Jurnal Mandiri IT
Vol. 14 No. 1, July (2025), pp. 149-158

ISSN 2301-8984 (Print), 2809-1884 (Online)
Published by Institute of Computer Science

Sentiment analysis of tourist reviews on google maps for pura besakih using machine learning algorithms

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ARTICLE INFO

Article history:

Received Jul 15, 2025
Revised Jul 22, 2025
Accepted Jul 29, 2025

Keywords:

Cultural Heritageh;
Machine Learning;
Pura Besaki;
Tourist Experience.

ABSTRACT

Tourist reviews on digital platforms have become a valuable source of information for understanding visitor experiences. This study applies sentiment analysis to 2,891 Google Maps reviews of Pura Besakih, Bali's largest and most sacred temple, collected between January 2023 and December 2024. The aim is to assess overall visitor sentiment and identify factors influencing satisfaction and dissatisfaction. Reviews were preprocessed using a standardized pipeline that included translation, cleaning, tokenization, stopword removal, and stemming. Sentiment labeling was conducted using the Indonesian Sentiment Lexicon (InSet), followed by classification using six machine learning models: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes, Decision Tree, Random Forest, and Neural Network. The SVM model achieved the highest performance with an accuracy of 76.3% and F1-score of 55.68%. Thematic analysis revealed positive feedback highlighting the temple's spiritual ambiance, architecture, and improved facilities, while negative sentiment was driven by issues such as unauthorized guides, misleading charges, and restricted access. These findings offer valuable insights for tourism stakeholders to improve visitor experience and support sustainable heritage tourism through data-driven decision-making.

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1. INTRODUCTION

Tourism is a vital component of Indonesia's economic development, and Bali stands out as a global tourism hub known for its spiritual, cultural, and natural heritage (Artayasa et al., 2024). Among the island's most iconic landmarks is Pura Besakih, widely regarded as the "Mother Temple of Bali." Located on the slopes of Mount Agung, this sacred site is not only a spiritual center for Balinese Hindus but also a major attraction for domestic and international tourists seeking cultural and religious experiences (WIBAWA et al., 2023). Each year, thousands of visitors are drawn to its grandeur, historical depth, and spiritual ambiance (Raditya et al., 2020). With increasing visitor numbers, maintaining and enhancing the quality of the tourist experience at Pura Besakih becomes essential for sustainable tourism development (WIBAWA et al., 2023). Traditional approaches to assessing tourist satisfaction such as structured surveys and interviews can provide valuable insights but often lack the depth, spontaneity, and scale needed to fully capture the diversity of visitor perceptions (Razali et al., 2024).

In contrast, the rise of user-generated content (UGC), particularly through platforms like Google Maps, offers new avenues for understanding tourist experiences in real-time (Strong, 2019). Tourists frequently leave publicly accessible reviews expressing both appreciation and criticism, making these platforms rich sources of data for tourism research and management (Yamali & Putri, 2020).

To effectively analyze these unstructured textual reviews, Sentymen Analis a subfield of natural language processing (NLP) has emerged as a powerful method (Dzulkarnain et al., 2024; Sudiatmika et al., 2021; Widodo & Hartono, 2023) . By automatically categorizing textual feedback into sentiment classes (positive, negative, or neutral) (Iqbal et al., 2023), sentiment analysis can reveal patterns and trends that might otherwise go unnoticed (Azzahra et al., 2024). While this approach is commonly applied in marketing and service industries, its use in evaluating tourist perceptions at cultural heritage sites in Indonesia remains limited (Alauthman et al., 2023; Basendwah et al., 2024; Cortez et al., 2024) .

This study aims to address that gap by applying sentiment analysis techniques to Google Maps reviews of Pura Besakih. The objective is to assess the emotional tone of visitor feedback, identify areas of satisfaction and concern, and provide data-driven insights to tourism stakeholders (Wiwin et al., 2020). Through this approach, the study contributes to a more nuanced understanding of how tourists experience Pura Besakih and demonstrates the potential of digital data in supporting sustainable cultural tourism management (Wiwin et al., 2020).

2. RESEARCH METHOD

This study adopts an experimental research approach, in which various machine learning algorithms are applied to perform sentiment classification on Google Maps review data specifically related to Pura Besakih (Dash et al., 2024; Rodríguez-Ibánez et al., 2023). The primary objective is to build, train, and evaluate several classification models—namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes, Decision Tree, Random Forest, and Neural Network—to determine their effectiveness in accurately identifying the sentiment expressed in visitor reviews (Iqbal et al., 2023). By applying these models to the same dataset, the research aims to perform a comparative analysis of their performance in classifying user sentiments as positive, negative, or neutral. The experimental aspect of this study is reflected in the structured training and testing environment, controlled preprocessing pipeline, and the application of standardized performance metrics such as accuracy, precision, recall, and F1-score (Anamisa et al., 2024). The systematic stages of the research methodology are outlined below and visually represented in Figure 1.

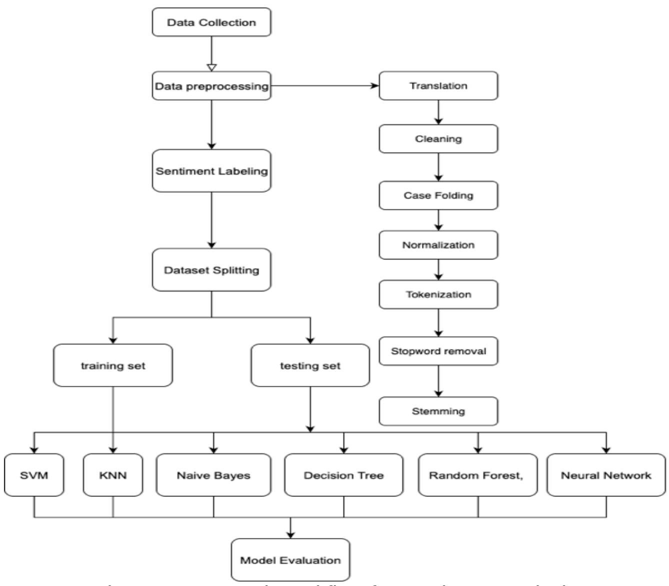

Figure 1. Research workflow for sentiment analysis

Data Collection

The data for this study were collected from publicly available user reviews on the Google Maps platform, focusing exclusively on Pura Besakih, one of the most prominent cultural and religious tourism destinations in Bali. Google Maps was selected as the primary data source due to its wide user base, high engagement level, and abundance of user-generated content that reflects genuine visitor experiences. The data collection process was carried out using the Python programming language, utilizing the Google Maps Application Programming Interface (API) (Yu et al., 2023) . A custom scraping script was developed to access the review section of Pura Besakih and extract relevant data points (Jain et al., 2023). For each review, the following information was retrieved: Star rating (on a scale of 1 to 5), Review text, Language of the review, Date of publication, Last edited date (if applicable).

The data were collected within a defined time frame (e.g., January 1, 2023 – December 31, 2024) to ensure the relevance and recency of user feedback. Prior to analysis, an initial data cleaning process was performed to remove irrelevant entries such as empty reviews, duplicate entries, and those containing only symbols or emojis without meaningful textual content (Mohan Kumar et al., 2022). This targeted and systematic data collection ensures the inclusion of recent and relevant visitor feedback, providing a solid foundation for sentiment analysis focused on the tourist experience at Pura Besakih.

An initial data cleaning process was carried out to remove irrelevant entries, such as empty reviews, duplicates, or those containing only emojis or non-informative symbols. The cleaned dataset was stored in CSV format to facilitate further preprocessing, sentiment classification, and statistical analysis (Rifa'i et al., 2021). This structured and time-bounded data collection approach ensured the inclusion of recent and relevant visitor feedback, enabling a comprehensive assessment of tourist perceptions and experiences at cultural heritage sites in Karangasem, Bali.

Data Preprocessing

The raw review data collected from Google Maps underwent a structured preprocessing pipeline to prepare it for sentiment analysis and machine learning classification. This process, as illustrated in the research flowchart, consists of several sequential steps: a) Translation, given the multilingual nature of tourist reviews, all non-English or non-Indonesian texts were translated into English using an automated translation service (Abrahams et al., 2021). This ensured uniformity of language for consistent processing (Amalia et al., 2023); b) Cleaning, the review texts were cleaned by removing unwanted characters, such as HTML tags, punctuation, numbers, emojis, special symbols, and redundant whitespaces (Hossain et al., 2023). This helped reduce textual noise and improve model interpretability (Hossain & Rahman, 2023); c) Case Folding, all text was converted to lowercase to normalize the input and reduce duplication of tokens due to letter casing; d) Normalization included correcting spelling variations, standardizing terms (e.g., "baliii" → "bali"), and replacing slang or informal terms with standardized equivalents using a manually curated lexicon; e) Tokenization, the normalized text was split into tokens (words or sub-phrases) using whitespace or language-specific tokenizers. This transformed the text into a format suitable for word-level analysis and vectorization; f) Stopword Removal, a custom stopword list was used to eliminate common words that do not contribute significantly to sentiment (e.g., "and," "the," "di," "yang"). This enhanced the focus on sentiment-bearing terms; g) Stemming, the remaining tokens were reduced to their root form using stemming techniques. For example, "walking," "walked," and "walks" were all reduced to "walk." In Indonesian, stemming was performed using libraries like Sastrawi.

Sentiment Labeling

Sentiment labeling was conducted using a lexicon-based approach with the help of an Indonesian sentiment dictionary called InSet (Indonesia Sentiment Lexicon). This method does not rely on machine learning models but instead calculates sentiment polarity based on the occurrence of positive and negative words in the text (Manullang et al., 2023). The lexicon was obtained from the open-source repository on GitHub, which contains a list of approximately 3,600 positive and 6,400 negative Indonesian words (Kirchner et al., 2024). Each review, after undergoing stemming, was analyzed by comparing its words with the entries in both the positive and negative lexicons (Yang et al., 2020).

The sentiment of each review was determined using the following steps: a) Token Matching: Each token in the review was compared with the positive and negative word sets; b) Scoring: A sentiment score was calculated as the difference between the number of positive and negative words in the review; c) Label Assignment: If the score > 0 → Positive, If the score < 0 → Negative, If the score = 0 → Neutral.

The sentiment score and corresponding sentiment label ("Positif", "Negatif", or "Netral") were then assigned to each review (Chen et al., 2023). This method ensures interpretability and transparency of sentiment classification, particularly suited for Indonesian-language datasets where labeled training data may be limited. This labeled output was later used as the target variable in training supervised machine learning models for evaluation.

Dataset Splitting

After the sentiment labeling process was completed, the dataset was divided into two subsets: a training set and a testing set. This step is essential for evaluating the generalization capability of machine learning models. The dataset was randomly split using a common 80:20 ratio, where 80% of the data was used for training and 20% was reserved for testing and validation (Setyawan & Fauzi, 2022). A stratified sampling approach was applied to ensure that the distribution of sentiment classes (Positive, Neutral, Negative) remained consistent across both subsets (Witjaksana et al., 2021). This technique minimizes the risk of class imbalance, which can negatively impact model performance. The splitting process was carried out using the train_test_split () function from the *scikit-learn* library with a fixed random seed to ensure reproducibility of results across different runs.

Model Training and Evaluation

Following dataset splitting, several supervised machine learning algorithms were trained to classify user review sentiments into three categories: Positive, Neutral, and Negative. The models implemented in this study included: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, Decision Tree, Random Forest, Neural Network.

All models were trained using preprocessed review text that had been transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) method (Rofiqi et al., 2019). This vectorization technique assigns importance to words based on their frequency in individual documents relative to their occurrence across the entire corpus, thereby enhancing the representation of semantically meaningful terms (Septiani & Isabela, 2022).

For the Neural Network model, a Multi-Layer Perceptron (MLP) was implemented using the MLPClassifier from the *scikit-learn* library (Wijaya et al., 2023). The architecture consisted of a single hidden layer containing 100 neurons, trained over a maximum of 500 iterations. The ReLU (Rectified Linear Unit) activation function was applied in the hidden layer, while the output layer used softmax activation for multi-class classification. The model employed the Adam optimizer for weight updates and used cross-entropy loss (*log loss*), which is appropriate for categorical output. Unlike deep learning frameworks such as Keras, this MLP implementation used full-batch training, as *scikit-learn* does not support mini-batch learning. Input features for the model were derived from TF-IDF vectorization, and model training was conducted using 80% of the dataset, while the remaining 20% was used for evaluation.

Model performance was assessed using standard classification metrics including accuracy, precision, recall, and F1-score. Additionally, confusion matrices were generated for each classifier to visualize the distribution of correct and incorrect predictions across sentiment classes. These evaluation metrics offered a comprehensive understanding of each model's ability to generalize to unseen data. The best-performing model, as determined by these metrics, was used to support deeper analysis and interpretation.

3. RESULTS AND DISCUSSIONS

A total of 2,891 user reviews of Pura Besakih were collected from Google Maps, covering the period from January 2023 to December 2024. Sentiment analysis revealed that 42.06% of the reviews (1,216) were classified as positive, 33.73% (975 reviews) as negative, and 24.21% (700 reviews) as neutral (see Figure 2). This distribution indicates that while a large proportion of tourists had favorable experiences, a significant number also expressed dissatisfaction or mixed feelings, as further illustrated in Figures 3 and 4.

A visual representation of sentiment distribution (Figure 2) confirms that positive sentiment dominates, reflecting overall tourist satisfaction with their visit to Pura Besakih. Nonetheless, the presence of neutral and negative feedback offers valuable insights for improving service quality and visitor management.

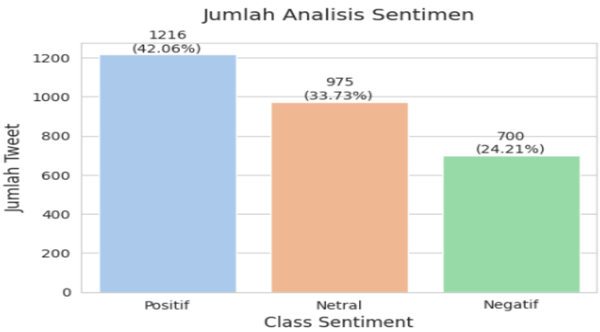

Figure 2. The number of sentiment analysis results

Figure 3. WordCloud Sentimen Positif

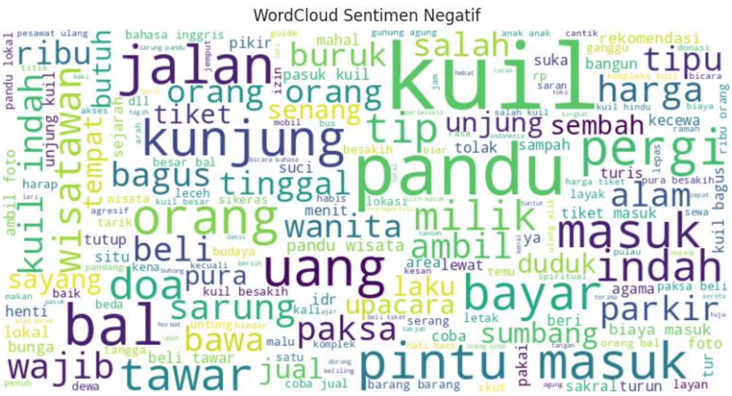

Figure 4. WordCloud Sentimen Negatif

Sentiment Classification Performance of Machine Learning Models

Six machine learning algorithms were implemented and evaluated for the sentiment classification task: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes, Decision Tree, Random Forest, and Neural Network. Performance metrics, including accuracy, precision, recall, and F1-score, were used to evaluate model effectiveness as presented in Tables 1 through 5.

Table 1. Classification report for k-nearest neighbors

Class	Precision	Recall	F1-Score	Support
Negatif	0.667	0.200	0.308	140
Netral	0.433	0.913	0.587	195
Positif	0.643	0.332	0.438	244
Accuracy			0.496	579
Macro avg	0.581	0.482	0.444	579
Weighted avg	0.578	0.496	0.457	579

Table 2. Classification report for naïve bayes

Class	Precision	Recall	F1-Score	Support
Negatif	0.593	0.593	0.593	140
Netral	0.748	0.441	0.555	195
Positif	0.627	0.832	0.715	244
Accuracy			0.642	579
Macro avg	0.656	0.622	0.621	579
Weighted avg	0.659	0.642	0.631	579

Table 3. Classification report for random forest

Class	Precision	Recall	F1-Score	Support
Negatif	0.759	0.471	0.581	140
Netral	0.729	0.744	0.736	195
Positif	0.693	0.832	0.756	244
Accuracy			0.715	579
Macro avg	0.727	0.682	0.691	579
Weighted avg	0.721	0.715	0.707	579

Table 4. Classification report for desicision tree

Class	Precision	Recall	F1-Score	Support
Negatif	0.759	0.471	0.581	140
Netral	0.729	0.744	0.736	195
Positif	0.693	0.832	0.756	244
Accuracy			0.715	579
Macro avg	0.727	0.682	0.691	579
Weighted avg	0.721	0.715	0.707	579

Table 5. Classification report for neural network

Class	Precision	Recall	F1-Score	Support
Negatif	0.775	0.614	0.685	140
Netral	0.695	0.795	0.742	195
Positif	0.800	0.803	0.802	244
Accuracy			0.755	579
Macro avg	0.757	0.737	0.743	579
Weighted avg	0.759	0.755	0.753	579

From the results, SVM outperformed all other models, achieving the highest accuracy and macro-averaged F1-score. This demonstrates that SVM provided the most balanced performance across all three sentiment classes (positive, neutral, and negative). The Neural Network model came second, showing competitive scores, particularly in recall. Decision Tree also performed well, especially in terms of class balance, though its overall accuracy was lower.

Conversely, KNN and Naive Bayes performed poorly, particularly in recognizing minority sentiment classes (negative and neutral), likely due to class imbalance and the limitations of these models in high-dimensional text data. Random Forest showed decent accuracy but lower sensitivity to negative and neutral sentiments.

These findings reaffirm the general effectiveness of SVM in text classification tasks, especially when working with unstructured, high-dimensional review data.

Thematic Analysis of Tourist Reviews

Positive Sentiment Themes

The dominant themes in positive reviews include: a) Aesthetic and spiritual admiration: Many tourists described Pura Besakih as "beautiful", "majestic", and "peaceful". The temple's architecture and natural setting on the slopes of Mount Agung impressed most visitors; b) Cultural appreciation: Reviews highlighted the temple's importance in Balinese Hinduism and praised the atmosphere as deeply spiritual and culturally rich; c) Improved facilities: Visitors noted enhancements such as organized parking, shuttle buses, and official guides. Some explicitly appreciated having knowledgeable local guides included with entry tickets.

Overall, these reviews suggest that visitors greatly value the visual and spiritual experience, and recent improvements in service infrastructure have positively influenced their perceptions.

Negative Sentiment Themes

In contrast, negative reviews frequently cited the following concerns: a) Aggressive or deceptive behavior by unofficial guides and vendors: Many visitors, particularly foreigners, reported being pressured into hiring unauthorized guides or buying items at inflated prices. Some mentioned being followed or shouted at when they declined services, describing the experience as intimidating and unwelcoming; b) Scam-related complaints: Tourists expressed frustration over being asked for large “donations” or forced to pay for services (e.g., sarong rentals) that should have been optional or included. Several reviewers perceived this as exploitation or “tourist traps.”; c) Restricted access to temple areas: Non-Hindu visitors were often not allowed into the innermost sanctums, which led to disappointment. Some felt misled or upset at paying full prices without being informed of access limitations. In a few cases, unauthorized individuals exploited the situation by offering "special access" in exchange for more money; d) Sanitation and stray animals: A few visitors mentioned trash in temple areas and the presence of stray dogs. Others commented on poorly maintained restrooms despite paying entrance fees.

Shown in figure 5, the Support Vector Machine (SVM) model demonstrates the highest accuracy in sentiment classification, reaching 76.7%. This confirms the reliability of SVM in handling high-dimensional textual data such as diverse Google Maps reviews. In second place, the Neural Network model achieved an accuracy of 75.5%, also showing competitive performance in detecting linguistic and sentiment patterns. The Random Forest and Decision Tree models obtained accuracies of 71.5% and 68.6%, respectively, indicating relatively stable performance though not as strong as SVM. Meanwhile, the Naive Bayes model achieved an accuracy of 66.2%, which is considered adequate for a simple probabilistic model. The K-Nearest Neighbors (KNN) model ranked the lowest with an accuracy of only 49.6%, suggesting that this method is less effective in dealing with the complexity and variability of textual review data. These findings indicate that the choice of classification model significantly affects the quality of sentiment analysis results, and in the context of this study, SVM has proven to be the most optimal model.

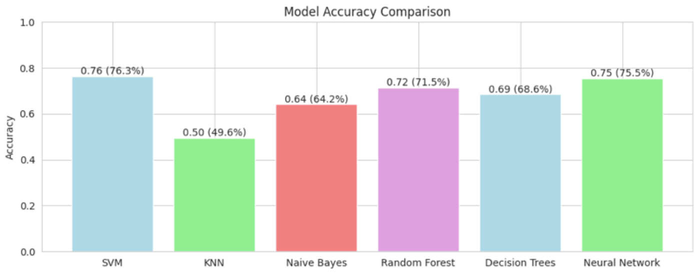

Figure 5. Comparison of sentiment classification model accuracy"

These findings directly align with the study’s objective to uncover key patterns in tourist sentiment and provide actionable insights for tourism stakeholders. By applying sentiment analysis to thousands of Google Maps reviews, this research not only reveals prevalent themes of appreciation and dissatisfaction but also offers a data-driven foundation for decision-making in the management of Pura Besakih. The ability to identify issues such as unauthorized guiding, misleading pricing practices, and access restrictions allows authorities to implement targeted interventions to improve visitor satisfaction while preserving the temple’s cultural and spiritual integrity. Moreover, the integration of machine learning models into tourism evaluation frameworks paves the way for scalable and continuous monitoring of public perception, which can inform long-term strategies for sustainable cultural tourism in Bali and beyond.

4. CONCLUSION

This study applied sentiment analysis techniques to 2891 Google Maps reviews of Pura Besakih, Bali, with the aim of understanding tourist perceptions and identifying factors influencing visitor satisfaction. The results showed that 42.06% of reviews were classified as positive, 33.73% as negative, and 24.21 %r as neutral. These findings indicate a predominantly positive visitor experience, highlighting the temple’s spiritual ambiance, scenic beauty, and improved infrastructure.

To classify sentiments, six machine learning models were tested: SVM, KNN, Naive Bayes, Decision Tree, Random Forest, and Neural Network. Among these, the Support Vector Machine (SVM) model achieved the best performance with an accuracy of **76.3%** and F1-score of **55.68%**, outperforming the others in classifying both majority and minority sentiment classes. The Neural

Network model followed closely, while KNN and Naive Bayes performed poorly, especially in recognizing neutral and negative reviews.

Thematic analysis revealed that while many tourists appreciated the temple’s architecture, spiritual value, and improved facilities, others expressed concern about aggressive unofficial guides, deceptive vendor practices, and limited access to sacred areas. These issues, though raised by a minority, can significantly affect the overall tourist experience if left unaddressed.

Based on the findings of negative sentiments related to tourist exploitation, the main policy recommendation that tourism managers can implement is the establishment of a fast and transparent complaint system This system should be easily accessible both online (via apps or websites) and offline (through complaint posts at the tourist site). Tourists should be provided with a safe and convenient space to submit complaints in real-time, and every report must receive clear, measurable, and publicly transparent follow-up. With such a mechanism in place, tourists' trust in destination management will increase, while also promoting accountability and continuous service improvement.

This research highlights the power of sentiment analysis in extracting actionable insights from user-generated content. The findings are expected to assist tourism stakeholders in improving service quality, ensuring visitor satisfaction, and promoting sustainable management of cultural heritage destinations. Future studies could incorporate deep learning models, sentiment trend analysis over time, or geolocation data to enhance the depth of visitor behavior analysis.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the Politeknik Negeri Bali for providing the facilities and academic support necessary to carry out this research. Special thanks are also extended to the reviewers whose constructive feedback greatly improved the quality of this paper. Lastly, the authors acknowledge the use of the InSet lexicon and Google Maps API as essential tools for data collection and sentiment labeling.

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