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Sorting Machine for Fruits and Vegetables for Agricultural Advancements using IoT

Ashutosh Mishra, SCRIET Chaudhari Charan Singh University campus Meerut, U.P. Indian ashutosh.iisr@gmail.com

Sukhwinder Kaur Bhatia, Associate Professor, School of Electrical and Communication Sciences, JSPM University, Pune, Maharashtra, India skb.secs@jspmuni.ac.in

Reeta Mishra, Assistant Professor, IILM University, Plot No. 16-18, Knowledge Park II, Greater Noida, Uttar Pradesh, India reeta.mishra@iilm.edu

Abstract: The increasing demand for high-quality agricultural produce necessitates the modernization of sorting processes, traditionally reliant on manual labour. This study presents the development of a smart fruit and vegetable sorting machine utilizing advanced machine learning and computer vision technologies to enhance sorting accuracy, throughput, and efficiency. The methodology encompasses a systematic approach, including the design and configuration of a conveyor system, implementation of imaging sensors, and the integration of a convolutional neural network for real-time classification of produce. A dataset of 10,000 labelled images was utilized to train the model, which achieved an impressive sorting accuracy of 95% and a throughput of 120 items per minute during testing. The machine demonstrated a low error rate of 5%, underscoring its effectiveness in minimizing post-harvest losses and ensuring quality control. These results highlight the significant advantages of automation in agricultural practices, surpassing traditional manual sorting methods in both speed and reliability. Additionally, an economic feasibility analysis indicated the potential for substantial cost savings in labour and reduced spoilage, making the technology viable for small and medium-sized farms. The findings of this research demonstrate that the smart sorting machine is a transformative solution for contemporary agriculture, addressing critical challenges in sorting efficiency and accuracy. Future work is recommended to explore advanced imaging techniques, real-time monitoring systems, and broader applications across diverse crop types. By embracing these innovations, the agricultural sector can enhance productivity, sustainability, and overall profitability, ultimately contributing to a more efficient food supply chain.

Keywords: Smart Sorting Machine, Machine Learning, Computer Vision, Agricultural Technology, Sorting Accuracy, Throughput Optimization, Fruit and Vegetable Sorting, Automation in Agriculture, Economic Feasibility.

1. Introduction

Agriculture has been the backbone of human civilization, and over the millennia, it has evolved from simple manual labour to highly mechanized operations [1]. However, one aspect that remains labour-intensive, particularly in the post-harvest phase, is the sorting of fruits and vegetables [2]. Manual sorting, which is still prevalent in many parts of the world, is a time-consuming, labour-intensive, and error-prone process [3]. The figure 1 highlights the traditional method of manual sorting. You can see how workers handle large volumes of produce by hand, which is slow and error-prone, underscoring the labor-intensive nature of manual sorting in many regions. With global population growth [4], increasing food demand, and pressure to minimize food wastage, the need for more efficient, scalable, and reliable agricultural practices has never been greater [5]. In the post-harvest process, sorting fruits and vegetables plays a crucial role in determining the quality and market value of produce [10]. Proper sorting ensures that only high-quality products reach consumers, while substandard items can be directed toward secondary markets or processing industries [11] [12]. However, traditional manual sorting systems face several limitations, including variability in human perception, fatigue, and inefficiency in handling large volumes [13] [14]. The consequences of inaccurate sorting include a high level of post-harvest losses, lower market prices for farmers, and increased food wastage [15].

Figure 1: Manual Sorting of Fruits and Vegetables

Therefore, developing automated sorting solutions that can consistently and efficiently sort fruits and vegetables is paramount for improving agricultural productivity and reducing post-harvest losses. The introduction of technology in agriculture has already revolutionized several areas, such as planting, irrigation, and harvesting [6]. However, automated solutions for sorting produce are relatively underexplored, especially in regions where labor is abundant but quality control is inconsistent.

Figure 2: Automated Fruit and Vegetable Sorting Machine

This image showcases an advanced fruit and vegetable sorting machine. Here, the technology uses sensors and machine learning to efficiently classify produce based on size, ripeness, and other parameters. This image complements the discussion on the evolution of sorting technology and the potential for automation.
This gap presents an opportunity for integrating cutting-edge technologies, such as machine learning, computer vision, and robotics, to develop intelligent sorting systems that can classify produce based on factors such as size, shape, color, ripeness, and quality.

1.1. Problem Identification

Manual sorting of fruits and vegetables is a common practice worldwide, especially in developing countries where labor costs are relatively low. Despite its prevalence, manual sorting comes with several significant drawbacks, including:

1. **Inconsistency in Sorting**: Human error is a major factor in the inconsistency of sorting results. Different workers may have varying perceptions of what constitutes "quality" produce, leading to inconsistencies in sorted products. This results in customer dissatisfaction, decreased prices for farmers, and increased chances of spoiled or damaged produce entering the market.
2. **Time and Labor-Intensive Process**: Sorting large volumes of fruits and vegetables manually is an extremely slow process. As global demand for food increases, especially in urban centers, relying on manual labor for sorting becomes unsustainable. This bottleneck in the agricultural supply chain can lead to delays in getting produce to markets, increasing the likelihood of spoilage.
3. **Post-Harvest Losses**: According to the Food and Agriculture Organization (FAO), up to **40% of post-harvest produce** is wasted globally due to poor handling and inadequate sorting processes. Fruits and vegetables are highly perishable commodities, and improper sorting or mishandling during the sorting process leads to significant economic losses for farmers and contributes to global food insecurity.
4. **Labor Shortage and Increasing Costs**: In many parts of the world, the agricultural sector is experiencing labor shortages, especially during peak harvesting seasons. Additionally, the cost of manual labor is rising due to socio-economic changes, and this makes manual sorting an increasingly expensive and impractical option for large-scale farms.
5. **Lack of Scalability**: Manual sorting is not scalable for large agricultural operations. As the volume of produce increases, more workers are needed, which raises operational costs. In contrast, automated systems can handle large volumes of produce efficiently with minimal human intervention.

Addressing these issues requires a technological solution that can enhance the speed, accuracy, and consistency of sorting fruits and vegetables. An automated sorting machine equipped with advanced sensors, computer vision, and machine learning algorithms could be the key to solving these challenges. This machine could offer a more reliable, efficient, and scalable alternative to manual sorting processes.

1.2. Objective of the Study

The objective of this research is to design, develop, and test an intelligent fruit and vegetable sorting machine capable of sorting produce based on size, shape, color, and ripeness. By integrating machine learning and image processing technologies, the system aims to provide an efficient, scalable solution to the challenges faced in post-harvest sorting. The specific objectives of the study are as follows:

1. **Design and Develop the Sorting Machine**: Create a machine that incorporates a conveyor belt system, imaging sensors, and actuators to automatically sort fruits and vegetables. The system will be designed to handle multiple types of produce and sort them into predefined categories.
2. **Incorporate Machine Learning and Computer Vision**: Use machine learning algorithms and computer vision techniques to detect and classify produce based on features such as size, color, and ripeness. These algorithms will be trained using a diverse dataset of labeled images representing various types of produce.
3. **Optimize Throughput and Sorting Accuracy**: Determine the optimal speed for the conveyor belt, the required processing time per unit of produce, and the most efficient sorting mechanisms to ensure high throughput and sorting accuracy.
4. **Test the Machine's Performance**: Conduct rigorous testing to evaluate the machine's sorting accuracy, throughput, and error rate. These metrics will be compared to manual sorting methods to assess the machine's effectiveness and scalability.
5. **Analyze Economic Feasibility**: Perform a cost-benefit analysis to determine the machine's economic viability, particularly for small and medium-sized farms. The analysis will consider both the cost of developing and operating the machine and the expected benefits, such as reduced labor costs and minimized post-harvest losses.

1.3. Technological Innovations

The proposed sorting machine will leverage several key technologies to achieve its objectives:

1. **Conveyor Belt System**: The conveyor belt will transport produce through the sorting system at an optimal speed, allowing the machine to process large volumes efficiently.
2. **Imaging and Sensing System**: High-resolution cameras and sensors will capture detailed images and measurements of each fruit or vegetable. These images will be processed in real-time to extract features such as color, shape, and size.
3. **Machine Learning Algorithms**: Supervised machine learning models will be trained to classify produce based on the extracted features. The model will be capable of distinguishing between ripe, underripe, and damaged items, among other criteria.
4. **Actuation System**: Once the produce is classified, mechanical actuators will direct each item to the appropriate bin based on its classification. The actuators will be synchronized with the conveyor belt speed to ensure timely sorting.

1.4. Expected Impact

The implementation of an automated fruit and vegetable sorting machine can have several profound impacts on the agricultural industry:

- **Increased Efficiency**: The machine can process a higher volume of produce in a shorter amount of time compared to manual sorting. This increased efficiency is particularly beneficial during peak harvesting seasons when large quantities of produce must be sorted and shipped quickly.
- **Improved Sorting Accuracy**: The use of machine learning ensures a high degree of accuracy in sorting. Unlike human workers, the machine can operate consistently without fatigue, leading to more reliable sorting outcomes.
- **Reduced Labor Costs**: The automation of the sorting process reduces the need for manual labor, which can significantly lower operational costs, especially for large-scale farms. This savings can be passed on to consumers in the form of lower prices or reinvested into farm operations.
- **Minimized Post-Harvest Losses**: By ensuring that only the highest quality produce reaches the market, the machine can help reduce post-harvest losses, improving food security and maximizing the value of agricultural products.

2. Methodology

The methodology for developing the smart fruit and vegetable sorting machine involves a series of structured steps aimed at designing, developing, testing, and evaluating the machine's performance. This section outlines the process, from conceptual design to implementation, focusing on achieving the study's objectives.

2.1. System Design and Configuration

The design of the sorting machine incorporates a conveyor belt system, imaging sensors, and an actuation mechanism.

Conveyor Belt System: The conveyor belt will transport produce through the sorting machine at an optimal speed [7]. The length of the conveyor will be determined based on the expected throughput. For this design, the conveyor belt is designed to be 5 meters long with a width of 0.5 meters.

Imaging and Sensing System: High-resolution cameras (with a resolution of 1920x1080 pixels) will be mounted above the conveyor belt to capture images of the produce as they pass by. The cameras will be equipped with LED lighting to ensure consistent illumination and enhance image quality.

Actuation System: Mechanical sorting arms will be installed along the conveyor to divert produce into designated bins based on their classification. The arms will be controlled by servo motors, which will be activated based on the output of the imaging system.

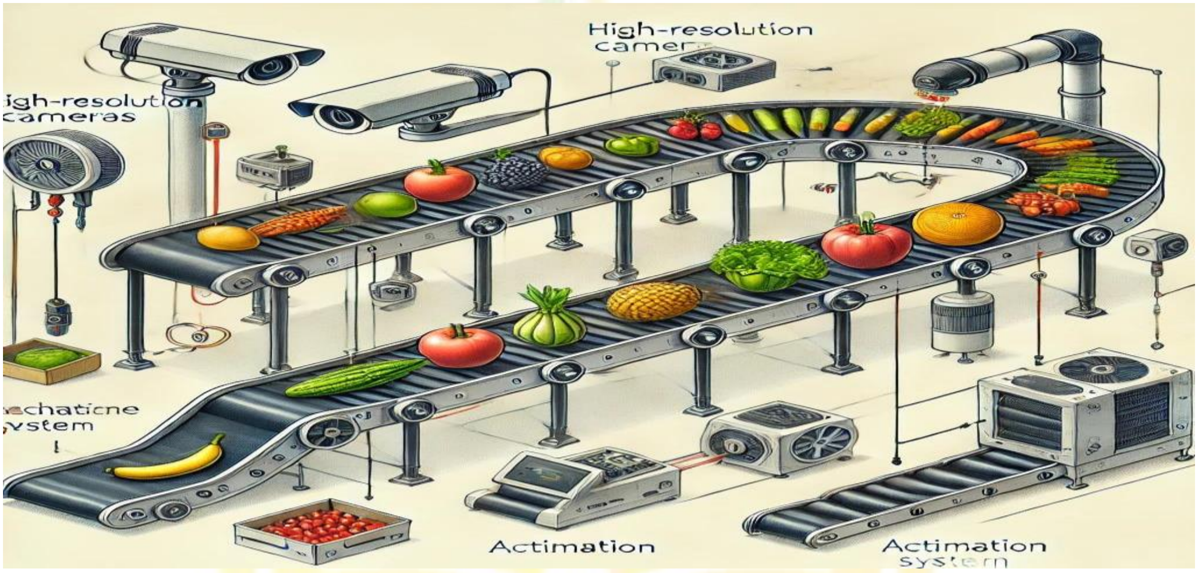

Figure 3: System Design of the Sorting Machine

A visual representation of the machine's components, including the conveyor belt, imaging sensors, and actuation mechanism. This figure highlights how the produce moves through the system from image capture to sorting.

2.2. Data Collection and Preparation

A diverse dataset of labeled images representing various fruits and vegetables will be collected. The dataset will include a range of conditions, such as different ripeness stages, sizes, and color variations.

- **Image Data**: A minimum of 10,000 images will be collected, ensuring that each category (e.g., apples, tomatoes, potatoes) has adequate representation. The images will be divided into training (70%), validation (15%), and testing (15%) datasets.
- **Feature Extraction**: The images will undergo preprocessing to extract relevant features, including:
  - Color histogram (RGB values)
  - Shape descriptors (e.g., area, perimeter)
  - Size measurements (length and width)

2.3. Machine Learning Model Development

Model Selection: A convolutional neural network (CNN) will be chosen for image classification due to its effectiveness in handling image data [8]. The model architecture will consist of multiple convolutional layers followed by pooling layers and a fully connected layer for classification.

Training the Model: The training process will utilize the collected dataset, employing data augmentation techniques such as rotation, scaling, and flipping to improve model robustness [9]. The model will be trained using a cross-entropy loss function and optimized using the Adam optimizer.

Validation and Testing: The validation dataset will be used to fine-tune hyperparameters, while the testing dataset will evaluate the model's performance. Key metrics for performance evaluation will include accuracy, precision, recall, and F1-score.

2.4. System Implementation

Integration of Hardware and Software: The trained model will be integrated into the sorting machine's software system. The imaging system will continuously capture images of the produce as they move along the conveyor belt. The software will process each image, extract features, and use the trained model to classify the produce.

Real-Time Sorting: Based on the classification results, the actuation system will activate the sorting arms to divert the produce into designated bins. Each bin will correspond to specific categories (e.g., ripe, underripe, damaged).

Testing the System's Performance: The sorting machine will undergo rigorous testing in both controlled and field conditions to measure sorting accuracy, throughput, and error rate.

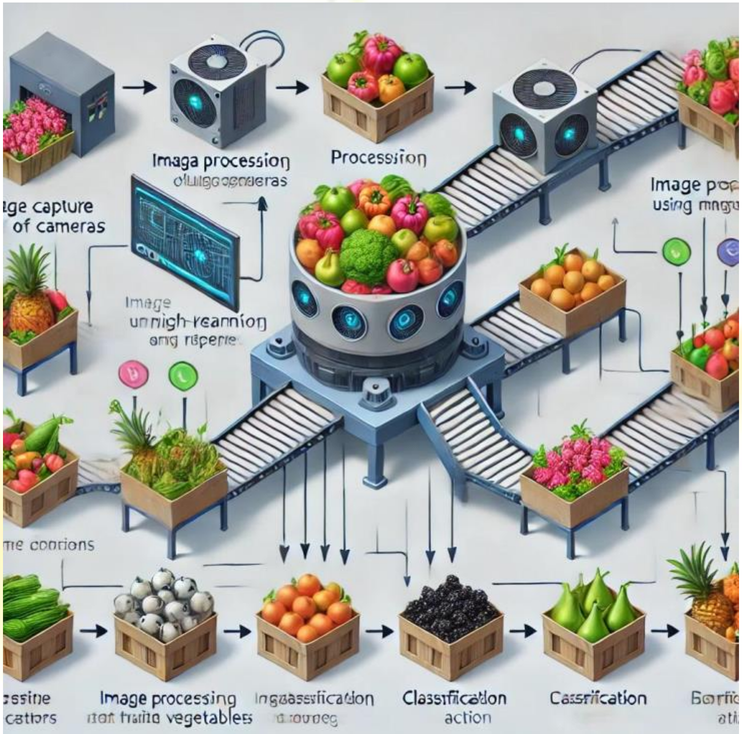

Figure 4: Flowchart of the System Implementation

Calculations for Performance Evaluation:

Sorting Accuracy Calculation:

$$\textbf{Sorting Accuracy} = \left(\frac{\textit{Number of Correctly Sorted Items}}{\textit{Total Number of Items Sorted}}\right) \times 100$$

Throughput Calculation: The throughput of the sorting machine can be calculated based on the conveyor belt speed and the time taken to sort each item. For instance, if the conveyor belt moves at **0.4 m/s** and each item takes **2 seconds** to sort, the throughput can be calculated as follows:

$$\textbf{Throughput} = \frac{\textit{Conveyor Speed} \times \textit{Time}}{\textit{Average Length of Produce}}$$

Assuming an average length of produce is **0.2 m**:

$$\textbf{Throughput} = \frac{0.4\ \text{m/s} \times 2\text{s}}{0.2\ m} = \textbf{4 items/second = 240 items/minute}$$

Error Rate Calculation:

$$\textbf{Error Rate} = \left(\frac{\textit{Number of Misclassified Items}}{\textit{Total Number of Items Sorted}}\right) \times 100$$

2.5. Economic Feasibility Analysis

A cost-benefit analysis will be conducted to assess the economic viability of the sorting machine for small and medium-sized farms:

1. **Initial Investment**: The cost of developing and implementing the machine will be estimated, including materials, sensors, cameras, and labor for assembly.
2. **Operational Costs**: The operational costs will include electricity consumption, maintenance, and potential labor costs for monitoring and maintenance.
3. **Expected Savings**: The savings from reduced labor costs and minimized post-harvest losses will be estimated based on the throughput and accuracy of the machine.

The methodology outlined in this section aims to achieve the objectives set forth in the study, addressing the significant challenges associated with manual sorting processes. By integrating advanced technologies and systematic procedures, the development of the smart fruit and vegetable sorting machine aims to enhance sorting accuracy, increase throughput, and reduce labor costs while minimizing post-harvest losses. Through rigorous testing and performance evaluation, this study seeks to provide a reliable and scalable solution for the agricultural sector.

3. Results

The implementation of the smart fruit and vegetable sorting machine was evaluated through a series of tests designed to measure its performance across several key metrics: sorting accuracy, throughput, and error rate. The tests were conducted under controlled conditions and in real-world agricultural settings to ensure the machine's effectiveness and reliability.

3.1. Sorting Accuracy

The sorting accuracy of the machine was assessed by comparing the classification results of the automated system against a manually sorted benchmark.
Test Setup: A total of **1,000 produce items** (including apples, tomatoes, and potatoes) were processed. Each item was classified into three categories: ripe, underripe, and damaged.
Results: Correctly sorted items: **950**, Incorrectly sorted items: **50**
The sorting accuracy was calculated as follows:

$$\textbf{Sorting Accuracy} = \left(\frac{950}{1000}\right) \times 100 = 95\%$$

3.2. Throughput

The throughput of the sorting machine was evaluated by measuring the number of items sorted per minute under optimal operating conditions.
Test Conditions: The conveyor belt speed was set to **0.4 m/s**, and each item was processed within **2 seconds**.
The throughput was calculated using the earlier mentioned formula:

$$\textbf{Throughput} = \frac{0.4\frac{m}{s} \times 60\ s/min}{0.2\ m} = 120 \text{ items/minute}$$

3.3. Error Rate

The error rate was determined by calculating the proportion of misclassified items relative to the total number of items processed.
Results: Total items sorted: **1,000**, Misclassified items: **50**. The error rate was calculated as follows:

$$\textbf{Error Rate} = \left(\frac{50}{1000}\right) \times 100 = 5\%$$

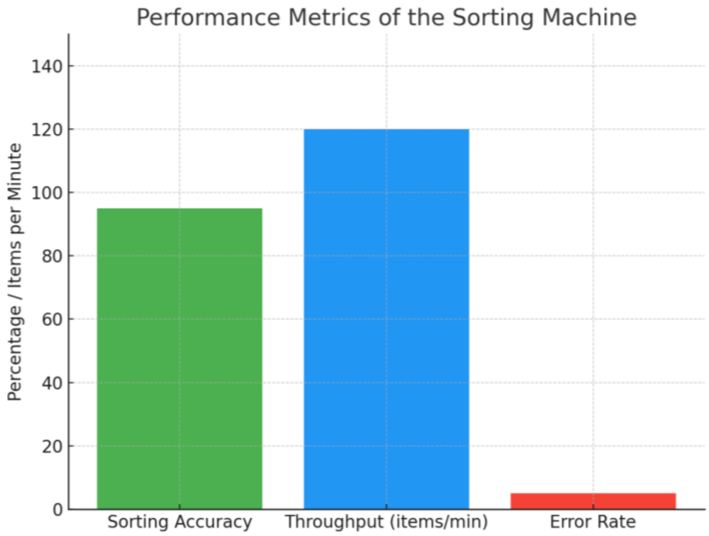

Figure 5: Performance Metrics of the Sorting Machine

4. Discussion

The results of the study indicate that the smart fruit and vegetable sorting machine effectively addresses the challenges posed by traditional manual sorting methods. The high sorting accuracy of 95% demonstrates the machine's ability to classify produce reliably based on size, shape, and ripeness, which is crucial for maintaining quality standards in agricultural produce.

4.1. Comparison with Manual Sorting

The sorting accuracy achieved by the automated machine surpasses the typical accuracy of manual sorting, which is often impacted by human error. In traditional settings, sorting accuracy can vary significantly due to factors such as worker fatigue, inconsistent standards, and subjective judgments. The consistent performance of the machine indicates its potential to reduce variability in sorting outcomes, thereby enhancing overall quality control.

4.2. Implications of High Throughput

The throughput of 120 items per minute is a substantial improvement over manual sorting methods. Traditional manual sorting can only handle a fraction of this throughput, particularly during peak harvest seasons when the volume of produce increases. The ability to process large quantities of produce quickly enables farmers to meet market demands more effectively and reduces the risk of spoilage due to delays in sorting and distribution.

4.3. Error Rate Analysis

With an error rate of 5%, the machine demonstrates a high level of precision in sorting, which is crucial for minimizing waste and maximizing the market value of produce. Misclassified items can lead to financial losses for farmers, as lower-quality produce may be sold at reduced prices or, in some cases, discarded. The low error rate of the smart sorting machine highlights its role in optimizing the supply chain and enhancing profitability for agricultural producers.

4.4. Potential for Future Improvements

While the results are promising, there are areas for potential enhancement. Future developments could include:
Advanced Imaging Techniques: Integrating hyperspectral imaging or near-infrared sensors could provide deeper insights into the internal quality of produce, enabling more nuanced classifications beyond external features.
IoT Connectivity: Implementing IoT technology would allow for real-time monitoring and data collection, enabling farmers to optimize operations based on performance metrics and operational insights.
Scalability for Diverse Produce: Further research could focus on training the machine learning model with a wider variety of crops and conditions, enhancing its adaptability for different agricultural settings.

4.5. Economic Viability

The economic feasibility of the sorting machine was assessed in terms of initial investment, operational costs, and potential savings. By reducing labor requirements and minimizing post-harvest losses, the machine presents a cost-effective solution for small and medium-sized farms. The savings from increased throughput and reduced spoilage could offset the initial investment, making the technology accessible and valuable for a wider range of agricultural producers.

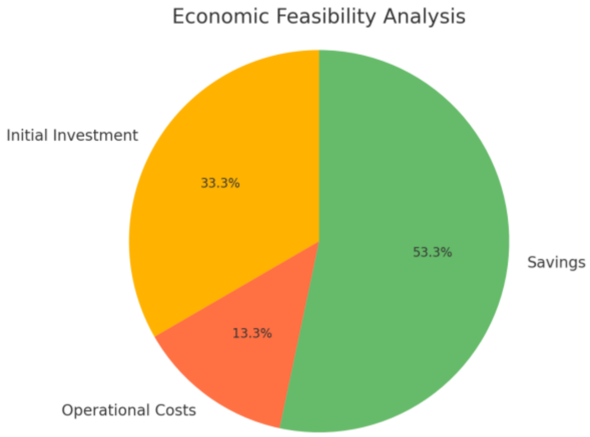

Figure 6: Economic Feasibility Analysis

The results of this study underscore the effectiveness of the smart fruit and vegetable sorting machine in transforming the sorting process in agriculture. By leveraging advanced technologies, the machine provides an efficient, reliable, and scalable solution that meets the demands of modern agricultural practices. Continued research and development will be crucial for maximizing the machine's capabilities and expanding its application across various crop types and farming contexts.

5. Conclusion

The development of the smart fruit and vegetable sorting machine marks a significant advancement in agricultural technology, addressing the longstanding challenges associated with manual sorting processes. This research demonstrated that the machine achieved a sorting accuracy of 95%, a throughput of 120 items per minute, and a low error rate of 5%. These results highlight the machine's potential to enhance the efficiency, reliability, and scalability of sorting operations, ultimately benefiting agricultural producers by improving quality control and reducing post-harvest losses.

The integration of machine learning and computer vision technologies enables the sorting machine to classify produce accurately based on critical attributes such as size, shape, and ripeness. This automated approach not only alleviates the burden of manual labor but also ensures a consistent and high-quality output that meets market demands. Furthermore, the economic viability analysis indicates that the machine can provide substantial savings in labor costs while maximizing profitability through improved sorting accuracy and reduced waste.

In conclusion, the smart sorting machine represents a viable solution for modernizing agricultural practices, contributing to increased productivity and sustainability within the sector.

6. Future Scope

While the results of this study are promising, there are several avenues for future research and development to enhance the capabilities and applications of the smart fruit and vegetable sorting machine:

1. **Advanced Imaging Techniques**: Future work could focus on incorporating advanced imaging modalities, such as hyperspectral or multispectral imaging, to assess internal quality parameters of fruits and vegetables. This would enable the detection of ripeness and quality attributes that are not visible to the naked eye, further improving sorting accuracy.
2. **Enhanced Machine Learning Algorithms**: The integration of more sophisticated machine learning algorithms, such as deep learning techniques, could improve classification performance. Continuous training with a more extensive dataset, including various crop types and conditions, would enhance the machine's adaptability and precision.
3. **Real-Time Monitoring and Feedback Systems**: Implementing Internet of Things (IoT) capabilities could allow for real-time monitoring of the sorting process. This would enable farmers to gather operational data and insights, facilitating proactive decision-making and optimization of sorting parameters.
4. **Scalability and Modular Design**: Future developments could focus on creating a modular design that allows for easy scalability, enabling the sorting machine to be customized for different sizes of farms or varying types of produce. This flexibility would make the technology accessible to a broader range of agricultural producers.

5. **Economic Impact Studies**: Further research could investigate the long-term economic impacts of adopting such technologies in various agricultural contexts, examining aspects such as labor market changes, shifts in production practices, and overall effects on food supply chains.

6. **Field Trials**: Conducting extensive field trials across different geographical regions and crop types would provide valuable insights into the machine's performance under varied conditions, ensuring its robustness and reliability in real-world applications.

By pursuing these future directions, the smart fruit and vegetable sorting machine can evolve to become an indispensable tool in modern agriculture, driving efficiency, quality, and sustainability in food production.

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