VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

MINI PROJECT REPORT
on

Mental Wellness Toolkit

Submitted by

MANYA VAID (1BM22CS150)
MARIA SAYEEMA(1BM22CS151)
N PRIYANKA(1BM22CS167)
NALLABOTHULA SAI SRUTHI(1BM22CS170)

Under the Guidance of
Dr. Pallavi G B
Associate Professor, BMSCE

in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B. M. S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU)
BENGALURU-560019

Sep-2024 to Feb-2025

B. M. S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the project work entitled "**Mental Wellness Toolkit**" carried out by MANYA VAID (1BM22CS150), MARIA SAYEEMA (1BM22CS151), N PRIYANKA (1BM22CS167), NALLABOTHULA SAI SRUTHI (1BM22CS170) who are bonafide students of **B. M. S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visveswaraiah Technological University, Belgaum during the year 2023-2024. The project report has been approved as it satisfies the academic requirements in respect of **Mini Project (23CS5PWMIP)** work prescribed for the said degree.

Signature of the Guide
Dr. Pallavi G B
Associate Professor,
CSE
BMSCE, Bengaluru

Signature of the HOD
Dr. Kavitha Sooda
Professor & Head, Dept. of
CSE
BMSCE, Bengaluru

External Viva

Name of the Examiner | Signature with date

1.______________________ ______________________

2. ______________________ ______________________

B. M. S. COLLEGE OF ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DECLARATION

We, Manya Vaid (1BM22CS150), Maria Sayeema (1BM22CS151), N Priyanka (1BM22CS167), Nallabothula Sai Sruthi(1BM22CS170), students of 5th Semester, B.E, Department of Computer Science and Engineering, B. M. S. College of Engineering, Bangalore, hereby declare that, this Project Work-1 entitled "Mental Wellness Toolkit " has been carried out by us under the guidance of Dr. Pallavi G B , Associate Professor, Department of CSE, B. M. S. College of Engineering, Bangalore during the academic semester September 2024- January 2025. We also declare that to the best of our knowledge and belief, the development reported here is not from part of any other report by any other students.

Signature

Manya Vaid (1BM22CS150)
Maria Sayeema (1BM22CS151)
N Priyanka (1BM22CS167)
Nallabothula Sai Sruthi(1BM22CS170)

TABLE OF CONTENTS

1. Introduction

The problem addressed here is that mental health support accessible and empathetic to stress, anxiety, and emotional issues has been absent. Traditional therapy is effective but costly, stigmatized, and inaccessible to most people. The gap results in many without access to support in a timely manner, thereby increasing the potential deterioration of mental health. Mental health has significant effects on well-being, relationships, and productivity; therefore, this is an urgent concern in society.

As part of the remedy, the current solution uses AI at its edge, using cutting-edge Google Generative AI that creates a supportive, empathizing conversationalist chatbot; it is hosted on a lean Flask framework while using state-of-the-art NL processing to respond with personalized care and emotional consideration. The conversation tool is designed around the safety concerns of users first, with such considerations as minimal data retention while ensuring encrypted session security.

This approach builds on the current AI-based mental health tools by addressing the limitations of generic, impersonal responses and weak privacy safeguards. The chatbot delivers context-aware, empathetic conversations, fostering trust and emotional validation. The results will demonstrate how AI can act as a scalable and accessible supplement to traditional mental health support, bridging the gap for those in need.

1.1 Motivation

Mental health is increasingly being adversely affected due to the increasing rapidity of life and constant digital connection. Most of the population feels anxious, depressed, lonely, or stressed but lacks easily accessible, cheaply available support structures. Adding stigma associated with mental illness, financial limitations, and geography does not help anyone who has this sort of problem but instead renders them helpless in an apparent void. We are bridging the gap between the two extremes-the needy and resources-available-to them-by an easily accessible platform, complete with helpline numbers and an interactive chatbot.

Our motivation was in the belief that every person would have access to mental health advice without judgment or barriers. Being able to take advantage of a world where AI has become a major discovery and online platforms are readily found, there is an opening to create a tool where immediate assistance is available coupled with personalized guidance in emotional betterment.

1.2 Scope of the Project

This project concerns the development of a resource website to become a clearinghouse for all resources in mental health. Among the main features are found:

Comprehensive Database of Helplines: categorised list of mental health helpline numbers from worldwide, arranged by regions, languages, fields of specialization such as crisis intervention, suicide prevention, counseling for addiction, and much more.

AI-Powered Chatbot: An intelligent chatbot that participates in empathetic discussion with users to learn about their mental health concerns before making recommendations, such as connecting them to the right helplines near them.

User-Friendly Interface: An easy-to-use interface that is accessible to people of all ages and intellectual level.

Privacy and Confidentiality: Measures to protect user data, ensuring secure interactions, and thus establishing trust in the platform.

This will require research, design, implementation, and testing of the website and chatbot on the grounds of meeting the demands of varied users, being ethical and legally compliant within the standards set for mental health care.

1.3 Problem statement

Mental health challenges affect many millions worldwide, but stigma, lack of resources, or deep feelings of isolation cause huge numbers to miss out on the help they urgently need. The current project bridges this gap by coupling the power of technology with empathy. It offers a comprehensive directory of mental health helplines along with an empathetic AI chatbot designed to create a supportive environment with no judgment.

The overall aim of this project is to provide emotional support immediately, encourage people to speak more about it, and get them in touch with professional help when needed. The chatbot always provides users with a safe and understanding space where they can freely come out and share their thoughts and feelings without fear or feeling left alone. That means this solution steps toward making the system of mental health support more approachable, personable, and accessible to anyone, because everyone should not need to face any struggle alone.

2. Literature Survey

Summary of the research papers:

1. Paper: Potential Benefits and Limitations of Machine Learning in Eating Disorders:

Link: https://link.springer.com/article/10.1186/s40337-022-00581-2

This paper uses ML for the detection and management of eating disorders, which focuses on supervised and unsupervised learning and neural networks. Therefore, ML demonstrates the power of complex data analysis involving social media, neuroimaging data, and genetic information. This research finds that predictive accuracy reaches 98% in early warning systems and has been effective in the symptoms of patients reduced by time with the use of chatbots. Despite its promise, limited generalizability, privacy, and dropout rates are among many limitations that restrict its possible scale and application.

2. Paper: An advanced Artificial Intelligence platform for a personalised treatment of Eating Disorders

Link: https://www.frontiersin.org/journals/psychiatry/articles/10.3389/fpsyt.2024.1414439/full

The research paper explains an AI integrated platform known as Master Data Platform. It used AIML concepts to identify risks, monitor symptoms and predict relapses. The chatbot is trained using NPL. It interacts with the patients, assesses their reports and monitors their treatment. Deep Learning is implemented to study complex data like neuroimaging and behavioral patterns from wearable sensors. It uses data obtained from various care centers in the Campania region as well as from wearable devices that monitor physiological conditions and behaviors such as heart rate and sleep patterns. The major cons of this project include difficulty in integrating the technologies required and cybersecurity risks.The main aim of the project was to increase the awareness of eating disorders. The platform improved the process of managing waiting lists and providing real time interventions to help the patients. The platform was successful in providing a promising solution to people struggling with eating disorders.

3.Paper: Application of machine learning methods in predicting schizophrenia and bipolar disorders: A systematic review

Link: https://onlinelibrary.wiley.com/doi/full/10.1002/hsr2.962

The paper reviews studies which have involved the usage Machine Learning models to detect schizophrenia and bipolar disorder. These studies were found in articles from PubMed, Scopus, and Google Scholar. It analyzed how each model behaved when complex data like neuroimaging, genetic information, and clinical features were fed into it. The studies analysed model performance using metrics like accuracy, precision, recall, or area under the curve (AUC).PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were used for selection and analysis of the studies. The selected studies used datasets that included genomic and neuroimaging data, and clinical records. Many of them depended on publicly available datasets, such as the ENIGMA Schizophrenia dataset. Some studies used custom data. The major cons include lack of standardization in ML and generalization problems. SVM and Random Forest performed well in predicting mental health disorders like schizophrenia and BD. Many studies achieved AUC values above 0.80. The paper emphasised on the need for larger and standardized datasets and better integration of various data types to enhance the performance of machine learning models in psychiatry

4.Paper: Automatic Diagnosis of Bipolar Disorder Using Optical Coherence Tomography Data and Artificial Intelligence

Link: https://www.mdpi.com/2075-4426/11/8/803

This study involved 17 patients that tested positive type 1 Bipolar disorder and 42 healthy people who were similar in age and gender. The study used a technique called Optical Coherence Tomography (OCT) to study the thickness of retina in various layers of the eye. Patients that had BD showed thinness in certain areas such as ganglion cells or inner plexiform layers This information along with Support Vector Machines was used to diagnose BD. This technique showed an accuracy of 95%. Other AI techniques such as g Gaussian Naive Bayes, K-nearest neighbors (KNN) were also used. The cons include that this study focused only on Type BD i.e a limited dataset and there was limited longitudinal data used. This study proved that OCT can be used as a powerful biomarker to diagnose BD.

5.Paper: A Novel Application for the Efficient and Accessible Diagnosis of ADHD Using Machine Learning

Link:https://ieeexplore.ieee.org/document/9311012

The study developed a system using pupillometry to study changes in the size of the pupil while performing memory tasks to detect ADHD. The study included 28 people diagnosed with ADHD and 22 healthy people who acted as the controls. The participants belonged to the age groups of 10-12 years. Leave-One-Out Cross-Validation was used to validate the data. The system showed high accuracy, with 82.1% sensitivity, 72.7% specificity, and 85.6% AUROC. It outperformed models like Random Forest and SVM. Focusing only on the pupil size may lead to ignoring other symptoms of ADHD. The system was implemented as a web app so it provided more accuracy, affordability, and accessibility than traditional methods.

6.Paper: Neuro Intel: A System for Clinical Diagnosis of Attention Deficit Hyperactivity disorder (ADHD) using Artificial Intelligence

Link:https://ieeexplore.ieee.org/document/10218313

The Neuro Intel system combines a hybrid AI model with a ML algorithm Decision Trees and knowledge-based rules to detect and diagnose ADHD. Complex cases are usually passed to experts. It used data from NHS mental health providers via tools such as GAD-7, PHQ-9,and CAARS ADHD scores. The model achieved 92% accuracy and transferred complicated cases to the experts. It helped in reducing clinical workload. The major drawback was the usage of a limited dataset. The model provided an accurate and efficient ADHD diagnostic tool by blending AI and expert knowledge

7.Paper: Machine Learning in ADHD and Depression Mental Health Diagnosis: A Survey

Link:https://ieeexplore.ieee.org/document/10214293

This paper explores ML models like SVM and Neural Networks to detect and diagnose depression and ADHD. It uses data from wearable (EEG) and non-wearable (MRI, speech, and video) modalities to train the ML models. It used multiple datasets like ADHD-200 dataset and DAIC-WOZ dataset for depression diagnosis. SVM models were particularly effective for EEG and MRI data, achieving up to 97.6% accuracy for ADHD detection.These methods outperform traditional approaches in accuracy, offering non-invasive and objective diagnostics. However, limited datasets and privacy concerns hinder broader applications.

8.Paper: Machine Learning based Detection of Post Traumatic Stress Disorder of Mental Health

Link:https://ieeexplore.ieee.org/document/10193036

The system involves the use of Gradient-Boosted Decision Trees,Logistic Regression and Random Forest algorithms to detect PTSD. The system uses a clinical dataset of trauma-exposed individuals and military personnel as well as data from 243,000 tweets shared by PTSD patients. The Random Forest algorithm showed the highest accuracy 97% and outperformed other methods like Bagging (95%) and SVM (91%). The study explains how Random Forest can detect Post Traumatic Stress Disorder using a combination of clinical data as well as social media.

9.Paper: Artificial-Intelligence based Prediction of Post-Traumatic Stress Disorder (PTSD) using EEG reports

Link:https://ieeexplore.ieee.org/document/10072671

This system uses EEG reports to predict PTSD. It involves collection, pre-processing, and extraction of relevant features from the data. A Convolutional Neural Network model is trained on this data to detect PTSD in the subjects. EEG data is used for tracking the activities of the brain. The model showed an accuracy of 85%. This system offers a highly accurate, non-invasive, and early diagnostic tool for PTSD using EEG data.

10.Paper: Potential benefits and limitations of machine learning in the field of eating disorders: current research and future directions

Link:https://link.springer.com/article/10.1186/s40337-022-00581-2

The paper covers various ML algorithms that have been used for helping people with EDs. SVM and logistic regression help in detecting eds. Transformers help by analyzing textual data .NN process neuroimaging information. The dataset used was derived from surveys, twitter, instagram and MRI scans. ML algorithms could predict disorders with 70-91% accuracy

11.Paper:Sentiment Analysis of Depression and Anxiety Social Media Tweets Using TF-IDF Weighting and Supervised Learning Algorithm

Link:https://ieeexplore.ieee.org/document/10687916

Tokenization, lemmatization, and stopword removal for text cleaning and TF-IDF Weighting for highlighting most used words were implemented. Convolutional layers and softmax activation were used for classification. 68,228 tweets from the Twitter API related to depression and anxiety were used. There were privacy concerns. It struggled with the concept of sarcasm. It has high accuracy (98.01%) and F1-Score (98%).

12.Paper:Artificial Intelligence based Anxiety Detection in Patient

Link:https://ieeexplore.ieee.org/document/9987310

Decision Tree, Random Forest, Logistic Regression, KNN, Boosting were used for prediction purposes. Basic NLP was used for data processing. PyCharm and Streamlit were used for designing user interface. A limited dataset from Kaggle was used.The system accurately classified users' mental health conditions and provided effective responses to user queries.

13.Paper:Mind Relaxation Chatbot for University Students by Using Dense Neural Network

Link:https://ieeexplore.ieee.org/document/9664678

NLP and a DNN were used for training a chatbot to provide emotional help to students. Therapeutic response based datasets were used. Pros include 24/7 Support and anonymity. Cons include limited empathy and struggles with synonyms. It achieved 99.99% accuracy in training

14.Paper:Exploring Machine Learning Algorithms for the Detection of Depression

Link:https://ieeexplore.ieee.org/document/10561447

the system uses SVM as well as LSTM models to detect signs of depression in tweets. These tweets are taken from Twitter and Kaggle. SVM offers clear decision-making. LSTM understands language context. SVM: 81.79% accuracy and LSTM 70% accuracy.

15.Paper:New breakthroughs in AI Chatbots and their potential in mental health services

Link:https://ieeexplore.ieee.org/document/10612516

Chatbot uses CBTto help the users via text as well as voice assistance. The chatbot uses the data that it derives using the user inputs during COVID-19 pandemic. There were certain ethical concerns. The chatbots couldn't handle complex cases. It offered non-judgmental, anonymous support to its users

16.Paper:From Brain Waves to Diagnoses: AI's Role in Schizophrenia Detection

Link:https://ieeexplore.ieee.org/document/10576096

EEGS and fMRI data from people who struggle with and don't deal with schizophrenia were analyzed for brain waves as well as detect trends associated with schizophrenia. CNNS were used for this purpose. There were ethical issues as well as the system's failure in addressing urgent and complicated cases. CNNS can detect schizophrenia with high accuracy. Some models have achieved accuracy rates as high as 98%.

17.Paper:AI-Powered Mental Health Diagnosis: A Comprehensive Exploration of Machine and Deep Learning Techniques

Link:https://ieeexplore.ieee.org/document/10515610

Mental Health related data was extracted from Reddit. 80% was used for training and the rest for testing. It was cleaned and tokenized. CNN, random forest, support vector classifier, and decision tree were used for the diagnosis part. layers like embedding, convolution, max-pooling, dense layers, and SoftMax were used. It may not be able to deal with data outside the social media platform. The random forest model achieved the highest accuracy of 0.907.

18.Paper:Machine Learning Approaches for Obsessive Compulsive Disorder Detection

Link:https://www.researchgate.net/publication/374719983_Machine_Learning_Approaches_for_Ob sessive_Compulsive_Disorder_Det ection

Various statistical methods were used to find out the probability that user inputs belonged to one of the predefined classes. Electroencephalogram(EEG), MRI, fMRI and DTI from people who had and did not struggle with schizophrenia were used SVM gives an accuracy of 83%. It required heavy computational resources

19.Paper: A comprehensive review for machine learning on neuroimaging in obsessive-compulsive disorder

Link:https://pmc.ncbi.nlm.nih.gov/articles/PMC10646310/pdf/fnhum-17-1280512.pdf

This paper focuses on studies that have used various AIML techniques such as Neural Networks to process data like neuroimaging data i.e MRI and EEG scans. It used Yale-Brown Obsessive-Compulsive Scale (Y-BOCS) for assessing OCD severity. Neurobiological markers associated with OCD were identified. A small and biased dataset was used. The results were not easily interpreted by clinical professionals.The accuracy rate of the model is 77.12%; in distinguishing between healthy people and high level OCD, the best accuracy rate of the model is 71.86%; in distinguishing low level OCD

3. Design

3.1 High Level Design

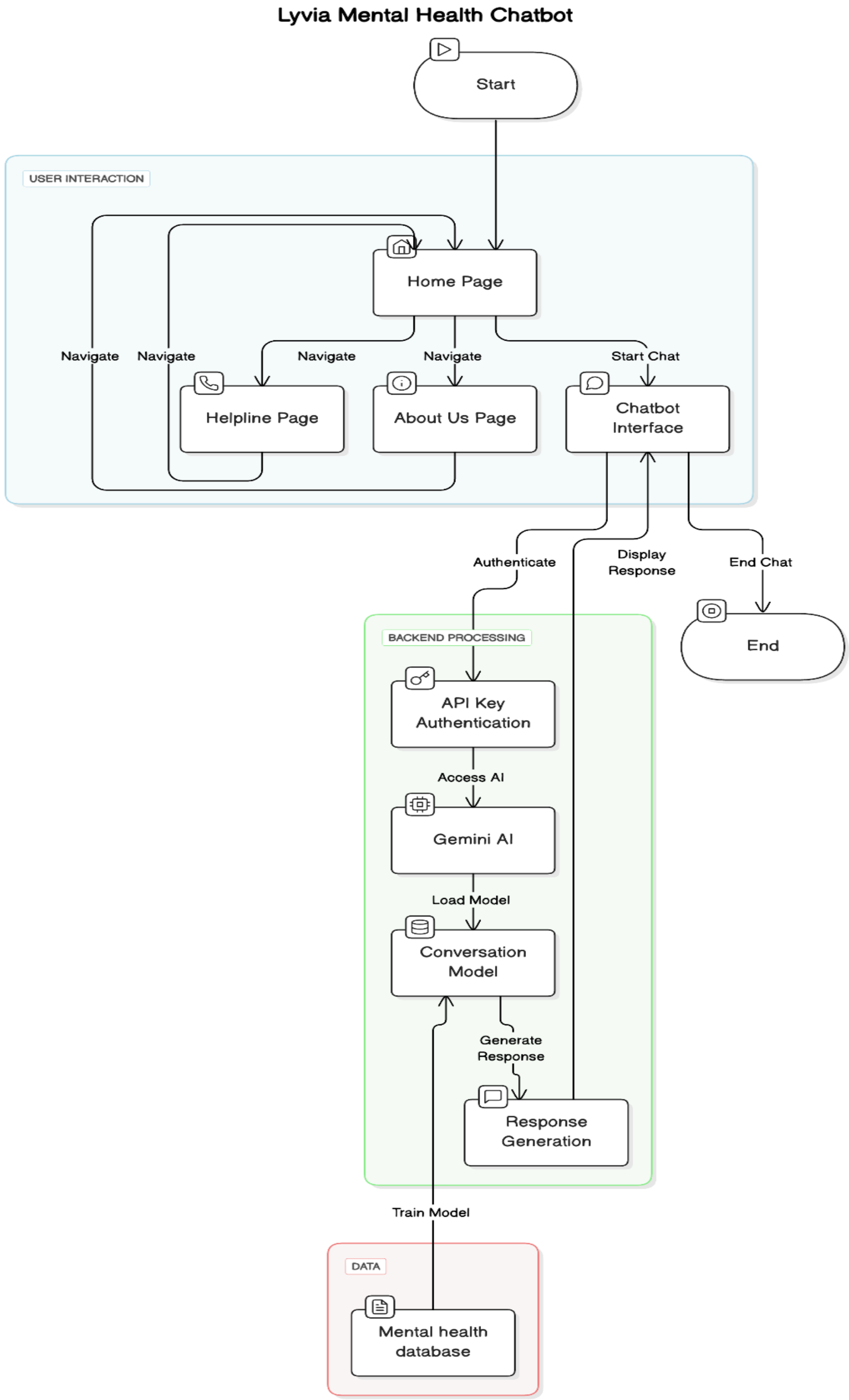

fig 3.1.1: High level design

This design describes the structure and workflow of the Lyvia Mental Health Chatbot, a platform designed to provide mental health support. Here's a comprehensive explanation:

1. User Interaction

On this section, various options are available to the user while interacting with the chatbot interface:

Start: The user begins the process at the start node.
Home Page: The central hub where users can choose different navigation options.
Helpline Page: The page contains the contact details for mental health helplines.
About Us Page: This page contains information on the purpose, creators, or organization behind the chatbot.
Chatbot Interface: The user initiates a conversation with the chatbot to receive help or support.
The session ends when the user closes the chat session.
All pages have the provision to go back to the Home Page to offer flexibility in exploring.

2. Backend Processing

This section describes the internal processes that occur when the user interacts with the chatbot:

API Key Authentication: It verifies that the chatbot has valid access credentials to interact with external AI services.
Gemini AI: It represents the AI service or framework responsible for handling the core functionalities of the chatbot.
Conversation Model: It is a trained machine learning model that enables the chatbot to understand user queries and generate appropriate responses.
Response Generation: The processed query data is converted into human-like responses, which are sent back to the chatbot interface for the user.

3. Data

The Mental Health Database is the training data for the Conversation Model. This database contains curated information on mental health, including FAQs, coping mechanisms, and resources.

Workflow Summary:

User Interaction: The user navigates through the interface to reach the chatbot.

Backend Processing: The chatbot checks the API key, processes the query through Gemini AI, and uses the Conversation Model to generate a response.

Response Delivery: The chatbot returns the response to the user.

End Session: The process is completed when the chat is ended.

This architecture provides a seamless and secure interaction with AI support for mental health.

3.2 Detailed Design

3.2.1 Use Case diagram

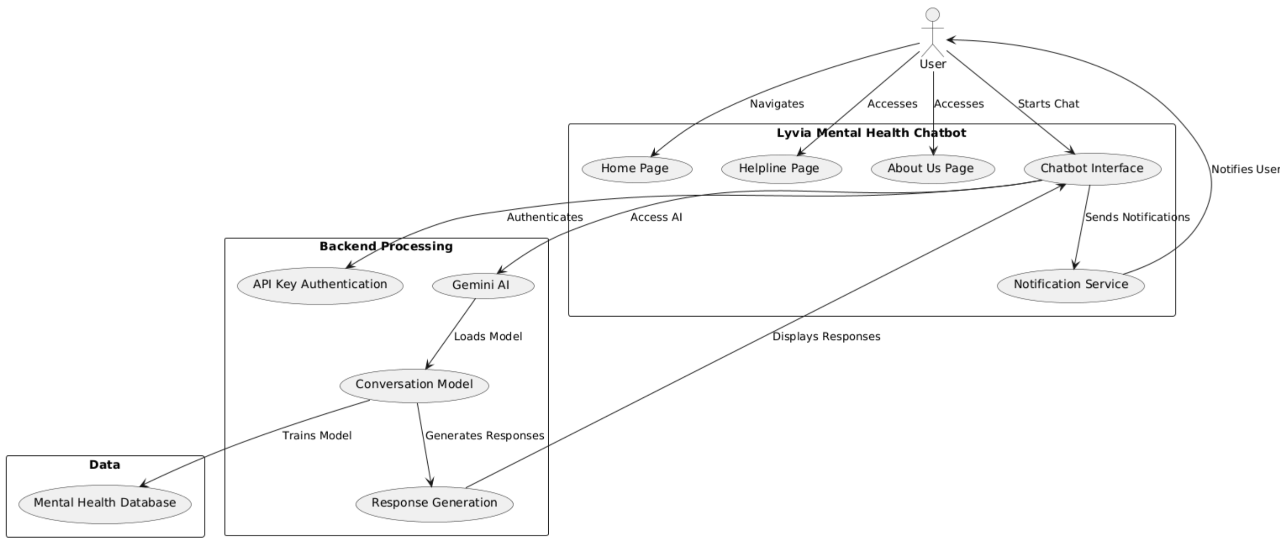

fig 3.2.1:Usecase diagram

This is a use-case diagram showing the components and interactions in the Lyvia Mental Health Chatbot system. Below is a description of each element and their interactions:

Main Components:

User:

The user interacting with the Lyvia Mental Health Chatbot.

He can move from one page to another, start a chat, and get notifications.

Lyvia Mental Health Chatbot:

This is a system that aims at helping users find answers about mental health using different interfaces.

Pages:

Home Page: The home page is the landing page where users start to explore.

Helpline Page: Quick access to the helpline resources.

About Us Page: Details related to the chatbot and services.

Chatbot Interface: core interactive platform where users interact with the chatbot.

Notification Service: Sends reminders or alerts to users based on the interactions.

Backend Processing:

The actual technology backbone of the chatbot system where it has been handled for AI, authentication as well as response generation.

API Key Authentication: Secure access control to backend services.

Gemini AI: This is an AI model powering the intelligence behind the chatbot.

Conversation Model: Trained on mental health data to output meaningful responses

Response Generation: Outputs replies targeted at the needs of the user

Data

Mental Health Database: Holds relevant data that is used to train and improve the conversation model

Interactions:

User to Chatbot

The user scrolls through pages, initiates a chat, and accesses mental health resources. Users can receive AI-generated responses as a result of their queries by using the interface of the chatbot.

The chatbot authenticates and loads conversation models using Gemini AI.

Response generation happens through trained AI models that depend on the Mental Health Database for accuracy and relevance.

Backend to Data:

The backend processes, trains and refine models using data from the Mental Health Database.

Notification Service:

Sends alerts or updates to the user, such as reminders for self-care or follow-up messages based on conversations.

This diagram represents the integration of frontend interfaces, backend processing, and a well-structured database to deliver a supportive and effective mental health chatbot experience.

3.2.2 Sequence diagram

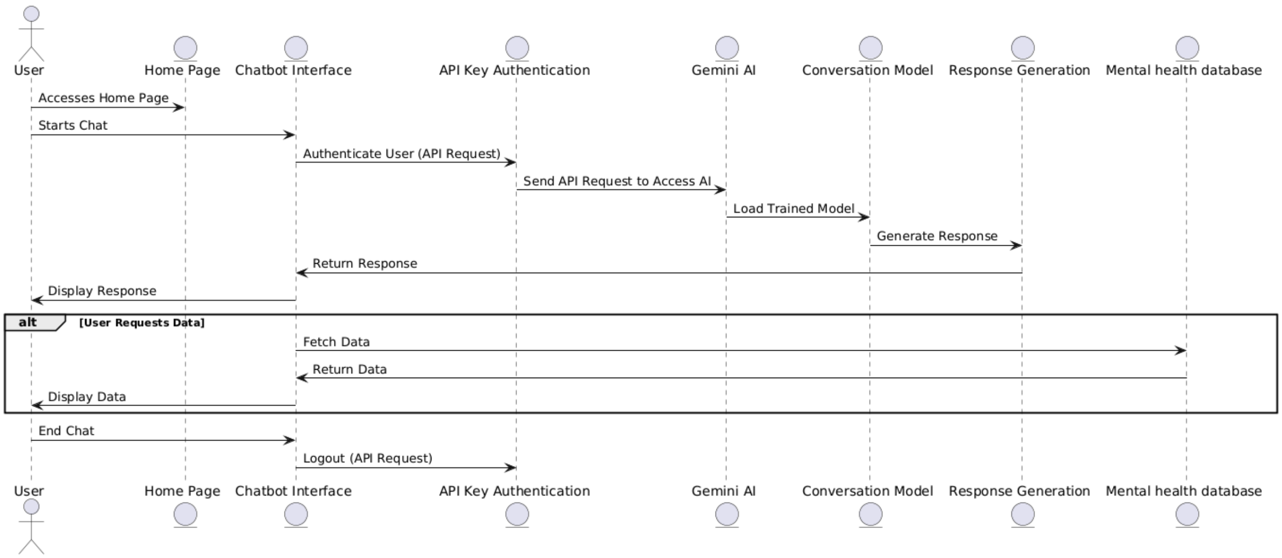

fig 3.2.2:Sequence diagram

This is a sequence diagram that explains how the Lyvia Mental Health Chatbot system processes user interactions. Here's a simplified explanation:

Main Steps:

User Access:

The user accesses the Home Page.

Starts a chat through the Chatbot Interface.

Authentication:

The chatbot sends an API request to the API Key Authentication service.

Once authenticated, the chatbot sends another API request to Gemini AI to access AI services.

AI Processing:

Gemini AI downloads the Conversation Model, which was trained on the Mental Health Database.

The Response Generation system is able to make an appropriate response to the question posed by the user.

Response Output:

The resultant response is forwarded back to the chatbot interface for display purposes to the user.

Alternate Flow (User Demands Data):

When the user wants more data.

The system retrieves data. It can be assumed to retrieve data from the Mental Health Database.

The data is returned to the chatbot and displayed to the user.

Terminating the Chat:

When the user ends the conversation:

The chatbot sends a logout request to the API Key Authentication service to end the session.

This sequence diagram depicts the flow of data and communication between the user, the chatbot interface, the AI backend, and the database. It ensures secure access, effective response generation, and user interaction support.

3.2.3 Activity diagram

fig 3.2.3:Activity diagram

This is an activity diagram that details the flow of a chatbot system. The following is the step-by-step explanation of the diagram:

Start Point:

When the user opens the chatbot, the process starts.

Display Home Page:

The chatbot will display the home page once opened.

Navigation Options:

The user can select any of the navigation options given below:

Helpline Page: This will display the helpline page with relevant information. After viewing the page, the user can again return to the home page.

About Us Page: Shows the information of the chatbot. Now, the user can come back to the home page.

Initiating Chat:

If the user wants to start a chat, the system invokes the chatbot interface.

Authentication

The API key is used for authentication. The system gets the access of the AI(Gemini AI) and loads the conversation model, if authentication is successful.

An error message will be displayed in case authentication is not successful and the process terminates.

Chat Flow:

Once the conversation model is loaded, the chat process starts.

It generates responses with the help of user input and displays them on the screen.

This continues till the user wants to end the chat.

Collecting Feedback:

Once the conversation is over, it asks the user for feedback

If feedback has been provided then it is saved in the system. Otherwise, the step is skipped

Final Point

The process will end up back at the original state or possibly exit altogether.

This diagram captures the logical flow of user interactions with a chatbot system, including navigation, authentication, chat handling, and feedback collection.

4. Implementation

Flask Framework Integration:

The backend was built using the Flask microframework, which is known for simplicity and scalability. The core strength of Flask is its lightweight nature, which lets developers integrate just the required libraries, thus cutting down on overhead. The application uses Flask for routing, template rendering, and session management. Session encryption is robustly protected by generating a dynamic secret key from os.urandom(24). Each application route is carefully crafted to perform certain tasks, like displaying the homepage or processing a chat (/chat). Routes are also modular and thus debuggable with ease, extendable for use in new areas of the application, and maintainable so they're up-to-date. This along with WSGI compliance under Flask, makes them very fast, compared to other heavier frameworks like Django, which loads overhead collections of pre-made modules, rather unnecessary in smaller, focused applications.

Google Generative AI Integration:

The application possesses a critical integration element: the Google Generative AI integration will allow for complex natural language processing and discussion creation. The application uses the gemini-2.0-flash-exp model, which is the latest generative model designed especially to optimize for interactive conversations. To begin with, it offers secure API key configuration using genai.configure(api_key="your_api_key"). The generation_config object is the key to fine-tuning the behavior of the AI. Parameters such as temperature control the randomness of responses, allowing the chatbot to balance creativity with predictability. Meanwhile, top_p and top_k parameters ensure diverse yet contextually relevant outputs, making the chatbot's responses feel natural and engaging. A high max_output_tokens limit ensures the AI can generate long, coherent responses, which are essential for therapeutic conversations.

The model is further directed by system instructions that specify its tone and behavior. Such instructions set up the AI as an empathetic conversational therapist, which places an emphasis on active listening, emotional validation, and thoughtful guidance. This way, the response will not only be contextually appropriate but also emotionally supportive. It will not be a typical chatbot with a generic conversational system.

Empathy-Driven Conversational Design:

This application is outstanding because it emphasizes empathy and user-centric interactions. Unlike the usual canned responses that are found in traditional chatbots, this implementation utilizes AI to simulate active listening and emotional validation. For instance, when a user expresses feelings of stress or sadness, the chatbot responds with phrases that validate the emotion and offer support, such as, “It sounds like you’ve been going through a tough time. I’m here to help.” The system’s pre-configured instructions guide the AI to reflect on user input, reinforcing the feeling of being heard. This design is crucial for mental health use cases where the user's needs are for interpretation and validation.

The conversational flow has been designed with user safety and respect in mind. The response never carries judgmental or prescriptive tones; it is instead focused on collaboration and support, building trust among the users while furthering meaningful interaction, a significant requirement for any mental health support application.

Front-End Integration and User Interaction:

Using Jinja2 templating engine in Flask, a powerful connection is developed between the frontend and the backend, injectively giving dynamic backend data to the HTML templates. Pages like the chatbot interface, homepage, or even helpline page thus have to be populated with real-time data. For instance, using forms on the user input, the chatbot interface sends all that information to the backend via POST request. JavaScript makes the application interactive by allowing asynchronous updates, which means that users experience minimal delays during their conversations.

The templates have been designed keeping in mind the accessibility of the interface, thereby making it simple and intuitive to users with diverse levels of technical know-how. Input fields, buttons, and chat windows have been structured with ease of use, while the use of CSS ensures a more visually appealing structure. The tightly integrated front-end and back-end components help avoid a fractured experience seen in systems loosely coupled at these layers. This kind of holistic design greatly enhances user satisfaction.

Security and Privacy Concerns:

Because mental health data is sensitive, the application has taken security and privacy very seriously. Flask's built-in session management is augmented with encryption so that user data cannot be accessed without permission. Session keys are generated using os.urandom, making session IDs unpredictable for added security. Importantly, the application adheres to a minimal data retention policy, avoiding the storage of sensitive user information. This design choice aligns with best practices in mental health technology, where safeguarding user privacy is paramount.

Google Generative AI uses secure API keys to store and access their APIs. This application also ensures graceful handling in cases of network failures or other issues with invalid responses from APIs. This, in turn, provides users with assurance that they will not encounter any data breach or service outage from the application.

Advantages Over Existing Solutions:

This solution is distinct compared with others that have existed previously. The majority of traditional chatbots are designed around pre-defined responses and generic AI models, offering a rather insensitive approach. What this application does use is Google's advanced generative AI with configurations customized to achieve empathetic and context-aware conversations. Compared with most therapy apps that use scripted interactions, this will produce dynamic, user-specific responses that make conversations more authentic and engaging.

More than this, Flask, as the choice of the backend framework, has ensured a light yet robust base. Its flexibility and speed in real-time applications make it preferable over heavier frameworks in terms of response time and scalability. What makes the application different is that it is placed under heavy stress while maintaining security and privacy for its users to have a safe platform to share thoughts and emotions.

4.1 Proposed methodology

This is a systematic, thoughtful process with each stage targeted to ensure every step of building the mental health chatbot would be aligned towards creating a supportive, secure, and user-friendly experience. The solution will be an integration of advanced AI with a user-centric approach and robust architectural development to fit the needs for mental health support.

The process begins with understanding the user's needs and challenges. Mental health is a sensitive domain, requiring a nuanced understanding of user emotions and expectations. The focus is on identifying the shortcomings of existing solutions, such as their inability to provide empathetic responses or maintain user privacy. Insights gathered from research shape the objectives of the chatbot, which include fostering trust, delivering personalized support, and ensuring data confidentiality.

The system architecture design is central to the achievement of these objectives. A modular and scalable architecture is developed, with Flask as the backend framework. This lightweight nature of Flask ensures fast response times and efficient session management, making it ideal for a chatbot application. The frontend, built using Jinja2 templates with HTML and CSS, is designed to offer a seamless and engaging user experience. This modular architecture has the capability for future scalability because the chatbot can change its nature and response based on future user needs as well as advancing technology.

Gemini, part of Google's Generative AI, uses **gemini-2.0-flash-exp** model which is specifically developed to create an empathetic or contextually correct response; most of all empathetic is ideal for a support chat on mental health. The parameters temperature and top_p are set so that there is a balance between creativity and coherence. System instructions are set to ensure that the AI will hold a tone of being supportive, understanding, and non-judgmental. This approach will make the chatbot be able to hold a meaningful conversation with the user and have it feel more human than traditional scripted chatbots.

One of the major elements of the chatbot's design is the **empathetic conversational flow**. The chatbot is designed to listen actively and reflect emotions as well as offer validation. For example, when a user has anxiety, the chatbot could say, "It sounds like you're feeling anxious. That's okay, and I'm here to help you through it." This flow is carefully constructed to make the user feel safe and trusting to open up to their feelings. The design emphasizes emotional validation and constructive dialogue, creating a supportive environment for users.

In the development phase, all the system components are integrated into a coherent application. The backend manages session handling, API calls to the AI, and routing, thus ensuring that communication between the user interface and the AI engine is smooth. Jinja2 templates render dynamic content and provide real-time updates on user inputs and responses. Error handling mechanisms are put in place to handle unexpected issues, such as invalid user inputs or API delays. This integration ensures that the chatbot runs efficiently and reliably.

With **security and privacy** considered at every level of development, it is possible to address the sensitive nature of mental health data. Encrypted sessions ensure that the user's interaction with the system is kept confidential. No personally identifiable information is stored or logged in the system. API keys used to access Google Generative AI are securely managed, and only authorized components can access the key. The privacy policies are made to ensure the users feel safe and protected while using the chatbot. This is aligned with ethical standards and will build trust among the users, a critical factor in mental health applications. This methodology focuses on the amalgamation of user-centered design, advanced technology, and secure practices to create a meaningful chatbot that supports users while also building trust in empathetic and meaningful interactions. The chatbot deals with key challenges and innovative solutions, thereby providing a reliable and transformative experience for mental health support.

4.2 Algorithm used for implementation

The chatbot will use advanced AI and secure backend algorithms to deliver empathetic, context-aware mental health support. Key components will include Google Generative AI, Flask for session management, and robust data encryption to ensure privacy and efficiency

- Google Generative AI (gemini-2.0-flash-exp):Generates empathetic and context-aware responses using fine-tuned conversational AI parameters.

- Flask Session Management: Encrypts data with randomly generated keys to ensure confidentiality of user sessions.
- NLP Tokenization:Breaks text into tokens to understand intent, sentiment, and context for processing user inputs.
- Response Generation Algorithm:Generates emotionally supportive replies using sequence-to-sequence modeling for tailored interactions.
- Data Encryption:Encrypts API calls and session data to protect user information and ensure secure communication.

4.3 Tools and technologies used

- **Development Framework:** Flask.
- **Machine Learning Algorithm**: Google Generative AI (gemini-2.0-flash-exp).
- **Frontend:** Jinja2, HTML, and CSS.
- **Data Security**: Flask Session Management and Data Encryption.
- **Backend and Hosting**: Flask and scalable cloud hosting platforms (e.g., AWS or Heroku).
- **Natural Language Processing**: NLP Tokenization for intent and sentiment analysis.
- **Data Source**: Kaggle.

4.4 Testing

4.4.1 Confusion Matrix Analysis:

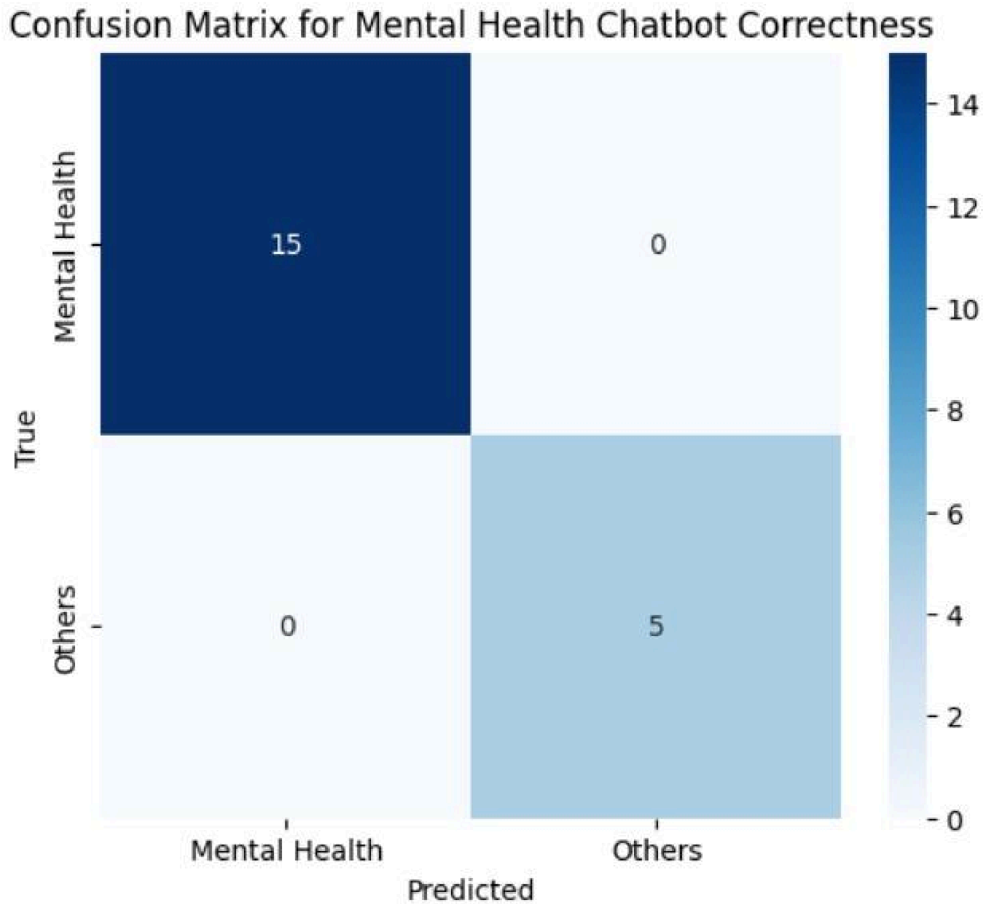

fig 4.4.1 Confusion matrix

The confusion matrix captures the chatbot's level of success in classifying and responding to mental health queries. They break down the results into four quadrants: True Positives (Rightly identified as Mental Health), True Negatives (Rightly identified as Others), False Positives, and False Negatives.

Insights:

- The chatbot achieved a perfect classification with 15 correct predictions for mental health-related queries and 5 correct predictions for non-mental-health queries.

- There were no misclassifications (i.e., no false positives or false negatives), which proved that the chatbot was very precise in differentiating between mental health-related and other types of queries.

There were no misclassifications (i.e., no false positives or false negatives), which proved that the chatbot was very precise in differentiating between mental health-related and other types of queries.

4.4.2 Relevance Score Analysis

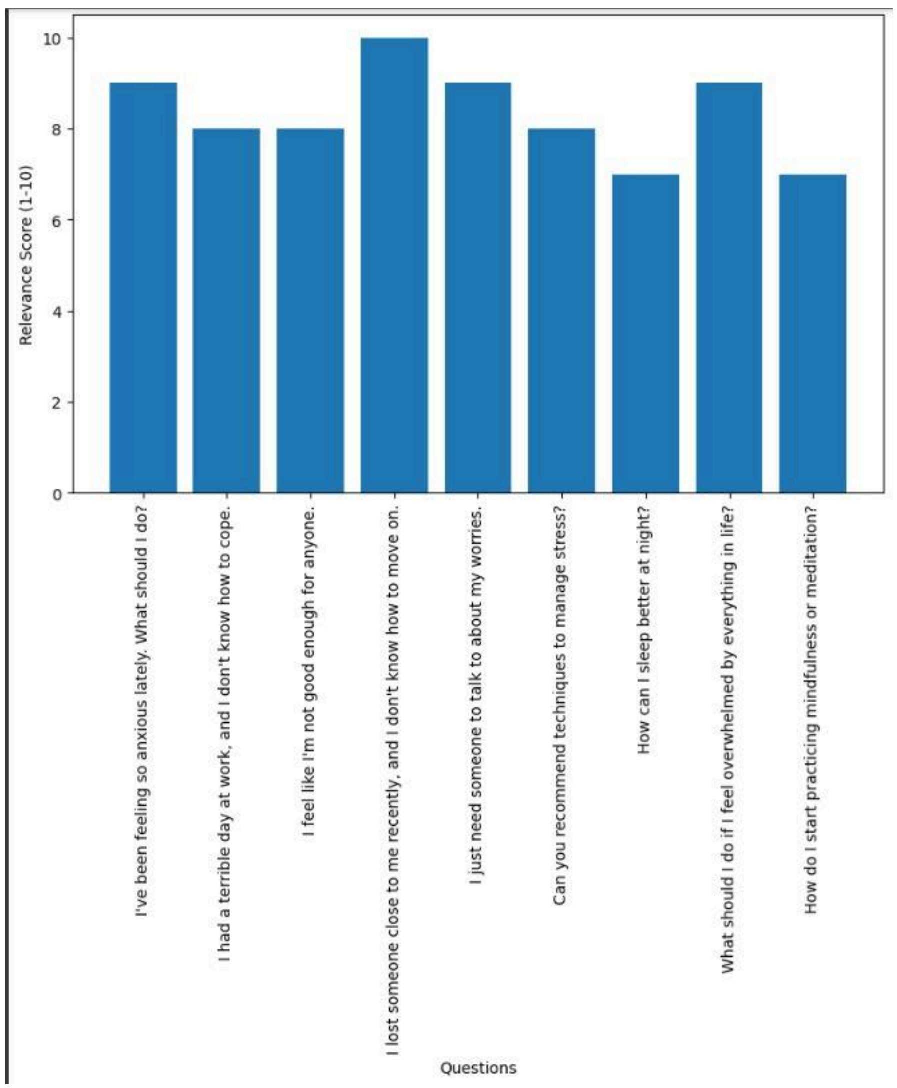

fig 4.2.2 : Relevance Score Analysis

The relevance score chart gives the ability of the responses to be on point in terms of empathy, clarity, and being useful for a human expectation. Scores, between 1 to 10, were generated based on cross-checking of answers generated by the chatbot against leading AI models-ChatGPT Gemini and Claude.

Main Observations:

- The relevance score for most responses ranged from 8 to 10 points for the chatbot.
- Queries such as "I just lost someone important to me; I don't know how I am going to get over them" scored maximum, 10, which highlights the empathic and supportive character of the replies given by this chatbot on the sensitive topics of life.
- More practical questions, for example, "How do I start practicing mindfulness or meditation?" received scores slightly lower (e.g., 8). This implies small room for improvement in offering greater detail and more action-oriented advice in such questions.

The evaluation underlines the chatbot's ability to deliver highly relevant and empathetic responses, especially for emotional and personal concerns. It also highlights its potential to evolve further in handling practical guidance with even greater dept

5. Results and Discussion

Here are the snapshots of the website LYVIA :

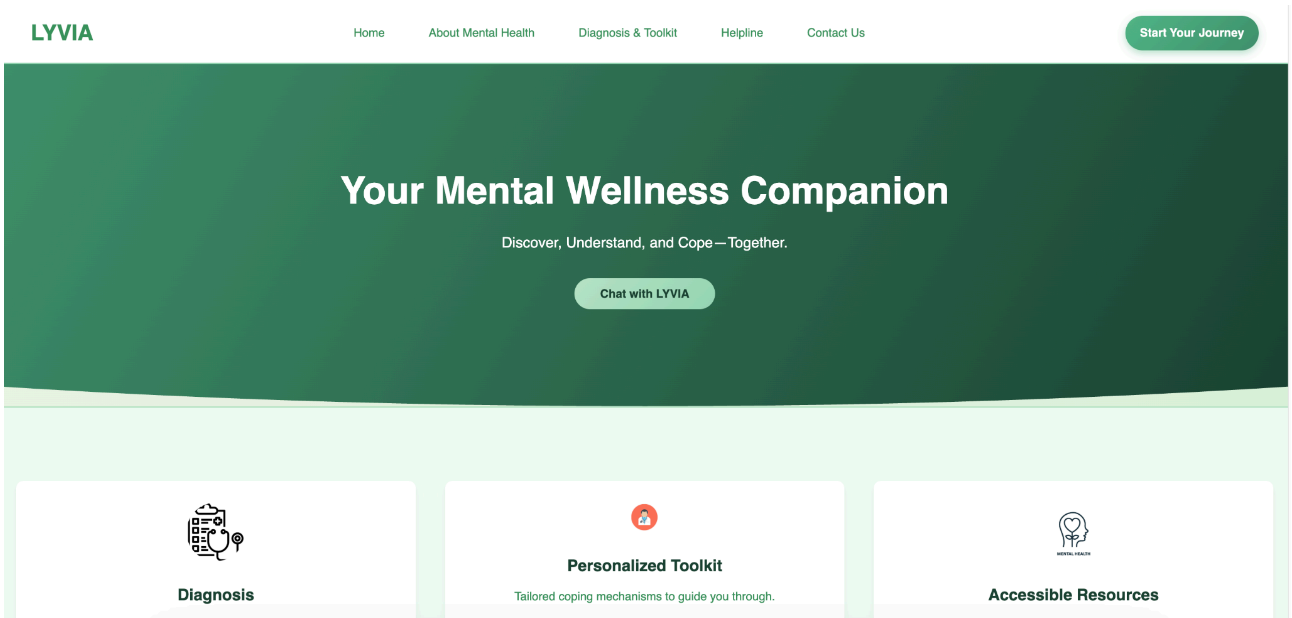

fig 5.1 output 1

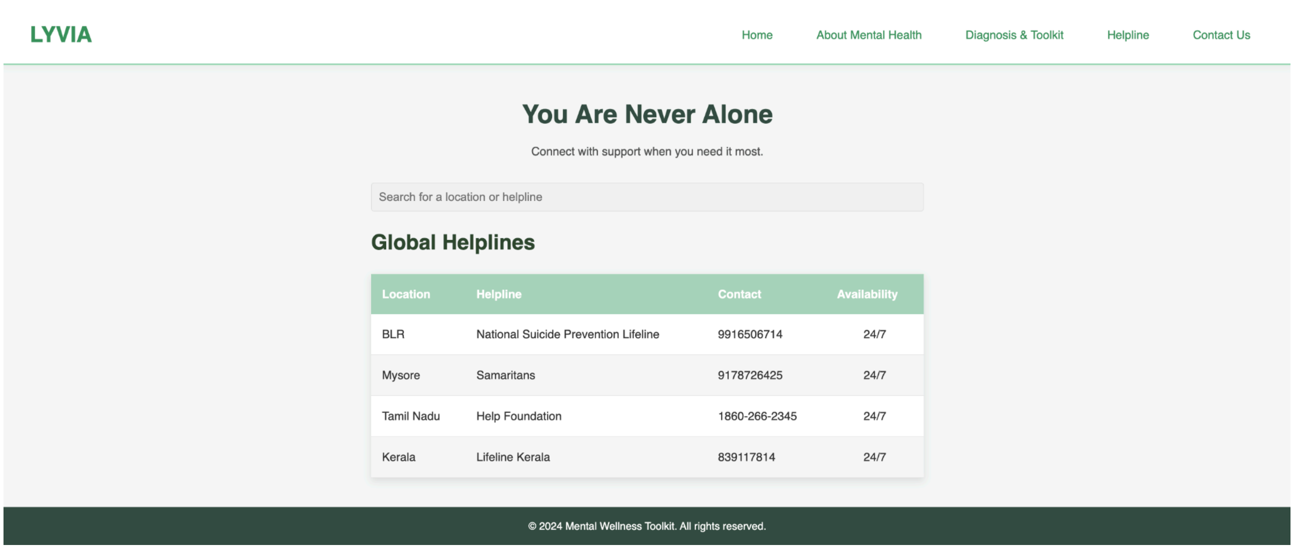

fig 5.2:output 2

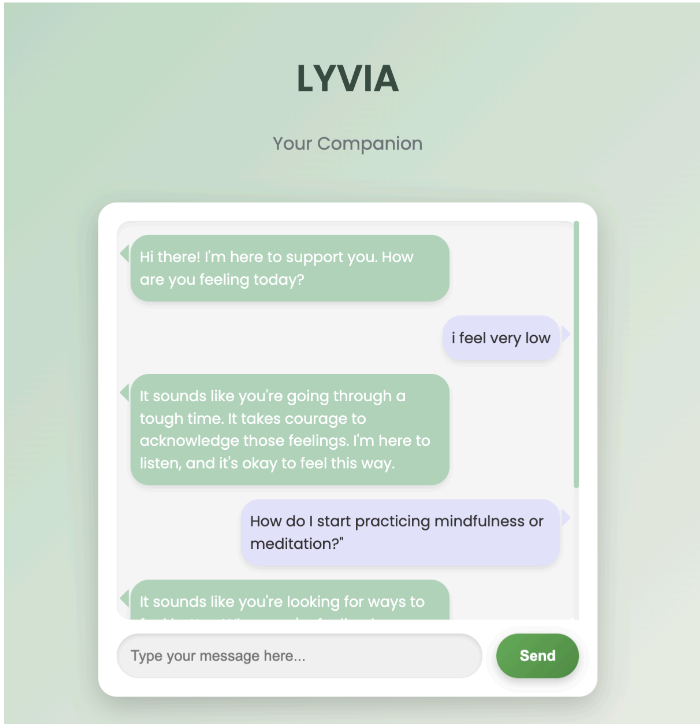

fig 5.3:output 3

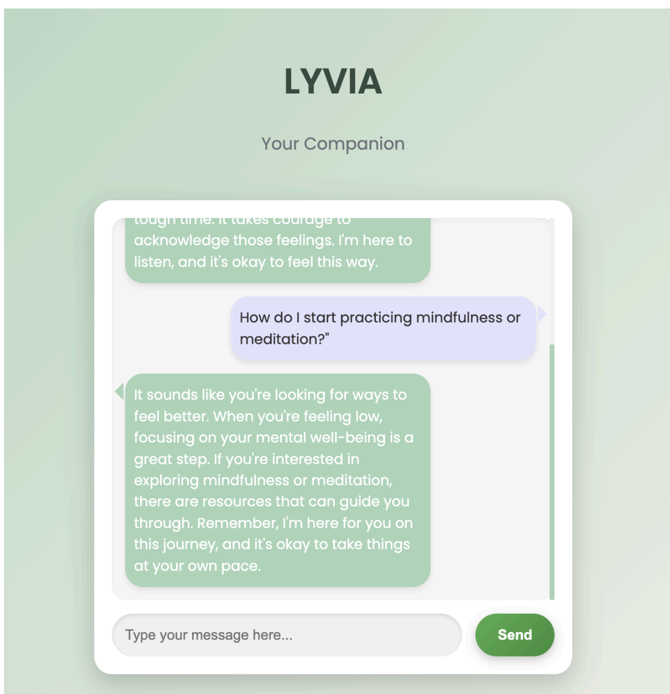

fig 5.4 output 4

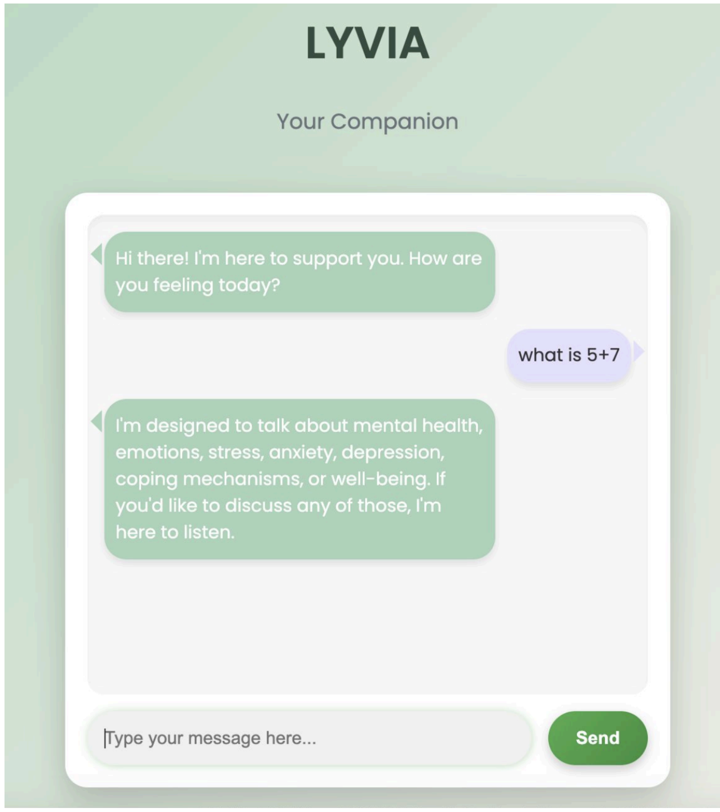

fig 5.5:output 5

5.2 Survey Results: Chatbot Performance Evaluation:

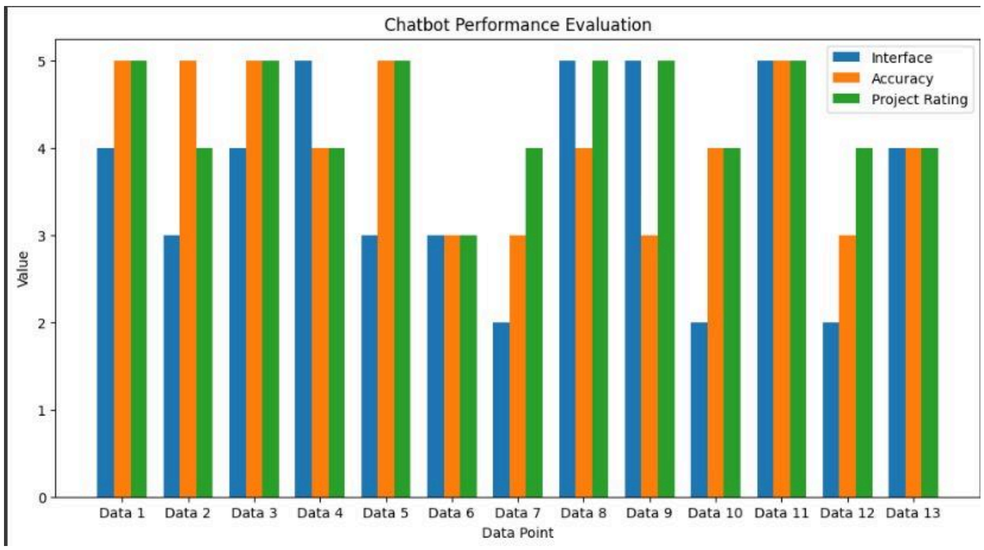

fig 5.2.1:Performance evaluation graph

To evaluate the performance of the chatbot and to ask for comments on its ease of use, the survey was conducted among classmates. The respondents were asked to try out the chatbot and provide a score based on three parameters: They were asked three questions :

- What is your view regarding the interface of the chatbot?
- Judging from your interactions , how would you interpret the responses made by the bot?
- Out of 5 how would you rate the project overall?

Insights from the Results:

The results obtained from the survey with regard to the bar graph presented above are as follows :

- **Interface Evaluation (Blue Bars):**In most cases the interface of the chatbot was rated highly, with most scores ranging from 4 to 5 . A few scores were lower, indicating possible target areas for enhanced user interaction or design features.As a whole, the interface was positively evaluated demonstrating its user-friendliness.

- **Accuracy of Responses (Orange Bars):**In comparison to other measures, accuracy remained one of the most highly rated components, with some participants scoring it a perfect 5.This serves as a confirmation of the ability of the chatbot to give users the emotional as well as the contextual understanding of their inquiries.
- **Overall Project Rating (Green Bars):**The project on the whole was rated well with most scores ranging from 4 to 5.This highlights the usefulness of the chatbot when it comes to counselling issues as well as the impression it left to the participants.

6. Conclusion and Future Work

Conclusion:

Mental Wellness Toolkit is a website integrated with an AI driven chatbot(Google Generative AI). named Lyvia that provides emotional support to users struggling with mental health. The website was developed using HTML, CSS, Python, NPL tokenization and Flask. Flask also provides encryption and session management. Lyvia provides contextually accurate replies to the input provided by the user. When the user enters an input that suggests suicide or self harm, Lvyia provides the helpline number that the user can contact for further help. Lyvia achieved relevance scores ranging from 1-10. According to the confusion matrix, the chatbot was able to differentiate between queries related to mental health and queries that were not related to mental health. The use of AI in this application proves that AI can be used along with mental health providers to help people with mental health issues as well as reduce the clinical load of doctors, nurses and other health staff.

Shortcomings

1.Lack of location specific hotline numbers:

Shortcoming: Lyvia does not provide location specific hotline numbers.

Solution:This can be solved by either using the location of the user or asking the location of the user and using the location given by the user to provide the nearest hotline number.

2.Limited support for complicated cases:

Shortcoming: The chatbot provides basic emotional support to the user. It may struggle to deal with cases of severe depression or suicidal thoughts.

Solution: This can be solved by implementing ML algorithms that can detect complex cases and immediately notify the nearest support.

3.Limited understanding of context

Shortcoming: The chatbot may not be able to understand sentences with cultural references or user specific situations

Solution: Using advanced NLP techniques to overcome this barrier.

4.Lack of personalization

Shortcoming: The chatbot may give generic responses to certain situations instead of something that is user specific.

Solution: Allowing users to create profiles and enter various type of information that can be used to provide specific responses.

5. Lack of voice messaging feature

Shortcoming: The chatbot solely relies on text. It cannot completely understand the user based on that. Allowing voice messaging will help the user to express themselves in a more elaborate manner. The chatbot can study the tone of their voice and provide support based on that

Solution: Implementing voice recognition technology along with text to speech and speech to text technology for more efficient communication

Future Work

1. Implementing technologies like Geolocation-based Services that can provide the users with the hotline numbers of the place they live in.
2. Implementing algorithms like RNN that can detect urgent cases and bring the attention of clinical professionals towards them
3. Using advanced NLP to allow the chatbot to understand the user's responses more clearly and give better responses.
4. Allowing the users to create profiles and providing information about their health, coping mechanism and personalities to provide user focussed treatment

5. Implementing voice recognition technology to allow voice messaging
6. Implementing text-to-speech and speech-to-text messaging to help people with visual impairments to also use the chatbot

References:

[1] Chakraborty, C., Gupta, A., Ghosh, S.K., and Zaman, S., "Machine Learning at the Core of Image and Video Analysis in the Healthcare Industry: An Outlook Beyond the COVID-19 Pandemic", SSRN, Page no. 1-25, 2022.

[2] Mahapatra, A., Sharma, P., and Tyagi, R., "Exploring Disordered Eating Behaviors through Social Media: A Machine Learning Perspective", Journal of Eating Disorders, Volume 10, Page no. 1-12, 2022.

[3] Amrani, A., Elharti, E., Zaki, S., and Zina, F., "Machine Learning Approaches for thePrediction of Depression: A Systematic Review", Frontiers in Psychiatry, Volume 15, Article 1414439, 2024.

[4] Fong, T., Li, H., and Sihota, M., "The Role of Artificial Intelligence in Cancer Diagnosis and Treatment: A Review of the Current State and Future Perspectives," Cancers, Volume 11, Page no. 803, 2021.

[5] Wang, Y., Zhang, Z., and Liu, C., "Artificial Intelligence in Health Care: Anticipating and Mitigating the Challenges", Health Services Research and Managerial Epidemiology, Volume 8, Page no. 1-9, 2021.

[6]Routhu, R. D., Likhita, C. K., Kranthi, G. K., & Lakshmi, A. (2022). Stress Management System. In 2022 IEEE Delhi Section Conference (DELCON) (pp. 1-5). IEEE. DOI: 10.1109/DELCON54057.2022.9753121.

[7]Nema, N. K., Shukla, V., Pimpalkar, A., & Tandan, S. R. (2024). Sentiment Analysis of Depression and Anxiety Social Media Tweets Using TF-IDF Weighting and Supervised Learning Algorithm. In 2024 OPJU International Technology Conference (OTCON) (pp.1-6). IEEE. DOI: 10.1109/OTCON60325.2024.10687916.

[8]Koneru, L. C., Dedeepya, R. R., Lakshmi, A., & Kumar, G. K. (2022). Artificial Intelligence based Anxiety Detection in Patients. In 2022 Sixth International Conference on I-SMAC (IoT in

Social, Mobile, Analytics and Cloud) (pp. 1-9). IEEE. DOI:10.1109/I-SMAC55078.2022.9987310.

[9]Bopage, H., & Weerakoon, C. (2021). Mind Relaxation Chatbot for University Students by Using Dense Neural Network. In 2021 5th SLAAI International Conference on Artificial Intelligence (pp. 1-7).

[10]Bala Krishna, N., Bhanu, M. I., Anjali, R., Yaswanth Kumar, R., Omprakash Reddy,P., & Reethu Reddy, P. (2024). Exploring Machine Learning Algorithms for the Detection of Depression. In 2024 International Conference on Smart Systems for Applications in Electrical Sciences (ICSSES) (pp. 1-6). IEEE. DOI: 10.1109/ICSSES62373.2024.10561447.

[11] C. L. Alves, A. M. Pineda, K. Roster, C. Thielemann, and F. A. Rodrigues, "EEG functional connectivity and deep learning for automatic diagnosis of brain disorders: Alzheimer's disease and schizophrenia", Journal of Physics: Complexity, vol. 3, no. 2, pp. 025001, 2022.

[12] H. Kour, "A hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM", Multimedia Tools and Applications, vol. 81, no. 17, pp. 23649-23685, 2022.

[13] S. K. Kar, B. Kumari, and A. Singh, "Multimodal augmentation approach with transcranial direct current stimulation in management of obsessive-compulsive disorder with depression and comorbid seizure disorder: A case report," Indian Journal of Psychological Medicine, vol. 44, no. 6, pp. 621–623, 2022.

[14] Abd-Alrazaq, A., Alhuwail, D., Schneider, J., Toro, C. T., Ahmed, A., Alzubaidi, M., et al. (2022). The performance of artificial intelligence-driven technologies in diagnosing mental disorders: an umbrella review. NPJ Digit. Med. 5:87. doi: 10.1038/s41746-022-00631-8

[15] Shaif, M. M., Rakhra, M., Singh, D., & Singh, A. (2022). AI-Based Prediction of PTSD Using EEG Reports. 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), 1073-1077. IEEE.

[16] Batsakis, S., Papadakis, E., Tachmazidis, I., Chen, T., Antoniou, G., & Adamou, M. (2023). Neuro Intel: A System for Clinical Diagnosis of ADHD Using AI. 2023 IEEE Conference on ICT

Solutions for eHealth (ICTS4eHealth), 1-6. IEEE.

[17] Makhdoomi, S. M., Rakhra, M., Singh, D., & Singh, A. (2022). Artificial-Intelligence-based Prediction of Post-Traumatic Stress Disorder (PTSD) using EEG Reports. 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), pp. 1-6. IEEE. DOI: 10.1109/IC3I56241.2022.10072671.

[18] Nagarajaiah, K., Krishnappa, M. H., & Asha, K. R. (2023). Machine Learning-based Detection of Post-Traumatic Stress Disorder of Mental Health. 2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 1-5. IEEE. DOI: 10.1109/ICESC57686.2023.10193036.

[19] Nash, C., Nair, R., & Naqvi, S. M. (2023). Machine Learning in ADHD and Depression Mental Health Diagnosis: A Survey. IEEE Access, vol. 11, pp. 82345-82357. Received July 11, 2023; accepted July 31, 2023; published August 10, 2023; current version August 17, 2023. DOI: 10.1109/ACCESS.2023.330423

APPENDIX:

Screenshot of the Plagiarism Check of the Report using Turnitin

Plagiarism should be less than 20%. (Screenshot to be attached and the plagiarism check to be done by respective Guides)