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ORIGINAL

Enhancing product predictive quality control using Machine Learning and Explainable AI

Mejora del control de calidad predictivo de los productos mediante el aprendizaje automático y la IA explicativa

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ABSTRACT

The integration of predictive quality and eXplainable Artificial Intelligence (XAI) in product quality classification marks a significant advancement in quality control processes. This study examines the application of Machine Learning (ML) models and XAI techniques in managing product quality, using a case study in the agri-food industry quality as an example. Predictive quality models leverage historical and real-time data to anticipate potential quality issues, thereby improving detection accuracy and efficiency. XAI ensures transparency and interpretability, facilitating trust in the model's decisions. This combination enhances quality management, supports informed decision-making, and ensures regulatory compliance. The case study demonstrates how ML models, particularly Artificial Neural Network (ANN), can accurately predict product quality, with XAI providing clarity on the reasoning behind these predictions. The study suggests future research directions, such as expanding datasets, exploring advanced ML techniques, implementing real-time monitoring, and integrating sensory analysis, to further improve the accuracy and transparency of quality control in various industries.

Keywords: Predictive Quality; Machine Learning; Explainable Artificial Intelligence; Agri-Food Industry.

RESUMEN

La integración de la calidad predictiva y la Inteligencia Artificial Explicable (XAI) en la clasificación de la calidad de los productos supone un avance significativo en los procesos de control de calidad. Este estudio examina la aplicación de modelos de aprendizaje automático (Machine Learning, ML) y técnicas de XAI en la gestión de la calidad de los productos, tomando como ejemplo un caso práctico de la calidad en la industria agroalimentaria. Los modelos predictivos de calidad aprovechan los datos históricos y en tiempo real para anticipar posibles problemas de calidad, mejorando así la precisión y eficacia de la detección. La XAI garantiza la transparencia y la interpretabilidad, facilitando la confianza en las decisiones del modelo. Esta combinación mejora la gestión de la calidad, favorece la toma de decisiones informadas y garantiza el cumplimiento de la normativa. El estudio de caso demuestra cómo los modelos de ML, en particular las redes neuronales artificiales (RNA), pueden predecir con precisión la calidad del producto, mientras que la XAI proporciona claridad sobre el razonamiento que subyace a estas predicciones. El estudio sugiere futuras líneas de investigación, como la ampliación de los conjuntos de datos, la exploración de técnicas avanzadas de ML, la implementación de la monitorización en tiempo real y la integración del análisis sensorial, para mejorar aún más la precisión y la transparencia del control de calidad en diversas industrias.

Palabras clave: Calidad Predictiva; Aprendizaje Automático; Inteligencia Artificial Explicable; Industria Agroalimentaria.

INTRODUCTION

The industrial sector has always been a pillar of major countries all over the word, and represents a significant contributor in economic growth, based on data World Bank, for 168 countries the average contribution of industrial value added on percentage of GDP is 13,4 %.[1]

Against the backdrop of globalization and economic integration, companies are deploying many strategies for promoting economic growth, as synergistic industrial agglomeration, which promotes the high-quality development of the manufacturing industry [2], indeed, companies are forced to balance between clean and quality production goals under the strategies of "high-quality development" and "dual carbon goals".[3] Producing high quality goods is one of the worldwide competitive edges in industrial sector, which requires innovative and systematic quality management approaches, in order to improve company performance.[4] The basic methods used to assess quality production, as end of line controls, part per millions follow up and systemic Non-conforming products analysis do not tie-in anymore with the actual customer or stakeholders requirements from continuous improvement strategy point of view.

The 20th century characterized by an inevitable trend, a stage of scientific, technological revolution and industrial change, which aims to build a smart industry.

The industry 4.0 enables industrial companies to collect huge amount of data via sensors implemented in production at an increasing rate and on a large scale. However, the real benefit does not come from the data itself, but from the insights it contains, which must be uncovered via data analysis.[5] This is what the Machine Learning (ML) is aimed at, it allows upsetting the role of quality management process by exploring data and predicting non-conforming products.

Predictive quality is a methodology, which considers process, product and data to enable proactive quality management in the field by highlighting irregular parameters before non-conforming product occurrence. The aim of predictive quality is the adoption of intelligent data-driven predictions as a basis for decision-making and action".[6] The objective is to optimize manufacturing processes, enhancing product quality, and ultimately improving overall competitiveness.[7]

This study aims to propose predictive quality strategy in industrial field by experimenting several Machine Learning algorithms commonly used in predictive modelling, all of which are used in this work for data analysis and prediction.

The following section of the article will delve into predictive quality and the array of techniques utilized in this domain to forecast product quality. It will explore methods to anticipate and mitigate the heightened costs associated with failures in the production process. By employing advanced predictive analytics, companies can not only improve the consistency and reliability of their products but also proactively manage potential issues, leading to enhanced efficiency and reduced operational costs. This comprehensive overview will cover both traditional and cutting-edge approaches, highlighting their applications and effectiveness in various industrial settings.

ML MODELS AND XAI

ML models and quality prediction

Improving internal performance is one of crucial conditions to remain competitive, sustainable and profitable in global market. Delivering value to the customer is one of lean management principals it consists on delivering good quality from customer point of view.

Superior quality is one of the greatest challenges for companies today. The success of the product on the global market can be achieved only with the fulfillment of customer requirements. This challenge takes another dimension with the constant battle against cost pressure, for that companies are forced to substitute the traditional way to manage quality, by a new method using data-driven analysis using Machine Learning algorithms. Data-driven analysis methods fused to actual typical procedures, we can lead to increase systematically performance of quality and failure management performance. There is a huge potential for enhancing quality.

The use of machine learning techniques is starting to take off on a large scale because of them acceptable and logical accuracy results, especially with revolution created by industry 4.0 and smart manufacturing which. Within this context, several machine-learning techniques were used to predict quality.

Wolfgang Rannetbauer et al.[8] have presented a case study with six machine learning models, trained and evaluated to assess their predictive capabilities. Linear Models (LMs), Generalized Linear Models (GLMs), Bayes Ridge Regression (BRR), Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GB). As for

Henrik Heymann & al 2022,[9] considers predicting product quality represents a common area of application of ML in manufacturing and gives us guideline for deployment of ML models for predictive quality in production (figure 1), he detailed each step of deployment guideline.

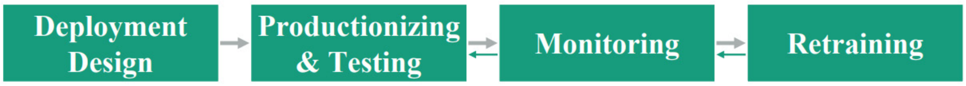

Figure 1. Deployment guideline components[9]

Artificial Neural Network

The artificial neural network is a Machine-Learning algorithm based functionally and architecturally on the biology of the human brain,[10] the latter having the capacity to process large-scale of data using the method of the human brain. It's a Machine-Learning process operating interconnected node networks in a structure with several layers that allow computers to learn from its recognition errors, and adapt automatically for continuous improvement.[11]

It takes multiple input signals, applies weights to these inputs, computes a weighted sum, and passes the result through an activation (transfer) function to produce an output. The activation function introduces non-linearity and allows the network to model complex relationships between inputs and outputs.[12]

The ANN have shown good results for decision-making in large scale of scientific and industrial field. Used for prediction of wear in cutting tools for boosting productivity and reducing manufacturing costs, predicting thermal-hydraulic performance of a solar air heater,[13] to control the speed of a brushless direct current motor motors[14] and to predict problems in the supply chain management.[15]

It is commonly used also for non-conforming products prediction in productions process. Traditional processes estimate quality control based on human auto-controls and quality wall checks that are consuming time, which are substituted by models that typically estimate quality control labels based on process data, such as machine control and sensor data.[16]

Random Forest

Random forest is a Machine-Learning algorithm. Proposed by Leo Breiman,[17] Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest.

It is an algorithm based on the assembly of decision trees. An algorithm which could handle both classification and regression tasks, depending on the nature of the data,[18] it provides a high classification accuracy, requires fewer parameters' settings, has a fast-training efficiency.[19]

Support Vector Machines

SVM is a very famous tool in machine learning, particularly for classification and regression tasks. Here's an overview of their role in prediction quality. SVM is a supervised learning algorithm used for classification and regression. Support vector machines (SVMs) are classic binary classification algorithms and have been shown to be a robust and well-behaved technique for classification in many real-world problems.[20]

Logistic Regression

Logistic Regression is a type of statistical model used for binary classification tasks, where the goal is to predict one of two possible outcomes. It's commonly used in situations where the dependent variable (the outcome you're trying to predict). Logistic regression is more popular than multiple linear regression in medical research because it can predict a dichotomous dependent variable from a set of binary explanatory variables. Unlike linear regression, the relationship among the explanatory variables in logistic regression does not need to be linear, and the variables do not have to follow a normal distribution.[21,22]

Predictive quality and agri-food industry

Predictive quality in the agri-food sector has seen significant advancements recently, driven by the integration of sophisticated technologies and data analytics. Machine learning algorithms and artificial intelligence are being increasingly employed to predict and enhance product quality, leading to more precise and timely interventions. Innovations in sensor technology allow for real-time monitoring of various parameters such as temperature, humidity, and chemical composition, providing critical data for predictive models. Additionally, blockchain technology is being utilized to ensure traceability and transparency throughout the supply chain, further enhancing the reliability of quality predictions. These advancements not only improve product consistency and safety but also reduce waste and optimize production processes, ensuring a more efficient and sustainable agri-food industry.

The AI approach offers numerous advantages, and the food sector has been leveraging it for decades, with increasing adoption in recent years. AI can replace traditional food production systems by either developing new AI models or adapting existing ones to address the unique challenges associated with producing meat, beverages, and cultured meat. This may involve creating models specifically designed to predict quality metrics, optimize manufacturing processes, or ensure regulatory compliance in food production.[23] By integrating feedback loops within AI systems, continuous learning from real-time data gathered during food production can be achieved. This enables AI systems to refine and improve their predictions and recommendations over time as they gain experience with the new technology.[24]

Since 2015, the innovation of AI applications in the food processing sector has accelerated. The use of Artificial Neural Networks (ANN) in various tasks within the industry has shown promising results, with all applications performing satisfactorily based on R2 values, demonstrating ANN's ability to deliver precise and reliable outcomes. Additionally, other machine learning (ML) techniques Linear Regression, Random Forest, Support Vector Machine, k-Nearest Neighbors Regression, Logistic Regression and others are utilized in the food industry. Studies have shown that ML applications have contributed to better decision-making, reduced sensory evaluation costs, and improved business strategies to meet consumer needs.[25]

Explainability with XAI

Explainability has become a central topic in machine learning research, with increasing emphasis on explainable AI (XAI) as the field evolves. The surge in interest can be attributed to the growing complexity of AI systems and their integration into critical decision-making processes. Researchers like[26] and[27] have highlighted the importance of making AI models interpretable to ensure they can be understood and trusted by users.

As AI technology continues to advance at a rapid pace, the challenge of achieving transparency and comprehensibility in these models has become more pronounced.[28] The complexity of modern AI systems—such as deep learning networks and ensemble methods—often results in models that act as "black boxes," where the decision-making process is obscured. This complexity complicates efforts to explain how models arrive at their predictions or decisions. Addressing this challenge is crucial for several reasons. Transparent AI models facilitate better understanding and trust among users, particularly in high-stakes applications where decisions need to be justified. Furthermore, explainability aids in identifying and correcting model biases, improving regulatory compliance, and ensuring ethical AI use. As AI systems become more embedded in various sectors, the development of robust XAI techniques is essential for maintaining accountability and fostering greater acceptance of AI technologies.[29]

The proposed model for qualitative classification of product:

To predict product quality using machine learning, particularly classification algorithms, an innovative model architecture could involve a hybrid approach combining deep learning and traditional machine learning techniques

The adopted model represents is based on a workflow for developing and selecting a quality classification model using machine learning techniques. This model is based on five main steps and result section:

Step 1: data used in training and prediction is used to train the machine learning models. It contains both the features (input variables) and the labels (output variables) needed for training. This dataset is trained to make predictions on new, unseen data. It contains only the features, and the model will predict the corresponding labels.

Step 2: this step involves preprocessing the data to make it suitable for training. It may include tasks such as cleaning the data, handling missing values, normalizing or standardizing the data, and other necessary transformations.

Feature Engineering & Modelling:

Step 3: This section involves creating new features or modifying existing ones to improve the model's performance. It's a crucial step where domain knowledge can be applied to extract the most informative features from the raw data. The modelling step involves selecting the type of model to be used and configuring it for training.

Step 4: The models chosen in this model are ANN, SVM, RF and LR. The choice is based on results of preselection between nine initial models.

Step 5: Scoring, Validation, and Explanation step involves evaluating the model's performance using various metrics as accuracy, precision and recall. Validation ensures that the model generalizes well to new data using cross-validation. The explanation sub-section refers to interpreting the model's predictions, which is increasingly important, especially in domains where understanding the decision-making process is crucial.

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Result Section- Choose the Quality Classification Model: Based on the scoring, validation, and explanation, the best-performing model is selected as the Quality Classification Model. This model is then used for future predictions on new data.

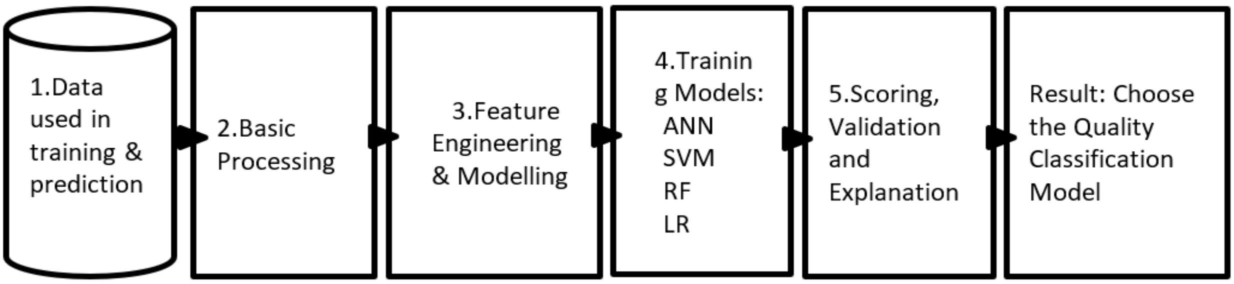

Figure 2. Case study architecture to Choose the best quality classification model

CASE STUDY

Dataset description:

This dataset, meticulously gathered through manual observations, is designed to support the development of machine learning models for predicting milk quality. It includes seven independent variables: pH, Temperature, Taste, Odor, Fat, Turbidity, and Color. Each of these variables plays a crucial role in determining the milk's grade or overall quality, making them essential for predictive analysis. The variables are defined as follows:

1. pH: The acidity or alkalinity level of the milk, influencing taste and shelf life.
2. Temperature: The storage temperature, affecting freshness and bacterial growth.
3. Taste: A subjective measure of the milk's flavor profile.
4. Odor: The smell of the milk, which can indicate spoilage or contamination.
5. Fat: The fat content, contributing to creaminess and nutritional value.
6. Turbidity: The clarity of the milk, which can signal impurities or spoilage.
7. Color: The visual appearance of the milk, which should be consistent and free from discoloration.

These parameters are vital for conducting thorough predictive analyses to assess milk quality. By understanding and analyzing these variables, robust models can be built to provide accurate predictions and insights into milk quality.

Quality Prediction and Target:

The primary target variable in this dataset is the Grade of the milk, which can be categorized based on quality. The grade indicates whether the milk is of high, medium, or low quality. For simplicity, the target variable can be classified as:

1. Low (Bad Quality)
2. Medium (Acceptable Quality)
3. High (Best Quality)

Prediction results:

The best model to predict the milk quality level:

The table compares the performance of four models: ANN, RF, LR, and SVM, in terms of accuracy and standard deviation. ANN emerges as the most reliable and consistent model, with the highest accuracy of 87,46 % and the lowest standard deviation of 0,027. RF follows with an accuracy of 82,18 % and a slightly higher standard deviation of 0,033, indicating more variability in its performance. LR shows a reasonable accuracy of 79,20 % and a standard deviation of 0,030, but it lags behind ANN in both accuracy and consistency. SVM, with the lowest accuracy of 69,66 % and a standard deviation of 0,032, is the least accurate and consistent model among the four. Therefore, ANN stands out as the best choice for this dataset.

Table 1. Calculated accuracy using the four chosen model

Model	Accuracy	Standard Deviation
ANN	87,46 %	0,027
RF	82,18 %	0,033
LR	79,20 %	0,030
SVM	69,66 %	0,032

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Table 2. Structured representation of the attribute weights

Attribute	Weight
Temprature	23,89 %
pH	12,44 %
Turbidity	7,68 %
Taste	3,80 %
Odor	3,08 %
Colour	2,88 %
Fat	2,79 %

These weights indicate the relative importance of each attribute in determining the quality or outcome in the model. For example, temperature has the highest weight at 23,89 %, suggesting it has the most significant impact, while attributes like fat and color have lower weights, indicating a lesser influence on the outcome.

Although machine learning (ML) models are effective in providing predictions, their lack of transparency can limit their utility. The attribute weights table shows that while certain factors like temperature and pH significantly impact predictions, understanding their specific roles is challenging with ML alone. This highlights the need for Explainable Artificial Intelligence (XAI). XAI techniques can clarify how these attributes influence model outcomes, making the decision-making process more transparent and comprehensible. Therefore, integrating XAI with ML is crucial for ensuring that predictions are not only accurate but also interpretable and actionable.

XAI and Important factors of milk quality:

The figures 3, 4 and 5 are a visualization related to milk data analysis. The different variables (Colour, Fat, Odor, Taste, Temperature, Turbidity, pH) are likely attributes of milk, and the charts on the right indicate how these attributes contribute to determining the quality of the milk, classified as "high," "medium," or "low". The most likely outcome, that the model predicts a 60 % likelihood that the milk quality is "high" based on the current settings of the variables.

Following figure 3, several factors contribute positively to its high quality. Fat content, pH level, color, turbidity, taste, and odor are all indicators that can signal superior milk quality. Higher fat content generally means richer milk, while a balanced pH level ensures freshness. A uniform color and low turbidity suggest purity and minimal contamination. Pleasant taste and mild odor further affirm high quality. Conversely, elevated temperatures can negatively affect milk quality by fostering bacterial growth, leading to spoilage and deterioration in taste and smell. Maintaining optimal temperature is crucial to preserving the milk's quality.

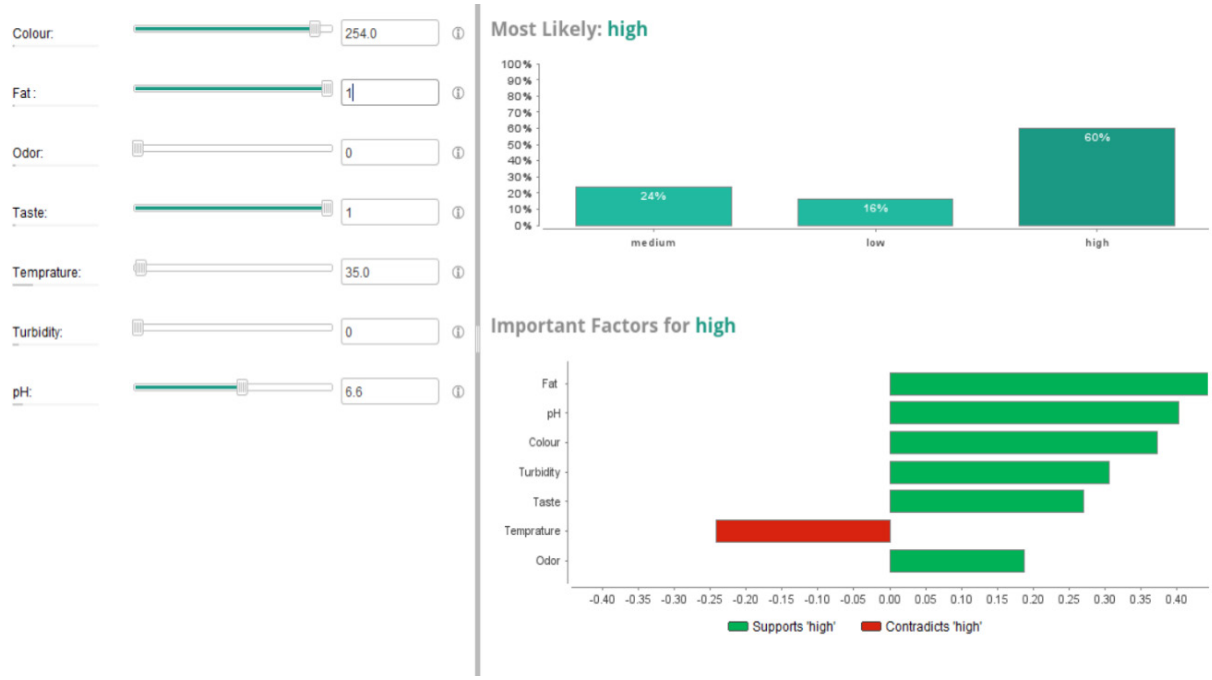

Figure 3. Important factors impacting high quality of milk

According to figure 4, two factors positively influence medium milk quality: pH level and taste. These indicators suggest that the milk is of medium quality. On the other hand, elevated temperatures negatively impact milk quality, while issues with color, fat content, and turbidity also signal a decline in medium quality.

Based on figure 4, temperature plays a crucial role in determining low milk quality. Elevated temperatures can lead to deterioration in milk, promoting bacterial growth and spoilage. Additionally, factors such as color, turbidity, fat content, and taste further contribute to lower milk quality. Discoloration may indicate contamination or spoilage, while high turbidity suggests the presence of impurities. An abnormal fat content can affect the milk's texture and richness, and an off-taste reflects potential quality issues. Together, these elements collectively signal a decline in milk quality.

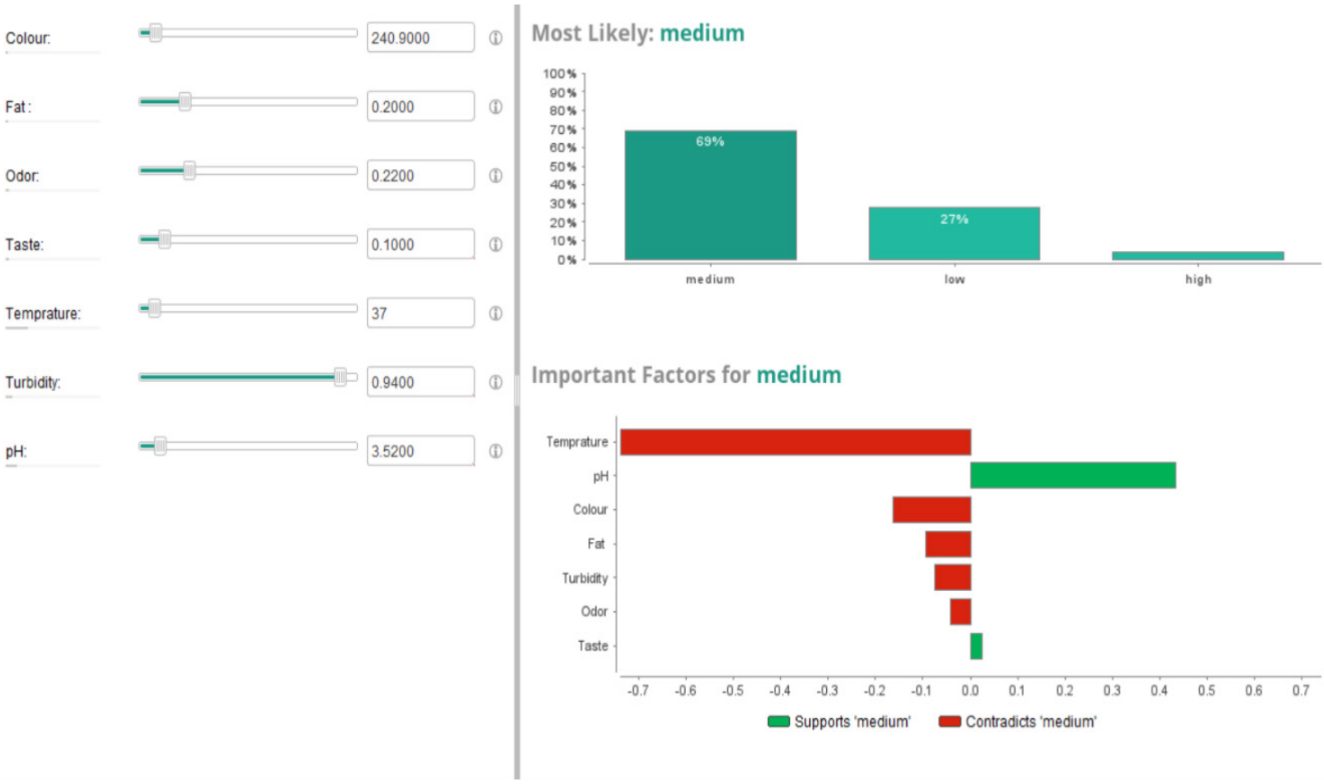

Figure 4. Important factors impacting medium quality of milk

The analysis presented in figures 3, 4, and 5 provides a comprehensive view of how various attributes—such as color, fat, odor, taste, temperature, turbidity, and pH—affect milk quality. The data suggests that the model predicts a 60 % likelihood of high-quality milk based on the current variable settings.

High-Quality Indicators: according to figure 3, several attributes positively influence high milk quality. Fat content, pH level, color, turbidity, taste, and odor are strong indicators of superior milk.

Overall, the figures illustrate a clear relationship between milk attributes and quality classification. High-quality milk is characterized by optimal fat content, balanced pH, desirable color, low turbidity, and pleasant taste and odor. Medium-quality milk shows a balance in pH and taste but suffers from issues like temperature effects and changes in other attributes. Low-quality milk is marked by elevated temperatures, poor color, high turbidity, abnormal fat levels, and off-taste. Effective management of these variables is essential for ensuring high-quality milk production. The figures demonstrate that high-quality milk is characterized by optimal fat content, a balanced pH level, desirable color, low turbidity, and a pleasant taste and odor. These indicators are essential for ensuring that the milk meets high-quality standards, reflecting freshness, purity, and minimal contamination.

For medium-quality milk, factors such as pH level and taste remain relatively stable, but other variables—such as temperature effects, changes in color, fat content, and turbidity—can influence the quality classification. Although the milk may still be acceptable, these factors indicate areas where improvements are needed to move towards higher quality.

Low-quality milk is identified by elevated temperatures, poor color, high turbidity, abnormal fat levels, and off-taste. These attributes point to significant issues such as spoilage, bacterial contamination, and degradation of milk quality. Addressing these problems is crucial for preventing quality decline and ensuring the milk remains safe and desirable for consumers.

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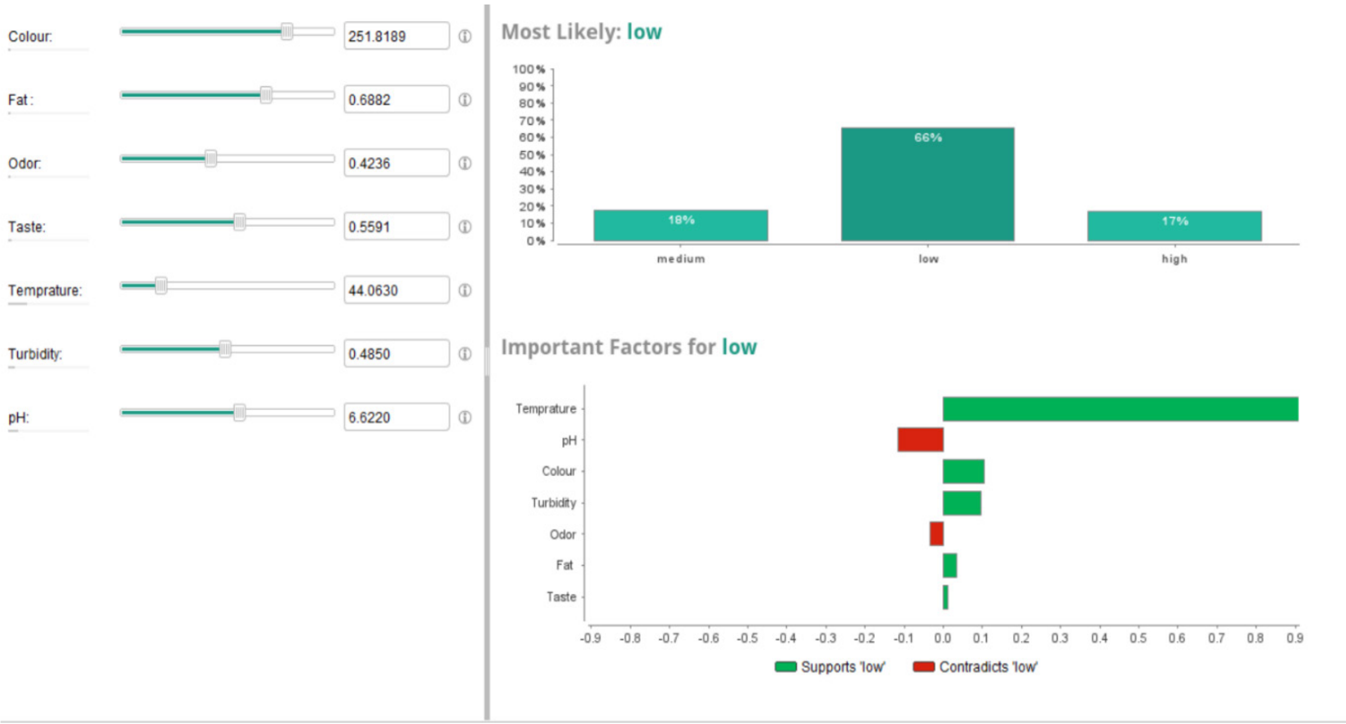

Figure 5. Important factors impacting low quality of milk

CONCLUSION

Machine learning models, particularly Logistic Regression, play a valuable role in predicting the quality of the product based on few attributes, supporting more precise decision-making and quality control.

The study highlights the importance of managing key product attributes to achieve high-quality standards, with a focus on Agri-food industry case study. Quality control is essential and depends on optimal factors. In milk industry, factors like optimal fat content, balanced pH levels, consistent color, minimal turbidity, and pleasant taste and odor define the quality of milk, reflecting its freshness and purity. Through a case study, the analysis shows that high-quality milk is achieved by maintaining these parameters, demonstrating the role of predictive models in effective quality management.

By using these predictive models, the industry can implement targeted improvements, such as temperature regulation to prevent spoilage, and careful monitoring of color and fat content to maintain high standards. Addressing the factors that contribute to lower quality helps prevent issues before they arise, ensuring consumer satisfaction and trust. Future research can enhance these predictive models, refining quality control practices and promoting efficient production especially in industry processes.

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DATA AVAILABILITY

Data set used in the case study is provided by an agri-food industrial company. Data will be made available on request.

COMPETING INTEREST

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AUTHOR CONTRIBUTIONS

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