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AI Mental Health Counselor

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Abstract:

In the modern-day scenario, mental health issues such as depression, anxiety, PTSD, and stress are increasingly prevalent, especially among students and working professionals. However, due to social stigma, lack of awareness, and limited access to mental health professionals, many individuals hesitate to seek help. With advancements in Artificial Intelligence and Natural Language Processing, intelligent chatbot systems can bridge this gap by providing accessible, non-judgmental, and immediate support.

This project proposes the development of a web-based AI chatbot that functions as a virtual therapist. The system begins with secure user authentication, followed by a conversational interface powered by a Large Language Model (LLM). As the user interacts with the chatbot, the system analyzes the chat data to identify potential mental health disorders. Based on the analysis, the chatbot classifies the disorder—such as depression, anxiety, stress, or PTSD—and stores the results in a secure database. It further suggests personalized remedies like meditation, journaling, physical activity, and breathing exercises to aid the user's mental well-being.

This intelligent, automated, and accessible solution addresses the urgent need for mental health support in today's fast-paced world, especially in educational institutions and digital health platforms.

Keywords: AI-based, Mental health counselor, Chatbot, Large Language Model (LLM), Emotional analysis, Mental health disorders

Introduction:

Over the last few years, mental health has become a vital issue that concerns individuals of all ages and backgrounds. Stress, anxiety, depression, PTSD, and suicidal ideation have increased, frequently undiagnosed or untreated as a result of social stigma, ignorance, or restricted access to expert assistance. With increasing development in Artificial Intelligence (AI) and Natural Language Processing (NLP), there is a strong potential to deliver scalable, accessible, and confidential mental health support.

This project deploys an AI-powered Web Mental Health Counselor that allows users to chat in real-time with a smart chatbot. The system interprets input from users based on sophisticated language models to recognize symptoms of mental health diseases and offer customized recommendations for betterment. It has a vital feature to recognize suicidal intentions and automatically notify a registered emergency contact if suicidal behavior is recognized. Also, an easily accessible dashboard colorfully monitors emotional improvement over time, assisting users in keeping track of well-being.

By integrating AI technology with the principles of mental health care, this project seeks to close the gap between those in need and the care they are entitled to, making early detection and timely intervention more accessible and effective than ever.

Literature Survey:

Paper 1

Title: Mental Health Chatbots Using NLP: A Review
Authors: Shruti Bhavsar, et al.
Conference: 2022 IEEE International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)

Survey of Existing System:

This paper gives an extensive overview of NLP-driven chatbots intended for mental health care. It explains how current systems apply sentiment analysis, keyword spotting, and rule-based response generation to interact with users and identify emotional cues. The systems reviewed here include early-stage therapy bots such as Woebot and Wysa, which are intended to provide Cognitive Behavioral Therapy (CBT) methods through chat. The article points out that such systems are built with minimal intent recognition, pre-designed scripts, and limited dynamic conversation adaptability.

Limitations / Research Gap:

- They use static data sets and template dialogues, leading to robotic and impersonal dialogue.
- They lack contextual awareness, frequently being unable to recognize subtle changes in emotions or ingrained psychological trends within long dialogue.
- There is little utilization of sophisticated LLMs (Large Language Models) that are capable of offering rich, natural, and empathetic responses.
- The paper concludes that although current tools serve as mental wellness aids, there is significant scope for improvement in personalization, diagnostic accuracy, and long-term user engagement.

Paper 2

Title: An Intelligent Chatbot for Depression and Anxiety Detection using Machine Learning
Authors: Akanksha Choudhary, et al.
Conference: 2021 IEEE Conference on Innovation and Technology in Computer Science Education (ITCSE)

Survey of Existing System:

This article presents a chatbot that applies machine learning methods to detect depression and anxiety symptoms from user interaction. The system utilizes a pre-trained model on manually labeled data and identifies mental illness through the use of sentiment polarity and emotional indicators. It engages the user via the chat interface and marks negative sentiments from word usage and phrases. The system then gives simple advice and encouragement to the user.

Limitations / Research Gap:

- The model relies mainly on keyword identification and sentiment analysis, which tends to result in false positives or failures to detect in more sophisticated conversations.
- It does not have contextual learning and cannot retain long-term memory or perceive user history, as is essential for mental health assessment.
- There is no backend database integration to save and monitor user diagnostics or offer customized remedies.
- The chatbot does not dynamically adjust while conversing and provides general tips instead of specific therapeutic recommendations.

Proposed System:

The AI Counselor project proposes a web-based solution for assessing mental health through real-time conversation analysis. The system leverages natural language processing (NLP) and deep learning algorithms to evaluate user inputs and classify emotional states such as stress, depression, anxiety, PTSD, and normal. The user-friendly interface allows seamless communication with the chatbot, while the back-end processes the input data, generates emotional health reports, and provides personalized feedback. By integrating technologies like Flask, TensorFlow, and NLTK, the system ensures efficient text processing and accurate mental health assessments, helping users understand their emotional well-being.

Analysis:

The AI Counselor project aims to assist users in assessing their mental health by analyzing their text-based inputs for signs of stress, depression, anxiety, PTSD, and overall emotional stability. The tool is designed to serve as an initial point of contact, providing insights into a user's mental state and flagging potential mental health issues that may require further attention.

Problem Statement:

With the rising prevalence of mental health issues, there is a need for accessible and easy-to-use solutions that help users understand their mental well-being. This AI-powered tool fills that gap by providing real-time analysis based on natural language inputs, offering users feedback on various mental health indicators.

Objectives:

1. Provide a platform where users can engage in a free-flowing conversation with a chatbot regarding their emotional state.
2. Evaluate the user's mental health through text sentiment analysis and generate an easy-to-understand report on five emotional parameters: stress, depression, anxiety, PTSD, and normal (neutral) state.
3. Create a predictive mechanism that displays the percentage of each parameter, helping the user understand their emotional balance.

Framework:

The framework for this project combines both front-end and back-end technologies to create an interactive and user-friendly web application.

Front-End:

- <u>HTML/CSS/JavaScript:</u> Used for building the user interface, allowing users to interact with the chatbot in real-time. The chat interface is simple and intuitive, guiding users through the interaction with the bot.

Back-End:

- <u>Flask:</u> A lightweight web framework built in Python that serves as the core back-end structure, facilitating communication between the chat inputs and the AI model.
- <u>TensorFlow/Keras:</u> These deep learning libraries are utilized for training and deploying the AI model. They handle the text processing and prediction tasks based on the user's inputs.
- <u>Langchain (Groq):</u> Utilized for building the chatbot's large language model (LLM). Langchain integrates Groq's capabilities to manage the conversational flow, enabling natural, context-aware interactions between the user and the AI Counselor.
- <u>Langchain (AI21):</u> Implemented for text embedding, which transforms the user's inputs into numerical vectors for efficient processing. The same is used to compare the user's input with the sentences from the database so as to predict the labels more efficiently.

Database:

- <u>MySQL:</u> Stores user data, chat histories, and mental health reports. This allows for secure storage of information, enabling users to retrieve previous reports if needed.

Algorithm:

The AI Counselor project leverages data generation, text embedding, and a deep learning model to analyze user inputs and classify their emotional state. Below is the detailed breakdown of the process:

1. Data Generation:

- Data Creation using Langchain (Groq): Initially, data was generated using Langchain's Groq-based LLM, which produced various sentences related to mental health conditions such as depression, stress, anxiety, PTSD, and normal (neutral) states. These sentences were saved into individual text files, with the file names corresponding to the emotional class (e.g., *depression.txt*, *stress.txt*).

2. Data Preparation:

- Converting Text Files to CSV: Each of the text files was opened and converted into CSV format. The resulting CSV files contained two columns: one for the sentence and another for the corresponding label (e.g., "depression" or "stress").
- Merging CSV Files: All the individual CSV files were merged into a single dataset containing a comprehensive list of sentences labeled by their respective emotional class.

3. Embedding Conversion:

- Sentence Embedding using Langchain (AI21): The sentences in the dataset were converted into embeddings using Langchain's AI21 embedding model. This step transforms each sentence into a numerical vector, enabling the model to understand the semantic meaning of the text.

4. Model Training:

- Training the TensorFlow Model: The embedded sentences were used to train a TensorFlow-based classification model. The model was trained to predict the emotional state (depression, stress, anxiety, PTSD, or normal) based on the sentence embeddings.

5. Real-Time Prediction:

- User Input Embedding: During chatbot interaction, the user's inputs are collected and converted into embeddings using Langchain AI21, similar to the training data.
- Class Prediction: The embedded user input is passed to the trained TensorFlow model, which predicts the emotional class for each sentence the user enters in the chat.

6. Report Generation:

- Class Counting and Percentage Calculation: As the user continues interacting with the chatbot, the model predicts the emotional class for each input sentence. The system keeps track of the number of predictions for each class (stress, depression, anxiety, PTSD, and normal).
- Percentage Display: The counts for each class are converted into percentages, providing a breakdown of the user's emotional state across the five categories. This percentage breakdown is presented to the user in a visual report, offering insights into their mental health condition.

Methodology:

Problem Understanding and Analysis:

- The primary challenge was to develop a chatbot that could assess the mental health of users based on their conversational inputs and classify their emotional state into categories like stress, depression, anxiety, PTSD, and normal.
- Analyzing the requirements for real-time user interaction and providing accurate emotional feedback led to the design of a system that integrates large language models (LLMs) and machine learning.

Data Generation and Preparation:

- **Data Creation**: To train the model, data was generated using Langchain Groq's large language model (LLM) to produce sentences representing different mental health states (depression, stress, anxiety, PTSD, and normal).

- **Data Processing**: The generated sentences were saved as individual text files, then converted into CSV files with columns for the sentence and its corresponding label. These CSV files were merged into a single dataset to build the model.

Text Embedding:

- **Langchain AI21 for Embedding**: The sentences were converted into vector embeddings using Langchain's AI21 embedding model, transforming raw text into a numerical format that the machine learning model could understand and process.
- This embedding technique captured the semantic meaning of the sentences, improving the ability of the system to distinguish between different emotional states.

Model Training:

- **TensorFlow-Based Classifier**: A TensorFlow deep learning model was developed and trained on the embedded dataset to classify the sentences into one of the emotional categories (stress, depression, anxiety, PTSD, normal).
- **Fine-Tuning and Validation**: The model was iteratively fine-tuned to improve its accuracy, using validation techniques to ensure reliable performance across different emotional categories.

Real-Time User Interaction:

- **Chatbot Integration**: Users interact with the chatbot through the web interface. As they type responses, the input is processed in real time and converted into embeddings using Langchain AI21.
- **Model Prediction**: The embeddings are passed to the trained TensorFlow model, which classifies each user input into one of the five emotional categories.

Report Generation and Feedback:

- **Class Count and Percentage Calculation**: For each user input, the system predicts the class and keeps track of the counts for each emotional category. The results are aggregated to produce a percentage breakdown of the user's emotional state.
- **Real-Time Reporting**: The system dynamically generates a visual report displaying the emotional health distribution of the user, allowing them to see their mental health condition at a glance.

System Architecture:

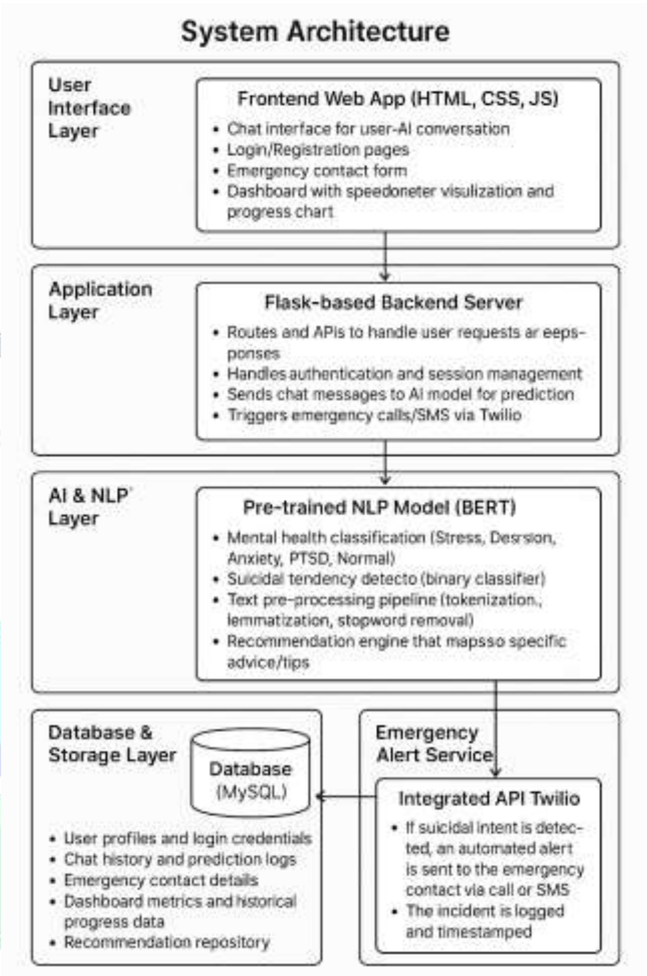

figure 1. System Architecture

Results & Analysis:

figure 2. Web Homepage

figure 3. User Registration Page

figure 4. Chatbot Interface

	precision	recall	f1-score	support
PTSD	1.0000	1.0000	1.0000	11847
anxiety	0.9988	1.0000	0.9994	11847
depression	0.9999	0.9993	0.9996	11847
normal	0.9722	0.9643	0.9682	11848
stress	0.9997	1.0000	0.9999	11848
suicide	0.9652	0.9722	0.9687	11847
accuracy			0.9893	71084
macro avg	0.9893	0.9893	0.9893	71084
weighted avg	0.9893	0.9893	0.9893	71084

figure 5. Performance Metrics

Conclusion:

The AI-based Web Mental Health Counselor project successfully demonstrates the application of artificial intelligence and natural language processing in the domain of mental healthcare. By allowing users to engage in a confidential conversation with an AI chatbot, the system intelligently analyzes their responses to predict possible mental health conditions such as depression, anxiety, stress, PTSD, and suicidal tendencies. It not only provides immediate emotional support and personalized suggestions for improvement but also offers an emergency alert mechanism for high-risk users, ensuring timely intervention. The project emphasizes the importance of early detection and support in mental health, especially in regions where awareness or access to professional care may be limited. With further development—such as multilingual support, integration with health professionals, and advanced analytics—this system has the potential to become a reliable virtual companion for mental well-being. Overall, this work bridges the gap between technology and psychology, offering a meaningful solution to an increasingly critical global issue.

Future Scope:

As mental health support through AI continues to evolve, the following points highlight the potential improvements, enhancements, and research directions that can strengthen and expand the system in future iterations:

Potential Improvements

- Improve Model Accuracy: Use larger and more diverse datasets (like social media, Reddit, therapy transcripts) to improve detection accuracy across different languages and cultural contexts.
- Better Emotion Recognition: Incorporate sentiment/emotion analysis models to detect subtle cues like sarcasm, mood swings, and hopelessness in user messages.

Future Enhancements

- Multilingual Support: Integrate NLP models to handle multiple Indian and global languages to make the system more inclusive.
- Voice-based Interaction: Allow users to speak instead of typing; integrate voice-to-text modules for accessibility.
- Professional Connect Feature: Enable auto-referral to licensed psychologists or counselors if user risk level is consistently high.

Recommendations for Further Work

- Clinical Validation: Collaborate with mental health professionals to validate the model outcomes and ensure ethical compliance.
- Real-time Chatbot Intelligence: Upgrade the LLM integration for more engaging, empathetic, and context-aware conversations.
- Dataset Contribution: Create a secure, anonymized dataset from users (with consent) for research and continuous model training.
- Gamified Mental Health: Introduce gamification techniques (e.g., goals, rewards, daily check-ins) to increase engagement and therapy adherence.

References:

[1] S. Bhavsar, M. Tanwar, S. Tandon and R. Sachan, "Mental Health Chatbots Using NLP: A Review," in 2022 IEEE International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), Greater Noida, India, 2022, pp. 1051–1056. doi:10.1109/ICCCIS56592.2022.10076148.

[2] A. Choudhary, R. Rawat and P. V. Dadhich, "An Intelligent Chatbot for Depression and Anxiety Detection using Machine Learning," in 2021 IEEE Conference on Innovation and Technology in Computer Science Education (ITCSE), Jaipur, India, 2021, pp. 135–140. doi:10.1109/ITCSE51865.2021.9455610.

[3] J. Yin, Y. Cao, Q. Zhang, M. Zhang and C. Liu, "Depression Detection Based on Sentiment Analysis in Social Networks," in 2020 IEEE International Conference on Smart Internet of Things (SmartIoT), Beijing, China, 2020,pp.117–121. doi:10.1109/SmartIoT49966.2020.00030.

[4] H. Al Hanai, M. Ghassemi and J. Glass, "Detecting Depression with Audio/Text Sequence Modeling of Interviews," in Interspeech 2018, Hyderabad, India, 2018, pp. 1716–1720. doi:10.21437/Interspeech.2018-2375.

[5] A. Trotzek, S. Koitka and C. M. Friedrich, "Utilizing Neural Networks and Linguistic Metadata for Early Detection of Depression Indications in Text Sequences," IEEE Transactions on Knowledge and Data Engineering, vol. 32, no. 3, pp. 588–601, March 2020. doi:10.1109/TKDE.2018.2876325.

[6] N. Calvo, J. Milne, and A. Hussain, "Natural Language Processing in Mental Health Applications Using Deep Learning," in Proc. 2017 International Conference on Intelligent Systems (IS), London, UK, Sept. 2017, pp. 118–123. doi: 10.1109/IS.2017.8077653.

[7] R. Gratch, S. Marsella, J. Rickel, and P. Petta, "Virtual Humans: A New Toolkit for Cognitive Behavioral Therapy," in Proc. 2016 IEEE International Conference on Affective Computing and Intelligent Interaction (ACII), Xi'an, China, Oct. 2016, pp. 1–7. doi: 10.1109/ACII.2016.7463792.