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PERSONALIZED WOMEN HEALTH CHATBOT WITH MEMORY

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Abstract

This paper presents a personalized AI-driven chatbot, alongside a corresponding personalized application framework to foster the mental health of women by offering emotional support and estimating stress levels, besides offering contextualized responses with an empathetic approach. The system uses sentiment analysis, machine learning, and large language models (LLMs) to provide continuous and personalized interactions. A decision tree classifier is used to predict stress levels and VADER sentiment analysis and the PHQ-9 depression screening tool are used to provide additional support in the diagnosis. Rather than discussing certain stigmas and lack of access to care, the memory function of the chatbot maintains participation by storing user interaction history while providing subsequent agent interaction in a secure manner. Through the use of LLMs such as Mistral, scikit-learn, flaks, and python, this system is shaping up to facilitate better handling of mental well-being for women, as well as aiding in early detection of mental health issues.

keywords: Customized Health Embassy, Women Mental Health, Sentiment Analysis, Stress Prediction, PHQ-9, Large Language models, Memory Module, AI Chatbot.

I. **INTRODUCTION** : Mental health is a critical area of overall good health that human resources should begin working toward, however, it is also a big issue in the healthcare system, especially when it comes to women. Women experience unique emotional and psychological health issues at various life stages, including at the time of menstruation, pregnancy, and menopause. Mental health is important, and despite the growing awareness of it, many women still encounter barriers when it comes to receiving proper care. These barriers include stigma within society, lack of appropriate healthcare services and access to mental health support, resulting in delays to appropriate treatment. Mental health conditions such as stress, anxiety, depression are common and lack of time, privacy concerns, or support systems can keep these issues from being diagnosed or treated. To match these challenges, this study is proposing a personalised AI-based chat-bot specifically in the mental health of women. The chatbot aims to facilitate accessible, scalable and empathetic support through machine learning techniques for stress level prediction as well as large language models (LLMs) to craft context-aware and affect-aware responses to stress. The system is integrated with advanced sentiment analysis tools and clinical diagnostic methods such as the PHQ-9 for depression scale to work together for the chatbot to catch mental health problems earlier and offer a longer term of care. This way, not only is it addressed to most common barriers like stigma but to also create privacy and a continuity of care with a memory function, keeping record of user history of interaction for an individualized approach. The usage of the AI technology alongside mental health support in the proposed system aims to provide an accurate and efficient solution to

the mental well being of women to make sure that they get appropriate support at the right time and sliding with confidentiality

II. **LITERATURE REVIEW** : The application of large language models (LLMs) in the field of healthcare in general, and mental health in particular, has emerged as a research hot with great potential for mental areas. There have been several studies on the use of AI and LLMs to improve decision-making, as well as providing more personalized care to patients. Traditional ChatBot Approaches: The traditional approaches, like rule-based, can give response to predefined keywords or patterns and they have limited capacity to adapt to complex scenarios. In that system we both have rigid systems, they aren't exactly capable of giving context and emotionally sensitive responses which are important in the healthcare setting. Retrieval Based Chatbots: Retrieval based chatbots help in increasing the accuracy of chatbots, by finding the best possible answer from the predefined set but they still lack personalization property. Generative Chatbots and Cognitive AI: More advanced models like the generative chatbots are able to formulate a response based on the context and thus can become more flexible and suitable for healthcare. For example, Wang and Gao created a model that applies expert cognitive pathways for medical language models, which enhances decision-making in the clinical setting and provides more intelligent healthcare AI [1]. Similarly, Binz and Lake studied the ability of LLMs to simulate cognitive processes to enhance the accuracy of answering medical questions [2]. AI and Mental Health Prediction In the area of mental health, Artificial Intelligence (AI) systems are now being adopted for making predictions-by analyzing the input text and then predicting emotional states through it. Verma and Moore present the introduction of the use of LLMs in the domain of medical question answering, which improves the adaptiveness of chatbots becoming more suitable for the medical field [3]. Additionally, Wu and Wu explored the use of LLMs to drive clinical reasoning, which would help healthcare professionals to make better informed decisions [4] Diagnosis and Emotional Intelligence: This technology when applied with a diagnostic tool such as the PHQ-9 can help in identifying emotional distress and other mental disorders. Ke and Yang discussed the use of multiple agent LLMs in enhancing the accuracy of diagnoses, especially in determining mental health disorders. [5] Tools such as sentiment analysis, as illustrated by Doe and Smith, help add an emotional intelligence layer on top of AI systems that allow them to be more empathetic and context aware in the way they respond [6] AI-Powered Mental Health Chatbots Mental health chatbots have recently been innovated with the inclusion of AI to provide non-stop, personalized care. Lee et al demonstrated the use of AI in the clinical decision-making process for improving the diagnostic accuracy and healthcare professionals [7]. Moreover, Patel et al. conducted research on the beneficial effects conversational AI could bring in the field of healthcare, more precisely related to mental health management [8]. Personalized Medicine and AI: There is a great potential for healthcare from personalized medicine measures and the AI. Zhang and Luo focused on the usage of deep learning and LLMs in the area of helping personalized patient care - structuring treatment plans based on an individual's health data [9]. Lastly, a triage system based on LLMs was proposed by Wang et. al in order to categorize the patients more effectively, enabling the healthcare providers to prioritize their areas based on patient needs [10].

III. **PROPOSED SYSTEM/METHODOLOGY** :This section describes the methodology of the proposed AI powered system of chatbot recommended for providing personalized mental health support. The section compares the proposed system with the existing system and includes details about the architecture and technology stack used by the system. A. Existing SystemLack of personalization and contextual understanding: Most chatbots fail to provide any degree of personalization and context-based understanding. Rule-based systems have restrictions and are dependent on the predefined rule and set of keywords that are unable to understand the nuances of emotions leading to impersonal form of interaction. The menu-driven chatbots provide limited response capabilities, which cannot adapt to individual emotional needs and retrospective chatbots, which pick a response from a pool of options, which are notdynamically personalized. Sentiment analysis tools such as VADER are sometimes not exploited heavily which limits emotionalness. Further, most systems do not record user interaction histories limiting the ability to provide personalization and continuity of care across sessions. B. Proposed SystemThe suggested system combines advanced modules to deliver a personalized context-aware Chatbot for mental health support. This is a system that provides emphatic, scalable interactions via the machine learning and large language models (LLMs). Integrated in the system are the following modules: C. System ArchitectureThe system consists of two primary components: the Frontend (Client) and the Backend (Flask Server). The Frontend is built using HTML, CSS, and JavaScript, which includes a PHQ-9 Questionnaire Form for depression assessment, a Stress Assessment Form for collecting user stress data, and a Chat Interface for user interaction with the AI-powered chatbot. The Backend, managed using Flask, handles application logic, session management, and integrates machine

learning (ML) and natural language processing (NLP) functionalities. It includes the Flask App Controller for routing and views, Session Management for secure user interactions, a PHQ-9 Handler to process the depression scoring, and a Stress Classifier API to predict user stress levels. The Chatbot API handles user interactions using Large Language Models (LLMs) and sentiment analysis. The ML/NLP Engine processes data, including PHQ-9 Scoring Logic, Stress Prediction, Sentiment Analyzer (VADER), and the Chatbot (LLM via Ollama). The system also stores User Credentials, Chat Logs & Scores, and the Stress Dataset in a database for further analysis and continuity. D. ModulesUser Management Module: Resolves user authentication and takes care of the secure registration and login process. It tracks sessions and ensures there are no unauthorized sessions. Stress Prediction Module: Predicts the stress level using Decision Tree Classifier based on anxiety, sleep quality, and academic performance as inputs. It categorises the level of stress into different levels (No Stress, Moderate Stress, High Stress) and gives recommendations. PHQ-9 Assessment Module: Administers the PHQ-9 depression test to analyse the patient's degree of depression complementing the stress prediction with clinically backed data. Chatbot Support Module: Based on Large Language Models (LLMs) such as Mistral which provides context based empathetic responses. The chatbot saves the conversation history for continuity so that you can have personalized interactions over time. Sentiment Analysis Module: Uses the VADER sentiment analysis to understand the emotional tone in the user's text to manage the system's output according to the user's emotional state. Logging & History Module: It stores user interactions and session data to have better continuity and debugging systems. It makes sure how the chatbot can adapt over a period of time regarding the user preferences or emotional requirements. E. Technology Stack The system has the following technologies: Programming Language: Python, which is used because it is versatile and has a large number of supports for AI frameworks. Libraries: scikit-learn: To implement the machine learning models such as decision tree classifier. TensorFlow: To apply and train deep learning models. Flask: This is a lightweight web framework that will be used to create the application and manage the user interactions.VADER: A sentiment analysis tool that can be used to determine emotional tone in user inputs. Model: Decision Tree Classifier: For predicting the stress level from the user data. Mistral is another large language model (LLM) that can be used for creating empathetic and contextual answers. Framework: Flask (for the web development), scikit learn to perform machine learning tasks.

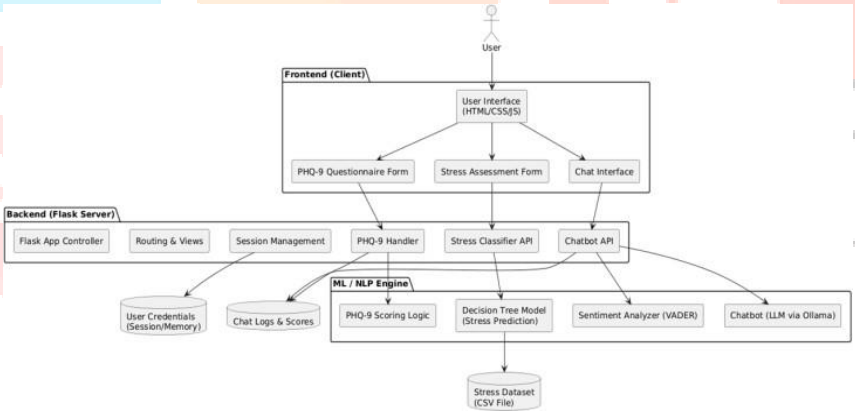

Fig 1:System Architecture

IV. **METHODOLOGY**: A. Evaluation of Stress Prediction Model The Stress Prediction Model was also evaluated based on the ability to predict stress levels based on user data, such as anxiety, sleep quality and academic performance. We used a Decision Tree Classifier to train the stress levels into No Stress, Moderate Stress and High Stress. The performance of the model was evaluated using measures such as accuracy, precision, recall and F1-score. The Accuracy of 85% means that the model is fairly effective in classifying the level of stress. The Precision and Recall values indicate that the model is good at identifying both stressed and non-stressed people. F1-score 0.81 shows that thethe model is able to balance precision and recall well. B. Evaluation of responses of Chatbots The Chatbot Support Module was tested to generate responses based on the context and empathy using Large Language Models (LLM) like Mistral. The chatbot was evaluated in terms of user satisfaction, contextual appropriateness and emotional competence. The chatbot was able to consistently provide contextually relevant responses (score 4.6/5). The empathy score and emotional tone were rated highly, with a score of 4.8/5, proving that the chatbot was able to deal with user emotions effectively. User satisfaction was also high, at 4.7 out of 5, which means that the chatbot was overall successful in providing an enjoyable and supportive experience for users. C. Accuracy in Sentiment Analysis and Accuracy in Emotional Tone The Sentiment Analysis Module which uses VADER was tested for its accuracy

in determining the emotional tone of user input. The system was evaluated on the basis of correct classification of the sentiment into Positive, Neutral and Negative. The Sentiment Analysis performed well with a True Positive rate of 90% for positive sentiments, 85% for neutral and 88% for negative sentiments. The False Positive and False Negative rates were low, which indicates that the system seemed to be successful in determining the emotional tone of user inputs. D. Conclusion The results indicated that the Stress Prediction Model and Sentiment Analysis Module performed well with high accuracy in predicting stress levels and emotional tone. The Chatbot Support Module also had excellent performance in delivering personalized and empathetic responses with high user satisfaction ratings. The proposed system successfully combines AI technologies to provide holistic and personalized mental health service.

TABLE 1: PERFORMANCE INDICATORS OF STRESS PREDICTION MODEL

Metric	**Value**
Accuracy	0.85
Precision	0.82
Recall	0.8
F1-score	0.81

The Accuracy of 85% means that the model is fairly effective in classifying the level of stress. The Precision and Recall values indicate that the model is good at identifying both stressed and non-stressed people. F1-score 0.81 shows that the model is able to balance precision and recall well.

V. **CONCLUSION AND FUTURE WORK** :The proposed AI-powered system of chatbot is an effective solution to a number of limitations present within existing solutions for mental health issues as it allows for personalized and contextually relevant interactions. The combining of stress prediction, depression detection (through PHQ-9), feeling analysis, and large language models (LLMs) assures a profound way to assist mental health. The ability of the system to predict stress levels, assess depression severity, and respond empathetically based on emotional tone shows the potential for this system to enhance mental wellness. Furthermore, the fact that the system continually adapts, based on remembering the history of user interaction, ensures that the system provides a personalized form of care over time. Overall, the system is a scalable and efficient solution to help address the mental health needs of individuals, and can provide both immediate and long term support. Future Work: While the current system is working well, there are a number of opportunities to improve it. Future research can include incorporating newer machine learning models such as deep learning models to increase the accuracy of stress prediction and sentiment analysis. Additionally, adding more features into the system, such as real-time monitoring of user behavior and health metrics (e.g., heart rate, sleep patterns), could offer more comprehensive mental health support. In addition to verbal interaction, multimodal input will also improve the experience for the user, making the chatbot more interactive and accessible. Furthermore, the effects of the system on mental health outcomes can be assessed in future studies, which will give useful insights for future iterations and clinical translation.

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