Project Phase 2 Report On

Depression Companion Chatbot

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Computer Science and Engineering

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CERTIFICATE

This is to certify that the project report entitled ***"Depression Companion Chatbot"*** *is a bonafide record of the work done by* ***Namitha Reji(U2003142), Navami Sunil(U2003144), Sandra Philna Sajiv(U2003185), Sreeranj S(U2003204)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

This study focuses on creating Depression Companion Chatbot, which aims to offer timely and compassionate care to people experiencing depression in the age of digital mental health solutions.Using state-of-the-art technologies, this chatbot analyzes user context to provide relevant and tailored responses.Furthermore, the chatbot is essential in anticipating possible crises and prompting users to get aid from professionals when needed. Context analysis and empathic communication are at the core of the Depression Companion Chatbot's development.The chatbot has access to a large collection of encouraging and understanding answers. It uses conversational techniques to provide users support, empathy, and encouragement. With the creation of our Depression Companion Chatbot, a publicly available and accepting platform for those struggling with depression is a step in closing the gaps in mental health care. By incorporating sophisticated context analysis and crisis response systems, it aims to improve the standard of care and, more crucially, to guarantee user safety by enabling prompt interventions when necessary.

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List of Abbreviations

LSTM - Long Short-Term Memory

GRU - Gated Recurrent Unit

BLEU - BiLingual Evaluation Understudy

RNN - Recurrent Neural Network

CNN - Convolutional Neural Networks

HAN - Hierarchical Attention Network

BiLSTM - Bidirectional Long-Short Term Memory

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Chapter 1

Introduction

This introduction chapter provides an overview of the research, defines the issue, and outlines the research's scope while highlighting its importance from both an academic and practical standpoint. The report's structure is briefly outlined and the study's societal and industrial significance is emphasized, laying the groundwork for more in-depth discussion in later chapters.

1.1 Background

Millions of people worldwide suffer from depression, a common mental health issue that is becoming more common in the contemporary period. The intricate relationship between stressors in modern life and the stigma associated with mental illness highlight the need for creative solutions. The rise in mental health disorders has made new methods of providing care for people necessary. Due to its widespread use, technology is now a major factor in the field of mental health. Acknowledging the shortcomings of conventional therapy methods, there is an increasing interest in utilizing technology to offer quick and easily available help. The emergence of digital mental health solutions paves the way for the creation of a Depression Assistant Chatbot, which is a practical reaction to the changing requirements of people dealing with mental health issues. A major motivator for creating a Depression Assistant Chatbot is the restricted availability of mental health providers. The need for creative solutions is made clear by the shortage of mental health professionals and the obstacles that prevent people from obtaining standard therapy. Furthermore, the requirement for prompt assistance, particularly in emergency scenarios, highlights the necessity for a tool that is available around-the-clock and can provide quick support.[6] The Depression Assistant Chatbot's main objective is to close the gap in mental health care by offering prompt, individualized assistance. The chatbot's integration of artificial intelligence—specifically, machine learning and natural language processing—aims to enable efficient comprehension of user input and customization of responses to suit individual needs. The Depression Assistant Chatbot is a cutting-edge creation that incorporates cutting-edge technologies. Intelligent language processing guarantees a sophisticated comprehension of customer inquiries. The design places a strong emphasis on a user-friendly interface and compassionate dialogues in order to increase user trust and participation.[7] A vital and relevant answer to the changing panorama of mental health issues is the creation of a Depression Assistant Chatbot. This initiative has the potential to significantly advance the assistance of people on their mental health journey by utilizing technology, raising awareness, and placing a high priority on ethical issues.

1.2 Problem Definition

Individuals experiencing depression may experience feelings of irritation, disinterest, insomnia, and even thoughts of suicide. Accessibility obstacles include things like a shortage of therapists, time, money, insurance, and transportation, as well as the stigma attached to mental health problems that sometimes keeps people from getting the care they need.

The Depression Assistant Chatbot project aims to close the gaps in traditional mental health care by creating an approachable, AI-powered tool that offers individualized, easily accessible help to people going through depression. By providing educational materials and encouraging open discussions, this project also seeks to raise user awareness of mental health issues and create a supportive environment.

1.3 Scope and Motivation

The Depression Assistant Chatbot project's scope includes the entire development and implementation of an AI-powered tool designed to tackle the complex problems related to depression. To help the chatbot comprehend user input, the project will make use of cutting-edge technology including machine learning and natural language processing. In terms of functionality, the chatbot will provide quick, individualised assistance.[8] It will also include tools for crisis intervention and ongoing enhancement via adaptive machine learning algorithms. The integration of educational components aims to provide materials on depression, promote mental health awareness, and aid in the destigmatization of mental illness. The project's ethical aspects include the implementation of emergency protocols in addition to strict privacy and data security safeguards. The initiative also establishes the framework for prospective extensions in the future, such as integration with wearable technologies.This extensive scope guarantees a creative and all-encompassing method of supporting people dealing with depression, emphasizing usability, responsiveness, and accessibility.

The urgent need to address the growing global mental health epidemic is the driving force behind the Depression Assistant Chatbot initiative. With millions of people affected by depression globally and accessibility issues with traditional mental health care, there is a significant gap that technology may help close.[9] By offering prompt, individualized support, the project aims to empower people while removing obstacles like remote locations and a shortage of mental health specialists. The goal is to lessen the stigma attached to depression by raising awareness and normalizing discussions about mental health.The project's ultimate motivation is a dedication to improving mental health on a larger scale by improving access to prompt, individualized care.

1.4 Objectives

- Offer Immediate and Tailored Support: The ability to respond promptly and provide tailored assistance, adjusting interactions according to user preferences to improve the effectiveness and significance of its answers.

- Promote Mental Health Awareness: Include instructional elements in the chatbot that provide details on depression in order to improve user comprehension and support more general initiatives to raise awareness of mental health issues.

- Normalize Talks about Mental Health: Construct a chatbot that facilitates open and de-stigmatized dialogues on mental health, offering a comforting atmosphere that encourages people to have these kinds of talks about their wellbeing.

- Develop a User-Friendly Chatbot: The Depression Assistant Chatbot should have an easy-to-use and accessible interface to encourage user participation among those in need of mental health assistance.

- Facilitate Support during crisis: Give the chatbot capabilities so that it can recognize and react to users who are experiencing distress, providing prompt assistance in urgent circumstances and putting them in touch with the right resources.
- Improve Accessibility to Mental Health Support: Create a Depression Assistant Chatbot with the goal of helping people who have limited access to traditional therapeutic services to get the quick, easily available support they need to bridge the gap in mental health treatment.

1.5 Challenges

Problems with ethics and user safety are major obstacles that require careful attention to detail in order to protect private mental health data and provide appropriate support. Accurately comprehending a wide range of user inputs, emotions, and contextual complexities in the setting of mental health is a challenging undertaking that demands advanced natural language processing capabilities. Furthermore, removing the stigma that society places on mental health and building confidence in a digital mental health solution are difficult tasks that call for the development of tactics that support openness, dependability, and empathy in order to guarantee the project's success.

1.6 Assumptions

- Inputs should be in text-format
- Input should be one to three sentences
- Input text should be in English
- Command specific interaction

1.7 Societal / Industrial Relevance

The Depression Assistant Chatbot initiative is highly relevant to society and business, filling critical gaps in mental health services and using technology to improve people's quality of life. Destigmatizing discussions about depression, the project advances society's conversation on mental health. [10]It offers readily available and prompt assistance, which is especially important in communities with a shortage of mental health specialists or where accessing conventional therapy may be hindered by social or cultural obstacles. Industries are realizing how important it is to use technology to provide mental health help as knowledge of mental health issues grows. The project is a pioneering attempt in the creation of cutting-edge AI applications, demonstrating chatbot technology's ability to offer individualized and scalable mental health support.[11] The initiative may help boost productivity and lessen the financial cost of untreated mental health concerns by taking a more proactive approach to addressing mental health issues. In the end, the Depression Assistant Chatbot project offers a timely and important response to current mental health issues by crossing the boundary between technical innovation and societal well-being.

1.8 Organization of the Report

Introduction of the project is covered in this chapter. The rest of the report is organized as follows: Chapter 2 briefs about the different literature available related to the project.Chapter 3 includes requirements.System architecture is explained in Chapter 4.System implementation is explained in Chapter 5.Chapter 6 includes the results and discussions.Chapter 7 includes the conclusion and future scope which is followed by references.

The project's main goal is to develop a Depression Companion Chatbot that, in the context of digital mental health solutions, can offer prompt, empathetic care to those who are depressed. The chatbot uses cutting-edge technologies and context analysis to provide personalized responses. The development places a high value on compassionate communication, employing a large library of uplifting responses and conversational strategies to offer assistance. The project's ability to de-stigmatize mental health, increase accessibility, and contribute to technology developments in mental health assistance highlight its significance to society and industry. Concerns about ethics, precise comprehension of user input, handling crises, and building trust are among the difficulties. Immediate support, raising awareness of mental health issues, normalizing conversations, user-friendly design, crisis intervention, and enhanced accessibility are all included in the goals. The Depression Assistant Chatbot project is a pioneering attempt to use technology for mental health assistance, tackle the difficulties related to depression, and improve society well-being.

Chapter 2

Literature Survey

2.1 A Mental Health Chatbot for Regulating Emotions (SERMO) - Concept and Usability Test[1]

2.1.1 Overview of SERMO within the Scope of Mental Health Chatbots:

In their 2020 paper, Denecke and colleagues introduce SERMO, a standout chatbot application grounded in the principles of Cognitive Behavioral Therapy (CBT), aimed at assisting users in managing their emotions. This review scrutinizes SERMO's role in the expanding domain of mental health chatbots, emphasizing its novel aspects, theoretical underpinnings, operational features, and the experience it offers to users.

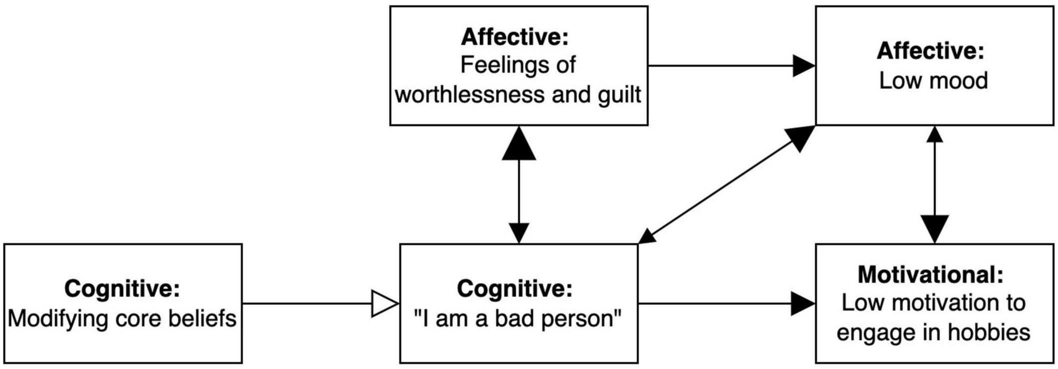

Figure 2.1: CBT Diagram.[1]

2.1.2 Unique Aspects of SERMO:

SERMO differentiates itself in the domain of mental health chatbots through several distinctive features: Focus on Emotion Regulation: SERMO's primary objective is emotion regulation, facilitated through personalized interventions based on daily emotional tracking, contrasting with general mental health chatbots. User Engagement Strategy:

SERMO requires active daily input from users regarding their emotions and events, promoting self-awareness, unlike other chatbots that rely on passive data collection. Integration of CBT Strategies: The chatbot encompasses specific CBT methods, including cognitive restructuring and behavioral activation, surpassing the basic conversational functionalities of standard chatbots.

2.1.3 Theoretical Base of SERMO:

The conceptual foundation of SERMO is anchored in CBT principles, featuring: Cognitive Patterns Modification: The chatbot aids in the recognition and modification of negative thought processes, enhancing cognitive adaptability. Encouragement of Behavioral Activation: It propels users to partake in activities that generate positive emotions, targeting avoidance behaviors. Mindfulness Practices: SERMO incorporates mindfulness techniques to boost awareness of the present moment and regulate emotions.

2.1.4 Functional Capabilities and Features of SERMO:

SERMO's functionalities are centered around aiding emotion regulation: Emotion Tracking Journal: A daily log helps users observe their emotional trends and pinpoint triggers. Customized Interventions: Depending on the emotional state, SERMO proposes tailored activities and informative materials. Educational Material Access: It provides resources on emotional understanding, CBT concepts, and coping mechanisms. Supportive Tools: The chatbot includes a glossary of emotions and a catalog of enjoyable activities to assist in self-guidance.[1]

2.1.5 Evaluation of Usability and User Experience:

Feedback from the usability test of SERMO revealed: Favorable User Response: The application was deemed effective, straightforward, and aesthetically pleasing by users. Strong User Involvement: Regular usage and positive emotional responses indicate significant user engagement and perceived value. Recommendations for Enhancement: Users suggested improvements in customization, a broader range of resources, and the possibility of including professional healthcare integration.

2.1.6 Advantages and Challenges of SERMO:

Prominent strengths of SERMO are: Foundation in Evidence-Based Practices: Its reliance on CBT offers a systematic and efficacious approach. Customization in Interventions: Tailored suggestions boost user engagement and relevance. Ease of Use in Design: The interface is user-friendly, enhancing accessibility.[1] Nonetheless, SERMO is confronted with challenges: Reliance on User-Provided Data: The effectiveness of interventions could be impacted by the accuracy of user input. Absence of Direct Professional Therapy: SERMO cannot replace formal therapy and requires users to understand its limitations. Concerns Over Data Security and Ethics: Careful management of user data and potential misuse is critical.

2.1.7 Prospective Research and Progression Pathways:

Future investigations into SERMO[1] should focus on: Assessing Long-Term Effectiveness: Examining its enduring effects on emotional health and reduction of symptoms. Combining with Other Digital Tools: Augmenting SERMO with additional features like biofeedback or direct communication with therapists. Refining Existing Limitations: Enhancing the personalization algorithm, incorporating professional support, and ensuring rigorous data protection.

2.1.8 Final Observations:

SERMO stands out as a progressive development in the field of mental health chatbots, notably for its proactive engagement in emotion regulation and individualized CBT-based interventions. Its innovative approach to user experience in mental health assistance marks a significant stride, yet continuous research is vital to refine its capabilities, maximize its long-term advantages, and guarantee responsible usage within the mental health technology sector.[1]

2.2 GENERATING AND ANALYZING RESPONSES USING NATURAL LANGUAGE PROCESSING[2]

2.2.1 Overview of Sequence-to-Sequence Approach in Customer Interaction:

This research introduces an innovative sequence-to-sequence learning technique for formulating responses to customer inquiries. This method transforms a sequence of input words (the customer's question) into a different word sequence (the response), effectively managing the varied lengths of customer interactions.

2.2.2 Utilization of Cutting-Edge Deep Learning Models:

The study incorporates three sophisticated deep learning models:

Long Short-Term Memory (LSTM): Essential for interpreting and remembering information over extended text sequences, LSTM is crucial for understanding intricate customer inquiries. Gated Recurrent Units (GRU): GRU, a streamlined version of LSTM, maintains effectiveness while modeling text sequences, making it well-suited for deciphering customer questions. Convolutional Neural Network (CNN): The integration of CNN into this framework is innovative. Renowned for its capability to identify patterns in input sequences, CNN significantly enhances the system's ability to interpret contextual elements in customer queries.

2.2.3 Encoding and Decoding Mechanisms:

The response generation involves a two-step process: Encoding Stage: Initially, the encoder network processes the customer's query, converting it into a concise context vector, which encapsulates the core elements of the query. Decoding Stage: Following this, the decoder utilizes the context vector to produce the output sequence, effectively forming a response aligned with the query's context. 4. Role of CNN in Enhancing Model Performance:

CNN's role in the sequence-to-sequence framework provides a distinct advantage. By recognizing local patterns in input sequences, CNN deepens the model's understanding of the linguistic intricacies within customer queries, leading to more accurate and context-aware responses.

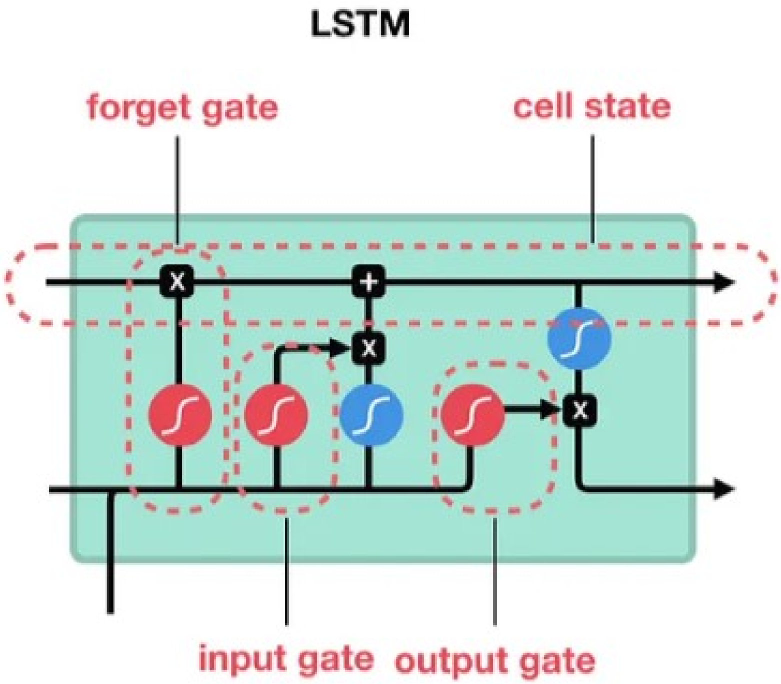

Figure 2.2: LSTM Architecture.[2]

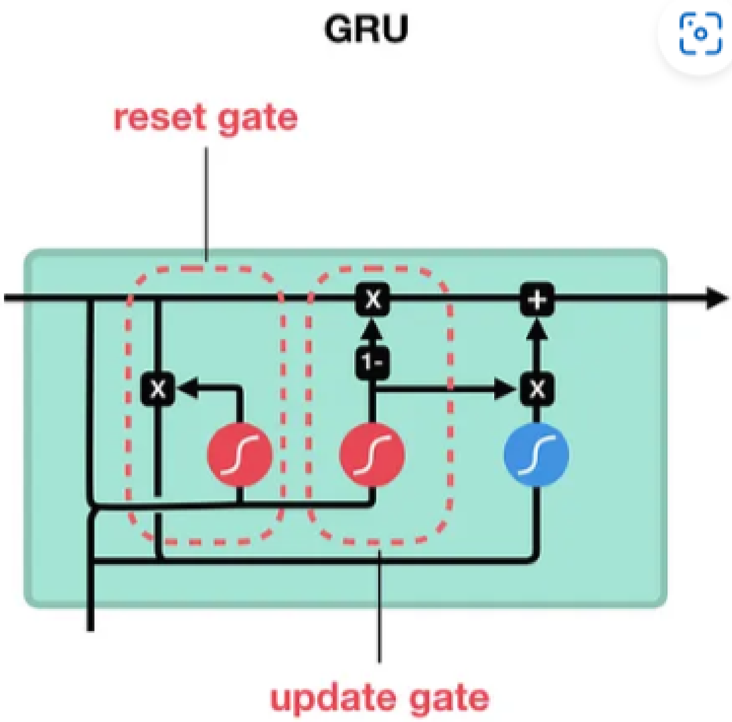

Figure 2.3: GRU Architecture[2].

2.2.4 Metrics for Assessing Response Quality:

The model's response effectiveness is measured using:

BLEU (Bilingual Evaluation Understudy) Score: This metric evaluates the linguistic precision and fluency of the machine-generated text against human responses. Cosine Similarity Measurement: It calculates the similarity between the vector representation of the produced response and an ideal response, indicating the model's effectiveness in capturing the query's essence and intention.

2.2.5 Benefits for Customer Service and Interaction:

The deployment of this deep learning method in customer service offers several advantages:

Improved Response Accuracy: The model's proficiency in generating contextually relevant and informative responses can significantly uplift the quality of customer service. Operational Efficiency: Automating responses while maintaining relevance and precision can enhance the efficiency of customer service systems. Future Prospects: This research lays the groundwork for further advancements in AI-powered customer service, aiming for more advanced and interactive communication systems.

2.2.6 Final Thoughts:

The investigation into utilizing sequence-to-sequence learning with LSTM, GRU, and CNN for crafting customer service responses signifies a noteworthy development in the field. The evaluation of model performance through BLEU scores and cosine similarity demonstrates the deep learning's potential in revolutionizing customer communication, heralding a new era of intelligent and responsive customer service solutions. [7]

2.3 ER-Chat: A Text-to-Text Open-Domain Dialogue Framework for Emotion Regulation[3]

An end-to-end discussion framework for managing emotions is called ER-Chat. Response conversation creation, response mood prediction, and response intent prediction are its three main modules.The dialogue's context is sent through the T5 decoder and encoder. The response generation module uses a contextual representation of the gold standard answer and cross-entropy loss to optimize response generation.

2.3.1 T5 or Text-to-Text Transfer Transformer

T5 is made up of a number of parts that come together to produce its remarkable performance. The attention mechanism, decoder, and encoder are some of these parts. T5's encoder module interprets the input text and uses embeddings, a high-dimensional representation, to extract the text's underlying meaning. Using the embeddings that the encoder produced, the decoder produces outputs that are tailored to the particular task at hand. When producing the output, T5 makes use of an attention mechanism to assess the significance of various passages in the input text.

2.3.2 Emotion and Intent Prediction

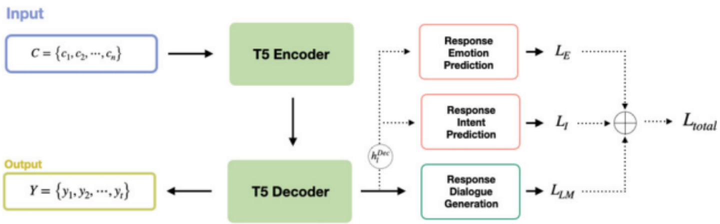

Figure 2.4: Framework structure diagram of ER-chat[3]

The goal of the Response Dialogue Generation (LLM) model is to produce responses that are as good as the gold standard response while also being contextually appropriate.Optimizing the emotions expressed by the generated replies is the main goal of the Response Emotion Prediction (LE). It guarantees that the answers match the intended emotional tone and are emotionally appropriate. Optimizing the purpose conveyed in the generated responses is the goal of the Response purpose Prediction (LI). It guarantees that the answers are in line with the discussion's stated aim or objective.

2.4 An AI-Based Medical Chatbot Model for Infectious Disease Prediction[4]

A deep feedforward multilayer perceptron-based AI chatbot interaction and prediction model is proposed by AI-based medical chatbot[4] for infectious illness prediction in order to support lifestyle improvement initiatives and treat infectious diseases. The goal of the model[4] is to include Covid-19 symptoms and give users a list of drugs and safety measures to take in case they become sick.

2.4.1 Long Short Term Memory

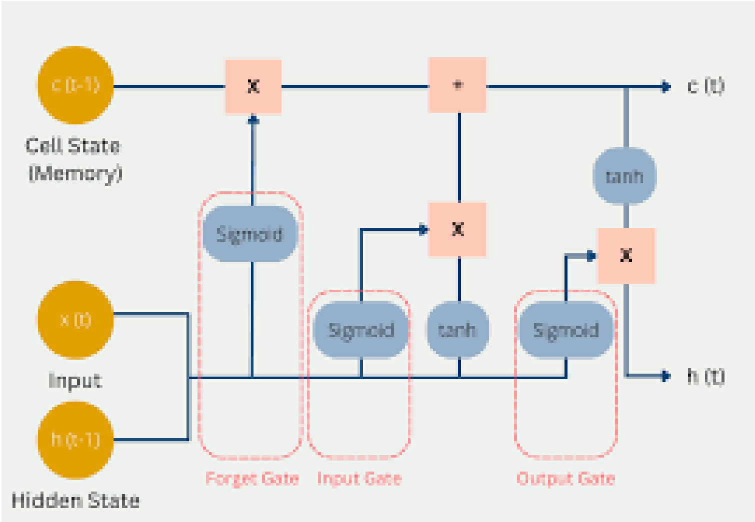

Figure 2.5: LSTM gates[4]

The LSTM[12] is a specific kind of Recurrent Neural Network (RNN) that is especially well-suited for tasks involving natural language processing because of its ability to capture long-term dependencies in sequential input. The first step in the procedure is gathering and preparing an appropriate dataset made up of pairs of input and output sequences, frequently taken from conversations. The network is thus able to selectively store and retrieve data across long sequences because to the implementation of the LSTM[13] architecture, which consists of memory cells and gating algorithms. By minimising the discrepancy between expected and actual outputs throughout the training phase, the LSTM chatbot refines its internal parameters and gains an understanding of the contextual subtleties of language.After being trained, the LSTM-based chatbot can produce coherent and contextually relevant responses, which makes for a more engaging and natural conversational experience for users.

2.4.2 Recurrent Neural Network

First, a dataset made up of conversational data pairs with input and output sequences is gathered. The problems of vanishing gradients are then addressed in the design of the RNN[14] model by utilising architectures such as the gated recurrent unit (GRU) or long short-term memory (LSTM). Through a procedure known as backpropagation[15], the weights of the network are changed to minimise the discrepancy between the expected and actual outputs, allowing the model to be trained on the dataset. Optimising hyperparameters and fine-tuning are essential to improving the chatbot's[4] performance. Furthermore, the textual material is preprocessed using natural language processing techniques like tokenization and word embeddings to improve its representation.

2.4.3 Decision Tree

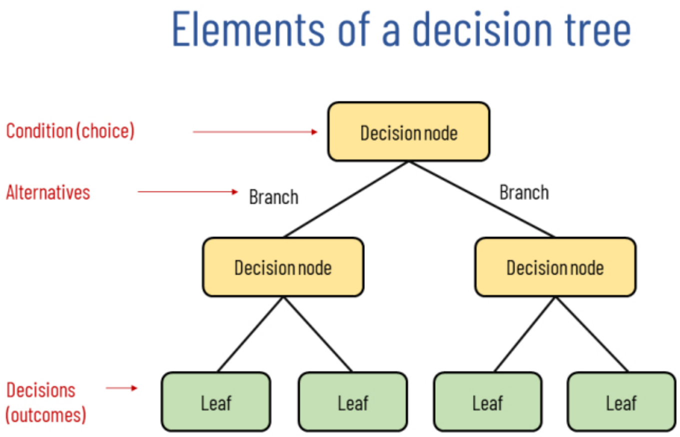

Figure 2.6: Branch and nodes of decision tree[4]

The first step in the procedure is gathering an appropriate dataset. A decision tree structure is constructed using the elements that were taken from these samples. The branches[16] that branch off of each node in the tree correspond to potential values or conditions for each feature, and each node itself represents a decision point depending on a particular characteristic. The ultimate choice or answer is contained in the leaves of the tree. Recursively partitioning the dataset according to the most informative characteristics is part of the training process for the decision tree chatbot[17], which makes sure the tree performs effectively when applied to new, untested data. Decision trees are appropriate for certain chatbot applications when specific rules can be provided because of their simplicity and interpretability.

According the analysis, the deep feedforward multilayer perceptron-based AI Chatbot interaction and prediction model[4] that was suggested had the best accuracy of 94.32 percentage and the lowest loss of 0.1232. LSTM method was found with best accuracy compared to RNN and decision tree methods. The paper's findings should aid researchers in better comprehending the design and uses of these cutting-edge technologies, which is necessary for ongoing enhancements to medical chatbot functionality and will help prevent COVID-19.

2.5 Detecting Mental Disorders in Social Media Through Emotional Patterns - The Case of Anorexia and Depression[5]

2.5.1 Bag of Sub-Emotions (BoSE)

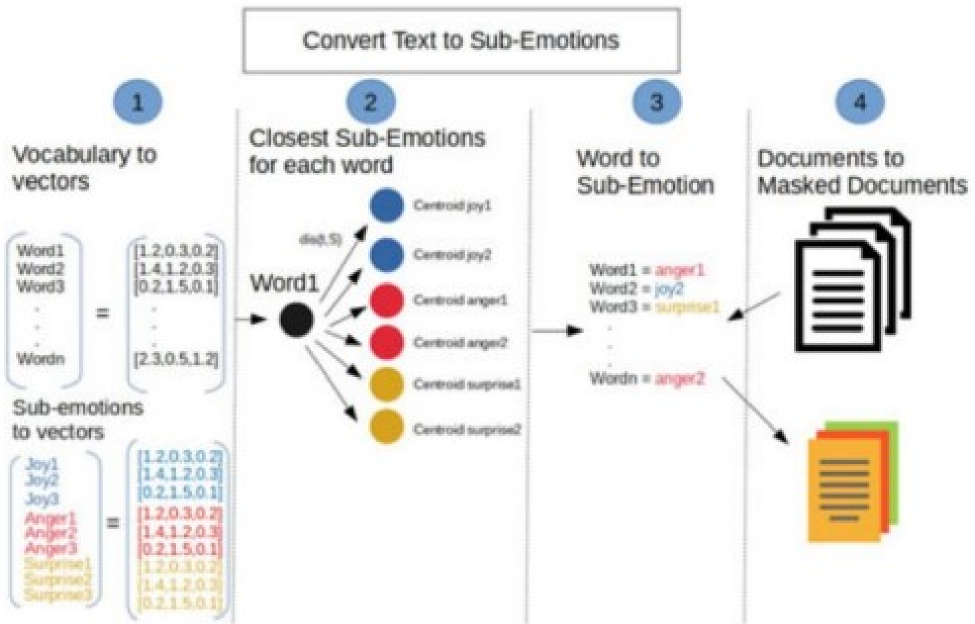

Figure 2.7: Procedure to transform the texts to sub-emotions sequences.[5]

The research[5] presents a method for identifying mental diseases, notably depression and anorexia, by collecting the emotional content of social media posts using the Bag of Sub-Emotions (BoSE) model. Documents are converted into vectors of weights corresponding to sub-emotions in order to create the BoSE representation. The weights of each document are computed in a tf-idf manner to determine the sub-emotions' relevance to the document. Each document[18] is represented as a vector of weights. The representation takes into account the existence of distinct sub-emotions, known as BoSE-unigrams, within the papers. It can also take into account the existence of sub-emotional sequences, or what are known as BoSE-ngrams.

The goal of the BoSE depiction is to convey the minute emotional variations that are essential to comprehending users' mental health. This method is predicated on the ideas that people with depression and anorexia typically demonstrate greater emotional diversity than healthy individuals, and that words assigned to coarse emotions in lexicons cannot reflect subtle emotional distinctions. In the identification of depression and anorexia, the BoSE representation has proven to be more effective than baseline methods[19] and deep learning models, suggesting that it may be able to identify useful emotional patterns associated with these mental illnesses.

2.5.2 Deep Bag of Sub-Emotions (D-BoSE)

The study proposes a representation called D-BoSE (Dynamic Bag of Sub-Emotions), which attempts to capture the temporal emotional patterns of social media users for the purpose of identifying mental diseases, particularly anorexia and depression. To calculate the D-BoSE representation, each user's post history is divided into n pieces, and the BoSE representation for each chunk is determined. A vector of statistical values that depict each sub-emotion's variations over the n-chunks sequence is then used to represent it. The variance, average, median, standard deviation, max-value, min-value, mean, and total are among these statistical values. A single vector with dimensions of 8 x m—where m is the number of sub-emotions—is created by concatenating the resultant D-vectors.

The modeling of emotional fluctuations that individuals with mental problems may continuously show is made possible by the D-BoSE representation[20]. This method is predicated on the idea that people with mental illnesses exhibit greater emotional fluctuation than people in good health. The efficacy of the D-BoSE representation in enhancing the identification of users exhibiting indications of anorexia and depression has been proven, highlighting the importance of taking into account the alterations in sub-emotions over time. It has also been demonstrated that combining the BoSE[5] and D-BoSE representations enhances the classification process's effectiveness, suggesting that both representations have the capacity to capture significant affective patterns associated with mental illnesses.In general, the D-BoSE representation offers a more thorough treat-

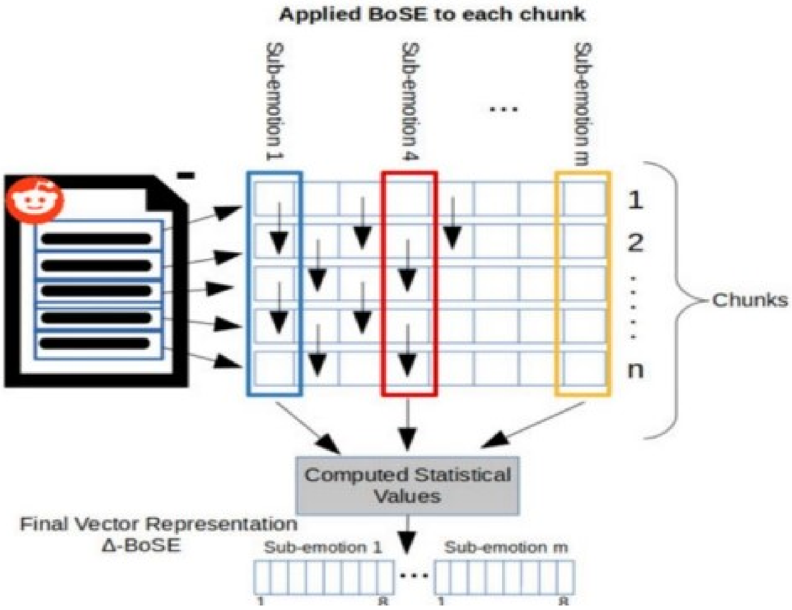

Figure 2.8: Construction Of D-BoSE Representation[5]

ment of the BoSE technique, enabling the modeling of temporal emotional patterns that may enhance the precision and promptness of the identification of mental disorders.

2.6 Summary and Gaps Identified

Gaps identified

- [1] To make SERMO better, it must respond to user feedback and trends, improve AI transparency, fortify data privacy, hone emotional intelligence, incorporate professional therapy, assess long-term efficacy, enhance customization, and guarantee data reliability—all of which are critical to the product's development and effectiveness.

- [2]In the development of mental health chatbots, crucial challenges include the need for ongoing updates and responsiveness to feedback, clarity in the AI's decision processes, robust protection of user data and privacy, and enhanced capability in discerning and reacting to emotional subtleties in communications.

- [3] As the ER-Chat functions as a "black box," it can be difficult to comprehend the underlying reasoning behind decisions made. To overcome ER-Chat's interpretability issue, a new paradigm is required. Creating a model that is more interpretable and transparent will boost user confidence and make it easier for people to comprehend how the model makes decisions.

- [4] Even while RNNs are good at identifying sequential dependencies, they frequently encounter issues like the vanishing gradient problem that make it difficult for them to discover long-term connections in conversational data.
- [5] The sequential order of the input data is ignored by the BoSE representation, which views it as an unordered series of events. This loss of sequential information can eventually make it more difficult to interpret user intent and context in chatbot talks, where context is essential. Additionally, the size of the event vocabulary has a direct bearing on how well BoSE representation works. Working with a big vocabulary can increase the dimensionality of the data, which could lead to increased processing needs and the dimensionality curse.

We reviewed important papers in chatbot technology and natural language processing in this chapter's literature review, with particular attention to SERMO[1] for mental health support, developments in AI language processing, ER-Chat for text-based emotional management, AI in medical diagnostics for disease prediction, and AI's function in social media mental illness detection. In addition to summarizing these ground-breaking discoveries, the chapter also pointed out areas in need of more investigation, underlining the broad and revolutionary potential of AI and NLP in healthcare and mental health services.

Table 2.1: Comparison table

Paper	**Method used**	**Comparison**
[1]	CBT,Daily Emotion Tracking	Advantages: CBT effectively alters negative thinking and behavior patterns,enhancing mental wellness. Disadvantages: Daily emotion tracking, though insightful, can be time-consuming and potentiallyoverwhelming, reducing user engagement.
[2]	LSTM,GRU,CNN	Advantages: CNN is excellent at recognizing localized patterns, GRU offers efficiency with a simpler structure and faster training, and LSTM records long-term dependencies. Disadvantages: These models are difficult to interpret and require a lot of processing power, which limits their use in some situations.
[3]	T5 model	Advantages: greater fluency, diversity , emotion awareness, generation of more human-like dialogue Disadvantages: require significant computational resources, lacks interpretability, fine-tuning complexity
[4]	LSTM,RNN,Decision tree	Advantages: Sequential Learning, Handling Long Term Dependencies, Memory Cells Disadvantages: Computational Complexity, Training Time, Limited Context
[5]	BoSE, D- BoSE	Advantages: Interpretability of results, More Flexible, Soft matching procedure Disadvantages: Loss of Sequence information, Limited context understanding, Vocabulary size impact

Chapter 3

Requirements

3.1 Hardware and Software Requirements

- 8 GB RAM: This amount of memory is essential for meeting the computing demands of the project, especially for managing large datasets and running complex algorithms.
- Core i5 Processor from Intel: The Intel Core i5 was chosen for its effectiveness in striking a balance between power consumption and performance. It can handle the computational complexities and demands of deep learning and data handling activities, as well as multitasking.
- 32GB Hard Drive: To handle the operating system, several software programs, the project's dataset, and additional space for transient processing data and outputs, a minimum 32GB hard drive capacity is needed.
- Google Colab or Visual Studio Editor:While Visual Studio Editor is installed locally and offers a variety of programming languages and tools, Google Colab is a cloud-based environment with ample resources and library accessibility.
- Windows 10 or 11: To guarantee compatibility with the most recent software and security upgrades, the project should run on one of these modern operating systems.
- Deep Learning Frameworks-TensorFlow, Keras: Together, Keras and TensorFlow make up a formidable team for creating deep learning models. They include an extensive array of libraries and tools that make the process of designing, training, and deploying models easier.
- Web Framework-Flask: This framework was chosen for web application deployment

due to its ease of use and versatility. Its compatibility with Python-based systems is one of the main reasons for its selection.

- Conversation dataset,intents.json: This particular dataset, which contains contextual data and conversational material, is essential for training and assessing machine learning models and guaranteeing the system's ability to comprehend and react appropriately in conversational contexts.

Chapter 4

System Architecture

This chapter presents a concise yet comprehensive overview of our system, covering its architecture, sequence diagram, module division, and work schedule. We begin with an introduction to the system's fundamental components and functionalities, then explore its architecture to understand how these elements interact. The sequence diagram offers a visual representation of operational flow, followed by an analysis of how the system is divided into modules. Finally, we outline the work schedule, detailing the development phases and key milestones. This chapter aims to provide a clear, cohesive understanding of the system's design and operational dynamics.

4.1 System Overview

Initial Interaction and Analysis of User Input: The commencement of the process is marked by the receipt of input from the user. This input undergoes a thorough analysis, aiming to uncover the user's fundamental objectives. During this phase, the system interprets the contextual clues within the message, pinpointing the user's precise needs. This initial analysis is pivotal, as it lays the groundwork for the stages that follow.

Detection of Emotional Cues, Management of Conversation, and Data Acquisition: Understanding the user's intention triggers two simultaneous operations within the system. The first is the detection of emotional undertones in the user's message, a critical step for crafting responses that are not only accurate but also emotionally attuned. In parallel, the system efficiently manages the ongoing conversation, maintaining relevance and coherence. For response formulation, the system accesses its repository of information, selecting data that corresponds to both the user's question and the identified motive.

Implementation of Responses and Delivery of Feedback: With the necessary information at hand, the system embarks on the execution of the appropriate action. This might involve answering queries, carrying out specific tasks, or even seeking further information for clarity. Post-action, the system assembles a well-thought-out response. This response is comprehensive, reflecting the conversation's progression, the emotional context, and the overall dialogue theme. This response is then communicated back to the user, thereby completing the interaction loop.

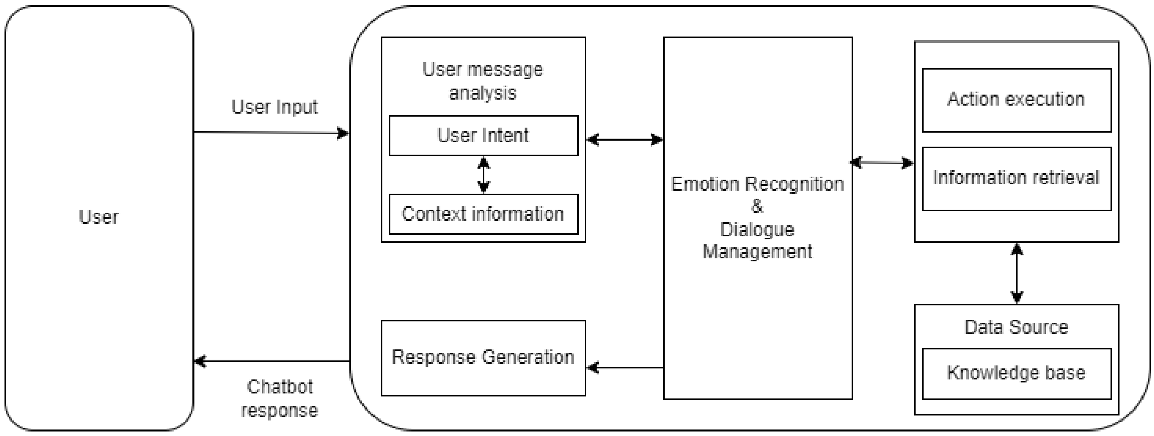

Figure 4.1: Architectural diagram

4.2 Architectural Design

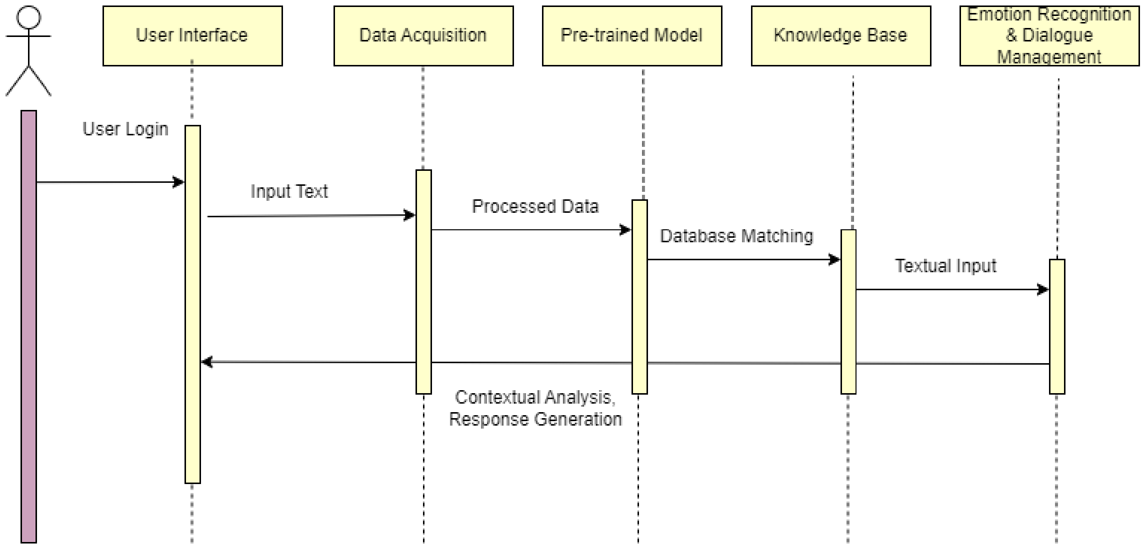

Figure 4.2: Sequence diagram

4.3 Module Division

1. User Interface Module

   - Input Interface: Handles user input through text or voice.
   - Output Interface: Presents information, responses, and suggestions to the user.

2. User Profile and History Module

   - User Profile Management: Keeps track of user preferences, history, and personalized information.
   - Feedback Mechanism: Users share experiences, helping customize support for individual needs.

3. Natural Language Processing (NLP) Module.

   - Text Processing: Tokenization, lemmatizing, and other preprocessing tasks.
   - Sentiment Analysis: Determines the sentiment of user input.
   - Intent Recognition: Identifies the user's intent or request.

It employs Natural Language Processing (NLP) modules for sentiment analysis to understand users' emotional states and tailor responses accordingly. It utilizes entity recognition modules to extract relevant information from user input, enhancing the chatbot' s ability to provide personalized and effective support.

4. Knowledge Base Module

    - Information Database: Stores information about depression, coping strategies, and related topics.
    - Content Retrieval: Retrieves relevant information to answer user queries.

    Comprehensive database covering mental health, depression symptoms, coping strategies, and professional resources. Regularly updated with the latest research for accurate and current information.

5. Emotion Recognition Module

    - Emotion Analysis: Analyzes user input to detect emotional states (e.g., sadness, anxiety).Employs sentiment analysis and language pattern recognition to gauge users' emotional states, tailoring responses based on detected cues and implementing risk assessment algorithms for intervention when necessary.It also considers conversation history and user feedback to continually refine its ability to provide empathetic and supportive interactions.
    - Empathy Responses: Tailors responses based on detected emotions.It utilizes empathetic language and validation techniques to acknowledge and understand users' emotions, fostering a supportive environment. Through personalized responses and compassionate engagement, it aims to provide comfort and companionship to users dealing with depression.

6. Therapeutic Support Module

    - Coping Strategies: Provides users with coping mechanisms, exercises, or suggestions.
    - Mindfulness Techniques: Introduces mindfulness and relaxation exercises.

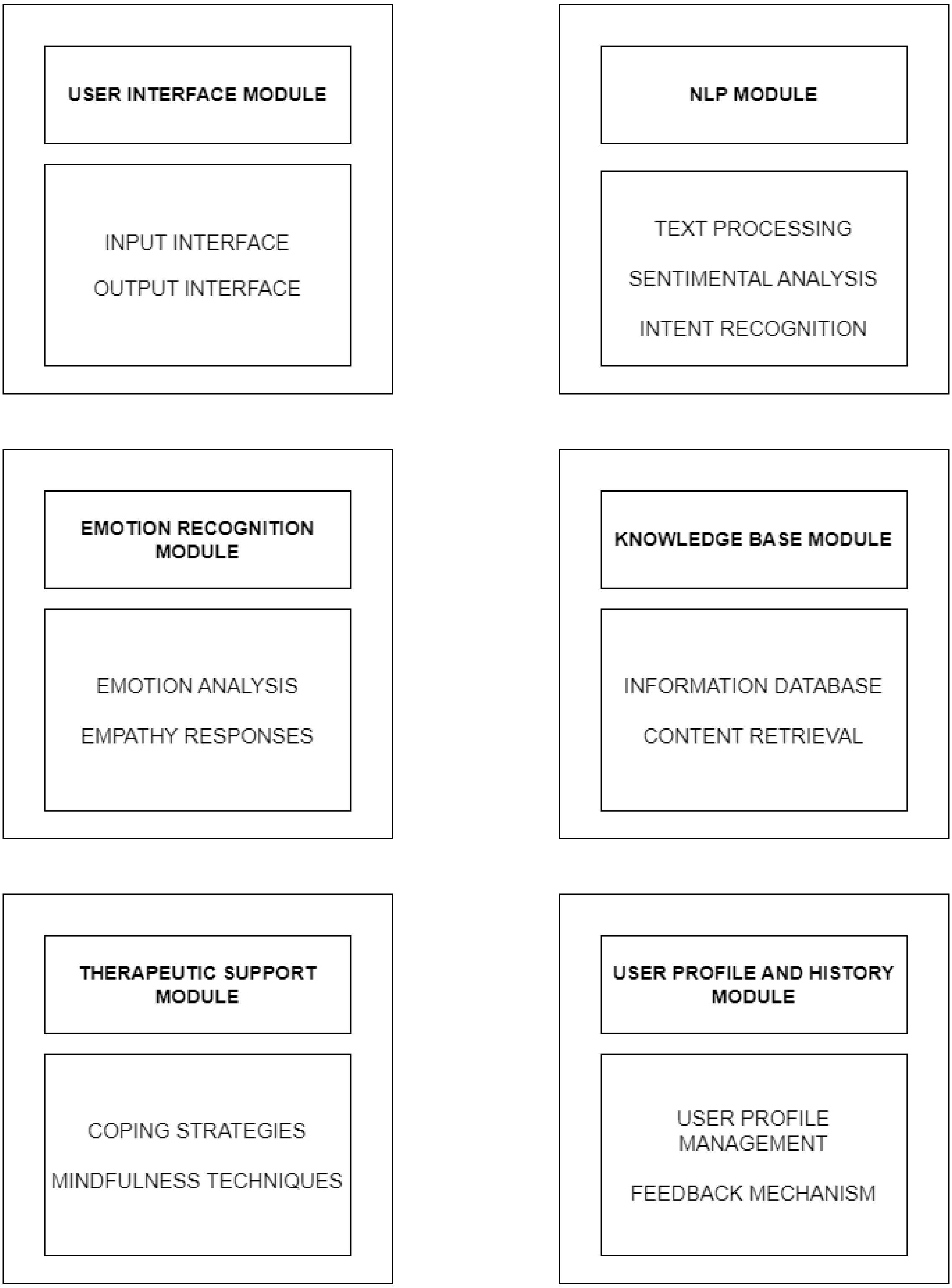

Figure 4.3: Module diagram

4.4 Work Schedule - Gantt Chart

Figure 4.4: Gantt Chart

In conclusion, the structure and operation of our system have been succinctly described in this chapter. It came with a thorough architectural diagram that showed how different system components are connected to one another. The system's partition into discrete modules was expounded upon, emphasizing their individual functions and inputs. The chapter also included a thorough work schedule that outlined the deadlines for the creation and implementation of each module. This well-structured framework lays the groundwork for our project's systematic and effective advancement, opening the door for more in-depth development and analysis in the ensuing chapters.

Chapter 5

System Implementation

In this chapter, we examine the datasets that are used in the project, explaining their importance. The methodologies associated with the work are also discussed. Next, we explore the UI design and provide an understanding of the interactive experience that consumers will have. We also explain the architecture of the database we used, providing justification for our choice of effective data management. Finally, we go over the many approaches that were used, along with some sample code to give readers an idea of how our project is actually run.

5.1 Datasets Identified

The mental health dataset used in the project is a comprehensive collection of conversations intended to train mental wellness-focused chatbot models. Because of its comprehensiveness, it covers a wide range of conversation types, such as standard exchanges, frequently asked topics regarding mental health, therapeutic dialogues, and general guidance intended for those who are experiencing anxiety or depression. Because of this diversity, the chatbot model may be trained on a broad range of circumstances, which guarantees that it will be able to respond to users who are seeking emotional comfort in a sympathetic and encouraging manner.

The dataset incorporates the concept of "intents",which represent the underlying purposes or emotions behind user messages. For example, if a user expresses feelings of sadness, the corresponding intent would be labeled as "sad." A collection of patterns, or sample messages that correspond with a certain purpose, is linked to each intent. The model uses these patterns as training data so that it can identify similar expressions of emotion in user messages. The matching responses, which the chatbot should produce when it detects a specific intent in a user's message, are displayed next to the patterns.

Through the definition of several intents, patterns, and answers, the model learns to comprehend user inputs more deeply and produces thoughtful, appropriate responses.

This dataset can be used by researchers and developers to train chatbot models that demonstrate a thorough comprehension of mental health issues. The chatbot can be trained on actual interactions to identify and react to different emotional states and provide users with personalized support. The ultimate goal is to develop a virtual conversational agent that can provide helpful guidance, and support to people facing the challenges of anxiety and depression.

This dataset's unique qualities are found in the wide variety of talks that have been thoughtfully chosen to cover a range of situations linked to mental health. o access the dataset and obtain additional information, kindly refer to the designated location for data retrieval and exploration.

The Depression Chatbot Dataset.xlsx is a key resource for teaching our customized Gemini Language Model. It contains conversations between users and a chatbot focused on helping people with depression. The dataset is organized with questions and answers, which are vital for training the model to respond with empathy and effectiveness to users' mental health issues. This ensures that the model can better understand and support users' mental health concerns.

5.2 Proposed Methodology/Algorithms

5.2.1 Sequential model

When creating a chatbot for mental health using a sequential model and JSON data, first the dataset is loaded. It is organized into patterns that reflect user inputs and the tagged answers that correspond to those inputs. After that, the dataset is preprocessed, which includes operations like tokenization, lowercasing, punctuation removal, and potentially stemming or lemmatization to standardize the text. When creating a chatbot for mental health using a sequential model and JSON data, the process is broken down into multiple parts. First, the dataset is loaded. It is organized into patterns that reflect user inputs and the tagged answers that correspond to those inputs. The dataset is preprocessed, which includes lowercasing, tokenization, punctuation removal, and lemmatization to standardize the text. A sequential model is built. Additional layers, such as Dropout layers for regularization or Dense layers for classification tasks, are added. The model is then trained as a result. The model is assembled using suitable loss functions, optimizers, and metrics specific to the job, like sequence generation or classification, once the dataset is divided into training and validation sets. Fit() is used to train on the training data, with batch size and epoch count specified. Accuracy and loss metrics are tracked on both the training and validation sets.

5.2.2 Sequential and Gemini pro model

First, the JSON-formatted dataset is loaded. It consists of patterns that represent user inputs and the tagged answers that go with them. Following that, operations related to data preprocessing are carried out, which include tokenization, lowercasing, punctuation removal, and lemmatization in order to standardize the text data. Next, the sequential model and the Gemini Pro Model API are incorporated into the model architecture. The Gemini Pro Model API is integrated into the design of a sequential model, which is built to handle sequential data, like text. The sequential model's input layer is set up to take numerical representations in sequence that are obtained from the text data that has been previously processed. The produced response is sent to the Gemini Pro Model API for additional improvement after being processed through the sequential model. Next, the sequential model is trained using a dataset that has been divided into training and validation sets. The model is assembled using task-specific metrics, optimizers, and loss functions. After training on the training set, the model is tested on an independent test set to check how well it performs on data that hasn't been seen before. The model's performance is examined after evaluation, and adjustments are made as necessary. After processing the input, the Gemini Pro Model API produces an improved response, which is then sent back to the chat interface as the user's final response.

5.2.3 RNN and LSTM

Data preparation is the first step in creating a mental health chatbot that uses LSTM and RNN layers within a sequential model. First, the dataset is loaded; it is usually organized in JSON format. This dataset includes patterns that indicate user inputs and matching responses—that is, the chatbot's replies—that are grouped under various tags. To normalize the text, the data is put through preprocessing procedures such tokenization, lowercasing, punctuation removal, and lemmatization. In the model architecture design to handle sequential data, like text, a sequential model is created. Sequences of numerical representations generated from the text data are accepted by the input layer. To capture the sequential dependencies present in the input data, the model makes use of LSTM and/or RNN layers. It may also include additional layers, like Dropout layers for regularization to avoid overfitting or Dense layers for classification jobs.

5.2.4 GPT 3.5 turbo

Token authorization is the initial step in the development process since it gives developers access to GPT-3.5 Turbo and lets them interact with the model's API. Establishing communication channels to transfer user input and receive generated responses is part of the integration process with the model. Usually, this entails creating HTTP requests and authenticating them with the token. Obtaining an appropriate dataset is essential for the chatbot's training process. The dataset for the chatbot include question and answer pairs. Every set of questions and answers depicts a dialogue between a client and a therapist. In order to fine-tune the GPT-3.5 Turbo model for the purpose of producing contextually relevant responses, it must be trained on the dataset of questions and therapist responses. When the model is fine-tuned, it learns to produce answers based on the input question while accounting for the intended tone and style of the therapist's responses as well as the context of the session. In order to develop the chat interface, a user-friendly platform for users to communicate with the chatbot must be created. Users should be able to input queries or concerns into the interface, submit them to the chatbot, and receive responses produced by the optimized model. The text and authentication token are delivered to the GPT-3.5 Turbo model when a user types a query or message into the chat interface. After analyzing the input text, the model produces a response that is delivered back to the conversation interface and shown to the user.

5.2.5 Customised Gemini Language Model

The Depression Companion Chatbot, powered by a customized Gemini Language Model (LLM), uses smart tools to understand how users feel and what they need. We gave Gemini a special custom message and response format based on our dataset of depression-related conversations, so it can provide more helpful and thoughtful responses. It adjusts its answers based on users' emotions, offering supportive listening, understanding emotions, helpful tips, and links to mental health resources. We created this chatbot because many people need mental health support, especially those dealing with depression. What makes this chatbot special is how easily it fits into a simple and friendly system, making it easy for users to get personalized help. It keeps learning and getting better at helping over time. Our goal is to help people feel better by giving them a kind and useful tool to manage their mental health. By combining smart technology with friendly design, the Depression Companion Chatbot helps build strong communities where everyone's mental health matters.

5.3 User Interface Design

Figure 5.1: Opening page

In order to provide customers with an aesthetically pleasing and user-friendly experience, we utilized HTML for layout structure and CSS for styling elements in the user interface (UI) design of our mental health chatbot. Users can enter their feelings and thoughts in the chat window on the main screen. The style of the design is clear and uncomplicated, with an input box where users can type their messages and a "Send" button to send them. The server processes the user's message, generates a response using the chatbot model, and sends the response back to the client. The chatbot's response is then displayed in the chat window. Users can also offer input on their experience by

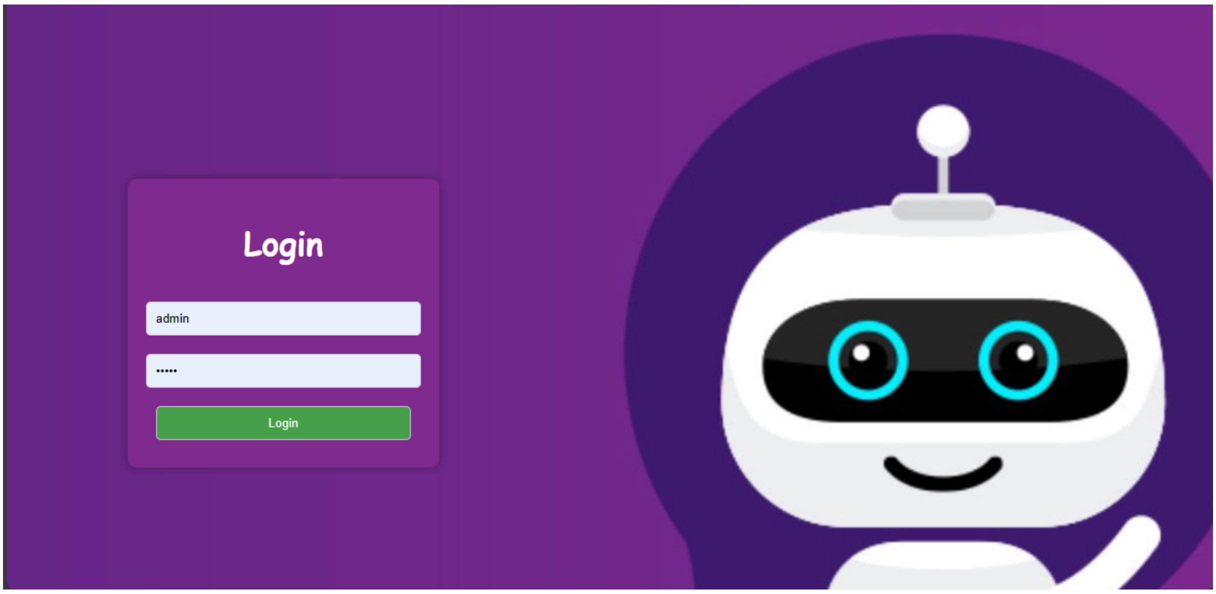

Figure 5.2: Login page

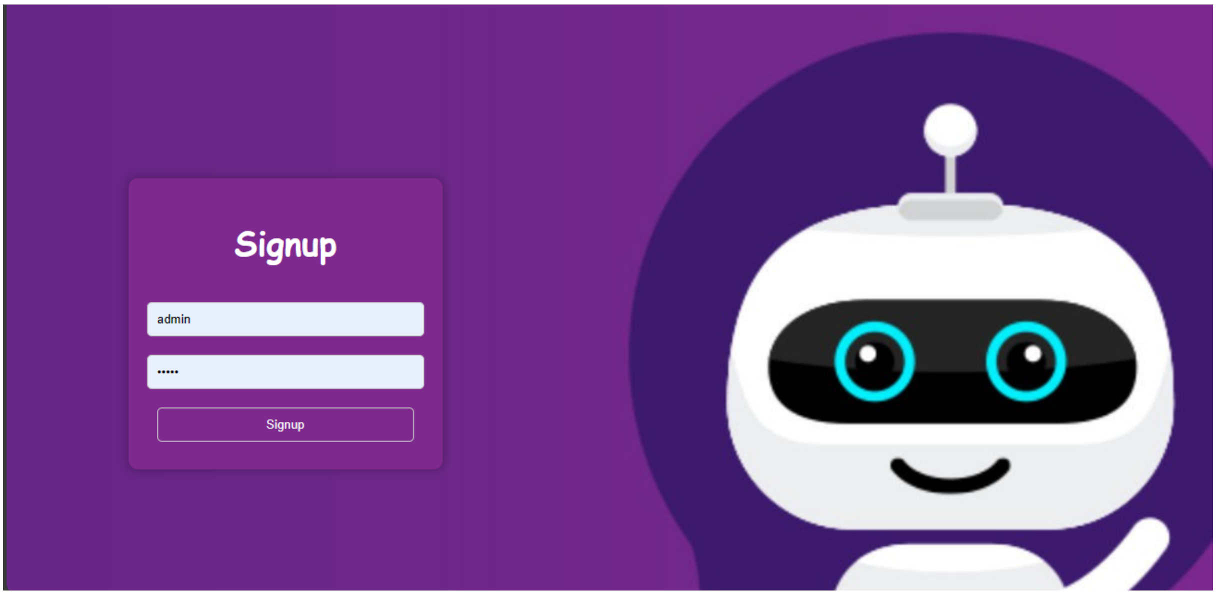

Figure 5.3: Sign up page

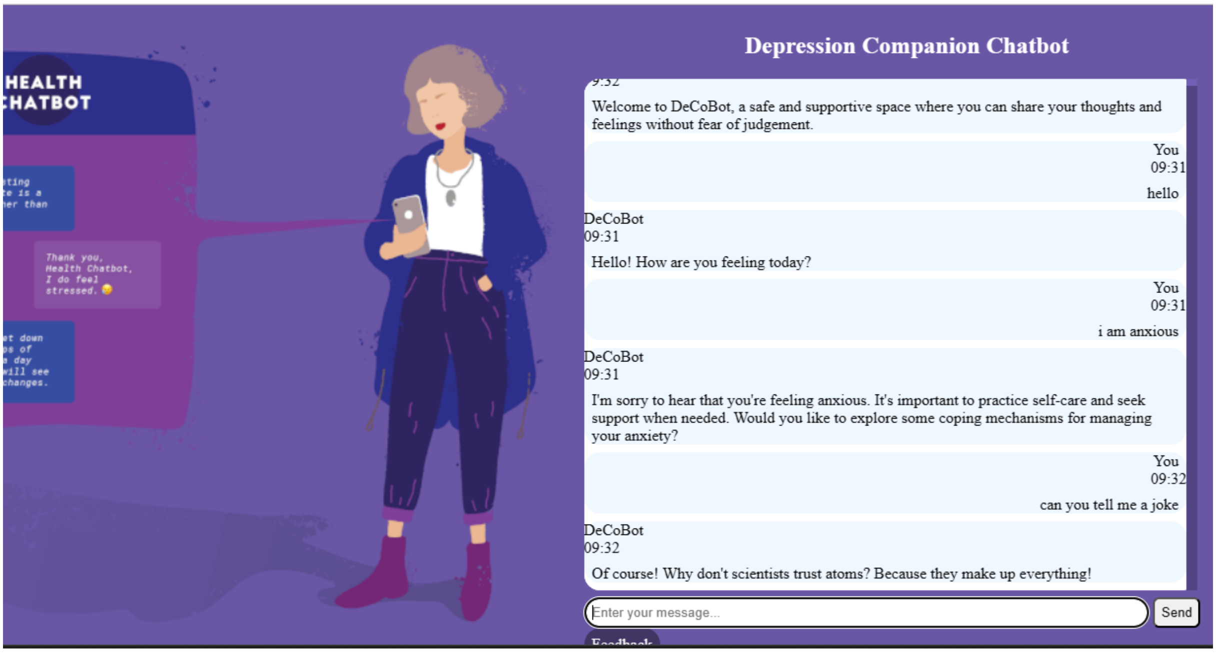

Figure 5.4: Conversation page

Figure 5.5: User feedback collection page

clicking the "Feedback" icon in the user interface. The user is redirected to the feedback form upon clicking the "Feedback" button. To further ensure that the discussion data is preserved for later use, a script is provided that activates a function to store the conversation whenever the user tries to close the tab or exit the page. This creates a user-friendly and visually appealing interface for interacting with the DeCoBot mental health chatbot, allowing users to engage in supportive conversations and receive guidance on managing their mental well-being.

5.4 Database Design

The database design revolves around MongoDB, chosen for its flexibility and scalability in handling document-based data. The primary repository is the chatbot-db database, which holds collections for user accounts and feedback entries. Secure authentication for registered users is made possible by the user account collection, named users, which keeps documents containing username and password fields. The username and password of a new user who registers via the /signup route are compared to already-existing records in the users collection. To create the user account, a new document is inserted if the username is unique. To collect user feedback, the program also has a /feedback route. Users' usernames and the content of their feedback are saved in the feedback collection when they submit it via a form. Username and feedback fields are included in every feedback entry, which enables the program to gather insightful data from users.

Both the MongoDB Atlas cluster at the given URI and the local database at localhost:27017 have their MongoDB clients initialized. Because of its dual design, the application may easily transition between local and cloud-based databases as needed, ensuring flexibility and scalability. The user and chatbot's ongoing interaction is dynamically recorded and stored in the conversation-history list. Starting with predetermined conversation pairs from the conversations list, this list records the message flow by adding the user's real-time input (msg). In order to preserve a chronological record of the conversation, the generated response based on the entire conversation history is then appended to the conversation-history list.

For the project, MongoDB was selected based on a number of factors. The document-based structure of MongoDB fits very nicely with the chatbot application's requirements, enabling the storage of dynamic and variable user data. Because of its scalability, the database can accommodate progressively more user data and input over time. The PyMongo module makes it simple to integrate MongoDB with Flask, which simplifies communication between the application and database backend.

5.5 Description of Implementation Strategies

Sequential model creates a chatbot with TensorFlow/Keras for natural language processing (NLP) and Python. In order to preprocess input text and train a neural network model to classify user intents, the code uses a bag-of-words (BoW) technique. Preprocessing the data and loading the intentions are the first steps. A JSON file with specified patterns and associated intents is read by the code. For every pattern, it generates a bag-of-words representation, tokenizes the patterns, and lemmatizes the words. Next, the data is divided into testing and training sets. TensorFlow/Keras is used to build the neural network model. To avoid overfitting, it is composed of densely coupled layers with dropout regularisation and ReLU activation functions. Stochastic gradient descent (SGD) is used as the optimizer and categorical cross-entropy is used as the loss function during model training. The code creates a Flask web application to function as the chatbot's interface when the model has been trained. Through the online interface, users can communicate with the chatbot by sending messages. Using the trained model, the chatbot determines the user's intent and then chooses a response from the list of pre-programmed responses. All things considered, this implementation strategy makes excellent use of web development frameworks, neural network models, and natural language processing techniques to build a chatbot that can comprehend and react to user input.

The LSTM and RNN with Sequential model creates a chatbot for natural language processing (NLP) tasks using Python and TensorFlow/Keras. It combines multiple features to classify intentions, identify emotions in input text, preprocess the text, and obtain relevant answers. To ensure consistency in word representation, the text preparation function tokenizes and lemmatizes phrases. In order to facilitate intent classification, the bag-of-words representation function converts input phrases into binary vectors. Prepared training data, which consists of labels and patterns taken from a JSON file, is used to train the model. To determine the relationship between input sentences and intents, it makes use of a neural network design that includes SimpleRNN, LSTM, and Dense layers. The Adam optimizer and categorical cross-entropy loss function are used to train the model. Through an interface on the command line, users communicate with the chatbot by entering messages that the trained model has classified. The chatbot produces suitable responses based on the anticipated intent and identified emotion. All things considered, this implementation strategy combines sentiment analysis, neural network models, and natural language processing to provide a chatbot system that is both responsive and successful.

Using TensorFlow for intent classification, Flask for the web interface, and Gemini Pro API with Sequential model for response creation, creates a chatbot. To start, text input is preprocessed, tokenized, and sentences are lemmatized for uniformity. Afterwards, TextBlob is used to identify the sentiment of the input sentences and classify them as "Happy," "Sad," or "Neutral," improving the chatbot's contextual comprehension. The classification model, which uses trained neural network models to predict phrase intent, benefits from the bag-of-words representation, which makes input easier to understand. Diverse interactions are produced by retrieving responses from a JSON file and selecting them at random based on the anticipated purpose. By taking into account user input and conversation history, integration with the Gemini Pro API enhances response creation. The interface is provided by the Flask web application, which processes input, renders HTML templates for user interaction, and sends responses. In general, this approach creates an interactive chatbot that can comprehend user input, identify emotions, and provide contextually relevant responses by fusing NLP techniques with external APIs.

The GPT-3.5 Turbo model from OpenAI is used by the chatbot_response function to respond to user messages. Setting up the infrastructure and utilising the OpenAI API for authentication comes first. The conversations list, which consists of pre-made question-answer pairings meant to mimic user-chatbot exchanges, is the central component of the service. These pairs address a wide range of mental health-related subjects, enabling the chatbot to react suitably to various user inputs. The function creates message_objects, a set of dictionaries that represent user and assistant messages, to make communication with the OpenAI API easier. Every message sent by a user is associated with the role tag "user," and every answer from an assistant is tagged with the role tag "assistant". After then, the GPT-3.5 Turbo model receives these message objects in order to be completed. The function adds the user's message to the list of message objects and sends the complete conversation history to the GPT-3.5 Turbo model for completion after receiving the message. Based on the context of the conversation, the model produces a response that takes into account the user's recent input in addition to the established interactions. The created response is finally returned by the function and shown in the chat interface.

In the customised gemini language model, we endeavored to address the pressing need for accessible mental health support, particularly for individuals grappling with depression. Leveraging a customized Gemini Language Model and meticulously curated dataset of depression-related conversations, we developed a Depression Companion Chatbot. This chatbot is seamlessly integrated into a framework designed to dynamically adjust its responses based on users' emotional states and specific needs.The chatbot's core functionalities include empathetic listening, validation of emotions, and the provision of personalized resources such as coping strategies and referrals to relevant support services. It is designed to create a supportive and understanding environment for users, providing them with the tools and assistance they need to navigate their mental health challenges effectively.By leveraging advanced AI technology in conjunction with empathetic design principles, our collaborative effort aims to empower individuals on their mental wellness journey. We believe that fostering resilience and holistic well-being within our communities is crucial, and our Depression Companion Chatbot plays a vital role in achieving this goal.

In conclusion, the DeCoBot chatbot embodies a novel approach to tackling mental health issues, presenting a comprehensive solution for enhancing users' mental well-being. Commencing with a diverse dataset, the chatbot exhibits the ability to understand and respond to diverse user intents with empathy. The incorporation of sophisticated algorithms like LSTM and RNN layers enriches the chatbot's cognitive capabilities, thereby improving its understanding and responsiveness. Furthermore, our exploration and evaluation of Gemini Pro Model API and GPT-3.5 Turbo served as a comparative analysis of distinct models, contributing to the enhancement of the chatbot's responses. Users derive substantial benefits from the chatbot's user-friendly interface, ensuring seamless interaction. Features such as feedback submission and discussion archiving augment user engagement and data acquisition. The implementation of secure authentication and efficient data management through MongoDB guarantees the confidentiality and protection of user data. Ultimately, DeCoBot strives to deliver personalized assistance and guidance tailored to meet individual mental health requirements, leveraging advanced AI technology and empathetic design principles to empower users along their mental wellness journey.

Chapter 6

Results and Discussions

In this chapter, we explore the outcomes of our study on the mental health chatbot. We'll discuss the qualitative results, examine graphical analyses, and delve into discussions about the different models we used to develop the chatbot and their respective results. Our goal is to provide a clear understanding of how effective these models were in enhancing the chatbot's functionality and supporting mental health-related interactions.

6.1 Overview

This chapter looks at what happened when we used different models to create a mental health chatbot. We tried out models like sequential, sequential with RNN, sequential with Gemini Pro model, and GPT-3.5 Turbo. After running several models, we were able to classify them based on their accuracy and determine which ones performed best for enhancing the chatbot and supporting mental health discussions. By looking at things like how they performed in tests and analyzing graphs, we figured out what each model did best and where they could be most useful in making better mental health chatbots.

6.2 Testing

```
You: i am stressed
1/1 [==============================] - 0s 81ms/step
Bot: Stress is a natural response to challenging situations, but it's important to find healthy ways to manage it. Conside
You: i failed in my exams
1/1 [==============================] - 0s 52ms/step
Bot: A decline in academic performance can impact overall well-being by causing stress, anxiety, and a negative impact on
You: i had a panic attack
1/1 [==============================] - 0s 53ms/step
Bot: If you have a paper bag or can cup your hands over your mouth and nose, try breathing into it slowly. This can help r
You: do you think i should consider therapy
1/1 [==============================] - 0s 52ms/step
Bot: Medication can be a helpful tool in managing depression, but it's important to discuss the potential benefits and sid
You: i am afraid of everything
WARNING:tensorflow:5 out of the last 5 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7fb04
1/1 [==============================] - 0s 57ms/step
Bot: Hey, hang in there. I know times are tough, but be patient and everything will fall into place. Here is a quote that
You: can you tell me a joke then
WARNING:tensorflow:6 out of the last 6 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7fb04
1/1 [==============================] - 0s 62ms/step
Bot: Sure! Here's a joke: Why don't skeletons fight each other? They don't have the guts!
You: i am sad
1/1 [==============================] - 0s 54ms/step
Bot: Sadness is a natural emotion, and it's okay to feel this way sometimes. Remember to be gentle with yourself and allow
You:
```

Figure 6.1: Output-Sequential model

```
1112/1112 [==============================] - 5s 4ms/step - loss: 0.1892 - accuracy: 0.935
Epoch 95/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1966 - accuracy: 0.9382
Epoch 96/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1792 - accuracy: 0.9427
Epoch 97/100
1112/1112 [==============================] - 4s 4ms/step - loss: 0.1818 - accuracy: 0.9436
Epoch 98/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1817 - accuracy: 0.9442
Epoch 99/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1811 - accuracy: 0.9382
Epoch 100/100
1112/1112 [==============================] - 4s 4ms/step - loss: 0.1707 - accuracy: 0.9469
Done
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your m
  saving_api.save_model(
```

Figure 6.2: Testing Accuracy-Sequential model

```
You: i am stressed
WARNING:tensorflow:6 out of the last 6 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7f3e1
1/1 [==============================] - 1s 503ms/step
Bot: What do you think is causing this?
You: i failed in my exams
1/1 [==============================] - 1s 537ms/step
Bot: Strategies for improving academic performance and addressing challenges include developing effective study habits, ti
You: i had a panic attack
1/1 [==============================] - 1s 510ms/step
Bot: Experiencing panic attacks or intrusive thoughts can be distressing, but therapy can help you learn techniques to man
You: do you think i should consider therapy
1/1 [==============================] - 1s 517ms/step
Bot: Why do you want to spend so much on this thought? I think it would be better to go on a vacation in your beautiful co
You: can you tell me joke
1/1 [==============================] - 1s 518ms/step
Bot: Sure! Here's a joke: Why don't skeletons fight each other? They don't have the guts!
You: i am afraid of everything
1/1 [==============================] - 1s 697ms/step
Bot: I hear you. It seems like you're feeling misunderstood. Let's try to bridge that gap.
You:
```

Figure 6.3: Output-Sequential with RNN,LSTM

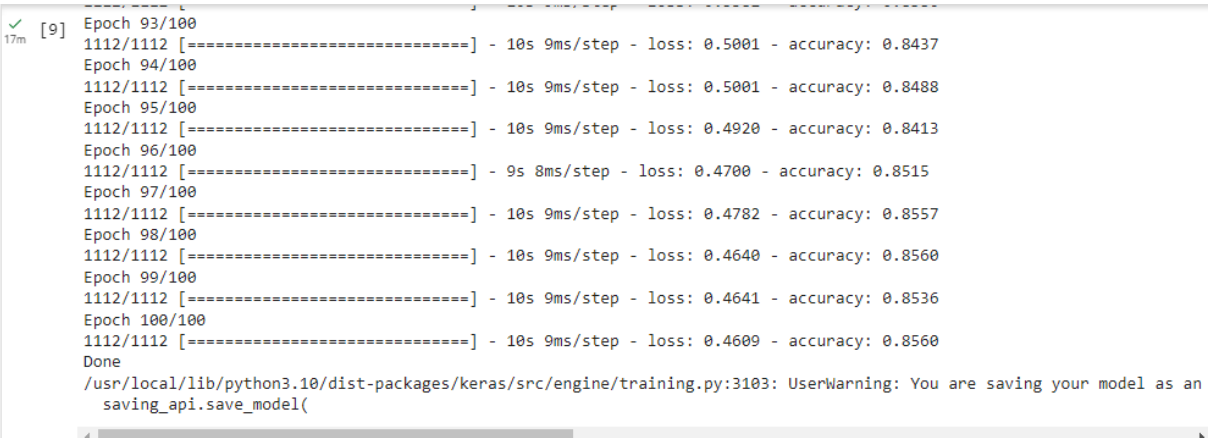

Figure 6.4: Accuracy-Sequential with RNN,LSTM

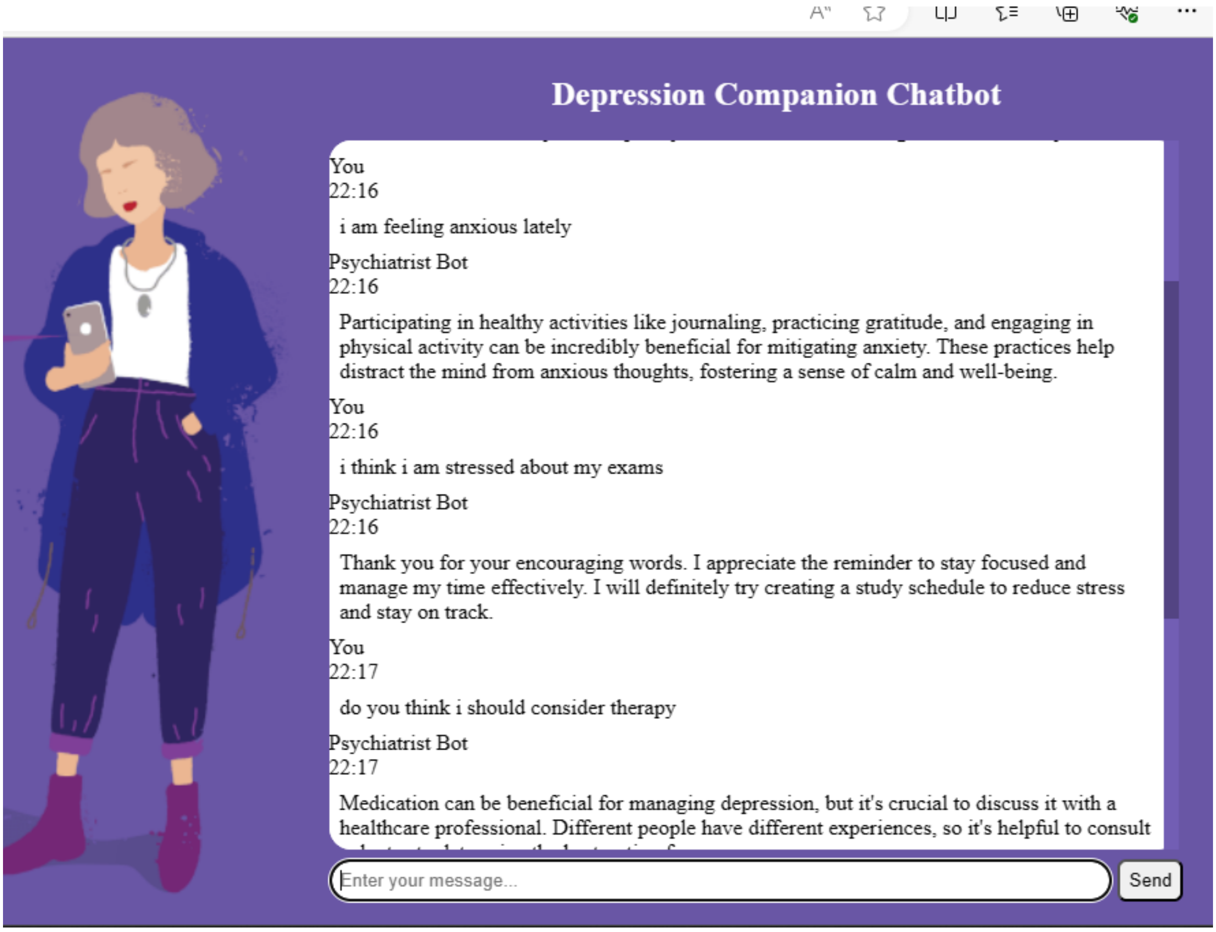

Figure 6.5: Output-Sequential with Gemini Pro model

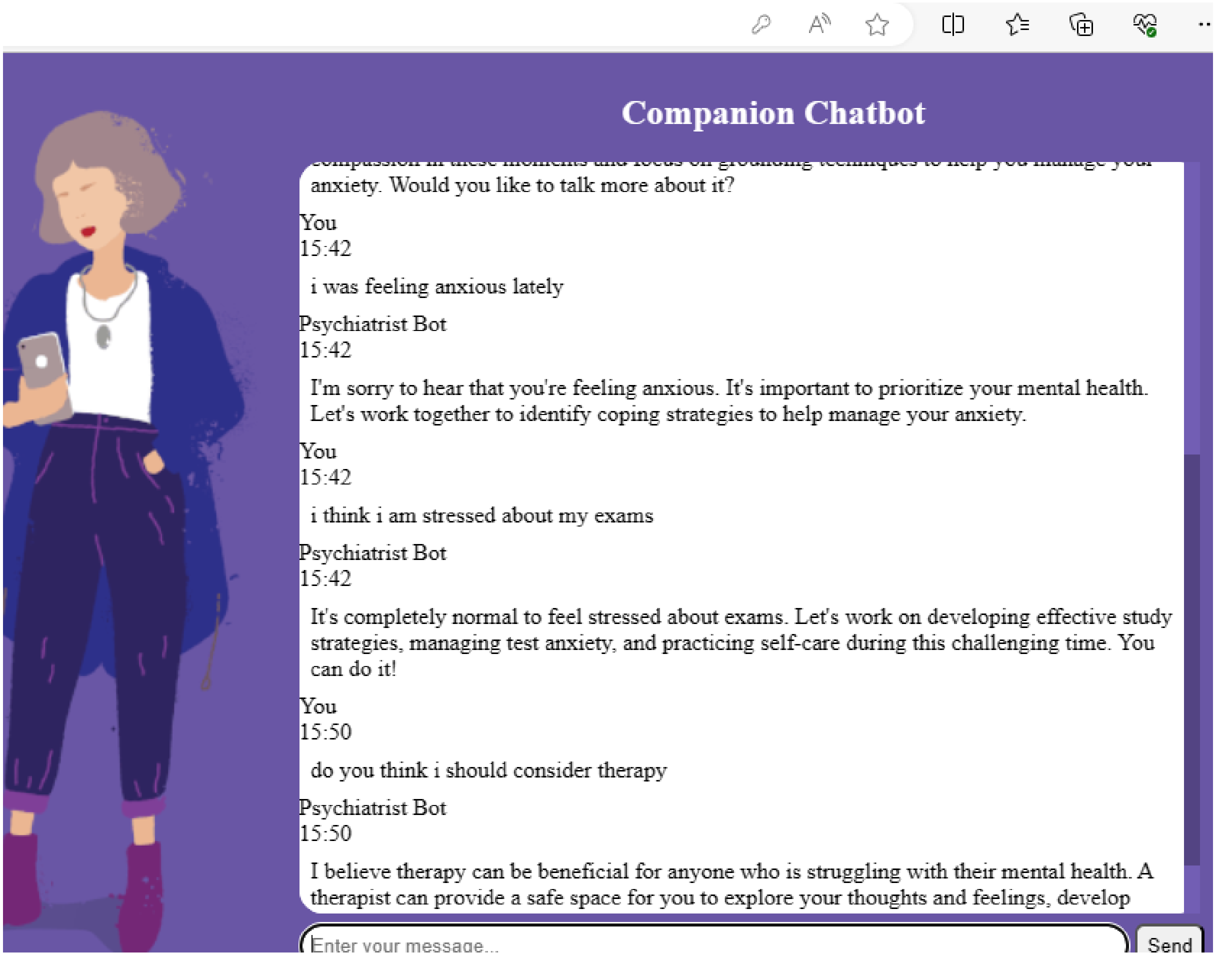

Figure 6.6: Output-Gpt 3.5 turbo

6.3 Quantitative Results

he Large Language Model (LLM) achieved a notable accuracy of 80 percentage, demonstrating its effectiveness in language-related tasks. In comparison, the Sequential model with RNN showcased an accuracy above 85 percentage, specifically excelling in image recognition rather than language tasks.

Conversely, the GPT 3.5 Turbo model exhibited the lowest accuracy among the models tested, with a rate of only 45 percentage even after 200 epochs of training. This considerable difference in accuracy highlights the LLM's superiority and the limitations of the GPT 3.5 Turbo model for practical applications.

6.4 Graphical Analysis

The graphs showing the model accuracy of all the models used for the comparative study are given below.

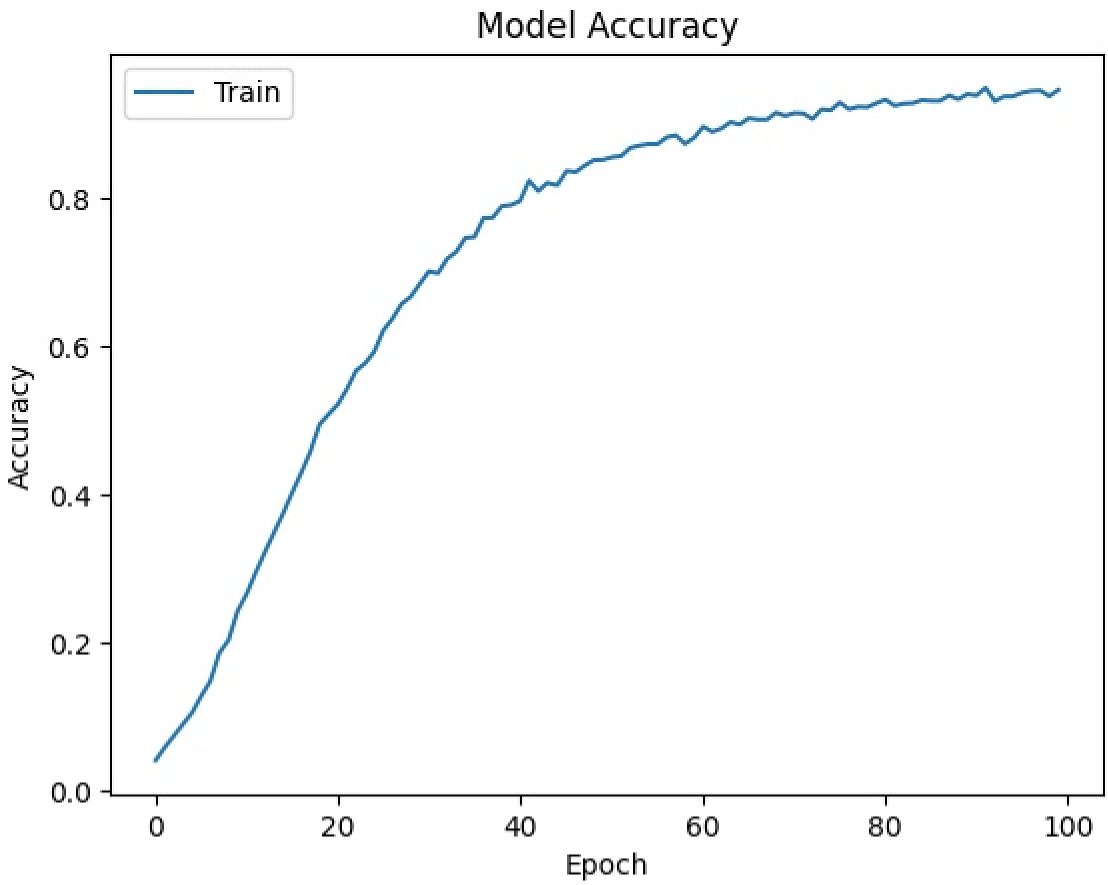

Figure 6.7: Sequential Model Accuracy Representation

The chart tracks progress of a step-by-step model, which we've identified as a sequential model, over multiple training sessions. It measures accuracy over time, with the x-axis showing the number of training rounds. The model's accuracy improves steadily, reaching up to 90 percentage by the end. However, achieving this accuracy level took a long time due to the size and complexity of the dataset, which we stored in JSON format. This highlights the challenge of balancing accuracy with the time needed to train large datasets, emphasizing the importance of finding more efficient training methods.

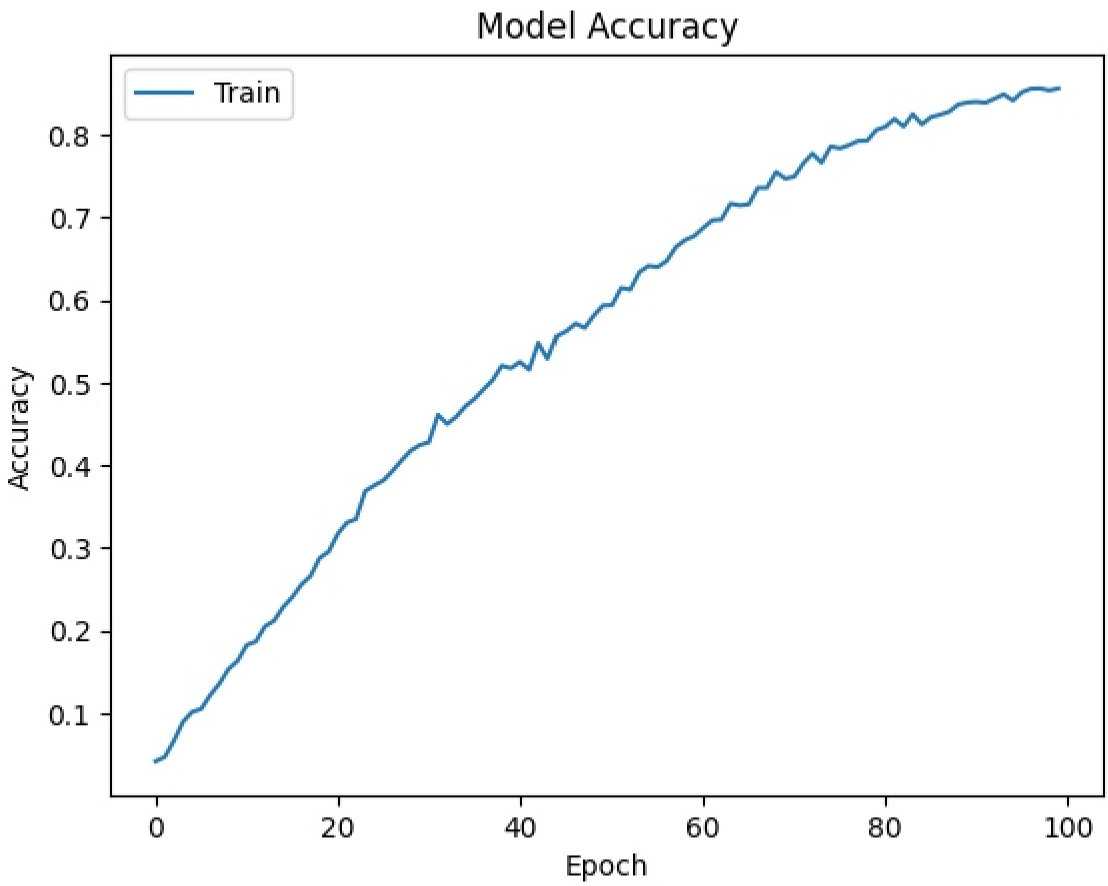

Figure 6.8: RNN Model Accuracy Representation

The graph shows the accuracy of a sequential model with recurrent neural networks (RNNs). On the vertical axis, we have accuracy, and on the horizontal axis, we have the number of epochs, which represent training rounds.

The graph tells us that initially, as we train up to 100 epochs, the model's loss decreases, which is good. However, after reaching around 200 epochs, the loss starts to increase again. This pattern isn't ideal for language generation tasks because we want the loss to keep decreasing as the model learns.

It's important to note that this model was tested mainly to compare accuracy, not for actual language generation tasks. Its primary use case is for generating images rather than text.

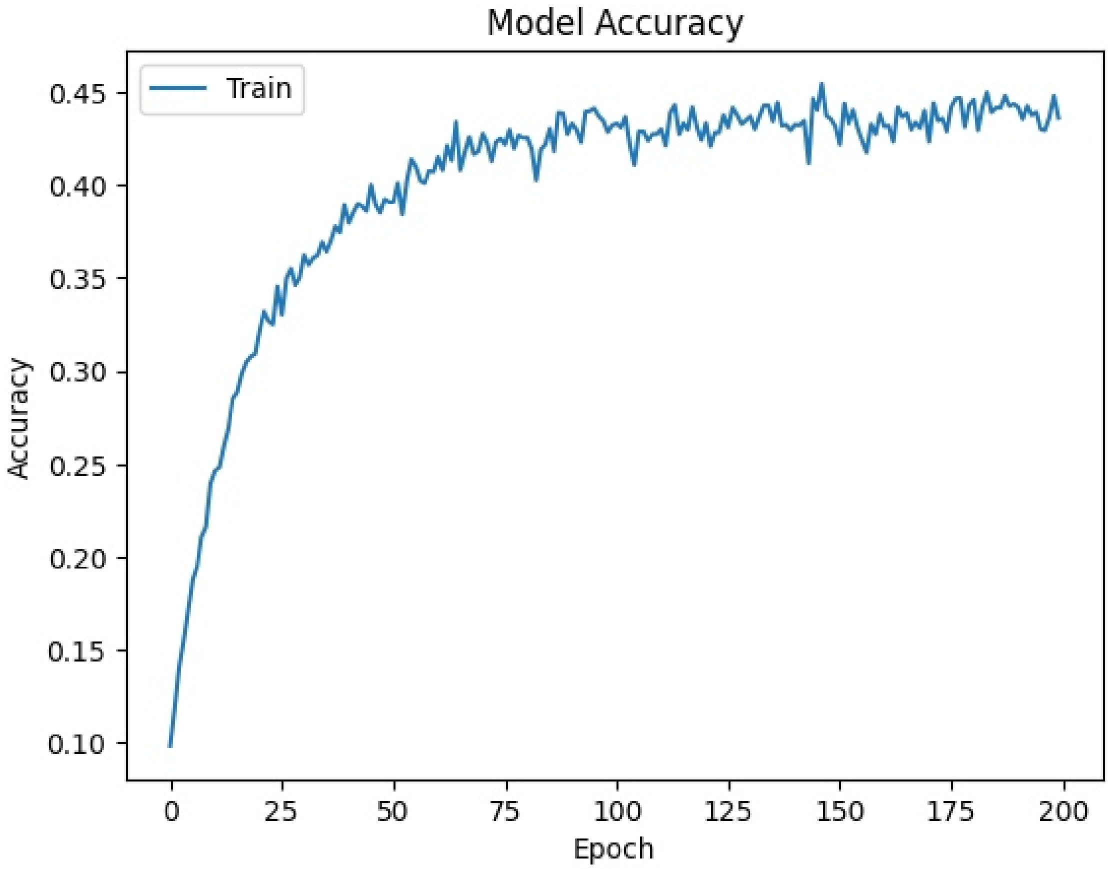

Figure 6.9: GPT 3.5 Turbo Model Accuracy Representation

The graph illustrates the progress of the GPT 3.5 Turbo model's accuracy over its training cycles. Accuracy, which measures how correct the model's predictions are, is plotted on the vertical axis, while the horizontal axis represents the number of training rounds, known as epochs.

Despite undergoing more than 200 epochs of learning, the model's accuracy stagnates at a relatively low level of around 45 percentage. This suggests that the model doesn't improve much beyond that point and isn't very accurate compared to other models available. As a result, it's not commonly used for tasks that require high levels of accuracy, especially those involving extensive datasets or complex problems.

The graph shows how accurate a big language model is as it learns over time. The

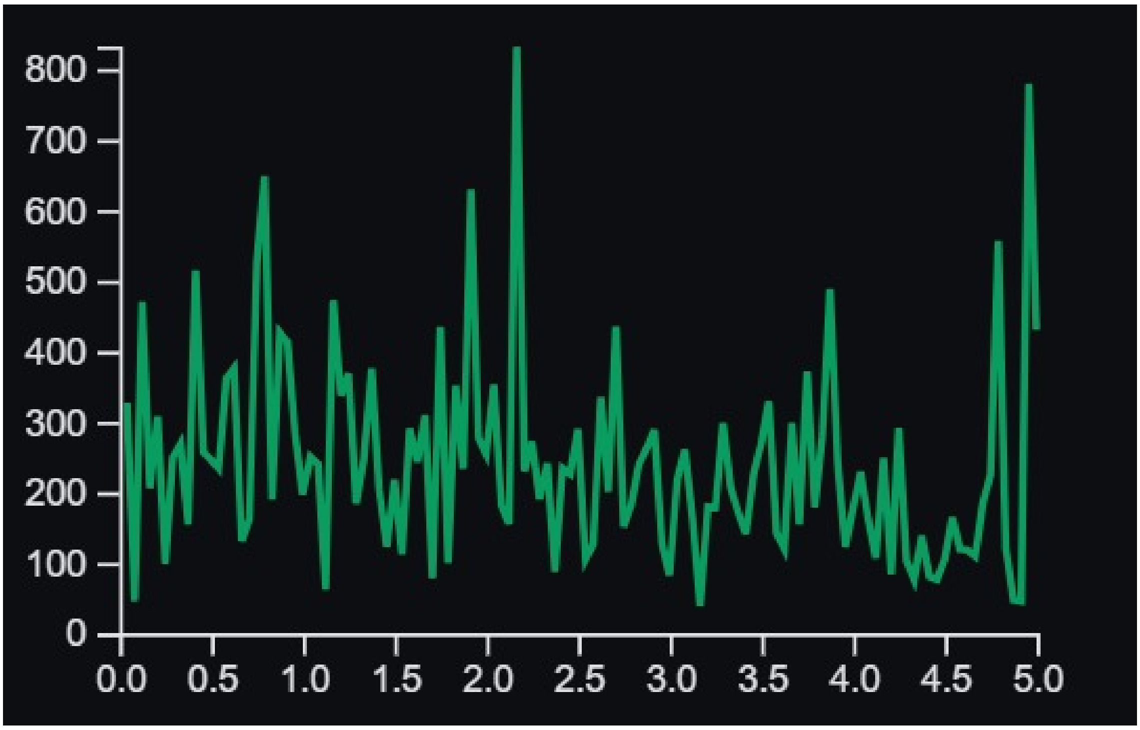

Figure 6.10: Large Language Model Accuracy Representation

y-axis is for accuracy, showing how often the model is right. On the x-axis, we have the number of learning sessions called epochs, which here goes up to 5000.

To get a good dataset for training, we had to manually make it bigger. This means we added more varied examples, which can make the training a bit up and down, causing the accuracy to go up and down too. Even with these challenges, the model still manages to reach an accuracy of about 80

This model stands out from others because it not only gets decently accurate but also does it faster. Plus, it can generate really good responses, making it a preferred choice compared to other models.

6.5 Discussion

The LLM model stands out with an impressive 80 percentage accuracy rate, showing its strength in handling language-related tasks well. On the other hand, the Sequential model with RNN excels more in recognizing images than in language tasks.

However, the GPT 3.5 Turbo model falls behind significantly with an accuracy of only 45 percentage, even after training for 200 epochs. This lower accuracy makes it less suitable for practical use, especially when compared to the more accurate LLM model.

In this chapter the testing results, graphical analysis and quantitative analysis of the models used in the study are provided. The results of sequential model, RNN model, Gemini pro, GPT 3.5 turbo and Large Language model are given in the chapter.

Chapter 7

Conclusions & Future Scope

In conclusion, the Depression Assistant Chatbot project is a significant advancement in the use of technology to address mental health issues, specifically depression. The goal of creating a sympathetic and context-aware chatbot is to provide prompt assistance, encourage open conversations, and aid in the de-stigmatization of mental health conditions. Through the use of cutting-edge technologies, the project is in line with the rapidly changing field of digital mental health solutions, meeting the requirements of those who encounter obstacles when attempting to access conventional therapeutic services. The project's focus on privacy, user safety, and ethical issues highlights its dedication to responsible development. Modern technologies like machine learning and natural language processing are used to make sure the chatbot can understand a variety of user inputs and answer in a relevant and empathic way. Developing an interface that is easy to use can improve accessibility even more, which fosters user confidence and involvement. The Depression Assistant Chatbot project has a lot of potential for growth and improvement in the future. Using wearable technology to monitor users' mental health indicators in real time is one possible extension. Collaborating with mental health specialists is another important area for the future. Creating a system that would allow the chatbot to automatically connect users with licensed experts when necessary could improve the continuum of care as a whole. Furthermore, adding multilingual functionality would increase the chatbot's accessibility and guarantee that people with various linguistic backgrounds may take advantage of its assistance. User feedback-driven continuous improvement is still a key component of the project's development. The responsiveness and efficacy of the chatbot will increase with the implementation of machine learning algorithms that adjust and learn from user interactions over time. In summary, the Depression Assistant Chatbot project not only tackles the issues surrounding mental health support today, but it also establishes the framework for a flexible and adaptable system that may grow with the needs of those who are experiencing depression. The project has the potential to significantly impact the nexus between cutting-edge digital solutions and mental health care as technology develops.

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Appendix A: Presentation

Depression Companion Chatbot
100% Project Presentation

Guide: Mr Biju Abraham

Group members: Namitha Reji, Navami Sunil, Sandra Philna Sajiv, Sreeranj S
Rajagiri School of Engineering and Technology

09/04/2024

Contents

1. Problem Definition
2. Objectives
3. Novelty of Ideas and Scope of Implementations
4. Gantt Chart
5. 30% Evaluation Work Done
6. 60% Evaluation Work Done
7. 100% Evaluation Results
8. Future Scope
9. Task Distribution
10. Conclusion
11. References
12. Status of Paper Publication

Problem Definition

- People having depression face feeling of frustration, loss of interest, sleep disturbances and even suicidal thoughts.
- Barriers that prevent people to seek help often include:
  - lack of available therapists
  - transportation
  - financial constraints
  - lack of time
  - stigma associated with mental health issues

Objectives

- **Personalized support**: Tailors responses to user profiles and preferences.
- **Educates on depression**: Imparts essential knowledge about the condition.
- **Empowers self-management**: Equips users with effective coping mechanisms.
- **Contributes to holistic well-being** Promotes overall mental and emotional health.

Novelty of Idea & Scope of Implementation

Our project is to improvise the existing mental health chatbots.

- **Comparison study of different models**: Trained using different models to improve the response generated.
- **On Demand Assistance**: Provides instant support without the need for appointments or waiting.
- **Comforting Environment**: Creates a non-intimidating atmosphere to encourage open communication.
- **Continuous Improvement**: Through user feedback, the chatbot can evolve to meet the needs of its users.

Literature Review

Paper	Method	Inference
A Mental Health Chatbot for Regulating Emotions (SERMO) - Concept and Usability Test[1]	CBT, NLP	Uses CBT principles to support individuals in managing their emotions. It uses natural language processing to determine users emotions and provides suggestions accordingly.

Literature Review

Paper	Method	Inference
ER-Chat: A Text-to-Text Open Domain Dialogue Framework for Emotion Regulation [2]	T5 (Text-to-Text Transfer Transformer)	The pretrained T5 model is fine tuned for dialogue generation. Ability to predict and respond to emotions in real time conversations.
Generating and Analyzing Chatbot Responses Using Natural Language Processing. [3]	LSTM,GRU,CNN	More accurate responses were provided by the LSTM model according to the evaluation techniques like, BLEU and Cosine similarity.

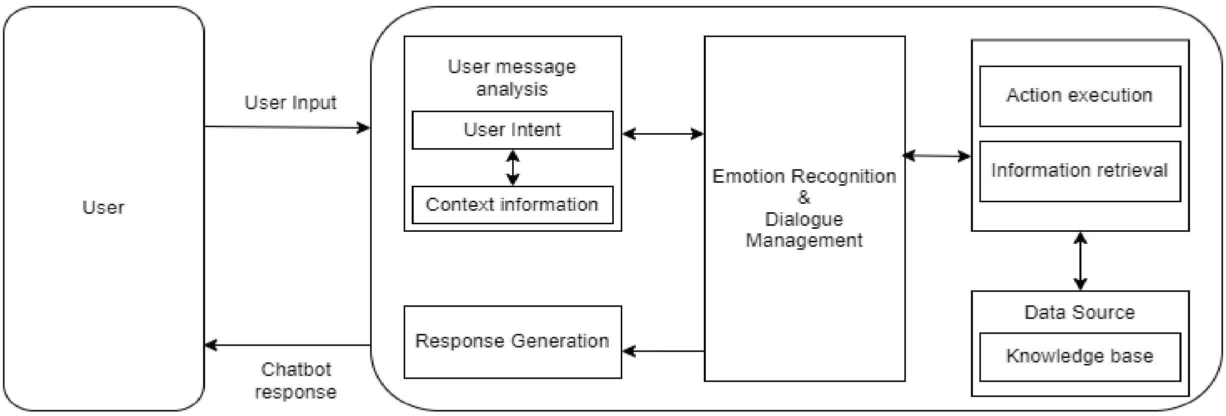
Literature Review

Paper	Method	Inference
Detecting Mental Disorders in Social Media Through Emotional Patterns - The Case of Anorexia and Depression[4]	BoSE & D- BoSE representations	BoSE method surpassed existing methods in identifying signs of anorexia and depression. Incorporating D BoSE enhanced detection accuracy.
An AI-Based Medical Chatbot Model for Infectious Disease Prediction [5]	LSTM,RNN, Decision tree	LSTM approach gives the best results in cases of interaction with users and getting the expected reply from a bot, providing a quicker response.

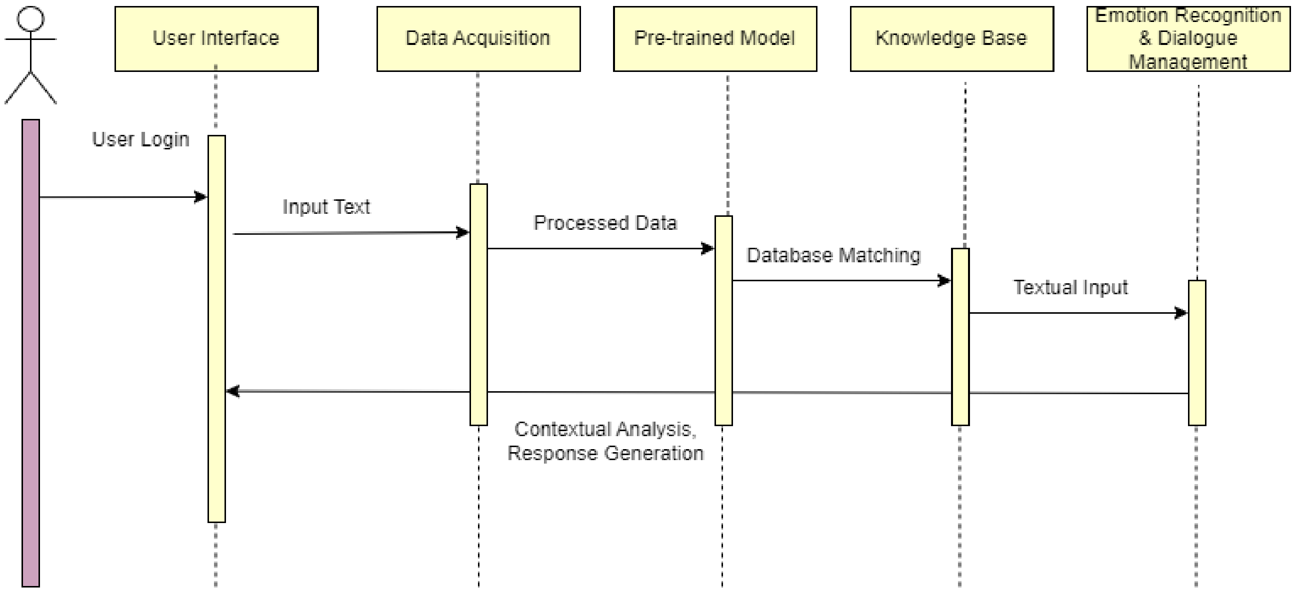
Methodolgy

- The Depression Companion Chatbot's methodology includes input processing and response generation for empathetic replies. It suggests personalized improvement techniques and promotes engagement with an interface.Feedback mechanism allows users to suggest areas for improvement.
- Implemented Sequential model, RNN model, Gemini pro, GPT 3.5 turbo, LLM model for comparison study of developing a mental health chatbot application.

Sequential Diagram



Architectural Diagram



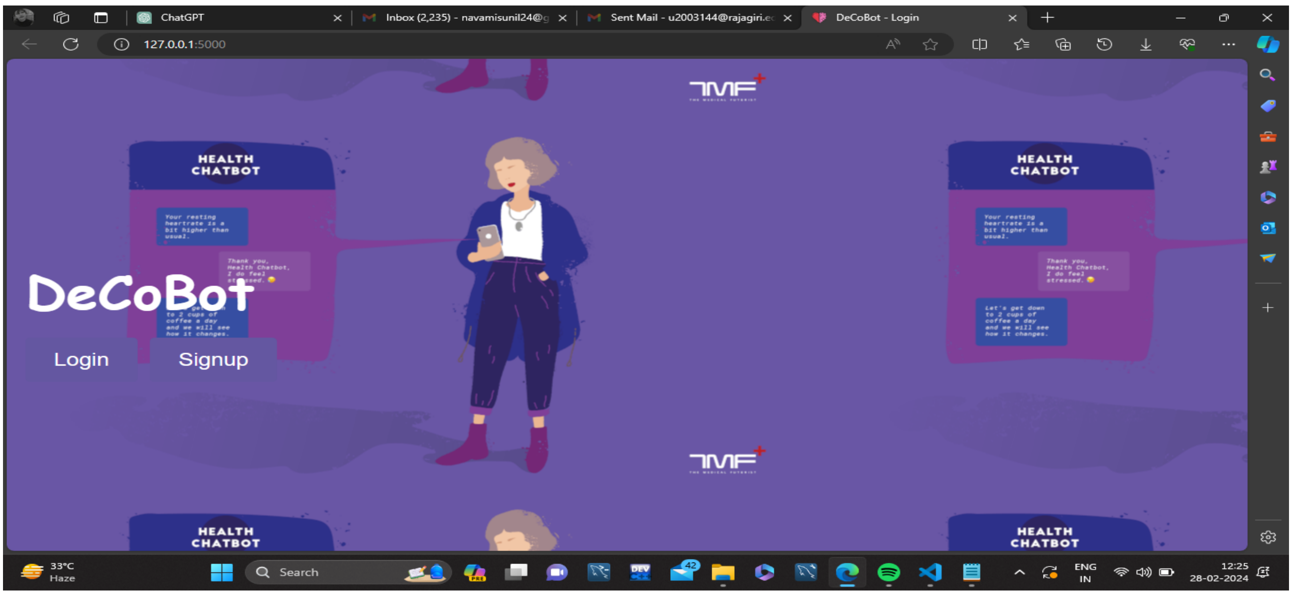
Result

- Implemented Sequential model, RNN model, Gemini pro, GPT 3.5 turbo, LLM model for comparison study of developing a mental health chatbot application.
  - Dataset used is in json format named as intents.json. It includes patterns and responses under each tag.
  - Data pre-processing.
  - Trained the model with pre-processed data.
  - Tested the models to find accuracy.

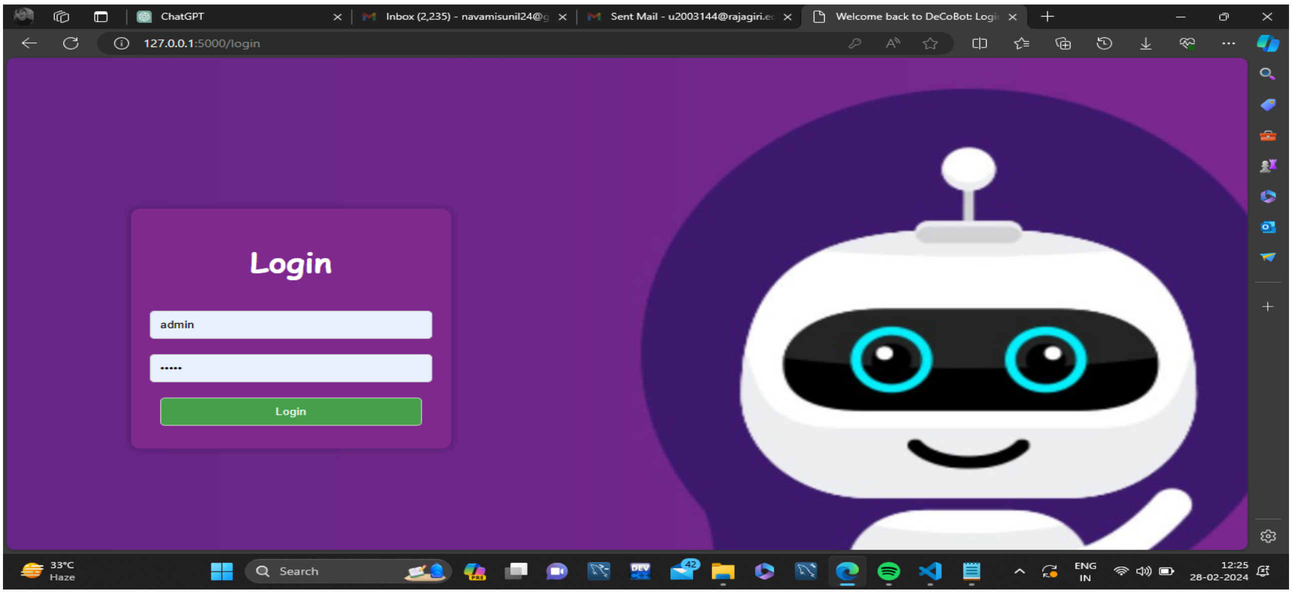
Result

- Developed web based UI for chatbot application.
  - First page
  - Feedback page
  - Conversation page
  - Login/Sign up page
- Storage in MongoDB Database
  - Username
  - Password
  - Conversation history
- Feedback collection from user
- Storage of conversation history

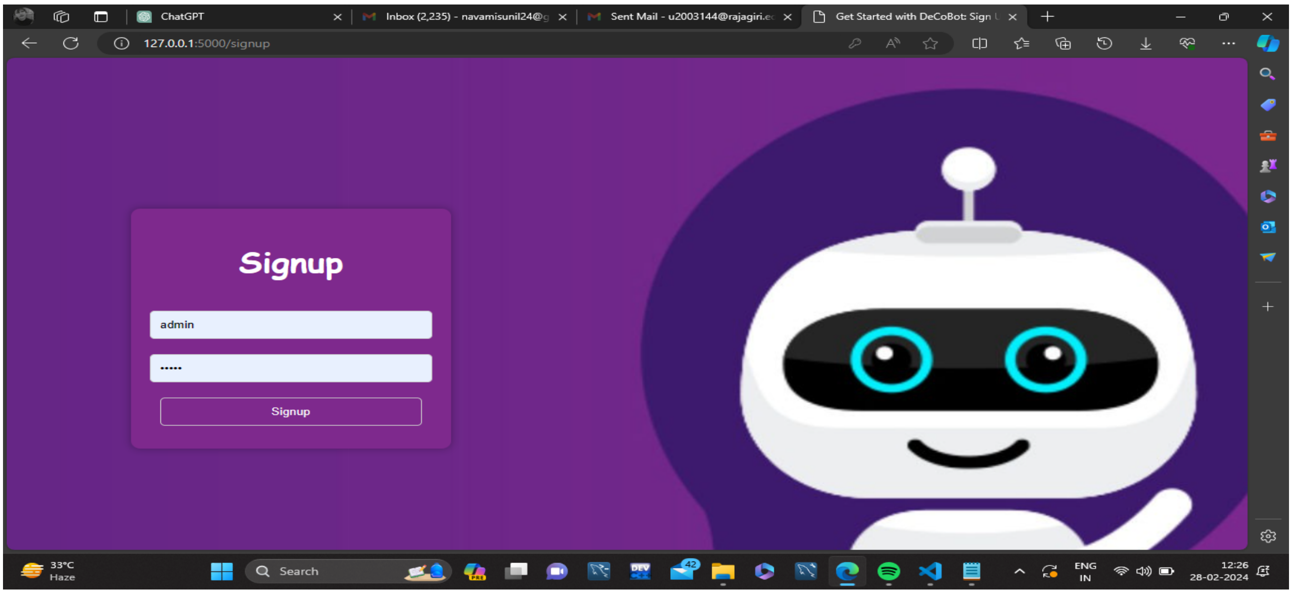
Result



Result



Result



Result

- Sequential model

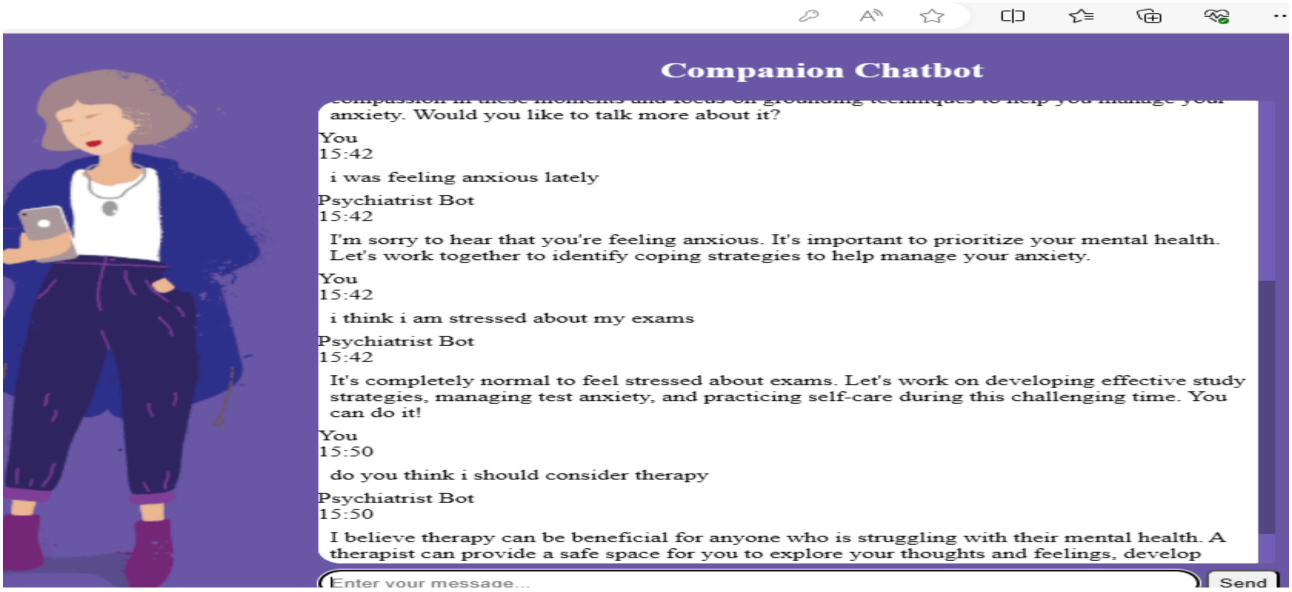
```
... You: i am stressed
    1/1 [==============================] - 0s 81ms/step
    Bot: Stress is a natural response to challenging situations, but it's important to find healthy ways to manage it. Conside
    You: i failed in my exams
    1/1 [==============================] - 0s 52ms/step
    Bot: A decline in academic performance can impact overall well-being by causing stress, anxiety, and a negative impact on
    You: i had a panic attack
    1/1 [==============================] - 0s 53ms/step
    Bot: If you have a paper bag or can cup your hands over your mouth and nose, try breathing into it slowly. This can help r
    You: do you think i should consider therapy
    1/1 [==============================] - 0s 52ms/step
    Bot: Medication can be a helpful tool in managing depression, but it's important to discuss the potential benefits and sid
    You: i am afraid of everything
    WARNING:tensorflow:5 out of the last 5 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7fb04
    1/1 [==============================] - 0s 57ms/step
    Bot: Hey, hang in there. I know times are tough, but be patient and everything will fall into place. Here is a quote that
    You: can you tell me a joke then
    WARNING:tensorflow:6 out of the last 6 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7fb04
    1/1 [==============================] - 0s 62ms/step
    Bot: Sure! Here's a joke: Why don't skeletons fight each other? They don't have the guts!
    You: i am sad
    1/1 [==============================] - 0s 54ms/step
    Bot: Sadness is a natural emotion, and it's okay to feel this way sometimes. Remember to be gentle with yourself and allow
    You:
```


Result

```
1112/1112 [==============================] - 5s 4ms/step - loss: 0.1892 - accuracy: 0.93
Epoch 95/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1966 - accuracy: 0.9382
Epoch 96/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1792 - accuracy: 0.9427
Epoch 97/100
1112/1112 [==============================] - 4s 4ms/step - loss: 0.1818 - accuracy: 0.9436
Epoch 98/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1817 - accuracy: 0.9442
Epoch 99/100
1112/1112 [==============================] - 4s 3ms/step - loss: 0.1811 - accuracy: 0.9382
Epoch 100/100
1112/1112 [==============================] - 4s 4ms/step - loss: 0.1707 - accuracy: 0.9469
Done
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your m
  saving_api.save_model(
```

Result

- GPT 3.5 Turbo



Result

- RNN

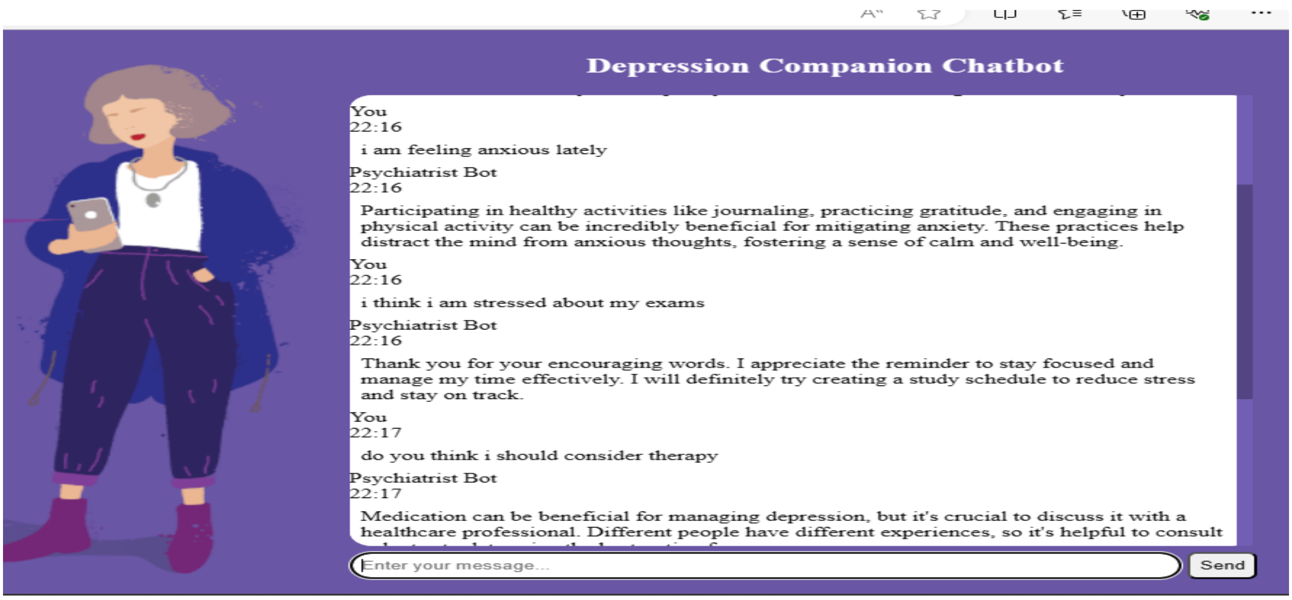
```
You: i am stressed
WARNING:tensorflow:6 out of the last 6 calls to <function Model.make_predict_function.<locals>.predict_function at 0x7f3e1
1/1 [==============================] - 1s 503ms/step
Bot: What do you think is causing this?
You: i failed in my exams
1/1 [==============================] - 1s 537ms/step
Bot: Strategies for improving academic performance and addressing challenges include developing effective study habits, ti
You: i had a panic attack
1/1 [==============================] - 1s 510ms/step
Bot: Experiencing panic attacks or intrusive thoughts can be distressing, but therapy can help you learn techniques to man
You: do you think i should consider therapy
1/1 [==============================] - 1s 517ms/step
Bot: Why do you want to spend so much on this thought? I think it would be better to go on a vacation in your beautiful co
You: can you tell me joke
1/1 [==============================] - 1s 518ms/step
Bot: Sure! Here's a joke: Why don't skeletons fight each other? They don't have the guts!
You: i am afraid of everything
1/1 [==============================] - 1s 697ms/step
Bot: I hear you. It seems like you're feeling misunderstood. Let's try to bridge that gap.
You:
```

Result

```
[9] Epoch 93/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.5001 - accuracy: 0.8437
Epoch 94/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.5001 - accuracy: 0.8488
Epoch 95/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.4920 - accuracy: 0.8413
Epoch 96/100
1112/1112 [==============================] - 9s 8ms/step - loss: 0.4700 - accuracy: 0.8515
Epoch 97/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.4782 - accuracy: 0.8557
Epoch 98/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.4640 - accuracy: 0.8560
Epoch 99/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.4641 - accuracy: 0.8536
Epoch 100/100
1112/1112 [==============================] - 10s 9ms/step - loss: 0.4609 - accuracy: 0.8560
Done
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103: UserWarning: You are saving your model as an
  saving_api.save_model(
```


Result

Sequential and Gemini Pro



Task Distribution

Namitha Reji

Feedback collection, Storage of conversation, Documentation, UI Development, Gpt 3.5 Turbo, Sequential & Gemini Pro model

Navami Sunil

User authentication, Documentation, UI Development, Sequential, RNN

Sandra Philna Sajiv

Feedback collection, Storage of conversation, Documentation, UI Development, Gpt 3.5 Turbo, Sequential & Gemini Pro model

Sreeranj S

User authentication, Documentation, UI Development, Sequential, RNN

Conculsion

In conclusion, the Depression Companion Chatbot is a significant stride in accessible mental health support.

- Accessible support
- Responsive companion
- Suggests improvement techniques
- Supportive environment

Future Scope

The Depression Assistant Chatbot project has a lot of potential for growth and improvement in the future.

- Using wearable technology to monitor users mental health indicators in real time.
- Collaborating with mental health specialists.
- Adding multilingual functionality.

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