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Design and Implementation of a Computer Vision System Using Convolutional Neural Networks for Sustainable Quality and Maturity Assessment of Bell Peppers

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Destructive testing is usually used for sorting and managing produce in a retail environment, which results in further damage and the misclassification of sensitive products. The quality of vegetables and fruits like bell peppers is reflected in their external features. Therefore, this research aims to develop a non-destructive method that uses a computer vision system and machine learning algorithms that can automatically determine the quality and maturity of bell peppers in real-time applications. This study implements two Convolutional Neural Network (CNN) machine learning models: YOLOv8 and EfficientNetV2 B0. Additionally, automated rollers are added to rotate multiple bell peppers, allowing the camera to capture different perspectives for more detailed classification. The YOLOv8 was used to obtain multiple images of bell peppers, which EfficientNetV2 B0 then classified. The bell peppers were categorized into four categories: (1) Ripe with good condition, (2) Unripe with good condition, (3) Ripe with bad condition, and (4) Unripe with bad condition. The accuracy of the device was tested in two supermarkets. In the first supermarket, the automated classification obtained an accuracy of 93.2 %, while manual classification obtained an accuracy of 90.6 %. For the second supermarket, the automated classification obtained an accuracy of 91.4 %, and the manual classification accuracy was 89.7 %. Overall, the automated classification achieves an accuracy of 92.3 %, surpassing the overall manual classification accuracy of 90.1 %.

1. Introduction

According to Harel et al. (2020), bell pepper comes in two classifications: ripe and unripe. In the Philippines, the bell pepper price has continued to increase from 2017 until now. In 2023, the price of bell peppers was PHP 143.41 /kg (Balita, 2024). Approximately 42% of vegetable harvests are spoiled at various stages, with 20–50% of losses occurring during the marketing phase due to inefficient transportation systems and inadequate storage facilities, as noted by Hoffman et al. (2021), and further exacerbated by improper packaging practices, according to Calora et al. (2019). Supermarkets experience postharvest losses when the quality and quantity of produce decline from the time it is harvested until it is sold to consumers. The quality examination of the bell peppers is done by human labor. In the Philippine National Standard document number 78 issued by BAFPS (2009), bell peppers should follow the set minimum requirement: good condition with no damage, no unwanted scent, correct ripeness, and handled properly (Bureau of Agriculture and Fisheries Standards, 2021). The Philippine National Standard for checking bell peppers is almost similar to the United Nations Economic Commission for Europe (UNECE) and United States Department of Agriculture (USDA). There are limitations to knowing whether the bell pepper is still in good quality or not. Checking is based on the presence of whether the bell pepper has shrivelling, foreign matter, scars, pests, etc. (UNECE, 2009). Considering the outside appearance of fruits and vegetables, human errors are sometimes made by the market employees as they thought that the quality of that product should be discarded as stated by Filimonau and Gherbin (2017). The output depends on a person's productivity and condition. As fatigue sets in, the expected output may change. As a result, their output is lower compared to when they first started working as stated by Collewet and Sauermann (2017).

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This study focuses on a non-invasive, AI-driven approach using convolutional neural networks for assessing the maturity and quality of bell peppers. These technologies allow for the evaluation of shape, size, color, texture, and flaws in fruits and vegetables, which is non-destructive and efficient (Bansal and Bhargava, 2021). In the study of Firouz et al. (2021), Multi-layer Perceptron Artificial Neural Network (MLP-ANN) was used to sort bell peppers according to their size and maturity levels. They gathered data that MLP is excellent at sorting the bell peppers. However, in classifying a class in bell peppers, the accuracy is low in the MLP-ANN algorithm. The bell pepper is also one-sided. As for Moon et al. (2021), they used MLP and Convolutional Neural Network (CNN) in classifying the bell peppers focused on the plant. You Only Look Once Version 5 (YOLOv5) was used for the collection of the data sets. In classifying the maturity and breaking of the bell peppers to the plants, the CNN algorithm obtained a high accuracy but not in immature bell peppers. Only the MLP can classify the immature bell peppers. EfficientNetV2 models can be used for the classification and grading of fruits (Kaharrudin et al., 2023). Adding machine vision to the fruit ripeness classification reduces the manual work of the people and time consumption. Compared to other models, EfficientNetV2 B0 gives an accuracy of 100 % as it does not need a large dataset to function (Le and Tan, 2021).
This research study aims to design an automated machine that can identify the quality and maturity of multiple bell peppers with the help of image processing. This research utilizes two CNN machine learning models specifically EfficientNetV2B0 which specializes on image classification and YOLOv8 which specializes on object detection. These machine learning models are chosen based on its efficiency, simplicity, and performance. Utilizing both specialize functions of the machine learning model, the researchers was able to produce a machine that can automatically assess multiple bell peppers on different angles. Unlike previous studies regarding bell pepper quality and maturity assessment which only assess single bell pepper on one angle.

2. Materials and Methods

Figure 1a shows a computer vision system using a Raspberry Pi 4 and a CNN to assess the quality and maturity of bell peppers. A camera captures images, which are processed in real-time by the Raspberry Pi 4 running a trained CNN model. The system classifies bell peppers based on maturity and quality. A laptop or mobile device connected via RealVNC can control the Raspberry Pi 4, view camera feeds, adjust settings, and access analysis data. Rotating cylinders ensure bell peppers are viewed from all angles for accurate classification.
The device is built inside a wooden enclosure as shown from Figure 1b. It uses PVCs with an enveloped rubber material for grip. The rollers are moved by motors (DC Motor and Relay Module) which are triggered by the Raspberry Pi 4. To obtain proper lighting, a ring light was integrated and attached to the ceiling of the enclosure that is powered by the Raspberry Pi 4. Additionally, a power bank is used as a power source of the Raspberry Pi 4. Lastly, the camera is placed at the middle of the ring light which captures most of the rollers.

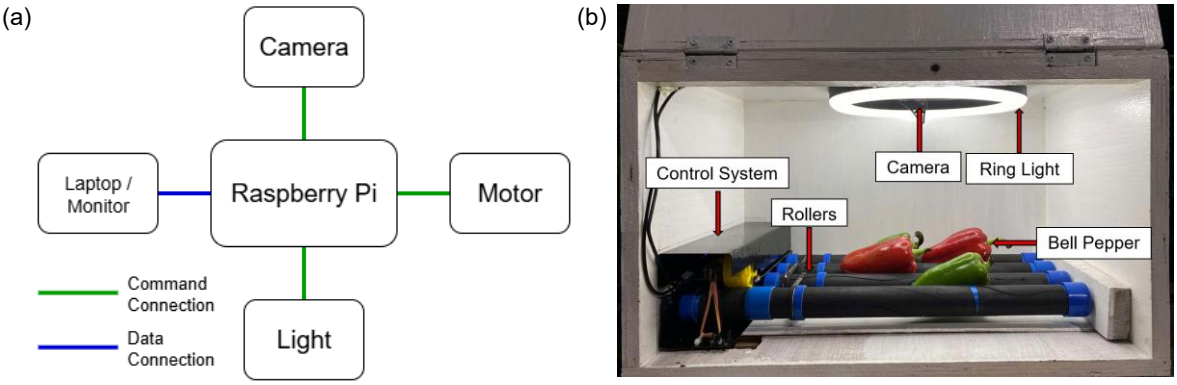


Figure 1: (a) Block Diagram (b) Actual Setup

2.1 The Machine

Figure 2a shows the machine's internal components, centered on the Raspberry Pi 4, which controls the relay module, DC motor, ring light, and camera. The relay manages voltage flow to the motor, rotating the wheels and PVC pipes. The camera and ring light are powered through USB ports on the Raspberry Pi 4. Power can be supplied via outlet or power bank. Figure 2b displays the external view of the machine, while Figure 2c shows the internal top view, with the camera positioned at the center of the ring light for better lighting. Figure 2d presents the camera's view used to assess the quality and ripeness of 4–6 bell peppers.

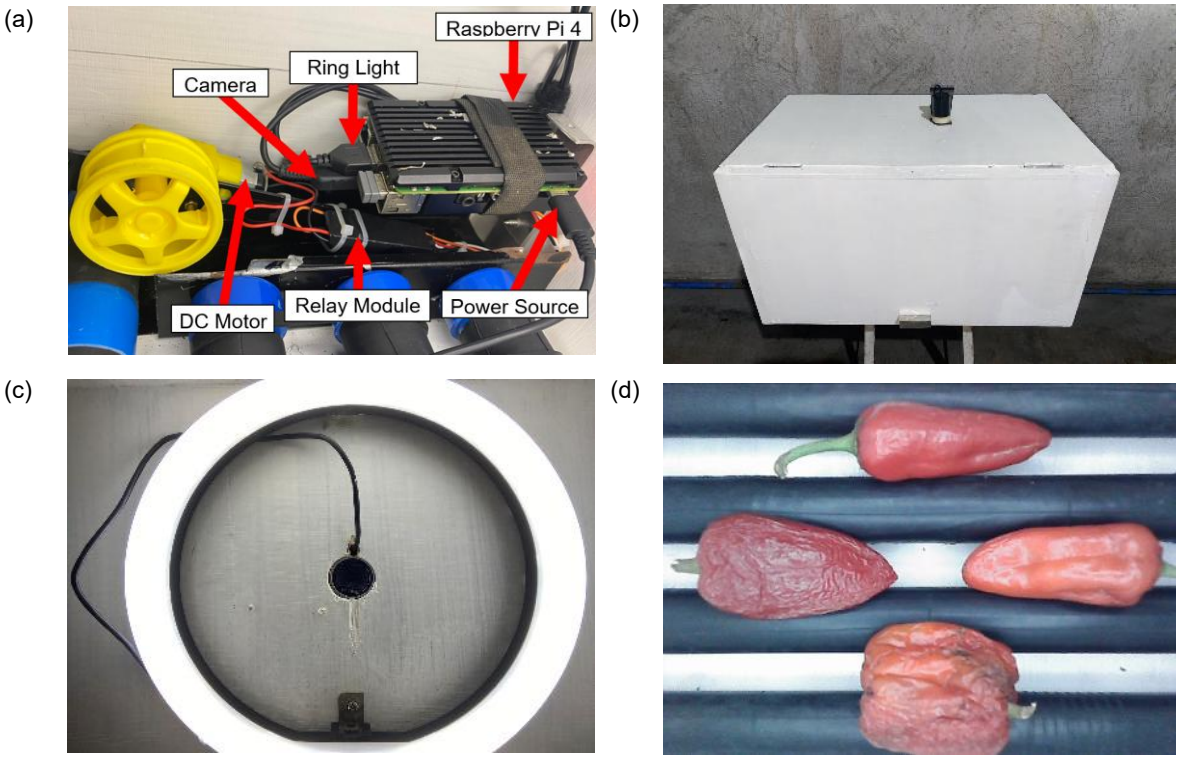


Figure 2: (a) Internal Subsystems (b) Outside Perspective (c)Inside Top View (d) Camera perspective

2.2 System Overview

This section demonstrates the step-by-step process of the system. It contains three stages to completely assess the maturity and quality of all the present bell peppers inside the machine. Stages 1 and 2 from Figure 3a have similar processes, except for the processed input image. Between Stage 1 and Stage 2, there is a roller motor function. The roller motors are made from PVCs, which are wrapped by rubber. This component has the purpose of rotating the bell peppers inside the machine so that the camera can capture multiple sides of the bell peppers.

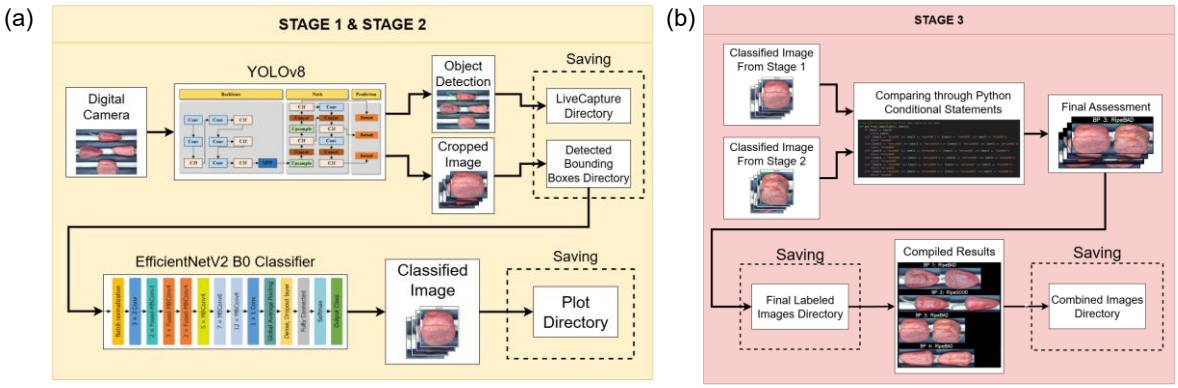


Figure 3: Automated Quality Analysis (a) Stage 1 and 2 (b) Stage 2

In Stage 1, it shows the first side of the bell pepper, and Stage 2 shows a different side of the bell pepper. Specifically, the A4Tech PK-910H 1080p Full-HD Webcam was used for capturing the Bell peppers inside the machine. For object detection, the YOLOv8 model was used to accurately detect the bell peppers. It uses two specific directories. The first directory is the “LiveCapture”, which contains two images that show the whole frame captured by the webcam with bounding boxes. The first image is from stage 1, and the second image is from stage 2. The second directory is the “Detected_Bounding_Boxes”, which stores the cropped images from the bounding boxes. In this directory, it has specific file names which are based on its Unique ID and cycle number. The cycle number is the reflection to its stage number (ex., Stage 1 is cycle 1). Additionally, Roboflow was used in labelling and indicating bounding boxes for training the pre-trained YOLOv8 model. Background

noises like tomatoes were implemented to enhance the model's capabilities to detect only bell peppers and ignore other fruits or vegetables that have a similar appearance to bell peppers. This procedure and practice can enhance the model's performance in capturing only bell pepper products. For the classification of bell peppers, a pre-trained model of EfficientNetV2B0 was used. It uses the images coming from the "Detected_Bounding_Boxes" directory as its input image. After classification, it was saved in the "Plot" Directory. The file name of each image remained the same, which was used in the next process. Stage 3 consists of two functions: the side comparison of each bell pepper and the compiled results. For the side comparison of the respective bell peppers, the program compared the two sides of the bell pepper and indicated its final decision. The two images are obtained from the "Plot" folder, which combined and matched the two sides of a similar bell pepper using the unique ID and cycle number indicated from the image's file name. Its decision is based on the conditional statement of the Python program. This conditional statement is based on the Philippine National Standard document number 78 issued by BAFPS (2009). Finally, it was saved in the "Final_Labeled_Images" directory. The last process is to compile all the images from the "Final_Labeled_Images" directory. This process produced one single image that contains all the bell peppers present inside the machine with its respective quality and maturity label as shown from Figure 3b. This image was saved in the "Combined_Images" directory.

3. Results and Discussion

3.1 Machine Learning Models

The datasets used in this study were sourced from both personal raw data and publicly available data from Kaggle which can be accessed in Villaluz et al. (2025). The bell pepper dataset comprises four distinct classifications: *Ripe Good*, *Unripe Good*, *Ripe Bad*, and *Unripe Bad*. This dataset was utilized for training and validating machine learning models, including EfficientNetV2B0 and YOLOv8. The machine learning that was used in this study was the EfficientNetv2 B0. To achieve acceptable results for EfficientNetV2B0 by only having minimum dataset, an approximate of 300 pictures per category is required. The validation depended to the 20-25 % of the trained data sets. The model dataset trained 4240 pictures and validated 1004 pictures of bell peppers. The calculation as seen in Eq(1) demonstrates the accuracy reading of the confusion matrix from the trained model. The trained model predicted a high accuracy of approximately 99.2 % for the four classifications of bell pepper (Ripe good, Ripe bad, Unripe good, and Unripe bad). There are slight errors in the unripe bad classification, as the model may need more datasets in terms of that part.

$$\text{Accuracy} = \frac{\text{Total number ofdatasets with errors}}{\text{Total number of datasets}} \times 100 \quad (1)$$

The graph below demonstrates the training output of the model through epoch. As shown in Figure 4a and 4b, fine-tuning has a significant contribution to enhance the model's performance.

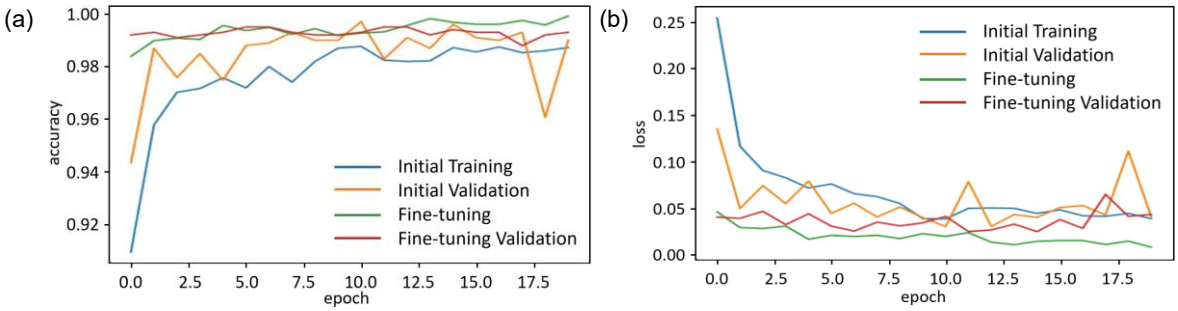


Figure 4: (a) Model Accuracy (b) Model Loss

The trained YOLOv8 for image extraction of bell peppers inside the enclosure achieved the ideal performance. The researchers were able to improve its performance by implementing background noise during the model's training. To achieve acceptable results for YOLOv8 by only having minimum dataset, an approximate of 100 pictures per category is required. The validation depended to the 20-25 % of the trained data sets. The model dataset used 1150 pictures and validated 230 pictures. Figure 5 illustrates the result, showing that the system accurately identified the bell pepper with a confidence level exceeding 80%, while successfully disregarding the presence of tomatoes. Even if it detects tomatoes, it does not exceed the 80 percent confidence level to consider it as a bell pepper.

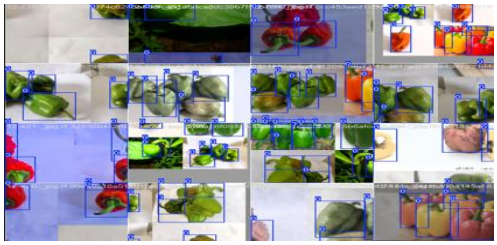
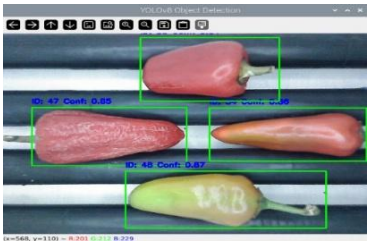
(a)  (b) 

Figure 5: (a) Batch Results (b) Actual Bounding Boxes

3.2 Statistical Tools

3.2.1 Confusion Matrices

In batch 1 out of 117 bell peppers 109 was correctly identified by the machine (automated) and 106 was correctly identified by the manual sorters. The machine achieved 93 % accuracy, with minor errors in classifying between good and bad conditions of unripe bell peppers. The worker's manual classification achieved 91 % accuracy, with major errors in classifying bad conditioned bell peppers. As for batch 2 out of 116 bell peppers 106 was correctly identified by the machine (automated) and 104 was correctly identified by the manual sorters. The machine achieved 91 % accuracy, with minor errors in determining between good and bad condition of a ripe and unripe bell peppers. The worker's manual classification achieved 90 %, with misclassifications coming from the bad conditioned bell peppers. The combined batch, averaging Batch 1 and 2, had an automated accuracy of 92 %. Minor errors were due to lighting, camera quality, and dataset. While it achieved a manual accuracy of 90 %. Misclassifications were due to bad condition of the bell peppers. The worker also relied on the hardness of the bell pepper despite having scratches and marks, which is not acceptable from the PH Standard of bell peppers. Table 1 follows the overall accuracy formula of the confusion matrix, which is the summation of the correctly identified samples (TP) over the total samples (TP + TN + FP + FN), where: TP (true positive), TN (true negative), FP (false negative) and FN (false negative) as seen in Eq(2).

$$\text{Overall Acuracy} = \frac{\sum \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2}$$

Table 1: Evaluation Metrics

Batch Number	Total Sample Size	Overall Accuracy (Automated)	Overall Accuracy (Manual)
1	117	0.932	0.906
2	116	0.914	0.897
Average	233	0.923	0.901

3.2.2 Cohen's Kappa

Cohen's Kappa (κ) is a measure of the two-rater agreement, used here to measure how well machine classification agrees with human sorting of bell peppers. To test the device's reliability, Batch 1 and Batch 2 bell peppers were bought from two supermarkets and sorted by store staff and the result is shown in Table 2.

- Batch 1: Kappa = 0.806 (SE = 0.043, $p < 0.001$, n = 117) indicating near-perfect agreement
- Batch 2: Kappa = 0.794 (SE = 0.044, $p < 0.001$, n = 116) indicating substantial agreement
- Combined (1 and 2): Kappa = 0.800 (SE = 0.031, test statistic = 21.390, $p < 0.001$) indicating strong significant agreement

As per the combined kappa, it confirms that the low standard error and high-test statistic indicate that the model outcomes are precise, and not random.

Table 2: Symmetric Measures

Batch Number	N of Valid Cases	Measure of Agreement	Asymptotic Standard Error	Approximate	Approximate Significance
1	117	0.806	0.043	15.193	<.001
2	116	0.794	0.044	15.078	<.001
Average	233	0.800	0.031	21.390	<.001

4. Conclusion

The machine learning model was able to classify the bell pepper in terms of condition and ripeness. However, in the trained EfficientNetV2 B0 model, some errors arise in classifying unripe good and unripe bad. There are instances where the model classifies unripe bad as unripe good. The misclassification is due to factors like lighting, camera quality, Raspberry Pi overheating, and lack of data variety. Poor lighting can affect the camera's visualization, potentially causing it to misclassify a poorly conditioned bell pepper as a good one. The same issue can occur with high-intensity brightness, as the bell pepper's skin may reflect light, affecting the classification and detection process. The trained YOLOv8 also performed better compared to its initial training. Due to the added background noises, the model was able to detect bell peppers and learned to ignore other fruits with similar features, like tomatoes. The Cohen's Kappa results validate the machine's high consistency and reliability in its classification system. With an overall Kappa score of 0.800, this indicates the system has substantial agreement with manual labelling and reduces random assignments. With that, the researcher can say the machine learning model in real-life classification is reliable and efficient. Lastly, the accuracy reading of the automated and manual classification indicates the machine gives a higher accuracy compared to the manual sorter. The overall accuracy of the machine was approximately 92.3%, while the manual sorter had an accuracy of 89.7%. Researchers observed that the manual sorter heavily relies on the hardness of the bell pepper rather than its physical appearance.

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