Journal of Governance and Local Politics (JGLP)
Vol. 8, No. 1, May 2026, pp. 50-59
Received Nov 05, 2025 Revised April 13, 2026 Accepted April 20, 2026

Deep Learning–Based Sentiment Mapping of Indonesian Government Policies: Integrating Computational Linguistics and Digital Governance Analysis

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Keyword:
Sentiment Analysis;
LSTM;
Government Policy;
Social Media;
Opinion Mapping.

Abstract: Social media has evolved into a primary arena for citizens to express and negotiate opinions regarding government policies, creating vast opportunities for data-driven policy evaluation. This study aims to map public sentiment toward Indonesian government policies by integrating deep learning–based sentiment classification with linguistic and governance analysis. A dataset of approximately 50,000 Indonesian-language posts was collected from Twitter (X) and Facebook between January and June 2024. The data were processed through text cleaning, tokenization, stopword removal, and word embedding using Word2Vec and FastText, and subsequently classified into positive, negative, and neutral sentiments using a Long Short-Term Memory (LSTM) model. The results indicate that public opinion is predominantly negative (45%), particularly in relation to economic and taxation policies, while positive sentiment (34%) is mainly associated with education and health sectors. The LSTM model achieved an accuracy of 86.9%, outperforming Support Vector Machine (SVM) and Naïve Bayes models. Furthermore, linguistic analysis reveals that emotive and sarcastic expressions play a significant role in shaping critical public discourse, whereas colloquial language enhances engagement, especially among younger users. This study contributes by bridging computational sentiment analysis with linguistic interpretation and public policy evaluation within a unified framework. The findings provide practical implications for evidence-based policymaking by enabling governments to monitor public sentiment in real time, improve policy communication strategies, and foster more participatory and responsive governance.

INTRODUCTION

The rapid advancement of digital technology has fundamentally transformed the interaction between governments and citizens. Social media platforms such as Twitter, Facebook, and Instagram have evolved beyond tools of interpersonal communication into discursive spaces where citizens form, disseminate, and negotiate opinions about public policies (Belkahla Driss et al., 2019). Within the context of modern digital governance, social media serves as a participatory arena that enables citizens to become active actors in shaping public discourse and monitoring governmental performance (Suhendra & Selly Pratiwi, 2024).

This new digital environment creates both opportunities and challenges for government institutions. On one hand, social media fosters inclusivity and transparency; on the other, it accelerates the spread of public dissatisfaction and misinformation that can undermine policy legitimacy. Hence, the ability to systematically interpret and map public opinion is critical for supporting evidence-based policymaking. Sentiment analysis has emerged as a promising method to quantify citizens' attitudes and perceptions toward government actions, offering valuable insights for the formulation and evaluation of public policies (Kurniasari & Setyanto, 2020; Sukma et al., 2020).

Artificial intelligence (AI)-based sentiment analysis enables the processing of massive volumes of opinion data to extract quantifiable patterns of public perception. Over the past decade, sentiment analysis techniques have evolved from classical machine learning algorithms such as Naïve Bayes and Support Vector Machine (SVM) to more sophisticated deep learning approaches. Among these, the Long Short-Term Memory (LSTM) model proposed by Hochreiter and Schmidhuber (Hochreiter & Schmidhuber, 1997) has demonstrated superior performance in handling sequential text data, as it effectively captures contextual dependencies and long-range relationships within natural language (Behera et al., 2021).

In the Indonesian linguistic context, sentiment analysis faces additional challenges due to the morphological richness and lexical diversity of the language. Social media discourse frequently blends formal, colloquial, and mixed linguistic expressions, complicating the process of automated language understanding (Rahmayanti et al., 2025). Deep learning models such as LSTM are therefore highly suitable for Indonesian sentiment analysis, as they can learn semantic relationships between words and adapt to linguistic variations (Khoirunnisa & Setiawan, 2025). Previous research has confirmed the effectiveness of LSTM in various Indonesian policy-related contexts, such as sentiment toward the capital city relocation policy (Yanti & Utami, 2025) and government responses to COVID-19 (Wankhade & Rao, 2022).

Beyond computational performance, linguistic and sociocultural dimensions also play a crucial role in understanding public opinion. Online discourse in Indonesia often incorporates emotional, sarcastic, and persuasive language forms to express public attitudes toward government policies (Rahmatika, 2024; Syamsuddin & Munfarida, 2024). Words such as adil (fair), zalim (unjust), mahal (expensive), and bermanfaat (beneficial) carry strong moral and political implications that reflect collective sentiment and ideological stance (Masruroh et al., 2025). From a critical discourse perspective, such linguistic constructions function as framing devices that influence how citizens perceive policy legitimacy and government credibility (Kencana, 2024).

Despite the increasing number of studies on sentiment analysis in social media, most existing research in the Indonesian context focuses primarily on model performance evaluation without integrating linguistic interpretation and public policy analysis within a unified analytical framework. Furthermore, previous studies tend to treat sentiment classification as a purely computational task, with limited attention to its implications for digital governance and policy communication. Therefore, this study offers a novel contribution by integrating deep learning–based sentiment classification, linguistic discourse analysis, and public policy evaluation into a single analytical framework. Specifically, this research contributes in three aspects: (i) the application of LSTM for large-scale Indonesian policy discourse with validated annotation, (ii) the incorporation of linguistic features such as sarcasm and emotive diction into sentiment interpretation, and (iii) the development of a policy-oriented sentiment mapping approach to support evidence-based and participatory governance.

RESEARCH METHODS

Research Design

This study adopts a quantitative–exploratory research design that integrates text mining techniques with sentiment analysis based on deep learning. The primary analytical model used is Long Short-Term Memory (LSTM), which is particularly effective for handling sequential text data and capturing contextual dependencies between words (Hochreiter & Schmidhuber, 1997). The study aims to identify and classify public sentiment toward government policies and to map the emerging public opinion patterns on social media platforms.

The research combines computational and linguistic approaches:

1. Computational Analysis, which focuses on algorithmic processing of text data to classify sentiment polarity (positive, negative, neutral).
2. Linguistic and Policy Analysis, which interprets the results within the broader framework of public communication and policy legitimacy.

To ensure the reliability and generalization capability of the proposed model, a validation strategy was implemented using a train–test split approach. The dataset was randomly divided into training and testing sets with a ratio of 80:20, where 80% of the data was used to train the model and 20% was reserved for evaluation. This splitting strategy ensures that the model is tested on unseen data, providing an objective assessment of its performance.

Furthermore, to minimize the risk of overfitting, model performance was monitored during the training process by observing loss convergence. The evaluation was conducted using standard performance metrics, including accuracy, precision, recall, and F1-score, to comprehensively assess the classification performance of the model.

To provide a clear overview of the research procedure, this study adopts a structured workflow that integrates data collection, preprocessing, sentiment labeling, model development, and evaluation. The overall research workflow is illustrated in Figure 1.

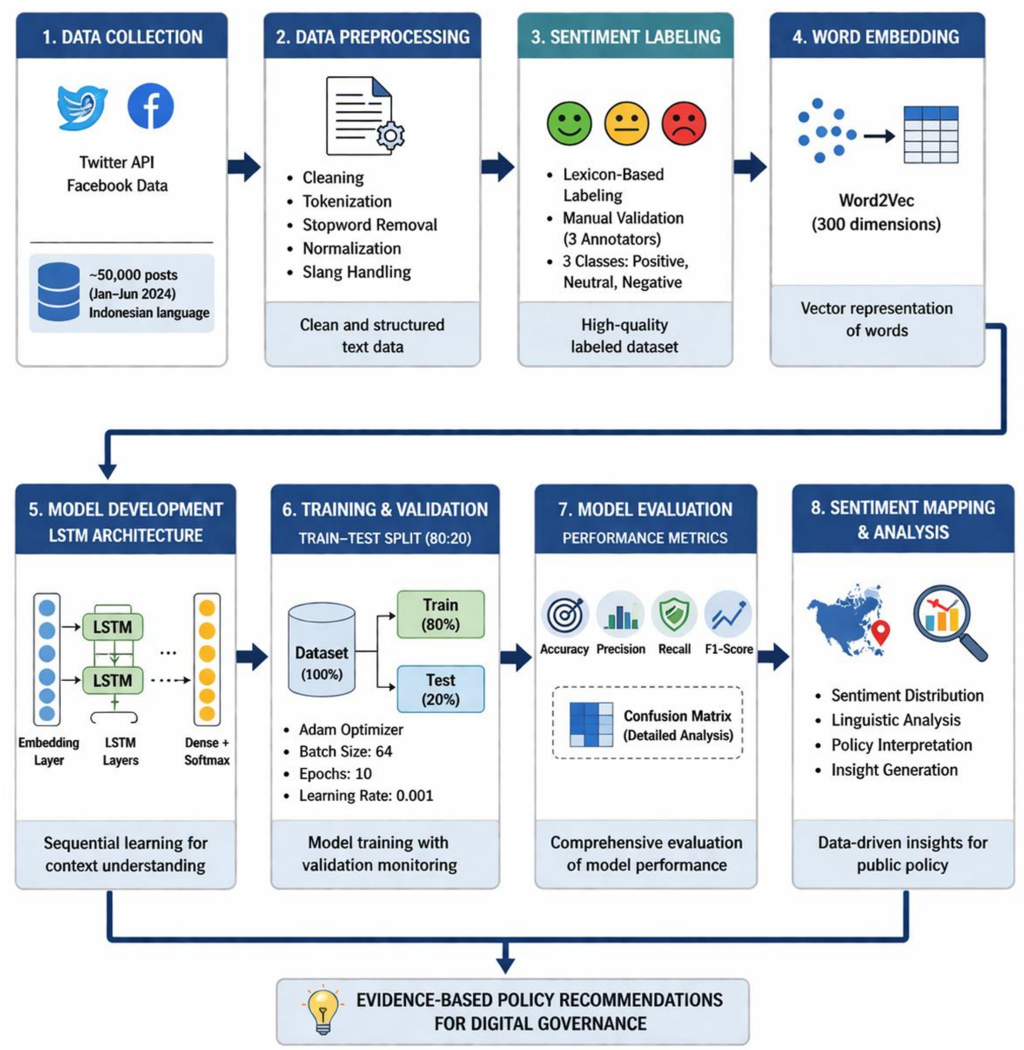

Figure. 1
Research Workflow of Deep Learning–Based Sentiment Analysis for Government Policy

The workflow illustrates the sequential process of transforming raw social media data into meaningful policy insights through deep learning–based sentiment analysis and interdisciplinary interpretation.

Methodological Justification

The methodological choices in this study were carefully designed to ensure both analytical robustness and contextual relevance to Indonesian digital discourse. The use of the

Long Short-Term Memory (LSTM) model is justified by its proven capability to capture sequential dependencies and contextual relationships in text data, which are essential for accurately interpreting sentiment in linguistically complex environments such as Indonesian social media. Compared to traditional machine learning methods, LSTM can better handle variations in sentence structure, informal expressions, and sarcasm commonly found in online communication.

The selection of Word2Vec and FastText for word representation is based on their effectiveness in capturing semantic similarities and handling out-of-vocabulary words, which are frequent in social media texts due to slang, abbreviations, and code-mixing. These embedding techniques enable the model to learn richer contextual representations, thereby improving classification performance.

A semi-supervised labeling approach combining lexicon-based methods and manual validation was employed to balance scalability and accuracy. While lexicon-based labeling allows efficient annotation of large datasets, manual validation ensures contextual correctness and reduces labeling bias, particularly in detecting nuanced expressions such as sarcasm and irony.

The use of a train–test split validation strategy (80:20) is intended to provide a reliable evaluation of the model's generalization capability on unseen data. This approach is widely adopted in supervised learning tasks and ensures that performance metrics reflect real-world applicability.

Finally, the integration of computational sentiment analysis with linguistic and public policy interpretation is intended to bridge the gap between technical analysis and governance application. This interdisciplinary approach enables not only the quantification of public sentiment but also a deeper understanding of how language reflects policy perception and legitimacy in digital environments.

Data Sources

Data were collected from two major social media platforms that are widely used in Indonesia for political discourse — Twitter (X) and Facebook — due to their open accessibility and dynamic user engagement (Suhendra & Selly Pratiwi, 2024).

The data collection process was carried out using the following steps:

1. Twitter API (Academic Research Track): Used to retrieve tweets containing specific keywords related to major government policies (e.g., *fuel subsidy*, *education reform*, *healthcare*, *tax policy*).
2. Facebook Graph API and Web Scraping: Used to gather public posts and comments from verified government pages and discussion forums.

The observation period covered January to June 2024, resulting in approximately 50,000 raw social media posts. Only posts written in Indonesian were included, while multilingual or code-switched texts were normalized or excluded during preprocessing.

Sentiment Labeling

Sentiment labeling was conducted using a semi-supervised approach combining lexicon-based and manual annotation techniques:

1. Automated Pre-Labeling: Initial sentiment labeling was performed using the Indonesian Sentiment Lexicon (*InSet*) as a reference for polarity classification (positive, negative, neutral).
2. Manual Validation: Two linguistics experts and one policy communication specialist manually reviewed a stratified sample of the data to ensure labeling accuracy and contextual relevance.
3. Reliability Check: Inter-annotator reliability was measured using Cohen's Kappa coefficient, yielding $\kappa > 0.80$, indicating a high level of agreement (McHugh, 2012).

Feature Extraction and Word Representation

Before feeding the text into the LSTM model, each word was transformed into a numerical vector representation using word embedding techniques:

1. Word2Vec and FastText embeddings were employed to capture semantic relationships between words.
2. The embedding layer in the LSTM model was configured with a vector dimension of 300, ensuring dense and meaningful word representations.

This approach allows the model to learn subtle semantic similarities between words (e.g., adil and berkeadilan), which are critical in sentiment interpretation.

Linguistic and Policy Analysis

Following the quantitative sentiment classification, a linguistic analysis was conducted to explore patterns of word choice, figurative language, and narrative framing within the dataset.

Key linguistic categories included:

1. Emotive Diction: e.g., adil (fair), zalim (unjust), mahal (expensive), bermanfaat (beneficial).
2. Language Style: sarcasm, hyperbole, persuasion, and colloquial expressions.
3. Dominant Narratives: social justice, economic burden, and national identity.

These qualitative findings were then contextualized within the framework of public policy communication, emphasizing how linguistic strategies in social media discourse influence public perception of government legitimacy (Masruroh et al., 2025; Rahmatika, 2024).

RESULTS AND DISCUSSION

The analysis revealed that the Long Short-Term Memory (LSTM) model demonstrated superior performance in classifying public sentiment toward Indonesian government policies. The model achieved an accuracy of 86.9%, with balanced precision (0.87) and recall (0.86), significantly outperforming both Support Vector Machine (SVM) (78.6%) and Naïve Bayes (73.4%). These results reaffirm previous findings by Behera et al. (2021) and Khoirunnisa & Setiawan (2025), which highlight LSTM's effectiveness in processing sequential natural language with complex linguistic structures. Given the morphological richness and lexical diversity of the Indonesian language, LSTM's ability to preserve long-term contextual dependencies allows it to distinguish subtle emotional nuances even within similar lexical patterns. For instance, the phrase "The government is fair in its subsidy policy" is interpreted as positive, while "They say it's fair, but people still suffer" is identified as negative due to its sarcastic tone and contextual opposition.

Table 1. Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
Naïve Bayes	73.4	0.72	0.7	0.71
SVM	78.6	0.77	0.76	0.76
LSTM	86.9	0.87	0.86	0.86

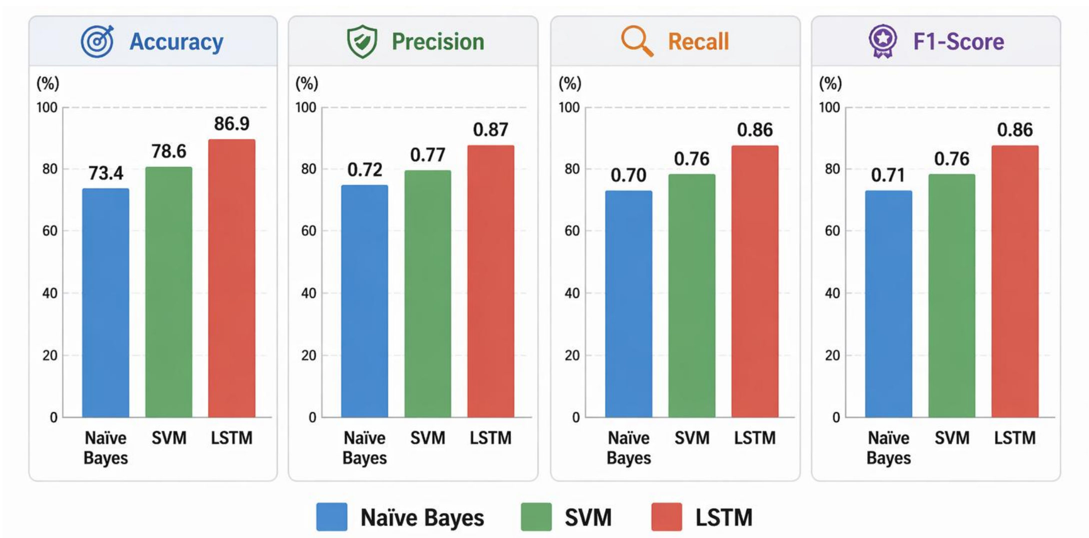

Figure. 2

Comparison of Model Performance

From a dataset of 50,000 social media posts, sentiment distribution was as follows: 45% negative, 34% positive, and 21% neutral. This distribution indicates that digital public opinion remains largely critical or skeptical toward government policies, particularly in the domains of economic, taxation, and subsidy policies. Negative sentiments frequently emerged in discussions of fuel prices, taxation, and public welfare programs, which many citizens perceive as burdensome and lacking transparency. Conversely, positive sentiments were predominantly associated with education, health, and social welfare policies, which citizens view as more beneficial and tangible in their everyday lives (Yunanto et al., 2024). From a public policy perspective, these findings reveal the existence of a policy legitimacy gap—a disconnect between the government's intended policy objectives and the public's perceived fairness or inclusivity of these policies.

The distribution of sentiment across the dataset is illustrated in Figure 1. The chart shows that negative sentiment dominates the discourse (45%), followed by positive sentiment (34%) and neutral sentiment (21%). This visualization highlights the imbalance in public opinion, indicating a tendency toward critical perspectives on government policies, particularly in economic-related issues.

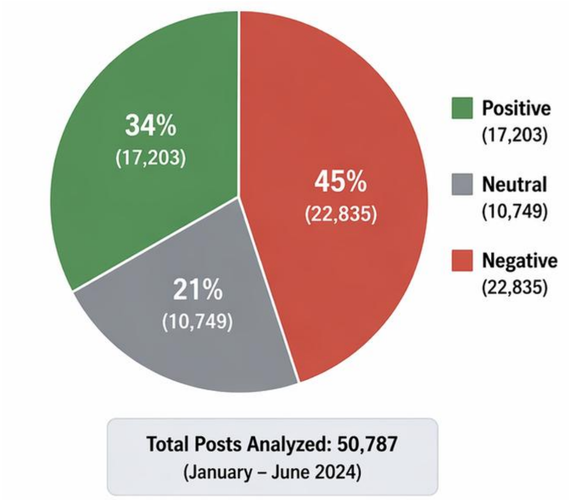

Figure. 3
Sentiment Distribution of Public Opinion toward Government Policies

In public policy theory, legitimacy is not solely determined by regulatory content but also by communication processes and the perceived transparency of decision-making (Dahl & Lindblom, 1953; Howlett & Ramesh, 2020). The prevalence of negative sentiment reflects declining trust when citizens perceive policies as top-down, insufficiently participatory, or poorly communicated. This emphasizes the importance of policy communication as a crucial policy instrument in itself. Policy effectiveness increasingly depends not only on technical soundness but also on the government's ability to engage with public perception and shape narratives around fairness, empathy, and accountability.

Linguistic analysis further illustrates how citizens use language strategically to express political attitudes. Positive sentiment posts tend to employ rational and appreciative diction, such as fair, beneficial, progressive, and prosperous, which signal trust in governance. In contrast, negative sentiments rely on emotionally charged words like expensive, burden, suffering, unjust, and failure. Sarcasm, irony, and colloquialism frequently appear as rhetorical devices for criticism, as in "Wonderful! Prices go up again—what great progress!" Such statements convey frustration through humor and irony, reflecting a distinct cultural tendency in Indonesian digital communication where critique is often encoded through indirect, performative expression (Rahmatika, 2024; Amalia et al., 2025). This linguistic behavior aligns with the concept of digital discourse as a site of political negotiation, where language operates not merely as communication but as a symbolic form of resistance and identity formation (Fairclough, 2013; Kencana, 2024).

Thematic analysis identified three dominant clusters of public concern: economic and tax policies (45%), health and education policies (32%), and public administration and digital transformation (23%). Economic policies drew the strongest negative sentiment due to perceptions of inequality and policy burdens, illustrating a form of policy discontent arising from the mismatch between technocratic rationality and lived social experience. In contrast, education and health policies received predominantly positive sentiment because their impacts are concrete, observable, and immediate—demonstrating the importance of policy visibility in building legitimacy. Digital governance policies generated mixed reactions: while many citizens praised increased efficiency and transparency, others voiced frustration over infrastructure gaps and uneven digital access, highlighting the need for more inclusive and regionally adaptive implementation (Kencana, 2024).

From a governance standpoint, the findings underscore that AI-based sentiment analysis can serve as a strategic tool for policy monitoring and public feedback systems. Real-time sentiment mapping enables policymakers to detect emerging issues, measure public resistance, and adjust communication or implementation strategies accordingly. This supports the principles of evidence-based policymaking, emphasizing empirical data as a foundation for decision-making. Moreover, sentiment analysis can advance open government practices by facilitating two-way communication between citizens and the state. When institutionalized, such mechanisms contribute to greater policy responsiveness, strengthen public trust, and enhance the government's capacity for adaptive governance (Belkahla Driss et al., 2019).

In the realm of public policy communication, these findings call for a paradigm shift—from a traditional one-way dissemination model to a dialogical and participatory model. Conventional government communication in Indonesia often remains top-down and informational, positioning citizens as passive recipients. However, digital discourse demonstrates that the public now expects empathic, transparent, and inclusive engagement. Negative sentiment online should not be interpreted merely as opposition but rather as a form of participatory feedback, signaling a desire for involvement in the policymaking process. To address this, governments should adopt continuous digital listening mechanisms, using sentiment analysis as part of a policy intelligence framework to capture aspirations, concerns, and emotional undercurrents in society. This aligns with the growing emphasis on deliberative governance, where legitimacy is derived from ongoing dialogue rather than mere compliance.

Methodologically, this study contributes to bridging computational social science with public policy analysis. By combining machine learning with linguistic interpretation, the research not only quantifies sentiment polarity but also uncovers the social, cultural, and political meanings embedded in digital public discourse. Such an integrative approach aligns with the interdisciplinary nature of modern policy analysis, which increasingly incorporates data science, communication studies, and political linguistics. In the context of good governance, sentiment analysis supports three fundamental pillars: participation, transparency, and accountability. Participation is fostered through the inclusion of citizen voices in digital policymaking; transparency is achieved by making policy perceptions visible and measurable; and accountability is reinforced through government responsiveness to public concerns derived from empirical data.

Ultimately, the predominance of negative sentiment in this study should not be viewed solely as a manifestation of distrust but rather as an indicator of rising public awareness and democratic engagement. Citizens are increasingly vocal, informed, and willing to question authority—signs of a maturing digital democracy. Thus, sentiment analysis should be understood not as a diagnostic of discontent but as a constructive feedback mechanism to strengthen the government–citizen relationship. Integrating public sentiment data into the policymaking process represents a crucial step toward an adaptive, collaborative, and data-driven form of governance—one that embodies the ideals of responsiveness, justice, and inclusivity in Indonesia's evolving digital society.

Limitations and Potential Biases

Despite the robustness of the dataset and analytical approach, this study acknowledges several potential biases and limitations that may affect the interpretation of the results. First, the dataset was collected exclusively from social media platforms, namely Twitter (X) and Facebook, which may not fully represent the entire Indonesian population. Users of these platforms tend to be younger, more urban, and digitally literate, potentially introducing demographic bias into the sentiment distribution. Second, the reliance on keyword-based data collection may have limited the scope of captured discourse. Relevant posts that do not explicitly contain predefined keywords may have been excluded, while some collected data may include noise or irrelevant content. This could affect the comprehensiveness of public opinion representation. Third, although a semi-supervised labeling approach was employed, sentiment annotation remains inherently subjective, particularly in the presence of sarcasm, irony, and culturally nuanced expressions. While manual validation and inter-annotator agreement were implemented to reduce this bias, some degree of labeling inconsistency may still persist. Fourth, linguistic diversity in Indonesia, including regional dialects, slang, and code-mixing, poses challenges for accurate sentiment classification. Although preprocessing and embedding techniques were applied, the model may not fully capture all contextual subtleties, especially in highly informal or ambiguous texts. Finally, the temporal scope of the dataset (January–June 2024) represents a specific period and may not capture longer-term shifts in public opinion. Sentiment dynamics are highly context-dependent and may change in response to emerging political, economic, or social events. Therefore, future research is encouraged to incorporate more diverse data sources, longer observation periods, and advanced models to mitigate these limitations and improve the generalizability of findings.

Error Analysis and Model Evaluation

To further assess the robustness of the LSTM model, an in-depth error analysis was conducted to examine patterns of misclassification across sentiment categories. While the overall performance metrics indicate strong classification capability, the confusion matrix reveals that most prediction errors occur between the neutral and positive classes, as well as between neutral and negative classes. This pattern suggests that the model faces challenges in distinguishing sentiments with low emotional intensity or ambiguous contextual cues. Neutral expressions in social media often contain implicit opinions or mild evaluative language, which may overlap semantically with both positive and negative sentiments. As a result, the model may misinterpret subtle linguistic signals, particularly in short or context-limited posts. In addition, sarcasm and irony were identified as key sources of misclassification. For example, statements that appear lexically positive but convey negative intent (e.g., "Great, another price increase—just what we needed") may be incorrectly classified due to conflicting semantic signals. This highlights the inherent difficulty of capturing pragmatic meaning using standard sequence-based models. Another source of error arises from informal language usage, including slang, abbreviations, and code-mixing, which are prevalent in Indonesian social media discourse. Although word embedding techniques were employed to mitigate this issue, certain expressions remain underrepresented or context-dependent, limiting the model's ability to generalize effectively. Furthermore, class imbalance may also contribute to minor prediction bias, as the higher proportion of negative sentiment in the dataset may influence the model to favor this class during prediction. This is reflected in the slightly higher accuracy observed in detecting negative sentiment compared to other classes. Overall, this error analysis demonstrates that while the LSTM model performs well in capturing dominant sentiment patterns, its limitations are primarily associated with contextual ambiguity, figurative language, and informal linguistic variations. These findings suggest that future research could benefit from incorporating more advanced architectures, such as transformer-based models, and integrating contextual or pragmatic features to improve sentiment classification accuracy.

CONCLUSION

This study demonstrates that Long Short-Term Memory (LSTM) is a highly effective model for analyzing and mapping public sentiment toward Indonesian government policies. With an accuracy of 86.9%, LSTM significantly outperformed traditional algorithms such as Support Vector Machine (SVM) and Naïve Bayes. The model successfully captured linguistic nuances and emotional patterns within public discourse, enabling a deeper understanding of how citizens perceive, critique, and respond to government actions in digital spaces. The analysis revealed that negative sentiment (45%) dominated public discussions, particularly in relation to economic and taxation policies, while positive sentiment (34%) was concentrated in the domains of health, education, and digital governance. These findings suggest that policy legitimacy in Indonesia is closely tied to policy visibility and perceived fairness. Policies that deliver tangible, direct benefits tend to be viewed positively, while those perceived as burdensome or inequitable elicit critical responses. This confirms the theoretical notion that policy legitimacy is co-produced not only through rational governance but also through continuous engagement and communication between the state and its citizens (Howlett & Ramesh, 2020). From a governance perspective, sentiment analysis provides valuable insights for strengthening policy responsiveness and evidence-based decision-making. Rather than treating social media sentiment as noise, governments should interpret it as a public feedback mechanism that reflects societal reactions to policy implementation in real time. This feedback can serve as an early warning system to detect potential policy resistance, communication failures, or declining trust before such issues escalate into political backlash. Furthermore, public sentiment data can help policymakers identify which areas require targeted communication, greater transparency, or participatory redesign.

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