Indonesian Journal of Data and Science

Volume 6 Issue 3
ISSN 2715-9936
https://doi.org/10.56705/ijodas.v6i3.366

Research Article

Comparison of Naïve Bayes and Random Forest in Sentiment Analysis of State-Owned Banks Management by Danantara on X and YouTube

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Received 18 October 2025; Accepted 20 December 2025; Published 31 December 2025

Abstract:
The advancement of digital technology has increased public engagement in expressing opinions and responding to issues on social media platforms such as X and YouTube. A prominent topic of recent public debate concerns Danantara's management of state-owned banks. This study analyzes public sentiment regarding this issue by comparing the performance of the Naïve Bayes and Random Forest classification methods. A dataset comprising 25,565 entries was collected from both platforms between January 2025 and May 2025. The data underwent text pre-processing, labeling with the InSet Lexicon, and feature weighting using term frequency-inverse document frequency (TF-IDF). The dataset was split at 80:20, and class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE) prior to classification. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics. The results demonstrate that Random Forest performed stably, achieving 84% accuracy both before and after sampling. In contrast, Naïve Bayes achieved 74% accuracy before sampling, which increased to 79% after sampling. These findings suggest that Random Forest is more robust to data imbalance than Naïve Bayes, which is more susceptible to bias toward the majority class.

Keyword: Sentiment Analysis, Naïve Bayes, Random Forest, Danantara, Stated-owned Bank.

1. Introduction:

Social media is a place where people can search for and share information, connect with people around the world, and express their opinions on current events. According to The Global Statistics, the number of social media users in Indonesia continues to grow, reaching 12.6% in 2024, an increase of 21 million compared to the previous year. Among Indonesians, the most widely used social media platforms are X and YouTube [1]. The X social media platform is often used to convey various personal and public opinions. Users utilize the X application to exchange messages and post opinions. Additionally, X is frequently used to search for trending information, with users often responding to it [2], [3]. The transfer of state-owned bank management to Danantara is one of the topics widely discussed by X users, with hundreds to thousands of posts ranging from opinions in support to questions. In addition to the X app, this topic is widely discussed on YouTube, the largest platform for sharing information in video format and a social media platform that allows users to watch [4], comment, share, and broadcast videos.

Recently, President Prabowo launched the Daya Anagata Nusantara Investment Management Agency (BPI Danantara), a strategic investment management agency tasked with consolidating and optimizing government investments to boost national economic growth [5]. This agency will also manage state-owned banks such as BNI, BRI, and Mandiri [6]. The transfer of management of state-owned banks to Danantara has become a contentious issue, with numerous opinions expressed by the public, both positive and negative. Although Danantara has not yet been officially implemented, the discussion has become the focus of public attention on various social media platforms. The opinions expressed on social media can significantly impact customer confidence in state-owned banks, ultimately affecting the government's image and that of its related financial institutions [7], [8].

Previous studies have compared these two methods but have not emphasized the issue of class imbalance, which frequently occurs in social media sentiment analysis. This imbalance can cause models to be biased toward the majority class, leading to inaccurate performance evaluations. Furthermore, prior research has not employed sampling techniques to assess how changes in data proportions affect the classification capabilities of each algorithm. This study addresses these gaps by comparing the performance of Random Forest and Naïve Bayes on an imbalanced Indonesian social media sentiment dataset and by applying SMOTE sampling to provide a more comprehensive and representative evaluation [9].

This comparison also seeks to identify the strengths and limitations of each method, thereby providing an objective assessment of their suitability for the dataset in question and determining whether public opinion regarding Danantara's management of state-owned banks is predominantly negative or positive [10], [11]. This study focuses on the use of comment data on the X and YouTube applications in Indonesian, where sentiment results will be categorized into two categories: negative and positive. This study does not encompass the entire discussion related to Danantara, but instead focuses on the keywords “Bank BUMN ke Danantara” and “Danantara BUMN”. This study contributes by comparing the Naïve Bayes and Random Forest methods for sentiment analysis of Danantara's management of state-owned banks. The comparison offers insights into each method's ability to handle unbalanced data and evaluate model performance. The findings are expected to reveal public opinion on Danantara's management of state-owned banks and provide an indication of public readiness to accept new policies [10].

2. Method:

The research methods used are Naïve Bayes and Random Forest. These two methods will be compared to evaluate their respective performances. The stages of this research are illustrated in **Figure 1**. The research began with collecting data using crawling techniques on the X and YouTube applications, focusing on two keywords: “Bank BUMN ke Danantara” and “Danantara BUMN,” and data collection began in January 2025 and ended in May 2025. Data crawling was performed using Google Colaboratory and Python. Collecting data from these two applications enabled additional sentiment analysis. After the data was successfully collected, a pre-processing stage was performed to remove unnecessary elements, such as symbols, emojis, numbers, URLs, and duplicate data. Duplicate data removal was identified based on text similarity, so that any opinion that appeared more than once was deleted, and only its first occurrence was retained. This stage was carried out to avoid bias in the analysis results and to reduce overfitting.

After the data passes the pre-processing stage, it is labeled using the InSet Lexicon, which is an Indonesian dictionary sourced from the X application. This dictionary also contains score weights for each word. The next stage involves dividing the data at an 80:20 ratio, bootstrapping with TF-IDF, and then sampling. The sampling approach method used in this study is the Synthetic Minority Over-sampling Technique (SMOTE). This sampling approach is used because it can balance sentiment classes without duplicating data excessively. By generating synthetic samples via interpolation of minority data, SMOTE reduces overfitting, improves model learning in minority classes, and improves metrics such as Recall and F1-Score. The next stage is classification using Naïve Bayes and Random Forest. Finally, the model is evaluated using a Confusion Matrix. This stage is carried out to determine the sentiment analysis results on Danantara's management of state-owned banks, specifically whether the sentiment is negative or positive, and to compare the two methods.

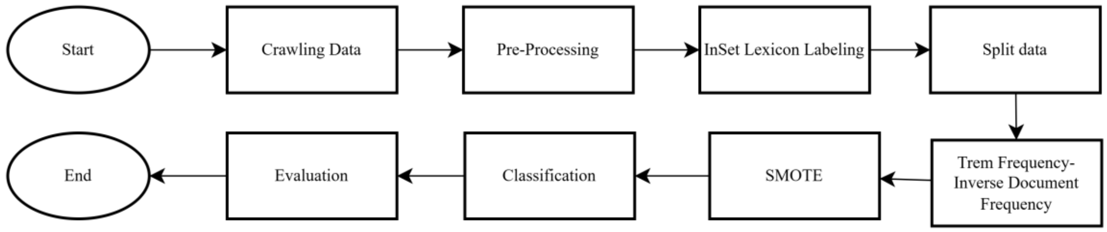

Figure 1. Research Flow

Sentiment Analysis

Sentiment analysis is a technique or process used to identify sentiment, emotions, and feelings contained in texts, such as articles, reviews, documents, and messages on social media [12]. The purpose of sentiment analysis is to study and measure people's emotional reactions or opinions on certain topics, products, services, or events. The analysis will be used to process data in order to gain a deeper understanding so that conclusions can be drawn. In the sentiment analysis process, there are three levels of sentiment analysis, namely document, sentence, and aspect. These three levels of sentiment are used to identify a number of negative, positive, and neutral areas in each sentiment [13], [14].

Naïve Bayes

Naïve Bayes is an algorithm that utilizes the concept of probability and is often applied in sentiment analysis classification, a technique commonly used for text classification [15]. This algorithm is based on Bayes' theorem, developed by the British scientist Thomas Bayes, which enables classification by calculating probabilities. The advantages of using the Naïve Bayes algorithm include a lower error rate when the dataset is large [16]. Additionally, Naïve Bayes achieves high accuracy when applied to larger datasets [17], [18]. The Naïve Bayes algorithm includes several variations, such as Multinomial Naïve Bayes, Bernoulli Naïve Bayes, Gaussian Naïve Bayes, Complement Naïve Bayes, and Categorical Naïve Bayes [19]. This analysis employs Multinomial Naïve Bayes for sentiment analysis. The Multinomial Naïve Bayes classifier is widely used in text mining due to its computational efficiency, straightforward implementation, and high effectiveness. It calculates the probability of a class based on its attributes and assigns the class with the highest probability. The classifier assumes that each attribute in the data is mutually independent [20].

Random Forest

The Random Forest Classifier algorithm is an extension of the Decision Tree algorithm that addresses its weaknesses, such as overfitting, by combining multiple decision trees to produce more stable and accurate predictions [21]. The Random Forest model generates many trees, and as the amount of data increases, so do the trees. Random Forest has several advantages, one of which is its ability to improve accuracy when data are missing. In addition, Random Forest includes a feature selection process that selects the best features to improve classification model performance. There are three main points in the Random Forest method, namely: (1) performing bootstrap sampling to build prediction patterns; (2) each decision tree makes predictions with random predictors; (3) then Random Forest makes predictions by combining the results of each decision tree using majority votes for classification or averages for regression. This study will build 200 decision trees to perform classification to improve accuracy and efficiency [22], [23].

Pre-Processing

Pre-processing is a crucial stage in text mining that aims to ensure the data can be used with high quality and accurately display the available information. This stage aims to reduce noise and data inconsistencies, enabling the use of the data for sentiment analysis [24]. The data pre-processing stage involves:

1) Cleaning: Cleaning is the stage of removing unnecessary characters, punctuation marks, and numbers. Examples include question marks, exclamation marks, commas and periods, as well as emojis and symbols.

2) Case Folding: Case Folding is the stage of converting all components in the text to lowercase letters.
3) Normalization: Normalization is the stage of normalizing non-standard words, which aims to restore the spelling of each word to match the Indonesian Dictionary (KBBI).
4) Tokenizing: Tokenizing is the stage of breaking sentences into single words, or tokens. Additionally, this stage removes certain characters, such as punctuation marks, and filters text based on its length.
5) Filtering/Stopword Removal: Filtering/Stopword Removal is the stage of removing or deleting terms that are not considered in sentiment analysis.
6) Stemming: Stemming is the stage of removing words that have prefixes to form the root word. This step also removes words with incorrect spelling [25].

InSet Lexicon Labeling

The Indonesian Sentiment Lexicon, also known as InSet Lexicon, is a lexicon-based system that utilizes an Indonesian sentiment dictionary developed in 2018 by Fadjri Koto and Gemala Y. Rahmaningtyas. InSet Lexicon contains a dictionary of approximately 10,218 words, comprising 3,609 positive sentiment words and 6,609 negative sentiment words [26]. The InSet Lexicon dictionary was compiled from data on social media X, with a weight value or polarity score ranging from -5 (very negative) to 5 (very positive) [27]**.** This dictionary was developed to identify written opinions and categorize them as positive or negative, which can be used to evaluate public sentiment towards certain topics, events, or products [28], [29]. Labeling in this study will be divided into two categories: negative and positive. Comments are classified as positive if the score is greater than 0 and negative if the score is less than or equal to 0.

Term Frequency-inverse Document Frequency (TF-IDF)

TF-IDF weighting is a method commonly used to determine the relationship between words (terms) and documents or sentences by assigning weights or values to each word. TF-IDF is a static model for evaluating the importance of words in a collection of documents, where TF represents the frequency of occurrence of a word in a text or document, and DF measures the importance of a word, balanced by how often a word appears in the entire dataset. IDF is the inverse of the DF value [30].

$$TF_t = (t, d) \tag{1}$$

$$IDF_t = log\frac{n}{df(t)} + 1 \tag{2}$$

$$TF\ IDF_t = TF_t \times IDF_t \tag{3}$$

3. Result and Discussion:

The initial stage of this research was data collection using crawling techniques on the X application and YouTube. Data collection on the X application and YouTube yielded 13,711 X data points and 11,854 YouTube data points. The data will later be combined into a single dataset to facilitate the analysis process, resulting in a total of 25,565 data points. Before conducting the direct testing process using the Naïve Bayes and Random Forest methods, the data is first divided into test data and training data. The data is divided into an 80:20 ratio, with 80% allocated for training data and 20% for test data. Then, a weighting process is carried out using TF-IDF. The classification process will be carried out in two stages: using the original data (unbalanced) and sampling data (balanced). This process is carried out to compare how the two methods handle unbalanced data.

Figures 2 and **3** show the results of the SMOTE process, with 7,907 negative and 3,523 positive data points before SMOTE was applied. After SMOTE sampling, there were 7,907 negative and 7,907 positive data points. With this sampling process, it is hoped that the classification model can learn more effectively about the patterns of both classes.

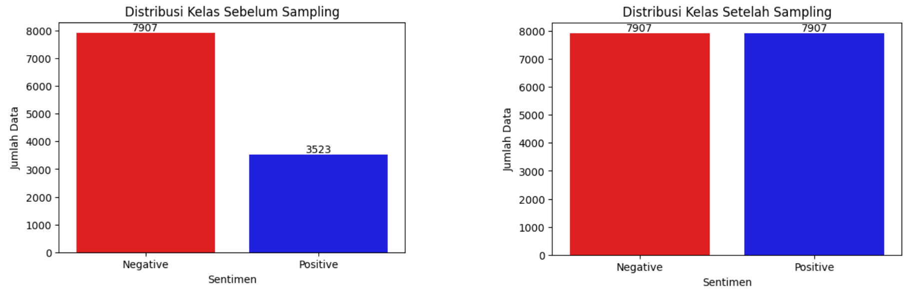

Figure 2. Class Distribution Before and After Sampling

After sampling using SMOTE, the next step is to perform classification using MultinomialNB (Naïve Bayes). The test achieved 74% accuracy with the original data, while the sample data produced 79%. Naïve Bayes performed better on sampled data than on the original data. This indicates that Naïve Bayes classification can identify and categorize sentiments more accurately and without bias towards any class. The Confusion Matrix was evaluated per sentiment class: TN (True Negative), TP (True Positive), FN (False Negative), and FP (False Positive). The following are the results of the Naïve Bayes Confusion Matrix before and after sampling:

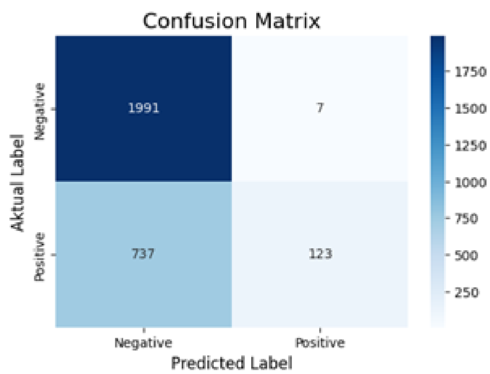

Figure 3. Naïve Bayes Confusion Matrix Before SMOTE

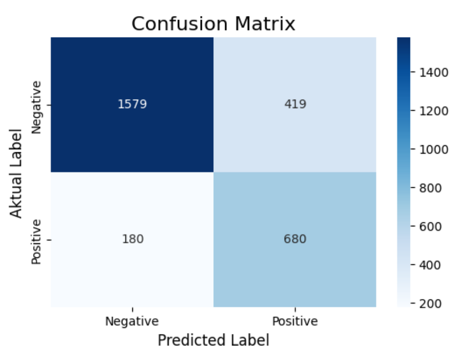

Figure 4. Naïve Bayes Confusion Matrix After SMOTE

The results of the model evaluation, as shown in **Figure 3**, indicate that the model successfully classified 1,991 true negatives and 123 true positives. Meanwhile, there were 737 false negatives and 7 false positives. **Figure 4** shows the results of 1,579 true negatives and 680 true positives. Additionally, there were 180 false negatives and 419 false positives. The overall evaluation results can be seen in the following **Table 1**.

Table 1. Naive Bayes Classification Results

Naïve Bayes	Data			
	Original		Sampling	
	Positive	Negative	Positive	Negative
Accuracy	74%	74%	79%	79%
Precision	95%	73%	62%	90%
Recall	95%	100%	79%	79%
F1 Score	25%	84%	69%	84%

Table 1 shows the results of Naive Bayes before and after sampling. Naive Bayes classification shows an improvement when the data used is balanced, achieving an accuracy of 79% compared to 74% previously. This demonstrates that Naive Bayes can help the model accurately recognize patterns in classes after the sampling process. After evaluation, the results of the analysis will be visualized using Pie Chart. This visualization is used to determine the percentage of sentiment results obtained through Random Forest classification, as well as to identify frequently occurring words that facilitate the analysis of patterns or common topics in text datasets.

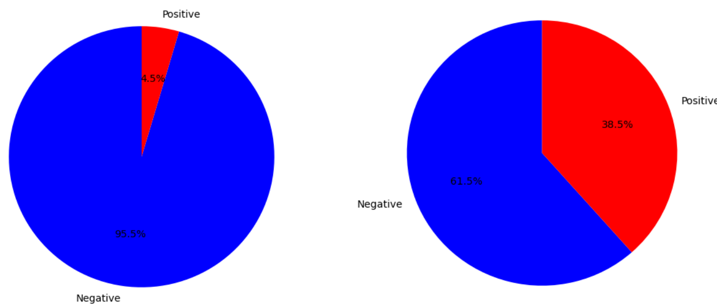

Figure 5. Naïve Bayes Result Before and After SMOTE

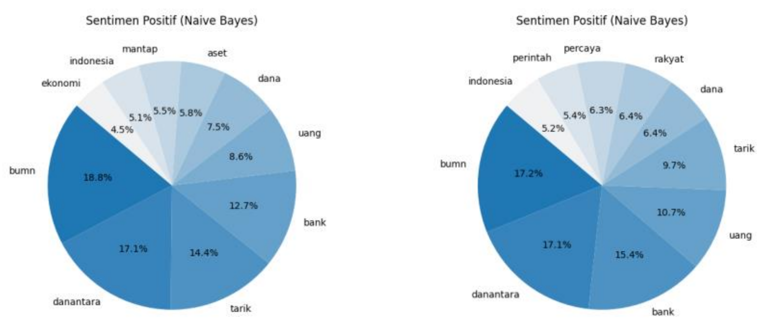

Figure 6. Positive Sentiment Word Naïve Bayes Classification Before and After Sampling

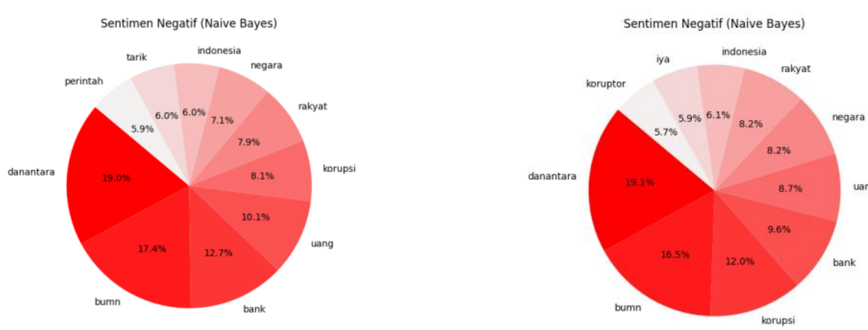

Figure 7. Negative Sentiment Word Naïve Bayes Classification Before and After Sampling

Figure 5 shows the results of Naive Bayes classification after sampling and before sampling. After sampling, the Naive Bayes method demonstrated an improvement in recognizing sentiment classes, with 1,099 positive sentiment results and 1,759 negative sentiment results following sampling, compared to 130 positive sentiment results and 2,728 negative sentiment results prior to sampling. **Figures 6** and **7** are visualizations of Pie Charts for the words that appear most frequently in positive and negative sentiments. From the diagrams above, we can see the ten most frequently appearing words, each with a different percentage depending on how often it appears in texts labeled as positive or negative

The second classification used is Random Forest. Random Forest classification is performed using n_estimator=200, meaning that the model will build 200 decision trees for classification. Random Forest achieved an accuracy of 84% for results using original data and sampled data. Random Forest classification provides more balanced results in this analysis process. These results demonstrate that the Random Forest method can effectively recognize classes, although there remains a slight tendency towards bias towards the majority class.

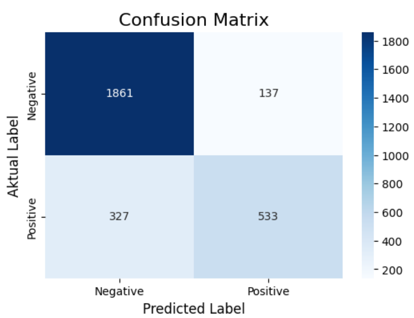

Figure 9. Random Forest Confusion Matrix After SMOTE

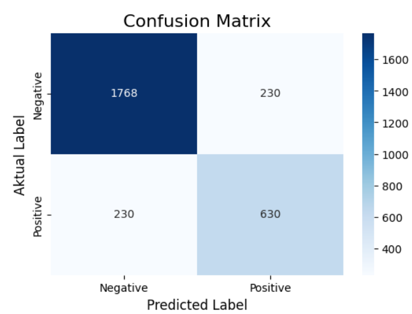

Figure 8. Random Forest Confusion Matrix Before SMOTE

The results of the model evaluation, as shown in **Figure 8**, indicate that the model successfully classified 1,861 true negatives and 533 true positives. Meanwhile, there were 327 false negatives and 137 false positives. Figure 8 shows the results of 1,768 true negatives and 630 true positives. Additionally, there were 230 false-negative data points and 230 false-positive data points. The overall evaluation results can be seen in the following table:

Table 2. Random Forest Classification Results

Random Forest	**Data**			
	Original		**Sampling**	
	Positive	**Negative**	**Positive**	**Negative**
Accuracy	84%	84%	84%	84%
Precision	80%	85%	73%	88%
Recall	62%	93%	73%	88%
F1 Score	70%	89%	73%	73%

Table 2 shows that the Random Forest method achieved an accuracy of 84%, with a precision of 85% and a recall of 89% for the negative class. For the positive class, the precision value obtained was 80%, and the recall was 62%. These results indicate that the Random Forest method yields more balanced outcomes compared to the Naïve Bayes method, although a slight bias towards the majority class remains. After evaluation, the results of the analysis will be visualized using Pie Chart. This visualization is used to determine the percentage of sentiment results obtained through Random Forest classification, as well as to identify frequently occurring words that facilitate the analysis of patterns or common topics in text datasets.

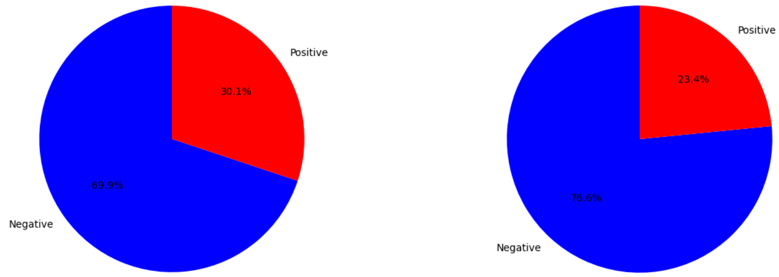

Figure 10. Random Forest Result Before and After

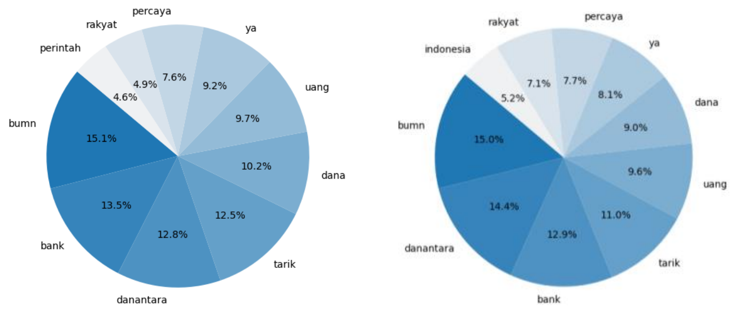

Figure 11. Negative Sentiment Word Random Forest Classification Before and After Sampling

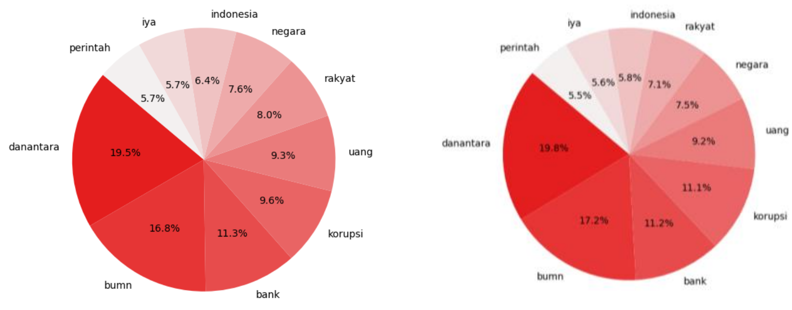

Figure 12. Positive Sentiment Word Random Forest Classification Before and After Sampling

Figure 10 shows the results of Random Forest classification after sampling and before sampling. After sampling, the Random Forest method demonstrated an improvement in recognizing sentiment classes, with 860 positive sentiment results and 1,998 negative sentiment results following sampling, compared to 670 positive sentiment results and 2,188 negative sentiment results prior to sampling. **Figures 11** and **12** are visualizations of Pie Charts for the words that appear most frequently in positive and negative sentiments. From the diagrams above, we can see the ten most frequently appearing words, each with a different percentage depending on how often it appears in texts labeled as positive or negative.

Discussion:

Based on the results of a comparative study of the Naïve Bayes and Random Forest methods, it was concluded that the highest data classification results were obtained by sentiment analysis using the Random Forest method, with an accuracy before and after sampling of 84%, and precision before and after sampling of 85% and 88%. The recall values before and after sampling were 93% and 88%, respectively, and the F1 scores before and after sampling were 89% and 88%, respectively. In comparison, the accuracy of the Naïve Bayes method was 74% before sampling and 79% after sampling. Similarly, the precision values before and after sampling were 73% and 90%. Then, the recall values before and after sampling were 100% and 90%, and the F1 scores before and after sampling were both 84%.

Overall, the comparison between the two methods reveals that the Random Forest method is superior in terms of both accuracy and handling unbalanced data. This method achieved 84% accuracy, while Naïve Bayes achieved 74% before sampling and 79% after sampling.

Random Forest is better at handling data imbalance than Naïve Bayes, which often shows bias towards the majority class. The findings of this study align with previous research comparing the performance of Naïve Bayes and Random Forests. Dina (2023) demonstrated that Naïve Bayes is limited in handling diverse Indonesian text data, achieving only 69.43% accuracy due to its sensitivity to unbalanced class distributions [31]. In contrast, Kurniasari (2024) reported that Random Forest achieved 99.38% accuracy in predicting student final grades, confirming its effectiveness in managing feature interactions and non-linear patterns [32]. Arisula (2024) also found that Random Forest performed more consistently than Naïve Bayes in sentiment analysis of the GetContact application. Collectively, these studies corroborate the present finding that Random Forest is superior to Naïve Bayes for Indonesian sentiment data, which is often unbalanced and lexically diverse [33].

Conclusion:

This study examines public sentiment regarding Danantara's management of state-owned banks using two classification methods: Naïve Bayes and Random Forest. The findings indicate that Random Forest is the most effective method, offering more stable performance and superior handling of class imbalance compared to Naïve Bayes. While Naïve Bayes' performance improved after data balancing, it remains less competitive in scenarios with complex data structures or imbalanced class distributions. The results confirm that ensemble-based models are better suited to the characteristics of Indonesian text, which exhibits significant lexical variation. A limitation of this study is the exclusion of a neutral class, which restricts the ability to capture ambiguous opinions. Future research should address this by introducing a neutral sentiment class and employing domain-specific lexicons for more nuanced sentiment analysis, including aspect-based evaluation. These enhancements will improve the robustness and detail of the findings, increasing their applicability in diverse real-world contexts.

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