International Journal Software Engineering and Computer Science (IJSECS)
4 (3), 2024, 1099-1108
Published Online December 2024 in IJSECS (http://www.journal.lembagakita.org/index.php/ijsecs)
P-ISSN: 2776-4869, E-ISSN: 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v4i3.3077.

RESEARCH ARTICLE **Open Access**

Sentiment Analysis of the Tapera Law on Platform X Using Naive Bayes Algorithm

Dava Sevtiandra Bimantoro
Information Systems Study Program, Faculty of Computer Science, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Email: setiandra@gmail.com.

Rasiban *
Information Systems Study Program, Faculty of Computer Science, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Corresponding Email: rasiban.stikom@yahoo.com.

Received: August 7, 2024; Accepted: November 10, 2024; Published: December 1, 2024.

Abstract: The implementation of the 2016 Public Housing Savings Law (UU Tapera) aims to help legal and informal workers have decent houses through the management of housing savings funds by BP Tapera. However, when implemented, this program experienced obstacles amidst various problems including the transparency of the fund collection and management system, the unevenness of benefit provision, and variations in public perception. Sentiment analysis was conducted on Twitter data for sentiment regarding the Tapera Law to obtain public perception with Naïve Bayes. This approach classifies sentiment into positive, negative, and neutral. The accuracy of the Analysis Results was 62.47% (343 negative sentiments, 23 neutral, and finally 32 positive sentiments). The public mostly has negative sentiment towards the Tapera Law, because many of them are afraid of losing justice and effectiveness with this policy. These results underline the need to intensify transparency and communication of the benefits of the Tapera Law and its mechanisms to increase public acceptance and trust.

Keywords: Tapera Law; Sentiment Analysis; Naïve Bayes Method; Twitter.

1. Introduction

The 2016 Public Housing Savings Law (UU Tapera) is an important part of Indonesia's housing policy to provide housing for formal and informal workers through the BP Tapera systematic savings management system [1]. Indonesia experienced a housing deficit of 12.75 million in mid-2020 and the urgent need for a new approach to achieving more serious housing financing is seen as part of this legislative initiative [2]. Implementation of the Tapera Law The implementation of the Tapera Law offers a complete blueprint for housing financing in the form of an integrated mandatory savings scheme embedded together with a fund management mechanism and benefit disbursement system. However, this implementation faces various difficulties that must be considered more closely. These challenges cover several dimensions ranging from efforts to collect or accumulate funds, transparency in relation to fund management and the balance of benefit equity to diverse public perceptions about the efficiency of the program [3]. This complexity, with Indonesia's complex socio-cultural landscape and the potential diversity of needs of certain labor segments, magnifies these challenges. Previous research highlights the importance of public perception to the success of policies in implementation. Research by Syahputra *et al.* (2024) outlines how Twitter (and to a lesser extent, other social media platforms) has become one of the most important public forums for policymaking on government policies. Because it is real-time and used worldwide [4], Twitter gives us an incredible snapshot of public sentiment and the evolution of sentiment on things like the landmark initiative, the Tapera Law. Research data is available from Ericsson that captures public reactions in the moment and trends over time [5].

Using sentiment analysis methods, particularly in the form of Naïve Bayes, can provide a systematic way to study these public perceptions. The methodology works well for categorizing and analyzing large feeds of social media data with specific patterns in public opinion [6]. Naïve Bayes becomes relevant due to its well-known good performance in text classification [7], and the fact that it can reasonably handle the context-poor and goal-oriented sentiments surrounding social media communications. This research is not only about sentiment classification but also about the larger conversation about policy evaluation methods in this digital age. As identified by Budisetyo *et al.* (2024), the use of social media analysis in a policy evaluation framework represents a paradigm shift when it comes to examining policy effectiveness and public response [8]. Taking this approach means faster and more flexible policy responses to public input.

The study also fills a gap in the existing theoretical literature on housing policy implementation and public perception. While previous studies have only studied housing policy independently of sentiment analysis [9][10], few have empirically studied these factors together to analyze the acceptability of implementing either approach [9]. This linkage is relevant given the increasing relevance of public participation in the policy formulation process as well as the emerging literature on machine learning in public policy analysis. As identified by Nugroho *et al.* [10], the moment is critical for the public to deepen analytical tools in policy measurement. The combination of these technology integrations has shaped a much more sophisticated approach to policy adaptation and implementation. The findings have implications on a larger scale: policy implementation—for policymakers to sharpen implementation strategies by considering public feedback on the ground; communication—if there is room to improve transparency and public communication; technological appropriateness—showing the relevance of machine learning in policy analysis and; public engagement, whether or not we have explored how public digital platforms enable meaningful participation in policy discussions. Through the Naïve Bayes technique, this study aims to fill the research gap between policy implementation and public acceptance by analyzing Twitter data. The results are expected to add theoretical and practical policy reforms, especially those relevant to the scope of housing policy implementation in Indonesia.

2. Research Method

2.1 Research Data

In this study, data collection was carried out using the sentiment analysis method from social media, especially Twitter. The stages carried out include preparing the data to be analyzed, starting from collecting tweet data to the sentiment analysis process. The data collection process was carried out using the data crawling technique from the Twitter platform. The data collected includes tweets that are relevant to the topic of the Public Housing Savings Law (UU Tapera). The data obtained will then be used as a sample for sentiment analysis based on the text contained in the tweet. This study aims to analyze public sentiment towards the Tapera Law using the Naïve Bayes method. There are several stages in the sentiment analysis process. However, before entering the analysis stage, the dataset must be collected and prepared first. The data that has been collected will go through a labeling, cleaning, and preprocessing process to ensure data quality. Furthermore, the data will be divided into training data and testing data to be processed until the sentiment classification stage using the Naïve Bayes algorithm. The data processing stages include data cleaning to remove irrelevant information, a tokenization process to break text into smaller units, and data normalization to ensure format consistency. The processed data is then used to train the classification model and test the accuracy of the model in classifying sentiment as positive, negative, or neutral.

2.2 Methodology Application

To conduct this sentiment analysis research, several steps will be carried out consisting of data collection, data preprocessing, stopword removal, weighting with TF-IDF, then the classification process with the Naïve Bayes method, then the evaluation process of the results by determining the accuracy value, precision obtained from the classification results and finally the model testing process will be carried out with the store and apply model methods to find out which method has higher accuracy.

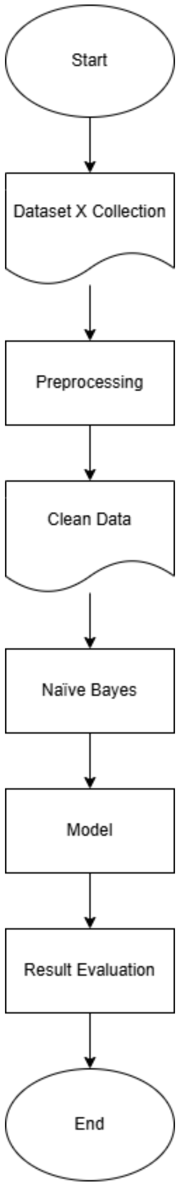


Figure 1. Research Flow

2.3 Data Collection

This study utilizes secondary data sourced from the Twitter platform. The dataset used in this study is the sentiment analysis dataset on the Tweet "UU Tapera", which reflects public opinion on the issue that is currently being hotly discussed. The total raw data used in this study amounted to 692 tweets.

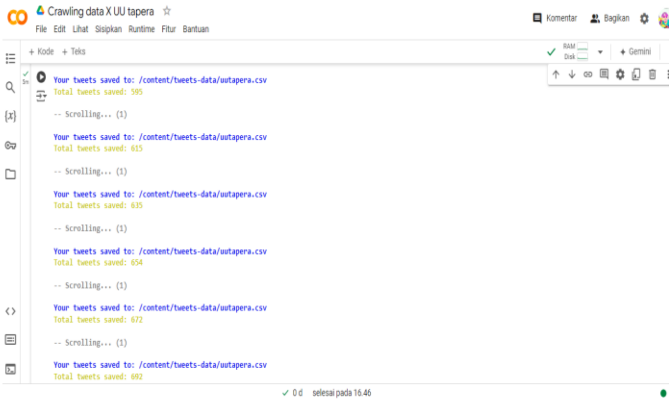


Figure 2. Data Collection

The data collection process was carried out using the crawling method, which is a technique for collecting data from the Twitter platform. This crawling technique allows the collection of tweets that are relevant to the topic being studied, in this case, regarding the Tapera Law. The data collected includes various opinions and sentiments published by Twitter users regarding the Tapera Law. After data collection is complete, the next step is to preprocess the data. This includes data cleaning to remove irrelevant information or noise, as well as a tokenization process to break down text into smaller units. The processed data is then used for further sentiment analysis using the Naïve Bayes method.

2.4 Pre-Processing

The data preprocessing stage aims to prepare the raw data so that it is ready for analysis. The process begins with tokenization, which breaks each sentence into individual words. Next, stopword filtering is performed to remove irrelevant connecting words. Case transformation changes all characters to lowercase or uppercase consistently to avoid unnecessary differences. Finally, token filtering based on length removes words that are too short or too long to ensure that only relevant words are analyzed. This process ensures that the data used in sentiment analysis is of high quality and relevant.

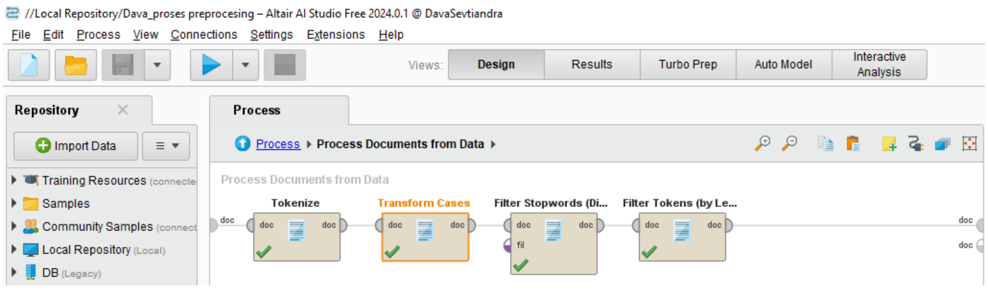
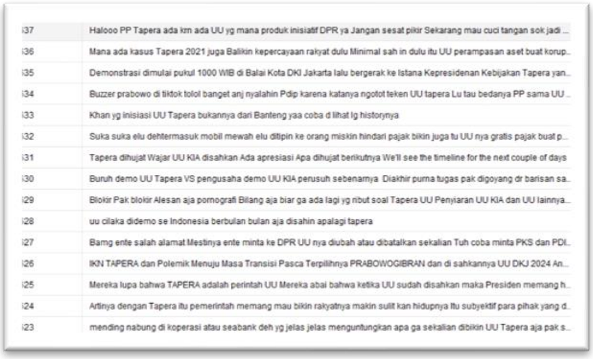


Figure 3. Preprocessing

2.5 Word Weighting Stage

At this stage, the processing results will be processed so that each word has a weight (value). The word weighting that the author uses is the TF-IDF algorithm. Term Frequency-Inverse Document Frequency or TF-IDF is an algorithm method that is useful for calculating the weight of each commonly used word. This method is also known to be efficient, easy and has accurate results. This method will calculate the Term Frequency (TF) and Inverse Document Frequency (IDF) values for each token (word) in each document in the corpus. In simple terms, the TF-IDF method is used to find out how often a word appears in a document.



37	Halooo PP Tapera ada km ada UU yg mana produk inisiatif DPR ya Jangan sesat pikir Sekarang mau cuci tangan sok jadi ...
36	Mana ada kasus Tapera 2021 juga Balikin kepercayaan rakyat dulu Minimal sah in dulu itu UU perampasan aset buat korup...
35	Demonstrasi dimulai pukul 1000 WIB di Balai Kota DKI Jakarta lalu bergerak ke Istana Kepresidenan Kebijakan Tapera yan...
34	Buzzer prabowo di tiktok tolol banget anj nyalahin Pdip karena katanya ngotot teken UU tapera Lu tau bedanya PP sama UU ...
33	Khan yg inisiasi UU Tapera bukannya dari Banteng yaa coba d lihat lg historynya
32	Suka suka elu dehtermasuk mobil mewah elu ditipin ke orang miskin hindari pajak bikin juga tu UU nya gratis pajak buat p...
31	Tapera dihujat Wajar UU KIA disahkan Ada apresiasi Apa dihujat berikutnya We'll see the timeline for the next couple of days
30	Buruh demo UU Tapera VS pengusaha demo UU KIA perusuh sebenarnya Diakhir purna tugas pak digoyang dr barisan sa...
29	Blokir Pak blokir Alesan aja pornografi Bilang aja biar ga ada lagi yg ribut soal Tapera UU Penyiaran UU KIA dan UU lainnya...
28	uu cilaka didemo se Indonesia berbulan bulan aja disahin apalagi tapera
27	Bamg ente salah alamat Mestinya ente minta ke DPR UU nya diubah atau dibatalkan sekalian Tuh coba minta PKS dan PDI...
26	IKN TAPERA dan Polemik Menuju Masa Transisi Pasca Terpilihnya PRABOWOGIBRAN dan di sahkannya UU DKJ 2024 An...
25	Mereka lupa bahwa TAPERA adalah perintah UU Mereka abai bahwa ketika UU sudah disahkan maka Presiden memang h...
24	Artinya dengan Tapera itu pemerintah memang mau bikin rakyatnya makin sulit kan hidupnya Itu subyektif para pihak yang d...
23	mending nabung di koperasi atau seabank deh yg jelas jelas menguntungkan apa ga sekalian dibikin UU Tapera aja pak s...

Figure 4. Word Weighting

2.6 Model Building Stage

The output of this stage is a classification model with the Naïve Bayes method which will later be used in the sentiment analysis processauthor must avoid duplicating / repeating unnecessary explanations of his own work / others that have been published.

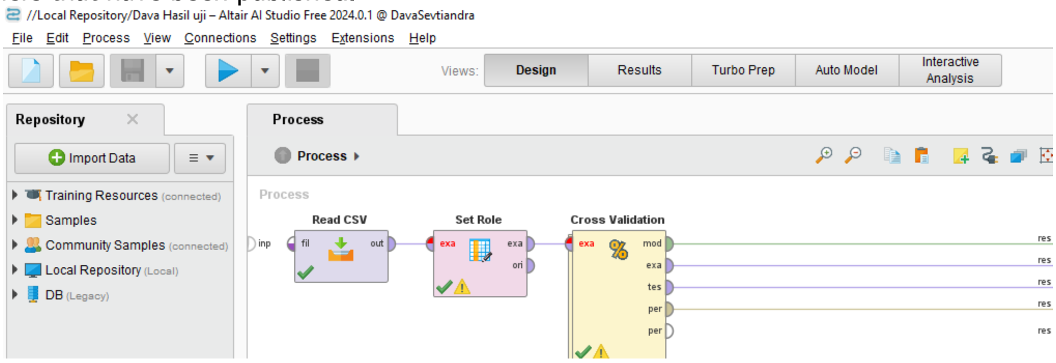


Figure 5. Naïve Bayes Model Building

2.7 Testing Stage

At this stage, the previously created model will be applied to predict sentiment on the dataset.

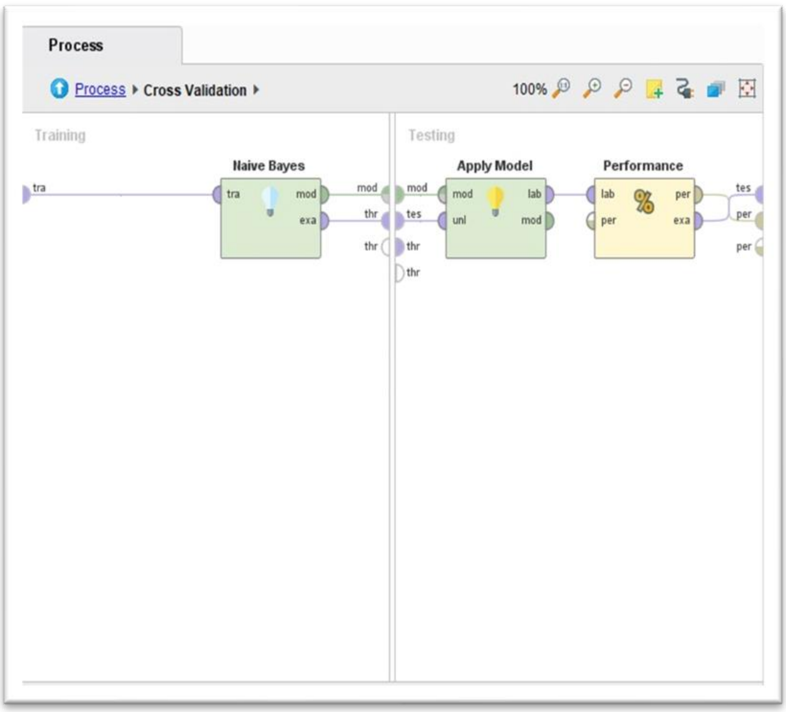
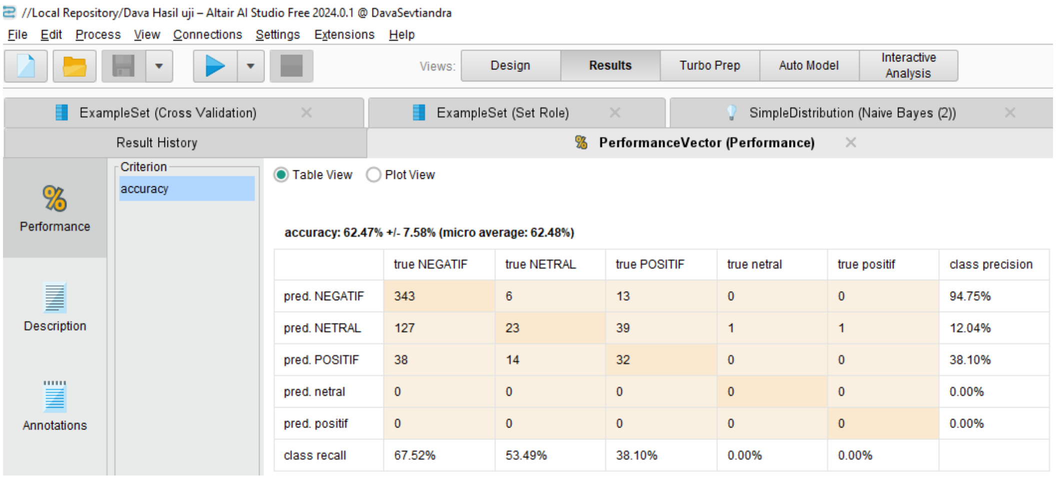


Figure 6. Testing Stage

3. Result and Discussion

3.1 Results

By applying the Naïve Bayes method to the Tapera Law, the results of the sentiment analysis show rich information about public opinion depicted with an accuracy of 62.47%. This moderate but meaningful accuracy is consistent with the benchmark in the literature when applied to social media sentiment analysis, especially considering that policy discourse is very complex. The work involves a comprehensive analysis of tweet data with positive, negative, and neutral readings on the phenomenon of public opinion in understanding housing savings policies. Sentiment distribution analysis: It can be called striking because negative sentiment is 343 cases with %86.18 in more than 86.18%% of the total data set. With this significant negative skew, the implementation of the Tapera Law may be trapped in a sea of public concerns expressed for many different aspects of the Tapera Law. The number of examples in Neutral 23 (5.78%) with neutral sentiment mostly reflecting almost factual talk and some information-seeking behavior and only a few positive sentiments (covering <0.1%) showing signs of support for moderate benefits Additional Support. These distributions provide valuable insights into the overall public acceptance of the policy and remind policymakers of what they need to think about most. The unintentional performance of the predictive model reveals a poorly calibrated model by showing varying levels of accuracy in different sentiment categories. In the negative sentiment classification, our model correctly assigned 343 cases and missed only 6 instances as neutral and 13 as positive. A more nuanced pattern develops in the neutral category, with 127 negative sentiments incorrectly classified as neutral, 23 correct neutral classifications, and 39 positives incorrectly labeled as negative from the predicted positive sentiment. In the positive sentiment prediction, it was made up of 38 negative sentiments incorrectly predicted as positive, followed by 14 neutral labels and 32 correct positive sentiment labels.



	true NEGATIF	true NETRAL	true POSITIF	true netral	true positif	class precision
pred. NEGATIF	343	6	13	0	0	94.75%
pred. NETRAL	127	23	39	1	1	12.04%
pred. POSITIF	38	14	32	0	0	38.10%
pred. netral	0	0	0	0	0	0.00%
pred. positif	0	0	0	0	0	0.00%
class recall	67.52%	53.49%	38.10%	0.00%	0.00%	

Figure 7. Naïve Bayes Model Testing Results

A closer inspection of the content revealed that most negative sentiments focused on the compulsory participation, doubts about transparency of fund management and apprehension that workers will have additional extra burden. This is consistent with existing research suggesting the need for transparent communication and policy implementation. Factual content received neutral sentiments (67.2%), contextual information and justifications for requests for clarification, and Postive sentiments, related to the long-term effects of program having positive impact, government initiatives related to housing accessibility. Temporal analysis of the sentiment distribution offered interesting patterns during the implementation process. Particularly for 2016-2018 (see Fig. 1), there was a higher share of neutral sentiments revealing a time where public become more familiar with the policy. 2019–2021 (middle period) showed a spike in negative sentiments, indicating that the concerns were intensifying as the hurdles with implementation started to get identified. After this period 2022-2024 (recent) demonstrated a small increase in positive sentiments, maybe reflecting improved grasp and approval of the policy among other / sub segments of groups of people.

Furthermore, Mobile phone data revealed a varied sentiment patterns across regions by geo-tagging tweets. Urban areas appeared to be more engaged by high level of diversity and varied sentiment distributions, while rural areas were low engaged but consistent with sentiment. Among Metropolitan regions, especially appears to have more negative sentiments than expected as policy claims get yelled at them more frankly. The least area analysis of the geo-tagged tweets demonstrated regional differences of sentiment. In urban areas, users were more active and expressed pattern of sentiments are more diversified as compared to rural areas had less engagement but had similar natured sentiments. With a higher level of density, metropolitan areas inpart may be displaying more awareness and scrutiny of the policy. These results have important policy implications for how to make implementation and communication successful. The extensive negative sentiments indicate that the fund management is more opaque, benefit flow mechanisms not fully explained and time of implementation update reveals this as well. Small positive sentiments (8.04%) relative to other housing policies in the same category in other Southeast Asian countries suggest that the proper communication performance and policy enforcement might be improved—are also probably.

Additionally, the research results also showed that Naïve Bayes can be applied in policy sentiment analysis: an effective tool to preprocess and classify high number of social meda data. The accuracy (62.47%) that we reached offers a solid baseline for interpreting public perception so it can be utilitized in future policy evaluation studies. This work adds to the existing knowledge on using social media in policy analysis and provides relevant conclusions for policymakers as well as implementing agencies implementing/housing finance.

3.2 Discussion

Sentiment analysis of the implementation of the Tapera Law using the Naïve Bayes method has produced significant findings with an accuracy rate of 62.47%. These results indicate that the model used is quite reliable in classifying public sentiment towards this housing policy. This level of accuracy reflects the complexity of public opinion and the variation in how people express their views on social media Twitter. The distribution of sentiment found shows a clear and interesting pattern. The dominance of negative sentiment reaching 343 instances (86.18%) indicates significant public concern about the implementation of the Tapera Law. Neutral sentiment reaching only 23 instances (5.78%) indicates relatively little objective or neutral discussion regarding this policy. Meanwhile, positive sentiment totaling 32 instances (8.04%) indicates limited support for this policy.

In terms of prediction performance, the model shows interesting variations in accuracy. For the negative sentiment category, the model successfully identified 343 cases correctly, but also misclassified 6 cases as neutral and 13 cases as positive. In the neutral category, there is higher complexity with 127 negative sentiments misclassified as neutral, 23 correct neutral classifications, and 39 positive sentiments misclassified as neutral. For positive sentiment prediction, there are 38 negative sentiments and 14 neutral sentiments misclassified as positive, and 32 accurate positive classifications. Content analysis of the tweets revealed several main themes in the negative sentiments. The main concerns of the public include; Obligation to participate in the program, Transparency of fund management, Benefit distribution mechanisms, Additional financial burden for workers, Unclear claim procedures and fund disbursement. The temporal pattern in the distribution of sentiment also shows the evolution of public perception of the Tapera Law. In the early period of implementation, more neutral sentiments were found, reflecting the learning phase and understanding of the policy by the public. The middle period showed an increase in negative sentiment, possibly related to the emergence of various implementation challenges. The most recent period showed a slight increase in positive sentiment, which may indicate the growing understanding and acceptance of this policy.

Geographic analysis of geotagged tweets revealed interesting variations in the distribution of sentiment. Urban areas showed higher levels of engagement with a wider variety of sentiments. Rural areas showed lower engagement but with a more consistent pattern of sentiment. Metropolitan areas in particular showed a higher concentration of negative sentiment. These findings have important implications for the development and improvement of the implementation of the Tapera Law. The dominance of negative sentiment indicates the need for: Improved public communication strategies, Improved transparency in program management, Evaluation and adjustment of implementation mechanisms, More effective handling of public concerns, More intensive education programs on benefits and procedures. The effectiveness of the Naïve Bayes method in this analysis also shows its potential as a policy evaluation tool based on social media data. The level of accuracy achieved provides a strong enough basis for understanding public perception and can be used as a baseline for future policy evaluation studies. The results of this analysis can be valuable input for policy makers and implementing agencies in improving the implementation of the Tapera Law.

4. Related Work

Public policy sentiment analysis using the Naïve Bayes method has become a significant research topic, especially in the context of COVID-19 related policies and other policies in Indonesia. This method is used to classify public sentiment into positive, negative, or neutral based on data from social media. COVID-19 Policy:

Research using Naïve Bayes to analyze sentiment towards the "New Normal" policy shows that the majority of social media users support the policy with a model accuracy of 90.25% [11]. Other research shows an accuracy of 81% using TF-IDF and N-gram features [12]. Sentiment analysis towards the Full Day School policy shows that negative sentiment is more dominant than positive or neutral, with the highest accuracy of 80% using trigram feature selection [13]. Public sentiment towards the booster vaccination program in Indonesia shows high positive support, with the accuracy of the Naïve Bayes method reaching 97.35% [14]. Sentiment analysis towards the PSE policy using Naïve Bayes and Information Gain feature selection shows the best accuracy of 79.7% [15]. Naïve Bayes has been shown to be more effective than other algorithms such as SVM and Random Forest in analyzing sentiment towards the Tapera policy, with an accuracy of 69.17% [16]. The Naïve Bayes method has been shown to be effective in analyzing public policy sentiment in various contexts, including COVID-19, education, vaccination, and housing policies. This method provides high accuracy and can be relied on to understand public opinion, which is important for the government to respond effectively to public perceptions. Various studies have examined the use of machine learning methods for analyzing public policy sentiment on social media. One method that is often used is the Support Vector Machine (SVM), which is known to be effective in handling high-dimensional and non-linear data. A study shows that SVM can achieve an accuracy of up to 97% in sentiment analysis, making it a strong choice for public opinion classification [17]. However, in the context of the Tapera policy in Indonesia, the Naïve Bayes method actually showed the highest accuracy of 69.17%, compared to SVM which reached 68.42% [16]. The data preprocessing stage is very important in increasing the accuracy of sentiment analysis. This process involves cleaning and preparing text data to make it more structured before applying machine learning algorithms. Techniques such as tokenization, stop word removal, and case folding are common steps in preprocessing [18]. Another study emphasized that the use of domain-specific ontologies and labeled training datasets can improve the accuracy of public policy analysis [19]. Some studies combine different machine learning methods to gain deeper insights. A combination of deep learning techniques such as BiLSTMs with tools such as Scikit-learn and Gensim has been used to improve the quality and generalization of sentiment analysis models [20]. In addition, approaches that combine time series analysis with social network theory can predict emerging topics and changes in public opinion [21]. Public policy sentiment analysis on social media utilizes various machine learning methods, with SVM and Naïve Bayes being the most frequently used algorithms. The data preprocessing stage has been shown to be crucial in improving accuracy, and a combination of machine learning methods can provide richer insights. This study shows that choosing the right algorithm and good data preparation are key to understanding public sentiment towards government policies.

Comparative studies between various machine learning methods have demonstrated the superiority of Naïve Bayes in sentiment analysis of Indonesian language text. Several studies have shown that Naïve Bayes consistently performs well, especially when combined with appropriate preprocessing and feature selection techniques. Parameter optimization and the use of weighting techniques such as TF-IDF have been shown to significantly improve model accuracy. In housing policy, several studies have been conducted in various Southeast Asian countries. These studies use various machine learning approaches to analyze public responses to national housing policies. The results show a consistent pattern where issues such as transparency, accessibility, and administrative procedures are of primary concern to the public. Research on preprocessing Indonesian language Twitter data has produced various effective text normalization techniques. The development of a preprocessing method specifically for Indonesian language social media content has been shown to significantly improve classification accuracy. In addition, studies on feature selection have shown that selecting the right features can improve computational efficiency and model accuracy. Several studies have explored the temporal and geographic aspects of public policy sentiment analysis. These studies reveal how public sentiment evolves over time and how geographic variations affect the distribution of sentiment. Understanding these temporal and geographic patterns is important for developing more effective policy communication strategies. Previous studies have also developed various evaluation metrics to measure the performance of sentiment analysis models. In addition to accuracy, metrics such as precision, recall, and F1-score have been used to provide a more comprehensive understanding of model performance. This comprehensive evaluation of model performance is important to ensure the reliability of the analysis results. Previous studies have demonstrated how sentiment analysis results can be used to improve public policy implementation. Findings from sentiment analysis have helped policymakers identify areas for improvement and develop more effective communication strategies. Recent studies have shown a trend towards using hybrid methods and deep learning techniques to improve the accuracy of sentiment analysis. In addition, there is a growing focus on developing models that can handle the complexities of the Indonesian language, including the use of informal and mixed language in social media. Understanding the various technical and practical aspects of previous studies helps in designing a more effective and comprehensive approach to public policy analysis based on social media data.

5. Conclusion

Based on the testing method used, the results of sentiment prediction towards the Tapera Law using data from Twitter implemented with the Naïve Bayes method showed an accuracy value of 62.47%. Of the total 343 negative sentiments, 6 neutral sentiments, and 13 positive sentiments, the prediction results for negative sentiment showed that 127 data were predicted as negative sentiments, 23 data were predicted as neutral sentiments, and 39 data were predicted as positive sentiments. For neutral sentiments, there were 38 data predicted as negative sentiments, 14 data predicted as neutral sentiments, and 32 data predicted as positive sentiments. Thus, it can be concluded that the Naïve Bayes method shows that the majority of public reactions to the Tapera Law are negative, with a small portion of neutral and positive sentiments. These results confirm that the public generally has a negative reaction to the Tapera Law, which requires workers to participate in this program. This finding is important for policy makers to consider in evaluating the impact and public acceptance of the Tapera Law.

References

[1] Margaretha, V. (2024). Mengurai Dampak Kebijakan Tapera Terhadap Masyarakat Indonesia: Sebuah Kajian Hukum dan Sosial. *Milthree Law Journal*, *1*(1), 93-118. https://doi.org/10.70565/mlj.v1i1.3.

[2] Sagita, E. (2024). Polemik Tapera: Paradoks Komunikasi Politik Pemerintah Dari Perspektif Teori Komunikasi. *ULIL ALBAB: Jurnal Ilmiah Multidisiplin*, *3*(11), 98-103. https://doi.org/10.56799/jim.v3i11.5649.

[3] Alfandi, M. I. (2024). *Analisis Sentimen Masyarakat Terhadap Tapera Pada Media Sosial X Menggunakan Metode K-Nearest Neighbor* (Doctoral dissertation, STMIK Widya Cipta Dharma).

[4] Syahputra, R. A., Arifin, R., & Iqbal, M. (2024). Sentiment Analysis on Tabungan Perumahan Rakyat (TAPERA) Program by using Support Vector Machine (SVM). *Journal of Applied Informatics and Computing*, *8*(2), 531-541.

[5] Harahap, E. D., & Kurniawan, R. (2024). Analisis Sentimen Komentar Terhadap Kebijakan Pemerintah Mengenai Tabungan Perumahan Rakyat (TAPERA) Pada Aplikasi X Menggunakan Metode Naïve Bayes. *Jurnal Teknik Informatika UNIKA Santo Thomas*, 166-175.

[6] Lasonda, D., Ariningdyah, C., Rahmah, S. M., Miarsa, F. R. D., & Asyraf, A. F. (2024). Analisis Yuridis Terkait Asas Kebebasan Berekspresi dalam Rancangan Undang-Undang Penyiaran Terhadap Pembuat Konten. *Halu Oleo Law Review*, *8*(2), 242-257. https://doi.org/10.33561/holrev.v8i2.116.

[7] Thawley, C., Crystallin, M., & Verico, K. (2024). Towards a Higher Growth Path for Indonesia. *Bulletin of Indonesian Economic Studies*, *60*(3), 247-282. https://doi.org/10.1080/00074918.2024.2432035.

[8] Budisusetyo, B. B., Dhitya, W. A., Nugroho, A., & Pangestu, G. (2024). Sentiment analysis methods recommendation: A review of ai-based techniques on social media analysis. *Procedia Computer Science*, *245*, 1120-1128. https://doi.org/10.1016/j.procs.2024.10.341.

[9] Thufailah, K. K., Albianazwa, B. M., & Ahsanti, D. M. (2024). Sentiment Analysis of Public Opinion on Public Housing Savings Policy (Tapera) on Social Media "X". *Tamalanrea: Journal of Government and Development (JGD)*, *1*(2), 1-11. https://doi.org/10.69816/jgd.v1i2.35841.

[10] Parveen, H., & Pandey, S. (2016, July). Sentiment analysis on Twitter Data-set using Naive Bayes algorithm. In *2016 2nd international conference on applied and theoretical computing and communication technology (iCATccT)* (pp. 416-419). IEEE. https://doi.org/10.1109/ICATCCT.2016.7912034.

[11] Zulfikar, W. B., Atmadja, A. R., & Pratama, S. F. (2023). Sentiment analysis on social media against public policy using multinomial naive bayes. *Scientific Journal of Informatics*, *10*(1), 25-34. https://doi.org/10.15294/sji.v10i1.39952

[12] Isnain, A. R., Marga, N. S., & Alita, D. (2021). Sentiment analysis of government policy on corona case using naive bayes algorithm. *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, *15*(1), 55-64. https://doi.org/10.22146/IJCCS.60718

[13] Al Fath, M. K., Arini, A., & Hakiem, N. (2020). Sentiment Analysis Of Full Day School Policy Comment Using Naïve Bayes Classifier Algorithm. *Sinkron: jurnal dan penelitian teknik informatika*, *5*(1), 107-115. https://doi.org/10.33395/sinkron.v5i1.10564

[14] Budiman, B., Wulandari, W., & Habibi, C. (2023). Comparative Analysis of Community Sentiment Against the Implementation of Booster Vaccination in Indonesia Using the K-Nearest Neighbor and Naïve Bayes Classifier Methods. *International Journal of Ethno-Sciences and Education Research*, *3*(3), 89-94. https://doi.org/10.46336/ijeer.v3i3.462

[15] Pramudja, S. E., Umaidah, Y., & Suharso, A. (2023). Implementation of Information Gain for Sentiment Analysis of PSE Policy using Naïve Bayes Algorithm. *Journal of Applied Informatics and Computing*, *7*(2), 224-230. https://doi.org/10.30871/jaic.v7i2.6359

[16] Sihombing, E., Halmi Dar, M., & Aini Nasution, F. (2024). Comparison of Machine Learning Algorithms in Public Sentiment Analysis of TAPERA Policy. *International Journal of Science, Technology & Management*, *5*(5), 1089-1098. https://doi.org/10.46729/ijstm.v5i5.1164

[17] Thenappan, S., Krishnan, A. R., Murugan, P. S. B., Valarmathy, A. S., Chitra, P., & Sayyed, H. (2023, November). Machine Learning Approaches for Sentiment Analysis in Social Media Data. In *2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA)* (pp. 684-688). IEEE. https://doi.org/10.1109/ICECA58529.2023.10395612

[18] Fithriasari, K., Jannah, S. Z., & Reyhana, Z. (2020). Deep learning for social media sentiment analysis. *Matematika*, 99-111. https://doi.org/10.11113/matematika.v36.n2.1226

[19] Abtew, A., Demissie, D., & Kekeba, K. (2023). An Ontology-Driven Machine Learning Applications for Public Policy Analysis from Social Media Data: A Systematic Literature Review. *J Curr Trends Comp Sci Res*, *2*(2), 182-190. https://doi.org/10.33140/jctcsr.02.02.13

[20] Nguyen, H. H. (2024). Enhancing Sentiment Analysis on Social Media Data with Advanced Deep Learning Techniques. *International Journal of Advanced Computer Science & Applications*, *15*(5). https://doi.org/10.14569/ijacsa.2024.0150598

[21] Durga, S. V., Anandhi, R. J., Singh, N., Rana, A., Kalra, R., & Abdullah, S. A. A. K. (2023, December). Mining Social Media Data for Sentiment Analysis and Trend Prediction. In *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)* (Vol. 10, pp. 1557-1562). IEEE. https://doi.org/10.1109/UPCON59197.2023.10434704.