum leaf size, thicker.

Jute Spinach:

- Young Age: oval-shaped, green, small, tender leaves.
- Semi-Matured Age: Larger leaves that are still green and have serrated edges.
- Mature Age: Deep green color leaves that fully formed, bigger, and have a thicker texture.

Malabar Spinach

- Young Age: Heart-shape, green leaves, tiny, tender

- Semi-Matured Age: larger leaves with distinct veining, tender.
- Mature Age: Fully grown, larger, with a richer shade of green.

Stem Amarnath:

- Young Age: Lanceolate green leaves, small, tender.
- Semi-Matured Age: Larger leaves with noticeable veins, still tender.
- Mature Age: Larger, more fully formed, with shades of deep green or red.

Colocasia:

- Young Age: Small, tender, few centimeters length.
- Semi-Matured Age: still tender.
- Mature Age: Larger, more fully formed, heart shaped or arrow shaped, deep green or reddish-purple shades with defining veining.

Red Spinach:

- Young Age: Small, tender, vibrant greenish red or maroon,
- Semi-Matured Age: larger than young, deeper maroon or red color, prominent veining.
- Mature Age: Maximum size, full red or maroon especially underside, elongate and lanceolate forms with defining veining.

Utilizing Image Processing for Feature Extraction:

Computer science and engineering's field of image processing focuses on analyzing, modifying, and altering digital images in order to either extract useful information or enhance their visual quality. In order to accomplish particular goals or tasks, it includes using a variety of algorithms and approaches to images. Numerous applications, including computer vision, medical imaging, remote sensing, surveillance, and more, heavily rely on image processing.

In this section, explore how image processing can be extracted significant from leafy vegetable images for analysis and identification using image processing methods coupled with transfer learning. Through a comprehensive technique, it is hoped to improve the accuracy and precision of leaf vegetable analysis.

The images are first standardized by being resized to a consistent dimension. Regardless of their the original dimensions, this step assures that each image is the same size. Standardization is essential because effective functioning of deep learning models like InceptionV3 and ResNet50 depends on inputs of uniform sizes. creating a uniform framework for the model to operate within by scaling the images, which makes it easier to extract useful features.

Then Normalization for pixel values is applied to the images. pixel values are scaled to a standard range, frequently between 0 and 1. In order to make the model more resilient and less sensitive to changes in pixel intensities, normalization is crucial since it prevents some pixel values from predominating the analysis. This phase makes sure that differences in brightness or contrast between different images do not affect the model's performance.

Additionally, during preprocessing, unwanted noise and artifacts that were present in the images are removed. Noise can obstruct the model's capacity to distinguish features precisely and may be brought on by poor imaging conditions or sensor constraints. I improve the images clarity and quality to make them better suited for further analysis by reducing noise and artifacts.

Utilizing knowledge gained from previously trained deep learning models, transfer learning is a potent technique. InceptionV3, ResNet50, and ConvNeXtSmall are examples of pre-trained models that have been used as feature extractors. These models have been trained on large datasets for general object recognition tasks.

The intermediate layers of the pre-trained models function as feature maps, capturing and encoding particular visual elements from the leaf vegetable images, such as color, shape, and size. These characteristics act as essential representations for upcoming analysis. Fine tune was not applied because of there is no overfit data.

4.4 Conclusion

In order to help the model efficiently recognize and make use of pertinent visual information, this section emphasizes the crucial role that image processing and transfer learning play in feature extraction. This method aids in the accurate identification and classification of numerous leafy vegetable species, which eventually helps the environment, agriculture, and food production.

CHAPTER 5

Evaluation and Result

5.1 Introduction

Different transfer learning algorithms have been implemented in this section to identify leafy vegetables. After putting all the models into practice, the classification of leafy vegetables performed better, enhancing human healthful eating. The Transfer Learning models are introduced in this study on the identification of leafy vegetables using a distinctive dataset.

5.2 Model Performance

Within the parameters of this research study, InceptionV3 has demonstrated exceptional performance in classifying a variety of leafy vegetables. With the help of its sophisticated convolutional neural network (CNN) and deep architecture, InceptionV3 has proven to be remarkably accurate at recognizing leafy vegetables. The model's strong performance can be attributed to its capacity to capture the complex features and patterns that are characteristic of leafy vegetables. When it comes to performing better on the classification assignment for leafy vegetables, using InceptionV3 has proven to be highly beneficial.

In this research, three transfer learning models are applied to the custom dataset of leafy vegetables. There are ConvNeXtSmall, ResNet50, and InceptionV3. Applied custom dataset for all of the aforementioned CNN-based architecture. However, InceptionV3 outperformed other CNN-based designs in terms of performance. As a result, a model using the InceptionV3 architecture is decided upon. Below, the performance of the three models is shown in Table 4.

TABLE 5.2: Model Performance

Transfer Learning model	Test Accuracy (%)	Test Loss
ConvNeXtSmall	77.02%	1.24556
ResNet50	94.19%	1.62405
InceptionV3	99.75%	0.05398

After evaluating all the models on custom dataset, the inceptionV3 model exhibited the highest predicted values. The accompanying figure 4 and 5 illustrates the output results achieved by the inceptionV3 model. These results emphasize the model's accuracy and proficiency in effectively identifying and classifying leafy vegetables. The superiority of the inceptionV3 model underscores its potential for practical implementation in leafy vegetable identification.

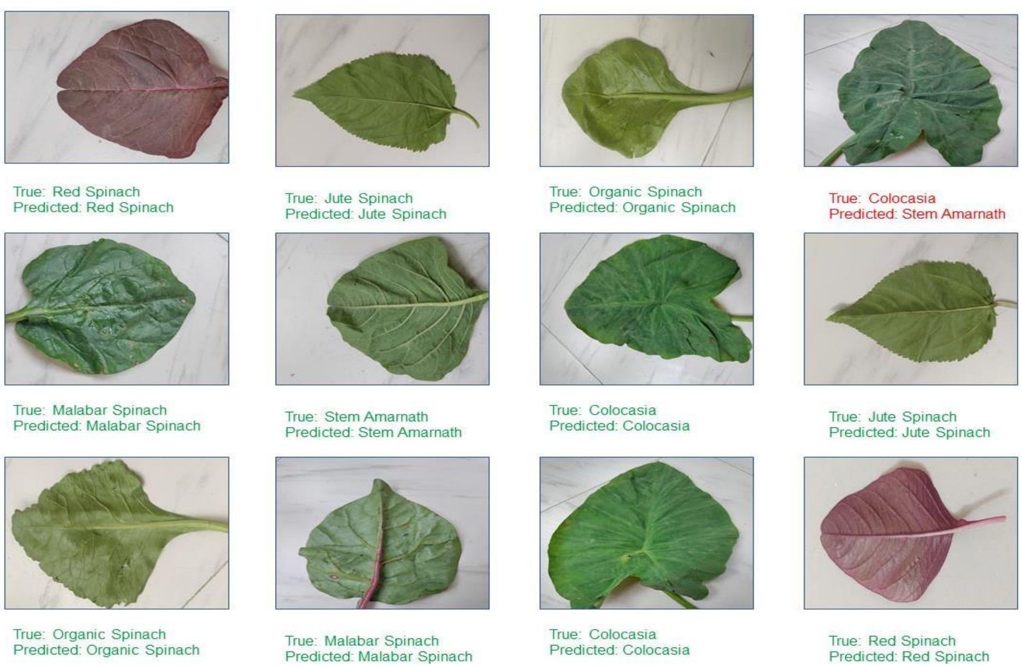

Fig 5.2.1: Predicted dataset with output 1

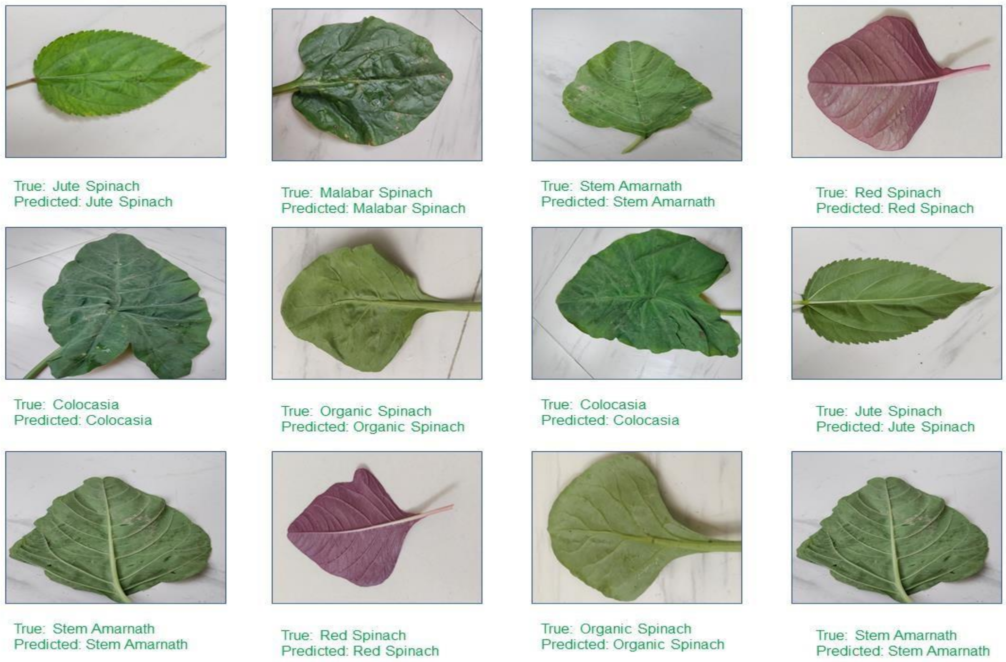

Fig 5.2.2: Predicted dataset with output 2

5.3 Generating Confusion Matrix

A confusion matrix is a method for comparing the anticipated and actual class labels for a given dataset to assess the overall performance of a classification model. It gives details regarding the accuracy and types of errors the model makes. The confusion matrix consists of four components that are True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). After a successful training session using a Custom dataset, a confusion matrix was generated to assess the performance of the used InceptionV3 model. The implementation's outcomes indicated that different leafy vegetables were able to be accurately identified. The model accurately predicted a specific number of cases for each class of leafy vegetables, including 61 instances of Colocasia, 66 instances of Jute spinach, 72 instances of Malabar spinach, 63 instances of and 61 instances of Red spinach, to

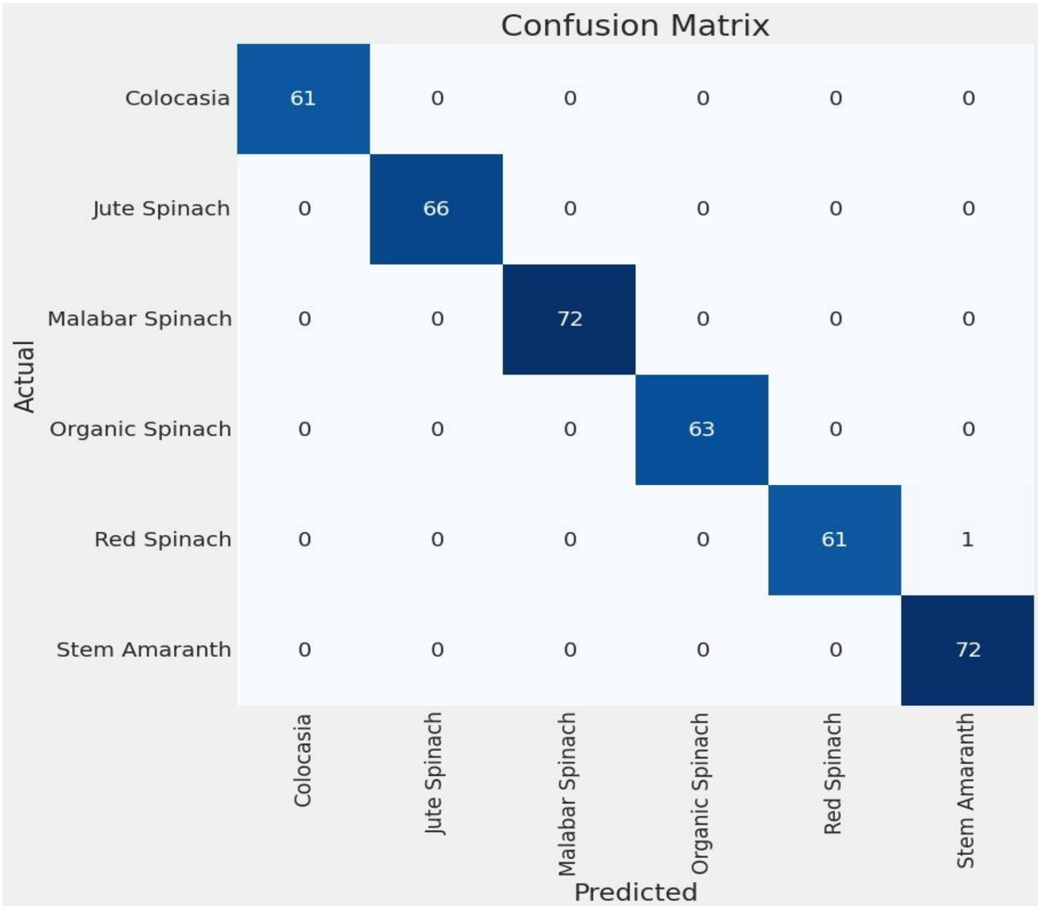

Fig 5.3: Heatmap of Confusion Matrix InceptionV3

evaluate the confusion matrix of InceptionV3. The Confusion Matrix, as represented in Figure 6, presents a comprehensive measurement of the InceptionV3 model's performance and effectiveness in leafy vegetable identification. It gives valuable perception into the overall performance of the model and gives a comprehensive understanding of its ability to accurately classify leafy vegetables.

5.4 Generating Classification Report

The classification report serves as vital for the study since it gives a thorough analysis of the model's performance, enabling researchers to evaluate the model's precision, recall, accuracy, and F1 score. It allows model comparison, confirms research assumptions, sets standards versus current techniques, and gives insights for deeper study and advancement. It improves the validity and dependability of studies in the field of classification by quantitatively assessing the model's categorization abilities. In this study, the classification report gives a summary of InceptionV3 and how the model can classify various leafy vegetables. Throughout the classification report, it is displayed that high precision ratings point to a low rate of false positives. The precision of 1.00 indicates reliable positive predictions for the majority of classes. The model appears to catch a significant fraction of true positive cases, according to the strong recall ratings. Recall scores for most classes are 1.00, implying accurate detection of positive instances. The Classification report visualizes in Table 5 below.

TABLE 5.4: CLASSIFICATION REPORT INCEPTIONV3

Class Name	precision	recall	f1-score	support
Colocasia	1.00	1.00	1.00	61
Jute Spinach	1.00	1.00	1.00	66
Malabar Spinach	1.00	1.00	1.00	72
Organic Spinach	1.00	1.00	1.00	63
Red Spinach	1.00	0.98	0.99	62
Stem Amarnath	0.99	1.00	0.99	72

Overall, the classification report demonstrates that the model did an excellent task of recognizing leafy vegetables. With few false positives and false negatives, it exhibits excellent precision, recall, and F1 scores. The model correctly recognizes and classifies the various leafy vegetable classes, demonstrating accuracy and dependability in its categorization abilities.

5.5 Training and Validation Accuracy & Loss Curve

Training and validation loss and accuracy curves are important for research. These curves are crucial for evaluating the model's performance during training on unseen data. It also helps to detect the overfitting and underfitting. Figure 7 displays the training and validation loss curve as well as figure 8 displays the training and validation accuracy curve. They give valuable insights for evaluating performance and model effectiveness in achieving the purpose of this study.

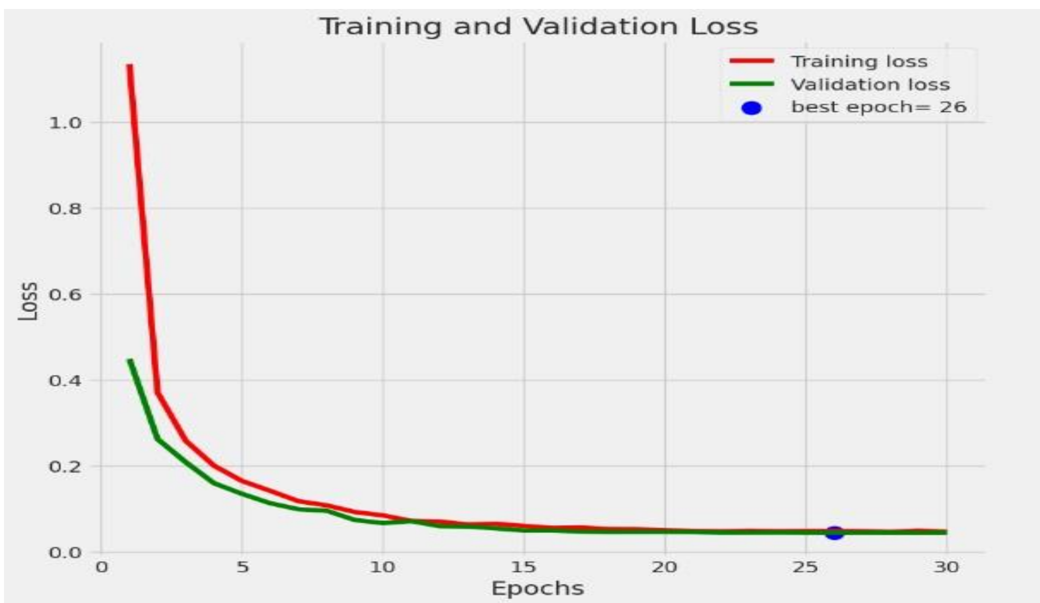

Fig 5.5.1: Training and Validation Loss Curve

The training loss curve demonstrates how the model's loss gradually lowers as it acquires knowledge from the training set. After training and validating the model for 30 epochs, the results are displayed in Figure 7 and 8.

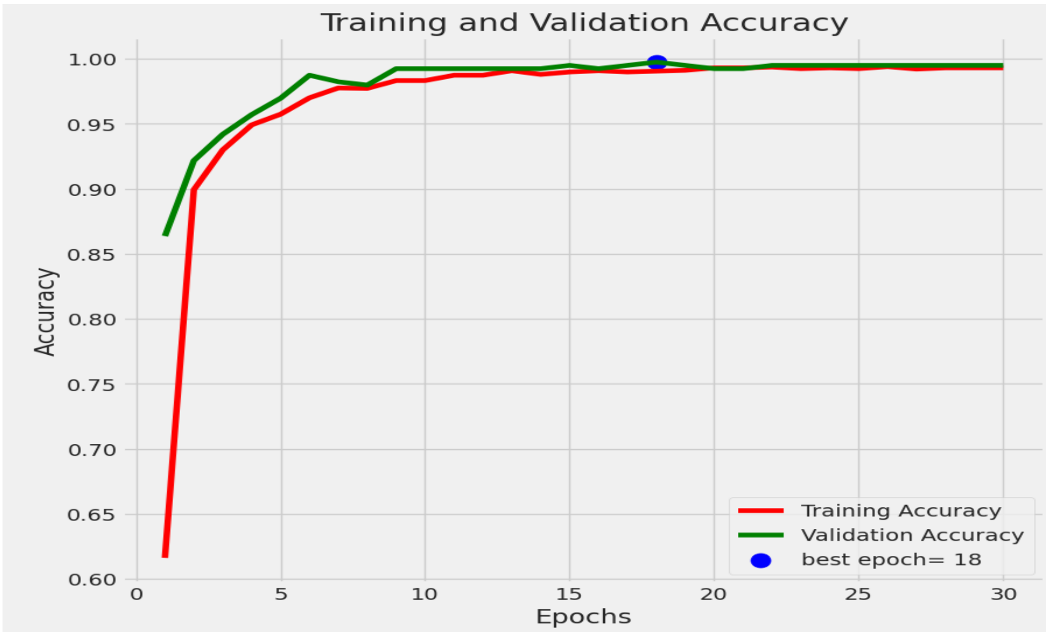

Fig 5.5.2: Training and Validation Accuracy Curve

It is demonstrated that the model has attained a high level of accuracy because both the training accuracy and the validation accuracy have reached their maximum values. The loss values, however, don't seem to be adequate, indicating that there is still potential for development in terms of error minimization.

The ability of the model to generalize to unseen data can be observed in the training and validation curves, which are used to measure model performance. It is crucial to comprehend and analyze these curves to assess and improve the model and make sure it helps reach the study's goals.

5.6 Discussion

ConvNeXtSmall, ResNet50, and InceptionV3 were three transfer learning models that I examined in this study for identifying leafy vegetables. With a stunning 99.75% accuracy on the test set, InceptionV3 stood out for its outstanding performance. It was able to accurately capture the intricate leafy vegetable features due to its advanced CNN architecture. InceptionV3 performed higher than the other two models when compared. ResNet50 obtained 94.19% accuracy, while ConvNeXtSmall achieved 77.02%. The confusion matrix's precision and recall scores of 1.00 for the majority of classes for InceptionV3 showed that it performed consistently. The classification report provided more evidence of InceptionV3's precision and reliability in recognizing numerous vegetable species.

InceptionV3 is a vital tool for agriculture because of its outstanding performance, which enables effective crop monitoring and disease diagnosis. To improve the identification of leafy vegetables, additional study can look into enlarging the dataset and using different models.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Introduction

This chapter explores the general implications of the experimental technique for leafy vegetable analysis. It has achieved impressive accuracy and efficiency in recognizing leafy vegetables by combining image processing methods with transfer learning models. This cutting-edge method has a great deal of potential to improve society, agriculture, and the environment. Consumers can make knowledgeable nutritional decisions by automating the identification process, promoting a healthier population. Additionally, better crop management and resource optimization can help the agriculture sector by lowering waste and environmental effect. Transfer learning and image processing together represent a significant advancement toward a more environmentally friendly and sustainable future.

6.2 Impact on Society

The implementation of a system for recognizing leafy vegetables using transfer learning models has the potential to significantly improve society. Since leafy vegetables are essential for sustaining a healthy lifestyle, it is crucial for people seeking nutrient-rich diets to ensure their accurate identification.

This method can help people make well-informed choices about the vegetables that they eat by automating the identifying procedure. With the suggested technique, users can save time and effort by not having to struggle to identify visually similar leafy vegetables apart. All age groups, especially those who are unfamiliar with leafy vegetables can benefit from this. A more varied and balanced diet may be encouraged by the system's increased accuracy in recognizing leafy vegetables, improving population health in the process.

The agricultural sector may benefit from the automated leafy vegetable identifying system. With the use of this technology, farmers and producers are able to ensure the reliability as well as the quality of their leafy vegetable products, giving consumers peace of mind regarding the food they are buying. The system can aid in fostering knowledgeable choices regarding food and promoting good eating habits, which will ultimately lead to a healthier society as a whole.

Additionally, the automatic leafy vegetable identification system could assist the food industry. This technology can be used by eateries, retailers, and food producers to ensure the quality and reliability of the leafy vegetables that they serve to customers. The approach can increase consumer trust in the food supply chain and raise general customer satisfaction by encouraging correct labeling and trustworthy information.

Besides the food industry and agriculture sector, the transfer learning model based identifying system of leafy vegetables can utilize different applications in various fields and industries. The technique can be used by nutritionists and healthcare professionals to inform patients and consumers about the nutritional advantages of certain leafy vegetables. It can be included into health applications or websites to offer individualized nutritional advice depending on user preferences and health objectives. The technique can be used by botanists, ecologists, and environmentalists to recognize and investigate different leafy vegetables in natural habitats. The protection of biodiversity can benefit from an understanding of the distribution and diversity of these plants. The application might be a useful educational resource for botany and plant identification classes. It can be used by scholars and researchers to carry out studies on ecological patterns and plant variety as well as to learn about various leafy vegetables. By assuring the accurate identification of leafy greens used in processed food items, the system can help with food safety and quality control procedures. Customers' confidence in their ability to choose the precise green vegetables they want reduces the possibility of mismatched online orders.

6.3 Impact on Environment

The automatic leafy vegetable identification system can benefit the environment, especially when used in conjunction with sustainable agricultural methods. The approach minimizes the likelihood of inefficient purchases and food waste by assisting consumers in making informed decisions. This may result in more conscientious eating habits and a reduction in the environmental impact of food production and disposal.

Furthermore, the identification of leafy vegetables is made possible by the application of sophisticated machine learning methods like transfer learning. This efficiency can lead to improved crop management techniques, resource optimization, and diminished environmental impact. Farmers may decide wisely when to sow and harvest, protecting priceless natural resources and reducing waste in the process.

Additionally, the system can promote sustainable farming methods and lessen the carbon footprint associated with the long-distance transportation of food by promoting the consumption of locally grown and seasonally available leafy vegetables.

6.4 Ethical Aspects

The automated leafy vegetable identification system adheres to the moral values of transparency and empowerment of customers. The system encourages moral consumer decisions by giving consumers reliable and truthful information. It makes sure that people can receive accurate information about the leafy vegetables they eat, empowering them to make moral and knowledgeable judgments about their dietary choices.

Additionally, using systems minimizes the possibility of biases or mistakes made by humans when identifying leafy vegetables. This promotes fair and uniform processes and ensures that consumers, irrespective of their location or skill, receive reliable information. Accurate information and ethical food labeling assist to foster consumer confidence in the food industry.

6.5 Sustainability Plan

A comprehensive strategy may be put into action to guarantee the long-term viability and impact of the leafy vegetable identification system. The machine learning models' accuracy and flexibility to shifting farming techniques and new leafy vegetable varieties will be improved through ongoing upgrades and improvements.

The performance of the system can be enhanced through cooperation with farmers, agricultural specialists, and nutritionists, who may also ensure that it is relevant to regional contexts and dietary demands. Involving with food industries and legislators can stimulate the implementation of the system to enhance food labeling processes and increase the consumption of healthier foods.

Furthermore, efforts should be taken to maximize the system's beneficial effects on society and the environment and assure its accessibility to reach a wider audience, in particular underserved communities.

In the long run, the system's sustainability and efficacy will be improved by continuous evaluation of the system's performance, input from customers, and environmental impact.

6.6 Conclusion

Our revolutionary method to leafy vegetable analysis using transfer learning-based image processing has significant implications for society, the environment, and sustainability. Automating the identification process enables customers to make knowledgeable and healthier food decisions, improving population health as a whole. The agricultural industry stands to benefit from better crop management and resource optimization, which lowers waste and has a positive influence on the environment. Additionally, this cutting-edge system can be used in a variety of fields, including botany, healthcare, food production, and safety. Consumers can trust the food sector because of its ethical underpinning, which guarantees accurate and fair information. A sustainability strategy with ongoing improvements, collaboration with experts, and an emphasis on serving underprivileged communities is in place to guarantee its long-term existence and influence. With this approach, we make a huge advancement toward a future that is sustainable and friendly to the environment.

CHAPTER 7

Conclusion and Future Scope

7.1 Introduction

This chapter explore the primary contributions of this study while also analysis its limitations. Furthermore, this study provides recommendations for future research directions to further advance the findings and broaden the work of this study. We have investigated new approaches to enhance the precision and effectiveness of leafy vegetable analysis throughout this research. I aimed to revolutionize the classification and recognition of leafy vegetables by utilizing transfer learning models and image processing techniques. The main findings of the study are presented in this chapter's last section, along with suggestions for further research and advancement. The ultimate objective is to create a strong and sustainable system that is advantageous to society, agriculture, and the environment and eventually encourages better lifestyles and sensible food consumption.

7.2 Summary of Main Finding

The key findings of this study emphasize the need of using transfer learning-based image processing to identify leafy vegetables. A growing distance between people and nature exists in today's technologically advanced society, which contributes to a lack of knowledge about many natural resources, including leafy vegetables. However, these vegetables are essential to an active and vigorous existence since they provide a healthy and balanced diet.

To address the challenges of analysis and identifying leafy vegetables, The study made use of convolutional neural networks (CNNs), which are well-known for their proficiency in object recognition. The CNN-based transfer learning model uses a pre-trained version that significantly reduces processing time and enhances classification performance. Three transfer learning models were applied to a customized dataset of six different leafy vegetables, and the results showed that InceptionV3 had the highest accuracy, achieving an amazing 99.75%. Precision, recall, and F1 score performance metrics all supported InceptionV3's better capacity to correctly identify and categorize leafy vegetables.

This study reveals how image processing and transfer learning methods could transform the way people identify leafy vegetables, so enhancing society and encouraging a healthy way of living. Future developments in this area are made possible by the InceptionV3 model's outstanding accuracy. To increase the value and effect of this newly developed technique, additional study is required to expand the dataset and explore different varieties of leafy vegetables.

7.3 Limitation

The study's limitations primarily revolve around data collection and dataset composition. Firstly, obtaining a suitable dataset of leafy vegetables presented challenges as it required fresh, attractive, and disease-free samples. Ensuring the availability of such high-quality data points for the study was difficult and might have limited the diversity of the dataset.

Secondly, the drawback lies in the fixed composition of the leafy vegetable dataset. With only six varieties of leafy vegetables included in the dataset, the study's scope might be limited in capturing the full range of leafy vegetable species. This fixed set of vegetables could restrict the model's ability to generalize well to new or previously unseen types of leafy vegetables, impacting its overall applicability and accuracy.

In conclusion, the study's limitations mainly originate from the difficulties in data collecting and the fixed character of the dataset, which may affect the model's functionality and ability to generalize to a wider variety of leafy vegetables. In order to construct more reliable and adaptable models for leafy vegetable analysis, future research ought to research into strategies to obtain more diverse and representative data.

7.4 Future Suggested Work

Further studies can reduce the limitation of research works. In this study, Dataset is considered a limitation. The custom dataset consists of six types of leafy vegetables: Colocasia, Red Spinach, Malabar Spinach, Jute Spinach, Organic Spinach, and Stem Amarnath. Future studies of this research are to expand the dataset with a wider range of leafy vegetables. By including more various types of leafy vegetables, the identification system can be trained to correctly identify the leafy vegetables. Additionally, a comparative analysis between different transfer learning models conducted can be provided comparative research. Furthermore, introduce a real-time application for practical implication. The next work for this research will also include optimizing the models for mobile and edge devices.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
IMPROVING LEAFY VEGETABLE ANALYSIS THROUGH IMAGE PROCESSING WITH TRANSFER LEARNING METHODS

Student ID: [201-15-3031]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **leafy vegetables identification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**

CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like InceptionV3, ConvNextSmall and ResNet50, enhancing pneumonia detection accuracy in chest X-ray images, crucial for computer-aided diagnosis.	**Page no:** [18-21] **Section:** [4.2] **Page no:** [1-5] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [32] **Section:** [3.2(B)]

					Page no: [33] **Section:** [3.4]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies, to advance pneumonia detection using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in pneumonia detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing pneumonia detection amidst multiple potential approaches.	**Page no:** [36-57] **Section:** [4.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory diseases like pneumonia, contributing to advancements in public health and healthcare practices which indicates **EP-4**.	**Page no:** [16-24] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics which ensures **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in pneumonia detection through transfer learning and deep CNNs.	**Page no:** [33-35] **Section:** [3.5]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This project contributes to society by improving healthcare through advanced pneumonia detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in pneumonia detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-10] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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