RESEARCH ARTICLE   **Open Access**

Social Media Sentiment Analysis of Twitter Regarding People's Housing Savings (TAPERA) Using Naïve Bayes

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Abstract: The advancement of technology has transformed how people interact and express opinions on social media platforms. This research examines Twitter conversations regarding Indonesia's government-initiated Housing Savings Program (TAPERA) through sentiment analysis. The study employed Naïve Bayes classification methodology, with data acquisition conducted via Google Colab platform utilizing the tweet-harvest library. The collection process yielded 1,800 tweets matching predetermined search parameters. Data underwent rigorous preprocessing, including text cleaning and manual sentiment annotation to establish reliable training datasets. Examination of 720 test tweets revealed 473 (65.69%) expressed negative sentiment while 247 (34.31%) conveyed positive sentiment toward the program. The implemented Naïve Bayes model achieved 84.17% accuracy, with negative class precision at 88.71% and recall at 88.60%, while positive class precision reached 78.54% with 76.08% recall. Results indicate the Naïve Bayes approach effectively categorizes public sentiment regarding the TAPERA program, offering valuable feedback for stakeholders responsible for program assessment and enhancement.

Keywords: Sentiment Analysis; Twitter; TAPERA; Naïve Bayes.

1. Introduction

Technological advancement has rapidly transformed various aspects of life, particularly how Indonesian society interacts and communicates. The internet, as a product of this progress, has become an inseparable part of daily activities, both for personal and professional purposes. By 2024, internet users in Indonesia have reached 221,563,479 individuals from a total population of 278,696,200 people [1]. In Indonesia, internet usage has experienced substantial growth, especially within the past year. This growth is supported by increasing smartphone penetration, wider internet network availability, and growing public awareness of internet benefits across various sectors, including education, business, entertainment, and communication. Social media serves as a primary platform for information dissemination, with Twitter being among the most popular. The presence of social media platforms like Twitter has become particularly relevant for information distribution. Last year, Twitter users in Indonesia reached 24 million [2], establishing this platform as an essential channel for spreading information among Indonesian society.

Twitter functions not only as a communication tool but also as a social media platform where people can express opinions on various issues. Recently, the Housing Savings Program (Tapera) policy has become a widely discussed topic in Indonesia, including in Twitter conversations. Tapera is a savings program implemented by participants continuously over a specified period and can only be used for housing financing. This policy came into effect after being enacted on Monday, May 20, 2024, requiring employers to register their employees with the Tapera Management Agency no later than seven years after the regulation takes effect. The Tapera contribution amount is regulated in Article 15 of Government Regulation Number 21 of 2024, with a contribution rate of 3% of the salary or wages of Worker Participants and income for Independent Worker Participants. Savings for Worker Participants are jointly borne by Employers at 0.5% and Workers at 2.5%, while for Independent Worker Participants, the 3% contribution is self-funded [3]. Sentiment analysis, commonly known as opinion mining, represents a field of computer science that analyzes opinions, assessments, attitudes, emotions, and evaluations toward products, services, organizations, individuals, public figures, or specific activities. The purpose of sentiment analysis is to assist in developing applications and services, as research results are obtained directly from public opinions based on their experiences, and these results can be used to optimize various products, work programs, or circulating issues [4].

Other research has utilized the Naïve Bayes method to analyze sentiment regarding the Jakarta-Bandung high-speed rail development on Twitter. Using 2,007 data points, this research identified 673 negative sentiments, 668 positive sentiments, and 665 neutral sentiments, with accuracy results of 71%, precision of 73%, and recall of 89% [5]. Research on sentiment toward Online Loans on Twitter also employed the Naïve Bayes method. Using 2,912 data points, this research produced 68.61% negative sentiment and 31.39% positive sentiment, with Twitter user sentiment analysis accuracy regarding Online Loans reaching 80% [6]. This research aims to examine Indonesian public perspectives toward the Tapera program, which offers assistance to low-income communities (MBR) for housing financing. By employing Naïve Bayes data classification, this study will analyze opinions that have not been previously researched, with the primary objective of understanding public responses to the program.

2. Related Work

Sentiment analysis serves as a tool for understanding public opinion on government policies and programs. Thufailah *et al.* (2024) analyzed public sentiment regarding the Tapera policy on "X" (formerly Twitter). Their work revealed how citizens responded to the housing savings program, emphasizing the value of public feedback for policy refinement. The researchers used sentiment classification to categorize responses, establishing a method for analyzing housing policy sentiment in Indonesia. Our study builds upon their foundation with a larger dataset and alternative methodological approach to better understand how people perceive Tapera [7].

International researchers have shown sentiment analysis helps interpret housing-related policies. Tetteh *et al.* (2023) examined social media data to assess public needs and views about energy efficiency retrofitting of existing buildings. They found that while people recognize retrofitting benefits, they worry about costs, implementation disruption, and health effects. Their approach to categorizing sentiment in housing discussions shapes our research framework [8]. Tan and Guan (2021) studied connections between housing prices, public sentiment, and activity frequency using Twitter data. They discovered areas with higher property values often show more positive public sentiment. Their spatial-temporal analysis offers methods for understanding how sentiment toward housing programs varies across economic settings [9]. Hannum *et al.* (2019) conducted spatial analysis of Twitter sentiment and district-level housing prices. Their work showed Twitter sentiment can indicate housing market trends and how people perceive property values. By linking online discussions with market conditions, they created a foundation for analyzing how public sentiment might reflect the effectiveness of housing programs like Tapera [10]. These studies from other countries provide methods that we can adapt to examine public sentiment toward housing policies in Indonesia.

Focusing on Tapera specifically, Syahputra *et al.* (2024) performed sentiment analysis using Support Vector Machine (SVM), creating a comparison point for our Naïve Bayes approach. As one of few studies directly examining public sentiment toward Tapera, their work relates closely to our research. They found mixed public sentiment about the program, with concerns about implementation and financial impact on workers. Though they used different methods, their findings help us interpret our results [11].

Research shows Naïve Bayes works well for sentiment analysis of Indonesian government programs. Florensius Sianipar *et al.* (2023) used Naïve Bayes to analyze sentiment about the Jakarta-Bandung high-speed rail on Twitter. From 2,007 posts, they found 673 negative, 668 positive, and 665 neutral sentiments, achieving 71% accuracy, 73% precision, and 89% recall. Their approach to processing Indonesian text and training the classifier guides our research design [5]. Similarly, Ghozali *et al.* (2023) applied Naïve Bayes to analyze sentiment toward Online Loans on Twitter. Using 2,912 posts, they found 68.61% negative sentiment

and 31.39% positive sentiment, with 80% accuracy. Their feature extraction and classification methods inform our analysis of Tapera-related tweets [6]. Several researchers have addressed how to handle Indonesian text for sentiment analysis. Najjichah *et al.* (2019) studied text preprocessing effects on automatic document summarization for Indonesian texts, showing the necessity of proper preprocessing for Indonesian language analysis. Their work shapes how we prepare Twitter data, especially when dealing with Indonesian language characteristics on social media [14]. Bayu Baskoro *et al.* (2021) analyzed hotel customer sentiment in Purwokerto using Random Forest and TF-IDF methods. Their study showed how sentiment analysis helps businesses understand customer feedback. Though focused on hospitality, their preprocessing and feature extraction techniques apply to our analysis of Tapera-related tweets [4].

While research on sentiment analysis for government programs and housing topics continues to grow, few studies examine public sentiment toward the Tapera program using Naïve Bayes classification. Syahputra *et al.* (2024) used SVM instead of Naïve Bayes [11], and Thufailah *et al.* (2024) took a different methodological approach [7]. Research by Tetteh *et al.* (2023)[8], Tan and Guan (2021)[9], and Hannum *et al.* (2019)[10] offers valuable methods for housing-related sentiment analysis, but these studies occurred in different economic and cultural environments [8][9][10]. Our research fills a gap by using Naïve Bayes classification to analyze Twitter sentiment about the Tapera program in Indonesia, building on established methods while focusing on a specific housing policy. Combining Naïve Bayes classification, which has worked well in previous Indonesian social media studies [5]-[6], with thorough preprocessing techniques for Indonesian text advances both methodology and practical understanding of how the public views the Tapera program.

3. Research Method

3.1. Sentiment Analysis

Sentiment Analysis is a discipline aimed at understanding opinion tendencies from a group of individuals or society, typically through comments or writings. With this technique, we can extract valuable information from unstructured data, in the form of opinions classified as positive or negative sentiments based on emotions contained in those opinions (Ramadhani & Suryono, 2024) [12]. Sentiment analysis is a method used to understand a person's views or opinions (Priansyah & Sutabri, 2024) [13]. This technique is very useful for identifying emotional expressions and user opinions. This research focuses on sentiment analysis of the Tapera program policy launched by the government. All comments related to the Tapera program posted on social media, particularly Twitter, will be collected and analyzed. These comment data will be processed and arranged in a more structured manner to provide useful insights for this research, as well as help understand public sentiment toward the Tapera program.

3.2. Preprocessing

Text preprocessing is a stage that aims to transform original text into a more structured format by applying various basic practices to modify or remove textual elements that are irrelevant for further processing (Najjichah *et al.*, 2019) [14]. The main purpose of text preprocessing is to extract keywords that represent the documents to be analyzed and understand the relationships between these documents. Several steps are needed to transform original text into text data ready for processing. The steps in text preprocessing are as shown in the following table example:

Figure 1. Diagram 1.1

The steps in text preprocessing include data cleaning to remove irrelevant or disruptive characters. The tokenization process is carried out to break text into units such as words or phrases. Case transformation is applied to standardize all letters into lowercase or uppercase. Stopword filtering is done to remove common words that do not provide meaning, while token filtering removes irrelevant tokens. The stemming process changes words into their basic forms. (Saputra & Hasan, 2024) [15]. By following these preprocessing steps, text documents are prepared for further analysis, thereby increasing the accuracy and effectiveness of the text data processing.

3.3. Naive Bayes

Naïve Bayes is a method for classifying data sets. This algorithm uses statistical principles and probability introduced by Thomas Bayes, a scientist from England (Firsttama *et al.*, 2024) [16]. The text classification process with the Naïve Bayes method involves two main stages: the training stage and the testing stage. In the training stage, analysis is conducted on sample data, including the selection of vocabulary that may appear in the sample data collection to represent the data. After that, prior probabilities for each group are determined according to the data specimens. In the testing stage, the category of data is determined based on terms that appear in the data being classified (Sulindawaty *et al.*, 2023) [17].

3.4. TF-IDF

The Term Frequency-Inverse Document Frequency (TF-IDF) method is a technique used in natural language processing and modeling. This method aims to assess how important a word (term) is in a piece of data within the context of a larger collection of documents. (Yutika *et al.*, 2021) [18]. The TF-IDF method considers two important factors: Term Frequency (TF) calculates how often a word appears in a piece of data, while Inverse Document Frequency (IDF) assesses how important the word is in the larger data collection. Words that rarely appear across the entire data collection have higher IDF values. In the TF-IDF method, the TF and IDF values are multiplied to produce a term weight for each word in a document. This weight reflects the level of importance of the word in a particular document compared to the wider collection of documents.

4. Result and Discussion

4.1 Results

4.1.1 Data Collection

This research collected data through the Google Colab platform using Python programming language. The tweet-harvest library was used to collect data from Twitter. The search keyword used was 'tapera lang:id'. This data collection process successfully gathered 1,800 tweets that matched the search criteria.

```
# Crawl Data

filename = 'Tapera.csv'
search_keyword = 'tapera lang:id'
limit = 2000

!npx --yes tweet-harvest@2.6.1 -o "{filename}" -s "{search_keyword}" -l {limit} --token {twitter_auth_token}
```

Figure 2. Data Collection

After the data was successfully collected, the next step was to save it in a format that could be accessed and analyzed further. The collected data was then stored in a CSV file named tapera.csv. This CSV file contains various important information from each collected tweet, including the tweet text, user, posting time, and other relevant metadata.

4.1.2 Data Labeling

After collecting a total of 1800 tweets, 720 tweets were selected to be manually labeled using Microsoft Excel based on opinions expressed on Twitter regarding the Public Housing Savings Program (Tapera). This labeling process was conducted by identifying whether each tweet showed positive or negative sentiment toward the program. The results of this labeling were then used as training data in the development of the sentiment analysis model. Information about the sentiment of each tweet was recorded and organized in Table 3.1 to provide a clear and structured picture of public perception toward the Tapera program.

Table 1. Data Labeling

Tweet Contents	Sentiment
Kebusukan dari program Tapera adalah agenda menyelamatkan bank plat merah Bank BTN yang dalam kondisi megap-megap Dengan memotong gaji PNS dan swasta 2 5 persen Dan semua tertuju pada Taperanya bukan pada kondisi Bank BTN diluar tanggungjawab pemerintahan Jokowi https://t\.co/FmMTGryKnx	Negative
Makin ngaco aja. Apaan coba pake ada PP No.25 tahun 2020 tentang Tapera. Gaji pekerja dipotong 3% tiap bulan buat tabungan rumah. Ini WAJIB buat ASN ataupun SWASTA!!. Nabungnya sampe kapan? Nyicil rumah jutaan perbulan aja lama apalagi dari potongan 3% https://t\.co/aCJEOSiMuX	Negative
Pada akhirnya kebijakan Tapera ini bertujuan untuk mencari jalan terbaik untuk menyelesaikan masalah hunian masyarakat. #LunchAtNewsroom	Positive
RUU Tapera Bertujuan Sejahterakan Rakyat: Kebutuhan dan ketersediaan rumah masih mengalami kesenjangan. https://t\.co/D3Z5rc81dp	Positive

4.1.3 Preprocessing

1) Data Cleaning

Data cleaning is the stage where incomplete, erroneous, and inconsistent data is removed from the dataset. At this stage, the combined data will undergo a cleaning process to eliminate various errors or anomalies that may exist. The data cleaning process was carried out using several specific sub-operators, one of which is the replace operator which functions to replace inappropriate text, and the trim operator which functions to remove unnecessary spaces.
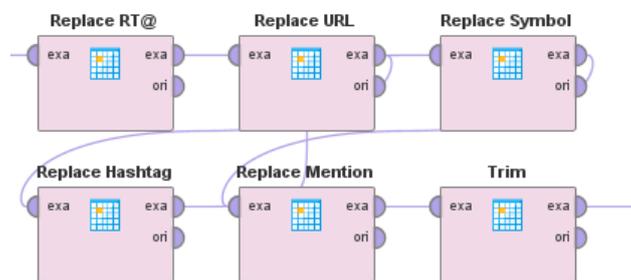

Figure 3. Data Cleaning

In Figure 3, the data cleaning process includes the following steps:
a) Replace RT@: This step removes sentences that begin with "@RT" using the code "RT @.*". The purpose is to remove sentences that start with "RT" followed by a specific username.
b) Replace URL: This step removes sentences that begin with "https" using the code "https.*?". The purpose is to remove URL links from the text.
c) Replace Mention: This step removes sentences that begin with "@" using the code "@.*?". The purpose is to remove usernames from the text.
d) Replace Symbol: This step uses special code "[!"#$%&'()*+,./:;<=>?@_`{|}~]" to remove irrelevant symbols from the text.
e) Trim Operator: This step ensures that the text is free from unwanted empty characters by removing additional spaces at the beginning and end of the text.

After the data cleaning stage is completed, the next step in data preparation is to prepare the text for further analysis. This stage is part of the preprocessing process and includes several important steps, as illustrated in Figure 3. These steps include tokenization, case transformation, stopword filtering, token filtering, and stemming.
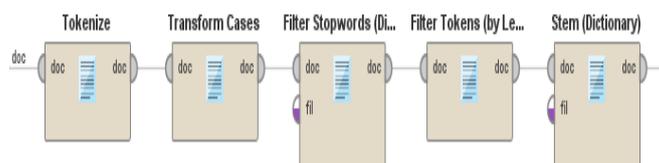

Figure 4. Data Preparation

2) Tokenize

The process of breaking down text into smaller parts, such as words, phrases, or symbols. This process aims to facilitate analysis by working with smaller and more structured text units. For example, the sentence "kami makan nasi" will be broken down into tokens "kami", "makan", "nasi", and "goreng". Tokenizing is an important step in natural language processing because it allows for more detailed and specific analysis. As shown in Table 2.

Table 2. Tokenize

Before Tokenize	After Tokenize
Kebusukan dari program Tapera adalah agenda menyelamatkan bank plat merah Bank BTN yang dalam kondisi megap-megap Dengan memotong gaji PNS dan swasta persen Dan semua tertuju pada Taperanya bukan pada kondisi Bank BTN diluar tanggungjawab pemerintahan Jokowi	'Kebusukan', 'dari', 'program', 'Tapera', 'adalah', 'agenda', 'menyelamatkan', 'bank', 'plat', 'merah', 'Bank', 'BTN', 'yang', 'dalam', 'kondisi', 'megapmegap', 'Dengan', 'memotong', 'gaji', 'PNS', 'dan', 'swasta', 'persen', 'Dan', 'semua', 'tertuju', 'pada', 'Taperanya', 'bukan', 'pada', 'kondisi', 'Bank', 'BTN', 'diluar', 'tanggungjawab', 'pemerintahan', 'Jokowi'

3) Transform Cases

The process of changing the form of letters in text to be uniform, such as changing all letters to uppercase or lowercase, aims to ensure consistency in analysis. In Table 3, all words have been converted to lowercase to maintain uniformity.

Table 3. Transform Cases

Before Transform Cases	After Transform Cases
Kebusukan dari program Tapera adalah agenda menyelamatkan bank plat merah Bank BTN yang dalam kondisi megap-megap Dengan memotong gaji PNS dan swasta persen Dan semua tertuju pada Taperanya bukan pada kondisi Bank BTN diluar tanggungjawab pemerintahan Jokowi	kebusukan dari program tapera adalah agenda menyelamatkan bank plat merah bank btn yang dalam kondisi megap megap dengan memotong gaji pns dan swasta persen dan semua tertuju pada taperanya bukan pada kondisi bank btn diluar tanggungjawab pemerintahan jokowi

4) Filter Stopword

The process step to remove common words that do not provide meaning, such as "saya", "aku", or "kamu". In the example in Table 4, the following words have been removed from the text to increase the relevance and meaning of the analysis.

Table 4. Filter Stopword

Before Stopword Filter	After Stopword Filter
Kebusukan dari program Tapera adalah agenda menyelamatkan bank plat merah Bank BTN yang dalam kondisi megap-megap Dengan memotong gaji PNS dan swasta persen Dan semua tertuju pada Taperanya bukan pada kondisi Bank BTN diluar tanggungjawab pemerintahan Jokowi	kebusukan program tapera adalah agenda menyelamatkan bank plat merah bank btn dalam kondisi megap megap memotong gaji pns swasta persen semua tertuju taperanya bukan kondisi bank btn diluar tanggungjawab pemerintahan jokowi

5) Filter Token

This process also includes filtering words based on their length, where very short or long words will be removed. As an illustration, in Table 5, only words with lengths between 3 and 25 characters are retained for further analysis.

Table 5. Filter Token

Before Token Filter	After Token Filter
Kebusukan dari program Tapera adalah agenda menyelamatkan bank plat merah Bank BTN yang dalam kondisi megap-megap Dengan memotong gaji PNS dan swasta persen Dan semua tertuju pada Taperanya bukan pada kondisi Bank BTN diluar tanggungjawab pemerintahan Jokowi	kebusukan program tapera adalah agenda menyelamatkan bank plat merah bank btn dalam kondisi megap megap memotong gaji pns swasta persen semua tertuju taperanya bukan kondisi bank btn diluar tanggungjawab pemerintahan jokowi

6) Stemming

The process of converting words to their base form, so that various forms of the same word can be identified as the same entity. This is shown in Table 6.

Table 6. Stemming

Before Stemming	After Stemming
Kebusukan dari program Tapera adalah agenda menyelamatkan bank plat merah Bank BTN yang dalam kondisi megap-megap Dengan memotong gaji PNS dan swasta persen Dan semua tertuju pada Taperanya bukan pada kondisi Bank BTN diluar tanggungjawab pemerintahan Jokowi	busuk program tapera adalah agenda selamat bank plat merah bank btn dalam kondisi megap megap potong gaji pns swasta persen semua tuju tapera bukan kondisi bank btn luar tanggungjawab pemerintah jokowi

7) Word Weighting

After the data goes through a series of text preprocessing processes, the next step is to perform word weighting using the TF-IDF (Term Frequency-Inverse Document Frequency) method on the Process Documents from Data operator. By using TF-IDF, words that frequently appear in one data but rarely appear in other data will be given higher weight, thus having a greater influence on the sentiment analysis results. The results of this word weighting will be used to train the sentiment analysis model, which allows the classification of data into negative or positive categories based on the occurrence of relevant words in the text.
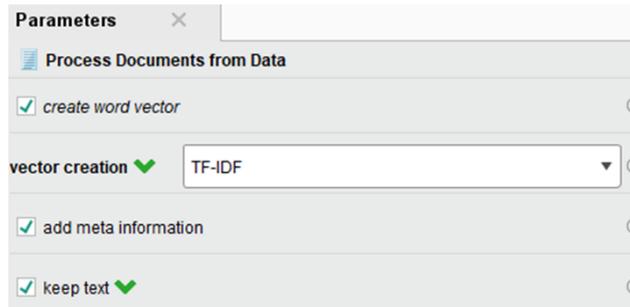

Figure 5. Word Weighting

8) Naive Bayes Implementation

The implementation of the Naïve Bayes algorithm for sentiment analysis is done by connecting the "Process Document from Data" operator to the "Naïve Bayes" operator. The next step is to direct the output from the "Naïve Bayes" operator to two "Store" operators. The first "Store" operator is used to save the results produced by the "Naïve Bayes" operator and is named "Store Training Data". It is used to save the results of the process performed on the test data.
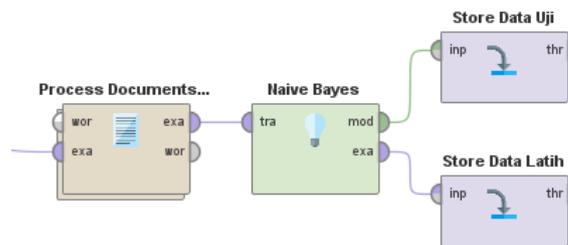

Figure 6. Naive Bayes Implementation

Next, the test data is combined with the prepared training data using the Union operator (Figure 6). After being combined, the data is further processed using the Filter Example operator to handle text with empty sentiment. To handle missing values, the Replace Missing Value operator is used with the default setting "zero", allowing the system to manage unfilled data. Finally, the Apply Model operator is applied to save and display the sentiment analysis results produced by the Naïve Bayes model.
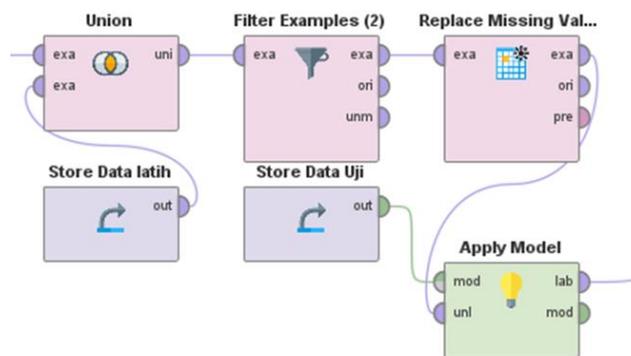
Figure 7. Testing Process

After the testing process is completed, the results provide a clearer picture of the sentiment distribution in the test data, which is important for further evaluation in sentiment analysis.

9) SMOTE Up Sampling and Cross Validation

The use of the SMOTE Up Sampling operator aims to address class imbalance in the dataset by generating synthetic samples from the minority class (Rachmatullah, 2023) [19]. This step is followed by connecting the SMOTE operator with the cross-validation operator using 10 folds, as shown in Figure 8. Cross-validation divides the dataset into several subsets, allowing for more accurate measurement of model performance.
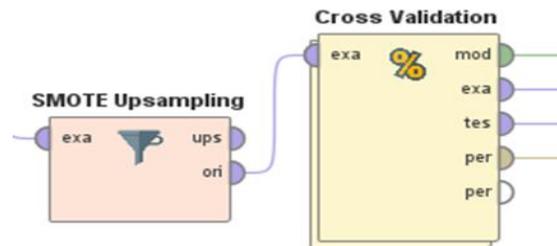

Figure 8. SMOTE Up Sampling and Cross Validation

10) Evaluation

In the model evaluation process using the cross-validation operator, there are several important operators to consider, one of which is the Naïve Bayes operator. In Figure 9, it is shown that this Naïve Bayes operator is connected to the Apply Model operator, which aims to apply the model that has been created. After the model is applied, the results from the Apply Model operator are then connected to the Performance operator. The function of the Performance operator is to measure the performance of the model in performing classification by presenting various evaluation metrics such as accuracy, precision, and recall.
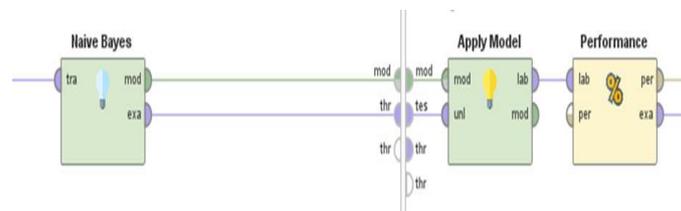

Figure 9. Evaluation

After the entire evaluation process is completed, based on the test data, out of a total of 720 test data, it was found that 473 data have negative sentiment, which is equivalent to approximately 65.69%, while 247 data have positive sentiment, which is equivalent to approximately 34.31%. The visualization of these results can be seen in Figure 10, which is presented in the form of a Pie Chart.
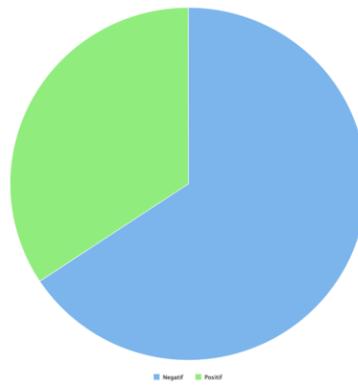
Figure 10. Results

The confusion matrix results from the test data, as displayed in Diagram (Figure 10), visualize a clear data diagram about how the Naïve Bayes model performs in classifying sentiment.

Table 7. Sentiment Classification

	True Negatif	True Positif	Class Precision
pred Negatif	412	61	87,10%
pred Positif	53	194	78,54%
Class Recall	88,60%	76,08%	

Accuracy $\frac{606}{720} = 0.8417 \ or \ 84.17\%$

Negative Class:
True Negative (TN) = 412
False Positive (FP) = 53
Precision = $\frac{TN}{TN+FP} = \frac{412}{465} = 0.8871 \ or \ 88.71\%$
Recall = $\frac{TN}{TN+FN} = \frac{412}{473} = 0.8860 \ or \ 88.60\%$
Positive Class:
True Positive (TP) = 194
False Negative (FN) = 61
Precision = $\frac{TP}{TP+FP} = \frac{194}{247} = 0.7854 \ or \ 78.54\%$
Recall = $\frac{TP}{TP+FN} = \frac{194}{255} = 0.7608 \ or \ 76.08\%$

4.2 Discussion

The sentiment analysis conducted on public opinions regarding the Tabungan Perumahan Rakyat (Tapera) program reveals significant insights into public perception. The analysis utilized the Naïve Bayes algorithm, which has been widely recognized for its effectiveness in sentiment classification tasks [12][13][17]. The research methodology began with data collection through Twitter (now X), gathering 1,800 tweets containing the keyword "tapera lang:id". From these, 720 tweets were manually labeled as either positive or negative. This approach aligns with similar studies that have used social media data to analyze public sentiment toward government policies [5][6][20]. As noted by Thufailah *et al*. (2024), social media platforms provide valuable insights into public opinion regarding housing policies like Tapera [7]. The preprocessing steps implemented in this study—including tokenization, case transformation, stopword removal, token filtering, and stemming—are essential for improving the accuracy of sentiment analysis models. These steps are consistent with best practices in text preprocessing for Indonesian language as highlighted by Najjichah *et al*. (2019), who emphasized the importance of proper text preprocessing for Indonesian language analysis [14].

The Naïve Bayes algorithm, combined with TF-IDF for word weighting, demonstrated strong performance in classifying sentiments about the Tapera program. The model achieved an overall accuracy of 84.17%, which is comparable to other sentiment analysis studies using similar methodologies [15][16][17]. This high accuracy indicates the model's reliability in capturing public sentiment toward the Tapera program. For the negative class, the model achieved a precision of 88.71% and a recall of 88.60%, while for the positive class, it achieved a precision of 78.54% and a recall of 76.08%. These metrics suggest that the model is more effective at identifying negative sentiments than positive ones, which could be attributed to the imbalanced nature of the dataset (65.69% negative vs. 34.31% positive). This observation is consistent with findings from Sulindawaty *et al*. (2023), who noted similar patterns in sentiment analysis of e-commerce reviews [17]. The

implementation of SMOTE Up Sampling to address class imbalance, as suggested by Rachmatullah (2023), likely contributed to the model's robust performance despite the uneven distribution of sentiment classes [19]. Cross-validation with 10 folds further ensured the reliability of the performance metrics by reducing the risk of overfitting.

The predominance of negative sentiment (65.69%) over positive sentiment (34.31%) in the dataset suggests significant public concern regarding the Tapera program. This finding aligns with Nugroho and Diahwahyuningtyas (2024), who discussed various aspects of Tapera including contribution rates and withdrawal conditions that have been subjects of public debate [3]. Similar patterns of public sentiment toward housing policies have been observed in international contexts. Tetteh *et al.* (2023) found that social media analysis can effectively capture public concerns about housing-related policies [8], while Tan and Guan (2021) demonstrated correlations between Twitter sentiment and housing prices [9]. Hannum *et al.* (2019) further established that sentiment analysis of social media data can provide valuable insights into housing market perceptions [10]. The negative sentiment observed may be attributed to concerns about the mandatory nature of contributions and their impact on take-home pay, as indicated in some of the sample tweets. For instance, tweets mentioning "Gaji pekerja dipotong 3% tiap bulan" (Workers' salaries cut by 3% each month) highlight financial concerns, while others question the program's implementation and benefits.

Our findings are consistent with Syahputra *et al.* (2024), who also conducted sentiment analysis on the Tapera program using Support Vector Machine (SVM) [11]. Their study similarly found a predominance of negative sentiment, though with different proportions. The consistency across different methodologies strengthens the validity of our findings regarding public perception of Tapera. Studies by Florensius Sianipar *et al.* (2023) and Ghozali *et al.* (2023) have demonstrated the effectiveness of Naïve Bayes in analyzing public sentiment toward other government initiatives and financial services in Indonesia [5][6]. These studies support our methodological approach and provide context for interpreting our results within the broader landscape of public opinion analysis in Indonesia. The significant proportion of negative sentiment identified in this study suggests that policymakers should address public concerns regarding the Tapera program. The specific issues mentioned in negative tweets, such as mandatory contributions and their financial impact, could guide policy refinements to improve public acceptance. As Bayu Baskoro *et al.* (2021) noted in their sentiment analysis study, understanding public opinion can provide valuable feedback for service improvement [4]. This feedback could inform communication strategies and potential policy adjustments to better align with public expectations and needs. The sentiment analysis of tweets regarding the Tapera program reveals predominantly negative public sentiment, with the Naïve Bayes model demonstrating strong performance in classifying these sentiments. The preprocessing techniques and model implementation followed established best practices in text analytics, resulting in reliable insights into public perception.

5. Conclusion

This research aimed to analyze Twitter conversations sentiment regarding the Public Housing Savings Program (TAPERA) using the Naïve Bayes classification method. Data collected through Google Colab platform and processed using the tweet-harvest library successfully gathered 1,800 tweets matching the search criteria. After data pre-processing steps, including data cleaning and manual sentiment labeling, the analysis revealed that of the 720 tested tweets, 473 tweets expressed negative sentiment (65.69%) and 247 tweets showed positive sentiment (34.31%) toward the TAPERA program. The Naïve Bayes model employed in the research demonstrated good performance with 84.17% accuracy, 87.10% precision for the negative class, 88.60% recall for the negative class, 78.54% precision for the positive class, and 76.08% recall for the positive class. The findings paint a clear picture of how the public responds to and perceives the TAPERA program. Such information proves valuable for relevant stakeholders to evaluate program effectiveness and design more targeted communication strategies.

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