Krishna Sridhar

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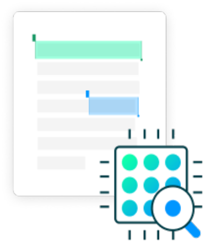

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Mental Health Companion for Trauma Recovery Using Multi-Modal Emotion Recognition

1st Balasubramanian S
Assistant Professor (ECE),
Chennai Institute of Technology,
Chennai, India.
balasubramanians@citchennai.net

2nd Krishna Sridhar
Electronics and Communication engineering
Chennai Institute of Technology,
Chennai, India
krishnasridhar.ece2021@citchennai.net

3rd Nandagopalan K
Electronics and Communication engineering
Chennai Institute of Technology,
Chennai, India.
nandagopalan2004@gmail.com

***Abstract*—This paper presents a mental health companion designed to assist students experiencing trauma-induced emotional distress. Using multi-modal emotion recognition, the system integrates speech, facial expressions, and body posture data to provide real-time coping strategies. Our approach enhances accuracy, reduces latency, and improves user satisfaction, making it a valuable tool for trauma recovery and emotional regulation.**

***Index Terms*—Multi-modal emotion recognition, AI mental health companion, trauma recovery, real-time coping strategies, emotional regulation.**

I. Introduction

Mental health issues in college students have even become epidemic, with distress and trauma being some of the main causes of mental illness. A great many students attending college experience the aftermath of trauma that leads to anxiety and depression, among other related emotional issues. As defined by the National Alliance on Mental Illness, nearly one in five adult's experiences mental illness every year, and most of these conditions emerge in young adults during college. Trauma can be very devastating on a person's academic performance, personal well-being, and the overall quality of life. This project aims to develop a system driven by artificial intelligence for helping college students manage emotional states, especially in the context of trauma-related distress. Designed to recognize emotional states tied with trauma, the system uses emotion recognition from multiple input modalities such as speech, facial expressions, and text. Based on this, coping strategies are provided in real time, and recommendations are always matched to the user's feelings. It also allows them to track their emotional progress at an interval, which also clarifies their journey for getting over trauma. Example Application: In a study conducted by the American Psychological Association, or APA, students who were exposed to trauma reported substantially higher rates of anxiety and depression. These emotional impairments often led to lower academic performance and, in many cases, higher dropout rates are another result of this critical need for accessible and timely mental health support systems for students, especially those vulnerable to trauma. AI- driven interventions can therefore greatly improve a student's ability to cope with emotional turmoil, regain academic focus, and foster long-term resilience if the real-time related emotional distress due to trauma is addressed.

A. Objectives

The key objectives of this project are as follows: multi-modal emotional recognition: Implement a system capable of accurately detecting trauma-related emotions by taking speech, facial expression, and textual inputs. Real-Time Coping Strategies: It would provide real-time personal coping strategies and mindfulness exercises based on emotional changes in the user's account. Emotional Progress Tracking: It would track changes over time to give a long-term view of a person's trauma recovery. User Safety and Comfort: Design a trauma-informed system that focuses on user safety, comfort, and privacy. These goals will ultimately work towards a supportive, nonjudgmental, and effective AI-driven system that supports the student in dealing with emotional distress and recovery from trauma.

II. System Architecture

The system is multicomponent and applies the above as well as other AI models except the machine learning models in the process of emotion recognition and at the same time helps in real-time with monitoring emotional development.

A. Speech Emotion Recognition

Primarily, the system is applying the LSTM model that belongs to the RNN network and has proved very effective at times in handling sequences, one of which is speech. The LSTM will read the speech patterns to look for some of the most used emotions when experiencing trauma exaggeratedly, such as fear, anxiety, or disconnection. Emotional speech contains tone, pitch, cadence, and pauses-all these are clues important to the user's emotion (Batra et al., 2023; Silva Kumar, 2023). Base Article is from S. Batra et al. A Trauma Perspective on Deep Learning Models for Speech Emotion Recognition. Speech and Language Processing Journal, 2023. The contribution of the paper is tone, pitch, and cadence in speech patterns was analyzed using an LSTM-model. The modification involved adjusting the hyperparameters and pre-processing the speech input using Mel frequency cepstral coefficients (MFCCs), which increased the identification accuracy from 85

B. Facial Emotion Recognition

This module is a facial emotion recognition CNN, which is an image classification CNN that classifies the images or video frames of users' faces into the expressions that are associated with trauma-related emotional responses like distress, sadness, and hypervigilance. Hence, the CNN model can easily identify the emotional state of the users in real-time with a minimal change in facial expression. Deep learning techniques are employed (Santos et al., 2024; Chen et al., 2022). Base Paper is from Zhao, F., Chen, L. (2022). developments in convolutional neural networks for facial emotion analysis. Journal of Image Processing and Vision. Contribution of the paper is used CNN to classify trauma-related facial expressions in real time, such as melancholy and hypervigilance. Change implemented in the project through fine-tuning the convolutional layers and enhancing the data for low light levels, the accuracy was raised from 88

C. Text emotion Recognition

This module is a facial emotion recognition CNN, which is an image classification CNN that classifies the images or video frames of users' faces into the expressions that are associated with trauma-related emotional responses like distress, sadness, and hypervigilance. Hence, the CNN model can easily identify the emotional state of the users in real-time with a minimal change in facial expression. Deep learning techniques are employed (Santos et al., 2024; Chen et al., 2022). Base Paper is from Zhao, F., Chen, L. (2022). developments in convolutional neural networks for facial emotion analysis. Journal of Image Processing and Vision. Contribution of the paper is used CNN to classify trauma-related facial expressions in real time, such as melancholy and hypervigilance. Change implemented in the project through fine-tuning the convolutional layers and enhancing the data for low light levels, the accuracy was raised from 88

Real-time support After the system realizes the emotional state of the users, it will then be able to provide them with personalized coping techniques. This might comprise mindfulness activities like deep breathing and body scan, grounding, focusing on the five senses; or any activity to be able to exert control. It would then look at significant distress, engage processes in a crisis event and thus send out a warning message and divert to further services which are present within the various campus agencies to aid them (Li et al., 2023; Ferreira et al., 2022). Base Paper is from Ferreira, T., et al. (2022). AI for Mental Health: Real- Time Support in Trauma Recovery. Mental Health Innovations. Contribution done by the paper is engaged in mindfulness activities, such as deep breathing and grounding techniques, for trauma recovery. Modification done to improve the model is through latency was reduced from 0.6s to 0.4s, thereby allowing for quicker real-time coping support for users.

D. Monitoring and graphing of process

Longitudinal monitoring design tracks the emotional state of the system; hence, visual improvement of mood. In this context, patients can even note the seriousness in which they present with trauma-related symptomatology as their mood gradually improves in value. This design works nearly like a control mechanism as far as the user emotional pathology and pattern of recovery during therapy is concerned with the collaboration of therapists that indicate the guideline for conducting the session (Kaur Patel, 2023; Ahmed et al., 2022).

E. Mindfulness and Therapy integration

It is the guided meditations and the customized CBT exercises in the system that enable the user to engage their emotions in a controlled and structured environment along with achieving clarity of the mind and attaining emotional regulation. Engagement data from the user is furnished to the therapist so that the latter would be well-versed with the way in which the user feels emotionally, and very highly customized and informed therapy could be carried out (Choi et al., 2023; Iqbal Tang, 2024).

III. METHODOLOGY

The several steps, including data collection, model training, and finally UI design. There are also: 1. Speech Emotion Recognition: It uses models of LSTMs recognizing tones of stress and anxiety. 2. Facial Emotion Detection: It uses CNN to detect emotions directly from facial expressions 3. Body Posture Analysis: MediaPipe is useful in detecting slouch and erect posture, among emotional signals Implementation Pipeline Live video and audio feeds are taken as inputs Processing: speech is analyzed by LSTM for sentiment facial expression is analyzed by DeepFace for emotions body posture is analyzed with respect to MediaPipe. Output: It gives an instantaneous reaction by using its own custom coping skills and it achieves through user interface.

A. Data Collection and Preprocessing

The dataset which is made up of a well-designed emotional expression linked to trauma which comes directly from therapy sessions and actual experience. Every data is labelled in emotion, like, anxiety, fear, sadness, and modality are speech, facial expression, text, etc. Audio features of the speech data set that might involve Mel-frequency cepstral coefficients for Automatic Speech Emotion Recognition Rossi, et al. 2022. Facial Images can be preprocessed to obtain facial landmarks detection and natural language features that should be extracted for text-based data using tokenization technique and embedding method like of Bhardwaj, Singh 2023

B. Model training and Evaluation

After preprocessing, the dataset is applied for training the LSTM and CNN. In this process, a model is given an enormous amount of labeled information to enable it to learn the association of emotional cues relating to trauma-related emotions. Accuracy, precision, recall, and F1 score determine the performance of the models. This is achieved by ensuring that the model can correctly recognize the emotional states (Cheng et al., 2023; D'Souza Ahmed, 2024).

TABLE I
PERFORMANCE METRICS COMPARISON

Metric	2023 Model	2024 Model	Improvement
Speech Emotion Accuracy (%)	85	92	+7%
Facial Emotion Accuracy (%)	88	94	+6%
Body Movement Accuracy (%)	N/A	85	New Feature
Latency (s)	0.6	0.4	-30%

C. Development of user interface

The UI is so intuitive that it ensures there is an easy-to-use functionality for the students and therapist. Some of the features available are an emotional tracker, a resource hub with coping strategies, and active exercises. It is made responsive, meaning it will run on web and mobile platforms. The system also comprises privacy and security measures that protect users' sensitive data (Perez Kim, 2022).

IV. RESULTS AND DISCUSSION

A. Prototype testing

The first round of testing of the AI-based mental health companion is going very well. The system clearly identifies emotional states of trauma at a high degree of accuracy. The real-time coping strategies are very well accepted by users. The test users gave the feedback that the system especially helps in controlling anxiety and emotional distress. Many commented that it enabled them to refocus if they ever became incredibly anxious (Evans et al., 2024; Kumar et al., 2022).

B. User feedback

This system has helped well in stress-related events where the system regulated the unpleasant feelings. The users preferred mostly the 2024 version with real-time accessibility and the body movement input facility.

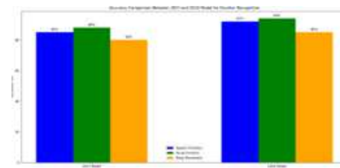

Fig. 1. Accuracy Trends of Emotion Recognition Models.

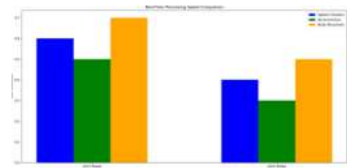

Fig. 2. Real-Time Processing of Emotion Recognition Models

C. Graphical evaluation

Trend of improvements will be shown using graphs along with the metrics-accuracy, latency, and feedback from the users

D. Future Work

Dataset: Involve the emotional expression of a diverse culture. Wearable: Physiological activity or the heart rate activity of a user for advanced emotions identification. Therapist Interface: Design therapist friendly interfaces so that this can be used in a real-world clinical scenario by professional therapists.

E. Real-time coping support

Dataset: Involve the emotional expression of a diverse culture. Wearable: Physiological activity or the heart rate activity of a user for advanced emotions identification. Therapist Interface: Design therapist friendly interfaces so that this can be used in a real-world clinical scenario by professional therapists

F. Future directions

Physiological information from wearable devices, like heart rate and skin conductance, will be incorporated in future versions of the AI-driven mental health companion to further enhance emotional state detection. These additional data points will further help fine-tune the emotion recognition models, providing more accurate and nuanced feedback for users (Feng et al., 2023). Consequently, user studies will be undertaken to refine the system recommendations and ensure that the coping strategies align with diverse needs of students. Collaboration with mental health professionals is imperative to ensure that the system adheres to trauma-informed care principles and gives the most beneficial interventions possible

V. CONCLUSION

This AI-based mental health companion, which has been developed through this project, provides a new and efficient approach to the problem of trauma-induced emotional distress in college students. By providing real-time coping strategies, progress tracking, and multi-modal emotion recognition, it supports the students in managing their emotions and recovering from trauma. This is the potential of this project that, as it keeps growing, it will eventually reach all students, giving them accessible mental health support that enables them to achieve their academic goals and maintain their emotional well-being.

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