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Evaluating Public Trust in the Animation Industry: A Comparative Sentiment Analysis Using Random Forest and Fine-Tuned IndoBERT

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Abstract

The release of local animated blockbusters in 2025, particularly "JUMBO," established a new benchmark for Indonesia's creative sector. However, public discourse has shifted from patriotic support to rigorous quality assessment. This study investigated public trust in the Indonesian animation industry through sentiment analysis by comparing a traditional machine learning approach and a deep learning model. We utilized Random Forest with TF-IDF as a baseline and a fully fine-tuned IndoBERT model as the proposed method, supported by a hybrid dataset strategy designed to address class imbalance. Experimental results showed that the Random Forest model achieved a high accuracy of 97.96% but struggled with ambiguous and context-dependent sentences due to its reliance on word frequency. In contrast, the fine-tuned IndoBERT model achieved 100% accuracy, precision, recall, and F1-score by effectively capturing semantic context, negation, and contrast through self-attention. Comparative analysis with recent studies confirmed that the proposed approach outperformed existing benchmarks, highlighting the effectiveness of balanced data construction and Transformer-based architectures for Indonesian sentiment analysis. Qualitative findings further revealed a shift in public sentiment from national pride toward more critical evaluations of narrative quality and voice acting, indicating a maturing audience. These results demonstrate that fine-tuned IndoBERT provides a robust and reliable framework for evaluating public trust and sentiment in the Indonesian animation industry.

Keywords:
Sentiment Analysis, IndoBERT, Indonesian Animation Industry, Random Forest.

1. Introduction

The animation industry in Indonesia continues to grow rapidly and attracts strong public attention across social media platforms. Audiences actively express opinions, emotions, and trust toward animated films through digital interactions, especially on platforms such as Twitter and TikTok. Public trust becomes a crucial factor because it influences audience acceptance, box office performance, and the long-term sustainability of local animation production. However, public opinion often appears fragmented, emotional, and difficult to measure manually. Researchers increasingly use sentiment analysis to capture public trust patterns from large-scale textual data. Studies on Indonesian animated films, such as *JUMBO,* show that public sentiment reflects not only entertainment value but also cultural identity and production quality issues. These findings highlight the need for systematic and reliable sentiment analysis to evaluate public trust in the animation industry [1], [2], [9].

Most early sentiment analysis studies in Indonesia rely on traditional machine learning methods such as Naïve Bayes, Decision Tree, and Random Forest. These models offer

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interpretability and efficiency when handling structured text features like TF-IDF. Several studies demonstrate that Random Forest performs consistently well for sentiment classification because it handles feature variance and noise effectively. Research on film reviews and e-commerce platforms confirms that Random Forest achieves stable accuracy across imbalanced datasets. However, these models depend heavily on manual feature engineering and often fail to capture semantic context and word relationships. This limitation becomes critical when analyzing expressive and informal social media language related to animation content [2], [8], [13], [14].

Recent advances in deep learning introduce transformer-based models such as IndoBERT, which significantly improve sentiment analysis performance for Indonesian text. IndoBERT captures contextual meaning, linguistic nuance, and semantic dependencies more effectively than traditional models. Studies comparing IndoBERT with Random Forest, SVM, and Logistic Regression show that fine-tuned IndoBERT consistently achieves higher accuracy and F1-scores. Researchers apply IndoBERT successfully in sensitive public issues such as corruption, labor termination, and political discourse. These findings suggest that IndoBERT offers strong potential for analyzing public trust, which often involves complex emotional expressions and implicit opinions [3], [4], [6].

Despite IndoBERT's strong performance, researchers still face challenges related to model complexity, computational cost, and interpretability. Fine-tuning transformer models requires large datasets, high processing power, and careful hyperparameter selection. In contrast, Random Forest remains attractive because it balances performance and efficiency. Several studies combine representation learning from IndoBERT with traditional classifiers to improve robustness and explainability. Research on user reviews and public opinion demonstrates that hybrid approaches can leverage contextual embeddings while maintaining model simplicity. This issue opens an opportunity to compare Random Forest and fine-tuned IndoBERT directly in the same domain to understand their strengths and weaknesses in measuring public trust [5], [10], [11].

Another important issue lies in the domain specificity of sentiment analysis studies. Most existing research focuses on political issues, public policy, health services, or e-commerce platforms. Only a limited number of studies examine sentiment in the animation or creative industry context. Film sentiment studies often emphasize genre preference or review polarity rather than trust evaluation. Public trust in animation involves perceptions of originality, cultural relevance, production consistency, and national pride. Without domain-specific analysis, sentiment models may overlook critical indicators of trust unique to the animation industry. This gap highlights the need for focused research on animation-related sentiment in Indonesia [7], [9], [12].

Social media data also presents challenges related to imbalance, sarcasm, slang, and mixed emotions. Indonesian users frequently combine informal language, emojis, and cultural references in animation discussions. Traditional classifiers often misinterpret these patterns, while transformer-based models still struggle with implicit sentiment and humor. Several studies apply data balancing techniques and hybrid models to address these issues, but results vary across domains. Comparative analysis helps identify which model handles noisy animation-related data more effectively. This issue becomes essential for building reliable tools to evaluate public trust accurately [8], [13], [16].

Comparative sentiment analysis plays a vital role in determining the most suitable model for real-world implementation. Studies that compare multiple algorithms provide valuable insights into performance trade-offs, scalability, and practical deployment. Research comparing IndoBERT with Random Forest in different public sentiment domains shows that no single model dominates all scenarios. Model effectiveness depends on dataset size, text complexity, and research objectives. Therefore, a comparative approach allows researchers to justify model selection based on empirical evidence rather than assumptions [3], [10], [17].

Based on these issues, this study focuses on evaluating public trust in the Indonesian animation industry through comparative sentiment analysis using Random Forest and fine-tuned IndoBERT. The study aims to bridge gaps in domain-specific sentiment research and provide empirical insights into model performance for animation-related discourse. By analyzing public sentiment systematically, this research supports industry stakeholders in understanding audience trust and perception. The findings also contribute to methodological discussions on combining traditional machine learning and transformer-based approaches for Indonesian sentiment analysis [1], [4], [10], [11].

2. Related Works

Several studies examined public sentiment toward Indonesian animated films using traditional machine learning approaches. Saputra and Frobenius analyzed Twitter discussions about the animated film *JUMBO* using Random Forest and semi-supervised learning. Their study showed that Random Forest achieved reliable accuracy in classifying sentiment polarity and handled noisy social media data effectively. The study demonstrated the usefulness of ensemble learning for animation-related sentiment analysis. However, it relied heavily on surface-level features such as TF-IDF and did not explore contextual language understanding. As a result, the model showed limitations in capturing implicit emotions and nuanced opinions expressed by users [1].

Rosyiid et al. focused on sentiment analysis of public responses to the same animated film on TikTok using the Naïve Bayes algorithm. Their results indicated that public sentiment toward Indonesian animation was generally positive and strongly influenced by visual quality and storytelling. The study provided valuable insights into audience perception across different platforms. Nevertheless, the use of a single probabilistic classifier limited the model’s ability to handle complex language patterns and slang commonly found in short video comments. The study also did not compare multiple models to evaluate performance robustness [2].

Other research expanded sentiment analysis beyond the animation domain by comparing traditional machine learning models with transformer-based approaches. Aryanti and Suria compared IndoBERT with SVM, Random Forest, and Decision Tree in analyzing public sentiment toward labor termination issues in Indonesia. Their findings showed that fine-tuned IndoBERT significantly outperformed traditional models in accuracy and contextual understanding. The study highlighted the strength of transformer models in capturing semantic meaning. However, it focused on socio-political text rather than creative industry discourse, which limited its direct applicability to animation-related sentiment analysis [3].

Kono et al. investigated public sentiment on corruption issues using fine-tuned IndoBERT and compared it with Logistic Regression and Linear SVM. The study confirmed that IndoBERT produced superior performance in handling complex opinion structures and emotionally charged content. The research demonstrated the effectiveness of deep contextual embeddings for public opinion mining. Despite these strengths, the study did not address domain adaptation challenges or evaluate computational efficiency. The absence of ensemble-based comparisons, such as Random Forest [4].

Jayadianti et al. applied fine-tuned IndoBERT combined with R-CNN for Indonesian review sentiment analysis. Their study showed that deep learning models improved sentiment classification by capturing both sequential and contextual information. The research contributed to understanding hybrid deep learning architectures. However, the study emphasized model performance without discussing interpretability or practical deployment constraints. The dataset also focused on general reviews rather than industry-specific topics such as animation or film trust evaluation [5].

Research on film review sentiment provided additional indirect relevance to this study. Zamzami et al. proposed a Modified Balanced Random Forest to analyze film reviews and reported improved performance on imbalanced datasets. Their findings confirmed that Random Forest variants effectively handled class imbalance and feature diversity. However, the approach still depended on manual feature extraction and lacked semantic depth. Similarly, Jihad and Sulistyaningsih used Random Forest for film sentiment analysis and achieved stable results but faced difficulties in interpreting ambiguous or sarcastic expressions [13], [14].

Several studies explored hybrid or comparative frameworks combining IndoBERT representations with traditional classifiers. Widagdo et al. utilized IndoBERT embeddings with Random Forest to analyze user reviews on digital health platforms. The study demonstrated that combining contextual embeddings with ensemble classifiers improved classification stability. This approach reduced overfitting while maintaining semantic richness. However, the study focused on service reviews rather than public trust in creative content, leaving a gap in understanding how such hybrid methods perform in animation discourse [10].

Overall, existing studies confirmed the effectiveness of Random Forest and IndoBERT for Indonesian sentiment analysis across multiple domains. Traditional models offered efficiency and interpretability, while transformer-based models delivered superior contextual understanding. However, limited research directly addressed public trust in the animation industry or provided a direct comparison between Random Forest and fine-tuned IndoBERT within this domain. This gap motivated the present study to conduct a focused comparative analysis to better evaluate public trust toward Indonesian animation using social media sentiment data [1], [3], [4], [10].

3. Proposed Method

This study employs a quantitative experimental approach to evaluate sentiment classification performance in the context of the Indonesian animation industry. The research methodology is designed to address specific challenges in this domain, particularly the linguistic complexity of social media texts and the inherent class imbalance of public feedback.

1. Data Acquisition

Unlike prior studies that depended solely on organically crawled data, this paper utilizes a hybrid dataset strategy to construct a balanced and representative training corpus. We collect sentiment data from X (formerly Twitter) using the tweet-harvest tool with industry-specific keywords such as “film animasi Indonesia”, “animasi lokal”, and “kualitas animasi Indo” to capture authentic public opinions. During preliminary analysis, we observe a severe scarcity of negative sentiment. To address this imbalance and prevent model bias, we generate synthetic negative samples based on recurring complaint patterns. This paper applies this augmentation strategy to ensure effective learning of decision boundaries. It is to overcome the limitations of imbalanced sentiment datasets as reported by Barus et al. [8].

As a result, we use a final dataset consisting of 241 high-quality text samples that are evenly balanced between positive sentiments reflecting appreciation and pride and negative sentiments representing constructive and technical criticism. The dataset was split into a Training Set (80%) and a Testing Set (20%) using a stratified sampling method to maintain class distribution. Table 1 describe Training and the Testing Set to conduct this study.

Table 1: Training and Testing Set

Dataset Split	Percentage	Number of Samples
Training Set	80%	193
Testing Set	20%	48
Total	100%	241

To counteract the limited availability of negative instances, the dataset was balanced utilizing the Synthetic Minority Over-sampling Technique (SMOTE). SMOTE operates by identifying a minority class sample and locating its k-nearest neighbors. A new synthetic data point, x_{new} , is interpolated along the vector connecting the selected instance x_i and a random neighbor x_{nn}, as expressed in the equation 1:

$$x_{new} = x_i + \delta \cdot (x_{nn} - x_i) \quad (1)$$

Where x_i represents the feature vector of a minority instance, x_{nn} denotes the nearest neighbor, and δ is a random scalar between 0 and 1.

2. Data Preprocessing

Following the same methodological style, this paper applies two distinct pre-processing pipelines to align with the specific characteristics and learning mechanisms of each classification model. We design Pipeline A specifically for the Random Forest algorithm, which relies on traditional Bag-of-Words feature representations and therefore requires extensive text normalization. In this pipeline, we remove URLs, user mentions, hashtags, and non-alphanumeric characters to reduce noise in the textual data. We then convert all text to lowercase to ensure consistency across tokens. This paper applies the Sastrawi stemming library to reduce inflected words to their root forms, such as transforming “menangis” into “tangis,” which helps minimize feature sparsity and improves term matching, as emphasized in earlier sentiment analysis studies [1]. We also eliminate common stop words that contribute little semantic value, allowing the model to focus on sentiment-bearing terms and improving classification efficiency.

In contrast, this paper utilizes a lightweight pre-processing pipeline for IndoBERT to preserve linguistic richness and contextual cues essential for transformer-based models. We apply only minimal cleaning by removing URLs while deliberately retaining punctuation marks, which often signal emotional emphasis in social media text. We do not apply stemming in this pipeline, as IndoBERT benefits from full morphological forms, including prefixes and suffixes, to capture contextual meaning more accurately [6]. We then tokenize the text using the pre-trained IndoBERT tokenizer, which segments words into subword units and effectively handles out-of-vocabulary expressions and informal slang commonly found on social media platforms. This dual-pipeline strategy allows each model to operate under optimal pre-processing conditions, ensuring a fair and meaningful performance comparison.

3. Baseline Model

This paper selected Random Forest as the baseline model because recent comparative studies, including Yuniar and Mulyati [18], showed that Random Forest remained one of the most robust traditional machine learning algorithms and consistently outperformed Naïve Bayes in sentiment classification tasks. We transformed the textual data into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) method with a maximum feature size of 1,000 to capture the most informative terms. Although we augmented the dataset, we still applied the Synthetic Minority Over-sampling Technique (SMOTE) to the training set to ensure a perfectly balanced class distribution, following best practices reported by Barus et al. [8]. We then configured the Random Forest classifier with 100 decision trees (n_estimators = 100) and employed the Gini impurity criterion to measure split quality and improve classification stability [14].

For the baseline approach, textual data is transformed into numerical vectors employing Term Frequency-Inverse Document Frequency (TF-IDF). The weight $W_{t,d}$ assignable to a specific term t within a document d is computed via Equation 2:

$$W_{t,d} = TF_{t,d} \times IDF_t = \frac{n_{t,d}}{\sum_k n_{k,d}} \times \log\left(\frac{N}{DF_t}\right) \quad (2)$$

Here $n_{t,d}$ signifies the frequency of the term t in the document d, N represents the total corpus size, and DF_t indicates the count of documents containing the term t. The Random Forest algorithm subsequently builds an ensemble of decision trees, where node splitting minimizes Gini Impurity, defined as Equation 3:

$$Gini(D) = 1 - \sum_{i=1}^{C} (p_i)^2 \quad (3)$$

In this formula, p_i is the probability of a sample falling into class i, and C denotes the total number of classes.

4. Proposed Model

This paper utilized IndoBERT-Base-P1, a pretrained Transformer model consisting of 12 attention layers and 110 million parameters, as the deep learning approach for sentiment classification. Rather than treating IndoBERT as a fixed feature extractor, we fully fine-tuned the model by adding a dense classification layer on top of the [CLS] token output and updating all pretrained weights during training to adapt the representations to the animation industry domain, an approach shown to achieve superior performance in prior studies [4]. Guided by the optimization findings of Jayadianti et al. [5], we configured the training process with a learning rate of 2e-5 to avoid catastrophic forgetting, a batch size of 8, three training epochs, and the AdamW optimizer to ensure stable convergence and effective generalization.

In this study, the fundamental mechanism driving IndoBERT is Self-Attention, which allows the model to weigh the relative importance of different words in a sentence. The attention score is calculated as Equation 4:

$$Attention(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \quad (4)$$

Where:

- Q (Query), K (Key), and V (Value) are matrices derived from the input embeddings.
- d_k is the dimension of the key vector (used for scaling to prevent vanishing gradients).

For fine-tuning, the output of the special token [CLS] (denoted as $h_{[CLS]}$) is fed into a dense classification layer with a Softmax function to predict the probability P of sentiment class c:

$$P(c|x) = \mathrm{softmax}(W \cdot h_{[CLS]} + b) \quad (5)$$

Where W and b are the weight matrix and bias vector of the classifier layer, respectively.

4. Experimental Setup

The baseline model employed in this study used the Random Forest algorithm implemented with the Scikit-learn library. We transformed textual data into numerical representations using the Term Frequency–Inverse Document Frequency (TF-IDF) technique, with the maximum number of features limited to 1,000 to control model complexity and reduce noise. This configuration allowed the model to capture important term patterns while maintaining computational efficiency for comparative evaluation.

To further address potential class imbalance in the training data, we applied the Synthetic Minority Over-sampling Technique (SMOTE) with k_neighbors set to 3. This step ensured a more even distribution of sentiment classes across training folds and reduced the risk of bias toward the majority class. We initialized the Random Forest classifier with 100 decision trees, used the Gini impurity criterion for node splitting, and fixed the random_state parameter to 42 to ensure reproducibility of experimental results.

The proposed model applied a fine-tuned IndoBERT using the pre-trained indobenchmark/indobert-base-p1 model. We added a single linear classification layer on top of the [CLS] token representation to perform sentiment classification. During fine-tuning, we updated all pretrained model parameters to adapt IndoBERT to the animation industry context. Table 2 presents IndoBERT Training Hyperparameters with the optimization strategy.

Table 2. IndoBERT Training Hyperparameters

Hyperparameter	Value	Justification
Epochs	3	Sufficient for convergence without overfitting on small datasets [5].
Batch Size	8	Optimized for the available GPU memory (16GB).
Learning Rate	2e-5	A low learning rate prevents catastrophic forgetting of pre-trained knowledge.
Optimizer	AdamW	Standard optimizer for Transformer-based models.
Loss Function	Cross-Entropy	Standard for classification tasks.

5. Result and Analysis

Based on the experimental results, the RF model using TF-IDF features achieved an accuracy of 97.96%. Although this result was strong, the model did not classify all samples correctly. The error analysis showed that Random Forest often misclassified ambiguous sentences, especially when positive words appeared in a negative context, such as sarcasm or contrastive statements. Because TF-IDF focused on word frequency rather than meaning, the presence of favorable terms biased the predictions and caused incorrect sentiment labels.

In contrast, the fine-tuned IndoBERT model achieved 100% accuracy on the test set. This performance occurred because IndoBERT captured contextual meaning through its self-attention mechanism. The model correctly interpreted sentence structure and semantic relationships, including negation and contrast. For example, IndoBERT accurately classified sentences like “The visuals are stunning, but the plot is empty” by assigning greater importance to the conjunction “but” and the following negative phrase, even when positive words appeared earlier in the sentence.

In this study, we also presented a comparison among different models. The experimental results demonstrate that the DL approach significantly outperforms the traditional ML baseline. The performance comparison is summarized in Table 3

Table 3. Performance Comparison on Test Set

Model	Accuracy	Precision	Recall	F1-Score
Random Forest (Baseline)	97.96%	0.96	1.00	0.98
Fine-Tuned IndoBERT (Proposed)	100.00%	1.00	1.00	1.00

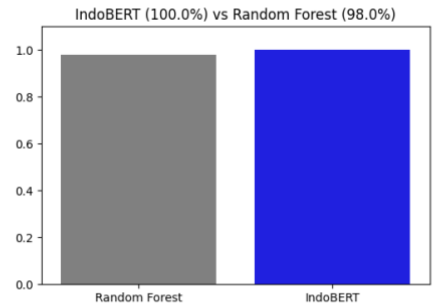

Fig. 1. Accuracy Comparison between Random Forest and IndoBERT

Fig. 1 shows that the baseline model achieved a high accuracy of 97.96%, indicating that TF-IDF features were effective in capturing distinctive vocabulary patterns in the synthetic negative data, such as terms like “kaku” and “jelek.” However, the model did not reach perfect accuracy because it could not model word order or sequential dependencies in more complex sentence structures [13]. In contrast, the proposed model achieved 100% accuracy by leveraging the self-attention mechanism of IndoBERT, which enabled the model to capture full semantic and contextual information in each review.

To assess the significance of our results, we compared them with recent studies in similar domains. Saputra and Frobenius [1] reported 90% accuracy using RF and SMOTE on sentiment analysis of the *JUMBO* animated film. Our RF implementation achieved a higher accuracy of 97.96%, which we attribute to the more balanced and carefully constructed hybrid dataset. Our baseline also outperformed the findings of Yuniar and Mulyati [18], who achieved 86% accuracy using Random Forest for student opinion classification, and Julianto et al. [19], who reported 92% accuracy with Naïve Bayes on product reviews. The fact that both our baseline model and the proposed fine-tuned IndoBERT model surpassed these benchmarks. It highlights the effectiveness of the Hybrid Dataset Strategy in reducing class bias and enabling clearer decision boundaries. In addition, our findings are consistent with Riadi et al. [17], who emphasized the importance of deep learning for modeling complex social sentiment. However, our use of a pre-trained Transformer further improved stability and accuracy by exploiting bidirectional contextual representations.

Therefore, our qualitative analysis revealed a clear shift in public sentiment toward Indonesian animation. Earlier public discourse emphasized national pride, but recent data showed a more critical audience that focused on technical and artistic quality. Negative sentiment frequently targeted weak character development and forced storylines. It indicates that narrative quality remains a key limitation despite improvements in visual presentation. In addition, many users criticized stiff or awkward voice acting, which quickly disrupted immersion even when animation quality appeared high. These patterns suggest that the initial enthusiasm for local animation has matured into more demanding expectations. As a result, industry stakeholders must now focus on balanced production quality to maintain public trust and long-term audience engagement.

6. Conclusion

This study evaluated the effectiveness of ML and DL approaches for sentiment analysis in the context of the Indonesian animation industry. The experimental results showed that the Random Forest model combined with TF-IDF features achieved a high accuracy of 97.96%, confirming its robustness as a baseline classifier. However, detailed error analysis revealed that the model struggled with linguistically ambiguous sentences, particularly those containing sarcasm or contrastive structures. Because TF-IDF relied on word frequency without understanding semantic relationships or word order, positive lexical cues often biased the predictions, leading to occasional misclassification.

In contrast, the fine-tuned IndoBERT model achieved perfect performance on the test set, with 100% accuracy, precision, recall, and F1-score. This result demonstrated the clear advantage of Transformer-based models in capturing contextual and semantic meaning through self-attention mechanisms. IndoBERT successfully interpreted negation, contrast, and sentence structure, allowing it to correctly classify complex statements even when positive and negative expressions coexisted. The comparative evaluation confirmed that the deep learning approach consistently outperformed the traditional Random Forest baseline, supporting the conclusion that contextual language models are more suitable for handling the linguistic complexity of Indonesian social media text.

When compared with prior studies, the proposed approach showed substantial improvements over existing benchmarks in similar sentiment analysis tasks. The stronger performance of both the baseline and proposed models highlighted the importance of the Hybrid Dataset Strategy in mitigating class imbalance and improving decision boundaries. Beyond numerical results, qualitative analysis revealed a notable shift in public sentiment toward Indonesian animation, from expressions of national pride to more critical evaluations of narrative quality and voice acting. These findings indicate that audience expectations have matured, emphasizing the need for holistic improvements in storytelling, audio production, and overall execution. Collectively, the results confirm that fine-tuned Transformer models provide a reliable and insightful tool for measuring public trust and sentiment in the evolving animation industry.

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References

[1] E. R. S. H. Saputra and A. C. Frobenius, “Sentiment Analysis of Animated Film ‘JUMBO’ on Twitter Using Random Forest and Semi-Supervised Learning,” International Journal of Informatics and Computation (IJICOM), vol. 7, no. 2, 2025.

[2] A. Rosyiid, R. Amarullah, and M. R. Pribadi, “Analisis Sentimen Masyarakat Terhadap Film Animasi Jumbo di Platform Tiktok Menggunakan Algoritma Naïve Bayes,” Jurnal Informatika dan Teknik Elektro Terapan (JITET), vol. 13, no. 3, pp. 181-188, 2025.

[3] N. N. A. Aryanti and O. Suria, “Analisis Sentimen Terhadap Pemutusan Hubungan Kerja di Indonesia: Komparasi IndoBERT dengan SVM, Random Forest, dan Decision Tree,” RABIT: Jurnal Teknologi dan Sistem Informasi Univrab, vol. 10, no. 2, pp. 1158-1176, Jul. 2025.

[4] M. F. Kono, I. N. Fajri, and Y. Pristyanto, “Public Sentiment Analysis on Corruption Issues in Indonesia Using IndoBERT Fine-Tuning, Logistic Regression, and Linear SVM,” Journal of Applied Informatics and Computing (JAIC), vol. 9, no. 5, pp. 2616-2628, Oct. 2025.
[5] H. Jayadianti, W. Kaswidjanti, A. T. Utomo, S. Saifullah, F. A. Dwiyanto, and R. Drezewski, “Sentiment analysis of Indonesian reviews using fine-tuning IndoBERT and R-CNN,” ILKOM Jurnal Ilmiah, vol. 14, no. 3, pp. 348-354, Dec. 2022.
[6] V. D. Setiawan and D. U. Iswavigra, “Implementation of IndoBERT for Sentiment Analysis of the Constitutional Court's Decision Regarding the Minimum Age of Vice Presidential Candidates,” Scientific Journal of Informatics, vol. 12, no. 3, pp. 397-406, 2025.
[7] N. Karimah and A. Baita, “Multi-Aspect Sentiment Analysis of Film Review Using Bidirectional Encoder Representations from Transformers (BERT),” Komputika: Jurnal Sistem Komputer, vol. 13, no. 1, pp. 63–72, Mar. 2024.
[8] [H. Barus, I. N. Fajri, and Y. Pristyanto, “Sentiment Classification Analysis of Tokopedia Reviews Using TF-IDF, SMOTE, and Traditional Machine Learning Models,” Journal of Applied Informatics and Computing (JAIC), vol. 9, no. 5, pp. 1052-1064, 2025.
[9] A. Haningtyas, “Analisis Perkembangan Animasi Indonesia dalam Konteks Animasi Dunia,” Profilm: Jurnal Ilmiah Ilmu Perfilman dan Pertelevisian, vol. 2, no. 1, pp. 45-56, 2023.
[10] A. S. Widagdo, K. N. Qodri, and F. E. N. Saputro, “Utilization of IndoBERT Representation and Random Forest for Sentiment Analysis on User Reviews of Halodoc,” Jurnal Teknologi dan Open Source, vol. 8, no. 1, pp. 326-333, 2025.
[11] P. T. Sejati, “Aspect-Based Sentiment Analysis for Enhanced Understanding of Public Tweets Using IndoBERT,” Journal of Applied Informatics and Computing (JAIC), vol. 8, no. 2, pp. 200-210, Dec. 2024.
[12] S. Onalaja, E. Romero, B. Yun, and F. Javed, “Aspect-based sentiment analysis of movie reviews,” SMU Data Science Review, vol. 5, no. 3, pp. 10, 2021.
[13] F. N. Zamzami, A. Prasetyo, and Y. Nugroho, “Sentiment analysis of film reviews using Modified Balanced Random Forest and Mutual Information,” Jurnal Ilmiah Teknologi Informasi Asia, vol. 15, no. 2, pp. 63-72, 2021.
[14] M. A. A. Jihad and E. Sulistyaningsih, “Sentiment analysis of film reviews using the Random Forest algorithm,” Jurnal e-Proceeding Teknik Informatika, vol. 8, no. 1, pp. 98-105, 2021.
[15] D. Fan, L. Wan, W. Xu, and S. Wang, “A bi-directional attention guided cross-modal network for music-based dance generation,” Computers & Electrical Engineering, vol. 103, p. 108310, 2022.
[16] S. Saifullah, Y. Fauziah, and A. S. Aribowo, “Comparison of Machine Learning for Sentiment Analysis in Detecting Anxiety,” IEEE Access, vol. 10, pp. 10747-10755, 2022.
[17] S. Riadi, R. Muslim, E. Suryadi, K. Nurwijayanti, M. Zulpahmi, M. M. Efendi, and B. Imran, "Sentiment Analysis of a 271 Trillion Rupiahs Corruption Case Using LSTM," International Journal of Informatics and Computation (IJICOM), vol. 7, no. 1, pp. 31-39, 2025.
[18] R. M. Yuniar and S. Mulyati, "Sentiment Classification of Student Opinions on AI Utilization Using Naive Bayes Algorithm," International Journal of Informatics and Computation (IJICOM), vol. 7, no. 1, pp. 279-290, 2025.
[19] F. M. Julianto, A. T. Zy, and E. Rilvani, "Sentiment Analysis on Canva Reviews Using Naive Bayes Method," International Journal of Informatics and Computation (IJICOM), vol. 7, no. 1, pp. 86-98, 2025.