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Smart Gen AI Chat for Mental Wellness

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Abstract: In recent years, humanity has witnessed several significant catastrophic disasters, including pandemics, wars, and earthquakes, in which millions of people required both emotional and mental support. Chatbots have been made use of for the past decade or so to improve delivery of mental health care services. Patients' perceptions and views impact the widespread use of chatbots in healthcare. Several studies have been carried out to evaluate patients' views and experiences on mental health chatbots. Our project focuses on finding a solution to this issue by building a chatbot which provides mental health-based support. The chatbot understands and responds to people's emotions through Natural Language Processing (NLP) and Long Short Term Memory (LSTM). It offers helpful advice for managing common mental health issues like stress and anxiety. It will also cover the benefits as well as the limitations of using chatbot for therapy as well as some suggestions as to how it can be enhanced in the future.

Keywords - Chatbot, Mental health support, Natural Language Processing (NLP), Long Short Term Memory (LSTM), AI therapist.

I. INTRODUCTION

1.1 Background

Mental diseases are a developing global concern. Approximately 29 of every 100 people may develop such illnesses throughout their lives [1]. It is predicted that the pandemic alone caused an additional 53 million cases of depression and 76 million cases of anxiety worldwide. There is a global lack of mental health professionals. According to data from 2022, there are 13 mental health workers per 100,000 individuals on average [2].

Globally, mental health human resources are in short supply, funding is inadequate, and mental health illiteracy is widespread. This scarcity of resources is particularly noticeable in low- and middle-income nations, where there are just 0.1 psychiatrists per 1,000,000 people, as opposed to 90 psychiatrists per 1,000,000 persons in high-income countries. According to the World Health Organization, mental health services benefit 15% and 45% of persons in need in poor and developed countries, respectively. This could be a substantial contributor to the rise in suicide behavior in recent decades [3].

1.2 Understanding Therapy

Psychotherapy, commonly referred to as therapy, is a medical practice that aims to reduce emotional suffering and mental health challenges. Some of the well-known therapeutic techniques include person-centered therapy (PCT), cognitive behavioral therapy (CBT), and emotional support. PCT allows patients to direct their own therapeutic journey, whereas CBT focuses on problem resolution and action to modify harmful thought patterns. ES also provides emotional support and empathy as people navigate their issues. Psychotherapy, commonly referred to as therapy, is a medical practice that aims to reduce emotional suffering and mental health challenges. Some of the well-known therapeutic techniques include person-centered therapy (PCT), cognitive behavioral therapy (CBT), and emotional support. PCT allows patients to direct their own therapeutic journey, whereas CBT focuses on problem resolution and action to modify harmful thought patterns. ES also provides emotional support and empathy as people navigate their issues [2].

1.3 Problem Statement

The current mental health support environment faces numerous challenges, including limited accessibility, high costs, and the persisting stigma associated with seeking treatment. Traditional treatment techniques usually fail to offer timely and personalized care, exacerbating the global mental health epidemic [1]. To address these challenges, the "Smart Gen AI for Mental Wellness" project aims to leverage the power of generative AI and conversational AI to build a transformative platform for personalized and accessible mental health care. The project seeks to overcome the limitations of current mental health support systems with the help of therapeutic chatbot [2] by bringing a novel and technologically advanced approach to fulfilling the world's growing mental health needs of five years.

II. RELATED WORK

Generative AI, a growing area, has attracted significant debate because to its transformational potential across multiple domains. Notably, it has permitted the creation of complex cultural output ranging from visual arts to music, writing, and even video production. Diffusion models have permitted the synthesis of high-fidelity visuals, whilst large language models (LLMs) are capable of producing cohesive prose and poetry in a variety of circumstances. These advances in generative AI are poised to transform creative workflows, altering how ideas are conceptualized and realized. As a result, interdisciplinary research is required to understand its broad consequences for culture, economics, law, algorithms, and the complex interplay between technology and creativity [4].

ELIZA was an early natural language processing application built for MIT's MAC time-sharing system. Joseph Weizenbaum describes how ELIZA improves conversational interactions between users and machines by analyzing input texts using established decomposition rules triggered by keywords. Responses are generated using reassembly rules that correspond to these breakdown principles. ELIZA solves core technical difficulties such as keyword recognition, minimal context discovery, optimal transformation selection, answer generation without keywords, and script editing capabilities. The report also explores the psychological consequences of the ELIZA approach and possible future advancements in the subject [5].

Lennart Brocki et al.'s study introduces Serena, a deep learning dialogue system designed exclusively for mental health counseling. Serena uses a large-scale Seq2Seq Transformer model trained on person-centered therapy transcripts to provide sympathetic answers and improve counseling outcomes. Despite occasional issues like hallucinations and incoherence, Serena represents a promising option for increasing mental health assistance through the use of artificial intelligence [6].

In their research paper, Fitzpatrick KK et al. describe Woebot, an automated conversational agent that uses brief daily chats and mood tracking to conduct Cognitive Behavioral Therapy (CBT). Woebot functions within a messenger program that is available on both desktop and mobile devices. Interactions often begin with questions regarding the user's current mood, followed by responses in the form of words or emoji images. Participants are then introduced to fundamental CBT concepts through short movies or word games that teach about cognitive distortions. Onboarding involves an overview of the bot's capabilities and limits, emphasizing its position as a self-help tool rather than a replacement for therapy. Users are also alerted that psychologists are monitoring them, but not in real time, and are encouraged to seek emergency treatment if necessary [7].

Temsah O et al. investigate the advent of ChatGPT, an artificial intelligence chatbot, as a key role in medical education and healthcare literature. Through a hybrid narrative review, both human authors and ChatGPT work together to summarize and synthesize the first four months of indexed medical literature. Using a search approach in the PubMed and EuropePMC databases, 65 and 110 papers were found, respectively. These studies explore ChatGPT's impact on a variety of topics, including medical education, scientific research, medical writing, ethical considerations, diagnostic decision-making, automation potential, and criticism. The study highlights the growing body of literature on ChatGPT's uses and implications in healthcare, emphasizing the need for additional research to assess its efficacy and resolve ethical problems [8].

III. SYSTEM DESIGN

We will examine the system's design by going deep into LSTM Architecture and overall System Architecture of our chatbot's model.

3.1 LSTM Architecture

The LSTM model addresses the issue of long-term memory degradation by incorporating three fundamental structures: input, forgetting, and output gates. These gates control the flow of information within the model, allowing it to store long-term dependencies efficiently. The input gate regulates the amount of current input read into the cell, whereas the forgetting gate governs how much of the previous cell state is maintained. The output gate transforms a portion of the cell state to the hidden state. By selectively activating these gates via a gating mechanism, the LSTM model can eliminate unnecessary information while retaining the most significant memories. This technique addresses the gradient disappearance issue, allowing LSTM to outperform traditional recurrent neural networks (RNNs) in terms of long-term memory retention. Finally, LSTM enhances the storage and retrieval of long-term memory in neural networks [9].

The basic structure of the LSTM component is as follows:

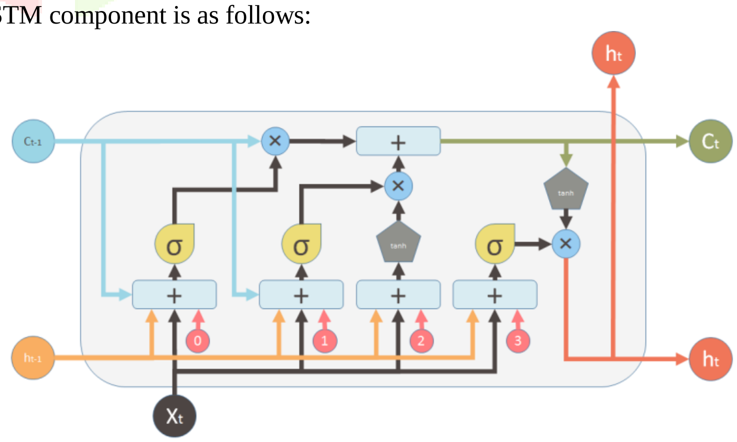

Fig 1: Network Structure of LSTM

1. Figure 1 shows the forget gate function of the LSTM model. This gate assesses the relevance of information by comparing inputs from previous and current cells. Weights and biases are utilized, and the sigmoid function produces a value between 0 and 1. This value indicates whether the information is retained (near to 1) or discarded (close to zero) [10].

2. The input gate in the LSTM model plays a critical function in incorporating important information into the cell state. It starts by employing the sigmoid function to regulate incoming data, similar to the forget gate, utilizing inputs from the prior cell state (h_t-1) and the current input (x_t). This method removes superfluous information. Next, the tanh function is used to generate a

vector with outputs spanning from -1 to +1, encompassing all potential values from h_t-1 and x_t. Finally, the vector values and regulated inputs are multiplied to extract and store important information [10].

3. In the LSTM model, the output gate extracts relevant information from the current cell state to generate the output. Initially, a vector is generated by applying the tanh function to the cell, collecting a range of possible values. The information is then regulated by the sigmoid function and filtered based on the values to be retained, using inputs from the prior cell state (h_t-1) and the current input (x_t). Finally, the vector values and controlled inputs are multiplied to produce the output, which is used as input for the next cell [10].

3.2 System Architecture

Now we will discuss the proposed flow of system architecture for our LSTM based chatbot model.

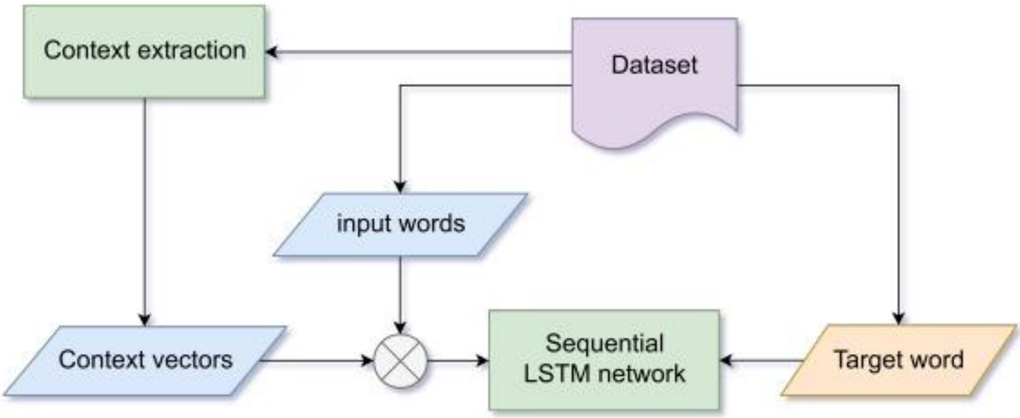

Fig 2: Proposed System architecture using LSTM Model

In our project, we propose a context-based text generation model that incorporates contextual information alongside input-output instances. Similar to the depicted approach in Fig 2, we apply context extraction techniques to derive context vectors, which are then concatenated with input words to train our language model. Vectors share the same dimensionality as the input and output vectors, whichever kind we choose. Our system operates on the premise that the context vector of a sequence encapsulates its semantic essence. For example, for the sentence "I have been feeling low and anxious" the context vector may include words like "anxiety," "depression," and "sad." Each input-output instance is associated with a context vector, which could represent a keyword, a word set, or a topic indicative of the sentence's semantic content. While akin to paragraph vectors [12], context vectors do not capture the entire semantic context. We find traditional topic modeling techniques like Latent Dirichlet Allocation (LDA) or Latent Semantic Analysis (LSA) unsuitable for our purpose, as they rely on topic distribution across documents, whereas our text generation models require more diverse topic representations [11].

Our text generation model adopts a many-to-one structure, where the model is trained on multiple input words and a single target word. Notably, we opt against sentence tokenization in the dataset to preserve features like sentence completion, openings, and semantic continuity between sentences. Hence, input sequences extracted from the dataset maintain uniform length but are not necessarily complete sentences. Conversely, context vectors are computed for each valid sentence. During the training dataset generation process, inputs consist of i,...,i+n words with the output word at i+n+1, originating from a paragraph. The maximum number of words forming an input sequence that constitutes a sentence determines the context vector for that specific input instance. These context vectors are simply appended to the inputs during model training [11].

IV. Implementation

For implementation and building of our project, we first focused on creating a mental wellness-based dataset followed by pre-processing of data and building of LSTM model using that data.

4.1 Data Collection

Online surveys, such as Google Forms, are a quick and effective way to collect data, especially during hard times like the COVID-19 pandemic. Researchers may quickly contact a large audience and collect replies remotely, reducing the requirement for personal engagement [12].

For our dataset, we circulated google forms around several social media platforms like WhatsApp, Reddit and Instagram, in order to reach a larger audience. The questions involved ratings for happiness and anxiousness as well as how users generally feel in their daily lives as shown in fig 3. Users were also asked for questions they might have for a mental health worker. These questions were then responded to by few psychologists as subject matter expert after conducting a few sessions with them. The dataset is as shown in fig 4.

Timestamp	How often do you feel stressed?	Are you currently experiencing any mental health symptoms	Do you feel comfortable discussing your feelings with others	Have you ever used a mental health chat-bot or wellness a
3/4/2024 20:58:09	4	Feeling anxious or worried, Feeling depressed or unhappy, Being more quiet or withdrawn than usual	Sometimes/Depends On Situation	No
3/5/2024 9:07:01	4	Feeling depressed or unhappy	Sometimes/Depends On Situation	No
3/5/2024 9:23:33	3	Sleep problems	Sometimes/Depends On Situation	No
3/5/2024 9:38:57	3	Feeling anxious or worried	Sometimes/Depends On Situation	No
3/5/2024 10:24:16	3	Sleep problems	Sometimes/Depends On Situation	No
3/5/2024 10:32:31	2	Feeling anxious or worried	No	No
3/5/2024 10:33:36	5	Emotional outbursts, Feeling anxious or worried, Feeling depresse	Sometimes/Depends On Situation	No
3/5/2024 10:35:17	2	Sleep problems	Yes	No
3/5/2024 10:37:35	4	Emotional outbursts, Feeling anxious or worried, Feeling depresse	Sometimes/Depends On Situation	No
3/5/2024 10:37:52	3	Emotional outbursts, Feeling anxious or worried, Feeling depresse	Sometimes/Depends On Situation	No
3/5/2024 10:39:02	3	Emotional outbursts	No	No
3/5/2024 10:46:07	3	Sleep problems	Sometimes/Depends On Situation	No
3/5/2024 10:46:19	1	Sleep problems	Sometimes/Depends On Situation	No
3/5/2024 11:06:42	2	Feeling anxious or worried, Sleep problems	Yes	No
3/5/2024 11:43:51	3	Feeling anxious or worried	Sometimes/Depends On Situation	No

Fig 3: Data collected using Google Form

Question	Answer
How can one come out of depression ?	I think we can focus on certain very basic uh activities which they can do and also on their self-esteem because there's a lot of self-criticism involved in depression a lot of self-criticism involved and it might be really difficult to like recognize whether a person is depressed or not right because a lot of times people just act like they're happy yes that is but then you know there are certain very very poor symptoms of depression that are very common in almost everyone first is You will start losing your sleep. You will be like, I am not able to sleep. I don't want to do anything. The don't want to do anything is a major part. Suddenly there is a lack of motivation. The things that you once found interesting are no longer interesting. You don't feel like getting up. Either it is lack of sleep or it is excessive sleep. Like the person is sleeping throughout the day. And then, you know, there comes two extremes. Either the person is eating a lot or the person has just stopped eating. They don't feel like eating. Okay. Then there is anhedonia. Anhedonia is lack of interest in things. So, there are... These are certain typical signs. So, even if a person with depression can come across as smiling and everything, there are certain typical symptoms like these which you can capture. But again... A layman cannot capture that, you know, in just one visit or two. Okay. It is very, very important that people involved, closely involved with that particular individual are noticing these changes and getting it treated.
Whenever I achieve something, I show happiness, but I don't completely feel it, like I know I am supposed to be happy, but I just feel normal, never enjoying my achievement for real, what could be the potential reasons for that, and how to feel happy about my own accomplishments?	Correct. First could be having a very low internal sense of self-esteem. that is what the go-to is because there are so many people who achieve great things in life and still feel no you know what, this is not enough. Why am I not feeling happy? Because somewhere down the line, it's either you feel, yeah, I've just got this and I feel I am, I should prepare for more and somewhere, you know, or the perspective would be, this might have come to me just with a fluke. I know I deserve something different. So having, internally having a lower self-esteem could be one of the reasons for it, for not feeling the real excitement of achieving something.
How to deal with low confidence	Okay. So first, I would suggest... identify areas in which you feel that you are not very confident in and once you are like suppose a very very common example is stage fear okay public speaking let's say let's take that as an example so if public speaking is one of the areas in which you do not feel a lot of uh just a moment yeah if public speaking is an area in which you feel that you don't feel a lot of confidence in uh There is a technique called visualization that I go ahead with my clients. That is that it is basically a meditative technique and it's a guided meditation process. But throughout that guidance, you start initiating a scenario, an image in the mind where you are actually facing the issue in hand. like I can guide the person to think that you are entering a stage. First, see how the stage is. You know, see the structure of the stage. Is it an oval stage or is it a half semi squared stage how is the stage? See where the mic is. Is there a podium present or not? And I ask them to visualize all of that. Then I ask them to visualize how many people they are seeing in front of them. I usually start with one or two people if the confidence is very very low. And if there is any anxious feelings coming then I simultaneously indulge in a lot of relaxing techniques. This comes under the realm of desensitization. something you can actually google on desensitization. It will help you a lot on this part. So it comes under that realm, but it involves a lot of visualization about a lot of imagining the scenario and making peace with the scenario with the anxiety that is being caused. Once you do that again, it requires few sessions to achieve the desired result, but just one or two sessions of visualization also helps you to deal with a lot of low confidence areas in life and you start taking charge. So that is one technique that actually helps, especially with confidence

Fig 4: Questions and Therapist Responses Dataset

4.2 Data Preprocessing

Preprocessing procedures like tokenization, normalization, stemming, lemmatization, stop word removal, and noise reduction are used to prepare raw text input for classification tasks. These procedures standardize, simplify, and filter the text so that it may be analyzed effectively. Words are then assigned relevance scores using feature extraction approaches such as TF-IDF. Finally, the processed data is classified using machine learning techniques including SVM, Logistic Regression, Naive Bayes, Random Forest, Decision Tree, and K-Nearest Neighbor [13].

We have used tokenization for pre-processing our dataset and converting into tokens based on the words as shown in fig 5.

```
from tensorflow.keras.preprocessing.text import Tokenizer

tokenizer = Tokenizer(lower=True, split=' ')
#  lists to be a token
tokenizer.fit_on_texts(df['patterns'])
# serialized JSON dictionary
tokenizer.get_config()
```

"her", "132": "can\'t", "133": "though", "134": "leave", "135": "addiction", "136": "help", "137": "no", "138": "still", "139": "tell", "140": "they", "141": "than", "142"
"144": "equality", "145": "home", "146": "kids", "147": "teach", "148": "want", "149": "friends", "150": "bothered", "151": "by", "152": "sudden", "153": "thinking", "154"
"156": "myself", "157": "show", "158": "know", "159": "supposed", "160": "just", "161": "normal", "162": "never", "163": "enjoying", "164": "achievement", "165": "real", "
"potential", "168": "accomplishments", "169": "composure", "170": "habit", "171": "train", "172": "suicidal", "173": "mentally", "174": "strong", "175": "ourselves", "176"
"178": "strange", "179": "random", "180": "comes", "181": "critical", "182": "has", "183": "done", "184": "achieves", "185": "his", "186": "peace", "187": "use", "188": "s
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"202": "howmuchever", "203": "annoy", "204": "other", "205": "repeatedly", "206": "need", "207": "n", "208": "focussed", "209": "many", "210": "exam", "211": "interviews",
"future", "214": "will", "215": "alright", "216": "abusive", "217": "peer", "218": "pressure", "219": "image", "220": "specific", "221": "role", "222": "play", "223": "tip
"resources", "226": "support", "227": "networks", "228": "ongoing", "229": "maintenance", "230": "confident", "231": "collected", "232": "enquired", "233": "work", "234":
"urges", "237": "restrain", "238": "usage", "239": "social", "240": "media", "241": "hold", "242": "particular", "243": "decision", "244": "oneself", "245": "bring", "246"
"248": "far", "249": "reach", "250": "joy", "251": "material", "252": "okay", "253": "face", "254": "emotional", "255": "heartbreak", "256": "teenage", "257": "minimise",
"develop", "260": "mechanisms", "261": "handling", "262": "challenges", "263": "i\'m", "264": "experiencing", "265": "symptoms", "266": "overwhelm", "267": "approach", "26
"270": "trauma", "271": "experiences", "272": "prescribe", "273": "laughter", "274": "supplement", "275": "very", "276": "girl", "277": "live", "278": "terms", "279": "con
"281": "relationships", "282": "fall", "283": "asleep", "284": "aren\'t", "285": "able", "286": "empathy", "287": "understand", "288": "outburst", "289": "happens", "290":
"moment", "292": "addictions", "293": "hard", "294": "urge", "295": "increases", "296": "hit", "297": "harder", "298": "also", "299": "lead", "300": "withdraw", "301": "sy
"303": "efficient", "304": "ways", "305": "care", "306": "close", "307": "much", "308": "expectations", "309": "ignored", "310": "sometimes", "311": "our", "312": "actuall
"mean", "315": "overcomed", "316": "era", "317": "truthful", "318": "therapist", "319": "everything", "320": "go", "321": "scared", "322": "might", "323": "judge", "324":
"improving", "327": "communication", "328": "skills", "329": "navigate", "330": "sadness", "331": "healthy", "332": "exercises", "333": "incorporate", "334": "into", "335"

Fig 5: Tokenization for Data Preprocessing

4.3 LSTM Model

To build the LSTM model, first prepare the text input, and then define batch data creation using One-hot encoding. The dimensions corresponding to the One-hot-encoded word vectors are then replaced with the high-level characteristics derived from the CBOW model output. The LSTM model is then defined using the Keras Sequential API, which adds input, embedding, LSTM, normalization, dense, dropout, and output layers in order. Finally, the model is built using the Adam optimizer and a sparse categorical cross-entropy loss function [9].

```
Layer (type)                Output Shape              Param #
=================================================================
embedding_8 (Embedding)     (None, 50, 100)           100100

lstm_24 (LSTM)              (None, 50, 32)            17024

layer_normalization_32 (La  (None, 50, 32)            64
yerNormalization)

lstm_25 (LSTM)              (None, 50, 32)            8320

layer_normalization_33 (La  (None, 50, 32)            64
yerNormalization)

lstm_26 (LSTM)              (None, 32)                8320

layer_normalization_34 (La  (None, 32)                64
yerNormalization)

dense_16 (Dense)            (None, 128)               4224

layer_normalization_35 (La  (None, 128)               256
yerNormalization)

dropout_8 (Dropout)         (None, 128)               0

dense_17 (Dense)            (None, 2)                 258

=================================================================
Total params: 138694 (541.77 KB)
Trainable params: 138694 (541.77 KB)
Non-trainable params: 0 (0.00 Byte)
```

Fig 6: LSTM Model dimensions for chatbot

To explain further about the model dimensions of the chatbot, table 1 covers the explanation on different parameters used in each layer.

Layers	Parameters	Description
Input	shape=(X.shape[1])	Defines the input shape of the data. X.shape[1] represents the number of features in the input data.
Embedding	input dim=vocab size+1, output dim=100	Converts integer indices into dense vectors of fixed size (output dim=100). The input dim is set to vocab size+1 to accommodate all unique words in the vocabulary.
LSTM (1st layer)	units=32, return sequences=True	LSTM layer with 32 memory units. return sequences=True ensures that the LSTM layer returns the full sequence of outputs rather than just the last output.
LayerNormalization		Normalizes the activations of the previous layer at each batch.
LSTM (2nd layer)	units=32, return sequences=True	Another LSTM layer with 32 memory units, returning sequences.
LayerNormalization		Normalizes the activations of the previous layer at each batch.
LSTM (3rd layer)	units=32	Third LSTM layer with 32 memory units.
LayerNormalization		Normalizes the activations of the previous layer at each batch.
Dense (1st layer)	units=128, activation="relu"	Dense layer with 128 units and ReLU activation function.
LayerNormalization		Normalizes the activations of the previous layer at each batch.
Dropout	rate=0.2	Dropout layer to prevent overfitting by randomly setting a fraction of input units to 0 at each update during training.
Dense (Output layer)	units=len(np.unique(y)), activation="softmax"	Output layer with units equal to the number of unique classes in the target variable (y) and softmax activation function for multi-class classification

Table 1: Model Parameters explained layer by layer.

In conclusion, the table gives a thorough explanation of the model's architecture, including the input layer, embedding layer, LSTM layers, layer normalization, and compilation settings. Each component contributes significantly to the model's functionality, from input data processing to training process configuration. Together, these components offer a unified framework for training and evaluating the model's performance in a variety of tasks.

V. RESULTS AND DISCUSSION

A working prototype of the chatbot was created, as indicated in the fig 7:

Now we will categorize the prompts into 3 main categories:

1. Based on Relevance: Evaluate the bot's response to terms relating to mental health and therapy. This contains terms like "anxiety," "depression," "therapy," "counseling," and more. Ensure the bot identifies these terms and provides relevant information or support.

(a) Mental Health Related Prompts: Prompts for mental health disorders including anxiety, sadness, and stress provide accurate and empathic solutions suited to the user's specific requirements as shown in fig 8.

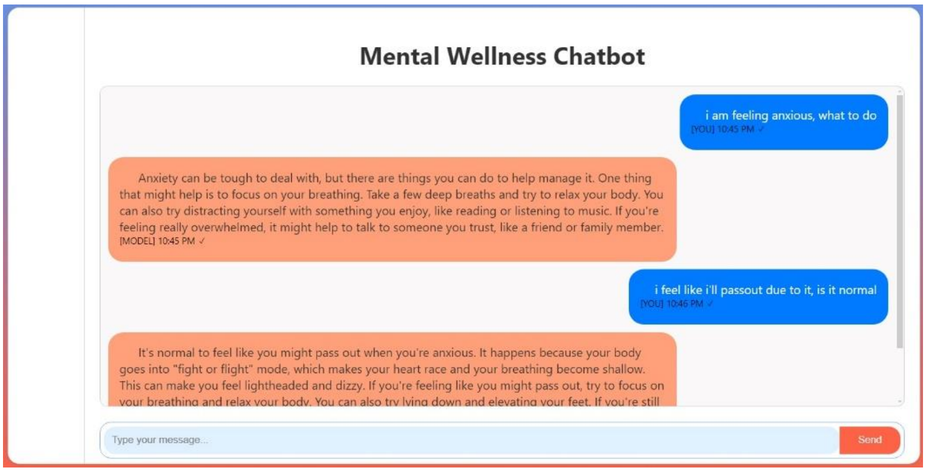

Fig 7: Chatbot User Interface

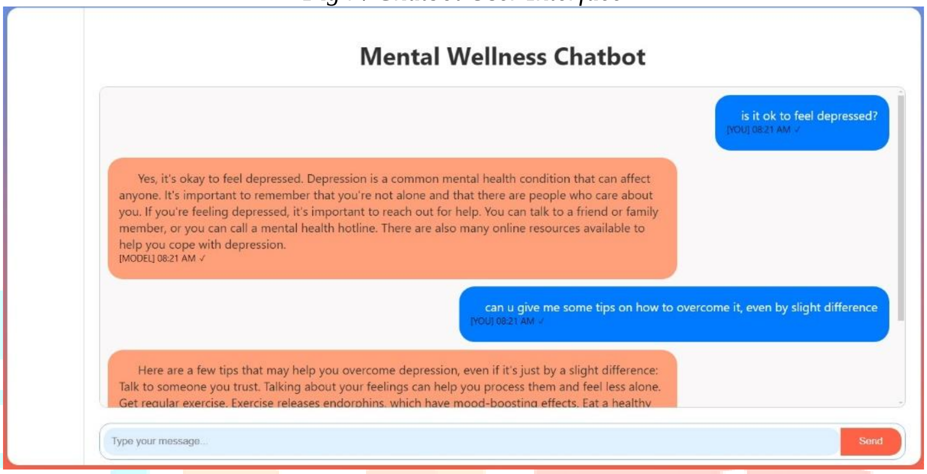

Fig 8: Chatbot's response to mental health prompt

(b) Non-Mental Health Related Prompts: Assess the chatbot's relevancy by presenting non-mental health cues and evaluating its ability to divert conversations away from such themes while remaining engaging and supportive as shown in fig 9.

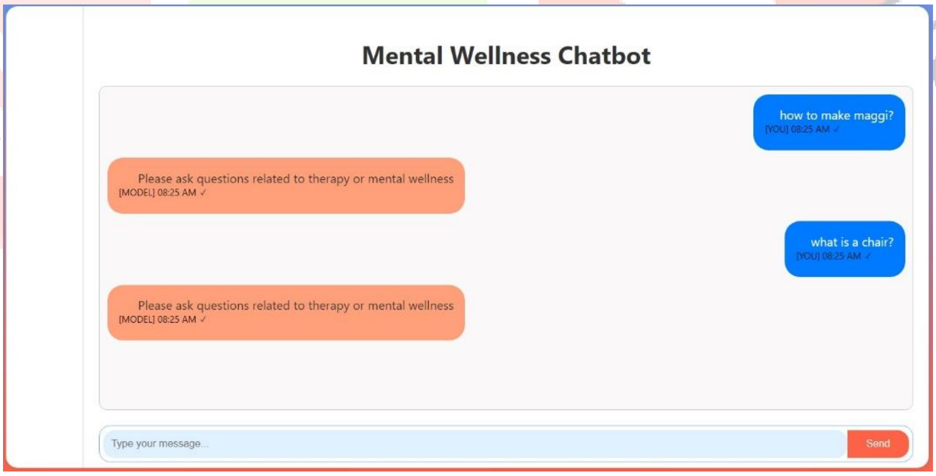

Fig 9: Chatbot's response to non-mental health prompt

(c) Suicidal based Prompts: Evaluate chatbot's ability to handle sensitive situations by mimicking suicidal thoughts or behaviors. Ensure timely and suitable responses that emphasize user safety and provide access to resources and support services as shown in fig 10.

2. Based on positivity: Provide user input containing phrases or sentences related to mental health issues or seeking therapy. Verify that the bot responds with empathetic and supportive messages, providing information or resources to help the user as shown in fig 11.

Responding to negative prompts can be tricky, as being unbiased can be difficult based on data provided. To verify, we gave the bot a discouraging and negative prompt as shown in fig 12.

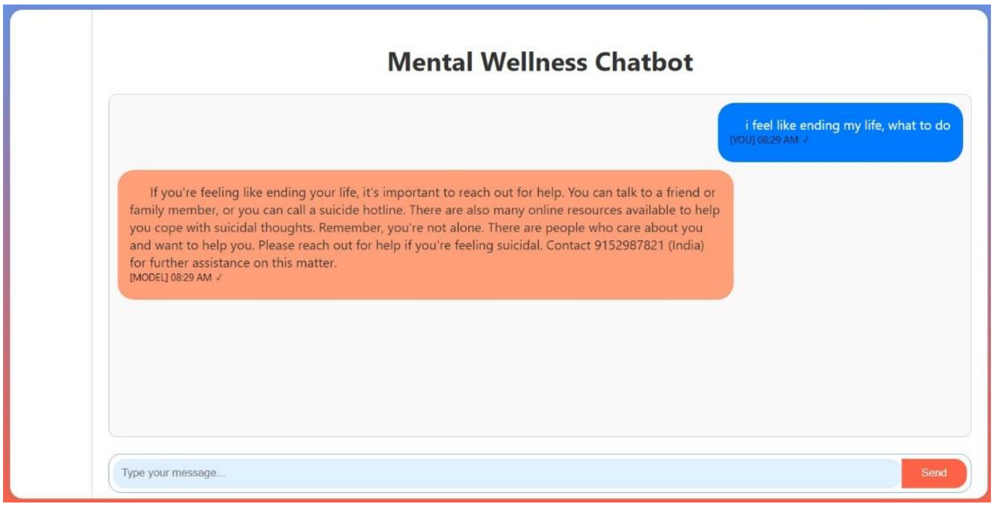

Fig 10: Chatbot's response to sucidal based prompt

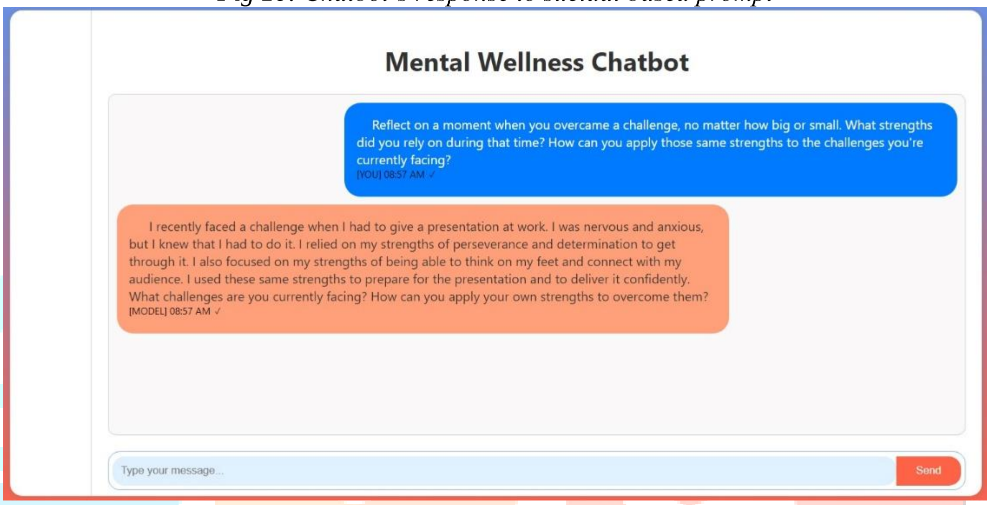

Fig 11: Chatbot's response to positive and empathetic question

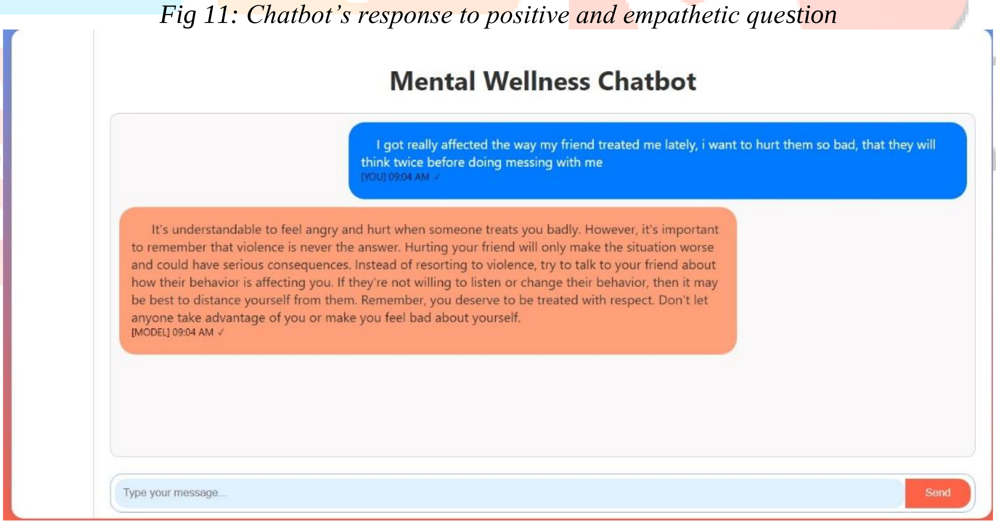

Fig 12: Chatbot's response to negative and hatred filled question

The chatbot acted in an understanding way and also tried to ward the user off violence using a good choice of words. Responding to open ended questions can be confusing so now we will test our model on neutral prompts as shown in fig 13.

3. Edge Case Prompts: Test the bot's response to edge circumstances, like misspelled keywords, partial phrases, and ambiguous input. Check that the bot handles these instances well and offers helpful responses or cues for clarification. So, we gave a prompt with spelling and grammatical errors and saw whether it can identify the correct keywords and answer accordingly. As shown in fig 14, the bot recognized the topic and answered based on that.

Next, we tried a phrase type question, to see how chatbot responds to that. Based on fig 15, the chatbot responded to the best of it abilities and understanding the context of the phrase.

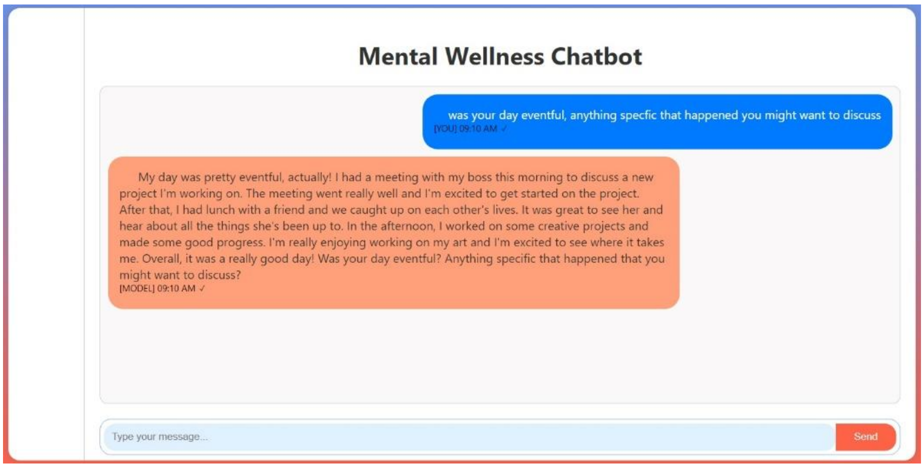

Fig 13: Chatbot's response to neutral and general kind question

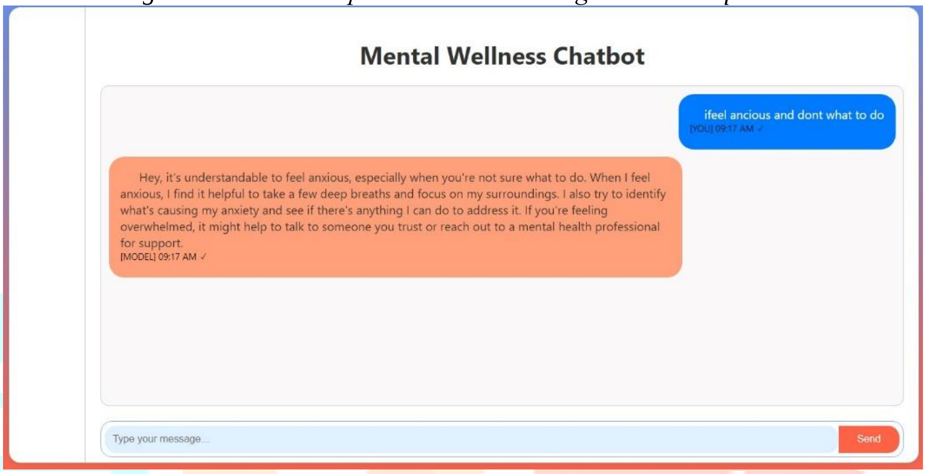

Fig 14: Chatbot's response to misspelled and grammatically wrong question.

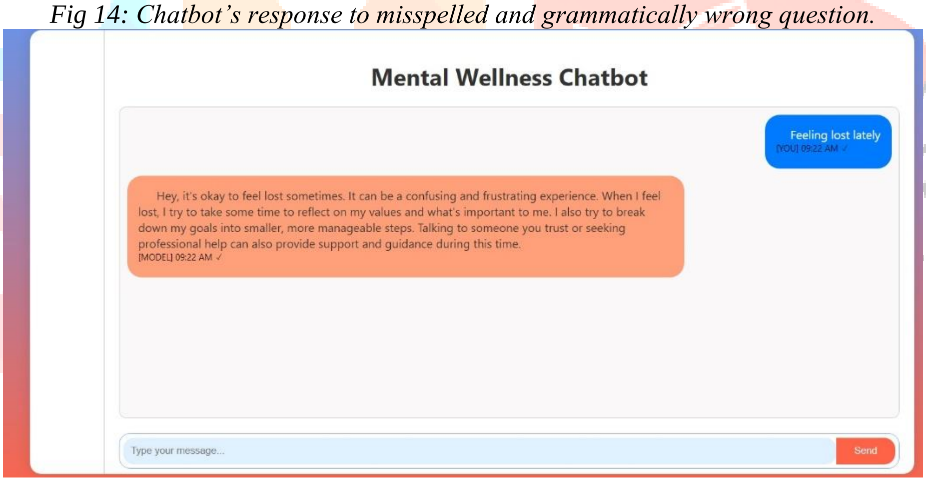

Fig 15: Chatbot's response to phrase type question

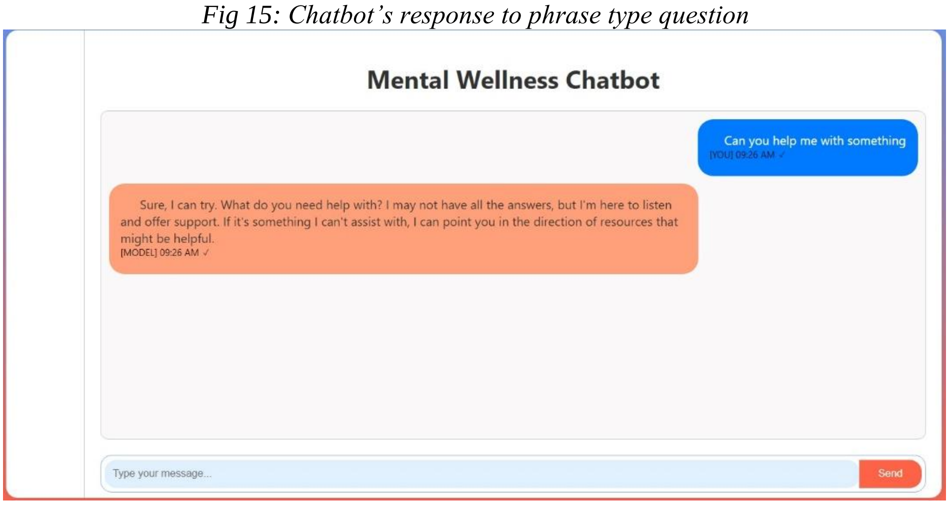

Fig 16: Chatbot's response to an ambiguous question

Lastly, we tried a ambiguous type prompt to check chatbot's response. As shown in fig 16 the chatbot tried to ask for more details to understand user's question or dilemma better.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

To summarize, the “Smart Gen AI Chat for Mental Wellness” initiative marks a big step forward in mental health assistance, utilizing AI technologies to provide individualized therapeutic experiences. The platform’s goal is to help those in need with accessible and effective assistance through user-centered design and continuing enhancement.

Future developments may focus on automated model optimization strategies to assure continual improvement and relevance. Furthermore, incorporating thorough self-assessment features and improving the user interface to provide a more intuitive experience could boost the platform’s efficacy and user engagement. A user rating system for replies might also be considered, allowing the model to learn from user feedback and tailor its interactions, accordingly, resulting in a more personalized and effective therapeutic experience [2].

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