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Personalized Balinese Food Chatbot with Sentiment and Preference Analysis

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Abstract: The rapid growth of digital technology has increased the adoption of chatbots across industries, including the culinary and tourism sectors. However, existing systems often lack integration of customer sentiment and user preferences, limiting recommendation relevance. This study develops a personalized chatbot by combining sentiment analysis of Google Maps reviews with user taste preferences for traditional Balinese cuisine. A dataset of 5,000 reviews was analyzed using the Naïve Bayes classifier, achieving 88% accuracy. User evaluation with 100 respondents showed positive perceptions of usability and engagement, though recommendation suitability scored lower. The findings highlight the potential of sentiment-driven personalization and suggest future improvements through advanced models, larger datasets, and multilingual features for tourism.

Keywords: Chatbot; Google Maps reviews; Naïve Bayes; Sentiment analysis; User preferences

INTRODUCTION

The development of digital technology has encouraged the use of chatbots across various fields, including culinary marketing. A chatbot is a service that operates based on specific rules and is sometimes supported by artificial intelligence, allowing users to interact through text-based conversations (Mayla & Nasution, 2023). In the food industry, chatbots can enhance service efficiency and automatically provide food recommendations to customers.

Recent industry reports highlight that the adoption of conversational AI in tourism and culinary sectors is increasing. OECD (2024) notes that 11% of travel agencies and tour operators had already implemented at least one AI technology in 2023, while adoption in accommodation and food services reached around 4% (OECD, 2024). At the same time, industry surveys show strong interest in chatbot adoption among restaurants. A study by Popmenu (2024) reported that about 79% of restaurant operators have implemented or are considering AI-based solutions for functions such as customer interaction, recommendations, and order management (Popmenu, 2024). These findings indicate a growing demand for automation and personalization in both tourism and culinary services.

However, existing chatbots still face limitations in understanding user preferences. These chatbots typically only recommend locations of traditional Balinese food vendors on Google Maps without considering customer experiences or reviews (Widhiyanti & Sekarini, 2024). In the culinary world, each customer has unique taste preferences and experiences when selecting food, such as spice level, sweetness, or other criteria. Additionally, customer reviews on Google Maps serve as valuable information for assessing the quality of service and taste offered by a food stall or restaurant.

Sentiment analysis is used to identify the tendency of an opinion, whether it leans more toward the positive or negative (Muttaqin & Kharisudin, 2021). By understanding positive and negative sentiments in customer reviews, business owners can evaluate and improve their service quality (Utomo et al., 2019). This information helps them identify what aspects customers like or dislike, allowing necessary improvements to increase customer satisfaction (Budiman et al., 2024).

Naïve Bayes is one of the commonly used algorithms in text classification, including sentiment analysis (Rahayu et al., 2022). Despite its simple working principle, Naïve Bayes has proven effective in performing sentiment analysis on various types of data, including reviews on Google Maps (Budiman et al., 2024). This algorithm estimates the probability of a review belonging to a certain category based on the words appearing in the text. By applying the assumption that each word is independent of others, the model can deliver sentiment predictions with a fairly high level of accuracy (Masripah & Utami, 2020).

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In this study, Naïve Bayes is applied to conduct sentiment analysis on Google Maps reviews and to analyze users' sentiments expressed through their taste preferences. The sentiment results are then used as chatbot outputs. With this approach, the chatbot does not merely recommend vendor locations but integrates two primary sources—customer reviews and user taste preferences—to provide more relevant and personalized food recommendations.

Based on these considerations, this study addresses several research problems, namely the lack of integration between sentiment analysis and user preferences in real-time culinary chatbots, the absence of empirical evidence on the performance of Naïve Bayes in classifying Balinese culinary reviews, and the limited evaluation of user satisfaction with personalized chatbot systems. The objectives of this research are to design and implement a personalized chatbot that combines sentiment analysis with user preferences, to measure the accuracy of Naïve Bayes in classifying customer sentiments, and to test user satisfaction with the system through a structured survey. The contributions of this study are both theoretical and practical: theoretically, it proposes a combined sentiment-preference framework for chatbot personalization, while practically, it provides an applied solution for traditional Balinese food vendors to enhance competitiveness through digital personalization.

LITERATURE REVIEW

Previous research has explored chatbots and sentiment analysis separately but rarely combined them in real-time culinary applications.

Table 1. Comparison of Previous Research

Author	Domain	Method	Weakness	Contribution
Kusnanda et al., 2023.	Hotel chatbot	NLP	No database integration	Contextual chatbot
Gilbert Darmawan, Syariful Alam, 2023	App reviews	Naïve Bayes	Not integrated with chatbot	High accuracy (91%)
Muhamad Mustaqim, Ari Gunawan, Yudistira Bagus Pratama, 2023	Public services	ML + NLP	No user preference	Efficient service chatbot
Widhiyanti, Anak Agung Sandatya, 2024	Balinese culinary	Rule-based	No sentiment/preference	Vendor location info
This study	Balinese culinary	Naïve Bayes + Preferences	Small dataset, simple model	Real-time personalized chatbot

International studies also highlight personalization. A study by Cach N. Dang et al. showed that integrating sentiment analysis from user reviews can significantly enhance the accuracy of a recommendation (Dang et al., 2021). Furthermore, research by Sana Yaqoob et al. proved that a hybrid approach combining various computational techniques can be more effective in analyzing sentiment from complex and informal reviews (Yaqoob et al., 2025). This finding is highly relevant to the culinary context where reviews are often subjective and varied. The novelty of this study lies in combining sentiment analysis of Google Maps reviews with user preferences for a real-time culinary chatbot.

METHOD

The method used in this study is illustrated in Figure 1, which outlines the research flow from problem identification to evaluation.

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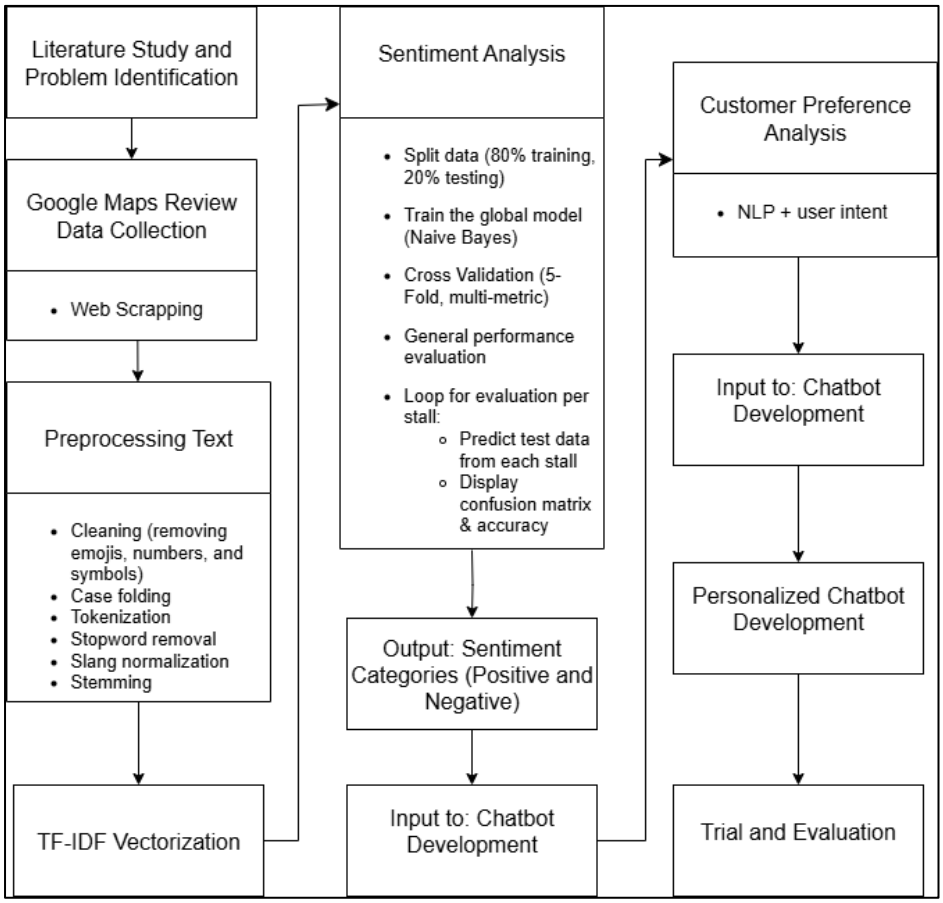

Fig. 1 Research Method

Literature Study and Problem Identification

The study began with a comprehensive literature review to identify research gaps and formulate the problem statement. This stage provided a strong theoretical foundation and justified the need for integrating sentiment analysis and user preferences into a personalized culinary chatbot.

Data Collection from Google Maps Reviews

The dataset consists of 5,000 reviews collected from 25 traditional Balinese food stalls between 12 June and 21 June 2025. Each stall selected had a minimum of 100 reviews. Reviews were retrieved using web scraping techniques, capturing both textual comments and numerical ratings as the primary data source for sentiment analysis. A similar method of collecting Google Maps reviews and applying Naïve Bayes has been used in "The Use of Naive Bayes Classifier in Sentiment Analysis at Indonesia's Super Priority Tourism Destinations Based on User Reviews" (2025), which processed tourist reviews to support evaluation platforms (Atmadji et al., 2025).

Text Preprocessing

Raw text was processed to clean and standardize the data. The procedures included cleaning (removing emojis, numbers, punctuation, symbols), case folding, tokenization, stopword removal, normalizing slang, and stemming using an Indonesian stemmer. The effectiveness of such preprocessing combined with TF-IDF and Naïve Bayes is supported by Penerapan Algoritma Naive Bayes dengan Teknik TF-IDF dan Cross Validation untuk Analisis Sentimen Terhadap Starlink (2025), which applied cross validation and proper preprocessing to improve model reliability (Khoerunnisa et al., 2025).

Feature Extraction with TF-IDF

Following preprocessing, the Term Frequency–Inverse Document Frequency (TF-IDF) method was used to transform text into numerical vectors. TF-IDF emphasizes informative terms by assigning higher weights to words that are frequent in a document but rare across the corpus, making it effective for text classification tasks (Kosala N, 2025).

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Sentiment Analysis

The processed dataset was divided (80% training / 20% testing) using stratified sampling. The sentiment classification used a Naïve Bayes classifier due to its efficiency and established performance for text analysis in Indonesian. While it performs well, limitations remain for class imbalance and nuanced expressions. The methodologies and metrics used (accuracy, precision, recall, F1-score, confusion matrix) are in line with several recent Indonesian studies such as Waterfront City Pangururan (2025), which achieved 90.48% accuracy using Naïve Bayes + TF-IDF on Google Maps reviews (Karo et al., 2025). To further validate the robustness of the model, this study also applied 5-Fold Cross Validation, which consistently confirmed strong overall accuracy but revealed that recall performance remained a challenge, particularly for negative reviews. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix, with both global results and per-stall performance analyzed for deeper insights (Nagar et al., 2025).

Customer Preference Analysis

After sentiment labeling, Natural Language Processing (NLP) and intent detection were used to capture user preferences, such as taste criteria (e.g., spiciness, sweetness) and service attributes. This step aimed to enhance personalization by aligning chatbot recommendations with both sentiment insights and individual user demands.

Chatbot Integration and Development

The results from sentiment analysis and preference modeling were integrated into a personalized chatbot system. The chatbot recommends food stalls and responds to user queries based on sentiment-driven and preference-based insights, thereby enhancing the relevance of recommendations.

System Testing and Evaluation

The chatbot was tested with 100 respondents, primarily local users, to evaluate usability and satisfaction. The evaluation covered sentiment classification accuracy, ease of use, engagement, trust, and recommendation suitability. This combination of algorithmic metrics and human-centered evaluation ensured that the proposed system achieved its research objectives and delivered practical value to traditional Balinese food vendors.

RESULT

Data Collection

A total of 5,000 Google Maps reviews were collected from 25 traditional Balinese food stalls, each with more than 100 reviews. Data was obtained using web scraping techniques with SerpAPI, which enables efficient retrieval of large-scale reviews in structured tabular format (Rizquina & Ratnasari, 2023) (Purnama et al., 2023). For each stall, around 200 reviews were extracted, including reviewer names, ratings, and textual comments.

Preprocessing

The dataset underwent preprocessing steps consisting of cleaning, case folding, tokenization, stopword removal, slang normalization, and stemming. These processes reduced noise and standardized the text for analysis. The output was stored in a structured CSV file for subsequent feature extraction and modeling.

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\User\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping corpora\stopwords.zip.
Melakukan preprocessing teks... Harap tunggu.
Data berhasil disimpan ke preprocessed_data.csv
```

Fig. 2 Preprocessing Process

Feature Extraction with TF-IDF

Reviews were converted into numerical vectors using Term Frequency–Inverse Document Frequency (TF-IDF). This technique assigns higher weights to terms that are frequent within a review but less common across the dataset, thereby emphasizing meaningful words (Ida Widaningrum et al., 2022).

Sentiment Analysis and Model Evaluation

The sentiment classification used an 80:20 train–test split with a Naïve Bayes classifier. Global performance evaluation showed an accuracy of 88%, with a precision of 0.89, recall of 0.99, and F1-score of 0.94 for positive reviews, while negative reviews achieved a precision of 0.83, recall of 0.33, and F1-score of 0.47. The confusion matrix heatmap (Figure 3) highlights that most errors occurred in misclassifying negative reviews as positive.

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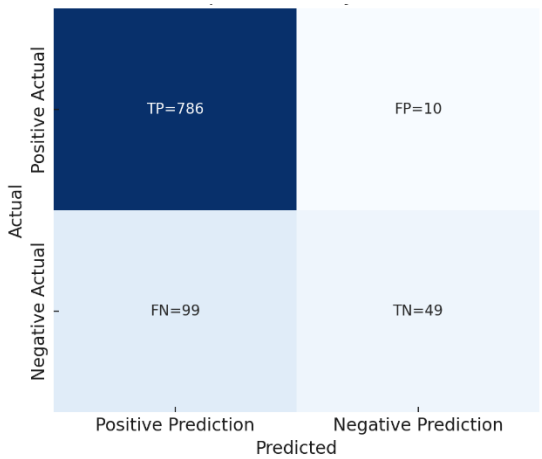

Fig. 3 Confusion Matrix Heatmap

To strengthen reliability, a 5-Fold Cross Validation was also conducted using accuracy, precision, recall, and F1-score as evaluation metrics. The average accuracy across folds was 89.15% (±0.74%), precision macro was 86.33% (±1.34%), recall macro was 68.60% (±2.41%), and F1-macro was 73.24% (±2.57%). These results confirm the robustness of Naïve Bayes combined with TF-IDF, though recall performance remained weaker for negative classes, indicating challenges in handling imbalanced datasets and subtle sentiment expressions (Figure 4).

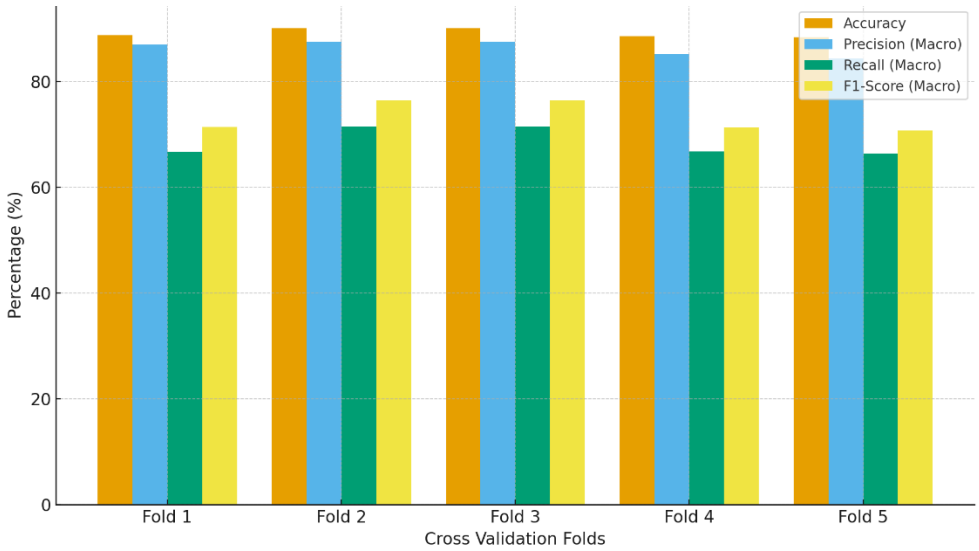

Fig. 4 5-Fold Cross Validation Results

Per-Stall Evaluation

Analysis per stall revealed variability in performance. Vendors with more homogeneous and consistent review styles achieved accuracies above 90%, while stalls with more diverse language expressions or mixed sentiments had accuracies ranging between 70–80%. Table 2 summarizes these results. This variation suggests that linguistic diversity and dataset balance significantly affect model accuracy.

Table 2. Evaluation Summary Per Stall

Stall ID	Accuracy (%)	Notes
W1	92.45	High accuracy, consistent review language
W3	72.97	Lower accuracy, reviews contain mixed sentiment
W5	95.24	Stable accuracy, reviews mostly positive
W8	95.00	Very high accuracy, homogeneous review style
W11	–	Not evaluated (all reviews belong to one sentiment class)

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W16	100	High accuracy, consistent sentiment distribution
W19	63.16	Lowest accuracy, reviews highly diverse and balanced
W21	73.91	Moderate accuracy, affected by varied review styles
W23	80.00	Borderline accuracy, more balanced sentiment distribution
W25	77.50	Lower accuracy, reviews contain slang and informal expressions
Others	88.00–100.0	Majority of stalls achieved strong accuracy (>88%)

Customer Preference Analysis

Beyond sentiment, an intent classification model was applied to identify customer preferences such as "spicy," "savory," or requests for specific dishes like babi guling or rujak kuah pindang. This analysis allowed the chatbot to align its recommendations not only with general sentiment but also with explicit user demands. Table 3 presents examples of intent classification results, showing the mapping of user text inputs to preference categories.

Table 3. Examples of Text and Classified User Intents

No.	Text	Intent
1	saya mau makanan pedas	pedas
2	saya mau makanan gurih	gurih
3	saya mau makanan yang ada rumput laut	rumput_laut
4	apa itu babi guling	deskripsi_babi_guling
5	apa itu be genyol	deskripsi_be_genyol
6	apa itu rujak kuah pindang	deskripsi_rujak_kuah_pindang
7	daftar makanan khas bali	menu_khas_bali
8	lokasi warung mujair nyatnyat	warung_mujair_nyatnyat
9	warung rujak kuah pindang di mana?	warung_rujak_kuah_pindang
10	saya mau beli bulung	warung_bulung

Personalized Chatbot Development

The sentiment and preference models were integrated into a chatbot system. The chatbot provided users with personalized recommendations, responded to queries, and visualized user preference profiles. Figure 5 illustrates the chatbot interface with recommendation and chat features.

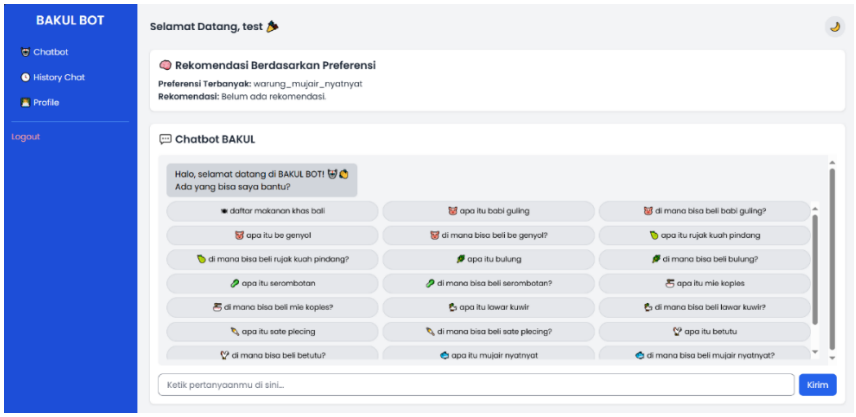

Fig. 5 Chatbot Page Views

Chatbot Evaluation

A user study involving 100 respondents was conducted with a seven-item Likert-scale questionnaire. Results indicated that ease of use (3.70), engagement (3.65), and reuse intention (3.62) were rated highest, showing that the chatbot was generally user-friendly and engaging. However, recommendation suitability (3.30) was rated Neutral/Fair, indicating that recommendations did not always meet user expectations. Information relevance (3.48) and trust (3.49) also scored moderately lower compared to usability, suggesting that personalization could be improved. These findings highlight the importance of expanding the dataset and enhancing the recommendation engine to better align with diverse user needs..

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DISCUSSIONS

The results confirm that Naïve Bayes combined with TF-IDF is effective for analyzing Balinese food reviews, achieving an overall accuracy of 88%. However, performance varies across stalls, with some achieving above 90% accuracy while others dropped to 63–77%. This variation is mainly caused by class imbalance, the presence of slang or local language, and the simplicity of the Naïve Bayes assumption. In addition to the train-test split evaluation, results from a 5-fold cross validation further validate the robustness of the model in terms of accuracy and precision; yet recall scores for negative classes remain relatively low, indicating persistent difficulty in detecting negative sentiment. Recent studies using deep learning and hybrid embedding techniques illustrate these limitations more clearly. For instance, Safar et al. (2024) improved performance in sentiment analysis of Indonesian texts by combining CNN, DNN, and LSTM models, showing better handling of sentiment subtleties than traditional classifiers (Safar et al., 2024). Also Lin and Nuha (2023) introduced a hybrid model based on text representations and various classifier combinations to address sentiment classification across multiple topics, achieving higher metrics especially in recall and F1 score (Lin & Nuha, 2023). From a theoretical perspective, this study contributes to the integration of sentiment analysis and user preference modeling in personalized chatbots, which is still underexplored in the culinary domain. The practical implications are significant: vendors can use chatbot-driven analytics to identify service strengths and weaknesses from customer reviews, while personalized recommendations improve customer engagement. Moreover, by developing multilingual and context-aware chatbot capabilities, the system could better support Bali's tourism sector by catering to both local users and international visitors who use diverse linguistic styles.

CONCLUSION

This study developed a personalized chatbot for Balinese cuisine by integrating sentiment analysis of Google Maps reviews with user preferences. The Naïve Bayes classifier combined with TF-IDF achieved an overall accuracy of 88% in the train–test split evaluation. Furthermore, a 5-fold cross validation confirmed the robustness of the model, with an average accuracy of 89.15%, macro-precision of 86.33%, macro-recall of 68.60%, and macro-F1 of 73.24%. These results indicate that the classifier consistently performed well in identifying positive reviews but struggled with recall for negative classes.The user evaluation involving 100 respondents also indicated generally positive perceptions, with usability (3.70) and engagement (3.65) rated highest. However, recommendation suitability scored only 3.30, reflecting the need for stronger personalization.The main limitations of this study include the relatively small dataset of 25 stalls, reliance on a simple Naïve Bayes algorithm, and evaluation limited to local respondents. Future research should expand the dataset, incorporate real-time review streams, adopt more advanced models such as LSTM or BERT to better capture complex language patterns, and involve more diverse participants, including international tourists, to enhance its relevance for Bali's culinary tourism sector.

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