AUTOMATED FRUIT QUALITY ASSESSMENT THROUGH COMPUTER VISION AND DEEP LEARNING

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "**AUTOMATED FRUIT QUALITY ASSESSMENT THROUGH COMPUTER VISION AND DEEP LEARNING**", submitted by Md. Ratul Parvez and Md. Ashraful Rahman 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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We hereby declare that this project has been done by us under the supervision of **Mr. Abdus Sattar (AS), Assistant Professor, Department of Computer Science and Engineering, 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.

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ABSTRACT

In agricultural field, automation is essential to raising a country's standard of living, economic expansion, and productivity. A large part of a person's diet is made up of fruits, and finding good fruit in the market can be challenging at the moment. Sorting and grading them has a big impact on customer preferences, choices, and market value. This affects both home consumption and export markets. While human grading and sorting is feasible, it is ineffective, arbitrary, and unreliable, increasing costs and the likelihood of errors brought on by external factors. Rather than employing embedded systems (sensors) or the labor-intensive manual methods of grading each fruit and vegetable by hand, which would take longer to complete, we chose to use a high-performance Android application for faster deployment in order to expedite data identification and improve usability. This comprehensive study investigates the application of deep convolutional neural networks (CNNs) in automating fruit quality assessments using computer vision techniques. With a dataset comprising 14,400 original fruit images, the research employs advanced augmentation methods to enhance dataset diversity, generating multiple images. The study evaluates the performance of five prominent CNN models ResNet50v2, VGG19, EfficientNetB0, InceptionV3 and a hybrid model of DenseNet121 & EfficieintB6. The hybrid model has achieved the highest accuracy of 92.43% but in terms of efficiency the hybrid model required much more computational power and as well more inference time which make it less efficient for mobile devices. On the other hand, EfficientB0 model which is far more superior in terms of efficiency was achieved 92.14% accuracy which is very close to what the hybrid model has achieved. While MobilenetV2 achieved slightly lower accuracy of 91.64% and it is as well very efficient as EfficientNetB0. InceptionV3 was also highly accurate, with accuracy of 90.63%. The accuracy of ResNet50v2 and VGG19 were slightly lower, measuring at 89.19% and 89.62%. Based on these EfficientNetB0 is the overall best model in terms of both accuracy and efficiency.

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ML	Machine Learning
SVM	Support Vector Machine
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
VGG	Visual Geometry Group
YOLO	You Only Look Once

CHAPTER 1
Introduction

1.1 Overview

The agricultural landscape is grappling with limitations in its fruit inspection and grading processes. Manual inspection, which can be laborious, subjective, and prone to human error, is a common component of traditional quality assessment techniques. In recent years, advancements in computer vision technology, coupled with the ubiquity of smartphones, have opened up new possibilities for automating and streamlining the quality assurance process. By investigating the creation of a real-time inspection and grading system, this research sets out to overcome these obstacles. An important development in the contemporary agriculture and food processing industries is the automated fruit grading assessment that uses computer vision and deep learning techniques. Fruit grading applications can greatly benefit from deep learning models, which have proven exceptionally adept at image recognition and classification tasks. Automated systems can quickly process large volumes of fruits, ensuring consistent grading standards and reducing reliance on manual labor. They also provide the possibility of real-time quality control and monitoring, allowing for prompt interventions to maximize efficiency and reduce waste in production processes. This study proposes a novel approach for real-time quality assurance of fruits using computer vision algorithms through an Android application. By harnessing the computational capabilities of smartphones and the power of computer vision, this system aims to provide a convenient, cost-effective, and accurate solution for assessing the quality of agricultural produce on the go.

1.2 Background and Present State

Traditionally, checking fruit quality has relied on people looking at each fruit, which takes a lot of time and can be inconsistent due to human error. This manual method can lead to differences in quality and affects how well fruits sell. Recently, computer vision technology has made it possible to automate this process. Computer vision uses algorithms to analyze visual information, and with deep learning, especially convolutional neural networks (CNNs), it can recognize and classify images accurately. This technology can evaluate fruit quality consistently and quickly, ensuring uniform standards. The widespread use of smartphones, with their powerful cameras and processors, makes them ideal for real-time quality assessment, providing a portable and cost-effective solution for farmers and food processors.

Today, automated systems using computer vision and deep learning are becoming common in agriculture. These systems analyze images of fruits to check for color, texture, size, shape, and defects, offering a fast and consistent grading process. This reduces the need for manual labor and minimizes errors. Real-time quality control allows for immediate corrective actions, optimizing production and reducing waste. Smartphone apps using computer vision are especially promising, as they can be used directly in the field for quick quality assessments. These apps are convenient, affordable, and particularly useful for small and medium-sized farms. The use of these technologies is transforming the way fruit quality is checked, making the process more efficient and reliable.

1.3 Problem Statement

Fruit quality assurance in the agricultural supply chain continues to be a major challenge, despite improvements in agricultural practices and food processing technologies. Manual inspection, which is labor-intensive, time-consuming, and subject to subjectivity, is a major component of traditional quality assessment methods. This manual approach often leads to inconsistencies in quality assessment and may result in the acceptance of substandard produce, leading to potential economic losses and consumer dissatisfaction. These difficulties are further exacerbated by the inability to make timely decisions about harvesting, processing, and distribution due to the lack of real-time quality assessment capabilities. A precise, automated system for quality assurance that can evaluate fruit quality in real-time is desperately needed to address these problems.

1.4 Objectives

The goal of this work is to create a reliable and efficient system for real-time fruit quality control using an Android application. This system aims to provide an automated, accurate, and consistent method for evaluating produce quality, addressing the limitations of traditional manual inspection techniques. Our specific objectives are:

- To improve consistency and accuracy by applying computer vision techniques to precisely analyze produce, reduce the possibility of human error.

- To increase accessibility by designing an Android application interface that is user-friendly and accessible to a wide range of users.

- To develop a comprehensive solution that leverages the power of computer vision technology to enhance efficiency, accuracy, and sustainability in the fruit supply chain.

1.5 Scope and Limitations

This research project uses computer vision and machine learning technologies to develop and implement a real-time fruit grading system. Analyzing existing grading methods, addressing their shortcomings, and developing original solutions are necessary to ensure accurate and efficient grading. The project involves developing a functional prototype system that can assess various fruit qualities instantly and implementing automation to streamline processes. The objectives are modernizing fruit grading, addressing issues facing the industry, and improving sustainability. The project's scope includes developing new technologies, putting them into practice, and validating them on various fruits to have a big influence on the market.

Despite advancements in fruit detection systems, several limitations and conflicts of interest must be acknowledged. One significant challenge is the high computational demand required for real-time performance on Android devices, potentially necessitating costly advanced hardware, especially burdensome for farmers in developing regions. Moreover, expanding the dataset to encompass a wide array of fruits from diverse regions and seasons poses difficulties in terms of resource-intensive data collection, annotation, and storage, often failing to achieve comprehensive coverage due to the immense diversity of fruit species and growing conditions. Scaling these systems for large-scale orchards and fields introduces additional complexities, as environmental variables like lighting and weather can significantly impact classification accuracy, demanding robust and adaptable algorithms. Furthermore, while designing a user-friendly interface for Android applications is crucial, addressing varying levels of technological literacy among farmers and agricultural workers remains a challenge.

1.6 Report Organization

Chapter 1: Introduction

- **Introduction:** This section provides an overview of the project, outlining its significance and relevance in the context of automated fruit quality assessment using computer vision techniques.

- **Problem Statements:** It identifies the specific challenges and gaps in the current methods of fruit quality assessment, highlighting the need for improved accuracy, efficiency, and objectivity.
- **Motivation and Objectives:** Discusses the reasons behind undertaking this project, such as addressing limitations in manual assessment, improving productivity in fruit sorting, and enhancing overall quality control.
- **Project Outcome:** Describes the expected deliverables and outcomes of the project, including the development of a novel computer vision model for fruit quality assessment.

Chapter 2: Literature Review

- **Literature Reviews:** Summarizes existing research and methodologies in automated fruit quality assessment, focusing on relevant studies in computer vision, image processing, and machine learning.
- **Gap Analysis:** Identifies the gaps and limitations in current literature, setting the stage for the project's contribution by proposing innovative solutions and improvements.

Chapter 3: Proposed Methodology.

- **Methodology:** Explains the approach taken in the project, including data collection methods, experimental design, and the framework for developing and evaluating the computer vision models.
- **Project Management & Financial Analysis:** Details the project planning, scheduling, and organizational structure, including roles and responsibilities of team members. Provides a budget overview, cost estimation, and resource allocation for the project

Chapter 4: Implementation

- **Training of Model:** Discusses the training process, including data preprocessing, model architecture selection, and training strategies employed.
- **Model Evaluation Metrics:** Presents the metrics used to evaluate the performance of the models, such as accuracy, precision, recall, and F1-score.

Chapter 5: Results and Analysis

- **Experimental Results:** Presents the findings from applying the developed models to real-world data, including quantitative results and visual representations.
- **Comparative Analysis:** Compares the performance of the developed models with existing methods or benchmarks, highlighting strengths, weaknesses, and areas for improvement.

Chapter 6: Impact on Society, Environment, and Sustainability

- **Impact on Society:** Discusses the potential societal benefits of automated fruit quality assessment, such as improved food safety, reduced waste, and enhanced product quality.
- **Impact on Environment:** Explores environmental implications, such as reduced use of chemicals through better sorting and grading techniques.
- **Sustainability:** Considers the long-term sustainability of the project's outcomes and their implications for the fruit industry and beyond.

Chapter 7: Conclusion

- **Conclusions:** Reiterates the conclusions drawn from the research, emphasizing the significance of the findings in addressing the project's objectives and solving identified problems.
- **Recommendations:** Provides practical recommendations for implementing the developed solutions in industry settings, as well as suggestions for future research directions to further advance automated fruit quality assessment.

1.7 Summary

Maintaining good quality in fruits is tough because it mostly relies on people checking them by hand. This method has problems like different opinions on quality, not enough time, and inconsistency. This introduction talks about a new system for checking fruit quality in real-time using computer vision and Android devices. Smartphones, with their powerful processing and portability, make the inspection process automatic. This new approach has big benefits: it speeds up the evaluation process and makes it more objective, reducing human bias.

CHAPTER 2

Literature review

2.1 Overview

The study of automated fruit grading systems that make use of computer vision and machine learning technologies has seen a noticeable uptick in interest in recent years. The increased attention is due to the realization of their enormous potential to transform and expedite the conventionally labor-intensive and time-consuming procedures linked to evaluating fruit quality. In light of this, this review of the literature begins with a careful analysis of a few working papers in this emerging field.

2.2 Related Works

Aherwadi, N. et al. [1], in their study, used two datasets of banana fruit, where they create the first dataset, and the second dataset is taken from Kaggle, named Fruit 360. There are 2100 photos in their dataset, divided into three groups (ripe, unripe, and over-ripe), with 700 photos each. An image augmentation approach is applied to increase the dataset size to 18,900. Both models are constructed using the AlexNet and Convolutional Neural Network. This model models in the original dataset had accuracy of 98.25% and 81.75%, and accuracy of 99.36% and 99.44% for enhanced dataset. These models also obtained accuracy of 81.96% and 81.75%, on the Fruit 360 dataset. So, in their study CNN is the best algorithm for classifying fruit maturity and detecting quality.

Varghese, Z. et al. [2] proposed a machine vision-based system to classify mangoes by their maturity level, aiming to replace manual sorting methods. The technology uses a Charge Coupled Device camera above a mango-carrying conveyor belt to evaluate video signals and extract pertinent information. From the 27 features that were initially selected, recursive feature elimination and a SVM classifier are used to identify the important features. Mangoes are then divided into four maturity categories based on these characteristics. Experiments with mangoes from different batches and locales show an average categorization accuracy of up to 96%.

Hossain, M.S. et al. [3] proposed a system which is built on top of two different deep-learning architectures. a six-layer convolutional neural network light model is proposed in the first and a deep learning model that has been pre-trained using visual geometry group-

16 is improved in the second, while. They evaluate the suggested framework using two datasets of color images, one of which is open to the public. The first dataset may contain fruit shots that are simple to recognize, whereas the second dataset may contain fruit images that are more challenging to identify. For the first dataset these models achieved 99.49% and 99.75% accuracies. While for dataset 2, achieved accuracy of 85.43% and 96.75%.

Robert G. de Luna et al. [4] proposed a method for identifying the presence of flowers and fruits on tomato plants growing inside the chamber. The tomato fruit maturity rating is likewise supported by the model. Two pre-trained transfer learning models Single Shot Detector (SSD) and Regional-based CNN (R-CNN) are utilized for fruit and floral recognition. Tomato fruit maturity level is classified using ANN, k-NN, and SVM. R-CNN's overall accuracy in fruit and flower detection is 19.48% and 1.67% while SSD's results are 100% and 99.99 percent. SVM achieved training and testing accuracies of 97.78% and 99.81%; KNN provides 93.78% and 99.32% and ANN provides 91.33% and 99.32% for tomato maturity grading.

Tu Shuqin et al. [5] used color and depth images, the algorithm's first stage recognizes passion fruit using Faster R-CNN. The combination of color and depth-based detections enhances the performance of detection. In the second stage, features are extracted and represented using a combination of Dense Scale Invariant Feature Transform and Locality Constrained Linear Coding. The RGB-DSFIT-LLC characteristics were also included for the linear SVM input to ascertain the fruit maturity. They achieved accuracy of 92.71% for detection and 91.52% for maturity.

Mauricio Rodriguez et al. [6] in his research used CNN to categorize the available fruit in their dataset according to its degree of ripeness. Oranges, red apples, bananas, strawberries, and green apples are among the fruits. Initially, two sets of images were created. The picture dataset was then used as input to train the CNN, and the data augmentation technique was then applied. Calculating all confusion matrix measurements serves as an evaluation of the system's performance. To find out how well the system is performing, all metrics are computed. The model's accuracy on average is 96.34%.

Dr. T. Vijayakumar et al. [7] present a CNN RESNET-152 application for dragon fruit mellowness identification. For training, they employed Python and TensorFlow. A variety of dragon fruit photos with varying degrees of mellowness were used to train the developed model. The model was subsequently assessed using a confusion matrix and region of convergence on an additional 100 images. When compared to training and testing accuracy using VGG16 or VGG19, the findings are as accurate as possible, and the testing epoch range is between 10 and 500.

Mazen, F.M. et al [8]. propose a method for utilizing an artificial neural network (ANN) to categorize the ripeness of bananas. The model is trained using an image dataset of bananas with labeled ripeness levels, allowing it to recognize and learn ripeness-related attributes. The results and consistency of the proposed model are compared with naive Bayes, discriminant analysis, k-NN, decision trees, and SVM classifiers. With a 97.75% accuracy rate, their model performs better than other approaches.

Rucha Thakur et al. [9] discussed a strawberry fruit sorting and analysis system that runs automatically. Strawberries are ripe to different degrees, according to CNN. Fruit surface color, fruit color, fruit size, fruit form, and other significant features are extracted for accurate CNN classification, and the color of the strawberry's surface indicates how ripe it is. The suggested model has a 91.6% accuracy rate thanks to CNN.

Suganya, V. et al. [10] present a method for evaluating the quality of fruit that uses the Faster Region Convolutional Neural Network (Faster R-CNN). They aim to improve the efficiency and precision of evaluating fruit quality in production environments. A softmax classifier, a speedier R-CNN method, and the Tensor-flow library are used for detection and quality classification. Using the quicker R-CNN algorithm, the objection task and the allregion proposals generation task are completed. Instead of feeding CNN with region proposals, they feed photos to create a convolutional map. Regarding fruit quality recognition, they outperformed CNN and DL algorithms with an accuracy of over 95%.

Payman Moallem, et.al [11] proposed a revolutionary method for rating delicious golden apples that are based on computer vision. The suggested technique was implemented in six steps. In order to construct a backdrop, non-apple pixels were first isolated from significant descriptors. The apple score was assessed through a comparative analysis of different categorization methods. The test findings demonstrated that the SVM strategy performed well when compared to numerous other classification strategies, with recognition rates of 89.2% and 92.5% for faulty and normal apples, respectively.

Ramos, R.P. et al. [12] employed DL methods to determine the grape maturation stage in their study. CNN, or VGG-19, is used to construct a system for classifying grapes. Images of grapes are gathered, examined, and arranged according to the degree of maturity. The parameters of the classification model are obtained by acquiring images with various illuminants. Cabernet Sauvignon and Syrah had mature categorization accuracy scores of 72.66% and 93.41%, respectively.

YuhangFu et al. [13] proposed grading methods for fruit freshness using CNN, YOLO, AlexNet, and VGG. The recommended algorithm might be able to stop fruit from going bad or keep fruit from being thrown away. They provide an in-depth review of the freshness rating system, which used deep learning and computer vision to rate fruit based on visual analysis of digital photographs.

Pallavi U. Patil et al. [14] proposed dragon fruit grading and sorting using machine learning algorithms, with an emphasis on SVM, CNN, and ANN. These algorithms accurately categorize fruits according to characteristics including size, color, shape, and disease symptoms, guaranteeing customer acceptance and preserving their outstanding quality for processing and marketing. The functioning of machine learning algorithms in Raspberry sorting systems which categorize fruits according to their maturity degrees to promote effective selling and processing is also covered in this research. To optimize these methods for particular fruit varieties and environmental conditions in sustainable agriculture practices, more study is required.

Arakeri, M.P.[15] proposed an automatic tomato fruit grading system based on computer vision. The hardware and software development phases make up the two stages of the suggested quality evaluation technique. The gear is designed to recognize a tomato by image and automatically send the fruit to the proper containers. The software is designed to examine the fruit for flaws and maturity using image processing techniques. Tests were run on multiple pictures of the tomato fruit. It was found that the suggested approach to assessing tomato quality was successful with 96.47% accuracy.

Madasamy, K. et al. [16] introduce a object monitoring system that uses drones fitted with an embedded system and YOLO algorithm. In this study, pre-trained YOLOV3 is used to train the model using drone pictures. The result indicates that the offered deep YOLO V3 is appropriate for the computer vision process. To extract improved characteristics, YOLOv3 leverages darknetrknet and residual networks. The proposed method uses IOU to forecast the confidence ratings of grid cells and bounding boxes simultaneously. Through the use of multi-scale predictions and backbone classifiers for enhanced classification, YOLO V3 achieved accuracy of 99.99%.

Ashok, V. et al. [17] provide a novel approach that blends deep learning algorithms with an Android application to enable real-time illness diagnosis in mango fruits. By utilizing deep learning algorithms and analyzing photographs of mango fruits obtained with a smartphone camera, the system can swiftly and accurately identify diseases. Farmers and other agricultural stakeholders will have an easy-to-use tool for monitoring the health of their mango crops and taking timely action to stop disease outbreaks and preserve crop quality thanks to the combination of these technologies. The system represents significant advancements in the detection and management of agricultural illnesses due to its real-time functionality and mobile application accessibility.

Al Ohali, Y.[18] have designed a computer vision-based date grading and sorting system. The date fruits' RGB pictures are used by the system. It automatically retrieves the previously described external date quality features from these photos. It divides dates into three quality groups. They have examined how well a backpropagation neural network classifier performs and evaluated the system's accuracy using pre-selected date samples. According to the test findings, the system can correctly sort 80% of dates.

2.3 Comparison between existing works

Table 1. Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Aherwadi, N. et al. [1]	CNN and AlexNet	AlexNet =99.44%
2.	Varghese, Z. et al. [2]	SVM	SVM=92.5%
3.	Hossain, M.S. et al. [3]	Six convolutional neural network layers, Fine-tuned visual geometry group-16	Fine-tuned visual geometry group-16 = 99.75%
4.	Robert G. de Luna et al. [4]	SSD, R-CNN for identification. ANN, k-NN, and SVM to classify the maturity level.	SSD= 100% for flower SSD=95.99 % for fruit

5.	Tu, S. et al. [5]	Faster R-CNN for detection of fruits DFSIT for maturity classification	Faster R-CNN for detection accuracy is 92.71% DFSIT for maturity classification accuracy is 91.52%.
6.	Rodriguez, M et al. [6]	Convolutional Neural Network	CNN=96.34%.
7.	Madasamy, K. et al. [16]	YOLOV3	YOLOV3=99.99%
8.	Mazen, F.M et al. [8]	ANN, Naive Bayes, SVM, k-NN, Decision tree.	ANN= 97.75%
9.	Suganya, V. et al. [10]	Faster R-CNN algorithm,	faster R-CNN=more than 95%
10.	Ramos, R.P. et al.[12]	VGG-19 CNN	VGG-19 CNN= 93.41% and 72.66% accuracy for both type of grapes

2.4 Open Issues

The existing research on automated fruit grading using computer vision includes a variety of approaches, such as deep learning algorithms and conventional image processing techniques. Convolutional neural networks have shown promise. But accuracy is still an issue especially when it comes to identifying fruits with a variety of ripeness levels, occlusions, or irregular shapes. The scarcity of large and varied datasets makes data acquisition difficult and requires well-annotated data for reliable model training. While real-time processing and user experience have made some progress, large-scale tasks, and smooth industry integration still require these areas to be further improved. It is necessary to improve defect detection and classification algorithms to correctly detect defects in a variety of fruit types. Our approach will be given a touch with modern models with an android based application for real time processing alongside a user-friendly interface that improve the user experience. There has not been much progress in creating automated fruit grading systems that are practical, inexpensive, and suitable for small and medium-sized farming enterprises. Many solutions discussed in the papers under evaluation are expensive and unavailable to small-scale farmers and producers since they depend on complex technology and software. There has not been much progress in creating automated fruit grading systems that are practical, inexpensive, and suitable for small and medium-sized farming enterprises.

2.5 Summary

The reviewed papers demonstrate how well computer vision and machine learning techniques work for automated fruit inspection and grading systems. Existing research demonstrates the feasibility of this approach for automating fruit classification and quality grading, potentially improving efficiency in agriculture and retail sectors. Several research papers explore the use of deep learning for fruit classification and quality assessment. Studies have shown success in identifying and classifying various fruits. Convolutional Neural Networks (CNNs) emerged as the dominant approach, demonstrating high accuracy in various studies (e.g., Aherwadi et al. [1], Hossain et al. [3], Rodriguez et al. [6], Thakur et al. [9]). Other techniques explored include YOLO (You Only Look Once) for object detection (Fu et al. [13], Madasamy et al. [16]), Support Vector Machines (SVM) (Varghese et al. [2], Moallem et al. [11]), and Artificial Neural Networks (ANN) (Mazen et al. [8]). Accuracy ranged from 72.66% for grape maturity (Ramos et al. [12]) to 99.99% for object detection using YOLOv3 (Madasamy et al. [16]). Studies by Aherwadi et al. [1] (98.25% - 99.44%), Hossain et al. [3] (99.49% - 99.75%), Rodriguez et al. [6] (96.34%), and Arakeri [15] (96.47%) achieved high accuracy in fruit maturity/ripeness classification using CNNs. Pre-trained models like VGG-19 and ResNet-152 were successfully employed for transfer learning (Hossain et al. [3], Dr. Vijayakumar et al. [7]). Artificial data augmentation techniques were widely adopted to increase dataset size and improve model robustness (Aherwadi et al. [1], Rodriguez et al. [6]). Several studies (e.g., Patil et al. [14]) highlight the need for further research to optimize algorithms for specific fruit varieties and environmental conditions. Integration with mobile platforms for real-time fruit analysis is an emerging trend (Ashok et al. [17]). Overall, the combination of AI, deep learning, and mobile technology offers a promising approach for developing automated fruit quality detection systems using Android applications.

CHAPTER 3

Methodology

3.1 Overview

The proposed method involves developing an Android app that utilizes computer vision technologies for real-time fruit grading and detection. The tasks include data collection, data preparation, and Android app creation. The program will have user-friendly interfaces for capturing and editing images. The deployment procedure will include thorough testing, user input, and regular updates to ensure optimum performance in real-world situations. The ultimate aim is to provide a reliable and effective method for fruit grading and detection in agricultural and food processing settings.

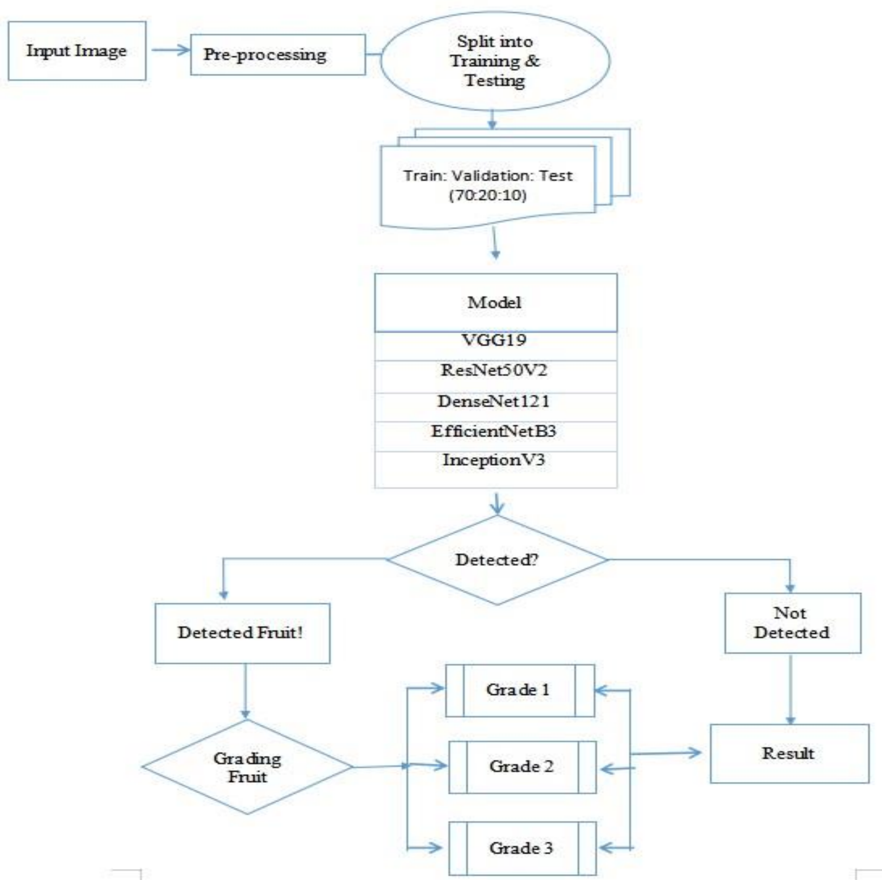

Figure 3.2.1: Methodology Diagram.

3.2 Proposed Methodology

A systematic approach is essential for conducting research on automated fruit grading using computer vision and deep learning methods. Here are the key steps involved:

3.2.1 Data Collection

Gathering a comprehensive dataset for assessing fruit quality requires careful planning. This includes selecting a diverse range of fruits based on consumer preferences, seasonal availability, and geographical variations. High-resolution images depicting various quality attributes are collected and meticulously labeled for model training.

Our research, which uses computer vision and deep learning for automated fruit grading assessment, used a multi-pronged method to compile a large datasets of fruit photos. This required combining web scraping tools with manual gathering methods.

A) Manual Collection: A portion of the datasets was meticulously curated through manual efforts. We used top-notch cameras and cellphones to take controlled photos of different fruits, making sure that the background, lighting, and camera settings were all the same. We were able to incorporate a wide range of fruit kinds, sizes, forms, colors, and quality factors in our datasets thanks to this practical technique.

B) Web scraping: We used web scraping techniques to supplement our personally gathered information and guarantee its diversity and breadth. Through the use of online markets, publicly accessible image repositories, and agricultural websites, we were able to compile a sizable collection of fruit photographs that represented various categories and circumstances.

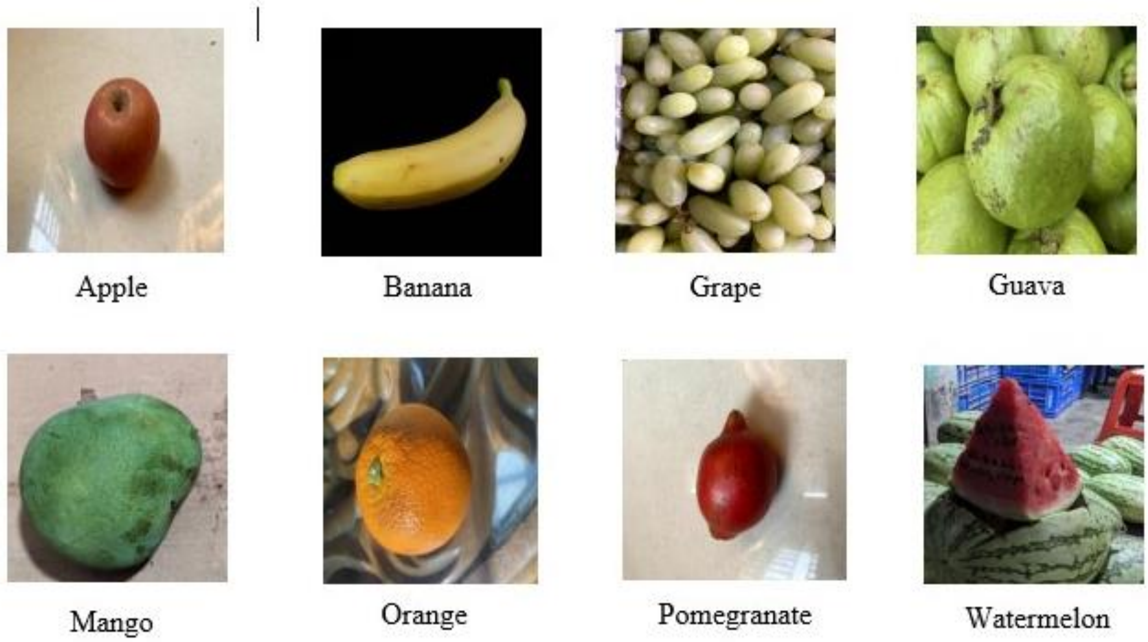

Fig 3.2.2: Sample Images of Grade 1 fruits

Fig 3.2.3: Sample Images of Grade 2 fruits

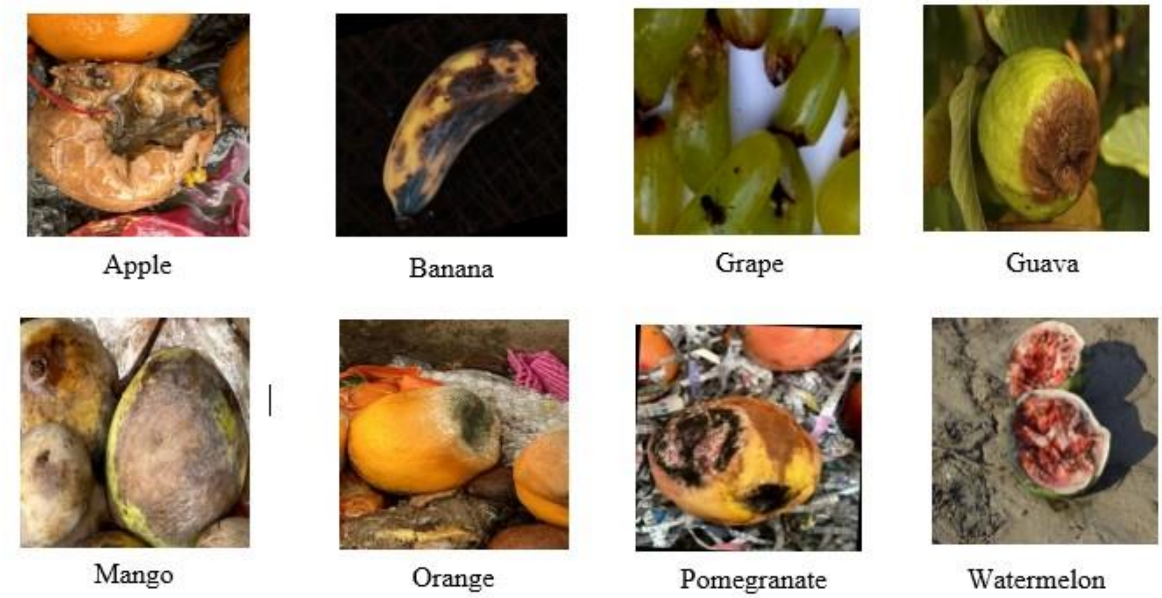

Fig 3.2.4: Sample Images of Grade 3 fruits

Classes Name	Quantity	Classes Name	Quantity	Classes Name	Quantity
Grade 1 Apple	145	Grade 2 Apple	135	Grade 3 Apple	132
Grade 1 Banana	138	Grade 2 Banana	134	Grade 3 Banana	149
Grade 1 Grape	135	Grade 2 Grape	156	Grade 3 Grape	130
Grade 1 Guava	140	Grade 2 Guava	142	Grade 3 Guava	128
Grade 1Mango	157	Grade 2 Mango	148	Grade 3 Mango	154
Grade 1 Orange	152	Grade 2 Orange	143	Grade 3 Orange	160
Grade 1 Pomegranate	131	Grade 2 Pomegranate	153	Grade 3 Pomegranate	131
Grade 1 Watermelon	158	Grade 2 Watermelon	150	Grade 3 Watermelon	140

Table 3.2.1: Collected images for each class (Total 3441)

We leveraged a combination of pre-processing techniques and data splitting strategies to prepare our datasets for model training and evaluation.

3.2.2 Data Pre-processing

To optimize training time and enhance model performance, we implemented several per-processing techniques on all images in the datasets:

A) Image Transformations

- **Auto-Orientation:** The images were automatically oriented to address any potential inconsistencies in image capture orientation
- **Resize:** All images were resized to a uniform dimension of 640x640 pixels. This standardization ensures consistency in the input data fed to the model.

B) Image Augmentation

To further enrich the training data and improve the model's ability to handle variations, we employed several image augmentation techniques:

- **Rotation:** Images were randomly rotated between **-15 and +15 degrees**, simulating natural variations in camera angles and improving the model's ability to generalize to objects captured from slightly off-center viewpoints.
- **Shear:** Images were randomly subjected to a **±10° horizontal and vertical shear**, expanding the dataset and enhancing the model's robustness to objects that may appear slightly distorted due to perspective variations.
- **Noise:** Up to **0.5% of pixels** were randomly altered, introducing a subtle level of noise that can improve the model's performance in real-world scenarios with less-than-perfect image quality.

By implementing these data analysis and pre-processing techniques, we aimed to create a well-annotated

Classes Name	Quantity	Classes Name	Quantity	Classes Name	Quantity
Grade 1 Apple	600	Grade 2 Apple	600	Grade 3 Apple	600
Grade 1 Banana	600	Grade 2 Banana	600	Grade 3 Banana	600
Grade 1 Grape	600	Grade 2 Grape	600	Grade 3 Grape	600
Grade 1 Guava	600	Grade 2 Guava	600	Grade 3 Guava	600
Grade 1Mango	600	Grade 2 Mango	600	Grade 3 Mango	600

Grade 1 Orange	600	Grade 2 Orange	600	Grade 3 Orange	600
Grade 1 Pomegranate	600	Grade 2 Pomegranate	600	Grade 3 Pomegranate	600
Grade 1 Watermelon	600	Grade 2 Watermelon	600	Grade 3 Watermelon	600

Table 3.2.2: Total data for each class after augmentation (14400)

C) Data Splitting

Following best practices, we employed a 70/20/10 train-validation-test split on our labeled datasets. This approach ensures:

- **70% Training Set:** The majority of the data (70%) is allocated for training the model, allowing it to learn the patterns and features within the images.
- **20% Validation Set:** This set (20%) is used for validation during the training process. It helps monitor the model's performance and prevent over fitting.
- **10% Test Set:** The remaining 10% of the data serves as the unseen test set. It is used for final evaluation of the trained model's generalization on unseen data

Table 3.2.3: Distribution between Training, validation and testing data.

	Training Data	Validation Data	Testing Data
For each Class	420	120	60

3.2.3 Model Development

Choosing and implementing appropriate deep learning architecture is the next step. Factors considered include computational resources, speed requirements, accuracy goals, and most importantly efficiency as these models are going to integrate with mobile devices.

3.2.3.1 EfficientNet

EfficientNet prioritizes achieving high accuracy for image classification tasks while minimizing computational cost. Unlike traditional CNN scaling methods focusing on increasing a single aspect (depth, width, or resolution), EfficientNet utilizes a compound scaling method that balances all three factors. This allows the network to achieve better performance with fewer parameters compared to other models with similar accuracy. The core building block of EfficientNetB3 is the Mobile Inverted Bottleneck Convolution (MBConv) block. This block is designed to be computationally efficient while maintaining good feature representation. It employs depthwise separable convolutions, which separate depthwise filtering (extracting features) from pointwise filtering (combining features across channels). This separation significantly reduces the computational cost compared to traditional convolutions. Additionally, EfficientNetB3 utilizes squeeze-and-excitation (SE) blocks to improve feature representation. These blocks learn the importance of each feature channel and dynamically scale the channel activations, focusing on informative features and suppressing less important ones. The compound scaling method in EfficientNetB3 involves scaling all three dimensions (depth, width, and resolution) with fixed ratios based on a baseline network. This ensures that the network maintains a balanced architecture while increasing its capacity. Compared to other models with similar accuracy, EfficientNetB3 requires fewer parameters and computations, making it a valuable choice for applications where resources are limited [19].

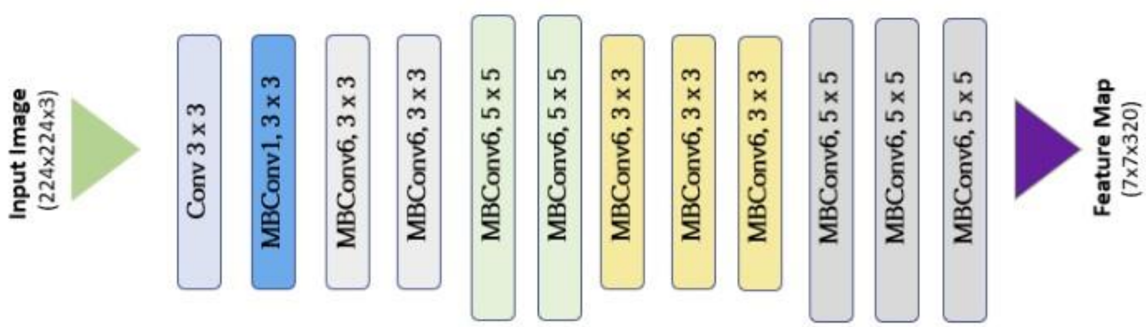

Figure 3.2.5: EfficientNet Architecture [19]

3.2.3.2 VGG19

VGG19, developed by the Visual Geometry Group, stands as a cornerstone of convolutional neural network (CNN) architectures. It gained recognition for its straightforward yet powerful design, achieving excellent performance on image classification tasks. VGG19 relies heavily on stacking numerous small convolutional layers (typically 3x3) with rectified linear units (ReLU) for activation. This repetitive structure allows the network to extract features progressively at various levels of complexity. The architecture is organized into five convolutional blocks, each containing several convolutional layers followed by a max-pooling layer for dimensionality reduction. These blocks progressively increase in complexity, using a fixed filter size (3x3) with a stride of 1 and padding of 1 to preserve spatial information. The max-pooling layers with a pool size of 2x2 and stride of 2 further reduce the image size while capturing dominant features. Following the convolutional blocks, VGG19 employs three fully-connected layers with ReLU activations. The final layer uses a SoftMax activation for classification tasks, outputting probabilities for each class. While effective, VGG19's reliance on numerous small convolutional layers makes it computationally expensive compared to more recent architectures. Additionally, its depth can lead to the vanishing gradient problem, hindering training in earlier layers [20].

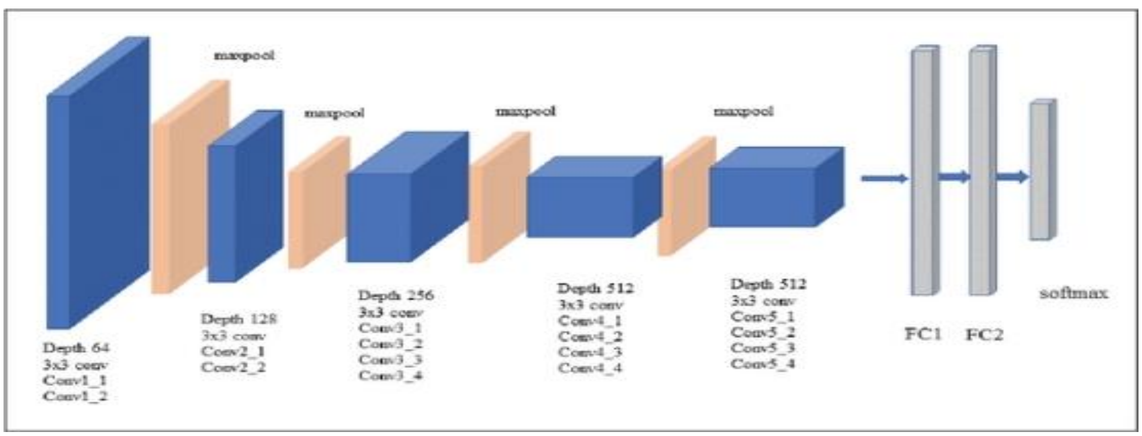

Fig 3.2.6: VGG19 Architecture [20]

3.2.3.3 ResNet50v2

ResNet50v2 addresses a significant challenge in deep neural networks: the vanishing gradient problem. This problem occurs when gradients become very small or zero as they propagate backward through the network during training. This makes it difficult for the network to learn effectively in earlier layers. ResNet50v2 introduces a concept called residual connections to tackle this issue. These connections bypass some layers in the network, allowing the gradients to flow directly through the identity function. This ensures that the gradients are not diminished as they propagate backward, enabling the network to learn the identity function and facilitating the flow of information throughout the entire architecture. The core building block of ResNet50v2 is the residual block. This block consists of two or three stacked convolutional layers followed by a shortcut connection that adds the input of the block to its output element-wise before the activation function. This architecture allows the network to learn the identity mapping efficiently, facilitating gradient flow and improving training performance. Compared to VGG19, ResNet50v2 achieves similar or better accuracy with a smaller number of parameters, making it a more efficient choice for many applications [21].

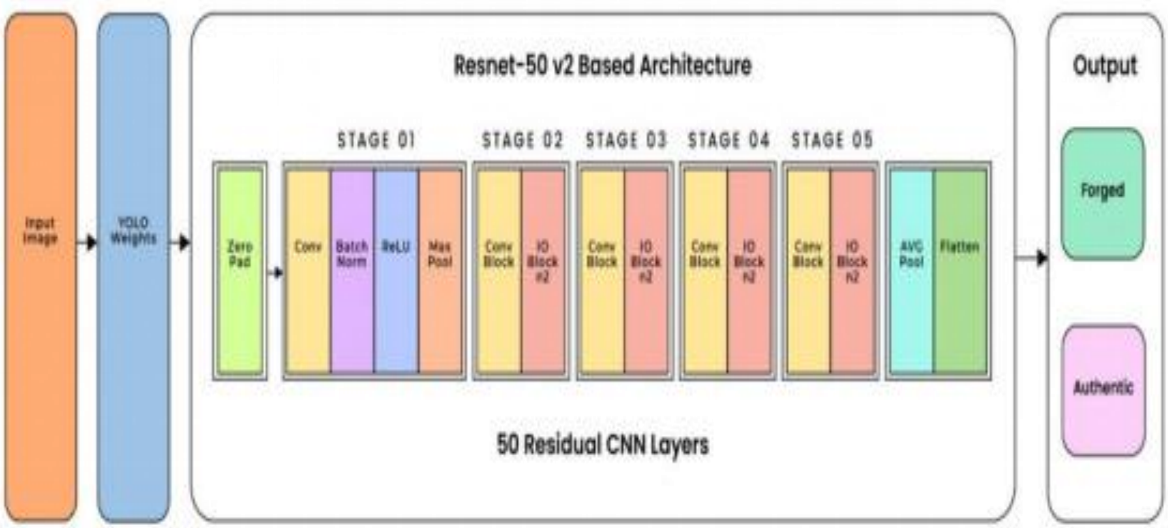

Figure 3.2.7: ResNet50V2 Architecture [21]

3.2.3.4 DenseNet121

DenseNet121 takes a unique approach to CNN architecture by connecting each layer to all subsequent layers in the network, fostering feature reuse and improving feature propagation. This dense connectivity contrasts traditional CNNs where each layer only connects to the subsequent layer. The core building block of DenseNet121 is the dense convolutional block. In these blocks, each layer receives the feature maps from all preceding layers as inputs and its own feature maps. This approach encourages feature reuse throughout the network, as each layer can learn from the features extracted by earlier layers and contribute to developing more complex features in later layers. Additionally, DenseNet utilizes bottleneck layers to reduce the number of channels before each convolutional layer, promoting efficiency by reducing the number of parameters in the network. Compared to traditional CNN architectures like VGG19, DenseNet121 achieves similar or better accuracy with a smaller number of parameters. This makes DenseNet a more efficient choice for applications where computational resources are limited. However, the dense connectivity can also increase the complexity of the network and make it more challenging to train [22].

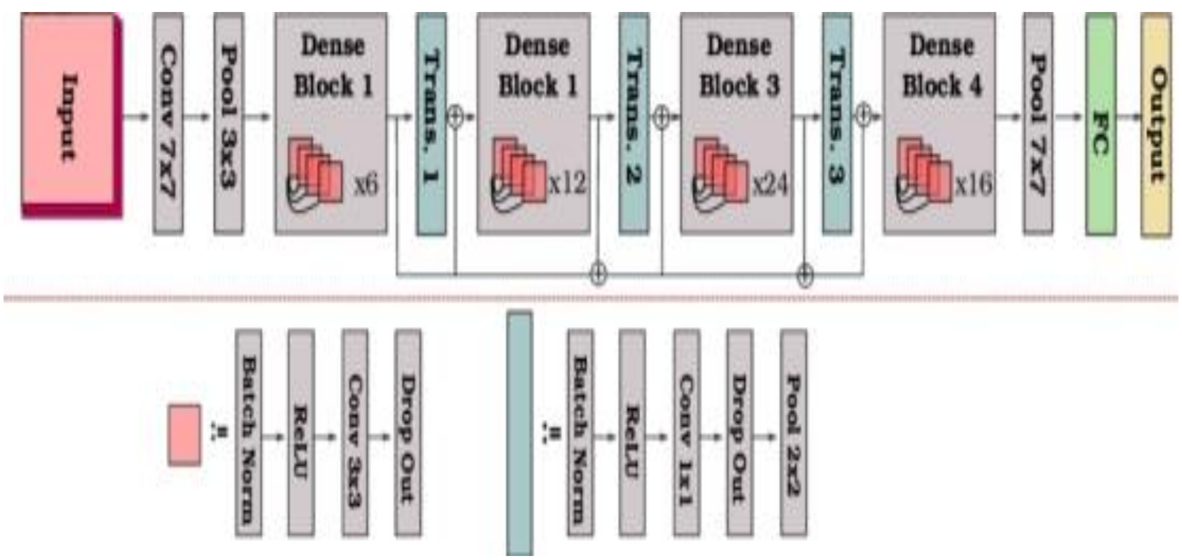

Fig 3.2.8: DenseNet121 Architecture [22].

3.2.3.5 MobilenetV2

MobilenetV2 stands out as a champion of efficiency in mobile image classification tasks. This convolutional neural network architecture achieves impressive results through a clever blend of techniques. Unlike traditional approaches, MobilenetV2 utilizes inverted residual blocks where the residual connection bridges thin bottleneck layers. This structure allows for efficient feature extraction while maintaining a compact model size. Within these blocks, depth wise separable convolutions play a starring role. They break down the typical convolution process into a two-act play: a depth wise convolution analyzes features, followed by a pointwise convolution to reduce channels. This significantly cuts down on computational cost compared to standard convolutions. But MobilenetV2 doesn't stop there. To further optimize efficiency, it incorporates a bottleneck design with linear activation within each block. This minimizes the number of channels processed by the depth wise convolution, squeezing even more efficiency out of the model. As an optional bonus, Squeeze-and-Excitation blocks can be integrated to prioritize important features and enhance overall accuracy. The result of these techniques is a lightweight model that achieves remarkable accuracy on image classification tasks. This makes MobilenetV2 perfectly suited for various mobile applications where image recognition is a key functionality, allowing for real-time processing on devices with limited resources [23].

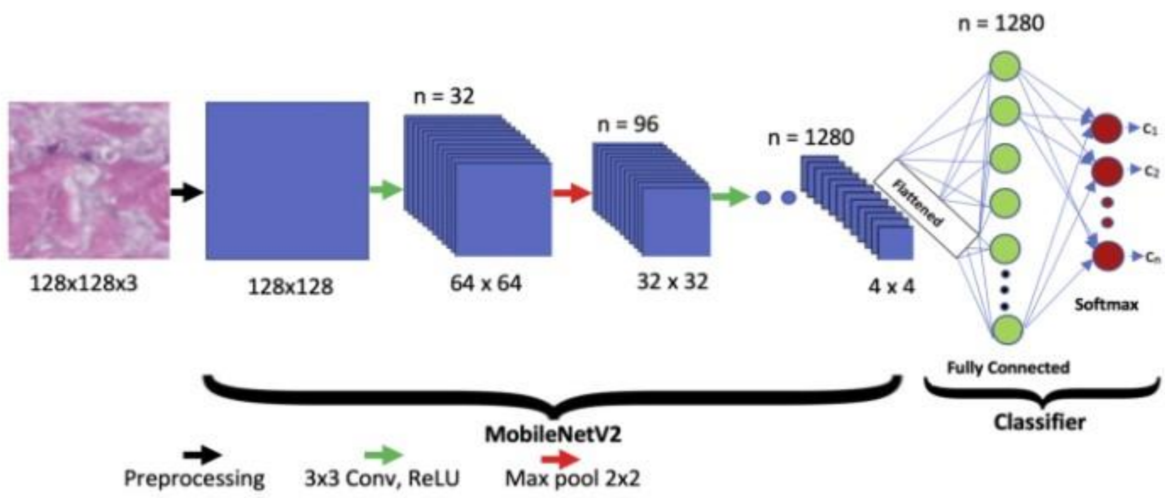

Fig 3.2.9: MobilenetV2 Architecture [23]

3.2.3.6 InceptionV3

InceptionV3 builds upon the Inception architecture, known for its use of inception modules. These modules combine convolutional and pooling layers in parallel paths, allowing the network to extract features at various scales and resolutions within an image. This multi-scale feature extraction is crucial for capturing diverse information in images, such as fine-grained details and global structures. The inception module in InceptionV3 is a grid-based structure containing multiple convolutional and pooling layers with different filter sizes. This allows the network to extract features of various sizes simultaneously, providing a richer representation of the image. Additionally, InceptionV3 employs batch normalization layers after each inception module, which helps to stabilize the training process and improve convergence. InceptionV3 utilizes multiple inception modules arranged in a hierarchical fashion. These modules progressively increase in complexity as the network goes deeper, allowing it to capture increasingly intricate features. Compared to earlier versions of the Inception architecture, InceptionV3 reduces the computational cost while maintaining good accuracy. This makes it a more practical choice for deployment in various applications [24].

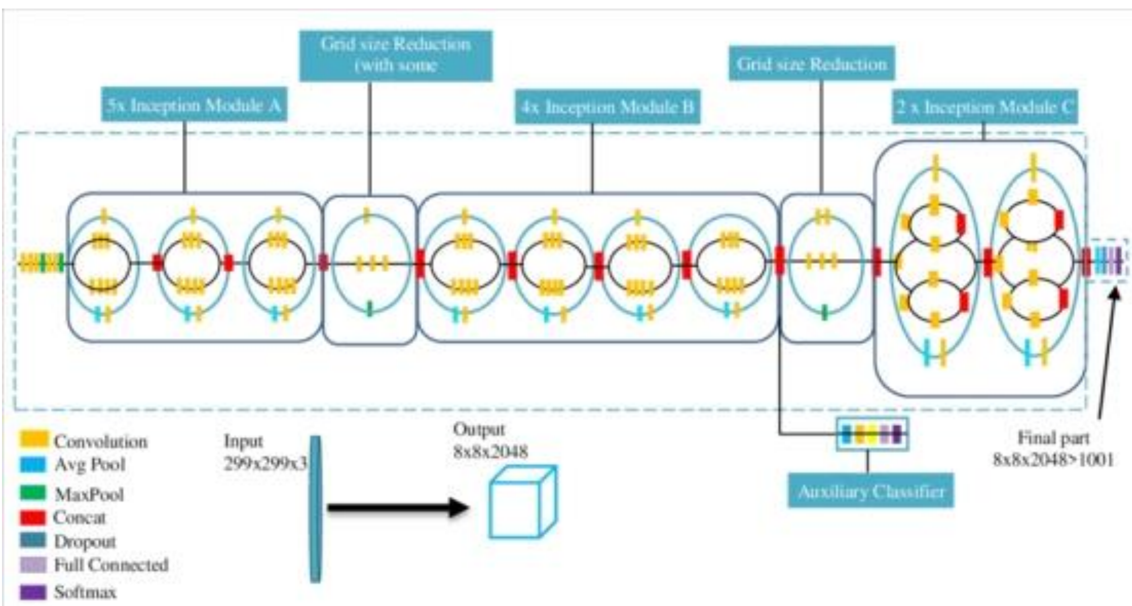

Fig 3.2.10: InceptionV3 Architecture [24]

3.2.4 Android Application Development

The Android application interface you described appears to be designed for image classification. Here's a breakdown of its elements and functionalities:

Interface Layout

- **Text Views:** There are two Text Views. One is for displaying a description "Classified as:", while the other text view shows the results of the image classification.
- **Image View:** Shows the captured or selected photos from gallery.

Buttons

- **Take Picture:** This button launches the device's camera app, allowing users to capture a new image for classification.
- **Launch Gallery:** This button opens the device's image library, enabling users to select an existing image for classification.

Overall Workflow:

- The user interacts with either the "Take Picture" or "Launch Gallery" button depending on whether they want to capture a new image or use an existing one.
- Following either action (camera or gallery), an image is obtained.
- The image is then sent for processing by the image classification model built into the app.
- The classification results are displayed in the second Text View.

Example Scenario:

- A user launches the app and wants to classify a fruit.
- They tap the "Take Picture" button, which opens the camera app.
- The user captures an image of the fruit and returns to the app.
- The app processes the image and displays the classification result in the second Text View. For instance, it might show "Classified as: G1ORANGE".

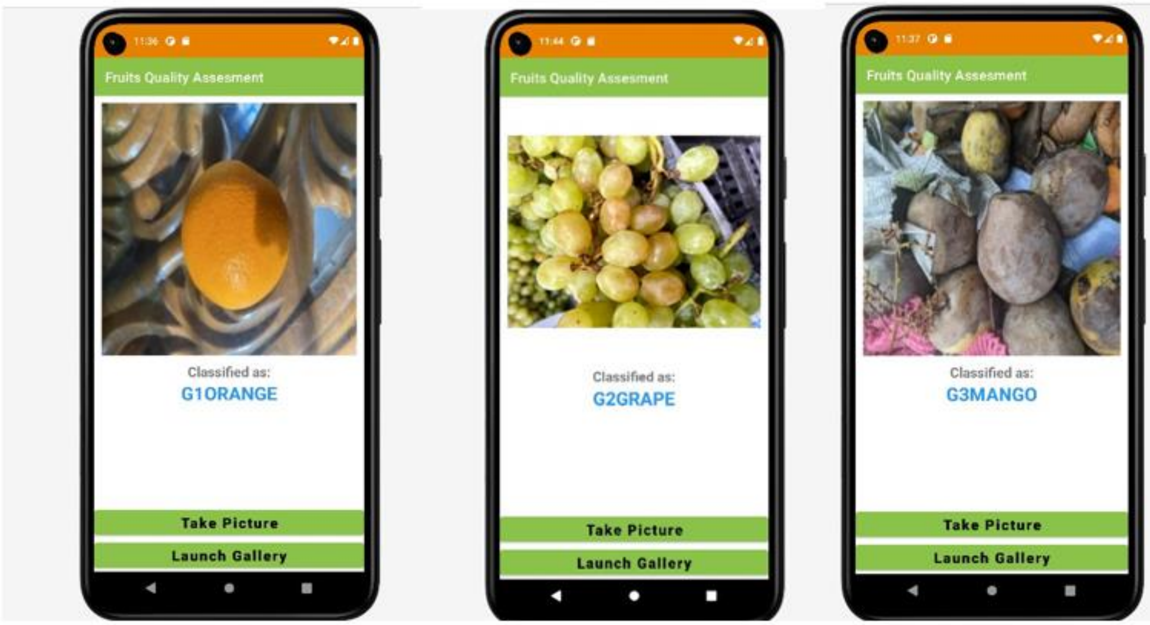

Fig 3.3.1: Interface of the Fruits Quality Assessment Android Application

3.3 Hardware/ Software Requirement

A. Hardware Requirement

- High-performance Computers
- High Speed Internet Connection

B. Software Requirements

1. Operating System

- Android OS version 8.0 (Oreo) or higher, to support the latest software development kits (SDKs) and APIs required for advanced image processing and machine learning.
- Windows 7 or higher

2. Development Environment

- Android Studio IDE (Integrated Development Environment) for Android application development.

- SDKs and libraries for computer vision and machine learning, such as TensorFlow Lite or PyTorch Mobile, for model deployment on mobile devices.

3. **Programming Languages**
   - Familiarity with Java or Kotlin for Android app development.
   - Familiarity with Python for model training and preprocessing tasks.

4. **Libraries and Frameworks**
   - OpenCV (Open-Source Computer Vision Library) for image processing and manipulation.
   - TensorFlow or PyTorch for implementing and deploying deep learning models.

5. **Documentation and Reporting**
   - Tools for documenting project progress, such as Microsoft Office or Google Workspace for creating reports, presentations, and project documentation.

These hardware and software requirements are essential for developing and deploying an Android-based automated fruit grading application using computer vision and machine learning technologies. Adjustments may be necessary based on specific project needs and the complexity of the models and algorithms used.

3.4 Project Management and Financial Analysis

3.4.1 Project Timeline:

A. Phase 1: Project Planning and Research (2-4 weeks)
B. Phase 2: Reviewing Existing Papers (6-8 weeks)
C. Phase 3: Image Data Collection (4-6 weeks)
D. Phase 4: Image Pre-Processing (10-14 weeks)
E. Phase 5: Selecting model (1-2 weeks)
F. Phase 6: Reviewing results and accuracy (2-4 weeks)
G. Phase 7: Application Design and Prototyping (4-6 weeks)
H. Phase 8: Application Development (8-10 weeks)
I. Phase 9: Testing and Deployment (1-2 weeks)

3.4.2 Resource Planning:

A. Equipment and Tools:

- High-performance Computers
- Processor: Intel Ryzen 5600
- RAM: 16GB
- Storage: 256 GB M.2 NV Me SSD, 1TB Hard Drive
- Graphics Processing Unit: RTX 3050
- High Speed Internet Connection

B. Software and Technologies:

- Google Collab
- Computer Vision
- Deep Learning
- Android Studio

C. Data and Content:

- Images Data: Gathered from local Market and super shop.
- Report Documentation: Written by the team.

D. Training and Skill Development:

Ensure that the development team has the necessary training and skills in machine learning, android application development, security, and database management.

Additional training on specific technologies and tools as needed.

Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project.

Here's a SWOT analysis for the e-commerce platform for agricultural products:

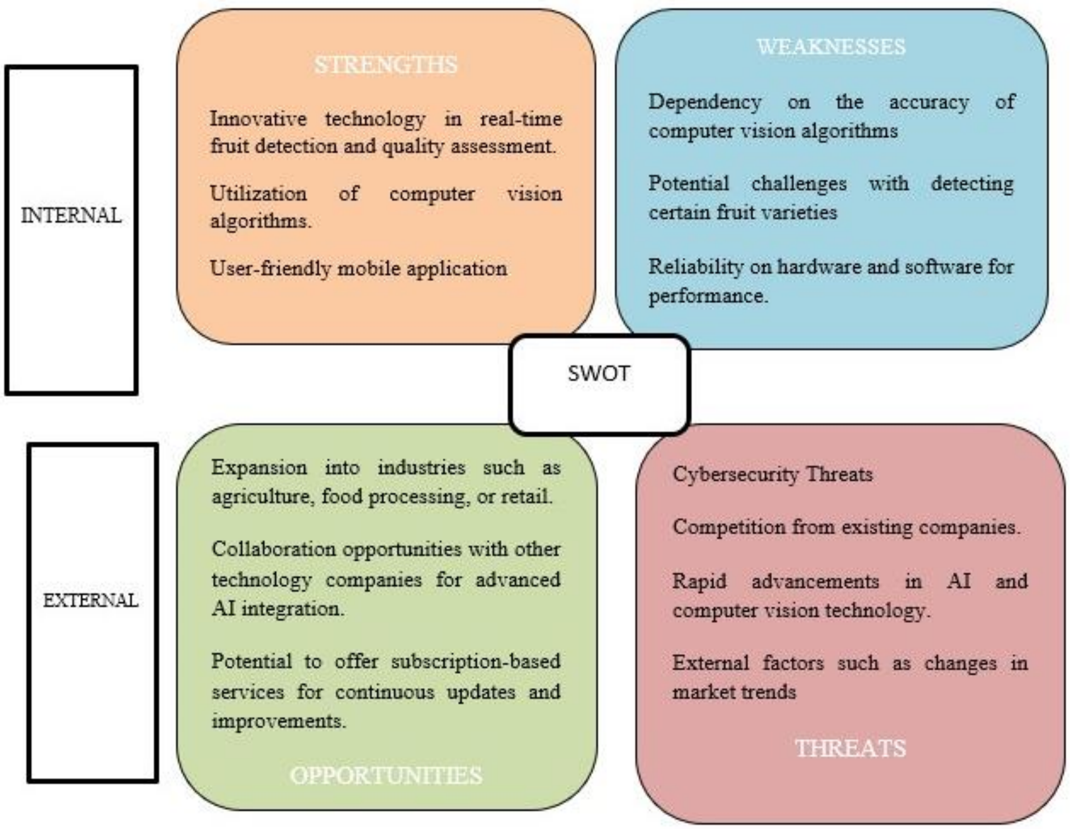

Figure 3.4: SWOT analysis

- **Communication Plan:**

A. Change Control Meetings:

Purpose: Discuss and approve any changes to the project scope or requirements.

Participants: Supervisor and team members.

Frequency: When change requests arise.

Table 3.4: Estimated Cost for this Project

SN	Components	Estimated Cost (BDT)
01.	Software and Tools	2000-3000
02.	Data Collection and Processing	2500-3000
03.	Documentation and Report Writing	1000-2000
04.	Miscellaneous	1500-2500
05.	Contingency	2000-3000
Total Estimated Cost		9,000-13,500

3.5 Summary

The methodology that is being given lays out a methodical way to conduct a study that uses computer vision and deep learning techniques to automate the assessment of fruit grading. The approach starts with collecting as much information as possible. After data gathering, annotations are added to these images to show quality aspects. Preprocessing techniques are then applied to enhance the dataset's diversity and normalize it. Model development is the next stage, which entails selecting and implementing appropriate deep-learning architectures. Subsequently, the trained model is included in an Android application to facilitate instantaneous image capture and quality assessment on mobile devices. The project management framework outlined here provides a systematic approach to conducting the study. A budget has also been curated for the overall project lifecycle. In a nutshell, the we seek to deliver precise and effective fruit quality assurance through the seamless integration of technological solutions.

CHAPTER 4
Implementation

4.1 Overview

The development of a robust fruit detection system using advanced machine learning techniques leverages architectures such as ResNet50v2, VGG19, EfficientNetB3, DenseNet121, and InceptionV3 for enhanced agricultural productivity and precision. Each pre-trained model was fine-tuned by unfreezing the appropriate last layers and incorporating additional layers such as global average pooling, batch normalization, dense layers with L2 regularization, dropout, and final SoftMax activation layers. These models were trained using a comprehensive dataset comprising diverse fruit images from various regions, seasons, and environmental conditions. Optimization with the Adam optimizer and strategic use of callbacks like Reduce learning rate and Early stopping ensured high accuracy and robust performance during training. Rigorous testing and evaluation, including metrics such as accuracy, precision, recall, and F1-score, alongside robustness testing, validated the models' generalization capabilities across different scenarios. The comprehensive evaluation of these systems demonstrates their readiness for deployment, with ongoing efforts focused on refining classification accuracy, optimizing computational efficiency, and incorporating user feedback. These sophisticated fruit detection systems represent significant advancements in precision agriculture, poised to enhance productivity and support informed decision-making for sustainable and efficient agricultural practices.

4.2 Train Model/ Prototype Design

The training methodology for the fruit detection model leverages the pre-trained VGG19, Resnet50v2, Densenet121, EfficientNetB3. InceptionV3 architectures from the TensorFlow Keras Applications module. These models, initialized with ImageNet weights and excluding its top classification layer, serves as the foundational feature extractor. To enhance its adaptability to the specific fruit detection task, the last few layers of the pre-trained model are unfrozen to allow fine-tuning, promoting improved performance by adjusting these layers to the new dataset's characteristics.

Subsequently, additional layers are appended to the pre-trained model. The output from These models undergoes global average pooling, followed by batch normalization to stabilize and accelerate the training process. A dense layer with 2048 units, utilizing the ReLU activation function and L2 regularization, is incorporated to learn complex patterns in the fruit images. A dropout layer with a 0.5 rate is added to mitigate overfitting by randomly disabling neurons during training. The final dense layer, employing the SoftMax activation function, outputs the probabilities for the 24 fruit classes, facilitating multi-class classification.

These models are compiled using the Adam optimizer with a learning rate of 0.0001, which balances the speed and stability of the training process. The loss function employed is sparse categorical cross-entropy, suitable for multi-class classification problems where class labels are provided as integers. The primary metric for evaluating model performance during training and validation is accuracy. To further refine the training process, two key callbacks are integrated: a learning rate scheduler and early stopping. The Reduce learning rate callback monitors the validation loss and reduces the learning rate by a factor of 0.5 if no improvement is observed over three epochs, with a minimum learning rate threshold of 0.00001. This adaptive learning rate adjustment aids in overcoming plateaus in the loss function, enhancing model convergence. The Early stopping callback halts training if the validation loss does not improve over five consecutive epochs, restoring the best weights observed during training to prevent overfitting.

These models undergo training over 30 epochs, with performance monitored using a validation dataset. Post-training, the model's efficacy is evaluated on a separate test dataset to assess its generalization capability, with the test accuracy serving as the primary metric. This comprehensive training methodology ensures a robust and effective fruit detection model, optimized for real-time performance on Android devices.

4.3 System Testing/ Model Evaluation

System testing and model evaluation are pivotal in ensuring the development of a robust fruit detection system. These processes are designed to confirm that the model performs not only effectively on the training data but also generalizes well to new, unseen data. The objective is to validate that the model can reliably identify and classify fruit images under diverse conditions. To comprehensively evaluate the model's performance, multiple metrics were employed. Each metric offers a different perspective on the model's effectiveness, providing a holistic assessment.

4.3.1 Accuracy

Accuracy is defined as the proportion of correctly classified images out of the total number of images in the test set. Accuracy provides an overall measure of how well the model performs in classifying the fruit images correctly.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

4.3.2 Precision

Precision is the proportion of true positive detections (correctly identified fruit classes) out of all positive detections (both true positives and false positives) made by the model. Precision indicates the model's ability to correctly identify only relevant instances of a particular class, minimizing false positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

4.3.3 Recall

Recall, also known as sensitivity, is the proportion of true positive detections out of all actual positives in the dataset. Recall measures the model's ability to identify all relevant instances of a class, minimizing false negatives.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

4.3.4 F1-Score

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both. The F1-score is particularly useful when there is an imbalance between precision and recall, as it provides a balanced measure of the model's performance across both metrics.

$$\text{F1-score} = \frac{2*(\text{Precision} * \text{Recall})}{\text{Precision} + \text{Recall}}$$

4.3.5 Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. The confusion matrix provides a detailed breakdown of the model's performance, highlighting specific areas where the model excels or needs improvement.

Structure: The matrix includes:

- True Positives (TP): Correctly predicted positive observations
- True Negatives (TN): Correctly predicted negative observations
- False Positives (FP): Incorrectly predicted positive observations
- False Negatives (FN): Incorrectly predicted negative observations

By employing these metrics, a comprehensive evaluation of the deep learning-based fruit detection model was performed. The goal was to ensure that the model is not only accurate but also precise, sensitive, and balanced in its performance across different classes. This detailed evaluation helps in understanding the strengths and weaknesses of the model, guiding further improvements and optimizations.

4.4 Summary

The development and evaluation of fruit detection systems based on ResNet50v2, VGG19, EfficientNetB3, DenseNet121, and InceptionV3 represent significant strides in precision agriculture. Leveraging each architecture's strengths through fine-tuning and additional layers such as global average pooling, batch normalization, dense layers with L2 regularization, dropout, and final SoftMax activation has led to models capable of achieving high accuracy and robust performance across diverse real-world scenarios. Rigorous testing and comprehensive evaluation using metrics like accuracy, precision, recall, and F1-score, alongside robustness testing, have confirmed these models' effectiveness in generalizing to new data. Ongoing efforts will concentrate on further enhancing classification accuracy, optimizing computational efficiency, and incorporating user feedback to maintain relevance and effectiveness.

CHAPTER 5
Result and analysis

5.1 Overview

This study focuses on leveraging deep convolutional neural networks (CNNs) for automated fruit quality assessments using computer vision techniques. With a dataset comprising 14,400 original fruit images, the research employs sophisticated augmentation methods to enhance dataset diversity, generating multiple images from each photograph. The evaluation centers on five prominent CNN models—ResNet50v2, VGG19, EfficientNetB3, DenseNet121, and InceptionV3 aimed at classifying fruit quality across various categories. Notably, EfficientNetB3 and DenseNet121 exhibit superior performance, achieving an impressive accuracy rate of 91%. ResNet50V2 and InceptionV3 achieved 88% and 89% respectively indicating a marginally decreased performance compared to their counterparts. While, VGG19 exhibited a slightly lower accuracy of 87%. The study comprehensively presents metrics such as training and validation loss graphs, confusion matrices, precision, recall, F1-score, and support for each class, offering detailed insights into the models' capabilities and performance.

5.2 Experimental Result

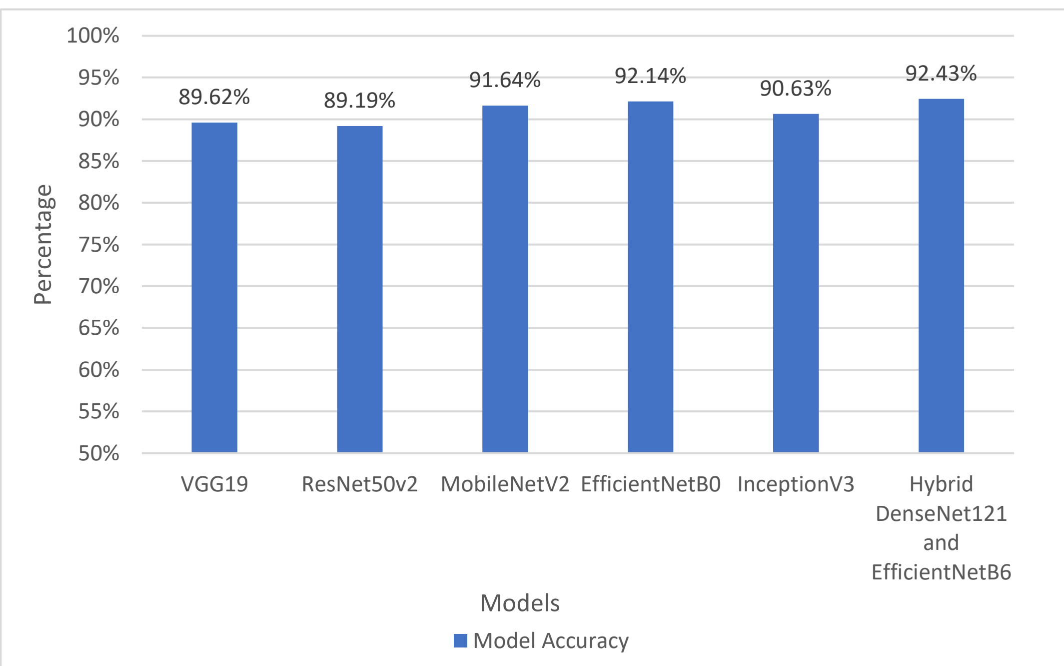

Figure 5.2.1: Test Accuracy for Classification of Individual model.

Table 5.2.1: Model Test Accuracy, Parameters, Depth, Time per Inference (CPU &GPU)

Architecture	Model Test Accuracy	Parameters	Depth	Time per Inference (CPU)	Time per Inference (GPU)
VGG19	89.62%	143.7M	19	84.8	4.4
ResNet50v2	89.19%	25.6M	107	58.2	4.6
MobileNetV2	91.64%	3.5M	105	25.9	3.8
EfficientNetB0	92.14%	5.3M	132	46.0	4.9
InceptionV3	90.63%	23.9M	189	42.2	6.9
Hybrid DenseNet121 and EfficientNetB6	92.43%	8.1M 43.3M	189 360	77.1 958.1	6.9 40.4

The comparative analysis of 5 well-known CNN models MobileNetV2, ResNet50v2, VGG19, EfficientNetB0, InceptionV3 and a hybrid model DenseNet121 & EfficieintB6 to accurately categorizing fruit quality across several classifications. The hybrid model has achieved the highest accuracy of 92.43% but in terms of efficiency the hybrid model required much more computational power and as well much more inference time which make it less efficient for mobile devices. On the other hand, EfficientB0 model which is far more superior in terms of efficiency was achieved 92.14% accuracy which is very close to what the hybrid model has achieved. While MobilenetV2 achieved slightly lower accuracy of 91.64% and it is as well very efficient as EfficientNetB0. InceptionV3 was also highly accurate, with accuracy of 90.63%. The accuracy of ResNet50v2 and VGG19 were slightly lower, measuring at 89.19% and 89.62%. So, we can say the EfficientNetB0 is the overall best model in terms of good accuracy and efficiency.

Table 5.2.2: Precision, Recall, F1-Score, and Support for each class of every model.

EfficientNetB0				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.92	1388
Macro avg	0.94	0.92	0.92	1388
Weighted avg	0.94	0.92	0.92	1388
VGG19				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.90	1388
Macro avg	0.91	0.89	0.89	1388
Weighted avg	0.91	0.90	0.89	1388
MobileNetV2				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.92	1388
Macro Avg	0.93	0.91	0.91	1388
Weighted avg	0.93	0.92	0.91	1388
ResNet50V2				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.89	1388

Macro avg	0.91	0.89	0.89	1388
Weighted avg	0.91	0.89	0.89	1388
InceptionV3				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.91	1388
Macro avg	0.92	0.90	0.90	1388
Weighted avg	0.92	0.91	0.90	1388

Hybrid DenseNet121 and EfficientNetB6				
Classes	Precision	Recall	F1-Score	Support
Accuracy			0.92	1388
Macro avg	0.94	0.92	0.92	1388
Weighted avg	0.94	0.92	0.92	1388

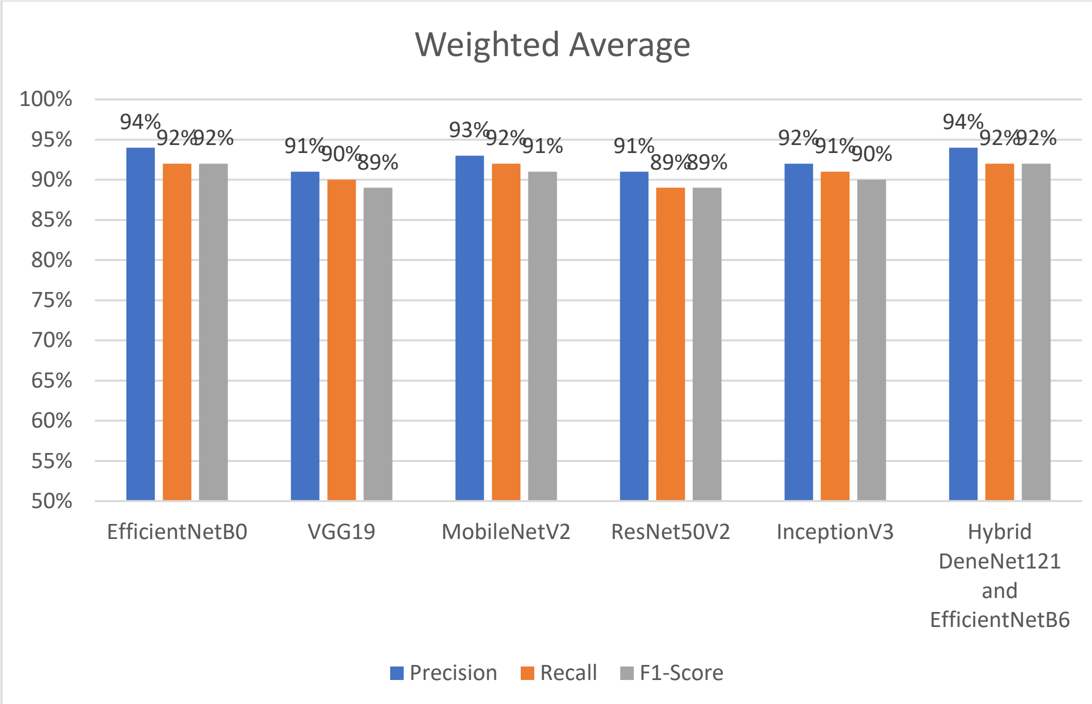

Figure 5.2.2: Comparison of Precision, Recall and F1-Score of models.

Figure 5.2.2 provides a comprehensive overview of the accuracy, macro average and weighted average achieved by five Convolutional Neural Network (CNN) architectures and a hybrid model. Additionally, Table 5.2.2 presents precision, recall, F1-score, and support values for each class, focusing on the MobileNetV2, ResNet50v2, VGG19, EfficientNetB0, InceptionV3 and DenseNet121 and EfficieintB6 hybrid model. EfficientNetB0 and hybrid model architectures exhibit remarkable performance, particularly evident in their precision values when applied to the test dataset. Specifically, these two models demonstrate superior precision, recall, and F1-score across various classes, affirming their effectiveness. MobilenetV2 and InceptionV3 models exhibit commendable performance as highlighted in the detailed breakdown. However, VGG19 and ResNet50v2, while part of the comprehensive comparison, yields a comparatively lower accuracy. The detailed insights from these table contribute valuable information for understanding the strengths and limitations of each model.

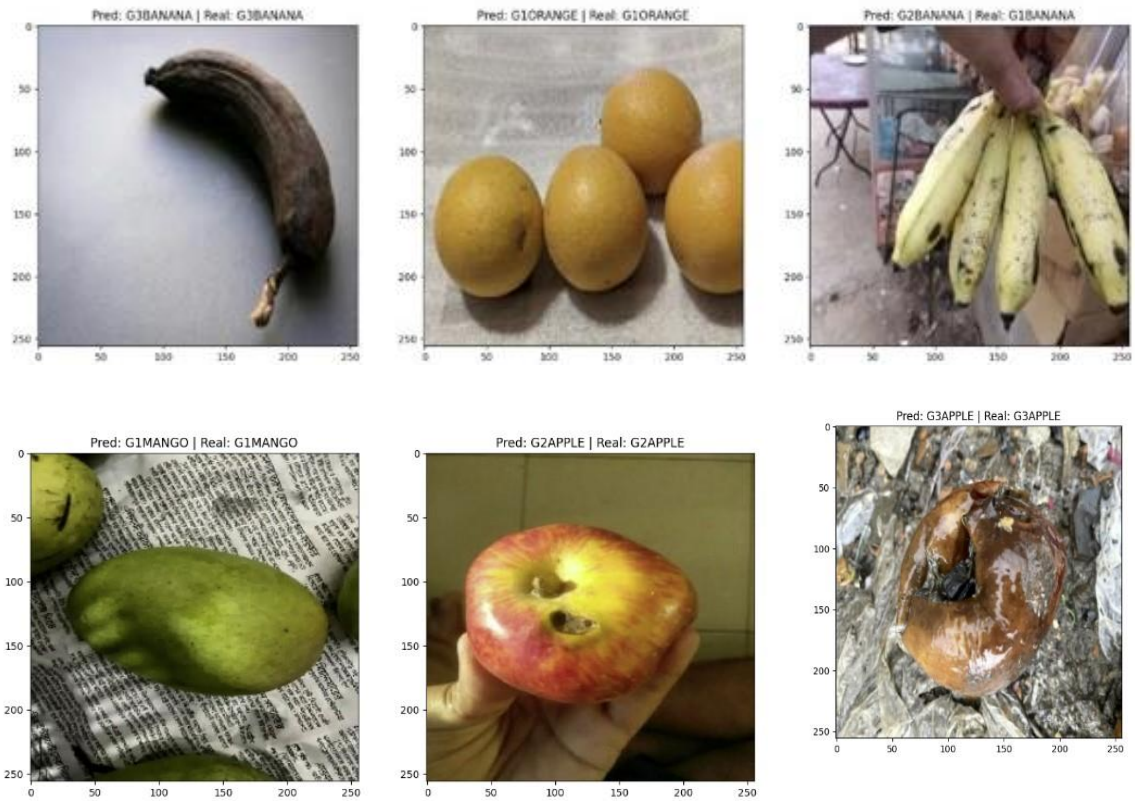

Figure 5.2.3: Test Results of the models.

5.3 Comparative Analysis

In this section, we present the training and validation accuracy and confusion matrix of all the models. For the training and validation accuracy and loss over the epochs for each model the number of epochs is plotted on the x-axis, while the accuracy and loss percentages are displayed on the y-axis. The figure clearly divides the training and validation data, providing a comprehensive view of model performance over time.

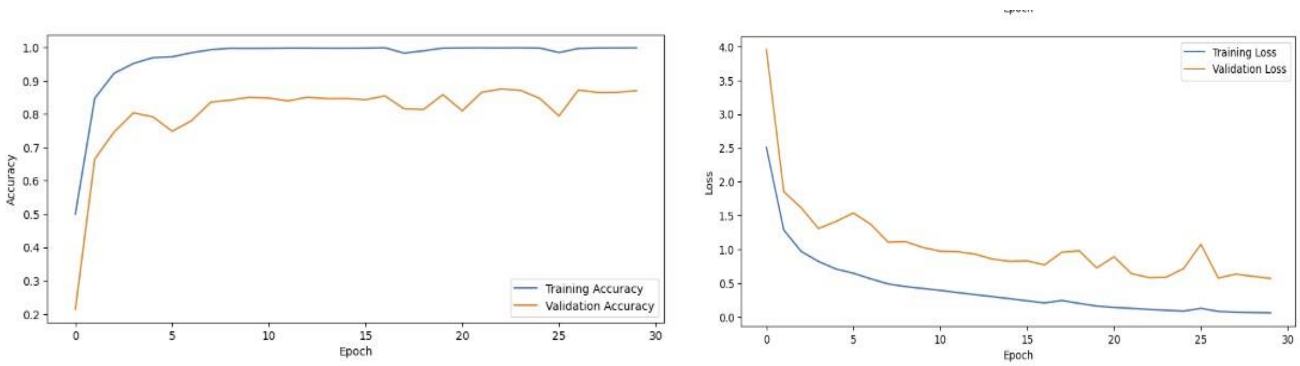

Figure 5.3.1 Training and validation accuracy and loss over the epochs (VGG19)

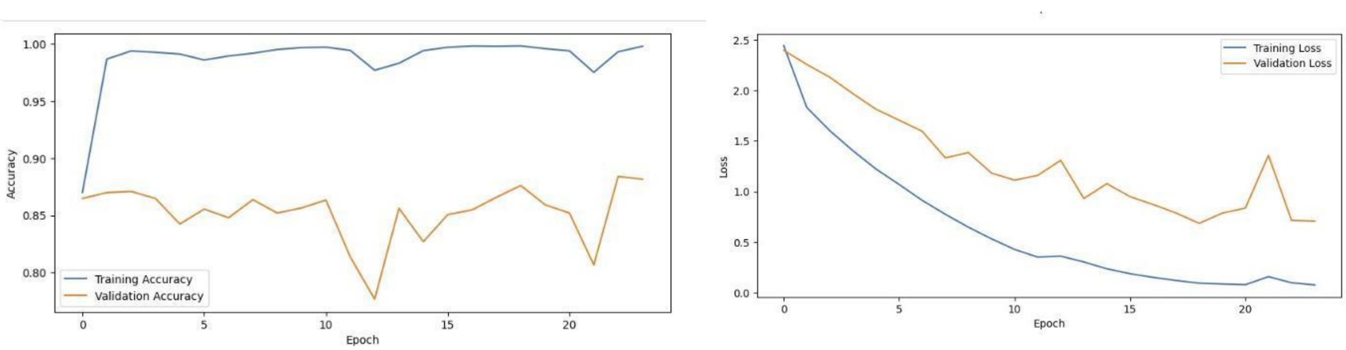

Figure 5.3.2 Training and validation accuracy and loss over the epochs (ResNet50v2)

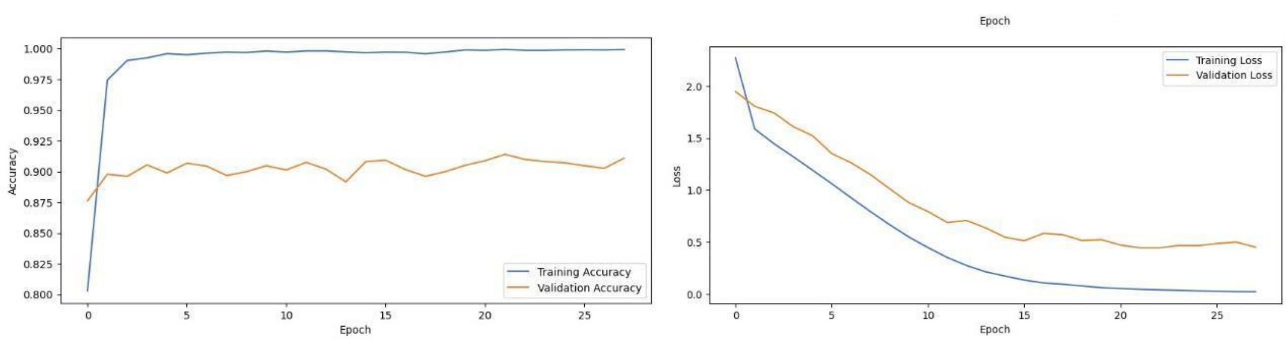

Figure 5.3.3: Training and validation accuracy and loss over the epochs (EfficientNetB0**)**

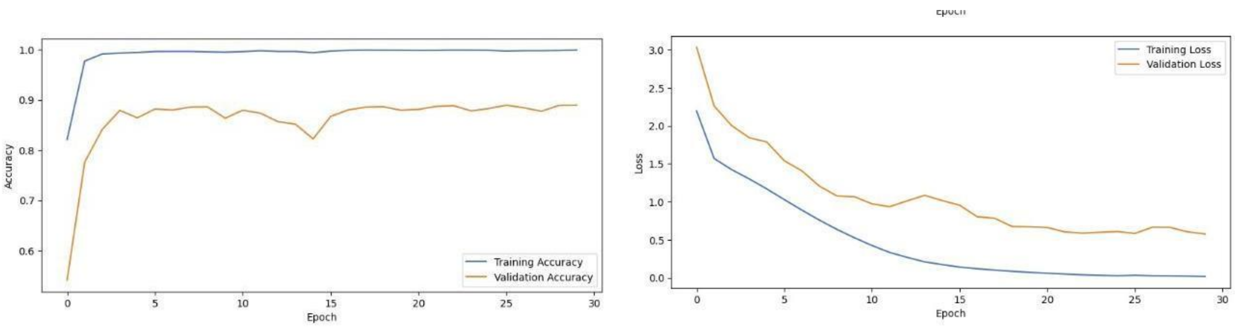

Figure 5.3.4: Training and validation accuracy and loss over the epochs (MobileNetV2).

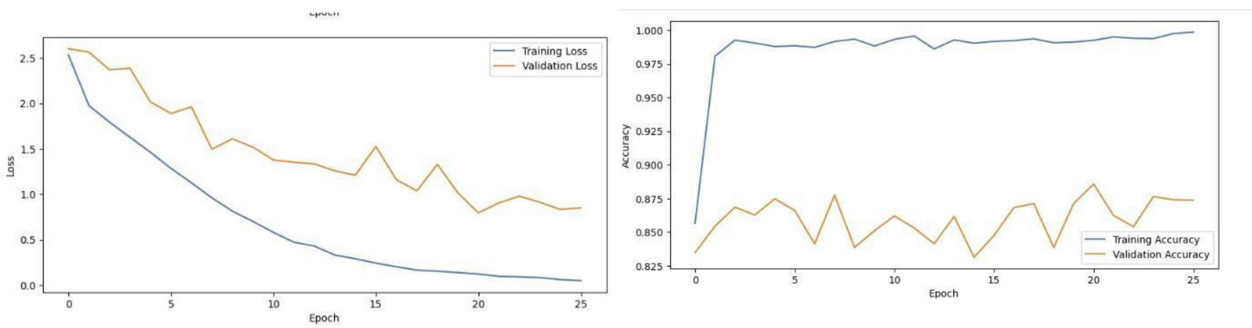

Figure 5.3.5: Training and validation accuracy and loss over the epochs (InceptionV3).

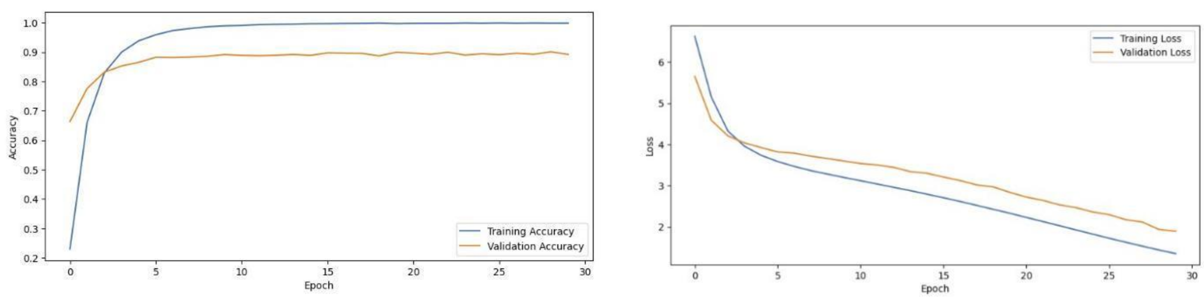

Figure 5.3.6: Training and validation accuracy and loss over the epochs (Hybrid Densenet121 and EfficientNetB6).

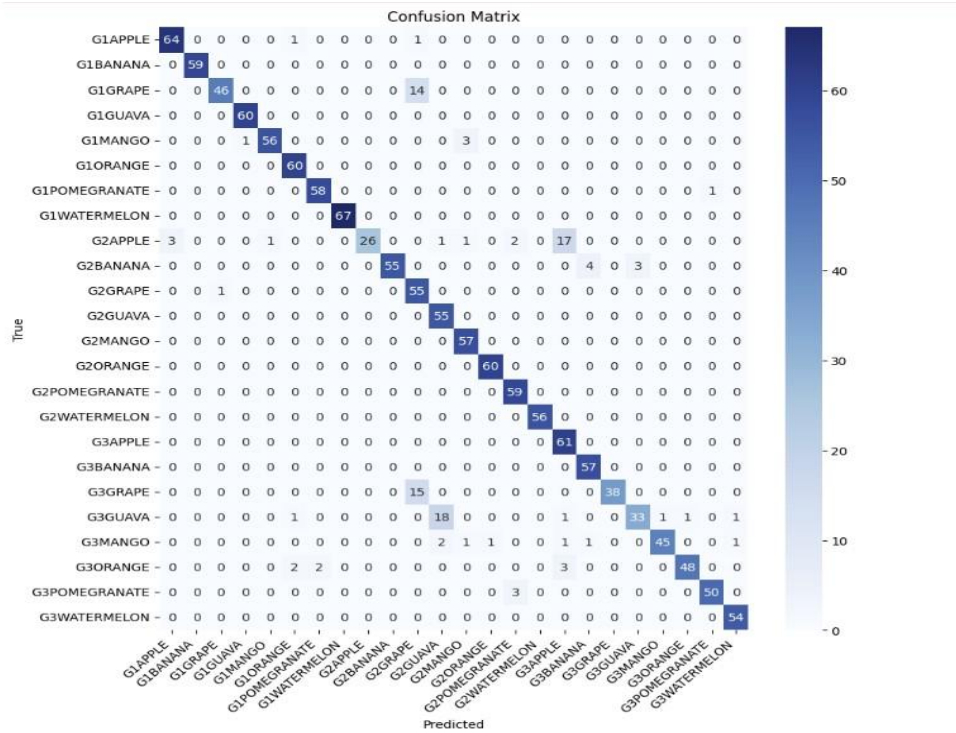

Figure 5.3.7: Confusion Matrix of EfficientNetB0

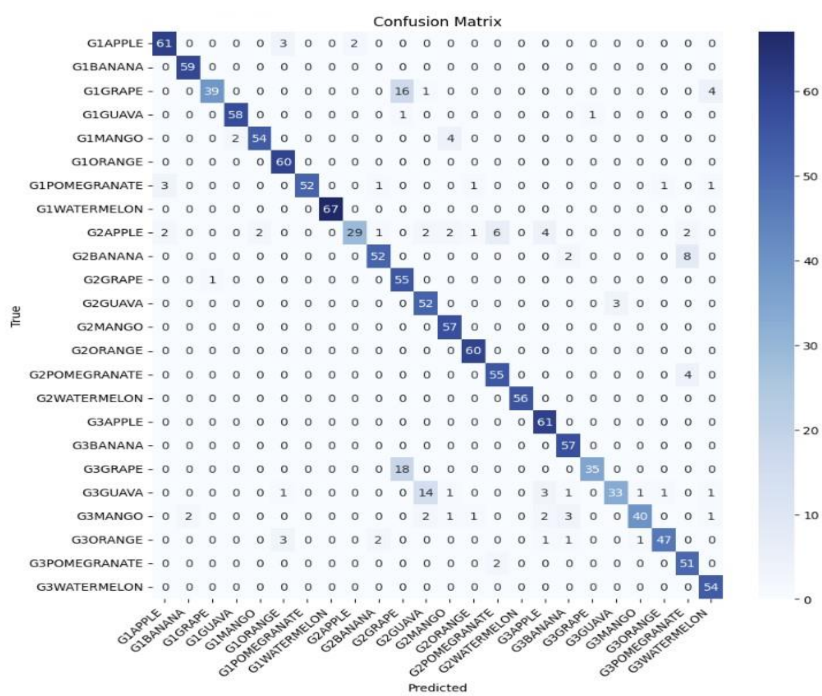

Figure 5.3.8: Confusion Matrix of VGG19

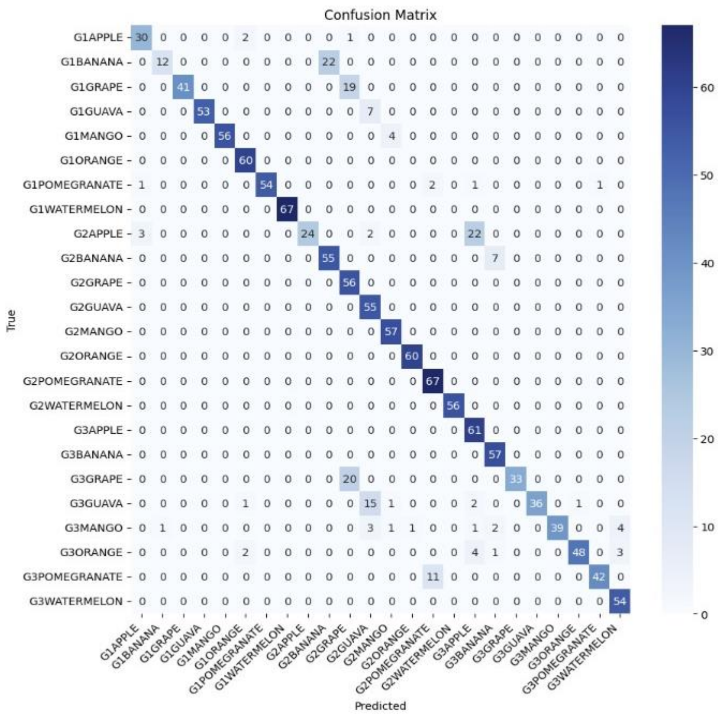

Figure 5.3.9: Confusion Matrix of Resnet50v2

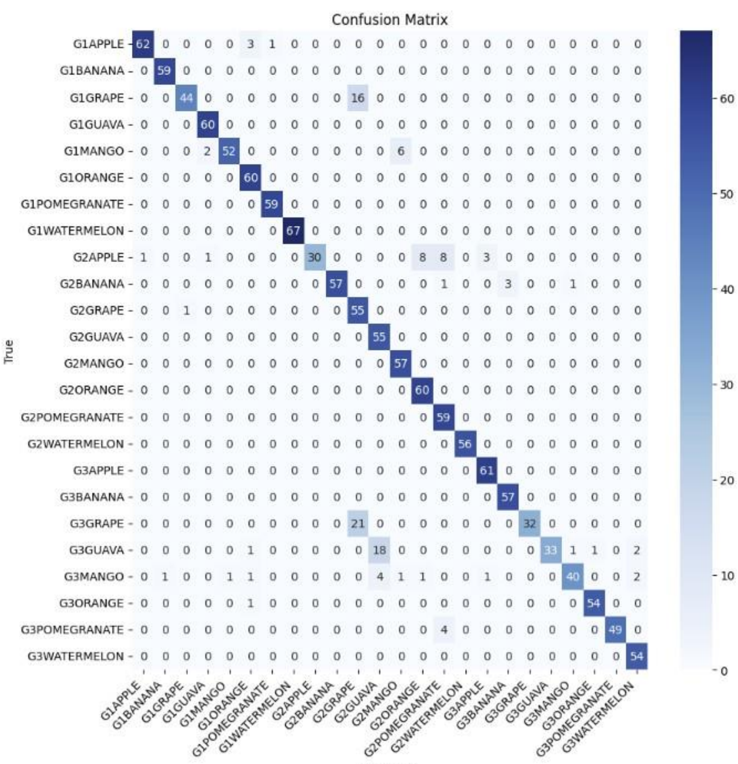

Figure 5.3.10: Confusion Matrix of MobileNetV2

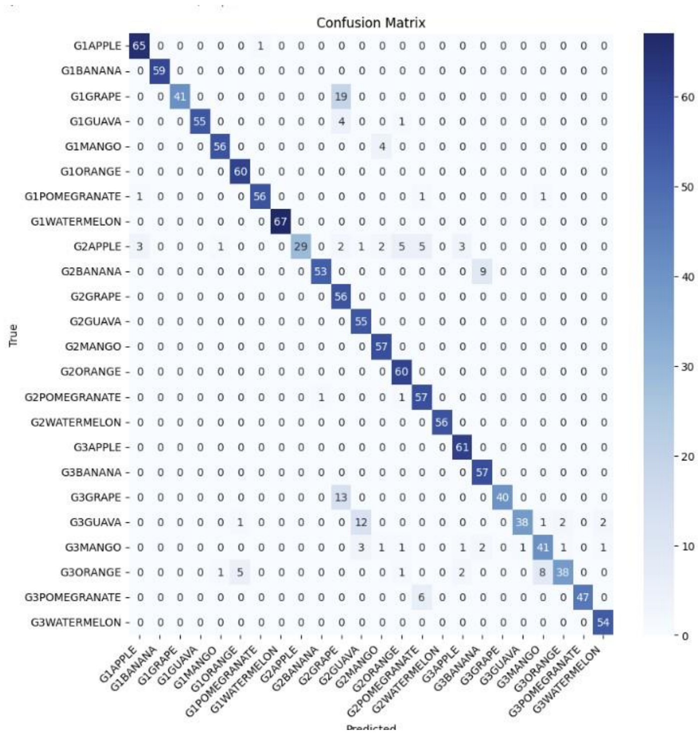

Figure 5.3.11: Confusion Matrix of InceptionV3

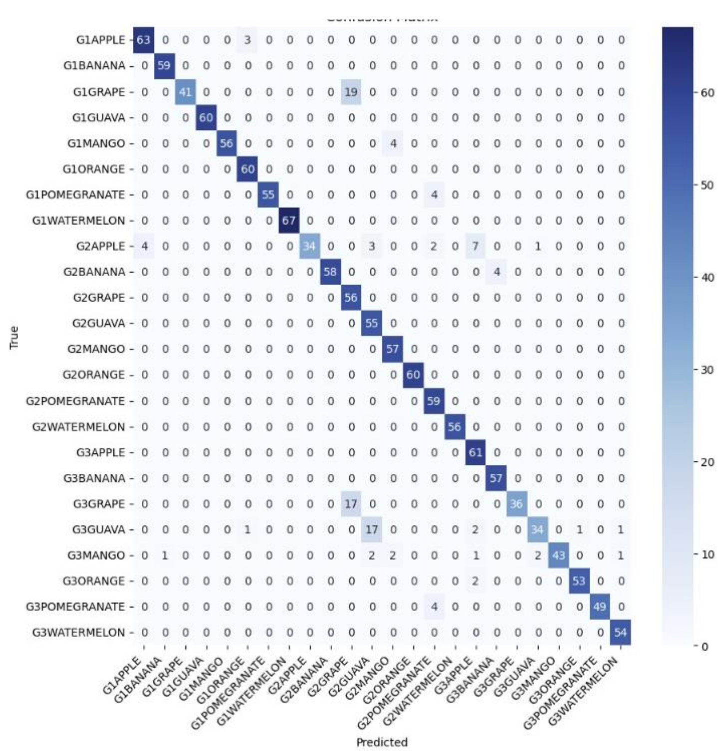

Figure 5.3.12: Confusion Matrix of Hybrid Densenet121 and EfficientNetB6

5.4 Summary

This comprehensive study investigates the application of deep convolutional neural networks in automating fruit quality assessments using computer vision techniques. The study evaluates the performance of five prominent CNN models ResNet50v2, VGG19, EfficientNetB3, DenseNet121, and InceptionV3 on the task of classifying fruit quality across multiple categories. Notably, EfficientNetB3 and DenseNet121 emerge as top performers, achieving a commendable accuracy rate of 91%. These findings are comprehensively illustrated through detailed metrics such as training and validation loss graphs, confusion matrices, precision, recall, F1-score, and support for each class. The study underscores the significance of transfer learning techniques, revealing varying performance trends across the evaluated architectures. This research provides valuable insights into leveraging deep learning for automated fruit quality assessment, highlighting avenues for further refinement and application in agricultural technology.

CHAPTER 6
Impact on society, environment and sustainability

6.1 Impact on Life

Automated fruit grading systems streamline operations, reducing the reliance on manual labor traditionally required for grading tasks. This shift has the potential to improve job satisfaction among agricultural workers by reallocating them to more skilled and rewarding roles within the production chain. Moreover, by automating repetitive and physically demanding tasks, these systems can enhance workplace safety and reduce occupational hazards, contributing to overall improved quality of life for workers in the agricultural sector. This technology empowers farmers by reducing post-harvest losses and ensuring they achieve fair market prices, thereby increasing income stability and improving their livelihoods. The project's emphasis on sustainability contributes to environmental health by minimizing food waste, optimizing the use of water, fertilizers, and other resources, and significantly lowering the agricultural carbon footprint. By integrating advanced technology into the agricultural supply chain, the project not only fosters innovation and operational efficiency but also encourages the adoption of precision farming practices. This leads to more effective crop management and higher yields. Furthermore, by adhering to ethical guidelines and utilizing efficient computational resources, the project supports sustainable development goals, contributing to economic prosperity, environmental preservation, and the overall well-being of communities. This holistic approach ensures a more sustainable and prosperous future, benefiting individuals, families, and society as a whole.

6.2 Impact on Society & Environment

From a societal perspective, automated grading systems ensure consistent quality and supply of fruits, thereby bolstering food security and meeting consumer expectations for high-quality produce. This reliability in grading standards supports economic stability within agricultural communities, fostering trust and satisfaction among consumers. This technology benefits farmers by reducing post-harvest losses, securing fair market prices, and improving economic stability.

Environmentally, the project promotes sustainability by reducing food waste, optimizing the use of natural resources like water and fertilizers, and lowering the agricultural carbon footprint. By integrating advanced technology and adhering to ethical guidelines, the project fosters innovation and efficiency in the agricultural supply chain. It encourages precision farming practices, leading to better crop management and higher yields. This holistic approach supports sustainable development goals, contributing to economic prosperity, environmental preservation, and the overall well-being of communities.

6.3 Ethical Aspects

The ethical implications of automating fruit grading encompass considerations of job displacement and fair labor practices. While automation may reduce the need for manual labor in certain tasks, it is essential to implement strategies that support affected workers through retraining programs and fair transition policies. Ensuring equitable distribution of benefits from technological advancements is crucial for maintaining social cohesion and ethical standards within the agricultural workforce. Additionally, the project adheres to ethical guidelines in AI development and deployment, ensuring that the technology is used responsibly and does not harm individuals or communities. By fostering transparency, accountability, and inclusivity, the project supports ethical agricultural practices that benefit society and the environment while promoting innovation and economic growth.

6.4 Sustainability Plan

A sustainable approach to deploying automated fruit grading systems involves continuous innovation in technology and processes. This includes ongoing research and development to enhance system accuracy and efficiency, as well as proactive engagement with stakeholders to address evolving societal and environmental challenges. Transparency in operations and adherence to sustainable practices are pivotal in ensuring that these systems contribute positively to long-term sustainability goals while minimizing adverse impacts on the environment and society.

6.5 Summary

Automated fruit grading systems are a big advancement in agriculture, offering many benefits. They improve productivity, quality, and worker safety, enhancing the lives of farming communities. These systems help farmers reduce losses, secure fair prices, and achieve economic stability. They also promote sustainability by reducing food waste, optimizing resources, and lowering the carbon footprint. It's important to use these technologies ethically, ensuring fair access, protecting privacy, and being transparent. Overall, this project supports a healthier, more sustainable, and prosperous future for everyone.

CHAPTER 7
Conclusion and future work

7.1 Conclusions

This study introduces a novel approach that uses computer vision and Android handsets to detect and assess the quality of fruits in real-time. By using the processing capability and portability of smartphones, the system automates the quality inspection process and incorporates objectivity into quality assessment, thereby mitigating human bias. The portability of smartphones enables the easy implementation of this solution in various environments, hence making it available to a wider variety of users. This extensive study employs deep convolutional neural networks (CNNs) to automate fruit quality evaluations through the application of computer vision techniques. The datasets consisted of 14,400 original fruit photos. To increase the diversity of the datasets, innovative augmentation methods were used, resulting in the generation of several images from each photograph. The study assessed the efficacy of five well-known CNN models—MobileNetV2, ResNet50v2, VGG19, EfficientNetB0, InceptionV3 and DenseNet121 and EfficieintB6 hybrid model in accurately categorizing fruit quality across several classifications. The hybrid model has achieved the highest accuracy of 92.43% but in terms of efficiency the hybrid model required much more computational power and as well more inference time which make it less efficient for mobile devices. On the other hand, EfficientB0 model which is far more superior in terms of efficiency was achieved 92.14% accuracy which is very close to what the hybrid model has achieved. While MobilenetV2 achieved slightly lower accuracy of 91.64% and it is as well very efficient as EfficientNetB0. InceptionV3 was also highly accurate, with accuracy of 90.63%. The accuracy of ResNet50v2 and VGG19 were slightly lower, measuring at 89.19% and 89.62%. So, we can say the EfficientNetB0 is the overall best model in terms of good accuracy and efficiency.

7.2 Further Suggested Works

Future research should focus on enhancing and optimizing the deep learning model to increase its precision and efficiency in automated fruit quality evaluation. This may involve employing several tactics, such as optimizing the model's hyper parameter to capture the intricate nuances in indices of fruit quality more effectively. Investigating different architectures may provide more efficient methods for processing and analyzing visual data, resulting in enhanced model performance.

The enlargement and broadening of the datasets utilized for training and evaluating the algorithms that judge fruit quality are of equal significance. An extensive dataset that includes a diverse range of fruit types, growth conditions, and quality indicators would enhance the creation of more reliable and widely applicable models. To ensure the model's ability to handle numerous scenarios and minimize any biases, it would be necessary to gather data from various geographic regions, climates, and agricultural techniques. The model's effectiveness in different agricultural settings would be greatly enhanced by incorporating a wide range of fruit appearances and conditions. This would result in more dependable and widespread use of automated fruit quality assessment systems.

Moreover, the implementation of additional features, including detailed fruit nutrition values and a voice assistant for visually impaired individuals, can significantly augment the functionality and accessibility of the system. Emphasizing real-time object detection capabilities for assessing fruit quality further underscores the importance of advanced technological integration in modern agriculture. Collectively, these efforts aim to create a comprehensive and sophisticated fruit detection system that addresses the multifaceted needs of contemporary agricultural practices. Additionally, designing a more intuitive and user-friendly interface for the Android application is crucial. Such an interface would enable farmers and agricultural workers to interact effortlessly with the fruit detection system, thereby enhancing usability and adoption.

7.3 Limitations

Despite the potential advancements in fruit detection systems, several limitations must be acknowledged. One significant limitation is the computational demand required for real-time performance on Android devices. Achieving high-speed and accurate detection may necessitate advanced hardware, which could be cost-prohibitive for many farmers, especially in developing regions. Additionally, the continuous expansion of the datasets to include a wider variety of fruits from different regions and seasons presents challenges related to data collection, annotation, and storage. This process is resource-intensive and may not always yield comprehensive coverage due to the vast diversity of fruit species and growing conditions.

Scaling up the fruit detection system for large-scale orchards and agricultural fields introduces further complexities. The variability in environmental conditions, such as lighting and weather, can affect classification accuracy, necessitating robust and adaptable algorithms. Moreover, designing a user-friendly interface for the Android application, while essential, may not fully address the varying levels of technological literacy among farmers and agricultural workers. Ensuring that the technology benefits a broad spectrum of users, rather than primarily serving large agricultural enterprises, is crucial to maintaining ethical standards and promoting inclusive agricultural development.

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Appendix A

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

Title: AUTOMATED FRUIT QUALITY ASSESSMENT THROUGH COMPUTER VISION AND DEEP LEARNING

Students ID: 203-15-14480, 203-15-14476

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**

CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

S N	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References

1.	EP1: Depth of Knowledge required	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting advanced CNN architectures.	**Page no:** [18-24] **Section:** [3.2.3]
				After completing different components types of integration, we will design an android application that covers **K5 and K6**	**Page no:** [25-26] **Section:** [3.2.4]
				We have studied existing works with similar goals which address the knowledge profile **K8**	**Page no:** [6-11] **Section:** [2.2, 2.3]
2.	EP2: Range of Conflicting Requirements	Yes	CO2, and CO7	Despite advancements, challenges remain in the development automated fruit grading systems. Issues such as variability in fruit appearance, environmental conditions, and hardware constraints pose significant hurdles to overcome.	**Page no:** [3] **Section:** [1.5]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	Navigating our project landscape proved challenging, notably due to the scarcity of research on similar fruit quality detection systems utilizing Android phones. With limited prior work to draw upon, we embarked on an extensive analysis to identify and adapt suitable algorithms, aiming to pioneer advancements in this under explored domain.	**Page no:** [35-45] **Section:** [5.2, 5.3]
4.	**EP4: Familiarity of Issues**	Yes	CO3	We encountered a notable gap in research within this domain. Few studies have delved into the intricacies of developing such systems. Particularly, we faced the challenge of determining effective methodologies to measure and assess fruit quality attributes using smartphone technology, requiring innovative approaches and careful consideration of various factors.	**Page no:** [11-12] **Section:** [2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders and involved**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO3	This project comprises several subsystems that depend on each other. These include tasks such as collecting data, processing it, training machine learning models, conducting predictive analysis, and developing a front-end application.	**Page no:** [14-26] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in fruits quality detection through computer vision.	**Page no:** [26,30] **Section:** [3.3, 3.4]

2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by ensuring the delivery of high-quality, disease-free fruits through advanced deep learning detection methods on Android platforms. It promotes environmental sustainability by reducing food waste, optimizing resource usage, and lowering the carbon footprint. By leveraging efficient computational resources and adhering to ethical guidelines, the project supports both consumer health and the economic well-being of farmers.	**Page no:** [48] **Section:** [6.3, 6.4]
5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in fruits quality assessments through computer vision, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [6, 11] **Section:** [2.2, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project meets CO4 by incorporating robust project management and financial oversight strategies. It ensures thorough planning, precise resource allocation, and accurate budget estimation, leading to optimal utilization of resources throughout the research lifecycle.	**Page no:** [26, 30] **Section:** [3.3, 3.4]
2	CO9	Yes	The project upholds ethical principles by ensuring the privacy of data, obtaining necessary consents, and transparently documenting the research process. This approach guarantees responsible dissemination of knowledge and promotes societal well-being through the ethical application of advanced technologies for fruit quality assessment, fully complying with CO9.	**Page no:** [48] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [14-45] **Section:** [3.2, 4.2, 5.2,5.3]

Automated Fruit Quality Assessment

ORIGINALITY REPORT

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