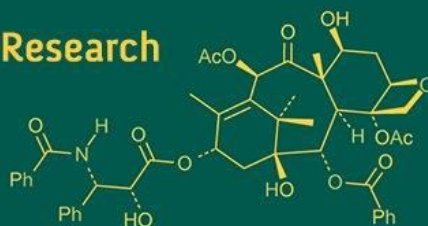


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AI-driven technologies in biochemical quality assessment and postharvest metabolic monitoring of horticultural crops

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Abstract

Horticultural crops play a vital role in global nutrition, providing essential vitamins, minerals, and bioactive compounds that support human health. However, their high perishability leads to significant postharvest losses, particularly in developing countries lacking adequate storage infrastructure. Traditional postharvest practices, such as manual grading and static storage, are often inefficient and fail to address crop-specific requirements. Artificial Intelligence (AI) offers a transformative solution by enabling predictive, data-driven management of postharvest systems. Through the integration of machine learning, sensors, imaging technologies, robotics, and cloud computing, AI facilitates real-time monitoring and decision-making to reduce spoilage and maintain quality. Additionally, the convergence of AI with IoT, big data, and blockchain enhances traceability, supply chain coordination, and resource efficiency. These intelligent systems shift postharvest management from reactive to proactive approaches, minimizing losses, improving food safety, and promoting sustainability in horticultural production and distribution systems.

Keywords: Horticultural crops, postharvest losses, artificial intelligence, smart storage systems, supply chain optimization

1. Introduction

Horticultural crops are indispensable to global nutrition, serving as primary sources of vitamins, minerals, antioxidants, and diverse bioactive compounds that contribute to human health and disease prevention (FAO, 2022; Slavin and Lloyd, 2012) [12, 48]. Fruits and vegetables are particularly rich in phenolics, flavonoids, carotenoids, and anthocyanins, which not only enhance dietary quality but also provide functional benefits such as reducing oxidative stress and lowering the risk of chronic diseases (Liu, 2013; Shahidi and Ambigaipalan, 2015) [46, 47]. However, the very biochemical richness that makes horticultural produce valuable also contributes to its perishability. High moisture content, active enzymatic systems, and sensitivity to environmental fluctuations render these commodities vulnerable to rapid deterioration (Kader, 2002) [19]. Consequently, postharvest losses remain a persistent challenge, especially in developing economies where cold chain infrastructure and advanced preservation technologies are limited (FAO, 2019) [49]. These losses manifest both quantitatively, through reduced marketable yield, and qualitatively, through diminished nutritional and sensory attributes (Kitinoja and Kader, 2015) [19]. Beyond economic implications, such wastage exacerbates environmental burdens by squandering inputs like water, fertilisers, energy, and labour, thereby increasing the carbon footprint of horticultural production systems (Gustavsson *et al.*, 2011) [50].

Traditional postharvest management strategies have historically relied on manual inspection, static storage protocols, and reactive interventions (Kader, 2002) [19]. Manual grading is inherently subjective and prone to inconsistency, while generalised storage conditions fail to account for crop-specific physiological responses (Abbott, 1999) [1]. Reactive interventions, such as applying chemical preservatives after visible spoilage symptoms appear, are often insufficient to prevent substantial losses (Parmar *et al.*, 2018) [51]. These limitations underscore the need for more adaptive, predictive, and data-driven approaches.

Artificial Intelligence (AI) offers precisely this paradigm shift (Russell and Norvig, 2016) ^[36]. By leveraging machine learning algorithms, deep learning architectures, and advanced data analytics, AI systems can process vast volumes of heterogeneous data, ranging from sensor readings and imaging outputs to environmental parameters and market trends (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. Through pattern recognition and predictive modelling, AI enables real-time decision-making that surpasses traditional manual systems, thereby transforming postharvest management from a reactive to a proactive discipline (Liakos *et al.*, 2018) ^[25]. The integration of AI with enabling technologies such as sensors, robotics, imaging systems, and cloud computing is redefining the postharvest landscape (Badia-Melis *et al.*, 2018) ^[4]. Smart sensors embedded in storage facilities continuously monitor temperature, humidity, and gas composition, transmitting data to AI platforms that predict spoilage trajectories and recommend corrective measures (Jedermann *et al.*, 2014) ^[17]. Robotics guided by computer vision and machine learning automates sorting and packaging processes with high precision and speed, reducing human error and labour costs (Zhang *et al.*, 2020) ^[44]. Imaging technologies, particularly hyperspectral and multispectral systems, coupled with deep learning models, enable non-destructive assessment of internal quality attributes such as sugar content, firmness, and microbial contamination (ElMasry *et al.*, 2012; Mahesh *et al.*, 2015) ^[11, 27]. Cloud computing integrates these diverse data streams, making them accessible across supply chains and enabling coordinated interventions from farm to retail (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. The convergence of AI with the Internet of Things (IoT), big data analytics, blockchain, and automation is giving rise to intelligent postharvest ecosystems (Wolfert *et al.*, 2017) ^[42]. IoT networks facilitate seamless communication between sensors, storage units, and logistics platforms, creating a dynamic feedback loop that continuously optimises storage conditions (Badia-Melis *et al.*, 2018) ^[4]. Big data analytics harness historical and real-time datasets to forecast demand, align supply chains, and minimise waste (Liakos *et al.*, 2018) ^[25]. Blockchain integration enhances transparency and traceability, ensuring that consumers and stakeholders can verify the origin, quality, and handling of produce (Tian, 2017) ^[40]. Automation driven by AI reduces reliance on manual labour while ensuring consistency and scalability (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. Collectively, these technologies not only minimise losses but also improve quality consistency, enhance food safety, and optimise resource utilisation (Jedermann *et al.*, 2014) ^[17].

Despite these advances, critical challenges remain. Data scarcity, particularly the lack of annotated datasets for diverse crops, limits the accuracy and generalisability of AI models (Liakos *et al.*, 2018) ^[25]. Infrastructure gaps in developing regions hinder the deployment of IoT-enabled cold storage and logistics systems (Kitinoja and Kader, 2015) ^[19]. High implementation costs restrict accessibility for smallholder farmers, who constitute most horticultural producers globally (FAO, 2019) ^[49]. Ethical concerns surrounding data ownership, privacy, and labour displacement further complicate adoption (Wolfert *et al.*, 2017) ^[42]. Addressing these challenges requires a multi-pronged approach that combines technological innovation with supportive policy frameworks, capacity building

initiatives, and inclusive system design to ensure equitable access and sustainable implementation (FAO, 2022) ^[12].

2. Conceptual Framework of AI in Postharvest Systems

Artificial Intelligence (AI) encompasses computational systems designed to replicate human cognitive functions such as perception, pattern recognition, reasoning, and decision-making (Russell and Norvig, 2016) ^[36]. Within postharvest horticulture, AI operates through a structured pipeline that transforms raw data into actionable insights (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. This pipeline typically involves five stages: data acquisition, preprocessing, model training, prediction, and decision execution (Liakos *et al.*, 2018) ^[25]. Each stage is critical to ensuring that AI systems can effectively manage the complexity and variability inherent in biological materials, particularly perishable horticultural commodities characterised by dynamic physiological changes (Kader, 2002) ^[19]. Data acquisition forms the foundation of AI-driven postharvest systems. A wide array of devices, ranging from sensors, cameras, and spectrometers to RFID tags and environmental monitoring units, collect diverse datasets (Jedermann *et al.*, 2014) ^[17]. These inputs capture both external attributes (colour, texture, size, shape) and internal parameters (moisture content, sugar levels, ethylene concentration, microbial activity) (ElMasry *et al.*, 2012) ^[11]. For example, hyperspectral imaging can generate hundreds of spectral bands that reveal subtle biochemical changes in fruits, enabling early detection of defects and maturity stages (Mahesh *et al.*, 2015) ^[27]. Similarly, IoT-enabled sensors continuously monitor temperature and humidity in storage facilities, providing real-time environmental data that influences respiration rate and shelf life (Badia-Melis *et al.*, 2018) ^[4]. The richness of these datasets allows AI systems to detect early signs of spoilage or quality deterioration that would be imperceptible to human inspection. Preprocessing is essential to transform raw data into usable formats. Biological datasets are often noisy, heterogeneous, and high-dimensional, requiring systematic refinement before model training (Jha *et al.*, 2019) ^[18]. Techniques such as data cleaning, normalization, feature extraction, and dimensionality reduction are applied to remove inconsistencies and highlight relevant variables (Liakos *et al.*, 2018) ^[25]. Principal component analysis (PCA), for instance, is widely used to reduce hyperspectral data into key components that strongly correlate with ripening stages or biochemical attributes (Mahesh *et al.*, 2015) ^[27]. Similarly, image preprocessing methods such as contrast enhancement, segmentation, and edge detection prepare visual datasets for machine learning algorithms, improving classification accuracy (Zhang *et al.*, 2020) ^[44]. Effective preprocessing ensures that models are trained on meaningful biological patterns rather than irrelevant noise. Model training represents the core of AI application. Machine learning algorithms, including Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN), are trained using historical or labeled datasets to establish correlations between environmental conditions and quality outcomes (Liakos *et al.*, 2018) ^[25]. Deep learning architectures, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image-based tasks such as bruise detection in apples and ripeness classification in bananas (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. Recurrent Neural Networks

(RNNs) and Long Short-Term Memory (LSTM) models are especially suited for time-series data, enabling prediction of spoilage trajectories based on continuous sensor inputs (Hochreiter and Schmidhuber, 1997; Wang *et al.*, 2021) ^[15, 52]. These models capture temporal dependencies in respiration rate, ethylene production, and temperature fluctuations, which are critical determinants of postharvest shelf life (Kader, 2002) ^[19]. Prediction and decision execution are the stages where AI systems demonstrate practical utility. Once trained, models generate real-time predictions regarding quality status, spoilage risk, or optimal handling strategies (Jedermann *et al.*, 2014) ^[17]. These outputs are integrated into decision-support systems that automate grading operations, adjust storage conditions, or trigger alerts for logistics managers (Badia-Melis *et al.*, 2018) ^[4]. For example, AI-guided storage management systems can recommend lowering temperature or modifying ventilation when ethylene concentrations rise, thereby slowing ripening and extending shelf life (Pathare and Opara, 2014) ^[32]. In automated sorting lines, AI-driven vision systems instantly classify produce into quality grades, ensuring consistency, efficiency, and reduced labor dependency (Zhang *et al.*, 2020) ^[44]. The success of AI in postharvest management depends on interdisciplinary integration. Plant physiology provides insights into biological processes such as respiration, ethylene biosynthesis, enzymatic browning, and microbial growth, which underpin quality changes during storage (Kader, 2002) ^[19]. Food science contributes to understanding of nutritional degradation, sensory attributes, and consumer preferences (Jha *et al.*, 2019) ^[18]. Computer science and electronics supply the algorithms, hardware, and data architectures necessary for AI deployment (Russell and Norvig, 2016) ^[36]. Logistics management ensures that AI-driven decisions are effectively implemented across supply chains (Jedermann *et al.*, 2014) ^[17]. Without this interdisciplinary foundation, AI models risk oversimplification and limited generalizability. For instance, predicting fruit ripening requires not only sensor data but also a mechanistic understanding of climacteric respiration patterns and ethylene sensitivity in different cultivars (Kader, 2002) ^[19].

3. Machine Learning Applications in Postharvest Management:

Machine learning (ML) constitutes the backbone of AI-driven systems in horticulture, enabling computational models to learn from data and make predictions or classifications without explicit programming. In postharvest management, ML algorithms are particularly valuable because they can capture complex, nonlinear relationships among biological, environmental, and logistical variables that influence produce quality and shelf life (Kumar *et al.*, 2021; Zhang *et al.*, 2020) ^[44]. By leveraging supervised, unsupervised, and reinforcement learning paradigms, ML provides a versatile toolkit for addressing diverse challenges in postharvest systems (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. Supervised learning techniques are the most widely applied in horticultural contexts. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), Artificial Neural Networks (ANN), and Gradient Boosting Machines (GBM) are trained on labeled datasets where input features (e.g., temperature, humidity, firmness, soluble solids content, microbial load) are linked to known outcomes such as shelf

life, defect categories, and ripeness stages (Liakos *et al.*, 2018; Misra *et al.*, 2020) ^[25, 28]. These models excel at classification and regression tasks. For instance, SVMs have been used to classify mangoes into ripeness categories based on spectral signatures (Rungpichayapichet *et al.*, 2016) ^[53], while Random Forests have demonstrated robustness in predicting apple shelf life under varying storage conditions (Zhang *et al.*, 2019) ^[44]. ANNs, with their ability to approximate nonlinear functions, are particularly effective in modelling complex physiological processes such as respiration rate and ethylene production (ElMasry *et al.*, 2012) ^[11]. Gradient Boosting, which builds ensembles of weak learners, has shown high accuracy in defect detection and quality grading of tomatoes and strawberries (Polder *et al.*, 2019) ^[54].

Shelf-life prediction models represent one of the most impactful applications of supervised learning. By analysing input parameters such as temperature, relative humidity, gas composition, respiration rate, firmness, soluble solids content, and microbial load, ML algorithms generate predictive models that estimate remaining shelf life under specific storage conditions (Kader, 2002; Rahman *et al.*, 2018) ^[19, 55]. These predictions are invaluable for supply chain stakeholders, enabling them to prioritise distribution, optimise storage, and reduce waste (Jedermann *et al.*, 2014) ^[17]. For example, predictive analytics integrated with ethylene monitoring systems has been shown to improve banana storage management and distribution planning (Pathare and Opara, 2014) ^[32]. Such proactive decision-making reduces losses and enhances consumer satisfaction. Unsupervised learning techniques, such as clustering algorithms, are employed when labelled datasets are unavailable. These methods group produce based on similarity in quality attributes, revealing natural patterns in the data (Jha *et al.*, 2019) ^[18]. K-means clustering, hierarchical clustering, and self-organising maps have been applied to categorise fruits and vegetables into quality clusters based on spectral or imaging data (Mahesh *et al.*, 2015) ^[27]. This categorisation aids in dynamic pricing strategies and market segmentation, where consumer preferences are matched with specific quality profiles (Kamilaris and Prenafeta-Boldú, 2018) ^[20]. For instance, clustering analysis has been used to differentiate premium-grade grapes for export markets from lower-grade batches intended for processing industries (Gómez *et al.*, 2016) ^[56]. Reinforcement learning (RL) is an emerging frontier in postharvest management. Unlike supervised or unsupervised learning, RL involves algorithms that learn optimal strategies through trial-and-error interactions with the environment (Sutton and Barto, 2018) ^[39]. In dynamic storage optimisation, RL agents continuously adjust environmental parameters such as temperature, humidity, and ventilation based on feedback from sensors (Wang *et al.*, 2021) ^[52]. Over time, the algorithm learns policies that maximise shelf life while minimising energy consumption. Studies have demonstrated that adaptive cooling strategies can improve leafy vegetable preservation while reducing electricity costs (Badia-Melis *et al.*, 2018) ^[4]. This adaptive capability is particularly valuable in contexts where environmental conditions fluctuate or where energy efficiency is a priority. The integration of ML into postharvest systems has already demonstrated tangible benefits. Predictive models reduce uncertainty in logistics, clustering algorithms enhance market efficiency, and

reinforcement learning enables adaptive storage management (Kamilaris and Prenafeta-Boldú, 2018; Liakos *et al.*, 2018) ^[20, 25]. However, challenges remain, including the need for large, high-quality datasets, the risk of overfitting in complex models, and the difficulty of transferring models across diverse crops and regions (Zhang *et al.*, 2020) ^[44]. Addressing these challenges requires interdisciplinary collaboration, combining expertise in plant physiology, food science, computer science, and supply chain management.

4. Deep Learning and Computer Vision in Quality Assessment:

Deep learning, particularly Convolutional Neural Networks (CNNs), has transformed visual inspection in postharvest management by providing objective, scalable, and highly accurate alternatives to traditional grading systems (LeCun *et al.*, 2015; Kamilaris & Prenafeta-Boldú, 2018) ^[20, 23]. Historically, grading and quality assessment of horticultural produce relied on human inspectors who evaluated attributes such as size, colour, shape, and visible defects. While human judgment can be nuanced, it is inherently subjective, inconsistent, and prone to fatigue-induced errors, especially when large volumes of produce must be assessed under time constraints (Patel *et al.*, 2012) ^[57]. AI-powered vision systems overcome these limitations by automating inspection processes, ensuring consistency, and enabling real-time decision-making across high-throughput packing lines (Li *et al.*, 2020) ^[24]. AI-powered vision systems capture high-resolution images of produce and analyse them using deep learning algorithms capable of recognising subtle patterns and defects. CNNs, with their hierarchical architecture, excel at extracting spatial features from images, making them particularly effective for tasks such as defect detection, ripeness classification, and quality grading (Krizhevsky *et al.*, 2012) ^[22]. These systems can detect bruises, fungal infections, cracks, colour variations, and maturity stages with accuracy often exceeding 95 per cent under controlled conditions (Zhang *et al.*, 2018) ^[44]. Unlike traditional machine learning approaches that rely heavily on handcrafted features such as colour histograms or texture descriptors, CNNs automatically learn relevant features during training, thereby improving robustness and generalizability across diverse crops and imaging environments (Mohanty *et al.*, 2016) ^[29]. Advanced architectures such as ResNet and YOLO have further enhanced object detection speed and precision, enabling real-time defect localisation on conveyor belts (He *et al.*, 2016; Redmon *et al.*, 2016) ^[14, 35].

Hyperspectral imaging combined with deep learning represents a significant advancement in non-destructive quality assessment (ElMasry *et al.*, 2012) ^[11]. Hyperspectral cameras capture hundreds of spectral bands across the visible and near-infrared spectrum, revealing biochemical and structural information invisible to the naked eye. When integrated with CNNs or hybrid deep learning models, hyperspectral data can be used to detect internal defects such as browning, watercore, or early-stage microbial contamination (Lorente *et al.*, 2012) ^[26]. For example, hyperspectral imaging has been successfully applied to apples to identify internal browning before external symptoms appear, enabling proactive sorting and reducing consumer complaints (Qin *et al.*, 2013) ^[33]. This capability significantly enhances quality assurance while minimising destructive sampling. Crop-specific applications illustrate

the versatility of deep learning in postharvest systems. In apples, CNN models have been trained to classify scab lesions, bitter pit, and bruising with high accuracy, while also quantifying severity levels to enable more nuanced grading (Zhu *et al.*, 2020) ^[45]. In tomatoes, deep learning models estimate ripeness stages based on colour transition from green to red by analysing subtle variations in hue and surface texture, thereby supporting optimal harvest timing and market segmentation (Rahnemoonfar & Sheppard, 2017) ^[34]. In bananas, vision systems detect mechanical damage such as cuts and abrasions, while predictive models estimate ripening progression based on peel colour and chlorophyll degradation patterns (Cubero *et al.*, 2014) ^[58]. Similarly, CNN-based approaches have been applied to detect fungal infections such as *Botrytis cinerea* in grapes and citrus canker in oranges, facilitating early intervention and minimising postharvest losses (Barbedo, 2019) ^[5]. Operational efficiency is another major advantage of deep learning-based vision systems. These systems can operate in real time on high-speed conveyor belts, inspecting thousands of units per hour without compromising accuracy (Li *et al.*, 2020) ^[24]. Automated grading lines equipped with CNNs reduce labour costs, improve throughput, and ensure uniformity in quality assessment. Integration with robotic arms further enables automated sorting and packaging, thereby streamlining postharvest workflows and reducing mechanical damage caused by manual handling (Bechar & Vigneault, 2016) ^[6]. Despite these advancements, critical considerations remain. Deep learning models require large, annotated datasets for effective training, and data collection and labelling are resource-intensive, particularly for crops exhibiting high variability in defect morphology (Kamilaris & Prenafeta-Boldú, 2018) ^[20]. Transfer learning, where models pre-trained on large benchmark datasets are fine-tuned for specific horticultural applications, offers a practical solution to limited data availability (Pan & Yang, 2010) ^[31]. Computational demand is another constraint, especially when processing hyperspectral data. However, advances in edge computing and lightweight CNN architectures are increasingly enabling real-time analysis on portable and embedded devices (Howard *et al.*, 2017) ^[59].

5. AI-Enabled Smart Storage Systems

Storage conditions exert a profound influence on the postharvest quality of horticultural crops. Temperature, relative humidity, oxygen, and carbon dioxide concentrations must be maintained within narrow ranges to slow physiological deterioration, suppress microbial growth, and preserve sensory attributes (Kader, 2002) ^[19]. Traditional cold storage systems typically operate on fixed setpoints that fail to account for dynamic changes in crop physiology or external environmental fluctuations. Such rigidity often results in suboptimal preservation, excessive energy consumption, and increased risk of physiological disorders such as chilling injury, moisture loss, and uneven ripening (Thompson *et al.*, 2018) ^[60].

AI-enabled smart storage systems represent a paradigm shift by integrating Internet of Things (IoT) sensors with predictive algorithms to continuously monitor environmental conditions and commodity responses (Verdouw *et al.*, 2016) ^[41]. Sensors embedded within storage chambers measure temperature, humidity, gas composition, and ethylene concentration in real time. These data streams are transmitted to AI platforms that analyse

trends, predict spoilage trajectories, and recommend corrective interventions (Misra *et al.*, 2020) ^[28]. Unlike static systems, smart storage units dynamically adjust refrigeration cycles, ventilation rates, and humidity control to maintain commodity-specific optimal conditions.

Reinforcement learning (RL) algorithms are particularly well-suited for dynamic storage optimization (Sutton & Barto, 2018) ^[39]. By interacting with the storage environment, RL agents learn optimal control policies through feedback mechanisms based on quality indicators such as firmness retention, weight loss, and microbial load. Over time, the algorithm converges on strategies that maximize shelf life while minimizing energy consumption. Such adaptive control systems are especially valuable in regions where ambient temperatures fluctuate widely or where energy efficiency is a strategic priority (Zhang *et al.*, 2021) ^[44].

Controlled atmosphere (CA) storage is another domain where AI integration has shown transformative potential. CA storage regulates oxygen, carbon dioxide, and nitrogen concentrations to slow respiration and delay ripening (Kader, 2002) ^[19]. AI systems predict ethylene accumulation, a critical ripening hormone in climacteric fruits such as bananas, mangoes, and apples, and adjust atmospheric composition accordingly (Saltveit, 2019) ^[37]. When ethylene levels exceed threshold values, AI algorithms can activate ventilation systems or ethylene scrubbers to prevent premature ripening. Fine-tuning gas composition reduces disorders such as superficial scald in apples, minimises moisture loss in leafy vegetables, and suppresses fungal growth in berries (Thompson *et al.*, 2018) ^[60]. Energy optimisation is an additional benefit of AI-enabled storage systems. Traditional refrigeration often operates continuously, leading to high electricity consumption and greenhouse gas emissions. AI-driven predictive models can schedule intermittent cooling cycles, balance compressor loads, and forecast peak demand periods to reduce operational costs (Acharjee *et al.*, 2017) ^[2]. Integration with renewable energy sources, such as solar-powered cold rooms, further enhances sustainability by reducing dependence on fossil fuels (Shukla & Jharkharia, 2013) ^[61]. Case studies demonstrate practical impacts. In India, IoT-integrated cold storage systems for onions and tomatoes have significantly reduced spoilage by dynamically adjusting humidity and ventilation based on real-time sensor feedback (Misra *et al.*, 2020) ^[28]. In Europe, reinforcement learning-based optimisation of apple storage conditions has extended shelf life while reducing energy consumption by approximately 15-20 per cent (Zhang *et al.*, 2021) ^[44]. In China, AI-supported smart warehouses for citrus have successfully predicted microbial outbreaks through environmental data modelling, enabling timely interventions and preserving fruit quality (Liu *et al.*, 2019) ^[62]. However, widespread adoption faces notable challenges. High initial investment in sensors, connectivity infrastructure, and AI platforms limits accessibility for smallholder farmers (Verdouw *et al.*, 2016) ^[41]. Data scarcity, particularly the absence of comprehensive crop-specific physiological datasets, constrains predictive accuracy. Interoperability issues between heterogeneous sensor networks and proprietary AI systems further complicate integration. Ethical and governance concerns regarding data ownership, privacy, and equitable benefit sharing across supply chains must also be addressed

(Wolfert *et al.*, 2017) ^[42]. Overcoming these barriers will require coordinated efforts among researchers, industry stakeholders, policymakers, and extension services to ensure inclusive and sustainable implementation of AI-driven smart storage technologies.

6. AI in Cold Chain Logistics and Supply Chain Optimisation

The cold chain represents a highly complex and interconnected network of storage facilities, refrigerated transport systems, distribution centres, and retail outlets designed to maintain optimal environmental conditions for perishable horticultural commodities from harvest to consumption (Kader, 2002; Thompson *et al.*, 2018) ^[19, 60]. However, temperature abuse during transit, inadequate monitoring, and logistical inefficiencies remain major causes of spoilage and quality deterioration (Aung & Chang, 2014) ^[3]. Even brief deviations from recommended temperature ranges can accelerate respiration rates, ethylene production, and microbial growth, leading to significant postharvest losses (Saltveit, 2019) ^[37]. AI-driven technologies are increasingly being deployed to address these challenges by enabling predictive, adaptive, and transparent management of cold chain logistics (Verdouw *et al.*, 2016; Wolfert *et al.*, 2017) ^[41, 42]. AI-powered logistics platforms integrate real-time data from GPS trackers, temperature sensors, and inventory management systems to provide continuous supply chain visibility (Misra *et al.*, 2020) ^[28]. Machine learning models analyse these data streams to detect anomalies, forecast transit delays, and recommend route adjustments (Choi *et al.*, 2018) ^[63]. For example, predictive analytics can anticipate traffic congestion or weather disruptions and reroute refrigerated trucks to minimise transit time and reduce thermal abuse (Ivanov & Dolgui, 2020) ^[16]. AI systems also estimate remaining shelf life upon arrival by combining transport conditions with physiological deterioration models (Jedermann *et al.*, 2014) ^[17]. This capability enables dynamic pricing strategies, redistribution decisions, and prioritisation of markets, thereby reducing waste and maximising profitability. Integration of AI with blockchain technology enhances traceability and transparency throughout the cold chain (Tian, 2017; Kamble *et al.*, 2019) ^[21, 40]. Blockchain systems create immutable digital ledgers that record temperature logs, humidity levels, handling practices, and transit histories at each stage of the supply chain. When combined with AI analytics, these datasets can be examined to identify risk patterns, ensure compliance with safety standards, and predict contamination events (Casino *et al.*, 2019) ^[9]. Consumers and retailers can access verified storage histories, thereby improving trust and food safety assurance. For instance, blockchain-enabled platforms allow buyers to verify whether strawberries were consistently stored below 4 °C during transit, reducing concerns regarding microbial proliferation and quality degradation (Aung & Chang, 2014) ^[3]. This transparency is particularly critical in export markets where stringent regulatory frameworks govern food safety and quality compliance.

Dynamic supply chain optimisation is another significant application of AI technologies. By integrating demand forecasting algorithms with cold chain monitoring systems, AI aligns supply volumes with market demand in real time (Choi *et al.*, 2018) ^[63]. Predictive models estimate consumer

demand based on historical sales data, seasonal patterns, promotional cycles, and exogenous factors such as holidays or climatic conditions (Carbonneau *et al.*, 2008) ^[8]. Reinforcement learning approaches are increasingly explored to optimise inventory turnover, balancing storage duration and market timing to minimise losses while maintaining product freshness (Sutton & Barto, 2018) ^[39]. Such adaptive systems enable perishable commodities to reach high-demand markets before quality deterioration occurs. Case studies highlight the tangible impact of AI-driven cold chain logistics. In Europe, AI-enabled apple distribution platforms have reduced spoilage by predicting shelf life and dynamically reallocating shipments to proximate markets (Jedermann *et al.*, 2014) ^[17]. In China, blockchain-integrated cold chain systems for citrus fruits have strengthened consumer confidence by providing transparent, verifiable quality records (Tian, 2017) ^[40]. In India, AI-supported logistics systems for mango exports have optimised routing and minimised transit delays, significantly lowering losses during international shipment (Kamble *et al.*, 2019) ^[21]. These examples demonstrate the adaptability of AI solutions across commodities and diverse supply chain environments. Despite these advancements, significant challenges remain. Effective AI deployment requires robust infrastructure, including reliable sensor networks, high-speed connectivity, and scalable computational platforms (Verdouw *et al.*, 2016) ^[41]. In developing economies, limited digital infrastructure and fragmented cold chain facilities constrain adoption (Aung & Chang, 2014) ^[3]. Data quality and standardisation are also critical, as inconsistent sensor calibration or incomplete records may compromise model reliability (Wolfert *et al.*, 2017) ^[42]. High capital investment requirements further restrict accessibility for smallholder farmers and cooperatives, highlighting the need for policy support and public-private partnerships. Ethical considerations surrounding data ownership, privacy, cybersecurity, and accountability in blockchain-enabled systems must also be addressed to ensure equitable participation and sustainable implementation across global horticultural supply chains (Casino *et al.*, 2019) ^[9].

7. Economic Implications of AI Adoption

The economic viability of Artificial Intelligence (AI) adoption in postharvest horticulture depends on a comprehensive cost-benefit assessment that balances substantial upfront investments against long-term financial and strategic returns (Wolfert *et al.*, 2017) ^[42]. Implementation of AI systems requires capital expenditure on hardware components such as sensors, machine vision cameras, robotic arms, servers, and networking devices, in addition to software development, cloud computing services, workforce training, and system maintenance (Misra *et al.*, 2020) ^[28]. These costs can be prohibitive, particularly for smallholder farmers operating in resource-constrained environments (Aung & Chang, 2014) ^[3]. However, the economic benefits of AI adoption extend beyond immediate profit gains, encompassing reduced postharvest losses, improved quality premiums, labour savings, enhanced energy efficiency, and increased competitiveness in domestic and export markets (Verdouw *et al.*, 2016) ^[41]. Reduced postharvest losses represent the most direct and measurable economic benefit of AI integration. Predictive shelf-life modelling, dynamic storage

optimisation, and real-time quality monitoring significantly minimise spoilage and extend marketable life (Jedermann *et al.*, 2014) ^[17]. Smart storage systems that regulate temperature and humidity according to commodity-specific physiological responses have been shown to reduce losses in highly perishable crops by 20-30% under optimised conditions (Kader, 2002; Thompson *et al.*, 2018) ^[19, 60]. Such reductions translate into higher effective yields, increased farmer incomes, and improved profitability across the supply chain. Improved quality premiums constitute another significant economic advantage. AI-driven grading and sorting systems enhance uniformity and classification accuracy, ensuring compliance with export standards and consumer quality expectations (Li *et al.*, 2020) ^[24]. Premium-grade produce commands higher prices in international markets, particularly where strict quality specifications are enforced (Aung & Chang, 2014) ^[3]. For example, AI-based vision systems used in apple grading improve market segmentation, enabling exporters to allocate high-quality produce to lucrative markets while directing lower grades to processing industries (Zhu *et al.*, 2020) ^[45]. This strategic allocation maximises overall revenue.

Labour savings and operational efficiency further enhance economic feasibility. Robotics and automated inspection systems reduce reliance on manual labour, which is often inconsistent and increasingly costly in many regions (Bechar & Vigneault, 2016) ^[6]. Automated packaging, palletising, and sorting systems increase throughput while reducing human error and mechanical damage (Li *et al.*, 2020) ^[24]. In contexts characterised by labour shortages or rising wage rates, these efficiency gains can offset initial capital investment within a relatively short payback period (Verdouw *et al.*, 2016) ^[41]. Energy efficiency represents another critical dimension of economic performance. AI-enabled smart storage systems optimise refrigeration cycles and ventilation patterns using predictive algorithms, reducing electricity consumption and operational expenses (Acharjee *et al.*, 2017) ^[2]. Improved energy management not only lowers costs but also contributes to sustainability objectives by reducing greenhouse gas emissions (Ivanov & Dolgui, 2020) ^[16]. Integration with renewable energy sources, such as solar-powered cold storage facilities, further enhances both economic resilience and environmental performance (Shukla & Jharkharia, 2013) ^[61]. Market competitiveness is strengthened through AI adoption in logistics optimisation, demand forecasting, and blockchain-enabled traceability (Kamble *et al.*, 2019) ^[21]. AI systems align supply with real-time market demand, reducing overstocking and waste (Carbonneau *et al.*, 2008) ^[8]. Blockchain integration improves transparency and compliance with international food safety regulations, thereby enhancing consumer trust and export potential (Casino *et al.*, 2019) ^[9]. Firms leveraging these technologies gain strategic advantages in global horticultural markets characterised by stringent quality requirements and intense competition. Adoption patterns, however, reveal significant disparities between large agribusiness firms and smallholder farmers. Large firms possess greater financial resources, technical expertise, and access to infrastructure, enabling rapid integration of AI into cold chain logistics, automated packing houses, and predictive analytics platforms (Wolfert *et al.*, 2017) ^[42]. Smallholders face barriers including limited capital, inadequate cold storage infrastructure, and low digital literacy (Aung & Chang, 2014) ^[3]. This digital divide

risks widening economic inequalities within horticultural supply chains.

Public-private partnerships (PPPs) and supportive policy frameworks are therefore essential for inclusive adoption (Verdouw *et al.*, 2016) ^[41]. Government subsidies for sensor deployment, tax incentives for AI-enabled equipment, and farmer training initiatives can accelerate technology diffusion in developing economies (Misra *et al.*, 2020) ^[28]. Community-based cold storage facilities equipped with AI monitoring systems represent cost-sharing models that reduce individual investment burdens. International development agencies and non-governmental organizations also contribute through pilot projects, funding mechanisms, and capacity-building programs aimed at strengthening technological adoption among marginalized producers. Case studies illustrate these dynamics. In Europe, large-scale apple exporters implementing AI-driven logistics platforms have reported measurable reductions in spoilage and enhanced competitiveness in global markets (Jedermann *et al.*, 2014) ^[17]. In India, government-supported AI initiatives in mango and onion supply chains have demonstrated improvements in loss reduction and market efficiency, although smallholder participation remains limited due to financial constraints (Misra *et al.*, 2020) ^[28]. In China, PPP-supported blockchain-integrated cold chain systems for citrus have enhanced supply chain transparency and consumer confidence (Kamble *et al.*, 2019) ^[21]. Future directions must prioritize affordability, inclusivity, and ethical governance. Development of low-cost sensor networks, mobile-based AI applications, and cooperative infrastructure-sharing models can make AI accessible to smallholders (Wolfert *et al.*, 2017) ^[42]. Addressing data ownership, privacy, and cybersecurity concerns is equally critical to ensure equitable participation and trust among stakeholders (Casino *et al.*, 2019) ^[9]. Policy frameworks should therefore balance innovation incentives with social equity considerations, ensuring that the economic benefits of AI-driven postharvest management are distributed across all participants in horticultural supply chains.

8. Technical Challenges

Data scarcity and inconsistency remain among the most significant barriers. AI models, particularly deep learning architectures, require large, annotated datasets to achieve high accuracy (LeCun *et al.*, 2015) ^[23]. However, horticultural datasets are often limited in size, fragmented across regions, and inconsistent in quality. For example, spectral imaging datasets for mango ripening may be abundant in one region but scarce in another, limiting model generalizability. Furthermore, inconsistencies in data collection methods, such as differences in sensor calibration, imaging resolution, or sampling protocols, introduce noise that reduces model reliability. Without standardised datasets, benchmarking across studies becomes difficult, and models trained in one context often fail when applied elsewhere (Mohanty *et al.*, 2016; Kamilaris & Prenafeta-Boldú, 2018) ^[20, 29]. Variability in cultivars, climatic conditions, and management practices further complicates AI model development. Horticultural crops exhibit significant genetic diversity, with cultivars differing in physiological traits such as respiration rate, ethylene sensitivity, and susceptibility to disorders. Climatic conditions, including temperature fluctuations, humidity levels, and rainfall patterns, influence postharvest

physiology and microbial dynamics. Management practices such as harvesting techniques, storage protocols, and packaging materials add additional layers of variability. AI models trained on one cultivar or region may not generalise to others, necessitating crop-specific customisation and localised training. This variability underscores the need for adaptive models capable of learning across heterogeneous datasets (Liakos *et al.*, 2018; Zhao *et al.*, 2016) ^[25, 64].

High computational requirements and energy demands pose another challenge. Deep learning models, particularly those used in hyperspectral imaging or real-time defect detection, require substantial computational resources for training and inference (LeCun *et al.*, 2015) ^[23]. Large-scale deployment in resource-constrained environments may be impractical due to limited access to high-performance computing infrastructure. Moreover, continuous monitoring systems generate massive data streams that demand real-time processing, further increasing computational load. Energy consumption associated with running AI systems, particularly in cold storage facilities, adds to operational costs and environmental impact. While advances in edge computing and lightweight neural architectures are mitigating these issues, scalability remains a concern (Shi *et al.*, 2016) ^[38]. Lack of standardised datasets and benchmarking frameworks impedes progress in the field. Currently, datasets are often proprietary, fragmented, or collected under varying protocols, making cross-comparison difficult. Without standardised benchmarks, it is challenging to evaluate the relative performance of different algorithms or to establish best practices. This lack of standardisation slows innovation and limits reproducibility, which are essential for scientific progress and commercial adoption (Kamilaris & Prenafeta-Boldú, 2018) ^[20]. Additional technical challenges include sensor reliability, data integration, and interoperability. Sensors deployed in storage facilities or transport vehicles must operate under harsh conditions, and their accuracy may degrade over time. Integrating heterogeneous data streams, such as imaging, spectral, and environmental data into unified AI models is technically complex. Interoperability between different sensor platforms, software systems, and supply chain stakeholders is often lacking, creating bottlenecks in implementation (Wolfert *et al.*, 2017; Zhao *et al.*, 2016) ^[42, 64].

9. Social and Ethical Considerations

The adoption of Artificial Intelligence (AI) in postharvest horticulture raises important social and ethical considerations that extend beyond technical feasibility and economic viability. While AI-driven systems promise efficiency, consistency, and sustainability, they also introduce challenges related to labor displacement, data ownership, privacy, and equitable access. Addressing these concerns is essential to ensure that the benefits of AI adoption are distributed fairly across stakeholders and that technological progress aligns with broader societal values (Kamilaris & Prenafeta-Boldú, 2018; FAO, 2022) ^[12, 20]. Labor displacement and employment concerns represent one of the most pressing social issues. Postharvest handling, grading, and packaging have traditionally relied on manual labor, particularly in developing economies where horticulture provides livelihoods for millions of workers. The introduction of robotics and automated vision systems reduces reliance on human graders and packers, potentially

leading to job losses or reduced demand for low-skilled labour. While automation alleviates issues of labour shortages and improves consistency, it also risks exacerbating unemployment and social inequality if alternative employment opportunities are not created (Brynjolfsson & McAfee, 2014) ^[7]. Collaborative robots (cobots) offer a partial solution by enabling human-robot cooperation, but broader policies are needed to retrain displaced workers and integrate them into higher-skilled roles within AI-enabled supply chains (World Bank, 2019) ^[43].

Data ownership and privacy present another critical ethical challenge. AI systems rely on vast datasets collected from sensors, imaging devices, and supply chain monitoring platforms. These datasets often include sensitive information about farm practices, storage conditions, and logistics operations. When shared across supply chain actors, questions arise regarding who owns the data, who has the right to access it, and how it can be used. Farmers may fear exploitation if their data are used by corporations to gain competitive advantage without fair compensation. Blockchain integration enhances transparency but does not automatically resolve ownership disputes. Ethical frameworks must establish clear guidelines for data governance, ensuring that producers retain agency over their information and benefit from its use (Wolfert *et al.*, 2017; OECD, 2019) ^[30, 42]. Privacy concerns also extend to consumers. Blockchain-enabled traceability systems allow consumers to access detailed storage histories and quality records, improving trust and food safety assurance. However, if consumer data, such as purchasing patterns or preferences are integrated into AI models, privacy risks emerge. Safeguards must be implemented to prevent misuse of personal information and to comply with data protection regulations such as the General Data Protection Regulation (GDPR) in Europe (European Union, 2016) ^[65].

Equitable access and inclusivity are essential to prevent widening the digital divide between large agribusiness firms and smallholder farmers. Large firms, with greater financial resources, rapidly adopt AI technologies, gaining competitive advantages in efficiency and market access. Smallholders, by contrast, face barriers related to cost, infrastructure, and digital literacy. Without inclusive policies, AI adoption risks marginalising small-scale producers, reducing their participation in high-value supply chains. Public-private partnerships, government subsidies, and cooperative models are necessary to democratize access and ensure that smallholders benefit from technological advancements (FAO, 2022; World Bank, 2019) ^[12, 43]. Ethical AI frameworks provide guiding principles for responsible adoption. These frameworks emphasise transparency, accountability, fairness, and sustainability. Transparency requires that AI systems be explainable, enabling stakeholders to understand how decisions are made. Accountability ensures that errors or biases in AI models are addressed and that responsibility is clearly assigned. Fairness demands that AI systems do not discriminate against specific groups or regions, while sustainability emphasises minimising environmental impact through energy-efficient algorithms and integration with green technologies (OECD, 2019) ^[30]. Policy interventions play a crucial role in operationalising ethical considerations. Governments and international organisations must establish regulations that protect labour rights, ensure fair data

governance, and promote inclusive adoption. Training programs can equip workers with digital skills, enabling them to transition into supervisory or technical roles within AI-enabled supply chains. Incentives such as subsidies for sensor deployment or tax breaks for AI adoption can encourage smallholder participation. Ethical guidelines must also address cross-border trade, ensuring that global supply chains adhere to uniform standards of transparency and fairness (FAO, 2022; OECD, 2019) ^[12, 30].

10. Future Directions

The adoption of Artificial Intelligence (AI) in postharvest horticulture raises important social and ethical considerations that extend beyond technical feasibility and economic viability. While AI-driven systems promise efficiency, consistency, and sustainability, they also introduce challenges related to labour displacement, data ownership, privacy, and equitable access. Addressing these concerns is essential to ensure that the benefits of AI adoption are distributed fairly across stakeholders and that technological progress aligns with broader societal values (Kamilaris & Prenafeta-Boldú, 2018; FAO, 2022) ^[12, 20]. Labour displacement and employment concerns represent one of the most pressing social issues. Postharvest handling, grading, and packaging have traditionally relied on manual labour, particularly in developing economies where horticulture provides livelihoods for millions of workers. The introduction of robotics and automated vision systems reduces reliance on human graders and packers, potentially leading to job losses or reduced demand for low-skilled labour. While automation alleviates issues of labour shortages and improves consistency, it also risks exacerbating unemployment and social inequality if alternative employment opportunities are not created (Brynjolfsson & McAfee, 2014) ^[7]. Collaborative robots (cobots) offer a partial solution by enabling human-robot cooperation, but broader policies are needed to retrain displaced workers and integrate them into higher-skilled roles within AI-enabled supply chains (World Bank, 2019) ^[43]. Data ownership and privacy present another critical ethical challenge. AI systems rely on vast datasets collected from sensors, imaging devices, and supply chain monitoring platforms. These datasets often include sensitive information about farm practices, storage conditions, and logistics operations. When shared across supply chain actors, questions arise regarding who owns the data, who has the right to access it, and how it can be used. Farmers may fear exploitation if their data are used by corporations to gain competitive advantage without fair compensation. Blockchain integration enhances transparency but does not automatically resolve ownership disputes. Ethical frameworks must establish clear guidelines for data governance, ensuring that producers retain agency over their information and benefit from its use (Wolfert *et al.*, 2017; OECD, 2019) ^[30, 42]. Privacy concerns also extend to consumers. Blockchain-enabled traceability systems allow consumers to access detailed storage histories and quality records, improving trust and food safety assurance. However, if consumer data, such as purchasing patterns or preferences are integrated into AI models, privacy risks emerge. Safeguards must be implemented to prevent misuse of personal information and to comply with data protection regulations such as the General Data Protection Regulation (GDPR) in Europe (European Union, 2016) ^[65].

Equitable access and inclusivity are essential to prevent widening the digital divide between large agribusiness firms and smallholder farmers. Large firms, with greater financial resources, rapidly adopt AI technologies, gaining competitive advantages in efficiency and market access. Smallholders, by contrast, face barriers related to cost, infrastructure, and digital literacy. Without inclusive policies, AI adoption risks marginalising small-scale producers, reducing their participation in high-value supply chains. Public-private partnerships, government subsidies, and cooperative models are necessary to democratize access and ensure that smallholders benefit from technological advancements (FAO, 2022; World Bank, 2019) ^[12, 43]. Ethical AI frameworks provide guiding principles for responsible adoption. These frameworks emphasise transparency, accountability, fairness, and sustainability. Transparency requires that AI systems be explainable, enabling stakeholders to understand how decisions are made. Accountability ensures that errors or biases in AI models are addressed and that responsibility is clearly assigned. Fairness demands that AI systems do not discriminate against specific groups or regions, while sustainability emphasises minimising environmental impact through energy-efficient algorithms and integration with green technologies (OECD, 2019) ^[30]. Policy interventions play a crucial role in operationalising ethical considerations. Governments and international organisations must establish regulations that protect labour rights, ensure fair data governance, and promote inclusive adoption. Training programs can equip workers with digital skills, enabling them to transition into supervisory or technical roles within AI-enabled supply chains. Incentives such as subsidies for sensor deployment or tax breaks for AI adoption can encourage smallholder participation. Ethical guidelines must also address cross-border trade, ensuring that global supply chains adhere to uniform standards of transparency and fairness (FAO, 2022; OECD, 2019) ^[12, 30].

11. Conclusions

Artificial Intelligence (AI) is rapidly transforming postharvest management in horticulture, offering unprecedented opportunities to enhance precision, efficiency, and sustainability across the supply chain. By integrating machine learning, deep learning, computer vision, robotics, IoT-enabled smart storage, and blockchain-based logistics, AI systems provide holistic solutions to long-standing challenges of perishability, quality inconsistency, and resource inefficiency. From automated grading lines capable of detecting subtle defects with near-perfect accuracy to predictive storage optimisation that dynamically adjusts environmental conditions, AI technologies are redefining the way horticultural commodities are handled, stored, and distributed. These innovations directly contribute to reducing postharvest losses, improving quality premiums, and strengthening food safety assurance, thereby advancing both economic viability and consumer trust. However, successful implementation of AI in postharvest systems requires overcoming a range of technical, economic, and social barriers. Technical challenges include data scarcity, variability across cultivars and climates, high computational demands, and the lack of standardised datasets for benchmarking. Economic barriers stem from the high initial costs of hardware, software, and infrastructure, which limit accessibility for smallholder

farmers. Social and ethical considerations, such as labour displacement, data ownership, privacy, and equitable access, must also be addressed to ensure that AI adoption does not exacerbate inequalities within horticultural markets. Without deliberate interventions, the benefits of AI risk are concentrated among large agribusiness firms, leaving smallholders marginalized. The path forward lies in responsible innovation and inclusive policy frameworks. Governments, research institutions, and industry stakeholders must collaborate to develop affordable, scalable AI solutions tailored to diverse production contexts. Public-private partnerships, subsidies, and cooperative models can democratize access, while training programs can equip workers with digital skills to transition into new roles within AI-enabled supply chains. Ethical AI frameworks emphasising transparency, accountability, fairness, and sustainability will be essential to guide responsible adoption.

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