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Depression Detection of Users in Social Media X using IndoBERTweet

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Abstract: According to the Ministry of Home Affairs, the population of Indonesia stands at 273 million, Indonesia has approximately 167 million active subscribers to virtual entertainment platforms, including YouTube, Facebook, Instagram, and X. The use of online entertainment is huge, particularly on X, and has been associated with mental health implications, such as depression. This research objective is to do a comprehensive study about the IndoBertweet deep learning framework to investigate the prevalence of depression in social media, focusing on X. Utilizing the DASS-42, the research estimates depression levels based on user interactions and reactions to tweets. The results of this research showed that the IndoBERTweet method achieved an accuracy rate of 82% in detecting depression using X data. This research highlights the importance of intervention strategies to support the mental health of social media users, emphasizing the importance of proactive measures in addressing mental well-being issues in the digital space.

Keywords: Social Media, Depression, X, DASS-42, IndoBERTweet

INTRODUCTION

According to the Ministry of Home Affairs, the population of Indonesia is approximately 273 million individuals (*273 Juta Penduduk Indonesia Terupdate Versi Kemendagri*, n.d.). Research titled "We Are Social" stated that a total of 167 million people actively engage with social media platforms (*Pengguna Media Sosial Di Indonesia Sebanyak 167 Juta Pada 2023*, n.d.). The same research highlights the current interest of Indonesians in various types of social media, including YouTube, Facebook, Instagram, and X. X, functioning as a social networking and microblogging service, enables users to disseminate information, promote businesses, and express viewpoints within the constraint of 140 characters known as Tweets. Additionally, X facilitates user interaction through comment sections and private direct messaging features (ELCOM;, 2010). Despite its widespread popularity, the use of social media has been associated with psychological impacts that may affect an individual's mental well-being, such as depression.

Depression is a prevalent mental disorder within society, characterized by symptoms such as sleep disturbances and decreased appetite (Lubis, 2016). Prolonged untreated depression can impose cognitive burdens and disrupt the immune system (Dirgayunita, 2016). (Suwistianisa et al., 2016) stated that patients unable to adapt to their illness may experience depression, leading to a decline in immune function and exacerbating their condition. While conventional methods, such as psychological tests, can be employed for depression diagnosis, the utilization of data science methods offers a more effective and efficient approach, as demonstrated in previous research endeavors.

In this research, the DASS-42 (Depression, Anxiety, and Stress Scales) questionnaire plays an important role as a measurement tool to detect and understand the level of depression among social media users, particularly on the X platform. The DASS-42 has been shown to be effective in measuring levels of stress, anxiety, and depression in individuals, providing a deep insight into one's emotional state (Ulfah, 2019). Engaging respondents on answering 42 carefully selected questions, this questionnaire provides accurate and quantitative information regarding levels of depression, anxiety, and stress. The use of the DASS-42 is also relevant for identifying behavioral patterns and user interactions on the X platform that may be associated with depressive symptoms. In addition, this study aims to establish a solid foundation for the development of more efficient diagnostic methods to detect depression in the context of social media, focusing on sensitivity to online interactions and social media behaviors.

This research utilizes the IndoBERTweet model to assess depression levels on X due to its proven effectiveness in previous research. Fikri Ilham utilized the BERT algorithm, achieving a precision of 52%, while Rafal Pos

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Winata and Michael Pelkiewicz improved upon BERT with the RoBERTa strategy, yielding a superior precision of 66.4%. In addition, Fajri Koto et al. demonstrated IndoBERTweet's success in sentiment analysis on Indonesian X with impressive accuracies of 86.2% (IndoLEM) and 90.4% (SmSA). Moreover, Sitti Saadah et al. applied IndoBERTTweet in public opinion sentiment analysis related to the COVID-19 vaccine, achieving notable accuracies of 73%. These outcomes showcase the reliability and proficiency of the IndoBERTweet model, justifying its selection for this study on depression detection in the Indonesian X environment.

LITERATURE REVIEW

Several studies have been conducted to diagnose depression using various algorithms. One such study was conducted by (Ilham & Maharani, 2022) using the BERT (Bidirectional Encoder Representations from Transformers) algorithm, stating its accuracy of 52%. The other research was conducted by (Poswiata & Perełkiewicz, 2022) using the RoBERTa method, an architectural development of BERT, which showed much better proficiency compared to previously published models. This is evidenced by an accuracy rate of 66.4%, surpassing the performance of the BERT architecture.

Fajri Koto, et al, implemented A Pretrained Language Model for Indonesian X with Effective Domain-Specific Vocabulary Initialization using the IndoBERTweet model. This research produces significant accuracy, namely the results of sentiment analysis using IndoBERTweet of 86.2% (IndoLEM) and 90.4% (SmSA) (Koto et al., 2021).

Sitti Saadah, et al, used the IndoBERT, IndoBERTTweet, and CNN-LSTM methods, to conduct public opinion sentiment related to the COVID-19 vaccine in Indonesia from X. The accuracy results using the IndoBERT method were 64% and an f1 score of 68%, then using IndoBERTweet of 73% and an f1 score of 73%, then using CNN-LSTM reached 66% and an f1 score of 61% (Saadah et al., 2022).

Referring to previous research, this research aims to describe the utilization of the deep learning framework, namely IndoBERTweet, for detecting depression among users on the X social media platform in Indonesia. Subsequently, the objective is to evaluate the accuracy and performance of the IndoBERTweet method in predicting the likelihood of depression among X users.

METHOD

This system is constructed utilizing deep learning techniques, specifically IndoBERTweet, which uses tweets as the main element to detect depression in X users. Figure 1. Illustrates the flowchart of the research methodology.

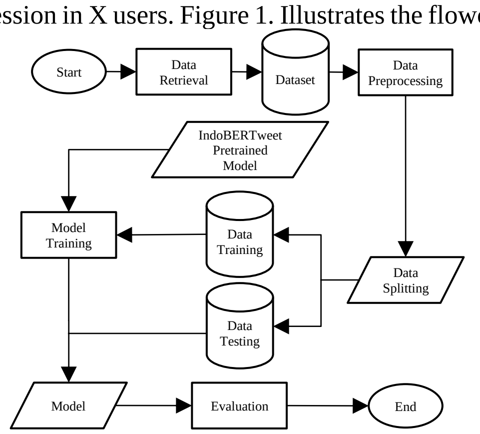

Fig. 1 Workflow

Data Retrieval

The data retrieval process began with collecting the information through the DASS-42 questionnaire for respondents, which included questions related to levels of depression, stress, and anxiety. After obtaining consent from respondents, user tweet data was crawled through the X social media platform. The data collected will be merged and saved in a CSV file format containing details such as usernames, tweets, and depression labels. The determination of the depression label was done by referring to the DASS-42 scale as the main guide in the data labeling process.

This research used the DASS-42 survey, a 42-item self-report scale designed by (Lovibond & Lovibond, 1995). The survey measures levels of stress, anxiety, and depression and was validated on a diverse sample of 1,044 people aged 17 to 69, including students, health professionals, and employees from various sectors. Although it is not standardized for individuals under 17, its simplicity makes it suitable for adolescents aged 12 and above. The DASS-42 is essential in clinical settings for assessing a person's depressive, anxious, and stressful states, providing high internal consistency and significant variance in various contexts (*Depression Anxiety Stress Scales – Long Form (DASS-42) – NovoPsych*, n.d.). Its application has proven to be beneficial for researchers and those

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monitoring changes over time, making it an appropriate choice for assessing mental health conditions in the context of social media.

Dataset

The data retrieval process began with collecting the information through the DASS-42 questionnaire for respondents, which included questions related to levels of depression, stress, and anxiety. After obtaining consent from respondents, user tweet data was crawled through the X social media platform. The data collected will be merged and saved in a CSV file format containing details such as usernames, tweets, and depression labels. The determination of the depression label was done by referring to the DASS-42 scale as the main guide in the data labeling process.

The resulting dataset includes sentences that describe users' emotional expressions and phrases. This dataset shows the informal characteristics and diversity inherent in the Indonesian language. The dataset demonstrates the blend of formal and informal language, which gives rise to the diversity of language expression on the X platform. This dataset forms the basis of analysis in our research, facilitating a deeper understanding of the diverse patterns of Indonesian language expression and content in the X environment. An illustrative representation of the content posted by X users can be seen in Table 1.

Table 1. Table User X

Tweet	Username	Score	Label
Hidup ini terasa berat. Saya ngerasa hmpa dan kehilangan semangattttt untuk melangkah ke depan. #Depresi 😵	@username_123	18	1

Preprocessing Dataset

Data Processing is to make sure that the developed model does not suffer from misrepresentation in sentences. This stage is after the data collection stage. Based on previous research conducted by (Ilham & Maharani, 2022). When performing depression detection, several processing steps can be carried out which are then complemented by adding several processing steps. The following steps are included in several techniques for pre-processing data: Lower Casing, Stop Word Removal, Replace Slang, Remove Elongation, Emoji to Word, Cleaning, Lemmatization, Tokenization, and Replace Typo. The result of this stage is indicated in Table 2.

Table 2. Result Of Pre-Processing Text

Stages	Result of Pre-Processing Stages
Actual Text	Hidup ini terasa berat. Saya ngerasa hmpa dan kehilangan semangattttt untuk melangkah ke depan. #Depresi 😵
After Lower Casing	hidup ini terasa berat. saya ngerasa hmpa dan kehilangan semangattttt untuk melangkah ke depan. #depresi 😵
After Stop Word	hidup terasa berat ngerasa hmpa kehilangan semangattttt melangkah #depresi 😵
After Replace Slang	hidup terasa berat merasa hmpa kehilangan semangattttt melangkah #depresi 😵
After Remove Elongation	hidup terasa berat merasa hmpa kehilangan semangat melangkah #depresi 😵
After Emoji to Word	hidup terasa berat merasa hmpa kehilangan semangat melangkah #depresi !wajah_pusing!
After Cleaning	hidup terasa berat merasa hmpa kehilangan semangat melangkah depresi wajah pusing
After Lemmatization	hidup terasa berat merasa hmpa kehilangan semangat melangkah depresi wajah pusing
After Tokenizing	“hidup”,”terasa”,”berat”,”merasa”, “hmpa”,”kehilangan”,”semangat”,” melangkah”,”depresi”,”wajah”, “pusing”

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After Replace Typo	“hidup”,”terasa”,”berat”,”merasa”, “hampa”,”kehilangan”,”semangat”,” melangkah”,”depresi”,”wajah”, “pusing”

IndoBERTweet

IndoBERTweet is a language model pre-trained specifically for the Indonesian language on the X platform. This model represents the first large-scale model tailored for Indonesian X, trained by expanding the monolingual BERT Indonesia. The primary focus lies in efficiently adapting the model under vocabulary mismatches and comparing various methods for initializing BERT embedding layers for new word types. The researchers discovered that initializing with the average embedding of BERT subwords renders pre-training five times more effective than the proposed methods for vocabulary adaptation in terms of extrinsic performance (Koto et al., 2021). Here is the architecture of IndoBERTweet in Figure 2

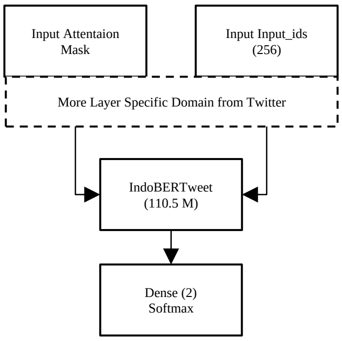

Fig. 2 Architecture IndoBERTweet

The architecture of IndoBERTweet is illustrated in Figure 3. This model comprises 128 layers with an exit value set at 0.5, utilizing a sigmoid function for the activation capability. The underlying concept of the design is that the method processes a sentence by passing it through a tokenization layer. This involves breaking down the sentence into tokens, each with 128 output dimensions, which then traverse the embedding layer of the Keras library.

The tokenization of information using the AutoTokenizer library from transformers with indolem/indobertweet-base-uncased as a boundary is a crucial phase in the development of the IndoBERTweet model in this study. Similar to BERT, the IndoBERTweet tokenizer follows a comparable design, incorporating closing tokens and prefixes, such as [CLS] tokens (*Depression Anxiety Stress Scales – Long Form (DASS-42) – NovoPsych*, n.d.). The evolution of tokens during the development phase is presented in Table III, and an encoded token was employed to configure the data for constructing the IndoBERTweet model.

Table 3. Result Of Pre-Processing Text

Text	Tokenize	Encode Token
“hidup”,”terasa”, ”berat”,”merasa”, “hampa”,”kehilangan”, ”semangat”,”melangkah”, ”depresi”,”wajah”, “pusing”	[‘[CLS]’,’hidup’, ’terasa’,‘berat’, ’merasa’,‘hampa’, ’kehilangan’,‘semangat’, ’melangkah’,‘depresi’, ’wajah’,‘pusing’,’[SEP]’]	[‘[3]’,’2025’, ’5776’,‘3314’, ’3052’,‘21937’, ’4297’,‘4650’, ’10370’,‘12108’, ’4570’,‘12693’,’[4]’]

Evaluation

Following the implementation of the IndoBERTweet modeling, an evaluation of the constructed model will be conducted. This evaluation aims to check the accuracy of the techniques used and determine the extent to which this model can be used effectively. If any shortcomings are identified, corrective measures will be taken. In this evaluation process, a confusion matrix will be used, using four common metrics, namely accuracy, recall, precision, and F1-score.

Confusion Matrix is a table used to characterize the exhibition of a grouping calculation, picture, and sum up the presentation of an order calculation. The consequences of the order are partitioned into 4 attributes, specifically Evident Positive (TP), Genuine Negative (TN), Bogus Positive (FP), and Misleading Negative (FN). The presentation of a framework is estimated in view of exactness, accuracy, review, and f1-score which can be determined in light of TP, TN, FP, and FN (Singh et al., 2021).

Accuracy addresses the proportion to be grouped with the formula (*A Look at Precision, Recall, and F1-Score | by Teemu Kanstrén | Towards Data Science*, n.d.)

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$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP + FP + TN + FN}} \quad (1)$$

Precision is the worth gotten from the exactness of a class with the all-out number of expectations for that class. The reason for accuracy is to see the level of importance of the arrangement results with the equation (Tatbul et al., 2018) :

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall is the worth gotten from the expectation precision of a class with the all-out number of realities for that class. Review can be determined by the formula (Tatbul et al., 2018) :

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-score is an evaluation calculation done by combining both precision and recall values. F1-score can be calculated with the formula (Tatbul et al., 2018):

$$f1 - score = \frac{2 * (Recall * Precision)}{Recall + Precision} \quad (4)$$

RESULT

Applying the IndoBERTweet method to X data, with an initial dataset of 4,892 entries, 9,691 additional data points were included, resulting in a dataset with a total of 14,583 entries from 184 users. This dataset consists of three columns: username, tweets, and labels. The username column consists of the user's username, then the tweet column contains the user's many tweets, and the label column contains the cumulative score derived from the DASS-42. In this labeling scheme, users who are identified as depressed are labeled 1, while users who are not depressed are labeled 0. The labeling stage is done manually based on the accumulated scores from the DASS-42.

Then, the dataset is adjusted to the input that can be accepted by BERT using a tokenizer. Then the indobertweet-base-uncased model is loaded. After that, implement the DocumentDepressionDataset class for data loading. which is used as a standardization of the length of subwords by cutting some subwords or adding padding tokens. It is necessary to implement a DocumentDepressionDataLoader that processes the list of subwords and depressions and outputs padded_subword, mask, and depression. The last step is to use fine-tuning techniques with the indobertweet-base-uncased model, in this research using the Transformers library provided by HuggingFace. This library provides thousands of pre-trained models that are used to perform depression detection in this research. And the main focus of the test scenarios in this research revolves around the preprocessing and evaluation stages of the IndoBERTweet method. The evaluation mainly concentrates on data partitioning to optimize performance on both testing and training datasets.

Classification Report

Each model is evaluated using several metrics in the classification report: accuracy, review, f1-score, and exactness. Recall is the ratio of true-positive predictions to true-positive data, and f1-score is the harmonic mean of precision and recall (Flach & Kull, 2015)(Wright, 2017). Precision is the ratio of true-positive data to the number of predicted positive data. The similarity value between the prediction and the actual measured value is known as accuracy (Beauxis-Aussalet & Hardman, 2014). Based on the division of the dataset, the evaluation of the IndoBERTweet classification report on the testing data is shown in Table 4.

Table 4. Classification Report Result

Split Data	Precision	Recall	F1-Score	Accuracy
60:40	79%	62%	56%	62%
70:30	81%	69%	65%	69%
80:20	**86%**	**82%**	**81%**	**82%**

Confusion Matrix

Confusion matrix is an assessment technique to calculate the execution of characterization cycles or assess the error in classifiers (Beauxis-Aussalet & Hardman, 2014). We evaluate the performance of the model with the test data and display it on a confusion matrix with the predicted and true labels, as shown in Table 5.

Table 5. Confusion Matrix Result

Split Data	True Negative	False Positive	False Negative	True Positive
60:40	10	0	8	3
70:30	3	5	0	8

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80:20	3	2	0	6

DISCUSSIONS

Evaluation with a 60:40 data split on Table 5. There were 10 True Negatives (TN), 0 False Positives (FP), 8 False Negatives (FN), and 3 True Positives (TP). These results indicate that the model tends to be accurate in identifying the negative class (TN), but has a significant error rate in recognizing the positive class (FP and FN). The model has difficulty recognizing signs of depression because the tweets analyzed by the model tend to contain words that have positive meanings, which are inversely proportional to the labels derived from the DASS-42. This will be challenges in the identification of depressive symptoms which are often manifested through ambiguous emotional expressions or expressed with language that does not directly reflect the psychological state that may be associated with depression.

In the 70:30 data split, there was a significant increase in True Positives (TP) to 8, but considerable increase in False Positives (FP) to 5. This may indicate an improvement in the model's ability to identify depression (TP), but also a tendency to make more errors by classifying non-depression data as depression (FP). While the model has proven to be very effective in recognizing signs of depression from users' tweets that contain negative meanings, it should be noted that negative user tweets are not necessarily congruent with the user's psychological state, as reflected in the DASS-42 results as labels.

In the 80:20 data split, it can be seen that True Positives (TP) increased to 6, while False Positives (FP) and False Negatives (FN) decreased. This can be interpreted as an improvement in the model's ability to recognize depression. The model has performed very well in recognizing signs of depression from negative user tweets. In addition, the decrease in False Positives (FP) and False Negatives (FN) could be due to the lack of variation in the test data. Furthermore, it should be noted that two users' negative tweets are not aligned with their psychological state, as based on the DASS-42 questionnaire assessment results as labeled.

The experimental results show that the IndoBERTweet model in this study managed to achieve the highest accuracy with a result 82%. In comparison, previous research using BERT with the same data division only achieved the highest accuracy of 71% (Ilham & Maharani, 2022).

CONCLUSION

This research employs the deep learning framework IndoBERTweet to detect depression among X users in Indonesia. The model demonstrates a commendable accuracy of 82% with an 80:20 data split, showcasing its effectiveness in identifying signs of depression based on user tweets. The evaluation encompasses model training, validation data, classification reports, and confusion matrices, providing a comprehensive understanding of the model's predictive outcomes. The findings reveal that certain X users exhibit depressive conditions, emphasizing the potential for proactive interventions to support mental health in the digital realm. Despite challenges observed, particularly in misclassifying non-depressed data as depressed, the model's performance improves at an 80:20 data split, highlighting its enhanced ability to recognize depression. This underscores the significance of leveraging IndoBERTweet as a valuable tool for mental health assessment on social media platforms

REFERENCES

273 Juta Penduduk Indonesia Terupdate Versi Kemendagri. (n.d.). Retrieved May 20, 2023, from https://dukcapil.kemendagri.go.id/berita/baca/1032/273-juta-penduduk-indonesia-terupdate-versi-kemendagri

A Look at Precision, Recall, and F1-Score | by Teemu Kanstrén | Towards Data Science. (n.d.). Retrieved December 20, 2023, from https://towardsdatascience.com/a-look-at-precision-recall-and-f1-score-36b5fd0dd3ec

Beauxis-Aussalet, E., & Hardman, L. (2014). Visualization of Confusion Matrix for Non-Expert Users. In *IEEE Conference on Visual Analytics*.

Depression Anxiety Stress Scales – Long Form (DASS-42) – NovoPsych. (n.d.). Retrieved May 20, 2023, from https://novopsych.com.au/assessments/depression/depression-anxiety-stress-scales-long-form-dass-42/

Dirgayunita, A. (2016). Depresi: Ciri, Penyebab dan Penangannya. *Journal An-Nafs: Kajian Penelitian Psikologi*, *1*(1), 1–14. https://doi.org/10.33367/PSI.V1I1.235

ELCOM;, T. A. O. T. (2010). *Twitter; Best Social Networking*. //libcat.uin-malang.ac.id%2F%2Findex.php%3Fp%3Dshow_detail%26id%3D18732

Flach, P. A., & Kull, M. (2015). Precision-Recall-Gain Curves: PR Analysis Done Right. *Advances in Neural Information Processing Systems*, *28*. http://www.cs.

Ilham, F., & Maharani, W. (2022). Analyze Detection Depression In Social Media Twitter Using Bidirectional Encoder Representations from Transformers. *Journal of Information System Research (JOSH)*, *3*(4), 476–482. https://doi.org/10.47065/JOSH.V3I4.1885

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 2, April 2024
DOI : https://doi.org/10.33395/v8i2.13354

e-ISSN : 2541-2019
p-ISSN : 2541-044X

Koto, F., Lau, J. H., & Baldwin, T. (2021). IndoBERTweet: A Pretrained Language Model for Indonesian Twitter with Effective Domain-Specific Vocabulary Initialization. *EMNLP 2021 - 2021 Conference on Empirical Methods in Natural Language Processing, Proceedings*, 10660–10668. https://doi.org/10.18653/V1/2021.EMNLP-MAIN.833

Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. *Behaviour Research and Therapy*, *33*(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

Lubis, N. L. (2016). Depresi : Tinjauan Psikologis. In *Kencana*. https://books.google.co.id/books?hl=id&lr=&id=p_pDDwAAQBAJ&oi=fnd&pg=PR5&dq=depresi+tinjauan+psikologis+Lubis+N+lumongga&ots=aNzLCRcYbf&sig=GxnzqgqzbIsGlMLjKadrgL8t_W8&redir_esc=y#v=onepage&q&f=false

Pengguna Media Sosial di Indonesia Sebanyak 167 Juta pada 2023. (n.d.). Retrieved May 20, 2023, from https://dataindonesia.id/digital/detail/pengguna-media-sosial-di-indonesia-sebanyak-167-juta-pada-2023

Poswiata, R., & Perełkiewicz, M. (2022). OPI@LT-EDI-ACL2022: Detecting Signs of Depression from Social Media Text using RoBERTa Pre-trained Language Models. *LTEDI 2022 - 2nd Workshop on Language Technology for Equality, Diversity and Inclusion, Proceedings of the Workshop*, 276–282. https://doi.org/10.18653/V1/2022.LTEDI-1.40

Saadah, S., Auditama, K. M., Fattahila, A. A., Amorokhman, F. I., Aditsania, A., & Rohmawati, A. A. (2022). Implementation of BERT, IndoBERT, and CNN-LSTM in Classifying Public Opinion about COVID-19 Vaccine in Indonesia. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *6*(4), 648–655. https://doi.org/10.29207/RESTI.V6I4.4215

Singh, P., Singh, N., Singh, K. K., & Singh, A. (2021). Diagnosing of disease using machine learning. *Machine Learning and the Internet of Medical Things in Healthcare*, 89–111. https://doi.org/10.1016/B978-0-12-821229-5.00003-3

Suwistianisa, R. '. (Rizki), Huda, N. '. (Nurul), & Ernawaty, J. '. (Juniar). (2016). Faktor-faktor yang Mempengaruhi Tingkat Depresi pada Pasien Kanker yang Dirawat di RSUD Arifin Achmad Provinsi Riau. *Jurnal Online Mahasiswa Program Studi Ilmu Keperawatan Universitas Riau*, *2*(2), 1463–1473. https://www.neliti.com/publications/188107/

Tatbul, N., Lee, T. J., Zdonik, S., Alam, M., & Gottschlich, J. (2018). Precision and Recall for Time Series. *Advances in Neural Information Processing Systems*, *2018-December*, 1920–1930. https://arxiv.org/abs/1803.03639v3

Ulfah, I. (2019). *krining masalah kesehatan jiwa dengan Kuesioner Dass-42 pada civitas UIN Syarif Hidayatullah Jakarta yang memiliki riwayat Hipertensi*. https://repository.uinjkt.ac.id/dspace/handle/123456789/53675

Wright, D. K. (2017). Accuracy vs. Precision: Understanding Potential Errors from Radiocarbon Dating on African Landscapes. *African Archaeological Review*, *34*(3), 303–319. https://doi.org/10.1007/S10437-017-9257-Z

*Warih Maharani