Non-Destructive Assessment of Raw Milk Quality Using Computer Vision and Artificial Intelligence

Ahmad Khoirul Umam[1*], Lilik Eka Radiati[1], Fitri Utaminingrum[2] and Dimas Firmanda Al Riza[3]

[1]Faculty of Animal Science, Universitas Brawijaya, Malang 65145, Indonesia
[2]Faculty of Computer Science, Universitas Brawijaya, Malang 65145, Indonesia
[3]Faculty of Agricultural Technology, Universitas Brawijaya, Malang 65145, Indonesia

Abstract. Milk quality plays a central role in determining dairy processing efficiency, product safety, and market value, with high-grade milk commanding premium prices. Conventional laboratory-based evaluations, including microbiological and physicochemical tests, provide accurate results but are time-consuming, costly, and impractical for real-time assessment at the farm level. Recent advances in computer vision and artificial intelligence (AI) offer non-destructive and rapid alternatives for food quality monitoring; however, applications specifically targeting raw milk remain underexplored. This study proposes a texture-based image analysis system to classify raw cow milk quality. A total of 1008 milk images were collected under controlled lighting conditions and categorized into three classes: (1) good quality with normal appearance, (2) non-defective but exhibiting abnormal opacity or thickness, and (3) defective samples with visible clots, sediment, or discoloration. Texture features were extracted using the Gray Level Co-occurrence Matrix (GLCM) at four pixel distances (1–4) and orientations (0°, 45°, 90°, 135°). Extracted parameters included contrast, correlation, homogeneity, dissimilarity, and energy. To reduce computational complexity, only the most relevant features were selected. Classification was conducted using a Decision Tree model, with the best performance achieved at pixel distance 3 and orientation 0°, yielding an accuracy of 81.68%. Statistical testing confirmed no significant differences across parameter variations, while confusion matrix analysis validated classification reliability across all categories. The results demonstrate the feasibility of combining GLCM-based texture features with decision tree models for rapid, non-destructive milk quality evaluation. This approach has strong potential for integration into precision dairy farming, although early-stage spoilage detection remains challenging.

Keywords: Computer vision, Machine learning, Non-destructive evaluation, Precision dairy farming, Texture analysis

* Corresponding author: a.khoirulumam@ub.ac.id

1 Introduction

Milk is one of the most important livestock products that directly contributes to human nutrition and food security. It provides essential nutrients, including high-quality proteins, fats, minerals, and bioactive compounds that support growth, health, and well-being [1]. In dairy production systems, the quality of milk is a crucial factor that determines both consumer acceptance and the profitability of farmers. High-quality milk ensures better processing characteristics for the dairy industry, resulting in superior dairy products such as cheese [2], yogurt and kefir [3], ice cream [4] and buttermilk, while also commanding higher prices in the market. Conversely, low-quality or contaminated milk not only reduces market value but also poses risks to food safety, public health, and consumer trust

Traditionally, raw milk quality has been assessed through physicochemical, microbiological, and sensory analyses, including fat, protein, lactose, acidity, somatic cell count, and microbial load. While accurate, these methods require laboratory facilities, skilled personnel, and significant time, making them impractical for on-farm or real-time monitoring. Manual inspection is also subjective and inconsistent. With increasing milk production volumes, there is a growing demand for rapid, objective, and non-destructive evaluation systems [5]. Ensuring high milk quality thus requires integrated management and technological monitoring systems. Recent advances in computer vision and artificial intelligence (AI) provide promising alternatives for rapid milk quality evaluation. Computer vision has been widely used in dairy sciences such as detection adulterant in milk and use-by date indicator for milk [6]. Applied to milk, image-based analysis offers a non-destructive approach to detect abnormalities such as discoloration, coagulation, or sedimentation. When combined with fluorescence imaging, it can also reveal subtle compositional and microbial changes.

Texture analysis has become an essential approach in food quality evaluation, particularly through the application of the Gray Level Co-occurrence Matrix (GLCM). This method extracts statistical features such as contrast, correlation, homogeneity, dissimilarity, and energy, which have been widely applied for the classification of fruits, vegetables, and meat products [7]. When integrated with artificial intelligence (AI) classifiers such as decision trees, GLCM-based features allow automated and interpretable classification, making them suitable for practical use in food quality monitoring. Within the livestock sector, such integration of digital tools reflects the growing trend of precision dairy farming, which relies on sensors, imaging, and AI to enable real-time monitoring of product quality.

Although deep learning approaches have recently gained prominence, they often require large datasets and high computational resources, which limit their applicability in smallholder farm contexts. In contrast, decision tree models remain attractive due to their interpretability, lower computational cost, and adaptability for farm-level decision-making [8]. However, despite their promise, only a limited number of studies have specifically applied GLCM-based texture features in combination with decision tree classifiers for the assessment of raw cow milk quality. This knowledge gap highlights the need for research that develops a non-destructive, computationally efficient system tailored for practical dairy applications.

In response to this gap, the present study employs computer vision and AI to establish a non-destructive method for raw cow milk quality evaluation. Specifically, the study aims to: (1) capture and analyze milk images under controlled conditions, (2) extract and select key visual features using GLCM, (3) classify milk samples into distinct quality groups with Decision Tree models, and (4) validate classification performance through statistical tests and confusion matrix analysis. By bridging livestock science with digital innovations, this work contributes to the advancement of precision dairy farming and provides a feasible framework for real-time milk quality monitoring in smallholder contexts.

2 Materials and methods

2.1 Materials

The raw material used in this study was fresh raw cow milk from Friesian Holstein crossbred dairy cows, obtained immediately after morning milking from local dairy farms located in Dau, Malang Regency, Indonesia. The milk samples were classified into three categories based on their storage duration at ambient temperature (25 ± 2 °C). The first category, representing good quality with normal appearance, consisted of samples stored for 0, 6, and 12 hours. The second category, classified as non-defective but with abnormal opacity or thickness, included samples stored for 18, 24, and 30 hours. The third category, considered defective samples containing clots, sediment, or discoloration, comprised milk stored for 36, 42, and 48 hours. The storage times (0–48 h, in 6 h intervals) were chosen to represent progressive stages of spoilage under ambient conditions, ranging from fresh to visibly defective milk, thereby allowing systematic evaluation of quality changes over time.

To enhance visualization of milk opacity and defects, methyl red dye (5%) was added in standardized amounts as a contrasting colorant. All samples were collected in sterile glass containers with airtight lids, handled under hygienic conditions, and prepared according to standardized laboratory procedures to minimize external contamination.

2.2 Methods

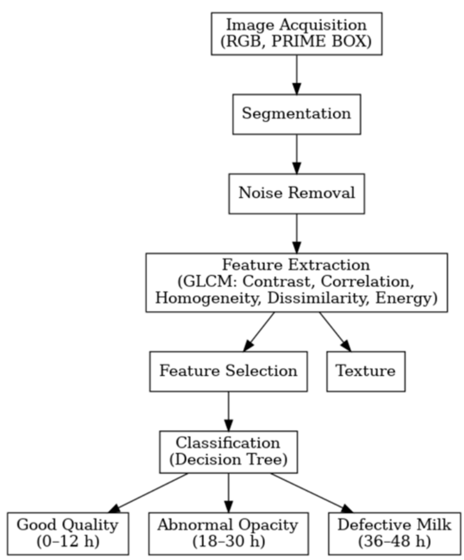

Fig. 1. Proposed system workflow for raw cow milk quality assessment using GLCM features and Decision Tree classification.

2.2.1 Image Acquisition

Image acquisition was conducted using a custom-designed PRIME BOX equipped with controlled illumination (Fig.2.). Each 15 mL raw milk sample was placed in a sterile 90-mm Petri dish with the addition of 0.5 mL of 5% methyl red indicator. After 30 s of mixing, images were captured using a fixed-focus camera mounted vertically at a 20 cm distance above the sample, aligned at 90° with the aid of a rigid jig. To ensure uniform illumination and minimize shadow artifacts, LED panels with diffusers (~6500 K) were installed along the four inner side walls of the box, surrounding the sample and producing lateral, evenly distributed light. Light baffles were included to reduce glare and direct reflection. The Petri dish was placed on a black matte background to enhance contrast, while a closing port on the top of the box prevented external light interference. This setup standardized geometry, lighting, and camera parameters across all acquisitions, ensuring reproducibility of the captured images.

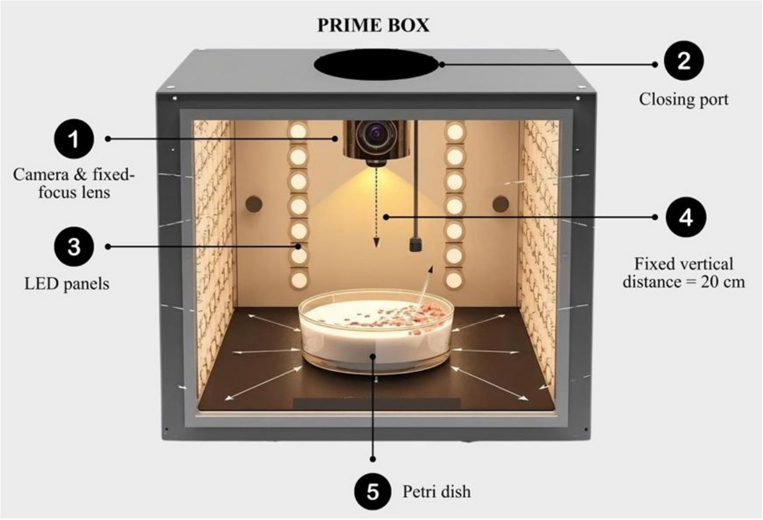

Fig. 2. Schematic of the PRIME BOX image acquisition system.

In total, 1,008 images of raw cow milk were collected and categorized into three quality groups according to storage duration at 25 ± 2 °C. The good quality group (0–12 h) comprised 336 images, with 112 images captured at each time point (0, 6, and 12 h). The abnormal opacity group (18–30 h) also consisted of 336 images, evenly distributed across 18, 24, and 30 h (112 images per time point). Finally, the defective group (36–48 h) included 336 images, with 112 images each at 36, 42, and 48 h. This systematic sampling ensured balanced representation of all quality stages, ranging from fresh to visibly spoiled milk

2.2.2 Object Segmentation

The captured images were pre-processed by cropping to remove irrelevant background regions and then resizing to 256 × 256 pixels to standardize input dimensions. All images were converted to grayscale to simplify texture representation, followed by contrast enhancement and Gaussian filtering to reduce noise and highlight relevant patterns. To improve dataset diversity, data augmentation was applied, including random rotations (±15°), horizontal and vertical flipping, as well as shear and skew transformations. After augmentation, the dataset increased from 336 original images to 1008 images used for analysis.

2.2.3 Feature Extraction

Texture features were extracted using the Gray Level Co-occurrence Matrix (GLCM) with four pixel distances (1, 2, 3, 4) and four orientations (0°, 45°, 90°, 135°). From each GLCM, five statistical features were calculated: contrast, correlation, homogeneity, dissimilarity, and energy. In total, 200 raw features were generated across all images. To minimize computational complexity and avoid redundancy, feature selection was applied using a two-step process. First, variance thresholding was used to remove low-variance features that contributed little discriminatory power. Second, pairwise correlation analysis was performed to eliminate highly correlated features ($r > 0.9$), ensuring that only non-redundant, informative features were retained for classification. This reduced the dimensionality of the dataset and improved model interpretability while maintaining predictive performance

2.2.4 Classification

The selected features were used as input for a Decision Tree classifier implemented in Python (scikit-learn). The dataset of 1008 images was randomly split into training (70%, n = 706 images) and testing (30%, n = 302 images) sets. To evaluate robustness, 20 independent sub-experiments were conducted with different random shuffling. The Decision Tree was configured with the following parameters: Gini index as the splitting criterion, maximum depth = 10, and minimum samples per leaf = 5 to prevent overfitting. Pruning was applied automatically using cost-complexity pruning (ccp_alpha = 0.01). Performance metrics included accuracy, precision, recall, and F1-score, while class-specific predictions were validated using a confusion matrix. To assess the statistical significance of performance differences across GLCM parameter variations, a paired t-test was performed with significance set at $p < 0.05$ using SPSS v26 and SciPy in Python.

3 Results and discussion

3.1 Visual and Physical Changes of Raw Cow Milk During Storage

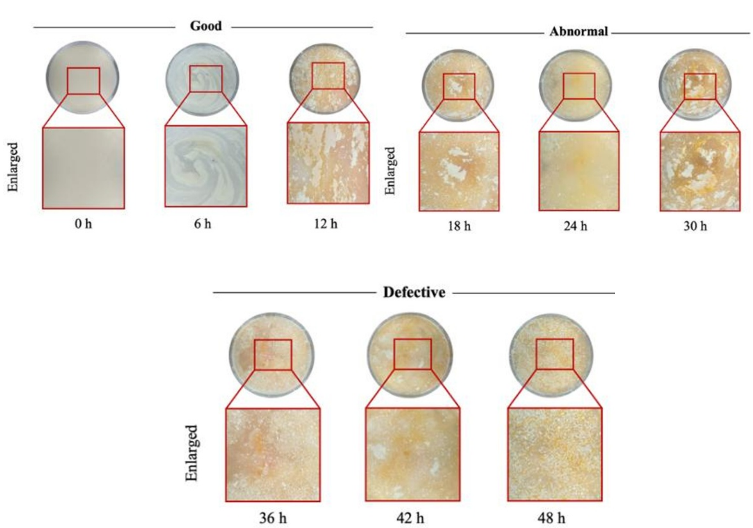

Fig. 3. The dataset sample of raw cow milk stored at ambient temperature (25 ± 2 °C) from 0 to 48 hours after adding the methyl red dye

The visual appearance of raw cow milk underwent progressive changes during storage at ambient temperature from 0 to 48 hours (Fig. 3). Methyl Red is a pH-sensitive dye that changes color from yellow at neutral pH to red under acidic conditions. Fresh raw cow milk (pH 6.6–6.8) appears yellowish after dye addition, reflecting its stable colloidal state. As storage at 25 ± 2 °C progresses, microbial fermentation of lactose lowers the pH, shifting the color toward orange (pH 6.0–6.2) during early spoilage (18–30 h) and red at advanced spoilage (pH <5.0, 36–48 h). This color transition, combined with visible textural changes such as turbidity, clotting, and sedimentation, enhances visual contrast and enables more accurate detection of milk deterioration through image analysis.

At 0–6 hours, the milk maintained its fresh characteristics with a uniform white color, smooth opacity, and homogeneous texture, representing good quality milk suitable for consumption and processing. By 12 hours, early signs of instability were observed, including slight increases in turbidity and surface heterogeneity, indicating the onset of structural changes in milk components. Between 18 and 30 hours of storage, more pronounced changes occurred, such as abnormal opacity, thickening, and the emergence of small clots or sediment. These alterations are consistent with the early stages of microbial proliferation and biochemical changes, particularly the reduction in pH due to lactic acid production, which leads to the destabilization of casein micelles. As the protein network weakens, milk loses its homogeneity, resulting in visible aggregation and phase separation [9]. At 36–48 hours, milk showed advanced spoilage with coagulation, sediment, and discoloration. These defects are strongly associated with microbial overgrowth, proteolytic and lipolytic enzyme activity, and advanced acidification, which promote protein denaturation and fat breakdown. Such conditions indicate that the milk is no longer safe for consumption and unsuitable for dairy processing.

These findings are in line with established dairy science, which emphasizes that the quality of raw milk is highly dependent on storage duration, microbial load, and environmental conditions. Previous studies have demonstrated that fresh raw milk can only maintain its physicochemical integrity for less than 12 hours at room temperature before spoilage indicators such as turbidity, clotting, and acidity become evident [10] evaluated the shelf-life of fresh and reconstituted milk under ambient (27–29 °C) and refrigerated (5–6 °C) conditions. Their findings indicated that fresh milk could be preserved for only about 9.5 ± 0.7 hours at room temperature, after which significant acidity development were observed, marking the onset of spoilage. [11] confirmed that both storage duration and temperature had a significant effect on the physicochemical and microbiological quality of raw milk. At higher ambient temperatures (26 °C), a rapid increase in total bacterial count and a decrease in pH were reported, leading to noticeable deterioration after only a few hours, as reflected by increased acidity and turbidity.

3.2 Texture Based Analysis Using GLCM Features

These findings are in line with established dairy science, which emphasizes that the GLCM analysis generated texture features, derived from pixel distances of (1, 2, 3, 4) and orientations of (0°, 45°, 90°, 135°). From each matrix, five statistical descriptors contrast, correlation, homogeneity, dissimilarity, and energy were extracted. Because using all features simultaneously could increase computational complexity and lead to redundancy, a feature selection process was applied based on variance thresholding and correlation analysis. This ensured that only the most informative features were retained for classification, while still preserving meaningful texture variation across milk quality categories. The textural properties of raw cow milk samples, extracted using GLCM, are summarized in Table 1. The analysis showed distinct differences among the three storage-based quality classes.

Table 1. Summary of GLCM texture features (mean ± SD) for raw cow milk at different quality classes. Statistical comparisons were conducted using one-way ANOVA followed by Tukey's post-hoc test ($p < 0.05$). Significant differences across classes are indicated by different superscript letters within each column.

Class	Correlation	Contrast	Homogeneity	Energy	Dissimilarity
Good (0–12 h)	0.95 ± 0.04^{a}	6.98 ± 4.00^{a}	0.72 ± 0.09^{a}	0.28 ± 0.06^{a}	1.31 ± 0.50^{a}
Abnormal (18–30 h)	0.88 ± 0.08^{b}	47.46 ± 33.47^{b}	0.40 ± 0.11^{b}	0.15 ± 0.04^{b}	4.41 ± 1.72^{b}
Defective (36–48 h)	0.83 ± 0.10^{b}	74.39 ± 56.11^{c}	0.33 ± 0.10^{b}	0.13 ± 0.03^{b}	5.70 ± 2.28^{c}

Note: Correlation reflects pixel intensity dependence, contrast indicates intensity variation, homogeneity represents texture smoothness, energy quantifies uniformity, and dissimilarity measures local variations. The large standard deviations observed in contrast for abnormal and defective classes reflect substantial heterogeneity in milk spoilage patterns, as clot formation and uneven opacity produced irregular textures at later storage times.

In Class 1 (0–12 h), milk samples demonstrated the highest correlation (0.95), the lowest contrast (6.98), and relatively high homogeneity (0.72), indicating a smooth and uniform texture. These characteristics reflect the physicochemical stability of fresh milk, in which casein micelles remain intact and proteins are evenly dispersed, thereby preserving the homogeneous appearance of the liquid. As storage progressed to Class 2 (18–30 h), a noticeable increase in contrast (47.46) and a reduction in homogeneity (0.40) were observed, accompanied by a decline in correlation (0.88). These changes suggest the onset of microbial activity and biochemical alterations, particularly acidification due to lactose fermentation by lactic acid bacteria [12]. The resulting decrease in pH weakens the casein micelle structure, leading to turbidity and increased thickness.

By Class 3 (36–48 h), the milk exhibited the highest contrast (74.39) and the lowest homogeneity (0.33), corresponding to advanced spoilage marked by clot formation, sedimentation, and discoloration. These phenomena are associated with intense microbial proliferation and enzymatic activity, which promote protein aggregation and fat breakdown. Taken together, the results demonstrate that longer storage time consistently leads to higher contrast, lower homogeneity, and reduced correlation, quantitatively capturing the progressive deterioration of milk quality [13]. Raw milk stored beyond 12 hours at room temperature rapidly deteriorates, as reported in dairy science literature. Integrating visual biomarkers with GLCM features provides a reliable, non-destructive method to identify milk quality stages and supports real-time monitoring in precision dairy farming.

3.3 Classification Performance and Confusion Matrix Analysis

The boxplot (Fig. 4) illustrates the distribution of classification accuracies for different pixel distances. At distance 1, the median accuracy was the lowest (0.69) with high variability. This indicates that short-range pixel relationships are insufficient to capture early structural changes in milk texture. Fresh milk (0–12 h) and milk with early opacity (18–30 h) often share subtle differences, which cannot be reliably detected using local pixel intensity variations alone. At distance 2, accuracy improved (0.74), reflecting the model's better ability to capture moderate irregularities in texture. This aligns with milk samples in the abnormal opacity stage (18–30 h), where microbial activity and pH reduction produce noticeable turbidity and thickening. These medium-scale variations are better detected by intermediate pixel distances.

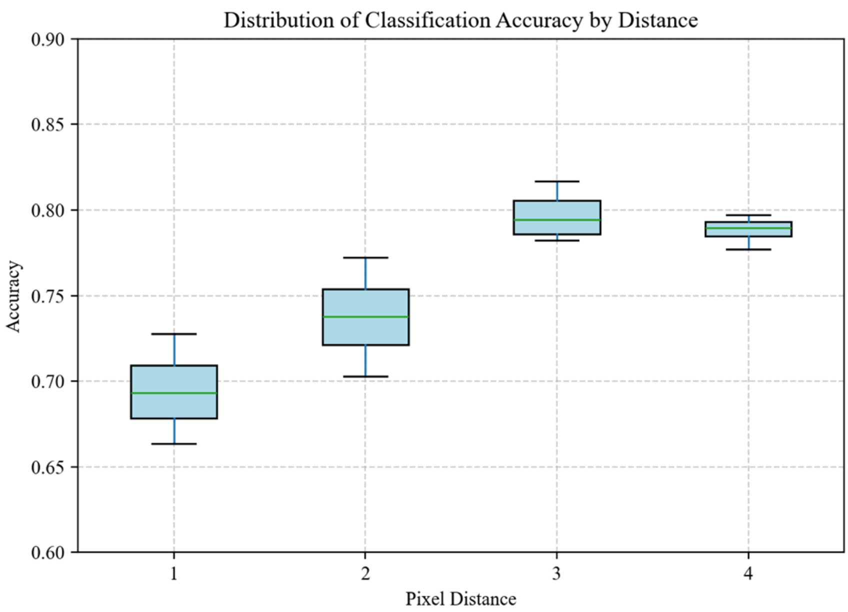

Fig. 4. Boxplot of classification accuracy across pixel distances. Distance 3 yielded the highest accuracy, effectively capturing spoilage features such as clots and sediment, while shorter distances struggled to detect subtle early changes in milk quality.

The best performance occurred at pixel distance = 3, where the median accuracy across 20 random train/test shuffles was 0.80 (80%), indicating low variability. The highest single-configuration result within these runs reached 81.68% (distance 3, angle 0°), which is the value reported in the abstract as the best single-case accuracy. Thus, the abstract highlights the peak performance, whereas this section summarizes the distribution using the median to reflect typical performance. This suggests that intermediate distances capture larger structural disruptions, such as clots and sediment found in defective milk (36–48 h). These advanced spoilage signs produce strong texture contrasts, making them more distinguishable by the classifier. At distance 4, the median accuracy (0.79) remained relatively high but slightly lower than distance 3. Longer distances may dilute fine local details, resulting in less precise discrimination of milk categories [14]

Overall, the results show that both distance and angle influence classification performance, although their impact was not statistically significant ($p > 0.05$, paired t-test). The confusion matrix analysis confirmed that the model consistently achieved the highest recall values for defective milk samples (36–48 h), whereas misclassifications were more common between good (0–12 h) and abnormal opacity (18–30 h) categories due to their subtle visual differences. This trend aligns with milk science observations, where early-stage spoilage is difficult to distinguish visually. Thus, the Decision Tree model combined with GLCM features provides a stable and computationally efficient method for non-destructive milk quality classification.

3.4 Integrated Perspective: Assessment of Raw Milk Quality Meets AI

From the dairy science perspective, storage duration drives progressive deterioration in raw milk quality, manifested as turbidity, thickening, clot formation, and sediment. These changes reflect microbial growth, acidification, and casein micelle destabilization, which are typically confirmed by laboratory analyses. Artificial intelligence extends this understanding by enabling rapid, non-destructive detection of these changes. GLCM-based texture features translated visual variations into measurable biomarkers, while the Decision Tree classifier achieved 81.68 %. accuracy in distinguishing fresh, early-stage spoiled, and defective samples. Defective milk was identified most reliably, whereas early spoilage stages remained challenging, consistent with visual inspection limits. This integration demonstrates how AI complements dairy science, offering real-time monitoring of milk quality before entering the distribution chain. Such systems strengthen the concept of precision dairy farming, ensuring both product safety and higher economic value for producers.

4 Conclusion

This study showed that computer vision and AI can serve as effective non-destructive tools for assessing raw cow milk quality. Using GLCM texture analysis and Decision Tree classification, samples were grouped into fresh, abnormal, and defective categories, with the best accuracy (81.68%) at a pixel distance of 3 and orientation of 0°. These findings confirm that spoilage can be tracked through texture features, enabling real-time monitoring to support precision dairy farming. Future work should use larger datasets, explore deep learning and multimodal approaches, and develop portable on-farm devices.

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