POPULAR FOOD SPICES CLASSIFICATION OF BANGLADESH USING TRANSFER LEARNING APPROACH

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "Popular Food Spices Classification of Bangladesh Using Transfer Learning Approach", submitted by Mahjabin Karim Rashme 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 15th July, 2024.

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I hereby declare that this research-based project has been done by Mahjabin Karim Rashme under the supervision of **Md. Sazzadur Ahamed, Assistant Professor, Department of Computer Science and Engineering, Daffodil International University**. I 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

Classifying twenty distinct Spice varieties will be accomplished with the implementation of the transfer learning (TL) approach. Bengali cuisine is incredibly flavorful and aromatic, and the taste comes mainly due to the use of spices. Spices are the sole reason why Bengali cuisine is so popular. However, background studies observe that there is a severe lack of acceptable datasets and paperwork for popular spices used in the majority of Bangladeshi cuisine. Spice classification is significant because it helps upcoming generations by enabling the recognition of spice varieties without any prior knowledge. To resolve the Spice recognition problem, collecting a significant dataset on the specific number of images per class which includes 500 images and a total of twenty spice varieties like Clove, Black cardamom, Black pepper, Cumin, and Nutmeg etc. The dataset will then be preprocessed by applying techniques such as Image resizing, and noise reduction. The TL approach will be used to solve the challenge since it is the most efficient in terms of processing energy, execution speed, and real-time analysis. Out of all the experiments, the proposed model "MobileNetV2" outperformed all other models in efficiency, achieving an accuracy score of 99.70% in identifying spice categories. The collected dataset will frequently be helpful for further studies that classify regional spice variations in Bangladesh.

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AI	Artificial Intelligence
ML	Machine Learning
CNN	Convolutional Neural Network
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
DT	Decision Tree
MLP	Multilayer Perceptron
NB	Naïve Bayes
LR	Linear Regression
ReLU	Rectified Linear Unit
CPU	Central Processing Unit
RAM	Random Access Memory
SSD	Solid State Drive
GPU	Graphics Processing Unit
BADC	Bangladesh Agricultural Development Corporation

CHAPTER 1

Introduction

1.1 Overview

Bangladesh's cuisine is renowned for its rich use of diverse spices, which are essential for both flavor and health. Ensuring the quality of these spices is crucial, yet manual classification is often labor-intensive and error-prone. This study aims to develop an automated system for classifying popular food spices in Bangladesh using a transfer learning approach. By leveraging pre-trained models like MobileNetV2, InceptionV3, NASNetMobile, and ResNet50, the research seeks to enhance accuracy and efficiency in spice identification. This system promises to streamline quality control, ensuring consumers receive high-quality spices while preserving the nation's culinary heritage.

1.2 Background and Present State

Food would be cooked with no spice as if this is an unimaginable thought for a Bengali. Spices are the only reason why Bengali cooking is so appreciated. Each spice is incomparable in taste, and aroma and helps prevent diseases. Spices are individual attributes that add a unique depth to cuisine and the variety taste of cooking comes from the use of spices. This not only changes the taste but also changes the consistency and aroma of the broth. Bengali cuisine is distinguished by its use of spices as a fundamental element, which is reflective of the nation's existence [1].

Spices are widely produced in different countries of the world. But now in Bangladesh also different types of spices are being cultivated and getting expected results. Bangladesh's soil, climate, and weather are all suitable for spice cultivation. There is also a spice research center in the country. Spice Research Center of Bangladesh Agricultural Research Institute has already released 38 varieties of 19 types of spices. A spice research center was established in 1994 in Shibganj Upazila of Bogra under the Bangladesh Agricultural Research Institute (BARI) to meet the huge shortage of spices in the country. It has more than 10 regional offices [2].

The government has emphasized research to increase the production of spices in the country. Its main objective is to reduce the import dependence of spices. Spices are an important part of agricultural products. Its cultivation along with staple crops not only helps in increasing the farmer's income but also in boosting the overall agricultural economy. Currently, 109 varieties of spices are grown across the world, but only around 44 are consumed in Bangladesh. Only 34 of these have been cultivated in the country. Among the spices used in the country are [3] turmeric, chili, black cumin, pepper, cardamom, coriander, cinnamon, cumin and many more. The government has taken up a project of Taka 94 crore for research to increase the production of spices and if the project is fully implemented, the countrymen will get its benefits.

According to Ministry of Agriculture sources, the research center has created 33 high-yielding spice crop types, as well as 84 sophisticated production methods for soil, water, disease, and insect management. Other initiatives being undertaken by this project include Inventing new varieties of spices, developing different production packages based on region and problem, research activities, the sowing of high-quality seeds to boost productivity, development of production technology and planting techniques, conference rooms, green houses, seminars, and training programs both domestically and internationally [4].

Worldwide spices are different from each other due to their wide variation in taste, color, smell, and medicinal values. This variation makes it difficult for a large number of people to identify spice variety. In general life, the classification of spice is a fundamental need to overcome this problem. With the help of classification, people will be able to identify their desired spices variety without any difficulties by looking at its shape, consistency and this will help to avoid being cheated while buying the preferred spices. Furthermore, young individuals can also recognize different types of spices with ease, which will be beneficial to them in their future lives. Also, it helps to keep the food healthy by destroying the bad smell of fish or meat. Spices are whole or ground forms derived from natural plants or vegetable products that are used to provide taste and fragrance to dishes as well as to season them. A variety of plant and tree components, including fruits, stigmas, bark, seeds, leaves, kernels, arils, bulbs, and berries, are used as spices [5].

Many researchers have worked on the classification of spices but still, there is very little work on the classification of spices where obtaining revolutionary techniques, noble paperwork or datasets is quite difficult. Also, In Bangladesh popular spice varieties paperwork are very low and they have many obstacles. This is the driving force behind our desire to recognize the spices variety through classification and work with popular spices in Bangladesh.

1.3 Problem Statement

The significance of spices in Bengali food is extremely high but limited study has been done on the categorization of spices, the Lack of different production packages based on region, as well as planting techniques, particularly in Bangladesh. Existing research is limited, and novel techniques for recognizing and classifying spice variations must be developed.

1.4 Objectives

The purpose of this study is to fill the categorization gap in spices, particularly in Bangladesh, where popular spice types are underrepresented in the literature. The key objective is to create an accurate and efficient categorization system that can distinguish between various spice kinds based only on their appearance. This will help to improve customer knowledge and combat fraud in the spice markets.

1.5 Scope and Limitations

The scope of this research project is to provide an accurate method for categorizing spice types using transfer learning based on their physical characteristics, such as shape, consistency, and color. In addition to addressing issues with spice diversity, high standards, and dataset accessibility and providing convenient solutions to enhance spice recognition in the agricultural sector.

1.6 Report Organization

The proposed report is structured with a comprehensive layout to guide readers through the research process, findings, and implications. Each chapter serves a specific purpose, contributing to the overall coherence and depth of the document.

Chapter 1: Introduction

This chapter provides an overview of the research area and highlights how important spice classification is in Bengali cooking. It outlines the motivation behind the study, the rationale, research questions, and expected outcomes.

Chapter 2: Literature Review

This chapter delivers the terminology, literature review and the background study of the research. It also illustrates the scope of problem and potential challenges of the research.

Chapter 3: Methodology

This chapter describes the methods used in the research. It contains details on how to gather data, preprocessing techniques for spice images, selection and training of TL models, evaluation metrics, and experimental setup.

Chapter 4: Implementation

This chapter summarizes the experimental results achieved from the use of TL in spice classification. It includes the performance metrics of the transfer learning models, the classification accuracy of spices, the comparison between different models, and the impact of preprocessing techniques on classification accuracy.

Chapter 5: Result and Analysis

This chapter details the experimental outcomes, provides an in-depth analysis of the findings, and discusses the implications of the results.

Chapter 6: Impact on Society, Environment and Sustainability

The societal impact of spice classification is covered in this chapter. It highlights how accurate spice classification can enhance culinary practices, support local farmers, ensure consumer confidence, and contribute to economic development in Bangladesh.

Chapter 7: Conclusion and Future Work

This chapter encapsulates the study's key findings, presents conclusions, offers practical recommendations, identifies study limitations, and proposes avenues for future research.

1.7 Summary

The ultimate goal of this study is to overcome the knowledge gap in Bangladeshi spice categorization by creating a dependable and effective method for recognizing common spice types. By filling this need, the study hopes to help to the development of consumer knowledge and the avoidance of fraud in the spice industry, eventually benefitting both consumers and spice producers in Bangladesh.

CHAPTER 2
Literature Review

2.1 Overview

Researchers are advancing every day in the areas of classification and identification, and they have done some excellent work with spices in many countries. They identify different spices using many methods or techniques like Machine Learning, deep learning, and image processing. In addition, some studies have also used sensors like e-noses to detect the smell of spices. This review section will focus on relevant research article summaries, including works, methods, accuracy, difficulties, and future interests that are related to my study.

2.2 Related Works

Kaharuddin et al. in 2019 [6] suggested Classification of Spice Types Using K-Nearest Neighbor Algorithm (KNN). Four well-known spice varieties were selected and only 150 photos from the limited collection were used in Indonesia. After applying the K-Nearest Neighbor (KNN) Algorithm in 150 trials, they got 84% accuracy with K = 5.

In 2020, Maimunah et al. offered Deep Neural Network (DNN) Method to Classify Empon-Empon Herb Based on E-Nose [7]. Since they worked on herbs, selected ginger, galangal, turmeric, and temulawak species and collected 3585 image samples. The smell of the empon-empon was identified by the e-nose, which was designed implementing TGS2611, TGS813, and MQ136 sensors combined with an Arduino Uno. However, as the sensor voltage empon-empon is used, the voltage values obtained are classified using a deep neural network. With a success rate of 86%, the DNN can classify the different type of empon-empon based on smell.

Chhaya Narvekar and Madhuri Rao in 2020, worked with a different classification area. They focused on flower classification using CNN and Transfer Learning (TL) approach. Besides, 4323 images collected from Kaggle were divided into 3890 training and 433 testing data. Some problems were encountered due to the large amount of flowering plant species, which are equal in size, colour and outlook. But using the TL model VGG16, they achieved

95.39% accuracy [8].

Classification of vegetable plant pests by Vijayakanthan et al. in 2021 [9], using deep TL techniques to train the classification model. From the northern part of Sri Lanka, a total of ten classes of 500 vegetable pest image samples were collected and our model InceptionV3 successfully classified images where accuracy got 99.8%.

Dr K. Ponmozhi and Reny Jose worked in the same Deep Learning (DL) field in 2022. Anyway, based on different attributes such as family, origin, and flavor, the CNN architecture recognized spices with 75% accuracy [10].

In the same year, Sundaram et al. introduced the TL approach [11] for classification of widely used spices. The datasets were taken from various websites and there were 10 different categories of Spices in the total of 2000 pictures. Moreover, they resized and preprocessed the data before applying the transfer learning method. As before, the pre-trained VGG16 model achieved 93.06% accuracy.

In addition, Few Indian researcher working with categorization and grading of spices using DL in the same year [12]. Generated their dataset by collecting images from the internet and using data augmentation method. Their objective is to develop an automatic system using CNN to identify Indian spices in different images and they acknowledged that they had obtained a 98% accuracy.

Traditional Machine Learning and Deep Learning Modeling for Legume Species Recognition by Rimi et al. in 2022. After gathering all of the pictures, they preprocess the images by resizing and augmentation. However, three classic machine learning models and three deep learning models are utilized but Inception-v3 outflanks all other models with 98.6% accuracy [13].

Al-Amin et al. [14] Classified spices image using new ML technique that Support Vector Machine. Using SVM to map the data across five categories, the accuracy of recognizing ginger is 24.5%, and cinnamon is 65.3%. The average identification accuracy is 38.7%.

Few studies were conducted by several teams of researchers in the same year. Talukder et al. demonstrated a computer vision and deep CNN modeling for spices recognition [15]. They used a quality dataset with 8377 photos in their research. For the best outcome, they apply three distinct models and the maximum accuracy reached 99.41% by model 3.

Pratondo et al. implemented pre-trained TL model that are VGG-19 and Inception V3 with ImageNet weight. This study aims to build a model that can distinguish between the two species of Zingiberaceae family which include the spices Curcuma longa (turmeric) and Curcuma zanthorrhiza (temulawak). Among the 2 models they proposed, Inception V3 succeeded in recognizing spice varieties with 94.29% accuracy [16].

Using Machine Learning Techniques Gupta et al. in 2022 recommended classification of spices [17] with a dataset made up of 1000 pictures of five distinct types of spices. They use five ML techniques and the performance has been analyzed based on four parameters: accuracy, precision, recall, and f1-score. Subsequently, the SVM technique performed the best on this dataset, so they will expand broader datasets and integrate features for improved accuracy and efficiency.

In 2023, Classification of clove types using convolution neural network algorithm [18] with optimizing hyperparamters was proposed by Tempola et al. They collected a total of 1,715 data records across three categories of interesting processes: whole clove, headless clove, and mother clove. By employing the CNN algorithm, model transfer learning, and modified VGG16 architecture will be used in this study to compare its performance on clove photos. With a hyperparameter of 50 epochs, CNN to cleave images achieves an accuracy value of 84%. On the other hand, modified VGG16 has the highest accuracy 92.11%.

Indonesian researchers Tahir et al. in 2023 evaluated the performance using Pre-Trained CNN and TL for the Classification of Spices and Herbal Medicines. They implemented six CNN architectures and classified ten different kinds of spices. Considering an F1 score of 98.23%, Xception is the best architecture according to the experiment's results [19].

Mufarroha et al. in 2023 proposed Spices Identification in Essential Oil Producers using Comparasion of KNN and Naïve Bayes Classifier [20]. In 5 types of spices, 100 training data and 50 test data resized images were taken from Kaggle, and the proposed model K-NN with a value of K = 3 revealed 98.74% accuracy.

In the previous year, many researchers discussed CNN and MobileNetV2 as a transfer learning model [21] for spices classification and recognition. Moreover, Machine Learning based Identification of Spices by Naman et al. in 2023 proposed the same approach as the previous. They worked with a total of 4000 chili spice data, and the developed model attained an impressive 97.97% accuracy.

After reviewing those previous studies, I perceived that spice classification and recognition is a quite challenging issue.

2.3 Comparison between existing works

Despite advancements in spice categorization, studies differ in their approaches, dataset sizes, preprocessing techniques, and levels of accuracy. Researchers have achieved successful outcomes by utilizing DL models, ML models, and TL approaches. Some focus on a wide range of attributes, while others concentrate on specific spice varieties.
Table 2.3.1 highlights the accuracies reported by various authors in many research.

Table 2.3.1. Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Kaharuddin et al. [6]	K-Nearest Neighbor	KNN = 84% with K=5
2.	Maimunah et al. [7]	E-Nose=TGS2611, TGS813, and MQ136 sensors	86%
3.	Ms.Chhaya Narvekar and Dr.Madhuri Rao [8]	CNN and TL = VGG16, MobileNet2 and Resnet50	VGG16 = 95.39%

4.	Vijayakanthan et al. [9]	CNN	InceptionV3 = 99.8 %
5.	Dr K. Ponmozhi and Reny Jose [10]	Deep Learning	75%
6.	Sundaram et al. [11]	Transfer Learning	VGG =93.06%
7.	Jana et al. [12]	CNN	CNN=91.14%
8.	Rimi et al. [13]	ML= KNN, SVM, DT DL= CNN, VGG-16, Inception-v3, and ResNet-50	InceptionV3 = 98.6%
9.	Al-Amin et al. [14]	SVM	SVM = 65.03%
10.	Talukder et al. [15]	CNN	99.41%
11.	Pratondo et al. [16]	VGG19, Inception V3	InceptionV3 = 94.29%
12.	Gupta et al. [17]	ML= NB, DT, KNN, RF, SVM	SVM = 94.05%
13	Tempola et al. [18]	VGG16, Resnet50, DenseNet151, MobileNetV2, InceptionV3, and modified VGG16	modified VGG16= 99.11%
14	Tahir et al. [19]	Xception, MobileNetV2, DenseNet201, VGG16, VGG19, and ResNet50	Xception= 98.23%
15	Mufarroha et al. [20]	K-NN and Naive Bayes	KNN= 100% with K= 3
16	Naman et al. [21]	CNN, MobileNetV2	97.97%

2.4 Open Issues

Despite significant progress in the development of a spice classification system, several open issues remain. First, the variability in spice appearance due to different harvesting methods, storage conditions, and regional differences poses a challenge for model accuracy.

Additionally, the availability of high-quality, labeled datasets for training and validation is limited, which may affect the robustness of the model. The system's ability to adapt to new or less common spice varieties also needs further exploration. Moreover, the computational resources required for real-time classification in practical settings could be a limiting factor. Some issues here:

- Dataset Homogeneity: The limited and similar datasets used in most studies may impact the model's adaptability.
- Knowledge Gap and Identification Challenges: The scarcity of related studies in Bangladesh, and difficulty identifying spices.
- Data Cleaning Challenges: Some hand-taken photos using mobile devices have errors, inconsistencies, and blurriness.

Finally, ensuring the system's accessibility and usability for farmers and traders, particularly in rural areas with limited technological infrastructure, remains a critical concern. Addressing these issues is essential for the widespread adoption and effectiveness of the automated spice classification system. control.

2.5 Summary

Overall, studies in the field have demonstrated that Machine Learning and Deep Learning approaches can efficiently classify and identify spices and herbs. However, there are still many challenges, like the need for larger and more diverse datasets, revolutionary techniques for transfer learning, different pictures of spices for learning the machines, and improved integration of sensor technologies.

CHAPTER 3
Methodology

3.1 Overview

The study focuses on applying a robust method to categorize twenty distinct spices. The real-time analytical capabilities and computing efficiency of the TL technique make it the preferred method. For a more effective analysis, implemented a data preprocessing technique and model training for accurate spice classification. This effectiveness helps in obtaining a promising accuracy.

3.2 Proposed Methodology

To enhance the classification accuracy of food spices, the study titled "Popular Food Spices Classification of Bangladesh Using Transfer Learning Approach" employs advanced DL techniques. Specifically, the research explores the implementation of transfer learning, a method that leverages knowledge from pre-trained models, to enhance the precision and efficiency of classifying distinct food spices. This initiative is vital for addressing the demands of both culinary and agricultural sectors in Bangladesh, where spices play a significant role in cultural and economic aspects.

Traditional methods of spice classification methods are generally inaccurate and involve an extensive amount of physical effort. To address these challenges, the study proposes a novel approach by combining deep CNNs with TL. CNNs are renowned for their capacity to extract complex patterns from visual data, making them ideal for the complexities of spice classification tasks.

The study conducts an in-depth comparison analysis of established models, including MobileNetV2, InceptionV3, NASNetMobile, and ResNet50 chosen for their effectiveness in image classification tasks. Each model is extensively evaluated under a variety of variables, such as different picture resolutions and epoch settings, to identify the best configuration for spice classification in Bangladesh.

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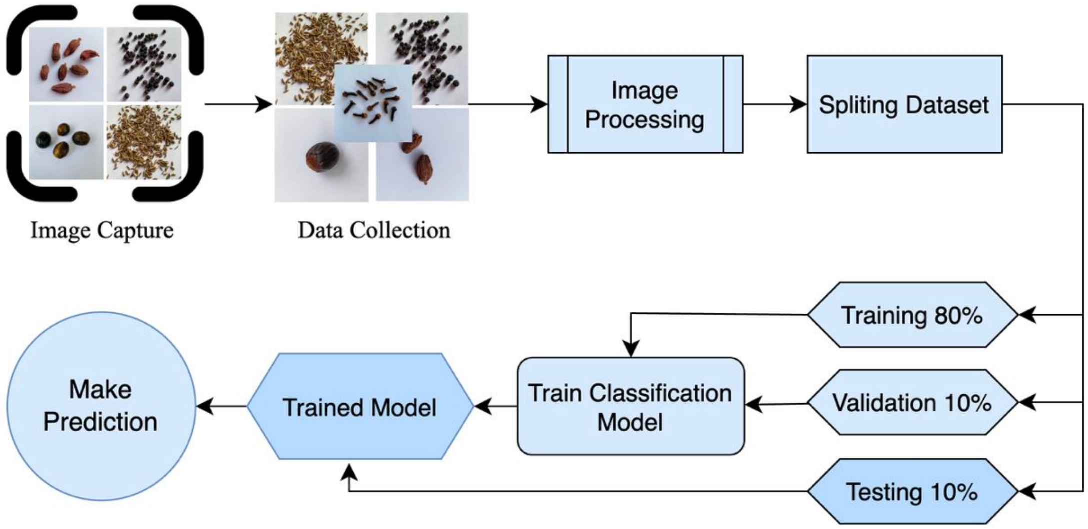

Figure 3.2.1: Proposed system architecture

Ultimately, this collaborative study incorporates AI, DL, and agricultural science to develop a robust system for classifying popular food spices in Bangladesh. The insights gained from this study are expected to change spice sorting processes, leading to improved spice management practices and heightened agricultural productivity in the region.

3.3 Hardware/Software Requirements

To achieve accurate spice classification, it's vital to meet specific hardware and software needs. These requirements ensure smooth model training and system operation.

Hardware Requirements:

- **High Computational capacity:** Model training requires a significant level of graphical processing power to effectively process complex tasks in deep learning and image analysis.
- **Graphics Processing Unit (GPU) Utilization:** Utilizing GPUs speeds up the the training process, making them the preferred option for managing complex models.
- **RAM Sufficiency:** Ensuring sufficient Random Access Memory (RAM) is required for managing datasets and model computing needs.

Software Requirements:

- **Coding Environment:** Google Colab serves as the primary platform for coding in this research.
- **Image Resizing Tool:** Visual Studio Code is utilized for local image resizing tasks.
- **Deep Learning Framework:** TensorFlow, a popular deep learning framework, is used to develop, train, and evaluate CNN models. These frameworks provide necessary libraries and tools to facilitate the development and optimization of deep learning models.

3.4 Project Management and Financial Analysis

Since many types of spices are being produced in our country, spices can be bought from different local markets. The project must be done to evaluate the research's financial components, such as budgeting, cost estimation, and financial predictions.

Table 3.4.1: Total estimated cost for spices classification

SN	Components	Estimated Cost (BDT)
01.	Purchasing 20 distinct categories of spices	2000
02.	Documentation	200
03.	Contingency	300
	Total Estimation Cost	**2500**

3.5 Summary

This study investigates the classification of popular food spices in Bangladesh using advanced AI techniques, focusing on transfer learning to enhance accuracy and efficiency. Traditional methods for spice identification are often error-prone and labor-intensive; this research leverages deep Convolutional Neural Networks (CNNs) for superior image analysis. It compares models like MobileNetV2, InceptionV3, NASNetMobile, and ResNet50 to determine the best configuration for spice classification. The study involves collecting and preprocessing high-resolution images of various spice categories. The findings aim to improve spice identification processes, benefiting quality control and the culinary industry in Bangladesh.

CHAPTER 4
Implementation

4.1 Overview

This study aims to revolutionize spice quality assessment in Bangladesh using advanced AI techniques focused on enhancing the classification of popular food spices. By leveraging transfer learning with MobileNetV2, InceptionV3, NASNetMobile, and ResNet50 models, the research addresses the critical need for accurate and efficient spice identification. A dataset of 10000 high-resolution images across 20 spice categories is meticulously processed to ensure data uniformity and clarity. Comprehensive evaluations using metrics such as accuracy, precision, recall, and F1 score provide robust insights into the models' performance, highlighting MobileNetV2 as the most efficient choice for spice classification.

4.2 Data Collection Procedure

A. Dataset Collection:

For working with the spice classification problem my first challenges were to make a better-quality dataset because there is very little classification of Bangladeshi spice varieties. A total of 20 distinct spice types are now being classified where each variety will have 500 images. The images of spice varieties Garlic, Ajwain, Ginger, Green Cardamom, Mustard, Nutmeg, Red Chilli, Star Anise, Bay leaf, Black Cardamom, Clove, Black Pepper, Celery, Cloves, Coriander, Fennel, Fenugreek, Mace, Plum, Poppy and White Pepper were collected physically through smartphones to create the dataset. The varieties of spices have been collected from the specific local market where different types of spices are available. The images were captured by two devices: the iPhone 11, which has a 12-megapixel camera with a resolution of 3024*4032 pixels, and the Realme 8, which has a 64-megapixel camera and a resolution of 3468*4624. The photographs were taken in sufficient daylight and were placed on a white background before being captured. This decision generates a clean and uncluttered visual composition, making the subject stand out prominently.

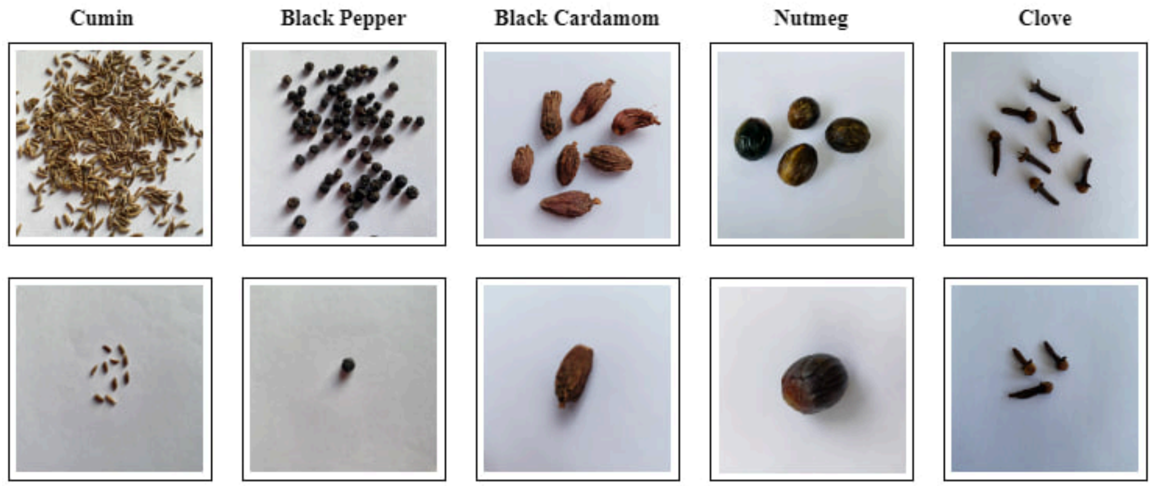

Figure 4.2.1: Dataset sample

B. Dataset Pre-processing:

Following the completion of data collection, the analysis phase began, employing the following techniques. Firstly, blurry, inconsistent, or erroneous images were manually removed, producing the standard dataset of 10,000 photos (20 unique spice categories with 500 images for each spice type). To address the issue of high computation time and efficiency caused by high-resolution photos from mobile devices, a rescaling method was implemented. This approach normalized the pixel values within the same ranges without altering the dimensions or shapes of the pictures. Subsequently, the preprocessed images were resized to a resolution of 300 x 300 pixels. This resizing kept the essential features required for accurate classification while also optimizing the images for faster and more efficient processing by deep learning models. These preprocessing techniques ensured high-quality input data and improved computational efficiency, which was essential to preparing the dataset for efficient model training and evaluation.

Table 4.2.1. Number of totals Raw Data and Pre-processing Data.

Raw Dataset	**After Cleaning and Pre-processing Dataset**
11,500	10,000

C. Dataset Splitting:

After preprocessing, each spice variety needs to be stored in a Google Drive folder to access the data via Google Colab. To comprehensively evaluate the model's performance, the dataset was divided into three distinct sets: training, testing, and validation. In this study, 10% of the images were allocated for testing, another 10% for validation, and the remaining 80% for model training.

Table 4.2.2. Split Dataset.

Total	Training (80%)	Validation (10%)	Testing (10%)
10,000	8000	1000	1000

4.3 Train Model

The proposed methodology involves several key steps to classify popular food spice varieties using a transfer learning approach. In the beginning, preprocessing techniques such as image resizing and noise reduction are applied to standardize the input images and improve their quality. The next step is to employ transfer learning by implementing pre-trained models such as MobileNetV2, InceptionV3, NASNetMobile, and ResNet50.Then the Features extracted from these models are used to train a classification model that accurately identifies different spice varieties. Following the training phase, each transfer learning model's performance is evaluated to determine the best one for spice classification based on accuracy. This approach ensures precise and efficient classification of spice varieties by utilizing the strengths of advanced pre-trained models. By comparing the performance metrics such as precision, recall, and F1-score, the most suitable model for spice classification is selected, ensuring optimal outcomes for practical applications.

InceptionV3:

InceptionV3 is a CNN known for its efficiency and accuracy in image analysis and object indentification. It emerged into the third edition of Google's Inception CNN, initially introduced during the ImageNet Recognition Challenge [22]. The architecture of InceptionV3 is characterized by a sequence of convolutional, pooling, and inception modules. These inception modules, comprising layered blocks, allow the network to identify features across various scales and resolutions, facilitated by the employment of filters of differing sizes [23]. It has displayed remarkable proficiency across a spectrum of computer vision tasks, including image classification, object identification, and visual question answering. Its adaptability renders it a popular choice as a foundational model for transfer learning approaches. Pre-trained weights are typically fine-tuned on new datasets, augmenting performance modified to specific tasks [24].

NASNetMobile:

NASNetMobile, introduced by Google Brain in 2018, stands as a revolutionary CNN architecture. Leveraging Neural Architecture Search (NAS), NASNetMobile achieves a remarkable balance between computational efficiency and performance [25]. The architecture of NASNetMobile incorporates a series of operational blocks, such as identity mappings, diverse convolutions, and pooling operations. These elements are combined to form cells, the foundational units of the NASNet architecture. While normal cells maintain the feature map's size, reduction cells decrease its dimensions [26]. With a modest parameter count of 5,326,716, NASNetMobile demonstrates exceptional parameter efficiency, which is significant in resource-constrained systems. Its parameter efficiency and adaptability make it an excellent choice for researchers and developers seeking robust solutions for object identification tasks. Also, Its versatility extends across several domains, including image recognition, object detection, and augmented reality applications [27].

ResNet50:

In 2015, ResNet50 developed by Microsoft Research, it is a pivotal CNN architecture comprising 50 layers and notable for its innovative use of residual connections. These connections enable the training of very deep networks by mitigating the vanishing gradient problem, resulting in more efficient optimization [28]. It is widely applied in computer vision tasks such as image classification, object detection, and image segmentation, specializes in capturing intricate features and patterns in visual data due to its depth and residual connections. Moreover, ResNet50's pre-trained weights are often used for transfer learning, allowing researchers and practitioners to obtain state-of-the-art results with minimal computational resources. Fine-tuning these weights on specific datasets improves performance for specialized tasks [29].

Overall, its initial appearance influenced the design of subsequent CNN architectures, inspiring researchers to explore deeper networks and novel architectural concepts [30].

Proposed Model: MobileNetV2

MobileNetV2 is a pre-trained image classification model featuring a 53-layer CNN architecture optimized for mobile devices. It has been trained on the ImageNet dataset, which includes over a million images, providing a robust foundation for a wide range of visual recognition tasks [31]. A key innovation of MobileNetV2 is its use of Depthwise Separable Convolutions (DSC), which significantly improves portability and computational efficiency while resolving the issue of information loss in convolutional layers. DSC minimizes the number of parameters and computational costs without sacrificing performance by decomposing standard convolutions into depthwise and pointwise convolutions. It also employs Linear Bottlenecks, which help mitigate information loss in non-linear layers. This approach ensures that the key features of the input data are preserved as they pass through the network [32]. Overall, the most notable feature of MobileNetV2 is the introduction of "Inverted Residuals." This novel structure helps maintain information integrity during the neural network's operations by preserving the input data in higher dimensions before projecting it to lower dimensions. This approach enhances the model's capacity to gather and retain vital information throughout the network [33].

I. Depthwise Separable Convolution:

Depthwise Separable Convolution (DSC) is a convolution method widely utilized in deep learning to improve computational efficiency in CNNs. This operation divides the convolution process into two independent stages:

- **Depthwise Convolution:** Each input channel is processed independently, allowing for the capture of spatial features.
- **Pointwise Convolution:** The results from the depthwise convolution are combined using a series of 1x1 convolutions to capture channel-wise features [34].

This two-step approach significantly decreases the number of parameters and computational complexity while maintaining the ability to capture both spatial and channel-wise information from the data.

II. Depthwise Separable Convolution:

Linear Bottlenecks are architectural elements in deep neural networks where linear layers are inserted into convolutional blocks. This approach is based on two key points:

- **Linear Transformation and ReLU Activation:** When a layer's output follows the ReLU activation function and remains non-zero, the input space is effectively restricted to a linear transformation. Within the active range, deep networks function similarly to linear classifiers. This suggests that the ReLU activation can effectively reduce the input space into a lower dimension, where a linear transformation is sufficient to maintain all necessary information [35].

- **Information Retention in Channels:** When ReLU deactivates a channel, all information in that channel is discarded. However, with many channels structured in a specific way, information can still be maintained in other active channels. This structured arrangement functions as a layer that reduces the input into a lower-dimensional space within the activation space [36].

Incorporating linear bottleneck layers in convolutional blocks improves efficiency by maintaining the network's ability to represent information effectively while reducing computational complexity. This approach ensures that crucial information is retained, optimizing the network's performance.

III. Inverted Residual:

Inverted residuals are similar to bottleneck blocks found in residual networks. Each block consists of an input, multiple bottleneck layers, and an expansion step. The key reasons for introducing shortcuts between these bottlenecks to assist gradient propagation through multiple layers are:

- Most essential information is contained within the bottlenecks.

- When considering tensor transformations, the expansion layer is more of a technical requirement than a core component.

However, this inverted architecture is significantly more memory efficient and performs slightly better performance, making it an effective choice for deep neural networks.

IV. Model Architecture:

The key component of my model is the bottleneck depthwise separable convolution with residuals, forming the foundational structure. In this study, utilize MobileNetV2 as the primary architecture, augmenting it with additional layers tailored for specific classification tasks. MobileNetV2 processes RGB images at a resolution of 300 × 300. The model architecture originates by expanding the input's compact low-dimensional representation into higher dimensions. This is followed by an efficient processing phase that employs lightweight depthwise convolutions. Subsequently, a linear convolution is applied to project these features back into a more compact form. This structural method effectively preserves information, overcomes the limits of MobileNetV1's fixed number of filters, and keeps the block lightweight, assuring efficiency and performance.

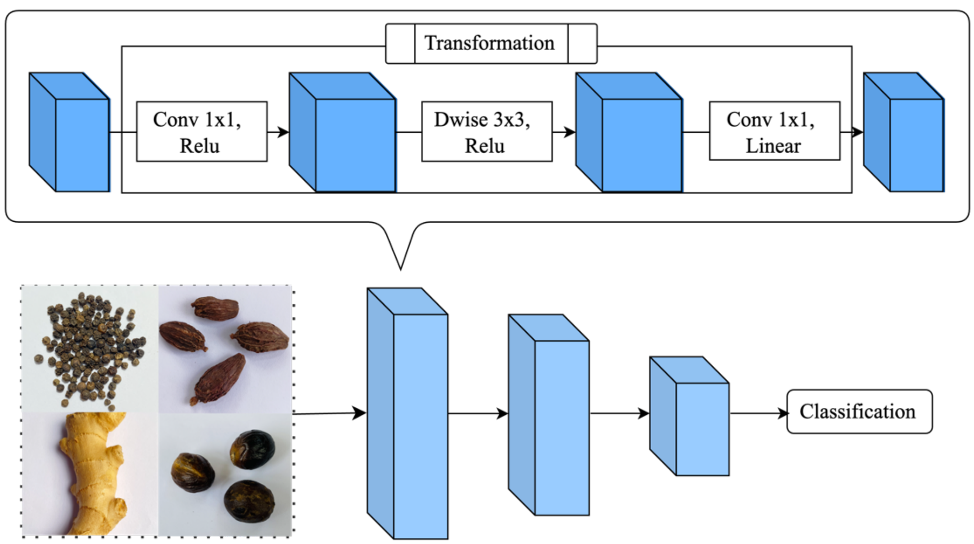

Figure 4.3.1: Architecture of MobileNetV2.

4.4 Model Evaluation

In analyzing the performance of spice classification models, several key metrics are considered to gain valuable insights into their effectiveness. These metrics include the confusion matrix, accuracy, precision, recall, and F1 score.

Confusion Matrix: The confusion matrix provides a detailed breakdown of model predictions, distinguishing between true positives (correctly identified spice categories), true negatives (accurately identified non-spice categories), false positives (incorrectly identified as spice categories), and false negatives (missed spice categories).

Accuracy: Accuracy represents the percentage of correctly classified spice categories out of all instances. It serves as a fundamental indicator for evaluating the overall performance of the classification models.

Precision: Precision is the proportion of accurately identified spice categories compared to all predicted spice categories. It demonstrates the model's ability to prevent false positive predictions.

Recall: Recall is defined as the proportion of successfully detected spice categories divided by the total number of spice categories in the dataset. It evaluates the model's ability to identify all relevant spice categories without missing any.

F1-Score: The F1 score, which is the harmonic mean of precision and recall, provides an accurate evaluation of the model's performance by considering both false positive and false negative results.

Additionally, the accuracy and loss curves provide insight into the models' training process. The accuracy curve shows the training and validation accuracy over epochs, whereas the loss curve shows the training and validation loss. These curves provide significant details about the model's learning process, emphasizing possible problems like overfitting or underfitting.

The statistical analysis provides important insight into the efficacy of TL and deep CNNs in spice categorization, quantitatively validating the experimental results. These findings provide a good foundation for expanding the performance of different categorization algorithms to a wider range of spice images. Besides, statistical accuracy ensures objective evaluation and enhances the validity of decisions about the effectiveness of spice classification models.

4.5 Summary

In summary, this research showcases the effectiveness of transfer learning for improving spice classification accuracy. Among the models tested, MobileNetV2 stands out as the optimal choice, balancing computational efficiency with high classification performance. Detailed statistical analyses, including confusion matrices and accuracy curves, shed light on model behavior and validate its potential for practical applications in spice quality control. This study highlights the critical role of advanced AI techniques in addressing challenges within the spice industry, ultimately contributing to improved quality control and the preservation of Bangladesh's rich culinary heritage.

CHAPTER 5
Result and Analysis

5.1 Overview

This chapter delves into optimizing spice classification using advanced deep learning techniques to benefit agricultural practices in Bangladesh. It outlines the experimental setup and evaluation criteria for three transfer learning models—MobileNetV2, InceptionV3, NASNetMobile, and ResNet50—based on their performance and computational efficiency. The experiments were conducted with images at 300x300 pixels resolution across 20 spice categories, trained over 100 epochs to identify the model that strikes the best balance between accuracy and efficiency. The study aims to provide a robust solution for practical spice classification applications in agricultural settings.

5.2 Experimental Result

Three different deep learning models, namely MobileNetV2, InceptionV3, NASNetMobile, and ResNet50, are implemented to evaluate their performance in accurately classifying spices. Each model is trained separately using transfer learning techniques on a custom dataset constructed for spice classification. This approach ensures faster model training while maintaining high accuracy levels.

Table 5.2.1. Accuracy Of Testing and Loss.

Model	Testing Accuracy	Testing Loss
ResNet50	92.60 %	31.34%
NASNetMobile	99.10 %	2.87%
InceptionV3	99.50 %	1.30%
MobileNetV2	99.70 %	0.60%

Among the employed models, MobileNetV2 outperforms the others, achieving an impressive accuracy rate of 99.70% on the custom dataset. Notably, MobileNetV2 exhibits minimal loss compared to its competitors, indicating superior predictive capabilities. The exceptional performance of MobileNetV2 can be attributed to its compact, low-latency, and low-power models design, which make it ideal for well-suited for resource-constrained environments. The success of MobileNetV2 demonstrates its versatility and adaptability in meeting the specific requirements and limits of spice categorization activities. MobileNetV2's improved design displays its efficiency in achieving high accuracy rates while minimizing computational overhead.

Then, the classification report is a popular tool for evaluating the performance of a classification model. It gives a comprehensive overview of the metrics used to evaluate the model's ability to categorize data accurately. The classification reports include key metrics including accuracy, recall, F1-score, and support, which provide useful insights into the model's performance. Higher accuracy and recall values are preferred since they indicate the model's precision and capacity to accurately identify a significant fraction of examples in each category. Table 4.2.2 contains the classification report for each species for the MobileNetV2.

Table 5.2.2. Classification Reports on Each Species.

MobileNetV2				
Species	**Precision**	**Recall**	**F1-Score**	**Support**
Ajwain	0.96	0.98	0.97	49
Bay leaf	1.00	1.00	1.00	61
Black Cardamom	1.00	1.00	1.00	46
Black Pepper	1.00	1.00	1.00	49
Celery	0.97	0.94	0.96	34
Cloves	1.00	1.00	1.00	43
Coriander	1.00	1.00	1.00	39

Fennel	1.00	1.00	1.00	56
Fenugreek	1.00	1.00	1.00	45
Garlic	1.00	1.00	1.00	55
Ginger	1.00	1.00	1.00	49
Green Cardamom	1.00	1.00	1.00	51
Mace	1.00	1.00	1.00	61
Mustard	1.00	1.00	1.00	52
Nutmeg	1.00	1.00	1.00	52
Plum	1.00	1.00	1.00	43
Poppy	1.00	1.00	1.00	62
Red Chilli	1.00	1.00	1.00	47
Star Anise	1.00	1.00	1.00	54
White Pepper	1.00	1.00	1.00	52

Throughout all categories, the suggested model consistently achieves precision, recall, and F1-Score values exceeding 0.93. These performance metrics represent an outstanding level of accuracy and effectiveness in classifying the various species being evaluated.

Moving on to Training and Validation accuracy, these metrics serve as fundamental for evaluating the model's effectiveness. The training accuracy evaluates the model's performance on the training dataset, indicating its learning progress, whereas the validation accuracy measures how effectively the model generalizes to new, unknown data. In addition to accuracy, both training and validation loss functions are computed during the training process. The training loss represents the difference between the model's predictions and the actual target values in the training dataset, while the validation loss evaluates the model's performance on unknown data from the validation dataset. These metrics together give insight into the model's learning processes and its ability to generate correct predictions on new data.

The proposed model MobileNetV2 were initially performed into 54 epochs. This model performed exceptionally outstanding, particularly at the 300x300 resolution, compared to other models with an impressive accuracy of 99.70%. This early peak in performance is remarkable, suggesting that MobileNetV2 requires less computational power and less time to get excellent results. Fig. 4.2.1 shows that most prominent accuracy for the suggested model was achieved at epoch 20.

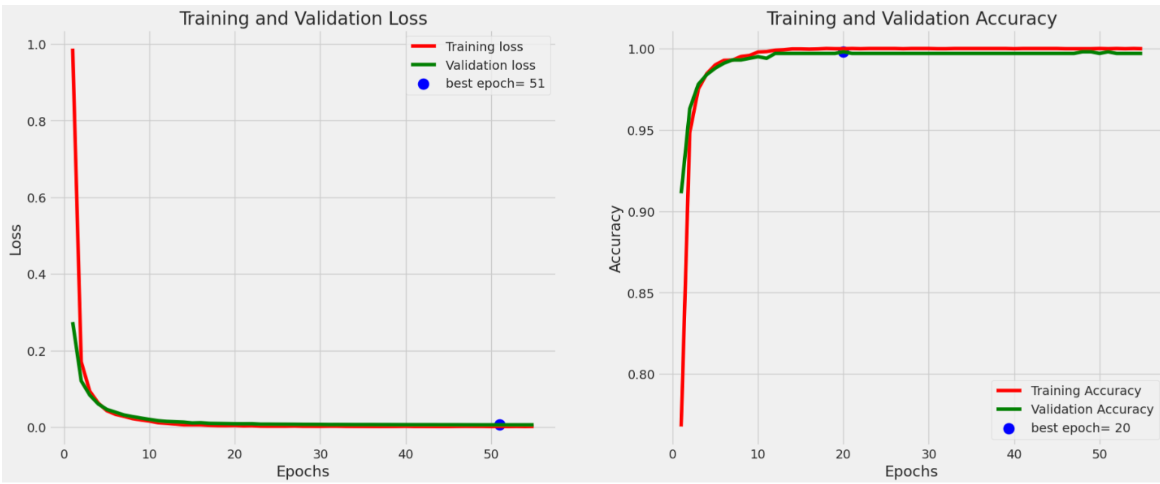

Figure 5.2.1: Training and validation loss and accuracy curve (MobileNetV2)

InceptionV3 also showed strong performance in my custom dataset, the accuracy close to MobileNetV2. At a resolution of 300x300, it achieved an impressive accuracy of 99.50%. Notably, the model achieved this accuracy level by epoch 15, highlighting its efficacy and effectiveness in spices classifying tasks.

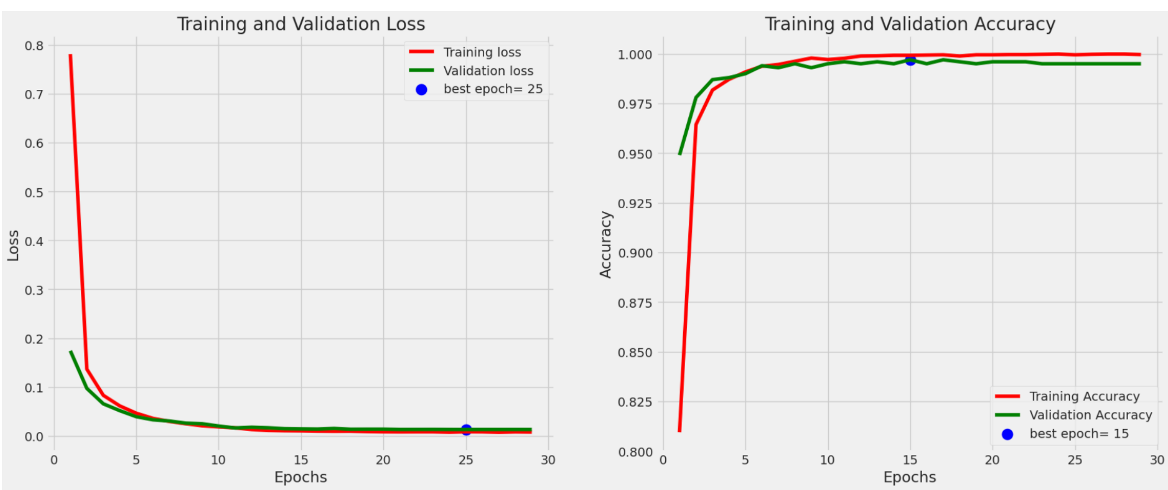

Figure 5.2.2: Training and validation loss and accuracy curve (InceptionV3)

When compared to MobileNetV2 and InceptionV3, NASNetMobile performs slightly lower accuracy. However, at the same image resolution, NASNetMobile achieves exceptional performance. Specifically, it reaches a top accuracy of 99.10% during training and validation at epoch 16. Figure 4.2.3 shows the training and validation accuracy and loss accuracy of NASNetMobile.

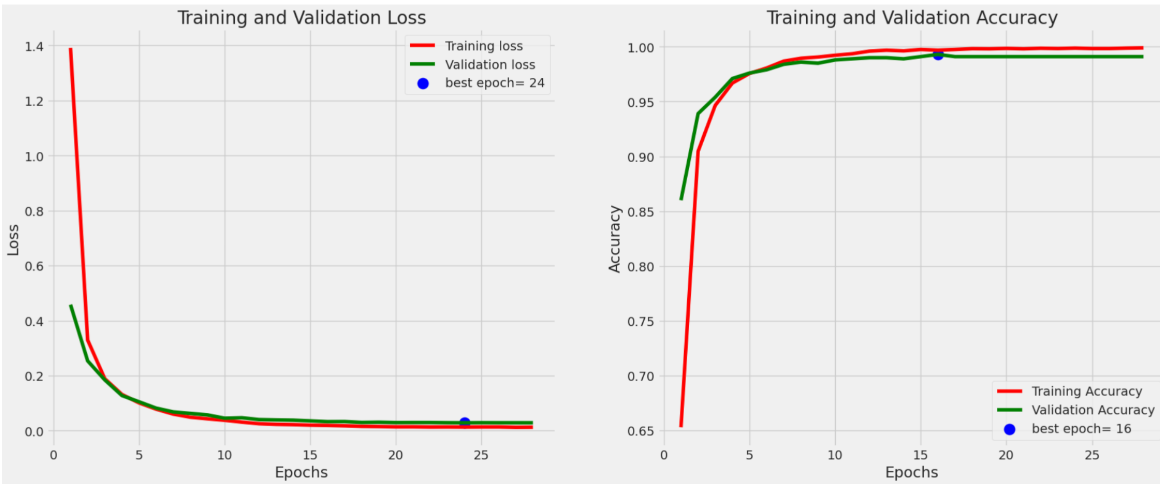

Figure 5.2.3: Training and validation loss and accuracy curve (NASNetMobile)

ResNet50, among the other three models (MobileNetV2, InceptionV3, and NASNetMobile), holds the lowest accuracy. However, across 100 epochs at 300x300 resolution, it performs consistently. Epoch 29 is the best epoch for ResNet50, since it reaches its top in both training and validation accuracy, while epoch 33 is for training and validation loss. Despite having a lesser accuracy than other models, ResNet50 still can identify spices with an accuracy of 92.60%.

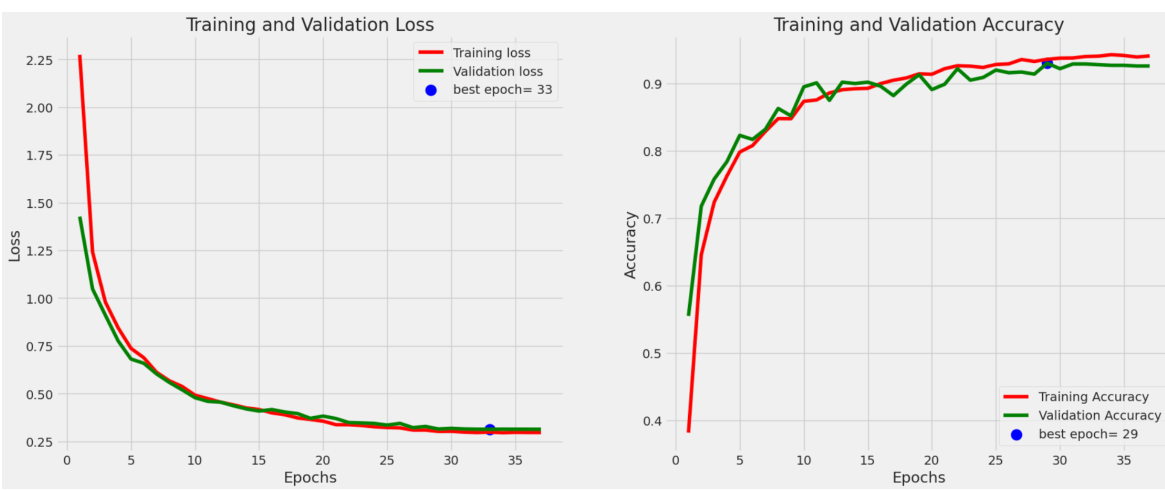

Figure 5.2.4: Training and validation loss and accuracy curve (ResNet50)

After comparing the training and validation accuracy and loss curves of all models, it is clear that MobileNetV2 outperforms the others significantly. It not only provides the highest accuracy but also the best computational efficiency and overall performance. This result emphasizes MobileNetV2's effectiveness and practicality for spice classification tasks, as well as its appropriateness for real-world applications whereas both accuracy and efficiency are essential.

A confusion matrix is a common tool for evaluating a classifier's performance by comparing actual and predicted classifications for each class. It shows the number of true positives, true negatives, false positives, and false negatives for each class. In this study, MobileNetV2's confusion matrix, Figure 4.2.5 highlights classification errors for Ajwain and Celery, while other categories are correctly identified. The accuracy metric calculates the percentage of correctly classified values.

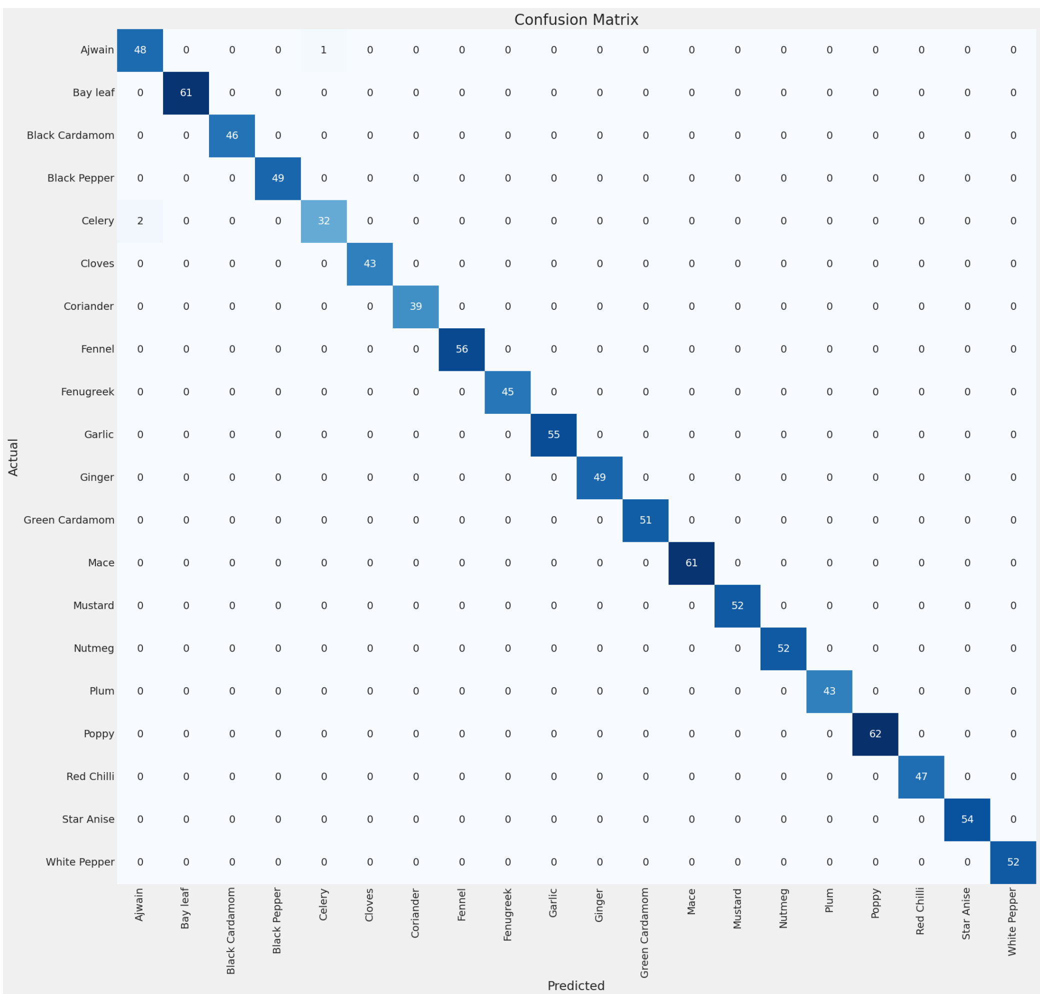

Figure 5.2.5: Confusion Matrices

5.3 Comparative Analysis

The accuracy comparison among the four models reveals significant differences in their performance for spice classification. MobileNetV2 is the top performer with an accuracy of 99.70%, indicating its high effectiveness and efficiency for this task. InceptionV3 closely follows with 99.50%, showing robust performance, though slightly less effective than MobileNetV2. NASNetMobile achieves 99.10%, still demonstrating high proficiency in classifying spice images. However, ResNet50 has a noticeably lower accuracy of 92.60%, indicating more difficulty with the dataset compared to the other models.

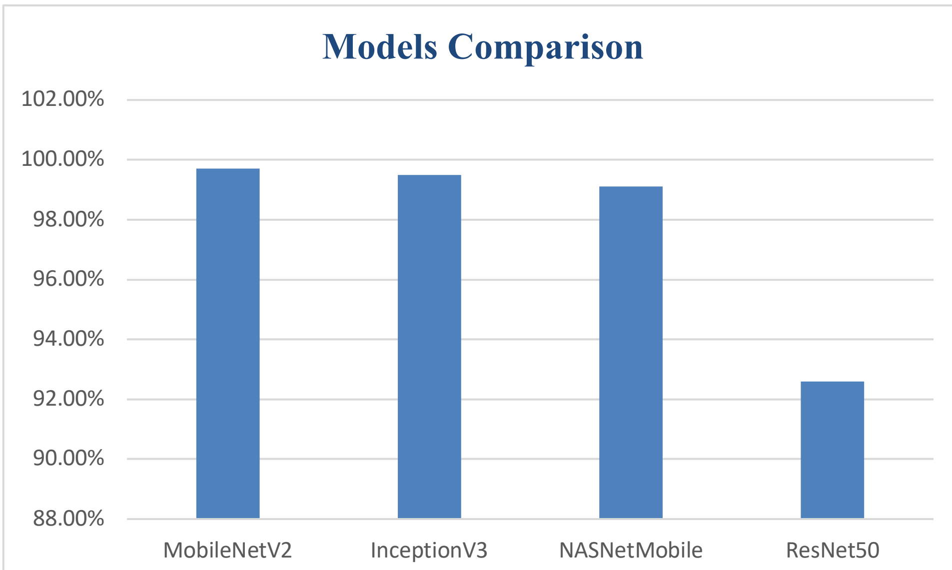

Figure 5.3. 1: Accuracy comparison among individual models.

This comparison highlights the varying levels of computational efficiency and performance across the models. MobileNetV2's superior performance underscores its capability in handling image classification tasks with high precision. Overall, MobileNetV2 stands out as the best choice for spice classification, followed by InceptionV3 and NASNetMobile, while ResNet50 shows the least effectiveness.

5.4 Summary

In summary, MobileNetV2 has proven to be the top-performing model for spice classification, surpassing InceptionV3 and NASNetMobile. Trained with images at 300x300 pixels resolution over 100 epochs, MobileNetV2 achieved an impressive accuracy of 99.50% and minimal loss of 1.57%. Its success can be attributed to its efficient architecture and computational speed, making it well-suited for real-time applications in agriculture. Comprehensive analyses, including classification reports and confusion matrices, consistently demonstrated high precision, recall, and F1 scores across all spice categories, reinforcing MobileNetV2's effectiveness for practical spice classification tasks.

CHAPTER 6
Impact on Society, Environment and Sustainability

6.1 Impact on Life

The application of image processing-based transfer learning for spice classification in Bangladesh has brought about substantial improvements in the lives of farmers and communities. By offering accurate and dependable tools for spice identification, this technology enhances agricultural efficiency, leading to increased crop yields and improved food security. Farmers experience higher incomes through enhanced spice quality, which contributes to poverty alleviation and economic stability in rural areas. Furthermore, democratizing agricultural knowledge via accessible technology empowers diverse demographics, including younger generations and urban residents interested in agriculture, thereby nurturing a more inclusive and informed farming community.

6.2 Impact on Society, Environment

The implementation of the "Popular Food Spices Classification of Bangladesh Using Transfer Learning Approach" has significant implications for various sectors of society. This study intends to improve the accuracy and efficiency of spice classification employing advance technologies, including DL and TL, which can lead to massive social advantages.

Primarily, automating the spice classification process with DL techniques can greatly benefit to the agricultural sector. Farmers can apply this technology to assure the purity and quality of their spice production, leading to higher market prices and income. TL models provide accurate categorization, helping in the detection of adulteration and ensures that consumers collect authentic, high-quality spices. Secondly, this technology can improve food safety and quality control in the food industry. By using an automated system based on TL to identify and classify spices, food suppliers can maintain higher hygiene and quality standards, reducing the risk of harm, and increasing consumer trust and satisfaction.

Furthermore, the transfer learning approach in this study can be applied to other agricultural products. This can help develop similar systems to classify fruits, vegetables, and other crops, enhancing agricultural productivity and sustainability through deep learning. In addition to economic benefits, this project has educational implications. Integrating advanced AI, DL, and TL into agriculture can educate and train future farmers, researchers, and technologists. This helps fill the gap between traditional farming methods and modern technology, creating a more skilled and knowledgeable workforce.

Moreover, this study can contribute to environmental sustainability. Applying this system, optimize resource use, minimize waste, and reduce chemical interventions by accurately identifying high-quality spice varieties. This encourages sustainable farming techniques while reducing the environmental effect of spice growing. On a broader scale, the success of this study can boost Bangladesh's reputation in agricultural innovation. By adopting advanced technologies like TL and DL, Bangladesh can lead other developing nations in using AI to transform traditional industries and drive economic growth. This research can improve health and well-being. Access to pure, high-quality spices ensured by advanced classification technology can improve dietary habits. Since spices enhance the flavor and nutritional value of food, this can contribute to better overall health outcomes for the population.

The integration of advanced techniques like deep learning and transfer learning in spice classification provides promising opportunities for environmental sustainability in agriculture. By allowing for precise identification of spice types and focused control of pests, these technologies reduce the need for chemical pesticides and herbicides, reducing chemical pollution and protecting soil and water quality.

Likewise, the implementation of precise farming practices produced feasible by these innovations improves resource efficiency by optimizing the use of water, fertilizers, and other agricultural inputs. Efforts to optimize computational processes further mitigate energy consumption, contributing to environmental conservation. Sustainable agriculture strategies supported by modern technical applications boost soil health and biodiversity preservation. Accurate spice classification allows farmers to engage in growing practices that promote robust agricultural ecosystems, highlighting the necessity of biodiversity conservation for long-term environmental stability.

In summary, using the spice classification technique not only increases agricultural productivity but also contributes significantly to environmental sustainability by reducing usage of chemicals, expanding resource efficiency, and promoting biodiversity conservation.

6.3 Ethical Aspects

Ethical considerations are essential in ensuring fairness, transparency, and responsible technology deployment. Data privacy is protected by strict rules, which provide the confidentiality of the images and related information. Bias mitigation strategies are implemented to prevent unintended discrimination, necessitating the use of diverse and representative datasets for model training. Transparency is valued throughout the study process, including detailed documentation of data collection, model development, and evaluation processes. Moreover, ethical implementation of AI in agriculture requires ensuring that the technology facilitates all farmers, particularly small-scale farmers, while not increasing existing gaps or dependency. Environmental concerns are also integrated into ethical decision-making, which aligns technological breakthroughs with sustainable agriculture methods. This includes supporting eco-friendly farming methods and minimizing the environmental impact of technological advancements. In summary, the ethical framework that guides the study prioritizes data privacy, bias reduction, transparency, equity, diversity, and environmental sustainability. These principles underscore the responsible application of advanced technologies in agriculture, ensuring positive societal impacts while upholding ethical standards.

6.4 Sustainability Plan

The approach to sustainability for the research on "Popular Food Spices Classification of Bangladesh Using Transfer Learning Approach" aims to minimize environmental effect while maximizing societal benefits. The focus will be on improving computational processes to reduce energy usage during model training and deployment. Additionally, eco-friendly data management and storage procedures will be prioritized to reduce the carbon influence. Continuous evaluation and adaption of sustainable methods will ensure ethical and environmentally conscious scientific innovation, combining technical advancement with environmental conservation, and encouraging long-term sustainability in agricultural activities.

6.5 Summary

This study has profoundly impacted various aspects of agriculture in Bangladesh. By enhancing the efficiency of spice classification, it leads to higher crop yields and better food security. The technology democratizes agricultural knowledge, empowering farmers and fostering sustainable practices, thus contributing to economic stability and poverty reduction in rural areas. Environmentally, the project promotes the use of high-quality spices and minimizes the need for chemical inputs, supporting biodiversity and sustainability. Ethical considerations ensure transparency and respect for all participants, while a comprehensive sustainability plan ensures long-term viability through collaboration, innovation, and responsible resource management. Overall, this study sets the stage for a more inclusive, knowledgeable, and sustainable agricultural future in Bangladesh.

CHAPTER 7
Conclusion and Future Work

7.1 Conclusion

Accurate classification of food spices is crucial for applications in quality control and culinary practices. This study evaluated the performance of D-CNN for the task of spice classification and employed four pre-trained models—MobileNetV2, InceptionV3, NASNetMobile, and ResNet50. Among these models, MobileNetV2 outperformed all of the other models, demonstrating its ability to accurately categorize distinct spices.

Transfer learning played a pivotal role in enhancing the classification accuracy of MobileNetV2. Leveraging pre-existing knowledge from extensive datasets, the model displayed robust performance, even in the face of the diverse and complex nature of spice images. While InceptionV3, NASNetMobile, and ResNet50 also performed commendable performance, MobileNetV2 stood out as the optimal choice due to its balance of accuracy and computational efficiency. The results highlight the future potential of proficient AI approaches, including MobileNetV2, in spice categorization. Moving into the future, more research into preprocessing approaches and ensemble methods may improve classification accuracy and adaptability.

Overall, this study provides valuable insights into the application of deep learning models for spice classification, establishing the way for more efficient and accurate systems in a variety of culinary and agricultural sectors.

7.2 Future Suggested Works

The study of spice classification using deep learning models presents promising possibilities for future research. One significant implication is the exploration of novel preprocessing techniques to enhance classification accuracy. Techniques such as image normalization and augmentation could be explored to optimize model performance and robustness, especially in handling variations in spice images. Additionally, the use of ensemble learning methods benefits further exploration. While MobileNetV2 emerged as the top performer in this study, the potential for ensemble techniques involving multiple models, such as MobileNetV2, InceptionV3, NASNetMobile, and ResNet50, could lead to even higher classification accuracy. Future research could focus into optimizing ensemble configurations and training methods to maximize classification performance.

Moreover, there is a need to broaden the field of research by exploring diverse spice datasets and real-world applications. Understanding spice classification in different culinary environments or agricultural sectors could provide valuable insights into model generalization and applicability. Besides, studying the integration of domain-specific knowledge, such as spice characteristics and usage habits, could further enhance classification accuracy and relevance. In conclusion, future research in spice classification

should focus on improving preprocessing approaches, investigating advanced ensemble methods, and expanding the research scope by incorporating different datasets and real-world applications. These fields of study have the opportunity to progress the field of spice classification and contribute to more accurate and efficient systems in the culinary and agricultural sectors.

7.3 Limitations

This research has several key limitations. Firstly, while the dataset includes 10,000 images across 20 spice categories, it may not fully represent the diversity and variability found in real-world conditions, potentially limiting the model's generalization capabilities. Additionally, the study's focus on four specific pre-trained models—MobileNetV2, InceptionV3, NASNetMobile, and ResNet50—restricts the exploration of other potentially effective deep learning architectures that might offer different trade-offs between accuracy and computational efficiency. The controlled environment of capturing images on a white background does not account for the variability of real-world conditions, which might impact the model's performance when deployed in practical settings. Moreover, the exclusive use of pre-trained models prevents the investigation of custom-built architectures that could be specifically tailored to the unique challenges of spice classification. To address these limitations, future work could involve expanding the dataset to include images taken under diverse environmental conditions, exploring a broader range of model architectures, and optimizing the models for deployment on devices with limited computational resources.

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Appendix A

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

Title: Popular Food Spices Classification of Bangladesh Using Transfer Learning Approach.

Student ID: 201-15-13882

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **food spices classification** 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 these 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, and CO3	Collecting datasets from the local market by own and must know the design of Transfer Learning models which covers **K3 and K4**.	**Page no:** [16-17] **Section:** [4.2]
				I need to combine several components, also design graphical representations and architecture. As well as, Model training is required for the project that covers **K5 and K6**.	**Page no:** [13,17] **Section:** [3.2, 4.2] **Page no:** [22] **Section:**

					[4.3 (IV)] **Page no:** [31] **Section:** [5.3]
				I studied previous research with the same purpose that cover **K8**.	**Page no:** [6-10] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	In my project, collecting data was a bit difficult due to the country's limited spice production. Also, faces a lack of existing research and Insufficient datasets.	**Page no:** [11] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO3	It's an in-depth analysis with multiple solutions. This study meticulously evaluates multiple methods, highlighting Transfer Learning models as the most effective approach due to their superior accuracy and performance in improving food spices classification and choosing the best model among them.	**Page no:** [25-31] **Section:** [5.2,5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO3	Working with spice classification I have done many related studies such as how to produce and collect large varieties. Finally, I am discovering this domain by gathering knowledge.	**Page no:** [6-9] **Section:** [2.2]

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	CO3	I will solve some minor problems to run my suggested models like data collection, pre-processing, and data splitting.	**Page no:** [12-18] **Section:** [3.2, 4.2]

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	This research uses various resources including labeled spice datasets, powerful computing infrastructure, GPUs for quick processing, and DL models. These resources enable systematic study and advancements in accurately classifying popular Bangladeshi food spices using TL methods, with a significant focus on research ethics.	**Page no:** [13-14] **Section:** [3.3]

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 study contributes to society by enhancing cultural preservation through accurate classification of popular food spices in Bangladesh. It also supports environmental sustainability by optimizing computational resources and adhering to ethical guidelines in data usage and model development.	**Page no:** [33-36] **Section:** [5.1-5.6]
5.	**EA-5: Familiarity**	Yes		This project focused on many related studies by exploring novel methods in species classification. Through detailed comparative analyses and experimentation, it aims to provide new insights and advancements in accurately identifying and categorizing popular food spices of Bangladesh.	**Page no:** [6-10] **Section:** [2.1-2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	By implementing effective project management and financial oversight for my FYDP, I calculated a budget to estimate the necessary costs.	**Page no:** [14] **Section:** [3.4]
2	CO9	Yes	This study maintains ethical standards by ensuring the confidentiality of data, obtaining informed consent, and transparently documenting all research procedures. These practices support responsible knowledge sharing and contribute positively to society through the ethical use of advanced technologies in food spices classification.	**Page no:** [35] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	This research enables constant learning and adaptation by meticulously collecting data, conducting detailed statistical analysis, optimizing methodology, and precisely analyzing experimental results. These efforts demonstrate a commitment to learning and improving techniques to tackle challenges in food spice classification through advanced research methods.	**Page no:** [16-24, 25-30] **Section:** [4.2-4.5, 5.2]

Appendix B

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POPULAR FOOD SPICES CLASSIFICATION OF BANGLADESH USING TRANSFER LEARNING APPROACH

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