AI-Powered Detection of Mental Health: A Multimodal System for Analyzing Social Media Activity and Physiological Data

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Abstract. — Mental health problems are still widespread all over the world and among the most frequent are depression, anxiety, and stress, etc. In some cases, however, the causative factor is not even recognized at all due to the social stigma surrounding the issue or the lack of professional treatment, which are the two predominant reasons for the problem remaining undetected. The situation has turned very urgent with the rising trend of mental health issues such that the demand for intervention and detection through sophisticated technologies that are going to tackle the problem right from its roots has already cropped up. The current paper presents a multimodal mental health detection system based on AI that merges behavior and physiological data to deliver psychological well-being with much better context and accuracy. The system leverages the power of Natural Language Processing (NLP) technology which, so to speak, scrutinizes the social media activity to spot the emotional tone, patterns of words, and conversation signals that may indicate mental distress. Moreover, the user's physiological data that user himself/herself provides, such as blood pressure, pulse rate, oxygen levels, sleep duration, sleep quality, etc., is processed by the system to display the user's mental state with great precision. The whole process of the insights obtained is then used to evaluate the risk levels based on percentage for various conditions like stress, anxiety, depression, suicidal risk, etc. The results of the analysis are then presented in a user-friendly report that not only provides the necessary information but also includes the specific recommendations for the user. A mental health assistant chatbot feature is also there. The find help feature further assists users in finding mental health professionals near them. This system has made it easier by providing the users with a combination of social media analysis and physiological wellness tracking.

Keywords: AI-powered Mental Health Detection, Social Media Activity Analysis, Mental Health Chatbot, Physiological Data Assessment, Mental Health Risk Prediction.

IICTDS 2025, December 19-20, Chandigarh, India
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DOI 10.4108/eai.19-12-2025.2362617

1 Introduction

There is a notable increase in the number of mental health disorders which are affecting people of all ages through stress, anxiety, depression, and suicidal ideation, among others. Nowadays, it is common to mention mental well-being, but the process of getting assistance is still hard for many individuals. Stigma, access to care issues, and lack of self-awareness, which act as significant barriers, are the main causes of this. The integration of Artificial Intelligence (AI) in mental health care is a great chance but it also entails unique challenges of proper deployment management which need to be attended to with utmost care. The traditional approaches of our current tools are mainly self-assessment and consulting, which people sometimes postpone or overlook for different reasons. Thus, the recognition of problems and the acquisition of help becomes too inconvenient.

Nonetheless, the globe has revolutionized in communication and health monitoring aspect. Text messaging has become a very dominant and critical means of communication, which has influenced people to prefer writing over talking on the phone, and sometimes even it has revealed emotional cues that are not so easily discerned in speaking. Besides, people have also been getting used to digital devices like smartwatches, fitness trackers, and phone health apps that enable them to monitor and log their various health parameters such as heart rates, blood pressures, oxygen levels, and sleep quality. When these two sources of information—textual behavior and physiological data—are studied together, they could very well be the ones to unravel early signs of mental health issues that otherwise would remain unreported.

1.1 Motivation

The paper is mainly motivated by the need to create a modern, data-based system that would be able to detect behavior through text and also intercede in the body's minor reactions to stress and emotional discomfort. Our plan is to employ Natural Language Processing (NLP) on social media sites, combine it with self-reported physiological data, and create a system that can identify warning signs before they advance to a serious issue. Moreover, we recognize that merely finding the problem is not enough; professional help has to follow. Therefore, the system contains a mental health chatbot for immediate conversational support as well as a find help function that helps users locate mental health professionals near their location when necessary. This links detection and action and thus, leads to assistance through insights.

1.2 Contributions

In this paper, we introduce a thorough model that is both complex and varied, along with physiological measurements for mental health assessment. Thus, the users are granted a better understanding of their emotional states. Among the principal contributions of the research:

- Treatment of social media communications with Natural Language Processing methods to reveal the emotional tone, stress level, and conversation-based signals of mental distress.
- Review of physiological factors like blood pressure, heart rate, oxygen saturation, duration of sleep, and quality of sleep to corroborate the findings of behavioral studies with health data.
- A hybrid scoring model that outputs percentage-based risk levels for stress, anxiety, depression, and suicidal ideation.

- Generation of a comprehensive mental health summary accompanied by personalized recommendations.
- Development of a mental health assistant chatbot designed to offer real-time support and guidance.
- Implement a doctor locator tool that helps users find certified mental health professionals in their area.

1.3 Organization of the Paper

The paper is laid out in the following manner:

- In Section II, the focus is on the present-day AI-based mental health detection and the current methods in using both chat and biometric data through the review of different approaches.
- Section III describes the major issues that the research has aimed to tackle such as the absence of proper diagnosis of mental health problems, the impact of social stigma, scarcity of affordable and timely medical care, and the lack of early detection tools that can be implemented on a large scale.
- Section IV provides a detailed explanation of the system architecture encompassing data gathering (WhatsApp chats and physiological metrics through Excel), preprocessing steps, feature fusion, classification algorithms, risk level determination, and the generation of system outputs such as reports, chatbot, and doctor locator.
- Section V exhibits the outcomes of working prototype including UI snapshots and a visually represented bar chart showing the classified risk levels in terms of depression, anxiety, and stress. It also explains how the system translates user input into actionable insights.
- Section VI summarizes the study's findings and impact, reinforces the significance of a multimodal AI approach to mental health detection, and discusses potential improvements and future work.

2 Background Survey

Mental health has become an essential aspect of our general well-being in recent years as stress, anxiety, and depression have grown more common, especially among teenagers, working professionals, and those under continuous stress, like academic pressure or isolation. Though individuals all around are growing more conscious of mental health issues, the medical system falls short in providing frequent, readily available psychological tests and treatments. Many people do not obtain help because it is stigmatized and poorly understood by society and people around them; the word mental is also sometimes misinterpreted and restricts access to mental health doctors. This has inspired specialists and scientists to develop approaches that do not require individuals to observe themselves constantly and may use the data people make regularly.

The rise of artificial intelligence (AI) and machine learning (ML) technology has enabled intelligent systems to identify subtle behavioral and emotional patterns that may detect mental health issues [1]. Studies have examined text-based data from Twitter, Reddit, and Facebook,

as well as physiological signs gathered via wearable devices like smartwatches and fitness bands [2]. Natural Language Processing (NLP) equipment is particularly efficient for recognising emotional signs like mood swings and depressing language in digital communication [3]. Moreover, the physiological data that are commonly monitored through devices such as smartwatches [4] include the heart rate, blood pressure, oxygen saturation level, pulse rate, and the total and qualitative hours of sleep and they also show the connection to the psychological states like anxiety, stress, depression, etc.

On the contrary, most of the techniques that are currently available have limited functions, mainly concentrating on textual sentiment or relying completely on physiological data [5], thus losing the more profound insights that could be obtained from a combined method. Also, only a small number of systems increase their scope by providing real-time assistance like context-aware chatbots [6], risk summaries, or expert care guidance. Social media data is one of the main sources of information where sentiment analysis techniques are applied to identify potential depression signs [7]. This creates a major research gap in developing a comprehensive, multi-sensory system that can not only detect but also treat mental health problems in a significant and personalized manner. This section is a review of the academic articles on AI-assisted mental health detection patient systems. Their approaches, drawbacks, and practical implementations are discussed here.

2.1 Comparative Analysis of Related Work

Table I shows the main conclusions of contemporary research, locating our solution proposal in the broader landscape of mental health technology.

Table 1. Comparative Analysis of Related Work

Reference	Description	Problems Addressed	Applications
[1]	Systematic review of AI applications in mental health care, highlighting benefits and challenges.	Challenges in early detection and intervention of mental health conditions; ethical considerations regarding data privacy and algorithm transparency.	Enhanced early detection and intervention for mental health conditions; improved patient engagement through AI-driven tools like chatbots.
[2]	Development of a system for real-time emotion analysis to assess mental health status.	There is a need for real-time monitoring and assessment of emotional states to detect mental health issues promptly.	Real-time emotion detection facilitates immediate mental health assessments and interventions.
[3]	Utilization of BERT transformers to detect depression indicators in Arabic social media posts.	Lack of practical tools for analyzing non-English content for mental health indicators.	Application of natural language processing to identify depression signs in Arabic text, aiding in broader demographic assessments.
[4]	Development of a smartwatch application to monitor and detect the psychological states of patients.	There is a need for constant, non-intrusive monitoring of patients' psychological states.	Wearable technology offers real-time surveillance of mental health indicators, providing data for immediate action.

[5]	Creation of 'Stress Sense,' an AI tool assessing stress levels using physiological data.	Difficulty in accurately assessing stress levels through traditional self-report methods.	AI-driven analysis of physiological data to objectively measure stress, aiding in stress management strategies.
[6]	Development of 'Empath.ai,' a chatbot providing emotional support by detecting user emotions contextually.	Limited availability of immediate emotional support resources; lack of context-aware interaction in existing chatbots.	AI-powered chatbot, giving customised emotional support, boosting accessibility to mental health resources.
[7]	Application of sentiment analysis techniques to detect depression indicators in social media data.	Challenges in identifying subtle linguistic cues indicative of depression in large volumes of text.	Leveraging AI for large-scale analysis of social media content to identify individuals at risk of depression.
[8]	The introduction of 'Proactive Emotion Tracker integrates BERT models and physiological signals for continuous mood monitoring.	There is a need for continuous, real-time monitoring of mood and emotions to detect early indicators of mental health disorders.	Combining natural language processing with physiological data allows full mood tracking, permitting early treatments.
[9]	Presentation of 'MHDeep,' utilizing wearable sensors and deep neural networks to diagnose mental health disorders.	Limitations in traditional diagnostic methods for mental health disorders; need for objective, data-driven diagnostic tools.	Integration of wearable technology and AI to detect disorders like schizoaffective, major depressive, and bipolar disorders, enhancing diagnostic accuracy.
[10]	Systematic review of AI tools in early mental health disorder detection emphasizes the need for human oversight.	Concerns regarding the reliability and ethical implications of AI-driven diagnostics without human intervention.	Highlighting the importance of combining AI tools with professional judgment to improve early detection and treatment outcomes.
(This Study)	Combines Social media activity analysis and physiological signals to assess risk for stress, anxiety, depression, and suicidal ideation. Includes chatbot support and doctor locator.	Data privacy and security, real-time integration challenges, and chatbot limitations.	Holistic mental health monitoring, support, and early intervention.

3 Problem Description

In the present-day digital world, mental health problems such as stress, anxiety, depression, and even suicidal thoughts are becoming very common phenomena so fast. The issue is becoming more and more visible but still, a large number of people avoid getting diagnosed and treated early because of stigma, societal pressure, lack of financial means, inadequate or no access to mental health professionals, or geographical isolation. Traditional ways such as

going to the doctor and taking self-assessment surveys at intervals are usually regarded as subjective, slow, and not appropriate for continuous monitoring.

However, digital communication and user-tracked health data can serve as a viable alternative. For example, WhatsApp not only provides a means for communication but also collects a huge amount of behavioral information such as emotional tone, linguistic patterns, and interaction styles, which might actually be reflecting the users' mental states. Moreover, physiological indicators, such as blood pressure, heart rate, oxygen saturation, sleep duration, sleep quality, etc, can effectively send signals about the mental and physical well-being of a person. Nevertheless, most of the existing systems are still not able to integrate these two data sources properly for the purpose of a wider analysis.

One of the main areas where the present research lacks is the multimodal integration—the combination of text-based behavioral insights with physiological data—while at the same time providing a user-friendly and accessible framework for the people. Some of the projects, though, are aimed at unifying models and signals for non-stop monitoring [8]. Still, a lot of the current tools either are restricted to analyzing social media text only or depend on real-time data from wearable sensors, which may not be accessible to every user. Advanced systems, on the other hand, may utilize wearable sensors and deep learning for diagnosis of specific disorders [9] but usually lack the applicability or support features that are broad enough. These systems also do not present personalized risk lists, do not make practical recommendations, and are seldom equipped with features for instant assistance or consulting a professional.

Besides this, the manual input of physiological data (such as through Excel files) is still very much an uncharted territory in the field of mental health monitoring despite its advantage of being more inclusive and less dependent on devices. Besides this, there is a scarcity of real-time support features, e.g., chatbots or doctor locator tools, that direct the users towards getting quick help. Nevertheless, trust and ethical issues related to AI diagnostics require careful handling and this frequently results in a demand for human oversight to the extent [10] in the interpretation and intervention processes.

The suggested way out of these problems is to set up a robust system that employs AI technology to spot mental health issues [11]:

- Utilizes Natural Language Processing (NLP) techniques to analyse social media chat data for signs of emotional distress.
- Accepts user-recorded physiological data in Excel to identify trends linked to mental health conditions.
- Calculates percentage-based risk scores for stress, anxiety, depression, and suicidal ideation.
- Generates a summarized mental health report with personalized feedback and recommendations.
- Provides an AI chatbot assistant for continuous support and conversation-based interaction.
- Offers a find help feature to connect and find nearby certified mental health professionals.

The utilization of non-intrusive monitoring techniques for mental health detection of the users—that is, without any sensors or medical devices—this system is responsible for not only detecting and reacting to but also delivering a complete and easy to access and maintain mental health care approach. AI has been the subject of intense study and development across different areas which is evident in [12-16].

4 Proposed Model

The recommended system is a groundbreaking AI-powered platform that merges various communication methods and is particularly aimed at mental health risk evaluation. It incorporates the user's Hinglish WhatsApp chat data along with the physiological parameters that are manually measured and documented in Excel. The goal of the model is to create a device that is small, privacy-conscious, and professionally supervised to facilitate individual risk evaluations for the four primary disorders: stress, anxiety, depression, and suicidal ideation. Moreover, in addition to risk classification, the system is capable of generating a detailed report that includes the presentation of the findings, individualized mental health guidance, an interactive mental health assistant chatbot, and a doctor locator function. The doctor locator helps users to find licensed doctors according to their location specified by a particular postal code.

4.1 System Architecture

The system's architecture consists of seven interconnected modules such as: data collection, preprocessing, feature extraction and fusion, risk classification, report generation and recommendation, chatbot interaction, and doctor locator services. The entire setup is built in a way that every module works in total harmony, thus allowing the capturing and interpretation of both biological and behavioral data to render the latter as having therapeutic value.

Behavioral and physiological data form the two main data streams that the Data Collection Module handles. The behavioral part comes from the social media chat log of the user, which is uploaded in .txt format. The entire data capture process is based on the use of emotionally expressive text written in Hinglish, an English and Hindi Latin script dialect that is widely used, thus making the process of data capture very efficient. The physician, on the other hand, receives the user's weekly health metrics that include systolic and diastolic blood pressure, pulse rate, blood oxygen saturation (SpO_2), sleep duration (in hours), and sleep quality (on a 1-5 scale) through an Excel sheet uploaded by the user as the physiological input. The design not only does away with the need for continuous monitoring by means of wearable devices but also ensures that the system is open to a greater diversity of users, especially those who have limited resource.

The Data Preprocessing Module functions as the main preparator of the inputs collected that have been prepared for the analysis. During the chat data processing, a variety of natural language processing (NLP) is applied, one of which is the deletion of system-generated metadata (like notifications about media not included) and another, the filtering of messages where the only writer was the user. Moreover, the processing involves converting the characters to lowercase, deleting emojis and timestamps, tokenizing the text, and eliminating stop-words. The physiology department’s data is still under processing with Pandas, one of the

libraries that are mostly used for data handling. The steps involved in this operation are treating missing data, assuring that all data inputs are in the same format, and scaling the data. User alerts and interpolation techniques are used in cases where data is not available. Moreover, blood pressure and sleep metrics trends are calculated over time to assist in time-series feature engineering.

The Feature Extraction and Fusion Module is the one that changes the raw data to feature vectors that have clinical significance. For chat data, this means sentiment classification (positive, neutral, or negative), emotion labelling (e.g. sadness, fear, anger), and identification of clinical expressions with weights determined by the usage of validated tools such as PHQ-9, GAD-7, and PSS (Perceived Stress Scale). Expressions such as "kabhi kabhi toh lagta hai sab chod du" (hopelessness) or "bahut zyada tension ho rahi hai" (anxiety), and so on, are recognized and weighted according to the severity of symptoms and the related condition. Meanwhile, the physiological data is measured against the established clinical thresholds (e.g. $SpO_2 < 90\%$ or heart rate > 110 bpm) and scored accordingly. Then all the features from each module are either concatenated or weighted merged to one vector, which represents the psychological and physiological states at the same time.

he Risk Classification Module receives these multimodal vectors and applies supervised machine learning techniques to process them, particularly Support Vector Machines (SVM), Random Forest, and deep neural networks. For each model training, either the annotated datasets or the synthetically generated samples are used, which are produced in accordance with clinical guidelines and grading systems. The scoring method consists of integrating the clinical symptom score (scaled outputs from PHQ-9, GAD-7, and PSS) with a physiological risk score (computed from the total weights of clinical threshold deviation). The two components are first subjected to a weighted linear summation, which is then followed by the application of sigmoid-based mapping in order to derive the final probabilities for depression, stress, anxiety, suicidal thoughts, and further:

$$P(d) = \frac{1}{(1+ e^{-Total_Risk})} \tag{1}$$

$$Total_Risk = 0.5 \times Clinical_Score + 0.5 \times Physiological_Risk \tag{2}$$

The result for each condition comes with probabilities and a combined mental health risk index as well. The Analysis and Recommendation Module compiles the classifier outputs into a coherent and easy-to-understand report. The report mentions the demographic, emotional, and physiological factors that caused the risk detection and represents them in visually interpretable forms like charts. Besides, the report contains a suggestion tool that proposes self-help methods (for example, journaling, meditation), lifestyle adjustments (for instance, sleeping, exercising), and professional treatments (like psychotherapy, counseling), all classified as short-term and long-term solutions. The recommendations are specifically crafted according to the diagnosed severity and type of issue.

To improve user interaction and provide continuous support, an NLP-powered Mental Health Assistant Chatbot is part of the system. This conversational bot powered by Natural Language Processing employs both the retrieval-augmented and the transformer-based models to provide empathetic and non-judgmental conversations. The chatbot conducts wellness check-ups, provides educational materials on stress and depression, and recommends evidence-based coping strategies like meditation or breathing exercises. It is a constant support companion that is available 24/7 and is most beneficial for users who are in need of immediate human help.

Moreover, the Doctor Locator Module is the final stage of the journey by which the users are led from diagnosis to treatment, as it links them to the nearby licensed mental health practitioners. Users receive a list of clinics, psychologists, or psychiatrists, along with their names, contact details, area of expertise, access to appointment portals, etc., after entering their pincode.

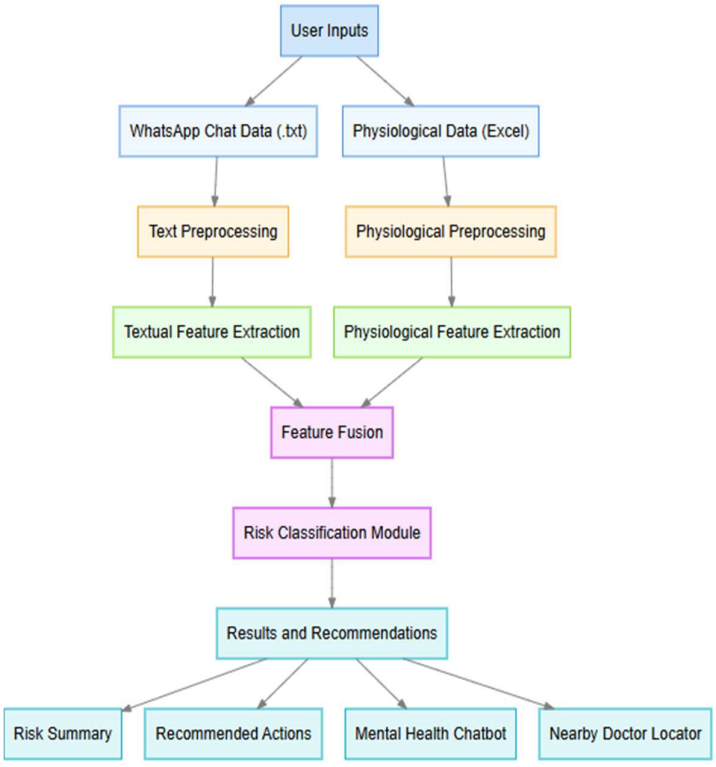


Fig. 1. Flowchart of the Working of the Proposed System.

4.2 Workflow of the Proposed System

At first, the user, Social media data like a WhatsApp chat history file and a structured Excel sheet with physiological data, are uploaded. The system then runs the preprocessing procedures that do the cleaning and organizing of text and numeric data. After that, each stream is subjected to feature extraction according to the predefined clinical criteria and language indicators. The features obtained are combined into a single representation that is presented to the classification engine. The classification output provides the probability score for each mental health condition, which is then interpreted to yield a detailed analysis report. Additionally, the system turns on the chatbot module for real-time interaction, and based on the user's input pincode, it suggests the nearest mental health doctors.

Proposed approach shown in Fig. 1 provides a seamless, user-friendly experience that from behavioural and biometric analysis goes to clinically grounded mental health evaluation while giving essential resources and conversational assistance. The integration of multi-source data, clinically validated scoring, and explainable outputs, makes the model an innovative, accessible, and valuable digital mental health diagnosis contributor.

5 Prototype Results

Through the establishment of a working web-based prototype, the proposed framework of multimodal mental health detection was validated. A personalized mental health assessment based on one's chat history and manually entered physiological data was made available to the user via secure and easy interaction. The construction of the platform was done with the use of standard full-stack technologies, where the data processing and machine learning inference were handled by a Flask-based Python backend, while a frontend was created using HTML, CSS, and JavaScript.

5.1 Website Interface

The system's homepage depicted in Fig. 2 gives a very simple and clean interface that directs the users to the two files they must upload for the analysis: a .txt file that includes their chat history on social media, and an .xlsx file with their weekly physiological metrics like blood pressure (systolic and diastolic), pulse rate, oxygen saturation, sleep duration in hours, and sleep quality rated on a numeric scale.

The system starts a background process after the files are uploaded that includes data cleansing, feature extraction, and risk classification. Visual progress indicators constantly update the viewer on the progress of the process, while organized and user-friendly results are displayed.

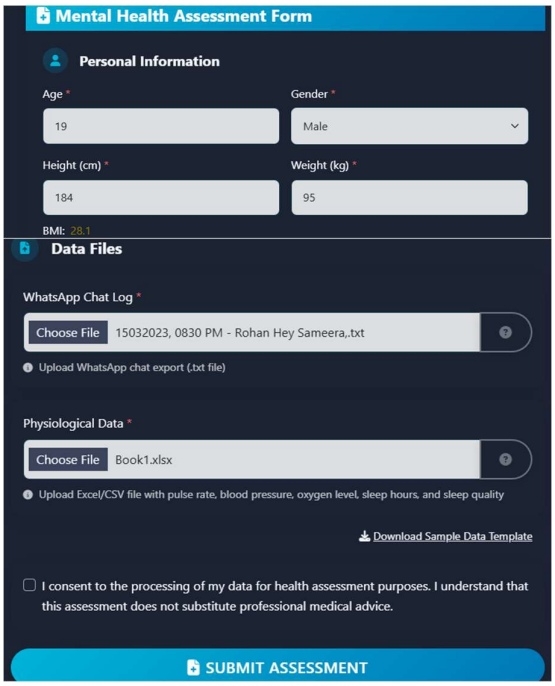


Fig. 2. Home page interface for uploading WhatsApp and Excel files.

5.2 Analytical Outputs

The report generated by the system after processing contains detailed information such as percentage scores reflecting the user's mental health risk in four primary categories: stress, anxiety, depression, and suicidal thoughts, as depicted in Fig. 3.

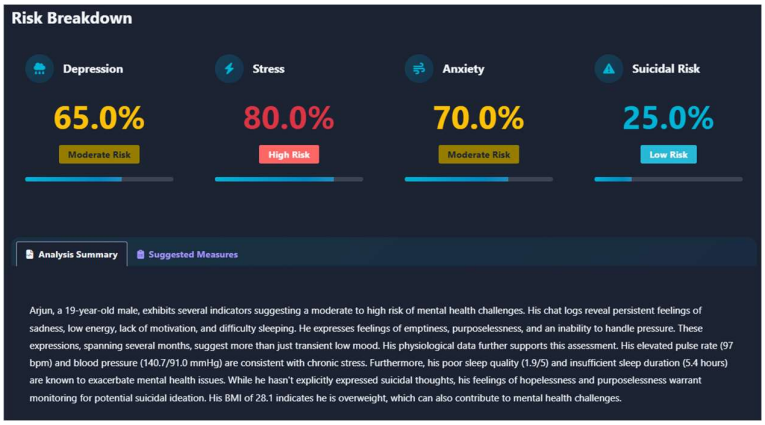


Fig. 3. Percentage-based risk scores of stress, depression, anxiety, and suicidal risk with sections for analysis summary and suggested measures.

The evaluation method includes clinical scales of the PHQ-9, GAD-7, and PSS in combination with weights and deviations assigned to health indicators that are physiological. The user's understanding is easier with the final output given in a clear percentage (for instance, 74%) rather than the probabilistic decimal outputs which are more difficult to comprehend. In this way, the method eases the clinical interpretation and at the same time shows the users the degree of impairments per category more clearly. The risk levels concerning depression, stress, and anxiety are graphically represented by a bar diagram placed on the results page, which is illustrated in Fig. 4. The height of each bar reflects the corresponding risk score in percentage terms, thereby granting the user instant visual comprehension of their mental health condition.

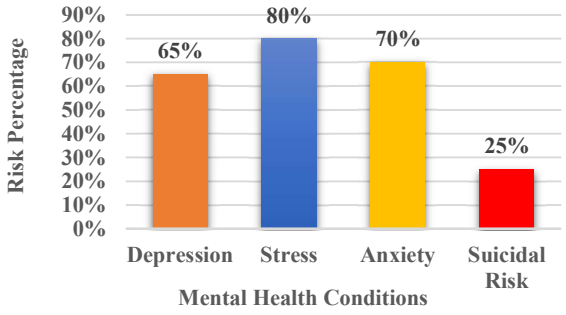


Fig. 4. Display of percentage-based risk scores with accompanying bar graph.

5.3 Chatbot Support

The mental health assistant chatbot depicted in Fig. 5 is integrated into the same platform and can be utilized after the evaluation. It has the functionality of conversing in real-time, providing tips based on cognitive-behavioural therapy, and leading users through activities like journaling or taking deep breaths. For the protection of the users, the chatbot uses transformer-based NLP models and works asynchronously while not keeping any sensitive chat dat.

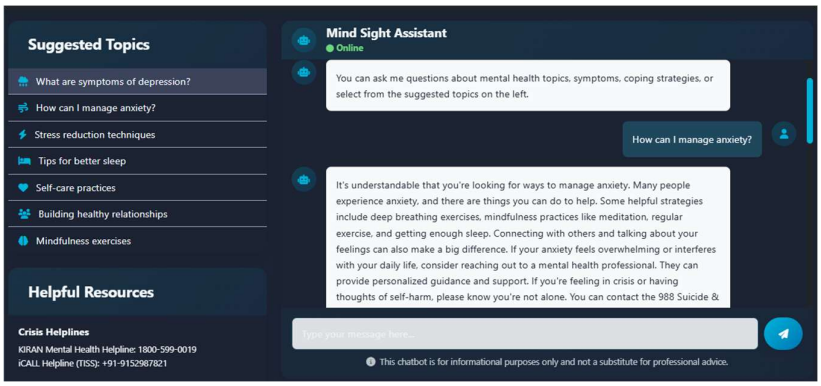


Fig. 5. Chatbot response interface for real-time mental wellness support

5.4 Doctor Finder

Contrary to typical map-based systems, the prototype features a pincode-based doctor locator as shown in Fig. 6.

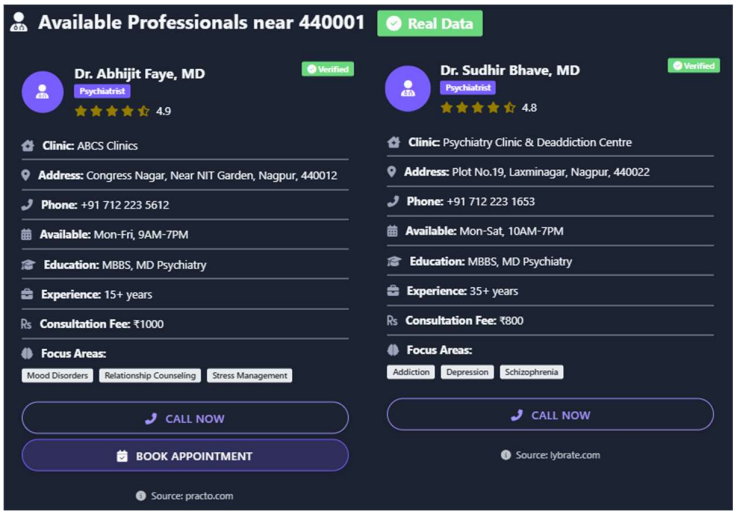


Fig. 6. The Doctor Finder interface shows available doctors for the pincode given by the user.

Once the mental health assessment is completed, users are allowed to input their postal code into a search box. Subsequently, the system searches the backend database and retrieves a list of certified mental health professionals located nearby. For every result, the physician's name, area of expertise, clinic location, education, and phone number (if available) are shown; in fact, there are also links to the online booking platforms.

6 Conclusion

The research presents a novel AI-controlled mental health risk self-assessment framework that integrates social media conversation logs' behavioral data and user's weekly pulmonary metrics. By merging different data sources and employing clinically-informed scoring methods based on PHQ-9, GAD-7, and PSS standards, the system delivers a customized assessment of an individual's risk for depression, anxiety, stress, and suicidal ideation. The new model is much more user-friendly than others as it does not require clinical interviews or wearable sensor data; instead, it gives much importance to people's convenience and their control over the process by allowing users to manually input data through software like Excel and WhatsApp, which are very common. The system's web-based prototype development and testing proved to be practical and user-friendly in the process. Non-technical users can easily understand their outcomes due to the use of percentage-based risk scores and bar graph visualizations. The mental health assistant chatbot and a pincode-based doctor locator were introduced as part of the digital detection and real-world care by giving immediate help and access to professional resources. The model proposes a combination of natural language

processing, physiological data analytics, and machine learning to produce an early mental health screening tool that is scalable. It is an indicator of progress in the field of AI-enhanced mental health care.

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