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Innovations in post-harvest disease detection: From molecular diagnostics to AI-based imaging

Abdelhak RHOUMA

Regional Centre of Agricultural Research of Sidi Bouzid, Sidi Bouzid, Tunisia

Post-harvest diseases are a major contributor to global food losses, accounting for 20-50% of perishable crops, thereby threatening food security and economic stability. Traditional disease detection methods, such as visual inspection and microbiological culturing, are often slow, subjective, and lack the sensitivity needed for early pathogen identification. Recent advancements in biotechnology and computational analytics have introduced transformative solutions, including molecular diagnostics, spectroscopic techniques, and artificial intelligence-powered imaging systems. Molecular methods such as polymerase chain reaction, loop-mediated isothermal amplification, and CRISPR-based assays enable rapid and precise pathogen detection at the genetic level. Meanwhile, non-destructive technologies like near-infrared spectroscopy and hyperspectral imaging capture biochemical and morphological changes in produce, allowing for real-time monitoring. AI and machine learning further enhance these approaches by automating disease recognition through deep learning models such as convolutional neural networks, improving accuracy and scalability. This review comprehensively examines these innovations, discussing their principles, applications, advantages, and current limitations. Additionally, it explores future trends, including the integration of multi-modal detection systems and edge computing for on-site diagnostics. By leveraging these cutting-edge technologies, the agricultural sector can significantly reduce post-harvest losses, enhance food safety, and optimize supply chain efficiency.

Keywords: polymerase chain reaction, loop-mediated isothermal amplification, CRISPR, hyperspectral imaging, near-infrared spectroscopy, artificial intelligence, machine learning, deep learning, convolutional neural networks, food security, pathogen detection, non-destructive testing

INTRODUCTION

Food security remains a critical global challenge, with post-harvest losses due to microbial spoilage, fungal infections, and physiological deterioration accounting for an estimated 20–50% of perishable crops worldwide (Taha et al., 2025). These losses not only reduce the availability of nutritious food but also contribute to significant economic waste, particularly in developing regions where storage and transportation infrastructure are inadequate. The primary culprits of post-harvest decay include fungal pathogens such as Botrytis cinerea, Penicillium expansum, and Aspergillus flavus, as well as bacterial and viral agents that thrive in storage conditions (González-Rodríguez et al., 2024). Traditional methods for detecting these pathogens—such as visual inspection, culturing on selective media, and biochemical assays—are often labor-intensive, time-consuming, and limited in sensitivity. Moreover, these techniques frequently fail to identify infections at early stages when interventions could still mitigate damage (Petcu et al., 2024).

The growing demand for sustainable food systems has driven the development of innovative diagnostic tools that offer rapid, accurate, and non-destructive detection of post-harvest diseases. Among these, molecular diagnostics—including polymerase chain reaction, quantitative PCR, loop-mediated isothermal amplification, and CRISPR-based systems—have revolutionized pathogen identification by enabling high-throughput, species-specific detection at the genomic level (Yuan et al., 2022; Mellikeche et al., 2024; Vo and Trinh, 2025). These methods significantly reduce diagnostic time while improving precision compared to conventional techniques (Hasanaliyeva et al., 2022). Parallel advancements in optical sensing technologies, such as near-infrared spectroscopy and hyperspectral imaging, allow for real-time, non-invasive monitoring of produce by detecting subtle biochemical and structural changes associated with disease (Zhang et al., 2019).

Perhaps the most transformative development in recent years has been the integration of artificial intelligence and machine learning into post-harvest disease detection (Yan et al., 2023). Deep learning algorithms, particularly convolutional neural networks, can analyze vast datasets from imaging and spectral sensors to classify disease symptoms with high accuracy (Nikzadfar et al., 2024). AI-powered systems are increasingly being deployed in smart storage facilities, where they combine environmental data (e.g., temperature, humidity) with real-time imaging to predict and prevent outbreaks (Botero-Valencia et al., 2025). Despite these advancements, challenges remain in making these technologies accessible to small-scale farmers and integrating them into existing supply chains (Ali et al., 2025). This review explores the evolution of post-harvest disease detection, from foundational molecular techniques to next-generation AI-driven solutions, while addressing current limitations and future opportunities for reducing global food waste.

MOLECULAR DIAGNOSTICS IN POST-HARVEST DISEASE DETECTION

The advent of molecular diagnostics has revolutionized post-harvest disease detection by enabling precise, rapid, and sensitive identification of pathogens at the genetic level. These techniques have largely supplanted traditional culture-based methods by offering species-specific detection, even in latent or early-stage infections where visual symptoms are absent. Among the most impactful molecular tools are polymerase chain reaction (PCR)-based methods, isothermal amplification techniques like LAMP, and the emerging CRISPR-based detection systems, each offering unique advantages for different post-harvest applications (Khadiri et al., 2024).

Polymerase Chain Reaction (PCR) and Quantitative PCR (qPCR)

PCR and its quantitative counterpart (qPCR) remain gold-standard methods for detecting post-harvest pathogens due to their exceptional sensitivity and specificity. These techniques amplify target DNA sequences unique to pathogens, allowing for the identification of fungal species like Botrytis cinerea (gray mold) in berries or Penicillium digitatum (citrus green mold) at concentrations as low as a few femtograms (Kabir et al., 2020). qPCR further enhances this capability by providing real-time quantification of pathogen load through fluorescent probes, enabling not just detection but also assessment of infection severity (Chen et al., 2022). For instance, qPCR assays targeting the β-tubulin gene of Colletotrichum species have been successfully used to monitor anthracnose development in mangoes during storage (Radomirović et al., 2025). However, these methods require sophisticated thermocycling equipment, DNA extraction protocols, and skilled personnel, limiting their use in field settings. Recent innovations like portable PCR systems and rapid DNA extraction kits are helping bridge this gap, making molecular diagnostics more accessible for point-of-need testing in packinghouses and storage facilities (Vo and Trinh, 2025).

Loop-Mediated Isothermal Amplification (LAMP)

LAMP has emerged as a powerful alternative to PCR, particularly for decentralized post-harvest disease monitoring. Unlike PCR, which requires thermal cycling, LAMP operates at a constant temperature (60–65°C) and can amplify DNA with high efficiency using just a heating block or water bath (Aglietti et al., 2024). This simplicity, combined with visual readouts (e.g., color changes from fluorescent dyes or turbidity), makes LAMP ideal for field applications. For example, LAMP assays targeting the polygalacturonase gene of Aspergillus flavus can detect aflatoxin-producing strains in peanuts within 30 min, significantly faster than traditional culturing (Mellikeche et al., 2024). Similarly, LAMP-based kits for Fusarium species in grains enable rapid on-site screening to prevent mycotoxin contamination during storage (Liu et al., 2022). Despite these advantages, LAMP can suffer from non-specific amplification if primer design is suboptimal, and its multiplexing capability (detecting multiple pathogens simultaneously) remains inferior to qPCR. Ongoing improvements in primer design and the integration of portable fluorescence detectors are addressing these limitations, expanding LAMP's utility in post-harvest pathogen surveillance (Bani et al., 2024).

CRISPR-Based Detection

The CRISPR-Cas system, renowned for its gene-editing capabilities, has been repurposed into a groundbreaking diagnostic tool for post-harvest diseases. Platforms like SHERLOCK (Specific High-sensitivity Enzymatic Reporter unLOCKing) and DETECTR (DNA Endonuclease Targeted CRISPR Trans Reporter) utilize CRISPR-associated enzymes (e.g., Cas12, Cas13) to cleave pathogen-specific nucleic acids, triggering fluorescent or lateral flow signals for easy interpretation (Xie et al., 2024). These systems combine the sensitivity of PCR with the simplicity of lateral flow tests, enabling ultrasensitive detection without complex instrumentation. For instance, CRISPR-Cas12 assays have been developed to identify Phytophthora infestans (potato late blight) in stored tubers with 10-fold greater sensitivity than conventional PCR (Yuan et al., 2022). Another breakthrough is the detection of Xanthomonas species in citrus fruits using CRISPR-based lateral flow strips, which provide results in under an hour with minimal training required. While CRISPR diagnostics are still in the early stages of commercialization, their potential for low-cost, high-accuracy field-testing is immense (Son, 2024). Current challenges include optimizing sample preparation for complex produce matrices and ensuring stability of reagents in varying climates—hurdles that are being actively addressed through lyophilized reagent formulations and integrated microfluidic devices (Farinati et al., 2024).

Synthesis and Future Directions

Molecular diagnostics have undeniably transformed post-harvest disease management, yet each technique presents a trade-off between accuracy, speed, and deployability. While PCR/qPCR remains the benchmark for lab-based confirmation, LAMP and CRISPR are paving the way for decentralized testing. Future innovations may focus on integrating these methods with automated sample processing and IoT-enabled devices to create end-to-end diagnostic systems for smart agriculture (Hernandez-Montiel et al., 2021). For example, combining LAMP's speed with CRISPR's specificity could yield next-generation assays for simultaneous detection of multiple pathogens in stored crops (Zhang et al., 2019; Hasanaliyeva et al., 2022). As these technologies mature, their adoption will hinge on cost reduction, user-friendly design, and validation across diverse crops and storage conditions—key steps toward minimizing global post-harvest losses (Hasanaliyeva et al., 2022; Moradinezhad and Ranjbar, 2023).

SPECTROSCOPY AND HYPERSPECTRAL IMAGING IN POST-HARVEST DISEASE DETECTION

The limitations of traditional destructive testing methods have driven significant innovation in optical sensing technologies for post-harvest quality control. Spectroscopy and hyperspectral imaging represent a paradigm shift in disease detection, offering rapid, non-contact, and non-destructive analysis of produce by capturing the unique biochemical fingerprints associated with pathogen infection (García-Vera et al., 2024). These techniques leverage the interaction between light and matter to detect subtle physiological changes that precede visible symptoms, enabling early intervention to prevent spoilage spread in storage facilities (Wan et al., 2022).

Near-Infrared (NIR) and Raman Spectroscopy

NIR spectroscopy (750-2500 nm) has emerged as a powerful tool for post-harvest disease management due to its ability to probe molecular vibrations of C-H, O-H, and N-H bonds in organic compounds. This technique detects disease-induced changes in carbohydrate, protein, and water content that occur during pathogen colonization (Yan et al., 2023). For instance, NIR has successfully differentiated sound and Fusarium-infected wheat kernels with >90% accuracy by identifying characteristic spectral shifts at 1200 nm and 1450 nm associated with starch degradation (Sohn et al., 2021). Portable NIR devices are now being integrated into sorting lines to automatically reject infected apples showing early signs of Penicillium rot based on their altered spectral profiles (Kasampalis et al., 2024).

Raman spectroscopy complements NIR by providing molecular specificity through inelastic scattering of monochromatic light. Its ability to detect vibrational modes of specific functional groups makes it particularly valuable for identifying fungal metabolites and toxins (Saletnik et al., 2024). Recent studies have demonstrated Raman's capability to detect Aspergillus flavus contamination in maize kernels at aflatoxin concentrations as low as 10 ppb by tracking signature peaks of fungal ergosterol at 1602 cm^{-1} (Yan et al., 2023). While traditionally limited by weak signals, advancements in surface-enhanced Raman spectroscopy (SERS) using nanoparticle substrates have improved sensitivity by 10^6-fold, enabling detection of single bacterial cells in produce wash water (Huang et al., 2025).

Hyperspectral Imaging (HSI)

HSI represents the convergence of spectroscopy and digital imaging, providing both spatial and spectral information across hundreds of contiguous wavelength bands. This technology creates chemical maps of produce surfaces where disease symptoms manifest first (García-Vera et al., 2024). In wheat, HSI in the 400-1000 nm range can distinguish harmless stem scars from early decay lesions caused by Fusarium pseudograminearum by analyzing chlorophyll absorption features at 675 nm and water content variations at 970 nm (Xie et al., 2021). Modern systems capture this data at speeds exceeding 100 fruits per minute, making the technology viable for commercial packing operations (Nikzadfar et al., 2024).

The true power of HSI emerges when combined with machine learning. Deep learning algorithms trained on spectral libraries can automatically classify multiple disease states in stored potatoes by recognizing complex patterns across spectral bands (Vignati et al., 2023). For example, convolutional neural networks processing 240-band HSI data achieve 97% accuracy in discriminating between late blight and dry rot infections based on their distinct spectral signatures in the 1000-2500 nm range. Recent innovations include portable HSI cameras that connect to smartphones, enabling real-time field diagnostics by comparing crop spectra against cloud-based disease databases (García-Vera et al., 2024; Nikzadfar et al., 2024).

Implementation Challenges and Future Outlook

While spectroscopic methods show tremendous promise, several barriers hinder widespread adoption (García-Vera et al., 2024). NIR systems struggle with moisture interference in high-humidity storage environments, while Raman requires careful calibration to avoid fluorescence background in pigmented produce (Kasampalis et al., 2024). HSI faces data dimensionality challenges, with single scans generating terabytes of information that demand sophisticated compression algorithms for practical use (García-Vera et al., 2024). Emerging solutions include:

- Hybrid systems combining NIR and Raman for cross-validated results.

- On-chip spectral sensors that reduce HSI system costs.

• Edge computing devices that preprocess spectral data before cloud transmission.

The next generation of spectroscopic tools will likely integrate with blockchain systems to create immutable quality records throughout the supply chain. As these technologies become more affordable and user-friendly, they will transform post-harvest disease management from reactive to predictive, potentially reducing global food losses by 30-40% in the coming decade (Huang et al., 2025). Future research should focus on developing universal spectral libraries for major crop-pathogen combinations and optimizing systems for use in developing country contexts where post-harvest losses are most severe.

AI AND MACHINE LEARNING IN POST-HARVEST DISEASE DETECTION

The integration of artificial intelligence (AI) and machine learning (ML) has revolutionized post-harvest disease detection by enabling automated, high-throughput, and increasingly precise identification of pathological conditions in stored crops (Botero-Valencia et al., 2025). These advanced computational approaches are transforming traditional quality control paradigms from subjective human visual inspection to objective, data-driven decision systems capable of detecting subtle disease indicators long before they become visible to the naked eye (Ngugi et al., 2024). The synergy between AI algorithms and modern sensor technologies is creating smart detection systems that not only identify existing infections but also can predict disease outbreaks based on environmental and physiological parameters, fundamentally changing how we approach post-harvest management (González-Rodríguez et al., 2024; Ali et al., 2025).

Deep Learning for Image Analysis

Deep learning architectures, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in analyzing visual data for disease detection (Wang et al., 2025). These algorithms excel at extracting hierarchical features from images, enabling them to distinguish between healthy tissue and various disease manifestations with human-level or superior accuracy. Modern implementations use multi-spectral imaging systems coupled with deep learning to detect early fungal infections in apples by identifying subtle changes in surface texture and spectral reflectance patterns that precede visible rot (Lee et al., 2023). For instance, a ResNet-50 architecture trained on 50,000 images of citrus fruits achieved 98.7% accuracy in differentiating between harmless blemishes and early citrus canker lesions, a task that even experienced graders struggle. Transfer learning approaches, where pre-trained models like VGG16 or EfficientNet are fine-tuned with smaller agricultural datasets, have proven particularly effective in overcoming data scarcity challenges common in post-harvest applications (Lee et al., 2024; Wang et al., 2025). Recent innovations include 3D CNN models that analyze temporal sequences of produce images to track disease progression in stored potatoes, enabling dynamic risk assessment throughout the storage period (Petcu et al., 2024). However, these systems face challenges including the need for large, diverse training datasets that account for varietal differences, environmental conditions, and the full spectrum of possible disease presentations (Opara et al., 2024).

IoT and Smart Sensors

The Internet of Things (IoT) ecosystem in post-harvest management combines distributed sensor networks with AI analytics to create responsive storage environments that actively prevent disease outbreaks (Kiobia et al., 2023; Ali et al., 2025). Modern smart warehouses deploy arrays of wireless sensors that continuously monitor critical parameters including temperature, humidity, ethylene concentration, CO_2 levels, and volatile organic compounds (VOCs) that serve as early chemical markers of pathogen activity (Tekeste et al., 2024). For example, metal-oxide semiconductor sensors can detect specific VOC fingerprints emitted by Fusarium-infected grains at concentrations as low as 1 ppm, triggering ventilation systems before visible mold appears. Edge AI devices installed directly in storage facilities process this sensor data in real-time using lightweight machine learning models, enabling immediate response without cloud dependency (Mahapatro et al., 2024; Platero-Horcajadas et al., 2024). A notable implementation involves piezoelectric sensors that detect the acoustic signatures of insect activity in stored grains, with recurrent neural networks (RNNs) classifying species based on their unique feeding vibrations (Orchi et al., 2022). The integration of blockchain technology with these IoT systems creates immutable records of storage conditions and quality assessments throughout the supply chain, enhancing traceability and compliance (Masood et al., 2023). Current research focuses on developing self-powered sensors using energy harvesting technologies and federated learning approaches that allow multiple facilities to collaboratively improve disease prediction models without sharing sensitive operational data (Nauman et al., 2023; Wang et al., 2025).

Implementation Challenges and Future Directions

While AI-driven systems offer tremendous potential, several technical and practical hurdles must be addressed for widespread adoption. The black-box nature of many deep learning models creates trust barriers among growers and regulators, prompting research into explainable AI techniques that provide interpretable decision rationales (Ali et al., 2025). Energy requirements for continuous IoT operation in remote storage locations drive innovation in low-power chips and energy harvesting solutions (Tekeste et al., 2024). Perhaps most critically, the development of standardized protocols for data collection and model validation across different crops and storage conditions remains an ongoing challenge (Wang et al., 2025). Future systems will likely incorporate digital twin technology, creating virtual replicas of storage facilities that simulate disease spread under various conditions to optimize intervention strategies. As 5G networks expand, real-time holographic imaging combined with AI analysis may enable remote quality assessment of stored crops with unprecedented detail. The convergence of these technologies promises to transform post-harvest disease management from a reactive process to a predictive, precision science capable of dramatically reducing global food losses while improving safety and quality throughout the supply chain (Petcu et al., 2024).

CHALLENGES AND FUTURE PERSPECTIVES IN POST-HARVEST DISEASE DETECTION TECHNOLOGIES

The remarkable advancements in post-harvest disease detection technologies, while transformative, face several critical challenges that must be addressed to achieve widespread adoption and maximize their impact on global food security (Yuan et al., 2024). Current limitations span technical, economic, and implementation barriers that hinder the transition from research prototypes to practical, scalable solutions (Palumbo et al., 2022). One of the most pressing technical challenges lies in the variability of produce characteristics across different cultivars, growing conditions, and storage environments, which can significantly affect the accuracy of both molecular and imaging-based detection systems (Hasanaliyeva et al., 2022). For instance, spectral signatures used in hyperspectral imaging may vary substantially between apple varieties, requiring extensive recalibration of machine learning models for different agricultural contexts (Wang et al., 2025). Similarly, molecular diagnostic techniques often struggle with inhibitor compounds present in certain produce that interfere with DNA amplification, necessitating the development of more robust sample preparation methods (Fang and Ramasamy, 2015). The high computational requirements of advanced AI algorithms also pose practical constraints, particularly in resource-limited settings where access to high-performance computing infrastructure is limited (Lebrini and Ayerdi Gotor, 2024; Khan et al., 2025). Economic barriers are equally significant, as many cutting-edge detection systems remain prohibitively expensive for small-scale farmers and developing economies where post-harvest losses are most acute (Portela et al., 2024).

Looking toward the future, several promising directions emerge to overcome these challenges and enhance the effectiveness of post-harvest disease management systems (Buja et al., 2021). The integration of multi-modal detection approaches that combine the strengths of molecular diagnostics, spectroscopic analysis, and AI-powered imaging represents a particularly promising avenue (Taha et al., 2025). Such hybrid systems could leverage nucleic acid detection for specific pathogen identification while using hyperspectral imaging for rapid, non-destructive screening of large produce volumes (Ljubobratović et al., 2022). Advances in edge computing and miniaturized sensor technologies are paving the way for truly portable diagnostic devices that can perform complex analyses directly in storage facilities or packing houses without requiring specialized laboratory infrastructure (Cano Marchal et al., 2021). The development of standardized, crop-specific spectral libraries and molecular marker databases would significantly reduce the calibration burden for new implementations, while federated learning approaches could enable continuous improvement of AI models across different facilities without compromising data privacy (Zhang et al., 2020; Taha et al., 2025). Another critical future direction involves the creation of closed-loop systems that not only detect diseases but also automatically trigger appropriate interventions, such as targeted antifungal treatments or adjusted storage conditions (Silva et al., 2025). Perhaps most importantly, future research must focus on making these technologies more accessible through cost-reduction strategies, simplified user interfaces, and localized training programs to ensure they reach the stakeholders who need them most (Orchi et al., 2023; He et al., 2025). As these innovations mature, they hold the potential to transform post-harvest management from a reactive process to a predictive, precision-based system capable of dramatically reducing global food waste while improving food safety and quality throughout the supply chain (Nturambirwe et al., 2021). The coming decade will likely see these technologies move from experimental settings to widespread commercial implementation, provided that researchers, industry stakeholders, and policymakers collaborate to address the existing barriers to adoption (Ouhami et al., 2021).

CONCLUSIONS

Post-harvest diseases remain a formidable challenge to global food security, contributing to substantial economic losses and decreased nutritional availability, particularly in developing regions where storage infrastructure is limited. However, the past decade has witnessed remarkable advancements in detection technologies that are transforming how we identify and manage post-harvest pathogens. Molecular diagnostics, including PCR, LAMP, and CRISPR-based systems, have enabled rapid, sensitive, and specific pathogen detection at the genetic level, overcoming many limitations of traditional culturing methods. Meanwhile, spectroscopic techniques such as NIR and hyperspectral imaging provide non-destructive, real-time monitoring of biochemical changes in produce, facilitating early disease identification before visible symptoms appear. The integration of artificial intelligence and machine learning has further enhanced these approaches, automating disease recognition through deep learning models and enabling predictive analytics via IoT-enabled smart storage systems. These innovations collectively represent a paradigm shift from reactive to proactive post-harvest management, with the potential to significantly reduce food waste and improve supply chain efficiency.

Despite these advancements, challenges remain in making these technologies universally accessible, particularly for smallholder farmers and low-resource settings. Issues such as high costs, technical complexity, and the need for crop-specific calibration must be addressed to ensure equitable adoption. Future research should focus on developing affordable, user-friendly devices that combine multiple detection modalities—such as molecular assays with spectral imaging—while leveraging edge computing for real-time decision-making in the field. Additionally, the creation of open-access databases for pathogen signatures and standardized protocols will be crucial for widespread implementation. As these technologies mature, their integration with blockchain for traceability and digital agriculture platforms for holistic farm-to-table quality control will further enhance their impact. The continued collaboration between researchers, industry stakeholders, and policymakers will be essential to translate these innovations into practical solutions that benefit the entire food supply chain. By harnessing the power of modern diagnostics, AI-driven analytics, and smart storage technologies, the agricultural sector can move closer to achieving sustainable food systems with minimized post-harvest losses, ensuring food security for future generations.

Ultimately, the fight against post-harvest diseases is not just a technological challenge but a global imperative. The innovations discussed in this review—from portable molecular tools to AI-powered imaging systems—demonstrate that solutions are within reach. With concerted effort and investment, these cutting-edge technologies can be scaled to create a transformative impact, reducing waste, improving food safety, and securing the global food supply in an era of climate uncertainty and growing population demands. The future of post-harvest management lies in smart, precise, and accessible detection systems, and the progress made thus far provides a strong foundation for the road ahead.

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