A Computer Vision and deep CNN Modeling for Spices Recognition

BY

Md. Maruf Hasan Talukder

ID: 191-15-12538

And

Tania Aktar Ria

ID: 191-15-12589

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

Supervised By

Dr. Fizar Ahmed
Associate Professor
Department of CSE
Daffodil International University

Co-Supervised By

Raja Tariqul Hasan Tusher
Assistant Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

26 JANUARY 2023

APPROVAL

This Project/internship titled **"A Computer Vision and deep CNN Modeling for Spices Recognition"**, submitted by Md. Maruf Hasan Talukder, ID No: 191-15-12538, and Tania Aktar Ria, ID No: 191-15-12589 to the Department of Computer Science and Engineering, Daffodil International University have been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 26 *January 2023*.

BOARD OF EXAMINERS

Chairman

____
Dr. Touhid Bhuiyan
Professor and Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

____
Sazzadur Ahmed
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner

____
Ms. Sharmin Akter
Senior Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

External Examiner

26.1.2023
____
Dr. Ahmed Wasif Reza
Associate Professor
Department of Computer Science and Engineering
East West University

DECLARATION

We hereby declare that this thesis has been done by us under the supervision of **Dr. Fizar Ahmed**, the Associate Professor, Department of CSE, and co-supervision of **Raja Tariqul Hasan Tusher**, Assistant Professor, and **Department of CSE** Daffodil International University. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Dr. Fizar Ahmed

Associate Professor
Department of CSE
Daffodil International University

Co-Supervised by:

Raja Tariqul Hasan Tusher

Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Md. Maruf Hasan Talukder

ID: 191-15-12538

Department of CSE
Daffodil International University

Ria

Tania Aktar Ria

ID: 191-15-12589

Department of CSE
Daffodil International University

ACKNOWLEDGMENT

First of all, we want to render our gratitude to the Almighty Allah for the enormous blessing that makes us able to complete the final thesis successfully.

We are really grateful and express our earnest indebtedness to **Dr. Fizar Ahmed**, the **Associate Professor**, Department of CSE Daffodil International University, Dhaka, Bangladesh. The Profound Knowledge & intense interest of our supervisor in the field of “Machine Learning & Deep Learning” made our way very smooth to carry out this thesis. Her remarkable patience and dedication, scholarly guidance, continual encouragement, vigorous motivation, direct and fair supervision, constructive criticism, valuable advice, and great endurance during reading many inferior drafts and correcting the work to make it unique pave the way for work very smoothly and ended with a great result.

We would like to express our gratitude wholeheartedly to **Prof. Dr. Touhid Bhuiyan**, Professor, and Head, Department of CSE, for his kind help to finish our thesis and also to other faculty members and the staff of the CSE department of Daffodil International University.

We would like to express thankfulness to fellow students of Daffodil International University, who took part in this discussion during the completion of this work. We would also like to thank the people who provide the done by us to collect the market real information.

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

ABSTRACT

In the countries of South Asia, there is a significant appetite for the consumption of spices. Each type of spice offers a distinctive flavor, aroma, and quality. People are unable to identify spices and do not make effective use of them, which leads to a loss of the benefits associated with certain spices and a waste of our time. Therefore, the identification of spices is necessary for the use of appropriate spices. In the context of this study, the model that we have proposed is capable of accurately detecting spices by utilizing computer vision and neural networks (CNNs) with the assistance of photographs. Within our dataset, we have 8377 photos that can be used to train our computer. We were able to achieve some fantastic results with the strategy, and despite the lack of test data and evaluation outcomes, we decided to go with the model that had the highest level of success. It achieved an accuracy of 99% using the model M1.

TABLE OF CONTENTS

CONTENTS	PAGE

Acknowledgment	iv
Abstract	v
List of Figure	vii
List of Table	ix
CHAPTER	
CHAPTER 1: INTRODUCTION	**PAGE NO.**
	1-3
1.1 Introduction	1
1.2 Motivation	2
1.3 Research Questions	2
1.4 Expected Outcome	2
1.5 Report Layout	3
CHAPTER 2: BACKGROUND STUDY	**4-9**
2.1 Introduction	4
2.2 Technology	4
2.3 Background Study	4
2.4 Comparative analysis and summary	7
2.5 Scope of the problems	8
2.6 Challenging	8
CHAPTER 3: RESEARCH METHODOLOGY	**10-16**
3.1 Introduction	10
3.2 Procedure of Data collection	11

3.3 Data Preprocessing	11
3.4 Dataset Analysis	13
CHAPTER 4: RESULT ANALYSIS	**17-32**
4.1 Introduction	17
4.2 Experimental Result	17
4.3 Evaluation	28
CHAPTER 5: SUMMARY, CONCLUSION, AND FUTURE WORK	**33**
5.1 Conclusion	33
5.2 Future Work	33
REFERENCES	34
CONFERENCE	36
APPENDIX	37
PLAGIARISM REPORT	38

LIST OF FIGURES

FIGURES	PAGE NO.
Figure 3.1: Methodology diagram of Research	10
Figure 3.2: Data augmentation	12
Figure 3.3: Testing Dataset Representation	13
Figure 3.4: Training Dataset Representation	14
Figure 3.5: Validation Dataset Representation	15
Figure 4.1 Training vs validation accuracy for Model 1	22
Figure 4.2 Training vs validation loss for Model 1	23
Figure 4.3 Training vs validation accuracy for Model 2	24
Figure 4.4 Training vs validation loss for Model 2	25
Figure 4.5 Training vs validation accuracy for Model 3	26
Figure 4.6 Training vs validation loss for Model 3	27
Figure 4.7 Representation of Evaluation	28
Figure 4.8 Bay leaf Detection	29
Figure 4.9 Black Cardamom Detection	30
Figure 4.10 Red chili Detection	30
Figure 4.11 Green Cardamom Detection	31
Figure 4.12 Nigella Seed Detection	31
Figure 4.13 Cinnamon Detection	32

LIST OF TABLE

TABLE	PAGE NO.
Table 4.1 Classification result for Model 1	18
Table 4.2 Classification result for Model 2	19
Table 4.3 Classification result for Model 3	21

CHAPTER 1
INTRODUCTION

1.1 Introduction

Compared to other countries, the use of spices in cooking and food is much higher in Bangladesh. The use of this spice started in the Mughal era and continues till now, and this use is increasing daily. There are many types of spices. Each has different properties, including different scents and use areas. To bring out its authentic flavor by using these qualities of spices, one must first recognize them. In our country, different spices are used in each type of cooking. For example, one spice is used for cooking fish, and there is a difference for meat. Similarly, for cooking vegetables, different and fewer spices are used. If you don't know about spices, then you can't use them properly. This can spoil the flavor of the cooking and can make the food unpalatable. It will waste time and spice. So, we all must first know the spices then we can use them properly. People in our country do not have much knowledge about spices. They don't know all the spices well. They do not know how many kinds of spices there are or their names and uses. The main reason is that most of them are not cultivated in Bangladesh. Each of the spices that entered the country from abroad came from twenty-two distinct places. Traders travel considerable distances to provide herbs to clients, typically beginning in India, a nearby country. Over one million twenty-six thousand metric tons of spices were brought in from 22 countries during the most recent fiscal year. The total amount of money in circulation in the home market is 1 lakh 181 crore takas.[1] So we have to import all these spices from our neighboring countries. As a result, our country's people cannot use good spices because they do not know the right spices. To get back the taste of cooking like Mughal cooking, the people of our country need to know the right spices. For this, we need to find something simple so people can easily recognize herbs. For this, we suggest a model that can quickly detect which spice it is by looking at the image of the herb. Everyone uses smartphones in the age of modern technology, so spice identification by taking pictures in this way is a current and straightforward process. It will save people time and hassle. By knowing the right spice and using it properly, you can find out its actual value. We have selected five commonly used spices for our research, which are: 'Red Chili,' Nigella Seeds,' 'Green Cardamom,' 'Bay Leaf,' 'Black Cardamom,' and 'Cinnamon'; their usage qualities and scents are different from others. There is a high demand for these spices in the regional cuisine, so we trained classic machine learning methods using pictures of them. Our proposed solution is built upon the deep learning framework. The usage of CNN is crucial to our method. We've devised a new defense mechanism and pricing system to protect our platform. We opted for the optimal solution since it provided the most reliable results. Overfitting in tests and evaluations should be taken into account. Successful rate consistency was accomplished. We created three distinct model designs. Our model's unique features are the result of fine-tuning numerous CNN layers and associated hyperparameters. Model 1 and Model 3 were the most successful in terms of precision. However, Model 3 was the clear winner when it came to calculating score categorization reports, therefore that's the one we've settled on for further analysis. Research efforts have increased deep learning models' accuracy in numerous graphical tasks. For the purpose of model implementation, we use TensorFlow, Pandas, and Keres. We've decided to use python as our main programming language for this endeavor.

1.2 Motivation

In the practical application of our proposed model, people can easily recognize spices. This will benefit everyone who sells herbs and those who use them. As people realize the right spices, they will now be able to use them properly. This will encourage people to use spices and reduce wastage much more than before. People can use it to increase the taste of cooking many times more than before. This will help you to identify the spices through pictures, and it will reduce the hassle and save time and proper use of herbs in cooking. With today's artificial intelligence (AI) and image recognition tools, we can create these solutions from the ground up. Therefore, our research effort reduces this obstacle and develops a system that would enable people to scan rapidly and obtain the final.

1.3 Research Question

- How to create a data set and make it usable for the program?
- What are the types of spices, and can the program sort them?
- How to differentiate between spices and other seeds?

- What benefits will this create for people?
- Which technology will be more accessible for people to use?

1.4 Expected outcome

We can use the most recent developments in AI and motion pictures to develop these systems from the ground up. This challenge is reduced, and a technique is designed to allow individuals to scan and obtain the findings. We have worked to create a deep-learning technological AI system to avoid this predicament. Our approach may detect species. The condition can be correctly detected in 99 percent of cases.

CHAPTER 2

BACKGROUND STUDY

2.1 Introduction

The background information required for understanding the concepts discussed here can be found in the history of the research. Because of this, the survey information grabs the reader's attention and shows why the research issue is significant. For instance, in the opening to a study, you might write about how various students' families' socioeconomic position affects their studying habits or the range of their final grades. This would be an example of how socioeconomic status influences students' academic performance. You are the most qualified person to select what material should be included in the background of the study; therefore, you should just use this as an illustration. This chapter provides a summary of the work done by a large number of knowledgeable specialists in the previous field.

2.2 Technology

Several studies have been conducted on identifying and preventing a wide variety of ailments caused by herbal remedies. One of the apps that are most frequently used for both master learning and profound learning is called Prediction. A substantial number of studies have been conducted that either predict or detect various plant diseases. The topic is addressed through the research by posing questions and utilizing a variety of different machine learning techniques. This section provides an overview of the significant work that many specialists in the field indicated above have done throughout their careers.

2.3 Background study

S. Jana et al. [1] developed an AI base system for detecting Indian spices among different photos, which dietitians can use better to assess the risks of poor nutrition and other factors. Numerous spices have been tested using this technique. With the help of a convolutional neural network, we were able to properly categorize the species (CNN). To sort data into categories, the proposed method uses a convolutional neural network model. Photos for the spices dataset were scraped from the web, and training examples were supplemented with data from four additional categories. They used a reach data set that contains 1024 photos. In their process, 640 images were applied for training, and 128 were for testing. During testing, the highest levels of accuracy and precision achieved 91.14 percent and 97.19 percent, respectively.

To directly translate input images into precise counts of fruits, S. Jana et al. [2] propose a new method that employs deep learning. The pipeline uses a crowdsourcing platform developed specifically for efficiently labeling massive datasets. A fully convolutional network-tuned blob detector examines the images to find regions of interest for extraction. Afterward, a counting algorithm is built on top of a second convolutional network to roughly estimate the total number of fruits in each area. The ability of their method to recognize hidden from-view fruits that would be challenging for human refill kits to recognize makes it applicable to both datasets.

For a comprehensive look at state of the art in deep learning methods for recognizing tiny objects, see Yang Liu et al. [3]. Using YOLOv3, Faster R-CNN, and SSD as examples, together with three substantial test datasets of small objects, this research examines the results of various deep-learning techniques for small object recognition. They describe the main deep learning approaches and discuss the difficulties and possible solutions for detecting small objects. However, their experiments show that despite the deep learning techniques' low detection effectiveness (less than 0.4) on small objects, Faster R-CNN still placed second only to YOLOv3.

Photos of ginger powder were used for fraud detection by Ahmad Jahanbakhshi et al. [4], who proposed a gated pooling function to enhance convolution neural networks (CNN). The primary method for creating CNNs uses pooling functions that include both average and maximum pooling. To improve classification results, CNNs use batch normalization (BN) methods. They offer data to support the claim that the iterative operation improves the ginger powder prediction model over the standard pooling approach. Classifiers using the MLP, fuzzy, SVM, GBT, and EDT algorithms were compared to those produced by CNN. Comparing the proposed CNN to earlier classifiers that used batch normalization via gated pooling, the results showed that it could grade images of ginger powder with an accuracy of 99.70 percent.

A model that uses ML and DL to identify legume species was proposed by Rimi et al. [5]. They employ one of three separate algorithms for machine learning, deep learning, and classical machine learning for each image they collect. They put the data through three unique algorithms for classical machine learning, deep learning, and other forms of machine learning. The system had a 99% accuracy rate for detecting legumes.

Images of herbs and spices can be detected using the smaller VGGNet convolutional neural network, which is very effective in image recognition tasks, according to a decision reached by D. C. Khrisne et. at. [6]. They generated a small VGGNet family in the layers that followed the convolutional layers by adding 1024 parameters and a few additional dropout layers. As a result, their database contains 3,574 images organized into 27 different categories. According to the findings, the performance of their algorithm is remarkable when it comes to categorizing herbs and spices, with an average labeling accuracy of 70%.

The methodology proposed by Frans P. Boogaard et al. [7] begins with applying a trustworthy node discovery technique based on a deep convolutional neural network. Both the recall and accuracy of the tested algorithm were 0.92 and 0.95, respectively. Nodes are scanned from several angles around the plant to handle complicated and messy plant environments and to address the possibility of nodes being obscured by other plant sections.

A brand-new method that combines deep learning and image processing algorithms was proposed by X. Jin et al. [8]. To begin, they utilized a trained CenterNet model that was able to identify veggies and drew a bounding box around the vegetables. This technique allows for a significant reduction in both the size of the training image collection and the level of complexity associated with weed detection. Next, image processing was employed to carry out color index-based segmentation, which allowed them to distinguish the weeds from the surrounding environment. A genetic algorithm (GA) was used to determine and assess the color indices utilized, and the results were based on the Bayesian classification error. During the in-field testing, the trained CenterNet model achieved an accuracy of 95.6 percent.

P. S. Duth et al. [9] developed efficient techniques for detecting vegetables; their primary focus is on detecting vegetable variants. They experimented with convolutional neural networks (CNNs) and used deep learning to extract and learn the recognition of vegetable category pictures. The results of the evaluation show that deep understanding is capable of effectively recognizing the vegetables in the group, with a rate of accuracy that is 95.50%.

Ahmad Jahanbakhshi et al. [10] In this study, picture data of turmeric powder was classified, and fakes were found using an improved convolutional neural network (CNN). The use of gated pooling has improved CNN. They also show how the proposed CNN becomes more effective and accurate when a combination technique based on the integration of mean and max pooling is used. Data augmentation was used to correct overfitting in CNN. Additionally, comparisons were made between the proposed CNN's performance and those of classifiers built using the MLP, fuzzy, SVM, GBT, and EDT algorithms. They demonstrated that the suggested CNN beat other classifiers in scoring photos of turmeric powder by a margin of 99.36%, showing that gated pooling may be employed without worrying about it.

2.4 Comparative analysis and summary

Because of these factors, we have decided to focus our research on computer vision and deep learning.

- After looking over a few different studies and initiatives, it seems to fit quite nicely with various categories, including small object detection, the natural world, and others. Moreover, it is the solution most congruent with what we all require to achieve our goals.
- When it comes to algorithms for the classification of images, CNN is the one that can achieve the highest levels of accuracy through its training.
- It is easy to use and can be developed further by utilizing various assets.

- The most successful method also involves comparing images, such as those inside or outside of boxes.
- We may achieve good outcomes and precision by carefully and thoroughly training deep-learning CNN layers.

2.5 Scope of the problems

Developing a system that is capable of identifying species in a hurry. As a result of our research, we were able to determine how effectively the Convolutional Neural Network functions. In the not-too-distant future, we will be able to implement such technology in various settings, one of which will be substantial agricultural endeavors.

We are going to simplify our processes and make them available to everyone. Using our technology, prosecutors can carry out their responsibilities more effectively in many parts of this country's agricultural industry and in culinary centers where a lot of species processing takes place.

2.6 Challenging

The most challenging aspect of our work is going to be getting the data sets ready for administration in the future. For the purpose of precisely determining our data set or any future revisions, we have utilized robust machine learning and image processing technology. A further issue in Bangladesh is that there is an insufficient supply of resources as well as jobs in corresponding fields.

Data Collection:

It is essential for deep learning to have efficient data collecting. Due to the fact that we needed a significant number of raw photographs for our research, it was a difficult task for us to gather all of the images from each of the different species. Because the maximum species are so few, it is really challenging for us to find an appropriate picture to use in our research. It was a challenging task to execute this system on a device or computer that was configured in a conventional manner. Because not all of the photos were present, the system requires the data we provide in a particular format in order to correctly categorize the images.

Model selection

It seems that there are many different models for deep learning. They bear a significant duty in terms of making sure the appropriate model is chosen. It is far less difficult to choose dependable data as well as the right model. Numerous models have been developed specifically for the purpose of classifying photos. In order to put our model into action, we make use of CNN as well as computer vision.

We are able to draw the conclusion that the processing method is complicated and sophisticated as a result of the fact that the system demands highly configured equipment.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This part will go over a variety of methods, as well as particular procedures, that can be implemented in research, and it will do so in an all-encompassing approach. We will also discuss the tools used for our project and the data collection process, the participants in the study, the preliminary processing, the analytical methods, and the potential implications of these findings. Illustrating the level of accomplishment attained in figure 3.1:

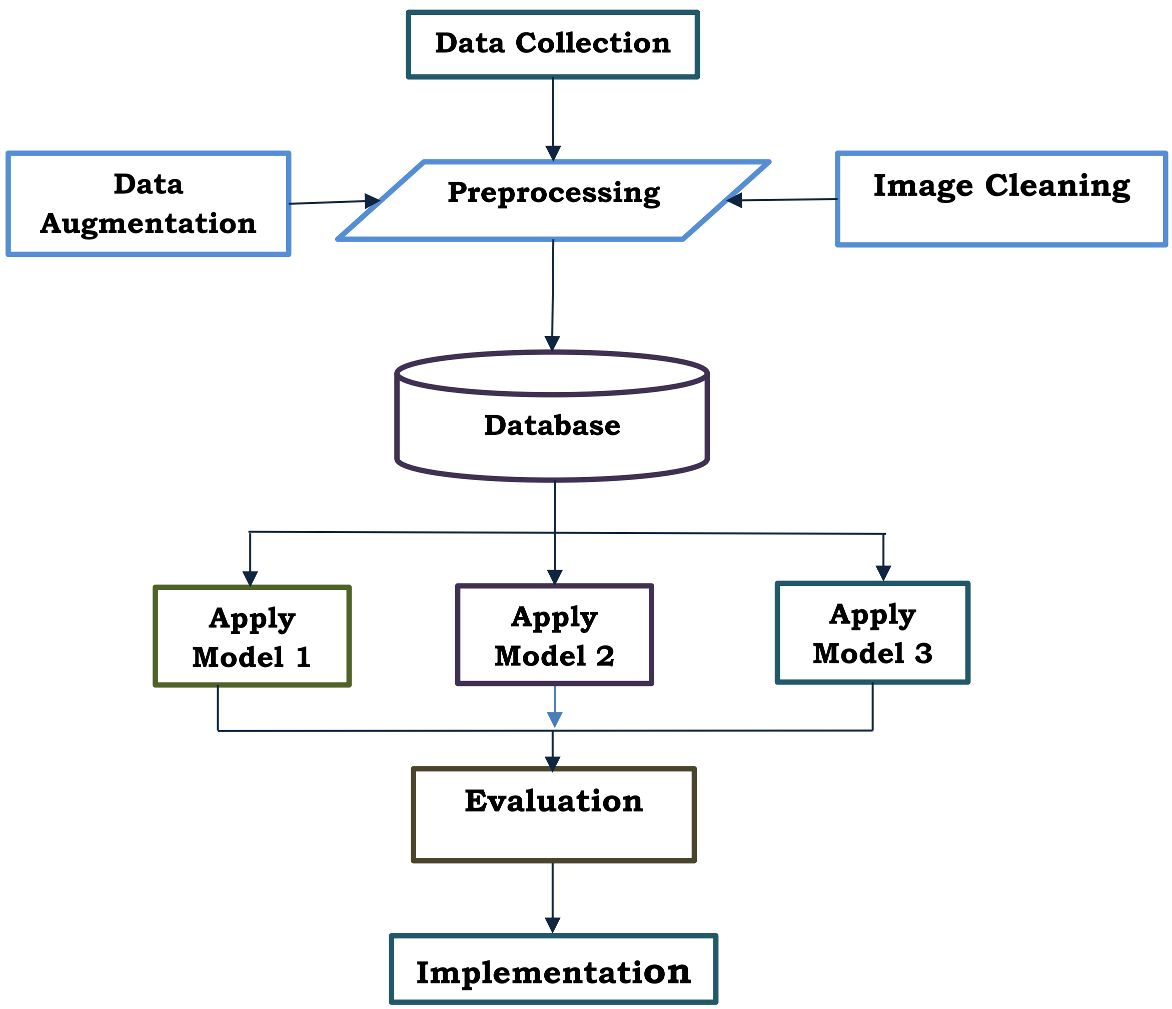

Figure 3.1 Methodology Diagram of Research

3.2 Procedure of Data Collection

In order to have a thorough knowledge, much as with machine learning, extensive volumes of data must be gathered. We gathered the data from a wide range of merchants and other retail places because Deep Learning demands a significant amount of data. When we took pictures of the species, we were by ourselves. In total, we shot close to 12,000 images. We picked six species and photographed them from various angles before deciding the ones we liked best. To achieve this, we had to visit several local markets and get the owners' permission before taking pictures of the species stalls inside. These stores are so busy during the day that we had to purchase some species to get better photos for our dataset. Even though it took a lot of time and money, the quality of our data considerably increased, and we collected many pictures for categorization. This data worked nicely for our study as a data set.

3.3 Data Pre-processing

At the end of the phase in which the data was collected, we subjected it to two separate processing procedures before applying the approach. Enhanced information. More data. The authors of the study believe that the use of preprocessing can, in the overwhelming majority of instances, reduce the likelihood of making an error in classification, which is an important finding. [10]

Data augmentation:

The data increase operation utilized an augmentation method that is depicted in figure 3.2. This strategy was employed during the data increase process. The process of growing the data used a variety of various approaches, including scaling, tilting, rotating the data, flipping it diagonally, and flipping it perpendicularly, among others. The quality of the data used in a project is essential to its success.

To the extent that data can be improved, the effectiveness of the program will increase.

Figure 3.2: Data augmentation

Our collection contained a significant amount of noise, which we cleaned out at this stage of the process. We have eliminated the image's background so that you can better see the data. This has made it easier for machines to comprehend. The image quality was then improved such that it could be used effectively at any magnification. We have made an effort to supplement the data in the most effective way possible so that the computer can comprehend it in a way that is simple and open to scrutiny.

3.4 Dataset Analysis

Following the completion of the procedure of enhancing the photographs, the total number of photos in our collection came to 12,000 altogether. In the photographs that make up our picture dataset, the backgrounds of the images have been cropped out, and the photographs have also been preprocessed and augmented. This collection also contains some of the data in its original form, which was obtained at the same time as the rest of the data. The following picture presents the data that we have been working on within the graphical form so that it may be more easily understood.

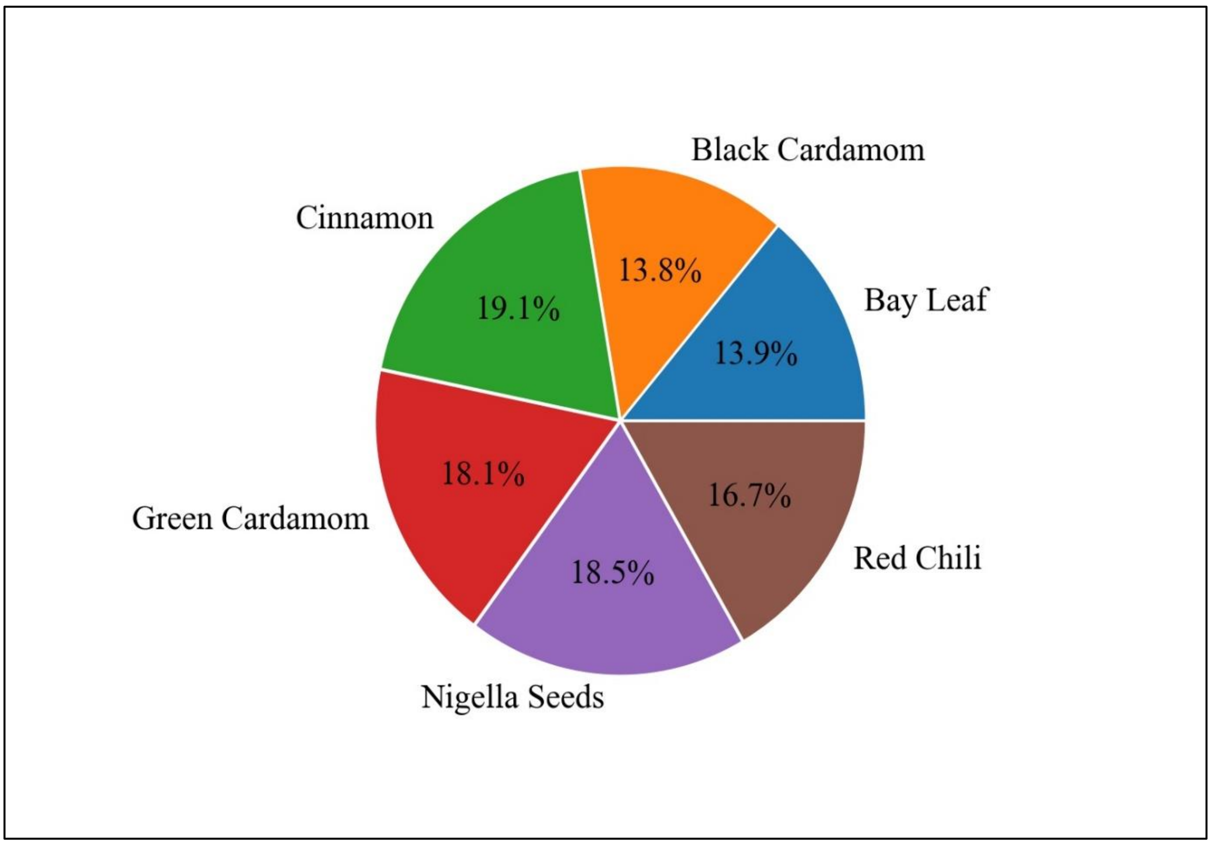

Figure 3.3 Testing dataset representation

Figure 3.3 shows our testing dataset. It also can be said that it is our main dataset representation. In this figure, there seems to be that all six levels of our data's combination are well. No high fluctuation among dataset levels.

It is a balanced dataset representation of twelve thousand images of six common species.

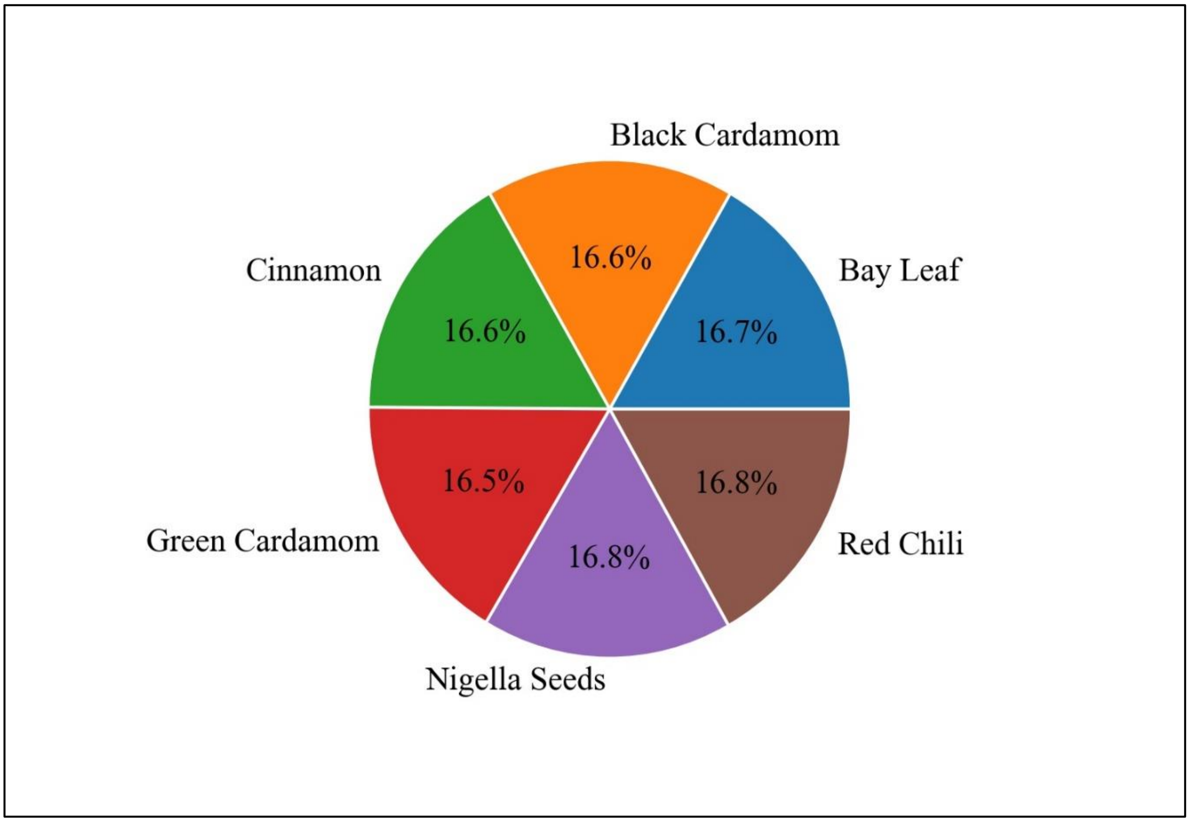

Figure 3.4 Training dataset representation

We divided all 12,000 of our images into one of these six categories as part of the process of displaying our training data set. To begin, cinnamon has a content density of 16.6%, green cardamom has a content density of 16.5%, and nigella seeds have a content density of 16.8%. The level of Red Chili is 16.8%, the level of Bay Leaf is 16.7%, and the level of Black Cardamom is 17.0%. In the end, we offered our best try at dividing the total number of photographs into an equal number for each category so that we could evaluate the results. When we trained on the dataset that we would be utilizing for our research, we discovered that it was actually a very good dataset. The dataset that we would be using for our research appears to be in good condition.

The representation graph for the training dataset may be found in Figure 3.3. This is the location where you can find it.

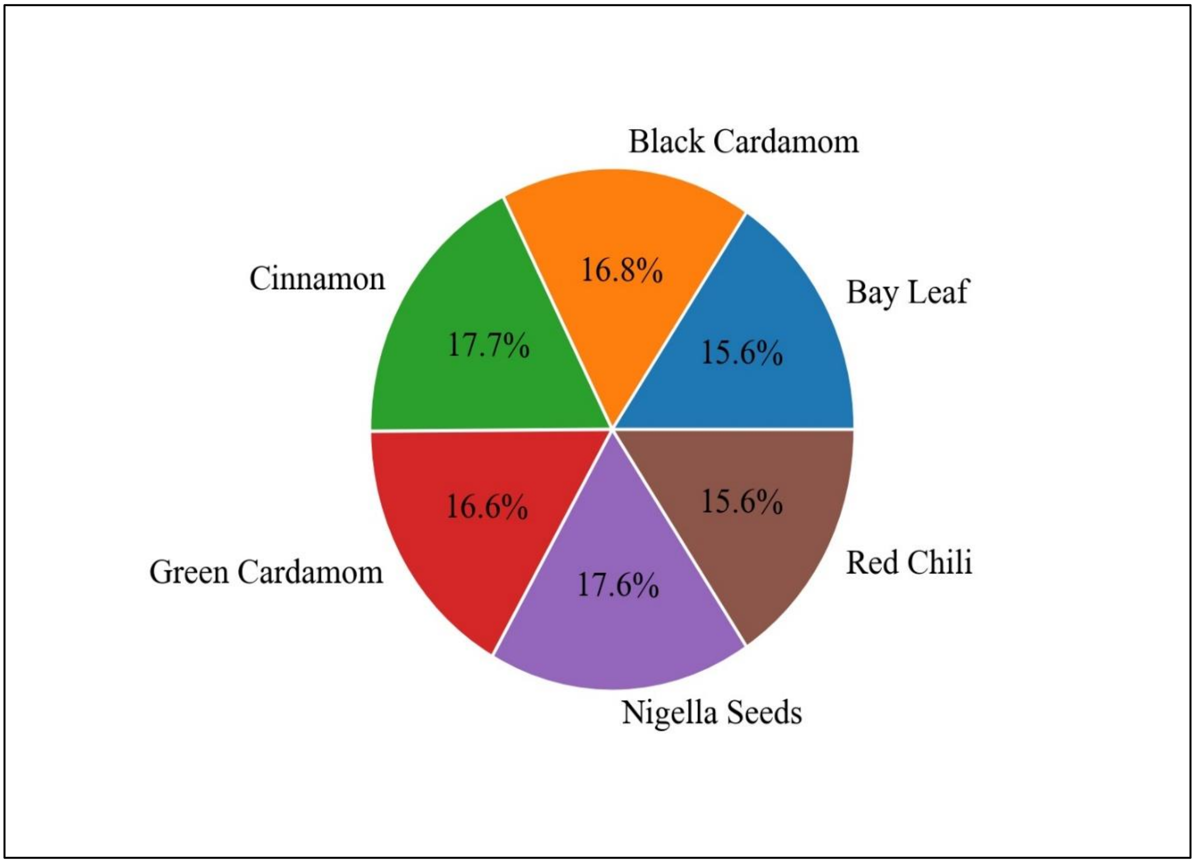

Figure 3.5 Validation dataset representation

In order to display our validation data set, we additionally classified each of the 12,000 photographs we used into one of these six groups. To start, the content density of cinnamon is 17.7%, that of green cardamom is 16.6%, and that of nigella seeds is 17.6%. The levels of red chili, bay leaf, and black cardamom are 15.6%, 15.7%, and 16.8%, respectively. In order to evaluate the outcomes, we decided to divide the entire number of images into an equal number for each category. We found that the dataset we would use for our research was a pretty nice dataset when we trained on it. The dataset that we would be utilizing for this study seems to be in decent shape.

This observation indicates that my dataset is top-notch. The training data and the validation dataset do not significantly differ. Nearly all of the values were the same. There was hardly any difference between the three levels, only a little one. This suggests that our dataset is understandable and practical.

Figure 3.4 shows the representation graph for the validation dataset. The place where you can find it is here.

CHAPTER 4

RESULT ANALYSIS

4.1 Introduction

This chapter's two main topics are the experimental design and the supporting data. When analyzing it, the results are the first thing we take into account. So that the reader is not required to be aware of the results or conduct any additional research on their own, the findings should be discussed in the Implications section. The section on research papers has some suggestions for further reading. The test's findings and outcomes will be documented in this chapter. The results should be given in the section titled "Implications," not made public or available to the reader. There may be some helpful information in the section devoted to research publications. Here, the test results and an analysis of them will be displayed. Here is a thorough description of each algorithm result and model that contributed to the success of my project. All the models and algorithms used in this part are explained.

4.2 Experimental Result

It is standard practice in research to try out various values for a set of independent variables in order to see what happens [9]. So, to conduct a machine learning experiment, you'll need more than just one training course, preferably in a wide range of conditions.

Now that we've applied the algorithm to my data, we can analyze the results and draw some conclusions. We do this to better grasp what the findings actually mean. The three groups present their individual perspectives on one of the three classification reports. Further, we employed several criteria for determining the accuracy of each model's output. In doing so, we could evaluate the results' reliability. The three models have reasonable settings for precision, recall, and f1, so the results they provide are both interpretable and satisfactory. The decision relied on three separate factors to establish the validity of my sweeping conclusions. When evaluating all three dimensions, the level of accuracy was relatively consistent.

Label name	**Precision**	**Recall**	**F1-Score**	**Support**
Bay Leaf	0.97	0.99	0.98	211
Black Cardamom	0.87	0.97	0.92	208
Cinnamon	1.00	0.96	0.98	286
Green Cardamom	0.97	0.92	0.94	270
Nigella Sed	0.99	0.98	0.99	277
Red Chili	1.00	1.00	1.00	251
Accuracy			0.97	1503
Macro avg	0.97	0.97	0.97	1503
Weighted avg	0.97	0.97	0.97	1503

Table 4.1 Classification result for Model 1

The following table, Table 4.1, shows the categorization report for Model 1. For the purpose of our study, we focused on six local species that are relatively common and examined the ways in which these various species differ from and are similar to one another. The precision, f1, and recall scores for the Red Chili uniform all result in 1, which is shown as the height value of all the other items. When it comes to the other five species, three of the criteria, namely Precision, Recall, and F1-Score, are performing pretty similarly to how they are being performed by the others. Cinnamon demonstrates that the precision is 1, the other parameter F1 is gaining 0.98%, and Recall attained 0.96%. Nigella Seed achieves a value that is highly comparable to our accuracy; it possesses precision, its F1 score is 0.99%, and its recall value reaches 0.98%. The precision content of Bay Leaf is 0.97%, while the content of Recall is 0.99%, and the content of F1 is 0.98%. In model 1, both black cardamom and green cardamom produce extremely unsatisfactory results.

The precision value of black cardamom is 0.87%, the F1 score gain it achieves is 0.92%, and the Recall it attains is 0.97%. When it comes to green cardamom, model 1 comes in with a precision value of 0.97%. The recall percentage is 0.92%, while the f1 score is 0.94% due to the fact that the findings for the other two metrics, Macro average. And Weighted avg. were quite comparable to one another, and it may be deduced that the accuracy is not exceptionally high. This demonstrates that our algorithms have produced findings that are incredibly erroneous in terms of their level of precision. According to our investigation, 4.1 Table was correct 97% of the time, out of a total of 1503 data sets that were examined. It demonstrates a lower level of accuracy in comparison to other models that we did not choose to use for another task that will occur in the future.

Table 4.2 Classification result for Model 2

Label name	**Precision**	**Recall**	**F1-Score**	**Support**
Bay Leaf	0.99	0.98	0.98	211
Black Cardamom	0.96	0.99	0.97	208
Cinnamon	0.99	0.97	0.98	286
Green Cardamom	0.97	0.98	0.97	270
Nigella Seed	1.00	0.99	0.99	277
Red Chili	1.00	1.00	1.00	251
Accuracy			0.98	1503
Macro avg	0.98	0.98	0.98	1503
Weighted avg	0.98	0.98	0.98	1503

The following table, Table 4.2, displays the classification report for Model 2. For the aim of our study, we concentrated on six local species that are rather common and explored the ways in which these distinct species differ from and are similar to one another. Red Chili's uniform has a precision, f1, and recall score of 1, which is represented as the height value of all other items. Three of the criteria, namely Precision, Recall, and F1-Score, show that the other five species are performing similarly to the others. The results from Cinnamon show that the accuracy is 0.99%, while F1 is improving by 0.98%, and Recall has reached 0.97%. Nigella Seed achieves a value that is substantially equivalent to our accuracy; it boasts Recall, its F1 score is 0.99%, and its Precision value reaches 1. Compared to Recall and F1, Bay Leaf has a 0.99% precision content, while both of those measures average 0.98%. The findings of both black and green cardamom in model 2 are vastly superior to those of model 1. The accuracy value of black cardamom is 0.96%, the F1 score gain it obtains is 0.97%, and the Recall it attains is 0.99%. When it comes to green cardamom, model 2 comes in with a precision value of 0.97%. The recall percentage is 0.98%, but the f1 score is 0.97% due to the fact that the findings for the other two metrics, Macro average. We can infer that the accuracy could be better because the Weighted avg. were very close to one another. This shows that our algorithms have generated extremely imprecise results. According to our analysis, 4.2 Table was right 98% of the time, out of a total of 1503 data sets that were reviewed. Its accuracy is better than model 1 but less than model 3, which we considered, but we ultimately decided against using it for a different future challenge.

Table 4.3 Classification result for Model 3

Label name	Precision	Recall	F1-Score	Support
Bay Leaf	0.97	0.99	0.98	211
Black Cardamom	0.97	0.99	0.98	208
Cinnamon	1.00	0.96	0.98	286
Green Cardamom	0.97	0.99	0.98	270
Nigella Sed	1.00	1.00	1.00	277
Red Chili	1.00	1.00	1.00	251
Accuracy			0.99	1503
Macro avg	0.99	0.99	0.99	1503
Weighted avg	0.99	0.99	0.99	1503

The following table 4.3 depicts the outcomes of the classification procedure applied to Model 3. Our research centered on comparing and contrasting six locally-common species, aiming to shed light on the similarities and differences between them. The uniformity of red chilies and Nigella seeds has a precision, f1, and recall of 1, which is equivalent to the height of all other levels. We can see that the other four species are performing similarly to the others on three of the criteria (Precision, Recall, and F1-Score). In addition to F1 improving by 0.98% and Recall reaching 0.96%, the data from Cinnamon also reveal that accuracy is at its maximum value of 1. Models 1 and 2 are inferior to the Bay Leaf, Black Cardamom, and Green Cardamom distribution. The F1 indicates a weight of 0.98%, the Recall value is 0.99%, and the precision is 0.97% across all three levels. Due to the findings for the other two metrics, the Macro average, the f1 score is 0.97% while the recall percentage is 0.98% since the Weighted average. We're so close to one another that we can deduce that the accuracy could be enhanced. This demonstrates that the outputs of our algorithms could be more accurate. Out of 1503 data sets examined, we found that 4.3 Table was exact 99% of the time. With its superior accuracy compared to the other two models we investigated, we have decided to use it in our subsequent work.

Model 1 Analysis

Figure 4.1 Training vs validation accuracy for Model 1

The degree of accuracy with which the first model was trained is illustrated in Figure 4.1. The accuracy of the validation is shown by the red line, while the green line shows the accuracy of the training. In this particular model, the accuracy of the training and validation phases steadily improves over time. Training and validation involve a lot of backtracking and zigzagging. In addition to this, there is not much of a distinction to be seen between the two lines. The rapid rate of learning exhibited by our dataset is highlighted by this incident. The accuracy of validation for our model 1 is 97.00 percent, which is the highest percentage that can be equaled by the accuracy of another model.

Figure 4.2 Training vs validation Loss for Model 1

One of the most common measurement combinations is a training loss vs a validation loss over time. Validation loss shows how well model 1 can develop novel data, in contrast to training loss which shows how well model 1 can duplicate the original data. That is, it measures how well model 1 generates new information. Figure 4.2 depicts one instance of testing the loss model 1 in training versus pushing it in validation. The guarantee losses and the activity losses from Model 1 were relatively smooth. As with training loss, validation loss is mitigated when epochs are allowed to run longer. Quick improvement is made, and there needs to be evidence that model 1 overfits the dataset in question. On the other hand, the findings show that a substantial quantity of information was lost during validation. The state is represented by the line of training loss. However, we lost a lot of information during validation. Therefore, there are better models for the data we have. So, I opted not to use it in my following implementation.

Model 2

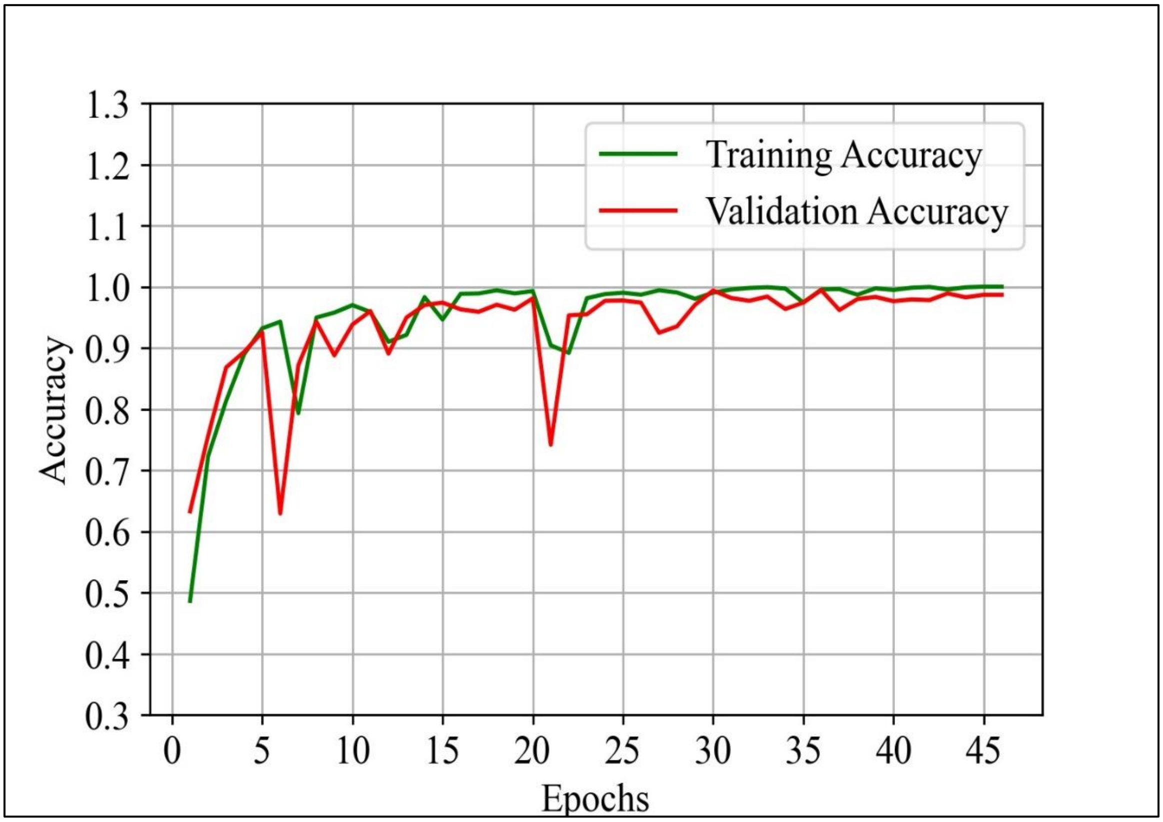

Figure 4.3 Training vs validation accuracy for Model 2

Figure 4.2 depicts the level of accuracy gained after training the initial model. The red line represents the validity of the validation, and the reliability of the training is the green line. Accuracy in both the training and validation stages of this model improves over time. As a result of training and validation, model 2 produces a line with more zigzags. Furthermore, the two series franchises each have their own unique characteristics. This occurrence has revealed that our dataset appears to have a slow pace of learning. Our model 2 has a validation accuracy of 98%, which is the best validation accuracy currently available. No competing model even comes close to matching our precision of ours. Nonetheless, it shows that the numbers in the collection are distributed in a variety of ways. For this dataset, model 2 does not show off extremely stable behavior. The results, however, show that the output is created with far greater efficiency than the model1.

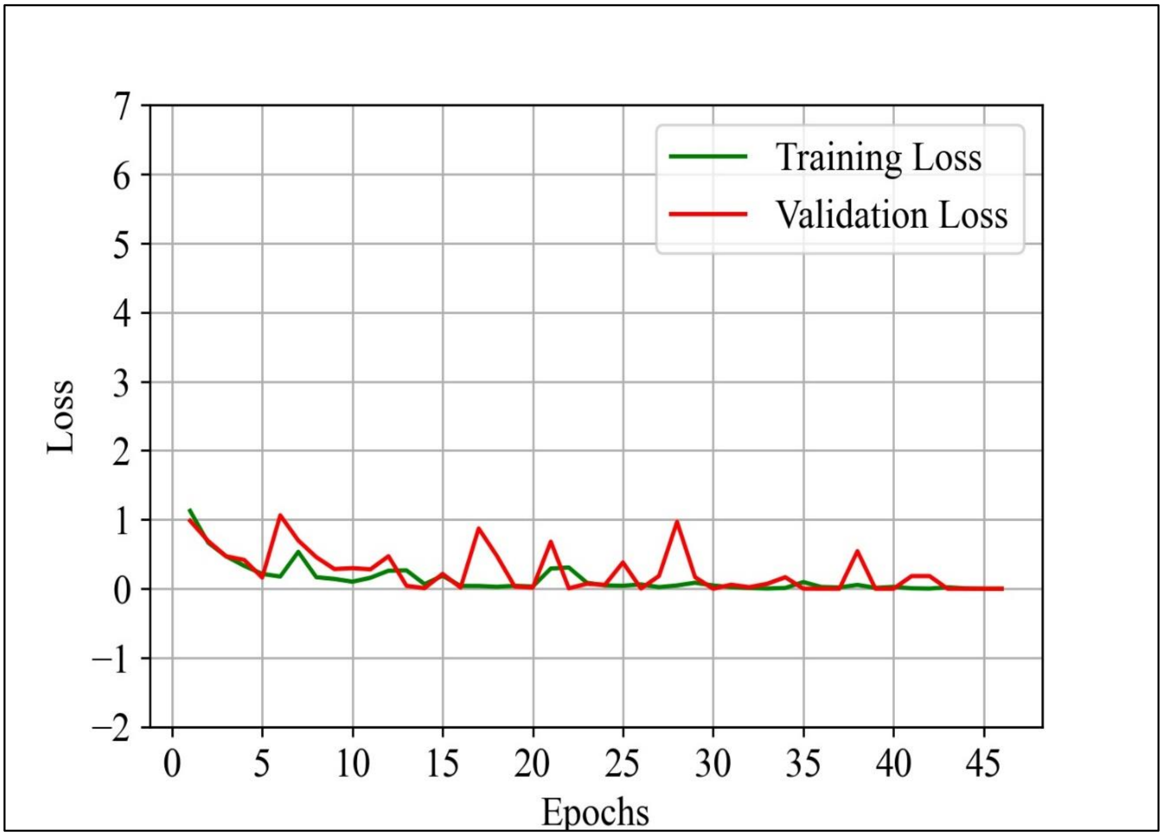

Figure 4.4 Training vs validation Loss for Model 2

Among the most popular measurement combinations is a training loss compared to a validation loss over time. The validation loss shows how accurately model 1 generates new data, as opposed to the training loss, which shows how accurately model 1 reproduces the initial data. In other words, it assesses how effectively model 1 generates new data. Figure 4.4 shows one instance of loss model 2's training versus validation. For both the guarantee losses and the activity losses, Model 1 generated relatively zigzagging curves. Similarly, to this, when the length of the epochs is spread out over longer amounts of time, the validation loss and the training loss are both decreased. Rapid learning occurs, and there is little evidence that model 2 has been excessively fitted to this data set. The outcomes, however, show that a sizable amount of data was lost throughout the validation procedure. The state is represented by the line of training loss. However, validation caused a substantial data loss, making it an inappropriate model for the dataset I have chosen. I consequently made the decision not to employ it in my later implementation.

Model 3

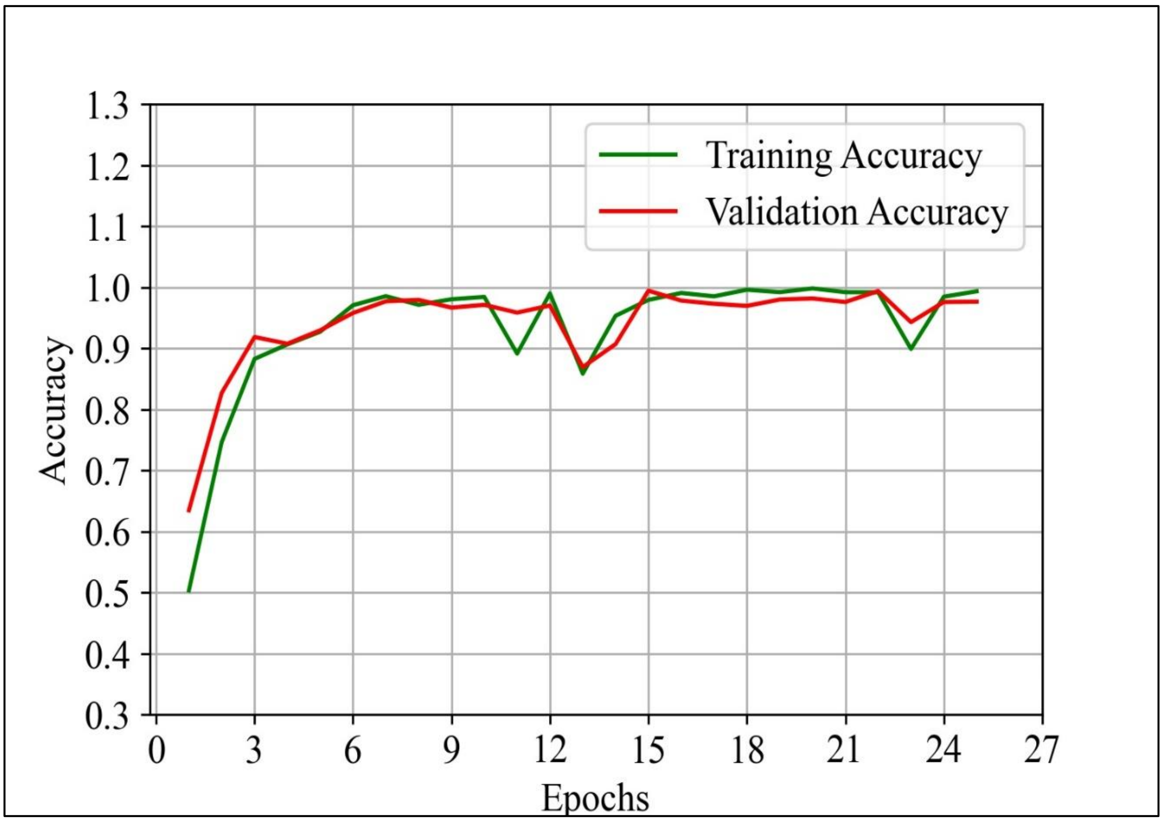

Figure 4.5 Training vs validation accuracy for Model 3

Figure 4.5 directly compares the Model 3 training and validation procedures. The training accuracy is depicted by the green line, while the validation accuracy is depicted by the red line. This algorithm's precision is steadily raised through the training and validation phases. There were no hiccups throughout either the proof or the training. The two lines appear identical to the naked eye. There is little to no difference between the validation accuracy and the training accuracy. That they are still making strides along the same path is shown by this. This occurrence exemplifies the impressive rate at which our dataset is maturing. Indicates how well the algorithm performs in terms of producing a good outcome. Our Model 3 validation is 99.0% accurate, which is the highest and most precise accuracy of any other method.

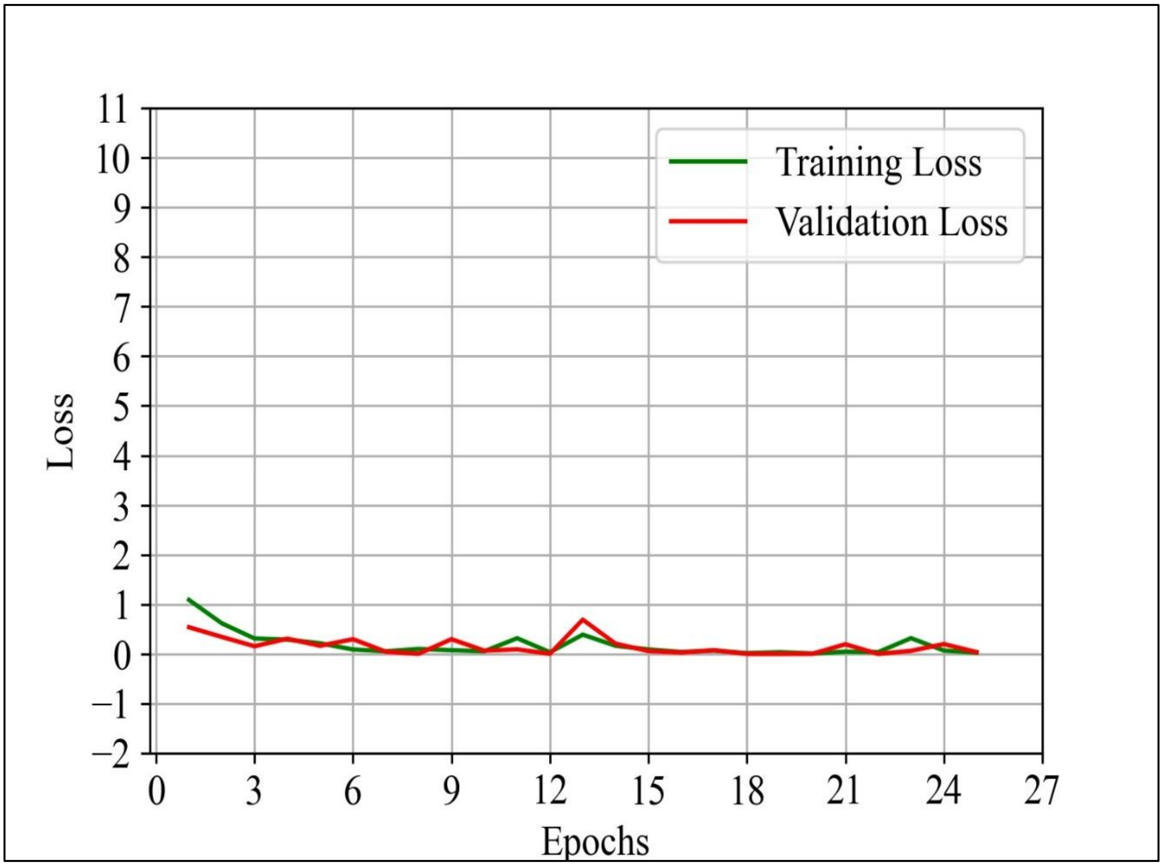

Figure 4.6 Training vs validation Loss for Model 3

Model 3's architecture is shown in Fig. 4.6 as a precaution during training to prevent validation loss. Model 3 outperforms competing algorithms by a wide margin. The validation loss is depicted as a straight line with little dips at certain times and significant dips at others. The loss comparison between Model 3 training iterations drops to a negligible value, and the two lines in the overlap line graph approach one another very closely as the number of iterations grows. Conversely, when comparing validation losses, a smooth curve emerges. Therefore, it clearly shows a loss curve that is flat during training and flat during validation. We have settled on Model 3 for the next venture, and this success determines the light of this success selected, and we have decided on Model 3 for the next experience.

4.3 Evaluation

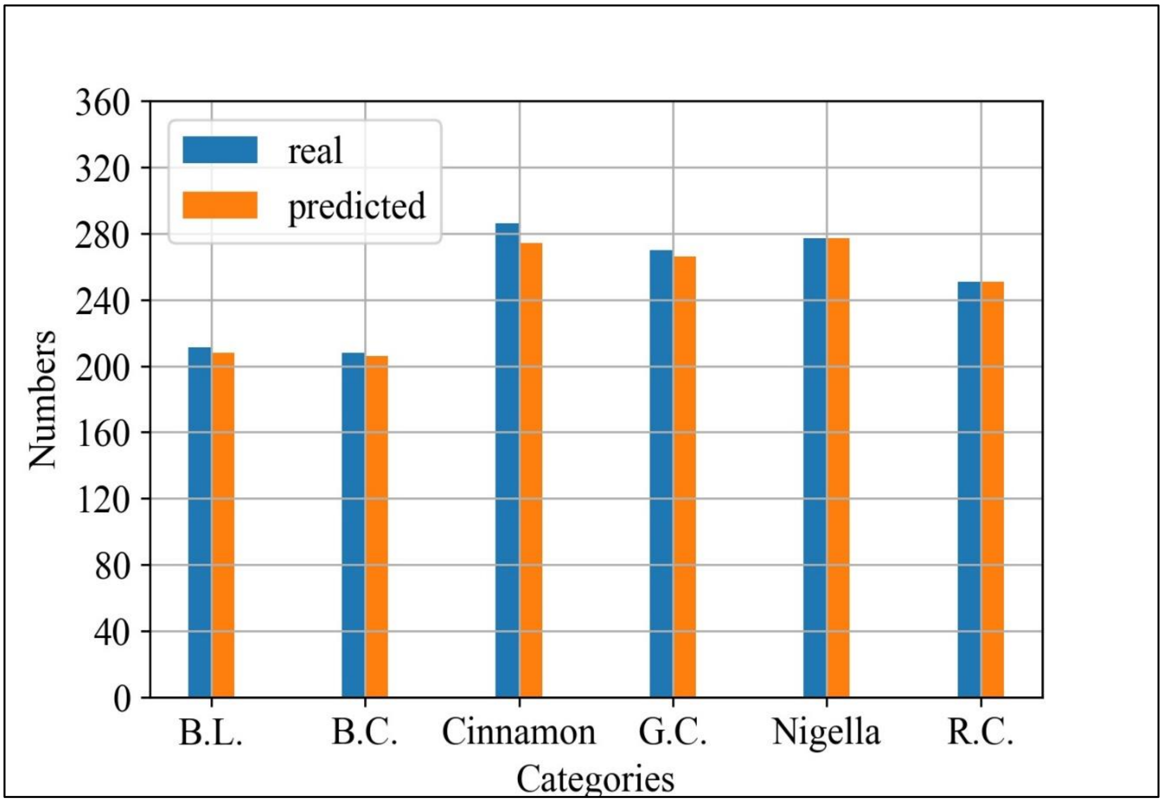

Figure 4.7 Representation of Evaluation

The selected Model 3 algorithm's performance was assessed using an ambiguity vector and a reliable data estimate. There are 210 reliable data points in our actual dataset on Bay Leaf. Our program is able to spot instances where there is missing data. Algorithmically, Nigella Seed and Red Chili can be caught as equivalent to preexisting data. There was not a single measurable discrepancy between the actual and predicted results. It demonstrates the precision with which Model 3's algorithms produce outcomes. Although the actual value of black cardamom is slightly greater than the expected value, the difference is not huge. Despite our algorithm's best efforts, it was unable to reduce the number of observed data from 210 to 199. Our dataset is a good fit for Model 3, the algorithm we utilized. It has a transparent ability to detect the outcomes. As a result, the Model 3 approach would be a better fit for our resource implementation.

Implications of our findings are discussed here. In the first place, we have shown that our algorithm can recognize distinct species. To that end, we first amassed the required training data and checked the efficacy of our constructed algorithm. With that information, the implementation model may quickly and easily build the names of the species and identify them with the name. In this section, you will learn about my project's overarching goal.

Bay Leaf

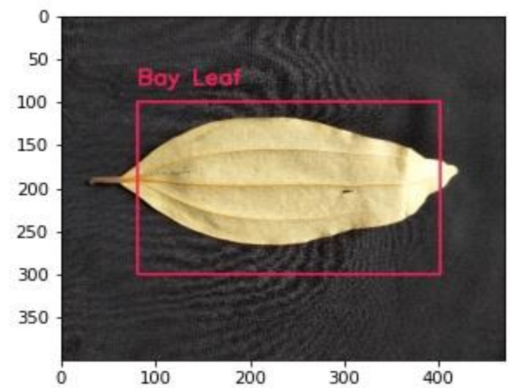

Figure 4.8 Bay Leaf Detect

The results of our first round of testing for the implemented method are shown in Figure 4.7. After deciding on a Bay Leafe for processing, we put the model we had selected into action. Incredible success is attained by it. It has excellent species-difference abilities. The red box depicts the actual species inspection. The ability to identify species names is also present and functional.

Black Cardamom

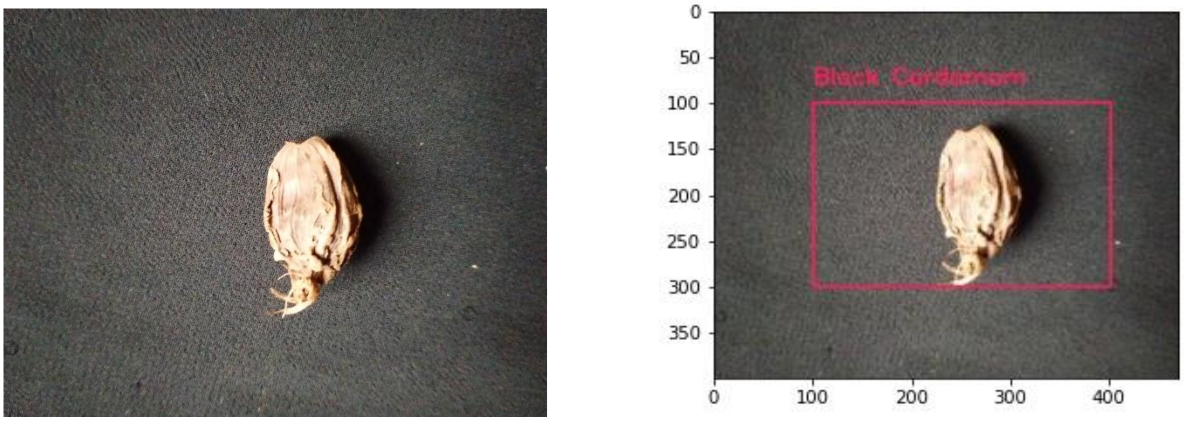

Figure 4.9 Black Cardamom detection

Figure 4.8 displays the outcomes of our second round of testing the developed procedure. We chose a Black Cardamom to process and then applied the model we had chosen. Again, outstanding success has been gained by it. It excels at distinguishing between different species. The actual species inspection is shown in the red box. The capacity to recognize species names is also functioning and existent.

Red Chili

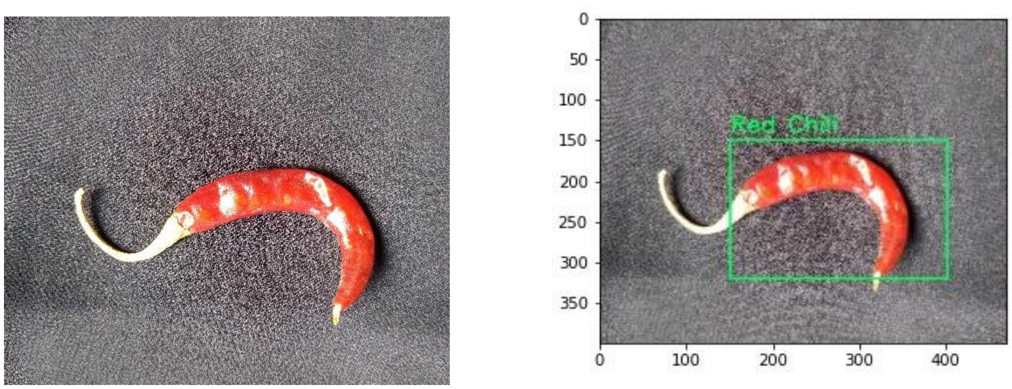

Figure 4.10 Red Chili detection

Figure 4.8 displays the outcomes of our third round of testing the developed procedure. We chose a Red Chili to process and then applied the model we had chosen. Again, outstanding success has been gained by it. It excels at distinguishing between different species. The actual species inspection is shown in the red box. The capacity to recognize species names is also functioning and existent.

Green Cardamom

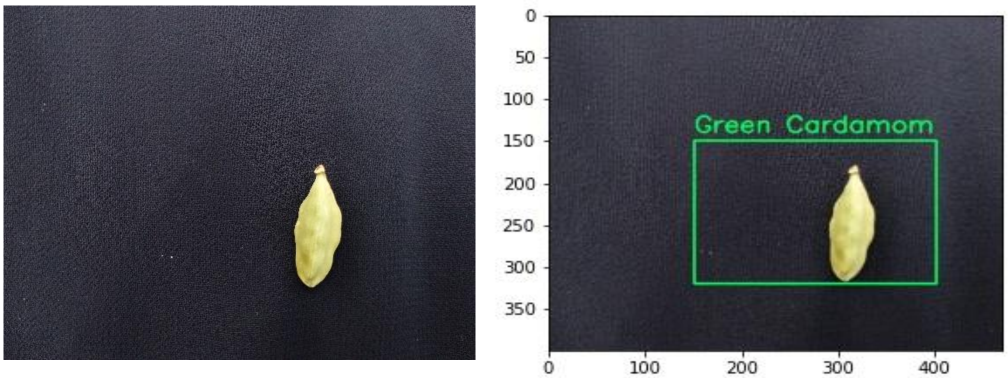

Figure 4.11 Green Cardamom detection

The data from our fourth round of testing the established process is shown in Figure 4.9. After selecting a Green Cardamom for processing, we put the model chosen to use. Once again, it has achieved remarkable results. The ability to tell one species from another is one of its many strengths. The red box represents the actual species inspection. The ability to correctly identify species is also active and authentic.

Nigella seed

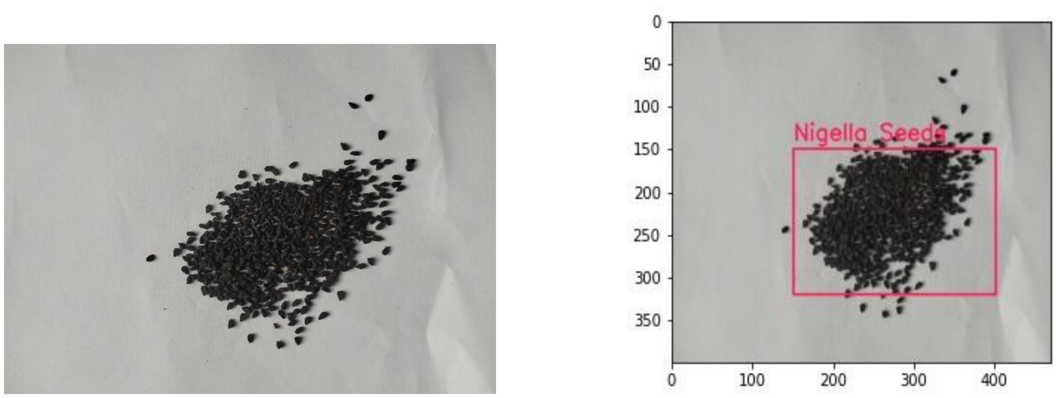

Figure 4.12 Nigella Seed detection

Figure 4.10 illustrates the findings that emerged from our fifth round of testing the conventional procedure. We started out by selecting a Nigella Seed for processing, and then we applied the model that we had already decided upon. Once more, it has accomplished something that is truly astounding. One of its numerous abilities is that it is able to discern different species apart from one another. The accurate inspection of the species is represented by the box in red. Active and genuine participation also includes having the capacity to identify species correctly.

Cinnamon

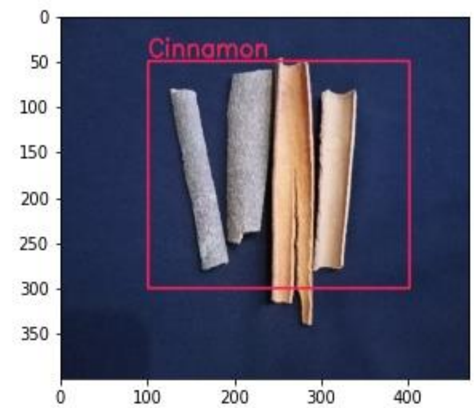

Figure 4.13 Cinnamon detection

The results of our final experiment testing the standard technique are shown in Figure 4.11. Initially, we chose Cinnamon for processing, and after that, we used the predetermined model. Another genuinely amazing feat has been done by it. Its ability to distinguish between several species is just one of its many skills. The box in red represents the precise examination of the species. The ability to correctly identify species is another requirement for true and active engagement.

CHAPTER 5

SUMMARY, CONCLUSION, AND FUTURE WORK

5.1 Conclusion

Our first objective has been met, which was to design a system that makes it simple for people to recognize different spices. We were able to develop our idea with the help of CNN's deep learning algorithm. The incredible accuracy of Model 3 was 99%, and it had improved score matrices such as f1-score, sensitivity, and specificity. Despite the fact that the other two models, model 1 and model 2, scored reasonably equally and well among model 1 and model 3, for score measurements model performed very well in test data, and model 1 and model 3 performed very well. As a result, we evaluated based on model 3. The result can be put to use to speed up the process of species identification when carried out by people. Because of our superior intelligence system, we will be able to recognize species far more quickly and accurately than humans. We are limited in our options due to the fact that we have only used six different spices. But a lot of data enhances a model's accuracy.

5.2 Future work

In the future, the outcome that we achieved will serve as the basis for the development of a mobile application system that will facilitate the selection of species in a more expedient manner. In addition to this, we broaden our dataset by including more spices and attempting a number of transfer learning strategies in our experiments.

REFERENCES

[1] S. Jana, P. Shanmukha Nagasai, K. Saravan Kumar and V. Mani Nageshwar, "Categorization and Grading of Spices Using Deep Learning," 2022 IEEE International Conference on Data Science and Information System (ICDSIS), 2022.

[2] S. W. Chen et al., "Counting Apples and Oranges With Deep Learning: A Data-Driven Approach," in IEEE Robotics and Automation Letters, vol. 2, no. 2, pp. 781-788, April 2017, doi: 10.1109/LRA.2017.2651944.

[3] Yang Liu, Peng Sun, Nickolas Wergeles, Yi Shang, A survey and performance evaluation of deep learning methods for small object detection, Expert Systems with Applications, Volume 172, 2021, 114602, ISSN 0957-4174,

[4] Ahmad Jahanbakhshi, Yousef Abbaspour-Gilandeh, Kobra Heidarbeigi, Mohammad Momeny, Detection of fraud in ginger powder using an automatic sorting system based on image processing technique and deep learning, Computers in Biology and Medicine, Volume 136, 2021, 104764, ISSN 0010-4825,

[5] Rimi, I.F., Habib, M.T., Supriya, S. et al. Traditional Machine Learning and Deep Learning Modeling for Legume Species Recognition. SN COMPUT. SCI. 3, 430 (2022).

[6] D. C. Khrisne and I. M. A. Suyadnya, "Indonesian Herbs and Spices Recognition using Smaller VGGNet-like Network," 2018 International Conference on Smart Green Technology in Electrical and Information Systems (ICSGTEIS), 2018, pp. 221-224.

[7] Frans P. Boogaard, Kamiel S.A.H. Rongen, Gert W. Kootstra, Robust node detection and tracking in fruit-vegetable crops using deep learning and multi-view imaging, Biosystems Engineering, Volume 192, 2020, Pages 117-132, ISSN 1537-5110,

[8] X. Jin, J. Che and Y. Chen, "Weed Identification Using Deep Learning and Image Processing in Vegetable Plantation," in IEEE Access, vol. 9, pp. 10940-10950, 2021.

[9] P. S. Duth and K. Jayasimha, "Intra Class Vegetable Recognition System using Deep Learning," 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), 2020, pp. 602-606.

[10] Ahmad Jahanbakhshi, Yousef Abbaspour-Gilandeh, Kobra Heidarbeigi, Mohammad Momeny, A novel method based on machine vision system and deep learning to detect fraud in turmeric powder, Computers in Biology and Medicine, Volume 136, 2021, 104728, ISSN 0010-4825,

CONFERENCE

Publisher: IEEE

Published in: 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT)

https://ieeexplore.ieee.org/document/9984338

APPENDIX

The first was to outline the procedures for the analysis, which presented a number of difficulties. The report was the first. Furthermore, no progress has been made in this area previously. Indeed. It wasn't your typical job. We couldn't find someone who could help us that much. Another stumbling block was data collection, which proved to be a huge issue for us. We created a data-gathering corpus because we couldn't locate an open-source Bangladesh text pre-processing program. We've begun manually collecting data. Furthermore, classifying the various postings is a difficult task. We might be able to achieve it after a long time of hard labor.

PLAGIARISM REPORT

A Computer Vision and deep CNN Modeling for Spices Recognition

ORIGINALITY REPORT

24%	17%	13%	12%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Md. Maruf Hasan Talukder, Tania Aktar Ria, Md. Mehedi Hasan, Md. Hamidur Rahman, Abdus Sattar. "A Computer Vision and Deep CNN Modeling for Spices Recognition", 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2022 Publication	9%
2	dspace.daffodilvarsity.edu.bd:8080 Internet Source	8%
3	Submitted to Daffodil International University Student Paper	3%
4	Submitted to Columbia High School Student Paper	1%
5	Submitted to National University of Singapore Student Paper	1%
6	Zhoujun Cao. "Deep Learning Methods for Objective Detection", 2022 IEEE 2nd	<1%