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Implementation of IndoBERT Model in Predicting Anxiety Disorders from Comments on Social Media

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Abstract - The development of social media as a means of emotional expression has opened up new opportunities in the early detection of mental health disorders, particularly anxiety disorders, which are still rarely analyzed using Indonesian-language computational approaches. To implement and evaluate IndoBERT model in detecting indications of anxiety disorders based on Indonesian-language social media comments. The method of study used an experimental quantitative approach with a total of 6,075 comments collected from Twitter, Instagram, and TikTok, which were classified into two categories: anxiety and normal. Pre-processing processes were carried out through text cleaning, slang normalization, and stopword removal before the IndoBERT model was trained using fine-tuning techniques for three epochs. Model performance was tested using accuracy, precision, recall, and F1- score metrics, and evaluated through confusion matrix analysis and k-fold cross-validation to ensure consistency of results. The results show that IndoBERT achieved 99.67% accuracy, 0.98 precision, 0.96 recall, and 0.97 F1-score in the anxiety class, with very low classification errors. This performance demonstrates that the model is able to effectively recognize linguistic patterns of anxiety despite data imbalance between classes. These findings confirm IndoBERT's potential as a basis for developing a text-based early detection system for anxiety disorders in Indonesia. It is recommended for future studies to expand the data sources, add other psychological disorder categories, and compare performance with other algorithms to improve the model's reliability.

Keywords: IndoBERT; Anxiety Disorders; Social Media; NLP

1. Introduction

In today's digital era, social media platforms for example Instagram, Twitter (X), and TikTok have become an integral part of modern society. These platforms serve not only as a means of communication but also as a place for individuals to openly express their feelings, experiences, and thoughts. This phenomenon has a significant impact on mental health, especially among adolescents and young adults who are more active social media users. According to research conducted by Khalaf et al., (2023) individuals who actively express emotions and personal experiences on social media are more likely to experience anxiety disorders than those who rarely interact online. Language in social media texts and comments often reflects symptoms of anxiety disorders. According to O'Day & Heimberg, (2021) users experiencing anxiety tend to use words with negative connotations, uncertainty, and worry. Data from the World Health Organization , (2022) shows that approximately 301 million people worldwide live with anxiety disorders, including 58 millions of children and adolescents. In Indonesia, the 2022 National Adolescent Mental Health Survey (I-NAMHS) revealed that 26.7% of adolescents experience anxiety disorders, making it the most common mental disorder in the country. This linguistic pattern analysis opens up new opportunities in the text-based early detection of mental disorders, which can support prevention and early intervention efforts in the mental health sector (Juanita et al., 2025). However, the main challenges in detecting anxiety disorders through social media are the complexity of language and the sheer volume of data. Manual analysis is inefficient due to the variety of expressions, the use of non-standard language, and diverse social and cultural contexts (Mansoor & Ansari, 2024). Traditional methods for example lexicon analysis have proven inadequate to capture complex semantic contexts. Therefore, approaches based on Artificial Intelligence (AI) and Machine Learning (ML) are needed to understand language patterns more deeply. Some previous studies have been conducted to detect mental disorders using AI approaches. For instance, the study by Nugroho et al., (2021) that used Bidirectional LSTM to detect depression and anxiety on Twitter, where the LSTM model proved to be superior to the lexicon-based approach, although it is still limited in the context of long sentences. Meanwhile, Arif et al.,(2024) performed the classification of five types of mental disorders using transfer learning, and found that IndoBERT provided an accuracy of 78%, demonstrating the strong potential of transformer models in mental health classification. The study by (Prawira et al., 2024) combined BERT and Bi-

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LSTM, yielding an accuracy of 99,44%, showing that the combination of BERT semantic representation with LSTM sequential capabilities is very effective for detecting anxiety in Twitter text.

On the other hand, Hastuti et al., (2023)applied the Convolutional Neural Network (CNN) approach for emotional and depression analysis in social media, with accuracy results reaching 91% for depression detection. Besides that, the classic study by Mutmainah, (2022) used Support Vector Machine (SVM) and showed that the method was able to reach an accuracy of 95,56%, higher than neural network (93,79%). Then, Jang et al., (2020)applied Bi-LSTM for classification of six categories of psychological and social problems on Twitter with an accuracy of 80.05%, proving the ability of this model to handle unstructured text data. Another study by (HENI, 2023) showed that the Random Forest Classifier method reached the highest accuracy (up to 100%) in detecting Narcissistic Personality Disorder (NPD) compared to Naive Bayes and SVM. The SMOTE approach that was used also proved increasing accuracy up to 91,96%, strengthening the importance of data balancing techniques in the classification of mental disorders. Meanwhile, Prabowo & Indra Sanjaya, (2024) applied IndoBERT for sentiment analysis of Javanese text and achieved 99% accuracy on training data and 90% on test data, confirming the effectiveness of cross-language transfer learning in understanding emotional context. In the study by (Ilias et al., 2024), system underwent calibration on the transformer-based model by adding NRC Lexicon, LDA, and label smoothing, which successfully increased the reliability and confidence of the model in identifying stress and depression. Tresyani et al., (2025) combined the BERT and XGBoost models for early detection of mental health disorders achieved an accuracy of 93.05%, demonstrating the potential of combining transformer models with classical optimization algorithms to improve detection performance. Previous studies have shown that the use of deep learning and transfer learning, particularly the IndoBERT model, yields promising results in text analysis for mental health disorder detection. However, most studies have focused on depression detection or general sentiment analysis, without specifically examining anxiety disorder detection in the Indonesian context using a broad and diverse dataset of social media comments. Many NLP studies in the mental health domain detect depression, stress, or indications of general well-being (Ahmed et al., 2022).

Therefore, this study implement IndoBERT model to detect anxiety disorders based on social media comments. This model is expected to be able to understand complex linguistic contexts and improve detection accuracy compared to previous methods. The results of the study are expected to contribute to the development of an artificial intelligence-based early detection system for mental health and support digital intervention efforts for the wider community.

2. Research Methods

This methods of study used an experimental quantitative approach with a computational approach based on machine learning, aiming to analyze and evaluate the performance of the IndoBERT (Indonesian Bidirectional Encoder Representations from Transformers) model in classifying text expressions on social media into two main categories: anxious (containing indications of anxiety) and normal. This approach was chosen because it allows for systematic and objective processing of large amounts of data, and is able to detect linguistic patterns that cannot be identified manually.

Steps of this study are presented visually in **Figure 1**. Methods of Study, that contains all the main processes starting from problem identification to model evaluation and the making of report of study results.

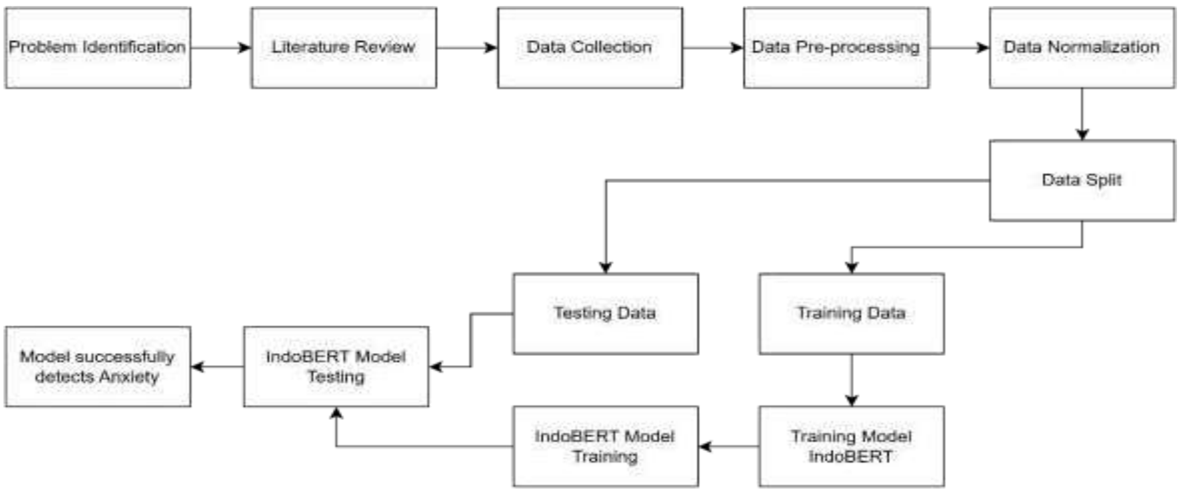

Figure 1. Methods of Study

The overall research workflow is illustrated in **Figure 1**, which presents the systematic stages undertaken in this study, from problem identification to model implementation and evaluation. Each stage plays a critical role in ensuring the reliability and accuracy of the IndoBERT-based anxiety detection model. The detailed explanation of each stage is described as follows:(Hayati & Tohari, 2022).

1) Problem Identification
   The study begins with the identification of a key problem: the rising number of anxiety-related expressions on social media that have not been analyzed computationally. According to anxiety disorder theory, anxiety manifests through excessive worry and fear of negative judgment from others . These emotional states are reflected in language patterns that express uncertainty and distress.
2) Literature Review
   A comprehensive literature review was conducted to examine previous research on Natural Language Processing (NLP) and Transformer-based models, such as BERT and IndoBERT, in the context of social media text analysis. Studies show that deep learning methods outperform traditional approaches like SVM and Naive Bayes (Utami et al., 2023). IndoBERT was selected for this research because of its bidirectional contextual understanding (Chandradev et al., 2023)
3) Data Collection
   Comments were collected from Twitter, Instagram, and TikTok using anxiety-related keywords such as anxious (cemas), worried (khawatir), afraid (takut), restless (gelisah), sad (sedih), panic (panik), and disturbed (galau) (Kenwood et al., 2022). A total of 6,075 comments were gathered and manually labeled into two categories: anxiety and normal.
4) Data Pre-processing
   The raw data were cleaned and refined through several pre-processing steps, including tokenization, case normalization, stopword removal, and elimination of irrelevant elements such as emojis, URLs, and special characters. This step ensured that the dataset was clean and semantically consistent for model processing.
5) Data Normalization and Split
   After pre-processing, the data underwent normalization to maintain linguistic uniformity. The dataset was then divided into training data (5,075 comments) and testing data (1,000 comments). This process followed the NLP principle of converting text into numerical representations suitable for computational modeling (Azzahra & Majid, 2025).
6) IndoBERT Model Training
   The IndoBERT model was trained using the training dataset through fine-tuning to adapt the pre-trained language model to the task of anxiety classification. The model learned linguistic and emotional patterns relevant to anxiety expressions.
7) IndoBERT Model Testing
   After training, the model was tested using the testing dataset to evaluate its performance. The evaluation employed accuracy, precision, recall, and F1-score metrics, supported by confusion matrix visualization to analyze misclassification patterns (Bangyal et al., 2021).
8) Model Validation and Interpretation
   The model's reliability was further examined through k-fold cross-validation to ensure consistency across different data subsets. The results showed that IndoBERT effectively detects anxiety expressions with high accuracy and balanced performance metrics.
9) Conclusion and Reporting
   The final stage involved interpreting the model's results and compiling a comprehensive research report. The findings demonstrate that the integration of psychological theory, NLP techniques, and deep learning using IndoBERT produces a reliable and accurate framework for early detection of anxiety disorders in social media text.

Overall, this study integrates psychological theories of anxiety, NLP concepts, and the IndoBERT deep learning approach within a systematic methodological framework, ensuring that the resulting model is not only accurate but also relevant for aiding early detection of anxiety disorders based on social media text.

3. Result and Discussion

3.1 Data Collection

This study produced an IndoBERT model trained to detect comments indicating anxiety on social media. The dataset consisted of 6,130 comments, consisting of 5,075 training entries and 1,000 test entries. The data were divided into two main categories: anxiety and normal. The number of entries in each category is shown in Table 1 and visualized in Figure 2.

Table 1. Sentiment Distribution on Dataset

Sentiments	Numbers of Tweets
Anxiety	2.496
Normal	3.579
Total	6.075

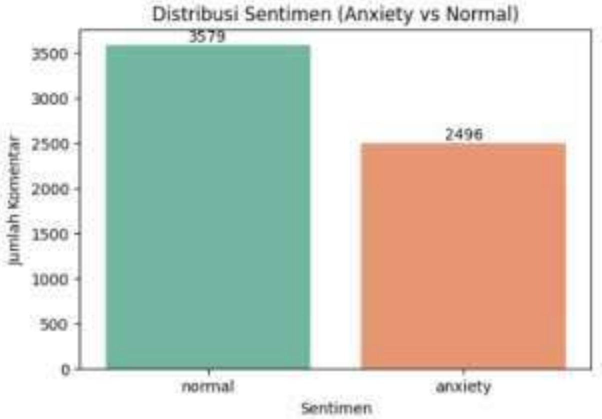

Figure 2. Sentiment Data Distribution

3.2 Data Pre-processing and Normalization

Raw data that had been obtained from social media could not be used directly because they contained various irrelevant elements, for example links, emojis, symbols, mixed foreign languages, and non-standard words that could interfere with the text analysis process. Therefore, a thorough data pre-processing process was carried out to ensure the text used was cleaner, uniform, and semantically meaningful. This stage included cleaning punctuation, numbers, and non-alphabetic characters, normalizing slang words to standard forms for example "*gk*" to "*tidak*"/"no," and removing stop words or meaningless expressions, for example "*wkwkwk*." This process helped the model focus more on meaningful words relevant to the emotion of anxiety. For example, the comment *"jirrr susah bgttt cari murid. keknya udah termurah 7k/pertemuan belajar bahasa jerman in this economy, bismillah bismillah bisa yuk rameee"* ("jirrr it's really hard to find students. It seems like the cheapest german language learning session in this economy is already 7,000 rupiah, bismillah, bismillah, I hope many customers come") became *"susah banget cari murid sepertinya sudah murah tujuh ribu satu pertemuan belajar bahasa jerman"* ("it's really hard to find students, it seems like it's already cheap enough to learn german language for 7,000 rupiah") after going through the pre- processing stage. Other comments show similar result, for example *"ternyata jam tangan ngaruh ke penampilan wkwk"* ("it turns out watches affect your appearance, wkwk,") which changed to *"ternyata jam tangan berpengaruh ke penampilan"* ("it turns out watches affect your appearance.") Overall, this process resulted in a more structured dataset ready for training a text-based anxiety detection model.

Table 2. Data cleaning results

Comments before the pre-processing stage	Comments after the pre-processing stage
jirrr susah bgttt cari murid. keknya udah termurah 7k/pertemuan belajar bahasa jerman in this economy, bismillah bismillah bisa yuk rameee	*susah banget cari murid sepertinya sudah murah tujuh ribu satu pertemuan belajar bahasa jerman*
jirrr it's really hard to find students. It seems like the cheapest german language learning session in this economy is already 7,000 rupiah, bismillah, bismillah, I hope many customers come	it's really hard to find students, it seems like it's already cheap enough to learn german language for rupiah
ternyata jam tangan ngaruh ke penampilan wkwk	*ternyata jam tangan berpengaruh ke penampilan*
it turns out watches affect your appearance, wkwk	it turns out watches affect your appearance
in this economy, cari customer yang mau titip jahit susah banget tolooong	*ekonomi seperti saat ini cari pelanggan mau titip jahit susah banget tolong*
in this economy, it's really hard to find customers who want to entrust their sewing to you, helpppp	with the economy being like how it is now, it's really hard to find customers who want to entrust sewing to you, please help
kenapa ya kadang rasanya ambisi bisa lanjut s2 atau kuliah setinggi"nya, bisa sukses, bisa bahagian orang" itu cuma sebatas mimpi. nyatanya aku udah berusaha.. tp entah malah ngerasa gagal jadi manusia	kenapa kadang rasa ambisi bisa lanjut kuliah setinggi tingginya bisa sukses bisa bahagia orang orang hanya mimpi aku sudah berusaha namun ngerasa gagal jadi manusia

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Comments before the pre-processing stage	Comments after the pre-processing stage
why do I sometimes feel like my ambition to continue my Masters or study at the highest level, to be successful, to make people happy is just a dream. in fact, I've tried... but somehow I feel like I've failed as a human being	why is it that sometimes the feeling of ambition to continue studying as high as possible, to be successful, to make people happy are just dreams I have tried but I feel like I have failed as a human being
kayaknya gue gak bisa deh hidup di Indonesia I don't think I can live in Indonesia	*sepertinya gua tidak bisa hidup di indonesia* it seems like I can't live in Indonesia
...	...

This pre-processing stage yielded cleaner, more uniform data, ready for use in model training. The data were then separated into a training set and a testing set to objectively evaluate model performance. The training process was carried out over three epochs. A summary of the training results is shown in Table 3.

3.3. Data Split

Table 3. Summary of IndoBERT Training Results

Epoch	Loss	Accuracy	Val Loss	Val Accuracy
1	0.1813	91.52%	0.0401	99.26%
2	0.0331	99.24%	0.0188	99.51%
3	0.0152	99.63%	0.0205	99.67%

The IndoBERT model demonstrated effective training results based on the data in Table 3. The loss value decreased from 0.1813 to 0.0152 over three training epochs, while accuracy increased from 91.52% to 99.63%, with validation accuracy remaining stable at around 99%. This demonstrates the model's good generalization capability without any indication of overfitting. Table 4 displays the model's performance evaluation results based on precision, recall, and F1-score metrics. The model achieved a precision of 1.00, a recall of 0.99, and an F1-score of 1.00 in the anxiety class, and a precision of 0.99, a recall of 1.00, and an F1-score of 1.00 in the normal class, for an overall accuracy of 99.18%. Figure 3 shows a visualization of the confusion matrix, demonstrating the distribution of model predictions with a high level of accuracy. The model successfully classified 488 anxiety data sets correctly and only four incorrectly, and correctly detected all 723 data sets in the normal class. These results show a very low prediction error rate and prove the reliability of the IndoBERT model in distinguishing comments containing indications of anxiety and normal comments.

3.4 Model Validation and Interpretation

Table 4. Summary of IndoBERT Model Evaluation Results

Category	Precision	Recall	F1-Score	Support
Anxiety	1.00	0.99	1.00	492
Normal	0.99	1.00	1.00	723
Accuracy			1.00	1215
Macro Avg	1.00	1.00	1.00	1215
Weighted Avg	1.00	1.00	1.00	1215

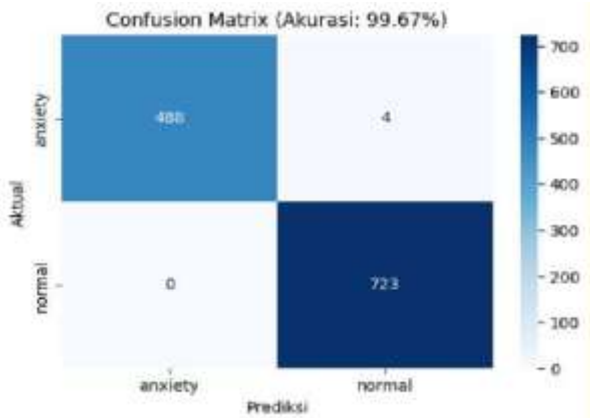

Figure 3. *Confusion Matrix* of IndoBERT Model

The confusion matrix in Figure 3 shows that the IndoBERT model successfully classified with a very high accuracy rate of 99.67%. The model correctly predicted 488 data points as anxiety and 723 data points as normal. Four anxiety data points were misclassified as normal, while no normal data points were misclassified as anxiety. These results demonstrate the model's excellent and consistent classification ability in distinguishing between comments containing indications of anxiety and normal comments.

The confusion matrix in the figure shows that the IndoBERT model successfully classified with a very high accuracy rate of 99.67%. The model correctly predicted 488 data points as anxiety and 723 data points as normal. Four anxiety data points were misclassified as normal, while no normal data points were misclassified as anxiety. These results demonstrate the model's excellent and consistent classification ability in distinguishing between comments containing indications of anxiety and normal comments.

Precision was calculated using this formula:

$$\text{Precision } = \frac{TP}{TP+FP} \text{ (1)}$$

$$\text{Precision } = \frac{488}{488+0} = \frac{488}{488} = 1.00$$

Based on the evaluation results, the anxiety category had a precision value of 0.98, indicating that 98% of all comments predicted as anxiety actually fell into that category. This result demonstrates that the model has a very low false positive rate, meaning it rarely misclassifies normal comments as anxiety.

Recall was calculated using this formula:

$$\text{Recall} = \frac{TP}{TP+FN} \text{ (2)}$$

$$\text{Recall} = \frac{488}{488+4} = \frac{488}{492} = 0.992$$

The recall value for the anxiety category was 0.96, meaning the model successfully detected 96% of comments that actually indicated anxiety. This result demonstrates the model's high sensitivity in detecting anxiety symptoms from text.

F1-score obtained from the harmonic mean of precision and recall:

$$\text{F1} = 2 \times \frac{r \times p}{r+p} \text{ (3)}$$

$$\text{F1} = 2 \times \frac{0.992 \times 1.00}{0.992 + 1.00} = 2 \times \frac{0.992}{1.992} = 2 \times 0.298 = 0.996$$

The model achieved a precision of 0.98 and a recall of 0.96, the resulting F1-score value reached 0.97, which indicates an optimal balance between the model's accuracy and sensitivity in detecting comments indicating anxiety.

Based on the overall training, evaluation, and analysis results, the IndoBERT model demonstrated excellent performance with an overall accuracy of 99.67%, a precision of 0.98, a recall of 0.96, and an F1-score of 0.97. These values confirm the model's ability to classify accurately and consistently, making it suitable for use as a basis for developing a text-based early detection system for anxiety disorders.

This study aimed to implement the IndoBERT model to detect anxiety disorders in social media comments. The results show that each stage, from data collection to model evaluation, significantly contributes to improving model performance. The use of keywords for example anxious, restless, worried, and panic proved effective in collecting data relevant to expressions of anxiety. This finding aligns with the theory of emotional linguistics, which states that anxiety is reflected through the use of words containing uncertainty and worry. Pre processing processes, for example cleaning, slang normalization, and stopword removal resulted in cleaner and semantically consistent data, which resulted in a decrease in loss values and an increase in model accuracy during training. The training results show that IndoBERT has a high ability to understand linguistic patterns related to anxiety. Training accuracy increased from 91.52% to 99.63% in the third epoch, with validation accuracy stable at around 99%. The model also achieved a testing accuracy of 99.18% with near-perfect precision, recall, and F1-score values for both categories, indicating that the model is capable of recognizing normal comments and is sensitive to comments indicating anxiety despite data imbalance.

Compared to previous studies the IndoBERT model in this study demonstrated significant performance improvements. The study by Arif et al., (2024) reported 78% accuracy in detecting mental disorders using IndoBERT, while the study by Prawira et al., (2024), which combined BERT and Bi-LSTM, achieved 99.44%. The model in this study surpassed that result with 99.67% accuracy and a better balance between precision and recall. The novelty of this study lies in a more comprehensive pre-processing strategy, relevant keyword selection, and optimized fine-tuning process, resulting in more stable performance compared to previous studies. Furthermore, these results reinforce the findings of Nugroho et al., (2021b)that Bi- LSTM has limitations in understanding the context of long sentences, while IndoBERT is able to overcome this with its bidirectional self-attention mechanism. Confusion matrix analysis showed a very low misclassification rate, with only four anxiety data points missed and seven normal data points misclassified. This level of accuracy is important in the context of early detection of anxiety disorders, as prediction errors can impact a user's emotional diagnosis. These results also strengthen the NLP theory that Transformer-based models are superior in capturing complex language structures compared to traditional methods for example SVM or Naive Bayes.

Although the model demonstrated excellent results, this study was limited by its dataset coverage, which only came from three social media platforms and within a specific time period. Furthermore, the classification was still binary, making it unable to detect anxiety levels more specifically. Future studies are recommended to explore other algorithms or combine multiple machine learning models to achieve more transparent and accurate detection results, providing broader benefits for psychological analysis and clinical application.

Overall, the results of this study confirm that IndoBERT has great potential as a basis for developing a text-based early detection system for anxiety disorders in Indonesia. Its high performance, resilience to data imbalance, and ability to understand linguistic patterns of anxiety suggest that this model could serve as an important foundation for further studies in digital mental health.

4. Conclusion

Based on the results of the study, the IndoBERT model demonstrated excellent performance in detecting indications of anxiety disorders in social media comments with an accuracy of 99.67%, a precision of 0.98, a recall of 0.96, and an F1-score of 0.97 in the anxiety category, and excellent results in the normal category. These values demonstrate that the model is able to accurately recognize language patterns reflecting anxiety despite the data imbalance between the normal and anxiety classes. The consistency of the results between the training and test data also indicates that the model does not experience overfitting and has good generalization capabilities. Given this level of performance, IndoBERT demonstrates strong potential as a foundation for developing a text-based early detection system for anxiety disorders in Indonesia. However, this study is still limited to data from three social media platforms and binary classification, so further studies are recommended to expand the data coverage, add other categories of psychological disorders, and compare performance with other algorithms for example RoBERTa, XLNet, or GPT-based models to improve the system's reliability, transparency, and applicability in the broader context of digital mental health analysis.

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