Automated Grading of Grapes Fruits Based on Internal and External Quality

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

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APPROVAL

This Project titled **"Automated Grading of Grape Fruits Based on Internal and External Quality"**, submitted by Juwel Rana Jony, ID no: 201-15-3487 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 January 24,2024.

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We, therefore, declare that this undertaking has been finished by us under the supervision of **Fahad Faisal, Assistant Professor,** Department of CSE, Daffodil International University. We further declare that neither an application nor an educational grant has been made anywhere for this project or any part of it.

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ABSTRACT

The harvesting time of fruits significantly affects their quality, flavor, and market value. Traditionally, this process relies on subjective human evaluation, which is both time-consuming and subjective. However, a solution to this challenge is offered through the application of deep learning. This study introduces an approach that utilizes a Customized Convolutional Neural Network (CNN) and the InceptionV3 architecture to differentiate between three stages of grapes. CNNs have proven to be effective tools for automating the assessment of fruit quality by analyzing visual features such as color, shape, and texture. The architecture incorporates multiple convolutional and pooling layers to extract hierarchical features from images, enabling the identification of subtle differences indicative of various quality stages. A dataset named Quality Grading Dataset was created, and the accuracy of various models was assessed: VGG16=96%, VGG19=98%, ResNet50=98%. The accuracy for InceptionV3 is reported to be 98%.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Grapes, scientifically identified as fruits, are delicious and flavorful fruits that have delighted palates across generations. Belonging to the vitaceae family, these petite, round or oval berries come in a diverse spectrum of colors, including red, green, and purple, each offering a distinct blend of sweetness and tartness. Beyond their delectable taste, grapes hold historical significance, having been cultivated for both winemaking and fresh consumption since ancient times. This adaptable fruit is enjoyed globally in various forms, from munching on fresh clusters to relishing them as raisins, in wines, and even as the foundation for grape juices. In this introduction, we will explore the varied characteristics, nutritional advantages, and cultural significance of grapes, uncovering the reasons for their enduring popularity throughout history. Grapes hold significant prominence in Bangladesh, and traditionally, the color of the fruit's skin has been a reliable indicator of its ripeness. However, manual sorting, a time-consuming process prone to random results, has been the standard practice. This study aims to showcase the effectiveness of using RGB images to assess the quality of cantaloupe fruit based on its skin color. Traditional manual sorting, reliant on color and physical traits, is not only time- consuming but also subjective, varying in skill levels among individuals. Due to this subjectivity, accuracy in determining fruit quality is compromised. Color is a key factor in assessing the quality and maturity of fruits, commonly used for evaluation. Even fruits from the same tree may exhibit uneven quality over different growing seasons. Recognizing fruit ripeness is essential for selective harvesting, as fruits at varying ripeness levels serve different purposes. Fully developed fruits are ideal for fresh food markets, while semi-mature fruits are better suited for long-distance delivery. Identifying ripeness also helps plan harvest schedules for precise harvesting and optimal profit. Early picking of fruit with dense flesh, for example, prevents damage during packing but may compromise its overall quality. The importance of allowing fruits to ripen on trees is emphasized, particularly in the case of peaches, as their flavor and aroma fully develop during the advanced stages of ripening. Packaging techniques consider factors such as color, size, and the presence of faults. While the finest grapes come from tree-ripened fruits, logistical challenges may lead commercial fruit farmers to rely on customers or merchants to complete the ripening process.

In conclusion, the ripeness and quality of grapes, as well as other fruits, are influenced by various factors, with color being a crucial indicator. The study explores the potential of utilizing technology for more accurate assessments, addressing the limitations of manual sorting and emphasizing the multifaceted considerations in determining fruit quality and maturity. In our nation, grapes stand out as the most significant fruit crop, and ensuring the production of top-quality yield is paramount for securing favorable market prices. The timing of the harvest plays a pivotal role not only in high-quality production but also in devising effective marketing strategies. Orchard management, cultural techniques, and post-harvest care further contribute to the overall success of grape cultivation. To minimize various pre- and post-harvest losses, it is essential to harvest grapes at the optimal stage of quality. Since grapes are climacteric fruits, they must be harvested at a physiological quality stage before ripening. This careful timing is crucial for achieving the desired quality during the ripening process. Identifying the quality stage of grape fruits involves considering several factors, including specific gravity, skin color, and the natural dropping of ripe fruit from the tree. These criteria collectively guide the determination of the ideal harvesting period for grapes.

1.2 Motivation

The categorization of grapes ripeness serves several crucial purposes. It facilitates the identification of the optimal quality stage, ensuring the best flavor and texture for an effective harvesting process. This categorization is instrumental in maintaining quality control throughout the entire supply chain, guaranteeing that only grapes at the correct ripeness level are selected and provided to customers. Furthermore, it allows for the implementation of appropriate post-harvest processing and storage techniques to enhance shelf life and reduce waste by accurately determining ripeness. Categorizing quality also aligns with consumer preferences, enabling merchants to offer grapes at the desired level of ripeness. Additionally, it ensures fair market pricing based on both quality and maturity. In conclusion, the systematic categorization of grapes ripeness is indispensable for assuring overall quality, meeting consumer preferences, and optimizing grapes production and distribution processes.

1.3 Rationale of the study

The rationale behind the issue of grapes quality categorization is rooted in the need to optimize various aspects of grape production, distribution, and consumption. By accurately identifying the quality stage of grapes, stakeholders in the industry can make informed decisions and take appropriate actions at different points in the supply chain. This precise categorization ensures that grapes are harvested at the right time, quality standards are upheld, and consumer preferences are met. Furthermore, effective categorization plays a pivotal role in reducing waste, optimizing shelf life, and establishing fair pricing practices that benefit both producers and customers. The overarching objective is to enhance productivity, ensure quality assurance, and bolster consumer satisfaction within the grape industry. Traditional grading methods often involve manual sorting and grading of fruits, which can be labor-intensive, time-consuming, and costly. Developing automated grading systems can help streamline this process, reduce labor costs, and improve overall efficiency. Research in automated grading contributes to the advancement of agricultural technology and innovation, driving improvements in production processes and quality control across the industry. the study aims to contribute to the development of efficient and reliable automated grading systems for grapes, which could have broad implications for the agricultural industry as a whole.

1.4 Research Question

- How the dataset is created?
- How to categorize the mango dataset?
- How many categories are in this dataset?
- How this works helps people agriculture industry and people?

1.5 Expected Outcome

This research focuses on the classification of grapes based on their quality, specifically categorizing them into two groups: fresh grapes and rotten grapes. The objective is to develop an advanced deep learning technique for accurately identifying the quality level of grapes. In this study, three Convolutional Neural Network (CNN) architectures have been employed, along with the InceptionV3 model, to enhance the precision of this classification task. The utilization of these models reflects a comprehensive approach to leveraging deep learning methodologies for the effective assessment and differentiation of grape quality.

1.6 Report Layout

- The subsequence chapters of this paper organized as follow:
- chapter 2: Discussion about related works, comparative analysis, scope of problems and challenges.
- chapter 3: Research Methodology, dataset description, proposed model.
- chapter 4: Result analysis.
- chapter 5: Impact on society, environment, sustainability of mango classification.
- chapter 6: says the conclusion of my research.

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

The classification of fruit quality stands as a crucial and noteworthy research topic, particularly in the context of identifying the best fruits for harvest and the agriculture industry. Extensive work has already been conducted in this domain, employing advanced techniques such as deep learning and machine learning. These research endeavors have yielded valuable insights and information, contributing to a deeper understanding of fruit quality assessment methods and their implications for the agricultural sector.

2.2 Related works

Xiao, H. et.al showed Utilizing Visible-Near Infrared Spectroscopy for the Assessment and Categorization of Grape Berries by Considering Various Internal Quality Factors. The study explored the potential of utilizing visible-near infrared (vis/NIR) spectroscopy within the wavelength range of 400 nm to 1100 nm to categorize grape berries based on multiple internal quality parameters [1]. The forecast outcomes indicated a correlation between the vis/NIR spectrum and the SSC and TP found in whole grape berries, with a prediction determination coefficient (RP^2) ranging from 0.735 to 0.823. Subsequently, the vis/NIR spectrum was employed to differentiate berries with varying SSC and TP levels through discriminant analysis using partial least squares (PLS-DA) with an accuracy exceeding 77%. This research offers a technique for categorizing stored grape quality classes by leveraging spectroscopy and the distributions of various internal quality parameters.

Sardar, H. et.al showed Fruit Quality Estimation by Color for Grading. Nowadays, ensuring the quality and standardization of fruits and their derived products is a crucial concern in food processing, particularly in relation to consumer health [2]. A logical and updated algorithm is proposed for assessing the quality and standard level of fruits, particularly spherical fruits like Guava, based on their external surface color using a non-destructive technique, such as soft computing. This algorithm aims to facilitate automated quality verification systems, which can be integrated into image processing for determining the fruit's quality, categorized as unripe, partially ripe, ripe, or overripe (bad fruit). The primary emphasis in this study is placed on the crucial role of color, while other parameters like size, shape, hardness, softness, daylight, day temperature, and colorization also contribute significantly to the quality analysis process. The research has practical applications in the grading and sorting of agricultural products through the utilization of digital images in various formats. The approach involves image analysis, visual examination, and inspection of color, providing valuable support for manufacturing different edible products based on the categorized quality levels of the fruits.

Valenzuela, G. A. L. et.al showed assessment of external and internal characteristics of blueberries through image analysis. The wide range of maturity levels in blueberries makes it important to explore non-destructive methods for evaluating both their internal and external characteristics in the postharvest period. Initially, images of harvested blueberries, encompassing four classes, including undamaged control berries, were captured to extract color and geometrical features. Subsequently, a sequential forward selection process was employed to choose relevant features for classifiers [3]. Ultimately, the outcomes underwent validation through external 10-fold cross-validation. Linear discriminant analysis, support vector machine, and a probabilistic neural network were utilized to successfully discern the orientation of blueberries in 96.5% of instances. The classifiers demonstrated average accuracies of 98.3%, 96.7%, and 93.3% for blueberries affected by fungal decay, shriveling, and mechanical damage, respectively.

Perpinello, G. P. et.al showed Relationship between sensory and NIR spectroscopy in consumer preference of table grape (cv Italia) [4]. The research explored the use of both near-infrared spectroscopy (NIR) instrument measurements and sensory analysis to forecast the solids soluble content (SSC, evaluated as Brix) and categorize preference in table grape variety Italia. For consumer testing, the chosen PLS model was employed to estimate the Brix value in a set of 400 berries. Subsequently, Discriminant Analysis (DA) was conducted to categorize berries based on preference, correlating NIR data with consumer judgment. The three predetermined preference clusters for berries were successfully classified, achieving 100% membership. During cross-validation, the accuracy decreased notably for class 1 (78.5%) and class 3 (75%), while class 2 maintained comparable values (98.7%). Our findings suggest that NIR technology holds promise for predicting SSC and providing insights into consumer preference for 'Italia' table grapes. This could lead to the application of efficient and cost-effective online instruments in the fruit industry.

Beghi, R. et.al showed Electronic nose and visible-near infrared spectroscopy in fruit and vegetable monitoring. In the past few decades, there has been a significant rise in the intake of fruits and vegetables because of their nutritional attributes, given that they are recognized as rich sources of vitamins, minerals, fiber, and antioxidants [5]. In this particular situation, it is crucial to maintain the quality of the product throughout its handling, processing, and storage stages. Consequently, the availability of rapid methods becomes essential to furnish valuable insights into process management. This review offers an overview of the utilization of commonly employed non-destructive techniques, specifically electronic nose and visible/near-infrared spectroscopy, for assessing the quality of fruits and vegetables. The text provides a brief overview of spectroscopic and electronic devices, accompanied by a range of applications. The conclusion of the review delves into future possibilities related to streamlining and utilizing these non-destructive techniques. Keywords: fruits and vegetables, non-destructive devices, postharvest, quality, shelf life

Nicolai, B. M. et.al showed A summary is provided on the application of near infrared (NIR) spectroscopy for assessing the quality characteristics of horticultural produce [6]. The statement discusses the resolution of challenges related to robustness, specifically those arising from orchard and species influences and varying temperatures. It introduces the issue of calibration transfer between spectrophotometers and outlines techniques to address it. While NIR spectroscopy has mainly been applied to nondestructively measure soluble solids content in fruits, achieving a root mean square error of prediction of 1° Brix, it is also applied in diverse areas such as texture, dry matter, acidity, and disorders of fruits and vegetables. The statement acknowledges the need for further research in identified areas.

Bayetto, M. et.al showed Electronic-Nose Applications for Fruit Identification, Ripeness and Quality Grading. Fruits generate a diverse array of volatile organic compounds, giving them distinct aromas and contributing to their unique flavor profiles [7]. We examine the chemical composition of volatile compounds in fruits throughout the entire agro-fruit production process. We discuss significant applications of electronic nose (e- nose) technologies in characterizing fruit aromas and provide an overview of recent research that utilizes e-nose data to assess their effectiveness in identifying fruits, distinguishing between cultivars, evaluating ripeness, and grading fruits to ensure quality in commercial markets.

Sravan, T. et.al showed Advances in Grading of Fruits. The grading of agricultural products, particularly fruits, has become a crucial aspect of cross-border trade. In India, the majority of fruit growers engage in manual fruit grading [8]. Farmers anticipate the availability of a sufficient agricultural product-grading machine to address labor shortages, enhance efficiency, and elevate the quality of graded produce. The process of grading fruits holds significant importance as it not only fetches higher prices for growers but also enhances packaging, management, and overall progress in the marketing system. Typically categorized by size, graded fruits find increased acceptance in the export market. The grading process contributes to minimizing risks during transportation and, in response to market demands, underscores the importance of improved quality assessment, leading to more precise grading and sorting methods. The process of categorizing fruit weight relies on specific gravity and density, while electronic color grading is employed for highly perishable fruits. Although this approach is costly, it offers a high level of precision in the grading process.

Scholer, F. et.al showed Automated 3D reconstruction of grape cluster architecture from sensor data for efficient phenotyping [9]. They suggest a method for the complete automation and sensor-driven 3D reconstruction of grape cluster structure, accompanied by an accurate, unbiased, and replicable extraction of phenotypic characteristics. Their methodology involves utilizing a detailed component-based model to describe the architecture of grape clusters. This model encompasses the interconnections among the components, the geometry of these components, and the constraints imposed by their structural and geometrical relationships. Leveraging this model, their approach enables the automated generation of comprehensive 3D reconstructions of observed grape clusters, even when faced with partial occlusions during sensor data acquisition. By obtaining a complete 3D reconstruction of a grape cluster, the method allows for the extraction of well-established phenotypic traits. Additionally, it facilitates the measurement and evaluation of novel phenotypic traits. Consequently, this approach holds significance for monitoring and estimating yields in vineyards, as well as for grapevine breeding purposes.

Zhang, R. et.al showed Nondestructive prediction of fruit detachment force for investigating postharvest grape abscission. Customers prefer table grapes due to their unique taste and valuable nutritional attributes [10]. Physiological indicators associated with FDF were scrutinized, leading to the identification of 10 closely linked indices, including aspects such as berry color, berry weight, and berry length. Subsequently, four machine learning models—multiple linear regression (MLR), principal component regression (PCR), back propagation (BP) neural networks, and genetic algorithm back propagation (GA-BP) neural networks—were utilized to forecast FDF based on these highly correlated physiological indicators. The outcomes indicated that the GA-BP model exhibited superior prediction efficiency, boasting a correlation coefficient (R2) of 0.833, root mean square error (RMSE) of 0.426, and mean absolute percentage error (MAPE) of 0.163. The final step involved the development of a nondestructive FDF prediction model using the GA-BP model, incorporating nondestructive apparent characteristics extracted through machine vision technology. This model demonstrated a commendable fitting effect, achieving R2 = 0.812, RMSE = 0.426, and MAPE = 0.334, respectively.

Consequently, an effective and nondestructive FDF prediction method has been successfully established for monitoring FDF changes during grape postharvest storage and predicting grape abscission. The writers assert that they do not have any identifiable conflicting financial interests or personal affiliations that might have seemed to impact the research presented in this article.

Kaiyan, L. et.al showed Review on the Application of Machine Vision Algorithms in Fruit Grading Systems. The computer executed image processing tasks, encompassing preprocessing, segmentation, as well as feature extraction and selection in the initial segment. The subsequent section outlined classification algorithms employed in machine vision for fruit grading [11]. These algorithms were categorized into supervised machine learning, unsupervised algorithms, and deep neural networks. Among supervised machine learning algorithms were Naive Bayes, K-nearest Neighbor, and Support Vector Machine. Unsupervised machine learning algorithms encompassed K-means Clustering and Principal Component Analysis. The deep learning component primarily introduced Artificial Neural Network and Convolutional Neural Network. This section comprehensively examined the characteristics and application potential of these classification algorithms, providing a comprehensive comparison of their advantages and disadvantages in fruit classification. The third segment delved into the challenges and difficulties encountered in fruit grading tasks utilizing machine vision technology, presenting prospective solutions. Finally, the paper summarized and analyzed machine vision algorithms within fruit grading systems, concluding that the integration of machine learning and deep learning with machine vision systems represents the primary developmental direction in fruit grading. This synthesis is anticipated to be a significant focus of research in the future.

Tripathi, M. K. et.al showed A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: A survey. Computer vision represents a reliable and sophisticated method for processing images, yielding favorable results and showcasing vast potential [12]. Its widespread adoption extends across diverse domains, including agriculture. They extensively analyze papers associated with fruits and vegetables in diverse horticulture products of agricultural fields. The examination encompasses a specific model, data pre-processing, data analysis methods, and overall performance accuracy assessed through a particular metric. Additionally, the research delves into various diseases affecting different types of fruits and vegetables. The focus extends to comparing different machine learning approaches using diverse performance metrics on the same dataset. The findings reveal that SVM outperforms other machine learning techniques in classification accuracy. The paper also introduces a generalized framework for grading the quality and detecting defects in multiple fruits and vegetables. In this comprehensive survey, ninety-eight papers closely related to computer vision in agriculture are reviewed. The survey underscores the pivotal role of computer vision in addressing challenges within the agricultural sector, highlighting its substantial potential. In their future endeavors, they aim to employ an alternative descriptor grounded in color, texture, shape, and size, amalgamating these factors to enhance precision. Additionally, they intend to incorporate the principles of deep learning techniques for both detection and classification purposes.

Ganguli, S. et.al showed Deep Learning Based Dual Channel Banana Grading System Using Convolution Neural Network. Deep learning is currently recognized as the cutting-edge technology in computer vision for categorizing images. The development of convolutional neural networks (CNNs) has streamlined the process of feature engineering [13]. The system has the capability to either substitute or assist human operators, allowing them to concentrate on selecting fruits. This study emphasizes the combined advantages of RGB and HSI (hyperspectral imaging) for categorizing bananas, suggesting their potential application as a model for classifying various horticultural produce. The rapid processing time of the multi-input model proves to be a convenient technique during postharvest procedures in the farm field. By employing a combination of CNN and MLP on data collected through RGB and hyperspectral imaging, the multi- input model reliably identifies bananas with an accuracy of 98.4% and an F1-score of 0.97. The AI algorithm accurately predicts the size (large, medium, and microscopic) and orientation (front or rear half) of banana classes with a 99% accuracy rate. In contrast to prior studies that solely utilized RGB imaging, this model underscores the significance of integrating both RGB imaging and HSI approaches.

2.3 Comparative Analysis and Summary

Indeed, the identification of fruit quality has been a focal point in related works, and researchers have employed a variety of machine learning and deep learning models for this purpose. Among the commonly used models are Naive Bayes Classifier, KNN, CNN, ResNet50, VGG16, AlexNet, GoogLeNet.

Table 2.2: Related Works table

Model	**Dataset**	**Classifier**	**Feature**	**Accuracy**
Xiao, H.	Grape Berries Dataset	SVM classifier	Shape and size	77%.
Sardar, H.	Fruit Quality Dataset	Support vector machine (SVM).	shape, size, color, hardness, softness	none
Valenzuela, G. A. L.	Blueberries Dataset	SVM and artificial neural network(ANN)	shape, size and color	98%
Perpinello, G. P.	Grape Dataset	Principal component analysis (PCA)	Size and color	98.7%
Ganguli, S.	Banana Dataset	ANN	size, texture, color, and shape	98.4%.
Tripathi, M. K.	fruits and vegetables Dataset	SVM and decision tree	size, texture, color, and shape	none
Kaiyan, L.	Fruit Dataset	SVM, K-NN	shape, size and color	none

2.3.1 Naive Bayes Classifier:

It stands out as a highly important algorithm for rapidly constructing machine learning models to swiftly make predictions. Operating on probability principles, it can be characterized as a probabilistic classifier. Key applications of the Naïve Bayes algorithm include effective usage in spam filtering, categorizing articles, demonstrating proficiency in face recognition, and contributing to accurate weather predictions. The Naive Bayes classifier is a simple probabilistic classifier based on Bayes' theorem with an assumption of independence among features. It's called "naive" because it makes the assumption that the presence of a particular feature in a class is unrelated to the presence of any other feature. Naive Bayes classifiers are commonly used in text classification, spam filtering, sentiment analysis, and other classification tasks, especially when the assumption of feature independence holds reasonably well or when computational resources are limited. Naïve Bayes algorithm is basically comprised of two words Naïve and Bayes. It is characterized as:

Naïve: The term "naive" is used to describe this algorithm because it assumes that the presence of one feature is independent of the presence of other features. For example, if a fruit is being identified based on its color, shape, and taste, a mango can be recognized as a yellow, oval, relatively tall fruit with a sweet flavor. In this naive approach, each individual characteristic contributes independently to identifying it as a mango, without taking into account any potential relationships with the other features.

Bayes: The principle of this algorithm is Bayes’ theorem. That’s it is called Bayes. Bayesian inference is widely used in various applications such as parameter estimation, hypothesis testing, machine learning, and Bayesian networks. It provides a powerful framework for reasoning under uncertainty and making informed decisions based on available evidence.

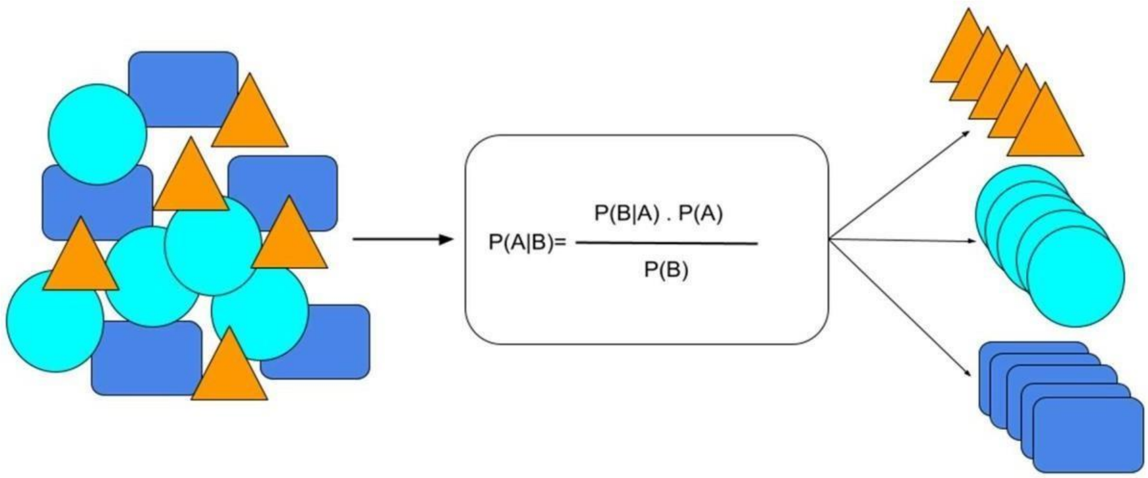


Figure 2.3.1: Naïve Bayes Classifier

2.3.2 K-Nearest Neighbor (KNN):

The K-NN algorithm functions with supervised data, assuming comparability between new instances and existing instances. It assigns the new instance to the category most closely resembling the existing ones. By retaining all available information and evaluating similarity, the K-NN algorithm adeptly classifies new input. This approach facilitates swift and precise categorization of new data into the relevant categories. The
K-NN algorithm is primarily utilized for classification and is considered a non-parametric algorithm because it does not make assumptions about the underlying data. The working method of K-NN, I can explain as:

- Choose the value of K, representing the number of neighbors to consider.
- Compute the Euclidean distance between the new data point and K nearest neighbors.
- Select the K neighbors with the smallest Euclidean distances.
- Tally the data points within each category among the K neighbors.
- Allocate the new data point to the category with the highest count among its neighboring points.
- This process results in the creation of a K-NN model used for classification purposes.

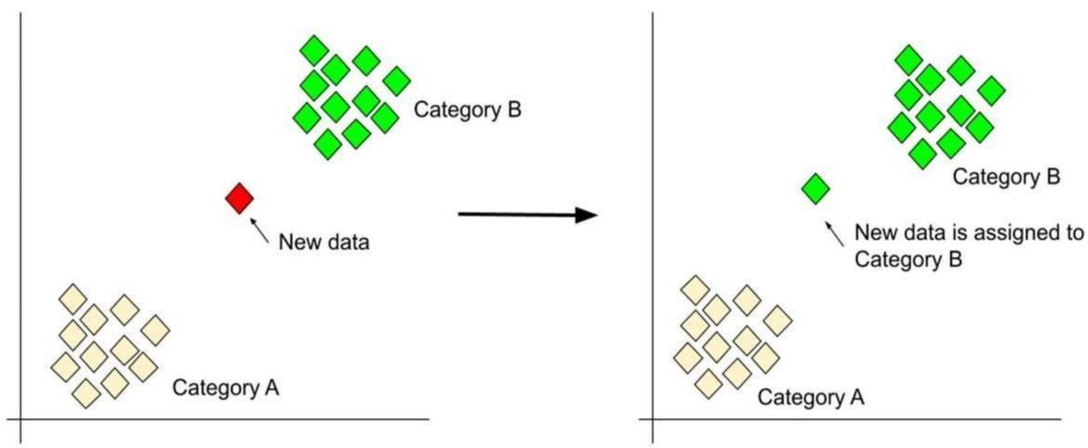


Figure 2.3.2: K-NN Algorithm

2.3.3 Convolutional Neural network (CNN):

A Convolutional Neural Network (CNN) is a class of deep learning network architecture designed for direct learning from images or data. CNNs extract features from images, enabling the identification of objects, classes, and categories. Taking inspiration from the human brain's visual cortex, CNNs are characterized by their use of convolutional layers. The distinctive feature of CNNs lies in their application of convolutional layers, where input data is processed through a set of learnable filters, also called kernels. These filters perform element-wise multiplications and summations while sliding over the input, extracting local features. The output is a feature map that highlights significant patterns or attributes in the input. CNNs can comprise numerous layers, often in the hundreds or thousands, to detect various features within an image. During training, each image undergoes processing with filters at different resolutions, and the resulting convolved image becomes the input for the next layer. Starting with basic properties like brightness and edges, the filters progressively convolute to identify increasingly complex characteristics specific to the image. This hierarchical approach allows CNNs to effectively learn and recognize intricate patterns in visual data.

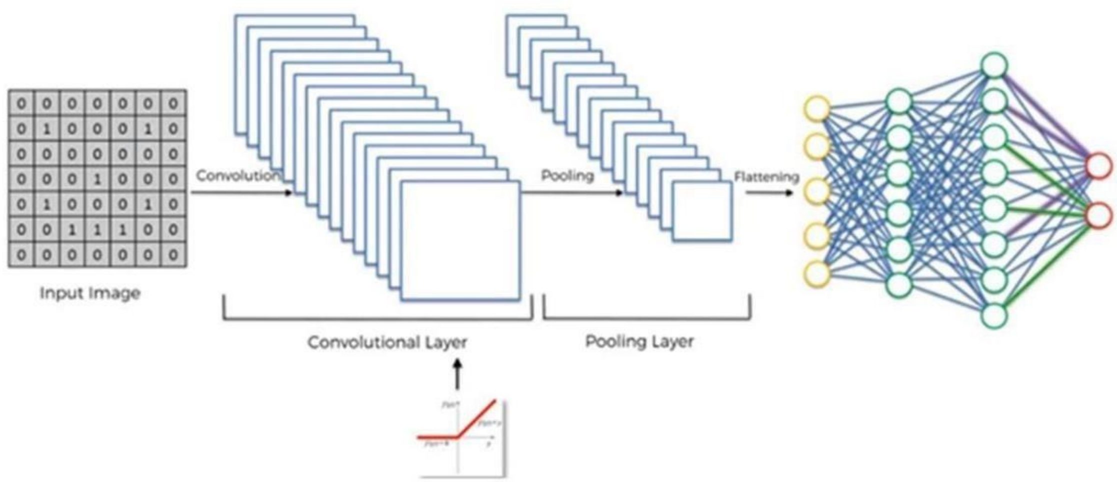


Figure 2.3.3: Basic CNN Architecture

2.3.4 ResNet50:

ResNet50 is a convolutional neural network (CNN) widely employed as a pretrained model, particularly well-suited for advanced computer vision tasks. The architecture of ResNet50 comprises 48 convolutional layers, one MaxPool layer, and one average pool layer, resulting in a 50-layer CNN. What sets ResNet-50 apart from conventional architectures is its incorporation of bottleneck building blocks. These bottleneck residual blocks, commonly referred to as "bottlenecks," efficiently decrease the number of parameters and matrix multiplications by incorporating 1x1 convolutions. This strategic design choice serves to enhance the model's efficiency without compromising its overall performance.

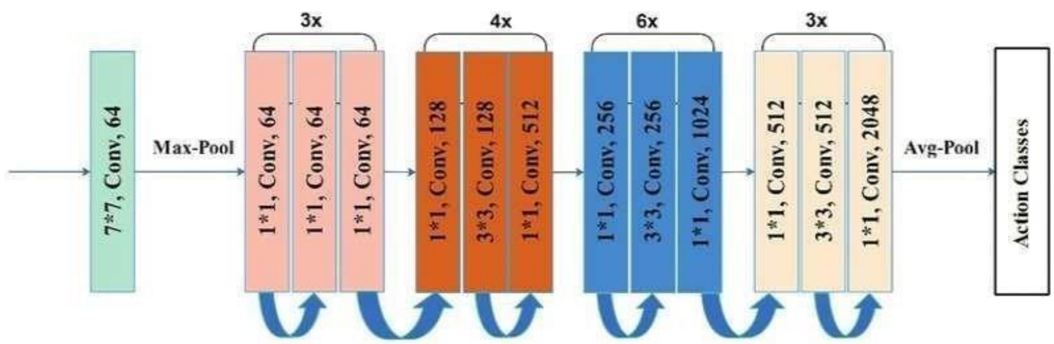


Figure 2.3.4: ResNet50 Model Architecture

To expedite the training speed, ResNet50 adopts a modified layer structure compared to the traditional two-level stack; instead, it incorporates three layers. The initial layer involves convolving a 7x7 kernel with 64 additional kernels using a stride of size 2, followed by a max pooling layer with a stride of size 2. Subsequent layers consist of nine convolutional layers, each utilizing 3x3 kernels and 64 channels, followed by another layer with 1x1 kernels and 64 channels, and a third layer with 1x1 kernels and 256 channels. This set of three layers is iterated three times. Additionally, twelve more layers involve 1x1 kernels with 128 channels, 3x3 kernels with 128 channels, and 1x1 kernels with 512 channels, repeated four times. Furthermore, eighteen more layers consist of 1x1 kernels with 256 channels and two sets of 3x3 kernels with 256 channels, along with 1x1 kernels with 1024 channels, repeated six times. Finally, nine additional layers comprise 1x1 kernels with 512 channels, 3x3 kernels with 512 channels, and 1x1 kernels with 2048 channels, repeated three times. This intricate layer structure contributes to the overall architecture of ResNet50, enhancing its efficiency during the training process.

2.3.5 VGG16:

The VGG model stands out as one of the notable contributions from the VGG group. As a deep neural network, it has gained widespread recognition and has been extensively employed as a benchmark for tasks such as image classification and object recognition. The VGG model has demonstrated state-of-the-art performance, solidifying its reputation as a significant contribution in the field.

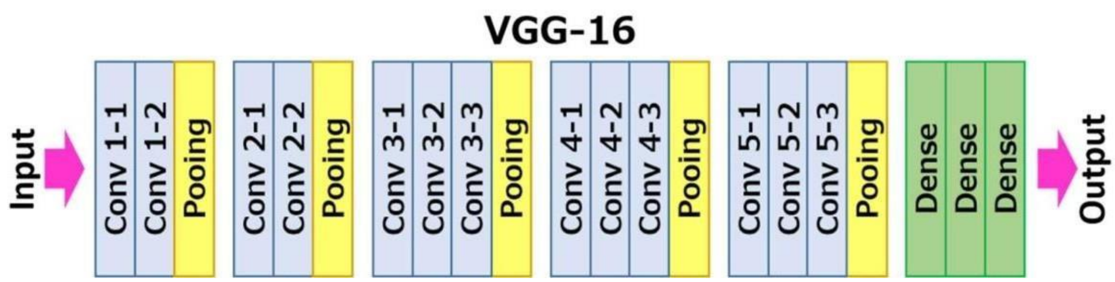


Figure 2.3.5: VGG16 Model Architecture

The VGG model achieves the capability to learn intricate features from input images by employing small 3x3 convolutional filters and adopting a deep architecture with up to 19 layers. In the case of VGG16, the designation "16" corresponds to the 16 weight layers within the model. In total, VGG16 comprises 21 layers, incorporating three Dense layers, five Max Pooling layers, and thirteen convolutional layers. However, only sixteen of these layers serve as weight layers or contain learnable parameters. VGG16 is designed to receive input tensors of size 224x224 with RGB channels.

A notable feature of VGG16 is its consistent utilization of the same padding and a 2x2 filter with a stride of 2 for the max pooling layers. Furthermore, it underscores the application of 3x3 filters with a stride of 1 for the convolutional layers, eliminating the need for a large number of hyper parameters. The arrangement of convolutional and max pooling layers maintains uniformity throughout the entire architecture. Following a stack of convolutional layers, VGG16 integrates three Fully-Connected (FC) layers. The third FC layer is tailored for 1000-way ILSVRC classification and comprises 1000 channels, each representing a specific class. The first two FC layers each contain 4096 channels. The final layer in the model is the soft max layer, commonly used for generating a probability distribution output.

2.3.6 AlexNet:

In 2012, AlexNet marked a groundbreaking achievement by winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), demonstrating a substantial reduction in error compared to previous state-of-the-art models. It achieved an impressive error rate of 15%, a significant improvement over the previous 26% error rate. The architecture of AlexNet comprises five convolutional layers, all followed by maximum pooling. Additionally, the model integrates three fully-connected (FC) layers. Throughout the network, Rectified Linear Unit (ReLU) activation functions are applied, addressing the vanishing gradient problem and enhancing the training process. AlexNet employs a diverse range of convolutional filter sizes, including the commonly used 3x3 filters as well as larger sizes such as 5x5 and 11x11. This variation in filter sizes enables the network to capture different levels of spatial information, detecting both local and global features in input images. The combination of architectural elements, including multiple convolutional layers with maximum pooling, three FC layers, ReLU activations, and the utilization of various filter sizes, contributed to AlexNet's remarkable performance. It played a pivotal role in popularizing deep learning for image recognition tasks and represented a significant advancement in the field.

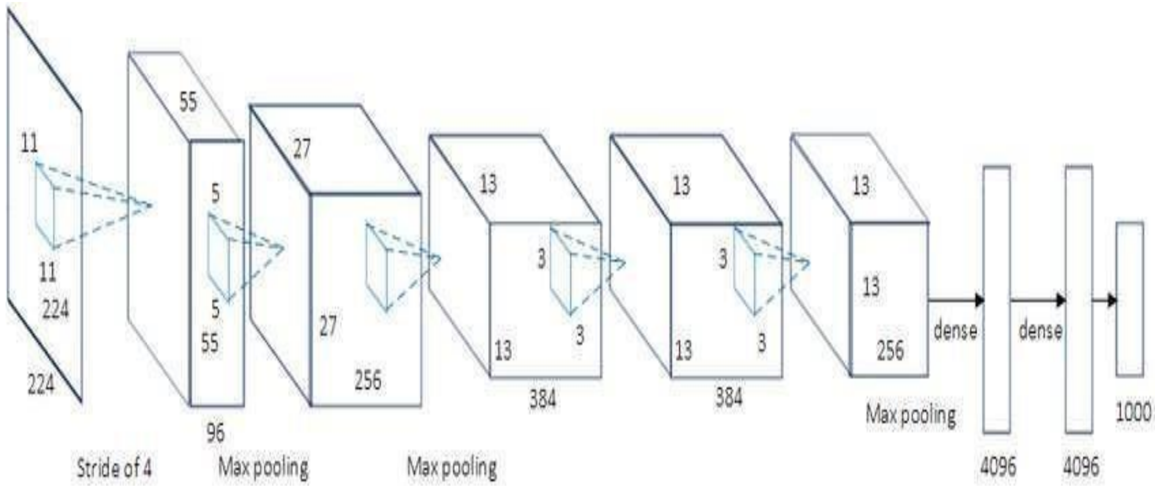


Figure 2.3.6: AlexNet Model Architecture

2.3.7 GoogLeNet:

In 2014, researchers at Google introduced GoogLeNet, a deep convolutional neural network renowned for its significant contributions. A noteworthy innovation is the Inception module, characterized by the integration of multiple parallel convolutional layers featuring distinct filter sizes. Subsequently, a pooling layer is applied, and the outputs are concatenated. This architecture enables the network to adeptly capture features at different scales and resolutions, effectively capturing information at different levels of granularity while maintaining manageable computational costs. The Inception module enhances feature learning efficiency by concurrently processing different receptive field sizes. Through concatenation of outputs, the network can capture both local and global features within a single layer. GoogLeNet also incorporates auxiliary classifiers at intermediate layers, serving dual purposes. Firstly, they act as regularization techniques by providing additional supervision during training, encouraging the network to learn more discriminative features. Secondly, they address the vanishing gradient problem by offering gradients from intermediate layers to earlier layers, facilitating improved information flow during backpropagation. By introducing the Inception module and auxiliary classifiers, GoogLeNet achieved state-of-the-art performance on the ImageNet dataset while showcasing computational efficiency. Its design principles have significantly influenced subsequent convolutional neural network (CNN) architectures, paving the way for the development of deeper and more accurate models.

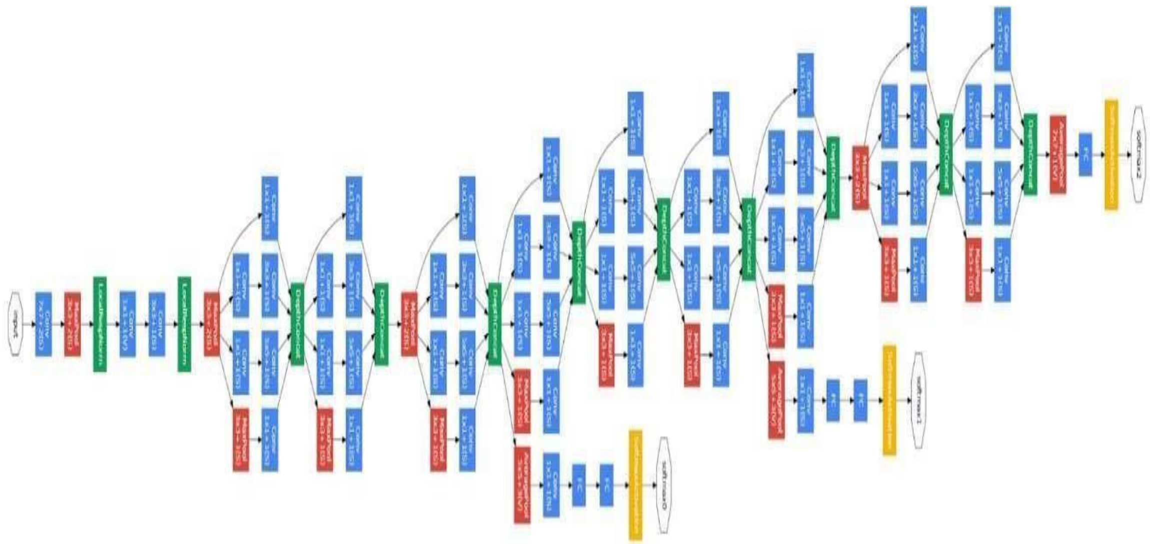


Figure 2.3.7: GoogLeNet Model Architecture

GoogLeNet builds upon the concepts introduced by earlier convolutional neural networks, including LeNet, which was one of the pioneering successful implementations of deep learning in computer vision. Notably, GoogLeNet surpasses LeNet in both depth and complexity, representing a substantial advancement in the evolution of convolutional neural network architectures.

2.4 Scope of the Problem

The grapes quality classification problem encompasses diverse aspects within the grapes industry, spanning from production to consumption. Key areas falling within the scope of this issue include agriculture and harvesting, supply chain management, quality control and sorting, consumer preferences and market demand, economic considerations, and research and technology. Moreover, the problem of grapes maturity classification is closely related, involving agricultural practices, supply chain management, quality control, consumer preferences, economic considerations, and advancements in research and technology. This multifaceted challenge involves multiple stakeholders and significantly influences various stages of the grapes industry.

2.5 Challenges

The primary challenge I encountered was data collection for my project. To compile a diverse dataset for grapes quality classification, I acquired grapes images from the market. However, some sellers were unwilling to allow me to take pictures of their grapes. To address this, I had to purchase grapes to capture the required images. For obtaining images of rotten grapes, I intentionally purchased overripe grapes and allowed them to spoil. Only after they reached the desired state of rot did I capture images for this category. Subsequently, I employed four distinct Convolutional Neural Network (CNN) architectures to determine the most accurate model for grapes quality classification.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This research is centered around the detection of fresh and rotten grapes using a Transfer Learning Approach. The study was carried out using programming tools such as Anaconda Prompt, Jupyter Notebook, and Google Colab to facilitate the necessary programming tasks.

3.2 Data Collection Procedure/Dataset Utilized

Researchers can ensure the collection of high-quality, reliable data for the automated grading of grape fruits based on internal and external quality parameters. This data forms the foundation for developing accurate and robust grading algorithms and systems in agricultural applications. To compile a Real Capture Image Dataset, I employed two cameras, namely the One plus nordCE2 lite, for capturing grape images. I visited various locations, including fruit markets and grape gardens, to purchase grape more than 5kg and take photos. To ensure clarity, I placed the grapes on white paper before capturing the images. The dataset comprises a total of 3000 images of raw grapes, 1500 images of fresh grapes, and 1500 images of rotten grapes. Notably, all the images are unique. The One plus NordCE2 lite camera specifications include a 48 MP primary camera with a 25mm f/1.8 lens, Sony IMX 582 Quad-Bayer 1/2" sensor featuring 0.8µm pixels, and PDAF, complemented by features like LED flash, HDR, and panorama.

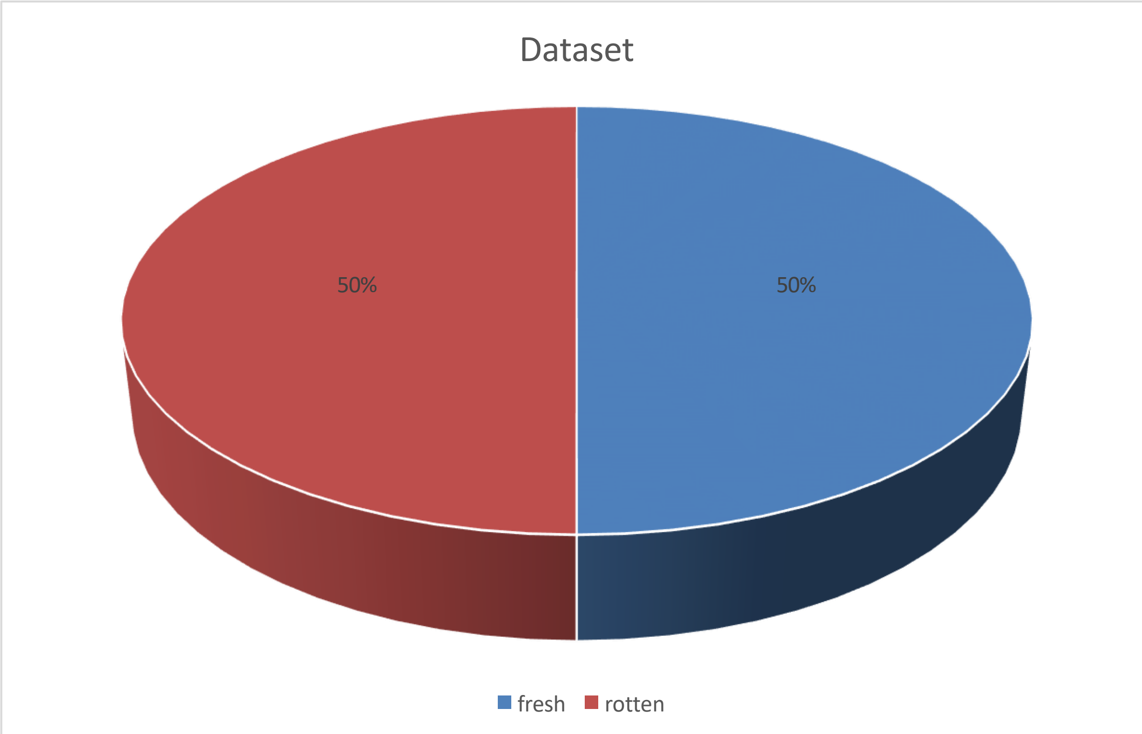
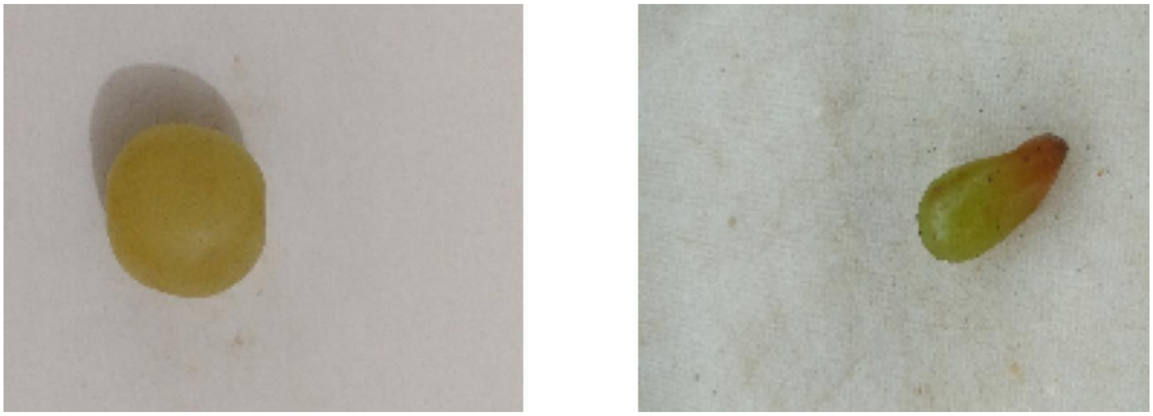


Figure 3.2: Classes of Dataset

3.3 Data Preprocessing

The Real Capture Image Dataset is organized into training, testing, and validation datasets, each comprising three classes: fresh grapes and rotten grapes. To preprocess this dataset, all images underwent resizing using the FastStone Photo Resizer tool, ensuring a reduction in megapixels while maintaining image quality. Subsequently, all images were cropped into 256x256 shapes. Following the preprocessing steps, image augmentation techniques were applied to enhance the diversity of the dataset. The distribution of these augmented images is allocated with 70% for the training dataset, 20% for testing, and 10% for validation, ensuring a balanced and representative division across the three classes.



Fresh Rotten

Figure 3.3: Processed Images

Table 3.3: dataset description

Dataset	Class	Original Data
Quality Grading Dataset	Fresh	1500
	Rotten	1500

3.4 Proposed Methodology/Applied Mechanism

The ResNet-50 model, short for Residual Network with 50 layers, is a popular deep neural network architecture. Its key innovation is the introduction of residual blocks, which help address the vanishing gradient problem during training. Below is a simplified outline of the working procedure of the ResNet-50 model:

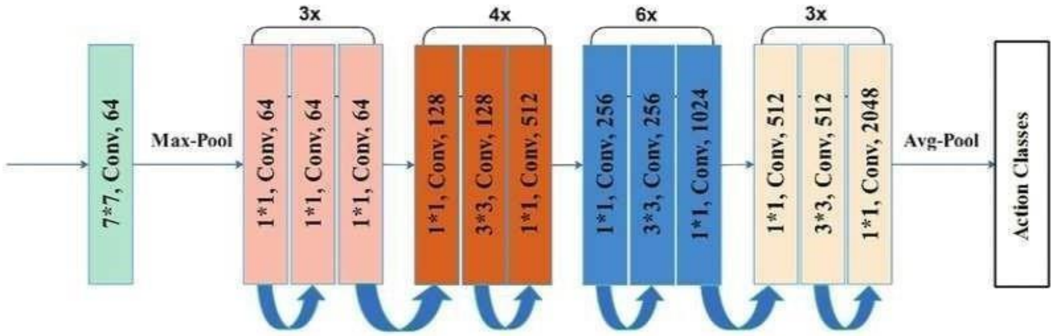


Figure 3.4: ResNet50 Architecture

- **Input Layer:**

  The model takes an input image typically of size 224x224 pixels with three color channels (RGB).
- **Convolutional and Pooling Layers:**

  The initial layers involve standard convolutional operations with 7x7 filters and a stride of 2. Max pooling is applied to down sample the spatial dimensions.
- **Residual Blocks:**

  The core of ResNet-50 consists of residual blocks. Each block contains multiple convolutional layers. Skip connections (shortcut connections) allow the gradient to flow directly through the block without encountering vanishing gradient issues.
- **Bottleneck Architecture:**

  ResNet-50 utilizes bottleneck building blocks to reduce the number of parameters and computational load. Bottleneck blocks include 1x1, 3x3, and 1x1 convolutions to capture different feature scales efficiently.
- **Multiple Stacks of Blocks:**

  The model is composed of several stacks of residual blocks, each containing different numbers of blocks. The deeper layers learn more abstract and complex features.

- **Global Average Pooling:**

  Global Average Pooling is applied to convert the 4D tensor output into a 2D tensor. This step reduces the spatial dimensions to 1x1, creating a compact representation.

- **Fully Connected (Dense) Layers:**

  Dense layers are added to perform the final classification based on the learned features. The output layer typically has 1000 neurons for ImageNet classification, representing the number of classes.

- **Soft max Activation:**

  The final layer uses the soft max activation function to convert the model's output into probability scores for each class.

- **Training:**

  The model is trained using a labeled dataset, adjusting its parameters (weights and biases) through backpropagation and optimization algorithms. Common optimization algorithms include stochastic gradient descent (SGD) or variants like Adam.

- **Fine-Tuning and Transfer Learning:**

  ResNet-50 is often used in transfer learning, where pre-trained weights on large datasets (e.g., ImageNet) are fine-tuned for specific tasks with smaller datasets.

The accuracy achieved by the customized ResNet50 on the Real Capture Image Dataset was 98%.

The image classification process of the VGG16 model unfolds through the subsequent steps:

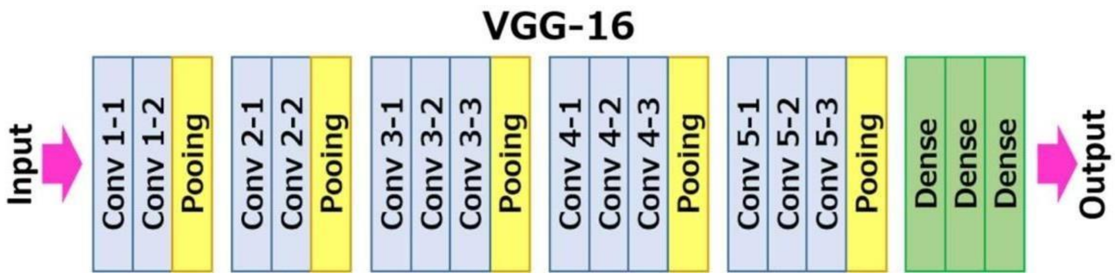


Figure 3.4.1: VGG16 Architecture

- **Input Layer:**
  The model takes an input image typically sized at 224x224 pixels with three color channels (RGB).
- **Convolutional Blocks:**
  VGG16 comprises several convolutional blocks, each housing multiple convolutional layers using small 3x3 filters. The employment of small filters aids in capturing intricate patterns while reducing the number of parameters.
- **Max Pooling:**
  After each set of convolutional layers, max-pooling is applied to reduce spatial dimensions.
- **Fully Connected (Dense) Layers:**
  Subsequent to the convolutional blocks, the model incorporates fully connected (dense) layers that progressively reduce spatial dimensions and learn high-level features.
- **Flattening:**
  Prior to entering the fully connected layers, the output from the convolutional layers undergoes a process of flattening, transforming into a one-dimensional vector.
- **Activation Functions:**
  Throughout the network, Rectified Linear Units (ReLU) serve as activation functions, introducing non-linearity.

- **Dropout:**
  To prevent overfitting, dropout layers may be introduced during training, randomly setting a fraction of input units to zero.
- **Soft max Activation:**
  The final layer commonly employs the soft max activation function for multi-class classification, converting the model's output into probability scores.
- **Training:**
  The model undergoes training using labeled datasets and optimization algorithms like stochastic gradient descent (SGD) to adjust weights and biases.
- **Fine-Tuning and Transfer Learning:**
  VGG16 is often employed in transfer learning, where pre-trained weights on larger datasets are fine-tuned for specific tasks with smaller datasets. The initial layers capturing general features are retained, and only the final layers are adapted for the new task.
- **Output:**
  The output of the VGG16 model is a probability distribution over the classes, indicating the likelihood of the input image belonging to each class.

The accuracy achieved by the customized VGG16 on the Real Capture Image Dataset was 96%.

The VGG19 model adheres to a sequential process for image classification:

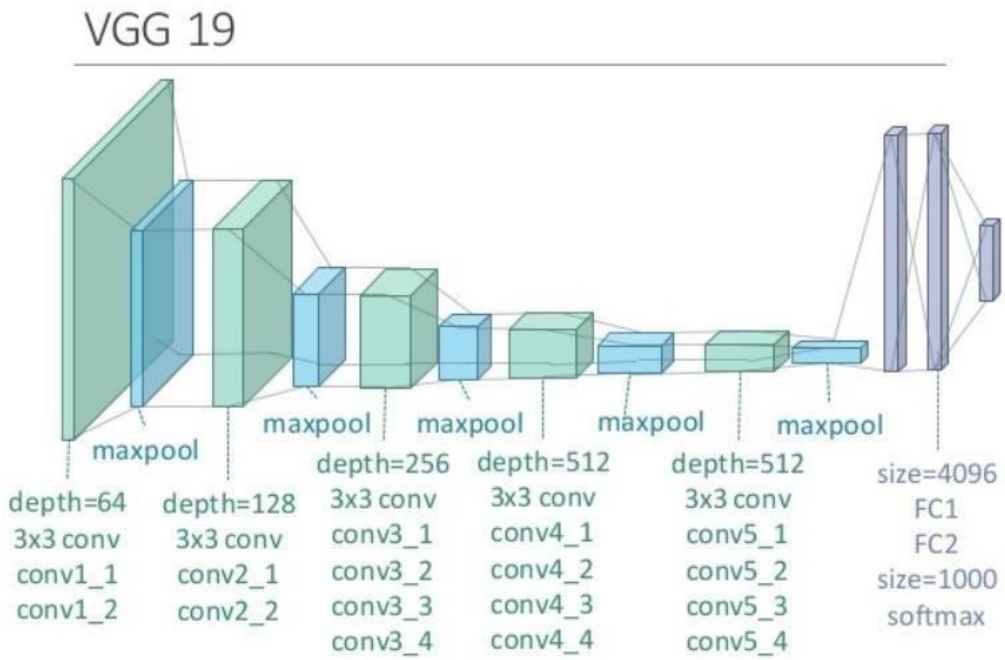


Figure 3.4.2: VGG19 Architecture

- **Input Layer:**

  The model receives an input image, typically sized at 224x224 pixels with three color channels (RGB).

- **Convolutional Blocks:**

  VGG19 comprises multiple convolutional blocks, each housing numerous convolutional layers with small 3x3 filters to capture intricate patterns and reduce parameters.

- **Max Pooling:**

  After each set of convolutional layers, max-pooling is applied to reduce spatial dimensions.

- **Fully Connected (Dense) Layers:**

  Following the convolutional blocks, fully connected (dense) layers progressively reduce spatial dimensions and learn high-level features.

- **Flattening:**

  Before reaching the fully connected layers, the output from the convolutional layers is flattened into a one-dimensional vector.

- **Activation Functions:**
- Throughout the network, Rectified Linear Units (ReLU) serve as activation functions to introduce non-linearity.
- **Dropout:**

  Dropout layers may be introduced during training to prevent overfitting by randomly setting a fraction of input units to zero.

- **Soft max Activation:**

  The final layer typically employs soft max activation for multi-class classification, converting the model's output into probability scores for each class.

- **Training:**

  The model undergoes training using labeled datasets and optimization algorithms like stochastic gradient descent (SGD) to adjust weights and biases.

- **Fine-Tuning and Transfer Learning:**

  VGG19 is often utilized in transfer learning, where pre-trained weights on larger datasets are fine-tuned for specific tasks with smaller datasets. The initial layers capturing general features are retained, and only the final layers are adapted for the new task.

- **Output:**

  The result from the VGG19 model is a probability distribution across classes, signifying the likelihood of the input image belonging to each specific class.

The accuracy achieved by the customized VGG16 on the Real Capture Image Dataset was 98%.

In my image classification project, I also employed the InceptionV3 model, which is a pre-trained deep neural network comprising 48 layers. This version, known as InceptionV3, is deeper compared to its predecessors, InceptionV1 and InceptionV2. The network operates by repeating blocks, where the output of one block serves as the input for the next. Each block is referred to as an inception block. By default, InceptionV3 expects images of size 299 x 299 pixels in RGB format. It extracts image features block by block. The achieved accuracy for InceptionV3 in my project is 98%.

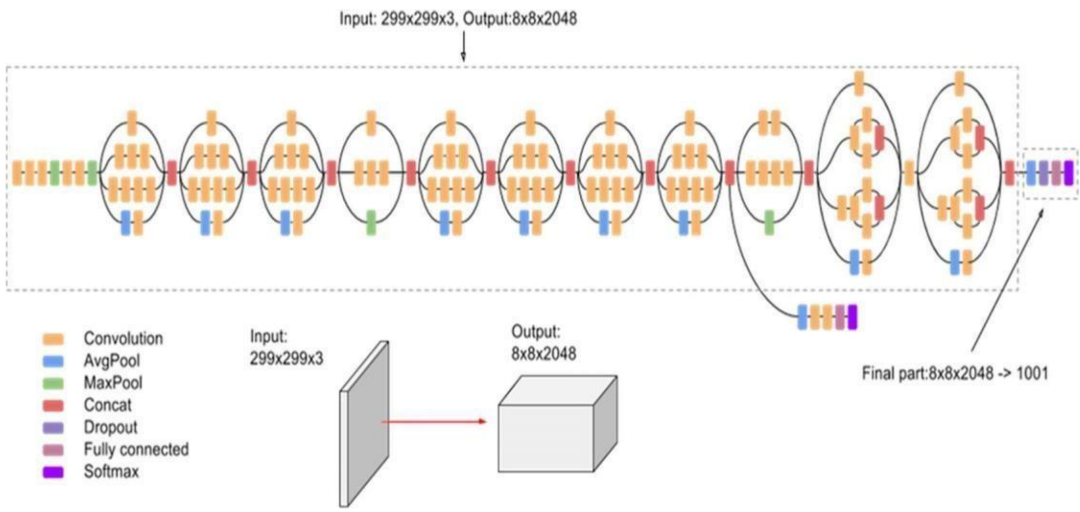


Figure 3.4.3: InceptionV3 Architecture

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Results & Analysis

Experimental results and analysis should provide a comprehensive evaluation of the automated grading system, demonstrating its effectiveness in accurately classifying grape fruits based on internal and external quality attributes. Thorough exploration into the detection of fruit quality has been undertaken to understand the longevity of fruits. In this study, Customized ResNet50, VGG16, VGG19, and InceptionV3 models were utilized with a dataset, employing 5 epochs for the training process. The sequential architecture and the accuracy graph are shown below.

For VGG16:

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14714688
flatten (Flatten)	(None, 25088)	0
dropout (Dropout)	(None, 25088)	0
dense (Dense)	(None, 1024)	25691136
dense_1 (Dense)	(None, 512)	524800
dense_2 (Dense)	(None, 2)	1026

Figure 4.1: Model Summary of VGG16

Figure 4.1 illustrates the model summary of VGG16. The total parameters for this model reach 40,931,650. The model has achieved an accuracy of 96%. The corresponding accuracy and loss graph for this model is presented below.

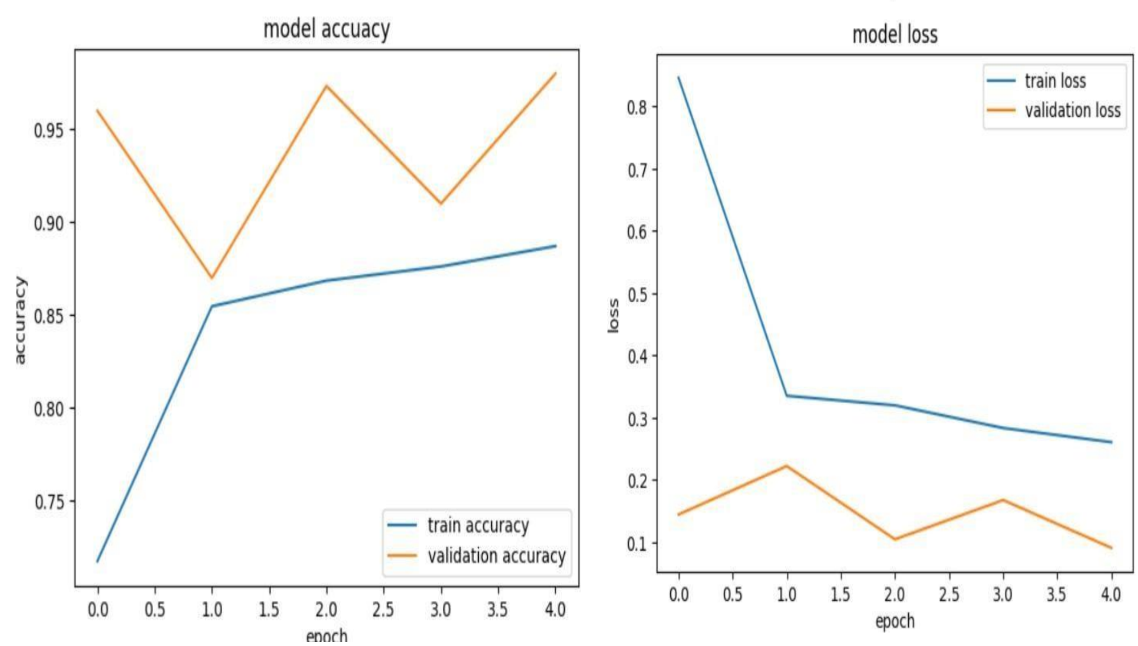


Figure 4.1.1: Accuracy and Loss Graph of VGG16

The graphs depicting the training and validation accuracy, along with the loss for VGG16, provide a visual representation of the model's performance during the training process.

For ResNet50:

The total parameters for this model reach 23,850,242. The model has achieved an accuracy of 98%. The corresponding accuracy and loss graph for this model is presented below.

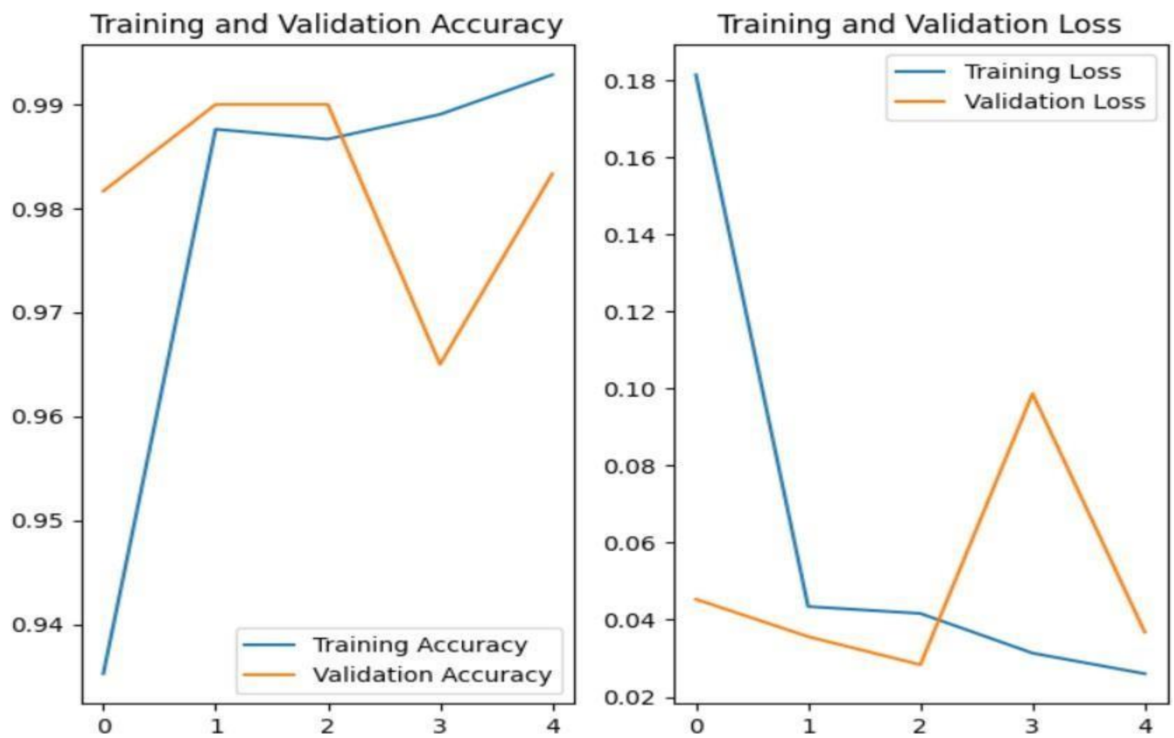


Figure 4.1.2: Accuracy and Loss Graph of ResNet50

The graphs depicting the training and validation accuracy, along with the loss for ResNet50, provide a visual representation of the model's performance during the training process. Here are two graphs as accuracy and loss. Accuracy are available for training and validation. Loss are available for training and validation. The graphs depicting the training and validation accuracy, along with the loss for ResNet50, provide a visual representation of the model's performance during the training process.

For VGG19:

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(None, 7, 7, 512)	20024384
flatten_1 (Flatten)	(None, 25088)	0
dropout_1 (Dropout)	(None, 25088)	0
dense_3 (Dense)	(None, 1024)	25691136
dense_4 (Dense)	(None, 512)	524800
dense_5 (Dense)	(None, 2)	1026

Figure 4.1.3: Model Summary of VGG19

Figure 4.1.3 illustrates the model summary of VGG19. The total parameters for this model reach 40,931,650. The model has achieved an accuracy of 98%. The corresponding accuracy and loss graph for this model is presented below.

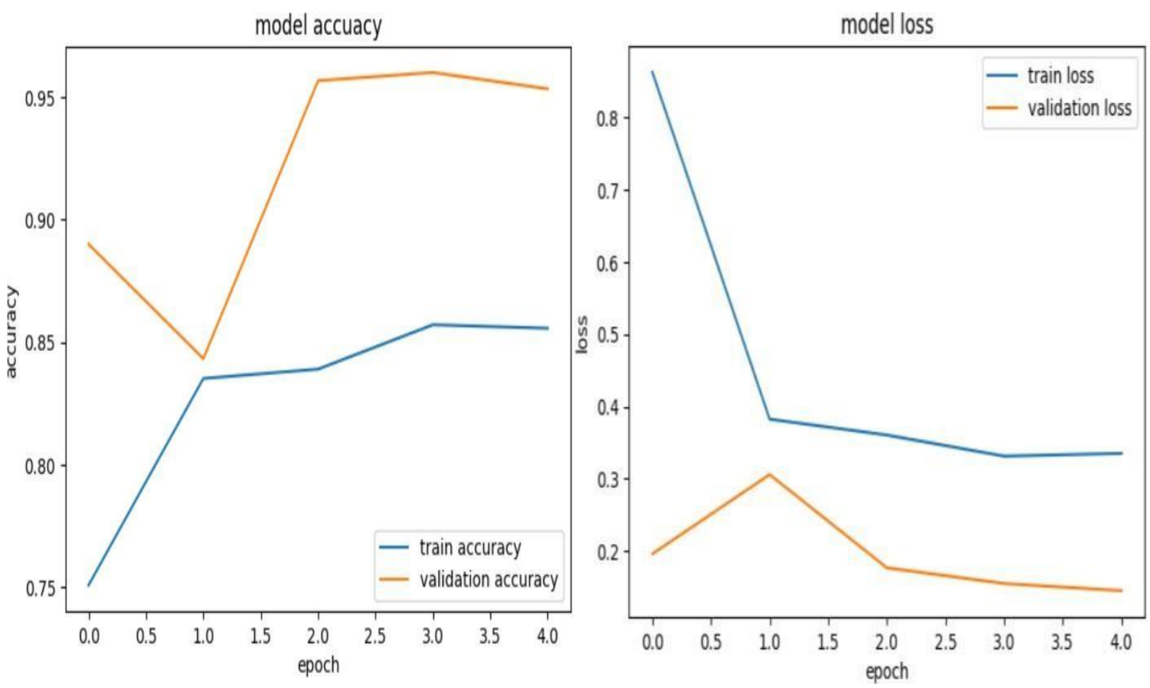


Figure 4.1.4: Accuracy and Loss graph of VGG19

The graphs depicting the training and validation accuracy, along with the loss for VGG19, provide a visual representation of the model's performance during the training process.

For InceptionV3 model:

Layer (type)	Output Shape	Param #
inception_v3 (Functional)	(None, 5, 5, 2048)	21802784
flatten (Flatten)	(None, 51200)	0
dropout (Dropout)	(None, 51200)	0
dense (Dense)	(None, 1024)	52429824
dense_1 (Dense)	(None, 512)	524800
dense_2 (Dense)	(None, 2)	1026

Figure 4.1.5: Model Summary of InceptionV3

Figure 4.1.5 illustrates the model summary of InceptionV3. The total parameters for this model reach 74,758,434. The model has achieved an accuracy of 98%. The corresponding accuracy and loss graph for this model is presented below.

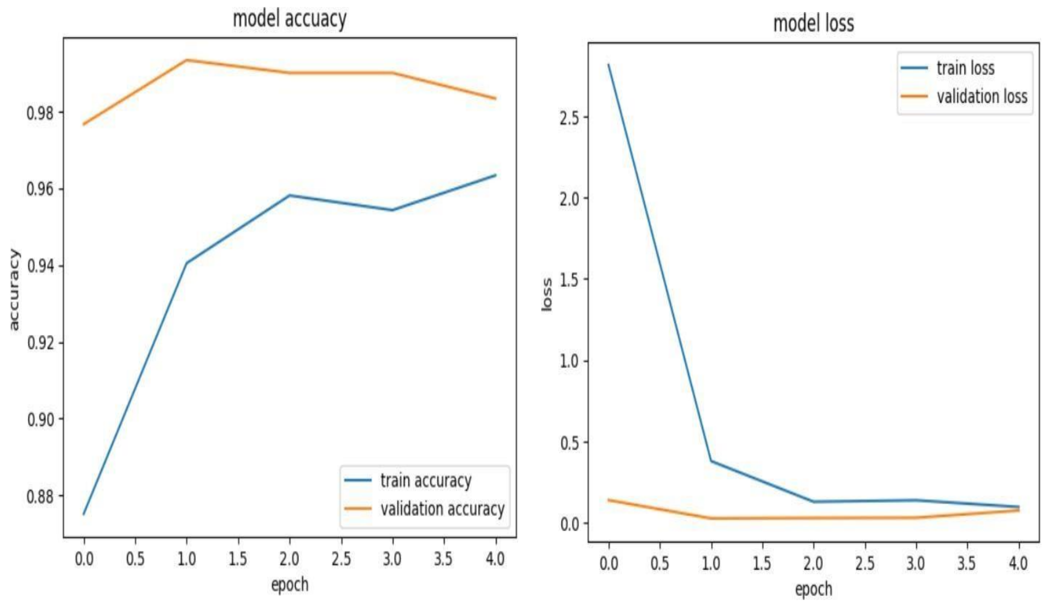


Figure 4.1.6: Accuracy and Loss Graph of InceptionV3

The graphs depicting the training and validation accuracy, along with the loss for InceptionV3, provide a visual representation of the model's performance during the training process.

Monitoring these graphs throughout the training process is crucial for assessing the model's performance. Each of these models has its unique characteristics and applications in the field of computer vision, with researchers and practitioners choosing models based on factors such as performance, computational resources, and specific task requirements. It allows for the identification of potential issues, such as overfitting, and informs decisions on adjusting hyper parameters or determining the optimal point to conclude the training for achieving the best results.

Table 4.1: Result Summary Table

Dataset	Model	Accuracy (%)
Quality Grading Dataset	ResNet50	98
	VGG16	96
	VGG19	98
	InceptionV3	98

4.2 Discussion

I employed four customized versions of ResNet50, VGG16, VGG19, and InceptionV3. In each model, I made adjustments to the layers, and variations in the accuracy percentage were observed. The accuracy is influenced by the number of layers and neurons in the dense layer, which subsequently impacts the model parameters. The percentage line graph is presented below.

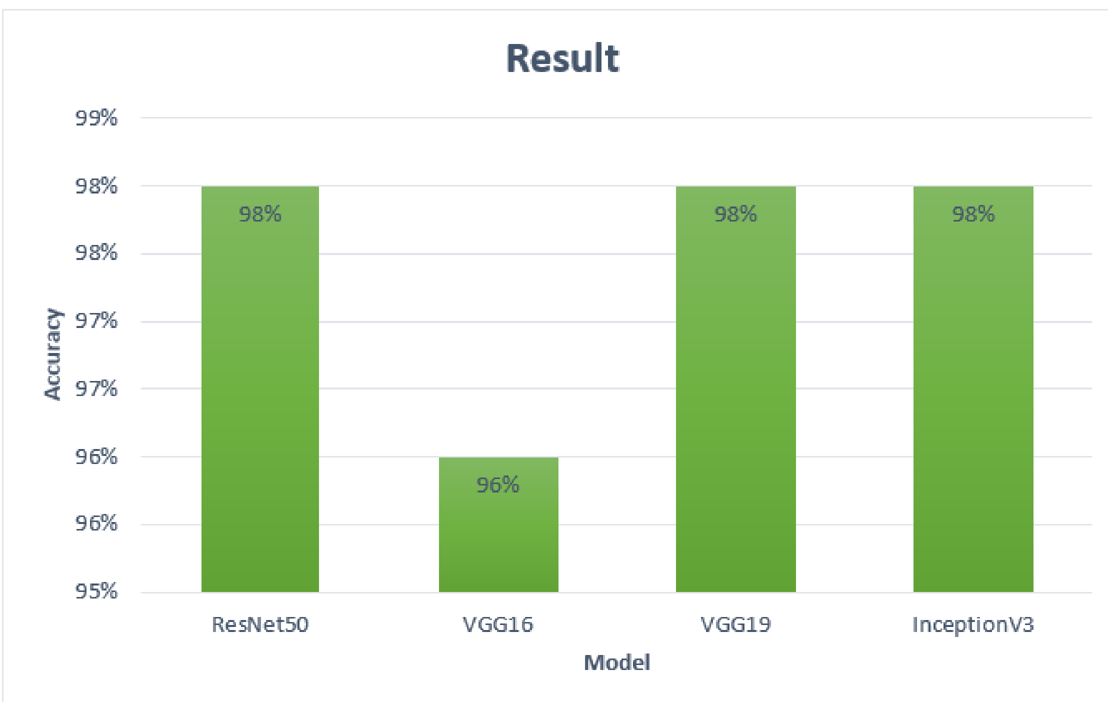


Figure 4.2: Percentage Line Graph

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The grading of grape quality holds substantial societal implications, contributing to improved food security, enhanced nutrition, economic growth, sustainable agricultural practices, increased consumer satisfaction, and a reduction in food waste. These positive outcomes play a vital role in fostering the overall well-being of individuals, communities, and the environment.

5.2 Impact on Environment

The environment benefits from the positive influence of grapes quality grading through the encouragement of sustainable agricultural practices. This involves minimizing chemical usage, reducing food waste, lowering carbon emissions, and actively contributing to the conservation of biodiversity. These combined efforts contribute to the development of a grapes industry that is both environmentally friendly and sustainable.

5.3 Ethical Aspects

The ethical dimensions of grapes quality grading involve factors such as fair trade, market transparency, consumer trust and safety, sustainable practices, worker welfare, and the societal and economic impact of the industry. Abiding by ethical principles in grapes quality grading promotes transparency, sustainability, and fairness throughout the supply chain. This approach brings benefits to both consumers and stakeholders, contributing to the development of a responsible and ethical grapes industry.

5.4 Sustainability Plan

Implementing a comprehensive sustainability plan for grape quality grading empowers the industry to make meaningful contributions to environmental conservation, social well-being, and economic resilience. This strategic plan supports the enduring viability of grape cultivation, builds consumer trust, and addresses ethical and sustainability challenges inherent in both grape production and consumption. Such an approach aligns with responsible and sustainable practices in the grape industry.

CHAPTER 6

CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Conclusion

Fruit quality grading plays a pivotal role in the fruit and vegetable industry and agriculture. Annually, a significant quantity of grapes is wasted due to premature harvesting. Traditionally, grapes are picked by individuals in orchards, relying on their experience; however, human judgment can be fallible and time-consuming. To address this challenge, I implemented deep learning models, including Convolutional Neural Networks (CNNs) and pretrained CNN base models. CNNs, inspired by the human brain, excel in tasks such as image classification, detection, and segmentation. Utilizing these models, such as CNNs and InceptionV3, for grapes quality grading has proven to be more accurate and time-efficient compared to traditional human methods.

6.2 Implication for Further Study

In my research, the primary focus was on discerning grapes quality through color and shape assessment. Nevertheless, I noted situations where color alone did not consistently depict the actual quality of the grapes. For instance, a grape could exhibit color defects but still be fresh, or conversely, appear fresh while having underlying defects. This observation indicates a potential avenue for further exploration, involving an in-depth investigation into the internal conditions of grapes to enhance the accuracy of quality grading.

REFERENCES

[1] Xiao, H., Feng, L., Song, D., Tu, K., Peng, J., & Pan, L. (2019). Grading and sorting of grape berries using visible-near infrared spectroscopy on the basis of multiple inner quality parameters. *Sensors*, *19*(11), 2600.

[2] Sardar, H. (2014). Fruit quality estimation by color for grading. *International Journal of Modeling and optimization*, *4*(1), 38.

[3] Valenzuela, G. A. L. (2013). *Assessment of External and Internal Quality of Blueberries Using Images* (Doctoral dissertation, Pontificia Universidad Catolica de Chile (Chile)).

[4] Parpinello, G. P., Nunziatini, G., Rombolà, A. D., Gottardi, F., & Versari, A. (2013). Relationship between sensory and NIR spectroscopy in consumer preference of table grape (cv Italia). *Postharvest biology and technology*, *83*, 47-53.

[5] Beghi, R., Buratti, S., Giovenzana, V., Benedetti, S., & Guidetti, R. (2017). Electronic nose and visible-near infrared spectroscopy in fruit and vegetable monitoring. *Reviews in Analytical Chemistry*, *36*(4), 20160016.

[6] Nicolai, B. M., Beullens, K., Bobelyn, E., Peirs, A., Saeys, W., Theron, K. I., & Lammertyn, J. (2007). Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review. *Postharvest biology and technology*, *46*(2), 99-118.

[7] Baietto, M., & Wilson, A. D. (2015). Electronic-nose applications for fruit identification, ripeness and quality grading. *Sensors*, *15*(1), 899-931.

[8] Sravan, T., & Tejaswini, V. (2020). Advances in Grading of Fruits. *In Vigyan Varta Vol*, *1*(8).

[9] Schöler, F., & Steinhage, V. (2015). Automated 3D reconstruction of grape cluster architecture from sensor data for efficient phenotyping. *Computers and Electronics in Agriculture*, *114*, 163-177.

[10] Zhang, R., Bian, Z., Wu, P., Liu, Y., Li, B., Xiong, J., ... & Zhu, B. (2024). Nondestructive prediction of fruit detachment force for investigating postharvest grape abscission. *Postharvest Biology and Technology*, *209*, 112691.

[11] Kaiyan, L., Chang, L., Huiping, S., Junhui, W., & Jie, C. (2021). Review on the Application of Machine Vision Algorithms in Fruit Grading Systems. In *Emerging Trends in Intelligent and Interactive Systems and Applications: Proceedings of the 5th International Conference on Intelligent, Interactive Systems and Applications (IISA2020)* (pp. 271-280). Springer International Publishing.

[12] Tripathi, M. K., & Maktedar, D. D. (2020). A role of computer vision in fruits and vegetables among various horticulture products of agriculture fields: A survey. *Information Processing in Agriculture*, *7*(2), 183-203.

[13] Ganguli, S., Selvan, P. T., Nayak, M. M., Chaudhury, S., Espina, R. U., & Ofori, I. (2022). Deep Learning Based Dual Channel Banana Grading System Using Convolution Neural Network. *Journal of Food Quality*, *2022*.

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