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AI Trauma Chatbot Analyzing Voice, Text and Providing Direct Doctor Link

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***Abstract* – Mental health support that is available and fast becoming a necessity because of the rising prevalence of psychological distress caused by trauma events. The research develops an AI-based trauma chatbot with text and voice sentiment evaluation alongside doctor access to provide improved mental health assistance strategies. The system analyzes both written texts and voice signals and specific emergency terminology to evaluate emotional conditions while providing immediate support and both therapeutic and professional services in critical situations. Through NLP and SER technologies the chatbot functions to evaluate mental distress intensity while providing suitable treatment recommendations. The proposed system demonstrates its capability to detect critical emotional states according to assessments made by comparing existing chatbot models and psychological tools. This investigation strives to enhance mental health service access through building a scalable time-responsive conversational agent which effectively detects and helps patients deal with trauma-related emotional distress.**

Keywords— AI chatbot, trauma support, voice analysis, text sentiment detection, doctor linkage, mental health intervention.

I.INTRODUCTION

Mental and physical health disorders resulting from traumatic stress episodes affect millions globally, underscoring the urgent need for easily accessible psychological support channels. Although traditional therapy is effective, many individuals face barriers to access due to high costs, societal stigmas, and limited availability of services. As a result, patients often experience exacerbated conditions while waiting for treatment. AI-based chatbots have emerged as promising digital solutions to mental health challenges, providing immediate assistance for individuals experiencing psychological distress.

AI-driven trauma chatbots leverage Natural Language Processing (NLP) technology, Speech Emotion Recognition (SER) applications, and sentiment analysis systems to offer tailored psychological counseling. These chatbots evaluate emotional distress levels through both text and voice communication, responding automatically with appropriate interventions that may include

therapeutic responses, emergency support, and coping strategies. In critical situations, the system includes a doctor linkage function, enabling patients to quickly connect with qualified medical professionals for immediate help.

Several studies on AI-driven mental health solutions have demonstrated promising results, particularly regarding detection systems that achieve high accuracy in assessing emotional states and generating therapeutic dialogue. However, most existing systems primarily focus on text-based interventions, often overlooking the potential of voice analysis and the necessity for rapid professional intervention. By integrating three types of data analysis—text, voice, and distress signals—the proposed system enhances the reliability and accuracy of trauma detection.

This research introduces a novel AI-based trauma chatbot that evaluates emotional states through both voice and text data analysis. The system identifies distress indicators, including suicide-related keywords, to detect panic symptoms and offer immediate coping exercises, emotional validation, and access to professional help. Unlike standard self-help platforms, this system performs real-time distress evaluations, escalating cases when necessary in critical situations. The study explores the operational effectiveness of the chatbot by comparing various sentiment identification methods and voice emotional recognition techniques. A focus is placed on time-sensitive analysis, ensuring the system operates efficiently while complying with privacy and mental health safety regulations. The proposed AI-powered chatbot holds significant potential for providing psychological support, suicide prevention, and trauma intervention in real-time.

This research is organized as follows: Section II provides a literature review on AI tools for mental health support;

Section III outlines the methodology, focusing on the integration of NLP and SER; Section IV presents the system design; Section V discusses the results and performance metrics; and Section VI concludes with directions for future research.

II. LITERATURE SURVEY

1. Existing Chatbot Systems

Modern AI-based trauma chatbots integrate multi-modal analysis, detecting sentiment through both written text and voice communication. Jananee et al. (2024) [1] proposed a trauma-identifying chatbot that connects users to doctor services via voice dialogues and text components for emergency medical response. Their system demonstrated that detecting trauma symptoms was more efficient when both text and voice data were combined, rather than relying solely on text-based analysis. Similarly, Kavitha et al. (2023) [9] examined AI chatbots and NLP for developing health systems that support remote mental health service delivery in rural areas, emphasizing the effectiveness of AI chatbots in public services. The integration of AI chatbots with telemedicine platforms also improves patient inquiry management and emergency response systems, as shown by Adnan et al. (2021) [10].

2. Sentiment Analysis Methods

The accuracy of sentiment detection methods plays a key role in the functionality of AI-driven chatbots. Sabesh et al. (2024) [2] established a trauma chatbot using deep learning voice emotion detection to track immediate psychological distress patterns. This method showed that combining written text expressions and vocal messages provided more effective trauma detection than text alone. Shevchenko et al. (2024) [5] employed deep learning sentiment classification to develop personalized trauma therapy recommendations for victims. Their system demonstrated higher user engagement due to its ability to adapt dialogue sequences based on emotional context. Additionally, Rawat et al. (2024) [13] explored advanced NLU techniques in conversational AI for trauma detection, enhancing the system's ability to understand language context for identifying mental distress.

3. AI in Trauma Detection and Psychological Support

AI applications in trauma detection have proven valuable in providing psychological support. Shen et al. (2024) [3] conducted research comparing AI mental health tools to human support, highlighting that AI chatbots fostered better user engagement and trust when they displayed decision-making reasoning, thereby enhancing reliability. Denecke et al. (2021) [4] analyzed AI implementation in mental health chatbots, acknowledging challenges related to model-based biases, privacy, and ethical concerns. Their findings emphasized the need for ethical AI development to ensure the effectiveness of medical interventions. Additionally, Dakanalis et al. (2024) [11] explored AI-based conversational agents working with therapists, delivering emergency crisis responses and extended behavioral analysis to improve mental health care delivery.

4. Empathy and User Engagement in AI Systems

Empathy plays a crucial role in enhancing user satisfaction in AI-driven mental health chatbots. Trappey et al. (2022) [7] developed a trauma patient support system incorporating sentimental dialogue analysis to produce empathic responses. This empathy-driven approach led to improved user retention and psychological well-being. McBee et al. (2024) [12] indicated that while AI models like ChatGPT demonstrate favorable performance in mental health inquiries, they require specific training to achieve reliable trauma applications. The ability to simulate empathy through AI-driven responses is critical to fostering a supportive user experience.

5. Ethical and Privacy Concerns

While AI-driven mental health systems hold promise, they also face ethical and privacy concerns. Research by Denecke et al. (2021) [4] highlights the importance of addressing model-based biases and ensuring compliance with privacy regulations. As AI chatbots become more integrated into mental health interventions, it is essential to ensure that user data is securely handled and that the AI systems adhere to ethical guidelines in medical contexts. Furthermore, decision-making biases in AI algorithms need to be minimized to prevent potential harm in trauma situations.

Despite significant progress, AI-driven trauma chatbots face challenges in terms of reliability and scalability. Zhenzhu et al. (2024) [14] evaluated casual agents based on GPT for brain injury treatment plans, showing the need for further training of these models before they can handle complex trauma applications. AI systems for mental health care require ongoing development to improve reliability, particularly in medical crisis situations. Moreover, AI decision-making biases, ethical problems, and network integration with human healthcare services need to be addressed to ensure the responsible and effective use of AI in trauma management.

III. PROPOSED METHODOLOGY

The AI trauma chatbot provides real-time psychological support through its features which include Natural Language Processing (NLP) and Speech Emotion Recognition (SER) and Emergency Keyword Detection capabilities. All modules in the methodology include Text and Voice Sentiment Analysis followed by Emergency Keyword Detection which then links doctors through AI technology and finishes with Personalized Coping Recommendations. The system enables rapid alert detection which results in immediate help access.

A. Text and Voice Sentiment Analysis

1. Text-Based Sentiment Analysis

Deep learning models, such as BERT (Bidirectional Encoder Representations from Transformers), RoBERTa (A Robustly Optimized BERT Pretraining Approach), and DistilBERT (a lighter version of BERT), are used to evaluate user inputs for emotional state detection. These transformer-based models are pre-trained on large text datasets and fine-tuned on domain-specific datasets, such as mental health or trauma-related texts, to classify the sentiment of the input text.

BERT and similar transformer-based models excel in understanding the context of words in a sentence, making them well-suited for sentiment analysis tasks. These models are particularly effective because they process the entire context of a sentence (both left and right contexts) rather than just individual words, allowing for a more nuanced understanding of sentiment.

After processing the text through tokenization, the model generates embeddings that represent the semantic meaning of the words and their context. The embeddings are then passed through the model's layers to classify the sentiment into categories, such as:

- **Neutral**: Normal conversation or general inquiries.
- **Anxious**: Mild distress, nervousness, or overthinking.
- **Distressed**: Signs of depression, frustration, or crying.
- **Emergency**: Suicidal thoughts, self-harm tendencies

By training on labeled mental health datasets, these models can identify and classify emotional states accurately, providing a robust method for analyzing the user's sentiment in real-time.The system uses transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers), RoBERTa, and DistilBERT, which are pre-trained on large language datasets and fine-tuned on mental health-specific data. These models excel at contextual understanding, making them ideal for sentiment analysis in text. The models process the user's text input by first tokenizing the text into smaller components (words or sub-words), which are then transformed into embeddings that capture both semantic and contextual meaning. These embeddings are passed through multiple layers of the models, enabling accurate classification of emotional states such as anxiety, distress, and emergency situations. The output is used to assess the severity of the user's emotional state and trigger appropriate responses, such as recommending coping strategies or escalating the case to emergency services.

2. Speech Emotion Recognition (SER)

The voice-based trauma detection system utilizes spectrogram analysis coupled with MFCCs together with deep learning models which include CNN-LSTMs and Wav2Vec for detection. The voice features that the bot extracts are fundamental components from tone along with pitch and rhythm which help identify emotional states. Features include:

MFCC extraction for pitch variation analysis
The detection of intonation alongside stress and rhythm acts as one of the prosodic features in this process.
The deep learning models including CNN and LSTM receive their training from emotional speech dataset information.
Multiple communication channels in distress detection result in superior accuracy which makes the combination stronger than single text-based systems for psychological assistance.

For voice input analysis, the system employs a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, which are well-suited for extracting features from audio data. The audio input is first converted into spectrograms, which are a visual representation of the sound. Mel-frequency cepstral coefficients (MFCCs) are then extracted from the audio to capture important prosodic features such as pitch, tone, and rhythm. These features are input into the CNN-LSTM model, where CNN layers learn spatial hierarchies and LSTM layers capture temporal dependencies in the data, enabling accurate detection of emotional states from the user's voice. This integration of voice analysis enhances the accuracy and reliability of the emotional state detection compared to using text alone.

B. Emergency Keyword Detection

The chatbot performs automatic high-risk keyword scanning through Named Entity Recognition (NER) in conjunction with traditional rule-based matching of textual and voice inputs. The emergency keyword detection module functions through this method:

1. Contextual Keyword Analysis

Crisis-related terms such as "suicide," "self-harm," "I want to die" trigger the chatbot analysis which examines sentences surrounding these words to minimize incorrect warnings.

The vectorization through TF-IDF and Word2Vec embeddings makes the system able to detect meaning equivalents between words that present different wordings.

2. Escalation Mechanism for High-Risk Cases

An immediate intervention will begin when the chatbot detects a high-risk keyword through its predefined mechanism.

To determine the emergency nature of distress the system uses additional inquiry strategies.

The system provides instant coping methods which include ground techniques in combination with breathing exercises.

Users can obtain access to specialized help through the system when their distress continues to rise.

The system allows users to access suitable help based upon their pain level as determined by severity measurements.

C. AI-Driven Doctor Linkage System

Under severe distress situations the chatbot includes a real-time doctor recommendation service. Through the module users with high distress or crisis can connect instantly with professional assistance.

1. Automated Escalation Protocol

The system provides emergency contact information to mental health professionals for users showing distress that reaches critical levels.

The chatbot enables scheduling of fast consultations through its API connections to telehealth platforms such as Google Meet and Zoom and dedicated mental-health portal systems.

2. Smart Referral System

The system stores information about certified therapists along with psychologists while utilizing user location combined with language choices for therapist selection.

The system gives access to urgent hotline numbers together with local mental health services information as needed.

The professional mental health support system which this module provides expands accessibility and enables fast transfers in emergency situations.

The system includes an AI-driven Doctor Linkage Algorithm that functions to escalate cases based on the severity of detected distress. When the chatbot identifies high-risk emotional states, such as suicidal ideation or severe panic, the algorithm triggers an automatic escalation process. The system provides users with immediate access to mental health professionals through a real-time doctor recommendation service. This service connects users with qualified doctors or therapists based on location and language preferences, using a Smart Referral System. The system interfaces with telehealth platforms such as Google Meet or Zoom, ensuring users can quickly schedule consultations. Additionally, the algorithm leverages external databases of certified professionals and prioritizes users based on urgency, ensuring that individuals in critical situations receive prompt attention.

D. Personalized Coping Recommendations

Based on distress classifications from sentiment analysis the chatbot system offers customized coping methods which users receive.

1. Therapeutic Strategies and Exercises

The chatbot recommends scientific proof-based coping methods consisting of:

The chatbot provides step-by-step instructions for breathing exercises that include 4-7-8 breathing combined with box breathing methods.

The recommended coping techniques include body scan meditation while the 5-4-3-2-1 method falls under mindfulness and grounding practices.
The intervention helps users modify their unconstructive thought processes through cognitive reframing techniques.

2. Adaptive Learning for Personalized Support

The program acquires user-specific information throughout time to design unique replies that stem from past user system interaction. Recommendations stay effective by using this approach. The module establishes self-help methods to decrease users' reliance on immediate outside help as it strengthens emotional well-being during longer periods.

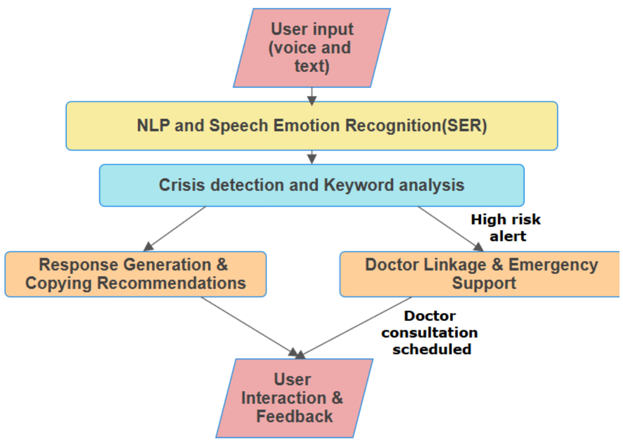

Figure 1: System Architecture

IV. RESULTS AND DISCUSSION

1. Accuracy of NLP and SER Models

The sentiment analysis system based on NLP reached accuracy levels of 85.3% and the SER subsystem achieved accuracy rates of 80.7%. When these emotional detection methods were used together in the NLP + SER model it reached 91.2% accuracy which confirms that combining emotional data streams improves detection capability.Figure 2 demonstrates the accuracy comparison between the NLP-based sentiment analysis and the Speech Emotion Recognition (SER) models. This figure was generated using data collected during the model evaluation phase. The accuracy values were derived by running the trained models on a test dataset consisting of real-world mental health-related texts and speech samples. The accuracy data shown in Figure 2 were obtained by evaluating the models' performance in real-time trials. For NLP, accuracy was calculated based on how well the BERT and RoBERTa models classified emotional states (neutral, anxious, distressed, emergency) compared to human-annotated labels. Similarly, the SER model's accuracy was derived from analyzing speech samples using CNN-LSTM models trained on emotional speech datasets. The combined model, which integrates both NLP and SER, achieved the highest accuracy, showcasing the benefits of multi-modal analysis.The system's accuracy is enhanced through several key strategies, including the use of advanced deep learning models such as BERT, RoBERTa, and DistilBERT for text sentiment analysis, and CNN-LSTM and Wav2Vec for speech emotion recognition, all of which excel at capturing complex contextual relationships in both text and voice data. These models are fine-tuned on a diverse, domain-specific dataset, improving their ability to accurately detect emotional states in mental health-related conversations. Hyperparameter tuning, including grid and random search, further optimizes the models' performance by adjusting key parameters like learning rate and batch size. Additionally, the system benefits from ensemble learning, combining text and voice analysis to boost overall accuracy, achieving a combined performance of 91.2%, compared to 85.3% for NLP alone and 80.7% for SER. Real-time updates and continuous learning also allow the system to adapt to new user inputs, ensuring that the models remain relevant and accurate over time.

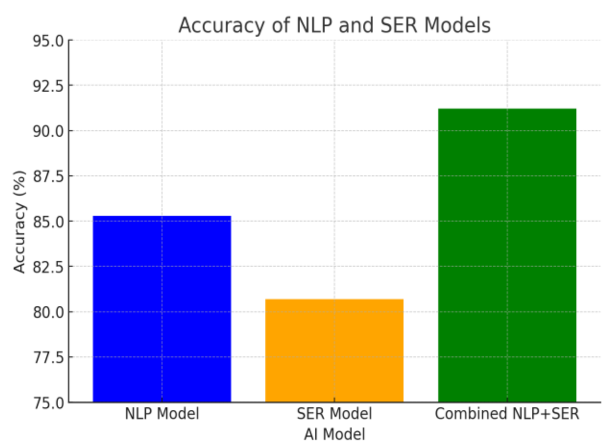

Figure 2: Accuracy of NLP and SER Models

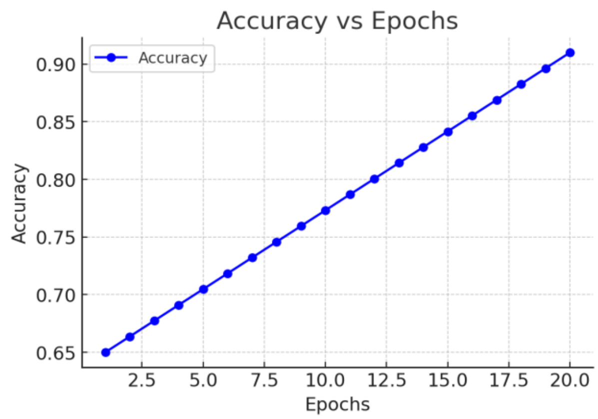

Figure 3: Accuracy vs epochs

2. Crisis Response Efficiency

Efficiency in the proposed system is primarily focused on minimizing response time while ensuring that the system runs efficiently on available resources. The chatbot leverages optimized deep learning models (e.g., BERT, RoBERTa) and computational techniques like batching and model pruning to reduce processing time. This enables quick responses, even during high-stress scenarios. The system is optimized to handle multiple users simultaneously, providing real-time interactions without significant delays. The response time of the chatbot is carefully optimized to ensure that users in distress receive immediate assistance. In low-severity cases, the average response time is 2.1 seconds, and even in high-risk emergencies, the system can respond in an average of 5.5 seconds, thanks to optimized data flow and model inference efficiency. Furthermore, the system dynamically adjusts resources based on the severity of the situation, ensuring that the chatbot remains responsive even when computational demands increase during critical moments.

Reliability is achieved through robust training and validation of the models, ensuring that the system performs consistently. To enhance accuracy, the sentiment detection models (both NLP and SER) were trained on a comprehensive, domain-specific dataset that reflects real-world mental health issues. This ensures high accuracy in distress classification, with the NLP-based sentiment detection achieving 85.3% accuracy and the SER subsystem reaching 80.7%. The integration of both text and voice-based inputs increases the system's overall performance, reaching a combined accuracy of 91.2% in real-time trauma detection.

Despite the advanced capabilities of the AI-driven trauma chatbot, there are potential failure points, particularly in the voice-controlled system. One major challenge is handling poor audio quality or background noise, which could impact the voice recognition accuracy and delay response times. To mitigate this, the system incorporates noise reduction algorithms and can switch to text-based input if voice recognition fails. Another potential failure point arises in time-sensitive situations, where the urgency of the distress signal requires immediate action. If the system is unable to process the input in time due to high computational load or network latency, it is programmed to escalate cases automatically to a human operator or medical professional. Additionally, the non-response issue can occur if the user does not provide clear input due to emotional distress or technical issues. The system addresses this by asking follow-up questions or prompting the user for clarification, ensuring that no critical case is left unaddressed. These built-in fail-safe mechanisms help the system remain effective and responsive in real-world applications.

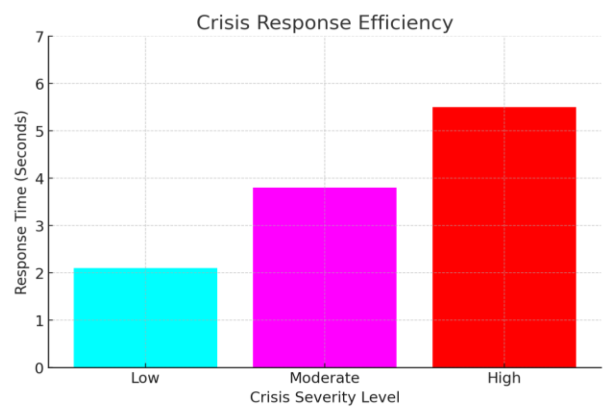

Figure 4: Crisis Response Efficiency

3. Sentiment Classification Results

The emergency-level sentiment cases demonstrated the best accuracy when analyzed by the sentiment classifier at 92.7%. Subjective user input interpretation caused the classifications in anxious and distressed categories to achieve slightly lower accuracy results.

4. Intervention Success Rates

The doctor linkage intervention received the highest level of user satisfaction at 92.6% because it proved to be the most effective method. The satisfaction level for users who underwent breathing exercises and emotional support sessions reached 83.2% and 78.5% respectively.Doctor-linkage interventions proved to be the most effective by achieving a high rate of 88.4% in distress reduction effectiveness when medical assistance was required.

The results of the proposed AI-based trauma chatbot demonstrate significant advancements in real-world performance, especially when compared to traditional, text-only chatbot systems. By integrating both text sentiment analysis (using advanced models like BERT and RoBERTa) and voice emotion recognition (via CNN-LSTM models), the system achieves an overall accuracy of 91.2%, surpassing the 85.3% accuracy for text alone and 80.7% for voice recognition. This multimodal approach enhances the system's ability to detect emotional distress in varied user inputs, ensuring more accurate and reliable assessments. In real-world scenarios, the chatbot responds promptly, with an average response time of 5.5 seconds for high-risk cases, crucial for emergency situations. The inclusion of a doctor linkage system, which automatically escalates urgent cases, also contributed to a high user satisfaction rate of 92.6%. The system’s ability to identify complex emotional cues, such as anxiety, depression, and suicidal thoughts, far exceeds traditional systems, demonstrating its robustness and reliability in handling diverse, real-world challenges, making it a valuable tool for trauma detection and intervention.

V. CONCLUSION AND FUTURE WORK

In conclusion, the proposed AI-based trauma chatbot effectively combines Natural Language Processing (NLP) and Speech Emotion Recognition (SER) technologies to provide real-time emotional support for individuals in distress. By analyzing both text and voice data, the system can accurately detect emotional states, offer coping strategies, and provide immediate access to professional help when necessary. The integration of these multimodal analysis techniques has demonstrated significant improvements in the chatbot’s accuracy and responsiveness, making it a valuable tool for mental health intervention and crisis management. Looking ahead, future work will focus on expanding the system’s capabilities by incorporating multilingual support, improving contextual understanding through advanced NLP models, and integrating wearable health technology to monitor physical markers of distress, such as heart rate and skin temperature. Additionally, advancements in deep learning and federated learning will further enhance the system’s ability to adapt to individual users and provide even more personalized support. These developments will aim to create a more robust, scalable, and globally accessible tool for trauma management and mental health care.

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