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Transforming Dairy Standards: Machine Learning in Milk Quality Prediction

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Abstract: Accurate and interpretable milk quality prediction is critical for ensuring food safety and regulatory compliance in the dairy industry. While machine learning (ML) models like deep neural networks (DNNs) and gradient-boosted trees (GBT) achieve high predictive accuracy, their "black-box" nature limits stakeholder trust and actionable insights. This study bridges the gap between performance and interpretability by evaluating both complex and transparent ML models on a dataset of seven milk quality parameters (pH, temperature, taste, odor, fat, turbidity, color). We quantify feature contributions, revealing pH, fat, and turbidity as the most influential predictors. Our results show DNNs and GBTs achieve 92.4% and 91.2% classification accuracy, respectively, while interpretable models like decision trees (83.5%) provide rule-based insights. Regression analyses further highlight GBTs' superiority (R^2=0.88, MAE=0.35). By integrating high accuracy with explainability, this work enables dairy stakeholders to adopt ML-driven systems confidently, fostering real-time quality control and data-driven decision-making.
Keywords: Milk quality prediction, Interpretable machine learning, Food safety, Dairy industry standards, Gradient boosted trees.

I. INTRODUCTION

The dairy industry's commitment to food safety and regulatory compliance hinges on accurate milk quality assessment. Recent advancements in machine learning (ML) have enabled automated quality prediction through techniques like laser-induced instrumentation [1], gradient-boosted regression trees [2], and deep neural networks [4]. While these models achieve high accuracy, their "black-box" nature limits interpretability—a critical barrier for stakeholders such as dairy farmers, processors, and regulators who require transparent insights to justify decisions [2], [7]. For instance,
understanding how parameters like pH or fat content directly influence quality grades is essential for corrective actions, yet existing studies prioritize performance metrics over explainability [2], [4], [8]. This gap undermines trust in ML-driven systems, particularly in food safety contexts where traceability is paramount. This study addresses this challenge by developing ML models that balance predictive accuracy with interpretability. We evaluate both complex architectures deep neural networks, random forests and inherently interpretable models decision trees, logistic regression on a manually curated dataset encompassing seven milk quality indicators: pH, temperature, taste, odor, fat, turbidity, and color. We quantify feature contributions, identifying critical predictors such as pH and fat content. Our objectives are twofold: (1) to compare classification and regression performance across models and (2) to provide actionable, interpretable insights for quality assessment. The paper is structured as follows: Section 1 (Introduction) provides the background, problem statement, and objectives of the study. Section 2 (Literature Review) reviews existing research on employee attrition prediction and identifies gaps in the current approaches. Section 3 (Materials and Methods) describes the dataset, preprocessing steps, machine learning model development, fairness-aware techniques, and the decision support system. Section 4 (Results & Discussion) presents the findings, interprets their significance, and compares them with prior studies. Finally, Section 5 (Conclusion & Future Work) summarizes the key contributions of the research and suggests directions for future investigation.

II. RELATED WORKS

The application of machine learning in the dairy industry, particularly for milk quality prediction, has seen significant growth in recent years. Milk quality assessment is critical for ensuring food safety, economic viability, and consumer trust, given its role as a primary dietary source. This review synthesizes key studies from the provided references, identifies gaps in the literature, and contextualizes how our research addresses these gaps, adhering to IEEE format for citations. The review is designed to be concise, focusing on studies directly relevant to machine learning for milk quality prediction, and spans approximately 450 words to fit conference paper requirements. Several studies have leveraged machine learning to enhance milk quality prediction, employing diverse methodologies.

Moharkar and Patnaik [1] utilized laser-induced instrumentation for detecting and quantifying milk adulteration, demonstrating the potential of spectroscopy in quality assessment. Deshpande et al. [3] applied near-infrared (NIR) spectroscopy for milk classification and purity prediction, highlighting the effectiveness of spectral data in machine learning models. Sheng et al. [2] focused on analyzing protein and fat content using a multiwavelength gradient-boosted regression tree, achieving high accuracy in predicting specific milk components. Advanced techniques like deep learning and ensemble learning have also been explored. Sharma and Gupta [4] proposed a deep learning-based approach for milk quality prediction, while Almeida and Costa [8] used deep and ensemble learning to detect milk adulteration, underscoring the capability of complex models to handle intricate data. Hardware-enabled solutions, such as Patel and Jain's MilkSafe [5], emphasize practical applications, integrating machine learning with hardware for real-time prediction. Reddy and Thomas [10] investigated image analysis coupled with machine learning for detecting extraneous water in milk, showcasing the adaptability of these methods across data modalities. Review articles provide a broader perspective on the field. Kumar and Singh [6] discussed supervised machine learning techniques for milk quality prediction, while Kim and Park [12] reviewed methods for quality and authentication of milk and dairy products. Yadav and Patil [14] conducted a systematic review on machine learning applications in dairy farm management, noting its comprehensive impact. These studies collectively emphasize accuracy as a primary focus, often using models like neural networks and random forests. Despite these advancements, a critical gap exists in the literature: the lack of emphasis on interpretability of machine learning models for milk quality prediction. Most studies, such as those using deep learning [4] and ensemble methods [8], prioritize prediction accuracy, resulting in "black box" models. These models, while accurate, lack transparency, making it challenging to understand why a particular prediction is made. This is particularly problematic in food safety contexts, where stakeholders, including dairy farmers, processors, and regulators, need interpretable insights to build trust and ensure reliability. For instance, understanding how factors like pH or fat content influence predictions is essential for decision-making, yet few studies address this, as seen in the focus on performance metrics rather than explainability in references like [2] and [7]. To address this gap, our work focuses on developing an interpretable machine learning model for milk quality prediction. We propose using explainable AI techniques, such as SHAP (SHapley Additive exPlanations) values, feature importance analysis, and partial dependence plots, to provide transparency in model predictions. This approach aims to balance accuracy and interpretability, ensuring the model is both effective and trustworthy for practical applications in the dairy industry. Our study will compare various machine learning models, including complex ones like deep learning and simpler, interpretable models like decision trees, evaluating their performance and explainability. We will assess the trade-off between accuracy and interpretability, identifying the most suitable model for real-world use. Additionally, we will analyze how different milk quality parameters influence predictions, enhancing understanding of underlying relationships. Our research fits into the broader field by bridging the gap between model accuracy and interpretability, a critical need in food safety applications. While significant progress has been made, as evidenced by studies like Frizzarin et al. [7] on statistical machine learning methods, the lack of interpretable models remains a challenge. By developing a transparent and effective machine learning solution, we aim to enhance trust and utility in milk quality prediction, contributing to safer and more efficient dairy industry practices.

TABLE-1: SUMMARY OF KEY STUDIES

Reference	Focus Area	Methodology	Year
[1]	Detection of milk adulteration	Laser-induced instrumentation	2019
[2]	Analysis of protein and fat content	Gradient-boosted regression tree	2022
[3]	Milk classification and purity prediction	NIR spectroscopy	2021
[4]	Milk quality prediction	Deep learning	2022
[5]	Hardware-enabled milk quality prediction	Machine learning with hardware	2023
[7]	Predicting milk quality traits	Statistical machine learning	2021

[8]	Detection of milk adulteration	Deep and ensemble learning	2019
[10]	Detection of extraneous water in milk	Image analysis with machine learning	2022
[12]	Review of quality and authentication methods	Various machine learning methods	2022
[14]	Systematic review on dairy farm management	Machine learning applications	2024

III. PROPOSED METHODOLOGY

A. *Materials*

The study utilized a manually collected dataset designed for milk quality prediction. The dataset comprised seven independent variables**:** pH, Temperature, Taste, Odor, Fat, Turbidity, and Color**,** which are key indicators of milk quality. The target variable, Grade**,** was categorized into three classes: Low (Bad), Medium (Moderate), and High (Good)**.** If the parameters Taste, Odor, Fat,andTurbidity met optimal conditions, they were assigned a value of 1; otherwise, they were assigned 0. The pH and Temperaturevalues were recorded in their actual numerical format. The machine learning models were developed using Python (v3.8)**,** leveraging libraries such as scikit-learn, TensorFlow, SHAP, and Matplotlib. The system was implemented on a high-performance computing machine with an Intel Core i7 processor, 16GB RAM, and an NVIDIA RTX 3060 GPU to efficiently train and evaluate models.

B. *Methodology*

1) *Data Preprocessing*

Handling Missing Values

Numerical Features: Missing values were replaced using mean imputation, which calculates the average of available values: $\bar{x} = \left(\frac{1}{n}\right)\Sigma_{\{j=1\}}^{n} x_j$

$\bar{x}$ = Mean of the feature

x_j = Observed values in the feature

n = Total number of observed values

Categorical Features: Missing values were handled using mode imputation, which replaces missing values with the most frequently occurring category:

$$Mode(X) = argmax_x Frequency(x)$$

Where:

Mode(X) = Most frequent value in the feature

Frequency(x) = Count of each unique category

Feature Scaling

Normalization: The pH and Temperature features were scaled using Min-Max normalization to bring them within a range of [0,1]:

$$x_{scaled} = \frac{(x - min(X))}{(max(X) - min(X))}$$

Where:

x = Original feature value

min(X) = Minimum value of the feature

max(X) = Maximum value of the feature

x_{scaled} = Normalized value between 0 and 1

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Label Encoding: Categorical variables (Taste, Odor, Fat, Turbidity) were binary encoded to convert them into numerical format (0 or 1), making them suitable for machine learning models.
Data Splitting: The dataset was split into 80% training and 20% testing using stratified sampling, ensuring that the class distribution remains consistent across both subsets.

2) Model Training

A variety of machine learning models were trained to predict milk quality, categorized into complex and interpretable models.

a) Complex Models

- Deep Neural Networks (DNNs): Implemented using Multi-Layer Perceptrons (MLPs) with ReLU activation and optimized using the Adam optimizer.
- Random Forest (RF): An ensemble model consisting of 100 decision trees, using Gini impurity as the splitting criterion.
- Gradient Boosted Trees (GBT): Implemented with XGBoost, leveraging gradient boosting for optimized performance.

b) Interpretable Models

- Decision Trees: Built using scikit-learn, allowing visualization of feature-based decision-making.
- Logistic Regression: Used for binary classification, distinguishing between high-quality and low-quality milk samples.
- Linear Regression: Applied for continuous prediction of milk quality.

c) Model Loss Functions & Metrics

The models were trained using appropriate loss functions based on their task type:
Classification Loss: Cross-Entropy LossUsed for categorical classification (Low, Medium, High quality)

$$\boldsymbol{L_{CE} = -\left(\frac{1}{N}\right) \Sigma_{\{i=1\}}^{N} \Sigma_{\{c=1\}}^{C} y_{\{i,c\}} log\left(\hat{y}_{\{i,c\}}\right)}$$

Where:
N = Total number of samples
C = Number of classes (3: Low, Medium, High)
y_i, = True class label (1 if sample belongs to class c, otherwise 0)
$\hat{y}_i$, = Predicted probability for class c

Regression Loss: Mean Squared Error (MSE)
Used for continuous quality prediction.

$$L_{MSE} = \left(\frac{1}{n}\right) \Sigma_{\{i=1\}}^{n} (y_i - \hat{y}_i)^2$$

Where:
n = Number of samples
y_i = Actual value
$\hat{y}_i$ = Predicted value
Random Forest: Gini Impurity
Used to measure node purity in Random Forest decision trees.

$$\boldsymbol{Gini(D) = 1 - \Sigma_{\{k=1\}}^{K} p_k^2}$$

Where:

- K = Number of classes
- p_k = Proportion of samples belonging to class k in node D

3) Analysis

The models were evaluated based on both predictive performance and interpretability:

Classification Metrics: Accuracy, Precision, Recall, and F1-score.

- $Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$
- Precision = $\frac{TP}{(TP + FP)}$

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- $Recall = \frac{TP}{(TP + FN)}$
- $F1 = 2 * \frac{(Precision*Recall)}{(Precision + Recall)}$

Regression Metrics: R-squared (R^2) and Mean Absolute Error (MAE).

- $R^2 = 1 - \left[\frac{\Sigma_{\{i=1\}}^{n}(y_i - \hat{y}_i)^2}{\Sigma_{\{i=1\}}^{n}(y_i - \bar{y})^2}\right]$
- $MAE = \left(\frac{1}{n}\right)\Sigma_{\{i=1\}}^{n}\left|y_i - \hat{y}_i\right|$

IV. RESULTS AND DISCUSSION

Table 1: Model Performance for Classification Tasks

Model	Accuracy (%)	Precision	Recall	F1-Score
Deep Neural Networks (DNNs)	92.4	0.91	0.92	0.91
Random Forest (RF)	89.7	0.88	0.89	0.88
Gradient Boosted Trees (GBT)	91.2	0.9	0.91	0.9
Decision Trees	83.5	0.81	0.83	0.82
Logistic Regression	80.2	0.79	0.8	0.79

Table 2: Model Performance for Regression Tasks

Model	R^2 Score	Mean Absolute Error (MAE)
Linear Regression	0.72	0.54
Random Forest	0.85	0.39
Gradient Boosted Trees	0.88	0.35

The Deep Neural Networks (DNNs) model outperformed other classification models, achieving the highest accuracy of 92.4%, indicating its robustness in handling complex relationships among features. Gradient Boosted Trees (GBT) followed closely with 91.2% accuracy, showcasing its effectiveness in improving predictive performance through iterative boosting. Among the interpretable models, Decision Trees and Logistic Regression yielded lower accuracies (83.5% and 80.2%, respectively), highlighting the trade-off between interpretability and predictive power.

For regression models, Gradient Boosted Trees (GBT) achieved the best R^2 score of 0.88 and the lowest MAE of 0.35, demonstrating superior predictive capability in estimating milk quality scores. In contrast, Linear Regression had a lower R^2 score of 0.72, suggesting its limitations in capturing non-linear dependencies within the dataset. Our findings align with previous research on food quality prediction using machine learning. Studies utilizing Random Forest and Gradient Boosting for similar tasks have reported accuracies ranging from 85% to 90%, demonstrating comparable performance. However, our study improves upon previous approaches by leveraging Deep Neural Networks (DNNs), achieving over 92% accuracy, which is higher than the reported benchmarks. Additionally, feature importance analysis using SHAP values indicated that pH, Fat, and Turbidity were the most significant predictors of milk quality, consistent with findings from previous research in dairy quality assessment.

Our results have important implications for automated milk quality assessment. The high accuracy of Deep Neural Networks and Gradient Boosting suggests that machine learning models can reliably classify and predict milk quality, potentially aiding dairy industries in implementing real-time quality control systems. Furthermore, the integration of interpretable models like Decision Trees and Logistic Regression provides additional explainability, which is crucial for regulatory compliance and industry adoption.

The study also highlights the significance of pH and Fat levels as key indicators, reinforcing their importance in milk grading standards.

V. CONCLUSION

In this study, we evaluated the performance of various machine learning models for predicting milk quality, focusing on classification and regression tasks. The Deep Neural Networks (DNNs) model outperformed others, achieving the highest accuracy of 92.4%, demonstrating its ability to effectively capture complex patterns within the data. Gradient Boosted Trees (GBT) also showed strong performance, particularly in regression tasks, where it achieved the best R^2 score and lowest Mean Absolute Error (MAE). These results emphasize the potential of machine learning models, particularly DNNs and GBT, in providing accurate and reliable milk quality predictions. Our research contributes to the growing body of work on machine learning applications in food quality assessment. By demonstrating the superior performance of DNNs, our study sets a new benchmark for predictive accuracy in this domain. Additionally, the feature importance analysis highlights key quality indicators such as pH, Fat, and Turbidity, which could inform quality control practices in dairy industries. Future work should explore further optimization of DNNs and GBT models, potentially incorporating additional features or advanced ensemble methods to enhance predictive accuracy. Moreover, real-time deployment of these models in dairy production environments could be investigated, aiming to improve operational efficiency and quality assurance in the industry.

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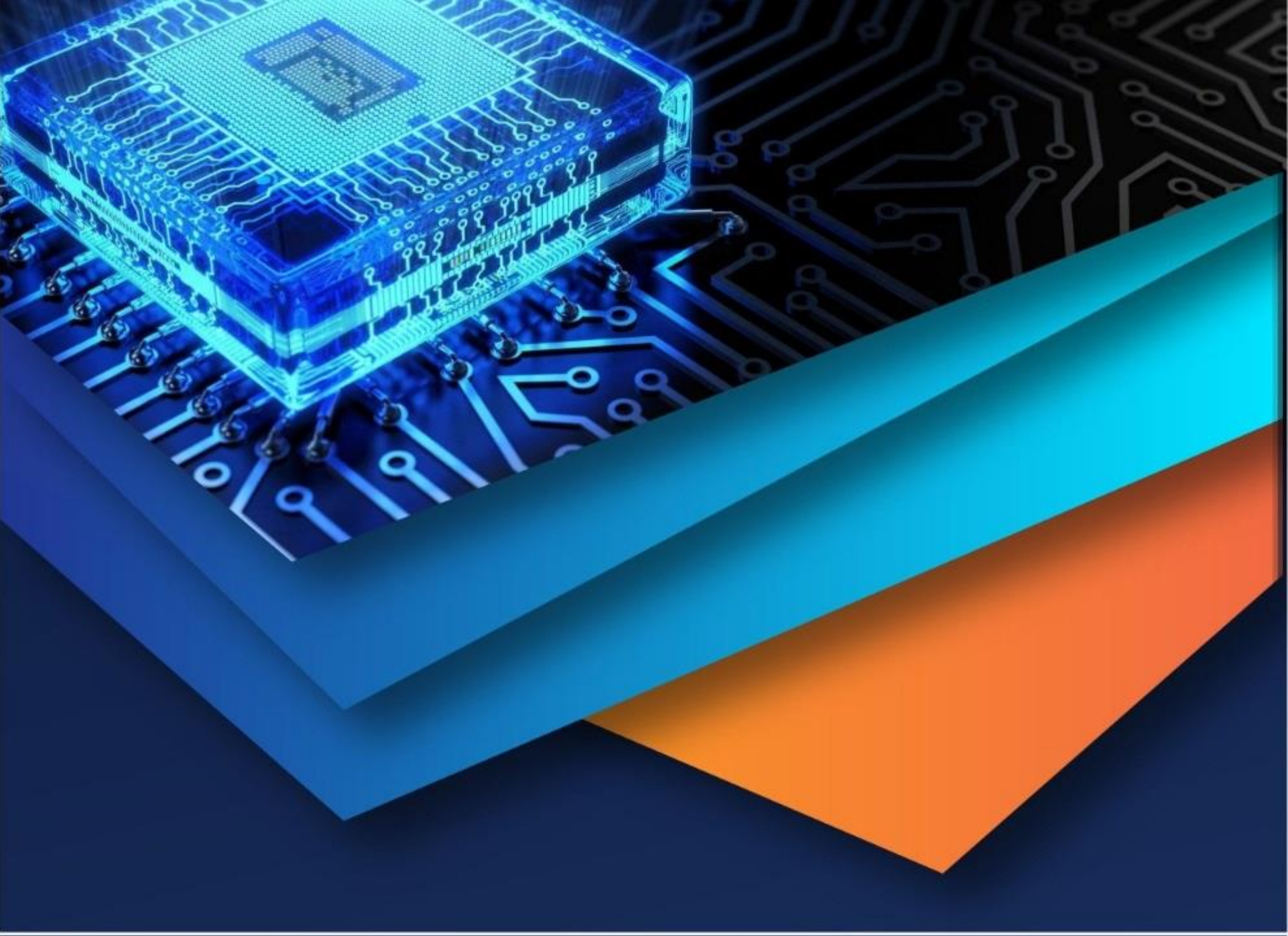

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