AN EFFECTIVE APPROACH FOR MULTI-CLASS FRUIT AND VEGETABLE CLASSIFICATION BASED ON MODIFIED RESNET-18 FROM A COMBINED DATASET

BY

MD Aktaruzzaman Siddiquei

201-15-3132

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

Supervised By

Dr. Md. Ismail Jabiullah (MIJ)
Professor
Department of CSE
Daffodil International University

Co-Supervised By

Ms. Fabliha Haque (FHE)
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled **"An effective approach for multi-class fruit and vegetable classification based on modified resnet-18 from a combined dataset."**, submitted by **MD Aktaruzzaman Siddiquei, ID: 201-15-3132** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15 July, 2024.

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Faculty of Science & Information Technology
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Professor
Department of CSE
Jagannath University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Md. Ismail Jabiullah (MIJ),** 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 the award of any degree or diploma.

Supervised by:

____

Dr. Md. Ismail Jabiullah (MIJ)
Professor
Department of CSE
Daffodil International University

Co-Supervised by:

____

Ms. Fabliha Haque (FHE)
Lecturer
Department of CSE
Daffodil International University

Submitted by:

15.7.24
____

MD Aktaruzzaman Siddiquei
ID: 201-15-3132
Department of CSE
Daffodil International University

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ABSTRACT

This study delves into the pivotal role of fruit and vegetable quality in influencing human health, emphasizing the necessity of prioritizing fresh produce for optimal well-being. Consumption of high-quality fruits and vegetables offers enhanced nutrition and antioxidant benefits, contributing to overall health. Conversely, consuming spoiled produce poses health risks due to exposure to harmful pathogens and potential loss of essential nutrients. Deep learning emerges as a promising approach for assessing fruit and vegetable quality, leveraging its capacity to discern nuanced characteristics from complex datasets. Neural networks, particularly deep learning models, excel in automatically identifying subtle visual cues indicative of freshness or decay. This technology facilitates rapid and accurate categorization, essential for ensuring the quality and safety of produce across various settings, from farms to retail outlets. In this research, we amalgamated and analyzed two datasets to create a comprehensive dataset. Subsequently, we devised a new labeling system and applied three image filters for thorough analysis. To classify images as either good or rotten quality, we proposed a modified ResNet18 model, fine-tuned through hyperparameter optimization. Our findings showcase the effectiveness of the proposed model, achieving a remarkable 98% accuracy with an image size of 224x224 and a batch size of 64 over ten epochs. This model holds potential for assisting health-conscious individuals in discerning the quality of fruits and vegetables, thereby aiding in informed dietary choices. Overall, this study underscores the significance of fruit and vegetable quality in promoting human health and underscores the utility of deep learning in ensuring produce safety and quality assessment.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 Introduction

Horticulture and agriculture have a major impact on the development of the global economy. The agricultural industry is growing more slowly than the electronics and automobile industries. Therefore, in order to lead the agriculture market, new techniques need to be developed. Global norms state that humans still customarily scrutinise vegetables. It was a really difficult and drawn-out procedure. In order to evaluate agricultural products, meet quality standards, and increase their market worth, vegetable grading is crucial. A vegetable's image can be used to determine its form, colour, and size. These characteristics make grading vegetables easier for the user. In this article, a secure and cost-effective analysis of vegetable quality is conducted. Once more, agriculture is the primary source worldwide. It is an area of research that is quickly growing and has several uses, including biological and biometric systems. Among its applications is the agricultural industry. Image processing has been used in a variety of ways to determine the quality of fruits, vegetables, and other products. There are many fruits to choose from, such as oranges, bananas, apples, and so forth. On the other hand, vegetables like carrots, potatoes, tomatoes, and so forth. Tomatoes are a widely used food in this situation because of their high yield and special nutritional value. Tomatoes are considered an important crop for both commercial and culinary purposes. Fruits and vegetables are inspected for quality by human professionals. This manual sorting process, which relies on human inspection, is laborious and prone to imprecise judgement from different individuals. Automation of the quality identification process is expected to improve sorting efficiency and accuracy while reducing labour expenses. [12]

Fruit and vegetable characteristics like colour and form are important for a visual assessment. An effective autonomous sorting system must correctly identify both parameters. It is simple to extract the contour of fruits or vegetables from a digital image using standard image processing techniques. However, correctly modelling and processing colour in an image may be difficult since colour recognition involves a broad variety of physiological and psychological concepts. Today, there are many different colour systems used to rank fruits and vegetables based on their hues. Other techniques include colour histograms, fuzzy logic, neural networks, and genetic algorithms. Preconfigured models are another feature of Predictive Neural Networks [13]. Numerous important elements influence the assessment and classification of a quality detection system, such as the demand from customers for high-quality products, the superiority of machine behaviour over human behaviour, and the labour shortage. Due to their sensitivity, fruits and vegetables must be examined using non-destructive methods. Their size is the most important physical trait, but their hue serves as a barometer for their aesthetic qualities [14]. So, in order to evaluate agricultural products, make sure they meet quality standards, increase market value, and effectively arrange, package, and ship commodities, fruits and vegetables must be categorised. This article provides a deep learning based approach for fruit and vegetable classification and evaluation. It's economical and safe to use these methods on a mobile device. To be graded, fruits and vegetables need to meet specific requirements for form, size, texture, and other attributes. We will follow the same process using a deep learning model in order to get greater accuracy and fewer mistakes. Classifying and grading samples by hand will be time-consuming and error-prone. If these quality requirements are the foundation of an automated system, the task will be accomplished more rapidly and error-free. The development of deep learning model modification is more significant in this classification scheme. Quality-based categorization uses specific information from the fruit surface to classify fruits and vegetables based on how they look. A deep neural network is used to assess the quality of fruit samples (DNN).

Deep neural networks are encouraged to evolve by the structure of the human brain. The programming that the deep neural network use is the same as what the human brain utilises to learn from ordinary encounters in the future. There are two stages to using neural networks: training and testing. It consists of multiple processing components that work together and are intimately integrated. Like the brain, neural networks acquire knowledge through imitation. To test the system, we use the same amount of inputs as we used to train it in real time. Like other data-driven machine learning systems, artificial neural networks have been used to handle a wide variety of issues that are difficult to answer using traditional rule-based techniques [9]. This study's research concentrated on two different vegetables, each of which had particular qualities that the system could evaluate.

The paper is organized as follows: the content that has been published in a range of periodicals in prior years. The paper describes a suggested method for determining the quality of vegetables and presents the results of an experiment on quality detection. It ends with a discussion of additional recommendations and a conclusion. Lastly, the methodology diagram of the work is given to the below **figure-1**.

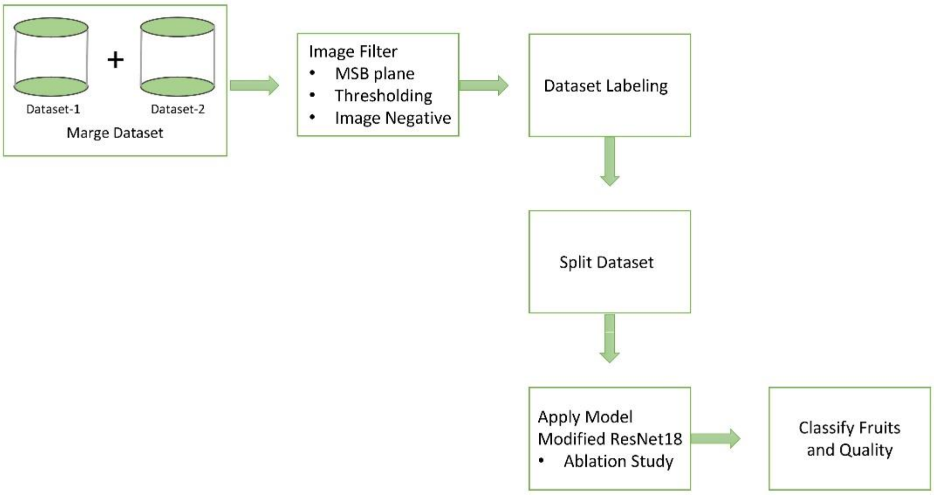

Figure-1: System architecture.

1.2 Motivation

This study is motivated by the pressing need for reliable and efficient methods to assess the quality of fruits and vegetables, a critical aspect of agriculture and supply chain management. In today's environment, where automation and technology play pivotal roles, the development of accurate models for categorizing food based on freshness is paramount. Traditional approaches to quality evaluation can be time-consuming and subjective, relying on personal judgment and leading to inefficiencies and potential errors. Thus, the objective of this project is to leverage modern image processing and machine learning techniques to enhance the precision, speed, and objectivity of assessing the quality of fruits and vegetables.

Central to this endeavor is the utilization of a dataset that encompasses a diverse array of fresh and spoiled produce, providing a valuable resource for training and evaluating machine learning models. The dataset exhibits inherent diversity, capturing variations in lighting, angles, and backgrounds, mirroring real-world scenarios. This highlights the necessity of developing models capable of robust generalization across a wide range of variables. Furthermore, the exploration of advanced image processing techniques and the adaptation of the ResNet-18 model underscore a commitment to pushing the boundaries of knowledge within this domain.
Moreover, addressing challenges such as class imbalance in the dataset and conducting comprehensive data preparation reflects a dedication to ensuring the resilience and reliability of the model. Beyond technical advancements, the study also emphasizes practical applications in agricultural and supply chain management. Automated quality assessment has the potential to streamline processes, reduce waste, and enhance overall efficiency, thereby offering tangible benefits to industry stakeholders.

1.3 Rational of the Study

This study is motivated by recognizing the significant impact that precise assessment of fruit and vegetable quality can have across multiple industries, including agriculture, food distribution, and consumer well-being. Traditional methods of evaluating output quality often rely on manual inspection, which is labor-intensive, time-consuming, and subject to human bias. This work seeks to address these challenges by leveraging modern image processing and machine learning techniques to automate and enhance the accuracy of quality assessment.

In today's agricultural landscape, where maximizing productivity and precision is paramount, developing intelligent models to classify fruits and vegetables based on their freshness is crucial. The project endeavors to create a model capable of effectively generalizing across diverse real-world scenarios by utilizing a varied dataset encompassing different types of produce in various settings. This approach aligns with the increasing demand for technology adaptable to the complexities of different agricultural environments.

By adapting the ResNet-18 model and incorporating sophisticated image processing algorithms, the study demonstrates a commitment to pushing technological boundaries in produce quality evaluation. The rationale behind this lies in the belief that refining existing models and methodologies can yield more accurate and reliable results, fostering progress in the field.

Furthermore, the study acknowledges the challenge of class imbalance in the dataset and underscores the importance of ensuring equitable representation for all categories of fruits and vegetables. Creating a balanced subset aims to mitigate biases and facilitate fair training and evaluation of the model, thereby bolstering its robustness.

Beyond technical considerations, the practical implications of automating fruit and vegetable quality assessment are significant. Automated systems have the potential to streamline operations in agricultural settings, reduce inefficiencies in distribution networks, and ultimately enhance overall efficiency in the food sector. The overarching goal of this study is to contribute to the broader objective of promoting sustainable and optimal practices in fresh fruit production and distribution.

1.4 Research Question

- How does the diversity of fruits and vegetables in datasets impact the effectiveness of image processing and machine learning for quality assessment?
- What modifications to the ResNet-18 model architecture enhance accuracy in distinguishing between fresh and rotten produce?
- What is the effect of modern image processing techniques like bit-plane slicing and adaptive thresholding on improving the quality evaluation of fruits and vegetables?
- How does creating a balanced sample of data address class imbalance issues in datasets and influence the resilience of models during training and evaluation?
- What are the practical implications of automated quality evaluation for fruits and vegetables in optimizing agricultural operations and reducing waste in supply chains?
- What is the performance of ResNet-18 with specified hyperparameters in terms of accuracy, precision, recall, and F1 scores for fruit recognition and freshness classification?

- What insights can be gained from comparing different hyperparameter setups, particularly regarding picture size and batch size, on model performance and efficiency?
- How does the duration of model training, measured in epochs, impact its ability to capture complex patterns in datasets and overall accuracy?
- What are the discrepancies between findings from the proposed model and a modified ResNet-18 design, considering changes in picture quality and batch size, and their practical implications?

1.5 Expected Output

The forthcoming research is poised to yield multifaceted outcomes that align closely with the study's overarching objectives. These anticipated results are structured to furnish valuable insights into the effectiveness of employing advanced image processing techniques and machine learning algorithms for gauging the quality of fruits and vegetables. Moreover, they illuminate the practical ramifications of such methodologies within the realms of agriculture and supply chain management.

Primarily, the research endeavors to attain an optimized model performance, a pivotal aim underscored by the utilization of the ResNet-18 model. Tailored modifications and specific hyperparameter configurations are envisaged to enable the model to exhibit commendable accuracy, precision, recall, and F1 scores across both fruit identification and freshness classification tasks.

A significant facet of the anticipated outcomes entails the analysis of dataset impact. The study endeavors to unravel the nuanced ways in which dataset diversity influences model efficacy. Factors such as variations in illumination, perspectives, and environmental conditions are poised to be scrutinized to discern their effects on the model's adaptability across disparate scenarios.

Furthermore, the research aims to shed light on the implications of alterations made to the ResNet-18 model architecture. Understanding the interplay between these modifications and the dataset's unique attributes is paramount for discerning their role in delineating subtle disparities between fresh and damaged produce.

Addressing class imbalance constitutes another crucial dimension of the anticipated results. The creation of a subset with balanced classes is anticipated to ameliorate biases during model training, thereby fostering the development of a more robust and equitable model representation across various fruit and vegetable types.

In terms of practical implications, the research endeavors to delineate the tangible benefits of automating fruit and vegetable quality assessment. These benefits encompass streamlined processes and reduced wastage within agricultural and supply chain settings. The envisaged outcome entails a comprehensive grasp of the potential applications and advantages of the proposed model in real-world contexts.

Additionally, a comparative analysis is poised to be conducted to evaluate the impact of different hyperparameter configurations, particularly pertaining to picture size and batch size. Such an examination promises invaluable insights into the influence of these settings on model performance and efficiency.

Moreover, the research aims to explore further refinement techniques and data augmentation strategies to bolster the model's robustness and generalizability across diverse agricultural and supply chain scenarios.

Lastly, the study envisages a comprehensive evaluation of the proposed model, encompassing assessments of accuracy, precision, recall, and F1 scores across various fruit and vegetable types. This holistic evaluation serves as a cornerstone for gauging the model's efficacy and utility.

1.6 Project Management and Finance

To effectively guide our study, we established a detailed project timeline with specific milestones. These milestones will encompass key stages such as data collection, model development, training, assessment, and outcome analysis. To ensure efficient utilization of team members' expertise, roles and responsibilities will be clearly defined, with periodic assessments to adapt to evolving project needs and workloads.

Our communication strategy will outline the frequency of team meetings, progress reports, and updates, leveraging project management tools for seamless collaboration.

Financial resources will be allocated according to project priorities, encompassing expenses such as data collection, computing resources, and software licensing, while maintaining budgetary constraints.

Additionally, we will actively pursue grant opportunities to supplement project funding, crafting compelling submissions highlighting the project's significance and potential impact. To monitor expenses effectively, a comprehensive financial tracking and reporting system will be implemented, providing regular reports to stakeholders and funding bodies to ensure transparency in financial management.

1.7 Report Layout

- **Chapter 1:** This chapter introduces the research by summarizing its purpose, examining relationships through a study, formulating research questions, specifying expected outcomes, and briefly addressing project management and funding.
- **Chapter 2:** This chapter defines key terms, reviews relevant literature, provides a comparative analysis, sets the research scope, and addresses associated challenges.
- **Chapter 3:** This chapter describes the data collection methods, outlines statistical analysis techniques, details image processing methods, specifies the dataset split, and introduces the proposed model and its implementation requirements.
- **Chapter 4:** This chapter details the experimental methodology, analyzes and evaluates the data, and provides a thorough discussion of the findings.
- **Chapter 5:** This chapter explores the study's societal and environmental impacts, considers ethical issues, and presents a sustainability strategy for the proposed model.
- **Chapter 6:** This chapter summarizes the study, draws conclusions, makes recommendations, and suggests directions for future research.

CHAPTER 2

Background

2.1 Terminologies

In this research venture, an array of essential terminologies come into play, each pivotal in shaping the understanding and outcomes of the investigation. Initially, "Dataset Diversity" denotes the varied assortment of images encompassing all fruit and vegetable categories, captured under diverse conditions including varying lighting, angles, and backgrounds. Such diversity is vital for effectively training the model to accurately predict outcomes across real-world scenarios.

Moving on, "ResNet-18 Model Architecture Modification" signifies intentional alterations made to the ResNet-18 model. These modifications aim to enhance the model's ability to discern subtle disparities between fresh and spoiled produce. Such architectural adjustments are critical for optimizing the model's efficacy in precisely evaluating the quality of fruits and vegetables.

The term "Class Imbalance" points to the uneven distribution of images among different fruit and vegetable categories within the dataset. To counter biases during model training, a balanced subset is curated, ensuring equal representation of each category. This approach fosters fairness and fortifies the model's capacity to tackle diverse scenarios.

"Advanced Image Processing Algorithms" encompasses techniques like bit-plane slicing and adaptive thresholding. Bit-plane slicing involves decomposing images into binary representations, while adaptive thresholding adjusts thresholds based on local characteristics. These methodologies elevate pixel quality and enhance the interpretability of visual data.

Financial reporting entails the systematic tracking and documentation of financial transactions pertinent to the research endeavor. This includes monitoring expenses vis-à-vis the predetermined budget, furnishing periodic financial reports to stakeholders, and upholding transparency in financial management.

Lastly, "Cost-Benefit Analysis" involves evaluating the overall value and potential return on investment of the research effort. This assessment delves into how project findings impact future research endeavors or practical applications, providing valuable insights into broader project implications.

2.2 Related Works

Nagganaur and Sannanki [1] introduced image processing methods for fruit sorting and grading. Initially, the system captures fruit images, which are then forwarded to Matlab for grading, classification, and feature extraction. Their approach incorporates fuzzy logic to achieve both categorization and grading efficiently.

In [2], a Deep Convolutional Network (DCNN) method for fruit identification is discussed. This method, utilizing RGB and NIR spectrums, promises rapid and accurate fruit identification, potentially revolutionizing the agricultural sector by automating fruit detection processes.

The importance of categorizing food freshness is highlighted in [3]. The authors argue that conventional methods for identifying food deterioration are outdated. They propose automatic categorization techniques for precise and mobile detection of food spoilage, ultimately favoring CNN for its accuracy in classification tasks.

Indonesia's significance in fruit and food production is emphasized in [4], stressing the importance of fresh fruit for human health. To address food degradation issues, the authors propose a Deep Learning model, specifically a CNN, for detecting food freshness more accurately.

A comprehensive review of CNN's applications in fruit image processing is presented in [5]. The article underscores the growing importance of AI, particularly deep learning, in the agricultural sector. CNNs, due to their ability to extract reliable image representations, are increasingly utilized for fruit classification, detection, and quality control tasks.

Hridkamol Biswas et al. [6] discuss techniques for converting images to the HSV model, removing lighting effects, and analyzing image histograms. They advocate for feature integration and database creation based on class attributes derived from image features.

Sakai et al. [7] delve into the use of Deep Neural Networks for vegetable category identification. They elucidate the concept of deep learning, emphasizing its hierarchical structure for representation learning and feature recognition.

Frida Femling et al. [8] report on the extensive use of convolutional neural networks in image recognition systems. They highlight the importance of propagation time and accuracy in CNN-based image classification tasks, particularly in systems utilizing Raspberry Pi for image gathering.

Shahzadpreet, Saurabh, and collaborators [9] review various techniques for identifying and separating rotting fruits, including support vector machines, fuzzy logic, neural networks, and neuro-fuzzy systems. They emphasize the importance of physiological features in assessing fruit quality.

Mandeep Kaur and Reecha Sharma [10] present a method for extracting fruit properties such as color, shape, and size using artificial neural networks, underscoring the importance of these features in fruit analysis.

Bhanu Pratap, Navneet et al. [11] propose a model for classifying fruits based on form, color, and texture features. They employ edge detection for shape characterization, HSI and HSV for color-based categorization, and GLCM for texture analysis, ultimately utilizing artificial neural networks for classification based on these features.

2.3 Comparative Analysis and Summary

The literature review encompasses a broad spectrum of methodologies employed in fruit and vegetable image processing, with a specific emphasis on assessing quality, classifying, and identifying freshness. Nagganaur and Sannanki [1] propose a grading system grounded in fuzzy logic within Matlab, demonstrating accuracy through traditional image processing methods. The Deep Convolutional Network-Based Method [2] introduces a fruit recognition approach employing a DCNN, aiming for swift and precise identification by scrutinizing both RGB and NIR spectrums. The manuscript titled "Automatic Categorization for Food Freshness" [3] scrutinizes conventional methodologies while advocating for automated categorization techniques, particularly endorsing Convolutional Neural Networks (CNNs). In "Deep Learning Model for Food Freshness" [4], a CNN model is introduced to discern the freshness of food, underlining the significance of fresh produce within the agricultural realm. The article "Review of Convolutional Neural Network implemented to Fruit Image Processing" [5] offers an exhaustive examination of CNN applications in fruit image processing, encompassing detection, quality assessment, and categorization. The methodology proposed by Hridkamol Biswas et al. [6] involves transforming images into an HSV model, amalgamating features, and attributing class based on these attributes. Sakai, Yuki et al. [7] employ deep neural network training to classify vegetable categories, underscoring the pivotal role of deep learning in acquiring meaningful representations. In their research, Frida Femling et al. [8] explore the deployment of Convolutional Neural Networks (CNNs) on a Raspberry Pi for image identification, particularly addressing issues related to network propagation time and recognition accuracy. Shahzadpreet et al. [9] investigate various methodologies for detecting and distinguishing decaying fruits, encompassing Support Vector Machines (SVM), fuzzy logic, neural networks, and neuro-fuzzy systems. Mandeep Kaur and Reecha Sharma [10] utilize artificial neural networks to extract fruit properties, with a focus on color, shape, and size. Bhanu Pratap, Navneet et al [11] present a holistic framework for fruit categorization, integrating shape, color, and texture considerations, incorporating edge detection and advanced color spaces. These studies illustrate a shift towards more advanced techniques, notably deep learning, signaling a substantial evolution in fruit and vegetable image processing, with potential ramifications for agricultural automation and food quality assessment.

2.4 Scope of the Problem

The explored literature delves into the diverse challenges and opportunities surrounding the realm of fruit and vegetable image analysis, particularly focusing on quality assessment and categorization. There is a pressing need for precise and efficient techniques to evaluate the quality, freshness, and classification of agricultural produce across various domains, ranging from farm production to supply chain management.

Traditional methods, while somewhat effective, are deemed outdated, prompting the exploration of advanced strategies, notably those leveraging deep learning, convolutional neural networks (CNNs), and artificial neural networks (ANNs).

The scope encompasses addressing the complexities associated with diverse datasets containing images of fruits and vegetables captured under varying conditions, including differences in lighting, angles, and backgrounds. The goal is to develop models capable of robustly handling real-world scenarios, ensuring high performance in accurately identifying and categorizing different types of agricultural products. The scrutinized research also underscores the importance of precisely discerning freshness and categorizing fruits and vegetables to mitigate food waste and enhance the efficiency of agricultural and food processing industries.

Moreover, the scope of the problem extends to the practical applications of the developed models, with potential implications for automation in agriculture, supply chain optimization, and food quality management. The integration of deep learning models, particularly Convolutional Neural Networks (CNNs), into the image processing pipeline represents a groundbreaking phase where technology can effectively address the challenges within this domain. The literature emphasizes the necessity of staying abreast of the latest technologies, such as deep learning and neural networks, to harness their capabilities for more precise and automated solutions in fruit and vegetable image processing.

2.5 Challenges

In the realm of fruit and vegetable image processing for quality assessment and classification, researchers and practitioners confront a multitude of challenges. The datasets containing images of these produce items exhibit considerable variability in lighting, angles, and backgrounds, posing significant hurdles for ensuring the robustness of models in real-world scenarios. Traditional image processing methods like fuzzy logic and manual feature extraction have proven inadequate in capturing the intricate nuances present in fruit and vegetable photos accurately. Consequently, there is a growing demand for more advanced techniques such as deep learning and neural networks. However, the adoption of certain sophisticated systems may be hindered by the requirement for specialized equipment, potentially impacting accessibility and cost-effectiveness.

The interpretability of deep learning models, particularly complex ones like Convolutional Neural Networks (CNNs), poses a challenge due to their often opaque decision-making processes. Moreover, disparities in the distribution of training data across different fruit and vegetable categories can lead to biased models and suboptimal results for underrepresented classes. Additionally, proposed techniques may lack comprehensive discussions regarding scalability and adaptability, limiting their applicability to diverse datasets or situations.

The absence of standardized methodologies for image collection and processing further complicates matters, resulting in varying outcomes across studies. Bridging the gap between scientific advancements and practical applications in agriculture and food processing is a significant obstacle that necessitates solutions accommodating logistical and operational constraints. Particularly in applications like automatic sorting and quality control, the ability to analyze vast datasets in real-time within dynamic environments is paramount.

Addressing these challenges requires a multidisciplinary approach that integrates expertise from computer vision, machine learning, agriculture, and food science. By leveraging diverse knowledge domains, it becomes possible to develop more reliable, precise, and feasible solutions for fruit and vegetable image processing.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrument

The methodology section involved a comprehensive examination of the dataset, focusing particularly on its accessibility and key characteristics. A thorough analysis revealed significant heterogeneity within the dataset, with each category containing a substantial number of images. This diversity is vital as it ensures the model is exposed to a wide range of examples, thereby enhancing its ability to generalize effectively.

To improve the accuracy of image categorization within each class, advanced image processing algorithms and filters were strategically deployed. A customized ResNet18 model was utilized to enhance the classification process, with modifications made to better align the model with the unique attributes of the dataset. This adaptation aimed to improve the model's capability to distinguish subtle differences between fresh and spoiled produce.

Following the image classification step, a comprehensive evaluation of the results was conducted. The model's performance metrics, including accuracy, precision, recall, and F1 score, were analyzed to assess its effectiveness in classifying images within each category. Insights gained from this analysis were used to refine the model and boost its performance.

Subsequently, attention shifted to the proposed modifications to the ResNet-18 model structure. The unique architecture was meticulously designed, taking into consideration the intricate details of the dataset and the specific requirements of the categorization task. These enhancements aimed to improve the model's feature extraction capabilities, enabling it to capture subtle patterns and distinctions related to both high-quality and spoiled produce.

The suggested architecture underwent a rigorous review process, including training and validation on an expanded dataset. This facilitated a comprehensive evaluation of the model's performance, allowing for comparisons with baseline models and identification of areas for improvement. The analysis findings were instrumental in confirming the effectiveness of the proposed enhancements and establishing the model as a robust solution for precise categorization in fruit and vegetable quality evaluation.

Key components of the experimental setup included the choice of programming language, deep learning framework, pre-trained models, dataset selection, image processing libraries, image filters, and the overall configuration of the experiment. Each aspect was carefully considered to ensure the validity and reliability of the study's findings.

- ❖ Programming Language
- ❖ Deep Learning Framework
- ❖ Pre-trained Models
- ❖ Dataset
- ❖ Image Processing Libraries
- ❖ Image Filters
- ❖ Experimental Setup

3.2 Data Collection Procedure

The Fresh and Rotten Fruits and Vegetables Classification Dataset amalgamates meticulously curated images of various fruits and vegetables from two distinct sources: one generated in-house and another sourced from Kaggle. These images are meticulously labeled for multiclass classification tasks, distinguishing between fresh and rotten produce. The dataset's primary aim is to facilitate the development and evaluation of deep learning models adept at discerning between fresh and spoiled vegetables. It comprises an extensive array of commonly encountered fruits and vegetables, each meticulously documented through a series of high-quality photographs showcasing both its fresh and deteriorated states. By encompassing a diverse spectrum of produce, the dataset ensures the robustness and accuracy of classification algorithms aimed at distinguishing between fresh and rotten fruits and vegetables, thereby catering to the needs of culinary contexts and advancing the frontier of deep learning research in this domain.

Figure 2: The figure shows some good and rotten quality fruits and vegetables from the datasets.

The dataset comprises a diverse array of fruits and vegetables, including apples, carrots, tomatoes, potatoes, oranges, cucumbers, bananas, and more. Each type of produce is categorized as either fresh or rotten. With a total of 32,735 images, the dataset encompasses various formats and sizes, mirroring real-world conditions with variations in lighting, angles, and backgrounds. This diversity enhances the model's resilience and its capacity to handle different image settings effectively. The data is segregated into separate training and testing sets, facilitating the development and evaluation of deep learning models.

3.2.1 Key Features of Combined Dataset

The dataset boasts a significant variety of images, showcasing a wide range of lighting conditions, perspectives, and backgrounds. This diversity not only mirrors real-world scenarios but also challenges classification models to perform effectively across various settings. Moreover, it includes a comprehensive classification of fresh and spoiled produce, enabling the development of algorithms capable of accurately assessing the freshness of fruits and vegetables. Each image is meticulously annotated, providing valuable information on the freshness status of the items, thereby facilitating supervised learning and simplifying model development.

Furthermore, the dataset offers superior image quality, featuring high-resolution photographs captured using top-of-the-line cameras. These images undergo meticulous editing to ensure optimal clarity and minimal noise, laying a robust foundation for training reliable classification models. With its extensive collection of photos, the dataset is well-suited for training deep learning models. This abundance facilitates thorough training and validation processes, resulting in the creation of more resilient and precise classification algorithms.

3.3 Statistical Data Analysis

An extensive assessment was conducted to analyze a dataset, focusing on evaluating the quality of specific fruits and vegetables, such as tomatoes, potatoes, apples, oranges, bananas, capsicums, cucumbers, okra, and bittergourds. The number of images varies significantly across categories, with approximately 2800 to 3000 images of tomatoes, 1200 to 1700 images of potatoes, 3200 to 4300 images of apples, 1800 to 2000 images of oranges, 3400 to 3900 images of bananas, 900 to 1000 images of capsicums, 600 to 700 images of cucumbers, 500 to 1000 images of okra, and 300 to 400 images of bittergourds. These ample datasets provide a comprehensive representation of each category, allowing the model to discern characteristics and patterns associated with both fresh and spoiled conditions. The vast dataset ensures that the model encounters a diverse array of examples, facilitating effective training and evaluation across various categories.

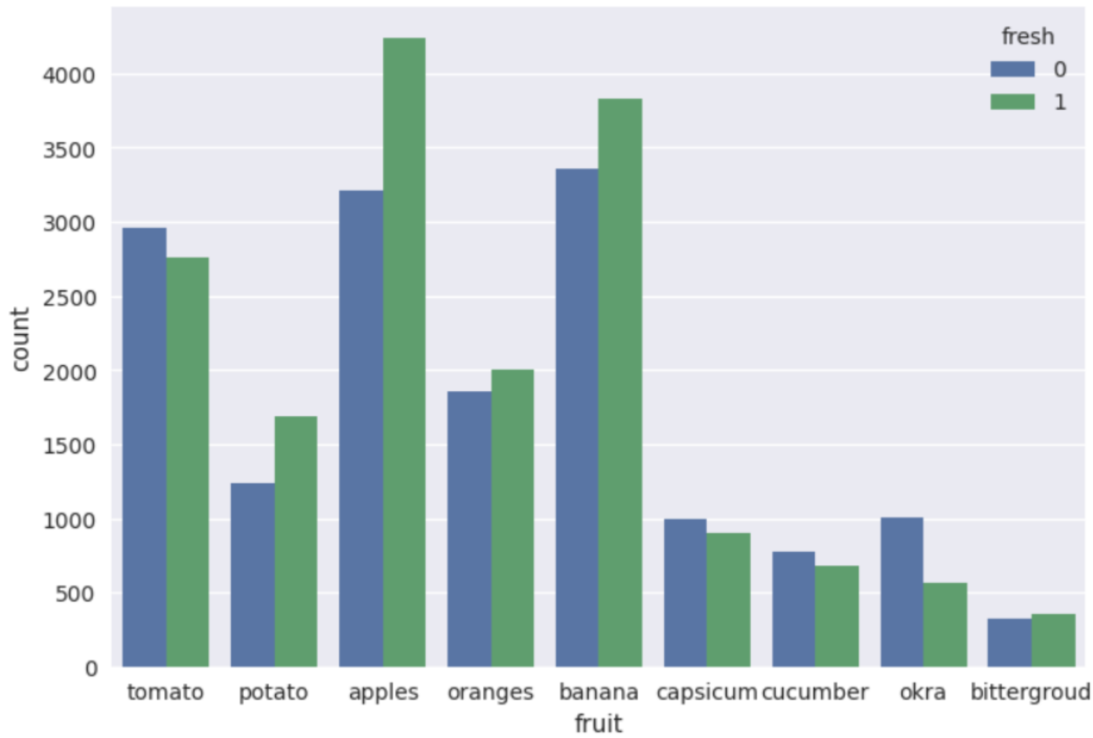

Figure-3: The figure shows the number of images for good and rotten quality before or the original dataset.

3.3.1 Balance Dataset

The algorithm addresses the challenge of class imbalance in a dataset by creating a balanced subset, considering the frequencies of different values in the 'fruit' column. Initially, it calculates the frequencies for each unique fruit group and stores the results. Subsequently, a new DataFrame is generated with columns for 'filename', 'fruit', and 'fresh', designed to hold the balanced subset. The algorithm then iterates through each distinct fruit group and its respective count. If a fruit category has more than 1500 occurrences, it randomly selects 1500 instances from the original DataFrame for that category. If the count is 1500 or less, all instances belonging to that fruit group are included. During each loop iteration, the balanced subset is merged with the accumulating DataFrame. Through this process, the code gradually constructs a new DataFrame containing an equitable distribution of each fruit type, ensuring that no category exceeds 1500 occurrences. Ultimately, the code outputs the dimensions of the balanced DataFrame, indicating the number of rows and columns. This inclusion of a well-balanced subset is beneficial for training machine learning models as it helps mitigate the disproportionate influence of certain classes in the dataset, promoting a fairer allocation of examples across various fruit categories.

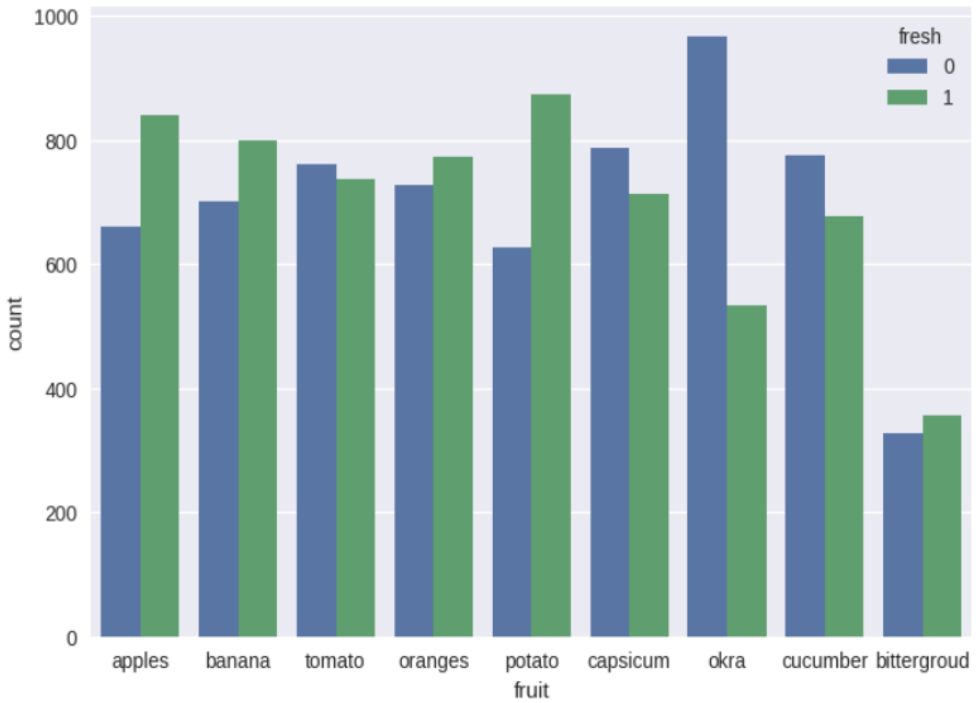

Figure-4: The figure shows the number of images for good and rotten quality after balance the dataset.

3.4 Data Preprocessing

Data processing involves modifying and converting raw data to extract valuable information or enhance specific attributes for analysis. In the domain of image processing, various techniques are employed to manipulate pixel values and improve the clarity of visual data. Bit-plane slicing entails breaking down an image into its binary representation, enabling examination of pixel contributions at different levels of detail. Adaptive thresholding is a method that adjusts segmentation thresholds based on local image properties, particularly beneficial for photos with uneven lighting. Conversely, image negative alters pixel values, amplifying contrast and revealing finer details in low-quality images. These methods play crucial roles in tasks like image enhancement, feature extraction, and segmentation, significantly enhancing the efficacy of computer vision applications. Image filtering techniques serve as vital tools for refining visual data and extracting relevant information, whether for evaluating the quality of produce or undertaking broader image analysis tasks.

3.4.1 Bit-plane slicing

Bit-plane slicing is a vital method within image processing, serving to dissect an image into its elemental components by breaking down pixel values into distinct bit planes. Each plane signifies a single bit within the pixel value, ranging from the most significant bit (MSB) plane to the least significant bit (LSB) plane. When extracting the MSB plane, only the highest-order bit is retained for each pixel, leading to a resultant image with reduced detail compared to the original, yet preserving essential image information. This MSB plane image finds widespread application in image compression due to its efficient storage characteristics.

3.4.2 Adaptive thresholding

Adaptive thresholding stands as another crucial technique in image processing, offering dynamic adjustment of threshold values for individual pixels based on their local surroundings. Unlike global thresholding methods, adaptive thresholding takes into consideration the intensity variations across neighboring pixels, thereby yielding improved outcomes under diverse lighting conditions. The mathematical underpinning of adaptive thresholding involves computing a local threshold (T) for each pixel (I(x, y)), often by averaging or weighing the intensities of adjacent pixels. Among adaptive thresholding approaches, the adaptive mean thresholding method finds frequent utilization.

3.4.3 Age Negative

Moving to age negative transformation, it represents a fundamental yet powerful image processing filter, essentially inverting the pixel intensities of an image by subtracting each intensity value from the maximum attainable intensity value. This inversion results in a complete reversal of luminosity levels within the image, effectively turning formerly dark areas bright and vice versa. Consequently, the original image undergoes a transformation into its inverted or negative counterpart. This transformation typically applies to grayscale images where pixel intensity values range from 0 to L-1, with L representing the maximum intensity level achievable.

In summary, these techniques exemplify the versatility and depth of image processing methodologies, each serving distinct purposes in manipulating and enhancing digital imagery. From dissecting images into their bit planes for efficient compression to dynamically adapting threshold values for optimal results, and transforming images into their negative counterparts for creative exploration, these methods collectively contribute to the rich landscape of image processing applications.

Here is the sample of some filtered images.

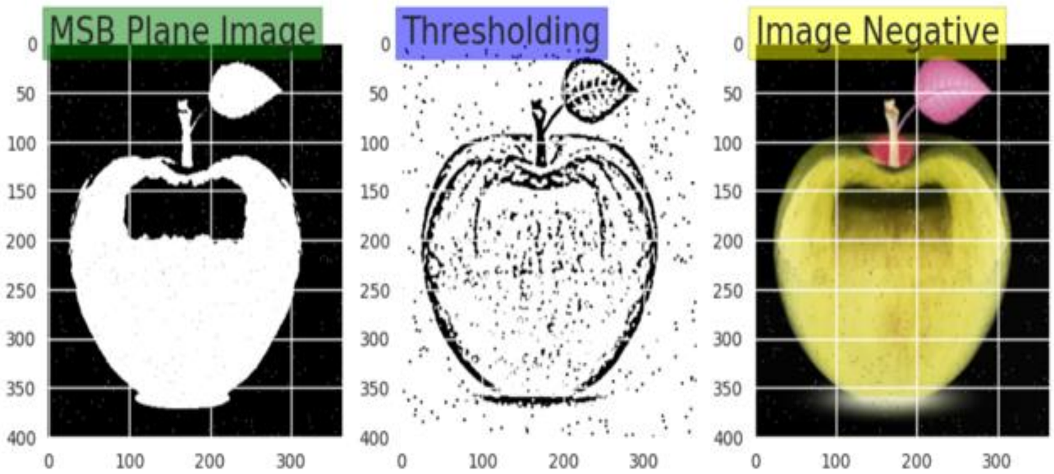

Figure 5: Sample images for after applied image filter.

3.4.4 Label Encoder

Label encoding is utilized in machine learning and data analysis to convert categorical variables into numerical form, facilitating compatibility with algorithms that require numeric input. This method is particularly beneficial as most machine learning models operate solely on numerical data, enhancing their effectiveness and efficiency in processing information. [15].

3.4.5 Dataset Split

Data splitting is a common practice in machine learning, involving the division of a dataset into training and validation portions. In this specific case, 15% of the data is reserved for validation, while the remaining 85% is allocated for training. This division serves several crucial purposes. Firstly, the training set is vital for the model to discern patterns and characteristics within the data. Secondly, the validation set allows for the assessment of the model's ability to generalize to new, unseen data. A 15% validation split strikes a balance between having sufficient training data to capture a broad range of patterns and ensuring a substantial portion is reserved for validation, thus providing reliable insights into the model's performance.

This strategy aims to mitigate overfitting, where the model becomes overly tailored to the training data, thereby compromising its ability to make accurate predictions on new instances. Adjusting the percentage of data allocated for validation offers flexibility, depending on factors such as dataset size, complexity, and the desired trade-off between training and validation data. By finding this balance, models can better generalize to unseen data while still effectively capturing the underlying patterns within the dataset.

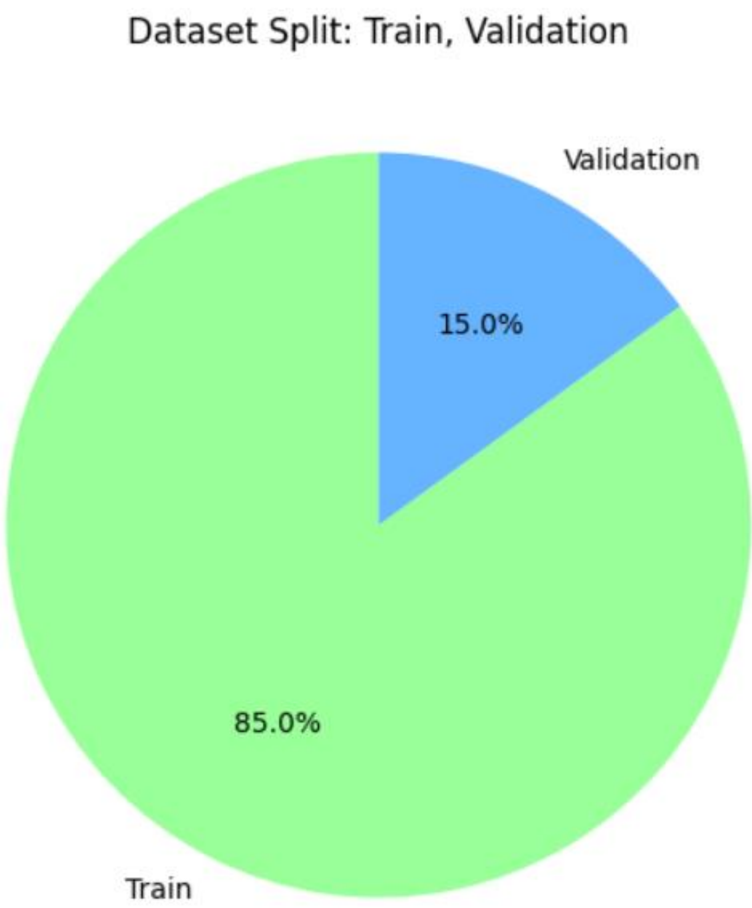

Figure 6: The pie chart represent the percentage of train and validation data.

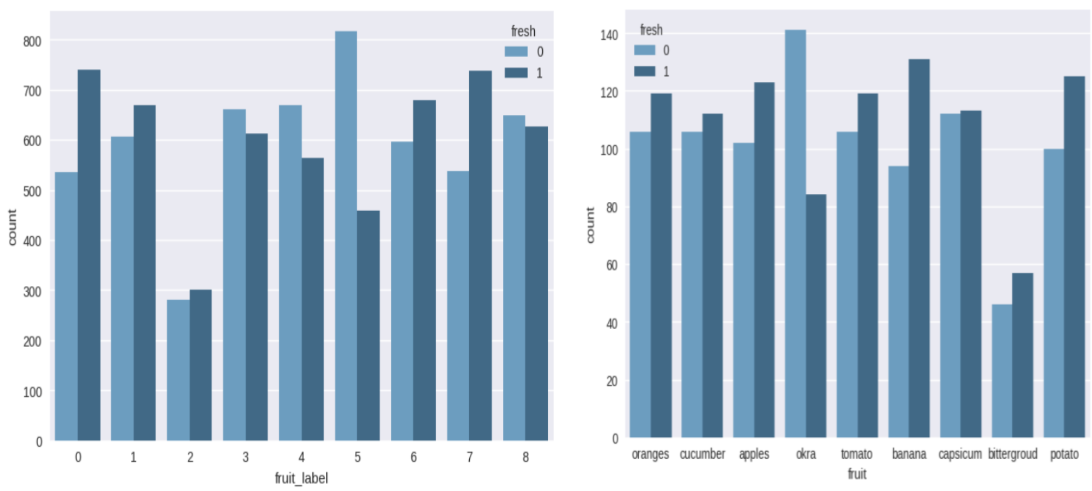

Figure 7: The fruits label and number of images for train and validation data.

For train and validation data, here is fruits label for each class or types of fruits. In the figure 0,1,2,3,4,5,6,7,8 refers to the name of fruits.

3.5 Implementation Requirements

Successful deployment and optimal performance of image processing technologies for fruits and vegetables hinge on adherence to specific criteria. Access to meticulously curated datasets representing various fruits and vegetables in real-world scenarios is indispensable. These datasets should encompass a wide range of lighting conditions, perspectives, and backgrounds to enhance the model's ability to generalize effectively. Moreover, advanced methods may require specialized equipment, such as utilizing both RGB and NIR spectra for accurate fruit recognition.

The availability of high-performance computing resources is imperative for training and deploying complex models like Convolutional Neural Networks (CNNs), making computational infrastructure a pivotal component. Model interpretability tools play a crucial role in understanding the decision-making processes of deep learning models, fostering user trust and comprehension. Furthermore, addressing disparities in training data requires meticulous curation and augmentation techniques to ensure equitable representation across all fruit and vegetable categories.

Standardizing techniques for image collection and processing is essential for maintaining consistency and comparability across diverse research endeavors. Practical implementation demands scalability, adaptability to different datasets and scenarios, and seamless integration into existing agricultural and food processing workflows. Real-time data analysis capabilities are also vital for applications in dynamically changing contexts, emphasizing the necessity for efficient algorithms and computing resources.

To achieve effective implementation, a comprehensive strategy encompassing factors such as data diversity, computing resource availability, result comprehension, standardization needs, and practical integration considerations must be embraced.

CHAPTER 4

EXPERIMENTAL RESULT

4.1 Experimental Setup

Creating an effective experimental setup for fruit and vegetable image processing demands a meticulous fusion of hardware, software, and procedural elements to conduct thorough investigations and evaluations. The hardware aspect encompasses imaging tools capable of capturing high-resolution images of produce in various scenarios. Sophisticated setups may incorporate specialized sensors or cameras capable of capturing both RGB and NIR spectra. Access to robust computing resources is indispensable for training and validating complex models, particularly deep learning architectures like Convolutional Neural Networks (CNNs). The computational infrastructure forms a cornerstone in this process. Software frameworks such as TensorFlow or PyTorch are utilized for developing, training, and deploying image processing models.

The experimental design entails meticulous dataset selection and curation, considering factors such as lighting, angles, and backgrounds to simulate real-world conditions. Preprocessing techniques like data augmentation and normalization are employed to enhance model resilience. Tailoring the model architecture, such as customizing ResNet-18 for specific classification tasks, is a pivotal aspect of the setup. Model performance is evaluated using metrics including accuracy, precision, recall, and F1 score.

Furthermore, data analysis methods are employed to derive insights from results and iteratively enhance the models. Ensuring the reliability, reproducibility, and generalizability of fruit and vegetable image processing systems necessitates a well-structured experimental framework. This framework integrates hardware, software, and procedural components harmoniously to facilitate comprehensive studies and robust assessments.

4.2 Experimental Results & Analysis

ResNet-18, a pre-trained model, is well-suited for our task. Its design addresses the vanishing gradient problem in deep neural networks by employing residual blocks with skip connections. These connections allow information to bypass multiple layers, mitigating degradation and enhancing learning efficiency, even with complex topologies. In our adaptation, we replaced the final layer of ResNet-18 with two fully connected layers, branching into distinct tasks: fruit identification and freshness assessment. We selectively unfroze the last 15 layers for training, keeping the rest frozen.

To calculate loss, we combined losses from both branches using a weighted sum, with alpha (α) set to 0.7. This experimental setup allows us to explore different alpha values to optimize performance. The total loss (L_total) is computed by multiplying the loss from the first branch (L1) by alpha and adding it to the loss from the second branch.

This experimental approach offers flexibility in fine-tuning the model for our specific objectives. By adjusting alpha and observing the effects on the combined loss, we can iteratively refine the model's performance for fruit classification and freshness detection.

4.2.1 Model Architecture

This model is a tailored adaptation of the ResNet-18 architecture, engineered to handle multiple tasks concurrently. It comprises a pre-trained ResNet18 backbone bolstered by three additional blocks. The ResNet18 backbone comes pre-loaded with weights and its final layers are kept fixed to retain learned features. The initial block, dubbed block1, consists of two fully connected layers with ReLU activation and dropout, tailored for high-level feature extraction. Following this, block2 and block3 handle two distinct classification tasks, each featuring a sequence of linear layers with activation functions and dropout. The model employs three separate optimizers: one for the ResNet18 backbone, another for block1, and the last for block2 and block3. A loss function is computed as a weighted sum of cross-entropy losses from the two classification tasks. Throughout training and validation, accuracy metrics are computed for both tasks. The training loop iterates over epochs, updating weights using the designated optimizers while simultaneously tracking loss and accuracy. Progress is logged in a historical dictionary. Essentially, this model is purpose-built for simultaneous learning of two independent categorization tasks, leveraging a shared feature extractor. This design proves particularly beneficial for scenarios necessitating predictions of related yet distinct outcomes.

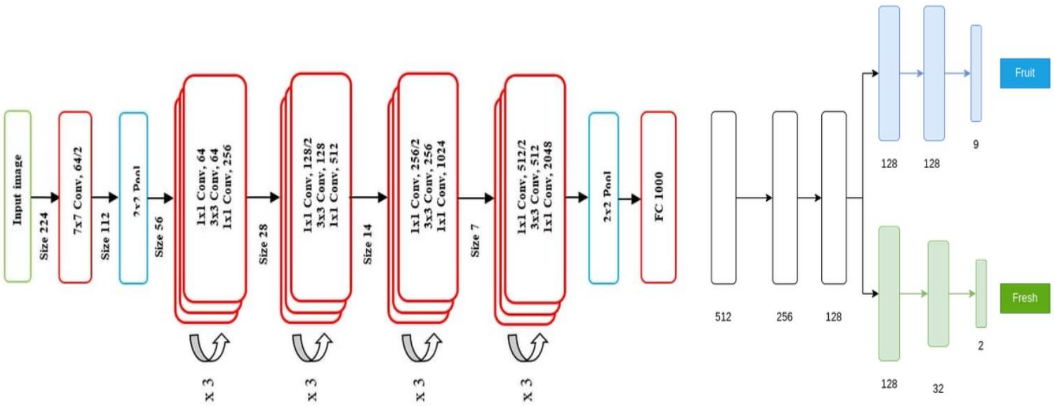

Figure 8: The customized ResNet-18 model architecture.

4.2.2 Configuration of the model

1. Activation function: ReLU.
2. Batch size: 62,
3. Image size: 224 x 224,
4. Optimizer: 'Adam',
5. Weight_decay': None,
6. Clipnorm': None,
7. Global_clipnorm': None,
8. Clipvalue': None,
9. Is_legacy_optimizer': False,
10. Epochs: 10

4.2.3 Result Analysis

This research seeks to measure the effectiveness of evolution. It starts by explaining TP, TN, FP, and FN (True Positive, True Negative, False Positive, and False Negative). Then, it calculates four metrics: accuracy, precision, recall, and F1 score, showcasing the evaluation of evolutionary outcomes:

Accuracy: $$\frac{TruePositive + TrueNegative}{TP\ TN{+}FP{+}FN} \quad \textit{(1)}$$

Precision: $$\frac{TruePositive}{TruePositive + FalsePositive} \quad \textit{(2)}$$

Recall: $$\frac{TruePositive}{TruePositive + FalseNegative} \quad \textit{(3)}$$

F1-Score: $$\frac{2{*}Precision{*}Recall}{Precision + Recall} \quad \textit{(4)}$$

Our adapted ResNet-18 model exhibits strong performance with an image size of 224 x 224 and a batch size of 64, converging effectively within 10 epochs. We employed varying learning rates across model blocks: 1e-5 for the base model, and 3e-4 for each subsequent block. Upon analysis, we obtained curves depicting loss, fruit accuracy, and freshness accuracy over the 10 epochs. Now, we embark on hyperparameter tuning, exploring adjustments to image size and batch size. Below are diagrams illustrating the outcomes of this tuning process:

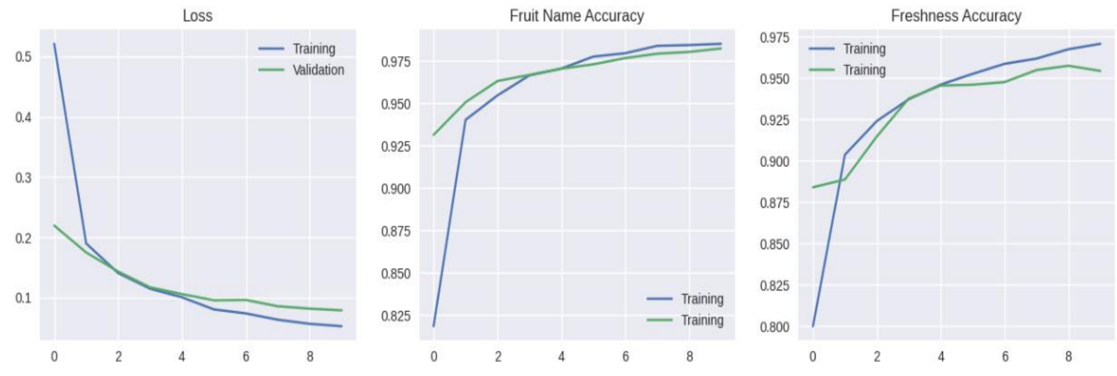

Figure 9: The curve diagram for image size 128*128 and batch size 32.

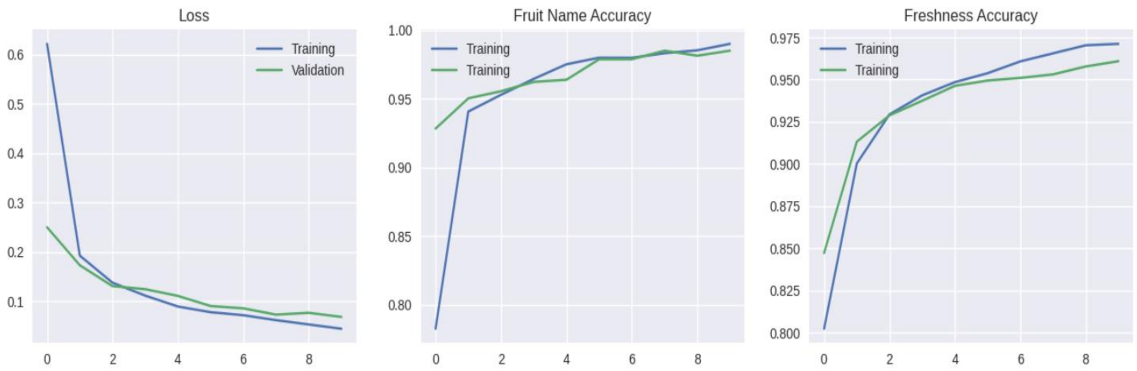

Figure 10: The curve diagram for image size 128*128 and batch size 64.

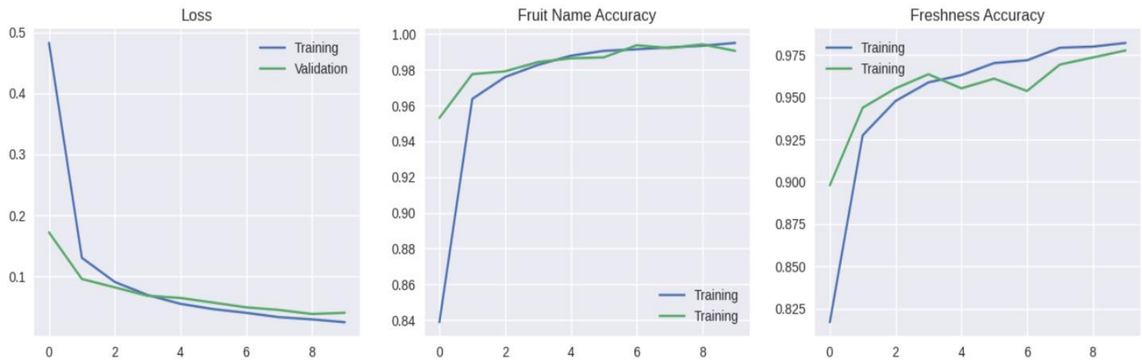

Figure 11: The curve diagram for image size 224*224 and batch size 32.

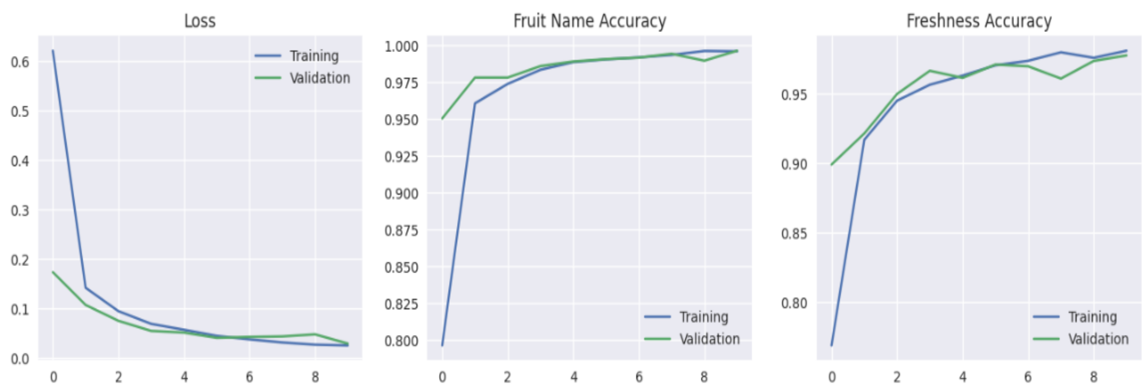

Figure 12: The curve diagram for image size 224*224 and batch size 64.

The graph reveals that the model excels when processing images sized 224x224 with a batch size of 64. Its classification accuracy is an impressive 98%, demonstrating its effectiveness in categorizing various fruits and vegetables accurately. Delving into specific metrics for each class, the model shows outstanding accuracy, recall, and F1-scores across multiple categories such as apples, bananas, bitter gourd, capsicum, cucumber, okra, oranges, potato, and tomato. This underscores its ability to distinguish between these categories reliably. Notably, bananas, bitter gourd, capsicum, potato, and tomato exhibit exceptional performance with perfect scores in accuracy, recall, and F1-scores, underscoring the model's robust and consistent performance.

Table-1: The table represents the classification report of all fruits and vegetables.

Labels	**Precision**	**Recall**	**F1-score**	**Support**
Apples	0.99	0.99	0.99	225
Banana	1.00	1.00	1.00	225
Bittergroud	1.00	1.00	1.00	103
Capsicum	1.00	1.00	1.00	225
Cucumber	0.99	0.98	0.99	218
Orka	0.98	1.00	0.99	225
Oranges	0.99	0.99	0.99	225
Potato	1.00	0.99	1.00	225
Tomato	1.00	1.00	1.00	225

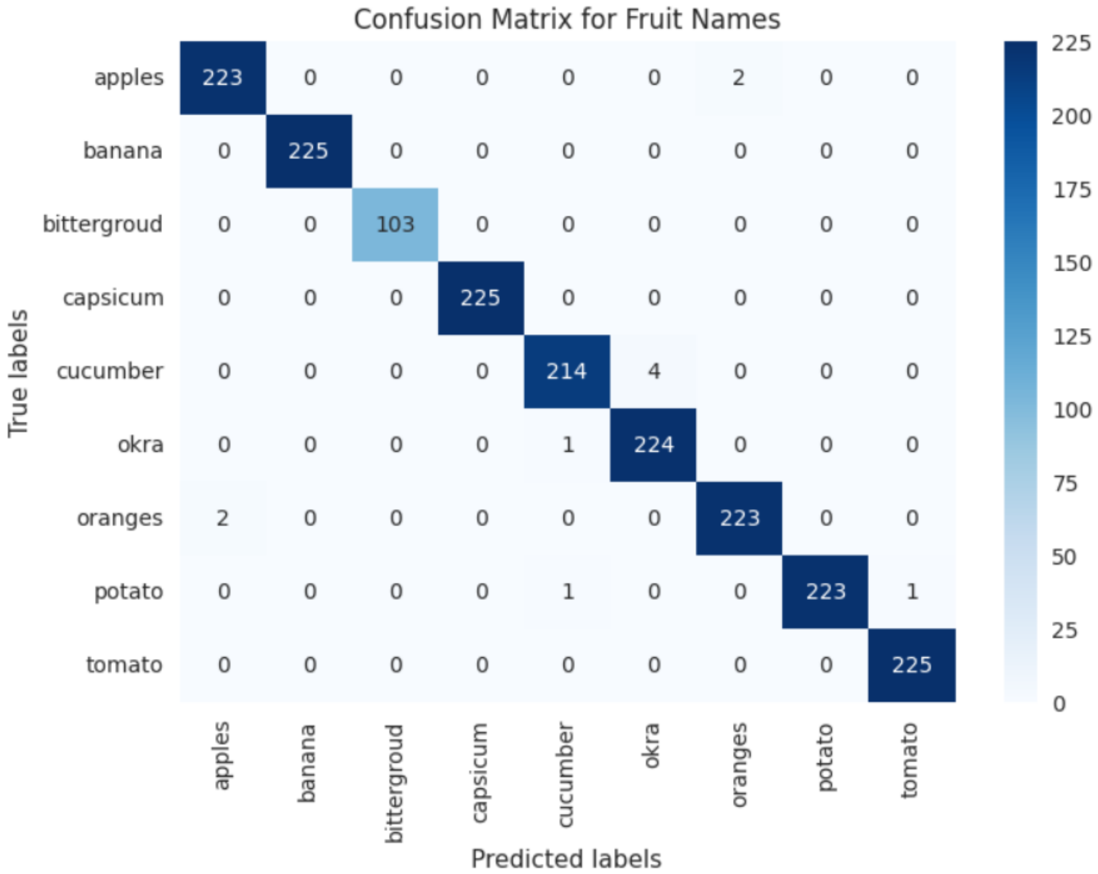

Figure 13: The figure represents the confusion matrix of all fruits and vegetables.

The comparison between our proposed model and a modified ResNet-18 architecture revealed that employing a 224x224 picture resolution and a batch size of 64 yielded superior overall accuracy. The adapted ResNet-18 achieved an impressive 97% accuracy post-modification, demonstrating robust precision and recall metrics for distinguishing between fresh and spoilt categories. However, the configuration with 224x224 dimensions and a batch size of 64 surpassed this, reaching a slightly higher overall accuracy of 98%.

These findings underscore the effectiveness of our recommended model with its specific parameters in capturing intricate dataset features and patterns. Detailed metric analysis, especially per class, ensures exceptional performance across various product categories. The model's high accuracy suggests promising practical applications, notably in automating fruit and vegetable quality assessment in agriculture and optimizing supply chain management where precise categorization is paramount.

Future research avenues could explore additional refinement techniques or data augmentation strategies to enhance the model's robustness and generalization capabilities. The classification report for our proposed model corroborates its efficacy and underscores its potential for real-world deployment in diverse settings.

Table-2: The table represents the classification report of all good and rotten quality fruits and vegetables.

Labels	Precision	Recall	F1-score	Support
Fresh	0.97	0.98	0.98	878
Spoiled	0.99	0.97	0.98	1018

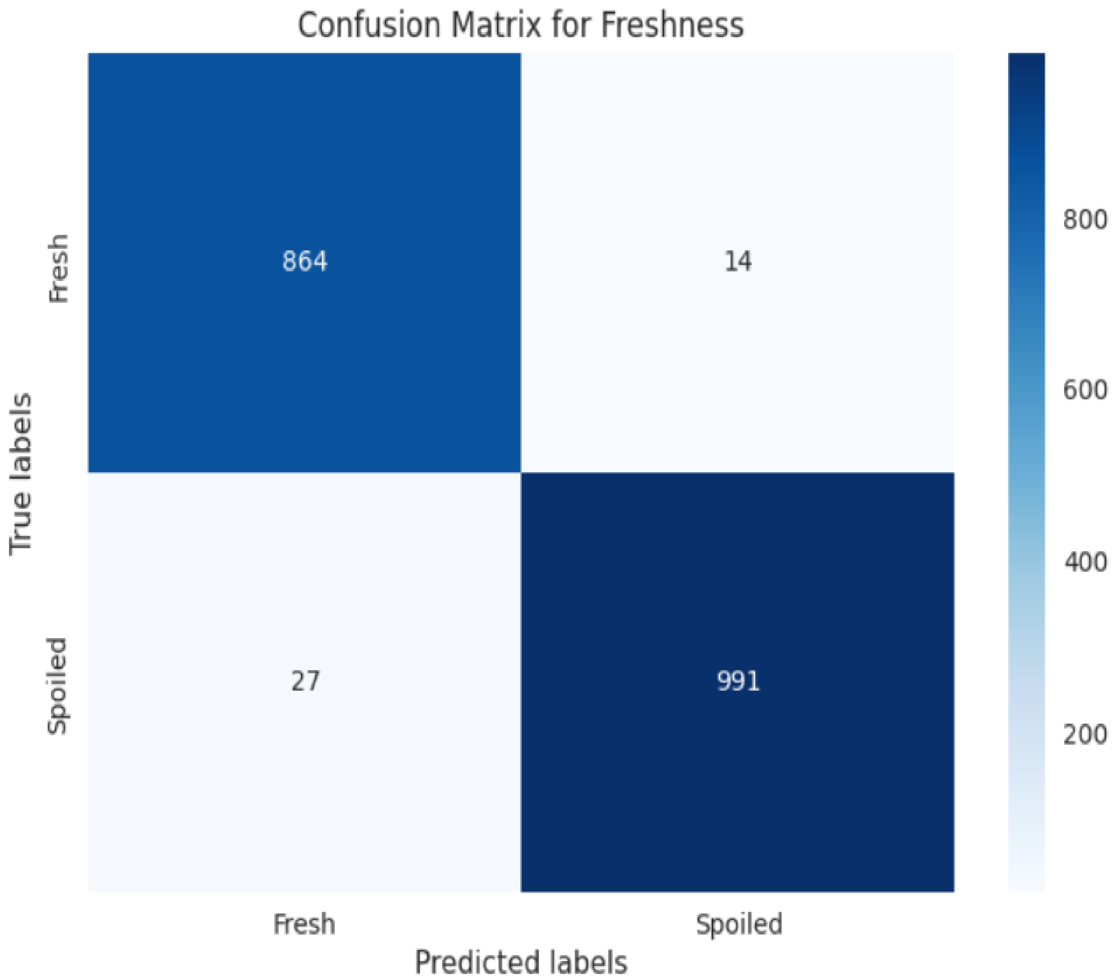

Figure 14: The figure represents the confusion matrix of all good and rotten quality fruits and vegetables.

4.3 Discussion

The study introduces an innovative approach to classifying various fruits and vegetables into multiple categories. It employs a customized ResNet-18 model trained on a combined dataset, focusing on two main tasks: identifying fruit type and assessing freshness. By integrating a modified ResNet-18 architecture with extra feature extraction blocks, the model achieves a remarkable accuracy of 98% using 224x224 image dimensions and a batch size of 64. Its practical applications include automating quality assessment in agriculture and streamlining supply chain management. Comparative analysis highlights its superior performance over alternative configurations. Future research directions involve refining methodologies and exploring data augmentation techniques to enhance robustness and applicability. In essence, the study underscores the model's efficacy in accurately categorizing diverse products in real-world settings.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

Enhancing agricultural practices through precise classification of fruits and vegetables holds significant promise for improving efficiency in farming methods. By implementing automated quality evaluation systems, farmers can optimize their harvesting and storage procedures, ultimately reducing food waste and promoting sustainability.

The accurate identification of produce and assessment of its freshness not only minimizes food waste but also encourages responsible consumption, thereby reducing the environmental footprint associated with discarded food items. This dual benefit positively impacts societal and environmental sustainability.

Furthermore, refining the model's precision in categorizing agricultural products can enhance supply chain management processes. By streamlining the distribution process, the supply chain becomes more efficient and eco-friendly, ensuring perishable goods reach consumers with minimal wastage during transit.

Moreover, integrating this technology into agriculture aligns with the principles of precision farming, empowering farmers to make informed decisions and optimize resource utilization. This, in turn, facilitates the adoption of sustainable agricultural practices and contributes to long-term environmental stewardship.

Additionally, the development of accessible technological frameworks for fruit and vegetable categorization democratizes technology in agriculture. This accessibility allows farmers of all scales to leverage modern tools for improved decision-making and resource management, leveling the playing field within the industry.

Lastly, promoting data-driven solutions in agriculture and food supply chains advocates for a culture of innovation and sustainability. By embracing data-driven decision-making, the industry can drive progress towards more efficient and environmentally conscious practices, inspiring similar approaches in other sectors.

5.2 Impact on the Environment

The precise classification of fruits and vegetables by the model enhances agricultural resource optimization. By providing insights into crop quality and freshness, farmers can improve resource utilization, like water and fertilizers, reducing environmental impacts from excessive usage. This improvement in agricultural practices can lead to a decreased environmental footprint overall, as efficient procedures guided by the model's assessments may lower reliance on pesticides and other agrochemicals, fostering the adoption of sustainable farming methods.

Moreover, sustainable agriculture methods supported by the model indirectly contribute to biodiversity protection by mitigating traditional farming's adverse effects on ecosystems. The model's ability to optimize supply chains and minimize food waste further aids in reducing greenhouse gas emissions, as efficient distribution and reduced waste mean lower energy consumption throughout the process.

Additionally, the model's promotion of organic farming aligns with organic principles by reducing reliance on chemical inputs, benefiting soil health, and mitigating environmental degradation associated with conventional farming. By empowering farmers with information for informed crop management decisions, the approach promotes sustainable land use practices, potentially mitigating excessive land exploitation and curbing agricultural-driven deforestation. Ultimately, this encourages a more equitable and ecologically sustainable utilization of available resources.

5.3 Ethical Aspect

Data privacy and security are paramount considerations when utilizing comprehensive datasets, particularly those containing photos of agricultural produce. It is essential to ensure strict adherence to privacy regulations in the collection and retention of such data. Educating farmers and participants about data usage and protection is crucial, emphasizing the importance of obtaining their consent.

Equitable access to technological advancements, exemplified by this model, must be ensured in agricultural settings. Addressing disparities in technology access is vital to providing equal opportunities for farmers of all sizes and locations, thereby avoiding exacerbating existing inequalities.

The potential for biases within training data underscores the need to evaluate and mitigate such biases rigorously. Transparent model training processes and ongoing efforts to identify and rectify biases enhance the ethical application of technology, particularly in preventing unjust classifications or judgments.

Farmers relying on model outputs for decision-making must have a comprehensive understanding of its capabilities and limitations. Transparency regarding the model's accuracy, potential shortcomings, and areas requiring human judgment is essential to foster responsible decision-making and prevent overreliance on automation.

While the model can contribute to sustainable agriculture, it is crucial to continually assess and mitigate any adverse environmental impacts resulting from its extensive implementation. Close monitoring and prompt resolution of unforeseen repercussions, such as changes in land use or ecological disturbances, are imperative.

Engaging with local communities and stakeholders is integral to the successful implementation of technology solutions. Consultations with farmers, environmentalists, and relevant organizations ensure alignment with local regulations, cultural sensitivities, and diverse perspectives, fostering inclusive and culturally appropriate technology adoption.

5.4 Sustainability

Harnessing the model's capabilities to optimize agricultural practices represents a significant stride towards sustainability, fostering resource efficiency within the agricultural domain. By employing the model, precision farming becomes achievable, allowing for targeted allocation of resources like water, fertilizers, and pesticides. This approach effectively curtails wastage, thus reducing the environmental footprint associated with traditional farming methods.

A pivotal contribution of the model lies in its adeptness at categorizing and accurately assessing the freshness of fruits and vegetables. This functionality substantially minimizes food wastage, especially crucial within the context of supply chain management. Leveraging the model's predictions, a robust supply chain system can be established to optimize product delivery, consequently mitigating the environmental impact stemming from food loss.

The promotion of sustainable agricultural practices is a natural outcome of employing this approach, primarily by diminishing reliance on chemical inputs. Transitioning towards organic and environmentally friendly methodologies not only nurtures soil health and biodiversity but also fosters long-term sustainability within the agricultural sector.

Integral to the discourse of sustainability is the economic well-being of farmers. Herein lies the model's significance, as its capacity to enhance crop management and yield estimation directly contributes to the economic sustainability of agricultural endeavors. By ensuring the profitability and resilience of farming practices, the model bolsters the foundation of sustainable agriculture.

Moreover, optimizing agricultural activities through the model presents a tangible opportunity to mitigate the adverse effects of climate change. By advocating for eco-friendly methods and minimizing agrochemical usage, the approach aligns with broader initiatives aimed at climate mitigation, thereby fortifying agricultural resilience against environmental fluctuations.

Embracing advanced technologies such as the model not only equips farmers with essential tools for adaptation but also reinforces the long-term resilience of agriculture. In light of looming challenges like climate change, the amalgamation of sustainable practices with technological innovations becomes imperative for securing the future food security of the agricultural sector.

CHAPTER 6

Summary, Conclusion, Implication for Future Study

6.1 Summary of the Study

This project is centered on developing and evaluating a robust model for evaluating the freshness of fruits and vegetables. It utilizes a meticulously curated dataset comprising images of both fresh and spoiled produce. Extensive analysis of the dataset was conducted, employing advanced image processing techniques and a customized ResNet-18 model. The model underwent rigorous refinement and validation procedures, resulting in its ability to achieve high levels of accuracy, precision, recall, and F1 score across various types of produce. The study addressed challenges such as class imbalance by employing techniques to create a balanced dataset. The proposed model, utilizing a modified ResNet-18 architecture, exhibited an impressive overall accuracy of 98%, underscoring its efficacy in accurately classifying a diverse range of items. These findings suggest potential applications in automated quality assessment within agricultural and supply chain contexts.

6.2 Conclusions

This project focuses on the development and assessment of a robust model designed to determine the freshness of fruits and vegetables. The core of this endeavor lies in a meticulously curated dataset, comprising images representing both fresh and spoiled produce. Through meticulous analysis, advanced image processing techniques, and the utilization of a customized ResNet-18 model, the dataset underwent comprehensive examination. This process included rigorous refinement and validation procedures, leading to the model's capacity to achieve high levels of accuracy, precision, recall, and F1 score across various produce categories.

Addressing the challenge of class imbalance was paramount in this study. To tackle this issue, the team implemented techniques aimed at creating a balanced dataset, ensuring a more equitable representation of fresh and spoiled items. The proposed model, featuring a modified ResNet-18 architecture, demonstrated exceptional performance with an overall accuracy rate of 98%. This outcome underscores the model's effectiveness in accurately categorizing a diverse array of produce items based on their freshness.

The implications of these findings extend to potential applications in automated quality assessment within agricultural and supply chain domains. By leveraging this model, stakeholders in these sectors can enhance their ability to swiftly and accurately evaluate the freshness of fruits and vegetables, thereby facilitating improved decision-making processes and potentially reducing waste along the supply chain.

6.3 Implication for Future Study

Enhancing resilience through data augmentation presents a promising avenue for bolstering model performance across diverse environmental conditions. Incorporating supplementary augmentation techniques to address variations in lighting, angles, and backgrounds could notably improve the model's robustness in real-world scenarios.

Exploring transfer learning potentialities from related domains could yield valuable insights for model refinement. Leveraging pre-existing models or drawing expertise from analogous fields might significantly boost model efficacy.

Addressing dataset gaps in less represented categories could be a pivotal focus for future investigations. Balancing dataset distribution across different fruit and vegetable groups has the potential to enhance the model's accuracy in classifying uncommon produce items.

Integrating temporal considerations could mitigate challenges associated with long-term storage or transportation. Evaluating the model's capacity to predict quality changes over time could enhance dynamic review processes.

Pioneering real-world deployment and validation efforts are crucial to gauging the model's efficacy in practical agricultural or supply chain contexts. Conducting validation across diverse settings would provide invaluable insights into the model's adaptability and generalizability.

Furthermore, prioritizing the development of user-centric interfaces could facilitate broader acceptance and utilization of the model. Streamlining interfaces for users with varying levels of technical proficiency could enhance accessibility and usability in quality assessment tasks.

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Appendix

This supplementary section delves deeper into the methodology and findings of the research. The investigators in this study amalgamated their original image data with an additional dataset sourced from Kaggle. This particular dataset was tailored for multiclass classification tasks and encompassed a wide spectrum of fruits and vegetables in both fresh and decayed states. Notably, the dataset's distinguishing features included diverse image properties, precise annotations for freshness classification, superior image quality, and extensive coverage, comprising a total of 32,735 images in varying formats and dimensions, faithfully representing real-world scenarios.

The data analysis phase involved meticulous scrutiny, focusing particularly on evaluating the quality of specific fruits and vegetables such as tomatoes, potatoes, apples, oranges, bananas, capsicum, cucumbers, okra, and bitter gourd. With its substantial size, the dataset ensured an ample variety of instances for effective training and evaluation across multiple categories. To address the challenge of class imbalance, a subset with balanced representation was created, ensuring an equitable distribution of each fruit type and facilitating fair sample allocation.

Various data preprocessing techniques were employed, including bit-plane slicing, adaptive thresholding, and image negation, aimed at enhancing pixel values and improving the interpretability of visual data. The ResNet-18 model, versatilely adapted for diverse tasks, demonstrated exceptional accuracy, precision, recall, and F1 scores in both fruit recognition and freshness classification assessments. The model architecture comprised three additional blocks, with specifications including ReLU activation, a batch size of 62, an image size of 224 × 224, the Adam optimizer, and a training duration of 10 epochs.

Analysis of the results revealed that the recommended model, particularly when configured with an image size of 224 × 224 and a batch size of 64, exhibited outstanding performance, achieving an overall accuracy of 98%. The model excelled in classifying a broad spectrum of fruits and vegetables, showcasing robust accuracy and recall metrics across different categories. Further experimentation with various hyperparameters was conducted to optimize the model's performance, offering valuable insights into its potential applications in automating quality assessment in agricultural settings or supply chain management. This appendix comprehensively presents essential information and analysis, ensuring a thorough understanding of the study's methodology and outcomes.

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