An automated system for sorting of freshly harvested tomato fruits

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Abstract: Fruit sorting determines market value. Farmers and traders commonly use physical-eye inspection and handpicking for sorting, but this is labour-intensive and ineffective. This research work aims to develop a sensor-based automated system for sorting freshly harvested tomato fruits. The automated system sorts tomato fruits into small, medium, and big sizes for market value. To evaluate the system performance, 115 fruits were machine-sorted and compared to eye-inspection and physical measurement. Physical measurement was done by measuring the minor, intermediate, and major diameters of each fruit with a Vernier calliper. While the eye-inspection was carried out by manual human examination with the eye. Results show average percentage error between physical measurement and automated sorting is 10.264%, which implies 89.736% accuracy. The influence of conveyor speed at three levels (2.8, 3.4, and 3.9) cm sec^{-1} on overall system performance was evaluated, and the optimum speed of 3.4 cm sec^{-1} was obtained.

Keywords: micro-controller, ultrasonic sensor, automated system, conveyor unit, control unit, stepper motor, Vernier calliper, tomato fruits sorting, sorting and grading, fresh tomato fruits, market value of fresh tomato fruits

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1 Introduction

In Nigeria and most Sub-Saharan African countries, smallholder commercial tomato farmers and traders adopt eye inspection and handpicking for sorting and grading fresh tomato fruits in order to determine their market value and sales. However, it is well-known that this method is laborious, time-consuming, and inefficient. A cost-effective, consistent, superior speed, and accurate sorting can be achieved using automation techniques before packaging and potential transportation (Nandi et al., 2014). As a potentially low-cost technology with less risk of mechanical failure, automation was well-suited to the agricultural environment, where different sensors can be employed to cover certain portions of the field, such as fruit sorting (Sabanci and Aydin, 2013). In automated fruit sorting, fruits are typically classified by their appearance (shape, colour, and size). According to Arjenaki et al. (2013), sorting tomatoes is one of the most crucial processes in the packaging line (including sizing). This operation needs the simultaneous identification and management of multiple parameters. Among these include shape, maturity, variety, size,

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colour, and defects. The effectiveness and efficiency of the sorting influence the quality standard of the packaging lines and the product, which in turn determines the marketability of the product.

Many researchers have adopted different methods for sorting and grading fresh tomatoes, with their respective merits and demerits. Zhang et al. (2009) used a machine learning method to extract nine features from each image of cherry tomatoes in order to automatically sort the tomatoes according to their maturity. There were three various kinds of tomatoes identified (unripe, half-ripe, and ripe). To differentiate between fully ripe, fully mature, and partially ripe tomatoes, a principal component analysis (PCA) was used. The system accurately classified 93.2% of the tomato sample. The processing time would have been shortened by using a colour sensor. Mehrdad et al. (2012) developed a tomato classification and sorting model and analyzed the automatic control of tomato quality using support vector machine (SVM), multi-layer perception, and learning vector quantization. A digital camera first captures images, then noise removal and contrast improvement operations are performed on them. Then, the tomato features were extracted, including redness, yellowness, greenness, first moment, second moment, third moment, and average, roundness, and surface area. Three different classifiers were used with the acquired features, and the resulting classifications were compared and analysed. The results demonstrated that SVM outperforms the two alternative methods. The images could have been captured with the colour sensor instead of the camera to reduce the processing time.

Hashim et al. (2013) proposed an image processing-based tomato inspection and grading system. The study consists of two steps: recognizing regions in colour photographs that are likely to include tomato skin and extracting information from these regions to locate the tomato in the image. The tomatoes were passed through inspection and grading systems through a brightness process that captures the images. After that, analysis was conducted using a MATLAB software toolbox for image processing. The system operates when it receives and compares the saved and captured images. Using machine vision to evaluate the shape, size, maturity, and faults, Arjenaki et al. (2013) developed a tomato sorting system that analysed images using a Visual Basic 2008 algorithm. Data were also retrieved based on the health, defect, shape, size, and colour of each image sample. It was capable of sorting 2,517 tomatoes per hour. Accuracy was low because only two classes were to be sorted in all forms of sorting, even though more were processed in combination sorting. Kalaivani et al. (2013) developed a MATLAB image processing algorithm to distinguish between good and bad tomatoes. They extracted features from the input data first, followed by thresholding, segmentation, and k-means clustering. They achieved 80% accuracy.

Dhanabal and Samanta (2013) used webcams and image processing techniques to create a computerized tomato rotting detection system. To rank images, three image processing features were used. Blossom End Rot is detected in healthy tomatoes using colour. There are two systems for sorting based on decisions. The colour image threshold and form factor accurately distinguish between good and bad tomatoes. The accuracy of defect detection was 94% and 96%. Furthermore, this is only applicable to BER tomatoes. Rokunuzzaman and Jayasuriya (2013) developed a low-cost machine vision system for sorting tomatoes using webcams and image processing algorithms. Colour features were used to distinguish good tomatoes from those with Blossom End Rot (BER), while form and quantity of green objects were used to distinguish calyx flaws from crack defects. Rule-based and neural network algorithms aid in decision-based sorting. The tomatoes were transported using a belt conveyor. To push faulty tomatoes, a cylinder pushrod connected to a solenoid was used. The colour image threshold approach with the form factor distinguishes between healthy and diseased tomatoes. The rule-based and neural network methods detected defects with 84% and 87% accuracy, respectively. After the algorithms inspected 180 tomatoes per minute, a prototype was created.

Ukirade (2014) created a tomato ripeness colour grading system. Colour was used to determine ripeness of tomatoes. System design included image acquisition, enhancement, and feature extraction. Photos were converted to hue saturation value (HSV) colour space to improve image quality. Based on their colour, tomatoes were categorized according to their age using a back propagation neural network. The investigation made use of the MATLAB image processing package. After training, the neural network performed well. When evaluated with a different set of photos than those used for backpropagation, the neural network correctly classified the model. The proposed method processes, evaluates, and identifies tomato colour. This operation was time-consuming. Bhavana and Reshma (2016) proposed methods for evaluating tomato quality using image processing techniques. The suggested technique utilized input tomato image structure and texture features. The retrieved features were compared using an artificial neural network (ANN) and the K-means clustering technique. The fresh and damaged tomatoes were identified using an edge detection algorithm. If the image had more edges, it was considered faulty; otherwise, it was considered acceptable. Ceh-Varela and Hernandez-Chan (2016) investigated the use of a tomato classifier with colour histograms. The study used computer vision and learning to classify tomatoes by colour. They used Google images to find the contour of each tomato, then created datasets based on a histogram of colour for each tomato to train and test a classifier. K-Fold cross-validation methods yielded a model that was 96% accurate.

This work aims at developing an indigenous, low tech and cost-effective method of sorting and grading fresh tomato fruits that local farmers and traders can easily adopt for market value determination and sales of fresh tomato fruits in Nigeria.

2 Materials and method

This work presents a model microcontroller-based system for sorting and grading freshly harvested tomato fruits based on their sizes, using an ultrasonic sensor. First, 115 tomatoes sorted at room temperature and 55% average humidity are introduced manually into the system through the hopper. A conveyor belt then carries them one after the other into the capture unit, where an ultrasonic sensor measures the diameter of each tomato fruit as they are placed within its range. The diameters of the 115 fresh tomato fruit samples were measured using a Vernier calliper in order to pre-define their sizes for classification, and three ranges of diameters were chosen as the criteria to be used for classification into small, medium, and big sizes, accordingly.

The microcontroller unit receives input signals of the diameter as captured by the ultrasonic sensor; it then compares the value with a set of predefined diameters as programmed and then classifies the fruit as either small, medium, or big size. Next, an actuator, which is a segregator attached to a stepper motor, separates the classified tomato fruit into the appropriate container at the end of the conveyor belt. A display attached to the microcontroller also displays the result of the sorted and classified fruit implemented by the actuator. The block diagram of the automated sorting system is shown in Figure 1.

The mechanical parts, shown in Figures 2 and 3, were designed using SolidWorks CAD software. The system consists of a battery, a tomato input chamber (hopper), a conveyor motor and belt, a sensor/capture chamber, a segregator and motor, containers for receiving sorted fruits, the control unit, and a common base on which the entire system components were mounted.

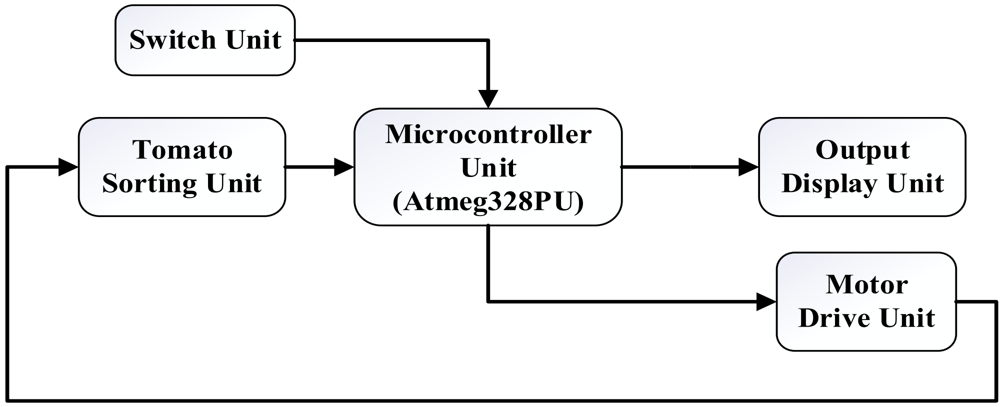

Figure 1 Block diagram of the automated sorting system

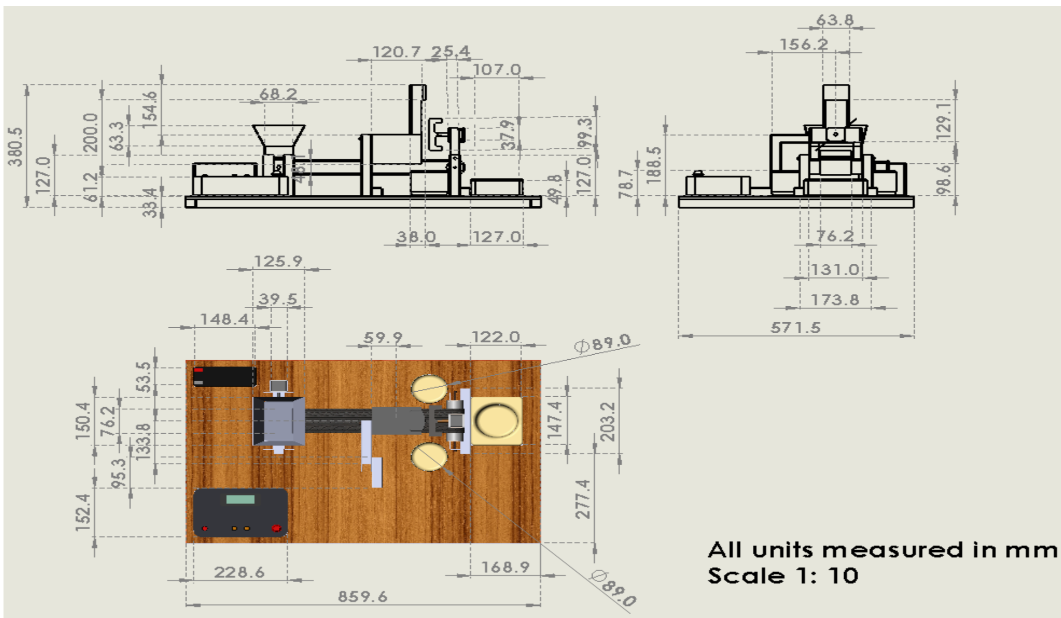

Figure 2 CAD design of the sorting and grading system in 2D

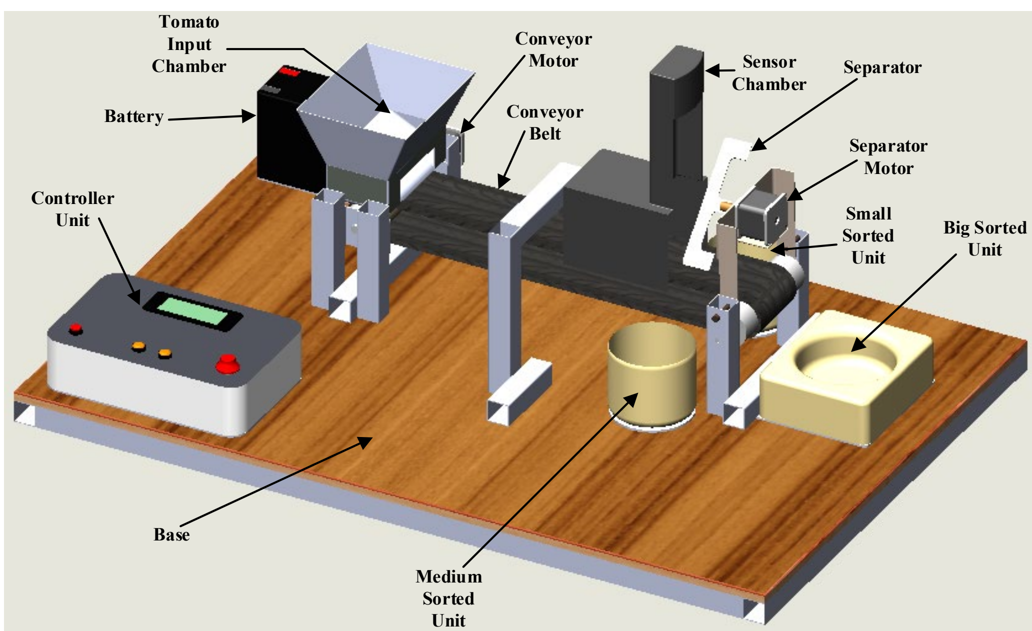

Figure 3 CAD design of the sorting and grading system in 3D

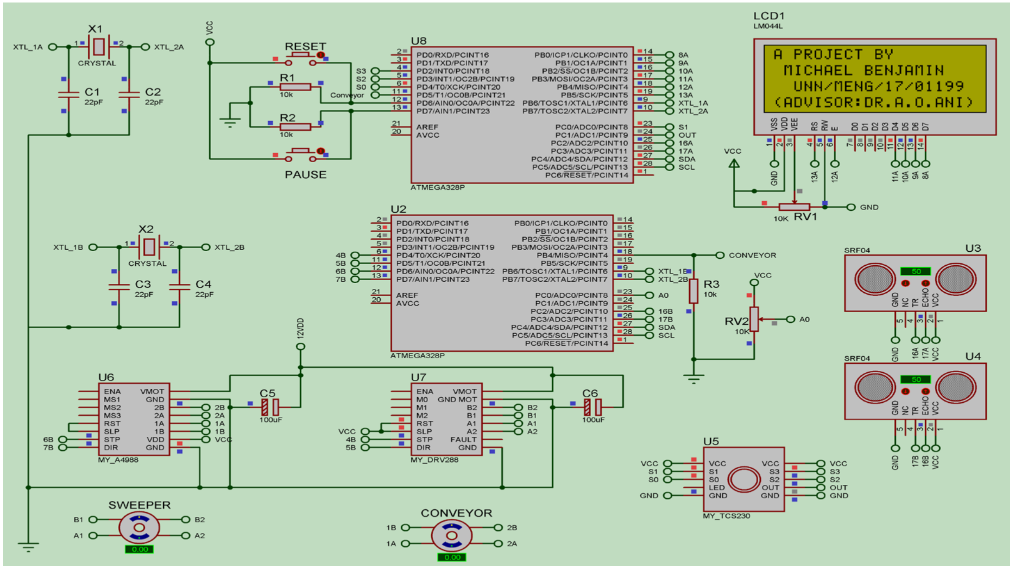

Figure 4 Interfacing circuitry for the control unit when switched On

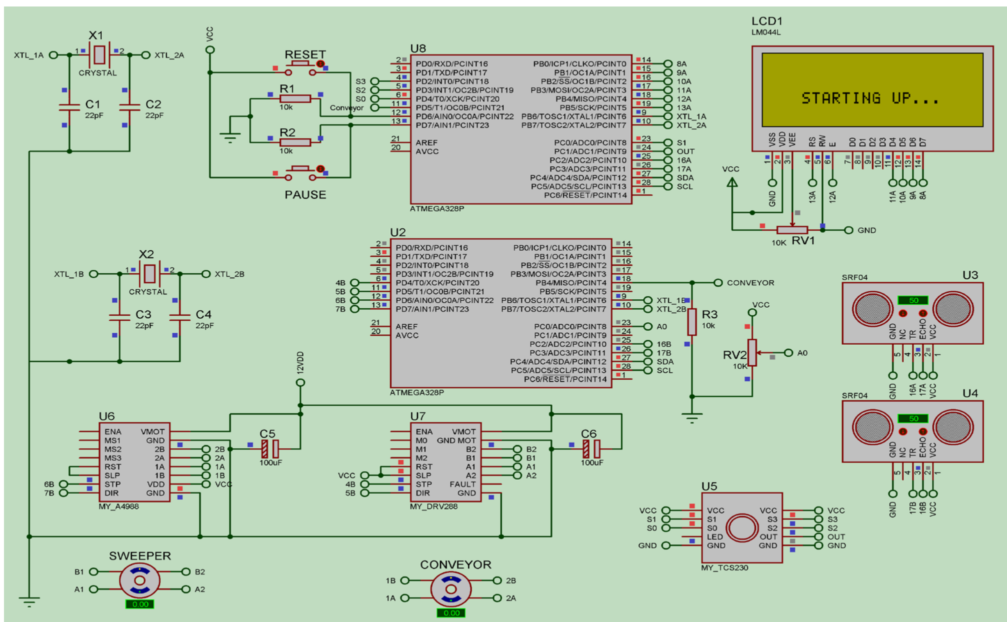

Figure 5 Interfacing circuitry for the control unit when sorting

The electrical and control systems are both embedded in the control unit. The control unit consists of the following components: ATmega328PU microcontroller chip, Vero board, motor driver 1 and 2 (DRIV), jumper wires, transistors, resistors, capacitor, LCD screen power on/off button, speed regulator, a pulse button, and a restart button. These are interconnected to communicate and function as an entity. The control unit had two power sources: a 12V adaptor and a 12V7.2AH rechargeable battery. Figure 4 shows the control unit interfacing circuitry connection design when the power switch was turned on using PROTEUS software. Figure 5 shows the control unit circuitry system as the stepper motor initialize and about to initiate the sorting procedure. Similarly, Figure 5 and Figure 6 depict the circuitry system of the control unit when the tomato sorting operation is suddenly pulsed in an emergency. While the sorting process is taking place, the LCD of the control unit is programmed to keep a record of the number of sorted tomato fruits. Figure 7 shows the constructed sorting machine. One hundred and fifteen fresh tomato fruit samples were sorted and graded using the built-in automated system. The results were evaluated and compared to the standard manual sorting by visual inspection. In addition, automated sorting was evaluated at three conveyor belt speeds in order to determine optimum belt speed.

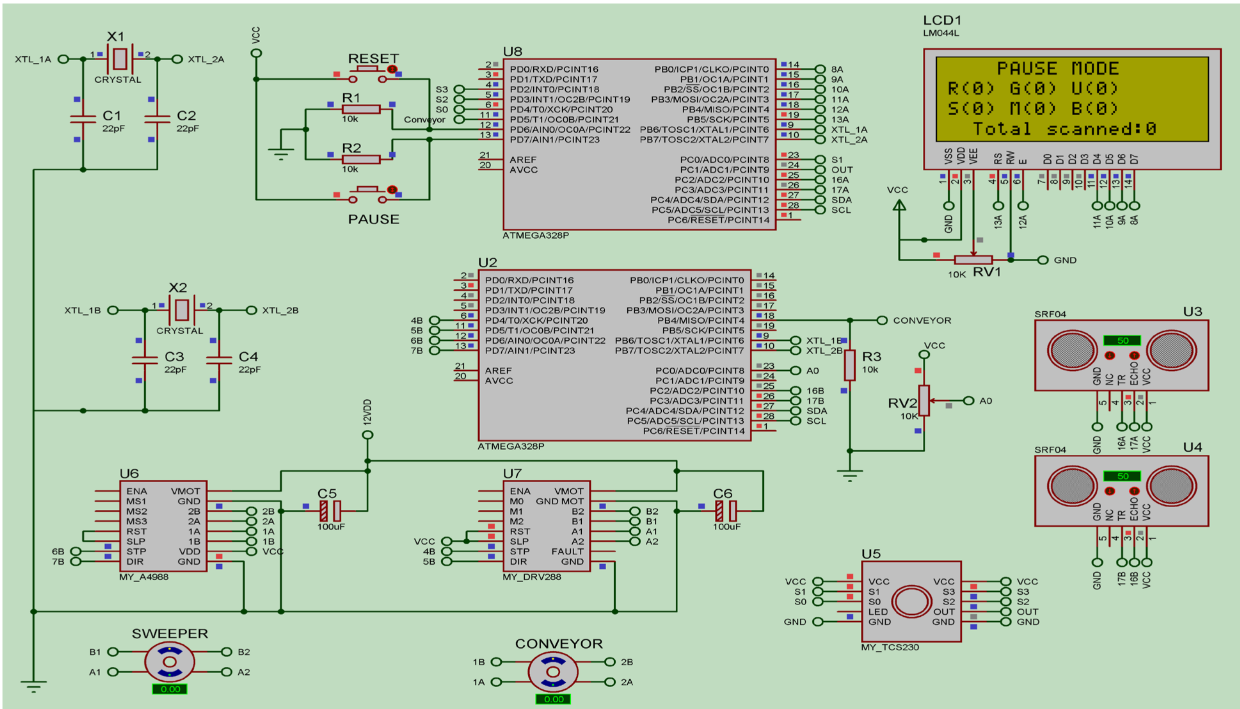

Figure 6 Interfacing circuitry for the control unit when the system is pulsed

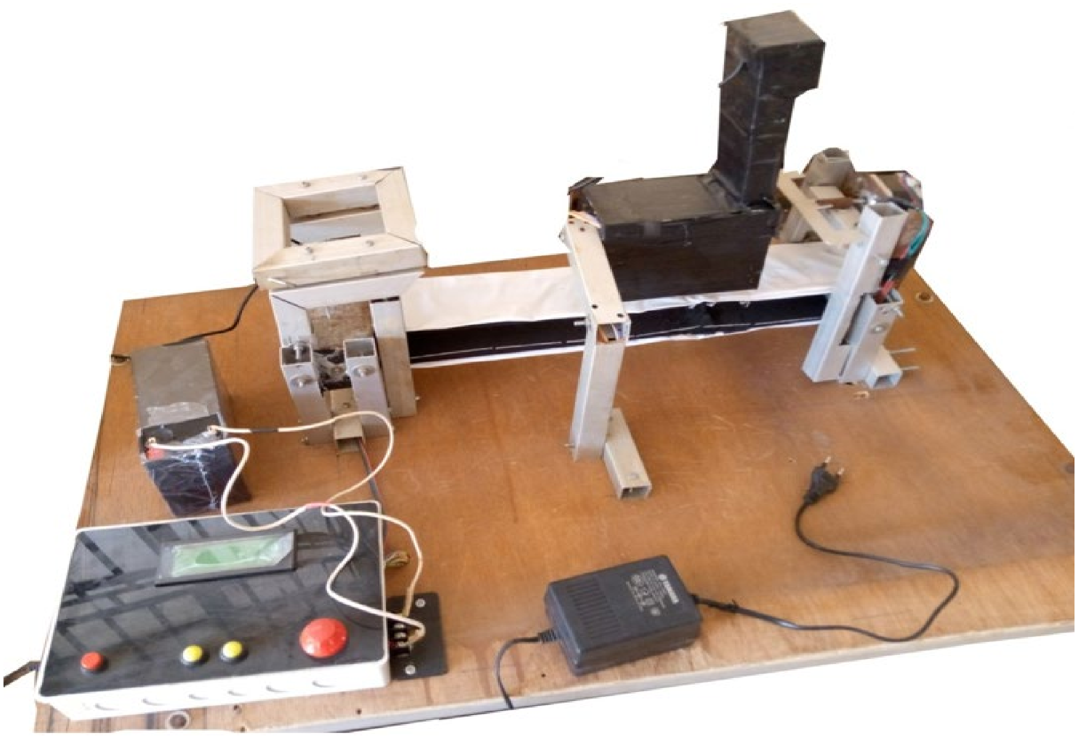

Figure 7 A Constructed automated system for sorting freshly harvested tomato fruits

3 Results and discussion

3.1 Sorting based on physical measurement

Result for sorting of tomato fruits based on the physical measurement of each fruit using a Vernier calliper are presented in Figure 8. These show the results of major, intermediate and minor diameter measurements taken and the three ranges chosen as control and hence basis for the classification of fruits into small, medium, and big sizes as $0 < x < 3.72$, $3.72 \leq x < 4.29$, $4.29 \leq x \leq \infty$, respectively, and are shown in Table 1. These ranges selected were used as basis for comparison and evaluation of how efficient the system works.

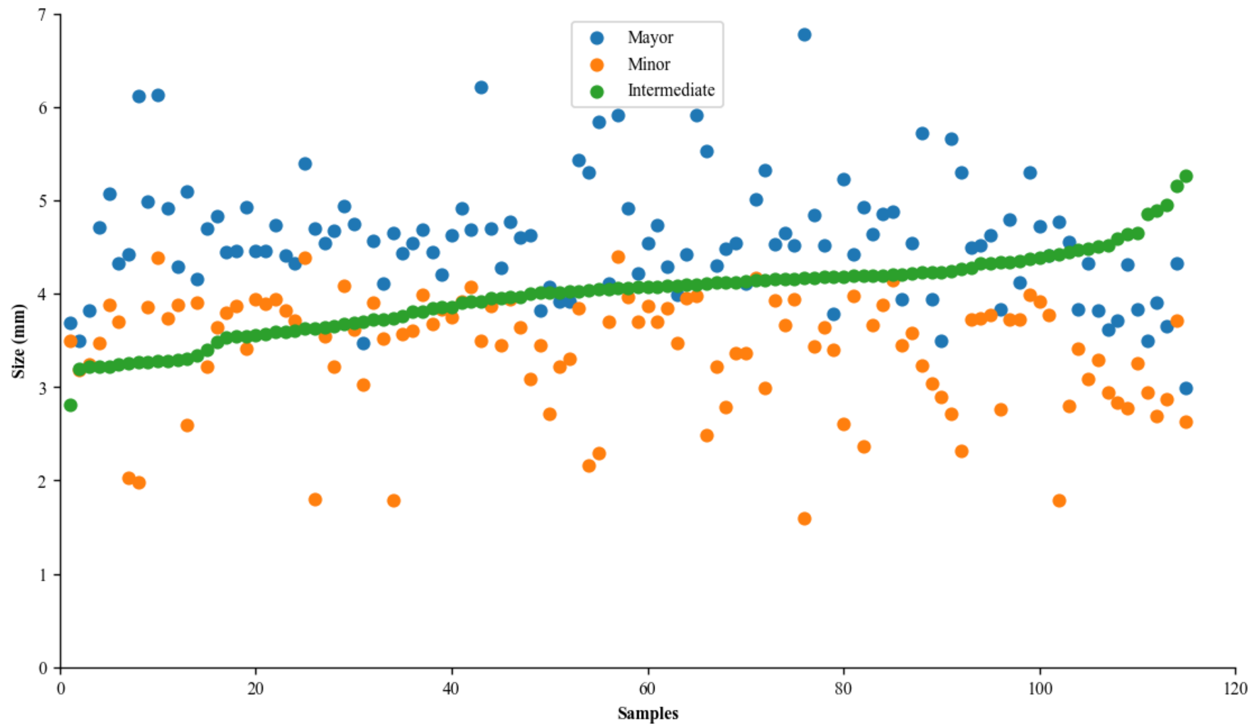

Figure 8 Results of major, intermediate, and minor diameter measurements of fresh tomato fruits using vernier caliper

Table 1 Tomato fruits classification based on physical measurement

Tomato size	Value of size
Small	32
Medium	52
Big	31

3.2 Sorting with the automated system

The influence of the conveyor speed on the overall performance of the machine is presented in Figure 9.

Three different speeds were evaluated to determine the optimal conveyor belt speed. At 2.8 cm sec^{-1}, the stepper motor was observed to be moving at a very low speed. This low speed caused the belt conveyor to move the tomato samples at a very slow rate, hence taking longer to sort the tomato fruits. It sorted the entire fruits as 32 small, 68 medium, and 15 big in 32 min. When the speed was increased to 3.4 cm sec^{-1}, it was observed that the stepper motor moved a little faster. This increased speed caused the belt conveyor to move tomato samples at a relatively fast rate, hence, cutting down the time spent sorting the tomato fruits. It sorted the fruits as 31 small, 58 medium, and 26 big in 23 min. After adjusting the belt speed to 3.9 cm sec^{-1}, it was observed that the stepper motor moved at a faster speed. This further increase in speed caused the belt conveyor to move tomato samples at a faster rate, further cutting down time spent sorting the tomato fruits. It sorted the fruits as 34 small, 61 medium, and 20 big in 22 min. But the accuracy level dropped.

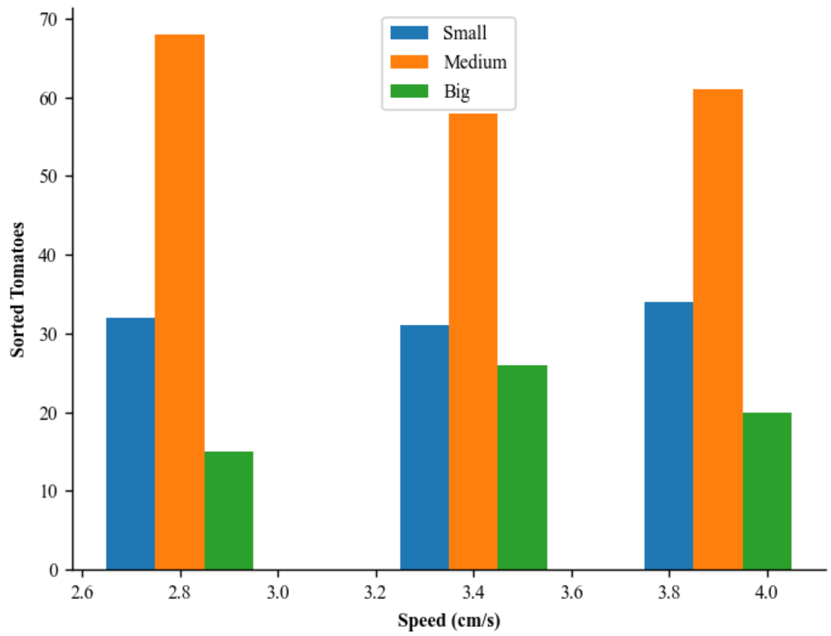

Figure 9 Bar chart showing the automated sorting of tomatoes at varying speeds

3.3 Manual sorting

Manual sorting of tomato fruits was also carried out by eye inspection and hand picking. It took 14 mins to sort the 115 tomato samples into 27 small, 45 medium, and 43 big. However, due to human fatigue, this method is laborious, less accurate as shown in Table 2, and will be inconsistent over time.

3.4 Comparison of automated sorting with manual sorting and physical measurement

Comparison of results obtained from automated sorting of tomato fruits and the results from manual sorting was done while using the physical measurement results as control, as shown in Figure 10.

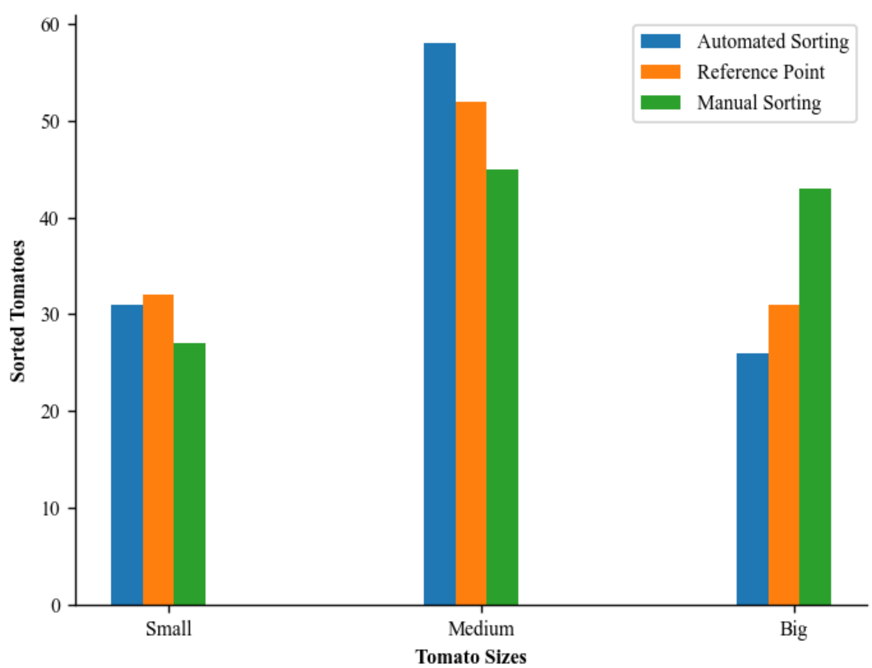

Figure 10 A bar chart of automated sorting at a varying speed with corresponding time

According to Figure 10, the physical measurement of small-graded tomatoes gave 32, while the automated sorting gave 31 and the manual sorting was 27. Physical measurement for medium-graded tomato fruits was 52, automated sorting was 58, and manual sorting was 45. While physical measurement was 31, automated sorting was 26, and manual sorting was 43 for large-graded tomato fruits. The results obtained from automated sorting of tomato fruits for small, medium, and big grades are closer to the results for physical measurement than for manual sorting. Compared to manual sorting, the automated system is more accurate, consistent and will be able to handle large quantity of tomatoes. However, the sorting time which suggests that manual sorting is better will be improved if the sorting chamber and hence the system is scaled up to be able to sort multiple fruits in each capture and the conveyor belt speed is better optimized.

3.5 Accuracy of the automated system and manual sorting

The error percentage of the manual sorting and automated system were computed, and the results are as shown in Table 2 and Table 3 respectively.

Table 2 Calculated percentage error for manual sorting

Tomato size	Automated sorting	Physical measurement	System %error
Small	27	32	15.625
Medium	45	52	13.462
Big	43	31	38.710

Average error for manual sorting system when compared to the physical measurements = (15.625% + 13.462% + 38.710%) / 3 = 22.599%

Percentage accuracy of the system = 32.203%

Table 3 Calculated percentage error for automated sorting

Tomato size	Automated sorting	Physical measurement	System %error
Small	31	32	3.125
Medium	58	52	11.538
Big	26	31	16.129

Average error for automated sorting system when compared to the physical measurements = (3.125% + 11.538% + 16.129%) / 3 = 10.264%

Percentage accuracy of the system = 89.736%.

The results, therefore, showed that the automated sorting system is 89.736% accurate in its operation, indicating a high level of precision in sorting and grading freshly harvested tomato fruits based on their sizes. In contrast, the manual sorting system had a percentage accuracy of only 32.203%, which highlights the limitations of traditional manual methods in achieving accurate and efficient sorting of large quantities of produce.

4 Conclusion

An automated system used for tomato sorting was developed using Arduino Uno microcontroller Atmeg328PU chip and ultrasonic sensor module to replace human intervention, which was a laborious process of sorting tomato fruits. The performance of the system was tested, and the result revealed 89.736% sorting accuracy while considering physical measurement with vernier calliper and a pre-set range as a reference. Given the ability of the ultrasonic sensor to capture and analyze one tomato at a time, the optimal conveyor speed was 3.4 cm s^{-1}. Based on the optimum speed the automated system accurately sorted 115 tomato fruits into 31 small-sized fruits, 58 medium-sized fruits, and 26 big-sized fruits in 23 min. By scaling the system to sort multiple fruits in each capture and by further optimizing conveyor belt speed, it is believed that the total sorting time of the system will be improved significantly.

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