JURNAL TEKNOLOGI DAN OPEN SOURCE
Vol. 8, No. 2, December 2025, pp. 639~649
e-ISSN: 2622-1659, accredited Four Grade by Kemenristekdikti, Decree No: 152/E/KPT/2023
DOI: https://doi.org/10.36378/jtos.v8i2.4596

Comparative Sentiment Analysis of Indonesian Leadership Transitions on Platform X Using LSTM and Naïve Bayes

Alief Ramadhan Dwi Putra[1], Afiyati Afiyati[2]
[1,2]Department of Computer Science, Mercu Buana University, Indoneisa

Article Info

Article history:

Received 05 25, 2025
Revised 08 15, 2025
Accepted 11 28, 2025

Keywords:

Sentiment Analysis
Long Short-Term Memory
Naïve Bayes
Social Media
Leadership Transition

ABSTRACT

Political sentiment analysis on social media has become a critical tool for understanding public perception during leadership transitions. This study compares the effectiveness of Long Short-Term Memory (LSTM) and Naïve Bayes algorithms in classifying sentiment related to Indonesia's 2024 leadership change using data from platform X (formerly Twitter). A total of 5,942 Indonesian-language tweets were collected and labeled through both lexicon-based and manual annotation. Manual labeling was crucial in capturing nuanced, context-dependent sentiments often missed by automated methods. LSTM was applied for its strength in modeling sequential patterns in text, while Naïve Bayes served as a lightweight probabilistic baseline. Both models were evaluated using accuracy, precision, recall, and F1-score. Results show that LSTM achieved 71.6% accuracy on lexicon-based data and 77.9% on manually labeled data, while Naïve Bayes reached 61.5% and 78.2%, respectively. LSTM offered better generalization across sentiment classes—especially neutral—whereas Naïve Bayes excelled in detecting clearly polarized sentiment. These findings highlight the importance of model selection based on data characteristics and labeling strategy. The study contributes practical insights for political analysts and institutions aiming to monitor digital public opinion and inform evidence-based policymaking.

Corresponding Author:

Afiyati Afiyati
Department of Computer Science
Mercu Buana University
Jakarta, Indonesia
Email: afiyati.reno@mercubuana.ac.id

1. Introduction

Political leadership plays a central role in shaping a nation's direction, stability, and public trust. In Indonesia, leadership transitions—especially during general elections—often trigger widespread public reactions, reflecting citizen expectations and offering insights for policymakers and analysts striving for democratic governance [1],[2].

The rise of social media platforms such as X (formerly Twitter), YouTube, and TikTok has transformed public political discourse into a dynamic, real-time digital conversation. These platforms host opinion-rich content, making them valuable sources for analyzing sentiment and gauging public mood[3],[4].

Sentiment analysis has emerged as a key computational method to extract emotional and attitudinal insights from such content. Earlier approaches used traditional machine learning algorithms like Naïve Bayes and Support Vector Machines (SVM). However, recent advances favor deep learning models—particularly Long Short-Term Memory (LSTM) networks—for their ability to capture sequential and contextual patterns in text[5], [6]. In the Indonesian context, characterized by informal expressions and dialectal variation, LSTM has demonstrated improved accuracy over conventional models [3], [7].

The 2024 Indonesian Presidential Election emphasized the need for robust sentiment analysis. Previous studies used Twitter data to monitor public reactions to debates and policy changes, revealing dynamic shifts in opinion aligned with political events [8]. However, there remains a lack of research directly comparing LSTM and Naïve Bayes performance on both lexicon-based and manually labeled Indonesian datasets. This methodological gap limits understanding of how labeling quality influences model performance in political domains [9], [10].

Manual annotation is more accurate but labor-intensive, while lexicon-based labeling offers automation with limited nuance. Comparing both models across these labeling types offers insights into the trade-offs between scalability, accuracy, and contextual sensitivity [11].

Therefore, this study aims to compare LSTM and Naïve Bayes algorithms in classifying political sentiment from Indonesian tweets related to leadership transitions. A dataset of 5,942 tweets was labeled using both lexicon-based and manual methods to evaluate the models under varying label quality. The findings are expected to inform future sentiment analysis strategies and assist researchers, analysts, and institutions in selecting appropriate methods based on data characteristics.

The remainder of this paper is organized as follows: Section 2 describes the research methodology, Section 3 presents the results and discussion, and Section 4 concludes the study.

2. Research Method

This study was conducted through a structured sequence of activities including data collection, preprocessing, sentiment labeling, model implementation, and evaluation. The main objective was to compare the effectiveness of two algorithms—Long Short-Term Memory (LSTM) and Naïve Bayes—in classifying public sentiment related to political leadership transitions in Indonesia.

The dataset consisted of tweets in Bahasa Indonesia, crawled from platform X (formerly Twitter), which serves as a major hub for political discourse. To ensure methodological rigor, two different labeling strategies—lexicon-based and manual annotation—were applied to the same dataset to assess how labeling quality influences model performance.

Each stage of the research process is elaborated in the following subsections.

2.1 Research Stages

The research followed five major stages as shown in Figure 1.

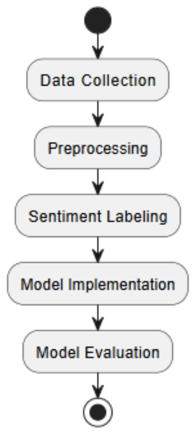


Figure 1. Research stages of sentiment classification model evaluation process.

A. Data Collection:

Tweets in the Indonesian language were collected using political keywords such as “Presiden baru”, “Pemimpin baru”, “Pemilu 2024”, and “Pergantian presiden”. The crawling process spanned from October 2024 to March 2025. After removing duplicates and irrelevant content, a total of 5,942 tweets were retained for analysis[12]. All data used in this study were publicly available and collected in accordance with ethical guidelines for social media research

B. Preprocessing:

The tweets were cleaned and normalized using standard Natural Language Processing (NLP) techniques. This includes lowercasing, punctuation and mention removal, stemming using Sastrawi, stopword filtering, normalization of slang words, and tokenization. These steps aimed to reduce noise and prepare the data for effective classification.

C. Sentiment Labeling:

Two labeling methods were employed. First, lexicon-based labeling was performed using curated sentiment word lists (positif.txt and negatif.txt). Second, manual labeling was conducted by two independent annotators with expertise in sentiment analysis. Disagreements were resolved by consensus or third-party adjudication. This dual-labeling strategy ensures both scalability and label quality [13], [14].

D. Model Implementation:

Two models were constructed:

1. Naïve Bayes using TF-IDF features and Multinomial classification;
2. LSTM, developed in Keras/TensorFlow, using embedding layers and sequential word representation to learn long-term dependencies in the data.

E. Model Evaluation:

Models were evaluated on both lexicon-based and manually labeled datasets. Evaluation metrics include accuracy, precision, recall, F1-score, and confusion matrices. For LSTM, early stopping and 10 training epochs were applied to prevent overfitting

2.2 Algorithmic Foundation

A. Naïve Bayes Classifier

Multinomial Naïve Bayes is a simple yet effective probabilistic classifier for text classification, especially suited to discrete input features like word counts or TF-IDF. It calculates the posterior probability of a class based on Bayes' theorem

$$P(c|d) = \frac{P(c) \, .\Pi_{i=1}^{n} P(w_i|c)^{Fi}}{P(d)} \tag{1}$$

Where :

1. $P(c \mid d)$: Posterior probability of class c given document d.
2. $P(c)$: Prior probability of class c
3. $P(w_i \mid c)$: Probability of word w_i given class c
4. F_i : Frequency of word w_i in document d.
5. n : Total number of distinct words

This classifier is computationally efficient and effective in many large-scale text classification settings [15], [16]

B. Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) designed to retain long-term dependencies using gating mechanisms. Its architecture enables it to learn context from sequences of words, which is essential in sentiment classification of informal text such as tweets [17], [18].

The core equations for LSTM operations are:

$$f^t = \sigma\left(W_f . \left[h_{t-1}, x_t\right] + b_f\right. \tag{2}$$

$$i^t = \sigma\left(W_i . \left[h_{t-1}, x_t\right] + b_i\right. \tag{3}$$

$$C^t = f_t \odot C_{t-1} + i_t \odot tanh\left(W_c . \left[h_{t-1}, x_t\right] + b_c\right. \tag{4}$$

$$\sigma^t = \sigma\left(W_o . \left[h_{t-1}, xt\right] + b_o\right. \tag{5}$$

$$h^t = o_t \odot \tanh(C_t) \tag{6}$$

These allow the model to capture context across time steps, making LSTM more robust in handling informal expressions, sarcasm, and evolving sentence structure common in social media [19], [20]

2.3 Data Preprocessing

The following steps were applied during preprocessing:

1. Lowercasing all text,
2. emoving punctuation, mentions, hashtags, and URLs,
3. Stemming using the Sastrawi library,
4. Stopword removal,
5. Slang normalization using a custom dictionary,
6. Tokenization using Keras Tokenizer() function.

Table 1. Example of Raw and Preprocessed Tweet Texts

Raw Tweet	After Preprocessing
@GunRomli Visi Presiden gak ada itu Visi Menteri masa pada lupa sih!	visi presiden visi menteri masa lupa
@hexagrap_id Langkah tegas Presiden Prabowo Pertamina bersih menyala	langkah tegas presiden prabowo pertamina bersih nyala

2.4 Sentiment Labeling Strateg

A dual-labeling strategy was applied:

1. Lexicon-based: Using curated sentiment dictionaries (positif.txt and negatif.txt), each tweet was automatically classified into positive, negative, or neutral based on keyword counts.
2. Manual annotation: Two trained annotators independently labeled each tweet based on its semantic content and tone. Discrepancies were resolved through consensus or a third reviewer.

Studies suggest combining both improves model reliability in political contexts [21], [22]

2.5 Model Training and Evaluation

Both models were trained and tested on the dataset using an 80/20 split:

1. Naïve Bayes: Implemented using Scikit-learn and TF-IDF vectorization.
2. LSTM: Built with Keras/TensorFlow, including an embedding layer, dropout, and categorical_crossentropy as the loss function.

Early stopping was used to avoid overfitting. Both models were evaluated using:

1. Accuracy
2. Precision
3. Recall
4. F1-Score
5. Confusion Matrix

These metrics allow for a comprehensive assessment of each model's performance under different labeling strategies

3. Result and Discussion

This section presents the experimental results and provides a comprehensive discussion on the performance of Long Short-Term Memory (LSTM) and Naïve Bayes algorithms in classifying public sentiment regarding political leadership changes. The analysis compares two labeling strategies: lexicon-based and manual annotation. Standard classification metrics such as accuracy, precision, recall, and F1-score are used for evaluation.

3.1 Word Cloud Visualization

Figure 2 presents a word cloud generated from the preprocessed tweets. The visualization highlights dominant terms such as “prabowo,” “presiden,” “pemilu,” and “pemimpin,” indicating the political focus of the discourse.

Figure 2. Word Cloud of Tweets Related to Leadership Transitions

3.2 Sentiment Distribution Overview

The sentiment distributions for both lexicon-based and manual labeling are shown to reveal differences in sentiment balance.

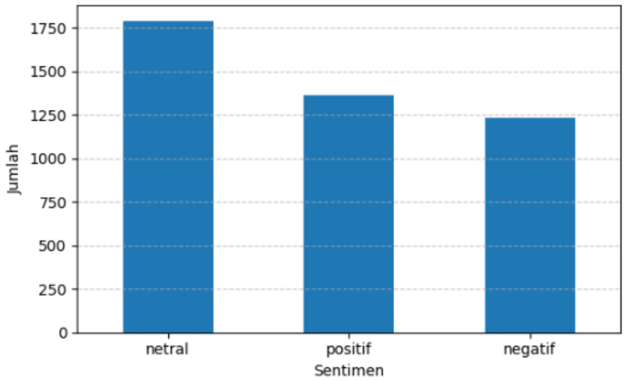
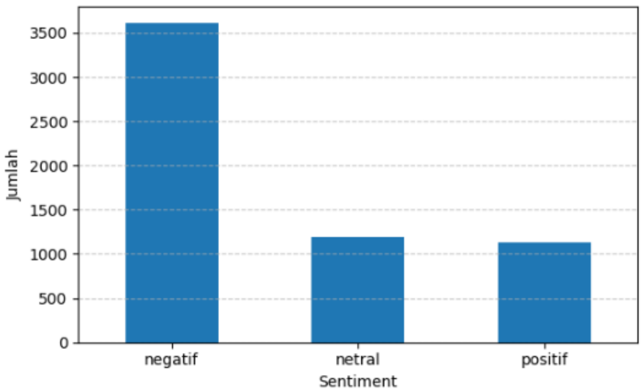


Figure 3. Sentiment Distribution from Lexicon-Based Labeling

This plot shows a neutral-dominant distribution, reflecting the limitations of lexicon-based sentiment detection.



.

Figure 4. Sentiment Distribution from Manual Annotation

The proportion of negative sentiment is significantly higher, possibly due to increased public criticism during the 2024 leadership transition.

3.3 Lexicon-Based Labeling Results

A. Naïve Bayes on Lexicon-Based Data

Naïve Bayes achieved 61.50% accuracy with lexicon-labeled data. The model handled polarized sentiment adequately but failed to capture neutrality and context-dependent language..

Table 2. Naïve Bayes Metrics on Lexicon-Based Data

Model	Labeling Type	Accuracy	Precision (Macro)	Recall (Macro)	F1-score (Macro)
Naive Bayes	Lexicon-Based	61.50%	0.67	0.59	0.60

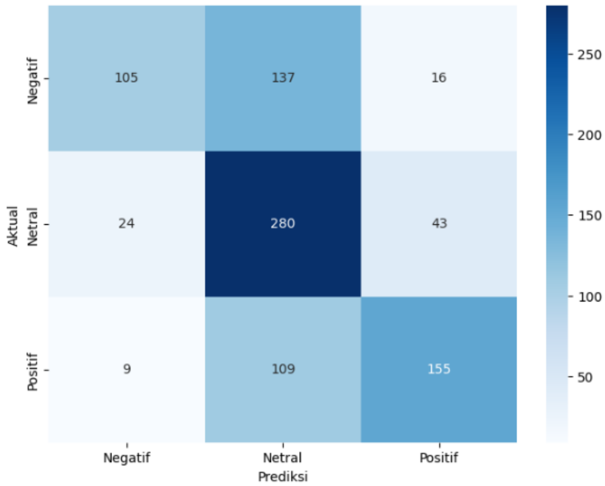


Figure 5. Confusion Matrix of Naïve Bayes (Lexicon-Based)

These results align with prior research indicating that Naïve Bayes is limited in modeling contextual dependencies, especially in political texts containing irony or ambiguity.

B. LSTM on Lexicon-Based Data

LSTM outperformed Naïve Bayes with 71.64% accuracy, leveraging its sequential processing to model sentence context and structure.

Table 3. LSTM Metrics on Lexicon-Based Data

Model	Labeling Type	Accuracy	Precision (Macro)	Recall (Macro)	F1-score (Macro)
LSTM	Lexicon-Based	71.64%	0.74	0.71	0.72

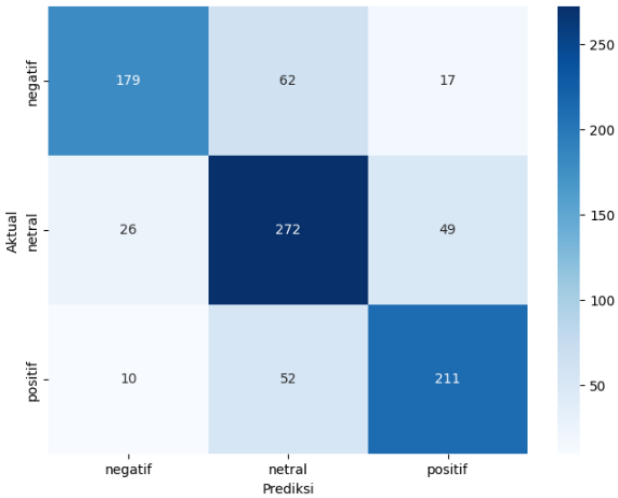


Figure 6. Confusion Matrix of LSTM (Lexicon-Based)

Although LSTM shows higher effectiveness, this comes with increased computational costs and sensitivity to overfitting, particularly with smaller datasets.

3.4 Manual Annotation Results

A. Naïve Bayes on Manual Data

With manually annotated labels, the performance of Naïve Bayes increased to 78.22%, demonstrating a significant improvement compared to the results obtained from automatically generated or noisy labels. This enhancement clearly indicates how strongly the model depends on the precision, consistency, and clarity of class annotations during training. When labels accurately represent the sentiment categories, the model can better learn distinguishing features, reduce misclassification, and produce more reliable predictions. This outcome further emphasizes that high-quality annotation plays a crucial role in optimizing traditional machine learning models, showing that even simple algorithms can achieve strong performance when supported by clean and well-structured training data.

Table 4. Naïve Bayes Metrics on Manually Annotated Data

Model	Labeling Type	Accuracy	Precision (Macro)	Recall (Macro)	F1-score (Macro)
Naive Bayes	Manual	78.22%	0.81	0.63	0.68

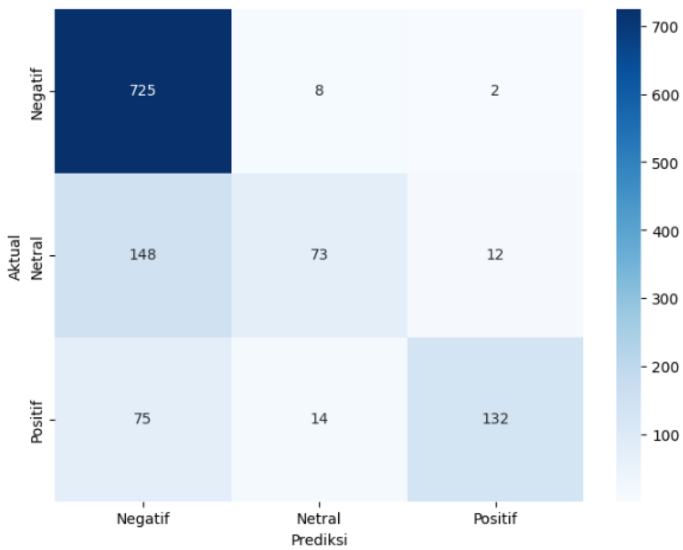


Figure 7. Confusion Matrix of Naïve Bayes (Manual Annotation)

This result demonstrates that even relatively simple models are capable of producing competitive performance when supported by high-quality labeled data, emphasizing that the accuracy of annotations plays a crucial role in sentiment analysis. Well-constructed datasets with consistent and precise labels enable models to better recognize linguistic patterns and reduce ambiguity during training. As a result, the reliability of predictions increases, even without complex architectures. This finding reinforces the idea that data quality often has a greater impact on model performance than model complexity, making careful annotation a fundamental component in building effective sentiment analysis systems.

B. LSTM on Manual Data

LSTM achieved 77.96% accuracy, slightly below Naïve Bayes, but offered more balanced performance across all sentiment classes. This consistency indicates that LSTM is better at capturing contextual patterns and sequential dependencies within the text, allowing it to generalize more effectively. Despite the lower overall accuracy, its stability across categories makes it valuable for multi-class sentiment tasks.

Table 5. LSTM Metrics on Manually Annotated Data

Model	Labeling Type	Accuracy	Precision	Recall (Macro)	F1-score (Macro)
LSTM	Manual	77.96%	0.73	0.71	0.72

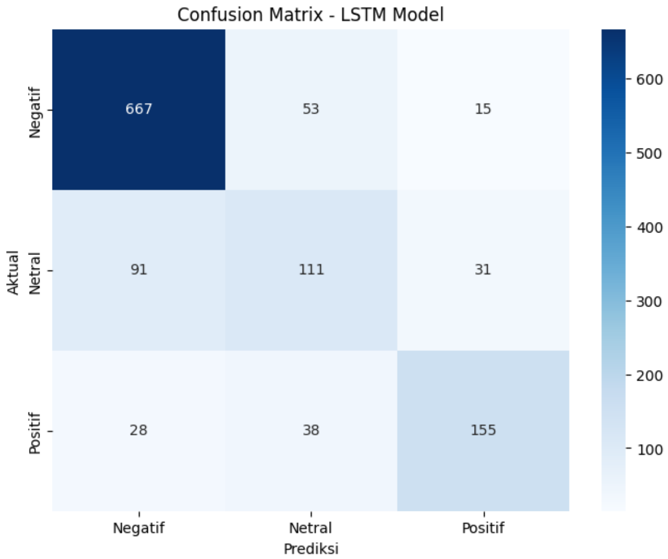


Figure 8. Confusion Matrix of LSTM (Manual Annotation)

This result indicates that the LSTM model performs strongly in identifying negative sentiments but still struggles to distinguish between neutral and negative classes. Although it achieves reasonable balance overall, there is room for improvement in handling more ambiguous or overlapping sentiment categories.

3.5 Comparative Analysis and Model Discussion

This section analyzes classification outcomes, model behaviors, and limitations across both algorithms under different labeling strategies.

A. **Impact of Labeling Quality:**

Both models showed performance gains with manual labels. Naïve Bayes improved by ~17%, while LSTM demonstrated improved detection of neutral sentiment.

B. **Algorithm Strengths and Limitations:**

1. LSTM excels in handling sequential patterns and informal syntax but requires more computational resources.
2. Naïve Bayes is efficient and performs well on clearly polarized and balanced datasets but lacks contextual sensitivity.

C. **Practical Implications**:

Accurate sentiment classification supports real-time policy evaluation and public opinion tracking. The choice of algorithm should consider resource availability and data characteristics.

D. **Limitations and Future Work:**

Limitations include the dataset size and subjective annotation. Future directions involve:

1. Expanding to multi-platform and multilingual datasets
2. Incorporating sarcasm detection and irony modelling
3. Experimenting with BERT or hybrid lexicon-deep learning models
4. Deploying real-time sentiment monitoring tools

3.6 Summary of Classification Accuracy

Table 6. Comparison of Classification Accuracy Between Naïve Bayes and LSTM

Model	Labeling Type	Accuracy
Naive Bayes	Lexicon-Based	61.50%
LSTM	Lexicon-Based	71.64%
Naive Bayes	Manual Annotation	78.22%
LSTM	Manual Annotation	77.96%

This comparison confirms that manual annotation improves classification quality across models. LSTM offers more balanced sentiment detection, while Naïve Bayes performs well with high-quality, polarized data.

4. Conclusion

This study evaluated the effectiveness of two machine learning algorithms—Long Short-Term Memory (LSTM) and Naïve Bayes—in classifying public sentiment related to leadership transitions in Indonesia. The analysis was based on 5,942 Indonesian-language tweets collected from platform X (formerly Twitter), labeled using two distinct strategies: lexicon-based and manual annotation. This dual approach allowed the study to assess the impact of label quality on model performance.

On lexicon-based data, LSTM achieved an accuracy of 71.64%, significantly outperforming Naïve Bayes at 61.50%. This result demonstrates LSTM's strength in modeling sequential dependencies and capturing context within noisy, informal text typical of social media. In contrast, on manually labeled data which offered higher label fidelity—Naïve Bayes slightly surpassed LSTM, achieving 78.22% versus 77.96% accuracy. This suggests that Naïve Bayes performs competitively when applied to clean and structured data.

Beyond raw accuracy, LSTM exhibited more balanced performance across sentiment classes, particularly in detecting neutral sentiment, indicating stronger generalization capabilities in linguistically complex environments. Meanwhile, Naïve Bayes proved effective for classifying polarized sentiment due to its probabilistic simplicity and computational efficiency.

This study contributes to the field of political sentiment analysis by highlighting how model performance is highly dependent on labeling strategy and data quality. The findings also provide practical guidance for model selection based on task complexity, resource availability, and annotation strategy.

However, several limitations should be noted. The dataset was confined to a single social media platform and covered a limited political timeframe. Additionally, manual annotation may introduce subjectivity, despite efforts to ensure consistency.

For future work, we recommend:

- Expanding the dataset to include multiple platforms and longer time spans,
- Incorporating multilingual sentiment analysis to account for dialectical variation,
- Exploring transformer-based models such as BERT or RoBERTa for deeper semantic understanding, and
- Implementing hybrid or semi-supervised labeling methods to improve scalability and annotation reliability.

These directions aim to further enhance the accuracy and applicability of sentiment analysis tools in supporting public opinion mining and political decision-making

References

[1]. D. Eryanto, I. van Eeden Jones, and K. Lasthuizen, “The troubling impact of political interference in Indonesian public sector institutions on ethical leadership credibility,” *International Journal of Public Leadership*, vol. 18, no. 4, pp. 319–336, Sep. 2022, doi: 10.1108/IJPL-10-2021-0056.

[2]. M. Murni, J. J. Ma’ruf, S. Utami, and S. Chan, “ANALYSIS OF POLITICAL COMMUNICATION, POLITICAL LEADERSHIP IN POLITICAL PARTIES, POLITICAL COSTS, GOVERNMENT SUPPORT FOR PUBLIC TRUST IN ACEH PROVINCE,” *Journal of Law and Sustainable Development*, vol. 12, no. 3, p. e1569, Mar. 2024, doi: 10.55908/sdgs.v12i3.1569.

[3]. A. N. Ma’aly, D. Pramesti, A. D. Fathurahman, and H. Fakhrurroja, “Exploring Sentiment Analysis for the Indonesian Presidential Election Through Online Reviews Using Multi-Label Classification with a Deep Learning Algorithm,” *Information (Switzerland)*, vol. 15, no. 11, Nov. 2024, doi: 10.3390/info15110705.

[4]. L. Damayanti and K. M. Lhaksmana, “Sentiment Analysis of the 2024 Indonesia Presidential Election on Twitter,” *Jurnal dan Penelitian Teknik Informatika*, vol. 8, no. 2, 2024, doi: 10.33395/v8i2.13379.

[5]. A. S. Wisnubroto, A. Saifunas, A. B. Santoso, P. K. Putra, and I. Budi, “Opinion-based sentiment analysis related to 2024 Indonesian Presidential Election on YouTube,” in *2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 2022, pp. 318–323. doi: 10.1109/ISRITI56927.2022.10052848.

[6]. K. Shanmugavadivel, M. Subramanian, and M. B. Sameer, “Beyond_Tech@DravidianLangTech 2025: Political Multiclass Sentiment Analysis using Machine Learning and Neural Network,” pp. 234–238, 2025.

[7]. M. David Angelo, R. Widyatna Harwenda, I. Budi, A. Budi Santoso, and P. Kresna Putra, “Sentiment Analysis and Topic Modeling of Public Opinion on Indonesia New Capital City Development Policies,” *Journal Eduvest*, vol. 5, no. 5, p. 2025, 2025, [Online]. Available: http://eduvest.greenvest.co.id

[8]. M. R. Ramadhan and K. Budiman, “Sentiment Analysis of Presidential Candidates in 2024: A Comparison of the Performance of Support Vector Machine and Random Forest with N-Gram Method,” *Recursive Journal of Informatics*, vol. 3, no. 1, pp. 34–42, Mar. 2025, doi: 10.15294/rji.v3i1.8385.

[9]. H. Ma’, A. Yudo Husodo, and B. Irmawati, “PERFORMANCE COMPARISON OF NAIVE BAYES AND BIDIRECTIONAL LSTM ALGORITHMS IN BSI MOBILE REVIEW SENTIMENT ANALYSIS,” *Jurnal Teknik Informatika (JUTIF)*, vol. 6, no. 1, pp. 159–172, 2025, doi: 10.52436/1.jutif.2025.6.1.4178.

[10]. M. Samantri and Afiyati, “Perbandingan Algoritma Support Vector Machine dan Random Forest untuk Analisis Sentimen Terhadap Kebijakan Pemerintah Indonesia Terkait Kenaikan Harga BBM Tahun 2022,” *Jurnal Teknologi Informasi dan Komunikasi)*, vol. 8, no. 1, p. 2024, 2024, doi: 10.35870/jti.

[11]. L. Aina, N. Voskarides, and R. Blanco, “Performance-Efficiency Trade-Offs in Adapting Language Models to Text Classification Tasks.” [Online]. Available: https://github.com/

[12]. A. R. Sembiring and C. K. Dewa, “Sentiment Analysis On Indonesian Tweets about the 2024 Election,” *Sinkron : Jurnal dan Penelitian Teknik Informatika*, vol. 9, no. 1, pp. 413–422, Jan. 2025, doi: 10.33395/sinkron.v9i1.14481.

[13]. P. Nandwani and R. Verma, “A review on sentiment analysis and emotion detection from text,” *Soc Netw Anal Min*, vol. 11, no. 1, p. 81, 2021, doi: 10.1007/s13278-021-00776-6.

[14]. Y. Romadhoni, K. Fahmi, and H. Holle, “Analisis Sentimen Terhadap PERMENDIKBUD No.30 pada Media Sosial Twitter Menggunakan Metode Naive Bayes dan LSTM,” *Jurnal Informatika: Jurnal pengembangan IT*, vol. 7, no. 2, 2022.

[15]. W. Yudha Patria, P. Harry Gunawan, and N. Aquarini, “Public Political Sentiment Post 2024 Presidential Election: Comparison of Naïve Bayes and Support Vector Machine,” *Technology and Science (BITS)*, vol. 6, no. 4, 2025, doi: 10.47065/bits.v6i4.6734.

[16]. C. Suhaeni, H. Wijayanto, and A. Kurnia, “Sentiment Classification on the 2024 Indonesian Presidential Candidate Dataset Using Deep Learning Approaches,” *Indonesian Journal of Statistics and Its Applications*, vol. 8, no. 2, pp. 83–94, Dec. 2024, doi: 10.29244/ijsa.v8i2p83-94.

[17]. A. Putra Prasetyo, C. S. Kusuma, and D. Rizki, “Analisis Sentimen Twitter terhadap Isu Penundaan Pemilu 2024 Menggunakan Metode Long Short-Term Memory (LSTM),” *JURNAL REPOSITOR*, vol. 6, no. 3, pp. 293–304, 2024.

[18]. A. Abdullah and E. B. Setiawan, “Performance of Deep Feed-Forward Neural Network Algorithm Based on Content-Based Filtering Approach,” *INTENSIF: Jurnal Ilmiah Penelitian dan Penerapan Teknologi Sistem Informasi*, vol. 8, no. 2, pp. 278–294, Feb. 2024, doi: 10.29407/intensif.v9i1.22999.

[19]. A. Alamsyah and F. Saviera, “A Comparison of Indonesia’s E-Commerce Sentiment Analysis for Marketing Intelligence Effort (case study of Bukalapak, Tokopedia and Elevenia),” *ArXiv*, 2021.

[20]. [20] V. R. Prasetyo, M. F. Naufal, and K. Wijaya, “Sentiment Analysis of ChatGPT on Indonesian Text using Hybrid CNN and Bi-LSTM,” *Jurnal RESTI*, vol. 9, no. 2, pp. 327–333, Apr. 2025, doi: 10.29207/resti.v9i2.6334.

[21]. A. Rahman *et al.*, “Analisis Perbandingan Algoritma LSTM dan Naive Bayes untuk Analisis Sentimen,” *JEPIN (Jurnal Edukasi dan Penelitian Informatika)*, 2022.

[22]. J. Ncib, *Comparative Insights from 12 Machine Learning Models in Extracting Economic Ideology from Political Text*. 2025. [Online]. Available: http://arxiv.org/abs/2501.09719

[23]. N. Pohan, P. A. Widya Purnama, and H. Kurnia AR, “Pengenalan Aplikasi Teknologi Komputer untuk Edukasi Islami bagi Anak-anak TPQ Nurul Huda Gunung Pangilun, Kota Padang”, MB, vol. 1, no. 3, pp. 99–109, Sep. 2025, Accessed: Oct. 07, 2025. [Online]. Available: https://yasiinpublisher.org/index.php/mandalabakti/article/view/56

[24]. W. Akbar, “Sinergi Mahasiswa Prodi Ilmu Hukum Universitas Islam Kuantan Singingi dan Aparatur Penegak Hukum dalam Mendukung Efektivitas Pelayanan Publik pada Bagian Pemulihan Aset dan Barang Bukti (PAPBB)Kejaksaan Negeri Kuantan Singingi””, MB, vol. 1, no. 3, pp. 110–118, Sep. 2025, Accessed: Oct. 07, 2025. [Online]. Available: https://yasiinpublisher.org/index.php/mandalabakti/article/view/69

[25]. Febri Haswan, Nofri Wandi Al-Hafiz, A. Mualif, Afrinald Rizhan, Yudio Prastio, and Paris Paizal, “Pelatihan Optimalisasi Layanan Berbasis Teknologi: Aplikasi Antrian PTSP dan Sidang di Pengadilan Agama Teluk Kuantan”, MB, vol. 1, no. 3, pp. 119–125, Sep. 2025, Accessed: Oct. 07, 2025. [Online]. Available: https://yasiinpublisher.org/index.php/mandalabakti/article/view/57