

# Artificial Intelligence-Enabled Smart Milk Quality Assessment: A Comprehensive Review of Sensing Technologies, Machine Learning Methods, and IoT Integration

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**Abstract** — Milk is a highly perishable, high-value food whose quality is affected by natural compositional variation, economically motivated adulteration with water, sugars, starch, urea or melamine, microbial spoilage during storage and transport, and udder diseases such as mastitis. Reference methods, including laboratory Fourier-transform infrared (FTIR) analysis, microbiological culture and chromatography, are accurate but centralised, slow and costly, which restricts routine testing at farm and collection-centre level. Artificial intelligence (AI), combined with rapid sensing and the Internet of Things (IoT), is increasingly proposed as a route to fast, on-site and continuous milk quality assessment. This paper presents a focused narrative review of verified peer-reviewed studies, prioritising 2022–2026 publications, that use AI for milk composition prediction, adulteration detection, spoilage assessment and udder-health prediction. The review examines three connected themes: sensing technologies (mid-infrared, near-infrared and fluorescence spectroscopy, low-cost multispectral chips, electronic noses and smartphone-based vibration sensing), learning methods (partial least squares chemometrics, classical machine learning such as support vector machines, random forests and gradient boosting, and deep learning such as convolutional neural networks), and IoT architectures with edge and cloud inference. The literature shows that spectroscopic data with machine learning or deep learning can detect single adulterants with reported accuracies of about 95–100 %, and that inexpensive 18channel spectral sensors calibrated against laboratory FTIR can estimate fat and protein with mean errors of about 0.07–0.14 %. Simple, interpretable models often perform as well as complex ones. However, most studies use small, single-region datasets, laboratory conditions, single adulterants and random data splits, and few report field validation, sensor drift, uncertainty or long-term IoT operation. The review contributes a comparative analysis of representative studies, a proposed conceptual farm-to-plant architecture that links multi-sensor acquisition, edge AI, IoT decision support and laboratory reference validation, and a prioritised agenda of research gaps and future directions.

**Keywords**— Milk Quality, Machine Learning, Spectroscopy, Adulteration Detection, Internet of Things, Edge Computing.

## I. INTRODUCTION

Milk is a nutritionally important and highly perishable commodity whose value depends on composition (fat, protein, lactose), hygiene, freedom from adulterants and residues, and the health of the producing animal. Quality failures arise from deliberate adulteration with water, sugars, starch, urea or melamine, from microbial growth during storage and transport, and from mastitis, which alters milk composition and somatic cell count (SCC) [1], [2]. Reference methods such as laboratory Fourier-transform infrared (FTIR) analysis, microbiological culture and chromatography are accurate but centralised, slow and expensive, which limits testing at farm and collectioncentre level [1], [3].

AI is now applied across the dairy chain, from herd health and yield prediction to processing quality control and product development [4]. For milk quality specifically, three developments converge: rapid spectroscopic and lowcost optical sensing, ML and DL models that map sensor signals to quality attributes, and IoT connectivity that moves measurements from laboratories to farms, tankers and plants [3], [5]. This review examines these three strands together, asks how mature the evidence is for on-site deployment, and proposes a conceptual architecture that addresses the weaknesses identified.

## II. REVIEW METHODOLOGY

A focused search of publisher platforms (MDPI, SpringerLink, IEEE, Elsevier, Wiley), PubMed Central, Crossref/OpenAlex

metadata and institutional repositories was carried out with combinations of the terms milk quality, adulteration, spoilage, mastitis, spectroscopy, electronic nose, machine learning, deep learning, IoT and edge computing, prioritising 2022–2026 publications. Studies were included when they reported milk-specific sensing or prediction with a stated method and quantitative outcome; reviews were used for context only. Every reference was verified against a publisher, DOI or repository record. Direct logged querying of Scopus and Web of Science was not possible, so the review is narrative rather than systematic, and study counts are not reported.

### III. SENSING TECHNOLOGIES FOR MILK QUALITY

#### 1. Laboratory and Portable Spectroscopy

Mid-infrared (MIR) spectroscopy is already routine in milk recording and offers non-destructive, multi-parameter prediction from a single spectrum with little sample preparation [1]. A review of MIR for adulterants and contaminants reports successful detection of sucrose, urea, melamine, foreign-species milk and some drug residues, but notes that added water remains difficult to quantify because water is the main milk constituent, and that MIR complements rather than replaces reference methods [1]. FT-MIR with Savitzky–Golay preprocessing and linear discriminant analysis (LDA) separated camel milk adulterated with cow milk down to 10 g/100 g in a 93sample study, while an artificial neural network (ANN) quantified the adulteration with a limit of detection of 3.27 g/100 g [6]. Near-infrared (NIR) spectroscopy with wavelength selection and partial least squares (PLS) regression quantified urea, melamine and starch in goat milk powder ( $R^2_p > 0.987$ ), and PLS2 handled simultaneous adulterants [7].

#### 2. Low-Cost Multispectral and Optical Sensors

Inexpensive multi-channel spectral chips (AS7265x, 18 bands from 410 to 940 nm) have been coupled with microcontrollers to estimate fat and protein on site. Using 100 samples from one region, gradient-boosting models reached  $R^2$  of 0.933 for protein and about 0.997–0.998 for fat [5]. A larger study of more than 600 raw-milk samples from over 80 farms, referenced to commercial FTIR results, found that simple linear regression outperformed decision trees, random forests and k-nearest neighbours, with mean errors of about 0.14 % for fat and 0.07 % for protein [3]. For spoilage, a handheld three-dimensional fluorescence spectrometer with a naive Bayes classifier distinguished fresh from spoiled milk with 95.4 % accuracy on an independent test set, although only twelve samples tracked over 48 h were used and labels were derived from a pH cutoff [8].

#### C. Gas, Electrochemical and Alternative Sensing

Volatile and physical signals offer complementary information. A quartz-crystal-microbalance electronic nose (e-nose) with polycomposite coatings predicted microbial counts in raw milk with errors of no more than 17 % using PLS regression, but on only 14 milk samples [9]. VibMilk used the vibration motor and inertial sensor of a smartphone with an InceptionTime DL model to classify 23 spoilage stages from pH 6.6 to 4.4 with 98.35 % accuracy, showing that ubiquitous hardware can capture viscosity-related changes [10]. On-farm, a patented sensor-driven HACCPstyle system monitored milk for four months and used MLbased outlier analysis to flag cows that differed by breed, recent calving or drug treatment [11].

### IV. MACHINE LEARNING AND DEEP LEARNING METHODS

#### 1. Chemometrics Versus Machine Learning

PLS regression and discriminant analysis remain strong baselines. On 730 MIR spectra from 622 cows, eleven regression and four classification methods were compared for fourteen technological and protein traits; ML reduced prediction error relative to PLS by only 0.18–3.67 %, the best method varied by trait, and support vector machines (SVM) gave the highest binary classification accuracy, with interpretable models recommended when performance is similar [12]. The superiority of simple linear regression in the multispectral study [3] supports the same conclusion: model complexity should be justified by data volume and validation results.

#### 2. Deep Learning

DL can learn directly from spectra. A one-dimensional convolutional neural network (CNN) trained on raw FTIR spectra of 4,846 samples, 2,376 of them adulterated with one of five substances, reached up to 98.76 % accuracy, outperforming random forest and gradient boosting on average, although adulterants were added singly and from one farm [13]. A hybrid blended DL model for milk spectral data reported 98.03 % accuracy and was benchmarked for energy use and inference on an NVIDIA Jetson Nano edge device [14].

#### 3. Validation Practice

Repeated measurements of the same animal, sample or batch can leak information between training and test sets and inflate accuracy [15]. In buffalo subclinical mastitis prediction from 3,891 test-day records, splitting by animal rather than by record was used to avoid leakage; accuracy remained moderate (about 74–76 %), with SCC history, differential SCC and electrical

conductivity as key predictors [2]. Such grouped validation is still uncommon in milk-sensing studies.

## V. IOT INTEGRATION AND EDGE DEPLOYMENT

IoT studies differ mainly in where inference runs. In the XGBoost multispectral system, the trained model ran on an Arduino Nano 33 BLE and results were forwarded by MQTT through an edge gateway [5]. The farm-to-factory sensor sent readings over NB-IoT with MQTT to a cloud IoT platform, where the regression model translated spectra into composition [3]. DL inference on Jetson-class hardware [14] and smartphone-based sensing [10] extend edge processing further. Edge inference reduces latency and dependence on rural connectivity, whereas cloud processing simplifies model updates and cross-site analytics; neither study above reported long-term operation in tanks, tankers or plants.

## VI. COMPARATIVE ANALYSIS

Table 1: Comparison of Representative AI-Based Milk Quality Studies

| Author, year                   | Objective                       | Sensing / method                   | Major reported findings                          | Limitations                        |
|--------------------------------|---------------------------------|------------------------------------|--------------------------------------------------|------------------------------------|
| Asseiss Neto et al., 2019 [13] | Detect five adulterants         | FTIR; 1D-CNN vs RF, GBM            | Up to 98.76 % accuracy; 4,846 samples            | Single adulterants; one farm       |
| Frizzarin et al., 2021 [12]    | Predict 14 quality traits       | MIR; 11 regression + 4 classifiers | ML gain over PLS 0.18–3.67 %; SVM best binary    | Moderate accuracy; trait-dependent |
| Zhao et al., 2022 [7]          | Quantify urea, melamine, starch | NIR; SPA + PLS, PLS2               | $R^2_p > 0.987$ for single adulterants           | Milk powder; lab only              |
| Yao et al., 2023 [6]           | Cow milk in camel milk          | FT-MIR; LDA, ANN                   | 100 % LDA at $\geq 10$ g/100 g; LOD 3.27 g/100 g | 93 samples; one region             |

|                             |                              |                                       |                                            |                                              |
|-----------------------------|------------------------------|---------------------------------------|--------------------------------------------|----------------------------------------------|
| Bobbo et al., 2023 [2]      | Predict subclinical mastitis | Milk recording + climate; SVM, RF, NN | $\approx 76$ % accuracy, animalwise split  | Six herds; SCC threshold label               |
| Shuba et al., 2024 [9]      | Estimate microbial load      | QCM e-nose; PLS                       | Error $\leq 17$ %                          | 14 milk samples                              |
| Wu et al., 2024 [10]        | Classify spoilage stage      | Smartphone vibration; InceptionTime   | 98.35 % over 23 stages                     | Controlled spoilage series                   |
| Mhapsekar et al., 2024 [14] | Milk quality from spectra    | Hybrid blended DL; Jetson Nano        | 98.03 % accuracy; energy profiled          | Dataset details not verified (abstract only) |
| Gillespie et al., 2024 [8]  | Fresh vs spoiled milk        | Handheld fluorescence; naive Bayes    | 95.4 % independent test                    | 12 samples; pH-based labels                  |
| Durgun, 2024 [5]            | On-site fat and protein      | AS7265x; XGBoost on MCU               | $R^2$ 0.933 protein, $\approx 0.997$ fat   | 100 samples; controlled conditions           |
| Fizza et al., 2025 [3]      | Farm-to-factory composition  | AS7265x; NB-IoT; linear regression    | Error $\approx 0.14$ % fat, 0.07 % protein | Lab-tested; one season and region            |

## VII. PROPOSED CONCEPTUAL ARCHITECTURE

Fig. 1 presents a proposed conceptual architecture derived from the reviewed systems. Milk is sampled or measured in-line at the farm tank, collection centre or plant (layer 1). Complementary sensors capture spectral, electrochemical, gas and temperature signals (layer 2), because no single modality covers composition, adulteration and spoilage [1], [9], [10]. An embedded acquisition unit timestamps and preprocesses signals (layer 3), and edge models perform composition regression,

adulteration or spoilage classification and anomaly detection with a confidence score (layer 4) [5], [14].

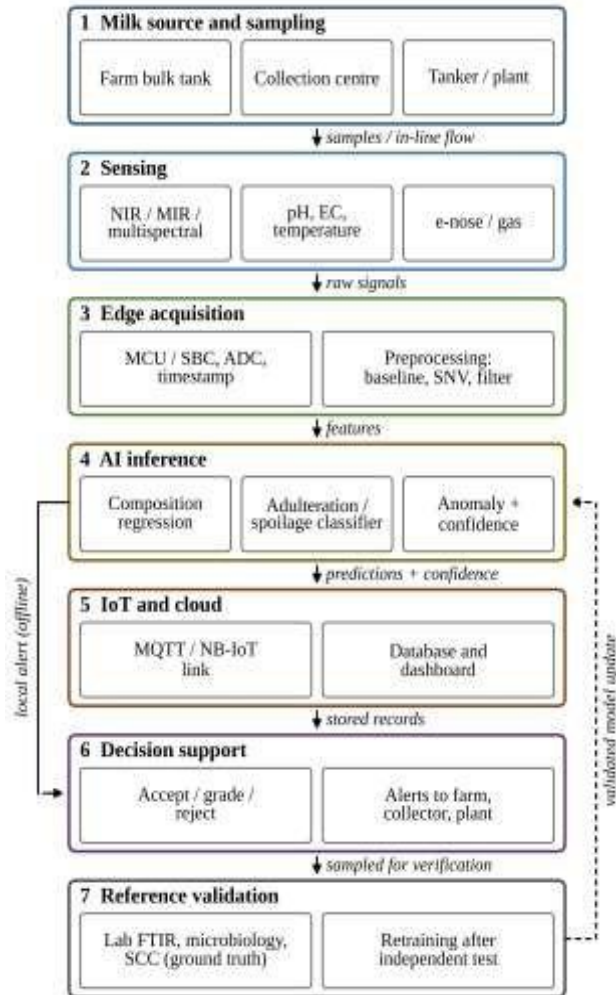


Fig.1. Proposed conceptual architecture for AI-enabled milk quality assessment from farm to plant (conceptual, not experimentally validated)

Results are transmitted by MQTT or NB-IoT to a database and dashboard (layer 5) [3], and decision rules support acceptance, grading or rejection with alerts (layer 6); a local alert path keeps working without connectivity. A sampled subset is verified with laboratory FTIR, microbiology or SCC (layer 7), and models are retrained only after independent re-testing, which addresses the calibration dependence highlighted in the literature [1], [3].

## VIII. RESEARCH GAPS AND FUTURE DIRECTIONS

Gaps supported by the reviewed evidence. (i) Small, single-region datasets: many studies use 12–100 samples or one farm or region [5], [6], [8], [9]. (ii) Laboratory rather than field validation: even IoT-oriented systems were tested on stored samples under controlled conditions [3], [5]. (iii) Simplified adulteration scenarios: adulterants are usually added singly, whereas fraud may combine substances [7], [13]. (iv) Weak validation practice: random splits of correlated samples risk leakage, and grouped splits remain rare [2], [15]. (v) Limited interpretability and uncertainty reporting, despite evidence that simple models often perform comparably [3], [12]. (vi) Difficult targets such as added water and low-level contaminants remain challenging for spectroscopy [1].

Directions requiring investigation. Priorities include multi-season, multi-region datasets with laboratory reference labels; field trials in tanks and tankers with drift and temperature compensation; multi-sensor fusion of spectral, gas and physical signals; calibrated confidence and out-of-distribution detection at the edge; transparent reporting of grouped validation; and data governance for shared dairy datasets, which a recent review identifies as a barrier to AI adoption [4].

## IX. CONCLUSION

AI-enabled milk quality assessment has progressed from laboratory chemometrics to compact spectral sensors, smartphone-based sensing and IoT-connected edge inference. Reported accuracies are high for specific tasks, such as single-adulterant detection and fat and protein estimation, but the evidence base is dominated by small, controlled, single-region studies with limited independent validation. Simple, interpretable models frequently match complex ones, and reference laboratory methods remain essential for calibration. Reliable deployment will require larger and more diverse datasets, field trials across the supply chain, grouped validation, multi-sensor fusion and continuous reference-based model maintenance, as reflected in the proposed conceptual architecture.

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