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Aspect-Based Sentiment Analysis of Tumpak Sewu Waterfall Tourist Reviews Using the Naive Bayes Classifier (NBC) Method

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ABSTRACT

With the increasing popularity of Tumpak Sewu Waterfall, the volume of visitor reviews on Google Maps continues to grow. These reviews contain valuable insights into tourists' experiences; however, conducting an in-depth manual analysis is inefficient. This study aims to perform aspect-based sentiment analysis on visitor reviews of Tumpak Sewu Waterfall using the Naive Bayes Classifier (NBC) method. This approach enables the classification of sentiments positive, negative, and neutral based on specific aspects such as facilities, accessibility, and natural scenery. Review data were collected from online platforms and processed through stages of text preprocessing and feature extraction before being trained using the NBC model. The results show that the model effectively classifies review sentiments with a high level of accuracy and provides detailed insights into which aspects most influence visitor satisfaction. These findings not only demonstrate the effectiveness of the Naive Bayes Classifier in aspect-based sentiment analysis tasks but also offer data-driven strategic recommendations for tourism managers to enhance service quality and improve visitor experience in the future.

Keywords: Tumpak Sewu Waterfall, Visitor Sentiment Analysis, Google Maps, NBC.

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INTRODUCTION

Tourism is a vital sector that contributes significantly to the economy, and natural destinations such as Tumpak Sewu Waterfall in Lumajang serve as major attractions for both domestic and international visitors. In today's digital era, online platforms such as Google Maps, TripAdvisor, and various social media channels have become the primary mediums for tourists to share their experiences and opinions through online reviews (Putra, Pranatawijaya, and Putra, 2024). This collection of review data serves as a valuable source of information that reflects visitors' perceptions and satisfaction toward the destination (Hizham, Asy'ari, and Urrochman, 2024). However, the large volume of data makes manual analysis inefficient and prone to subjectivity (Wijayanto, Prabowo, Kristiyanto, and Fathoni, 2023).

On the other hand, tourism destination managers require a deep understanding of tourist sentiments to make informed decisions aimed at improving the quality of services and facilities. (Arianto and Budi, 2022). Sentiment analysis, a subfield of Natural Language Processing (NLP), offers a solution

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to automate this process. Aspect-based sentiment analysis enables more specific identification of opinions, for instance, distinguishing negative sentiments toward road conditions from positive sentiments regarding natural beauty. Therefore, this study implements the Naive Bayes Classifier (NBC) method to conduct an in-depth analysis of visitor reviews of Tumpak Sewu Waterfall, with the aim of providing data-driven strategic recommendations for tourism managers (Assiva, 2024).

Based on the background described above, the research questions of this study are as follows:
1. How can an aspect-based sentiment analysis system be designed and implemented for reviews of Tumpak Sewu Waterfall using the Naive Bayes Classifier (NBC) method?
2. How can the Naive Bayes Classifier model classify sentiments (positive, negative, and neutral) for each aspect of the reviews, such as facilities, road access, and natural beauty?
3. Which aspects most dominantly influence the positive and negative sentiments of tourists toward Tumpak Sewu Waterfall?

A study conducted by (Pratama, Bachtiar, and Setiawan, 2018) entitled "Sentiment Analysis of Customer Opinions on Tourism Aspects of South Malang Beach Using TF-IDF and Support Vector Machine" reported that sentiment classification testing using the SVM algorithm on general, road, crowd, wave, and cleanliness aspects produced good average values for accuracy, precision, recall, and F1-Score—87%, 85%, 87%, and 85%, respectively. Another study (QORITA, 2022) entitled "Aspect-Based Sentiment Analysis on Tourist Attraction Reviews in Yogyakarta," found that SVM achieved better accuracy than the Multinomial Naïve Bayes algorithm, with results of 66.49% for the accessible aspect, 69.35% for amenities, and 90.39% for ancillary services. Furthermore, research by(Baihaqi, Ratnawati, and Hanggara, 2022) "Sentiment Analysis of Batu City Square Tourism Using the SVM Algorithm," showed an accuracy of 89.58%, precision of 90.73%, recall of 89.48%, and F-measure of 89.45%. Another study by (Hizham, Kartika Murni, and Qori'atunnadyah, 2024) which analyzed reviews of Puncak B29 on Google Maps using the Backpropagation Neural Network, obtained the best evaluation results for accuracy, recall, and F1-score after 50 iterations, with average values of 97.33%, 100.00%, and 98.47%, respectively. Meanwhile, the best precision value was achieved at 10 iterations, with an average of 99.72%, indicating that evaluation metrics tend to improve as the number of iterations increases during the classification process.

METHOD

There are several methodological stages that can be described as follows:

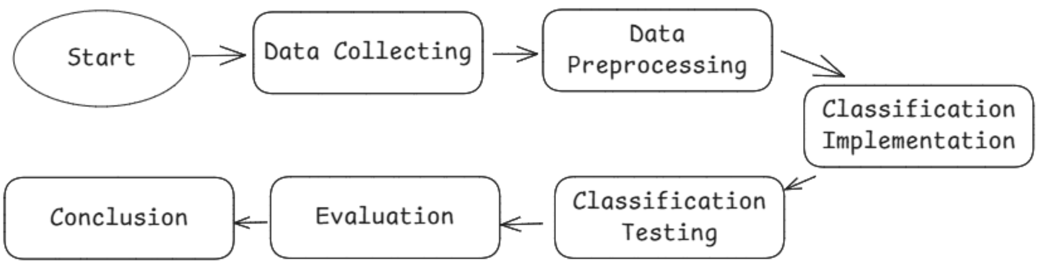

Figure 1. Research Flow Diagram

Data Collection and Preprocessing

This research began with data collection from the Tumpak Sewu Waterfall tourist destination, located in Pronojiwo District, Lumajang Regency. The review data were collected using two approaches: Google Maps API web scraping and direct field interviews. The dataset was obtained through scraping reviews from the Google Maps API, which included users' review scores and textual comments. In addition, data were also gathered through direct interviews with visitors at the tourism site. The interviews aimed to gain a deeper understanding of the review context, identify specific aspects that were important to visitors, and validate the sentiment data obtained online. This dual approach was essential to ensure the quality and validity of the data used for model training.

Text Pre-Processing

The next stage is data preprocessing, which in the context of sentiment analysis is referred to as text preprocessing. This stage aims to clean and standardize review texts to improve the accuracy of the classification model. The text preprocessing process includes the following steps:

1. Data Cleaning: Removing empty reviews that contain only ratings without textual comments.
2. Case Folding: Removing punctuation marks and non-alphabetic characters, and converting all text to lowercase to ensure data uniformity.
3. Tokenization: Breaking sentences into smaller units of words or "tokens."
4. Stopwords Removal: Eliminating common words that are irrelevant and carry no significant sentiment meaning (e.g., "yang," "dan," "di") to reduce feature dimensionality and improve system performance.
5. Stemming: Converting inflected words into their root or base form (e.g., "berjalan" becomes "jalan"). The stopwords removal and stemming processes in this study utilized the Sastrawi library in Python.

After the text preprocessing stage, the next step is word weighting. This stage assigns scores to the occurrence of words using the Process Document from Data operator, which applies the Term Frequency–Inverse Document Frequency (TF-IDF) method. The TF-IDF approach quantifies the importance of a word within a document relative to its frequency across the entire dataset, allowing the model to emphasize terms that are more informative for sentiment classification (Al Rasyid and Ningsih, 2024). Term Frequency (TF) Term Frequency (TF) is used to calculate the frequency of word occurrences within a single document, while Inverse Document Frequency (IDF) measures the importance of that word across the entire collection of documents. The formula for calculating TF-IDF is presented in Equation (1).

$$tf.idf\ (t, d, D) = \left(1 + \log(f_{t,d})\right)\left(log\frac{N}{df_t}\right)$$

Keterangan:

$f_{t,d}$ = the number of occurrences of term t in document d

N = the total number of documents in the document collection

df_t = the number of documents containing the term t; if the term does not appear in any document (0), its value is set to 1.

Acpect Classification

In this study, the classification testing was carried out by implementing the Naïve Bayes Classification (NBC) algorithm. The Naïve Bayes Classification (NBC) algorithm is a probabilistic classification method based on Bayes' Theorem (Assiva, 2024). It is referred to as "naïve" because it assumes that all features or attributes in the dataset are mutually independent. (Hizham, Kartika Murni, and Qori'atunnadyah, 2024), although this assumption is rarely satisfied in practice. In brief, the working mechanism of NBC can be described as follows:

1. Calculating Prior Probabilities: The algorithm first computes the probability of occurrence for each class in the dataset.
2. Calculating Conditional Probabilities: Next, the algorithm calculates the probability of each feature appearing within a specific class.
3. Classifying New Data: When new data are introduced, NBC combines the prior and conditional probabilities to compute the posterior probability that the data belong to each class.
4. Determining the Class: The new data are then classified into the class with the highest posterior probability.

Model Evaluation

After the method was implemented, the next step was to measure the classification performance using a confusion matrix. Based on the confusion matrix, the values of accuracy, precision, and recall were obtained. Accuracy measures the overall correctness of the classification, calculated as the ratio of correctly classified positive and negative data to the total number of data. Precision measures the relevance of the retrieved data to the required information, while recall evaluates how well the system successfully retrieves relevant information. The confusion matrix is presented in Table 1.

Table 1. ***Confusion Matrix***

		Kelas Aktual	
		True	**False**
Kelas Prediksi	**True**	TP (*True Positive*)	FP (*False Positive*)
	False	FN (*False Negative*)	TN (*True Negative*)

Description:
True Positive (TP) : When the predicted data are positive and match the actual positive value.
False Positive (FP) : When the predicted data do not match the actual value (predicted as positive but
False Negative (FN) : When the data are predicted as negative but are actually positive.
True Negative (TN) : When both the prediction and the actual value are negative.

The measurement of accuracy, precision, recall, and F-measure values based on the confusion matrix is formulated in Equations (1) to (4):

$$\text{Accuration} = \frac{TP + TN}{TP + FN + FP + TN} \quad (1)$$

$$\text{Presisi} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FP} \quad (3)$$

$$\text{F-Measure} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (4)$$

RESULTS AND DISCUSSION

Data Collection Results

The initial stage before implementing the method was to collect review data about the Tumpak Sewu Waterfall in Lumajang, obtained through the Google Maps API. The data collection was conducted using a scraping method through the Outscrapper platform. From the scraping results, a total of 6,985 reviews were collected, with ratings ranging from 1 to 5 stars. Specifically, there were 159 one-star reviews, 45 two-star reviews, 147 three-star reviews, 697 four-star reviews, and 5,937 five-star reviews.

In this study, the classification based on review scores was divided into two sentiment categories: positive sentiment for reviews with 3–5 stars, and negative sentiment for reviews with 1–2 stars. In addition, data collection was also carried out through direct interviews with visitors at the tourist site. Combining both scraping and interview results, a total of 7,000 reviews with varying ratings (1–5 stars) were obtained.

Table 2. Interview Results and Aspect-Based Sentiment Classification

No	Interview Result	Aspect	Label
1	The waterfall scenery is truly stunning, like a giant curtain. However, the access road is steep and quite slippery.	Scenery, Accessibility	Positive (scenery), Negative (accessibility)
2	The entrance ticket is affordable for such a beautiful tourist destination.	Ticket Price	Positive
3	The toilet facilities are poorly maintained, and the water often does not flow.	Facility	Negative
4	The atmosphere is calm and the air is cool, making it perfect for relaxation.	Atmosphere	Positive
5	The parking area is small, and there are no attendants to manage the vehicles.	Facility, Service	Negative

After the data collection stage, the next phase is text preprocessing. In this stage, preprocessing is performed through four main steps: case folding, tokenizing, stopword removal, and stemming. All processes were conducted using the Python programming language. The dataset was imported using the pandas library and processed through the following series of preprocessing steps:
1. Case Folding: This step converts all text into lowercase letters and removes non-alphabetic characters (a–z), such as symbols, numbers, and emojis.
2. Tokenizing: This process splits the text into individual words (tokens).
3. Stopword Removal: Common and non-informative words are removed to improve the efficiency of text analysis.
4. Stemming: This stage reduces words to their root form to group together words with the same base meaning but different inflected forms.

Since some of the reviews were written in English, the processes of stopword removal and stemming were performed using the WordNet Lemmatizer, Porter Stemmer, and Lancaster Stemmer from Python. The next stage involved assigning weights to each word in the dataset using the TF-IDF (Term Frequency–Inverse Document Frequency) method.

From a total of 6,985 reviews that had undergone text preprocessing, several reviews were found to be empty due to specific preprocessing steps, and some contained personal contact information. To ensure data privacy, such reviews were also removed. The TF-IDF weighting was then carried out by calculating the Term Frequency (TF) values based on the frequency of word occurrences within each review.

Table 3. TF Calculation Results

Data	TF(blue)	TF(crater)	TF(fire)	TF(beautiful)	TF(view)
1	1	2	0	1	0
2	1	2	1	0	2
3	0	0	0	0	0
4	1	2	0	0	1
5	0	0	0	0	0
6	0	0	0	0	0
7	2	0	2	0	0
8	0	0	0	1	0
9	0	0	0	0	0

10	1	4	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
6.985	0	0	0	0	0

After obtaining the Term Frequency (TF) values, the next step is to calculate the Document Frequency (DF). The DF value is determined by counting the number of documents in the dataset that contain the corresponding term, where the term's occurrence frequency is greater than zero. The results of the DF calculation are presented in Table 3.

Table 4. DF Value

DF(blue)	DF(crater)	DF(fire)	DF(beautiful)	DF(view)
804	663	640	606	604

After calculating the Document Frequency (DF) values, the next step is to compute the Inverse Document Frequency (IDF) for each keyword. The IDF value is used to balance the influence of frequently occurring words across the dataset by taking the base-10 logarithm of the total number of documents divided by the DF value of the corresponding word. The larger the DF value, the smaller the resulting IDF value, and vice versa. Based on the DF values presented in Table 7, the corresponding IDF values for each word are shown in Table 4.

Table 5. IDF Value

IDF(blue)	IDF(crater)	IDF(fire)	IDF(beautiful)	IDF(view)
0,5796	0,6634	0,6787	0,7024	0,7038

After calculating the Inverse Document Frequency (IDF) values, the next step is to compute the Term Frequency–Inverse Document Frequency (TF-IDF). The TF-IDF value is obtained by multiplying the Term Frequency (TF) by the corresponding IDF value. For example, for the word "crater" in dataset entry number 10, the TF value is 4, while the IDF value for the word "crater" is 0.6634. Thus, the TF-IDF value for that word is calculated as $4 \times 0.6634 = 2.6536$. The complete TF-IDF calculation results for all words are presented in Table 5.

Table 6. TF-IDF Calculation Results

Dataset	TF-IDF (blue)	TF-IDF (crater)	TF-IDF (fire)	TF-IDF (beautiful)	TF-IDF (view)
1	0,5796	1,3268	0	0,7024	0
2	0,5796	1,3268	0,6787	0	1,4076
3	0	0	0	0	0
4	0,5796	1,3268	0	0	0,7038
5	0	0	0	0	0
6	0	0	0	0	0
7	1,1592	0	1,3374	0	0
8	0	0	0	0,7024	0
9	0	0	0	0	0
10	0,5796	2,6536	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮
3054	0	0	0	0	0

NBC Classification Implementation

The classification implementation was carried out using the Python programming language on the Google Colab platform. The initial step before performing the classification was to import the prepared dataset, which had been converted into a .csv file format, into Python. The Pandas library

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was utilized for importing and managing the dataset within the program. The code snippet used for importing the dataset is presented in Table 7.

Table 7. Code for Importing the NBC Library

Baris	Kode
1	!pip install Sastrawi sklearn pandas numpy matplotlib
2	
3	import pandas as pd
4	import numpy as np
5	import re
6	import string
7	from nltk.corpus import stopwords
8	from nltk.stem import WordNetLemmatizer, PorterStemmer, LancasterStemmer
9	from sklearn.model_selection import train_test_split
10	from sklearn.feature_extraction.text import TfidfVectorizer
11	from sklearn.naive_bayes import MultinomialNB, BernoulliNB, GaussianNB
12	from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
13	import warnings
14	warnings.filterwarnings('ignore')

Tabel 8. Load Dataset

Baris	Kode
1	df = pd.read_csv('/content/tumpak_sewu.csv') #
2	df.dropna(inplace=True)
3	df.head()

Performance Test Results

This study utilized three variations of the Naive Bayes Classifier algorithm: Multinomial Naive Bayes (MNB), Bernoulli Naive Bayes (BNB), and Gaussian Naive Bayes (GNB). All three were tested to determine the model with the best performance in classifying the sentiment of Tumpak Sewu Waterfall Lumajang tourist reviews into three categories: positive, neutral, and negative. The data was split into 80% training data and 20% testing data. Subsequently, a word weighting process was carried out using TF-IDF after the text preprocessing stage (which included case folding, tokenizing, stopword removal, and stemming/lemmatization). Evaluation was conducted using four primary metrics: accuracy, precision, recall, and F1-score, the results of which are presented in the following Table.

Table 9. Performance Test Results of Naïve Bayes Classifier Models

NBC Model	Acuration (%)	Precision (%)	Recall (%)	F1-Score (%)
Multinomial Naive Bayes	87.45	86.32	85.76	85.92
Bernoulli Naive Bayes	84.12	82.45	81.98	82.15
Gaussian Naive Bayes	79.96	78.54	77.92	78.10

From the performance test results presented in Table 1, it can be observed that the Multinomial Naive Bayes (MNB) model achieved the highest accuracy score of 87.45%, with a precision value of 86.32%, recall of 85.76%, and an F1-score of 85.92%. The Bernoulli Naive Bayes (BNB) model showed reasonably good performance, yet slightly lower compared to MNB. In contrast, Gaussian Naive Bayes (GNB) exhibited the lowest performance, likely due to its unsuitability for discrete TF-IDF data.

These results indicate that Multinomial Naive Bayes is the most appropriate algorithm for text-based sentiment analysis cases, such as tourist reviews. This is because the MNB model is more effective in handling text data represented by word frequencies (TF-IDF), enabling it to more accurately distinguish between words representing positive, negative, and neutral sentiments. Overall, it can be concluded that the MNB model with TF-IDF weighting yields the best results and can be utilized for aspect-based sentiment analysis of Tumpak Sewu Waterfall Lumajang.

Performance Test Results Based on Aspect

In addition to analyzing overall sentiment, this study also conducted an evaluation based on four main aspects frequently appearing in tourist reviews: road access, cleanliness, facilities, and ticket price. This aspect-based approach aims to determine tourists' perceptions of each service dimension within the Tumpak Sewu Waterfall Lumajang tourist area. The optimal model used for this analysis was the Multinomial Naive Bayes (MNB) with TF-IDF weighting, as it demonstrated the highest performance in the overall testing.

Table 10. Performance Test Results of Models Based on Aspect

Aspect	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Description
Road Access	86.22	84.90	84.12	84.51	The path to the location is considered quite good, but slippery during the rainy season.
Cleanliness	89.18	88.45	87.92	88.10	Tourists rated the tourist area as clean and well-maintained.
Facilities	85.37	84.22	83.71	83.96	Some visitors highlighted the lack of toilets and dining/food areas.
Ticket Price	90.05	89.76	89.11	89.43	Tourists generally rated the ticket price as affordable.

Analysis of Aspect-Specific Results

1. Road Access Aspect
   The results indicate that the model was able to classify sentiment for this aspect with an accuracy of 86.22%. Positive reviews largely highlighted the paved condition of the road, whereas negative reviews were associated with slippery roads and steep inclines during the rainy season.
2. Cleanliness Aspect
   The cleanliness aspect achieved the second-highest result with an accuracy of 89.18%. Tourists generally provided positive assessments regarding the cleanliness of the tourist area, although there were a few complaints concerning litter in the parking area.
3. Facilities Aspect
   Facilities encompass toilets, parking areas, and dining locations. The model's accuracy for this aspect was 85.37%, with a dominance of negative reviews mentioning the limitations of public facilities.
4. Ticket Price Aspect
   This aspect exhibited the highest performance, achieving an accuracy of 90.05%. The majority of tourists rated the entrance ticket price as highly affordable considering the facilities and beauty provided.

CONCLUSION

Based on the results of this study, it can be concluded that the Naive Bayes Classifier (NBC) method is effective for classifying the sentiment of Tumpak Sewu Waterfall Lumajang tourist reviews.

Among the three variants tested—Multinomial Naive Bayes, Bernoulli Naive Bayes, and Gaussian Naive Bayes—the Multinomial Naive Bayes model demonstrated the best performance with an accuracy of 87.45%, a precision of 86.32%, a recall of 85.76%, and an F1-score of 85.92%. The aspect-based analysis also yielded good results, where the Ticket Price aspect achieved the highest accuracy at 90.05%, followed by Cleanliness (89.18%), Road Access (86.22%), and Facilities (85.37%). Generally, tourists expressed positive sentiment towards cleanliness and affordable ticket prices, while facilities remain the most frequently complained-about aspect.

For future research, it is recommended that the development of sentiment analysis models utilize other classification methods such as Support Vector Machine (SVM), Random Forest, or deep learning approaches like Bidirectional LSTM to enhance accuracy and achieve a deeper understanding of text context. Subsequent researchers could also increase the number of analysis aspects to include service, security, and comfort, and refine the text preprocessing process to minimize data loss due to text cleaning. Furthermore, the integration of analysis results with spatial data or real-time social media can be developed as a dynamic tourist opinion monitoring system, enabling the research findings to contribute tangibly to decision-making and the quality improvement of tourist destinations in the future.

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