AI-Integrated Spectroscopic Detection and Practical Quality Assurance of Mycotoxins in Dairy and Milk-Based Ready-to-Eat Foods

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Abstract—Mycotoxin contamination in dairy and milk-based ready-to-eat products is a critical public health concern, particularly in India where food supply systems span vast geographies. Aflatoxin M1 (AFM1), the hydroxylated form of AFB1, is the primary regulatory concern: it carries over from contaminated feed, survives pasteurisation and fermentation due to heat stability, and is classified as a Group 1 human carcinogen by IARC. Other mycotoxins including ochratoxin A (OTA), zearalenone (ZEN), fumonisins, and deoxynivalenol (DON) also persist in dairy products, posing chronic health risks, especially for children. Conventional detection methods such as HPLC and ELISA are expensive, slow, and impractical for real-time industrial monitoring. In Indian dairy operations, a single AFM1 test by HPLC costs INR 6,000–15,000 and takes 6–24 hours, by which time contaminated milk may already be in the processing line. This paper reviews AI-integrated spectroscopic platforms—NIR, FTIR, Raman, SERS, and fluorescence spectroscopy—as practical tools for rapid, non-destructive mycotoxin detection in dairy systems. It covers platform principles, AI architectures, cost comparisons in INR, realistic implementation pathways for Indian processors, key challenges including matrix variability and regulatory gaps, and future directions toward IoT and portable sensing. The findings demonstrate that AI-spectroscopic systems can screen 100% of incoming milk batches at INR 1–5 per test, compared to INR 6,000–15,000 for conventional HPLC, with results available in under 30 seconds, offering a transformative pathway for Indian dairy food safety infrastructure.

Index Terms—*Mycotoxin detection; Aflatoxin M1; NIR spectroscopy; FTIR; SERS; machine learning; dairy food safety; milk-based ready foods; internet of things; India; deep learning; food quality assurance.*

I. INTRODUCTION

India is the world's largest milk producer, generating over 220 million tonnes annually through cooperative networks such as Amul, Saras, and Verka [1]. Approximately 6 billion people worldwide consume dairy products, and in India these form a core dietary staple across both rural and urban populations [2]. This scale creates enormous nutritional reach but also a substantial food safety challenge that has historically not received adequate technological attention.

Mycotoxin contamination is one such challenge. These low-molecular-weight toxic compounds are produced by toxigenic fungi—mainly Aspergillus, Fusarium, and Penicillium—when cereal feed grains or silage are stored under high humidity, poor ventilation, or temperature stress [3]. India's monsoon climate and inadequate grain storage infrastructure create frequent conditions for mycotoxin development in cattle feed, particularly in Rajasthan, Maharashtra, and the Indo-Gangetic plains during and after the rainy season [4].

When cattle consume AFB1-contaminated feed, the toxin is hydroxylated in the liver and passes into milk as AFM1 at a carryover rate of approximately 1–3% [5]. IARC classifies AFM1 as a Group 1 carcinogen; the EU limit in milk is 0.05 µg/kg (EU Regulation 1881/2006), while FSSAI permits 0.5 µg/kg. AFM1 survives pasteurisation at 72°C, UHT at 135°C, and fermentation, making point-of-reception screening the only effective intervention.

AI-integrated spectroscopic platforms offer a practical solution. These tools measure light-sample interactions to generate spectral patterns that machine learning algorithms can scan for contamination

signatures, returning concentration estimates in seconds without reagents. For Indian dairy plants receiving hundreds of tanker loads daily, this transforms what food safety monitoring can realistically achieve.

This paper reviews AI-assisted spectroscopic detection in the Indian dairy and milk-based food context: platform principles and dairy matrix adaptations, AI/ML extraction of toxin signals, implementation challenges including costs in INR, and the trajectory toward IoT-integrated, field-deployable food safety systems.

II. MYCOTOXINS IN DAIRY MATRICES: OCCURRENCE, STABILITY, AND HEALTH EFFECTS

A. Principal Mycotoxins and Occurrence in Dairy

Of more than 400 known mycotoxins, six groups attract primary regulatory and public health attention in dairy: AFM1, OTA, ZEN, fumonisins, DON, and patulin. AFM1 has been detected in 20–60% of global raw milk samples above the detection limit [6]. A systematic review by Srivastava et al. [7] covering 47 Indian studies found that 74% of raw milk samples contained detectable AFM1, with 14.8% exceeding the FSSAI limit of 0.5 µg/kg, with Rajasthan, Gujarat, and Maharashtra showing the highest contamination frequencies. Internal surveillance at Saras Dairy identified peak contamination during the post-monsoon months of July–September.

OTA concentrations of 0.02–1.8 µg/kg have been recorded in European dairy surveys. Fumonisin B1 has been measured at 0.1–2.3 µg/L in bulk tank milk in maize-growing regions [8]. A significant concern in Indian dairy is co-contamination: when multiple toxins are present simultaneously, combined risk can exceed single-toxin model predictions.

Table I. Major Mycotoxins in Dairy Matrices with Regulatory Limits

Mycotoxin	Producing Fungi	Heat Stability	EU Limit (µg/kg)	FSSAI Limit	Health Effect
AFM1	A. flavus, A. parasiticus	Survives pasteurisation, UHT, fermentation (up to 270°C)	0.05 (milk)	0.5 µg/kg	Group 1 carcinogen; hepatocellular carcinoma; immunosuppression
OTA	A. ochraceus, P. verrucosum	Partially survives; concentrates in cheese curd	3.0 (cereals)	Not established for milk	Nephrotoxic; immunosuppressive; genotoxic (Group 2B)
ZEN	F. graminearum	Stable at dairy pH; persists in yoghurt	75 (raw grain)	Not established for dairy	Oestrogen receptor agonist; endocrine disruption; reproductive toxicity
DON	F. graminearum, F. culmorum	Partially degraded at high pH/heat; partial rumen degradation	1,750 (grain)	1,000 µg/kg (grain)	Ribotoxic; GI inflammation; immune modulation
FB1+FB2	F. verticillioides, F. proliferatum	Stable in milk; water-soluble; heat-resistant	200 (maize)	Not established for dairy	Sphingolipid disruption; hepatotoxic (Group 2B)
Patulin	Penicillium expansum	Reduced by LAB; unstable at alkaline pH	50 (apple juice); 10 (infant food)	50 µg/kg	GI toxicity; immunotoxic; genotoxic

B. Behaviour of Mycotoxins During Dairy Processing

Standard dairy processing steps—pasteurisation, UHT, and fermentation—alter but do not eliminate mycotoxins. Lactic acid bacteria can bind AFM1 to some degree (up to 36% reduction reported for L. rhamnosus GG [9]), but no processing step has been officially recognised by FSSAI as a validated

decontamination method. OTA concentrates in the fat-rich curd during paneer and cheese making, while fumonisins remain in the whey fraction. Paneer preparation can result in AFM1 concentrations 2–4 times higher than the original milk, while commercial ghee typically contains AFM1 below 0.01 µg/kg due to the aqueous-phase separation. Products like shrikhand and khoa concentrate milk solids further, warranting close monitoring.

C. Health Impacts

AFM1 forms DNA adducts at the N7 position of guanine in liver cells, initiating mutagenic pathways linked to hepatocellular carcinoma. Children's estimated AFM1 exposure runs 2–3 times higher than adults on comparable diets due to greater milk consumption relative to body weight and underdeveloped liver detoxification systems [10]. OTA damages kidneys and suppresses immune function. ZEN disrupts endocrine function in children and adolescents. Fumonisins interfere with sphingolipid biosynthesis affecting neural tube development. Co-contamination can produce additive or synergistic effects [11], making Indian dairy—where multiple mycotoxins frequently co-occur—a particularly high-concern food safety environment.

III. SPECTROSCOPIC DETECTION PLATFORMS: PRINCIPLES AND DAIRY MATRIX ADAPTATIONS

A. Near-Infrared (NIR) Spectroscopy

NIR spectroscopy (780–2500 nm) measures overtone and combination band absorptions from C-H, O-H, and N-H bonds. It is the most familiar spectroscopic tool in Indian dairy labs, already deployed for fat, protein, lactose, and moisture analysis, making extension to mycotoxin screening primarily a software/calibration challenge rather than a capital investment [12]. Magan et al. [13] showed PLS-DA on NIR spectra of spiked milk samples achieved >90% classification accuracy. Kos et al. [14] achieved a LOQ of 0.08 µg/kg for AFM1 in raw milk using temperature-controlled transflectance NIR cells with PLSR—sufficient for FSSAI compliance screening. Patel et al. [15] demonstrated three-way PLS chemometrics on NIR spectra achieving simultaneous AFM1 prediction (RMSEP 0.012 µg/kg) and OTA prediction (RMSEP 0.041 µg/kg) within a single calibration model.

B. FTIR/MIR Spectroscopy

Mid-infrared FTIR (2500–25,000 nm; 400–4000 cm-1) with ATR accessories allows direct milk analysis in ~60 seconds without sample preparation. FTIR instruments are widely deployed across Indian cooperative laboratories for compositional analysis under ISO 9622 methodology. Aflatoxins show characteristic absorption bands at ~1690 cm-1 (lactone C=O), 1635 cm-1 (C=C stretching), and 1020 cm-1 (C-O-C ether). Cozzolino et al. [16] reported detection of AFM1 at 0.04 µg/kg—below the EU limit—with appropriate preprocessing. The FOSS MilkoScan FT3, widely used in Indian cooperatives, supports mycotoxin screening model integration without hardware changes [17]. Adulteration-robust model development using training sets that include representative adulterated samples is essential for Indian deployment.

C. Raman Spectroscopy and SERS

Conventional Raman struggles in dairy matrices due to fluorescence interference from fat and protein chromophores. Surface-enhanced Raman spectroscopy (SERS) overcomes this through adsorption of target analytes onto nanostructured metal surfaces, providing signal amplification of 10^6 to 10^10. Aptamer-functionalised SERS substrates can detect AFM1 in milk at femtomolar concentrations, with LODs below 0.001 µg/kg [18]. Li et al. [19] demonstrated pH-normalised SERS substrates for simultaneous AFM1 and OTA quantification in processed dairy. Magnetic SERS nanoparticles improve LOD values by approximately one order of magnitude through matrix pre-concentration [20].

D. Fluorescence and Hyperspectral Imaging

Aflatoxins are naturally fluorescent under 365 nm UV light. Excitation-emission matrix (EEM) fluorescence spectroscopy with PARAFAC decomposition enables simultaneous quantification of AFM1, OTA, and ZEN without chromatographic separation [21]. Synchronous fluorescence spectroscopy paired with PLS regression has achieved AFM1 LODs of 0.02 µg/kg in milk with 10-second measurement times [22]. For solid dairy products (paneer, hard cheese, butter), hyperspectral imaging combined with CNN classifiers detects mycotoxin hotspots across product surfaces within seconds [23]. Time-resolved fluorescence

spectroscopy exploits AFM1's fluorescence lifetime of ~3.8 ns to distinguish it from shorter-lived matrix autofluorescence [24].

IV. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING FOR SPECTRAL ANALYSIS

A. From Spectral Data to Contamination Decisions: The AI Pipeline

Classical chemometric approaches—PLSR, PCA, and SVM—have long underpinned spectroscopic food analysis by reducing high-dimensional spectral data (1,000–10,000 wavelength variables per spectrum) and building calibration models linking spectral features to reference mycotoxin concentrations [25]. CNNs have increasingly outperformed classical chemometrics: Wu et al. [26] reported a five-layer CNN on NIR spectra of aflatoxin-contaminated corn achieving 97.3% classification accuracy versus 91.2% for PLS-DA. LSTM networks treating wavelength as a sequential dimension have shown strong results for dairy mycotoxin regression tasks. Transformer-based attention mechanisms provide interpretable wavelength-region identification, increasingly important for regulatory acceptance [27].

Transfer learning significantly reduces the data burden in Indian dairy settings. Birse et al. [28] showed transfer learning from a large cereal NIRS database to a smaller milk AFM1 dataset achieved equivalent predictive accuracy using only 15% of the training data otherwise required—a critical advantage for new implementation sites.

B. AI Model Validation and Performance

Training data diversity is the primary determinant of AI model reliability in dairy mycotoxin spectroscopy. Indian dairy uniquely processes both zebu cow milk (~3.5–4.5% fat) and buffalo milk (~6–8% fat) in often-mixed streams, requiring training data that reflects this breed and seasonal variation [7]. Cross-validation stratified by supplier, season, and processing conditions gives more accurate field performance estimates than random splits. Published FTIR and NIR models report RMSEP values for AFM1 in milk of 0.005–0.025 µg/kg when properly validated.

XAI techniques—particularly SHAP values and Grad-CAM applied to spectral CNN models—highlight which wavelength regions drive contamination predictions, providing the mechanistic transparency increasingly expected by food safety regulators [29].

Table II. Comparative Performance of AI/ML Architectures for Spectroscopic Mycotoxin Detection in Dairy

Model	Best RMSEP (AFM1)	Classification Accuracy	Interpretability	Training Data Need
PLSR	0.008–0.025 µg/kg	88–94%	High (loadings)	Low (n≥60)
SVM	0.010–0.030 µg/kg	91–96%	Medium (kernel SHAP)	Low-Medium (n≥100)
Random Forest	0.009–0.022 µg/kg	92–95%	Medium (feature importance)	Medium (n≥150)
1D-CNN	0.005–0.018 µg/kg	94–97%	Low-Medium (Grad-CAM)	High (n≥500)
LSTM	0.006–0.020 µg/kg	93–97%	Low (attention maps)	High (n≥500)
Transfer Learning CNN	0.007–0.015 µg/kg	95–98%	Low-Medium	Very low (n≥80 fine-tune)
Transformer/Attention	0.004–0.012 µg/kg*	96–99%*	Medium (self-attention)	Very High (n≥1000)

*Emerging; limited published dairy validation to date.

V. PRACTICAL IMPLEMENTATION IN INDIAN DAIRY OPERATIONS

A. Operational Context

A large cooperative such as Saras Dairy (RCDF) in Rajasthan receives milk from thousands of village-level cooperative societies across multiple districts. Current quality checks typically include temperature measurement, platform adulteration tests, and selective laboratory sampling on a periodic basis. A single HPLC AFM1 test costs INR 6,000–15,000 and takes 6–24 hours, making routine testing of every incoming tanker financially and operationally

impractical. In practice, most plants test under 1% of total incoming volume. A single large-scale contamination recall can cost several crore rupees—far exceeding the capital cost of AI-spectroscopic screening systems.

B. Cost-Benefit Analysis

Table III. Cost Comparison: Conventional HPLC-MS/MS versus AI-Spectroscopic Monitoring in Indian Dairy

Parameter	Conventional HPLC-MS/MS	AI-NIR/FTIR Inline
Capital cost	INR 85–2,10,000	INR 12–38 lakh
Cost per test	INR 6,000–15,000	INR 1–5
Samples per day	20–50	Continuous; unlimited (one per tanker <30 s)
Time to result	6–24 hours	<30 seconds
Batch coverage	<1% of daily production	100% of incoming milk batches
Annual operating cost	INR 15–30 lakh	INR 1–3 lakh
LOD AFM1 in milk	0.002–0.005 µg/kg	0.01–0.08 µg/kg (platform-dependent)
ROI timeline	N/A (cost centre)	12–18 months

A medium-scale cooperative processing 5 lakh litres per day typically spends INR 20–25 lakh annually on HPLC testing covering <1% of incoming milk. An AI-integrated NIR system at capital cost INR 15–25 lakh can reduce annual operating costs to INR 1–2 lakh while achieving full batch screening coverage, with ROI typically within 12–18 months.

C. Phase-by-Phase Implementation Roadmap

Phase 1 (Months 1–6): Site risk assessment and spectral database building. Deploy portable or benchtop NIR at reception dock; archive all spectra alongside HPLC reference values to build a site-specific seasonal database.

Phase 2 (Months 6–18): Model development and shadow mode operation. Develop PLSR or SVM calibration models on a minimum of 150–200 independently validated samples. Run AI predictions in shadow mode alongside concurrent HPLC results to identify systematic biases.

Phase 3 (Months 18–36): Full deployment with risk-stratified confirmation. Screen 100% of incoming raw milk. Batches below a conservative threshold (e.g., 0.1 µg/kg, 20% of FSSAI limit) are cleared; above triggers HPLC confirmation. This approach typically reduces HPLC workload by 80–90% while maintaining equivalent regulatory safety.

Phase 4 (Year 3+): IoT connectivity, predictive risk scoring from farm-level feed quality and weather data, and federated model improvement through inter-cooperative data sharing.

VI. CASE STUDY: FTIR-AI MONITORING IN A COOPERATIVE DAIRY PLANT

This section presents a conceptual case study built on published data and operational experience from Indian dairy settings. The scenario involves an FTIR-AI monitoring system at a cooperative plant processing 80,000 litres/day of standardised pasteurised full-fat milk, representative of medium-sized cooperatives in Rajasthan, Gujarat, and Punjab.

An existing FTIR instrument used for routine fat/protein/lactose analysis was connected to the LIMS via Ethernet. Spectral data from 12 months of milk reception testing (~1,800 spectra) were exported alongside HPLC AFM1 values ranging from below 0.005 to 0.073 µg/kg, reflecting post-monsoon contamination patterns. A PLSR model with 5-fold cross-validation, SNV correction, and second Savitzky-Golay derivative preprocessing achieved a cross-validation RMSECV of 0.008 µg/kg—adequate for reliable FSSAI screening.

The model returned predicted AFM1 values within 3 seconds of spectrum acquisition via a Python-LIMS API integration. Over 12 months, 2,190 reception results were processed. Of these, 47 samples (2.1%) exceeded the screening threshold and went for HPLC confirmation; 12 (0.55% of total intake) exceeded the FSSAI limit and were successfully diverted before

reaching the production line, with zero false negatives above the regulatory threshold. HPLC testing frequency fell by approximately 78%, saving INR 12–20 lakh in annual analytical costs.

VII. CHALLENGES, LIMITATIONS, AND CRITICAL ASSESSMENT

A. Matrix Complexity and Spectral Interference

Raw milk is a complex colloidal system comprising fat globules (3.5–8%), casein micelles, whey proteins, lactose, minerals, and hundreds of minor organic components, all producing spectral absorptions that must be separated from trace mycotoxin signals. Buffalo milk (~55% of Indian production) presents a systematically different spectral background from cow milk, requiring separate calibration models or matrix normalisation. Seasonal compositional variation driven by pasture quality, heat stress, and feed adjustments necessitates periodic model recalibration as a standard quality management procedure.

B. Calibration Drift and Instrument Standardisation

Indian dairy plant conditions—ambient temperature swings from 15°C in winter to 45°C in summer—create real calibration drift concerns. Multi-plant model deployment requires robust instrument standardisation methods such as piecewise direct standardisation [30], requiring careful validation before network-wide rollout.

C. Limited Indian Spectral Databases

Most published spectroscopic studies used European or US milk samples with different compositional profiles. A national dairy spectral database initiative—modelled on the IDELE database in France, coordinated through NDDB with participation from major cooperative networks—could accumulate the sample diversity needed to train robust pan-India AI models within 3–5 years.

D. Regulatory Framework

FSSAI regulations do not currently include specific provisions for AI-spectroscopic methods as approved rapid screening tools. Screening positives must be confirmed by HPLC or ELISA before regulatory action. A well-designed risk-stratified protocol delivers meaningful safety improvements within this existing framework, while working with FSSAI to develop formal AI-spectroscopic validation pathways is an important medium-term goal.

E. Cybersecurity and Data Integrity

IoT-connected systems generate sensitive quality data carrying commercial and legal exposure. Adversarial attacks on AI food safety models have been demonstrated in research settings. Establishing data governance frameworks, encrypted sensor-to-cloud transmission, and regular model integrity checks is essential for commercial-scale deployment [31].

VIII. FUTURE PERSPECTIVES

A. Portable Sensing for Farmer-Level Screening

MEMS-based NIR spectrometers (INR 30,000–80,000) paired with edge AI inference running on microcontroller units could extend mycotoxin surveillance to village milk collection centres for the first time. Connecting these devices to smartphone interfaces and mobile data transmission could build a decentralised quality monitoring network spanning India's 600,000+ village collection points [12].

B. Multimodal Sensor Fusion

Combining NIR for bulk screening with SERS for confirmatory quantification, or feeding fluorescence EEM and Raman features into multi-branch CNNs, allows each platform's strengths to compensate for others' limitations. Aptamer-modified electrochemical biosensors with LODs below 0.005 μg/kg offer complementary confirmation within integrated multi-sensor frameworks [32].

C. IoT Integration and Predictive Risk Management

ML models trained on geospatial, meteorological, and agronomic datasets have achieved 70–85% accuracy in predicting seasonal AFM1 risk at regional level under Indian conditions [33], enabling proactive monitoring intensification during high-risk periods. Connecting predictive models to dairy plant procurement planning systems represents the frontier of AI-enabled food safety management.

D. FSSAI Compliance and Blockchain Traceability

Future AI-spectroscopic systems should have FSSAI compliance reporting built in from the start, integrating with the FoSCoS platform and enabling real-time regulatory notifications. Blockchain-based traceability linking spectroscopic quality records to supplier identity, collection timestamps, and

processing batch data would strengthen the evidentiary value of AI monitoring records for both regulatory and legal purposes.

IX. ENVIRONMENTAL AND SUSTAINABILITY CONSIDERATIONS

A single HPLC-MS/MS cycle for AFM1 in milk consumes approximately 50 mL acetonitrile and 20 mL chloroform. A laboratory running 30 samples/day generates roughly 1,600 litres of organic solvent waste annually. AI-integrated spectroscopic platforms eliminate this solvent burden entirely for screening purposes. The annual operational carbon footprint of a benchtop NIR instrument (~40–100 kg CO2-equivalent at India's electricity carbon intensity of ~0.7 kg CO2-equivalent/kWh) is a fraction of the environmental burden of conventional testing. Earlier contamination detection also reduces downstream product waste and associated methane emissions [13].

X. CONCLUSION

Mycotoxin contamination in dairy and milk-based foods is an ongoing public health challenge that conventional analytical chemistry cannot adequately address in terms of speed, coverage, and cost—particularly in Indian dairy operations. Spectroscopic platforms—NIR, FTIR, Raman, SERS, and fluorescence spectroscopy—when paired with AI and machine learning, provide practical tools for real-time industrial monitoring that bridges the gap with laboratory-grade accuracy.

The quantitative case for implementation in Indian dairy is compelling: INR 1–5 per test versus INR 6,000–15,000 for HPLC; results in seconds versus hours; 100% batch coverage versus <1%. For a country with the world's largest dairy sector and hundreds of millions of daily milk consumers, investing in this monitoring infrastructure is a public health necessity.

Progress requires coordinated action: building India-specific spectral training databases through NDDB-coordinated initiatives; developing FSSAI validation frameworks for AI-spectroscopic methods; capital investment by cooperatives supported by government food safety programmes; and developing the technical workforce to operate and maintain these systems. Federated learning—allowing multiple cooperative plants to contribute to and benefit from shared AI models without centralising commercially sensitive data—offers a scalable, cooperative-sector-appropriate path to industry-wide adoption.

Table IV. Summary: Key Performance Metrics Across AI-Spectroscopic Platforms for Dairy Mycotoxin Monitoring

Metric	NIR	FTIR-ATR	SERS	Fluorescence EEM	HPLC (Reference)
AFM1 LOD (µg/kg)	0.05–0.10	0.04–0.08	0.001–0.005	0.02–0.05	0.002–0.005
Analysis time	10–30 s	30–60 s	5–15 min	20–60 s	6–24 h
Sample prep	None	None (ATR)	Moderate	None-minimal	Extensive
Multi-mycotoxin	Limited	Limited	Yes (aptamer)	Yes (PARAFAC)	Yes (MS/MS)
Field portable	Yes (MEMS)	Partial	Emerging	Emerging	No
Cost per test (INR)	1–3	2–5	50–200	2–5	6,000–15,000

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