Sentimen Politik Pasca Pemilihan Presiden 2024: Perbandingan Pendekatan Naïve Bayes dan Support Vector Machine

Tugas Akhir
diajukan untuk memenuhi salah satu syarat memperoleh gelar sarjana
pada Program Studi Informatika
Fakultas Informatika
Universitas Telkom

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Universitas Telkom

Bandung

2025

LEMBAR PENGESAHAN

Sentimen Politik Pasca Pemilihan Presiden 2024: Perbandingan Pendekatan Naïve Bayes dan Support Vector Machine

Political Sentiment Post 2024 Presidential Election: Comparison of Naïve Bayes and Support Vector Machine Approaches

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Bandung, 16 Januari 2025
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LEMBAR PERNYATAAN

Dengan ini saya, Widya Yudha Patria, menyatakan sesungguhnya bahwa Tugas Akhir saya dengan judul **Sentimen Politik Pasca Pemilihan Presiden 2024: Perbandingan Pendekatan Naïve Bayes dan Support Vector Machine** beserta dengan seluruh isinya adalah merupakan hasil karya sendiri, dan saya tidak melakukan penjiplakan yang tidak sesuai dengan etika keilmuan yang belaku dalam masyarakat keilmuan. Saya siap menanggung resiko/sanksi yang diberikan jika di kemudian hari ditemukan pelanggaran terhadap etika keilmuan dalam Laporan TA atau jika ada klaim dari pihak lain terhadap keaslian karya,

Bandung, 16 Januari 2025

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Building of Informatics, Technology and Science (BITS)
Volume 99, No 99, Bulan 2023 Page: 999−999
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v9i9.999

Public Political Sentiment Post 2024 Presidential Election: Comparison of Naïve Bayes and Support Vector Machine

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Abstract−One nation with a democratic political system is Indonesia. The public is able to express themselves freely. The public's use of social media is expanding quickly, particularly among users of platform ‘X’. The now trending tweets concern the 2024 presidential election. The reaction to the results of the 2024 presidential election has ranged from positive to negative to neutral. Large numbers of tweets can be used as a source of information to do their sentiments analysis. It is possible to know if people, in general, are satisfied or unsatisfied with the outcome of the presidential election thanks to the emotion categorization. This study aims to analyze public sentiment regarding the election result utilizing machine learning methods which will provide insights into public opinion that can be useful in political strategy as well as in public discourse assessment. In this paper, we will compare the Naïve Bayes Classifier (NBC) and the Support Vector Machine (SVM) algorithms for tweet classification of platform ‘X’ sentiment. This study presents the performed data analysis on 2193 data points (from platform X) that have been classified into neutral, positive, and negative categories using the Naive Bayes Classifier (NBC) and Support Vector Machine (SVM) techniques. Balancing SMOTE is used to address data imbalance, and TF-IDF is applied for feature extraction. Results depicts that Naïve Bayes Classifier (NBC) gives an accuracy of 62.41% whereas Support Vector Machine (SVM) gives 62.19% accuracy. This accuracy on these creations demonstrates how able models can be when classifying varying public sentiments between political events, highlighting the abilities, but also weaknesses of such efforts in sentiment classification. This paper contributes to the further development of sentiment analysis by providing an assessment of how effective these algorithms are, and by stressing the need for unbalance data treatment on research utilizing social media.

Keywords: Naïve Bayes Classifier; Support Vector Machines; 2024 Presidential Election results; X; Dataset; TF-IDF; Sentiment Classification

1. INTRODUCTION

Democracy is a system of government in which political power is held collectively by the people [1]. Indonesia is a country that adheres to a democratic system. The democratic system is characterized by periodic general elections. On February 14, 2024, Indonesia will hold simultaneous elections to choose the president and vice president. The presidential and vice presidential elections in 2024 will be a historic moment for the Indonesian people. Following the election, speculation and debates emerged regarding the results. In addition to speculation and debate, there were also pros and cons regarding the existing government policies.

Sentiment analysis [2] is crucial in this research as it provides a systematic way to understand public opinion regarding the results of the 2024 Indonesian presidential election, which is a significant political event. Following the election, social media platforms like X became a hub for the public to express their views, leading to a surge in opinions, debates, and even polarized discussions. Analyzing this data helps uncover sentiment toward the election results and government policies, offering insights into societal reactions and public discourse. By applying sentiment analysis, this research aims to address the challenges of understanding large-scale public feedback and identifying key trends in sentiment, which can inform policymakers and stakeholders about the perspectives and concerns of the population during a pivotal moment in Indonesia's democratic process.

The government is an institution that has already utilized social media to gather input or ideas from the public [3]. X, as a popular social media platform, has become a venue for the public to express views, opinions, and sentiments related to political issues, including the presidential and vice-presidential elections [4]. The data generated by X provides a meaningful representation of public sentiment towards political issues post the 2024 presidential election. Therefore, sentiment analysis using the Naïve Bayes approach becomes important to understand public opinion post the 2024 Presidential election.

The significance of this research lies in its ability to provide actionable insights into the dynamics of public sentiment during a critical political event, such as the 2024 presidential election [5]. While traditional opinion polls capture a limited scope of public opinion, sentiment analysis on social media offers a more dynamic, real-time understanding of the public's perspectives. This study not only highlights the role of social media as a reflection of societal views but also explores the effectiveness of machine learning techniques in processing unstructured data. By identifying the sentiments and opinions expressed on X, this research contributes to the growing field of social media analytics, demonstrating its potential to guide policymakers, enhance political strategies, and foster informed public discourse in Indonesia's democratic landscape.

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Volume 99, No 99, Bulan 2023 Page: 999−999
ISSN 2684-8910 (media cetak)
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Therefore, a comparison between the Naïve Bayes Classifier (NBC) [6] and Support Vector Machine (SVM) [7] methods is conducted to classify public sentiment on social media platform X. Naïve Bayes Classifier has many advantages, one of which is its speed in calculations, a simple algorithm, and the ability to produce high accuracy [8]. However, a previous study on the implementation of X sentiment analysis for movie reviews using the Support Vector Machine (SVM) algorithm, a stable accuracy rate of up to 76% was achieved, which is better than the Naïve Bayes Classifier (NBC) algorithm that only stabilized at 75% [9].

This research was conducted to classify public opinion on Twitter regarding the results of the 2024 presidential election. The aim of this study is to classify public sentiment among Twitter users towards the results of the 2024 Presidential election by comparing the Naïve Bayes Classifier (NBC) method and the Support Vector Machine (SVM) method. The outcome of this research is the accuracy value of public sentiment towards the 2024 Presidential election results and to determine which method is considered to have higher accuracy.

Previous study related to sentiment classification include research using the Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM) methods in sentiment analysis on the impact of the covid-19 virus in X, with NBC achieving an accuracy of 81.07% and SVM 79.96% [10]. A study conducted sentiment analysis research on KAI access reviews using NBC and SVM, with NBC achieving an accuracy of 82.23% and SVM 91.63% [11].

From several previous studies conducted, the Naïve Bayes Classifier method achieved a high accuracy rate. However, other research has also proven that the support Vector Machine (SVM) can achieve higher accuracy than the Naïve Bayes Classifier (NBC) method. By comparing the Naïve Bayes Classifier (NBC) and Support Vector machine (SVM), it can be determined which method is most effective in assessing the pros and cons in society, particularly among X users, regarding the results of the 2024 Presidential election.

2. RESEARCH METHODOLOGY

2.1 Research Stages

To illustrate the research flow, a flowchart is needed. The flowchart consists of several steps to complete the research on order to achieve efficient results. The steps are data crawling, data labelling, data preprocessing, splitting data into training and test data, feature extraction using TF-IDF, modelling using Naïve Bayes Classifier (NBC), modelling using Support Vector Machine (SVM), and performance evaluation. In the preprocessing stage, it consists of cleaning, case folding, normalization, stopword removal, and stemming. The flowchart sequence from the beginning to the end is shown in figure 1.

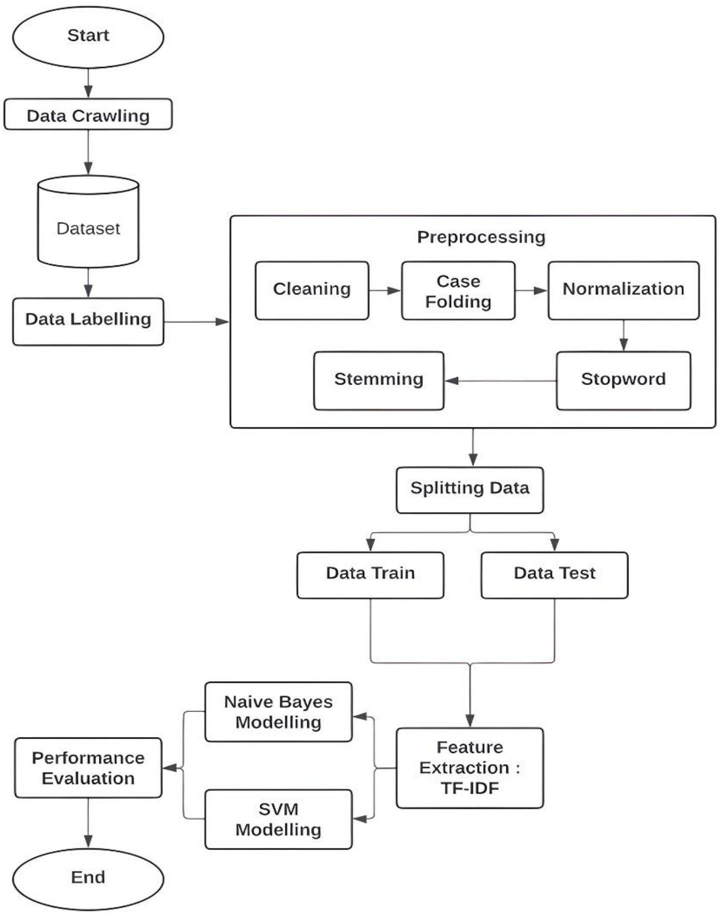

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Figure 1. Flowchart System

2.2 Data Collection

The data obtained is the result of data crawling on X. Data crawling is a stage carried out to retrieve or collect from the X server using the available API [4]. Data crawling was conducted using the keywords 'prabowo', 'gibran samsul', 'prabowo gibran', 'dukung prabowo', and 'fufufafa'. Then, total of 2193 data points were obtained. Table 1 shows the raw data, the result of the crawling.

Table 1. Dataset from Crawling X

Full Text
@saktiawanferi25 Iru urusan Prabowo soal pemilu curang loe bangga blom dilantik jd presiden definitif, tp gw bicarakan presiden ndablegh gak punya malu, paham kau ?
Semua elemen masyarakat dukung Hasil Pemilu 2024 Prabowo-Gibran Presiden dan Wakil Presiden terpilih #pemilupenuhdamai #PemiluIndonesia https://t.co/ifXwdPKhni
@DindinSofyant PDIP menolak Gibran Cawapres Karena Tidak Memenuhi Ambang Batas Usia Minimum Bambang. Jangan kau bolak balikkan fakta, yg nyatanya owi owo omar dan samsul berkomplot merubah konstitusi.
@IMachjar @mohmahfudmd @gibran_tweet @prabowo Gibran msh banyak yg milih. Masih aja sakit hati wahai manusia kalah.
Karena tak berotak maka aku hanya mampu bagi-bagi susu. Karena tak berotak maka aku gugup dan gagap menghadapi wartawan. Karena tak berotak maka menjadi Fufufafa adalah satu-satunya keahlianku. Selamat siang. Fufufafa terlekat selalu diberitamu. Rela? Ga terhina? :)

2.3 Data Labelling

Before entering data preprocessing, the crawled data will be labelled. The purpose of this data labelling is to facilitate the data classification process. In this labelling, data containing neutral tweets will be labelled "0", data containing positive tweets will be labelled "1", and data containing negative tweets will be labelled "2". Table two shows the number of each label in the dataset. Label "0" has 657 instances, label "1" has 511 instances, and label "2" has 1025 instances. Table 2 presents the quantity of data corresponding to each positive, negative, and neutral label.

Table 2. Dataset from Crawling X

Label	Total
0	657
1	511
2	1025
Total	2193

2.3 Pre-Processing Data

Before Preprocessing is a process where the dataset collected from social media X will be cleaned of unnecessary elements so that it will obtain data of high quality and according to what is desired [12]. The preprocessing process is divided into several stages, cleaning, case folding, normalization, removing stopword, and stemming.

1. Cleaning is a step for data cleansing on each tweet from URLs, punctuation, emoticon, etc.
2. Case folding makes all datasets lowercase.
3. Normalization is the process of standardizing non-standard words into standard words. Normalization is the process of standardizing non-standard words into standard words.
4. Stopwords removal allows for the removal of conjunctions.

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Volume 99, No 99, Bulan 2023 Page: 999−999
ISSN 2684-8910 (media cetak)
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5. Stemming is the stage of removing affixes to obtain the root word. Stemming is a stage to remove affixes and reduce words to their base form.

Data before preprocessing and results after preprocessing are shown in table 3.

Table 3. Before and After Preprocessing

Before Preprocessing	After Preprocessing
"@H4T14K4LN4L42 @jokowi @prabowo TERKUTUKLAH WAHAI KAU LAKNAT!!!"	terkutuklah wahai kau laknat
"@FaGtng @AgusYudhoyono @jokowi @prabowo Beda dg yg ini ketika sdh waras https://t.co/naM7a0piJb"	beda dengan yang ini ketika sudah waras
"Semua menghormati kemenangan prabowo https://t.co/7fDLPyFeam"	semua hormat menang prabowo

2.4 Feature Extraction TF-IDF

TF-IDF weighting is the stage of determining the weight value of each token in the document used for classification testing [13]. While the Inverse Document Frequency (IDF) approach computes the logarithm of the inverse proportion of documents in the corpus that contain a given word, the Term Frequency (TF) method counts the frequency with which a certain word occurs in a document [14]. Combining the two, TF-IDF generates a way to assess a word's significance in a document in relation to a group of other documents. The formula for calculating weights in the TF-IDF method can be formulated as follows:

$$tf = 0{,}5 + 0{,}5 \times \frac{tf}{\max(tf)} \quad (1)$$

$$idf = \log\left(\frac{D}{df_t}\right) \quad (2)$$

$$W_{d,t} = tf_{d,t} \times IDF_{d,t} \quad (3)$$

tf is the number of times a word is searched in a document. $\max(tf)$ represents the highest occurrence of a term in the same document. The value of D is the total number of documents. df_t is the number of documents that contain term-t. IDF (Inversed Document Frequency) is the value of $\log\left(\frac{D}{df_t}\right)$. d is the d-th document. t is the t-th word of the keyword. W is the weight of the d-th document against the t-th word.

TF-IDF Vectorizer [15] is used in this study to extract text features. To ascertain the range of N-grams as features in the extraction procedure, TF-IDF Vectorizer makes use of the N-gram range option. The N-gram, which is made up of textual sequences of n-words, help the model in better identifying word patterns. This study uses a two kind of n-gram. Table four shows an example of using the N-gram parameter in TF-IDF [16]. Examples of N-gram parameter combinations in TF-IDF are shown in table 4.

Table 4. TF-IDF N-Gram

N-Gram	Tweet
Unigram + Bigram	[prabowo], [fufufafa], [gibran], [prabowo, fufufafa]
Unigram + Trigram	[prabowo], [fufufafa], [gibran], [prabowo, fufufafa, gibran]
Unigram	[prabowo], [fufufafa], [gibran]

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Unigrams capture individual word frequencies, making them effective for recognizing simple word-level mood cues. Bigrams and trigrams, which represent sequences of two and three words, respectively, help in understanding contextual word pairs and common phrases related to public political sentiment. By combining unigram, bigram, and trigram, the model acquires a more comprehensive understanding of both individual word sentiment and context-dependent sentiment patterns, improving its ability to categorize sentiment more successfully.

2.5 Model Classification

After the dataset passes through the preprocessing and feature extraction stages, it will be classified using the Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM) classification algorithms. The Naïve Bayes Classifier (NBC) is a classification method with simple probability that applies Bayes' theorem with high independence [17]. Naïve Bayes analyzes data sentiment using sentence-level classification as negative, positive, or neutral [18]. The polarity of statements (positive, negative, neutral) is calculated based on the features selected using n-gram [19]. In this study, Unigram + Bigram is used.

Support Vector Machine (SVM) is one of the message-to-natural language translation techniques that eliminates the expression of supervised learning techniques with atypical quality and accuracy, thereby minimizing noise at the good stages, making it an algorithm [20]. SVM is a supervised learning algorithm widely used in classification problems with reliability [21]. The accuracy of the Support Vector Machine (SVM) model depends on the characteristics and parameters of the kernel [22]. This research uses SVM with the 'linear' kernel was selected for several reasons.

Indeed, the linear kernel is very powerful for high-dimensional data, which is what usually text classification problems reduce at the end, a sparse feature matrix obtained by means of techniques like TF-IDF vectorization. The first is the linear kernel, which is a very simple method that attempts to find an optimal hyperplane that keeps data points of different classes separate from each other, making it computationally efficient and well-suited to large text datasets. The linear kernel is simple and consequently comes with a lower training cost than more complex alternatives like the Radial Basis Function (RBF) or polynomial that entails further parameter tuning. The linear kernel is naturally interpretable, providing the means to extract the words contributing to classification decisions.

2.6 Evaluation

This study assessed the performance of the Naïve Bayes Classifier (NBC) and the Support Vector Machine (SVM) algorithms through a train/test split method applied to the sentiment classification models developed in this work. 2.193 tweets were split in training and testing sets. This approach allows us to maximize training on most of the data whilst maintaining a separate set of data to assess generalization performance.

Balancing SMOTE was used to balance sentiment classes (positive, negative, and neutral) in the training data as we recognized the likelihood of bias occurring because of imbalanced data. Replication of minority class instances by this strategy has yielded a more uniform class distribution and prevents models from biasing toward majority classes.

The performance evaluation of this research uses a confusion matrix. The confusion matrix can estimate how well the model distinguishes between classes by comparing the actual and predicted classifications from the model [15]. The confusion matrix consists of 4 values: True Negative (TN), False Negative (FN), True positive (TP), and false positive (FP). These 4 values are employed to assess the classification model of the NBC and SVM algorithms. The four values that are the results are Accuracy, Precision, Recall, and F1-score.

1. Accuracy

$$\frac{(TP+TN)}{(TP+FP+FN+TN)} \tag{4}$$

2. Precision

$$\frac{TP}{(TP+FP)} \tag{5}$$

3. Recall

$$\frac{TP}{(TP+FN)} \tag{6}$$

4. F1-score

$$2 \times \frac{Recall \times Precision}{Recall \times Precision} \tag{7}$$

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3. RESULT AND DISCUSSION

In this research, several test scenarios will be carried out on two classification models, namely Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM). The first scenario is carried out by dividing the test data and training data into 10:90, 20:80, 30:70, 40:60, and 50:50.

The second scenario was conducted using TF-IDF for word weighting with unigram - bigram and unigram - trigram. The third scenario was carried out using random oversampling. Random oversampling aims to ensure that the data is not imbalanced. Random over sampling uses SMOTE to make the positive instances more densely distributed in order to make the boundaries more well defined [23].

3.1 Experiment Results

The first scenario is to split the test data and the training data. The Naïve Bayes Classifier (NBC) used is Complement Naïve Bayes with 5-fold cross-validation. Meanwhile, the Support Vector Machine (SVM) uses a 'linear' kernel.

In table 5, Naïve Bayes Classifier (NBC) achieved the highest accuracy (62.41%) with a split ratio of 40:60, demonstrating its robustness when given a balanced training set to help mitigate bias from imbalanced distributions. This feature makes Naïve Bayes Classifier (NBC) an excellent choice for exploratory analyses or when computational efficiency is important.

Support Vector Machine (SVM) got the highest accuracy of 62.19 percent while using a split ratio of 20:80 and this process demonstrates how well SVM generalizes with limited training data This kind of makes SVM useful for features that are more complex.

The 20:80 split ratio performed well for Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM) during the scenario of this study, that ratio was selected when trying out the other performance splits. Naive Bayes Classifier (NBC) had the most accuracy at 62.41% with the 40:60 ratio, but the 20:80 will give the most balanced generalization versus size of the training set.

Table 5. Results of First Scenario Test

Splitting Ratio	Accuracy	
	NBC	SVM
10:90	60.00%	60.00%
20:80	60.82%	**62.19%**
30:70	62.16%	62.16%
40:60	**62.41%**	61.16%
50:50	61.62%	61.62%

Table 6 shows the evaluation metrics on the NBC and SVM models with a test and train data split of 20:80.

Table 6. Results of the Confusion Matrix

Model	Metrics		
	Precision	Recall	F1-Score
NBC	61.22%	59.36%	59.77%
SVM	**61.71%**	**62.52%**	**62.04%**

The second scenario is to apply a combination of n-gram parameters. The combinations used are unigram-bigram and unigram-trigram. Table 7 shows the results of the second scenario, which has the best accuracy with the Unigram-Bigram combination in the NBC model with an accuracy of 60.82% and in the SVM model with an accuracy of 62.19% based on a 20:80 splitting ratio.

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NBC uses conditional prababilities, which work well with simple feature representations like unigrams. This is because NBC assumes feature independence, reducing its reliance on complex contextual patterns. In this situation, NBC did reasonably well with both Unigram-Bigram (60.82%) and Unigram-Trigram (61.05%) combinations, indicating its ability to detect fundamental patterns in the data.

SVM performs well in instances with complex feature spaces, such as those formed by N-gram pairings. SVM uses a linear kernel to determine the best hyperplane for separating sentiment classes, allowing it to effectively manage sparse and multidimensional data. The Unigram-Bigram combo scored the highest SVM accuracy (62.19%) demonstrating the capacity to balance individual word-level sentiment markers with contextual insights from bigrams.

The results of this scenario indicate that NBC is a reliable solution for scenarios needing quick, interpretable results, especially when the dataset is simple or lacking complex patterns. Meanwhile, SVM is more suited for problems involving complex data patterns, where the contextual relationships between words are critical to proper categorization.

Table 7. Results of Combination N-gram

N-Gram	Accuracy	
	NBC	**SVM**
Unigram - Bigram	60.82%	**62.19%**
Unigram - Trigram	**61.05%**	61.73%
Bigram	51.94%	51.94%

The third scenario is by applying random oversampling. Random oversampling addresses data imbalance by creating a more evenly distributed dataset. This random oversampling uses SMOTE. After random oversampling, each label—positive, neutral, and negative—amounts to 825. Figure 2 shows the data visualization after balancing SMOTE.

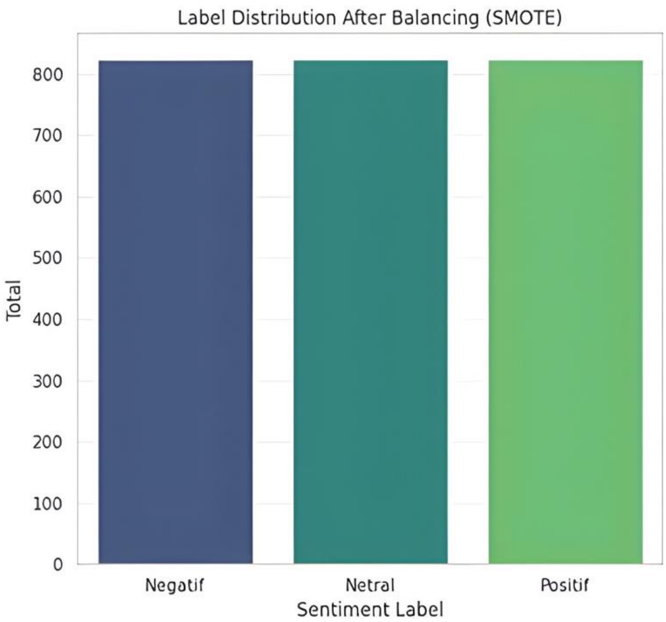

Figure 2. Label Distribution of Balancing (SMOTE)

Table 8 shows the results of the third scenario by implementing random oversampling uses SMOTE. In the NBC model, an accuracy of 59.91% was achieved, and in the SVM model, an accuracy of 59.68% was achieved. SMOTE was constructed using the 'imblearn' library in Python. Using 'k_neighbours' of 5, the number of nearest neighbours used to generate synthetic samples, and 'sampling_strategy' auto, all classes are balanced by majority class size. In addition, a 'random_state' of value 12 to a fixed seed with high probability is utilized to ensure that the findings are consistent.

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In this scenario, NBC scored 59.91% accuracy. Because of its simplicity and independence assumption, NBC is robust when dealing with balanced datasets. While its performance increases marginally after balancing, NBC's reliance on feature independence can occasionally restrict its capacity to record nuanced interplay between features. This explains why the accuracy does not much improve after balancing.

The SVM model scored 59.68% accuracy. SVM is a sophisticated classifier that can handle high-dimensional data, although it is more susceptible to noisy or overlapping classifications. In this situation, even when SMOTE balances the dataset, synthetic samples can occasionally add minor noise, affecting the SVM's performance. Furthermore, while using a 'linear' kernel in SVM is computationally efficient, it may not fully capture the complicated relationships in the data after oversampling.

Table 8. Model's Accuracy After Balancing

Model	Accuracy
NBC	**59.91%**
SVM	59.68%

3.2 Analysis

Through a variety of testing scenarios, the NBC model in this study exhibited greater accuracy and stability. Balancing SMOTE, the ideal N-gram value combination with TF-IDF, and splitting ratio were the testing scenarios used to identify the optimum model. The accuracy values for each testing scenario are presented in Figure 3.

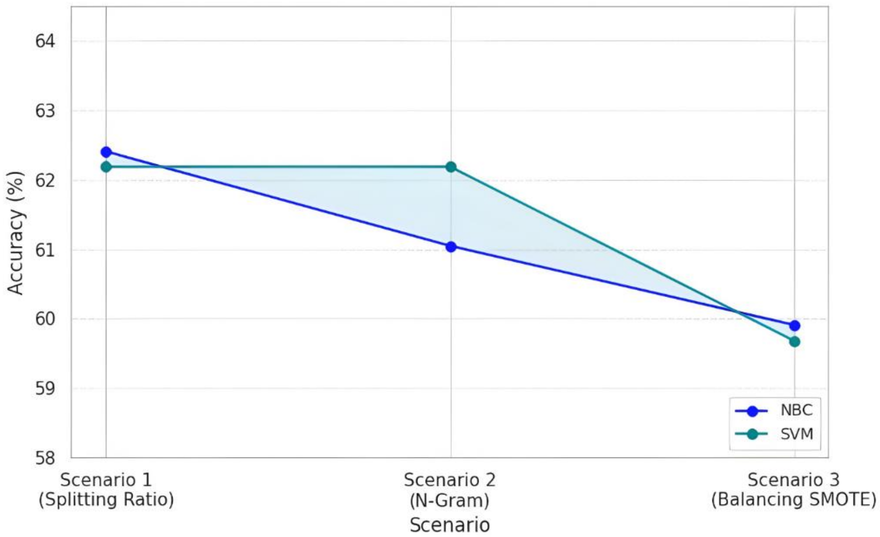

Figure 3. Distribution Labels of All Scenarios

The Naïve Bayes Classifier (NBC) model achieved its greatest accuracy of 62.41% in the first test scenario when splitting using a 40:60 ratio. With a 20:80 splitting ratio and an accuracy of 62.19%, the Support Vector Machine (SVM) model, on the other hand, obtained the highest accuracy. The accuracy of the Naïve Bayes Classifier (NBC) model dropped by 2.18% to 61.05% with a Unigram – Trigram combination in the second test scenario with a TF-IDF N-gram combination. In the meantime, the Unigram-Bigram combo generated an accuracy of 62.19% for the Support Vector Machine (SVM) model, which held steady from the initial test scenario. In the third scenario with balancing SMOTE, the Naïve Bayes Classifier (NBC) model decreased by 1.87% to 59.91%. In the meantime, the Support Vector Machine (SVM) model's accuracy dropped by 4.04% to 59.68%. The decrease in the Naïve Bayes Classifier (NBC) model from the first to the third scenario remains relatively stable, with an average decrease of 2.03%, whereas the Support Vector Machine (SVM) model decreases by 4.04%.

According to a number of test scenarios that have been carried out. When compared to the Support Vector Machine model, the Naïve Bayes Classifier (NBC) model performs better and more consistently. The Support Vector Machine (SVM) model's performance is initially rather consistent before experiencing a notable fall of 4.04%, which is larger than the Naïve Bayes Classifier (NBC) model's performance decline of only 2.03%.

The research suggests that the Naïve Bayes Classifier (NBC) model is more effective due to its accuracy and stability. Class imbalance can be addressed with balancing SMOTE, which balances the class distribution in the data by duplicating new samples. NBC efficiently learns the pattern of each class using a balanced distribution.

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4. CONCLUSION

This study makes use of data from platform "X" regarding the presidential election results in 2024. The sample included 2,193 tweets, with 1,025 classified as negative, 657 as neutral, and 511 as positive. The dataset was evaluated using Naïve Bayes Classifier (NBC) and Support Vector Machine (SVM) models, with TF-IDF used for feature extraction. The Naïve Bayes Classifier (NBC) model had the highest accuracy of 59.91% after using balancing techniques like SMOTE. In three testing scenarios, the Naïve Bayes Classifier (NBC) outperformed the Support Vector Machine (SVM) model for accuracy and stability. Furthermore, the results of this study can classify tweets about the 2024 presidential election on platform 'X' as neutral, good, or positive. These findings are critical for sentiment analysis in elections, as understanding public opinion can provide valuable information for political campaigns and media analysis. For example, NBC's consistent performance demonstrates reliability when balance is available, whereas SVM's performance under certain conditions demonstrates its applicability to datasets with high complexity. Despite these benefits, this study has limitations. The dataset is restricted to the ‘X’ platform, which may not accurately reflect popular mood across all social media platforms. While SMOTE helps decrease data imbalance, it also introduces synthetic samples, which might have an impact on the performance of some models, such as SVM. Feature extraction technique and other hyperparameter optimization strategies might be investigated to enhance the model’s performance.

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Building of Informatics, Technology and Science (BITS)
Volume 99, No 99, Bulan 2023 Page: 999−999
ISSN 2684-8910 (media cetak)
ISSN 2685-3310 (media online)
DOI 10.47065/bits.v9i9.999

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