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REVIEW ARTICLE

Advanced robotic automation and sensor technologies for postharvest sorting of perishable foods: innovations, case studies, and future perspectives

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ABSTRACT

The significant postharvest loss of perishable foods, mainly due to inefficiencies in handling, sorting, and quality assessment, underscores the critical need for advanced automation solutions in the food supply chain. This paper explores developing and implementing robotic systems for postharvest handling and sorting perishable foods, focusing on innovations in sensor technology, machine learning, and soft robotics to improve quality retention and reduce damage. It provides an overview of the challenges faced in postharvest logistics and examines the role of automated systems in enhancing efficiency and scalability within the agricultural sector. Integrating quality-assessment sensors, such as hyperspectral imaging, and machine-learning algorithms facilitates real-time produce sorting based on key quality indicators. At the same time, soft robotics offer a solution for gently handling fragile items. Through case studies and performance evaluations, this study illustrates how robotic systems can effectively address labor shortages, minimize food waste, and improve supply chain transparency, ultimately contributing to sustainable food systems and increased profitability for stakeholders across the value chain.

Keywords: Robotic systems, Postharvest handling, Perishable foods, Automated sorting

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INTRODUCTION

Perishable products are prone to spoilage and loss of freshness postharvest. Approximately 1.3 billion metric tons of food produced for human consumption are wasted annually, leading to an estimated US$1 trillion in spoils (Durán-Sandoval et al., 2023). Globally, food supply routes are increasingly being threatened due to the entry of pollutants, contaminants, and toxic elements. Modern consumers are grossly inconvenienced by purchasing perishables whose intrinsic and extrinsic qualities are masked or hidden and, therefore, find it difficult to correctly assess the actual decay state (Makanjuola et al., 2020). Speedy and efficient sorting and segregation of food commodities are apparent needs for all stakeholders involved from training, appraising, research, and extension perspectives (Kaur et al., 2023; Daszkiewicz, 2022; Khan et al., 2024; Adedeji, 2022).

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Automation in the postharvest handling of fruits and vegetables is the most effective solution for minimizing or eliminating food waste for the retailer or the consumer (Krishnamma et al., 2024). Interest in handling food through technological intervention shows a paradigm shift in the commercial philosophy of operation. In addition to working with rural produce such as fruits and vegetables, it provides an opportunity to transfer value to individual farmers who aspire to have a more significant role in the food production chain. Modern and advanced robotic-based systems, with their better speed and efficiency, are beneficial to fulfilling the demand for quick sorting of fruits and vegetables without causing any damage to the products (Zhou et al., 2022) (Chauhan et al., 2022). The robotic systems for postharvest handling have more advantages than traditional methods, which can grade the products based on several physical, mechanical, and electrical properties. The computer vision and machine learning-based sorting systems also provide high-quality product grading at a lower cost. These systems have a crucial effect on lowering postharvest losses significantly and greatly help decision-making (Singh et al., 2022; Vrochidou et al., 2022).

OVERVIEW OF POSTHARVEST CHALLENGES WITH PERISHABLE FOODS

Postharvest food processing is the first stage of a complex chain of events between harvest at the farm and final consumption by the customer. A prolonged time delay from harvest creates food quality challenges for fruits and vegetables, which are mainly at risk from the following types of postharvest spoilage:

1. Physical injury and damage during harvesting, handling, and mechanical processing after harvest;
2. Increased susceptibility to microbial and fungal infections;
3. Undesirable phenotypic changes in ripening, including colour and starch accumulation and flesh softening.

Enhanced perishability and the potential for physical damage result in low economic returns when the fruits and vegetables are finally placed on the market (Etefa et al., 2022). Growing demand for a constant supply of high-quality fruit and vegetable products with varying ripeness adds complexity and uncertainty to postharvest logistics. The average worldwide rate of postharvest wastage in fruits and vegetables is 25% and 30%, respectively; in the agricultural setting, up to 40% of edible food volume is wasted (Ali et al., 2021). The inefficiency of hard manual labor for crop handling worsens substantial postharvest food losses. Traders with few alternatives regard crop distress and spoilage during transport and roadblocks, particularly as an unavoidable aspect of handling fresh goods. Field-to-market fruits and vegetables may feedstock various industries and factories from the initial harvest to the final consumer. Early damage disqualifies many crop products planned for processing, and the ones that go through processing are eventually separated (Opara et al., 2021). Perishability alone means that goods such as potatoes and carrots experience rapid decomposition during field processing due to moisture loss and physical injury. Particularly in subtropical climates, evacuating the field and beginning the transportation process is sometimes not economically feasible (Lufu et al., 2020).

SIGNIFICANCE OF AUTOMATION IN REDUCING POSTHARVEST LOSSES

Significant postharvest losses are reported in perishable foods like fruits, vegetables, and tea, attributed primarily to poor handling and sorting during postharvest operations (Anand & Barua, 2022). Automation, particularly robotic systems, helps to address some of the issues related to handling and sorting operations. Automation can replace a considerable amount of manual labor, which is tiresome and time-consuming, and reduce human errors. This will streamline and bring more efficiency to the operations, which ultimately helps in delivering an enhanced quality of the food products to the consumer. Timely handling of perishable foods in the postharvest phase will also help extend the shelf life of the produce, thus reducing wastage and postharvest losses (Bisht & Singh, 2024). Moreover, sorting makes the packaging process simpler and more accurate and maximizes the food quality produced. This restoration also reduces operational and packaging costs as it minimizes workers' need for hands-on sorting (Pokhrel, 2021).

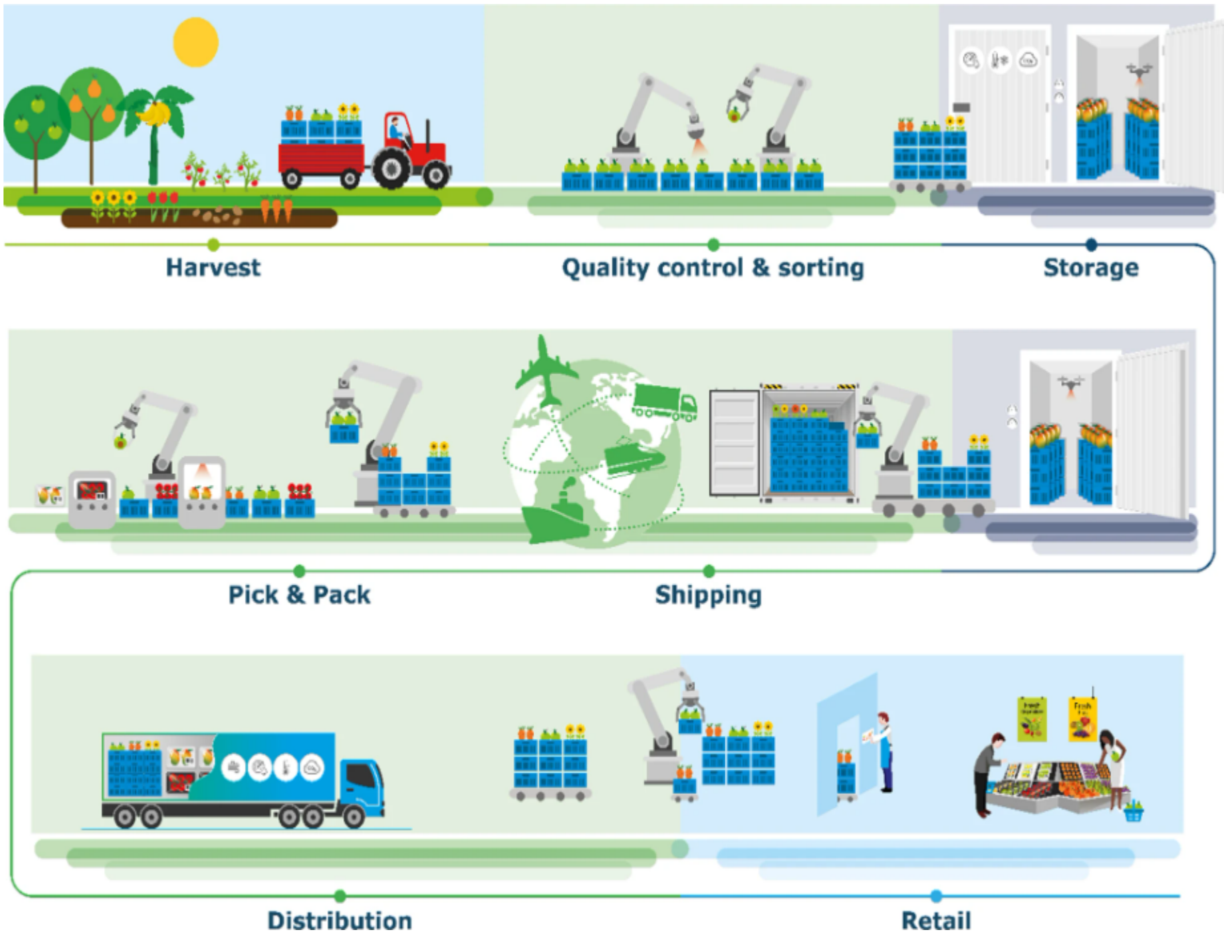

Figure 1: Representation of the roles of robotics in the post-harvest supply chain.

Automation can also make on-time sorting of the produce, as a result of which traceability of the food items in the supply chain can be maintained throughout the storing, processing, and transportation in pre- and post-market phases (Bhutta & Ahmad, 2021; Balamurugan et al., 2022). In developing societies, the implication of automation is more heavily acknowledged than in developed societies. Automating the overall sorting system and the treatment process had no adverse effects on profitability; instead, it improved the industry's competitive edge. The advancement of automated technology developments and the move towards sustainability objectives through technical progress and research have broad implications for the agricultural commodities sector (Haji et al., 2020; Behnke & Janssen, 2020).

In the last few years, several robotic systems for post-harvest handling and sorting have been proposed to balance the growing demand for food and labor scarcity (Chauhan et al., 2022; Zhou et al., 2022). Most of these studies are lab-scale to explore new issues or investigate the implementation of specific devices or new vision techniques. The research in robotics has undergone several development phases, starting from the study of robot hardware, the introduction of sensors and intelligent systems to ensure robots can interact more efficiently with the environment, the design of new strategies to control the components and the entire system, and new business models to ensure rapid market placement of products (Fei & Vougioukas, 2021). Research into more efficient, integrated post-harvest methods is limited to minimising physiological deterioration of non-damaged products, consequently extending the freshness, safety, and shelf life of foods. Despite the efforts and high potential of the current environment and food robotic technologies, the sophistication of the post-harvest management process, improvement of aesthetic quality, and on-time delivery to the market are still temporary bottlenecks. There is diversity in the methods employed, and the design objectives of technological tools, and the primary motivation is to improve food handling efficiency (Faheem et al., 2021). Therefore, while many studies have been conducted on robot handling efficiency, there are no unified or standardized research methodologies to compare the performance of developed robotic systems versus traditional food handling operations for specific post-harvest fruit handling operations (Bharad & Khanpara, 2024; Vrochidou et al., 2022).

ROBOTIC SYSTEM DESIGN AND SPECIFICATION

Robot and robotic system design is fundamental to realizing the agility of picking for various perishable products. This robotic system must have mobility properties to swiftly move along so-called rails near the vertically suspended products in their bulk storage space or on a wired 3D path(Chauhan et al., 2022). The system should also be very dexterous to robotically handle different types of vegetables or fruits of different sizes and shapes, such as cauliflower, cucumber, tomato, and broccoli. For autonomous operation, this robot should be capable of automated and remote control and designated location with automated fruit selection based on ripeness and autofluorescence from fungi and insects. To facilitate the pick module, the prototype robot was tested during the summer by humans, who controlled it using a state-of-the-art virtual robot control interface. In contrast, the waste pack zone was manually controlled separately. The human-operated waste pack system is a development platform and can be substituted with automated waste packing to facilitate early deployment (Haji et al., 2020).

It is essential to understand and analyze the requirements, which are based on the actual needs of the farm and have also been informed through a survey of farmers and a dedicated user engagement large group meeting. Engineering simulations, tools used in toppling handling, robotic design considerations, and how initial prototypes are integrated into the system in a preliminary real-world demonstration are also discussed. Such a robotic design control philosophy is based on seven engineering principles, including durability, enhancement, dexterity, versatility, and automation, as described in the objectives. An overview of the avatars of robots presenting the robotic aids for the commodity system is shown. The concept for a dedicated robot picker system is depicted. The stages planned to develop the robotic system for toppling are presented.

Integration of sensors for quality assessment (ripeness, color, size)

To perform the sorting of perishable food fully automatically, a robotic system requires sensor technology to assess the quality of food items: ripeness, color, and size. Several studies have been conducted in which different sensor technologies have been assessed for quality assessment.

Table 1: Case Studies on Sensor Technologies for Quality Assessment in Perishable Food Sorting

Case Study	Sensor Technology	Quality Parameters Assessed	Methodology	Key Findings	Challenges
Sorting Tomatoes (Garg et al.2022)	Visual Sensors	Ripeness, Color	Visual light spectrum sensors capture color, texture, and shape data of tomatoes	Visual sensors effectively assess ripeness and uniformity in tomatoes, with high-speed processing	Limited detection of internal defects, reliance on ambient lighting
Citrus Fruits Sorting (Nikzadfar et al.2024)	Hyperspectral Imaging	Ripeness, Size, Defects	Hyperspectral sensors capture visible and NIR data for quality grading	Combines spatial and spectral data; detects ripeness and hidden defects such as bruises or fungal infections	High cost and sensitivity to environmental conditions (dust, temperature, moisture)
Avocado Maturity Assessment) (Walker et al.2023)	NIR Spectroscopy	Internal Ripeness, Texture	Near-infrared sensors analyze internal properties based on reflected light	Successfully distinguishes between ripe and unripe avocados, minimizes handling damage	Requires calibration for different varieties, influenced by external factors (humidity, temperature)
Apple Grading System (Yu et al.2024)	Visual and Color Sensors	Size, Color, Shape	Color space analysis and size measurements to classify apples	Efficiently sorts apples based on color uniformity, size, and shape consistency for market specifications	Limited to external quality traits; does not assess internal ripeness or early signs of decay
Strawberry Bruising Detection (Nikzadfar et al.2024)	Hyperspectral and UV Sensors	Damage, Ripeness	Combines hyperspectral and UV sensors to detect bruising and ripeness indicators	Detects surface and subsurface bruising effectively, reducing waste by eliminating damaged strawberries early	Requires controlled lighting and calibration; complex data processing

Poor environmental conditions can impact the performance of the technology by limiting the number of quality-related food traits that can be obtained from it. Enormous research efforts are required to enhance the accuracy of sorting technologies in robotic systems (Chen & Yu, 2021; Kumar et al., 2021; Van Hilten & Wolfert, 2022; Zhang et al., 2020).

Development of Soft Robotics for Gentle Handling

The development of soft robotics is essential for robotic grippers to handle and pick up perishable foods gently. The reasoning is that if a product is gripped too hard or in the wrong place, skin and tissues can burst, resulting in immediate bruising or developing a bruise that grows during storage and results in low product quality at the time of purchase. The softness of the gripper material is essential for handling fresh produce, as it has been found to reduce the risk of tissue damage from bruising. Most describe the use of flexible materials like silicones and urethane elastomers. The different flexural modulus and the coefficient of friction of those materials were tested and compared. Simulations and models of new gripper designs are used to predict the performance of the design for food applications. The materials with the best performance are then selected and tested.

Table 2: Overview of Soft Robotic Grippers for Gentle Handling of Fresh Produce

Case Study	Focus Area	Material Used	Testing Protocols	Key Findings	Challenges
Handling of Fresh Produce with Soft Grippers (Elfferich et al., 2022)	Material Flexibility and Grip	Silicone, Urethane Elastomers	Performance simulations and flexural modulus testing	Silicone and urethane materials effectively reduce bruising by adapting to fruit shape and texture	Flexibility varies under temperature changes; some materials degrade quickly with use
Robotic Grippers for Delicate Fruits (Navas et al.2021)	Gripper Surface Texture	Micro- and Nano-fabricated Si-based materials	Controlled experiments with load cells and surface interaction testing	Increased surface roughness improves grip strength and minimizes slippage for delicate fruits	Requires high-precision manufacturing, making it costly to implement
Impact Assessment for Peaches and Apples (Zhang et al.2020)	Testing Fragility and Impact	Composite Elastomers with Paper Coating	High-speed camera and sensor data capture for indentation analysis	High-speed imagery showed that softer materials reduce bruising in peaches due to controlled force distribution	Apples withstand higher stress than peaches; testing shows variation in force needed per fruit type
Adaptive Materials for Soft Grippers (Chen et al., 2022)	Reversibility and Adaptability	Bio-inspired Adaptive Polymers	Repetitive grip-release tests and durability measurements	Bio-inspired polymers show high adaptability and reversible adhesion, ideal for fragile produce handling	Limited by polymer lifespan and environmental sensitivity
Testing Soft Grippers on Mixed Produce (Elfferich et al., 2022)	Mixed Produce Handling	PVA, PVEV, PVALV polymers	Multi-fruit trials with force sensors and indentation measurement	PVA-based polymers perform well under repetitive use, allowing for efficient gentle handling of diverse produce types	Limited resistance to high elongation; may lose elasticity with long-term use

Overall, soft robotics can aid in finding a balance between theory and practice in speeding up development and improving the efficiency and product quality maintenance of end-effectors for robotic systems. More research on the combination of material and mechanical properties is also needed.

Sensor Technology for Automated Quality Sorting

Sensor Technology for Automated Quality Sorting One of the key steps in the post-harvest handling of perishable foods is the assessment of quality, which determines the subsequent treatment of individual foodstuffs. Automated quality assessment is a critical factor in further developing automated robotic systems in food logistics and shall improve quality in post-harvest handling of foods (Duong et al., 2020). The application of machine learning algorithms allows the integration of multiple sensor signals and the more efficient application of models and patterns during the quality assessment process. This will be a significant step for developing automated sorting applications (Hassoun et al., 2023; Bader & Rahimifard, 2020).

Sensors combined with suitable algorithms are a potential key technology in automated food sorting applications. There are some sensor technology approaches to automate food quality estimation or classification. These technologies can be classified according to sensor type, such as visual, hyperspectral, and multispectral sensors. These sensors have been examined for several applications in horticulture to assess their potential. The data collected by sensor systems must be processed. In the case of simple food sorting operations, the data is typically a measure of product color, size, and basic shape. The data can pass the product through or to a reject bin in these cases. Automated sorting generally increases throughput speed as well as accuracy. The finer levels of processing decrease sorting times, reduce waste and improve product quality. The following table explores sensor technology in food sorting systems in greater detail (Ling et al., 2024).

Table 3: Comparison of Sensor Technologies for Automated Quality Sorting in Perishable Foods

Case Study	Sensor Type	Quality Parameters Assessed	Methodology	Key Findings	Challenges
Apple Quality Sorting (Yu et al.2024)	Visual Sensors	Color, Shape, External Damage	Visible light sensors capture color and shape to assess visual quality	Effectively sorts apples based on visible quality, like uniform color and shape, for retail specifications	Limited in detecting internal defects or decay not visible on the surface
Citrus Ripeness and Decay (Shaikh et al., 2022)	Hyperspectral Imaging	Ripeness, Bruising, Fungal Infection	Spectral imaging combines visual and NIR data to detect internal decay	Hyperspectral sensors accurately assess ripeness and detect early signs of fungal decay in citrus fruits	High cost of hyperspectral equipment and sensitivity to environmental conditions
Fat-Rich Produce Sorting (Avocados)(Ismail & Malik, 2022)	Spectral Sensors	Internal Composition, Ripeness	NIR sensors measure molecular structure variations in fat content	Successful in distinguishing fat-rich, ripe avocados, helping reduce damage during sorting	Requires calibration for each variety; affected by external temperature and humidity
Tomato Sorting for Freshness (Shaikh et al., 2022)	Multispectral Sensors	Color, Texture, Ripeness	Combines visual, NIR, and infrared data to assess ripeness and firmness	Provides consistent sorting by ripeness, reducing waste and ensuring optimal market quality	Multispectral sensors are sensitive to environmental changes and require frequent recalibration
Berry Quality Sorting for Minimal Bruising (Ashtiani et al.2021)	Visual and Hyperspectral Sensors	Surface Bruising, Maturity	High-resolution imagery and spectral analysis for bruise and ripeness assessment	Accurately detects bruising and sorts berries by maturity level, preserving quality during packaging and transport	Limited in outdoor settings where lighting and temperature vary; hyperspectral data requires large storage

Machine learning algorithms for automated sorting

One step further in terms of automation is the implementation of machine learning algorithms as part of the system for detecting the product's internal and external characteristics for postharvest handling and quality assessment purposes (Singh et al., 2022). A faster and more precise machine-learning mechanism is necessary when using high-resolution sensors. Using the data gathered by several sensors that show external and internal product attributes, machine learning algorithms can better predict the product's quality features (Chen et al., 2024). The filters used in machine learning can identify patterns in the data and make better decisions for sorting the product than what is usually visible in the case of human-operated sorting lines. Another way to use machine learning algorithms is to detect external pattern symptoms that are characteristic of the product's deterioration appearance. The comprehensive review by Pandey et al. (2023) outlines the fundamentals and potential of machine learning techniques in fruit and vegetable preservation, underscoring their effectiveness as emerging tools in food safety.

Complexity and non-linearity are the critical triggers while designing machine learning algorithms and workflows. Using large-scale datasets for training, machine learning algorithms can better predict the characteristics and attributes of the food product along with defects and quality. Data is an important driver when working with machine learning modules in the postharvest domain; it has to be carefully and accurately recorded in order to ensure that the algorithms are well-trained for a particular application

Table 4: Machine learning algorithms applied in automated sorting of perishable foods (Ngongoma, 2024; Miraei Ashtiani et al., 2021)

Produce Type	Algorithm	Quality Parameters Assessed	Methodology	Key Findings	Challenges
Tomatoes	Convolutional Neural Network (CNN)	Ripeness, Color	CNN-based models process images to classify ripeness based on color and texture.	Achieved high accuracy in identifying ripeness, reducing sorting time.	High computational requirements; sensitive to image quality.
Apples	Support Vector Machine (SVM)	Size, Shape, Color	SVM trained on spectral data for shape and size classification.	Accurately classifies apples based on size and shape, reducing manual errors.	Requires regular calibration; does not detect internal defects.
Avocados	K-Nearest Neighbors (KNN)	Internal Maturity, Firmness	Uses sensor data (NIR) and KNN algorithm to assess firmness levels.	Improved sorting accuracy and reduced handling damage.	Sensitive to environmental factors like humidity and temperature.
Citrus Fruits	Decision Tree	Ripeness, Bruising	Decision tree classifies ripeness and detects bruising using hyperspectral data.	Enhanced ability to detect early signs of decay and bruising.	High cost of hyperspectral equipment; requires frequent updates.
Strawberries	Random Forest	Surface Bruising, Maturity	Random Forest model processes multispectral data to detect bruising.	Accurately detects surface damage and maturity, preserving quality.	Sensitive to environmental conditions, impacting data consistency.

Continuous learning is crucial when working with this module type; data should be recorded and periodically updated for optimized performance. With a correctly trained algorithm, the system can predict whether a characteristic is in the regular stage or not and the next stage level of deterioration of the defect or parameter.

DISCUSSION

A robotic system designed for handling and sorting perishable foods should preferably outweigh traditional methodologies to be widely accepted by producers, packers, manufacturers, and consumers. Robotic post-harvest handling and sorting systems are demonstrated to be superior to traditional handling methods in many ways. A robotic system that performs pick-and-place tasks enhances the process's flexibility in collecting data. Using a perforated container to vacuum and deliver food products to a centralised location in the process line is comparable to an automated line used by vendors. Robots can grasp objects with more excellent care and less pressure than before. Data suggest that robotic systems can boost fruit operational efficiency to the most significant degree.

Labour efficacy is improved, and the quality of sorted products is also increased. They are in good agreement with existing systems. A vision system to assess internal quality will improve product quality. Vision technology is costly and requires much time to program for each data set. Whole object learning is used to create and implement a deep learning framework, saving researchers time and resources. Conveyors and rigid paths are more efficient, resulting in reduced time penalties. Robots created to deal with the post-harvest scenario can be scaled to address a variety of dynamics. Logistics and cost are two main concerns that must be addressed. Sterile handler arms are a new idea. This robotic system improves operations. Worker support has been enhanced, and how we work is also beginning to improve. Only various scenarios have been inspected up to this point. Only a few stations on the processing line have been mechanised. Until now, only some stations in the post-harvest line have been improved. To the same degree, manufacturing has been shown to improve it.

Comparison with traditional handling methods

Traditional handling methods in agriculture are less efficient than automated systems. Manual sorting or grading requires significantly higher labor requirements, as manual dexterity and concentration are necessary. Physical sorting, especially dragging from one place to another, substantially damages fruit properties.

Table 5: Comparison between Traditional Handling Methods and Automated Systems in Postharvest Sorting

Aspect	Traditional Handling Methods	Automated Systems
Labor Requirements	High; requires significant manual dexterity and focus	Low; automation reduces manual labor and reliance on human operators
Efficiency	Lower efficiency, especially with increased worker fatigue	Higher efficiency; faster sorting and grading with vision systems
Impact on Product Quality	Physical sorting and dragging increase risk of damage, bruising, and loss of quality	Reduces physical damage and handling-related bruising
Fatigue Factor	Workers experience fatigue over long hours, leading to decline in sorting quality	Not affected by fatigue; maintains consistent quality in sorting
Speed	Slower; typically lower throughput	Faster sorting throughput, saving up to 370 hours annually with optimised sorting speed
Damage Statistics (e.g., Kiwifruit)	Physical sorting can damage up to 45% of fruits; handlers apply force, causing drop damage up to 18%	Automated systems with conveyors and sensors reduce the need for manual contact, thus lowering drop damage significantly
Skill Retention	Requires ongoing skill training to maintain quality in sorting and grading	Minimal skill retention needed; automated systems can handle consistency in sorting
Financial Modeling	Lower initial investment but shorter ROI (5 years or less for manual sorting houses)	Higher initial investment, but longer ROI (10–15 years), with improved long-term cost savings
Scalability	Limited scalability due to labor constraints and physical demands	Highly scalable; automation can adapt to larger volumes and operate continuously
Consistency	Variable quality due to human factors	High consistency with programmed sorting standards

CONCLUSION

The advancements in robotic systems for the postharvest handling and sorting of perishable foods represent a paradigm shift in agricultural logistics and food quality management. Robotic systems with advanced sensor technology and machine learning algorithms provide a highly efficient and scalable alternative to traditional, labour-intensive handling methods. Deploying quality-assessment sensors and applying soft robotics for gentle handling is crucial in minimising damage, reducing waste, and maintaining fresh produce's nutritional and aesthetic quality. Despite the high initial investment, the long-term benefits, including lower operational costs, extended shelf life, and enhanced marketability of produce, make robotic systems a promising solution for the agricultural industry.

However, widespread adoption requires overcoming scalability, cost, and workforce retraining barriers. Collaboration among technology providers, industry stakeholders, and regulatory bodies is essential to standardise best practices and facilitate industry-wide integration. Future research should focus on refining sensor accuracy, exploring adaptive soft robotics for varied produce, and developing cost-effective models to broaden accessibility. As these technologies continue to evolve, robotic systems hold the potential to revolutionise postharvest operations, supporting a more resilient and sustainable food supply chain.

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