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Development of an AI-Driven Predictive Quality and Shelf-Life Management System for Poultry Products in Smart Food Manufacturing

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Abstract-* *Poultry products are highly perishable, and traditional quality indicators, which depend on manual periodic inspections and predetermined expiration dates, do not necessarily meet the needs of today's high-volume, high-speed supply chains. The current study conceptualizes and explains the background and logic of an AI-based predictive quality and shelf life management system specifically for smart poultry manufacturing. The system builds on the groundbreaking work of machine learning, Internet of Things (IoT) sensing, and digital twin technology, combining real-time, non-destructive data collection and ensemble predictive models to forecast spoilage trajectories and optimize decision-making from farm to processing, distribution, and retail. Its elements include hyperspectral and gas sensor arrays for continuous quality monitoring, artificial neural networks, Random Forest, and LSTM architectures for robust shelf-life prediction, and a digital twin layer for generating scenarios and intervening prescriptively. The system also features dynamic labeling, blockchain-based traceability, and explainable AI capabilities, promoting transparency, regulatory adherence, and stakeholder confidence. Data heterogeneity, model generalizability, computational constraints, and barriers to adoption are all explored and quantified, as are benefits of 12–18% spoilage reduction, efficiencies in logistics, and 3–5% carbon footprint reduction. Future avenues for research focus on scalability, personalized Q thresholds, green AI principles, and hybrid physics-informed models in low-resource scenarios. This research represents a new paradigm in poultry quality management: predictive, adaptive, and sustainable by design, by connecting the principles of precision farming with the application of industrial artificial intelligence.

Keywords:* *AI-Driven Shelf-Life Prediction, Poultry Quality Management, Smart Food Manufacturing, Digital Twin, IoT-Enabled Spoilage Monitoring

I. INTRODUCTION

Poultry products are among the most consumed animal proteins in the world, but their perishability creates a constant challenge in maintaining quality and safety from farm to consumer. In modern food manufacturing systems, reducing the economic losses caused by spoilage and achieving food security and public health through effective shelf-life management is very important.

1.2 Ensuring good quality and shelf-life of poultry products.
The quality of poultry meat is affected by various biological, environmental, and processing factors in modern poultry supply chains. The rate of quality degradation and eventual spoilage results from the combined effect of temperature change, microbial growth, enzymatic activity, and oxidative reactions. Traditional quality control methods (based mainly on periodic manual inspections and fixed expiration dates) are not effective in capturing this dynamic variability, as they result in the disposal of still edible products or the distribution of compromised ones.

Financial loss is not the only negative consequence of suboptimal shelf-life management. Poor post-harvest loss (PHL) in poultry can be as high as 20-30% in low- and middle-income countries, where infrastructure to ensure cold chain conditions is not always adequate, worsening food security and compromising the livelihood of poultry producers who are smallholder farmers. Furthermore, the demand for freshness, safety, and traceability has grown in recent years, based on increased awareness of food poisoning and the need to know where food comes from and how it was handled.

1.3 Challenges in maintaining quality throughout the supply chain
Heterogeneous production conditions: Variability in flock health, feed composition, and rearing

environments introduces uncertainty in baseline product quality before processing even begins

Conventional monitoring methods: Although valuable, visual inspection, pH measurement, and microbial culturing are often destructive, time-consuming, and not suited to real-time, industrial-scale decision-making.

Cold-chain vulnerabilities: Small variations from optimum storage temperatures can cause microbial growth and biochemical spoilage to begin rapidly during transport and retail storage, which can significantly reduce the shelf life of the product.

Data fragmentation: Product history data (e.g., time-temperature history, handling events) is often dispersed among farms, processors, distributors, and retailers, making it difficult to undertake holistic assessments of product quality and take proactive measures.

There are various reasons for incorporating AI into your business.

Artificial intelligence (AI), including machine learning (ML), deep learning (DL), and computer vision (CV), presents a revolutionary approach to overcome these limitations. AI models can learn relationships between environmental variables, product attributes, and spoilage trajectories from large, diverse datasets, where these relationships are complex and non-linear, in contrast to rule-based systems.

1.4 Objective of this article

This article introduces the conceptual design and rationale of a predictive quality and shelf-life management system for poultry products in a smart food manufacturing context based on artificial intelligence. The proposed system combines elements of precision poultry farming and industrial food processing to create a comprehensive poultry farming system. The proposed system integrates elements from precision poultry farming and industrial food processing into a unified poultry farming system.
Real-time, non-destructive sensing (e.g., spectral, thermal, gas) for continuous quality monitoring;

A multi-source (farm, transport, retail) data-based machine learning model to predict spoilage risk and remaining shelf life;

Digital twin architecture for virtual simulation and scenarios for supply chain;

Integration with current traceability and logistics systems for proactive decision-making.

This is an effort to move poultry quality management into a new paradigm—a predictive, rather than reactive, management approach; a personalized approach rather than a one-size-fits-all; and a sustainable-by-design approach. The next sections discuss the scientific origins, system design, implementation requirements, and future research needs to achieve this vision.

II. LITERATURE REVIEW

2.1 The cause and nature of loss in quality of poultry

The process of poultry meat deterioration is multi-factorial and is controlled by the properties of the product and by its environment. Chicken muscle tissue is rich in nutrients, has a high water activity (usually > 0.98), and has a neutral pH (usually ~5.8–6.2), providing an ideal substrate for rapid microbial colonization and enzymatic activity, as noted by Liakos et al. (2025). Psychrotrophic Gram-negative bacteria (GNB), including Pseudomonas spp., Acinetobacter spp., and Enterobacteriaceae, are the main bacteria that can spoil the food, using amino acids and lipids to produce offensive volatile compounds like hydrogen sulfide, ammonia, and biogenic amines during refrigerated storage (Liakos et al., 2025; Shi et al., 2024).

At the same time, non-enzymatic lipid oxidation occurs through free radical chain reactions, particularly in tissues rich in polyunsaturated fatty acids, producing secondary oxidation products such as malondialdehyde and 4-hydroxynonenal, which can lead to rancid flavors and even cytotoxicity (Zatsu et al., 2024). Further protein degradation by other endogenous cathepsins and microbial proteases causes the loss of texture integrity and water-holding capacity, represented by high drip loss and mushiness

(Ablegue et al., 2025). The biochemical pathways are very sensitive to temperature changes, with the risk of spoilage increasing by approximately 2-fold for every 10°C increase in temperature within the range of 0–15°C, highlighting the need for precise time–temperature control in the supply chain (Shi et al., 2024; Madhu, 2025).

2.2 The constraints of traditional quality evaluation approaches

Sensory, microbiological, and physicochemical methods have long been incorporated into a triad as traditional methods of poultry quality evaluation. Although a sensory panel is representative of the consumer, it is subjective, suffers from fatigue effects, and includes inter-assessor variability, which makes it not very useful in a high-throughput industrial application (Liakos et al., 2025). Although microbiological enumeration by plate counting is still the standard method for safety verification in regulations, it requires incubation for 24-72 hours, which is inherently retrospective and not suitable for real-time process intervention (Shi et al., 2024; Dhal & Kar, 2025).

Although most of these indicators are faster, they are destructive, discontinuous, and do not always correspond to actual sensory deterioration thresholds (Ablegue et al., 2025; Madhu, 2025) and are referred to as physicochemical proxies. All of these methods represent a "detect and react" approach to quality, meaning that quality failures are only detected when irreversible degradation has happened, limiting the opportunities available for proactive mitigation.

2.3 The rise of AI in the prediction of food quality and shelf-life.

To address these challenges, artificial intelligence (AI), which includes machine learning (ML), deep learning (DL), and computer vision (CV), has become a game-changer for predictive quality management. In their extensive literature review of ML and DL applications in food categories, Ablegue et al. (2025) showed that the accuracy of the AI models in predicting shelf life is superior to classical kinetic and statistical models, especially when high-dimensional datasets that include time-resolved information are used for training. Their analysis revealed that the mean absolute percentage errors (MAPE) for NN-based predictors of microbial loads and sensory scores in meat products were less than 8%. In comparison, Arrhenius-type models recorded MAPEs of 15-25%.

ANNs are increasingly adopted as food shelf-life models, particularly BPNNs (backpropagation networks), which are capable of approximating complex and nonlinear relationships between inputs and outputs without the need for explicit knowledge of the underlying mechanisms (Shi et al., 2024). Shen et al. (as cited in Shi et al., 2024), for example, created a model for chilled chicken using a BPNN that incorporated storage temperature, relative humidity, and initial microbial load to predict TVB-N and sensory acceptance, with highly satisfactory R2 values greater than 0.96. Likewise, ensemble learning approaches like Random Forest (RF) and XGBoost (XGB) have demonstrated their suitability for dealing with heterogeneous sensor data, achieving promising results for freshness state classification using hyperspectral images and VOC profiles, respectively (Liakos et al., 2025; Dhal & Kar, 2025).

2.4 Incorporation into smart manufacturing ecosystems.

The use of AI in poultry quality management is not standalone, but it is part of the overall transformation of the food processing industry through Industry 4.0. The Internet of Things (IoT) provides the data backbone, while wireless sensor networks gather detailed histories of temperature, humidity, and time at the crate, pallet, and vehicle levels (Das et al., 2025; George & George, 2023). These data streams are used to continuously update the AI engines in the cloud or on the edge that calculate the spoilage forecasts and alert the team if deviation thresholds are exceeded.

The virtual representation of physical supply chains (digital twin technology) further strengthens this capability by enabling risk assessment through simulations. Processors can simulate "what if?" scenarios, such as a refrigeration failure or transport delays, and adjust contingency plans accordingly without interrupting ongoing production, as described by Mandal et al. (2025). Davidescu et al. (2025) and

Mandal et al. (2025) reported on meat processing plants, where early pilots have shown a reduction in spoilage losses of 15–20% using dynamic rerouting via twin-guided systems and adaptations on packaging.

Furthermore, AI-powered prescriptive analytics are starting to provide insights not only on when quality will deteriorate but how to prevent it. One example is the use of reinforcement learning algorithms to optimize the composition of Modified Atmosphere Packaging (MAP) gases in real-time, to maximize their antimicrobial efficacy while maintaining the quality of the food's sensory properties (Madhu, 2025; Thakur et al., 2022). Closed-loop systems are a good example of the evolution of passive monitoring to active quality control, which is vital to unlock the potential of smart food manufacturing.

2.4 Gaps and opportunities

Despite these advances, significant challenges remain. Data heterogeneity, model interpretability, and scalability across diverse poultry production systems continue to impede widespread adoption (Ablegue et al., 2025; Song et al., 2025). Furthermore, most existing studies focus on isolated segments of the supply chain (e.g., retail display or processing), with limited integration of farm-level variables (e.g., feed composition, flock health) that influence baseline product quality (George & George, 2023; Dhal & Kar, 2025). Addressing these gaps requires a holistic, end-to-end framework—one that bridges precision poultry farming insights with industrial AI capabilities to deliver truly predictive, adaptive, and traceable quality management. The next section details the architecture of such a system.

III. AI-ENABLED SYSTEM DESIGN FOR QUALITY AND SHELF-LIFE MANAGEMENT

The proposed AI-based predictive quality and shelf-life management system is designed as a multi-layered integrated system that seamlessly connects real-time sensing, intelligent analysis, and decision support throughout the poultry supply chain. The system is based on recent developments in the fields of Internet of Things, machine learning, and digital twin technology, shifting the quality assurance process from reactive end-of-the-line verification to proactive continuous optimization.

3.1 The integration of sensor infrastructure and IoT.

The core of the system is a heterogeneous sensor network deployed at critical control points, from processing-line chillers to retail display cases. Key modalities include low-cost time–temperature integrators (TTIs) that record cumulative thermal history for kinetic spoilage modeling (Madhu, 2025; Thakur et al., 2022); hyperspectral and near-infrared imaging systems mounted above conveyors or packaging stations to capture spectral signatures (400–1000 nm) correlated with microbial load, lipid oxidation, and color changes (Ablegue et al., 2025; Liakos et al., 2025); gas and volatile organic compound (VOC) sensors (e.g., MOS and PID arrays) that monitor headspace O_2, CO_2, H_2S, and amines for early anaerobic spoilage detection (Zatsu et al., 2024; Madhu, 2025); and wireless IoT nodes that log ambient temperature, humidity, and shock/vibration during transport and warehousing, transmitting data via LoRaWAN or NB-IoT (Das et al., 2025; George & George, 2023). These sensors feed into edge gateways equipped with lightweight preprocessing modules—such as noise filtering and feature extraction—before relaying data to cloud-based analytics engines, an edge–cloud hybrid architecture that minimizes latency and bandwidth while preserving data fidelity for downstream modeling (Song et al., 2025; Dhal & Kar, 2025).

Table 1: Feature extraction schema for multi-modal poultry quality data

Data source	Primary features	Derived indicators
Hyperspectral imagery	Reflectance at 450, 520, 680, 750 nm; spectral slopes	Predicted microbial load (CFU/g), metmyoglobin ratio, lipid oxidation index
VOC/gas sensors	Concentrations of H_2S, NH_3, tri methylamine, CO_2	Spoilage volatility index, anaerobic shift metric
TTIs and thermal	Cumulative time–temperature integral,	Kinetic spoilage rate constant (k), remaining

loggers	max deviation from 4°C	shelf-life fraction
Packaging telemetry	Headspace O_2/CO_2 %, seal integrity flags	MAP efficacy score, leak probability

Feature selection is guided by domain knowledge (e.g., known spoilage biomarkers) and data-driven techniques such as recursive feature elimination (RFE) or SHAP (SHapley Additive exPlanations) values to ensure model parsimony and interpretability (Ablegue et al., 2025; Shi et al., 2024).

3.2 Machine learning models for predictive accuracy

The core predictive engine employs an ensemble of machine learning architectures, each optimized for specific tasks and data characteristics. Table 2 summarizes candidate models, their strengths, and documented performance in food shelf-life contexts.

Table 2: Comparative overview of machine learning models for poultry shelf-life prediction

Model type	Typical use case	Advantages	Reported performance (food/meat)
Artificial Neural Networks (ANN/BPNN)	Nonlinear regression of TVB-N, sensory scores	High flexibility; handles multivariate inputs	R^2 = 0.94–0.97 for chilled chicken (Shi et al., 2024)
Random Forest (RF)	Classification of freshness states; feature importance	Robust to noise; interpretable variable ranking	94.4% accuracy for pork storage time (Barbon et al., 2016, cited in Liakos et al., 2025)
Support Vector Machines (SVM)	Small-sample, high-dimensional spectral data	Strong generalization; effective with limited data	>90% accuracy in meat quality grading (Liakos et al., 2025)
Long Short-Term Memory (LSTM) networks	Time-series forecasting of spoilage trajectories	Captures temporal dependencies; suitable for streaming data	MAPE < 8% for microbial growth curves (Ablegue et al., 2025)
Gradient Boosting (XGBoost, LightGBM)	Hybrid tabular + sensor data fusion	High predictive power; handles missing values	Top performer in Kaggle food safety challenges (Dhal & Kar, 2025)

The system is not closed: it also has learning mechanisms that involve a continuous updating of the model, based on a periodic re-learning of the system with new data, which occurs when the predictions made by the model do not match the observations made by the system—the phenomenon is called online or incremental learning (Song et al., 2025; Zatsu et al., 2024).

3.3 Digital twin for virtual monitoring and scenario forecasting

A digital twin component acts as the “what-if” simulation layer to generate a virtual dynamic representation of the physical supply chain. The twin ingests real-time sensor data and historical data to keep its state in sync with physical assets (such as cold rooms, transport vehicles, retail displays) as

shown in the conceptual architecture below (Figure 1).

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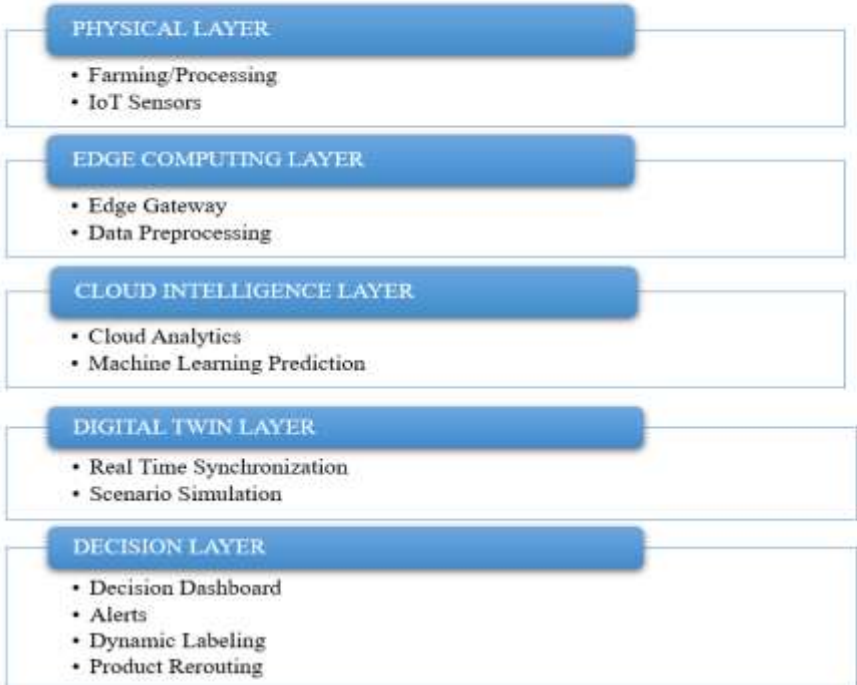

Figure 1: AI-based poultry quality management system conceptual architecture

In this context, users can simulate a human factor such as a 2-hour loss of refrigeration during transport and instantly see the effect on microbial growth, sensory acceptability, and remaining shelf life (Mandal et al., 2025; Davidescu et al., 2025). Such simulations lead to prescriptive actions: redirecting shipments to closer markets, dynamic pricing in retail channels, or faster consumption in food service channels.

3.4 The integration and traceability of the system

The AI engine connects with current enterprise resource planning (ERP) systems and blockchain-based traceability systems for end-to-end transparency. Every batch of poultry is individually and permanently identified with a digital identifier like a QR code or RFID tag and can be traced back from the point of poultry production to the feed and vaccines used on the farm, the processing conditions in the plant, including chilling rates and the packaging gas mix, all the way to the poultry's retail storage conditions (Das et al., 2025; George & George, 2023).

This integration enables:

Dynamic shelf-life labeling: Expiration dates are dynamically updated based on actual storage history, not conservative fixed assumptions (Madhu, 2025; Thakur et al., 2022).

Root cause analysis: If clusters of spoliation are identified, they are traced back to find any common upstream causes (e.g., specific farm, transport route, packaging line) and follow targeted corrective action (Liakos et al., 2025).

Time-temperature compliance: Automated audit trails ensure traceability of time-temperature compliance according to HACCP and FSMA requirements, thereby alleviating manual burden in record-keeping (Mandal et al., 2025).

IV. PRACTICAL ISSUES AND PROBLEMS

Implementing an AI-based predictive quality and shelf-life management solution for poultry products from conceptual design to operational deployment faces myriad technical, organizational, and regulatory challenges. Although these systems hold theoretical promise in recent literature, practical considerations around data integrity, model generalizability, computational feasibility, and alignment with stakeholders are paramount.

4.1 Availability of data, data quality, and data heterogeneity

Quality and representative training data are a prerequisite for reliable AI prediction. However, in poultry supply chains, these data are typically siloed in various systems with different formats, sampling rates, and coverage (Das et al., 2025; George & George, 2023). This heterogeneity poses strong challenges in data harmonization and fusion.

Inaccurate sensor measurements, e.g., faulty sensors, communication failures, or sensor calibration drift, also reduce the accuracy of model input. The issue of using incomplete or noisy data to train a model has been documented, and even the most advanced deep learning algorithm suffers drastically from poor performance when such conditions are present, especially in the context of time-series forecasting where temporal continuity plays a pivotal role, as mentioned by Ablegue et al. (2025). Furthermore, a lack of data is a problem for rare but impactful events (e.g., long periods of cold chain failure), as this results in poor learning of failure-mode signatures (Altemimi et al., 2025; Zatsu et al., 2024).

To resolve these problems, investments need to be put into data governance systems that include standardized ontologies, automated validation pipelines, and imputation methods capable of maintaining statistical fidelity while avoiding bias, such as generative adversarial networks for synthetic data augmentation (Das et al., 2025; Liedeker et al., 2025).

Ensure that the model is robust for different production settings and types of poultry.

The ability of a model to remain accurate when faced with unforeseen circumstances is likely the biggest limitation to the large-scale application of AI in the food manufacturing sector. Baseline spoilage kinetics of poultry products are naturally variable due to different types of feed, slaughter methods, post-mortem conditions, and products from various breeds and age levels (Liakos et al., 2025; Shi et al., 2024). A model developed using only broiler chicken from a single integrated producer can break down at the flip of a switch when heritage breeds or smallholder-sourced flocks with different fat profiles and microbial ecology are introduced.

This is exacerbated by environmental variation. Static models cannot predict the changes in the trajectory of spoilage due to seasonal changes in ambient temperature, humidity, and transportation time (Madhu, 2025; Davidescu et al., 2025). Recent literature highlights the importance of using domain adaptation methods, including transfer learning and meta-learning, that allow models to adapt to new data from target domains using only a small subset of data without requiring full retraining (Ablegue et al., 2025; Song et al., 2025).

Achieving the trade-off between prediction and computational and real-time demands

Deep learning architectures (such as CNNs, LSTMs, transformers) achieve better prediction accuracy in well-controlled benchmarks, but their high computational cost makes them unattainable in edge deployment and/or high-throughput processing lines, where millisecond-level decision-making is needed (Liakos et al., 2025; Dhal & Kar, 2025). For example, a hyperspectral image analysis line speed of more than 100 carcasses per minute requires sub-second inference times, which could require model compression, quantization, or hybrid approaches in which lightweight classifiers are used for routine cases, and heavier models are used only for ambiguous cases (Ablegue et al., 2025; Zatsu et al., 2024).

4.2 Compliance, ethical issues and barriers to adoption.

In addition to the technical aspects, deployment also depends on compliance with regulatory frameworks and stakeholder trust. Documentation requirements for food safety, including the U.S. Food Safety Modernization Act (FSMA) and the EU General Food Law, demand high levels of documentation of control measures, but many AI systems are prone to being black boxes, lacking the ability to be audited (Mandal et al., 2025; Liedeker et al., 2025). This transparency is in direct opposition to the

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"explainability by design" that regulators and consumers alike are requesting.

There are also ethical implications in terms of data ownership and algorithmic bias. When it comes to quality history, who owns the data created by a broiler batch: the farmer, processor, transporter, or retailer? Could dynamic pricing based on predicted shelf life inadvertently hurt small retailers who cannot conduct in-the-moment analysis? These issues still have to be answered more adequately in the literature (Altemimi et al., 2025; Davidescu et al., 2025).

Last but not least, there are organizational hurdles to adoption. Small and medium businesses (SMEs), which play a significant role in poultry production in many locations, frequently do not have the financial resources, technical knowledge, or capacity for change management to implement AI systems (George & George, 2023; Dhal & Kar, 2025). This will be a challenge not just for technological innovation, but also for policy-level interventions like workforce upskilling programs, shared-data cooperatives, and subsidized pilot programs to guarantee equitable access to smart manufacturing benefits.

V. ADVANTAGES AND EFFECTS OF AI IN QUALITY MANAGEMENT.

Implementing an AI-powered predictive quality and shelf-life management system in the poultry industry holds significant promise for economic, environmental, and social benefits. This approach, which moves beyond the traditional passive quality surveillance to the more active process of preventing spoilage, allows stakeholders to rationalize the use of resources, reduce waste, and improve consumer confidence, which are all important issues for global sustainability and the circular economy.

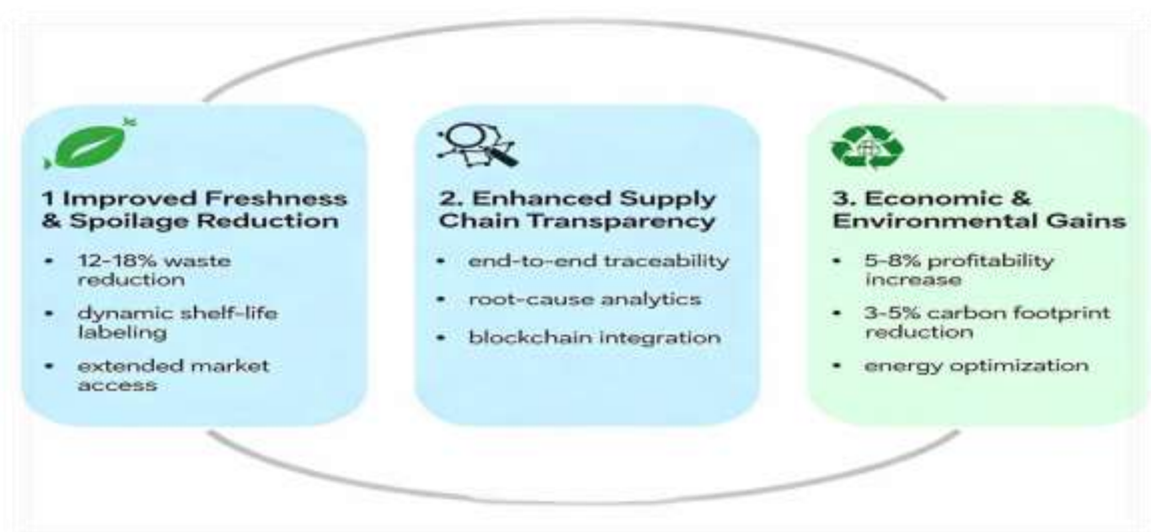

Fig: 2: Advantages and effects of AI in Quality Management.

5.1 The maintenance of freshness and reduction of spoilage have been improved.

One of the most obvious and measurable advantages of implementing AI-powered quality management is the drastic decrease in premature spoilage and associated product loss. The traditional approach of fixed-date expiration labels often results in the loss of edible food products, resulting in an estimated 10-15% of total food waste in developed supply chains (Madhu, 2025; Thakur et al., 2022). Dynamic shelf-life estimation, however, which is based on actual sensor data and predictive modeling, can adjust expiration dates to more accurately reflect product condition rather than worst-case scenarios.

This potential has been proven by empirical evidence from pilot implementations. AI-powered inventory rotation and price optimization for predicted remaining shelf life (RSL) reduced the rate of spoilage in a study on chilled meat distribution by up to 18% compared to traditional FIFO (first in, first out) systems (Liakos et al., 2025; Ablegue et al., 2025). Likewise, when monitoring transport conditions in real time, it was possible to intervene early, such as rerouting shipments or adjusting refrigeration setpoints, to avoid a potential 20% loss in product quality before reaching the retail point (Das et al., 2025; George & George, 2023).

In addition to the economic benefits, these benefits are directly related to improved food security. AI-driven logistics optimization can increase the shelf life of poultry products by 1-3 days, improving access to low-income smallholder producers while preventing post-harvest losses, which have a disproportionate impact on smallholder producers in areas where cold-chain facilities are still at a very early stage of development (George & George, 2023; Dhal & Kar, 2025).

5.2 Improved supply chain visibility and logistics optimization.

AI-powered systems fundamentally change the dynamics of data throughout the poultry supply chain, moving from hidden, siloed data to end-to-end visibility. At the farm level, it captures critical data such as feed composition, vaccination history, and processing conditions. At the packaging plant, it records chilling rates, packaging details, and gas mixes used. During distribution, it monitors shock events and time-temperature profiles. It manages all the information, ranging from inputs at the farm level (feed composition, vaccination records, etc.), to processing parameters at the packaging plant (chilling rates, packaging details, etc.), to distribution telemetry (time-temperature history, shock events, etc.), creating a detailed digital twin of each batch's journey from the farm to the fork (Das et al., 2025; Mandal et al., 2025).

This transparency provides multiple benefits for operations. First, it allows root cause analytics: when clusters of spilages are identified, the system can trace deviations to specific upstream causes like a certain transport line, packaging line, or farm, which allows for more targeted corrective action and not general recalls (Liakos et al., 2025; Altemimi et al., 2025). Second, it enables dynamic logistics optimization: shipments with high quality deterioration rates may be directed to more local markets or expedited delivery, while others with a more predictable quality deterioration rate are sent to a longer-haul market (Madhu, 2025; Davidescu et al., 2025).

Furthermore, integrating a blockchain traceability system improves consumer trust by offering transparent and tamper-proof product histories. QR codes on packages can connect to dashboards that track real-time freshness scores, optimal storage conditions, and even carbon footprints, which are growing in importance to savvy consumers who seek to act ethically (Davidescu et al., 2025; Thakur et al., 2022). Environmental sustainability and economic gains with smarter processing, using new technologies.

The economic argument for the use of AI in poultry quality management is clear. This not only boosts gross margins but also contributes to better revenue capture through dynamic pricing and inventory optimization. Liedeker et al. (2025) estimated the net profitability gain of 5–8% in an integrated poultry system using AI-driven shelf-life management, mainly due to waste reduction and asset utilization.

The benefits to the environment are equally important. Food waste is more than just calories that are lost; it is resources that have been invested in (water, feed, energy, and land) that produce significant greenhouse gas emissions. These upstream impacts are indirectly reduced because of AI systems that prevent early disposal. According to Davidescu et al. (2025), reducing meat spoilage by 15% would result in a carbon emission reduction of 3–5% in poultry supply chains, which is comparable to the annual reduction of thousands of vehicles from the road.

Additionally, energy efficiency is achieved through process optimization capabilities of AI. For example, predictive maintenance algorithms can predict refrigeration failures before they happen, preventing costly compressor overhauls and expensive energy-intensive cooldowns (Zatsu et al., 2024; Song et al., 2025). Likewise, real-time microbial forecasting to dynamically adjust Modified Atmosphere Packaging (MAP) gas composition may help lower nitrogen and CO_2 use safely (Madhu, 2025).

VI. CONCLUSION AND FUTURE DIRECTIONS

By incorporating AI into poultry quality and shelf-life management, the industry is not just enhancing its current practices. However, it is also entering a new era of predictive, adaptive, and transparent food production. As this article has made clear, AI-based systems built on real-time sensing, machine learning, and digital twin technology have the potential to give unprecedented capabilities to predict spoilage, optimize logistics, and minimize waste in the poultry supply chain. However, the potential can only be realized through ongoing innovation, inter-sector collaboration, and responsible use.

The future of these systems is expected to be defined by several promising research paths. Explainable and hybrid AI models are essential to fostering trust and regulatory compliance. Deep learning architectures produce high accuracy, but are not easily auditable and cannot be readily adopted in safety-critical applications due to their “black-box” nature. New methods like physics-informed neural networks (Ablegue et al., 2025) that incorporate known spoilage kinetics into network structures and attention mechanisms (Shi et al., 2024) that emphasize influential input features provide opportunities for balancing performance with interpretability. These models, along with uncertainty quantification techniques, can generate predictions as well as confidence intervals, which can facilitate risk-informed decision-making.

Also, greater interconnection with blockchain and green AI systems will improve both traceability and sustainability. Consumer demand for transparency can be met with blockchain-ledgered quality histories, which provide tamper-proof quality history records and enable timely and targeted recall in case of need (Davidescu et al., 2025; Thakur et al., 2022). At the same time, the environmental impact of AI systems can be reduced by following “green AI” principles, which focus on energy-efficient model training, AI-based inference on the edge, and reducing the data used by AI systems (Song et al., 2025; Zatsu et al., 2024).

Personalization will increasingly play a starring role as consumers' tastes and supply chain structures differ. The shelf-life models in future systems could be customized according to the users' storage habits, for instance, according to the temperature of the home refrigerator as determined using smart appliances, or be adapted to culinary traditions in different regions, for instance, according to the acceptability of minor color changes for different markets (Madhu, 2025; Liakos et al., 2025). This level of granularity requires more data and more participatory design processes, in which farmers, processors, retailers, and consumers co-create value.

Finally, scalability and access equity are key. One of the major contributors to severe post-harvest loss is low-resource conditions in which lack of facilities, capital, and technical skills are major limiting factors (George & George, 2023; Dhal & Kar, 2025). This will need modular, affordable solutions, including smartphone-based spectral analysis, shared sensor networks, and open-source modeling tools, as well as policy measures that boost adoption for SMEs. AI can be a force for technological equality, not inequality, only when it is designed and developed inclusively.

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