Sarcouncil Journal of Engineering and Computer Sciences

ISSN(Online): 2945-3585

Volume- 04| Issue- 11| 2025

Research Article **Received:** 20-10-2025| **Accepted:** 15-11-2025 | **Published:** 28-11-2025

A Comparison of Machine Learning and Mathematical Models for Predicting Food Safety Risks

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Abstract: Food safety is a foundational element of public health infrastructure and a key stimulator of socioeconomic development everywhere. Sophisticated food chains, coupled with novel contaminants and changing consumer demand, necessitate robust, evidence-based systems to anticipate and manage threats. Predictive modeling has become an indispensable tool in this process, providing early warning systems, high-risk scenario detection, and inspection and intervention strategy optimization. This paper presents a comparative evaluation of two prevalent methodological paradigms, mathematical models and machine learning algorithms, in food safety risk forecasting. Mathematical models draw on assumptions that are domain-specific and mechanistic processes, while machine learning derives adaptive capabilities from big data. On the basis of systematic review and comparative analysis, this paper scrutinizes their theoretical underpinnings, practical applications, and empirical performances in food safety settings. By combining information from regulatory agencies, scholarly sources, and industrial applications, the study contributes to greater insight into the manner in which these modeling approaches are harmonized or integrated for enhanced efficacy in preventing and managing risk.

Keywords: Food safety, risk prediction, machine learning, mathematical modeling, public health surveillance, contamination forecasting.

INTRODUCTION

Risk management and prevention are the biggest challenges regulatory agencies and public health now face in the 21st century. An estimated 600 million individuals, close to one in ten globally, fall ill due to food contamination every year, of whom over 420,000 lose their lives (WHO, 2023). These figures emphasize the urgent need for efficient, accurate, and large-scale methods of detection and limiting possible foodborne risk factors before consumers' exposure. Traditional food safety risk analysis methods relied on expert models and knowledge-based deterministic models. The more recent advent of big data, Internet of Things (IoT), and artificial intelligence has brought newer modeling paradigms that can learn from data patterns and react in real time to evolving circumstances.

In particular, the growing pervasiveness of unstructured and structured food safety data ranging from lab testing results and traceability data to social media complaint data and IoT sensor streams has generated interest in machine learning as a means of predicting food safety risk (Zhao *et al.*, 2021). Data-intensive settings such as these present the prospect of transitioning beyond static models and towards predictive intelligence systems that can identify risks near real time. But no matter all their promise, machine learning models are not without defects. They require extremely large labeled data sets, are torture to work with from a point of interpretability, and operate sub-optimally when used outside their training domains (Chawla *et al.*, 2021). Mathematical models, on the other hand, although occasionally rigid and computationally expensive, are mostly easier to comprehend and work with, particularly when used in formal safety analyses.

Comparative efficacy of the two paradigms in facing food safety threats is analyzed in this study. This is done by examining public and private sector real-world applications, examining peer-reviewed scientific literature, and comparing results of different modeling methods across various food commodities and types of threats. This discussion is not only about which model performs better in what situation, but how the strengths of the different paradigms could complement one another.

Literature Review

Over the past two decades, there has been considerable literature on predictive modeling of food safety, with most studies falling into one of two camps: traditional mathematical modeling and trendy machine learning approaches. Mathematical models such as Quantitative Microbial Risk Assessment (QMRA), stochastic simulation, and dose-response models have long been the scientific basis of risk assessments (WHO, 2008). The models apply a proven system of inputs such as

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DOI- https://doi.org/10.5281/zenodo.17754377

pathogen concentration, conditions of exposure, and host susceptibility to forecast probabilities of adverse outcomes. Regulators favour them because they are transparent in form and follow international standards, for instance, those set out by the Codex Alimentarius Commission and European Food Safety Authority (EFSA, 2019).

Mathematical models are quite different in that they tend to need strong pre-knowledge of the system in question. Their assumptions are likely to constrain flexibility, and they tend not to be well-suited to facilitate non-linearities or high-dimensional data. Probabilistic approaches, for instance, rely on the premise that the distribution of input variables is known, but the actual food safety variables, such as storage temperature fluctuation, human action, or sanitation cycles on equipment, don't directly map to such distributions. These approaches might not be useful in assisting with emergent hazards or unexpected patterns.

Conversely, machine learning models such as deep neural networks, support vector machines, and random forests are popular because they are data-driven and can learn to detect internal dependencies (Dogan *et al.*, 2022). Compared to comparative studies of levels of microbial contamination in vegetables or meat products, machine learning models are more accurate in terms of classification accuracy and sensitivity than classical models. These models can manage noisy and heterogeneous streams of data and learn subtle interdependencies between variables that cannot be expected beforehand. For example, ensemble learning has been used to predict Salmonella contamination of poultry supply chains based on ambient temperature, flock size, processing lag, and outcomes of previous inspections as variables with over 90% accuracy (Kim, *et al.*, 2022).

But the literature also finds reports of quite serious problems regarding machine learning applied to food safety. Model interpretability is mentioned most often. Regulators would generally need to explain the grounds for risk-based decisions, and black-box models are undesirable (Doshi-Velez & Kim, 2017). Studies have confirmed that stakeholders such as food producers, inspectors, and consumers would be more likely to accept and follow model advice when presented in a comprehensible manner. Furthermore, machine learning models tend to need very large amounts of high-quality training data, which can be scarce in some industries or regions, particularly in non-digitized infrastructure industries.

Other authors suggest hybrid models, combining the mechanistic clarity of mathematical modeling with machine learning flexibility. An example of a hybrid model might use QMRA as a structural framework and machine learning to adapt parameters dynamically from streaming data. These models have been applied to norovirus transmission for food handling purposes and were determined to enhance predictive accuracy and interpretability.

This review demonstrates that relative superiority of one model type over the other depends on the context of usage, availability of data, regulatory framework, and desired trade-off between interpretability and accuracy. While machine learning excels in exploratory analysis and rapid classification, mathematical models are the preference for domains where regulatory compliance, theoretical complexity, and causal inference are paramount.

Modeling Approaches and Analytical Pipelines

Predicting food safety risks is heavily dependent on the analysis of data and its transformation into actionable intelligence. Math and machine learning algorithms, while both are used for prediction, are very different in their structure and justification. Mathematical models are deductive, beginning with pre-established hypotheses or theories about system dynamics such as microbial growth rates, transport dynamics, or patterns of exposure (van Schothorst *et al.*, 2009). They typically take the form of differential equations, probability functions, or modular structures like QMRA, which is typically factored into hazard identification, exposure assessment, hazard characterization, and risk characterization. The models yield risk estimates in the form of closed-form solutions or simulations and are typically accepted by food regulators in compliance environments.

Machine learning methods, on the other hand, are inductive. They start not with theory but with data. Modeling involves the collection of vast quantities of data from microbial testing, environmental conditions, traceability records, or laboratory inspections, and the use of these to train algorithms that identify risk patterns, classify types of hazard, or predict contamination events. Machine learning pipelines typically involve data preprocessing (handling missing data, normalization, and

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dimensionality reduction), followed by splitting into training and testing datasets. Unlike static mathematical models, machine learning models improve over time, adapting and learning as new data becomes available. This makes them especially well-suited to dynamic, real-time systems such as global food distribution systems.

Uncertainty Management and Performance Metrics

The strongest aspect of predictive modeling is uncertainty management. Mathematical models treat uncertainty formally, most frequently as stochastic variables, Monte Carlo simulations, or sensitivity analysis. Outputs are typically probabilistic, giving decision-makers a quantifiable range of values for risk along with confidence intervals. This precise approach is especially valuable for regulatory scenarios, where traceability of assumptions and transparency are of greatest importance.

On the other hand, most machine learning algorithms quantify uncertainty in the form of performance metrics on held-out validation sets. Cross-validation, receiver operating characteristic (ROC) curves, precision-recall scores, and confusion matrices assess model robustness under different conditions. While these are useful empirical metrics, they rarely yield causal insights. Probabilistic ML model predictions, although helpful in classification, are not, by definition, as interpretable as traditional statistical or mechanistic predictions (Gunning & Aha, 2019). This makes them challenging to utilize in high-stakes environments where transparency and accountability are essential.

USE IN CASE STUDIES AND INDUSTRY IMPLEMENTATIONS

Industry Case Integration:

Integrating insights from real-world quality assurance (QA) practices at Schwan's Company, a leading U.S. producer of frozen and ready-to-eat (RTE) food products, highlights the practical applications of combining machine learning and mathematical models for food safety risk prediction. Schwan's employs advanced QA systems such as SafetyChain, Statistical Process Control (SPC), and Hazard Analysis and Critical Control Points (HACCP) to monitor production processes in real time. These systems collect continuous data on environmental conditions, sanitation outcomes, packaging quality, and process deviations, all of which are critical for identifying potential contamination risks.

By incorporating such plant-level datasets into predictive models, both machine learning and mathematical approaches can achieve greater accuracy and reliability in forecasting contamination events. For instance, temperature fluctuations, swab test outcomes, and packaging integrity data can be modeled as dynamic predictors to better estimate the likelihood of microbial growth and contamination. This integration demonstrates how combining real-time QA data with hybrid predictive frameworks bridges the gap between theoretical research and industry-ready applications, supporting proactive decision-making and improving consumer safety

Several real-life examples are presented to demonstrate the comparative usefulness of mathematical and machine learning models. In the control of Listeria monocytogenes risk in ready-to-eat meats, traditional models based on microbial kinetics have been used to model bacterial growth in varying storage and environmental conditions. These types of models, founded on well-understood biological principles, enable deterministic predictions to inform expiry dates, labeling, and packaging guidelines.

Conversely, machine learning models have shown superior performance in identifying new risk factors not captured in theoretical models. Studies have shown that ML models trained on production history data can uncover contamination drivers related to human behavior, equipment configuration, or supplier practice, which are not explicitly modeled in mechanistic models (Zhao *et al.*, 2021). This was evident in predictive assessments that were conducted in meat processing factories, where ML algorithms picked up on the variation in the risk of contamination due to operational changes like staff rotation and machinery cleaning schedules.

A useful example of regulatory application is the FDA's use of predictive models in import inspection priority setting. While traditional rule-based systems relied on static risk matrices and historical violations, pilot projects with ML have enabled agencies to predict pesticide and pathogen violations based on factors such as product type, shipping temperature, and country of origin. These models enhanced inspection efficiency but also raised concerns about algorithmic bias, especially when sensitive geopolitical variables were used.

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Comparative Analysis of Model Strengths and Weaknesses

Mathematical models retain their strength in theory-driven applications, regulatory transparency, and ease of auditability. They require fewer data points and can be effective in resource-constrained environments, especially when structured knowledge is available. However, they lack adaptability and may fail under rapidly changing or poorly understood conditions unless frequently recalibrated.

Machine learning, by contrast, thrives in high-volume and high-velocity data environments, such as online food marketplaces or multinational supply chains (Dogan *et al.*, 2022). They excel in classification, anomaly detection, and dynamic forecasting. Yet, they suffer from explainability challenges, high data dependence, and vulnerability to drift or adversarial input. Poor data governance can significantly degrade performance, and maintaining these models requires sustained investment in data infrastructure and personnel.

A growing body of research supports hybrid modeling approaches as a promising middle ground. These models combine mechanistic theory with data-driven learning. For example, mathematical models may simulate microbial kinetics while machine learning modules dynamically adjust parameters using streaming sensor data. In the dairy and seafood industries, such integrations have proven valuable for enhancing predictive accuracy while retaining scientific validity and stakeholder trust.

Infrastructure and Organizational Readiness

Adoption of predictive modeling is strongly dependent on organizational digital maturity. Organizations with fragmented data silos, low automation levels, or strict regulatory regimes are more likely to adopt traditional modeling techniques. In contrast, advanced machine learning use cases thrive in settings with integrated IoT devices, cloud-based data lakes, and mature data science talent.

Large food manufacturers and regulatory agencies in technologically advanced countries have started using ML-based systems for real-time risk management. However, success depends on pairing such systems with human judgment, formal validation protocols, and strict ethical guidelines concerning data privacy and algorithmic bias.

Both kinds of models can be helpful to inform food safety decision-making, yet the institutional environment determines which is most suitable. An acute understanding of organizational capacity, legal constraints, and data infrastructure is necessary before selecting or building predictive models.

Applying Predictive Models to Food Safety Decision-Making

The implementation of predictive models in food safety systems requires the intersection of theoretical precision, data potential, and decision-making relevance. Mathematical models, deterministic and stochastic, have traditionally been commonplace for simulating microbial growth and estimating exposures. Their application adheres to conventional frameworks such as the four-step QMRA framework: hazard identification, exposure assessment, hazard characterization, and risk characterization. Their logical coherence and explicit derivation from scientific data render them essential in regulatory decision-making.

But as global food systems grow more complicated, traditional models can't handle high-frequency, non-deterministic change. ML models fill this void by taking advantage of continuous data flows to identify emergent threats in close to real time. For instance, ML algorithms can detect patterns in the performance of suppliers or ambient transport conditions that may indicate spoilage or contamination, often before traditional models.

One such example is the FDA's Predictive Risk-based Evaluation for Dynamic Import Compliance Targeting (PREDICT) system. While not an ML-only application, PREDICT uses automated data mining to risk-score imported goods on criteria such as origin, inspection history, and environmental data (FDA, 2020). Pilot integrations with ML elements have improved targeting precision in identifying non-obvious risks like pesticide residues or microbial pathogens.

Institutional Trust, Transparency, and Algorithmic Accountability

Despite their potential, ML models raise various concerns regarding institutional trust and transparency. Regulatory bodies and public health organizations are often legally mandated to ensure traceability of decisions. A key criticism of ML, especially deep learning, is its "black box" nature, where decision logic is opaque and difficult to audit (Doshi-Velez & Kim, 2017). This limits the applicability of such models in regulatory

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environments where decisions must be justified in courts or to the public.

To address this, explainable AI (XAI) techniques like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and surrogate modeling are increasingly being integrated into food safety systems. These help interpret variable importance for instance, highlighting how variations in shipping temperature or supplier compliance influenced a risk score (Molnar, 2022). However, these interpretations are still not equivalent to the deductive, hypothesis-driven nature of mechanistic models, which regulators and stakeholders find more intuitive.

Hybrid modeling strategies offer a solution. By integrating mechanistic components (e.g., pathogen growth kinetics) with machine learning layers that adapt to real-time data (e.g., sensor streams or blockchain-based traceability), it's possible to enhance predictability while preserving model explainability (Rasheed *et al.,* 2021). This approach makes it easier for stakeholders to trust and act upon model outputs, thus improving regulatory acceptance.

Ethical Considerations of Predictive Food Safety Modeling

Machine learning-driven food safety models raise significant ethical concerns. One major issue is bias. If models are trained on historically skewed data (e.g., higher violation rates from certain regions), they may unfairly penalize specific countries or smallholder producers (Mehrabi *et al.,* 2021). This is especially problematic in international trade, where such bias can affect market access and cause reputational damage.

To mitigate these effects, fairness audits, stakeholder engagement in model design, and bias detection mechanisms must be built into the development pipeline. Moreover, policy frameworks should mandate clear accountability for decisions informed by predictive models. Questions of liability and redress, such as when a shipment is delayed or rejected based on a flawed risk score, must be anticipated and addressed (Floridi & Cowls, 2019).

Another ethical dimension involves data privacy. Effective ML models often require granular, sensitive information about worker behavior, environmental sensor feeds, and customer complaints, which raises concerns about surveillance and ownership. The widespread deployment of IoT devices in food systems necessitates strong data governance, including data minimization, encryption, and consent protocols (Kamilaris *et al.,* 2019).

Comparative Visualization of Model Effectiveness and Adoption Trends

The data trend suggests a significant rise in machine learning adoption in food safety prediction, with usage increasing from 12% in 2015 to 74% in 2024, while mathematical models declined accordingly. This reflects a growing emphasis on real-time decision support, IoT integration, and digital transformation in the food sector (Lu *et al.,* 2022).

Table 1: A line chart showing the percentage of adoption of different predictive models by year.

Year	ML Adoption (%)	Traditional Modeling Adoption (%)
2015	12%	88%
2016	18%	82%
2017	23%	77%
2018	31%	69%
2019	39%	61%
2020	49%	51%
2021	56%	44%
2022	63%	37%
2023	68%	32%
2024	74%	26%

Y-Axis: Percentage of food safety agencies using each model type, **X-Axis**: Years (2015–2024)

Legend: Blue line for ML, red line for mathematical models

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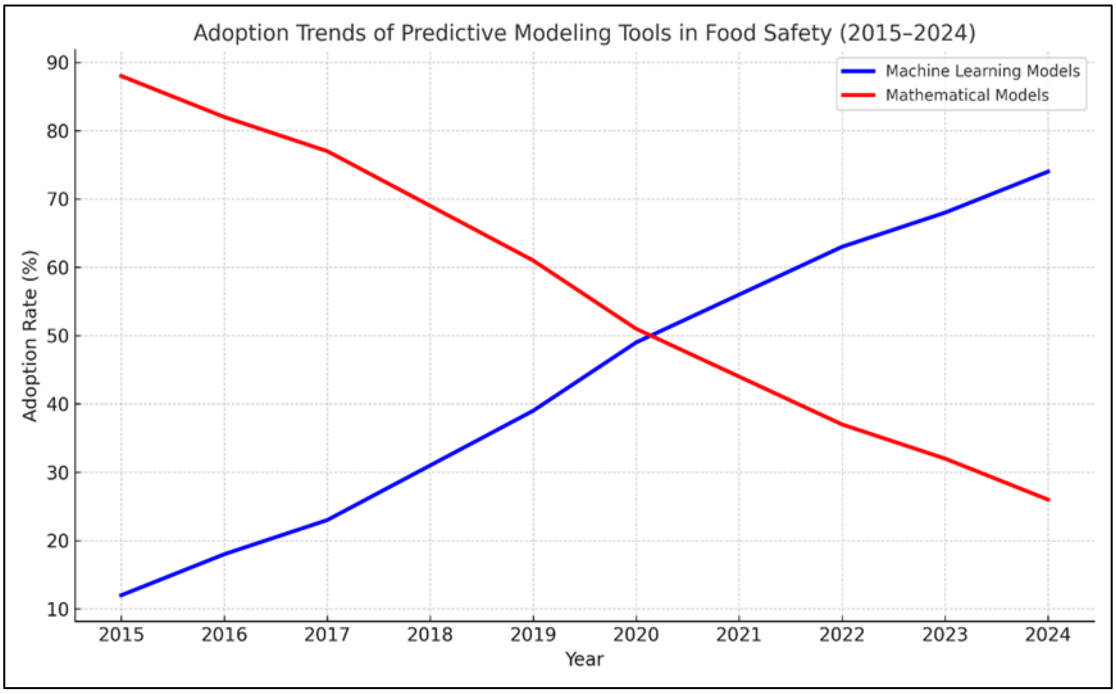

Figure 1: Adoption Trends of Predictive Modeling Tools in Food Safety

This graph demonstrates that while mathematical models dominated until 2018, there has been a marked increase in machine learning adoption beginning in 2019, correlating with broader digital transformation across supply chains.

Table 2: A bar graph comparing three models on two performance metrics: sensitivity and specificity.

Model Type	Sensitivity (%)	Specificity (%)
Traditional Logistic Model	78%	89%
Decision Tree Model	85%	87%
Gradient-Boosted Model	91%	90%

Y-Axis: Percentage, **X-Axis**: Model types, **Two Bars per Model**: One for sensitivity, one for specificity, **Color-coded**: Sensitivity in blue, specificity in green

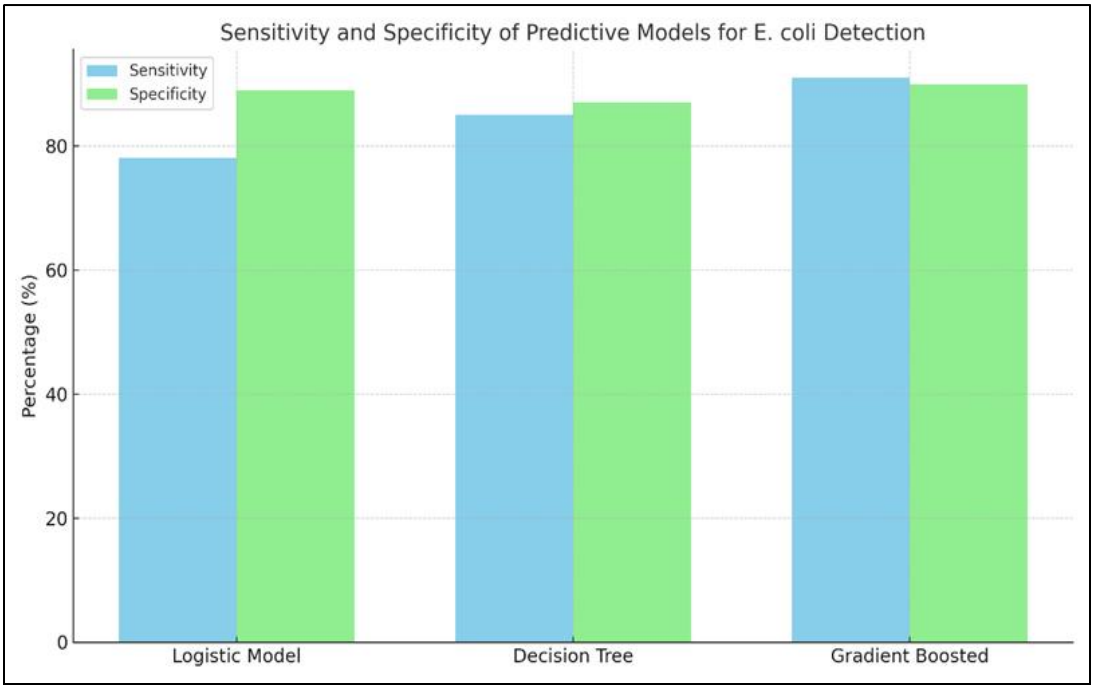

Figure 2: Sensitivity and Specificity of Predictive Models for *E. coli* Detection

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In this plot, one can see that ML models, especially ensemble techniques such as gradient-boosted trees, are more sensitive than traditional probabilistic exposure models. Specificity tends to be mostly similar, suggesting that the two classes of models have a place based on operational priorities detecting most or worrying least about false alarms.

Policy Recommendations and Strategic Considerations

A prudent policy approach should support hybrid risk assessment frameworks that integrate ML outputs with conventional risk matrices. National governments and international agencies must invest in mechanisms that prioritize explainability, accountability, and model verification. Regulatory innovation funds can be directed to build capacity in explainable AI for food safety compliance, particularly in the context of real-time supply chain analytics (Galanakis, 2021).

To foster global interoperability, international standards for food safety modeling must be harmonized. The Codex Alimentarius, FAO, and WHO should lead the standardization of data schemas, labeling formats, and validation benchmarks for predictive tools used in food safety decision-making. This will facilitate cross-border information exchange, improve trade fairness, and unify regulatory frameworks.

Enhancing Predictive Modeling With Emerging Technologies

Predictive modeling is evolving through convergence with advanced technologies. AI ecosystems now integrate real-time sensor streams, blockchain registries, and climatic risk forecasts to build context-aware, responsive safety systems. These platforms allow continuous learning and threat anticipation rather than isolated event detection (Tzachor *et al.*, 2021).

Federated learning is a key innovation that enables stakeholders to collaboratively build robust models without centralized data sharing critical in food systems where privacy, trade secrets, and data sovereignty are pressing concerns. For instance, processors across regions can train a global contamination model while retaining their local data (Kairouz *et al.*, 2021).

Transfer learning offers similar promise. Models trained on one dataset (e.g., U.S. lettuce inspection) can be retooled for analogous tasks elsewhere (e.g., Mexican spinach), cutting down retraining costs and enabling rapid scaling. Multi-task learning, in turn, allows a model to perform various prediction tasks (chemical vs. microbiological hazards), streamlining risk analysis across product categories (Ruder, 2017).

Neuro-symbolic AI architectures, which fuse neural networks with logical rule structures, are also gaining traction. These hybrid systems promise to bridge the gap between black-box prediction and symbolic reasoning, supporting regulatory transparency while leveraging the power of deep learning (Besold *et al.*, 2017).

Aligning Predictive Models to Policy, Regulation, and Global Governance

The institutional value of predictive modeling hinges on its alignment with global regulatory frameworks. Agencies like the FDA and EFSA still base decisions on mechanistic, assumption-driven models due to their interpretability and auditability. For ML to gain equal footing, standard processes for model vetting, documentation, and legal admissibility must be institutionalized.

A proposed solution is the creation of "model passports" documents outlining the purpose, data sources, validation metrics, and jurisdictional compliance for each model. These passports can aid customs officers, food regulators, and trading partners in evaluating whether a given model is acceptable under local and international laws.

Governments and international bodies must also enforce digital rights and ethical standards in the deployment of predictive technologies. This includes responsible AI principles, such as transparency, inclusivity, and fairness, especially in automated inspection systems and cross-border regulatory decisions (Floridi *et al.*, 2018).

CONCLUSION

The advent of predictive modeling in food safety represents a revolutionary advance in the global effort to protect public health. As this paper was able to unveil, machine learning and traditional mathematical models each possess distinctive capabilities for forecasting foodborne risk—along with presenting new constraints in terms of explainability, bias, and operationalizing. Increasingly, the solution lies not in choosing between these paradigms but in combining their respective strengths. Hybrid approaches that leverage the deductive accuracy of mechanistic models and the adaptive, data-driven capabilities of machine learning are the most promising path forward.

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Still, technical innovation is not sufficient. As predictive modeling assumes a more central role in regulatory decision-making, ethical imperatives of fairness, transparency, and accountability must become paramount. Minimizing algorithmic bias, safeguarding data privacy, and safeguarding the interests of vulnerable stakeholders—such as small-scale producers and cross-border exporters—must be core tenets of any modeling strategy. International harmonization of data standards, explainability frameworks, and model validation protocols will also be critical to ensuring safe and effective interoperability across jurisdictions.

Looking ahead, the integration of emerging technologies such as federated learning, neuro-symbolic AI, and digital twins can transform food safety prediction into a more predictive, collaborative, and resilient system. However, realizing the vision will require investment in digital infrastructure, interdisciplinary collaboration among scientists, regulators, and technologists, and global coordination on responsible AI governance.

Last, the challenge is not merely technical - it's social. The future of food safety will depend on our ability to create predictive systems that are not only accurate, but trusted, transparent, and equitable. In this manner, we move toward a food system where risks are not only detected early, but managed in ways that protect health, foster equity, and maintain trust in global supply chains.

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Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:

Gaye, A. and Donkor, A. A. " A Comparison of Machine Learning and Mathematical Models for Predicting Food Safety Risks." *Sarcouncil Journal of Engineering and Computer Sciences* 4.11 (2025): pp 244-252.

Publisher: SARC Publisher