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False Negatives, Real Consequences: Risk Profiles of AI-Driven Food Safety and HACCP Monitoring in Animal-Source Foods

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PRESENTATION

- APPLICATIONS OF AI AND MACHINE LEARNING IN FOOD SAFEY AND HACCP MONITORING
- WHAT AI PROMISES IN HACCP MONITORING
- CONCRETE RISKS
- FALSE NEGATIVES AND DETECTION GAPS
- DATA QUALITY AND GARBAGE-IN FAILURES
- POOR INTERPRETABILITY (“BLACK BOX” SYSTEMS)
- OVERRELIANCE AND AI BIAS
- REGULATORY AND ACCOUNTABILITY GAPS
- CONCLUSIONS

APPLICATIONS OF AI AND MACHINE LEARNING IN FOOD SAFEY AND HACCP MONITORING (1)

- Artificial intelligence is transforming HACCP in meat processing by replacing manual, paper-heavy documentation with automated, predictive safety systems. AI integrates with facility sensors and computer vision to monitor Critical Control Points (CCPs) in real-time, preventing pathogen outbreaks and streamlining compliance audits.

- The most common application is documentation automation. HACCP requires food manufacturers to document every potential hazard in a production process, identify the critical control points (CCPs), and define exactly what happens when those controls fail. Historically, this work has been manual. Teams maintain binders, update spreadsheets, and rebuild plans from scratch when processes change. The volume of documentation scales with facility complexity, and a single ingredient or supplier change can trigger a cascade of updates.

- AI-powered tools now ingest existing SOPs, process flowcharts, and product specifications, then use that information to generate HACCP frameworks automatically. A complete HACCP plan can be generated in under some minutes by a system analyzing a company’s product and process data. A facility could potentially move from paper records to a structured digital food safety system in under a week.

- AI analyzes historical data and real-time sensor feeds to identify subtle temperature fluctuations in cold storage or cooking phases before they breach critical limits.

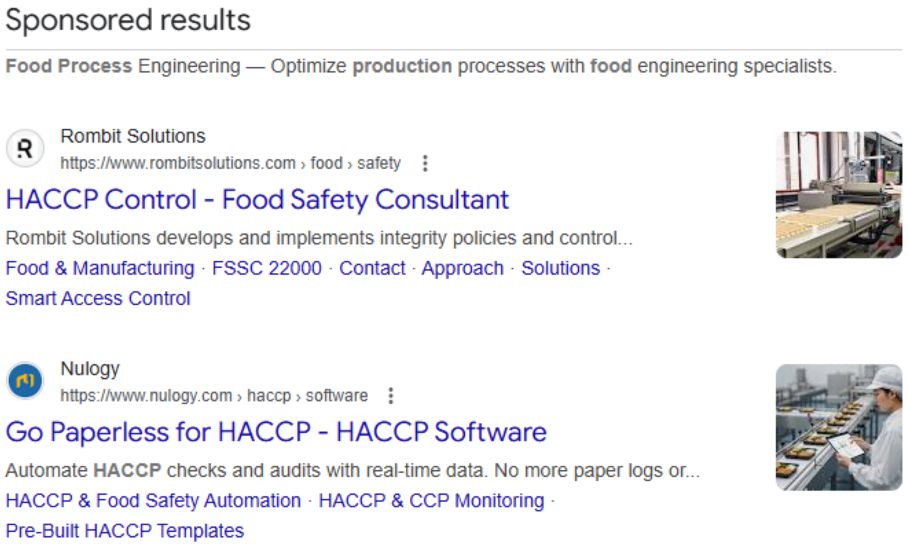
** Source 1 and 2

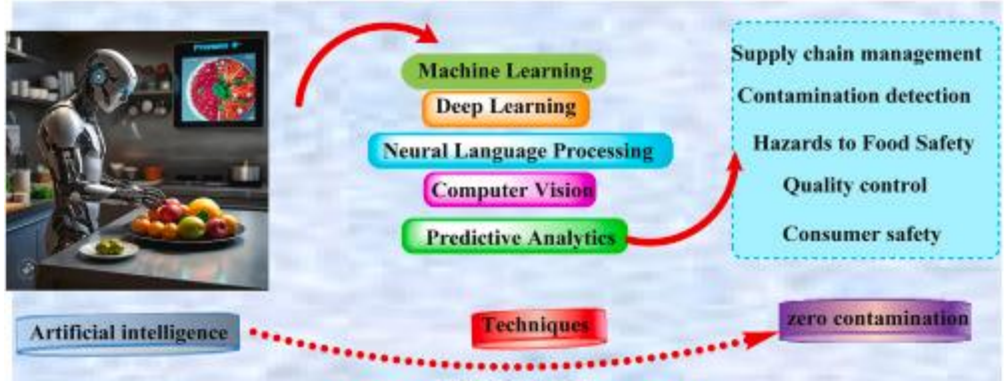
APPLICATIONS OF AI AND MACHINE LEARNING IN FOOD SAFEY AND HACCP MONITORING (2)

Here are the most common AI technologies used in food manufacturing and how they're applied:

- **Machine learning (ML):** Machine learning algorithms analyze historical data to predict trends, potential issues, deviations, and identify unusual patterns.
- **Computer vision:** Computer deviation systems use cameras to visually inspect food items for contamination and irregularities and automatically sort and grade products.
- **Natural language processing (NLP):** NLP looks at textual data, like customer feedback, product details, or quality reports to gain insights or identify potential issues.
- **Robotics:** When combined with AI, robotics can help automate repetitive and manual tasks, such as quality assurance testing processes to ensure more consistent checks.
- **Internet of Things (IoT)**: IoT devices such as sensors collect real-time data on various manufacturing stages and analyze that data to monitor the quality of the product and environment.
- **Blockchain**: Blockchain technology helps provide transparency in the food supply chain, offering possible map of the entire supply chain.

APPLICATIONS OF AI AND MACHINE LEARNING IN FOOD SAFEY AND HACCP MONITORING (3)





Sobia Naseem, Muhammad Rizwan,
The role of artificial intelligence in advancing food safety: A strategic path to zero contamination,
Food Control, Volume 175, 2025, 111292, ISSN 0956-7135

WHAT AI PROMISES IN HACCP MONITORING (1)

- **Real-time monitoring:** AI devices can monitor facility or storage specifics, such as temperature and humidity to ensure spoilage or contamination are avoided.
- **Supplier evaluation:** Manufacturers can use AI to help analyze data on raw materials received from suppliers, reducing the risk of contamination.
- **Compliance:** By continuously monitoring processes and records, AI can help ensure a facility meets compliance and regulation requirements.
- **Shelf-life prediction:** Optimize storage by leveraging AI to help analyze factors that affect shelf life, such as packaging, storage conditions, ingredients, or transportation.
- **Automated inspection:** AI-powered systems can automate otherwise cumbersome food inspection processes to ensure the consistency and accuracy of assessments.

WHAT AI PROMISES IN HACCP MONITORING (2)

38% of EU meat processing companies are applying AI driven solutions (baseline 2026) in their operations to improve food safety. Accidents and recalls have economic and reputational costs. Food operators are constantly careful to implement strategies of risks mitigation (3);

1) **Computer Vision**: Real-time carcass and processed products inspection at line speed. Possibility to detect contamination invisible to the human eye. Already used and integrated in processing plant. Effective.

2) **IoT Sensor Networks**: continuous temperature, humidity, pH monitoring across the entire cold chain. In the vast majority of cases, reports are still analyzed by internal quality control.

3) **Predictive Analytics**: Early warning of pathogen risk spikes based on environmental and historical patterns. Quite new and not applied at large scale.

4) **NLP Audit Trails**: Automated analysis of HACCP records, NCRs and supplier documentation. Quite new and some tests already performed. Useful if well managed.

But every promise carries a shadow risk

CONCRETE RISKS

The Core Question analysed in this presentation:

"What happens when the algorithm is wrong and nobody notices?"

1) Mistakes can happen also in human management. The most important thing is to be conscious of such a possibility

2) Risks identified both in the literature and in concrete cases

Risk category	Potential impact on HACCP systems
Algorithmic bias	Incorrect hazard identification
Black-box AI	Difficulty in auditing and validation
Sensor errors	Failure to detect CCP deviations
Overfitting	Poor performance outside training datasets
Cybersecurity	Manipulation of HACCP data
Excessive automation	Reduced human oversight
Lack of explainability	Regulatory non-compliance
Incomplete datasets	Microbiological false negatives
Dependence on generative AI	Incorrect or non-contextualized HACCP procedures

FALSE NEGATIVES AND DETECTION GAPS

- AI systems can fail without raising any alert: the most dangerous failure mode
- Training data bias: over-representation of common pathogens, certain seasons, specific species
- Under-trained on rare events: novel Salmonella serovars, emerging STEC strains
- A false negative at a CCP means contaminated product clears the line undetected
- Unlike equipment failure, AI failure generates no error signal. It produces a confident wrong answer.
- Computer vision vs. human inspection for carcass contamination: Studies on hyperspectral and multispectral imaging systems report sensitivities of 85 - 95% for detecting visible fecal contamination on beef carcasses, but sensitivity drops sharply (to ~60 - 70%) for small or atypically distributed contamination spots. Human inspectors under standard line speeds show similar or lower sensitivity for small lesions but perform better on novel or unexpected anomalies.

Concrete case: test performed in an Eastern European facility. Overreliance in the system led to lack of detection of Listeria. Human follow-up based on in-house procedures helped to detect the contamination before the batch was dispatched.

DATA QUALITY AND GARBAGE-IN FAILURES

In HACCP terms: if the monitoring data is unreliable, the entire control system is compromised.

- Faulty sensors feed incorrect temperature/pH values without triggering alarms
- Missing data fields handled by imputation: model fills gaps with statistical assumptions
- Mislabeled training data produces systematically biased outputs
- AI has no mechanism to "know" its inputs are wrong. Outputs carry false confidence

Concrete case: detection of a cold chain failure based on human inspection. The system failed to detect a cold-chain gap. 16K € production lost. If human inspection lacked, the production could have entered into the market.

POOR INTERPRETABILITY ("BLACK BOX" SYSTEMS)

The algorithm can't justify its decision

- Deep learning models do not produce interpretable decision pathways
- HACCP requires documented, traceable decision rationale at each CCP
- Regulatory audits cannot accept "the model said so" as a corrective action
- XAI (Explainable AI) tools exist but add complexity and may still obscure root causes
- A 2023 meta-analysis published in *Food Control* found that ML-based Listeria monocytogenes prediction models in RTE facilities achieved AUC values of 0.78–0.89 on validation sets, which still implies a meaningful false negative rate (10–22% of positive environmental samples misclassified as safe), especially when applied to facilities not represented in training data.

Concrete case: test of an AI tool to design HACCP plan lacked 3 critical control points compared to the existing plan.
In a pilot with 12 EU meat processors, NLP-based audit tools missed on average 2.3 critical gaps per HACCP plan that manual review caught (5).

OVERRELIANCE AND AI BIAS

The biggest risk which is absorbing all the others: the human stops watching because the machine is watching

- Operators systematically defer to AI outputs, even when anomalous
- Vigilance degradation: reduced manual checks at AI-monitored CCPs
- Automation bias is well-documented in aviation and healthcare: now entering food safety
- Risk amplified when AI has high historical accuracy: "it's always been right before"

Concrete case: a cooked ham meat line where AI approves internal temperature. But the sensor was miscalibrated for 5 hours. Mistake detected during quality control and after shipment of the product. The company revised the HACCP procedures and came back to a less automated process.

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CAN AI DETECT NEW OR PREVIOUSLY UNSEEN RISKS?

- **What AI can do?** Detect **deviations from learned patterns:** e.g., a temperature profile that statistically resembles conditions preceding a prior contamination event. This is powerful for known CCPs under normal operating conditions.

- **What AI cannot do:** Recognise a **genuinely new hazard** for which no training signal exists. There is no mechanism by which a supervised ML model trained on historical HACCP data can flag a novel pathogen, an unprecedented contamination route, or an emerging chemical hazard.

- Unsupervised anomaly detection models (autoencoders, isolation forests) *can* in principle flag "*something unusual is happening*" without knowing what it is, but in practice, these generate high false positive rates in food manufacturing (lots of legitimate process variation), leading operators to disable or override them.

HAZARDS THAT ARE UNDER-DETECTED

- **Novel Salmonella serovars**: Most AI/ML food safety models are trained predominantly on S. Typhimurium and S. Enteritidis, which together account for ~60% of EU Salmonella isolates. Emerging serovars such as S. Infantis (now dominant in broilers across several EU member states) and monophasic S. Typhimurium variants are consistently under-represented in training datasets, meaning AI systems tuned on historical data will underperform precisely when the epidemiological landscape shifts. EFSA's One Health Zoonoses reports document the rise of these variants since 2016, providing a clear before/after benchmark.

- **STEC beyond O157:H7**: AI models trained on clinical and food chain data are heavily biased toward STEC O157, while non-O157 STEC (O26, O103, O111, O145, O104) account for an increasing share of EU outbreaks. These strains are often missed because their virulence gene profiles differ and their environmental persistence patterns in processing plants are less documented.

- **Novel pathogens**: For a truly emerging threat (e.g., a newly identified norovirus strain or an unexpected zoonosis), AI systems provide zero early warning. They can only detect patterns they have encountered. This is the structural limitation: AI is excellent at interpolation but blind to extrapolation.

REGULATORY AND ACCOUNTABILITY GAPS

- Who is responsible when the algorithm fails? When a recall occurs, can the competent authority determine whether the AI system performed as validated?
- Current EU food law assigns responsibility to the FBO. But AI adds a software liability layer
- No harmonised standard for AI integration into HACCP plans (ISO, Codex Alimentarius gap)
- Liability chain: FBO → AI software vendor → hardware provider → cloud service
- EU AI Act (Reg. 2024/1689): food safety AI likely "high-risk“, but sector-specific guidance is absent

CONCLUSIONS (1)

Why Animal-Source Foods Are a sensitive case to assess and why FBOs are so careful in the Implementation of new tools?

- Intrinsic biological variability: Microbial loads vary widely by species, age, season and farm practices, making AI generalisation harder

- Complex, multi-stage supply chain: Farm → Slaughter → Processing → Cold Chain → Distribution: each handoff is a potential AI monitoring gap

- Zoonotic and One Health dimension — *Salmonella*, *Campylobacter*, STEC, *Listeria*: AI failures in this sector have direct public health consequences

- AI models trained predominantly on large industrial facilities show 15–30% accuracy drops when applied to different production environments.

CONCLUSIONS (2)

What Good Looks Like

- **AI is a very powerful tool:** but to work perfectly, it needs to be programmed, and an early detection of risks helps to make it work.
- **Human-in-the-Loop at Critical CCPs:** AI cannot be the sole decision-maker at critical control points. Mandatory human validation for high-risk triggers.
- **Model Validation and Periodic Retraining:** Define performance benchmarks and schedule retraining when the epidemiological context changes
- **Explainable AI (XAI) as a Requirement:** Only interpretable models should be accepted for HACCP monitoring. If a decision can't be explained, it can't be audited.
- **EFSA Role: Benchmark Datasets & Guidance:** Develop reference datasets for AI validation, sector-specific risk guidance, and a registry of approved AI tools

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THANK YOU FOR YOUR ATTENTION !