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Fruits Freshness Classification System using Computer Vision and AI on Jetson Nano and Edge Impulse

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ABSTRACT

The classification of fruit freshness is commercially important in the food industry. Due to a lack of automation systems in this industry, this process is often done by human labour, resulting in inefficiency and inaccuracy in fruit freshness assessment, which can lead to food waste. As a result, this project will focus on developing a deep learning model that is reliable and accurate at identifying the freshness of fruits and categorizing them as fresh or rotten using two different datasets, as well as evaluating the model's performance in real-time on the Jetson Nano board to set a benchmark against existing models. The model was created using MobileNetV2, a well-known image classification architecture based on Convolution Neural Network (CNN). Data augmentation and pre-processing were already used in both datasets, resulting in 12196 and 13588 images from the Kaggle dataset and the Mendeley dataset, respectively. The model's hyper-parameter was tuned and analysed to classify 6 and 16 fresh and rotten classes from both datasets, respectively. In classifying 6 and 16 classes of various fresh and rotten fruits, the developed model achieved remarkable accuracy of 98.92% and 99.11%, respectively.

Keywords: Artificial Intelligence (AI), Classification Fruit Freshness, Computer Vision, Convolution Neural Network (CNN), MobileNetV2.

1. INTRODUCTION

The quality, flavour, and nutritional content of fruits are all influenced by how fresh they are, which is an important factor. However, assessing the freshness of fruits by hand can be a time-consuming and arbitrary task. As a result, to enable effective quality control and reduce food industry waste, a system that can automatically evaluate fruit freshness is required. Agriculture and food processing are just two of the many industries that have been transformed by computer vision and artificial intelligence (AI) technology in recent years. One of the application systems that significantly contributes to the profit rate of a business is the classification of fruit freshness [1]. Now that advanced and powerful hardware platforms like the Jetson Nano are available for deep learning algorithms, it is possible to create intelligent systems that can instantly analyse visual data.

Hand and eye classification of fruits and plants by type and characteristics is common [1]. While images are the most basic approach for physical classification and identification of food in the representation of human brain concepts [2], they are not the only approach. These methods are often time-consuming, arbitrary, and susceptible to human error. The proposed project intends to build a Classification of Fruits Freshness System using computer vision and AI technologies

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using the Jetson Nano module. This method will allow for the automatic evaluation of fruit freshness based on visual cues such as colour, texture, and surface flaws.
Using computer vision algorithms, the system will be able to capture photos or video streams of fruits and extract relevant elements that indicate freshness. Modern machine learning algorithms will then be applied to the retrieved features to classify the fruits into fresh and rotten states. When it comes to modern machine learning, the deep learning method is the most used because it can handle large datasets of images.

CNN (Convolutional Neural Network) has produced excellent results in image classification tasks, and it will be used in the proposed project. By learning to extract discriminative features from fruit images, CNN models can distinguish between fresh and rotten fruits. Transfer learning, which allows pre-trained CNN models to be improved using fruit specific datasets, has grown in popularity as a method for classifying the freshness of fruits and allows for effective training even with small datasets.

For the edge computing devices, NVIDIA Jetson Nano functions in real time and makes sure that the work is more sustainably done [1]. NVIDIA's Jetson Nano AI development board was released in 2019. Its 128 core MAXWELL GPU delivers significant AI computing capability for the device. Jetson Nano also supports several well-known machine learning frameworks and algorithms for image recognition [3]. The system also made use of the Raspberry Pi Camera Module V2 as an external connection device for the Jetson Nano development board. This camera module has a maximum resolution of 3280 x 2464 and can catch light from the visible spectrum [400- 700] nm [4]. It is connected directly via the CSI interface, whose bus supports high-rate serial data transmission and is equipped with a 15-pin ribbon connector [4]. The Jetson Nano and Raspberry Pi Camera Module V2 is an affordable and cost-effective embedded computing device that offers high-performance AI processing capabilities. Real-time inference is made possible by its GPU-accelerated design, which makes it the best option for deploying computer vision models in contexts with limited resources.

The Classification of Fruits Freshness System had many useful uses since it is developed successfully. It is included into sorting and grading equipment in the food sector to automate the quality control procedure, increasing productivity and decreasing waste. Consumers might gain from it by receiving trustworthy information regarding the freshness of fruits, which enables them to make wise purchasing decisions.

This paper presents a Classification of Fruits Freshness System using Computer Vision and AI on Jetson Nano. The remainder of the paper is organized as follows. Section II presented the methodology approach for this research work. Section III discussed the experimental result of a Classification of Fruits Freshness System using Computer Vision and AI on Jetson Nano performance. Finally, section IV provides the concluding remarks and points out the ideas for future extension of this work.

2. METHODOLOGY

This project research methodology was carried out for two phases where the 1st phase involves Step 1 to Step 5 while the 2nd phase involves in Step 6. All these phases will be processed on the Edge Impulse platform are shown in Figure 1.

2.1 Model and Data

The dataset is one of the most important things in data-driven techniques for implementing computer vision and AI. Because the classification of fresh and rotten fruits is usually done by eye, a large dataset is required to build a better classification model. The dataset provides a visual representation of both fresh and rotten fruits in a hyperspectral order of images for this project [5]. Although there are numerous datasets of fresh and rotten fruits available, the datasets used in this project were obtained from Kaggle and Mendeley Data as shown in Table 1.

The Kaggle dataset contains three types of fruits (apple, banana, and orange), each divided into fresh and rotten categories. The dataset contains 13,588 images after removing some impractical image samples with the same hash, which are used by 80% for training and 20% testing from total number of images.

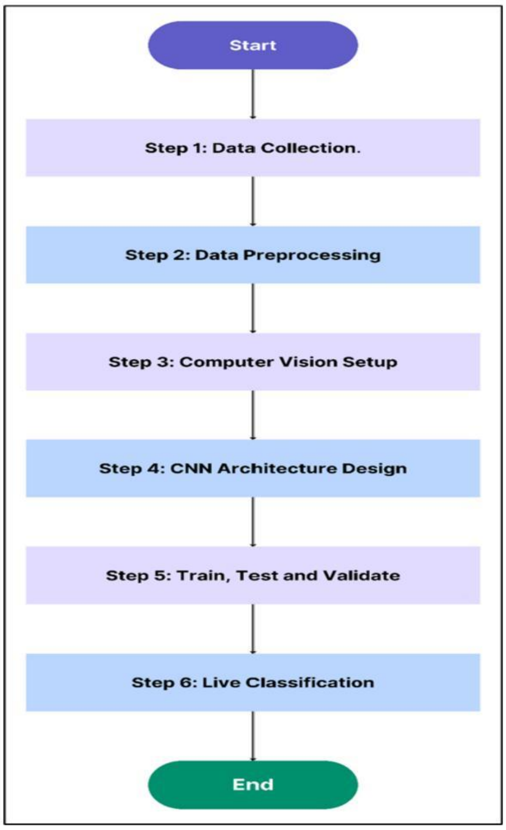


Figure 1. Overall steps for classification of Fruits Freshness system

The training dataset has 10,901 images, and the testing dataset has 2,687 images with 6 classes each. Mendeley Data's dataset includes eight different types of fruits (apple, banana, grape, guava, jujube, orange, pomegranate, and strawberry), each of which is divided into fresh and rotten categories. The dataset now has 12,196 images after some removal. The training dataset has 9,825 images which is 81%, and the testing dataset has 2,371 images which is 19% of total number of images with 16 classes each.

Table 1 Summary of datasets

Dataset Name	Total No. of Classes	Total No. of Images	Total No. of Training Images	Total No. of Testing Images
Kaggle	6	13,588	10,901	2,687
Mendeley Data	16	12,196	9,825	2,371

2.2 Data Pre-processing

Both datasets were evaluated separately to determine which dataset would provide the best efficiency in terms of performance and accuracy. In the Edge Impulse platform, these datasets will be automatically divided into training and testing sets. Because the datasets received were already enhanced, there is no need to rotate, shear, or otherwise manipulate the images. Figures 2 and 3 show some sample images from both datasets. To implement computer vision, image acquisition methods include the extraction of three features used: colour, morphological, and texture features. Images are captured in RGB colour codes for colour features, where R is red, G is green, and B is blue. Each image is divided into red, green, and blue planes, and the mean, median, standard deviation, and other statistics are calculated using these planes [6]. The YIQ colour space has three components: brightness (Y), which contains grey scale information, hue (I), and saturation (Q), which contains signal information [7]. It also includes the HSV colour space. HSI is also an excellent tool for creating natural-looking color-based image processing algorithms. Shape and size are morphological characteristics. Size features are physical dimension measurements that reveal information about the appearance of an object and [7].

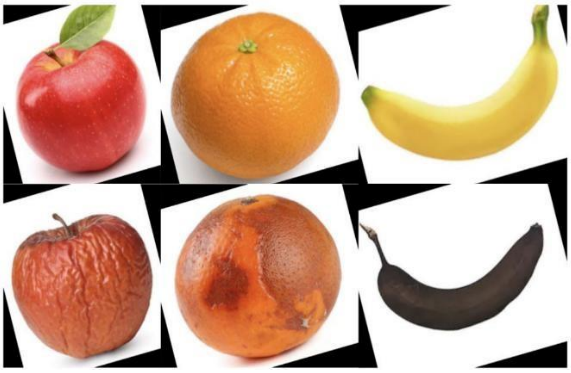


Figure 2. Sample images in Kaggle dataset

Figure 3. Sample images from Mendeley dataset

Area, perimeter, main and minor axis lengths, and aspect ratio are commonly used as morphological features [6]. Roundness ($4\pi \times \text{Area}/\text{Perimeter}^2$), aspect ratio (Major Axis/Minor Axis), and compactness ($\text{Perimeter}^2/\text{Area}$) are shape features that are measured [8]. Finally, texture features such as contrast, roughness, orientation, entropy, and so on are important in predicting the surface of fruits.

2.3 Computer Vision Setup

Computer vision is used to extract attributes from images captured in the real world. It is a field that encompasses methods for collecting symbolic and numerical data by acquiring, processing, analysing, and comprehending images. Its primary goal is to electronically perceive, comprehend, and classify images in order to mimic the effect of human vision [9]. Based on Figure 4, a computer vision system is made up of five parts: lighting, a camera, an image capture board (also known as a frame grabber or digitizer), computer hardware, and software [10]. To save time, computer vision of defect detection frequently involves automatic processing [11].

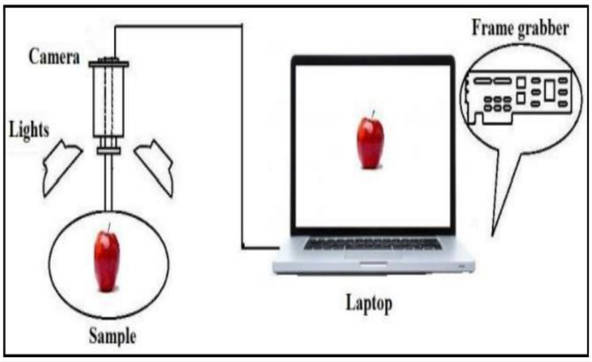


Figure 4. The computer vision's component [12]

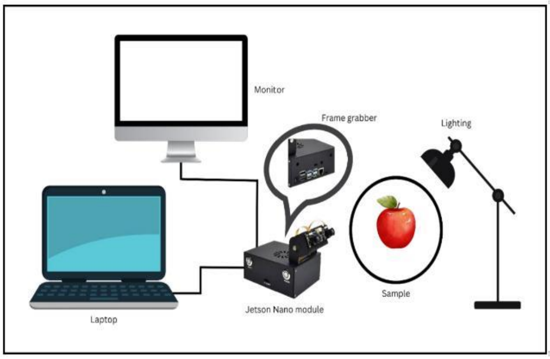


Figure 5. The computer vision setup for this project

To implement the computer vision algorithm, the Jetson Nano module is linked to a laptop and an additional monitor via the frame grabber on the back of the Jetson Nano, as shown in Figure 5. To ensure that the project runs smoothly, a Dell Inspiron 15 3505 laptop with an AMD Athlon Silver processor and an AMD Radeon graphics processor was used. An extra monitor is used to project the Jetson Nano's first boot up to activate a Raspberry Pi camera attached to the Jetson Nano for live classification with room lighting.

2.4 CNN Architecture Design

CNN is a type of deep neural network that uses supervised learning and is trained using backpropagation algorithms. CNNs are commonly used in computer vision to learn feature spatial hierarchies. CNNs are made up of three layers: convolution layers, pooling layers, and fully connected layers [13]. Convolution layers scan input images using filters that can perform convolution operations. Pooling layers are frequently used to save detected features or to down sample feature maps. Finally, fully connected layers collect results from previous images and label them accordingly. With the usage of deep learning architecture in the field of image recognition, CNN, one of the common deep learning models used for transfer learning, performs well in picture classification. CNN has several architectures that are being developed in conjunction with evolving technologies, one of which is Inception-V3 [14]. CNN extracts an image feature and scales it down in terms of dimension. CNN uses a sequence model to build a network and eventually provides a fully connected layer where all sensors are connected, and the results are processed. Unlike other pixel vector algorithms, CNN avoids a lot of spatial interaction between pixels by effectively down sampling the image first by convolution and then by using a prediction layer at the end [14].

This project used Edge Impulse platform; the CNN architecture used is MobileNetV2. CNN is a link formed sequentially from convolution layers, pooling layers, and fully connected layers. The Neural Network (NN) architecture combines all of the layers. CNN is composed of two parts: feature extraction and classification. The input layer, as well as convolution and pooling layers, are used in feature extraction, while fully connected layers and the output layer are used in classification. All these layers have already been pre-trained in MobileNetV2 to efficiently classify images. The image input size for this model network is 96×96. The input layer is represented by a matrix with values ranging from 0 to 255. This input layer has three channels: red, green, and blue. Each matrix is 96×96 in size. The total data or number of features provided by the input layer is 96×96×3, i.e., 27648. The number of neurons in the model's final dense layer can be changed because it has a significant impact on the model's size. To avoid overfitting and underfitting, the value is set to 40. The dropout rate is then set to 0.15 to avoid overfitting and embrace the model's performance.

2.5 Train Test and Validate

Edge Impulse and Jetson Nano are used to train, test, and validate the developed Machine Learning model. Edge Impulse is a new technology that combines machine learning algorithms, sensor data, and embedded systems to create intelligent and efficient solutions [15]. It enables machine learning models to be deployed directly on edge devices such as smartphones, wearable devices, or Internet of Things (IoT) devices, eliminating the need for continuous access to a remote server [16]. Because of its capabilities, Edge Impulse is an appropriate solution for addressing the problem of classifying fruit freshness.

Edge Impulse is a cutting-edge machine learning platform for developing and deploying intelligent edge applications [17], [18]. It offers developers an intuitive interface as well as a comprehensive set of tools for collecting, processing, and analysing data to create machine learning models [16]. Edge Impulse enables machine learning at the edge, allowing devices to make real-time decisions without requiring continuous cloud access [15]. The platform supports a wide range of edge devices, including microcontrollers, development boards, and sensors, enabling developers to leverage the power of machine learning in resource-constrained environments [16] and other application such crowd sensing[19].

Edge Impulse can be used by developers to train and deploy models for a wide range of applications such as predictive maintenance, anomaly detection, motion identification, and more [16]. The platform also supports the training and optimisation of machine learning models using widely used techniques such as neural networks, decision trees, and support vector machines [16]. It offers a user-friendly interface for configuring model parameters, evaluating model performance, and optimising models for deployment on edge device.

At first glance, a model is created by starting a new project in Edge Impulse. The target device has been set to Jetson Nano in the dashboard. Image data has been selected on the Data Acquisition page. The dataset used in this project were obtained from Kaggle and Mendeley Data [20] described in previous sections has now been uploaded. As shown in Figure 6, data for 6 and 16 classes of fresh and rotten fruits have been uploaded.

Figure 6. The total collected and train/test split ratio for both dataset.

The impulse is generated by first increasing the image size to 7676 and then adding image processing and learning blocks suitable for image classification models. To generate features, training images are used. Feature extraction considers between 6 and 16 image classes. The following step is to build the classifier. The number of training cycles, learning rate, and validation set size are the classifier's input parameters. It trains the model and calculates the training accuracy and loss. It also computes and displays the following on-device performance metrics: inference time, peak RAM usage, and Flash usage. The values of these parameters are shown in the next part.

2.6 Live Classification

The last step for the project is to deploy the model created in Edge Impulse into the Jetson Nano module. All the dependencies needed to connect Jetson Nano to the Edge Impulse platform have been installed. After installing the firmware, it was connected to an Edge Impulse project via the terminal command. The Raspberry Pi camera is used to capture images to classify new live data that will be evaluated by the model created in Edge Impulse. After uploading the model, the camera was accessed, and images were taken to classify the output that will be displayed in the Edge Impulse. Previously, the model was tested with a laptop connected to the Jetson Nano.

3. RESULTS AND DISCUSSION

The result shows the outcomes that provide a thorough evaluation of the developed system. It starts with a look at the training performance accuracy, which is backed up by a confusion matrix to provide a more detailed picture of the model's performance. The feature explorer is used to learn about the most important features for the classification task. The model's efficiency and effectiveness in a real-world setting are evaluated using on-device performance. The section then delves into the model testing results, using a confusion matrix once more to gain a detailed understanding of the model's predictive capabilities. To provide insight into the model's configuration and its impact on performance, a summary of the model's parameters is provided. Finally, the section concludes with real-time classification results that demonstrate the model's ability to classify the freshness of fruits. This section aims to provide a comprehensive and transparent assessment of the system's performance across various metrics and scenarios.

3.1 Training model performance

The first type of result is the Edge Impulse screens that show the model parameters: percentage accuracy, loss, the classification plots, and the on-device performance parameters: peak RAM usage, flash usage. Figure 7 shows the performance of Linux powered Jetson Nano running Edge Impulse platform.

Figure 7. Total data collected and train/test split ratio for both dataset.

The model illustrates a good training performance as shown in Table 2. Feature explore shown the subset of training set (2000 of 10901 samples) that classified by the neural network. The items in green are classified correctly while the items in red are misclassified. The model testing result is shown on Table 3.

Table 2 Model performance and confusion matrix based in settings used

Last training performance (validation set)						
Accuracy	99.2%		**Loss**		0.02	
Confusion matrix (validation set)						
	Fresh Apple	***Fresh Banana***	***Fresh Orange***	***Rotten Apple***	***Rotten Banana***	***Rotten Orange***
Fresh Apple	98.9%	0%	0.6%	0.6%	0%	0%
Fresh Banana	0%	100%	0%	0%	0%	0%
Fresh Orange	0%	0%	99.3%	0%	0%	0.7%
Rotten Apple	1.1%	0%	0.2%	98.3%	0%	0.4%
Rotten Banana	0%	0.2%	0%	0%	99.8%	0%
Rotten Orange	0%	0%	0.3%	0%	0.3%	99.4%
F1 Score	0.99	1.00	0.99	0.99	1.00	0.99

Table 3 Model testing results and confusion matrix of the model

Model Testing Results							
Accuracy	98.92%						
Confusion matrix							
	Fresh Apple	***Fresh Banana***	***Fresh Orange***	***Rotten Apple***	***Rotten Banana***	***Rotten Orange***	***Uncertain***
Fresh Apple	97.7%	0%	0%	1.2%	0%	0%	1.0%
Fresh Banana	0%	100%	0%	0%	0%	0%	0%
Fresh Orange	0.3%	0%	98.4%	0%	0%	0.5%	0.9%
Rotten Apple	1.0%	0%	0%	98.7%	0%	0.3%	0.2%
Rotten Banana	0%	0%	0%	0%	100%	0%	0%
Rotten Orange	0%	0%	0.8%	0.3%	0%	98.5%	0.5%
F1 Score	0.98	1.00	0.99	0.99	1.00	0.99	

3.2 Performance Evaluation on Different Dataset

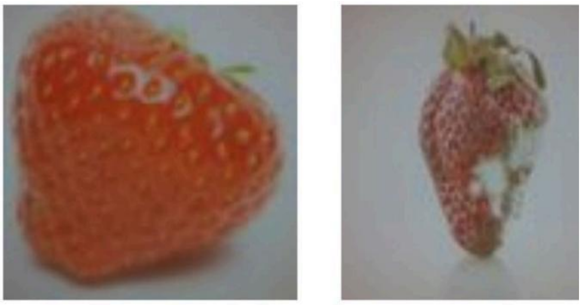
This project uses two different dataset which is Kaggle and Mendeley datasets. There are several common metrics such as these metrics of f1-score, accuracy, loss and confusion matrix for classification problems to obtain valuable information about algorithm performance and conduct a comparative analysis. With 20 epochs, both datasets performed admirably, with minor losses as shown in Table 4. Because the model was deployed on the same Jetson Nano module, the peak RAM and flash usage are the same for both datasets. These outputs have been used in the Edge Impulse Live Classification feature to record some new samples for classification from the camera connected to the Jetson Nano. For each sample, the model should be able to correctly identify the class.

Table 4 Summary of performance of different datasets

Dataset	**Epochs**	**Training Accuracy**	**Testing Accuracy**	**Loss**	**Peak RAM Usage (bytes)**	**Flash Usage (bytes)**
Kaggle	20	99.2%	98.92%	0.02	947.8K	1.7M
Mendeley Data	20	97.3%	99.11%	0.09	947.8K	1.7M

3.3 Live Classification Results

The Figure 8 to Figure 11 show the results of live fruit freshness classification using Edge Impulse for four different fruits in both datasets: strawberry, pomegranate, banana, and orange. The goal of the analysis is to assess the model's real-time performance and determine the effects of limiting image resolution optimisation to 96x96 pixels on classification accuracy.



Fresh Strawberry (0.98) Rotten Strawberry (0.87)

Figure 8. F1 score of live classification of fresh and rotten strawberry

Fresh Banana (1.00) Rotten Banana (1.00)

Figure 9. F1 score of live classification of fresh and rotten banana.

Fresh Pomegranate (0.99) Rotten Pomegranate (0.86)

Figure 10. F1 score of live classification of fresh and rotten pomegranate.

Fresh Orange (1.00) Rotten Orange (1.00)

Figure 11. F1 score of live classification of fresh and rotten orange.

The slight blurriness of the fruit images reflects the inherent limitation of Edge Impulse's optimisation up to 96x96 pixels. This constraint, while beneficial for resource efficiency, poses difficulties in accurately capturing fine details and textures. Balancing computational efficiency and image quality highlights the importance of understanding the impact of resolution on model performance. Also, these figures show that different fruits have varying degrees of success in live classification. Strawberries present a more difficult classification challenge due to their small size and detailed surface features. In contrast, bananas, and oranges, which have simpler textures, consistently produce clearer classification results. Pomegranates, with their combination of complex textures and larger surface areas, fall somewhere in the middle, reflecting the nuances of each fruit type. The live classification process demonstrates the model's ability to make decisions in real time. Despite the images' inherent blurriness, the system's responsiveness suggests its viability in dynamic environments requiring quick assessments of fruit freshness, such as supply chain management or retail settings.

Future iterations should investigate optimizing model parameters, incorporating additional training data, and experimenting with advanced image pre-processing techniques to improve the model's robustness and accuracy. Addressing these issues may reduce the impact of resolution constraints, improving the system's ability to handle difficult scenarios such as blurry or low-resolution images. Despite its resolution limitations, the live classification system has practical applications. Its ability to distinguish between fresh and rotten fruits in real time opens possibilities for low-cost quality control systems in agriculture and the food industry.

Continuous refinement, on the other hand, is required to adapt the model to various real- world scenarios and improve overall reliability.

The performance evaluation results provide a comprehensive evaluation of the system's performance. The model performance section contains positive training and testing results, demonstrating the model's effectiveness in classifying fruit freshness. The performance metrics summary compares the Kaggle and Mendeley Data datasets' training and testing accuracy, as well as loss. This comparison sheds light on the model's performance across various datasets. The live classification result section shows the system's real-time performance with the Raspberry Pi Camera Module V2, with the model achieving a high F1-score. This suggests that the system works well in a live environment, accurately classifying fruit freshness in real time.

4. CONCLUSION

In conclusion, this project introduced an innovative classification of fruits freshness system that integrates computer vision and AI and is designed for deployment on the Jetson Nano. The first goal was achieved by creating a deep learning model capable of accurately classifying fruits as fresh or rotten based on visual cues from a diverse dataset. However, image resolution constraints highlighted the delicate balance required between computational efficiency and image quality. The second goal was to evaluate real-time fruit freshness classification on the Jetson Nano, demonstrating the system's responsiveness within the constraints of the embedded device. The importance of considering the computational capabilities of the deployment platform was highlighted by optimization efforts tailored to the Jetson Nano. The benchmarking analysis, which fulfilled the third objective, positioned the system favourably in terms of accuracy, responsiveness, and robustness when compared to existing models. While promising, future research should concentrate on refining image resolution constraints and optimizing parameters to improve adaptability across different fruit types and real- world scenarios. This system makes an important contribution by demonstrating the power of embedded AI applications in addressing practical problems in agriculture, supply chain management, and retail.

In future project developments, priority should be given to increasing image resolution and quality within the constraints of the Jetson Nano. Exploring advanced preprocessing techniques and incorporating higher-resolution samples into the dataset may help to address the issues associated with image blurriness. To improve the model's adaptability, efforts should also be directed towards expanding the dataset to include a broader range of fruits and environmental conditions. Dynamic model optimisation strategies, which adjust parameters in real time based on available computational resources, have the potential to improve system efficiency even further. The incorporation of temporal data and the investigation of collaborative processing across multiple edge devices may contribute to a more robust and scalable solution. Furthermore, creating a user-friendly interface and seamlessly integrating with existing systems would make practical applications easier to implement. Finally, extensive field tests and evaluations in real-world settings are required to quantitatively assess the system's performance and validate its utility under a variety of operational conditions.

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