International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 11 | Nov - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

A Survey of Internet of Things, Machine Learning and Blockchain Approaches for Milk Adulteration Detection and Dairy Supply Chain Transparency

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Abstract—Milk safety depends on detecting adulteration, measuring composition and preserving trustworthy records across a fragmented dairy supply chain. This focused critical survey combines secondary literature with a full-text analysis of five core publications on low-cost sensor classification, continuous milk-tank monitoring, machine-learning-assisted quality grading and blockchain-based traceability and governance. A four-sensor Raspberry Pi study reports 91.2% accuracy for five-class adulteration classification under controlled conditions, a spectroscopic Internet of Things (IoT) device reports fat and protein errors of ±0.14 and ±0.07 percentage points, and an Ethereum milk-chain prototype reports 99.69% accuracy for three-grade quality prediction; these results address different targets and cannot be directly ranked. The review offers a task-aware taxonomy, comparative evidence tables, a proposed integration workflow and six research gaps. Its key finding is that recorded-event integrity does not establish the truth of physical measurements, and field-ready quality-to-batch traceability remains insufficiently demonstrated in the examined sources. It is a focused narrative review, not a systematic review.

Keywords—milk adulteration, Internet of Things, machine learning, blockchain, dairy traceability, sensor provenance.

I. INTRODUCTION

Milk is a major nutritional and economic product, yet its quality can be compromised by dilution, added substances, microbial activity and inadequate handling. Water, urea, detergents and starch are among the adulterants considered by sensor-based research [1]. Chemical and spectroscopic laboratory methods can be informative [2], [3], but their cost, sampling requirements and turnaround time motivate field-deployable sensing. In parallel, milk is combined, stored, processed and distributed across organizations, so a reading that lacks reliable batch linkage may be of limited value for recall or dispute handling [4], [5]. Recent reviews examine traceability in the dairy industry [6], [7] and the role of blockchain in dairy supply and value chains [8].

Three outcomes must be kept distinct. Adulteration classification predicts an unauthorized addition or class; composition estimation measures properties such as fat or protein; and quality grading assigns an overall categorical label. A reported percentage accuracy for one is not directly comparable with an error expressed in percentage points for another. Traceability is an additional system-level function rather than an inherent outcome of an accurate sensor [1], [4], [9].

This review contributes (i) a task-aware taxonomy linking measurement, analytics, record trust and dairy operations; (ii) a critical comparison of five directly examined sources together with secondary related literature; (iii) explicit separation of reported results, conceptual architectures and future proposals; and (iv) a measurable validation agenda for low-resource dairy deployment. The remainder of this paper is organized as follows: Section II reviews the literature, Section III describes the review method, Section IV presents the comparative results, Section V discusses research gaps, an evaluation framework and limitations, and Section VI concludes.

II. LITERATURE REVIEW

A. Measurement and Adulterant Signatures

pH, turbidity, total dissolved solids (TDS) and temperature give complementary signals [1]. Water dilution and added soluble or scattering substances can shift more than one reading, but natural variation

and spoilage can produce overlapping signatures. Therefore, learning from multiple calibrated measurements may be more informative than fixed thresholds. The four-sensor model of Korde et al. [1] illustrates this approach; it does not establish universal identification of all possible additives.

B. Record Integrity Versus Sensor Truth

An append-only signed log or distributed ledger can make subsequent changes detectable, but neither guarantees that the original sample was representative nor that a sensor was calibrated. Incorrect farmer identifiers, mislabeled samples, device compromise and batch mixing can all undermine traceability before data reach the ledger. Governance, encryption, permission boundaries and operator usability therefore matter alongside technical immutability [5], [10].

Further context is provided by a milk-adulteration health review [11] and a Food Safety and Standards Authority of India (FSSAI) surveillance announcement [12]; neither establishes a universal current unsafe-sample percentage. Dairy monitoring, classical learning and traceability studies [13]–[19] also motivate the distinctions in this survey.

C. Taxonomy of Approaches

The four-layer organization used in this review is summarized in Fig. 1. Sensing ranges from analyzers and chemistry to low-cost arrays and optical spectroscopy. Learning ranges from rule systems [20] to Random Forest [14], support vector machines (SVM) [21], gradient boosting [15] and regression models [9]. Trust options span signed centralized records, permissioned ledgers, public networks and hybrid designs. Operations add sample identification, batch splits and merges, transfer custody, offline operation and consumer-facing verification through Quick Response (QR) codes [1], [4], [5], [9], [10].

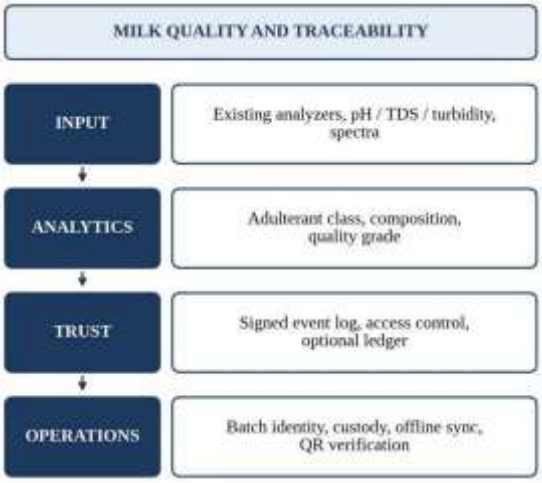


Fig. 1. Four-layer taxonomy synthesized from the reviewed milk-quality and traceability literature; proposed analytical classification, not a deployed system [1], [4], [5], [9], [10].

D. Sensor- and Machine-Learning-Based Milk Quality

1) Classical and Optical Approaches

The secondary literature reports work on electrical impedance for urea detection [22], [23], multispectral and hyperspectral milk analysis [2], [3], infrared spectral classification [24], fuzzy-logic sensing [20], sensor fusion [25] and laboratory-derived SVM models [21]. More recent work includes a multispectral sensor with an artificial neural network for starch adulteration in raw milk [26], a recurrent neural network with IoT for adulteration detection [27], and a lightweight deep learning framework for edge devices that is applied to milk species identification and adulteration detection [28]. Such methods differ substantially in instrumentation, training labels, sample preparation and deployment environment. Numeric results from secondary sources are not revalidated here, and reported performance should not be generalized across tasks or hardware.

2) Four-Sensor Adulterant Classification

Korde et al. [1] describe a Raspberry Pi 3A+ system integrating pH, turbidity, TDS and temperature sensors, an ADS1115 interface and a Flask-SocketIO browser dashboard. The paper reports 1,500 controlled laboratory observations across five classes: pure, urea, detergent, starch and water-diluted milk. On the authors' evaluation, Random Forest achieved 91.2%, XGBoost 90.4% and linear SVM 89.0% accuracy, as listed in Table I. Confusion involving starch and water-diluted samples indicates overlapping signatures. The reported laboratory performance does not quantify generalization to mixed adulterants, seasonality or long-running rural deployment. An IoT milk-grading analyzer that measures pH, temperature, humidity, TDS and gas levels also compared six classifiers and reported Random Forest as the best performer [29].

TABLE I. REPORTED CLASSIFICATION RESULTS ON THE SAME FOUR-SENSOR DATASET [1]

Model	Target	Accuracy
Random Forest	5 adulterant classes	91.2%
XGBoost	5 adulterant classes	90.4%
Linear SVM	5 adulterant classes	89.0%

3) Continuous Fat and Protein Monitoring

Fizza et al. [9] designed a milk-tank sensor using an 18-channel low-cost spectrometer, light-emitting diode (LED) illumination, a microcontroller and Narrowband IoT (NB-IoT) and Message Queuing Telemetry Transport (MQTT) connectivity. A machine-learning translator estimates fat and protein from spectral readings, with reported experimental errors of ±0.14 percentage points for fat and ±0.07 percentage points for protein. The work is relevant to farm tanks, pickup trucks and depots; it estimates composition rather than identifying the chemical class

of an adulterant. Cleaning, calibration and deployment durability require attention when transferring this setup to new operating conditions.

4) Quality-Grade Prediction

Nukapeyi et al. [4] use CatBoost on tabular features, including pH, temperature, fat, turbidity and subjectively entered taste, odor and color, to predict low, medium or high milk-quality grades. The results section reports 99.69% classification accuracy, whereas an earlier methodology sentence mentions 100%; this discrepancy should be checked by the source authors. Neither figure can be used as evidence of 99.69% accuracy for identifying urea, detergent or other specific adulterants. The manually entered attributes also pose data-quality challenges. A blockchain-enabled deep residual network that grades milk from IoT data reports a testing accuracy of 0.931 on a public milk-grading dataset [30]; as with [4], grade labels are not adulterant identities.

E. Blockchain-Based Dairy Traceability

1) Ethereum Milk Chain Prototype

Nukapeyi et al. [4] present a local Ethereum demonstration using Solidity contracts, Remix, Ganache, MetaMask and Web3.js. Milk producers, processing or cooperative actors, retailers and consumers record or retrieve milk-related events under a common identifier. Screenshots demonstrate a workflow on a test environment; the study does not establish field-scale transaction latency, privacy protection, sensor authenticity or real supply-chain outcomes. Other dairy-specific designs include Ethereum and Quorum smart contracts for cheese production with consumer verification through QR codes [31], a private Ethereum system with smart contracts for dairy waste accountability [32], an IoT and blockchain design that uses long-range radio to record milk quality at rural sites [33], and a hybrid blockchain and artificial intelligence traceability prototype [34]. These works are prototypes or proofs of concept, so the distinction between record integrity and sensor truth discussed above still applies.

2) Indian Dairy Blockchain Architecture

Khanna et al. [5] propose a dairy-specific blockchain supply-chain platform integrating QR identification, smart contracts and possible IoT capabilities. Their paper discusses milk, cheese and butter, along with social, economic, operational and sustainability dimensions. It also illustrates a structured literature review with explicit research questions and a database search description. Proposed benefits should be differentiated from independently measured reductions in contamination or fraud.

3) Agri-Food Systematic Review and Governance

Khoualdi et al. [10] independently screened 41 agri-food publications using a PRISMA approach. Their reported subset includes 61% public-permissionless and 39% permissioned or consortium blockchain solutions; 75% did not adequately discuss solution governance. They propose a conceptual hybrid architecture employing controlled access, protected off-chain storage and public verifiability. They explicitly recognize that tamper-evident storage cannot establish the truthfulness of initial sensor input.

III. METHODOLOGY

A. Review Design and Scope

The manuscript is a focused narrative and critical survey. Five distinct full-text documents were directly examined: Nukapeyi et al. [4], Korde et al. [1], Khoualdi et al. [10], Khanna et al. [5] and Fizza et al. [9]. A duplicate of [10] was excluded. Twenty-nine additional items are included as secondary contextual literature; their full texts were not independently examined, and results attributed to them are reported as stated by their authors.

Selection of the five core studies was purposive rather than the outcome of an exhaustive database search. No independent Scopus, IEEE Xplore or Web of Science search log, exclusion count, or Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow is claimed. The 41 articles included in the systematic review by Khoualdi et al. [10] are that publication's study set, not 41 articles separately screened by the present authors. This limitation prevents a claim of comprehensive systematic coverage.

B. Research Questions and Extraction

Five guiding research questions (RQ) structured extraction: RQ1 Which property or class is predicted? RQ2 How were measurements and models evaluated? RQ3 What data provenance or traceability mechanism is demonstrated? RQ4 Which field-deployment restrictions remain? RQ5 What would constitute meaningful end-to-end validation? For each core source, the analysis records inputs, target, model or ledger, evaluation setting, and evidenced limitations.

IV. RESULTS

Table II compares the five directly examined studies in terms of observed evidence and principal limitation. The reported outcomes address three different targets: five-class adulterant classification with 91.2% accuracy [1], fat and protein estimation with errors of ±0.14 and ±0.07 percentage points [9], and three-grade quality prediction with 99.69% accuracy [4]. The remaining two sources contribute a dairy-specific conceptual architecture [5] and a systematic synthesis with a hybrid proposal [10]. These outcomes are not directly comparable.

TABLE II. CORE FULL-TEXT STUDIES: NONCOMPARABLE OUTCOMES AND MATURITY

Study	Observed evidence	Principal limitation
Korde et al. [1]	1,500 lab observations; five-class Random Forest 91.2%.	No documented mixed-adulterant field trial or batch chain.
Fizza et al. [9]	Fat and protein errors ±0.14 / ±0.07 percentage points.	Composition, not adulterant-class detection.
Nukapeyi et al. [4]	99.69% grade model; local Ethereum workflow.	Manual inputs; no production evaluation.
Khanna et al. [5]	Dairy-specific blockchain conceptual model.	Limited measured integrated outcomes.
Khoualdi et al. [10]	41-study systematic synthesis; hybrid proposal.	General agri-food focus; input truth unresolved.

V. DISCUSSION

A. Interpretation of Findings

The technical insight is that good prediction, accurate measurement and immutable event storage solve different problems. Accuracy percentages are only meaningful within the same labels and dataset, while composition error must be judged against laboratory reference values. A quality grade computed from manual fields cannot verify chemical safety. Similarly, a verifiable QR history is reliable only if the sample-to-batch linkage and source measurements are credible [1], [4], [5], [9], [10].

B. Research Gaps and Challenges

G1. Integration and interoperability: The core sources do not jointly establish a field-tested system that connects automatic adulterant classification, continuous quality monitoring and complete batch genealogy. Existing dairy testing machines need validated, device-specific interfaces [1], [4], [9].

G2. Field validity and mixed adulterants: Lab-separated labels may not describe blended adulterants, changing milk composition, seasonal conditions, sensor drift or abnormal microbiological states. Future studies need multi-site blind tests with certified reference methods [1].

G3. Source-data integrity: Secure records should bind calibrated devices, operator identities, sample identifiers, timestamps and immutable raw readings. Device attestation and independent consistency checks must be evaluated rather than assumed [10].

G4. Batch genealogy: Mixing, splitting, conversion to dairy products, quarantine and recall must preserve parent-child associations; QR lookup alone is not enough. Researchers should quantify trace-back completeness and correctness [5].

G5. Rural operations: Offline collection, idempotent synchronization, low-cost maintenance, sensor sanitation, language accessibility and operator training require realistic pilot evaluation [1], [9].

G6. Governance and privacy: Access rules must distinguish regulator, farmer, dairy, logistics and consumer data. A ledger should be justified against signed centralized logs using a transparent threat model, operational costs and consortium governance [10].

C. Proposed Evaluation Framework

A future research workflow, derived from these findings and not presented as implemented work, has eight steps: (1) verified farmer, sampling event and device identification; (2) acquisition of original analyzer or sensor readings with calibration metadata; (3) task-specific quality inference with recorded model version; (4) signed raw measurement and decision events; (5) batch creation with parent-child genealogy; (6) monitored storage, processing and transport handovers; (7) privacy-filtered QR verification; and (8) auditable recall reports. Blockchain, permissioned anchoring and signed append-only databases should be compared empirically before deployment. The minimum reportable metrics for each evaluation domain are given in Table III.

TABLE III. PROPOSED FIELD-VALIDATION CHECKLIST; NOT EXPERIMENTAL RESULTS

Evaluation domain	Minimum reportable metrics
Detection	Sensitivity, specificity, F1 score by adulterant and concentration; mixed samples
Composition	Absolute error versus reference lab; cross-device calibration drift
Traceability	Event completeness; batch split/merge correctness; recall trace-back
Operations	Offline sync success; latency; cost per liter/center; operator workload
Trust/privacy	Tamper detection; role access failures; key recovery; audit reproducibility

D. Limitations and Threats to Validity

The five core studies were selected purposively rather than retrieved systematically. Related references outside that set were not independently read in full, so the present review cannot estimate overall publication trends or claim exhaustive coverage. Metrics were taken from source reports, not recalculated or reproduced. The included papers span prototypes, conceptual models and a secondary systematic review; no common benchmark permits cross-task ranking. These limitations should be addressed through an auditable literature search, citation verification and independent field datasets before this work can be presented as a comprehensive systematic review.

VI. CONCLUSION

Published research supports promising sensor-based adulterant classification [1], continuous compositional monitoring [9] and milk-chain

traceability concepts [4], [5], while the broader IoT/blockchain evidence underscores unresolved privacy and governance issues [10]. The strongest research opportunity is to join trustworthy measurement capture with correct batch genealogy, task-appropriate machine learning, resilient rural operation and privacy-preserving auditability. Future experiments should evaluate the complete chain against laboratory ground truth and independently verified transfer events. This article provides an evidence-grounded focused synthesis, not a claim of a deployed or experimentally validated integrated system.

ACKNOWLEDGMENT

The authors acknowledge academic guidance and institutional support from the Departments of Computer Engineering and Electronics and Telecommunication Engineering, SVPM's College of Engineering, Malegaon (Bk).

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