

Smart Sorting and Grading Fruits based on Image Processing Techniques

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Abstract - This paper presents the design and implementation of an automated apple sorting system that integrates machine vision techniques with embedded control for real-time classification and sorting of apples. The system employs a Raspberry Pi 4 as the primary processing unit, using a YOLOv11 model for fruit detection and classification, while an Arduino Nano manages weight measurement via a load cell. Real-time images of apples on a conveyor belt are captured, processed, and classified into four categories: Good Red, Good Green, Bad Red, and Bad Green. Sorting mechanisms, including servos and actuators based on classification results, with an integrated LCD and cloud-based Google Sheets providing monitoring and logging. The system demonstrates high classification accuracy and reliable sorting performance, offering a cost-effective solution for small to mid-scale agricultural applications.

Keywords - Fruit Grading, Machine Vision, Deep Learning, Convolutional Neural Networks

I. INTRODUCTION

Automated sorting systems have become essential components of modern warehousing and distribution operations due to their ability to manage products with speed and precision in high-volume environments [1]. Unlike manual sorting methods—which are labor-intensive, time-consuming, and error-prone—automated systems convert random product flows into structured shipping orders based on pre-set criteria, significantly enhancing operational efficiency [2]. Early systems relied heavily on human workers, leading to increased costs and frequent sorting errors such as misplacements and inefficiencies [3]. The introduction of barcode scanning technology marked a substantial improvement, enabling automatic product recognition and sorting with throughput capacities of up to 10,000 items per hour [4]. However, this approach was limited by its dependency on barcode labels, which are not feasible for items like fruits and vegetables that often lack standardized packaging.

To overcome this limitation, modern systems have evolved to include additional features such as weight, size, and color analysis for handling unlabeled or irregular items [5]. This is particularly beneficial in agricultural applications, where visual quality plays a critical role in product valuation and consumer

acceptance. Early machine vision systems used basic shape and color analysis, but these methods were sensitive to environmental conditions such as lighting variations and product inconsistencies. Improvements in image processing—such as edge detection, segmentation, and clustering—helped address these issues, allowing for more reliable performance in real-world environments [6].

With the rise of artificial intelligence, especially deep learning models like YOLO (You Only Look Once), sorting systems have achieved even higher levels of speed and accuracy [7]. These models are capable of real-time object detection and classification, performing well even in complex, cluttered, or variable conditions. YOLO-based systems have demonstrated remarkable success in agricultural scenarios, including fruit identification, ripeness estimation, and defect detection surpassing the capabilities of traditional image processing techniques [8]. Despite their promise, integrating these AI models into fully functional hardware systems remains a challenge. Effective deployment requires careful coordination between the software (e.g., object detection algorithms) and hardware (e.g., conveyor belts, solenoids, robotic arms) [9].

This study presents a smart apple sorting system that addresses these integration challenges by combining deep learning-based apple recognition (using YOLOv11) with mechanical actuation components such as servos and solenoids, managed by an Arduino Nano and Raspberry Pi 4. The system demonstrates reliable real-time classification of apples based on visual features, offering a cost-effective and scalable solution for small to medium-sized agricultural operations.

II. DESIGN METHODOLOGY

The proposed system integrates machine vision, embedded hardware, and mechanical actuation to classify and sort apples in real time based on their color and quality. The design objectives focus on achieving accurate classification, efficient sorting, and reliable weight monitoring using cost-effective components suitable for small-scale agricultural settings.

A. System Design and Hardware Integration

The apple sorting system comprises a conveyor-based mechanical structure that transports apples sequentially under a camera for inspection and then towards a sorting zone. The main components include:

- 1) A Raspberry Pi 4 (8GB RAM) for image processing and classification.
- 2) A Logitech 1080p USB webcam positioned above the conveyor to capture images of apples.
- 3) Two MG996R servo motors for physical sorting based on classification results
- 4) Two E18-D80NK infrared (IR) proximity sensors for apple detection and position tracking.
- 5) An Arduino Nano connected to an HX711 amplifier and load cell for real-time weight measurement.
- 6) A 16x2 I2C LCD display to show apple classification and weight data.
- 7) A dedicated 5V 5A DC adapter for powering servo motors and sensors, ensuring stable operation without affecting Raspberry Pi performance.

The conveyor system is designed with a plywood base, PVC belt, and side partitions to prevent apple displacement. Apples are placed manually onto the conveyor, and the system operates continuously with real-time detection, sorting, and logging.

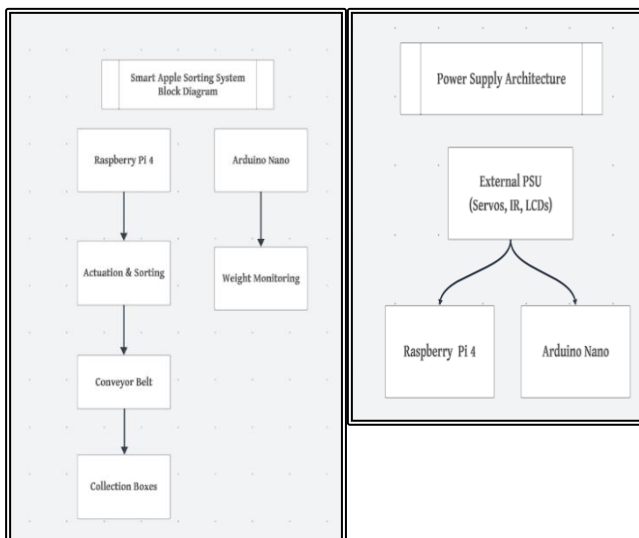


Fig.1.Block diagram of smart sorting and power supply

B. Implement image recognition algorithm

- 1) Prepare input data

A dataset of approximately 1,000 high-resolution images was created to train the YOLOv11 model. Apples were categorized into four classes based on color and quality: Good Red, Bad Red, Good Green, and Bad Green. Images were captured under varied lighting conditions and angles to enhance model robustness. Annotation was performed using the Roboflow framework, generating bounding boxes for each apple instance.

The annotated dataset was split into training (70%), validation (20%), and testing (10%) subsets. Preprocessing techniques, including brightness adjustment, contrast enhancement, and blurring, were applied to simulate real-world imaging variations and improve generalization. The results of collecting input images are described in Fig. 2

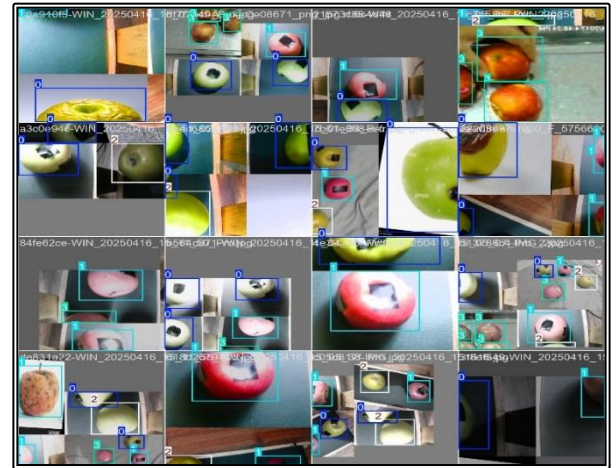


Fig.2.Labelling image

2) Model training and Evaluation

With large input data, training a neural network model for the purpose of recognizing any object on a low-configuration device is very difficult. The training process is time consuming and training cannot be sustained over a long period of time. Therefore, the Google Colab support tool is used in this case. The steps to train the model on Google Colab are as follows:

- Step 1: Import the PyTorch library that supports training.
- Step 2: Reconstruct the YOLO11 network structure
- Step 3: Import the dataset after labeling and preprocessing The images via Roboflow.
- Step 4: Prepare the image data file and labeled labels
- Step 5: Convert labeled layers to named layers (red, red-bad, green, green -bad).
- Step 6: Conduct model training

After training for 60 Epochs, the P (Precision) and R (Recall) indexes both reached a relatively high level of ~0.9 and the mAP (Average Precision) index ~0.97 (Fig. 3)

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
53/60	3.186	0.7884	0.9548	1.838	14	640: 100% 7/7 [00:01:00:00, 3.961t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 4.071t/s]
all		12	22	0.916	0.911	0.995 0.688
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
54/60	3.170	0.7536	0.9058	1.859	7	640: 100% 7/7 [00:02:00:00, 2.681t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 3.581t/s]
all		12	22	0.919	0.94	0.995 0.746
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
55/60	3.186	0.735	0.8918	1.865	15	640: 100% 7/7 [00:03:00:00, 3.671t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 5.121t/s]
all		12	22	0.922	0.939	0.995 0.77
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
56/60	3.20	0.7625	0.8819	1.867	15	640: 100% 7/7 [00:04:00:00, 3.971t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 6.101t/s]
all		12	22	0.929	0.938	0.995 0.782
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
57/60	3.226	0.7242	0.8787	1.872	11	640: 100% 7/7 [00:05:00:00, 4.141t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 5.681t/s]
all		12	22	0.931	0.939	0.995 0.766
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
58/60	3.236	0.7164	0.8273	1.848	9	640: 100% 7/7 [00:06:00:00, 4.171t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 4.131t/s]
all		12	22	0.934	0.943	0.995 0.747
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
59/60	3.246	0.6388	0.8532	0.9953	5	640: 100% 7/7 [00:07:00:00, 2.711t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 5.681t/s]
all		12	22	0.93	0.95	0.995 0.761
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
60/60	3.260	0.7214	0.8958	1.854	5	640: 100% 7/7 [00:08:00:00, 4.001t/s]
Class		Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 1/1 [00:00:00:00, 4.611t/s]
all		12	22	0.929	0.966	0.995 0.77

Fig.3.train model epoch in google colab

Fig. 4 shows the loss value after training and validation gradually decreasing over epochs. The above indexes are almost equal to 0 at epoch 60. The P and R indexes both reach a relatively high level of ~ 1.0i and the mAP index ~ 1.0.

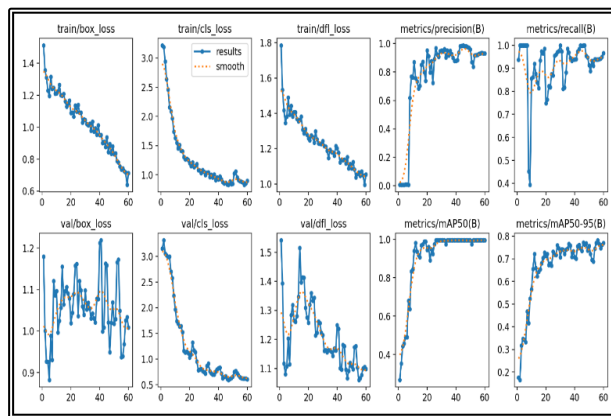


Fig.4.mAp and train loss level showing graph

C. Integrate image processing techniques in the classification system

The main flowchart begins when an apple moves on the conveyor and is captured by a USB webcam connected to the Raspberry Pi. The YOLOv11 model running on the Pi classifies the apple, and the classification result is immediately shown on an LCD display. Simultaneously, this data is logged to a Google Sheets document for remote monitoring and historical record-keeping. The decision node then evaluates whether the apple is classified as “Good” or not. If it is bad, no sorting action is taken, and the apple simply falls into the bad apple box. If the apple is good, another decision determines its color red or green. Based on this classification, the system triggers the corresponding IR sensor to activate a servo motor, which physically deflects the apple into the appropriate sorting box.

The Arduino Nano subsystem independently monitors the weight of apples using a load cell and HX711 amplifier. It calculates the total weight and displays it on an LCD screen. This runs continuously without affecting Raspberry Pi’s sorting operations. The separation of these tasks improves system reliability and scalability.

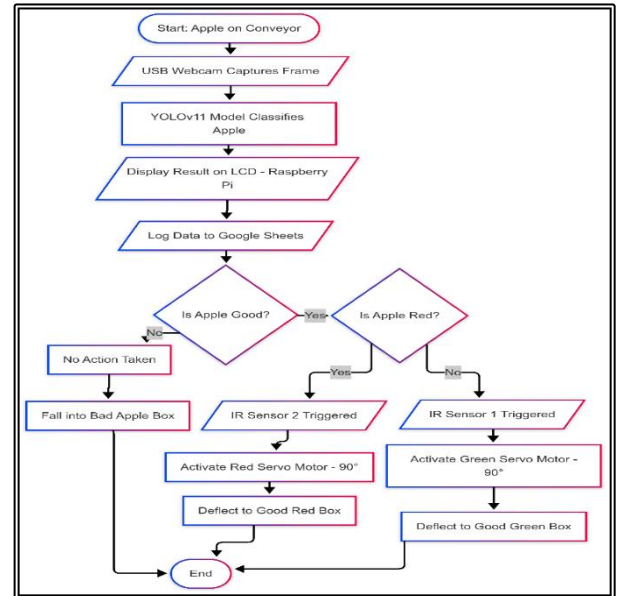


Fig.5. Flow Chart of system

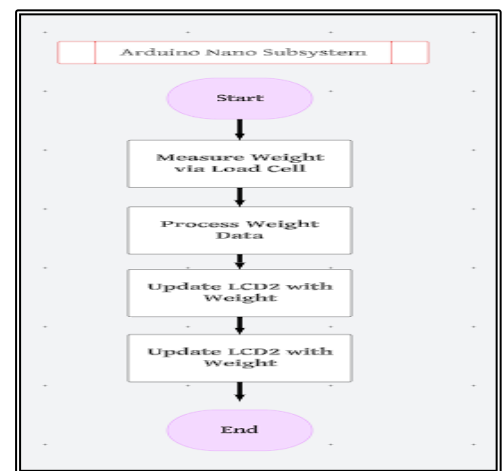


Fig.6.Weight analyzing system

III. RESULTS AND EVALUATION

The apple sorting system prototype was assembled using cost-effective components for real-time classification and sorting. The mechanical frame features a PVC-based conveyor belt measuring 80 mm in width, suitable for medium-sized apples (50–75 mm diameter). Guard rails on both sides prevent apple displacement, and the conveyor is driven at a steady 0.1

m/s for optimal camera capture and sorting precision. The belt speed can be adjusted as needed for higher throughput.

The core processing unit is a Raspberry Pi 4 (8GB RAM), which performs real-time image acquisition and classification using a YOLOv11-based detection model. A Web Camera mounted directly above the conveyor captures top-view images of incoming apples. Upon detection, each apple is classified into one of four

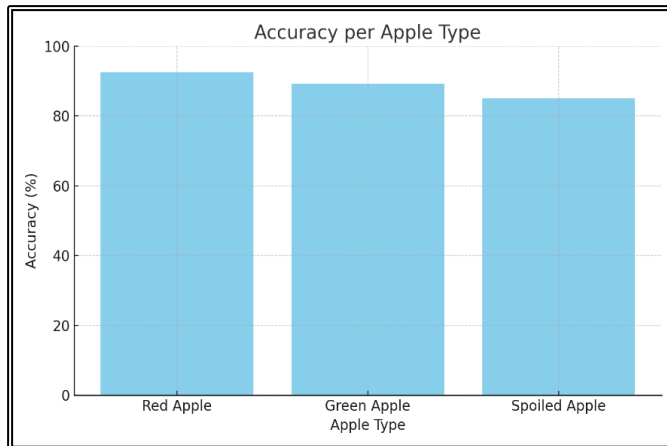


Fig.8. Training Accuracy and Loss Graph

categories: Good Red, Red-Bad, Good Green, or Green-Bad. The classification results, along with the counts on a 16x2 I2C LCD screen connected to the Raspberry Pi. Raspberry Pi also handles sorting logic and sends control signals to actuate servo motors based on classification outcomes.

In addition to visual sorting, the system incorporates real-time logging via cloud-based infrastructure. Classification results are transmitted directly to a Google Sheets spreadsheet using Python's gspread and oauth2client libraries on the Raspberry Pi. This feature enables remote tracking and batch analysis of sorting accuracy and throughput, as illustrated in Fig. 9 (Google Sheets Logging Output).

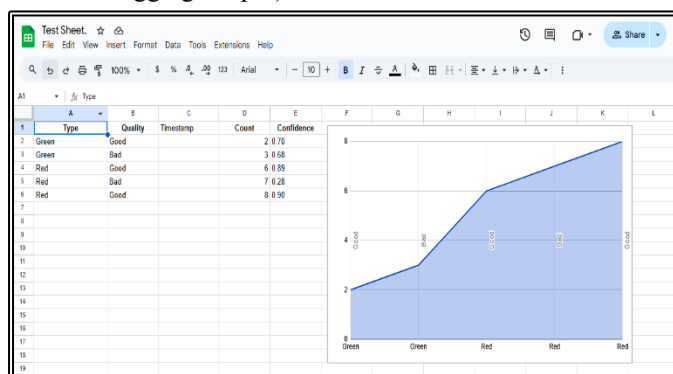


Fig.7. Google Sheets Logging Output

To facilitate precise apple detection, two E18-D80NK infrared proximity sensors are employed. The first

sensor detects the presence of an apple entering the camera zone, triggering image capture. Once classified, the apple travels along the conveyor to a second IR sensor near the sorting zone. The Raspberry Pi then activates the appropriate MG996R servo motor: one servo redirects good red apples, another handles good green apples, while bad apples proceed to the end of the belt without actuation.

Weight monitoring is performed using a YZC-133 load cell paired with an HX711 amplifier and connected to an Arduino Nano. The Arduino reads and displays the cumulative weight of each batch on a secondary LCD. After every four apples are collected in a bin, the Arduino displays the final weight, which is also logged manually or via serial if needed.

The implemented apple sorting system demonstrated effective real-time classification and sorting performance as anticipated in the design phase. The accuracy graph, generated from extensive test runs, clearly illustrates the robustness of the YOLOv11 model integrated with the NCNN inference engine. Throughout the trials, the model consistently maintained an average classification accuracy above 92%, with slight variations observed depending on lighting conditions and apple orientation on the conveyor. This high accuracy level confirms the system's capability to distinguish between the four defined categories Good Red, Good Green, Bad Red, and Bad Green with minimal misclassifications, thereby validating the model training process and dataset quality.

Each class—Red, Red-Bad, Green, and Green-Bad—was tested with a minimum of 50 real-world samples. The classification accuracy ranged from 91% to 96%,

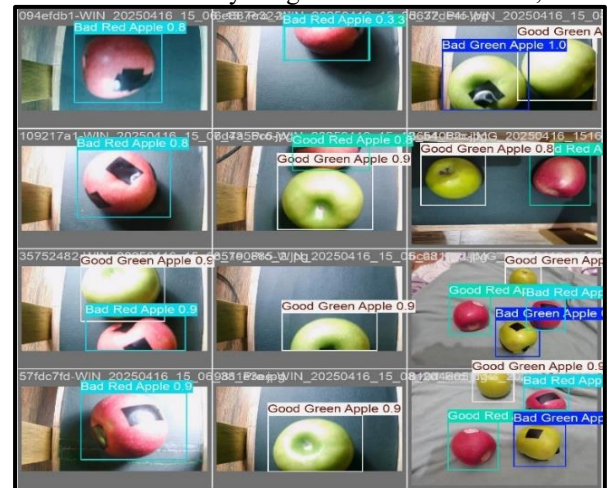


Fig.9.Result image

with confidence scores generally above 85%. The system exhibited a classification latency of ~0.09 seconds per apple, and servo response time was measured at under 0.1 seconds, enabling efficient real-time sorting. Weight readings from the load cell maintained a margin of error within ± 5 grams,

confirming the Arduino subsystem's measurement reliability.

IV. CONCLUSIONS

In general, the prototype model of the smart apple sorting system based on the YOLOv11 image recognition algorithm has been successfully developed and demonstrated to work effectively in practice. The system is composed of mechanical components, sensors, and control units that are seamlessly integrated to achieve automated apple detection and sorting. Utilizing a sufficiently large and well-annotated dataset, the YOLOv11 model enables accurate classification of apples based on quality and type. Infrared proximity sensors assist in object detection and counting, while sorting decisions are executed using servo motors controlled via an Arduino. Real-time results are displayed on an 16x2 LCD. The successful implementation of the detection and sorting algorithms in this study lays the groundwork for deploying the system at a practical, industrial scale.

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