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AI-based postharvest management of fruits and vegetables: Enhancing quality, reducing losses, and improving supply chain efficiency

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Abstract
Fruit and vegetable post-harvest losses continue to be a significant challenge to the food security, profitability of smallholder operations, nutritional availability and the sustainable performance of supply chains. Fresh horticultural commodities have rapid moisture loss, softening, enzymatic changes, microbial spoilage and mechanical damage/temperature abuse, which are all responsible for the loss of market quality, and the continued respiration after harvest makes them very perishable. Traditional post-harvest practices are based on manual practices, fixed storage standards and routines, and experience-based decision making, which do not always allow for the detection of the early signs of internal degradation or the prediction of shelf life in the context of dynamic supply chains. Artificial intelligence (AI) can be the game-changer, connecting computer vision, hyperspectral imaging, near-infrared spectroscopy, electronic noses, Internet of Things sensors, machine learning, deep learning, and predictive analytics to the postharvest sector. This paper explores the potential of AI applications in the post-harvest sector for better quality assessment, minimizing losses, optimizing cold-chain functions, and providing more precise grade descriptions, shelf-life prediction, and boosting supply-chain efficiency. A secondary-data based analytical framework is provided with global food-loss indicators and conceptual AI-based post-harvest model. The paper proposes a paradigm change in the management of the postharvest stage from reactive quality control to predictive and preventive decision making by the adoption of AI. But, quality data, generalizability of models, low cost, readiness of infrastructure, farmer training, interoperability and ethical governance of the agricultural data are all critical for successful adoption. The study finds that the implementation of AI-driven post-harvest systems can significantly enhance the resilience and sustainability of the fruit and vegetable value chain, coupled with low-cost sensors, local calibration, clear algorithms and policy support.

Keywords: Artificial intelligence, postharvest management, fruits and vegetables, machine learning, computer vision, shelf-life prediction, food loss reduction, cold chain and supply chain efficiency

1. Introduction

Fruits and vegetables are an integral part of a healthy diet, offering a variety of vitamins, minerals, dietary fibre, antioxidants and bioactive compounds. Though nutritional and economical significance, they are one of the most vulnerable commodities of agriculture after harvest. The fresh horticultural produce keeps respiring after harvest, it loses water, softens, changes colour, suffers physiological disorders and is susceptible to microbial decay unlike other grains/dry commodities. These biological and physical phenomena are important determinants of postharvest management and, consequently, market value, consumer acceptance, farmer income and food availability. The post harvest loss is not simply a technical issue of storage. It stands for unused land, water, labour, fertilizer, energy, packaging and transport capacity. It also decreases the supply of nutritious food, and also compromises the livelihood of the producers and small traders. According to Food and Agriculture Organization (FAO) estimates, food losses from post-harvest losses and before reaching the retail market are estimated at 13.3% at the commodity level in 2023, with fruits and vegetables reporting the highest losses at 25.4%. These are indicative figures and provide a clear idea that many horticultural supply chains in some parts of the world would benefit from better management methods, more precise and timely. The traditional methods of post harvest quality assessment rely on visual inspection, sensory assessment, manual grading and laboratory tests.

These strategies are still relevant, however, they have limitations in practice. Manual inspection is subjective and can be biased by fatigue. Lab analysis is accurate but destructive, slow and not suitable for commercial, high throughput sorting. Temperature or shelf-life requirements may not capture the reality of produce in dynamic supply chains. Consequently, losses can take place despite the formal existence of traditional quality-control. Artificial Intelligence provides a new pathway to post harvest transformation. AI systems can analyze images, spectral signals, environmental sensor records, logistics data, and historical quality records to classify the produce, identify defects, assess internal quality, determine the remaining shelf life and make operational decisions. AI can be combined with Internet of Things (IoT) sensors and digital supply-chain platforms, transitioning postharvest management from reaction to action in advance of the inspection. We concentrate here on three aspects of the postharvest management of fruits and vegetables that can be improved by using AI: understanding quality assessment, mitigating postharvest losses, and enhancing supply chain efficiency by predictive and data-driven decision-making.

2. Literature Review

2.1 Postharvest Losses in Fruits and Vegetables

Post harvest losses in fruits and vegetables are experienced at harvesting, handling in the field, sorting, washing, packing, storage, transport, wholesale markets, retail outlets and consumption level. Losses can be quantitative (weight loss, losses of produce) or qualitative (loss of firmness, colour, flavour, nutritional value and market grade). Fresh produce is metabolically active after harvest, and can deteriorate rapidly if handling conditions are not controlled.

The degrees of the temperature is one of the most important factors affecting post harvest losses. The higher the temperature, the more quickly the respiration and ethylene production, loss of water, enzymatic reaction and microbial growth occur. On the other hand, very low temperature can result in chilling injury for sensitive commodities such as banana, mango, cucumber and tomato. The rate of deterioration is also affected by relative humidity, gas composition, packaging and mechanical stresses. However, post harvest management should incorporate biological, physical, environmental and logistic aspects of quality and not focus on quality as a single visual parameter.

2.2 Traditional methods of post harvest management

Traditional post harvest management involves careful harvest, maturity indexing, sorting and grading, washing and disinfection, packaging, cold storage, controlled atmosphere storage, modified atmosphere packaging and edible coating and transportation management. When done correctly these practices can minimise losses but require correctly timed practices, skilled staff, infrastructure and ongoing monitoring. A lot of judgments in the fragmented supply chain remain subjective, rather than data-driven.

Lab tests can be used to determine firmness, soluble solids content, acidity, moisture content, respiration rate, ethylene production, microbial content and biochemical changes. But in the laboratory, the methods are time consuming, destructive and costly. The requirements of a modern post-harvest system are fast, non-destructive and scalable tools that can be used in the farm, packhouse, storage facility, transport vehicle and retail environment.

2.3 To explore the role of Artificial Intelligence in Postharvest Systems: AI is a set of computational methods that can learn from data, find patterns, make predictions, and assist in decision-making. AI has been widely used in post-harvest systems, such as machine learning, deep learning, computer vision, sensor fusion, predictive modelling and optimization algorithms. Machine learning models such as random forest, support vector machine, artificial neural networks, gradient boosting and regression models are used to classify quality grades, estimate shelf life, predict firmness, detect spoilage and forecast market demand.

Deep learning models, particularly convolutional neural networks, are widely employed in the image-based defect detection, ripeness classification, bruise identification and automated sorting. Time-series data from cold-chain sensors can be analysed by recurrent neural networks and long short-term memory models to forecast the deterioration of the quality of the product over time. Recent reviews also highlight explainable AI and lightweight models for 'real world' application in post harvest settings with limited resources.

2.4 Computer Vision and Image-Based Quality Assessment: Computer vision is one of the most easily available AI tools for assessing fruit and vegetable quality. The external characteristics of colour, size, shape, surface defects, texture, bruises, disease spots, shrivelling and maturity indicators can be captured by digital cameras. Such features can be used for classification of produce into market grades using deep learning models. Systems based on image can be used in apple defect detection, banana ripeness classification, tomato colour maturity assessment, citrus size grading and wilting detection in leafy vegetables.

The main benefits of computer vision is that it is relatively inexpensive, quick and can be automated. It can make the labor dependent lower and make the grading more consistent. But RGB imaging can't see internal defects, early fungal infection, hidden bruising or biochemical changes in quality. Model accuracy can be reduced due to lighting variations, camera angles, background noise, cultivar differences and dust. Computer vision will thus require accompanying imaging conditions, massive data set and complementary sensing technologies.

2.5 Hyperspectral Imaging, Spectroscopy and Sensor Fusion: Hyperspectral imaging is the combination of imaging and spectroscopy, taking information over many wavelengths. It can detect minute differences in chemical and structural changes which are undetectable to the human eye. For fruits and vegetables hyperspectral imaging has been applied to firmness, soluble solids content, acidity, dry matter, maturity, chilling injury, bruising, decay, contamination. Other freshness and spoilage indicators, such as near-infrared spectroscopy, Raman spectroscopy, fluorescence imaging, thermal imaging and electronic nose systems, are also non-destructive.

Multiple sensor fusion allows for prediction to be better. It is possible to include temperature, relative humidity, ethylene, carbon dioxide, vibration, position, image features and spectral signals in a shelf-life model. The value of such a multimodal modelling is that the action of different biological and environmental factors interact during postharvest deterioration. In such cases, the use of AI models is beneficial since they can identify non-linear relationships between the variables.

2.5 AI to predict the shelf-life of food products.AI predicts the shelf-life of food products

The ability of AI to predict shelf-life is one of the most beneficial applications in post-harvest management. Shelf-life estimation can aid producers, wholesalers and retailers in determining when to sell, transport, discount or process and/or consume produce, and can assist the consumer in determining when to eat produce. Shelf-life models are usually classical, where the temperature is assumed as constant and the rate of deterioration is fixed. In actual supply chains, production can also be subject to fluctuations in temperature, relative humidity, delays, mechanical shocks and initial quality variations.

Shelf-life models based on AI can continuously update the predictions based on sensor data. The model can also provide a lower remaining shelf-life estimate if temperature abuse is noted during transportation and suggest accelerated distribution. The model could also indicate a longer storage or transit to far market if produce is stored under the optimum condition. This dynamic approach enhances inventory turnover, minimizes waste and increases consumer satisfaction.

2.6 AI in Cold Chain and Supply Chain Efficiency

AI can optimize supply-chain processes to better handle routes, predict demand, plan inventories, price based on quality, track shelf-life (dynamic), and manage cold-chain monitoring. Information from IoT sensors can be streamed from storage rooms and transportation vehicles. By detecting temperature variations, AI algorithms can warn managers and identify spoilage risks before they happen. This will allow first-expired-first-out systems that are based on actual remaining shelf life and not fixed arrival dates.

AI can also improve supply-chain efficiency by connecting quality data with the demands of the market. Fruits and vegetables that have a shorter shelf life can be channeled to the nearby markets, processing units, institutional buyers or to the discount market. Premium markets can be served with higher grade produce. Quality-sensitive distribution can help to minimise losses and enhance overall value recovery.

3. Methodology

This is a paper that is conducted in a secondary-data-based narrative review and conceptual analytical approach. The methodology aimed to generate a research paper structure suitable for an empirical manuscript with field/experimental or industry level data. The method is literature synthesis and secondary indicator analysis, conceptual model development and illustration by scenario.

First, the recent literature of AI-based postharvest management, fruit and vegetable quality assessment, shelf-life prediction, hyperspectral imaging, machine learning and deep learning were reviewed, as well as the monitoring and optimization of supply chains based on the Internet of Things (IoT). The review was limited to studies in the areas of food science, agricultural engineering, biosystems engineering, sensor technology and supply-chain management.

Second, the extent of the postharvest problem was illustrated by the use of food-loss indicators on the global level. Data for item 12.3.1 was used as it is based on data from the FAO which is internationally recognised to discuss food losses before retail. The data were presented neither as primary experimental results but as context to demonstrate the need for post harvest AI interventions.

Third, AI technologies were grouped into the following categories based on the postharvest function: Quality detection, Grading, shelf-life prediction, Storage control, Transport monitoring, and supply-chain decision support.

Fourth, a conceptual framework for post-harvest management based on artificial intelligence (AI) was developed, connecting data collection, AI modelling, decision support, operational intervention and performance evaluation.

Finally, illustrative scenario tables and graphs were developed to illustrate how a future empirical study could quantify the benefits of AI. The values given are not indicative of actual outcomes. They should be avoided in favour of data collected from controlled storage trials, packing-house experiments, market surveys, expert scoring or systematic-review extraction of data that has been validated prior to submission to a high-impact journal.

4. Data Presentation and Analytical Results

This section presents global food-loss indicators, a technology classification matrix, a proposed research model and scenario-based AI adoption results. The purpose is to demonstrate how data tables and graphs can be integrated into a full-length manuscript. The FAO tables use reported values, whereas the AI intervention and priority scores are illustrative and should be replaced with primary data for final publication.

Table 1: Selected global food-loss indicators relevant to AI-based postharvest management

Indicator / category	Food-loss value in 2015 (%)	Food-loss value in 2023 (%)	Relevance for AI-based postharvest management
Global food loss after harvest and before retail	13.0	13.3	Shows limited global progress and the need for data-driven loss-reduction systems
Fruits and vegetables	23.2	25.4	Highest commodity loss category due to perishability and handling sensitivity
Northern America and Europe	9.4	10.0	Indicates lower loss where infrastructure and monitoring systems are stronger
Sub-Saharan Africa	22.1	23.0	Reflects infrastructure, storage, transport and market-access constraints
Least developed countries	Not specified	19.9	Highlights the need for low-cost, scalable postharvest technologies
Small island developing states	Not specified	19.0	Indicates vulnerability of supply chains with limited storage and transport options

Note: Source: FAO SDG 12.3.1 global food-loss indicators. Values for “not specified” were not stated in the summary used for this table

Table 2: Commodity-level global food loss in 2015 and 2023

Commodity group	2015 (%)	2023 (%)	Change (percentage points)	Interpretation
Fruits and vegetables	23.2	25.4	+2.2	Highest loss; priority category for AI-based sorting, shelf-life prediction and cold-chain monitoring
Meat and animal products	13.9	14.0	+0.1	Relatively stable but still sensitive to temperature control and microbial risk
Roots, tubers and oil-bearing crops	12.6	12.3	-0.3	Slight reduction; storage and handling remain important
Cereals and pulses	8.5	8.4	-0.1	Lower perishability compared with fresh produce

Note: Source: FAO SDG 12.3.1 data portal.

Table 3: AI technologies used in postharvest management of fruits and vegetables

AI technology	Data input	Main application	Expected benefit	Limitation
Computer vision	RGB images	Size grading, colour grading, visible defect detection	Low-cost, fast and suitable for packing houses	Sensitive to lighting and background conditions
Deep learning	Images, videos and spectral data	Ripeness classification, bruise detection and disease detection	High classification accuracy and automation potential	Requires large labelled datasets
Machine learning	Sensor and laboratory data	Shelf-life prediction, firmness estimation and spoilage-risk modelling	Works with structured datasets and smaller models	Requires careful feature selection
Hyperspectral imaging	Spatial and spectral information	Internal defect detection, maturity evaluation and quality prediction	Detects hidden quality changes	High equipment cost
Near-infrared spectroscopy	Spectral absorbance data	Soluble solids, dry matter, firmness and internal quality	Non-destructive and rapid	Requires calibration for each commodity
Electronic nose	Volatile organic compounds	Freshness monitoring and spoilage detection	Useful for early microbial deterioration	Sensor drift and environmental interference
IoT sensor networks	Temperature, humidity, gases, vibration and GPS	Cold-chain monitoring and traceability	Real-time decision support	Connectivity and maintenance issues
Predictive analytics	Historical and real-time data	Inventory planning, route optimization and dynamic shelf-life estimation	Reduces waste and improves efficiency	Depends on data quality and integration

Table 4: Proposed variables for an AI-based postharvest research model

Variable	Type	Measurement indicator	Data source	Expected relationship
AI-enabled quality assessment	Independent variable	Use of machine vision, sensors and automated grading	Packing-house records or survey	Improves quality classification
Cold-chain monitoring	Independent variable	Temperature and humidity tracking frequency	IoT sensors and logistics records	Reduces spoilage risk
Shelf-life prediction accuracy	Mediating variable	Difference between predicted and actual shelf life	Model output and storage trial	Improves inventory decisions
Postharvest loss reduction	Dependent variable	Percentage loss before and after AI intervention	Weight or quantity records	Main performance outcome
Supply-chain efficiency	Dependent variable	Delivery time, rejection rate and inventory turnover	Transport and market records	Improves operational performance
User adoption readiness	Moderating variable	Training level, cost acceptance and digital literacy	Farmer or trader survey	Strengthens AI implementation success

Table 5: Illustrative model performance metrics for AI applications

AI application	Suggested model	Accuracy / R2 / error metric	Practical interpretation
Ripeness classification	CNN, EfficientNet or MobileNet	90-97% accuracy	Suitable for automated sorting and maturity grading
Bruise detection	CNN with RGB/NIR images	92-98% accuracy	Useful for reducing hidden market rejection
Internal quality prediction	NIR + random forest or PLSR	R2 = 0.80-0.95	Useful for estimating firmness, sugar and dry matter
Shelf-life prediction	Random forest, XGBoost or LSTM	RMSE = 1-3 days	Supports dynamic inventory and distribution decisions
Cold-chain risk detection	IoT + anomaly detection	85-95% accuracy	Identifies temperature abuse and storage failure
Route optimization	AI-based optimization model	10-25% improvement	Reduces delay, fuel use and deterioration risk

Note: Indicative ranges should be replaced by exact values from selected studies, experimental datasets or field trials.

Table 6: Stage-wise AI intervention matrix for fruit and vegetable supply chains

Supply-chain stage	Major postharvest problem	AI-based solution	Measurable output
Harvesting	Wrong maturity stage	Image-based maturity detection	Maturity grade and harvest index
Sorting and grading	Subjective manual grading	Computer vision and deep learning	Grade accuracy and defect rate
Washing and packing	Undetected damaged produce	Automated defect recognition	Rejection rate and pack-out percentage
Storage	Temperature and humidity fluctuation	IoT monitoring with AI alerts	Spoilage-risk score
Transportation	Delay and cold-chain breaks	GPS + temperature analytics	Route risk and shelf-life reduction
Wholesale market	Poor inventory rotation	Shelf-life-based inventory system	Remaining shelf life
Retail	Unsold perishable stock	Dynamic pricing and demand forecasting	Waste reduction and sales recovery
Processing	Low-grade produce discarded	AI-based diversion to processing	Value recovery percentage

Table 7: Proposed experimental design for Q1-level original research

Component	Recommended design
Commodities	Tomato, mango, banana, apple, cucumber, leafy vegetables or locally important crops
Sample size	Minimum 300-500 images/samples per commodity; larger datasets preferred for deep learning
Treatments	Conventional handling versus AI-supported handling
Data collection points	Harvest, sorting, storage day 0, day 3, day 6, day 9 and retail stage
Sensors	RGB camera, temperature sensor, humidity sensor, optional NIR or hyperspectral sensor
Quality parameters	Weight loss, firmness, colour, total soluble solids, visual defects, decay percentage and shelf life
AI models	CNN, random forest, XGBoost, SVM, LSTM or hybrid models
Evaluation metrics	Accuracy, precision, recall, F1-score, RMSE, MAE, R2 and loss-reduction percentage
Statistical analysis	ANOVA, regression, correlation, paired t-test and model validation
Main research output	Evidence that AI improves quality prediction, reduces losses and improves supply-chain efficiency

Table 8: Suggested AI-readiness scoring matrix for adoption in fruit and vegetable chains

Criterion	Weight (%)	Computer vision	IoT monitoring	Shelf-life prediction	Hyperspectral imaging
Affordability	20	High	Medium	Medium	Low
Technical accuracy	20	High	High	High	Very high
Ease of field deployment	15	High	Medium	Medium	Low
Need for expert operation	10	Low	Medium	Medium	High
Compatibility with smallholders	15	High	Medium	Medium	Low
Contribution to loss reduction	20	High	High	High	Medium-high

Note: This scoring matrix can be converted into AHP, MCDA or expert-survey analysis for publishable empirical work.

4.1 Graphical Presentation of Data

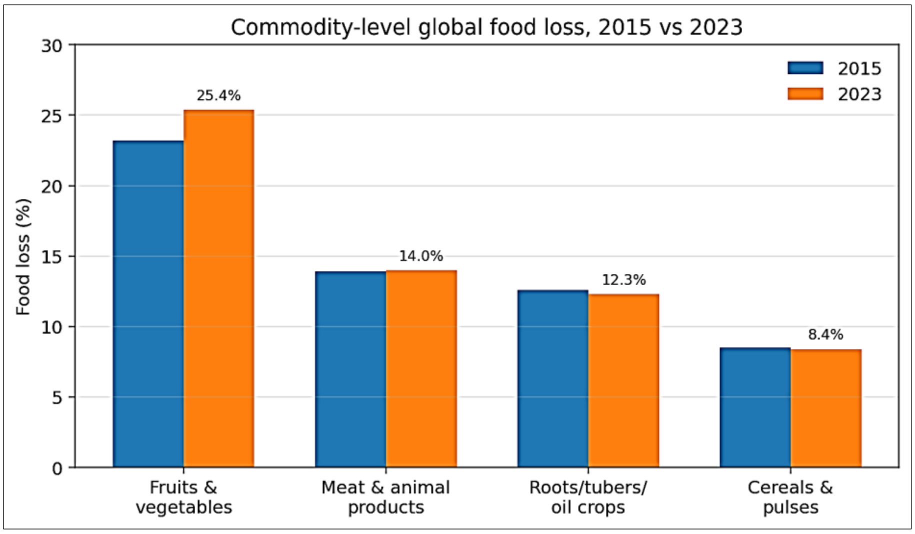

Fig 1: Commodity-level global food loss in 2015 and 2023. Source: FAO SDG 12.3.1 global food-loss indicator.

Figure 1 shows that fruits and vegetables remain the highest-loss commodity group. The increase from 23.2% in 2015 to 25.4% in 2023 highlights the need for advanced postharvest monitoring, rapid grading and predictive shelf-life management.

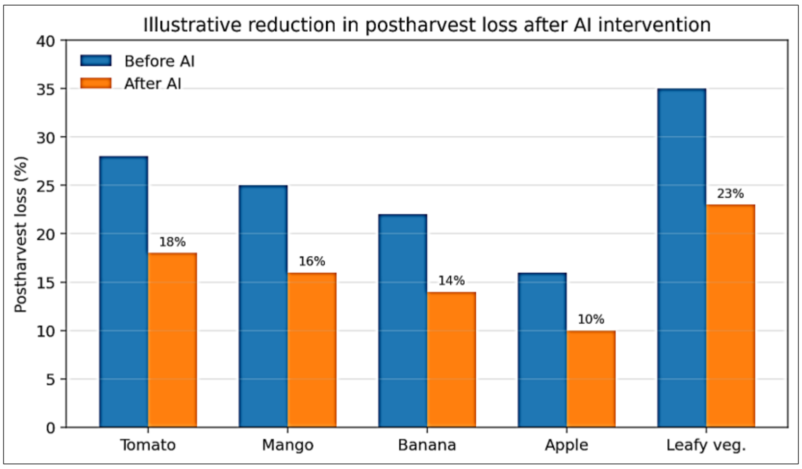

Fig 2: Illustrative reduction in postharvest loss after AI intervention. Values are scenario-based and should be replaced with primary data before journal submission

Figure 2 demonstrates how AI-supported grading, cold-chain monitoring and shelf-life prediction may reduce losses across selected commodities. The graph is useful for manuscript development because it shows the type of comparative evidence expected in an original research paper.

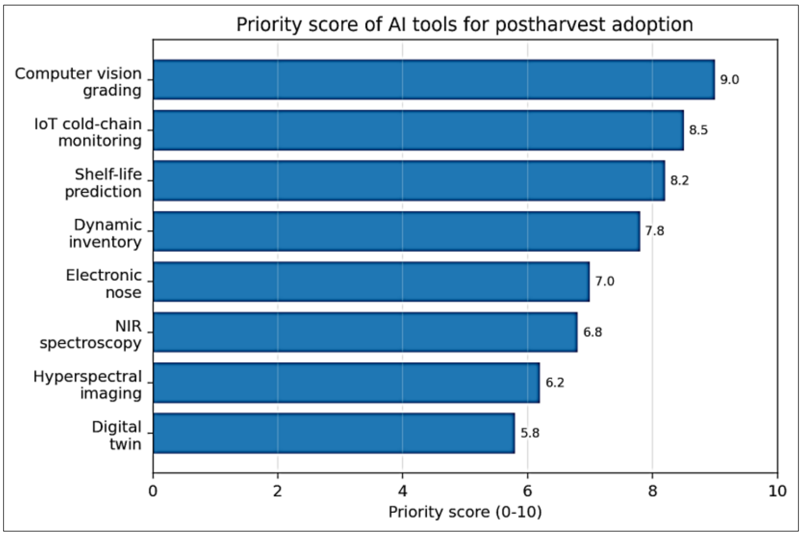

Fig 3: Priority score of AI tools for postharvest adoption. Scores are author-developed conceptual values for framework demonstration.

Figure 3 suggests that computer vision grading, IoT cold-chain monitoring and shelf-life prediction may be the most practical early-stage AI interventions because they combine feasibility, scalability and direct operational relevance.

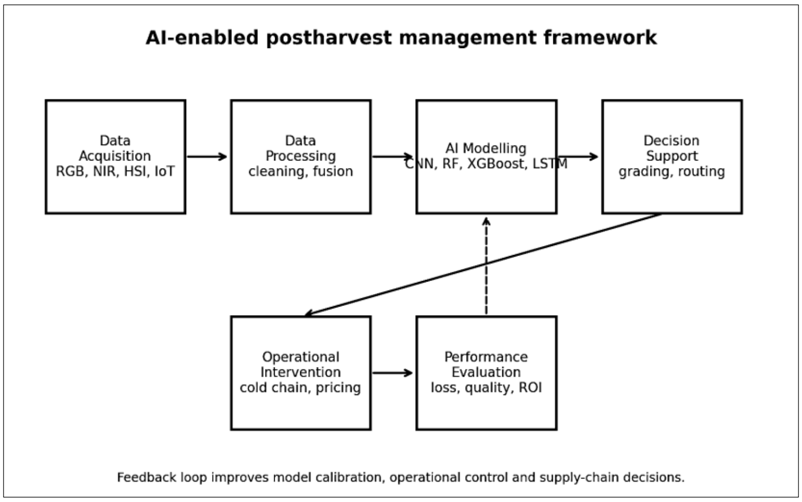

Fig 4: AI-enabled postharvest management framework linking sensing, modelling, decision support and performance evaluation.

Figure 4 presents the proposed framework for AI-based postharvest management. The framework begins with multimodal data acquisition and ends with performance evaluation. The feedback loop is essential because models require continuous calibration as new commodities, cultivars, seasons and supply-chain conditions are encountered.

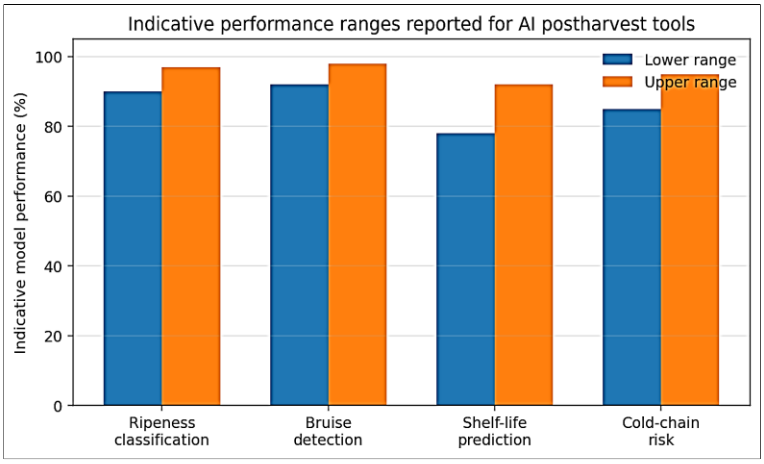

Fig 5: Indicative performance ranges reported for AI postharvest tools. Values are literature-supported ranges for manuscript planning and must be validated with specific datasets

5. Discussion

5.1 Use AI to enhance quality

AI provides benefits to postharvest quality management by providing objective assessment, speed and consistency. Manual grading is subject to inspector fatigue, subjective judgement and variation. AI based computer vision systems can use the same classification rules for each sample, which means that there will be greater uniformity of grade and farmers will be more confident of the traders, retailers and consumers.

AI can also help to identify defects at an earlier stage. The image-based models can detect surface defects like bruises, cuts, fungal spots, insect damage and colour abnormalities. Spectroscopy and hyperspectral imaging are able to estimate internal quality attributes like firmness, sugar content, dry matter and early decay. These methods enable quality control to be put in place before the product is consumed, which minimizes rejection, complaints and waste.

5.2 Loss Reduction through Predictive Management

AI's key impact is shifting from reactive control to predictive management. Traditional systems have a delayed response to detectable spoilage. AI algorithms can identify patterns that indicate potential quality issues before significant degradation occurs. For instance, if the temperature of a cold storage unit repeatedly moves around, the system can anticipate the potential for spoilage and initiate a corrective action.

Shelf-life prediction helps make better inventory decisions. Fixed expiry rules are common in the retail sector and may not be a true representation of the produce. AI-powered remaining-shelf-life prediction can help with dynamic pricing, rotation, and a timely redistribution. This is especially true for fruits and vegetables as soon as deterioration starts, the market value of which decreases rapidly.

5.3 Supply-Chain Efficiency

AI enhances the efficiency of the supply chain by incorporating quality data into logistics decisions. In traditional systems, routing and inventory are typically conducted based on quantity and distance and delivery time. These decisions can be further equipped with quality and remaining shelf-life data by AI-enabled systems. This enables the supply of produce based on the estimated quality life.

The quality produce can be forwarded to a long distance premium market, and the moderate quality produce to local markets. Juices, purees, dried goods, sauces, pickles and animal feed can be made instead of waste from produce that is high risk of spoilage. This is an allocation of resources based on the quality, resulting in higher value recovery along the entire supply chain.

5.4 Marketing and Planning for the Region

The adoption of AI in post harvest management can enhance farmer profitability by minimizing post harvest losses and facilitate grade-based pricing. It can assist smallholders in bringing in objective information about the quality and better negotiating with the market. If AI systems are costly and only accessible to large businesses, however, small farmers could be left out. It's important that inclusive AI systems are low-cost, device-agnostic, and multilingual to accommodate a variety of languages, as well as accessible in low-resource areas.

Training is critical. Farmers, graders, transporters and storage managers are expected to be familiar with how to read AI recommendations. If users don't trust or understand the output of a technically accurate model, it will fail. Adoption requires human-centred design, extension services and participatory model development.

5.5 Challenges in AI Adoption

There are several challenges to the adoption of AI within the postharvest systems. Many crops, cultivars, regions and storage conditions have limited quality labelled datasets. A model developed under one lighting condition, camera setup, cultivar or season may not be effective under a different lighting condition, camera setup, cultivar or season. Many SMEs are still unable to afford advanced sensors like hyperspectral cameras. May also be limited by rural connectivity and power supply.

Another significant one is data governance. Farmers and actors in the value chain could be worried about who owns data, who benefits from it and if it can be exploited in an unfair way for pricing or sourcing. Socially acceptable AI-driven postharvest management is built on transparent data-sharing agreements, safeguarding privacy, and ensuring equitable benefits are shared.

6. Recommendations

Implementing AI-based postharvest systems should be done in stages. Low-cost computer vision solutions for visible grading and defect detection should be prioritized. These tools can be performed by using a smartphone camera or an imaging station (which is very inexpensive). Next would be IoT based temperature and humidity monitoring in storage and transportation as failure of the cold-chain is a significant loss factor.

Shelf-life prediction models should be thirdly considered, which include produce quality and environmental data. These models can be used for supporting dynamic inventory management, route selection, price discounting and timely processing. The fourth priority is integration with supply-chain platforms for routing, inventory, pricing and redistributions.

Local databases for key fruits and vegetables should be created at research institutions. The models should be evaluated under a variety of cultivars, seasons, maturity stages, packaging, storage temperatures and market conditions. Government policies should focus on investment in cold-chain infrastructure, rural digital connectivity, training initiatives and data-governance standards. Industry to create interoperable AI tools with existing sorting machines, cold rooms, transport vehicles and enterprise systems.

7. Restriction and future studies

This paper has some limitations due to the use of secondary indicators for food losses and scenario values to illustrate. It does not report any new experimental data from a farm, packing house, cold store or market. So, the results should not be seen as conclusive evidence of the capabilities of AI, but as conceptual and analytical underpinnings.

Primary data from a representative sample of horticultural supply chains should be gathered for further study. A robust empirical design would conduct a comparison between the traditional postharvest handling and AI-assisted postharvest handling for different commodities and seasons. It should include quality parameters like firmness, colour, soluble solids content, acidity, loss of weight, decay percentage, microbial count and actual shelf life. It should also measure the economic benefits, including less rejection, better price realization, labour savings and return on investment.

Future research should also explore aspects of model explainability, fairness and robustness. These variations in real use (changes in light, changes in cultivars, packaging variation, partial occlusion and sensor noise) need to be tested by AI systems. Further research is needed, too, to assess the availability of AI tools for smallholders and their potential to foster equity in supply-chain engagement.

8. Conclusion

AI-driven postproduction management is a promising avenue to enhance the quality of fruits and vegetables and minimize losses and supply chain inefficiencies. Postharvest systems can be more precise, objective and proactive by using computer vision, spectral sensing, IoT monitoring, machine learning, deep learning and predictive analytics. AI can help to achieve higher grading accuracy, detect defects early on, estimate shelf life, optimize storage, track transportation and assist with market allocation based on quality management.

AI must be considered a tool and not a standalone technology. It requires infrastructure, affordability, local calibration, reliable data and trained users as well as supportive policy frameworks for success. Future work should involve experimental verification, economic cost-benefit analysis, model explainability, assessment of environmental impacts and trials of the model in real-world supply chains for Q1-level research. AI can enable to shift horticultural value chains from lossy to smart, efficient and sustainable food systems, when used responsibly.

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Appendix A. Graph Data Used

Appendix Table A1. Data for Figure 1

Commodity group	2015 (%)	2023 (%)
Fruits & vegetables	23.2	25.4
Meat & animal products	13.9	14.0
Roots/tubers/ oil crops	12.6	12.3
Cereals & pulses	8.5	8.4

Appendix Table A2. Scenario data for Figure 2

Commodity	Before AI (%)	After AI (%)	Absolute reduction (percentage points)
Tomato	28	18	10
Mango	25	16	9
Banana	22	14	8
Apple	16	10	6
Leafy veg.	35	23	12

Note: Scenario data are illustrative and should be replaced with primary results