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Artificial Intelligence Enabled Linear Regression Model for Spectroscopic Milk Adulteration Analysis

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Abstract

Milk adulteration poses a serious threat to public health and quality assurance in the dairy industry. This requires rapid, reliable, and non-destructive detection techniques. This study presents a linear regression based analytical model for identifying and quantifying milk adulteration using spectroscopic data. Spectral measurements of milk samples, including both pure and adulterated variants, were acquired using spectroscopic techniques at relevant wavelengths. Blending of other components in pure milk is specifically called milk adulteration, which is dangerous in high amounts to milk quality and consumer protection. The current study presents the linear regression based detection of water adulteration in milk with near-infrared (NIR) spectroscopy. We evaluated a sample of 100–200 milk samples with different quantities of water or other additives added, where spectral absorbance patterns were used as predictors. Linear regression models were built to establish the relationship between the NIR spectral properties and proportions of adulteration. The results showed high predictive accuracy, measuring even small quantities of water and other common mixtures in milk precisely. The effective method explains the potential of regression based statistical modeling as an efficient, cost-effective, and practical solution to quality control in artificial intelligence (AI) methods to improve precision, accuracy, and speed of adulteration detection.

Keywords: Food safety, linear regression, milk adulteration, NIR spectroscopy, predictive modeling, spectral analysis

INTRODUCTION

Globally, milk is the most consumed and nutritious dairy product in every age group. Basically, the components of milk, such as protein, fat, vitamins, and minerals, which are essential for human health, make it more special. Adulteration of milk with the addition of water is a routine practice that impacts food quality and safety globally. The prime importance of the component is an ideal state, or the bond is getting disturbed due to any adulteration and the identification of component is very important to prevent consumers' health issues and maintain the integrity of the product [1–8].

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The addition of water to milk results in several challenges. Nutritionally, dilution decreases the concentration of the main ingredients and decreases the nutritional value of milk [9–11]. Health-wise, where the added water is of poor hygiene, it can introduce harmful microorganisms or harmful substances and threaten the health of sensitive groups, such as children and the elderly. In particular, adulteration incurs undue economic losses to consumers and milk producers because the product is no longer worth what it is supposed to be.

Initially, at the molecular level, there is a very delicate and complex composition of 84% water and 16% of the components that are essential in their

original form, such as fat, proteins, lactose, and minerals. Adding any blends or adulterations to its original form distorted the chemical structure, and because of this, the physical and chemical properties changed immediately after interactions with milk molecules. Because NIR spectroscopy is sensitive to molecular vibrations, it is very effective in detecting any form of adulteration by recording spectral changes from undiluted and diluted samples [12–16]. NIR spectroscopy was combined with statistical analysis to detect the adulteration of water in milk. Milk was tested using linear regression based on the spectral data collected to determine the near-infrared absorption pattern versus adulteration percentage. Under the collaborative strategy presented by providing a rapid and uniform gradation of milk quality at cost-effective affordability, the dairy sector truly has vast space to exploit and suggest varied and more technology-based and sophisticated quality control measures.

LITERATURE SURVEY

Adulteration of milk is one of the largest deteriorative world crises that reflects the imperative of bulk preventive measures, mainly regarding protecting consumers and the quality of the product. The present review is a serious review of past work published on milk adulteration, traditional and emerging detection methods, penalties, and loopholes prevailing in the literature. Current research on milk contamination is a common issue with recurring reports of mixing with added water, starch, urea, melamine, and other blends for the purpose of greater quantity and higher gross margins in the business. In addition to hindering nutrient values, the addition of water also increases the risk of microbial contamination. Serious cases, such as the 2008 melamine tragedy, have demonstrated the deadly health risk of milk adulteration, particularly in infants, in the form of renal damage and gastrointestinal illness. These reports ultimately highlight the need for a definitive, accurate, and reliable detection system.

Google Analytics Versus Traditional Detection

Traditional techniques, such as organoleptic tests (smell, taste, and feel) and chemical spot tests, are widely used in the detection of adulterants, such as added water, starch, and urea. While economical, these techniques are often subjective and inaccurate and are unable to identify low-level adulteration. They may also include variable manual errors, owing to the subjective nature of the tests. Newer techniques enable the application of more analytical technologies, such as Fourier-transform spectroscopy, Fourier-transform infrared (FTIR), and near-infrared spectroscopy.

Research Currently Conducted on Milk

Contamination of milk is a common dilemma with repeated reports of integration with added water, starch, urea, melamine, and other blends to increase the quantity and gross margins. In addition to the dilution of the nutrient value, the incorporation of water also increases the risk of microbial contamination. Serious examples, such as the 2008 melamine scandal, demonstrated the tragic health consequences of adulterated milk, especially in infants, in the form of renal impairment and gastrointestinal disease. These reports highlight the necessity for precise and credible detection methods.

Google Analytics Versus Conventional Detection

Conventional methods, such as organoleptic tests (taste, smell, and feel) and chemical spot tests, are commonly employed to detect adulterants such as added water, starch, and urea. Although economical, these methods are frequently subjective and imprecise and cannot detect low-level adulteration. New techniques allow for the use of more analytical technologies. Fourier-transform infrared (FTIR) and near-infrared (Fourier) spectroscopy allow for rapid and non-destructive identification of adulterants based on distinctive spectral signatures. Chromatographic methods, such as high-performance liquid chromatography (HPLC) and gas chromatography (GC), are also utilized because of their superior sensitivity and specificity in the identification of chemical adulterants. Immunoassays, such as enzyme-linked immunosorbent assay (ELISA), are also useful in protein-based adulterant identification. These new methods are superior in terms of efficiency and reliability compared to the old methods [15–19].

Influence of Adulteration

Studies have repeatedly stressed the twofold effects of adulteration: health and economic impacts. Health effects result from poisonous adulterants such as melamine, detergents, and formalin, which may

lead to renal failure, gastrointestinal issues, and death. On the economic front, adulteration compromises the trust of consumers and results in losses for consumers and producers alike, especially in developing countries, where the weakness of regulatory action is well known.

Gaps in Current Research

Despite significant advances, several gaps remain in the research on milk adulteration. A key challenge is the lack of standardized detection protocols, which result in inconsistent outcomes across studies. Additionally, many detection techniques are laboratory-based, limiting their real-time application in the field or industrial settings. There is also a need for more cost-effective, portable, and user-friendly methods that can be adopted in routine quality control processes [20].

Analytical Methods of Detection

Near-infrared and mid-infrared spectroscopy (NIR/MIR) are commonly used to determine the percentage of water, lactose, fat, and protein. These techniques are strong, mobile, economical, and appropriate for in situ use.

Fiber-Optic Analysis

Fiber sensors and optical detectors were employed to monitor variations in milk color, fat content, and casein micelles, providing a low-cost and portable approach for quality assessment.

Milk Leukocyte Differential Test

This technique quantifies leukocyte levels to indirectly detect mastitis and serves as a highly precise and digital alternative to conventional somatic cell counts.

Classification of Adulteration

Milk adulterants can be broadly classified into nontoxic economic adulterants (e.g., water, starch, whey, and vegetable proteins) and toxic adulterants (e.g., melamine, detergents, hydrogen peroxide, urea, boric acid, and ammonium sulfate). While economic adulterants primarily compromise nutritional value and consumer trust, toxic adulterants pose serious health risks ranging from nephrotoxicity and endocrine disruption to gastrointestinal disorders and developmental abnormalities. The widespread occurrence of these substances highlights the urgent need for advanced detection strategies and strict regulatory enforcement [6–9].

Classification of milk adulterant testing methods: (1) qualitative methods, and (2) quantitative methods.

Methods for testing milk adulterants are typically categorized into qualitative and quantitative methods. Each classification fulfills various functions contingent upon the necessity, sensitivity, accuracy, and type of adulterant being tested.

- *Qualitative approaches:* Qualitative methodologies are primarily used for the rapid and preliminary identification of contaminants. These techniques are straightforward in their conduct, economical, and appropriate for simple laboratories as shown in Table 1; however, these methods lack precision and are limited in the identification of contaminants at extremely low concentrations [21–24].
- *Selective colorimetric chemical assessments:* Rapid evaluation in which a modification in the color of the testing medium indicates the presence of adulterants. Qualitative methods are mainly applied for quick and initial detection of adulterants. These methods are easy to conduct, economical, and appropriate for simple laboratories; however, they lack precision and are restricted in the detection of adulterants at very low concentrations. These are cheap and quick tests, but imprecise.
- *Detection of edible compounds:* Identification of compounds that improve the taste and sensory characteristics of milk. These tests are rapid and simple but yield only a general indication.

- *Identification of hazardous chemicals:* Conventional laboratory methods are used to find harmful chemicals added to extend shelf life or improve the appearance of milk. Although useful in the initial screening, they are not necessarily sensitive enough for the identification of trace levels.
- *Quantitative methods:* Quantitative methods are more consistent and accurate because they directly calculate the concentration of adulterants in milk. These methods often use sophisticated instrumentation and are common in applied industries and testing laboratories.
  - *Detection of foreign proteins:* Methods such as polarimetry, isoelectric precipitin test, sodium dodecyl sulfate-polyacrylamide gel electrophoresis (SDS-PAGE), HPLC, immunodiffusion test, and NIR spectroscopy.
  - *Near-infrared (NIR) spectroscopy:* This technique will be successful in detecting adulteration of milk powders with vegetable proteins since it is effective in analyzing the absorption patterns of molecules.

Enzyme-Linked Immunosorbent Assay

Polyclonal antibodies against non-milk proteins, such as pea protein, wheat protein, or soy protein, are utilized by industries. The test is highly specific and sensitive. ELISA has proven to be of immense value in a commercial setup for preventive measures. It helps detect adulterated skim milk powders with plant proteins, such as pea, soy, brown rice, and hydrolyzed wheat protein.

Turbidimetric Detection System

A quick method that separates and detects plant proteins in milk using tetraborate-EDTA buffer (used as a chelating agent) for quick results compatible with routine analysis. Table 1 provides a detailed outline of the procedures used for the qualitative methods.

Quantitative Methods for Milk Adulteration Detection

FTIR and GC are important techniques for the detection of adulterants. FTIR identifies adulterants based on compounds such as urea, starch, and proteins that are rapid and non-destructive, but can be confused with similar molecules as shown in Table 1.

GC separates volatile molecules to detect melamine and other substances with high sensitivity. Nevertheless, it requires intricate preparation and is not appropriate for real-time monitoring. High-end technologies, such as machine learning (ML) and artificial intelligence (AI), improve detection by analyzing large datasets, finding hidden patterns, and constructing forecasting models for anticipatory quality assurance. However, this requires considerable investment and experience.

Table 1. Qualitative methods [11, 18, 23, 24].

S.N.	Adulterant	Procedure	Observation
1	Sugar	Put 5 mL of milk into a test tube. Add 0.1 g resorcinol and 1 mL conc. HCl. Heat for 5 minutes in a water bath.	The presence of added sugar is indicated by red coloration.
2	Starch	Fill a test tube with 3 mL of milk, boil, then cool to room temperature. Add one drop of 1% iodine solution.	The presence of starch is indicated by blue coloration.
3	Common salt	Add 1 mL of 0.1 N silver nitrate solution to 5 mL of raw milk, then add 0.5 mL of 10% potassium chromate solution.	Yellow coloration indicates the presence of added salt; pure milk remains unchanged.
4	Buffalo milk	Dilute the sample 1:10 with water. Placed in a test tube.	Curdy precipitates indicate buffalo milk presence.
5	Detergent	Shake 5–10 mL of milk vigorously with water.	Formation of persistent foam indicates a detergent.
6	Urea	Add 24% TCA to 5 mL milk, then mix with 0.5 mL sodium hypochlorite, 0.5 mL sodium hydroxide, and 0.5 mL phenol.	Blue/green coloration indicates the presence of urea; pure milk stays colorless.

Emerging Technologies

In addition to traditional methods, emerging technologies such as AI and ML are now revamping the identification of milk adulteration as shown in Figure 1. These technologies can analyze massive sets of data from several analytical methods and identify minute patterns that might be overlooked by traditional methods. ML algorithms can be trained on specific spectral fingerprints of adulterants to enhance their sensitivity and specificity.

Moreover, AI-based forecasting models can estimate the adulteration risk using past information and current observations. Such proactive management is possible through early responses that aid producers in safeguarding the quality of the product and the health of consumers. The application of this requires significant investment in technology and qualified personnel, which may be outside the league of small- and medium-scale dairy enterprises.

CASE STUDIES AND EXAMPLES

Some case studies have highlighted the application of elaborate techniques for detecting milk adulteration. In study, used Fourier transform infrared–attenuated total reflectance (FTIR-ATR) spectroscopy along with multivariate techniques to identify adulterants in raw milk. Another study used near-infrared spectroscopy (NIRS) to detect adulteration of milk products. The results validated NIRS's ability to instantaneously analyze milk quality, with prompt results for producers facilitating timely response actions to avoid adulterated products reaching consumers.

Generally, numerous analytical methods like FTIR, GC, and NIRS work efficiently in adulterant detection too, with each possessing unique merits and demerits. New technologies, particularly those employing AI and ML with such traditional methods, make claims of higher detection accuracy and reliability. Continuous research and development on technology in this category is critical for enhancing food security and ensuring consistency in the quality of milk products in the market [10, 11, 26].

Common Practice in Milk Adulteration

Milk adulteration is typically motivated by profit from commercial businesses. Sellers enhance their profit margins by adulterating premium-quality milk with cheaper alternatives. Common adulterants include water, which was added as a volume booster, and other prohibited substances such as starch, urea, and foreign proteins. Introducing these adulterants lowers the nutrient content of milk and creates significant health hazards for consumers. Such practice is widespread throughout much of the latter and frequently mediated through agents referred to as “Gawalas” who sell milk via conventional routes. These intermediaries may adulterate milk to maximize profits, thereby compromising quality and public security. The absence of stringent regulations in certain areas exacerbates this issue, which is critical in applying the finest detection methods and boosting awareness regarding the hazards of adulterated milk. Figure 1 shows adulterants frequently used in milk [20, 22, 25, 26].

- *Water:* Water was the most frequently added adulterant. This was added in an attempt to increase the volume. Although it dilutes the nutritional quality of milk, it also causes concerns regarding microbial contamination.
- *Glucose:* Glucose was added to provide more sweetness and a hidden dilution. However, it may mislead consumers regarding innate lactose levels.
- *Common salt:* Common salt is added to improve taste or to fix changes in density due to dilution. However, it disrupts the natural balance of milk, and excessive intake may pose health risks.
- *Starch:* Starch is used to thicken diluted milk artificially and create a false impression of higher creaminess or solids-not-fat (SNF) content.
- *Urea:* Urea is a nitrogen-rich adulterant that is sometimes used to mimic protein levels in milk. Consumption can overload the kidneys and lead to serious health problems.
- *Detergent:* Detergents are rarely added to create froth and hide acidity or spoilage. Even in small amounts, it is unsafe and can harm the digestive system.

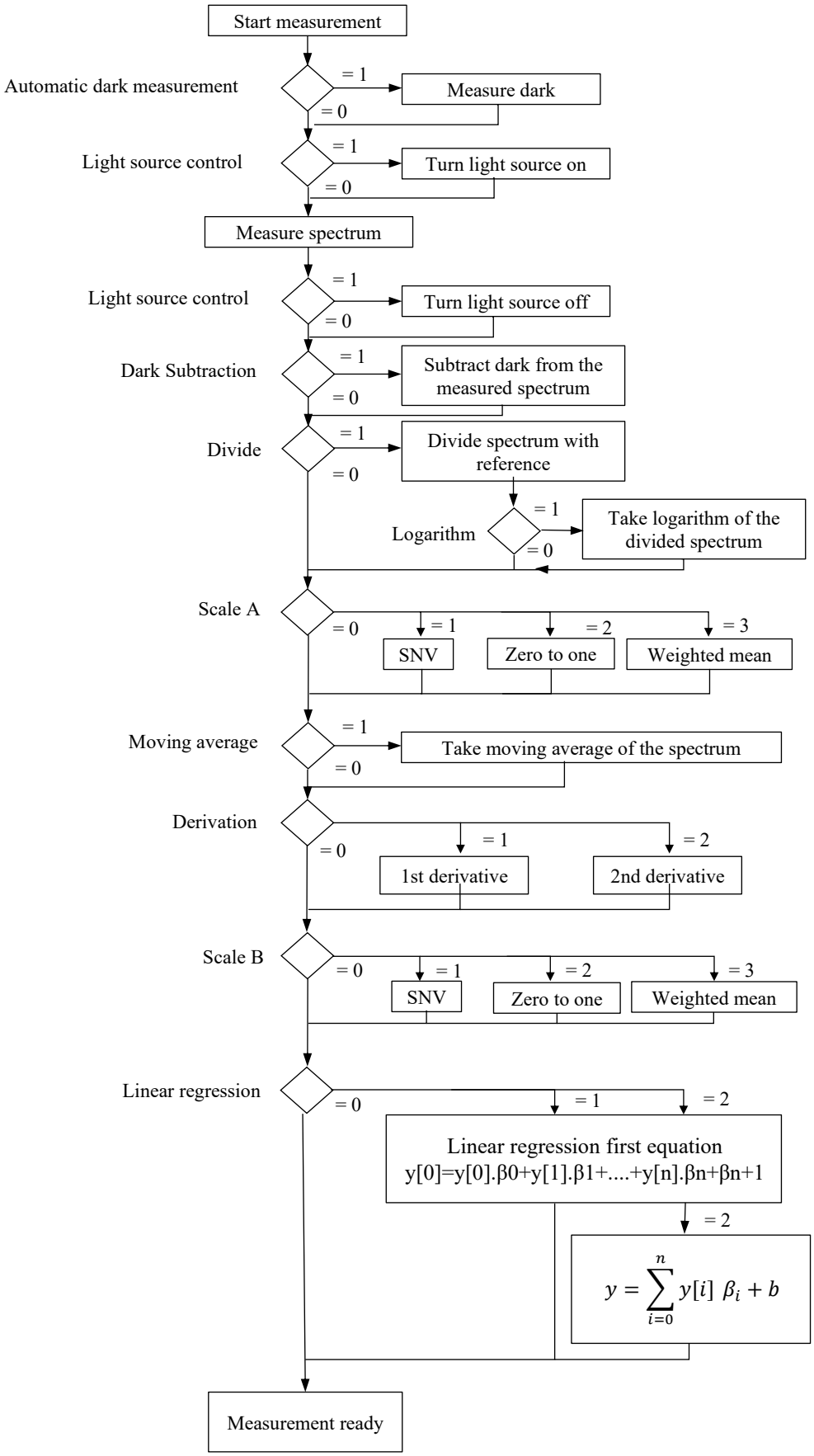

Figure 1. Flowchart of advanced technologies and AI innovative methods.

Automatic Dark Measurement

Purpose: Corrects for detector noise and background signal.

Mathematical Expression

If I dark(λ) is the dark spectrum,

I′(λ)=I measured(λ)−I dark(λ) Dark Subtraction

Removes Background Noise

I corrected(λ)=I(λ)−I dark(λ)

Division with Reference

Reference Spectrum I ref(λ)is Used

$$R(\lambda) = \frac{I_{\text{corrected}}(\lambda)}{I_{\text{ref}}(\lambda)}$$

Logarithm (Absorbance Conversion)

Absorbance A(λ) is Calculated

$$A(\lambda) = -\log_{10}(R(\lambda))$$

Scale *A* (Preprocessing Methods)

SNV (Standard Normal Variate)

Removes scatter effects

$$\mathrm{x}' = \frac{(\mathrm{x} - \mu)}{\sigma}$$

Where, μ=mean of spectrum, σ= standard deviation.

Zero to One Normalization

$$\frac{(\mathrm{x} - \min \mathrm{x})}{\max \mathrm{x} - \min \mathrm{x}} = \mathrm{x}'$$

Weighted Mean centering

Spectra are centered using weight functions.

$x' = x - \sum w_i x_i$

Moving average (noise reduction) smooths spectral data.

$$S_k(x_i) = \frac{1}{n} \sum_{i=k-\frac{(n-1)}{2}}^{k+\frac{(n-1)}{2}} x_i$$

Derivative Spectroscopy

First Derivative

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h}$$

Second Derivative

$$f''(x) = \frac{f(x+h) - 2f(x) + f(x-h)}{h^2}$$

Linear Regression Models

Multiple Linear Regression

$$y = y_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$$

Simple Linear Regression

$$y = m.\ x + b$$

Identification of milk substances using ML and deep learning technologies. The application of ML and deep learning algorithms has transformed the detection of milk adulterants. These methods are computationally efficient when handling bulk data analysis and identifying fine patterns that other methods fail to catch. This entails how it is performed, an example of the right algorithm, and its straightforward pseudocode.

How Detection Works

Computer learning software can interpret vibrational information from vibrational techniques such as FTIR and NIRS. These algorithms identify the distinctive spectral indications of certain adulterants. By aligning the spectra related to the milk sample with such usual signs, the algorithm can identify the presence of impurities. Deep learning, as a subtype of ML, improves this ability by utilizing neural networks to tackle nonlinear and high-order relationships within the data, and it works particularly well in identifying adulterants, even when their spectral properties are not clearly different. Milk adulteration detection is a field that is constantly advancing at a rapid rate owing to technological developments.

Among these developments, machine intelligence, deep learning, and ML are becoming the cornerstones in enhancing the accuracy and effectiveness of adulteration detection methods. These technologies can screen big data using different analytical protocols, allowing for the identification of refined patterns that tend to signal the presence of adulterants. Subsequently, we describe the role of convolutional neural networks (CNNs), random forests, and support vector machines (used to detect contaminants in milk, accompanied by detailed explanations and algorithms. Table 2 shows the methods used for milk adulteration detection and the spectroscopic techniques.

- *Common adulterant:* Lists of substances often added to milk to increase volume or change its properties.
- *Milk component affected:* Indicates which part of the milk is mainly impacted by the adulterant.
- Spectroscopic Methods Used: Highlights the techniques used for finding specific adulterants in milk.
- *Raman spectroscopy:* Used to detect chemical composition through vibrational modes.
- *Mass spectrometry:* Provides information on other components.
- *NIR:* Analyzes moisture, protein, and fat content in milk.
- *FTIR:* Identifies organic and inorganic compounds in milk.
- *Observations:* Describe the physical and chemical changes in milk due to the presence of adulterants.

Table 2. Methods for milk adulteration detection and spectroscopic techniques [12, 17, 14, 27].

Adulterant	Affected	Used	Observations
Water	Water (diluent)	Raman spectroscopy, Gas Chromatography (GC), Mass Spectrometry (MASS), Near-Infrared Spectroscopy (NIR)	Increased quantity of serum
Melamine	Non-protein nitrogen	FTIR, NIR, High-Performance Liquid Chromatography (HPLC), GC, Raman	Artificially increased protein Content
Vegetable oil	Fat content	GC, FTIR, NIR, HPLC, MASS	Increased density of serum
Urea, starch, sugar	Non-protein nitrogen	FTIR, NIR, HPLC, GC, Raman	Increased density of lactose and content

GC, gas chromatography; MASS, mass spectrometry; NIR, near-infrared spectroscopy; FTIR, Fourier-transform infrared spectroscopy; HPLC, high-performance liquid chromatography

Proposed Method

The regression model shows how to identify the water level in the milk. A flowchart of the proposed system is shown in Figure 2. The steps involved collecting a large amount of data samples while considering small changes in the position of the beaker on the sensor. This is performed in a controlled environment to obtain a solid set of data for processing. The collected real-time data were processed using various tools. These values serve as references for spectroscopy to investigate unknown levels of water added to different samples.

From Figure 2, we can understand the process of adulterant water detection in milk. The spectroscopic sensor used is the SCR series sensor, which works based on the NIR spectroscopic principle. The dataset was created using 100–150 samples. Only a few samples are shown in Figure 3. Here, we can clearly observe that the raw milk is added with water as shown in Figure 3.

After the plot showed an increase in the added water, the plots declined. This is observed in readings 2, 3, 4, 5, and 6. Step 4 in Figure 2 calculates the average of the plots from the given graph in Figure 3. This average helps to determine the approximate level of water in milk. Next step of the flowchart displays the testing of unknown samples for water level detection.

Table 3 highlights the success rates of this regression method. This method was tested using buffalo milk and cow milk, which have different SNF. Figure 5 shows the unknown milk samples tested using the sensor. The average values from the reference datasets were used to determine the water levels in unknown milk samples. Figure 4 shows the actual spectra of raw milk samples with adulterants obtained using the sensor. A mobile-based milk-testing model using linear regression combines portable spectroscopy with trained mathematical calibration.

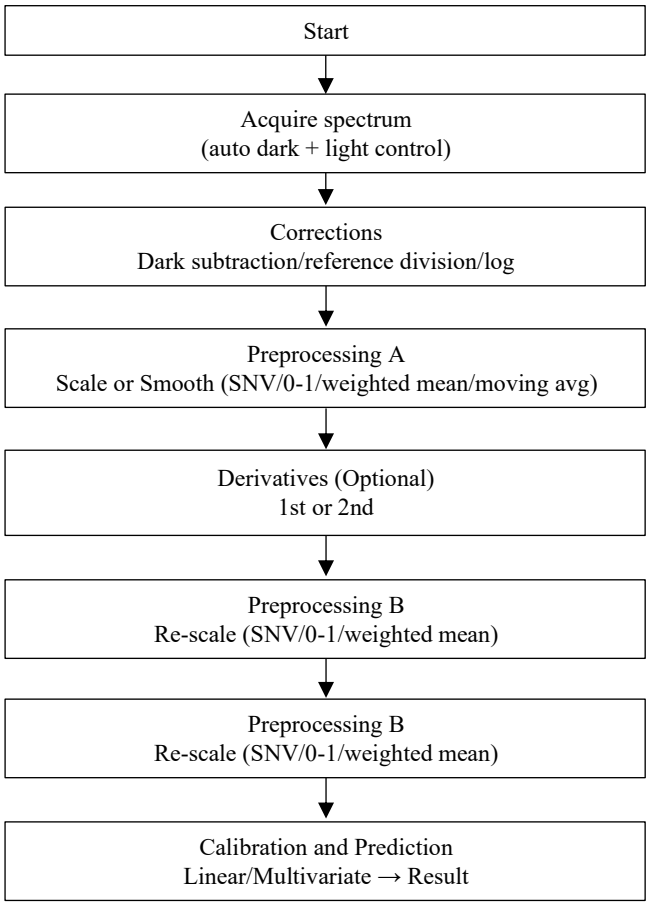

Figure 2. Flowchart of the process followed to detect adulteration in milk.

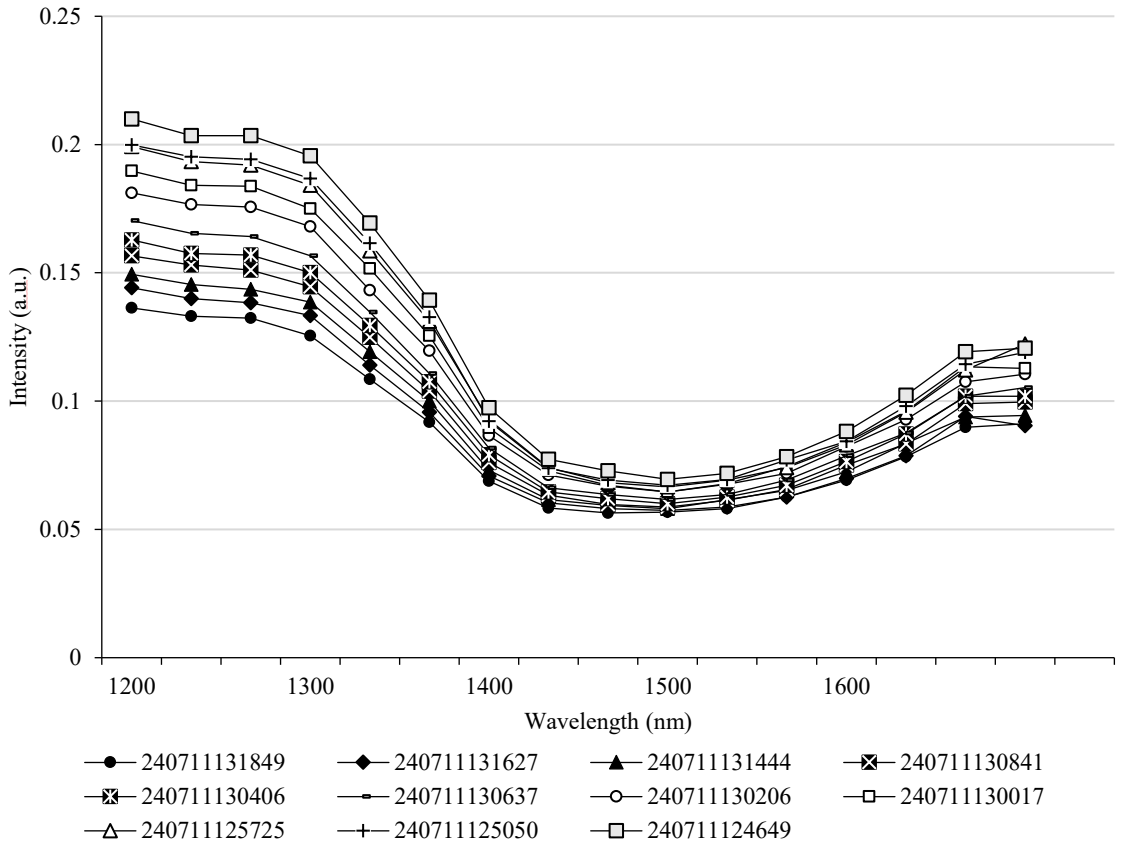

Figure 3. Spectra of raw milk with water adulterant.

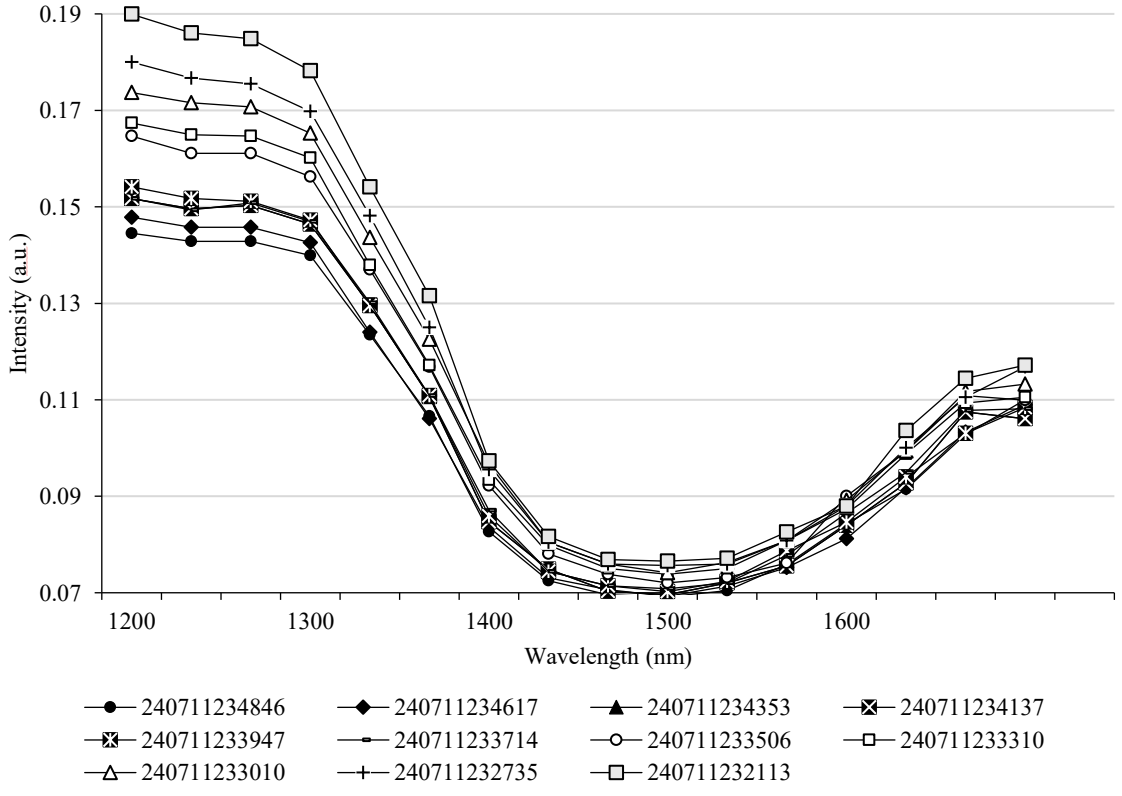

Figure 4. Spectra of raw milk with added salt adulterant.

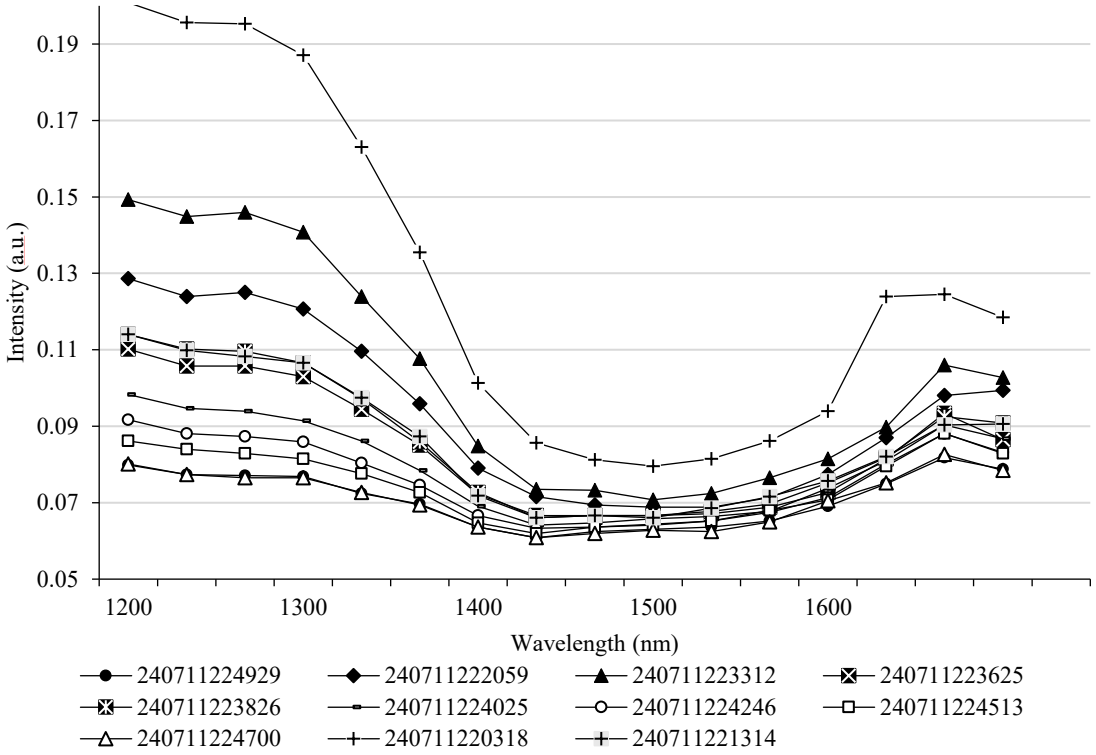

Figure 5. Spectra of raw milk with added sugar adulterant.

Figure 6. Testing of samples with a sensor.

First, the spectrum of the milk sample was captured using a small sensor connected to a smartphone. This raw spectrum undergoes preprocessing to remove noise, correct dark readings, and scale it for consistency. During the calibration phase, the spectra from known milk samples were matched with laboratory-tested values of fat, protein, or adulterants. A linear regression model was developed using these data pairs.

This can be a simple regression with one spectral variable or a multivariate regression with multiple wavelength bands. The regression coefficients were then integrated into a mobile app as shown in figure 6 and 7. When a new sample is tested, the application uses the stored regression equation on the newly captured spectrum to instantly predict the quality parameters of milk. These parameters include fat percentage, protein content, and the level of adulteration, such as water, salt, sugar, vegetable oil, starch, or urea.

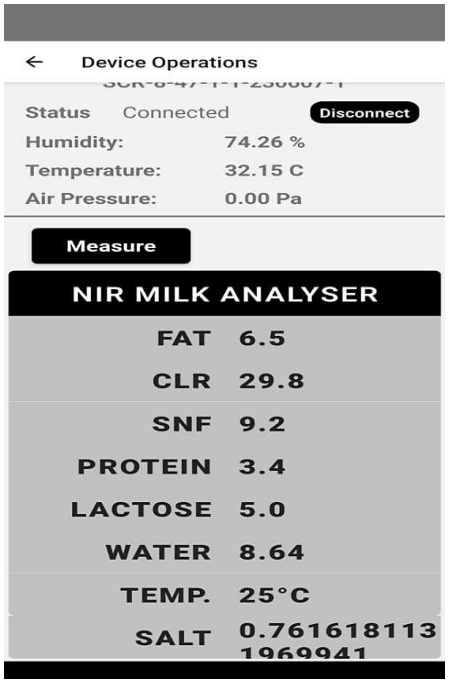

Figure 7. Result displaying on the mobile app for raw milk.

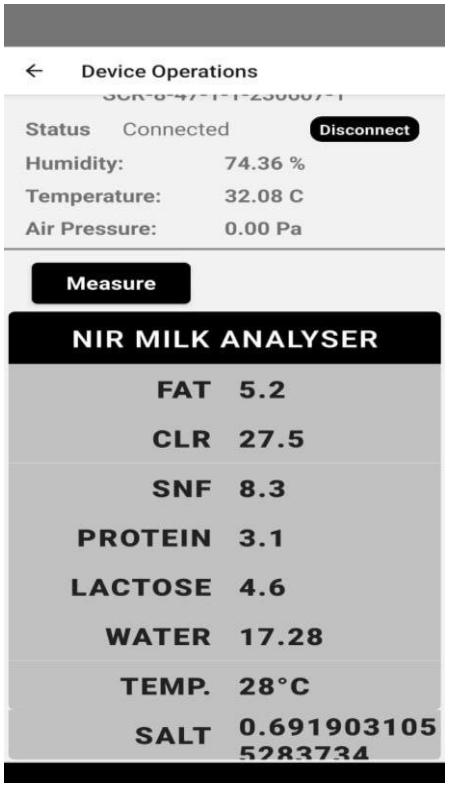

Figure 8. Result displaying on the mobile app for adulterated milk.

This approach makes testing quick, portable, and affordable, allowing farmers, dairy collection centers, and consumers to check milk purity in real time without requiring a laboratory. instantly. These parameters include fat percentage, protein content, and the level of adulteration, such as water, salt, sugar, vegetable oil, starch, or urea as shown in Table 3. This approach makes testing quick, portable, and affordable, allowing farmers, dairy collection centers, and consumers to check milk purity in real time without requiring a laboratory.

Table 3. Success rate calculation based on 100 random sample experiment.

Parameters of milk	Raw milk success rate (%)	Adulterated milk success rate (%)
Fat	6.5	5.2
Solids-not-fat (SNF)	9.2	8.3
Protein	3.4	3.1
Lactose	5.0	4.6
Water level	8.64	17.28

ANALYSIS

- Fat, SNF, protein, and lactose had slightly lower success rates in adulterated milk than in raw milk as shown in Figures 7 and 8.
- This suggests that adulteration caused spectral variability, which decreased the prediction accuracy of the linear regression model.
- The water level showed the opposite trend. The success rate increased significantly in adulterated milk from 8.64% to 17.28%. This is expected because the added water creates a clear spectral signature with strong O–H absorbance in the NIR region, making linear regression more effective for detecting adulteration.
- Overall, linear regression is better at detecting adulterants such as water than at predicting natural milk components such as fat, protein, lactose, and SNF. The predictions for these components are more complex owing to the spectral overlaps.

CONCLUSION

The linear regression model showed a moderate ability to predict the milk constituents in raw milk. However, its effectiveness declines when adulteration occurs because of the increased complexity of spectral data.

The model is very sensitive to water adulteration, achieving a much higher success rate for adulterated samples than for raw samples. This indicates that, while basic linear regression works well for detecting added water, more sophisticated techniques, such as partial least square (PLS) or Polymerase Chain Reaction (PCR), may be required to improve the accuracy of fat, protein, lactose, and SNF in both raw and adulterated milk.

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