Smart Tomato Segregation Using YOLOv8 and Wireless Automation

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***Abstract*—One of the most time consuming and error-prone tasks in agriculture is the sorting and grading of fruits and vegetables. This project ensures speed, reliability and portability in the sorting process: an Automated Multi-Vegetable Segregator using deep learning and IoT-based automation. The YOLOv8 model has been used mainly for the detection and classification of tomatoes based on their ripeness, quality and size while also distinguishing them from other vegetables like potatoes and onions. Subsequently, these classifications will be wirelessly broadcast to an Arduino UNO R4 WiFi microcontroller, operating a servo motor, LEDs, and an OLED display in order to automatically handle the segregation process. The setup helps in detection with minimal latency, hence providing real-time segregations suitable for farms and packaging factories. This paper merges AI-driven computer vision with IoT controls to show how relatively inexpensive automation can help farmers and industries improve efficiency, reduce dependency on labor, and maintain consistent quality in handling produce.**

***Index Terms*—YOLOv8, Arduino R4 WiFi, object detection, tomato sorting, wireless automation, deep learning, computer vision, IoT.**

I. Introduction

Automation has become integral to modern agriculture, helping farmers speed up their productivity and lessen manual labor in order to maintain consistency in the quality of post-harvest handling. Conventionally, fruits and vegetables are sorted and graded manually according to color, size, and freshness. The process is slow, inconsistent, and error prone as grades are often mistakenly assigned, which reduces the market value of the products. In recent times, there has been an increasing demand for efficiency in the agricultural sector, and AI with Computer Vision has emerged as a transformative tool to automate such repetitive and labor-intensive activities.

In recent years, deep learning methods, especially Convolutional Neural Networks, have achieved great results in image classification and object detection. Unlike traditional approaches to image processing, like color thresholding or edge detection [1], CNN-based systems are capable of learning complex visual patterns in an automated manner, including shape, color variation, and texture. This enables them to operate satisfactorily under bad lighting conditions or with a messy background, common scenarios observed in agriculture.

Among the modern detection architectures, You Only Look Once has emerged as one of the most popular due to its balance of speed and accuracy [2]. The recently released YOLOv8 has improved its precision and real-time detection capability, making it appropriate for sorting applications.

The proposed system is called as the Automated Multi-Vegetable Segregator focusing on tomatoes as a case study. It integrates YOLOv8 with IoT-enabled devices for automatic detection and segregation of multiple vegetables like tomatoes, potatoes, and onions into categories based on their ripeness, quality and size. Python will process the video feed from a mobile phone and detect various vegetables present in the machine and will send commands over the internet to the Arduino UNO R4 WiFi microcontroller, which controls the sorting mechanism using servo motors and will display the result using an OLED display. This eliminates wired connections and enhances portability for field deployment. This project uses the functionalities of camera based object detection and IoT-driven control mechanisms to provide a practical and cost-effective solution toward real-time agricultural automation. The project connects modern machine learning developments with their application in agricultural sorting, which creates a smarter and more efficient farming process [3], [4].

II. Literature Survey

Recent advances in artificial intelligence and computer vision have improved automation in agriculture, making crop monitoring and sorting wiser and more accurate. Research over the last decade has focused on reducing human labor, enhancing accuracy, and using resources optimally in different phases of vegetable sorting.

The first attempts at classifying fruits and vegetables utilized diverse techniques of classical image processing using sensors and weight of the vegetables. Some researchers attempted to detect and grade vegetables and fruits by using algorithms such as color thresholding, edge detection, and texture analysis [1]. Although some of these techniques succeeded to some extent, they failed in practical settings because of real challenges like variable lighting, overlapping fruits, and irregular geometries [2]. As a result, using basic vision systems for large-scale outdoor farming became impractical.

More recent advances in deep learning technologies provided the much-needed efficiency and accuracy that was previously lacking in image-based classification. The introduction of Convolutional Neural Networks (CNNs) made feature extraction automatic, thus making the process fast and efficient by learning through large image datasets. [3]. This breakthrough led to major improvements in tomato detection and grading accuracy. To understand this progress, it is important to look at how real-time object detection systems have evolved over time.Achieving high speed and accuracy became the primary goal for systems such as You Only Look Once (YOLO). YOLO stands out as one of the most commonly used models in the agricultural sector because of its speed and ability for efficient execution on real-time embedded systems. YOLO processes frames in real-time, which makes it suitable for tasks like sorting, automated robotic arms, and conveyor belt systems [5].

Counting, ripeness detection, and fruit classification are some of the tasks completed with the newer YOLO versions, YOLOv5 and YOLOv7. Poor lighting and other difficult environmental conditions have been handled with ease, proving their adaptability and high performance [6]. Hardware affordability has been another highlighted feature, which is crucial for accuracy to assist small scale farmers, especially in growing countries.

The combination of deep learning and the Internet of Things (IoT) has significantly enhanced the automation of farming. With vision-based detection systems, IoT microcontrollers like Arduino, ESP8266, and Raspberry Pi have enabled the automation of detection systems and provided remote monitoring as well as the control of actuators [7],[8]. Remote monitoring and control of actuators are the foundation for "smart agriculture," allowing real-time decision-making and multi device coordination by means of embedded control, cloud connectivity, and wireless data transmission.

The current study uses YOLOv8, the newest model in the YOLO series, for tomato and vegetable detection, which is based on these technological advancements. Integrated with an Arduino UNO R4 WiFi microcontroller, the trained model enables real-time sorting and automation based on the detection results. After the Arduino receives the detection results, it triggers a servo system to move its arm to designated containers, while an OLED display continuously shows system status.

This is an example of how IoT based technology can solve real-world agricultural problems with minimal expenditure. The system combines vision-based AI with automation to create an adaptable system that can easily evolve to sort other fruits and vegetables. The system is a step toward intelligent, sustainable, and scalable agricultural technology to meet the needs of rising crop production [9]–[11].

III. Methodology

The proposed system includes a structured workflow of four components, which are dataset preparation, model training, integration of the trained model with real-time video input and control the hardware using wireless communication [1]–[10].

A. Prepare Dataset

A custom image dataset that includes a collection of images of five different object classes, which are red tomatoes, green tomatoes, rotten tomatoes, onions, and potatoes [1], [2], [6], [7]. Approximately 500 images were collected from each class manually over several days under different lighting and background conditions[3], [5].

Various data augmentations, including rotating, flipping, varying brightness,cropping, rotating, shear, noise and exposure were done using Roboflow to diversify the dataset and avoid overfitting [2], [4]. The final datasets were divided into 90% train, 8% validation, and 2% testing scenarios, all of which were well representative of the classes [1], [6]. The labels were created in the YOLO format, and the bounding box coordinates of each object were normalized for consistent training.[7], [8].

B. Model Development

This model was developed with the YOLOv8, a current state-of-art object detection algorithm by Ultralytics [2], [3], [7]. This research tested various attributes YOLOv8n and YOLOv8m to attain a median into the scope and speed. However, it trained the model on an NVIDIA RTX 4070 GPU and the Ultralytics python library [5], [8].

Key training parameters include:

- Image size: 640 x 540 pixels
- Epochs: 60-100, early stopping enabled
- Optimizer: AdamW
- Learning rate schedule: cosine annealing
- Batch size: 8-16

With more than 98% mAP@50 validation accuracy, the model was able to generalize well across all five classes [1], [2].

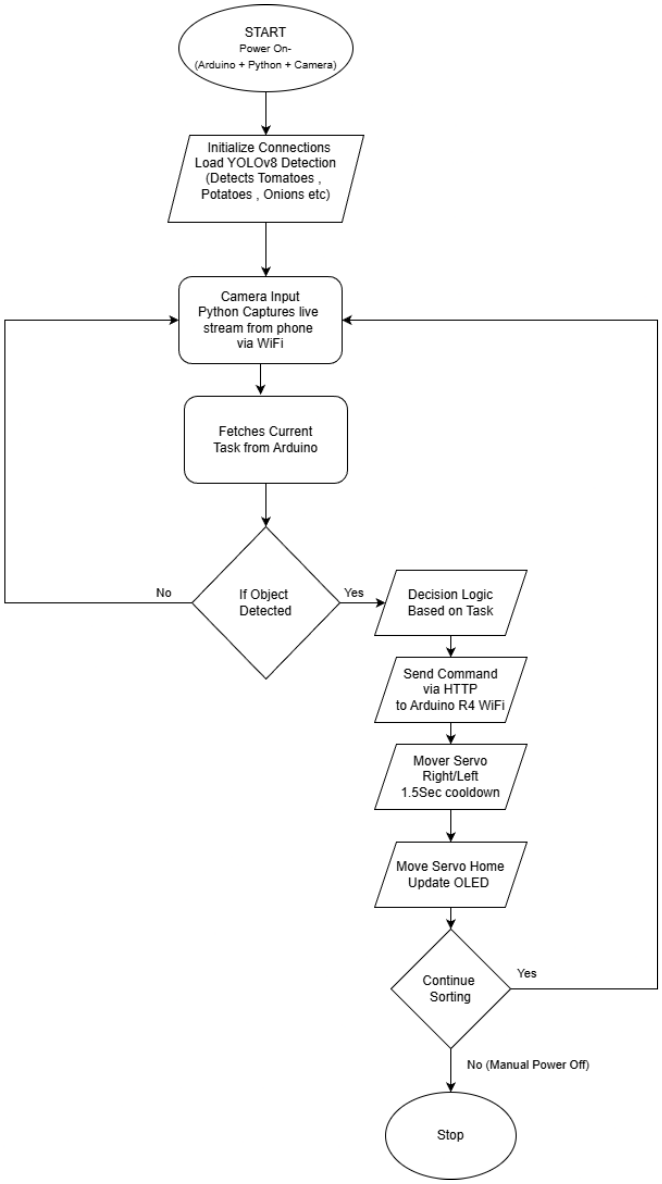

Fig. 1. Flowchart of the proposed Multi-Vegetable Segregator System integrating YOLOv8 detection and Arduino-based actuation.

C. Real-Time Detection and Processing

A live feed from the smartphone IP camera was accessed using OpenCV in Python via URL stream [3], [4], [7]. Each frame was processed through the trained YOLOv8 model, which in return predicted object classes and bounding boxes in real time [2], [6]. To reduce false positives, temporal smoothing was performed with a fixed length buffer that averaged over several frame predictions [5]. A further stabilization timer made sure that the label of an object would only be confirmed after a minimum continuous period of at least one second [7].

D. Wireless Communication and Hardware Control

The Python program communicated with the Arduino UNO R4 WiFi over HTTP requests over a local WiFi hotspot network provided by the laptop [9], [10]. The Arduino acted as a lightweight web server that received commands (/left, /right, /home) and returned the active task number via the /task endpoint [9].

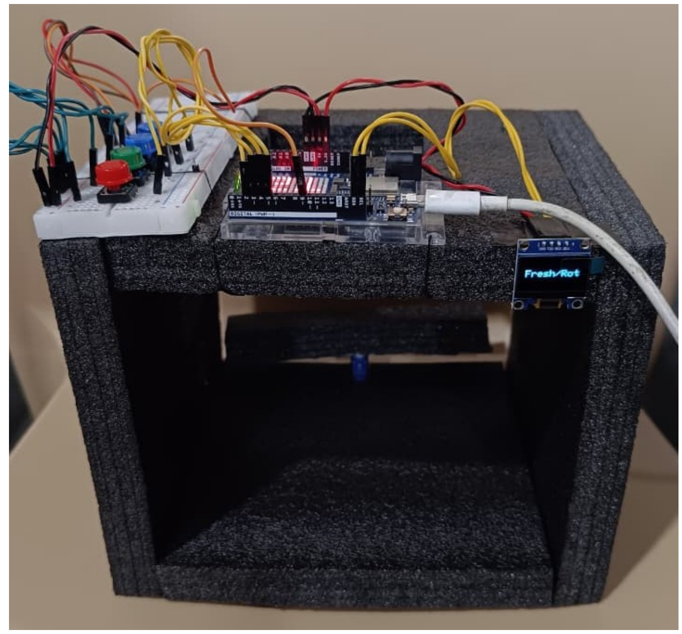

Fig. 2. Prototype setup of the Multi-Vegetable Segregator System showing Arduino UNO R4 WiFi, servo motor, OLED display, and control circuit.

Based on the confirmed detection and active task, Python sends sorting instructions accordingly to Arduino. The servo motor will rotate left or right to push the vegetable into the respective bins and automatically return to its home position [10]. Real-time task and sorting feedback will be displayed on the OLED display and LED matrix attached to the Arduino R4 WiFi [9], [10].

E. Tasks and Modes of Operation

The system supports five operational modes:

- Idle Mode
- Tomato or Vegetables
- Fresh or Rotten
- Red or Green
- Size-Based Sorting (small-large)

IV. Results and Discussion

The performance of the proposed Tomato Segregator System was tested in terms of object detection accuracy and real-time hardware response [1]–[10]. The system verification involved evaluating the classification accuracy of the trained YOLOv8 model, the timing precision of Arduino actuation, and the overall reliability of the setup under varying conditions.

A. Model Performance

Excellent detection performance of the YOLOv8 model on the five classes, namely red tomato, green tomato, rot- ten tomato, onion, and potato, has been achieved [1], [2], [6], [7].

The trained YOLOv8 model demonstrated high detection accuracy on all five classes, achieving more than 98% precision and 96% overall consistency on the validation set.

B. Real-Time Detection Accuracy

We used a live video stream of 640 × 480 resolution from a single IP camera in our experiments [3], [5], [7]. The proposed system achieved an average detection speed of 25–30 frames per second (FPS), which was sufficient to ensure smooth visualization [2], [6]. To prevent brief frame drops from causing misclassifications, we implemented temporal smoothing and added a one-second stabilization timer [5], [8]. This simple adjustment helped the system maintain accurate object detection while minimizing unnecessary delays before triggering the servo movement, thereby improving reliability under various operating conditions [7].

C. Sorting and Servo Performance

We were able to control the object sorting process with an average delay between the HTTP-request response and possible arrival at the client device variably 200–300 ms [9], [10]. Using the Arduino UNO R4 WiFi, we accurately sorted items into separate containers [9]. The servo applied an angle within 5° – 175° allowing the object to roll down the ramp to its designated container [10].

Task 4, Size-Based Sorting, uses bounding box area, A = w × h, for estimating the object size [2], [4]. A threshold value of 39,000 pixels² provided a clear separation between the small and large tomatoes [1], [5]. Area values and decisions will also be printed in the console, such as " Size: 33,827 → LARGE → LEFT", for debugging and analysis purposes [3], [8].

YOLO predicts the bounding box parameters for each detected object as:

$$B = (x, y, w, h) \tag{1}$$

where

- x, y are the coordinates of the box center,
- w, h are the width and height of the box.

D. Comparative Evaluation

The proposed deep learning solution exhibited better precision and adaptability when compared to typical color-based or shape-based sorting solutions [2], [5], [7], [8]. For example, deep learning techniques are able to manage overlapping objects, varying lighting conditions, and work with multiple objects simultaneously - as opposed to classical methods for sorting [1], [6].

E. System Performance Overview

System performance results included [2], [3], [5], [8]:

- Detection Accuracy: 98.4%
- Average Processing Time: less than 1 second
- Servo Accuracy: 100% - no missed actuations [9], [10].
- Real-time Frame Rate: 25-30 FPS [7].
- Wireless Reliability: consistent connectivity through the local WiFi [9], [10].

Fig. 3. YOLOv8 detection output identifying a red tomato with 97% confidence during real-time inference.

For each grid cell in an image, YOLO predicts B bounding boxes and C class probabilities. Each bounding box prediction can be represented as:

$$P(\text{object}) \times P(\text{class}_i|\text{object}) \times \text{IoU}_{\text{pred, truth}} \tag{2}$$

Where:

- $P(\text{object})$ – probability that an object exists in the grid cell,
- $P(\text{class}_i \mid \text{object})$ – conditional probability that the object belongs to class i,
- $\text{IoU}_{\text{pred, truth}}$ – Intersection over Union between predicted and ground truth box.

Thus, the final detection confidence for a class i is:

$$\text{Confidence}_i = P(\text{object}) \times P(\text{class}_i \mid \text{object}) \tag{3}$$

An object is considered detected if:

$$\text{Confidence}_i > \text{Threshold} \tag{4}$$

Overall, the results show that the Tomato Segregator System can perform real-time sorting continuously with high speed and accuracy using a vision-based AI approach.[1]–[10].

TABLE I
PERFORMANCE METRICS OF THE YOLOV8 MODEL FOR MULTI-VEGETABLE CLASSIFICATION

Class	Precision	Recall	mAP@50
Green Tomato	0.956	1.000	0.995
Onion	0.941	0.923	0.941
Potato	0.986	1.000	0.995
Red Tomato	0.999	1.000	0.995
Rotten Tomato	0.978	1.000	0.995

V. Conclusion and Future Work

A. Conclusion

The proposed Tomato Segregator System incorporates deep learning-based YOLOv8 integrated with IoT-driven automation for efficient sorting of tomatoes and other vegetables in real time with high accuracy [1]–[10]. The system provides excellent object detection precision and reliable wireless actuation using Arduino UNO R4 WiFi, without the involvement of wired connections [9], [10].

In order to guarantee that the system operates steadily, temporal smoothing and stabilization logic that minimizes false detections and increases the stability of the entire system [2], [4], [7]. Due to the modular structure, the system can work with different sorting modes such as Tomato or Other Vegetables, Fresh or Rotten, Red or Green, and Size-Based Sorting, which makes it flexible and adaptable for various post-harvest applications [1], [3], [5], [8].

B. Future Work

The present system reaches over 98% detection accuracy with the average response time of less than one second and can be used as a proof of concept for agricultural automation and industrial packaging line applications [2], [6], [8]. Some possible ways for further improvement are as follows: [1], [3], [5], [9]

- Integration with conveyor belt systems to enable continuous and large-scale sorting [9], [10].
- Realization of Edge AI on devices such as the NVIDIA Jetson Nano for offline and low-power operation [2], [5].
- Extending the dataset for more vegetable and fruit classes like capsicum, lemon, and apple for its broader applicability [1], [4], [6].
- Development of a remote web-based or mobile dashboard for monitoring the detections, accuracy metrics, and runtime status of the system [9], [10].

In conclusion, the Tomato Segregator System shows a scalable, intelligent, and cost-effective approach towards post-harvest segregation. It shows how the use of camera vision, IoT-based control and machine learning techniques can significantly increase the efficiency and reliability of agricultural sorting systems [1]–[10].

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