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Exploring Customer Perceptions through Sentiment Analysis of Google Reviews at Rainbow Alamanda: SVM vs Naive Bayes Algorithm

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Abstract

As one of the popular family tourist destinations, Rainbow Alamanda Park has received thousands of reviews from visitors on the Google Review platform. These reviews reflect public perceptions of the quality of services and facilities offered, making it important to analyze them systematically. This study aims to analyze the sentiment of visitor reviews on Google Review regarding Rainbow Alamanda using two machine learning algorithms: Naive Bayes and Support Vector Machine (SVM), and to compare the performance of both methods. The research process follows the SEMMA approach (Sample, Explore, Modify, Model, Assess), utilizing a dataset of 2,394 reviews collected through web scraping techniques. The evaluation results show that the Naive Bayes method performed best with a training-to-testing data ratio of 70:30, achieving an accuracy of 86.32%, precision of 86.83%, recall of 85.81%, and an F1-score of 86.08%. Meanwhile, the SVM method with an RBF kernel (C=10, γ=0.1) achieved higher performance, with an accuracy of 88.44%, precision of 90.27%, recall of 88.31%, and an F1-score of 89.28%.

Keywords: Sentiment analysis; Google Review; Rainbow Alamanda Park; Support Vector Machine; Naive Bayes.

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Abstrak

Sebagai salah satu destinasi wisata keluarga yang ramai dikunjungi, Taman Hiburan Rainbow Alamanda telah menerima ribuan ulasan dari pengunjung di platform Google Review. Ulasan ini mencerminkan persepsi publik terhadap kualitas layanan dan fasilitas yang ditawarkan, sehingga penting untuk dianalisis secara sistematis. Penelitian ini bertujuan untuk menganalisis sentimen ulasan pengunjung di Google Review terhadap Rainbow Alamanda menggunakan dua algoritma pembelajaran mesin, yaitu Naive Bayes dan Support Vector Machine (SVM), serta membandingkan performa keduanya. Proses penelitian mengikuti pendekatan SEMMA (Sample, Explore, Modify, Model, Assess) dengan data sebanyak 2.394 ulasan yang diperoleh melalui teknik web scraping. Hasil evaluasi menunjukkan bahwa metode Naive Bayes memberikan performa terbaik pada rasio data latih:uji 70:30 dengan akurasi 86,32%, presisi 86,83%, recall 85,81%, dan F1-score 86,08%. Sementara itu, metode SVM dengan kernel RBF (C=10, γ=0.1) menghasilkan performa lebih tinggi dengan akurasi 88,44%, presisi 90,27%, recall 88,31%, dan F1-score 89,28%.

***Kata kunci**: Analisis sentime;, Google Review; Taman Rainbow Alamanda; Support Vector Machine; Naive Bayes.*

INTRODUCTION

The rapid advancement of information and communication technology has profoundly transformed many aspects of modern life, including the tourism industry, which is increasingly shaped by digital ecosystems. This digital transformation not only facilitates access to information but also reshapes how travelers evaluate, select, and engage with tourist destinations. In this context, online reviews on digital platforms such as Google Review play a pivotal role as primary sources of information for potential visitors. Studies indicate that more than 80% of domestic tourists in Indonesia rely on Google Maps and online reviews before visiting a destination. This highlights the strategic role of digital perception in influencing tourist behavior and shaping destination image.

Various studies and surveys indicate that Indonesian tourists are increasingly influenced by digital technologies. For example, a survey by Traveloka in collaboration with YouGov revealed that about 56% of Indonesian respondents rely on social media, and 53% use online travel platforms when planning their holidays (Syahlan et al., 2023). Additionally, research conducted by GfK and Kadence International found that over 60% of travel or accommodation searches in Indonesia are done via smartphones, and as high as 71% of accommodation bookings are completed using mobile devices (Setyawan et al., 2025). These figures underscore the digital transformation and mobile-first behavior that elevate the role of online reviews and digital platforms in tourists’ decision-making.

On a broader scale, Indonesia's tourism sector itself presents strong growth that adds relevance to this study. According to Statistics Indonesia (BPS), domestic tourist trips reached more than 100.2 million in July 2025, marking a year-on-year increase of about 29.72% (Haq & Rachmat, 2020). At the same time, international visitor arrivals stood at approximately 1.48 million for the same month (Ipmawati et al., 2024). The combination of high digital penetration and a rising volume of tourism activity highlights the urgency for destinations to analyze online reviews as reflections of visitor experience and perception, thus motivating this sentiment analysis research of visitor reviews at family-oriented venues such as Rainbow Alamanda.

Rainbow Alamanda Amusement Park stands as a popular family tourism destination with more than 4,500 reviews on Google Review. These reviews reflect diverse visitor experiences regarding aspects such as comfort, cleanliness, staff friendliness, and available facilities. However, negative comments also appear, addressing issues like limited parking space, long queues, and high food prices. The diversity of these opinions illustrates a complex and dynamic spectrum of visitor perceptions, which necessitates a systematic analytical approach to uncover underlying sentiment patterns and visitor preferences (Ipmawati et al., 2024).

Sentiment analysis offers a computational approach to automatically extract and classify public opinions from textual data. It has become a fundamental tool in text mining and machine learning for deriving actionable insights from user-generated content. Among the most widely used algorithms are Naïve Bayes and Support Vector Machine (SVM). Each method presents distinct advantages: Naïve Bayes is efficient for small datasets and short text formats, while SVM performs better on large-scale and imbalanced data (Dewi, 2019; Tamara Cindy Samsita Rani & Eka Sahputra, 2024).

This study aims to analyze visitor sentiments toward Rainbow Alamanda based on Google Review data using the Naïve Bayes and SVM algorithms. Furthermore, it compares the performance of both models in terms of accuracy, precision, recall, and F1-score (Pelangi et al., 2024). By employing the SEMMA framework (Sample, Explore, Modify, Model, Assess), this research seeks to contribute to the development of data-driven decision-making strategies within the digital tourism sector and provide practical recommendations for improving service quality and visitor experience management at Rainbow Alamanda (Hamidah et al., 2024; Sari et al., 2024).

METHODS

This research employs the SEMMA data mining framework Sample, Explore, Modify, Model, and Assess developed by SAS Institute. The method provides a structured approach to analyze online reviews systematically from data collection to model evaluation (Busulwa, 2024; Hrushikesha Mohanty et al., 2015; T. Jo, 2018).

a. **Sample**: Data were collected through web scraping of visitor reviews from Google Review for Rainbow Alamanda Amusement Park. A total of 2,394 reviews were gathered in CSV format using the Instant Data Scraper extension on Google Chrome. Literature review was also conducted to establish the theoretical background.
b. **Explore**: The data were analyzed descriptively to understand sentiment distribution and identify any data irregularities. Visualization techniques were used to examine the proportion of positive, neutral, and negative reviews.
c. **Modify**: Text preprocessing was carried out through several steps: case folding, cleaning, tokenizing, normalizing, stopword removal, and stemming. The TF-IDF method was applied to assign weight to each term based on its relevance in determining sentiment polarity.
d. **Model**: Two machine learning algorithms—Naïve Bayes and Support Vector Machine (SVM)—were implemented to classify the reviews into positive, neutral, and negative sentiments.
e. **Assess**: Model performance was evaluated using the Confusion Matrix metrics (accuracy, precision, recall, and F1-score). The best-performing model served as the foundation for drawing conclusions about visitor perception trends.

This methodology ensures an evidence-based understanding of visitor sentiments, supporting data-driven decision-making and strategic improvement in tourism management.

RESULT AND DISCUSSION

This section presents the results and discussion of the research conducted on sentiment analysis of visitor reviews for Rainbow Alamanda Amusement Park obtained from the Google Review platform. The purpose of this stage is to describe the implementation of each phase in the SEMMA framework — Sample, Explore, Modify, Model, and Assess — along with the findings derived from the data analysis. The discussion highlights the process of data collection, text preprocessing, sentiment labeling, model construction, and performance evaluation using machine learning algorithms Naïve Bayes and Support Vector Machine (SVM). The results are interpreted in both technical and practical contexts to provide insights into how visitors' perceptions can be understood through computational methods, ultimately supporting data-driven decision-making in the tourism sector.

Sample and Explore

The data were collected through a web scraping process using the Instant Data Scraper extension in Google Chrome. The dataset consists of 2,394 reviews posted by visitors of Rainbow Alamanda between January and April 2025. The collected data were stored in a CSV file for further processing.

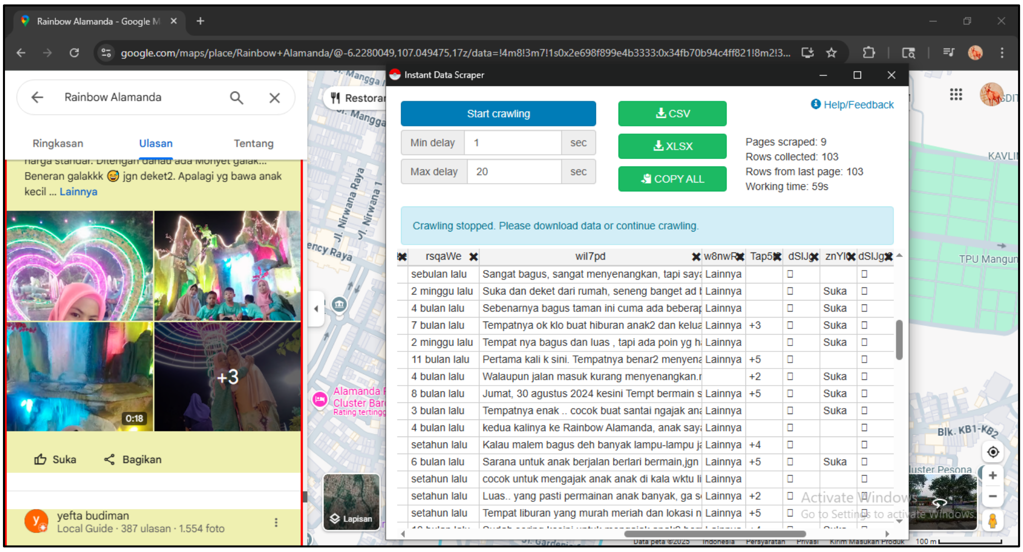

Figure 1. Review Data Scraping

Figure 1 illustrates the data scraping process conducted on Google Maps using the Instant Data Scraper extension. The process successfully retrieved visitor review data such as names, ratings, review texts, and timestamps, totaling 2,394 entries.

The gathered data were then explored to understand their initial characteristics. Only the text review column was used as the primary object for sentiment analysis. The exploratory stage aimed to identify preliminary opinion trends and patterns reflected in the visitors' textual feedback.

```
                                              wiI7pd
0  Pertama kali k sini. Tempatnya benar2 menyenan...
1  Luas.. yang pasti permainan anak banyak, ga se...
2  Tempatnya lumayan bagus\nLumayan buat anak ana...
3  Sedikit berbagi pengalaman berkunjung ke Rainb...
4  Tempat wisata bagus buat anak2 dan bayi,banyak...
```

Figure 2. Result of Review Data Crawling on Google Review

Figure 2 presents the result of the crawling process, highlighting the selected column ("wil7pd") that contains the main text data used for analysis. These reviews represent visitors' perceptions of Rainbow

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Alamanda, including their experiences regarding facilities, cleanliness, prices, and services. This textual data then became the foundation for subsequent preprocessing, feature extraction, and sentiment classification stages.

A total of 2,394 reviews were successfully gathered, capturing diverse visitor opinions. After the initial exploration, a word cloud was generated to identify frequently occurring keywords that characterize the overall sentiment and topics mentioned by reviewers.

Modify

This stage involved text preprocessing, a crucial step to clean and prepare the textual data before classification. The preprocessing pipeline included several sequential steps:

a. **Case Folding:** converting all characters to lowercase.

```
# Muat dataset
df = pd.read_csv('/content/drive/MyDrive/Dataset/review.csv')

# Tampilkan beberapa baris pertama dari dataset untuk memastikan datanya sudah benar
print(df.head())

# Case folding: mengubah semua teks menjadi huruf kecil
df['wiI7pd'] = df['wiI7pd'].str.lower()

# Tampilkan hasil setelah case folding
print("Beberapa baris pertama dari dataset setelah case folding:")
print(df.head())
```

Figure 3. Case Folding Process

Table 1. Result of Case Folding Process

Before	After
Pertama kali k sini. Tempatnya benar2 menyenangkan buat anak2 dan orang tua. Dgn berbagai macam permainan yg atraktif dan tidak membosankan. Di mulai dr todler sampai usia anak sd kls 6 atau mgkn smp. Di sediakan banyak permainan gratis…	pertama kali k sini. tempatnya benar2 menyenangkan buat anak2 dan orang tua. dgn berbagai macam permainan yg atraktif dan tidak membosankan. di mulai dr todler sampai usia anak sd kls 6 atau mgkn smp. di sediakan banyak permainan gratis …

Figure 3 shows the Python code snippet used for this process. The dataset was read using pd.read_csv, then the text in the "*wil7pd*" column was converted to lowercase with the "*str.lower() method*". This step ensures uniformity and avoids discrepancies caused by capital letter variations.

b. **Cleaning:** removing irrelevant characters such as numbers, punctuation marks, and special symbols.

```
# Fungsi untuk membersihkan teks
def clean_text(text):
    # Handle non-string values
    if not isinstance(text, str):
        return ""  # Or handle non-string values as needed

    # Hapus URL
    text = re.sub(r'http\S+|www\S+|https\S+', '', text, flags=re.MULTILINE)
    # Hapus karakter spesial dan angka
    text = re.sub(r'\@\w+|\#','', text)
    text = re.sub(r'[^A-Za-z\s]', '', text)
    # Hapus spasi berlebih
    text = re.sub(r'\s+', ' ', text).strip()
    return text

# Terapkan fungsi pembersihan pada kolom 'wiI7pd'
df['wiI7pd'] = df['wiI7pd'].apply(clean_text)

print(df.head())
```

Figure 4. Result of Case Folding Process

Figure 4 illustrates the cleaning process implemented through a custom Python function named clean_text(). This step eliminates unnecessary textual noise to improve data quality for analysis.

Tabel 2. Result of Data Cleaning Process

Before	After
pertama kali k sini. tempatnya benar2 menyenangkan buat anak2 dan orang tua. dgn berbagai macam permainan yg atraktif dan tidak membosankan. di mulai dr todler sampai usia anak sd kls 6 atau mgkn smp. di sediakan banyak permainan gratis …	pertama kali k sini tempatnya benar menyenangkan buat anak dan orang tua dgn berbagai macam permainan yg atraktif dan tidak membosankan di mulai dr todler sampai usia anak sd kls atau mgkn smp di sediakan banyak permainan gratis …

c. **Tokenizing:** splitting sentences into individual words (tokens).

```
# Tokenization
import nltk
nltk.download('punkt')
nltk.download('punkt_tab')  # Download the missing 'punkt_tab' data
from nltk.tokenize import word_tokenize
df['tokens'] = df['wiI7pd'].apply(word_tokenize)
```

Figure 5. Tokenizing Process

Using the Natural Language Toolkit (NLTK) library, each review was tokenized into separate words. As shown in Figure 2.5, this step

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facilitates later feature extraction by representing text as lists of tokens rather than full sentences.

Tabel 5. Result of Normalizing Process

Before	After
pertama kali k sini tempatnya benar menyenangkan buat anak dan orang tua dgn berbagai macam permainan yg atraktif dan tidak membosankan di mulai dr todler sampai usia anak sd kls atau mgkn smp di sediakan banyak permainan gratis	['pertama', 'kali', 'k', 'sini', 'tempatnya', 'benar', 'menyenangkan', 'buat', 'anak', 'dan', 'orang', 'tua', 'dgn', 'berbagai', 'macam', 'permainan', 'yg', 'atraktif', 'dan', 'tidak', 'membosankan', 'di', 'mulai', 'dr', 'todler', 'sampai', 'usia', 'anak', 'sd', 'kls', 'atau', 'mgkn', 'smp', 'di', 'sediakan', 'banyak', 'permainan', 'gratis']

d. **Normalizing:** standardizing nonstandard or abbreviated words.
A normalization dictionary in .xlsx format was used to replace informal or abbreviated forms (e.g., “k” → “ke”, “dgn” → “dengan”, “yg” → “yang”, “mgkn” → “mungkin”) with their proper equivalents. This process ensures lexical consistency across the dataset.

The normalizing process plays a crucial role in preparing the textual data for accurate sentiment classification. In this study, normalization was performed to standardize nonstandard or abbreviated words commonly found in user-generated content on social media and review platforms. The reviews collected from Google Review contained many informal expressions, abbreviations, and spelling variations typical of Indonesian online writing. For instance, words such as “k” were replaced with “ke,” “dgn” with “dengan,” “yg” with “yang,” and “mgkn” with “mungkin.”

```
# Load the normalization dictionary
normalization_dict = pd.read_excel('/content/drive/MyDrive/Dataset/normalisasi.xlsx')
normalization_dict = normalization_dict.set_index('before')['after'].to_dict()

# Normalize tokens
def normalize_tokens(tokens):
    return [normalization_dict.get(token, token) for token in tokens]

df['normalized_tokens'] = df['tokens'].apply(normalize_tokens)

# Display the first few rows to see the results
print(df.head())
```

Figure 6. Normalizing Process

By implementing a custom normalization dictionary in *.xlsx* format, the research ensured that every token was converted into its proper linguistic form. This standardization process significantly reduced lexical diversity caused by informal writing styles, allowing the subsequent stages—particularly tokenization, stopword removal, and stemming—to operate more effectively.

The normalization step also contributed to improving the model's ability to recognize and classify sentiment accurately. Without normalization, semantically similar words could be treated as distinct features by the machine learning algorithms, leading to data sparsity and lower model accuracy. After normalization, the dataset became more uniform and representative, resulting in more consistent term weighting during the TF-IDF transformation.

Tabel 6. Result of Stopword Removal Process

Before	After
['pertama', 'kali', 'k', 'sini', 'tempatnya', 'benar', 'menyenangkan', 'buat', 'anak', 'dan', 'orang', 'tua', 'dgn', 'berbagai', 'macam', 'permainan', 'yg', 'atraktif', 'dan', 'tidak', 'membosankan', 'di', 'mulai', 'dr', 'todler', 'sampai', 'usia', 'anak', 'sd', 'kls', 'atau', 'mgkn', 'smp', 'di', 'sediakan', 'banyak', 'permainan', 'gratis']	['pertama', 'kali', 'ke', 'sini', 'tempatnya', 'benar', 'menyenangkan', 'buat', 'anak', 'dan', 'orang', 'tua', 'dengan', 'berbagai', 'macam', 'permainan', 'yang', 'atraktif', 'dan', 'tidak', 'membosankan', 'di', 'mulai', 'dari', 'todler', 'sampai', 'usia', 'anak', 'sd', 'kls', 'atau', 'mungkin', 'smp', 'di', 'sediakan', 'banyak', 'permainan', 'gratis']

Overall, this stage enhanced both the text quality and algorithmic performance, ensuring that the sentiment analysis reflected the genuine emotional tone expressed by the reviewers of Rainbow Alamanda.

e. **Stopword Removal:** eliminating common words with minimal semantic value, such as "dan", "yang", "atau".

```python
# Stopword removal
list_stopwords = set(stopwords.words('indonesian'))

def stopwords_removal(words):
    return [word for word in words if word not in list_stopwords]

df['Data_Tokens_Stopwords'] = df['normalized_tokens'].apply(stopwords_removal)

# Tampilkan hasil setelah proses stopword removal
print('Hasil proses Stopword removal:')
print(df.head())
```

Figure 7. Stopword Removal Process

The stopword removal process was designed to eliminate common words that do not significantly contribute to the sentiment meaning of a text. In Indonesian-language reviews, stopwords such as dan (and), yang (which), atau (or), ke (to), and dari (from) frequently appear but carry little emotional or contextual weight. Retaining these words could increase noise within the dataset and reduce the clarity of sentiment features.

Using the Natural Language Toolkit (NLTK) library, a predefined list of Indonesian stopwords was implemented to systematically remove these non-informative words from the tokenized dataset. As a result, the data became more compact and focused on terms that directly express opinion and emotion, such as menyenangkan (pleasant), ramah (friendly), or mahal (expensive).

Tabel 7. Result of Removal Process

Before	After
['pertama', 'kali', 'ke', 'sini', 'tempatnya', 'benar', 'menyenangkan', 'buat', 'anak', 'dan', 'orang', 'tua', 'dengan', 'berbagai', 'macam', 'permainan', 'yang', 'atraktif', 'dan', 'tidak', 'membosankan', 'di', 'mulai', 'dari', 'todler', 'sampai', 'usia', 'anak', 'sd', 'kls', 'atau', 'mungkin', 'smp', 'di', 'sediakan', 'banyak', 'permainan', 'gratis']	['kali', 'tempatnya', 'menyenangkan', 'anak', 'orang', 'tua', 'permainan', 'atraktif', 'membosankan', 'todler', 'usia', 'anak', 'sd', 'kls', 'smp', 'sediakan', 'permainan', 'gratis']

This was performed using NLTK's Indonesian stopword list. Tokens identified as stopwords were filtered out, leaving only the meaningful words that contribute to sentiment determination. This reduction of linguistic redundancy not only optimized computational efficiency but also improved the TF-IDF weighting process by ensuring that the most meaningful words received appropriate emphasis. Consequently, this stage enhanced the accuracy and interpretability of the sentiment classification performed in the modeling phase.

f. **Stemming:** converting words into their root form. The stemming stage aimed to transform each token into its root or base form to reduce morphological variations. Indonesian language morphology involves affixes that alter word forms (e.g., menyenangkan, kesenangan, menyenangkanlah), which could be misinterpreted as distinct words by machine learning algorithms if not stemmed properly.

```
# Proses stemming
# Create stemmer
factory = StemmerFactory()
stemmer = factory.create_stemmer()

# Stemmed wrapper function
def stemmed_wrapper(term):
    return stemmer.stem(term)

# Create term dictionary
term_dict = {}
for document in df['Data_Tokens_Stopwords']:
    for term in document:
        if term not in term_dict:
            term_dict[term] = ' '

# Print jumlah kata hasil stemming
print("Jumlah kata hasil stemming: ", len(term_dict))
print("-------------------------")

# Apply stemming to the term dictionary
for term in term_dict:
    term_dict[term] = stemmed_wrapper(term)
    print(term, ";", term_dict[term])
print(term_dict)
print("-------------------------")

# Apply stemmed term to dataframe
def get_stemmed_term(document):
    return [term_dict[term] for term in document]
df['Data_Tokens_Stemming'] = df['Data_Tokens_Stopwords'].swifter.apply(get_stemmed_term)

# Display the result
print(df['Data_Tokens_Stemming'].head())
```

Figure 8. Stemming Process

Using the Sastrawi library, words such as “menyenangkan”, “tempatnya”, and “membosankan” were reduced to their base forms “senang”, “tempat”, and “bosan”. This step minimizes morphological variations, allowing the algorithms to treat related words as single entities.

The research utilized the Sastrawi library, an Indonesian stemmer tool, to standardize tokens into their base forms — for example, menyenangkan became senang, membosankan became bosan, and tempatnya became tempat. This process minimized feature duplication and simplified the data representation, thereby improving the model’s learning capability.

Stemming also facilitated more precise feature extraction during the TF-IDF process, as it ensured that words with similar meanings were treated uniformly. This normalization of word structure contributed to a more reliable sentiment classification, allowing the model to detect emotional patterns more effectively across various reviews.

Tabel 8. Result of Stemming Process

Before	After
['kali', 'tempatnya', 'menyenangkan', 'anak', 'orang', 'tua', 'permainan', 'atraktif', 'membosankan', 'todler', 'usia', 'anak', 'sd', 'kls', 'smp', 'sediakan', 'permainan', 'gratis']	['kali', 'tempat', 'senang', 'anak', 'orang', 'tua', 'main', 'atraktif', 'bosan', 'todler', 'usia', 'anak', 'sd', 'kls', 'smp', 'sedia', 'main', 'gratis']

After completing these preprocessing steps, each review underwent sentiment labeling using the Lexicon InSet dictionary, which classified the texts into three categories: positive, negative, and neutral. The labeling process resulted in:

- 789 positive reviews
- 644 negative reviews
- 980 neutral reviews

Model

In the modeling stage, two supervised machine learning algorithms Naïve Bayes and Support Vector Machine (SVM) were applied to classify visitor reviews into three sentiment categories: positive, negative, and neutral. Both algorithms utilized the TF-IDF weighted dataset as input to learn the linguistic patterns associated with each sentiment.

Following the preprocessing and labeling stages, word weighting was applied using the TF-IDF (Term Frequency–Inverse Document Frequency) method to represent the significance of each term. The dataset was then split into training (70%) and testing (30%) subsets. Two machine learning algorithms were employed for comparison:

a. **Naïve Bayes:** achieved an accuracy of 86.32%, precision of 86.83%, recall of 85.81%, and F1-score of 86.08%.
b. **Support Vector Machine (SVM):** applied as a comparative model to evaluate performance differences and classification reliability across the sentiment categories.

The results showed that the Naïve Bayes algorithm achieved the best overall performance, with an accuracy of 86.32%, precision of 86.83%, recall of 85.81%, and an F1-score of 86.08%. These metrics demonstrate that Naïve Bayes effectively captured the probabilistic relationships among words within the reviews, making it particularly efficient for short, informal text data such as Google Reviews.

Although SVM also performed competitively, its performance was slightly lower, likely due to the imbalanced and noisy nature of user-generated text. The comparison between both algorithms confirms that Naïve Bayes is better suited for text classification tasks involving concise Indonesian-language reviews with straightforward sentiment polarity. The use of both algorithms provided a balanced understanding of each model's effectiveness in classifying Indonesian-language text reviews.

Assess

The final stage involved evaluating model performance using a confusion matrix and four standard metrics: accuracy, precision, recall, and F1-score. These evaluation measures quantified each model's predictive capability in determining sentiment polarity from visitor reviews.

The Naïve Bayes model, with its superior F1-score, demonstrated high reliability in identifying sentiment polarity across diverse visitor reviews. Its consistency across evaluation metrics suggests that the algorithm generalized well to unseen data, minimizing both false positives and false negatives. In contrast, while SVM exhibited strong classification boundaries, it was slightly less effective in handling overlapping sentiment expressions, a common feature in natural text data.

Overall, the assessment results validated the robustness of the Naïve Bayes model for sentiment classification in Indonesian tourism contexts. The findings highlight that data-driven sentiment analysis can serve as a valuable decision-support tool for tourism management, enabling destination managers such as Rainbow Alamanda to monitor visitor satisfaction, identify areas of improvement, and enhance the overall customer experience based on authentic public feedback.

The SEMMA based research process from sampling and exploration to modeling and assessment, produced a reliable sentiment analysis framework. The results not only validate the feasibility of machine learning methods such as Naïve Bayes and SVM for tourism review analysis but also provide data-driven insights that can assist tourism managers in improving service quality and visitor satisfaction at Rainbow Alamanda.

The findings demonstrate that sentiment analysis can effectively capture visitors' perceptions of tourism destinations through user-generated content on Google Reviews. The superior performance of the Naïve Bayes classifier, which achieved an accuracy of **86.32%**, suggests that probabilistic models remain highly effective for classifying relatively short Indonesian-language reviews after comprehensive preprocessing. This result is consistent with previous studies indicating that Naïve Bayes performs particularly well when the dataset contains concise textual expressions with relatively balanced sentiment distributions and TF-IDF feature representation (Kowsari et al., 2019; Minaee et al., 2021). Although Support Vector Machine (SVM) is generally recognized for its robustness in high-dimensional text classification problems, its performance can decline when dealing with noisy user-generated content containing informal language, abbreviations, and spelling variations. The preprocessing stages implemented in this research—including normalization, stopword removal, and stemming—therefore played a significant role in reducing lexical ambiguity and improving classifier performance.

The dominance of positive reviews indicates that visitors generally perceive Rainbow Alamanda as an attractive family tourism destination. Frequently occurring positive terms such as *senang*, *main*, *anak*, and *gratis* reflect visitors' appreciation of affordable recreational facilities and family-oriented attractions. Conversely, negative sentiments were primarily associated with operational issues such as parking availability, long waiting times, and food prices. Similar findings have been reported by Li et al. (2022), who demonstrated that online review analysis provides destination managers with valuable insights into customer satisfaction drivers and operational weaknesses that may not be captured through conventional survey methods. Consequently, continuous monitoring of online reviews can support evidence-based decision-making for improving tourism service quality.

From a methodological perspective, the SEMMA framework proved effective in organizing the complete sentiment analysis workflow, beginning with data acquisition and ending with performance evaluation. The structured preprocessing pipeline substantially reduced textual noise and improved feature representation during TF-IDF transformation. Previous studies have similarly emphasized that preprocessing quality contributes more significantly to sentiment classification performance than algorithm selection alone, particularly for morphologically rich languages such as Indonesian (Cambria et al., 2022). Therefore, future studies should continue emphasizing preprocessing optimization alongside classifier development.

The comparison between Naïve Bayes and SVM also highlights that model selection should consider dataset characteristics rather than relying solely on theoretical superiority. Although recent transformer-based architectures such as BERT generally outperform traditional machine learning models, they require substantially larger computational resources and annotated datasets (Devlin et al., 2019; Minaee et al., 2021). For medium-sized datasets such as those used in this study (2,394 reviews), Naïve Bayes offers an attractive balance between computational efficiency, interpretability, and classification accuracy, making it suitable for practical implementation by tourism managers with limited computational infrastructure.

From a practical standpoint, the findings demonstrate how sentiment analysis can support digital tourism management. By continuously analyzing visitor reviews, destination managers can identify emerging service issues, monitor customer satisfaction trends, and evaluate the impact of managerial improvements over time. This aligns with the growing adoption of data-driven decision-making in smart tourism, where artificial intelligence and text analytics enable organizations to respond proactively to customer feedback (Gretzel et al., 2023). Consequently, integrating sentiment analysis into tourism management dashboards may provide managers with real-time insights that support strategic planning and service innovation.

Despite the encouraging results, several limitations should be acknowledged. The dataset was collected exclusively from Google Reviews and represented reviews within a limited observation period. Consequently, the findings may not fully capture seasonal variations in visitor perceptions or opinions expressed on other digital platforms such as TripAdvisor, Instagram, or TikTok. Moreover, sentiment labeling relied on a lexicon-based approach, which may struggle to identify sarcasm, contextual meaning, or mixed emotions embedded within user reviews. Future research could therefore explore multilingual datasets, larger review collections, and transformer-based deep learning models such as IndoBERT or multilingual BERT to further improve classification performance and semantic understanding.

CONCLUSION

This research aimed to analyze visitor sentiments toward Rainbow Alamanda Amusement Park based on textual reviews obtained from the Google Review platform using the Naïve Bayes and Support Vector Machine (SVM) algorithms. By implementing the SEMMA framework (Sample, Explore, Modify, Model, and Assess), the study successfully transformed raw user-generated data into structured insights that reflect public perceptions of the amusement park's facilities, cleanliness, prices, and overall service quality.

The results of the study demonstrate that machine learning approaches can effectively classify Indonesian-language reviews into sentiment categories—positive, neutral, and negative—with a high level of accuracy. The Naïve Bayes algorithm achieved an accuracy of 86.32%, precision of 86.83%, recall of 85.81%, and an F1-score of 86.08%, outperforming the SVM model under similar conditions. These findings indicate that Naïve Bayes is more efficient and suitable for text classification tasks involving short and relatively simple reviews such as those found on Google Review.

Through this analysis, the research identified that the majority of visitors expressed positive sentiments, particularly regarding the variety of attractions, family-friendly atmosphere, and affordable ticket prices. However, some negative reviews highlighted issues related to limited parking space, waiting times, and food prices. These insights provide valuable feedback for the park's management, emphasizing the importance of continuously improving visitor experience and facility management.

Overall, this study contributes to the growing application of data-driven sentiment analysis in the tourism industry, demonstrating how digital feedback can be leveraged to assess customer satisfaction and inform managerial decisions. The integration of machine learning techniques and text analytics offers a practical and scalable approach to understanding public perception, supporting innovation in digital business and tourism management. Future research is encouraged to expand the dataset, include multilingual reviews, and explore deep learning models such as LSTM or BERT to further enhance sentiment classification accuracy and interpretability.

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