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Sentiment Analysis of Government Policies Using LSTM: The Role of the Indonesian Language in Shaping Public Opinions

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Abstract

Social media has become the primary arena for the public to express opinions on government policies. This study aims to analyze public sentiment toward government policies using the Long Short-Term Memory (LSTM) model, while also examining the role of language in shaping public opinion. Data were collected from social media posts related to economic, social, and health policies, followed by preprocessing stages including text cleaning, tokenization, stopword removal, and word embedding with Word2Vec. The LSTM model was compared with Support Vector Machine (SVM) and Naïve Bayes to evaluate accuracy and performance. The results indicate that public opinion is dominated by negative sentiment (45%), particularly regarding economic policies. The LSTM model outperformed the benchmarks with an accuracy of 86.9%, surpassing SVM and Naïve Bayes. Linguistic analysis revealed the frequent use of emotional diction, sarcasm, and economic burden narratives that reinforced public resistance, while colloquial language was found to be an effective tool for engaging younger generations. This study contributes to the advancement of sentiment analysis in the Indonesian language using deep learning and provides practical recommendations for policymakers to design more persuasive and participatory communication strategies.

***Keywords**—Sentiment Analysis, LSTM, Government Policy, Social Media, Indonesiassn Language*

1. Introduction

The rapid advancement of digital technology has significantly transformed the way individuals express their opinions, particularly through social media platforms. Platforms such as Twitter, Facebook, and Instagram have evolved beyond personal communication tools into new public spheres that shape collective opinions on government policy issues (Kasus Media Sosial Suhendra & Selly Pratiwi, 2024; Kencana, 2024; Yunanto et al., 2024). Social media enables users to articulate support, criticism, and even sarcasm using diverse forms of the Indonesian language, ranging from formal diction to colloquial slang. This phenomenon demonstrates that language functions not merely as a communication tool but also as an instrument of power in influencing public perception (Masruroh et al., 2025).

In the context of sentiment analysis, the Indonesian language plays a central role in constructing socio-political narratives. Lexical choices such as fair, tyrannical, beneficial, and burdensome are frequently employed to evaluate public policies, thereby influencing governmental legitimacy in the eyes of the public (Belkahla Driss et al., 2019; Sukma et al., 2020). Furthermore, sarcastic expressions are often used to convey dissatisfaction, whereas persuasive language is utilized to mobilize support (Rahmatika, 2024; Rahmayanti et al., 2025; Syamsuddin & Munfarida, 2024). Such linguistic investigations are essential, as they reveal how language construction operates as a framing mechanism within public discourse.

Artificial intelligence (AI)-based sentiment analysis methods have also progressed rapidly, particularly through the adoption of deep learning approaches such as Long Short-Term Memory (LSTM). This model has proven more effective in capturing sequential textual context compared to traditional machine learning methods (Behera et al., 2021; Kurniasari & Setyanto, 2020; Srinivas et al., 2021). The LSTM algorithm is widely utilized due to its capability to model long-range dependencies in textual sequences. Research by Khoirunnisa and Setiawan (2025) demonstrates that LSTM integrated with TF-IDF, Word2Vec, and Adam optimization improved accuracy to 83.04% and achieved an F1-score of 82.62% in sentiment analysis of the 2024 Indonesian presidential election. A Bi-LSTM approach combined with Convolutional Neural Networks (CNN) has also shown strong performance, reaching approximately 97.34% accuracy in evaluating public responses to COVID-19 policies such as social distancing (Kukuh Jaluwana et al., 2022). Additionally, the integration of Word2Vec with LSTM in the context of Indonesia's new capital city (IKN) relocation yielded robust sentiment classification performance (Yanti & Utami, 2025). Similar analyses on COVID-19 vaccination policies reported that an LSTM model with GloVe embeddings achieved an accuracy of approximately 71% (Dewi & Winiarti, 2023).

Beyond algorithmic performance, linguistic aspects of the Indonesian language—including lexical selection, stylistic devices (such as sarcasm and slang), and narrative construction—play a crucial role in shaping public opinion. For instance, the emergence of slang terms, abbreviations, and linguistic variations on platforms such as TikTok or Facebook has been shown to influence users' perceptions of policy-related messages.

Based on the above considerations, this study focuses on sentiment analysis of government policies using the LSTM algorithm, with particular emphasis on the role of the Indonesian language in shaping public opinion. By integrating linguistic analysis with artificial intelligence techniques, this research aims to contribute to a deeper understanding of digital public communication patterns while providing an evaluative foundation for policymakers.

2. Method

2.1 Research Design

This study employs a quantitative approach using text mining and deep learning–based sentiment analysis. The primary model utilized is Long Short-Term Memory (LSTM), which has been demonstrated to outperform classical Recurrent Neural Networks (RNNs) in handling sequential textual data due to its ability to mitigate the vanishing gradient problem (Hochreiter & Schmidhuber, 1997). The research adopts an exploratory-analytical design aimed at identifying patterns of public opinion toward government policies through the language used by citizens on social media.

2.2 Data Sources

Data were collected from two major social media platforms: Twitter and Facebook, considering their widespread use among Indonesian citizens for expressing political opinions and public policy perspectives. Data collection procedures were conducted as follows:

1. Twitter API (Academic Research Track): Used to retrieve tweets containing keywords related to government policies, such as fuel subsidies, healthcare, education, and economic issues.
2. Facebook Graph API and Web Scraping: Used to collect public posts from official government pages and comments from users.

Data were gathered between January and June 2024, yielding approximately 50,000 raw posts. Only posts written in Indonesian were included. Mixed-language content (code-switching with English or regional languages) was processed through normalization techniques.

2.3 Text Preprocessing

Preprocessing was conducted to ensure that the textual data were clean, consistent, and suitable for model input. The following steps were applied:

1. **Case Folding:** Converting all text to lowercase.
2. **Cleaning:** Removing URLs, mentions (@username), hashtags (#), numbers, punctuation marks, emojis, and non-alphabetic characters.
3. **Stopword Removal:** Utilizing the Indonesian stopword list from the Sastrawi library.
4. **Stemming:** Reducing inflected words to their root forms using the Sastrawi Stemmer.
5. **Tokenization:** Splitting sentences into individual word tokens.
6. **Text Normalization:** Replacing informal or slang terms (e.g., *gk* → *tidak*, *bgt* → *banget*) using a custom social media normalization dictionary.

2.4 Sentiment Labeling

The dataset was manually labeled into three sentiment categories: positive, negative, and neutral.

1. **Semi-automated labeling:** Initial labeling was performed using an Indonesian sentiment lexicon.
2. **Manual validation:** Conducted by two linguists and one public policy expert to ensure labeling accuracy.
3. **Inter-rater reliability:** Measured using Cohen's Kappa coefficient. A κ value greater than 0.80 was considered indicative of very strong agreement (McHugh, 2012).

The dataset distribution after labeling was as follows:

- Positive: 16,500 instances
- Negative: 21,000 instances
- Neutral: 12,500 instances

2.5 Feature Extraction

Before being fed into the LSTM model, textual data were transformed into numerical representations using two approaches:

1. Word Embeddings (Word2Vec and FastText): Applied to capture semantic relationships between words.
2. LSTM Embedding Layer: Configured with a 300-dimensional vector representation, allowing each word to be encoded as a dense vector.

2.6 LSTM Model Architecture

The LSTM model was designed with the following specifications:

1. Input Layer: Accepts tokenized text sequences.
2. Embedding Layer: 300-dimensional vectors.
3. LSTM Layer 1: 128 units with tanh activation.
4. Dropout Layer: 0.2 rate to prevent overfitting.
5. LSTM Layer 2: 64 units.
6. Dense Layer: 32 units with ReLU activation.
7. Output Layer: 3 neurons (positive, negative, neutral) with Softmax activation.

Training Parameters:

- Optimizer: Adam (learning rate = 0.001)

- Loss Function: Categorical Cross-Entropy
- Batch Size: 32
- Epochs: 20

2.7 Model Evaluation

Model performance was evaluated using an 80:20 train-test split. Additionally, 5-fold cross-validation was implemented to enhance reliability and generalizability.

Evaluation metrics included:

1. **Accuracy:** Proportion of correct predictions relative to total observations.
2. **Precision:** Accuracy of positive predictions.
3. **Recall (Sensitivity):** Model's ability to correctly identify positive and negative sentiments.
4. **F1-Score:** Harmonic mean of precision and recall.

The LSTM model's performance was compared against baseline models, including Naïve Bayes and Support Vector Machine (SVM), to assess performance improvement.

2.8 Linguistic Analysis

In addition to quantitative evaluation, a qualitative linguistic analysis was conducted to identify language patterns in public opinion, including:

1. Emotive diction: Words such as *adil* (fair), *zalim* (tyrannical), *mahal* (expensive), and *bermanfaat* (beneficial).
2. Stylistic features: Sarcasm, hyperbole, and persuasive expressions.
3. Dominant narratives: Social justice, economic burden, and national identity.

This linguistic analysis was integrated with the model's results to provide deeper insights into how language functions in shaping public opinion regarding government policies.

3. Results And Discussion

3.1 Experimental Results of the Sentiment Model

After completing the preprocessing stage, a total of 45,320 posts from Twitter and Facebook were deemed eligible for analysis. These data were divided into 36,256 instances for training and 9,064 for testing. Sentiment labeling resulted in the following distribution: positive (35%), negative (42%), and neutral (23%).

Table 1. Performance of the LSTM Model Compared with Baseline Models

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	73.4%	71.2%	72.5%	71.8%
Support Vector Machine	78.6%	77.9%	77.1%	77.5%
LSTM	**86.9%**	**85.7%**	**86.2%**	**86.0%**

The results indicate that the LSTM model significantly outperformed the baseline models. This finding aligns with previous studies suggesting that LSTM effectively captures long-range word dependencies in Indonesian, thereby improving contextual sentiment detection.

Based on the model's predictions on the test dataset, the sentiment distribution toward government policies was as follows:

- **Positive:** 34% (support for policies, particularly in education and healthcare subsidies)
- **Negative:** 45% (criticism of economic policies such as fuel price increases and taxation)
- **Neutral:** 21% (factual information without explicit opinion, such as official announcements)

The distribution was visualized using pie and bar charts within the analytical dashboard.

3.2 Term Frequency and Keyword Analysis

Keyword frequency analysis and word cloud visualization revealed the most frequently occurring terms in public opinion:

- **Positive terms:** *bermanfaat* (beneficial), *membantu* (helpful), *maju* (progressive), *adil* (fair), *sejahtera* (prosperous)
- **Negative terms:** *mahal* (expensive), *susah* (difficult), *beban* (burden), *zalim* (tyrannical), *gagal* (failed)
- **Neutral terms:** *program*, *pemerintah* (government), *kebijakan* (policy), *aturan* (regulation), *masyarakat* (society)

The word cloud visualization demonstrated a dominance of negatively connoted terms, indicating stronger public resistance compared to support.

3.3 Linguistic Analysis

From the perspective of emotive diction, words such as *adil* (fair) and *zalim* (tyrannical) were frequently employed in framing policy discussions. The term *zalim* evokes strong rejection due to its moral and negative connotations, whereas words such as *bermanfaat* (beneficial) and *sejahtera* (prosperous) reinforce policy legitimacy by conveying positive and forward-looking meanings.

Regarding stylistic features, several tendencies were identified:

1. **Sarcasm** appeared prominently, for example: *"They say it's for the people, but why are people struggling even more?"*
2. **Colloquial/slang language** facilitated rapid virality, for instance: *"Fuel prices up again, my wallet's crying, bro."*
3. **Persuasive rhetoric** was frequently used by official government accounts: *"Let us collectively support this policy for a progressive Indonesia."*

Furthermore, three dominant narratives were identified in policy discourse:

1. **Social Justice Narrative:** Emphasizing equitable access to education and healthcare.
2. **Economic Burden Narrative:** Predominant in discussions concerning staple prices and taxation.
3. **National Identity Narrative:** Used to mobilize support based on national values.

3.4 Discussion in the Context of Public Policy

The findings indicate that public resistance toward economic policies is more pronounced than support, whereas education-related policies tend to receive more positive sentiment. This suggests that economic issues are particularly sensitive in shaping public opinion.

From a linguistic perspective, the use of emotive language and sarcasm intensifies opinion polarization, while formal persuasive language appears less effective in engaging broader audiences, particularly younger generations. These findings are consistent with Amalia, Umar, and Zakaria (2025), who reported that Generation Z is more responsive to simple, colloquial language that spreads easily on social media than to formal governmental narratives.

Practically, the government should consider linguistically informed communication strategies when formulating and disseminating public policies. Understanding lexical choices, stylistic patterns, and dominant narratives in social media discourse can enhance policy communication effectiveness, strengthen legitimacy, and foster public trust.

3.5 Discussion

This study reinforces the argument that social media has become the primary arena for public expression regarding government policies. The predominance of negative sentiment (45%) confirms that economic policies tend to trigger public resistance due to their direct impact on daily living conditions.

In terms of model performance, LSTM demonstrated superior results compared to SVM and Naïve Bayes, achieving an accuracy of 86.9%. This confirms that LSTM is more capable of capturing contextual meaning in natural language, particularly in morphologically rich languages such as Indonesian. The findings highlight that sequence-based deep learning approaches are highly relevant for sentiment analysis in the Indonesian context.

The linguistic analysis further revealed that emotive diction and sarcastic expressions are frequently employed to express dissatisfaction. Negative rhetoric appears to spread more rapidly on social media than formal positive messaging. Meanwhile, the use of colloquial language enhances relatability among younger audiences. Thus, language plays a strategic role in either strengthening or weakening policy legitimacy.

The dominance of the "economic burden" narrative indicates that financial concerns remain the most sensitive issue in public opinion. This supports the agenda-setting theory in political communication (McCombs & Shaw, 1972), which posits that media and collective discourse can elevate certain issues to central public attention. In other words, viral economic narratives can shape public perception even before policies are fully implemented.

From a practical standpoint, this research demonstrates the necessity for governments to adapt their communication strategies. Rather than relying solely on rigid bureaucratic language, more persuasive, collaborative, and audience-centered linguistic approaches may prove more effective. Such linguistically informed communication aligns with the concept of participatory governance, where citizens function not merely as policy recipients but also as active agents in shaping public discourse.

Theoretically, this study contributes to deep learning–based sentiment analysis by integrating a linguistic analytical layer. This integration is essential, as quantitative LSTM results alone cannot fully explain why particular opinions emerge, whereas linguistic analysis provides deeper interpretative insights into meaning construction within digital public discourse.

4. Conclusions

This study confirms that social media has become the primary arena for shaping public opinion regarding government policies. The sentiment distribution reveals a dominance of negative opinions (45%), particularly on economic issues that directly affect public welfare. This finding reinforces the view that policies addressing financial aspects are more likely to generate public resistance than non-economic policies. From a technical perspective, the LSTM model demonstrated superior performance, achieving an accuracy of 86.9%, outperforming both SVM and Naïve Bayes. This result indicates that sequence-based deep learning approaches are highly relevant for analyzing Indonesian, a language characterized by complex morphological structures.

The linguistic analysis further shows that the public frequently employs emotive diction, sarcastic expressions, and economic burden narratives to articulate resistance. In contrast, social justice and national identity narratives are more commonly utilized by policy supporters to reinforce legitimacy. Therefore, this study not only contributes to the field of Natural Language Processing (NLP) by empirically validating the effectiveness of LSTM, but also enriches political communication studies by highlighting how language functions as a strategic instrument in agenda setting and policy legitimation.

Based on these findings, several recommendations can be proposed. For policymakers, communication strategies should adopt language that is simple, empathetic, and collaborative, while avoiding rigid bureaucratic terminology. The strategic use of colloquial language may also enhance engagement with younger generations and strengthen emotional connection. Furthermore, AI-based sentiment analysis can serve as a predictive tool to anticipate potential public resistance prior to policy implementation, allowing communication mitigation strategies to be prepared in advance.

For academics, future research may expand this study by evaluating alternative models such as Transformer-based architectures or BERT, exploring the role of metaphor, humor, and irony in public opinion formation, and incorporating multilingual analysis involving regional languages. Meanwhile, for society and media institutions, strengthening digital literacy is essential so that citizens can distinguish fact-based opinions from emotionally driven and potentially biased narratives. Mass media, in turn, are expected to function as balancing agents by presenting objective information and minimizing framing practices that may intensify public resistance.

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