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Advances in Sensor-Based and Machine Learning Techniques for Automated Tomato Sorting and Grading: A Review

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ABSTRACT

The increasing demand for high-quality tomatoes necessitates the implementation of efficient sorting and grading systems to meet market standards. Traditional manual sorting methods are labour-intensive and susceptible to inaccuracies, thereby highlighting the need for automated solutions. This review examines advancements in sensor-based technologies and machine learning algorithms for automated tomato sorting and grading. A variety of methodologies, including the utilization of RGB colour sensors, convolutional neural networks (CNNs), and hybrid models, were evaluated for their efficacy in classifying tomatoes based on size, colour, ripeness, and defects. The review examines systems that achieve classification accuracies of up to 97.5%, with sorting capacities of up to 2807 tomatoes per hour. Challenges such as variability in performance across different tomato varieties and high implementation costs were identified as significant barriers to widespread adoption. The findings suggest that further research should concentrate on enhancing the scalability, adaptability, and affordability of these systems, with potential improvements through the integration of emerging technologies such as artificial intelligence (AI) and the Internet of Things (IoT). Overall, automated sorting systems hold considerable promise for improving quality control in tomato production and ensuring a consistent supply for global markets.

Keywords: *Tomato · automated sorting · sensor technology · machine learning.*

1. Introduction

Tomatoes serve as a staple in human diets owing to their rich content of essential nutrients, along with minerals including calcium, magnesium, and potassium, as well as vitamins A, B1, B2, B6, C, and E. Also, they have bioactive substances like lycopene and beta carotene, which have contributed to several health advantages including the protection of some malignancies and cardiovascular illnesses [1]. As a result, there is always a demand for good quality tomatoes in both domestic and international markets. Tomato quality must be preserved during processing, which calls for effective sorting and grading according to factors such as size, colour, maturity, and the absence of defects [2]. Given that millions of people eat tomatoes every day and that the demand for them is rising faster than supply due to a growing global population, sorting techniques must be concentrated on to boost production.

Tomatoes have traditionally been sorted and graded manually through visual inspection, wherein individuals classify tomatoes based on their physical characteristics. However, this method is time-consuming, labour-intensive, and susceptible to inconsistencies due to human error, fatigue, and subjective assessment [3, 4]. Moreover, manual sorting and grading often results in lower precision and higher operational costs, making it less suitable for large-scale agricultural operations. Given the growing demand for quality assurance in food production-particularly in high-volume markets, there is a pressing need for more efficient and accurate methods.

An effective remedy for these problems is the emergence of automated sorting and grading systems. These systems leverage sensor technology, machine-vision and machine learning algorithms to classify agricultural products, including tomatoes, on several properties such as size, colour, and surface defects. Numerous advantages of automated approaches include reduced labour costs and decreased human errors, as well as improvements in sorting speed, accuracy, and consistency [5].

Despite the promising potential of these systems, challenges remain in terms of optimizing their accuracy and applicability across different tomato varieties and conditions. Recent advancements, particularly in the fields of machine learning and deep learning, have shown significant improvements in the classification of tomatoes based on ripeness, defects, and maturity [6]. However, further research is necessary to refine these models and ensure they can be scaled effectively for real-world applications.

This paper aims to review the current state of tomato sorting and grading technologies, focusing on sensor-based and machine learning approaches. It will analyze the performance of various systems in terms of accuracy, speed, and cost-effectiveness while highlighting the potential for future advancements in the field. By exploring both existing methods and novel approaches, this review seeks to provide a comprehensive understanding of the opportunities and challenges associated with automated tomato sorting and grading. The material is fed into the system by means of a conveyor mechanism, for instance, a vibrating feeder. The material is then transported further, for example, by a conveyor belt. Sensor-based data acquisition also takes place during this transport phase. The sensor data are processed with the goal of detecting and classifying individual particles in the material stream. The classification result serves as the basis for the sorting decision, which is executed by means of actuators as shown in Fig. 1.

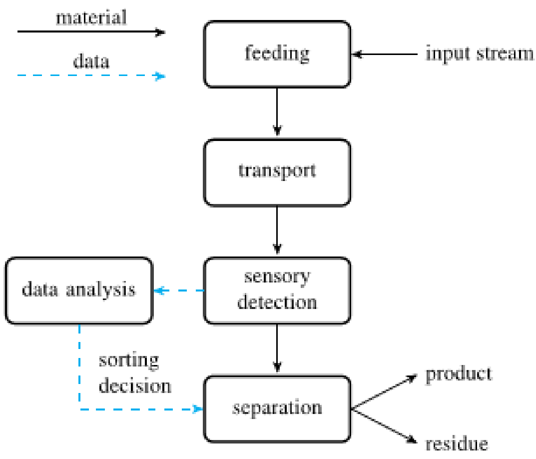


Figure 1: Schematic illustration of the sensor-based sorting process

2. Review of Related Literature

With the growing need for high-quality food products and efficient agricultural practices, the adoption of automated systems using machine vision and sensor technology has become a key area of research and development. To maximize efficiency and reduce misclassifications, agricultural marketing requires precise computerized classification of agricultural products. Nevertheless, computer applications in agriculture and food industries are applied within the areas of sorting, grading, detection of defects like cracks, dark spots and bruises on fruits and seeds [7]. Fruits are sorted and graded primarily to meet market demands by being divided into two or more grades according to factors like weight, form, colour, and obvious flaws. Therefore, a means for distinguishing tomato sizes and colours are needed by tomato sellers.

2.1 Manual Sorting and Grading

In small businesses, sorting fruits, vegetables, eggs, and other food goods by hand is a common practice. Compared to mechanical grading, it requires a smaller initial investment, but a greater running cost [7]. A low-cost manual grading machine for tomatoes using locally available materials was designed and constructed by [8]. The machine was able to solve the problems associated with manual grading, and consists of a feeding compartment (drum), sieves and collector. The machine was designed for grading UC 82-B and Roma VF tomatoes. It was based on major and minor diameters in which different tomato with different sizes will pass.

2.2 Automated Sorting and Grading Technologies

Machine vision assisted sorting and grading systems offer an alternative to manual methods, providing significant advantages in terms of speed, accuracy, and cost-effectiveness. These systems typically employ cameras, sensors, and machine learning algorithms to classify fruits like tomatoes based on characteristics such as colour, size, shape, and defects. A study conducted by [9] demonstrated the effectiveness of a sensor-based tomato sorting machine, which used RGB colour sensors and size sensors to classify tomatoes with an average sorting capacity of 1,915 tomatoes per hour and accuracy rates of 70% to 86% for colour sorting and 58% to 68% for size sorting across different tomato varieties. Similarly, [10] designed an automatic colour sorting machine that uses RGB sensors and robotic actuators to sort tomatoes based on colour. This machine achieved high sorting speeds and reduced the need for human intervention, further supporting the potential for automation in tomato processing. Moreover, [11] developed a sorting system using the TCS34725 RGB colour sensor and Arduino Uno microcontroller, achieving a sorting performance of 2,807 tomatoes per hour with an accuracy rate of 97.8%.

In addition to sensor-based sorting, machine learning algorithms have gained attention for their ability to enhance the accuracy and precision of classification tasks. A hybrid approach proposed by [12] combined traditional machine learning algorithms like support vector machines (SVM) and convolutional neural networks (CNNs) for tomato quality sorting. The hybrid model achieved 97.5% accuracy in binary classification (healthy vs. rejected tomatoes) and an accuracy of 96.67% in more than one grouping as ripe, unripe, or rejected tomatoes. Another study by [13] utilized deep learning algorithms, comparing CNN and recurrent neural networks (RNN) for sorting tomatoes based on ripeness. The RNN outperformed CNN, offering better accuracy for green, ripe, and unripe classifications.

2.2.1 Tomato classifier by machine learning algorithm

A new approach combining CNN based feature extraction with traditional machine learning classification for tomato quality sorting and grading was recommended by [12]. Tomato image dataset were generated by NVIDIA Jetson TX1 single-board computer as shown in figure 2. Image pre-processing and fine-tuning methods were employed to authorize deep layers for analysis and focus on challenging and significant characteristics. Next, support vector machines (SVM), random forests (RF), and k-nearest neighbours (KNN) classifiers were used to categorize the generated attributes. An accuracy of 97.50% for classifying tomatoes as healthy or rejected was achieved when the CNN-SVM perform better than others, amidst the suggested models. Also, 96.67% accuracy when a feature extractor called Inceptionv3 was employed in the grouping classifies them as ripe, unripe, or rejected. In classifying tomatoes as ripe, unripe, old, or damaged, a 97.54% accuracy was attained by the suggested hybrid model (CNN-SVM) once other dataset was used. Again, when a feature extractor called Inceptionv3 was employed it performs better than other hybrid models. The performance measures (accuracy, F1-score, precision, recall and specificity) of the best-performing suggested hybrid model were assessed.

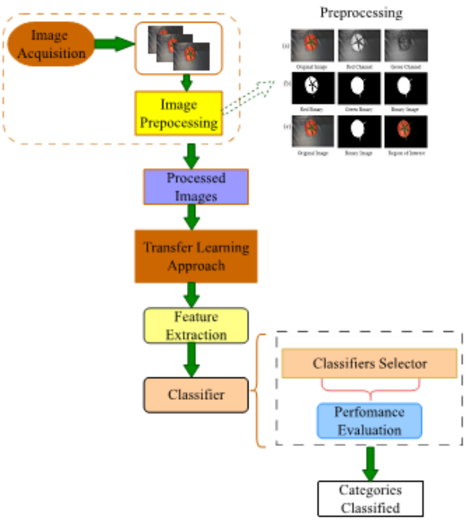


Figure 2: An overview of the proposed system for tomato classification

Automated sorting of tomatoes using deep learning algorithm (DLA) was carried out by [13]. The study uses convolution neural network (CNN) and recurrent neural network (RNN) algorithms to improve the accuracy of the tomato sorting, and provide better quality tomatoes accepted by the market. Based on their colour, they are differentiated into green, ripe and unripe. The accuracy and timing speed were increased using python programming, when framework was used to realize the feature extraction of tomatoes. The green, ripe, and unripe classifications were not accurately categorized by the CNN algorithm. Hence, the CNN generated a detection accuracy rate of 100% but the RNN algorithm provides better result as shown in table 1. The identity of ripe tomatoes from immature and half-ripe accuracy is shown in table 2. The study concurrently considered one algorithm’s size, form and faults as sorting factor.

Table 1. Comparison between CNN and RNN algorithm

Method	Data ratio	Accuracy	Sensitivity	Precision
CNN	75:70	87%	95%	75%
RNN	78:73	99.98%	96%	95%

Table 2. Calculated accuracy of each sorting type

Sorting type	Expert identification		System identification		Accuracy
	Good	Bad	True	False	
Defect	68	32	90	12	90.00%
Shape	40	15	50	5	92.90%
Size	28	27	52	3	95.54%
Maturity	37	13	46	4	95.00%

A low-cost tomato sorter by a monochromatic camera and Arduino was developed by [14]. As shown in figure 3, the monochrome image was refined into a binary, then size and colour differentiation were executed. Colour differentiation was achieved by the dominant colour method and a threshold for deep and light red colour intensities was set, while size differentiation was obtained by ellipse fitting and thresholds for big, medium and small size tomatoes were also set. For size differentiation and system control, MATLAB app was advanced as a user input interface. A multi-quality decision-making theory to perform sorting into four grades was taking into the system. The suggested method is made up of Arduino motor shield, conveyor belt, a duo of light barriers, a monochrome camera, illumination source, sorter (gripper) and a power source. An Arduino microcontroller and a computer controls the system. 0.937 and 0.924 showed size and colour sorting accuracies respectively. A success rate of 100% at 0.920 highest accuracy was average time to sort one tomato at about 3s.

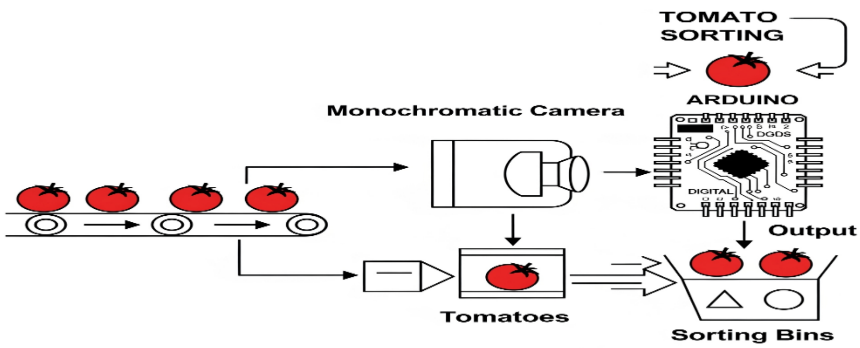


Figure 3: Diagram structure of automatic tomato sorting system

Plate 1 shows an online tomato sorting based on shape, maturity, size and surface blemishes developed by [15]. The system utilizes machine vision, a CCD camera, a microcontroller, sensors and a computer. An algorithm was used to analyze the pictures that was developed using Visual Basic 2008. 210 tomato samples were used to assess the system's performance and algorithmic precision. All images were applied with every detection method. Information regarding the class and of every representative picture, wholesome or unhealthy, long or curved, tiny or huge, and colour were extracted. The outcomes of overall system accuracy is 90%, with shape, size and defect detection algorithm of 90.9, 94.5 and 84.4% in that order. 2517 tomatoes were approximated at the system's sorting functionality per hour with one line.

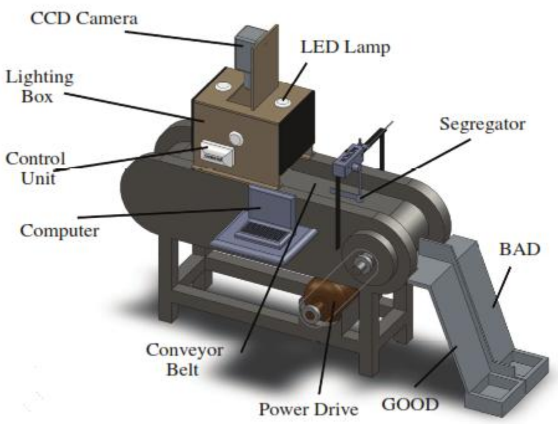


Plate 1: An experimental machine vision system for sorting tomatoes

A low-cost vision technology system for classifying of tomatoes (figure 4) was developed by [16]. One tomato per second was the sorting speed by the control program, because of the parallel port programming and simplicity in the algorithm. 180 tomatoes min^{-1} was the examination speed reached by the algorithm. The overall accuracy of defect detection reached by the rule-based approach was 84%, while that of neural network method was 87.5%. The process of colour image threshold was found effective for the tomato sorting application since the faults can be noticed based on colour. Area threshold can be used to find the difference between blossom end rot (BER) defected and good tomatoes. But due to resemblance in the colour distribution, threshold, area and number of green objects were found unfit of detecting calyx's differences from crack defects. Hence, the shape form was used for its differentiation.

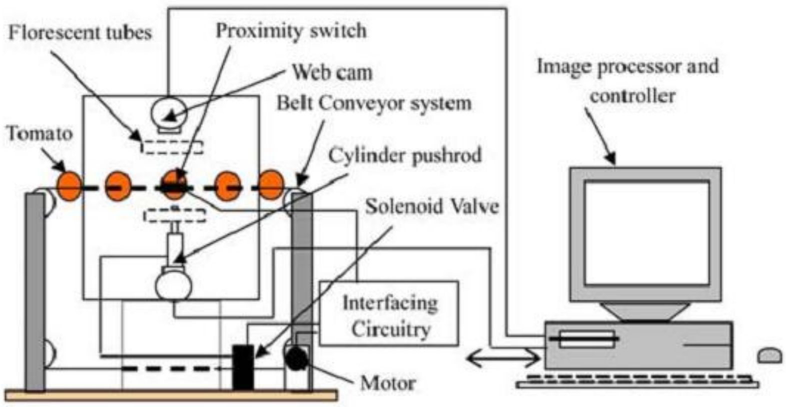
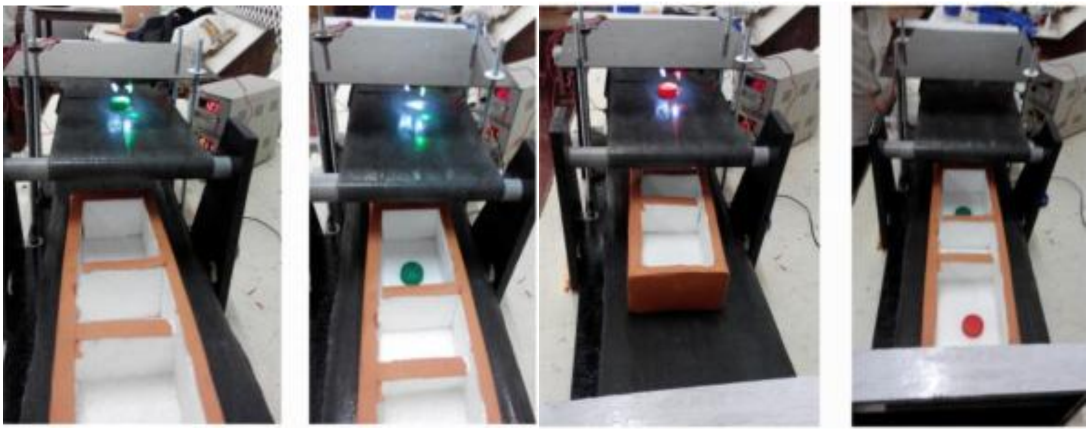


Figure 4: Schematic of the defect detection and sorting system prototype

2.2.2 Tomato classifier by weight, diameter and colour

A prototype for using a microcontroller and TCS230 colour sensor, an automatic colour sorting device was designed by [17]. Using a PIC16F628A microcontroller to control the full program and the sensor was used to detect the product's colour. The identity of the hue is on the basis of the study of the TCS230 sensor's frequency output. As shown in plate 2, a pair of conveyor belts were used, each managed by a different DC motor. For placing the intended product analyzed using the colour sensor, a first belt had been used and also, there is a second belt with distinct compartments for transporting the container, ready to split the products. The outcomes of the experiment confirmed the prototype would satisfy the necessities for increased creation as well as accurate excellence in the automation space.



(a) (b) (c) (d)

Plate 2: (a) The colour sensor identifying the colour of object 1, (b) The object 1 (Green) falls into the first section of the container, (c) The colour sensor identifying the colour of object 2, and (d) The object 2 (Red) falls into the third section of the container.

Figure 5 shows a general block diagram and subsystems an intelligent tomato classifier based on weight, diameter and colour developed by [18]. The framework optimized the required data processing techniques for tomatoes in order to maximize productivity. The test model was capable to attain rapid categorization (12.5 ratings/second) utilizing friendly and inexpensive commercial machinery. As it reduces by a factor of four the duration of hand sorting and is not sensitive to the categorized tomato variety. As the method made easier the procedures for standardization and quality control, rises the competitiveness among tomato plantations and influence completely regarding profitability.

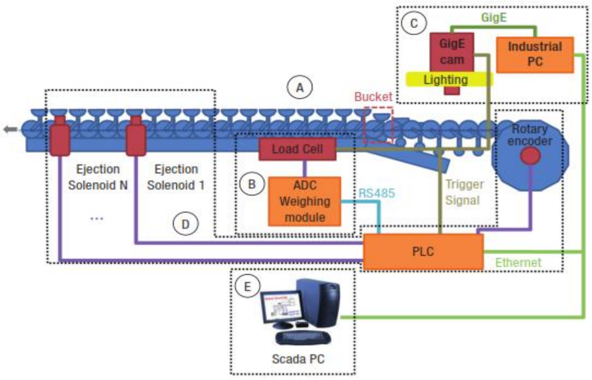


Figure 5: General block diagram. Subsystems: A) transportation and support, B) weighing, C) vision, D) control of synchronization and ejection, E) monitoring

2.2.3 Tomato sorter by colour, shape, size and maturity

To classify the ripeness of tomatoes, a fusion technology with multiple modes for tomato ripeness evaluation was suggested by [19]. The haptic data, image, and Vis/NIR spectrum results were gathered. When comparing with the multimodal fusion approach, a desirable achievement of 94.2% was attained with the formation of three-single modal designs. Also, a 5.2% improvement and the highest classification accuracy of 99.4% was achieved, when a completely connected, neural network was found using multimodal fusion model. Classifying tomato maturity, the multimodal fusion network outperforms the three conventional single-modal designs with 99.4% accuracy, 99.3% precision, and 99.4% recall. Specifically, in the event of incompatible maturity both within and outside, the categorization exactness comes to 94.4%. The outcomes demonstrate that multiple modes fusion technology can be able to get over the shortcomings of classes that are singular modal as well emphasizes its peculiar benefits. As the process recognized different matured tomatoes, enhanced the quality of food, created a novel way of guiding quick and non-invasive tomato ripeness assessments, yet arranged an establishment for the ideal harvest period and to maximize the worth of tomato produce. Also, the process may be able to be used as a source for different future fruits and veggies, such as cucumber, kiwi, and persimmon. Figure 6 shows the sorting process.

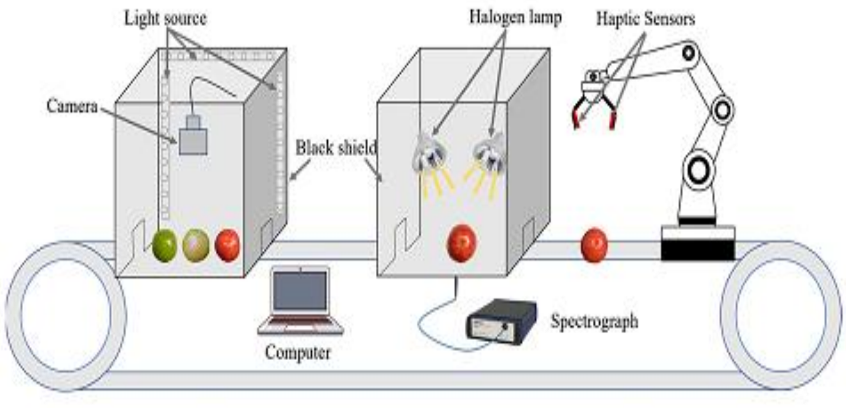


Figure 6: Diagram of data acquisition device

2.2.4 Tomato sorter by colour and size

A machine that sorts tomatoes according to size and colour that majorly consists of electrical and mechanical systems as shown in figure 7, was developed by [9]. PIC16F887A microcontroller, colour sensor (TCS230 RGB), size sensor, position sensors, and tomato collecting plates constitutes the electrical system in the machine. The whole process was controlled by the PIC16F887A and the colour of tomato was detected by the TCS230 RGB. The physical dimension and position of the tomatoes were shown by LDRI (size sensor) and the LDR2, LDR3, LDR4 and LDR5 (position sensors) respectively. Also, the mechanical system consists of a conveyor that is controlled by the electrical system. 1915 tomatoes were the sorting capacity estimated per hour with one-line pass on the conveyor, as the tomatoes pass in a straight line to the sorting point. Colour sorting accuracy was 70%, 74% and 86% and accuracy of size sorting was 68%, 58% and 58% for Roma VF, UC 82-B and Divar tomato varieties respectively. The precision was 70%, 75% and 82% for colour sorting and the precision for size sorting was 68%, 58% and 58% for Roma VF, UC 82-B and Divar respectively.

Parts No	Parts Name
1	Frame
2	Hopper
3	Pulley
4	Collector Platform
5	Collector Plate
6	Shaft 1
7	Sorting Platform
8	Electric Motor
9	Control Box
10	Collector Bottom Board
11	Belt
12	Collecting Plate
13	Steeper Motor

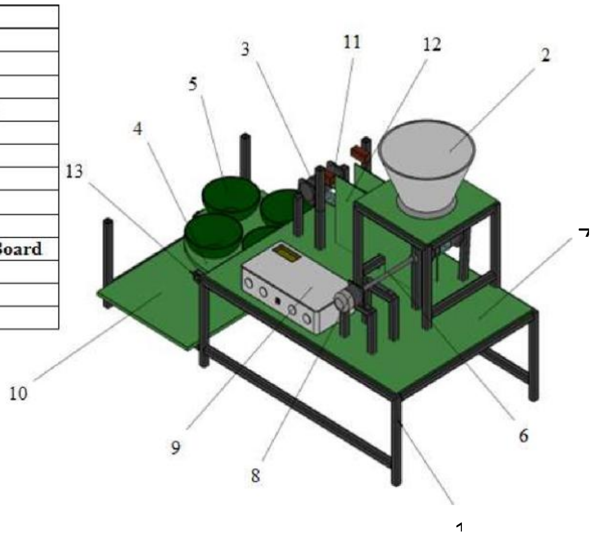


Figure 7: Isometric view of the tomatoes sorting machine

[10] designed and developed a conveyor belt-driven automatic sorting device. The device comprising four sections: small robotic manipulator, conveyor belt, and colour sensor by driving the servo

motor and linear actuator with the help of L293D motor driver and a DC motor as shown in plate 3. The outputs and inputs of these parts were interfaced using Arduino. Primarily, RGB colours were sorted using the colour sorting machine. The device separated different coloured things and arranges them into appropriate cups. As the entire process is carried out by machine, the largest benefit of the process is less time required to sort the product, there is little capability of error and smaller man power demand.

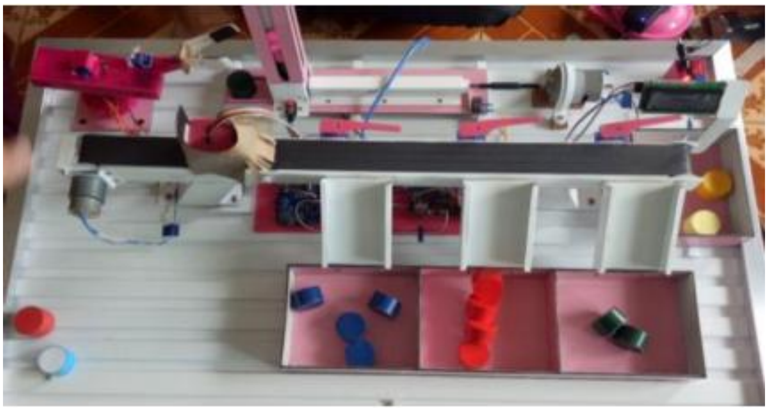


Plate 3: Colour sorting machine

An automatic tomato sorting machine based on colour sensors comprising an Arduino Uno board, a conveyor system, sorting unit, TCS34725 RGB colour sensor (plate 4) was designed and developed by [11]. ATmega328 microcontroller-based PIC development board controls the complete procedure and the colour of the tomato was detected by the colour sensor. The tomatoes moved in-line on the conveyor to the sorting point. The authentication of the hue is on the basis of the examination of the colour sensor's output frequency. As the tomato was sorted as ripe or unripe on the basis of the frequency of the colour intensity that the sensor recorded. Machine sorting yielded 2807 tomatoes per hour with 1-line with an overall system accuracy of 97.8%.

Plate 4: Schematics and photo of the prototype of the colour sorting machine

Authors in [20] designed and constructed a tomato sorting system that divided tomatoes into three sizes: small (<30 mm diameter), medium (≤50 mm diameter) and large (≥50 mm diameter) as shown in figure 8. The machine works on the belt and pulley system that feeds tomatoes through a feeding tray. With a 94% accuracy rate, the system was able to correctly classify tomatoes into three grades at 6° feeding tray angle, but for higher angles (i.e. 10°, 15°) there is a sharp increase in percentage error, a mistake that lowers the accuracy with a rise in the sorting rate. Additionally, the manual sorting rate is 0.45 tonnes/hour while the machine sorting rate is 2.7 tonnes/hour. Potato experiments demonstrate that other vegetables, such as chickoo, lemon, and onion, can also be sorted by the suggested device.

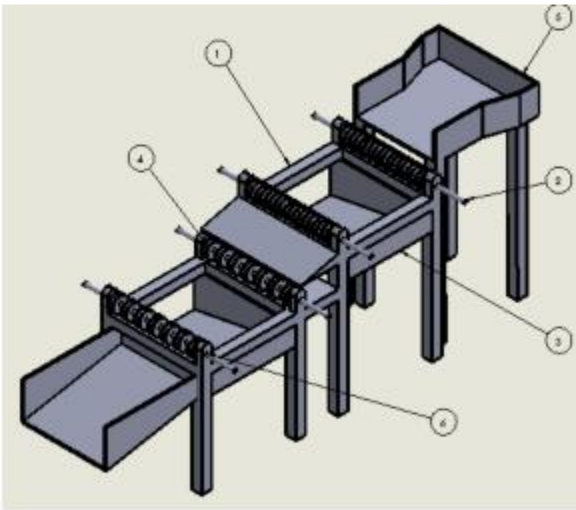


Figure 8: Assembly of tomato sorting machine with description of 1) Frame, 2) Shaft, 3) Collecting bin, 4) Pulley, 5) Feeding tray, 6) Deep groove ball bearing

A study on the sorting of tomatoes according to their colours using optical systems was carried out by [21]. The machine comprises of five subunits, namely; a band conveyor, a computer unit, a directing mechanism, a lighting system and an optic-electrical system. The units of the system were eventually united and the entire system was examined collectively. The method was able to sort out two colours (red and green). To rate the surface colours of each ripeness rate for tomatoes, accuracy in colour sorting was calculated. The average accuracy in colour sorting was 75%.

3. Challenges and Future Directions

While significant progress has been made in developing automated tomato sorting and grading systems, challenges remain in optimizing the performance of these technologies. For example, some systems struggle to achieve high precision across different tomato varieties or environmental conditions, such as variations in lighting and temperature [18]. Additionally, high costs associated with advanced sensor technologies and machine learning models may limit their widespread adoption, particularly in developing countries where resources are limited [8]. Future studies ought to concentrate on improving the scalability of these systems to handle larger datasets and higher sorting speeds, as well as reducing the costs of implementation. Researchers are also encouraged to explore the potential of new technologies like the internet of things (IoT) and artificial intelligence (AI), to further improve the efficiency and effectiveness of automated sorting systems [9].

4. Conclusion

The growing demand for high-quality tomatoes in global markets has made traditional manual sorting methods inadequate due to inefficiency, high labour costs and human error. Automated sorting systems using advanced sensor technologies and machine learning algorithms significantly improve accuracy, speed and consistency. This review shows that technologies like convolutional neural networks (CNNs) and hybrid models have achieved classification accuracy of up to 97.5% in sorting tomatoes via size, colour and ripeness. However, challenges remain in optimizing these systems for different tomato varieties and environmental conditions, as well as in reducing implementation costs to increase accessibility in resource-constrained regions. Future research should enhance the scalability and adaptability of these systems, efficiency and efficacy could be further enhanced by artificial intelligence (AI) and the internet of things (IoT). Overcoming these challenges would establish automated tomato sorting systems as essential tools for improving quality control and ensuring a consistent supply of premium tomatoes to meet global market demands.

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