Chapter 5

IOT-Driven Innovations in Fruits and Vegetables Quality Monitoring: From Sensors To Edge AI

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Chapter DOI:

https://doi.org/10.47715/978-93-86388-87-2/ch5

Abstract

This review highlights recent advances in sensing technologies, embedded systems, and machine learning for the automated quality assessment of fruits and vegetables, with a particular focus on Internet of Things (IoT)-enabled solutions. These systems support real-time monitoring, remote alerts, and improved supply-chain visibility. The survey encompasses diverse sensing modalities, including visual, gas/e-nose, optical, mechanical/texture, and spectroscopic methods, as well as embedded and edge architectures. It further examines data analytics approaches, ranging from classical machine learning to lightweight convolutional neural networks optimized for edge devices. Representative implementations are discussed, along with practical challenges such as power efficiency, sensor calibration, selectivity, and data reliability. The review also explores future directions, including edge AI, digital twins, federated learning, and sustainable hardware. Overall, findings reveal a clear progression from basic environmental monitoring toward multimodal, AI-enabled edge devices that deliver actionable insights on freshness and grading to stakeholders across the agricultural value chain.

Keywords: Fruits and Vegetables, Fruits and Vegetables, Food Quality Monitoring, Computer Vision, Machine Learning / Deep Learning, Edge Computing, Digital Twins in Agriculture.

5.1 Introduction

Maintaining the quality of fruits and vegetables from farm to fork is a critical challenge in modern agriculture, as it directly impacts food waste reduction, nutritional preservation, consumer safety, and overall supply-chain efficiency [1], [2]. Conventional inspection methods remain largely manual, subjective, and labor-intensive, often leading to inconsistencies in grading and late detection of spoilage [3]. Automated systems, by contrast, offer the potential for objective, repeatable, and continuous quality monitoring [4].

The rapid convergence of low-cost sensing technologies, ubiquitous wireless connectivity, and increasingly powerful edge processors has paved the way for Internet of Things (IoT)-enabled quality assessment devices [1], [6]. These systems are capable of detecting ripeness, decay, and defects, while transmitting results in real-time to cloud platforms, dashboards, or mobile applications for timely decision support [6], [8], [11]. Unlike traditional single-parameter monitoring, which is typically limited to environmental factors such as temperature and humidity, emerging systems employ multimodal sensing strategies that integrate vision-based inspection, gas/e-nose technologies, and spectroscopic techniques [4], [5], [8]. When combined with machine learning and edge artificial intelligence (AI), these solutions enable more accurate, scalable, and nondestructive quality assessment [6], [7].

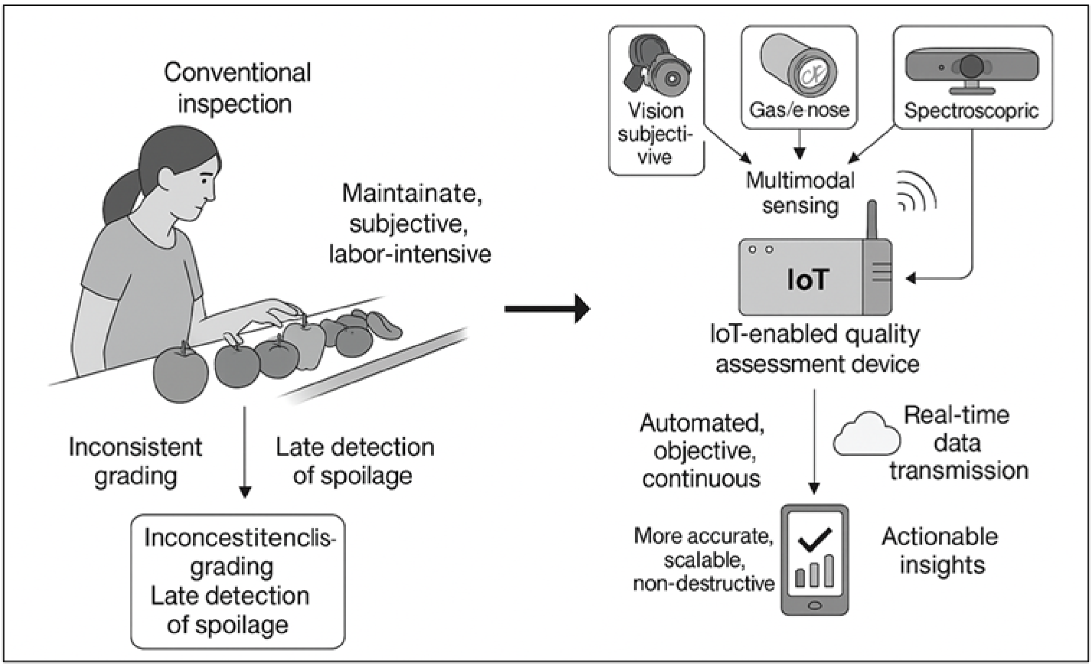

Figure 5.1: Conventional versus IoT-enabled fruit and vegetable quality inspection

Figure 5.1 illustrates the contrast between traditional manual inspection methods and modern IoT-based approaches for assessing produce quality. Conventional inspection is often subjective, labor-intensive, and prone to inconsistencies, leading to delayed detection of spoilage. In comparison, IoT-enabled systems integrate multimodal sensing, real-time data transmission, and AI-driven analysis to provide accurate, scalable, and continuous monitoring. This transformation enables proactive quality management, reduces waste, and delivers actionable insights across the supply chain. Recent literature reflects this paradigm shift, demonstrating a clear evolution from basic environmental monitoring toward smart, AI-driven, IoT-integrated systems capable of delivering actionable insights across the entire agricultural value chain [3], [8]. These advances not only enhance quality assurance but also provide predictive intelligence for post-harvest handling, logistics, and storage, thereby reducing losses and ensuring safer, fresher produce for consumers [9]–[11].

5.2 Sensing Modalities for Produce Quality

5.2.1 Vision and Computer Vision

Camera-based inspection systems are among the most widely adopted nondestructive techniques for assessing the external quality of fruits and vegetables. These systems analyze surface features such as color, size, shape, spots, and texture to evaluate ripeness, detect defects, and classify produce into commercial grades. Traditional feature-based approaches, relying on thresholding or handcrafted descriptors, have been mainly superseded by deep convolutional neural networks (CNNs), which offer superior accuracy and robustness under variable lighting and background conditions [3], [4].

Recent developments in model compression, pruning, and lightweight architectures (e.g., MobileNet, EfficientNet) now enable these algorithms to run on smartphones and microcontrollers. Such edge-optimized models provide real-time inference, reduce latency, and minimize bandwidth usage, making them suitable for field deployment and integration into IoT-based quality monitoring systems [5], [6], [7].

5.2.2 Gas Sensors and Electronic Noses (E-noses)

The spoilage of fruits and vegetables is often accompanied by the release of volatile organic compounds (VOCs) such as ethanol, ethylene, ammonia, hydrogen sulfide (H_2S), and carbon dioxide (CO_2) [4]. Metal-oxide semiconductor (MOS) chemiresistive gas sensors and electronic noses (e-noses), which combine multiple sensor arrays, have been widely employed to detect these gaseous markers [5].

Data from these sensors are typically analyzed using pattern recognition and machine learning algorithms, including Principal Component Analysis (PCA), Support Vector Machines (SVM), and Artificial Neural Networks (ANN), to classify freshness levels, ripeness stages, or soluble solids content [6]. While MOS sensors are valued for their low cost and high sensitivity, they also face challenges such as low selectivity, baseline drift, and cross-sensitivity to humidity and temperature [7]. These limitations necessitate careful calibration protocols and the use of advanced signal processing strategies [8].

5.2.3 Spectroscopic and Optical Methods

Spectroscopic and optical sensing methods provide nondestructive and highly accurate assessments of internal fruit and vegetable quality attributes that are invisible to external inspection. Near-infrared (NIR) spectroscopy, hyperspectral imaging, and fluorescence-based techniques are commonly used to estimate parameters such as soluble sugar content (SSC), dry matter, acidity, and internal defects [9]. While these methods deliver richer information compared to visual or gas sensors, they are relatively costly and often require controlled conditions. As a result, their application is more practical in centralized grading facilities, high-value produce chains, or shared-service models, rather than for low-margin commodities or smallholder farmers. Nevertheless, integration of portable and miniaturized spectrometers with IoT platforms is gaining traction, expanding their feasibility for decentralized deployment [10].

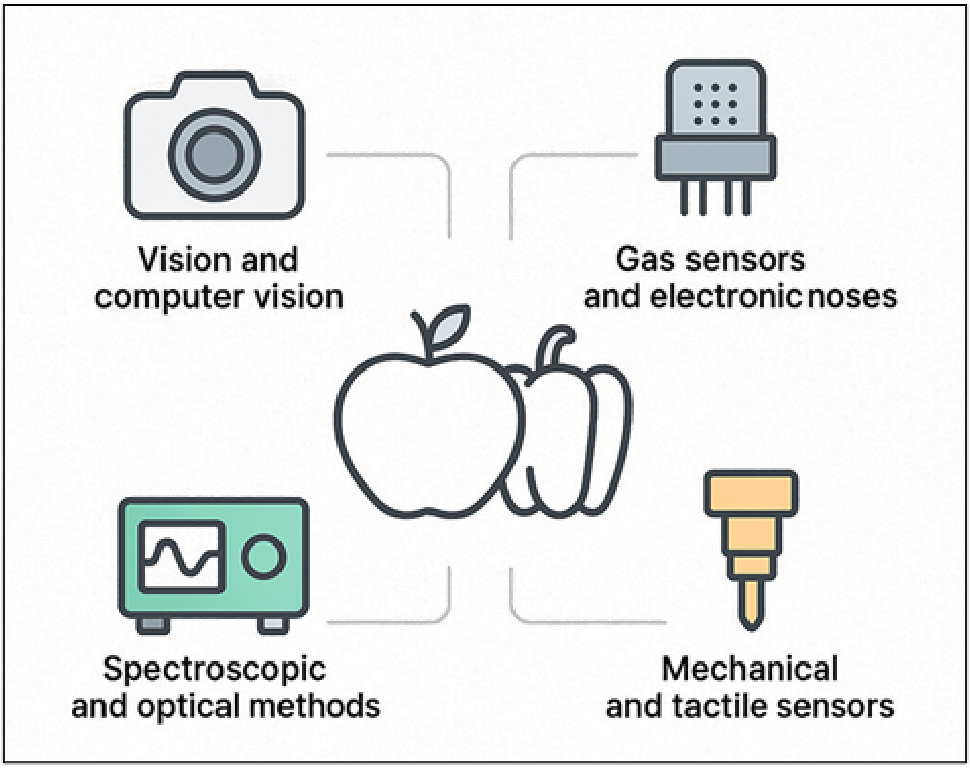

Figure 5.2: Sensing modalities for nondestructive quality assessment of fruits and vegetables

Figure 5.2 illustrates four primary sensing modalities applied in produce quality monitoring. Vision and computer vision techniques capture external features, while gas sensors and electronic noses detect volatile organic compounds linked to freshness. Spectroscopic and optical methods offer insights into internal quality parameters, including sugar and moisture content. Mechanical and tactile sensors assess firmness and texture, providing complementary information for a comprehensive nondestructive evaluation.

5.2.4 Mechanical and Tactile Sensors

Mechanical and tactile sensing methods provide objective measurements of textural properties such as firmness, elasticity, compression resistance, and acoustic response, all of which are strong indicators of ripeness and damage. Advanced prototypes utilize force sensors, piezoelectric actuators, and magneto-resistive tactile arrays to quantify these properties with high repeatability and accuracy.

When combined with visual and gas-sensing data, tactile measurements significantly improve the accuracy and reliability of classification models. Such multimodal fusion systems offer holistic assessment, capturing both external appearance and internal freshness indicators. Emerging IoT-enabled tactile sensors, designed as portable handheld probes or robotic grippers, further extend the scope of nondestructive quality monitoring in real-world settings (Frontiers).

5.3 IOT Architectures & Edge Design Patterns

The architecture of an IoT-enabled quality assessment device integrates sensing, edge processing, connectivity, and cloud intelligence into a unified framework. The design must strike a balance between accuracy, real-time decision-making, cost, and energy efficiency, depending on whether the application is for farm-level grading, cold-chain monitoring, or retail inspection [1], [2].

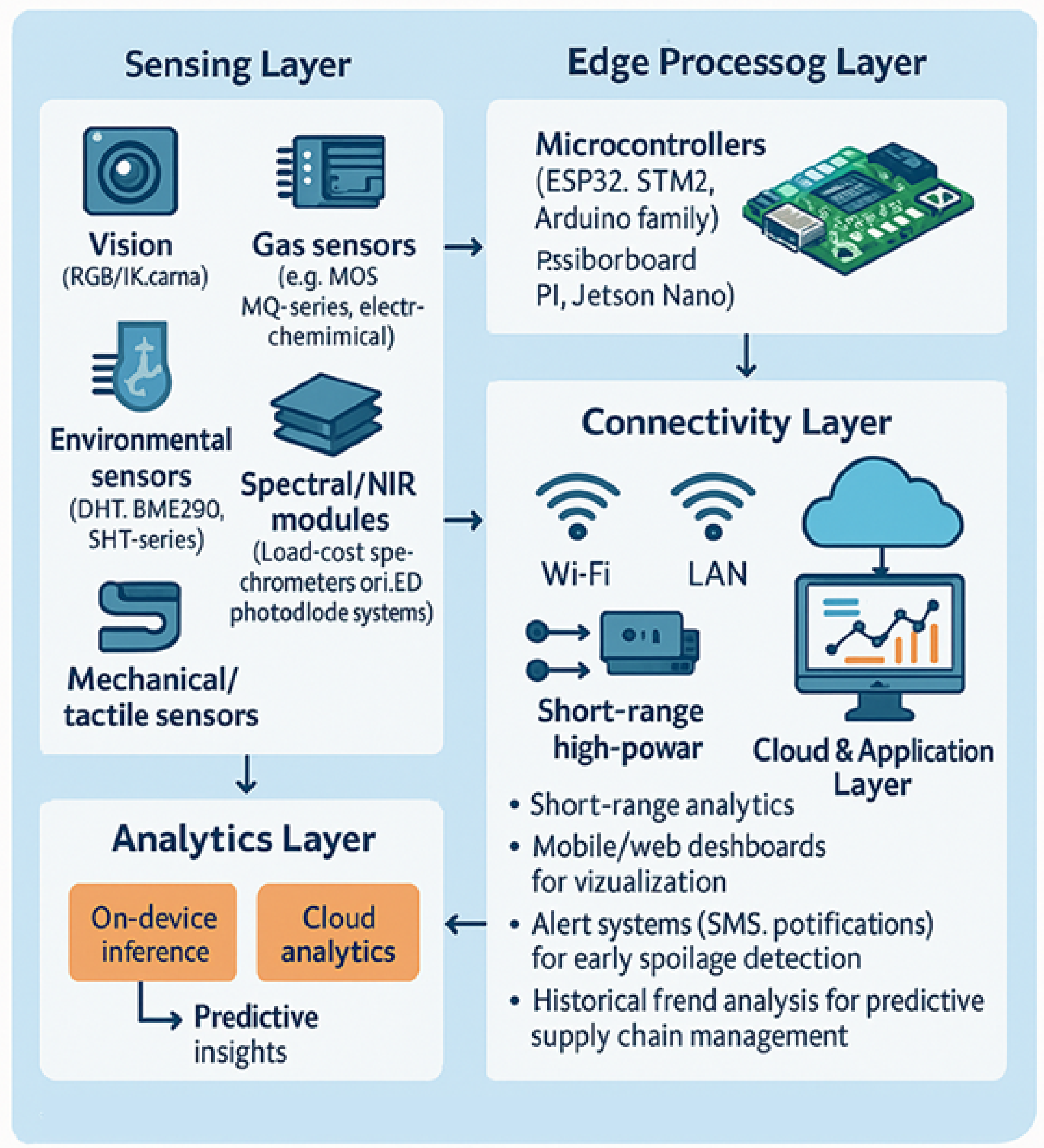

Figure 5.3: IoT architectures and edge design patterns for produce quality monitoring

Figure 5.3 depicts the multilayered architecture of IoT-enabled quality assessment systems, integrating sensing, edge processing, connectivity, cloud, and analytics components. The sensing layer collects multimodal data from various sensors, including vision, gas, environmental, spectral, and tactile sensors. Edge processors provide real-time inference, while connectivity protocols ensure data transfer under diverse deployment conditions. Cloud platforms manage storage, visualization, and alerts, complemented by analytics for model retraining and predictive insights. Together, these layers strike a balance between accuracy, cost, energy efficiency, and scalability to optimize farm-to-fork quality monitoring.

5.3.1 Core Components

Sensing Layer:

- The front-end sensors capture multimodal information related to quality attributes. Common components include:
- Vision sensors (RGB/IR cameras) for colour, shape, and surface texture analysis [3].
- Gas sensors (e.g., MOS, MQ-series, electrochemical) for ethylene, ammonia, CO_2, or ethanol detection [4].
- Environmental sensors (DHT, BME280, SHT-series) to measure temperature and humidity affecting freshness [5].
- Spectral/NIR modules (low-cost spectrometers or LED-photodiode systems) for nondestructive sugar or dry matter estimation [6].
- Mechanical/tactile sensors such as load cells, strain gauges, or piezoelectric elements to assess firmness and bruising [7].

Edge Processing Layer:
Microcontrollers (ESP32, STM32, Arduino family) or single-board computers (Raspberry Pi, Jetson Nano) process data locally. Modern MCUs with neural accelerators (e.g., Kendryte K210, ARM Cortex-M with TinyML support) enable efficient on-device inference of CNN or machine learning models [8].

Connectivity Layer:
Data is transmitted via communication protocols depending on the deployment context:

- Short-range, high bandwidth: Wi-Fi, BLE for packhouses, retail, and farms with infrastructure [9].
- Long-range, low-power: LoRaWAN, NB-IoT for field-level or cold-chain applications with limited connectivity [10].
- Hybrid setups: Gateways aggregate local data and forward it to cloud systems using MQTT or HTTP protocols [11].

Cloud & Application Layer:
Cloud servers (AWS IoT, Azure IoT Hub, Google Cloud IoT, or open-source platforms like Things Board and Thing Speak) provide:

Data storage and analytics.

- Mobile/web dashboards for visualization.

- Alert systems (SMS, push notifications) for early spoilage detection.
- Historical trend analysis for predictive supply chain management [2], [5].

Analytics Layer:

- On-device inference: Real-time grading and freshness assessment with low latency and minimal bandwidth [6], [8].
- Cloud analytics: Aggregated datasets enable retraining of models, trend analysis, and federated learning across distributed devices [9], [11].

5.3.2 Design Trade-offs

Designing an IoT-based fruit and vegetable quality device requires careful consideration of competing requirements [1], [2].

Edge vs Cloud Processing:
Edge benefits include lower latency, reduced data transmission, better privacy, and uninterrupted operation in low-connectivity zones [3]. Cloud benefits lie in supporting heavy computation for retraining ML models, centralized analytics, and model sharing across devices [4], [5].

Power Consumption:
Battery-powered systems, standard in transit and cold-chain logistics, require low-energy radios (LoRa, NB-IoT) and energy-efficient sampling [6]. Mains-powered setups, such as packhouses and warehouses, can support higher data rates and continuous sensing [7].

Cost vs Accuracy:
Low-cost sensors (MQ gas sensors, basic RGB cameras) provide affordable monitoring but require calibration, signal denoising, and advanced feature extraction [8]. High-end sensors (NIR spectrometers, hyperspectral cameras) deliver higher accuracy for biochemical attributes but may only be justified in centralized grading lines or premium produce applications [9], [10].

Scalability vs Customization:
Standardized IoT platforms enhance scalability, but domain-specific models (e.g., for mango ripeness versus tomato spoilage) often require custom datasets and fine-tuning [11].

5.4 Data Analytics and Machine Learning

Traditional machine-learning techniques—particularly principal component analysis (PCA), support-vector machines (SVM), and ensemble trees such as Random Forest—retain considerable utility for small or clearly structured datasets, owing to their efficient performance and the straightforward interpretability they afford [4], [5]. However, their predictive power tends to diminish as the structural complexity and noise density of the learning environment increase. By contrast, hierarchical architectures of deep learning, particularly convolutional neural networks (CNNs) such as YOLO and MobileNet, demonstrate superior capability in defect detection and classification, routinely attaining predictive accuracies exceeding 90% in controlled laboratory and field conditions [6], [7]. Techniques for model size reduction—including pruning, quantization, and the TinyML framework—facilitate the deployment of these models on edge devices such as smartphones and microcontrollers with minimal performance sacrifice [8]. The fusion of multimodal inputs—visual, gas, and spectroscopic—yields additional performance gains, although the integration process imposes increased computational and latency overhead [9]. Contemporary research directions also spotlight federated learning to enable collaborative, privacy-conserving model training that circumvents the transmission of sensitive data and self-supervised learning paradigms that leverage large, unlabeled corpora to enrich feature extraction without substantial labeling effort [10], [11].

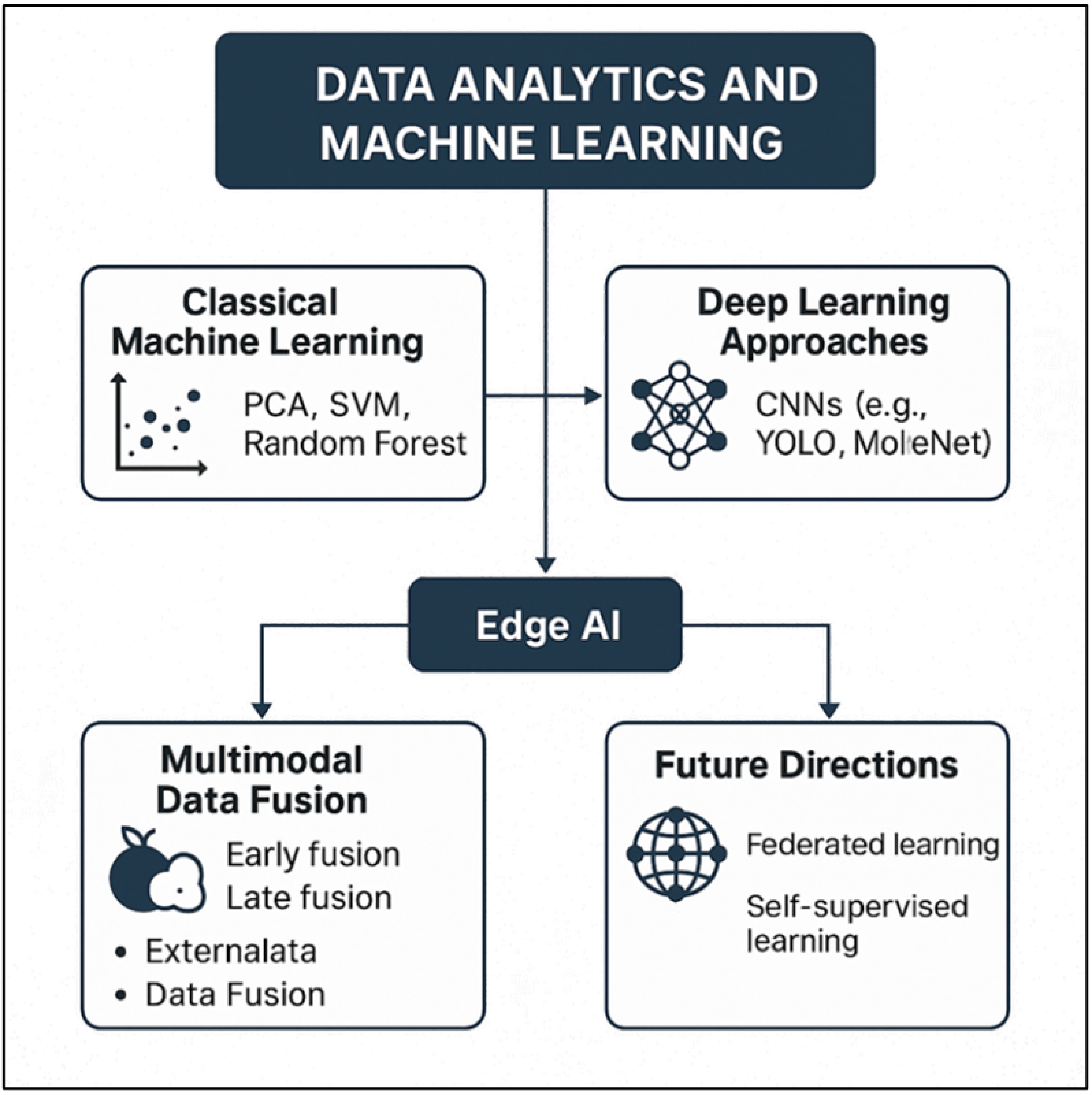

Figure 5.4: Data analytics and machine learning approaches for IoT-enabled produce quality monitoring

Figure 5.4 illustrates the role of data analytics and machine learning in fruit and vegetable quality assessment. Classical machine learning methods, such as PCA, SVM, and Random Forest, support the efficient analysis of small datasets. Deep learning approaches, such as CNNs, YOLO, and MobileNet, enable robust visual grading and edge deployment through model optimization. Multimodal data fusion and emerging trends, such as federated and self-supervised learning, enhance accuracy, scalability, and privacy in IoT-based monitoring systems.

5.4.1 Classical Machine Learning

Traditional ML methods such as Principal Component Analysis (PCA), Support Vector Machines (SVM), and Random Forests remain relevant in scenarios where datasets are limited or sensor signals are lower-dimensional [3]. For instance, electronic nose (e-nose) arrays producing volatile gas patterns, or handcrafted image descriptors (color histograms, texture features, shape descriptors), can be effectively analyzed with these algorithms [4]. Their advantages include interpretability, lower computational cost, and suitability for embedded processors with limited resources. However, performance may degrade in complex, unstructured environments where variability in produce type, lighting, or handling is high [5].

5.4.2 Deep Learning Approaches

In recent years, Convolutional Neural Networks (CNNs) have become the dominant choice for visual grading and defect detection [6]. Architectures such as YOLO and lightweight Mobile Net variants have demonstrated robust classification and localization capabilities in real-time applications [7]. These methods outperform classical approaches by automatically learning discriminative features, reducing the need for manual feature engineering [8].

Model Optimization: To enable deployment on low-power IoT edge devices, techniques like model pruning, quantization, and TinyML frameworks are widely adopted [9]. These strategies reduce memory footprint and inference time while maintaining acceptable accuracy.

Reported Performance: Studies have consistently shown high grading accuracies (>90%) when datasets are well curated and domain shifts (such as lighting changes, crop varieties, or camera differences) are minimized [10].

5.4.3 Multimodal Data Fusion

A key trend is the integration of multiple sensing modalities, such as combining visual data with gas or spectroscopic measurements [4]. This multimodal fusion allows systems to detect subtle internal defects, hidden bruises, or early microbial spoilage that are not visible externally [5].

Fusion Strategies:

Early fusion integrates raw or pre-processed features before feeding them into the model, enabling joint representation learning.

Late fusion combines predictions from separate models, offering flexibility when sampling rates or modalities differ [6].

Trade-offs: Early fusion often provides richer joint representations but can increase computational complexity. Late fusion is computationally lighter and resilient to missing modalities, though sometimes less accurate [7].

5.4.4 Future Directions

Emerging research highlights the importance of federated learning for collaborative model improvement across distributed IoT nodes, reducing data transfer while preserving privacy [8]. Moreover, self-supervised learning is gaining traction to leverage large amounts of unlabeled sensor data for pretraining, with downstream fine-tuning on smaller annotated datasets [11].

5.5 Representative Implementations & Case Studies

The integration of IoT and AI technologies in assessing the quality of fruits and vegetables has been demonstrated through multiple prototype systems and practical deployments [1], [2]. Key representative implementations include:

5.5.1 Low-Cost IoT Prototypes

Numerous studies report that Arduino/ESP8266-based systems, which combine DHT11/22 temperature-humidity sensors with MQ-series gas sensors, are used for spoilage detection and freshness monitoring [3]. Data transmission is often implemented through platforms such as ThingSpeak, Blynk, or Firebase, enabling real-time alerts and visualization [4]. These low-cost solutions are highly suitable for small warehouses, cold rooms, and retail refrigerators where budget constraints are a critical factor. However, sensor drift, calibration challenges, and cross-sensitivity limit long-term accuracy, necessitating periodic recalibration and advanced signal processing [5].

5.5.2 Edge AI Smartphone/Mobile Applications

Lightweight Convolutional Neural Network (CNN) architectures (e.g., MobileNet, EfficientNet-lite, YOLO-tiny) have been embedded in smartphone-based applications for real-time fruit and vegetable grading [6]. Farmers can capture images directly on mobile devices, enabling on-field classification without extra hardware. Research indicates >90% accuracy in class-specific grading (e.g., apple varieties, mango ripeness stages) when models are trained on large, curated datasets [7]. On-device inference ensures low latency and offline usability, making this approach highly attractive for smallholder farmers in regions with poor internet connectivity [8].

5.5.3 Supply-Chain Level Monitoring Systems

At the commercial scale, IoT-enabled trackers and loggers are deployed in crates, pallets, or shipping containers to continuously record temperature, humidity, and gas concentrations [9]. Data is transmitted periodically to cloud dashboards, enabling retailers, logistics operators, and wholesalers to assess storage conditions, predict shelf life, and proactively manage inventory [10]. Studies highlight the importance of optimizing battery life, measuring intervals, implementing data redundancy strategies, and tolerating intermittent connectivity for reliable deployment across long transit durations [11]. Such systems have been shown to significantly reduce post-harvest losses and improve cold-chain efficiency in perishable supply chains [2].

5.6 Practical Challenges

Ongoing challenges continue to hinder progress in low-label malodour monitoring technology. Metal-oxide semiconductor (MOS) sensors remain susceptible to drift and exhibit poor selectivity across chemical backgrounds, thereby undermining sustained operational reliability over an extended time horizon[3]. Concurrently, vision-based pipelines exhibit susceptibility to biases inherent in training datasets, which limits the transferability of neural network architectures across disparate cultivars, illuminative spectra, and background settings[6]. The Internet of Things (IoT) platforms themselves are constrained by energy budgets and intermittent connectivity, especially in off-grid rural environments[2]. Meanwhile, the prohibitive capital and operational costs of miniature-room-temperature and wavelength-modulated spectroscopy—when fused with machine-learning inference—leave smallholders without an economically viable monitoring solution[9]. System improvements to enable scalable deployment therefore demand comprehensive drift compensation, lightweight yet generalizable machine-learning architectures, and hardware platforms designed from the outset with cost, power, and ease of fabrication optimization [5], [8].

5.6.1 Sensor Selectivity and Drift

Metal-oxide semiconductor (MOS) gas sensors, widely used for detecting ripeness and spoilage markers, often suffer from cross-sensitivity to temperature and humidity fluctuations [4]. This leads to unstable readings over time and necessitates frequent recalibration. While advanced material engineering and pattern-recognition algorithms improve reliability, they cannot eliminate these maintenance requirements [5].

5.6.2 Dataset Biases and Generalization

Computer vision models trained on controlled laboratory datasets often perform poorly when exposed to real-world conditions, such as variable lighting, diverse backgrounds, or variations in fruit surface [6]. This domain shift limits scalability across farms and supply chains. Solutions such as domain adaptation, transfer learning, and creating large, diverse, and context-rich datasets are critical to enhancing generalization [7].

5.6.3 Power and Connectivity Constraints

IoT devices deployed in remote agricultural fields or during long-haul transport must operate under strict energy constraints [8]. Limited access to power sources and unreliable network coverage demand ultra-low-power designs, energy harvesting, and robust store-and-forward communication strategies to prevent data loss [9].

5.6.4 Integration and Cost Factors

High-end sensing systems, especially those based on spectroscopy (NIR, hyperspectral imaging), provide richer and more reliable data compared to low-cost alternatives [10]. However, their high purchase and maintenance costs hinder large-scale adoption in smallholder and resource-limited contexts. Practical deployment often requires clear demonstrations of return on investment (ROI), cooperative ownership models, or hybrid approaches that combine low-cost sensors with selective high-end validation [11].

5.7 Future Directions

5.7.1 Edge AI and Tiny-ML

The miniaturization of AI models through compression, pruning, and hardware acceleration is expected to enable on-device grading and multimodal fusion further. Such approaches allow real-time decision-making directly at the farm or storage site, eliminating the need for high-bandwidth connectivity and reducing latency. This trend is particularly relevant for resource-constrained agricultural environments, where cloud access may be unreliable.

5.7.2 Federated Learning and Privacy-Aware Model Updates

Federated learning frameworks are emerging as a practical way to update and improve models across multiple stakeholders without centralizing raw data. By sharing only model parameters, farmers, cooperatives, and retailers can collectively benefit from improved performance while ensuring data privacy and ownership. This is especially useful in supply-chain ecosystems where sensitive operational data cannot be easily shared.

5.7.3 Digital Twins and Predictive Shelf-Life Modeling

The integration of IoT sensor streams with digital twin frameworks and predictive models for shelf life is gaining momentum. By simulating quality decline under varying conditions, these tools can provide actionable insights for optimizing routing, storage, and distribution strategies, thereby minimizing losses and improving consumer satisfaction.

5.7.4 Advanced Sensing Materials

Research into organic/inorganic nanomaterials, selective coatings, and hybrid composites is addressing the longstanding limitations of MOS gas sensors, particularly their issues with selectivity and high-temperature operation. Next-generation materials aim for room-temperature stability, faster response times, and enhanced resistance to environmental cross-sensitivity, enabling more accurate detection of spoilage and defects.

5.7.5 Sustainable Hardware Design

Beyond software and sensing innovations, sustainability in hardware design is gaining equal importance. Future IoT nodes are envisioned as modular, repairable, and energy-harvesting systems, capable of extending their lifespan and minimizing electronic waste in agricultural deployments. Incorporating solar, kinetic, or RF energy harvesting can further enhance self-sufficiency, reducing dependence on frequent battery replacement in remote or large-scale field deployments.

5.8 Conclusion

IoT-integrated quality-checking devices for fruits and vegetables have evolved into multimodal systems that merge environmental monitoring, electronic noses, computer vision, and embedded AI. Their practical deployment is shaped by trade-offs in cost, energy efficiency, connectivity, and robustness. Looking ahead, broader adoption is likely to be driven by edge AI, federated learning, and next-generation sensing materials, which together promise to reduce food waste and enhance decision-making throughout the supply chain.

For large-scale impact, however, emphasis must be placed on real-world trials, standardized calibration protocols, diverse and representative datasets, and sustainable hardware design. By addressing these challenges, IoT-enabled quality assessment systems can play a crucial role in ensuring food safety, reducing post-harvest losses, and empowering stakeholders in the agricultural and retail sectors.

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