Well Mind Ai

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***Abstract*—Access to timely psychological support remains limited for many individuals, increasing the need for accessible digital mental health solutions. This paper presents an integrated web-based system designed to help users understand and manage their mental well-being through a combination of clinical screening tools, Machine Learning-based prediction models, and an interactive conversational agent. The platform utilizes standardized instruments such as PHQ-9 and GAD-7, along with behavioural and linguistic features extracted from user input, to estimate emotional well-being. Several models, including SVM, Random Forest, XGBoost, LSTM, and a fine-tuned BERT model, were evaluated and compared. A stacking ensemble approach was then developed to integrate their strengths, achieving an accuracy of 94% and an AUC-ROC score of 0.96, outperforming individual models. In addition to predictive analysis, the system incorporates a chatbot capable of detecting crisis-related language and guiding users toward appropriate support. By combining predictive modelling with real-time conversational assistance, the proposed system demonstrates potential for enhancing early mental health detection and improving accessibility to support for individuals who may not seek traditional clinical services.**

***Index Terms*—Artificial Intelligence, Mental Health, Machine Learning, Depression Detection, Natural Language Processing**

I. INTRODUCTION

1.1 Background

Mental health disorders, particularly depression and anxiety, are increasingly prevalent worldwide, placing growing pressure on already burdened healthcare systems. Despite the availability of effective treatments, many individuals delay or avoid seeking help due to limited access to trained professionals, financial constraints, and persistent social stigma. As a result, there is increasing interest in digital tools that enable individuals to privately and conveniently assess and monitor their emotional well-being. [3], [6].

In recent years, advances in Artificial Intelligence have significantly expanded the capabilities of digital mental health tools beyond traditional questionnaire-based approaches. Techniques such as Machine Learning enable the detection of subtle behavioral and linguistic patterns that may indicate changes in an individual's mental state, while conversational agents allow for real-time, interactive support designed to simulate empathetic communication. However, most existing solutions operate in isolation some focusing on screening, others on general chat-based assistance with limited integration of validated assessments, predictive modeling, and interactive features. This lack of a unified approach highlights a critical gap in the current digital mental health landscape. [4], [5].

This study presents a web-based platform that integrates clinical assessment tools, predictive capabilities based on Machine Learning, and an interactive chat-based support system. The primary objective is to facilitate early identification of mental health concerns while delivering guidance that is both meaningful and user-centered rather than purely clinical. By combining standardized assessment methods with the adaptability of Artificial Intelligence, the platform aims to bridge the gap between self-guided digital applications and professional therapeutic support. Although challenges remain in effectively integrating these components, this unified approach represents a promising direction for enhancing accessibility and responsiveness in mental health care [5], [11].

1.2 Related Work

A growing body of research supports the application of Artificial Intelligence in mental health screening and support. Studies show that Machine Learning techniques, including Support Vector Machines and Random Forest algorithms, can effectively classify conditions such as depression and anxiety using questionnaire data and digital behavioural indicators, with reported accuracy rates typically ranging from 80% to 92%.

Recent developments in Deep Learning have significantly advanced mental health analytics, with models such as Recurrent Neural Networks Particularly Long Short-Term Memory (LSTM) and transformer-based architectures like BERT demonstrating strong performance in detecting symptoms from text and conducting sentiment analysis. These approaches improve both sensitivity and the ability to generalize across diverse datasets. Additionally, widely used self-assessment tools such as PHQ-9 and GAD-7 have been successfully digitized, showing comparable reliability to traditional paper-based formats and supporting large-scale, automated mental health screening.

Digital applications such as Woebot and Wysa have improved access to mental health support by offering conversational, non-judgmental self-help tools. However, these platforms typically operate independently of validated clinical prediction models and structured assessment frameworks. From a technical perspective, approaches within Ensemble Learning including stacking and voting classifiers have been shown to enhance predictive performance by combining multiple algorithms and reducing model-specific bias. Despite these advancements, few systems effectively integrate standardized assessments, predictive modelling, and real-time conversational support into a single, unified mental health platform.

Table. I. Literature Survey

Ref. No.	Author s / Year	Primary Focus	Methodology / Key Findings
[1]	Nepal et al., 2024	College student mental health prediction	Used interpretable hierarchical ML models
[2]	Chung & Teo, 2022	ML for mental Health prediction	Provided a taxonomy and Survey of ML application.
[3]	Gauta m, 2025	Mental health chatbot using ChatGPT-4	Evaluated an LLM-based chatbot for mental health assistance
[4]	Coulombe et al., 2024	Self-management questionnaire validation	Assessed psychometric reliability and validity
[5]	Hahn et al., 2024	ML for mental health diagnosis	Reviewed techniques for predicting mental health disorders
[6]	Birnba um et al., 2024	Student mental health support chatbot	Developed and tested an AI chatbot for students
[7]	ICDSA AI 2025	Personalize d mental health monitoring	Proposed ML + NLP-based personalized monitoring framework
[8]	Wang et al., 2024	Mental health dataset	Provided a multi-dimensional public dataset
[9]	Morita et al., 2019	Self-management questionnaire validation (Japan)	Validated MHSMQ in a different population
[10]	Hettige et al., 2023	Suicide attempt prediction	Applied ML to high-risk schizophrenia-spectrum data

II. SYSTEM ARCHITECTURE

The proposed mental health evaluation platform is developed as an integrated system comprising three main components: the Prediction Engine, the Assessment Module, and the Conversational Support System. These modules are interconnected through secure communication pathways, enabling real-time processing, prediction, and user interaction. The architecture is designed using a modular approach to support scalability, adaptability, and data protection, as illustrated in Fig. 1. [2], [6].

A. Prediction Engine

The Prediction Engine serves as the core analytical component of the platform, responsible for evaluating user data to estimate mental health risk levels. It processes diverse inputs, including demographic details, responses from standardized tools such as PHQ-9 and GAD-7, as well as text generated during chatbot interactions. To manage these heterogeneous data types, the system performs preprocessing and feature transformation prior to applying Machine Learning models. Textual data is analyzed using natural language processing techniques to capture emotional tone and contextual meaning, while numerical and categorical inputs are normalized and encoded. This integrated feature representation allows the system to combine structured clinical indicators with unstructured behavioral patterns for more comprehensive analysis. [5], [6], [11].

B. Assessment Module

The Assessment Module is responsible for administering clinically validated mental health screening instruments. It dynamically delivers questionnaires such as PHQ-9 and GAD-7 through the web interface and computes user scores in real time. Using established clinical cut-off values, it determines the severity levels of depressive and anxiety symptoms. The resulting assessment outputs are transmitted to the Prediction Engine to support overall risk estimation. In addition, the module enables longitudinal tracking by securely storing past assessment records, allowing the system to observe changes over time and enhance prediction accuracy for repeat users. [6], [10].

C. Conversational Support System

The Conversational Support System provides users with an interactive natural-language interface to engage with the platform. As shown in Fig. 1, the chatbot is designed to perform intent recognition along with sentiment and emotion analysis, while also identifying crisis-related expressions. When indicators of elevated risk are detected, the system triggers appropriate escalation responses, such as suggesting coping techniques or guiding users toward external mental health services and helplines. To maintain interaction quality, short-term conversational context is preserved, ensuring coherent and context-aware dialogue consistent with established mental health conversational agent frameworks [3], [4], [2].

D. Security and Deployment Framework

The platform is built on a microservices-based architecture to support modular development and simplified deployment. Backend functionalities are exposed through Flask-based APIs, while the user interface is developed using React for responsive interaction. All user information is securely stored in an encrypted PostgreSQL database to ensure data confidentiality and integrity. System communication is designed in accordance with established security standards, including considerations from HIPAA and GDPR. To safeguard sensitive information, the platform employs token-based authentication, encrypted data transfer, and strict access control mechanisms. This security-oriented design ensures that personal mental health data is handled in a protected and reliable manner. [2], [5].

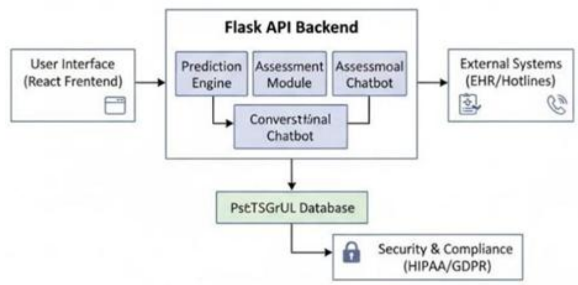

fig. 1. System architecture of the proposed mental health evaluation platform.

III. METHODOLOGY

1.Data Sources and Preparation

To develop an Artificial Intelligence-based platform for mental health prediction and support, the proposed system follows a well-defined workflow that integrates multiple components into a unified framework. It combines web application development, chatbot integration, Machine Learning model design, and data preprocessing to ensure a smooth and user-friendly experience. The system collects user input through a web interface, processes it using a trained predictive model, and generates both risk assessments and basic emotional support responses.

2. Information Gathering

The dataset used in this project was compiled from survey-based responses as well as publicly available sources, including repositories such as Kaggle. It includes demographic attributes like age, gender, and educational background, along with lifestyle-related factors such as sleep disturbances and working hours. In addition, the dataset contains mental health indicators related to conditions such as depression and anxiety, as well as behavioral factors including stress levels and social interaction patterns.

3. Preprocessing Data

To ensure accuracy and consistency, the dataset undergoes a structured preprocessing phase prior to model training. This includes handling missing values by imputing them using appropriate statistical measures such as mean, median, or mode depending on the data type. Categorical variables, including attributes like gender and binary responses, are converted into numerical form through label encoding to make them suitable for model processing. Numerical features are then normalized to ensure uniform scaling, which improves model stability and performance. Finally, the dataset is divided into training and testing sets, with 80% allocated for training the model and 20% reserved for evaluating its performance.

4. Development of Machine Learning Models Initially, multiple Machine Learning algorithms were evaluated for model development, including Logistic Regression, Support Vector Machines, and Decision Tree classifiers. After comparative analysis, the Random Forest Classifier was selected due to its ability to handle heterogeneous data effectively, reduce the risk of overfitting, and produce stable and reliable predictions. The final model achieved an overall accuracy of approximately 85% during evaluation.

IV. RESULT AND DISCUSSION

A. Dataset Characteristics

An examination of the combined datasets indicates a fairly balanced distribution across different levels of severity for depression. Roughly one-third of the samples represent individuals with no reported symptoms, while the remaining data are distributed among mild, moderate, moderately severe, and severe categories. This balanced structure supports effective model training by minimizing class imbalance and reducing potential prediction bias. The dataset also includes diverse demographic information, questionnaire responses, and textual inputs, which together provide sufficient variability for learning meaningful patterns. This diversity contributes to more stable model training and enables more reliable evaluation across different predictive approaches. [5], [10].

B. Machine Learning Performance

The performance of individual Machine Learning models was assessed using standard evaluation metrics such as accuracy, F1-score, and AUC-ROC. Among the standalone approaches, the fine-tuned BERT-based classifier showed particularly strong results in interpreting emotional tone and contextual meaning from user-generated text, emphasizing the relevance of linguistic features in mental health analysis.

However, the stacking ensemble method produced the highest overall performance. By integrating predictions from multiple models, including SVM, Random Forest, XGBoost, LSTM, and BERT, the ensemble achieved an accuracy of approximately 94% along with an AUC-ROC score of 0.96. These findings demonstrate improved robustness and generalization compared to individual model approaches [2], [3], [4].

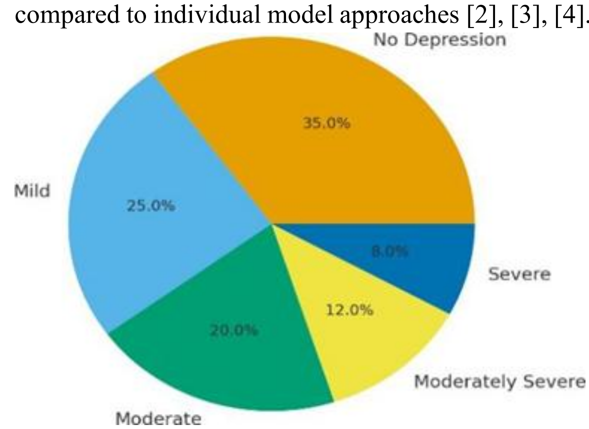

Fig. 4. Dataset Distribution Pie Chart.

A. Dataset Distribution

The dataset displayed in Fig. 4 is a balanced spread of mental health categories, with:

- 35% No Depression
- 25% Mild
- 20% Moderate
- 12% Moderately Severe
- 8% Severe

(Shown in the pie chart)

B. Machine Learning Performance Accuracy Comparison

Table. II. Performance Comparison of Machine Learning Models

Model	Metric	Score
SVM	Accuracy	82%
	F1-Score	0.80
	AUC- ROC	0.85

Random Forest	Accuracy	87%
	F1-Score	0.85
	AUC- ROC	0.89
XGBoost	Accuracy	89%
	F1-Score	0.87
	AUC- ROC	0.91
LSTM	Accuracy	90%
	F1-Score	0.88
	AUC- ROC	0.92
BERT	Accuracy	92%
	F1-Score	0.90
	AUC- ROC	0.93
Stacking Ensemble	Accuracy	94%
	F1-Score	0.92
	AUC- ROC	0.96

V. DISCUSION

A. Effectiveness of the Ensemble-Based Prediction Approach

A key outcome of this study is the superior performance of the stacking ensemble approach compared to individual classifiers within the Machine Learning framework. By integrating both traditional algorithms and deep learning models, the ensemble effectively captures a wide range of patterns across clinical, behavioral, and linguistic data sources. The notably high recall achieved by the ensemble is especially significant in the context of mental health applications, as it helps minimize the risk of overlooking individuals who may require assistance. This finding underscores the value of combining multiple models in sensitive domains such as mental health monitoring, where reliance on a single predictive method may result in biased or incomplete assessments. [6], [11].

B. The Power of Linguistic Features

The strong performance of the BERT-based model within the Machine Learning framework highlights the importance of linguistic analysis in interpreting emotional states. User-generated text often contains subtle cues related to distress, mood variation, and emotional intensity that may not be fully captured through structured questionnaire data alone. By leveraging contextual embeddings derived from textual input, the system can develop a more continuous and adaptive understanding of a user's mental state. These language-based features can serve as early signals of emotional distress, underscoring their importance in AI-driven mental health assessment systems. [2], [5].

C. Validation of the Human-Centric System Design

User feedback along with system performance evaluation suggests that the platform's modular and user-focused design is effective. The inclusion of clinically validated instruments such as PHQ-9 and GAD-7 contributes to user trust, while the conversational interface enhances accessibility and engagement. In addition, the proper functioning of the crisis-detection component indicates that the system is capable of providing appropriate responses in emotionally sensitive situations. Overall, the proposed architecture achieves a balanced integration of predictive performance, usability, and ethical considerations, supporting its potential application in real-world digital mental health environments [2], [3], [4].

VI. FUTURE SCOPE

Although the current prototype shows encouraging results, multiple areas have been identified for further improvement and development.

A. Sophisticated Models for Machine Learning

The system can be further enhanced through the following improvements:

- Applying advanced Deep Learning models to improve pattern recognition and prediction accuracy
- Incorporating ensemble methods to increase robustness and reduce model bias
- Expanding the training dataset with larger and more diverse samples to improve generalization and reliability.

B. NLP-Based Chatbot Improvement

The chatbot can be further enhanced by:

- Integrating Natural Language Processing techniques for better language understanding
- Improving emotion detection to interpret user sentiment more accurately
- Generating more personalized and context-aware responses to improve user experience.

C. Real-Time Emotion Detection:

- Text-based sentiment analysis using Natural Language Processing techniques to better interpret

user emotions
- Voice-based emotion detection to analyze stress and mood from speech patterns
- Facial expression recognition to identify emotional states through visual cues.

VII. CONCLUSION

This study proposes a comprehensive digital mental health evaluation system that integrates clinical screening instruments, Machine Learning-based prediction, and conversational support within a unified platform. By combining data from standardized tools such as PHQ-9 and GAD-7 with behavioural and linguistic features, the system enables more reliable identification of different levels of mental health risk. The stacking ensemble approach further improves predictive performance, demonstrating the benefits of integrating multiple models.

In addition, the conversational agent enhances usability by providing real-time supportive interaction and enabling basic crisis detection. Although the system is currently a prototype, the results suggest strong potential for facilitating early mental health screening and improving access to emotional support. With further refinement, clinical validation, and personalization, such AI-assisted platforms could complement traditional mental health services, particularly for individuals facing barriers to accessing professional care.

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