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A SYSTEMATIC REVIEW OF DEEP LEARNING METHODS FOR EMOTION RECOGNITION ON EEG DATA

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Abstract:
Electroencephalography (EEG) has emerged as a powerful modality for emotion recognition, offering a direct window into the neural correlates of affective states that is difficult to consciously mask, unlike facial expressions or speech. In recent years, deep learning has largely replaced traditional handcrafted-feature-and-classifier pipelines as the dominant approach in this field, owing to its ability to automatically learn discriminative spatial, spectral, and temporal representations from raw or minimally processed EEG signals. This paper reviews the evolution of deep learning methods applied to EEG-based emotion recognition . Multi-modal and multi-scale models improve recognition by learning different representations from multiple input sources. EEG-based emotion recognition, in particular, provides detailed insights into brain responses, allowing for noninvasive and continuous emotional state monitoring. Hybrid models that combine spatial, channel-wise, and graph-based attention can assist solve signal variability and noise issues. Modern emotion detection systems seek for accuracy, scalability, and explainability to fulfill the needs of real-world applications.

***Index Terms* -** Emotion, EEG, CNN, Transformer, Multimodal

I. INTRODUCTION

Emotions play an important role in many aspects of our daily lives, such as learning, decision-making, and interpersonal interactions. The choices and actions we take are often influenced by the emotional signals we perceive. This emotional exchange enhances the effectiveness and fluidity of information transmission. Human to human communication is fundamentally based on emotions, which also provide important signals to allow us to transmit our messages. Our daily lives now more involve interactions between people and machines as technology develops, not merely between people. In human-to--human contacts, humans can clearly understand and react to emotional signals, guaranteeing smooth communication; in human-to--machine interactions, the same cannot be asserted. The often static and predetermined responses of machines can leave users feeling unsatisfied and agitated. This study intends to improve computer understanding of human emotions and recognition. Though they are vital for our daily existence, the way the brain handles emotions is yet unknown. From psychology to engineering, the study of emotional recognition via electrophysiological responses has drawn interest in many fields. In this paper, we build a thorough model for electroencephalography (EEG) emotion detection utilising cutting-edge machine learning approaches. As cognitive science has developed, EEG has become an important instrument for investigating the inner workings of the brain concerning perception, memory, and attention [1]. For years, people have argued about whether or not emotions affect cognitive functions. Because of the inherent difficulties in studying emotions, scholars typically disregarded the study of emotional states until the late 20th century [2]. The study intends to increase a computer's capacity to exactly recognise and comprehend human emotions. psychiatrist and physiologist [3]. Originally, clinical environments mostly employed EEGs to identify brain-related disorders such Alzheimer's disease, ADHD, and epileptic seizures. Due in great part to the high cost and immobility of EEG devices as well as the necessity for knowledge in data collecting, its use was limited in the medical field for many years. But because to recent technological developments, wearable, portable, wireless user-friendly EEG equipment have become available. These developments have made it simpler for people to record their EEG on their own without professional help, therefore extending its application beyond medical diagnosis to include personal entertainment. Though still very costly, other brain imaging techniques including functional near-infrared spectroscopy (fNIR), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI) are nevertheless largely used in clinical settings. Although brain diagnoses in healthcare mostly rely on EEG, its present uses span several spheres, including: a) cognitive enhancement, b) entertainment, c) brain-computer interfaces (BCI), d) analysing humanoid aspects, e) marketing, and f) rehabilitation. For user amusement, businesses including Emotiv [4] and NeuroSky [5] have developed EEG-based games. In healthy people as well as in stroke patients or those with drug addiction, EEGdriven neurofeedback sessions have been used to improve cognitive functions [6–7]. Researchers have also used EEG to maximise working settings and by economists to grasp consumer behaviour. Affective brain-computer interfaces (ABCI) are the main topic of this dissertation [8], with a more general focus on EEG-based BCI. By creating a direct link between the brain and a machine, brain-computer interfaces (BCIs) allow individuals to communicate with machines directly, avoiding the peripheral nervous system. An aBCI integrates emotional elements into this interaction. Ideally, such an interface can sense a user's emotional state from involuntary EEG signals and adjust its responses based on those emotions. the precise timing capabilities of EEG devices enable real-time tracking of a user's emotional state. Consequently, for scenarios requiring instant emotion detecAt the heart of affective Brain-Computer Interfaces (aBCI) is EEG-driven emotion detection. human emotions are intricate experiences that lead to both physical and psychological changes, often manifesting in behaviors such as gestures, facial expressions, and variations in voice tone. Historically, the identification of human emotions primarily relied on these outward displays, such as speech patterns and facial cues [9]. However, these expressions can be consciously altered or masked by individuals, making such emotion recognition methods potentially inconsistent. In contrast, EEG-based emotion detection offers insights into an individual's genuine inner emotions, as it directly captures fluctuations in brain activity. Furthermore, EEG driven methods may be the more favourable approach.

II.EEG SIGNAL

The electrical activity produced by nerve cells is reflected in biological signals called electroencephalograms, or EEGs. The electrical activity of the brain, as shown in Figure 1, represents the total electrical potentials generated by different brain areas. However, interference from sources other than the brain can also affect EEG data. These undesired impulses, originating from the electrical grid, muscles, or eyes, are known as artefacts.

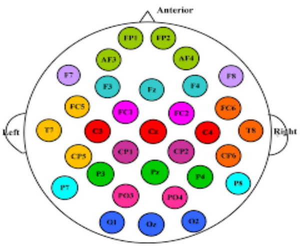

Fig 1 Electrode of Brain

III. CHALLENGES OF EEG PROCESSING

Because EEG signals are complex and difficult to decipher, accurate analysis requires expert judgement. Research indicates that the brain is constantly electrically active, and changes in EEG frequency reflect an individual's mental state. When a person is awake or focused on a task, beta (β) waves 14–30 Hz) predominate, whereas alpha (α) waves (8–14 Hz) are more prominent when the person is relaxed with their eyes closed. Important EEG rhythms include theta (θ) waves (4–8 Hz), which appear in infants during alertness, in adults under stress, and during hand movements, and delta (δ) waves (0–4 Hz), which are observed during deep leep (see Table 1.1). Amplitude fluctuations in scalp-based EEG readings typically range from 1 to 100 units. The frequency range of these signals is 0.5 to 100 ists in clinical and physiological settings typically focus on the 0.5 to 30 Hz range, as frequencies above this limit are considered to lack significant components [10]. Figure 1: Electrode of brain [11].

IV. EEG PROCESSING USING DEEP LEARNING METHODS

The paper aims to improve EEG-based emotion recognition while making the classification process interpretable. Many deep learning models achieve high accuracy but behave like "black boxes." The authors propose a method that not only recognizes emotions from EEG signals but also explains which EEG features and brain regions contribute most to the prediction. [15] The primary objective of this study is to evaluate the effectiveness of deep learning models for predicting user responses from EEG signals. The authors aim to determine which neural network architecture performs best for EEG time-series classification while maintaining high prediction accuracy for Brain–Computer Interface (BCI) applications. [16]Although cross-subject performance improved, EEG among individuals remains a significant challenge. [17] A new method is introduced using a classifier-dependent feature selection approach to classify valence, arousal, and dominance states using three different classifiers. A highest accuracy of 75%, 73.8%, and 75% is achieved for classifying valence, arousal, and dominance states, respectively. This study is used a relatively small experimental dataset, which may limit generalization. [18] The primary objective of this paper is to develop a real-time EEG-based emotion recognition (EEG-ER) system that works effectively with both high-density EEG systems (32 channels) and low-cost consumer-grade EEG devices (5 channels). The study focuses on recognizing emotions quickly and accurately, making EEG emotion recognition practical for real-world applications [19] The study proposes an EEG-based human emotion recognition system using Fast Fourier Transform (FFT) for feature extraction and the K-Nearest Neighbor (KNN) algorithm for emotion classification. The study relies on a relatively simple KNN classifier, whose performance depends on the choice of the value of k and the quality of the extracted features. Additionally, the model was evaluated on a limited dataset and does not address cross-subject variability, which may reduce its generalizability to real-world EEG emotion recognition applications. [20]. The work focuses on binary classification of Valence and Arousal, rather than recognizing a wider range of discrete emotions. Ahmad Chaddad et al., 2023 [21] conducted a thorough assessment of several works on EEG signal processing. Amer et al. [22] hope to inform practitioners about the best practices and possible future directions for enhancing the accuracy of automatic diagnostic systems. focuses specifically on medical and healthcare applications of EEG signal analysis and emphasizes how signal processing and machine learning support clinical diagnosis Suveetha Dhanaselvam et al., 2023 [23] conducted a study examining the different EEG pretreatment strategies presented in the published work focusing on the most appropriate preprocessing mode for any given application.highlighting how cleaning noisy EEG signals is essential before feature extraction and classification.

The paper proposes a deep learning-based automated system for detecting abnormal EEG signals associated with neurological disorders, particularly epilepsy, using a 1D Convolutional Neural Network (1D-CNN). Evaluates only a CNN architecture; newer models such as Transformers,[24] . Dagdevir et al. [25] proposed enhancing pre-processing methods to raise MI-BCI systems accuracy and time-cost performance. Preprocessing is thought to involve modifiable parameters such as time window-step size, time interval, theta frequency band, and mu and beta frequency bands. The Taguchi method is used to generate an experimental design that is used for the pretreatment processes. In order to diagnose one or two neurological illnesses simultaneously, Fahd A. Alturki et al. [26] suggested developing a single system. To help with the precise diagnosis of epilepsy and autism spectrum disorder (ASD), two neurological brain disorders, a number of EEG feature extraction and classification methods are being researched. Single-channel and multi-channel EEG signal types are used to assess epilepsy and ASD. It discusses both traditional machine learning and emerging deep learning methods for EEG analysis across applications such as brain–computer interfaces, emotion recognition, epilepsy detection, and sleep monitoring. This gives comparative analysis of several methods, we also analysing its outcome. Chaddad, A., Wu, Y., Kateb, R., & Bouridane, A. (2023) [27].

Singh, A. K., & Krishnan, [28], This review provides a comprehensive overview of feature extraction techniques used in EEG signal analysis, categorizing them into time-domain, frequency-domain, time–frequency, and nonlinear methods. It discusses the effectiveness of these techniques across applications such as brain–computer interfaces (BCIs), emotion recognition, epilepsy detection, sleep stage classification, and cognitive workload assessment. Electrooculogram and ECG artifacts are typical sounds encountered during the recording of EEG data, and they have a significant impact on the collection of useful details. Xiaozhong Geng et al., [29] present a technique for analyzing EEG data that combines ICA, WT, and comparable spatial patterns. Initially, the ICA technique is utilized to break down the electrical brain wave signals into individual elements, which are subsequently degraded by WT to produce the wavelet transform coefficient for each component.Yuvaraj et al. [30] addressed this by assessing the capacity to classify the dependability of a wide variety of EEG data sets for recognizing mental states according to arousal and valence. For five EEG feature sets statistical characteristics, FD, Hjorth parameters, HOS, and those produced by wavelet reconstruction the categorization accuracy was assessed

Table 1 EEG Data Preprocessing Methods

Reference	Pre-processing Technique(s)	Dataset	Accuracy (%)	Limitation
Ahmed, M. Z. I., et al. [21]	Comprehensive review of denoising techniques	DEEP & SEED	97.10%	Highlights limitations and future prospects of preprocessing methods
Syamsundararao, T., et al. [24]	Deep 1D CNN preprocessing pipeline	EEG	85.48%	The model uses only single-channel EEG data and short 60-second segments, which may limit generalization across diverse multi-channel or longer-duration EEG recordings.
Dagdevir, E., et al. [25]	Taguchi method for optimizing time window, frequency bands, etc.	IV-2b dataset	82.58%	Identified time window-step size as most impactful preprocessing factor
Alturki, F. A., et al. [26]	ICA for artifact removal, elliptic band-pass filtering	EEG dataset	99.9%	The study relies on pre-recorded datasets with limited sample diversity, which may affect generalizability across broader populations

V. DATABASE OF EEG SIGNAL

Three popular benchmark EEG datasets frequently used in emotion categorisation research are the SJTU Emotion EEG Dataset-IV (SEED-IV) and the Dataset for Emotion Analysis using hysiological Signals (DEAP). These datasets have been widely utilised in research related to the analysis and categorisation of emotions and include physiological signals such as EEG.

DEAP Dataset , Researchers investigating the classification of emotions using physiological signals can greatly benefit from the DEAP dataset. This dataset was developed by recording EEG and peripheral physiological signals from 32 subjects while they watched 40 one-minute videos. Several approaches for choosing channels that enable emotional recognition have been investigated, including those put forth by [13–14].

SEED-IV Dataset, The BCMI Laboratory provides a collection of EEG datasets known as SEED. For this study, the SEED-IV dataset was selected from among the SEED, SEED-IV, SEED-V, SEED-VIG, SEED-FRA, and SEED-GER datasets. Understanding the data is the first and most crucial step in EEG research. The SEED-IV dataset consists of EEG signals recorded from 15 participants across three sessions, with each session involving the viewing of 24 videos. EEG data were collected from 62 channels, and this extensive dataset is used for emotion classification.

MAHNOB-HCI is a multimodal dataset for emotion recognition and implicit affective tagging, created for studying human responses to emotionally evocative video stimuli. The dataset includes 27 usable participants (11 male, 16 female, aged 19–40) out of an original 30 recruited — three subjects didn't complete data collection, so most studies use only the 27 complete sets.

VI. OBJECTIVES OF THE PROPOSED SYSTEM

The main objective of the proposed system is to improve the robustness and accuracy of emotion classification by means of a new hybrid deep learning architecture. The system seeks to extract fine-grained, multi-modal emotional indicators from EEG signals, facial expressions, and voice data by merging Multi-Cross Vision Transformers (ViT) with Attention-Driven Saliency Mapping (ADSM). While the ADSM mechanism recognises the most emotionally salient places in the input, hence enhancing focus and interpretability, the Multi-Cross ViT module captures long-range dependencies and multi-scale contextual qualities across modalities. This approach ensures a more whole and interpretable feature representation, hence enhancing the explainability and performance of emotion identification algorithms. Another objective is to create a scalable and generalisable system able to regularly operate over several datasets and emotional states. This review also provides a detailed methodological information on various DL-EEG processing. This system offers the means for practical applications in emotional computing, mental health monitoring, and human-computer interaction by means of improved categorisation performance and explainable artificial intelligence components.

VII. CONCLUSION

This paper gives systematic review of papers from reputed conferences and journals about deep learning approaches for EEG-based emotion recognition. EEG based emotion recognition becomes increasingly popular because it enables numerous applications in affective computing and mental health monitoring as well as human-user interaction (HUI). .

Across the literature, EEG continues to be a preferred modality for affective computing due to its high temporal resolution and its ability to capture involuntary neural correlates of emotion that are difficult to consciously suppress or fabricate, making it especially valuable for applications in mental health monitoring, adaptive human-user interaction systems, and neuro feedback-based interventions. Standard deep learning approaches have achieved notable progress yet they fail to recognize fundamental spatial relationships which naturally occur within EEG datasets. This review also provides detailed methodological information on various DL-EEG processing Standard deep learning approaches have achieved notable progress yet they fail to recognize fundamental spatial relationships which naturally occur within EEG datasets. This review also provides a detailed methodological information on various DL-EEG processing The reviewed literature demonstrates that while conventional deep learning architectures including CNNs, RNNs, and LSTM-based models have delivered measurable improvements in classification accuracy over traditional machine learning pipelines, they largely treat EEG channels as independent or loosely structured input streams. This design choice systematically overlooks the spatial topology of electrode placement on the scalp, along with the inter-channel dependencies and cross-hemispheric interactions that are neurologically meaningful for emotion processing. As a result, many existing models fail to capture the full spatial-spectral- temporal structure inherent in EEG signals, which likely constrains their generalization across subjects and recording sessions — a limitation consistently reported across the studies surveyed. Emerging architectures, particularly graph neural networks and transformer-based models capable of modeling spatial relationships through attention or adjacency-based representations, show promise in addressing this gap.

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