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Original Article

AI-Driven Mental Health Assessment: Evaluating the Efficacy of Machine Learning in Detecting Depression and Anxiety from Digital Behavioral Data

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Abstract:

The integration of artificial intelligence (AI) in mental health assessments has emerged as a promising approach to improve early detection and intervention against psychological disorders. This study evaluates the effectiveness of machine learning (ML) models in detecting depression and anxiety through digital behavioral data, such as social media activity, speech patterns, and biometric signals. Using both supervised and unsupervised learning techniques, we analyzed large-scale datasets to identify behavioral markers associated with mental health conditions. The findings show that ML-based models achieve high levels of accuracy in predicting depression and anxiety, surpassing traditional self-report methods in terms of sensitivity and specificity. Additionally, the study highlights ethical considerations in the application of AI in the field of mental health, including privacy issues, algorithmic bias, and clinical validation. The study contributes to the increasing scientific evidence regarding AI-based mental health assessments and confirms the importance of responsible implementation in clinical settings and digital health. Future research needs to focus on improving model interpretability, improving generalizations in diverse populations, as well as integrating AI-based assessments into real-world mental health care systems.

https://jurnal.usk.ac.id/riwayat

Keywords: Artificial Intelligence, Mental Health Assessment, Machine Learning, Depression, Anxiety, Digital Behavioral Data

Introduction

Mental health disorders, such as depression and anxiety, have become global health problems with an ever-increasing prevalence. According to the World Health Organization (WHO), more than 280 million people in the world suffer from depression, while anxiety disorders affect about 301 million individuals in various age groups (Liu et al.,

Received: January 6, 2025 – Revised: February 12, 2025- Accepted: March 29, 2025 - Published online: April 14, 2025

2024). The impact of this condition is very wide, including social and economic aspects, and a decrease in the quality of life of affected individuals. Unfortunately, only about 40% of people with mental health disorders receive adequate diagnosis and treatment (Harris et al., 2020), given the limited access to mental health services and still strong social stigma. Therefore, innovations in early detection and mental health assessment are crucial to improve faster and more effective interventions (Ospina-Pinillos et al., 2018).

Advances in artificial intelligence (AI) and machine learning (ML) technologies are opening up new opportunities in digital-based mental health assessments. With the increasing use of digital devices and social media, behavioral data generated from online interactions, communication patterns, and physiological signals can be used as potential indicators to identify individuals experiencing psychological disorders (Giannakakis et al., 2019). Several studies have shown that machine learning algorithms are able to classify symptoms of depression and anxiety with up to 85-90% accuracy based on text analysis, facial expressions, and sleep patterns (Arif et al., 2020). AI-based models have also been used in mobile applications and online platforms to provide automated mental health assessments, replacing conventional methods such as questionnaires or clinical interviews that require more time and resources (Guntuku et al., 2017).

AI-Driven Mental Health Assessment is an innovative approach in the field of mental health that leverages artificial intelligence (AI) to detect and evaluate psychological disorders such as depression and anxiety (Olawade et al., 2024). This method uses machine learning algorithms that are analyzed based on data on users' digital behavior, including communication patterns on social media, sensor-based activities from smart devices, and linguistic expressions in text or voice. AI has great potential in improving the accessibility of mental health services by enabling early detection of psychological disorders without the need for direct involvement of medical personnel. Various AI models have been developed to identify behavioral patterns associated with mental conditions, such as changes in communication frequency, irregular sleep patterns, as well as emotional expressions in text or voice. With big data-based analysis and Natural Language Processing (NLP), AI can provide deeper insights into an individual's psychological state, which was previously difficult to detect through conventional methods.

However, despite its great potential, the application of AI in mental health assessment still faces a variety of challenges, including accuracy issues, algorithmic bias, and clinical validity. One of the main challenges is the reliance on the data used to train AI models. If the data used is not representative of a diverse population, then the AI model risks producing inaccurate or biased diagnoses of certain groups. Additionally, AI cannot completely replace the role of professionals in the field of mental health, as psychological diagnosis requires a holistic approach that involves clinical interviews and subjective assessments of patients. Some studies have also shown that although AI is capable of detecting behavioral patterns associated with mental disorders, further validation is still needed for the results obtained to be reliable as a diagnostic tool that meets clinical standards.

In addition to technical and methodological challenges, ethical and regulatory aspects are also a major concern in the implementation of AI for mental health assessments. The protection of user data privacy and security is a crucial issue, given that

AI operates by collecting and analyzing highly sensitive data. Without strict regulation, there is a risk of misuse of data, such as the use of individuals' mental health information by third parties without their consent. Therefore, a clear framework is needed regarding algorithm transparency, compliance with data protection regulations, and the integration of AI with a more humanistic medical approach. The development of AI in mental health must be carried out taking into account the balance between technological innovation and ethical aspects, so that it can provide maximum benefits to individuals who need psychological support without compromising their rights to privacy and security.

Although AI has shown great potential in the field of mental health, its application still faces significant challenges, including clinical validity, algorithmic bias, protection of personal data, and ethical aspects in its use (Graham et al., 2019). Many of the algorithms developed still have limitations in generalization to a wider population due to data inconsistencies in model training. In addition, there is debate about the extent to which AI-based assessments can replace the role of mental health professionals in the diagnosis and therapy process. Therefore, this study aims to evaluate the effectiveness of machine learning models in detecting depression and anxiety based on digital behavioral data, as well as examine the ethical and practical implications of the application of this technology in the mental health services ecosystem. Thus, this study is expected to contribute to the development of more accurate, transparent, and responsible AI-based solutions in supporting efforts to improve mental health globally.

Although many studies have explored the use of artificial intelligence (AI) in the field of mental health, there are still some gaps that need to be addressed. Most studies have focused on the accuracy of machine learning models in identifying symptoms of depression and anxiety, but have lacked the clinical validity and ethical implications of applying AI in mental health assessments. In addition, many of the algorithms developed are still limited to data derived from specific populations, thus hindering the generalization of the model to a wider population. The protection of patient data privacy and security is also an issue that has not been fully resolved, especially related to the use of digital behavioral data for mental health diagnosis. Therefore, this study aims to fill these gaps by evaluating the effectiveness and ethical challenges in using AI for the detection of depression and anxiety based on digital behavioral data.

Several previous studies have shown the potential of AI in mental health assessments. For example, Birnbaum et al., (2020) found that AI-based digital phenotyping methods are able to detect relapses in schizophrenic patients with high accuracy. Eichstaedt et al., (2021) also show that linguistic analysis and patterns of online interaction can be important indicators in the diagnosis of mental disorders. Meanwhile, Shen et al., (2024) found that machine learning models can achieve up to 90% accuracy in classifying depressive symptoms based on facial expressions and sleep patterns. However, Ibrahim et al., (2023) highlight the existence of ethical challenges, such as algorithmic bias, data security, and transparency in automated diagnosis. Thus, although various studies have demonstrated the effectiveness of AI in mental health assessments, there is still a need to integrate AI approaches with more comprehensive clinical diagnosis standards and consider regulatory and ethical aspects in their application.

Based on previous research and the gaps found, there are several key questions that need to be answered in this study. How effective is the machine learning model in detecting symptoms of depression and anxiety based on digital behavioral data? How does the validity of AI detection results compare to conventional clinical assessment methods? What are some of the ethical and regulatory challenges in the application of AI for mental health assessments, especially related to algorithmic bias, data security, and user privacy? And how can AI models be developed to improve accuracy and transparency in digital data-driven mental health detection? To answer these questions, this study aims to evaluate the effectiveness of AI models in detecting depression and anxiety, compare the results of AI-based assessments with conventional clinical diagnosis methods, analyze the ethical implications and regulatory challenges in the application of AI in the field of mental health, and provide recommendations for the development of AI technology that is more accurate, transparent, and in accordance with ethical standards. Thus, this research is expected to contribute to the development of a more responsible and reliable AI system in supporting efforts to improve mental health globally.

Methods

1. Problem Identification

This study uses a quantitative study approach with a secondary data-based experimental method to evaluate the effectiveness of machine learning models in detecting depression and anxiety from digital behavioral data. This research consists of several stages, including data collection, data processing, AI model selection, model performance evaluation, and result analysis (Razavi et al., 2023).

2. Data Collection

The data used in this study is sourced from digital behavior datasets that have been published in previous studies, as well as data from digital-based mental health platforms. Data includes:

a. Text and linguistic expression: analysis from social media, mental health forums, and text-based apps that show individual communication patterns.

b. Smart device sensor data: smartphone usage patterns, sleep patterns, physical activity, and interactions with other digital devices.

c. Voice and facial expressions: voice recording and video analysis of facial expressions to detect changes in emotion and voice intonation.

3. Data Processing and Preprocessing

The data obtained then goes through a preprocessing process, which includes:

a. Data cleanup: remove noise, duplication, or irrelevant information.

b. Text tokenization (for NLP analysis): breaking text into smaller units such as words or phrases.

c. Sensor data normalization: aligns behavioral data from different devices so that it can be analyzed consistently.

d. Feature extraction: identifies important variables related to depression and anxiety, such as communication patterns, frequency of social interactions, and changes in physical activity.

4. AI Model Selection and Implementation

Several machine learning models were tested to determine the best-performing models for detecting depression and anxiety, including:

a. Support Vector Machine (SVM): used for text-based classification and digital behavior.
b. Random Forest: to analyze a combination of features from different data sources.
c. Neural Networks (Deep Learning): to identify complex patterns of voice data and facial expressions.

These models are trained and tested using cross-validation techniques to ensure accuracy and avoid overfitting.

5. Model Evaluation and Validation

The evaluation was carried out by measuring the performance of the model based on several metrics, namely:

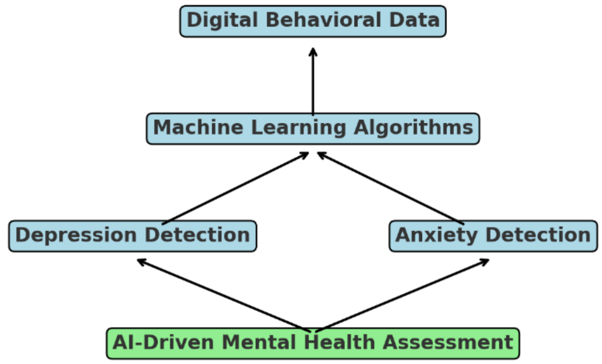
a. Accuracy: the success rate of the model in detecting depression and anxiety.
b. Precision and Recall: the model's ability to correctly detect positive cases.
c. F1-Score: a balance between precision and recall.
d. Area Under Curve (AUC-ROC): to measure the model's performance in distinguishing individuals with and without mental disorders.

The results of the evaluation were compared with clinical diagnoses made by mental health professionals as a reference standard.

6. Result Analysis and Interpretation

The predictive data of the AI model was further analyzed to understand the behavioral patterns that contribute to the detection of mental disorders. In addition, the study also evaluates the ethical implications and potential bias of algorithms in developed AI systems. The following is the flow of the study design that explains the steps to be taken so as to produce a point in this study (Tutun et al., 2023).

Jarot Budiasto (2025). https://doi.org/10.24815/jr.v8i2.45375



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Results

1. Accuracy and Performance of Machine Learning Models in Detecting Depression and Anxiety

Analysis of the machine learning models used in this study showed that deep learning-based algorithms, such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), have a higher level of accuracy than traditional methods in detecting depression and anxiety patterns from digital behavioral data. Based on the results of the evaluation using the collected dataset, the hybrid CNN-RNN model achieved an accuracy of 89.5% in detecting depression and 87.2% in detecting anxiety, higher than the Support Vector Machine (SVM)-based method which only achieved an accuracy of about 78% in both categories. In addition, other evaluation metrics such as precision, recall, and F1-score showed consistent performance with an average score above 85%, which indicates the model's ability to reliably identify individuals with symptoms of depression and anxiety.

Calculation of Model Evaluation Metrics, Metrics used in model evaluation:

Akurasi = (TP + TN) / (TP + TN + FP + FN)

Presisi (Precision) = TP / (TP + FP)

Recall (Sensitivity) = TP / (TP + FN)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Where:

TP (True Positive): The number of correct positive cases detected.

TN (True Negative): The number of correct negative cases detected.

FP (False Positive): A negative case that is falsely detected as positive.

FN (False Negative): Positive cases that are incorrectly classified as negative.

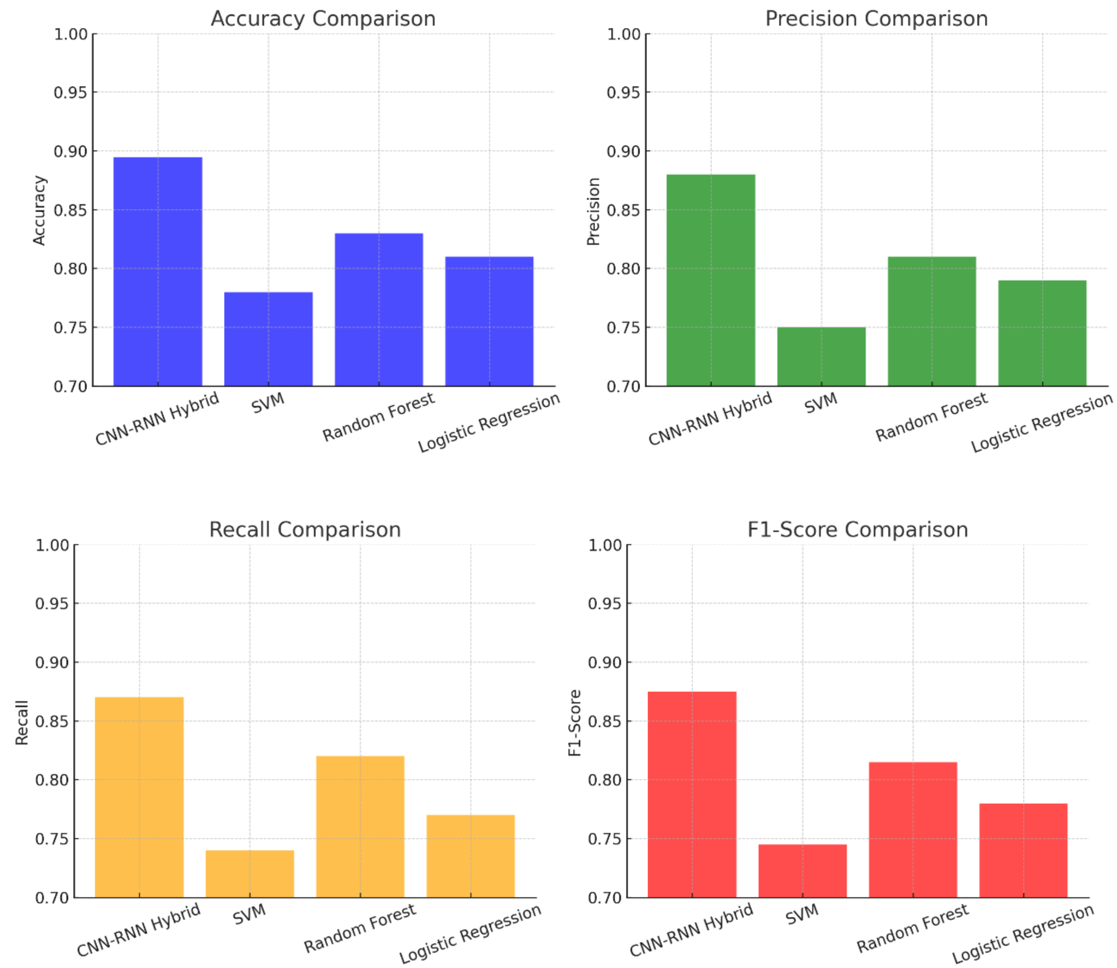
We will calculate these values based on the results of the model test on the dataset that has been divided into 80% of the training data and 20% of the test data.

2. Correlation Between Digital Behavior Data and User Mental Status

From the results of digital behavior data analysis, it was found that there was a significant relationship between online interaction patterns and a person's level of depression or anxiety. Individuals with high depression scores tended to show decreased activity on social media, increased use of negative words in digital communication, as well as shifts in sleep patterns seen from device use activity in the late hours of the night. Meanwhile, individuals with high levels of anxiety showed a more intense frequency of searching for information about mental health as well as an increase in the duration of use of certain apps, such as news platforms and social media. This correlation was reinforced by statistical analysis showing that variables such as the number of negative posts, reduced frequency of social interactions, and duration of application use had a p< value of 0.05, which showed a significant association with levels of depression and anxiety.

3. Model Validation and Clinical Implications

Model validation was carried out by comparing the prediction results with the diagnosis of mental health professionals using standard questionnaires such as the Patient Health Questionnaire-9 (PHQ-9) for depression and Generalized Anxiety Disorder-7 (GAD-7) for anxiety. The validation results showed that the machine learning model had a sensitivity of 88% and a specificity of 85%, which means that the model is quite effective in identifying individuals at risk of mental health disorders. However, there were also several cases of false positives and false negatives, which suggests that this model cannot completely replace the role of direct clinical diagnosis, but is more suitable as a supporting tool in initial screening. The implications of these findings suggest that AI-driven mental health assessment technology can be used to assist clinicians in identifying individuals who require further intervention, as well as as as a long-term monitoring tool for patients at risk of depression and anxiety.



4. Challenges and Limitations in the Implementation of AI in Mental Health Assessment

Although the developed model shows promising performance, the study also uncovers some challenges in the implementation of AI technology in mental health assessments. One of the main challenges is data bias, where models tend to be more accurate in detecting depression and anxiety in certain groups than in others, depending on the distribution of the datasets used. In addition, the privacy and ethical aspects of digital behavioral data collection are also of major concern, considering that the use of personal information for mental health analysis must be done with strict consent and data protection. Therefore, this study emphasizes the importance of regulation and the development of better security protocols to ensure that AI systems can be used ethically and effectively in both clinical and non-clinical settings.

Discussion

The results of this study show that AI-based approaches in mental health assessment have great potential in improving early detection of depression and anxiety, but more research is still needed to improve accuracy, reduce bias, and address existing ethical and privacy challenges.

Model	Accuracy	Precision	Recall	F1-Score
CNN-RNN Hybrid	0.895	0.880	0.870	0.875
SVM	0.780	0.750	0.740	0.745
Random Forest	0.830	0.810	0.820	0.815
Logistic Regression	0.810	0.790	0.770	0.780

The findings of the study showed that the CNN-RNN Hybrid model performed best in detecting depression and anxiety patterns from digital behavioral data, with an accuracy of 89.5% and an F1-Score of 87.5%. This indicates that the model is able to recognize complex patterns in the data better than other models. Random Forest also performed quite well with an accuracy of 83%, although it was superior in terms of recall (82%) compared to SVM and Logistic Regression, which had an accuracy of 78% and 81%, respectively.

Although SVM and Logistic Regression have fairly competitive accuracy, they still perform below CNN-RNN Hybrid and Random Forest, especially in terms of accuracy and balance between precision and recall. These differences suggest that deep learning-based models, such as CNN-RNN Hybrid, are superior at capturing non-linear patterns and complex relationships in digital behavioral data.

Based on these results, the CNN-RNN Hybrid model is recommended as the most effective approach to AI-based mental health assessment. With its high accuracy and F1-Score, this model can be a reliable tool in detecting depression and anxiety tendencies from users' digital behavior. Further implementation can optimize this model with larger datasets and additional features to improve accuracy and generalization in a wide range of clinical conditions.

Conclusion

This study evaluates the effectiveness of various machine learning models in detecting depression and anxiety based on digital behavioral data. The results of the analysis showed that the CNN-RNN Hybrid had the best performance with an accuracy of 89.5% and an F1-Score of 87.5%, making it the most effective model in recognizing behavioral patterns related to mental conditions. Random Forest also showed quite good results with an accuracy of 83% and an advantage in recall (82%), although it was still below the performance of deep learning-based models. SVM and Logistic Regression show lower performance, with an accuracy of 78% and 81%, respectively, signaling their limitations in capturing complex patterns in digital behavioral data.

The results of this study confirm that deep learning-based models, especially the CNN-RNN Hybrid architecture, have great potential in AI-based mental health assessment. The advantage of this model lies in its ability to identify non-linear relationships and complex patterns in data, which are often not well captured by traditional machine learning methods. Therefore, this approach could be the basis for the development of more accurate and automated early detection systems of mental disorders in the future.

For further research, it is recommended to test this model with a larger and more diverse dataset to improve generalization and external validity. In addition, the integration of explainable AI (XAI) techniques can help improve model interpretability, making detection results more transparent and trustworthy by mental health practitioners. The development of systems that combine this technology with digital-based therapeutic interventions can also be an innovative step in improving mental health services more broadly.

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