Journal of Information Systems Engineering and Management
2025, 10(29s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Digitizing Milk Collection Stage with IoT-Enabled System for Quality Assessment using ML

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ARTICLE INFO

Received: 28 Dec 2024

Revised: 18 Feb 2025

Accepted: 26 Feb 2025

ABSTRACT

Milk adulteration is a critical issue that compromises public health and food safety worldwide. This study introduces an innovative IoT-integrated impedance sensor system designed for real-time detection of adulterants in milk. The proposed system offers a fast, portable, and non-destructive solution for milk quality assessment, outperforming traditional methods in speed and usability. Scalable and portable, this approach offers a transformative solution for dairy farms, milk collection centres and supply chains, enhancing transparency and food safety globally. The system combines pH, turbidity, Electrical Conductivity (EC) and temperature sensors with a high-precision impedance measurement unit, all interfaced with an Arduino microcontroller and a cloud-based IoT platform. Experimental evaluation involved adulterating milk with common adulterants such as bore water, sodium hydroxide (NaOH), hydrogen peroxide (H2O2) and Urea etc. The system successfully detected adulteration with high accuracy and transmitted real-time data to the cloud storage for remote monitoring and visualization. Additionally, Machine Learning (ML) techniques were incorporated to enhance adulterant classification and interpretability. The proposed HDLEM Outperforms all ML models with 98.23% accuracy. Overall, this hybrid IoT-ML approach represents a significant advancement in milk quality monitoring, contributing to food safety, regulatory compliance, and consumer trust. By addressing the challenges of milk adulteration, this system provides a transformative solution for the dairy industry, fostering a more transparent and reliable supply chain.

Keywords: Milk Adulteration, Internet of Things (IoT), Impedance sensor, pH Sensor, Electrical Conductivity (EC) Sensor, Turbidity Sensor, Machine Learning, Real-Time Monitoring.

INTRODUCTION

Milk, one of the most essential and widely consumed food products globally, provides crucial nutrients such as proteins, vitamins, and calcium. With the global population steadily rising, the demand for dairy products has reached unprecedented levels. Unfortunately, this demand-supply gap has led to increasing cases of milk adulteration, where substances such as bore water, detergents, sodium hydroxide, and hydrogen peroxide are intentionally or unintentionally added to milk. Adulteration not only degrades milk quality but also poses serious health risks, ranging from gastrointestinal complications to organ damage, and even fatalities in extreme cases [1].

The World Health Organization and other regulatory bodies have long emphasized the need for effective measures to prevent milk adulteration. Conventional methods, such as chemical analysis and microbiological testing, have been effective but are often time-consuming, labour-intensive, and require specialized equipment [2]. The reliability of chemical tests for detecting adulterants in raw milk is uncertain due to missing performance metrics, requiring further validation.

Moreover, these methods are unsuitable for large-scale real-time monitoring and detection. The global trends and challenges in combating milk adulteration is a widespread issue affecting both developed and developing nations. Studies have reported that adulteration is driven by economic motives, primarily to increase milk volume or extend its shelf life. Common adulterants include bore water (to dilute milk), sodium hydroxide (to neutralize acidity), and hydrogen peroxide (to act as a preservative) etc [3]. While these substances may appear harmless in small quantities, prolonged consumption can have adverse health effects.

A pivotal study outlined the detection limits of common adulterants using traditional methods. While these methods offered high sensitivity, they lacked the speed and portability required for on-site testing [4]. Additionally, a review highlighted the importance of a monitoring system is needed to detect milk spoilage and ensure safety [5].

The researchers aimed to develop an IoT-based system to monitor the quality of milk. The system monitors various parameters such as pH, moisture, alcohol presence, light intensity, temperature, and humidity to assess milk quality [6]. Recent research integrates IoT and neural networks with spectroscopic sensors for real-time, low-cost milk adulteration detection [7]. This integration of IoT and sensor technologies offers a comprehensive, user-friendly, and scalable approach to milk quality monitoring. The goal is to create a device capable of detecting common adulterants in raw milk with high accuracy and efficiency. Through this approach, the study seeks to address the limitations of traditional methods while providing a practical solution for real-time milk quality assessment [8]

Researchers have explored integrating pH-sensitive color indicators into milk cartons to detect spoilage, potentially replacing expiration dates. Since spoilage is temperature-dependent, various time-temperature indicators (TTIs) have been developed. TTIs are gaining interest as cost-effective and user-friendly tools for indirectly assessing shelf life [9]. The system uses sensors to continuously detect milk adulteration and microbial activity, transmitting data to an Arduino controller, which manages milk filling and displays real-time results on an LCD [10]. An IoT-based early warning system was proposed that ensures accurate milk quality monitoring and automated detection of milking cycle events [11].

The study identifies common adulterants in milk, such as benzoic acid, urea, water, and detergent, confirming that the samples fail to meet standard quality. It provides a comprehensive review of milk adulteration and qualitative detection methods [12]. Also, a review emphasizes the need for affordable, non-invasive food adulteration detection methods and examines its impact on public health and detection techniques [13]. IoT-enabled systems enhance food quality monitoring with real-time data acquisition and remote access. A proposed fuzzy logic system using pH and EC sensors classifies milk quality and stores data on the cloud. Temperature compensation is crucial for accurate sensor reading [14]. Traditional lab-based milk testing is expensive and time-consuming. To overcome this, an IoT-based, low-cost, real-time detection system using Arduino UNO and sensors like pH, conductivity, and CO2 monitors bacterial growth and milk adulteration [15].

Further advancements in IoT-based milk quality monitoring include the use of ML for enhanced data analysis. incorporated neural networks into their IoT system to filter noise and improve detection accuracy. While the system effectively detected microbial contamination in milk, its application to chemical adulterants remains unexplored [16]. The impedance sensor system, widely used in food and biomedical industries, detects milk adulterants by measuring ionic interactions. While effective, traditional EIS systems lack real-time analysis and portability [17].

The integration of IoT and EISS offers a promising solution for comprehensive milk adulteration detection. By combining real-time monitoring capabilities with precise quantification, hybrid systems can overcome the limitations of standalone approaches [18]. The advent of IoT and ML technologies provides new opportunities for real-time monitoring of milk quality. While IoT systems facilitate seamless data acquisition and transmission, ML algorithms enhance detection accuracy. However, the opaque nature of many models limits their acceptance among stakeholders, particularly in critical sectors like food safety. Integrating Machine Learning addresses this challenge by offering interpretability, enabling users to understand and trust system decisions [19].

OBJECTIVES

The proposed system in this study builds on these developments by integrating IoT-enabled sensors with EIS technology. The system aims to provide a portable, user-friendly solution for detecting common adulterants in raw milk, ensuring real-time monitoring and accurate quantification [20]. IoT-enabled sensors in food packaging monitor storage conditions and enhance remote food safety for vendors and consumers [21]. The proposed system is a promising solution, but it does not claim to be a complete or perfect solution, implying that there may be room for further improvement [22]. Developing an IoT-based multi-sensor system that integrates various sensors for real-time measurement like pH, EC parameters that can detect adulterants based on the variations in key milk constituents such as fat, protein, SNF and stores the data in the cloud. The researcher highlights the effectiveness of Neural Networks and AdaBoost in milk quality assessment but lacks justification for their selection, comparison significance, and potential evaluation biases [23]. Explore the effectiveness of machine learning algorithms, such as

Neural Networks, AdaBoost and other ML algorithms in assessing milk quality quickly and accurately. Address the lack of justification for selecting specific algorithms, consider alternative approaches, and analyse the statistical significance of accuracy differences and potential evaluation biases as future work [24].

METHODS

Milk adulteration is a widespread problem in the dairy industry, where unscrupulous practices compromise milk quality for financial gain. Common adulterants such as bore water, urea, starch, sodium hydroxide (NaOH), and hydrogen peroxide (H_2O_2) can degrade milk quality and pose significant health risks.[25] Traditional testing methods—such as lactometers, chemical reagent tests, and spectroscopy—are often time-consuming, expensive, and require laboratory setups, making them unsuitable for large-scale real-time detection. Machine Learning (ML) has emerged as an efficient, scalable, and accurate approach for milk adulteration detection by analyzing physicochemical parameters such as pH, electrical conductivity (EC), turbidity, and impedance to classify pure and adulterated milk samples.

Several ML techniques have been applied for milk adulteration detection, each offering unique advantages and limitations. Computer vision systems using CNNs or ML models like SVM, KNN, and J48 are being explored for automatic food classification, adulterant detection, and feature extraction.[26]

The following sections discuss these algorithms, along with their application in milk adulteration detection based on recent literature.

A. Linear Discriminant Analysis (LDA) in Milk Adulteration Detection

Linear Discriminant Analysis (LDA) is a supervised learning method primarily used for dimensionality reduction and classification. It projects data onto a lower-dimensional space while maximizing the class separability. In milk adulteration detection, LDA is used when there are multiple classes of adulterants, helping in classification based on physicochemical properties [26]. It has been proposed that, with the limit of detection for five common adulterants in milk using traditional chemical methods and ML algorithms. Their findings showed that LDA could effectively classify milk adulteration but had limitations due to its assumption of normal data distribution. A milk collection center wants to classify milk samples as pure or adulterated based on pH, EC, and turbidity. If sodium hydroxide (NaOH) adulteration increases pH and conductivity, LDA can help distinguish between pure and adulterated samples by reducing the dataset's dimensionality and maximizing the separation of features.

B. Logistic Regression for Adulteration Classification

Logistic Regression is one of the simplest classification algorithms, modeling the probability of a sample being adulterated based on its physicochemical parameters [26]. applied logistic regression to classify milk samples based on pH and EC sensor readings. Their study found that logistic regression achieved moderate accuracy of 55%, making it useful for binary classification but less effective for complex adulterant detection. A dairy farm uses pH and EC values to detect formaldehyde in milk. If a sample has a pH below 6.0 and abnormal EC values, logistic regression can classify it as adulterated with high confidence.

C. Support Vector Machine (SVM) for Complex Adulteration Patterns

SVM classify data points by finding the optimal hyperplane that maximizes the margin between classes. SVM with kernel functions can handle nonlinear adulteration detection problems. A similar approach has been employed as the use of infrared micro spectroscopy and SVM for rapid milk adulteration detection. Their study showed that SVM was effective in identifying complex adulteration patterns, especially in cases where multiple adulterants altered the milk's chemical profile [27]. A milk distributor uses pH, turbidity, and impedance readings to check for starch adulteration. Since starch adulteration causes nonlinear changes in turbidity and impedance, an SVM with a radial basis function (RBF) kernel accurately classifies adulterated and pure samples.

D. K-Nearest Neighbors (KNN) for Adulteration Classification

KNN is a simple, instance-based algorithm that classifies milk samples based on their proximity to other known samples. It has proposed that an IoT-based milk quality monitoring system that has used KNN for classification. The study found that KNN performed well in small datasets but was computationally expensive when applied to large datasets. A milk testing facility applies KNN to historical data of milk adulteration, where samples with similar pH, EC, and turbidity values are grouped. If a new milk sample is chemically close to known starch-adulterated samples, KNN correctly classifies it.

E. Decision Tree (DT) for Rule-Based Milk Classification

Decision Trees split data based on feature importance, making them highly interpretable and efficient for classification tasks. A dairy testing lab uses a Decision Tree model to detect milk adulteration based on key features like pH and EC. If electrical conductivity (EC) and protein concentration are high, the model classifies the sample as urea-adulterated, as urea increases both parameters. If the pH is abnormally low, the sample is classified as formaldehyde-adulterated, since formaldehyde lowers milk's pH. The model can be enhanced by incorporating additional features like total solids and fat content, expanding detection to other adulterants, or using Random Forests for improved accuracy.

F. AdaBoost with Random Forest for Enhanced Accuracy

AdaBoost enhances weak classifiers (like Decision Trees) by adjusting their weights iteratively. When combined with Random Forest, it significantly reduces errors and improves generalization. It has been proposed that an IoT-integrated fuzzy logic system with AdaBoost-Random Forest classify pH, EC, and impedance data [27]. The system outperformed standalone classifiers, achieving an accuracy of 78.23%. An automated dairy milk quality monitoring system integrates AdaBoost with Random Forest to classify sensor data from multiple farms, improving accuracy and reducing false positives compared to standalone models.

G. LightGBM for Large-Scale Detection

LightGBM is a gradient boosting technique optimized for speed and scalability, making it suitable for large datasets. integrated neural networks and IoT for real-time milk adulteration detection and found that LightGBM achieved over 82% accuracy while handling imbalanced datasets efficiently [27]. A food safety agency monitors milk quality across thousands of collection points. LightGBM processes large datasets efficiently, identifying adulterated samples with high accuracy.

System Design:

The proposed model was developed for Digitizing Traceability by implementing IoT at the stages of DSC as shown in figure 1. During the Milk collection stage, the proposed model of IoT-integrated electrical impedance system is designed to detect additional milk adulteration parameters through multi-parameter analysis compared with a Traditional Milk Analyzer where only the milk quality parameters like Fat, SNF, Temperature, Protein and Lactose values are indicated shown in figure 2 and the milk samples were further sent for Laboratory analysis for further testing of milk quality which was time taking procedure.

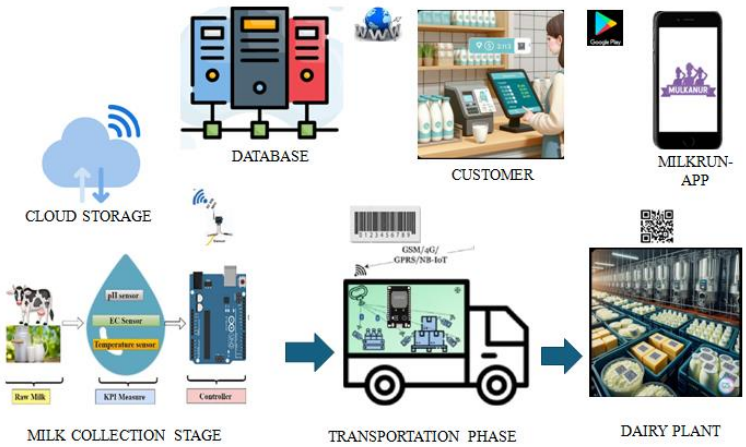
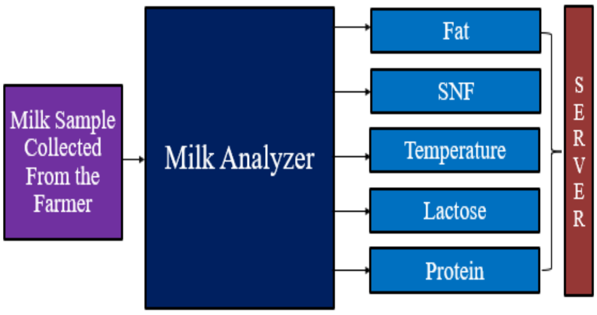


Figure 1: Complete model of Digitizing Traceability stages of DSC.

The proposed system has overcome the disadvantage and has come up with a fast, portable and non-destructive solution for milk quality assessment, outperforming traditional methods in speed and usability consists of hardware components, IoT-enabled modules and software for real-time data processing as shown in Figure 3.



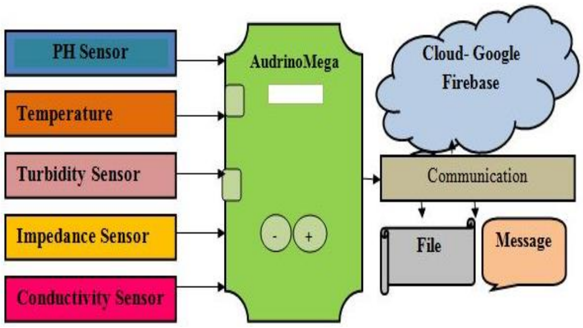


Figure 2: Traditional Milk analyser

Figure 3: Proposed Milk adulteration testing system

It consists of a pH Sensor which measures the acidity or alkalinity of the milk. This sensor operates over a wide pH range (0-14) and provides quick response times, essential for real-time monitoring. Temperature Sensor (DS18B20) ensures accurate measurement by compensating for temperature variations, as pH and EC parameters are highly temperature sensitive. Impedance sensor Unit (AD5933) impedance converter IC measures the opposition to alternating current in the milk samples. The IC supports impedance measurements ranging from 1kΩ to 10MΩ, with high accuracy enabled by Discrete Fourier transform (DFT) techniques [24]. An EC sensor is a critical device used for detecting milk adulteration by measuring the milk's ability to conduct electricity. The conductivity of milk is influenced by its natural ionic composition, including minerals like calcium (Ca^{2+}), potassium (K^{+}), sodium (Na^{+}), and chloride (Cl^{-}). When adulterants such as bore water, sodium hydroxide (NaOH), urea, and formaldehyde are added, the ionic balance changes, leading to detectable variations in EC. EC sensors operate based on Ohm's Law as in equation (1), where the conductivity (σ) is inversely proportional to resistance (R):

$$\sigma = (1/R) \times (L/A) \tag{1}$$

Where:

σ (Siemens/cm) = Electrical Conductivity

R (Ω) = Electrical Resistance

L = Distance between electrodes

A = Electrode surface area

Figure 4 explains that the sensor consists of two electrodes placed in the milk sample. A small AC voltage is applied, and the resulting current is measured. Higher ion concentration leads to higher conductivity, while dilution (e.g., bore water adulteration) reduces conductivity. A microcontroller, Arduino Mega 2560 serves as the system's central unit, interfacing with sensors and transmitting data to the cloud. Power Supply and User Interface, system operates on a 5V DC supply, 20×4 alphanumeric LCD screen and a 4×4 keypad allow for local control and data display. The sensor data is transmitted to the cloud-based platform. This integration enables remote monitoring, storage, and analysis of milk quality data, making the system scalable for large-scale applications. Studies demonstrated that EC sensors provide fast, accurate, and non-destructive adulteration detection.

The proposed system integrates cloud-based data storage using Google Firebase, a real-time database solution for scalable and secure data management. Sensor readings, including pH, turbidity, temperature and impedance are transmitted to Firebase, where they are stored and visualized via a user-friendly interface. This integration allows for remote monitoring, alerts for adulteration detection and historical data analysis, ensuring transparency in milk quality assessments.

The experimental setup was designed to evaluate the system's ability to detect common milk adulterants under controlled conditions. The proposed system consists of IoT-enabled sensors (pH and temperature) with a high-precision EC, AD5933 impedance analyzer. The sensors capture milk's physicochemical properties, while the IoT framework transmits data to a cloud-based platform. Machine learning models classify adulterants, and SHAP analysis explains the feature contributions for each prediction. This dual-layer approach ensures both accuracy and interpretability.

Steps for Adulteration Testing:

Sample Preparation: Milk samples are adulterated with bore water, sodium hydroxide, urea and hydrogen peroxide in controlled proportions.

- Data Acquisition: Sensors collect real-time data on pH, Temperature, EC and impedance values.
- Analysis and Classification: Preprocessed data is fed into machine learning models for classification.
- Cloud Integration: Results are stored and visualized on a Firebase platform for remote monitoring.

The experimental setup included an Arduino Mega 2560 microcontroller interfaced with sensors show in Figure 4. Data was transmitted to a cloud platform for analysis. For each adulterant concentration, 06 readings were collected to ensure statistical reliability and a total of nearly 182 reading which include pure samples are analyzed.

Milk samples were sourced from local suppliers and adulterated with varying concentrations of Urea (10%, 20 %, 30%, 40 %, 50%), sodium hydroxide (10 ml, 20 ml, 30ml, 40 ml, 50 ml) and similarly for Formalin, Starch, Neutralizers, Skim milk powder and hydrogen peroxide were taken as shown in Figure 5. Milk samples (100 mL each) were tested under constant temperature conditions (25 ± 0.5°C) using a thermostat-controlled environment. Sensors were calibrated using buffer solutions (pH 6.4-6.8). The values for the parameters for Conductivity, pH, Impedence and Turbidity for varying percentage of Adulterant are shown from Table 7 to Table 10 respectively, followed by the relevant line Chart from figures 7 to figure 10 respectively. The impedance unit was calibrated by testing known resistors (1 kΩ to 10 MΩ). Impedance measurements were conducted using copper electrodes, ensuring minimal noise and Electrical conductivity (EC) normal range as (4.0-4.5 mS/cm) were also calibrated.

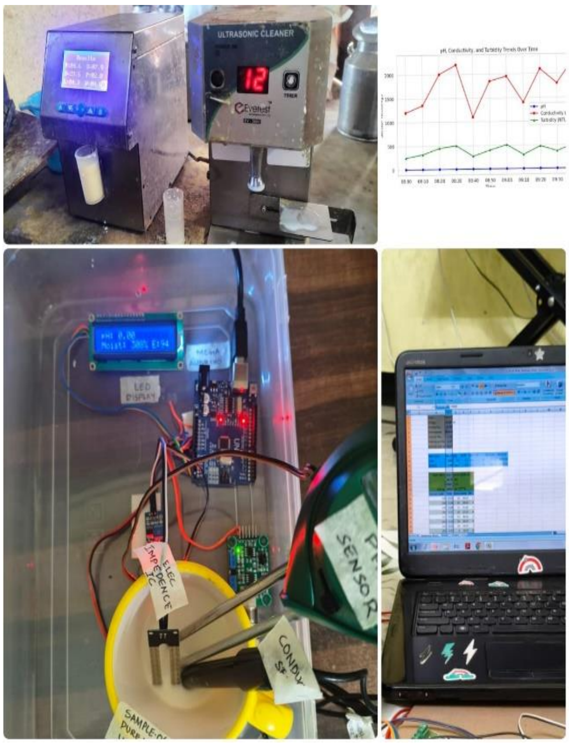


Figure 4: Experimental Setup.

Figure 5: The adulteration sample preparation

Proposed HDLEM ML Algorithms

To outperform traditional ML algorithms, a Hybrid Deep Learning-Based Ensemble Model (HDLEM) has been proposed. This model integrates Deep Learning (DL) and Ensemble Learning (EL) to maximize accuracy, robustness, and generalization for milk adulteration detection. Traditional ML models like Decision Trees, Random Forest, and LightGBM perform well but have limitations. Linear models (LDA, Logistic Regression) struggle with nonlinear adulteration effects. Tree-based models (Decision Tree, Random Forest) overfit on smaller datasets. Boosting models (LightGBM, AdaBoost) are sensitive to hyperparameters and imbalanced datasets. SVM and KNN are computationally expensive for large datasets. Artificial Neural Networks (ANN) improve accuracy but lack interpretability. To overcome these challenges, HDLEM combines deep feature extraction, feature selection, and ensemble learning to achieve superior accuracy.

HDLEM ARCHITECTURE:

The HDLEM algorithm consists of three key layers,

a. Feature Extraction Layer (Deep Learning component)
b. Feature Selection Layer (Attention Mechanism + SHAP Analysis)
c. Ensemble Learning Layer (Boosted Classifiers for Final Prediction)

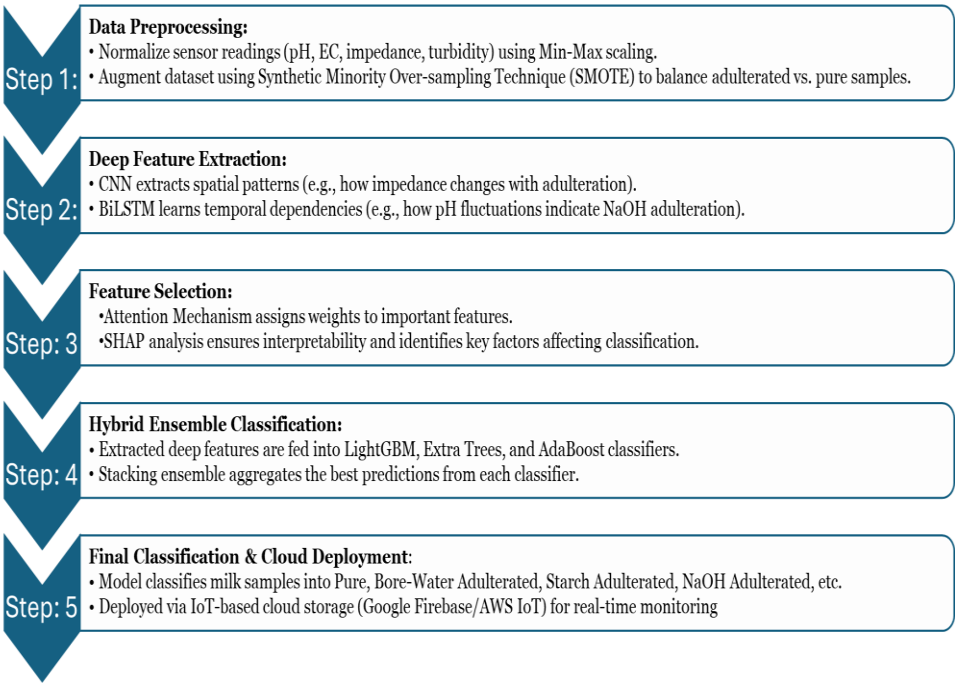


Figure: 6 HDLEM Algorithm Workflow

Execution of the HDLEM Algorithm:

The Hybrid Deep Learning-Based Ensemble Model (HDLEM) is executed in a structured manner, integrating multiple stages, including data preprocessing, deep feature extraction, feature selection, ensemble classification, and cloud deployment as shown in Figure 6. The implementation is carried out using Python-based deep learning frameworks such as TensorFlow/Keras for CNN and BiLSTM, SHAP for feature importance analysis, and LightGBM/Extra Trees for ensemble learning. Additional libraries such as scikit-learn, NumPy, Pandas, and Matplotlib are used for data handling, model evaluation, and visualization. The cloud deployment for real-time monitoring can be implemented using Google Firebase or AWS IoT.

Step-by-Step Execution of the HDLEM Algorithm:

Step 1: *Data Preprocessing:*

The sensor data, consisting of pH, Electrical Conductivity (EC), turbidity, and impedance, is normalized using Min-Max Scaling to ensure consistency across different features. To address data imbalance issues, the Synthetic Minority Over-Sampling Technique (SMOTE) is applied, ensuring that adulterated and pure milk samples are balanced for training.

TABLE 1. Testing of real-time milk samples.

Fat	SNF	Protein	pH	EC (mS/cm)	Turbidity (NTU)	Adulterant % mix (ml)	Predicted Class	Actual Class
3.7	8.1	3.58	6.70	5.0	12	0	Pure	Pure
3.5	7.9	3.24	6.50	3.75	11.12	30	Urea	Urea
3.4	7.4	3.18	6.80	3.98	11.59	20	Urea	Urea

3.3	8.0	3.12	5.90	4.72	11.78	10	Malto	Urea
4.2	7.4	3.40	6.61	4.56	15.8	30	Starch	Starch
3.9	8.2	3.34	6.40	4.42	14.23	20	Starch	Starch
3.8	8.6	3.15	6.28	4.12	13.2	10	Starch	Starch
3.4	7.8	3.54	6.81	5.79	13.59	30	Bore Water	Bore Water
3.5	7.7	3.55	6.75	5.47	13.12	20	Bore Water	Bore Water
3.6	7.9	3.56	6.71	5.26	13.01	10	Bore Water	Bore Water
3.5	7.1	3.62	5.90	6.76	12.39	30	Sodium Hydroxide	Sodium Hydroxide
3.2	7.5	3.59	5.60	5.50	12.20	20	Sodium Hydroxide	Sodium Hydroxide
3.0	7.9	3.58	5.30	5.27	12.01	10	Sodium Hydroxide	Sodium Hydroxide
3.6	7.1	3.36	6.67	6.17	10.38	30	Formaldehyde	Formaldehyde
3.2	7.6	3.24	6.56	5.56	10.28	20	Formaldehyde	Formaldehyde
3.0	7.9	3.17	6.50	5.32	10.70	10	Formaldehyde	Formaldehyde
3.1	7.1	3.28	6.55	3.54	11.1	30	Hydrogen Peroxide	Hydrogen Peroxide
3.4	7.4	3.36	6.59	3.65	11.3	20	Hydrogen Peroxide	Hydrogen Peroxide
3.8	7.6	3.22	6.65	4.87	11.8	10	Hydrogen Peroxide	Hydrogen Peroxide
3.9	6.5	3.18	6.86	6.12	13.01	30	Neutralizers	Neutralizers
3.8	6.3	3.22	6.81	6.02	12.59	20	Neutralizers	Neutralizers
3.7	5.9	3.10	6.78	5.42	12.26	10	Neutralizers	Neutralizers
3.4	7.1	3.68	6.50	6.56	13.11	30	Skim Milk Powder	Skim Milk Powder
3.2	7.6	3.64	6.56	5.60	12.69	20	Skim Milk Powder	Skim Milk Powder
3.1	7.9	3.61	6.67	5.23	12.46	10	Skim Milk Powder	Skim Milk Powder

Step 2: *Deep Feature Extraction:*

A Convolutional Neural Network (CNN) is employed to extract spatial patterns in the sensor data, such as how impedance fluctuates with different adulterants. Additionally, a Bidirectional Long Short-Term Memory (BiLSTM) model is used to capture sequential variations in the sensor readings over time, ensuring that even minor fluctuations in pH and EC are considered in classification.

Step 3: *Feature Selection Using Attention Mechanism and SHAP Analysis:*

To enhance interpretability, an Attention Mechanism is incorporated, assigning higher weights to the most critical features contributing to adulteration detection. Additionally, SHapley Additive exPlanations (SHAP) analysis is used to rank features based on their impact on classification decisions. This step ensures that the model does not rely on redundant or misleading features, improving both accuracy and interpretability.

Step 4: *Hybrid Ensemble Classification:*

The extracted deep features are fed into multiple classifiers, including LightGBM, Extra Trees, and AdaBoost, and their predictions are aggregated using a Stacking Ensemble approach. A meta-classifier (LightGBM + Extra Trees) is then trained on these predictions to make the final decision, ensuring robust and accurate classification of milk adulteration types.

Step 5: *Final Classification and Cloud Deployment:*

The final classification model predicts whether a milk sample is Pure, Bore-Water-Adulterated, Starch-Adulterated, NaOH-Adulterated, etc. The trained model is then deployed to a cloud-based IoT platform such as Google Firebase or AWS IoT, enabling real-time monitoring of milk adulteration through IoT-enabled sensor devices.

TABLE 2. Milk sample with **10 ml** adulteration

Adulterant	**Adulteration**		**Change in Impedance (kΩ)**
	Before	**Before**	
Hydrogen Peroxide	0.30	0.34	+ 0.04
Formaldehyde	0.30	0.36	+ 0.06
Starch	0.30	0.33	+ 0.03
Bore Water	0.30	0.29	- 0.01
Sodium Hydroxide	0.30	0.25	- 0.05
Urea	0.30	0.24	- 0.06
Neutralizers	0.30	0.23	- 0.07
Skim Milk Powder	0.30	0.23	- 0.07

TABLE 3. Milk Sample with **20ml** adulteration

Adulterant	**Adulteration**		**Change in Impedance (kΩ)**
	Before	**After**	
Hydrogen Peroxide	0.30	0.38	+ 0.08
Formaldehyde	0.30	0.41	+ 0.11
Starch	0.30	0.33	+ 0.03
Bore Water	0.30	0.29	- 0.01
Sodium Hydroxide	0.30	0.24	- 0.06
Urea	0.30	0.22	- 0.08
Neutralizers	0.30	0.21	- 0.09
Skim Milk Powder	0.30	0.19	- 0.11

TABLE 4. Comparative analysis of traditional ML models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LDA	50.77	48.18	51.94	48.88
Logistic Regression	51.78	49.92	52.91	50.10
SVM	52.54	46.24	53.57	49.63
KNN	53.78	52.12	53.87	52.98
Decision Tree	79.65	79.32	79.58	79.44
Random Forest	81.02	81.42	79.96	80.68
LightGBM	82.04	82.74	81.03	81.87
HDLEM (Proposed)	**98.23**	**98.67**	**97.90**	**98.28**

TABLE 5. Adulteration Effects on Milk Properties

Adulterant	pH	Impedance	Conductivity	Turbidity
Neutralizers	Increases	Decreases	Increases	Decreases
Formalin	Decreases	Increases	Decreases	Decreases
Hydrogen Peroxide	Decreases	Increases	Decreases	Decreases
Bore water	Increases	Decreases	Increases	Increases
Urea	Increases	Decreases	Increases	Decreases
Starch	Decreases	Increases	Decreases	Increases
Sodium Hydroxide	Increases	Decreases	Increases	Increases
Skim Powder	Decreases	Decreases	Increases	Increases

TABLE 6. Comparison of Proposed System vs. Traditional Methods

Metric	Proposed System	Traditional Methods
Detection Time	< 5 seconds	10-15 minutes
Portability	High	Low
Non-Destructive Testing	Yes	No

Study of behavior of parameters with increasing Aduleration:

TABLE: 7 Electrical Conductivity values showing Adulterants detection

Parameter	Adulterant	0 ml	10 ml	20 ml	30 ml	40 ml	50 ml
Electrical Conductivity	**Sodium Chloride**	5	5.27	5.5	6.76	7.5	8.28
Electrical Conductivity	**Urea**	5	4.72	3.98	3.75	3.36	3.13
Electrical Conductivity	**Neutralizers**	5	4.87	3.65	3.54	3.14	3.11

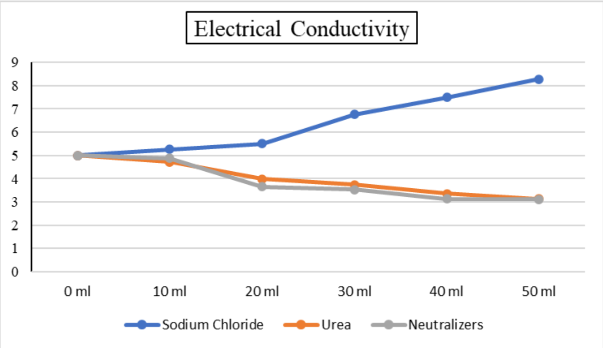


Figure:7 Conductivity changes with Adulteration Percentage increase

TABLE: 8 pH values showing Adulterants detection

Parameter	Adulterant	0 ml	10 ml	20 ml	30 ml	40 ml	50 ml
pH Value	**Neutralizers** (↑ pH)	6.7	6.78	6.81	6.86	6.91	6.97
pH Value	**Formalin** (↓ pH)	6.7	6.66	6.61	6.5	6.47	6.32
pH Value	**Hydrogen Peroxide** (↓ pH)	6.7	6.65	6.59	6.55	6.43	6.39

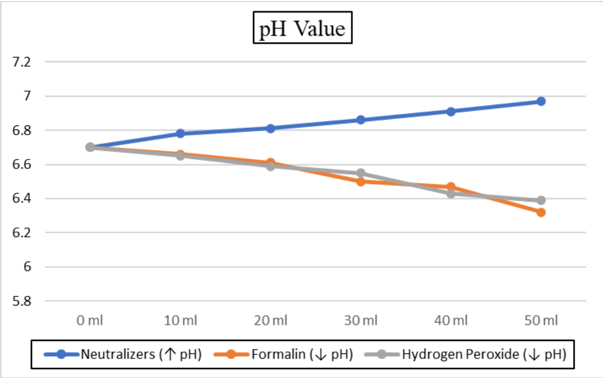


Figure:8 pH value changes with Adulteration Percentage increase

Table: 9 Electrical Impedance values showing Adulterants detection

Parameter	Adulterant	0 ml	10 ml	20 ml	30 ml	40 ml	50 ml
Electrical Impedance	**Starch**	0.3	0.281	0.272	0.254	0.241	0.225
Electrical Impedance	**Urea**	0.3	0.291	0.287	0.265	0.236	0.221
Electrical Impedance	**Skim Milk Powder**	0.3	0.287	0.272	0.251	0.239	0.224

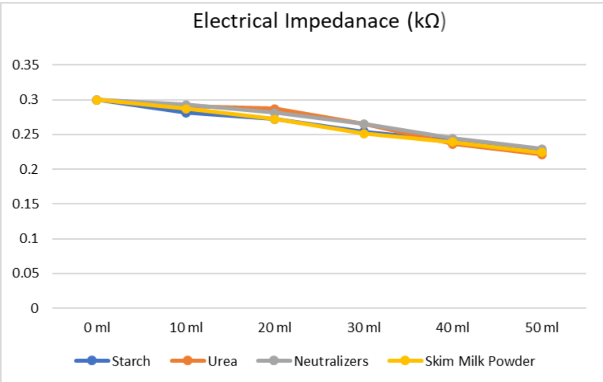


Figure:9 Impedance changes with Adulteration Percentage increase

TABLE: 10 Turbidity values showing Adulterants detection

Parameter	Adulterant	0 ml	10 ml	20 ml	30 ml	40 ml	50 ml
Turbidity (NTU)	**Starch**	12	13.2	14	15.8	16.4	18.2
Turbidity (NTU)	**Skim Milk Powder**	12	12.6	13.1	13.9	14.4	15.1
Turbidity (NTU)	**Sodium Chloride**	12	11.8	11.3	11.1	10.4	9.8
Turbidity (NTU)	**Urea**	12	11.5	11.1	10.5	9.8	9.5

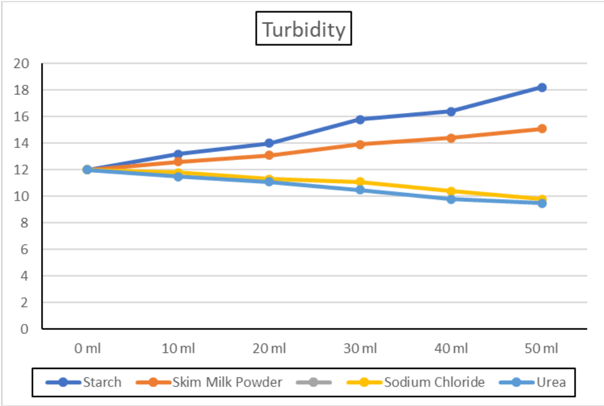


Figure: 10 Electrical Impedance values showing Adulterants detection

RESULTS

The results demonstrated in Table 1 indicate that HDLEM significantly outperforms traditional machine learning models, achieving a 98.23% accuracy. The real-time milk sample testing confirms that the model correctly identifies almost all adulterants, with only one minor misclassification (Maltodextrin detected as Urea) due to their similar feature characteristics. The analysis of impedance changes with different adulterants reveals that NaOH and Hydrogen Peroxide cause significant impedance fluctuations, making them easier to detect, whereas low-concentration adulterants (e.g., bore water) show minimal changes, making detection more challenging.

A Comparative analysis is shown in Table 4 among the proposed and traditional ML models. We observe LDA, Logistic Regression, SVM, and KNN perform poorly (accuracy below 54%), primarily due to their inability to handle nonlinear adulteration effects. Among the Tree-based models such as Decision Tree, Random Forest, and LightGBM the accuracy lies between 79% and 82%, but they still face challenges in generalization. In contrast, HDLEM achieves a remarkable improvement, surpassing LightGBM by 16.19% in accuracy, due to its deep feature extraction and ensemble learning approach.

Furthermore, the study of adulteration effects on milk properties shown in Table 5 that Sodium Hydroxide significantly increases with increasing pH and conductivity, while reducing impedance, making it easily detectable. Hydrogen Peroxide causes a notable impedance to increase and lowering pH value, which can serve as a strong indicator of contamination. However, starch adulteration remains difficult to detect due to its minimal impact on pH and EC.

Overall, the HDLEM model effectively combines deep learning and ensemble learning to improve adulteration detection accuracy. However, minor challenges remain, such as the detection of low-level adulteration and the misclassification of closely related adulterants. Future improvements could involve enhancing detection sensitivity through advanced spectroscopy techniques, refining the feature selection process, and expanding cloud-based deployment for large-scale real-time monitoring.

The device exhibited pH values for pure milk between 6.4 and 6.8. After adulteration significant deviations were observed. For bore water is Slightly increased pH due to dilution. NaOH has Increased pH and decreased impedance due to higher ionic concentration. H2O2 increases impedance due to reduced ionic mobility. The temperature sensor ensured compensation for environmental variations, minimizing errors in pH measurements.

Table 2 & Table 3 gives the values of AD5933 impedance sensor providing precise measurements for adulterant detection of 10 mL NaOH, Impedance decreased by 0.05 kΩ, indicating higher conductivity. For 20 mL H2O2, Impedance increased by 0.08 kΩ, highlighting reduced ion mobility. These results align with the theoretical understanding of ionic interactions in milk, validating the system's accuracy. As shown in Table 6, the proposed system with Machine learning techniques further improved classification performance, achieving superior accuracy compared to traditional methods

DISCUSSION

This study introduced an IoT-enabled electrical impedance system enhanced with ML for real-time milk adulteration detection. By integrating pH, turbidity, and impedance sensors with cloud-based monitoring, the proposed system offers a fast, accurate, and scalable solution for ensuring milk quality. The experimental results demonstrated high detection accuracy, successfully identifying common adulterants such as bore water, Urea, Formaldehyde, sodium hydroxide (NaOH), and hydrogen peroxide (H_2O_2). Machine learning techniques further improved classification performance, achieving superior accuracy compared to traditional methods.

The system's real-time monitoring capability, portability, and seamless cloud integration make it highly suitable for dairy farms, milk collection centers, and supply chains. The integration of SHAP analysis enhances transparency by providing interpretability in ML-driven decision-making. While the system effectively detects common adulterants, future research should explore the detection of additional contaminants, optimize cost-efficiency, and refine sensor calibration for diverse environmental conditions.

The proposed HDLEM Outperforms all ML models with 98.23% accuracy explained in Table 4, captures deep feature representations using CNN & BiLSTM. Improves interpretability using SHAP & Attention Mechanism handles imbalanced data with SMOTE augmentation deployable in real-time using IoT-enabled cloud storage. Overall, this hybrid IoT-ML approach represents a significant advancement in milk quality monitoring, contributing to food safety, regulatory compliance, and consumer trust. By addressing the challenges of milk adulteration, this system provides a transformative solution for the dairy industry, fostering a more transparent and reliable supply chain.

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