Multi-Label Classification of Fruits and Vegetables Using Advanced Machine Learning Algorithms

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Abstract

In today's world, ensuring the freshness and safety of fruits and vegetables is critical for reducing food waste and maintaining public health. However, accurately determining the freshness and safety of these perishable items remains a significant challenge, contributing to significant food waste each year. Traditional manual sorting methods are inefficient and cannot meet the growing demand for reliable quality assessment. To address this challenge, this paper proposes a novel model leveraging Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), which are effective in extracting and interpreting complex image data to enhance the accuracy of classifying and determining the freshness of fruits and vegetables. By integrating these advanced machine learning algorithms, this model offers a reliable and efficient solution to combat food waste. The proposed model was evaluated using a dataset of apples, bananas, tomatoes, and cucumbers obtained from Kaggle. It achieved 100% accuracy in classifying fruit types and 98.9% accuracy in determining freshness with the CNN model. Similarly, results using the ViT showed 100% and 97.9% accuracy in classifying fruit types and determining freshness, respectively. These results demonstrate that the model can accurately categorize both fresh and rotten fruits and vegetables, highlighting its potential utility in the food and agriculture sectors. The expected outcome is a reliable, efficient, and scalable system for reducing food waste and ensuring the safety of perishable goods.

Keywords: convolutional neural network; vision transformer; machine learning; fruit classification; fruit and vegetable freshness

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1.0 Introduction

Every year, tons of nutritious food go to waste due to confusing expiration labels. Consumers discard safe, wholesome, and high-quality food because they are unsure how to interpret date labels during the retail and consumption stages, significantly contributing to global food waste [1]. Over 1.6 billion tons of food are wasted worldwide, of which 81% is deemed fit for human consumption. Fresh fruits and vegetables are the primary contributors to these high levels of food waste. Studies show that fruits and vegetables account for 85% of food waste by volume but only 46% of the wasted carbon footprint [2].

Food waste is a primary problem from an economic, environmental, and food security perspective. Fruit quality refers to the characteristics influencing nutritional value and safety, which are essential to both the industry and consumers. For the industry, quality impacts profitability and competitiveness in the marketplace. Additionally, the produce market is highly competitive, with customers being pickier than ever, expecting fruits that meet their standards for flavor, appearance, and nutritional value. Manufacturers' and distributors' reputations rely on product quality. Customers pleased with the quality of the fruits are more likely to buy from the company again and refer others, strengthening the brand's reputation and boosting sales. Quality also ensures food safety, as poor-quality produce is more susceptible to contamination by bacteria and rotting microorganisms, which can lead to foodborne disease outbreaks and damage the industry's reputation. For consumers, quality is crucial because it affects the nutritional value, flavor, and safety of the fruits they consume. High-quality fruits and vegetables are more likely to be incorporated into a healthy diet due to their superior taste and nutritional value [3].

Recognizing rotten fruits is crucial for consumer satisfaction, quality control, sustainability, economics, and health and safety. Moreover, there will be significant losses if rotten fruits ruin the fresh ones. Because manually sorting rotting fruits is a labor-intensive, time-consuming, inefficient, and exhausting process, technology-driven methods are needed to complete the task [4]. An effective, automated, and technology-driven approach is needed to precisely estimate each item's quality based on its observable attributes to ensure fresh food is consumed at the ideal point in the supply chain to maximize nutritional benefits. This study aims to develop machine learning models that can be trained to evaluate and classify the quality of fresh fruits and vegetables using classification algorithms to create a more reliable basis for food safety. While previous studies focused on developing models to classify the quality of fruits and vegetables, their datasets were limited to a single variety of the specific fruit or vegetable being studied [5, 6, 7]. This study will address the constraints of earlier research by identifying various types of fruits and vegetables based on their category and quality rather than focusing on particular varieties, resulting in a multi-label model. This contribution to determining the quality of fruits and vegetables is expected to benefit small agro-industrial companies, traders, farmers, and customers.

The rest of this paper is organized as follows. Section 1 concludes with a discussion of the limitations of this study. Section 2 reviews the literature on fruit quality classification methods. Section 3 outlines the deliverables of the project. Section 4 describes the proposed techniques. Section 5 covers the empirical studies. Section 6 presents the results and discussion. Finally, Section 7 concludes the findings and proposes directions for future work.

1.1 Limitations

This study aims to address the limitations of previous research by evaluating multiple types of fruits and vegetables, rather than focusing on individual fruit/vegetable types. However, due to the constraints of the original dataset, the proposed work still has certain limitations. Although the dataset contains a variety of fruits and vegetables, it does not include all subtypes. For example, some sub-varieties of specific fruits are not represented. Additionally, while this model can distinguish between ripe and unripe samples, it cannot compute numerical shelf-life durations.

2.0 Review of Related Literatures

Several studies have aimed to develop machine learning models for the classification of fruit and vegetable quality. The following section provides a summary of previous research in this field.

A study by El-Bendary et al. [5] presented an automated multi-class classification method for determining and measuring tomato ripeness by looking at and categorizing the various maturity/ripeness phases. The suggested method can categorize tomatoes at various stages of maturity. This system uses color features to distinguish between various tomato maturity stages in a multi-class scenario. The method suggested in this article employs the Principal Components Analysis (PCA) technique for feature extraction and the Support Vector Machines (SVMs) and Linear Discriminant Analysis (LDA) algorithm for classification. The genuine sample photos of tomatoes at various stages that were gathered from several farms located in Minya City in Egypt served as the basis for creating the dataset utilized in the tests. A total of 250 photos made up the training and testing datasets, which were cross-validated ten times. Five classes, each representing a distinct state of tomato ripening, make up the training dataset. According to experimental results, the suggested classification strategy achieved ripeness classification accuracy of 90.80% when utilizing the one-against-one (OAO) multi-class Support Vector Machines algorithm with linear kernel function, 84.80% when utilizing the one-against-all (OAA) multi-class Support Vector Machines algorithm with linear kernel function, and 84% when utilizing the Linear Discriminant Analysis algorithm. Consequently, it can be said that the OAO multi-class Support Vector Machines technique yielded a higher level of ripeness classification accuracy than both the Linear Discriminant Analysis and OAA multiclass Support Vector Machines approaches.

A study by Castro et al. [6] aimed to automate the classification of Cape gooseberry fruits based on their ripeness level using machine learning algorithms and several color spaces. The authors collected a dataset of 925 Cape gooseberry fruit samples and manually classified each fruit into one of seven ripeness classes. The color values of the fruit images in RGB, HSV, and Lab* color spaces were recorded for training and validation. Four machine learning approaches were evaluated: artificial neural networks, support vector machines, decision trees, and k-nearest neighbor algorithms. The results showed that the choice of color space and classification technique significantly influenced the accuracy of the classification. Models based on the Lab* color space and support vector machines achieved the highest f-measure, indicating better precision and recall. The combination of color spaces using principal component analysis improved model performance but increased complexity. While specific accuracy values were unavailable, the study proved the efficacy of the suggested method in automating the categorization of Cape gooseberry fruits based on maturity.

A study by Mazen and Nashat [7] delivered an automated computer vision system for the ripeness classification of bananas. They prepared a homemade four-class database comprising different ripening levels of bananas. The dataset was used to train an artificial neural network (ANN) model, which incorporated color, the growth of brown spots, and Tamura statistical textural elements extracted from the banana images. The performance of the suggested system was contrasted with existing approaches, such as support vector machines (SVM), naive Bayes, k-nearest neighbours (KNN), decision trees, and discriminant analysis classifiers. However, the system was not compared to CNN. The findings showed how the ANN-based approach had the greatest overall recognition rate, with an accuracy of 97.75%. This research contributes to the development of intelligent techniques for fruit quality assessment and provides valuable insights for fruit industrial companies and consumers concerned about the quality of fresh banana fruit.

A recent study by Kumar S. Krishna et al. [8] focused on using an effective classification algorithm of supervised learning technique with high accuracy for finding the quality of fruit. This study used various algorithms to detect the quality of fruit, such as k-mean clustering, Edge Detection algorithm, Artificial Neural Networks (ANN), Support Vector Machine, convolutional neural network algorithm (CNN), and Machine vision technology. For the early system, it can only classify the fruits as good and rotten with an accuracy of 87.4%. On the other hand, the CNN algorithm started by taking a fruit image through the pi camera of the raspberry pi. The image is transformed to base64 format (String) of a web server using the Python flask framework and it is given as the input to the training model. So, the features are extracted based on the parameter from the sample image, some examples of the features are color, size, and shape. CNN is used for checking the quality by using the features of fruits. The results will be good, moderate, and rotten. The study used a Kaggle dataset website that contains bananas, apples, and oranges. The dataset consists of nearly 11000 images, which are used as training and testing mode using a CNN algorithm, moreover, its results were obtained with an accuracy level of 94.6%, and it achieves the highest accuracy than the earlier system.

Another study was conducted by Santi Behera et al. [9], The main purpose of this research is to propose a new non-destructive maturity status classification of papaya fruits. They examined the performance by using the machine learning approach which consists of three feature sets and three classifiers, each with a different kernel function. Machine learning features used are local binary pattern (LBP), histogram of oriented gradients (HOG), Gray-Level Co-occurrence Matrix (GLCM), with the classifiers k-nearest neighbor (KNN), support vector machine (SVM), Naı̈ve Bayes, respectively. Another approach was used also, which is the transfer learning approach, and it includes seven pre-trained models such as ResNet101, ResNet50, ResNet18, VGG19, VGG16, GoogleNet, and AlexNet. The experiment is carried out with a dataset of 300 papaya fruit sample pictures, 100 from each of the three maturity stages. The result of this study using the machine learning approach is that the weighted KNN with HOG feature outperforms the other machine learning-based classification models, with 100% accuracy and 0.0995 seconds of training time. As for the transfer learning approach, From the experimentation, it is observed that the VGG19 performs better among the other classification models of transfer learning with 100% accuracy. Finally, the limitation of this study is that is intended to classify the maturity status of a single fruit; it would be preferable to enhance it and make it assist all types of fruits.

Arun Kumar [1, B] and Varsha Bhole[1, A] [10] developed a novel method to improve the accuracy of fruit shelf-life prediction. The suggested architecture combines machine learning algorithms, RGB imaging, and visual inspection with a specific focus on "Kesar" mangoes. The research makes use of a specially created dataset that has been divided into 19 classes, each of which represents a distinct remaining useful life (RUL) stage. One class is dedicated to fruits that have no remaining RUL. In order to record intrinsic fruit features such as internal defects, bruises, texture, and colour, thermal imaging is used as a non-destructive method. To enhance the RUL-based classification tasks, transfer learning is implemented. The investigation involves a comparative analysis of three prominent lightweight CNN models—Squeeze Net, Shuffle Net, and MobileNetv2. Bhole and Kumar report an impressive highest achievable accuracy of 98.15±0.44%, showcasing the success of the model in accurate shelf-life prediction with computational efficiency. This research not only contributes to advancements in agriculture and the food industry but also offers a potential solution to optimize fruit shelf-life prediction, thereby minimizing waste in the supply chain.

Another study by I. B. Iorliam et al. [11] aimed to predict the shelf life of Okra using machine learning techniques. The study emphasizes the importance of accurate prediction due to the health risks associated with the consumption of Okra after its shelf life. The dataset utilized in the study was generated in the laboratory by Ogbaji and Iorliam [12], and it consisted of data on Okra parameters such as weight loss, firmness, titrable acid, total soluble solids, vitamin C/ascorbic acid content, and pH. These parameters were used as inputs into the machine learning models after the dataset was pre-processed to remove noise and filter out undesirable parameters. The study employed several algorithms, such as the Support Vector Machine (SVM), Naïve Bayes, Decision Tree, Logistic Regression, and K-Nearest Neighbour. The SVM, Naïve Bayes, and Decision Tree algorithms demonstrated exceptional performance, accurately predicting the shelf life of Okra with accuracy rates of 100%. On the other hand, the Logistic Regression and K-NN algorithms achieved relatively lower accuracies of 88.89% and 88.33%, respectively. The results confirmed the effectiveness of machine learning techniques, particularly SVM, Naïve Bayes, and Decision Tree, in accurately predicting the shelf life of Okra. These techniques can contribute to ensuring food safety, reducing post-harvest losses, and minimizing waste.

Tsega, Matteo, Valentina, Francesco, and Stefano [13] conducted a study to prepare a new way to create a machine learning-based digital twin (DT). It used two techniques to create DT, the first technique is by using a deep convolutional neural network (CNN), and the second technique is by using a thermal camera as a data source. This study focuses on the second technique which is the thermal camera. Because of its ability to identify surface and physiological changes in fruits after storage, it has been utilized as a data-collecting technique. Images taken with the FLIR device were used to construct the dataset. The dataset of fruit images from a single thermal camera was divided into four categories: fresh, good, bad, and rotten. Moreover, 3968 images represent the dataset, while 496 images with four labels each were used to build the test and validation datasets. Eighty percent of the original training set's records represent the training dataset, with the remaining twenty percent going to the validation and test dataset. In this study, a machine learning-based DT approach for banana fruit has been tested using SAP intelligent technology. This technique has demonstrated increased accuracy. As a result, 99% prediction accuracy was attained, demonstrating the technique's promise for creating digital twins of fruit. In order to reduce waste in the food supply chain, a machine learning-based digital twin of fruit can be created by applying thermal imaging techniques as a data source.

The research by Worasawate et al. [14] offers a method for using supervised and unsupervised machine learning techniques to evaluate the maturity stage of "Nam Dok Mai Si Tong" mangos. In all phases of ripeness—unripe, ripe, and overripe—this variety has yellow skin. This study aimed to develop models that could be used to predict, in addition to physical (skin color, weight), electrical (voltage, capacitance), and chemical characteristics, the maturity stage of mangoes at harvest. They developed four popular machine learning (ML) classifiers— the feed-forward artificial neural network (FANN), support vector machine (SVM), k-mean, and naïve Bayes—that were designed to categorize mangoes according to their level of ripeness during harvest. 120 mangoes were used, and ten variables of mango characteristics present in the data set used in the study were measured: weight, color (red, green, and blue), TSS–TA ratio, titratable acidity (TA), total soluble solids (TSS), capacitance, voltage, and capacitance to weight ratio. They assessed the machine learning classifiers using electrical and physical data after they were trained on biochemical data. The information gathered from 100 mango fruits was used to train the FANN, GNB, and SVM algorithms using fourfold cross-validation. Consideration was given to the percentage of corrected forecasts. Based on biochemical features, the k-means algorithm was able to differentiate between the ripening phases of mangos: ripe and unripe or into ripe, unripe, and overripe. Compared to the support vector machine and Gaussian naïve Bayes methods, the feed-forward artificial neural network was able to categorize the data with considerably greater accuracy. Compared to the other classifiers, the FANN classifier had a mean accuracy of 89.6% for the ripe, overripe, and unripe classifications. Out of the four classifiers that were employed, the Gaussian naïve Bayes classifier performed the worst.

A comparison study conducted by Binder et al. [15] aimed to evaluate the effectiveness of Convolutional Neural Networks (CNNs) and feature-based machine learning methods for classifying the ripeness of strawberries. The researchers utilized a balanced dataset comprising three ripeness classes: unripe, ripe, and overripe strawberries. CNNs, which process raw image data, outperformed most feature-based classifiers in terms of classification accuracy. The penalized multinomial regression achieved the highest accuracy of 86.27% without hyperparameter tuning. Interestingly, different methods demonstrated varying degrees of accuracy for specific ripeness classes, with CNNs excelling in classifying unripe strawberries and penalized discriminant analysis and penalized multinomial regression performing best for ripe and overripe strawberries, respectively. The findings highlight the significance of selecting appropriate algorithms based on ripeness classes to achieve accurate classifications.

In a study by Sanath Shenoy et al. [16] a new technique for predicting fruit shelf life using object detection methods based on Deep Learning models was presented. The study focuses on developing a model for estimating the shelf life of Cavendish bananas, which could significantly assist the food industry achieve its goal. To accomplish this goal, two object detection algorithms, Faster R-CNN and You Only Look Once (YOLO) are used, and their performance is compared in this study. The YOLO method, known for its efficiency, is contrasted to the Faster R-CNN, which is recognized for identifying very fine features. As for the dataset that has been used in this research, it has been developed by collecting images of bananas throughout their life cycle and categorizing them according to their maturity. The data collection process consisted of taking images of bananas every day for six days, from day zero to day five. To guarantee consistent lighting conditions, pictures were taken each day at 4:00 pm GMT+5.5H using a typical white light. The camera was placed in a fixed position to provide constant video collection from the same angle. The experiment outcomes for both models demonstrate that object detection models with customization can help in real-world use cases of shelf-life detection of bananas or other fruits of interest with an acceptable level of accuracy. Furthermore, the results indicate that Yolov5 and Faster RCNN can forecast shelf life with accuracy mAP50 and mAP50-95 greater than 80%. It has also been observed that faster R-CNN performs better with a larger number of repetitions and demands more computational hardware. Yolo, on the other hand, offers model options that do not require high computer hardware. Despite the impressive accuracy of deep learning models in predicting fruit shelf life, researchers can work to improve the model architecture or incorporate more data factors to increase the accuracy percentage.

A recent study by A. Khorramifar et al. [17] focused on detecting the shelf life and quality changes of potatoes during storage using an electronic nose (e-nose) and machine learning algorithms in a non-destructive manner. The study utilized datasets from three potato cultivars (Sprit, Santé, and Agria) that were harvested and stored under controlled conditions. The aroma data from the potato samples was collected using an electronic nose with nine metal oxide sensors. The quality parameters, including sugar and carbohydrate contents, were evaluated every 15 days over six storage periods. The study employed several machine learning algorithms, including principal component analysis, linear data analysis, support vector machine, artificial neural networks, quadratic discriminant analysis, and multivariate discrimination analysis. They used a confusion matrix to validate and evaluate the models and found that the LDA, ANN, QDA, and MDA all achieved 100% accuracy in individual cultivar classification. QDA and MDA achieved 98.89% accuracy when applied to all cultivars, outperforming LDA (91.85%). SVM attained accuracies of 91.11% and 88.15% for training and validation of all cultivars. Overall, the study demonstrated that a combination of e-nose and proper machine learning can be used effectively to classify potato quality changes without requiring destructive chemical analysis.

A research paper by S. Mamidala [18] developed a correlation between actual food spoilage time and the dates on food packaging labels. The study used machine learning to predict spoilage more accurately than traditional dates by considering sensory observations and specific food features. The study used a private dataset collected through experimentation on five common foods: bananas, bread, milk, eggs, and leafy greens. Each food was assigned 3–7 measurable characteristics to determine if the food was spoiled or not. Linear regression analysis and Pearson's correlation coefficient were applied to develop mathematical models of spoilage for each food based on the dataset. The results showed strong relationships between certain spoilage characteristics and time, aligning well with published research on typical spoilage times and confirming the model's accuracy. The regression graphs of the spoilage scores closely matched observed degradation patterns. A key finding was that for all tested foods, the time until spoilage significantly exceeded the labeled expiration dates. The project yielded the development of a smartphone application and a test kit. These tools enable consumers to monitor their food's shelf life through simple measurements, which can help effectively reduce food waste and its environmental impact.

2.1 Literature Review Summary Table

Table 1: Literature Review Summary

Ref.	Authors	Year	Title	ML Techniques	Dataset	Results
[5]	Nashwa El-Bendary, Esraa El Hariri, Aboul Ella Hassanien, and Amr Badr	2015	Using machine learning techniques for evaluating tomato ripeness	Principal Components Analysis (PCA), Support Vector Machines (SVMs), Linear Discriminant Analysis (LDA)	The dataset used for training and testing in the study consisted of 250 images	90.80% accuracy using the SVMs algorithm
[6]	Wilson Castro, Jimy Oblitas, Miguel De-la-Torre, Carlos Cotrina, Karen Bazán, and Himer Avila-George	2019	Classification of Cape Gooseberry Fruit According to Its Level of Ripeness Using Machine Learning Techniques and Different Color Spaces	Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and K-nearest Neighbour Algorithms (KNN)	925 Cape gooseberry fruit samples from a plantation in Peru.	Models based on Lab* color space and SVM achieved highest f-measure, while PCA combination of color spaces improved performance with increased complexity.
[7]	Fatma M. A. Mazen , Ahmed A. Nashat	2019	Ripeness Classification of Bananas Using an ANN	Artificial Neural Network, Image Processing, Computer Vision	Homemade four-class banana image database	97.75% accuracy using ANN
[8]	S. Krishna Kumar, J. Kaviya, K. Srinivasan, G. Dilip Prakash	2020	Fruit quality detection using machine vision techniques	k-mean clustering, Edge Detection algorithm, Artificial Neural Networks (ANN), Support Vector Machine, Convolutional Neural Network (CNN), and Machine vision technology.	Kaggle dataset website for banana, apple, and orange. The downloaded set consist of nearly 11000 images	94.6% accuracy using CNN

Ref.	Authors	Year	Title	ML Techniques	Dataset	Results
[9]	Santi Kumari Behera, Amiya Kumar Rath, Prabira Kumar Sethy	2020	Maturity status classification of papaya fruits based on machine learning and transfer learning approach	k-nearest Neighbour (KNN), Support Vector Machine (SVM), Naïve Bayes, Transfer learning	300 papaya fruit sample pictures, 100 from each of the three maturity stages	KNN with HOG feature with 100% accuracy
[10]	Varsha Bhole, Arun Kumar	2021	A Transfer Learning-based Approach to Predict the Shelf life of Fruit	Convolutional Neural Network (CNN), Transfer Learning	images of "Kesar" mangoes, specifically Mangifera Indica Linn cv. Kesar.	Highest achievable accuracy of 98.15±0.44%
[11,12]	Iveren Blessing Iorliam, Barnabas Achakpa Ikyo, Aamo Iorliam, Emmanuel Odeh Okube, Kenneth Dekera Kwaghtyo, Yahaya I. Shehu	2021	Application of Machine Learning Techniques for Okra Shelf Life Prediction	Support Vector Machine (SVM), Naïve Bayes, Decision Tree, Logistic Regression, and K-Nearest Neighbour	The dataset was generated in the laboratory by Ogbaji and Iorliam	SVM, Naïve Bayes, and Decision Tree algorithms achieved 100% accuracy; Logistic Regression and K-NN achieved 88.89% and 88.33%, respectively.
[13]	Tsega Y. Melesse, Matteo Bollo, Valentina Di Pasquale, Francesco	2022	Machine Learning-Based Digital Twin for Monitoring Fruit Quality Evolution	machine learning-based DT	The dataset of fruit images was classified into four. 3968 images represent the dataset, while 496 images with four labels	99% accuracy using DT

Ref.	Authors	Year	Title	ML Techniques	Dataset	Results
	Centro, Stefano Riemmaa					
[14]	Denchai Worasawat, Panarit Sakunasin, and Surasak Chiangga	2022	Automatic Classification of the Ripeness Stage of Mango Fruit Using a Machine Learning Approach	k-Means, Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM), Feed-Forward Artificial Neural Network (FANN)	The dataset used in the study consisted of 120 mangoes of the "Nam Dok Mai Si Tong" variety	89.6% accuracy rate using FANN classifier
[15]	Leon Binder, Michael Scholz, Roman-David Kulko	2022	A Comparison of Convolutional Neural Networks and Feature-Based Machine Learning Methods for the Ripeness Classification of Strawberries	CNNs, Feature-based classifiers	The researchers utilized a balanced dataset comprising three ripeness classes: unripe, ripe, and overripe strawberries.	CNNs outperformed most classifiers, with penalized multinomial regression achieving the highest accuracy of 86.27%
[16]	Sanath S Shenoy, Radhika Mishra, Ruchi Chaturvedi	2023	Comparative Analysis for Predicting Shelf life of Fruits Using Advanced Deep Learning Approaches	Deep learning, Faster R-CNN and You Only Look Once (YOLO)	Images of cavendish bananas	Yolov5 and Faster RCNN with accuracy mAP50 and mAP50-95 greater than 80%.
[17]	Ali Khorramifar, Mansour Rasekh, Hamed Karami, Jesús Lozano,	2023	Determining the shelf life and quality changes of potatoes (Solanum tuberosum) during storage	Principal Component Analysis (PCA), Linear Data Analysis (LDA), Support Vector Machine (SVM), Artificial	Three potato cultivars (Sprit, Sante´, and Agria)	LDA, ANN, QDA, and MDA achieved 100% in individual classification; QDA

Ref.	Authors	Year	Title	ML Techniques	Dataset	Results
	Marek Gancarz, Ewa Łazuka, Grzegorz Łagód		using electronic nose and machine learning	Neural Network (ANN), Quadratic Discriminant Analysis (QDA) and Multivariate Discrimination Analysis (MDA)		and MDA led with 98.89% across all cultivars.
[18]	Srilekha Mamidala	2023	The SLED (Shelf Life Expiration Date) Tracking System: Using Machine Learning Algorithms to Combat Food Waste and Food Borne Illnesses	Linear Regression Analysis and Pearson's Correlation Coefficient	Private dataset collected through experimentation on five common foods: bananas, bread, milk, eggs, and leafy greens.	Sensory observations were able to detect spoilage accurately, proven by the strong correlations with the day these observations were taken from the regression graphs.

2.2 Literature Survey Outcome

After reviewing many prior research papers on classifying fruit and vegetable quality, we found that past studies had some limitations in their datasets and scope. Specifically, many studies focused exclusively on a single fruit or vegetable type, disregarding cultivar diversity [5, 7, 9]. In addition, several datasets were restricted to local regions, capturing a narrow range of growing environments [5]. As a result, models exhibited constrained generalizability as they examined only one food type using limited datasets. Additionally, some studies mainly considered controlled storage rather than real-world conditions [17]. This research aims to address these gaps. It will leverage a dataset covering multiple fruit and vegetable varieties to develop models with broader applicability. While previous studies focused solely on predicting ripeness [7,14,15] the proposed model has the additional objective of classifying fruits and vegetables based on their quality and type, creating a multilabel model.

3.0 Deliverables of the Project

This section shows the deliverables of the project:

Table 2: Deliverables of the Project

Deliverable	To whom	Delivery Media	Duration	Date
Literature Review (Homework-1)	Dr. Nawaf Alharbi	Softcopy	2 weeks	16/02/2024
Project Proposal			1 week	27/02/2024
Project Proposal Presentation			2 weeks	14/03/2024
Description of Selected ML Algorithms			2 weeks	30/03/2024
Final Project Report			1 month and 2 weeks	18/05/2024
Final Project Presentation			1 day	19/05/2024

4.0 Description of the Proposed Techniques

When evaluating the quality of fruits and vegetables, two machine learning algorithms are better to utilize which are Convolutional Neural Networks (CNNs) and Vision Transformer (ViT). A thorough explanation of the algorithms employed in this study can be found in the section that follows.

4.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specialized branch of Artificial Neural Networks (ANNs) known for their deep feed-forward architecture and remarkable generalization capabilities. Operating within a supervised learning framework, CNNs learn from labeled datasets. The unique aspect of CNNs lies in their design, which is influenced by the way organisms visually interpret their surroundings. CNNs outperform networks with only fully connected layers in terms of generalization, making them ideal for detecting objects and learning the abstracted features of spatial data. A deep CNN is composed of multiple processing layers, each built to handle inputs with a grid arrangement, like images, where there's a significant reliance on the spatial relationships within sections of the grid [19]. These layers can learn different input data characteristics at several abstraction levels. Furthermore, a traditional convolutional neural network (CNN) is structured around two combinations of basic building blocks. It incorporates a convolution block and a fully connected block.

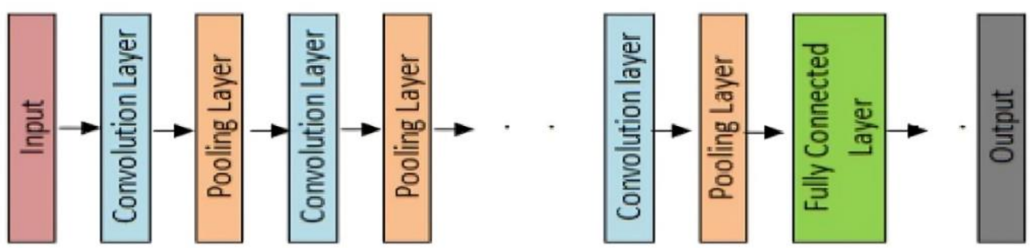

Figure 1: Conceptual model of CNN [20]

The convolutional block is the core component, consisting of both the Convolution Layer and the Pooling Layer, important in extracting features from the input images. Moreover, Convolution layers build upon one another to acquire intricate features. The initial layers identify edges, the layers after them combine to identify forms, and the layers after that integrate this data. The Pooling layer chooses a single value, usually the maximum or average, from a set of values. This reduces the output matrix's dimensions. In a CNN architecture, a Pooling layer is typically placed between consecutive convolutional blocks. Its purpose is to gradually lower the spatial size of the data representation, thereby decreasing the network's computational demands and the total number of parameters needed. The Fully Connected Block, composed of a basic, fully connected neural network design, serves as the CNN architecture's output layer or classifier. It receives a set of metrics (feature maps) from the final convolutional or pooling layer, which are then flattened to create a vector. This vector is fed into the Fully Connected (FC) layer, which performs classification tasks using the input from the convolutional block [20]. The FC layer learns to use the features extracted by the convolution layers to accurately classify the images. Finally, the sophisticated layering of convolutional and fully connected blocks in CNNs is essential for image analysis and classification. This complex architecture enables accurate and efficient processing of image datasets, dramatically improving prediction accuracy.

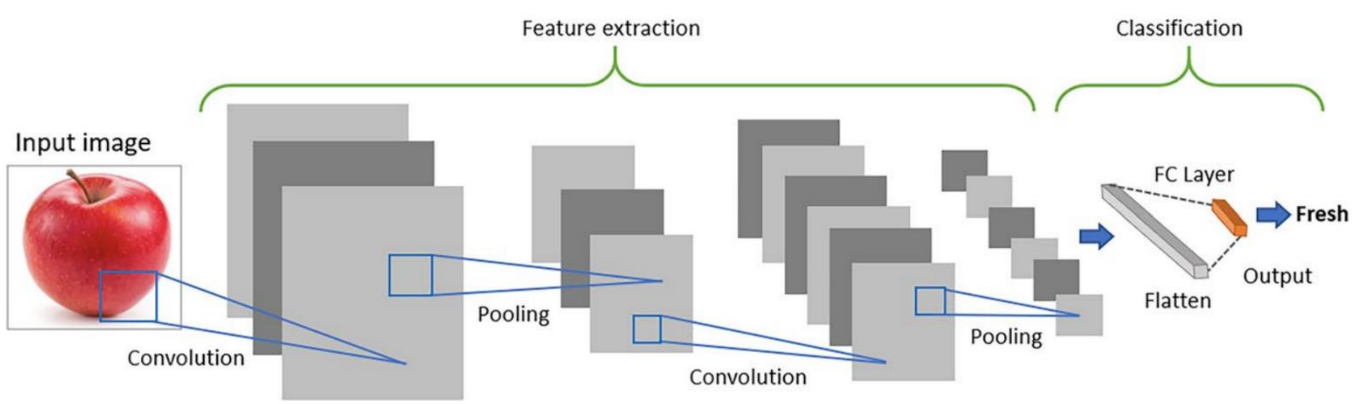

Figure 2: Building blocks of a typical CNN [21]

4.2 Vision Transformer (ViT)

The Vision Transformer (ViT) is a powerful deep-learning model that is popular in the computer vision field. It utilizes multi-head self-attention and transformer encoders to process image data without requiring image-specific biases. By splitting the images into positional embedding patches, ViT can understand both local and global features of the image. It has demonstrated higher precision rates and reduced training time on large datasets. Also, it is particularly suited for tasks involving image data, making it a suitable choice for optimizing quality classification for fruits and vegetables. By training the model on labeled images, it will learn to recognize visual cues that indicate freshness or spoilage. During the training process, the Vision Transformer's parameters will be updated using an optimization algorithm, enabling it to map input images to corresponding quality classes. The model can then make predictions on new images by passing them through the network. The Vision Transformer's ability to capture dependencies, handle variations, and achieve impressive performance makes it a promising choice for accurate quality classification in this project [22].

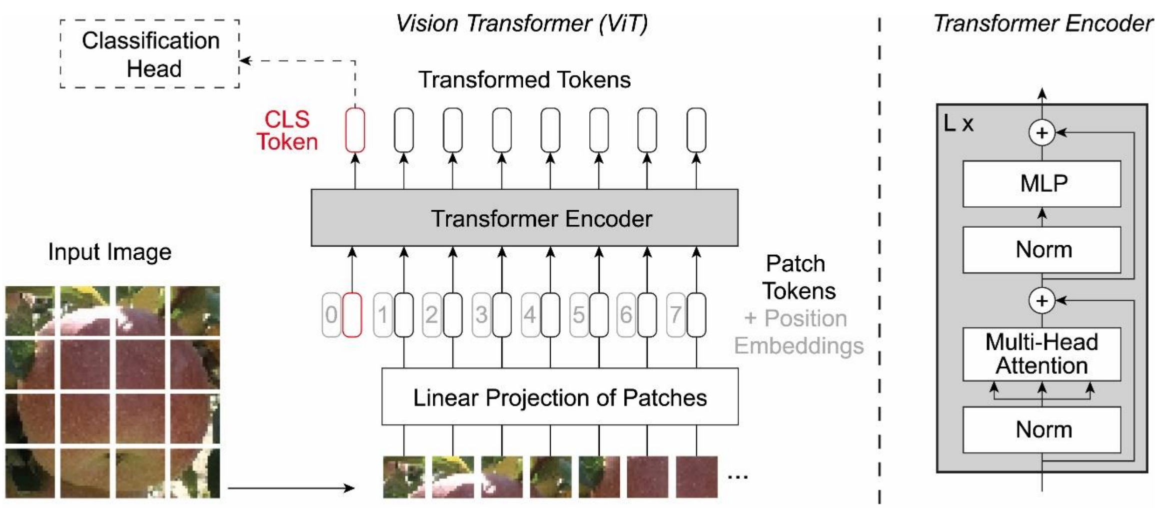

Figure 3: Vision Transformer Architecture [23]

5.0 Empirical Studies

5.1 Description of dataset

The original dataset utilized in this study comprises a vast number of images of various fruits and vegetables, such as apples, bananas, oranges, tomatoes, carrots, okra, and cucumbers. Each fruit in the dataset was captured with high-resolution cameras in multiple images representing both fresh and rotten states, with varying angles and lighting to allow for more accurate model training. This dataset was collected from multiple sources by SWOYAM SIDDHARTH NAYAK on Kaggle [24]. In this study, a diverse sample of this data was taken to ensure the generalizability and robustness of the classification models, including apples, bananas, cucumbers, and tomatoes. Each type received 60 images, for a total of 480 images in the dataset. These images were split into two sets: a training set comprising 384 images (80% of the image sample) and a testing set comprising 96 images (20% of the image sample).

5.1.1 Statistical Analysis of the Dataset

The statistical analysis of the dataset is presented in the table below. The number of each fruit and vegetable images in the dataset are presented.

Table 3: Statistical Analysis of the Dataset

	Apple	Banana	Cucumber	Tomato	Total
Fresh	60	60	60	60	240
Rotten	60	60	60	60	240
Total	120	120	120	120	480

5.2 Experimental Setup

This section discusses the stages and techniques used in developing the model for predicting the quality and category of fruits and vegetables. Essential preprocessing steps were undertaken to extract clean data from the Kaggle dataset for effective model training. Given the imbalance in the original dataset, undersampling was employed to ensure equal representation for each category, providing a fair and balanced view of all fruit and vegetable types. The dataset was carefully divided into two parts: 80% for training and 20% for testing. Experiments were conducted using Google Colab, which provided a reliable and user-friendly computing environment. The graph below includes a comprehensive flow diagram that illustrates the step-by-step workflow, aiding in the understanding and replication of the experimental method.

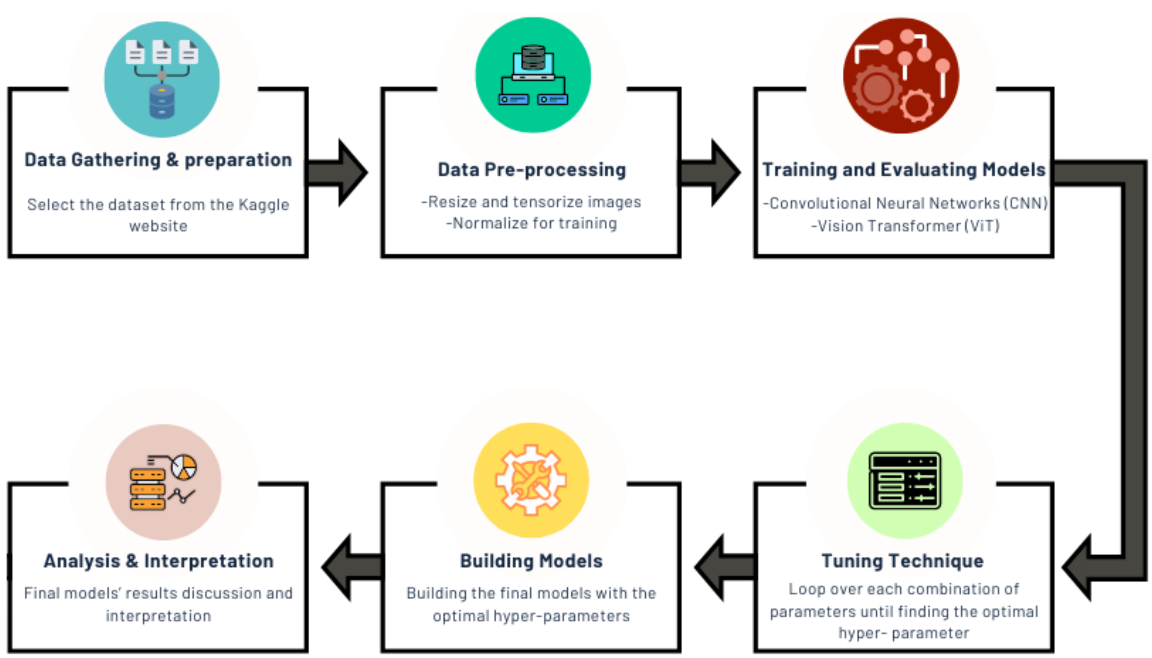

Figure 4: Workflow Diagram

5.3 Performance Measures

Several metrics, including accuracy, precision, recall, F-Score, and a confusion matrix, are used to evaluate the model's performance. These measures assess the overall performance of the model, accuracy of positive predictions, sensitivity, and the balance between precision and recall. The confusion matrix facilitates visualization of the model's performance across different classes, providing a clear depiction of true and false predictions. These methods are essential for a thorough and consistent evaluation and are commonly recommended for balanced datasets.

Accuracy Formula:

$$\frac{Tp + Tn}{Tp + Tn + Fp + Fn}$$

Precision Formula:

$$\frac{Tp}{Tp + Fp}$$

Recall Formula:

$$\frac{Tp}{Tp + Fn}$$

F-Score Formula:

$$\frac{2 * recall * precision}{recall + precision}$$

The scikit-learn library's built-in functions were utilized to compute these evaluation metrics. Given that the dataset used to train and test the model was balanced, the 'average' parameter was set to 'micro' in the accuracy and recall calculations. As will be demonstrated in the results section, using micro-averaging yields the same results for all three metrics: accuracy, precision, and recall [25].

5.4 Optimization strategy

Finding hyperparameters that enhance model performance was a crucial part of the optimization strategy. This involved adjusting key parameters and observing their impact on accuracy. In this section, plots illustrate how accuracy changes with these adjustments, concluding with a table of the optimal parameters. This strategy ensures that the model performs efficiently under the optimal settings.

The learning rate is a crucial hyperparameter used in neural network models, and it was adjusted during the model's optimization process. The effect of different learning rates on the model's accuracy is shown in the graph. The learning rate is represented on the x-axis, plotted on a logarithmic scale from 10^{-5} to 10^{-3}. The mean final accuracy is represented on the y-axis, ranging from 0.90 to 1.00. This graph illustrates that as the learning rate increases from 10^{-5} to 10^{-4}, there is a significant improvement in accuracy, which stabilizes around 1.00 as the rate approaches 10^{-3}.

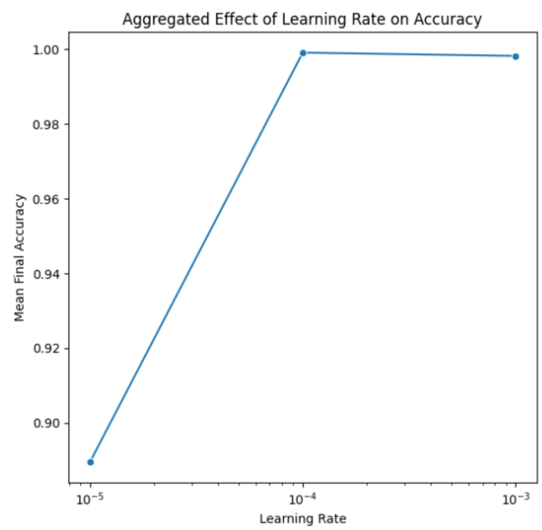

Figure 5: Hyper-parameter Search for the Learning Rate

In machine learning, the batch size refers to the quantity of data processed before the model's parameters are updated. The graph displays how different batch sizes affect the model's accuracy. On the x-axis, the batch size is plotted from 40 to 120, and on the y-axis, the mean final accuracy is plotted from 0.93 to 0.99. This graph illustrates that as the batch size increases, the mean final accuracy decreases. This indicates an adverse correlation between the batch size and the model's accuracy.

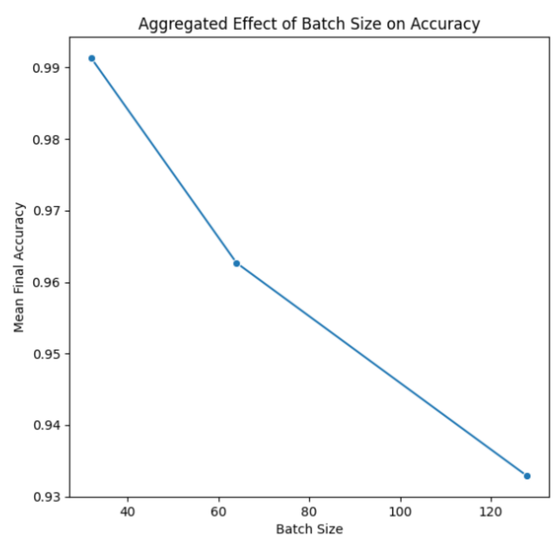

Figure 6: Hyper-parameter Search for the Batch Size

The number of epochs is a hyperparameter that controls how many times the training dataset is processed by the learning algorithm. The epochs are represented on the x-axis, plotted on a linear scale from 5 to 15. The mean final accuracy is represented on the y-axis, ranging from 0.92 to 0.99. As shown in the graph, the accuracy of training the model for 5 epochs reached approximately 92%. The model achieved a significant improvement in accuracy when the number of training epochs was increased to 10, reaching almost 99%. However, as the number of epochs increased further, the accuracy began to decrease.

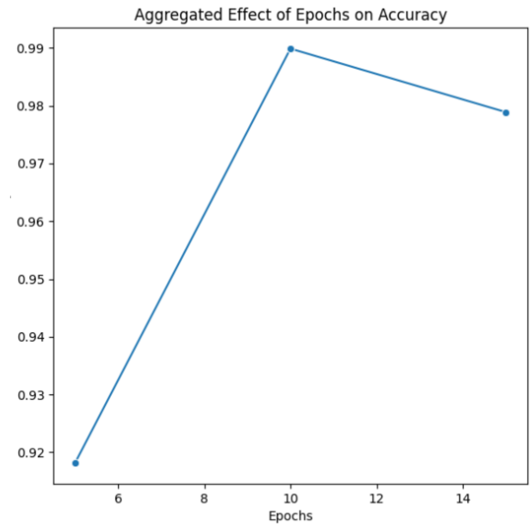

Figure 7: Hyper-parameter Search for the Epoch

The table below displays the best combination of hyperparameter values for learning rate, batch size, and epoch selected for this model, as determined through our hyperparameter tuning process.

Table 4: Optimum Parameters for the Proposed Model

Parameters	Optimal Value chosen
Learning Rate	10^{-3}
Batch Size	64
Epoch	10

5.5 Tools

In this study, a machine learning model was developed using the Python programming language in a Google Colab notebook to classify the quality and category of fruits and vegetables. Numerous visuals were produced using Canva, and documentation was prepared in Microsoft Word with the integrated Mendeley Reference Manager. The laptop computer most frequently used throughout the study has the following characteristics:

1. **Hardware Resources**
   - Device: IdeaPad S340-15IWL
   - Processor: Intel(R) Core (TM) i5-8265U CPU @ 1.60GHz 1.80 GHz
   - Graphic Card: Intel(R) UHD Graphics 620
   - Memory: 8.00 GB RAM

2. **Software Recourses**
   - Edition: Windows 10 Home
   - Version: 22H2
   - Python 3.10.12 on Google Colab
   - Frameworks used: Pandas, Matplotlib, Seaborn, Torch, Torchvision, Numpy
   - Time required: The code execution took approximately one hour.

6.0 Result and discussion

This section presents the results from the evaluation of the CNN and Vision Transformer (ViT) models, followed by a discussion of the findings. The primary focus was on classifying fruits and determining their freshness, leveraging both CNN and ViT architectures.

6.1 Discussion of Final Results

Performance Metrics:

After determining the optimal hyperparameters, 20% of the dataset was used to evaluate the models. The performance was assessed using multiple metrics: accuracy, precision, recall, and F-Score. However, accuracy served as the primary metric for comparing the effectiveness of the CNN and ViT models. Below are the results obtained from the experiments:

Table 5: Performance Metrics Results

Model	Fruit Classification					Freshness Classification				
	Accuracy	Precision	Recall	F1	Total	Accuracy	Precision	Recall	F1	Total
CNN	100%	100%	100%	100%	100%	98.9%	99%	99%	99%	99%
Vision Transformer (ViT)	100%	100%	100%	100%	100%	97.9%	98%	98%	98%	98%

Both models demonstrated exceptional performance, achieving a perfect accuracy of 100% in classifying the types of fruits and vegetables. However, in the more complex task of predicting the freshness of the produce, the Convolutional Neural Network (CNN) slightly outperformed the Vision Transformer (ViT). The CNN achieved an accuracy of 98.9%, while the ViT recorded an accuracy of 97.9%. This demonstrates how well the CNN can handle the complex aspects of this classification task and offers a reliable approach for accurate freshness detection. Even with the small performance variance, the high accuracy rates demonstrate the effectiveness of both models.

Confusion Matrix and Classification Report

Confusion matrices and classification reports were also generated to provide a detailed analysis of the model performance across different classes.

- **CNN Model confusion matrices**

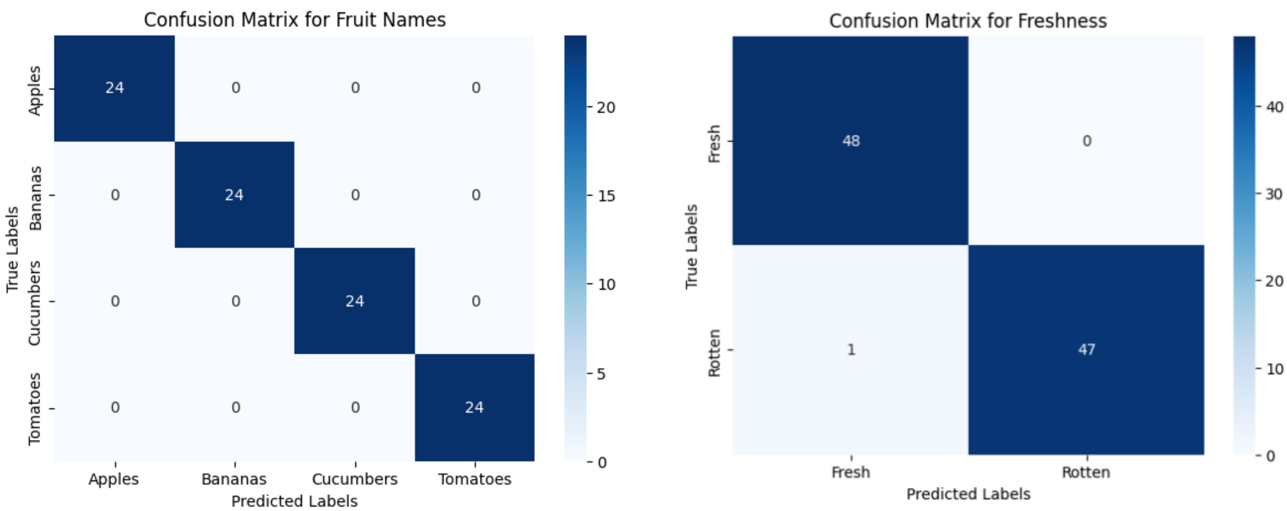

Figure 8: CNN Model Confusion Matrices

- **ViT Model confusion matrices**

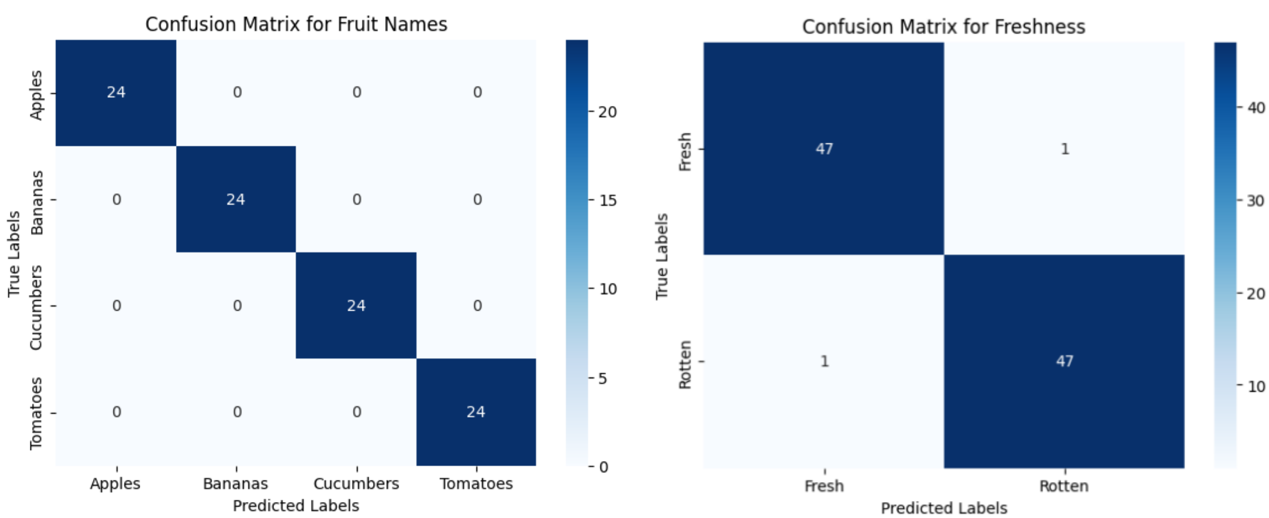

Figure 9: ViT Model Confusion Matrices

The confusion matrices illustrate that both models performed exceptionally well in classifying fruit types, achieving 100% accuracy. The classification of freshness showed slight misclassifications, particularly in distinguishing between slightly rotten and fresh fruits.

Implications and Benefits

The high accuracy achieved by both models in classifying fruit types and determining freshness has significant implications:

1. **Reduction in Food Waste:** By accurately determining the freshness of fruits, these models can help reduce food waste by ensuring that only fresh and high-quality items reach consumers. This can potentially save tons of food from being discarded unnecessarily.
2. **Enhanced Food Safety:** Improved classification helps reduce the chances of spoiled fruits entering the supply chain, thereby enhancing food safety. Consumers are less likely to purchase or consume spoiled fruits, reducing the risk of foodborne illnesses.
3. **Efficient Quality Control:** These models can automate the quality control process, making it more efficient and reliable compared to manual sorting. This automation can save time and reduce labor costs for companies involved in the distribution of fruits and vegetables.

6.2 Alignment with the requirements:

The intelligent solution implemented in this project aligns well with the specified requirements. The use of CNN and ViT models addresses the need for accurate and reliable fruit classification and freshness detection. This not only helps in reducing food waste and ensuring food safety but also enhances the efficiency of quality control processes in the food industry.

7.0 Conclusion and Future Work

The use of machine learning techniques to build a predictive model for classifying the quality and type of fruits and vegetables holds great promise for a beneficial impact on the agricultural and food industries. This study addresses critical issues of food waste and security through the use of convolutional neural networks (CNNs) and Vision Transformers (ViT). The CNN model achieved remarkable accuracies of 100% in classifying fruit and vegetable types and 98.9% in assessing freshness. The Vision Transformer model also performed well, achieving accuracies of 100% and 97.9% in these categories, respectively. However, the CNN model demonstrated superior performance in freshness classification. The impact of this research is significant. By accurately determining fruit type and freshness, these models can drastically minimize food waste by ensuring that only fresh and high-quality items reach customers. Furthermore, they improve food safety by reducing the possibility of spoiled goods entering the supply chain. The adoption of such technologies also streamlines agricultural processes, resulting in better supply chain management and more efficient resource usage.

For future work, we aim to incorporate a more diverse and extensive range of fruit and vegetable types to enhance the generalizability and robustness of our model. Additionally, we plan to expand our project to include the shelf life of these fruits and vegetables, providing more comprehensive insights and practical applications. To further improve the accuracy of our predictions, we intend to refine the dataset by incorporating a greater number of high-quality images and detailed annotations. This enhancement will help in refining our models and achieving superior performance in both classification and shelf-life estimation tasks.

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