

Sentiment Analysis of Mikie Holiday Funland Visitor Reviews Using the Naïve Bayes Algorithm

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Abstract

Mikie Holiday Funland is one of the tourist destinations in North Sumatra that receives numerous visitor reviews through digital platforms such as Google Maps and TikTok. The large number of available reviews makes manual analysis less effective, creating the need for sentiment analysis to identify visitors' perceptions of the facilities and services provided. This study aims to classify visitor reviews of Mikie Holiday Funland into positive, negative, and neutral sentiment categories using the Naïve Bayes method. This research adopted the CRISP-DM framework, with data processing stages including text preprocessing, lexicon-based sentiment labeling, TF-IDF weighting, and classification using the Naïve Bayes algorithm. The data used in this study were collected from Google Maps reviews and TikTok comments from February 2025 to February 2026, totaling 4,876 reviews. Model evaluation was conducted using a confusion matrix and classification report. The results showed that the Naïve Bayes method achieved an accuracy of 73% in classifying review sentiments. Of the 4,876 reviews analyzed, 849 reviews (17.4%) were classified as positive, 1,466 reviews (30.1%) as negative, and 2,561 reviews (52.5%) as neutral. The dominance of neutral sentiment indicates that most reviews were informative and did not express strong opinions. Furthermore, the analysis results were successfully implemented in a Streamlit-based application to provide interactive sentiment visualizations. These findings are expected to serve as evaluation material for improving the quality of tourism facilities and services, as well as a source of information for prospective visitors in making decisions about visiting Mikie Holiday Funland.

Keywords: *Sentiment Analysis, Visitor Reviews, Mikie Holiday Funland, Naïve Bayes, TF-IDF.*

1. Introduction

The tourism sector has become one of the major contributors to economic growth in many countries, including Indonesia. Advances in information technology and digital communication have significantly transformed the tourism industry by enabling visitors to easily access information and share their travel experiences through online platforms. Nowadays, digital platforms such as Google Maps, TikTok, and other social media applications have become important sources of user-generated content that reflects visitors' perceptions, experiences, and satisfaction with tourism destinations[1]. Mikie Holiday Funland is one of the most popular amusement parks in North Sumatra, Indonesia, attracting thousands of domestic tourists every year. Visitors frequently express their opinions regarding attractions, facilities, cleanliness, ticket prices, and service quality through online reviews on Google Maps and TikTok. These reviews provide valuable information for evaluating tourism services and understanding visitor satisfaction. However, the increasing number of online reviews makes manual analysis inefficient, time-consuming, and prone to subjective interpretation[2]. applications of Natural Language Processing (NLP) and text mining, sentiment analysis aims to classify opinions into predefined sentiment categories, such as positive, negative, and neutral[3]. This approach has been widely adopted in various domains, including healthcare, education, e-commerce, transportation, and tourism, because it enables organizations to understand public perception and support data-driven decision-making[4].

Among various machine learning algorithms, the Naïve Bayes classifier remains one of the most widely used methods for sentiment classification due to its computational efficiency, simplicity, and competitive performance in text classification tasks. Although the algorithm assumes feature independence, numerous studies have demonstrated that Naïve Bayes performs well when combined with appropriate text preprocessing and feature extraction techniques such as Term Frequency-Inverse Document Frequency (TF-IDF)[5]. Furthermore, TF-IDF effectively represents textual information by assigning greater importance to discriminative words while reducing the influence of frequently occurring but less informative terms[6].

Several previous studies have demonstrated the effectiveness of the Naïve Bayes algorithm in tourism-related sentiment analysis.[7] analyzed Google Maps reviews of hospital services and reported an accuracy of 84%.[8] classified visitor reviews of the Mandalika Circuit

using Naïve Bayes and achieved an accuracy of 70.96%.[9] analyzed public sentiment toward Aceh tourism using social media data and obtained an overall accuracy of 81%. Applied Naïve Bayes to classify visitor reviews of Bukit Merese tourism and reported an accuracy of 89%, demonstrating that the algorithm performs reliably for tourism-related sentiment classification[10]. Although previous studies have successfully applied sentiment analysis in various tourism contexts, research focusing specifically on Mikie Holiday Funland remains limited. Moreover, most existing studies rely on a single data source, whereas visitor opinions are distributed across multiple digital platforms. Integrating reviews collected from Google Maps and TikTok provides a richer and more representative dataset because each platform captures different styles of user interaction and expression. Consequently, a multi-source sentiment analysis is expected to provide a more comprehensive understanding of visitor perceptions[11]. This study proposes a sentiment classification framework based on the Cross-Industry Standard Process for Data Mining (CRISP-DM). The research consists of six stages, namely business understanding, data understanding, data preparation, modeling, evaluation, and deployment. Text preprocessing techniques, lexicon-based sentiment labeling, TF-IDF feature extraction, and the Naïve Bayes classifier are employed to analyze 4,876 visitor reviews collected from Google Maps and TikTok between February 2025 and February 2026. Model performance is evaluated using a confusion matrix and classification report[8]. The main contributions of this study are threefold. First, it presents a comprehensive sentiment analysis of Mikie Holiday Funland using reviews collected from two different online platforms. Second, it evaluates the effectiveness of combining TF-IDF feature extraction with the Naïve Bayes classifier for multiclass sentiment classification. Third, the proposed framework is implemented in a Streamlit-based web application that provides interactive visualization of sentiment distribution, enabling tourism managers to evaluate visitor satisfaction and supporting prospective visitors in making informed travel decisions

2. Research Method

This study employed the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework to develop a sentiment classification model for visitor reviews of Mikie Holiday Funland. CRISP-DM was selected because it provides a systematic and structured methodology for data mining projects, covering all stages from business understanding to deployment. The research workflow consisted of six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment[12].

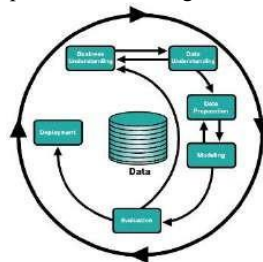


Fig. 1: Research Framework Based on CRISP-DM

2.1 Business Understanding

The primary objective of this study is to analyze visitor opinions regarding the facilities and services provided by Mikie Holiday Funland. The large number of reviews published on online platforms makes manual analysis impractical and inefficient. Therefore, an automated sentiment classification model is required to categorize visitor opinions into positive, negative, and neutral sentiments. The resulting information can support tourism managers in evaluating service quality and improving visitor satisfaction.

2.2 Data Understanding

The dataset used in this study consists of visitor reviews collected from Google Maps and TikTok between February 2025 and February 2026. The reviews were obtained through a web scraping process using Python. After the data collection stage, the dataset was cleaned and validated to remove duplicate and incomplete records, resulting in a total of 4,876 valid reviews for subsequent analysis. The collected dataset contains four primary attributes, namely the anonymized username, review date, review text, and data source. These reviews represent visitors' opinions regarding various aspects of Mikie Holiday Funland, including attractions, facilities, cleanliness, ticket prices, staff services, accessibility, and overall visitor experiences.

Table 1: Dataset Distribution

Username	Date	Review	Sumber Data
N*** ****i	14-02-2026	pengalam baruu dann seru!! kebetulan pas datang gak terlalu rame jadi bebas main sampe sore🌈...	Google Maps
A*****a	31-01-2026	Pelayan nya kurang puas karena sabtu itu kami ribut di mikie holiday karena satu karyawan cakap nya sombong kali kepada kami semua	Google Maps
I*** ****r	20-01-2026	Mantap buat liburan keluarga	Google Maps
L*****u	02-01-2026	trauma pulang dari mikie aku sakit seminggu🤒🤒🤒	TikTok
A*****a	10-11-2025	Tempat yang asik untuk liburan bersama keluarga selain wahananya yang seru" juga nyaman dan bersih	Google Maps
W****n	14-09-2025	tempat main anak tidak bebas asap rokok. banyak pengunjung merokok. staff sombong.	Google Maps
U*****3	30-03-2025	ga cocok buat org yg gampang pusing+muntah"🤢🤢🤢	TikTok
R*****e	22-01-2026	pusing bet kak🤕	TikTok
I** ***i	11-04-2025	Seruuu sekali Wahana permainan nyaa banyak Rekomendasi tmpt liburan seru bareng	Google Maps

Username	Date	Review	Sumber Data
I*****a	01-01- 2026	keluarga	TikTok
M*****3	09-10-2025	berapa tiketnya kak?	TikTok
M*****f	08-01-2026	udah pernah naik semua permainan yg disana taoi pulang nya pingsan karna permainan nya puter-puter semua 🤖 🤖 🤖 🤖	Google Maps
N*****_	05-10-2025	AKU SAMA KELUARGA SERING BGTT KE SI TU IHH EMNG BAGUS BGTT 🍗 SERU JUGAA	TikTok
M****g	14-10-2025	tempat nya bersih,keamanan nya terjamin,pelayanan nya bagus dan banyak wahanaaa gemec 🎡 🎡 ...	Google Maps
M*****n	10-04-2025	Biasa aja	Google Maps

Table 1 presents representative samples of the collected raw dataset before preprocessing. Since online reviews commonly contain informal language, abbreviations, emojis, punctuation marks, and other textual inconsistencies, text preprocessing is required to improve data quality before feature extraction and sentiment classification.

2.3 Data Preparation

Data preparation is a crucial stage in sentiment analysis because the collected reviews are unstructured and contain various forms of textual noise that may reduce classification performance. Therefore, several preprocessing techniques were applied to transform the raw reviews into a structured representation suitable for feature extraction and machine learning algorithms. These preprocessing steps were performed sequentially using Python following common practices in text mining and Natural Language Processing (NLP). The preprocessing pipeline consisted of six main stages: cleaning, case folding, tokenization, normalization, stopword removal, and stemming.

2.4 Modeling

Following the preprocessing stage, the cleaned textual data were transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) weighting technique. TF-IDF is widely used in text mining because it assigns higher weights to terms that frequently appear within a document while reducing the influence of commonly occurring words across the entire corpus. Consequently, TF-IDF provides an effective representation of textual information for machine learning algorithms[13].

2.5 Evaluation

The performance of the proposed sentiment classification model was evaluated using a confusion matrix, which compares the predicted sentiment labels with the actual sentiment labels. The confusion matrix provides a comprehensive assessment of the classifier by identifying correctly and incorrectly classified instances for each sentiment category[15]. Based on the confusion matrix, four evaluation metrics were calculated, namely accuracy, precision, recall, and F1-score. Accuracy measures the overall proportion of correctly classified reviews, while precision evaluates the proportion of correctly predicted instances within each predicted class. Recall measures the classifier's ability to identify all relevant instances of each sentiment class, whereas the F1-score represents the harmonic mean of precision and recall, providing a balanced performance measure [18].

The calculated evaluation metrics were used to assess the effectiveness of the proposed Naïve Bayes model in classifying visitor reviews into positive, negative, and neutral sentiment categories. The experimental results and performance analysis are presented in the following section.

2.6 Deployment

The final sentiment classification model was deployed using the Streamlit framework to provide an interactive web-based application. The developed system enables users to upload review datasets, perform sentiment analysis automatically, visualize sentiment distributions, display word clouds, and predict the sentiment of new visitor comments[16]. This deployment allows tourism managers to monitor visitor opinions efficiently and supports decision-making based on real-time sentiment information.

3 Results and Discussion

3.1 Data Collection Results

The visitor review dataset was collected from two online platforms, namely Google Maps and TikTok, using web scraping techniques. Google Maps reviews were extracted using a Python-based scraping program with the Selenium library, while TikTok comments were collected using the TikTok Comment Scraper tool. The collected data include user names, review dates, ratings (Google Maps), and visitor comments related to facilities and services at Mikie Holiday Funland. The data collection covered the period from February 2025 to February 2026 and produced 4,876 visitor reviews, which were subsequently used for sentiment analysis. The collected reviews represent various visitor opinions regarding attractions, cleanliness, staff services, ticket prices, facilities, and overall travel experiences.

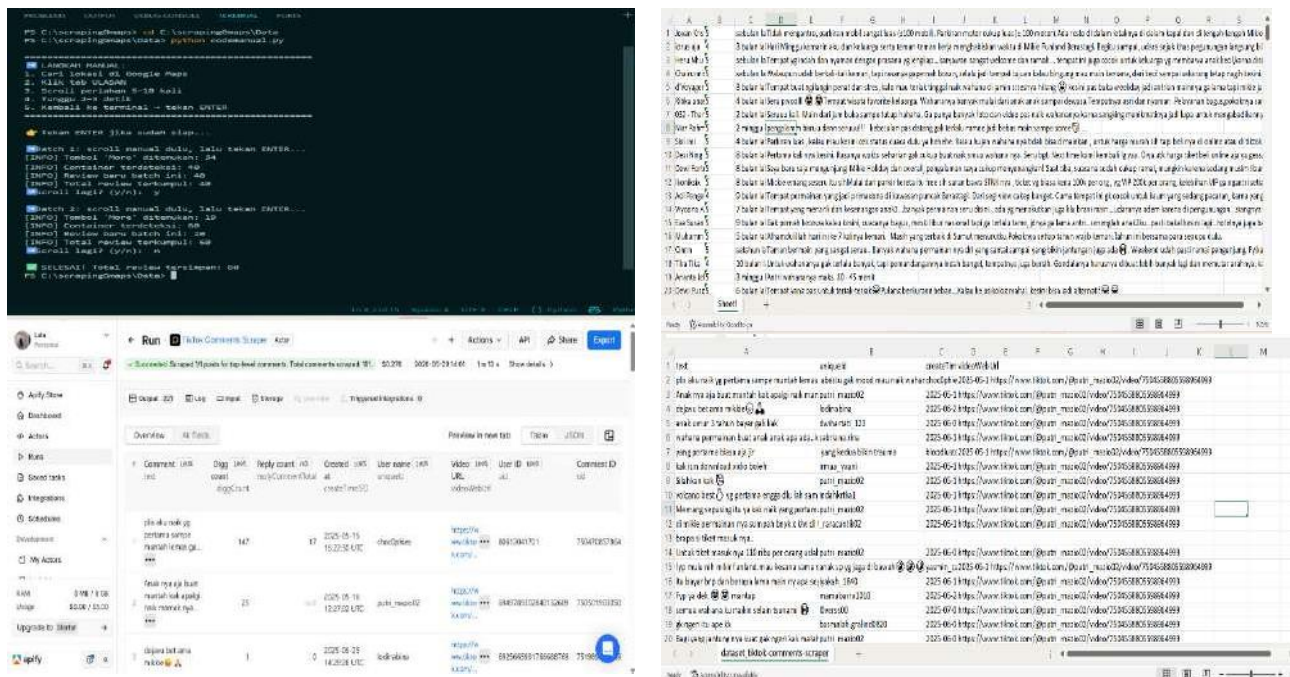


Fig. 2: Google Maps and TikTok Data Collection Process

Figure 2 illustrates the data acquisition process from Google Maps and TikTok. The scraping process successfully collected visitor reviews from both platforms and exported them into spreadsheet format for further preprocessing and sentiment classification. The use of two different data sources provides a more comprehensive representation of visitor opinions regarding Mikie Holiday Funland.

3.2 Text Preprocessing Results

Before feature extraction and sentiment classification, all collected reviews underwent a text preprocessing stage to improve data quality and remove textual noise. The preprocessing pipeline consisted of cleaning, case folding, tokenization, normalization, stopword removal, and stemming. These processes transformed unstructured visitor reviews into normalized textual data that were more suitable for machine learning analysis.

Table 2: Text Preprocessing Results

No	Sebelum Text Preprocessing	Sesudah Text Preprocessing
1.	Pelayan yang asik untuk liburan bersama keluarga tempat wahananya yang seru" juga nyaman dan bersih	asyik libur keluarga wahana seru nyaman bersih
2.	Pelayan nya kurang puas karena sabtu itu kami ribut di mikie holiday karena satu karyawan cakap nya sombong kali kepada kami semua	layan kurang puas ribut karyawan sombong
3.	trauma pulang dari mikie aku sakit seminggu 🤔🤔🤔	trauma pulang sakit minggu
4.	tempat nya bersih,keamanan nya terjamin,pelayan nya bagus dan banyak wahanaaa gemes 🐱🐱 ...	bersih aman jamin layan bagus wahana gemas
5.	berapa tiketnya kak?	tiket

Table 2 presents several examples of visitor reviews before and after preprocessing. The preprocessing stages successfully removed unnecessary symbols, standardized informal words, eliminated stopwords, and converted words into their root forms. Consequently, the processed reviews became more structured and suitable for TF-IDF feature extraction.

Review	clean_text	case_folding	tokens_raw	tokens_normalized	tokens_final	tokens	tokens_stopword	stemming
Tidak mengantre, parkir mobil sangat luas (2...	tidak mengantre parkir mobil sangat luas mob...	tidak mengantre parkir mobil sangat luas mob...	[tidak, mengantre, parkir, mobil, sangat, lu...	[tidak, mengantre, parkir, mobil, sangat, lu...	[tidak, mengantre, parkir, mobil, sangat, lu...	[mengantre, parkir, mobil, luas, mobil, park...	[mengantre, parkir, mobil, luas, mobil, park...	antre parkir mobil luas mobil parkir motor luas...
Hari Minggu kemarin aku dan keluarga serta tem...	hari minggu kemarin aku dan keluarga serta tem...	hari minggu kemarin aku dan keluarga serta tem...	[hari, minggu, kemarin, aku, dan, keluarga, se...	[hari, minggu, kemarin, aku, dan, keluarga, se...	[hari, minggu, kemarin, aku, dan, keluarga, se...	[hari, minggu, kemarin, aku, dan, keluarga, se...	[minggu, keluarga, teman, kerja, menghib...	minggu keluarga teman teman kerja hahi mikie ...
Tempat yg indah dan nyaman dengan prasana yg l...	tempat yg indah dan nyaman dengan prasana yg l...	tempat yg indah dan nyaman dengan prasana yg l...	[tempat, yg, indah, dan, nyaman, dengan, pra...	[tempat, yang, indah, dan, nyaman, dengan, pra...	[tempat, yang, indah, dan, nyaman, dengan, pra...	[tempat, yang, indah, dan, nyaman, dengan, pra...	[indah, nyaman, prasana, lengkap,karyawan, welc...	indah nyaman prasana lengkapkaryawan welcome r...
Walaupun udah berkali...	walaupun udah berkali...	walaupun udah berkali...	[walaupun, udah, berkali...	[walaupun, udah, berkali...	[walaupun, udah, berkali...	[walaupun, udah, berkali...	[kali, kali, kemari, enqgak pernah...	kali kali kemari enqgak pernah

Fig. 3: Text Preprocessing Results

Figure 3 presents the output of each preprocessing stage. During the cleaning stage, punctuation marks, numbers, and unnecessary symbols were removed from the reviews. Case folding converted all characters into lowercase letters, tokenization separated each review into individual words, normalization replaced informal words with their standard forms, stopwords removal eliminated words with little semantic contribution, and stemming reduced each word to its root form. These transformations produced consistent textual data that were ready for TF-IDF feature extraction and sentiment classification.

3.3 Sentiment Labeling Results

Following the text preprocessing stage, each visitor review was labeled using the Indonesian sentiment lexicon to classify the reviews into three sentiment categories: positive, negative, and neutral. The labeling process was performed by calculating the sentiment score of each review based on the polarity values of the words contained in the lexicon. The accumulated sentiment score was then used to determine the final sentiment label for each review. The labeled dataset serves as the ground truth for training and evaluating the Multinomial Naïve Bayes classifier.

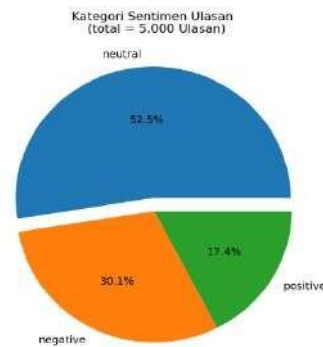


Fig. 4: Sentiment Label Distribution

Figure 4 presents the distribution of sentiment labels obtained from the lexicon-based labeling process. The results indicate that neutral sentiment is the dominant category with 2,561 reviews (52.5%), followed by negative sentiment with 1,466 reviews (30.1%), and positive sentiment with 849 reviews (17.4%). The predominance of neutral sentiment suggests that most visitors provide descriptive or informational reviews regarding their experiences at Mikie Holiday Funland, whereas fewer reviews explicitly express positive or negative emotions.

polarity neutral 2561 negative 1466 positive 849 Name: count, dtype: int64	1 yg [tempat, ya, dan indah, dan nam nyaman, dengan pra...]									
	2 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	3 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	4 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
5 [tempat, ya, dan indah, dan nam nyaman, dengan pra...]	6 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	7 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	8 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	9 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
10 [tempat, ya, dan indah, dan nam nyaman, dengan pra...]	11 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	12 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	13 [tempat, yang, indah, dan, nyaman, dengan, pra...]									
	14 [tempat, yang, indah, dan, nyaman, dengan, pra...]									

Fig. 5: Labeling Results

Figure 5 shows examples of the sentiment labeling results generated using the Indonesian sentiment lexicon. Each visitor review was assigned a sentiment category according to the total sentiment score calculated from the constituent words. These labeled reviews were subsequently used as the target labels during the supervised learning process.

3.4 TF-IDF Feature Extraction

After the sentiment labeling process, the preprocessed reviews were transformed into numerical feature vectors using the Term Frequency–Inverse Document Frequency (TF-IDF) weighting method. TF-IDF evaluates the importance of each word based on its frequency within an individual review and its occurrence across the entire document collection. Consequently, highly informative terms receive greater weights, while commonly occurring words receive lower weights, enabling more effective feature representation for sentiment classification.

Matriks TF-IDF data latih:

	seru	wahana	banget	tiket	kali	pengin	pusing	takut	cocok	main
0	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	1.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	1.0	0.0	0.0
9	1.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
10	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
12	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
13	0.0	0.161043	0.179223	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	0.0	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.476057	0.000000	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Fig. 6: TF-IDF Feature Matrix

Figure 6 illustrates the TF-IDF feature matrix generated from the preprocessed training dataset. Each review was converted into a numerical vector representing the relative importance of each term within the corpus. These feature vectors were subsequently used as input for the Multinomial Naïve Bayes classifier during the model training and testing stages.

3.5 Naive Bayes Classification Results

The performance of the proposed Multinomial Naïve Bayes classifier was evaluated using the testing dataset after the training process was completed. The evaluation aimed to measure the model's capability in classifying visitor reviews into positive, negative, and neutral sentiment categories. The performance assessment was conducted using several evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix, to provide a comprehensive analysis of the classification results.

Akurasi Model: 0.73

Laporan Klasifikasi:

	Presisi	Recall	F1-Score	Jumlah Data
negatif	0.88	0.51	0.65	314.00
netral	0.68	0.97	0.80	483.00
positif	0.83	0.47	0.60	179.00
accuracy	0.73	0.73	0.73	0.73
macro avg	0.80	0.65	0.68	976.00
weighted avg	0.77	0.73	0.71	976.00

Fig. 7: Model Evaluation Results

Figure 7 presents the Model Evaluation Results of the proposed Naive Bayes model. The evaluation results indicate that the classifier achieved different performance levels across the three sentiment categories. The neutral class obtained the highest recall, indicating that the model was highly effective in recognizing neutral reviews. Meanwhile, the positive and negative classes exhibited lower recall values due to the similarity of expressions among visitor reviews.

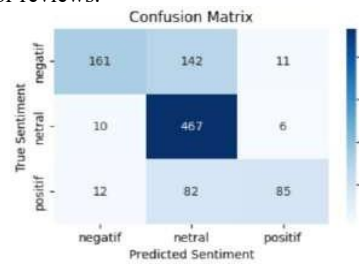


Fig. 8: Confusion Matrix

Figure 8 illustrates the confusion matrix generated during model evaluation. The matrix shows that the classifier correctly predicted the majority of neutral reviews, whereas several positive and negative reviews were incorrectly classified because they shared similar vocabulary and contextual meanings. These findings indicate that distinguishing between positive and negative sentiments remains more challenging than identifying neutral opinions.

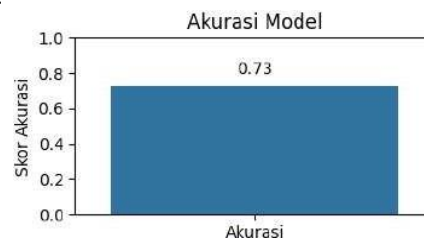


Fig. 9: Model Accuracy

Figure 9 presents the overall classification accuracy achieved by the proposed model. The Multinomial Naïve Bayes classifier obtained an accuracy of 73%, indicating that the model correctly classified most visitor reviews in the testing dataset. Although the overall performance is satisfactory, several misclassifications still occurred, particularly between positive and negative sentiment classes due to overlapping linguistic characteristics.

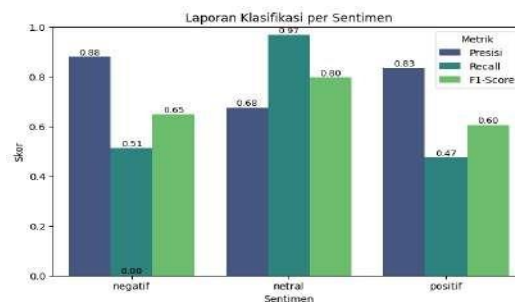


Fig. 10: Classification Performance by Class

Figure 10 compares the precision, recall, and F1-score obtained for each sentiment category. The results demonstrate that the neutral class achieved the highest overall performance, with a precision of 0.68, recall of 0.97, and F1-score of 0.80. In contrast, the positive class

achieved a precision of 0.83, recall of 0.47, and F1-score of 0.60, while the negative class obtained a precision of 0.88, recall of 0.51, and F1-score of 0.65. These results indicate that the proposed model is more effective in identifying neutral reviews than distinguishing between positive and negative sentiments.

3.6 System Implementation

The proposed sentiment analysis model was implemented as a web-based application using the Streamlit framework to provide an interactive platform for sentiment analysis of visitor reviews. The application integrates all stages of the proposed methodology, including data preprocessing, sentiment labeling, TF-IDF feature extraction, Naïve Bayes classification, model evaluation, and sentiment prediction. The system was designed to simplify the analysis process while allowing users to visualize classification results and predict the sentiment of new visitor reviews efficiently.

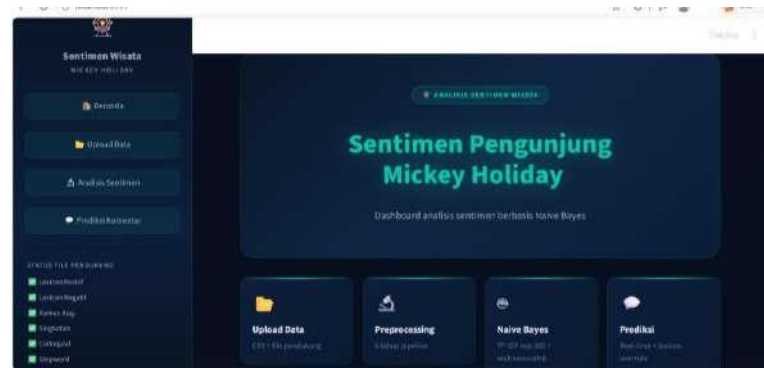


Fig. 11: Main Interface of the Sentiment Analysis Application

Figure 11 presents the main dashboard of the developed sentiment analysis application. The dashboard provides navigation to the primary system features, enabling users to access data preprocessing, sentiment analysis, model evaluation, and sentiment prediction modules through an intuitive web interface.

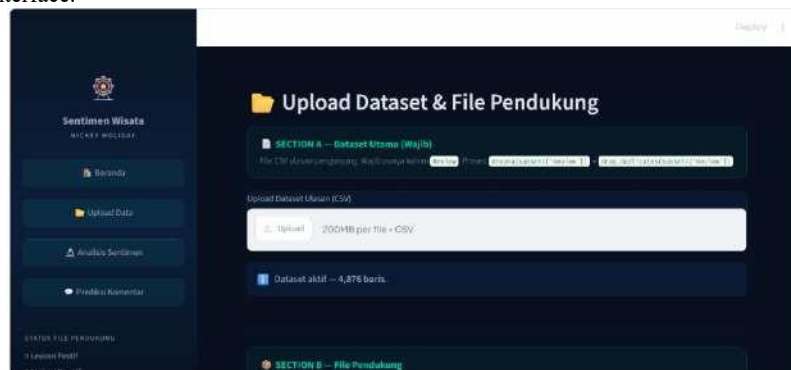


Fig. 12: Dataset Upload Module

Figure 12 presents the dataset upload module of the developed web-based application. This module allows users to upload the primary dataset in CSV format containing visitor reviews of Mikie Holiday Funland. After the dataset is successfully uploaded, the system automatically validates the file structure, counts the number of available records, and confirms that the dataset is ready for the sentiment analysis process. This validation step helps ensure that only valid datasets are processed by the classification model.



Fig. 13: Supporting File Upload Module

Figure 13 illustrates the supporting file upload module, which enables users to upload the required resources for sentiment analysis, including the positive lexicon, negative lexicon, slang dictionary, colloquial lexicon, and Indonesian stopword list. Once all supporting files have been successfully uploaded, the application verifies their availability and notifies the user that the analysis environment is fully

prepared. These supporting resources play an important role in improving text preprocessing quality and the accuracy of the sentiment labeling process.

After the dataset and all supporting resources have been successfully uploaded, the system proceeds to the sentiment analysis stage. This module integrates the entire sentiment analysis workflow, including text preprocessing, sentiment labeling, TF-IDF feature extraction, Naïve Bayes classification, and visualization of the analysis results. The generated outputs enable users to evaluate visitor opinions interactively through a web-based interface.

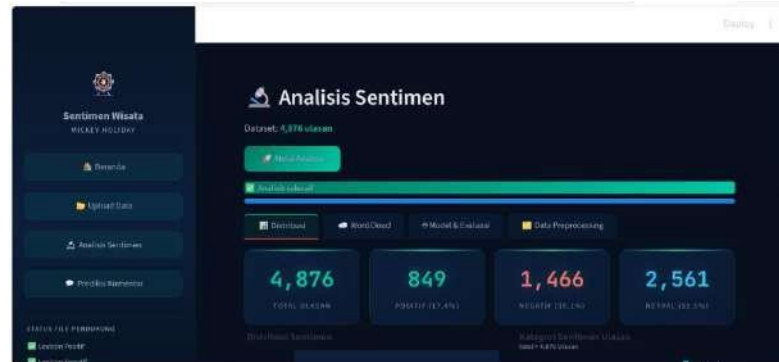


Fig. 14: Sentiment Analysis Module

Figure 14 presents the sentiment analysis module implemented in the Streamlit application. The system automatically executes each processing stage and displays various analytical results, including sentiment distribution, word cloud visualization, classification performance, and evaluation metrics. This integrated workflow simplifies the analysis process and allows users to obtain sentiment analysis results without requiring manual data processing.



Fig. 15: Sentiment Analysis Module

Figure 15 illustrates the sentiment distribution using both a bar chart and a pie chart. The bar chart presents the number of reviews in each sentiment category, whereas the pie chart shows their corresponding proportions. The results indicate that neutral sentiment dominates the dataset with 2,561 reviews (52.5%), followed by negative sentiment with 1,466 reviews (30.1%) and positive sentiment with 849 reviews (17.4%). These visualizations enable users to understand the overall distribution of visitor opinions more intuitively.



Fig. 16: Word Cloud Visualization

Figure 16 presents the overall word cloud generated from the visitor reviews. The visualization highlights the most frequently occurring terms within the dataset, where larger words indicate higher occurrence frequencies. This feature helps users quickly identify the dominant topics discussed by visitors, such as attractions, facilities, ticket prices, and overall travel experiences.



Fig. 17: Word Cloud by Sentiment Category

Figure 17 illustrates the word cloud generated for each sentiment category. This visualization allows users to compare the dominant terms associated with positive, negative, and neutral reviews. Consequently, users can identify the most frequently discussed aspects within each sentiment category and gain deeper insights into visitor perceptions.

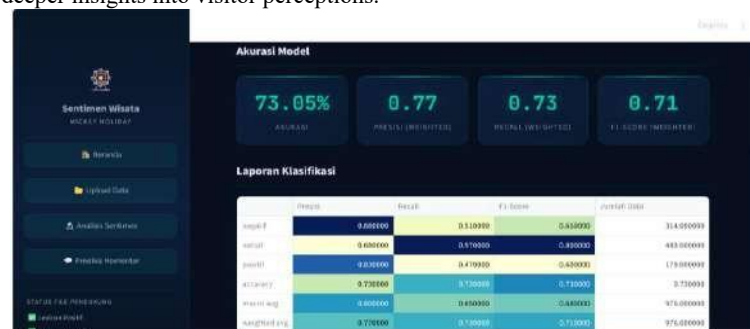


Fig. 18: Model Evaluation Dashboard

Figure 18 presents the model evaluation dashboard implemented in the application. The dashboard displays the classification accuracy, precision, recall, F1-score, classification report, and confusion matrix, allowing users to evaluate the overall performance of the Multinomial Naïve Bayes classifier directly through the web interface.



Fig. 19: Model Evaluation Dashboard

Figure 19 summarizes the classification performance of the proposed model. The application achieved an overall accuracy of 73%, while the evaluation metrics indicate that the neutral sentiment class achieved the highest recall and F1-score among all sentiment categories. These results demonstrate that the proposed model performs effectively in identifying neutral visitor reviews.



Fig. 20: Confusion Matrix Visualization

Figure 20 presents the confusion matrix visualization generated by the application. Most neutral reviews were classified correctly, whereas several positive and negative reviews were misclassified due to similarities in textual expressions. The confusion matrix provides a comprehensive overview of the classification performance for each sentiment category.



Fig. 21: Text Preprocessing Module

Figure 21 presents the text preprocessing module implemented in the Streamlit application. The system displays the preprocessing results for each review after applying cleaning, case folding, tokenization, normalization, stopword removal, and stemming. By presenting the processed text, users can compare the original and transformed reviews, thereby improving the interpretability and reliability of the sentiment analysis workflow.

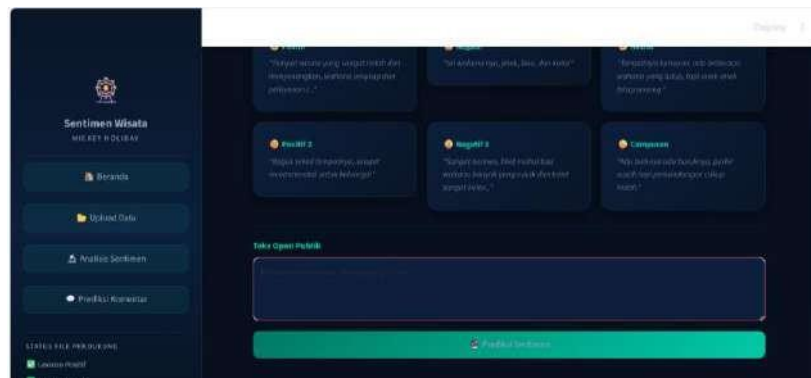


Fig. 22: Comment Prediction Module

Figure 22 illustrates the comment prediction module of the developed application. Users can enter a new review into the input field, and the system automatically performs text preprocessing, feature extraction, and sentiment classification using the trained Multinomial Naïve Bayes model. The predicted sentiment is then displayed immediately, allowing users to evaluate new visitor opinions in real time.

4 Conclusion

This study proposed a sentiment analysis system for visitor reviews of Mikie Holiday Funland by integrating data collected from Google Maps and TikTok. A total of 4,876 visitor reviews were processed through several text preprocessing stages, including cleaning, case folding, tokenization, normalization, stopword removal, and stemming. The processed reviews were transformed into numerical feature vectors using the TF-IDF weighting method and subsequently classified using the Multinomial Naïve Bayes algorithm. The experimental results demonstrated that the proposed model achieved an overall classification accuracy of 73%, indicating that the Naïve Bayes classifier is capable of effectively classifying visitor reviews into positive, negative, and neutral sentiment categories. Furthermore, the sentiment analysis revealed that neutral sentiment dominated the dataset, followed by negative and positive sentiments, suggesting that most visitors provided descriptive opinions regarding their experiences.

The developed sentiment analysis model was successfully implemented as a web-based application using the Streamlit framework. The application integrates dataset upload, text preprocessing, sentiment labeling, TF-IDF feature extraction, sentiment visualization, model evaluation, and real-time sentiment prediction into a single interactive platform. This implementation demonstrates the practical applicability of the proposed approach in assisting tourism managers to monitor visitor feedback and identify service strengths and weaknesses more efficiently. Future research may improve the classification performance by employing larger datasets, advanced text representation techniques such as contextual word embeddings, and deep learning-based classification models to achieve higher predictive accuracy and better semantic understanding of visitor reviews.

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