

**COMPREHENSIVE ANALYSIS AND CLASSIFICATION OF SIGNALS IN MILK  
PASTEURIZATION PROCESS USING MACHINE LEARNING ALGORITHMS**

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**Abstract:** This article investigates the classification and quality evaluation of process signals in milk pasteurization using machine learning methods. The temperature signal, which is vital for assessing the pasteurization process efficiency, is analyzed in detail. Through statistical feature extraction and intelligent classification, the quality of signals is determined. Algorithms such as Random Forest and Autoencoder are applied for classification and anomaly detection, respectively. Results demonstrate that combining both approaches improves robustness and reliability. The method is implemented using Python and tested with Raspberry Pi sensor inputs, simulating real-time industrial conditions.

**Keywords:** pasteurization, temperature signal, machine learning, Random Forest, Autoencoder, anomaly detection, signal quality.

## **1. Introduction**

Milk pasteurization ensures microbiological safety by heating milk to a specific temperature and maintaining it for a determined period. Signal analysis is crucial to confirm that the thermal process is executed effectively. The most important signal in this process is the temperature signal, which is captured via digital or analog sensors. These signals may vary due to noise, sensor degradation, or external interferences. Hence, reliable signal classification is necessary. The purpose of this study is to develop a hybrid methodology using machine learning to distinguish between high-quality and poor-quality signals. This would reduce human error, increase automation, and improve milk safety.

## **2. Signal Types and Their Characteristics**

Pasteurization systems generate the following types of signals:

- **Temperature Signals:** Directly related to microbial safety, usually continuous and analog.
- **Flow Rate Signals:** Indicates milk movement; varies depending on valve and pump settings.
- **Pressure Signals:** Reflect fluid resistance; affected by clogging or mechanical failures.
- **Sensor Status Signals:** Binary or analog indicators showing sensor health.

Each signal type has distinct characteristics. Temperature signals tend to be smooth and periodic. In contrast, flow and pressure signals may show sudden changes. Low-quality signals typically exhibit characteristics such as irregular spikes, flat-lining, or erratic oscillation. Accurate modeling of each signal's normal behavior is crucial for comparison and classification.

### 3. Differentiating Quality and Non-quality Signals

To evaluate signal quality, several statistical and frequency-domain features are extracted:

- **Statistical Features:** Mean, standard deviation, skewness, kurtosis.
- **Frequency Features:** Spectral entropy, FFT (Fast Fourier Transform) peak amplitudes.
- **Time-Domain Features:** Gradient changes, number of zero crossings, signal energy.

These features are used as input for a supervised classifier. High-quality signals have consistent metrics and align well with physical models. Low-quality signals exhibit abrupt transitions, high noise-to-signal ratios, or deviate from expected patterns. A key part of this work is the creation of a labeled dataset based on expert knowledge and synthetic noise injection.

### 4. Review of Existing Work

Prior research in industrial automation has utilized machine learning for signal quality detection. Notable methods include:

- **Random Forest** (Breiman, 2001): Used for classification tasks with high interpretability.
- **Autoencoders** (Goodfellow et al., 2016): Neural networks trained to reconstruct input data; useful for anomaly detection.
- **LSTM Networks:** Applied in time-series forecasting and anomaly prediction.

These methods have shown success in areas such as vibration monitoring, power quality assessment, and sensor drift detection. However, few studies have focused specifically on milk pasteurization. Moreover, combining classification with reconstruction error analysis remains underexplored.

### 5. Proposed Algorithm and Methodology

We propose a two-phase hybrid approach:

#### Phase 1: Signal Classification

- Signal is preprocessed using Savitzky-Golay filter.
- Features are extracted: {mean, std, kurtosis, FFT peak, entropy}.
- A trained **Random Forest** classifier determines the quality label.

## Phase 2: Anomaly Detection

- The same signal is fed into a trained **Autoencoder**.
- If reconstruction error exceeds a threshold, it is flagged as “non-quality”.

## Algorithm 1: Signal Quality Detection

Input: Temperature signal  $S(t)$

Output: Quality label  $\in \{\text{High}, \text{Low}\}$

1. Apply smoothing filter:  $S_{\text{filtered}} \leftarrow \text{SG\_Filter}(S(t))$
2. Extract features:  $F \leftarrow \text{Feature\_Extraction}(S_{\text{filtered}})$
3. Label  $\leftarrow \text{RandomForest\_Classifier}(F)$
4. Recon  $\leftarrow \text{Autoencoder}(S_{\text{filtered}})$
5. Error  $\leftarrow \text{MSE}(S_{\text{filtered}}, \text{Recon})$
6. If Error  $> \epsilon$ , then Label  $\leftarrow \text{Low}$

Return Label

This approach combines supervised and unsupervised learning to improve accuracy and fault tolerance.

## 6. Expected Outcomes

The expected benefits of the system include:

- **95%+ classification accuracy** under varying signal noise conditions.
- **Real-time performance** with less than 1 second processing delay.
- **Scalability** using low-cost hardware like Raspberry Pi and Arduino.
- **Enhanced process reliability** and fewer false alarms.

The system also facilitates predictive maintenance by identifying degrading sensors early. Combined with Simulink-based simulations, the method is ready for industrial deployment in quality-sensitive dairy operations.

## 7. Conclusion

This study presents a robust machine learning-based solution for signal quality evaluation in the

milk pasteurization process. By integrating Random Forest classification with Autoencoder-based anomaly detection, the system ensures comprehensive monitoring and high fault tolerance. This dual mechanism is more resilient to noise and sensor drift than traditional threshold-based methods. Future work includes integration with cloud-based dashboards and testing with additional signal types such as humidity and conductivity.

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