

# Sentiment Analysis of the Sheikh Zayed Grand Mosque's Visitor Reviews on Google Maps Using the VADER Method

Elinda<sup>1</sup>, Herman Yuliansyah<sup>2</sup>, Muhammad Iqbal Abu Latiffi<sup>3</sup>

<sup>1,2</sup>Department of Informatics, Universitas Ahmad Dahlan, Indonesia

<sup>3</sup>Center for Artificial Intelligence and Technology, Universiti Kebangsaan Malaysia, Malaysia

## Article Info

### Article history:

Received Apr 04, 2024

Revised Apr 19, 2024

Accepted Apr 26, 2024

### Keywords:

Lexicon  
Opinion Mining  
Religious Tourism  
Social Network Analysis  
Text Classification

## ABSTRACT

The Sheikh Zayed Grand Mosque in Solo is a replica of the Zayed Grand Mosque in Abu Dhabi. Many people have provided reviews on Google Maps after visiting the mosque. This research aims to determine the sentiment results regarding visitors' reviews by developing a sentiment analysis model using a combination of the Valance Aware Dictionary for Sentiment Reasoning (VADER) and Deep Translator methods. This research was conducted in two phases. The first phase proposed a sentiment analysis model using VADER and Deep-Translator with public datasets. Later, the resulting sentiment analysis model was applied in the second phase to analyze the dataset of mosque visitor reviews and determine public perceptions. This research compares two preprocessing models (PPTV1 and PPTV2) and continues with the translation and sentiment prediction processes. The evaluation results show the proposed model (PPTV2) achieved the best average accuracy values of 72%, precision of 83%, recall of 72%, and F1-Score of 75% for the three examined datasets. The results of visitor review sentiment obtained showed 84.1% positive, 8.4% neutral, and 7.5% negative. The analysis findings show that people are amazed by the beauty and majesty of the mosque. However, some people provide negative reviews of the mosque's facilities.

*This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.*



## Corresponding Author:

Herman Yuliansyah,  
Department of Informatics,  
Universitas Ahmad Dahlan,  
Jl. Ringroad Selatan, Kragilan, Tamanan, Kec. Banguntapan, Kabupaten Bantul, Daerah Istimewa  
Yogyakarta 55191  
Email: herman.yuliansyah@tif.uad.ac.id

## 1. INTRODUCTION

The Sheikh Zayed Grand Mosque in Solo was built as a replica of the Sheikh Zayed Grand Mosque located in Abu Dhabi, United Arab Emirates. The construction of this mosque is part of the donation given by the Government of the United Arab Emirates to the Government of Indonesia. One of the distinctive characteristics of this mosque is the use of batik motifs on each component of the building, such as Kawung, flower, and Bokor Kencono motifs. This characteristic distinguishes it from the original mosque and adds to its uniqueness and beauty [1]. The city of Solo's residents and surroundings feel very enthusiastic about this mosque because its magnificent building and beautiful ornaments interest people who want to worship and visit it for tourism. Visitors have provided reviews on Google Maps to provide an impression of their experience when visiting the mosque.

Google Maps is a free application in the form of a map service developed by Google that users can access via a web browser and mobile application. This application can provide road directions when traveling on foot, by motorbike, or by car. Because there are many reviews from visitors to the Sheikh Zayed Solo Mosque, these reviews can be used as data and processed to determine the public's response to the Sheikh Zayed Solo Mosque.

Sentiment analysis implements text classification as a subfield of text mining. Sentiment analysis analyzes opinions, evaluations, attitudes, and review / perceptions about products, services, objects, events, issues, etc [2]. Sentiment analysis aims to understand positive, negative, or neutral reviews [3], [4]. Sentiment analysis is developed using two approaches: lexicon-based and machine learning-based. The lexicon-based text classification approach is divided into two categories: dictionary-based, which involves manually collecting opinion words and then processing them to find antonyms and synonyms; and corpus-based, which entails including opinion words in the corpus and then identifying other opinion words within the corpus to aid in determining opinions that are contextually appropriate [5], [6], [7].

Previous sentiment analysis research has been conducted using Twitter and Google Play Store dataset. These studies include analyzing sentiment analysis of people's emotions towards Covid-19 [8], pig farming during the African swine fever outbreak [9], comments in the Klik Indomaret application during the Covid-19 pandemic [10], government efforts in dealing with Covid-19 [11], and horror stories of KKN students in Java East [12]. Other research that uses VADER is analysis of customer reviews in determining customer satisfaction in the digital market [13], public opinion about the new educational curriculum [14], and reviews of the PLN Mobile application [15] which produces high accuracy scores on VADER performance. The results of using the VADER method can achieve an accuracy of 88%, precision of 94%, Recall of 93%, and F1-Score of 88%.

VADER is a lexicon-based and rule-based sentiment analysis method. The advantages of VADER are that it does not require training data, supports emoji for classification, requires fewer resources, is computationally intensive, and does not suffer from a speed-performance tradeoff. VADER works better for text from social media and other web sources. VADER is also a simple rule-based model for sentiment analysis [16].

The main objective of this research is to propose a sentiment analysis model by combining the VADER and Deep-Translator methods and conduct a sentiment analysis of visitors' reviews of the Sheikh Zayed Grand Mosque in Solo. The sentiment analysis results are sentiment classification, which includes positive, negative, and neutral and is accompanied by a total score (compound). The research presents two key contributions: first, developing a sentiment analysis model using VADER with a translator. Second, it delivers the analysis outcomes categorizing sentiments into positive, negative, and neutral, alongside visualizing comments corresponding to each emotion.

The rest of this study is organized by outlining the research methodologies implemented in Section 2, illustrating the outcomes of sentiment analysis model evaluations from publicly available data, analyzing sentiment results, and generating word cloud visualizations based on the examined data in Section 3. The conclusion of this research encompasses the findings of sentiment analysis outlined in Section 4.

## 2. RESEARCH METHOD

This research proposed a sentiment analysis model by combining the VADER and Deep-Translator methods [17] in Phase 1 and Phase 2 to conduct a sentiment analysis of visitors' reviews of the Sheikh Zayed Grand Mosque in Solo using the model proposed in Phase 1, as shown in Figure 1. Preprocessing is the most critical stage in text processing. This stage is used to normalize the text so that the sentiment analysis results are more accurate and make the weighting stage easier [18]. The VADER method takes into account punctuation and context in words [19].

This research examines two preprocessing methods before performing text translation and sentiment prediction with VADER. The first sentiment analysis model is PTTV1, and the second is

PTTV2. The terms PTTV1 and PTTV2 is interpreted as sentiment analysis models with preprocessing, translation, and VADER version 1 and version 2.

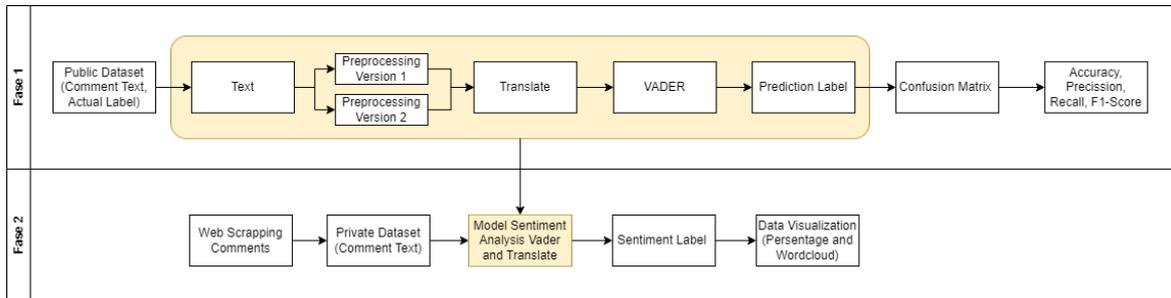


Figure 1. Research Method

2.1 Dataset

In Phase 1, 3 public datasets were obtained from Github (<https://github.com/rizalespe/Dataset-Sentimen-Analisis-Bahasa-Indonesia>): the cyberbullying Instagram comments dataset, the TV show tweet dataset, and the film opinion tweet dataset, as shown in Table 1. VADER is a lexicon-based sentiment analyzer that has been trained and does not depend on the context of the opinion. It uses a dictionary of words and defined rules to determine a text's sentiment score, deciding whether a text is positive, negative, or neutral [20], [21]. This research used a public dataset based on the Indonesian language to evaluate the proposed model in Phase 1. The dataset was selected based on the criteria that it was Indonesian language and sourced from published articles published in open access.

Table 1. Public Dataset

Dataset	Number of data	Attribute	Label Positive	Label Negative	Ref
komentar instagram cyberbullying	400	{Id, Sentiment, Instagram Comment Text}	50%	50%	[22]
tweet tayangan tv	200	{Id, Sentiment, Text Tweet}	50%	50%	[23]
tweet opini film	400	{Id, Sentiment, Acara TV, Jumlah Retweet, Text Tweet}	50%	50%	[24]

In Phase 2, the dataset of visitors' reviews of the Sheikh Zayed Grand Mosque in Solo was obtained using Web Scrapper [25] which uses the instant data scrapper extension [26] for Google Maps reviews. The Web Scrapper obtained 2753 reviews of mosque visitors. The dataset obtained is in the form of review text, as shown in Table 2. Later, this dataset is analyzed using the sentiment analysis model obtained in Phase 1.

Table 2. Private Dataset

Reviews	
1	Dibalik segala kemacetan dan kesemrawutan lalu lintas menuju ke sini, mungkin ini adalah masjid terbesar dan terindah yang pernah saya kunjungi.
2	Masjid wakaf dari Sheikh Zayed, selain sebagai tempat ibadah juga menggerakkan perekonomian di daerah sekitar sebagai tempat wisata religi.
3	Indah, megah..cuma area parkir yang terbatas
4	Alhamdulillah bisa ngerasain ibadah di mesjid ini. MasyaAllah bagus. Tempatnya indah, megah, mewah, didalam pun sejuk, tempat wudhu harus turun ke bawah. Ada Al Qur'an besar sekali. Insyallah mau kesini lagi kalau ke solo
5	Masjidnya bagus,
5	Bagus buat wisata dan photo2 hehe...
6	Malah belum sempat sengaja ibadah di sini 😊 ...
6	Masjid yang untuk beribadah dan wisata religius
...	
...	
...	
2752	Luas dan bersih, arsitekturnya juga cakep. Cuma ramenanya subhanallah
2753	Masjid megah dengan bentuk bangunan yang sangat bagus dengan konsep Timur Tengah, dengan toilet dan tempat wudhu yang luas juga bersih

## 2.2 Preprocessing Version 1

In the model with preprocessing, translation, and VADER version 1 (PTTV1), several steps are conducted in the preprocessing stages, such as Case Folding, Tokenization, Normalization, and Stemming. This Case Folding stage changes uppercase/capital letters to lowercase/lowercase letters, as shown in Figure 2.

```
# Case Folding: changes uppercase/capital letters to lowercase/lowercase letters
data['Case Folding'] = data['text_cleaning'].str.lower()
```

Figure 2. Case Folding

For this Tokenization stage, NLTK installation and word\_tokenizing import are conducted. This Tokenization stage is breaking down a text or document into smaller units. The tokenizing stage separate phrases, words, symbols, and other essential entities, as shown in Figure 3.

```
import nltk
from nltk.tokenize import word_tokenize
nltk.download('punkt')

# Tokenizing: process of breaking down a text or document into smaller units
data['Tokenizing'] = data['Case Folding'].apply(word_tokenize)
```

Figure 3. Tokenization

The results of Tokenization are processed in the third stage, namely Normalization, as shown in Figure 4. In this Normalization stage, stopwords and regex are imported to remove special characters and numbers.

```
from nltk.corpus import stopwords
import re
nltk.download('stopwords')

# Normalization: remove special characters and numbers
stop_words = set(stopwords.words('indonesian'))
data['Normalized'] = data['Tokenizing'].apply(lambda tokens: [word for word in tokens if word.isalpha() and word not in stop_words])
```

Figure 4. Normalization

Normalization results are continued with the Stemming stage by installing the literary library used to decompose a word into its basic word form, as shown in Figure 5.

```
pip install Sastrawi

from Sastrawi.Stemmer.StemmerFactory import StemmerFactory
# Stemming: decompose a word into its basic word form
factory = StemmerFactory()
stemmer = factory.create_stemmer()
data['Stemming'] = data['Normalized'].apply(lambda tokens: [stemmer.stem(word) for word in tokens])
```

Figure 5. Stemming

## 2.3 Preprocessing Version 2

Preprocessing for PTTV2 is conducted in several steps, namely changing uppercase letters to lowercase, deleting text links, deleting special characters, replacing double spaces with single spaces, and deleting Twitter marks [27], as shown in Figure 6.

```
#preprocessing
import re

# Teks lower
data['text_cleaning']=data['text_cleaning'].str.lower()
# Code to remove the Hashtags from the text
data['text_cleaning']=data['text_cleaning'].apply(lambda x:re.sub(r'\B#\S+', '',x))
# Code to remove the Special characters from the text
data['text_cleaning']=data['text_cleaning'].apply(lambda x: ' '.join(re.findall(r'\w+', x)))
# Code to substitute the multiple spaces with single spaces
data['text_preprocessing']=data['text_cleaning'].apply(lambda x:re.sub(r'\s+', ' ', x, flags=re.I))
```

Figure 6. Preprocessing Version 2

In PTTV1, sentence cleaning is conducted by deleting affixes and conjunctions to produce only the basic words. Meanwhile, in PTTV2, sentence cleaning is conducted by tidying up the sentences, such as changing to lower text, deleting hashtags, deleting special characters, and replacing double spaces with single spaces. PTTV2 produces complete sentences without eliminating conjunctions and affixes. Comparing the two proposed models aims to determine which preprocessing method effectively improves classification score results.

## 2.4 Translate

After preprocessing stage, the clean data is translated into English. This process requires installing Deep-Translator and importing Google Translator into the Python workspace. Each text is checked using auto-source parameters according to the original language and translated into English, as shown in Figure 7. VADER uses an English word dictionary while the data examined is Indonesian language text. Therefore, the proposed model is combined with a translational model. This translation model is used to translate preprocessed text using existing preprocessing text models for Indonesian, such as NLTK and Sastrawi on PPTV1. This combination of VADER and Deep Translator is considered better than carrying out translations manually using a web-based translator service, as a previous researcher has conducted [11].

```
%pip install deep-translator
from deep_translator import GoogleTranslator

df['text_trans'] = df['text_cleaning'].apply(lambda x: GoogleTranslator(source='auto', target='english').translate(x))
df
```

Figure 7. Translate Process

## 2.5 VADER

Valence Aware Dictionary for Sentiment Reasoning (VADER) is a sentiment analyzer that can identify variations in data through the intensity of emotional strength according to the available Lexicon data dictionary [21], [28]. The VADER method was introduced by C.J. Hutto et al. [29] in 2014, which combines qualitative analysis and empirical validation using research and human wisdom. Each word in the data is given a weight according to the English lexicon dictionary, and then the compound value results is obtained [30], [31], [32], as shown in Figure 8.

```
# Import the lexicon
from nltk.sentiment.vader import SentimentIntensityAnalyzer

# Create an instance of SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()

df['polarity_score'] = df['text_trans'].apply(lambda x: analyzer.polarity_scores(x))

def predict_sentiment(text):
    polarity = "neutral"

    if(text >= 0.05):
        polarity = "positive"

    elif(text <= -0.05):
        polarity = "negative"

    return polarity

# Run the predictions
df["sentiment_predicted"] = df["compound"].apply(predict_sentiment)
df
```

Figure 8. VADER Classification

The classification process is conducted by installing SentimentIntensityAnalyzer, which is used to calculate the polarity score. These calculations' results are positive, neutral, negative, and compound values. The criteria for classifying compound value results are three sentiments, namely:

$$\begin{array}{l} \text{Compound} \\ \text{Value (CV)} \end{array} = \begin{array}{ll} \text{positive} & CV \geq 0.05 \\ \text{neutral} & -0.05 < CV < 0.05 \\ \text{negative} & CV \leq -0.05 \end{array}$$

## 2.5 Evaluation

The evaluation stage is used after the VADER method obtains the prediction label. This evaluation uses a confusion matrix to measure the performance of a classification method. This evaluation compares the actual labels from the dataset and the predicted labels from the VADER method, as shown in Figure 9.

```
from sklearn.metrics import accuracy_score, classification_report

accuracy = accuracy_score(df['Sentiment'], df['vader_prediction'])

print("Accuracy: {}".format(accuracy))

# Show the classification report
print(classification_report(df['Sentiment'], df['vader_prediction']))
```

Figure 9. Confusion Matrix

The confusion matrix evaluates sentiment results and groups them into four categories:

*TP* (True Positive) = The actual feasible value and the predicted feasible value.

*FP* (False Positive) = The actual value is not feasible, but the predicted value is feasible.

*FN* (False Negative) = Actual worthy value and non-worthy prediction value.

*TP* (True Positive) = The actual value and the predicted value are not feasible.

The confusion matrix has four evaluation matrices: Accuracy, Precision, Recall, and F1—Score. Accuracy is comparing the number of items predicted correctly with the total number of predictions made. Precision is the ratio of the number of items correctly identified as favorable to the number of items positively identified. Recall is the ratio of the number of relevant items correctly identified to all correct items. F1-Score is a comparison of Precision and Recall results between the predicted category and the actual category.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$$

## 2.6 Data Visualization

After obtaining the sentiment results in Phase 2, the next step is to visualize the data on the review text according to the sentiment labeling. The visualization used is a pie chart to display the percentage of sentiment, as shown in Figure 10. Word cloud to display words that often appear in the text, as shown in Figure 11 [33].

```
import matplotlib.pyplot as plt

# Count the number of positive, negative, and neutral sentiments
positif_count = df[df['vader_prediction'] == 'positive'].shape[0]
negatif_count = df[df['vader_prediction'] == 'negative'].shape[0]
netral_count = df[df['vader_prediction'] == 'neutral'].shape[0]

# Compile sentiment and label data
sentimen = [positif_count, negatif_count, netral_count]
labels = ['Positive', 'Negative', 'Neutral']

# Determine the color for each sector
colors = ['#55a868', '#c44e52', '#4c72b0']

# Creating a Pie Chart
plt.pie(sentimen, labels=labels, colors=colors, autopct='%1.1f%%', startangle=90)

# Add title
plt.title('Percentage of Predicted Sentiment Analysis')

# Display Pie Chart
plt.axis('equal')
plt.savefig(f'percentage-predicted-sentiment-analysis.png')
plt.show()
```

Figure 10. Visualization Pie Chart

```
# Create data subsets for each sentiment category
df_neutral = df[df['vader_prediction'] == 'neutral']
df_negative = df[df['vader_prediction'] == 'negative']
df_positive = df[df['vader_prediction'] == 'positive']

# Merge all words in the "text_cleaning" column for each sentiment category
text_neutral = ' '.join(df_neutral['text_cleaning'])
text_negative = ' '.join(df_negative['text_cleaning'])
text_positive = ' '.join(df_positive['text_cleaning'])

# Create WordCloud objects for each sentiment category
wordcloud_neutral = WordCloud(width=800, height=400).generate(text_neutral)
wordcloud_negative = WordCloud(width=800, height=400).generate(text_negative)
wordcloud_positive = WordCloud(width=800, height=400).generate(text_positive)

# Display wordcloud for each sentiment category separately
plt.figure(figsize=(8, 4))
plt.imshow(wordcloud_neutral, interpolation='bilinear')
plt.title('Wordcloud - Neutral Sentiment Analysis')
plt.axis('off')
plt.savefig(f'wordcloud-neutral-sentiment-analysis.png')
plt.show()

plt.figure(figsize=(8, 4))
plt.imshow(wordcloud_negative, interpolation='bilinear')
plt.title('Wordcloud - Negative Sentimen Analysis')
plt.axis('off')
plt.savefig(f'wordcloud-negative-sentimen-analysis.png')
plt.show()

plt.figure(figsize=(8, 4))
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.title('Wordcloud - Positive Sentimen Analysis')
plt.axis('off')
plt.savefig(f'wordcloud-positive-sentimen-analysis.png')
plt.show()
```

Figure 11. Visualization Word Cloud

### 3. RESULTS AND DISCUSSION

The results and discussion section is divided into the evaluation results of the sentiment analysis model in Phase 1 and the implementation of the sentiment analysis model 1 in Phase 2.

#### 3.1 Model Sentiment Analysis using VADER and Deep Translator

The public dataset consists of 3 datasets with comment and sentiment text attributes. The next stage is preprocessing to normalize the text and more accurately examine the sentiment analysis results. The normalized comments are then translated into English because VADER is a lexicon dictionary that uses English, as shown in Table 3-5.

Table 3. Instagram Comments Cyberbullying Dataset

Sentiment	Text	Preprocessing Version 1	Translate Version 1	Preprocessing Version 2	Translate Version 2
negative	<USERNAME> TOLOL!! Gak ada hubungan nya keguguran dgn pake hijab syar'i yg lo bilang bayi nya panas dalem kepanasan didalem gak ada hubungan nya woyyyy!! Otak sama jempol lo gak sinkron sih ya jadinya asal nulis komentar!	username tolol gak hubung nya gugur dgn pake hijab syar i yg lo bilang bayi nya panas dalem gak hubung nya woyyyy otak jempol lo gak sinkron sih ya nulis komentar	Stupid username doesn't have a connection but it doesn't work if you wear a sharia hijab. What you said is that the baby is hot inside doesn't have a connection, wow, your thumb brain isn't in sync, okay? Write a comment	username tolol gak ada hubungan nya keguguran dgn pake hijab syaryg lo bilang bayi nya kepanasan didalem gak ada hubungan nya woyyyy otak sama jempol lo gak sinkron sih ya jadinya asal nulis komentar	Stupid username has nothing to do with miscarriage and wearing a hijab, you said the baby was hot inside, there's no connection, wow, your brain and thumb are not in sync, so that's why I just wrote a comment
negative	Geblek lo tata...cowo bgt dibela2in balikan...hadeww...ntar ditinggal lg nyalahin tuh cowo...padahal kitenya yg oon.	geblek lo tata cowo bgt balik hadeww ntar tinggal lg nyalahin tuh cowo kitenya yg oon	You're so hot for a guy who's really good at coming back, then you'll just have to blame the guy for being the one	geblek lo tata cowo bgt dibela2in balikan hadeww ntar ditinggal lg nyalahin tuh cowo padahal kitenya yg oon	You're so mean to a guy when you defend him back then he's left and he blames the guy even though we're the one who's the one

Sentiment	Text	Preprocessing Version 1	Translate Version 1	Preprocessing Version 2	Translate Version 2
positive	yang sabar yaa.. insya Allah menjadi pembuka pintu syurga dan penghalang api neraka bagi kedua orang tuanya	sabar yaa insya allah buka pintu syurga halang api neraka orang tua	Be patient, God willing, open the gates of heaven and block the fire of hell for the parents	yang sabar yaa insya allah menjadi pembuka pintu syurga dan penghalang api neraka bagi kedua orang tuanya	Those who are patient, God willing, will open the gates of heaven and prevent the fire of hell for both parents
positive	Lagu barunya mbak tata kan kisah nyatanya rumah tangga mbak tata.... jadi rasanya mbak tata bener2 sayang get sama suaminya... syukur kalau baikan.... semoga awet...	lagu baru mbak tata kisah rumah tangga mbak tata mbak tata sayang get suami syukur baik moga awet	Miss Tata's new song, Sis Tata's household story, Miss Tata, love, get husband, thank goodness, hope it lasts	lagu barunya mbak tata kan kisah nyatanya rumah tangga mbak tata jadi rasanya mbak tata bener2 sayang get sama suaminya syukur kalau baikan semoga awet	Ms. Tata's new song tells the true story of Ms. Tata's household, so it feels like Ms. Tata really loves her husband, I'm thankful that it's better, I hope it lasts

Table 4. Tweet TV Views Dataset

Sentiment	Text	Preprocessing Version 1	Translate Version 1	Preprocessing Version 2	Translate Version 2
negative	Sesat pikir para pengamat #taxamnesti #ILCtvone	sesat pikir amat taxamnesti ilctvone	Very misguided thinking taxamnesty ilctvone	sesat pikir para pengamat	observers are mistaken
negative	berbicara kelamaan ribet #ILC	bicara ribet ilc	Talk about complicated ILC	berbicara kelamaan ribet	talking for too long is complicated
positive	ih lucu, mas kick andy nya senyum2 aja	ih lucu mas kick andy nya aja	It's funny bro, just kick Andy	ih lucu mas kick andy nya senyum2 aja	It's funny, bro, Kick Andy, he's just smiling
positive	nonton pak hasan Merkids di kick andy sangat menginspirasi salut pak hasan	nonton hasan merkids kick andy inspirasi salut hasan	watching hasan merkids kick andy inspiration salute hasan	nonton pak hasan merkids di kick andy sangat menginspirasi salut pak hasan	Watching Mr Hasan Merkids on Kick Andy was very inspiring, salute Mr Hasan

Table 5. Tweet Opinion Film Dataset

Sentiment	Text	Preprocessing Version 1	Translate Version 1	Preprocessing Version 2	Translate Version 2
negative	Jelek filmnya... apalagi si ernest gak mutu bgt actingnya... film sampah	jelek film si ernest gak mutu bgt actingnya film sampah	Ernest's film is bad, the acting isn't very good, it's a trash film	jelek filmnya apalagi si ernest gak mutu bgt actingnya film sampah	The film is bad, especially when Ernest doesn't act very well, it's a rubbish film
negative	Film king Arthur ini film paling jelek dari seluruh cerita King Arthur	film king arthur film jelek cerita king arthur	king arthur movie bad movie king arthur story	film king arthur ini film paling jelek dari seluruh cerita king arthur	This King Arthur film is the worst film of all the King Arthur stories
positive	Keren bang flm lo @radityadika persahabatan, keluarga dan cinta kentel banget. Tokoh pemain pas	keren bang flm lo radityadika sahabat keluarga cinta kentel banget tokoh main pas keren bang	How cool is your film, Radityadika, a friend of the family, Cinta, really cool, the characters playing	keren bang flm lo radityadika persahabatan keluarga dan cinta kentel banget tokoh pemain pas semua	Your film Radityadika's film is really cool, family friendship and love are really strong, the

Sentiment	Text	Preprocessing Version 1	Translate Version 1	Preprocessing Version 2	Translate Version 2
	semua keren bang		are really cool, bro	keren bang	cast of characters are all cool, bro
positive	Habis nonton film Kong: Skull Island 2017. Lumayan greget filmnya, 7.5 deh.. layak buat nobar	habis nonton film kong skull island lumayan greget film deh layak nobar	After watching the film Kong Skull Island, it's quite an exciting film, it's worth watching	habis nonton film kong skull island 2017 lumayan greget filmnya 7 5 deh layak buat nobar	After watching the film Kong Skull Island 2017, the film is quite exciting, 7 5, it's worth watching

The next stage is the sentiment classification process using VADER. In this process, text is classified by calculating the weight of words (positive, neutral, and negative) and then producing a compound value. The compound value results are categorized into positive, neutral, and negative. The result of text classification is shown in Figure 12.

Sentiment	text_cleaning	text_trans	polarity_score	neg	neu	pos	compound	sentiment_predicted	
0	negative	jelek filmnya apalagi si ernest gak mutu bgt a...	The film is bad, especially when Ernest doesn't...	{'neg': 0.315, 'neu': 0.685, 'pos': 0.0, 'comp...}	0.315	0.685	0.000	-0.6737	negative
1	negative	film king arthur ini film paling jelek dari se...	This King Arthur film is the worst film of all...	{'neg': 0.24, 'neu': 0.76, 'pos': 0.0, 'compou...}	0.240	0.760	0.000	-0.6249	negative
2	negative	beekuanlin sepanjang film gwa berkata kasar t...	beekuanlin throughout the movie was rude to h...	{'neg': 0.273, 'neu': 0.727, 'pos': 0.0, 'comp...}	0.273	0.727	0.000	-0.4588	negative
3	negative	ane ga suka fast and furious menurutku kok jel...	I don't like Fast and Furious, I think it's a...	{'neg': 0.608, 'neu': 0.392, 'pos': 0.0, 'comp...}	0.608	0.392	0.000	-0.8523	negative
4	negative	baekhyun36 kan gua ga tau film nya lu bilang p...	baekhyun36 I don't know the film, you said war...	{'neg': 0.394, 'neu': 0.606, 'pos': 0.0, 'comp...}	0.394	0.606	0.000	-0.9136	negative
...	...	...	...	...	...	...	...	...	...

Figure 12. Public Dataset Classification Results

The evaluation result with the confusion matrix on three datasets is shown in Table 6. Comparison between the sentiment analysis model with preprocessing, translation, and VADER version 1 (PTTV1) and preprocessing, translation, and VADER version 2 (PTTV2) obtained results that are suitable for implementing the sentiment analysis model because the accuracy and F1-Score are above 70%. Apart from that, the precision and recall values also reached more than 80%. However, the average value of PTTV2 outperforms that of PTTV1.

Table 6. Model Evaluation Results

Model	Dataset	Accuracy	Precision	Recall	F1-Score
PTTV1	Instagram	0,74	0,81	0,74	0,75
	Opini Film	0,70	0,80	0,70	0,74
	Tayangan TV	0,65	0,86	0,65	0,73
	Average	0,70	0,83	0,70	0,74
PTTV2	Instagram	0,73	0,795	0,73	0,73
	Opini Film	0,74	0,81	0,74	0,77
	Tayangan TV	0,70	0,86	0,70	0,75
	Average	<b>0.72</b>	<b>0.83</b>	<b>0.72</b>	<b>0.75</b>

### 3.2 Sentiment Analysis Google Maps Reviews

The sentiment analysis model developed in Phase 1 named PTTV2 was implemented on the Sheikh Zayed Solo Mosque visitor review dataset on Google Maps, as shown in Table 7.

Table 7. Google Maps Review Compound Value

Review Text	Text Cleaning	Translate	Compound
Dibalik segala kemacetan dan kesemrawutan lalu lintas menuju ke sini, mungkin ini adalah masjid terbesar dan terindah yang	dibalik segala kemacetan dan kesemrawutan lalu lintas menuju ke sini mungkin ini adalah masjid terbesar dan	Behind all the traffic jams and chaos to get here, this is probably the biggest and most beautiful mosque I have ever	0.1263

Review Text	Text Cleaning	Translate	Compound
pernah saya kunjungi.	terindah yang pernah saya kunjungi	visited	
Masjid wakaf dari Sheikh Zayed, selain sebagai tempat ibadah juga mengerakkan perekonomian di daerah sekitar sebagai tempat wisata religi.	masjid wakaf dari sheikh zayed selain sebagai tempat ibadah juga mengerakkan perekonomian di daerah sekitar sebagai tempat wisata religi	Sheikh Zayed's Waqf Mosque, apart from being a place of worship, also stimulates the economy in the surrounding area as a religious tourism spot	0.4939
Di balut nuansa religi madinah	di balut nuansa religi madinah	wrapped in Medina religious nuances	0.0
Baru pertama kali kesini pas jumat'an eh gak taunya ada Pak Jokowi 😊 ...	baru pertama kali kesini pas jumat an eh gak taunya ada pak jokowi	This was my first time here on Friday, but I didn't know Pak Jokowi was there	0.0
Bersih,indah,cuma pengunjungnya kurang ditertibkan.. masih nampak tiduran di teras masjid dan kenapa ada kolam sebelum masjid ya?	bersih indah cuma pengunjungnya kurang ditertibkan masih nampak tiduran di teras masjid dan kenapa ada kolam sebelum masjid ya	it's clean, beautiful, but the visitors are not disciplined and can still be seen lying on the mosque terrace and why is there a pool before the mosque?	-0.3182
Masjidnya bagus, super ramai, tapi kamar mandi bau, dan yang sangat mengecewakan petugasnya supernya galak galak, Nih ya contoh ada kolam air bilangnyanya tidak boleh dimasuki kaki, katanya banyak obatnya, logika nya obat apa??? kenapa ga dikasih tulisan dilarang masukan kaki, atau mending kolamnya dikasih ikan terapi kan lebih bermanfaat Fasilitas dan tempat bagus tapi tidak didukung dengan SDM yang ramah, SDM yg sudah hilang Marwahnya dari "kejawen" yang halus dan santun	masjidnya bagus super ramai tapi kamar mandi bau dan yang sangat mengecewakan petugasnya supernya galak galak nih ya contoh ada kolam air bilangnyanya tidak boleh dimasuki kaki katanya banyak obat nya obat apa kenapa ga dikasih tulisan dilarang masukan kaki atau mending kolamnya dikasih ikan terapi kan lebih bermanfaat fasilitas dan tempat bagus tapi tidak didukung dengan sdm yang ramah sdm yg sudah hilang marwahnyanya dari kejawen yang halus dan santun	The mosque is nice, super busy, but the bathroom smells and what really disappoints is that the staff are super fierce, for example, there is a water pool that says you can't put your feet in, it says there's a lot of medicine, what's the logic behind the medicine? Why isn't it written that it's forbidden to put your feet in? Or it's better to have therapy fish in the pool, isn't it more useful? Good facilities and place but not supported by friendly human resources that have lost their refined and polite Javanese character	-0.3677
...	...	...	...

The dataset consists of 2753 review data, then the preprocessing stage carried out and 2634 reviews are obtained. The results of data labeling from 2643 review data showed positive sentiment of 2223 reviews (84.1%), neutral sentiment of 222 reviews (8.4%), and negative sentiment of 198 reviews (7.5%), as shown in Figure 13.

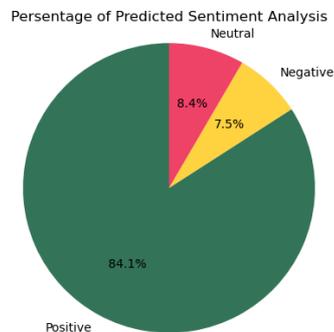


Figure 13. Percentage of Predicted Sentiment Analysis

Wordcloud is used to identify keywords from several text data. In this research, the sentiment results from each class are visualized via a word cloud to display the words that appear



The neutral sentiment is shown in Figure 15. Words that often appear are “parking,” “mosque,” “prayer,” and “solo.” From these words, the review that occurs is shown in Table 9. The UAE government funds the Sheikh Zayed Mosque in the city of Solo.

Table 8. Neutral Sentiment Review

#	Review
1	The only mosque that does not receive financial aid, all the operational needs of the mosque are covered by the UAE government and the APBD, Masyaallah
2	Access to parking if you take the bus is a little far if you walk
3	Come here, when you are going for noon prayers, the inside of the mosque is opened for noon prayers. The mosque is quite large, with batik patterned carpets
4	The coolest mosque I've ever visited has complete facilities
5	could become a religious tourism destination in Solo
6	It is very majestic and the place next to the main road is always busy with visitors from various regions
7	Equipped with goods storage, the prayer area detector is opened only during prayer time
8	Solo mosque which is often visited by young people and old people
9	If you go to Solo for out-of-town business, you always make time to stop by here to pray
10	one of the places you must visit if you are in Solo

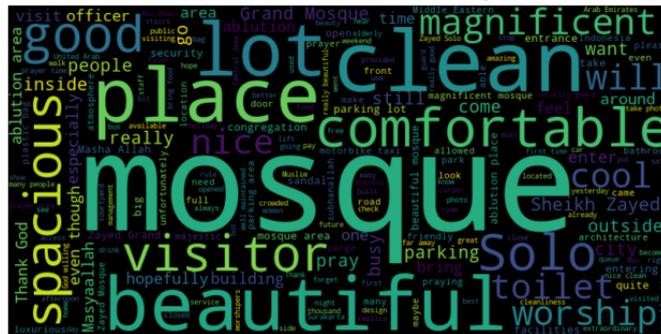


Figure 16. Wordcloud Negative Sentiment

The positive sentiment is shown in Figure 16. Words that often appear are “mosque,” “beautiful,” “comfortable,” “place,” “clean,” and “visitor.” From these words, the reviews that appear are shown in Table 10. Many visitors are amazed by the beauty and luxury of the mosque because its interior is beautiful, spacious, neat, and comfortable, and there is also a large Al-Quran.

Table 9. Positive Sentiment Review

#	Reviews
1	Thank God, I can feel the worship at this mosque, masyaallah, the place is beautiful, majestic, luxurious, the inside is cool, the place for ablution has to go downstairs, there is a very large Al-Quran, God willing, I will come here again if I go to Solo
2	spacious and clean, the architecture is also beautiful, but it's busy, subhanallah
3	a nice and beautiful mosque with good security and cleanliness, everything is well organized, the ablution place is also good and adequate
4	Masyaallah the mosque is really beautiful, majestic, spacious and clean when you go there, you can park inside, so it's nice to be close to the mosque and pay as willingly as possible, but during the day the floor is very hot when you enter the mosque, it's cool, comfortable
5	The mosque is magnificent and the building is cool, there are lots of toilets
6	wonderfully magnificent and the facilities are good. I hope it is well maintained and we can visit again
7	A magnificent and comfortable mosque for prayer and other worship
8	Very majestic and beautiful mosque, God's house for worship. FYI, it is recommended not to visit on holidays because it will be very busy
9	This is my first time here and it turns out the building is very magnificent. During the fasting month there is a Ramadan festival. The mosque is always busy, especially starting in the afternoon during the fasting month
10	Masha Allah, the mosque is really nice, at first I didn't know, I just opened a tourist reference in Solo, but I came across a review of the Sheikh Zayed Grand Mosque, the atmosphere is nice, cool, especially if you come on a weekday, it tends to be a bit quiet, so you can enjoy it more, on weekends it tends to be busy because there are lots of tourists coming from far away too

#### 4. CONCLUSION

This research proposed a sentiment analysis model using VADER and Deep-Translator. The results of the VADER sentiment analysis model evaluation performed well. The reviews of mosque visitors on Google Maps implemented the proposed method to classify the sentiment of

reviews. The sentiment analysis results on mosque visitor reviews are positive, neutral, and negative. This sentiment is in the form of various public opinions regarding the mosque's existence. The beautiful and majestic Sheikh Zayed Mosque in Solo makes people want to visit it. However, there are also problems with the mosque, such as the parking lot being far from the mosque. Hence, visitors have to walk a long way, there are expensive parking fees, a lack of security even though CCTV has been provided, and officers in front of the mosque are less than friendly. This sentiment evaluates future mosque management to make it even better and become one of the religious attraction's tourists visit in Solo.

Future research can propose other lexicon-based sentiment analysis models, such as Bert and transformer. This model can evaluate visitor reviews for other famous tourist attractions in Indonesia. Remember that Indonesia has many tourist attractions that continue to develop and become famous. Investigating the impact of sentiment on visitor satisfaction or conducting qualitative analysis in visitor reviews can also enrich discussions about other tourist attractions.

#### DATA AVAILABILITY

Dataset used in this study is openly available and can be found online at [Mendeley Data](#).

#### ACKNOWLEDGEMENTS

The authors extend their appreciation to Universitas Ahmad Dahlan, Indonesia, for their support of this research through grant number: PD-239/SP3/LPPM-UAD/VIII/2023.

#### REFERENCES

- [1] A. E. Subhan, E. Dan, E. Wisata, S. Masjid, R. Sheikh, and Z. Solo, "Eksistensi Dan Efektivitas Wisata Syariah Masjid Raya Sheikh Zayed Solo," vol. 7, no. 1, pp. 42–55, 2024, doi: 10.31943/afkarjournal.v7i1.877.
- [2] Samsir, "Analisis Sentimen Pembelajaran Daring Pada Twitter di Masa Pandemi COVID-19 Menggunakan Metode Naïve Bayes," *J. Media Inform. Budidarma*, vol. 5, no. 1, pp. 157–163, 2021, doi: 10.30865/mib.v5i1.2604.
- [3] N. S. Fathullah, "Analisis Sentimen Terhadap Rating dan Ulasan Film dengan menggunakan Metode Klasifikasi Naïve Bayes dengan Fitur Lexicon-Based," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 4, no. 2, pp. 590–593, 2020.
- [4] F. Fazrin, N. O. Pratiwi, and R. Andreswari, "Perbandingan Algoritma K-Nearest Neighbor dan Logistic Regression pada Analisis Sentimen terhadap Vaksinasi Covid-19 pada Media Sosial Twitter dengan Pelabelan Vader dan Textblob," *J. e-Proceeding Eng.*, vol. 10, no. 2, pp. 1596–1604, 2023.
- [5] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams Eng. J.*, vol. 5, no. 4, pp. 1093–1113, 2014, doi: 10.1016/j.asej.2014.04.011.
- [6] Y. Qi and Z. Shabrina, "Sentiment analysis using Twitter data: a comparative application of lexicon- and machine-learning-based approach," *Soc. Netw. Anal. Min.*, vol. 13, no. 1, p. 31, Feb. 2023, doi: 10.1007/s13278-023-01030-x.
- [7] R. Bose, P. S. Aithal, and S. Roy, "Survey of Twitter Viewpoint on Application of Drugs by VADER Sentiment Analysis among Distinct Countries," *Int. J. Manag. Technol. Soc. Sci.*, no. March 2021, pp. 110–127, 2021, doi: 10.47992/ijmts.2581.6012.0132.
- [8] A. J. Nair, G. Veena, and A. Vinayak, "Comparative study of Twitter Sentiment on COVID - 19 Tweets," *Proc. - 5th Int. Conf. Comput. Methodol. Commun. ICCMC 2021*, pp. 1773–1778, 2021, doi: 10.1109/ICCMC51019.2021.9418320.
- [9] E. M. Baesa, E. R. Raro, V. Q. Parillas, J. M. Berina, and T. D. Palaoag, "Sentiment Analysis of Hog Raisers during African Swine Fever using Vader Lexicon-Based Methods," *Proc. 2022 IEEE 7th Int. Conf. Inf. Technol. Digit. Appl.*, 2022, doi: 10.1109/ICITDA55840.2022.9971165.
- [10] A. G. Budianto, B. Wirjodirdjo, I. Maflahah, and D. Kurnianingtyas, "Sentiment Analysis Model for KlikIndomaret Android App During Pandemic Using Vader and Transformers NLTK Library," *IEEE Int. Conf. Ind. Eng. Eng. Manag.*, vol. 2022-Decem, pp. 423–427, 2022, doi: 10.1109/IEEM55944.2022.9989577.
- [11] P. A. Sumitro, Rasiban, D. I. Mulyana, and W. Saputro, "Analisis Sentimen Terhadap Vaksin Covid-19 di Indonesia pada Twitter Menggunakan Metode Lexicon Based," *J-ICOM - J. Inform. dan Teknol. Komput.*, vol. 2, no. 2, pp. 50–56, 2021, doi: 10.33059/j-icom.v2i2.4009.
- [12] R. Arief and K. Imanuel, "Analisis Sentimen Topik Viral Desa Penari pada Media Sosial Twitter dengan Metode Lexicon Based," *J. Ilm. MATRIK*, vol. 21, no. 3, pp. 242–250, 2019.
- [13] K. Barik and S. Misra, "Analysis of customer reviews with an improved VADER lexicon classifier," *J. Big Data*, vol. 11, no. 1, p. 10, Jan. 2024, doi: 10.1186/s40537-023-00861-x.
- [14] F. Paian Sitorus, E. Utami, and M. Parwanto Kurniawan, "Public Sentiment Analysis about Independent Curriculum with VADER Annotations using the Naive Bayes and K-Nearest Neighbor Methods," *Int. J. Innov. Sci. Res. Technol.*, vol. 8, no. 8, 2023, doi: 10.5281/zenodo.8310746.
- [15] Y. Asri and M. Fajri, "Sentiment Analysis of PLN Mobile Review Data Using Lexicon Vader and Naive Bayes

- Classification,” in *2023 International Conference on Networking, Electrical Engineering, Computer Science, and Technology (IConNECT)*, Aug. 2023, pp. 132–137. doi: 10.1109/IConNECT56593.2023.10327064.
- [16] V. Bonta, N. Kumares, and N. Janardhan, “A Comprehensive Study on Lexicon Based Approaches for Sentiment Analysis,” *Asian J. Comput. Sci. Technol.*, vol. 8, no. S2, pp. 1–6, 2019, doi: 10.51983/ajcst-2019.8.s2.2037.
- [17] H. Yuliansyah, S. A. Mulasari, S. Sulistyawati, F. A. Ghozali, and B. Sudarsono, “Sentiment Analysis of the Waste Problem based on YouTube comments using VADER and Deep Translator,” *J. Media Inform. Budidarma*, vol. 8, pp. 663–673, 2024, doi: 10.30865/mib.v8i1.6918.
- [18] M. Fahmi, S. Hidayat, and A. F. Hidayatullah, “Application of Lexicon Based for Sentiment Analysis of Covid-19 Booster Vaccinations on Twitter Social Media Using Naïve Bayes Method,” *J. Tek. Inform.*, vol. 3, no. 4, pp. 1119–1124, 2022, doi: 10.20884/1.jutif.2022.3.4.565.
- [19] M. R. Ningsih, K. A. H. Wibowo, A. U. Dullah, and J. Jumanto, “Global recession sentiment analysis utilizing VADER and ensemble learning method with word embedding,” *J. Soft Comput. Explor.*, vol. 4, no. 3, pp. 142–151, 2023, doi: 10.52465/josce.v4i3.193.
- [20] C. Hutto and E. Gilbert, “VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text,” in *Proceedings of the International AAAI Conference on Web and Social Media*, May 2014, vol. 8, no. 1, pp. 216–225. doi: 10.1609/icwsm.v8i1.14550.
- [21] S. Elbagir and J. Yang, “Twitter sentiment analysis using natural language toolkit and Vader sentiment,” in *Lecture Notes in Engineering and Computer Science*, 2019, vol. 2239, pp. 12–16.
- [22] W. A. Luqyana, I. Cholissodin, and R. S. Perdana, “Analisis Sentimen Cyberbullying pada Komentar Instagram dengan Metode Klasifikasi Support Vector Machine,” *J. Pengemb. Teknol. Inf. Dan Ilmu Komput.*, vol. 2, no. 11, pp. 4704–4713, 2018, [Online]. Available: <https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/3051>
- [23] W. E. Nurjanah, R. S. Perdana, and M. A. Fauzi, “Analisis Sentimen Terhadap Tayangan Televisi Berdasarkan Opini Masyarakat pada Media Sosial Twitter menggunakan Metode K-Nearest Neighbor dan Pembobotan Jumlah Retweet,” *J. Pengemb. Teknol. Inf. Dan Ilmu Kompute*, vol. 1, no. 12, pp. 1750–1757, 2017, [Online]. Available: <https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/631>
- [24] P. Antinasari, R. S. Perdana, and M. A. Fauzi, “Analisis Sentimen Tentang Opini Film Pada Dokumen Twitter Berbahasa Indonesia Menggunakan Naive Bayes Dengan Perbaikan Kata Tidak Baku,” *J. Pengemb. Teknol. Inf. Dan Ilmu Komput.*, vol. 1, no. 12, pp. 1733–1741, 2017, [Online]. Available: <https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/629>
- [25] C. Prakoso and A. Hermawan, “Perbandingan Model Machine Learning dalam Analisis Sentimen Ulasan Pengunjung Keraton Yogyakarta pada Google Maps,” *Kaji. Ilm. Inform. dan Komput.*, vol. 4, no. 3, pp. 1292–1302, 2023, doi: 10.30865/klik.v4i3.1419.
- [26] T. Dzulkarnain, D. E. Ratnawati, and B. Rahayudi, “Penggunaan Metode Naïve Bayes Classifier pada Analisis Sentimen Penilaian Masyarakat Terhadap Pelayanan Rumah Sakit di Malang,” *J. Teknol. Inf. dan Ilmu Komput.*, vol. 10, no. 7, pp. 1453–1460, 2023, doi: 10.25126/jtiik.1077979.
- [27] M. Hayaty and A. H. Pratama, “Performance of Lexical Resource and Manual Labeling on Long Short-Term Memory Model for Text Classification,” *J. Ilm. Tek. Elektro Komput. dan Inform.*, vol. 9, no. 1, pp. 74–84, 2023, doi: 10.26555/jiteki.v9i1.25375.
- [28] A. Ria Devina Endsuy, “Sentiment Analysis between VADER and EDA for the US Presidential Election 2020 on Twitter Datasets,” *J. Appl. Data Sci.*, vol. 2, no. 1, pp. 8–18, 2021, doi: 10.47738/jads.v2i1.17.
- [29] E. Hutto, C.J. and Gilbert, “VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text,” *Eighth Int. AAAI Conf. Weblogs Soc. Media*, pp. 216–225, 2014.
- [30] R. D. Tan *et al.*, “LMS Content Evaluation System with Sentiment Analysis Using Lexicon-Based Approach,” *2022 10th Int. Conf. Inf. Educ. Technol. ICIET 2022*, pp. 93–98, 2022, doi: 10.1109/ICIET55102.2022.9778976.
- [31] V. Nurcahyawati and Z. Mustaffa, “Vader Lexicon and Support Vector Machine Algorithm to Detect Customer Sentiment Orientation,” *J. Inf. Syst. Eng. Bus. Intell.*, vol. 9, no. 1, pp. 108–118, 2023, doi: 10.20473/jjisebi.9.1.108-118.
- [32] M. Isnan, G. N. Elwirehardja, and B. Pardamean, “Sentiment Analysis for TikTok Review Using VADER Sentiment and SVM Model,” *Procedia Comput. Sci.*, vol. 227, pp. 168–175, 2023, doi: 10.1016/j.procs.2023.10.514.
- [33] F. Illia, M. P. Eugenia, and S. A. Rutba, “Sentiment Analysis on PeduliLindungi Application Using TextBlob and VADER Library,” *Proc. Int. Conf. Data Sci. Off. Stat.*, vol. 2021, no. 1, pp. 278–288, Jan. 2022, doi: 10.34123/icdsos.v2021i1.236.
- [34] O. Abiola, A. Abayomi-Alli, O. A. Tale, S. Misra, and O. Abayomi-Alli, “Sentiment analysis of COVID-19 tweets from selected hashtags in Nigeria using VADER and Text Blob analyser,” *J. Electr. Syst. Inf. Technol.*, vol. 10, no. 1, 2023, doi: 10.1186/s43067-023-00070-9.