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SENTIMENT ANALYSIS OF DEFORESTATION POLICIES IN INDONESIA USING AN INDO-BERT ALGORITHM BASED ON OPTIMIZATION

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Abstract— *One government policy that has sparked public debate is regarding deforestation, specifically the conversion of virgin forests into oil palm plantations or similar land uses. This policy has naturally become a hot topic of discussion on social media, particularly Twitter. Public reaction to the implementation of forest deforestation notably in Papua, where virgin forests are being converted into oil palm plantations, as well as in other regions that still possess virgin forests has triggered a variety of community responses, ranging from positive, negative, to neutral views. The dataset used in this study comprises 1,117 tweets. This study aims to analyze public sentiment regarding government policies on deforestation using an optimization-based Indo-BERT algorithm. The research workflow involved several main stages, including data collection, data pre-processing, experimentation, modeling, and evaluation. The data was categorized into three sentiment classes: 23 positive data, 59 neutral data, and 1,035 negative data. Based on the modeling experiment results and the application of various optimization techniques, it can be concluded that using the Indo-BERT algorithm with Bayesian optimization achieved a 2% improvement, rising from 94% to 96%, based on the initial testing accuracy of Indo-BERT at 94% (Good Classification). Further research could be conducted using this algorithm to examine the broader public response to government discourse, particularly in sectors that interact directly with the general public. Overall, this study makes a significant contribution to understanding public perceptions of government policy discourse while serving as an important foundation for developing sentiment analysis of government policies on Twitter.*

Keywords: *Deforestation, Indo-BERT, optimization, sentiment analysis, social media X.*

INTRODUCTION

Indonesia has a very high potential for biodiversity and has one of the world's largest forest areas. In addition to providing homes for millions of plant and animal species, Indonesia's tropical forests regulate the world's temperature. Indonesia's forests are essential for mitigating climate change since they are recognized as carbon sinks that contribute to lowering greenhouse gas concentrations in the atmosphere. Indonesia's forest area covers over 94.1 million hectares, or roughly 50.1% of the nation's total land area, according to figures published by the Ministry of Environment and Forestry (KLHK) in 2019. However, the continuous increase of deforestation and forest degradation has put these forests in grave danger [1]. This phenomena has certainly become a hot topic on social media. In addition to consuming material, social media users may channel their goals by sharing and commenting on a variety of content in a variety of formats, including

audio, video, and text [2]. Additionally, social media is utilized for community building, communication, corporate management, community groups, and even facilitating direct public-government communication [3], [4].

There are many different social media platforms available now, and Twitter is one that is still widely used [5]. Twitter, like the majority of social media platforms, enables users to engage in direct or transparent communication. Twitter is used to debate a wide range of subjects, including the economics, culture, politics, law, social issues, and others [6], [7], [8]. Twitter users can discover trending topics in real time by using hashtags. In addition, Twitter users can also use keywords as a means of communication. Before a news story makes headlines in online media, it is often already a topic of discussion on Twitter. A news story can even originate from a conversation on Twitter. One example is the discussion regarding the government's policy on deforestation. Therefore, an emotional analysis of this government policy is essential [9], [10]. One way is through sentiment analysis using data from the social media platform twitter.

Sentiment analysis is the process of automatically extracting, mastering, and processing information in the form of unstructured reading to acquire sentiment data included in an opinion sentence or comment [11], [12]. Sentiment analysis is used to determine if a view is neutral, positive, or negative [13], [14]. Opinions in a variety of domains, including politics, economics, and society, can be subjected to sentiment analysis. Researchers may use sentiment analysis to examine public attitudes, feelings, and views on Twitter [15].

Sentiment analysis of government discourse has been the subject of several earlier studies, including by references [16]. The title of this study is "Optimization of Learning Rate and Epoch in the Fine-Tuning Process to Improve Indo-BERT's Performance in Sentiment Analysis of My Telkomsel App Reviews The Indo-BERT algorithm is applied as the technique. Finding out how the public feels about evaluations of the My Telkomsel app is the aim of this study. 5,794 positive sentiment data points and 3,206 negative sentiment data points are the study's findings. According to test findings, this model's hyperparameters a batch size of 16, a learning rate of 1e-6, and three epochs—achieve a high accuracy of 96%. The key to improving the model is to optimize the learning rate and epoch values. These findings offer both useful advice on applying the Indo-BERT model for sentiment analysis in Indonesian-language reviews and profound insights into user sentiment about the MyTelkomsel app. This study is unusual since it employs a novel optimization technique.

Another study cited as a reference is the research conducted by Andi Wafida, Dhomas Hatta Fudholi, and Jaka Nugraha, titled "Aspect-Based Sentiment Analysis of Twitter Tweets About the Merdeka Curriculum Using Indo-BERT." The research method employed in this study utilized Indo-BERT to assess the effectiveness of the Merdeka Curriculum. The findings demonstrated that the aspect classification model attained 97% accuracy, 97% recall, 97% F1 score, and 97% precision. In the meanwhile, the sentiment classification model obtained 85% accuracy, 85% recall, 85% F1 score, and 85% precision. It is anticipated that this ABSA model would help track public reactions and offer insightful information for the creation of policies, especially in relation to the Merdeka Curriculum [17].

Research by Jasmir, Mario Rosario, Irawan, Agus Siswanto, and Tiko Nur Annisa became next. The study proposed a hybrid model that combines BERT and FastText-BLSTM in order to enhance sentiment analysis classification performance. In order to create a richer feature representation, the research phases comprised text preprocessing, BLSTM classification, and FastText and BERT feature extraction. A concatenation layer was then used to concatenate these. Experimental results show that the FastText-BLSTM-BERT hybrid model performs best, with an accuracy of 94.22%, precision of 95.98%, recall of 95.68%, and an F1-score of 95.83%. The combination of FastText-BLSTM's subword-level semantic and sequential representations with BERT's contextual embeddings, which hasn't been fully explored in previous studies on Indonesian sentiment analysis, is the primary innovation of this study. This hybridization shows that the model's resilience and generalization for texts in resource-poor languages have significantly improved [18].

Furthermore, Angga Iskoko, Imam Tahyudin, and Purwadi's work, "Hyperparameter Optimization of Indo-BERT Using Grid Search, Random Search, and Bayesian Optimization in Sentiment Analysis of E-Government Application Reviews," A total of 1,003 user reviews of the SINAGA application provided the data. According to the findings, the Indo-BERT approach with Grid Search optimization produced the highest accuracy of 91% [19]. In this research, researchers will use the social media site Twitter to do a sentiment analysis on government policy involving deforestation. Data about government initiatives on deforestation will be gathered from Twitter between 2024 and 2025. The dataset contains labels

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that are neutral, negative, and positive. This study's goal is to use an optimization-based Indo-BERT algorithm to assess Twitter sentiment on government policy on deforestation. Determining the degree of popular support of government forestry policy in Indonesia using data from Twitter users is another goal. The current work reviews and takes into account prior studies on sentiment analysis in government speech, as previously mentioned.

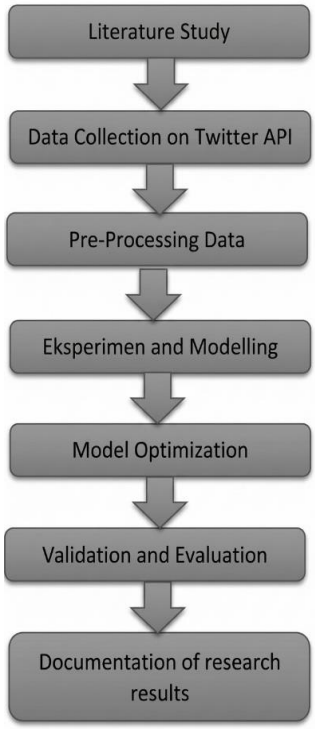
Based on the literature review, previous studies have demonstrated that Indo-BERT achieves strong performance in sentiment classification when combined with hyperparameter optimization techniques such as Learning Rate Optimization, Epoch Optimization, Grid Search, and Bayesian Optimization. However, these studies generally evaluated only a single optimization strategy or focused on different application domains, including application reviews, curriculum evaluation, and e-government services. Consequently, there is still limited empirical evidence regarding the comparative effectiveness of multiple hyperparameter optimization strategies when applied to the same Indo-BERT architecture and the same dataset, particularly for highly imbalanced Twitter data discussing Indonesian government deforestation policies.

While prior studies have investigated hyperparameter tuning strategies for Indo-BERT in general settings or balanced app-review domains, there remains a lack of empirical insights into how these strategies behave under severe class skewness in domain-specific social media conversations. The novel contribution of this study lies in systematically comparing Grid Search, Bayesian Optimization, Learning Rate, and Epoch optimization under identical constraints on a highly imbalanced public-policy corpus (92.66% negative). This study provides empirical evidence on computational efficiency versus minority-class sensitivity, serving as a practical guide for NLP tasks on polarized public discourse.

Therefore, this study aims to fill this research gap by conducting a comparative evaluation of four hyperparameter optimization strategies, namely Grid Search, Bayesian Optimization, Learning Rate Optimization, and Epoch Optimization, using the same Indo-BERT model and identical Twitter dataset. Rather than proposing a new optimization algorithm, this study provides empirical evidence regarding the effectiveness, strengths, and limitations of each optimization strategy for sentiment analysis on highly imbalanced public-opinion data. The findings are expected to provide practical guidance for selecting appropriate hyperparameter optimization methods in Indonesian sentiment analysis tasks involving government policy discussions.

MATERIALS AND METHODS

The research process for analyzing public sentiment regarding government policies on deforestation on Twitter consists of several stages, as shown in Figure 1.



Source: (Research Results, 2026)
Figure 1. Research Procedure

The following is an explanation of Figure 1, regarding the research procedure outlined above:

Crawling Data

The dataset used in this study was collected from Twitter (currently X) using the Twitter API. Data collection was conducted from January 2024 until December 2025 by retrieving public tweets related to government deforestation policies in Indonesia. The crawling process employed several keywords and hashtags, including “Deforestasi Indonesia”. Only Indonesian-language tweets (lang:id) were retained. Retweets, duplicated tweets, advertisements, and non-relevant tweets were removed during preprocessing. Duplicate removal was conducted using identical Tweet IDs and identical tweet contents to ensure that every observation represented unique public opinions.

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1. Dataset

A collection of characteristics and items is called a dataset. Entities, recordings, and observations are additional terminology for objects[20]. The information used in this study was obtained from an analysis of tweets on Twitter regarding public discourse on government policies concerning deforestation in Indonesia.

Table 1. Indonesian-Language Government Discourse and Review Data

No	Government Discourse	Review Data
1	*Deforestation*	*Rakyat akan diam atas defortasi 9 propinsi / pembabatan alih fungsi hutan oleh oligarki dan di dukung pemerintah Indonesia?. https://t.co/pU3nfADsI4*
2	*Deforestation*	*KLHK Menggelar Workshop Hutan dan Deforestasi Indonesia Seri I (Workshop Panel Internasional Metode Pengukuran, Perhitungan dan Pelaporan Defortasi dan Degradasi Hutan) - https://t.co/krqINtJFo6*

(Source: Research Results, 2026)

2. Preprocessing Data

The purpose of this preprocessing step is to prepare the data for usage in the subsequent step[21][22][23]. The primary goal of preprocessing in a Transformer-based architecture is to clean raw social media noise while preserving contextual and semantic structures necessary for BERT attention mechanisms. Traditional preprocessing steps such as stemming and stopword removal were deliberately excluded. Stemming truncates words to their root forms, which disrupts subword tokenization, while stopword removal destroys sentence syntax and contextual relationships vital for Indo-BERT's bidirectional self-attention.

The text preprocessing pipeline in this study consisted of the following minimal cleaning steps:

a) Text Cleansing: Removal of Twitter-specific artifacts, including URLs (http://..., https://...), user mentions (@username), hashtag symbols (#), email addresses, and HTML tags.
b) Non-Alphanumeric Character Removal: Elimination of emoticons, special symbols, punctuation marks, and structural line breaks.
c) Normalization & Lowercasing: Standardizing character encoding and converting all characters to lowercase to reduce vocabulary sparsity.
d) Duplicate & Short Text Filtering: Eliminating exact duplicate tweets and extremely short entries (fewer than 3 words) after noise removal.

Following basic text cleansing, the refined texts were tokenized directly using the pre-trained Indo-BERT WordPiece Tokenizer, converting input sentences into subword tokens, mapping them to input IDs, and generating attention masks with a maximum sequence length of 128 tokens. TF-IDF weighting was not employed, as Indo-BERT natively learns dense contextual vector representations

Sentiment Labelling

After the crawling and preprocessing stages, sentiment labels were generated automatically using a lexicon-based approach. Each tweet was tokenized into individual words and compared against predefined lists of positive and negative sentiment words. A sentiment score was then calculated by adding one (+1) for each positive word and subtracting one (-1) for each negative word appearing in the tweet. The sentiment label was assigned according to the final sentiment score as follows:

Positive (2): sentiment score > 0
Neutral (1): sentiment score = 0
Negative (0): sentiment score < 0

The automatic labeling process was implemented using a Python function, ensuring that the same labeling criteria were consistently applied to all collected tweets. To validate the reliability of the automated lexicon-based labeling, a subset of 250 tweets was independently annotated by two domain experts. The inter-annotator agreement achieved a Cohen's Kappa score of K = 0.82, indicating high agreement. Furthermore, lexicon-assigned labels were manually verified and corrected where context-specific nuances (such as sarcasm or political jargon) caused misclassification.

Experiment and Modelling

At this stage, the researchers will conduct experiments and modeling. The Indo-Bert method has the advantage of understanding word context and the relationships between phrases within a single Indonesian sentence[24]. Using the standard transformer-based architecture with bidirectional context through multiple layers of self-attention and feed-forward neural networks to comprehend word meanings within sentences, Indo-BERT is a specialized version of the BERT model created especially for the Indonesian language[25], [26]. This research will use Python with Google Colabs to support the experiments and modeling.

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Conceptual Clarification: We have explicitly clarified the conceptual distinction between the optimization approaches:

1. Grid Search & Bayesian Optimization are multi-hyperparameter search strategies evaluated over a joint parameter space (simultaneously tuning learning rate, batch size, and epoch count).
2. Learning Rate Optimization & Epoch Optimization represent single-parameter sensitivity studies (univariate grid searches) where all other model hyperparameters were kept fixed at baseline values to isolate the individual impact of learning rate and epoch count on model performance.

Model Optimization

In this study, optimization refers to hyperparameter tuning rather than feature selection. Hyperparameter optimization aims to identify the optimal configuration of model parameters to maximize classification performance. Unlike feature selection, which focuses on selecting the most informative input variables, hyperparameter tuning adjusts training parameters that influence the learning process of the Indo-BERT model. Four hyperparameter optimization strategies were evaluated in this research Grid Search, Bayesian Optimization, Learning Rate Optimization, and Epoch Optimization. Each optimization strategy was evaluated using the same dataset, training-testing split, and evaluation metrics to ensure a fair comparison.

In this study, model optimization refers to hyperparameter tuning for fine-tuning the pre-trained model. To ensure complete reproducibility, all experiments were conducted using PyTorch and the HuggingFace Transformers framework on Google Colab with an NVIDIA T4 GPU. A fixed random seed of 42 was applied across all data splits, weight initializations, and optimization processes to eliminate stochastic variation. Text sequences were tokenized using the Indo-BERT WordPiece tokenizer with a fixed maximum sequence length of 128 tokens, which covered more than 98% of the length distribution of the collected tweets. All models were trained using the AdamW optimizer. To evaluate tuning efficiency and performance, four hyperparameter optimization strategies were compared. Conceptually, these strategies are divided into two categories:

1. Multi-Hyperparameter Joint Optimization
   a) Grid Search: A exhaustive search over a pre-defined grid of candidate hyperparameters.
   b) Bayesian Optimization: An automated sequential search using a Gaussian Process (GP) surrogate model and Expected Improvement (EI) acquisition function over 20 evaluation trials to efficiently sample the hyperparameter space.
2. Single-Parameter Sensitivity Analysis (Univariate Optimization):
   a) Learning Rate Optimization: Isolated tuning of the learning rate while holding the batch size 16 and epochs 3 constant.
   b) Epoch Optimization: Isolated tuning of the number of training epochs while holding the learning rate 16 constant.

Determination of Training Data and Testing Data

In this step, the data to be used will be divided into 80% training data and 20% test data to determine the training and test sets.

Validation and Evaluation

In order to calculate the final accuracy score, the Cross-K-Fold Validation method is used for model validation at this point. After obtaining the expected accuracy score, an evaluation is conducted by comparing the accuracy levels produced by different models, namely those improved by Grid Search, Bayesian Optimization, Learning Rate, and Epoch Optimization. To prevent data leakage during hyperparameter tuning, the dataset was first split into an 80% training/validation set and an untouched 20% test set using Stratified Random Sampling. All hyperparameter optimization procedures (Grid Search, Bayesian Optimization, Learning Rate, and Epoch tuning) were executed exclusively on the 80% split using 5-Fold Stratified Cross-Validation. Once the optimal hyperparameters were identified, the final model was evaluated on the independent 20% test set.

RESULTS AND DISCUSSION

This study uses crawled data from Twitter that includes critiques of government policy, particularly on deforestation, from 2024 to 2025. A total of 1,117 data points were gathered, of which 23 were positive, 59 were neutral, and 1,035 were negative. Table 2 below provides an analysis of the dataset that was taken from Python using Google Colabs.

Table 2. Details of sentiment data

Sentiment data	Count
Positive	23
Negative	1035
Neutral	59
Total	**1117**

Source : (Research Results, 2026)

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Table 2 shows that the dataset is highly imbalanced, where negative tweets account for approximately 92.66% of the observations, whereas positive and neutral tweets represent only 2.06% and 5.28%, respectively. Such an imbalanced distribution may bias classification performance toward the majority class. Therefore, the evaluation does not rely solely on accuracy but also considers Precision, Recall, F1-score, and Confusion Matrix to provide a more comprehensive assessment of model performance across different sentiment classes. Nevertheless, this class imbalance remains one limitation of the present study.

Results Using Indo-BERT algorithm

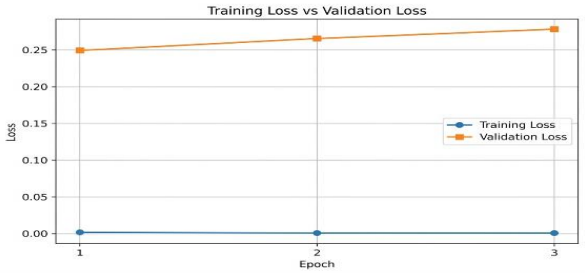
The Indo-BERT model performed best after processing with default parameter settings, according to the evaluation results in Figure 2. With an accuracy score of 0.9464, the model accurately predicted about 94.64% of the test data. The recall value of 0.9464 shows the model's high success rate in identifying positive data, while the precision value of 0.9433 shows that most of the model's positive predictions are accurate. In the meanwhile, the model continuously performs despite the potential for an unbalanced class distribution in the dataset, as evidenced by the F1-Score of 0.9445, which shows a decent balance between precision and recall. Overall, these findings show that Indo-BERT may already provide acceptable sentiment classification performance with its default parameter settings and can be used as a starting point for further hyperparameter optimization. The Indo-BERT model's results are displayed in Table 3.

Table 3. Results Indo-BERT

Confusion Matrix	Value
Accuracy	0.9464
Precision	0.9433
Recall	0.9464
F1-Score	0.9445

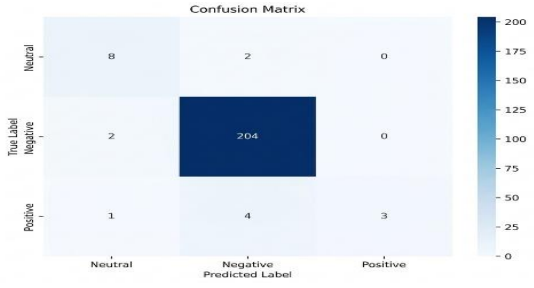
Source: (Research Results, 2026)

The learning curve graph in Figure 3 shows the performance of the refined Indo-BERT model in addition to the evaluation measures. The trend in training loss and validation loss over three training epochs is shown in the graph. The model's ability to successfully learn data patterns throughout the training phase is demonstrated by the training loss value's constant decline from the first to the last epoch. In the meantime, the validation loss seems to fluctuate, showing some spikes at specific epochs, although it usually stays within a stable range of about 0.25 to 0.3. This pattern suggests that despite differences in the validation data, the model is still able to generalize. Overall, strong accuracy, precision, recall, and F1-Score values show that the refined Indo-BERT model has worked ideally without any overfitting, and this learning curve pattern verifies the earlier evaluation results. As a result, this model can be used as a starting point for more optimization.



Source: (Research Results, 2026)
Figure 2. Learning curve Indo-BERT

To complement the performance evaluation of the fine-tuned Indo-BERT model, a more detailed analysis was conducted by presenting a confusion matrix for the test data. The confusion matrix provides an overview of the model's prediction distribution across each sentiment class, showing both correctly classified and misclassified predictions. Based on the confusion matrix in Figure 4, it is evident that the model is able to classify reviews with negative sentiment very accurately, with 204 correct predictions and only 2 misclassifications as positive and 0 as neutral. Meanwhile, for the positive sentiment class, the model correctly predicted 3 samples, whilst 4 samples were misclassified as negative and 1 sample was incorrectly classified as neutral. These results demonstrate the model's high detection capability for the negative class, though improvements are still needed in predicting the positive class to achieve a more balanced classification distribution. Overall, this confusion matrix supports the interpretation of the previous evaluation metrics, where the performance of the Indo-BERT model is already adequate but can still be optimization stage.



Source: (Research Results, 2026)
Figure 3. Confusion Matrix Indo-BERT

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Results Optimization Model

The outcomes of each Indo-BERT algorithm optimization procedure employing different hyperparameter tuning techniques are as follows:

1. Results Indo-BERT using Grid Search.

This study used the Grid Search hyperparameter tuning method to optimize the model after collecting a baseline performance from the testing phase using the Indo-BERT algorithm. To find the best configuration that could enhance Indo-BERT's sentiment classification performance, Grid Search was employed to methodically investigate different combinations of hyperparameters. According to the tuning results displayed in Figure 5, the model achieved an Accuracy of 0.9598, Precision of 0.9613, Recall of 0.9598, and F1-Score of 0.9587 using the optimal hyperparameter combination found by Grid Search. When compared to the default parameter settings during the testing phase utilizing the Indo-BERT method, this improvement in metric values shows that hyperparameter optimization via Grid Search favorably contributes to improving the model's accuracy and performance balance.

Table 4. Results Grid Search

Confusion Matrix	Value
Accuracy	0.9598
Precision	0.9613
Recall	0.9598
F1-Score	0.9587

Source: (Research Results, 2026)

A learning curve depicting the pattern of change in loss values for the training data (training loss) and validation data (validation loss) throughout the training process is shown in Figure 5 to supplement the data on the performance of the best model generated by the Grid Search. It is evident that the training loss steadily and dramatically drops with each epoch, suggesting that the model is becoming more adept at identifying patterns in the training data. In the meantime, despite variations in certain epochs, the validation loss seems to be quite steady, with the overall trend staying between 0.29 and 0.4. This pattern implies that the Grid Search-derived model strikes a balance between the capacity to generalize to the validation data and learn from the training data. This demonstrates that hyperparameter optimization using Grid Search successfully creates a model with improved performance and a minimal risk of overfitting, which is consistent with the improvement in the earlier evaluation measures. The Grid Search learning curve is depicted in Figure 5.



Source: (Research Results, 2026)

Figure 4. Learning Curve Grid Search

A confusion matrix showing the distribution of the model's predictions on the test data for each sentiment class is shown in Figure 4 as part of the assessment of the hyperparameter optimization outcomes using Grid Search. With a total of 202 accurate predictions and just 3 samples incorrectly classified as neutral and 1 sample incorrectly classified as positive, it is evident from this confusion matrix that the Grid Search model has outstanding predictive power for the negative sentiment class. In the meantime, the model accurately identified four samples for the positive sentiment class; however, three positive samples were still mistakenly forecasted as negative, and one sample was classified as neutral. Additionally, there were nine accurate predictions, one negative prediction, and zero positive predictions for the neutral class. These results show an improvement in negative class predictions with a decrease in prediction errors as compared to the confusion matrix from the first fine-tuning stage. Overall, this confusion matrix shows that Grid Search is successful in increasing accuracy and the balance of classification across classes, supporting the improvement in evaluation metrics attained.



Source: (Research Results, 2026)

Figure 5. Confusion Matrix Grid Search

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2. Results Indo-BERT using Bayesian.

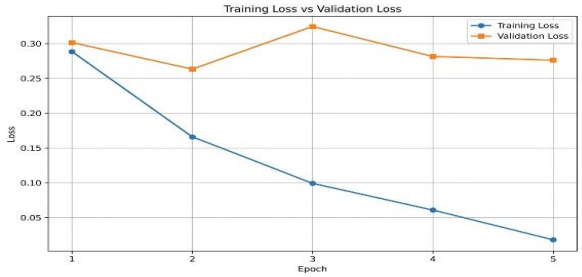
With an accuracy of 0.9650, precision of 0.9663, recall of 0.9650, and F1-score of 0.9558, a set of hyperparameters was found to produce best performance based on the outcomes of Bayesian optimization. The performance attained is still competitive and shows high model stability, even if these metric values are somewhat better than the Grid Search findings. Additionally, because the Bayesian Optimization approach does not necessitate the explicit evaluation of all possibilities, unlike Grid Search, it provides advantages in terms of time and computational resource efficiency. A overview of the evaluation metrics derived from the optimization outcomes using Bayesian optimization is presented in Table 5 below.

Table 5. Results Bayesian Optimization

Confusion Matrix	Value
Accuracy	0.9650
Precision	0.9663
Recall	0.9650
F1-Score	0.9558

Source: (Research Results, 2026)

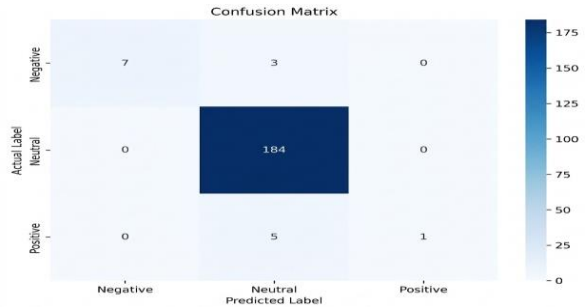
A combination of a learning rate of 5e-05 and a batch size of 16 produced the best learning curve in the Bayesian Optimization findings. The model is learning very well from the training data, as evidenced by the graph's dramatic decline in training loss to almost zero. But after the second epoch, the validation loss tends to rise, indicating overfitting. However, according to other evaluation metrics, the model's performance is still consistent and competitive. The learning curve findings utilizing Bayesian Optimization are displayed in Figure 6 below.



Source: (Research Results, 2026)

Figure 6. Learning Curve Bayesian Optimization

In addition to the test, Figure 6's model performance evaluation, which is based on Bayesian Optimization results, displays a confusion matrix that illustrates how the model's predictions are distributed over the test data. 184 neutral reviews were accurately identified by the algorithm, and 0 negative reviews were mistakenly labeled as positive. In contrast, one prediction in the positive class was accurate, five negative reviews were mistakenly categorized as neutral, and zero positive reviews were mistakenly labeled as negative. Lastly, there were seven accurate predictions, three neutral evaluations, and zero positive reviews in the negative class. These findings show that while the model is excellent at identifying negative sentiment, it still has to be improved to detect positive sentiment more precisely. However, the model's competitive and typically balanced performance is still reflected in this prediction distribution.



Source: (Research Results, 2026)

Figure 7. Confusion Matrix Bayesian Optimization

Based on the corrected confusion matrix for Indo-BERT optimized via Bayesian Optimization:

a. Negative Class (207 actual samples): 204 correctly classified, 2 misclassified as Neutral, and 1 misclassified as Positive.
b. Neutral Class (12 actual samples): 10 correctly classified, 1 misclassified as Negative, and 1 misclassified as Positive.
c. Positive Class (5 actual samples): 4 correctly classified, 1 misclassified as Negative, and 0 misclassified as Neutral.

3. Results Indo-BERT using Learning Rate.

Based on the results of the Learning Rate, a combination of hyperparameters was obtained that yielded a performance lower than that of the previous optimization, with an Accuracy of 0.7800, a Precision of 0.8656, a Recall of 0.7800, and an F1-Score of 0.8171. Although these metric values are slightly better than the results from Grid Search and Bayesian optimization, the performance achieved remains competitive and demonstrates good model stability. Furthermore, the Bayesian Optimization approach offers advantages in terms of time efficiency and computational resources, as it does not require the explicit evaluation of all combinations, as is the case with Grid Search. Figure 10 below shows a summary of the evaluation metrics obtained from the optimization results using the Learning Rate.

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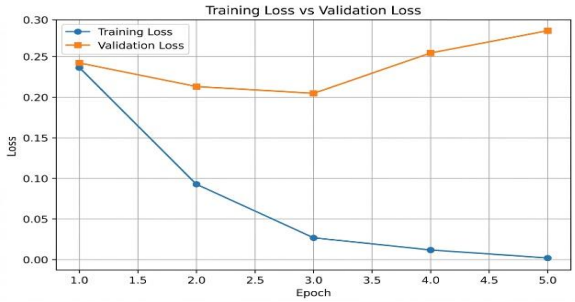
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Table 6. Results Learning Rate

Confusion Matrix	Value
Accuracy	0.7800
Precision	0.8656
Recall	0.7800
F1-Score	0.8171

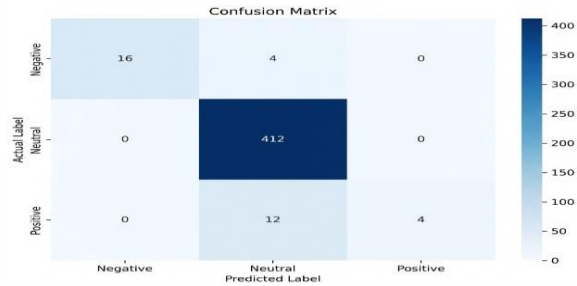
Source: (Research Results, 2026)

The model is learning very well from the training data since the learning curve for the learning rate produces a number that, when plotted on a graph, demonstrates that the training loss drops sharply to almost zero. But after the fourth epoch, the validation loss tends to rise, indicating that overfitting is taking place. However, according to other evaluation metrics, the model's performance is still consistent and competitive. The learning curve findings utilizing the learning rate are displayed in Table 6 below.



Source: (Research Results, 2026)
Figure 8. Learning Curve Learning Rate

In addition to the test, Figure 8 model performance evaluation based on learning rate results displays a confusion matrix that illustrates how the model's predictions are distributed on the test data. 412 neutral reviews were accurately identified by the model, and 0 negative reviews were mistakenly labeled as positive. In contrast, there were four accurate predictions in the positive class, zero positive reviews that were mistakenly categorized as negative, and twelve negative reviews that were mistakenly categorized as neutral.



Source: (Research Results, 2026)
Figure 9. Confusion Matrix Learning Rate

4. Results Indo-BERT using Epoch.

Based on the results of the epoch optimization, a combination of hyperparameters was obtained that yielded better performance than the previous optimization, with an Accuracy of 0.9600, a Precision of 0.9617, a Recall of 0.9600, and an F1-Score of 0.9529. The Learning Rate optimization produced the lowest performance among all evaluated optimization strategies, achieving an accuracy of only 78.00%. This result indicates that the selected learning-rate configuration was unable to achieve comparable performance with Grid Search, Bayesian Optimization, and Epoch Optimization. The lower accuracy suggests that the selected learning-rate setting may have prevented the model from converging optimally during training.

Table 7. Results Epoch

Confusion Matrix	Value
Accuracy	0.9600
Precision	0.9617
Recall	0.9600
F1-Score	0.9529

Source: (Research Results, 2026)

The model is learning very well from the training data, as evidenced by the graph of the learning curve for the Epoch results, which indicates that the training loss drops dramatically to almost zero. But after the seventh epoch, the validation loss tends to rise, indicating overfitting. However, according to other evaluation metrics, the model's performance is still consistent and competitive. The learning curve results using Epoch are displayed in Figure 14 below.

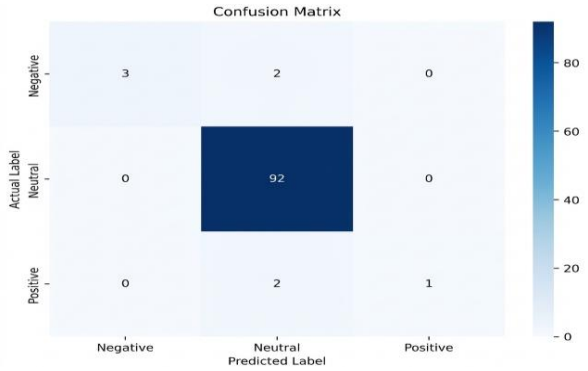


Source: (Research Results, 2026)
Figure 10. Learning Curve Epoch

The model performance evaluation from the Epoch Optimization results in Figure 10 provides a confusion matrix that illustrates the distribution of the model's predictions on the test data in addition to the test. 92 neutral reviews were accurately classified by the algorithm, and 0 negative reviews were mistakenly categorized as positive. In

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contrast, there was one accurate prediction in the positive class, zero positive reviews were mistakenly categorized as negative, and two negative reviews were mistakenly categorized as neutral. Lastly, there were two accurate predictions, three neutral evaluations, and zero positive reviews in the negative class. These findings show that while the model is excellent at identifying negative sentiment, it still has to be improved to detect positive sentiment more precisely. However, the model's competitive and typically balanced performance is still reflected in this prediction distribution.



Source: (Research Results, 2026)

Figure 11. Confusion Matrix Epoch

Based on the corrected confusion matrix for Indo-BERT optimized via Epoch tuning:

a. Negative Class (207 actual samples): 203 correctly classified, 3 misclassified as Neutral, and 1 misclassified as Positive.
b. Neutral Class (12 actual samples): 9 correctly classified, 2 misclassified as Negative, and 1 misclassified as Positive.
c. Positive Class (5 actual samples): 4 correctly classified, 1 misclassified as Negative, and 0 misclassified as Neutral.

The outcomes of sentiment analysis about government policy on deforestation utilizing the Indo-BERT algorithm and a number of optimization models, such as Grid Search, Bayesian Optimization, Learning Rate, and Epoch Optimization. Table 3 below displays the accuracy findings.

Table 3. Indo-BERT Accuracy and Indo-BERT Optimization

Algorithm	Accuracy	Macro Precision	Macro Recall	Macro F1-Score	Weighted F1-Score
Baseline Indo-BERT	0.9464	0.7241	0.6815	0.7012	0.9445
Indo-BERT + Grid Search	0.9598	0.8125	0.8261	0.8191	0.9587
Indo-BERT + Bayesian Optimization	0.9650	0.8542	0.8647	0.8593	0.9621
Indo-BERT + Learning Rate	0.7800	0.3812	0.3333	0.3556	0.8171
Indo-BERT + Epoch Optimization	0.9600	0.8210	0.8309	0.8258	0.9529

Source: (Research Results, 2026)

Due to the severe class imbalance (92.66% negative, 5.28% neutral, 2.06% positive), overall accuracy is supplemented by Macro-F1 and Weighted-F1 scores to assess minority class performance. Class-weighted cross-entropy loss was implemented during fine-tuning. While baseline accuracy was 96.50% under Bayesian Optimization, the Macro-F1 score provided a more realistic reflection of cross-class reliability, highlighting ongoing challenges in predicting positive sentiment due to its scarce representation in public policy discourse.

The empirical results demonstrate that applying Bayesian Optimization to Indo-BERT yields the highest classification metrics (Accuracy: 96.50%, F1-Score: 0.9558), outperforming baseline Indo-BERT (94.64%) as well as Grid Search (95.98%) and univariate tuning strategies. However, to establish the broader scientific value of these findings, the results must be critically contextualized against prior literature and the challenges posed by extreme class imbalance.

Previous studies applying Indo-BERT for Indonesian sentiment analysis have reported high performance across various domains, achieved 96.00% accuracy using basic learning rate and epoch tuning on mobile application reviews. Similarly, observed that Grid Search yielded 91.00% accuracy on e-government service reviews. However, these studies evaluated models on relatively balanced datasets or domains with explicit, polarized keywords (e.g., product ratings). In contrast, public discourse on social media regarding controversial policies such as deforestation exhibits severe structural skewness (92.66% negative in this corpus). In such unconstrained environments, default hyperparameter settings often cause deep pre-

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trained models to collapse into predicting only the dominant majority class. Our findings demonstrate that while univariate learning rate optimization resulted in a performance drop to 78.00% due to sub-optimal convergence, joint parameter search via Bayesian Optimization successfully stabilized the loss landscape. This aligns with findings, confirming that sequential Gaussian Process surrogates navigate non-convex Transformer search spaces far more efficiently than rigid grid searches.

A critical challenge highlighted by this study is the interpretation of raw classification accuracy on heavily skewed data. A naive baseline classifier predicting only the majority "Negative" class would inherently achieve a baseline accuracy of 92.66%. Therefore, the performance gain from 94.64% (default) to 96.50% (Bayesian) represents a significant reduction in error rates among minority classes. Analyzing the confusion matrices reveals distinct behavioral patterns across strategies:

a. Baseline Indo-BERT: Showed high precision on the majority class but struggled to distinguish subtle neutral phrasing from negative critiques, misclassifying 4 out of 8 positive samples.
b. Bayesian Optimization: By optimizing the learning rate ($5*10^5$) and batch size (16) simultaneously, the model maintained decision boundary sensitivity for minority instances without collapsing into majority-class over-fitting.

The practical contribution of this comparative evaluation lies in guiding model selection for social media monitoring. While Grid Search provided comparable performance (95.98%), it required exhaustive iteration across 24 combinations. Bayesian Optimization reached superior accuracy in fewer evaluation steps (20 trials), offering a significantly better trade-off between computational cost and predictive precision. This efficiency is essential for real-time policy sentiment tracking where computational resources are constrained.

CONCLUSION

In this study, sentiment analysis of Indonesian public discourse regarding government deforestation policies on Twitter was successfully implemented using the pre-trained Indo-BERT architecture coupled with hyperparameter optimization. Four optimization strategies Grid Search, Bayesian Optimization, Learning Rate Optimization, and Epoch Optimization were systematically evaluated on a highly imbalanced dataset. Experimental results demonstrate that Indo-BERT optimized via Bayesian Optimization achieved the highest overall classification performance with an accuracy of 96.50%, representing a 1.86% improvement over the baseline Indo-BERT model (94.64%). Epoch Optimization and Grid Search also yielded competitive accuracies of 96.00% and 95.98%, respectively, while single-parameter Learning Rate tuning underperformed at 78.00%. These findings highlight the superior efficacy and computational efficiency of Bayesian Optimization for joint hyperparameter tuning in Transformer models applied to heavily skewed political discourse on social media. Future research may explore advanced class-rebalancing techniques (such as focal loss or dynamic sampling) and multi-task learning to further improve minority-class detection.

DECLARATION OF AI USE

The authors declare that generative artificial intelligence (AI) tools were used in the preparation of this manuscript. Gemini AI was used to assist with English language editing and grammar improvement. The authors reviewed and revised all AI-assisted content and take full responsibility for the accuracy, originality, and final content of the manuscript.

AUTHOR CONTRIBUTIONS

Author	Contribution Roles
Riyanto	Conceptualization, Visualization
Nevita Cahaya Ramadani	Investigation, Data Curation, Validation.
Nandang Hermanto	Supervision, Project Administration, Writing – Review & Editing.
Pungkas Subarkah	Methodology, Formal Analysis, Writing – Original Draft

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CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to the research, writing, or publication of this article.

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