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Advancing real-time predictive systems for listeria and *E. coli* detection in meat processing facilities across the USA

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Abstract
Ensuring the safety of meat products is a critical priority in the United States due to the persistent threats posed by *Listeria monocytogenes* and *Escherichia coli* contamination. These pathogens are major contributors to foodborne illnesses, leading to severe health risks, economic losses, and regulatory challenges. This paper explores the development and implementation of real-time predictive systems for detecting *Listeria* and *E. coli* in meat processing facilities. It proposes an integrated framework that leverages advanced technologies, including biosensors, Internet of Things (IoT) devices, and machine learning (ML) algorithms, to enable rapid and accurate microbial detection. The proposed system incorporates predictive analytics to identify contamination patterns based on historical and real-time data, enabling proactive interventions and minimizing contamination risks. Biosensors and nanotechnology-based platforms provide high sensitivity and specificity, while IoT-enabled devices facilitate continuous monitoring and data transmission. Machine learning algorithms enhance predictive accuracy by analyzing trends and anomalies, offering real-time alerts for corrective actions. This framework also emphasizes blockchain-enabled traceability to secure data integrity and improve transparency across supply chains. Additionally, it aligns with Hazard Analysis and Critical Control Points (HACCP) protocols and USDA Food Safety and Inspection Service (FSIS) guidelines to ensure regulatory compliance. Workforce training and capacity-building programs are integrated to optimize system adoption and operational efficiency. By combining innovative technologies with existing food safety practices, this framework aims to modernize microbial risk management, reduce recalls, and enhance consumer confidence. Future research directions include exploring artificial intelligence (AI)-driven adaptive systems and expanding predictive models to address emerging pathogens. This approach represents a transformative step toward safer meat production and distribution systems in the United States.

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1. Introduction
Food safety remains a critical aspect of meat processing due to its direct impact on public health and industry sustainability (Adefila *et al*., 2024) [3]. Meat products, being highly perishable, are particularly susceptible to microbial contamination, which can lead to severe foodborne illnesses. Among the most concerning pathogens are *Listeria monocytogenes* and *Escherichia coli* (*E. coli*), both of which pose significant risks to consumers. *Listeria monocytogenes* is known for its ability to survive and proliferate under refrigeration, while *E. coli*, particularly the O157:H7 strain, is associated with outbreaks of severe gastrointestinal illness and even life-threatening complications (Toromade and Chiekezie, 2024) [3].

The prevalence of these pathogens in meat processing facilities underscores the urgent need for effective detection, monitoring, and prevention strategies to ensure food safety and compliance with regulatory standards.

Despite advances in food safety protocols, the early detection and prevention of microbial contamination remain formidable challenges (Ogunyemi and Ishola, 2024) [43, 47]. Traditional methods, such as culture-based testing, often require extended incubation periods, delaying results and increasing the risk of contaminated products reaching consumers. Furthermore, these methods are labor-intensive and prone to errors, limiting their reliability in large-scale processing environments. Rapid detection technologies, including biosensors and molecular techniques, have shown promise, but their integration into routine monitoring systems is still limited (Ishola *et al*., 2024) [43]. Consequently, there is a pressing need to develop and implement real-time predictive systems capable of enhancing detection accuracy, reducing response times, and minimizing contamination risks. Addressing these gaps is essential for safeguarding public health and strengthening consumer confidence in meat products (Adewale *et al*., 2024) [7].

These aims to develop and assess real-time predictive systems for microbial detection in meat processing facilities. Specifically, it focuses on leveraging advanced technologies such as artificial intelligence (AI), machine learning (ML), and sensor-based monitoring systems to enhance detection capabilities. Designing and testing predictive algorithms to identify contamination risks (Okedele *et al*., 2024) [50]. Evaluating the effectiveness of AI-driven models in providing rapid and accurate detection of *Listeria monocytogenes* and *E. coli*. Integrating sensor-based technologies with predictive analytics to enable continuous monitoring and early intervention. Recommending best practices for adopting these technologies in compliance with regulatory frameworks. The scope of this review is limited to microbial detection and monitoring systems targeting *Listeria monocytogenes* and *E. coli* contamination in U.S. meat processing facilities. It evaluates both technological advancements and regulatory frameworks to determine their effectiveness in enhancing food safety standards. Key focus areas include the performance assessment of AI and ML-based detection systems, the feasibility of real-time monitoring through sensor networks, and the alignment of these technologies with existing regulations enforced by the U.S. Department of Agriculture (USDA) and the Food and Drug Administration (FDA). The findings are expected to provide actionable insights for industry stakeholders, policymakers, and researchers in improving microbial safety protocols. This seeks to bridge the gap between traditional and modern detection methods by introducing innovative, technology-driven solutions for microbial risk management. Through rigorous evaluation and practical recommendations, it aims to support the meat processing industry in achieving higher standards of safety, efficiency, and regulatory compliance (Toromade and Chiekezie, 2024) [3].

2. Risks and Impacts of *Listeria* and *E. coli* Contamination

Listeria monocytogenes and Escherichia coli (*E. coli*) are pathogenic bacteria that pose significant risks in food safety, particularly in meat processing environments (Ishola *et al*., 2024) [43]. Listeria monocytogenes is a Gram-positive bacterium that causes listeriosis, a severe foodborne illness. It primarily infects humans through contaminated food, including raw or undercooked meat, dairy products, and ready-to-eat items. Listeria has the ability to cross the intestinal barrier, placenta, and blood-brain barrier, leading to invasive infections. Conversely, *E. coli*, particularly the Shiga toxin-producing strains (STEC), such as *E. coli* O157:H7, cause hemorrhagic colitis and hemolytic uremic syndrome (HUS). Transmission occurs through contaminated water, undercooked meat, and cross-contamination in food processing. Both pathogens thrive in food processing environments. Listeria monocytogenes can survive and grow at refrigeration temperatures (0–45 °C), making it a persistent risk in cold storage facilities. It also forms biofilms, which protect it from cleaning agents (Anjorin *et al*., 2024) [17]. *E. coli*, though less tolerant to cold, grows rapidly at temperatures between 7–46 °C and can also persist in biofilms on equipment and surfaces. Poor sanitation practices and inadequate temperature control create favorable conditions for the proliferation of these pathogens.

Listeriosis is associated with symptoms such as fever, muscle aches, and gastrointestinal distress, but it can lead to severe complications, including meningitis, septicemia, and miscarriage (Ogunyemi and Ishola, 2024) [47]. The fatality rate for listeriosis is approximately 20-30%, particularly among vulnerable populations. *E. coli* infections typically result in severe abdominal cramps, diarrhea, and vomiting. In severe cases, STEC infections can lead to HUS, causing kidney failure and death, especially in children and the elderly. Pregnant women, newborns, the elderly, and immunocompromised individuals are most susceptible to both pathogens. Long-term effects include chronic kidney disease from HUS in *E. coli* infections and neurological damage from invasive listeriosis. Persistent health issues can impose a lifelong burden on affected individuals and their families. Contamination events often trigger costly product recalls, impacting manufacturers and retailers. Recalls not only result in direct financial losses but also lead to lawsuits and settlements, adding to the economic strain. For instance, high-profile outbreaks linked to *E. coli* in beef and Listeria in processed foods have led to millions of dollars in damages. Public awareness of contamination incidents can erode consumer trust, reducing sales and market confidence. Companies may suffer reputational damage that is difficult to recover from, especially in competitive markets. Market instability can also affect suppliers and distributors, highlighting the broader economic ripple effects of contamination incidents (Adefila *et al*., 2024) [3]. The risks associated with Listeria and *E. coli* contamination in meat processing environments underscore the need for stringent food safety measures. Understanding microbial characteristics, health impacts, and economic consequences is essential for developing effective prevention strategies. Enhanced monitoring, sanitation, and employee training are critical to mitigating these risks and ensuring food safety. By addressing these challenges, the food industry can better protect public health and maintain consumer confidence (Ishola, 2024) [43].

2.1 Existing Detection Methods and Their Limitations

Detection of pathogens, pollutants, or other biological markers is crucial across various fields, including public health, environmental monitoring, and food safety. Over time, numerous detection methods have been developed, each with its strengths and limitations as shown in figure 1 (Billington *et al*., 2022; Ogunyemi and Ishola, 2024) [43, 47].

These methods generally fall into three categories: traditional techniques, molecular methods, and current monitoring practices. While each approach has its utility, challenges remain, necessitating ongoing research and innovation to improve efficiency, accuracy, and applicability. Culture-based methods and biochemical assays have been foundational in microbiological analysis. Culture-based methods involve isolating microorganisms on selective media, followed by identification based on colony morphology, biochemical tests, or staining techniques (Okedele *et al*., 2024) [50]. These methods are widely used for identifying bacteria, fungi, and viruses in clinical, environmental, and food samples. Biochemical assays, on the other hand, often measure enzymatic reactions or metabolic products specific to a target organism.

However, traditional techniques come with significant time delays and are labor-intensive. The time required for cultures to grow can range from hours to days, especially for slow-growing or difficult-to-culture microorganisms (Avwioroko *et al*., 2024) [21]. Furthermore, biochemical assays often require multiple steps, which increases the complexity of the process and the risk of human error. This delay in pathogen detection can result in missed opportunities for early intervention, particularly in time-sensitive scenarios like outbreak management. Moreover, these methods generally lack sensitivity in detecting low concentrations of pathogens, leading to false negatives in some cases.

With the advancement of molecular biology, Polymerase Chain Reaction (PCR) and its more sensitive version, quantitative PCR (qPCR), have revolutionized pathogen detection. PCR amplifies small amounts of genetic material, making it possible to detect even trace amounts of pathogens (Abass *et al*., 2024) [1]. qPCR further enhances this by allowing for real-time quantification of the target DNA, providing detailed information about pathogen load in a sample. These molecular methods offer high specificity and sensitivity, and they can be applied to a wide range of biological and environmental samples. Despite their advantages, PCR-based methods are not without cost and scalability challenges. The equipment required for PCR analysis, such as thermocyclers and fluorescence detection systems, can be expensive, especially for high-throughput applications. Moreover, reagents for PCR and qPCR are often costly and require precise storage conditions, increasing operational costs. These factors limit the widespread adoption of PCR-based techniques, particularly in resource-limited settings. Additionally, while PCR provides high sensitivity, it does not always differentiate between live and dead microorganisms, which could result in an overestimation of the actual threat in certain contexts (Ajirotutu *et al*., 2024) [13]. Furthermore, the need for trained personnel to interpret results adds to the complexity of implementation.

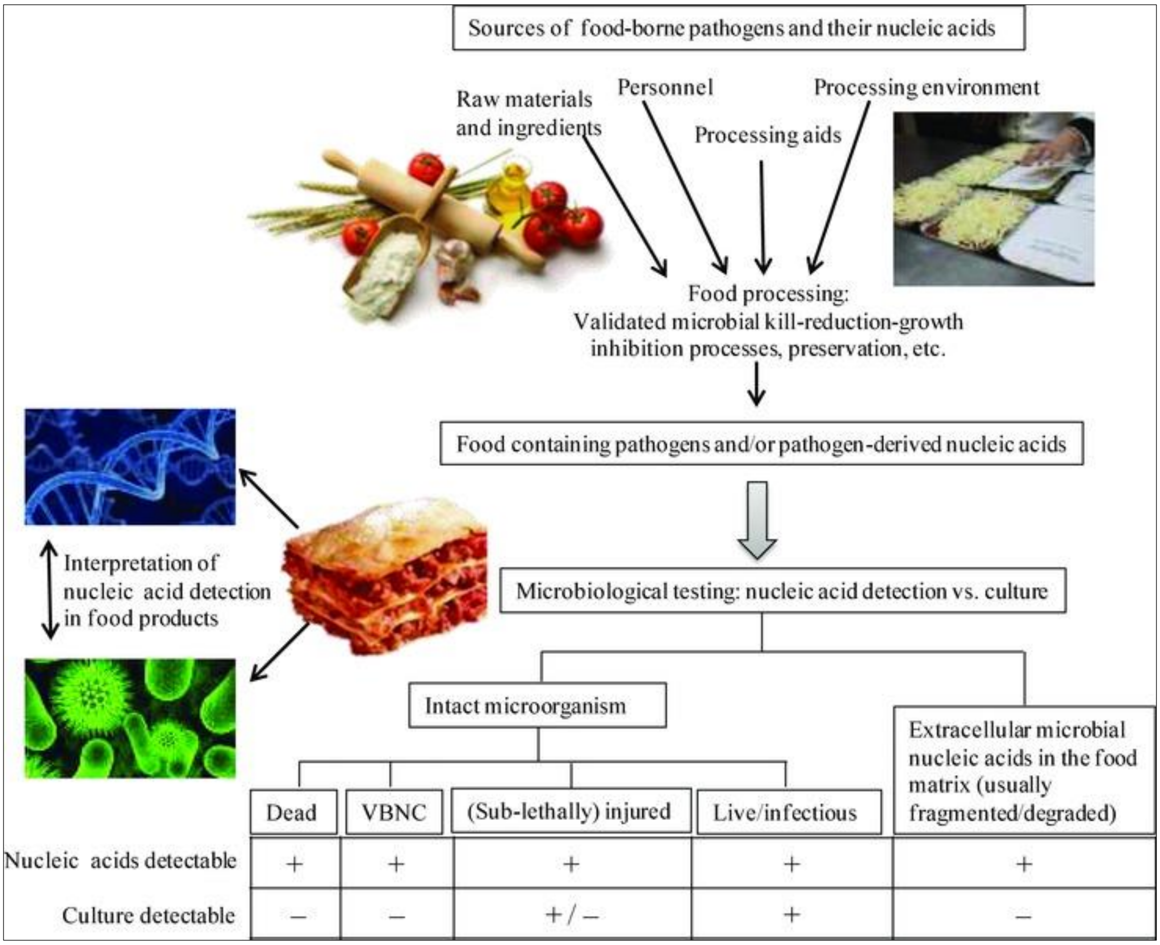

Fig 1: An outline of potential food contamination pathways with microbial pathogens and/or their nucleic acids, along with potential repercussions for detection using culture-based and nucleic acid-based techniques (Billington *et al*., 2022) [29]

Current monitoring practices often rely on periodic sampling rather than continuous surveillance. In environmental monitoring, for example, water samples are typically collected at fixed intervals to assess contamination levels

(Agupugo *et al*., 2024) [11]. While this approach offers useful snapshots of contamination levels, it fails to capture real-time fluctuations in pathogen or pollutant concentrations, which can be crucial for timely decision-making. Continuous surveillance, on the other hand, involves real-time data collection, often through sensors or automated systems. This method is more suited for environments that require constant monitoring, such as in industrial settings or critical public health infrastructure. However, even with continuous surveillance, gaps in traceability and response time remain. Although continuous data can provide a more accurate reflection of environmental or biological conditions, the vast amount of data generated can overwhelm analysts, especially in real-time settings. Moreover, there is often a lack of integrated systems for data analysis, which can delay the detection of anomalies or trends. Furthermore, even with automated monitoring systems, the time between detecting a potential threat and initiating a response remains a significant challenge. In many cases, there is a delay in interpreting the data or in implementing corrective measures, which can mitigate the effectiveness of continuous monitoring (Bassey and Ibegbulam, 2023) [22]. Detection methods in fields like microbiology and environmental monitoring have come a long way, but each method whether traditional, molecular, or current monitoring practices has inherent limitations. Traditional culture-based methods and biochemical assays suffer from time delays and labor-intensive processes, making them less effective for real-time applications. While molecular methods like PCR and qPCR offer high sensitivity, they are often hindered by high costs and scalability issues. Current monitoring practices, including periodic sampling and continuous surveillance, face challenges with traceability and response times. Overcoming these limitations will require the development of more cost-effective, efficient, and scalable detection systems, as well as improvements in real-time data analysis and response strategies.

2.2 Proposed Real-Time Predictive Framework

In the evolving landscape of industrial and environmental monitoring, the need for real-time predictive systems has grown considerably (Folorunso *et al*., 2024) [36]. This proposes a comprehensive framework that integrates cutting-edge technologies to enable efficient and timely detection of anomalies, hazards, and risks. The proposed framework leverages technological foundations such as the Internet of Things (IoT), Machine Learning (ML), and Artificial Intelligence (AI), alongside advanced detection systems, data-driven predictive modeling, and blockchain-enabled traceability as illustrated in figure 2 (Shinde *et al*., 2023) [53]. Together, these components offer a robust solution for proactive monitoring and rapid decision-making in various sectors.

At the heart of the proposed predictive framework is the use of Internet of things (IoT), which enables sensor-based monitoring. IoT technology involves interconnected sensors and devices that collect real-time data from the environment or specific assets (Toromade *et al*., 2024) [3]. These sensors can measure variables such as temperature, pressure, humidity, and chemical concentrations, providing a constant stream of data essential for early detection of potential issues. The sensors are connected via wireless networks, ensuring that the data is transmitted promptly to central systems for analysis. In conjunction with IoT, Machine learning (ML) and Artificial intelligence (AI) play a pivotal role in predictive analytics. These technologies can process vast amounts of data generated by IoT devices to identify patterns, forecast potential risks, and offer actionable insights. ML algorithms can be trained to recognize trends in historical data and apply this knowledge to predict future events. AI, particularly deep learning, enhances this by automating decision-making processes, enabling systems to learn and adapt over time without explicit programming. Together, IoT, ML, and AI form the technological foundation for a real-time predictive framework that is both adaptive and scalable (Abass *et al*., 2024) [1].

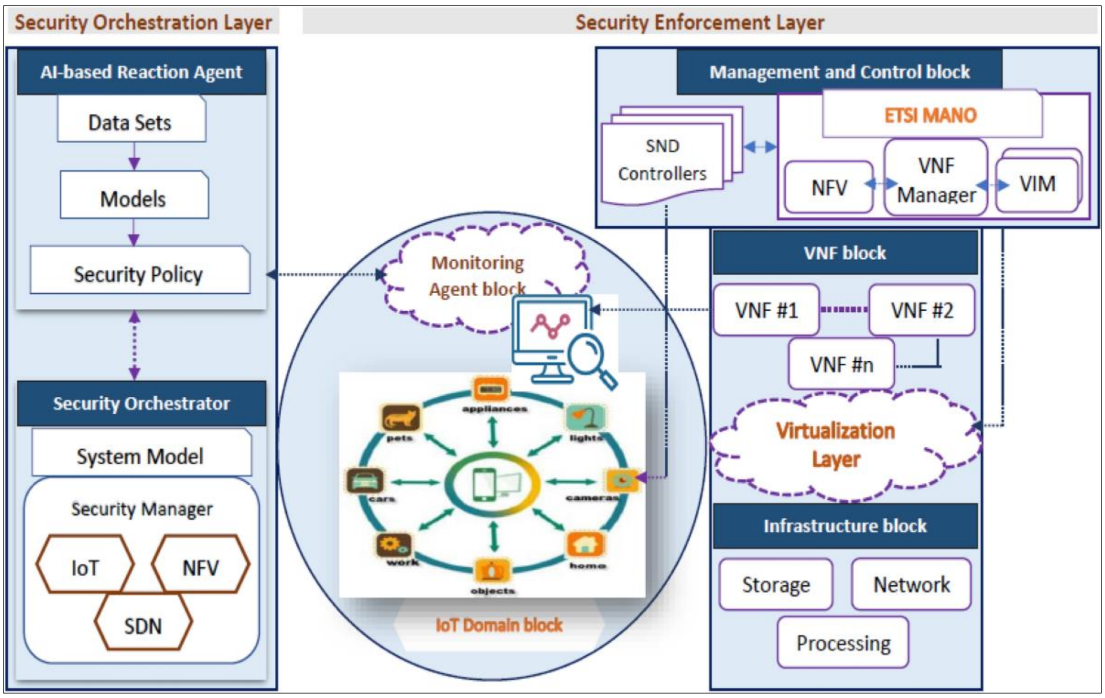

Fig 2: Cutting-edge detection systems, data-driven predictive modeling, blockchain-enabled traceability, and technical underpinnings like the Internet of Things (IoT), machine learning (ML), and artificial intelligence (AI). (Shinde *et al*., 2023) [53]

An essential feature of the proposed framework is the use of advanced detection systems, which significantly enhance the capability of real-time monitoring. Biosensors and nanotechnology-enabled rapid testing are emerging as powerful tools in this regard. Biosensors can detect biological markers, toxins, or pollutants with high sensitivity, while nanotechnology improves the detection limit by using engineered nanoparticles to interact with the target substance. This combination ensures faster, more accurate detection of environmental or health-related hazards, facilitating immediate intervention (Bassey, 2023) [22]. Moreover, portable spectroscopy and fluorescence-based systems allow for rapid on-site testing. These systems use light to detect the presence of specific compounds in samples, providing real-time data on their concentration. Spectroscopy and fluorescence techniques are highly versatile, offering applications across various industries, from environmental monitoring to healthcare diagnostics. Wireless monitoring networks are another crucial aspect of advanced detection systems. These networks enable real-time alerts by transmitting sensor data to centralized platforms via secure communication channels. Such systems can promptly notify operators or stakeholders about emerging risks, enhancing situational awareness and allowing for faster response times in critical situations. The backbone of a real-time predictive framework is the integration of historical data for risk forecasting. By combining past incident records, sensor data, and environmental conditions, predictive models can identify trends and predict future risks with higher accuracy. The integration of this data enables a comprehensive understanding of potential hazards, whether they are related to equipment failures, environmental disasters, or health outbreaks. AI algorithms further enhance the framework's predictive capabilities by performing anomaly detection and trend analysis (Agupugo *et al*., 2022) [9]. Anomaly detection algorithms are trained to spot deviations from established norms, flagging irregularities that might indicate a developing issue. Trend analysis, on the other hand, involves examining patterns over time to anticipate future behaviors. When combined, these techniques allow for highly accurate and dynamic risk forecasting, offering organizations the foresight necessary to prevent costly or dangerous events.

In addition to predictive analytics, the proposed framework incorporates blockchain-enabled traceability to secure data integrity across supply chains and systems. Blockchain, with its decentralized and immutable ledger, ensures that all data collected from IoT sensors, detection systems, and predictive models is securely recorded (Ajirotutu *et al*., 2024) [13]. This prevents tampering or manipulation of data, which is critical in industries where trust and transparency are paramount, such as healthcare, food safety, and environmental protection. Blockchain also enhances transparency and accountability by providing an auditable trail of every transaction or data point. This allows stakeholders to track and verify the origin, quality, and movement of goods or materials throughout the supply chain. By integrating blockchain with IoT, ML, and AI systems, the framework ensures a reliable, transparent, and accountable process for real-time monitoring and early detection. The proposed real-time predictive framework offers a comprehensive solution for monitoring and early detection across various industries. By integrating IoT, ML, AI, advanced detection systems, data-driven predictive modeling, and blockchain, this framework enables faster response times, improved risk forecasting, and enhanced transparency. The combination of these technologies not only improves operational efficiency but also ensures that potential hazards are detected before they escalate into more significant problems. As industries continue to face increasingly complex challenges, the integration of these cutting-edge technologies will be crucial in maintaining safety, sustainability, and accountability (Folorunso *et al*., 2024) [36].

2.3 Implementation Strategies

The implementation of real-time detection systems in sectors such as public health, food safety, and environmental monitoring is crucial for timely decision-making and intervention. Effective deployment requires a multifaceted approach, addressing infrastructure, workforce training, and integration with existing safety protocols (Bassey, 2023) [22]. These strategies must align with operational objectives, ensuring the systems are functional, sustainable, and able to provide real-time insights for risk management.

The design and deployment of real-time systems require robust infrastructure to support sensor networks and data systems. Sensors are the backbone of real-time detection, providing continuous data on environmental factors such as temperature, humidity, contamination levels, or pathogen presence. For these sensors to function effectively, reliable and scalable communication networks are essential, facilitating the transmission of sensor data to centralized or cloud-based systems for processing and analysis (Agupugo *et al*., 2022) [9]. Additionally, the data infrastructure must include high-performance computing systems to manage large volumes of real-time data and sophisticated algorithms to analyze and interpret it. Developing standard operating procedures (SOPs) for data collection and response is equally critical. SOPs ensure consistency and accuracy in data acquisition, reducing the risk of errors. They must outline protocols for sensor calibration, data storage, and routine system maintenance, as well as how to handle unexpected events or failures. Furthermore, SOPs should provide guidelines for response protocols, detailing how to react to anomalous readings, including automated responses (e.g., system shutdowns or alerts) and manual interventions when necessary (Toromade *et al*., 2024) [3]. This structured approach to data collection and response improves operational efficiency, reduces downtime, and ensures that the system delivers actionable insights in a timely manner.

Workforce training is essential for the successful operation and sustainability of real-time detection systems (Eruaga, 2024) [30]. Operators must be thoroughly educated in the functioning of the systems, including how to troubleshoot equipment issues, perform routine maintenance, and optimize the performance of sensors and data networks. Regular training sessions should be conducted to ensure personnel remain up-to-date with evolving technologies and system upgrades. This continuous education fosters confidence in system use and enhances its effectiveness in detecting and mitigating risks. Additionally, training should include protocols for rapid decision-making and intervention. In situations where immediate action is required, such as during pathogen outbreaks or hazardous environmental conditions, employees need clear, concise guidelines on how to assess data, interpr*et al*erts, and execute appropriate interventions. These protocols should emphasize decision-making speed without sacrificing accuracy, ensuring that the response is both timely and correct. Simulations and role-playing exercises can be valuable tools for building these skills, as they provide practical experience in handling high-pressure situations.

An effective real-time detection system cannot operate in isolation; it must be seamlessly integrated with existing safety protocols to ensure that the response to detected risks is aligned with industry standards. For instance, in the food industry, systems must be harmonized with Hazard Analysis and Critical Control Points (HACCP). HACCP is a preventative approach to food safety that identifies potential hazards and establishes critical control points to mitigate those risks. Real-time detection systems can enhance HACCP by providing continuous monitoring of critical control points, allowing for immediate corrective actions when deviations occur (Toromade *et al*., 2024) [3]. The integration ensures that the detection system supports, rather than replaces, established safety practices, enhancing overall food safety management. Compliance with regulatory bodies is another critical aspect of integration. For instance, systems used in food production must comply with USDA Food Safety and Inspection Service (FSIS) guidelines. These guidelines set the standards for food safety, including requirements for pathogen monitoring, traceability, and sanitation practices. A real-time detection system must be designed to meet these regulatory standards, ensuring that any data collected can be used to verify compliance. This integration not only helps ensure legal compliance but also builds trust with stakeholders, including consumers and regulatory agencies. The implementation of real-time detection systems requires careful consideration of infrastructure, workforce training, and integration with existing safety protocols. A robust infrastructure, including well-designed sensor networks and data systems, provides the foundation for effective monitoring and response. Workforce training ensures that personnel are equipped to operate the system efficiently and make rapid, informed decisions. Integration with established safety protocols, such as HACCP and FSIS guidelines, ensures that the real-time system enhances existing practices and meets regulatory requirements (Eruaga *et al*., 2024) [30]. By addressing these key elements, organizations can successfully deploy and maintain real-time detection systems that improve safety, efficiency, and risk management across various industries.

2.4 Evaluation and Performance Monitoring

The effectiveness of safety and quality systems in industries such as food processing, healthcare, and manufacturing relies heavily on ongoing evaluation and performance monitoring. This ensures that systems not only operate efficiently but also continue to improve over time. A comprehensive approach to performance monitoring involves defining Key Performance Indicators (KPIs), implementing continuous improvement mechanisms, and conducting benchmarking against industry standards (Adepoju *et al*., 2019) [5]. These elements form the foundation for evaluating system effectiveness and driving progress toward enhanced safety and quality outcomes. The first step in performance monitoring is the establishment of Key Performance Indicators (KPIs), which offer quantifiable measures of system performance. KPIs are essential for assessing the success of safety and quality systems in real-time, particularly in high-risk sectors like food safety and healthcare. One critical KPI is detection accuracy, which measures the ability of the system to correctly identify hazards or issues. For example, in food safety systems, detection accuracy refers to the system's capacity to identify contaminants or potential foodborne pathogens. Alongside accuracy, detection speed is a vital KPI, as quicker identification leads to faster interventions, reducing the likelihood of contamination spreading or affecting large populations. Additionally, false-positive rates, the frequency with which the system incorrectly flags harmless substances as hazardous, are a key KPI. Minimizing false positives is crucial for ensuring the efficiency and reliability of the system, preventing unnecessary actions that could disrupt operations. Another important KPI in safety and quality systems is the reduction in contamination incidents and recalls. By tracking the frequency and severity of contamination-related issues, organizations can gauge the effectiveness of their systems in preventing safety hazards (Agupugo *et al*., 2021) [8]. A reduction in recalls, which often incur significant financial costs and damage to a brand’s reputation, directly reflects the success of the system in mitigating risks.

For any system to remain effective over time, continuous improvement mechanisms must be in place. These mechanisms enable organizations to identify areas for enhancement and ensure that the system evolves in response to changing conditions and emerging threats. Feedback loops are an integral part of continuous improvement (Eruaga *et al*., 2024) [30]. These loops allow operators to provide data and insights back into the system, enabling it to adapt and refine its processes. For instance, when an issue is detected, the system can analyze the root cause and implement corrective actions to prevent recurrence. This feedback-driven approach ensures that the system becomes more effective with each iteration. System updates are another key component of continuous improvement. As new challenges arise, and as technologies advance, safety and quality systems must be updated to incorporate the latest practices, methodologies, and tools. Regular updates to the system software, hardware, and protocols help address evolving risks and optimize operational efficiency. Incorporating emerging technologies and practices into the system is also a critical element of continuous improvement (Bassey, 2023) [22]. Technologies like Artificial Intelligence (AI), blockchain for traceability, and advanced sensors can be integrated to enhance the detection, analysis, and monitoring capabilities of existing systems. By adopting cutting-edge tools, systems can stay ahead of emerging risks and maintain the highest standards of safety and quality.

To ensure that performance remains at a global standard, systems must be regularly benchmarked against industry standards. This process involves comparing the performance of a given system with established best practices and standards within the relevant industry, such as food safety frameworks or healthcare regulations. Comparative analysis with international food safety frameworks allows organizations to evaluate how their safety systems measure up to global standards (Bassey *et al*., 2024) [27]. Frameworks such as the Hazard Analysis and Critical Control Points (HACCP) or ISO 22000 provide guidelines for identifying and mitigating risks in food production. Benchmarking against these frameworks helps organizations identify gaps in their existing systems, ensuring that they comply with international safety regulations and deliver optimal protection to consumers. Moreover, recommendations for global best practices should be generated through this benchmarking process. By analyzing the best-performing systems worldwide, organizations can adopt strategies and technologies that have been proven to deliver superior results. These recommendations serve as a roadmap for continuous improvement, ensuring that organizations stay competitive and aligned with global standards in their respective industries. Evaluation and performance monitoring are critical for maintaining and improving the effectiveness of safety and quality systems. By establishing relevant Key Performance Indicators (KPIs), implementing continuous improvement mechanisms, and benchmarking against industry standards, organizations can ensure their systems remain effective in detecting and mitigating risks. The integration of feedback loops, system updates, and emerging technologies further strengthens the system, enhancing its adaptability and accuracy. Benchmarking against international frameworks helps ensure that systems comply with global best practices, enabling continuous progress towards better safety and quality outcomes. Through these comprehensive evaluation and monitoring strategies, organizations can protect consumers, improve operational efficiency, and foster a culture of continuous improvement (Oyewale and Bassey, 2024) [27].

2.5 Challenges and Future Directions

The development and implementation of real-time detection systems have made significant strides in industries such as public health, environmental monitoring, and food safety (Bassey, 2022) [23]. However, several challenges remain, spanning technological, economic, regulatory, and adaptive considerations. Addressing these challenges is essential to improving the effectiveness, affordability, and scalability of these systems. Future directions in real-time detection will focus on overcoming these barriers and leveraging emerging technologies to create more responsive, efficient, and robust systems.

One of the primary challenges in the implementation of real-time detection systems is the high costs of deployment and maintenance (Bassey *et al*., 2024) [27]. The infrastructure required to support these systems including sensors, data storage, communication networks, and processing units can be expensive, particularly when considering the need for regular maintenance and calibration. These costs can be prohibitive for smaller organizations, limiting the widespread adoption of advanced detection systems. Additionally, the need for specialized personnel to operate and maintain the systems adds to the ongoing financial burden, particularly in resource-constrained environments (Folorunso, 2024) [36]. Another significant challenge is the scalability of real-time systems for small and medium-sized enterprises (SMEs). Many detection systems are designed for large-scale operations, and adapting them to the needs of smaller enterprises presents a challenge in terms of both cost and complexity. For SMEs, the lack of technical expertise and financial resources can hinder their ability to adopt and implement these systems, despite the potential benefits. To address this, future systems must focus on designing more cost-effective and scalable solutions, incorporating modular components that can be customized to fit the specific needs and resources of smaller organizations. Innovations in sensor technology and cloud computing could help make real-time systems more affordable and accessible for SMEs, ultimately expanding their reach and impact. As real-time detection systems become more integrated into industries like food safety and healthcare, aligning these systems with evolving regulations presents a significant challenge. Regulatory frameworks are continually updated to address new risks, emerging technologies, and industry needs, creating a dynamic landscape for organizations to navigate. Real-time systems must be designed to meet these evolving regulations, ensuring that the data collected is compliant with industry standards and legal requirements. This requires ongoing monitoring of regulatory changes and adapting systems to remain compliant, which can be resource-intensive (Adepoju *et al*., 2018) [6]. Moreover, there is a need to balance innovation with standardization. As new technologies, such as artificial intelligence (AI) and machine learning, are integrated into detection systems, there is a risk that rapid innovation may outpace the development of regulatory frameworks. This can lead to discrepancies between cutting-edge technological capabilities and established compliance requirements. Future development should focus on harmonizing innovation with regulatory standards to ensure that new technologies can be adopted without compromising safety or compliance. Collaborative efforts between industry stakeholders, regulatory bodies, and technology developers will be essential to create frameworks that support both innovation and standardization (Eruaga *et al*., 2024) [30].

Emerging risks, such as antimicrobial resistance (AMR) and evolving pathogens, pose significant challenges to real-time detection systems. AMR is a growing concern in both clinical and environmental settings, as pathogens evolve to resist conventional treatments (Anozie *et al*., 2024) [18]. Real-time detection systems must be able to quickly identify and monitor these evolving threats to enable timely interventions. Similarly, pathogens themselves are constantly evolving, which requires detection systems to adapt to new strains or variants that may not have been previously encountered. This need for adaptive systems to detect novel or resistant strains adds a layer of complexity to the design and maintenance of these systems (Folorunso, 2024) [36]. AI-driven adaptive models represent a promising direction for proactive risk management. AI can be used to analyze vast amounts of data from real-time monitoring systems, identifying patterns and predicting potential risks before they materialize. By leveraging machine learning algorithms, these systems can continuously evolve and improve their predictive capabilities, responding to emerging threats in real time. AI models can also be integrated with real-time detection systems to facilitate rapid decision-making, providing actionable insights and recommendations for intervention. However, the deployment of AI models must be carefully managed to ensure they are properly trained, validated, and transparent, to avoid the risk of false positives or inaccurate predictions. The challenges facing real-time detection systems are significant but not insurmountable. Overcoming technological and economic barriers, such as high deployment costs and scalability issues for SMEs, will require innovation in sensor technology, data processing, and system design. Addressing regulatory and compliance issues involves aligning real-time systems with evolving regulations while ensuring that innovation is balanced with standardization. Finally, emerging risks such as AMR and evolving pathogens highlight the need for adaptive systems, with AI-driven models offering proactive solutions for risk management. As these challenges are addressed, real-time detection systems will become more effective, accessible, and responsive, driving improvements in safety, health, and environmental protection across industries (Itua *et al*., 2024).

2.6 Methodology

The detection of pathogens such as *Listeria* and *E. coli* in meat processing facilities is a critical concern for food safety (Avwioroko, 2023; Folorunso *et al*., 2024) [36, 20]. Real-time predictive systems offer the potential to enhance pathogen detection, providing immediate insights into contamination risks, improving response times, and reducing public health risks. This outlines a methodology for studying the advancement of these systems in detecting *Listeria* and *E. coli* in meat processing facilities across the USA, focusing on system design, data collection, analysis, and future trends in technology integration.

The first step in studying the advancement of real-time predictive systems is understanding the design and integration of sensor networks. These systems rely on sensors to continuously monitor the environment in meat processing facilities. Sensors should be strategically placed at critical points, such as meat contact surfaces, air quality monitors, and water systems, to detect the presence of pathogens or environmental factors conducive to microbial growth. The sensor network must integrate seamlessly with data systems that store and analyze the incoming data in real-time. To ensure effective pathogen detection, sensor types (e.g., biosensors, electrochemical sensors, and optical sensors) should be selected based on their ability to detect specific biomarkers or environmental conditions indicative of contamination (Agupugo *et al*., 2024) [11]. The predictive model should leverage these data streams to predict pathogen proliferation patterns based on environmental variables such as temperature, humidity, and sanitation practices. The design of this model must account for known factors that influence pathogen survival and growth, such as the inherent variability in meat processing operations and fluctuations in facility conditions (Avwioroko, 2023) [20].

Effective data collection is fundamental to the success of real-time predictive systems. The study should begin by selecting relevant parameters to monitor, including environmental data (e.g., temperature, humidity, pH levels), microbial levels (e.g., *Listeria* and *E. coli* counts), and operational factors (e.g., cleaning schedules, equipment usage). These parameters must be collected using automated sensors that feed real-time data into a centralized system. Data should be aggregated from different stages of the meat processing line, including slaughter, cutting, packaging, and storage, to identify contamination hotspots. To evaluate the system's effectiveness, data collection should include both quantitative and qualitative aspects. Quantitative data involves pathogen counts, temperature readings, and other numeric metrics, while qualitative data can include observations of cleaning practices, worker behavior, and compliance with food safety protocols. These datasets should be continuously updated and processed through real-time monitoring systems that flag deviations from acceptable safety thresholds.

Once data collection processes are established, the next step is developing and refining predictive models that can assess the likelihood of pathogen presence in the facility based on real-time inputs (Ajirotutu *et al*., 2024) [13]. Machine learning (ML) and artificial intelligence (AI) models, such as support vector machines (SVM), neural networks, and decision trees, can be used to analyze historical and real-time data to identify trends and predict pathogen outbreaks. The development of these models requires extensive data on pathogen behavior, environmental factors, and operational variables within the facility. To ensure accuracy and reliability, the predictive model should undergo rigorous validation and testing. This can be achieved by comparing the predictions made by the system with actual laboratory testing results of *Listeria* and *E. coli* samples taken from the facility. The model should also account for the facility's unique operational conditions, allowing for the adjustment of thresholds and parameters in response to changing conditions over time (Ijomah *et al*., 2024). A robust system will also include feedback loops to improve prediction accuracy as new data is integrated into the model.

To assess the practical application of the predictive system, field studies and pilot testing should be conducted in various meat processing facilities across the USA. This should involve multiple facilities of varying sizes, production volumes, and processing methods to understand how the system performs across different environments. During the pilot phase, the system should be integrated with existing safety and monitoring protocols to ensure that it complements current practices without disrupting operations (Toromade *et al*., 2024) [3]. Data gathered during pilot testing should be used to evaluate the real-time response capabilities of the system, including how quickly it identifies contamination risks and alerts facility operators. Success metrics for pilot testing should include the system's accuracy in detecting pathogens, its speed in providing actionable insights, and its impact on reducing contamination levels through timely interventions.

Regulatory compliance is an essential component of advancing predictive systems. The study must ensure that the system aligns with USDA Food Safety and Inspection Service (FSIS) guidelines and HACCP (Hazard Analysis and Critical Control Points) principles. This alignment ensures that the system's predictions lead to actionable interventions that are legally and operationally sound (Eruaga *et al*., 2024) [30]. Furthermore, the review should examine how industry stakeholders such as meat producers, regulators, and technology providers can collaborate to support the integration of these predictive systems into existing infrastructure.

Looking ahead, future research should focus on enhancing the AI-driven capabilities of real-time predictive systems. Incorporating more advanced machine learning algorithms can refine prediction models to better handle complex and dynamic operational environments. Additionally, the study should investigate the role of Internet of Things (IoT) devices in facilitating smart manufacturing practices, such as real-time monitoring of worker practices and facility conditions, to prevent pathogen contamination from occurring in the first place (Folorunso *et al*., 2024; Toromade *et al*., 2024) [36, 3]. Global harmonization of predictive systems will be a crucial future direction. As international trade increases, the development of standardized predictive safety systems will be necessary to ensure consistency and reliability in meat safety practices across borders. Collaborative efforts between global stakeholders will ensure that real-time predictive systems are universally effective in mitigating foodborne diseases. Advancing real-time predictive systems for pathogen detection in meat processing facilities offers significant promise for improving food safety. The methodology for studying these systems includes sensor design, data collection, predictive modeling, field testing, and regulatory integration. As these systems evolve, they hold the potential to significantly reduce the risks of *Listeria* and *E.*

coli outbreaks, benefiting both public health and the meat processing industry. Future advancements will focus on refining AI-driven models, enhancing scalability, and fostering international collaboration to standardize food safety practices across the globe (Eruaga *et al*., 2024; Ajirotutu *et al*., 2024) [30, 13].

2.8 Conclusion
In conclusion, the implementation of predictive systems in food safety has emerged as a transformative approach to modernizing the industry. These systems leverage real-time data and advanced analytics to proactively identify risks, enhancing food safety and reducing the occurrence of foodborne illnesses. The ability to anticipate potential threats enables faster, more effective interventions, thereby improving public health outcomes and contributing to economic stability. As the food industry faces increasing global challenges, predictive systems offer significant potential to safeguard consumers and streamline production processes.

To accelerate the adoption of these systems, it is crucial for policymakers and industry leaders to collaborate on strategies that promote their widespread use. Offering incentives for the adoption of advanced technologies, along with regulatory support that aligns with evolving food safety standards, can encourage greater investment in predictive systems. Additionally, fostering partnerships between technology providers and food processors is essential for integrating these innovations into existing production lines, ensuring that both technical expertise and industry needs are addressed.

Looking forward, future research directions will likely focus on the development of AI-enhanced predictive models that can further improve the accuracy and efficiency of risk assessment in food safety. The integration of these models with smart manufacturing practices could lead to more automated, responsive, and adaptive production systems. Moreover, global harmonization of predictive safety systems will be essential to standardize practices and ensure consistency in food safety monitoring across different regions, especially in an increasingly interconnected global market. Predictive systems hold immense promise in shaping the future of food safety, but achieving this potential will require concerted efforts from stakeholders across technology, policy, and industry.

3. References

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