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Using Sentiment Analysis with BERT and SVM for Detect Mental Health Detection on Social Media

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ABSTRACT

Mental health is an important aspect of an individual's life that can affect overall quality of life. In the current digital era, social media has become the main platform for individuals to express their thoughts and feelings. The increasing use of social media opens up opportunities for individuals to share personal experiences, but it also creates negative influences on oneself that can affect the mental health of other users. The symptoms experienced by sufferers include fatigue, headaches, and decreased productivity. but if not handled quickly and properly, it can lead to something dangerous for themselves, such as self-harm or suicide. Based on these issues, a system is needed that can quickly determine the diagnosis experienced by the patient. This study aims to develop a sentiment analysis-based system for early detection of mental health indicators using Bidirectional Encoder Representations from Transformers (BERT) and Support Vector Machine (SVM). The dataset, obtained from Kaggle, consists of 62,301 social media posts categorized into anxiety, depression, stress, and normal classes. Preprocessing techniques such as text cleaning, tokenization, and feature extraction with BERT were applied before classification using SVM. Experimental results indicate that the BERT+SVM model achieved an accuracy of 93.49%, outperforming traditional machine learning approaches. Notably, challenges remain in distinguishing normal and anxiety-related content due to semantic overlap. The findings highlight the potential of sentiment analysis in enhancing mental health screening tools. Future research should explore hybrid deep learning architectures and multilingual datasets to improve classification robustness and applicability across different populations.

INTRODUCTION

Mental health is a condition where a person is free from various symptoms of mental disorders, allowing them to utilize their potential to meet life's needs and fulfill social roles optimally (Fathe & Wahyu, 2023). Social media has become an integral part of modern society, providing a space for users to openly express their thoughts and feelings. However, it is also a medium where psychological conditions like anxiety, stress, or depression are indirectly revealed through posts, comments, and interactions. (Dan et al., 2024).

The rise of social media usage has enabled individuals to share personal experiences more freely. While this fosters openness, it also increases the presence of distressing content, potentially affecting users' mental well-being. However, these interactions provide valuable data that can be leveraged for detecting early signs of mental disorders. Depression and anxiety are among the most prevalent mental health disorders, affecting millions worldwide and significantly reducing quality of life (Garcia-Ceja et al., 2018). According to WHO (2019), over 280 million people suffer from depression, and 264 million experience anxiety disorders. Given the rising prevalence, early detection through digital platforms such as social media is crucial for timely intervention and mental health management (WHO, 2019).

In Indonesia, the 2018 Riskesdas survey reported that 9.8% of individuals over 15 years old experience emotional mental disorders, highlighting the need for early intervention strategies (Badan Penelitian dan Pengembangan Kesehatan Kemenkes RI, 2018). Mental disorders, if left untreated, can escalate into severe conditions, including substance abuse, self-harm, or suicide (Azhari, 2021). While professional mental health treatment remains essential, the use of sentiment analysis on social media offers a complementary approach to identifying at-risk individuals before their conditions worsen (Mubarok, 2022).. Given these risks, early detection is critical. This study explores how sentiment analysis on social media, using BERT and SVM, can serve as an early warning system for identifying individuals at risk of mental health disorders (Nopi et al., 2022).

Previous studies have utilized lexicon-based methods to detect depression symptoms on Twitter and among student communities, leading to the development of depression lexicon dictionaries. However, such approaches often struggle with understanding complex emotional contexts, limiting their effectiveness in detecting nuanced mental health indicators. To address this gap, our research leverages BERT for contextual feature extraction and SVM for classification, aiming for higher accuracy in mental health detection (Cha et al., 2022). In addition Previous studies have explored classical machine learning methods such as k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Random Forest, and Logistic Regression for sentiment analysis, achieving accuracy between 78% and 85% depending on the dataset (Primadhani Tirtopangarsa & Maharani, 2021), (Darmawan et al., 2023), (Nijhawan et al., 2022). More recent approaches have shifted towards deep learning models like Bidirectional LSTM (BiLSTM) and CNN, which better capture emotional context. However, these models often require extensive labeled data and computational resources, making them less practical for real-time applications. To address these challenges, this study integrates BERT for contextual feature extraction and SVM for classification, leveraging BERT's deep linguistic understanding while maintaining SVM's efficiency in classification tasks. For example, the BiLSTM model was used to detect depression and anxiety from Indonesian-language Twitter data, achieving an accuracy of 94.12% (Nugroho et al., 2023), (Abdurrahim & Fudholi, 2024). Meanwhile, large language models (LLMs) such as RoBERTa and GPT are not only capable of detecting mental disorders but also predicting potential future disorders, with higher F1-scores compared to traditional methods (Abdullah & Negied, 2024). The ensemble learning approach, which combines several models simultaneously, also shows improved accuracy in detecting mental disorders through sentiment and emotion analysis on social media (Ogunleye et al., 2024). Additionally, topic modeling techniques such as Latent Dirichlet Allocation (LDA) have also been used to identify relevant topics in text data, providing deeper insights into the social context related to the mental health of social media users (Bokolo & Liu, 2023). Research that combines these techniques with deep learning and machine learning-based sentiment analysis shows better results, both in terms of accuracy and generalization capability (Tiwari et al., 2021).

From previous research results that used various approaches such as lexicon-based analysis, machine learning, and deep learning, it can be concluded that although there has been significant progress, there are still challenges in terms of accuracy and the model's ability to understand complex emotional contexts. Therefore, the aim of this research is to address these limitations by leveraging the power of BERT in capturing deeper language context and the capability of SVM in performing more precise classification. This research aims to develop a more accurate and efficient mental health indicator detection model, particularly in detecting depression and anxiety on social media platforms (Sankar et al., 2024).

RESEARCH METHODS

This research method consists of data collection, preprocessing, BERT feature extraction, SVM classification, and evaluation. Here is an explanation of each stage.

Data Collection

The first stage of the research is data collection. The dataset used in this study was obtained from Kaggle, consisting of 62,301 text entries from social media X. The dataset includes tweets and comments related to mental health, categorized into four classes Anxiety, Depression, Stress, and

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Normal. These data were collected based on relevant keywords to ensure coverage of mental health discussions. The sources of tweets vary, including public figures, mental health advocacy groups, and general users. Providing a well-balanced dataset was a priority to ensure model performance across different psychological conditions

Pre-processing data

The second stage of the research is data pre-processing. This stage includes cleaning and simplifying the text so that it can be processed further. The goal of this stage is to improve data quality by removing non-letter characters, standardizing words, and reducing vocabulary volume, so that the results of the sentiment analysis model are expected to be better. In this research, the pre-processing stages include text cleaning, case folding, stopwords removal, stemming, tokenization, normalization, tokenizing, and deduplication, which are carried out sequentially to ensure that the collected data is ready for use (Prakoso et al., 2023)

BERT Feature Extraction

The third stage of the research is BERT feature extraction. BERT was selected due to its superior ability to capture contextual semantics in text, outperforming traditional word embedding models. Feature extraction using BERT is carried out through several key steps to produce rich and meaningful text representations. The process begins with tokenization using the built-in BERT tokenizer, which divides the text into tokens that the model can understand while also adding special tokens like CLS and SEP to help the model comprehend the context and structure of the text. After that, the length of the text is standardized by adding padding to shorter texts or truncating overly long texts to ensure consistent input dimensions. The BERT model then generates embeddings, which are numerical representations of these tokens, capable of capturing contextual relationships between words in the text. The features extracted usually come from the last layer of the BERT model, particularly the CLS token vector, which represents the entire text (Mann et al., 2023).

Classification SVM

The fourth stage of the research is Classification with SVM. Sentiment classification using the Support Vector Machine (SVM) algorithm with BERT features is carried out through several stages. SVM was chosen for classification due to its robustness in handling high-dimensional feature spaces, as demonstrated in previous sentiment analysis studie. The initial step is to divide the dataset into two parts, with 80% for training data and 20% for testing data, ensuring a proportional data distribution for accurate evaluation. Next, Hyperparameter tuning was performed using grid search with 5-fold cross-validation to optimize the SVM classifier. The evaluated parameters included the kernel type (linear, polynomial, RBF), regularization parameter (C = {0.1, 1, 10, 100}), and gamma values for the RBF kernel (gamma = {scale, auto}). The best configuration was determined based on F1-score, ensuring a balanced trade-off between precision and recall. For BERT, fine-tuning was conducted with a batch size of 16, learning rate of 2e-5, and a maximum sequence length of 128 tokens, following best practices outlined in prior NLP studies. After the model has been trained, test data is used to evaluate the model's performance by comparing the predicted results against the original labels. The model's performance is measured using evaluation metrics such as accuracy, precision, recall, and F1-score to ensure the effectiveness of the sentiment classification performed (Gupta & Rattan, 2023).

Evaluation

The fifth stage of the research is evaluation. After the SVM classification stage is complete, the process continues with evaluation using the Confusion Matrix to calculate the accuracy, precision, recall, and F1-Score on the previously processed training and testing data in order to obtain optimal results and assess the quality of the sentiment analysis model that has been created (Bello et al., 2023).

RESULTS AND DISCUSSION

In this study, the researchers aim to evaluate the model's ability to detect mental health indicators on social media using BERT and SVM methods. From the research stages described in the

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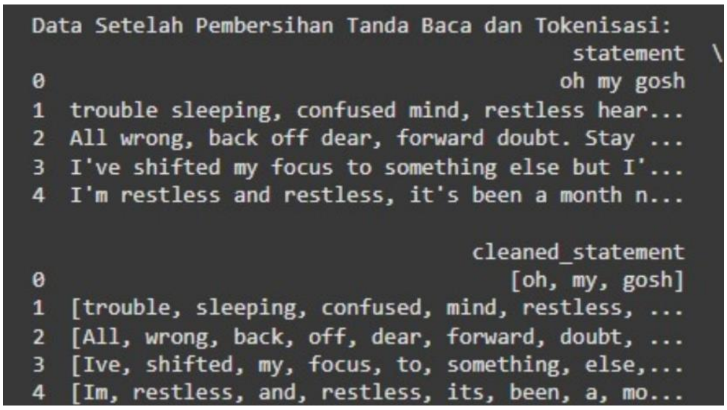
research methodology above, the following discussion results were obtained. At the initial stage of data collection, the researcher gathered data from the Kaggle dataset.

Table 1. Dataset

No	Statement	Status
1.	Trouble sleeping, confused mind, restless hear…	Anxiety
2.	All wrong, back off dear, forward doubt. Stay ...	Anxiety
3.	I've shifted my focus to something else but I'...	Anxiety
4.	I'm restless and restless, it's been a month ...	Anxiety

Next, the data cleaning process is carried out. The process carried out involves the removal of irrelevant elements, such as common words (stop words) that do not contribute significantly in the context of sentiment analysis, as well as special characters that can disrupt model processing. For example, words like all, restless, something and etc. as well as symbols or punctuation marks like commas, periods, and exclamation marks are removed. After this process, the text becomes more concise and focuses on words that have significant meaning in detecting emotional conditions related to mental health.



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Data Setelah Pembersihan Tanda Baca dan Tokenisasi:
                                           statement  \
0                                         oh my gosh
1  trouble sleeping, confused mind, restless hear...
2  All wrong, back off dear, forward doubt. Stay ...
3  I've shifted my focus to something else but I'...
4  I'm restless and restless, it's been a month n...

                                   cleaned_statement
0                                    [oh, my, gosh]
1  [trouble, sleeping, confused, mind, restless, ...
2  [All, wrong, back, off, dear, forward, doubt, ...
3  [Ive, shifted, my, focus, to, something, else,...
4  [Im, restless, and, restless, its, been, a, mo...
```

Figure 1. Data Cleaning

After the text was cleaned, the data was divided into two parts: 80% for training and 20% for testing. The BERT-SVM and SVM models were then trained and tested using this data. Evaluation was conducted based on metrics commonly used in measuring the performance of classification models, namely accuracy, precision, recall, and F1-score.

```
[ ] Akurasi: 0.9349206349206349

    Laporan Klasifikasi:
                         precision    recall  f1-score   support

              Anxiety       0.96      0.94      0.95       383
               Normal       0.82      0.91      0.86        45
  Personality disorder       0.91      0.93      0.92       202

             accuracy                           0.93       630
            macro avg       0.90      0.93      0.91       630
         weighted avg       0.94      0.93      0.94       630
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Figure 2. Model Evaluation BERT and SVM

The BERT and SVM classification models applied in the research shown in figure 2 demonstrate very satisfactory performance, with an overall accuracy reaching 93.49%. Based on the evaluation results, the Anxiety class shows the best performance, with a precision value of 0.96, recall of 0.94, and F1-score of 0.95, indicating the model's excellent ability to detect anxiety disorders. Meanwhile, for the Personality Disorder class, the model also shows good results, with a precision of 0.91, recall of 0.93, and F1-score of 0.92. The performance of the Normal class was lower than other categories, with a precision of 0.82 and an F1-score of 0.86. One primary reason for this discrepancy is the class imbalance, as indicated by the smaller number of samples in this category, leading to insufficient learning representation. Additionally, the semantic overlap between Normal and Anxiety classes may contribute to misclassification, as certain linguistic patterns expressing mild distress could be misinterpreted. Overall, the average macro average precision, recall, and F1-score are 0.90, 0.93, and 0.91 respectively, indicating consistent performance across all classes, regardless of data distribution. Meanwhile, the weighted average precision, recall, and F1-score reaching 0.94 show that the model maintains optimal performance despite the imbalance in data distribution among classes.

```
[ ] Akurasi SVM: 0.8684879288437103

    Laporan Klasifikasi SVM:
                         precision    recall  f1-score   support

              Anxiety       0.87      0.93      0.90       940
               Normal       0.80      0.56      0.66       131
  Personality disorder       0.87      0.84      0.86       503

             accuracy                           0.87      1574
            macro avg       0.85      0.77      0.80      1574
         weighted avg       0.87      0.87      0.87      1574
```

Figure 3. Model Evaluation SVM

The Support Vector Machine (SVM) model applied in the research shown in figure 3 demonstrates an overall accuracy of 86.85%. Evaluation of the model's performance based on precision, recall, and F1-score metrics shows good results for the Anxiety and Personality Disorder classes, with F1-scores of 0.90 and 0.86, respectively. In the Anxiety class, precision is recorded at 0.87, recall at 0.93, and F1-score at 0.90, indicating the model's excellent ability to detect individuals with anxiety disorders. A similar trend is observed in the Personality Disorder class, with precision at 0.87, recall at 0.84, and F1-score at 0.86, indicating that the model is quite reliable in recognizing personality disorders. However, in the Normal class, the model showed lower performance, with precision 0.80, recall 0.56, and F1-score 0.66. This indicates that the model is less effective in accurately detecting this class, likely due to the smaller amount of data in this class (support: 131) compared to other classes. This imbalance in data distribution has the potential to cause model bias towards the class with a larger amount of data. Overall, the macro average values for precision, recall, and F1-score are 0.85, 0.77, and 0.80 respectively, indicating that although the average model performance is quite good, there is an imbalance in performance across classes. On the other hand, the weighted average precision, recall, and F1-score, which each reached 0.87, indicate that the model performs more optimally when considering the data distribution in each class.

Of the two models compared, the BERT classification model and SVM have overall better performance with an accuracy of 93.49%, compared to the SVM model which only reached an accuracy of 86.85%. In the Anxiety class, the BERT and SVM models excelled with an F1-score of 0.95 compared to the SVM model which only had 0.90. For the Normal class, the BERT and SVM models showed much better performance (F1-score 0.86) compared to the SVM model (F1-score 0.66), which was caused by the low recall of the SVM (0.56). Similarly, for the Personality Disorder class, Model 1 excelled with an F1-score of 0.92 compared to the SVM model with 0.86. On average (macro average), Model 1 has an F1-score of 0.91, higher than the SVM Model which only reaches 0.80, indicating that Model 1 is more consistent across all classes and more reliable for classifying psychological conditions.

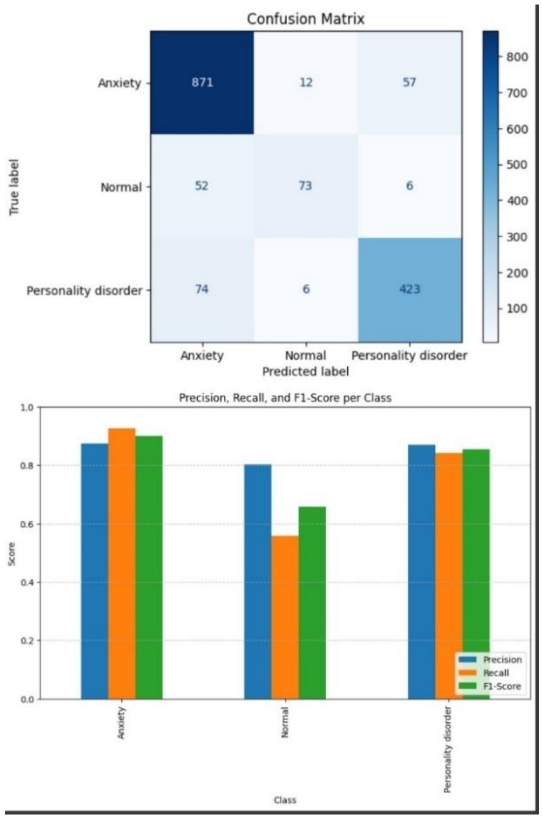

Figure 4. Confusion Matrix

Figure 4 illustrates the confusion matrix and evaluation metrics graph (precision, recall, and F1-score) for the classification model consisting of three classes: Anxiety, Normal, and Personality Disorder. Based on the confusion matrix, the Anxiety class shows very good predictive performance, with 871 samples correctly classified, while only 12 samples were misclassified as Normal and 57 as Personality Disorder. On the other hand, for the Normal class, although there were 73 samples correctly classified, the model struggled to differentiate this class, as evidenced by 52 samples misclassified as Anxiety and 6 as Personality Disorder. Meanwhile, the Personality Disorder class had 423 samples correctly classified, with minor errors, namely 74 samples misclassified as Anxiety and 6 as Normal.

The evaluation metric graph further clarifies the findings in the confusion matrix. Precision, recall, and F1-score for the Anxiety class are all above 0.9, indicating that the model performs very well for this class. Conversely, the Normal class has the lowest performance, with a recall value of around 0.56, indicating that many samples of this class are misclassified as other classes. The Personality Disorder class shows stable metrics, with precision, recall, and F1-score values ranging from 0.86 to 0.87. Overall, these results indicate that the model performs very well in detecting the Anxiety and Personality Disorder classes.

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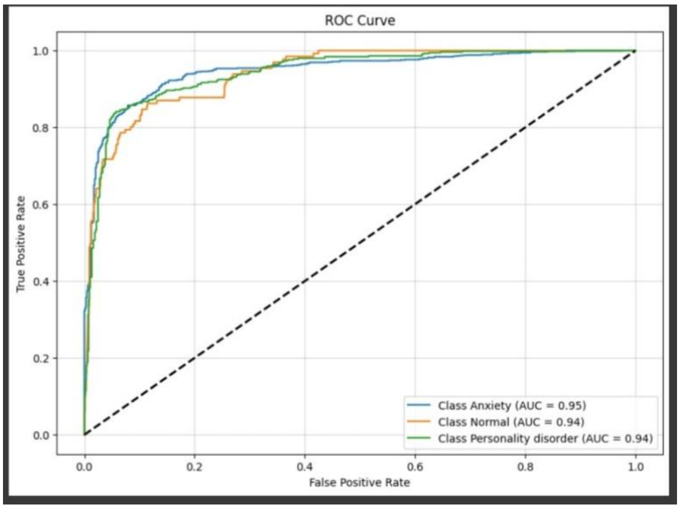

Figure 5. ROC Curve

Figure 5 illustrates the performance of the classification model in distinguishing three classes, namely Class Anxiety, Class Normal, and Class Personality Disorder. ROC is used to evaluate the trade-off between True Positive Rate (TPR) or sensitivity, and False Positive Rate (FPR) at various thresholds. (threshold). Based on the existing curves, the model shows very good performance with high Area Under Curve (AUC) values for each class. The AUC value for the Anxiety Class is 0.95, indicating that the model is very effective in distinguishing anxiety cases from other classes. Meanwhile, the Normal Class and Personality Disorder Class have AUC values of 0.94 each, showing nearly equivalent classification performance between these two classes. The curve that is close to the top left corner of the diagram indicates that the model has high sensitivity while maintaining a low level of false positive rate. This indicates that the model is capable of providing very accurate predictions for all tested classes.

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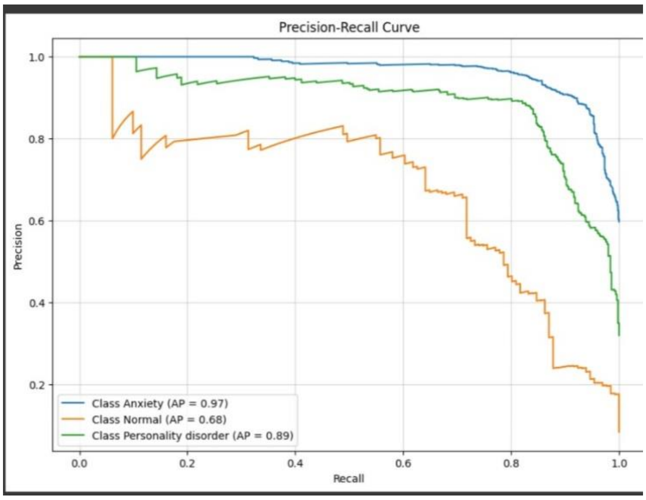

Figure 6. Precision-Recall Curve

Figure 6 is used to evaluate the performance of the classification model based on precision and recall metrics. This curve provides insights into the model's ability to maintain a balance between precision and recall at various thresholds. (threshold). From the curve, Class Anxiety shows the highest Average Precision (AP) value of 0.97, indicating that the model is very effective in identifying anxiety cases with consistent accuracy. On the other hand, Class Personality Disorder has an AP of 0.89, which reflects good performance although slightly lower than Class Anxiety. Conversely, Class Normal shows a lower AP value of 0.68, indicating that the model faces difficulties in accurately predicting the normal class. Overall, the model demonstrates good capability in detecting anxiety and personality disorder cases, but its performance on the Normal Class still needs improvement.

While sentiment analysis provides promising capabilities for detecting mental health indicators, its application to social media data raises several ethical concerns. One primary issue is user privacy, as many individuals may not be aware that their public posts are being analyzed for mental health classification. Additionally, the risk of misclassification could lead to negative consequences, such as falsely labeling a healthy individual as distressed or failing to detect someone in need of urgent support. To address these concerns, mental health detection systems should be designed with strict data privacy protocols, ensuring user anonymity and transparency in how predictions are made. Moreover, integrating these tools into professional mental health services rather than using them as standalone diagnostic systems can help mitigate risks. By functioning as early detection support for clinicians, mental health organizations, and crisis intervention teams, sentiment analysis can contribute valuable insights without replacing expert judgment. Given these considerations, the integration of into mental health services must be approached carefully. However, when implemented responsibly, these models have the potential to revolutionize mental health monitoring. The following section explores practical applications where sentiment analysis can support mental health professionals and improve access to timely interventions.

CONCLUSION

This research demonstrates that social media data can serve as an effective indicator for detecting mental health conditions such as anxiety and personality disorders. The developed BERT+SVM model achieved a high accuracy of 93.47%, making it a promising tool for sentiment-based mental health assessment. However, challenges remain, particularly in the classification of normal conditions, where the model exhibited lower precision due to data imbalance and semantic overlap with anxiety-related posts. To enhance practical applications, mental health professionals should consider integrating sentiment analysis as a complementary tool in digital mental health platforms, ensuring that human oversight is maintained. Additionally, policy makers and ethical committees should establish clear data privacy guidelines to protect users while leveraging for public health monitoring. These findings make an important contribution to efforts to improve community well-being through an interdisciplinary approach that combines technology with the field of mental health.

CONFLICT OF INTEREST

The author(s) declare(s) that there is no conflict of interest.

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