

Implementation of IndoBERT in Sentiment Analysis for Pre Election 2024 on X Platform with Generative AI Based Narrative Explanation

William Rayhan Harsono¹, Aditiyawan^{1,2}

¹Universitas Multimedia Nusantara

²Badan Riset dan Inovasi Nasional (BRIN)

*Email aditiyawan@lecturer.umn.ac.id

Abstract—This research aimed to analyze public sentiment towards three Indonesian presidential candidates Prabowo Subianto, Ganjar Pranowo, and Anies Baswedan during the early pre-election phase of 2024. Data was collected from Platform X in April 2023, comprising 10,000 Indonesian-language tweets per candidate posted between October 2022 and April 2023. This period was selected as a historical baseline to understand initial sentiment dynamics, with the potential for adapting the methods to more current data. The fine-tuned IndoBERT model showed strong performance, achieving an average F1-score of over 80% for all three candidates. Its highest performance was recorded on the Prabowo Subianto dataset, with an F1-score of 84.32%. Crucially, the integration of generative AI successfully translated technical analysis results into clear, communicative narratives, making the findings more accessible to non-technical users like political analysts and policymakers. The study's findings highlight IndoBERT's potential for new data-driven sentiment analysis, contributing to the development of an accurate, transparent, and practical framework for Indonesian political sentiment analysis. This approach offers promising avenues for supporting real-time public opinion monitoring systems.

Index Terms—Generative AI, IndoBERT, Political Sentiment Analysis, Pre-Election 2024, Social Media

I. INTRODUCTION

DIGITAL technology has reshaped political discourse, with social media platforms becoming central to public opinion formation [1], [2]. In Indonesia, this shift amplifies political participation but also introduces challenges from the spread of biased content that can destabilize democratic processes [3], [4]. Platform X (formerly Twitter) is the epicenter of this debate, especially for the 2024 election, hosting over 70% of online political discussions [5], [6]. Its complex linguistic environment, rich with informal language and political slang, renders conventional sentiment analysis methods like Support Vector Machines or Naive Bayes ineffective [7].

To overcome these limitations, the *Bidirectional Encoder Representations from Transformers* (BERT) architecture, specifically its Indonesian variant *IndoBERT*, offers a robust solution [8]. *IndoBERT* has demonstrated superior accuracy (87-92%) in classifying nuanced Indonesian political text, significantly outperforming traditional models [9]–[11]. However, the inherent “black-box” nature of such models hinders trust and adoption, a critical issue in sensitive domains like

politics. To address this opacity, we integrate a *generative AI* module to provide human-readable, narrative explanations for the model's predictions, a method shown to enhance user trust [12], [13].

This paper proposes and evaluates an integrated framework combining a fine-tuned *IndoBERT* for high-accuracy binary sentiment classification with a generative AI component for interpretability. Using a tweet dataset from the 2024 Indonesian election cycle (Oct 2022–Apr 2023), this work develops a sentiment analysis tool that is not only accurate but also transparent and accountable, offering a more reliable method for understanding public opinion.

II. THEORETICAL BASIS

A. Sentiment Analysis

Sentiment analysis is a computational process aimed at identifying and classifying opinions within a text to determine the writer's attitude towards a topic, entity, or event [14]. In politics, it enables researchers to gauge public opinion towards candidates or policies using data from digital platforms [15]. This field has evolved from lexicon-based methods to deep learning approaches, which offer higher accuracy by learning complex linguistic features and patterns from data [16].

B. Platform X (Twitter)

Platform X, formerly Twitter, is a microblogging social media service where users post and interact with short messages known as *tweets* [1]. Its features, such as hashtags, mentions, and retweets, facilitate the rapid dissemination of information and public discussion [2]. In Indonesia, Platform X is a primary digital space for political discourse, especially during election periods, making it a rich and relevant data source for analyzing public opinion [17].

C. Text Preprocessing

Text preprocessing is a fundamental step to clean and standardize raw text data for effective processing by machine learning models. This process includes several steps such as *tokenization* (splitting text into tokens), *normalization* (e.g., lowercasing, correcting slang), *stopword removal* (removing common, meaningless words), and cleaning *noise* like URLs,

mentions, and hashtags [18]. This stage is crucial for improving the quality of the input and the performance of the sentiment analysis model.

D. Transformer

The Transformer is a deep learning architecture introduced by Vaswani et al. [19]. It revolutionized natural language processing by introducing the *self-attention* mechanism, which allows the model to weigh the importance of every word in a sentence simultaneously. Its main advantages are efficient parallel processing and its ability to capture long-range contextual dependencies in text, overcoming the limitations of sequential models like RNNs [20].

E. BERT (Bidirectional Encoder Representations from Transformers)

BERT is a Transformer-based language model developed by Google [8]. Its key innovation is the ability to understand word context bidirectionally (from both left-to-right and right-to-left) during its pre-training phase. This is achieved through two tasks: *Masked Language Modeling (MLM)* and *Next Sentence Prediction (NSP)*. After being pre-trained on massive text corpora, BERT can be adapted for various specific NLP tasks through a process called *fine-tuning*, consistently achieving state-of-the-art performance [8].

F. IndoBERT

IndoBERT is an adaptation of the BERT model specifically pre-trained on a large Indonesian language corpus, which includes formal sources like news and Wikipedia, as well as informal content from social media [18], [21]. The model was developed to handle the unique linguistic characteristics of the Indonesian language that cannot be optimally captured by multilingual models. IndoBERT has been shown to have superior performance on various Indonesian NLP tasks, including sentiment analysis [21].

G. Language Model Fine-tuning

Fine-tuning is the process of adapting a pre-trained language model (like IndoBERT) for a more specific task by re-training it on a smaller, labeled dataset [22]. This process leverages the model's general language knowledge acquired during pre-training and tailors it to a specific domain, such as political sentiment. Fine-tuning typically involves adding a classification layer on top of the base model and training all parameters with a small learning rate to prevent overfitting [23].

H. Generative AI for Narrative Explanations

Generative AI refers to AI models capable of creating new, original content, such as text or images, based on patterns from training data [24]. In this research, a generative language model like GPT (*Generative Pre-trained Transformer*) is utilized to transform quantitative sentiment analysis results into coherent narrative explanations. This approach aims to enhance model interpretability and transparency, making the analysis results more accessible to non-technical users and bridging the gap between data analysis and qualitative insights [25].

I. Indonesian Presidential Election 2024

The 2024 Indonesian Presidential Election was a significant political contest marking a national leadership transition [26]. The pre-election period was a crucial phase where public opinion was formed and sentiment dynamics towards candidates intensified, especially on social media platforms like X [27]. Sentiment analysis during this period provides real-time insights into public perception, complementing traditional opinion polling methods.

J. Evaluation Metrics

To quantitatively measure the performance of the sentiment classification model, several standard metrics derived from a *confusion matrix* are used. The confusion matrix summarizes prediction results with four main components: *True Positive (TP)*, *True Negative (TN)*, *False Positive (FP)*, and *False Negative (FN)*.

- 1) **Accuracy:** Measures the proportion of total correct predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- 2) **Precision:** Measures the exactness of the positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

- 3) **Recall (Sensitivity):** Measures the model's ability to identify all actual positive samples.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

- 4) **F1-Score:** The harmonic mean of Precision and Recall, providing a single score that balances both metrics, which is especially useful for imbalanced datasets.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

III. RESEARCH METHODOLOGY

A. Research Workflow

The research follows the structured workflow illustrated in Figure ???. The workflow commences with a conceptual phase involving a literature review, followed by data collection, model design and implementation, testing and evaluation, and concludes with the final reporting of the documented findings.

B. Literature Review

A systematic literature review was conducted to build a robust theoretical foundation. The primary focus was on scientific publications from 2019 to 2023 covering political sentiment analysis, Transformer models, the application of IndoBERT for the Indonesian language, and the use of generative AI for Explainable AI (XAI). This review references relevant studies such as [28] and [?] to identify the advantages of the chosen methods and to formulate the research contribution.

C. Data Collection and Annotation

1) *Data Sourcing*: Raw data, consisting of Indonesian-language tweets, were collected from Platform X using the Twitter API v2. The data collection spanned from January to April 2023, using the names of the three presidential candidates as keywords: "Prabowo Subianto," "Ganjar Pranowo," and "Anies Baswedan." This process yielded over 15,000 relevant tweets related to the pre-election political discourse.

2) *Dataset Annotation*: From the collected data, a subset of 3,000 tweets (1,000 per candidate) was randomly selected for manual annotation. The annotation was performed by two annotators (informatics students) to label each tweet into binary sentiment classes: positive (1) or negative (0). The quality and consistency of the annotation were validated using an inter-annotator agreement metric, achieving a *Cohen's Kappa score* of 0.85, which indicates substantial agreement.

D. Model Design and Implementation

The detailed system implementation flow is depicted in Figure ??.

1) *Model Architecture*: The sentiment analysis model is built upon the *indolem/IndoBERT-base-uncased* version of the IndoBERT architecture, which features 12 Transformer layers, 12 attention heads, and a hidden size of 768. A linear classification layer with a Softmax activation function was added on top of the output from the [CLS] token to produce binary sentiment probabilities.

2) *Training Process*: The annotated dataset was split into a training set (80%) and a testing set (20%) using stratified sampling to maintain the proportion of sentiment classes. The fine-tuning process was conducted with optimized hyperparameters: a learning rate of $2e-5$, a batch size of 16, and 4 epochs. The AdamW optimizer was used for training efficiency. To prevent overfitting, regularization techniques such as dropout with a probability of 0.1 and an early stopping mechanism monitoring the validation loss were implemented.

3) *Generative AI Integration*: For the narrative explanation functionality, the system was integrated with the Google Generative AI API, leveraging the Gemini model. The quantitative analysis results (sentiment distribution, influential tweet examples) from IndoBERT were used as input prompts for the generative model to produce a qualitative narrative summary explaining sentiment trends and patterns.

E. Testing and Evaluation

1) *Evaluation Protocol*: The model's performance was evaluated on the 20% test set, which was held out during the training process. The evaluation involved calculating standard performance metrics from the resulting confusion matrix. The analysis also included an examination of prediction errors (false positives and false negatives) to understand the model's weaknesses.

2) *Performance Metrics*: Four key metrics were used to assess the model's performance, as defined in Chapter 2 (Equations 1 through ??):

- **Accuracy**: The proportion of overall correct predictions.

TABLE I
MODEL PERFORMANCE COMPARISON FOR THE THREE CANDIDATES
(80:20 VALIDATION)

Metric	Anies Baswedan	Ganjar Pranowo	Prabowo Subianto
Accuracy	80.89%	80.90%	84.08%
Precision	81.83%	81.75%	84.68%
Recall	80.89%	80.90%	84.08%
F1-Score	81.16%	81.27%	84.32%

- **Precision**: The model's ability to avoid labeling a negative sample as positive.
- **Recall**: The model's ability to find all positive samples.
- **F1-score**: The harmonic mean of precision and recall.

The F1-score is particularly important for providing a balanced assessment, especially in cases of imbalanced class distribution.

IV. RESULTS AND DISCUSSION

A. Sentiment Analysis Model Performance

The evaluation was conducted on three separately fine-tuned IndoBERT models, one for each candidate, using an 80:20 training-to-test data ratio. The overall performance of the models is summarized in Table I.

The results indicate that the model trained on the Prabowo Subianto dataset achieved the highest performance across all metrics, with an F1-Score of 84.32.

The stability of the training process was also evaluated via loss and F1-score curves (Figure 4). The Prabowo Subianto model not only achieved the highest peak performance but also demonstrated the most stable and efficient learning curve.

B. Narrative Explanation Results from Generative AI

A key output of this research is the narrative explanation generated by the generative AI system (Gemini model) to interpret the technical metrics. The following is a sample narrative produced for the best-performing model (Prabowo Subianto).

This study analyzed public sentiment towards Prabowo Subianto on the X platform leading up to the election, using an artificial intelligence technology named IndoBERT. Think of IndoBERT as a doctor skilled at diagnosing diseases; it was trained to analyze text and determine if the sentiment expressed within is positive or negative. The evaluation results show that the IndoBERT model achieved an average accuracy rate of 84.1%. Imagine this as a doctor who correctly diagnoses 84 out of 100 patients... The average F1-score of 84.2% indicates a good balance between precision and recall. In conclusion, this model can be a reliable tool for analyzing public sentiment in the social media context...

This narrative successfully simplifies technical concepts like "accuracy" and "F1-score" using relatable analogies, making the research findings more accessible to a non-technical audience.

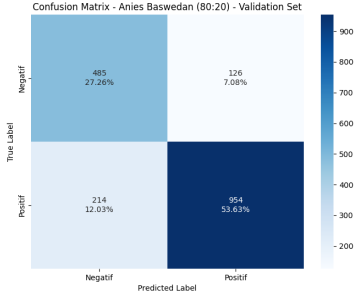


Fig. 1. CM Anies B.

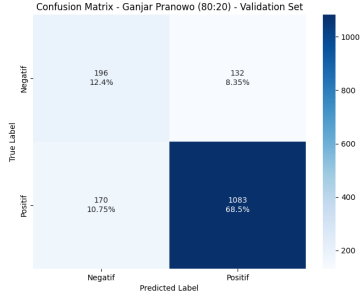


Fig. 2. CM Ganjar P.

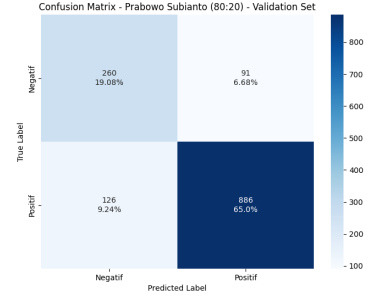


Fig. 3. CM Prabowo S.

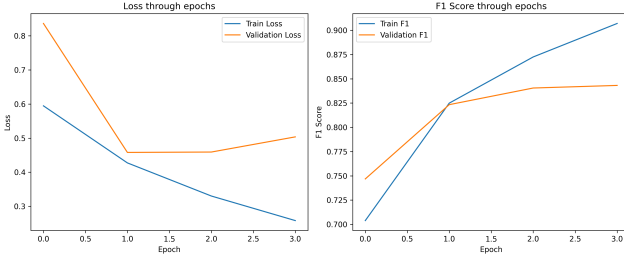


Fig. 4. Loss and F1-Score Progression During Prabowo Subianto Model Training

TABLE II
SAMPLE PREDICTION RESULTS OF PRABOWO SUBIANTO MODEL FOR NEW TWEETS

Tweet	Predicted Sentiment	Confidence
"Mr. Prabowo has a great program for Indonesia"	Positive	98.25%
"Prabowo failed to handle the riots in '98"	Negative	99.04%
"cool, mr. prabowo"	Positive	96.52%

C. Validation and Comparative Analysis

1) *Testing on New Data:* To test generalization capabilities, the models were evaluated on new, unseen data. Table II shows the Prabowo Subianto model consistently delivering accurate predictions with high confidence levels.

2) *Comparison with Previous Research:* The performance of the IndoBERT model was compared against results from a previous study by Firdaus et al. (2023), which used SVM and Naïve Bayes methods on a similar dataset. Figure 5 shows the accuracy comparison.

The IndoBERT model demonstrated highly competitive and often superior performance. For example, on the Anies Baswedan dataset (90:10 ratio), IndoBERT achieved an accuracy of 84.04%, surpassing SVM-Linear (80.00

D. Discussion

The research findings indicate that a fine-tuned IndoBERT model is effective for political sentiment analysis in Indonesia, achieving F1-scores between 81-84%. The superior performance of the model on the Prabowo Subianto dataset is likely influenced by its dataset characteristics, which featured tweets with the highest average word count (18.4 words), providing richer context for the model to learn from. Conversely, the

slightly lower performance on the Ganjar Pranowo dataset highlights the challenge of class imbalance (79% positive), where the model tended to be biased towards the majority class.

Qualitative error analysis revealed that the model's primary challenges lie in understanding sarcasm, implicit sentiment, and complex political context—a common limitation in current NLP models. The main contribution of this research, the integration of a narrative explanation system, proved effective. This system successfully bridges the gap between complex technical metrics and the need for insights that are understandable to the public, political analysts, and policymakers, thereby enhancing the practical value of sentiment analysis.

V. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

This research successfully developed a web-based expert system for preliminary tuberculosis diagnosis using the *certainty factor* method. The system classifies eight TB types based on user-reported symptoms, implemented with CodeIgniter 4 framework and validated by medical expert dr. Selvy Mayadyana from UPT Puskesmas Jatiuwung.

The system achieved 80% diagnostic accuracy through expert validation using ten test case scenarios, with eight scenarios matching expert diagnosis. User satisfaction evaluation using the *end user computing satisfaction* (EUCS) method reached 85.36% from 34 respondents, with all dimensions rated as very satisfied: content (86.77%), accuracy (83.53%), format (85.29%), ease of use (85.30%), and timeliness (85.89%).

The findings demonstrate promising potential as a preliminary TB screening tool, particularly for resource-limited settings. The combination of reasonable diagnostic accuracy and high user satisfaction indicates effective public health intervention capability. However, the system should be implemented with appropriate disclaimers emphasizing its role as a diagnostic aid rather than replacement for professional medical evaluation. Future improvements should focus on expanding TB classifications and refining symptom weights to enhance diagnostic precision.

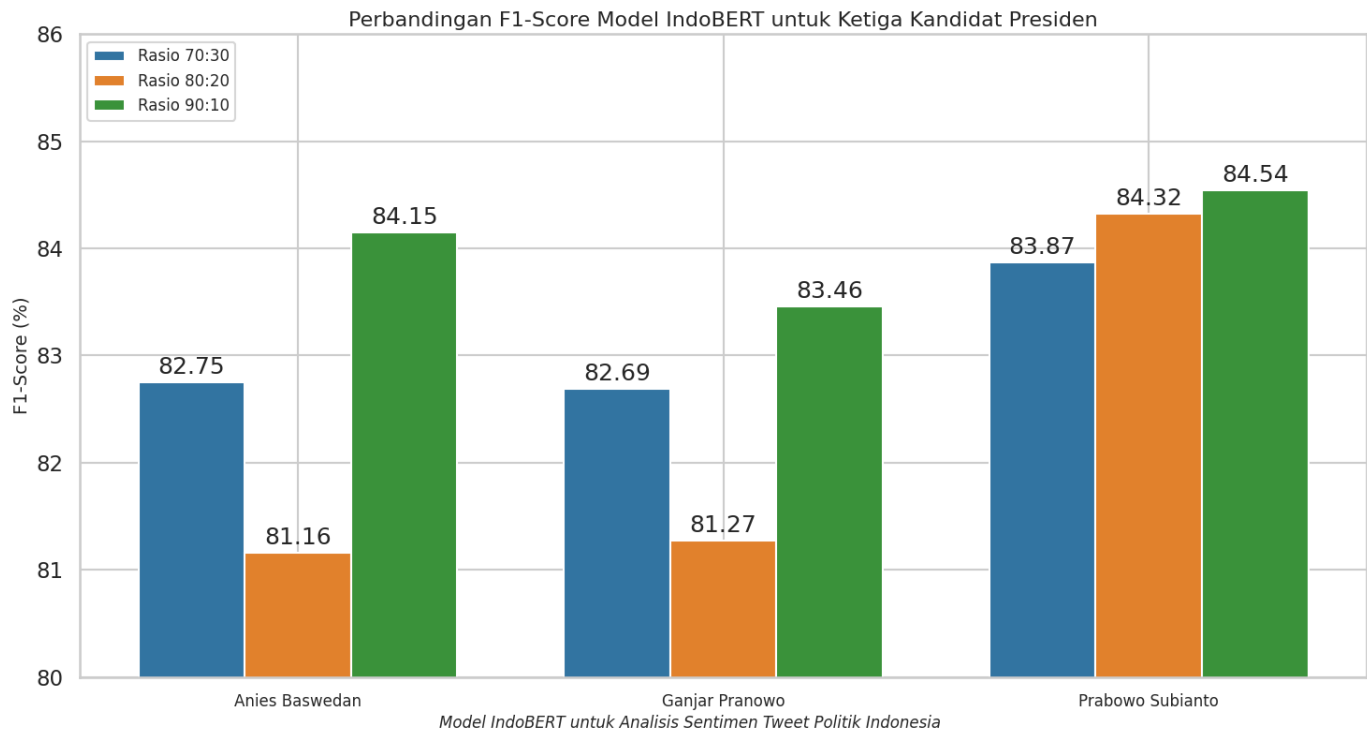


Fig. 5. Comparison of IndoBERT F1-Scores with Varying Data Split Ratios

B. Recommendations

- 1) **Mobile Application Development:** Future work should focus on developing a mobile-based expert system application to improve system accessibility for the general public. Given the high smartphone usage in Indonesia, a mobile application would facilitate public access to TB diagnosis systems anytime and anywhere, including in remote areas where healthcare access is limited.
- 2) **Healthcare Service Integration:** The system should incorporate integration features with healthcare services such as doctor appointment scheduling and electronic referral systems to nearby community health centers or hospitals. This feature would streamline medical follow-up for users who receive positive TB diagnosis results, enabling faster and more effective treatment processes.
- 3) **Machine Learning Algorithm Exploration:** Future research should explore the implementation of machine learning algorithms to improve TB diagnosis accuracy by leveraging larger datasets. Subsequent studies could implement algorithms such as neural networks, support vector machines, or random forests that can automatically learn from TB patient data patterns, potentially achieving higher diagnostic precision than rule-based systems.
- 4) **Knowledge Base Expansion:** The system's knowledge base should be expanded by adding more comprehensive TB categories such as miliary TB, pericarditis TB, and ocular TB. This expansion would increase the system's diagnostic coverage and reduce misclassification risks

for TB cases with uncommon manifestations.

ACKNOWLEDGMENT

The author would like to express sincere gratitude to **Multimedia Nusantara University** for providing the support and resources that made this research possible. Deepest appreciation is extended to **Mr. Aditiyawan, S.Kom., M.Si.**, for his invaluable guidance, insightful feedback, and unwavering support throughout this research journey. Finally, the author is grateful to their family and friends for their continuous encouragement and support.

REFERENCES

- [1] A. M. Kaplan and M. Haenlein, "Users of the world, unite! The challenges and opportunities of Social Media," *Business Horizons*, vol. 53, no. 1, pp. 59–68, 2010.
- [2] J. H. Kietzmann, K. Hermkens, I. P. McCarthy, and B. S. Silvestre, "Social media? Get serious! Understanding the functional building blocks of social media," *Business Horizons*, vol. 54, no. 3, pp. 241–251, 2011.
- [3] H. Allcott and M. Gentzkow, "Social Media and Fake News in the 2016 Election," *Journal of Economic Perspectives*, vol. 31, no. 2, pp. 211–236, 2017.
- [4] F. Fadli, "Analisis Sentimen terhadap Isu Politik di Media Sosial: Studi Kasus Pilpres 2019," *Jurnal Politik Indonesia*, vol. 8, no. 1, pp. 45–60, 2020.
- [5] Kementerian Sekretariat Negara, "Politik Digital: Keterlibatan Media Sosial dalam Meningkatkan Partisipasi Politik Generasi Muda pada Pesta Demokrasi 2024," Jan. 15, 2024. [Online]. Available: https://www.setneg.go.id/baca/index/politik_digital_keterlibatan_media_sosial.
- [6] N. Ramadhany, "Analisis Big Data: 70% Diskusi Politik Indonesia Berlangsung di Platform X," *Kompasiana*, Feb. 10, 2024. [Online]. Available: <https://www.kompasiana.com/naomiramadhany/analisis-big-data-politik-indonesia>.

- [7] A. Putra and N. Lestari, "Strategi Fine-Tuning Model Deep Learning untuk Klasifikasi Sentimen pada Data Imbalanced," *Jurnal Ilmu Komputer*, vol. 14, no. 4, pp. 203–220, 2020.
- [8] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proc. 2019 Conf. North American Chapter Assoc. Comput. Linguistics (NAACL)*, 2019, pp. 4171–4186.
- [9] S. M. Isa, G. Nico, and M. Permana, "IndoBERT for Indonesian Fake News Detection," *ICIC Express Letters*, vol. 16, no. 3, pp. 289–297, 2022.
- [10] I. Chandra and S. Wibowo, "Evaluasi Kinerja IndoBERT dalam Analisis Sentimen pada Diskursus Politik," *Jurnal Teknologi Informasi*, vol. 9, no. 3, pp. 145–160, 2022.
- [11] D. Suryani *et al.*, "Pemanfaatan Model BERT untuk Analisis Opini Publik di Media Sosial Indonesia," in *Prosiding Seminar Nasional Teknologi Informasi*, 2021, pp. 232–245.
- [12] R. Mahendra and L. Setiawati, "Integrasi Generative AI dalam Meningkatkan Interpretabilitas Model NLP," *Jurnal Teknologi dan Inovasi*, vol. 3, no. 2, pp. 115–130, 2022.
- [13] S. Kurnia and A. Rahman, "Explainable AI untuk Model BERT: Studi Kasus pada Analisis Sentimen Politik," *Jurnal Kecerdasan Buatan Indonesia*, vol. 4, no. 1, pp. 77–90, 2022.
- [14] B. Liu, *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*, 2nd ed. Cambridge: Cambridge University Press, 2020.
- [15] A. Ceron, L. Curini, S. M. Iacus, and G. Porro, "Every tweet counts? How sentiment analysis of social media can improve our knowledge of citizens' political preferences with an application to Italy and France," *New Media & Society*, vol. 16, no. 2, pp. 340–358, 2014.
- [16] S. M. Mohammad, "Practical Text Analytics: Quantifying Language Data for Research, Applications, and Recommendations," *Natural Language Engineering*, vol. 28, no. 1, pp. 1–36, 2022.
- [17] M. Lim, "Freedom to hate: social media, algorithmic enclaves, and the rise of tribal nationalism in Indonesia," *Critical Asian Studies*, vol. 49, no. 3, pp. 411–427, 2017.
- [18] B. Wilie, K. Vincentio, G. I. Winata, S. Cahyawijaya, X. Li, Z. Y. Lim, S. Soleman, R. Mahendra, P. Fung, and S. Bahar, "IndoNLU: Benchmark and Resources for Evaluating Indonesian Natural Language Understanding," in *Proc. 1st Conf. Asia-Pacific Chapter Assoc. Comput. Linguistics and 10th Int. Joint Conf. Natural Language Process.*, 2020, pp. 843–857.
- [19] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention is All You Need," in *Advances in Neural Information Processing Systems*, 2017, pp. 5998–6008.
- [20] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, *et al.*, "Transformers: State-of-the-art Natural Language Processing," in *Proc. 2020 Conf. Empirical Methods Natural Language Process.: System Demonstrations*, 2020, pp. 38–45.
- [21] F. Koto, A. Rahimi, J. H. Lau, and T. Baldwin, "IndoLEM and IndoBERT: A Benchmark Dataset and Pre-trained Language Model for Indonesian NLP," in *Proc. 28th Int. Conf. Comput. Linguistics*, 2020, pp. 757–770.
- [22] J. Howard and S. Ruder, "Universal Language Model Fine-tuning for Text Classification," in *Proc. 56th Annual Meeting Assoc. Comput. Linguistics (Volume 1: Long Papers)*, 2018, pp. 328–339.
- [23] C. Sun, X. Qiu, Y. Xu, and X. Huang, "How to Fine-Tune BERT for Text Classification?," *Chinese Computational Linguistics*, pp. 194–206, 2019.
- [24] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, *et al.*, "Language Models are Few-Shot Learners," *Advances in Neural Information Processing Systems*, vol. 33, pp. 1877–1901, 2020.
- [25] M. Madsen and S. Gregor, "Generating Narrative Explanations: A Case Study of Explaining AI-based Financial Decisions," *International Journal of Human-Computer Studies*, vol. 166, p. 102889, 2022.
- [26] Komisi Pemilihan Umum, "Tahapan Program dan Jadwal Penyelenggaraan Pemilihan Umum Tahun 2024," *Peraturan KPU No. 3 Tahun 2022*, 2023.
- [27] E. Aspinall and D. Fossati, "Indonesia's 2024 Election: Issues, Personalities, and the Race for Power," *Contemporary Southeast Asia*, vol. 45, no. 1, pp. 1–17, 2023.
- [28] A. Wibowo, B. Trisaktimulya, A. Mulyana, and M. Syarif, "Sentiment Analysis of Indonesian Tweets Using Deep Learning Approach," in *Proc. 5th Int. Conf. Sustainable Information Engineering and Technology*, 2020.