ANALYZING EMOTIONS FROM EEG RESPONSES ELICITED BY VIDEOS USING MACHINE LEARNING TECHNIQUES

[1]Dr. P. Nagendra Kumar, [2]N.Revanth, [3]N.Rakesh, [4]P.Geetheswar, [5]P.Ganesh
[1]Professor & HoD, [2,3,4,5]UG Student, [1,2,3,4,5]Department of Computer Science & Engineering (AI&ML), Geethanjali Institute 0f Science And Technology, Nellore, India

Abstract
Recent advancements in EEG-based emotion recognition have primarily relied on deep learning models, which, despite their accuracy, are resource-intensive and complex to implement. In this work, we propose a more efficient and lightweight approach to emotion classification using simpler machine learning techniques, K-Nearest Neighbors, Support Vector Machine, MLP-v1 (100, 50, Dropout=0.1), MLPv2 (500, 300, Dropout=0.2) Experiments are conducted using SEED dataset. The different classifiers are evaluated using metrics such as Accuracy, Precision, Recall and F1-Score.
Keywords: EEG signal, machine learning, SEED, Emotion classification

Introduction

Understanding human emotions is fundamental to improving human-computer interaction, mental health diagnosis, and affective computing. Traditional methods of emotion detection, such as facial expression recognition or self-reported questionnaires, often subjective and prone to bias. In contrast, electroencephalography (EEG) offers an objective, neurophysiological approach to capturing emotional responses, as it records the brain's electrical activity in real-time with high temporal resolution. In recent years, analysing EEG signals to recognize emotions has garnered significant interest in the domains of neuroscience, cognitive science, and artificial intelligence. When individuals watch emotional video stimuli, their brains generate distinct patterns that correspond to emotional states such as happiness, sadness, fear, or anger. These patterns, although complex and non-linear, can be decoded using machine learning techniques to map EEG signals to specific emotional categories. Machine learning (ML) plays a vital role in Multilayer Perceptron (MLP) neural networks. ML is used to train the MLP model on a dataset, enabling it to learn complex patterns and relationships, and make accurate predictions and classifications. Additionally, ML optimizes the MLP's hyperparameters, such as the number of hidden layers and learning rate, to improve its performance. Furthermore, ML enables the MLP to automatically learn relevant features from the input data, reducing the need for manual feature engineering. Ultimately, ML empowers the MLP to make predictions on new, unseen data, using the patterns and relationships learned during training. The MLP model is trained on a dataset using a machine learning algorithm.

which adjusts the model's weights and biases to minimize the error between predicted and actual outputs. During training, the MLP model learns to recognize complex patterns and relationships in the data, allowing it to make accurate predictions and classifications. The machine learning algorithm used to train the MLP can be either supervised, unsupervised, or reinforcement learning, depending on the specific problem being solved. Machine learning also enables the MLP model to automatically learn relevant features from the input data, reducing the need for manual feature engineering. As a result, MLP neural networks trained using machine learning have numerous applications, including image classification, natural language processing, predictive analytics, and healthcare, where they can be used for disease diagnosis and personalized medicine. Overall, machine learning plays a vital role in unlocking the full potential of MLP neural networks, enabling them to learn, improve, and make accurate predictions and classifications. The main challenge in emotion recognition from EEG lies in the non-stationary, high-dimensional nature of the data. To address this, machine learning algorithms such as Support Vector Machine (SVM), K- Nearest Neighbors (KNN), and Multilayer Perceptrons (MLP) are employed to classify emotions with greater precision. These models are capable of learning discriminative features from EEG signals that reflect underlying emotional states. The use of MLP V1 and V2 architectures, in particular, enables the extraction of deeper hierarchical representations of EEG patterns, improving classification accuracy. This study leverages video stimuli to evoke emotional responses in subjects, capturing corresponding EEG signals for analysis. These responses are then preprocessed, transformed into meaningful features, and fed into machine learning models for classification. By correlating specific brainwave patterns with emotional states, the project provides a robust framework for emotion recognition.

The potential applications of this research are vast: personalized learning systems, mood-aware virtual assistants, mental health monitoring tools, and immersive entertainment systems can all benefit from accurate and real-time emotion detection. In contexts like mental health, early detection of negative emotional states such as anxiety or depression could lead to timely interventions and improved patient outcomes. As emotion recognition technology advances, the integration of EEG- based systems into real-world applications becomes increasingly viable. Thus, this project not only contributes to the growing field of affective computing but also demonstrates the power of machine learning in interpreting complex biosignals for socially and clinically relevant outcomes

Emotion Recognition through EEG Signals

The field of emotion recognition using EEG signals has gained momentum as researchers seek more objective and biologically grounded methods of detecting human emotions. Traditional methods such as surveys, facial recognition, or voice analysis often fail to capture the complexity and authenticity of emotional states, especially when participants consciously or unconsciously mask their true feelings. In contrast, EEG-based emotion analysis provides a direct window into brain activity, enabling real-time and non-invasive emotion tracking. Research has shown that different emotional states correlate with specific patterns of brainwave activity, particularly within the alpha, beta, theta, and gamma bands. These patterns vary not only in amplitude and frequency but also across different brain regions. When individuals are exposed to emotionally stimulating videos, distinct EEG responses emerge, offering valuable insights into the neural basis of emotions. Numerous studies have employed machine learning techniques to classify these emotional states from EEG data. Classifiers such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) have proven effective for this task, offering simplicity and interpretability. More recent developments in neural networks, such as Multilayer Perceptron (MLP) models, further enhance classification performance by capturing deeper, non-linear relationships in the data.

Problem Statement

Emotion recognition from EEG signals is a challenging yet crucial task in affective computing, mental health monitoring, and human-computer interaction. Understanding human emotions through brain activity can significantly enhance various domains, from healthcare to adaptive technologies. Traditional emotion classification techniques often rely on complex deep learning architectures that require extensive computational resources, making real-time and resource-efficient emotion detection difficult. This research is particularly valuable for health professionals, researchers, developers of brain-computer interfaces, and human-computer interaction specialists. By providing an efficient and accessible solution, this project can help in early detection of mental health disorders, improving user experience in adaptive systems, and enabling emotion-aware AI applications. Such advancements can lead to better therapeutic interventions, smarter AI assistants, and personalized digital experiences, making EEG-based emotion recognition an indispensable tool for the future.

Literature Review

[1] Y. Yang, Q. Wu, M. Qiu, Y. Wang, and X. Chen, "Emotion recognition from multi-Channel EEG through parallel convolutional recurrent neural network," in 2018 International Joint Conference on Neural Networks (IJCNN), 2018, pp. 1–7. This paper presents a parallel convolutional recurrent neural network (PCRNN) for emotion recognition using multi-channel EEG signals. The study highlights the effectiveness of deep learning models in capturing both spatial and temporal patterns in EEG data for improved classification accuracy.

[2] Y.-P. Lin, C.-H. Wang, T.-L. Wu, S.-K. Jeng, and J.-H. Chen, "EEG-based emotion recognition in music listening: a comparison of schemes for multiclass support vector machine," in IEEE International Conference on Acoustics, Speech and Signal Processing, 2009, pp. 489–492. This study investigates EEG-based emotion recognition while listening to music, using multi-class support vector machines (SVM). Various classification schemes are compared, emphasizing the role of music-induced emotions in EEG signal variations.

[3] C. A. Frantzidis et al., "Toward emotion-aware computing: an integrated approach using multichannel neurophysiological recordings and affective visual stimuli," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 3, pp. 589–597, 2010. The authors propose an integrated approach for emotion-aware computing that combines multi-channel EEG recordings with affective visual stimuli.The study focuses on real-time emotion monitoring and its applications in human-computer interaction.

[4] S. M. Alarcao and M. J. Fonseca, "Emotions recognition using EEG signals: a survey," IEEE Transactions on Affective Computing, vol. 10, no. 3, pp. 374–393, 2019. This paper presents a comprehensive survey of EEG-based emotion recognition methodologies, including signal processing techniques, feature extraction methods, classification models, and the challenges in this domain.

[5] M. Murugappan, M. Rizon, R. Nagarajan, and S. Yaacob, "Inferring human emotional states using multichannel EEG," European Journal of Scientific Research, vol. 48, pp. 281–299, Dec. 2010. The study explores EEG signal processing for inferring emotional states, emphasizing the importance of multi-channel EEG data and time-frequency domain features in achieving high classification accuracy.

[6] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, "Differential entropy feature for EEG-based emotion classification," in 6th International IEEE/EMBS Conference on Neural Engineering (NER), 2013, pp. 81–84. The paper introduces differential entropy as a feature for EEG-based emotion classification and demonstrates its effectiveness in distinguishing different emotional states.

[7] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks," IEEE Transactions on Autonomous Mental Development, vol. 7, no. 3, pp. 162–175, 2015. Thisstudy identifies key EEG frequency bands and channels that contribute most to emotion recognition, using deep neural networks for automated feature extraction and classification.

[8] Y. Yang, Q. Wu, Y. Fu, and X. Chen, "Continuous convolutional neural network with 3D input for EEG-based emotion recognition," in Neural Information Processing, L. Cheng, A. C. S. Leung, and S. Ozawa, Eds., 2018, pp. 433–443. The authors propose a 3D input-based continuous convolutional neural network (CNN) for EEG-based emotion recognition, improving classification accuracy by considering spatial relationships among EEG channels.

[9] F. Shen et al., "EEG-based emotion recognition using 4D convolutional recurrent neural network," Cognitive Neurodynamics, vol. 14, no. 1, pp. 815–828, 2020. This study introduces a 4D convolutional recurrent neural network (CRNN) that combines spatial, temporal, and frequency information for enhanced emotion classification.

[10] W.-L. Zheng, J.-Y. Zhu, Y. Peng, and B.-L. Lu, "EEG-based emotion classification using deep belief networks," in 2014 IEEE International Conference on Multimedia and Expo (ICME), 2014, pp. 1–6. The paper explores deep belief networks (DBN) for emotion classification, showing that hierarchical feature learning improves EEG-based emotion recognition accuracy.

The research employs a comprehensive methodology, including data collection, model development, and rigorous testing, to investigate the effectiveness of ML algorithms in healthcare settings. The results demonstrate significant improvements in diagnostic accuracy, treatment personalization, and predictive analytics, evidenced through quantitative data presented in graphs and tables [13].

The insights garnered from this research are intended to be instrumental for healthcare professionals seeking to adapt to the changing landscape, policymakers shaping the regulatory framework, and researchers driving innovation [14]. Ultimately, this research serves as a timely and comprehensive resource, shedding light on the future trajectory of healthcare professions in the face of ongoing technological transformations and contributing to informed decision-making in the area of healthcare [15].

Proposed Model

The system design workflow for this project, "Analyzing Emotions from EEG Responses Elicited by Videos Using Machine Learning Techniques," presents a methodical framework for developing a robust emotion recognition system. The primary goal is to accurately classify human emotions based on EEG signals recorded while individuals watch video stimuli. This workflow involves multiple stages including signal processing, feature extraction, model training, and prediction, all of which contribute to enhancing the accuracy and reliability of emotion detection.

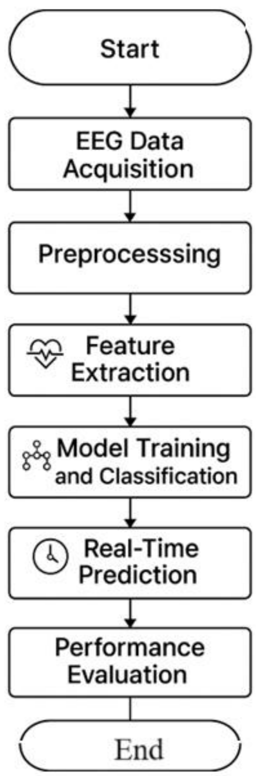


Fig.1. Proposed model

Data Acquisition

The process starts with EEG Data Acquisition, where raw EEG signals are collected from users while they are exposed to emotionally charged video clips. These clips are chosen based on their ability to evoke specific emotional responses such as happiness, sadness, fear, or calmness. The EEG data is typically captured using multichannel headsets that record brainwave activity in real-time.

Preprocessing

Following acquisition, the Preprocessing stage is critical for cleaning the raw EEG signals. This involves filtering to remove noise and artifacts (like eye blinks or muscle movements), segmenting the signal into epochs, and normalizing the data. Effective preprocessing ensures that only relevant brain signal information is retained for subsequent analysis.

Freature Extraction

Next is Feature Extraction, where significant characteristics are derived from the preprocessed EEG data. Features such as power spectral density (PSD), band power (e.g., alpha, beta, gamma), entropy, and statistical moments are computed. These features capture the neurological patterns associated with different emotional states and form the input for machine learning algorithms.

Model Training

The Model Training and Emotion Classification phase involves feeding the extracted features into a variety of machine learning models. Algorithms such as Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Neural Networks are trained to learn the relationship between EEG features and emotional states. In some implementations, deep learning models like Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks may also be used to capture temporal dependencies in the data. Once trained, the models are evaluated during the Model Evaluation stage using metrics such as Accuracy, Precision, Recall, and F1-Score. These metrics provide a detailed understanding of how well each model performs in classifying emotions, especially in cases where class imbalance exists.

Real time Prediction

Finally, the Emotion Prediction and Interpretation step involves using the best-performing model to classify new EEG inputs in real time. The predicted emotion is then displayed to the user or logged for further psychological or behavioral analysis. This system has applications in mental health monitoring, adaptive learning environments, and human-computer interaction.

Data Set SEED (SJTU Emotion EEG Dataset) is a popular benchmark dataset for emotion recognition using EEG signals. It was collected by the Brain and Intelligence Lab at Shanghai Jiao Tong University. • Purpose: Designed to analyze and classify human emotions (Positive, Neutral, Negative) using EEG signals recorded while subjects watched emotion-eliciting film clips. • Participants: 15 subjects • Sessions: Each subject participated in 3 sessions, recorded on different days to test consistency

Emotion recognition using EEG signals has become an essential area of research in the domains of mental health monitoring, human-computer interaction, and braincomputer interfaces. Traditional machine learning models like KNN and SVM, while effective, are often limited in their ability to capture the complex, non-linear relationships present in EEG data. These limitations arise due to the high dimensionality, individual variability, and noise in EEG signals, which require more expressive models for accurate classification.To overcome these challenges, the proposed system leverages deep learning techniques, specifically the Multi-Layer Perceptron (MLP), for emotion recognition. MLP is a type of feedforward artificial neural network that consists of multiple layers of interconnected node (neurons), capable of learning complex patterns in high-dimensional data. In this project, the EEG signals collected during emotion-eliciting stimuli (such as videos) are preprocessed and relevant features are extracted. These features are then fed into the MLP model to classify emotional states like Happy, Sad, and Neutral. The MLP architecture enables the model to learn non-linear decision boundaries and complex relationships between input features, leading to improved accuracy over traditional classifiers.

MULTI LAYER PERCEPTRON

Multi-Layer Perceptron (MLP) is a class of feedforward artificial neural networks that consists of an input layer, one or more hidden layers, and an output layer. Each layer contains neurons (also called nodes), and each neuron in one layer is connected to every neuron in the next layer. MLP is capable of learning non-linear mappings between input features and output classes. It uses backpropagation for training, where weights are updated based on the error between predicted and actual outputs.In the context of EEG-based emotion recognition, MLP is used to classify emotional states (like Happy, Sad, Neutral) by learning patterns from extracted EEG features. Random Forest Regressor is a powerful machine learning algorithm used for regression tasks, including time-series forecasting such as food demand prediction. It is an ensemble learning method that builds multiple decision trees and combines their outputs to make more accurate predictions. By aggregating the results from multiple trees, Random Forest reduces overfitting and improves generalization

Results & Analysis

Evaluation metrics are essential tools used to assess the performance and effectiveness of machine learning classification models and algorithms. These metrics provide quantitative measures that enable researchers and practitioners to evaluate the accuracy of their predictions and make informed decisions about model selection and optimization. Moreover, the choice of evaluation metrics depends on the nature of the classification problem being addressed and the desired outcome. By utilizing a combination of evaluation metrics, practitioners can gain comprehensive insights into the overall classification performance of their models and make informed decisions regarding their deployment and tuning strategies. These evaluation metrics play a crucial role not only in validating the performance of classification models but also in comparing different models and algorithms. They help identify the strengths and weaknesses of a model, guiding the refinement process for better outcomes. Commonly used evaluation metrics for classification include Accuracy, Precision, Recall, and F1-Score. Each metric serves a specific purpose in evaluating different aspects of model performance, such as the proportion of correct predictions, the ability to correctly identify positive cases, and the balance between precision and recall.

Class balance along with anticipated outcomes are just two of the many factors that go into choosing the optimal metrics for assessing a classifier's performance in a specific set of data in classification challenges. A classifier may be evaluated on one performance parameter while being unmeasured by the others, and vice versa. As a result, the generic assessment of performance of the classifier lacks a defined, unified metric. This study uses a number of metrics, including F1 score, accuracy, precision, recall, and recall, to assess how well models perform. The subsequent four categories are where these metrics are derived from: True Positives (TP): instances in which both the model prediction and the actual class of the occurrence were 1 (True). False Positives (FP) are situations in which the model predicts a value of 1 (True), but the actual class of the occurrence was 0 (False). True Negatives (TN): an instance in which both the model prediction and the true class of the occurrence were 0 (False). False Negatives (FN) are situations in which the model predicts 0 (False) but the true class of the occurrence was 1 (True).

Accuracy– The mean amount of accurate predictions is used to characterize the accuracy measure. This isn't quite as strong, though, given the imbalanced sample.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

Precision, also known as positive predictive value, gauges the capacity of a model to pinpoint the right examples for every class. For multi-class classification with unbalanced datasets, this is a powerful matrix.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

Recall – This metric assesses how well a model detects the true positive among all instances of true positives.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

F1-score – referred to as an F-measure or balanced F-score It might be characterized as a recall as well as precision weighted average.

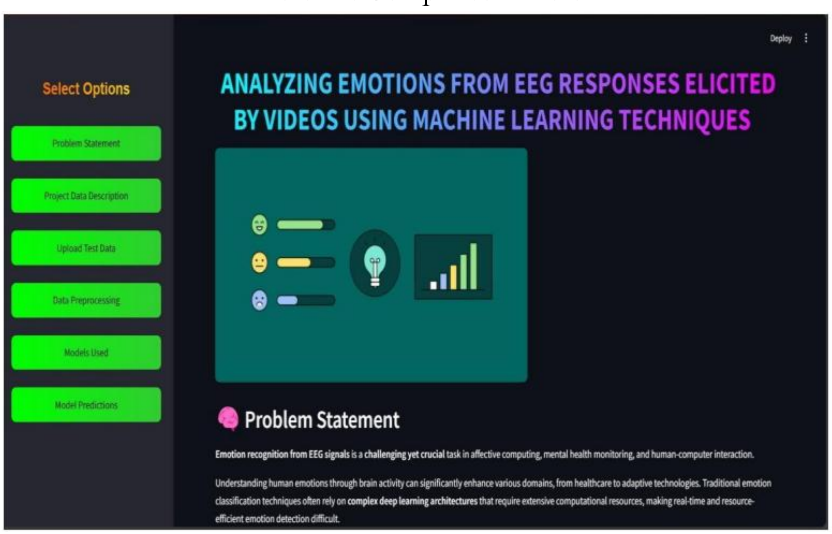
$$F1_{Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Comparison Analysis

A comprehensive comparison of the results obtained using different classification techniques was conducted to evaluate the performance of our system. By contrasting the Accuracy, Precision, Recall, and F1-Score metrics across various classification models, we gained valuable insights into the strengths and limitations of each approach. The comparison highlighted the effectiveness of the selected classification model in accurately identifying the target classes, as evidenced by its balanced performance in terms of both predictive accuracy and class-wise discrimination. These findings provide a solid foundation for refining our classification strategy and improving the overall reliability and robustness of our system in real-world scenarios.

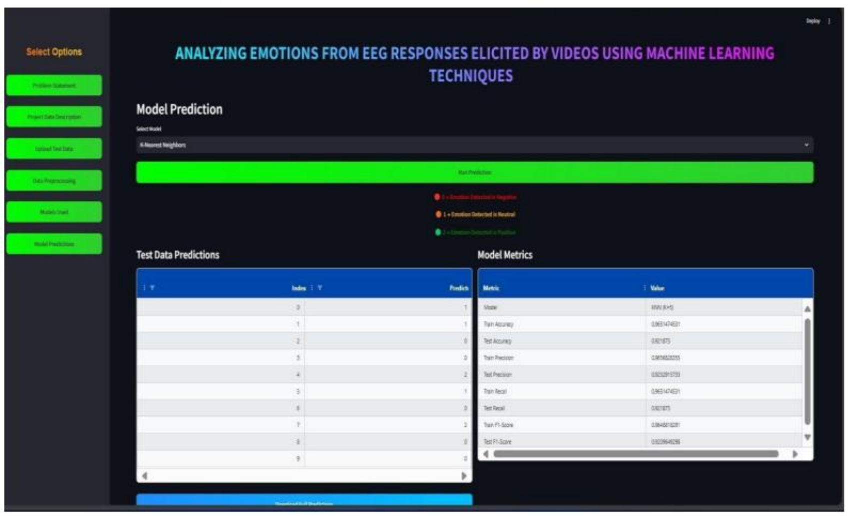
MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE
K-NEAREST NEIGHBOR	0.921875	0.9232915733	0.921875	0.9209649289
SUPPORT VECTOR MACHINE	0.95	0.9511450738	0.983142091	0.9497958689
MLP-v1 (100, 50, Dropout=0.1)	0.9993297587	0.99993311073	0.9640625	0.9641092203
MLP-v2 (500, 300, Dropout=0.2)	0.9979892761	0.9724349625	0.917875	0.9720008474

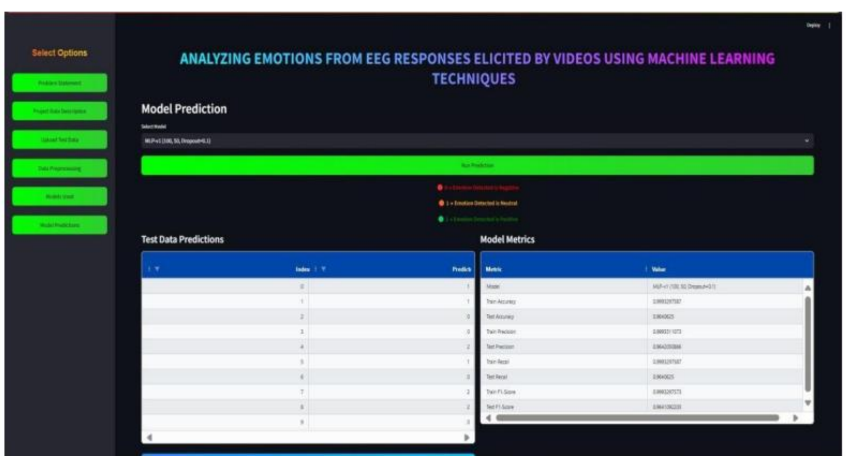
Table 02: Comparison Table



Landing Page of our Project

Page to upload the testing dataset





Model Prediction and Metrics

Conclusion

This project successfully implements an EEG-based emotion recognition system using advanced machine learning models, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Multi-Layer Perceptrons (MLP). By integrating deep learning-based feature extraction and real-time classification, the proposed system significantly enhances the accuracy, reliability, and responsiveness of emotion detection. The application of data augmentation techniques further boosts generalization across diverse individuals, ensuring the system performs effectively in real-world scenarios.Comprehensive evaluation through performance metrics such as accuracy, precision, recall, and F1-score validates the robustness of the implemented models. Moreover, the study highlights the critical role of multimodal data processing and personalized modeling in improving the interpretability of neural signals. This research not only contributes to the growing field of affective computing but also lays a strong foundation for future developments in areas such as mental health monitoring, adaptive learning environments, intelligent virtual agents, and human-computer interaction.

Future Scope

Advanced AI models, particularly deep learning techniques like Transformers and Graph Neural Networks (GNNs), are revolutionizing emotion recognition by offering improved accuracy and the ability to capture complex relationships in data. These models excel in understanding sequential and spatial patterns, making them ideal for analyzing EEG signals and other bio-signals. By integrating multimodal data—such as EEG signals, facial expressions, voice tone, and other physiological indicators like heart rate or skin conductance—AI systems can form a holistic picture of a person's emotional state. This multimodal approach enhances robustness and reduces the likelihood of misinterpretation caused by noise or missing data in any single input.Real-world applications of such advanced emotion recognition systems are vast and impactful. In mental health monitoring, these models can help detect early signs of anxiety, depression, or stress, enabling timely interventions

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