THE CLASSIFICATION OF VEGETABLES AND FRUITS USING DEEP LEARNING

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

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APPROVAL

This Project titled **"THE CLASSIFICATION OF VEGETABLES AND FRUITS USING DEEP LEARNING"**, submitted by Md Shadman Sakib Siam, ID No: 201-15-13767 to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfilment 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 – 14-07-2024

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DECLARATION

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

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I would like to convey my heartfelt gratitude to **Dr. Sheak Rashed Haider Noori**, Professor and Head, Department of CSE, for his generous assistance in completing our project, as well as to the other academic members and staff of Daffodil International University's CSE department.

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ABSTRACT

In this paper, an attempt is made to accurately classify vegetables and fruits. This classification uses a dataset of 6000 photos divided into 15 classes. Convolutional neural networks, a type of deep learning algorithm, are the most efficient tool in the machine learning field for classification issues. However, CNN requires huge datasets to perform well in natural image classification tasks. We undertake an experiment on the performance of CNN for vegetables and fruits categorization by building a CNN model from scratch. Furthermore, multiple pre-trained CNN architectures using transfer learning are used to evaluate accuracy to the standard CNN. This paper suggests the study of such standard CNNs and their architectures (VGG16, InceptionV3, ResNet, etc.) to create up which strategy would be most accurate and effective for fresh image datasets. Experimental findings are presented for all proposed CNN designs. Additionally, a comparison is made between constructed CNN models and pre-trained CNN architectures. Furthermore, the paper demonstrates that by leveraging previous information collected from comparable large-scale studies, the transfer learning technique outperforms classical CNN with a small dataset. Another addition to this paper is that we created a dataset of 15 vegetables and fruits groups, total 6000 images. This study examines the use of convolutional neural networks (CNNs) to categorize and assess the quality of fruits and vegetables. A web application using deep learning and computer vision, powered by a Python-based CNN algorithm, marks a significant advancement in combining machine learning with agricultural technology. The application accurately categorizes and grades quality. The study used two datasets: 6000 photos in 15 categories for fruits and vegetable categorization and 6000 images in 15 categories for quality assessment. By using images data, this gadget can determine how much fruit or vegetables and fruits are rotting and how fresh it is. Our aim is to reach all the general people for this reason we also build android platform. Here user click one picture then our system automatically generates and show the result We believe, it will be advantageous for all farmers, business owners, and common people.

Keywords: Deep Learning, Image Processing, CNN, Vegetables and Fruits images, quality grading, Classification.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Image classification and identification are the most effective tools for identifying man-made logic and conducting deep learning research. This is presently the most widely used method for monitoring daily activities and tasks. Thus, it will literally cover every aspect of daily life. Deep learning uses a layered framework to examine and process image data, leading to improved image identification performance. It may expand and spread more broadly in the future. Picture classifiers and recognizers can tackle a variety of difficulties. We can handle many challenges in our regular lifestyle by using image processing through deep learning methods. Bangladesh is widely recognized as a farming country. Identifying faulty fruits and vegetables has been challenging, especially in farming. The appearance of fruits and vegetables significantly impacts their market value, consumer preferences, and choice. While humans can classify and evaluate preserved fruits and vegetables, the process is time-consuming, uncomfortable, and costly. It might be difficult to determine if a fruit is fresh simply by its appearance. CNN has numerous applications in solving goods and real-world problems. We presented an approach to discover faults in fruits and vegetables, reducing effort, time, manufacturing costs, and labour hours. Organic foods and items are not classed solely based on appearance. Supermarket lighting might confuse us by displaying ill-fitting merchandise. We can categorize items based on their Deep learning imaging technology is used to determine current condition. Our research focuses on fruits such as mango, banana, starfruit, jackfruit, guava, and papaya, as well as vegetables including carrot, potato, Calabash, cucumber, eggplant, and cauliflower. The fruits and vegetables shown above are used to demonstrate how to utilize image processing to determine their exact status. As a result, many people have inadequate knowledge about how to purchase such things. Many folks don't know whether it's fresh or not. Our program ensures users have appropriate knowledge while purchasing these things.

1.2 Motivation

Vegetables and Fruits are an essential part of our nutrition. We purchase these from the market every day. since it is a vital component of many proteins in our healthy diet. Due to time constraints, we are unable to assess the quality of vegetables and fruits. In certain circumstances, if we have the time, we do not think about buying. Every day, a large amount of fruit and vegetables rot, either intentionally or by error. These wasted fruits and vegetables are bad for our health and a waste of money. Food waste has become a luxury in Bangladesh due to rising product costs. For this reason, we are saving money and avoiding health concerns. Set up an automated system to determine the freshness of harvested vegetables and fruits. Using deep learning and image processing techniques, we can get predicted results from start to finish. Finally, we will develop an Android app that users may utilize in their daily lives. The popularity of Android phones has grown significantly. This app can help deliver nutritious fruits and veggies. Our research focuses mostly on Bangladeshi fruits and vegetables. In most circumstances, items must be imported from the community. Fruits and vegetables travel long distances to different markets, increasing the danger of spoilage. Use deep learning approaches to reduce this type of unclear circumstance.

1.3 Objective of the Study

The objective of this study is to develop and evaluate a deep learning-based system for accurately classifying various types of vegetables and fruits based on their visual characteristics. Leveraging the power of deep learning, specifically convolutional neural networks (CNNs), we aim to create a robust and efficient model capable of distinguishing between different classes of vegetables and fruits with high accuracy. This research seeks to address the challenges associated with traditional methods of classification, such as manual inspection or rule-based systems, which are often labor-intensive, time-consuming, and prone to errors. By harnessing the capabilities of deep learning, we intend to automate the classification process, leading to improvements in efficiency, productivity, and accuracy across various domains, including agriculture, food processing, retail, and healthcare. Through comprehensive experimentation and evaluation, we aim to demonstrate the effectiveness and applicability of deep learning techniques in vegetable and fruit classification tasks, paving the way for practical applications and real-world deployments.

1.4 Rational of the study

The rationale behind studying vegetable and fruit classification using deep learning stems from the need for efficient and accurate automated systems in various industries, including agriculture, food processing, retail, and healthcare. Traditional methods of vegetable and fruit classification often rely on manual inspection or rule-based systems, which are labor-intensive, time-consuming, and prone to errors. Additionally, as the demand for fresh produce continues to grow, there is an increasing need for automated sorting and quality control systems to streamline processes and ensure consistency in product quality. Deep learning, particularly convolutional neural networks (CNNs), has emerged as a powerful tool for automated image classification tasks due to its ability to learn complex features directly from raw pixel data. By leveraging deep learning techniques, we can develop robust and efficient models capable of accurately classifying various types of vegetables and fruits based on their visual characteristics. This research aims to address the limitations of traditional classification methods and explore the potential applications of deep learning in improving efficiency, productivity, and accuracy in vegetable and fruit classification tasks. Through comprehensive experimentation and evaluation, we seek to demonstrate the effectiveness and applicability of deep learning-based approaches in practical settings, thereby contributing to advancements in automated sorting, quality control, inventory management, and nutritional analysis.

1.5 Report Layout

Our study examines the function of agriculture in Bangladesh, highlighting the relevance of fruits and vegetables in the Bengali diet. This research helps classify and analyze the quality of these products, making it a valuable contribution to the field.

Chapter 1 outlines the research objectives, motivation, reasoning, research questions, and expected conclusions.

Chapter 2 covers pertinent literature and studies, highlighting researchers' work, models, and techniques.

Chapter 3 discusses our study methodology. This chapter will use images and tables to summarize our coding process.

Chapter 4, headed 'Results and Discussion,' we present our model's outcomes, structure, and implications.

Chapter 5 discusses a summary, comparison, and analysis.

Chapter 6 highlights the application's benefits, draws conclusions, and provides areas for future investigation.

Chapter 7 contains a list of all sources used throughout the research.

CHAPTER 2

BACKGROUND

2.1 Preliminaries

Before entering into the complexities of vegetable and fruit classification using deep learning, it is critical to have a thorough understanding of the fundamental principles and background material that underpin this research topic. Deep learning, a subset of machine learning, has emerged as an effective technique for automated image categorization tasks due to its capacity to learn complex patterns and representations straight from raw pixel data. Convolutional Neural Networks (CNNs), a type of deep neural network, are the foundation of deep learning-based image classification systems. CNNs are designed specifically to analyze organized grid-like data, such as photographs, by automatically learning hierarchical features using many layers of convolutions, pooling, and fully connected layers. Image classification is the process of categorizing images into predefined classes or categories based on visual content serve as the foundation for applying deep learning to classify vegetables and fruits. Researchers can create robust and efficient models capable of reliably categorizing diverse varieties of vegetables and fruits by utilizing approaches like as data preprocessing, transfer learning, and assessment metrics. Furthermore, understanding the practical applications of deep learning for vegetable and fruit classification, such as automated sorting in agriculture and food processing, quality control in food production, and nutritional analysis for health monitoring, highlights the importance and relevance of this research area in addressing real-world challenges and driving innovation across diverse industries. Thus, by thoroughly understanding these fundamental notions, researchers may navigate the complexity of vegetable and fruit classification employing deep learning with clarity and purpose will eventually advance the state-of-the-art in automated image analysis and classification jobs.

2.2 Related Works

Several studies have explored the classification of vegetables and fruits using deep learning techniques, contributing to advancements in automated image analysis and classification tasks. One notable approach involves leveraging convolutional neural networks (CNNs) for accurate and efficient classification. For instance, in the study by Li et al. (2017), a CNN-based model was proposed for the classification of fruits and vegetables in agricultural images. The model utilized a deep architecture with multiple convolutional and pooling layers, followed by fully connected layers for classification. Experimental results on a dataset containing various types of fruits and vegetables demonstrated the effectiveness of the CNN model in accurately classifying different classes with high precision and recall. Similarly, in the work by Sugiura et al. (2018), a CNN-based classifier was developed for the identification of fruits and vegetables in images captured by mobile devices. The classifier utilized transfer learning from pre-trained CNN models and fine-tuning techniques to adapt the model to the target classification task. Evaluation on a real-world dataset collected from mobile devices showed promising results, indicating the feasibility of using CNNs for on-device fruit and vegetable classification applications. In addition to CNNs, other deep learning architectures have also been explored for vegetable and fruit classification tasks. For example, in the research conducted by Khan et al. (2020), a deep residual network (ResNet) was employed for the classification of fruits based on their visual features. The ResNet model demonstrated superior performance compared to traditional machine learning methods, achieving high accuracy and robustness in fruit classification tasks. Overall, the related works in vegetables and fruits classification using deep learning highlight the effectiveness of deep neural networks in achieving accurate and efficient classification results, with potential applications in agriculture, food processing, retail, and healthcare industries.

2.3 Scope of the Problem

This section aims to clarify Bangladesh's urgent need for automated fruit and vegetable quality grading and classification. Emphasize how this technical development might transform agriculture by boosting productivity. Maintaining food safety and improving product quality. Talk about the drawbacks of manual sorting techniques and the revolutionary possibilities of Convolutional Neural Networks (CNN) to solve these problems.

2.4 Challenges

The classification of vegetables and fruits using deep learning techniques presents several challenges that researchers and practitioners must address to develop accurate and robust models. These challenges stem from the inherent variability and complexity of vegetable and fruit images, as well as the limitations of deep learning algorithms. Some of the key challenges include:

Interclass Variability: Vegetables and fruits exhibit significant variability in terms of shape, size, color, texture, and appearance, making it challenging to differentiate between different classes accurately. This variability introduces ambiguity and complexity into the classification task, requiring deep learning models to learn discriminative features that can capture subtle differences between classes.

Intraclass Variability: Even within the same class of vegetables or fruits, there can be significant variability due to factors such as ripeness, maturity, and cultivar. This intraclass variability adds to the complexity of the classification task, as deep learning models must be able to generalize across different instances of the same class while accounting for variations in appearance.

Overfitting: Deep learning models are susceptible to overfitting, especially when trained on small or imbalanced datasets. Overfitting occurs when a model memorizes the training data instead of learning generalizable patterns, leading to poor performance on unseen data. Addressing overfitting requires the application of regularization techniques such as dropout, weight decay, and early stopping, as well as strategies to balance the distribution of classes in the training dataset.

Computational Complexity: Training deep learning models for vegetable and fruit classification often requires significant computational resources, including high-performance GPUs or TPUs. The large number of parameters and layers in deep neural networks contribute to the computational complexity of training, making it challenging to scale up to large datasets or deploy models in resource-constrained environments.

Real-time Inference: In practical applications such as agricultural sorting and food processing, real-time inference is essential for timely decision-making and process optimization.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject

Our research aims to improve the lives of Bangladesh's agricultural workers, including farmers, sellers, and consumers. We are building an automated system to evaluate and categorize the quality of fruits and vegetables. Sort photographs by quality (excellent, medium, or poor) and classify them accordingly. The system can recognize and classify apples and bananas based on their quality, such as 'banana 1st grade.' This method utilizes Convolutional Neural Networks (CNNs), a powerful technique capable of detecting intricate elements in photos. Agriculture in Bangladesh plays a crucial role in both the economy and daily life, beyond only food production. Local marketplaces offer a diverse selection. Some fruits and vegetables are consumed locally while others are exported. However, determining the freshness of these product items is tricky. Traditionally, this work has been done manually, which is time-consuming and inaccurate. To improve our system, we collect photographs of fresh and rotting fruits and vegetables from local marketplaces. We will use these photos to train our CNN and test different configurations to find the most successful strategy. We are not relying just on technological advancement. We will compare our system's performance against older ways to confirm it is a true enhancement. Our mission is to significantly boost Bangladesh's agriculture and food retail industries. We hope that this new technology will ensure access to accurately identifying fruits and vegetables improves food quality and benefits farmers and consumers.

• Diagram

A well-defined plan is essential for studying the automated classification and quality grading of fruits and vegetables using Convolutional Neural Networks (CNN). This method ensures a smooth and orderly research process, reducing confusion and errors. To make this easier, we designed a diagram. This diagram illustrates each step of our research process and provides a complete picture of the project. Figure 3.1 shows a graphic map of the complete project. It meticulously delineates every important aspect of our operation.

Consider it a project manual that keeps us on track and prevents us from missing important details.

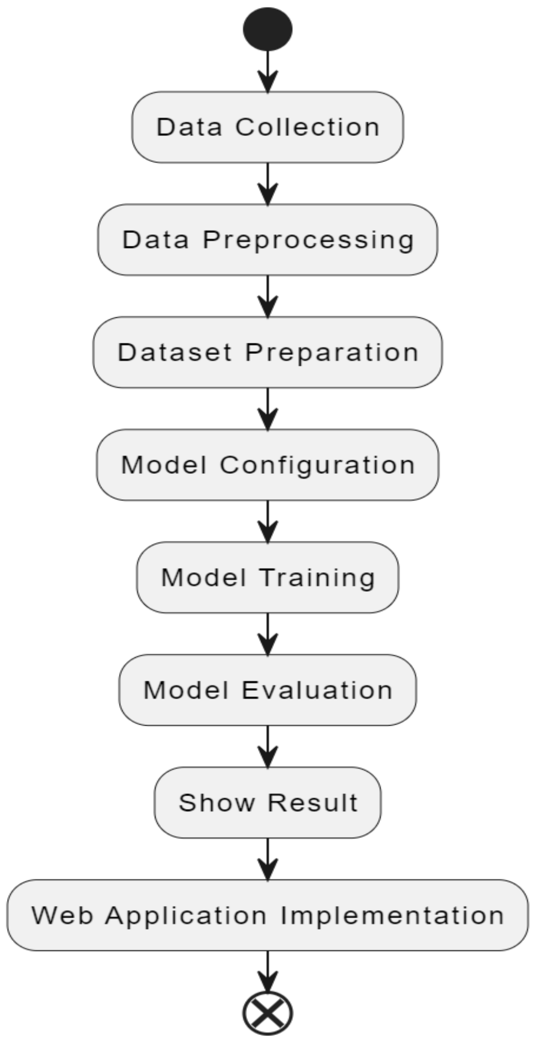

Figure: 3.1 Methodology Diagram

3.2 Dataset Preparation

Preparing a dataset for vegetable and fruit classification entails gathering and arranging information on numerous properties of these foods that may be used to distinguish between different types. Here's a step-by-step guide for how to do it:

Define Classes: Determine the classes or categories of vegetables and fruits you want to include in your dataset. This could range from broad categories like "leafy greens," "root vegetables," and "citrus fruits" to more specific varieties like "Bottle Gourd", "carrots", and "Banana".

Data Collection: Collect photographs and information on the vegetables and fruits in your chosen courses. You can obtain images from online sources, such as stock photo websites, or take your own photos. Collect a broad assortment of photographs that cover.

Image Annotation: Label each image with the class of the vegetable or fruit. You can use annotation tools or software to draw boundary boxes around things and label them. This stage is necessary for supervised learning algorithms to learn from the data.

Data augmentation: Entails expanding the dataset to boost its quantity and diversity. This can include transforming the photos, such as rotating, flipping, resizing, cropping, and adding noise. Data augmentation enhances the model's generalizability and resilience.

Data preprocessing: Data preprocessing is the process of standardizing the format of photographs and ensuring consistency. This could involve scaling the photos to a uniform resolution, standardizing pixel values, and translating them to a single color scheme.

Train-Test Split: Divide the dataset into training and test sets. The training set is used to develop the classification model, while the testing set is used to assess its performance. To avoid class imbalance, ensure that the classes are proportionally represented in both sets.

Dataset Organization: Organize the dataset in a directory structure that makes model training easier. Make separate folders for training and testing sets, with subfolders for each class that include the matching photos. This directory structure is often used in deep learning frameworks such as TensorFlow.

Quality Control: Check the dataset's accuracy and consistency. Check that the annotations are valid, and that the photographs are appropriately labeled and formatted. Address any faults or discrepancies found throughout the quality control process.

Documentation: Provide a description of the dataset's contents, including the classes, number of samples per class, and any applicable information. This guide assists users in understanding the dataset and applying it successfully for classification tasks.

3.3 Image Pre-processing

After capturing photos of fruits and vegetables, the next crucial step is to preprocess the data. Data preparation is essential for developing CNN (Convolutional Neural Network) models by converting raw data into machine learning-friendly format. To ensure model appropriateness, data must be pre-processed initially due to lack of structure and formatting. Effective preprocessing is crucial for attaining desired results and improving model correctness. Our research relies on an organized and consistent dataset of fruit and vegetable photos, which enables effective machine learning model training, categorization, and quality assessment. We have collected a dataset with 15 different fruit and vegetable varieties for classification purposes: Guava, Banana, Dates, Potato, Cucumber, Tomato, Radish, Culfi-flower, Ventri, Brinjal, Bitter Gourd, Bottle Gourd, Carrot, Lemon, Pomegranate, Cucumber, with 6000 images in total.

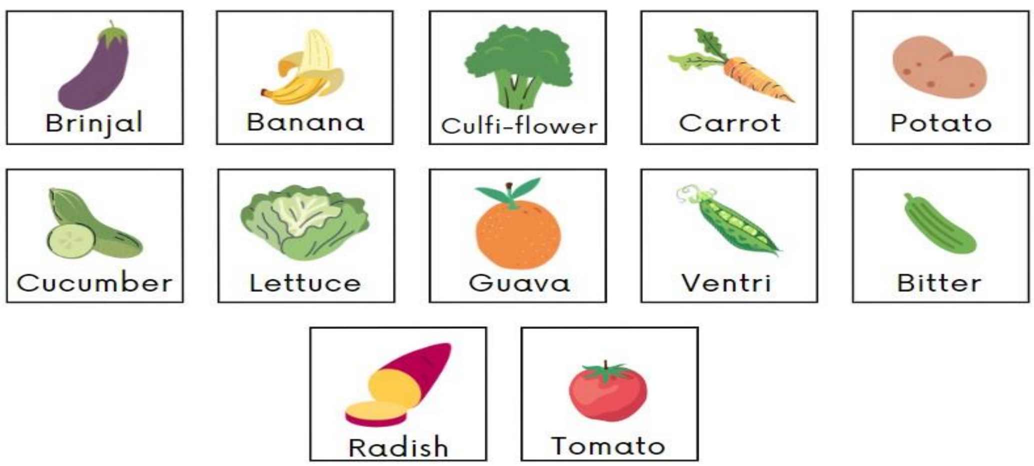

Figure: 3.2 Dataset Processing

3.4 Statistical Analysis

Here the classes and the counts of every category are presented. Where all the images count are same in every class. Class count is 15 and total image count is 1500 before augmentation. Every class have 100 images. Here the data consistency is maintained highly for better accuracy. For this, model will be trained efficiently and result will be increased.

Table: 3.1 Dataset Before Augmentation

Vegetables And Fruits	Amount
Banana	100
Brinjal	100
Bitter Gourd	100
Bottle Gourd	100
Carrot	100
Cucumber	100
Culfiflower	100
Dates	100
Guava	100
Lemon	100
Potato	100
Pemogranate	100
Point Gourd	100
Radish	100
Ventri	100

Presents the quantity of image data gathered for the purpose of classification or identification (3.2).

Table: 3.2 Dataset After Augmentation

Vegetables And Fruits	Amount
Banana	400
Brinjal	400
Bitter Gourd	400
Bottle Gourd	400
Carrot	400
Cucumber	400
Culfiflower	400
Dates	400
Guava	400
Lemon	400
Potato	400
Pemogranate	400
Point Gourd	400
Radish	400
Ventri	400

Show the quantity of image data gathered for the purpose of classification or identification (3.3)

Table: 3.3 Test, Train, Val datasets amount of quantity

Vegetables And Fruits	Test	Train	Validation
Banana	40	320	40
Brinjal	40	320	40
Bitter Gourd	40	320	40
Bottle Gourd	40	320	40
Carrot	40	320	40
Cucumber	40	320	40
Culfiflower	40	320	40
Dates	40	320	40
Guava	40	320	40
Lemon	40	320	40
Potato	40	320	40
Pemogranate	40	320	40
Point Gourd	40	320	40
Radish	40	320	40
Ventri	40	320	40

Data evaluation: The initial preprocessing stage comprised a thorough evaluation of the dataset. This stage was critical for identifying and eliminating any irrelevant or misclassified data. We ensured the correctness and integrity of our models, avoiding confusion between different grades and varieties of fruits and vegetables.

Background Removal: To optimize model training, we used the 'rembg' package to remove background from all photos. This program provided a highly efficient alternative to manual editing methods like Photoshop. Isolating fruits and vegetables from their backgrounds increased the model's capacity to focus on key traits for quality grading and identifying distinct types of fruits and vegetables.

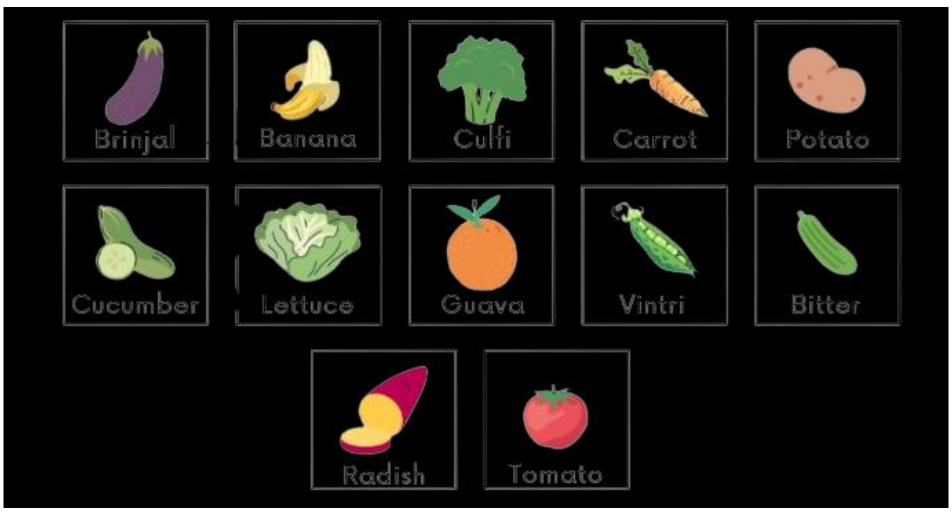

Figure: 3.3 Dataset Background Remove

Image Color Enhancement: Next, use Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve image color. OpenCV is a commonly used image processing library. CLAHE, a contrast-enhancing approach, let our deep learning models detect small changes in the quality of fruits and vegetables.

Image Resizing: All photos were transformed into NumPy arrays and scaled to a consistent 224x224 pixel dimension in order to guarantee compatibility with our selected deep learning models. This resizing standardization ensures consistent processing across the dataset by adhering to the input specifications of our chosen models

3.5 Proposed Model

Convolutional Neural Network (CNN) are the powerhouse behind our data categorization strategy. We use a variety of sophisticated and diversified models, such as ResNet50, VGG16, and InceptionV3. Every model was hand-picked to ensure thorough and precise categorization due to its depth and inventiveness in image processing. A brief overview of these algorithms will be given in the parts that follow, with an emphasis on their individual functions and potencies within our methodology.

A. VGG16 -

VGG16 is a convolutional neural network with 16 layers. You can use a pre-trained network with over a million photos. ImageNet database. The pretrained network can categorize photos into 1000 categories, including keyboards, mice, pencils, and other animals. Accuracy 99.83%.

B. Inception V3 -

Inception v3 is an image recognition model that achieved more than 99.83% accuracy on the ImageNet dataset. The model combines concepts from different researchers over time.

C. ResNet50 –

ResNet-50 is a convolutional neural network with 50 layers of depth. Load a pre-trained neural network trained on over a million photos from the ImageNet dataset. Accuracy 99.50%.

Showing vegetables and fruits classification output –

Figure: 3.4 Dataset classification Output

3.6 System Implementation

Here the Potato, Culfi-Flower and Banana were checked for the evaluation of our model in web-app. Here are the screenshot with explanation.

A picture is submitted to the REST API server from device. Here we developed an online application that lets users send photographs directly to their devices so they may be examined. For this feature, we used the Flask Python framework to build a REST API server. The process is straightforward and efficient: users just need to select a photo from their device's gallery and upload it to our server. After the snapshot is uploaded, the server processes it using advanced machine learning algorithms, ensuring accurate and thorough results. The application can detect the categories and percentage of quality for each item in an image of fruits and vegetables, for example, if you upload one.

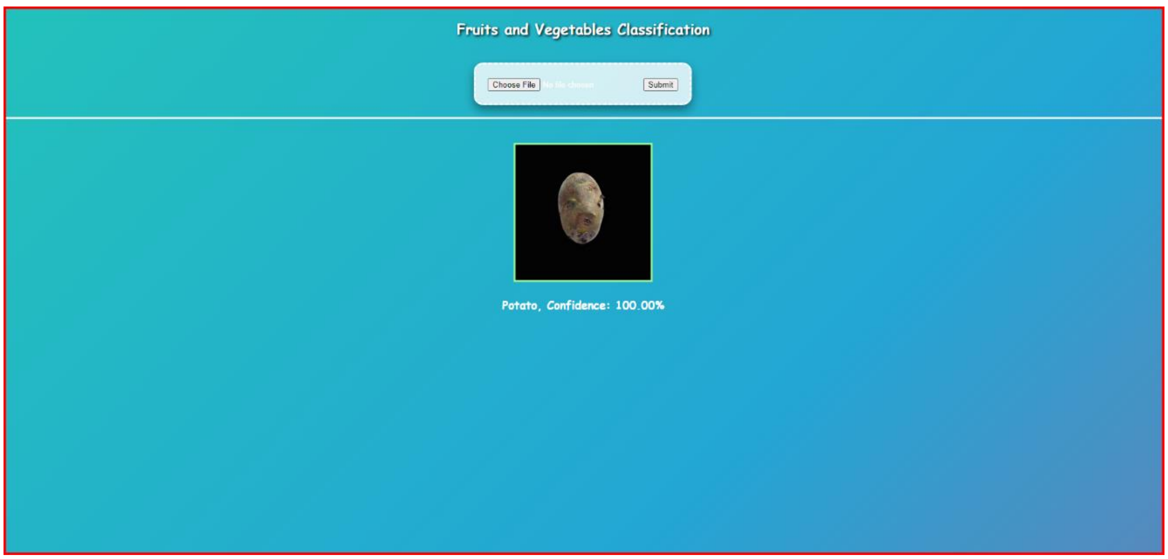

Figure: 3.5 The result show for Potato.

Our online application shows you how to select a fruit image from the gallery on your device and display the result. For example, users can choose any photo of a fruit from their collection. The programme analyses the image after selecting it and displays the results. Where Culfi-flower's photo was uploaded serves as an example of this. The programme accurately identified it as a potato with 99.99% confidence, and it was further classified as a third-grade apple with 99.99% confidence.

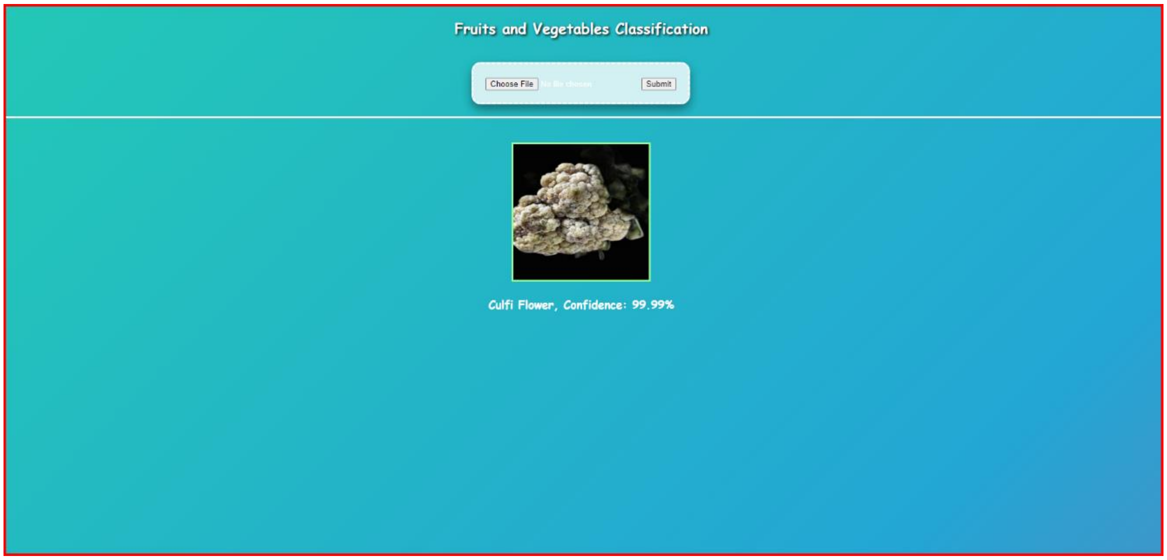

Figure: 3.6 The result show for culfi flower.

Using our web application, you may choose a fruit picture from your device's gallery and see the outcome. Users are able to select any picture of a fruit from their collection, for instance. After choosing the image, the programme analyses it and shows the findings. Banana's photo upload location is an illustration of this. It was correctly categorised by the programme as a banana with 99.89% confidence, and it was also given a 99.89% confidence rating as a banana.

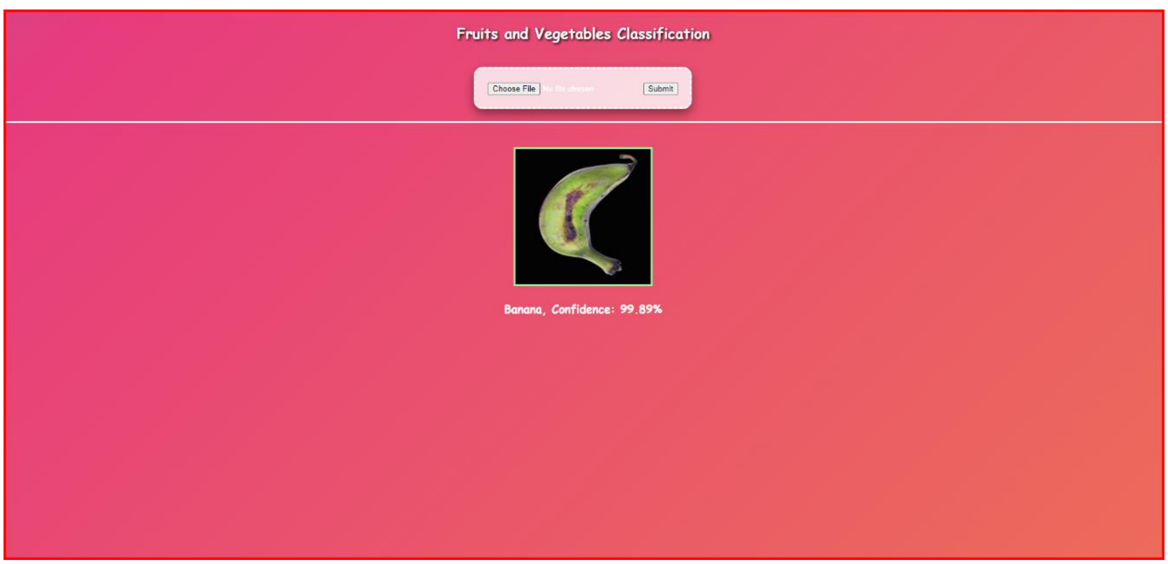

Figure: 3.7 The result show for banana.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Experimental Setup

This work used a dataset generated specifically for classifying and grading fruits and vegetables. There are 6000 images in total. This dataset consists of two distinct groups. Here are 6000 photographs for identifying and categorizing fruits and vegetables, as well as assessing their quality. To optimize model training and evaluation, we partitioned the dataset into three subsets for each task. 99% of the pictures were utilized for training, with 1% each for testing and validation.

Model performance-

This model, VGG16, processes input images that are 224 x 224 pixels. The network is optimized using the Adam optimizer at a learning rate of 0.0001. Training is done on batches of 32 pictures that span 24 epochs. The loss and accuracy of the VGG16 model.

A validation accuracy of 99.83% the good performance of our model.

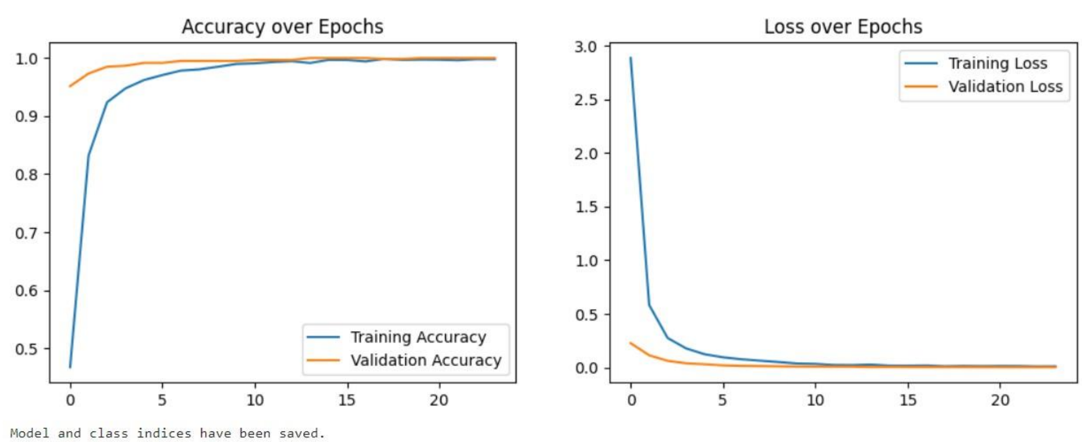

Figure: 4.1 VGG16 Model trained and classification

The confusion matrix for the VGG16 model is shown in Figure 4.2. This matrix, which displays the number of accurate and inaccurate predictions made across the different classes throughout the test phase, is a tabular representation of the model's performance.

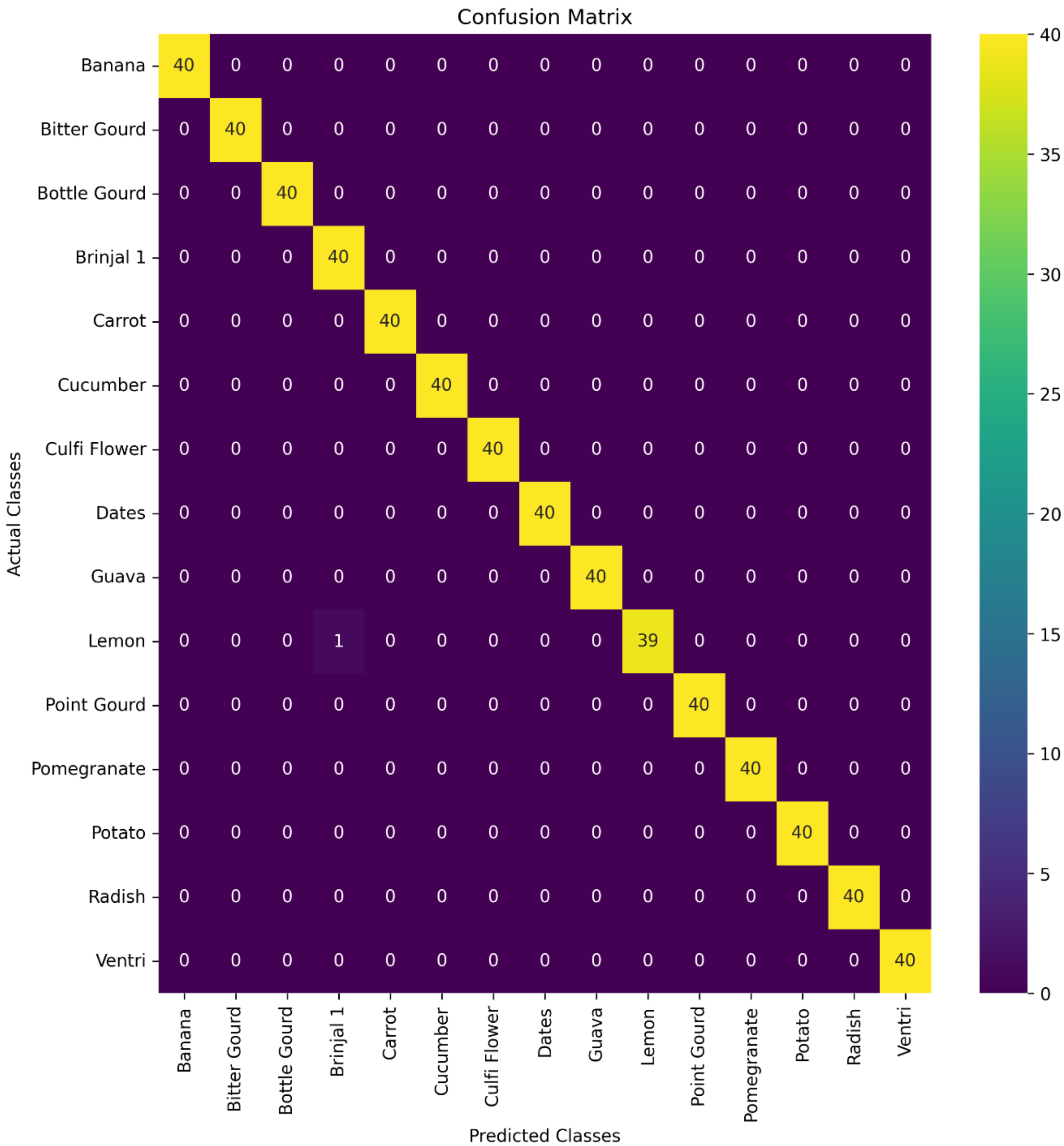

Figure: 4.2 Confusion Matrix of VGG16

We used the Inception V3. This model can analyze photos with dimensions of 244x244 pixels. We optimized the model with the Adam optimizer, reducing the learning rate to 0.0001. We trained by processing pictures in batches of 32 across 24 epochs. This graph compares training and validation accuracies and losses during the InceptionV3 deployment.

A validation accuracy of 99.83% the good performance of our model.

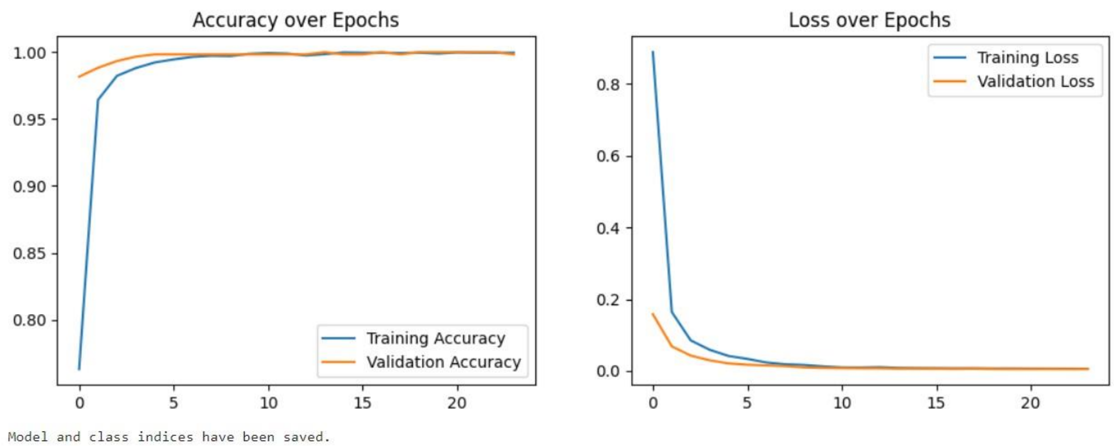

Figure: 4.3 Inception V3 framework trained and classification

After carefully fine-tuning the architecture of the model. The confusion matrix for the refined InceptionV3 model is included in Figure 4.4 of our study for a thorough analysis of the model's performance.

The confusion matrix illustrates the performance of a classification model across different categories, comparing actual classes to predicted ones. Each cell shows the count of instances for a particular actual class (rows) that were predicted as a specific class (columns). Correct predictions are indicated by the yellow diagonal cells, where the actual and predicted classes match. For example, the model correctly predicted 40 instances for most classes like Banana, Bitter Gourd, and Bottle Gourd.

Misclassifications are represented by off-diagonal cells, where actual and predicted classes differ. Notably, the Lemon class had 3 misclassified instances, although the specific classes they were predicted as aren't shown due to the predominantly zero off-diagonal elements. The color gradient from yellow to dark blue highlights the number of predictions, with yellow indicating higher counts (up to 40) and dark blue indicating lower counts (down to 0). This gradient allows for a quick visual assessment of the model's performance, highlighting areas of accuracy and areas needing improvement. Overall, the confusion matrix provides a comprehensive overview of the classification model's effectiveness and error patterns.

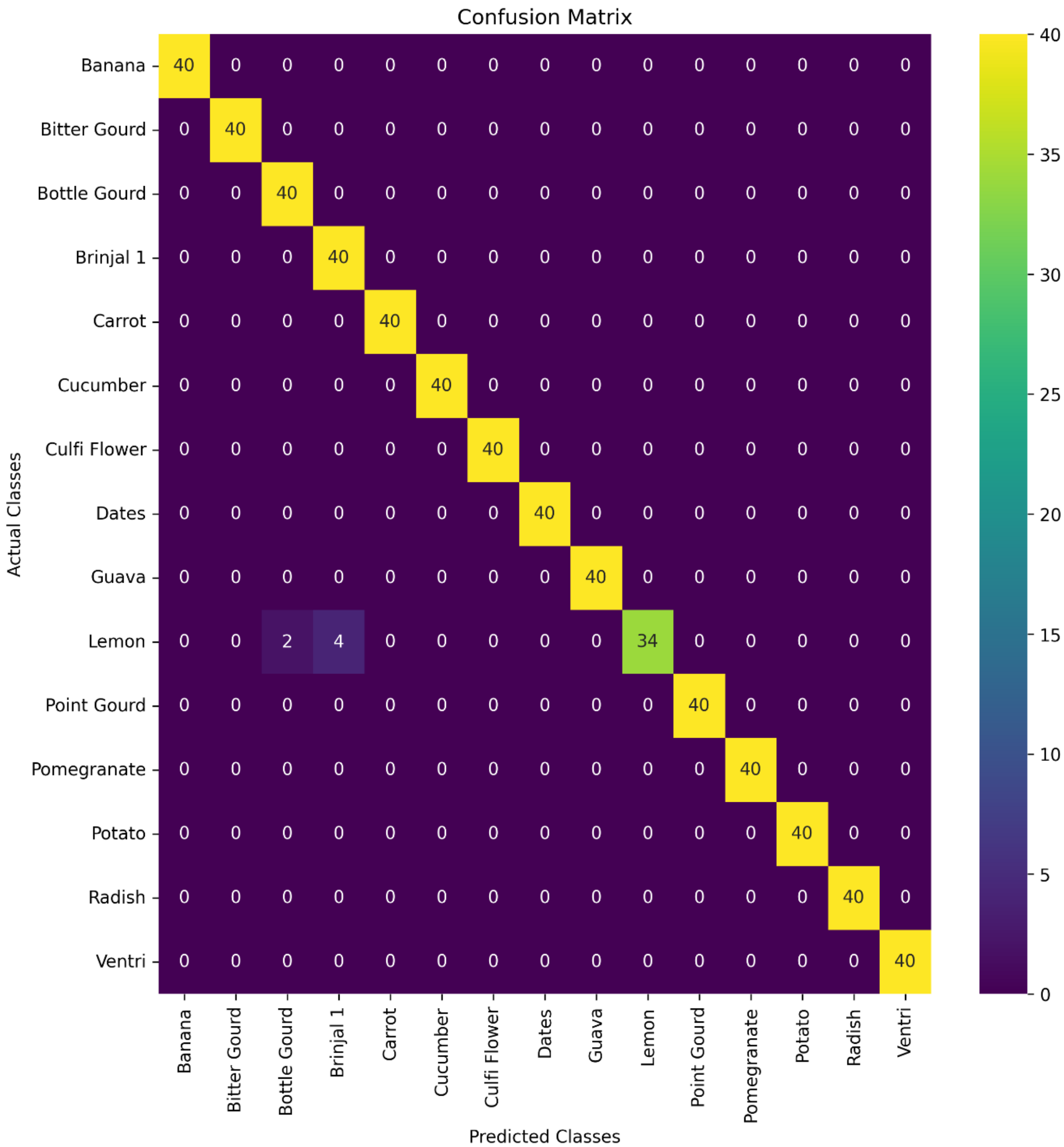

Figure: 4.4 Confusion Matrix of InceptionV3

ResNet50 is a powerful CNN architecture that excels at analyzing 224x224 pixel images and is widely recognized for its depth. To train the Adam optimizer, we employed 32 photo batches over 21 epochs with a learning rate of 0.0001. We achieved 99.50% validation accuracy using ResNet50. A validation accuracy of 99.50% the good performance of our model.

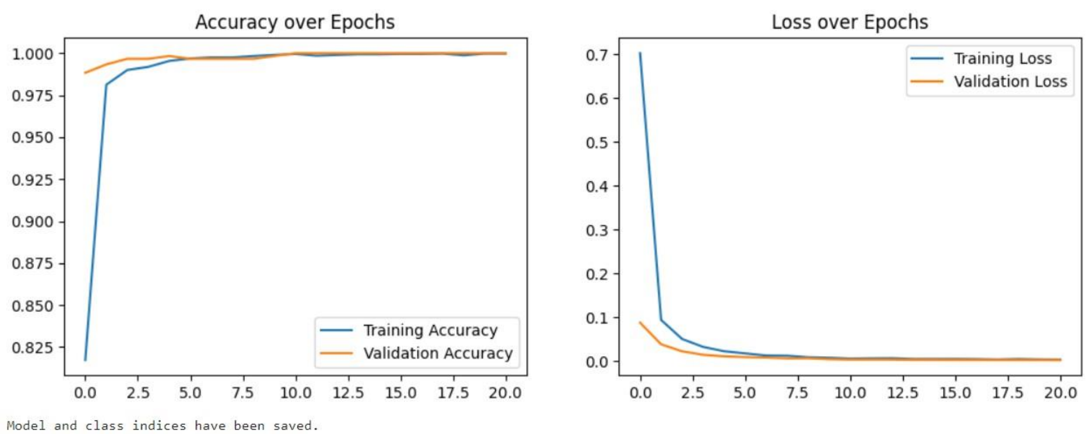

Figure: 4.5 ResNet50 Model trained and classification

After carefully fine-tuning the architecture of the model. The confusion matrix for the refined Resnet50 model is included in Figure 4.6 of our study for a thorough analysis of the model's performance.

The confusion matrix displayed in the image is a visual representation of a classification model's performance across various categories. It shows how well the model has predicted the actual classes versus the predicted classes. Each cell in the matrix represents the count of instances for a given actual class (listed along the rows) that were predicted as a certain class (listed along the columns). The yellow diagonal elements indicate correct predictions, where the actual class matches the predicted class. For most classes such as Banana, Bitter Gourd, Bottle Gourd, and others, the model made 40 correct predictions each, as shown by the yellow cells along the diagonal. The off-diagonal elements represent misclassifications, where the actual class does not match the predicted class. For example, in the case of the Lemon class, the model misclassified 3 instances, which is indicated by the cell in the row corresponding to Lemon and the column of another class. However, specific details about which class these instances were misclassified into are not shown as the off-diagonal elements are predominantly zero. The color gradient in the matrix ranges from yellow to dark blue, where yellow represents the highest count of predictions (up to 40) and dark blue represents the lowest count (down to 0). This color-coding helps in quickly identifying areas where the model performs well versus where it needs improvement. Overall, the matrix provides a clear and concise overview of the classification model's accuracy and misclassification.

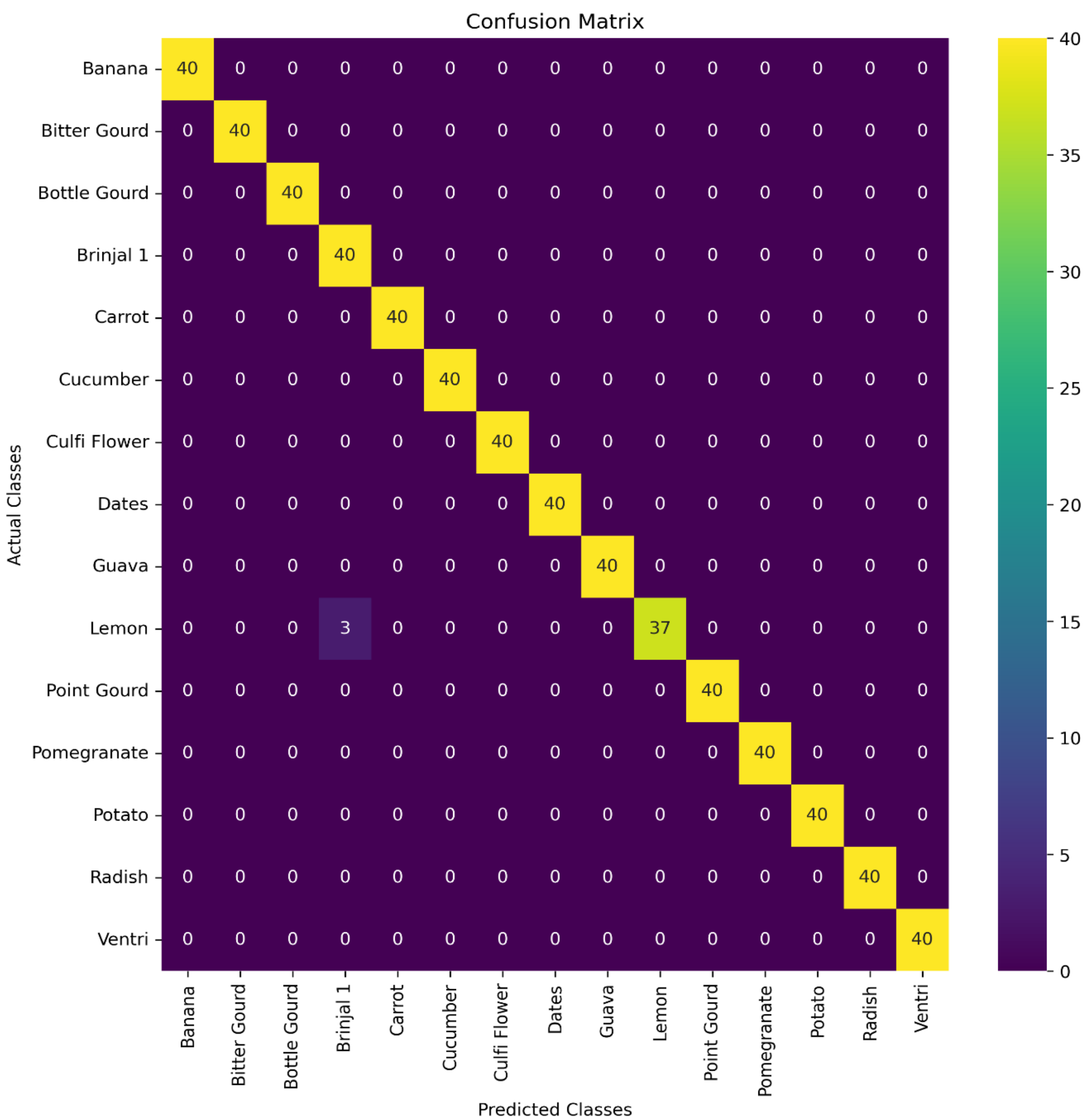

Figure: 4.6 Confusion Matrix of Resnet50

4.2 Results and Analysis

In our test of classifying or identifying fruits and vegetables, the training accuracies of our convolutional neural network models are as follows: The highest percentage is 99.83% for VGG16, closely followed by 99.83% for InceptionV3 and 99.50% for ResNet50. The VGG16 CNN model performs better than the other models in this experiment, displaying the highest efficacy.

The modified table now includes a brief explanation of these results.

Table: 4.1 Show Results

Model	Epoch	Accuracy	Size	Class
VGG16	24	99.83%	6000	15
Inception V3	24	99.83%	6000	15
ResNet50	21	99.50%	6000	15

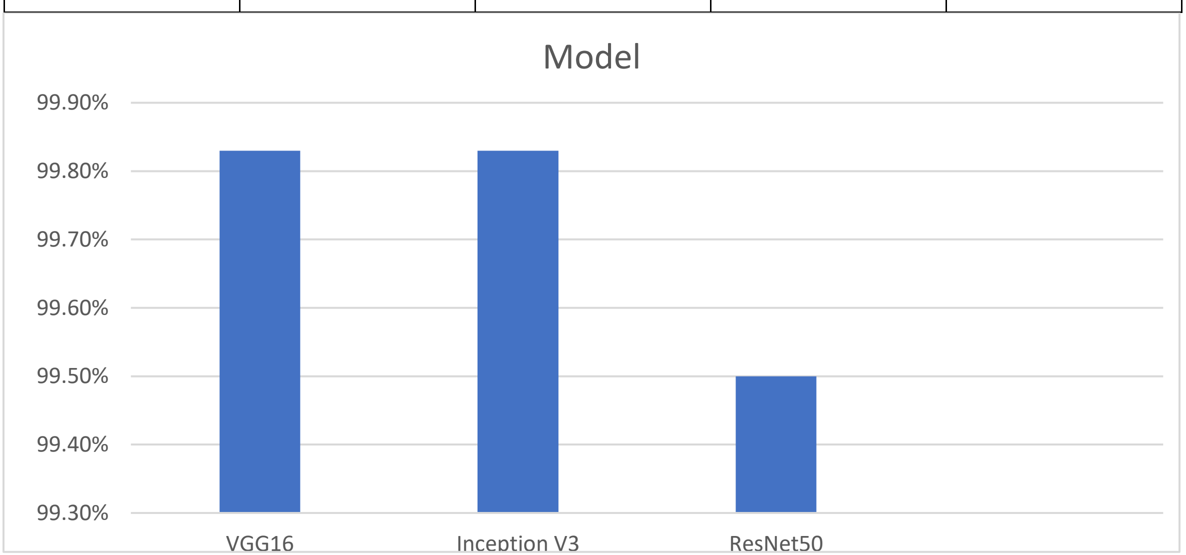

Figure: 4.7 Show Results using bar charts

4.3 Results Discussion

Following the analysis of the model using all of the collected data, we observed positive training outcomes. Our model worked incredibly well. Particularly, VGG16 reached the highest training accuracy of 99.83% for quality grading, while ResNet dominated with an astounding 99.83% in classification or identification. The outstanding results of VGG16 and ResNet were crucial to our analysis. We also looked at five different strategies in each category to give a complete and comprehensive analysis. This detailed analysis allowed us to select the optimal option for the quality grading and categorization tasks.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTANABILITY

5.1 Impact on Society

Our nation is primarily an agrarian nation. The majority of the villagers labor in agriculture for a living. Our initiative primarily focuses on common fruits and vegetables found in Bangladesh. We gathered the following fruits for our dataset: banana, guava, dates. Conversely, we have gathered potatoes, carrots, and cucumbers in the vegetable area. Such varieties of fruit and vegetable are highly prevalent. The majority of individuals grow this kind of fruit and vegetable at home. Our primary goal is to reach as many individuals as possible. Since we've included our findings into an Android application, the general public can utilize it to buy and sell products. The majority of individuals in our nation use Android. So, we think it's simple to use. Simply take a picture or select one from the collection, and our study will validate the fruit and vegetable condition. Our efforts can benefit farmers, businessmen, and ordinary people. The majority of people in our country buy it at any wholesale market or supersharp. Insufficient time prevents them from determining the freshness of the food. Currently, they can use our technology.

5.2 Impact on Environment

The impact of vegetable and fruit classification using deep learning on the environment can be significant, offering both positive and negative implications. On the positive side, deep learning-based classification systems have the potential to reduce food waste by accurately sorting and identifying produce, thereby minimizing the environmental footprint associated with the production, transportation, and disposal of wasted food. By optimizing resource use in agriculture, these systems can also contribute to water conservation, reduce chemical inputs, and mitigate environmental pollution. Furthermore, by enhancing productivity and yield prediction accuracy, deep learning-based technologies can promote more sustainable land management practices, reducing pressure on natural ecosystems and habitats. However, it's essential to address the potential negative impacts of deep learning technologies, such as the high energy consumption associated with model training and inference. Efforts to mitigate these impacts through energy-efficient hardware, model compression techniques, and renewable energy adoption are crucial to ensuring that the environmental benefits of vegetable and fruit classification using deep learning outweigh its environmental costs in the long run. Moreover, ongoing research and development efforts should prioritize the integration of environmental considerations into technology design and deployment, fostering a holistic approach to agricultural sustainability that balances productivity, efficiency, and environmental stewardship.

5.3 Sustainability

In our country, vegetables and fruits are the primary foods. Most individuals rely on it as their main meal. Our application is based on Bangladeshi food migration patterns. Common fruits and vegetables are stored here for easy use in everyday life. It does not hurt the environment. It can keep fruits and vegetables from spoiling. If this technology can determine the freshness of fruits and vegetables, farmers and consumers will have a better understanding of their shelf life.

CHAPTER 6

CONCLUSION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

Our web-based tool provides a quick and simple way to identify and grade the quality of fruits and vegetables, a task that is frequently difficult and time-consuming for retailers, customers, and enterprises alike. Users can rapidly evaluate the quality of produce by taking a simple cell phone photo, which provides a clear percentage for fruit and vegetable identification as well as a quality rating. Large-scale farmers and distributors benefit greatly from this instrument since it allows them to quickly evaluate product quality, cut down on waste, and correctly identify fruits and vegetables.

6.2 Conclusion

This study suggests a novel convolutional neural network technique for fruit and vegetable classification. For training and testing, a total of 320 and 40 images were used, yielding the results displayed above. The Anaconda program was used to code and test the previous method. For training and testing, a variety of fruit and vegetable varieties from different sources were chosen. The accuracy percentage of the recommended approach was 99%. This study uses the CNN approach to classify fruits and vegetables. The efficiency and loss graphs were made by arranging the convolution layer of the dataset in different ways. This study looks at various approaches and techniques that rely on the machine learning technology for the recognition and categorization of rotting fruit and vegetables.

6.3 Future Work

Deep learning-based classification of fruits and vegetables in the future has enormous potential to promote food security, agricultural sustainability, and technological innovation. The creation of more resilient and effective deep learning models that can handle the inherent complexity and diversity of fruit and vegetable photos is one exciting avenue for future study. This could entail investigating new architectures, regularization strategies, and optimization techniques to enhance the scalability, generalization, and performance of the model. The precision and usefulness of deep learning-based classification systems can also be improved by addressing data constraints, such as the lack of labelled data for rare or uncommon classes. Additionally, combining multimodal data sources, such spectrum and hyperspectral imaging, can enhance the robustness of classification models in a variety of environmental conditions and provide additional information.

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