Global Journal of Computer Sciences and Artificial Intelligence

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

AI-Powered Food Contaminant Detection: A Review of Machine Learning Approaches

Khuram Shehzad[1], Akhtar Munir[2], Umair Ali[3*]

[1]Ravensbourne University, London

[2]University of Agriculture, Faisalabad, Pakistan

[3]Islamia university of Bahawalpur, Pakistan

[1]khuramshehzad6166@gmail.com, [2]akhtar.munir@uaf.edu.pk, [3]umair.ali@iub.edu.pk

open access

Corresponding Author

Umair Ali
umair.ali@iub.edu.pk

Article History:
Submitted: 14-01-2025
Accepted: 16-02-2025
Published: 19-02-2025

Keywords:
Artificial intelligence, food safety, machine learning, contaminant detection, real-time monitoring, block chain, IoT, regulatory compliance

ABSTRACT

Food safety is being transformed by artificial intelligence (AI), which is boosting contamination detection, real time monitoring and transparency of food supply chain. AI based techniques like machine learning, deep learning and computer vision help to detect chemical, microbial and physical contaminants in food more accurately and efficiently. These advancements have led processes to be automated, minimize the impact of human error and facilitate better decision taking. Other innovations include rapid, automated detection and traceability using AI driven spectroscopy, sensor based monitoring and block chain integration. Challenges in adopting AI, however, include fragmented and proprietary data, lack of model interpretability, the sheer implementation costs, and regulatory hurdles. Implementing AI has cost and technical challenges for small and medium sized businesses. Also, the AI models must be explainable and FMV compliant to provide the necessary transparency and reliability. Future research will consist of building upon the AI models developed in this thesis, incorporation of AI with IoT and edge computing for real time monitoring as well as setting up of ethical and regulatory frameworks. Trust in AI driven food safety will be developed with standardized AI regulations, unbiased predictions, and data privacy protections. Although AI presents some hurdles, it has the power to contribute in building a much safer, more efficient and transparent global food supply chain.

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

INTRODUCTION

Food safety is a significant international challenge and millions of people fall sick every year as a consequence of consuming contaminated food [1]. Contamination by biological agents (bacteria, viruses and fungi), chemical substances (pesticides, heavy metals and toxins) or physical hazards (glass, plastic, metal, etc.) is possible in food products. To eliminate the risks to health and economic losses associated with inadequate food safety, accurate, efficient, and effective detection of contaminants in food and feed is of paramount importance. Detection of food contaminants using chromatography, spectroscopy as well as microbiological assays has been reliable and useful but is often time consuming, laborious, and costly. There is recently a lot of technological advancements in terms of artificial intelligence (AI) and machine learning (ML) and these are well implemented in many industries including food safety and quality control. Automated, high speed and precise detection of contaminants is possible through the use of machine learning techniques for speeding up the food safety monitoring systems. AI powered approaches can utilize large datasets in conjunction with advanced pattern recognition to identity contamination patterns, classify food samples as well as predict contamination risks before they become critical issues [2].

This review outlines the use of machine learning in food contamination detection through different techniques of AI and their applications in food safety domain. AI powered detection methods have many advantages over the conventional laboratory-based techniques, as noted in the paper, such as improved accuracy, real-time monitoring, and cost-effectiveness [3]. Moreover, it analyzes how different machine learning techniques like supervised learning (e.g., neural networks, support vector machines), unsupervised learning (e.g., clustering algorithms), and deep learning (e.g., convolutional neural networks) have been used for food quality inspection and contamination identification [4].

While promising, AI driven food contaminant detection has some challenges that need to be overcome such as needing large, high quality datasets, model interpretability, and regulatory concerns. The successful implementation of AI to ensure food safety relies on the collective effort of the researchers, industry professionals and the politicians to develop standard protocols and respond to the ethical concerns [5]. This presents a review and the current state-of-the-art technologies utilizing machine learning techniques for the detection of food contaminants, challenges, and future directions. Review of the existing research and case studies will identify the potential utilization of AI-powered solutions to improve food safety and secure public health.

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

OVERVIEW OF FOOD CONTAMINANTS

Food contaminants are substances that are unwanted and any contamination to food can compromise food safety causing serious health risks and economic losses. Contaminants can be introduced anywhere in the food supply chain at any of production, processing, packaging, transportation, or storage. Similarly, they are broadly divided into three main types' biological, chemical and physical contaminants [6]. It is necessary to know about these contaminants, the possible sources and the associated risks to then be able to implement efficient detection and prevention strategies. Biological contaminants consist of chemical and physical agents mistakenly referred to as biological agents, as well as microorganisms such as bacteria, viruses, fungi and parasites that can cause foodborne illnesses. Bacterial pathogens common to humans include Salmonella, Escherichia (E.) coli, Listeria monocytogenes, and Clostridium (C.) botulinum. If these bacteria have favorable conditions, they can multiply quickly to cause food poisoning or even worse. They can also be contaminated by viruses, such as norovirus and hepatitis A, spread through poor hygiene and poor practice in handling. It produces mycotoxins, toxic compounds that may cause liver damage and cancer, and in the case of fungal contamination, including mold growth [7].

The most common of biological contamination are those which occur as a result of poor food handling, not cooked properly, cross contamination or unhygienic processing environment. These are often transmitted through contaminated water or uncooked or poorly cooked food and poor personal hygiene practices [8]. For the controlling of biological contamination in food products, effective measures of detection and control, such as rapid microbial testing, AI based image analysis and predictive modeling are needed. Chemical contaminants refer to toxic substances that may be intentionally or unintentionally introduced in food. Pesticide residues, heavy metals (lead, mercury, arsenic, and cadmium), food additives and industrial pollutants are also included in this list. In agriculture, chemical pesticides are strongly used to protect crops of from pests and diseases [9]. To be fair, pesticides help in controlling these pests but exposure to dangerous levels of pesticides can also cause some long term health problems like cancer, some neuro disorders and imbalances in hormones.

Heavy metals contamination of soil is largely due to environmental pollution, industrial waste or contaminated water sources generally. These metals can build up in the body over time and are toxic. Artificial additives, used by some food manufacturers to enhance flavor, color or shelf life, are another potential contributor to the different state of antioxidant protein in the plasma [10]. Nevertheless, any

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

misuse or prohibited substance in the product (such as melamine in milk products) is very harmful to health. We have therefore developed AI powered analytical techniques including spectroscopy based machine learning models and chemical fingerprinting as means to do so with high precision [11].

Foreign objects included as physical contaminants are glass shards, plastic fragments, metal pieces, and stones that mistakenly enter food products. It is often contamination from this case, since poor manufacturing practices, bad equipment or improper packaging of the product can cause these contaminants. Choking may occur from physical contaminants, and physical contaminants may cause injuries or gastrointestinal damage [12]. Increasingly, advanced AI driven imaging technologies such as X- ray inspection, hyper spectral imaging, deep learning based object detection etc are being used to detect physical contaminants in the food processing lines, leaving no room for any doubt regarding product integrity and consumer safety. Food contaminants may pose health effects including foodborne illnesses, organ damage, developmental disorders and increased cancer risks if presented [13].

As such, in order to ensure food safety, global regulatory agencies like the Food and Drug Administration (FDA), European Food Safety Authority (EFSA), and World Health Organization (WHO) have set strict guidelines and permissible limits for different contaminants. There are now AI powered food safety systems being embedded into compliance frameworks for better monitoring and enforcement of food safety rules [14]. To effectively develop detection and prevention strategies, it is important to understand food contaminants and sources of contaminants. Modern AI and machine learning technologies are becoming increasingly important for contamination detection and thus improving the food safety of the consumers all over the world [15].

MACHINE LEARNING IN FOOD CONTAMINANT DETECTION

Machine learning (ML) has started to play a critical role in food safety by replacing traditional methods of compounds detection by removing traditional techniques of compounds detection which are expensive, slow and lack accuracy. With the help of large datasets, ML algorithms can uncover the contamination patterns, classify food samples and can predict contamination risks. Unlike conventional analysis methods based on extensive laboratory testing, ML models can process such data in real time at nominal cost to food safety monitoring [16]. Advanced data processing techniques using machine learning become essential to automate and improve the process of food contaminant detection. At a high level, it identifies the contamination utilizing pictorial, sensor, and chemical

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

compositions through the recognition of patterns. By integrating ML powered models to the spectroscopy, hyper spectral image, biosensors, etc., food safety assessment can be done more accurately and efficiently [17].

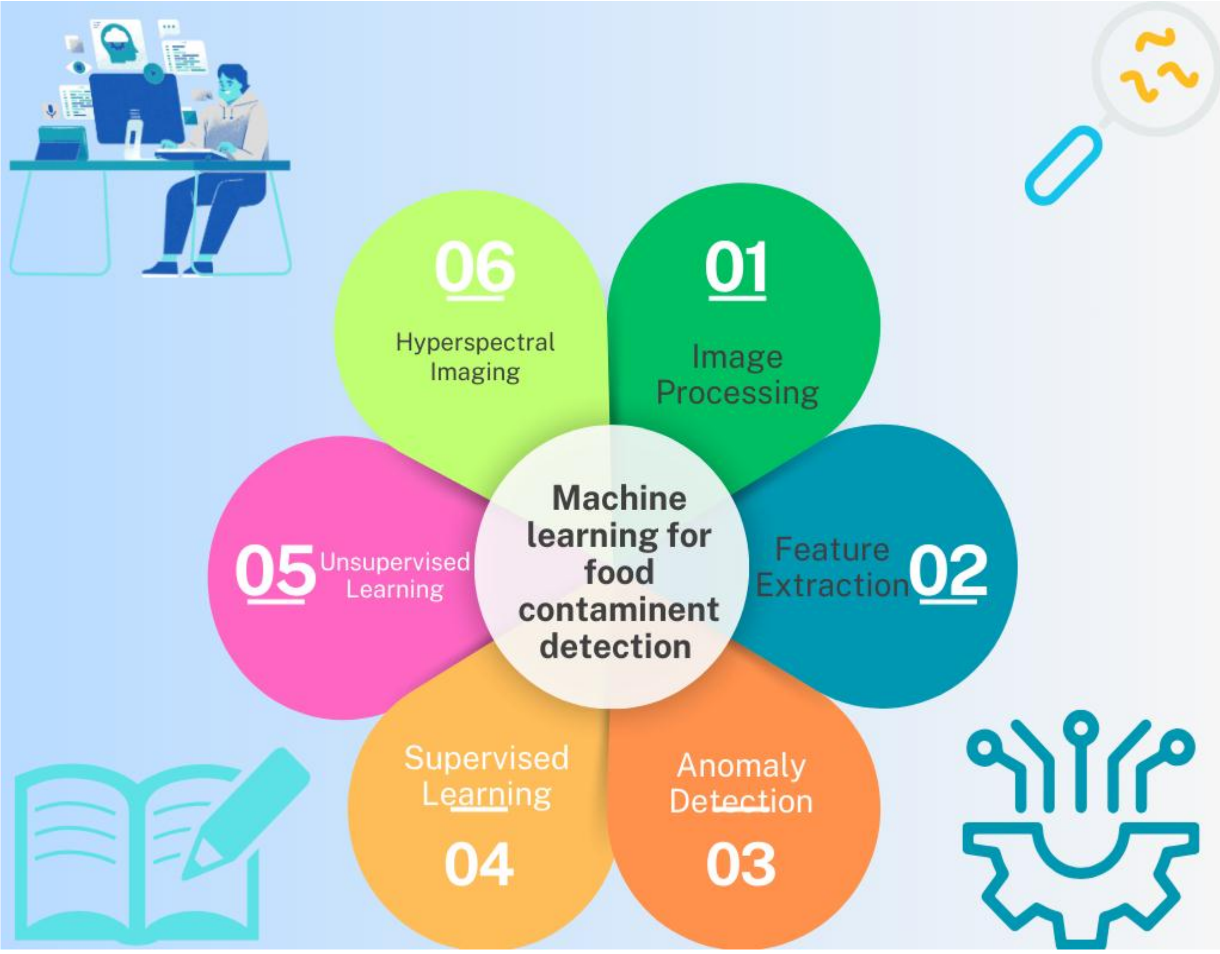

Figure: 1 showing machine learning for contaminant food detection

Traditional methods cannot detect the smallest amounts of contaminants, but ML algorithms can. Food samples can be analyzed right there with AI powered systems and the results are pretty fast, requiring no extensive lab testing. Historical data can be used by ML models to forecast potential contamination risks and therefore prevent foodborne outbreaks [18]. Labor and operational costs are reduced through the use of automated detection systems, which also promote detection efficiency. The functioning of the ML models depends on diverse and high quality datasets. key data sources for training ML models for food contaminant detection are as follows:

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

Near-Infrared (NIR) and Raman spectroscopy spectral fingerprints of food samples can be used by chemical contaminants that ML detects. Detecting plastic, glass or metal fragments is widely performed using hyper spectral and X-ray imaging. These images are analyzed by ML algorithms to detect the foreign objects [19]. ML can analyze the chemical composition or bacterial growth pattern and identify bacterial contamination or toxic chemical substances. Utilizing Internet of Things (IoT)-enabled sensors, real time environmental data of temperature, humidity, and emissions of gases are collected and ML models are utilized for spoilage and contamination risk forecasting. To enhance food safety measures, machine learning is sometimes coupled with other cutting edge technologies such as Convolutional Neural Networks (CNN's) for analyzing food images for contaminants and defects [20].

Food safety reports and consumer complaints can be analyzed by applying NLP techniques for identifying the contamination trends. Block chain, combined with AI powered systems, boosts traceability improving checks so that contaminating food products are quickly highlighted and prevented from entering the food supply chain [21]. Large, diverse and well labeled data set can be difficult to obtain for ML models. They have been designed as 'black boxes'; i.e., it is hard to explain how the model reaches a conclusion. AI for compliance must be explainable to regulatory bodies. Training and deployment of ML models effectively requires high performance computing resources. In order to implement AI based food safety solutions, there are strict food safety regulations which are in place and are mandatory for all parties; however, these are different from one country to another or across various regions [22].

However, in light of advances in AI and data science, we can expect machine learning to continue to have a strong role to play for food safety. With better data collection techniques and advances in developing more robust and interpretable AI models, AI powered food contaminant detection systems will be more reliable [23]. Next, applying ML to edge computing and IoT is intended to allow for real time food safety monitoring at every stage in the food supply chain. To sum it up, machine learning has redefined the way food contaminants are detected by providing more efficient, accurate and automaton ways of doing it without much reliance on the traditional methods. However this is envisaged to be an ongoing challenge, advances in AI and ML technologies being made will continue to offer safer and more transparent food safety practices for the benefit of the consumer, as well as the industry stakeholders [24].

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

MACHINE LEARNING TECHNIQUES FOR CONTAMINANT DETECTION

With the aid of machine learning (ML) techniques, the detection of food contaminant has been greatly improved by automated, high speed, and highly accurate contaminant identification. They are classified as supervised learning, unsupervised learning, and deep learning, with unique use for food safety. One of the most commonly used approaches of ML in food safety is that of supervised learning. It is training a model on labeled datasets, where the algorithm learns to look into known contaminant patterns, and applies it to new data [25]. Several supervised learning methods commonly applied include: SVM is useful for classifying food spectrum, chemical or image data to determine whether they had been contamination. Spectroscopy–based contaminant detection is widely used and they are employed [26].

ANNs involve modeling the human brain which is very effective in the detection of contaminants in complicated food matrices through recognizing complex patterns in large data sets. The algorithms used are designed to classify food samples based on key contamination indicators such as pesticides, microbial contamination and heavy metals in food. In case of large well labeled data, supervised learning approach is most fitting [27]. However, their quality is dependent on the quality and diversity of the training data. If the data on which you will be learning cannot be labeled, then unsupervised learning is utilized. These models do not learn from predefined categories but instead learn what patterns are and what is strange enough regarding the data, and thus may be employed to detect contamination in dynamic environments [28].

The clustering algorithms reveal food samples with similar properties and detect abnormal patterns that might reveal contamination. For instance, in microbiological testing clustering can show abnormal growth in bacteria of food samples. Typically, anomalous models detect anomaly in normal food properties which represents spoilage issue in food, adulteration of food and contamination of food. Unsupervised learning is a very valuable technique for sensor based food monitoring systems as it allows the discovery of unknown contamination patterns but may need further validation to verify the results [29]. ML subset: deep learning has gained interest in food contaminant detection particularly owing to its ability to analyze complex dataset with close to no human intervention. First, these models, that is, neural networks, are most effective in processing visual and spectral data.

It is well known that CNNs are used for image based contamination detection. For example, they analyze hyper spectral images as well as X-ray images in an effort to detect foreign objects (glass,

Global Journal of Computer Sciences and Artificial Intelligence
ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

plastic, metal, etc.) in food products. RNNs, which are used when processing sequential data, allow to perform such kind of time-series analysis as monitoring trends of contamination in food supply chains. Deep learning has proved effective for anomaly detection in predicting when food has been adulterated and spoiled by reconstructing data and picking up deviations [30]. Although they are quite accurate in contamination detection, deep learning models can only be run with large amounts of data and high computational power. Food contaminant detection is revolutionizing with the help of machine learning techniques as they provide an advance over traditional methods in terms of analytical capabilities. Supervised learning has been the most used technique to detect known contaminants but unsupervised and deep learning have become key to detect new, complicated contamination patterns. As AI and data science continue to advance, the future of ML based food safety seems quite promising to provide a cleaner, safer and the most transparent food supply chain [31].

APPLICATIONS OF AI IN FOOD SAFETY

The food safety industry has been revolutionizing by the intelligence of artificial intelligence (AI) that has improved contamination detection and developed monitoring systems and ensured supply chain transparency. Machine learning (ML), block chain, computer vision, are among the developing AI driven technologies that are redefining detection and control of food contaminants [32]. Following are some of the key uses of AI in food safety:

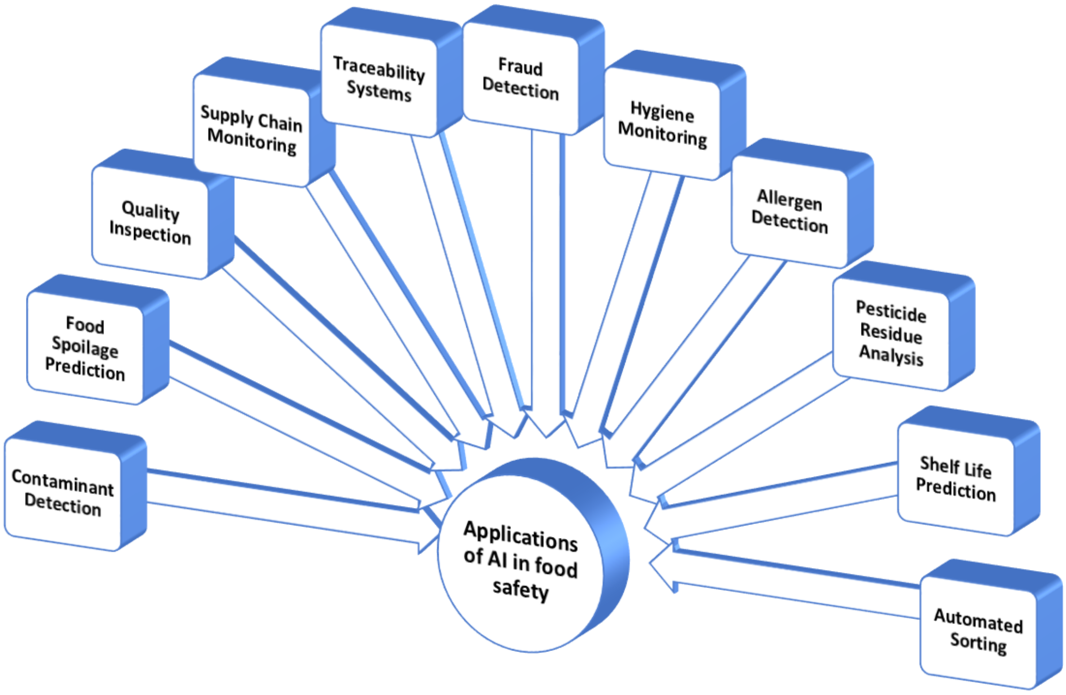

Figure: 2 showing applications of AI in food safety

Global Journal of Computer Sciences and Artificial Intelligence

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

AI-POWERED SPECTROSCOPY AND IMAGING FOR CONTAMINANT DETECTION

There are widespread uses of spectroscopy and imaging techniques to detect chemical and physical contaminants in food. These methods are enhanced with AI-powered systems that can study large datasets very accurately. AI powered hyper spectral imaging is used to identify contaminants like pesticide residues, heavy metals, and microbial growth in food samples by analyzing spectral fingerprints [33]. Machine learning algorithms in X-ray and Computer Vision are used to detect foreign objects like glass, plastic, metal etc in processed food.'

This is Raman Spectroscopy with AI, where AI is combined with laser-based spectral analysis to identify chemical adulterants in such foods as dairy and oils, for example. Real time food quality monitoring is widely done by the use of AI powered sensors. Data on temperature, humidity, gas emissions, and microbial growth is collected by these smart sensor before contamination can spread [34]. AI integrated IoT sensors monitor the perishable food products during the storage and transportation in order to minimize the risks of spoilage and contamination. AI enhanced biosensors are capable of detecting pathogens and toxins present in food samples timely to avoid the spread of pathogens that may lead to poisoning. On the other side, AI in conjunction with a block chain acts as an efficient tool to provide food traceability in order to make the supply chain transparent [35].

AI decodes block chain records to detect origin of food source, to find the contamination origin. AI Powered Block chain Solutions: Solutions that check that food producers and distributors are minimizing fraud and mislabeling by adhering to regulations for safety. However, AI in food safety also needs to overcome several hurdles before it can be more widely implemented. Large, high quality datasets are required for training AI models [36]. Currently, data on food safety is often fragmented, inconsistent, or proprietary and thus is less effective for applying ML algorithms. Food regulators are having a hard time interpreting why AI models make certain decisions because many AI models are 'black boxes.' Explainable AI is necessary for compliance with food safety laws and regulatory agencies come in for them as well. AI based food safety solution deployment involves huge technology, infrastructure, and skilled personnel investment. However, these solutions are not within the reach of many small and medium sized SMEs (SMES) [37].

Researchers and industry experts focusing on different areas of advancement to overcome the current challenges and for improvement in food safety. Hybrid machine learning and deep learning approaches are being worked upon to further improve the accuracy for food contaminant detection in

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

the next generation of AI models. Together, AI, IoT, and edge computing will help to quickly and continuously monitor food contaminants in real time and remove the need for centralized processing systems to perform this task [38]. With guidelines as noted above, policymakers and regulatory agencies are working on guidelines to ensure ethical use of AI in ensuring food safety which mainly involves transparency, data privacy and compliance to safety standards.

As such, AI fueled technologies are transforming food safety through advanced contaminant detection, real time monitoring and toward better traceability. Challenges yet exist, including data limitations, interpretability of the models, and high implementation costs, however, AI advances food safety practices [39]. The reliability and accessibility of AI driven food safety solutions will continue to improve as these are coupled with future advancements in other technologies como AI, IoT e sua regulamentação. But, in the end, with AI being integrated into the food industry, it will result in safer foods for consumers around the globe – losses to the economy, as well as health risks related to food contamination will be reduced [40].

CHALLENGES AND LIMITATIONS OF AI IN FOOD SAFETY

The AI food contaminant detection and safety monitoring has made great advance; however, there are still challenges for their application and adoption. This can be anything from data issues, to regulatory issues or to the implementation costs. These are obstacles that need to be addressed so as to ensure the successful integration of AI in food safety systems [41].

Data Availability and Quality Issues

The availability and quality of data is one of the main challenges to AI driven food safety. They are dependent on large datasets, diverse, and well annotated, in order to work. However, in the food industry, data is frequently:

Data is fragmented: it is collected in different points of the supply chain, thereby rendering the format and structure inconsistent. Many food manufacturers and regulatory bodies do not have full datasets of areas within a facility to test for each type of contamination, therefore limiting the data required for an AI model to be effective to detect each type of contamination [42].

Many companies are proprietary: Companies hold their food safety data privately, thus not allowing data sharing for research and model development. Inaccurate poor data leads to inaccurate

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

AI predictions, thus reducing the reliability of contaminant detection systems. To address this challenge, all industry stakeholders must agree upon standardized data collection practices and alternatively make an effort to encourage teamwork between food safety organizations, researchers, and AI developers [43]. The decision making of the AI models, more often deep learning systems, often also functions as a ‘black box’, i.e. the process to make decisions are not easily explainable. Regulatory agencies and food safety authorities are faced with this lack of transparency regarding how the AI comes to its conclusion, as they need to vet and approve its use for critical food safety applications [44].

Key regulatory concerns

There is Lack of Explain ability as regulatory bodies mandate AI models to have human comprehensible explanations for the predictions. The consequence of the lack of this is that it’s hard to rely on AI for food safety assessments [45].

Compliance with Food Safety Standards: The food safety standards established by the FDA, the EFSA and the WHO must be respected, and the AI based detection method must comply with these existing regulations. Currently, there are no standardized guidelines for AI-driven food safety [46]. If an AI model is trained on biased or incomplete datasets, it may not effectively identify all the contaminants, which will make it lead to unsafe food getting to the consumers.

To overcome these drawbacks, researchers are currently devising explainable AI (XAI) techniques that provide regulators and food safety professionals with access to AI’s decision making process [47].

Cost and Implementation Challenges

So, implementing AI driven food safety solutions is going to be an expensive process, requiring huge investment with respect of technology, infrastructure and skill set. There are several factors creating high cost of AI adaptation [48]. AI based contaminant detection systems need imaging devices, sensors and cloud computing infrastructure in order to function, which obviously can get expensive. There is a requirement for employees being trained to operate AI driven food safety tools and this brings up in initial cost of investment for food manufacturers [49].

Global Journal of Computer Sciences and Artificial Intelligence

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

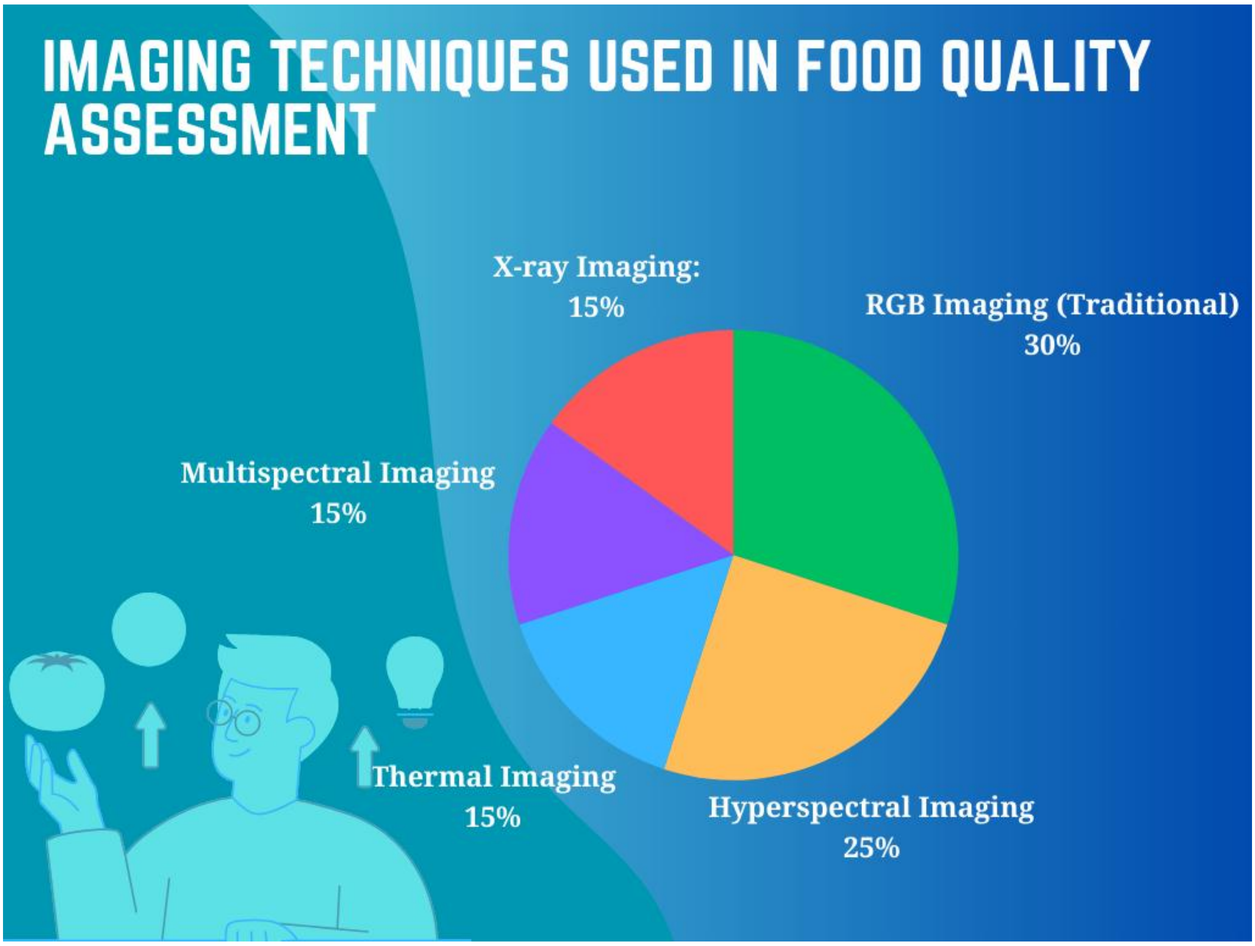

Figure: 3 showing imaging techniques used in food quality assessment

Large scale implementation of AI in food safety needs AI to work together with the existing food processing and quality control systems maintaining the same level of consistency and thus poses scalability issues. Many small and medium size enterprises (SMEs) cannot afford to use their financial resources to implement AI solutions [50]. To alleviate these issues, industry parties are currently testing out cost efficient means of AI deployment such as outsourcing to cloud based AI services or the use of AI powered mobile applications that enable smaller companies to access AI powered food safety services without having to invest in extensive infrastructure [51].

ETHICAL AND PRIVACY CONCERNS

Typically, the data is collected from many places such as supply chain, manufacturer, and consumers and so on, thus making use of AI food safety solutions. This has ethical and privacy concerns: Who own the data collected by AI-driven food safety system? Should regulatory bodies be tasked with reviewing food safety data in regards to food companies? If AI powered systems are collecting consumer feedback on food safety then data privacy and security needs to be ensured [52]. If AI

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

models trained for assisting in regulatory actions on food are trained with biased datasets, then the regulatory actions on food producers may disproportionately affect some of these food producers.

Ethical AI frameworks must be developed, and compliance with data protection laws (like GDPR in Europe) maintained in order to foster public trust in food safety systems driven by AI. Although AI holds great promise to disrupt food safety, its broad market penetration is constrained by barriers such as availability of data, regulatory hurdles, high implementation costs and the ethical implications. To address these challenges they need to be solved by joining forces between researchers, regulatory bodies and food industry stakeholders [53]. However, these limitations may be overcome by future advancements in explainable AI, standardized data-sharing frameworks, and low cost deployment strategies to enable the transformative use of AI in global food safety [54].

FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES IN AI-DRIVEN FOOD SAFETY

With further advances of AI, its applications in food safety are anticipated to grow and enhance the accuracy and efficiency in dealing with food safety issues as well as regulatory compliance. However, there is still a lot of research and development to be done on some areas. Future studies will include refining AI models, leveraging AI with rapid technological adoptions, and creating ethical and legally acceptable frameworks related to responsible AI implementation in food safety [55].

Food contaminant detection is improving with the help of AI, but more scope is there to make model more accurate, faster, and reliable. Future research will focus on:

Hybrid AI models: These incorporate several machine learning tools like deep learning and reinforcement learning; they help to increase the detection accurateness and reduce the number of false positives [56].

Explainable AI (XAI): To enhance regulatory and food industry stakeholder trust, trust, developing AI models with the ability to justify their predicted outputs with human understandable reasoning's will be crucial [57].

Adaptive AI Systems: Adaptive AI systems learning from new data, including the effects of data tampering or real world contaminatisation, will further enable improvement of the models' capability to detect new classes of contaminants as they emerge [58]. The AI model can be trained on data that

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

remains encrypted across multiple decentralized servers, according to Federated Learning for Data Privacy, instead of centralizing food safety data. Use of AI to interface Internet of Things (IoT) and edge computing will, in turn, revolutionize real time food safety monitoring and contamination prevention. An AI augmented sensor would embed on the food storage and transportation systems and continuously monitor the measures like food temperature, humidity, and gas emissions to prevent spoilage and contamination [59].

Edge AI for Real Time Analysis: Prides itself in computing on local devices and thus enabling real time contamination detection without the need for internet. This is especially useful to those living in remote areas or food production sites [60]. By combining block chain and AI, food traceability will be enhanced to eep out contaminated food products from the market in a timely manner. Block chain records will be analyzed by AI in order to detect the risk of different things such as fraudulent food labeling or contamination events [61]. AI integration with IoT and edge computing will make food safety monitoring faster, more automated, and less dependent on centralized infrastructure, for both large-scale manufacturers and small food producers.

ETHICAL AND REGULATORY FRAMEWORKS FOR AI-DRIVEN FOOD SAFETY

With the spreading use of AI in food safety, ethical guidelines and regulations for how the AI should be deployed will be of crucial importance. Some key focus areas include:

Lack of Standardization in AI Regulations: There are various country specific food safety regulations today which make AI based solutions hard to be deployed on a global level. Standardized AI regulations must be created to avoid inconsistent AI marketing across different international markets [62]. When creating guidelines that will help to prevent biased AI models in food safety applications, regulatory agencies will have to outline guidelines that require diverse, representative training datasets.

Food Safety Data and AI: Food safety is very necessary as world population is increasing rapidly [63-66] and growing population is demanding more food. It goes without saying that AI relies heavily on huge amounts of food safety data, whether it's from food industry or from the customers. It is critical that these data are protected and kept secure. As per traditional quality control measures, food safety audits should be pursued for AI driven food safety system just as we have for food audits [67].

This will help develop ethical and regulatory frameworks for using AI in controlling these processes

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

as well as building consumer trust in AI-powered food safety systems, and using them fairly and responsibly in the food industry. Future of AI in food safety is promising with further development in AI models, IoT integration and regulatory framework, which will lead to a better food safety monitoring and contaminant detection [68]. AI accuracy will be improved, real time monitoring would be enabled by IoT and edge computing and global regulatory standards would be set up by the food industry through AI to ensure a safer and more transparent food supply chain. To realize AI's potential in serving public health and enhancing global food security, further research and working with food safety regulators and industry stakeholders will be needed.

CONCLUSION

Artificial intelligence (AI) has been incorporated into the development of food safety, a field in which it has presented great advances in contaminant detection and real time monitoring, as well as supply chain transparency. Methods based on AI, including machine learning and deep learning, as well as computer vision, improve the accuracy and the efficiency for detecting chemical, microbial and physical contaminants in food. Issues associated with automation of traditional food safety practices, most directly, due to accelerated capacity for detection, reduced human error, and rapid decision making through emerging technologies. Nevertheless, some concerns need to be resolved to make sure AI can thrive in the food industry.

The first challenge is data availability and quality. This is where the food industry is and AI need large, well labeled, diverse data set, data sources in the food industry however are scattered, inconsistent and sometime proprietary. Standardized data sharing framework is necessary for realizing AI powered food safety systems. Further, the complexity of many AI models and their 'black box' output make them difficult to regulate, as food safety authorities as well as more general regulatory authorities will require explainable AI (XAI) to achieve transparency in decision making processes. The challenge for developing regulatory compliant and widely industry adopted AI model is to build interpretable AI models with clear and interpretable justifications of predictions.

Barriers to implementing AI driven food safety systems include cost and implementation challenges especially to small and medium enterprise SMEs. The costs of AI infrastructure such as advanced sensors, computing resources and personnel may be cost prohibitive for the initial investment. However, cloud-based AI services, federated learning, and AI enabled mobile applications are emerging technologies that make AI accessible, affordable for all sizes of food manufacturers to

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

leverage the advantages of AI technology. A further exciting development is the integration of AI with Internet of Things (IoT) devices and edge computing for real time food safety monitoring without dependence on the availability of centralized data processing. These will greatly enhance contamination monitoring, food storage monitoring and the overall supply chain management.

With the growth of AI adoption, ethics and regulation must be kept in mind. In order to sustain trust in AI driven food safety solution, ensuring data privacy, preventing AI bias and establishing global AI standards will be the most important components. Therefore, policymakers and industry stakeholders have to jointly devise comprehensive guidelines for the use of AI applications in food safety and foster innovation and efficiency. Furthermore, AI models need to be thoroughly tested and validated to guarantee accuracy in real world scenarios, so that people's lives across the country are not risked. There is an opportunity for AI to do for food safety what it's doing in healthcare: to deliver faster, better, more automated contaminant detection and monitoring solutions. Nevertheless, to overcome obstacles like data limitations, regulatory concerns, and implementation costs, research is continuously evolving and paving the way towards an easy incorporation of AI into the food industry. Working in tandem, researchers, policymakers, and food manufacturers will continue to collaborate to leverage AI food safety solutions to help improve the global food supply chain to more safe, resilient, and transparent.

REFERENCES

[1]. Talib A, Samad A, Hossain MJ, Muazzam A, Anwar B, Atique R, Hwang YH, Joo ST. Modern trends and techniques for food preservation. Food and Life. 2024;2024(1):19-32.

[2]. Rayhan, A. (2023). AI and the environment toward sustainable development and conservation. Research Gate. https://doi.org/10.13140/RG.2.2.12024.42245

[3]. Santhuja, P., Reddy, E. G., Choudri, S. R., Muthulekshmi, M., & Balaji, S. (2023). IIntelligent personalized nutrition guidance system using IoT and machine learning algorithm. In Proceedings of the, second international conference on Smart Technologies for Smart Nation (SmartTechCon), Singapore, 18–19 August 2023 (pp. 250–254).

[4]. Piscataway, NJ, USA: IEEE. Seyedghorban, Z., Tahernejad, H., Meriton, R., & Graham, G. (2020). Supply chain digitalization: Past, present and future. Production Planning & Control, 31(2–3), 96–114. https://doi.org/10.1080/09537287.2019.1631461

[5]. Shahare, P. (2022). Relationship management: A quantitative investigation of role of artificial intelligence in marketing and customer relationship management: A quantitative investigation of recent. Ijfans, 11(1), 912–936. https://doi.org/10.48047/IJFANS/S1/103

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

[6]. Shinde, K. J., & Pardeshi, I. L. (2014). Fuzzy logic model for sensory evaluation of commercially available jam. Journal of Ready to Eat Food, 1(2), 78–84. Sohail, M., Sun, D. W., & Zhu, Z. (2018). Recent developments in intelligent packaging for enhancing food quality and safety. Critical Reviews in Food Science and Nutrition, 58(15), 2650–2662. https://doi.org/10.1080/10408398.2018.1449731

[7]. Soltani-Fesaghandis, G., & Pooya, A. (2018). Design of an artificial intelligence system for predicting success of new product development and selecting proper marketproduct strategy in the food industry. International Food and Agribusiness Management Review, 21(7), 847–864. https://doi.org/10.22434/IFAMR2017.0033

[8]. Vilela, A., Bacelar, E., Pinto, T., Anjos, R., Correia, E., Gonçalves, B., & Cosme, F. (2019). Beverage and food fragrance biotechnology, novel applications, sensory and sensor techniques: An overview. Foods, 8(12), 1–51. https://doi.org/10.3390/foods8120643

[9]. Zhu, J., & Wang, G. (2023). Artificial intelligence technology for food nutrition. Nutrients, 15(21), 4562. Zhu, L., Spachos, P., Pensini, E., & Plataniotis, K. N. (2021). Deep learning and machine vision for food processing: A survey. Current Research in Food Science, 4(December 2020), 233–249. https://doi.org/10.1016/j.crfs.2021.03.009

[10]. Sood S, Singh H. Computer vision and machine learning based approaches for food security: a review. Multimedia Tools Appl. 2021; 80:27973–99.

[11]. Kakani V, et al. A critical review on computer vision and artifcial intelligence in food industry. J Agric Food Res. 2020; 2: 100033.

[12]. Fracarolli JA, et al. Computer vision applied to food and agricultural products. Rev Ciência Agronômica. 2020; 51: e20207749.

[13]. Squara, S. et al. Valorisation of premium Italian wines by volatile signature exploration with GC× GC-TOF MS and Computer Vision. In: 14th Multidimensional Chromatography Workshop Guide Book, 2023 (pp. 74–74).

[14]. Russom P. Big data analytics. TDWI Best Pract Rep. 2011; 19:1–34. 62. Marvin HJP, et al. Big data in food safety: an overview. Crit Rev Food Sci Nutr. 2017; 57:2286–95.

[15]. Jin C, et al. Big data in food safety—a review. Curr Opin Food Sci. 2020; 36:24–32.

[16]. Donaghy JA, et al. Big data impacting dynamic food safety risk management in the food chain. Front Microbiol. 2021; 12: 668196.

[17]. Sharma S, et al. Sustainable innovations in the food industry through artifcial intelligence and big data analytics. Logistics. 2021; 5:66.

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

[18]. Rose K, Eldridge S, Chapin L. The internet of things: an overview. Int Soc (ISOC). 2015; 80:1–53.

[19]. Li S, Xu LD, Zhao S. The internet of things: a survey. Inf Syst Front. 2015; 17:243–59. 68. Xia F, et al. Internet of things. Int J Commun Syst. 2012; 25:1101–11.

[20]. Bouzembrak Y, et al. Internet of things in food safety: literature review and a bibliometric analysis. Trends Food Sci Technol. 2019; 94:54–64.

[21]. Liu Y, et al. An Internet-of-things solution for food safety and quality control: a pilot project in China. J Ind Inf Integr. 2016; 3:1–7.

[22]. Doinea M, et al. Internet of things based systems for food safety management. Informatica Econ. 2015; 19:87–94.

[23]. Dias, R.M.; Marques, G.; Bhoi, A.K. Internet of things for enhanced food safety and quality assurance: a literature review. In: proceedings of the international conference on emerging trends and advances in electrical engineering and renewable energy. Springer, Singapore, 2020; pp. 1–8.

[24]. Palakurti NR. AI applications in food safety and quality control. ESP J Eng Technol Adv. 2022;2:48–61. 75. Ataei Kachouei M, Kaushik A, Ali MA. Internet of things-enabled food and plant sensors to empower sustainability. Adv Intell Syst. 2023; 5:2300321.

[25]. Taneja A, et al. Artifcial intelligence: implications for the agri-food sector. Agronomy. 2023; 13:1397

[26]. Huberts, L. W. J. C. (2018). Integrity: What it is and why it is important. Public Integrity, 20(sup1), S18–S32. https://doi.org/10.1080/10999922.2018.1477404

[27]. IBM Food Trust. (2024). Data – the world's most essential ingredient Accessed on 03 September 2024. Accessed via: https://www.ibm.com/products/supply-chain-intelligence-suite/food-trust.

[28]. Iheanacho, C. A., & Vincent, O. R. (2022). Classification and recommendation of food intake in West Africa for healthy diet using deep learning. In Proceedings of the 5th Information Technology for Education and Development (ITED), Abuja, Nigeria, 1–3 November 2022 (pp. 1–6). Piscataway, NJ, USA: IEEE.

[29]. Jadhav, H. B., Alaskar, K., Desai, V., Sane, A., Chaudhary, P., Annapure, U., Nayik, G. A. (2024). Transformative impact: Artificial intelligence in the evolving landscape of processed food-a concise review focusing on some food processing sectors. Food Control, 110803. https://doi.org/10.1016/j.foodcont.2024.110803

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

[30]. Khan, R. (2021). Artificial intelligence and machine learning in food industries: A study. Journal of Food Chemistry And Nanotechnology, 07(03). https://doi.org/10.17756/jfcn.2021-114

[31]. Kirk, D., Kok, E., Tufano, M., Tekinerdogan, B., Feskens, E. J. M., & Camps, G. (2022). Machine Learning in Nutrition Research. Advances in Nutrition (Bethesda, Md.), 13 (6), 2573–2589.

[32]. Kumar, I., Rawat, J., Mohd, N., & Husain, S. (2021). Opportunities of artificial intelligence and machine learning in the food industry. Journal of Food Quality, 2021. https://doi.org/10.1155/2021/4535567

[33]. Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2022). IoT, big data, and artificial intelligence in agriculture and food industry. IEEE Internet of Things Journal, 9(9), 6305–6324. https://doi.org/10.1109/JIOT.2020.2998584

[34]. Nunes, C. A., Ribeiro, M. N., de Carvalho, T. C., Ferreira, D. D., de Oliveira, L. L., & Pinheiro, A. C. (2023). Artificial intelligence in sensory and consumer studies of food products. Current Opinion in Food Science, 50, Article 101002. https://doi.org/10.1016/j.cofs.2023.101002

[35]. Ore Areche, F., Flores, D. D. C., Quispe-Solano, M. A., Nayik, G. A., CruzPorta, E. A. D. L., Rodríguez, A. R., Roman, A. V., & Chweya, R. (2023). Formulation, characterization, and determination of the rheological profile of loquat compote Mespilus Germanica ´ L. through sustenance artificial intelligence. Journal of Food Quality, 2023(1), Article 3344539.

[36]. Papadopoulos, T., Sivarajah, U., Spanaki, K., Despoudi, S., & Gunasekaran, A. (2022). Editorial: Artificial Intelligence (AI) and data sharing in manufacturing, production and operations management research. International Journal of Production Research, 60 (14), 4361–4364. https://doi.org/10.1080/00207543.2021.2010979

[37]. Prakash, G., Mishra, R. K., Meena, P., Pandey, D., & Pandey, V. K. (2023). Application of computer-aided artificial intelligence techniques in food industry. Current Journal of Applied Science and Technology, 42(34), 23–31. https://doi.org/10.9734/cjast/2023/v42i344230

[38]. Caldwell DG, editor. Robotics and automation in the food industry: current and future technologies. Amsterdam: Elsevier; 2012.

[39]. Mohammad-Razdari A, Ghasemi-Varnamkhasti M, Izadi Z, Rostami S, Ensafi AA, Siadat M, et al. Detection of sulfadimethoxine in meat samples using a novel electrochemical biosensor as a rapid analysis method. J Food Compos Anal. 2019; 82:103252.

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

[40]. Pikkemaat MG, Rapallini MLBA, Karp MT, Elferink JWA. Application of a luminescent bacterial biosensor for the detection of tetracyclines in routine analysis of poultry muscle samples. Food Addit Contam Part A. 2010; 27(8):1112-1117.

[41]. Tang D, Tang J, Su B, Chen G. Ultrasensitive electrochemical immunoassay of Staphylococcal enterotoxin B in food using enzyme-nanosilica-doped carbon nanotubes for signal amplification. J Agric Food Chem. 2010; 58(20):10824-10830.

[42]. Wang Y, Zhang L, Peng D, Xie S, Chen D, Pan Y, et al. Construction of electrochemical immunosensor based on gold-nanoparticles/carbon nanotubes/chitosan for sensitive determination of T-2 toxin in feed and swine meat. Int J Mol Sci. 2018; 19(12):3895.

[43]. Dinçkaya E, Akyilmaz E, Kemal Sezgintürk M, Nil Ertaş F. Sensitive nitrate determination in water and meat samples by amperometric biosensor. Prep Biochem Biotechnol. 2010; 40(2):119-128.

[44]. Mansouri M, Fathi F, Jalili R, Shoeibie S, Dastmalchi S, Khataee A, et al. SPR enhanced DNA biosensor for sensitive detection of donkey meat adulteration. Food Chem. 2020; 331:127163.

[45]. Hartati YW, Suryani AA, Agustina M, Gaffar S, Anggraeni A. A gold nanoparticle-dna bioconjugatebased electrochemical biosensor for detection of sus scrofa mtdna in raw and processed meat. Food Anal Methods. 2019; 12(11):2591-2600.

[46]. Ruiz-Valdepeñas Montiel V, Gutiérrez ML, TorrenteRodríguez RM, Povedano E, Vargas E, Reviejo ÁJ, et al. Disposable amperometric polymerase chain reaction-free biosensor for direct detection of adulteration with horsemeat in raw lysates targeting mitochondrial DNA. Anal Chem. 2017;89(17):9474-9482

[47]. Das AK, Nanda PK, Das A, Biswas S. Hazards and safety issues of meat and meat products. In: Food safety and human health. Elsevier; 2019. p. 145-68.

[48]. Pradhan SR, Patra G, Nanda PK, Dandapat P, Bandyopadhyay S, Das AK. Comparative microbial load assessment of meat, contact surfaces and water samples in retail chevon meat shops and abattoirs of Kolkata, WB, India. Int J Curr Microbiol Appl Sci. 2018; 7:158-164.

[49]. Ali AA, Altemimi AB, Alhelfi N, Ibrahim SA. Application of biosensors for detection of pathogenic food bacteria: a review. Biosensors. 2020; 10(6):58.

[50]. Zhao X, Lin CW, Wang J, Oh DH. Advances in rapid detection methods for foodborne pathogens. 2014.24(3):297-312.

[51]. Rajapaksha P, Elbourne A, Gangadoo S, Brown R, Cozzolino D, Chapman J. A review of methods for the detection of pathogenic microorganisms. Analyst. 2019; 144(2):396-411.

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

[52]. Batani G, Bayer K, Böge J, Hentschel U, Thomas T. Fluorescence in situ hybridization (FISH) and cell sorting of living bacteria. Sci Rep. 2019; 9(1):18618.

[53]. Sionek B, Przybylski W, Banska A, Florowski T. Applications of biosensors for meat quality evaluations. Sensors. 2021; 21(22):7430.

[54]. Poghossian A, Geissler H, Schöning MJ. Rapid methods and sensors for milk quality monitoring and spoilage detection. Biosens Bioelectron. 2019; 140:111272.

[55]. Weng X, Neethirajan S. Ensuring food safety: Quality monitoring using microfluidics. Trends Food Sci Technol. 2017; 65:10-22.

[56]. Sonwani, E., Bansal, U., Alroobaea, R., Baqasah, A. M., & Hedabou, M. (2022). An artificial intelligence approach toward food spoilage detection and analysis. Frontiers in Public Health, 9, Article 816226. Sydoruk, A. (2023). Artificial Intelligence (AI) in retail & ecommerce: Use Cases with Examples Accessed on 01 September 2024. Accessed via: https://smarttek.solutions/blog/ai-in-retail-ecommerce/.

[57]. Thapa, A., Nishad, S., Biswas, D., & Roy, S. (2023). A comprehensive review on artificial intelligence assisted technologies in food industry. Food Bioscience, 56(June), Article 103231. https://doi.org/10.1016/j.fbio.2023.103231

[58]. Toro, M., Weller, D., Ramos, R., Diaz, L., Alvarez, F. P., Reyes-Jara, A., … Adell, A. D. (2022). Environmental and anthropogenic factors associated with the likelihood of detecting Salmonella in agricultural watersheds. Environmental Pollution, 306, Article 119298. https://doi.org/10.1016/j.envpol.2022.119298

[59]. Van Erp, M., Reynolds, C., Maynard, D., Starke, A., Iba´nez ˜ Martín, R., Andres, F., Bosma, U. (2021). Using natural language processing and artificial intelligence to explore the nutrition and sustainability of recipes and food. Frontiers in Artificial Intelligence, 3, Article 621577.

[60]. Singh A, Poshtiban S, Evoy S. Recent advances in bacteriophage based biosensors for food-borne pathogen detection. Sensors. 2013; 13(2):1763-1786

[61]. Ivnitski D, Atanassov P. Biosensors based on direct bioelectrocatalysis for environmental monitoring. Biosens Bioelectron. 1999; 14:599-624.

[62]. Alamer S, Eissa S, Chinnappan R, Herron P, Zourob M. Rapid colorimetric lactoferrin-based sandwich immunoassay on cotton swabs for the detection of foodborne pathogenic bacteria. Talanta. 2018; 185:275- 280.

[63]. Samad A, Kim SH, Kim CJ, Lee EY, Kumari S, Hossain MJ, Alam AN, Muazzam A, Hwang YH, Joo ST. From Farms to Labs: The New Trend of Sustainable Meat Alternatives. Food Science of Animal Resources. 2025 Jan 1;45(1):13.

ISSN : 3079-5753
Volume 1, Number 2, February, 2025
https://doi.org/10.70445/gjcsai.1.2.2025.01-22

[64]. Samad A, Alam AN, Kumari S, Hossain MJ, Lee EY, Hwang YH, Joo ST. Modern Concepts of Restructured Meat Production and Market Opportunities. Food Science of Animal Resources. 2024 Mar;44(2):284.

[65]. Samad A, Kumari S, Hossain MJ, Alam AM. RECENT MARKET ANALYSIS OF PLANT PROTEIN-BASED MEAT ALTERNATIVES AND FUTURE PROSPECT. JAPS: Journal of Animal & Plant Sciences. 2024 Aug 31;34(4).

[66]. Samad A, Kim S, Kim CJ, Lee EY, Kumari S, Hossain MJ, Alam AN, Muazzam A, Bilal U, Hwang YH, Joo ST. Revolutionizing cell-based protein: Innovations, market dynamics, and future prospects in the cultivated meat industry. Journal of Agriculture and Food Research. 2024 Aug 22:101345.

[67]. Oh SY, Heo NS, Shukla S, Cho HJ, Vilian AE, Kim J, et al. Development of gold nanoparticle-aptamer-based LSPR sensing chips for the rapid detection of Salmonella typhimurium in pork meat. Scientific Reports. 2017; 7(1):10130.

[68]. Zhang G. Foodborne pathogenic bacteria detection: an evaluation of current and developing methods. The Meducator. 2013; 1(24).