Intellibot: A Personalized Behavioral Analysis Chatbot Framework Powered by GPT-3

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***Abstract*—This paper is focused on helping individuals with autism, paranoid personality disorder (PPD), and other mental illnesses practice and improve their communication skills by offering them a friendly, intelligent, and comfortable environment in them to express their needs and overcome their daily communication struggles by practicing. The research aims to construct a personalized Chatbot based on GPT-3 technology to provide professional help to individuals with psychological issues. We proposed implementing an advanced system that chats with the user, detects their emotion, and replies accordingly; it also sees negative thoughts during user sessions and automatically terminates the session while referring the individual to a professional psychiatrist if needed. The paper discusses the whole process of developing the Chatbot from the preprocessing steps for the training data to an overview of GPT-3 and its capabilities. Our top priority is to guarantee the safety and well-being of our users; therefore, the paper addresses the challenges faced during the development of the Chatbot, including the unintentional encouragement of negative thoughts and how we overcame these challenges by implementing proactive measures. Additionally, the paper describes text classification using RoBERTa, voice classification using the "asapp/sew-d-base-plus-400k-ft-ls100h" model, and a Hidden Markov Model to analyze user emotions and provide appropriate responses. Ultimately, the proposed Chatbot aims to create a friendly and comfortable environment for users while offering professional support, enabling fulfilling connections, and improving their quality of life.**

***Index Terms*—GPT-3, Artificial intelligence, Chatbot, Psychology, Markov model, behavioral analysis.**

I. Introduction

It is hard to imagine experiencing the struggle of communicating one's most basic needs and desires, feeling a sense of isolation and misunderstanding, and encountering challenges in establishing authentic relationships. communication difficulties can be a daily struggle for individuals with autism, paranoid personality disorder (PPD), and other mental illnesses. Usually, individuals who suffer from these disorders have trust issues and cannot deal with the community and people around them as they are always in fear of being betrayed or taken advantage of, especially autistic people because of their sensory sensitivities that can make certain social situations overwhelming for them. They also struggle to form and maintain long-lasting human relationships. The need for mental healthcare services is increasing worldwide. Unfortunately, the shortage of mental health professionals and the association of social stigma with mental illness made it difficult for individuals to access professional help. However, artificial intelligence (AI) is currently involved in technology-facilitating services. AI can boost many learning systems that can automate tasks that humans perform. Most Chatbots rely on experts to continually update their systems [1]. AI Chatbots differ utterly from conventional conversational and messenger chatbots (e.g., Siri). Nevertheless, AI chatbots will argue through a deep understanding of the data provided, miming human-like conversation. AI Chatbots have become a valuable solution to cater to the mental health requirements of individuals. Numerous researchers and scholars have explored this topic; one suggested using virtual reality to discover the crucial social skills of stating social contact, recognizing emotion, and appropriate behaviors. Nine studies that used arbitrary measures and participants' body language were included in the review [2]. Another proposed study by [3]aimed to assist children with autism spectrum disorders (ASD) recognize and express emotions through a serious game. The game design targets the emotion recognition learning cycle and involves a character animation pipeline and facial expression analyzer. The paper's primary goal is to use a new strategy to address the numerous communication difficulties that people may encounter. We have dedicated our efforts to improving conversation abilities by implementing an AI-powered chatbot based on GPT-3 technology. We have focused on providing users with a friendly and comfortable environment while offering professional help if necessary. This personalized communication method can transform these people's lives by creating the conditions for fulfilling connections, a higher standard of living, and more promising futures.

II. Related work

Authors in [4] presented a Chatbot called EMMA, designed to elevate the user's overall well-being by developing the Chatbot to be aware of the user's emotions and consider them in its responses. EMMA utilizes natural language processing and machine learning techniques to understand the user input, detect emotion and generate an empathetic response. The Chatbot's development involved several stages. Firstly, a large dataset of user conversations was collected. Then, they employed a hybrid approach that combined rule-based techniques and machine learning algorithms for emotion detection. The system also utilized sentiment analysis and named entity recognition to enhance the contextual understanding of user messages. The Chatbot responds using predefined rules and machine learning-based techniques. In their work, they used two main evaluation metrics. The first metric was accuracy, which measured the Chatbot's ability to detect user emotions accurately.

The second metric was user satisfaction, determined through a user survey that gauged participants' satisfaction with the Chatbot's responses. The results indicated that EMMA achieved an accuracy rate of 85% in emotion detection, showing its effectiveness in understanding user emotions. The user satisfaction survey revealed that 75% of the users were satisfied with the experience. While Emma showed promising results, the paper acknowledged a few limitations. First, the Chatbot's performance might vary depending on the complexity of user emotions and the accuracy of the emotion detection models. Second, the predefined rules for generating responses could limit the Chatbot's ability to provide personalized and nuanced interactions. Lastly, the study primarily focused on English-speaking users, potentially limiting its applicability to other languages and cultural contexts.

Anzar Abbas et al. [5] presented an observational study that uses smartphones to detect facial and vocal markers of schizophrenia remotely. The researchers used smartphone applications that prompted participants to perform specific tasks and record themselves. The tasks were designed to detect facial and vocal expressions commonly observed in individuals with schizophrenia. The collected data was then analyzed using different algorithms and audio-processing techniques to identify any potential markers of the disorder. The paper employed several evaluation metrics, including specificity, sensitivity, and positive and negative predictive value, which measured the accuracy of smartphone-based assessments in identifying individuals with schizophrenia. The results of the study showed promising findings. The assessments achieved a sensitivity of 80%, demonstrating the ability to identify people who have schizophrenia with accuracy using facial and vocal markers. The specificity approached 90%, implying a high accuracy level in correctly identifying those who do not have schizophrenia. The positive predictive value was 75%, and the negative predictive value was 93%. The paper acknowledged many research limitations. The study sample size was limited, which may impact the findings' generalizability. The study focused solely on detecting accuracy without considering other clinical factors typically used for diagnosing schizophrenia.

Robert Dale et al. [6] provided an overview of the current state of commercial Natural Language Generation (NLG) systems as of 2020. they examined the capabilities and advancements in NLG technology, highlighting its applications across various industries and domains. The researchers conducted a thorough survey of commercial NLG systems available in 2020. They investigated the systems' features, approaches, and underlying methodologies. The researchers conducted a comprehensive survey of commercial NLG systems available in 2020. They analyzed the features, techniques, and underlying methodologies these systems employ. The study involved gathering information from vendors, product documentation, and public demonstrations to gain insights into the current landscape of NLG technology. The study made no explicit reference to any evaluation metrics. Instead, it summarised the features, functions, and application scenarios of various commercial NLG systems. The rating was based on the reported capabilities and developments in the systems surveyed. The research summarised the significant results concerning the business situation of NLG in 2020. It emphasized that NLG systems had advanced significantly and are now widely utilized in finance, e-commerce, and healthcare. According to the findings, commercial NLG systems can produce coherent and contextually relevant natural language output for various tasks, such as report generation, customer service, and content creation. Since the study relied on publicly available information and vendor documentation, biases or incomplete representation of specific NLG systems may exist. The report also did not detail the performance or comparative analysis of the examined NLG systems, which may have limited the depth of the evaluation.

Thuong Le-Tien et al. focused in their paper [7] on describing the development of a Chatbot system designed explicitly for university consultancy purposes. The system employs deep learning techniques to efficiently support users pursuing guidance and information related to universities and educational consultancy. Their proposed system is trained on a large dataset containing relevant information about universities, admission procedures, courses, and other consultancy-related topics. Recurrent neural networks (RNNs), or transformer models, are utilized to understand user queries, generate appropriate responses, and continuously improve the Chatbot's performance over time. The paper defined the evaluation metrics, including user satisfaction measures such as response time and accuracy. The paper discussed potential weaknesses, including training in deep learning models, limitations in the availability or accuracy of the training dataset, and the need for ongoing maintenance and updates to keep the Chatbot system up-to-date with the dynamic nature of university data and consultancy requirements

Maen Alrashdan et al. [8], used data analysis techniques to improve speech recognition in IPAs. They gathered and analyzed many user speech inputs and corresponding IPA responses. The data is processed with automatic speech recognition (ASR), natural language processing (NLP), and machine learning algorithms. The goal is to identify patterns, user preferences, and expectations from the speech data to enhance the IPA's performance. The paper may suggest using specific evaluation metrics to measure the effectiveness of the improved speech recognition system and analyze user expectations. These could include assessing speech recognition accuracy, word error rate (WER), or the system's ability to understand user queries and generate appropriate responses.

User satisfaction can also be evaluated through feedback ratings and surveys. The results highlight improvements in speech recognition accuracy and performance achieved through enhanced data analysis techniques; they also report insights and patterns identified from the user speech data that contribute to a better understanding of user expectations. User satisfaction metrics and feedback ratings may indicate the system's effectiveness in meeting user needs. Some potential limitations or drawbacks of the research include challenges in obtaining a representative and diverse dataset, limitations in the accuracy of speech recognition algorithms, and the need for ongoing updates and improvements to adapt to evolving user expectations.

III. Proposed Work

The main aim of this paper is to construct a clever reactive Chatbot that generates responses according to user behavior And helps individuals with psychological issues such as autism. This section describes the sources and preprocessing procedures for the datasets used for training and evaluation. The training data includes various user interactions, and its quality is improved through labeling and annotation.

A. Pre-processing

To enhance the accuracy of the generated replies, we made sure that the data was preprocessed by the methods below:

- Loading and Concatenating Datasets: The code loads three separate datasets containing GoEmotions data and combines them into one data frame named "df".
- Reshaping the DataFrame.
- Filtering Zero Emotion Scores.
- Removal of unnecessary spaces and null values through regular expressions.
- Converting all text into lowercase.
- Creating User Sequences: we gather data from different user inputs, classify their emotions, and add them to a unique data set personalized for each user to train our model to have more tailored responses.

B. Overview of GPT3

GPT-3, or Generative Pre-trained Transformer 3, is a state-of-the-art language model developed by OpenAI. Released in June 2020, GPT-3 represents a significant advancement in natural language processing and generation. It builds upon the success of its predecessor models, such as GPT-2, and is currently one of the largest and most powerful language models available. GPT-3 uses a deep learning architecture known as the transformer model, which has proven highly effective in various NLP tasks. It is trained unsupervised on a massive corpus of text data from the internet, allowing it to learn patterns, grammar, and context in various topics and writing styles. One of the distinguishing features of GPT-3 is its enormous size, with a staggering 175 billion parameters. This vast number of parameters enables GPT-3 to generate highly coherent and contextually relevant text, often indistinguishable from human-written content. It has been praised for its ability to produce natural language responses, answer questions, complete sentences, write essays, translate languages, and even engage in creative writing. GPT-3 excels in tasks that require understanding and generating human-like text. It has been successfully applied in various domains, including Chatbots, virtual assistants, content generation, language translation, and code generation. Its flexibility and adaptability make it a versatile tool for various applications. However, GPT-3 has limitations. Despite its impressive capabilities, it can sometimes produce incorrect or nonsensical responses. It may also exhibit biases in the training data, requiring careful consideration and mitigation when deploying it in real-world applications. In conclusion, GPT-3 represents a significant advancement in the field of language modeling and has the potential to revolutionize how we interact with natural language interfaces. Its size, flexibility, and ability to generate human-like text make it a powerful tool for various NLP tasks. However, consideration must be given to its limitations and potential biases when utilizing it in practical applications.

C. challenge

While developing a Chatbot that responds to user behavior and emotion, we faced a significant challenge during the experimental phase. We discovered that some of the Chatbot's responses were unintentionally causing negative thoughts in users, which raised concerns about their well-being. To solve this problem, we implemented a solution by limiting the conversation flow. We added a mechanism to identify negative thoughts expressed by users, and if detected, the Chatbot would immediately end the session and offer appropriate resources. These resources include referring the user to a psychiatrist or mental health professional for further support and assistance. Our proactive approach prioritizes the user's safety and mental well-being throughout their interaction with the Chatbot.

D. Text Classification using RoBERTa:

Our proposed Chatbot uses a pre-trained model called IsaacZhy/roberta-large-goemotions to analyze the user emotion from their text input. The dataset we used is the GoEmotions dataset. It is unique in its annotation approach, as it includes a fine-grained labeling schema with 28 emotion categories. These categories cover a comprehensive spectrum of emotions which are (admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise, and neutral). Each text sample in the GoEmotions dataset is labeled with one or more emotion categories, allowing for multi-label emotion classification tasks. The dataset allows one to explore the complexities of emotion expression, as multiple emotions can be present in a single text sample.

TABLE I
COMPARISON OF EMOTION CLASSIFICATION ACCURACY

Classifier	Accuracy (%)
CNN	85.2
SVM	79.6
Decision Tree	71.3
RoBERTa	90.7

We tested various classifiers and found that the RoBERTa classifier performed better than the others, as seen in Table I. To use the model, we first train it and then input user text. The model will then provide the appropriate emotional category. We use the associated context file and feed it to the next stage.

E. voice Classification using asapp/sew-d-base-plus-400k-ft-ls100h model:

The "asapp/sew-d-base-plus-400k-ft-ls100h" pre-trained model uses the SEW-D (Sentiment Emotion Word Disambiguation) architecture, which is a deep learning-based model designed explicitly for analyzing sentiment and emotion in text. The SEW-D model combines word embeddings and contextualized representations to accurately capture the sentiment and emotional information in both vocal and textual data. We input user queries using audio input. The model will then provide the appropriate emotional category. We use the associated context file and feed it to the next stage.

F. Emotion prediction using Hidden Markov model

The code trains a Hidden Markov Model (HMM) on the augmented dataset, a collection of text messages labeled with one or more emotions using the RoBERTa pre-trained model mentioned earlier. The model uses emotions as observations and learns the probabilities of transitioning from one emotion to another as hidden states. After training the model, the code takes an input text, uses a sentiment analysis model to determine the current emotion, and then uses the HMM to predict the next emotion. The HMM uses the current emotion as an input and outputs the probabilities of transitioning to each of the other emotions as hidden states. The most probable next emotion is then selected based on these probabilities.

G. Answering questions using GPT3

Generative Pre-trained Transformer (GPT) is a powerful tool for implementing chatbot systems and answering user questions. GPT is highly skilled in generating coherent and relevant responses to user queries due to its ability to comprehend natural language. GPT is pre-trained on massive amounts of text data, which enables it to learn complex patterns and semantic relationships, allowing it to understand the subtleties of user queries. Consequently, GPT is valuable in developing Chatbots that engage in meaningful conversations and provide informative answers. GPT is a versatile tool that adapts to different domains and languages, making it helpful in building Chatbots for various applications, such as customer support and virtual assistants. By utilizing GPT's language generation capabilities, Chatbots can deliver accurate and human-like responses to questions, enhancing the user experience and improving the overall effectiveness and usability of the Chatbot system.

IV. WORK MODEL

A. System Overview

Our proposed framework, as described in Fig.1, involves the following system overview: The user interacts with the user interface (UI) by providing input through either speech or text. In the case of speech input, the system converts it into text using a speech-to-text conversion module since the framework solely operates on text data. The Chatbot manager receives the text input and the extracted emotion from the user's text and stores this information in a database. The Chatbot manager retrieves relevant data from the database if any previous user data exists.

The Chatbot manager processes the user's input and generates appropriate responses based on the stored knowledge and learned behaviors. The feedback from the Chatbot is then sent to the dialogue analysis component, which analyzes the overall interaction and generates a weekly analysis report. The report is presented to the user through a dashboard, providing valuable insights and feedback on their conversations with the Chatbot. Additionally, if the user's input was originally in speech format, the text response from the Chatbot can be converted back to speech, creating a seamless conversational experience. Our reactive system caters to the needs of both individuals and commercial organizations. It benefits individuals by assisting them in staying organized, completing daily tasks, and promoting psychological well-being while preventing feelings of loneliness. Furthermore, the system offers various entertainment possibilities, enhancing the user experience. This framework also holds the potential for commercial organizations to enhance customer support, provide personalized assistance, and improve overall user satisfaction.

B. GPT-3 Model architecture

The architecture of GPT-3 consists of multiple layers of self-attention and feed-forward neural networks. It is a deep, autoregressive model that predicts the next word in a sequence

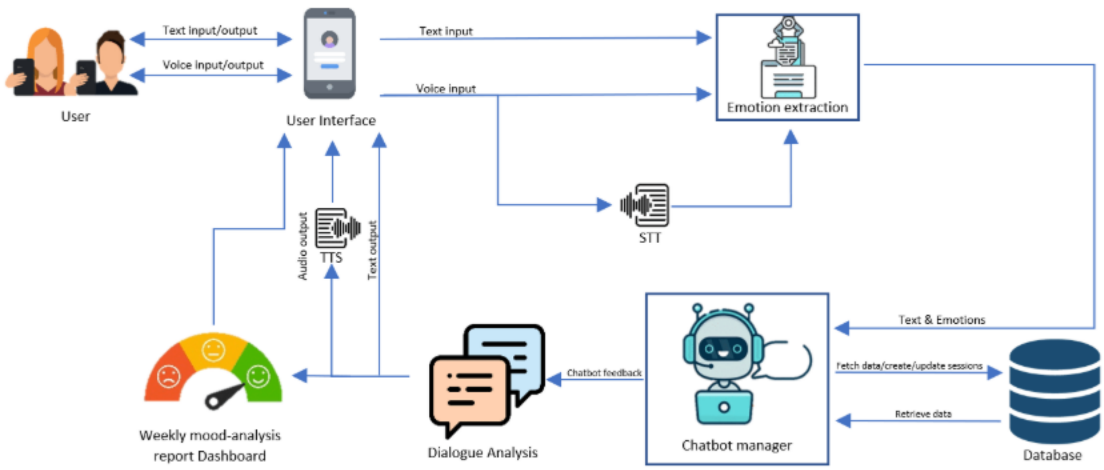

Fig. 1. System Overview

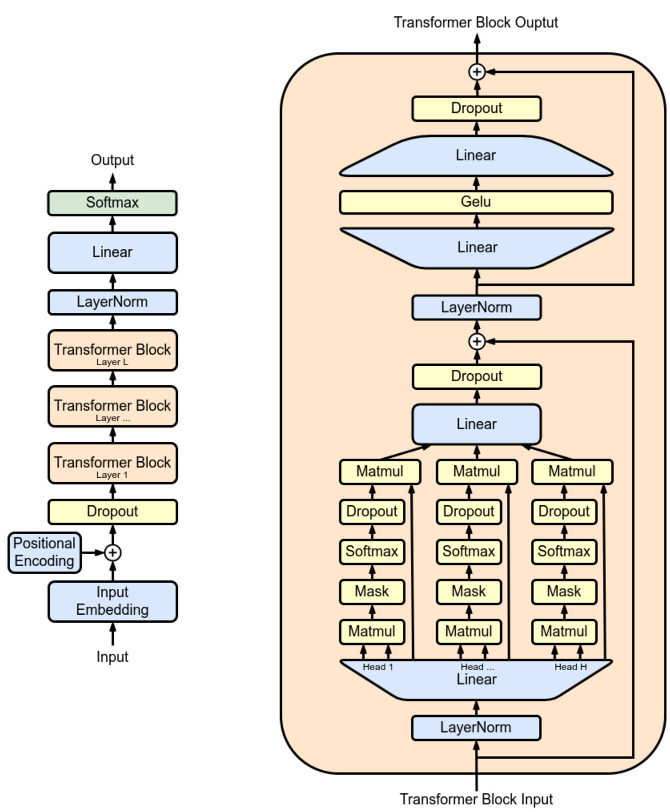

Fig. 2. GPT-3 Model Architecture [9]

based on the previous words. The model is trained on a massive amount of text data from the internet, allowing it to learn a language's patterns, grammar, context, and semantics. GPT-3 has a staggering number of parameters, with up to 175 billion in its most giant version. This extensive size enables it to capture and generate complex language patterns accurately. The model can process input sequences and generate coherent and contextually appropriate responses.

CONCLUSION AND FUTURE WORK

This article discusses individuals' difficulties with autism, paranoid personality disorder (PPD), and other mental illnesses when expressing their needs and building relationships. It emphasizes the growing need for mental healthcare services and suggests that AI chatbots could be a potential solution to these challenges. The paper explores using AI chatbots to provide mental health support, making it more accessible and removing barriers to care. It also introduces a smart reactive Chatbot that uses behavior modeling approaches to provide tailored responses based on user behavior. The Chatbot can understand and respond to user inputs contextually appropriately, resulting in a more personalized and engaging conversational experience. The evaluation shows that the intelligent reactive Chatbot successfully adapts its responses based on user behavior, dynamically modifying its responses to align with user preferences; this ultimately leads to a more efficient and effective mental health support system.

However, there are various opportunities for further developing the capabilities of the intelligent reactive Chatbot:

- Enhanced Behavior Modeling: We can enhance our comprehension and forecasting of user behavior by delving into more advanced behavior modeling techniques. Exploring reinforcement learning or deep learning approaches is beneficial, as they allow the Chatbot to learn and adapt to user interactions more intricately.
- User-Centric Evaluation: To improve the performance of the intelligent reactive Chatbot, it is essential to conduct user studies and collect feedback from real users; This will provide valuable insights into the effectiveness of the Chatbot and the level of user satisfaction. The Chatbot's performance can be enhanced by incorporating user preferences into the response generation process and analyzing user feedback.
- Handling Ambiguity and Uncertainty: Dealing with unclear user inputs and vague contexts is still tricky. To provide more accurate responses, we need to make some improvements. Developing methods to handle and clarify ambiguous queries and incorporating techniques for estimating and managing uncertainty is essential.
- Scaling and Generalization: To improve the Chatbot, it is essential to expand its abilities to handle a broader range of topics, languages, and cultures. To achieve this, we can explore transfer learning and domain adaptation techniques, which can help the Chatbot become more adaptable and responsive.
- Ethical Considerations: It is crucial to continually assess and address ethical considerations related to privacy, fairness, and bias in chatbot interactions. Creating transparent and accountable decision-making mechanisms is essential to ensure responsible deployment and use of the intelligent reactive Chatbot.

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