AI-Driven Chatbot for Mental Health Analysis Using Transformer Models

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ABSTRACT

This Mental Wellness Chatbot is a software-based solution created for the purpose of solving the incomplete alleviation of depression symptoms in a person. This mental wellness Companion is a chatbot that act as a normal chatbot while mainly focus on the mental health of the user. To accomplish this, we are going to be use various techniques and algorithms to create this chatbot. We are going to use API token of a pre-trained hugging face model in order to create this chatbot rather than using the Large Language Model (LLM) locally since executing the chatbot locally requires a lot of GPU power in the device in order to create and embed the data that we are providing as a dataset. Mainly we are going to be using a pre-trained model from the open-source hugging face model and we are not going to be using OpenAI for completing it. For the database we are going to be using the vector database Facebook AI Similarity Search (FAISS) instead of Mangodb. The mental health Chatbot app is like a reliable friend in the pocket, always ready to lend an ear and offer support whenever you need it. Through gentle questions and personalized suggestions, it helps to navigate the emotions and find ways to feel better. By tracking persons progress over time, it creates a valuable record of emotional journey, empowering to understand oneself better. With 24/7 availability and a commitment to privacy and confidentiality, it provides a safe space for a person to express openly and honestly. Whether the person looking for coping strategies, educational insights, or connections to additional resources, the Chatbot app is there to guide a person on their path to emotional well-being.

Keywords: Mental health chatbot, Transformer-based NLP, FAISS vector embeddings, Langchain integration, Sentiment analysis

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Introduction

The development of the Mental Wellness Chatbot represents a significant step forward in leveraging technology to address the unmet needs of individuals experiencing incomplete alleviation of depression symptoms. Through a comprehensive approach that integrates assessment, treatment, and support functionalities, the work presented in this article offers a personalized and accessible solution to augment existing mental health care services.[1,2]

This article explores a new chatbot called Mental Wellness Companion to help doctors take care of people's mental health. This chatbot talks like a friend and uses smart technology to understand what people say. This chatbot is like having a helpful friend who's always there to listen and give good advice. It makes it easier for doctors to take care of people's mental well-being, which is super important for everyone's health. The prevalence of mental health disorders continues to rise globally, necessitating innovative approaches to support individuals in managing their mental well-being. In response, this study introduces the development of a novel chatbot application, titled "Mental Wellness Companion" designed to assist healthcare professionals and doctors in mental health assessment and treatment. The algorithms used in the reference paper was discussed by reviewing lot of related works.[1–10]

The use of Transformers in the chatbot was very useful since the old Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN) techniques[3] used in are less effective. The chatbot leverages natural language processing (NLP) and machine learning algorithms to engage users in conversation-based interactions, enabling efficient and accessible mental health support. This was already done in accomplishing the adobot from which a user-friendly interface, healthcare professionals can utilize the chatbot to administer assessments, monitor patient progress, and deliver personalized treatment recommendations.[4]

In the Mental health department, the problem of incomplete alleviation of depression symptoms, attrition, and loss of follow-up persist as significant obstacles. Despite advancements in therapeutic techniques and interventions, a gap remains between those seeking help and those effectively receiving and maintaining treatment. To bridge this divide, integration of Artificial Intelligence (AI) in the form of a chatbot is tailored to address these pressing issues. Using of FAISS as vector database was inspired from the work in since the FAISS was proven to be more effective when it comes to the purpose of storage.[5] Along with it the proposed system going to use Hugging Face Transformer as it is proved to be more effective and mainly due to the fact that it is an open-source work.

Related Work

H Kazi, B.S Chowdhry et al developed automatized medical chatbots,[6] designed with technology in mind, hold promise in reducing healthcare costs and improving access to medical services. One such chatbot, a diagnosis bot, engages patients in conversations about their medical queries and problems, offering individualized diagnoses based on manifested symptoms and patient profiles. The system achieves a standard precision of 65%, with identified symptoms recalled at 65% precision and 71% recall. This suggests that a conversational medical bot could be effective, potentially playing a significant role in healthcare. While K-Nearest Neighbours (KNN) isn't typically used directly for chatbot construction due to its supervised

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learning nature, it could serve as a classifier for identifying user query intents or for response retrieval in a retrieval-based chatbot system.

Data acquisition and model deployment are crucial steps, involving obtaining specialist knowledge, defining test criteria, and conducting acceptance tests before deploying the certified model to an API. However, limitations in understanding context and the risk of misinterpretation or misdiagnosis highlight potential challenges. Nonetheless, developing a prototype chatbot system for evaluation, such as on the WeChat platform, could pave the way for further advancements in automated medical assistance. Improved mental health outcomes for affected individuals.

In H.B. Essel et al developed Unified Medical Language System (UMLS) based Chatbot for Medical Students.[7] The design of interactive tutoring systems emphasizes the importance of natural dialogue, particularly in addressing student queries within a specific task domain. This article focuses on the development of a chatbot tailored for medical students, utilizing the Artificial Intelligence Markup Language (AIML) based Chatterbean framework and drawing on the UMLS as its knowledge source. By customizing Chatterbean to convert natural language queries into SQL queries and utilizing the extensive medical terminology and concepts within UMLS, the chatbot can provide relevant responses to student queries in a conversational manner.

A survey of student queries informs the design, targeting common template queries for efficient handling. The system utilizes both UMLS and AIML-based chatbot functionality to ensure comprehensive coverage and accurate responses within the medical education domain.[6] While advantageous in leveraging the rich UMLS knowledge base and offering tailored support for medical students, the chatbot's limitations include its restricted scope of understanding and the potential for providing inaccurate responses, especially if the underlying knowledge base is not regularly updated. Nonetheless, the application of this chatbot promises to alleviate the workload of instructors by addressing a large volume of student queries effectively.

In a research article Towards Chatbot-based Interactive What- and How-Question Answering Systems: The Adobot Approach the paper addresses the limitations of existing question-answering systems (QASs) by proposing an interactive question answering (QA) system, particularly suited for technical support and training domains.[4] This system facilitates exchanges between users and the system to clarify intents and enable follow-up questions, aiming to provide coherent responses to complex queries. It employs a chatbot-based approach, integrating pattern-based, retrieval-based, and generative models, along with an ontology-based knowledge base.

Evaluation utilizes two datasets focusing on user message understanding and dialogue quality. Adobot, the resulting system, emphasizes interactive and conversational experiences, leveraging advanced Natural Language Processing (NLP) techniques for accurate understanding of user queries. However, its reliance on sophisticated NLP models may pose resource challenges and limit deployment on less powerful platforms. While proficient in handling straightforward queries, Adobot may encounter difficulties with complex or ambiguous inquiries. The application process involves data collection, pre-processing, model training, development, deployment, and evaluation, aiming to address the pressing need for an interactive QA system in technical support and training domains.

An AIML chatter bot Knowledge-Base starting from a FAQ and a Glossary[5] the paper focuses on the development of chatterbots using AIML, outlining a methodology to automatically generate AIML knowledge bases from Frequently Asked Question (FAQ) files and glossaries.

The proposed algorithm involves extracting relevant categories from FAQ questions, calculating possible branches, extracting answers, and generating AIML. Advantages include structured knowledge organization and efficient content selection from FAQs and glossaries, facilitating the creation of AIML patterns and enriching the chatterbot's understanding. However, limitations include a potentially restricted scope and flexibility in handling diverse queries beyond the predefined content, as well as maintenance challenges related to updating the knowledge base. The applications of this approach span various domains, including medical diagnosis, content creation, education, and virtual assistance.

Implementation of interactive healthcare advisor model using chatbot and visualization[8] the paper delves into the integration of artificial intelligence data in the medical field through the development of an Interactive Healthcare Advisor Model (IHAM) and a chatbot-based IHAM. Biological information from users, including body temperature, oxygen saturation, pulse, and electrocardiogram data, is collected and analysed using biological sensors and chatbot interactions. This data is then utilized to provide personalized medical advice aimed at enhancing general health. The approach combines the IHAM framework with chatbot technology to engage users in natural language conversations and present health insights through visualization tools. While offering personalized healthcare guidance and enhancing user engagement and understanding, challenges include the complexity of implementation and integration, as well as privacy and data security concerns associated with handling sensitive health data. The applications of this model span various domains, including maintenance assistance, quality control, inventory management, and training.

Crime Awareness and Registration System Using Chatbot[9,10] focuses on implementing a crime awareness and registration system using a chatbot with voice recognition capabilities. The system aims to raise awareness about crime by providing access to blogs, crime rates, news related to crime, and facilitating the reporting of crimes. Through the chatbot-based web service, users can file complaints, gather information

about various types of crimes, and submit verification documents, enabling authorities to cross-verify the information provided.[11,12] Leveraging a custom named entity recognition model, the system extracts structured information such as location, time, and crime type from unstructured complaints, aiding authorities in comprehending complaints more effectively.

The process involves tokenization, segmentation, parsing, stemming, lemmatization, and manipulation of text to generate relevant responses. Advantages include providing comprehensive understanding of crime-related behaviours, access to crime data disclosure, and contributing to crime prevention through increased awareness. However, there are limitations, such as dealing with immigration difficulties and advising bank personnel on legal issues, which may not directly align with crime awareness and registration. Overall, the application of this system enhances crime awareness and facilitates the registration process, contributing to public safety initiatives.

An Educational Chatbot in a Blended Learning Environment.[2,7] The article explores the educational potential of chatbots as interactive learning tools, focusing on their application in facilitating self-paced learning within a blended learning environment, particularly in programming language courses. It discusses the didactic principles underlying the development of chatbots and outlines the process flow within the chatbot interface, emphasizing its role in personalized communication, process automation, and cognitive learning promotion. The methods employed include linear chatbots, generative chatbots, and service chatbots, each serving different functions within educational contexts. The advantages highlighted encompass the automation of repetitive tasks, provision of technical support, personalized communication, and promotion of cognitive learning. The application of chatbots in education extends to various courses, aiding in teaching, course management, and answering common queries. Overall, chatbots serve as educational assistants, alleviating the workload of instructors by addressing student queries and promoting self-paced learning.

The related works highlight various implementations of chatbot systems in the medical domain. The first system focuses on an automatized medical chatbot designed for diagnosis, achieving a standard precision of 65% by using K-Nearest Neighbours (KNN) for classification. The second system tailors a chatbot for medical students, leveraging the UMLS and AIML-based Chatterbean framework to provide relevant responses to student queries, alleviating instructors' workload. The third system proposes an interactive question answering system, Adobot, integrating pattern-based, retrieval-based, and generative models with an ontology-based knowledge base to address complex queries in technical support and training domains. The fourth system develops chatterbots using AIML, automatically generating knowledge bases from FAQs and glossaries, facilitating structured knowledge organization and efficient content selection. Finally, an interactive healthcare advisor model (IHAM) combines AI with chatbot technology to collect and analyse biological information for personalized medical advice, enhancing user engagement and offering health insights through visualization.

These systems demonstrate the versatility of chatbots in healthcare, from diagnosis and education to interactive QA and personalized healthcare guidance, each employing distinct methodologies and technologies to address specific challenges within the medical domain, albeit with considerations such as accuracy, scope, and user engagement.

The summary showcases a wide array of chatbot applications within the healthcare domain. A virtual nurse chatbot aims to offer personalized healthcare advice and support, potentially alleviating pressure on healthcare professionals. Another focus lies on mental health support, where empathetic chatbots provide psychoeducation, coping strategies, and referrals, enhancing accessibility to mental health resources and reducing stigma. In the realm of medication adherence, chatbots remind patients to take medications, track adherence, and provide information, thereby improving health outcomes. Additionally, emergency response chatbots offer immediate first-aid guidance during medical emergencies, potentially saving lives by complementing traditional emergency systems. Each implementation utilizes diverse methodologies, from natural language processing for understanding user queries to integration with existing healthcare systems for personalized recommendations. These systems collectively aim to enhance accessibility, efficiency, and effectiveness of healthcare services, catering to diverse needs and scenarios within the healthcare landscape.

Methodology

The major modules involved are described in this subsection. A query is asked by the user the query gets analysed semantically and then it gets embedded. The embedded query is sent to the model (Figure 1). In the model which is connect to the vector database checks the embedded value with the other embedded value it has which was received from the document that was provided as data. The provided data first gets split into chunks and then split chunks is embedded while maintain its or their semantic relationship between the chunks. This is then stored in the vector database so, when the model receives the user's embedded query it compares with the embedded data in the vector database.

The vector database FAISS used here has irreplaceable role it stores the embedded data provided by us and also the embedded data/query given by the user, the pre-trained model uses the vector database as memory storage. Since FAISS organizes the vectors into an index structure it allows for fast nearest neighbor search. Using this fast nearer neighbour search, the system can quickly match the user's embedded query with the embedded data provided as Knowledge base for the chatbot.

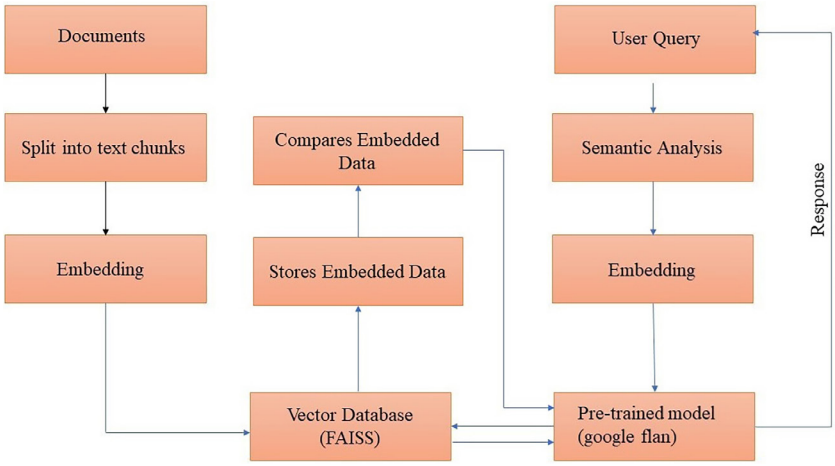

Fig 1 | Work flow diagram of mental wellness companion

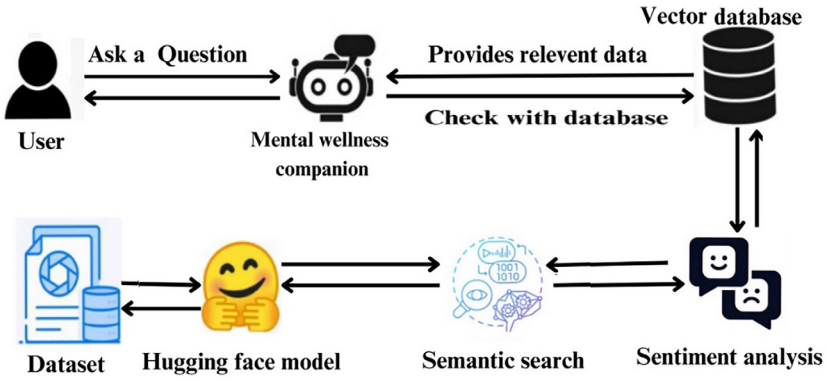

Fig 2 | Architecture diagram of proposed approach

BERT Model

BERT is a powerful language model designed to understand the context of words within sentences, which enhances its accuracy in language comprehension tasks. Unlike traditional models that analyse words in isolation, BERT considers the surrounding context to grasp the intended meaning more accurately. This contextual understanding is achieved through pre-training on vast amounts of text data, allowing BERT to learn the intricate relationships between words and their context without the need for task-specific annotations.

One of the key strengths of BERT lies in its ability to be fine-tuned for various natural language processing tasks such as question answering, sentiment analysis, and text classification. Fine-tuning involves training BERT on specific datasets for targeted tasks, allowing it to adapt its learned representations to perform optimally for those tasks. This flexibility enables BERT to excel in understanding and processing language in diverse ways, making it a highly versatile tool for a wide range of natural language understanding tasks.

Hugging Face Hub

Hugging Face Hub is like a big library of computer brains that anyone can access. It is library that contains several pre-trained models that can be chosen and use it for the need, since it is an open source, anyone can use it for their purpose at no cost, this proposed system is going to use this library for selecting a pre-trained model. For the needs and specification, a pre-trained free of cost model named "google flan". Google flan is a LLM based pre-trained model that is Instruction tuning approach to fine-tune language models.

Langchain

Langchain is a method used for creating a chatbot from the own data. Langchain is an opensource just like Hugging Face. Mainly Langchain model is a framework that focus on combining powerful LLM's like GPT-3, BERT to an array of external data sources or in other words linking the LLM with the own data is the primary and main work of a langchain model. The given data undergoes several processes like chunk, embedding before it is given as an array of external data source. The architecture diagram of proposed idea is depicted in Figure 2, the first and foremost step done after a query is asked by the user the query gets analysed semantically and then it gets embedded. The embedded query is sent to the model. In the model which is connect to the vector database checks the embedded value with the other embedded value it has which was received from the document that was provided as data. The provided data first gets split into chunks and then split chunks is embedded while maintain its or their semantic relationship between the chunks. This is then stored in the vector database so, when the model receives the user's embedded query it compares with the embedded data in the vector database.

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Let's break down how this system work from Figure 2, the system helps you with your mental health questions. Imagine you're talking to a friendly robot who understands you. First, you ask your question. This robot then dives into a giant storage of information, like a super library, to find what might be helpful. But instead of just searching for exact words, it uses a clever tool to grasp the true meaning behind what you're saying. On top of that, it listens closely to how you phrase your question, like if you sound frustrated or down. By understanding both the meaning and your feelings, the robot can pinpoint the most relevant information from its mental health knowledge base. Finally, just like a supportive companion, it shares this information with you, potentially offering additional resources or support if needed.

One might think that there won't be any formulas required in the creation of a chatbot, it is just simply

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an assumption of people but there are lot mathematical calculations needed while creating the chatbot for our purpose. For example, while considering a word embeddings like Word2Vec or Glove they use complex mathematical concepts such as Vector Space Models, here this won't be using those embeddings system but instead would need the help of mathematical calculation for creating probabilistic models. In that case would also need to use formulas such as Hidden Markov Models or Conditional Random Fields to make the chatbot answer in Human way.

Proposed System and Results

The robust chatbot aims to tackle the persistent challenges associated with incomplete alleviation of depression symptoms, attrition, and loss of follow-up in mental health treatment. By integrating advanced technology into mental health interventions, the project seeks to improve treatment outcomes, enhance patient engagement, and increase adherence to therapy. This work accepts voice as input and provide as output to make the conversation livelier. The proposed chatbot uses Sentiment Analysis, it will provide personalized interventions and coping strategies based on individual needs and responses. This chatbot will have a follow-up system to maintain continuous engagement with patients' post-treatment. Utilize chatbots to deliver periodic check-ins, assess treatment efficacy, and provide ongoing support and resources to prevent relapse. This chatbot would have robust security systems to protect the patient's data.

A chatbot created that runs on a cloud server and people can either use it from a software or they can purchase a voice chatbot that listens and speaks back to create a livelier conversation and to make the user to access or use it without any complication since it provides ease of access. This chatbot will have a follow-up system to maintain continuous engagement with patients' post-treatment. Utilize chatbots to deliver periodic check-ins, assess treatment efficacy, and provide ongoing support and resources to prevent relapse. Given below are the four major components in the proposed system that are going to implemented.

1. Creating a Knowledge Base
2. Using LangChain Model
3. Conversation Memory
4. Sentiment Analysis

1. *Creating a Knowledge Base*: First and foremost, step is to collect information's about mental health, their symptoms, prevention or treatment techniques to be used, etc, Convert the collected information's into separate PDF document and categorize it, is shown in Figure 3.
2. *Using Langchain Model*: This model is using Langchain model since it's a language model capable of generating high-quality, contextually relevant text across various domains and applications. Since the targeted users are probably with depression using this model would ease the conversation in a way that the user doesn't get lonely. Langchain model is a language model capable of generating high-quality, contextually relevant text across various domains and applications. Since the targeted users are probably with depression using this model would ease the conversation in a way that the user doesn't get lonely.
3. *Conversation Memory*: Designing the chatbot to handle multi-turn conversation by maintaining context across user interactions. Enabling users to ask follow-up questions and receive responses throughout the conversation. Designing the chatbot to handle multi-turn conversations by maintaining context across user interactions. Enabling users to ask follow-up questions and receive responses throughout the conversation.
4. *Sentiment Analysis*: Sentiment analysis is a main task since it plays a major role in detecting the sentiment. The Langchain model would be developed with sentiment analysis using Deep Learning. This ensures early detection of any depression or any other symptoms. Sentiment analysis is a main task since it plays a major role in detecting the sentiment. The Langchain model would be developed with sentiment analysis using Deep Learning. This ensures early detection of any depression or any other symptoms.

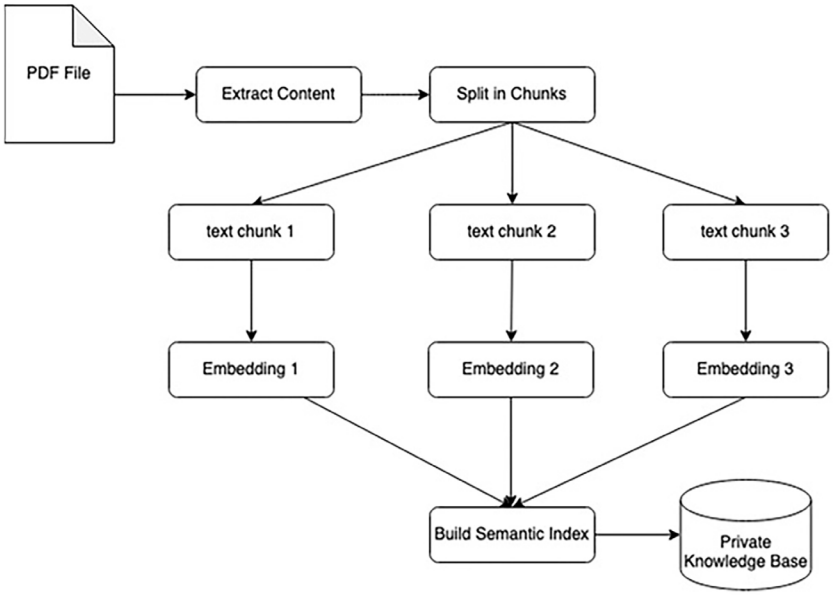

Fig 3 | Knowledge base generation form input PDF files

Module Description

The proposed system has proved to more effective compared to the existing system in terms of both time and accuracy or relevant. The Existing mostly used FAQs as a data and they trained it with their model and created the chatbot thus making the chatbot's knowledge less and its knowledge only fix around with those given FAQ's. The existing system's provided answers while some of them to be relevant most of it was irrelevant or the chatbot replied with "Sorry, I don't know".

This was one of the major backdrops of the existing system but, the proposed system overcame this and proved to be running efficiently and the provided answers were relevant and the accuracy level of chatbot was high mainly due to the fact that the algorithm or method used was different and efficient.

The model used here was pre-trained model thus making it more efficient and also the main major change was that all the existing chatbots executed their model locally making their response time and processing time more, but the proposed system uses API tokens thus executing the model in the hugging face model instead of downloading large models and executing it locally.

For comparing the performance variation, some experiments on proposed work and compared it with the other existing project to compare the performance of the chatbots. These are some of the experiments done for evaluating the performance.

From the Table 1, it can infer that average time taken to process was 70s and average response time was found to be 4.25s. While comparing it with the other chatbots the process time was more when compared with proposed chatbot but the response time of their project was found to be less comparatively. The Figure 4 shows the user interaction window with sample query-response result.

The experimental analysis with respect to complex query and irrelevant query are illustrated in Figure 5.

While testing this experiment even though response time was more the accuracy was always 97% and whatever the query maybe the chatbot can answer precisely. The existing chatbots cannot answer complex queries and their accuracy was low. When it comes to follow up question those chatbots cannot answer follow up questions since they do not have a conservation memory in them. Now let's compare the accuracy with other chatbot. Let us consider these experiments to conclude that the proposed chatbot is more efficient and effective than the existing chatbots.

Approach A is the existing system paper[6] and approach B is the paper.[8] This gives us a clear picture of performance analysis that proposed chatbot is more efficient. The experiment A is about the time taken to process datasets of different sizes. When the user asks a question *"I am feeling* depressed for a *while now what should I do?"* This query's response time is also recorded as shown in Table 2. The query gets split into chunks and then the chunks gets embedded without damaging the semantic relationship between the chunks, so then the embedded chunk gets compared with the data provided as a knowledge base and then the pre-trained model forms a response and this response is displayed to the user. The time taken to produce this answer is known as response time.

Table 1 | Testing with different size of datasets

Dataset Size	Process Time	Response Time
128 kb	10s	2s
512 kb	12s	2s
1.4 mb	25s	3s
5.2 mb	232s	10s

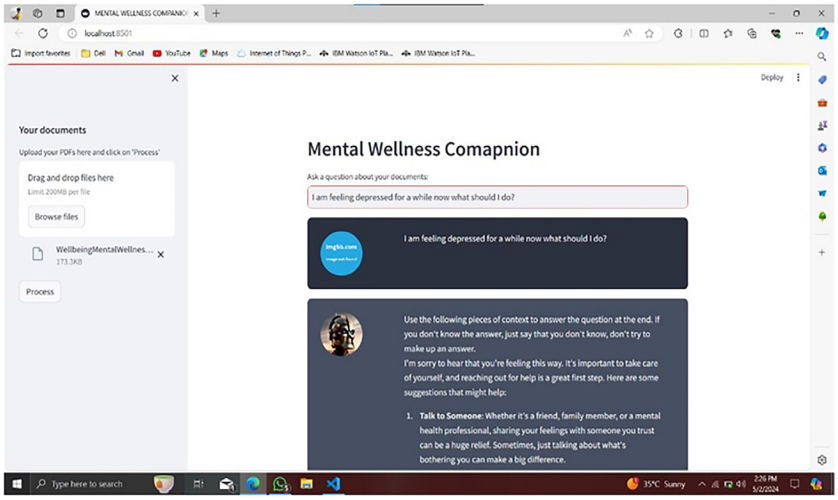

Fig 4 | Sample response for the user query

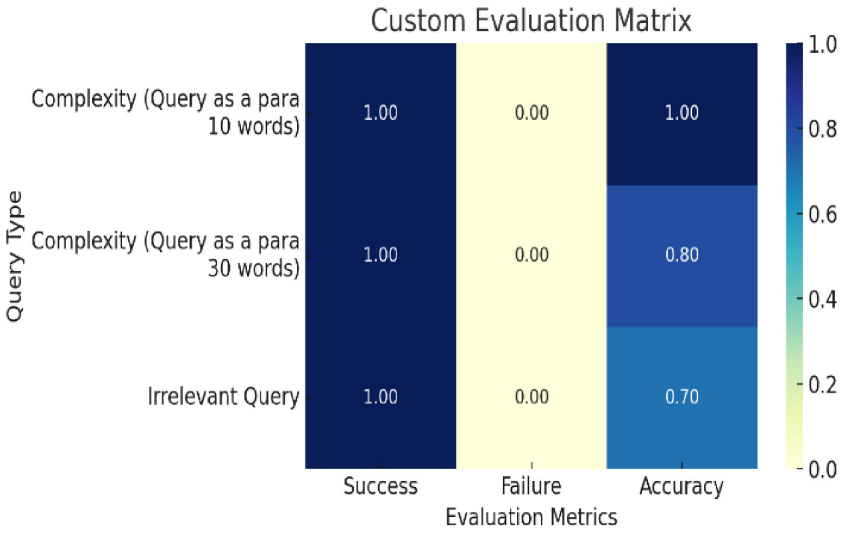

Fig 5 | Confusion matrix results of various types of queries

Table 2 | Testing with complex query

Parameter	Approach A	Approach B	Proposed Approach
Increased Data size	90s	110s	70s
Complex Queries	82	90	97
Conversation Memory	No	No	Yes
Response Time	6.72s	5.51s	4.25s

Conclusion and Future Work

This proposed work has demonstrated the potential of the Mental Wellness Companion to provide meaningful support to individuals struggling with depression. The chatbot's ability to engage users in personalized conversations, deliver psychoeducation, offer coping strategies, and monitor progress has been shown to enhance overall well-being and empower users to take control of their mental health journey. By leveraging

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advancements in natural language processing, machine learning, and data analytics, the Mental Wellness Companion adapts and evolves over time to meet the changing needs of users. Its user-centered design, privacy safeguards, and integration with existing mental health services ensure that it remains a trusted and reliable companion for individuals seeking support for their depression symptoms. However, it is important to acknowledge the limitations of the Mental Wellness Companion and the challenges that lie ahead. While the chatbot shows promise in improving access to mental health care and enhancing treatment outcomes, it is not a substitute for professional medical advice or therapy. Its effectiveness may vary depending on individual preferences, cultural factors, and the severity of depression symptoms. Moving forward, further research is needed to validate the efficacy of the Mental Wellness Companion through rigorous clinical trials and real-world deployments. Additionally, ongoing efforts are required to refine the chatbot's algorithms, expand its repertoire of therapeutic techniques, and ensure its accessibility and inclusivity for diverse user populations. In conclusion, the development of the Mental Wellness Companion represents a significant contribution to the field of mental health care technology. By harnessing the power of chatbot technology, this can create innovative solutions to support individuals with depression and ultimately improve their quality of life. As a continuation to innovate and collaborate, the idea moves closer to a future where mental health support is readily accessible to all who need it. In future work, the need to host the chatbot in cloud to decrease the process response time and need to use OpenAI model to make the accuracy still more high.

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