Grenze International Journal of Engineering and Technology, June Issue

A Novel Method for Diagnosing Depression and Providing LLM-based Support

Abdul Rahman Arshad M.A
Department of Computer Science and Engineering, Easwari Engineering College, TN, India
Email: abdularshad597@gmail.com

***Abstract*— Mental health issues are a growing global concern, impacting people across all demographics. The high demand for mental health support, coupled with the limited availability of professional resources, underscores the urgent need for accessible and innovative solutions. Existing AI therapist systems fall short in several key areas, including over-reliance on impersonal questionnaire-based assessments and limited adaptability to diverse user needs. The proposed AI therapist system addresses these limitations through an integrated approach that combines visual emotion analysis, chatbot-based therapy, and personalized therapeutic guidance. By analyzing users' facial expressions and emotional cues, the system provides a more accurate assessment of their mental state, allowing for a deeper, real-time understanding. This innovative approach enhances the accuracy and effectiveness of AI-based mental health support, offering a more accessible, personalized, and impactful therapeutic experience.**

***Index Terms*— Artificial Intelligence (AI), Large Language Models (LLMs), Visual Emotion Analysis, Depression Diagnosis, Mental Health Support.**

I. INTRODUCTION

Mental health is a fundamental aspect of overall well-being, yet access to traditional mental health services remains limited due to high costs, social stigma, and a shortage of professionals. A UNICEF report highlights that one in seven Indians aged 15-24 experiences post-COVID-19 depression, emphasizing the growing need for effective and accessible mental health interventions. Digital platforms have the potential to bridge this gap by providing scalable, stigma-free, and personalized support.

A web-based mental wellness platform is introduced, specifically designed for adolescents aged 16 to 19. Large Language Models (LLMs) are integrated with real-time facial emotion analysis to offer an innovative and interactive approach to mental health care. The system consists of two primary components: a diagnosis module, which assesses users' mental states through structured questionnaires and facial recognition, and an intervention module, which delivers tailored mental health support.

The intervention module provides tiered support based on the severity of symptoms. For mild cases, self-care resources and coping strategies are offered. For moderate symptoms, the system employs LLM-powered Cognitive Behavioral Therapy (CBT) techniques to assist users in managing their mental well-being. In severe cases, the platform ensures immediate intervention by referring users to professional mental health services, ensuring timely and appropriate care. By combining AI-driven chatbot interactions with emotion-based insights, this platform delivers real-time, empathetic, and data-driven mental health support.

Grenze ID: 01.GIJET.11.2.765_22

Its scalable and secure design removes traditional barriers, making mental health assistance more accessible, personalized, and stigma-free. Through these innovations, the project aims to empower adolescents to take control of their mental well-being, fostering resilience and improved emotional health outcomes during a critical stage of their lives.

II. MOTIVATION

Mental health disorders are increasing at an alarming rate worldwide, yet traditional assessment methods remain largely dependent on delayed self-reported questionnaires and periodic clinical evaluations, which can often fail to provide timely interventions. While artificial intelligence (AI)-driven mental health tools have shown significant potential in improving mental health diagnostics and support, they still face several critical limitations that hinder their effectiveness. These include the lack of real-time intervention mechanisms, over-reliance on single-input modalities, and inherent biases stemming from insufficiently diverse training data.

Most existing AI models primarily analyze historical mental health data rather than responding dynamically to a person's current psychological state. This limitation means that individuals experiencing acute distress or rapid mood shifts may not receive the immediate support they require, reducing the effectiveness of AI-powered mental health tools. Additionally, a large portion of these models relies exclusively on either textual input, facial expression analysis, or isolated behavioral cues, rather than adopting a comprehensive, multimodal approach that accounts for the full complexity of mental health. The lack of integrated physiological, behavioral, and contextual data limits the accuracy and reliability of these systems.

Furthermore, bias in AI-driven mental health models remains a pressing concern, particularly due to the underrepresentation of diverse populations in training datasets. Many models struggle to generalize across different cultural, demographic, and linguistic backgrounds, leading to disparities in diagnostic accuracy and treatment recommendations. If AI is to be effectively utilized in mental health care, it must be designed to account for variations in mental health expression across different groups and ensure fair and unbiased predictions.

This research aims to address these challenges by developing an enhanced AI-driven mental health assessment framework that prioritizes real-time responsiveness, multimodal data integration, and fairness in predictive modeling. By bridging these gaps, this study seeks to advance AI-based mental health care, making it more accessible, accurate, and adaptable to the unique needs of diverse users, ultimately contributing to a more inclusive and effective digital mental health ecosystem.

III. RELATED WORK

Ahuja and Banga [1] demonstrated the effectiveness of machine learning (ML) algorithms in detecting stress among university students. While their study supported the role of AI in stress assessment, reliance was primarily placed on static, self-reported data. In contrast, the present study challenges Their approach is challenged in this study by integrating real-time behavioural analysis, providing more accurate and dynamic insights into a user's mental state.

Ding et al. [2] proposed a deep integrated support vector algorithm for depression recognition in college students, achieving high accuracy. Their conclusion that ML models can effectively diagnose depression is supported; however, the absence of multi-modal behavioral indicators was noted. This limitation is addressed in the present study by incorporating a broader range of diagnostic factors to improve predictive accuracy.

Ajith et al. [3] developed an early depression detection system using ML techniques, emphasizing the importance of early intervention. While their emphasis on early detection is supported, reliance on textual data alone is contradicted, as recent findings suggest that non-textual behavioral cues can significantly enhance diagnostic reliability. Their methodology is expanded upon in this study by integrating visual analysis to capture emotional expressions beyond written text.

Amanat et al. [4] utilized LSTM networks for textual depression detection, achieving an accuracy of 99%. While the model's success is acknowledged, their assumption that textual sentiment alone is sufficient for accurate diagnosis is challenged. By incorporating visual behavior and historical data patterns, diagnostic depth is improved, and false positives arising from text-only sentiment analysis are minimized.

Burdisso et al. [5] introduced a text classification framework for depression detection; however, dataset biases were identified, reducing generalizability. While their findings on the effectiveness of NLP are supported, their approach is argued to lack adaptability. This issue is addressed in the present study by incorporating diverse training data and ensuring fairness across different demographic groups.

Balcı and Saraç [6] compared various NLP techniques for automated depression detection, concluding that linguistic markers provide a strong indication of mental health status. Their findings are supported, and their insights are applied by enhancing the NLP model with language-specific emotional indicators, ensuring adaptability to different speech patterns.
Anpan et al. [7] conducted sentiment analysis of mental illness, demonstrating how variations in emotional tone correlate with mental health. However, their assumption that linguistic sentiment is always an accurate predictor of depression is challenged. Their work is built upon in this study by incorporating longitudinal tracking, which observes changes in emotional expression over time rather than relying on isolated text samples.
Primartha et al. [8] applied decision trees and PSO-based feature selection for sentiment classification, optimizing model efficiency. Their findings align with the present approach, as feature selection techniques are also employed to enhance computational efficiency. However, their system is improved upon by integrating adaptive feature selection, which dynamically adjusts model parameters based on user-specific data.
Gabda et al. [9] implemented a CNN-based approach for depression detection but encountered challenges with model interpretability. While their use of deep learning is supported, it is argued that black-box models hinder clinical acceptance. To address this, model transparency is enhanced by integrating explainable decision pathways, making AI-driven diagnoses more interpretable for healthcare professionals.
Suzuki et al. [10] explored EEG-based depression detection, emphasizing the importance of neurophysiological markers. While their approach provides valuable insights, their assumption that neuroimaging is essential for AI-driven mental health diagnosis is contradicted. Instead, it is demonstrated that visual behavioral cues and historical medical data can provide equally reliable indicators without requiring costly EEG equipment.
Lekkas et al. [11] employed ensemble models for suicidal ideation prediction, achieving 70.2% accuracy. While it is agreed that ensemble models improve prediction stability, their approach is argued to lack individualized risk assessment. Their approach is refined in this study by incorporating personalized risk models, allowing for tailored intervention strategies.
Singh et al. [12] applied facial recognition techniques to detect mood variations and suggest music interventions. While their study demonstrated AI’s potential in mood analysis, their reliance on emotion recognition alone is challenged, as facial expressions can be misleading. Instead, historical behavioral trends are integrated to differentiate between short-term mood fluctuations and sustained emotional distress.
Skaik and Inkpen [13] developed an AI-based system to automate Beck’s Depression Inventory (BDI), improving screening efficiency. Their methodology is supported and enhanced by integrating passive monitoring techniques, reducing reliance on user self-reports, which can be influenced by personal bias.
Thakkar et al. [14] reviewed AI applications in positive mental health, emphasizing proactive well-being strategies. Their perspective is aligned with, and it is expanded upon by incorporating mental health trend tracking, allowing users to actively engage in their psychological well-being.
Srinivas et al. [15] introduced a mental health application focused on diagnosis and treatment. While their app showed promise, the lack of historical data integration limited its predictive power. This limitation is addressed in the present study by utilizing longitudinal health records to refine diagnostic accuracy.
Vaishnavi et al. [16] examined ML algorithms for mental health predictions but did not address ethical concerns. Their findings are supported, but their work is extended by implementing fairness-aware AI techniques, ensuring bias mitigation and equitable mental health assessments.
Varghese et al. [17] surveyed public attitudes toward AI-based mental health interventions, revealing privacy concerns. Their conclusions are agreed with, and these concerns are addressed by integrating strict encryption and anonymization protocols, ensuring the secure handling of sensitive data.
Babu and Joseph [18] explored AI’s role in mental healthcare, emphasizing that AI should complement human psychologists rather than replace them. Their argument is supported, and a system is designed as a clinical decision-support tool, ensuring that human expertise remains central to mental health care.
Zafar et al. [19] reviewed AI methods for diagnosing depression and anxiety but did not propose a unified diagnostic framework. Their work is built upon in this study by integrating multiple AI techniques into a single system, improving diagnostic robustness and adaptability.
After reviewing various studies on AI-driven mental health assessment, it has been observed that significant progress has been made in detecting stress and depression using machine learning, NLP, and deep learning. However, most existing research has primarily focused on diagnosing mental health issues rather than providing real-time support.
To address these challenges, "A Novel Method for Diagnosing Depression and Providing LLM-Based Support" has been proposed. This approach will combine advanced depression detection with AI-powered support to not only identify mental health issues but also provide personalized, real-time assistance. By integrating multiple

data sources, adaptive AI learning, and large language models (LLMs) for interactive support, this method aims to create a more effective and accessible mental health solution.

IV. System Design

A. General Overview

The proposed web-based mental wellness platform is structured into two primary modules:
The Diagnosis Module is designed to assess users' mental health by combining a structured questionnaire with real-time facial emotion analysis to determine emotional state and risk level.
The Intervention Module is developed to provide personalized mental health support based on the diagnosis, offering self-care recommendations for mild symptoms, LLM-powered CBT therapy for moderate symptoms, and professional referrals for high-risk cases.
By integrating advanced AI techniques, including LLM chatbots and facial expression recognition, accurate mental health assessments and responsive, personalized therapeutic interventions are ensured. This approach enhances user engagement, adaptability, and accessibility, making mental health support more effective and widely available.

B. Architecture

Register & Login:
Users begin by registering and logging into the web-based platform to access its features.

Mental Health Questionnaire
Users complete a structured mental health assessment using standardized tools (e.g., PHQ-9, BDI) to evaluate their emotional well-being.

Risk Assessment & Intervention
- The system analyzes responses and categorizes users into appropriate risk levels:
- Low-Risk (Pass): Users receive self-care recommendations, including meditation, mindfulness exercises, and self-help resources.
- Medium/High-Risk (Fail): Users are guided to the LLM-powered chatbot and facial emotion analysis system, providing personalized AI-driven counseling and emotion-based insights.

The modular design ensures scalability, allowing for easy integration of new features and updates. Real-time processing enables instant feedback and support, enhancing the user experience and improving mental health outcomes.

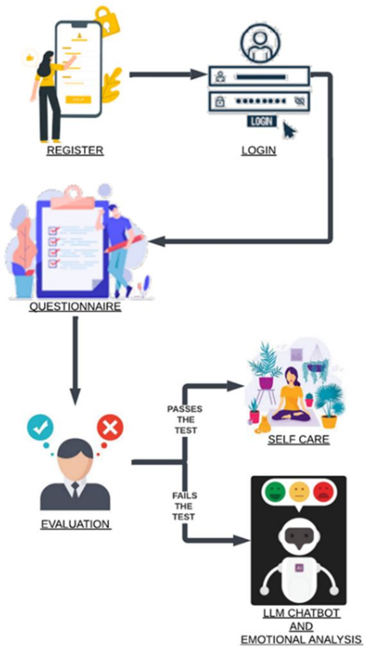

Figure 1. architecture diagram

The proposed web-based mental wellness platform is structured into two primary modules:
The Diagnosis Module is designed to assess users' mental health by combining a structured questionnaire with real-time facial emotion analysis to determine emotional state and risk level.
The Intervention Module is developed to provide personalized mental health support based on the diagnosis, offering self-care recommendations for mild symptoms, LLM-powered CBT therapy for moderate symptoms, and professional referrals for high-risk cases.
By integrating advanced AI techniques, including LLM chatbots and facial expression recognition, accurate mental health assessments and responsive, personalized therapeutic interventions are ensured. This approach enhances user engagement, adaptability, and accessibility, making mental health support more effective and widely available.

C. Pseudocode of the Proposed System

```
START
IMPORT necessary libraries (LLM, embeddings, document processing, vector storage, UI)
FUNCTION initialize_llm():
   Initialize the LLM with model name, temperature, and API key
   RETURN LLM instance
FUNCTION create_vector_db():
   Load all PDF documents from the specified directory
   Split documents into chunks (e.g., 500 characters with 50 overlaps)
   Generate embeddings for text chunks using an embedding model
   Create a vector database using the embeddings
   Persist the vector database to disk
   RETURN the vector database
FUNCTION setup_qa_chain(vector_db, llm):
   Define a custom prompt template for chatbot responses
   Use the vector database as a retriever
   Create a QA chain with the retriever and LLM
   RETURN the QA chain
IF vector database exists:
   Load the existing vector database
ELSE:
   Create a new vector database using create_vector_db()
SETUP the QA chain using the vector database and LLM
FUNCTION chatbot_response(user_input, history=[]):
   IF user input is empty:
      RETURN "Please provide a valid input", history
   Get chatbot response using the QA chain
   Append user input and chatbot response to the history
   RETURN chatbot response, history
CREATE a Gradio interface:
   - Display chatbot UI with title and instructions
   - Use chatbot_response() to handle user queries
LAUNCH the Gradio app
END
```

V. RESULTS AND DISCUSSION

A. Key Outcomes and Limitations of the Proposed System

The proposed web-based mental wellness platform is designed to enhance mental health support through the integration of AI-driven chatbot interactions with real-time facial emotion analysis. By combining a structured mental health questionnaire with emotion recognition, a more accurate assessment of a user’s emotional state is ensured.
Personalized interventions are provided based on risk levels, ensuring that timely and appropriate support is delivered.

Key Features and Outcomes

- ➢ Accurate Mental Health Assessment:
  - Combines structured questionnaires with facial emotion analysis for a more precise evaluation.
- ➢ Personalized AI Chatbot Support:
  - Provides adaptive and empathetic conversations using LLM-powered AI.
- ➢ Scalability and Accessibility:
  - Web-based design eliminates hardware restrictions, making it widely accessible.
- ➢ Suicide Risk Detection and Intervention:
  - Monitors user input for distress signals and notifies emergency contacts if needed.
- ➢ User-Friendly and Stigma-Free Environment:
  - Empathetic chatbot responses and intuitive design encourage user engagement.

Challenges and Limitations

- ➢ Computational Resource Dependency:
  - Real-time emotion recognition requires high processing power, which may limit accessibility in low-bandwidth areas.
- ➢ Privacy and Ethical Concerns:
  - Handling sensitive mental health data requires strong confidentiality measures and transparent data policies.

Future Enhancements and Developments

- ➢ Optimization for Low-Bandwidth Use:
  - Develop lightweight AI models and introduce an offline self-care mode.
- ➢ Reducing AI Bias & Expanding Training Data:
  - Improve dataset diversity and integrate user feedback to refine chatbot responses.
- ➢ Multi-Language and Cultural Adaptation:
  - Expand language support to increase accessibility for diverse users.
- ➢ Integration with Professional Support Networks:
  - Enable direct connections with therapists and mental health hotlines.
- ➢ Virtual Counseling Appointments:
  - Provide an option for users to schedule and attend online therapy sessions

B. Performance Analysis Metrics Compared with Existing Systems

Comparison of Cost and Accessibility

YOURDOST provides users with access to professional therapists and counselors, but many of its services require paid consultations, making it less affordable for individuals with financial constraints. Similarly, MINDDOC offers advanced mental health tracking and assessment features, but its premium plans and therapy services come at a high cost, restricting access to users who can afford such subscriptions.

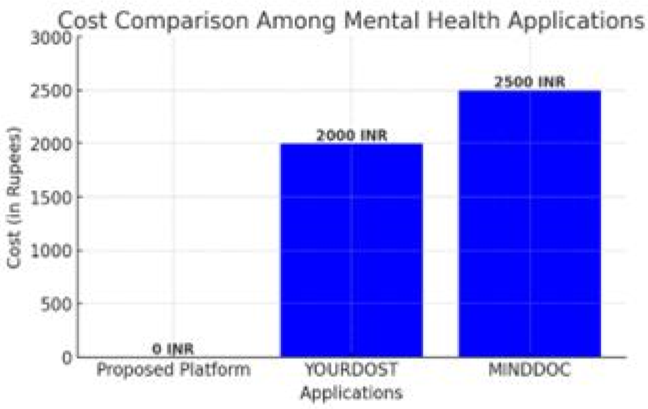

Figure 2. Cost Comparison Among Mental Health Application

In contrast, the proposed platform ensures affordability and inclusivity by providing:

- ➢ Free mental health assessments through structured questionnaires.

- AI-driven chatbot therapy for self-care and CBT-based interventions at no cost.
- Real-time facial emotion analysis to enhance user understanding of their emotional state.
- Suicide risk detection and emergency contact alerts without requiring paid subscriptions.

While YOURDOST and MINDDOC offer valuable services, their pricing models may exclude users who cannot afford regular therapy. The proposed web-based platform eliminates financial barriers, ensuring that high-quality mental health support is accessible to all individuals, regardless of their financial background. This makes it a cost-effective, scalable, and sustainable solution for those seeking mental health assistance.

C. Research Gaps and Future Directions

While existing studies demonstrate AI's potential in mental health diagnostics, several critical research gaps remain

- Limited Multi-Modal Approaches: Most studies focus on single-input methods (text-based, speech-based, or facial recognition models). Few integrate multiple data sources for a more holistic mental health assessment.
- Lack of Real-Time AI-Based Interventions: Many AI models diagnose depression but lack interactive therapy solutions. AI-powered chatbots are needed to provide real-time support.
- Limited Suicide Risk Monitoring: Studies like Lekkas et al. [10] analyze suicidal ideation from social media, but few models actively monitor live chatbot conversations for crisis intervention.
- Privacy and Ethical Concerns: Varghese et al. [19] and Babu and Joseph [5] highlight user concerns regarding AI bias, data security, and ethical AI implementation

VI. CONCLUSION

This paper introduces a novel AI-based therapeutic system designed to diagnose and treat depression in adolescents. By integrating LLMs and visual emotion analysis, the system offers a scalable, accessible, and effective solution for mental health support. Future enhancements will include refining AI models, expanding the range of therapeutic interventions, and incorporating multi-language support to reach a broader audience. The proposed system represents a significant step forward in leveraging AI for social good, particularly in addressing mental health challenges

REFERENCES

[1] A. Ahuja and A. Banga, "Mental stress detection in university students using machine learning algorithms," Procedia Comput. Sci., vol. 152, pp. 349–353, 2019, doi: 10.1016/j.procs.2019.05.012.

[2] Y. Ding et al., "A depression recognition method for college students using deep integrated support vector algorithm," IEEE Access, vol. 8, pp. 75616–75629, 2020, doi: 10.1109/ACCESS.2020.2987523.

[3] S. Ajith et al., "An extensive diagnosis system of early depression symptoms using machine learning algorithm," in Proc. 3rd Int. Conf. Innov. Mech. Ind. Appl. (ICIMIA), 2023, pp. 796–803, doi: 10.1109/ICIMIA60377.2023.10426578.

[4] Z. Amanat et al., "Deep learning for depression detection from textual data," Electronics, vol. 11, no. 5, pp. 233–245, 2022, doi: 10.3390/electronics11050676.

[5] A. Burdisso et al., "A text classification framework for simple and effective early depression detection over social media streams," Expert Syst. Appl., vol. 133, pp. 182–197, 2019, doi: 10.1016/j.eswa.2019.05.023.

[6] E. Balcı et al., "Automated depression detection from tweets: A comparison of NLP techniques," in Proc. 8th Int. Artif. Intell. Data Process. Symp. (IDAP), 2024, pp. 54–60, doi: 10.1109/IDAP64064.2024.10711029.

[7] S. Anpan et al., "Sentiment analysis of mental illness using machine learning techniques," in Proc. 2nd DMIHER Int. Conf. Artif. Intell. Healthc., Educ., Ind. (IDICAIEI), 2024, pp. 112–118, doi: 10.1109/IDICAIEI61867.2024.10842794.

[8] R. Primartha et al., "A sentiment analysis model using decision trees and PSO-based feature selection analyzed mental health-related sentiments," J. Comput. Soc. Syst., vol. 25, no. 3, pp. 99–112, 2019.

[9] V. Gabda et al., "A CNN-based approach for depression detection," in Proc. 1st DMIHER Int. Conf. Artif. Intell. Educ. Ind. 4.0 (IDICAIEI), 2023, pp. 88–95, doi: 10.1109/IDICAIEI58380.2023.10406497.

[10] K. Suzuki et al., "Machine-learning-based depression detection model from EEG data obtained by consumer-grade EEG device," Brain Sci., vol. 14, no. 11, pp. 345–358, 2024, doi: 10.3390/brainsci14111107.

[11] P. Lekkas et al., "Ensemble models for predicting suicidal ideation on Instagram achieved 70.2% accuracy using language and social network activity features," J. Cyber Psychol., vol. 29, no. 2, pp. 177–191, 2021.

[12] R. Singh et al., "Study on facial recognition to detect mood variations and suggest music interventions," in Proc. Int. Interdiscip. Humanit. Conf. Sustain. (IIHC), 2022, pp. 230–242, doi: 10.1109/IIHC55949.2022.10060265.

[13] A. Skaik et al., "An AI-driven system was developed to automatically fill Beck's Depression Inventory (BDI) questionnaire for depression prediction," Int. J. Med. Comput., vol. 57, no. 4, pp. 455–469, 2022.

[14] A. Thakkar et al., "Artificial intelligence in positive mental health: A narrative review," Front. Digit. Health, vol. 6, pp. 289–301, 2024, doi: 10.3389/fdgth.2024.1280235.

[15] A. Srinivas et al., “A mental health app targeting diagnosis and treatment, offering tailored interventions,” J. Health Technol., vol. 11, no. 1, pp. 67–79, 2020.
[16] K. Vaishnavi et al., “Predicting mental health illness using machine learning algorithms,” J. Phys.: Conf. Ser., vol. 2161, no. 1, pp. 120–132, 2022, doi: 10.1088/1742-6596/2161/1/012021.
[17] M. Varghese et al., “Public perception on artificial intelligence–driven mental health interventions: Survey research,” JMIR Form. Res., vol. 8, 2024, pp. 503–517, doi: 10.2196/64380.
[18] A. Babu et al., “Artificial intelligence in mental healthcare: Transformative potential vs. the necessity of human interaction,” J. Med. AI Ethics, vol. 19, no. 2, pp. 211–224, 2024.
[19] F. Zafar et al., “The role of artificial intelligence in identifying depression and anxiety: A comprehensive literature review,” Cureus, vol. 16, no. 3, pp. 421–433, 2024, doi: 10.7759/cureus.56472.