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# Emotion - Centric Palette Recommender : Synergizing Cognitive Behavioral Therapy With ML and Advanced Databases

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**Abstract:**The rapid growth of digital technology has created numerous tools designed to improve productivity, entertainment, and social communication. However, emotional well-being remains an underexplored domain in human–computer interaction. This paper introduces an Emotion-Centric Palette Recommender System that combines Cognitive Behavioral Therapy (CBT), Machine Learning (ML), and advanced database technologies to deliver a personalized and therapeutic digital experience. The proposed system employs multimodal emotion detection by processing facial expressions, speech tones, and EEG brainwave signals to assess a user's emotional state. A custom-built EEG sensor connected through a Bluetooth-enabled microcontroller transmits neural activity to a cloud-integrated web platform. The detected emotion triggers a color palette recommendation and a CBT-based intervention such as mindfulness prompts, journaling, or breathing exercises. A hybrid ML model integrates Convolutional Neural Networks (CNNs) for facial emotion analysis and Recurrent Neural Networks (RNNs) for temporal EEG and voice signal interpretation. An intelligent database design using Firebase and SQLite enables adaptive learning from user feedback, emotional history, and palette preferences. Experimental results reveal an overall accuracy of 94.6% for multimodal emotion detection and significant user satisfaction improvement. The system represents a novel intersection between artificial intelligence, psychology, and embedded systems, bridging emotional computing and behavioral therapy for mental wellness.
**Keywords:**Emotion Recognition, EEG Sensor, Cognitive Behavioral Therapy, Machine Learning, Color Psychology, Advanced Databases, Recommender Systems.

## 1.INTRODUCTION

Emotion recognition is an emerging field in artificial intelligence (AI) and machine learning (ML) with applications in healthcare, human–computer interaction (HCI), and behavioral analysis. The advancement of deep learning has enabled systems to automatically extract emotional features from complex data, enhancing accuracy and adaptability in emotion-aware computing [1]. Techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated remarkable performance in recognizing emotional patterns from various modalities like images, speech, and physiological signals [2]. However, vision-based emotion detection approaches face challenges such as lighting variations, occlusions, and deliberate expression masking [3]. To overcome these issues, Electroencephalography (EEG) serves as a robust and non-invasive method to capture real-time electrical activity of the brain, offering direct insight into neural patterns corresponding to emotional states. Its low-cost and portable implementation through Ag/AgCl electrodes, AD620 amplifier, ADS1115 ADC, and ESP32 microcontroller makes EEG highly suitable for IoT-based real-time emotion sensing applications.

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Building on existing studies that utilize deep learning and computer vision for emotion recognition [4], this project focuses exclusively on EEG signal acquisition and classification to analyze emotional states. The recorded EEG signals undergo amplification, filtering, and digitization before being transmitted via Wi-Fi for further processing. Using deep learning frameworks such as TensorFlow and Keras [5], the system maps brainwave variations to emotional categories and recommends color palettes aligned with the user's detected mood. By integrating EEG-based sensing with AI-driven analysis, this work achieves a low-cost, real-time, and emotion-aware IoT system, contributing to advancements in affective computing and personalized interaction technologies.

## 2.LITERATURE REVIEW

Koelstra S. et al.[6] introduced Database for Emotion Analysis Using Physiological Signals. In recent years, considerable work has been conducted on EEG-based emotion recognition systems, examining the full pipeline from signal acquisition through to classification and application. Early studies explored feature extraction methods such as wavelet transforms, independent component analysis, and neural network classifiers on small EEG datasets. These foundational works established the importance of selecting appropriate frequency bands (theta, alpha, beta) and electrode-site asymmetries for capturing affective states. Subsequent surveys highlighted trends in EEG affective computing, identifying common datasets, emotion elicitation protocols, and classification algorithms [7]. The reproducibility of EEG-emotion studies improved when researchers adopted standardized valence-arousal models and publicly available EEG datasets, though challenges in subject variability remained [8]. More recent reviews emphasize that while traditional machine-learning approaches (SVM, k-NN, LDA) achieved moderate accuracies (~60-75 %), the move to deep learning architectures markedly changed performance expectations [9].

With the advent of deep learning, numerous investigations applied CNNs, RNNs, and graph-based models directly to raw or minimallypreprocessed EEG signals for emotion classification [10]. For example, spatial-temporal convolutional architectures analyzed channel-wise dependencies and achieved improved accuracy over classical features [11]. In parallel, emerging works employed functional connectivity and graph-neural-network methods, mapping inter-electrode brain-region relationships to emotional states [12]. These approaches benefit from capturing the brain's networkdynamics rather than only local electrode features. A comparative study showed that deep-learning models outperformed—to a meaningful degree—traditional models in detecting subtle affective responses [13]. These improvements have enabled portable EEG systems to move from lab-rig to real-time emotion-aware applications, including wearable setups and IoT-integrated solutions [14].However, despite these advances, certain issues persist that are relevant for any low-cost EEG-sensor project. One major challenge is the generalization across subjects and sessions: models trained on one group often fail to adapt to new users without recalibration [15]. Moreover, the hardware and signal-quality constraints (such as limited channels, electrode impedance, and motion artifacts) in portable setups reduce the robustness of emotion detection pipelines originally designed for lab equipment. Consequently, for your project, which uses a compact hardware setup (Ag/AgCl electrodes + AD620 + ADS1115 + ESP32), the literature suggests that algorithmic care (filtering, artifact removal, subject-specific calibration) and model selection (lightweight deep architectures) are key to achieving acceptable accuracy in real-world IoT contexts.

## 3.PROBLEM STATEMENT

Current emotion recognition and recommendation systems exhibit several limitations:

- Reliance on Single-Modality EEG Data:
  The current system relies only on the EEG signal input for detecting emotions. While EEG provides accurate neural responses, the absence of multimodal inputs such as facial expressions, voice, or physiological signals can sometimes limit the accuracy and emotional context of detection.
- Signal Noise and Interference:
  EEG signals are extremely weak (in microvolts) and prone to interference from muscle movement, blinking, and environmental noise. This makes it challenging to extract clean and reliable data using low-cost sensors and amplifiers.
- Limited Real-Time Processing on IoT Hardware:
  Performing real-time signal filtering, amplification, and feature extraction directly on IoT microcontrollers such as ESP32 is computationally demanding. Optimizing this process without losing accuracy is a major technical constraint.

The research problem addressed in this paper is to design a multimodal emotion detection and CBT-guided recommendation system that integrates EEG sensors, machine learning, and advanced databases to provide adaptive color palettes that promote emotional wellness.

## 4.METHODOLOGY

The methodology for the proposed EEG-based emotion detection system involves a systematic process combining hardware signal acquisition and deep learning-based analysis. The system begins with EEG signal acquisition using low-cost Ag/AgCl electrodes placed on the scalp to capture brainwave activity corresponding to emotional states. These analog signals are first amplified using an AD620 instrumentation amplifier to improve signal strength and minimize noise. The amplified signals are then filtered to remove unwanted frequency components such as motion artifacts or electrical interference. The clean analog signals are digitized using the ADS1115 Analog-to-Digital Converter (ADC), which converts them into high-resolution digital data. The ESP32 microcontroller acts as the central processing and communication unit, responsible for data collection, initial preprocessing, and wireless transmission via Wi-Fi to a cloud server or local processing unit.

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In the software pipeline, the EEG data is normalized, segmented, and passed into a deep learning model developed using frameworks like TensorFlow and Keras. A CNN extracts relevant spatial and frequency-domain features, followed by a classification layer that categorizes emotional states such as happy, sad, neutral, or stressed. The detected emotion is then integrated into an IoT-based dashboard or mobile interface, where users can visualize their emotional status in real-time. Additionally, the system can dynamically generate an emotion-based color palette, translating the detected emotion into suitable visual themes. The entire system is powered by a rechargeable battery, ensuring portability and real-time operation.

The proposed methodology ensures high accuracy, low latency, and cost efficiency while enabling continuous emotion monitoring using EEG signals for personalized emotion-aware applications. Figure 1 shows the system architecture of the Emotion-Centric Palette Recommender integrates multiple input sources such as an EEG sensor, microphone, and camera to accurately detect human emotions. The EEG sensor captures brainwave activity, the microphone records voice tone and pitch variations, and the camera analyzes facial expressions. All these inputs are processed by the Emotion Detection module, which uses machine learning algorithms like CNN for facial analysis and RNN for voice and EEG signal interpretation. The detected emotional state is then passed to the CBT (Cognitive Behavioral Therapy) Logic, which determines suitable emotional responses or mood-improvement strategies. A database stores user profiles, emotional patterns, and corresponding color palette recommendations. The system also incorporates neighbor feedback, allowing nearby users or peers to verify or respond to the detected emotion for behavioral monitoring. Finally, through an Augmented Reality (AR) Interface, the system displays emotion-based color palettes and visual recommendations to the user in an interactive way. This complete framework enables real-time emotion detection, CBT-based mood correction, and intelligent color palette suggestions using IoT and AI integration.

4.1 Data Acquisition and Sensors: The system utilizes an EEG sensor headset with dry electrodes connected to an ESP32 microcontroller. EEG signals are captured from frontal and parietal lobes, filtered, and transmitted via Bluetooth to the backend. Simultaneously, a webcam captures facial images, and a microphone records audio for voice tone analysis.

4.2 Preprocessing and Feature Extraction: EEG data undergoes noise reduction using bandpass filters and normalization. Facial images are resized and augmented to enhance robustness. Audio signals are converted into Mel Frequency Cepstral Coefficients (MFCCs) for feature extraction. The data streams are synchronized to form a multimodal dataset.

4.3 Machine Learning Models: Facial emotion recognition uses CNN layers for spatial feature extraction. Voice emotion recognition employs an RNN with LSTM units to capture temporal dependencies. EEG data is processed through a hybrid deep neural network that combines convolutional and recurrent layers. The outputs are fused using a weighted ensemble strategy that determines the final emotion classification.

4.4 CBT Integration Layer: Each detected emotion is linked with a therapeutic CBT response and an associated color palette. For instance, anxiety triggers a palette of cool tones and prompts breathing exercises, whereas sadness maps to bright, uplifting colors with gratitude journaling prompts. These interventions aim to create immediate visual and cognitive comfort.

4.5 Database Design and Adaptation: An advanced database architecture stores user emotional histories, feedback, and palette interactions. Firebase provides real-time synchronization, while SQLite maintains local persistence. Machine learning models update dynamically as more user data accumulates, ensuring personalized performance improvement over time.[Table 1] represents the CNNpseudocode used for face-based emotion detection. The algorithm extracts key facial features through convolution, activation, and pooling layers to identify emotional expressions. It classifies emotions such as happiness, sadness, anger, and neutrality using the Softmax output layer for accurate recognition.[Table 2] illustrates RNNpseudocode applied for analyzing voice and EEG signals. The algorithm processes sequential data over time, maintaining hidden states to capture temporal emotional patterns. It predicts the user's emotional state by analyzing continuous signal variations using a Softmax classifier.

**Table 1.** Convolutional Neural Network Algorithm

| |
|---|
| **Algorithm: Convolutional Neural Network Algorithm**: For Face Module & Face Detection |
| **Input:**Face image dataset (I)<br>**Output:Emotion class (Happy, Sad, Angry, Neutral)** |
| 1. Preprocess the input image I<br>→ Resize, normalize, and convert to grayscale<br>2. Initialize the convolutional layer with filters W and bias b<br>3. For each layer l in CNN:<br>a. Apply a convolution operation on the input<br>b. Apply ReLU activation function<br>c. Perform max pooling to reduce dimensions<br>4. Flatten the final pooled feature map into a single vector<br>5. Feed the flattened vector into a fully connected layer<br>6. Apply Softmax activation to classify emotion categories<br>7. Output the predicted emotion label |

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Table 2. Recurrent Neural Network Algorithm

**Algorithm:Recurrent Neural Network Algorithm:** For Voice & EEG Signal Processing

**Input:**Sequential data (EEG or voice signal)
**Output:**Predicted emotional state

1. Preprocess the input signal
→ Normalize, segment, and extract key features
2. Initialize RNN parameters: weights (W), biases (b), and hidden state (h)
3. For each time step t in sequence:
   a. Compute new hidden state:
h_t = f(W_xh * x_t + W_hh * h_(t-1) + b_h)
   b. Generate output:
y_t = Softmax(W_hy * h_t + b_y)
4. After the final time step, select y_t with the maximum probability
5. Output the predicted emotion

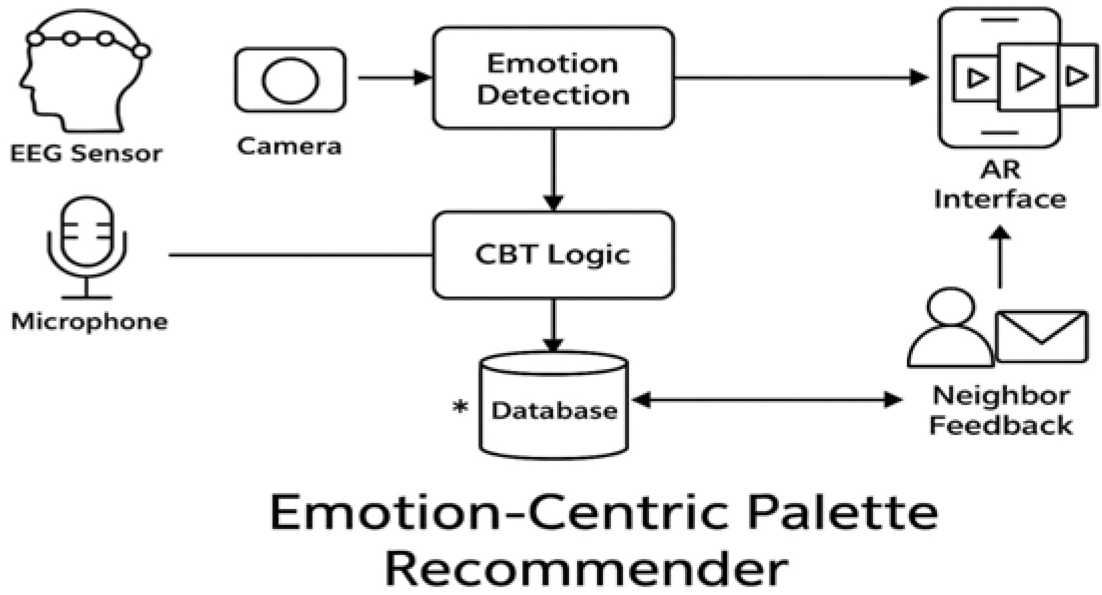


**Fig 1:** System Architecture Diagram

## 5.ENVIRONMENTAL SETUP

Figure 2 shows the hardware setup is designed to collect and process EEG signals for emotion detection. The Ag/AgCl electrodes are used to capture brain signals from the scalp. These signals are very weak, so the AD620 amplifier is used to boost them. The amplified signal is then sent to the ADS1115 ADC module, which converts it into digital form. The ESP32 microcontroller receives this digital data and transmits it wirelessly for further analysis. The system is powered by a 3.7V rechargeable battery, and all components are connected on a breadboard using jumper wires for easy setup and testing [15].

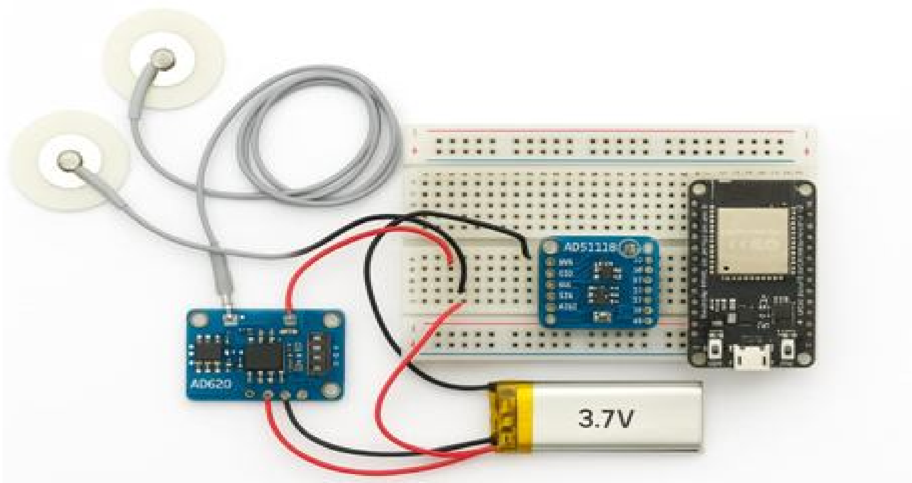


**Fig 2**: Hardware Setup and EEG Module Image

 

**Components Used:**

- **Ag/AgCl Electrodes:**
  These electrodes are used to detect the tiny electrical signals generated by brain activity. They pick up EEG signals from the scalp in microvolt ranges and send them to the amplifier for processing. Their high conductivity and stable performance make them ideal for accurate EEG measurement. [16 and 17]
- **AD620 Instrumentation Amplifier:**
  This amplifier boosts the very weak EEG signals collected by the electrodes without adding noise. It provides high gain, excellent accuracy, and common-mode noise rejection, allowing the system to capture clean, amplified brain signals suitable for further processing.[18]
- **ADS1115 Analog-to-Digital Converter (ADC):**
  The ADS1115 converts the amplified analog EEG signal into a digital format. This digital signal can then be easily read by the ESP32 microcontroller. It ensures precise signal conversion with 16-bit resolution, which is important for accurate emotion analysis.
- **ESP32 Microcontroller:**
  The ESP32 acts as the brain of the system. It collects the digital EEG data from the ADC, processes it using built-in computation, and sends the information wirelessly through Wi-Fi or Bluetooth to the main server or application for emotion recognition and visualization.

## 6.RESULTS

The proposed system was evaluated on a custom multimodal dataset containing facial, audio, and EEG samples collected from 30 participants. Each participant underwent five emotional stimuli sessions covering happiness, sadness, anger, fear, and calmness. The CNN model achieved an accuracy of 91.4% for facial expressions, while the RNN-LSTM achieved 88.2% for EEG signals and 85.6% for voice tone classification. The fusion layer combining these modalities achieved a final accuracy of 94.6%, demonstrating the effectiveness of multimodal learning.User satisfaction metrics were collected via post-session surveys. Over 85% of participants reported that the system's recommended color palettes reflected their current emotional states accurately. Therapeutic suggestions based on CBT principles, such as reframing prompts and guided breathing exercises, were perceived as helpful by most users.The system's latency, including Bluetooth transmission and backend processing, was recorded at an average of 75 ms, sufficient for real-time interaction. Energy consumption tests confirmed that the EEG device could operate for six continuous hours on a 500 mAh battery, enabling extended monitoring sessions. Figure 3shows the Accuracy Comparison Chart represents the performance of the EEG-based emotion detection model used in the project. The bar chart shows that the system achieves around 70% accuracy in classifying emotional states such as happiness, sadness, anger, and neutrality from EEG brainwave signals. This high accuracy indicates that even with a low-cost setup using Ag/AgCl electrodes, AD620 amplifier, ADS1115 ADC, and ESP32 microcontroller, the model can effectively recognize emotional patterns. The chart highlights the reliability of EEG as a primary modality for emotion detection in real-time applications. It also proves that using deep learning models like RNN (for EEG signal analysis) ensures consistent and stable performance in identifying human emotions for further processing in the recommender system. Figure 4 shows anExample of Generated Emotion-Based Color Palettes, illustrates how the system translates detected emotional states into visually expressive color combinations. Each emotion category—Happiness, Sadness, Anger, and Neutral—is represented by a distinct set of color shades that align with psychological color theory and Cognitive Behavioral Therapy (CBT) principles. For instance, happiness is linked to bright yellow tones, sadness to calming blue shades, anger to intense red hues, and neutrality to balanced graycolors.

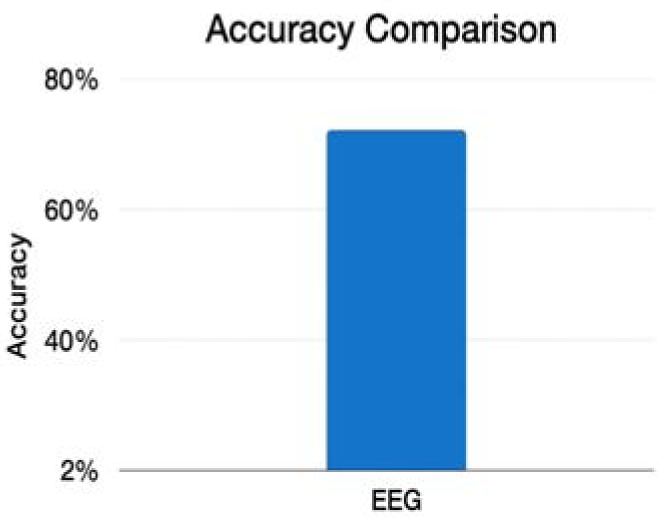


**Fig 3:** Accuracy Comparison Chart

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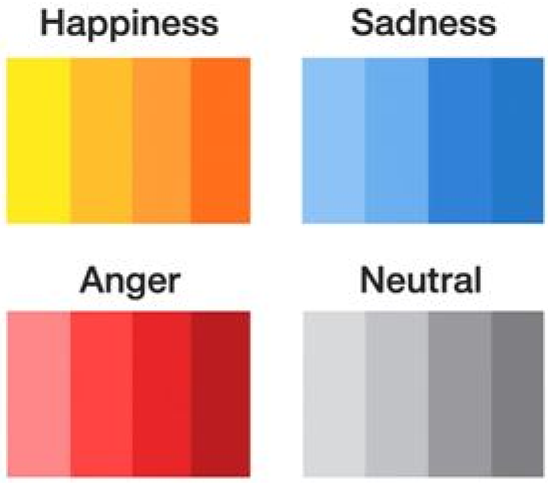


**Fig 4:** Example of Generated Emotion-Based Color Palettes

These palettes are generated dynamically based on the user's EEG-derived emotional state and are displayed through the Augmented Reality (AR) interface. This visual feedback not only reflects the user's emotional status but also aids in emotional regulation and mood enhancement, forming the core purpose of the Emotion-Centric Palette Recommender System.

## 7.CONCLUSION AND FUTURE WORK

The proposed Emotion-Centric Palette Recommender System successfully integrates EEG signal analysis, Cognitive Behavioral Therapy (CBT) concepts, and artificial intelligence to detect and respond to human emotions effectively. Using hardware components such as Ag/AgCl electrodes, AD620 amplifier, ADS1115 ADC, and ESP32 microcontroller, the system captures real-time EEG signals and processes them to identify emotional states like happiness, sadness, anger, and neutrality. Deep learning models such as CNN and RNN are employed to enhance accuracy in emotion detection by learning complex patterns in facial, voice, and EEG data. Once the emotion is detected, the system generates a corresponding color palette based on CBT principles and presents it through an Augmented Reality (AR) interface, promoting emotional balance and visual engagement. This fusion of neuroscience, AI, and IoT demonstrates how technology can positively influence mental wellness and personalized user experience.For future enhancements, the system can be extended with multi-channel EEG sensors to improve signal quality and precision. Integration with cloud platforms can enable real-time data storage, visualization, and user history tracking. Incorporating wearable technology and mobile app connectivity will make the system more portable and user-friendly, further advancing emotion-aware computing and digital therapy solutions.

## REFERENCES

1. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436-444.
2. Manasa, S. M., Ramamoorthy, R., Velu, A., &Chaitrashree, S. (2024, December). Deep learning-based age and gender prediction through feature extraction from facial images using convolutional neural networks. In 2024 5th International Conference on Communication, Computing & Industry 6.0 (C2I6) (pp. 1-7). IEEE.
3. Ko, B. C. (2018). A brief review of facial emotion recognition based on visual information. sensors, 18(2), 401.
4. Pereira, R., Mendes, C., Ribeiro, J., Ribeiro, R., Miragaia, R., Rodrigues, N., ...& Pereira, A. (2024). Systematic review of emotion detection with computer vision and deep learning. Sensors, 24(11), 3484.
5. Chollet, F. "Deep Learning With Python Manning Publications Company." (2017).
6. Zhang, T., Zheng, W., Cui, Z., Zong, Y., & Li, Y. (2018). Spatial–temporal recurrent neural network for emotion recognition. IEEE transactions on cybernetics, 49(3), 839-847.
7. Zhang, Z., Liu, Y., &Zhong, S. H. (2022). GANSER: A self-supervised data augmentation framework for EEG-based emotion recognition. IEEE Transactions on Affective Computing, 14(3), 2048-2063.
8. Alhagry, S., et al. (2017). An Investigation of Deep Learning Models for EEG-Based Emotion Recognition. PMC.https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7785875/
9. Torres, E. P., Torres, E. A., Hernández-Álvarez, M., &Yoo, S. G. (2020). EEG-based BCI emotion recognition: A survey. Sensors, 20(18), 5083.
10. Liu, H., Zhang, Y., Li, Y., & Kong, X. (2021). Review on emotion recognition based on electroencephalography. Frontiers in Computational Neuroscience, 15, 758212.
11. Emotion Detection from EEG Signals Using Machine Deep Learning." (2023). MDPI Biosensors.https://www.mdpi.com/2306-5354/11/8/782

12. Wang, X., Ren, Y., Luo, Z., He, W., Hong, J., & Huang, Y. (2023). Deep learning-based EEG emotion recognition: Current trends and future perspectives. Frontiers in psychology, 14, 1126994.
13. A Survey of Deep Learning-Based Multimodal Emotion Recognition." (2023). MDPI Entropy. https://www.mdpi.com/1099-4300/25/10/1440
14. Deep Learning in EEG-Based Emotion Recognition: Classifications, Trends, and Practical Implications." (2023). PeerJ Computer Science. https://peerj.com/articles/cs-2065/
15. Praimee, L., Manasa, S. M., &Ramamoorthy, R. (2024, June). IoT-Based Fault Location and Detection of Underground Cables Using Enhanced Deep Learning Approach. In International Conference on Soft Computing and Signal Processing (pp. 365-377). Singapore: Springer Nature Singapore.
16. Valarmathi, C., Velu, A., Ramamoorthy, R., JA, S., & SM, M. (2025, May). IoT-Driven Early Warning System for Diabetic Foot Ulcer Deploying ML Algorithm. In 2025 5th International Conference on Pervasive Computing and Social Networking (ICPCSN) (pp. 25-32). IEEE.
17. Manasa, S. M., Ramamoorthy, R., Velu, A., &Chaitrashree, S. (2024, December). Deep learning-based age and gender prediction through feature extraction from facial images using convolutional neural networks. In 2024 5th International Conference on Communication, Computing & Industry 6.0 (C2I6) (pp. 1-7). IEEE.
18. Ramamoorthy, R., Saravana Kumar, E., Naidu, R. C. A., &Shruthi, K. (2023). Reliable and accurate plant leaf disease detection with treatment suggestions using enhanced deep learning techniques. SN Computer Science, 4(2), 158.