

Public sentiment analysis of government subsidy policies on Twitter using the Naïve Bayes classifier

Putri Natahsya Amelia^{1*}, Nayyara Bunga Aatiqah², Afrina Hasibuan³

^{1,2,3} Department of Informatics, Universitas Satya Terra Bhinneka, Medan, Indonesia

ABSTRACT

Government subsidy policies are one of the important instruments in maintaining economic stability and improving public welfare; however, they often generate diverse responses in the public sphere. These differing perspectives arise because subsidy policies directly affect the social and economic lives of the community. In the digital era, social media particularly the Twitter platform has become a medium for the public to express opinions, criticisms, and information in real time regarding such policies. This study aims to analyze public sentiment toward government subsidy policies on the Twitter platform using the Naïve Bayes Classifier method with text preprocessing stages. The research data consist of Indonesian-language tweets collected from the Twitter platform during a specific period in 2024. The text preprocessing stages include case folding, tokenization, filtering/stopword removal, and stemming to eliminate irrelevant words before the sentiment classification process into positive, negative, and neutral categories. The results show that out of 87 analyzed tweets, neutral sentiment dominates with a percentage of 66.67%, followed by positive sentiment at 19.54% and negative sentiment at 13.79%. The dominance of neutral sentiment indicates that most tweets are informational in nature, while expressed opinions tend to be more positive than negative. Overall, these findings demonstrate that the Naïve Bayes Classifier method is able to provide an objective overview of public sentiment trends toward government subsidy policies on the Twitter platform and can be utilized as a references for policy evaluation.

ARTICLE INFO

Keywords:
Sentiment Analysis,
Government Subsidy Policy,
Naïve Bayes Classifier, Text
Preprocessing, Twitter

Histori:

Received: 18 January 2026
Accepted: 30 January 2026
Published: 10 Februari 2026

* Corresponding Author at Department of Informatics, Universitas Satya Terra Bhinneka, Medan, Indonesia.
E-mail address: putrinatahsya51@gmail.com (author#1), nayyarabunga@gmail.com (author#2),
afrinahasibuan05@gmail.com (author#3)

1. INTRODUCTION

The Governments frequently issue various subsidy policies in an effort to maintain economic stability, assist specific social groups, or stimulate strategic sectors. These policies, despite their positive intentions, often trigger diverse reactions and perspectives among the public. Understanding this public response is crucial, as it serves as an indicator of a policy's success, shortcomings, and level of acceptance (Siti Salasatu Sa'diyah et al., 2025).

Twitter, a social media platform categorized as an alternative media, is an information network consisting of 140-character messages called 'tweets.' It offers a new and easy way to discover the latest news or current events, especially those related to your interests. Twitter was founded in March 2006 by Jack Dorsey, and the social networking site was officially launched in July. Literally, the word 'twitter' means 'to chirp.' The site utilizes a micro-blogging concept (Zukhrufillah, 2018). Twitter also features several unique characters in its short messages, such as RT (retweet), hashtags (#), and usernames (@). Every day, millions of tweets provide an instantaneous reflection of public sentiment regarding current issues, including government subsidy policies. However, the massive volume of data and the inherently unstructured nature of text make manual sentiment analysis highly inefficient and prone to bias.

Sentiment analysis of government subsidy policies can serve as an evaluation tool to determine the level of public acceptance. The social media platform Twitter provides real-time public opinion data that can be analyzed using the *Naïve Bayes Classifier* method to categorize sentiments as positive, negative, or neutral (Ritonga & Sriani, 2025). This study proposes the use of sentiment analysis by utilizing *Text Preprocessing* techniques to clean and standardize data, alongside *machine learning* classification methods. The chosen method for this research is the Naïve Bayes Classifier (NBC).

The Naïve Bayes Classifier is a machine learning algorithm that utilizes the probabilistic principles of Bayes' Theorem for classification tasks. This method employs a supervised learning technique to classify future objects by assigning class labels to instances or records based on conditional probability. Conditional probability is a measure of the likelihood of an event occurring, given that another event has already occurred (based on assumptions, presumptions, statements, or evidence). By applying the NBC after the Text Preprocessing stage, this study aims to objectively measure and analyze the trends of public sentiment namely positive, negative, or neutral on the X platform regarding government subsidy policies (Gan et al., 2021). Through this analysis, it is expected that an accurate overview of public acceptance will be obtained, providing valuable insights for the government in evaluating and formulating future subsidy policies.

This study aims to: (1) implement and evaluate the optimal *Text Preprocessing* stages for Indonesian-language tweets regarding government subsidy policies; (2) build and test the performance of the *Naïve Bayes Classifier* model in classifying public sentiment toward government subsidy policies; and (3) produce quantitative and qualitative sentiment analyses as a representation of public opinion on the Twitter platform regarding government subsidy policies.

2. LITERATURE REVIEW

2.1. Government Subsidy Policy and Public Perception

Government subsidy policies play a crucial role in maintaining economic stability and supporting vulnerable social groups. Subsidies are commonly implemented to control prices, enhance purchasing power, and protect strategic sectors such as energy, food, and transportation. Despite their economic objectives, subsidy policies frequently generate diverse public responses due to their direct impact on daily life and government expenditure efficiency.

Previous studies indicate that public perception toward subsidy policies significantly influences policy legitimacy and long-term sustainability (Huber et al., 2020). Subsidy policies often become a source of public debate because of issues related to targeting accuracy, fiscal burden, and perceived fairness. Consequently, understanding public sentiment toward subsidy policies is essential for evaluating policy effectiveness beyond conventional economic indicators.

There are two types of subsidies, namely direct and indirect subsidies (Siti Salasatu Sa'diyah et al., 2025). A direct subsidy is a grant consisting of actual cash payments made to specific individuals, groups, or industries. A simple example of a direct subsidy is providing funds to small business owners to scale their operations. With this assistance, they can hire more employees and produce a higher volume of goods than usual. An indirect subsidy is a benefit with a predetermined monetary value that is not tied to an actual cash outlay to the recipient. These subsidies encompass various policies designed to lower the prices of goods or services needed by the public as a whole. This means beneficiaries can purchase one or more products at a price below the current market value.

2.2. Social Media as a Medium for Public Opinion Analysis

The rapid growth of social media has transformed the way public opinion is expressed and disseminated. Platforms such as Twitter enable users to share opinions, reactions, and information in real time, making them a valuable source for analyzing societal responses to public policies. Twitter is particularly suitable for opinion mining due to its open-access nature, short text format, and high engagement in political and economic discussions (Tsai & Wang, 2021).

Several international studies have demonstrated the effectiveness of Twitter data in capturing public sentiment toward government policies. Twitter discussions often reflect real-world political attitudes and collective reactions. Therefore, Twitter-based sentiment analysis provides an alternative and complementary approach to traditional survey-based public opinion studies. Twitter provides programmatic access to its data for companies, developers, and users through an API (Application Programming Interface).

An API is essentially a way for computer programs to "talk" to one another so they can request and deliver information (Sunardi et al., 2019). This process works by allowing software applications to call endpoints, which are specific addresses associated with certain types of information provided by the platform. Twitter grants this access so that people can build software integrated with its ecosystem such as solutions that help a company respond to customer feedback directly on Twitter.

2.3. Sentiment Analysis in Public Policy Research

Sentiment analysis is a text mining technique used to identify and classify opinions expressed in textual data into sentiment categories such as positive, negative, or neutral. In public policy research, sentiment analysis has been increasingly adopted to measure public reactions to government decisions and social issues. Sentiment Analysis, frequently referred to as opinion mining, is a comprehensive field of study dedicated to analysis the opinions, sentiments, evaluations, assessments, attitudes, and emotions that individuals express toward various entities. These entities can include products, services, organizations, individuals, social issues, specific events, topics, or particular activities (Kusuma & Nugroho, 2021). In a more technical sense, sentiment analysis is the computational process of identifying and categorizing the polarity of text within a document or a sentence. By employing this process, researchers can determine whether the expressed sentiment falls into specific categories, namely positive, negative, or neutral.

Furthermore, the primary objective of performing sentiment analysis is to provide a data-driven benchmark or reference point. Organizations utilize these insights to strategically enhance their service delivery, refine their business models, and significantly improve the overall quality of their products based on direct consumer feedback. Sentiment analysis enables large-scale opinion analysis by transforming unstructured text into structured information. Recent studies have applied sentiment analysis to assess public sentiment toward fuel subsidies, tax reforms, and social assistance programs, highlighting its potential as a policy evaluation tool. However, the accuracy of sentiment analysis heavily depends on data preprocessing techniques and the classification algorithms used (Harwenda et al., 2025).

2.4. Text Preprocessing and Feature Representation

Text preprocessing is a fundamental step in sentiment analysis, particularly when dealing with noisy social media data. Tweets often contain slang, abbreviations, hashtags, and informal language, which can negatively affect classification performance if not properly processed. Common preprocessing steps include case folding, tokenization, filtering/stopword removal, and stemming. Beyond cleaning the text, feature representation is a critical transition phase where textual data is transformed into a structured numerical format that machine learning algorithms can interpret. While simple models like Bag of Words (BoW) count word frequency, they often fail to distinguish which words are truly important (Albab et al., 2023).

In addition, feature representation plays a critical role in transforming textual data into numerical form. Term Frequency–Inverse Document Frequency (TF-IDF) is one of the most widely used feature extraction techniques in text classification. TF-IDF effectively highlights discriminative terms while reducing the influence of common words, thereby improving classification performance (Rosid et al., 2020).

To overcome this, Term Frequency–Inverse Document Frequency (TF-IDF) is utilized. This technique operates on two levels namely, Term Frequency (TF) for measures how often a word appears in a specific tweet, and Inverse Document Frequency (IDF) for measures how unique or rare a word is across the entire dataset. By multiplying these two factors, TF-IDF effectively highlights discriminative terms

words that are specific to certain sentiments while automatically penalizing or reducing the influence of common words that appear everywhere (Albab et al., 2023). This mathematical weighting ensures that the Naïve Bayes Classifier can focus on the most impactful vocabulary, thereby significantly improving the precision and recall of the final classification results.

2.5. Naïve Bayes Classifier for Sentiment Classification

The Naïve Bayes Classifier (NBC) is a probabilistic machine learning algorithm based on Bayes' theorem and the assumption of feature independence. Despite its simplicity, NBC has been widely used in sentiment analysis due to its computational efficiency and robustness, especially when applied to text data (Agustya Dewi Utami et al., 2021).

Despite the fact that language is inherently contextual and words are rarely independent, this simplicity is precisely what grants NBC its remarkable computational efficiency. It requires a relatively small amount of training data to estimate the necessary parameters, making it incredibly fast and scalable for real-time applications, such as monitoring millions of daily tweets.

Several empirical studies have shown that Naïve Bayes performs competitively compared to more complex classifiers in sentiment classification tasks. For instance, Naïve Bayes achieves reliable performance in document classification with relatively small datasets. However, its assumption of conditional independent may limit its ability to capture contextual and semantic nuances, particularly in informal social media text (Gan et al., 2021).

However, the power of Naïve Bayes is also its primary constraint. The conditional independence assumption serves as a double-edged sword; while it simplifies computation, it inherently limits the model's ability to capture contextual and semantic nuances. In the world of social media, where communication is rife with sarcasm, double negatives, and complex slang, the "meaning" of a sentence often lies in the relationship *between* words rather than the words themselves.

2.6. Research Gap and Contribution

Although numerous studies have explored sentiment analysis of public policies using social media data, several gaps remain. First, many existing studies focus on large-scale international datasets, while sentiment analysis of Indonesian-language tweets related to government subsidy policies remains limited. Second, prior research often emphasizes classification accuracy without sufficiently interpreting the dominance of neutral sentiment in policy-related discussions.

Furthermore, there is a lack of focused analysis on how Naïve Bayes Classifier performs in capturing public sentiment toward subsidy policies specifically, considering the prevalence of informational rather than opinionated tweets. Therefore, this study addresses these gaps by analysis Indonesian-language Twitter data related to government subsidy policies using systematic text preprocessing and the Naïve Bayes Classifier approach.

This research contributes by providing empirical evidence on public sentiment distribution, highlighting the predominance of neutral sentiment, and demonstrating the applicability of Naïve Bayes Classifier as a practical tool for public policy.

3. METHOD, DATA, AND ANALYSIS

3.1. Research Type and Approach

This research applies a mixed-method approach, systematically combining quantitative and qualitative elements. Quantitative research provides measurable data that can be analyzed statistically, while qualitative research deeply explores the meanings, perceptions, and experiences of the subjects (Setiawan et al., 2025). The quantitative approach focuses on gathering a large volume of tweet data and utilizing a machine learning algorithm, specifically the Naïve Bayes Classifier (NBC), to classify sentiments in a structured manner (positive, negative, and neutral).

The quantitative results consist of model performance scores (accuracy) and the percentage of public sentiment polarity. Meanwhile, the qualitative approach is used in the initial stages, literature review and observation, as well as in the final stage of result analysis. This approach functions to provide contextual interpretation and understanding of the quantitative findings, such as analyzing the content of representative tweets to explain why a certain policy receives a specific sentiment, thereby producing a comprehensive analysis.

3.2. Data Collection and Labeling Methods

The research data is sourced from the Twitter platform, specifically targeting Indonesian-language public opinions regarding specific government subsidy policies during a certain period in 2015 or 2025. Data collection is conducted through a crawling process using the Twitter API. The raw data obtained then undergoes a manual labeling stage into three categories: positive, negative, and neutral (Gupta & Joshi, 2021). Subsequently, the data is divided into two parts: training data to build the model and testing data to measure the classification performances.

To retrieve this data, a web crawling and scraping process is executed by interfacing with the Twitter API (Application Programming Interface). This programmatic approach ensures that the collection is both scalable and precise, utilizing specific keywords and hashtags related to subsidies to filter out irrelevant content. Data crawling on the Twitter platform is the systematic and automated process of retrieving or downloading vast amounts of information directly from Twitter's servers. By leveraging the Twitter API (Application Programming Interface), researchers and developers can access a structured stream of information that includes both user metadata (such as profile descriptions, location, and follower counts) and tweet data (including the text content, timestamps, and engagement metrics like likes and retweets).

The technical execution of data crawling involves developing a specialized script or program typically written in languages such as Python that serves as a bridge between the researcher and the database. The process begins by defining specific search queries or keywords that act as filters. These keywords are

essential because they instruct the API to ignore irrelevant "noise" and only capture tweets that align with the specific objectives of the study, such as public opinion on government subsidies (Sunardi et al., 2019). This programmatic approach is far superior to manual collection, as it allows for the gathering of thousands of data points in a fraction of the time, providing a statistically significant sample for subsequent Sentiment Analysis.

3.3. Text Preprocessing and Feature Extraction

The preprocessing stage is conducted to remove noise from the text through several phases: case folding, tokenization, filtering/stopword removal, and stemming (Fani et al., 2021). Once the data is cleaned, feature extraction is performed using the Term Frequency – Inverse Document Frequency (TF-IDF) method (Albab et al., 2023). TF-IDF is a statistical method used in natural language processing and information retrieval to evaluate the importance of a word to a document within a larger collection of documents, and it is calculated using the following formula:

$$TF - IDF(t, d, D) = TF(t, d) \times IDF(t, D) \quad (1)$$

Where TF measures how frequently a word appears in a document. Meanwhile, IDF reduces the weight of common words across multiple documents while simultaneously increasing the weight of rare words. Feature extraction is an essential stage in document processing for search engines, as it significantly determines the success of the overall text mining process. The goal of feature extraction is to transform unstructured text data into a structured format that can be effectively processed by various data mining algorithms. In document processing, a piece of text is typically represented as a collection of words, a model known as a Bag of Words (BoW). This representation results in a high-dimensional feature space, where each unique word serves as a separate dimension within the data (Albab et al., 2023).

3.4. Naïve Bayes Classifier

The TF-IDF weighted data is processed using the NBC algorithm. The Naïve Bayes Classifier demonstrates remarkably strong performance in the field of text classification. This method also takes weighting information into account; consequently, the classification results tend to be more accurate compared to methods that rely solely on a single decision-making factor (Gan et al., 2021). This model predicts class membership probabilities by seeking the maximum value of conditional probability, based on Bayes' Theorem. Bayes' Theorem provides the conditional probability, which is defined as follows:

$$P(y|X) = \frac{P(X|y) \cdot P(y)}{P(X)} \quad (2)$$

Where $P(y|X)$ is the probability of class y given feature X . $P(X|y)$ is the likelihood probability of feature X given class y . $P(y)$ is the prior probability of class y , and $P(X)$ is the likelihood or marginal evidence (Lubis et al., 2022).

3.5. Evaluation and Data Analysis

The model performance evaluation is conducted using a 3×3 Multiclass Confusion Matrix. The measured metrics include Accuracy to observe the overall proportion of correct predictions, Precision to measure the

accuracy of predictions for each class, and Recall to assess the model's ability to retrieve information within the actual classes (Farhadpour et al., 2024). The final stage of the research involves a quantitative analysis of sentiment distribution and a qualitative analysis through findings validation to produce robust conclusions for policymakers.

Accuracy serves as the baseline indicator of overall correctness, representing the proportion of total instances correctly identified across all classes. Precision is employed to measure the "*exactness*" of the model, calculating the ratio of true positive results to all instances predicted as a specific class. This ensures that when the model identifies a sentiment, it is highly likely to be correct, thereby reducing "*false alarms*" or False Positives. Conversely, Recall assesses the model's "*completeness*" or its ability to retrieve all relevant instances within the actual classes. High recall is particularly vital in policy-related research, as it ensures that critical public sentiments especially dissenting or negative ones are not overlooked by the system. By balancing these metrics, the study ensures that the model is both precise in its labeling and comprehensive in its data retrieval (Azhari et al., 2021).

The final stage of the research transitions from technical evaluation to applied intelligence through a dual-track analytical approach. First, a quantitative analysis is performed to map the distribution of sentiments, providing policymakers with a clear, statistical overview of public opinion trends and volume. This is followed by a qualitative analysis involving findings validation, where automated results are cross-referenced with human context to account for linguistic nuances such as sarcasm or regional dialects. This hybrid methodology ensures that the final conclusions are not only statistically significant but also contextually "*robust*." Ultimately, these insights provide a reliable evidence base for policymakers to craft data-driven strategies and respond effectively to public needs.

3.6. Research Flow

The entirety of this study, spanning from the initial problem identification to the final synthesis of conclusions, is structured within a comprehensive and systematic research framework. This logical progression ensures that each phase of the study builds upon the previous one, maintaining data integrity and analytical rigor throughout. The journey begins with the data acquisition phase, where raw information is harvested through automated web crawling techniques to capture real-time public discourse. Once the raw dataset is compiled, it undergoes a rigorous text preprocessing stage. The complete research flow can be observed in Figure 1.

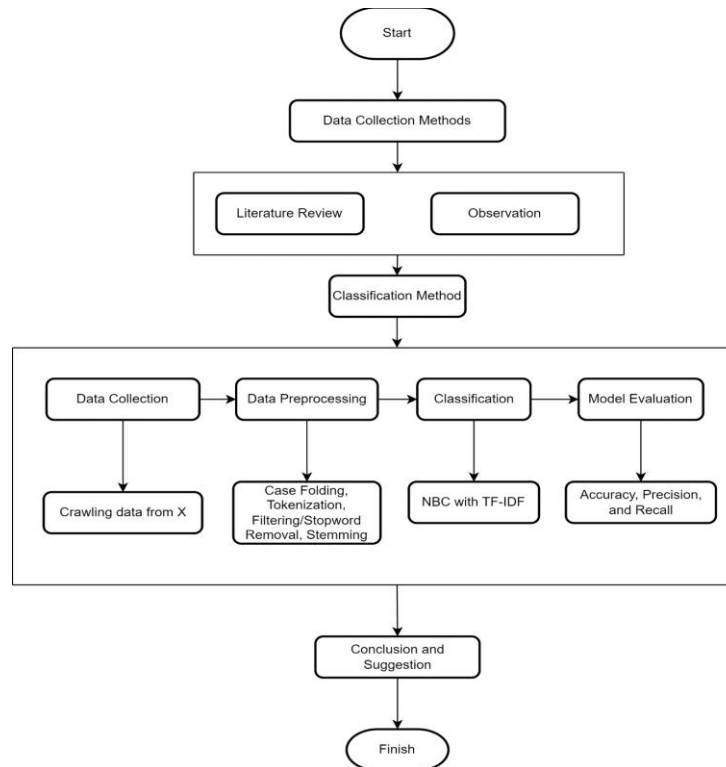


Figure 1. Research Flow Diagram

Source: Author’s research design (2025)

4. RESULT AND DISCUSSION

4.1. Data Selection

In the initial stage of the research, a total of 87 raw data entries were obtained through the crawling process via the Twitter platform API. Data within Twitter must be collected first for subsequent analysis and information extraction. To perform this information gathering, a web data collection technique known as crawling can be utilized. This data is unstructured, thus requiring a preprocessing phase so that it can be processed by the Naïve Bayes Classifier algorithm.

Table 1. Data Sample

No	Date	User	Tweet
1	04-12-2025	@neVerAl0nely	Bantuan Pemerintah terus mengalir ke berbagai lokasi bencana, maka akan semakin cepat upaya penanganan dan pemulihan pasca bencana.\n#SemangatIndonesia
2	04-12-2025	@AnjuRNaisya	jual premium dengan niat subsidi membantu, ternyata malingnya main di bahan baku. Sawit, alasan gampang dibuat kalo sudah ketemu duit, demi cuan, demi

			lapangan kerja dll. Tapi tidak ada yg pernah mengukur: efisiensi. 1 saw.
3	03-12-2025	@indepSumatera	bantuan pemerintah lambat banget
4	03-12-2015	@parkjihoot	Jadi selama ini tk kita ga di subsidi pemerintah#kecewa
5	03-12-2015	@arifbalikpapan1	Subsidi yang disetujui semua pihak termasuk DPR&MPR, masi ada untuk mereka.

Source: Primary data processed (2015-2025)

4.2. Data Preprocessing

The collected data will undergo a preprocessing stage.

a. Case Folding

Case folding is the phase that converts all letters in the document into lowercase; only letters from 'a' to 'z' are accepted (Zhu & Luo, 2023). Characters other than these letters are removed and treated as delimiters.

Table 2. Case Folding

Before Case Folding	After Case Folding
Bantuan Pemerintah terus mengalir ke berbagai lokasi bencana, maka akan semakin cepat upaya penanganan dan pemulihan pasca bencana. \n#SemangatIndonesia	Bantuan pemerintah terus mengalir ke berbagai lokasi bencana maka akan semakin cepat upaya penanganan dan pemulihan pasca bencana

Source: Primary data processed (2025)

b. Tokenization

Tokenization is the process of splitting sentences into individual words, which are referred to as tokens (Budiman & Widjaja, 2020). The primary objective of this process is to break down the syntactic structure of the language into a format that a computational model can interpret and quantify. By isolating each word, tokenization allows the model to perform frequency counts, identify patterns, and prepare the data for further stages like stop-word removal and classification. Without effective tokenization, the algorithm would treat an entire sentence as a single, incomprehensible string, making it impossible to derive meaningful insights from the data.

Table 3. Tokenization

Before Tokenization	After Tokenization
bantuan pemerintah terus mengalir ke berbagai lokasi bencana maka akan semakin cepat upaya penanganan dan pemulihan pasca bencana	['bantuan', 'pemerintah', 'terus', 'mengalir', 'ke', 'berbagai', 'lokasi', 'bencana', 'maka', 'akan', 'semakin', 'cepat', 'upaya', 'penanganan', 'dan', 'pemulihan', 'pasca', 'bencana']

Source: Primary data processed (2025)

c. Filtering/Stopword Removal

Filtering or Stopword Removal is the stage of extracting important words from the tokens by using a stoplist algorithm (removing insignificant words) or a wordlist algorithm or retaining significant words (Almutairi et al., 2024). Rather than retaining these redundant words within a dataset, it is considered a best practice to remove them entirely to improve computational efficiency. This removal process is carried out by filtering the text against a predefined dictionary, commonly referred to as a stopwords list, which contains all the terms designated for exclusion.

Table 4. Filtering/Stopword Removal

Before Filtering/Stopword Removal	After Filtering/Stopword Removal
['bantuan', 'pemerintah', 'terus', 'mengalir', 'ke', 'berbagai', 'lokasi', 'bencana', 'maka', 'akan', 'semakin', 'cepat', 'upaya', 'penanganan', 'dan', 'pemulihan', 'pasca', 'bencana']	['bantuan', 'pemerintah', 'lokasi', 'bencana', 'cepat', 'upaya', 'penanganan', 'pemulihan', 'pasca']

Source: Primary data processed (2025)

d. Stemming

Stemming is the process of mapping and decomposing various word forms into their base or root form (Albab et al., 2023). In the context of computational linguistics, this process aims to reduce morphological complexity by stripping away affixes such as prefixes, inflections, and suffixes thereby unifying words that share the same semantic core. This ensures that the model recognizes different forms of the same word as a single feature, which is crucial for achieving high consistency in sentiment analysis and information retrieval.

Table 5. Stemming

Before Stemming	After Stemming
['bantuan', 'pemerintah', 'lokasi', 'bencana', 'cepat', 'upaya', 'penanganan', 'pemulihan', 'pasca']	['bantu', 'perintah', 'lokasi', 'bencana', 'cepat', 'upaya', 'tangan', 'puluh', 'pasca']

Source: Primary data processed (2025)

4.3. NBC Classification

The core of the analytical phase involves the classification process, which is executed by implementing the Naive Bayes Classifier (NBC) algorithm. This algorithm is applied to the textual data only after it has successfully transitioned through the rigorous preprocessing stages, ensuring that the input is free from noise and irrelevant features.

```
import pandas as pd
import re
from Sastrawi.Stemmer.StemmerFactory import StemmerFactory
from Sastrawi.StopWordRemover.StopWordRemoverFactory import StopWordRemoverFactory
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, accuracy_score
import matplotlib.pyplot as plt
df = pd.read_csv("tweets_subsidi_sample.csv", encoding="utf-8", on_bad_lines="skip")
print("Jumlah data:", len(df))
print(df.head())
a = StemmerFactory().create_stemmer()
stop = set(StopWordRemoverFactory().get_stop_words())
def clean(t):
    t = str(t).lower()
    t = re.sub(r"http\S+|www\S+", "", t)
    t = re.sub(r"@w+", "", t)
    t = re.sub(r"#w+", "", t)
    t = re.sub(r"[^a-zA-Z\s]", "", t)
    t = re.sub(r"\s+", " ", t)
    t = " ".join([w for w in t.split() if w not in stop])
    t = a.stem(t)
    return t
df["clean_text"] = df["text"].apply(clean)
vec = TfidfVectorizer()
x = vec.fit_transform(df["clean_text"])
y = df["sentiment"]
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
model = MultinomialNB()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)
print(classification_report(y_test, y_pred))
print("Akurasi:", accuracy_score(y_test, y_pred))
df["sentiment"].value_counts().plot(kind='bar')
plt.title("Distribusi Sentimen")
plt.xlabel('Kategori'), plt.ylabel('Jumlah'), plt.show()
```

Figure 2. Sentiment Analysis Dashboard Code

Source: Author’s calculation using Python (2025)

The data processing results using the NBC algorithm on 87 tweets yielded a varied mapping of opinions. The visualization of these findings is presented in two primary forms: a sentiment analysis result table and a pie chart.

```
Memuat file hasil analisis: hasil_analisis_sentimen.csv...

=== Analisis Sebaran Sentimen ===
Jumlah (Frekuensi) Sentimen:
prediksi_sentimen
Netral      58
Positif     17
Negatif     12
Name: count, dtype: int64

Persentase Sebaran Sentimen:
prediksi_sentimen
Netral      66.67%
Positif     19.54%
Negatif     13.79%
Name: proportion, dtype: object

=== Tabel Hasil Analisis Sentimen ===
          Jumlah  Persentase
prediksi_sentimen
Netral          58    66.67%
Positif         17    19.54%
Netral          58    66.67%
Positif         17    19.54%
Negatif         12    13.79%
```

Figure 3. Sentiment Analysis Results

Source: Author’s calculation (2025)

Based on the figure above, a specific distribution of numbers for the three sentiment categories is clearly visible. The data shows that 58 tweets are classified as neutral, 17 tweets as positive, and 12 tweets as

negative. This indicates that the neutral category dominates the dataset, accounting for 66.67% of the total data.

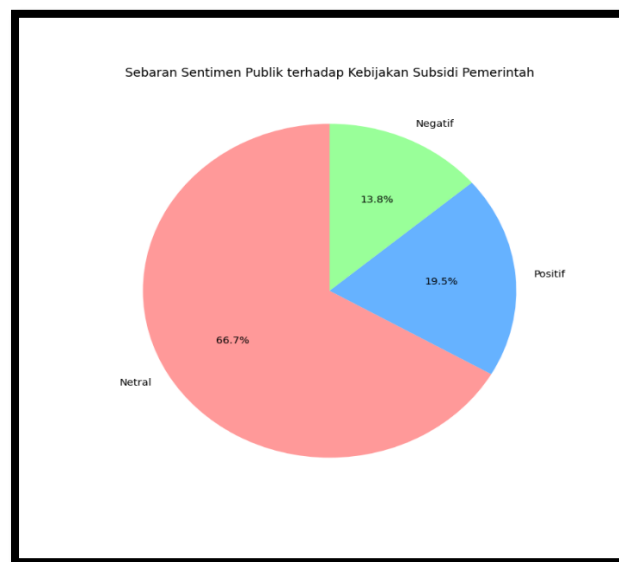


Figure 4. Pie Chart

Source: Processed from Twitter data using Python (2025)

5. CONCLUSION AND SUGGESTION

Based on the results of the sentiment analysis of 87 public tweets regarding government subsidy policies on the Twitter platform, it is concluded that the implementation of text preprocessing and the Naïve Bayes Classifier method is capable of effectively mapping general public opinion. The classification results show that neutral sentiment dominates the discussion with a percentage of 66.67%, indicating that the majority of tweets are informative and do not clearly express either support or rejection.

Meanwhile, among tweets containing specific opinions, positive sentiment (19.54%) is higher than negative sentiment (13.79%), suggesting that public opinion is relatively more supportive of the government's subsidy policy. Nevertheless, this research has limitations, particularly the relatively small number of tweets and the use of the Naïve Bayes Classifier method, which does not yet fully capture linguistic contexts such as sarcasm or implicit meanings. Therefore, future research is encouraged to utilize larger datasets and implement or compare other classification methods to achieve more accurate and representative sentiment analysis results.

Based on the limitations of this study, future research is recommended to use larger and more diverse Twitter datasets to obtain more representative sentiment analysis results. In addition, the application or comparison of other classification methods beyond the Naïve Bayes Classifier is suggested to better capture contextual language patterns such as sarcasm and implicit sentiment. From a practical perspective, sentiment analysis results can be utilized by policymakers as a complementary tool to monitor public responses and support the evaluation of government subsidy policies.

REFERENCE

- Agustya Dewi Utami, Y., Sihombing, V., & Halmi Dar, M. (2021). Implementasi Algoritma Naive Bayes Classifier (NBC) untuk Analisis Sentimen Komentar. *MEANS (Media Informasi Analisa Dan Sistem)*, 6(1). http://ejournal.ust.ac.id/index.php/Jurnal_Means/
- Albab, M. U., P., Y. K., & Fawaiq, M. N. (2023). Optimization of the Stemming Technique on Text Preprocessing President 3 Periods Topic. *Jurnal Transformatika*, 20(2), 1–12. <https://doi.org/10.26623/transformatika.v20i2.5374>
- Almutairi, T., Saifuddin, S., Alotaibi, R., Sarhan, S., & Nassif, S. (2024). Preprocessing Techniques for Clustering Arabic Text: Challenges and Future Directions. *International Journal of Advanced Computer Science and Applications*, 15(8), 1301–1314. <https://doi.org/10.14569/IJACSA.2024.01508126>
- Azhari, M., Situmorang, Z., & Rosnelly, R. (2021). Perbandingan Akurasi, Recall, dan Presisi Klasifikasi pada Algoritma C4.5, Random Forest, SVM dan Naive Bayes. *JURNAL MEDIA INFORMATIKA BUDIDARMA*, 5(2), 640. <https://doi.org/10.30865/mib.v5i2.2937>
- Budiman, A. E., & Widjaja, A. (2020). Analisis Pengaruh Teks Preprocessing Terhadap Deteksi Plagiarisme Pada Dokumen Tugas Akhir. *Jurnal Teknik Informatika Dan Sistem Informasi*, 6(3). <https://doi.org/10.28932/jutisi.v6i3.2892>
- Fani, S. M., Santoso, R., & Suparti, S. (2021). PENERAPAN TEXT MINING UNTUK MELAKUKAN CLUSTERING DATA TWEET AKUN BLIBLI PADA MEDIA SOSIAL TWITTER MENGGUNAKAN K-MEANS CLUSTERING. *Jurnal Gaussian*, 10(4), 583–593. <https://doi.org/10.14710/j.gauss.v10i4.30409>
- Farhadpour, S., Warner, T. A., & Maxwell, A. E. (2024). Selecting and Interpreting Multiclass Loss and Accuracy Assessment Metrics for Classifications with Class Imbalance: Guidance and Best Practices. *Remote Sensing*, 16(3), 533. <https://doi.org/10.3390/rs16030533>
- Gan, S., Shao, S., Chen, L., Yu, L., & Jiang, L. (2021). Adapting Hidden Naive Bayes for Text Classification. *Mathematics*, 9(19), 2378. <https://doi.org/10.3390/math9192378>
- Gupta, I., & Joshi, N. (2021). Real-Time Twitter Corpus Labelling Using Automatic Clustering Approach. *International Journal of Computing and Digital Systems*, 10(1), 519–532. <https://doi.org/10.12785/ijcds/100150>
- Harwenda, R. W., Angelo, M. D., Budi, I., Santoso, A. B., & Putra, P. K. (2025). Sentiment Analysis on Government Public Policies: A Systematic Literature Review. *Dinasti International Journal of Education Management And Social Science*, 6(5), 4192–4211. <https://doi.org/10.38035/dijemss.v6i5.4699>
- Huber, R. A., Wicki, M. L., & Bernauer, T. (2020). Public support for environmental policy depends on beliefs concerning effectiveness, intrusiveness, and fairness. *Environmental Politics*, 29(4), 649–673. <https://doi.org/10.1080/09644016.2019.1629171>
- Kusuma, A., & Nugroho, A. (2021). Analisa Sentimen Pada Twitter Terhadap Kenaikan Tarif Dasar Listrik Dengan Metode Naive Bayes. *Jurnal Ilmiah Teknologi Informasi Asia*, 15(2), 137–146. <https://doi.org/10.32815/jitika.v15i2.557>
- Lubis, A. R., Nasution, M. K. M., Sitompul, O. S., & Zamzami, E. M. (2022). The feature extraction for classifying words on social media with the Naive Bayes algorithm. *LAES International Journal of Artificial Intelligence (IJ-AI)*, 11(3), 1041. <https://doi.org/10.11591/ijai.v11i3.pp1041-1048>
- Ritonga, R. R., & Sriani, S. (2025). Public Opinion Sentiment Analysis Towards Government Budget Efficiency Policy on Twitter (X) Using the Naive Bayes Classifier Algorithm. *Journal of Information Systems and Informatics*, 7(3), 2496–2515. <https://doi.org/10.51519/journalisi.v7i3.1234>
- Rosid, M. A., Fitrani, A. S., Astutik, I. R. I., Mulloh, N. I., & Gozali, H. A. (2020). Improving Text Preprocessing For Student Complaint Document Classification Using Sastrawi. *IOP Conference Series: Materials Science and Engineering*, 874(1), 012017. <https://doi.org/10.1088/1757-899X/874/1/012017>
- Setiawan, A., Jailani, S., & Risnita. (2025). Penelitian Metode Campuran (Mixed Method). *Arus Jurnal Sosial Dan Humaniora*, 5(2), 1484–1491. <https://doi.org/10.57250/ajsh.v5i2.1263>
- Siti Salasatu Sa'diyah, Eli Apud Saepudin2, Resma Cahya, Siti Lita Rosita, & Nova Qurrota Ayun. (2025). Kebijakan Subsidi BBM. *Ekopedia: Jurnal Ilmiah Ekonomi*, 1(2), 286–293. <https://doi.org/10.63822/bbs6f165>
- Sunardi, S., Riadi, I., & Raharja, P. A. (2019). Analisis Application Programming Interface Pada Mobile E-Voting Menggunakan Metode Test-Driven Development. *Techno (Jurnal Fakultas Teknik, Universitas*

- Muhammadiyah Purwokerto*, 20(2), 87. <https://doi.org/10.30595/techno.v20i2.4266>
- Tsai, M. H., & Wang, Y. (2021). Analyzing Twitter Data to Evaluate People's Attitudes towards Public Health Policies and Events in the Era of COVID-19. *International Journal of Environmental Research and Public Health*, 18(12), 6272. <https://doi.org/10.3390/ijerph18126272>
- Zhu, L., & Luo, D. (2023). A Novel Efficient and Effective Preprocessing Algorithm for Text Classification. *Journal of Computer and Communications*, 11(03), 1–14. <https://doi.org/10.4236/jcc.2023.113001>
- Zukhrufillah, I. (2018). Gejala Media Sosial Twitter Sebagai Media Sosial Alternatif. *Al-I'lam: Jurnal Komunikasi Dan Penyiaran Islam*, 1(2), 102. <https://doi.org/10.31764/jail.v1i2.235>