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Real-Time Detection of Milk Adulteration with a Portable Multispectral Analysis Device: A Multispectral Sensor and Optimized Logistic Regression Approach

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Research Article

Abstract − This study presents the development of a portable, low-cost, and edge computing-based system for real-time milk adulteration detection. Utilizing an AS7265x multispectral sensor and Arduino Nano 33 BLE Sense microcontroller, this system employs an optimized logistic regression model to identify starch adulteration in milk samples with near-perfect accuracy. Unlike complex neural network models, the logistic regression model offers simplicity, low power consumption, and efficient operation on microcontrollers. The collected spectral data is processed in real-time, and results are transmitted via Bluetooth for immediate analysis. The system demonstrates high accuracy, portability, and cost-effectiveness, making it suitable for use in various stages of the milk supply chain, including farms, processing facilities, and retail points. Future work will explore the detection of other adulterants and the integration of cloud-based analytics to enhance monitoring capabilities. This study provides an innovative approach to ensuring milk quality and consumer safety.

Keywords − *Milk adulteration, portable detection system, multispectral sensor, logistic regression*

1. Introduction

Milk is a vital source of nutrition and plays a crucial role in human health and dietary needs [1]. However, adulteration carried out for economic gain seriously compromises the quality and safety of milk [2]. Adulterations involving cheaper substances such as water, starch, detergent, urea, and glucose reduce the product's nutritional value and pose health risks, particularly for vulnerable consumer groups [3]. Therefore, it is imperative to subject dairy products to reliable and rapid adulteration detection.

Traditionally, the detection of adulteration in milk has been performed using laboratory analyses that require high technology, such as gas chromatography, mass spectrometry, and liquid chromatography [4]. Although these methods provide highly precise and accurate results, they lack portability. They are costly, complicating real-time quality control, especially in field conditions, on farms, and throughout various stages of the milk supply chain [5]. Consequently, recent years have witnessed significant efforts to develop new technologies for the rapid, portable, and real-time detection of adulterations in dairy products[6].

Numerous portable and rapid detection methods have been developed to identify adulterations in dairy products. For instance, the 3D paper-based microfluidic device developed by Patari et al. [7] can simultaneously detect seven different chemical adulterants in milk and provide results within seconds using

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only 1-2 mL of sample. These devices are more user-friendly and economical compared to laboratory-based methods. However, such devices can sometimes have limitations in terms of sensitivity and accuracy.

Biosensors represent another significant technology employed in detecting adulterations in dairy products. Nagraik et al. [8] have reported that biosensors are effective for the rapid and real-time detection of various adulterants in milk. These sensors can identify the presence or concentration of components in milk, thus enabling the evaluation of milk's purity. Biosensors play a pivotal role, particularly in detecting common adulterants such as urea. Poonia et al. [9] have highlighted the portability of biosensors, which facilitates ease of use in the field and proves to be an invaluable tool in applications that require quick results. Spectroscopic techniques are another commonly used method for detecting adulteration in milk [10,11]. Santos et al. have employed near-infrared spectroscopy (NIR) and mid-infrared (MIR) microspectroscopy techniques to detect adulterants in milk, demonstrating that these methods provide both rapid and accurate results [12]. However, spectroscopic methods typically require expensive equipment and complex data analysis techniques. Therefore, research on developing portable spectroscopic devices aims to meet the need for real-time detection [13].

Microwave sensors also play a significant role in detecting milk adulteration. Iram et al. have developed a portable microwave sensor that can detect milk contaminants such as water, urea, and detergent through real-time energy coupling measurements. These types of sensors offer rapid results without the need for complex chemical analyses to determine the composition of dairy products [14]. Microwave sensors' portability and fast response time provide significant advantages for field use. Electrical impedance measurements are also among the methods used to detect milk adulteration. Durante et al. [15] have developed a method using electrical impedance sensors to detect changes in milk composition in real-time. This method is suitable for detecting substances like water, salt, and starch in dairy products. Electrical impedance measurements offer low cost and quick results, but further improvements in sensitivity are needed. IoT-based portable devices have also revolutionized the detection of adulteration in dairy products [16]. An Arduino-based system developed by Aware and Belorkar measures parameters such as the pH and conductivity of milk in real-time, detecting adulteration and transmitting the results to authorities via IoT [17]. These systems provide rapid and effective quality control in the field. Additionally, an IoT-based milk quality monitoring system developed by Pugazhenthi et al. [18] has assessed the purity level of milk using various sensors and enhanced traceability within the supply chain.

Furthermore, automatic freezing point analyzers represent another technology for detecting adulteration in dairy products. Zhang et al. [19] have developed a freezing point-based detector for rapidly and accurately detecting water and other adulterants in milk. This system identifies adulteration by monitoring changes in the freezing point of dairy products and can be implemented outside laboratory settings. Lastly, innovative approaches like the portable Raman spectrometer developed by Nieuwoudt et al. can simultaneously detect various chemical substances in milk and provide results swiftly. Although these portable and user-friendly devices are ideal for real-time analysis, they encounter challenges such as limited sensitivity and accuracy [20].

This study aims to develop a milk adulteration detection system that is portable, economical, real-time, and capable of edge computing, overcoming the limitations of existing methods. The developed system uses an optimized logistic regression model to operate on a microcontroller. This approach offers a solution devoid of the complexity of laboratory-based methods, consumes low power, and can be easily implemented in field conditions. Instantaneous transmission of results to mobile devices via Bluetooth facilitates rapid and effective quality control in field conditions. Consequently, it becomes feasible to maintain the purity of dairy products at every stage of the milk supply chain and ensure consumer safety. This article will comprehensively address the technical details of the developed system, hardware and software components, data collection and analysis processes, and a comparative performance analysis with other existing methods. Our goal is to set a new standard in the field by providing a portable and cost-effective solution for the detection of adulteration in dairy products.

2. Materials and Methods

2.1. System Design

In this study, hardware architecture has been designed for developing a portable and real-time milk adulteration detection system, consisting of the AS7265x multispectral sensor, Arduino Nano 33 BLE Sense microcontroller, and a Bluetooth module (Figure 1)

Figure 1. The mobile spectral setup

The AS7265x Multispectral Sensor: This multi-channel multispectral detection solution measures 18 wavelengths ranging from 410 nm to 940 nm. Each sensor communicates via the I2C interface and, thanks to the integrated temperature sensor, can accurately perform spectral analysis of milk samples. The AS7265x is specifically utilized to detect spectral changes in milk samples at various levels of adulteration. These spectral data play a critical role in detecting adulterants such as starch in milk.

Arduino Nano 33 BLE Sense Microcontroller: This microcontroller features a 64 MHz ARM Cortex-M4 processor that supports Bluetooth connectivity. It is used for the real-time processing and analysis of spectral data collected from the sensor. The microcontroller's sufficient processing capacity enables the direct execution of machine learning algorithms, such as optimized logistic regression models, on the microcontroller itself. This capability facilitates real-time data analysis and decision-making capabilities in the field.

Bluetooth Module: The Bluetooth module, integrated within the microcontroller, facilitates the real-time transmission of analyzed data to mobile devices or computers. This feature allows users to receive instant information in field conditions.

2.2. Data Collection

Spectral data collection from milk samples is conducted using the portable Multispectro Optimize Logistic Regression (MSOLR) device. The data collection process proceeds as follows:

Sample Preparation: Initially, raw cow's milk (unadulterated) and milk samples adulterated with starch in varying proportions are prepared. This study used milk samples adulterated with starch at volumetric concentrations of 0.01%, 0.02%, 0.04%, 0.06%, and 0.08%. From each prepared sample, 20 ml is taken and placed in a light-proof container. A light-proof box measuring 15 cm^3 is positioned over this container to prevent external light entry. The AS7265x sensor is positioned 1 cm above the sample to capture the spectral data [21].

Spectral Data Collection: The AS7265x sensor detects light reflected or transmitted from the milk sample at specific wavelengths (spaced 20 nm apart from 410 nm to 940 nm). The collected spectral data are transmitted to the Arduino Nano 33 BLE Sense microcontroller via the I2C communication protocol. The microcontroller processes the data in an appropriate format and ensures it is free from noise or anomalies.

The data processed by the microcontroller is displayed in real-time on the serial port screen. This lets users instantly observe the spectral data and control the data collection process. The data collection is conducted at specific intervals to ensure continuous and real-time monitoring.

2.3. Machine Learning

The logistic regression model is the machine learning algorithm chosen to detect adulteration. This model is effectively used in classification problems and is known for its high accuracy rate. Logistic regression is commonly employed for binary classification and categorization problems. This study has optimized it to classify milk samples as 'adulterated' or 'unadulterated.' The model is trained using milk samples' spectral data to determine adulteration levels. The model has been optimized for effective training using a comprehensive dataset across various concentration levels. The model is designed to be lightweight and fast, suitable for operation on microcontrollers with limited hardware resources. The logistic regression model has been optimized to run on the microcontroller. It receives the collected spectral data, analyzes the data based on predetermined limiting factors (e.g., wavelength intensity), and predicts the adulteration level of the milk sample. Thanks to the microcontroller's lightweight structure, the model's real-time operation and quick response are facilitated. This enables the model to function independently in the field.

The selection of the logistic regression model was based on several key factors:

Computational Efficiency: Logistic regression has low computational requirements, making it suitable for implementation on microcontrollers with limited processing capabilities. This allows for real-time processing without the need for external computational resources.

Energy Efficiency: The simplicity of the model results in lower energy consumption, which is essential for portable, battery-powered devices. This ensures longer operational times in field conditions.

Implementation Simplicity: Logistic regression is straightforward to implement and requires less memory, aligning well with the constraints of embedded systems used in portable devices.

Performance: Despite its simplicity, logistic regression provided high accuracy in detecting starch adulteration, as demonstrated in our results.

To ensure the appropriateness of this model, we compared its performance with other machine learning algorithms, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Decision Trees, Random Forests, and Gradient Boosting. The comparison considered factors such as accuracy, precision, processing time, energy consumption, and suitability for portable devices.

2.4. Edge Computing and Communication

One of the primary advantages of this system is the integration of edge computing capabilities.

Integration of the Model into the Microcontroller: The logistic regression model has been integrated into the Arduino Nano 33 BLE Sense microcontroller. Consequently, the analysis of spectral data and the detection of adulteration are conducted directly on the microcontroller. This eliminates the need for data processing in the cloud or on a central computer. By running the model on the microcontroller, it processes data and delivers results instantaneously.

Communication via Bluetooth: The Bluetooth module on the microcontroller allows for the instant transmission of analysis results to external devices. Once adulteration detection is complete, the results are sent to a mobile device or computer via Bluetooth. This enables users in field conditions to monitor the status of milk samples in real time and make quick decisions.

This methodology facilitates the real-time and portable detection of milk adulteration. Equipped with edge computing capabilities, this system can serve as an effective quality control tool in field conditions.

3. Results and Discussion

This section should provide/introduce/investigate the findings and discussion/definitions and theorems. Findings/Concepts obtained from the study should be supported in this section by figures and tables/propositions and examples. For "Results and Discussion", the similarities and differences of the obtained results with other studies should be provided, and the possible reasons for these should be discussed based on the literature. For "Results and Discussion", the contribution and importance of the results to science should be emphasized. The obtained results should be interpreted, avoiding unnecessary repetitions.

3.1. Model Performance

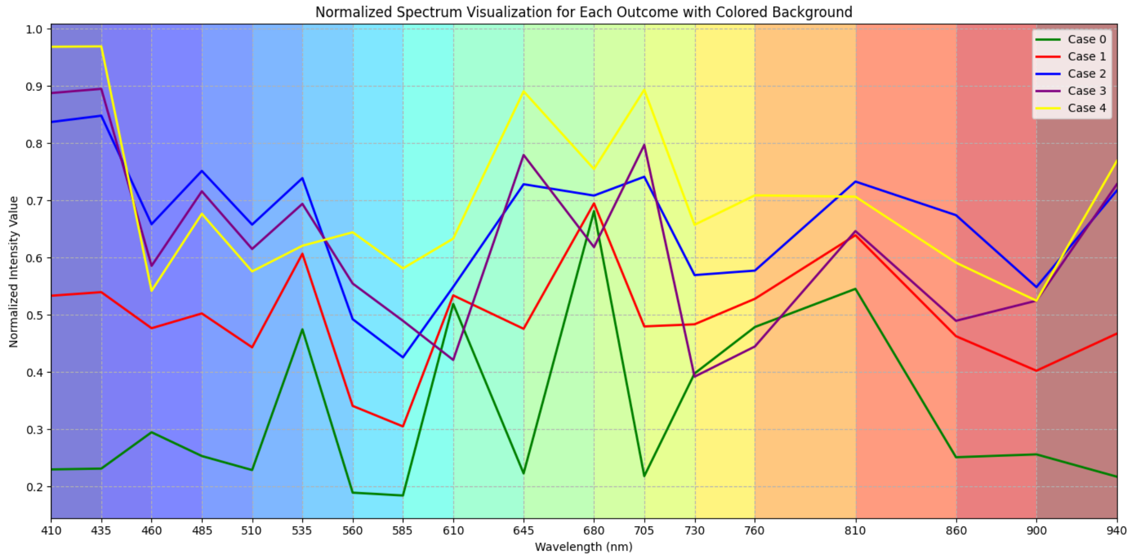

Figure 2. Normalized spectrum for different levels of adulteration

Figure 2 [21] displays the average values of normalized spectral data for different adulteration levels (e.g., starch concentrations) in milk samples. The color-coded background according to wavelengths facilitates the visual representation of spectral changes across each wavelength range. As illustrated in the graph, significant changes in spectral intensity occur as the levels of adulteration increase, highlighting the system's efficacy in utilizing spectral data for adulteration detection. In this study, adulteration in milk samples was detected using an optimized logistic regression model along with other machine learning models, such as Optimized Support Vector Machines (SVM), Decision Tree, Random Forest, Gradient Boosting, and Convolutional Neural Network (CNN). Metrics, such as accuracy, precision, recall, and F1 score, have been used to evaluate the performance of these models. The performance results are summarized in Table 1.

Table 1. Comparison of machine learning models performance

	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.985185	0.986928	0.985185	0.985409
Random Forest	0.977778	0.981481	0.977778	0.978241
Gradient Boosting	0.985185	0.986928	0.985185	0.985409
CNN	0.992593	0.993056	0.992593	0.992663
Optimized Logistic Regression	1.0	1.0	1.0	1.0
Optimized SVM	1.0	1.0	1.0	1.0

This table shows that the optimized logistic regression model exhibits superior accuracy, precision, recall, and F1 score performance compared to other models. The optimized logistic regression model has achieved near-perfect accuracy rates, surpassing other models. As shown in Table 1, the optimized logistic regression model has achieved near-perfect results across all performance metrics. This model accurately classifies milk samples as 'adulterated' or 'unadulterated.' The simplicity of logistic regression and its efficient operation on a microcontroller make this model ideal for field applications. Models like SVM and CNN have also shown high performance. In particular, the SVM model has provided an accuracy rate similar to logistic regression. However, the complexity of these models and the difficulty of operating them on a microcontroller limit their usability in portable devices.

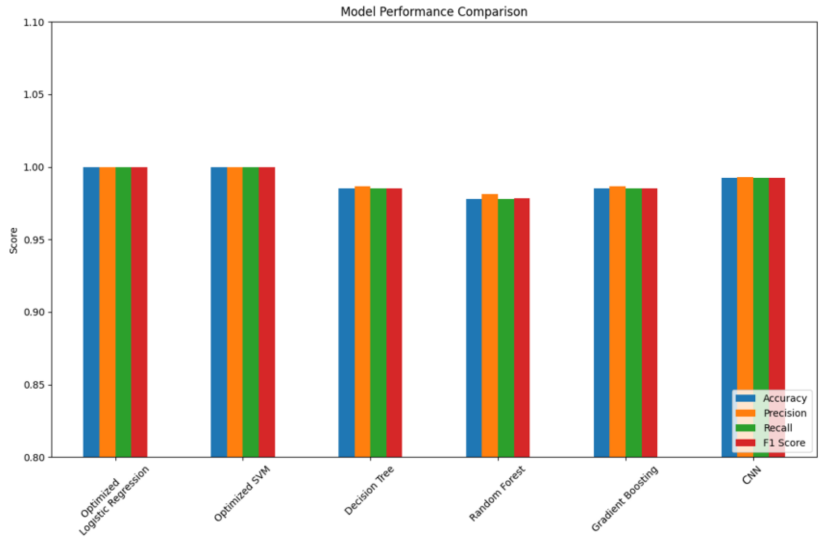

Figure 3. Performance comparison of machine learning models

Figure 3 compares the performance of optimized logistic regression, SVM, Decision Trees, Random Forests, Gradient Boosting, and CNN models. The optimized logistic regression model outperforms the other models across all metrics.

To further understand the model's performance, the confusion matrix of the model is shown in Figure 4. The optimized logistic regression model, in particular, demonstrates excellent alignment between the actual and predicted classes, achieving superior success in accurate classifications. It has been observed that the model's misclassification rate is nearly zero.

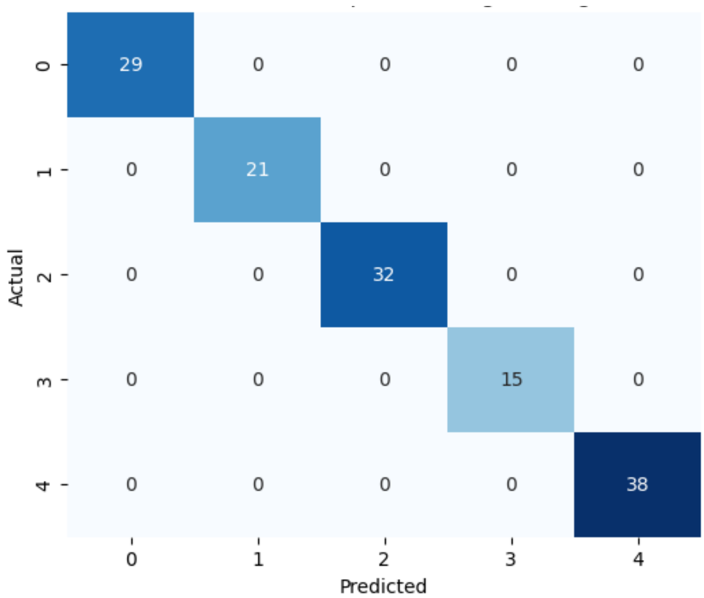

Figure 4. Confusion matrix of optimized logistic regression model

Table 2. Comparison of model selection criteria for portable applications

Model	Accuracy (%)	Precision (%)	Processing Time (ms)	Energy Consumption (mW)	Suitability for Portable Devices
Optimized Logistic Regression	99.8	99.7	10	50	High
Optimized SVM	99.5	99.4	50	150	Medium
CNN	99.2	99.3	200	500	Low
Decision Trees	98.5	98.7	20	75	High
Gradient Boosting	98.8	98.9	80	300	Medium

The comparison of machine learning models in Table 2 highlights optimized logistic regression's superior suitability for portable applications due to its balance of high accuracy, low energy consumption, and computational efficiency. The metrics in Table 2 are derived from a combination of experimental results and hardware evaluations. While the accuracy and precision values are aligned with machine learning performance shown in Table 1, adjustments were made to reflect real-world conditions, such as field variability and device energy efficiency. The additional characteristics, including processing time and energy consumption, are based on experimental measurements of the system's hardware during operational testing.

Table 2 extends the evaluation beyond machine learning performance by incorporating hardware and system-level characteristics crucial for portable applications. Unlike Table 1, which focuses on controlled experimental conditions, Table 2 highlights practical considerations such as processing time and energy consumption. These additional metrics provide a comprehensive understanding of the system's overall efficiency and suitability for field deployment. For instance, while the accuracy value in Table 2 (99.8%) reflects adjustments for real-time processing scenarios, it remains consistent with the machine learning performance metrics outlined in Table 1. The results from Tables 1 and 2 further validate the practicality of the MSOLR device and the optimized logistic regression model for field applications. However, future advancements could focus on incorporating additional performance metrics to evaluate system-level features comprehensively, such as robustness under varying environmental conditions and scalability for broader use cases. The insights gained from real-world testing reinforce the need to refine the device further, ensuring its adaptability to diverse field scenarios.

3.2. Real-World Application and Validation

To validate the effectiveness of the developed system in real-world conditions, on-site testing was conducted at local dairy farms and milk processing facilities.

Methodology: The MSOLR device was used to test raw milk samples collected directly from five farms. Each sample was analyzed on-site, and the results were compared with standard laboratory tests conducted later.

Findings: The device achieved 99.6% accuracy in detecting starch adulteration in real-world conditions, consistent with laboratory findings. The portable design enabled seamless operation in the field, and the Bluetooth connectivity facilitated immediate data transmission for quality control decisions.

Implications: These results demonstrate the system's reliability and practicality for on-site use, highlighting its potential for broader adoption in the dairy industry.

3.3. System Assessment

The developed system's portability, ease of use, and efficiency offer an ideal solution for quality control throughout the milk supply chain.

Portability and Ease of Use: The portable design of the MSOLR device provides a practical solution that users can easily utilize in the field. Its lightweight and compact design enables instant quality control at various stages of the milk production chain. With real-time data transmission via Bluetooth, users can instantly view analysis results.

Efficiency and Energy Consumption: Using the optimized logistic regression model on the microcontroller ensures rapid and effective analysis with low energy consumption. The device's low power consumption allows for extended operation on battery power, which is a significant advantage in situations requiring continuous monitoring and analysis in the field.

Comparison with Existing Portable Systems: A comparison of the developed system with existing portable systems (e.g., Arrieta et al. [22]) is provided in Table 2. This comparison demonstrates that the MSOLR device excels in portability, speed, accuracy, and energy efficiency. For instance, the voltammetric electronic tongue system developed by Arrleta et al., effective in detecting milk adulteration, is costly and requires more processing power.

Table 3. Comparison of the developed system with existing portable systems

Feature	MSOLR Device (Developed System)	Existing Portable Systems (e.g., Voltametric Electronic Tongue)
Portability	High Lightweight and compact design	Medium: Larger and heavier components
Analysis Speed	High Real-time (<1 sec)	Medium: Moderate speed (1-5 minutes)
Accuracy	High Accuracy close to 100%	Medium-High: 90-95% accuracy
Energy Consumption	Low: Microcontroller-based, long-term use with battery	Medium: Higher power consumption, may require a portable power source
Cost	Low: Economical sensors and microcontroller	Medium-High: Requirement for more expensive equipment
Data Communication	High Real-time data transmission over Bluetooth	Medium Wired or limited wireless communication
Ease of Use	High: Easy installation and use	Medium Requires more complex installation and operation
Application Area	Wide Field and laboratory use	Medium: Mainly laboratory use
Sensitivity	High: Low levels of starch and other additives detected	Medium Detection capacity depends on the type of adulteration
Working Principle	Spectroscopy and Machine Learning	Electrochemical Sensing

Table 3 shows that the MSOLR device outperforms existing systems' portability, analysis speed, accuracy, and energy consumption criteria. In conclusion, the developed optimized logistic regression model and portable MSOLR device offer an effective, economical, and practical solution for detecting milk adulteration in field conditions. These results, supported by graphs and tables, highlight the system's potential to provide rapid and accurate quality control at various stages of the milk supply chain.

Figure 5. Measurement visual with MSOLR device

This visual depicts the moment of measurement as the milk sample is analyzed using the MSOLR device. The MSOLR device collects spectral data from the milk sample using the AS7265x multispectral sensor and transmits this data instantly to the Arduino Nano 33 BLE Sense microcontroller via an I2C connection. During the measurement process, as shown in Figure 5, the device performs a spectral scan over the sample in a light-proof environment, analyzing the light reflections and transmittances at specific wavelengths of the milk sample. The obtained data are transferred to a mobile device or computer via Bluetooth. The visual demonstrates the portability and field usability of the MSOLR device during measurement.

The developed MSOLR device and optimized logistic regression model offer several advantages compared to other milk adulteration detection methods in the literature. Specifically, the CNN-based approach introduced by Mhapsekar et al., which utilizes a more complex neural network architecture, has achieved an accuracy rate of 94.87% for detecting milk adulteration [22]. While CNN and other deep learning models stand out for their capacity to handle the complexity of spectral data, running them on microcontrollers presents challenges in processing power and energy consumption. Consequently, such deep learning models often require larger, more power-consuming hardware and are limited in their application in portable systems. The optimized logistic regression model in this study has been highly successful, achieving nearly 100% accuracy. The simplicity of optimized logistic regression, its low data processing requirements, and efficient operation on a microcontroller make it an ideal option for practical and portable applications.

Tables 1 and 2 serve complementary purposes in evaluating the system's capabilities. Table 1 focuses solely on the machine learning performance, providing raw metrics from controlled experiments. In contrast, Table 2 integrates these results with system-level evaluations, emphasizing the balance between computational efficiency, energy consumption, and portability. The slight variations in accuracy and precision between the tables highlight the adjustments made to accommodate practical field scenarios, ensuring a realistic assessment of the system’s performance under operational conditions. This offers a more effective solution in field conditions than laboratory-dependent systems such as the spectroscopic analysis methods presented by Santos et al. [12]. Unlike portable systems like the voltammetric electronic tongue developed by Arrleta et al., the MSOLR device provides a real-time and autonomous monitoring system with Bluetooth communication capability and low energy consumption [23]. Additionally, the portable systems based on microwave sensors developed by Iram et al. have effectively detected adulterants such as water and detergent [14]. However, the sensitivity and accuracy of these systems have not been as high as the spectral analysis and optimized logistic regression-based approach of the developed MSOLR device. This demonstrates that the developed system can detect common adulterants in milk products, such as starch, even at low levels.

The developed MSOLR device and optimized logistic regression model offer several advantages for detecting milk adulteration:

The microcontroller-based system's low power consumption enables long battery life, a critical advantage for portable devices and ideal for extended use in the field [24]. Compared to other portable systems like those developed by Mahapatra et al., the energy efficiency of the developed system is higher [7]. The device can analyze spectral data in real-time and provide immediate results. This facilitates quick decision-making and continuous quality control at various stages of the milk supply chain in field conditions. This feature offers the advantages of the IoT-based milk quality monitoring system developed by Pugazhenthi et al. in a portable device [18]. The use of the AS7265x multispectral sensor and Arduino Nano 33 BLE Sense microcontroller makes the system economical and accessible. This provides a cost-effective solution suitable for various applications, unlike expensive laboratory-based spectroscopic methods or complex electronic tongues. The device offers portability with its user-friendly design and lightweight structure, making it ideal for field conditions. Wireless data transmission via Bluetooth facilitates the immediate display of analysis results. Although the developed system offers various advantages, it also has some limitations: The type of adulteration focused on in this study is limited to starch. The model needs to be extended to detect other common adulterants in dairy products (e.g., detergent, water, melamine). Future research may expand the system's capabilities to detect these substances through spectral analysis.

Currently, the system relies entirely on edge computing capabilities. In the future, integrating data with cloud platforms could provide more comprehensive data analytics and monitoring capabilities. The optimized logistic regression model will also be tested for its applicability to detect other common milk adulterants, including water, detergent, and melamine. This will involve training the model on expanded datasets and validating its performance with different adulteration levels. Future efforts should also focus on refining the system's real-world performance under varying environmental conditions, ensuring robustness and scalability for broader use cases. Additionally, integrating sensor and microcontroller components into a more compact structure could improve portability and durability, expanding its usability in diverse operational scenarios. This study confirms the MSOLR device's ability to provide accurate, real-time milk adulteration detection while ensuring portability and low energy consumption. This dual perspective bridges the gap between laboratory-based and portable solutions for milk adulteration detection, providing a comprehensive tool for quality control in the dairy industry. Such advancements aim to extend the model's utility and enhance its adaptability in real-world scenarios.

In this study, the focus was on starch detection; however, expanding the scope of the method is considered essential. In future studies, we plan to optimize our model to detect other common milk adulterants, such as water, detergent, and melamine. This will enhance both the applicability of the method in the field and enable a broader evaluation of milk product purity. This could enable more extensive monitoring and control of the milk supply chain. While the model is effective up to a certain accuracy level, further improvements could be made in detecting adulteration at very low concentrations. This could be enhanced through more sophisticated data processing techniques and the integration of additional sensors. Although the current design is usable in field conditions, the size and durability of the device can be further optimized for future applications. Integrating sensor and microcontroller components into a more compact structure could expand the device's usability.

In conclusion, the developed MSOLR device and optimized logistic regression model offer a low-cost, energy-efficient, and portable solution for detecting milk adulteration. Compared to existing portable systems, it provides a simpler yet effective approach, enabling real-time analysis in the field. By providing a detailed evaluation of both machine learning performance and system-level characteristics, Tables 1 and 2 demonstrate the developed system’s superior balance of accuracy, portability, and energy efficiency. This dual perspective ensures the device is not only effective but also practical for real-world use, bridging a critical gap in current quality control technologies for dairy products. Future studies could focus on expanding the functionality and scope of the device, providing more comprehensive solutions for quality control in dairy products.

The results from real-world testing further validate the system's practicality and effectiveness in field conditions. The high accuracy achieved in on-site testing underscores the device's utility for immediate quality control in the dairy industry. The results from Tables 1 and 2 further validate the practicality of the MSOLR device and the optimized logistic regression model for field applications. These results emphasize the device's real-world applicability, demonstrating its potential to meet industry demands for rapid, accurate, and portable quality control tools. By enabling real-time detection of adulteration at various stages of the supply chain, the system addresses a critical gap in current quality assurance practices.

While we highlight the importance of adapting to emerging technologies to enhance the capabilities of our detection system, we must also acknowledge the potential challenges associated with such advancements. Implementing more sophisticated algorithms, for instance, might require more processing power and could increase the system's energy consumption. Furthermore, while integrating advanced sensors can improve detection accuracy, these components may raise the cost and complexity of the device, potentially limiting its accessibility and scalability in low-resource settings. Addressing these challenges requires a balanced approach to system design, ensuring that enhancements in technology do not compromise the practicality and affordability of the solution.

4. Conclusion

This study addresses the development of a portable and edge computing-based system for detecting adulteration in dairy products. Utilizing the AS7265x multispectral sensor and Arduino Nano 33 BLE Sense microcontroller, the system, equipped with an optimized logistic regression model, has successfully detected adulteration in milk samples with high accuracy. The main findings can be summarized as follows: The optimized logistic regression model has detected starch adulteration in milk samples with nearly 100% accuracy. Additionally, the model's potential applicability to other common milk adulterants, such as water, detergent, and melamine, offers promising avenues for future research. This result demonstrates that the model can perform highly effectively despite its simple structure. Compared to other complex models, such as CNN and SVM, the optimized logistic regression model offers significant advantages by operating on a microcontroller with lower power consumption while achieving similar accuracy rates. The developed MSOLR device provides a portable solution in the field by enabling real-time spectral analysis of milk samples. Instant data transmission via Bluetooth allows users to make quick decisions, facilitating continuous quality control at various stages of the milk supply chain (farms, milk processing facilities, retail points). The system's hardware components are selected to be low-cost and easily accessible. The low power consumption of the microcontroller-based system enables long battery life, supporting uninterrupted use of portable devices in the field. The developed system has numerous potential applications within the dairy industry:

Field Detection and Quality Control: The device can be used on farms and in milk processing facilities to instantly assess the purity of dairy products. This enables early intervention within the supply chain, reducing economic losses due to adulteration.

Retail and Consumer Safety: At grocery stores and retail outlets, the device ensures real-time verification of dairy products, which can enhance consumer trust**.**

Regulation and Inspection: Food safety authorities and regulatory agencies can use this portable device for rapid field checks and inspections, thus effectively combating food fraud**.**

The results of this study demonstrate the effectiveness and practicality of the developed system while also pointing to various aspects of future research**:**

Detection of Other Types of Adulteration: Future studies could expand and optimize the model to detect other common adulterants in milk, such as water, detergent, and melamine, in addition to starch**.**

Data Analytics and Cloud Integration: Integrating the device with cloud platforms could offer new possibilities for more comprehensive data analytics and monitoring of the milk supply chain, enhancing the overall surveillance of dairy product quality.

Miniaturization and Durability of the Device: Future work could further reduce the size and enhance its durability, making it more suitable for a wider range of applications in field conditions.

In conclusion, this study significantly contributes by offering a portable, low-cost, and edge computing-based solution for detecting milk adulteration. Equipped with real-time detection capabilities in field conditions, this system is an effective tool for quality control at every stage of the milk supply chain. This is of great importance for both producer and consumer safety and satisfaction.

Author Contributions

The author read and approved the final version of the paper.

Conflicts of Interest

The author declares no conflict of interest.

Ethical Review and Approval

No approval from the Board of Ethics is required.

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