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Real-Time Iot and AI Systems for Monitoring Food Freshness in Supply Chains

Kumar Rahul[1], Shubham Singh Patel[1], Vikas Malik[2], Ramjee Prasad Gupta[3], Neeraj Arora[4], Surender Kumar Kulshrestha[5]
[1]Department of Interdisciplinary Sciences, NIFTEM, Kundli 131028, India
[2]Department of Agriculture and Environmental Sciences
[3]Department of CSE, BPS Mahila Vishwavidyalaya, Sonepat 131001, India
[4]Department of Electrical Engineering, MIT Muzaffarpur 842003, India
[5]School of Science and Technology, VMOU, Kota 324010, India
[6]School of Humanities and Social Sciences, VMOU, Kota 324010, India
[1]kumar.rahul@niftem.ac.in; [1]shubhamnotshubham@gmail.com; [2]vikassmalik@gmail.com
[3]rpgupta@mitmuzaffarpur.org; [4]neeraj.arora007@gmail.com; [5]skulshrestha@vmou.ac.in;
*Corresponding author E-mail: kumar.rahul@niftem.ac.in

Abstract
Ensuring the freshness of food products throughout the supply chain remains a critical concern in the modern food industry. With increasing globalization and complex logistics, real-time monitoring systems integrating Internet of Things (IoT) and Artificial Intelligence (AI) technologies have emerged as promising solutions. These systems enable continuous tracking of environmental parameters, predictive analytics, and automated decision-making, thus helping reduce spoilage, improve traceability, and ensure food safety. This paper presents a comprehensive literature review on recent developments in real-time IoT and AI systems for monitoring food freshness across the supply chain. The review highlights key technologies, application domains, research findings, and existing challenges. It further identifies the research gaps and outlines the methodological approaches for future studies. This review aims to provide a consolidated reference for researchers and practitioners interested in deploying intelligent and real-time food monitoring systems.
Keywords: *Food freshness; Internet of Things; Artificial Intelligence; Supply chain; Real-time monitoring; Food safety*

1. INTRODUCTION

Food freshness plays a pivotal role in ensuring the quality, safety, and consumer satisfaction of perishable goods. However, maintaining freshness throughout the entire supply chain—from farm to fork—remains a challenging task due to varying environmental conditions, logistical delays, and lack of transparency. In recent years, the convergence of the Internet of Things (IoT) and Artificial Intelligence (AI) has created transformative opportunities for real-time monitoring of food freshness [1]. IoT technology enables the deployment of interconnected sensors that collect real-time data on critical environmental parameters such as temperature, humidity, gas concentration (e.g., ethylene, CO2), and light exposure [2]. These data are essential for assessing food quality, especially for perishables like fruits, vegetables, dairy, and meat products. Simultaneously, AI algorithms—ranging from machine learning (ML) to deep learning (DL) models—facilitate predictive analytics, anomaly detection, and automated decision-making processes [3]. For instance, AI can be used to process complex sensor data in near real time to detect anomalies indicative of spoilage or improper storage conditions [4]. The importance of such monitoring systems is underscored by statistics from the Food and Agriculture Organization (FAO), which estimates that approximately one-third of all food produced globally is wasted, with a significant proportion due to spoilage during transportation and storage [5]. By deploying real-time IoT and AI systems, stakeholders can identify potential risks earlier, optimize logistics, and enforce timely interventions, thereby reducing food waste and improving supply chain efficiency. Moreover, predictive models can enable proactive decision-making rather than reactive responses, which is critical for time-sensitive perishable goods [6]. In practice, these technologies have been implemented in diverse settings, including cold chain logistics, smart packaging, and warehouse management [12]. For instance, RFID and NFC-enabled sensors have been utilized for tracking shipment conditions, while AI-driven computer vision systems have been employed for visual freshness evaluation [7]. Wireless communication technologies like Bluetooth, ZigBee, LoRaWAN, and 5G support seamless data transmission, while cloud and edge computing infrastructures provide storage and computational capabilities [4]. Edge computing, in particular, offers benefits in latency-sensitive scenarios such as spoilage detection during long-haul transport [11].

Despite their potential, several challenges hinder the large-scale adoption of IoT-AI systems. These include energy constraints in sensor devices, data privacy and security concerns, standardization issues, integration with legacy systems, and the need for cost-effective deployment models [6]. Additionally, sensor calibration inconsistencies and the high variance in environmental conditions across geographic regions complicate universal implementation [8]. Moreover, developing accurate AI models for food freshness prediction requires extensive, high-quality datasets and domain-specific knowledge [9]. This paper reviews the state-of-the-art research in real-time IoT and AI systems for monitoring food freshness in supply chains. The objective is to synthesize existing work, identify research gaps, and propose directions for future investigations.

Section 2 Presents the literature review, including a summary table of key contributions.
Section 3 Outlines the primary research problems.
Section 4 Discusses the research methodology to address these challenges, and
Section 5 Concludes the review with insights into future trends.

2. LITERATURE REVIEW

Recent studies have explored various technological frameworks combining IoT and AI for enhancing food freshness monitoring. For instance, [1] integrated a wireless sensor network with a deep learning model to predict the freshness of strawberries in cold storage. Similarly, the authors proposed a hybrid model using gas sensors and ML algorithms to detect spoilage in packaged meat [10]. These technologies often rely on real-time data capture, intelligent pattern recognition, and integration with cloud or edge processing systems [3].

Table 1. Studies on IoT and AI for monitoring food freshness

References	Technologies	Results	Challenges
Zou et al. (2021)	WSN Deep Learning	Accurate prediction of strawberry freshness in cold storage	Sensor calibration and battery constraints
Ghosh et al. (2022)	Gas sensors ML	Detected spoilage in meat with 91% accuracy	Need for calibration with different meat types
Kim et al. (2020)	RFID AI	Real-time tracking of milk freshness across distribution centers	Data synchronization and transmission delays
Liu et al. (2019)	IoT CNN	Freshness grading of vegetables using visual cues	Model overfitting with limited datasets
Sharma et al. (2023)	Lowpower WAN Predictive Analytics	Low-power system for tracking fruits in rural areas	Network coverage and latency
Wang et al. (2021)	Smart packaging AI	Shelf-life prediction for dairy products using embedded sensors	Packaging material compatibility
Ahmed et al. (2022)	Edge AI Wireless Sensors	Reduced data transmission costs with localized AI inference	Limited edge processing power
Li et al. (2020)	Cloud computing SVM	Centralized prediction of fish freshness using spectral data	Latency and dependency on internet
Garcia et al. (2021)	Image sensors AI	Visual analysis of fruit ripeness with 95% accuracy	Image variability due to lighting conditions
Mohan et al. (2023)	5G IoT ML	Fast response time for perishable shipments tracking	High infrastructure cost
Tan et al. (2022)	NFC AI	Identified freshness of bakery items in retail	Limited read range of NFC
Rajan et al. (2020)	Bluetooth Time-series ML	Temperature trend prediction for refrigerated transport	Signal interference in crowded networks

3. Research Problem

The rapid evolution of smart supply chains has led to an increasing reliance on real-time data-driven systems for maintaining food quality. Despite notable advancements, there remains a significant research gap in developing integrated, scalable, and cost-effective IoT-AI solutions for food freshness monitoring. A key issue is the fragmentation of current technological solutions, which are often designed for specific types of food or isolated segments of the supply chain [10]. This limits the generalizability and interoperability of such systems across different logistical environments.

One of the primary challenges involves sensor limitations. Most freshness-monitoring sensors are sensitive to particular environmental conditions or chemical markers. Their deployment in dynamic and heterogeneous food logistics scenarios—such as refrigerated trucks, open-air markets, or cross-border shipments—presents inconsistencies in data collection and accuracy [1][8]. Moreover, many sensors face power efficiency issues that restrict their long-term usability, especially in settings where battery replacement or charging is infeasible. Another significant barrier is the limited integration between IoT hardware and AI models. In many cases, sensor data are collected but not processed in real time due to the absence of sufficient computing power at the edge [4]. Cloud processing, while powerful, introduces latency and dependency on stable internet connections, which are often unavailable in remote or underdeveloped areas [11]. Furthermore, the lack of standardized data formats and protocols hinders the development of universally deployable AI solutions [6]. On the AI front, model development is hampered by the scarcity of high-quality, annotated datasets that reflect real-world conditions. Existing datasets often lack diversity in food types, spoilage conditions, and environmental variables. This reduces model accuracy and limits applicability in diverse settings [9]. Additionally, training robust models for perishable goods requires not only large datasets but also domain-specific knowledge to interpret sensor data patterns correctly [3]. Data security and privacy represent another critical concern. As sensor networks grow, so does the potential for cyber threats, data manipulation, and unauthorized access. Implementing secure communication protocols, blockchain for traceability, and compliance with data protection regulations (e.g., GDPR) adds further complexity and cost to deployment [2]. Finally, economic and infrastructural constraints inhibit widespread adoption. Many stakeholders in developing regions lack the financial and technical resources to implement end-to-end IoT-AI solutions [6]. There is a need for low-cost, energy-efficient, and modular platforms that can be customized for various food products and supply chain configurations. Overall, the research problem centres around the need to create an integrated, secure, scalable, and intelligent system for real-time food freshness monitoring that functions reliably across diverse operational contexts. Addressing this gap requires interdisciplinary collaboration between engineers, computer scientists, supply chain experts, and food technologists.

4. RESEARCH METHODOLOGY

To address the identified challenges, the research methodology will follow a hybrid approach combining experimental design, simulation modelling, and system prototyping. This section outlines the key stages.

4.1 System Architecture Design

The study begins by designing a modular system architecture composed of four core layers: (i) sensing and data acquisition, (ii) edge and cloud computing, (iii) AI analytics, and (iv) visualization and decision-making. Sensors will capture real-time data (temperature, humidity, gas concentration, etc.), which will be transmitted via wireless protocols (LoRa, ZigBee) to edge devices for preliminary processing. The processed data will be further relayed to cloud platforms for model training and long-term analytics [4].

4.2 Dataset Development and Feature Engineering

Fresh produce and dairy items will be monitored under controlled spoilage experiments to generate a representative dataset. Sensors and imaging devices will record environmental and visual indicators of freshness. Manual quality inspection (visual, olfactory, and microbial tests) will serve as ground truth. Feature extraction techniques such as PCA, FFT, and histogram analysis will be employed to preprocess data before feeding it into AI models [9].

4.3 Model Training and Optimization

Multiple machine learning algorithms—including support vector machines (SVM), convolutional neural networks (CNN), and ensemble learning methods—will be implemented to develop freshness prediction models. These models will be evaluated using metrics such as accuracy, F1-score, and RMSE. Transfer learning and data augmentation will address the limitations of small datasets [3].

4.4 Prototype Implementation and Testing

A low-power IoT device prototype will be built using microcontrollers (e.g., ESP32) integrated with sensor modules and edge AI accelerators (e.g., Coral TPU). Real-time monitoring will be tested across different logistics environments (cold storage, transport, retail). The prototype's performance will be compared against traditional quality control methods to validate its efficacy [10].

4.5 Risk Analysis and Security Integration

Cybersecurity protocols such as data encryption, blockchain for traceability, and multi-factor authentication will be incorporated. Risk analysis will evaluate vulnerabilities in data transmission and storage to ensure system robustness [2].

5. CONCLUSION AND FUTURE DIRECTIONS

The integration of IoT and AI technologies into food supply chains offers unprecedented capabilities for real-time freshness monitoring, quality control, and waste reduction. This review has highlighted significant progress in sensor deployment, predictive modeling, and communication infrastructure. However, technical, economic, and logistical barriers persist—particularly around system integration, data quality, energy efficiency, and scalability. Future research should focus on enhancing edge AI capabilities, creating open-source datasets across multiple food categories, and standardizing protocols for data sharing and model interoperability. Additionally, interdisciplinary collaboration between AI researchers, agricultural scientists, and supply chain professionals is essential to translate prototypes into commercial-scale solutions. A particular emphasis should be placed on developing affordable, plug-and-play systems that can be deployed in resource-constrained environments. With continued innovation, IoT-AI systems have the potential to transform food supply chains into intelligent, adaptive networks capable of ensuring freshness, safety, and sustainability on a global scale.

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Conflict

The authors declare no conflict of interest.

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