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Automated Bell Pepper Quality Assessment: Robotic Gripper Sorting System with Transfer Learning

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Abstract

Sorting is an activity during post-harvest that separates fresh produce depending on certain parameters. If this activity is manually done, it is time-consuming and sometimes inconsistent. The marketability of fruits and vegetables often relies on customers' standards and satisfaction. When these standards are not met, this will result in food wastage in the long run. In this study, the researchers aim to develop a sorting system using three (3) transfer learning algorithms with a robotic gripper application – which has not been majorly explored in previous studies. Moreover, this study also intends to aid bell pepper retailers in preventing food loss due to unsatisfied customer preferences. The process starts with image acquisition for data gathering. The collected data is subjected to data splitting for training and testing. Three pre-trained algorithms were used namely; VGG-16, Resnet50, and GoogleNet. Each of which undergone three train-test splits of; 70:30, 75:25, and 80:20 to see their accuracy. VGG-16 obtains an accuracy of 98.38% for both 70:30 and 75:25 train-test split. GoogleNet on the other hand, has the highest accuracy on 80:20 split with 97.84%. ResNet50 has the lowest accuracy having 90.23% for train-test split of 75:25.

Keywords: bell pepper, sorting, food loss, transfer learning, robotic gripper

1. INTRODUCTION

Sweet bell pepper (Capsicum annuum L.), recognized as the second most important vegetable globally after tomatoes, is cultivated extensively in tropical and subtropical regions [1-2]. It is esteemed for its diverse-colored fruits and is predominantly represented by Capsicum annuum, among various cultivated chili species [3-4].

Bell peppers experience substantial postharvest losses, estimated at 25-35% of total production, attributed to their perishable nature and vulnerability to various issues such as flaccidity, wilting, and fungal infections [5-6]. These losses occur across the entire supply chain, from harvest to home consumption, highlighting the need for improved handling and preservation methods [7].

Bell peppers are prone to postharvest diseases, leading to significant losses [8]. Common defects include rotting and damage caused by black mold and grey mold [8-9], as well as drying [10], which reduces freshness and firmness. Fresh produce must maintain an appealing appearance throughout the supply chain to meet consumer standards, with customers scrutinizing ripeness, color, and defects such as rot, dryness, and damage.

Sorting is a post-harvest activity that classifies fresh produce according to certain parameters [11]. This can be done manually, but it is time-consuming, subjective, and inconsistent [12]. Recent studies about sorting have focused more on classifying fruits and vegetables based on color, shape, and size only. Others are limited only to using machine vision and image acquisition techniques. Robotic arm applications with machine vision are not majorly explored.

The objective of this study is to develop a bell pepper sorting model designed to aid retailers by conducting a systematized quality assessment utilizing a transfer learning algorithm and a robotic gripper. Moreover, a camera is used for image acquisition, and a developed Graphic User Interface (GUI) displays the quality of the bell pepper. The proponents believe that the model will help reduce food loss due to unbought bell peppers that are not able to satisfy consumers' purchase preferences.

This paper is divided into six sections. Section II discusses the review of the related works. In Section III, the methods are explained. The results and discussion are presented in Section IV. Lastly, the conclusion and recommendation for future works related to the topic are discussed in Section V and Section VI respectively.

2. REVIEW OF RELATED WORKS

2.1 Existing Works

Bell peppers, also known as Capsicum, belong to the Solanaceae family, specifically the Solaneae tribe and Solanoicleae subfamily, and are rich in water and carbohydrates, offering a low-calorie option with minimal protein and fat content [13].

Color and pungency indicate capsicum quality, influencing consumer preference [14]. Bell peppers, like other perishable vegetables, are prone to defects from pre-harvest to postharvest stages, leading to food losses [15]. These defects include morphological, physiological, mechanical, internal, and pathological disorders [16]. Common post-harvest diseases in bell peppers include Grey Mold, Black Mold, and Internal Fruit Rot [8].

2.2 Lacking in Approaches

Artificial Intelligence is extensively applied in agriculture, industry, and services for faster and more efficient production, leading to enhancements in the quality of both service and agricultural sectors [17].

In enhancing the cultivation of bell pepper farming, artificial intelligence is one of the ways to improve its efficiency and productivity. The following is a summary of the application of AI: growth estimation [18], sorting [11], maturity estimation [19], leaf area modeling [20], color sorting [21], automatic harvesting [22], leaf disease detection [23].

Grippers can be designed to handle a variety of objects, from fruits and vegetables [24] to fabrics [25] and even eggs [26]. Some grippers use advanced technology, like force feedback and slip detection, to ensure a secure and delicate grip [27]. Others are simpler and focus on tasks like cutting [28] or quality assessment. While others are designed for certain operations such as mass production and harvesting, they are rarely used in bell pepper sorting. This offers an opportunity for innovation and technological integration in bell pepper sorting procedures.

Modern tools like neural networks, support vector machines [29-30], NIRS [29], hyperspectral imaging [31-32], RGB Cameras [30], and SRS [33] are used to assess fruit quality. Agricultural innovation includes soft gripper [34] with precise performance measurements, while terahertz time-domain spectroscopy [35] is employed for non-invasive assessment of fresh fruit quality, like cherries, based on chemical concentrations. However, there is a gap in the information regarding defect assessment in bell peppers and the application of gripper for this specific purpose in agricultural practices.

3. METHODOLOGY

This section will tackle robotic gripper utilization, data collection, and model development to classify and sort the fresh and non-fresh bell pepper.

3.1 Hardware

The design utilizes the A4Tech PK-910H image sensor, Arduino UNO R3 microcontroller, and a gripper. The robotic arm consists of six Tower Pro MG996R servos, controlled by a 16-channel, 12-bit PWM servo driver (PCA9685) connected to the Arduino. A DC-DC buck converter (LM2596S) serves as the voltage regulator for the gripper system design.

Battery specifications are critical to the robot's stability and functionality. A 5V, 10A lithium-ion battery was selected to power the servo motors, with payload and load capacity considerations ensuring stable operation.

3.2 Software

Proponents used C++ language for development of robotic arm and gripper, particularly the yaw, pitch, and roll. These functionalities will be embedded into the microcontroller controlled by PyCharm through a serial communication signal. Google Colaboratory was employed for training models using the TensorFlow and Keras libraries.

Python programming is also utilized for tasks such as capturing and recording images through OpenCV library, model training, the integration of two subsystems, and graphical user interface (GUI) for user-end functionalities.

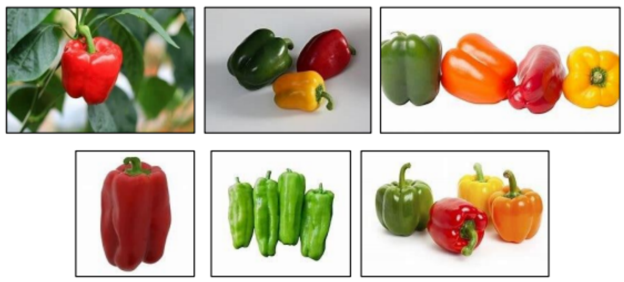


Figure 1 Images from Fresh Category

Figure 2 Images from Not Fresh Category

3.3 Dataset Description

The study employs diverse datasets from VegNet [36], Kaggle [37-38], and a self-generated dataset captured using a 108 MP Android camera under natural lighting at a 20 cm distance from the bell pepper. Images were filtered and classified as fresh or not fresh based on appearance and quality. The Figure 1 and Figure 2 shows the representative images from these datasets classified by the proponents.

The total number of images shown in Table 1 gathered in the study is 1872 images comprised of 808 images for fresh category and 1064 images for the not-fresh category.

Table 1 Summary of the Number of Images per Class

Total Images	Training-Testing Ratio		
	80:20	75:25	70:30
1872	1498:374	1404:468	1310:562

3.4 System Overview

Figure 3 shows the overview of the proposed system consisting of image acquisition, data normalization and augmentation, model creation, model evaluation, and the desired robotic arm output.

3.4.1 Image Acquisition

Bell peppers were captured on a platform situated 27cm far from the camera, placed adjacent to the maximum reach of the gripper to avoid potential collisions. The camera has a specification of 16-megapixel at 1080p video and a resolution of 4608 x 3456 pixels. The images will be acquired utilizing OpenCV libraries in Python and recorded upon capturing the object for widening the dataset further.

3.4.2 Data Preprocessing and Splitting

The images underwent normalization of pixel values, augmentation through adjustments of shear intensity, zoom range, and horizontal flipping for a robust dataset for training models. The distribution of samples was set at 70:30, 75:25, and 80:20 for the training and testing sets, respectively. Then, it was resized to dimensions suitable for the models, with the proponents standardized the dimensions to 128 x 128 for the process.

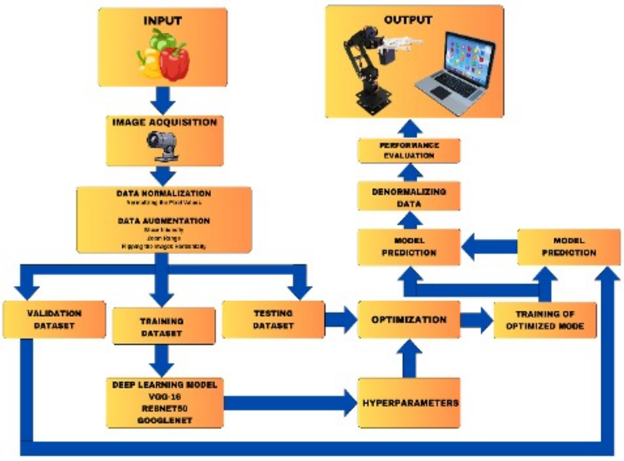


Figure 3 Overview of the Proposed System

3.4.3 Development of Classification Models

The proponents utilized pre-trained models commonly used for classification tasks, namely VGG-16, ResNet50, and GoogleNet initialized with weights obtained from the ImageNet dataset.

VGG-16 (Visual Geometry Group) architecture was developed from the AlexNet architecture at which it enhanced the convolutional and pooling layer's performance. ResNet (Residual Neural Network) builds upon VGGNet by incorporating additional layers, leading to a network that includes 152 convolutional, pooling, and fully connected layers. However, variations in the number of layers can have a significant impact to the accuracy due to reduced image quality [39].

In contrast, the GoogleNet architecture is also recognized as Inception that introduces a complex design featuring Inception module which allows the model to determine the optimal size of each convolutional layer [40].

For training the model, different splitting ratios of dataset were explored for the development of each model. Table 2 shows the ratio of images in different sets of training and testing.

Table 2 Image Distribution to Training-Testing Ratio

Total Images	Training-Testing Ratio		
	80:20	75:25	70:30
1872	1498:374	1404:468	1310:562

The training development for each model will utilize these ratios of training images as shown above, followed by optimization using testing images to achieve optimal performance of the model.

3.5 Testings and Parameters

3.5.1 System Setup and Calibration

Regular maintenance of hardware and software is essential for optimal functionality, involving systematic testing and manual calibration of sensors and the gripper. Each servo motor is calibrated by determining its rotation angle prior to robotic gripper assembly to prevent breakage.

Additionally, training the model with a curated dataset enhances its generalization to unseen data, thereby improving performance in sorting fresh and unfresh fruit. This decision-making process is critical given Arduino's limited image processing capabilities. Therefore, the Arduino is interfaced with a laptop. The Figure 4–6 below show the system setup.

3.5.2 Data Preparation

Bell peppers meeting the specified variations and quality criteria were assembled. The data collection process involved selecting images from existing datasets and capturing detailed images with a camera to document visual characteristics. These images demonstrate the rigorous methods employed to construct our datasets.

3.5.3 Performance Evaluation Metrics

The system is evaluated using multiple performance metrics such as accuracy, recall, precision, F-1 score, and confusion matrix to ensure robust system performance through model's generalization capabilities to the unseen image data.

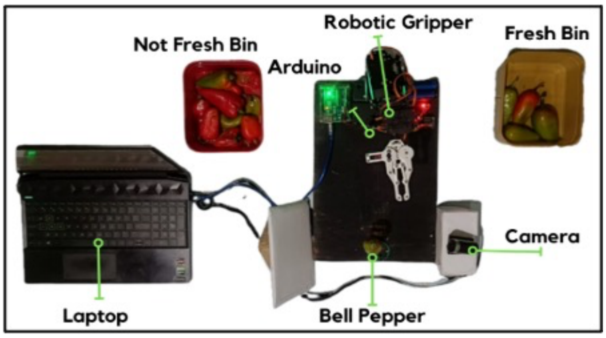
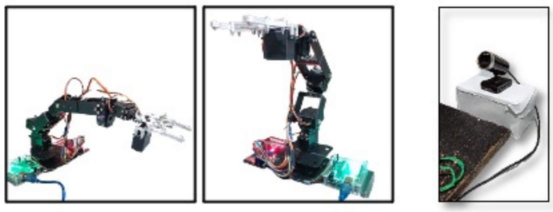
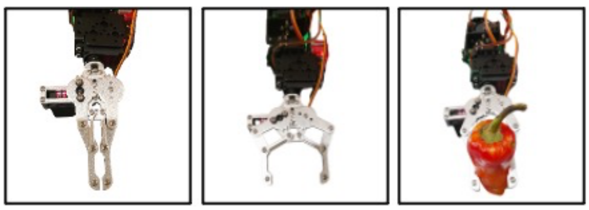


Figure 4 Actual Set Up of i-Cap



(a) Going Down and Default   (b) Camera Setup

Figure 5 Robotic Arm Position



(a) Closed   (b) Opened   (c) Grabbing

Figure 6 Robotic Gripper Position

3.5.4 Deep Learning Parameters

To enhance model performance, various parameters were optimized, including regularization to prevent overfitting, GlobalAveragePooling for dimensionality reduction, and ReLU activation to introduce non-linearity. Dropout layers were incorporated to mitigate overfitting, while softmax activation enabled multi-class classification. Learning rate adjustments and early stopping optimized convergence, while fine-tuning improved feature extraction. Additionally, 5-fold cross-validation ensured model generalization by validating performance across multiple subsets. These techniques collectively contributed to a well-balanced model, minimizing both underfitting and overfitting.

4. RESULTS AND DISCUSSION

The robotic arm starts from its default position, guided by the laptop processor that commands the camera to take a picture of the bell pepper. Once it verifies the pepper's freshness category, the arm lowers, opens the gripper to pick up the pepper, places it in the assigned bin, and then goes back to its initial position.

4.1 Software Development

4.1.1 Training of Models

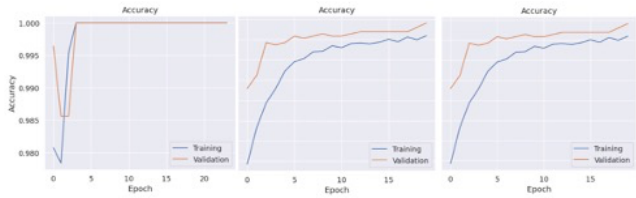
The three deep learning models utilized by the proponents are the VGG-16, ResNet50, and GoogleNet initially trained on the ImageNet weights. The gathered datasets from various sources are distributed in different training-testing ratio shown in Table 3. The proponents standardized the parameters in training models for uniformity as shown below.

Table 3 Standard Training Parameters

Standard Parameters	Name/Size
Batch Size	32
Learning Rate	0.00001
L2 Regularization	0.0001
Optimizer	Adam
Fine-tune epochs	40

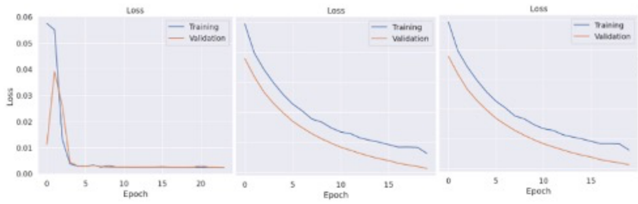
- VGG-16 Performance

Figure 7 and Figure 8 shows the accuracy and loss plot on ratios 70:30, 75:25, and 80:20 in VGG-16 model, respectively. By comparison, the 70:30 ratio had the better training results based on its learning curve compared to other ratios that show overfitting.



(a) 70:30 (b) 75:25 (c) 80:20

Figure 7 VGG-16 Accuracy Plot



(a) 70:30 (b) 75:25 (c) 80:20

Figure 8 VGG-16 Loss Plot

After training development, the VGG-16 is evaluated using separate 374, 468, and 562 test images for 70:30, 75:25, and 80:20 ratios, respectively.

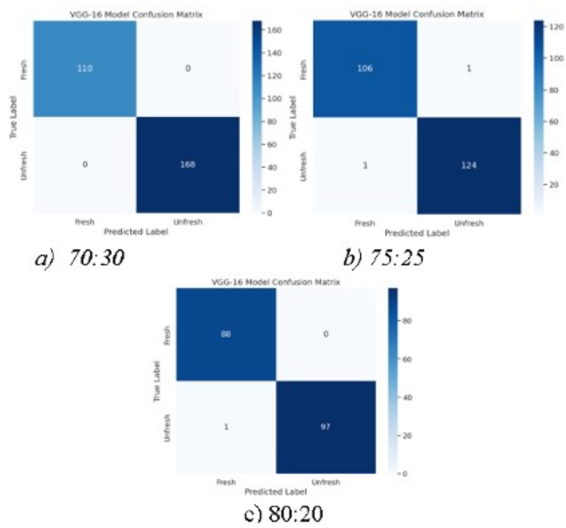


Figure 9 VGG-16 Confusion Matrix

Figure 9 VGG-16 Confusion Matrix shows the performance of each ratio on VGG-16 through confusion matrix and summarized its training results in Table 4.

Table 4 VGG-16 Training Results Summary

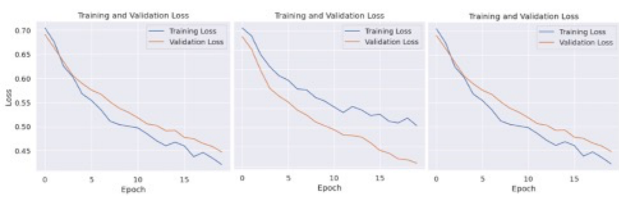
Train (%)	Test (%)	Epoch	P (%)	R (%)	F1 (%)	Acc. (%)
70	30	70	98.3	98.3	98.38	98.38
75	25	70	98.28	98.28	98.28	98.28
80	20	70	98.6	95.5	95.56	95.56

- ResNet50 Performance

Figure 10 and Figure 11 shows the accuracy and loss plot on ratios 70:30, 75:25, and 80:20 in ResNet50 model, respectively. By comparison, the ratio 70:30 and 80:20 has the better training results based on its learning curve compared to other that overfits.

(a) 70:30 (b) 75:25 (c) 80:20

Figure 10 ResNet50 Accuracy Plot

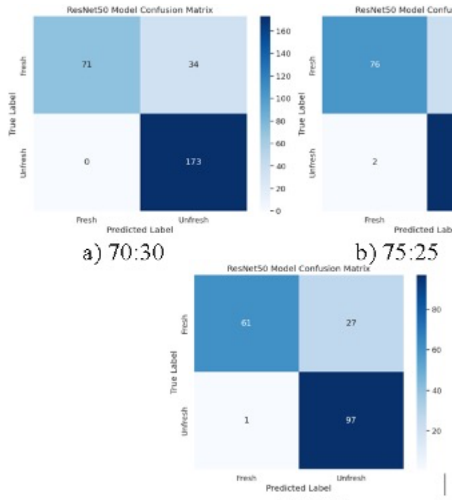


(a) 70:30 (b) 75:25 (c) 80:20

Figure 11 ResNet50 Loss Plot

After training development, the ResNet50 are evaluated using separate 374, 468, and562 test images for 70:30, 75:25, and 80:20 ratios, respectively.

Figure 12 shows the performance of each ratio on ResNet50 through confusion matrix and summarized its training results in Table 5.



a) 70:30 b) 75:25 c) 80:20

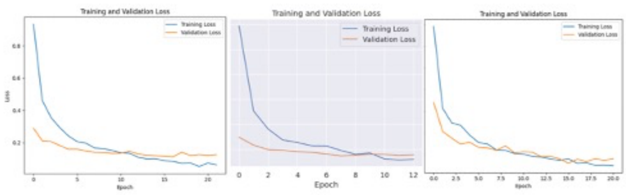
Figure 12 Resnet50 Confusion Matrix

Table 5 ResNet50 Training Results Summary

Train (%)	Test (%)	Epoch	P (%)	R (%)	F1 (%)	Acc. (%)
70	30	20	88.67	86.69	86.33	86.69
75	25	20	90.23	89.22	88.87	89.22
80	20	20	89.89	88.65	88.07	88.65

(a) 70:30 (b) 75:25 (c) 80:20

Figure 13 GoogleNet Accuracy Plot



(a) 70:30 (b) 75:25 (c) 80:20

Figure 14 GoogleNet Loss Plot

- GoogleNet Performance

Figure 13 and Figure 14 show the accuracy and loss plot on ratios 70:30, 75:25, and 80:20 in GoogleNet model, respectively. By comparison, the ratio 70:30 has the better training results based on its learning curve. In addition, the other ratio indicates a well-fitting model.

After training development, the GoogleNet is evaluated using separate 374, 468, and562 test images for 70:30, 75:25, and 80:20 ratios, respectively.

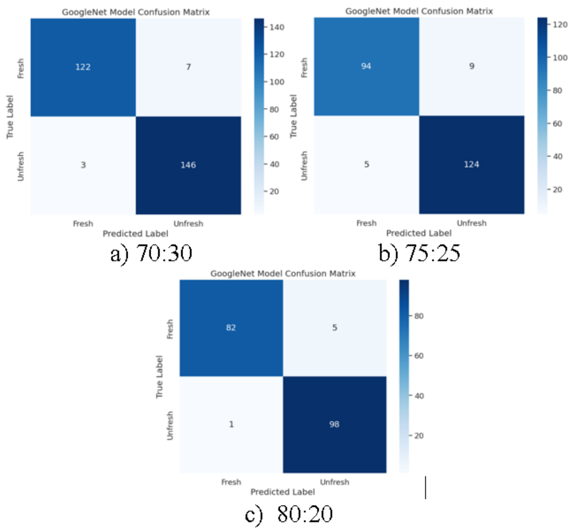


Figure 15 GoogleNet Confusion Matrix

Figure 15 shows the performance of each ratio on GoogleNet through confusion matrix and summarized its training results in Table 6.

Table 6 GoogleNet Training Results Summary

Train (%)	Test (%)	Epoch	P (%)	R (%)	F1 (%)	Acc. (%)
70	30	30	97.84	97.84	97.84	97.84
75	25	30	93.57	93.53	93.51	93.53
80	20	30	95.21	95.14	95.15	95.14

4.1.2 Summary of Training

The table 7 shows the summary of training on VGG-16, ResNet50, and GoogleNet trained with ratios 70:30, 75:25, and 80:20. It indicates the architecture (Arch), train-test-split ratio, epoch (Eph), precision (P), recall (R), F1-score (F1), and accuracy (Acc).

Table 7 Summary of Training on the three model

Arch	Ratio	Eph	P	R	F1	Acc
VGG-16	80-20	70	98.6	95.5	95.56	95.56
VGG-16	**75-25**	**70**	**98.2**	**98.2**	**98.28**	**98.28**
VGG-16	**70-30**	**70**	**98.3**	**98.3**	**98.38**	**98.38**
Resnet50	80-20	20	86.6	86.3	86.69	88.67
Resnet50	75-25	20	89.2	88.8	89.22	90.23
Resnet50	70-30	20	88.6	88.0	88.65	89.89
GoogleNet	**80-20**	**30**	**97.8**	**97.8**	**97.84**	**97.84**
GoogleNet	75-25	30	93.5	93.5	93.53	93.57
GoogleNet	70-30	30	95.1	95.1	95.14	95.21

Three models at various ratios during the training, testing, and validation phase are explored. Upon evaluation, it was concluded that the VGG-16 architecture with a ratio of 70:30 is the best classifier model for having a consistent level of accuracy. It surpassed the performance of the other two models and thus established as the preferred model for quality assessment classification of the bell pepper fruits.

4.2 Hardwar Development

The graphical user interface (GUI) of the system will show the classifiers' model prediction as visual representation below to the end-user if the system detected (a) fresh or (b) unfresh as shown in Figure 16.

4.3 Subsystem Testing

This pertains to the integration of live video feed, classifier model, and the robotic gripper. The system is programmed featuring a delay before it classifies the object. Upon detection, the system captures the frame from live video feed and initially recording it.

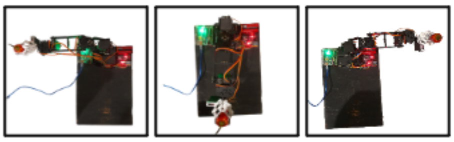
Subsequently, it will undergo image processing as discussed before it employs to the model for prediction. As it predicts the object, it will reflect on the developed GUI as shown in Figure 16. Simultaneously, the robotic gripper will function based on the prediction as for the hardware output.

Figure 17 shows the Robotic Gripper Movements of the proposed system. With proper programming, compatible components, robot's payload, platform's load capacity, the desired functionality of robotic gripper in terms of yaw, pitch, and roll is achieved.

(a) Fresh (b) Unfresh

Figure 16 GUI Of I-Cap

(a) Yaw (b) Roll



(c) Pitch

Figure 17 Robotic Gripper Movements

5. CONCLUSION

This paper presents a comprehensive approach to an automated bell pepper quality assessment and classification system. The hardware development section shows the successful implementation of a robotic arm with a versatile gripper and a strategically positioned camera for efficient data gathering.

Three deep learning models pretrained on ImageNet dataset were implemented in classifying quality in the generated dataset of bell pepper. These models are VGG-16, ResNet50, and GoogleNet, which are commonly used for classifying fruits. A total of 1872 images comprised of 808 for fresh and 1064 for not fresh were used in training, testing, and validation of all models in different split ratios. VGG-16 recorded a 70:30–75:25–80:20 accuracy of 98.38%–98.28%–95.56%, ResNet50 with 89.89%–90.23%–88.67%, and 95.21%–93.57%–97.84% for GoogleNet. The VGG-16 model demonstrates an outstanding performance in classifying fresh and unfresh compared to the two other models. Thus, it is considered as the best model for classifying the quality of the bell pepper fruit.

6. RECOMMENDATON

The researchers provide the following suggestions as they conclude and summarize the execution of the system's development, training, and validation. These recommendations are intended to offer insights and guidance for future work in this area.

- Assess the system's generalization and robustness by conducting tests on a more extensive and diverse dataset.
- Consideration of alternative gripper, such as vacuum gripper or soft gripper, is proposed to minimize potential damage to bell peppers during the sorting process.
- Regular updates to the system, incorporating new data and models, are advised to ensure its alignment with the latest advancements and trends in the field.
- Further experimentation with models or algorithms with enhanced precision is suggested for comprehensive testing and identification of the most accurate model.

- The use of conveyor belts enabled high-throughput, simultaneous processing of bell peppers.

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