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Tomato Quality Classification

Amrutha G S[1], Bharath Raj S[2], Chandana S R[3], Lekhana M Ichangi[4], Victor Jeyaseelan D[5]

[1234] U.G students, [5]Assistant Professor

Department of Electronics and Communication Engineering, AMC Engineering College

amruthags2002@gmail.com[1], braj0643@gmail.com[2], chandanasr1745@gmail.com[3], lekhana.ichangi@gmail.com[4], victorjeyaseelan@gmail.com[5]

Abstract

This project explores the viability of utilizing You Only Look Once version 5 (YOLOv5), a state-of-the-art object detection algorithm, for classifying tomato ripeness. Accurate and automated tomato quality assessment based on ripeness is essential in the agricultural sector for optimizing harvesting, sorting, and pricing. Traditional methods often rely on manual inspection, which is labour-intensive, subjective, and susceptible to human error. This project proposes a deep learning-based approach using YOLOv5 to address these limitations. YOLOv5 offers a good balance between accuracy and real-time performance, making it appropriate for deployment in automated sorting systems. The project will involve creating a comprehensive tomato image dataset encompassing various stages of ripeness (half ripe, green, fully ripe) with diverse lighting conditions, backgrounds, and potential blemishes. This dataset will be utilized for training a YOLOv5 model for identifying and categorizing individual tomatoes within an image while simultaneously assigning a ripeness stage based on colour and morphological features. The project will evaluate the model's performance using metrics like precision. The achievement of this project would demonstrate the possibilities of YOLOv5 for real-time, non-destructive tomato quality assessment based on ripeness, laying the groundwork for its integration into smart agriculture solutions for improved efficiency and reduced waste within the food supply chain.

Keywords - Tomato; YOLOv5; Quality; Classification; Ripeness

1.Introduction

One of the primary advantages of this method is its adaptability and scalability. The system can be readily customized to accommodate different tomato varieties, in addition to adjusted to meet specific quality standards or grading criteria set by producers or regulatory bodies. Furthermore, the conveyor belt system can be integrated with existing sorting and packaging infrastructure, facilitating a seamless transition towards automated quality control processes.

At the core of this project lies the powerful YOLOv5 (You Only Look Once version 5) object detection algorithm. Trained on a vast dataset of tomato images spanning various ripeness levels, this deep learning model can accurately identify and localize tomatoes as they move along the conveyor belt. By leveraging advanced computational techniques, the system analyses visual characteristics such as colour, texture, and shape to categorize each tomato into one of three distinct classes: green, half-ripe, or fully ripe.

The flawless merging of the YOLOv5 model with the automated conveyor belt system enables real-time processing and classification of tomatoes. As the produce moves along the belt, high-resolution cameras take pictures that are subsequently fed into the deep learning model for analysis. The system's ability to process multiple tomatoes simultaneously ensures efficient throughput, minimizing bottlenecks and maximizing productivity.

2. Proposed Methodology

The proposed methodology involves a hardware setup consisting of an Arduino Uno microcontroller board as the central control unit, a regulated power supply to power the components, an LCD (Liquid Crystal Display) for displaying grading results and system status, a motor driver module (such as L293D) to control the direction and speed of a DC motor, and the DC motor itself to drive the conveyor belt. The conveyor belt, made of a suitable material like PVC or rubber, will transport the tomatoes, with adjustable speed control to accommodate different flow rates. Image acquisition and processing play a vital role in this methodology. A high-resolution camera mounted above the conveyor belt will capture pictures of the tomatoes as they move along the belt. These images will be processed by the YOLOv5 object detection model, which has been pre-trained to identify and categorize tomatoes based on their ripeness levels (green, half-ripe, fully ripe). The YOLOv5 model, a state-of-the-art real-time identification and categorization of objects algorithm, will be integrated into the Arduino Uno system to process the captured images and provide the classification results. Based on the YOLOv5 model's output, the Arduino Uno will determine the appropriate grading category for each tomato according to its ripeness level. The grading information will be displayed on the LCD, and the Arduino Uno will control the conveyor belt's movement to sort the tomatoes into respective bins or collection areas based on their ripeness levels (green, half-ripe, fully ripe). A user-friendly interface will be developed, allowing operators to monitor the system's status, adjust settings, and view grading statistics, with manual overrides and controls for exceptional cases. The system will log grading data, including the quantity of tomatoes processed, their ripeness levels, and any errors or exceptions encountered. This data can be analysed to identify trends, optimize the grading process, and make data-driven decisions for quality control and supply chain management. Extensive testing and calibration of the system will be performed using a diverse range of tomatoes at different ripeness levels to ensure accurate grading and sorting. The YOLOv5 model's performance will be evaluated, and necessary adjustments or retraining will be conducted to improve its precision and dependability in classifying tomato ripeness levels.

3. Block Diagram

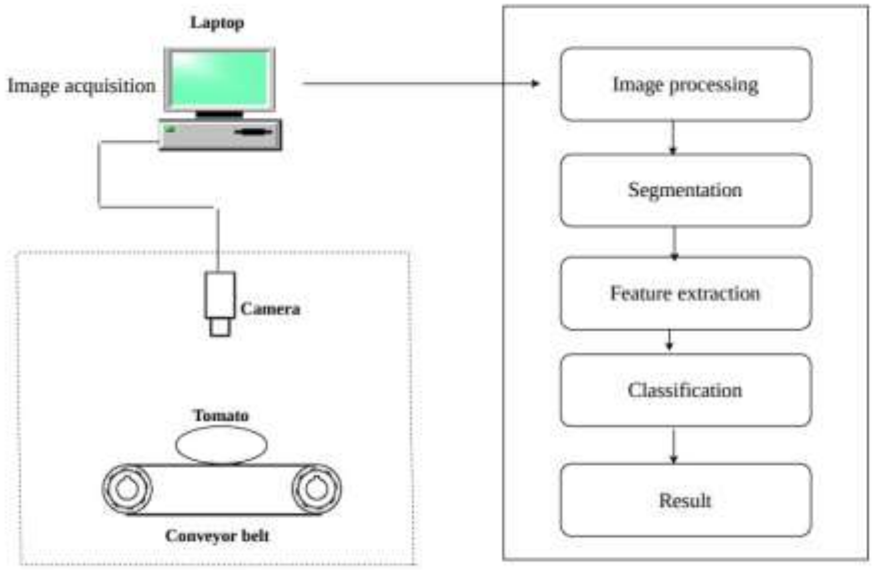

Fig 1: Block diagram

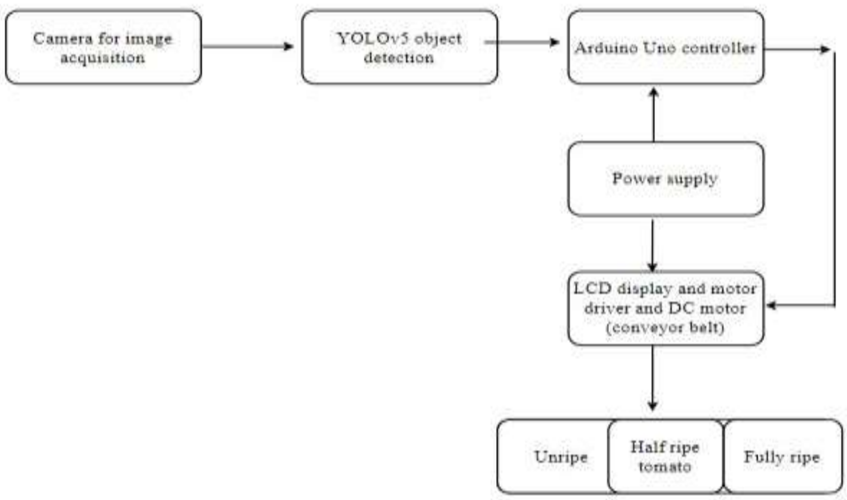

Fig 2: Flowchart

The schematic diagram represents a system designed to evaluate the standard of tomatoes on a conveyor belt using computer vision techniques. The procedure initiates with the acquisition of images, where a camera is positioned to capture images of tomatoes as they move along the conveyor belt. This particular phase entails crucial as the standard of the acquired images directly impacts the following phases of the process. The images captured by the camera are then fed into an image processing module. This module performs various operations on the images, such as resizing, color correction, and noise removal, To improve the caliber and prepare them For additional examination. After Image processing techniques are utilized to extract pertinent features from the image, such as color, texture, and shape characteristics of the tomatoes. The The features that have been extracted are subsequently transmitted to a segmentation module, which aims to separate the tomatoes from the background and other objects within the image. Segmentation algorithms, such as thresholding, edge detection, or regionbased methods, are employed to achieve this task. The segmented tomato regions are then isolated and prepared for the classification stage. The classification module is responsible for analyzing the segmented tomato regions and determining their quality based on predefined criteria. In this project, the YOLOv5 object detection algorithm is employed for classification. YOLOv5 it's a system for real-time object detection, capable of precisely recognizing and categorizing objects within images or videos.That is trained on a dataset of tomato images with various quality levels, enabling it to classify the tomatoes as either high-quality or low-quality based on their visual characteristics.

4. Implementation

Tomato dataset:

The Tomato Dataset comprises a total of 905 images, with 6,800 cluster instances of tomatoes distributed across various classes. Among these images, the test folder contains 89 images, the train folder contains 632 images, and the valid folder contains 184 images. This distribution results in a training-to-testing ratio of approximately 7:1, indicating a significant emphasis on training data compared to testing data.

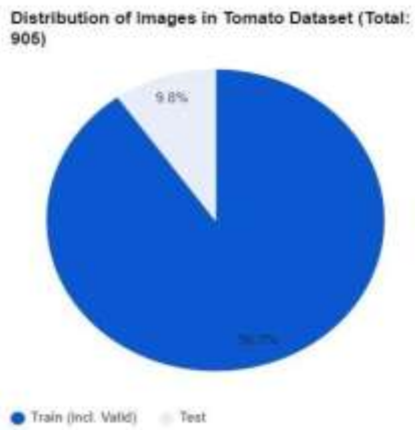

Fig 3: Tomato Dataset (Train vs Test)

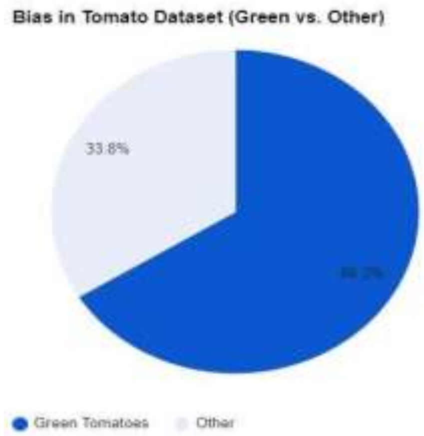

Fig 4: Tomato Biasness (Green vs Other)

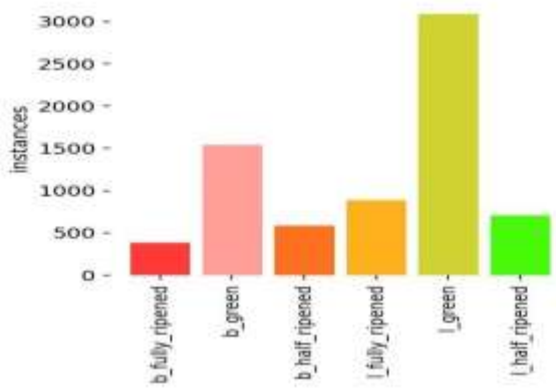

Fig 5: Tomato Class (Instances)

Within the dataset, there are six classes of tomatoes, including 'b_fully_ripened', 'b_green', 'b_half_ripened', 'l_fully_ripened', 'l_green', and 'l_half_ripened'. However, to illustrate, just three will be used. classes, namely 'b_fully_ripened', 'b_green', and 'b_half_ripened', were selected. Notably, the dataset exhibits bias towards 'b_green' and 'l_green' tomatoes, which collectively account for 4,500 instances out of the total 6,800 instances of tomato clusters. Every image within the dataset underwent pre-processing steps, including auto-orientation of pixel data with EXIF-orientation stripping and resizing to a uniform standard dimension of 640x640 pixels. It's noteworthy that no image augmentation methods were utilized. during the pre-processing stage, indicating that the dataset maintains its original characteristics without artificially generated variations.

5. Results

Figure 6 shows the training loss vs Epochs chart depicting the classification models. Over 101 epochs, the tomato dataset training observed a considerable drop in objective loss, decreasing from 9.33% to 4.10%. This decline signals improved accuracy in predicting tomato-related attributes, highlighting the model's enhanced proficiency in understanding and categorizing tomato characteristics

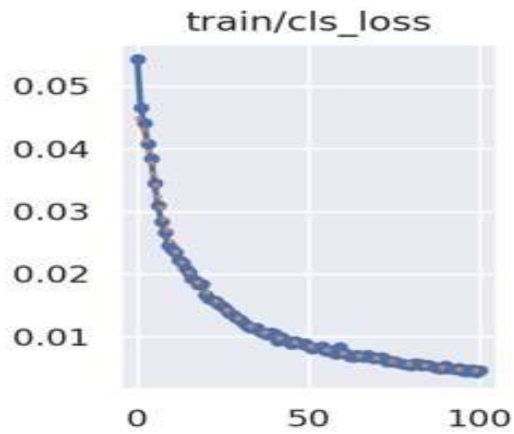

Fig 6: (Classification Loss vs Epochs) Graphs

Figure 7 shows the metrics/mAP_0.5 stands for "mean Average Precision at IoU (Intersection over Union) threshold of 0.5. Over 101 training sessions, the tomato dataset saw a big boost in its ability to accurately spot tomatoes in images, with its precision climbing from 0.96% to an impressive 69.17%. This progress shows that the model got much better at recognizing tomatorelated stuff in the pictures, what constitutes as a big step forward

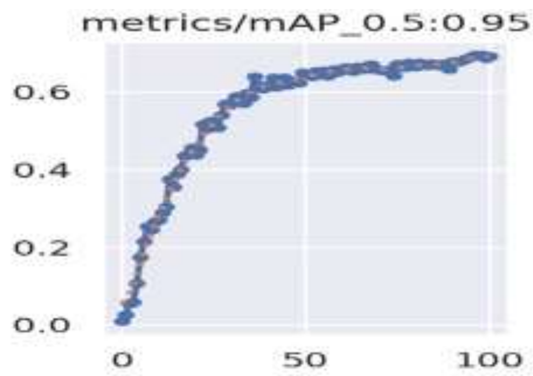

Fig 7: (mAP across IOU Thresholds) Graphs

Figure 44 shows the confusion matrix evaluates a classification model's performance. For "fully ripened," it achieved an 80% true positive rate but misclassified as "half ripened" 17% of the time. "Half ripened" tomatoes had a 73% true positive rate but were misclassified as "fully ripened" (10%) and "green" (11%). "Green" tomatoes had a 73% true positive rate but were sometimes misclassified as "half ripened" (21%). Overall, the matrix sheds light on the model's accuracy in distinguishing between tomato ripeness stages .

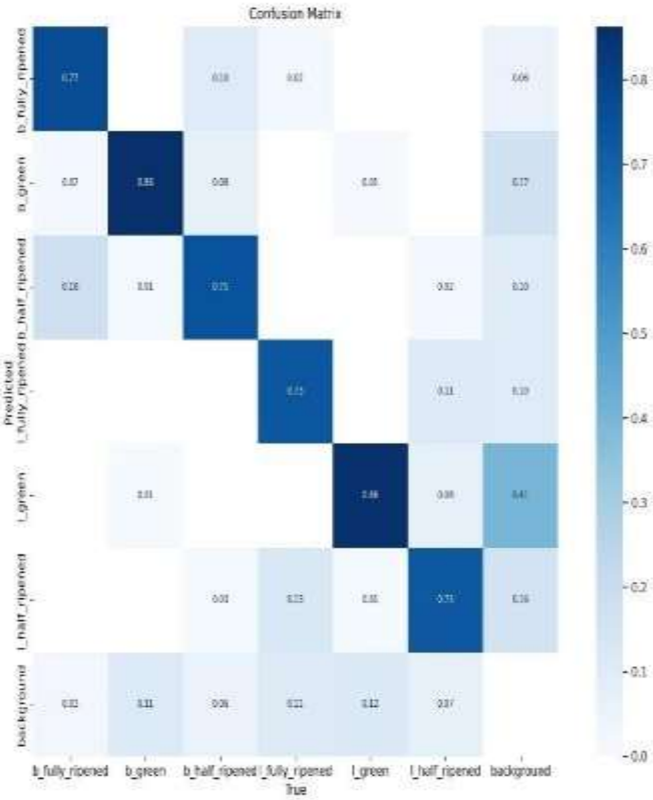

Fig 8: Confusion Matrix

Fig 9 shows the model identified the objects with a high confidence level (0.97) as green tomato, (0.98) as half ripened tomato, (0.96) as fully ripened tomato.

Fig 9: Different ripening stages of tomato

Conclusion

The proposed tomato quality classification system, which utilizes YOLOv5 and a conveyor belt setup to sort tomatoes by ripeness levels, marks a major advancement in the agricultural industry. By leveraging advanced computer vision techniques and object detection algorithms, this project presents an innovative approach to efficiently sort and grade tomatoes, boosting productivity and maintaining consistent quality of the product.

Yet, the real strength of this system is its capacity to adapt and evolve alongside emerging technologies and changing industry needs. Ongoing exploration and incorporation of advanced computer vision models, like Mask R-CNN, YOLO-X, or transformer-based architectures, could further refine the system's accuracy and robustness, enabling reliable performance even in challenging environments with varying lighting conditions, occlusions, or complex backgrounds.

Expanding the classification capabilities to encompass a broader range of quality parameters, including size, shape, defects, and disease detection, would elevate the system's value proposition. By providing a comprehensive assessment of tomato quality, this improvement would not only streamline sorting and grading processes but also contribute to enhanced product quality, increased customer satisfaction, and overall competitiveness in the market.

Adapting the system through transfer learning techniques would unlock its potential to be applied across various agricultural domains, classifying different types of produce or crops. This versatility would allow for efficient deployment and rapid adoption, minimizing the requirement for comprehensive data gathering and training efforts, thereby reducing time-to-market and associated costs.

Seamless integration with robotic systems and real-time processing capabilities would position this solution as a viable option for industrial-scale operations. By enabling efficient and accurate classification at production speeds, coupled with automated sorting and handling mechanisms, the system could drive significant improvements in efficiency, productivity, and cost savings, revolutionizing traditional agricultural practices.

7. Future Scope

The current project employs YOLOv5, an advanced object detection algorithm, to classify tomatoes based on their ripeness levels (green, half-ripe, and fully ripe) on a conveyor belt setup. While this approach offers an efficient and accurate solution, the future scope of this project presents numerous exciting opportunities for further development and enhancement.

One promising direction for future exploration is the integration of state-of-the-art computer vision techniques and cutting-edge object detection models. As the domain of computer vision rapidly evolves, incorporating models such as Mask R-CNN, YOLO-X, or transformer-based architectures could significantly improve the system's precision, durability, and performance, especially in difficult situations involving variable lighting conditions, occlusions, or complex backgrounds.

Additionally, expanding the classification capabilities beyond ripeness levels would be a valuable endeavor. By incorporating the capacity to detect and classify tomatoes based on other quality parameters, such as size, shape, defects (blemishes, cracks, bruises), and diseases, the system could offer a more thorough evaluation of tomato quality. This would enable more efficient sorting, grading, and quality control processes, ultimately leading to improved product quality and customer satisfaction.

Further development could focus on adapting and fine-tuning the system through transfer learning techniques. This approach would enable the classification model to be tailored to different types of produce or agricultural products, expanding its applicability across various domains. By leveraging existing knowledge and quickly adapting the model, the necessity for extensive data gathering and training from scratch could be reduced, facilitating rapid deployment in new areas.

To increase the system's scalability and practical application in industrial settings, future work could concentrate on real-time processing capabilities and integration with robotic systems or sorting mechanisms. Enabling efficient and accurate classification at production speeds, coupled with seamless interfacing with automated sorting and handling systems, would streamline processes, reduce manual labor, and improve overall efficiency and productivity.

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