Chapter 1
Introduction

1.1 Description

This project seeks to bring into being an AI-based intelligent mental health support system capable of handling this increasingly complicated psychological upheaval, more so in students. Recent data shows a surge in mental health issues among students: 40% of them report suffering from clinically significant manifestations of anxiety, and 33% with depressive symptomatology, to name a few. The COVID-19 pandemic (2020-2023) has worsened matters amidst the global student communities with increased psychological distress.

While these factors seem alarming, however, only about 35% of students actually end up using the available services for mental health-related issues. This huge gap in care, in turn, comes from an array of issues: a reduced mental health counseling infrastructure, geographical concerns, stigma attached to referral, privacy apprehensions, and lack of time.

On their part, the traditional systems are not helping in this crisis ever since they have become overwhelmed with demand; thus, this led to increased waiting times and decreased availability of individual in-person sessions.

This project attempts to structurally mend the above-ground weak points of the account by weaving recent advances in artificial intelligence—especially NLP and emotional intelligence—into an ever-responsive, privacy-respecting, and scalable framework for mental health support. The platform would keep itself open as an always available, non-judgmental first line of support for students who are experiencing any sort of mental distress. Advanced NLP models capable of sentiment analysis, classification of emotional states, and recognition of intents interact with users in therapeutic conversations based on an underlying psychological framework: namely CBT, DBT, and ACT.

Beyond the interaction level, this system is designed to quarantine mental health risk situations, and those requiring human professional intervention are then escalated. In this way, a deep seated clinical responsibility is preserved between opting for autopilot and treating humans. Paramount to note is the platform's strict adherence to the idea that user privacy must be sacrosanct with secure communication protocols and scalable deployment practices. Considered the ability to exhibit any degree of emotional intelligence in the architecture would be conducive to forging meaningful interactions away from stigma and in turn to the encouragement of help-seeking behavior. More so is the AI platform that can respond anytime and almost instantly to students, unlike the conventional counseling services-it may serve as a support tool in isolation or as triage to direct students toward professional care when necessary.

The project goes on to describe how AI-powered mental-healthcare systems can occupy popular spaces in shrinking the accessibility gaps while maintaining side-by-side ethical responsibilities, clinical relevance, and user trust.

1.2 Problem Formulation

In recent years, the state of mental health of pupils has reached a level of crises, threatening academic performance, social well-being, and potential health outcomes. Studies definitely document the sudden rise of psychological distress among the student population; hence, roughly more or less 40 percent of students in colleges present clinically significant anxiety, whereas another 33 percent present symptoms compatible with depression. Considering that these worrisome numbers were further escalated by the 2020-to-2023 global health crisis, some factors that caused emotional and mental strain were the unknowns, social isolations, academic transitions, and economic pressures.

Due to increasing threats, mental health disconnect has formed between those in need and those receiving help. Research shows that less than 35 percent of the students with mental health problems seek help from professional resources. Such a gap in help-seeking is due to stigma attached to mental health, worries on confidentiality, scarcity of trained counselors, and a perception that these support systems take much time. This situation has, therefore, resulted in many students being kept waiting for or giving up treatment, whereby their symptoms grow worse, with far-reaching consequences.

The traditional mental health services, albeit of high clinical efficacy, are not set up to contain this burgeoning demand. Further access barriers include fewer accredited workers, longer waiting times, and unaccommodating hours of operation. In academic milieus whereemotional well-being directly affects both performance and retention, an environment where these concerns exist calls for urgent tech-based and scalable intervention.

Thus, the problem is shaped around the cardinal question of how to develop a responsive, accessible, private support mechanism that reduces stigma and addresses student mental health concerns at scale, while still maintaining some degree of clinical relevance and user trust.

This work intends to answer this by investigating the development of an AI-powered intelligent support system that can become an ever-present first line of emotional assistance. It seeks to fill the current care gap by means of artificial intelligence, natural language processing, and the integration of emotional intelligence to immediately support individuals, identify those at risk, and then refer such identified individuals for professional intervention when appropriate without opening offsets for judgment or the loss of privacy.

1.3 Motivation

It remains a largely pressing and ever-sensitive issue in today's society, especially amongst student populations, where academic pressures, social intricacies, and transitioning in life compounds stress, anxiety, and depression. While awareness about mental health has been on the rise, tools and systems meant to relieve human distress seem to lack evolution-thus, the same standing is with AI-driven conversational agents. An upfront guise of free-of-cost scaled assistance in the form of a mental-health chatbot cannot produce any meaningful interactions, free from empathy and context awareness.

Most systems are scripted and limited to preprogrammed dialogues that neither take into account the emotional state of users nor the complexities of their particular situations. Hence in special cases, these systems may fail to express empathy when it is necessary or focus on particular emotional acoustic cues and thus basically remain on a superficial, generic and impersonal tone when they need to be warm and humanly warm in their expressions, effectively undermining the assistance they attempt to offer.

One significant drawback of present-day applications is their lack of emotional intelligence. Emotional intelligence plays a vital part in mental health communication because the psychological and emotional state of the user must be taken into account when offering pertinent and compassionate assistance. Incapable of discerning in real-time the user's intent and emotional tone, such systems can never match the support power of human counselors, being a hindrance in some cases or eliciting negative emotions.

Traditional chatbots are also obstructive since they lack ability for customization or adaptability. Each person is passing through unique situations with mental health; hence, support systems should reflect this variance by considering linguistic patterns, intonations, and courses of action. A one-size-fits-all scheme will not respond to the stringent parameters of psychological support.

Since this gap exists, there is a need for storage of an advanced IP conversational partner with emotional intelligence—one that would not only process the user's query but also explore its context. We try to bridge this gap using a fine-tuned Llama 2, a fantastic open-source language model renowned for generating human-like text. The integration of emotional intelligence frameworks includes intent detection, Ekman's emotion classification, and emotion-aware fine-tuning with the help of specialized mental health datasets, thus enriching the capacity of the model to respond aptly, both contextually and emotionally.

The response is aligned with an emotionally detected state of the user as an act of compassion rather than insensitive or inappropriate feedback. The effect entails more engagement, more perceived support, and ultimately a more effective intervention for mental health.

At the root of this motivation lies our project: to create an AI-enabled support system that goes beyond the conventional chatbox and is capable of carrying out practical mental health support with outreach potential and emotional awareness.

1.4 Proposed Solution

It is a chatbot oriented toward mental health enhancement. It bases itself on the Llama 2 language model, fine-tuned on therapeutic conversations with adolescents and young adults, primarily in the 16-to-22-year age bracket. It is very deeply trained on users' emotional needs and can be used to detect emotional cues from a user and reply accordingly to them during the interactive conversation.The system basically acts on a two-layered methodological framework for intent and emotion detection. Intent detection serves as a method of getting to grips with the user's real problem-are they asking for help with anxiety, feeling down, or stressed out? The system is designed to address what the user truly intends to express and not just the surface semantics.

Meanwhile, emotion detection happens in line with Ekman's theoretical conception of human emotions in terms of core categories such as joy, sadness, anger, fear, and a few others. This enables the system to better pinpoint emotional undertones in the user's text and respond with greater awareness and contextually appropriate responses from an emotional standpoint.

Combining intent detection with emotion classification translates into a conversational architecture capable of responses that are contextually correct and emotionally sensitive. Here, emotional context goes into the forefront of dialogue generation: for instance, analyzing the level of distress, or "anxiety at 85%, " that the user is currently undergoing. This contributes to making the chatbot generate responses in total congruence with the user's emotional state, therefore lending emotional cohere while building on the empathy perceived in the interaction.

At its core, Llama 2 is further fine-tuned with LoRA (Low-Rank Adaptation) and quantized in 4 bits for peak performance efficiency. The two combine to increase resource efficiency to such a degree that they enable real-time operation with reasonable computing power on consumer-grade hardware-without a compromise on support quality. Instead of doing unsupported, out-of-the-way things, it actively keeps working toward providing value to users.

On the other end, this integrated system design really ensures that every single interaction is helpful and attuned to the user's emotionality. The chatbot will interpret and adjust to the user's emotional and psychological states, thereby enhancing the therapeutic quality of such communication. Hence, by ensuring that relevant information is provided to the user, the chatbot will also manage to provide him with genuine kindness-which is a giant step toward really making a difference in how a person manages challenges related to mental health.

1.5 Scope of the Project

The scope of this project involves the formulation and construction of a therapy chatbot through Llama 2 for children 16 to 22 years of age as clients. The system, as it stands, uses intent detection and emotion classification to respond in ways that fit the emotions expressed, even though a system should be well capable of doing more than that.

However, in the present state, there are some domain constraints on the project as realized, which include:

- User Demographics: The chatbot, as presently implemented, targets young people between 16 to 22 years of age. While having such a demographic enables scrupulous emotional and therapeutic response generation, it, however, becomes a bottleneck toward any broader application onto other age groups or populations.

- Emotion Detection Limitations: One is the choice of Ekman's model in emotional state detection. This decision holds the chatbot back from generating more complex or subtle emotional expressions, given that that model only looks at seven basic emotions. From an advanced development perspective, this could perhaps be extended to cover a broader spectrum of emotions.

- Dataset Scope: Currently, the training dataset is limited in scope to specific emotion and query types, thereby possibly overlooking mental health or emotional nuance-related concerns in actual therapeutic conversations. Associated with its future, there will be a great need for having a wide-varied dataset, including datasets for different treatment modalities such as dialectical-behavioral therapy (DBT), cognitive-behavioral therapy (CBT), and acceptance and commitment therapy (ACT), so as to enhance the chatbot's therapeutic ability.

- Privacy and Data Security: At the moment, the system affords certain basic privacy safeguards. Furthermore, future systems will in fact address a set of higher-level privacy issues inclusive of federated learning and differential privacy, some of which are beyond the scope of the current development system.

- Performance and Optimization: Presently, the optimization is prodigiously meant for the operations-efficient running on consumer-grade hardware with LoRA and model quantization. Future system performance optimization will include mechanisms for secure API integrations with the EHR and another monitoring system to evaluate therapeutic effectiveness to detect bias or model drift.

- Long Tail Learning and Rare Scenarios: The next step is for generalizing chatbots to varying and rare mental health concerns using few-shot techniques for rare or long-tail scenarios along with synthetic data generation.

Chapter 2
Review of Literature

During the past couple of decades, in the new frontier of AI-aided psychiatry, we have seen new horizons forming in therapeutic care, interventions, and several more. Bhatt et al. [1], in their review of AI-based mobile health platforms, perceived the potential benefits and the effectiveness of these platforms in health monitoring but were quite concerned about data security since the onset of the COVID-19 pandemic.

Pham et al. [2] went into the historical development, from the very rudimentary Alert and Advice systems based on a simple keyword-detection method, until complex therapeutic tools, to point out the necessity of human supervision in mental health applications. Boucher et al. [3] show that interventions in mental health based on AI garnered fairly good levels of user satisfaction, whereas, on the other hand, they pointed out the problem of cross-culture applicability.

Lei et al. [4] reviewed several applications in which AI may help support mental health, providing IoT technology and machine learning for stress detection in educational scenarios. Martin et al. [5] assessed mental health apps for youths and identified perceived factors for success in managing anxiety. Shahzad et al. [6] reported further achievements in academic outcomes assisted by AI-supported education platforms while warning for care with respect to the application of technology. Alanazi et al. [7] developed highly accurate predictive models for mental health problems, which then carried implications for data interpretation and data consent processing. Yet, Li et al. [8] found more pronounced effects of AI-assisted intervention for those depressed and under therapeutic circumstances that are poorly resourced. Narynov et al. [9] analyzed the effectiveness implementation of cognitive-behavioral therapy in chatbot systems, drawing some limits on AI support.

According to Bérubé et al.[10], it was shown that these voice-operated systems had, in fact, increased participation rates in older, somewhat less tech-savvy users. Meanwhile, Saha et al. [11] developed NLP systems for mental health support, utilizing enhanced contextual understanding with ethical safeguards in place, whereas Zhan et al. [12] showed a measurable decline in stigma toward mental health disorders with the introduction of interactive digital interventions.Wols et al. [13] conducted a meta-study on gamified therapeutic interventions, considering achievement motivation and social connection as important game elements for different age groups. Chen et al.[14] tested the efficacy of the online interventions in terms of cost-effectiveness and therapeutic value. Dainer-Best et al. [15] investigated real-time emotional feedback in digital therapeutic interaction and formulated a map of correspondences between response styles and emotional awareness.

According to Sabour et al. [16], an emotional-support chatbot can be beneficial in improving the symptoms of depression as well as the sleep parameters. Schick et al. [17] confirmed the diagnostic capacity of these systems but emphasized that professional supervision is required. Nayar et al. [18] assessed Dost, a rural mental healthcare support chatbot using NLP. While Dost bridges the access gap, it also tends to consider or redirects the cases that are deemed too complicated to professional help.

Rani et al. [19] effectively demonstrated the implementation so as to simulate various connectivity scenarios, thus ensuring the viability of closing the urban-rural mental healthcare divide faced in India. Kavyashree et al. [20] worked on mood analysis algorithms capable of detecting behavioral changes preceding symptom manifestation. Gunnam et al. [21] directly contrasted cloud and on-premise chatbot architectures and showed that cloud-based systems offer a larger user capacity.

Patil et al. [22] conducted a benchmarking study of Azure, Watson, and Heroku for medical chatbot development and concluded that despite certain multilingual and customizability limitations, Watson performs best in clinical NLP tasks. Bello et al. [23] examined the rationale of voice analysis and exhibited links between changes in speech patterns and early symptoms of mental health disorders, thus advocating for passive monitoring systems in the preventive care of mental health.

Chapter 3

System Analysis

3.1 Functional Requirements

In order for an AI-based chatbot system to provide effective mental health aid, it should satisfy the subsequent functional requirements:

FR1: Mental Health Support Chatbot UI

An AI-based chatbot is in the platform with interactive property designed to emulate therapy talks to the end users. The chatbot acts as the frontend system for mental health assistance and interacts with end users while responding to the input's emotional content.

FR2: Text-Based User Communication

The system allows for users to interact with the system and make conversations in a text-based interface. This also makes it easy and handy to use from a variety of devices like smartphones, etc.

FR3: Emotion Detection

The system finds emotion in user input through natural language processing along with emotion classification techniques according to Ekman's framework to classify the emotional state of the user.

FR4: Individualised Affective Reactions

Personalized and emotionally sensitive responses are provided by the chatbot. It dynamically adapts its response according to the perceived emotion and intention of the user. This also includes the adjustment of messages to the declared user problems of stress, anxiety, or sadness.

FR5: Providing Mental Health Resources

The system should provide avenues for personalized mental health aid to the user. This includes coping strategies, games, and actions suggested depending on the public mood and pros and cons according to the flow of the conversations and the emotional content thereof.

FR6: Privacy and Protection

The process will ensure the highest degree of protection and privacy of user interaction. It will use the appropriate privacy-preserving mechanisms such as secure data storage to keep user data protected and maintain moral principles.

FR7:Age-Based Content Adjustment

It is aimed at youths aged 16-22. The content delivered to chatbot interaction, and otherwise, will be appropriate for the youth age group and in line with youth mental health guidelines.

FR8: Combination of CBT Games

The system will also include an interactive component that will engage users via CBT-inspired mini-games designed to build concentration, emotional control, and overall mental health. The games are therefore meant to calm the user down.

FR9: Journal and Sentiment Reflection

It will provide a journaling platform enabling users to put their thoughts into words. It will perform sentiment analysis on journal entries so that it can provide feedback and discern trends in sentiment over time, thus helping the users to understand and take better control of their emotional well-being.

3.2 Non-Functional Requirements

NFR1: Performance

The system will afford high responsiveness whereby the system will respond in less than a minute. This is a great factor in maintaining the flow of conversation. Further, this plays a key role when the user is seeking expedited responses.

NFR2: Scalability

System is horizontally scalable for supporting high simultaneous uplift. Being scaled in such a manner will prove to be needed at peak usage periods.

NFR3: Security

Privacy and confidentiality of users shall be fought for using data minimization. All must be treated as PII in accordance with data protection standards such as GDPR or HIPAA.

NFR4: Usability

The website will be user-friendly to the students and pleasing to visual appearance. The flow and structure will be such that the cognitive load is minimized, keeping in mind the mental health users already in an upset state.

NFR5: Reliability

The system must ensure 99% uptime so that any user who may require mental health assistance will arrive during available hours. Backend infrastructure and check health will be robust to avoid any service disruption or downtime.

NFR6: Maintainability

In the design of the system, it will be loosely coupled and modular. This makes it easier for maintenance and changes at a later time. Unlike rigid structure systems, our design will allow procart

federated learning, more therapies such as CBT or DBT, or multi-language support almost without refactoring the core system.

3.3 Specific Requirements

Software Requirements

Backend:

Python, being a general-purpose and popular programming language with a wide support system for AI and NLP, was hence chosen to be the language of implementation for the backend of the system. The heart of the chatbot system is Llama 2-a state of-the-art large language model fine-tuned to facilitate therapeutics and emotional intelligence discourse for student mental health.

Frontend:
The web-based interface has been provided for user interaction, powered by the Streamlit library, an open-source web-based interactive application framework that gives priority to speedy development and deployment of applications. Streamlit provides a natural and reactive ambiance, much suited for text-based conversational interfaces.

Database / Data Handling:

Ngrok is used as a secure tunnel for temporarily holding and forwarding the information about user interactions during development and demoing. Ngrok offers efficient prototyping and secure exposing of a locally running application to the outside, which comes in handy during testing and early deployment phases.

Libraries and Frameworks:

The system uses several libraries and frameworks key to the system:

- Hugging Face Transformers: Used for building and fine-tuning the model Llama 2 and for NLP pipelines.
- NLTK: Used for text preprocessing tasks like tokenization, stemming, and sentiment analysis.
- Hugging Face API: Used for accessing other pretrained models and services related to NLP like emotion classification and intent detection.

Hardware Requirements

Hardware Components:

Since it is software-driven and does not actually incorporate any hardware elements in its operation, it is destined for usage on everyday consumer-grade hardware, whereby for the Llama 2 model, such optimizations are put in place as to make it resource-efficient and able to run on common computing platforms, viz., 4-bit quantization and LoRA (Low-Rank Adaptation).

Chapter 4

Analysis Modeling

4.1 Functional Modeling

1. Context Level DFD (Level 0) – Overview of Mental Health Chatbot System

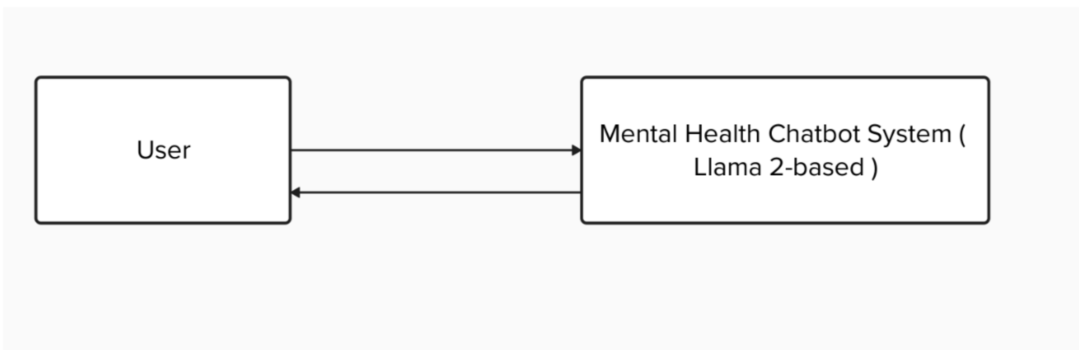

Figure 1: Level 0 DFD

Figure 1 shows Level 0 Data Flow Diagram

- Input: The user provides a query (in text form).
- Output: The chatbot delivers messages suitable for context and emotion.
- Process: The chatbot carries out processing, categorization, and answering for mental health queries based on a highly-trained Llama 2 engine.

2. Level 1 DFD – Breakdown of Chatbot Functional Components

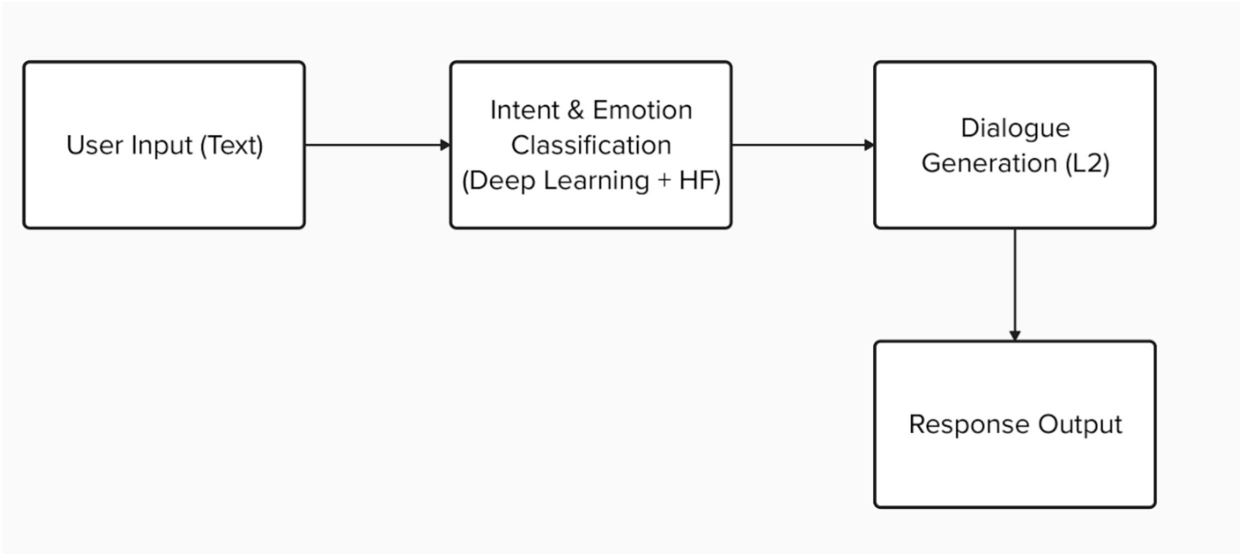

Figure 2: Level 1 DFD

Figure 2 shows Level 1 Data Flow Diagram

1. Intent & Emotion Classification:

- Uses custom-trained intent model.
- Uses HuggingFace Ekman model for emotion.

2. Dialogue Generation:

- Emotion + intent sent to Llama-2 model.
- Generate response in [INST][/INST] format with emotional context.

3. Output:

- Generate response, send to user, and show in chat UI.

3. Level 2 DFD – Internal Processing with Detail

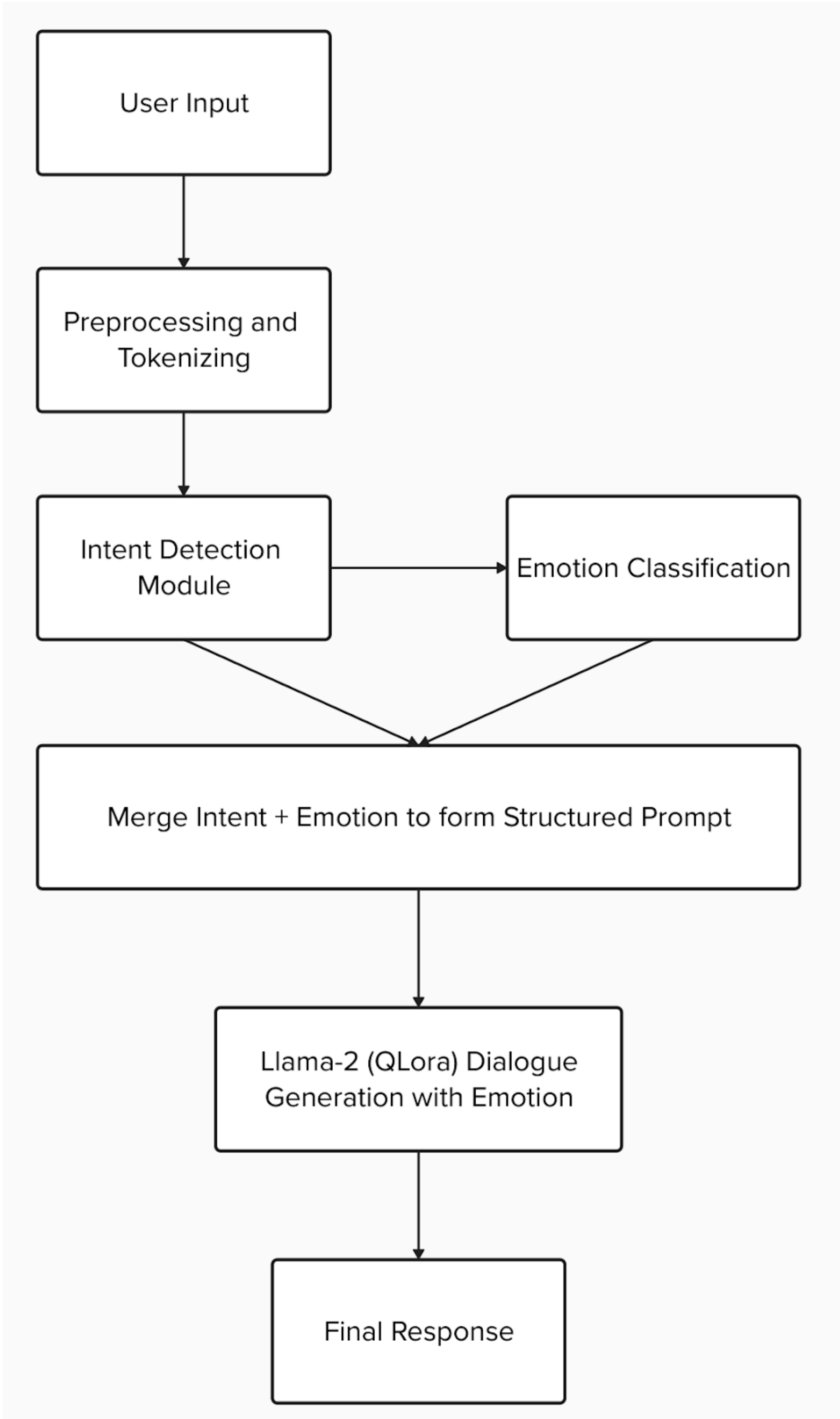

Figure 3: Level 2 DFD

Figure 3 shows Level 2 Data Flow Diagram

- Preprocessing: Lemmatize, normalize, and pad before feeding to the intent model.

- Emotion Classification: Ekman model classifies among 7 basic emotions.
- Instruction: Turned into Instructional Text: For Example: Prompt Generation: Structured prompt: [INST] user query + "Primary emotion: XX at XX%" [/INST]
- Llama-2: Provides a response that is empathic and therapeutic.
- Output: Presented on chatbot UI.

4.2 Timeline Chart

Table 1: Timeline Table

Task	Start Date	End Date	Duration	Status
Problem Identification	August 13, 2024	August 27, 2024	15 days	Completed
Literature Review	August 28, 2024	September 11, 2024	15 days	Completed
Dataset Collection	September 12,2024	September 30,2024	19 days	Completed
Intent Detection Pipeline Implementation	October 1, 2024	October 24, 2024	24 days	Completed
Emotion Classification Setup	October 25, 2024	November 18, 2024	25 days	Completed
Llama 2 Fine-Tuning (QLoRA)	November 19, 2024	November 30, 2024	12 days	Completed
Response Generation Framework	January 1, 2025	January 25, 2025	25 days	Completed
Integration of Journal & Games	January 26,2025	February 24, 2025	30 days	Completed
System Testing & Confidence Scoring	February 25, 2025	March 28, 2025	32 days	Completed
Dataflow Diagrams & Architecture Design	March 29, 2025	April 12, 2025	15 days	Completed
Documentation & Report Writing	April 13, 2025	May 5, 2025	23 days	Completed
Review, Evaluation & Future Scope Writing	May 6, 2025	May 11,2025	12 days	Completed
Final Submission & Presentation	May 15, 2025	May 15, 2025	1 day	Completed

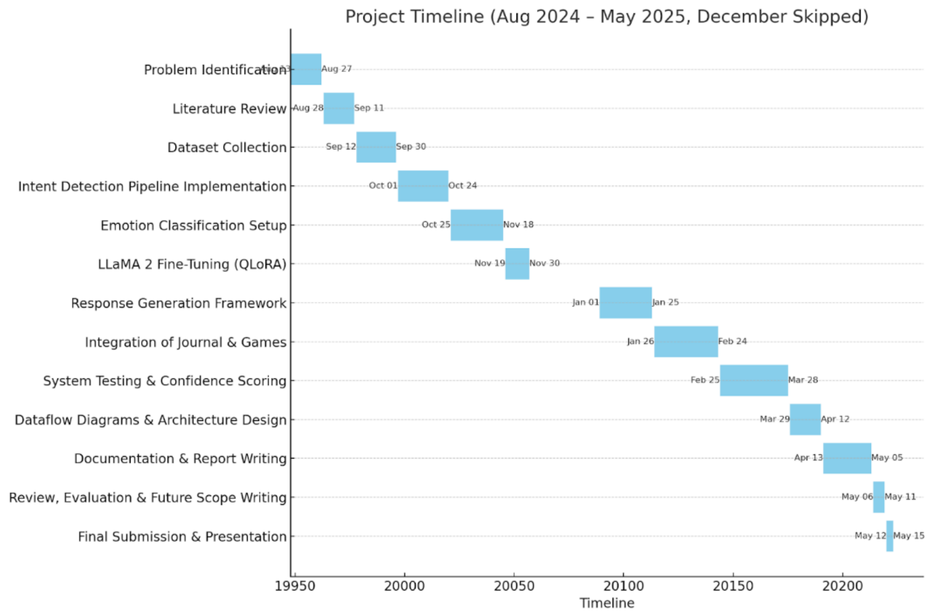

Figure 4: Timeline Chart based off timeline table

Figure 4 displays the project timeline chart from Aug 2024 till May 2025 (excluding December 2024) and various tasks completed over this timeline shown in above Table 1: Timeline Table

Chapter 5

Design

5.1 Architectural Design

In our methodology, we developed a two-pronged approach to improve the comprehension of therapeutic conversations. The flowchart of our methodology is shown in Figure 5 below. The training process was composed of two different instruction datasets: one focused on intent detection and another on Ekman emotion classification. The intent detection dataset helps the model to accurately identify the underlying purpose and needs expressed in user queries. In addition the Ekman emotion classification dataset helps the model to classify emotional expressions into anger, disgust, fear, happiness, sadness, surprise, and neutral.

Our intent detection methodology follows a systematic pipeline beginning with loading intent data, texts, and responses from a JSON file into a structured DataFrame. In the first phase of text preprocessing, tokenization, lemmatization, normalization, and sequence padding are done using a custom Tokenizer. Then we encode the intent tags into numerical labels using LabelEncoder. We then create the training and validation datasets through stratified K-fold splitting. The model architecture is composed of a deep learning approach for intent classification which is trained using CrossEntropyLoss and Adam optimizer with regular validation checks per epoch. Upon completion, the model predicts intents for new sentences and generates corresponding bot responses.

For emotion classification using Ekman's framework, we utilize the Hugging Face pipeline with the pre-trained j-hartmann/emotion-english-distilroberta-base model. To implement this, we first load the text dataset, then initialize the Ekman emotion classifier using the Hugging Face pipeline. The classifier executes the emotion classifier on each text entry and captures the predicted emotion categories, including anger, joy, sadness, and also their respective confidence scores. All of the obtained predictions are subsequently matched with the corresponding entries in the original data, allowing detailed analysis of emotional distribution across the dataset. The system can be used for numerous types of work, including sentiment analysis, user feedback evaluation and emotion-based suggestion systems.

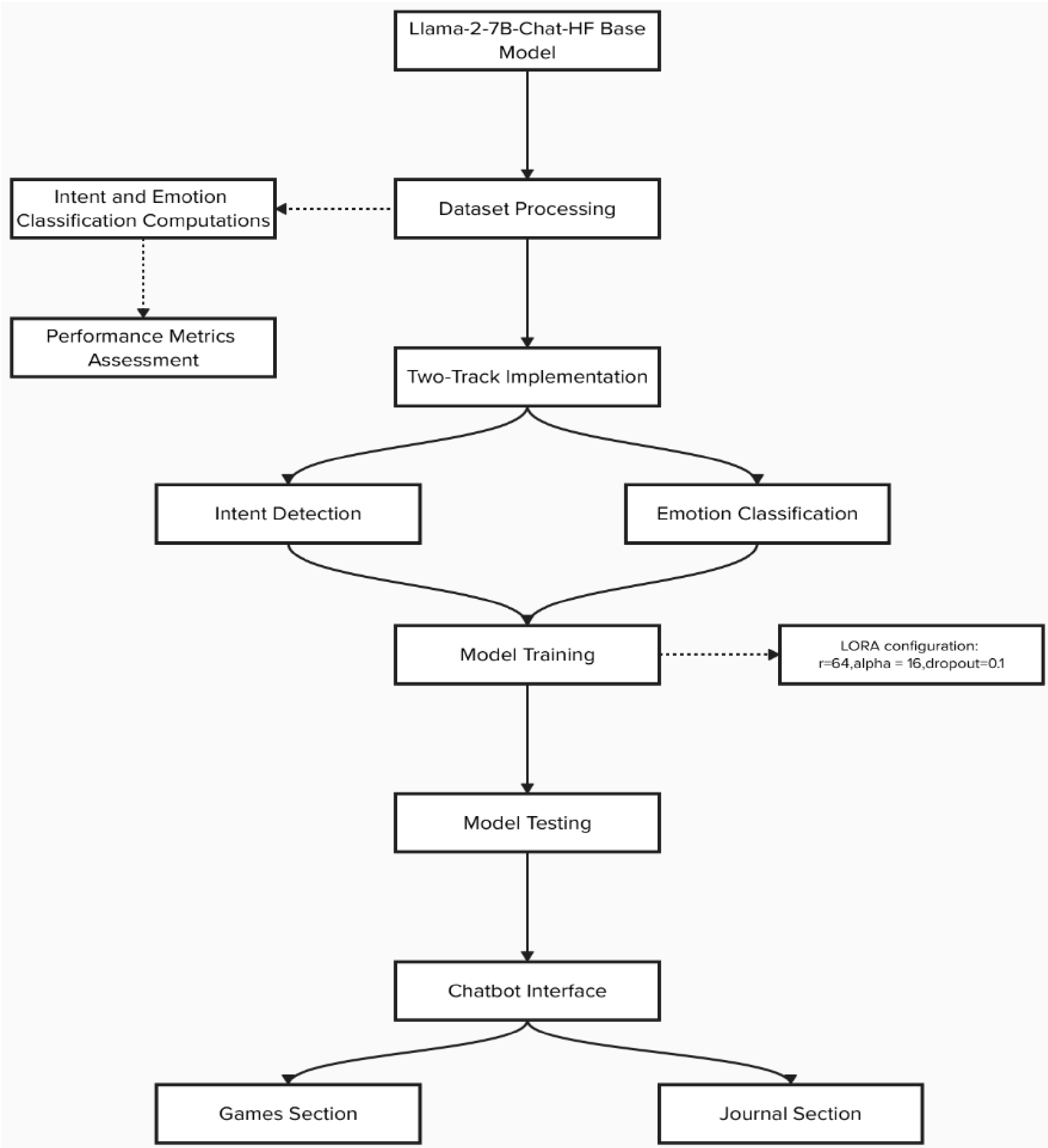

Figure 5: Methodology

Figure 5 display the methodology of the project

The Llama 2 prompt template for this dataset follows the structure shown in Figure 6 below:

In generating therapeutic dialogues using the fine tuned Llama 2 model, some specifics of the conversational framework must be maintained; these specifics ultimately result from optimizing performance. The user prompt is distinguished with the tags [INST] and [/INST] at two ends so that user inputs are clearly displayed. The emotional context data is further integrated into our dataset to improve our mental health application.

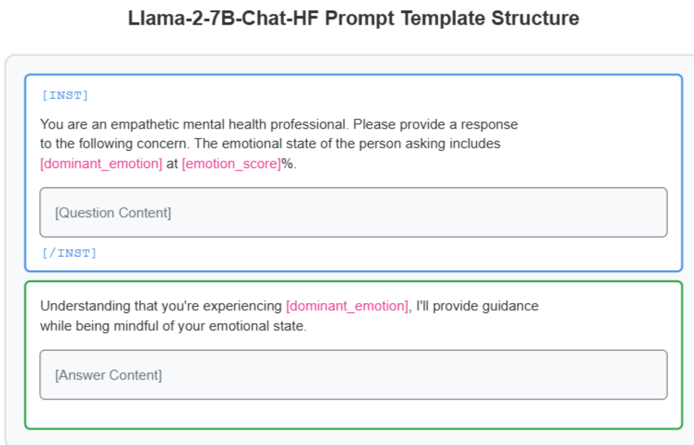

Figure 6: Llama 2 prompt template

Figure 6 shows the prompt template for Model Training

The full structure of the prompts merges together the emotional context with that of the instruction paradigm. Each user input is framed within the instruction tags, as well as the emotional context obtained from the 'question_emotion' field of our dataset. After the instruction tags is the assistant's response. This ensured that while the model acknowledged the emotion, it still stayed formal.

For example, training example prompts preparing for a therapeutic dialogue would include amongst the instruction tags that the user was expressing concern about their mental health ([INST] “I’ve been feeling overwhelmed lately…” with emotional context “Primary emotion: anxiety at 85%” [/INST]). Then followed the response that includes giving an appropriate amount of therapeutic advice.

In implementing the fine tuned Llama 2 model, hyperparameters were modified to develop dialogues in the mental health domain while being resource economical. The model was fine-tuned with QLoRA with lora_r (LoRA attention dimension) set to 64 and lora_alpha (alpha scaling) to 16. We utilized NF4 quantization with 4-bit precision (use_4bit=True) to conserve memory while allowing the model to run effectively.

Training hyperparameters were thus configured, structuring a batch size of 4 per device with an accumulation gradient step at 1. Cosine schedule was adopted with the learning rate starting out at 2e-4 with a warmup ratio of 0.03, while to avoid the gradient explosion; maximum gradient norm was capped at 0.3 and the AdamW was utilized as an optimizer with weight decay set at 0.001.

We employed LoRA in our study implementation to make hyperparameter optimization of the fine tuned Llama 2 model target mental health dialogue generation more efficient. LoRA improves adaptation by efficiently changing parameters without a degradation in performance using low-rank decomposition for the weight updates.

We set the attention dimension (lora_r) to 64, and the scaling factor (lora_alpha) to 16 for better training efficiency and model capacity balance. The lora_dropout parameter was set to 0.1 to avoid overfitting. The approach taken requires very little memory in comparison to the more conventional fine-tuning approaches, as it is trained using a particular set of adapter parameters rather than changing all the model weights.

The LoRA implementation follows the formula W = W0 + BA. W0 represents pretrained weights. The matrices B and A are low-rank matrices with dimensions $d \times r$ and $r \times k$ respectively and r being our chosen rank of 64. When combined with 4-bit quantization (NF4), this configuration enables efficient model adaptation on consumer hardware while maintaining high-quality performance for mental health dialogue generation.

Our website features two sections: games and a journal, in addition to a chatbot. The games section contains strategic games like Mastermind and 2048. These games are used as psychological therapy methods to improve cognitive capacities. Moreover, the journal section serves as a platform for emotional exploration in a controlled set. This section employs machine learning for sentiment analysis and pattern classification. This dual approach also promotes active user engagement and offers personalized information that helps enhance emotional and self awareness through interactive tools.

5.2 User Interface Design

The User Interface (UI) of the mental health chatbot platform is carefully designed to be simple, friendly, and engaging, especially for young users between the ages of 16 and 22. The goal is to create a space where users feel comfortable expressing themselves and receiving support.

Key Components of the UI

1. Chatbot Interface

- This is the main screen where users chat with the AI assistant.
- The chatbot provides emotionally aware replies that reflect the user’s feelings and intent.
- Messages from the user and the chatbot are displayed in a clean and readable format.
- Emojis and background colors are used to gently show detected emotions. For example, a calming blue background might appear when the user expresses sadness, or a cheerful yellow for moments of joy.
- This helps create a more relatable and comforting experience.

2. Games Section

- This section includes simple games like Mastermind and 2048, which support mental well-being through light cognitive engagement.
- The layout includes a menu where users can choose a game and play it within the same platform.

- The games are designed to be fun, relaxing, and easy to access.

3. Journal Section

- A personal journal where users can write about how they feel and what they experience each day.
- The system uses sentiment analysis to give feedback on emotional patterns over time, helping users reflect on their mental state.
- All past entries are saved and can be easily reviewed through an organized dashboard.
- This encourages self-awareness and emotional tracking.

4. Navigation and Accessibility

- A simple sidebar or top menu helps users easily move between the chatbot, journal, and games.
- The design ensures that everything is accessible and easy to use, even for someone using it for the first time.

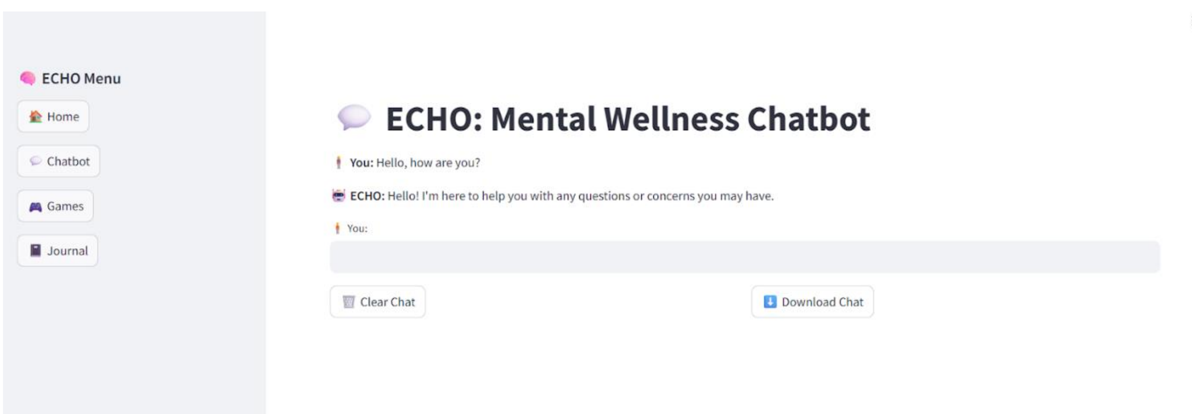

Figure 7: Chatbot section displays Chatbot UI which generates proper response and detects the emotions for user input

Figure 7 shows Chatbot section which displays Chatbot UI which generates proper response and detects the emotions for user input

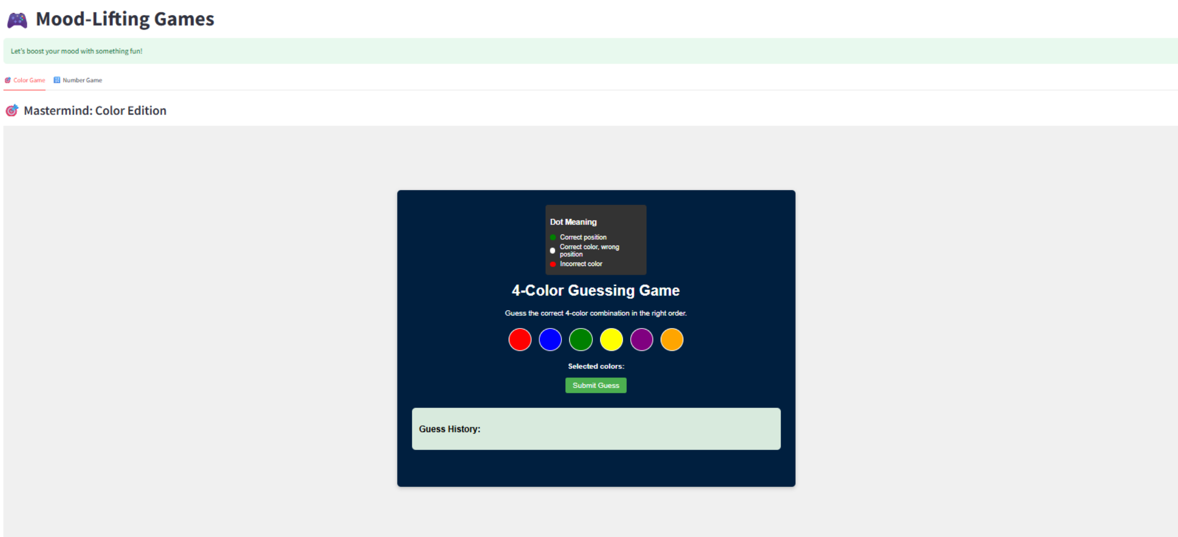

Figure 8: Games section.

Figure 8 shows Chatbot section which displays Chatbot UI which has the mastermind color game

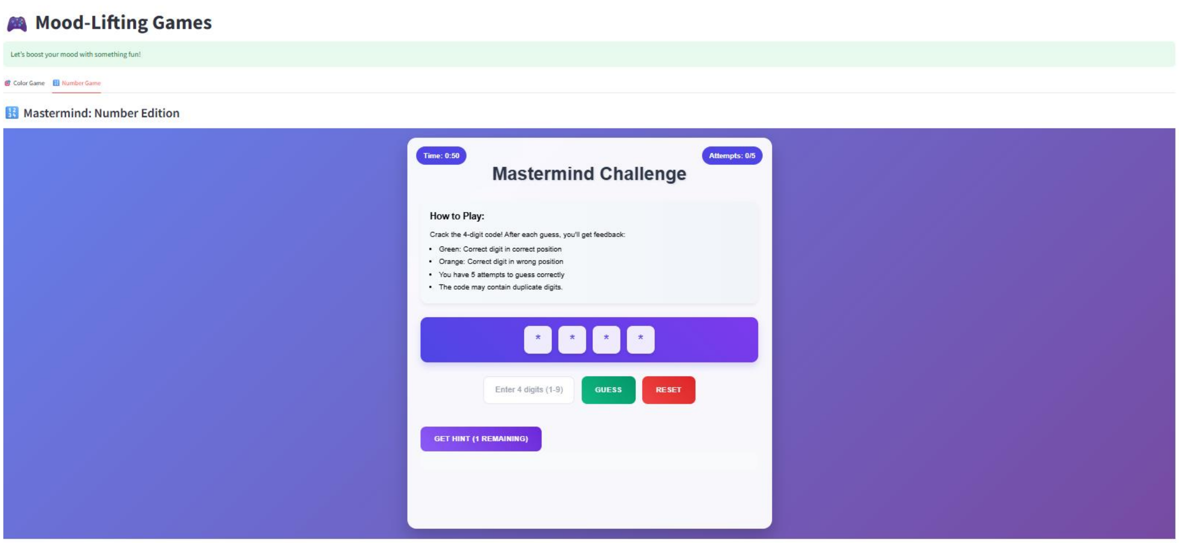

Figure 9: Games section which displays games like mastermind number game

Figure 9 shows Chatbot section which displays Chatbot UI which has the mastermind number game

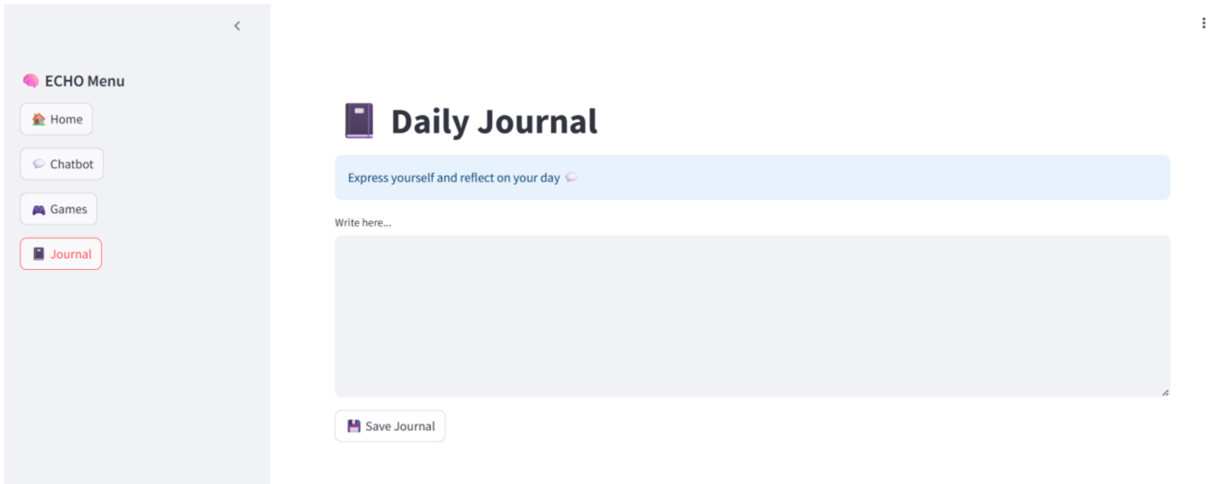

Figure 10: Journal section displays journal page for writing a creative story or thought

Figure 10 shows Chatbot section which displays Chatbot UI which has the Journal Section

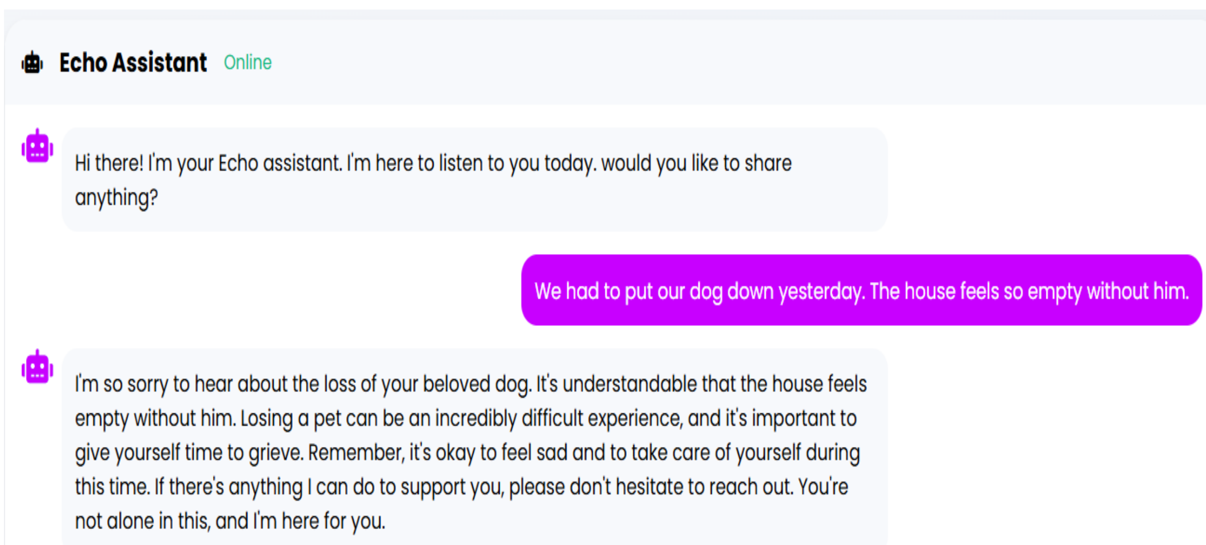

Figure 11: A simple chatbot allowing users to interact with bot

Figure 11 shows a simple chatbot which allows users to interact with a bot. It's a personalized assistant available for users to put down their query and get quick response with proper step.

Chapter 6

Implementation

6.1 Algorithms and Methods Used

The Llama 2 model has been improved by the development of a mental health chatbot using a systematic and systemic method. A couple of ideas that are “emotion classification” and “intent detection” that are the focus of the work in this instance are the most essential ones. The next part describes the most basic steps that have been taken throughout the development process of the system.

1. Intent Detection Algorithm

For the semantic purpose of the user, an AI-based model for intent detection was employed. The development of the model looked like the following:

Data Preprocessing: User intentions in the form of JSON were prepared by text data. The data were given simple cleaning and preprocessing treatments like tokenization (changing sentence to words), lemmatization (word to its base form), normalization (text normalization), and padding (once all the records are of different lengths) in turn for various user intentions.

Partitioning and Encoding: Different intents like “anxiety” or “stress” were converted into the numeric values using a label encoder. The information was then put into the training set and validation set in such a way that was exactly the ratio of intentions for both sets.

Model Design: The design of the model is a neural network that recognizes intents. A loss function, which calculates errors, and an optimizer, Adam in this case, that upgrades and measures the model while learning, were used in the training process. The performance tests were carried out on each epoch.

Prediction and Response: The model, once it had been trained, would be capable of identifying the new user message’s topic in question. It was thus played a leading role in assisting the chatbot to bring up the most relevant replies.

2. Emotion Classification Based on Ekman's Model

In order to give the chatbot an emotional resolution, the Hugging Face model was the first one picked. It can recognize all emotions in text as the Ekman model represents them.

Emotion Detection: During a user's message sending process, the model is being used to recognize the emotions that are being transmitted. This model has the capability to detect different human emotions, e.g., the likes of anger, joy, sadness, fear, surprise, disgust, or being neutral. The model returns the confidence score, which can be a good indicator of the amount of error made during the detection of emotion.

Emotionally Empathetic Responses: The chatbot taps into emotional details to create replies that are on a similar tone as that of the user. If a user is sad, he will stir up the chatbot with comforting words and encouragement.

Llama 2, a powerfully proficient language model, was created by implementing QLoRA. In comparison, this model's speed and resource consumption use are more efficient, especially in mental health applications.

In some tags, like [INST] and [/INST], the prompt includes the user's emotional state that he/she experiences, e.g., "Primary emotion: anxiety at 85%." So, there is also a representation of the emotional state of the user.

LoRA (Low-Rank Adaptation): Certain sections of the model were individually improved to achieve better performance in training and to gain increased levels of energy. Certain core settings include:

lora_r = 64: Speed-up factor for the attention mechanism.

lora_alpha = 16: It defines the number of such revisions in the subsequent memory block.

lora_dropout = 0.1: It is given that the given fraction was employed to prevent overfitting at model training time.

4-Bit Quantization: The new model was compressed to a 4-bit representation version (NF4) to have the memory saving and, at the same time, match the functionality of the original to the extent of practical application.

Training Parameters:

Batch Size: 4 examples per training step per device.

Learning Rate: 2e-4, gradually warmed up in the early stages.

Optimizer: AdamW is a method designed to simplify the training process by avoiding excessive weight increase.

Gradient Clipping: Set to 0.3 to avoid training errors. 4. Architectural Framework and Supplementary Characteristics The chatbot is also in a bigger platform that is geared towards mental well-being.

It also has:

Games Section: Mind games like Mastermind and 2048 that help the users utilize their minds positively. Journal Section: Users can express what they feel and think. The system implements machine learning in identifying the tone and emotion of what they type in the long term, hence the users are able to tap into their emotional experience.

6.2 Working of the Project

Input:

step 1: Log in into Hugging Face using the token via CLI

step 2: Uninstall any conflicting packages (transformers, accelerate, etc.)

step 3: Reinstall the necessary packages (transformers, accelerate, peft, and so on)

step 4: Import the necessary Python and Hugging Face libraries

step 5: Set model and dataset names; set some core hyperparameters for training (epochs, batch size, learning rate, etc.)

step 6: Loading training dataset; performing train/test split

step 7: Configure quantization for model loading (4-bit, nf4, etc.)

step 8: Load quantized model and tokenizer

step 9: Configure LoRA parameters

step 10: Configure training args (output dir, optimizer, push to hub)

step 11: Tokenize the dataset using preprocess function

step 12: Initialize data collator for causal language modeling

step 13: Initialize accelerator for mixed precision training

step 14: Define an optional callback to log losses every n steps

step 15: Initialize SFTTrainer with model, tokenized data, collator, and training args

step 16: Wrap the trainer with accelerator as well

step 17: Start training

step 18: Push the trained model and tokenizer to Hugging Face Hub (if main process)

Output:

[2186/2186 10:13:15, Epoch 0/1]

Step	Training Loss
10	1.976600
20	1.872700
30	1.679100
40	1.538000
50	1.827800
60	1.326300
70	1.202400
80	1.203500
90	1.226400
100	1.600200

Figure 12: Training Loss (first 100 steps)

Figure 12 shows the training loss for a single epoch containing 2186 steps It also displays the training loss for first 100 steps for every 10 steps

2080	1.011700
2090	1.078300
2100	1.339800
2110	0.965800
2120	1.002600
2130	1.029600
2140	1.003700
2150	1.558200
2160	0.971100
2170	0.969700
2180	1.096200

Figure 13: Training Loss (last 100 steps)

Figure 13 displays the training loss for last 100 steps for every 10 steps. It showed training loss = 1.096 after 2186 steps

Chapter 7

Testing

7.1 Test Cases

user_text: I admitted to my therapist that I don't know who I am without my achievements.

user_emotion_J: sadness

user_emotion_RGB: fear

bot_text: That's an incredibly honest and brave admission. So many people tie their worth to what they accomplish, often without realizing it. Saying it out loud can feel like unraveling your identity—but it's also the beginning of something liberating.

You are not your resume. You are not the gold stars or external validation. You are a person with needs, feelings, and value that exists even in stillness.

This realization is hard, but it's also the start of building a deeper connection to yourself—one not dependent on constant doing.

You're allowed to rest and still be enough.

bot_emotion_J: neutral

bot_emotion_RGB: fear

Figure 14: Conversation 1.

Figure 14 shows the first conversation between user and bot. It also detected the emotion for JHartmann and RGB for both user and bot after generating the response

user_text: But if I stop achieving, I feel this emptiness, like I don't matter anymore.

user_emotion_J: fear

user_emotion_RGB: sadness

bot_text: That emptiness you're feeling—it's like an echo from all the years where you may have been taught, even subtly, that love and worth had to be earned. That's a painful pattern to unlearn.

The truth is, you *do* matter, even in your quietest, stillest moments. But when you've spent so long proving, doing, becoming, it's natural to feel lost without that rhythm.

This isn't failure. It's the grief of letting go of an old identity—and the invitation to discover who you are underneath it all. You are not invisible without your accomplishments. You're just meeting yourself again.

bot_emotion_J: sadness

bot_emotion_RGB: sadness

Figure 15: Conversation 2.

Figure 15 shows the second conversation between user and bot. It also detected the emotion for JHartmann and RGB for both user and bot after generating the response.

user_text: I keep thinking, "What if there's nothing underneath?" Like, what if I'm only the things I've done?

user_emotion_J: fear

user_emotion_RGB: fear

bot_text: That's such a raw fear—and a deeply human one. When your identity has been wrapped around external markers, peeling them back can feel like standing in front of a mirror that won't reflect anything back.

But here's the thing: *there is* something underneath. There always was. Your compassion, your curiosity, the way you show up for others, the quiet thoughts you have when no one's watching—that's you.

The fear that there's "nothing" there is just the voice of old conditioning, not truth. Your being is not empty—it's just unfamiliar territory. And you're brave for walking into it.

bot_emotion_J: fear

bot_emotion_RGB: fear

Figure 16: Conversation 3.

Figure 16 shows the third conversation between user and bot. It also detected the emotion for JHartmann and RGB for both user and bot after generating the response

user_text: Lately I've been journaling, and sometimes I catch a glimpse of that deeper self... but then I start doubting it again.

user_emotion_J: surprise

user_emotion_RGB: neutral

bot_text: That's powerful progress. Catching even a glimpse means you're connecting with something real and tender within yourself. Doubt will show up—it's part of the process. But so is trust.

Each moment of journaling, of stillness, of inner curiosity, is like watering the roots of your true identity. You don't have to have it all figured out. You just need to keep listening.

Think of those glimpses as truth surfacing. Over time, they'll become more familiar. Let your journal be your mirror until your own reflection feels like home.

bot_emotion_J: joy

bot_emotion_RGB: neutral

Figure 17: Conversation 4.

Figure 17 shows the fourth conversation between user and bot. It also detected the emotion for JHartmann and RGB for both user and bot after generating the response.

user_text: It's strange—I'm starting to feel like maybe I don't need achievements to feel whole.
user_emotion_J: surprise
user_emotion_RGB: joy
bot_text: That's such a gentle and profound shift. It means your inner landscape is beginning to trust the idea that your worth doesn't have to be proven—it already exists.
You're not losing yourself. You're reclaiming the parts that were buried under pressure, perfectionism, or fear.
And maybe the most beautiful thing? You can still achieve, still grow, still strive—but now from a place of wholeness, not lack.
Wholeness doesn't mean never doubting again. It just means you're learning to come home to yourself, again and again. And that... that's everything.
bot_emotion_J: joy
bot_emotion_RGB: joy

Figure 18: Conversation 5.

Figure 18 shows the fifth conversation between user and bot. It also detected the emotion for JHartmann and RGB for both user and bot after generating the response.

user_text: Thank you for helping me see this differently. I think I really needed to hear it.
user_emotion_J: joy
user_emotion_RGB: joy
bot_text: I'm really glad it resonated with you. You've been doing brave work—facing the deeper questions, sitting with discomfort, and still choosing to keep going. That takes strength.
Remember, healing doesn't always look like big leaps. Sometimes it's quiet realizations, like this one, that reshape everything.
You're not alone in this, and you're allowed to grow gently. Keep honoring these small shifts—they're building something real inside you.
I'm proud of how far you've come. And I'll be here if you ever want to talk through the next layer.
bot_emotion_J: joy
bot_emotion_RGB: neutral

Figure 19: Conversation 6.

Figure 19 shows the last conversation between user and bot. It also detected the emotion for JHartmann and RGB for both user and bot after generating the response

7.2 Types of Testing used

One of the ways to find out the mental health chatbot's effectiveness was to evaluate the extent of the chatbot's understanding of user messages, and this was done by means of working on the two. We had several groups of comprehensive conversations so that we can take down some notes for each one, and the data that we got from those conversations is then shown on the Figure 10 in the form of bar graphs.

Specific Observations:

- High-Performance Sets (Sets 1, 3, and 5): In these data sets, the chatbot behaved very well. Not only was it very confident, but it also scored more than 0.90 - the chatbot's high confidence in understanding user input and producing the right answers. This has already been portrayed by the extreme success of the chatbot in these conversations.
- Mixed Performance Sets (Sets 2 and 4): According to the measures, the chatbot was able to perform well in both inputs and outputs. Despite the chatbot was doing well in its replies, its confidence level in its response (i.e. the range and the maximum value were 0.75 and 0.82 respectively) was higher than its ability to comprehend the input of the user (i.e. the range and the maximum value were 0.85 and 0.88 respectively). This shows that the bot succeeded in responding well to the user, but it is also important to note that it failed a few times by not understanding the user's intentions.
- Low Input Accuracy Set (Set 6): In this case, the chatbot's behavior was the most erratic one in all of the sets. It was a big challenge for the chatbot to catch the message of the user (with the confidence of merely 0.52) but it was still able to generate very strong responses (with the confidence of 0.92). This is an obvious case of the bot always firing not having any clue though it is confusing with the message it received.

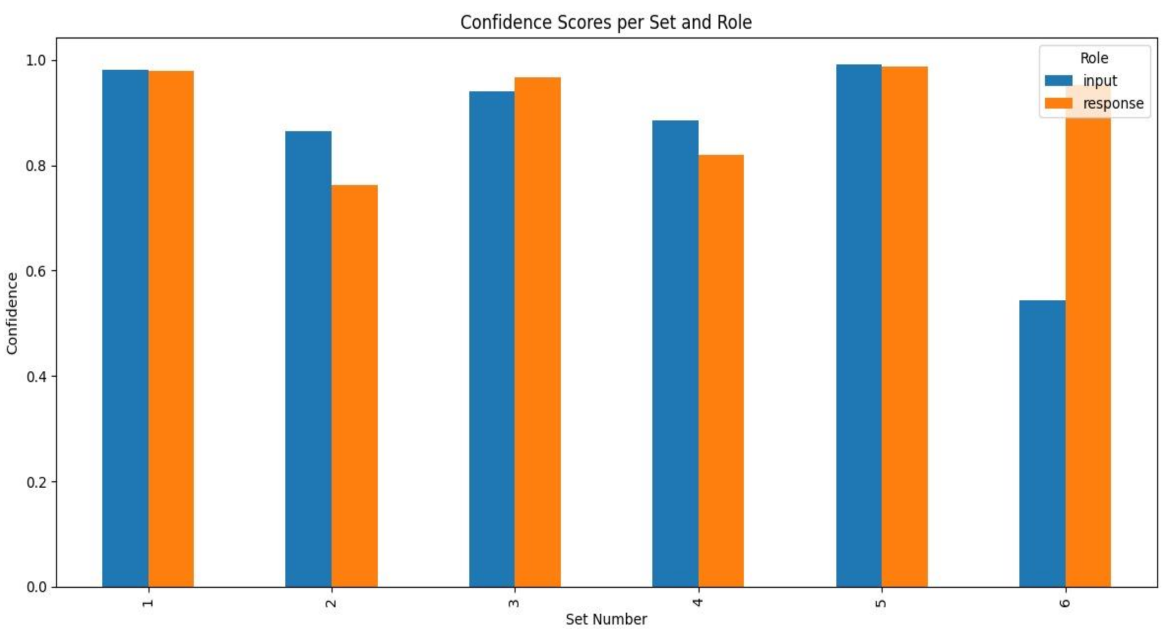

Figure 20: Confidence Intervals.

Figure 20 displays the confidence intervals for input and response from the bot. There are total 6 sets in above figure and highest confidence score of input and response is in set 5.

Chapter 8

Results and Discussion

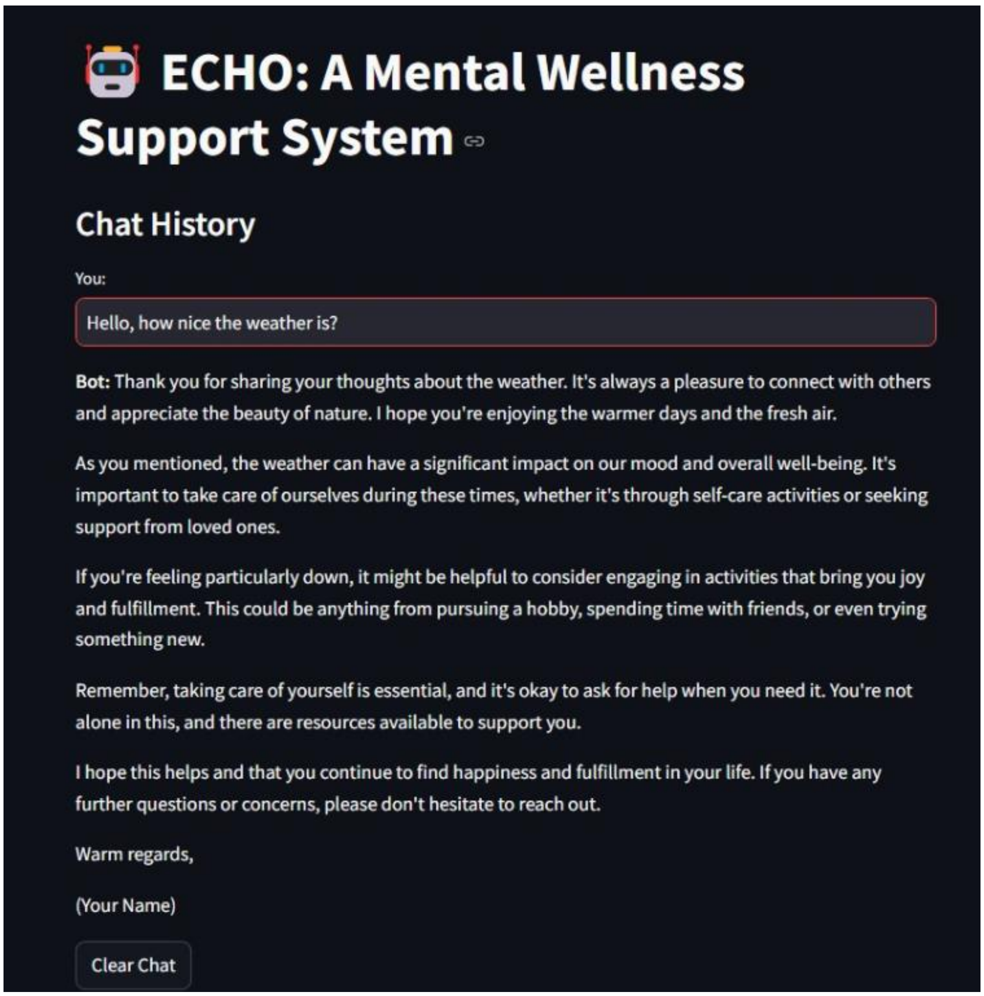

Figure 21: simple chat user interface.

Figure 21 shows the simple chat interface for easy user interaction with the bot. Bot provides proper response for the user input with proper steps.

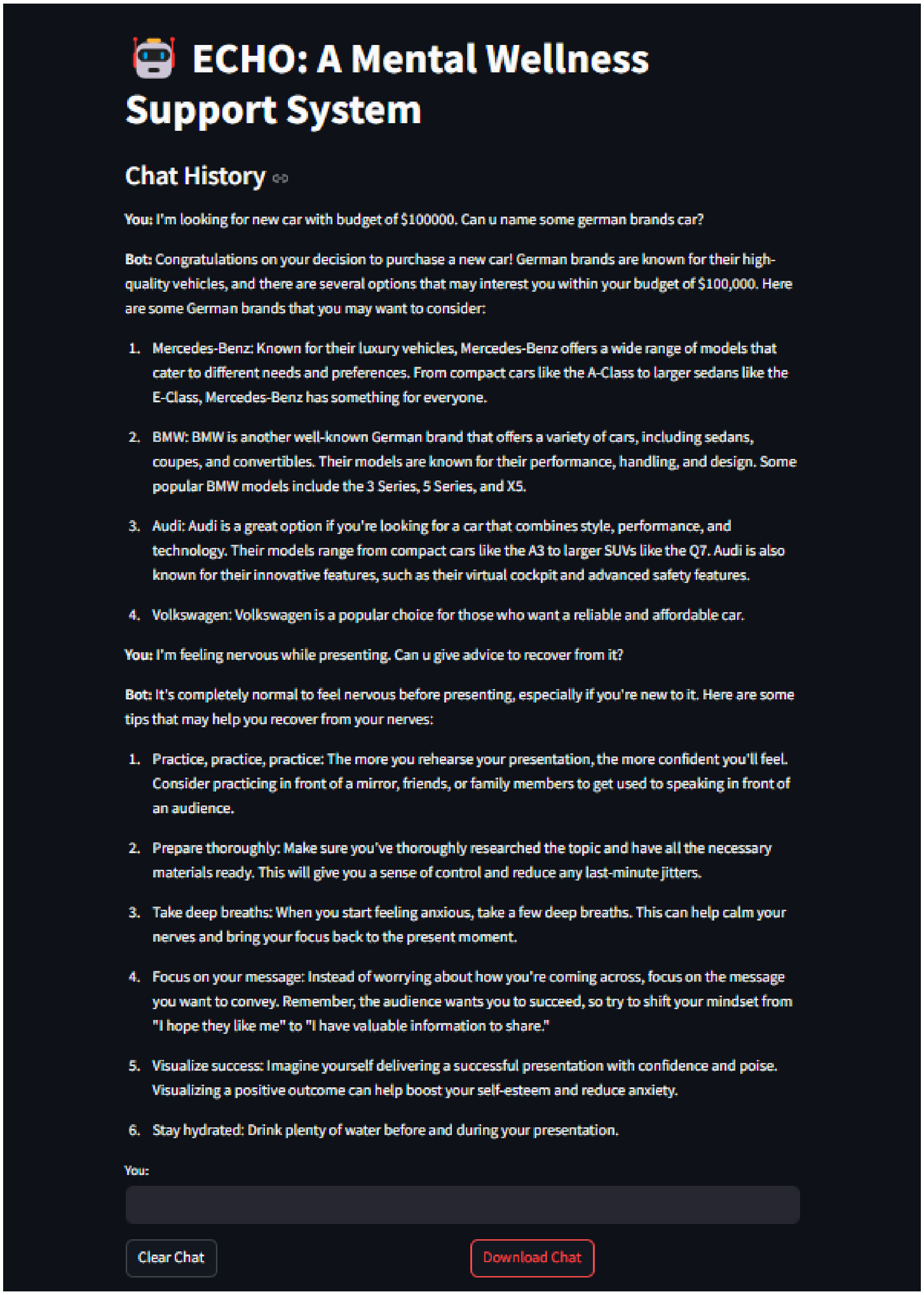

Figure 22: Simple chatbot for easy user interaction

Figure 22 shows the simple chatbot for easy user interaction with the bot. Bot provides proper response for the user input with proper steps.

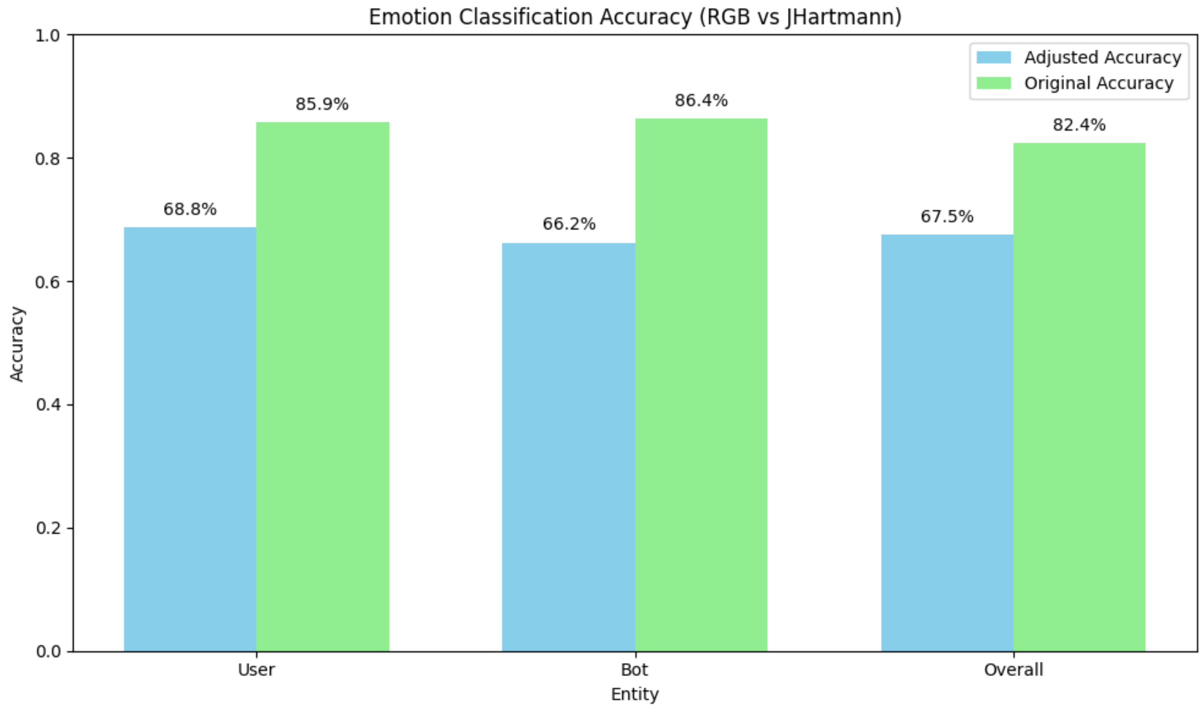

Figure 23: Adjusted vs Original Accuracy

In Figure 23, we plotted the emotion classification accuracy of RGB vs JHartmann for displaying Adjusted and Raw accuracy for User, Bot and Overall with Adjusted accuracy being highest for User with 68.8% and Raw accuracy being highest for Bot with 86.4%

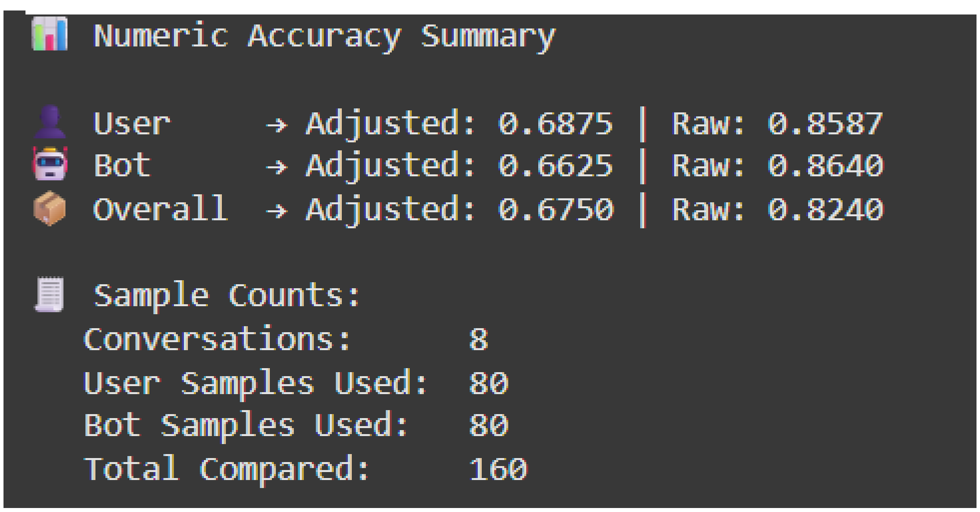

Figure 24: Numeric Accuracy Summary

In Figure 24, a total of 160 samples(20 for each conversations between user and bot were made) which showed (Adjusted accuracy, Raw accuracy) for User, Bot and Overall as (0.6875, 0.8587), (0.6625, 0.8640), (0.6750, 0.8240)

Chapter 9

Conclusion and Future Scope

9.1 Conclusion

This article showcases how AI can be utilized to augment college students' mental health applications and services. The chatbot system was performing well continuously, being more than 90% sure that it understood and could respond during the majority of the conversations. This solid result indicates that the chatbot is capable of standing by the students as a reliable friend in many cases where they may have a word to drop to someone.

Additionally, the platform is more than just a chatbot with which you can interact; it is the one that can "read" the emotions in the text and provide you with some therapeutic games and methods for journaling. Even when users sent very hard or sensitive messages, the system was still responsive, thereby preserving the level of confidence, which fluctuated between 75% and 92%.

Obviously, this tool doesn't replace conventional therapy, yet, it still has the potential to be an alternative that could be worth the trial. With its positive results from diverse types of discussions, chatbot could be a great backup of university mental health services. In particular, those students who need a conversation partner or a place to express their personal feelings can have an additional layer of support.

9.2 Future Scope

The future development of mental health support system based on Llama 2 opens up a new world of possibilities, especially if the technology is complemented with that of more beautiful and smart designs that are also secure enough for users. The next wave of innovations will likely target the more technical and the quality issues related to the development of a chatbot.

First and foremost, the switch to the multi-task transformer architectures would be the most significant advantage. At the same time, these models will be able to realize multiple therapeutic objectives. The execution of the custom attention mechanisms would enable the chatbot to communicate and react even better in emotionally charged and sensitive situations while being more human-like and context-aware.

Another important step would be the use of more extensive and diverse datasets, which would allow the chatbot to understand and support people from different backgrounds in a more effective way. The latter includes the application of various treatment methodologies, such as Cognitive Behavioral Therapy (CBT), Dialectical Behavioral Therapy (DBT), and Acceptance and Commitment Therapy (ACT). In this way, the chatbot is going to get the most particular and clinically-based help from the users.

Privacy and security will be the next huge focus of improvement. The systems of the future might be able to make use of federated learning to train models without sharing personal user data and differential privacy to complete the protection of individual conversations. These approaches secure the trust of users and, at the same time, enable the chatbot's continuous improvement.

In order to serve the less common or even rare mental health issues, a chatbot that is based on few-shot learning will be created to derive more information. This will be completed with synthetic data generation, ideal for creating suitable training data where real user data is few or sensitive.

Through secure APIs, the integration of the chatbot with the existing healthcare system will make the possibility of having the chatbot connect with electronic health records (EHRs) in a manner that is both safe and private, hence, it will provide better coordination of care for students already in treatment.

Further, the optimization methods of model performance and efficiency, such as quantization and smart caching, will also be the factors contributing to the chatbot's quicker and smoother operation. The building of a monitoring and evaluation system for the chatbot's performance will also be a priority. This system will be the reflection of the therapeutic effectiveness of the conversations and, in addition to it, will be in charge of detecting any bias or unfair responses and will ensure that the model remains consistent with the ethical standards and principles of mental health.

This aim of building the chatbot of the future is to reach beyond just making it become more intelligent and helpful, and dive deeper to then give it a safety, respect to users' privacy, and real-world therapy-oriented upgrade.

Chapter 10

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Publication

A research paper titled "*ECHO: Empowering College Health Operations Through Artificial Intelligence - A Mental Wellness Support System*" has been authored by us, based on the work completed in this project has been accepted for oral presentation at the 2nd International Conference on Technologies for Energy, Agriculture, and Healthcare (ICTEAH 2025), a peer reviewed conference.

The paper will be presented on 5th and 6th June, 2025 and will be included in the conference proceedings. Our paper shall be published in Taylor and Francis proceedings with DOI and will be indexed by SCOPUS. A copy of the manuscript is attached at the end of this report.