IntelliCART

(AI Enabled Smart Cart)

FYP-1 REPORT

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Abstract

Agriculture supports our fundamental needs for food, fuel and is the cornerstone of human civilization. With innovative technologies and sustainable practices, agriculture can feed a growing global population while preserving the planet for future generations. Agriculture, being a critical sector of the economy, employs almost half of the workforce of a nation. One of the main products in the agriculture industry are the fruits and vegetables. Fruits and vegetables are an essential part of a healthy and balanced diet, and they offer numerous benefits for our overall health and well-being like they are nutrient-rich, have antioxidants, helps in hydration, low in calories, and are versatile. This research proposes the development of real time fruit and vegetable quality assessment named IntelliCART which utilizes Artificial Intelligence, Computer Vision and Deep Learning for accurate and efficient quality assessment of fruits and vegetables. IntelliCART focuses on assessing quality of most common and widely grown fruits and vegetables (Apples, Banana, Oranges, Tomato and Green Chili). The objective of this project is to assess quality of plants and vegetables through image analysis using Computer Vision and Deep Learning. To achieve this goal, we trained and evaluated several models such as MobileNet, Inception-V3, ResNet, AlexNet, VGG-16, VGG-19. After comparing and evaluation of accuracy of models we found MobileNet yielding high precision, achieving accuracy rate of 94.925%. As a result, we integrated into our IntelliCART for quality assessment. IntelliCART will provide vendors and consumers with user friendly interface to capture and analyze images of fruits and vegetables in real time allowing for assessing fruit and vegetable quality. With this application seller can increase their sales, gain customer loyalty and customers can easily access to healthy fruits and vegetables with satisfaction. To achieve this, implemented state of art deep learning models.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

1. Background

The modern agricultural industry has evolved remarkably with technological advancements. This leads to growing interest in using computer vision and deep learning techniques to various aspects of agriculture such as farming and supple chain. Fruits contain vitamins and dietary 3bers, a vital source of the human die [1]. The quality assessment of fruits and vegetables results a critical factor for both seller and customers. Traditionally the assessment of fruits and vegetable quality heavily relies on experienced manual labor inspection which is time consuming, subjective, and often prone to errors. This way of assessment also results in maintaining consistency, and scalability especially in large scale operations. The emergence of innovative technologies particularly in field of Artificial Intelligence, Machine Learning, and Computer Vision has introduced a way of to revolutionize the assessment of fruits and vegetables. This offer potential to automate and streamline the assessment process, ensuring high accuracy, and scalability.

2. Importance of Fruit Quality Assessment

In today's marketplace, the fruits and vegetable quality assessment holds immense importance across various domains including customer satisfaction and preferences, ensuring food safety and health, and impacting economy significantly.

2.1 Consumer Preferences and Expectations

Consumer expects fresh, visual appealing, best quality fruits and vegetable when making their purchases. Thus quality assessment plays an important role in meeting these expectations as it provides consumer with satisfaction regarding overall condition of fruits and vegetables. The quality of fruits and vegetable impact consumer perception of values. Fruits and vegetable that are fresh and have high quality tend to fetch better prices and are preferred by customers resulting in increased sales and customer satisfaction. Delivery of high quality fresh produce results in customer loyalty and repeat business. When customers trust the quality of fruits and vegetable purchased they more likely to return to same seller.

2.2 Impact on Food Safety and Healthy

Fresh and high quality fruits and vegetables holds more nutrients contributing to better health outcomes. Poor quality, contaminated or spoiled poses great risk and threat to health of customers. Effective high quality assessment helps in segregating such risks. Thus results in safety from risks caused by consuming low quality fruits and vegetables.

2.3 Economic Significance

High quality fruits and vegetables results in better marketability and prices. Venders selling high quality fruits and vegetable attract more customers and can sell them at good rates resulting in good revenue. Effective quality assessment contributes to more efficient supply chain. By accurately assessing quality it can streamline distribution, reduce inventory holding costs and ensures quality items reach the consumer. Improved quality assessment practices lead to more feasible agriculture practices, improved profitability for sellers and better resource utilization.

3. Challenges in Fruit Quality Assessment

The assessment of fruits and vegetable quality presents several challenges impacting the efficiency and accuracy of evaluation. These challenges include subjectivity in assessment, time consuming and labor intensive highlighting the importance for more objective and efficient solutions.

3.1 Subjectivity and Variability

Traditional methods of fruit and vegetable quality assessment relied on human assessment which is subjective. Difference individual may have different judgement and assess quality differently resulting inconsistent grading and classification. Standards of assessing quality can differ across regions, markets and cities. This difference complicates standardization of assessment criteria and results variation in quality evaluation. Fruits and vegetable have natural variation in color, size texture and other attributes making it challenging for establishing standardized criteria for quality assessment.

3.2 Time and Labor Intensive

Traditional methods involve manual inspection which is time consuming and requires more workforce for large scale operations. This involve sorting, grading each fruit individually leading to time wastage, labor costs and operational difficulties. In areas such as markets the manual assessment of large quantity of fruits and vegetable becomes impractical and not efficient resulting in bottlenecks and delays.

3.3 Need for Objective and Efficient Solutions

With increased demand for high quality fruits and vegetables there is need for standardized methods that can ensure unanimous quality assessment across different markets. The market demands real time evaluation of quality of fruits and vegetable minimize delays in distribution and ensure fresh fruits and vegetables reaching consumers. Manual methods fall short in meeting these demands. Using technological advancement such as machine learning, artificial intelligence and computer vision can result in promising solutions for efficient and automated quality assessment These technologies have potential to standardized assessment criteria and reduce human subjectivity.

4. Role of Computer Vision and Deep Learning

In agriculture sector the integration of computer vision and deep learning technologies provide transformative solution for fruits and vegetable quality assessment. These technologies provide approach for automation, precision, improved efficiency and accuracy resulting in showing immense potential for integration with industry. The latest advanced computer vision technology with the utilization of deep neural networks can be used for object discovery and semantic picture division [2].

4.1 Automation and Precision

Computer vision provides a way to automate analysis of images of fruits and vegetables allowing for processing large quantity. From that algorithms can identify and extract relevant features such as color, texture, size and defects without human input. By using defined algorithms and computer vision systems we can facilitate standardized evaluation methods minimizing subjectivity. Deep learning models trained on extensive dataset can accurately classify fruits and vegetables based on quality parameters. These models can differentiate between differences in quality such as ripeness, blotch or bruised with high accuracy.

4.2 Enhancing Efficiency and Accuracy

Computer vision system equipped with deep learning models can process images at high speed reducing time for quality assessment. Rapid processing enhances efficiency of assessment process. Deep learning models continuously learn and adapt on data leading to improved accuracy over time. As these models are trained on diverse dataset they can accurately identify and classify a wide range of quality parameters that cannot be done through human capabilities.

4.3 Potential for Industry Integration

Integrating computer vision system into fruits and vegetables supply chain can optimize various stages from production to distribution. Real time quality assessment allows timely assessing quality and ensuring delivery of high quality fruits and vegetables to customers. Beyond traditional markets computer vision and deep learning find application in different sectors including precision agriculture, food processing industries and online retail. These technologies enable quality assessment resulting evolving consumer demands,

5. Objectives

- To identify quality of fruits and vegetables through image analysis using computer vision and deep learning
- To train and evaluate certain models i.e. MobileNet, Inception-V3, ResNet152, AlexNet, VGG-16, VGG-19 for fruit and vegetable classification
- To compare and evaluate the performance of each deep learning models across various classes of fruits and vegetables (Apple, Banana, Orange, Tomato, Green Chili) to determine their effectiveness in quality assessment based of defined metrics accuracy, recall and precision.
- To integrate the most effective model into our IntelliCART application for quality assessment of fruits and vegetables.
- To provide a user friendly and efficient solution for real time quality assessment ultimately leading to increased sales of vendors, increase customer satisfaction and loyalty and improved economic benefits in agriculture industry.

RELATED WORK

The state of the art in agriculture, and more specifically, the field of fruit and vegetable quality assessment, is presented in this chapter:

This paper [3] implements an automatic classi3cation and detection of fruits using neural network approaches. This system can be used for children for educational purposes, industries and supermarkets and for people to know different fruits for learning purposes. the primary contributions of this work are described as follows: (i) Automatic fruit detection and classi3cation system have been developed by using two datasets, i.e., open-source FIDS-30 of 30 classes and collected custom dataset of eight categories of fruits. (ii) For classi3cation, we used VGG16 and ResNet50 neural network models. YOLOv3 and YOLOv7, deep learning frameworks, have been employed to detect multiple fruits in the image. (iii) The domain adaptation technique is applied so that the proposed deep learning-based fruit classi3cation model can cope with real-world problems of diverse domains. Using this method, different sets of images of various fruits were used to train and test the proposed model. (iv) The web framework of the proposed automatic fruit classi3cation and detection system is created with the help of a flask. (v) A Python-based API has been utilized to develop an Android smartphone application, which uses the phone's camera for instantaneous detection and recognition of fruits.

This study presents a deep-learning system for multiclass fruit and vegetable categorization based on an improved YOLOv4 model that first recognizes the object type in an image before classifying it into one of two categories: fresh or rotten. The proposed system involves the development of an optimized YOLOv4 model, creating an image dataset of fruits and vegetables, data argumentation, and performance evaluation. Furthermore, the backbone of the proposed model was enhanced using the Mish activation function for more precise and rapid detection. Compared with the previous YOLO series, a complete experimental evaluation of the proposed method can obtain a higher average precision than the original YOLOv4 and YOLOv3 with 50.4%, 49.3%, and 41.7%, respectively [4]. The proposed system has outstanding prospects for the construction of an autonomous and real-time fruit and vegetable classification system for the food industry and marketplaces and can also help visually impaired people to choose fresh food and avoid food poisoning.

This paper is focused on improving the accuracy of the automatic mango grading system by doing multi-level grading using Deep Learning, Computer Vision and Image processing techniques [5]. The proposed system is based on the mango maturity ripening stage, shape, texture features, colour and defects to identify the mango variety and classify based on quality. The maturity ripening stage of the mango is extracted using the Convolutional Neural Network (CNN). Computer Vision and Image processing techniques are used to extract shape, texture features and defects. The extracted features are input to the Random Forest classifier to identify the mango variety and grade the mango quality into three classes Notfit, Average and Good. The system has been validated on the dataset created for this study across three different varieties, Banganapalli, Neelam and Rumani, the most popular in Tamil Nadu. The proposed system using features extracted from CNN enhanced the system's efficiency with an accuracy of 93.23% for variety recognition and 95.11% for quality grading. Hence the proposed system is fully automated, commercially viable and has improved accuracy in variety recognition and quality grading of mangoes across different varieties.

Kamble, P. R. et al. (2020) used CNN to identify if the fruit is raw or ripe from the fruit image [6]. The authors did it for three different types of fruits mango, banana and apple, using a pre-trained network like VGG16. They achieved 92% accuracy in classifying mango fruit as raw or ripe. Srinivasan, D. and Yousef, M. (2020), using the pre-trained ReNnet-50 CNN model, could classify if the apple fruit is fresh or rotten with about 97.92% accuracy [7]. The authors used 5031 images for classification, with 2088 images for fresh apples and 2943 for rotten apples.

In this paper, [8] a novel deep learning-based architecture Fruit-CNN has been proposed to identify the type of fruit and their quality assessment of real world images in multiple visual variations which achieves a test accuracy of 99.6%. The proposed architecture takes minimal time to train the large dataset and test fruit images in comparison with state-of-the-art deep learning models which proves its wide applicability in precision agriculture. More images belonging to various classes can also be trained with fewer parameters which result in fast training of models and less processing time.

In recent work, early and late fusion methods were investigated in the development of the multi-model Faster RCNN method for fruit detection utilizing RGB and near infrared images [9]. In another work, M. Afonso et al. used Intel RealSense cameras to demonstrate a Mask-RCNN-based deep learning approach for tomato fruit detection and their counting in production greenhouse [10]. With practical implementation of detection mechanism, a Faster R-CNN based object identification framework was applied for fruit detection in orchards, including apples, almonds, and mangoes [11]. A model with ResNet-101 as the backbone which performed semantic segmentation on apple and apple branches obtained an accuracy of 77.2% [12]. Other methods either use basic computer vision techniques, like colour-based segmentation, or sensors such as hyperspectral, 3D or LWIR etc.

In a recently published study, Wu et al. [13] took a modified AlexNet model with an 11-layers structure, aiming to identify and detect defects in apples. Furthermore, as a comparison of the classification, they use three known algorithms—backpropagation neural networks (BP), particle swarm optimization (PSO), and support vector machine (SVM). The dataset consists of laser-induced backscatter images (i.e., speckle images of 5472 × 3648 pixels), where the acquisition process is carried out with a laser system with a beam expander, a complementary metal-oxide-semiconductor (CMOS) color camera with a zoom lens, and a polarizer. The dataset has a total of 500 apple samples of about a similar size (equatorial diameter 80–100 mm). The proposed CNN model for apple detection achieves a recognition rate of 92.50%, which is higher than other algorithms commonly used, such as BP, SVM, and PSO algorithm.

Hou et al. [14] proposed the VegFru dataset for fine-grained visual categorization (FGVC). VegFru is a domain-specific dataset that covers 25 upper-level categories and 292 subordinate classes of vegetables and fruits, containing more than 160,000 images. Moreover, they presented a framework called HybridNet comprised of two DCNNs for separate classification by exploiting the label hierarchy of the FGVC. They compare HybridNet, with VGGNet and CBP-CNN, for 292, 100, and 200 sub-classes of VegFru Dataset. The accuracy of HybridNet was better in all tests: VGGNet 77.12%–84.46%–72.32%, CBP-CNN 82.21%–87.49%–84.91%, and HybridNet 83.51%–88.84%–85.78%.

Manali R. Satpute and Sumati M. Jagdale (2016) Built a system for Defect detection in tomato based on the automatic fruit quality inspection system for detection of defected tomato and sorting and grading of tomato. In First step they have segment the tomato, segmentation based on OTSU algorithm. After segment the tomato, next step is extract the feature. Author use two feature extraction algorithms size detection and colour detection. Dilation and Erosion (Morphological operation), use for size detection. After that shape feature are used for size detection like small, medium and large. Colour detection based on Red, green and yellow tomato use for sorting the tomato. [15]

In this work, [16] they have exploited the concept of Densely Connected Convolutional Neural Networks (DenseNets) for fruit quality assessment. The feature propagation towards the deeper layers has enabled the network to tackle the vanishing gradient problems and ensured the reuse of features to learn meaningful insights. Evaluating on a dataset of 19,526 images containing six fruits having three quality grades for each, the proposed pipeline achieved a remarkable accuracy of 99.67%. The robustness of the model was further tested for fruit classification and quality assessment tasks where the model produced a similar performance, which makes it suitable for real-life applications.

In this paper, [17] they utilize the concept of transfer learning in fruits and vegetable quality assessment. The transfer learning concept applies the idea of reuse the pre-trained Convolutional Neural Network to solve a new problem without the need for large-scale datasets for training. Eight pre-trained deep learning models namely AlexNet, GoogleNet, ResNet18, ResNet50, ResNet101, Vgg16, Vgg19, and NasNetMobile are fine-tuned accordingly to evaluate the quality of fruits and vegetable. To evaluate the training and validation performance of each fine-tuned model, we collect a dataset consists of images from 12 fruits and vegetable samples. The dataset builds over five weeks. For every week 70 images collected therefore the total number of images over five weeks is 350 and the total number of images in the dataset is (12*350) 4200 images. The overall number of classes in the dataset is (12*5) 60 classes. The evaluation of the models was conducted based on this dataset and also based on an augmented version. The model's outcome shows that the Vgg19 model achieved the highest validation accuracy over the original dataset with 91.50% accuracy and the ResNet18 model scored the highest validation accuracy based on the augmented dataset with 91.37% accuracy.

Table 1 Overview of most important Papers

Published in year	Classes	Method	Features	Classifiers
2022	123 different classes	Object Detection using Deep Learning	Data Pre-processing and augmentation	U-Net ResNet VGG19
2022	6 Fruits and 6 Vegetables	Object Detection	Grids, Blocks, Union Over Intersection (IOU)	YOLOv4 - tiny
2022	Total 30 fruit classes	Convolutional Neural Networks	Object isolation, bounding boxes, feature vectors	ResNet50 VGG16 YOLOv3
2022	Apple, Banana, Guava, Lime, Orange, Pomegranate	Convolutional Neural Networks	Class Activation Map (CAM), texture and color	DenseNet
2021	Fig Fruit	Deep Learning and Object Detection	Colored bounding boxes, confidence threshold	Faster R-CNN YOLOv3 YOLOv4
IRJET 2021	Apple, banana, Mango Disease	K-means clustering technique to cluster the images	color, morphology, Color Coherence Vector (CCV)	Support Vector Machine (SVM).
ICIRCA 2020	Banana disease	identifying diseases in banana plants at an earlier stage to protect neighboring plants from the same diseases.	Feature extraction is primarily dependent on pattern recognition.	Artificial Neural Network (ANN)
2016	3 classes (background, sweet pepper, rock melon)	Deep Convolutional Neural Networks, Object Detection	RGB Colors, Near Infrared (NIR) images, bounding boxes	Faster R-CNN

METHODOLOGY

The methodology of project involved obtaining a dataset of fruit and vegetables and preprocessing the images to a size of 256x256 pixels. We then trained Six different models MobileNet, Inception-V3, ResNet152, AlexNet, VGG-16, VGG-19) on the preprocessed data to classify fruits and vegetables quality. Assessed each model's performance by calculating measures such as accuracy, precision, recall, and F1 score. Based on the results, selected the top performing model for further analysis.

To perform fruit and vegetable quality assessment, we trained a YOLOv8 model on the fruit and vegetables dataset. The trained model was used to detect the fruits and vegetable quality. Finally, integration all the results done and app will be developed for customers and seller to upload an image or get real time quality of fruits and vegetable. The app used the trained model for classification and quality assessment and displayed the results to the user in a most user friendly way.

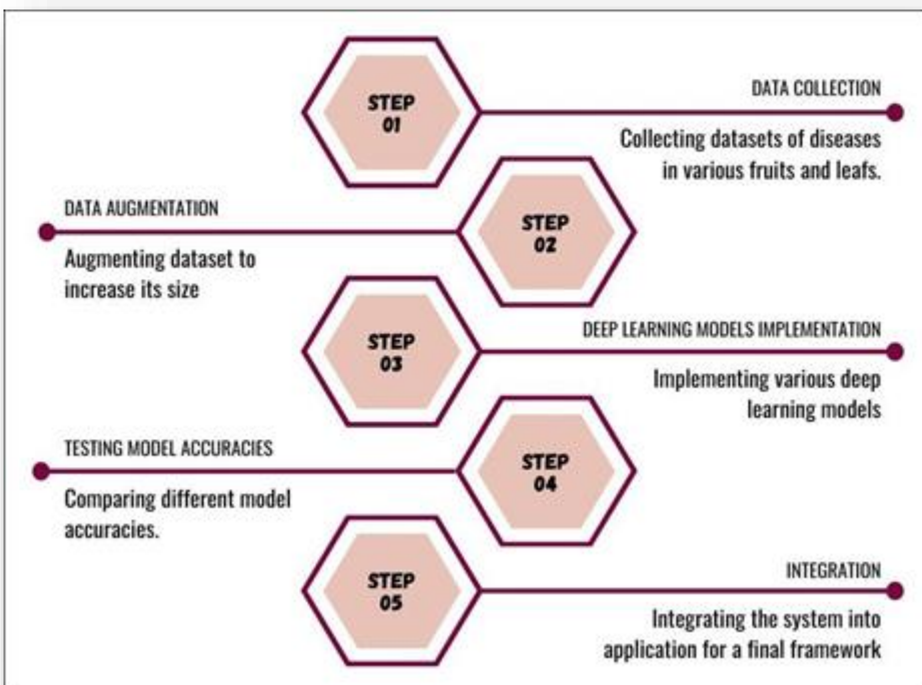


Figure 1 Overview of Methodology

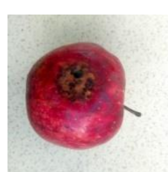
1. Dataset Collection

The dataset comprises 10155 images of fruits and vegetables (Apples, Banana, Oranges, Tomato and Green Chili). Some images were taken from online sources while other are taking by going on dataset drives using mobile camera. All images had resolution of 256x256 pixels and were divided into test and train folders.

The dataset contains 19 classes which are used to classify fruits and vegetable quality. Common quality like blotch, scab, rotten, greening and many more as mentioned in below table were included in classes. The images were preprocessed before training to optimize results and ensure consistency and performance

Table 2 Fruits and Vegetable quality division in 19 classes

FRUITS AND VEGETABLES	**CLASSES**
Apple	Apple Blotch Apple Healthy Apple Scab Apple Rotten
Banana	Banana Heavily Bruised Banana Slightly Bruised Banana Firm
Orange	Orange Greening Orange Healthy Orange Rotten
Tomato	Tomato Damaged Tomato Old Tomato Ripe Tomato Unripe
Green Chili	Green Chili Damaged Green Chili Dried Green Chili Ripe Green Chili Unripe Green Chili Old

CLASS	**QUANTITY**	**SNAPSHOTS**			
Apple Blotch	Train (284) Test (64)				

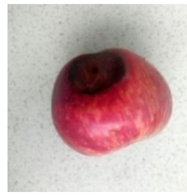
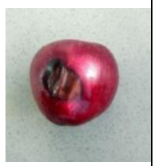
Apple Scab	Train (180) Test (42)				
Apple Rotten	Train (641) Test (136)				
Apple Healthy	Train (515) Test (137)				

Figure 2 Apple Dataset

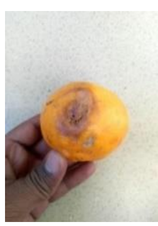
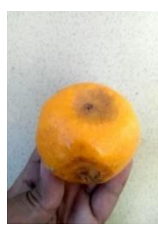
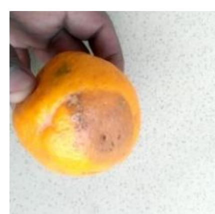
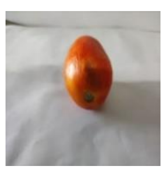
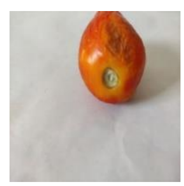
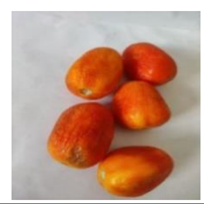
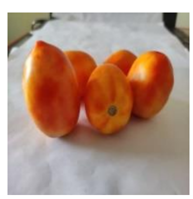
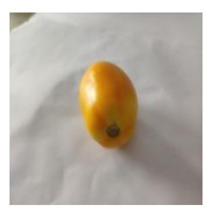
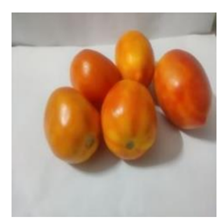
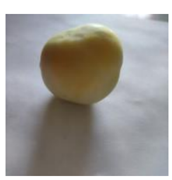
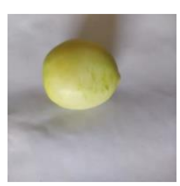
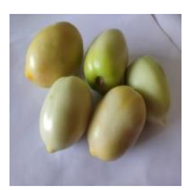
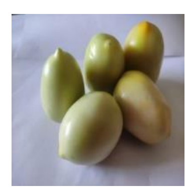
CLASS	QUANTITY	SNAPSHOTS			
Orange Healthy	Train (257) Test (71)				
Orange Rotten	Train (977) Test (247)				
Orange Greening	Train (573) Test (136)				

Figure 3 Orange Dataset

CLASS	QUANTITY	SNAPSHOTS			
Banana Firm	Train (588) Test (148)				
Banana Slightly Bruised	Train (634) Test (159)				
Banana Heavily Bruised	Train (542) Test (136)				

Figure 4 Banana Dataset

CLASS	QUANTITY	SNAPSHOT			
Tomato Damaged	Train (23) Test (4)				
Tomato Ripe	Train (765) Test (190)				
Tomato Unripe	Train (116) Test (29)				

Tomato Old	Train (987) Test (247)				

Figure 5 Tomato Dataset

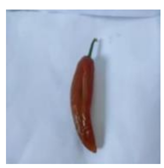
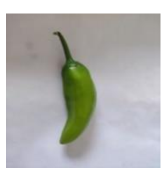
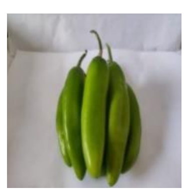
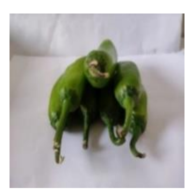
CLASS	QUANTITY	SNAPSHOTS			
Green Chili Damaged	Train (111) Test (27)				
Green Chili Dried	Train (400) Test (100)				
Green Chili Old	Train (209) Test (52)				
Green Chili Ripe	Train (161) Test (40)				
Green Chili Unripe	Train (182) Test (45)				

Figure 6 Green Chili Dataset

2. Dataset Preprocessing

We preprocessed the data to make sure it was in a format that the models could use for learning before we trained them. The photos underwent resizing to a standard 224x224 pixel size, grayscale conversion, and normalization of pixel values. In order to increase data diversity and decrease overfitting, we also employed data augmentation techniques like rotation, flipping, and zooming.

Next, we used an 80:20 ratios to split the data into training and testing sets. The models were trained on the training set; the models' performance during training was assessed on the validation set, and the top-performing model was selected for further examination.

In this project, data preprocessing was essential because it made sure the models were trained on high quality data for classifying quality of fruits and vegetables.

3. Deep Learning Models

Most of these automatic fruit classi3cation works used a wide range of deep learning-based neural network frameworks. For instance, in a recent work [18], the authors designed an automatic model to recognize vegetables by image processing and computer vision approaches. First, the authors compare 24 different types of vegetables in the dataset by using pictures. First, the authors trained the, and then, preprocessed the images by resizing and normalizing. Next, they implemented the convolutional neural network (CNN) [19] learning model. Any deep learning project must include the critical step of model selection as it directly affects the model's performance and accuracy. Using a preprocessed dataset of pictures of fruit and vegetables, we trained six different models in this study—AlexNet, VGG-16, VGG-19, Mobile Net, and Inception-V3, ResNet152—to classify various fruit and vegetable quality. We evaluated the performance of each model by computing metrics including F1 score, accuracy, precision, and recall. We selected the best-performing model for additional research based on the findings. After weighing the trade-off between computational efficiency and accuracy, as well as the model's ability to successfully generalize on unobserved data, a decision was made. To verify our findings, we also performed a comparison study between the chosen model and earlier research.

3.1 MobileNet

MobileNet is a small neural network architecture designed for efficient processing on mobile and embedded devices. To reduce the number of parameters and calculations required during training and inference, it employs depth-wise separable convolutions. The MobileNet architecture is made up of convolutional layers, pointwise convolutional layers, a global average pooling layer, and a fully connected layer. The architecture was designed with minimal latency, small size, and low power consumption in mind.

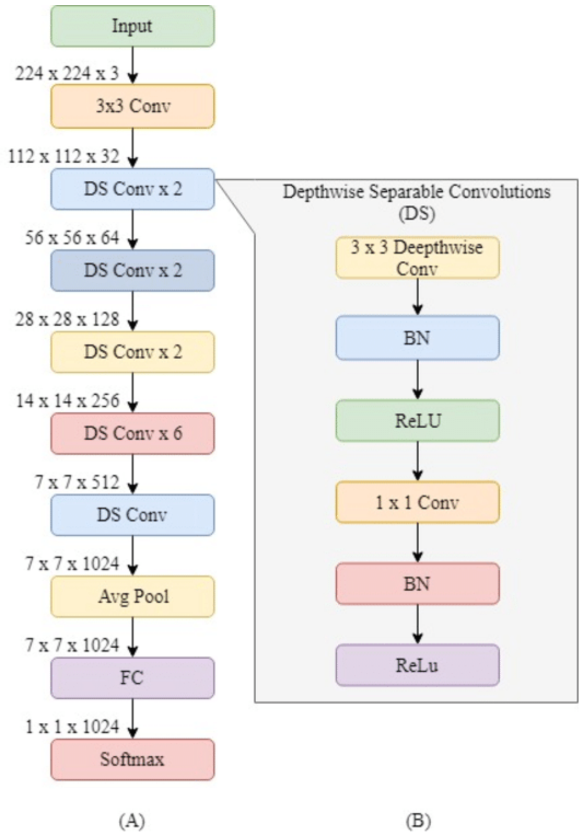


Figure 7 MobileNet Architecture

3.2 Inception V3

Inception-V3 is a deep convolutional neural network architecture introduced in 2015. It is a highly accurate and efficient image classification model that has found widespread application in a variety of computer vision tasks. Inception-V3's architecture is made up of many convolutional layers, pooling layers, and fully linked layers. The model is trained using a large dataset of labeled images to learn the key features of different objects and patterns. Inception-V3 uses a technique called "factorized convolution" which reduces the computational cost and improves the efficiency of the model.

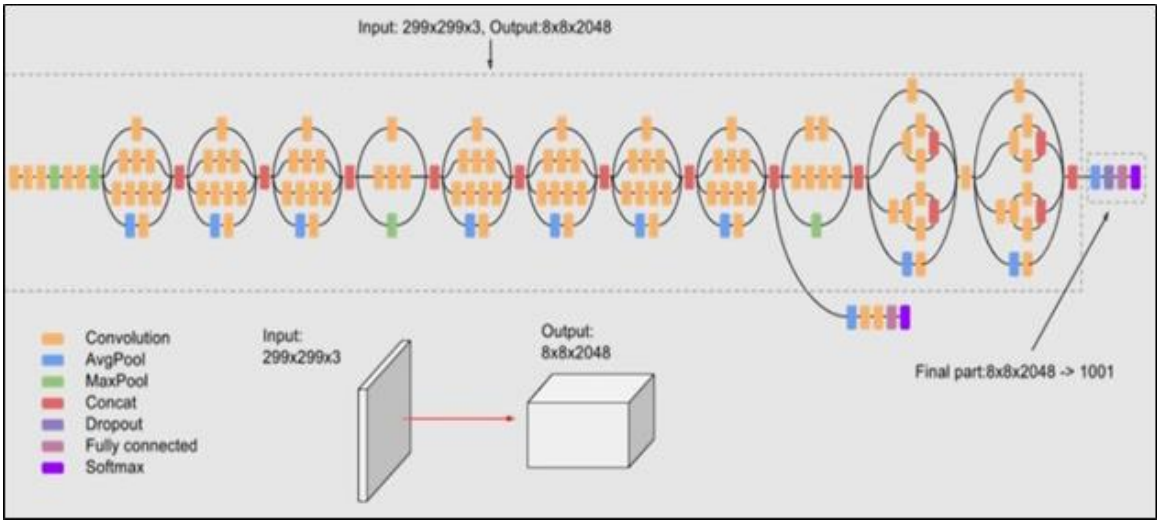


Figure 8 Inception V3 Architecture

3.3 VGG-16

The VGG-16 is a sixteen-layer convolutional neural network model. The architecture of VGG-16 includes several convolutional layers with 3x3 filters, followed by max pooling layers. The model also includes fully connected layers towards the end. This architecture is deeper than some of the earlier models, such as AlexNet, and has shown to perform well in various image classification tasks.

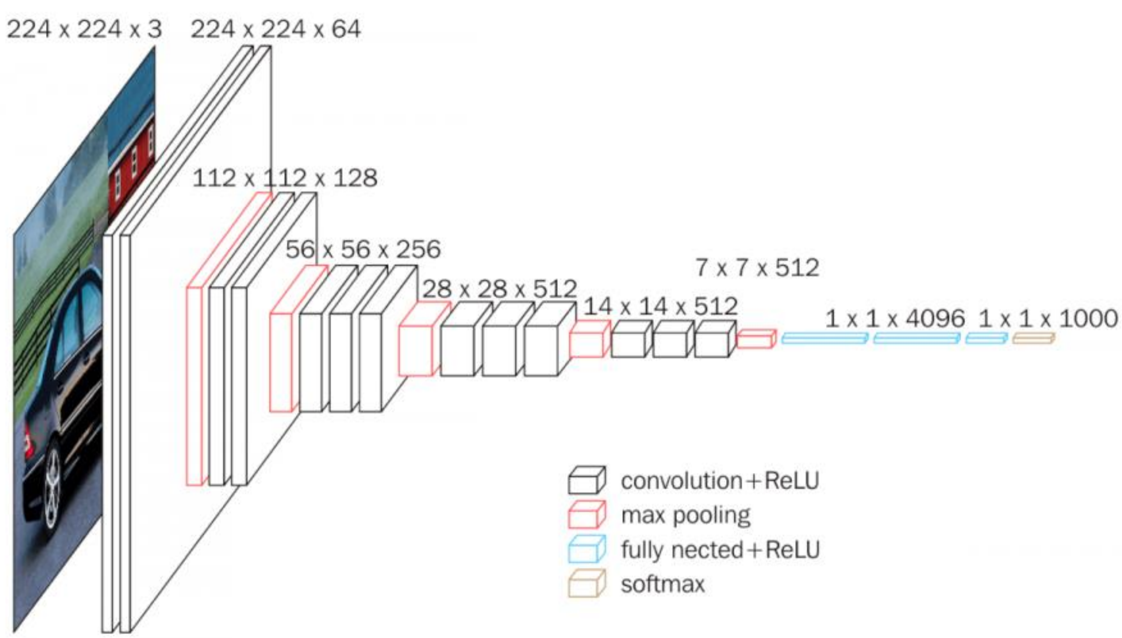


Figure 9 VGG-16 Architecture

3.4 VGG-19

The VGG-19 deep convolutional neural network architecture was created by the Visual Geometry Group (VGG) at the University of Oxford. It is made up of nineteen convolutional and pooling layers, which are followed by three fully linked layers. VGG-19 has a simple and uniform architecture, with small convolutional filters (3x3) used throughout the network, and pooling layers applied after every two convolutional layers.

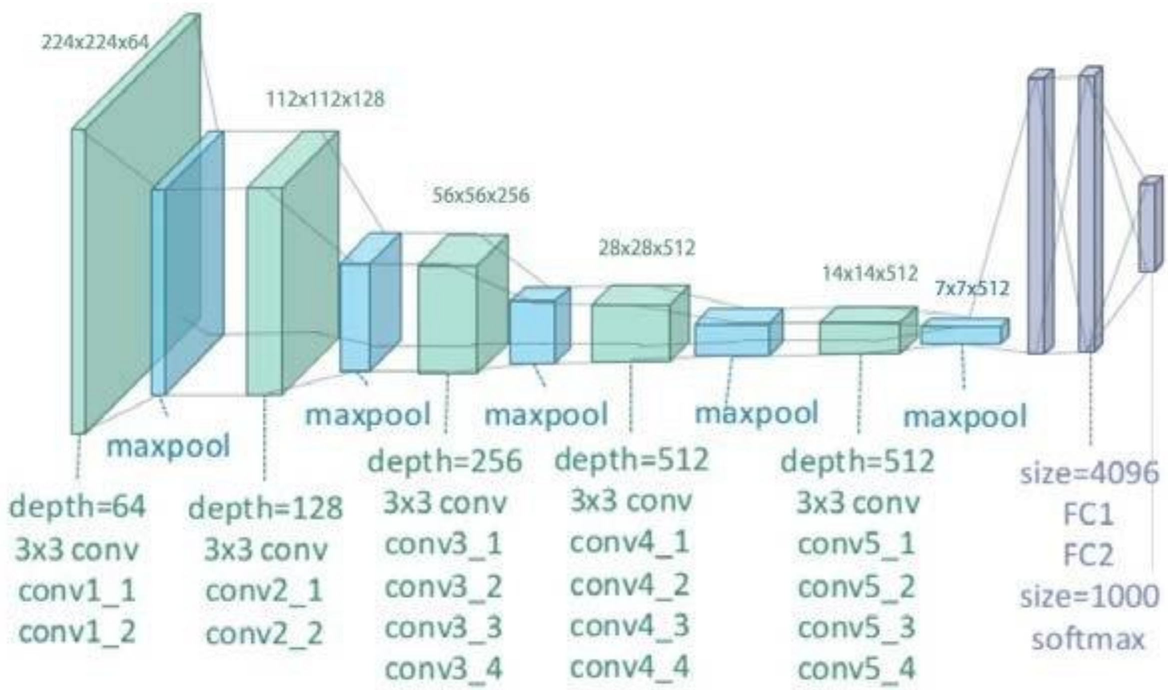


Figure 10 VGG-19 Architecture

3.5 AlexNet

AlexNet is a convolutional neural network (CNN) architecture that Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton proposed in 2012. AlexNet's design is built on an eight-layer deep CNN (convolutional neural network). The first five layers are convolutional layers, with three fully linked layers following. To maintain the spatial dimensions of the input, the convolutional layers use tiny filters (11x11, 5x5, and 3x3) with a stride of four pixels and zero-padding. Each convolutional layer's output is routed through a ReLU activation function, which introduces nonlinearity into the model.

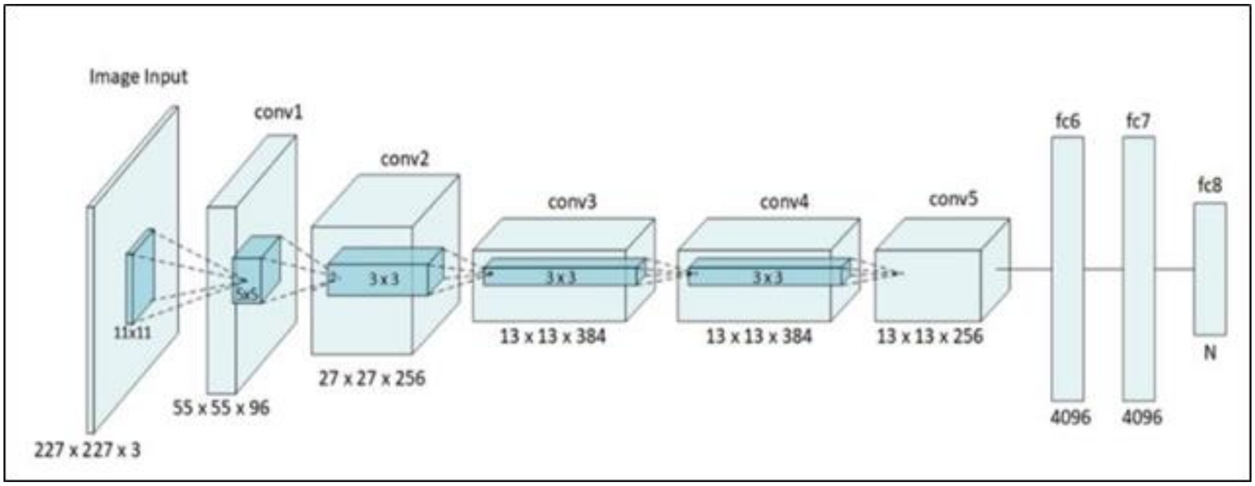


Figure 11 AlexNet Architecture

3.6 ResNet152

To enhance the accuracy for quality assessment of fruits and vegetables, we used ResNet152 system, that is known for its unique function ResNet, short for Residual Network, introduced a revolutionary concept of residual learning. Unlike traditional neural networks where each layer learns how to directly map input to output, ResNet includes residual blocks, in order to form shortcuts or skip joins These connections enable the network to learn residual tasks, making it easier to very deep networks will be trained without risk of gradient extinction occurring. ResNet152, in particular, has 152 layers, each of which occurs on top of the residual block structure. The ability of this algorithm to capture complexity at different layers played an important role in the skill of our model. Skip connections reduce the complexity associated with training deep connections, making ResNet152 a unique and highly efficient choice for complex image classification tasks such as fruit and vegetable quality assessment.

ResNet152 showed promising results in our use case. Model was trained with a validation accuracy of 93.93%, while training accuracy was 98.74%.

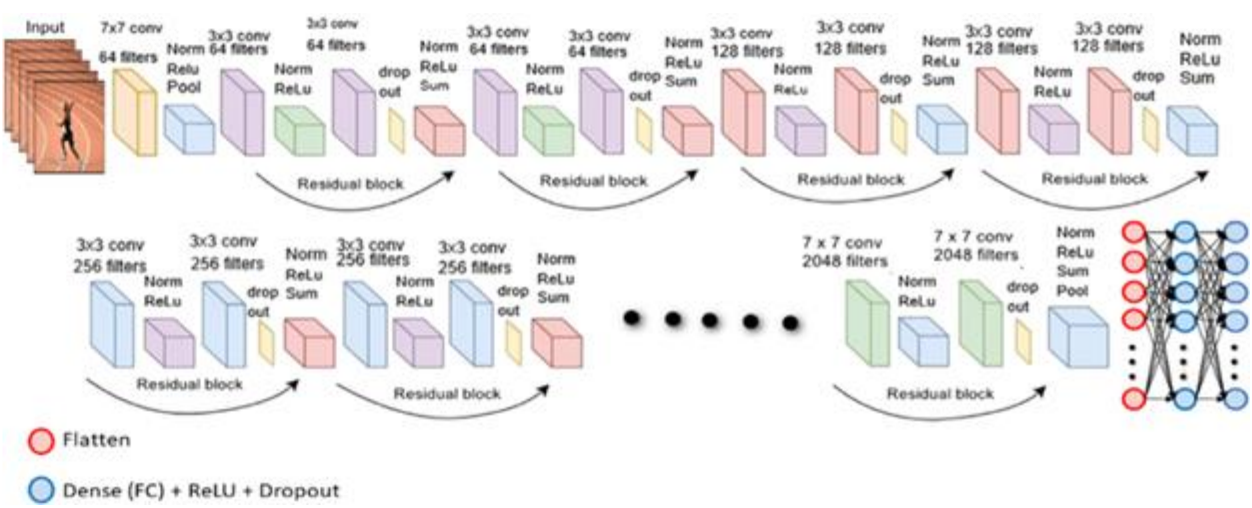


Figure 12 ResNet Architecture

4. Selecting Best Model

Once, we had trained and tested all above mentioned six well known Neural Network models (AlexNet, MobileNet, VGG1, VGG19, Inception V3, ResNet 152) on our preprocessed dataset of fruits and vegetables' images, next step was to analyze and compare the results acquired from these models and choose the best model for our use case. The selection criteria for the best model were based on a tradeoff between accuracy and performance. We aimed to choose a model that was accurate in classifying the fruits based on their quality, but also efficient and fast.

After assessing various evaluation metrics, it became evident that MobileNet surpassed other models in terms of both accuracy and performance. Its superiority is attributed to a smaller parameter count and optimization for mobile device usage, resulting in enhanced speed and efficiency. MobileNet achieved an impressive accuracy of 94.93% and a macro F1 score of 0.91, the highest among the models under consideration. With a 28-layer architecture utilizing depth wise convolution for efficient computation and parameter reduction, MobileNet strikes a commendable balance between model accuracy and computational efficiency.

The architecture of MobileNet employs depth wise convolution, a two-step process:

1. **Depth wise Convolution:** This step involves convolving the input volume with a distinct filter for each input channel. Each input channel undergoes independent convolution, yielding feature maps with the same number of channels as the input.
2. **Pointwise Convolution:** Following depth wise convolution, a 1x1 convolution with a set of filters is applied to the output. Pointwise convolution facilitates the mixing and combination of features from different channels, enabling the network to learn intricate interactions between features.

Further scrutiny involved calculating Inter-Quartile Ranges (IQR) for all models based on True Positive Rates (TPR), False Positive Rates (FPR), True Negative Rates (TNR), and False Negative Rates (FNR). MobileNet exhibited the highest TPR and TNR, approaching 1, while maintaining the lowest FPR and FNR, close to 0, outperforming other models.

Table 3 MobileNet IQR Analysis

TPR average	0.9058942945130736
FPR average	0.002858193302300445
TNR average	0.9971418066976995
FNR average	0.0941057054869264

In-depth examination of confusion matrices reinforced the indication that MobileNet excels in classification tasks, solidifying its selection as the optimal model for fruit disease classification. This choice is deemed suitable for real-world applications where both speed and precision are pivotal considerations.

Table 4 Deep Learning Models Used and Their Configuration

Model	Number of Layers	Input Image Size	Activation Function	Convolutional Layers	Pooling Layers	Fully Connected Layers
MobileNet	88	224*224	softmax	multiple	multiple	1
VGG-16	16	224*224	softmax	13	5	3
VGG-19	19	224*224	softmax	16	5	3
InceptionV3	159	224*224	softmax	multiple	2 max-pooling layers, 11 inception modules, 1 average pooling layer	2
AlexNet	8	224*224	softmax	5	3	3
ResNet 152	152	224*224	softmax	151	3	1

5. Object Detection

Following the training and evaluation of the deep learning classification models, we trained a highly efficient YOLOv8 model to perform real time object detection of the fruits and vegetables. YOLOv8 model was employed to precisely identify and classify the fruits and vegetables based on their quality classes. YOLOv8 is a popular object detection model that is widely used in computer vision applications. Since it is highly precise and computationally efficient, it is appropriate for real-time applications. We specifically chose YOLOv8 because it has an overall improved accuracy and higher speed than its predecessors. YOLOv8 is an open source model designed by ultralytics, hence it is easily customizable.

To train this object detection model, whole data was annotated by precisely creating bounding boxes around each instance. Then the images were scaled to 640x640 pixel size to make it easily usable input for YOLOv8. Keeping the high performance of YOLOv8 in consideration, we kept the number of epochs minimum to keep it least resource intensive, thus at last 20 epochs were set to be optimal.

Finally, we obtained following results:

(Specially mAP50 i.e. mean Average Precision with IoU threshold at 0.50, obtained was 0.955 after 20 epochs).

```
                 all       1419       1984      0.872      0.892      0.922      0.784

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      20/20      7.18G     0.5041     0.3682      1.011         21        640: 100% 311/311 [03:02<00:00,  1.70it/s]
               Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 45/45 [00:32<00:00,  1.39it/s]
                 all       1419       1984      0.889      0.892      0.929       0.79

20 epochs completed in 1.284 hours.
Optimizer stripped from runs/detect/train/weights/last.pt, 52.0MB
Optimizer stripped from runs/detect/train/weights/best.pt, 52.0MB

Validating runs/detect/train/weights/best.pt...
Ultralytics YOLOv8.0.221 🚀 Python-3.10.12 torch-2.1.0+cu118 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 218 layers, 25849024 parameters, 0 gradients, 78.7 GFLOPs
               Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 45/45 [00:35<00:00,  1.28it/s]
                 all       1419       1984      0.889      0.892      0.929      0.789
        apple_blotch       1419         72      0.824      0.722      0.853      0.804
       apple_healthy       1419        135      0.834      0.891      0.923      0.883
        apple_rotten       1419        158      0.979      0.981      0.993      0.949
          apple_scab       1419         50      0.989       0.98      0.994       0.94
         banana_firm       1419         80      0.854      0.804      0.892      0.591
 banana_heavilybruised     1419        207      0.902      0.843       0.94      0.672
banana_slightlybruised     1419         61      0.738      0.785       0.78      0.536
   greenchilli_damaged     1419         24      0.952      0.832      0.917      0.666
      greenchilli_ripe     1419         96      0.917      0.927      0.967      0.703
       orange_greening     1419        219      0.904       0.95      0.981      0.876
        orange_healthy     1419        156      0.757      0.942       0.94      0.864
         orange_rotten     1419        295      0.935      0.971      0.986      0.947
        tomato_damaged     1419         25          1      0.752       0.85      0.744
          tomato_old       1419        110      0.746      0.982      0.928       0.84
         tomato_ripe       1419        209      0.914      0.914      0.931      0.816
       tomato_unripe       1419         87      0.983          1      0.984      0.797
Speed: 0.2ms preprocess, 9.4ms inference, 0.0ms loss, 1.7ms postprocess per image
Results saved to runs/detect/train
```

Figure 13 Results of training YOLOv8 Model on the dataset consisting of apple, oranges, Tomato, Green Chili and bananas comprising of 19 classes.

This trained YOLOv8 model was also tested using real time camera to identify and classify the fruits and vegetables based on their quality. Thus this would be used in a camera mounted on the fruit and vegetables' cart and would be integrated in a mobile application to help fruit vendors and customers to provide a transparent and smooth selling and buying experience.

Table 5 Initialization Parameters for YOLOv8

Hyper-Parameters	***Value***
Epochs	20
Warm-up bias learning rate	0.1
Batch size	16
Input Image size	640
Weight Decay	0.0005
Momentum	0.937

5.1 Bounded Boxes:

A bounding box is a graphical representation of the position of an object in an image. Each image's bounding box includes the ascribes listed below.

1. Dimensions

2. Measurements
3. Class (rotten_apple, bruised_banana, fresh_oranges, etc.).

Figure 14 Bounded Box Example

TESTING AND RESULTS

1. Deep Learning Models Results

The project's results revealed that MobileNet had the highest accuracy among the six models tested, with an overall accuracy of 94.93%. ResNet had the second highest accuracy with 93.930%, followed by AlexNet with 92.437%, VGG-16 with 92.288%, VGG19 with 92.039%, and Inception-V3 with 89.203%.

Table 6 Accuracies of Deep Learning Models Implemented

Model	**Epochs executed**	**Accuracy**
MobileNet	10	94.925%
ResNet	10	93.930%
AlexNet	30	92.437%
VGG16	10	92.288%

VGG19	10	92.039%
Inception-V3	10	89.203%

Following are the graphs showing their accuracy and loss.

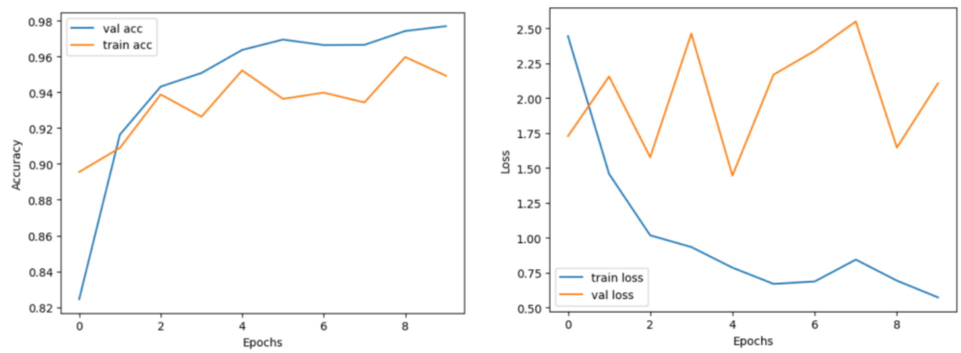


Figure 15 Graphs showing (a) Accuracy and (b) Loss of MobileNet.

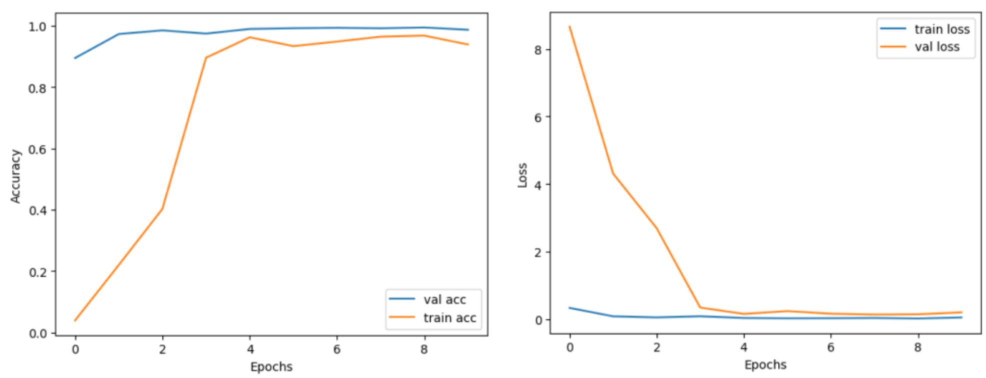


Figure 16 Graphs showing (a) Accuracy and (b) Loss of ResNet.

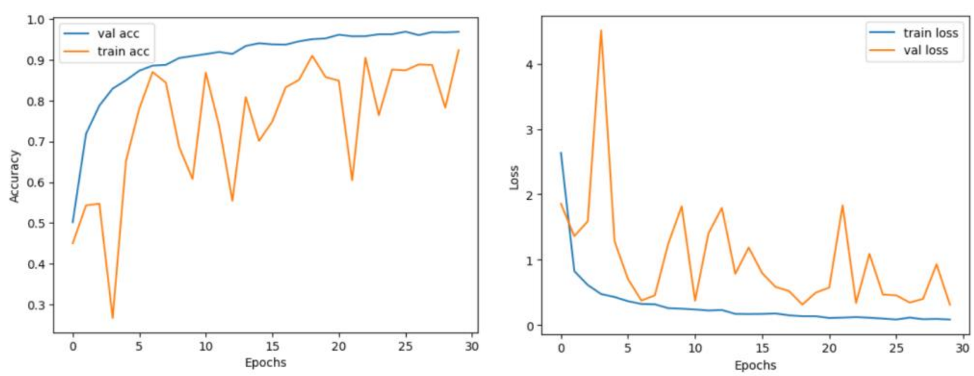


Figure 17 Graphs showing (a) Accuracy and (b) Loss of AlexNet.

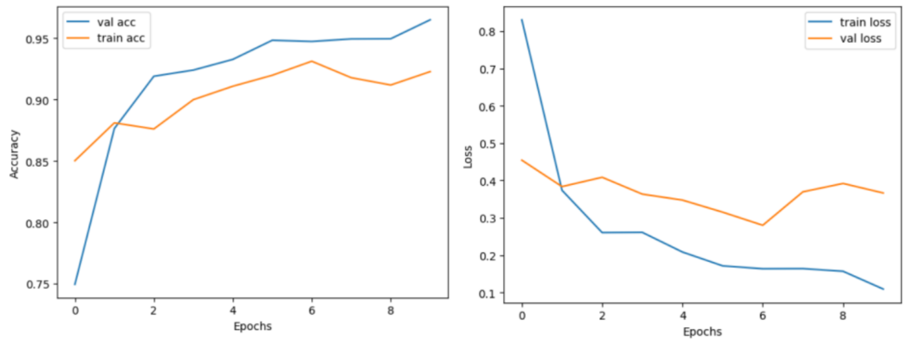


Figure 18 Graphs showing (a) Accuracy and (b) Loss of VGG16.

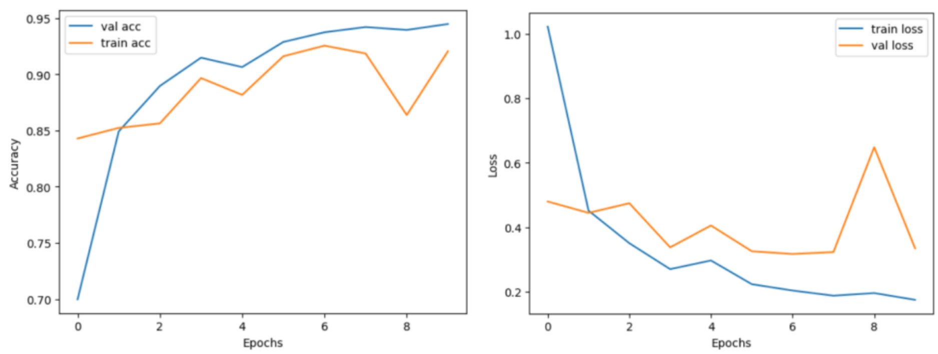


Figure 19 Graphs showing (a) Accuracy and (b) Loss of VGG19.

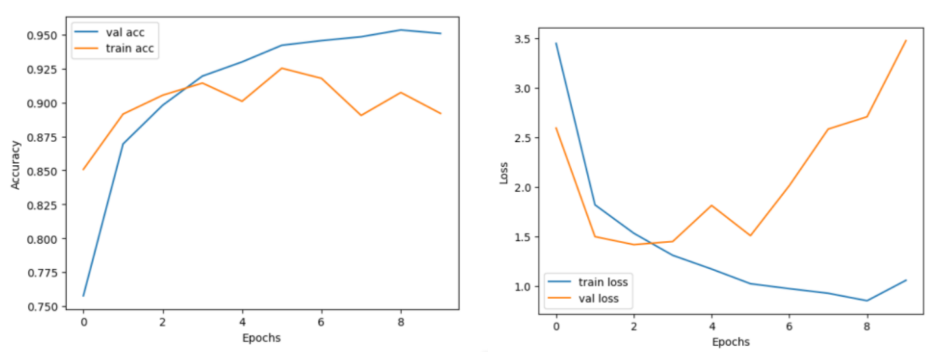


Figure 20 Graphs showing (a) Accuracy and (b) Loss of Inception-V3.

MobileNet, with its simple and efficient architecture, achieved the highest accuracy of all models. It is also one of the best deep learning models implemented in the ImageNet competition held at an international level. As MobileNet is a lightweight model it would be easy to deploy it on a mobile application as well.

2. YOLOv8 Results

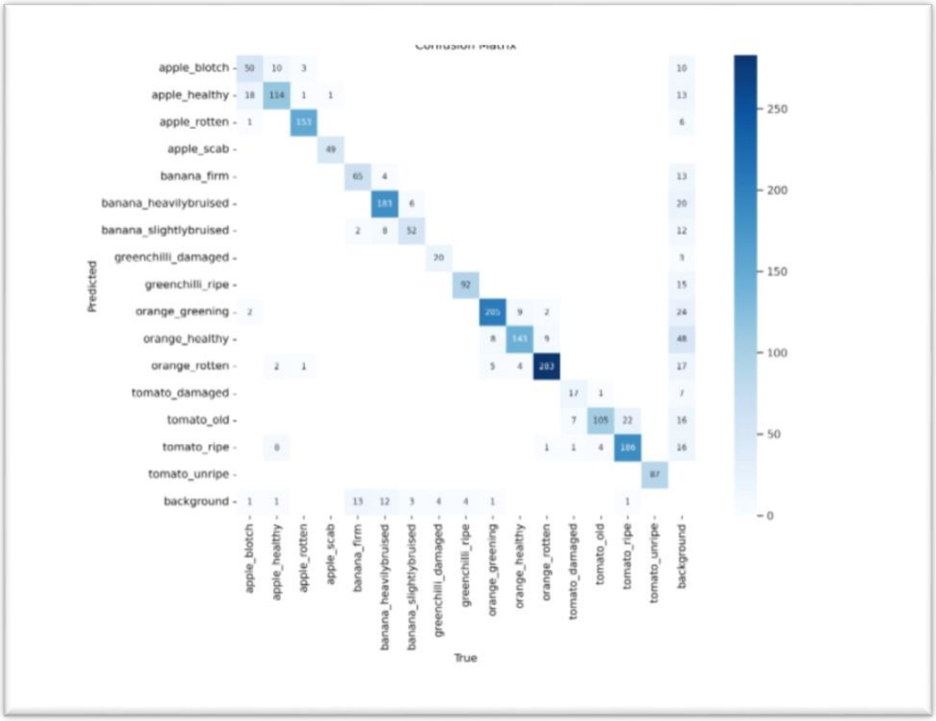


Figure 21 Confusion Matrix of YoloV8 Results

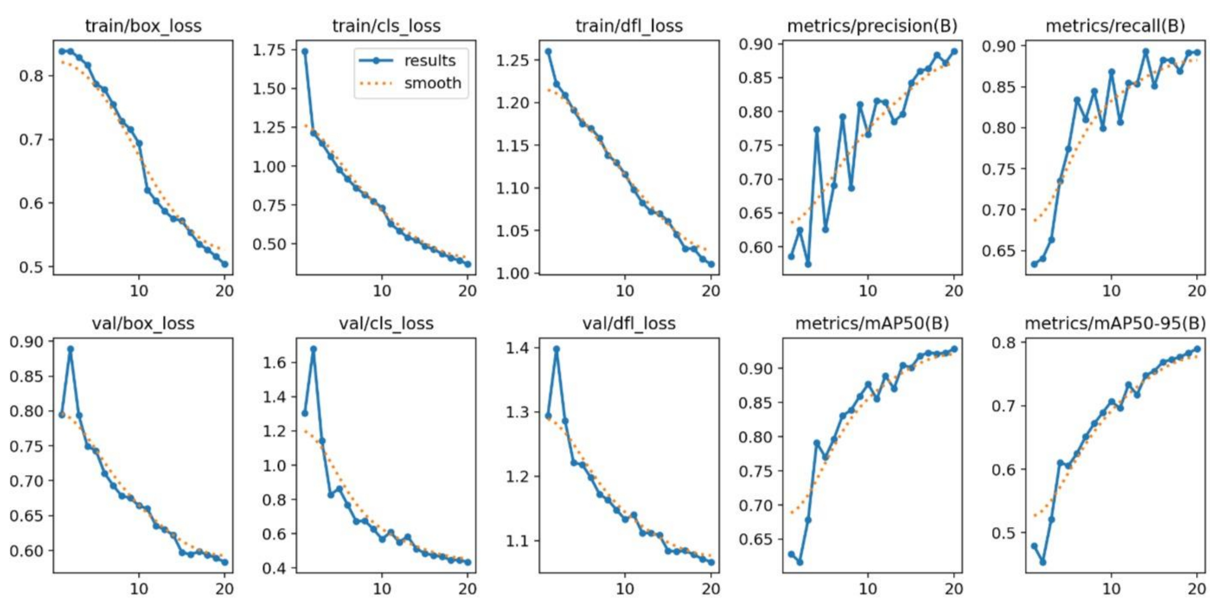


Figure 22 Validation and Loss Results

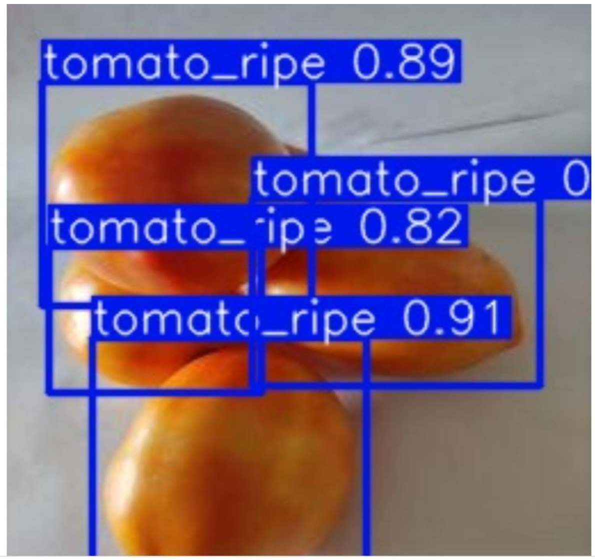


Figure 23 Some Results Sample of Tomato

SYSTEM DIAGRAM

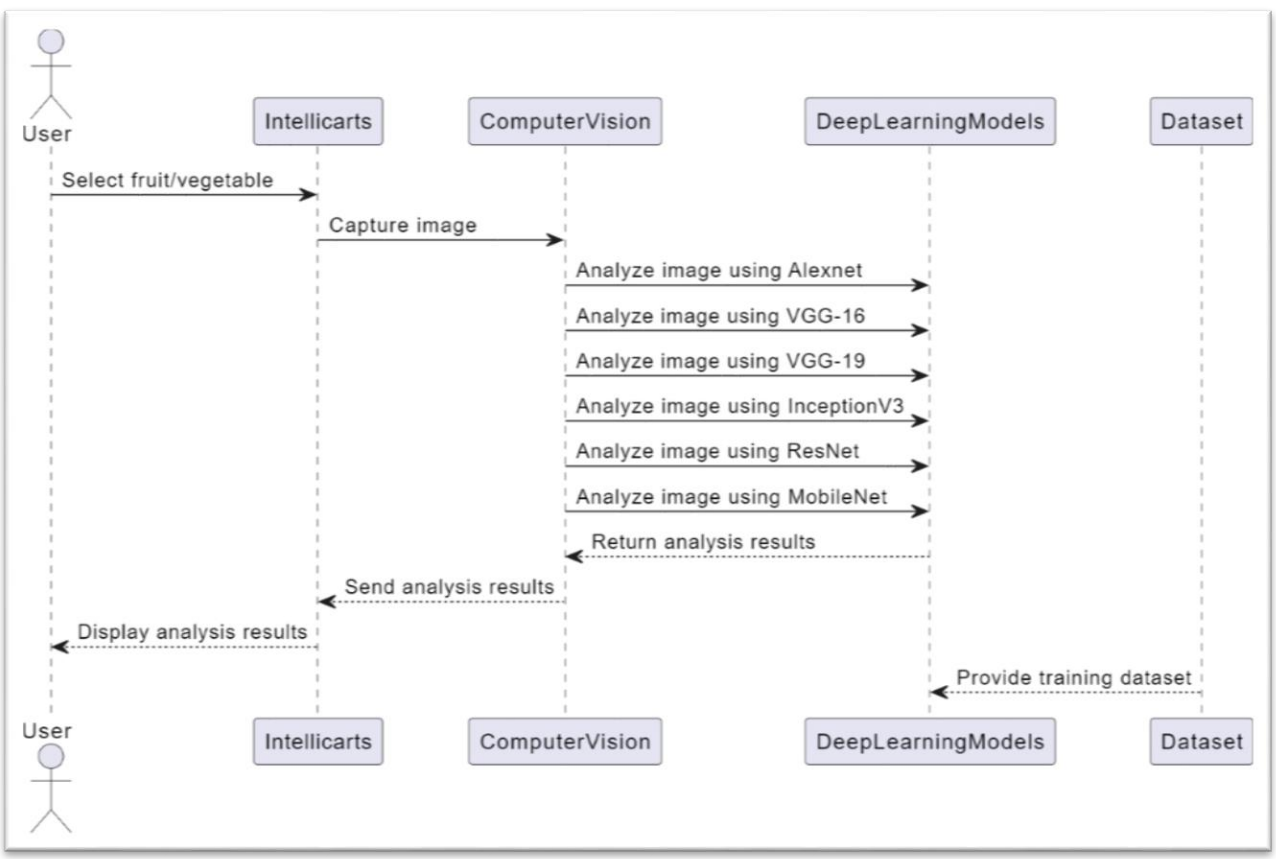


Figure 24 System Diagram showing each Component Involved in Implementation

- **Computer Vision:** This part involves the use of methods and approaches to analyze, process and extract information from images. It is crucial, for extracting features in evaluating the quality of fruits and vegetables.
- **Deep Learning Models:**
  - AlexNet, VGG 16, VGG 19, MobileNet ResNet152, InceptionV3: These are trained deep learning architectures that are used for extracting features and classifying the quality of fruits and vegetables. Each model offers its advantages in identifying patterns within the dataset.
- **Training and Testing Datasets:** Selected datasets that consist of categorized images of fruits and vegetables based on their quality parameters. These datasets are used to train, validate and test the learning models.
- **Users:** End users who oversee the project. They provide input. Utilize the system for monitoring/utilizing purposes or to give feedback.
- **IntelliCART:** Refers to the platform equipped with the implemented quality assessment system. These carts use the deployed models to evaluate the quality of fruits and vegetables in time. This enhances convenience. Builds trust, between sellers and customers.

GOAL FOR FYP-II

Following are the planned goals to be achieved in FYP-II:

1. **Integration of Classification Models:**
   Seamlessly integrate the fruit disease classification model (MobileNet) and the fruit quality classification model (YOLOv8) into the application infrastructure.
   Establish efficient communication between the models and the application's backend for real-time processing.
2. **Development of User-Friendly Interface:**
   Design an intuitive and user-friendly mobile application interface accessible to both sellers and customers.
   Incorporate features for sellers to mark the availability of their current stock and for customers to browse, select, and place orders based on fruit quality indicators.
3. **Seller-Specific Functionality:**
   Provide sellers with a dedicated interface for marking the availability of fruits.
   Implement an IoT-based camera system mounted on the fruit cart to enable real-time fruit quality assessment.
4. **Real-time Fruit Quality Assessment with IoT:**
   Develop an IoT-based camera system mounted on the fruit cart to capture snapshots of fruits and vegetables for real-time quality assessment.
   Integrate the captured images with the YOLOv5 model to evaluate fruit and vegetable quality indicators on the spot.
5. **Customer-Centric Features:**

Enable customers to access a catalog of fruits and vegetables with real-time quality assessments captured by the IoT-based camera system.

Implement a user-friendly ordering system, allowing customers to place orders based on assessed fruit quality.

6. **Real-time Updates:**

   Establish a real-time update system to notify both sellers and customers about stock availability, fruit quality assessments, and any relevant updates.

   Implement push notifications for timely communication and to enhance the overall user experience.

7. **Data Security and Privacy:**

   Implement robust data security measures to safeguard user information, captured images, and any sensitive data.

   Comply with privacy regulations and standards to ensure the confidentiality of user and image data.

8. **Testing and Quality Assurance:**

   Conduct thorough testing of the integrated system, including the IoT-based camera system, to identify and resolve any bugs or performance issues.

   Perform user acceptance testing (UAT) to ensure the application meets the expectations and requirements of both sellers and customers.

9. **Documentation and User Guides:**

   Create comprehensive documentation outlining the application architecture, integration process, and user guides for both sellers and customers.

   Ensure that the documentation is clear, concise, and easily accessible for future reference.

10. **Feedback Mechanism:**

    Implement a feedback system to gather input from both sellers and customers regarding the application's usability and effectiveness.

    Use feedback to make iterative enhancements to the application's functionality and user experience.

11. **Project Presentation and Demonstration:**

    Prepare a detailed presentation showcasing the application's features, development process, and the real-time fruit quality assessment system.

    Conduct a live demonstration to highlight key functionalities and address any queries or feedback.

By achieving these goals, the project aims to deliver a comprehensive mobile application with real-time fruit and vegetable quality assessment capabilities using an IoT-based camera system mounted on the cart, benefiting both sellers and customers in the fruit and vegetable market.

CONCLUSION

In the journey from FYP I deliverables to FYP II goals, our research and development efforts have converged into a promising trajectory, marking significant progress towards the realization of our intelligent fruit and vegetable quality assessment and e-commerce application. In FYP I, we successfully trained and evaluated robust deep learning models, specifically MobileNet for fruits and vegetables classification based on their quality and YOLOv8 for fruit and vegetable reliable detection in different environment conditions. These models exhibited commendable accuracy and efficiency, forming the foundation for the subsequent phase of our project.

Building upon these accomplishments, FYP II introduces an ambitious expansion of our project scope, incorporating real-world applicability and user-centric design. The integration of classification models into a user-friendly mobile application aims to bridge the gap between sellers and customers, facilitating a streamlined process for assessing fruit quality and making informed purchasing decisions. The inclusion of an IoT-based camera system mounted on the fruit cart introduces a novel dimension, enabling real-time fruit quality assessment on-site.

The development of dedicated interfaces for both sellers and customers reflects our commitment to inclusivity, providing tailored experiences that cater to the distinct needs of each user group. By empowering sellers with tools for inventory management and real-time updates on stock availability, and customers with access to dynamically assessed fruit quality information, we aim to revolutionize the fruit and vegetable market experience.

The feedback-oriented approach incorporated into the project's goals underscores our commitment to continuous improvement. User feedback will serve as a compass guiding iterative enhancements, ensuring that the final product aligns closely with user expectations and industry standards.

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