International Journal of Frontline Research in
Life Sciences
Journal homepage: https://frontlinejournals.com/ijfrls/
ISSN: 2945-4832 (Online)

(Review Article)

Evaluating the effectiveness of AI-driven anomaly detection in food safety compliance monitoring

Adama Gaye [1], Barnabas Narteh Apaflo [2] and Alice Ama Donkor [3, *]

[1] *FSQ (Food Safety Quality) Analyst, SFC Global Supply Chain Inc (Schwan's) – Florence, Kentucky, USA.*
[2] *Department of Computer Science and Engineering, Texas A & M University, Texas, USA.*
[3] *Department of Computer Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.*

International Journal of Frontline Research in Life Science, 2025, 03(02), 001-009

Publication history: Received on 07 April 2025; revised on 28 June 2025; accepted on 30 June 2025

Article DOI: https://doi.org/10.56355/ijfrls.2025.3.2.0022

Abstract

Food safety compliance is a critical matter of public health and regulatory oversight, which requires strict monitoring to protect against contamination, ensure quality, and maintain standards across the industry. Conventional food safety monitoring methods typically depend on manual inspections and rule-based systems, which can be labor-intensive, time-consuming, susceptible to human error, and ineffective in identifying complex or evolving anomalies. This research investigates the effectiveness of AI-driven anomaly detection systems in food safety compliance monitoring, focusing on their capacity to improve real-time monitoring, enhance detection accuracy, and risks of non-compliance. It evaluates the performance of AI-based anomaly detection vs. traditional monitoring approaches using key metrics including detection accuracy, response time, and false-positive rates. Additionally, it also discusses the challenges of adopting AI in food safety applications, such as data quality limitations, model interpretability and regulatory restrictions. Through an analysis of case study comparisons and industry observations, the findings highlight that AI-driven technologies such as machine learning, deep learning, and computer vision significantly enhance food safety compliance through automation of contamination detection, optimizing processing parameters, and supply chain traceability. Different applications of AI mentioned in this research study have demonstrated success in reducing food spoilage, improving shelf-life prediction and quality control, as evidenced by improved accuracy of contamination detection and compliance with regulations. Nevertheless, challenges remain in terms of data availability, model interpretability, regulatory restrictions, and the high cost of AI adoption. Through a thorough analysis, this research addresses the indicators and practical uses of AI automation in food safety compliance monitoring and its potential impact on existing food safety standards.

Keywords: AI-Driven Anomaly Detection; Food Safety Compliance; Machine Learning in Food Safety; Regulatory Monitoring Systems

1. Introduction

Food safety stands as a major worldwide concern as foodborne diseases affect millions of individuals annually, resulting in serious health consequences and substantial economic losses. The World Health Organization (WHO) reports that an estimated 600 million people, which equals 1 in 10 worldwide, become sick yearly from contaminated food, resulting in 420,000 deaths [1]. The burden on healthcare systems continues to grow significantly as a result of these incidents and highlights the pressing need for more efficient food safety compliance practices necessary to avoid contamination, fulfill regulatory adherence, and maintain consumer confidence.

* Corresponding author: Alice Ama Donkor

In attempts to address food safety, the implementation of strict regulatory frameworks by governments and international organizations has been established. In the United States, the Food Safety Modernization Act (FSMA), enacted through the Food and Drug Administration (FDA), focuses on preventing food safety hazards [2]. Similarly, the European Food Safety Authority (EFSA) and Hazard Analysis and Critical Control Points (HACCP) guidelines provide systematic protocols to identify, evaluate, and control food safety risks [3].

Despite these existing regulatory frameworks, traditional food safety monitoring processes depend on manual and reactive methods. Human interventions in food safety inspections, laboratory testing, and quality control checks create delays and are prone to errors while being inefficient in identifying evolving risks in real time [4]. Moreover, the complex global food supply chains and the rising frequency of food recalls require advanced data-driven approaches to reduce risks and adhere to compliance.

2. The Growing Role of AI in Food Safety Compliance

In recent years, Artificial Intelligence (AI) has become a powerful transformational asset in numerous fields, including healthcare and finance, while it now progressively enters the domain of food safety compliance monitoring. AI technologies are used to boost crop yield and quality and enhance nutritional value while also increasing safety, traceability, and reducing resource consumption [5]. Some companies like IBM's Watson, Google's DeepMind, and Alibaba's AI-powered safety platform have begun to use AI in food supply chains to enhance traceability capabilities while detecting contaminants and automating quality assurance processes. Studies demonstrate that AI technology in food safety surveillance leads to fewer product recalls and reduced health hazards while supporting regulatory adherence [6-8].

Despite its potential, the development of AI-powered anomaly detection systems for food safety compliance remains nascent, with multiple challenges preventing its broad implementation. Traditional food safety monitoring systems depend on structured historical datasets, while AI models need continuous data feeds and large labeled datasets to enhance their precision. The lack of explainability in black-box AI models means that food regulators struggle to trust automated decisions [9]. Additionally, substantial financial resources and extensive preparation in infrastructure, workforce skill development, and regulatory harmonization are needed to integrate AI into food safety compliance systems. The adoption of AI solutions presents significant challenges for food industries, especially small and medium enterprises (SMEs), because of steep costs and insufficient AI expertise. Moreover, regulatory agencies need to revise current regulations to accommodate AI-based compliance systems that ensure fairness and accountability alongside transparency [10].

The objective of this research is to investigate AI-driven anomaly detection for food safety compliance through evaluating its effectiveness in regulatory compliance monitoring and improving regulatory adherence, comparing its efficiency with traditional assessment methods, and recognizing challenges associated with its acceptance and adoption. In addition, this research investigates the limitations and challenges hindering AI adoption on a large scale for food safety compliance, including issues surrounding data availability, interpretability of AI-generated insights, and regulatory acceptance. The significance of this research delivers value to several key stakeholders, including manufacturers who produce food products, regulatory bodies, and researchers working with AI technology.

3. Overview of Food Safety Compliance and Monitoring

The global food industry is governed by a complex set of regulations designed to protect human health and safety. In the U.S., the Food Safety Modernization Act (FSMA) permits the Food and Drug Administration (FDA) to enforce preventive controls across food supply chains. The Hazard Analysis and Critical Control Points (HACCP) also provides a methodical process for identifying and controlling potential hazards, focusing on prevention over final product testing. Notwithstanding the existence of these regulatory frameworks, the food industry and its supply chains still face a significant burden of compliance. The complex nature of supply chains, often involving multiple nations and various stakeholders, makes it more challenging to implement uniform safety standards. In addition, variability in regulatory requirements can differ from one jurisdiction to another, adding another layer of difficulty to navigate differing standards and enforcement practices. Resource constraints, especially for small and medium-sized enterprises (SMEs), further hinder these compliance efforts as they have limited financial and technical resources, making it challenging to implement comprehensive food safety systems. These challenges have sparked a multidisciplinary rethinking of food safety compliance, pushing beyond current practices towards enhanced food safety compliance and monitoring solutions. Integration of advanced technologies such as Artificial Intelligence (AI) applications in food safety monitoring and compliance systems offers promising paths for improvement in the detection and mitigation of food safety issues to strengthen compliance and safeguard public health.

4. Traditional Techniques in Anomaly Detection for Food Safety

Traditional analytical methods have contributed to ensuring food quality and safety through the detection of contaminants like pesticides, heavy metals, mycotoxins, and microbial toxins. These traditional approaches involve chemical methods such as chromatography and mass spectrometry, which provide high sensitivity and specificity but require significant sample preparation, specialized instruments, and high operational costs [11]. Labor-intensive and time-consuming biological methods like enzyme-linked immunosorbent assay (ELISA) and polymerase chain reaction (PCR) have been developed for the identification of microbial contaminants with high specificity [12]. Physical techniques such as molecular spectrometry, X-ray, and hyperspectral imaging offer rapid non-invasive analysis but may be insufficiently sensitive in situations of low-level contaminants. Although they can perform effectively, these traditional methods introduce constraints like high maintenance costs and limited throughput [13]. The application of artificial intelligence (AI) technology offers a significant positive approach to address these challenges by automating data analysis, minimizing human-induced errors, and enabling real-time monitoring. AI, specifically machine learning, can contribute to improving food safety by detecting patterns of contamination and strengthening responsiveness to prevent food contamination, hence addressing bottlenecks in traditional methods and making food contaminant analysis more cost-efficient, faster, and more accurate [14].

Table 1 Advantages and disadvantages of traditional dynamic models and machine learning

Chemical kinetics	Total plate count (TPC)	Simple form, suitable for various shelf life predictions	Usually used in conjunction with the Arrhenius equation, only considering the effect of temperature on quality changes.	[15]
Microbial kinetics	Specific spoilage organism	In addition to temperature, the impact of environmental factors such as humidity and pH value on shelf life was also considered	Microbial indicators are highly correlated with changes in food quality and are not suitable for predicting the shelf life of fresh food with shorter storage times	[16]
BP neural network, Support Vector Regression Machine	Sensory, physicochemical, and microbiological indicators	No need to understand the specific underlying principles that cause good quality decay, reducing errors caused by insufficient research on the principles	Unable to express and analyze the internal relationship between input and output	[17; 18]

5. AI in Anomaly Detection for Food Safety Compliance

Through the leveraging of technologies like machine learning (ML), natural language processing (NLP), computer vision (CV), and reinforcement learning (RL), AI is transforming the food industry by improving quality, safety, and security [19]. It enables real-time detection and prevention of contamination, automates defect detection, optimizes processing parameters, and assures batch consistency. AI also enhances food security through better resource management, crop yield predictions, and transparency in supply chains. Moreover, AI-driven optimization of advanced food processing methods in food safety and quality control, such as high-pressure processing (HPP), ultraviolet treatment, cold plasma, and pulsed electric fields (PEF), ensures the quality and safety of food products. By dynamically detecting and modulating parameters in sterilization applications such as ultrasonic treatment and irradiation, AI assists in optimizing energy, minimizing waste, and enables conditions to extend the shelf life of food while maintaining food safety and quality [19].

Figure 1 Artificial Intelligence (AI) In Food and Beverage Industry Market Size 2025-2029 [20]: Artificial intelligence (AI) in food and beverage industry market size is forecast to increase by USD 32.2 billion at a CAGR of 34.5% between 2024 and 2029

Supervised learning models in predictive analytics allow for food safety risks to be detected early. Contamination indicators such as pesticide residues and microbial growth, are analyzed using algorithms such as Support Vector Machines (SVM) and Decision Trees, allowing for preemptive prevention [21-24]. Similarly, predictive models such as Multiple Linear Regression (MLR) models are used to predict shelf life by examining environmental factors, including storage and transportation conditions, leading to precision in quality control and reduction in spoilage [25]. Advanced techniques such as Random Forests also enhance quality assurance through the detection of anomalies in food products, ensuring only quality items are delivered to consumers that meet the necessary regulatory standards [26-28]. In addition, time-series forecasting models further refine food security by predicting disruptions in supply chains, where Logistic Regression and SVMs are leveraged to predict pathogen outbreaks, thus strengthening preventive interventions against foodborne illness [29-31]Additionally, unsupervised learning techniques like clustering and anomaly detection provide significant advancement in food safety that helps in recognizing hidden patterns and major anomalies in extensive datasets. Also, clustering algorithms such as K-means have been effectively applied to other microbial profiling, showing successful results in terms of early detection of bacterial contamination in dairy products with an accuracy rate of 95% [32]. Likewise, DBSCAN has been used for shelf-life prediction through the evaluation of temperature and humidity fluctuations, keeping storage conditions in check and minimizing spoilage rates [32].

Anomaly detection models like One-Class SVM and Isolation Forest help in detecting contaminants and monitoring supply chains. For instance, One-Class SVM reveals about 90% accuracy in detecting unusual pesticide residue in fruit samples, allowing regulatory agencies to intercept potentially contaminated batches even before they are distributed [33]. Isolation Forest has also been applied in cold-chain logistics, successfully identifying deviations in temperature and reducing the spoilage of seafood during transportation by 30% [34]. The Gaussian Mixture Models have further reinforced quality management in beverage production through more accurate identification of equipment malfunctions, which negatively affect product consistency, resulting in a quantifiable decrease in defective outputs [35].

Reinforcement learning (RL) models like Q-Learning and Deep Q-Networks (DQN) have proven beneficial in improving compliance monitoring and contamination detection by facilitating real-time machine monitoring to identify any failure even before food safety is compromised. RL-driven predictive maintenance ensures optimal running and cleanliness of equipment's which decreases the chance of foodborne diseases [36]. Also, training platforms powered with RL have enhanced the responsiveness of staff to contamination scenarios with a 30% faster reaction time and a 15% increase in food safety regulatory compliance [37]. RL also facilitates food recall processes by determining any contaminated products in real-time, minimizing public health risk and reducing the overall impact of food recall by 25% [36].

Deep Learning (DL) is a subfield of AI that uses multi-layered neural networks to model and interpret patterns in complex data. A significant field in which DL is applied in food safety and quality is detecting and predicting foodborne diseases. Large data sets from sources such as social media, healthcare records, and sensor data are analyzed using CNNs and RNNs [38]. With the ability to recognize patterns and anomalies in large datasets, such models can identify and predict outbreaks at an early stage, enabling timely intervention and mitigation strategies. Another important area in which DL makes a significant impact is in the analysis of ingredient similarity. Autoencoders and CNNs compare chemical properties and compositions of food production ingredients and make graphed correlations of their nutritional value, minimizing the potential for adverse reactions and contamination.

6. Case Studies

A notable case study that demonstrates the effectiveness of AI-driven anomaly detection in food safety compliance monitoring is the application of Artificial Neural Networks (ANN) for shelf-life prediction of paneer tikka, a perishable dairy product, which is an exotic kebab of Indian cottage cheese. In their experimental study [39], they proposed an ANN model to investigate and forecast the degradation of paneer tikka over time, where moisture content, titratable acidity, free fatty acid levels as well as tyrosine content were utilized as physicochemical input variables and overall acceptability scores for the output variable. In observing patterns associated with shelf-life estimation, data from 42 observations were split into training (38 samples) and test sets (4 samples), enabling the artificial neural network (ANN) model in a learning process. This optimal configuration comprised two hidden layers with 25 neurons per layer, producing high predictive accuracy with root mean square error RMSE=0.0945 and a coefficient of determination (R^2) of R^2=0.9642. The high level of precision shows that the AI-based models can significantly improve monitoring and compliance within food safety by proactively conducting quality control, which reduces the possibilities of human error and ensures timely intervention in food spoilage.

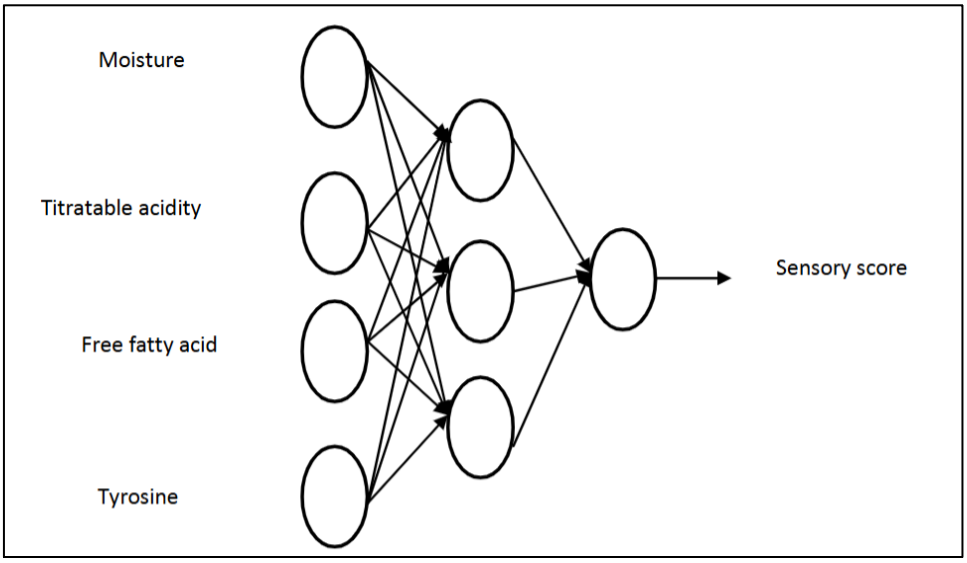

Figure 2 Input and output parameters of the ANN model

In another case study, the effectiveness of AI-driven anomaly detection in food safety compliance monitoring is demonstrated through the application of Computer Vision Systems (CVS) for quality control in frozen mixed berries. Traditionally, quality control in this sector depended heavily on manual labor to count and sort individual berries to avoid improper ingredient ratios. This method is slow, subject to human error, and lacks scalability. Ricauda Aimonino et al. (2013) developed an AI-based computer vision system (CVS) to automate the task of counting and classifying berries, leveraging digital imaging and color calibration techniques. For the image acquisition, the system used a Nikon D5100® digital camera with a dome lighting system to provide even illumination and a flatbed scanner for additional image acquisition. To obtain accurate classification, the RGB color data of the images were improved to the CIELab colorimetric space by using polynomial regression models to remove the inconsistencies associated with device-dependent color representations. The use of the polynomial regression model significantly optimized the accuracy in color measurement, resulting in E (color difference), a substantial decrease in values below the human perceivable threshold of 2.2. Higher-order polynomial models (p19, p20, p21) produced the least color differences, with some models reducing the E values below 1, highlighting that the AI-driven system produced more consistent and repeatable results than manual human evaluations. The system was able to recognize different types of berries and the percentages of each type in a mixture with color differences as little as or less than human perceptual sensitivity, demonstrating a high level of accuracy. This signifies how AI-driven anomaly detection through image processing can enhance food safety compliance and quality assessment by ensuring value chain uniformity, minimizing manual labor, and making quality assessments more reliable. In addition, this highlights the potential of AI to enable a shift from human inspections to standardized and automated evaluations that improve efficiency in food production and maintain regulatory compliance.

7. Practical Implementation of AI in Quality Assurance at Schwan's Company

At Schwan's Company, as a Quality Assurance (QA) professional, I work with food safety and compliance monitoring systems that integrate AI-driven methodologies. The application of AI in QA operations, particularly in hazard analysis and critical control points (HACCP) compliance, has enhanced real-time monitoring and decision-making for food safety compliance.

One of the key AI-based tools implemented in our facility is Safety Chain, a cloud-based food safety and quality management software that leverages AI to streamline compliance monitoring and automate data collection. Safety Chain enhances traceability by integrating real-time quality checks and allowing predictive analytics to detect potential safety hazards before they escalate. This ensures a proactive approach to food safety monitoring, reducing the likelihood of regulatory non-compliance.

In my role, I also utilize Statistical Process Control (SPC) techniques to analyze production data and identify deviations that might indicate contamination risks. AI-driven anomaly detection in SPC enables us to recognize patterns in production that human inspectors might overlook. By integrating machine learning models into SPC, we have been able to minimize product defects and ensure consistency in food quality.

Furthermore, the use of HACCP principles, combined with AI-based predictive analytics, has allowed us to refine food safety interventions. AI algorithms assess historical data to predict critical control point (CCP) deviations, allowing for timely corrective actions. This has resulted in a significant reduction in food safety risks and a more efficient compliance management process.

7.1. Impact on Food Safety Compliance and Monitoring

AI has significantly improved the reliability of food safety monitoring at Schwan's Company. By leveraging machine learning algorithms, the system can automatically flag potential compliance violations, reducing the reliance on manual inspections. Additionally, AI-driven automation has enhanced the speed and accuracy of reporting, ensuring that non-compliance incidents are addressed promptly.

The integration of AI in quality assurance has also optimized resource allocation. Instead of spending excessive time on manual quality control, QA professionals can focus on high-risk areas identified by AI-based predictive models. This shift has increased operational efficiency and improved food safety outcomes.

Overall, the implementation of AI-driven anomaly detection systems in food safety compliance at Schwan's Company has demonstrated the potential for industry-wide adoption. By continuously refining AI models and integrating them into existing food safety frameworks, we can enhance regulatory compliance and consumer safety while reducing waste and operational inefficiencies.

7.2. Challenges and Limitations of AI in Food Safety Compliance Monitoring

Notwithstanding its potential benefits, AI-driven anomaly detection for food safety compliance monitoring encounters technical, ethical, economic, and regulatory obstacles that prevent its widespread adoption and successful implementation. The reliance of AI-driven models on large amounts of data introduces concerns related to data quality, as errors in the sensor data may compromise the resulting predictions, and thus, not enable the mitigation of contamination risks. Another challenge lies in the limitations of algorithms, as machine learning models may not generalize well beyond what they were trained on, reducing the chances of detecting a new anomaly. Further, AI systems mostly require high computational capabilities, which may be unattainable for institutions with limited infrastructure. The integration with legacy systems is also another challenge, as many food processing facilities are using outdated technology that cannot seamlessly be connected to modern AI solutions. Additionally, the lack of interpretability and algorithm transparency, specifically with deep learning models, generates concerns about their trustworthiness and compliance, as regulatory authorities require clear justifications for decisions made by artificial intelligence. Legal and regulatory challenges also make AI adoption in food safety compliance and monitoring even harder, with frameworks like FSMA (Food Safety Modernization Act) and GDPR (General Data Protection Regulation) imposing stringent data governance and compliance requirements. Ethical issues also arise regarding data privacy, security, and the potential for biased AI models that could, in turn, lead to discriminatory decisions, based on those AI assessments, in supplier evaluations or on the assessment of product quality, for example. In addition, the economic burden of AI implementation, with onboarding costs, varying ROI, and constant workforce retraining, poses yet another hurdle to its adoption within the food industry, particularly for SMEs. Moreover, the scalability and adaptability of many AI solutions become a problem as food safety risks are evolving, and AI models must continuously be updated to new threats in the food industry.

7.3. Future Considerations

Strengthening dataset quality and standardization throughout the industry will ensure that AI models are trained on reliable and accurate information. Advancements in explainable AI (XAI) will also increase algorithm transparency and make AI-based decisions more interpretable for regulators and food safety practitioners. Furthermore, Modular AI solutions can be integrated into existing food systems, enabling compatibility with legacy infrastructure, offering a smoother integration process, and allowing for compatibility. At the same time, strengthening cybersecurity protocols and adherence to privacy regulations such as GDPR and CCPA will alleviate ethical concerns around data security and consumer trust. On the other hand, organizations can adopt incremental AI implementation strategies to ease financial burdens by going through several pilot projects on a small scale before full-scale deployment and adoption. In addition, cloud-based AI solutions can reduce costs even more by offering scalable computing resources without the need for heavy infrastructural investment. Finally, collaboration between industry leaders, regulatory bodies, and AI researchers will be vital to creating clear regulations that encourage technological development while ensuring compliance with food safety standards, so AI can be developed and implemented as a widely available tool for public health protection within the food industry.

8. Conclusion

AI-driven anomaly detection has proven to be a transformative solution in food safety monitoring and compliance, improving contamination detection, response time, and overall risk management. Through the integration of real-time monitoring and predictive analytics, AI allows for proactive interventions that mitigate threats both to public health and reduce burdens on the environment. Its ability to automate quality control processes and enhance regulatory compliance highlights AI's potential to transform food safety standards. Nonetheless, responsible implementation of AI tends towards technological advancement without losing sight of this imperative to balance such progress with ethical considerations to ensure fairness, trust, and transparency in decision-making processes. While the challenges of food contamination and food safety continue to grow with rising populations and urbanization, AI has been and will continue to be part of a solution to ensure that the needs of an ever-more complex global food system are safely met.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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