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Recent Progress in Human Emotion Recognition Using EEG Signals: A Brief Review

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***Abstract*— During cognitive and emotional activities, the rhythmic, spontaneous impulses of neurons in the brain generate electrical potentials. These electrical potentials can be detected as brain waves using various instruments. Among those instruments, EEG is widely used for emotion recognition. The process of EEG-based emotion recognition generally consists of several steps: data collection using EEG, preprocessing the data, feature extraction, feature dimensionality reduction, and classification. With the advancement of information technology, these steps have been improved significantly. New approaches such as new machine learning and deep learning models are being employed in this field. Moreover, through continuous research, new theoretical ideas of emotions are being proposed for the use of EEG-based emotion recognition. In recent years, the field of EEG-based emotion recognition has seen significant progress. This article explores these advancements and gives an overview of current trends and progression in EEG-based emotion recognition.**

Keywords—EEG, emotion recognition, review, recent trends

I. Introduction

Emotions are central to human cognition and behavior. Emotions play major roles in different aspects of daily life, including decision-making, problem-solving, and communication [1], [2]. The emotional state of an individual is closely associated with their overall well-being. Accurately recognizing emotions is crucial in various applications, including mental health diagnosis, human-computer interaction, and affective computing [3], [4], [5]. One of the widely used tools for emotion recognition is Electroencephalography (EEG). It is popular because of its availability, cost-effectiveness, portability, and ease of use. Additionally, its non-invasive nature makes it an ideal choice for emotion recognition tasks [5], [6]. However, the method has several limitations, including noise sensitivity, individual and session-specific variations in signal patterns, and the difficulty of interpreting the high-dimensional data [6]. These limitations reduce the tool's effectiveness, hinder the generalizability of emotion recognition models, and make it challenging to adopt EEG for diverse real-life applications. The good news is that recent developments in artificial intelligence, especially in machine learning and deep learning, have shown promise in overcoming many of these limitations. This paper explores these advancements and provides a comprehensive overview of the latest technical innovations in the process of emotion recognition using EEG. Additionally, as new theories of emotions are being adopted in this field, the current paper also explores these theories.

II. Model of Human Emotion

Before detecting something, one needs to have a clear idea of what they are looking for. This is where theoretical models of emotion become relevant. It should be noted that these models are psychological theories of defining, categorizing, and measuring emotions. So, here they are mentioned as ‘theoretical models’. As emotions are subjective experiences, theoretical models of emotions are often based on arbitrary measures and ideas that can often vary from culture to culture or even from person to person. To categorize and represent emotions, several theoretical models have been proposed in the literature. One of the models known as Ekman’s classification of discrete emotions, gained influence as it was widely adopted in EEG-based emotion detection studies. Ekman determines 6 basic emotions namely anger, fear, sadness, joy, surprise, and disgust [7]. Izard, Levenson, Panksepp, and Watt also proposed similar theoretical models of basic emotions, which mostly overlap with Ekman’s and each other’s models but have a few differences [8].

However, EEG emotion detection studies based on these other theoretical models are limited. Several datasets were developed to evoke emotions from test subjects, such as SEED and DEAP datasets. This was done to standardize the emotion-evoking stimuli across different studies. Among the two datasets, the SEED dataset is focused on the categorical classification of emotions [9]. Some studies tried to integrate standardized psychological scales (i.e. Beck Depression Inventory) in EEG-based emotion recognition but the application was fairly limited [10], [11]. Several contemporary approach suggests using dimensional models that define emotions on two or three-dimensional planes [6]. Russell's circumplex model is a well-known dimensional model that uses an arousal scale to express sensations of activity and inactivity and a valence scale to indicate positive to negative emotions.

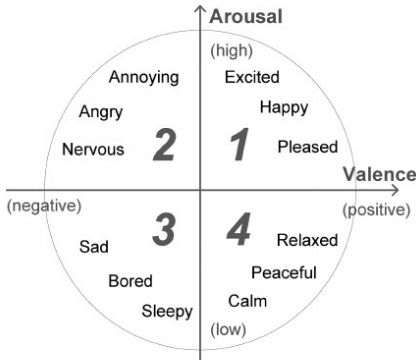

Fig. 1. Russel's the 2D valence-arousal emotion space [13]

Emotions are therefore interpreted based on each scale's values. Without being restricted to a certain emotion category, this kind of dimensional model allows researchers to concentrate on emotion recognition tasks [12]. Among the datasets for evoking emotions, the DEAP dataset focuses on the dimensional approach (valence-arousal) to characterize emotions [9]. Despite the presence of various theoretical models for emotions; there are disagreements over a general consensus [12].

III. Learning Systems for Emotion Recognition

The advent of artificial intelligence has revolutionized emotion recognition, with machine learning and deep learning algorithms advancing EEG-based emotion detection. [14]. Typically, after feature extraction, the extracted features are fed into the classifier. Several machine learning algorithms have been applied as emotion classifiers. AdaBoost from the ensemble classifier category, CNN (convolutional neural network) from the neural networks category, kNN (k-nearest neighbors) from the nearest neighbor classifier category, and SVM (support vector machine) from the linear classifier category are the most commonly used classifiers [15], [16], [17]. After a machine learning model is trained, the results of this classification are generally evaluated using performance metrics so that various researchers can understand and compare the performances of the models. The most commonly used performance evaluation metrics are confusion matrix, accuracy, error rating, and other metrics derived from the confusion matrix, including precision, recall, specificity, receiver operating characteristics- area under the curve (ROC-AUC), and F-measure [6], [15].

Deep learning has become an increasingly popular approach for analyzing EEG data, often replacing or complementing traditional feature extraction methods. One of DL's benefits is the ability to employ multimodal systems successfully and efficiently. There are two main types of emotion recognition systems. - unimodal system and multimodal system. To detect emotions, unimodal systems only use one source of data, such as speech, facial expressions, or physiological signs. But the amount of information is low and these systems frequently perform poorly. Unimodal algorithms are vulnerable to input data fluctuation and noise. So, a multimodal approach was necessary. However, it was extremely difficult until the introduction of DL. Using DL algorithms, Researchers are now able to extract complex patterns and nuanced details from multimodal data using DL algorithms. Multimodal emotion recognition (MER) systems can combine information from multiple modalities such as facial expressions, speech patterns, and physiological signals to enhance the accuracy of the emotion recognition process [18].

IV. Improvement of Recognition accuracy

Several new approaches and algorithms are being employed for the detection of emotion from EEG data for the purpose of improving the accuracy of the models. This section offers a concise overview of recent approaches and models reviewed in the current paper, highlighting their contributions to advancing EEG-based emotion recognition.

A. CATM

A study introduces the cross-scale attention convolutional model (CATM), which incorporates a cross-scale attention module, a frequency-space attention mechanism, a feature transition framework, a temporal feature extraction component, and a depth classification unit. It captures spatial features at various scales, prioritizes key channels and locations, extracts temporal patterns, and classifies EEG signals into emotions. On the DEAP dataset, CATM achieved 99.70% (valence) and 99.74% (arousal) in binary classification, and 97.27% in four-class classification. With only five channels, it reached 97.96% (valence), 98.11% (arousal), and 92.86% (four-class). The results outperform recent methods and demonstrate strong performance even with fewer channels [19].

B. 4D-CRNN

Another innovative approach integrates frequency, spatial, and temporal information using a four-dimensional convolutional recurrent neural network (4D-CRNN). Differential entropy features are transformed into 4D structures for training, with CNN capturing frequency-spatial data and LSTM extracting temporal dependencies. This method achieves state-of-the-art accuracy on SEED and DEAP datasets under intra-subject splits. The 4D-CRNN model achieved an average accuracy of 94.74% on the SEED dataset 94.22% for valence classification and 94.58% for arousal classification on the DEAP dataset [20].

C. SVM, CSP, and Entropy-Energy Features

High accuracy can be achieved even with previously established methods like SVM and CSP by refining the pipeline. For example, a study applied CSP to emotion recognition to extract features from narrowband EEG waves (theta, alpha, beta, gamma) and found that higher frequency bands (beta and gamma) were more effective for emotion recognition than lower bands like theta and alpha. Using short-time entropy and energy for feature capture and SVM for classification, the method achieved 96.15% valence and 96.47% arousal accuracy on the DEAP dataset, and 99.95% on the SEED dataset [21].

D. CapsNet and LSTM

Similarly, hybrid deep learning models are making strides in multi-channel EEG emotion recognition. For example, capsule networks (CapsNet) combined with attention mechanisms and LSTM networks improve multi-channel EEG emotion recognition by extracting spatial features with

CapsNet and temporal features with LSTM. Channel-wise attention further enhances performance, achieving superior results on the DEAP dataset, with accuracies of 97.17%, 97.34%, and 96.50% for valence, arousal, and dominance, respectively. [22].

E. Graph Neural Networks (GNNs)

Another promising area involves applying graph neural networks (GNNs). GNNs are better at handling dynamic, variable-sized data. Leveraging the biological topology of brain regions, dynamical graph convolutional neural networks (DGCNNs) outperform traditional methods like SVMs and CNNs, achieving a 95% average accuracy with faster training times, thus showing potential for further research [23].

F. Ensemble methods

Furthermore, it has been proposed that novel ensemble methods may capture the spatial-temporal characteristics of EEG signals. Incorporating spatial-temporal characteristics of EEG signals, a novel ensemble approach uses a multi-class common spatial pattern (MCCSP) for signal processing and autoencoders with CNN layers for classification. Tested on custom-collected datasets, it achieves 99.44% accuracy for classifying positive, negative, and neutral emotions, outperforming previous methods and suggesting promising applications for brain-computer interfaces (BCIs) [24].

G. CNN and GRU Hybrid Models

Lastly, hybrid models combining CNN and GRU improve preprocessing, feature extraction, and classification stages. Techniques such as independent component analysis (ICA) and discrete wavelet transform (DWT) enhance signal quality and feature selection, respectively, leading to precise and sensitive emotion classification for human-computer interaction systems. The result showed CNN-GRU leads with the highest accuracy (78%), followed by SVM (70%) and KNN (65%) [25]. The methods used to improve recognition accuracy are briefly presented in "Table 1".

TABLE I. COMPARISON OF DIFFERENT ALGORITHMS

Method	Key Feature(s)	Dataset(s)	Accuracy
CATM [19]	Multi-feature, cross-scale attention CNN	DEAP	DEAP: Valence: 99.70% Arousal: 99.74%
4D-CRNN [20]	CNN (spatial), LSTM (temporal)	SEED DEAP	DEAP: Valence:94.22% Arousal: 94.58% SEED: 94.74%,
SVM + CSP + Entropy-Energy Features[21]	Multi-band CSP, entropy-energy features, SVM	DEAP, SEED	DEAP: Valence:96.15%, Arousal: 96.47%; SEED: 99.95%
CapsNet + LSTM [22].	Spatial (CapsNet), temporal (LSTM)	DEAP	Valence: 97.17%, Arousal: 97.34%,
GNNs [23]	Dynamical GCNs, biological topology	Custom	95%
Ensemble [24]	Multi-class CSP, autoencoders with CNN	Custom	99.44%
CNN + GRU [25]	ICA(preprocessing) DWT (feature selection)	Custom	78%

V. Enhancement by Generalization

A. Domain-Invariant Adaptive Graph regularized Label Propagation (DIAGLP)

The EEG signal patterns for the same emotion vary between individuals and even for the same person across sessions, limiting the generalizability of emotion recognition models. To address this, a study proposes DIAGLP (domain invariant adaptive graph regularized label propagation), a method designed to adapt models trained on one domain (e.g., a specific person's data) to work on another domain (e.g., different individuals or sessions). Unlike traditional methods that handle feature alignment and label adjustment separately, DIAGLP integrates both tasks into a single system, using soft labels for flexible predictions and an adaptive probability graph to propagate accurate emotion labels. This unified framework improves adaptability to new people or situations, enhancing the real-world applicability of emotion recognition systems [26].

B. AIGC with Pre-trained Transformers

Artificial intelligence for generative content (AIGC) is enhancing EEG data augmentation and model performance. A novel workflow using generative pre-trained transformers (EEGPT) generates time-invariant components, while a contrastive learning strategy ensures subject-invariant data alignment. These methods improve deep learning generalization across datasets [27]."Fig 2" provides A brief overview of the theories, datasets, the methods used for increasing accuracy, and the methods used for improving generalization.

VI. Discussion

This article provides a comprehensive overview of recent progress in EEG-based emotion recognition summarizing key publications to highlight progress in the field. EEG is widely used in the fields of neuroscience, computer science, health, and behavioral science. However, the presence of noise, high dimensional data complexity, and individual variations remains a challenge. For EEG-based emotion recognition, at present, there is no universally accepted theory to classify human emotion. but dimensional models, such as valence-arousal, have gained traction in recent studies. Recently, the integration of machine learning and deep learning has greatly improved the process.

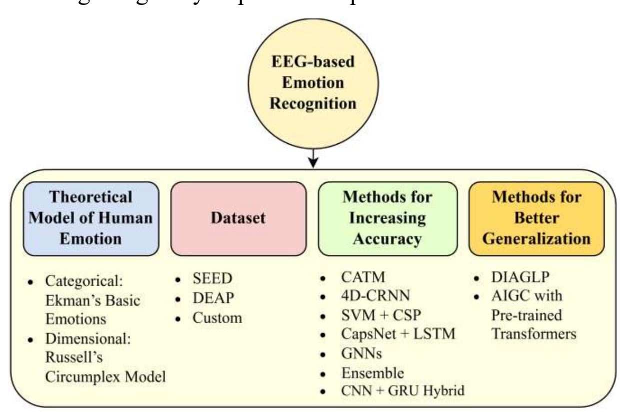

Fig. 2. Diagram illustrating the models, datasets, and methods

Some machine learning algorithms such as AdaBoost, CNN and SVM, and deep learning techniques like 4D-CRNN and hybrid models, such as CapsNet with LSTM, have been used with great accuracy in emotion classification with some of the models achieving accuracy over 99%. Accuracy is also enhanced by using ensemble methods and graph neural networks. MER systems, which combine EEG with other modalities such as facial expressions and speech have gained prominence due to their ability to handle complex patterns and improve system robustness. New methods for improving generalizations of the models such as DIAGLP, and AIGC have been developed to increase generalizations. These advancements make EEG-based emotion recognition more adaptable and effective for real-world applications. This research recommends future studies to focus on developing standardized, universally accepted theories of emotion. Researchers can focus on biological parameters, such as neurotransmitter and hormone secretions to define affective states rather than depending on subjective descriptions. Future studies can also focus on following newer approaches such as developing self-reflecting models like DeepSeek's R1, but tailored for emotion recognition using EEG.

VII. CONCLUSION

To conclude, the rapid progress in EEG-based emotion recognition is being fueled by new approaches, algorithms, and models that are improving accuracy and adaptability. These advancements are opening the door for the incorporation of this technology into real-life applications such as mental disorder detection, assessment of mental fitness, etc. As research continues to explore the frontiers of EEG-based emotion recognition, it is destined to play a pivotal role in diverse areas, from healthcare and human-computer interaction to adaptive technologies and beyond.

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