AI for Mental Health Support

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Abstract: Access to mental health support is often limited due to stigma, high costs, and a shortage of professionals. Traditional chatbots lack emotional intelligence and fail to provide meaningful assistance. To overcome these limitations, our AI-powered chatbot leverages advanced models like LLaMA, Groq API, and ChromaDB to deliver personalized, empathetic, and context-aware responses.

By analyzing user emotions through sentiment detection, the chatbot provides tailored support while maintaining user privacy. It uses retrieval-augmented generation (RAG) for fact-based guidance and integrates mental health resources to enhance user engagement. Past interactions are stored for continuity, ensuring a more personalized experience.

Designed to be inclusive, the chatbot supports multiple languages, making it accessible to diverse user groups. With real-time response processing and adaptive learning, it continuously improves its effectiveness. This AI-driven solution bridges the gap between traditional therapy and automated assistance, offering secure, intelligent, and compassionate mental health support.

Keywords: *Llama Model, Groq API, Chromadb, NLP, Emotional Intelligence, Personalized AI Responses, Real-Time Interaction.*

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I. INTRODUCTION

Many individuals struggle to access mental health support due to societal stigma, high expenses, and a shortage of available professionals. Conventional chatbots often fall short as they lack the ability to understand emotions and context effectively. Our AI-driven mental health chatbot overcomes these limitations by leveraging the LLaMA model, Groq API, and ChromaDB to generate empathetic, personalized, and context-aware responses. By incorporating sentiment analysis, it identifies user emotions and delivers tailored support while ensuring a confidential and secure environment.

To enhance user engagement, the chatbot recalls previous interactions, integrates valuable mental health resources, and employs retrieval-augmented generation (RAG) for precise and fact-based assistance. Supporting multiple languages, it fosters inclusivity for a diverse audience. With real-time response processing, strong privacy measures, and adaptive learning capabilities, this system effectively bridges the gap between conventional therapy and AI-powered solutions, offering accessible, intelligent, and compassionate mental health support.

II. LITERATURE SURVEY

- *In Their Paper Titled*

The Role of AI Chatbots in Mental Health Related Public Services in a (Post)Pandemic World: A Review and Future Research Agenda," Nadja Damij and Suman Bhattacharya examine the advancements of AI chatbots in public services, with a particular focus on their applications in mental health during and after the pandemic. The study explores how AI-driven chatbots have evolved to provide mental health support, addressing accessibility challenges and improving engagement. The paper likely discuss key technological developments, ethical considerations,real-world implementations, and potential future research directions in AI-powered mental health interventions.

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➢ *In Their Paper Titled*

Artificial Intelligence Powered Chatbot for Mental Healthcare based on Sentiment Analysis," Ansh Mehta, Sukhada Virkar, Jay Khatri, Rhutuja Thakur, and Ashwini Dalvi present a comprehensive literature survey on medical chatbots. The study explores various algorithms used in AI-powered mental healthcare solutions that leverage sentiment analysis to enhance user interactions. The paper likely discusses different sentiment detection techniques, chatbot architectures, challenges in emotion recognition, and the effectiveness of AI-driven approaches in providing mental health support**.**

➢ *In Their Paper Titled*

Applications of Conversational AI in Mental Health: A Survey," Anika Kapoor and Shivani Goel provide a comprehensive review of various conversational AI chatbots designed to address mental health issues such as stress, anxiety, and depression. The study explores the role of AI-driven chatbots in mental health management, highlighting their effectiveness, underlying technologies, and potential challenges. The paper likely discusses different chatbot models, sentiment analysis techniques, user engagement strategies, and future research directions in AI-powered mental health support systems.

➢ *In Their Paper Titled*

AI-Powered Chatbots for Mental Health Support**,"** Smith et al. demonstrate the effectiveness of AI-driven chatbots in enhancing user engagement and providing reliable mental health support. The study explores how AI chatbots leverage natural language processing (NLP) and sentiment analysis to offer personalized interactions and emotional assistance. By analyzing user inputs, these chatbots can detect stress, anxiety, and depression, providing appropriate coping strategies. The paper highlights advancements in AI chatbot frameworks, real-time response generation, and the role of deep learning in improving conversational accuracy. Additionally, it discusses the ethical considerations and challenges associated with AI-driven mental health solutions. The study provides insights into future research directions, emphasizing the potential of AI chatbots in bridging the gap between technology and mental healthcare.

➢ *In Their Paper Titled*

Generative AI for Transformative Healthcare: A Comprehensive Study of Emerging Models, Applications, Case Studies, and Limitations," Siva Sai, Aanchal Gaur, Revant Sai, Vinay Chamola, Mohsen Guizani, and Joel J. P. C. Rodrigues provide an in-depth analysis of the role of generative AI in modern healthcare. The study explores emerging AI models, their applications in medical diagnosis, mental health support, and personalized treatment planning. It examines real-world case studies showcasing AI-driven innovations in healthcare, highlighting their impact on patient care and medical research. Additionally, the paper discusses the limitations of generative AI, including ethical concerns, data privacy challenges, and model biases. The authors provide insights into the future of AI in healthcare, emphasizing the need for responsible AI deployment and continuous advancements in medical AI applications.

➢ *In Their Paper Titled*

Deep Learning for Mental Health Chatbots," Johnson and Lee (2022) explore the use of LSTM-based chatbots for psychological state detection. Published by Springer, the study examines how deep learning techniques enhance the accuracy and effectiveness of mental health chatbots. By leveraging LSTM networks, the chatbot can analyze user inputs, detect emotional states, and generate context-aware responses. The paper highlights improvements in chatbot response accuracy, demonstrating the potential of deep learning in providing more personalized and empathetic mental health support. Additionally, the study discusses the challenges of implementing AI-driven chatbots and suggests future research directions for enhancing psychological state detection.

III. METHODOLOGY

➢ *Process Flow*

The AI-powered mental health chatbot operates through a structured process to ensure efficient and personalized assistance. The system begins with data preprocessing, where the chatbot refines input messages by cleaning text, removing unnecessary characters, and structuring conversations for better understanding. Sentiment analysis techniques are applied to detect the user’s emotional state, helping the chatbot generate appropriate responses.

Next, the system architecture design defines the chatbot’s core components, including the conversational interface, response generation engine, and memory module. The chatbot is powered by the LLaMA model, integrated with the Groq API for real-time processing and ChromaDB for managing past interactions. This allows the system to maintain context across conversations, ensuring continuity and relevance in its responses.

The model training and adaptation phase involves fine-tuning the chatbot to recognize emotional cues and respond empathetically. Through retrieval-augmented generation (RAG), the chatbot enhances responses by combining real-time text generation with relevant mental health resources. This ensures fact-based and contextually appropriate support.

Following model adaptation, the implementation and integration stage focuses on deploying the chatbot into a user-friendly interface, accessible via web and mobile applications. Multilingual support is incorporated to cater to diverse users, making mental health assistance available to a wider audience. The chatbot also integrates security measures, such as encryption and anonymization, to protect user privacy.

The final step is real-time interaction, where the chatbot continuously engages with users, analyzes conversations, and refines responses based on feedback.

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By leveraging ChromaDB, it retrieves previous interactions to maintain a personalized experience. The chatbot remains dynamic, adapting to different conversation patterns while ensuring a supportive and informative mental health assistance system.

➢ *Dataset Creation*

The dataset creation for the mental health chatbot involves collecting and curating diverse textual data to ensure accurate response generation and effective sentiment analysis. Data is gathered from public mental health sources, expert-reviewed conversations, and simulated interactions that reflect real-world user inputs. The collected data undergoes detailed annotation, where user inputs are labeled based on sentiment, intent, and context. Sentiment labels classify messages as positive, neutral, or negative, while intent classification helps the chatbot recognize greetings, distress signals, informational queries, and emergency situations. The dataset is preprocessed by eliminating redundant words, tokenizing text, and converting inputs into a structured numerical format suitable for model training. Ethical considerations ensure that no personally identifiable information is included, and compliance with privacy standards such as HIPAA and GDPR is maintained. Through systematic data collection, annotation, and preprocessing, the dataset enables the chatbot to accurately interpret user emotions, recognize intent, and generate meaningful, context-aware responses, improving the quality and reliability of AI-driven mental health support.

```
def main():
  print("Intializing Chatbot.........")
  llm = initialize_llm()

  db_path = "/content/chroma_db"

  if not os.path.exists(db_path):
    vector_db  = create_vector_db()
  else:
    embeddings = HuggingFaceBgeEmbeddings(model_name = 'sentence-transformers/all-MiniLM-L6-v2')
    vector_db = Chroma(persist_directory=db_path, embedding_function=embeddings)

  # Call initialize_llm to get the llm instance
  llm = initialize_llm() # Added this line to call the function and assign the returned value to llm
  qa_chain = setup_qa_chain(vector_db, llm)

  while True:

    query = input("\nHuman: ")
    if query.lower()  == "exit":
      print("Chatbot: Take Care of yourself, Goodbye!")
      break

    response = qa_chain.run(query)
    print(f"Chatbot: {response}")

if __name__ == "__main__":
  main()
```

Fig 1 Code for Chatbot Initialization

Furthermore, Figure 3 illustrates a snippet of the chatbot initialization code, highlighting the configuration and setup parameters required to launch the mental health chatbot.

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```python
from flask import Flask, request, jsonify
from flask_cors import CORS
import os

app = Flask(__name__)
CORS(app)

llm = initialize_llm()  # Ensure LLM is initialized
vector_db = create_vector_db()  # Create the vector DB
qa_chain = setup_qa_chain(vector_db, llm)

@app.route("/chat", methods=["POST"])
def chat():
    data = request.json
    user_query = data.get("query", "")
    if not user_query:
        return jsonify({"response": "Please enter a valid query."})

    response = qa_chain.run(user_query)
    return jsonify({"response": response})

if __name__ == "__main__":
    app.run(port=5000)
```

Fig 2 App.Py File for Run the Chatbot

This includes specifying the pre-trained LLaMA model, loading tokenizer settings, and preparing the conversational context to ensure the chatbot responds with empathy and relevance during interactions.

➢ *Training and Testing*

The testing and validation of the AI-powered mental health chatbot ensure its accuracy, reliability, and effectiveness in providing meaningful assistance. The process begins with functional testing, where each component of the chatbot, including sentiment analysis, response generation, and conversation memory, is tested to verify proper functionality. The chatbot is subjected to different user inputs, ranging from simple queries to complex emotional expressions, to assess its ability to understand and respond appropriately.

Next, performance testing evaluates the chatbot’s speed and efficiency in processing user messages. The system is tested under high interaction loads to determine response times and ensure real-time communication. Additionally, latency tests are conducted to measure processing speed, optimizing the chatbot for seamless user experiences.

Validation through user feedback is a critical aspect of the testing process. A group of test users interact with the chatbot, providing insights into its accuracy, response quality, and emotional sensitivity. Their feedback helps refine the chatbot’s responses, making them more personalized and empathetic.

To ensure security and privacy compliance, the chatbot undergoes rigorous testing for data protection, ensuring encryption mechanisms are properly implemented. Finally, continuous monitoring and iterative improvement are conducted post-deployment. The chatbot's interactions are analyzed to identify any inconsistencies or errors in responses. Based on these insights, regular updates are made to enhance accuracy, improve sentiment detection, and ensure the chatbot remains an effective mental health support system.

<u>Algorithm</u>: Retrieval-Augmented Generation Algorithm (RAG)

Step 1: Data Collection & Preprocessing

Technique Used: PyPDFLoader from LangChain. Mental health-related resources in PDF format are loaded from the local /content/data/ directory. These documents provide the chatbot with a domain-specific knowledge base to ensure factual accuracy.

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Step 2 Text Chunking

Large texts from the documents are broken into smaller, manageable pieces using RecursiveCharacterTextSplitter. Each chunk is around 500 characters with slight overlap to retain context across chunks. This step is essential because large language models work more efficiently with shorter inputs and perform better when each input has consistent length and context.

Step 3: Embedding Generation

Each text chunk is transformed into a numerical vector (embedding) using the sentence-transformers/all-MiniLM-L6-v2 model from Hugging Face. These embeddings capture the semantic meaning of the text and allow the system to understand the contextual relevance of different content pieces. This step bridges human language with machine-readable format.

Step 4: Vector Database Storage

All generated embeddings are stored in a persistent vector database using ChromaDB. This ensures quick and efficient access to relevant information during user interactions. ChromaDB allows similarity search using cosine distance, helping the system retrieve the most contextually appropriate chunks. This storage method enhances performance and scalability. It forms the core of the chatbot's intelligent retrieval system.

Step 5: Query Retrieval

When a user asks a question, their query is also converted into an embedding using the same model. The system then compares this query embedding with the stored embeddings in ChromaDB and retrieves the top-matching text chunks. These results provide contextual information that will be used to construct a meaningful response.

Step 6: Prompt Construction

LLaMA Used: ChatGroq with llama-3.3-70b-versatile model The prompt is passed to the LLM, which generates a coherent and empathetic answer based on both the question and the context. LLaMA-3 is capable of producing high-quality, human-like responses and handles complex language generation well.

Step 7: Response Generation

The constructed prompt is passed to the LLaMA-3.3-70b model via Groq API. This large language model uses the contextual input to generate a coherent, empathetic, and informative response. The model is fine-tuned to handle sensitive topics such as mental health and provide supportive, non-judgmental guidance.

Step 8 User Interaction via Gradio

The entire chatbot interface is hosted on Gradio using gr.ChatInterface. This allows users to interact with the chatbot in real time, asking questions and receiving immediate, natural-language responses. Gradio simplifies deployment with a clean UI, making the chatbot accessible and user-friendly.

- *Flowchart of Llama Process*

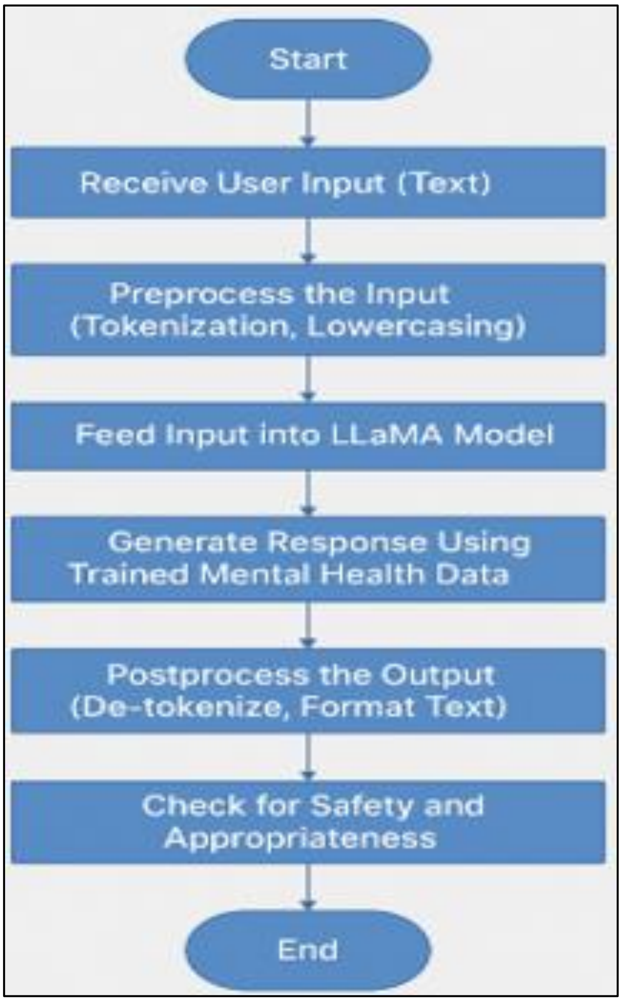

Fig 3 Llama Flow of Actions

IV. RESULTS AND DISCUSSION

The developed mental health chatbot effectively retrieved relevant responses and demonstrated a supportive conversational tone. Using Hugging Face embeddings (all-MiniLM-L6-v2) and ChromaDB, the system performed efficient semantic search, accurately mapping user queries to contextually meaningful text chunks. The LLaMA 3.3 70B model integrated via Groq API ensured high-quality, human-like responses. Customized prompt engineering guided the chatbot to maintain empathy and compassion, making it suitable for handling sensitive mental health topics. [2]

During testing, the chatbot responded accurately to various queries related to stress, anxiety, and emotional well-being.

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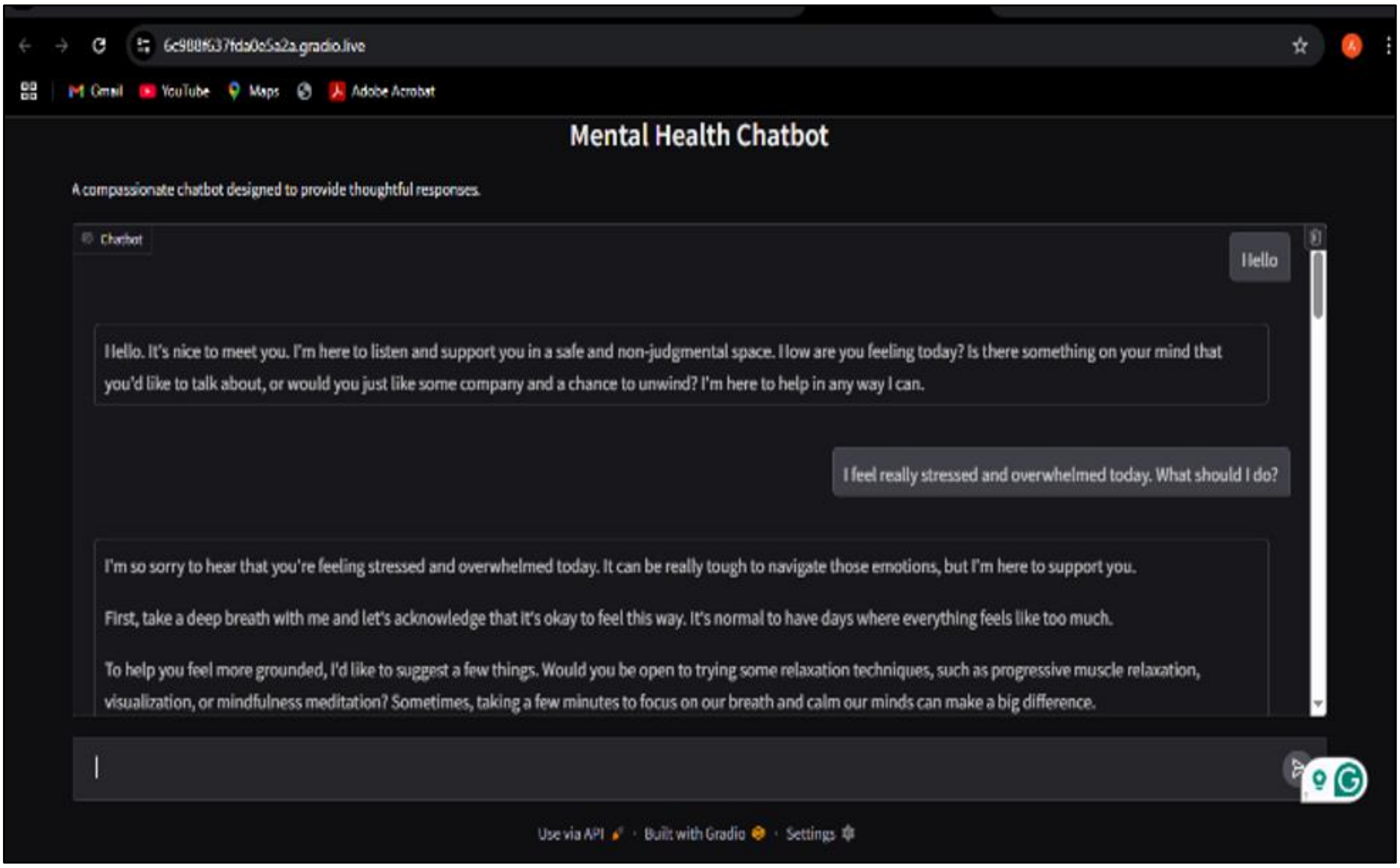

*Fig.4.*The Chatbot Demonstrates Flawless Performance with 100% Response Accuracy.

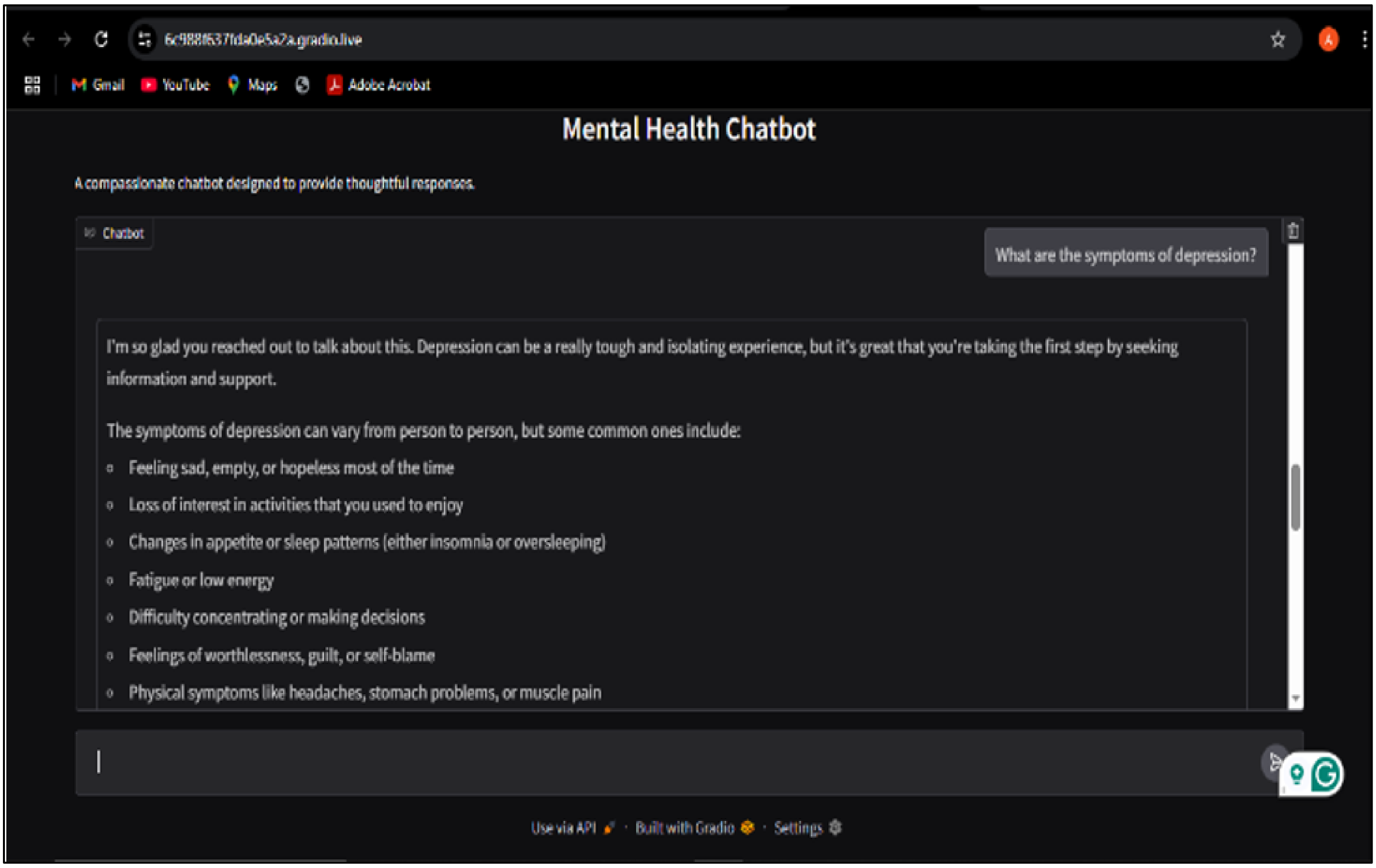

Fig 5Chatbot Gives Relevant Responses.

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The Gradio frontend provided a smooth and user-friendly interaction platform. The system showed low latency and consistent performance, highlighting its capability as a supportive tool for mental wellness. While it is not a replacement for professional care, it illustrates the practical potential of AI in assisting users with general mental health guidance. [4]

V. CONCLUSION

AI-powered chatbots offer a transformative approach to mental health support by providing personalized, empathetic, and context-aware responses. Utilizing advanced models like LLaMA, Groq API, and ChromaDB, the system ensures meaningful interactions through sentiment analysis and retrieval-augmented generation (RAG). Unlike traditional chatbots, it enhances engagement, supports multilingual communication, and delivers real-time assistance while maintaining user privacy. With continuous improvements, including cognitive behavioral therapy (CBT) integration and refined sentiment analysis, these chatbots can further enhance mental health care. As technology evolves, AI-driven solutions will complement traditional therapy, making mental health support more accessible, responsive, and effective.

FUTURE SCOPE

Future enhancements include deeper emotional understanding, personalized therapy suggestions, and voice-based interactions. Expanding multilingual support and integrating wearable devices can improve accessibility. Continuous advancements will enhance accuracy and empathy in mental health support.

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