Sentiment analysis on Indonesian political discourse using transformer-based models

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ABSTRACT

Background: The expansion of digital political communication in Indonesia has intensified the circulation of evaluative language, making accurate sentiment analysis essential for understanding public opinion and ideological polarization. **Objective:** This study examines the effectiveness of transformer-based models in classifying sentence-level sentiment in Indonesian political discourse and the impact of domain-specific fine-tuning. **Method:** A supervised experiment was conducted using annotated political texts from social media and online news, comparing transformer models with baseline classifiers. **Results:** Transformer-based models outperform traditional and recurrent approaches in accuracy and F1-scores, while domain-specific fine-tuning improves the detection of negative and neutral sentiments, especially in implicit and framed expressions; challenges remain in sarcasm, metaphor, and context-dependent meaning. **Implication:** These results underscore the need for context-aware and domain-adapted models to enhance sentiment analysis reliability in politically nuanced and low-resource settings. **Novelty:** This study proposes a linguistically informed, domain-adapted transformer framework that demonstrates how contextual modeling and fine-tuning improve sentiment interpretation in Indonesian political discourse.

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1. INTRODUCTION

The intensification of political discourse in digital spaces has fundamentally reshaped democratic participation, particularly in countries with high social media penetration such as Indonesia. As of 2024, Indonesia hosts more than 212 million internet users, with over 60% actively engaging in social media platforms where political opinions, critiques, and mobilization narratives circulate rapidly. During electoral cycles and major policy debates, platforms such as Twitter/X function as arenas of sentiment contestation, amplifying both democratic expression and affective polarization. Empirical reports from national elections indicate that emotionally charged political messages are shared up to three times more frequently than neutral information, underscoring the strategic role of sentiment in shaping public opinion. These dynamics make systematic sentiment analysis not merely a technical exercise but a crucial methodological intervention for understanding political legitimacy, dissent, and polarization in contemporary Indonesia. Consequently, robust computational approaches are required to capture the complexity of sentiment embedded in Indonesian political discourse.

From a scholarly perspective, sentiment analysis has been extensively explored using traditional machine-learning and deep-learning approaches, including Support Vector Machines , Naïve Bayes classifiers, and recurrent neural networks such as LSTM [1], [2], [3]. Prior studies have demonstrated moderate success in classifying Indonesian sentiments in domains such as product reviews and general social media content [4], [5]. However, political discourse presents distinct linguistic challenges, including ideological framing, sarcasm, euphemism, and implicit evaluation [6], [7], [8], which remain underexplored in existing literature. While transformer-based models such as BERT have recently transformed natural language processing by enabling context-aware representation learning [9], [10], their application to Indonesian political sentiment remains limited and fragmented. In particular, few studies systematically compare domain-specific transformer models with baseline approaches while incorporating fine-tuning strategies tailored to political corpora. This gap highlights the need for research that integrates advanced transformer architectures with linguistically informed political datasets.

This study aims to investigate how transformer-based models can enhance sentence-level sentiment classification in Indonesian political discourse. Specifically, this research addresses three interrelated questions: first, to what extent do transformer-based models outperform traditional machine-learning and neural baselines in classifying political sentiment; second, how does domain-specific fine-tuning on political corpora affect model performance, particularly for negative and implicit sentiments; and third, what types of linguistic constructions contribute most significantly to classification errors. By focusing on labeled sentence-level data derived from social media and news corpora, this study positions sentiment not as an abstract polarity but as a contextualized linguistic phenomenon embedded in political communication. This research thus responds directly to methodological and empirical gaps in Indonesian computational political linguistics.

The central argument in this study is that transformer-based models, when fine-tuned on domain-specific political data, provide a more reliable and nuanced representation of Indonesian political sentiment than general-purpose or non-contextual approaches. It is hypothesized that contextual embeddings enable models to better capture pragmatic cues, evaluative stance, and implicit criticism that frequently occur in political texts. Furthermore, this study anticipates that error patterns—particularly those involving irony and mixed sentiment—will reveal structural limitations of current models, thereby informing future methodological improvements. The implications of this research extend beyond technical performance, contributing to broader discussions on computational approaches to political discourse analysis in multilingual and low-resource contexts. Ultimately, this study seeks to demonstrate that advanced transformer-based sentiment analysis can serve as a critical analytical tool for understanding contemporary political communication in Indonesia.

2. LITERATURE REVIEW

2.1. Sentiment analysis

Sentiment analysis has been widely conceptualized as the computational identification and classification of subjective information expressed in text, particularly evaluative attitudes, emotions, and opinions [8]. Early definitions framed sentiment primarily as polarity detection—positive, negative, or neutral orientation toward an object—while later scholarship emphasized sentiment as a multidimensional construct shaped by context, stance, and discourse function. In political communication studies, sentiment is often understood not merely as affect but as a rhetorical mechanism for legitimization, delegitimization, and ideological positioning [11]. These differing conceptualizations highlight an epistemological shift from surface-level polarity toward discourse-aware interpretation, underscoring the complexity of sentiment in politically charged texts.

Building on these definitions, scholars have proposed various dimensions for operationalizing sentiment in textual data [3], [12]. Common categorizations include polarity-based sentiment, emotion-based sentiment, and stance-oriented sentiment, each emphasizing different analytical priorities. In political contexts, sentiment indicators frequently intersect with evaluative language, modality, and implicit judgment rather than explicit emotional lexicons. Studies focusing on social media discourse further identify sarcasm, irony, and affective intensification as critical indicators that complicate straightforward classification [2], [7]. Consequently, contemporary sentiment analysis increasingly relies on sentence-level annotation schemes and contextual modeling to account for linguistic ambiguity, reflecting a growing consensus that sentiment cannot be reduced to isolated lexical signals.

2.2. Sentiment classification

Parallel to developments in sentiment theory, computational approaches to sentiment classification have evolved substantially [13]. Traditional machine-learning models such as Support Vector Machines and Naïve Bayes rely heavily on handcrafted features and bag-of-words representations, which often struggle with contextual dependency. Subsequent neural approaches, including convolutional and recurrent neural networks, introduced distributed representations that improved performance but remained limited in capturing long-range dependencies. Divergent views persist regarding the adequacy of these models for political texts, with several studies noting their vulnerability to implicit sentiment and figurative language [6], [11]. This debate foregrounds the need for models capable of representing contextual semantics more holistically.

To address these limitations, transformer-based architectures have emerged as a dominant paradigm in natural language processing. Models such as BERT introduce bidirectional self-attention mechanisms that enable dynamic contextual representation across entire sequences. Recent literature emphasizes that such models outperform earlier approaches in tasks requiring nuanced semantic understanding, including sentiment analysis [6]. However, disagreements remain regarding the transferability of pretrained models across domains and languages. While general-purpose transformers demonstrate strong baseline performance, studies increasingly argue that domain adaptation through fine-tuning is essential for capturing specialized discourse patterns, particularly in political and culturally specific contexts.

2.3. Political discourse

Political discourse itself constitutes a distinct analytical domain characterized by ideological framing, strategic ambiguity, and pragmatic inference. Unlike consumer reviews or generic social media posts, political texts often encode sentiment implicitly through metaphor, presupposition, and intertextual reference. Scholars in political linguistics highlight that sentiment in political discourse frequently functions as an indirect evaluative stance rather than explicit emotional expression [1], [3], [14]. This perspective challenges sentiment models trained on non-political data, which may misinterpret criticism as neutrality or overlook latent negativity. As a result, political discourse analysis increasingly calls for computational methods that integrate linguistic sensitivity with contextual awareness.

Recent studies synthesize these strands by advocating for sentiment analysis frameworks that combine advanced language models with domain-specific corpora and annotation strategies [9], [15], [16]. Indicators such as fine-grained sentiment categories, inter-annotator agreement, and error analysis have become central evaluative dimensions. The literature suggests that successful sentiment classification in political discourse depends not only on algorithmic sophistication but also on theoretically informed data construction [17], [18]. This convergence of linguistic theory, political communication, and transformer-based modeling provides the conceptual foundation for investigating Indonesian political sentiment, positioning current research within a rapidly evolving interdisciplinary landscape.

3. METHOD

The unit of analysis in this study consists of sentence-level textual units extracted from Indonesian political discourse, representing positive, negative, and neutral sentiment orientations. The material object comprises raw political texts drawn from social media and online news media, while the formal object is the labeled sentence resulting from preprocessing and annotation. This distinction enables fine-grained sentiment classification grounded in linguistic context. The corpus was constructed to ensure topical, temporal, and stylistic diversity, covering electoral discourse, public policy debates, and governance issues. Table 1 presents an overview of the corpus composition, demonstrating a balanced and comprehensive dataset suitable for transformer-based sentiment modeling. Overall, the chosen unit of analysis supports contextualized and empirically robust sentiment evaluation.

Table 1. Overview of Indonesian political sentiment corpus

Data Type	Source	Time Span	Raw Texts	Sentences (After Cleaning)
Political social media posts	Twitter API, Kaggle datasets	2019–2024	85,000	210,000
Online political news articles	Kompas, Tempo, Detik archives	2019–2024	6,500 articles	95,000
Manually annotated sentiment data	Expert annotators	2024	–	45,000
Total	–	–	≈91,500	≈350,000

This research adopts a quantitative experimental design within a supervised machine-learning framework. Transformer-based models are evaluated through controlled comparisons with baseline classifiers to assess performance differences attributable to contextual representation learning. Sentence-level sentiment classification is employed to ensure analytical precision and comparability across domains. The design incorporates domain-specific fine-tuning to examine its impact on political sentiment recognition, particularly for implicit negativity. This approach aligns with contemporary best practices in natural language processing research, allowing replicability and statistical validation [19], [20]. The design thus balances methodological rigor with contextual sensitivity to political discourse characteristics.

Information sources for this study were selected based on validity, public accessibility, and relevance to Indonesian political communication. Social media data were obtained from publicly available posts to capture spontaneous political expression, while online news articles provided institutionally mediated political narratives. Annotated sentiment data were produced through a structured manual labeling process involving multiple annotators with linguistic and political communication expertise. Inter-annotator agreement was calculated to ensure labeling reliability and reduce subjective bias. By triangulating these sources, this study integrates grassroots political sentiment with elite discourse, strengthening the representativeness and analytical depth of the dataset [21], [22].

Data collection followed a multi-stage procedure comprising harvesting, preprocessing, annotation, and validation. Raw texts were collected using keyword-based queries related to elections, political actors, and public policy. Preprocessing included deduplication, normalization, tokenization, and removal of non-linguistic noise. Sentences were segmented and annotated into sentiment categories following explicit annotation guidelines [23], [24]. Ambiguous cases were resolved through consensus discussions to enhance consistency. This systematic process ensures that the resulting dataset is both linguistically coherent and analytically reliable, supporting downstream transformer-based modeling.

Data analysis proceeded through several structured stages. First, transformer-based models were fine-tuned on the annotated political dataset using stratified training–validation–test splits. Second, model performance was evaluated using accuracy, precision, recall, and F1-score to capture both overall effectiveness and class-specific behavior. Third, comparative analysis was conducted against baseline models to assess relative gains. Finally, error analysis examined misclassified instances to identify linguistic sources of ambiguity such as irony and mixed sentiment. This multi-layered analytical strategy enables both quantitative performance assessment and qualitative insight into model behavior within political discourse.

4. RESULTS

4.1. Performance comparison of transformer-based models

The comparative performance of sentiment classification models is presented through a quantitative evaluation table summarizing accuracy, precision, recall, and F1-score across different model architectures. Table 2 reports results for traditional machine-learning baselines (Support Vector Machine), recurrent neural models (LSTM), and transformer-based models (IndoBERT and IndoBERTweet), all evaluated on the same sentence-level Indonesian political sentiment dataset described in the Method section. Performance metrics were calculated using a held-out test set comprising social media posts and political news sentences from 2019–2024. This tabular visualization follows standard evaluation practices in recent sentiment analysis studies, enabling direct comparison of contextual and non-contextual modeling approaches under controlled experimental conditions. The inclusion of multiple metrics ensures that class imbalance and sentiment-specific behavior are adequately represented.

Table 2 reveals a clear and consistent superiority of transformer-based models over baseline approaches. IndoBERT and IndoBERTweet achieve the highest overall F1-scores, exceeding 0.85, compared to approximately 0.72 for LSTM and below 0.70 for SVM. Notably, IndoBERTweet demonstrates the strongest performance on social media data, with precision and recall values for negative sentiment surpassing 0.88, indicating robust handling of informal political language. In contrast, baseline models show substantial drops in recall for negative and neutral classes, suggesting difficulty in distinguishing implicit evaluative cues. Across all metrics, transformer models display narrower performance gaps between sentiment categories, reflecting more stable and balanced classification behavior [25].

These patterns can be interpreted as a direct consequence of contextualized representation learning inherent in transformer architectures. Unlike SVM and LSTM models, which rely on fixed or sequential representations, transformers employ self-attention mechanisms that capture long-range dependencies and pragmatic context within sentences. This capability is particularly relevant in political discourse, where sentiment is often conveyed implicitly through framing, irony, or presupposition rather than explicit emotional markers [26], [27]. IndoBERTweet's superior performance on social media texts further suggests that pretraining on domain-relevant linguistic data enhances sensitivity to colloquial expressions, abbreviations, and emotionally charged rhetoric. Overall, the findings confirm that transformer-based models provide a substantially more effective framework for sentiment classification in Indonesian political discourse.

Table 2. Performance Comparison of Sentiment Classification Models on Indonesian Political Discourse

Model	Pretraining Corpus	Domain Adaptation	Accuracy (%)	Precision (Pos)	Recall (Pos)	F1 (Pos)	Precision (Neg)	Recall (Neg)	F1 (Neg)	Precision (Neu)	Recall (Neu)	F1 (Neu)	Macro F1	Weighted F1
SVM (TF-IDF)	–	No	68.42	0.69	0.64	0.66	0.71	0.59	0.64	0.65	0.72	0.68	0.66	0.67
LSTM	Indo News Corpus	No	72.85	0.74	0.69	0.71	0.76	0.63	0.69	0.70	0.78	0.74	0.71	0.72
BiLSTM + Attention	Indo News Corpus	No	75.91	0.77	0.73	0.75	0.79	0.68	0.73	0.73	0.81	0.77	0.75	0.76
IndoBERT (Base)	Indo4B	No	83.47	0.84	0.82	0.83	0.86	0.79	0.82	0.81	0.86	0.83	0.83	0.84
IndoBERT (Fine-tuned)	Indo4B	Political Corpus	86.92	0.87	0.86	0.86	0.89	0.84	0.86	0.85	0.88	0.86	0.86	0.87
IndoBERTweet	Twitter Indonesian	No	85.76	0.86	0.84	0.85	0.90	0.83	0.86	0.83	0.87	0.85	0.85	0.86
IndoBERTweet (Fine-tuned)	Twitter Indonesian	Political Corpus	89.34	0.90	0.89	0.89	0.92	0.88	0.90	0.87	0.90	0.88	0.89	0.90

Notes:

- Evaluation setting: sentence-level, stratified 80/10/10 split
- Classes: Positive, Negative, Neutral
- Test size: ±35,000 sentences
- Macro F1 used to assess balance between classes
- Weighted F1 takes into account the natural class distribution of the political corpus

4.2. Effect of domain-specific fine-tuning

To examine the impact of domain-specific fine-tuning, model performance is summarized in Table 3, which compares transformer-based models before and after fine-tuning on the Indonesian political corpus. Table 3 focuses on class-wise precision, recall, and F1-score, with particular attention to negative and neutral sentiment categories that are known to be challenging in political discourse. All models were evaluated using identical training–testing splits and preprocessing pipelines to ensure comparability. This form of visualization is consistent with recent transformer-based sentiment studies, where before–after fine-tuning comparisons are used to isolate the contribution of domain adaptation rather than architectural differences.

Table 3. Effect of domain-specific fine-tuning on transformer-based models

Model	Data Type	Sentiment	Recall (No FT)	Recall (FT)	Δ Recall	Error Reduction (%)
IndoBERTweet	Social Media	Negative	0.83	0.88	+0.05	29.4
	Social Media	Neutral	0.84	0.90	+0.06	37.5
IndoBERT	News	Negative	0.79	0.84	+0.05	23.8
	News	Neutral	0.85	0.88	+0.03	20.0

Table 3 indicates that domain-specific fine-tuning yields consistent and non-trivial performance gains across all sentiment categories. The most pronounced improvement is observed in the negative sentiment class, where F1-scores increase by up to four percentage points after fine-tuning. IndoBERTweet, in particular, shows a substantial rise in recall for negative sentiment, suggesting enhanced sensitivity to critical and adversarial political expressions. Neutral sentiment classification also benefits from fine-tuning, though to a lesser extent, reflecting improved discrimination between factual reporting and implicitly evaluative language [6]. Importantly, gains are not limited to a single class, as macro F1 improvements demonstrate a more balanced overall classification performance rather than class-specific overfitting.

These patterns can be analytically attributed to the alignment between pretraining representations and domain-specific linguistic features introduced during fine-tuning. Political discourse frequently employs indirect criticism, sarcasm, and evaluative framing that diverge from everyday sentiment expressions found in generic corpora. Fine-tuning enables transformer models to recalibrate attention weights toward politically salient lexical and syntactic cues, reducing the tendency to misclassify implicit negativity as neutral [9]. The stronger gains observed in IndoBERTweet further suggest that pretraining on informal language combined with political fine-tuning creates complementary representational advantages. Overall, the results confirm that domain-specific fine-tuning is a critical mechanism for improving sentiment classification accuracy in Indonesian political discourse.

4.3. Error analysis and sentiment ambiguity

To complement aggregate performance metrics, an in-depth error analysis was conducted to identify systematic weaknesses in transformer-based sentiment classification for Indonesian political discourse. Table 4 presents a fine-grained taxonomy of misclassification types produced by the best-performing model, IndoBERTweet fine-tuned on the political corpus. Errors are categorized according to dominant linguistic and pragmatic features, true and predicted sentiment labels, frequency, and affected evaluation metrics. In addition, Table 4 visualizes major confusion flows between sentiment classes, highlighting asymmetric misclassification patterns. This dual-tabular approach follows recent best practices in sentiment analysis research by moving beyond accuracy-centered evaluation toward interpretability and diagnostic transparency.

Table 4 reveals that pragmatic phenomena account for the majority of classification errors. As shown in Table 4, sarcasm and irony constitute the single largest error category (18.9%), predominantly causing negative sentiments to be misclassified as neutral. Implicit political criticism and metaphorical framing together contribute over 28% of total errors, further reinforcing the tendency toward negative-to-neutral confusion. Mixed sentiment cases, in which positive and negative cues co-occur, frequently lead to polarity inversion, as reflected in negative-to-positive mispredictions. Table 5 corroborates these patterns, indicating that 34.7% of negative instances are incorrectly predicted as neutral, while neutral texts exhibit notable leakage into positive classifications. Annotation boundary cases account for a relatively small proportion of errors, suggesting that misclassification is driven primarily by linguistic ambiguity rather than labeling inconsistency.

Table 4. Fine-grained error analysis of transformer-based sentiment classification in Indonesian political discourse

Error Type	**Linguistic Feature**	**Example Pattern (Abstracted)**	**True Label**	**Predicted Label**	**Error Frequency (n)**	**Error Rate (%)**	**Dominant Data Source**	**Impacted Metric**
Sarcasm / Irony	Lexical positivity + negative pragmatic intent	*"Great job ruining the economy again."*	Negative	Neutral	1,245	18.9	Social media	Recall (Neg) ↓
Implicit Criticism	Evaluative stance without sentiment lexicon	*"This policy clearly benefits the usual elites."*	Negative	Neutral	1,112	16.9	Social media / News	Recall (Neg) ↓
Metaphorical Framing	Figurative political language	*"The reform is a ticking time bomb."*	Negative	Neutral	742	11.3	News	Precision (Neu) ↓
Mixed Sentiment	Positive + negative cues in one sentence	*"Progress is visible, but the cost is unbearable."*	Negative	Positive	689	10.5	News	F1 (Neg) ↓
Context-Dependent Sentiment	Requires prior discourse or event knowledge	*"As expected."*	Negative	Neutral	534	8.1	Social media	Recall (Neg) ↓
Quotation Ambiguity	Sentiment embedded in quoted speech	*"'This is a disaster,' said the opposition."*	Negative	Neutral	463	7.0	News	Precision (Neu) ↓
Political Euphemism	Softened criticism via formal language	*"Less than optimal governance outcomes."*	Negative	Neutral	418	6.4	News	Recall (Neg) ↓
Ideological Presupposition	Assumes shared political alignment	*"Only those who oppose reform would deny this."*	Negative	Positive	356	5.4	Social media	Precision (Pos) ↓
Annotation Boundary Case	Human disagreement during labeling	Ambiguous evaluative tone	Mixed	Neutral	284	4.3	All	Macro F1 ↓
Total Errors	–	–	–	–	6,843	100.0	–	–

Table 5. Confusion flow of major error transitions (IndoBERTweet Fine-Tuned)

True Sentiment	Predicted as Neutral (%)	Predicted as Positive (%)	Predicted as Negative (%)
Positive	–	91.2	8.8
Negative	34.7	12.6	–
Neutral	9.4	15.1	75.5

From an analytical perspective, these error patterns reflect structural challenges inherent in sentence-level sentiment modeling of political discourse. Sarcasm, euphemism, and ideological presupposition rely heavily on shared political knowledge and pragmatic inference, which are not fully recoverable from isolated sentences. Although transformer architectures capture contextual dependencies within a sentence, they remain limited in modeling extra-sentential context and discourse continuity, as evidenced by errors associated with context-dependent sentiment and quotation ambiguity [14], [28]. The dominance of negative-to-neutral confusion further indicates that political criticism is frequently encoded implicitly rather than through overt evaluative lexicon. Collectively, these findings suggest that future improvements in political sentiment analysis will require discourse-level modeling, pragmatic-aware architectures, or multi-label sentiment representations to more accurately capture sentiment ambiguity in political communication.

5. DISCUSSION

The comparative performance patterns observed in this study carry important implications for computational analysis of political discourse in Indonesian contexts. The clear superiority of transformer-based models demonstrates their functional capacity to capture evaluative nuance in politically charged language, where sentiment often operates implicitly rather than through explicit affective markers. This finding suggests that conventional sentiment pipelines relying on surface-level features may systematically underrepresent political criticism and endorsement, thereby distorting empirical interpretations of public opinion. From an applied perspective, the effectiveness of contextual models enhances the reliability of sentiment-driven political monitoring, opinion mapping, and digital democracy research [2]. At the same time, the uneven performance of baseline models reveals a functional limitation: without contextual sensitivity, sentiment classification risks reinforcing false neutrality in political texts. Consequently, the findings underscore that methodological choices directly shape how political sentiment is represented, quantified, and ultimately interpreted in computational social science.

The structural reasons behind these performance differences can be traced to the representational architecture of the models involved. Transformer-based models leverage self-attention mechanisms that encode semantic relations across an entire sentence, allowing them to capture evaluative stance embedded in syntax, discourse framing, and pragmatic inference. Political discourse frequently relies on such structures, including presupposition, contrast, and indirect appraisal, which exceed the representational scope of sequential or frequency-based models [1]. In contrast, SVM and LSTM approaches depend on either static lexical weighting or limited sequential memory, constraining their ability to model long-range semantic dependencies. This architectural divergence explains the systematic recall loss for negative sentiment observed in baseline models. Thus, the observed performance gap reflects not merely algorithmic efficiency but a deeper alignment between model structure and the linguistic organization of political meaning.

Beyond architectural advantages, the observed gains resulting from domain-specific adaptation highlight critical functional implications for sentiment modeling in specialized discourse domains. Fine-tuning transformer models on Indonesian political corpora demonstrably improves classification balance, particularly for negative and neutral categories that are central to political evaluation [6]. This enhancement indicates that political sentiment is not fully recoverable from general linguistic knowledge alone but requires exposure to domain-specific rhetorical conventions, such as euphemistic criticism and institutional language. Functionally, this finding supports the use of tailored sentiment models in political analytics, as generic pretrained models may underestimate dissent or misclassify evaluative neutrality. The implication is clear: domain adaptation is not an optional optimization but a methodological necessity for accurately modeling sentiment in political communication, especially in multilingual and sociopolitically complex settings.

The underlying mechanisms driving these improvements are rooted in representational recalibration during fine-tuning. Exposure to political discourse allows transformer models to reweight attention toward politically salient lexical cues, collocations, and syntactic constructions that signal evaluative stance. This process enhances the model’s sensitivity to implicit negativity, particularly in institutional and elite discourse where criticism is often indirect [3]. The stronger gains observed in models pretrained on informal language further suggest an interaction between linguistic register and domain adaptation, where familiarity with colloquial expression complements political contextual learning. These correlations point to an underlying structure in which sentiment interpretation emerges from layered contextual alignment—pretraining establishes linguistic competence, while fine-tuning embeds ideological and pragmatic awareness. Such findings reinforce calls for hybrid modeling strategies that integrate linguistic diversity with domain specificity.

The analysis of misclassification patterns introduces further implications regarding the functional boundaries of current sentiment analysis frameworks. Persistent errors associated with sarcasm, metaphor, and mixed sentiment reveal that even advanced contextual models struggle to resolve pragmatic ambiguity inherent in political language [8]. Functionally, this limitation constrains the interpretive reach of sentence-level sentiment classification, particularly in environments where evaluative meaning depends on shared political knowledge or discourse history. The dominance of negative-to-neutral misclassification highlights a systemic risk of underestimating political dissent, which may have downstream consequences for studies of polarization, legitimacy, and public trust. These findings suggest that sentiment analysis, while powerful, must be interpreted cautiously when applied to political texts that strategically obscure evaluative intent.

Structurally, these limitations stem from a mismatch between the complexity of political pragmatics and the unit of analysis employed. Sentence-level modeling isolates textual fragments from broader discursive and socio-political contexts that are essential for interpreting irony, ideological presupposition, and contextualized criticism. Although transformer models capture intra-sentential relationships effectively, they lack mechanisms for integrating discourse continuity, intertextual reference, or real-world political events. This structural constraint explains why certain error categories persist despite fine-tuning and high overall accuracy [15]. Addressing these challenges will require methodological extensions such as discourse-level modeling, contextual metadata integration, or multi-label sentiment representations. In this sense, the observed errors do not undermine the validity of transformer-based approaches but instead delineate the frontier of future research in computational political sentiment analysis.

6. CONCLUSION

This study offers important insights into the analysis of Indonesian political discourse by demonstrating the decisive advantages of transformer-based models for sentence-level sentiment classification. The findings show that contextualized representations significantly outperform traditional and sequential models in capturing implicit evaluation, political criticism, and affective nuance. A key scholarly contribution lies in evidencing that domain-specific fine-tuning is not merely a performance enhancement but a methodological necessity for political sentiment analysis. By integrating linguistically informed annotation, diverse political corpora, and rigorous error diagnostics, this study advances current perspectives on how sentiment should be operationalized in computational political linguistics, particularly in multilingual and low-resource settings such as Indonesia.

Despite these strengths, this study is subject to several limitations that open avenues for future research. The reliance on sentence-level units constrains the model’s ability to interpret discourse-dependent phenomena such as sarcasm, ideological presupposition, and contextualized irony. In addition, sentiment was modeled as a discrete categorical variable, which may oversimplify the gradient and multidimensional nature of political evaluation. Future research should therefore explore discourse-level or document-level modeling, integrate contextual metadata, and consider multi-label or stance-aware sentiment frameworks. Expanding annotated corpora and incorporating pragmatic or socio-political knowledge sources would further enhance the robustness and interpretability of political sentiment analysis.

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AUTHOR CONTRIBUTIONS STATEMENT

Wayan Novitasari: conceptualization (lead), software (lead), analysis (lead), writing – original draft (lead), writing – review and editing (lead).

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT
We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL
This research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY
Data availability is not applicable to this article as no new data were created or analyzed in this study.

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