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Public Sentiment Toward VAT Increase in Indonesia: A Machine Learning Analysis of YouTube Comments

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ABSTRACT

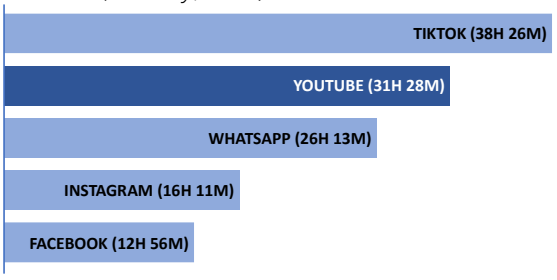
This study analyzes public sentiment toward the VAT increase in Indonesia by examining YouTube comments, using machine learning models to validate the consistency of an initial lexicon-based sentiment labeling. Given the rapid growth of social media use in Indonesia, particularly on YouTube, the platform serves as a rich source of real-time public opinion data. The primary objective is to determine public sentiment regarding the VAT increase and evaluate the performance of the Support Vector Machine (SVM) and Naive Bayes models in classifying this sentiment. The initial labeling reveals a significant negative sentiment, with 58.3% of comments expressing dissatisfaction with the VAT increase. To assess whether this pattern was systematic rather than an artifact of the labeling method, SVM and Naive Bayes were trained and evaluated on the labeled data: SVM achieved an accuracy of 86.83% and an F1-score of 87.26%, outperforming Naive Bayes, which achieved an accuracy of 83.19% and an F1-score of 83.33%, supporting the internal consistency of the initial sentiment labels. These findings underscore the importance of incorporating public sentiment into policy-making and highlight the potential for using social media data to inform and refine taxation policies.

Keywords: VAT increase, public sentiment, machine learning, YouTube comments, SVM, Naive Bayes

1. INTRODUCTION

Indonesia has seen rapid social media growth, making platforms such as X (Twitter), YouTube, and Facebook valuable sources of real-time public opinion data. In early 2024, YouTube was Indonesia's second most-used social media platform, with Indonesians spending an average of more than 31 hours per month on the platform (Meltwater, 2024), as shown in Figure 1. Moreover, Indonesia has around 139 million YouTube users, accounting for 75% of its total internet user base (DataReportal, 2024).

Figure 1
Top 5 Social Media Apps Based on Time Spent in Indonesia (January, 2024)



Note. Source: Social Media Statistics for Indonesia, (Meltwater, 2024)

Social media platforms are not only used for entertainment but also serve as spaces for discussing important issues. They enable people to share their opinions on various subjects,

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generating vast amounts of unstructured data (Yadav & Vishwakarma, 2020). This provides a rich dataset for analyzing public sentiment through comments and discussions on economic issues, policies, and taxation. VAT is a tax levied on the value added to goods and services at each stage of production and distribution. It serves as a major source of government revenue, contributing to the financing of public services and infrastructure development. However, changes in VAT rates can be controversial and affect consumer purchasing behavior and business operations. According to Winata et al. (2023), VAT-related tax evasion cases are prevalent, underscoring the significance of VAT in total tax revenues. Tax compliance behavior is significantly influenced by factors such as government trust, taxpayers' knowledge of taxation, tax system fairness, and rewards, while compliance costs negatively impact compliance (Mebratu, 2024). Understanding these factors is essential for policymakers when designing effective taxation policies.

Given the complexity of tax policies, particularly those involving VAT increases, it is crucial for policymakers to consider public opinion. Public opinion can significantly influence the acceptance and effectiveness of these policies. Social media platforms such as YouTube contain substantial amounts of real-time public opinion data that can be analyzed to understand public sentiment. According to Aufar et al. (2020), some companies view YouTube as an effective tool for promoting their products through various methods such as pop-up advertisements, banner advertisements, and company-specific channels that allow users to review their offerings. This indicates the potential for government policies to also leverage YouTube as a platform for public service announcements and educational campaigns, thereby maximizing their reach and public engagement. In this context, this study uses machine learning techniques to analyze YouTube comments related to VAT increases, providing insights into public attitudes and potential areas for policy improvement. Observing public perception in the digital age, especially through comments on social media platforms such as YouTube, is essential for sentiment analysis (Sholihah et al., 2023).

Recent studies have begun to examine public sentiment toward Indonesia's VAT increase on other social media platforms. Astuti and Erfina (2025) analyzed Twitter (X) data using an Indonesian RoBERTa-based classifier; Hasan and Bimby (2025) compared Naive Bayes, Support Vector Machine (SVM), and Logistic Regression on X data related to the VAT increase; and Manoppo et al. (2025) combined data from X, Instagram, and TikTok using a fine-tuned IndoBERT model. These studies consistently identify negative sentiment as the dominant sentiment, though findings vary across platforms and modeling approaches.

However, these studies center on short-form microblogging content, which differs structurally from the longer, context-rich discourse found in comment sections of curated news videos on YouTube. Furthermore, none of these studies combines lexicon-based sentiment labeling with independent validation through multiple supervised classifiers, an approach this study adopts to strengthen label reliability beyond single-model classification. This research addresses these gaps by applying a lexicon-based labeling approach, with the labels evaluated using SVM and Naive Bayes classifiers, to longer-form public discourse in YouTube comment sections, a combination of content type and validation approach that has not yet been examined together in existing VAT-sentiment studies. The resulting model is intended to provide actionable insights for informed, evidence-based policymaking.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 Sentiment Analysis

Sentiment analysis involves the process of determining and categorizing the emotions and attitudes conveyed in opinions about a specific topic. This technique has gained importance alongside advances in technology, enabling businesses and other entities to assess public opinion on products, services, and topics of public interest (Chakraborty et al., 2020). By tracking the emotions behind social media posts, sentiment

analysis helps researchers understand the context in which users respond, providing valuable insights into public reactions and trends. This information can be crucial for organizations, including governments, to adjust their strategies, improve products, and enhance customer satisfaction.

2.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a widely used supervised machine learning algorithm that excels in classification tasks, including sentiment analysis. SVM operates by identifying an optimal hyperplane that separates classes within the feature space. By maximizing the margin between different classes, SVM provides a robust solution to classification challenges. SVM is effective in high-dimensional spaces and can achieve high accuracy in text classification, including sentiment analysis. For example, SVM has been used to analyze sentiments in Twitter (X) data, achieving high accuracy by incorporating both vocabulary and latent semantic information (Han et al., 2020). The capability of SVM to manage extensive feature sets and its proven effectiveness across various applications underscore its popularity in sentiment analysis.

2.3 Naive Bayes

Naive Bayes is another supervised machine learning algorithm commonly used for text classification tasks such as sentiment analysis. Leveraging Bayes' theorem, it operates under the assumption of feature independence, which simplifies computational processes and proves effective across various practical applications. Noted for its simplicity, efficiency, and capability to handle large datasets, Naive Bayes classifiers are frequently employed to categorize text into sentiments such as positive, negative, and neutral. Research indicates that Naive Bayes can achieve high accuracy in sentiment analysis, especially when integrated with additional methods to address feature dependencies and enhance performance (Kiran Kumar et al., 2021).

2.4 Tax Burden and Fairness Theory

Prior research indicates that individuals' attitudes toward taxation are shaped less by the absolute size of the tax burden than by perceptions. Of its fairness: a tax burden judged unreasonable relative to one's ability to pay tends to generate negative attitudes, an effect partially mediated by perceptions of social fairness (Guo & Gong, 2024). Guo and Gong (2024) also draw on fiscal illusion theory, according to which taxpayers underestimate their true tax burden when its cost remains obscured. A VAT increase may reduce this illusion by making an otherwise embedded consumption tax visible to consumers at the point of purchase. This mechanism is directly reflected in the Indonesian context: survey evidence regarding individual taxpayers' perceptions of the increase in the VAT rate to 12% in 2025 found that respondents disagreed that the policy reflected the principle of tax fairness, even while acknowledging its potential benefit for national development. This disagreement was attributed largely to the disproportionate increase in the nominal tax burden on daily necessities for lower- and middle-income taxpayers (Febiola, 2024). The marginal tax rate, a concept specific to progressive income taxation, has no structural analog in VAT's single-rate structure, so this study instead draws on VAT regressivity as the relevant tax-burden concept.

2.5 VAT Regressivity

This perceived unfairness aligns with VAT's broader characterization as a regressive tax, whose burden falls proportionally heavier on lower-income groups, which spend a larger share of their income on consumption (Blasco et al., 2023). Given the importance of perceived fairness in shaping public attitudes toward taxation, this regressivity has been identified as a defining source of the controversy surrounding VAT policy worldwide (Swistak & de la Feria, 2024).

2.6 Hypothesis

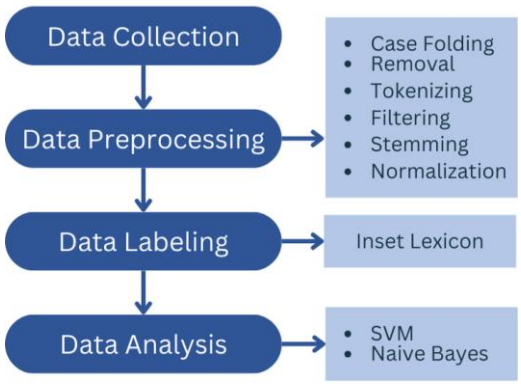
Developing hypotheses based on the literature review and theoretical framework is important for

guiding this study. Given that perceived unfairness in the distribution of the tax burden is closely associated with negative public attitudes, and that VAT's regressive nature has been identified as a defining source of controversy surrounding its increase, this study hypothesizes that the majority of YouTube comments concerning the VAT increase will express negative sentiment.

3. RESEARCH METHODOLOGY

This study followed a step-by-step approach to collecting, cleaning, labeling, and analyzing data to understand public sentiment about VAT increases. This process began with collecting data from YouTube, a prominent platform for sharing opinions in Indonesia. The data were then cleaned and prepared using the Natural Language Toolkit (NLTK) to improve data accuracy and relevance.

Figure 2
Research Method of Sentiment Analysis



Note. Source: Processed data by Author

By utilizing Machine Learning and feature extraction, the study aimed to provide a comprehensive analysis of public sentiment. Each step in the methodology, which is shown in Figure 2, was designed to build on the previous one, ensuring a clear and efficient process.

3.1 Data Collection

The data collection process began with a manual keyword-based search on YouTube, using 20 Indonesian-language search terms[1] related to the planned VAT increase. The search was restricted to videos published between January and May 2024 to capture public sentiment during the initial phase of policy discourse before the VAT rate was implemented in 2025. Videos were required to have more than 200 comments, a threshold established to ensure reliable per-video sentiment estimation and provide sufficient data for machine learning model training. Videos also had to be non-Shorts YouTube videos (duration ≤60 seconds), as comment patterns on Shorts differ substantially from standard-length videos. Videos were selected from well-known news channels such as Metro TV, KompasTV, CNN Indonesia, tvOneNews, and CNBC Indonesia, which were selected for their editorial credibility and broad reach as established national broadcasters, as opposed to personal commentary or content-aggregator channels. The keyword-based search yielded 267 candidate videos after likely Shorts were excluded; these candidates included all nine videos retained for the present analysis. Of the 12 videos that met the 200-comment threshold, nine were published by the five selected national broadcast channels and retained for analysis. The remaining three were excluded because they originated from channels that did not meet the predefined selection criteria. Table 1 also reports each video's title framing and the corresponding proportion of negative comments to assess whether title valence, rather than underlying public sentiment, influences comment negativity (see Limitations, Section 6.2).

Comments were extracted using the YouTube API v3. An API consists of a set of protocols that facilitate communication between software applications, granting developers access to video, channel, and user interaction data (Google Developers, 2021). Researchers frequently

[1] Search terms spanned four thematic categories: VAT rate/numeric variants (e.g., "PPN naik," "PPN 12 persen," "tarif PPN naik"), public impact and reaction (e.g., "dampak kenaikan PPN," "daya beli PPN naik," "reaksi masyarakat PPN naik"), government policy framing (e.g., "kebijakan PPN 12 persen," "alasan pemerintah naikkan PPN"), and scope of affected goods/services (e.g., "barang jasa kena PPN 12%").

Table 1
YouTube List Descriptions

No	Channel	Title	Comment Count	Title Valence	% Negative
1	METRO TV	Turun Kelas Akibat Pajak Naik	943	Negative	65.0%
2	tvOneNews	Laporan Utama: Atas Nama Keberlanjutan Pajak Naik Lagi | Kabar Petang tvOne	516	Negative	54.3%
3	KOMPASTV	PPN Akan Naik 12 Persen Tahun Depan, Barang dan Jasa Apa Saja yang Terdampak?	415	Neutral	55.4%
4	CNBC Indonesia	PPN Siap Naik, Pengusaha Menjerit	345	Negative	54.2%
5	CNBC Indonesia	2025, PPN Naik Jadi 12%: Kas Negara vs Daya Beli Warga	313	Neutral	57.8%
6	KOMPASTV	Tarif PPN Naik Jadi 12 Persen Tahun 2025, Sudah Tepatkah?	285	Neutral	57.9%
7	CNN Indonesia	Komentar Warga soal Rencana PPN 12% Mulai 2025	263	Neutral	51.3%
8	CNBC Indonesia	Kelas Menengah RI Wajib Waspada Efek Ngeri PPN Naik Jadi 12%	241	Negative	67.6%
9	CNN Indonesia	PPN 12% Bakal 'sambut' Warga di Tahun 2025	207	Negative	49.3%

Note. Source: Processed data by Author

utilize the YouTube API to collect data for analyzing social behavior and media consumption, as platforms like Twitter and YouTube provide extensive datasets via their APIs for academic and practical studies (Kready et al., 2020). The data retrieved included the video ID, timestamp (published at), comment text, and the date (updated at). Note that if a comment was not edited, the timestamp and date would be identical.

3.2 Data Preprocessing

Data preprocessing is a crucial step to ensure the quality and consistency of the dataset. This process was implemented using the Natural Language Toolkit (NLTK), a Python library that offers a comprehensive range of text-processing tools for classification, tokenization, stemming, tagging, and semantic analysis (Bird et al., 2009). NLTK's robust text processing features are particularly suited to sentiment analysis, enabling researchers to analyze YouTube comments and derive insights into public opinion (Hardeniya et al., 2016). The following steps were implemented using Python:

1) Case Folding: All text was converted to lowercase to maintain uniformity. This step helps ensure that words are treated consistently, regardless of their original casing.
2) Removal Processes: Several data-cleaning steps were performed to remove HTML tags, numbers, punctuation, whitespace, and empty lines. These steps ensure the data is uniform and free from extraneous elements that could skew the analysis.
3) Tokenizing: Each comment was tokenized into individual words. This process breaks down the text into manageable pieces, facilitating further processing and analysis.
4) Stopwords Filtering: The NLTK library was used to filter out common Indonesian stopwords. The list of stopwords was extended with additional terms that might have sentiment implications to ensure those words are not inadvertently filtered out. Stopwords that are meaningful in sentiment analysis, such as 'sementara' (while), were retained.
5) Stemming: The Sastrawi library was applied for stemming, reducing words to their base

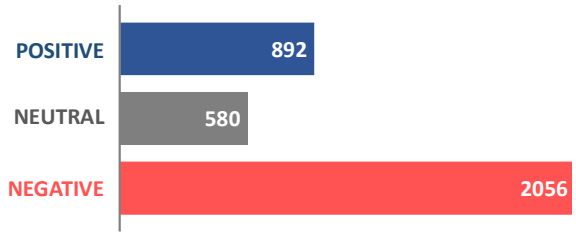
form by removing suffixes and prefixes. For example, "meningkat" (increasing) would be reduced to "tingkat" (increase). The Sastrawi library is a well-regarded tool specifically designed for stemming Indonesian words (Robbani, 2016).

6) Normalization: Slang words or informal terms were replaced with their standard equivalents using a "Kamus Alay", a dictionary for slang words (Salsabila et al., 2018). This step ensures that colloquial expressions are converted into their formal counterparts, aiding in accurate sentiment analysis.

A comparison of YouTube comments before and after data preprocessing is shown in Table 2, highlighting the impact of these steps on the dataset's quality and consistency.

Figure 3

Comment Distribution by Sentiment Labels



Note. Source: Processed data by Author

3.3 Data Labeling

Comments were labeled using a lexicon-based approach, in which words are assigned sentiment scores based on a predefined dictionary of positive and negative terms. Koto and Rahmaningtyas (2017) developed the Indonesian Sentiment Lexicon (InSet) comprises 3,609 positive words and 6,609 negative words, each assigned a score based on its positive or negative connotations. The sentiment score for each comment was calculated by summing the scores of its constituent words according to the InSet Lexicon. A comment was classified as positive when the total score was greater than zero, negative when the total score was less than zero, and neutral when the total score equaled zero. This labeling helped identify the sentiment of each comment, as shown in Figure 3 and Table 3.

Although this method was efficient for processing large datasets, it had several limitations. Automated labeling might not accurately detect sarcasm, irony, or the overall sentiment conveyed by complex expressions, leading to potential misclassification. Moreover, context-specific meanings and idiomatic expressions or phrases used in certain topics might not have been correctly understood, affecting the reliability of the sentiment analysis.

Table 2

Comparison of YouTube Comments Before and After Data Preprocessing

No	Before	After
1	Apa apa rakyat di pajaki . Beli barang mewah dikit kena pajak. Bangun rumah sendiri kena pajak.. Pakai jalan kena pajak	kena pajak rakyat pajak beli barang mewah dikit bangun rumah pakai jalan
2	Logikanya darimana ppn naik semua pasti ikutan naik,, yg betul itu dicari uang negara pada lolos kemana ckckkckc pajak bertumpuk2 emang nyusahin ini	logika darimana ppn ikut cari uang negara lolos mana pajak tumpuk memang susah
3	Rakyat makin menjerit ...sementara mereka berpesta pora	rakyat jerit sementara pesta pora
4	Disyukuri aja, setiap manusia sudah ada rejekinya masing-masing. Niscaya kita akan diberikan banyak rejeki dengan bersyukur. Barangkali kebutuhan dana untuk IKN dll meningkat, makanya pajak naik.	syukur manusia ada rejeki niscaya rejeki syukur barangkali butuh dana ikn dll tingkat pajak
5	Ketika biaya produksi dan lainnya naik, otomatis harga produknya pun naik... Masalah pajak pasti ada efek domino nya	biaya produksi otomatis harga produk pajak ada efek domino

Note. Source: Processed data by Author

Table 3
Sample of Label Results

Cleaned Comment	Label
kena pajak rakyat pajak beli barang mewah dikit bangun rumah pakai jalan	Negative
logika darimana ppn ikut cari uang negara lolos mana pajak tumpuk memang susah	Negative
syukur manusia ada rejeki niscaya rejeki syukur barangkali butuh dana ikn dll tingkat pajak	Positive
biaya produksi otomatis harga produk pajak ada efek domino	Positive

Note. Source: Processed data by Author

3.4 Data Processing

Due to the imbalance in the dataset, where certain sentiment labels were more prevalent than others, the neutral label was omitted. The negative label was reduced using the resampling function from the "scikit-learn (sklearn)" library. Specifically, the negative label, the majority class, was undersampled without replacement to match the size of the positive label (892 comments each), since the final classification task involved only the positive and negative categories once neutral was excluded from modeling. This ensured a balanced distribution of each label, improving the performance and reliability of the models. This process yielded a final balanced dataset of 1,784 comments (892 positive and 892 negative), as shown in Table 4, compared to the original 3,528 labeled comments in Figure 3, reflecting the undersampling and neutral-exclusion steps described above. The distribution between the training and testing datasets is shown in Table 4.

The preprocessed and balanced data were analyzed using machine learning models. Term Frequency-Inverse Document Frequency (TF-IDF) vectorization was employed to transform the textual data into numerical representations that are suitable for machine learning algorithms. This technique calculates the importance of a term within a document by considering both its frequency in the document (TF) and its rarity across the document collection (IDF). TF is calculated as the ratio of a term's frequency in a document to the total number of terms in that document. In contrast, IDF is determined by taking the logarithm of the ratio of the total number of documents to the number of documents containing the term. This approach effectively highlights terms significant to specific documents while reducing the impact of commonly occurring, less informative words (Rustam et al., 2021).

The application of supervised machine learning for sentiment classification builds on prior research applying similar methods to social media data (Chakraborty et al., 2020; Yadav & Vishwakarma, 2020). In the context of taxation, SVM and Naive Bayes have been used to classify public sentiment toward Indonesia's VAT increase, with SVM outperforming both Naive Bayes and Logistic Regression (Hasan & Bimby, 2025). Accordingly, this study employed an SVM model to classify the sentiment of the comments based on their features. Additionally, a Naive Bayes model was also used for sentiment classification to compare which model performed better.

Table 4
Distribution of Training or Testing Dataset

Phase	Number of Comments
Training	1,427
Testing	357
Total	1,784

Note. Source: Processed data by Author
Note: 1,784 = balanced dataset after undersampling negatives to 892 (matching positives) and excluding neutral (Section 3.4).

3.5 Evaluation

The performance of the SVM and Naive Bayes models was evaluated using four standard classification metrics: accuracy, precision, recall, and F1 score, as shown in Table 6. These metrics were used to assess how well the models

performed in classifying sentiments of YouTube comments concerning VAT increases.

Through this methodological approach, the study aimed to provide a comprehensive analysis of public sentiment towards VAT increases, offering valuable insights for policymakers.

4. RESULTS AND DISCUSSIONS

The initial sentiment labeling of YouTube comments concerning the VAT increase, as shown in Table 5, revealed the distribution of positive, neutral, and negative comments. This distribution provides an overview of the public's overall reaction and provides a foundation for subsequent analysis using machine learning models.

The preliminary analysis indicated that negative comments accounted for a substantial proportion of the dataset (58.3%), suggesting a predominant negative sentiment towards the VAT increase. This substantial negativity reflects the public's discontent and possible concerns about the economic impact of the tax adjustment. Possible concerns include reduced purchasing power, inflationary pressures, and dissatisfaction with government fiscal policies. However, these underlying concerns cannot be conclusively identified through sentiment classification alone and require further investigation. Understanding these underlying reasons for negative sentiment is crucial for policymakers and businesses as they navigate the potential implications of the VAT increase. Furthermore, the prevalence of negative comments may suggest better public communication and engagement strategies to address public concerns and clarify the rationale, objectives, and anticipated benefits of the tax adjustment.

To validate the initial sentiment labeling, two machine learning models, Support Vector Machine (SVM) and Naive Bayes, were employed. To maintain balanced data, the neutral label was excluded, and the negative label was reduced using sampling, as explained in Section 3.4. The resulting dataset was divided into training and testing sets using an 80:20 ratio. The test set comprised 357 comments, including 180 negative and 177 positive comments, on which model performance was subsequently evaluated. The performance of these models was evaluated using confusion matrices and various metrics.

The SVM model demonstrated better performance across all metrics compared to the Naive Bayes model. The accuracy of the SVM model was 86.83%, with a precision of 83.85%, recall of 90.96%, and an F1-score of 87.26%, indicating robust performance in classifying sentiments accurately. In contrast, the Naive Bayes model showed an accuracy of 83.19%, precision of 81.97%, recall of 84.75%, and an F1-score of 83.33%, making it slightly less effective than SVM but still a reliable model for sentiment analysis.

Table 5
Sentiment Label Distribution

Sentiment Label	Count	Percentage
Positive	892	25.3%
Neutral	580	16.4%
Negative	2056	58.3%
Total	3,528	100.0%

Note. Source: Processed data by Author

Table 6
Performance Comparison of SVM and Naive Bayes Models on Sentiment Classification

Metric	SVM	Naive Bayes
Accuracy	86.83%	83.19%
Precision	83.85%	81.97%
Recall	90.96%	84.75%
F1-Score	87.26%	83.33%

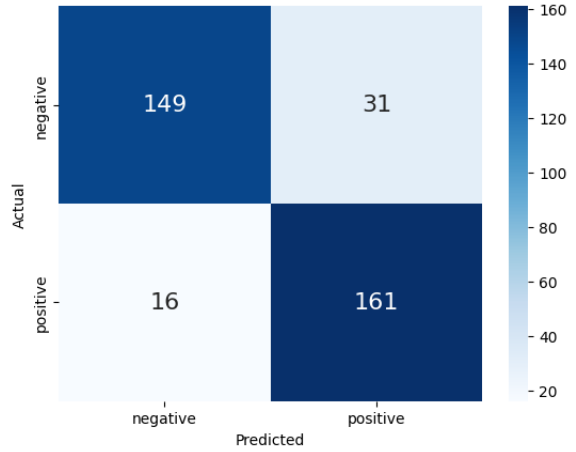
Note. Source: Processed data by Author

To assess whether these results depend on a particular train-test split, 5-fold stratified cross-validation was performed on the same balanced dataset and TF-IDF feature representation, with the vectorizer refit on each training fold to avoid data leakage. Across the five folds, the SVM model achieved a mean accuracy of 85.1% (SD = 2.1%)

and a mean F1-score of 85.1% (SD = 1.9%), while the Naive Bayes model achieved a mean accuracy of 80.4% (SD = 3.1%) and a mean F1-score of 80.1% (SD = 3.3%). These results are consistent with the single train-test split reported in Table 6, confirming that SVM's performance advantage over Naive Bayes is stable across data partitions rather than an artifact of one particular split.

Figure 4

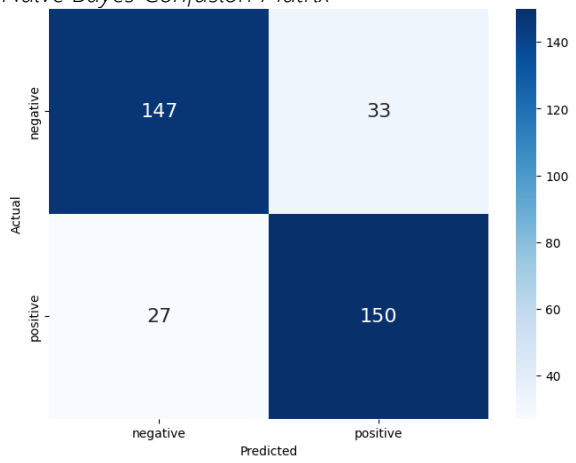
SVM Confusion Matrix



Note. Source: Processed data by Author

Figure 5

Naive Bayes Confusion Matrix



Note. Source: Processed data by Author

As shown in the confusion matrices (Figures 4 and 5), of the 180 negative-labeled test comments, SVM correctly classified 149 (true negatives) and misclassified 31 as positive (false positives); of the 177 positive-labeled comments, SVM correctly classified 161 (true positives) and misclassified 16 as negative (false negatives). Naive Bayes correctly classified 147 negative comments (33 false positives) and 150 positive comments (27 false negatives). The gap between the two models is concentrated in the positive class: SVM produced fewer false negatives than Naive Bayes (16 versus 27), meaning it missed fewer genuinely positive comments, while false-positive rates were comparable between the two models (31 versus 33). This indicates SVM's advantage over Naive Bayes stems primarily from more reliably distinguishing positive comments rather than from a general improvement across both classes.

Table 7

Top 10 Word Frequencies in Negative-Labeled Comments

Rank	Word	Meaning	Frequency
1	*pajak*	tax	586
2	*rakyat*	people/citizens	391
3	*naik*	increase/rise	252
4	*ppn*	VAT	229
5	*negara*	state	209
6	*pemerintah*	government	147
7	*miskin*	poor	105
8	*gaji*	salary	103
9	*korupsi*	corruption	99
10	*joget*	dancing	92

Note. Source: Processed data by Author
Note: *Descriptive word frequencies from preprocessed negative-labeled comments (Section 3.2); not a causal or topic model.*

As shown in Table 7, a word frequency analysis of the negative-labeled comments identified recurring terms beyond the immediate subject of taxation itself. While the most frequent terms (*pajak*, *rakyat*, *naik*, *ppn*, *negara*) reflect the topic under discussion, subsequent terms point to more specific grievances: economic hardship (*miskin*, *gaji*), distrust toward government institutions (*pemerintah*, *korupsi*), and sarcastic commentary toward officials (*joget*). This pattern suggests that negative sentiment toward the VAT increase was shaped not only by its direct financial burden but also by broader public frustration with

government conduct. The sentiment analysis, supported by both SVM and Naive Bayes models, confirms that the majority of comments regarding the VAT increase are negative, with this word-level pattern offering a preliminary account of the themes underlying that negativity.

5. CONCLUSION

This study aimed to analyze public sentiment towards the VAT increase in Indonesia using YouTube comments and validate the initial sentiment labeling with machine learning models. The main findings from the sentiment analysis revealed a predominant negative sentiment, with 58.3% of the comments expressing dissatisfaction with the VAT increase. Both the Support Vector Machine (SVM) and Naive Bayes models were trained on the lexicon-labeled data and evaluated on a held-out test set. This approach assesses whether the initial labeling reflected a consistent, learnable pattern rather than arbitrary lexicon-based noise.

The SVM model outperformed Naive Bayes, achieving an accuracy of 86.83% and an F1-score of 87.26%, compared with 83.19% and 83.33%, respectively, for the Naive Bayes model. These results indicate that the sentiment patterns underlying the 58.3% negative proportion were systematic and reliably distinguishable from positive sentiment, lending support to the validity of the initial lexicon-based labeling rather than confirming the 58.3% figure as an independent measurement (see Section 6.2). Overall, this study underscores the importance of understanding public opinion in policy implementation and the need for strategies to address public concerns.

6. IMPLICATIONS AND LIMITATIONS

6.1 IMPLICATIONS

The findings of this study have several important implications for policymakers and stakeholders involved in the implementation of the VAT increase in Indonesia:

- Policymakers should treat the negative sentiment identified in this study as evidence of public concerns regarding the perceived inequity in the distribution of the VAT burden, rather than merely as generalized dissatisfaction with government policy (Guo & Gong, 2024; Febiola, 2024). This distinction shapes which policy responses are likely to be effective. Furthermore, these findings capture anticipatory public sentiment, as the comments were collected before the VAT rate was formally increased to 12% in January 2025.
- Enhanced transparency and public communication efforts should specifically target the distrust toward government institutions identified in the word-frequency analysis (*pemerintah*, *korupsi*; Section 4, Table 7), for example, through public reporting mechanisms that provide clear information on the allocation and expenditure of VAT revenue.
- Explaining the rationale behind the tax increase should be paired with evidence addressing VAT's regressive character (Blasco et al., 2023; Swistak & de la Feria, 2024), since public skepticism appears rooted in fairness concerns rather than a simple lack of information.
- Beyond general communication strategies, policymakers could consider mechanisms such as targeted real-time VAT compensation for lower-income households at the point of purchase, an approach shown to reduce the regressive impact of VAT increases without requiring a full redesign of the tax base (Swistak & de la Feria, 2024). Such targeted measures would directly address the economic-hardship concerns (*miskin*, *gaji*) identified in the word-frequency analysis (Section 4, Table 7), complementing broader efforts such as phased implementation strategies to improve compliance and reduce resistance.

Understanding and addressing public sentiment is vital for the successful implementation of policy changes and for maintaining public trust in government actions.

6.2 LIMITATIONS

Despite the valuable insights provided by this study, several limitations should be acknowledged. First, the dataset was limited to comments collected from nine YouTube videos within a

specific timeframe and according to predefined selection criteria, as explained in Section 3.1 (data collection). A related concern is headline bias: negatively framed video titles may disproportionately attract negative commentary independent of underlying public sentiment, consistent with findings on news framing effects on political attitudes (Lecheler & De Vreese, 2012). A per-video comparison (Table 1) did not show negative-comment share increasing monotonically with negative title framing, suggesting headline framing alone does not fully account for the observed sentiment; this comparison should be read as descriptive rather than conclusive, given the small number of videos and the use of explicit lexical cues rather than a validated coding scheme for title valence.

Second, the automatic labeling process using positive and negative word libraries has inherent limitations. Although computationally efficient, this method cannot detect sarcasm, irony, or the overall sentiment conveyed in complex sentences. The thematic analysis of negative sentiment presented in Section 4 (Table 7) was likewise based on descriptive word frequency rather than a formal causal or topic-modeling approach.

Third, the SVM and Naive Bayes results confirm that the lexicon-based labels reflect a systematic, learnable linguistic pattern rather than random noise, but this does not substitute for independent human validation of individual labels, which this study did not perform. Future work could strengthen this further through human-annotated validation.

These limitations suggest the need for a more comprehensive approach in future studies, including a broader dataset, more sophisticated sentiment analysis techniques, causal or topic-modeling approaches to thematic analysis, and possibly integration of human experts to improve the accuracy and reliability of sentiment classification.

REFERENCES

Astuti, S., & Erfina, A. (2025). Analisis sentimen pandangan publik terhadap kenaikan pajak 12% dari Twitter menggunakan Indonesian RoBERTa base classifier. *Smart Comp: Jurnalnya Orang Pintar Komputer*, *14*(3), 698–706.

Aufar, M., Andreswari, R., & Pramesti, D. (2020). Sentiment analysis on YouTube social media using decision tree and random forest algorithm: A case study. In *2020 International Conference on Data Science and Its Applications (ICoDSA)*, (pp. 1–7).

Bird, S., Klein, E., & Loper, E. (2009). *Natural language processing with Python: Analyzing text with the natural language toolkit*. O'Reilly Media.

Blasco, J., Guillaud, E., & Zemmour, M. (2023). The inequality impact of consumption taxes: An international comparison. *Journal of Public Economics*, *222*, Article 104897.

Chakraborty, K., Bhattacharyya, S., & Bag, R. (2020). A survey of sentiment analysis from social media data. *IEEE Transactions on Computational Social Systems*, *7*(2), 450–464.

DataReportal. (2024). *Digital 2024: Indonesia*. https://datareportal.com/reports/digital-2024-indonesia

Febiola, L. (2024). Analisis persepsi wajib pajak orang pribadi terhadap kebijakan kenaikan tarif pajak pertambahan nilai menjadi 12% di tahun 2025. *Journal of Social and Economics Research*, *6*(1), 1863–1876.

Google Developers. (2021). *Youtube Data API*. https://developers.google.com/youtube/v3

Guo, Y., & Gong, T. (2024). The impact of tax burden on welfare attitudes: Micro evidence from welfare states. *PLOS ONE*, *19*(11), Article e0311047.

Han, K.-X., Chien, W., Chiu, C.-C., & Cheng, Y.-T. (2020). Application of support vector machine (SVM) in the sentiment analysis of Twitter dataset. *Applied Sciences*, *10*(3), Article 1125.

Hardeniya, N., Perkins, J., Chopra, D., Joshi, N., & Mathur, I. (2016). *Natural language processing: Python and NLTK*. Packt Publishing.

Hasan, M. A., & Bimby, N. (2025). Analisis sentimen publik terhadap kenaikan pajak PPN di Indonesia tahun 2024 menggunakan algoritma machine learning: Analisis sentimen. *Jurnal Fasilkom*, *15*(1), 179–184.

Kiran Kumar, P., Jahna Tejaswi, N., Vasanthi, M., Srihitha, L., & Phanindra Kumar, B. (2021). Sentimental analysis on multi-domain sentiment dataset using SVM and Naive Bayes algorithm. In *International Advanced Computing Conference* (pp. 201–213).

Koto, F., & Rahmaningtyas, G. Y. (2017). INSET lexicon: Evaluation of a word list for Indonesian sentiment analysis in microblogs. In *2017 International Conference on Asian Language Processing (IALP)* (pp. 391–394).

Kready, J., Shimray, S. A., Hussain, M. N., & Agarwal, N. (2020). YouTube data collection using parallel processing. In *2020 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW)* (pp. 1119–1122).

Lecheler, S., & De Vreese, C. H. (2012). News framing and public opinion: A mediation analysis of framing effects on political attitudes. *Journalism & Mass Communication Quarterly*, *89*(2), 185–204.

Manoppo, M. R., Kolang, I. C., Fiat, D. N. N., Mawara, R. M. C., Sumarno, A. D. P., Yusupa, A., & Tarigan, V. (2025). Analisis sentimen publik di media sosial terhadap kenaikan PPN 12% di Indonesia menggunakan IndoBERT. *Jurnal Kecerdasan Buatan dan Teknologi Informasi*, *4*(2), 152–163.

Mebratu, A. A. (2024). Theoretical foundations of voluntary tax compliance: Evidence from a developing country. *Humanities and Social Sciences Communications*, *11*(1), 1–8.

Meltwater. (2024). *Social media statistics for Indonesia [Updated 2024]*. https://www.meltwater.com/en/blog/social-media-statistics-indonesia

Robbani, H. (2016). *Sastrawi: Library for stemming Indonesian (Bahasa) text*. https://pypi.org/project/Sastrawi/

Rustam, F., Khalid, M., Aslam, W., Rupapara, V., Mehmood, A., & Choi, G. S. (2021). A performance comparison of supervised machine learning models for COVID-19 tweets sentiment analysis. *PLOS ONE*, *16*(2), Article e0245909.

Salsabila, N. A., Winatmoko, Y. A., Septiandri, A. A., & Jamal, A. (2018). Colloquial Indonesian lexicon. In *2018 International Conference on Asian Language Processing (IALP)* (pp. 226–229).

Sholihah, N., Abdulloh, F. F., Rahardi, M., Aminuddin, A., Asaddulloh, B. P., & Nugraha, A. Y. A. (2023). Feature selection optimization for sentiment analysis of tax policy using SMOTE and PSO. In *2023 3rd International Conference on Smart Cities, Automation & Intelligent Computing Systems (ICON-SONICS)* (pp. 44–48).

Swistak, A., & de la Feria, R. (2024). *Designing a progressive VAT*. International Monetary Fund.

Winata, Y. G., Noor, F., Bahar, M. F., Budi, A., & Santoso, E. S. (2023). Application of data mining to taxpayers issuing fictitious tax invoice using classification techniques. In *International Tax Conference G20 Indonesian Presidency: Achieving a Stronger and More Sustainable World Recovery through International and National Tax Reform*.

Yadav, A., & Vishwakarma, D. K. (2020). Sentiment analysis using deep learning architectures: A review. *Artificial Intelligence Review*, *53*(6), 4335–4385.