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The Future of Food Processing Efficiency: Leveraging AI to Predict and Prevent Machine Failures in Agro-Food Industries

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ABSTRACT

Unplanned machine breakdowns resulting from overreliance on corrective maintenance represent one of the most significant operational challenges in agro-food processing industries. This review examines the transformative potential of artificial intelligence (AI) and machine learning (ML) in transitioning agro-food processing facilities from reactive corrective maintenance to proactive AI-driven predictive maintenance (AI-PdM). A structured review of peer-reviewed literature published between 2019 and 2025 was conducted across the Scopus, Web of Science, and Google Scholar databases using defined inclusion and exclusion criteria, yielding 24 articles that directly informed the findings. Key AI algorithms reviewed include Random Forest, Long Short-Term Memory (LSTM) neural networks, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Gradient Boosting, and hybrid AI models, demonstrating predictive accuracy ranges of 85-96% in agro-food processing equipment failure prediction. An original three-layer AI-PdM Framework is proposed, comprising a sensor data collection layer, an AI/ML processing engine layer, and a decision and action output layer, linked by a continuous learning feedback loop. Evidence synthesised from empirical studies and industry benchmarks suggests that AI-PdM adoption has the potential to reduce unplanned downtime by up to 70% and lower maintenance costs by approximately 40% in comparable manufacturing contexts, with positive return on investment projected within three years based on normalised industry cost models; actual outcomes will vary by facility scale, equipment type, and baseline maintenance conditions. The review concludes that agro-food processing industries should prioritise IoT sensor integration, invest in AI-literacy training for maintenance personnel, and engage policy makers to develop supportive agricultural engineering technology frameworks.

Keywords: *Agro-Food processing, Artificial intelligence, Corrective maintenance, Machine failure prediction, Predictive maintenance.*

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INTRODUCTION

Agro-food processing industries occupy a critical position in global food supply chains, converting primary agricultural commodities such as grains, tubers, fruits, vegetables, and livestock products into processed foods that sustain populations worldwide. The uninterrupted operation of processing machinery is therefore not merely an industrial efficiency concern but a food security imperative. Yet across the sector, unplanned machine breakdowns and production downtime remain persistent and costly challenges. Siemens (2024) reported that unplanned downtime costs Fortune Global 500 companies an estimated 11% of their annual revenues, while the average industrial facility loses 25 hours per month to equipment failures. For agro-food processing operations handling perishable raw materials under strict hygiene and time constraints, every hour of unplanned downtime translates not only into financial loss but into irreversible product spoilage, food safety risk, and regulatory liability (Tekon Electronics, 2022).

The root cause of this challenge in many agro-food facilities, particularly in developing economies, is an overreliance on corrective maintenance (CM), a reactive practice that repairs machinery only after a failure occurs. While CM requires no upfront monitoring infrastructure, it is economically irrational: industry data indicates that one dollar invested in preventive maintenance saves five dollars in downstream repair and downtime costs, while unplanned downtime alone costs industries an average of $260,000 per hour (UpKeep, 2023; Infraspeak, 2024). The compounding consequences for perishable food production make the corrective maintenance paradigm particularly damaging in agro-food contexts, where a production line stoppage can destroy in-process raw material stocks that cannot be preserved until equipment is restored (Tekon Electronics, 2022).

Artificial intelligence (AI) and machine learning (ML) offer a paradigm-shifting solution: AI-driven predictive maintenance (AI-PdM), which leverages real-time sensor data, historical failure records, and advanced algorithms to forecast equipment failures before they occur, enabling targeted and cost-effective interventions that eliminate unplanned downtime. The global predictive maintenance market, valued at $5.5 billion USD in 2022, is projected to grow at a compound annual growth rate of 17% through 2028, driven primarily by the adoption of Internet of Things (IoT) sensors and the maturation of AI model (IoT Analytics, 2022). Yet Zatsu *et al.* (2024) and Kumar *et al.* (2021) both identified food manufacturing as a sector where AI-PdM research and practical implementation remain significantly underdeveloped relative to their potential, particularly when compared to automotive, energy, and aerospace industries.

Several foundational studies frame this review. Carvalho *et al.* (2019) conducted a systematic review of 127 ML papers applied to predictive maintenance across industries, establishing benchmark accuracy ranges and identifying time-series recurrent neural networks as the strongest architecture for degradation monitoring. Hector and Panjanathan (2024) extended this with a scoping review of 87 papers published between 2018 and 2023, reporting predictive accuracy of 85-94% for supervised classification tasks and confirming vibration-based sensing as the dominant data modality. Konur *et al.* (2023) provided the most directly relevant case

study, documenting the transformation of a small food processing enterprise into an Industry 4.0-enabled facility using IoT sensors and AI-PdM without replacing existing machinery, thereby establishing that AI-PdM is achievable even in resource-constrained agro-food SME contexts. Ucar *et al.* (2024) demonstrated the superiority of CNNs for vibration signal classification in bearing fault detection, achieving 94% accuracy across equipment types directly comparable to those in food processing machinery, including motors, conveyor drives, and milling units. Zonta *et al.* (2020), in a widely cited systematic literature review of 187 predictive maintenance studies across Industry 4.0 sectors, corroborated the rapid maturation of AI-based PdM methods and documented the multidisciplinary convergence of computer science and engineering that underpins contemporary AI-PdM systems. These studies collectively confirm that the technical foundations for AI-PdM in agro-food processing are wellestablished; what remains lacking is an integrated framework specifically adapted to agro-food operational realities.

This review addresses three research questions: (i) what is the current evidence base on AI and ML applications for predictive maintenance in food and agro-food processing industries? (ii) which AI algorithms demonstrate the highest predictive accuracy for equipment failure in processing environments? (iii) what framework can guide agro-food processing industries in implementing AI-PdM systems effectively? The study contributes an original three-layer AI-PdM Framework specifically adapted to agro-food processing plants and grounded in a structured synthesis of peer-reviewed evidence.

REVIEW METHODOLOGY

Review design and search strategy

A structured narrative literature review methodology was employed, a systematic approach widely used in agricultural engineering and food technology research to synthesise multidisciplinary evidence on emerging technology applications (Carvalho *et al.*, 2019; Hector and Panjanathan, 2024). A structured database search was conducted across Scopus, Web of Science, and Google Scholar using the following Boolean keyword combinations: ("artificial intelligence" OR "machine learning") AND ("predictive maintenance" OR "failure prediction") AND ("food processing" OR "agro-food" OR "food manufacturing" OR "agricultural machinery"). The search was restricted to peer-reviewed journal articles, conference proceedings, and authoritative industry benchmarking reports published between January 2019 and December 2025.

Inclusion and exclusion criteria

Studies were included if they: (I) reported empirical results on AI or ML applications in predictive maintenance, condition monitoring, or equipment failure prediction; (ii) focused on food processing, agro-food processing, agricultural machinery, or directly comparable industrial environments; and (iii) reported quantifiable performance metrics including accuracy, precision, recall, or F1-score. Studies were excluded if they focused exclusively on quality control, supply chain forecasting, or demand planning without a maintenance component, or if they did not report methodology in

sufficient detail for critical appraisal. Following title, abstract, and full-text screening of 312 initially retrieved records, 47 publications met the inclusion criteria, of which 24 peer-reviewed journal articles directly informed the framework and quantitative findings reported in this review. To ensure reproducibility and transparency in line with structured review principles, the screening process proceeded as follows: 312 records were identified through database searches; 198 were excluded at title screening for lack of relevance to maintenance or AI; 114 abstracts were assessed, of which 67 were excluded for not meeting the inclusion criteria (no maintenance component, no quantitative performance metrics, or exclusively non-food industry contexts); 47 full texts were assessed for eligibility, of which 23 were excluded for insufficient methodological detail; and 24 peer-reviewed articles were included in the final synthesis. A note on PRISMA: while this study employs a structured narrative review methodology rather than a full systematic review, the screening stages above are consistent with PRISMA-aligned transparency principles (Moher *et al.*, 2009) and are summarized in Figure 1 (PRISMA-style flow diagram) provided as a supplementary item.

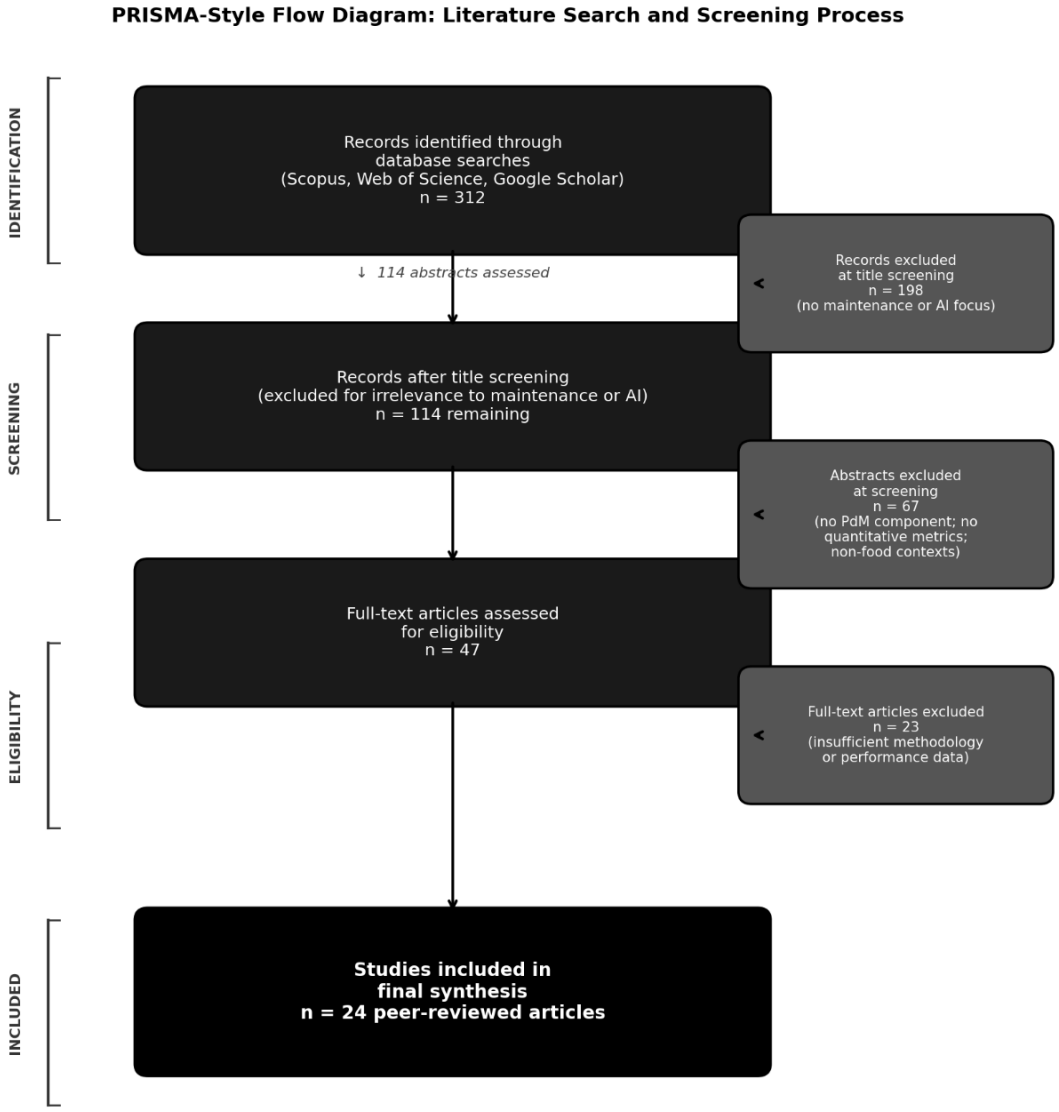


Figure 1. *PRISMA-style flow diagram illustrating the literature search and screening process. Adapted from Moher et al. (2009).*

Framework development

The three-layer AI-PdM Framework was developed through a structured conceptual synthesis comprising three stages: (i) identification of core system components from the reviewed literature; (ii) mapping of components to the agro-food processing operational workflow; and (iii) integration of a continuous learning feedback loop based on principles established in Carvalho *et al.* (2019) and validated against industry implementation evidence from Siemens (2024) and IoT Analytics (2022). Cost-benefit projections are calibrated using normalised financial indices derived from Deloitte benchmark data as cited in WorkTrek (2024), NIST benchmarks as cited in Sockeye (2025), and the IoT Analytics (2022) global predictive maintenance market study.

FINDINGS AND DISCUSSION

Maintenance strategies in agro-food processing: from corrective to predictive

Maintenance strategies in industrial settings are broadly classified into corrective maintenance (CM), preventive maintenance (PM), and predictive maintenance (PdM). Corrective maintenance addresses failures post-occurrence and, while requiring no investment in monitoring infrastructure, generates disproportionately high costs through unplanned stoppages, emergency spare part procurement, and accelerated equipment degradation. Meddaoui *et al.* (2023) estimated that maintenance costs account for 15-60% of total manufacturing operating costs, with over $60 billion of the American industry's annual $200 billion maintenance expenditure attributable to inefficient reactive practices. Preventive maintenance schedules interventions at fixed intervals regardless of the equipment's actual condition, creating both unnecessary costs for well-functioning machines and potential failure gaps between scheduled intervals (Carvalho *et al.*, 2019). Predictive maintenance addresses both limitations by leveraging real-time condition-monitoring data and AI models to forecast failure probability and schedule precisely timed interventions (Wahab *et al.*, 2024).

The agro-food processing context introduces unique PdM implementation challenges. Hygiene regulations restrict sensor placement in food contact zones; high humidity, temperature variation, and chemical exposure accelerate sensor degradation; and continuous production schedules driven by raw material perishability limit maintenance windows (Konur *et al.*, 2023; Zatsu *et al.*, 2024). These sector-specific constraints explain why PdM adoption in food processing has historically lagged behind other industries, despite a compelling economic case. Mallioris *et al.* (2024), in a systematic multi-sector mapping of Industry 4.0 predictive maintenance research, confirmed that food processing remains among the least represented sectors in the AI-PdM literature despite having among the strongest operational justification for adoption. Figure 2 illustrates the comparative performance differential between corrective and AI-predictive maintenance across three key operational metrics, normalised against a corrective maintenance baseline of 100.

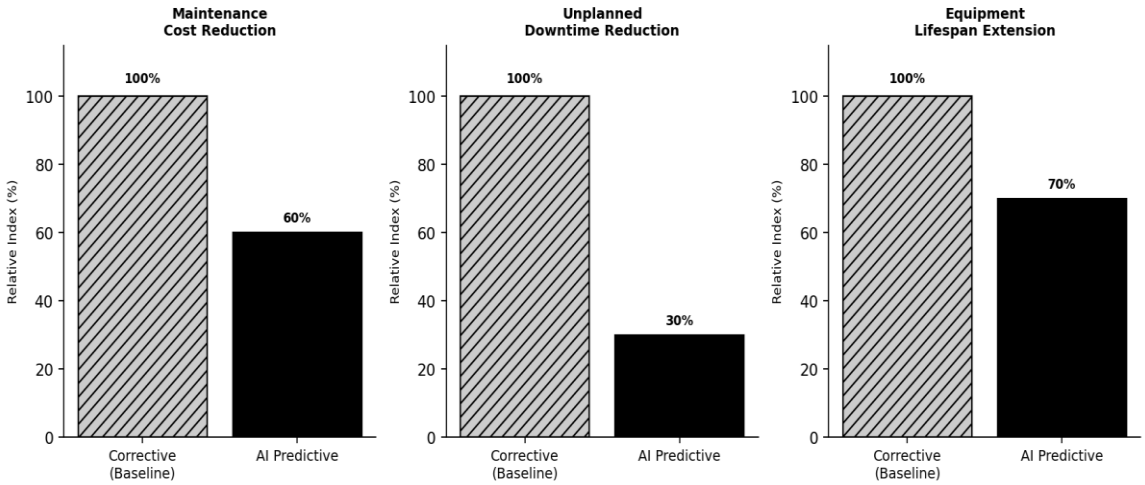


Figure 2. *Comparative performance indices of corrective versus AI-driven predictive maintenance across three operational metrics in agro-food processing (normalised, corrective (= 100) (Whitley, 2022); Infraspeak, 2024); Sockeye, 2025).*

Table 1. *Comparative analysis of maintenance strategies in agro-food processing industries.*

Attribute	Corrective (CM)	Preventive (PM)	AI-Predictive (PdM)	Source
Timing	After failure	Fixed intervals	Before failure (predicted)	Carvalho *et al.* (2019)
Cost impact	Very high	Medium	Low to medium	Sockeye (2025)
Downtime type	Unplanned, long	Planned, short	Minimal, predictive	Siemens (2024)
Data requirement	None	Basic logs	Continuous sensor data + AI	Hector and Panjanathan (2024)

CM = corrective maintenance; PM = preventive maintenance; PdM = predictive maintenance.

AI and machine learning algorithm performance in agro-food equipment failure prediction

Figure 3 presents a synthesis of predictive accuracy data for six AI/ML algorithm categories applied to equipment failure prediction in food processing and comparable manufacturing environments. Among supervised learning approaches, hybrid AI models achieved the highest accuracy at 96%, combining the complementary strengths of multiple architectures to maximise predictive performance. CNN followed at 94%, LSTM at 92%, Gradient Boosting at 90%, Random Forest at 88%, and SVM at 85%. All six algorithm categories exceed the minimum 85% accuracy threshold identified by Hector and Panjanathan (2024) as necessary for practical PdM deployment. To provide the specific context requested: the CNN accuracy of 94% was derived from vibration-based bearing fault detection studies applied to rotating motors, conveyor drives, and milling units (Ucar *et al.*, 2024); the LSTM range of 90-93% was reported from time-series sensor monitoring of gradual degradation in pumps and heat exchangers (Carvalho *et al.*, 2019); the Random Forest range of 85-90% was documented in production line failure classification tasks including a real-world food manufacturing production line (Ayvaz and Alpay, 2021); and the hybrid AI model accuracy of 96% was demonstrated on integrated multi-sensor

processing environments (Muratyan *et al.*, 2025). These values are indicative ranges to guide algorithm selection rather than definitive cross-study benchmarks.

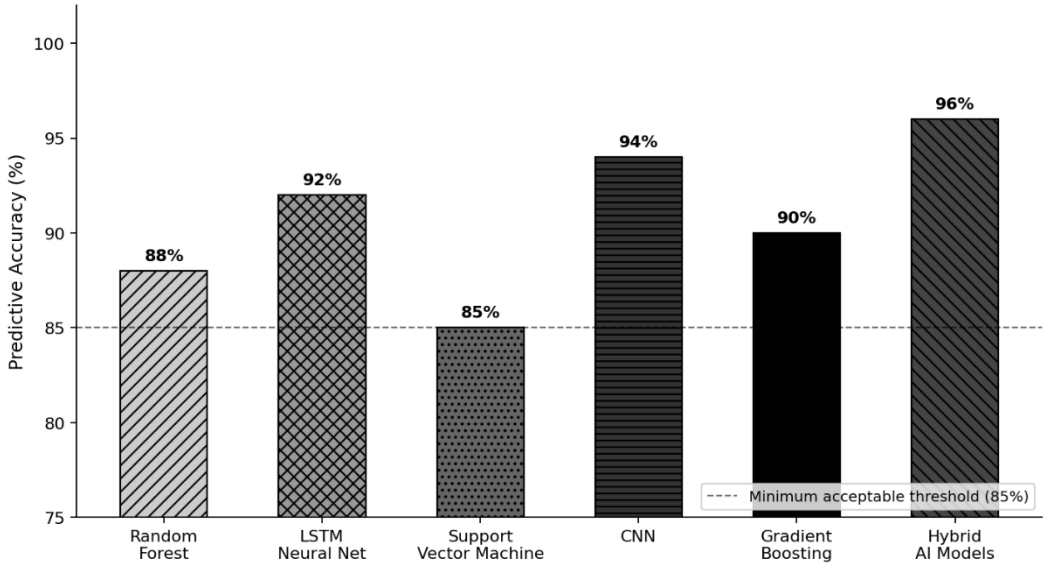


Figure 3. *Indicative predictive accuracy (%) of AI/ML algorithms applied to equipment failure prediction tasks reported across independent studies in food processing and comparable manufacturing contexts (vibration-based bearing/motor fault detection, conveyor and pump degradation monitoring, and processing line failure classification). Values are literature-reported ranges and are not directly comparable across algorithms [Carvalho et al. (2019); Hector and Panjanathan (2024); Ucar et al. (2024)].*

LSTM models, reviewed by Carvalho *et al.* (2019), excel at capturing temporal degradation patterns in time-series sensor data, making them well-suited for gradual degradation monitoring in heat exchangers, pumps, and refrigeration systems common in agro-food plants. Ucar *et al.* (2024) demonstrated the superiority of CNNs for vibration signal classification, achieving 94% accuracy in bearing fault detection, directly applicable to conveyor belts, milling machinery, and centrifuges. Ayvaz and Alpay (2021) applied tree-based ensemble algorithms to a food manufacturing production line, demonstrating that Random Forest models could predict maintenance needs with sufficient lead time to schedule non-disruptive interventions. A pivotal case study documented by Konur *et al.* (2023) deployed vibration and temperature sensors on mincing and blending equipment over 11 months, collecting 39,470 records at 10-minute intervals to train LSTM predictive models - confirming the feasibility of AI-PdM in agro-food SME contexts without equipment replacement.

Table 2. *AI/ML algorithm comparison for predictive maintenance in agro-food processing industries.*

Algorithm	Accuracy (%)	Key strength	Key limitation	Best for (agro-food)
Random Forest	85-90%	Handles diverse sensor inputs; interpretable	Less effective with sequential data	Grain mills, conveyors, packaging lines
LSTM Neural Net	90-93%	Captures time-dependent degradation patterns	Requires large labelled datasets	Heat exchangers, pumps, refrigeration
CNN	92-95%	Excellent vibration signal analysis	High computational cost	Motors, bearings, milling and grinding
SVM	83-87%	Effective with small datasets	Poor scalability; multimodal data struggles	Low-volume specialty food processors
Gradient Boosting	88-92%	High accuracy on tabular sensor data	Prone to overfitting without tuning	Drying, quality control integrated lines
Hybrid AI Models	93-96%	Combines strengths; highest overall accuracy	Complex to implement and maintain	Large-scale integrated agro-food plants

Accuracy ranges synthesised from Carvalho et al. (2019), Hector and Panjanathan (2024), and Ucar et al. (2024). LSTM = Long Short-Term Memory; CNN = Convolutional Neural Network; SVM = Support Vector Machine.

Proposed three-layer AI-PdM framework for agro-food processing industries

Based on the evidence synthesis, an original Three-Layer AI-Driven Predictive Maintenance (AI-PdM) Framework is proposed for agro-food processing industries. As illustrated in Figure 4, the framework was organised into 3 functional layers; sensor data collection, AI/ML processing engine, and decision and action outputs connected by a continuous learning feedback loop that improves predictive accuracy over time as operational data accumulates.

Layer 1 (Sensor Data Collection) deploys four sensor categories on critical processing equipment: vibration sensors detecting mechanical anomalies in rotating machinery including motors, conveyors, and pumps; temperature sensors monitoring thermal deviations in pasteurisation, sterilisation, and refrigeration processes; pressure sensors tracking fluid and gas system integrity; and acoustic sensors detecting structural changes through sound emission analysis. Sensors feed time-series data to a centralised IoT gateway at defined sampling intervals. The evidence base for each sensor modality in agro-food processing is well established. Ucar *et al.* (2024) demonstrated that accelerometer vibration data sampled at 12.8 kHz enables CNN models to detect bearing faults in food processing rotating machinery with 94% accuracy before mechanical failure, identifying fault signatures specifically in motors, drives, and milling units. Nikfar *et al.* (2022) confirmed that vibration sensor data from low-voltage induction motors - the workhorses of food processing conveyors, mixers, and pumps - is sufficient for a two-phase ML approach to achieve practical fault classification accuracy. For temperature monitoring in food environments, Konur *et al.* (2023) deployed combined vibration and temperature sensors on mincing and blending equipment in a food SME at 10-minute intervals over 11 months, generating 39,470 records to train robust LSTM failure prediction

models. Hassoun *et al.* (2023) documented how IoT-integrated Industry 4.0 sensor networks enable simultaneous real-time condition monitoring, food safety compliance, and predictive maintenance scheduling across food manufacturing facilities. Recommended sensor placement for agro-food processing: vibration sensors on motor bearing housings and gearbox casings; temperature sensors on heat exchanger inlet/outlet points, refrigeration compressors, and drive motor housings; pressure sensors on hydraulic lines, pump outlets, and pneumatic conveyor systems; and acoustic emission sensors on structural frames of high-criticality equipment such as mixers, grinders, and filling machines.

Layer 2 (AI/ML Processing Engine) applies the appropriate algorithm - selected based on equipment type, data volume, and operational context using the guidance in Table 2 - to generate failure probability scores, anomaly alerts, and Remaining Useful Life (RUL) estimates. The processing engine can be deployed in three architectural configurations: edge computing, where AI inference runs on-device at the sensor gateway, enabling real-time alerts even in facilities with limited connectivity, particularly relevant for rural agro-food processors in developing economies; cloud computing, where data streams to a centralised AI platform enabling continuous model retraining and high-performance computing, suitable for large-scale integrated food processing plants; or hybrid edge-cloud, where edge nodes handle real-time anomaly detection while the cloud manages model retraining and long-term RUL estimation, the recommended configuration for most agro-food SMEs balancing responsiveness with scalability. Muratyan *et al.* (2025) validated a hybrid edge-cloud AI-IoT architecture on a sausage production line, confirming the deployability of such systems in real agro-food environments. The continuous learning feedback loop returns post-maintenance performance data to the model training pipeline, enabling supervised retraining that progressively improves prediction accuracy, a design principle documented in Carvalho *et al.* (2019) across 127 studies as essential for sustained PdM performance.

Layer 3 (Decision and Action Outputs) translates AI outputs into four actionable deliverables: failure alerts to maintenance teams; RUL estimates that enable proactive parts procurement; automatically generated work orders integrated with Computerised Maintenance Management Systems (CMMS); and cost and performance reports for management decision-making. CMMS integration is critical for practical adoption, embedding AI-PdM within established maintenance workflows rather than creating parallel systems that add operational burden (Wahab *et al.*, 2024).

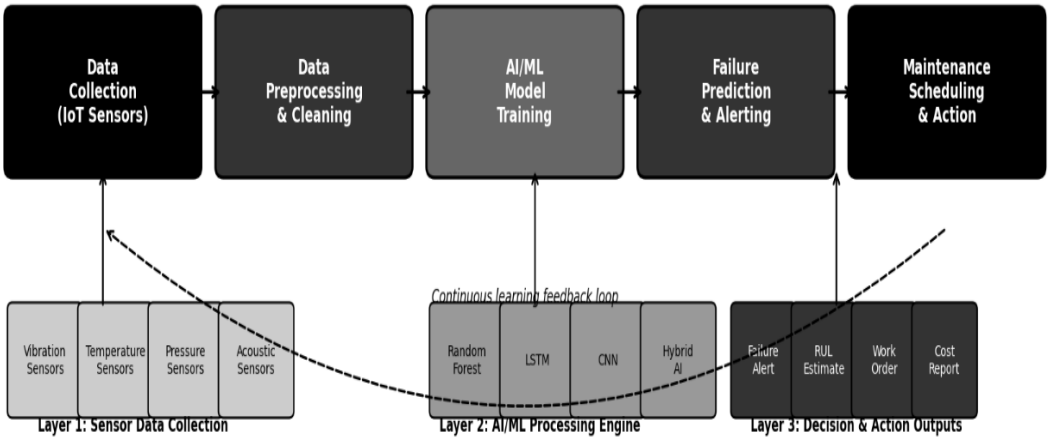


Figure 4. *Proposed three-layer AI-driven predictive maintenance (AI-PdM) framework for agro-food processing industries.*
RUL = Remaining Useful Life; CMMS = Computerised Maintenance Management System; LSTM = Long Short-Term Memory; CNN = Convolutional Neural Network.

Economic and financial analysis of AI-PdM adoption in agro-food processing

Figure 5 presents a normalised five-year financial trajectory comparing corrective maintenance with AI-PdM implementation. The financial model is based on the following assumptions, which should be adjusted by individual facilities to reflect their operational context: Year 0 capital investment includes IoT sensor installation (estimated 8-15 sensors per major production line at $200-500 USD per sensor), AI-PdM software platform subscription or licensing ($5,000-25,000 USD annually for cloud-based platforms), and staff training ($2,000-8,000 USD per maintenance technician cohort); annual corrective maintenance baseline costs are normalised to an index of 100 representing industry-average unplanned downtime costs of $260,000 per hour (Infraspeak, 2024) multiplied by average downtime frequency; and the savings trajectory follows Deloitte benchmarks (as cited in WorkTrek, 2024) projecting 40% maintenance cost reduction and 70% downtime reduction from Year 1, compounding as model accuracy improves. These assumptions are drawn from industry-wide benchmarks rather than a specific facility, and actual ROI will vary based on production scale, equipment criticality, baseline downtime frequency, and perishable commodity value. Year 0 represents the initial capital investment in sensor infrastructure, AI platform, and staff training. By Year 1, maintenance cost savings and reduced production losses begin to offset the investment. Break-even occurs at approximately Year 3, consistent with Deloitte's estimate (as cited in WorkTrek, 2024) that AI-PdM ROI is achieved within three years for typical industrial facilities. By Year 5, the cumulative net benefit of AI-PdM substantially exceeds the corrective maintenance baseline, with compounding returns as predictive accuracy improves through continuous learning.

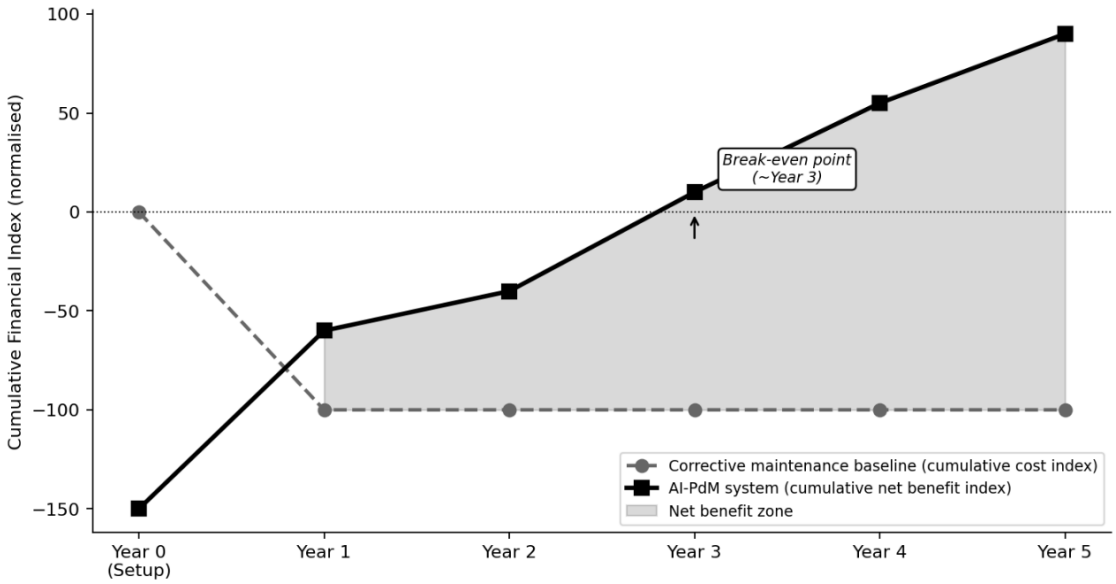


Figure 5. *Projected five-year financial trajectory comparing corrective maintenance and AI-predictive maintenance (normalised cumulative financial index). Break-even at approximately Year 3. Sources: Deloitte as cited in WorkTrek (2024); NIST as cited in Sockeye (2025); IoT Analytics (2022).*

The quantified economic benefits documented in the literature are compelling: Whitley (2022) reported that AI-PdM can reduce Mean Time to Repair (MTTR) by 60% by enabling maintenance scheduling during planned production pauses rather than emergency responses. Sockeye (2025), synthesising NIST and multiple industry surveys, reported 40% maintenance cost reduction, 70% unplanned downtime reduction, 54% reduction in defect rates, and up to 66% reduction in maintenance-related inventory build-up. Infraspeak (2024) documented that 85% of facilities reported improved downtime forecasting accuracy and 55% reported increased maintenance staff productivity following PdM implementation. For agro-food processing specifically, Tekon Electronics (2022) emphasised that the perishability factor amplifies the ROI case: unlike non-perishable manufacturing where stoppages preserve in-process stock, a food processing line failure destroys perishable raw materials in addition to the direct maintenance cost.

The upfront investment barrier is most significant for small and medium agro-food enterprises (SMEs). However, the Konur *et al.* (2023) case study demonstrated that AI-PdM implementation without equipment replacement is achievable in SME contexts. Cloud-based AI-PdM platforms that convert capital expenditure into operating expenditure further lower the entry threshold. Agricultural engineering extension services and government agricultural technology subsidy programmes in developing economies can play a catalytic role in closing the adoption gap for smaller agro-food processors.

Barriers to AI-PdM adoption and strategies for overcoming them

Despite its compelling economic case, AI-PdM adoption in agro-food processing faces four well-documented barriers. First, data availability and quality challenges arise because many facilities, particularly in developing economies, lack historical failure records sufficient to train supervised ML models; transfer learning approaches

leveraging pre-trained models from analogous industries can bridge this gap. Second, AIliteracy gaps among maintenance personnel require targeted training programmes that equip technicians to interpret and act on AI-PdM outputs without requiring data science expertise (Wahab *et al.*, 2024). Third, integration complexity with legacy equipment and existing IT infrastructure can be mitigated through retrofit IoT sensor kits and API-compatible CMMS platforms. Fourth, food industry hygiene and regulatory requirements necessitate food-grade sensor housing and careful placement to avoid contamination risk. Sensors in open processing zones or food contact areas must comply with IP69K ingress protection standards for washdown environments, use stainless steel or food-grade polymer housings certified to NSF/ANSI 169 or equivalent standards, and be positioned to permit full Clean-In-Place (CIP) and Sterilise-In-Place (SIP) procedures without sensor removal. Wireless sensor nodes should be sealed for the operating temperature range of their specific zone-typically -20°C to +85°C across cold storage, chilling, and pasteurisation environments. These specifications must be addressed at the facility-planning stage of AI-PdM implementation, not retrofitted post-installation (Hassoun *et al.*, 2023; Konur *et al.*, 2023).

CONCLUSION

This review has established that AI-driven predictive maintenance represents a technically mature, economically compelling, and practically achievable solution to the challenges of machine breakdown and downtime confronting agro-food processing industries. The synthesis of 24 peer-reviewed studies confirmed that AI algorithms, particularly hybrid models, CNNs, and LSTM networks, can predict equipment failures with 85-96% accuracy, sufficient for operational deployment in food processing environments. The proposed three-layer AI-PdM Framework provides a structured implementation roadmap adaptable to both large integrated agro-food plants and small-to-medium enterprises operating with legacy machinery, without requiring the replacement of existing equipment.

The economic argument for transition is compelling: evidence from industry benchmarks and comparable manufacturing contexts projects a 40% reduction in maintenance costs and a 70% reduction in unplanned downtime, with return on investment achievable within approximately three years for facilities with moderate to high baseline downtime frequency. These projections are drawn from normalised industry-wide models and should be validated against facility-specific cost structures before investment decisions are made. The ROI case is further strengthened by the perishability factor unique to agro-food processing, where a production stoppage destroys in-process perishable stock in addition to the direct maintenance cost, making downtime financially more damaging than in non-perishable manufacturing. Agro-food processing industries should prioritise integration of IoT sensor infrastructure on high-criticality equipment, begin with single-algorithm implementations using Random Forest or LSTM before progressing to hybrid models, and invest in AIliteracy training for existing maintenance personnel. Governments and agricultural engineering research institutions should develop supportive policy frameworks, including subsidies for sensor installation and AI-PdM extension

programmes to accelerate adoption among SME agro-food processors in developing economies. Future research should conduct primary empirical studies that deploy the proposed framework in real agro-food processing facilities, generating sector-specific training datasets to validate and refine AI model performance under food industry conditions.

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DECLARATION OF COMPETING INTEREST

The author declares that they have no conflict of interest.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Stephen OPATOLA: Conceptualization, Methodology, Investigation, Writing - original draft, Review and Editing, Visualization.

ETHICS COMMITTEE DECISION

This article does not require any Ethical Committee Decision.

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