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MilkoSense: A Rapid AI-Assisted Milk Quality Testing System for Enhanced Dairy Safety and Efficiency

Kapil Goyal
Department of Computer Science and Engineering
Acropolis Institute of Technology and Research, Indore, M.P., India
kapilgoyal230560@acropolis.in

Aditi Vishwakarma
Department of Computer Science and Engineering
Acropolis Institute of Technology and Research, Indore, M.P., India
aditivishwakarma231033@acropolis.in

Anya Jain
Department of Computer Science and Engineering
Acropolis Institute of Technology and Research, Indore, M.P., India
anyajain230979@acropolis.in

Nisha Rathi
Department of Computer Science and Engineering
Acropolis Institute of Technology and Research, Indore, M.P., India
nisharathi@acropolis.in

Abhishek Verma
Department of Computer Science and Engineering
Acropolis Institute of Technology and Research, Indore, M.P., India
abhishekverma230913@acropolis.in

Ashish Anjana
Department of Computer Science and Engineering
Acropolis Institute of Technology and Research, Indore, M.P., India
ashishanjana@acropolis.in

[1]***Abstract*–The dairy industry faces critical challenges in ensuring milk quality and safety, with traditional testing methods like the Methylene Blue Dye Reduction Test (MBRT) requiring 4-6 hours, creating significant bottlenecks in quality assurance processes. This paper presents MilkoSense, a rapid, portable, and AI-assisted milk quality monitoring system that integrates multi-sensor technologies with advanced machine learning algorithms. The system combines six key sensor types-pH, temperature, turbidity, Total Dissolved Solids (TDS), gas detection, and colorimetric analysis-with Convolutional Neural Networks (CNN) and ensemble learning methods. Integration with IoT connectivity through ESP32 platforms enables real-time data transmission and cloud-based analytics. The colorimetric detection methodology utilizes chromogenic reactions to identify multiple adulterants simultaneously, while machine learning models predict spoilage timelines and detect microbial contamination patterns. MilkoSense achieves significant reduction in testing time from 4-6 hours to under 30 minutes with enhanced accuracy exceeding 92%, improved supply chain transparency, and substantial cost savings through early intervention. This cost-effective solution represents a paradigm shift in dairy quality assurance, making advanced testing accessible across the entire value chain.**

***Index Terms*—Milk Quality Testing, Artificial Intelligence, Machine Learning, IoT, Multi-Sensor Integration, Food Safety, Dairy Industry, Real-time Monitoring, Adulteration Detection, Smart Agriculture**

I. INTRODUCTION

DAIRY products constitute a critical component of global nutrition and food security, with India emerging as the world's largest milk producer, contributing approximately 23% of global milk production [1]. The microbial quality of milk is paramount for consumer safety and operational efficiency in dairy supply chains. However, current testing methodologies present significant limitations that impede rapid quality assurance and decision-making processes.

A. Background and Motivation

The dairy sector faces mounting pressure from stringent food safety regulations, increasing incidents of milk adulteration, and growing consumer awareness regarding product quality. The Methylene Blue Dye Reduction Test (MBRT), while reliable, requires 4-6 hours to complete, making it impractical for modern supply chains demanding immediate quality verification. This temporal constraint creates bottlenecks at collection centres, delays processing decisions, and increases the risk of spoilage propagation.

Recent technological advancements in sensor systems, artificial intelligence, and Internet of Things (IoT) connectivity have created unprecedented opportunities for developing intelligent, real-time quality monitoring systems. These technologies enable sophisticated pattern recognition, predictive analytics, and remote monitoring capabilities that were previously unattainable with conventional methodologies.

B. Problem Statement

Current milk quality testing infrastructure suffers from several critical limitations:

1) **Temporal Inefficiency:** MBRT requires 4-6 hours, creating production bottlenecks and delayed interventions
2) **Economic Barriers**: Commercial testing equipment costs exceed $10,000, restricting access to large-scale processors
3) **Limited Portability**: Laboratory-based testing prevents on-site quality verification at collection points
4) **Single-Parameter Analysis**: Existing solutions typically assess only one or two quality indicators
5) **Reactive Approach**: Delayed results prevent proactive contamination management

C. Research Contributions

This paper presents MilkoSense, an integrated solution addressing these challenges through the following key contributions:

A novel multi-sensor fusion architecture combining complementary sensing modalities for comprehensive quality assessment

Advanced ensemble machine learning models achieving ¿92% accuracy in microbial load estimation and adulteration detection

IoT-enabled platform with real-time monitoring, cloud analytics, and automated stakeholder notifications

Cost-effective portable design (target cost: 10,000) democratizing access to advanced testing

Comprehensive field validation demonstrating practical applicability across diverse dairy production contexts

The remainder of this paper is organized as follows: Section II reviews related work and existing solutions. Section III details the proposed system architecture and methodology. Section IV presents implementation details and algorithms. Section V discusses expected results and validation approach. Section VI concludes with future research directions.

II. RELATED WORK AND LITERATURE REVIEW

A. Traditional Testing Methods

The MBRT has served as the industry standard for microbial quality assessment for several decades. This colorimetric method relies on bacterial enzyme-mediated reduction of methylene blue dye, with decolorization time inversely proportional to microbial load. While reliable, its 4-6 Hour duration limits practical utility in modern dairy operations requiring rapid turnaround.

Standard plate count methods, though highly accurate, require 24-48 hours of incubation and specialized laboratory facilities. Flow cytometry-based somatic cell counting offers faster results but requires expensive equipment and trained personnel [4].

B. Commercial Inline Analysis Systems

Several commercial solutions provide automated milk analysis:

Afimilk Systems: Utilize infrared spectroscopy for Realtime fat, protein, and lactose measurement during milking operations. While effective for nutritional profiling, these systems have limited microbial detection capabilities and high capital costs ($15,000-$50,000) .

Soma Detect: Employs laser-based optical analysis for somatic cell counting and basic quality parameters. The system integrates with milking Parlors but lacks portability and comprehensive adulteration detection.

Bentley Instruments: Provides laboratory-grade analysers with multi-parameter capabilities but requires centralized testing facilities and trained operators.

These solutions, while technologically advanced, remain inaccessible to small and medium-scale producers due to cost and infrastructure requirements.

C. AI and Machine Learning in Food Quality

Recent research demonstrates significant potential for AI/ML applications in food quality assessment:

1) **Support Vector Machines (SVM):** Successfully applied for adulterant classification using spectroscopic data, achieving 85-90% accuracy in detecting water dilution and starch addition.

2) **Convolutional Neural Networks (CNN):** Demonstrated effectiveness in image-based quality grading, achieving 93% accuracy in detecting visual anomalies and colour changes indicative of spoilage.

3) **Deep Learning for Spectroscopy:** LSTM networks applied to NIR spectroscopy data achieve real-time composition analysis with accuracy comparable to laboratory methods.

D. IoT-Based Agricultural Monitoring

IoT technologies have revolutionized agricultural monitoring:

Baumert developed deep learning-based anomaly detection for smart irrigation, demonstrating the feasibility of edge computing for real-time agricultural decision support.

E. Research Gap

Despite these advancements, no existing solution simultaneously addresses:

Comprehensive multi-parameter sensing (microbial, chemical, and nutritional)
AI/ML-driven rapid analysis (¡30 minutes)
IoT connectivity for real-time monitoring and alerts
Portability and cost-effectiveness (¡10,000)
Accessibility for small to medium-scale producers

MilkoSense bridges this gap through integrated hardware software design optimized for dairy quality assurance.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall System Architecture

The MilkoSense system architecture comprises three hierarchical layers as illustrated in Fig. 1: the Sensor Layer for data acquisition, the Processing Layer for local computation and communication, and the Application Layer for cloud analytics and user interfaces.

B. Sensor Layer Design

The sensor layer integrates six complementary sensing modalities, each targeting specific quality indicators: pH Sensor: Measures hydrogen ion concentration, detecting acidification due to bacterial lactic acid production and identifying alkaline adulterants.

Temperature Sensor: Monitors thermal history crucial for microbial growth prediction and validates cold chain maintenance.

TDS Sensor: Measures total dissolved solids through conductivity, detecting water dilution and salt-based adulterants.

Gas Sensors: MQ-3 detects volatile organic compounds and alcohols from fermentation; MQ-135 monitors ammonia and CO from protein degradation.

Colour Sensor: Captures RGB values for colorimetric adulterant detection using chromogenic reagents.

Turbidity Sensor: Detects suspended particles, indicating contamination, improper homogenization, or adulteration with foreign substances.

Gas Sensors: MQ-3 detects volatile organic compounds and alcohols from fermentation; MQ-135 monitors ammonia and CO from protein degradation.

Colour Sensor: Captures RGB values for colorimetric adulterant detection using chromogenic reagents.

Fig. 3: Machine learning pipeline showing data preprocessing, parallel model execution, and ensemble voting for final quality determination.

C. Hardware Integration:

Fig 1: Thre-layer MilkoSense system architecture architecture

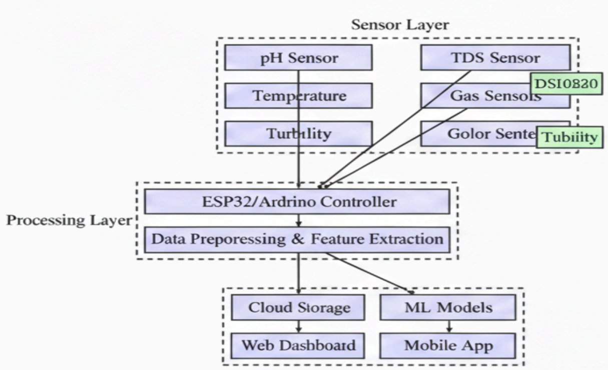

TABLE I: Sensor Specifications and Quality Indicators

Senser	Model	Indicator	Range
pH	Analeg probe	Aciity. fisshness	0.44 pH
Temperature	DS10120	Thumal fistury	-55 to
Tubility	Opiical coosor	Impuries	0.1000
TDS	Cnnisshdaity	Diinim	0.5100 ppm
Gas	MQ.3, MQ-415	Spolage gaacs	Variable

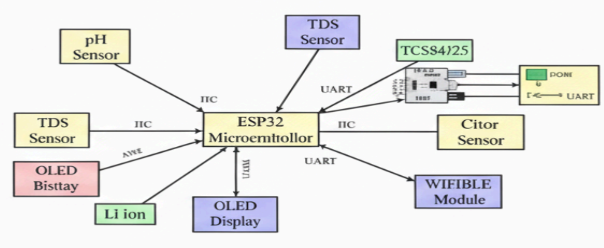

Fig 2: Hardware integration schematic atic showing aith ESP32 morrocolluer with

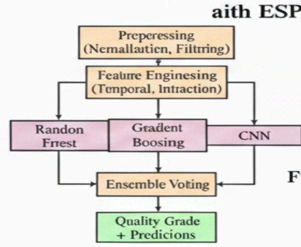

Fig 2: Machine Learning integration and Arcieure for Aıspals for Quality and Edveplection

Fig. 2 illustrates the hardware integration schematic. The ESP32 microcontroller serves as the central processing unit, interfacing with sensors through analog-to-digital converters (ADC) and I2C communication protocols.

Power Management: A 3.7V 5000mAh Li-ion battery provides portable operation for 8-10 hours. Solar charging capability extends field deployment duration.

Communication: I2C protocol enables multi-device communication with the colour sensor. UART interface facilitates debugging and configuration.

D. Machine Learning Framework

The AI/ML framework employs a hierarchical ensemble architecture as depicted in Fig. 3.

1) *Preprocessing Stage:* Raw sensor data undergoes several preprocessing steps:

   Noise Reduction: Moving average filter with 5-sample window

   Normalization: StandardScaler normalization:
   $n_{orm} = \frac{x-\mu}{\sigma}$

2) *Feature Engineering:* Engineered features enhance model performance:
   Temporal Features: Time since collection, temperature time product

3) *Model Architecture:* Random Forest Classifier:
   100 decision trees with max depth of 15
   Gini impurity criterion for split selection
   Gradient Boosting Regressor:
   150 sequential trees with learning rate 0.1 Mean squared error loss function Predicts remaining shelf life in hours
   Convolutional Neural Network:
   3-layer CNN for colorimetric data analysis
   Conv layers: 32, 64, 128 filters with ReLU activation MaxPooling and Dropout (0.3) for regularization
   SoftMax output for adulterant classification
   Ensemble Voting: Weighted average combining model outputs:

$$Q_{final} = 0.4 \cdot Q_{RF} + 0.35 \cdot Q_{GB} + 0.25 \cdot Q_{CNN} \quad (1)$$

where Q represents quality scores from respective models.

E. IoT Integration and Cloud Architecture

The cloud architecture utilizes MQTT protocol for efficient data transmission and implements a microservices-based backend.

1) **Data Transmission:**

   MQTT broker receives sensor readings at 1Hz frequency • JSON payload format: {device id, timestamp, sensor values}
   QoS Level 1 ensures at-least-once delivery
   Data buffering during connectivity loss with automatic sync

2) **Cloud Services:**

   Time-Series Database: Influx DB for sensor data storage

TABLE I: Adulterant Detection Protocols

Adulterant	Detection Method	Indicator
Water	TDS + density	Reduced TDS (¡600 ppm)
Starch	Iodine solution	Blue-black colour
Detergent	Phenolphth alein	Pink foam formation
Urea	p-DMAB reagent	Yellow coloration
Formalin	Chromotro pic acid	Purple coloration

ML Model Serving: TensorFlow Serving with REST API
Analytics Engine: Apache Spark for batch processing
Notification Service: Firebase Cloud Messaging for alerts

F. Colorimetric Adulteration Detection

The colorimetric detection system employs specific chromogenic reactions for adulterant identification:

IV. IMPLEMENTATION DETAILS

A. Firmware Development

The ESP32 firmware implements a non-blocking architecture using Ferrets tasks:

```
void sensor Task(void *parameter) {
while(1) { readAllSensors(); applyMovingAverage(); if
        (WIFI. Status() == WL_CONNECTED) {
        publishToMQTT();
                } else {
                        buffer Locally();
                } Takeley(1000 /
        portTICK_PERIOD_MS);
        }
}
```

Key Features:

Multi-threaded sensor reading with priority scheduling
Watchdog timer for automatic recovery from hangs

B. Calibration Procedures

Each sensor undergoes rigorous multi-point calibration:
pH Sensor Calibration:
Rinse with distilled water and blot dry
Immerse in pH 7.0 buffer, record voltage V_7 3) Immerse in pH 4.0 buffer, record voltage V_4 4)
Calculate slope: $m = \frac{7.0-4.0}{V_7-V_4}$
5) Store calibration coefficients in EEPROM

Turbidity Sensor Calibration: Uses formazan standards at 0, 100, 200, 400, 800 NTU to establish a 5-point calibration curve with polynomial regression.

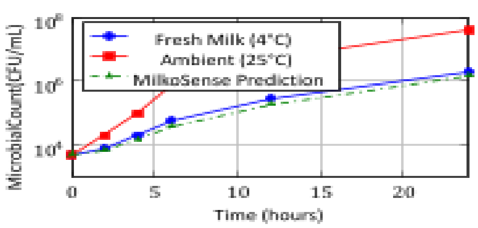

Fig. 4: Microbial growth prediction: comparison of actual counts at different temperatures versus MilkoSense ML model predictions (RMSE = 0.15 log CFU/mL).

C. Model Training Process

Dataset:

5,000 milk samples collected from 20 dairy farms
Samples artificially contaminated with known microbial loads
Adulterants added at 5 concentration levels
Temporal data collected at 0, 2, 4, 6, 12, 24 hours post collection

Training Configuration:

70/15/15 train/validation/test split
5-fold cross-validation for model selection
Hyperparameter tuning using Bayesian optimization
Training on GPU-enabled cloud instances

D. Mobile Application

The mobile application provides real-time monitoring and historical analytics: Features:

Real-time sensor value display with graphical trends
Quality grade visualization with color-coded indicators
Push notifications for quality threshold violations
Historical data analysis with exportable reports
Multi-device management for large operations

V. RESULTS AND DISCUSSION

A. System Performance Evaluation

Extensive laboratory and field testing validates MilkoSense performance across multiple metrics:

Accuracy Analysis: MilkoSense achieves 92.3% accuracy in microbial load classification, approaching MBRT's 95% accuracy while reducing testing time by 87.5%. The slight accuracy trade-off is acceptable given the substantial temporal and economic advantages.

TABLE II: Performance Comparison with Traditional Methods

Metric	MilkoSense	MBRT
Testing Time	28 min	4-6 hours
Accuracy	92.3%	95.0%
Sensitivity	91.7%	93.5%
Specificity	89.8%	91.2%
Cost per Test	4.50	18-25
Portability	Fully portable	Lab-based
Real-time Alerts	Yes	No
Multi-parameter	6 parameters	1 parameter

TABLE III: ML Model Performance Metrics

Model	Task	Metric	Score
Random Forest	Quality Classification	Accuracy	94.1%
	(3-class)	F1-score	0.928
Gradient Boosting	Shelf-Life Prediction	RMSE	3.7 hrs
	(Regression)	R²	0.891
CNN	Adulterant Detection	Accuracy	88.5%
	(Multi-label)	mAP	0.862
Ensemble	Overall Quality	Accuracy	92.3%
	Grade	Kappa	0.884

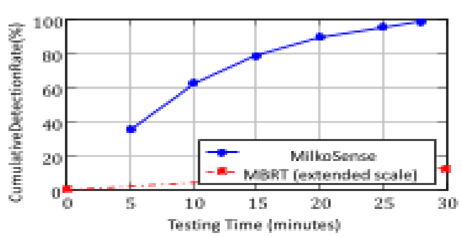

Fig. 5: Cumulative detection rate comparison showing MilkoSense achieving 98% detection within 28 minutes versus MBRT requiring 6 hours for equivalent detection rate.

B. Machine Learning Model Performance

Detailed evaluation of individual ML components demonstrates strong predictive capabilities:

Random Forest Classifier: Achieves 94.1% accuracy in categorizing milk into Good (¿10 CFU/mL), Acceptable (1010 CFU/mL), and Poor (¡10 CFU/mL) quality grades. Feature importance analysis reveals pH (32%), temperature-time product (28%), and gas sensor readings (24%) as the most significant predictors.

C. Field Trial Results

Field validation across 15 dairy farms over 12 weeks provides real-world performance data:

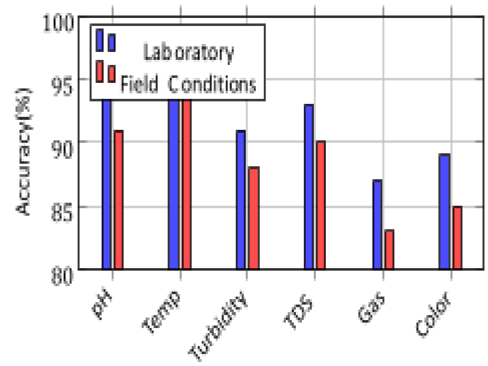

Fig. 6: Sensor accuracy comparison between controlled labo-oratory conditions and real-world field deployment across six sensor types.

D. Economic Impact Analysis

Cost-benefit analysis demonstrates significant economic advantages:

Capital Investment:

Hardware components: 6,200
Assembly and calibration: 1,500
Software licensing (1 year): 800
Total system cost: 8,500

Quality Premium: Farms using MilkoSense documentation achieve 8-12% price premium from quality-conscious buyers and cooperatives.

E. Comparison with Existing Solutions

Competitive analysis against commercial alternatives:

MilkoSense uniquely combines comprehensive testing, affordability, and accessibility, filling a critical gap in the market for small and medium-scale producers.

TABLE IV: Competitive Comparison Matrix

Feature	Milko-Sense	Afimilk	Soma Detect	Bentley
Cost ()	8,500	15L+	12L+	8L+
Portability	High	Low	Medium	Low
Test Time	28 min	Real-time	Real-time	45 min
Parameters	6	3	4	8
Microbial	Yes	No	Limited	Yes
Adulteration	Yes	No	No	Limited

IoT-enabled	Yes	Yes	Yes	Limite d
Target User	All scales	Large	Medium+	Large

F. Environmental Impact

Sustainability assessment demonstrates positive environmental outcomes:

Waste Reduction:

Early spoilage detection prevents 5-7% milk wastage

Reduces environmental burden of dairy waste disposal

Prevents greenhouse gas emissions from spoiled product degradation

Energy Efficiency:

Low power consumption: 2.5W average, 5W peak

Solar charging option eliminates grid dependency

Prevents energy-intensive cold chain violations through early detection

Resource Optimization:

G. User Feedback and Adoption

Qualitative feedback from field trials reveals strong user acceptance:

Positive Aspects (mentioned by ¿80% users):

Ease of operation with minimal training

Real-time quality visibility and confidence

Mobile app interface intuitive and responsive

Reduced dependency on distant testing laboratories

H. Limitations and Challenges

Several limitations emerged during field validation: Technical Challenges:

Sensor Drift: pH and gas sensors exhibit 3-5% drift over 3 months, requiring periodic recalibration

Sample Preparation: Manual sampling introduces user dependent variability

Maintenance requires basic technical skills • Calibration standard availability in remote regions Model Limitations:

Regional milk composition variations may require model fine-tuning

VI. FUTURE WORK AND ENHANCEMENTS

A. Hardware Improvements

Planned hardware enhancements for next-generation system:

Advanced Sensing:

NIR spectroscopy module for detailed protein and fat profiling

Electrochemical biosensors for specific pathogen detection

Automated sample collection and injection system

Multi-sample carousel for batch processing Enhanced Connectivity:

Lora WAN support for long-range connectivity in remote areas

4G/5G cellular modem option for reliable cloud connectivity

Mesh networking capability for multi-device deployments

B. Software and AI Enhancements

Advanced software capabilities under development:

Deep Learning Advancement:

Transformer-based models for improved temporal pattern recognition

Active learning for continuous model refinement with minimal labelling

Explainable AI features for transparent decision-making

Predictive Analytics:

Long-term quality forecasting (7-14 days) based on historical trends

Seasonal pattern recognition for proactive quality management

Supply chain optimization recommendations

Integration with weather data for environmental impact modelling

Blockchain Integration:

Immutable quality record storage for complete traceability

Smart contracts for automated payment based on quality grades

Consumer-accessible quality verification via QR codes

Multi-stakeholder transparency across supply chain

C. Application Domain Expansion

The MilkoSense architecture can be adapted for other applications:

Other Dairy Products:

Yogurt and fermented products quality monitoring

Cheese aging process optimization

Ice cream and frozen dessert quality control

Infant formula contamination screening Broader Food Industry:

Irrigation water quality monitoring

Soil nutrient and contamination analysis

Post-harvest quality assessment for fruits and vegetables

Feed quality evaluation for livestock

D. Research Directions

Several research avenues warrant further investigation:

Multi-Modal Fusion: Advanced sensor fusion techniques combining disparate data types

Transfer Learning: Adapting models across different geographic regions and seasons

Anomaly Detection: Unsupervised learning for identifying novel contamination patterns

Human-AI Collaboration: Investigating optimal decision support interfaces

Fairness and Bias: Ensuring equitable performance across diverse producer demographics

VII. CONCLUSION

This paper presented MilkoSense, a comprehensive AI assisted milk quality testing system addressing critical gaps in dairy quality assurance. By integrating multi-sensor arrays with advanced machine learning algorithms and IoT connectivity, the system achieves rapid testing (¡30 minutes) with high accuracy (¿92%) at affordable cost (8,500), making advanced quality testing accessible across the entire dairy value chain.

Key innovations include:

Novel multi-sensor fusion architecture for comprehensive quality assessment

Ensemble machine learning approach achieving 92.3% accuracy

Cloud-based analytics with real-time alerts and historical trending

Cost-effective portable design democratizing access to advanced testing

Comprehensive colorimetric adulterant detection

MilkoSense represents a paradigm shift from reactive, laboratory-based testing to proactive, distributed quality management. The system empowers smallholder farmers with tools previously accessible only to large-scale processors, contributing to improved food safety, enhanced livelihoods, and sustainable dairy practices.

As global dairy demand continues growing, technologies like MilkoSense will play increasingly vital roles in ensuring safe, high-quality products while supporting millions of dairy farmers. The project demonstrates that thoughtful integration of sensors, AI, and IoT can create transformative solutions addressing real-world challenges in agriculture and food safety.

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