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Public Sentiment Analysis on TikTok about Tapera Policy using Random Forest Classifier

[1]Isnaini Muhandhis*, [2]Alven Safik Ritonga
[1,2]Informatics Engineering Study Program, Faculty of Engineering, Universitas Wijaya Putra
[1,2]Raya Benowo 1 – 3, Surabaya, Indonesia
*e-mail: imuhandhis@gmail.com

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Abstract

At the beginning of 2024, the Tapera policy proposed by the government sparked widespread public debate, resulting in both pros and cons. To improve the quality of public services, it is crucial for the government to evaluate policies to align with the needs and expectations of the community. This study aims to analyze public sentiment on the social media platform TikTok regarding the Tapera policy. Comment data was collected from several TikTok videos discussing the Tapera policy with high view counts. These videos received various responses in the form of comments, expressing positive, neutral, and negative sentiments about Tapera. A total of 5,036 comments were successfully scraped. The Random Forest Classifier was used for sentiment classification. This method was chosen for its ability to maintain high predictive accuracy, minimize overfitting, and perform effectively in classification tasks. The study results showed that negative sentiment dominated TikTok users' opinions, accounting for 82%, followed by neutral sentiment at 10% and positive sentiment at 8%. Many expressed disapproval for various reasons, including concerns about potential corruption, the ineffectiveness of contributions due to inflation, and the policy being burdensome amid a sluggish economy. Neutral sentiment was dominated by questions related to Tapera, such as the amount of Tapera deductions and whether participation is mandatory for those who already own a house. Positive sentiments expressed support for the Tapera policy and willingness to pay the contributions. However, the proportion of supporters of this program was significantly smaller than those opposing it. The training results of the classification model using the Random Forest Classifier achieved an accuracy of 89%. The highest F1-score for detecting negative sentiment was 94%, while the F1-score for detecting neutral sentiment was 17% and for positive sentiment, it was 32%. This disparity is due to the dataset composition being dominated by negative sentiment. The proportion of sentiment significantly influences the training of the classification model. A balanced proportion for each sentiment would enable the model to better learn and recognize the words frequently associated with each sentiment.

Keywords: *corruption, decision tree, social media, negative, positive*

1 Introduction

In early 2024, the issue of the Public Housing Savings (Tapera) contribution policy proposed by the government became a heated topic. That year, President Joko Widodo issued regulations under Government Regulation (PP) No. 21 to address inequality in homeownership and the housing backlog. Based on PP No. 25 of 2020, which was updated through PP 21/2024, all workers earning at least the regional minimum wage (UMR) and aged 20 years or older are required to participate in Tapera. Each month, their income will be deducted by 3%, with 2.5% paid by the employee and 0.5% by the employer, while self-employed workers are responsible for the entire deduction. However, despite the government's good intentions to provide housing for the people through this policy, its implementation has not been effective, leading to mixed reactions and debates among the public.

The debate surrounding the policy is reflected, among other things, in TikTok video content related to Tapera, which has garnered a variety of comments from TikTok users. According to research by HG Putra [1], the nationally implemented Tapera program has not effectively addressed housing affordability for civil servants in Jakarta. Similarly, Yohanes [2] highlighted that the public's limited understanding of the policy, the complexity of administrative procedures, and economic constraints remain significant barriers to public acceptance of the program. To improve the quality of

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public service delivery, the government must evaluate each policy to ensure it aligns with the expectations and needs of the people.

Based on this background, this study aims to analyze public sentiment on the social media platform TikTok regarding the Tapera policy. Sentiment analysis has become increasingly important in the digital era as it enables organizations to gain insights from large volumes of textual data, including customer reviews, social media comments, and news articles. This type of analysis provides valuable feedback on products, services, policies, or the success of an organization's campaigns. Sentiment analysis has been widely applied to evaluate government policies, such as the analysis of sentiments regarding the "Kampus Merdeka" policy [3] and the IKN policy [4].

The sentiment classification process in this study employs a classification model using the Random Forest method. Random Forest is a supervised learning algorithm used for classification, regression, and other tasks through decision trees. It is particularly suitable for handling large and complex datasets, managing high-dimensional feature spaces, and providing insights into feature importance. Its ability to maintain high prediction accuracy while minimizing overfitting makes it a popular choice across various domains. Random Forest has demonstrated robust performance in sentiment analysis tasks [5] [6]. The urgency of this research lies in providing the government with an overview of public responses and sentiments on TikTok concerning the Tapera policy, aiding in policy evaluation and improvement.

This study aims to understand public sentiment on the social media platform TikTok regarding the Tapera policy implemented by the government. This is achieved through sentiment analysis using the Random Forest algorithm, which classifies sentiments into positive, negative, or neutral categories. By understanding these sentiment patterns, the study seeks to identify factors of public concern, such as the level of acceptance, perceived benefits, or challenges faced. Furthermore, the study also aims to uncover potential improvements for the Tapera policy based on indirect feedback from the public expressed through digital platforms, ensuring the policy better aligns with the needs and expectations of society.

The findings of this study are expected to provide positive contributions to the government in evaluating and enhancing the effectiveness of the Tapera policy. Sentiment analysis can offer deep insights into public perceptions of the policy, helping the government understand specific issues that concern the public, such as administrative complexity, financial burdens, or perceived benefits. Additionally, this research can serve as a reference for policymakers in designing more effective communication strategies to convey policies to the public. Academically, this study can expand the literature on the application of sentiment analysis in evaluating government policies and provide empirical evidence of the effectiveness of the Random Forest algorithm in the context of analyzing social media data, particularly TikTok.

2 Literature Review

Sentiment analysis is the process of categorizing emotions expressed in a document to gather insights, with the goal of translating this information into everyday language. Fundamentally, sentiment analysis is a form of classification, but it is more complex than standard classification due to linguistic challenges such as sarcasm or implicit irony [7]. Words can have multiple meanings, tone is absent in text, and language continually evolves. Many studies have utilized sentiment analysis as a tool to evaluate government policies.

Prastyo's study [8] analyzed public sentiment regarding the government’s COVID-19 handling policies. The findings revealed that, from an economic perspective, the public generally supported the government’s approach, although dissatisfaction with overall government performance remained. The SVM algorithm with a Normalized Poly Kernel was effective in classifying sentiments in this research.

Samantri [9] investigated public sentiment regarding fuel price increases. Public sentiment varied significantly, with some Twitter users understanding the rationale behind the price hikes and supporting the government’s decision, while others opposed the increase. The study concluded that sentiment toward the fuel price hike was predominantly negative, and the K-Nearest Neighbor algorithm was shown to be effective in classifying sentiments.

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Serli [10] analyzed public reactions to the closure of TikTok Shop. The results indicated that most sentiments expressed by the public were of disapproval and disappointment. Many negative comments highlighted the loss of a favored shopping platform and restricted access. Although a minority expressed support for the policy, negative views overwhelmingly dominated.

Studies [11] analyzed sentiment related to the Tapera policy on the social media platform X (formerly Twitter) using the commonly employed Naïve Bayes method. However, there has been limited research using TikTok data as a sample, particularly with a different methodology such as the Random Forest algorithm. A distinctive characteristic of TikTok users is their tendency to critique political issues using satire or sarcasm [13]. One of the trending topics among TikTok users is Tapera, with related content garnering high views and diverse comments from the TikTok community.

Thus, this study aims to analyze public sentiment on TikTok regarding the Tapera policy using the Random Forest Classifier method. Random Forest has proven to be accurate in sentiment classification, as demonstrated in previous studies [10] [9] [5] [6].

3 Research Method

The research method involves several steps: scraping comments from TikTok, storing the data into a CSV file, preprocessing the raw data by removing noise, performing case folding, and normalizing the text. Subsequently, sentiment labeling is conducted to create the output dataset. The next stage involves training the Random Forest classification model, followed by data visualization, as illustrated in Figure 1.

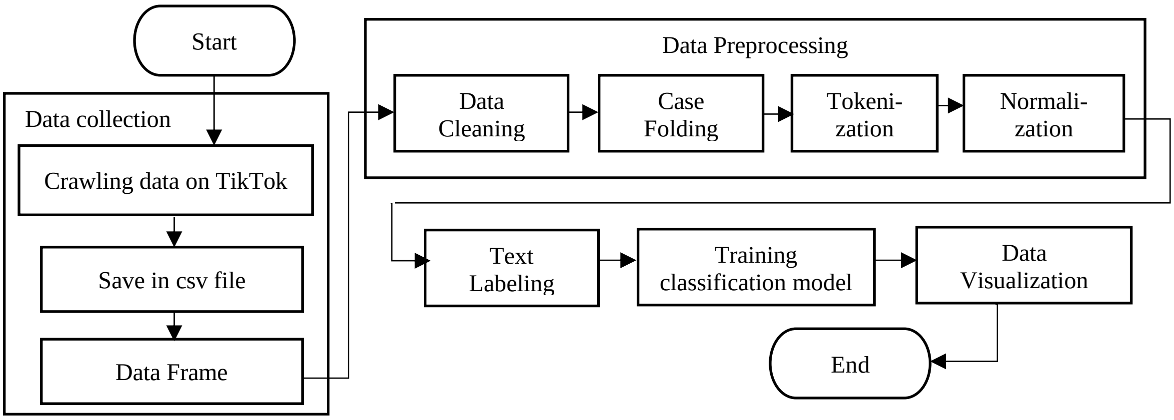

Figure 1. Research stages

3.1 Data Collection

This study collects data from the social media platform TikTok. TikTok is a social media platform that allows users to create short video content with a maximum duration of three minutes. Many TikTok users express their criticism of political issues using sarcasm [13]. This social media platform is often used as a space to share opinions on public policies through video content, which receives various responses in the form of comments, whether positive, neutral, or negative about the discussed topic. Several TikTok videos discussing the Tapera policy with high view counts were selected, and the comment sections were scraped. The tool used for scraping TikTok comments is Apify, which is capable of downloading over 2,000 comments in a single process.

3.2 Research Scope

This study discusses the analysis of public sentiment on the social media platform TikTok regarding the Tapera policy proposed by the government. The scope of this research is to analyze TikTok users' comments about the Tapera policy. Data is collected from several TikTok videos that discuss their views on the Tapera policy, with a high number of views. These videos have received thousands of comments from TikTok users expressing their opinions on the policy. The comment data represents various social groups who use TikTok as their social media platform. Sentiments are classified into three categories: positive, negative, and neutral. The expected outcome of this study is to determine the distribution of public sentiment towards the Tapera policy and identify the main

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reasons why people support or oppose the policy. This research is expected to provide insights for policymakers to understand public opinion and formulate policies that are more responsive to the needs of society.

3.3 Sentiment Analysis Method

Sentiment analysis methods are processes for identifying, extracting, and categorizing opinions in text into specific sentiments, such as positive, negative, or neutral. Here are the methods commonly used in sentiment analysis.

3.3.1 Data Preprocessing

Raw data preprocessing aims to transform unstructured raw data into semi-structured data. Structuring text data can assist in training classification models. The stages involved in text data preprocessing are:

a. Cleaning: Removing noise from the text data, including hashtags, usernames, URLs, links, emojis, numbers, punctuation marks, and special characters.
b. Case Folding: Converting all uppercase letters to lowercase.
c. Tokenization: Converting a sentence into a collection of words stored in an array.
d. Normalization: Converting all non-standard language and abbreviations into standard, complete forms.

3.3.2 Text Labeling

Text labeling plays a crucial role in the field of Natural Language Processing (NLP) and machine learning. This process categorizes and annotates or labels textual data, enabling machines to effectively understand and interpret human language. In this sentiment analysis, text data is labeled as positive, negative, or neutral. In this study, sentiment labeling on the text data uses the model ‘ayameRushia/bert-base-indonesian-1.5G-sentiment-analysis-smsa’. This model is a fine-tuned version of the BERT transformer used for sentiment analysis tasks specifically in the Indonesian language. It was developed by the Hugging Face community. This model was chosen due to its good performance in Indonesian sentiment classification [14].

3.3.3 Training Classification Model

Model training is the process of teaching a machine learning algorithm to process a dataset and optimize the algorithm in identifying specific patterns or outputs. In this case, the Random Forest Classifier method is trained to classify public comments regarding the Tapera policy, including negative, positive, or neutral sentiments.

Random Forest is a machine learning algorithm designed to classify large datasets. It is an extension of the Decision Tree method. While a Decision Tree creates a single decision tree to make predictions, Random Forest divides the data into several decision trees and combines them to obtain more stable and accurate prediction results. The term 'forest' in Random Forest refers to a collection of decision trees that are typically trained using the bagging method.

Bagging (Bootstrap Aggregating) is an ensemble method in machine learning aimed at improving model accuracy by combining the prediction results from multiple models trained separately. This process begins with randomly selecting several subsets of data from the original training dataset. Each subset is used to train the same model but with slightly different data. Once these models are trained, their prediction results are combined. In classification problems, the final prediction is usually determined by majority voting, meaning the class most frequently chosen by the models. In regression problems, the result is the average of all model predictions. This method is effective in reducing variance and overfitting, as well as increasing the model's resilience to data variation.

Random Forest (RF) is an advanced version of the bagging method in the context of decision trees. Unlike regular bagging, Random Forest adds an additional step in the random sampling process. In addition to randomly selecting data samples to build classification trees, independent variables are also randomly selected to determine the best split when forming the trees. This approach is expected to produce more accurate predictions compared to previous methods [15].

To evaluate the performance of a classification model, one of the methods that can be used is the Confusion Matrix. The confusion matrix compares the classification results obtained from the model with the true classification of the data and measures metrics such as F1-score, precision, recall, and accuracy. Accuracy measures the ratio of correct predictions to the total data tested. Precision

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measures the level of correctness between the requested data and the results or answers provided by the system. Meanwhile, recall is used to calculate the number of data correctly classified into a particular class compared to the total data that should belong to that class. The F1-score is used to assess the balance between precision and recall, especially when there is class imbalance (e.g., when the number of data in one class is much higher than in other classes). Figure 2 is an example of a confusion matrix for classification with three classes.

Classes		*Predicted Classification*		
		A	B	C
Actual Classification	A	TN	FP	TN
	B	FN	TP	FN
	C	TN	FP	TN

Figure 2. Confusion matrix

As shown in Figure 2, the condition where the prediction is correct for class B is called True Positive (TP), while a mistaken prediction for class B is called False Negative (FN). A False Positive (FP) occurs when another class is predicted as class B. True Negative (TN) occurs when another class is not predicted as class B. The formulas for calculating accuracy, precision, and recall for a class can be formulated as follows:

$$precision = \frac{TP}{TP+FP} \tag{1}$$

$$recall = \frac{TP}{TP+FN} \tag{2}$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

In addition to measuring accuracy, precision, and recall, the evaluation process also calculates the F1-Score to assess the model's performance by combining precision and recall values. The F1-Score reflects how well the model performs predictions, with a value of 1 indicating good performance, while a value of 0 indicates unsatisfactory performance. In binary classification, the F1-Score formula can be expressed as follows:

$$F1 - Score = 2 * \frac{presiisi*recall}{presisi+recall} \tag{4}$$

3.3.4 Data Visualization

Data visualization of sentiment analysis results is often presented in the form of graphs or charts to facilitate the understanding of the distribution of public sentiment, as well as word clouds for each sentiment. A word cloud is a visual representation of a set of words that shows the frequency or importance of words in a text. Words that appear frequently in the data are displayed in a larger size, while words that appear less frequently are displayed in smaller sizes. This helps to quickly identify key themes or terms related to the sentiment expressed in the text.

4 Results and Analysis

4.1 *Preprocessing* data

The data obtained from the scraping process consists of 6000 tweets, and after removing duplicate data, 5036 tweets remained. This data is raw and needs to be processed further. Data preprocessing is performed to transform raw data into a more structured format, allowing for more effective and efficient training of the classification model. The preprocessing steps carried out include cleansing, case folding, tokenizing, and formalization. The results of the data preprocessing can be seen in Table 1. Formalization is useful for replacing slang with standard language, and common

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abbreviations are expanded into full words, which is expected to help the machine understand the context of the sentences.

Table 1. Text data before and after preprocessing

Raw Data	After *preprocessing*
Gaji kita hanya 2 juta pak,belum LG untuk kebutuhan anak dan istri..🥺 😢	gaji kita hanya juta pak belum lagi untuk kebutuhan anak dan istri
Setuju. Terutama poin terakhir, kenapa tidak menteri & dpr aja yg dipotong untuk kebutuhan rakyat 👍	setuju terutama poin terakhir kenapa tidak menteri dpr saja yang dipotong untuk kebutuhan rakyat
berubah mulai awal lagi. modal lagi. hasil yg sebelumnya dimangkrakin gt aja. apa bedanya dg sebelum"nya. 🤣 tiap ganti presiden kok perubahan. browsing aja. mangkraknya di era sby	berubah mulai awal lagi modal lagi hasil yang sebelumnya dimangkrakin begitu saja apa bedanya dengan sebelumnya tiap ganti presiden kok perubahan browsing saja mangkraknya di era sby

4.2 Text Labeling

Labeling is the process of annotating or labeling raw data so that the model can learn from it. In this research, each comment is labeled as "negative," "positive," or "neutral" to help the model recognize similar comments in the future. Labeling is crucial in supervised machine learning, where the model requires labeled data to learn the relationship between input and desired output. Labeled data helps algorithms understand patterns and make more accurate predictions.

The labeling of data is performed automatically using the model ‘ayameRushia/bert-base-indonesian-1.5G-sentiment-analysis-smsa’. This model is a fine-tuned version of the BERT transformer used for sentiment analysis tasks specifically in Indonesian. The model has been trained on a large dataset in the Indonesian language, enabling it to understand context in Indonesian. This model is reliable in providing accurate sentiment. It was chosen because the data does not need to be translated into English first, unlike with Textblob, which has lower accuracy [16]. The results of the labeled classes can be seen in Table 2.

Table 2. Text labeling result

Data	Label
kalau pun bisa dicairkan setelah puluhan tahun apa nominalnya bisa dibelikan rumah saat uang diterima harga sudah melambung tinggi bisa buat beli motor saja	Negative
tujuan bagus cuma siapa yang percaya nabung di lembaga pemerintahan	Negative
firasat saya mengatakan uang dari iuran dana tapera itu untuk membangun ikn karena sejauh ini para investor sudah tidak mau nanem modal di indonesia pemerintah sudah pusing jalan satu nya ya tapera	Negative
memang kembali tapi kan kalau yang gajinya kecil kasian mending kalau bisa diambil kapan saja ini menguntungkan yang kelola si uangnya sama mereka bisa diputer buat usaha banyak loh kalau ditotal seluruh karyawan se indo	Negative
saya mau tanya buat saya yg berpenghasilan jtbln punya istri anak batita dan tanggungan kpr yang tahun depan bunganya floating mengikuti suku bunga bank bi apa manfaat tapera ini buat saya	Neutral
jadi sistem tapera itu mengumpulkan ana masyarakat lewat tabungan tapera nah dana yang terkumpul nantinya dipinjamkan berupa kredit rumah	Neutral
jangan lupa bayar tapera bang	Neutral
intinya sifat nya sama kayak bpjs tk tetap ada manfaatnya manfaat jangka panjang coba kalau tidak ada pas pada berhenti kerja emang pada punya tabungan tidak kan untung ada tabungan bpjs tk	Positive

From the results of the text labeling, the majority of the public have a negative sentiment

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towards the Tapera policy. The unfavorable economic conditions have made the public sensitive to policies that cut their salaries. The proportion of each sentiment can be seen in Figure 3. The negative sentiment constitutes 4141 comments, or 82%, the neutral sentiment is 517 comments, or 10%, and the positive sentiment is 378 comments, or 8%.

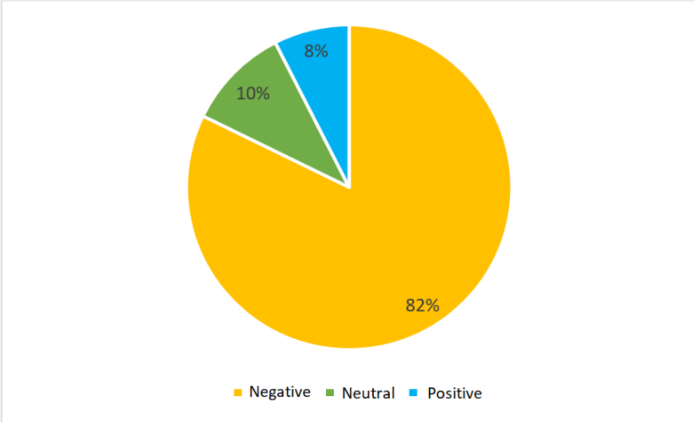

Figure 3. Sentiment proportion of dataset

4.3 Sentiment Classification with Random Forest Classifier

This study consists of 5036 data points, which are split into two parts: 75% for training data and 25% for testing data. Essentially, computers can only make predictions on numerical data, as computers are sophisticated calculators. The data used in this study is textual, so the data needs to be converted into a numerical form.

One way to convert text/sentences into numerical values is by using TF-IDF. TF-IDF is chosen because the dataset is relatively small and the pattern is not too complex. TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical technique used in text mining and information retrieval to evaluate the importance of a word within a document relative to a collection of documents or corpus.

TF-IDF assigns a score to each word in a document based on its frequency in the document and how rare the word is across the entire corpus. Words that appear frequently in a specific document but rarely across the entire corpus will receive a high TF-IDF score. This technique aids in feature extraction for machine learning models that require a numerical representation of textual data. TF-IDF is commonly used as a feature in machine learning algorithms for sentiment analysis, text classification, and similar tasks. The results of converting text data using TF-IDF can be seen in Figure 4. The output data, which includes negative, neutral, and positive sentiments, is converted into numerical values: 0 for negative, 1 for neutral, and 2 for positive using the Label Encoder library.

```
(0, 3413)     0.252683544436012
(0, 2982)     0.19913813328102795
(0, 618)      0.30667488242786645
(0, 6735)     0.30667488242786645
(0, 1424)     0.30667488242786645
(0, 1534)     0.6133497648557329
(0, 7549)     0.2617048901916403
(0, 6350)     0.18340624996623567
(0, 7747)     0.1973867298958059
(0, 8024)     0.054866555674475834
(0, 3179)     0.30667488242786645
(1, 8024)     0.04935240551273877
(1, 6163)     0.24626760676683498
(1, 877)      0.24038062685339726
(1, 8072)     0.15516811680767975
(1, 6137)     0.253472687874 6301
(1, 6411)     0.26276165299625714
(1, 3674)     0.3353773525298049
(1, 846)      0.2534726878746301
```

Figure 4. The result of converting text data to numeric using TF-IDF

Random Forest has quite good performance in sentiment analysis [5] [6]. Essentially, Random Forest is an extension of the Decision Tree method. A Decision Tree creates a decision tree for classification purposes. Random Forest, on the other hand, divides that decision tree into multiple smaller decision trees.

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The results of the model training can be seen in Figure 5. The model achieves an accuracy of 89%. The highest F1-score for detecting negative sentiment is 94%. The F1-scores for detecting neutral sentiment and positive sentiment are 17% and 32%, respectively. This is because the dataset composition is predominantly negative sentiment. The proportion of sentiment in the dataset affects the performance of the classification model [17]. A balanced proportion of each sentiment allows the model to better learn and recognize the words that frequently appear in each sentiment category.

	precision	recall	f1-score	support
0	0.89	1.00	0.94	884
1	0.71	0.10	0.17	103
2	0.80	0.20	0.32	20
accuracy			0.89	1007
macro avg	0.80	0.43	0.48	1007
weighted avg	0.87	0.89	0.85	1007

Figure 5. Classification report model random forest

The confusion matrix from the model testing can be seen in Figure 6. A confusion matrix is a table used to evaluate the performance of a classification model. This matrix compares the true labels (actual labels) with the predicted labels by the model. A model with more numbers in the diagonal of the matrix has better performance. The model successfully predicted 879 negative sentiments out of 884, 10 neutral sentiments out of 103, and 4 positive sentiments out of 20. The model performs best in identifying negative sentiment. This is because the proportion of negative sentiment is higher compared to the other sentiments..

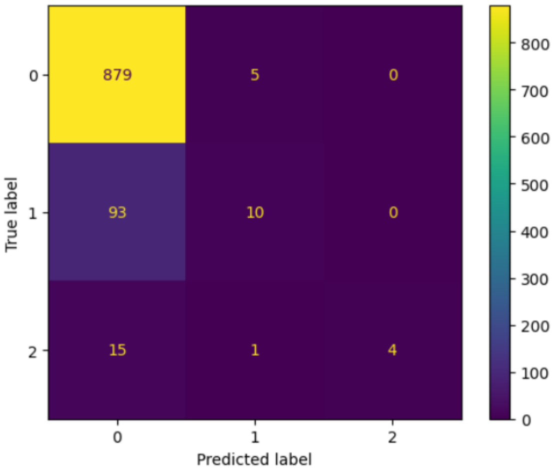

Figure 6. Confusion matrix

4.4 Data Visualization

A word cloud is a visualization tool used to represent the frequency of words in a text dataset. In the case of sentiment analysis, a word cloud allows us to quickly see the most frequently used words in the text data. Words that appear more often are displayed larger, providing a clear visual representation of the main issues discussed by the public. Figure 7 shows the word cloud from the entire dataset.

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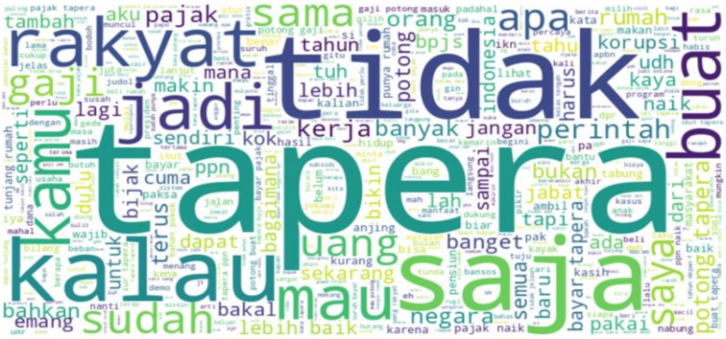

Figure 7. Word cloud of tapera policy

From the word cloud of the entire dataset in Figure 7, the most frequent word is ‘tapera’, as Tapera is the central topic of this study. The second most frequent word is ‘rakyat’, referring to the people who are directly affected by the Tapera policy. The third word is ‘gaji’ (salary), as Tapera is funded by a 3% salary deduction from employees. Comments related to salary express objections to the salary deduction for Tapera, with some even inquiring about the exact amount of salary affected by Tapera. The fourth word is ‘pajak’ (tax), where people complain that their salaries are already taxed, and now Tapera will also be deducted. The fifth word is ‘pemerintah’ (government), with most comments stating that the government is imposing the Tapera policy. The sixth word is ‘negara’ (country), with many people commenting that the Tapera deduction is to cover the state budget shortfall, assist in the development of the new capital (IKN), and so on.

To explore the sentiment further, each sentiment category was visualized in its own word cloud, which was then analyzed based on the comments. The word cloud for negative sentiment can be seen in Figure 8. The word 'tapera' is often satirized as "Tabungan pemeras rakyat" (People's Exploitation Savings) or "Tabungan penderitaan rakyat" (People's Suffering Savings). The word 'pemerintah' (government) is frequently mentioned, with most comments expressing that the government is imposing its will to carry out the Tapera program and is looking for additional funds for the state budget (APBN).

Figure 8. Word cloud of negative sentiment

The word cloud for neutral sentiment is shown in Figure 9. Neutral sentiment is mainly dominated by questions related to Tapera. The word 'potong' (cut) represents comments asking about the amount of salary deductions required for workers. The word 'rakyat' (people) mostly represents comments discussing the full name of Tapera, "Tabungan Perumahan Rakyat" (People's Housing Savings). Some comments suggest that if the program is for the people, it would be better if houses were provided first or at least the locations were disclosed so that the people could occupy and pay for them through Tapera. The word 'kalau' (if) also appears frequently, asking various questions like "If I already have a house, what happens?" "What is JHT for if Tapera works like this?" and "If this goes through, we hope my salary in the city will increase by 3 million; that would be acceptable," and similar inquiries.

Figure 9. Word cloud of neutral sentimen

The word cloud for positive sentiment is shown in Figure 10. The most frequent words are ‘tapera’, ‘kalau’ (if), ‘kelola’ (manage), ‘perintah’ (order), ‘rakyat’ (people), ‘bpjs’, ‘alhamdulillah’ (thank God), and ‘semangat’ (spirit). In general, positive comments express support for the Tapera policy, with people stating that they are ready for their salaries to be deducted according to the regulations. Some comments compare it to BPJS Kesehatan (Health Insurance), stating that the funds are well-managed and benefit many people. However, the proportion of positive sentiment is not comparable to the dominant negative sentiment.

Figure 10. Word cloud of positive sentiment

Based on the data analysis results, negative sentiment dominates the public’s view of the Tapera policy. The public disagrees with the policy for various reasons, including: (1) the widespread cases of corruption involving the government, which makes the public distrustful of the management of Tapera funds, similar to the ongoing Jiwasraya and Bumiputera cases, (2) the public perceives that the 3% deduction over time, until the age of 58, will not accumulate much due to inflation, meaning that even when the funds are released, they will not be enough to purchase a house, (3) the Tapera deduction is seen as a burden on the public amidst a sluggish economy, consistent with research findings [18] , (4) Tapera funds are considered as additional funds to cover the APBN deficit, and others.

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5 Conclusion

Based on the research results, a total of 5036 comment data were successfully downloaded from the TikTok social media platform regarding the Tapera policy and used for this study. The sentiment distribution shows that the majority of the public holds a negative sentiment towards the Tapera policy. The unfavorable economic conditions make the public sensitive to policies that cut their wages. The number of negative sentiments is 4141, or 82%, neutral sentiments amount to 517, or 10%, and positive sentiments total 378, or 8%.

The public disagrees with the Tapera policy for various reasons, including: (1) widespread corruption cases within the government have made the public distrustful of Tapera fund management, (2) the public believes that the 3% wage deduction until the age of 58 will not accumulate much due to inflation, so even when it is disbursed, it may not be sufficient to purchase a house, (3) the Tapera deduction is seen as a burden on the public amid the sluggish economic conditions, (4) the Tapera fund is viewed as additional funding to cover the deficit in the state budget (APBN), and so on.

Neutral sentiments are dominated by questions related to Tapera. The word "potong" (cut) represents comments inquiring about the amount of salary deduction workers have to make. The word "kalau" (if) frequently appears, asking various questions such as "if I already have a house, what happens," "what is the purpose of JHT (Jaminan Hari Tua - old age benefit) if Tapera works like this," "if this becomes a policy, can my salary be increased by 3 million, that's fine," and similar inquiries.

Meanwhile, positive sentiment expresses support for the Tapera policy. Similar to BPJS Health, which helps many people, the Tapera program is hoped to assist lower-income individuals in purchasing homes. However, the proportion of those supporting the program is not as large as those who oppose it.

Based on the classification model training using Random Forest, the model achieved an accuracy of 89%. The best F1-score for detecting negative sentiment was 94%. The F1-scores for detecting neutral and positive sentiment were 17% and 32%, respectively. This is due to the dataset being dominated by negative sentiment. The proportion of sentiments influences the training of the classification model. A balanced proportion for each sentiment allows the model to learn better and recognize the words frequently associated with each sentiment.

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