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Edge AI and IoT-Enabled Smart Food Manufacturing System for Adaptive Process Control, Real-Time Quality Monitoring, and Sustainable Production

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Abstract: Edge Artificial Intelligence (Edge AI) and the Internet of Things (IoT) are revolutionizing the smart food manufacturing landscape, offering enhanced adaptive process control, real-time quality monitoring, and more sustainable production processes. Food manufacturers must make quick and accurate decisions to ensure product consistency, safety, and operational efficiency in their food manufacturing processes. Smart use of IoT-based infrastructure, with its sensors and edge-based analytics, can process data near its source, thereby reducing latency and enabling instant responses to process changes. This paper reviews the system architecture for smart food manufacturing enabled by Edge AI, focusing on physical sensing, local data collection, Edge AI intelligence, and cloud connectivity, and highlighting communication protocols and deployment considerations. It also focuses on the use of artificial intelligence (AI) for developing adaptive control strategies, including predictive modeling, anomaly detection, and closed-loop feedback for process optimization and quality assurance. Furthermore, the article discusses the benefits of minimizing waste, conserving energy, and predicting maintenance needs. Lastly, the following key challenges are addressed: security, interoperability, scalability, and integration complexity, as well as future opportunities such as 5G, blockchain, and digital twins for smart and resilient food systems.

Keywords: AI for the Edge, Internet of Things (IoT), smart food manufacturing, adaptive process control, real-time quality monitoring, sustainable production, food safety.

1. INTRODUCTION

As consumer and regulatory expectations rise, the food manufacturing industry is under increasing pressure to deliver higher-quality products, ensure food safety, reduce food waste, and become more sustainable. These needs have fueled interest in smart food production, in which digital technologies enhance efficiency, responsiveness, and data-driven production processes. AI and IoT technologies, along with intelligent systems, have become more prevalent in recent years to boost efficiency, quality management, and sustainability in food production and manufacturing settings (Agrawal et al., 2025; Canatan et al., 2025; Mansour et al., 2025).

Of all these changes, Edge AI and IoT are becoming key enabler technologies for real-time monitoring and adaptive process control. IoT sensors can continuously monitor key process and product parameters such as temperature, humidity, pressure, vibration, and flow conditions. At the same time, edge computing enables data processing near the source, providing faster response times and lower latency. This is particularly relevant in food manufacturing, where timely intervention can prevent defects, ensure food safety, and help to maintain consistency in production (Ataei Kachouei et al., 2023; Pandey et al., 2025; Yazdi, 2024). Moreover, edge intelligence is not dependent on cloud resources, which means that more trustworthy local decision-making can be achieved than in cloud-only systems, especially in time-critical industrial setups (Rahman et al., 2025; Vermesan et al., 2022).

AI combined with IoT further uplifts food systems quality monitoring and process optimization. Anomaly detection, prediction of deviations from the process state, and closed-loop feedback control are among the benefits that AI-based models can provide, enabling manufacturers to act proactively when process conditions change (Subramanian, 2023; Okuyelu & Adaji, 2024). These features are beneficial in food-specific applications, such as traceability, rejection analysis, process consistency, and microbial or fermentation control, where slight inconsistencies can impact the final product quality and safety (Dakhia et al., 2025; Huang et al., 2025; Nasrudin et al., 2025; Yee et al., 2025). Meanwhile, distributed and connected technologies like blockchain and federated learning are being investigated to enhance collaboration, traceability, and trust in the smart food supply chain (Ding et al., 2025).

The article thus explores the potential of Edge AI and IoT for integration into smart food manufacturing systems to enable adaptive process control, real-time quality monitoring, and sustainable production. It has centered on the system's architecture, AI-driven control systems, and the sustainability advantages it offers, as well as implementation challenges such as interoperability, security, scalability, and deployment complexity. The article aims to summarize existing knowledge and assess the value of intelligent edge-enabled systems for the future of a safe, efficient, and sustainable food manufacturing industry.

2. LITERATURE REVIEW

Smart food manufacturing is a concept that relies on and extends the convergence of artificial intelligence, Internet of Things (IoT), and edge computing in the broader effort to enhance the visibility, responsiveness, and sustainability of food manufacturing. Over the last several years, research has increasingly focused on food manufacturing as a data-driven process in which continuous monitoring, rapid response, and adaptive optimization are vital to ensuring food safety and quality (Agrawal et al., 2025; Canatan et al., 2025; Mansour et al., 2025). As this literature shows, there has been a transition in the field of automation from simple systems to intelligent systems that learn and take action in real time based on process data.

One of the key topics in the literature is the application of AI and IoT for process monitoring and quality control. The operational data from an IoT sensor network can be used in real time, and AI models can convert the data into actionable insights for identifying defects, predicting quality, and optimizing processes (Subramanian, 2023; Okuyelu & Adaji, 2024; Pandey et al., 2025). This is especially helpful in the food processing industry where product quality can be affected by slight variations in environmental and operational conditions. AI-powered food production is also being shown to enhance traceability and consistency throughout the manufacturing process, helping detect issues at an early stage and minimize losses in downstream stages of the food supply chain (Dakhia et al., 2025; Huang et al., 2025; Nasrudin et al., 2025).

Another significant trend in the literature is the shift in the focus from cloud analytics to edge intelligence. Edge computing is a technology that enables data from sensors and machines to be processed at the edge, thereby reducing latency and improving reliability in time-critical environments (Yazdi, 2024; Vermesan et al., 2022). In the food manufacturing industry, this is particularly important because it can lead to spoilage, nonconformance, or waste. The empirical research on edge AI for industrial systems indicates that local analytics can enhance the speed of anomaly detection, control performance, and operational resilience, particularly in the context of a digital twin and an industrial automation system (Pal, 2024; Rahman et al., 2025).

AI- and IoT-powered food systems are also known for their sustainability benefits. Research confirms that smart sensing and intelligent control can lead to energy savings, minimize raw material wastage, and enable predictive maintenance, enhancing economic and environmental efficiency (Ataei Kachouei et al., 2023; Agrawal et al., 2025; Alghamdi & Haraz, 2025). Moreover, distributed technologies such as blockchain and federated learning are becoming prominent for their potential to enhance transparency, data sharing, and trust in food supply networks while maintaining privacy (Ding et al., 2025). The developments point to a new trend in which sustainability is becoming part of the design purpose in intelligent food manufacturing, rather than just an additional value.

Despite these advances, many challenges remain unaddressed in the literature. Food manufacturing settings are frequently characterized by a diverse array of sensors, devices, and legacy systems, with limited compatibility between them (Dakhia et al., 2025; Canatan et al., 2025). Security and privacy are also critical, especially if production data is shared with multiple stakeholders in a supply chain or crosses the edge and cloud (Ding et al., 2025). Another hurdle is the lack of practical implementation due to issues with scalability, model robustness, and deployment complexity, particularly when AI models must consistently deliver high accuracy across varying process conditions and within constrained edge computing resources (Rahman et al., 2025; Vermesan et al., 2022).

In summary, all the literature reviewed suggests that Edge AI and IoT are a viable platform for the future of food production. While existing studies have demonstrated the benefits of real-time monitoring, adaptive control, and sustainable optimization, they have also highlighted the critical importance of system integration, data governance, and operational reliability when implementing these in practice (Agrawal et al., 2025; Canatan et al., 2025; Mansour et al., 2025). This article takes that as a starting point. It highlights the potential of integrating these technologies to enable adaptive process control, real-time quality monitoring, and sustainable production in smart food manufacturing systems.

3. SYSTEM ARCHITECTURE

The proposed smart food manufacturing system comprises four interconnected layers: Sensing and Data Acquisition, Edge Analytics, Cloud Coordination, and Control Execution. This multi-layered approach enables quick local responses, long-term cloud storage, model retraining, and analytics across sites. This configuration is particularly beneficial in the food production industry, where process parameters can fluctuate rapidly and need to be adjusted immediately to prevent loss or degradation of food quality (Yazdi, 2024; Rahman et al., 2025).

The sensing layer consists of physical devices that sense the continuous process data in the production environment. Commonly used inputs include temperature, humidity, pressure, vibration, flow rate, pH, and conductivity, as well as visual or spectral outputs to assess product quality. These streams are then preprocessed at the edge by filtering out noise, extracting features, and applying screening thresholds, thereby reducing communication overhead and enabling faster decision-making (Ataei Kachouei et al., 2023; Pandey et al., 2025). This can then be used to identify abnormal conditions, segment product conditions, or estimate the process outcome at the plant level (Subramanian, 2023; Okuyelu & Adaji, 2024).

The cloud layer is not an edge; it serves complementary roles. It facilitates enterprise-wide optimization across production lines or facilities, large-scale data archiving, model training, and dashboard data visualization. The hybrid architecture aligns with ongoing research on the Industrial Internet of Things (IoT), digital twins, and distributed intelligence, in which autonomy is strengthened by centralized learning and coordination (Pal, 2024; Rahman et al., 2025; Ding et al., 2025). This balance is crucial for food manufacturing, as it enables real-time process control and improvement.

The protocol for communication between devices, between edge nodes, and to a cloud service can be MQTT, OPC UA, HTTP/REST, or industrial wireless links, depending on the requirements for latency, bandwidth, and integration. Variations in protocols affect reliability, interoperability, and scalability across heterogeneous devices. However, in reality, food factories typically require architectures that can accommodate real-time message exchange, secure authentication, and flexible expansion across various production areas, or zones (Dakhia et al., 2025; Canatan et al., 2025).

Table 1: Architecture comparison

Layer	Main function	Example technologies	Relevance to food manufacturing
Sensing and data acquisition	Capture process and product data	IoT sensors, cameras, RFID, spectroscopy	Enables continuous monitoring of quality and process conditions (Ataei Kachouei et al., 2023; Nasrudin et al., 2025).
Edge analytics	Local preprocessing and AI inference	Embedded AI, gateways, microcontrollers	Supports low-latency anomaly detection and adaptive control (Vermesan et al., 2022; Subramanian, 2023).
Cloud coordination	Storage, training, visualization, fleet optimization	Cloud platforms, digital twins, analytics dashboards	Supports long-term optimization and multi-site management (Rahman et al., 2025; Ding et al., 2025).
Control execution	Automated adjustment of process parameters	PLCs, actuators, controllers	Maintains product consistency and reduces waste through feedback control (Okuyelu & Adaji, 2024; Pandey et al., 2025).

The AI models deployed at the edge are typically lightweight enough to run under constrained computational resources while still delivering useful predictions or classifications. Common model types include anomaly detection networks, regression models for process estimation, and computer vision models for product inspection. Studies in smart manufacturing and food computing indicate that these models are most effective when aligned with specific process variables and integrated into a feedback loop that automatically triggers control actions (Subramanian, 2023; Dakhia et al., 2025; Huang et al., 2025). In this sense, the architecture is not only a data pipeline but also a decision-making system.

4. ADAPTIVE CONTROL AND QUALITY MONITORING

Adaptive control in smart food manufacturing relies on continuous sensing, real-time inference, and closed-loop decision-making. In this approach, IoT sensors gather process data, AI models on the edge network detect deviations, and control systems regulate operating parameters before quality issues arise. In the food sector, this method is particularly beneficial for ensuring product safety, quality, and consistency while also addressing process drift, which can negatively impact product characteristics such as texture, microbial stability, and safety (Subramanian, 2023; Okuyelu & Adaji, 2024; Pandey et al., 2025).

A key component of this section is the use of AI to build predictive models, enabling the system to anticipate outcomes rather than respond to errors. With historical and real-time sensor data, models may predict product quality, identify outlier events, and predict equipment or process instabilities. In the field of intelligent industrial systems and food computing, studies demonstrate that edge-based AI can be beneficial for classifying and detecting faults in a short time and minimizing the need for remote cloud processing (Vermesan et al., 2022; Dakhia et al., 2025; Rahman et al., 2025). This can translate to enhanced rejection accuracy, fewer off-spec batches, and improved process reliability.

It is important to have a closed-loop feedback structure to convert predictions into control action. If abnormal conditions are detected, the system can initiate changes in temperature, pressure, flow, humidity, speed, etc., based on the process. This aligns with recent studies demonstrating that AI can enhance manufacturing efficiency by enabling timely, targeted interventions (Ayomide & Ozurumba, 2024; Agrawal et al., 2025). Feedback loops are especially significant in food processing for maintaining uniformity of batch and continuous systems.

The literature also notes that multiple sensing modalities should be combined to achieve the best monitoring quality. Product data, spectroscopic measurements, environmental sensing, and visual inspection can be combined to give a more comprehensive picture of product condition. The application of smart technologies in food quality and traceability has been studied, with attention paid to the merits of integrating these inputs into food inspection systems to enhance inspection accuracy and facilitate tracing food origin (Huang et al., 2025; Nasrudin et al., 2025). The multimodal approach can help detect surface defects, spoilage characteristics, contamination, and process irregularities earlier than traditional inspection.

Table 2: Monitoring functions

Monitoring function	Role in the system	Typical output	Relevant benefit
Anomaly detection	Identifies abnormal process behavior in real time	Alert, flag, risk score	Prevents defects and downtime (Subramanian, 2023; Okuyelu & Adaji, 2024).
Predictive modeling	Estimates likely product or process outcomes	Quality prediction, failure probability	Supports proactive intervention (Pandey et al., 2025; Agrawal et al., 2025).
Visual inspection	Detects surface-level quality issues	Defect class, reject/accept decision	Improves inspection consistency (Huang et al., 2025).
Environmental tracking	Monitors conditions affecting product stability	Temperature, humidity, pH, pressure trends	Maintains safety and process stability (Ataei Kachouei et al., 2023; Yee et al., 2025).
Closed-loop control	Adjusts process parameters automatically	Setpoint update, actuator command	Reduces waste and improves uniformity (Ayomide & Ozurumba, 2024; Vermesan et al., 2022).

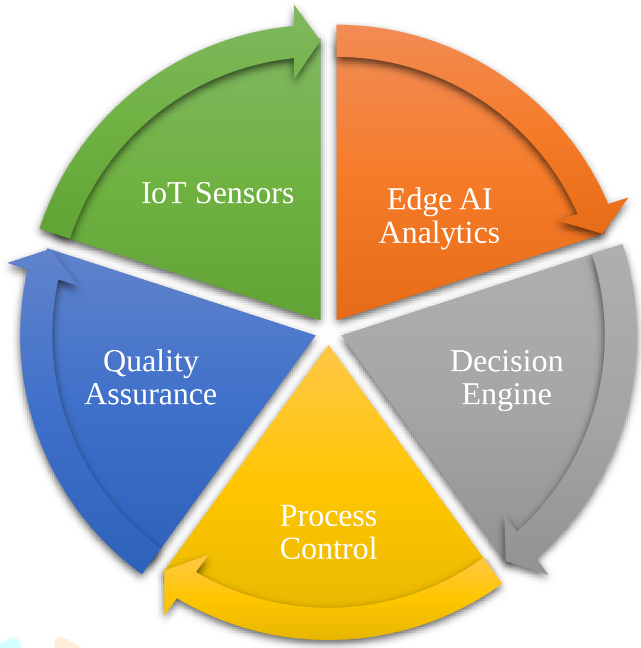

Fig 1: Adaptive AI-Driven Closed-Loop Control Framework for Smart Food Manufacturing

5. SUSTAINABILITY IMPACT

The combination of Edge AI and IoT in smart food manufacturing has significant sustainability connotations as it enables more efficient use of energy, water, raw materials, and labor, and minimizes waste throughout the production process. Sustainability is not restricted to environmental performance in food systems; it also encompasses operational resilience, resource efficiency, and the capacity to maintain product quality while minimizing losses. Recent studies reveal how intelligent manufacturing technologies can aid food producers in achieving these objectives by enabling continuous process monitoring, optimization, and rapid corrective actions in the event of inefficiencies (Agrawal et al., 2025; Ataei Kachouei et al., 2023; Alghamdi & Haraz, 2025).

A key sustainability advantage is waste reduction. Real-time monitoring and edge-processing analysis can help identify deviations earlier, enabling timely adjustments to the process before defective products are produced or raw materials are wasted. This is especially crucial in the food manufacturing industry, where timing matters, as any delay in response can result in substantial losses due to spoilage, contamination, or process instability (Okuyelu & Adaji, 2024; Pandey et al., 2025; Nasrudin et al., 2025). Edge AI minimizes off-spec batches and enables more precise rejection decisions, helping manufacturers reduce material waste and disposal costs.

Another key part of the impact is on energy efficiency. Smart control systems can optimize heating, cooling, mixing, drying, and other energy-intensive processes based on current production conditions rather than a set schedule. This dynamic control helps eliminate unnecessary energy use and enhances process responsiveness. In the literature on intelligent industrial systems and food production, there is increasing focus on the potential to contribute to more sustainable operations by optimizing energy use in line with actual production needs (Mansour et al., 2025; Agrawal et al., 2025; Vermesan et al., 2022). From a practical perspective, this translates to saving energy without compromising performance, but by making production more precise.

Fig 2: Sustainability benefits

Predictive maintenance is also a significant part of sustainability. Rather than waiting for equipment failure, AI models can identify early signs of wear, instability, or abnormal machine behavior and decide to schedule maintenance before the equipment fails. This helps minimize downtime, prolong the life of assets, and avoid unnecessary, resource-intensive emergency repairs. Research highlights the potential of predictive maintenance to enhance equipment reliability and mitigate environmental and economic losses caused by poor equipment performance (Vermesan et al., 2022; Rahman et al., 2025). This is particularly useful for food plants, where machine downtime may affect product quality and lead to waste throughout the production line.

This also contributes to sustainability by providing greater traceability and transparency in the supply chain. Blockchain and federated learning are gaining popularity as complementary technologies in distributed production networks (Ding et al., 2025), facilitating secure data sharing, provenance verification, and coordinated decision-making. They are valuable in food production for sustainability objectives, which are closely tied to transparency and accountability in the processes, as well as the ability to track inefficiencies or safety concerns back to their origin. It is also easier to plan resources and adhere to regulations in a more transparent system.

The sustainability potential of smart food manufacturing therefore lies in its ability to make production systems more adaptive, precise, and accountable. Rather than relying on reactive responses, manufacturers can use intelligent sensing and local analytics to reduce losses at the source and improve long-term operational efficiency. This positions Edge AI and IoT not only as productivity tools but also as enablers of greener and more resilient food manufacturing systems.

6. CHALLENGES AND FUTURE DIRECTIONS

While Edge AI and IoT have great promise for smart food manufacturing, several barriers to widespread adoption remain. Interoperability is one of the most important challenges because food production environments may need to integrate different types of sensors, controllers, legacy machines, and software platforms that may not interact easily with one another. This can make integration challenging and time-consuming across facilities with varying degrees of digital maturity.

Ensuring the security and privacy of data is another critical issue. The attack surface grows as production data flows across devices, edge nodes, and cloud services, giving attackers more opportunities to access, manipulate, or disrupt the service. Food manufacturing applications are particularly vulnerable because they can impact the safety of the food product, traceability, and business continuity. Therefore, from the start, the system architecture must be designed for secure authentication, encryption, and governance.

Another significant concern is scalability. Many Edge-AI scenarios work well in the pilot environment but become more complex when operating across multiple production lines or facilities. With a growing number of sensors, the system should maintain low latency, ensure model accuracy, and still communicate without consuming too much of the edge's or network resources. This challenge is closely related to efficient design of the model, modular architecture of the system, and resource management.

The combination of Edge AI, 5G, blockchain, and digital twins is expected to influence future developments. Enhanced network connectivity speeds and reliability will enable better real-time synchronization between devices and control systems, and blockchain can bolster traceability and data integrity in the supply chain. Digital twins can provide virtual copies of food manufacturing processes for simulation, predictive analysis, and scenario testing prior to making changes on the manufacturing floor. All these technologies can contribute to the real gap between experimentation and industrial scale-up.

One potential area for further improvement is the development of AI models with greater capabilities and interpretability for industrial food applications. Manufacturers require systems that are not only good but also produce results that are easy to interpret and can be trusted by their quality engineers and managers. In safety-sensitive food environments, decisions must be justified, auditable, and comply with regulations and standards. Future studies could thus aim to balance model performance, transparency, resilience, and usability in practice.

Future studies should move beyond proof-of-concept demonstrations and incorporate integrated, scalable, and secure deployments in a real food manufacturing environment. Advancements in this field rely on improved synergies between food engineers, data scientists, automation experts, and food industry participants. This cooperation will be crucial to bringing the promise of Edge AI and IoT into reliable, secure infrastructures for smart and sustainable food production.

7. CONCLUSION

Edge AI and IoT provide a solid basis for the continued development of a smart food manufacturing system that can shift to adaptive process control, monitor quality in real-time, and produce sustainably. These technologies bring intelligence closer to the data source, minimizing latency, enhancing responsiveness, and enabling quicker corrective actions where quality and safety rely on timely decisions. The literature reviewed indicates that this approach can boost process visibility, minimize waste, and improve operational efficiency in various food manufacturing environments (Agrawal et al., 2025; Dakhia et al., 2025; Pandey et al., 2025).

This central theme of the article is that smart food manufacturing is not just about automation; it is about creating a system that can sense, analyze, and react intelligently in real time. Data acquisition through an IoT approach lays the groundwork for continuous monitoring, and Edge AI enables predictive modeling, anomaly detection, and closed-loop control at the production site. This arrangement enhances product uniformity and minimizes the potential for product defects, spoilage, and waste of resources, especially in industries with tight production schedules like fermentation, beverage manufacturing, and packaged food production (Subramanian, 2023; Okuyelu & Adaji, 2024; Yee et al., 2025; Nasrudin et al., 2025).

The sustainability value is also important. The use of intelligent control will not only help lower energy usage but also limit material losses and enable predictive maintenance, all of which will make the manufacturing process more resource-efficient. Furthermore, the use of traceability-enhancing technologies such as blockchain and federated learning can increase transparency and trust in food production systems, thereby making it more feasible to achieve sustainability at scale (Ding et al., 2025; Ataei Kachouei et al., 2023; Alghamdi & Haraz, 2025). The developments demonstrate the growing connection between digital intelligence and sustainability in today's food manufacturing approach.

However, the shift to full-scale deployment is limited by security, interoperability, scalability, and implementation complexity. The growth of the industry will rely on the development of robust architectures, interoperable platforms, explainable AI models, and better integration with new technologies such as 5G and digital twins. Ongoing interdisciplinary efforts are crucial to translating these demonstrations into reliable industrial systems for real-world production environments (Rahman et al., 2025; Canatan et al., 2025; Vermesan et al., 2022).

In conclusion, the integration of Edge AI and IoT offers a promising avenue for achieving smarter, more efficient, and sustainable food production systems. As they are integrated, they can transform the future of food production, monitoring, and optimization over the next decade, leading to safer food, reduced environmental footprint, and increased resiliency.

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