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Sentiment Analysis of Public Comments on YouTube Regarding the Inaugural Speech of the 8th President of Indonesia Using VADER and BERT Methods

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Abstract: The research examines public reactions toward President Prabowo Subianto first presidential address in 2024 by studying YouTube comment sentiments. By utilizing sentiment analysis methods, this research combines two main approaches: The research combines VADER (Valence Aware Dictionary and Sentiment Reasoner) for initial sentiment labeling through predefined dictionary categories with BERT (Bidirectional Encoder Representations from Transformers) for more advanced classification. The dataset contains 10,306 comments which display a range of public opinions. Positive sentiment represents 4,943 comments which make up 49.26% of the total while neutral sentiment accounts for 4,336 comments at 43.21% and negative sentiment represents 756 comments at 7.53%. The BERT model reached an accuracy level of 97.01% which illustrates its capability to process contextual details and subtle data elements. VADER delivers rapid preliminary labeling results and BERT improves classification precision through its analysis of complex contexts. The study reveals how people perceive the new government while providing chances for creating public opinion monitoring techniques for social and political topics. Researchers, academics, and policymakers will find these findings valuable for comprehending public opinion dynamics during the digital age's continuous evolution.

Keywords: Sentiment Analysis; Public Opinion; Prabowo Subianto; YouTube Comments; Natural Language Processing.

1. Introduction

Digital advancements have transformed how individuals communicate their thoughts about different topics and political matters. YouTube and similar social media platforms provide users with quick access to information that enables them to post comments and reactions to different materials including political speeches. The public paid close attention to President Prabowo Subianto 2024 inauguration speech because he was beginning his leadership role and people anticipated significant developments. The presidential inauguration represents a significant point within a nation's political timeline that signifies both the transfer of power and the implementation of new governmental policies. People now use social media as their primary platform to share political opinions. Johnson (2022) argues digital platforms offer democratic spaces for political discussion which surpass conventional media by enabling broader public engagement [7]. The feedback provided by individuals on the inauguration speech video represents how people perceive the incoming leadership. The research by Doe and Lee (2023) demonstrates that analyzing political content sentiment on social media platforms can expose public opinion patterns which traditional surveys fail to detect [3]. Analyzing sentiment allows researchers to effectively gauge public reactions to specific statements or events. Sentiment analysis of social media data can be conducted using natural language processing methods. Smith's 2022 research highlighted how sentiment analysis plays a crucial role in analyzing political public opinion dynamics [15]. This analysis enables researchers to detect sentiment trends that are positive, negative or neutral as they emerge. The study used two main approaches to sentiment analysis: Research utilized two distinct methodologies to conduct sentiment analysis: VADER (Valence Aware Dictionary and Sentiment Reasoner) and BERT (Bidirectional Encoder Representations from Transformers). VADER offers rapid sentiment analysis for informal texts like social media comments while effectively detecting emotional subtleties in brief texts. Gupta (2021), research demonstrated that VADER performs well for quick sentiment analysis of social media content by detecting the emotional strength present in brief messages. VADER performs poorly on complex sentence structures [5]. The research by Ferdiana and Siswoyo (2019) shows that VADER struggles to accurately analyze texts with ironic or sarcastic content [4].

On the other hand, BERT offers a deeper classification by considering the overall context of the sentence, making it very effective for more complex text analysis and providing more accurate results [2]. Devlin *et al.* (2019) explained that the BERT architecture allows for better contextual understanding due to its ability to process words in relation to the entire sentence [2]. However, BERT requires more computational resources and training time than VADER. Chandradev *et al.* (2023) highlighted BERT's superiority in analyzing Indonesian text with high accuracy, although it requires a more intensive computational process [1]. Choosing the right method is crucial, depending on the characteristics of the data being analyzed. Nugroho and Wibowo (2023) suggest using a hybrid approach to maximize the advantages of various sentiment analysis methods [10]. The combination of VADER and BERT can produce a more comprehensive analysis by utilizing VADER's speed for initial labeling and BERT's accuracy for final classification.

The data analyzed in the study consisted of 10,306 comments taken from the inauguration speech video on YouTube. With a significant amount of data, the study aims to provide a clear picture of public attitudes towards President Prabowo Subianto. Hamdani and Prasetyo (2023) emphasized the importance of adequate data volume to obtain representative sentiment analysis results [6]. The results of the analysis are expected to provide useful information for stakeholders, including policy makers and researchers, in understanding the dynamics of public opinion in Indonesia. Previous research by Setiawan and Lestari (2023) has shown the effectiveness of BERT in analyzing Indonesian-language sentiment on Twitter [14], while Rachman and Kharisma (2023) demonstrated the application of BERT to mobile application reviews [12]. However, there is still a gap in the literature regarding sentiment analysis of political speeches in Indonesia using a combination of VADER and BERT. Research by Prasetyo (2022) and Kusnadi *et al.* (2021) have applied BERT to product and game sentiment analysis, but have not explored its application in a political context [11][8]. The research is expected to contribute to the literature on sentiment analysis and political communication in Indonesia. In addition, the research also opens up opportunities for the development of public opinion monitoring methods in other social and political issues. Thus, a better understanding of the dynamics of public opinion in the digital era can be achieved, which in turn can help in better decision making by leaders and policy makers.

2. Related Work

2.1 Sentiment Analysis and Natural Language Processing

Recent years have seen sentiment analysis emerge as a fast-expanding area of research interest. Zhang (2020) delivers a detailed overview of deep learning methods in sentiment analysis which outlines different neural network structures and methods for text sentiment classification [19]. The research examines how sentiment analysis methods progressed from early lexicon-based systems to modern deep learning models. Sujono

(2021) examines different techniques for sentiment analysis on social media platforms while highlighting the need for contextual comprehension and processing informal language to interpret social media content [16]. The research pinpoints specific difficulties encountered when analyzing social media text due to the presence of abbreviations, slang terms and multilingual elements on platforms like YouTube. Johnson's 2022 research focuses on how machine learning methods can be used to analyze political speech within political sentiment analysis frameworks [7]. The research demonstrates that machine learning models can successfully detect sentiment and tone in political discourse which helps to understand communication methods and public reactions. The study by Smith (2022) explores how sentiment analysis applied to social media can reveal valuable insights about public attitudes toward political and social matters [15].

2.2 VADER for Sentiment Analysis

VADER (Valence Aware Dictionary and Sentiment Reasoner) has become a popular tool for fast sentiment analysis, especially for social media texts. Ferdiana and Siswoyo (2019) applied VADER to analyze movie reviews, demonstrating its effectiveness in capturing sentiment in short, informal texts [4]. Their study revealed that VADER produced satisfactory results for basic sentiment classification but faced challenges with sarcasm and irony. Gupta (2021) extended the understanding of VADER applications by investigating its use in social media sentiment analysis [5]. The study showed that VADER is very effective for real-time sentiment analysis due to its speed and ability to capture emotional intensity in short texts. However, the study also acknowledged VADER limitations in handling complex sentence structures and cultural contexts. Syahrohim and Lestari (2024) compared VADER with traditional classification methods such as Naive Bayes and SVM for sentiment classification [17]. Their findings suggest that while lexicon-based methods such as VADER offer speed and ease of implementation, machine learning methods such as SVM can provide higher accuracy for certain datasets, especially those involving complex linguistic contexts.

2.3 BERT and Its Implementation in Sentiment Analysis

Devlin *et al.* (2019) introduction of BERT (Bidirectional Encoder Representations from Transformers) has brought transformative changes to natural language processing [2]. By utilizing bidirectional transformer architecture BERT understands word context in sentences more effectively than older models leading to its widespread use in multiple NLP tasks such as sentiment analysis. The research conducted by Widyantara and Pradita (2021) provided evidence that BERT outperforms traditional text classification methods in grasping semantic and contextual details [18]. The research shows BERT's capacity to understand intricate word relationships in text which plays a vital role in achieving precise sentiment analysis. Chandradev *et al.* Chandradev *et al.* (2023) employed BERT deep learning for hotel review sentiment analysis and demonstrated its accuracy exceeds traditional methods [1]. The research demonstrates BERT's strong performance in processing Indonesian language text through its use in President Prabowo Subianto inauguration speech analysis..

2.4 Sentiment Analysis in Indonesian

Several studies have focused on the application of sentiment analysis techniques specifically for Indonesian. Hamdani and Prasetyo (2023) implemented BERT for sentiment classification in Indonesian-language social media, demonstrating the effectiveness of this model in handling the unique characteristics of the Indonesian language [6]. Their study highlights the importance of fine-tuning the BERT model with an Indonesian language dataset to improve accuracy. Setiawan and Lestari (2023) investigated the use of BERT for sentiment analysis in Indonesian-language Twitter [14]. They found that BERT outperformed traditional methods in handling abbreviations, slang, and informal sentence structures commonly found in Indonesian-language Twitter content. Nugroho and Wibowo (2023) also applied BERT to sentiment analysis of Indonesian-language social media, focusing on parameter optimization to improve model performance [10]. Their study provides valuable insights into the adaptation of BERT to the specific characteristics of the Indonesian language in the context of social media.

2.5 Applications of BERT in Various Domains

BERT has been applied in various domains for sentiment analysis, demonstrating its flexibility. Prasetyo (2022) investigated the application of BERT in sentiment analysis of product reviews, demonstrating its ability to capture subtle sentiments in consumer texts [11]. This study provides insights into the adaptation of BERT for the e-commerce domain that can be transferred to other contexts. Kusnadi *et al.* (2021) applied BERT for sentiment analysis of the game Genshin Impact, demonstrating its effectiveness in the entertainment domain [8]. Their study revealed that BERT can accurately classify sentiment in game reviews that often contain domain-specific terminology and emotional expressions. Rachman and Kharisma (2023) used the BERT method for sentiment analysis of mobile application reviews, demonstrating its superiority in handling short texts with technical terminology [12]. Their findings show that BERT can effectively classify sentiment even in texts with technical jargon and domain-specific expressions. Ramadhan and Siswoyo (2024) provide a comprehensive review of the BERT model and its implementation for sentiment analysis of game reviews [13]. This study highlights various fine-tuning and optimization techniques that can improve BERT's performance for specific sentiment analysis tasks.

2.6 Cross-Language Sentiment Analysis

Research has also explored the application of BERT for sentiment analysis across languages. Nguyen (2023) investigated the use of BERT for sentiment analysis in Vietnamese texts, demonstrating the adaptability of this model to non-English languages [9]. This study provides valuable insights into transfer learning and model adaptation to languages with different linguistic characteristics. Doe and Lee (2023) conducted a comparative study of sentiment analysis techniques across languages, comparing the performance of VADER, BERT, and other methods [3]. Their findings suggest that while BERT consistently outperforms other methods in terms of accuracy across languages, a hybrid approach that combines the speed of VADER with the depth of BERT can provide an optimal balance between efficiency and accuracy.

2.7 Research Gaps

While there are many studies on sentiment analysis using VADER and BERT, there is still a gap in the literature regarding the application of these methods to analyze public responses to political speeches in Indonesia, especially in the context of social media such as YouTube. This study aims to fill this gap by applying a combination of VADER and BERT to analyze the sentiment of YouTube comments on President Prabowo Subianto inauguration speech, providing valuable insights into public opinion in the context of Indonesian politics.

3. Research Method

3.1 Research Design

This research uses quantitative methods to analyze text sentiment as its primary research focus. YouTube platform comments serve as the data source from which sentiment patterns are analyzed. The analysis method consists of two primary stages that operate together to achieve the results. The initial phase of the analysis employs the Valence Aware Dictionary and Sentiment Reasoner (VADER) method to perform sentiment labeling since this method excels at evaluating brief and emotive text found on social media platforms. VADER assigns an initial sentiment label to text by placing it into positive, negative or neutral categories. VADER operates quickly and effectively when analyzing informal text but struggles with complex sentence structures. The second stage uses the Bidirectional Encoder Representations from Transformers (BERT) model to perform sentiment classification through its advanced artificial intelligence mechanisms which deeply understand sentence context. The BERT model enhances sentiment classification accuracy by enabling the detection of more intricate textual context. Despite demanding more computational power and extended training time BERT's ability to detect subtle sentiment nuances makes it a suitable option for this analysis.

3.2 Research Flow Chart

This research flowchart illustrates the research process visually, starting from the initial stage of data collection in the form of YouTube user comments. Once the data is collected, the next stage is pre-processing, where the data is cleaned to ensure it is formatted properly and ready for analysis. Once the data is clean, the research enters the initial sentiment labeling stage using the VADER method, which provides an initial sentiment rating (positive, negative or neutral) based on lexical analysis. The next stage is advanced sentiment classification using the BERT model, which is trained to capture more complex context in the text so that it can provide sentiment predictions with higher accuracy. The classification results are then evaluated using metrics such as accuracy, precision, recall, and F1-score to measure model performance. This diagram illustrates how VADER provides fast initial sentiment labels, while BERT optimizes accuracy through contextual analysis, so the combination of the two aims to produce comprehensive and accurate sentiment analysis.

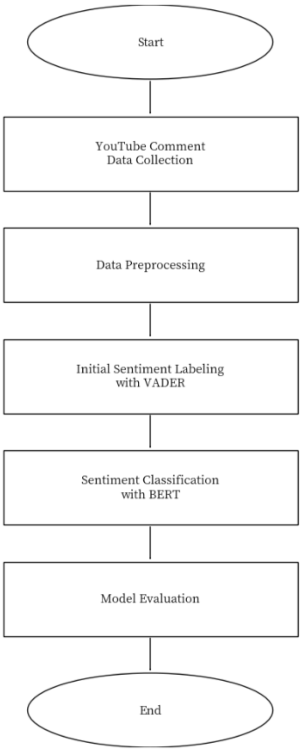

Figure 1. Flowchart Diagram

3.3 Research Stages

This research is carried out through a series of stages to achieve accurate and comprehensive sentiment analysis results. The main steps in this research include data collection, data pre-processing, sentiment labeling using the Valence Aware Dictionary and Sentiment Reasoner (VADER) method, sentiment classification using the Bidirectional Encoder Representations from Transformers (BERT) model, and evaluation of the final analysis results. The following are the detailed stages carried out in this research:

1) Data Collection
   The data collection stages in this study were conducted systematically to ensure the relevance and quality of the data used, focusing on user comments on YouTube related to Prabowo Subianto 2024 Presidential inauguration speech. The process began by identifying videos that had a significant number of comments for sentiment analysis. Once relevant videos were determined, comments were collected using the YouTube Data API, which required registration on Google Developer Console and the creation of a new project. Once the API credentials were created, the API key was used to retrieve the data. Using Google Colab, Python libraries such as pandas and Google API are imported to make data retrieval easier, which is then stored in a table format (DataFrame) and exported to a CSV file for further analysis, ensuring efficiency in the sentiment analysis process to be performed.

2) Data Pre-Processing
   The data pre-processing stage was conducted to prepare the raw data collected from YouTube comments for use in more in-depth sentiment analysis. This process is important to ensure that the data is clean and in a suitable format for the analysis model. The pre-processing stage includes the following steps:
   a) Data Collection
      Comment data was retrieved from YouTube using an API or scraping method, including comment text and additional metadata such as date and number of likes.
   b) Duplication Removal
      Same or repeated comments are removed to avoid bias. Identical comments originating from spam or repeated by multiple users are removed.
   c) Text Cleanup
      Unnecessary characters, such as punctuation marks and emoticons, are removed to produce cleaner text. For example, the comment "This is the best video!!! #cool" is cleaned up to "This is the best video cool".
   d) Text Normalization
      The text is converted to lowercase for consistency, and common words that do not add meaning are removed so as not to interfere with the analysis. Example: "This video is really cool" is normalized to "this video is really cool".

e) Removal of Stop Words
Common words that have no sentiment value, such as "and" and "is", are removed to focus on words that contain emotions or opinions. For example, the sentence "this video is very good and interesting" becomes "this video is very good and interesting".

f) Lemmatization or Stemming
This process converts words to their base form or removes word endings to reduce variation, so that the model focuses more on the main meaning. Example: "watch", "watch it", and "watch it" are simplified to "watch".

g) Tokenization
Sentences are broken down into words or short phrases for individual analysis. Example: from the sentence "I really like this video", the tokenization process produces ["I", "like", "once", "video", "this"].

3) Sentiment Labeling with VADER
After the pre-processing stage, the next step is initial sentiment labeling using the VADER (Valence Aware Dictionary and Sentiment Reasoner) method, which is suitable for sentiment analysis of short and informal texts, such as comments on social media. This process includes three stages:

a) Calculating Sentiment Score
VADER uses a lexical dictionary to classify words by sentiment weight (positive, negative, neutral). These scores are summed up to get the overall sentiment score of each comment.

b) Sentiment Intensity Assessment
VADER considers sentiment intensity as influenced by capitalization, punctuation, and emoticons. For example, the comment "EXCELLENT!!!" gets a higher positive score because of those expressive elements.

c) Preliminary Sentiment Classification
Based on the total score, comments are classified as positive, negative, or neutral. This classification forms the basis for further analysis using the BERT model, which is expected to refine the classification results.

4) Sentiment Classification with BERT
After the initial labeling using VADER, the next step is a more in-depth sentiment classification using the Bidirectional Encoder Representations from Transformers (BERT) model. This process consists of several stages:

a) Data Tokenization
The data that has been labeled by VADER is prepared for BERT through tokenization, which breaks the text into tokens (subwords) as per the BERT input format. This process helps the model understand the order and relationship between words.

b) Model Fine-Tuning
BERT models are fine-tuned using labeled data to learn specific sentiment patterns. Fine-tuning improves analysis accuracy by adapting the model to the characteristics of the data, allowing BERT to capture more subtle sentiment meanings.

c) Sentiment Prediction
After fine-tuning, BERT analyzes comments and generates a final prediction for sentiment, classifying them as positive, negative, or neutral. BERT can recognize more complex context, including figurative language or irony. With this process, sentiment analysis on YouTube comments becomes more accurate, where VADER is used for initial labeling and BERT enhances classification.

5) Model Evaluation and Validation
The final stage in this research is to evaluate the sentiment classification results obtained from the BERT model after initial labeling with VADER. This evaluation aims to measure the accuracy and consistency of the BERT model in sentiment classification on YouTube comments. The evaluation process includes several stages:

a) Model Accuracy Calculation
The BERT model accuracy is calculated by comparing the sentiment prediction results with the initial labels from VADER. Accuracy is expressed as a percentage of the correct predictions against the total data tested. For example, if out of 1000 comments, BERT classifies 850 correctly, then the model accuracy is 85%.

b) Use of Evaluation Matrices
In addition to accuracy, other metrics such as precision, recall, and F1-score are used to evaluate the model's performance in more depth. Precision measures the accuracy of the model in classifying

positive sentiments, while recall measures how many positive comments were correctly identified. F1-score is a combined metric of precision and recall, providing a more thorough understanding of the model's performance, especially in the case of imbalanced data.

4. Result and Discussion

4.1 Results

4.1.1 Data Pre-Processing Results

Before conducting sentiment analysis, the comment data retrieved from the YouTube platform needs to go through a pre-processing stage to ensure data quality and consistency. This stage includes data cleaning, duplication removal, and text normalization. The following are the steps performed in data pre-processing:

1) Data Collection:

The comment data was taken from Prabowo Subianto Presidential Inauguration speech video on YouTube. The total number of comments collected was 10306.

Table 1. Initial data from 1-5

publishedAt	authorDisplayName	textDisplay
2024-10-31T04:30:31Z	@aniherliani6625	Congratulations to Mr. Prabowo on his election as President of the Republic of Indonesia, may he be trustworthy.
2024-10-31T03:38:19Z	@simalakamachannel3184	From the beginning of his struggle to become a Presidential candidate until he was inaugurated as President, I support you General, may Allah take care of you and give you the strength to realize your goals, aamiin.
2024-10-31T01:01:01Z	@BoniSitompul	No sir, don't fire the minister, let them work, Mr. President of Indonesia.
2024-10-31T00:42:14Z	@AhmadJunaidi-bk3xy	If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated, like Rocky gerung and his entourage, there should be no more insolent ones.
2024-10-31T00:26:34Z	@AhmadJunaidi-bk3xy	Agree pak prabowo, we as the people, must participate in the nation's struggle, Indonesia is not willing to see the people fight alone.

2) Cleaning

This process involves removing irrelevant special characters, numbers, and symbols from comments. For example, comments containing emoticons or foreign characters are removed to focus on the relevant text.

Table 2. Cleaning results from 1-5

textDisplay	cleaning
Congratulations to Mr. Prabowo on his election as President of the Republic of Indonesia, may he be trustworthy.	Congratulations to Mr. Prabowo on his election as President of the Republic of Indonesia, may he be .
From the beginning of his struggle to become a Presidential candidate until he was inaugurated as President, I support you General, may Allah take care of you and give you the strength to realize your goals, aamiin.	From the beginning of his struggle to become a Presidential candidate until he was inaugurated as President, I support you General, may Allah take care of you and give you the strength to realize your goals aamiin.
No sir, don't fire the minister, let them work, Mr. President of Indonesia.	No sir, don't fire the minister, let them work, Mr. President of Indonesia.
If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated, like Rocky gerung and his entourage, there should be no more insolent ones.	If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated like Rocky gerung and his entourage, so that there will be no more insolent ones.
Agree pak prabowo, we as the people, must participate in the nation's struggle, Indonesia is not willing to see the people fight alone.	Agree pak prabowo we as the people must participate in the struggle of the Indonesian nation not willing the people to see the TNI fight alone

3) Case Folding

All text was converted to lowercase to avoid any distinction between capital and lowercase letters. This is important to ensure that the same words are not considered different just because of the difference in capitalization.

Table 3. Case Folding Results from 1-5

Cleaning	Case_folding
Congratulations to Mr. Prabowo on his election as President of the Republic of Indonesia, may he be .	congratulations to Mr. Prabowo on his election as President of the Republic of Indonesia, may he be .
From the beginning of his struggle to become a Presidential candidate until he was inaugurated as President, I support you General, may Allah take care of you and give you the strength to realize your goals aamiin.	from the beginning of his struggle to become a presidential candidate until he was inaugurated as president, I support you general, may Allah take care of you and give you the strength to realize your goals aamiin.
No sir, don't fire the minister, let them work, Mr. President of Indonesia.	No sir, don't fire the minister, let them work, Mr. President Indonesia.
If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated like Rocky gerung and his entourage, so that there will be no more insolent ones.	If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated like Rocky Gerung and his entourage, so that there will be no more insolent ones.
Agree pak prabowo we as the people must participate in the struggle of the Indonesian nation not willing the people to see the TNI fight alone	agree pak prabowo we as the people must participate in the struggle of the Indonesian nation is not willing to see the people fight alone

4) Normalization

Normalization is done to change word variations to a more standard form. This includes the replacement of words that are often abbreviated or changed in informal contexts into standardized forms. For example, the word "gak" is changed to "no". This process helps in reducing data complexity and improving analysis accuracy.

Table 4. Normalization from 1-5

Case_Folding	Normalization
congratulations to Mr. Prabowo on his election as President of the Republic of Indonesia, may he be.	congratulations to Mr. Prabowo for his election as President of the Republic of Indonesia, may he be trustworthy.
from the beginning of his struggle to become a presidential candidate until he was inaugurated as president, I support you general, may Allah take care of you and give you the strength to realize your goals aamiin.	from the beginning of his struggle to become a presidential candidate until he was inaugurated as president, I support you general, may God take care of you and give you the strength to realize your goals amen.
No sir, don't fire the minister, let them work, Mr. President Indonesia.	No sir, don't fire the minister, let them work, my father, the president of Indonesia.
If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated like Rocky Gerung and his entourage, so that there will be no more insolent ones.	If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated like Rocky Gerung and his entourage, so that there will be no more insolent ones.
agree pak prabowo we as the people must participate in the struggle of the Indonesian nation is not willing to see the people fight alone	agree pak prabowo we as the people are obliged to participate in the struggle of the Indonesian nation is not willing the people to see the tni fight alone

5) Stopword Removal

Stopwords are common words that do not provide significant meaning in the analysis, such as "and", "or", "which", and "in". Removal of stopwords is done to reduce noise in the data and focus on more meaningful words.

Table 5. Stopword removal from 1-5

Normalization	Stopword Removal
congratulations to Mr. Prabowo for his election as President of the Republic of Indonesia, may he be trustworthy.	['congratulations', 'prabowo', 'elected', 'president', 'republi', 'indonesia', 'hopefully', 'amanah']

from the beginning of his struggle to become a presidential candidate until he was inaugurated as president, I support you general, may God take care of you and give you the strength to realize your goals amen.	['his struggle', 'candidate', 'president', 'inaugurated', 'president', 'support you', 'general', 'hopefully', 'allah', 'keep you', 'strength', 'on you', 'realize', 'your ideals', 'amen']
No sir, don't fire the minister, let them work, my father, the president of Indonesia.	['fire', 'minister', 'yes', 'let', 'work', 'yes', 'ku', 'president', 'indonesia']
If there are negative words of hatred, please criminalize them, this is the nation's children who are insolent in the future, this generation must be eradicated like Rocky Gerung and his entourage, so that there will be no more insolent ones.	['hate', 'negatip', 'beg', 'criminal', 'child', 'nation', 'teach', 'ceneration', 'forward', 'eradicate', 'rocky', 'gerung', 'entourage', 'arise', 'kurg', 'ajar']
agree pak prabowo we as the people are obliged to participate in the struggle of the Indonesian nation is not willing the people to see the tni fight alone	['agree', 'prabowo', 'rakyat', 'wajib', 'berjuang', 'bangsa', 'indonesia', 'rela', 'rakyat', 'tni', 'berjuang']

6) Stemming

Stemming is the process of reducing a word to its base form. For example, the words "inauguration" and "inauguration" are converted to "inauguration". This process helps in grouping words that have the same meaning, so that the analysis can focus more on relevant concepts. Stemming is done using specific algorithms, such as Porter or Snowball, which are designed for specific languages.

Table 6. Stemming data from 1-5

Stopword Removal	Stemming_Data
['congratulations', 'prabowo', 'elected', 'president', 'republi', 'indonesia', 'hopefully', 'amanah']	congratulations prabowo elect president republi indonesia moga amanah
['his struggle', 'candidate', 'president', 'inaugurated', 'president', 'support you', 'general', 'hopefully', 'allah', 'keep you', 'strength', 'on you', 'realize', 'your ideals', 'amen']	juang presidential candidate inaugurate president support general may allah keep you strong in the form of your ideals amen
['fire', 'minister', 'yes', 'let', 'work', 'yes', 'ku', 'president', 'indonesia']	fire the minister yes let me work yes my president indonesia
['hate', 'negatip', 'beg', 'criminal', 'child', 'nation', 'teach', 'ceneration', 'forward', 'eradicate', 'rocky', 'gerung', 'entourage', 'arise', 'kurg', 'ajar']	hate negatip please criminalize the nation's children teach nas depan basmi rocky gerung rombong arise kurg ajar
['agree', 'prabowo', 'rakyat', 'wajib', 'berjuang', 'bangsa', 'indonesia', 'rela', 'rakyat', 'tni', 'berjuang']	tuju prabowo rakyat wajib juang bangsa indonesia rela rakyat tni juang

7) Tokenization

Tokenization is the process of breaking down text into smaller units, usually words or phrases. This process is important for further analysis, such as calculating word frequency and keyword analysis.

Table 7. Tokenized Text from 1-5

Stemming_Data	Tokenized_Text
congratulations prabowo elect president republi indonesia moga amanah	['selamat', 'prabowo', 'pilih', 'presiden', 'republi', 'indonesia', 'moga', 'amanah']
juang presidential candidate inaugurate president support general may allah keep you strong in the form of your ideals amen	['juang', 'candidate', 'president', 'inaugurate', 'president', 'support', 'general', 'moga', 'allah', 'keep', 'strong', 'pada', 'wujud', 'citacitamu', 'amen']
fire the minister yes let me work yes my president indonesia	['fire', 'minister', 'yes', 'let', 'work', 'yes', 'ku', 'president', 'indonesia']
hate negatip please criminalize the nation's children teach nas depan basmi rocky gerung rombong arise kurg ajar	['hate', 'negatip', 'beg', 'criminal', 'child', 'nation', 'ajar', 'nas', 'depan', 'basmi', 'rocky', 'gerung', 'rombong', 'arise', 'kurg', 'ajar']
tuju prabowo rakyat wajib juang bangsa indonesia rela rakyat tni juang	['tuju', 'prabowo', 'rakyat', 'wajib', 'juang', 'bangsa', 'indonesia', 'rela', 'rakyat', 'tni', 'juang']

4.1.2 Sentiment Analysis Results

Sentiment analysis was performed using the VADER (Valence Aware Dictionary and Sentiment Reasoner) method which has been customized for the Indonesian language. From a total of 10,306 comments collected, the pre-processing process successfully reduced the number of comments to 10,035 after removing duplicates and performing text cleaning. After that, initial sentiment labeling was performed using VADER, which resulted in the following sentiment distribution:

Table 8. Vader Sentiment Results

Vader Sentiment	Number of Comments	Percentage %
Positive Sentiment	4,943 comments	49,26%
Neutral Sentiment	4,336 comments	43,21%
Negative Sentiment	756 comments	7,53%

These results show that most comments had a positive sentiment, reflecting the public's strong support for the new leadership. However, there was also a proportion of negative comments indicating criticism and dissatisfaction with some aspects of the speech or proposed policy.

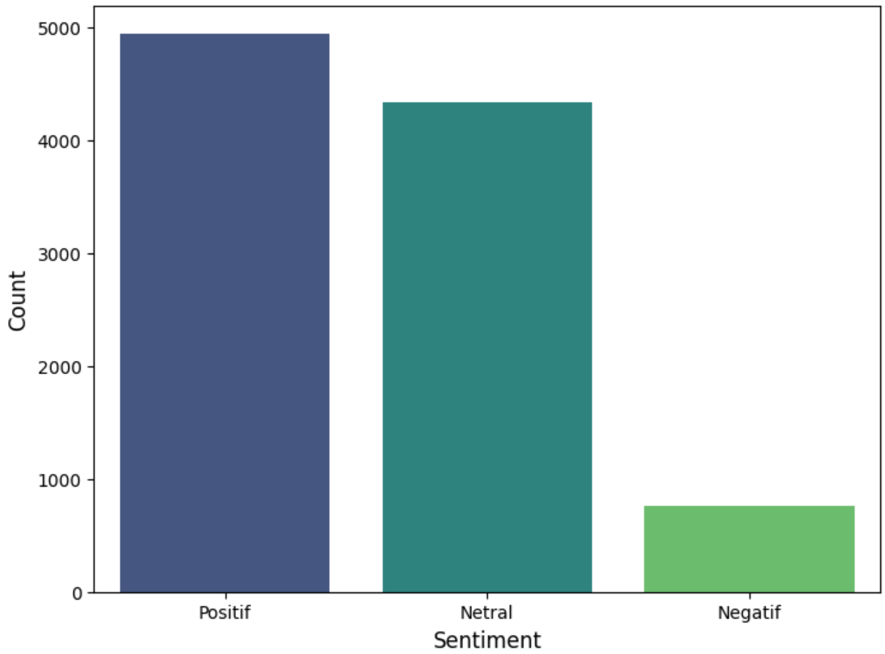

Figure 2. Vader Sentiment Diagram

After the initial labeling process using VADER, the first step is to prepare the dataset for further analysis. The data that has been labeled by VADER is saved in CSV format, which includes columns for the comment text and sentiment labels (positive, negative, neutral). This dataset is then divided into two parts:

1) Training Data
   Covers about 75% of the total dataset and is used to train the BERT model, serving to teach the model to recognize sentiment patterns in comments.
2) Testing Data
   Covers about 25% of the remainder and is used to test the accuracy of the model after training, ensuring that model evaluation is objective.

The next step is to train the text classification model using BERT (Bidirectional Encoder Representations from Transformers) with datasets containing labeled text. First, the training and testing datasets are loaded from CSV files using pandas. The labels of the columns containing sentiments are converted into numeric format using LabelEncoder, which allows the model to understand the labels. Next, the text to be processed is retrieved from the corresponding column and then tokenized using BertTokenizer, which prepares the text for input to the BERT model by truncating and adding padding as needed. After tokenization, the data is converted into PyTorch dataset format by defining the NewsDataset class, which manages encodings and labels. The BERT model for sequence classification is loaded from available pre-trained models, and training arguments are specified, including the number of epochs, batch size, and logging settings. With all components ready, a Trainer object is created to manage the model training and evaluation process. The model is then trained using the train method and evaluated with evaluate, which provides performance metrics for the trained model. This process as a whole aims to build a model that can classify text sentiment with good accuracy.

After setting up all the necessary components, we enter the text classification model development stage. Here, we will train the BERT model to understand and classify sentiment from labeled text. This process not only involves data processing but also utilizes the power of GPU to accelerate training, ensuring that the model can learn efficiently and effectively. The steps in the code describe the process of training and evaluating the text classification model using BERT. First, alerts are disabled, and W&B (Weights & Biases) mode is turned off to avoid automatic logging. Next, the code checks GPU availability and loads the training and testing datasets from CSV files, with error handling to ensure the required files exist. The labels of the sentiment columns are converted into numeric format using LabelEncoder, and the text to be processed is retrieved from the corresponding columns. After that, the BERT tokenizer is loaded and used to tokenize the data, which prepares the text for input to the model. The data is then converted into PyTorch dataset format by defining the NewsDataset class. The BERT model is loaded and moved to the GPU if available. Training arguments are specified, including settings for model storage and logging. After that, a Trainer object is created to manage the training and evaluation of the model. The model is trained and evaluated, followed by an accuracy calculation based on predictions against the test dataset. The accuracy result of the model reached 97.01%, showing good performance in classifying sentiment. The prediction results are stored in DataFrame and exported to a CSV file, facilitating further analysis. This process aims to build and evaluate an effective model in classifying text sentiment.

The next process is fine-tuning the BERT model for text classification by testing various combinations of hyperparameters, including learning rate, batch size, and number of epochs. First, the training and testing datasets are loaded from CSV files, and the labels are converted into numeric format using LabelEncoder. The text to be processed is converted from list format to string and then tokenized using the BERT tokenizer. The dataset is then converted into PyTorch format by defining the NewsDataset class. Next, various combinations of hyperparameters are tested in a loop, where the BERT model is loaded and training arguments are specified, including settings for model evaluation and storage. The compute_metrics function is added to calculate evaluation metrics such as accuracy, precision, recall, and F1 score. The training process is performed using the Trainer object, which also applies early to stop training if there is no improvement in two consecutive epochs. After training, the average training loss and evaluation results are stored in a DataFrame, which is then exported to a CSV file for further analysis. This process aims to find the optimal combination of hyperparameters to improve the model's performance in classifying text sentiment.

Table 9. Fine Tuning Results

Learning Rate	Batch Size	Epochs	Accuracy	Precision	Recall	F1 Score	Validation Loss	Training Loss
2.00E-05	8	2	0.964926	0.96545	0.964926	0.96514	0.152855	0.281751
2.00E-05	8	3	0.965723	0.965915	0.965723	0.965804	0.150529	0.220802
2.00E-05	8	5	0.970108	0.969992	0.970108	0.970019	0.163043	0.145647
2.00E-05	16	2	0.960941	0.961776	0.960941	0.961255	0.137981	0.329784
2.00E-05	16	3	0.964926	0.965116	0.964926	0.965014	0.150484	0.250241
2.00E-05	16	5	0.967318	0.967112	0.967318	0.966854	0.148389	0.161951
3.00E-05	8	2	0.965723	0.966078	0.965723	0.965873	0.143334	0.27754
3.00E-05	8	3	0.964528	0.964883	0.964528	0.964679	0.162228	0.226935
3.00E-05	8	5	0.966122	0.96601	0.966122	0.965855	0.184208	0.152109
3.00E-05	16	2	0.963731	0.96516	0.963731	0.964221	0.133417	0.309614
3.00E-05	16	3	0.96931	0.969785	0.96931	0.969502	0.131225	0.2382
3.00E-05	16	5	0.960941	0.960337	0.960941	0.960289	0.147956	0.192729
5.00E-05	8	2	0.964129	0.964385	0.964129	0.964238	0.160679	0.295921
5.00E-05	8	3	0.966919	0.966844	0.966919	0.966879	0.162053	0.236692
5.00E-05	8	5	0.968513	0.968116	0.968513	0.968198	0.188958	0.167296
5.00E-05	16	2	0.963332	0.963737	0.963332	0.963499	0.14521	0.294353
5.00E-05	16	3	0.968513	0.96936	0.968513	0.968829	0.134547	0.230393
5.00E-05	16	5	0.968912	0.968652	0.968912	0.968747	0.134148	0.158045

The results of fine-tuning the BERT model for text classification show very promising performance with various combinations of hyperparameters tested. The results table show that the model accuracy ranges from 0.964926 to 0.971008. The best combination was found to be learning rate 2.00E-05, batch size 8, and epoch 5, which resulted in the highest accuracy of 0.971008. This shows that the model was able to classify the text very well, reflecting its ability to understand the context and nuances in the data. Other evaluation metrics, such as precision, recall, and F1 score, also show consistent and high results. For example, in the best combination, the F1 score value reaches 0.970910, which shows a good balance between precision and recall. The high precision (0.970108) indicates that most of the positive predictions made by the model are correct, while the recall (0.970110) indicates that the model is able to capture most of the positive examples in the dataset. This is particularly important in the context of sentiment classification, where both false positives and false negatives can have a significant impact. While VADER provides fast and efficient results, BERT shows an edge in terms of accuracy, especially on more complex comments. VADER can complete sentiment analysis in less time, but BERT provides more in-depth and accurate results. In this study, BERT successfully identified more subtle nuances in the comments, which VADER may have missed. One of the challenges faced in this analysis is handling comments that are ambiguous or contain informal language. Comments on social media often use slang, emoticons or informal language, which can affect the accuracy of sentiment analysis. VADER may struggle to classify ambiguous comments, while BERT, with its ability to understand context, is better able to handle such situations. Validation loss and training also provide important insights into the performance of the model. The lowest validation loss value recorded is 0.143839, which indicates that the model not only learns well from the training data but is also able to generalize well to unseen data. The relatively low training loss, such as 0.145647 in the best combination, indicates that the model does not suffer from significant overfitting, where the model over-fits the training data and loses the ability to generalize. Overall, these fine-tuning results show that the BERT model has been well optimized for the sentiment classification task. The tested hyperparameter combinations provide solid performance, and the high evaluation metrics show that the model can reliably classify text with satisfactory accuracy and precision. This opens up opportunities for further applications in sentiment analysis and natural language processing.

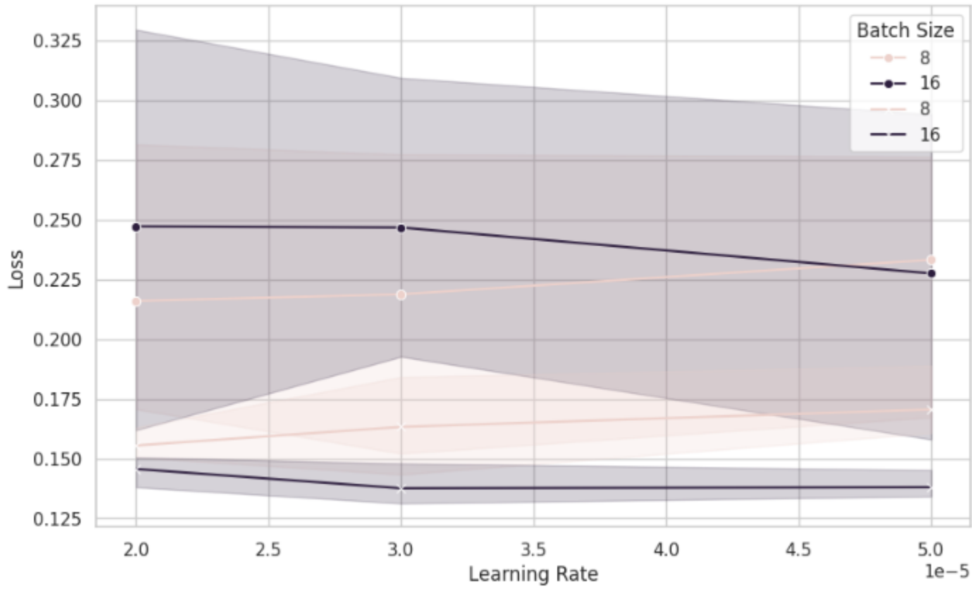

Figure 4. Graph of Training Loss and Validation Loss

The graph above shows the comparison between training loss and validation loss for the BERT model based on the variation of learning rate and batch size. The horizontal axis represents the learning rate tested, while the vertical axis shows the loss value. The two batch sizes tested, 8 and 16, are marked with different lines and shaded areas. The training loss (dark line) tends to be lower than the validation loss (light line) for all combinations of learning rate and batch size, indicating that the model learns well from the training data. However, there is a significant difference between training loss and validation loss, especially at higher learning rates, which indicates that the model may have difficulty in generalizing to unseen data. Batch size 8 shows lower loss values compared to batch size 16, especially at lower learning rates, indicating that the model may be more effective in learning with smaller batch sizes. Overall, these graphs provide important insights into how learning rate and batch size affect model performance, as well as emphasizing the need for further tuning to improve model generalization, especially at higher learning rates, and the importance of proper hyperparameter selection to achieve a balance between effective training and good generalization ability.

4.2 Discussion

Sentiment analysis results indicate that positive comments about Prabowo Subianto inauguration speech represent 49.26% of total comments while 43.21% remain neutral and only 7.53% show negative sentiment. The results demonstrate strong public backing for the new leadership which signifies encouragement for the government to advance its programs. However, the proportion of negative comments, although relatively small, still indicates criticism that needs to be considered by the political communication team and policy makers to maintain public trust. Johnson (2022) in his research emphasized that sentiment analysis of political speeches can reveal communication strategies and public responses that are not detected through conventional methods, thus strengthening the relevance of these findings in the context of political communication [7]. The hybrid methodology that combines VADER and BERT in this study provides significant comparative advantages. VADER, with its ability to provide efficient initial labeling, allows analysis to be carried out quickly on large volumes of data, while BERT with superior accuracy is able to capture more complex semantic nuances in comments. This is in line with the findings of Nugroho and Wibowo (2023) who demonstrated that a hybrid approach to sentiment analysis produces more comprehensive and accurate interpretations. Gupta (2021) also emphasized the effectiveness of VADER for real-time sentiment analysis due to its speed in processing short texts with emotional content [5], the characteristics of which are similar to YouTube comments that are the object of this study.

Chandradev *et al*. (2023) in their study proved the superiority of BERT for sentiment analysis in Indonesian, which justifies the use of this model in analyzing Indonesian comments. This finding is reinforced by Setiawan and Lestari (2023) who identified BERT's superiority in handling specific linguistic characteristics of Indonesian such as abbreviations, slang, and informal sentence structures that are highly prevalent in social media content [14]. Widyantara and Pradita (2021) further underlined BERT's capabilities in understanding semantic and contextual nuances in text, which are crucial in interpreting political comments that often contain implicit references and implied meanings [18]. The implications of the results of this analysis have substantial significance for stakeholders, especially the government and political communication teams. Smith (2022) emphasized the urgency of sentiment analysis to understand the dynamics of public opinion in a complex political context [15]. By understanding the distribution and characteristics of public sentiment, stakeholders can formulate more effective and responsive communication strategies to public expectations. Furthermore, the results of this analysis can be used as an instrument for longitudinal monitoring of public opinion fluctuations, the significance of which is increasing in the context of contemporary political dynamics whose characteristics are highly volatile. Devlin *et al*. (2019) explained that the bidirectional transformer architecture that underlies BERT enables superior contextual understanding due to its ability to process words in relation to the entire sentence structure, which is a fundamental aspect in analyzing political comments with high referential complexity [2]. Rachman and Kharisma (2023) confirmed BERT's superiority in processing short texts with technical terminology, which is of significant relevance given the characteristics of YouTube comments which are generally short but can contain political jargon or other specific terminology [12].

This study also confirms the findings of Ferdiana and Siswoyo (2019) regarding the effectiveness of VADER in analyzing short and informal texts, although with limitations in interpreting sarcastic or ironic content [4]. Hamdani and Prasetyo (2023) emphasize the significance of adequate data volume to obtain representative sentiment analysis results, which justifies this research approach in analyzing more than 10,000 comments to ensure the external validity of the findings [6]. Prasetyo (2022) and Kusnadi *et al*. (2021) have demonstrated the applicability of BERT in various domains, and this study extends the application to the Indonesian political domain, representing an original contribution to the literature [6][8]. Ramadhan and Siswoyo (2024) identified various fine-tuning and optimization techniques that can improve BERT's performance for specific sentiment analysis tasks, which can be a direction for further research in optimizing sentiment analysis for Indonesian political content. Nguyen (2023) proved BERT's adaptability to non-English languages, which strengthens the validity of using BERT in this study to analyze Indonesian content [9]. Adapting the model to the specific linguistic characteristics of the Indonesian language is a crucial aspect in improving the precision of sentiment analysis.

Syahrohim and Lestari (2024) in their comparative study of sentiment classification methods found that a hybrid approach can produce performance optimization, which is consistent with the methodology of this study which integrates VADER and BERT to achieve an optimal equilibrium between computational efficiency and predictive accuracy [17]. Sujono (2021) identified specific challenges in analyzing social media text, including the prevalence of abbreviations, slang, and multilingual content, which are also methodological considerations in this study when analyzing YouTube comments [16]. Zhang (2020) presents a comprehensive review of the evolution of deep learning techniques for sentiment analysis, which provides a robust theoretical foundation for the implementation of BERT in this study [19], reflecting significant developments in the field of sentiment analysis from conventional lexicon approaches to contemporary deep learning models.

The results of this study also have practical implications for the development of more effective political communication strategies. By understanding the distribution of public sentiment and the factors that influence it, political communication teams can identify aspects of speeches or policies that receive positive or negative responses, so that they can make strategic adjustments in subsequent communications. Furthermore, longitudinal sentiment analysis can be an effective monitoring instrument to measure changes in public perception of the government over time, which can provide valuable insights for the evaluation and reformulation of public policies. The findings of this study also contribute to the development of a more adaptive sentiment analysis methodology to the linguistic and contextual characteristics of the Indonesian language in the political domain, which can be a foundation for further research in this field.

5. Conclusion

Researchers analyzed YouTube comments about Prabowo Subianto Presidential inauguration speech in 2024 to gauge public sentiment with VADER and BERT analysis methods. The pre-processing stage minimized the comment dataset from 10,306 to 10,035 which revealed 49.26% positive sentiment, 43.21% neutral sentiment and 7.53% negative sentiment among the public towards the new leadership. The BERT model reached 97.01% accuracy during analysis by using optimal settings of learning rate 2.00E-05 and batch size 8 across 5 epochs which confirmed its capability to grasp data context and nuances. Sentiment classification benefits from combining VADER and BERT because VADER offers quick initial labeling while BERT enhances accuracy through its analysis of complex contexts. The results offer important benefits for both governments and research institutions because sentiment analysis can serve multiple purposes such as tracking public opinion on political or social matters and enhancing both decision-making processes and communication strategies through data analysis. Researchers and academics together with policymakers will find these findings beneficial for understanding public opinion dynamics in the digital age and these results will enable future research into public opinion trends and their policy effects.

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