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# Smart Postharvest Management: Leveraging AI for Reduced Food Loss, Waste, and Improved Quality

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ARTICLE INFO	ABSTRACT
Article history: Received: June 23, 2025 Accepted: August 16, 2025 Published: August 25, 2025 Keywords: food loss, Internet of Things, Machine learning, Postharvest management, smart sensors	Food loss continues to be a major global challenge that impacts environmental sustainability, economic stability and food security. An inventive strategy for lowering food loss across the supply chain is Al-driven monitoring. The foundation of human civilization has always been agriculture, which supplies the vital resources needed for growth and nutrition. Higher quality crops with improved nutritional value, increased resilience to pests and diseases and improved adaptability to varying climatic conditions are in greater demand as the world's population continues to grow. Despite their effectiveness, traditional agricultural methods frequently fail to effectively meet these objectives; therefore, an innovative strategy for raising crop quality is the incorporation of artificial intelligence (Al) into agricultural operations. This paper examines the role of Al-driven monitoring in reducing food loss, focusing on its applications, benefits and implications for the food industry. Al driven technologies like machine learning, IoT-based smart sensors and computer vision can enhance efficiency in food production, storage, transportation and retail. By utilizing Al-driven solutions, stakeholders can optimize resource utilization, reduce waste, and contribute to sustainable food systems. Al-assisted processing can optimize various stages of crop production, from planting and growing to harvesting and postharvest management, thereby improving the overall quality of agricultural produce.
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#### 1. Introduction

The rapid advancement of artificial intelligence (AI) is transforming agriculture, especially in crop production and postharvest management, with significant potential to reduce global food loss and waste (Onyeaka et al., 2023; Pandey & Mishra, 2024). Postharvest management which includes storage, transportation, quality inspection, and packaging aims to preserve quality, extend shelf life, and ensure food safety from harvest to consumer (Augustin et al., 2016; Osei-Kwarteng & Ogwu, 2024). Despite improvements in agricultural practices (Nath et al., 2024), postharvest losses remain a major issue, with about one-third of all food produced for human consumption lost or wasted annually, according to the Food and Agriculture Organization (FAO) (Ishangulyyev et al., 2019). These losses can occur at various supply chain stages, including harvesting, storage, shipping, and retail (Mesterházy et al., 2020).

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In postharvest management, preserving the freshness of fresh produce is crucial. Produce quality is increasingly being evaluated using AI-based technologies such as thermal imaging and computer vision (Pathmanaban et al., 2023). These tools detect flaws, track ripeness, and identify early signs of spoilage, enabling prompt interventions (Khan et al., 2024). Additionally, AI systems facilitate automated sorting and grading, ensuring only superior goods reach the market, which enhances the marketability of fresh produce and improves customer satisfaction. Such AI advancements guarantee safer and fresher products (Lalam et al., 2025).

Al-powered technologies play a critical role in optimizing postharvest processes more broadly (Pathmanaban et al., 2023; Dwivedi et al., 2024). The integration of machine learning (ML), data analytics, and Internet of Things (IoT) devices enables real-time monitoring and regulation of key variables such as temperature, humidity, and ethylene levels, helping to maintain food freshness and quality (Shuprajhaa, 2024; Kanna et al., 2024). Predictive analytics and Al-driven monitoring allow for accurate spoilage prediction, optimal storage recommendations, and improved supply chain logistics, reducing discrepancies between production and consumption (Kanna et al., 2024; Seyedan & Mafakheri, 2020). By analyzing historical and real-time data, Al systems support informed decision-making, such as inventory adjustments and timely deliveries (Nweje & Taiwo, 2025), which enhance distribution efficiency and ensure perishable goods reach consumers while still fresh (Şimşek, 2024).

Al also enhances food quality and safety through rapid, reliable vision-based inspections (Chhetri, 2024) and traceability solutions (El-Ramady et al., 2015), minimizing human error and enabling swift responses to food safety issues (Agnisarman et al., 2019). These Al-driven systems analyze diverse data sources, including supply chain records, public health data, and customer reviews, to identify hazards and prevent foodborne illnesses (Dhal & Kar, 2025). Furthermore, Al-based predictive analytics and packaging solutions help forecast demand, optimize production, extend shelf life, and reduce overproduction and waste, thus supporting sustainability and resource efficiency in the food industry (Anwar et al., 2023; Taneja et al., 2023; Elgalb & Gerges, 2024).

Integrating AI into postharvest management streamlines operations, minimizes food loss and waste, enhances food safety, and contributes to the sustainability of the global food system (Onyeaka et al., 2023; Kasera et al., 2024).

#### 2. Literature Review

Food loss and waste are major worldwide issues that affect food security, economic stability, and environmental sustainability. Approximately one-third of all food produced for human consumption is wasted or lost, which increases greenhouse gas emissions and wastes resources (FAO, 2019).

A significant amount of this waste is caused by postharvest losses, which happen during different phases such as harvesting, storage, transportation, and retail (Mesterházy et al., 2020).

In agriculture, artificial intelligence (AI) has become a transformative technology that provides creative ways to improve sustainability and productivity. In postharvest management, AI is very important since it helps preserve produce quality, increase shelf life, and guarantee food safety (Mishra & Mishra, 2023; Pandey & Mishra, 2024).





The shortcomings of conventional techniques, which frequently fall short of the increasing demands for higher-quality crops with improved nutrition, pest resistance, and climatic adaptation, are addressed by the incorporation of AI technology into agricultural systems (Addas et al., 2024).

#### 3. Materials and Method

A systematic methodology, adapted from the approach outlined by Tawakalitu et al. (2025), was employed. The process involved a comprehensive and structured search, screening, and synthesis of relevant literature. Specifically, peer-reviewed journal articles, conference proceedings, and industry reports published between 2015 and 2025 were systematically identified through advanced searches across multiple reputable academic databases, including Scopus, Web of Science, ScienceDirect, and Google Scholar.

Clearly defined inclusion and exclusion criteria guided the selection of sources to enhance the reliability, transparency, and reproducibility of the findings.

#### 4. Result and Discussion

#### 4.1. Reducing Food Loss with Al-Driven Monitoring

Food loss and waste are serious problems that have a negative impact on environmental sustainability, economic stability and global food security (Sawaya, 2017). Its effects are extensive and include food insecurity, environmental damage and financial losses (Baspakova et al., 2024). Artificial intelligence has become a potent instrument in the development of methods to address these problems, including creative approaches to supply chain management and postharvest monitoring (Das et al., 2025). By offering real-time data analysis, predictive analytics and automated interventions through automated tracking, Al-driven monitoring systems present a game-changing solution and have the potential to drastically lower postharvest losses (Pathmanaban et al., 2023; Zong & Guan, 2024). Because of human error, inefficiencies and a lack of real-time data, traditional monitoring techniques frequently fail to meet these problems (Mohanty et al., 2024)

Research has demonstrated that large data sets are analyzed using machine learning algorithms to predict variables such as demand fluctuations, optimal storage conditions, and spoilage rates that contribute to food waste (Elgalb & Gerges, 2024). It has been reported that, in an effort to minimize waste, suppliers and retailers are employing predictive analytics to facilitate informed decision-making (Agu et al., 2024). Additionally, studies indicate that Al-powered cameras are utilized within computer vision systems to evaluate the freshness and quality of food products (Dhal & Kar, 2025).

These systems are said to identify early signs of contamination, defects, or spoilage, thereby ensuring that only viable items are allowed to progress through the supply chain (Pal & Kant, 2020). Furthermore, it has been observed that smart sensors integrated within Internet of Things (IoT) devices continuously monitor various factors, including temperature, humidity, and gas emissions.

These sensors provide AI models with real-time data, which allows for automated adjustments to transportation and storage conditions, ultimately enhancing the shelf life of food items.





### 4.2. Applications of Al-Driven Monitoring

Recent studies suggest that employing artificial intelligence (AI) technologies within food monitoring systems presents a viable approach to mitigating food loss. Researchers, such as Ataei et al. (2023), indicate that these systems gather real-time data on crucial factors such as temperature, humidity, and ethylene levels through a combination of Internet of Things (IoT) sensors, cameras, and other devices during storage and transit. The data collected is continuously transmitted to cloud-based platforms, where AI algorithms analyze it to identify any deviations from optimal conditions (Singh et al., 2024). Consequently, these technologies are essential in preserving product quality and preventing spoilage by ensuring that food is transported and stored in ideal environments.

Furthermore, it has been highlighted by Titirmare et al. (2024) that drones and satellite imagery equipped with AI capabilities play a critical role in assessing crop health, predicting harvest dates, and optimizing fertilization and irrigation. This proactive monitoring contributes to reducing postharvest losses by facilitating timely and effective harvesting processes (Das et al., 2025). In addition, these AI-driven systems enhance cold chain logistics by maintaining appropriate humidity and temperature levels (Fatorachian & Pawar, 2025). Automated alerts and real-time tracking further enable swift actions to prevent spoilage during transportation and storage (Abdel Qader, 2023). Retailers are also leveraging AI to enhance inventory management, as detailed by Şimşek (2024). They optimize restocking schedules, monitor expiration dates, and track stock levels, thus improving demand forecasting. This minimizes both overstocking and understocking, which in turn reduces food waste in supermarkets and restaurants. A significant aspect of AI-driven monitoring is the application of predictive analytics, as reported by Sathishkumar et al. (2024). This technology forecasts potential spoilage, fluctuations in demand, and other critical events by utilizing both historical and real-time data.

Moreover, machine learning models analyze patterns and provide relevant insights to stakeholders, thereby aiding decision-making processes aimed at reducing food wastage. For instance, predictive models may recommend adjustments in transit routes or storage conditions to avert spoilage (Arowosegbe et al., 2024). Kuppusamy et al. (2024) emphasize the autonomy of AI systems in executing automated actions. These systems can independently adjust environmental controls such as temperature and humidity to restore ideal conditions whenever deviations are detected. Similarly, AI technologies are capable of performing automated grading and sorting, thereby identifying and discarding contaminated or defective produce (Ogidi et al., 2025). Streamlining postharvest procedures is another benefit of Al-driven monitoring systems. By reducing the necessity for manual inspections and interventions, these technologies contribute to maintaining produce quality more consistently and efficiently. Tasks such as sorting, grading, and environmental management can be automated, which ultimately lowers labor costs and diminishes human error (Garcia-Herrero et al., 2018). Reducing food loss through AI not only promotes sustainability but also supports resource optimization by decreasing the need for additional production to compensate for losses (Onyeaka et al., 2023). Moreover, these Aldriven solutions enhance supply chain operations and help lower greenhouse gas emissions associated with food waste, thereby encouraging environmentally sustainable practices.





### 4.3. Optimizing Waste Management through Al Algorithms

Waste management has become a critical global challenge, particularly in the context of postharvest operations (Stathers & Mvumi, 2020). The optimization of waste management practices is essential for achieving sustainable development, especially as global populations increase and environmental issues intensify (Hajam et al., 2023). A key area of innovation involves the integration of AI into waste management systems. This approach holds significant promise for enhancing productivity, minimizing resource waste, and fostering environmental sustainability (Olawade et al., 2024). Postharvest activities encompass a wide range of activities; however, these processes are not without their challenges. They often result in substantial organic waste due to inefficiencies within the supply chain or spoilage (Yahia et al., 2019; Kaur and Watson, 2024). Traditional waste collection and sorting methods typically rely on manual labor and predetermined schedules, leading to a host of inefficiencies. Such inefficiencies can include contamination in recycling streams and less-than-optimal routing, ultimately undermining the effectiveness of waste management strategies (Mohanty et al., 2023).

In discussing these issues, it becomes evident that the conventional approaches to waste management need to evolve. The incorporation of AI technologies could significantly streamline these processes by providing data-driven insights that optimize routing, reduce spoilage, and enhance sorting accuracy. This transformation not only addresses the immediate challenges of waste management but also contributes to a broader framework of sustainable agricultural practices. By aligning technological advancements with ecological considerations, stakeholders can work towards a more sustainable future, where waste is minimized, and resources are utilized efficiently. Overall, the intersection of AI, waste management, and postharvest practices signifies a promising frontier in the pursuit of environmental sustainability. Emphasizing this relationship can encourage further research and innovation, paving the way for effective solutions to one of the most pressing challenges of our time.

#### 4.4. Crop Quality Improvement with AI-Assisted Processing

Researchers highlight that AI-powered precision agriculture provides a means to track and manage variations within crop fields (Sishodia et al., 2020). They indicate that using AI algorithms allows farmers to collect and analyze real-time data regarding plant health, nutrient content, moisture levels, and soil health (Sarma et al., 2024). It has been noted that drones and sensors equipped with AI capabilities can capture high-resolution images of agricultural fields, facilitating early detection of pest infestations or disease outbreaks (Verma & Kishor, 2024). Analysts explain that machine learning models offer actionable insights following data analysis, helping to mitigate potential losses (Rolnick et al., 2022). The significant advantage of AI-assisted processing lies in its ability to improve crop growth conditions, as AI systems predict weather patterns, suggest optimal planting times, and recommend suitable crop varieties (Javaid et al., 2023). In the realm of crop breeding programs, it has been reported that these initiatives aim to develop new cultivars with traits such as higher yields, better nutritional value, and disease resistance.

Traditional breeding methods, which require substantial time and effort, can be expedited by AI, as it identifies promising candidates and forecasts the outcomes of different breeding combinations (Crossa et al., 2021). AI-powered genomic selection utilizes genetic data to predict the performance of various plant genotypes, enabling breeders to make informed decisions and accelerate the development of





improved crop varieties (Xu et al., 2022). Moreover, AI technology significantly impacts quality control and postharvest processing. It is suggested that computer vision and machine learning algorithms facilitate automated sorting and grading systems to assess the quality of harvested crops based on attributes like size, color, and texture. Researchers note that these technologies ensure that only high-quality products reach the market, increasing consumer satisfaction and reducing postharvest losses (Kutyauripo et al., 2023). It is emphasized that the use of AI-assisted processing enhances agricultural sustainability. AI technologies help to lessen the environmental impact of farming by optimizing resource use, including water, fertilizers, and pesticides (Gryshova et al., 2024). Researchers advocate that AI-driven insights can encourage eco-friendly practices that improve soil health and biodiversity, such as crop rotation and intercropping (Shankar et al., 2020). Overall, sustainable agriculture is seen as essential for ensuring the long-term viability of farming ecosystems (Muhie, 2022).

#### 4.5. Al-Enabled Predictive Maintenance for Postharvest Equipment

Recent technological advancements are driving a significant transformation in the agriculture sector, focusing on enhancing sustainability and productivity. Researchers like Abiri et al. (2023) emphasize that ML and AI have become integral to these developments, particularly in the area of predictive maintenance. They explain that predictive maintenance utilizes data-driven insights to foresee equipment breakdowns and maintenance needs, which minimizes downtime and optimizes postharvest resources, a concept supported by Goel et al. (2024). Schmidt et al. (2023) noted that the effectiveness and reliability of equipment directly impact the quantity and quality of harvested products sold, highlighting the approach's importance in postharvest activities. In the realm of smart postharvest management for horticultural crops, Shuprajhaa (2024) pointed out that predictive maintenance serves as a proactive strategy for equipment management. They elaborated that AI and ML technologies are employed to monitor machine conditions and predict potential breakdowns. Senoo et al. (2024) corroborated this by stating that AI algorithms can analyze data from embedded sensors to detect patterns indicating early signs of wear or potential failures. This proactive maintenance enables timely repairs, reducing downtime and enhancing the operational lifespan of postharvest equipment, as indicated by Gidiagba et al. (2024). The Boston Consulting Group's 2018 study revealed that implementing Al-driven predictive maintenance can decrease maintenance costs by 25–30% and reduce equipment failures by up to 70%, underscoring the effectiveness of this approach.

### 4.6. Real-Time Data Analytics for Postharvest Decision Making

Farmers are reported to improve pest management, optimize irrigation schedules, and enhance supply chain logistics through the utilization of real-time data (Tantalaki et al., 2019). Advanced technologies such as big data, machine learning, and the Internet of Things (IoT) are said to enable real-time data analytics to provide continuous monitoring and analysis of postharvest conditions (Tiwari, 2024). This approach is described as facilitating the quick detection of issues like spoilage, pest infestations, and suboptimal storage conditions by gathering and evaluating data from various sensors and devices (Tiwari, 2024). Consequently, it reportedly allows for timely corrective actions, thereby reducing losses and improving the overall quality and marketability of agricultural products (Pandey & Mishra, 2024). The use of real-time data analytics in postharvest decision-making is considered not only a technological advancement but also a paradigm shift in agricultural practices (Schmidt et al., 2024). It is noted that





real-time data analytics equips farmers, supply chain managers, and policymakers with actionable insights, fostering a culture that prioritizes resilience, sustainability, and efficiency (Ajayi et al., 2024).

### 5. Benefits and Challenges of AI in Postharvest Management

The integration of Artificial Intelligence (AI) into postharvest management systems is rapidly transforming the agricultural value chain, providing innovative solutions to the enduring problems of food loss, quality deterioration, and supply chain inefficiencies (Pandey & Mishra, 2024). All is positioned as a key facilitator of sustainable postharvest activities due to its applications in grading and sorting, storage monitoring, transportation optimization, and quality verification.

The primary benefit of artificial intelligence is its capacity to improve product quality and extend shelf life. Storage facility environmental parameters including temperature, relative humidity, and atmospheric gas composition can be managed by real-time monitoring systems powered by artificial intelligence (AI). By maintaining these factors within optimal thresholds, perishable items can minimize the rate of deteriorating and prolong their sensory and nutritional qualities (Onyeaka et al., 2023). Because AI makes it possible to detect flaws and microbial contamination early, it also helps to reduce food losses. By automatically sorting produce according to visual quality criteria, computer vision systems can separate faulty goods before they contaminate healthy supply. Moreover, predictive models can anticipate deterioration trends using historical and sensor-generated data, allowing stakeholders to take proactive measures such as re-routing shipments or adjusting storage conditions (Pandey & Mishra, 2024). Another critical advantage is enhanced operational efficiency across the supply chain. AI-driven logistics platforms can analyze demand patterns, transportation routes, and storage capacities to optimize product flow, thereby reducing delays and wastage.

Despite these benefits, the widespread adoption of AI in postharvest systems remains constrained by several technological, economic, and social challenges. A primary barrier is the high cost of implementation; starting from procuring AI-compatible equipment, installing advanced sensors, and maintaining data infrastructure require substantial capital investments, which are often beyond the reach of smallholder farmers and small-to-medium agribusinesses in developing regions (Onyeaka et al., 2023). Infrastructural limitations further hinder effective deployment. Stable electricity supply, reliable internet connectivity, and well-developed cold chain logistics which are prerequisites for AI functionality—are lacking in many rural agricultural zones. Additionally, limited technical expertise poses a significant challenge. AI systems require skilled personnel for data management, model training, and hardware maintenance. The shortage of such expertise means that even when AI technologies are introduced, they may not be utilized to their full potential (Kilinc et al., 2025).

#### 6. Conclusion

The integration of artificial intelligence into agricultural and postharvest operations presents a transformative opportunity to address the persistent challenges of food loss, waste management, and crop quality improvement. Al driven monitoring systems, leveraging machine learning, IoT-based smart sensors, and computer vision, enable real-time data analytics, and automated interventions that optimize every stage of the food supply chain from production and storage to transportation and retail. These technologies not only enhance efficiency and reduce human error but also support informed decision making, improve food safety, and promote sustainability by minimizing resource waste and





greenhouse gas emission. As global populations grow and environmental concerns intensify, the adoption of Al-powered solutions in agriculture is essential for building resilient, sustainable, and secure food systems for the future.

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