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Public Sentiment Toward Rupiah Redenomination on Social Media X

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ABSTRACT
This study examines public sentiment toward the proposed Indonesian Rupiah redenomination policy using data collected from Social Media X. The research applies a structured computational sentiment analysis pipeline, beginning with automatic sentiment labeling using a transformer-based language model, followed by classification using a Support Vector Machine with Term Frequency–Inverse Document Frequency feature representation. The dataset was collected over a one-day period from 7 November 2025 to 8 November 2025 to capture immediate public reactions to the policy discourse. Experimental results show that the classification model achieved an accuracy of 0.68 with balanced classification performance. Rather than aiming to optimize predictive accuracy, this study focuses on identifying general sentiment tendencies and patterns of public opinion regarding currency redenomination. The findings indicate that negative sentiment dominates the discourse, reflecting public concern and hesitation toward the policy, while a substantial proportion of neutral sentiment suggests ongoing evaluation and uncertainty among users. These results highlight the complexity of public responses to monetary policy communication and demonstrate the potential of social media analysis to provide an indicative overview of public sentiment in the digital public sphere. The study also acknowledges limitations related to automatic labeling and the inherent ambiguity of social media language, emphasizing that the findings should be interpreted as exploratory insights rather than definitive conclusions.

Keywords: Rupiah redenomination, sentiment analysis, Social Media X, IndoBERT, Support Vector Machine

I. Introduction

Redenomination refers to adjusting currency denominations without changing real value, as in the proposed conversion of Rp. 1,000 to Rp. 1 in Indonesia. In economic literature, redenomination is defined as a monetary policy aimed at simplifying nominal currency values while maintaining purchasing power, with the objective of improving transaction efficiency and monetary clarity [1]. Such a policy aims to simplify transactions, improve financial clarity, and modernize currency structure. However, public perception plays a crucial role in policy acceptance, particularly in emerging economies where inflation expectations and monetary trust can influence public confidence in government decisions.

Social media has become a primary arena for citizens in Indonesia to express views regarding government actions and economic issues [2]. Prior studies show that digital discussions reflect public responses toward official regulations, including mobility restrictions and public governance measures [3], [4]. Sentiment analysis has also been applied to evaluate reactions to public systems and national initiatives, demonstrating its usefulness in capturing societal responses and public perspectives on government platforms [5], [6], [7]. In a broader context, similar sentiment-analysis approaches have been widely adopted in international research to examine public opinion toward socio economic and policy related issues across different linguistic and cultural settings [8], [9], [10].

Machine learning techniques have been widely used for sentiment classification in Indonesian text. Support Vector Machine (SVM) and Naïve Bayes remain popular due to their effectiveness in text classification and stability across various datasets [11], [12], [13]. Other research in Indonesian computing and data analysis domains also reports consistent performance of classical machine-learning approaches across multiple social media and text processing applications [14], [15]. Comparative studies highlight the strengths of these classical algorithms in Indonesian computational linguistics research [11], emphasizing their suitability in public opinion analysis contexts [5].

In recent years, transformer-based language models have enhanced sentiment analysis performance by improving contextual understanding for Indonesian language input. IndoBERT has demonstrated superior semantic capability for interpreting public sentiment on social platforms [2], while its advantages over traditional models have been noted in Indonesian NLP applications [16]. Hybrid approaches combining modern language models with efficient classical classifiers have also been explored to balance accuracy and computation in text classification tasks [17], [18].

Despite growing research on public sentiment regarding government programs and social regulations in Indonesia [4], studies specifically analyzing public attitudes toward Rupiah redenomination remain limited. This gap indicates a need to examine how the public perceives currency restructuring and to assess whether reactions align with economic objectives. Understanding these responses is essential to anticipate communication challenges and ensure smooth policy execution [19].

This study addresses that need by analyzing public sentiment on Social Media X toward the proposed redenomination. A hybrid approach is employed, involving transformer-based automated text labelling followed by SVM with TF-IDF features for classification. This combination leverages contextual language understanding while maintaining efficient text-classification performance, making it suitable for sentiment analysis in the Indonesian socio-economic context.

II. Related work

Recent studies on public sentiment analysis in Indonesia increasingly utilize social media as a primary data source for understanding public response toward government programs and national events. Research has shown that platforms such as X (formerly Twitter) effectively capture public expressions related to policy enforcement, mobility restrictions, and social regulations [3], [4]. Other works analyze sentiment in digital public-service systems, reflecting digital trust and citizen evaluation of government platforms [5], [6], [7]. These studies demonstrate that sentiment mining provides a data driven lens for monitoring public perception toward policy decisions in Indonesia.

A substantial portion of Indonesian sentiment-analysis research applies classical machine learning methods. Support Vector Machine (SVM) and Naïve Bayes are frequently selected due to their stability, interpretability, and competitive performance on Bahasa Indonesia datasets [11], [12], [13]. Further investigations in Indonesian computational studies reinforce the reliability of traditional classifiers across diverse text-processing and social media scenarios [14], [15]. Comparative analysis also highlights the consistency of classical models in handling high dimensional linguistic features, supporting their relevance in public opinion research [5], [11].

Alongside classical approaches, modern neural architectures particularly transformer-based models have gained momentum in Indonesian NLP. IndoBERT has demonstrated strong contextual understanding for Indonesian sentiment classification on social media datasets and offers advantages over statistical models in capturing nuanced language patterns [2], [4]. Several studies explore hybrid approaches combining language models with lightweight classifiers to balance accuracy, computational cost, and inference efficiency [17], [18]. These findings show an ongoing shift toward deeper semantic modelling in Indonesian sentiment research, driven by transformer advancements.

Evaluation practices also reflect an emphasis on rigorous performance measurement. Studies frequently employ accuracy, precision, recall, and confusion matrix validation to evaluate sentiment models in Indonesian contexts [17], [19]. This supports the development of more reliable and reproducible sentiment pipelines for real world applications in policy monitoring and public engagement analysis.

While existing studies successfully analyze sentiment toward public policies, government systems, and socio economic events [3], [4], [5], [6], [7], no prior work specifically examines public sentiment surrounding the proposed Indonesian Rupiah redenomination policy. Most literature concentrates on pandemic management, taxation systems, digital service platforms, and regional public programs instead of monetary denomination reforms. Therefore, there remains a clear gap in computational examination of public attitudes toward currency restructuring. This study addresses that gap by leveraging transformer assisted labelling and SVM classification to analyze sentiment on Social Media X regarding Rupiah redenomination discussions.

III. Material and Methods

This study follows a structured computational pipeline to analyze public sentiment toward the proposed Indonesian Rupiah redenomination policy discussed on Social Media X. The process consists of data acquisition, preprocessing, automated sentiment annotation, feature extraction, model training, and performance evaluation.

A. *Data Collection*

Tweets related to the Rupiah redenomination discourse were collected from Social Media X using the tweet-harvest tool during a one-day collection period, from 7 November 2025 to 8 November 2025. The data were retrieved based on relevant keywords associated with the redenomination topic and subsequently processed for sentiment analysis.

B. *Text Preprocessing*

A text cleaning pipeline was applied to normalize social media text. Preprocessing included lowercasing, removal of URLs, mentions, hashtags, punctuation, numbers, and excess whitespace. This step aimed to standardize textual input and reduce noise for subsequent modelling.

C. *Sentiment Annotation*

Sentiment annotation was performed automatically using a pre-trained Indonesian transformer-based language model, namely w11wo/indonesian-roberta-base-sentiment-classifier, accessed through the HuggingFace transformers pipeline. The cleaned Indonesian text data were processed individually, with each input truncated to a maximum of 512 characters to comply with model constraints. The model produced probabilistic outputs for predefined sentiment classes, and the final sentiment label was assigned by selecting the class with the highest predicted probability. No additional confidence thresholds or post processing rules were applied in the labeling process.

Although automatic labeling enables efficient large-scale annotation, it may introduce label noise due to contextual ambiguity, implicit expressions, or sarcasm commonly found in social media text. In this study, the automatically generated labels were directly used for subsequent classification without human annotation or manual verification. This limitation is acknowledged as a methodological constraint and may contribute to error propagation and moderate classification performance.

D. *Feature Extraction*

Text data was converted into numerical form using the TF-IDF vectorization technique to represent word importance across the corpus while handling sparse text efficiently.

E. *Classification Model*

Sentiment classification was performed using a Support Vector Machine (SVM) with a linear kernel due to its effectiveness in handling high-dimensional and sparse textual features generated by the TF-IDF representation. In this study, SVM was selected as a stable and interpretable classifier suitable for sentiment analysis with automatically generated labels, which may contain noise. Compared to more complex deep learning models, SVM offers reliable performance on medium sized datasets while remaining computationally efficient. Accordingly, SVM was employed as a baseline analytical classifier to examine sentiment patterns rather than to achieve state-of-the-art predictive performance. To address class imbalance in the sentiment distribution, class weighting was applied during model training, and a stratified train test split was used to preserve class proportions.

F. *Evaluation Metrics*

Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis to assess classification capability across sentiment classes. Accuracy was reported to provide an overall performance overview, while precision, recall, and F1-score were used to better reflect classification effectiveness under imbalanced sentiment class distribution. The confusion matrix was employed to analyze class-wise prediction behaviour and misclassification patterns. The trained model and TF-IDF vectorizer were exported for reproducibility and future deployment. The research workflow is described in Figure 1.

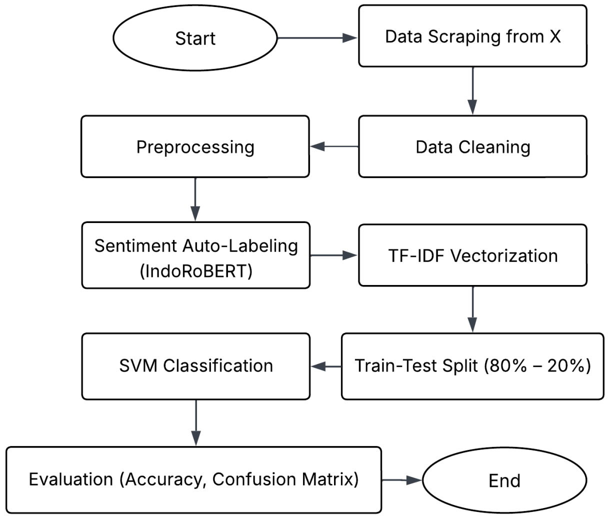

Figure 1. Research Workflow.

IV. Results and Discussion

This section presents the empirical findings of the sentiment analysis experiment and interprets public perceptions toward the Rupiah redenomination based on social-media data.

A. Dataset Overview

A total of 1,094 tweets relevant to the redenomination discourse were collected. After preprocessing and filtering non-informative text, 1,077 clean entries were retained for analysis. The size of the processed dataset ensures sufficient representation of public reactions within the study period. The dataset was split into 80% training (861 tweets) and 20% testing (216 tweets) using stratified sampling to preserve sentiment label distribution across folds.

B. Sentiment Distribution

Sentiment labels generated by IndoRoBERT indicate that public responses to the redenomination discussion were predominantly negative.

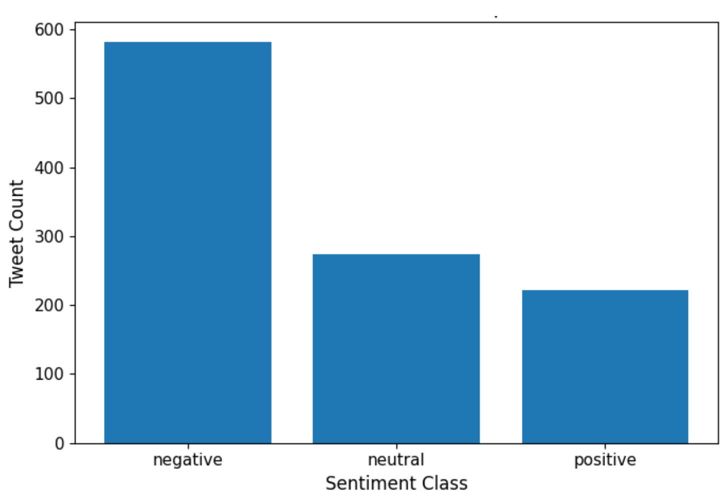

Figure 2. Public sentiment distribution toward the Indonesian Rupiah redenomination on Social Media X.

The high proportion of negative sentiment suggests the presence of scepticism and concerns among users, potentially influenced by uncertainty regarding price rounding, inflation expectations, and perceived disruption to financial transactions. However, the neutral portion indicates a substantial segment adopting an observational stance, reflecting cautious public evaluation of the policy.

C. Model Performance

The SVM classifier trained on TF-IDF features achieved the following performance shown in Table 1 above. The revised SVM model demonstrated improved classification performance compared to the initial experiment, achieving an overall accuracy of approximately 68% on the test dataset.

Table 1. SVM classification performance for Rupiah redenomination sentiment.

Sentiment Class	Precision	Recall	F1-Score	Support
Negative	0.70	0.85	0.77	116
Neutral	0.62	0.42	0.50	55
Positive	0.63	0.53	0.58	45
Accuracy	-	-	0.68	216
Macro Avg	0.65	0.60	0.62	216
Weighted Avg	0.67	0.68	0.66	216

This improvement is primarily attributed to better handling of class imbalance through the application of class weighting and the use of optimized hyperparameters selected via weighted F1-score optimization. Rather than focusing solely on accuracy, the evaluation emphasizes precision, recall, and F1-score to provide a more balanced assessment of model performance across sentiment classes.

D. Confusion Matrix Analysis

The confusion matrix illustrates the ability of the SVM classifier to distinguish between sentiment categories, as shown in Figure 3. The results indicate that negative sentiment is recognized more consistently than other classes, suggesting that explicit expressions of criticism or concern related to the redenomination policy are more easily captured by the model.

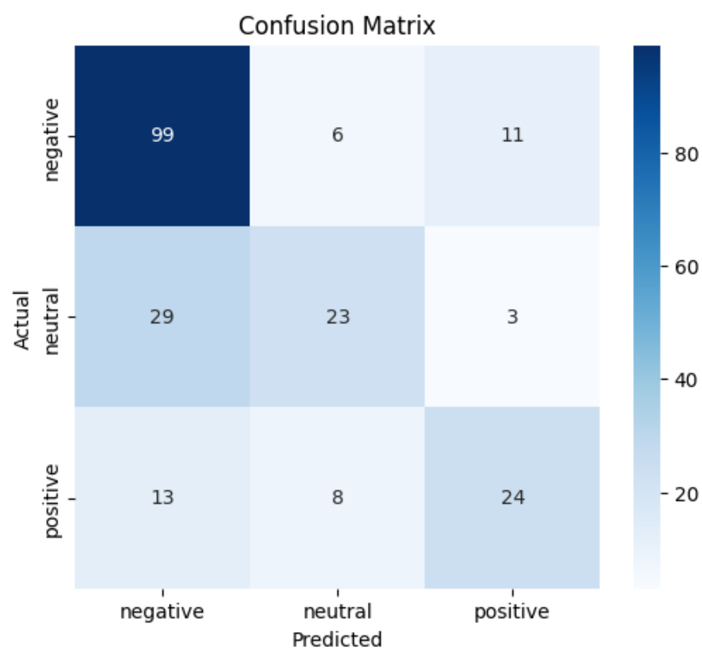

Figure 3. Confusion Matrix of SVM Sentiment Classification Results.

In contrast, neutral sentiment remains more challenging to classify accurately due to the presence of linguistically ambiguous and evaluative expressions that often overlap with negative sentiment. This limitation is influenced by the inherent characteristics of social media language as well as the use of automatic sentiment labelling without manual validation. Overall, while the revised model demonstrates improved balance in classification performance, challenges persist in distinguishing nuanced or mixed-tone expressions, particularly within the neutral class.

E. Interpretation of Findings

The dominance of negative sentiment suggests hesitation and public concern toward the redenomination plan. This finding aligns with perspectives in behavioural economics, which indicate that currency reforms may trigger psychological reactions related to inflation expectations, uncertainty, and levels of trust in monetary authorities. Negative expressions on social media therefore reflect not only opposition but also apprehension regarding the potential implications of the policy.

However, the presence of a sizeable proportion of neutral sentiment indicates that public opinion on redenomination remains under evaluation and has not yet become fully polarized. This neutral stance may represent informational gaps, cautious attitudes, or ongoing public learning regarding the objectives and consequences of the policy, as observed in previous studies on economic governance debates in Indonesia. These findings should be interpreted as an indicative representation of public discourse on Social Media X rather than a comprehensive reflection of societal attitudes, given the platform specific scope and limited data collection period.

In addition, sentiment labels were generated through an automatic transformer-based approach without human annotation or manual verification, which may introduce classification noise due to linguistic ambiguity, implicit expressions, or sarcasm commonly found in social media text. Although the revised classification model demonstrates improved balance across sentiment categories, classification performance particularly accuracy is not treated as the primary objective of this study. Future research may enhance robustness by incorporating manually annotated datasets, fine-tuned transformer models, and multi-platform data sources to obtain a more comprehensive understanding of public opinion toward monetary policy reforms.

V. Conclusion

This study examined public sentiment toward the proposed Indonesian Rupiah redenomination policy using social media data from Social Media X and a hybrid computational approach. The findings indicate that negative sentiment dominates the public discourse, reflecting concerns and hesitation related to currency restructuring and its potential implications. At the same time, the presence of a substantial proportion of neutral sentiment suggests that public opinion has not fully polarized and remains under evaluation, indicating ongoing public deliberation rather than immediate acceptance or rejection of the policy.

The sentiment classification results demonstrate that the applied analytical framework can capture general patterns of public opinion in social media discussions. However, several limitations must be acknowledged. The sentiment labels were generated through an automatic labelling process without human annotation, which may introduce label noise and affect classification reliability, particularly in distinguishing neutral expressions. In addition, class imbalance and the inherently ambiguous and informal nature of social media language present further challenges for accurately interpreting nuanced sentiment. These factors highlight the importance of cautious interpretation of the results.

Despite these limitations, this study provides an indicative overview of public sentiment trends surrounding the redenomination discourse in Indonesia. The results contribute to a broader understanding of how monetary policy proposals are perceived in the digital public sphere and underscore the relevance of social media as a source for public opinion analysis. Future research may incorporate human-validated annotations, longer observation periods, or more advanced modelling approaches to enhance analytical robustness and deepen insights into public responses to economic policy communication.

Conflicts of Interest

The author declares no conflicts of interest.

Author Contributions Statement

The author independently carried out the data collection, preprocessing, sentiment modelling, analysis, and manuscript preparation.

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