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Design and Development of a Predictive AI Model for Early Detection of Mental Disorders in Adolescents

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ABSTRACT
Adolescents are a vulnerable age group for mental disorders such as depression, anxiety, and stress. Early detection is crucial to enable timely and appropriate interventions. This study aims to design and develop a predictive artificial intelligence (AI) model capable of identifying potential mental health issues in adolescents. The research applies a quantitative experimental approach, collecting data through the locally validated DASS-21 questionnaire. The data were analyzed using Random Forest, Support Vector Machine, and Multilayer Perceptron algorithms, evaluated by accuracy, precision, recall, and F1-score metrics. The findings indicate that the Random Forest model achieved the highest accuracy at 87.4%. The system was designed with a user-friendly interface that delivers prediction results along with initial intervention recommendations. This study offers a significant contribution to preventive efforts in adolescent mental health through adaptive, accurate, and ethical AI-based technology.
Keywords: mental disorder, adolescents, artificial intelligence, prediction, Random Forest, DASS-21

INTRODUCTION

Adolescent mental health has become an increasingly important global issue, especially as adolescence is a critical developmental stage that is highly influenced by both internal and external factors, such as academic pressure, social environment, and digital media exposure (Mardini et al., 2025). According to the World Health Organization (WHO, 2023), more than 10% of adolescents worldwide experience mental health disorders, yet over half remain undiagnosed and receive no early intervention (Liu et al., 2025). In the Indonesian context, limited access to psychological services and persistent social stigma make early detection of mental health issues particularly challenging. Alongside technological advancements, artificial intelligence (AI) has begun to be utilized across various fields, including mental health, as a tool to help detect psychological symptoms more quickly, objectively, and at scale (Yang et al., 2025).

Previous studies have demonstrated the potential of AI in identifying mental health disorders. Guntuku employed AI-based linguistic analysis of social media to detect depression(Guntuku et al., 2019), while Nguyen developed a multimodal deep learning approach to identify anxiety using text and audio data (Nguyen & Phung, 2021). In Indonesia, Ririn applied the Random Forest algorithm to predict stress levels among university students using questionnaire data (Ririn et al., 2025). Abimanyu utilized the Support Vector Machine (SVM) method to classify depressive symptoms based on DASS-24 scores (Satria et al., 2023), and Sudrajat developed an ensemble model to detect tendencies toward depression among high school students (Sudrajat & Zakariyah, 2024). While these studies offer valuable contributions, they exhibit several limitations, such as focusing solely on a single disorder (most commonly depression), lacking cultural and linguistic localization, and not integrating AI results into systems that are directly usable by non-technical users such as adolescents, teachers, or counselors.

Some researchers have concentrated on developing algorithms for single-disorder detection, and few have implemented a predictive multi-label approach locally within Indonesia. There is a limited number of studies that have addressed the development of an AI-based early detection system capable of identifying depression, anxiety, and stress simultaneously, while also presenting results in a youth-friendly interface that considers ethical and data privacy aspects (Sharma et al., 2025). Therefore, this study aims to design and develop a multi-label predictive AI model based on local Indonesian data to detect three major types of mental disorders among adolescents using machine learning algorithms, with an interface system that supports ethical and informative result interpretation. The novelty of this research lies in the development of a multi-label predictive model based on Indonesian local data that simultaneously integrates the detection of depression, anxiety, and stress, accompanied by a user-friendly interface specifically designed for adolescents, taking into account language, cultural context, as well as data security and ethical principles.

METHODOLOGY

This study employs a quantitative experimental approach based on the development of a machine learning model using predictive algorithms for the early detection of mental disorders in adolescents (Tate et al., 2020). The model was constructed and validated through a series of tests using primary data collected from psychological questionnaires, as well as supporting secondary data. Prior to implementation, the study received ethical approval from the university's ethics committee, including informed consent from both participants and their parents or guardians. All data were stored anonymously and encrypted to ensure user confidentiality.

The stages of this research are illustrated in Figure 1 below.

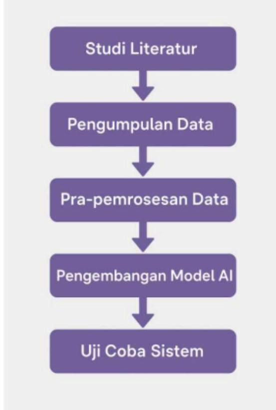

Figure 1: The stages of this research

1. **Literature Review**

This stage involves examining AI methods that have been used for detecting mental disorders and developing the system architecture along with interface mock-ups.

2. **Data Collection**

Data are gathered through three sources:

- The Indonesian-language version of the standardized Depression Anxiety Stress Scale (DASS-21) (Lovibond & Lovibond, 1995; adapted by Listiyandini (Listiyandini et al., 2024)).
- A brief demographic form recording age, gender, and school of origin.
- Limited observation of digital-behavior patterns (optional and only with written consent).

The study population comprises adolescents aged 13–18 years from several junior and senior high schools in urban and semi-urban areas. Purposive sampling is employed with the following criteria:

- Age between 13 and 18 years;
- Willingness to complete the questionnaire and provide consent (including parental or guardian approval);
- Not currently undergoing active psychiatric treatment.

The target sample is 300 respondents, divided into 70 % for training, 15 % for validation, and 15 % for testing.

3. **Data Pre-processing**

Before model training, the data undergo:

- Data cleaning**:** removal of empty or invalid entries.
- Encoding**:** conversion of questionnaire scores into risk labels (high, moderate, low).
- Normalization**:** Min–Max scaling to standardize feature ranges.

4. AI Model Development

Models are built with three algorithms:

- Random Forest Classifier, robust against overfitting and suitable for categorical and numerical data (Rahma et al., 2025).
- Support Vector Machine (SVM)**,** effective for high-dimensional data.
- Multilayer Perceptron (MLP), a simple deep-learning approach.

Multi-label classification is applied because respondents may exhibit symptoms of more than one disorder simultaneously (e.g., depression and anxiety). Models are compared using accuracy, precision, recall, and F1-score, and the best model is integrated into the system.

5. System Testing

Data analysis is performed in Python using:

- Scikit-learn for machine-learning modeling and evaluation;
- Pandas and NumPy for data manipulation and cleaning;
- Matplotlib/Seaborn for visualizing classification results and data correlations.

Model performance is assessed with:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-score = 2 × (Precision × Recall) / (Precision + Recall)

RESULTS AND DISCUSSION

1. Data Preprocessing Results

Out of 300 adolescent respondent entries, 278 valid datasets were successfully used after undergoing cleaning and validation processes. The distribution of psychological symptoms is as follows:

- 32% showed symptoms of mild to severe depression,
- 41% exhibited signs of anxiety,
- 26% indicated stress-related symptoms.

The labels were determined based on scores from the DASS-21 questionnaire and were subsequently converted into a multi-class label format for classification purposes.

2. AI Model Training Results

Three machine learning algorithms were compared to identify the best-performing model. The evaluation results on the testing set (15% of the total data) are as follows:

Table 1
Results on the testing set

Algoritma	Akurasi	Precision	Recall	F1-Score
Random Forest	87.4%	85.1%	86.8%	**85.9%**
Support Vector Machine	82.6%	80.3%	79.7%	80.0%
Multilayer Perceptron	84.1%	82.5%	81.2%	81.8%

The results indicate that the Random Forest algorithm delivered the best performance in terms of stability and interpretability, making it the most suitable choice for the initial implementation of the system.

3. Feature Analysis (Feature Importance)
The analysis of feature importance, as identified by the Random Forest model, reveals that the following variables play a dominant role in predicting potential mental health disorders: (AlSagri & Ykhlef, 2020)

- Depression Score (DASS-21) – This feature has the highest predictive weight, highlighting the strong link between self-reported depressive symptoms and the likelihood of mental health issues. Higher scores often correlate with increased risk, making this metric a critical diagnostic indicator.
- Frequency of Psychosomatic Complaints (Optional) – Although optional, the presence of frequent physical complaints without clear medical causes can be an early sign of psychological distress. Psychosomatic symptoms often manifest as a response to prolonged stress or anxiety.
- Sleep Patterns – Irregular or poor-quality sleep strongly correlates with mental health disturbances. Disruptions in sleep cycles can either be a symptom or a contributing factor to conditions such as depression and anxiety.
- Social Activity – Reduced engagement in social activities is a common behavioral change among individuals experiencing mental health challenges. Social withdrawal often reflects or exacerbates emotional distress.
- Duration of Online Time – Extended periods of internet usage, particularly for non-work-related activities, can be linked to social isolation, disrupted sleep, and heightened exposure to negative content, all of which may affect mental health.

These findings collectively indicate that both psychological indicators (e.g., depression scores, psychosomatic symptoms) and daily behavioral patterns (e.g., sleep, social activity, online habits) are strongly associated with mental health conditions. Practically, this means that early detection and intervention efforts should incorporate both types of data to provide a more comprehensive understanding of an individual's mental well-being.

4. System Interface Development

The system was implemented as a simple web-based prototype using Python–Flask for the backend and React for the frontend. The user interface includes the following components:

- A questionnaire input page
- Risk prediction results (displayed with visual icons and color codes)
- Initial suggestions (e.g., "try consulting a school counselor," "ensure adequate rest")
- An option to share results with a counselor or parent (with the user's consent)

The interface design is illustrated in Figure 2 below:

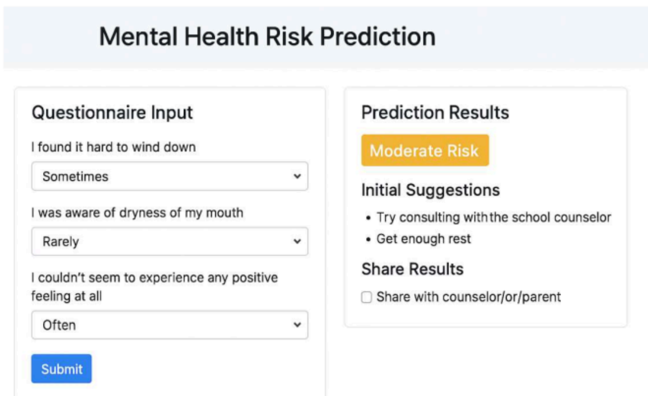

Figure 2: The interface design

5. Discussion

This study demonstrates that the Random Forest–based AI model is effective in the early detection of potential mental health issues among adolescents, particularly within the Indonesian cultural context (Toharudin et al., 2024). In contrast to previous studies that focused solely on depression, this model is capable of simultaneously identifying three major disorders: depression, anxiety, and stress. The adoption of a multi-label approach enhances the diagnostic capacity of early screening (Chougrad et al., 2020).

The strengths of this study include:

- Validation of data within the local Indonesian cultural context,

- A user-friendly system design accessible for adolescents and their caregivers,
- Strong emphasis on ethical considerations and privacy, including informed consent procedures.

However, the system still presents several limitations:

- It does not utilize multimodal data sources (e.g., social media text),
- The sample size remains limited,
- Long-term testing of the system's effectiveness as a psychological screening tool has not yet been conducted.

This study demonstrates that the predictive artificial intelligence model based on the Random Forest algorithm is capable of detecting early risks of mental health disorders in adolescents with high accuracy and strong local validity, making it an adaptive and relevant approach within the context of education and mental health in Indonesia (Jackins et al., 2021). By integrating prediction results into a simple and ethical system interface, this research offers not only a theoretical contribution to AI systems grounded in psychometrics, but also practical value in supporting targeted early interventions for students, school counselors, and teachers. This approach opens new opportunities for developing data-driven technologies to empower adolescent mental health in a preventive, sustainable, and inclusive manner (Upreti et al., 2022).

CONCLUSION

This study successfully developed a predictive AI-based system using the Random Forest algorithm for the early detection of adolescent mental health disorders. The system was able to predict the risk of depression, anxiety, and stress with an accuracy of 87.4%. The prediction results are displayed through an intuitive user interface and can serve as a supporting tool for early intervention by adolescents, school counselors, and parents. Future development should include integration of multimodal data sources, such as social media text or voice recordings. Greater involvement of professional psychologists is recommended for the evaluation and validation of system results. Developing the system into a mobile application is essential to broaden accessibility and reach more users.

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