Comparison of SVM and Naive Bayes in Public Sentiment Analysis Regarding Budget Efficiency

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Abstract— The The budget efficiency policy through Presidential Instruction No. 1 of 2025 has generated various public responses on social media, particularly X. Understanding public sentiment is important for assessing the level of public acceptance and supporting government decision-making and communication strategies. This study aims to classify public sentiment towards the policy using the Naïve Bayes and Support Vector Machine (SVM) algorithms. A total of 9,261 tweets were collected and processed through pre-processing, removal of duplicate data and texts with only two words, and removal of neutral categories, resulting in 6,596 clean data. Labeling was done using the InSet dictionary, while feature extraction used Term Frequency–Inverse Document Frequency (TF-IDF). The data was divided into 70% training data and 30% test data, and the Synthetic Minority Over-Sampling Technique (SMOTE) was applied to address class imbalance. The results showed that the SVM–Linear SVC model achieved the highest accuracy of 94%, outperforming Multinomial Naïve Bayes with an accuracy of 86%. Although Naïve Bayes has faster training and prediction times, SVM provides more stable and accurate classification performance. These findings indicate that machine learning methods can be used effectively to analyze public sentiment towards government policies and have the potential to become a reference in the development of Indonesian language sentiment analysis research.

Keywords—Sentiment Analysis, Naive Bayes, Support Vector Machine, Budget Efficiency

I. INTRODUCTION

The Prabowo-Gibran administration issued Presidential Instruction Number 1 of 2025 (Inpres 1/2025) aimed at implementing savings in the 2025 State Revenue and Expenditure Budget (APBN) as well as Regional Revenue and Expenditure Budgets (APBD) so that the budget is more effective and allocated to priority programs [1]. This policy requires ministries, institutions, and regional governments to reduce spending considered less strategic, such as operational costs, business travel, and procurement of goods, but employee expenditures and social assistance remain excluded to avoid disrupting main services. The government targets savings of Rp306.7 trillion, consisting of Rp256.1 trillion from ministries/institutions and Rp50.5 trillion from regional transfers [2].

The dissemination of information in the current digital era heavily relies on the internet, along with the increasing number of users utilizing this technology. In 2021, the number of X/Twitter users in Indonesia was recorded at 10,645,000 users. Social media has become one of the primary means of information distribution, with one of the most frequently used platforms by Indonesian people being X/Twitter, which is a social media platform that allows users to share short messages containing up to 280 characters called tweets [3]. Currently, it is estimated that X users at the beginning of 2025 will reach 25.2 million users. Sentiment analysis (opinion mining) is a machine learning-based NLP technique for categorizing opinions or emotions into negative, positive, or neutral [4]. This method helps assess public opinion on social media regarding budget efficiency, thereby making the public's response to policies clearer. Thus, sentiment analysis becomes an effective and useful tool in examining budget efficiency issues.

The purpose of this research is to examine public opinion on the X application regarding the Indonesian-language budget efficiency issue and to evaluate the performance of Naïve Bayes and SVM algorithms in sentiment classification. Naïve Bayes works with a probabilistic approach, while SVM uses weighting for data separation. This study compares the performance of both models on tweets with the keyword "budget efficiency".

As for previous research, conducted by Oca Meilika Wulandari et al. in 2025, which analyzed public opinion sentiment regarding the fake Jokowi diploma issue on Twitter using the Naïve

Bayes and Support Vector Machine (SVM) methods, this study found that the Naïve Bayes algorithm achieved 65% accuracy, while Support Vector Machine (SVM) was higher at 69.23% [5]. Then there was research conducted by Acuan Supian et al. in 2024 that compared the performance of Naïve Bayes and Support Vector Machine (SVM) algorithms in sentiment analysis related to the Capital of the Archipelago on Twitter, the study proved that SVM was able to maintain accuracy up to 94%, surpassing Naïve Bayes with 91%. This shows the effectiveness of SVM is better in measuring public opinion regarding the Capital of the Archipelago [6]

Studies show that the Naïve Bayes and Support Vector Machine (SVM) algorithms have proven capable of providing high accuracy in various sentiment analysis topics, such as product reviews, application reviews, political opinions, and public service assessments. However, the topic of budget efficiency has different characteristics because it relates to sensitive public policy issues, a broad scope of discussion, and a variety of opinions influenced by social, economic, and political factors. In addition, this issue uses many technical terms related to state finances, government regulations, and the pros and cons of austerity policies that rarely appear in other topics. These conditions make sentiment data from social media more diverse, complex, and critical in nature. This study focuses specifically on the Indonesian context, so the scope of analysis is limited to public opinion in that country. Thus, the application of these two algorithms is intended to test their consistency in performance on the issue of budget efficiency in Indonesia. The results of this study are expected to be useful for the public, academics, and the government in understanding public perceptions and formulating more effective communication and budget management strategies.

II. RESEARCH METHODS

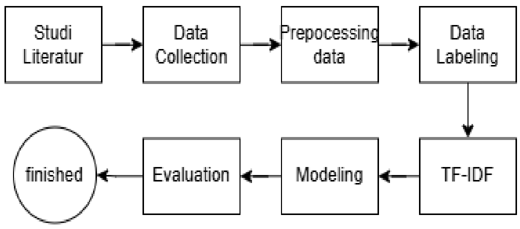

Figure 1. Methodolgy Flow

This research process consists of several stages starting with data collection from platform X (Twitter) as the basis for dataset formation. The collected data then undergoes a preprocessing stage. After that, the data is labeled using word weights based on three sentiment categories, namely positive, negative, and neutral. The next stage is feature extraction using the Term Frequency–Inverse Document Frequency (TF-IDF) method. The TF-IDF extraction results are then divided into training data and testing data for modeling using Naïve Bayes and Support Vector Machine (SVM) algorithms. The final stage of this process is to evaluate the model testing results.

A. Studi Literatur

This stage aims to understand and select appropriate research methods to solve the problems that are the subject of the study, which is conducted through the collection and analysis of relevant references such as journals, books, articles, and previous studies regarding public sentiment analysis on social media X (Twitter) by applying Naïve Bayes and Support Vector Machine (SVM) algorithms.

B. Data Collection

Data collection was conducted using scraping techniques through the Tweet Harvest v20.18.3 script created by Helmi Satria. Scraping X data is the process of data retrieval through the X (Twitter) API. Data collection used the keyword "Budget efficiency" with a time range from

January 10, 2025 to May 30, 2025, and was conducted over a two-day period on July 29 and 30, 2025, utilizing 1 X (Twitter) account.

C. Prepocessing Data

After obtaining the scraping results from X (Twitter), the next step is to perform data preprocessing. This cleaning and refinement stage, known as preprocessing, is conducted to process raw data that is typically unstructured and contains numerous characters. This process aims to remove noise and prepare the data to be optimally processed by algorithms, thereby resulting in better performance and accuracy. Preprocessing becomes a crucial step as it helps simplify the data and reduce the impact of irregularities or imbalances that may exist in the dataset [7]

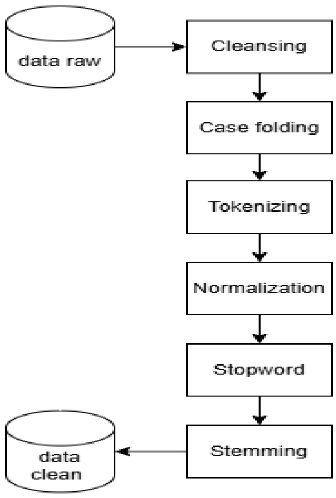

Figure 2. Prepocessing Flow Stages

The preprocessing stages in this research consist of cleansing, case folding, tokenizing, normalization, stopword removal, and stemming. Preprocessing is performed to prepare text data before analysis. This process includes cleansing to remove punctuation, URLs, hashtags, and irrelevant elements [8], case folding to standardize text to lowercase [9], tokenization which breaks sentences into words, for example the sentence "saya sangat boros" will become "saya", "sangat", "boros", with this tokenization computers can more easily process each word in the review text [8], Normalization to standardize non-standard words to standard form [10], stopword removal removes common words that are not significantly meaningful [11], and stemming to replace derivative words to their base form [12]. These stages are performed using NLTK and Sastrawi libraries

D. Data Labeling

Data labeling is the process of assigning initial categories to data before model classification. This stage aims to classify each sentence into positive, negative, or neutral sentiment according to its meaning. Labeling is done using the InSet Lexicon, which is an Indonesian lexical dictionary for sentiment analysis containing 3,609 positive words and 6,609 negative words. Each word is manually assigned a weight between -5 and 5. Sentiment determination is based on the total word weight in the text: values above 0 are categorized as positive, below 0 as negative, and a value of 0 is considered neutral [13].

E. TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) is a feature extraction technique that measures the importance of a word in a document. TF records the frequency of word occurrences in the document, while IDF weights based on the word's rarity across the corpus [14]. The TF-IDF calculation can be seen in the formula below:

$$TF.IDF(t) = tf_d^t \, x \log \frac{N}{df^t} \quad (1)$$

Where $tf_d^t \, x \, log \frac{N}{df^t}$ represents the frequency of term t in document d. The symbol N denotes the total number of documents in the corpus, while df refers to the number of documents containing term t, which is calculated in the TF-IDF computation. In this research, TF-IDF is used to represent text in numerical form so that the Naïve Bayes and Support Vector Machine (SVM) algorithms can work more accurately and effectively.

F. Modeling

At this stage, a sentiment classification model is designed by applying two machine learning algorithms, namely Naive Bayes and Support Vector Machine (SVM). Before model implementation, the training data is first processed using SMOTE to address data imbalance by creating synthetic samples in the minority class, thus achieving a balanced distribution between classes and enabling the model to learn optimally for all categories.

Naïve Bayes algorithm is a classification method that predicts the probability of an event based on previously available information or historical data, this approach refers to Bayes' theorem, which functions to calculate the probability of a hypothesis against a specific case[15].

$$Rumus : P(A \mid B) = \frac{P(B \mid A)(A)}{P(B)} \quad (2)$$

In this context, A is data that does not yet have a class label, while B is the hypothesis that data A belongs to a specific class. The value P(A|B) represents the posterior probability, which is the likelihood that the hypothesis is correct given the existing conditions. P(B|A) is the likelihood or the probability that data B appears if hypothesis A is correct, and P(B) is the prior probability of hypothesis B [16].

The Support Vector Machine (SVM) algorithm is a commonly used technique for data classification. The main principle of this algorithm is to find and maximize the separating margin (hyperplane) between data groups. SVM operates by using a set of hypotheses consisting of linear functions in high-dimensional feature space [17]. The following is the equation of SVM (LinearSVC):

$$f(x) = w^T x + b \quad (3)$$

w = weight vector (sought by the algorithm)
x = feature vector (for example, TF-IDF result from text)
b = bias (intercept)
Prediction result: sign$(w^T x + b)$

G. Confusion Matrix Evaluation

The evaluation in this study aims to assess the performance level of the developed model. The evaluation approach used is the confusion matrix, which is a table showing the comparison between model prediction results and actual classifications. By using the confusion matrix, the number of test data that are correctly classified and data that experience errors in the classification process can be identified[18]. The equations for accuracy, precision, recall, and f1-score are shown as follows

$$Akurasi\ \frac{(TP+TN)}{TP+TN+FP+FN} \times 100\% \quad (4)$$

$$Presisi = \frac{TP}{TP+FP} \times 100\% \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (6)$$

$$F1 - Score = 2\left(\frac{Presisi \times Recall}{Presisi + Recall}\right) \quad (7)$$

In the confusion matrix, True Positive (TP) represents the number of positive data that is correctly predicted as positive, while False Positive (FP) describes negative data that is incorrectly classified as positive. False Negative (FN) is positive data that is incorrectly detected as negative, while True Negative (TN) indicates negative data that is accurately predicted as negative [19].

III. Results and Analysis

A. Data Collection Results

A total of 9,261 tweets were successfully collected. Below is an example of data taken from X./twitter.

"full_text"	"created_at"
"Presiden Prabowo menekankan kepada jajarannya...	"Tue Jan 07 08:50:33 +0000 2025"
"Langkah tegas Presiden dalam memangkas angga...	"Wed Jan 08 13:26:16 +0000 2025"
" Kerja sama dan komitmen untuk betul-betul bi...	"Fri Jan 10 08:19:28 +0000 2025"
"Dedi Mulyadi yang baru saja ditetapkan sebaga...	"Fri Jan 10 09:18:41 +0000 2025"
"Selain itu dalam rapat tersebut juga disosial...	"Mon Jan 13 03:41:10 +0000 2025"

Figure 3. Data Collection Results

The data collected only includes the full_text and created_at columns, which are then used in the data preprocessing or cleaning process.

B. Data Prepocessing Results

The dataset that will be analyzed and has undergone the data preprocessing stage, namely cleaning, case folding, tokenizing, normalization, stop word removal, and stemming

Table 1. Data Prepocessing Results

Stages	Raw Data	Results
Cleansing	Pimpinan DPR Pusing Lembaganya Kena Efisiensi Anggaran Rp13Triliun Bingung Bayar Gajian https://t.co/Jvj0wWsRkb	Pimpinan DPR Pusing Lembaganya Kena Efisiensi Anggaran Rp Triliun Bingung Bayar Gajian
Case Folding	Pimpinan DPR Pusing Lembaganya Kena Efisiensi Anggaran Rp Triliun Bingung Bayar Gajian	pimpinan dpr pusing lembaganya kena efisiensi anggaran rp triliun bingung bayar gajian
Tokenizing	pimpinan dpr pusing lembaganya kena efisiensi anggaran rp triliun bingung bayar gajian	['pimpinan','dpr','pusing','lembaganya','kena','efisiensi','anggaran','rp','triliun','bingung', 'bayar', 'gajian']
Normalization	['pimpinan','dpr','pusing','lembaganya','kena','efisiensi','anggaran','rp','triliun','bingung', 'bayar', 'gajian']	['pimpinan','dpr','pusing','lembaganya','kena','efisiensi','anggara

		n','rp','triliun','bingung', 'bayar', 'gajian']
Stopword	['pimpinan','dpr','pusing','lembaganya',' kena','efisiensi','anggaran','rp','triliun','b ingung', 'bayar', 'gajian']	['pimpinan','dpr','pusing','lemba ganya','kena','efisiensi','anggara n','rp','triliun','bingung', 'bayar', 'gajian']
Stemming	['pimpinan','dpr','pusing','lembaganya',' kena','efisiensi','anggaran','rp','triliun','b ingung', 'bayar', 'gajian']	pimpin dpr pusing lembaga kena efisiensi anggar rp triliun bingung bayar gaji

After going through the preprocessing stage, including the removal of duplicate data and data consisting of only two words, the number of data decreased from 9,261 to 8,605 clean data ready to be processed to the next stage.

C. Data Labeling Results

In this labeling, data from preprocessing results is categorized into three classes: positive, negative, and neutral. The data labeling process uses the InSet lexicon, which produces 4183 negative class instances, 2413 positive class instances, and 2009 neutral class instances

Table 2.Sentiment Labeling Results

Stemming	Text Sentiment	Score	Sentiment
jangan lupa potong efisiensi	Jangan lupa potong	-2	Negatif
support efisiensi langkah positif lebih cerah	Support langkah positif lebih	4	Positif
efisiensi habis lebaran	habis	0	Netral
efisiensi acara seremonial		0	Netral

Table 2 shows examples of the sentiment labeling process results using the Lexicon InSet dictionary based on score values. A total of 8,605 data were classified into three sentiment categories, namely positive, negative, and neutral. Comments with a score of exactly 0 were removed from the dataset as they were considered neutral and did not contain clear indications of support or rejection of the policy. This decision was made to maintain the focus of the analysis on opinions with clear emotional tendencies, thus preventing the model from experiencing confusion during the learning process due to data with gray polarity. However, it should be noted that the removal of neutral opinions is a limitation of this research, as neutral responses are also part of the overall picture of public opinion. Therefore, the results of this study more represent polar sentiments (positive or negative) and do not include the group of people who are neutral towards the policy.

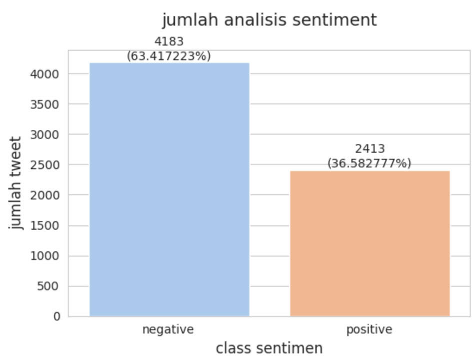

Figure 4. Sentiment Class Distribution

Figure 4 shows the data distribution after labeling and filtering, with a total of 6,596 data categorized as positive and negative used for the model classification stage. Meanwhile, 2,009 data labeled as neutral (score 0) were removed because they did not have sentiment tendency.

D. TF-IDF Weighting Results

TF-IDF weighting is performed on each data, the process is carried out by calculating the frequency of occurrence of a word in a document, while assigning a smaller weight value for words that are commonly found in many documents, the more repeated words in the data, the higher their weight value. To see the characteristics of dominant words in each sentiment class, visualization is done using a TF-IDF-based wordcloud. This approach is chosen so that the words displayed not only represent the frequency of occurrence, but also the level of importance of words in distinguishing each sentiment class.

Figure 5. Wordcloud for positive class

Figure 6. Wordcloud for positive class

Figures 5 and 6 show the TF-IDF weight-based WordCloud visualization for positive and negative sentiment. In the positive sentiment, words with high weights such as more, support, step, grow, wise, benefit, realize, and success are visible, reflecting public support for budget efficiency policies as a wise and appropriate step. Meanwhile, in the negative sentiment, words such as not, increase, impact, not, don't, waste, cause, cut, wrong, educate, and road appear, indicating public rejection, criticism, or dissatisfaction with the impact of budget efficiency, for example in education, fund cuts, and public burden.

E. Evaluation of Naive Bayes and SVM Models

Evaluation was conducted using confusion matrix measurements, namely accuracy, precision, recall, and f1-score based on classification results against test data. This was done through a data division scheme with a training dataset of 70% of the total data to train model parameters, and a testing dataset of 30% to test model performance. The 70:30 ratio was chosen considering the balance between sufficient training data availability to produce a representative model and adequate test data to reliably evaluate performance. On the training data, SMOTE technique was also applied to address class imbalance by generating synthetic data for the minority class, resulting in a more even data distribution between classes and allowing the model to learn balanced across all classes.

Table 3. Algorithm Performance Results

Model	Accuracy	Precision	Recall	F1-Score
NB	0.87	0.83	0.82	0.83
SVM	0.94	0.94	0.92	0.93

Based the evaluation results in Table 3 show that although Naïve Bayes performs quite well with an accuracy of 0.87 and precision, recall, and F1-score of 0.83, 0.82, and 0.83, respectively, its performance is still below that of SVM. The SVM model achieved the highest results with an accuracy of 0.94, precision of 0.94, recall of 0.92, and F1-score of 0.93. These findings indicate that Naïve Bayes is capable of delivering solid performance, but SVM remains superior in classifying sentiment more accurately and consistently.

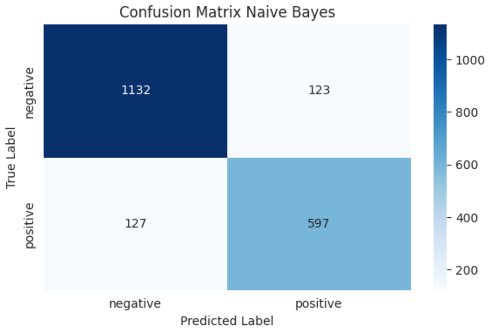

Figure 7. Naive Bayes Confusion Matrix

Based on Figure 7, the confusion matrix evaluation results for the Naive Bayes algorithm indicate that the model can perform data classification quite well and accurately, with 1132 true negatives and 597 true positives. However, there are still prediction errors in the form of 123 false positives and 127 false negatives. Overall, the model is more accurate in recognizing negative sentiment compared to positive sentiment, but its overall performance is already adequate for sentiment analysis.

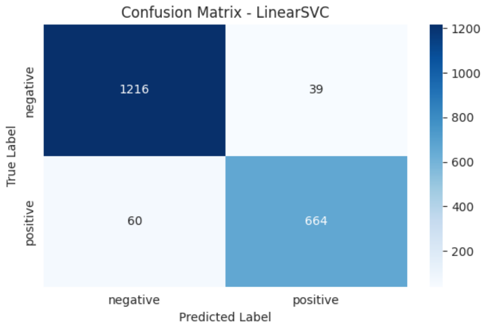

Figure 8. SVM Confusion Matrix

Based on Figure 8, the evaluation of the confusion matrix for the LinearSVC algorithm shows very good classification performance, with the model successfully predicting 1216 negative and 664 positive data correctly, while relatively small errors, namely 39 false positives and 60 false negatives. This demonstrates that LinearSVC has high accuracy and balanced capability in recognizing both negative and positive sentiments, making it superior to Naive Bayes in sentiment analysis.

In addition to evaluation based on accuracy and other performance metrics, algorithm efficiency is also compared by looking at the training time and prediction time of each mode

Table 4. Training Time and Model Prediction

Model	Training Time	Prediction Time
NB	0.0034 sec	0.0007 sec
SVM	0.0247 sec	0.0006 sec

Table 4 shows that the Naïve Bayes algorithm has the shortest training and prediction time, while SVM shows the longest training and prediction time but produces the highest accuracy

Testing results prove that the SVM algorithm achieves the best accuracy of over 0.94, outperforming Naïve Bayes which reaches 0.87. The superiority of SVM comes from its ability to optimally separate high-dimensional data, while Naïve Bayes is less effective due to the assumption of independence between features. However, Naïve Bayes is superior in terms of efficiency with very short training and prediction times, which is caused by its calculation nature based on word frequency and simple conditional probability, while SVM requires longer time because it involves quadratic optimization to determine the best hyperplane, especially on large and high-dimensional datasets. Thus, Naïve Bayes is suitable for fast or real-time classification, while SVM is more appropriate when accuracy becomes the main priority.

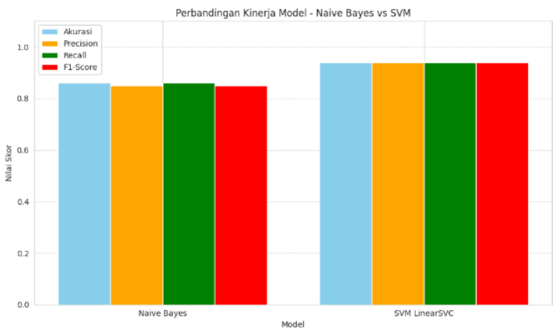

Figure 9. Bar Chart Comparison of Models

Figure 9 shows a visualization of performance metric comparison between Naïve Bayes and SVM algorithms. It can be seen that SVM-LinearCSV shows the highest score in all metrics.

To evaluate the model's performance more comprehensively, an error analysis was conducted on the prediction results from the test data. This analysis aims to identify examples of texts that were misclassified by both the Naïve Bayes and SVM algorithms, thereby providing a deeper understanding of the characteristics of data that is difficult to classify accurately. This approach also helps to reveal patterns or factors that influence the performance differences between the algorithms.

Table 5. Model Prediction Errors

Stemming	Initial Label	NB Prediction	SVM Prediction
Langkah efisiensi sangat bantu ekonomi negara	Positif	Negatif	Positif
Kurang anggaran banyak proyek rakyat terbengkalai	Negatif	Negatif	Positif
semangat efisiensi tumbuh disiplin baru birokrasi	Positif	Positif	Negatif
opini rakyat pikir rasional maksud bijak efisiensi inpres nomor kurang mubazir penuh sejahtera masyarakat	Negatif	Positif	Negatif

Table 5 shows some examples of comments that were misclassified by one algorithm but correctly classified by others. Naïve Bayes tends to struggle when words have context-dependent meanings, thus potentially misjudging sentiment polarity. Conversely, SVM sometimes fails to detect idiomatic meanings or phrases that rarely appear in the training data. This error analysis is important for understanding the limitations of each model and can serve as a basis for improvement, for example by expanding the sentiment dictionary or adding context-based feature engineering.

IV. CONCLUSION

From the research results, it can be concluded that the Support Vector Machine (SVM) algorithm has the best performance in classifying public sentiment on budget efficiency issues compared to the Naïve Bayes algorithm. The analysis process was conducted on 6,596 tweet data from social media X that had undergone preprocessing, sentiment labeling using InSet dictionary, and feature extraction using TF-IDF. The model was trained using 70% of the training data and evaluated with 30% of the test data. The evaluation results show that SVM - Linear SVC achieved 0.94 accuracy, outperforming Naive Bayes - Multinomial NB with 0.87 accuracy. In terms of efficiency, Naïve Bayes shows faster training and prediction times, making it suitable for real-time implementation, although its accuracy is slightly lower. Meanwhile, SVM requires more time but provides more accurate and consistent classification. The implications of these findings affirm that machine learning algorithms can be used as an analysis tool to understand public opinions about government policies more effectively and efficiently. This classification result can also be used by policymakers as input in developing public communication strategies. In the academic field, these findings can serve as a reference in the development of Indonesian-language text-based sentiment analysis systems. The results of this study need to be understood by considering several limitations, especially in terms of data coverage which was only collected for two days and using one main keyword, namely "budget efficiency". This limits the broader and more diverse representation of public opinion. Furthermore, the crawling process only used one account, which technically limits the volume and variety of data that can be obtained. For further research development, it is recommended to extend the data collection period, use several relevant keywords, and utilize more than one account or more comprehensive scraping methods. Use of other algorithms, for example the Ensemble method or deep learning,can also be considered to improve the accuracy and generalization of the model.

REFERENCES

[1] Inpres, *Instruksi Presiden Republik Indonesi Nomor 1 Tahun 2025*. indonesia, 2025.

[2] G. M. Rizky, V. J. Tanzil, A. Rafi, D. Pasara, R. Kusumo, and E. J. Tiasono, “Dampak efisiensi anggaran pada ATR/BPN Kota Tangerang: optimalisasi layanan pertanahan dan iklim investasi,” *IKRAITH-HUMANIORA : jurnal sosial dan humaniora*, vol. 9, no. 2, pp. 326–342, Jul. 2025, doi: https://doi.org/10.37817/ikraith-humaniora.v9i2.

[3] A. Kartino, M. K. Anam, Rahmaddeni, and Junadhi, “Analisis Akun Twitter Berpengaruh terkait Covid-19 menggunakan Social Network Analysis,” *Jurnal RESTI*, vol. 5, no. 4, pp. 697–704, Aug. 2021, doi: https://doi.org/10.29207/resti.v5i4.3160.

[4] E. Hokijuliandy, H. Napitupulu, and F. Firdaniza, “Analisis sentimen menggunakan metode klasifikasi support vector machine (SVM) dan seleksi fitur Chi-Square,” *SisInfo : Jurnal Sistem Informasi dan Informatika*, vol. 5, no. 2, pp. 40–49, Aug. 2023, doi: 10.37278.

[5] O. M. Wulandari, I. Maulana, F. Syamsudin, and R. Waluyo, “Perbandingan Algoritma Naive Bayes dan SVM dalam Analisis Sentimen Twitter terhadap Isu Ijazah Jokowi Palsu,” *Jurnal Manajemen Informatika, Sistem Informasi dan Teknologi Komputer (JUMISTIK)*, vol. 4, no. 1, pp. 392–400, Jun. 2025, doi: https://doi.org/10.70247/jumistik.v4i1.145.

[6] A. Supian, B. Tri Revaldo, N. Marhadi, and L. Efrizoni, “Perbandingan kinerja Naïve Bayes dan SVM pada analisis sentimen twitter Ibukota Nusantara,” *Jurnal ilmiah informatika (JIF)*, vol. 12, no. 1, pp. 15–21, Mar. 2024, doi: https://doi.org/10.33884/jif.v13i01.

[7] T. H. Suprapti and R. Narasati, “IMPLEMENTASI ALGORITMA NAIVE BAYES UNTUK ANALISIS SENTIMEN ULASAN PRODUK MAKANAN DAN MINUMAN DI TOKOPEDIA,” *Jurnal Mahasiswa Teknik Informatika*, vol. 8, no. 1, pp. 111–118, Feb. 2024, doi: https://doi.org/10.36040/jati.v8i1.8237.

[8] A. Fauzi and A. H. Yunial, "Analisis aentimen US Airline pada media sosial Twitter/X menggunakan perbandingan algoritma data mining," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 10, no. 2, pp. 277–286, Aug. 2024, doi: https://doi.org/10.26418/jp.v10i2.

[9] Yunita Rani and Kamayani Mia, "Perbandingan Algoritma SVM dan Naïve Bayes pada analisis sentimen kebijakan penghapusan kewajiban skripsi," *Indonesian Journal of Computer Science(IJCS)*, vol. 12, no. 5, pp. 2879–2890, Oct. 2023, doi: https://doi.org/10.33022/ijcs.v12i5.

[10] Ditami Rachma Gientry, E. F. Ripanti, and Sujaini Herry, "Implementasi Support Vector Machine untuk analisis sentimen terhadap pengaruh program promosi Event Belanja pada Marketplace," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 8, no. 3, pp. 508–516, Dec. 2022, doi: https://doi.org/10.26418/jp.v8i3.

[11] H. Junianto, R. E. Saputro, B. A. Kusuma, and S. D. I. Saputra, "Eksplorasi Sentimen Publik terhadap Film 'Dirty Vote' melalui Metode Naïve Bayes dan Logistic Regression," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 10, no. 3, pp. 362–370, Dec. 2024, doi: https://doi.org/10.26418/jp.v10i3.

[12] D. Rifaldi, A. Fadlil, and H. Herman, "Teknik preprocessing pada text mining menggunakan data tweet 'Mental Health,'" *Decode: Jurnal Pendidikan Teknologi Informasi*, vol. 3, no. 2, pp. 161–171, Sep. 2023, doi: https://doi.org/10.51454/decode.v3i2.131.

[13] N. M. F. Fathoni, E. Y. Puspaningrum, and N. A. Sihananto, "Perbandingan performa labeling Lexicon InSet dan VADER pada analisa sentimen Rohingya di Aplikasi X dengan SVM," *Modem : Jurnal Informatika dan Sains Teknologi*, vol. 1, no. 3, pp. 62–76, Jul. 2024, doi: https://doi.org/10.62951/modem.v1i3.112.

[14] C. V. Angkoso, N. M. A. Thrisna, B. D. Satoto, and A. Kusumaningsih, "Optimasi Klasifikasi Sentimen Menggunakan Random Forest dengan Preprocessing K-Means Clustering dan SMOTE," *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, vol. 10, no. 3, pp. 389–400, Dec. 2024, doi: https://doi.org/10.26418/jp.v10i3.

[15] R. A. Chaerudin, E. Ermatita, and B. R. M. Wadu, "Implementasi Algoritma Naïve Bayes untuk analisis klasifikasi survei kesehatan mental (Studi Kasus: Open Sourcing Mental Illness)," *Jurnal Informatik : Jurnal Ilmu Komputer (IFTK)*, vol. 19, no. 1, pp. 1–10, Apr. 2023, doi: https://doi.org/10.52958/iftk.v19i1.

[16] B. A. Maulana, M. J. Fahmi, A. M. Imran, and N. Hidayati, "Analisis sentimen terhadap aplikasi Pluang menggunakan Algoritma Naive Bayes dan Support Vector Machine (SVM)," *MALCOM: Indonesian Journal of Machine Learning and Computer Science*, vol. 4, no. 2, pp. 375–384, Apr. 2024, doi: https://doi.org/10.57152/malcom.v4i2.1206.

[17] R. Noviana and I. Rasal, "Penerapan algoritma naive bayes dan svm untuk analisis sentimen boy band bts pada media sosial twitter," *JTS (Jurnal Teknik dan Science)*, vol. 2, no. 2, pp. 51–60, Jun. 2023, doi: 10.51903.

[18] M. I. Fikri, T. S. Sabrila, and Y. Azhar, "Perbandingan metode Naïve Bayes dan Support Vector Machine pada analisis sentimen twitter," *SMATIKA Jurnal : STIKI Informatika Jurnal*, vol. 10, no. 2, pp. 71–76, Dec. 2020, doi: https://doi.org/10.32664/smatika.v10i02.

[19] F. Rifaldy, Y. Sibaroni, and S. S. Prasetiyowati, "Effectiveness of Word2Vec and TF-IDF in Sentiment Classification on Online Investment Platforms Using Support Vector Machine," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 10, no. 2, pp. 863–874, Mar. 2025, doi: https://doi.org/10.29100/jipi.v10i2.6055.