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Research Article

A Mental Health Support Platform Powered by Artificial Intelligence

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Abstract: Mental health has an important role in our overall well-being leading to a balanced, healthy life and contributing meaningfully to society. However, mental health problems are quite common with the World Health Organization reporting an increasing trend in mental health disorders; yet, many people avoid treatment options due to stigma associated with mental health issues in society, long wait periods, as well as limited access to timely and personalized support. Therefore, it is essential to steer towards an Artificial intelligence (AI) based innovative, accessible and personalized solutions to mental health disorders. This paper introduces an AI-powered mental health platform designed to provide comprehensive mental health assistance through several key features: a conversational chatbot, educational content, self-assessment tools, emotion tracking and counselor recommendations. The AI chatbot, built by fine-tuning Llama 3.2 (3B) on mental health conversations, engages users in real-time, offering relevant guidance. Users can gain insights into their mental state through validated surveys, while the emotion detection module uses natural language processing and sentiment analysis to track mood patterns over time. The emotion classification attained an accuracy and F-score of 88%. The platform aims to close the mental health support gap by leveraging AI to promote self-awareness, proactive management and ongoing support.

Keywords: Mental Health Support; AI for Mental Health; Machine learning; Mental health assistant; Natural language processing; Sentiment and Emotion Analysis.

1. Introduction

Mental health incorporates into its ambit our psychological, emotional and our social well-being. It takes into consideration our way of feeling, thinking, interacting, handling stress, building and maintaining relationships and making decisions. Good mental health boosts resilience, productivity and quality of life, while poor mental health affects both our physical health as well as our daily functioning. Because mental and physical health are closely connected, mental health issues can worsen conditions like heart disease, diabetes and weakened immunity. When people have good mental health, they are more likely to build strong relationships, feel a sense of purpose and engage confidently in social settings. It also strengthens resilience, helping individuals adapt to change, overcome challenges and approach life with a positive mindset. Promoting mental health not only supports personal well-being but also contributes to stronger, more resilient communities. Prioritizing mental well-being leads to a balanced, healthy life and contributing meaningfully to society. However, mental health problems are common and can affect anyone. Nowadays, depression, stress disorder (post-traumatic or not), anxiety, bipolar disorder and schizophrenia are widespread. The World Health Organization has highlighted in its reports that depression is one of the foremost causes of disability and suicide is the fourth major reason of death among people aged 15 to 29 [1]. In spite of this, people are still discouraged from seeking therapy because mental health issues are stigmatized. Expensive mental health services, long wait periods, and limited access to mental health professionals exacerbate the fact that many people suffer in silence. Therefore, innovative and accessible solutions are needed to make mental health issues accessible and supportive.

Artificial intelligence (AI) has been extensively used in providing accessible personalized and scalable solutions to mental health disorders by analyzing text, audio or video input [2]. AI processes and identifies complex patterns from huge amount of data making it a powerful tool in mental healthcare providing deeper insights into human behavior; supporting early detection of mental health issues and enabling personalized treatments through virtual platforms [2]. AI based mental health platforms can be used to monitor and track mood patterns and detect any emotional crises. By analyzing behavioral and psychological data both users and clinicians will obtain data-driven insights into an individual's emotional well-being over time. This will help identify early warning signs of depression or anxiety which will help in timely interventions.On the basis of this data, AI platforms will be able to recommend guided meditations, relaxation techniques, or professional resources. AI based online tools have been used to deliver customized recommendations based on individual needs remotely thereby addressing the challenges of stigma associated with mental disorders. It has also addressed the high costs of treatment as well as treatment options and has helped reach even remote areas with a basic smart phone and an internet connection. Through self-assessment tools, emotional tracking and custom recommendations, AI is reshaping mental health support to be more accessible and responsive to individual needs. The various AI based mental health tools [3] can be classified into the following categories:

[i] *Support Tools*: These mental health tools help individuals manage their own well-being. Examples include mobile apps and AI-powered chatbots that are designed to offer coping strategies and relaxation techniques. Tools like these allow users to reflect on their emotions, develop healthier thinking patterns and access support anytime, without needing an appointment. Mood Journaling apps (such as Daylio [4], Reflectly [5]) allow users to record emotions, thoughts and habits, thus recognizing emotional patterns and triggers. AI Chatbots and virtual assistants, for example Woebot [6] and Wysa [7], can simulate conversations and guide the users of the system through cognitive behavioral therapy (CBT) exercises, helping them deal with anxiety, stress, or low mood in a private and accessible way.

[ii] *Mental Health Assessment Tools*: Some digital tools are focused on helping users better understand their mental health through assessments and screenings. These tools often involve questionnaires or AI-driven analysis that evaluates mood, thought patterns, or behavioral data. By identifying early signs of conditions such as anxiety or depression, these platforms support early intervention. Some tools can analyze language, speech or phone usage patterns to detect subtle emotional changes, helping users recognize when they might need professional help. Tools like Mindstrong [8]

can detect even subtle signs of anxiety or depression which can help prevent the escalation of the mental health issues based on a feedback mechanism.

[iii] *Monitoring and Predictive Tools*: Some mental health tools such as mobile apps and wearable devices (Moodfit and Bearable) are designed to observe and analyze behavioral and physical patterns over time. These tools collect and interpret data by tracking different physical and other activities like sleep patterns, daily habits and mood changes. Smartwatches and other wearable devices (Fitbit or Apple Watch) help in monitoring different physiological signals like oxygen levels, heart rate, etc. These ongoing tracking helps in getting an early information regarding mental health issues thereby helping individuals get prompt interventions. The AI based platform Ginger [9] tries to predict individuals who are at risk of mental health issues while IBM's Watson Health [10] uses artificial intelligence to predict the disease progression and their treatment options.

[iv] *Online Counselling and Therapy Platforms*: These help users connect to professional healthcare personnel or mental health services via chats, phone, audio or video sessions maintaining the privacy of individuals such as BetterHelp and Talkspace. Some therapy based platforms such as Sanvello and Happify offer guided and structured lessons on meditation and mindfulness exercises.

[v] *Community Support Tools*: The emotional well-being of a person is directly connected to the social connectivity that the person has. With the surge in loneliness factors post Covid as well as due to the rise in time spent by a person online, many people have become disconnected from their peers and communities. Therefore, platforms have surged to foster online peer support communities like the 7 Cups, Supportiv [11] and Reddit which connects individuals topeers, trained professionals or people with similar experiences. These platforms provide a space to share experiences, thoughts and stories without the fear of judgement.

Natural Language Processing (NLP) is a subset of AI that focuses on making computers able to interpret, understand and generate human languages [13]. It combines linguistics and machine learning to process human language and is widely applied in chatbots, translating languages, analyzing text, answering questions, summarizing text, analyzing sentiments and emotions etc. NLP has been extensively used in the mental health domain to aid in the diagnosis, monitoring, treatment of people suffering from mental health challenges and also as an identification and support tool for individuals at clinical risk for depression or suicidal ideation. It has evolved as a powerful tool for making AI based mental health chatbots and assistants [14] using Large Language Models (LLMs), like GPT and LLaMA [15, 16]. LLMs applies advanced neural network techniques on huge text data. They use an uderlying transformer architecture consisting of encoder-decoder with self attention capabilities that help extract meanings and undertsand relationships of words and phrases in a sequence of text. LLMs can engage in conversations in a context aware manner almost like a human which helps them detect subtle signs of mental ailments, provide tailored support and help in monitoring [17-20]. Sentiment analysis extracts subjective information from textual data classifying it as positive, negative, or neutral, while emotion classification recognises emotions and classifies them into the corresponding categories of anger, sadness, surprise, happiness, disgust, or fear. Studies have concluded that there is an inverse relationship between depression severity and positive/negative emotions [21] and hence the information about emotions will also be a guiding factor in mental illness diagnosis. Powered by LLMs and large scale labeled datasets, these techniques help the AI systems diagnose and predict mental health conditions. Our work builds on such techniques by developing an AI-powered platform that integrates conversation, emotion tracking, and expert recommendations for an accessible, destigmatised real-time mental health support system. We also try to address the challenges of ethical concerns and regulations by maintaining the privacy of the users of the system and proper consents taken from participants in the study process.

In this paper, we present our AI-driven mental health platform that aims to deliver an accessible and personalized support by using AI tools to analyze conversations, monitor emotional well-being and guide the users who are in need of professional help towards trained clinicians. The contributions of this work are:

(i) To develop an AI powered mental health platform that supports an AI chatbot capable of conversing with users about various topics, gauge the emotional state of the individuals, offer emotional support and give answers to questions regarding mental health.

(ii) To provide self-assessment tools and questionnaires to users for assessing their own mental state, stress, anxiety or depression conditions.

(iii) To provide strategies to manage the conditions and treatment options available including our on board doctors, counselors and therapists.

(iv) To provide emotion tracking, monitoring and detecting subtle signs of mental illness symptoms.

With the help of adaptive recommendations and mental health tracking, this work seeks to develop a platform that continuously supports users throughout time. The platform engages the user in a seamless conversation providing much needed encouragement and support. It helps the users in their mental health journey by monitoring and tracking their moods, emotions and experiences. It detects subtle signs of depression and anxiety based on pre-validated clinical assessment tools and tracks the users progress and recommends solutions and treatment options in response to any change in the mental health data of the users.

2. Materials and Methods

The focus of this work is to design and develop an AI-powered mental health support platform that offers a destigmatized and accessible mental health care in collaboration with healthcare providers or clinicians. Our mental health support platform allows users to interact with an AI powered chatbot which services as a conversational assistant providing much needed support, friendship and encouragement alongwith an access to reliable mental health information and solutions. It also has features like assessment of mental conditions through validated clinical tools, monitoring of emotional well-being through emotion and sentiment tracking and detection along with recommending and scheduling counseling sessions with professional experts and receive personalized recommendations. Our AI powered mental health support platform aims to bridge the gap between mental health patients and clinical services by delivering timely, user-friendly support and treatment options even in a virtual environment if the user decides so.

Our mental health support platform has multiple modules with both web (SurvUday) and mobile interfaces (SarvUday) designed for patients, counselors and administrators. Among its different features, the AI chatbot offers interactions, depression screening and session summaries. It has a centralized data that stores privacy preserved user profiles, chat history and clinical assessments, while the backend APIs handles the user authentication modules, payment modules and data exchange modules. The platform has two main layers: Frontend and Backend. The frontend for patients/users i.e.,user interface allows users to book sessions, chat and access information related to mental health. The counselor interface supports video consultations, summaries and emotion analysis. The admin interface manages system operations. Each connects securely to the backend for seamless service delivery. The backend of both SarvUday and SurvUday platforms manages core functionalities, including authentication, data storage and service delivery. It features secure login modules for users, counselors and administrators, ensuring role-based access. Data is stored in both relational databases (for structured data like user profiles and appointments) and non-relational databases (for unstructured data such as chat history and emotion analysis). Key functional modules include video consultation for live sessions, AI-powered summarization of session data, emotion detection, chatbot support, mental health resources, assessment tools, appointment scheduling and payment processing. These modules interact with the respective authentication and database systems to ensure secure and seamless operations. Non-functional requirements include scalability for large user bases, strong data encryption, compliance with privacy regulations (like HIPAA and GDPR), a user-friendly interface and fast API responses under 200 milliseconds. The architecture of the framework for our mental health support platform is illustrated in Figure 1.

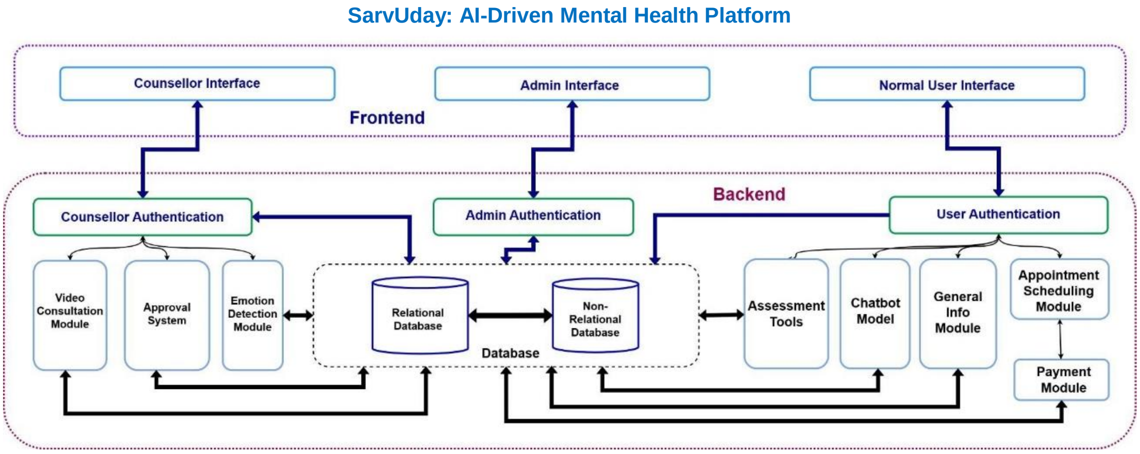

Figure 1. Architecture of our AI powered mental health support platform

2.1. Datasets Used

Two types of data were used in this work: (i) conversational, text summarization and emotion classification datasets sourced primarily from Kaggle (https://www.kaggle.com/datasets/thedevastator/synthetic-therapy-conversations-dataset) and (ii) user-generated data collected through standard clinical questionnaires.

To build an effective mental health chatbot, a comprehensive conversational dataset was prepared, combining mental health-related and general conversations. This approach ensures that the fine-tuned model responds specifically to mental health queries and filters out unrelated topics. Approximately 30,000 dialogue samples were used to train the base chatbot model, with each sample containing 5-10 related question-answer pairs, maintaining a 4:1 ratio of mental health to non-mental health dialogues [22]. An additional 30,000 samples were later used for further fine-tuning, keeping the same ratio. For the summarization component, around 15,000 dialogue-summary pairs were sourced from Kaggle and split into training set and validation set in 4:1 ratio. Emotion classification data, also obtained from Kaggle, included 10,000 samples for each of eight emotional categories: anxiety, bipolar, depression, fear, grateful, happy, sad and stress. This data was also split into training set and validation set in the same 4:1 ratio.

The data preparation process involved text cleaning and formatting to ensure suitability for each task. For depression analysis, user data was gathered through structured questionnaires designed using standardized clinical scales such as the Beck Depression Inventory (BDI) [23], Hamilton Depression Rating Scale (HAM-D) [24] and Patient Health Questionnaire-9 (PHQ-9) [25]. These questions were adapted for conversational ease while maintaining clinical accuracy. The questionnaire focused on key domains- mood, behavior and cognition- with responses scored from 0 to 4, enabling real-time scoring and personalized feedback. To ensure reliability, mental health professionals validated the content and the questionnaire was refined through pilot testing with a diverse group of users. Ethical approval was obtained and strict privacy standards, including informed consent and data confidentiality, were upheld. Users were clearly informed that the tool is supportive and not a substitute for professional diagnosis.

2.2. AI Models Used

Large Language Models (LLMs) [15] and NLP [13] have been coupled to create AI-powered chatbots for mental health while BERT [26] was used for emotion and sentiment analysis.

2.2.1. LLaMA 3.2 for Chatbot and Text Summarization

Meta's LLaMA 3.2 (3B) [15] is a 3-billion-parameter language model built for high and efficient performance across various NLP tasks. It follows a decoder-only transformer design, using multi-head self-attention, feedforward layers and learned positional embeddings to generate contextually accurate outputs. Trained with a causal language modeling objective on large-scale datasets, it balances computational efficiency with strong language understanding. The model supports 4-bit quantization, which lowers memory demands and allows fine-tuning on limited hardware. Additionally, it incorporates Low-Rank Adaptation (LoRA), a method that updates only small subsets of parameters, making fine-tuning more resource-efficient. LLaMA 3.2 performs well in areas like text generation, summarization, classification and translation. The chatbot (Model 1) was developed using the lightweight 4-bit quantized version (via Unsloth library) for training on Google Colab.A total of 24,000 mental health conversations and 6,000 general conversation samples from Kaggle [16]were used for training using CrossEntropyLoss, Adam optimizer, a linear learning rate scheduler and batch size of 4, 0.0002 learning rate with0.01 weight decay.

Model 2 includes a text summarization model which employs the LLaMA-3.2 model in two versions, one with 1 billion and the other with 3 billion parameters, with the larger model delivering better performance. The 4-bit quantized version of the model was used to optimize training speed and resource usage. The dataset of conversational dialogue had a total of 15000 samples along with their summaries. Cross Entropy loss function was used to train the model with a batch size of 4, while the Adam optimizer was chosen with 0.0002as the learning rate and 0.01 asweight decay to prevent overfitting.

2.2.2. BERT for Sentiment Analysis

Bidirectional Encoder Representations from Transformers (BERT) [26], developed by Google, is a powerful model based on transformers that processes input bidirectionally and interpreting words based on their full context. Its architecture consists of multi-layer Transformer encoder which employs bidirectional self-attention that help model the relationships between words. The pre-training is done by masking some of the input tokens at random, and then predicting them, referred to as Masked Language Modeling (MLM). To understand sentence relationship the binarized Next Sentence Prediction (NSP) is employed. BERT is pre-trained on huge text corpora where from it learns to understand the meanings of words and structure and relationship of sentences. For classification BERT uses the special (CLS) token, to represent the entire input sequence. BERT is able to aquire the essence and meaning of words and sentences w.r.t. their contex makes it apt for sentiment analysis.

Model 3 focused on emotion classification leveraging the power of a pre-trained BERT model. A dataset of 80,000 samples across 8 distinct emotion classes was divided in the ratio of 4:1 for training and validation sets. Here, the summarizer model is being used to summarise the users' conversation before doing sentiment analysis due to token limit of BERT model.

3. Results and Discussion

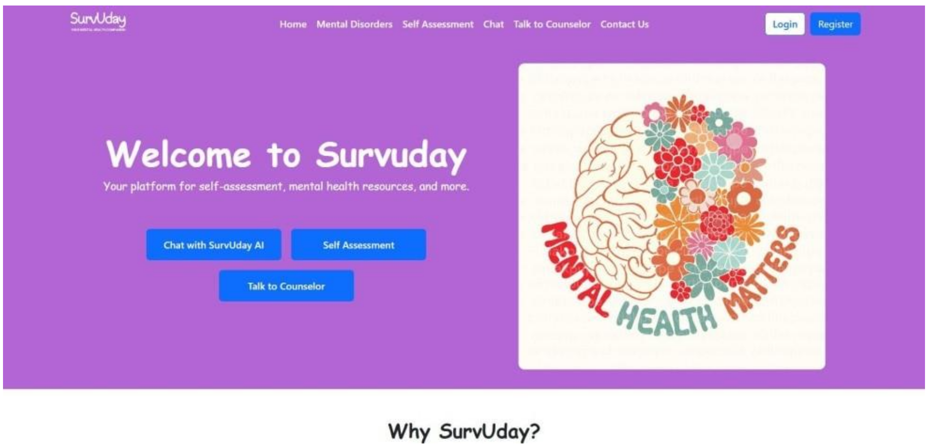

Figure 2. Web interface of SurvUday

The interfaces of both the mobile and web versions of our mental health support platform is designed for a fast, intuitive user experience, offering access to chatbot interactions, mental health assessments, emotion tracking and expert support. It features a streamlined integration between the frontend and backend for optimal performance. The web interface is built using React.js, while the mobile app uses React Native, enabling efficient, cross-platform development with native-like performance on both iOS and Android. React's component-based architecture ensures rapid and modular UI design, while React Native allows for code reuse across platforms. The backend is developed using FastAPI, a high-performance Python framework that supports asynchronous operations, real-time response handling and automatic data validation. This system architecture connects AI models, the FastAPI backend and frontend applications into a cohesive framework. Users interact through the web or mobile apps, with inputs routed to AI models via the backend, generating real-time responses for a responsive and scalable experience. The web application, along with the chatbot, questionnaire and emotion detection modules, is illustrated in Figures 2-4, while the corresponding mobile versions are shown in Figures 5-8.

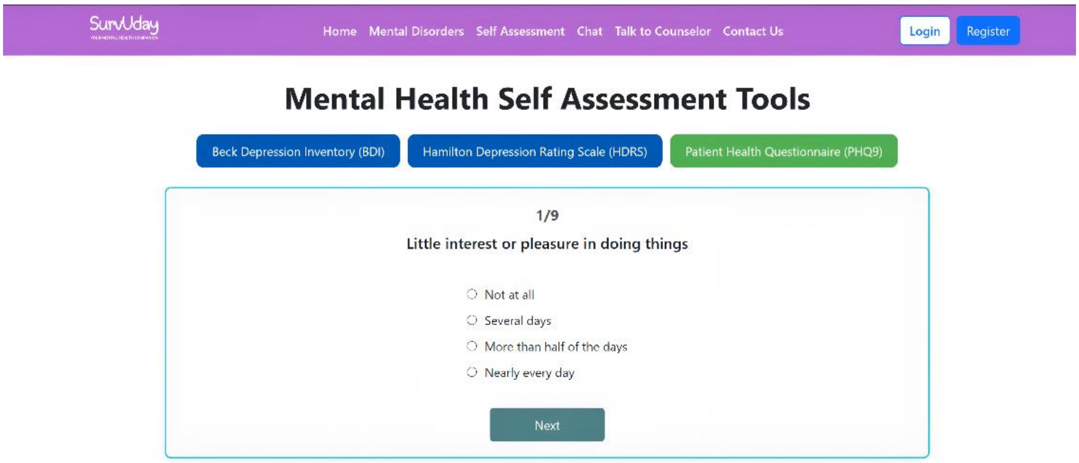

Figure 3. Mental Health Self Assessment Tool

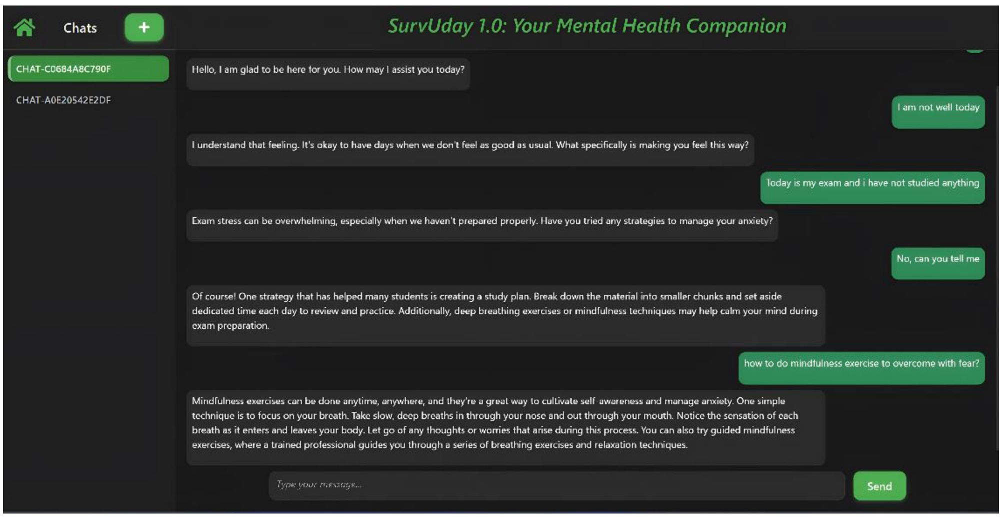

Figure 4. SurvUday Chatbot

Our AI-powered mental health platform (both web and mobile versions) helps users manage their emotional well-being through a combination of intelligent tools. It features a conversational assistant, emotion and sentiment analysis, mental health assessments, personalized counseling recommendations and real-time emotional tracking. Leveraging technologies like NLP, sentiment analysis and large language models such as LLaMA 3.2, the system delivers context-aware, emotionally responsive support. Emotion classification enables personalized guidance, while clinically validated assessments help detect issues like anxiety, depression and stress. The platform also tracks emotional trends over time, offering insights for early intervention and tailored mental health care.

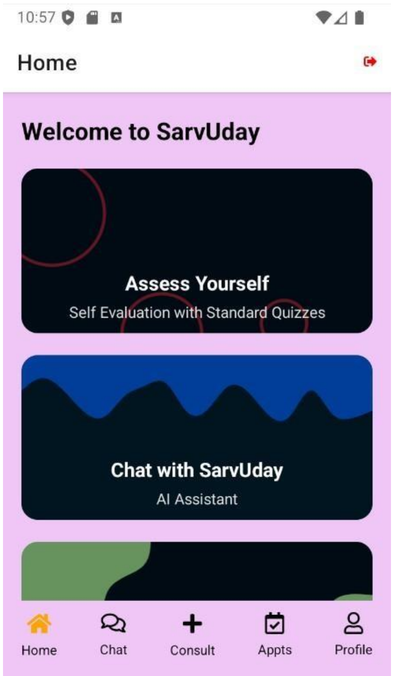

Figure 5. SarvUday Mobile Interface main menu

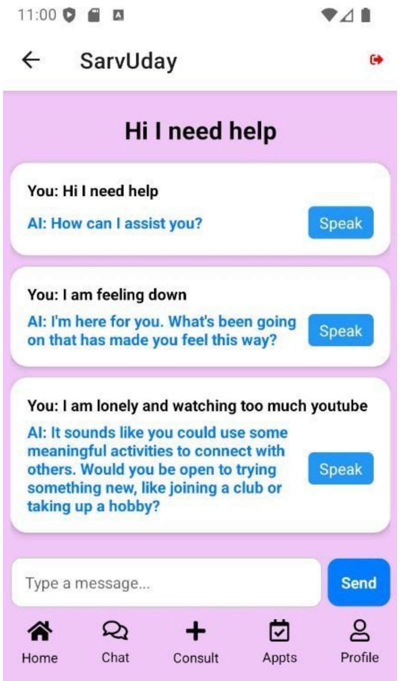

Figure 6. The chat window of the Mobile Interface

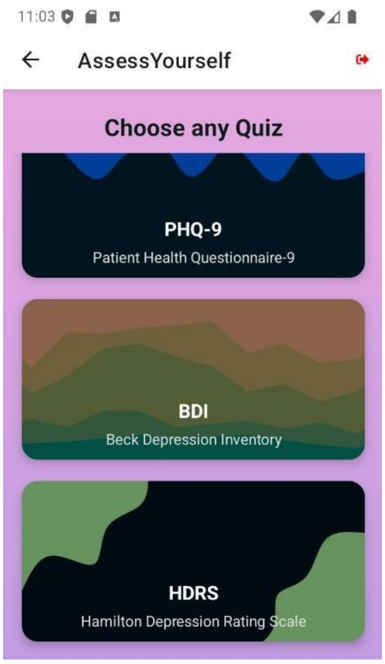

Figure 7. The assessment tools of the Mobile Interface of SarvUday

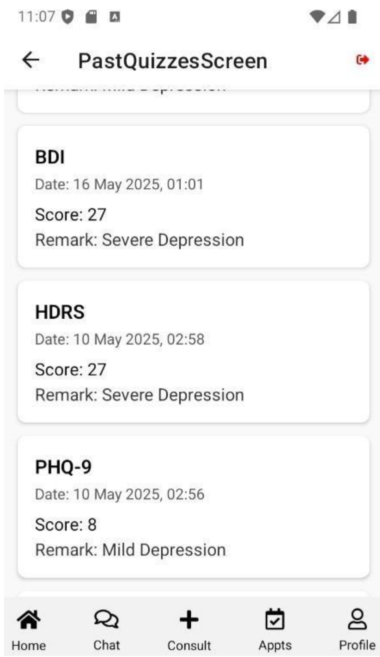

Figure 8. Example scores according to different assessment tools of an user in SarvUday

Model 3 was trained with 64 batch size for over 5 epochs using CrossEntropyLoss and the Adam optimizer (learning rate: 0.00001). It achieved a strong performance, with precision of 89%, 88% of recall of 88%, an F1 score of 88% and an accuracy of 88%. As shown in Figure 9, the training loss steadily declined, while validation loss began increasing after the third epoch, indicating potential overfitting. Similarly, training accuracy improved throughout, but validation accuracy plateaued, suggesting the model generalized well initially. Overall, the model performs effectively, though further training beyond 3 epochs may not offer additional benefits.

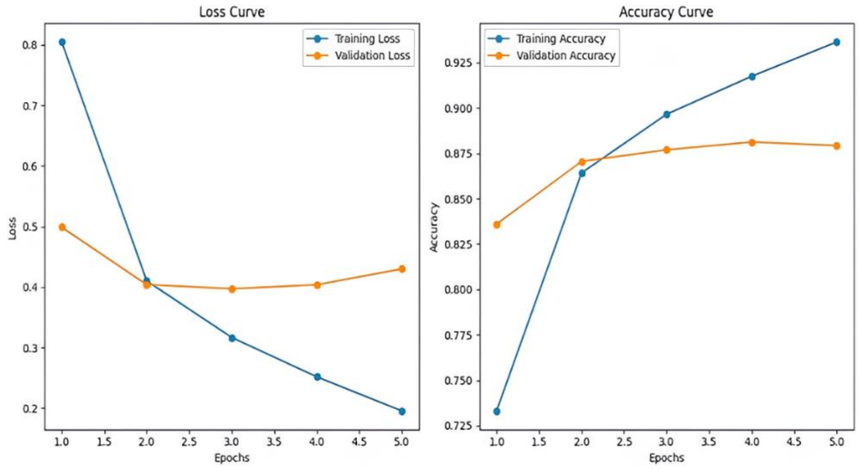

Figure 9. Loss and Accuracy Curve for the Sentiment Model

The confusion matrix in Figure 10 illustrates the model's performance across eight emotion classes: anxiety, bipolar, depression, fear, grateful, happy, sad and stress with darker colors indicating accurate predictions and lighter shades the misclassifications. Diagonal values show high true positives, such as 9,224 for "fear" and 8,978 for "sad," indicating accurate predictions. Misclassifications mostly occur between similar emotions—e.g., "stress" is often predicted as "bipolar" (897 times) and "anxiety" as "sad" (487 times). Minor confusion is also seen between "grateful" and "happy." The color bar adjacent to the confusion matrix in Figure 10 represents the frequency of predictions, with darker shades indicating higher counts and lighter shades indicating lower counts. For instance, the darkest cells along the diagonal correspond to the highest number of correct predictions for each class. Even though the model performs well, more fine-tuning could reduce the overlap between the classes which are emotionally similar.

The AI chatbot converses with users and provides a destigmatized, safe, non-judgmental space where the users of the system can share their feelings and experiences, gain emotional support and access various mental health e-resources as well. The self-assessment tools and questionnaires validated by healthcare professionals, help the users of the system to assess their own mental state and manage their health with recommended coping strategies or treatment options. The emotion tracker could effectively detect subtle signs of emotional change with an accuracy of 88% thereby enabling individuals manage their own emotional well-being with support from our mental health support platform.

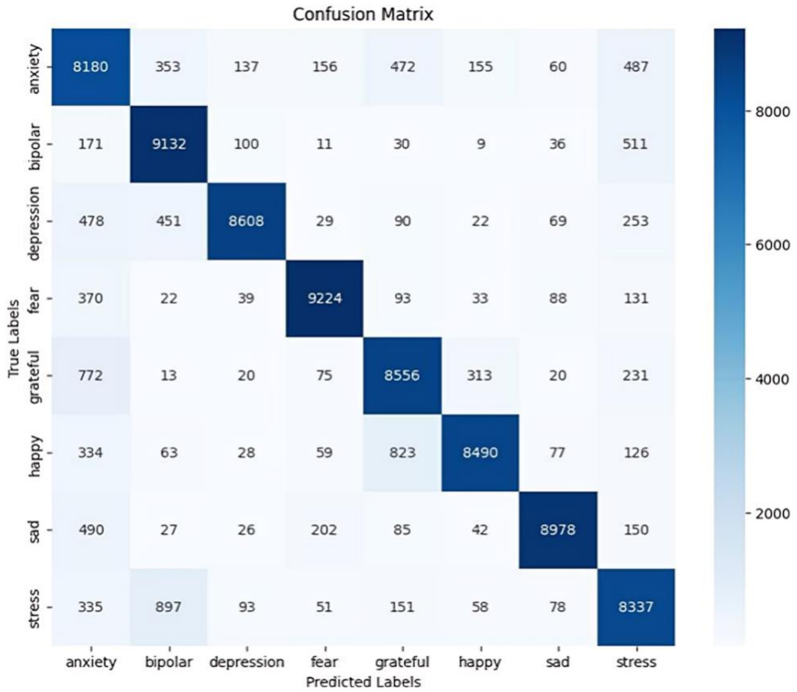

Figure 10. Confusion Matrix for Sentiment Model, x-axis indicating the predicted labels, and y-axis, the true labels, The numbers indicate the predicted number of samples that have been classified of a particular label. Diagonal elements indicate the number of predicted labels which match the true labels. The dark blue colors show that huge number of samples (>8000) have been correctly classified according to their true labels.

4. Conclusions

This paper presents both the mental health platforms, SurvUday (web version) and SarvUday (mobile version), which leverages the power of NLP in summarization, emotion and sentiment analysis. It provides a chatbot capable of carrying conversations with users, giving personalized support as well as directing them to seek professional help in case of severe mental health conditions with our onboard clinicians. Other features of our mental health platforms include the self-psychological assessment based on the three validated clinical assessment tools [23-25] and emotional tracking. The platform is user friendly and helps users obtain personalized responses, solutions and treatment options by analyzing the chat sessions of the users. The system has been enhanced to send sentiment analysis results from the past specified days to the counselor instead of the summarized patient conversations used in the prototype version. Additionally, SarvUday and SurvUday versions introduces several new features, including a persistent backend and integrated databases, marking a significant improvement in functionality and data management. While it shows strong performance, challenges such as emotion recognition accuracy, the need for human support in critical cases remain as it is up to the user to opt for advanced clinical care offered by our on board clinical consultants. The platform's ability to monitor emotional trends over time supports early intervention, making mental health care more accessible, proactive and user-focused.

Interpreting complex emotions remains challenging due to nuances like sarcasm, cultural context and subtle language cues. Enhancing model accuracy requires better algorithms and more diverse data. Given the sensitivity of mental health data, strong privacy measures such as encryption and anonymization are essential. While the AI platform offers helpful support, it cannot replace professional care; users should always have access to licensed mental health experts, especially for urgent or specialized needs which is why our onboard clinicians are licensed mental health experts.

Multidisciplinary Domains

This research covers the domains: (a) Psychiatry, and (b) Computer Science.

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Conflicts of Interest

The authors have no conflicts of interest.

Declaration on AI Usage

This manuscript has been prepared without the use of AI.

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