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AI Powered Chatbot For Mental Health Treatment

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***Abstract*—In the recent days, most people of all ages have their mental health affected by various factors like stress, anxiety, depression, fear, phobia and trauma. Hence it is mandatory for people to take care of their mental health. People may hesitate to approach therapists in real life due to societal stigmas. As many people are unable to access or afford mental health services, our research work aims at developing a SAAC Mental health chatbot to mimic a therapist to provide personalized support and guidance, learn about an individual's unique needs and preferences, and tailor their responses accordingly with 24/7 support by handling speech and text queries. SAAC chatbot also maintains chat history and notifies users by sending alerts to ensure follow-ups.**

***Index Terms*—Anxiety, Chatbot, Depression, Fear, Mental Health, Phobia, Speech, Therapist, Trauma**

I. Introduction

This section gives introduction about mental health, cognitive behavioral therapy and need for chatbots to assess mental health. In recent years, the meeting point of technology and mental health therapy has resulted in a seismic change in how people receive resources and help for their well-being.

A. Mental Health

Mental health includes a person's mental, social, and emotional health. It involves the way individuals think, feel, and act in various situations, in addition to how they deal with pressure and connect with others. Good mental health is essential for a good standard of life, since it determines how people deal with barriers, make decisions, and keep up connections. This changes over time and is impacted by genetics, environment, and personal experiences. Prioritising mental health involves acknowledging and managing one's emotions, getting help when required, and taking part in self-care practices to sustain emotional resilience and mental health. the most common types of mental health disorders include Anxiety disorders, Attention-deficit/hyperactivity disorder (ADHD), Autism spectrum disorder, Depression, bipolar disorder and other mood disorders, Disruptive behavior disorders, such as oppositional defiant disorder and conduct disorder, Eating disorders, Obsessive-compulsive disorder (OCD), Personality disorders, including borderline personality disorder and antisocial personality disorder, Post-traumatic stress disorder (PTSD), Schizophrenia and other psychotic disorders, and substance use disorders including drug addiction and alcohol.

B. Research Challenges

Our SAAC chatbot is designed considering the following factors namely Real Time Environment, Tailored Response, Accuracy and Privacy and confidentiality.

1) In real-time circumstances, mental health chatbots experience several challenges that have a direct impact on the efficacy of their product or service. One such difficulty is speed of response, in which users believe quick responses to their queries. Delays in responding can cause irritation and potentially aggravate the user's discomfort. As a result, chatbots must be properly set to ensure quick and flawless interactions, even during periods of high demand or system pressure.

2) Tailored Response - The constantly evolving nature of human emotions and mental health issues makes it difficult to predict customer requirements and tastes throughout time. Furthermore, successfully personalizing replies necessitates a thorough awareness of cultural differences and variations among people. Chatbots must carefully handle these cultural sensitivities to avoid causing offense or confusion.

3) Accuracy - Chatbots must provide reliable data as well as suggestions to users requesting mental health support.

4) Privacy and confidentiality - Safeguarding user confidentiality and privacy is critical in mental health services.

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II. Related Work

This section discusses about the existing mental health chatbots and research work addressing various mental health issues. Wysa [10] is a conversational AI chatbot designed to create an anonymous, safe space to work through worries and stressors, preventing them from escalating in severity and towards illness, thereby providing mental health support. Youper [11] chatbot, designed to help maintain mental health and mental wellness, allows individuals to express their feelings, ideas, and worries in a setting that is safe and free of judgement. Talkspace [12] allows users to communicate with licensed therapists via text, audio, or video. With the use of this platform, people may quickly and easily get assistance with their mental health from the convenience of their own homes. Ginger [13] app uses automation and artificial intelligence to enhance the overall user experience to ensure personalised therapy, the platform links users with providers based on their specific needs and preferences using AI-driven algorithms. 7 cups of Tea [14] chat-based connections in which users can securely and cost-free sign up with trained listeners who provide respectful guidance and compassion.Woebot [15] Health provides mental health guidance and emotional wellbeing, which has its foundations in cognitive behavioural therapy (CBT), provides users with scientifically proven therapies and approaches to help them deal with mental health concerns like depression, anxiety, stress, and other mental health issues.

[1] presented their work on suicidal ideation detection holds great potential for improving mental health support systems. [2] implemented an AI-powered mental health chatbot, which marks a significant milestone in the realm of psychological support, particularly for individuals grappling with depression.The chatbot's conversational engine, fuelled by AIML, enables seamless interactions, understanding user inputs, and delivering contextually appropriate responses. [3] makes use of the integration of Artificial Intelligence technology into mental health services has emerged as a promising way to improve the quality and accessibility of mental health services. In the field of analysis, Artificial Intelligence techniques like Natural Language Processing and Machine Learning algorithms have shown great potential for the analysis of big data such as electronic medical records (EMRs) and social media posts. Use of NLP in psychotherapy and compare the responses provided by chatbots to a set of predefined user inputs related to well-being and mental health queries and compare existing systems [4].

At the heart of Saarthi is a chatbot, which uses advanced AI algorithms to provide personalized and empathetic support to patients. The chatbot is trained in various therapeutic techniques, and can help patients manage their symptoms, improve their wellbeing, and access the resources they need to live a fulfilling life [5]. In recent years, there has been a proliferation of works on human action classification from depth sequences. These works generally present methods and/or feature representations for the classification of actions from sequences of 3D locations of human body joints and/or other sources of data, such as depth maps and RGB videos [6]. Automating the vaccine counseling session, with conversational agents, may provide a method for standardizing and formalizing dialogue with health consumers, and provide an efficient means to communicate health information that could improve patient satisfaction and patient health literacy [7]. [8] determine the prevalence and nature of the harm that could result from patients or consumers using conversational assistants for medical information

III. Methodology

Figure 1 shows the architecture diagram of SAAC chatbot leveraging natural language processing and deep neural networks to enhance the quality of life of human, constituting three components namely User Interface, Sequential Model and Chat Response.

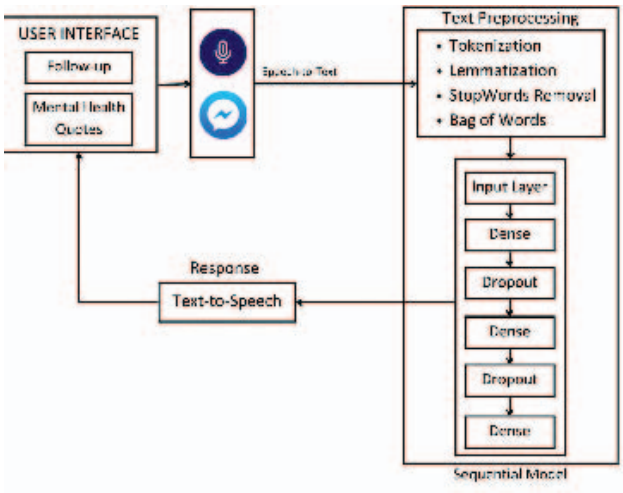

Fig. 1. Architecture Diagram of SAAC Mental Health Chatbot

A. User Interface

User interface is the front-end layer of the chatbot system, providing the platform for users to interact with text and voice-enabled web-based SAAC chatbot. The user interface includes various elements such as buttons, input fields, and chat windows, facilitating different modes of interaction with the chatbot. Additional features like Follow-up and Mental Health Quotes section enhance user engagement and provide value-added services beyond basic conversation.

B. Sequential Model

This component forms the heart of chatbot intelligence. It performs tasks like Input processing and Text processing. SAAC chatbot makes use of Keras sequential deep learning model which serves as the core component responsible

for understanding user input and generating appropriate responses. During the training process, the sequential model learns to identify patterns and relationships between tags-patterns-response relations.

The neural network model was configured using TensorFlow's Sequential API, comprising an input layer with 128 neurons and relu activation, followed by two hidden layers with 128 and 64 neurons respectively, both using relu activation and a dropout rate of 0.5 to prevent overfitting. The output layer was configured with a softmax activation function to handle multi-class classification. The model was compiled using the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.01, momentum of 0.9, and Nesterov momentum enabled. The loss function used was categorical_crossentropy, and the primary evaluation metric was accuracy. Training was conducted over 200 epochs with a batch size of 5.

During training, the dataset was randomly shuffled to ensure a good mix of data. The performance of the model was monitored using accuracy and loss metrics to ensure effective learning. The final trained model was saved for future use. This approach ensured the development of a robust chatbot capable of understanding and responding to various mental health-related queries effectively.

1) Input Processing: Users can input their queries through either speech or text, offering flexibility and convenience in communication. Speech input is facilitated by integrating the Google Speech Recognition and Transcription component, which converts spoken words into text, enabling hands-free interaction with the chatbot. Textual input is directly accepted by the system, allowing users to type their queries using the keyboard.

2) Text Preprocessing: Text preprocessing is crucial for converting the raw input text into a format that can be effectively analysed and understood by machine learning models. Techniques employed in text preprocessing include stopwords removal, tokenization, Lemmatization and Bag of Words representation for intent classification which contains the tags with corresponding patterns and responses. StopWords removal is to eliminate noise and improve the efficiency of subsequent processing steps. Tokenization enables the chatbot to analyze and process the text at a more granular level. Lemmatization improves chatbot's ability to understand and respond semantically to similar queries.

Bag of Words representation converts the text into a numerical representation, often a vector, where each dimension corresponds to a unique word in the vocabulary, enabling machine learning models to process textual data efficiently. The value of each dimension corresponds to the presence or absence of that word in the input text, in this case, the value is binary. These techniques collectively enhance the quality and usability of textual data for various natural language processing tasks. Pickle dump functions are used to store and load NLP components such as tokenizers and lemmatizers, and optimize text preprocessing for efficiency and scalability.

3) Output Processing: After generating the chat response, the chatbot presents to the user in text format directly within the chat window. Additionally, the text output can also be converted into speech using Text-to-Speech (TTS) component, leveraging the Web Speech API. Text-to-Speech enhances user experience by providing an alternative mode of communication, particularly useful for users with visual impairments or those preferring auditory interaction. The user is notified for Follow-ups to have a good mental health well-being. Chat history is also made available to the user, based on which users can analyze their mental state over time.

IV. RESULTS AND DISCUSSION

This section discusses about the various components involved in the development of SAAC mental health chatbot.

A. USER INTERFACE

The chatbot is developed using Vanilla JS cross-platform framework with HTML5 for content structure and CSS3 for styling, ensuring a responsive and visually appealing interface. CSS3 is used to style mental health quotes and chatbot buttons to process text and voice, along with images. Voice is converted to text using Web Speech API. Python packages nltk, tensorflow, and pickle are essential to build SAAC chatbot. The intents are in the tag-patterns-responses format.

All the intents present in the JSON file is loaded into the training sequence. For each pattern in the intent, the words are tokenized using nltk.word_tokenize(). Further, the words are lemmatized using WordNetLemmatizer() function to extract unique value and standardize the words which is put into a list. Another list is made comparing the tags and wordlist and put into a list called documents.

The model is trained by randomly shuffling the word and document list. Sequential model is imported using tf.keras.Sequential() function. The input layer of the model is added to the neural network along with a dense fully connected layer with 128 units/neuron. ReLU activation function is used at the hidden layer and softmax at the output layer. SGD optimizer is used for convergence. The model is compiled and saved as chatbotmodel.keras. The chatbotmodel.keras model is imported for bag of words representation. After the user input is fed into the sequential model, it compares the tags and patterns to generate the relevant chat response. Figure 2 gives information about Home page of SAAC Chatbot where user can get information about mental health.

Fig. 2. SAAC Chatbot Home Page

As a result of SAAC chatbot initialization, the user is presented with a chat interface. The first greeting of the bot is conveyed with the user's name. Now, the user can respond to the bot with their queries in the input box at the bottom of the chat interface. Additionally, the application supports audio inputs or queries from the user. Once the input is registered from the user, the bot generates a meaningful response as shown in Figure 3

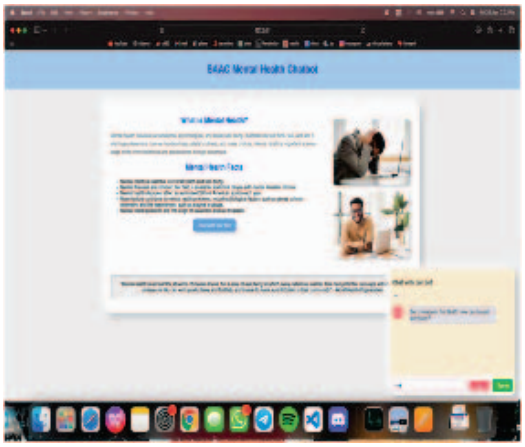

Fig. 3. SAAC Chatbot Initialization

B. CHAT RESPONSE

The text output generated from the model is sent to the user interface where the text is converted into voice using Web Speech API. Scenario of response generation is shown in Figure 4. The user enters a message about his/her concern on being lonely. The bot then asks descriptive questions about the user's feelings. As the user responds further, the bot then decides to comfort the user and shows that it can be a listener or therapist to the user. The bot also motivates the user to open up and let out what's in their minds.

As the user communicates with the bot, the chat history gets automatically saved to a .txt file as shown in Figure 5. This

Fig. 4. Response Generation

application gives importance to data retaining and hence this feature has been implemented. Furthermore, these text files as chat history can be forwarded to mental health therapist for analysis and prescription.

Fig. 5. Chat History

C. USER NOTIFICATION

The application prioritizes the user's general health and hence sends the user, useful reminders. These reminders are supplied whenever the user is prone to be idle. The notification messages are essentially pop-ups, relayed in a scheduled manner as shown in Figure 6.

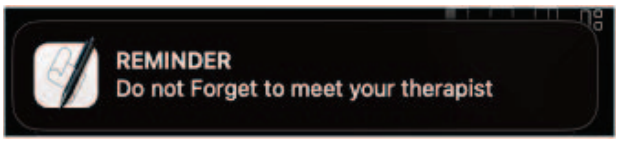

Fig. 6. User Notification

V. CONCLUSION AND FUTURE WORK

The developed AI powered SAAC Mental health chatbot mimics a therapist to provide personalized support and guidance, in an age where people may hesitate to approach therapists in real life due to societal stigmas. The web-based application is designed to learn about the unique needs and preferences of an individual. This extensive work provides conversational records which are further utilised by mental health professionals. Additionally, the application tailors its responses providing 24/7 support with speech as well as text queries. In the near future, chatbot may be extended as a mobile application to behave like a Pocket-Doctor. Chat history can be made more secure using Blockchain technology. Moreover, the chatbot's capabilities can be expanded to include more sophisticated features such as sentiment analysis, predictive analytics, and integration with other health monitoring tools. These enhancements would enable a more comprehensive approach to mental health support, potentially identifying early signs of distress and recommending timely interventions. Through continuous improvement and adaptation, the SAAC Mental Health Chatbot aims to bridge the gap between individuals and mental health services, offering accessible, reliable, and empathetic support.

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