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AI-Powered Emotion-Aware Mental Health Guardian

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Abstract: The rising rates of stress, anxiety, and depression in contemporary culture have made mental health a major worldwide concern. In order to prevent serious psychological problems, early detection and prompt care are essential. It is now feasible to create intelligent systems that can use computational methods to analyze human emotional states because to developments in artificial intelligence, machine learning, and deep learning. This research introduces an AI-Powered Emotion Aware Mental Health Guardian that uses multimodal data sources to track and evaluate emotional well-being.

Three primary modalities are used by the suggested system to detect emotions: text-based sentiment analysis, spoken emotion identification, and facial expression analysis. While Mel-Frequency Cepstral Coefficients (MFCC) in conjunction with deep learning models are utilized to extract emotional aspects from voice signals, Convolutional Neural Networks (CNNs) are utilized to determine emotions from facial photos. Additionally, textual input is analyzed and emotional states are classified using transformer-based models like BERT. An overall mood score and emotional intensity level are calculated by integrating the results from these separate models through a fusion mechanism.

The system offers tailored suggestions, such as stress-relieving activities, music selections, relaxation techniques, and encouraging messages, based on the identified emotional intensity. This method guarantees that the system not only detects emotional distress but also provides proactive support to enhance mental health. When compared to single-modality systems, the incorporation of multimodal emotion detection improves prediction accuracy and dependability.

The AI-Powered Emotion Aware Mental Health Guardian shows how deep learning may be used in real-world mental health monitoring and emotional support systems. It is an intelligent supportive tool that can help users manage stress and emotional imbalance, but it does not take the place of a professional psychological diagnosis. The study demonstrates how AI-driven solutions may support mental health and create emotionally intelligent digital systems..

Index terms *- Emotion Recognition,Mental Health Monitoring,Multimodal Emotion Detection,Deep Learning,Artificial Intelligence*

1. INTRODUCTION

Mental health has become one of the most important facets of human well-being in recent years. People's levels of stress, anxiety, and depression have dramatically grown due to rapid technological breakthroughs, competitive academic and professional contexts, and lifestyle changes. However, due to a lack of awareness or prompt monitoring mechanisms, many people are unable to identify early emotional discomfort. Manual observation, questionnaires, and expert consultation are the mainstays of traditional mental health assessment techniques, which may not always be readily available or prompt.

The development of machine learning (ML), deep learning (DL), and artificial intelligence (AI) has made it feasible to use computational models to study human emotions. In order to determine underlying emotional states, emotion detection algorithms can decipher textual content, speech patterns, and facial expressions. By combining textual, auditory, and visual signals, multimodal emotion recognition enhances prediction accuracy.

The AI-Powered Emotion Aware Mental Health Guardian is a multimodal intelligence system that uses textual input, audio signals, and facial photos to identify human

emotions. The system uses transformer-based models like BERT for text emotion classification, Mel-Frequency Cepstral Coefficients (MFCC) with deep learning models for audio analysis, and Convolutional Neural Networks (CNN) for facial emotion recognition. These models' outputs are used to provide a single mood score and emotional intensity level. The system offers tailored suggestions, including workouts, music selections, calming activities, and encouraging messages, based on the identified emotional state.

This experiment shows how proactive mental health care and early emotional assessment can be supported by AI-driven platforms. The method serves as a helpful tool to assist people in tracking and managing their emotional well-being, but it does not take the place of expert psychiatric consulting..

2. LITERATURE SURVEY

Recent developments in artificial intelligence, machine learning, and deep learning techniques have drawn a lot of attention to the field of emotion recognition and mental health monitoring. Various academics have proposed different ways for identifying human emotions utilizing facial expressions, audio signals, and textual analysis. A review of pertinent studies on multimodal emotion recognition and AI-based mental health monitoring systems is presented in this chapter.

2.1 Deep Learning-Based Facial Emotion Recognition

Facial expression analysis is one of the most researched fields in emotion recognition. Convolutional Neural Networks (CNNs) have been widely employed by researchers to classify facial emotions from RGB and grayscale photos. Deep learning models that recognize emotions including happy, sorrow, anger, fear, surprise, disgust, and neutrality are frequently trained using the FER-2013 dataset.

Research has demonstrated that CNN architectures perform better in image-based emotion detection than conventional machine learning techniques like Support Vector Machines (SVM) and k-Nearest Neighbors (kNN). By automatically extracting hierarchical features from facial photos, deep learning algorithms eliminate the need for human feature engineering. However, in situations with low illumination, occlusions, or changes in facial posture, facial expression identification systems may be less accurate. These drawbacks emphasize how crucial it is to integrate facial data with other modalities in order to enhance performance.

2.2 MFCC and Neural Networks for Speech Emotion Recognition

Another significant area of study in affective computing has been Speech Emotion Recognition (SER). To extract useful patterns from voice transmissions, researchers have used audio signal processing techniques like spectral contrast, chroma characteristics, and Mel-Frequency Cepstral Coefficients (MFCC). Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) are examples of machine learning or deep learning models that receive these features.

Speech emotion models have been trained and evaluated using datasets like RAVDESS and EMO-DB. Research findings reveal that MFCC features paired with deep learning classifiers considerably boost recognition accuracy. However, in the presence of background noise or fluctuations in voice modulation, speech-based systems by themselves may misclassify emotions. This restriction implies that multimodal systems are necessary to improve dependability.

2.3 Transformer Models for Text-Based Emotion Recognition

With the advent of transformer-based architectures and Natural Language Processing (NLP) approaches, text emotion identification has advanced dramatically. Previous methods relied on traditional machine learning techniques and lexicon-based sentiment analysis. For contextual emotion identification, however, contemporary methods make use of transformer models like BERT (Bidirectional Encoder Representations from Transformers), RoBERTa, and GPT-based models. Google Research introduced the GoEmotions dataset, which offers detailed emotion labeling for several categories. Because of their capacity to comprehend contextual meaning and semantic links in text, transformer models trained on such datasets exhibit great accuracy. Text-only models are effective, but they are unable to capture non-verbal emotional cues like tone of voice or facial expressions. As a result, combining text analysis with other modalities increases the overall resilience of the system.

2.4 Systems for Multimodal Emotion Recognition

In order to create reliable emotion identification systems, recent research has concentrated on integrating several modalities, including face, speech, and text. To produce final predictions, multimodal systems combine characteristics from several sources and use fusion techniques like early fusion, late fusion, or hybrid fusion. Research indicates that when it comes to accuracy and dependability, multimodal techniques perform noticeably better than unimodal systems.

Weighted fusion procedures, in which each modality contributes proportionately to the final emotion score, have been used by researchers. In practical situations when one modality may not be dependable, such systems are especially helpful. However, to guarantee real-time performance, multimodal systems need rigorous synchronization, feature alignment, and computing efficiency.

2.5 AI-Powered Monitoring and Suggestion Systems

For Mental Health Numerous studies have investigated AI-driven mental health assistance systems in addition to emotion recognition. These systems evaluate psychological states using chatbot conversations, behavioral tracking, and sentiment analysis. Certain applications offer treatment support, relaxation suggestions, and dashboards for tracking mood. Nevertheless, a lot of current systems lack multimodal integration and just use text-based analysis.

An important development in mental health technology is the combination of recommendation systems and deep learning-based emotion recognition. AI systems can provide proactive emotional support instead of passive monitoring by fusing emotion detection with tailored recommendations like workouts, music, and stress-relieving activities.

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3. METHODOLOGY

i) Proposed Work:

To address the shortcomings of current systems, a multimodal deep learning-based system called AI-Powered Emotion Aware Mental Health Guardian is being developed. To improve forecast accuracy and dependability, the system combines three distinct modalities: text emotion classification, spoken emotion identification, and facial expression recognition.

The facial emotion identification module leverages Convolutional Neural Networks (CNN) trained on facial image datasets to identify expressions such as happy, sorrow, anger, fear, surprise, and neutrality. The voice emotion detection module employs deep learning models to categorize vocal emotions by extracting Mel-Frequency Cepstral Coefficients (MFCC) from audio signals. The text emotion identification module analyzes contextual meaning and identifies emotional states from textual input using transformer-based architectures like BERT. An overall mood score is calculated by combining the signals from all three modules using a weighted fusion process. The approach categorizes emotional intensity levels, such as Low, Moderate, or High stress, based on this score. In contrast to current systems, the suggested system goes beyond emotion detection by offering tailored suggestions, such as stress-relieving activities, relaxation techniques, music selections, and encouraging messages.

The following are the main benefits of the suggested system: • Multimodal integration leads to increased accuracy. • Sturdy performance in a range of environmental circumstances. • The ability to identify emotions in real time. • A system for personalized recommendations. • Offline features that don't require an external API. • A scalable architecture that may be implemented as a mobile or online application. Therefore, the suggested approach offers a thorough AI-driven framework for emotional evaluation and assistance with mental health.

ii) System Architecture:

The proposed AI-Powered Emotion Aware Mental Health Guardian is a multimodal system designed to monitor and analyze a user's emotional state using different input sources such as facial expressions, speech signals, and textual input. The system captures facial images through a camera and analyzes them using Convolutional Neural Networks (CNN) and DeepFace models to detect emotional expressions. Speech input is recorded through a microphone, where audio features such as Mel-Frequency Cepstral Coefficients (MFCC) are extracted using Librosa, and emotional patterns are identified using Long Short-Term Memory (LSTM) networks. In addition, user-provided textual data is processed using BERT, a transformer-based model capable of understanding contextual sentiment and emotional meaning. The outputs from these three emotion detection models are integrated

through a multimodal fusion mechanism, which combines the predictions to generate a comprehensive emotional interpretation. Based on this fusion, the system calculates a Mood Index that represents the overall emotional intensity of the user. Depending on the detected mood level, the Adaptive Support System provides personalized recommendations such as calming music, motivational content, relaxation techniques, or suggestions for professional help. Finally, the results are displayed on a dashboard interface, enabling users to monitor their emotional state and receive proactive support for improving mental well-being.



Fig.1. Proposed Architecture

iii) MODULES:

1. Face Emotion Detection Module

The Face Emotion Detection Module is responsible for identifying emotions from the user's facial expressions. This module captures facial images through a camera and processes them using **Convolutional Neural Networks (CNN) and DeepFace models**. The CNN model extracts important facial features such as eye movement, mouth shape, and facial muscle patterns. Based on these features, the system classifies emotions into categories such as happiness, sadness, anger, surprise, fear, or neutrality. This module plays a crucial role in understanding the user's emotional state through visual cues.

2. Speech Emotion Recognition Module

The Speech Emotion Recognition Module analyzes emotional patterns from the user's voice. Audio signals are recorded using a microphone and processed using Librosa, a Python library for audio analysis. Important audio features such as Mel-Frequency Cepstral Coefficients (MFCC) are extracted from the speech signals. These features are then analyzed using Long Short-Term Memory (LSTM) neural networks to detect emotional variations in tone, pitch, and speech rhythm. This module helps identify emotions expressed through speech, improving the accuracy of emotional analysis.

3. Text Emotion Analysis Module

The Text Emotion Analysis Module focuses on detecting emotions from textual input provided by the user. The system uses BERT (Bidirectional Encoder Representations from Transformers), a powerful transformer-based natural language processing model. BERT understands contextual meaning in text and classifies the sentiment or emotional state of the user. The module can detect emotions such as positive, negative, or neutral sentiment, helping the system understand the emotional tone behind the user's written messages.

4. Multimodal Fusion Module

The Multimodal Fusion Module combines the outputs from the face, speech, and text emotion detection modules. Since emotions can be expressed differently through facial expressions, voice, and text, integrating these modalities provides a more reliable and accurate emotional assessment. This module aggregates the predictions from all models and calculates a combined emotional output that represents the user's overall emotional condition.

5. Mood Index Calculation Module

The Mood Index Calculation Module evaluates the integrated emotional results obtained from the multimodal fusion module. It calculates an overall **Mood Index score**, which indicates the emotional intensity level of the user. Based on this score, the system categorizes the user's emotional state into different levels such as positive mood, neutral mood, or negative mood. This module provides a simplified representation of the user's emotional condition.

6. Adaptive Support Recommendation Module

The Adaptive Support Recommendation Module provides personalized suggestions based on the user's emotional state. If the system detects signs of stress, sadness, or emotional imbalance, it recommends suitable activities such as calming music, motivational messages, relaxation exercises, or stress relief techniques. In severe emotional

conditions, the system may suggest seeking professional psychological support. This module ensures that the system not only detects emotions but also provides proactive assistance to improve mental well-being.

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iv) IMPLEMENTATION:

The implementation phase involves transforming the system design into a functional software solution. In this project, the AI-Powered Emotion Aware Mental Health Guardian is implemented as a multimodal deep learning system capable of analyzing facial expressions, speech signals, and textual input to detect emotional states. The system integrates individual modules for face, speech, and text emotion recognition, followed by a fusion mechanism and recommendation module.

The implementation is carried out using Python-based frameworks and libraries. Each module is developed and tested independently before integration into the backend API using FastAPI. The modular design ensures maintainability, scalability, and ease of debugging.

Overall System Architecture Implementation

The system is implemented using a modular structure consisting of the following components:

1. Face Emotion Detection Module
2. Speech Emotion Recognition Module
3. Text Emotion Classification Module
4. Fusion Module
5. Severity Mapping Module
6. Recommendation Module
7. API Integration Module

Each module performs a specific task and communicates with the main application server.

Dataset Description:

The performance and accuracy of the AI-Powered Emotion Aware Mental Health Guardian depend significantly on the quality and relevance of the datasets used for training and evaluation. The project utilizes three publicly available datasets corresponding to the three modalities: facial images, speech audio signals, and textual data.

1.Facial Emotion Dataset

For facial emotion recognition, the system uses the FER-2013 dataset. This dataset consists of grayscale facial images categorized into seven emotional classes: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral.

Dataset Characteristics:

- Image size: 48 × 48 pixels
- Grayscale images
- Labeled emotion categories
- Large number of training and testing samples
- Suitable for training Convolutional Neural Networks

The dataset is preprocessed by converting images to normalized pixel values in the range [0,1]. Data augmentation techniques such as rotation and horizontal flipping may also be applied to improve generalization.

2. Speech Emotion Dataset

For speech emotion recognition, the RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) dataset is used. This dataset contains emotional speech recordings performed by actors expressing different emotions.

Dataset Characteristics:

- Audio format: WAV
- Emotions: Neutral, Calm, Happy, Sad, Angry, Fearful, Disgust, Surprised
- Balanced dataset across emotions
- High-quality recordings

The audio signals are processed to extract Mel-Frequency Cepstral Coefficients (MFCC), which represent the short-term power spectrum of sound.

3. Text Emotion Dataset

For text-based emotion classification, the GoEmotions dataset is used. This dataset contains Reddit comments labeled with multiple fine-grained emotions.

Dataset Characteristics:

- Large-scale textual dataset
- 27 emotion categories + neutral
- Suitable for transformer-based models
- Context-rich annotations

The text data is tokenized using a BERT tokenizer and converted into input IDs and attention masks before being passed to the transformer model.

Mathematical Formulations Used in Implementation

The system implementation involves various mathematical operations and deep learning computations. The important formulas used are described below.

1. Convolution Operation (CNN for Face Emotion Recognition)

The convolution operation is defined as:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-m, j-n) \cdot K(m,n)$$

Where:

- I= Input image
- K= Kernel (filter)
- $S(i,j)$= Feature map output

This operation extracts spatial features from the facial image.

2. Activation Function (ReLU)

The Rectified Linear Unit (ReLU) activation function is defined as:

$$f(x) = \max(0, x)$$

It introduces non-linearity into the neural network and prevents vanishing gradient problems.

3. Softmax Function (Emotion Classification)

The Softmax function converts raw output scores into probability values:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where:

- z_i= Logit value for class i
- n= Number of classes

This ensures the output probabilities sum to 1.

4. Cross-Entropy Loss Function

The loss function used for classification is:

$$L = -\sum_{i=1}^{n} y_i \log(p_i)$$

Where:

- y_i= True label
- p_i= Predicted probability

This measures the difference between predicted and actual values.

5. Transformer Attention Mechanism (Text Model)

The attention mechanism in BERT is defined as:

$$Attention(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where:

- Q= Query matrix
- K= Key matrix
- V= Value matrix
- d_k= Dimension scaling factor

This mechanism allows the model to focus on important words in the sentence.

6. Weighted Fusion Formula

The final mood score is computed using weighted fusion:

$$MoodScore = (w_1 \cdot C_{face}) + (w_2 \cdot C_{speech}) + (w_3 \cdot C_{text})$$

Where:

- w_1, w_2, w_3= Weights assigned to each modality
- C= Confidence score of each model

In implementation:

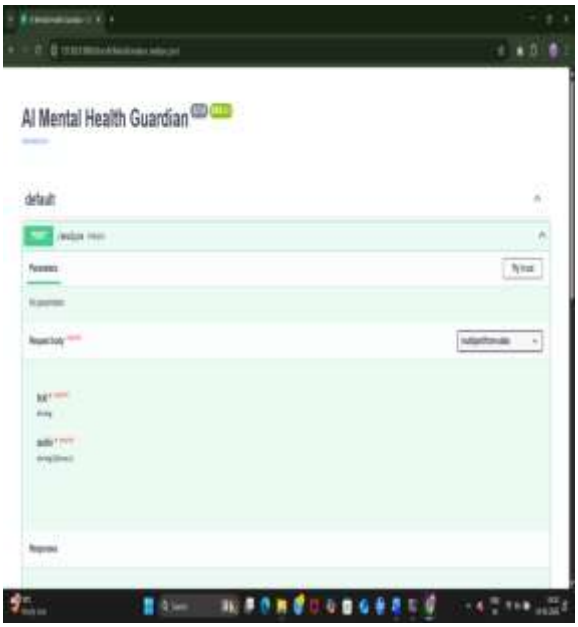
$$MoodScore = (0.35 \times Face) + (0.25 \times Speech) + (0.40 \times Text)$$

7. Severity Classification

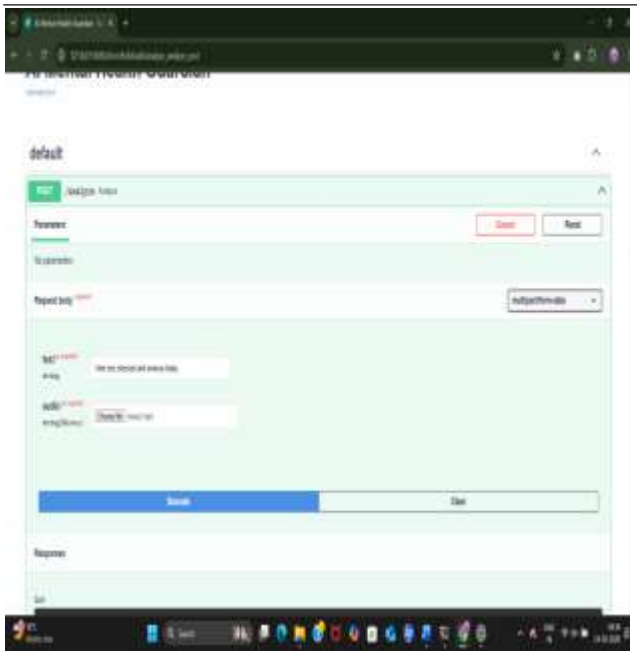
Severity is determined as:

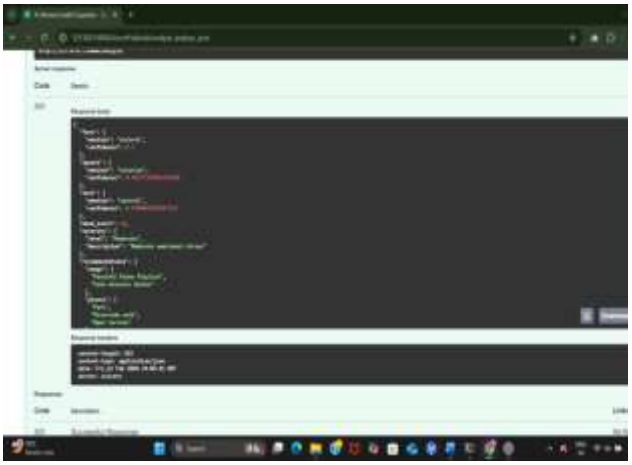
$$Severity = \begin{cases} Low, & 0 \le Score \le 40 \\ Moderate, & 41 \le Score \le 70 \\ High, & 71 \le Score \le 100 \end{cases}$$

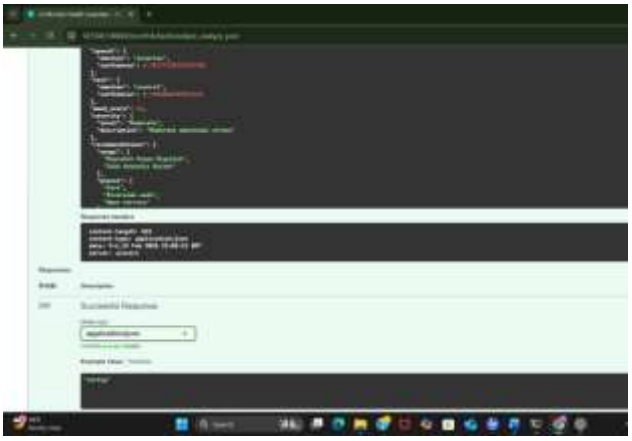
4. EXPERIMENTAL RESULTS



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{
 "face": {
  "emotion": "neutral",
  "confidence": 0.5
 },
 "speech": {
  "emotion": "surprise",
  "confidence": 0.49277156591415405
 },
 "text": {
  "emotion": "neutral",
  "confidence": 0.3306066393852234
 },
 "mood_score": 42,
 "severity": {
  "level": "Moderate",
  "description": "Moderate emotional stress"
 },
 "recommendations": {
  "songs": [
   "Peaceful Piano Playlist",
   "Calm Acoustic Guitar"
  ],
  "places": [
   "Park",
   "Riverside walk",
   "Open terrace"
  ],
  "exercises": [
   "Light yoga",
   "Neck and shoulder stretches",
   "10-minute walk"
  ],
  "activities": [
   "Listening to music",
   "Reading",
   "Journaling"
  ]
 },
  "support_message": "You seem a bit overwhelmed. Would you like to try a calming exercise?"
}

5. CONCLUSION

The AI-Powered Emotion Aware Mental Health Guardian effectively illustrates how deep learning and artificial intelligence may be applied to the field of emotional analysis and mental health monitoring. The system combines text-based sentiment analysis, spoken emotion detection, and facial expression recognition into a single

multimodal framework. When multiple modalities are combined, the system outperforms single-modality methods in terms of accuracy and dependability. The application of transformer-based text models, MFCC-based voice processing, and convolutional neural networks demonstrates how well contemporary AI systems comprehend human emotions.

The project's main goal of identifying emotional states and assessing the severity of mental health issues is successfully accomplished. The system's fusion technique guarantees that the face, speech, and text modules contribute equally, producing a complete mood score. The approach categorizes emotional problems into suitable severity categories, such as Low, Moderate, and High, based on this score. Users are able to comprehend their emotional condition more clearly and understandably because to this methodical assessment.

In addition to emotion detection, the system expands its capabilities by delivering individualized recommendations such as relaxation exercises, stress-relief activities, music selections, and supportive messages. The suggested system differs from conventional emotion detection algorithms that merely identify emotions without providing assistance because of its proactive approach. The project fosters healthy coping methods and emotional well-being by implementing a recommendation mechanism.

Careful dataset selection, model training, system integration, and thorough testing were all part of the development process to guarantee performance reliability. The efficacy of the model was evaluated using metrics like accuracy, precision, recall, and F1-score. The system successfully managed multimodal integration through API-based development and showed steady performance across a range of input situations. Scalability and maintainability for upcoming enhancements are guaranteed by the modular architecture.

To sum up, the AI-Powered Emotion Aware Mental Health Guardian is a big step toward smart, tech-driven mental health support systems. It is a preventive and helpful tool for emotional monitoring, but it does not take the place of expert psychological services. The system has great potential for practical use in businesses, educational institutions, and healthcare settings with additional improvements including real-time tracking, recommendations based on reinforcement learning, and mobile deployment..

6. FUTURE SCOPE

The incorporation of Reinforcement Learning (RL) to offer tailored and adaptive recommendations is one of the system's main future improvements. At the moment, the system makes recommendations using rule-based mappings and predetermined severity levels. The system may continuously improve its recommendations by learning from user feedback through the application of reinforcement learning techniques. For instance, the system may give preference to similar recommendations in subsequent sessions if a user reacts favorably to particular exercises or musical selections. This adaptive process would boost the efficacy of emotional support and enhance personalization.

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