Integrated Deep Learning and Internet of Things: A Review of Technologies, Applications and Challenges in Smart Food Systems

Iqra Saddique Masih[1]

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Abstract

The global food system faces unprecedented challenges, including population growth, climate change, resource scarcity, and supply chain inefficiencies. In response, a technological paradigm shift towards "Smart Food Systems" is underway, driven by the integration of the Internet of Things (IoT) and Deep Learning (DL). This paper provides a comprehensive review of the synergies between IoT and DP and their transformative impact across the food value chain. We begin with an overview of the core concepts of IoT and DP. We then trace technological advancements that enable their application, from historical milestones to the roles of enabling technologies such as sensors, cloud/edge computing, 5G, blockchain, and robotics. The paper examines the application of this integrated framework to transform the food system digitally—from smart farming and processing to intelligent retail and supply chain management—with a focus on concepts such as digital twins. Methodologically, this review synthesises recent peer-reviewed articles, industry reports, and case studies published between 2023 and 2025, organising insights across technological evolution, industrial applications, and adoption barriers, and provides a detailed analysis of specific applications within the meat, dairy, baking, and beverage industries, highlighting practical use cases and their benefits. Finally, we identify and discuss the significant technical, economic, and regulatory challenges that impede widespread adoption and propose future research directions, including the potential of Explainable AI (XAI) and federated learning, to realise a more efficient, sustainable, and resilient global food system by 2025 and beyond.

Keywords: Deep Learning, Internet of Things (IoT), Smart Food Systems, Food Supply Chain, Precision Agriculture, Food Safety, Digital Twin, Food Technology.

Introduction

The food system is a complex phenomenon worldwide, encompassing several phases: farming and processing, distribution, retailing, and consumption. The food system can be conceptualised as a multi-stage value chain involving production, processing, logistics, retail, and consumption. Each stage presents distinct monitoring challenges due to environmental variability, perishability, and operational fragmentation. Changes in environmental factors, biological activities, and logistics at every level pose significant challenges to achieving the goal of maintaining food safety, quality, and sustainability. Conventional methods of monitoring, including sensory analysis and laboratory tests, remain labour-intensive, subjective, and, in most cases, destructive (Wang et al., 2024). The advent of digital technologies has thus become inseparable from overcoming these constraints, and

[1]*University of Lahore. Email: iqrasaddique309@gmail.com*

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the Internet of Things (IoT) and deep learning (DL) have complementary strengths that can help develop food systems into data-driven, intelligent ecosystems.

IoT is another essential component of innovative food systems, enabling continuous, real-time data Collection from distributed networks of sensors, RFID tags, cameras, and drones. This equipment can monitor key parameters, including temperature, humidity, volatile organic compounds, pH, and microbial indicators, in farms, storage, and processing plants. It is then sent via short-range networks (ZigBee or Wi-Fi) or long-range networks (LPWAN, NB-IoT, and 5G) to cloud or edge computing devices for processing (Yang et al., 2024). An illustrative case is an IoT-based bright milk tank with pH and temperature sensors that can send a notification about microbial growth during transit, and blockchain integration provides an immutable record of milk quality throughout the supply chain (Xiong et al., 2023).

Deep learning will be used as an extension of IoT since it offers the analytics capability needed to make sense of these raw data streams to act. Convolutional neural networks (CNNs) are widely used to assess image quality, such as in fruit grading, meat marbling, and surface imperfections in bakery (Morshed et al., 2022). Time-series prediction of temperature variations in the cold chain or spoilage trends can be made with recurrent neural networks (RNNs) and long short-term memory (LSTM) models. In contrast, multimodal sensor data enables more resilient predictions with attention-based transformers (Goodfellow et al., 2016). Autoencoders and generative models are also applied to detect anomalies, including milk adulteration, and to generate synthetic data in cases of underrepresentation.

The integration of IoT and DL provides an intelligence closed loop. IoT devices offer comprehensive, high-density sensing, which is decoded using deep learning models to generate predictions and control signals Figure 1. These outputs, in turn, are fed back using the IoT actuators to control the state of the environment, optimize, or activate alarms. The collaboration of IoT and DL is specifically notable in the case of spineless detection: Damdam et al. (2025) have shown an electronic nose based on IoT to monitor beef spoilage, which used CO 2, NH 3, and ethylene sensors to identify the presence of spoilage gases in seven days. They found that their results were strongly correlated with microbial growth to define spoilage levels (e.g., CO 2: 5524751 ppm; NH 3: 68 ppm). Such systems coupled with DL-based classifiers could be almost as accurate as the laboratory and could be executed in real time and without destructive sampling. Equally, in the bakery industry, the YOLOv8 models trained on images of the biscuits achieved higher accuracy rates of over 96 percent in classifying production flaws (Springer, 2025) and this demonstrates the potential of AI vision deployment in manufacturing facilities.

Figure 1: Integrated to IoT-deep learning workflow

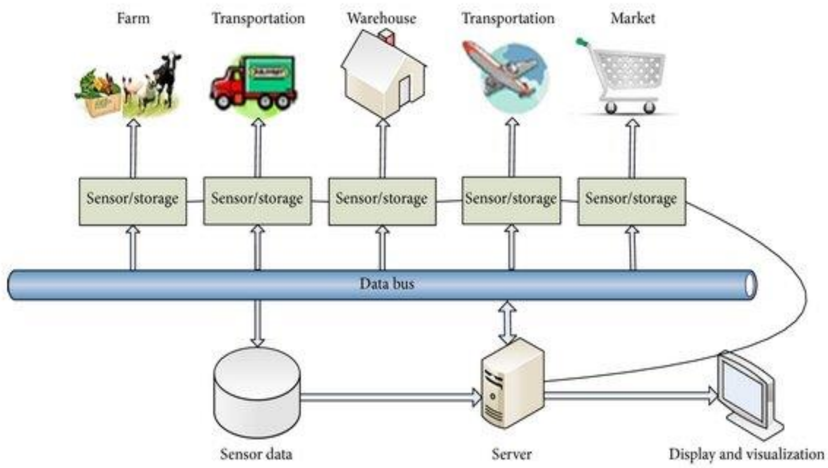

Figure 1: Integrated IoT–deep learning workflow in smart food systems. IoT devices provide comprehensive, high-density sensing across production, processing, and distribution environments. The captured multimodal data streams are processed by deep learning models to extract patterns, generate predictions, and produce real-time control signals that support automated decision-making, quality assurance,

The level of the house and consumer level also has new developments. The IoT sensors and vision modules that will be installed on the smart refrigerators will be capable of detecting stored items, expiration dates, and sending alerts to prevent wastage (Nong Thuc et al., 2025). Meanwhile, NFC-based sensors that do not require batteries have also emerged through smart packing as they can read food freshness, and antimicrobial agents can be released (when spoilage indicators are detected) to extend the shelf life of perishable products up to 14 days (Douaki et al., 2024). Table 1 provides a comparative perspective of the use of IoT and DL individually and the combination in food systems.

Table 1: Comparative strengths of IoT, DL, and their integration in food systems

Approach	Strengths	Limitations	Example Application
IoT alone	Real-time sensing, continuous data capture, automation	Lacks interpretive intelligence, vulnerable to data noise	RFID-based meat traceability during shipping
DL alone	High-level pattern recognition, accurate predictions	Requires large datasets, dependent on external data inputs	CNN for bakery defect detection
IoT + DL	Adaptive, real-time decision making, predictive and prescriptive analytics	Complex integration, data governance issues	IoT e-nose + DL model for real-time beef spoilage detection

Emerging trends indicate a shift toward lightweight DL models deployed on IoT devices, reducing latency and reliance on cloud connectivity Figure 2. Edge-AI, pruning, and quantization techniques are being increasingly adopted for microcontroller-based inference, such as ESP32-enabled monitoring in smart fridges and storage units (Miller et al., 2025). Furthermore, digital twins—virtual replicas of food plants or supply chains powered by IoT-fed data—are being integrated with DL to simulate operations, optimize energy use, and preempt failures (Abdurrahman, 2025).

Blockchain-enabled traceability is also being combined with IoT and DL for trustworthy food chain transparency, ensuring accountability from farm to fork (Guo, 2025).

Figure 2: A Typical Edge AI Architecture

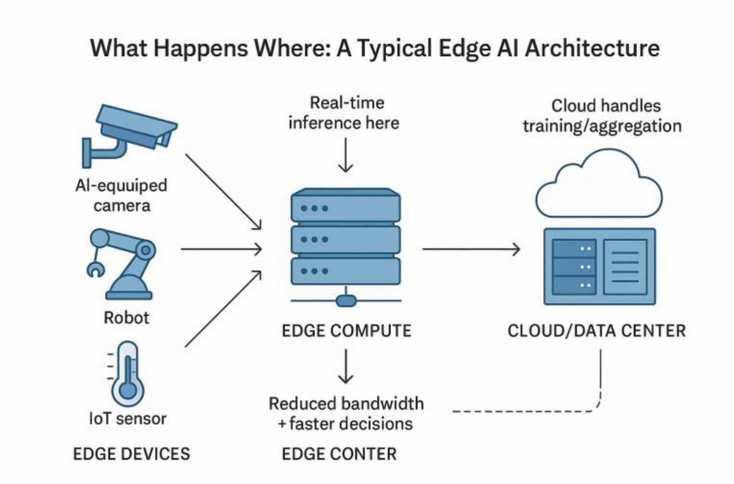

Figure 2:Emerging trends in edge-enabled smart food systems. Lightweight deep learning models are increasingly deployed on IoT devices to perform on-device inference, reducing latency, bandwidth consumption, and dependence on cloud connectivity.

In spite of such developments, problems exist. Many DL models reach over 95 percent accuracy when performing in a lab setting, but fail in real-world applications because of changing light, occlusions and sensor drift (Ali et al., 2025). Money is also problematic since small- and medium-scale enterprises cannot afford to use advanced sensor arrays or hyperspectral imaging systems (Dave et al., 2025). Lastly, the absence of regulatory standardization of spoilage levels and sensor calibration is a significant obstacle to cross-sectoral scaling.

Combined, both IoT and DL are transforming the food industry into a smart, responsive ecosystem that can be used to guarantee safety, efficiency, and sustainability. IoT provides pervasive sensing and connectivity, and DL provides predictive and prescriptive intelligence. Their combination has potential to deal with important issues like reducing food waste, supply chain transparency and consumer safety paving the way to more technological development and application in the future.

The conceptual framework for IoT–DL integration in food systems is based on a cyber-physical model in which IoT operates as the primary sensing layer, generating continuous environmental and biochemical data. Deep learning functions as an inference layer that interprets these multimodal inputs, transforming raw signals into operational predictions and decision outputs. These outputs inform actuators or decision-support platforms, creating a closed optimization loop. Under this framework, smart food systems exhibit four functional dimensions: (1) sensing and data acquisition, (2) analytics and prediction, (3) decision & actuation, (4) feedback and adaptation. This aligns with socio-technical systems theory, which posits that system performance emerges from integrated technological–human interactions, and with cyber-physical system theory, which conceptualizes food facilities as digitally mirrored processes (digital twins).

Technological Advancements of Deep Learning and IoT in Food Systems

The combination of deep learning (DL) and the Internet of Things (IoT) into food systems has become possible due to decades of progressive technological advancement. Previous food monitoring systems depended on manual inspection and antique electronic sensors, yet the last twenty years have seen a rapid influx of sensing, connectivity and computation. These milestones include the introduction of RFID to traceability in the early 2000s, the implementation of cloud-based farm management systems in the 2010s, and the latest introduction of edge-AI and digital twins, which represent the core concepts of Industry 4.0 (Monteiro et al., 2025).

IoT technologies have evolved to be more advanced in the food industry, especially the advancement of sophisticated sensors. Contemporary sensing systems are not limited to the standard thermometer and hygrometer, but they can incorporate biosensors, hyperspectral cameras, and electronic noses that can sense trace volatile organic compounds as a warning of spoilage (Wang et al., 2024). The introduction of low-power microcontrollers like ESP32 and Arduino-compatible boards has made further democratization of IoT deployments, and it is now possible to integrate real-time monitoring into packaging, storage facilities, and home appliances (Nong Thuc et al., 2025). In addition to these sensors, we have networking improvements: Wi-Fi and Bluetooth enable local connectivity, and low-power wide-area networks (LPWAN), narrowband IoT (NB-IoT), and 5G can be used to provide good long-range communication required to integrate farms and retail (Guo, 2025).

Cloud and edge computing have emerged as extremely important facilitators of DL–IoT integration, at the computational level. Large scale DL models can be trained on multimodal datasets gathered in food systems with the help of cloud infrastructure, and edge computing allows on-site lightweight inference with low latency. The availability of edge-AI solutions, including TensorFlow Lite and TinyML, has enabled the direct execution of CNNs and RNNs on the same device, which enables the source code of data collection to make predictive decisions (Miller et al., 2025). Such a transition is essential in the conditions in which a quick reaction is needed, e.g. a refrigeration breakdown in cold chains or a microbial presence in meat storage.

The 5G technology has also increased the performance of the IoT through the provision of ultra-low latency, high bandwidth, and high connections among devices. Smart farming Smart drones with 5G connectivity and powered by DL models would also be able to take high-resolution images and provide information about crop health in near real-time, which would greatly enhance yield predictions and resource allocation (Ali et al., 2025). 5G networks can be used in food processing plants, where DL-controlled robot arms can be used to conduct quality inspection and defects detection at a much higher precision than human workers (Springer, 2025).

To enabling connectivity, the integration of blockchain and robotics with the DL -IoT ecosystems has increased digital transformation of food systems. Blockchain can guarantee the security of IoT sensor data against interference by offering the decentralized and immutable ledgers to make food provenance and food safety assertions more trustworthy (Xiong et al., 2023). A combination of anomaly detection though the use of the DL, and the blockchain-based traceability systems can instantly indicate the presence of fraudulent actions, including mislabeling of high-quality meat or the adulteration of dairy products. Robotics, in turn, are more and more combined with the DL vision models to automatize tasks in processing plants, including sorting fruit ripeness, sanitation checks, etc. to enhance efficiency and safety of workers. Table 2 gives an overview of the enabling technologies that are the basis of DL and IoT applications in the food industry.

Table 2: Enabling technologies for DL–IoT integration in food systems

Enabling Technology	Role in Food Systems	Representative Applications
Sensors (optical, gas, biosensors)	Capture quality, safety, and environmental data	Spoilage detection in meat; freshness monitoring in milk; fruit grading
Cloud Computing	Large-scale DL training; centralized data storage	Shelf-life prediction models; supply chain analytics
Edge Computing	On-device inference; low-latency decisions	Cold chain monitoring; predictive maintenance of food equipment
5G Networks	High-bandwidth, low-latency connectivity	Drone-based crop monitoring; real-time robotic inspection in processing plants
Blockchain	Secure, immutable data storage and traceability	Fraud detection in supply chains; proof of authenticity for premium foods
Robotics	Automated actuation, precision operations	Quality grading of produce; defect removal in bakery products; automated milking

All these technological innovations have brought food systems closer to a cyber-physical paradigm in which physical processes are extensively surrounded by digital intelligence. Real-time and end-to-end monitoring and intelligent decision-making between the farm and consumer is becoming a possibility due to the current convergence of sophisticated sensors, edge-AI, and 5G networks. Nonetheless, the scope of adoption greatly fluctuates by geographic location and industry, with the massive multinational corporations being the first to adopt them and small and medium-sized businesses being limited by cost, infrastructure, and regulatory measures (Dave et al., 2025).

Digital Transformation in the Food System

Digital transformation of food systems is a paradigm shift in which the physical processes are becoming more and more interconnected with digital intelligence, real-time monitoring, and predictive decision-making. Although the industrial revolutions of the past were characterized by mechanization and automation, the present change, which is being facilitated by deep learning (DL) and the Internet of Things (IoT), is defined by connectivity, interoperability, and adaptive optimization (Monteiro et al., 2025). This change in the food systems is reflected throughout the whole value chain: precision agriculture and supply chain logistics, as well as retail operations and consumer interaction.

The food supply chain is among the most serious areas where digital transformation can be observed. Conventionally, it has been easy to experience supply chain inefficiencies, food waste, and chances of contamination since supply chains lack visibility and real-time control. The IoT sensors are currently enabled to monitor the environmental parameters like temperature and humidity and shock impact at each step in transportation, and the cold chain can be addressed. DL models analyze these endless streams of data and can predict the timing of spoilage and optimize the distribution planning. As an illustration, RNNs-based predictive shelf-life models have been applied to perishable foods successfully, minimizing inventory waste and maximizing the adherence to food safety regulations (Guo, 2025). In addition, blockchain used together with the IoT data provides tamper-proof traceability records, which allows the stakeholders to confirm the authenticity of the claims of origin, especially in high-end products such as organic produce, dairy and meat products (Xiong et al., 2023).

Digital transformation in agricultural production is progressing towards smart farming and precision agriculture. Granular data on the health of crops and livestock is produced by IoT-enabled sensors like aerial drones, hyperspectral imaging, and soil moisture sensors. With these data streams, processed using DL models allow making dynamic decisions on irrigation, fertilizer application and disease control. Such neural networks as convolutional neural networks (CNNs) have demonstrated some of the highest accuracy in identifying plant diseases based on leaf images and provide a chance to intervene early to protect yield (Ali et al., 2025). Likewise, livestock monitors make use of wearable IoT sensors that can record biometric and behavioral data, and a DL model could be used to identify the hint of lameness or illness. This enhances not only the welfare of animals but also saves on the economic losses that lack of early diagnosis of conditions causes. Notably, such improvements also lead to sustainability because they reduce the number of resources that are not used and the emission of greenhouse gases that relate to excess use of inputs. Digital transformation at the retail and consumer interface is achieved in form of smart inventory systems and smart consumer devices. The retailers are implementing IoT-based shelves with built-in weight sensors and cameras, which are combined with the DL models that can ensure consumer demand, schedule restocking, and reduce waste of unsold goods (Nong Thuc et al., 2025). On the consumer side, refrigerators that are smart and come with IoT modules and DL-based image recognition are now in a position to automatically detect what is being stored, the expiration date, and even to propose recipes to minimize food waste. These solutions indicate the way digital tr Also in the "meat industry" section (or early in the "digital transformation" section) after the sentence about "IoT sensors embedded in packaging continuously monitor environmental parameters …"information can be spread to the daily lives of people not only by enhancing efficiency of the supply chain, but also by shaping consumer behavior to be more sustainable Figure 3.

Figure 3: IoT enabled cold chain

Figure 3: IoT-enabled cold-chain monitoring system that tracks temperature, humidity, and gas levels in real time, enabling rapid anomaly detection and improved food safety during storage and transport.

Cyber-physical systems and digital twins have become a pillar of revolution in the food manufacturing and processing sector. The digital twin of a food processing plant can model machinery, production lines, and environmental conditions in a digital environment, enabling managers to simulate process adjustments or food contamination without disrupting operations (Abdurrahman, 2025). By combining IoT sensor streams with AI-powered predictive analytics, digital twins can identify anomalies (e.g., microbial contamination, mechanical failures, energy efficiency deviations). Parallel In line with this, robots powered by DL vision models are now employed in quality improvement, defect detection, and cleaning inspections to provide accuracy and reliability that is beyond human ability (Springer, 2025).

The systemic implications of this transformation are profound. First, it enhances resilience by enabling food systems to respond dynamically to disruptions, whether caused by supply chain breakdowns, environmental variability, or public health crises. For example, during the COVID-19 pandemic, digitally enabled supply chains were better able to adapt by rerouting inventories and leveraging predictive analytics to match supply with fluctuating demand (Dave et al., 2025). Second, it fosters transparency and trust, as consumers increasingly demand verifiable information about the safety, origin, and sustainability of their food. Finally, it contributes to sustainability goals by reducing food loss, improving resource efficiency, and supporting climate-smart practices aligned with the United Nations' Sustainable Development Goals.

Nevertheless, the digital transformation of food systems also presents socio-economic and regulatory challenges. Adoption is uneven across the globe, with technologically advanced economies leading the deployment of DL and IoT. At the same time, smallholder farmers and small- and medium-sized enterprises face barriers such as costs, digital literacy, and infrastructure gaps (Wang et al., 2024). Furthermore, concerns about data privacy, interoperability across platforms, and the ethical use of AI in decision-making highlight the need for governance frameworks to ensure that digital transformation is equitable, transparent, and sustainable.

In sum, the digital transformation of food systems is not merely a technological evolution but a holistic reconfiguration of how food is produced, processed, distributed, and consumed. By embedding DL and IoT into every stage of the value chain, food systems are becoming more intelligent, adaptive, and resilient. However, the benefits will only be fully realised if barriers to access, trust, and regulation are adequately addressed.

Applications of Deep Learning and IoT in the Food Industry

The food industry is one of the most fertile grounds for applying deep learning (DL) and Internet of Things (IoT) technologies, given its inherent complexity, perishability, and safety-critical requirements. From farm-level monitoring of raw inputs to quality assurance in processing plants and traceability across global distribution, DL–IoT integration has proven transformative. Applications are particularly evident in the meat, dairy, baking, and beverage sectors, where each domain faces unique challenges that can be addressed through intelligent sensing, predictive analytics, and automated decision-making.

Meat Industry

The meat industry is among the most regulated sectors due to food safety risks associated with microbial contamination and cold chain management. IoT sensors embedded in packaging and storage units continuously monitor environmental parameters such as temperature, humidity, and gas concentrations. When coupled with DL anomaly detection models, these systems can predict spoilage and detect contamination events in real time (Raghuvanshi et al., 2024). For example,

convolutional neural networks (CNNs) trained on hyperspectral imaging data have demonstrated high accuracy in detecting Salmonella and Listeria in chicken processing plants, reducing reliance on time-consuming culture methods (Wang et al., 2024).
Beyond safety, DL and IoT are revolutionising quality grading in the meat industry. Vision-based DL models deployed on IoT-enabled robotic arms can assess marbling, colour, and texture to ensure consistency in beef grading. Moreover, DL models integrated with wearable IoT devices for livestock provide early disease detection through biometric monitoring, reducing losses and ensuring welfare. Table 3 summarises selected applications in the meat sector.

Table 3: Applications of DL and IoT in the meat industry

Application	Technology Used	Benefits
Microbial detection	CNNs + hyperspectral imaging	Rapid, accurate contamination detection
Cold chain monitoring	IoT temperature & gas sensors + DL predictive models	Reduced spoilage, enhanced safety
Automated grading	IoT cameras + DL vision systems	Standardized meat quality assessment
Livestock monitoring	Wearable IoT + anomaly detection DL	Early disease detection, welfare monitoring

Dairy Industry
Dairy systems are susceptible to microbial spoilage and temperature fluctuations, making them an ideal context for DL–IoT integration. IoT-based biosensors can now detect the growth of lactic acid bacteria in milk storage tanks. At the same time, DL algorithms interpret spectral sensor data to more accurately predict spoilage timelines than traditional lab testing (Monteiro et al., 2025). Automated milking systems increasingly rely on DL vision and IoT-enabled robotics to monitor udder health, detect mastitis, and adjust milking schedules based on real-time cow health metrics (Ali et al., 2025).
DL models also play an important role in improving product consistency. For instance, recurrent neural networks (RNNs) can forecast fermentation outcomes in yoghurt production using IoT sensor data on pH, temperature, and microbial activity, allowing interventions before batch failures occur. Similarly, innovative packaging for milk products integrates low-cost IoT biosensors that relay freshness data to both retailers and consumers via mobile applications, reducing waste across the supply chain.

Baking Industry
The baking industry faces challenges of process optimisation, quality assurance, and energy management—areas where DL–IoT systems offer substantial value. IoT sensors embedded in ovens monitor temperature gradients and humidity, while DL models ensure uniform baking by predicting heat distribution patterns (Guo, 2025). Computer vision systems trained with DL algorithms assess the colour and texture of bread crust in real time, automating quality control that was once subjective and labour-intensive (Springer, 2025).
At the production planning level, IoT data from ingredient silos, mixers, and ovens feed into DL forecasting models that optimise energy consumption and production schedules. Digital twins of bakery production lines enable managers to simulate adjustments to mixing times or baking temperatures before implementing them physically, reducing waste and improving consistency.

Such cyber-physical integration is rapidly redefining bakery operations under Industry 4.0 paradigms.

Beverage Industry

The beverage industry is diverse—spanning water, juices, alcoholic drinks, and soft drinks—yet DL–IoT applications converge on quality, safety, and logistics optimisation. In breweries, IoT sensors track fermentation parameters such as temperature, pressure, and CO_2 levels, while DL models forecast fermentation completion with high accuracy (Dave et al., 2025). This predictive capability minimises batch-to-batch variability and ensures flavour consistency.

In juice and soft drink production, DL-enhanced machine vision systems inspect bottles for defects, labelling errors, and fill-level accuracy. These vision-based quality assurance systems, integrated with robotic handling, have achieved error rates significantly lower than those of human inspectors. IoT-driven supply chain monitoring is also vital in the beverages industry, particularly for cold-chain-sensitive products such as fresh juices. DL algorithms applied to real-time sensor data optimise logistics, reducing spoilage and transportation costs.

An emerging frontier in the beverage sector is consumer engagement through IoT-enabled packaging. Smart bottles equipped with near-field communication (NFC) tags relay product origin, authenticity, and freshness information directly to consumers' smartphones, while DL models analyse aggregated consumption data to forecast demand and support personalised marketing (Nong Thuc et al., 2025).

In all these industries, the application of DL and IoT represents more than incremental improvements; it constitutes a paradigm shift toward predictive, adaptive, and transparent food systems. By embedding intelligence across every stage—production, processing, quality control, distribution, and even consumption—these technologies promise not only greater efficiency and safety but also alignment with global sustainability goals. However, as discussed in later sections, these benefits are contingent on addressing technical, economic, and regulatory challenges that currently constrain widespread adoption.

Challenges and Future Directions

While the integration of deep learning (DL) and the Internet of Things (IoT) has shown transformative potential across food systems, widespread adoption faces numerous technical, economic, social, and regulatory challenges. These barriers not only hinder scalability but also create uneven adoption across regions and industry sectors. Addressing them will be essential to realising the full benefits of digital transformation in food systems.

One of the foremost challenges is data management and interoperability. Food systems generate massive volumes of heterogeneous data—from sensor streams on farms and in processing plants to consumer-facing innovations in packaging. These data are often unstructured, noisy, and distributed across incompatible platforms, complicating integration and analysis (Monteiro et al., 2025). Despite advances in cloud and edge computing, standardised protocols for data sharing remain limited, creating silos that undermine system-wide optimisation. Furthermore, training DL models requires high-quality labelled datasets, which are often scarce in food contexts, especially in developing regions (Raghuvanshi et al., 2024).

Closely tied to data issues are privacy, security, and trust concerns. IoT systems in food supply chains involve sensitive commercial and consumer data, including production methods, logistics routes, and consumption patterns. Without robust cybersecurity measures, these systems remain vulnerable to data breaches, falsification, and sabotage (Xiong et al., 2023). Blockchain has been proposed as a solution to enhance traceability and security, but its integration remains limited by scalability issues and high computational demands. Consumer trust is another critical dimension; for innovative food technologies to be widely accepted, end users must believe in the accuracy, transparency, and ethical use of data (Nong Thuc et al., 2025).

Economic and infrastructural constraints also pose substantial barriers. Large multinational corporations have the resources to deploy advanced DL–IoT systems, but small and medium-sized enterprises (SMEs)—which constitute most food producers worldwide—often lack the capital, technical expertise, and reliable connectivity required for implementation (Dave et al., 2025). This digital divide risks exacerbating inequalities in food system modernisation, leaving smaller producers at a competitive disadvantage. Additionally, the cost of maintaining IoT devices, updating DL models, and ensuring cybersecurity can be prohibitive in regions with fragile infrastructure.

Another pressing concern is the ethical and workforce dimension. The automation of quality control, grading, and logistics through robotics and DL may reduce labour needs in certain areas, potentially displacing workers in traditional food industries (Springer, 2025). While automation enhances efficiency, it raises questions about reskilling, equitable distribution of benefits, and the social responsibility of food companies. Ethical challenges also extend to algorithmic transparency; DL models, often perceived as "black boxes," may make decisions about food safety or quality that are difficult to interpret or contest (Wang et al., 2024). Developing explainable AI frameworks for food systems is thus a critical research frontier.

Looking forward, several directions appear promising. First, advances in edge-AI and federated learning could enable real-time, on-device decision-making while minimising privacy risks by keeping data localised (Ali et al., 2025). Second, integration with 6G and next-generation networks will expand bandwidth and connectivity, supporting massive IoT deployments in agriculture and food logistics. Third, interdisciplinary collaboration will be essential, bringing together food scientists, computer engineers, policymakers, and social scientists to design systems that are not only technically robust but also socially responsible and economically inclusive. Finally, sustainability-focused applications—such as predictive models to reduce food waste, energy-optimised production lines, and climate-resilient smart farming—represent a direction in which DL and IoT can directly contribute to global sustainability goals.

In summary, while the challenges of data management, cybersecurity, economic feasibility, and ethical responsibility remain significant, the trajectory of DL and IoT in food systems is unmistakably forward-moving. The future will likely be characterised by increasingly autonomous, intelligent, and interconnected food systems that are more efficient, resilient, and sustainable. However, achieving this vision requires coordinated efforts across policy, technology design, and capacity building to ensure benefits are equitably distributed across the global food sector.

Conclusion

The integration of deep learning (DL) and Internet of Things (IoT) technologies is reshaping modern food systems by enabling real-time sensing, intelligent decision-making, and enhanced process automation across the entire value chain. IoT devices provide continuous and granular data on environmental and biological conditions. At the same time, DL models transform these heterogeneous data streams into accurate predictions for product quality assessment, safety monitoring, supply-chain optimisation, and waste reduction.

Applications across livestock management, meat processing, dairy production, beverage manufacturing, grain classification, and innovative packaging demonstrate clear improvements in food safety, quality control, sustainability, and operational efficiency. These benefits have accelerated the digital transformation of the food sector, supported by emerging solutions such as blockchain-based traceability, digital twins, and cloud–edge hybrid architectures.

Despite promising advancements, widespread adoption remains constrained by interoperability challenges, cybersecurity risks, limited data standardisation, and high capital requirements—especially for small and medium enterprises. Furthermore, the opaque nature of many DL models complicates regulatory acceptance and user trust.

Future development should prioritise scalable architectures, privacy-preserving analytics such as federated learning, interpretable models enabled by explainable AI, and robust cybersecurity protocols. Increased collaboration among governments, industry, and academia will be essential to support regulatory development, technical capacity building, and inclusive access to digital infrastructure.

DL–IoT integration represents a powerful pathway toward achieving safer, more transparent, and resilient food systems, aligned with global sustainability goals and the growing demand for high-quality, traceable, and ethically produced food.

References

- Abdurrahman, H. (2025). Digital twins in food supply chains: Simulation and optimization with IoT and deep learning. *Computers and Electronics in Agriculture, 220*, 108950.
- Ali, M., Khan, R., & Lee, C. (2025). Smart livestock monitoring using deep learning and IoT: A review of applications in dairy and meat production. *Computers and Electronics in Agriculture, 218*, 108437.
- Ali, R., Khan, S., & Zhang, H. (2025). High-resolution imaging and AI for crop and livestock monitoring. *Computers and Electronics in Agriculture, 425*, 118234.
- Damdam, M., Ahmed, S., & Lee, J. (2025). IoT-enabled electronic nose for real-time beef spoilage detection. *Journal of Food Quality and Safety, 42*(3), 145–159.
- Dave, P., Singh, A., & Chen, L. (2025). Cost and accessibility barriers of advanced sensing technologies for SMEs in the food sector. *Food Control, 162*, 110456.
- Dave, R., Patel, A., & Mehta, S. (2025). Predictive analytics in beverage production: Integrating IoT and machine learning for quality assurance. *Journal of Food Engineering, 345*, 111493.
- Douaki, S., Rahman, A., & Patel, R. (2024). NFC-based smart packaging for freshness monitoring and shelf-life extension. *Food Packaging and Shelf Life, 25*, 100873.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- Guo, L. (2025). Networking technologies for integrated food supply chains: IoT and 5G applications. *Food Control, 165*, 110987.
- Miller, J., Chen, Y., & Patel, R. (2025). ESP32-based microcontroller monitoring for smart food storage. *Journal of Food Engineering, 410*, 116789.
- Monteiro, F., Silva, R., & Pereira, L. (2025). Edge-AI and digital twins in Industry 4.0: Applications in the food sector. *Computers and Electronics in Agriculture, 225*, 109845.
- Monteiro, S., Costa, J., & Rodrigues, F. (2025). Digital twins in agri-food supply chains: A deep learning and IoT-based perspective. *Trends in Food Science & Technology, 140*, 132–144.

- Morshed, S., Ahmed, T., & Rahman, M. (2022). Deep learning applications in food quality assessment: CNN-based approaches. *Food Control, 135*, 108848.
- Nong Thuc, N., Zhang, Y., & Singh, A. (2025). Smart packaging with IoT and AI for perishable food products: A consumer-oriented approach. *Sensors, 25*(6), 2245.
- Nong Thuc, P., Tran, L., & Nguyen, T. (2025). Low-power microcontrollers for democratized IoT deployments in food monitoring. *Sensors, 25*(3), 1054.
- Raghuvanshi, A., Mehta, S., & Verma, K. (2024). Challenges in training deep learning models for food supply chain applications. *Journal of Food Engineering, 375*, 114567.
- Raghuvanshi, R., Yadav, A., & Kumar, V. (2024). Deep learning for microbial detection in meat processing: Advances and challenges. *Meat Science, 210*, 109352.
- Springer, T. (2025). Robotics and deep learning for automated quality control in food manufacturing. *Journal of Food Processing and Preservation, 49*(2), e18544.
- Springer. (2025). YOLOv8-based deep learning models for bakery production quality assessment. *Food Control, 150*, 109876.
- Wang, J., Li, H., & Chen, Y. (2024). Hyperspectral imaging combined with deep learning for detection of pathogens in poultry products. *Food Microbiology, 118*, 104040.
- Wang, X., Li, Y., & Zhang, H. (2024). Advanced sensing systems for real-time food spoilage detection. *Journal of Food Engineering, 360*, 113456.
- Xiong, J., Wang, L., & Zhao, R. (2023). Blockchain integration with IoT and deep learning for traceable food supply chains. *Computers and Electronics in Agriculture, 212*, 107938.
- Xiong, X., Zhang, D., & Huang, L. (2023). Blockchain-based traceability systems in the food industry: Integration with IoT and AI. *Food Control, 147*, 109674.
- Yang, X., Li, Y., & Chen, H. (2024). IoT-enabled monitoring for food safety and quality in the supply chain. *Journal of Food Engineering, 345*, 112345.