

AI-Based Mental Health Assessment System Using Machine Learning and Natural Language Processing

Vishal Kumar Sharma*, Ghanshyam Saini**, Rahul Misra***

*Department of Computer Science and Engineering, Jagannath University, Jaipur

**Department of Computer Science and Engineering, Jagannath University, Jaipur

***Associate Professor, Department of Engineering & Technology, Jagannath University, Jaipur

vishalsharma27106@gmail.com, ghansyam858@gmail.com, rahul.misra@jagannathuniversity.org

ABSTRACT

Mental health disorders represent one of the most critical and underdiagnosed challenges in modern healthcare. The absence of timely assessment tools and limited availability of professionals often delays diagnosis. This research proposes an AI-Based Mental Health Assessment System leveraging Machine Learning (ML) and Natural Language Processing (NLP) to automate screening of depression, anxiety, stress, and emotional burnout. Users interact through a conversational interface; responses are analyzed using NLP models to extract psychological indicators. Classification algorithms including SVM, Random Forest, and a fine-tuned BERT-based transformer model categorize mental health status across severity levels. The system uses Python and Flask for backend, React.js and Tailwind CSS for frontend, achieving 93.1% classification accuracy on benchmark datasets. The system also provides personalized resource suggestions, severity reports, and professional referral recommendations based on assessment outcomes.

Keywords — Mental Health Assessment, Machine Learning, Natural Language Processing, BERT, Depression Detection, Anxiety Classification, AI in Healthcare, SVM, Emotional Analysis.

1. Introduction

Mental health is a fundamental component of overall human well-being, yet it remains one of the most neglected areas of healthcare, particularly in developing nations. According to the World Health Organization (WHO), more than 970 million people worldwide suffer from a mental health disorder, and only a small fraction receive adequate treatment [1]. The growing gap between demand for mental healthcare and available professional support has created an urgent need for accessible, scalable, and cost-effective mental health screening tools.

Traditional mental health assessment methods rely entirely on in-person consultations with licensed psychiatrists and psychologists. These methods are time-consuming, expensive, and often inaccessible for individuals in rural areas or low-income groups. Additionally, social

stigma associated with mental health prevents many individuals from seeking help. Digital mental health platforms and AI-assisted tools offer promising alternatives that can bridge this critical gap by providing preliminary assessments in an anonymous, comfortable, and convenient manner [2].

Artificial Intelligence and Natural Language Processing have demonstrated remarkable potential in the healthcare domain, particularly in analysing patient-generated text and speech for detecting emotional and psychological states. Recent advancements in transformer-based language models such as BERT and GPT have made it possible to achieve human-level understanding of complex linguistic patterns associated with mental health conditions [3].

The primary objective of this research is to design and implement an intelligent mental

health assessment system that can automatically analyse user responses, detect linguistic and semantic indicators of mental distress, classify the severity of mental health conditions, and provide personalized recommendations. The proposed system aims to serve as a first line of mental health screening, enabling users to understand their psychological state and seek appropriate professional support when required.

2. Literature Review

Significant research has been conducted over the past decade in the area of automated mental health assessment using computational methods. Early approaches employed lexicon-based sentiment analysis techniques to identify emotional polarity in text. Tools such as LIWC (Linguistic Inquiry and Word Count) were widely used to extract psychological features from written text and were found to correlate with clinically validated depression scores [4].

Machine learning approaches significantly improved assessment accuracy compared to rule-based methods. Studies by Coppersmith et al. demonstrated that social media data could be used to predict depression onset using SVM and logistic regression classifiers with reasonable accuracy [5]. These works highlighted the importance of temporal patterns in user-generated content for mental health prediction tasks.

Deep learning methods further advanced the field by enabling automatic feature extraction from raw text without manual feature engineering. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks were applied to mental health text classification tasks with improved performance. Attention mechanisms that allow models to focus on relevant parts of the input sequence have been shown to outperform fixed-feature classifiers across language understanding benchmarks [6].

The introduction of BERT by Devlin et al. marked a major milestone in NLP-based mental health analysis [7]. BERT-based

models fine-tuned on mental health datasets such as CLPsych, SMHD, and eRisk have demonstrated superior performance in detecting depression, PTSD, and anxiety from online text. Despite these advancements, most existing systems are research prototypes that lack user-friendly interfaces and personalized feedback mechanisms. The proposed system bridges this gap.

3. Methodology

The proposed AI-Based Mental Health Assessment System is designed as a multi-component pipeline comprising user input collection, text preprocessing, feature extraction, machine learning classification, severity scoring, and feedback generation. The overall architecture follows a client-server model where the frontend handles user interaction and the backend performs AI-based analysis.

A. Dataset and Preprocessing: The system is trained on multiple publicly available mental health datasets including CLPsych 2015, the SMHD (Self-reported Mental Health Diagnoses) dataset, and the DAIC-WOZ dataset. Preprocessing steps include tokenization, stop word removal, stemming, lemmatization, and removal of personally identifiable information to ensure user privacy.

B. Feature Extraction: Two parallel feature pipelines are implemented. The first extracts handcrafted linguistic features including sentiment scores, LIWC-based psychological word counts, readability indices, negation patterns, and grammatical distributions. The second employs a pre-trained BERT model to generate contextual embeddings that capture deep semantic relationships in the input text.

C. Classification Models: Three machine learning models are implemented: SVM with an RBF kernel, Random Forest Classifier, and a fine-tuned BERT model with a classification head trained on labeled mental health text. An ensemble voting mechanism combining all three models produces the final classification output.

D. Severity Scoring: The system classifies mental health status into four severity levels: Normal, Mild, Moderate, and Severe. These categories align with PHQ-9 (Patient Health Questionnaire) for depression and GAD-7 (Generalized Anxiety Disorder Scale) for anxiety. A weighted scoring function maps model confidence values to severity thresholds.

E. System Architecture: The backend is implemented using Python and Flask REST API, while the frontend uses React.js and Tailwind CSS. User sessions are managed through JWT-based authentication. MongoDB is used for anonymized assessment history storage. The system is containerized using Docker for scalable deployment.

4. Implementation & Experimental Results

The proposed system was implemented and tested on benchmark mental health datasets. The BERT model was fine-tuned for 10 epochs using a batch size of 16 and a learning rate of $2e-5$ with the AdamW optimizer. Training was performed on an NVIDIA Tesla T4 GPU with 16GB VRAM. The dataset was split into 70% training, 15% validation, and 15% testing partitions.

The system interface presents users with structured questionnaire prompts derived from standardized tools including PHQ-9, GAD-7, and PSS (Perceived Stress Scale). Users provide free-text responses to these prompts, which are then analysed by the NLP pipeline. The conversational interface was designed to be empathetic, non-judgmental, and supportive to encourage honest responses.

Experimental evaluation demonstrated that the proposed ensemble model outperformed individual classifiers across all evaluation metrics. The fine-tuned BERT model alone achieved 91.4% accuracy, significantly surpassing the SVM baseline of 84.7%. The ensemble approach further improved overall accuracy to 93.1% by combining the complementary strengths of linguistic feature-based and embedding-based models.

Table I: Model Performance Comparison

Model	Acc.%	Prec.%	Rec.%	F1
SVM	84.7	83.2	82.9	0.830
Random Forest	87.3	86.8	86.1	0.864
BERT	91.4	90.9	91.0	0.909
Ensemble	93.1	92.7	92.5	0.926

The system was also evaluated using a user study involving 50 volunteers who completed assessments on the platform. Post-assessment surveys indicated that 88% of participants found the interface easy to use, 84% reported that the severity feedback was understandable, and 79% expressed willingness to use the tool regularly as a self-monitoring resource.

5. Discussion

The experimental results confirm that AI-based approaches, particularly transformer-based language models, are highly effective for automated mental health assessment. The proposed system demonstrates that combining deep contextual embeddings from BERT with handcrafted linguistic features produces more robust and accurate classification than either approach alone. The ensemble model's strong performance across depression, anxiety, and stress categories confirms that the underlying psychological language patterns generalize well across conditions.

An important consideration in the design of the proposed system is the balance between accessibility and clinical validity. The system is explicitly intended as a preliminary screening and self-awareness tool and is not designed to replace professional psychiatric diagnosis. Clear disclaimers and professional referral recommendations are integrated into all high-severity assessment outcomes to ensure responsible deployment.

Privacy and data security are critical concerns in mental health applications. The proposed system implements end-to-end encryption for all user communications, anonymizes stored assessment data, and does not retain personally identifiable information beyond the active user session. These design choices align with global data protection frameworks including GDPR and HIPAA guidelines.

6. Conclusion & Future Scope

This paper presents an AI-Based Mental Health Assessment System that integrates Machine Learning and Natural Language Processing to provide automated, accessible, and privacy-preserving mental health screening. The proposed ensemble model achieved a classification accuracy of 93.1%, demonstrating the effectiveness of hybrid AI approaches in mental health analysis. The system provides severity-level assessment reports, personalized resource recommendations, and professional referral guidance within a user-friendly web interface.

Future work will focus on extending the system to support regional Indian languages to improve accessibility. Integration of multimodal inputs including voice tone analysis and facial expression recognition will be explored. A longitudinal monitoring feature that tracks mental health trends over time and provides early warning alerts will also be developed. Collaboration with clinical institutions for validation against professional psychiatric assessments is planned to strengthen the clinical credibility of the platform.

Acknowledgment

The authors would like to express their sincere gratitude to Dr. Rahul Misra for his valuable guidance, continuous support, and encouragement throughout the development of this research work. His expert mentorship in the domain of Artificial Intelligence and healthcare applications played an important role in shaping the direction and quality of this research.

The authors also extend their heartfelt thanks to Dr. Om Prakash Sharma, Dean, Faculty of Computer Science and Engineering, for his constant motivation and academic support. The authors are sincerely thankful to the Department of Computer Science and Engineering, Jagannath University Jaipur, for providing the necessary resources and academic environment required for conducting this research successfully.

References

- [1] World Health Organization, "World Mental Health Report: Transforming Mental Health for All," WHO Press, Geneva, 2022.
- [2] A. G. Reece and C. M. Danforth, "Instagram photos reveal predictive markers of depression," *EPJ Data Science*, vol. 6, no. 1, p. 15, 2017.
- [3] G. Coppersmith, M. Dredze, and C. Harman, "Quantifying Mental Health Signals in Twitter," *ACL Workshop on Computational Linguistics and Clinical Psychology*, 2014.
- [4] J. W. Pennebaker, M. E. Francis, and R. J. Booth, "Linguistic Inquiry and Word Count: LIWC 2001," Mahwah, NJ: Erlbaum, 2001.
- [5] M. De Choudhury et al., "Predicting Depression via Social Media," *Proceedings of the ICWSM*, 2013.
- [6] A. Vaswani et al., "Attention Is All You Need," *NeurIPS*, 2017.
- [7] J. Devlin et al., "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *NAACL-HLT*, 2019.
- [8] K. Losekoot et al., "Detecting Depression from Social Media using Deep Learning," *Journal of Biomedical Informatics*, 2021.
- [9] R. Misra, "Deep Learning-Based Image Recognition Systems: A Comprehensive Study," *International Journal of Engineering Trends and Applications (IJETA)*, vol. 13, no. 2, pp. 15–18, 2026.
- [10] R. Misra and N. Sharma, "Emerging Cybersecurity Threats and Advanced Defense Technologies: Challenges, Risks and Future Security Solutions," *International Journal of Engineering Trends and Applications (IJETA)*, vol. 13, no. 3, pp. 61–71, 2026.
- [11] A. Agarwal, R. Joshi, H. Arora and R. Kaushik, "Privacy and Security of Healthcare Data in Cloud based on the Blockchain Technology," *2023 7th International Conference on Computing Methodologies and*

- Communication (ICCMC), pp. 87-92, 2023.
- [12] H. Kaushik, "Artificial Intelligence in Healthcare: A Review", *International Journal of Engineering Trends and Applications (IJETA)*, Vol. 11, Issue. 6, pp. 58-61, 2024.
- [13] R. Misra, N. Sharma, G. K. Soni, H. Arora, S. Chauhan and A. Biswas, "A Hybrid and Ensemble Machine Learning Framework for Enhanced Brain Tumor Detection," 2026 *International Conference on Electronics and Renewable Systems (ICEARS)*, pp. 1583-1588, 2026.
- [14] S. Soni, "Enhancing Digital Platforms Using Artificial Intelligence-Based Recommendation Systems," *International Journal of Engineering Trends and Applications (IJETA)*, vol. 13, no. 2, pp. 52–56, 2026.
- [15] R. Misra and P. K. Sharma, "Recent Trends, Applications and Challenges of the Internet of Things," *International Journal of Engineering Trends and Applications (IJETA)*, vol. 12, no. 6, pp. 55–61, 2025.
- [16] R. Joshi and R. Misra, "Artificial Intelligence Enabled Advances in Wireless Communication Systems," *International Journal of Engineering Trends and Applications (IJETA)*, vol. 12, no. 6, pp. 50–54, 2025.
- [17] R. Misra and N. Sharma, "Artificial Intelligence Driven Cybersecurity Techniques: Challenges and Future Directions," *International Journal of Engineering Trends and Applications (IJETA)*, vol. 13, no. 1, pp. 11–16, 2026.