

Assessment of Milk Quality Optimization of Yogurt Fermentation

Sejal Gilda¹, Meghali Waghmode^{2*}, Arpita Sable³

Abstract

In the creation of new products, yogurt makers need to prioritize consumer preferences to enhance their market share. An advanced prediction method will help in grasping the fundamental connection between consumer preferences and sensory attributes. This study introduces a new deep learning approach that employs an autoencoder to derive product features from expert-scored sensory attributes. These sensory features are then analyzed through support vector machine regression to align them with consumer preferences. Manual distance measurement is often prone to human error. This project aims to achieve precise and consistent measurements for short distances. The device can measure distances between 0.5 meters and 4 meters with an accuracy of 1 cm. This project employs ultrasonic sensors to determine distance by emitting ultrasonic waves at a frequency of 40 kHz. The circuit, which is controlled by an ATmega microcontroller, calculates the distance using the speed of sound at 25°C, factoring in the ambient temperature and the time taken for the waves to return. The measured distance is then displayed on an LCD module. The importance of this project lies in its capability to accurately measure distances to different obstacles. This device is applicable in numerous fields, including construction for distance measurement, robotics, car sensors for obstacle avoidance, and many other uses.

Keywords: Yogurt, model-train, consumer preference, autoencoder, support vector machine

INTRODUCTION

Machine learning (ML) methods have become crucial in the food industry, particularly for maintaining quality control and ensuring food safety standards. An important application in this field is the precise identification of milk and yogurt, which are both essential products in the dairy industry. This distinction is not just a matter of convenience; it is crucial to preserve product quality, avoid contamination, and ensure authenticity in the dairy industry. To address this challenge and harness the power of ML, a thorough approach was utilized [1–3]. The initial phase of developing an ML model to

differentiate between milk and yogurt involves gathering a thorough dataset. This dataset typically includes images, spectroscopic data, and the chemical properties of both milk and yogurt. Collecting a wide array of data is crucial for ensuring the accuracy of the model across different real-world situations. After collection, the data underwent thorough preprocessing, which included removing noise, standardizing data formats, and ensuring consistency throughout the dataset. Different ML algorithms were employed with a clean and well-structured dataset. These include support vector machines (SVM), random forests, and deep learning models such as Convolutional Neural Networks (CNNs) [4]. The algorithms were subsequently trained on the preprocessed dataset to

*Author for Correspondence

Meghali Waghmode
E-mail: meghali.waghmode1@gmail.com

¹⁻³Student, Department of Electronics & Telecommunication Engineering, Smt. Kashibai Navale College of Engineering, Pune, Maharashtra, India

²Assistant Professor, Department of Electronics & Telecommunication Engineering, Smt. Kashibai Navale College of Engineering, Pune, Maharashtra, India

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create a robust model that can accurately differentiate between milk and yogurt. The use of ML to predict milk quality and optimize yogurt fermentation processes has many benefits [5]. This goes beyond just differentiating between the two dairy products. The primary objectives include boosting the efficiency of the dairy industry, maintaining high product quality, and promoting innovation in a constantly changing environment [6] ML, through data-driven insights, paves the way for more efficient, sustainable, and competitive practices in dairy production.

The key elements of the Milk and Yogurt Fermentation Detection Project include the following.

- *ASPECT 1: Importance in the food industry*–Utilizing ML for milk and yogurt detection is crucial for maintaining quality control and food safety in the food industry.
- *ASPECT 2: Differentiation Challenge* - The main challenge is to accurately distinguish between milk and yogurt, which is essential for quality control, prevention of contamination, and ensuring product authenticity.
- *ASPECT 3: Data Collection* - A diverse and thorough dataset of images, spectroscopic data, and chemical properties of both milk and yogurt was gathered.
- *ASPECT 4: Data Preprocessing* - The collected data underwent preprocessing to eliminate noise, standardize data formats, and ensure consistency throughout the dataset.
- *ASPECT 5: ML Algorithms* - Various ML techniques have been applied, including SVM, random forests, and deep learning models such as CNNs.
- *ASPECT 6: Motivation* - This project aims to enhance product quality, refine processes, ensure consumer safety, and drive innovation in the dairy industry through data-driven insights.
- *ASPECT 7: Efficiency and Sustainability* - The goal is to achieve more efficient, sustainable, and competitive practices in dairy production.
- *ASPECT 8: Quality Prediction*: One objective is to create an ML model that predicts the quality of milk based on various parameters.
- *ASPECT 9: Fermentation Analysis* - Another objective is to use ML techniques to analyze and optimize the yogurt fermentation process.
- *ASPECT 10: Multidisciplinary Approach* - Reaching these objectives requires a blend of domain expertise, data engineering skills, and advanced ML methods.

The history of mental health extends to ancient civilizations where various cultures have rudimentary concepts of mental illness. The development of modern psychiatry began in the late 19th and early 20th centuries [7].

Throughout the 20th century, diagnostic tools such as the Diagnostic and Statistical Manual of Mental Disorders (DSM) and various psychological assessment tests have been developed, offering standardized methods for diagnosing mental health conditions. In the late 20th and early 21st centuries, significant advancements in computing power and data analytics occurred, enabling the use of ML algorithms across various fields, including healthcare. However, its popularity surged in the 1990s because of its effectiveness in classification tasks, particularly in domains with high-dimensional data, such as genetics, image processing, and text classification. With the integration of ML in Healthcare as a ML technique, researchers and healthcare professionals began exploring their potential in diagnosing and managing medical conditions. This progress has resulted in the creation of predictive modeling and decision support systems in healthcare. Simultaneously, there is an increasing awareness of the need for ongoing monitoring and early intervention in mental health care [8].

Various technologies, including mobile applications and wearable devices, have been developed to collect data on individuals' behavior, physiological signals, and self-reported experiences. The application of SVM in Mental Health researchers started by applying SVM and other ML algorithms to mental health data for tasks such as predicting treatment outcomes, detecting mood disorders, and assessing suicide risk.

The SVM's capacity to manage high-dimensional data and nonlinear relationships makes it especially effective for analyzing complex mental health datasets. Development of Mental Health Trackers Building upon advancements in both mental health care and ML, developers began integrating SVM algorithms into mental health tracking applications. These trackers utilize data from various sources, including self-reports, activity levels, sleep patterns, and social interactions to provide personalized insights and early warnings for individuals at risk of mental health issues. Continued Refinement and Validation of the development of Mental Health Trackers using SVM continue to evolve, with ongoing efforts focused on refining algorithms, improving data collection methods, and validating the effectiveness of these tools in real-world settings through clinical trials and longitudinal studies [9].

HISTORY

The history of milk quality prediction and yogurt fermentation is intertwined with broader histories of dairy science, microbiology, and food technology. The following is a brief overview.

1. *Early beginnings:* The history of dairy production and fermentation dates back thousands of years. Historically, milk has been primarily consumed as a fresh product or converted into fermented products such as yogurt, cheese, and kefir. Early civilizations, including the Sumerians and ancient Egyptians, were thought to have engaged in basic methods of dairy fermentation.
2. *Scientific discoveries:* Understanding microbiology in the 19th century paved the way for significant advancements in dairy science. Researchers, such as Louis Pasteur, have elucidated the role of microorganisms in fermentation processes.
3. Pasteurization, named after Louis Pasteur, has become a crucial technique for killing harmful bacteria in milk while preserving its quality.
4. *Quality prediction:* The development of techniques for predicting milk quality has emerged alongside advancements in microbiology and analytical chemistry. These techniques involve the assessment of various parameters, such as bacterial counts, somatic cell counts, fat content, and protein content. Over time, these methods have become more sophisticated and rely on automated systems and sensor technologies to provide real-time quality assessments [10–12].
5. *Yogurt fermentation:* Yogurt fermentation has a long history, and its origins are believed to be traced back to ancient Mesopotamia. Traditionally, yogurt is prepared by allowing milk to ferment naturally, often in warm environments. However, the industrialization of yogurt production has led to the development of standardized fermentation processes and the use of starter cultures containing specific strains of bacteria, notably *Lactobacillus bulgaricus* and *Streptococcus thermophilus*.
6. *Industrialization and modernization:* The 20th century witnessed significant industrialization and modernization of dairy production processes, including milk quality control and yogurt fermentation. This period saw the development of standardized testing methods, pasteurization techniques, and large-scale commercialization of yogurt production.
7. *Technological advancements:* In recent decades, technological advancements have transformed the prediction of milk quality and yogurt fermentation.
8. Automation, data analytics, and ML algorithms have been applied to optimize production processes, improve product consistency, and ensure that quality standards are met [13, 14].
9. *Current trends:* Today, there is an increasing focus on sustainability, health, and innovation in the dairy industry. This has led to the exploration of alternative milk sources (such as plant-based milk) and the development of probiotic-rich yogurt with additional health benefits. Moreover, there is ongoing research on predictive modeling and AI-driven systems for milk quality assessment and fermentation control, aiming to further enhance efficiency and product quality.

Overall, the history of milk quality prediction and yogurt fermentation reflects a journey of scientific discovery, technological innovation, and cultural evolution in dairy production and food science. The system architecture of the proposed model is shown in Figure 1.

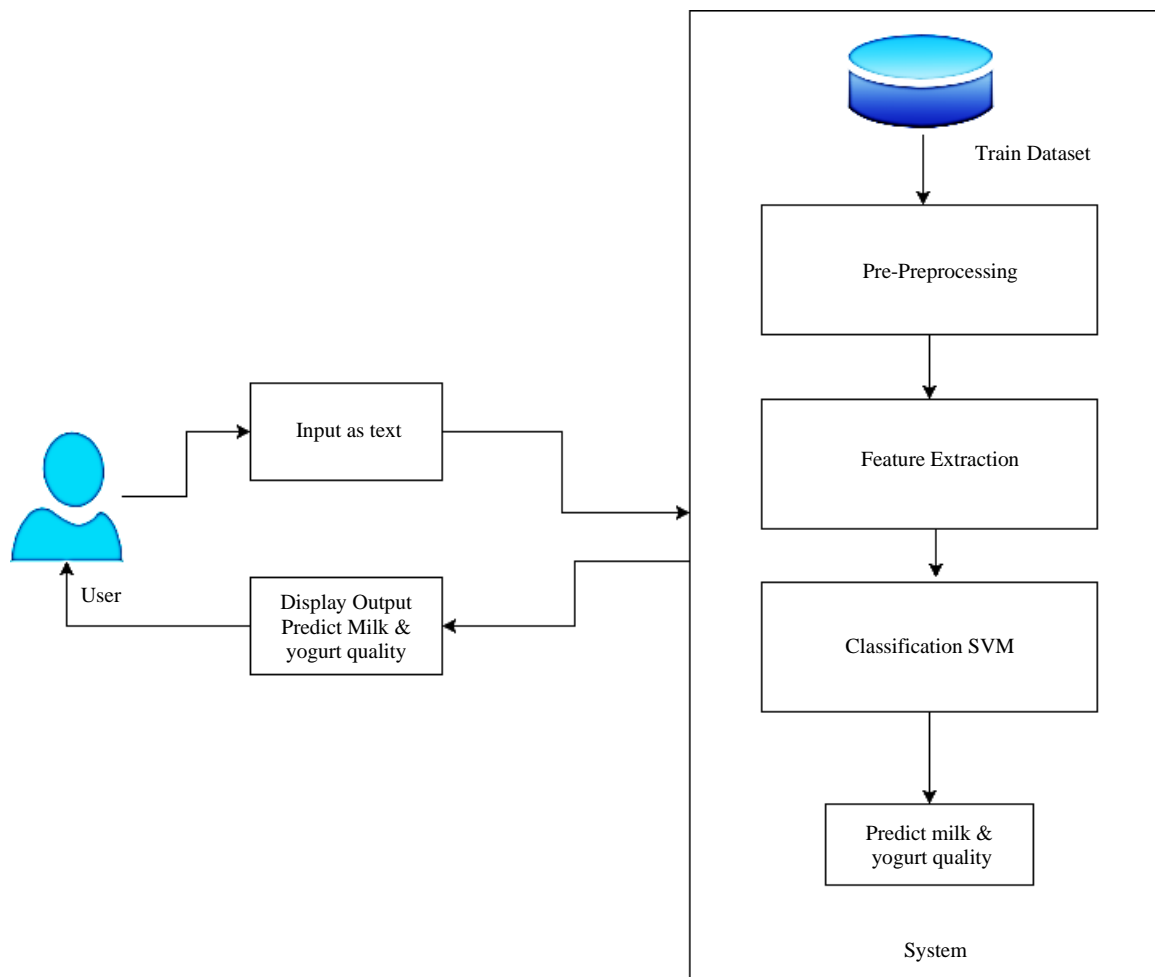


Figure 1. System architecture of the proposed model.

Data Collection and Preprocessing

- Gather diverse datasets for milk and yogurt.
- Clean, standardize, and format data, including noise removal and feature extraction.

ML Model Development

- Predict Milk Quality and optimize Yogurt Fermentation.
- Using ML algorithms like SVM, and Random Forests.

Integration and Deployment

- Integrate ML models into production processes.
- Deploy real-time detection system on-premises cloud.

Feedback Loop

- Continuously monitor and adapt the system to changing conditions.
- Incorporate insights from domain experts.

User Interface and Reporting

- Provide a user-friendly interface for real-time interaction.
- Generate reports for decision-making and quality control.

Security and Authentication

- Implement data security measures and user authentication.

FUTURE SCOPE AND ITS APPLICATIONS

The future scope and applications of milk quality prediction and yogurt fermentation are promising, driven by advancements in technology, increasing consumer demand for high-quality and healthy dairy products, and growing emphasis on sustainability and efficiency in food production. There are several potential future directions and applications [15, 16].

1. *Precision Dairy Farming*: Precision agriculture techniques, including sensor technologies, data analytics, and AI-driven systems, can be applied to monitor various parameters related to milk production and quality in real-time. This could enable dairy farmers to optimize feeding regimes, detect health issues in cows early, and improve the overall milk quality.
2. *Predictive Modeling*: Advanced ML and predictive modeling algorithms can be utilized to develop highly accurate models for milk quality prediction. These models can incorporate diverse datasets, including environmental factors, cow health data, and milk composition, to precisely forecast milk quality. These models can help dairy farmers make informed decisions about milk processing and distribution.
3. *Value-Added Products*: Beyond traditional yogurt, there is room for innovation in the development of novel dairy products with unique flavors, textures, and nutritional profiles. Fermentation technologies can be used to create functional dairy products enriched with probiotics, prebiotics, vitamins, and other bioactive compounds.
4. *Global Health Initiatives*: In regions with limited access to high-quality dairy products, advancements in milk quality prediction and yogurt fermentation could contribute to improving public health outcomes. Affordable and accessible dairy products fortified with essential nutrients can help address nutritional deficiencies and promote overall well-being.
5. In summary, milk quality prediction and yogurt fermentation hold tremendous potential for leveraging technology, innovation, and sustainable practices to enhance dairy production, product quality, and consumer satisfaction. By embracing these advancements, the dairy industry can meet evolving market demands while addressing the challenges related to food security, health, and environmental sustainability.

METHODOLOGY

The methodology for milk quality prediction and yogurt fermentation involves a multidisciplinary approach that incorporates techniques from dairy science, microbiology, analytical chemistry, data science, and food technology. A generalized methodology can be adapted and refined based on specific research objectives and available resources.

Data Collection and Preprocessing

Other relevant data sources include milk composition data, environmental factors (e.g., temperature and humidity), cow health records, and fermentation parameters (for yogurt production).

Prepare and preprocess the data by eliminating noise, addressing missing values, and maintaining consistency across variables.

Feature Selection and Engineering

Determine the relevant features (variables) that could impact milk quality or fermentation results. These may include factors such as pH, temperature, bacterial count, somatic cell count, fat content, protein content, and lactose content.

Feature engineering is conducted to create new and valuable features or refine existing features to improve the model's performance.

Model Development for Milk Quality Prediction

Suitable ML or statistical modeling techniques are selected depending on the characteristics of the data and research goals. Common approaches include regression analysis, classification algorithms, and time series forecasting methods.

Training predictive models using historical data on milk quality and associated factors. We consider using techniques such as cross-validation to evaluate model performance and prevent overfitting. Explore ensemble methods or deep learning architectures for capturing complex relationships in the data if necessary [17].

Model Validation and Evaluation

Evaluation of predictive models using distinct datasets or cross-validation techniques. Examine performance metrics, such as accuracy, precision, recall, F1-score, and area under the ROC curve (for classification tasks). Make adjustments and optimizations of the models based on the validation results if needed.

Real-time Monitoring and Control

Deploy sensor technologies and IoT devices for real-time tracking of milk quality parameters or fermentation conditions.

Create algorithms for automated decision-making and control systems to enhance process parameters and ensure consistent product quality.

Yogurt Fermentation Optimization

Experiments were conducted to optimize the fermentation conditions for yogurt production, considering factors such as temperature, pH, inoculum concentration, incubation time, and starter culture selection.

We applied statistical design of experiments (DOE) or response surface methodology (RSM) to systematically investigate the effects of various variables and determine the optimal conditions for fermentation.

Process Scale-up and Commercialization

Expand optimized fermentation processes from laboratory- or pilot-scale setups to full-scale industrial production facilities. Pilot trials and quality assurance tests were conducted to ensure consistency and scalability of the production process. Quality control protocols and monitoring systems should be established to ensure product quality during large-scale production.

Continuous Improvement and Innovation

Continuously gather feedback from production processes and consumer preferences to drive further improvement and innovation. Explore emerging technologies and research advancements to stay at the forefront of milk quality prediction and yogurt fermentation.

Throughout the methodology, collaboration between experts from diverse fields is essential to effectively leverage the domain knowledge and technical expertise. Additionally, adherence to regulatory standards and food safety guidelines is critical for ensuring the quality and safety of dairy products [18].

CONCLUSION

In summary, applying ML to the dairy industry, especially for forecasting milk and yogurt quality and examining fermentation processes, can greatly enhance efficiency, product quality, and consumer safety. Accurate differentiation between milk and yogurt presents a crucial challenge that can be addressed using effective ML models. Success in these areas requires a multidisciplinary approach that integrates domain expertise, data engineering skills, and advanced ML techniques. A varied dataset encompassing images, spectroscopic data, and chemical properties essential for effective model training. Appropriate data preprocessing, including noise reduction and standardization, is vital. Different ML methods, including SVM, random forests, and deep learning models such as CNNs, can

be used to build these systems. These models can be implemented in real-time in production lines, dairy farms, or retail settings to swiftly address issues such as mislabeling or contamination, thus maintaining product authenticity and quality.

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