

Emotion Recognition Based on Electroencephalography: survey

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ABSTRACT

Electroencephalography (EEG) is considered as a standard method for recording human brain activity in the form of electric pulses over time. The significant attention in emotion recognition based on EEG has grown meaningfully, owing to its potential applications in brain-computer interfaces, mental health monitoring, and human-computer interaction. This article provided a comprehensive literature review of emotion recognition using EEG data, investigating datasets, classification techniques, challenges, and real-world applications. Various publicly available EEG datasets, including Database for Emotion Analysis using Physiological Signals (DEAP), Shanghai Jiao Tong

University Emotion EEG Dataset (SEED), and Multimodal Dataset for Emotion Recognition (DREAMER), are investigated in terms of their structure, features, and labeling techniques. Additionally, we also investigated various classification methods, from conventional machine learning algorithms like support vector machines (SVM) to sophisticated deep learning models such as convolutional neural networks (CNN) and recurrent neural networks (RNN). Even with significant advances, issues like inter-subject variability, data noise, and the necessity for reliable feature extraction techniques continue to pose major obstacles to attaining improved recognition accuracy. Furthermore, the review underscored the expanding use of EEG-based emotion recognition in fields such as affective computing, neurofeedback systems, and adaptive learning environments. This study offered valuable insights into future research directions for enhancing EEG-based emotion recognition systems by synthesizing recent advancements and challenges. Finally, our findings can be summarized as: mapping the current research landscape, evaluating the effectiveness of tools and techniques, identifying challenges and limitations, and recommending future paths for researchers and developers.

Introduction

The electroencephalography (EEG) signal is a complex, noninvasive signal with various applications in biomedical fields, such as sleep studies and the brain-computer interface (BCI) [1]. Facial expressions are one of the most potent, instinctual, and immediate means by which humans communicate emotions and intentions [2]. They mirror mental states shaped by both internal stimuli, like past memories, and external stimuli, such as video content [3].

Among Human Computer Interface (HCI) technologies, BCI is crucial for recognizing emotions [4], which is a communication system that uses computers to analyze signals generated by the neural activity of the central nervous system (CNS) [5].

Today, one of the subjects generating considerable discussion in psychology, medicine, and computer science is the analysis of emotional mechanisms and the automatic identification of emotional states [6]. To sum up, the identification of emotions using EEG is a technology with great potential in health monitoring and medical measurements [7].

EEG is a preferred method for assessing the brain's reactions to emotional stimuli due to its non-invasiveness, speed, and affordability. EEG signals are frequently used to recognize emotions as they provide valuable insights into various aspects of emotions such as frequency bands, electrode placements, and temporal details [8]. As a result, our understanding of human emotions from a scientific perspective has advanced over the last twenty years. Emotion detection methods and theories and emotion recognition techniques have been commonly used in EEG, skin impedance measurements, blood pressure, heart rate, eye activity, and motion analysis. [9].

This research emphasizes on existing and upcoming trending methods and converses how these methods may influence both researchers and practitioners, which conducted relying on feature extraction methods, and datasets, application. Several methods are focused on in this study concerning EEG-based emotion detection, such as classifier method, machine learning, Artificial Intelligence. Also, some of the issues and challenges that faces each level of the process are mentioned. In conclusion of this study, it is noted that human emotion detection using EEG signals is one of the most reliable and used techniques nowadays, especially in psychiatry field concerning those patients whom emotions impossible to read using traditional ways like facial expression and nature of voice.

1. Methodology

To recognize emotions based on EEG, it is important to have a clear understanding of the concepts and features of EEG signals, emotion models, and methods for

inducing emotions. The subsequent section presents a comprehensive overview of each of these areas.

1.1 Electroencephalography Signal

EEG signals are frequently used to identify emotions because they may be utilized to explore various components of emotions based on frequency band, electrode position, and temporal information [8]. The CNS is responsible for generating EEG signals, which are known to respond rapidly to changes in emotions [10]. Early studies on animal brain activity conducted by Richard Caton in the nineteenth century served as the basis for his subsequent work. In 1929, Hans Berger took the first human EEG and published the first article on the subject. He invented the term "electroencephalogram" as a major in the field [11]. His findings were progressively supported by electrophysiologists and neurophysiologists, which sped up the advancement of EEG research in clinical medicine and brain science. The electrodes in the device are arranged around the head based on the 10-20 system [12], as in Figure 1 demonstrated.

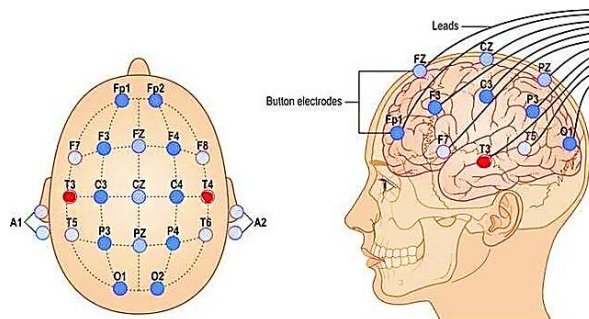


Figure 1: The 10-20 system for EEG [12].

This device is used to monitor brain activity and record signals from the brain [13]. The recorded signals can be transmitted to computers through wired, wireless, or other forms of communication. Researchers and scientists then analyze the data to draw conclusions and recognize emotions [14].

1.2 Emotion Model

Emotions can be viewed from a categorical viewpoint or a dimensional viewpoint to understand the kinds of emotions. From the categorical viewpoint, Ekman presented six of the basic emotions: sadness, happiness, anger, disgust, fear, and surprise [13]. Also, Plutchik divided emotion into two kinds: basic emotions (anticipation, joy, confidence, sadness, fear, surprise, anger, disgust) and secondary emotions (aggression, submission, contempt, dread, and others) that are certation of basic emotions [6]. He evolved an emotion wheel representation method, which is shown in figure 2.

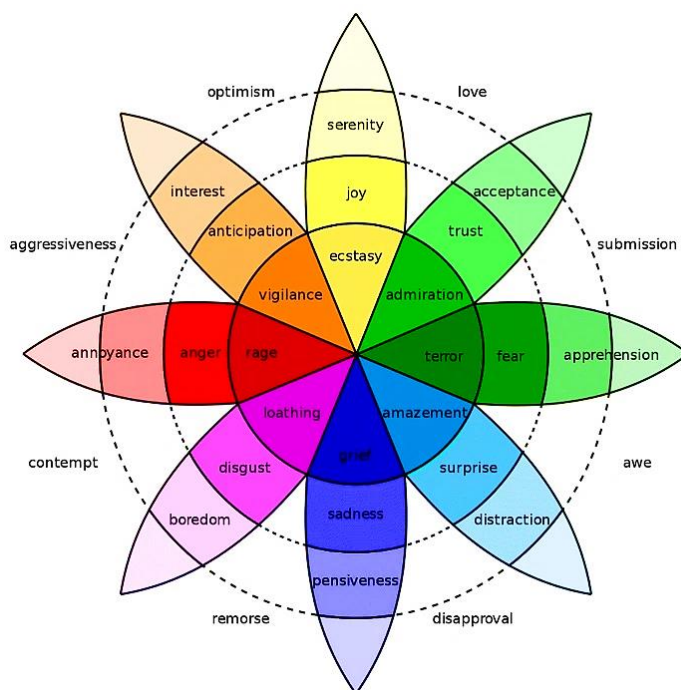


Figure 2: Emotion wheel representation method [6].

1.3 Emotion induction

To recognize emotions, it is necessary to obtain EEG signals associated with the specific emotional state of interest. This can be achieved by inducing the corresponding emotional state and recording the resulting EEG signals. Various methods are currently used to induce emotions, video induction, music induction and picture induction [14]. The main advantage of this method is that it takes less time to elicit different emotions and has a more pronounced effect [15]. However, the subjects may exhibit different facial expressions when watching the videos, resulting in significant noise interference such as Electromyography (EMG) and Electrooculogram (EOG), which can make data preprocessing more challenging [16]. For individuals with little exposure to music, music induction may not produce consistent results [17]. Picture induction involves presenting various images to elicit different emotional states in participants while recording their EEG signals. To ensure the effectiveness of the images in inducing emotions, they must possess notable emotional characteristics or be capable of producing strong stimulation. The widely recognized International Affective Picture System (IAPS) is a prime example of this type of imagery, as it undergoes rigorous screening to ensure distinct emotional expressions and is a valuable tool in emotional research [18] [19]. As stated by Bradley and Lang, the valence of an emotion signifies which system (the defensive or the appetitive) is activated, while the arousal dimension indicates the intensity of that activation. Figure 3 below shows that arousal and valence have a boomerang relationship: as images become more unpleasant or pleasant, arousal ratings rise. To put it differently, Bradley and Lang (2007) indicate that when either system is activated, the arousal ratings are also elevated. In the absence of activation of the motivational systems, individuals experience low arousal levels and a neutral valence [20].

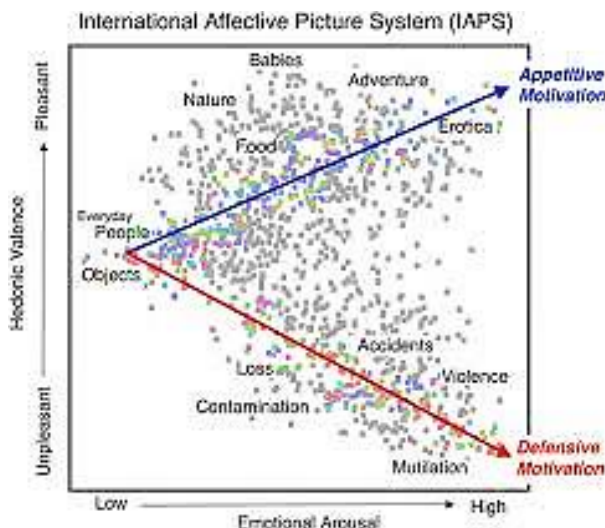


Figure 3: Relationship between Valence and Arousal for IAPS [20]

1.4 Datasets

There are many public sentiment datasets that anyone can download and analyze without requiring anyone's permission or involvement in the organization's work. We described some popular emotion detection datasets based on EEG signals.

a) DREAMER

Dreamer is the inaugural database of EEG and ECG signals that records reactions to audiovisual prompts designed to evoke emotions [21]. It employs cost-effective, commercially available wearable devices for data gathering, enabling signal analysis in everyday environments. Participants viewed film excerpts and assessed their feelings using three different scales. Supervised classification was applied to EEG and ECG data to establish a baseline [22]. This study aims to provide datasets for emotion research using low-cost wearables, evaluate their performance against that of medical-grade devices, and demonstrate the practicality of incorporating affective computing into everyday applications.

b) AMIGOS

The AMIGOS dataset records neurophysiological signals from participants reacting to emotional film snippets. This dataset comprises EEG, ECG, and GSR data, along with frontal HD videos and whole-body RGB and depth videos [23]. All components are meticulously synchronized for research on emotions, personality, and mood across multiple modalities. Participants viewed short videos on their own, while they watched long videos either individually or collectively. The Big Five Model was used to evaluate personality, while PANAS was used to assess mood. Emotional annotations comprised self-assessments along with external ratings of valence and arousal. Physiological signals were captured with handheld sensors, guaranteeing a natural environment. This dataset can be used for academic research purposes [24].

c) SAFETY

SAFE - EEG dataset for the selection of stable emotional features. For each topic, the data set includes several recording sessions spread over multiple days [25]. To evaluate the affective brain-computer interface (aBCI) long-term cognitive performance, multiple sessions were documented across various days. We demonstrated with this dataset that, during long-term use, the detection accuracy of aBCI declines when readjustment is not included. We proposed a stable trait selection method that chooses the most stable affective traits in order to minimize accuracy loss and maximize aBCI performance over time

d) GAMEEMO

The GAMEEMO dataset comprises EEG and physiological signals collected from participants engaged in video games for the purpose of examining emotion recognition [26]. It encompasses various forms of data, including EEG, ECG, and galvanic skin response (GSR), which reflect emotional states while playing the game. Emotions of participants were annotated through self-assessments and external evaluations using valence and arousal scales.

The dataset makes it possible to study affective computing, emotion recognition in gaming, and human-computer interaction. It is useful for creating emotion-aware gaming experiences and enhancing adaptive game design [27].

e) DEAP

The DEAP (Dataset for Emotion Analysis using Physiological Signals) dataset comprises EEG and physiological recordings of participants viewing music videos for emotion recognition research. It comprises multimodal data including EEG, ECG, GSR, respiration rates, skin temperature measurements, and facial videos. Participants evaluated their emotions using scales for valence, arousal, dominance, and liking. The dataset aids in the development of emotion-aware applications and supports research in affective computing, brain-computer interfaces, and emotion-based human-computer interaction. [28].

f) ASCERTAIN

The ASCERTAIN dataset serves the purposes of emotion recognition and personality assessment, and it is multimodal in nature. It encompasses EEG, ECG, GSR, and facial expression data collected as participants viewed affective movie clips [29]. The Big Five Personality Traits and PANAS (Positive and Negative Affect Schedule) were also used to assess participants in order to examine the connection between personality and emotions. Self-assessments based on valence, arousal, and dominance were used to derive emotion labels. ASCERTAIN holds significance for studies in affective computing, human-computer interaction, and tailored emotion-aware systems [30].

g) HCI MAHNOB-HCI

The MAHNOB-HCI dataset serves as a multimodal resource for human-computer interaction (HCI) and emotion recognition. It encompasses EEG, ECG, GSR, respiration, skin temperature, eye gaze, and facial videos captured

as participants viewed emotional videos and carried out implicit tagging tasks. Participants evaluated their emotional reactions in terms of valence, arousal, dominance, and tagging relevance. Because the dataset is synchronized across modalities, it can be used for research in affective computing, emotion-aware systems, and human-computer interaction applications [31]. From 27 people he collected data while viewing 20 videos and photos. Data collected are EEG signals (32 channels), ECG signals (3 signals), ERG (2 channels), GSR (2 channels), respiratory capacity, and skin temperature signals. This experiment was carried out on his two parts. In the first session, participants were asked to watch a video clip and then to fill out a questionnaire about their feelings after watching the video. At the same time, in the second session, videos and images were displayed with correct and incorrect labels and without labels [32].

h) SEED

The SEED (SJTU Emotion EEG Dataset) serves as a multimodal dataset aimed at recognizing emotions through EEG signals [33]. It includes EEG recordings of participants viewing emotionally charged movie clips classified as positive, neutral, and negative emotions. The dataset was gathered through 62-channel EEG recordings, and participants' emotional states were confirmed via self-assessments. SEED serves as a valuable resource for research in affective computing, brain-computer interfaces, and emotion-aware AI systems, facilitating the study of emotion classification through deep learning and machine learning methods [34]. Table 1 below offered a clear and organized summarizing of the datasets, focusing on key aspects such as modalities, emotion labels, types of stimuli, participants, and applications.

Table 1: summarizing and comparing the datasets we mentioned for Emotion Recognition Based on EEG

dataset	Modalities	Emotion Labels	Stimuli Type	Participants	Annotations	Key Applications
DREAMER	EEG, ECG	Valence, Arousal, Dominance	Audiovisual (Movie Clips)	23	Self-assessment	Emotion recognition with portable, low-cost devices
AMIGOS	EEG, ECG, GSR, Facial Videos, Depth Videos	Valence, Arousal, Personality Traits	Short & Long Videos	40	Self & External	Emotion, personality, and mood analysis
SAFETY	EEG, ECG, GSR, Respiration	Valence, Arousal	Driving Simulation	Varies	Self-assessment	Driver state monitoring and safety applications
GAMEEMO	EEG, ECG, GSR	Valence, Arousal	Video Games	Varies	Self & External	Emotion-aware gaming and adaptive game design
DEAP	EEG, ECG, GSR, Respiration, Skin Temp, Facial Videos	Valence, Arousal, Dominance, Liking	Music Videos	32	Self-assessment	Affective computing and human-computer interaction
ASCERTAIN	EEG, ECG, GSR, Facial Expressions	Valence, Arousal, Personality Traits	Movie Clips	58	Self-assessment (Big Five & PANAS)	Emotion-personality correlation study
MAHNOB-HCI	EEG, ECG, GSR, Respiration, Skin Temp, Eye Tracking, Facial Videos	Valence, Arousal, Dominance, Tagging Relevance	Emotion Videos & Tagging Task	30	Self-assessment	Multimodal emotion recognition and HCI

1.5 Classification Methods

With the growth of artificial intelligence (AI) and the significant advancements in computer vision and deep learning (DL) in recent years, CAD applications in the medical industry have proliferated and are crucial for illness diagnosis [35]. Initially, EEG signals are acquired from the subject using an EEG headset while inducing one of the emotions in the first stage. Subsequently, the received EEG signals are processed in the second stage to eliminate artifacts and extract features, including statistical, temporal, frequency, and time-frequency-based features, from the preprocessed EEG signals. These features are then split into training and testing samples, which are employed as input for classification models to identify emotional states [36].

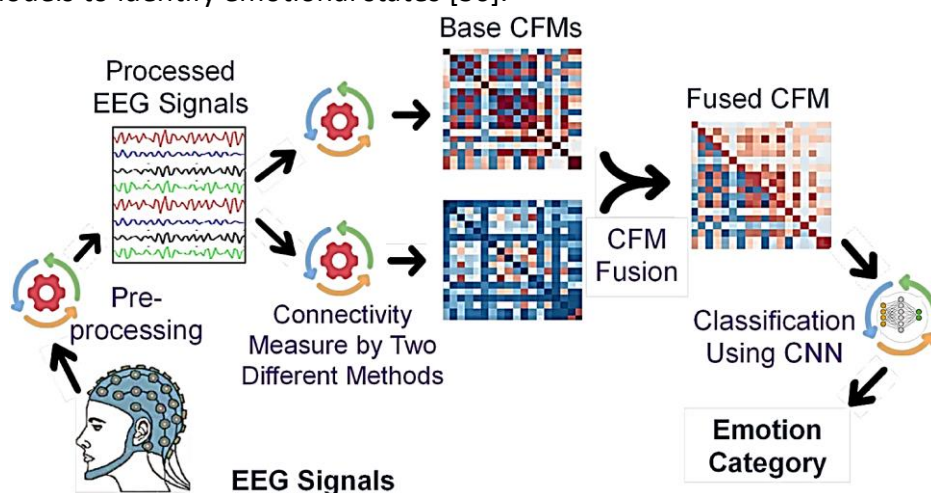


Figure 4: The overall process of emotions classification based on EEG [36].

Different classifiers have been used to classify EEG signals for the purpose of emotion recognition. These classification techniques can be grouped into several categories based on the classifiers used, including ANNs, CNN, kNN, SVM, and DWT. This current review uses an approach that entails searching the most commonly used academic search engines and databases: specifically, Google Scholar, IEEE Explore, and ScienceDirect—with keywords such as “EEG” or “EEG” + “Emotion” + “Recognition” or “Classification” or “Detection,” for

publications dated 2020 to 2023. The resulting papers from this search are carefully assessed and scrutinized to remove redundant works by the same author and keep only significant novel contributions to EEG-based emotion recognition. Due to the large number of features that can be derived from EEG signals, a range of classification techniques have been explored for categorizing EEG data according to the differences in these features. Some of the classification methods mentioned in this review are highlighted in the following section.

a) Linear Discriminant Analysis (LDA): is a commonly used technique for EEG classification. It involves finding a linear combination of the EEG features that maximally separates the classes of interest. LDA assumes that the data is normally distributed and that the covariance matrices of the classes are equal [37].

LDA's advantages: Easy & Quick: Effective for datasets that are small to medium in size. Interpretability: Generates linear decision boundaries that are simple to understand. Dimensionality reduction preserves class-discriminatory information while reducing feature space.

b) Support Vector Machines (SVM): is a supervised classification algorithm known for its strong scalability. Through predictive analysis, it assigns fresh data elements to predefined groups. Within the SVM algorithm, every data point is represented in an n-dimensional space, where 'n' signifies the number of features. Each feature's value corresponds to a specific coordinate. Subsequently, the classification process involves identifying a hyper-plane that effectively separates the two classes. The data points in close proximity to this hyper-plane are referred to as support vectors [38]. SVM's advantages: Effective in High-Dimensional Spaces: Works well when the number of features exceeds the number of samples. Robust to Overfitting: Especially with proper kernel and regularization. Versatile with

Kernels: Can model linear and non-linear decision boundaries using kernel functions (e.g., RBF, polynomial).

c) Artificial Neural Networks (ANNs): are essential for recognizing emotions based on EEG data, as they learn intricate patterns from brain signals [39]. Due to the high non-linearity and inter-individual variability of EEG data, ANNs prove effective for feature extraction and classification. Architectures of deep learning such as CNNs and LSTMs assist in capturing spatial and temporal dependencies within EEG signals, leading to enhanced recognition accuracy. Artificial Neural Networks (ANNs) improve real-time emotion detection in fields like brain-computer interfaces and affective computing. Artificial neural networks (ANNs) facilitate the creation of more adaptive and personalized emotion-aware systems—thereby enhancing human-computer interaction and mental health monitoring—by managing noise and high-dimensional data effectively [40].

ANN's advantages: Universal Purpose Approximation: With enough architecture and data, it can represent extremely complicated, non-linear interactions. Feature learning eliminates the need for manual feature engineering by automatically learning hierarchical feature representations. Adaptability: The ability to modify an architecture's number of layers, neurons, and activation functions to suit a variety of activities and data modalities.

d) Convolutional Neural Networks (CNNs): are commonly employed in EEG-based emotion recognition because of their capability to extract spatial and spectral features from brain signals. CNNs learn representations automatically from raw or preprocessed EEG data, enhancing classification accuracy, in contrast to traditional machine learning methods that depend on handcrafted features [41]. Before being input into CNNs, EEG signals are often converted into 2D representations like spectrograms, time-frequency maps, or EEG topographic images. While pooling layers reduce

dimensionality and computational complexity, the convolutional layers identify local patterns in these representations. Due to their ability to capture spatial correlations across EEG channels, which are essential for understanding emotional states, CNNs excel [42]. A major benefit of CNNs is their robustness in managing high-dimensional, noisy EEG data, rendering them suitable for practical applications. They are often combined with Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks to represent the temporal dynamics of EEG signals [43]. CNN-based models have found successful applications in brain-computer interfaces (BCIs), monitoring mental health, and affective computing, facilitating real-time detection of emotions. Their ability to learn complex patterns from EEG data with great efficiency renders them a potent tool for the enhancement of emotion recognition systems [44].

CNN's advantages: Excellent at identifying spatial hierarchies and local patterns in data, particularly in pictures and EEG topographic maps, is spatial feature extraction. Parameter Efficiency: Compared to fully connected networks, fewer parameters are needed thanks to shared weights and local receptive fields. Excellent Performance: Cutting-edge precision in a variety of signal processing and visual applications, such as emotion recognition based on EEG.

2. Related Work

A wide range of studies have been carried out on emotion recognition based on EEG, examining different datasets, methods for feature extraction, and classification approaches. The subsequent section examined important related works in the last decade to underscore the progress and major contributions in this domain.

In 2015, Mikkelsen et al. [45], assessed the effectiveness of ear-EEG, a technique for recording electroencephalograms from the outer ear, as a possible method for EEG monitoring in natural environments. Various paradigms, such as auditory

onset response, mismatch negativity, auditory steady-state response, and alpha power attenuation, involved simultaneous recordings from 32 scalp electrodes and 12 ear electrodes. The results showed that ear-EEG signals mirrored cortical activities comparable to those from nearby scalp electrodes, especially for sources close to the ear.

In 2016 Bashivan et al. [46], presented a new approach for deriving representations from multi-channel EEG time-series data in their 2015 research. They converted EEG activities into sequences of multi-spectral images that preserve topology, capturing spatial information that is often neglected in standard EEG analyses. The sequences were subsequently processed with a deep recurrent-convolutional network, drawing inspiration from cutting-edge video classification methods, in order to learn robust representations that preserve spatial, spectral, and temporal structures. Their method, when used for a cognitive load classification task, led to major enhancements in classification accuracy compared to current best-in-class techniques.

In 2017, Schirrmeister et al. [47], utilized CNN to decode EEG signals, avoiding the use of handcrafted features. They reached a mean decoding accuracy of 84.0%, exceeding the commonly used filter bank common spatial patterns (FBCSP) algorithm, which had an accuracy of 82.1%. By means of visualization techniques, it was shown that ConvNets learned to make use of spectral power modulations at alpha, beta, and high gamma frequencies, offering insights into the spatial topography of EEG features.

In 2018, Acharya et al. [48], created a 13-layer deep CNN in their 2018 research to automatically categorize electroencephalogram (EEG) signals as normal, preictal, and seizure. The CNN reached an accuracy of 88.67%, specificity of 90.00%, and sensitivity of 95.00% when using the EEG database from Bonn University. This method illustrates how deep learning can improve the detection and diagnosis of seizures from EEG signals.

In 2019, Craik, He et al. [49], conducted a systematic examination of the use of deep learning techniques for electroencephalogram (EEG) classification tasks. Their analysis of 90 studies revealed five main application domains: emotion

recognition, motor imagery, mental workload, seizure detection, and sleep scoring. The review found that in terms of classification accuracy, CNNs, RNNs, and deep belief networks (DBNs) generally outperformed stacked auto-encoders and multi-layer perceptron neural networks. The writers covered different input formulations and preprocessing techniques applied in training these networks. They offered useful advice on choosing hyperparameters to direct future studies on the use of deep learning for EEG analysis.

In 2020, Liu et al. [50], put forward an emotion recognition algorithm that does not rely on subjects, utilizing a Dynamic Empirical CNN (DECNN). This method tackles the difficulties of emotion recognition by utilizing DECNN to examine electroencephalogram (EEG) signals, with the goal of enhancing the accuracy and generalization of emotion classification among various individuals.

In same year Ali et al. [51], employed sLORETA to examine EEG source regions and frequency bands related to emotion recognition. Using an SVM, they extracted six features from the time and frequency domains from 26 Brodmann areas designated as ROIs. Source-region features demonstrated enhanced accuracy compared to EEG sensor-based features in experiments conducted on DEAP and TYUT 2.0.

In 2021, Tian et al. [52], suggested a multimodal fusion emotion detection approach that integrates EEG and ECG data through Dempster-Schafer Evidence Theory. SVM was used to classify EEG features, while a bidirectional LSTM network was employed for ECG. The experimental findings demonstrated enhanced accuracy in the arousal and valence dimensions, surpassing the performance of single-modal models by 2.64% and 2.75% for EEG, and by 7.37% and 8.73% for ECG. Simultaneously, Another model for classifying emotional intensity based on self-reports was proposed by Vahan et al. (2021) [53], utilizing SVM and CNN classifiers. The results indicated that SVM reached an accuracy of 85% and CNN 81% when classifying four emotion classes. SVM and CNN achieved 70% and 69% accuracy for 12 emotional response classes, surpassing existing emotion classification systems. Satyanarayana et al.

In 2022 [54], proposed a method for identifying emotions based on electroencephalogram (EEG) signals classified by a Support Vector Machine (SVM) classifier. Gamma band frequencies linked to emotional states were the focus of the study, which used the SEED dataset. The approach used involved smoothing features with a linear dynamical system (LDS) prior to classification. With a classification accuracy of 79.38%, this method illustrates the promise of integrating wavelet analysis with neural network classifiers for successful emotion recognition. They achieved accuracy rates of 87.14% for valence and 86.31% for arousal emotional states. The F-score values were even more impressive, with 90.45% for valence and 92.03% for arousal emotional states. These achievements underscore the strength of their approach in effectively discerning emotions from EEG data.

Concurrently, Anitha et al. (2022) [55], created a system for identifying emotions that leverages multichannel electroencephalogram (EEG) signals and artificial neural networks (ANN). The system analyzes EEG data to identify and categorize human emotions, with the goal of improving human-computer interaction through precise interpretation of emotional states. The suggested ANN model showed considerable promise for emotion recognition, aiding progress in affective computing and real-time emotion detection applications.

In 2023, Pawan and Rohtash Dhiman [56], introduced a method for selecting EEG channels in BCI systems using the Pearson correlation coefficient (PCC), with an emphasis on the sensorimotor area. Wavelet packet decomposition (WPD) and approximate entropy (ApEn) were used to extract features. The method was categorized using SVM and K-NN, resulting in accuracies of 91.66% with SVM and 90.33% with K-NN. The method, evaluated using BCI competition-IV-Dataset I, surpassed earlier techniques in classifying motor imagery signals.

At the same year, Song et al. [57], proposed a self-supervised framework for the purpose of decoding natural images from electroencephalography (EEG) signals to facilitate object recognition. Using contrastive learning, the framework aligns image and EEG modalities by extracting features from paired image stimuli and their corresponding EEG responses using image and EEG encoders. When assessed on a comprehensive EEG-image dataset, the model attained a top-1 accuracy of

15.6% and a top-5 accuracy of 42.8% in difficult 200-way zero-shot tasks. In the study, attention modules were added to capture spatial correlations and provide insights into brain activity based on EEG data. These results provide important insights for neural decoding and brain-computer interfaces in practical situations. In 2024, Liu et al. [58], presented EEG2Video, a framework aimed at reconstructing dynamic visual experiences from EEG signals. The SEED-DV dataset was created by the researchers and contains EEG recordings from 20 individuals who were exposed to 1,400 video clips representing 40 different concepts. EEG2Video employs a sequence-to-sequence architecture to effectively match the high temporal resolution of EEG data with dynamic visual content. With a 2-way semantic classification accuracy of 79.8% and a Structural Similarity Index (SSIM) of 0.256, the model represents a considerable progress in decoding dynamic visual perception from EEG signals.

Same in 2024, Kim et al. [59], presented EEG-GPT, a new method that utilizes large language models (LLMs) for the classification and interpretation of EEG. EEG-GPT demonstrated performance on par with leading deep learning techniques for the classification of normal versus abnormal EEGs, with particular excellence in few-shot learning situations where it utilized merely 2% of training data. EEG-GPT goes beyond mere classification by providing intermediate reasoning steps and incorporating specialized EEG tools at various scales, thereby improving transparency and interpretability in clinical settings.

In 2025 Zhu et al. [60], explored the practicality of employing ear-EEG to decode auditory attention in multi-speaker settings. While EEG data were gathered simultaneously with scalp-EEG and ear-EEG (cEEGrids) systems, participants were directed to concentrate on one of four speakers who were spatially separated from one another in an anechoic chamber. The analysis showed that the temporal response functions (TRFs) associated with the attended speech were greater in magnitude than those linked to unattended speech. Over a 60-second window, the ear-EEG system attained a decoding accuracy of 41.3%, exceeding the chance level of 25%. Further examination of electrode placement and quantity revealed that while the positioning of electrodes has a considerable effect on decoding accuracy,

the number of electrodes affects it to a lesser extent. Moreover, the research evaluated the STAnet auditory spatial attention detection approach on the ear-EEG dataset, resulting in a decoding accuracy of 93.1% using a 1-second window. The results imply that ear-EEG can serve as a viable substitute for traditional scalp-EEG when it comes to decoding auditory attention in complex auditory situations.

Latest, Shukla et al. (2025) [61], performed an extensive survey on the fusion of EEG signals with generative AI, examining applications in image and text generation. This research looks into progress made in EEG-based brain-computer interfaces (BCIs) and how they work together with deep generative models like GANs and diffusion models to reconstruct images and produce text based on neural activity. they highlighted challenges in data scarcity, model interpretability, and real-time processing while discussing potential improvements in feature extraction and multimodal learning. By offering insights into future enhancements for generative AI-driven EEG decoding, the survey lays the groundwork for brain-to-content systems that are more intuitive and efficient.

Table 2. comparison of Emotion Recognition Based on Electroencephalography

Authors	Year	Dataset	Focus	Methods/Techniques	Key Findings
Mikkelsen et al. [45]	2015	Ear-EEG dataset	Ear-EEG signal characterization	Signal processing, statistical analysis	Demonstrated the feasibility of EEG recording from the ear
Bashivan et al. [46]	2016	DEAP dataset	EEG representation learning	Deep (RCNN)	Improved feature extraction for EEG classification

Schirrmeister et al. [47]	2017	BCIC IV 2a dataset	EEG decoding and visualization	CNNs	Achieved high accuracy in decoding EEG signals
Acharya et al. [48]	2018	Bonn EEG dataset	Seizure detection and diagnosis	CNNs	Automated seizure detection with high accuracy
Craik et al. [49]	2019	Multiple datasets	EEG classification tasks review	CNNs, RNN	Provided a comprehensive review of EEG-based deep learning methods
Liu et al. [50]	2021	SEED dataset	Emotion recognition from EEG	Dynamic empirical CNN	Subject-independent emotion recognition with improved accuracy
Ali et al. [51]	2020	Custom dataset (Dyslexic children EEG)	Dyslexia detection	sLORETA source localization	Identified visual mismatch negativity in dyslexic children
Tian et al. [52]	2021	Custom high-density EEG dataset	Cognitive event segmentation	EEG-based VR film analysis	Investigated EEG patterns in VR-based cognitive segmentation

Babushkin et al. [53]	2021	Custom dataset	Emotion intensity classification	EEG-based classification using machine learning	Developed EEG-based intensity classification models
Satyanarayana et al. [54]	2022	DEAP dataset	Emotion recognition	Support vector machine (SVM) classifier	Achieved emotion classification through EEG signals
Anitha et al. [55]	2022	Custom EEG dataset	Emotion detection	Artificial neural networks (ANNs)	Improved multichannel EEG-based emotion detection
Pawan et al. [56]	2023	Multiple datasets	EEG-based BCI	Machine learning techniques review	Provided a systematic review of EEG-based BCI methods
Song et al. [57]	2023	Custom dataset	EEG-based object recognition	Deep learning for natural image decoding	Developed methods for object recognition from EEG signals
Liu et al. [58]	2024	Custom dataset	Visual perception decoding	EEG2Video framework, neural processing	Developed a method for decoding visual perception from EEG

Kim et al. [59]	2024	Multiple datasets	EEG-based language model interpretation	EEG-GPT, large language models	Explored the potential of LLMs for EEG classification
Zhu et al. [60]	2025	Ear-EEG dataset	Auditory attention decoding	Ear-EEG, multi-speaker analysis	Used Ear-EEG for auditory attention detection
Shukla et al. [61]	2025	Multiple datasets	EEG and Generative AI	Generative AI, EEG bridging methods	Reviewed EEG-GANs and EEG-based text/image generation

3. Challenges and Limitations

The EEG faces numerous inherent challenges, including the elimination of additive noises (i.e., EEG artifacts) that can arise from various sources such as muscle movements or electric line interferences [62]. One of the most essential subjects in emotion classification is the capacity to detect emotions from physiological signals. Emotions can be detected through various means, such as facial expressions, writing, vocal cues, and EEG signals [63]. Because EEG signals are internal signals from the brain that a person cannot control, the challenge has increased for psychologists, computer science researchers, and others. However, it also presents several significant challenges:

1. **Complexity of Emotions:** Emotions are complex and multifaceted, making it challenging to identify and classify them accurately based on EEG signals alone. Emotions can vary in intensity and can be influenced by individual differences, cultural factors, and context.

2. **Data Quality and Noise:** EEG signals are susceptible to various sources of noise, such as muscle artifacts, eye movements, and environmental interference. Ensuring high-quality EEG data is essential for accurate emotion recognition. Several techniques have been used in the data filtering process.
3. **User Comfort and Acceptance:** Wearing EEG electrodes can be uncomfortable, and user acceptance is a critical factor for the practical use of EEG-based emotion recognition systems. Finding ways to make EEG devices more user-friendly is essential.
4. **Lack of Standardization:** There is a lack of standardization in EEG data collection and preprocessing techniques across different studies, which can make it difficult to compare results and develop robust emotion recognition models [62].

4. Applications

The application of Emotion Recognition based on EEG holds significant potential in various fields. EEG-based emotion recognition involves analyzing brainwave patterns to identify and interpret emotions. Here are a few potential applications:

1. **Healthcare and Mental Health:** By offering objective assessments of emotional state, EEG-based emotion recognition can assist in diagnosing and tracking mental health disorders like anxiety and depression, thereby facilitating individualized treatment. Through brain activity, EEG serves as an effective means of detecting genuine emotions. Along with entertainment, music therapy has a significant effect on mental health by affecting emotions. Recent studies concentrate on the identification of music moods, the analysis of emotional impact, and the interpretation of emotions through data mining and machine learning techniques. Music therapy is a promising method for emotion regulation that includes EEG-based semantic analysis. This approach offers valuable insights into physiological emotional responses and aids in advancing research related to emotional health [63].

2. **Human-Computer Interaction (HCI):** By adapting interfaces to users' emotions, the incorporation of EEG-based emotion recognition technology into human-machine interaction (HCI) systems allows for more intuitive interactions. Emotions are crucial in daily life, affecting communication and well-being. Automatic emotion recognition aids machines in understanding emotions, thereby improving human-machine interaction (HCI) and assisting in diagnosing emotional disorders. Recognition methods encompass non-physiological signals (like facial expressions and speech) as well as physiological signals (such as GSR, RR, ECG, and EEG), with EEG providing an objective means of detecting emotional state. Emotions have been connected to EEG through psychophysiological research, and improvements in dry cell technology have made it easier to gather EEG data, leading to a heightened interest in emotion recognition technology based on EEG [4].
3. **Market Research and Advertising:** by examining consumers' emotional reactions to products and ads, emotion recognition via EEG can bolster market research and aid companies in refining their strategies. Affect is vital in perception, decision-making, and communication. Conventional methods of evaluating marketing, like surveys and interviews, can carry a bias because consumers might not reveal their genuine sentiments. EEG-based neuromarketing addresses these limitations by providing objective insights through the measurement of brain activity. EEG is a valuable tool in modern marketing research due to its low cost and high temporal resolution, which make it effective for understanding emotional states and enhancing strategies related to sales, advertising, pricing, and package design [64].
4. **Neurofeedback and Stress Management:** Neurofeedback from EEG-based systems can assist in stress management by offering real-time feedback on stress levels. This method uses EEG to record brain activity and enables users to manage their brain's electrical signals. It has shown effectiveness in addressing ADHD, sleep disorders, and emotional regulation. Emotion

regulation (ER) encompasses the identification and management of emotions to avert emotional vulnerability. Emotional responses can be altered through cognitive strategies such as attention shifting, distancing, and reappraisal. Emotional regulation can also be supported by reality testing and physical activities like running. EEG-based techniques hold promise for wellness and relaxation industries by enhancing stress management and emotional well-being [65].

5. **Security and User Authentication:** By confirming identity via exclusive brainwave patterns, biometric authentication based on EEG provides an additional security layer. EEG signals are more secure than fingerprints or iris scans because they cannot be easily counterfeited or stolen. While traditional biometric systems can be deceived with counterfeit fingerprints or images, EEG signals necessitate a living, functioning brain, thereby blocking unauthorized entry. EEG functions by tracking electric activity in the brain via electrodes positioned on the scalp, which capture unique oscillatory patterns. Subsequently, these signals undergo analysis for the purpose of authentication. EEG-based biometrics, due to their uniqueness and high security, offer a promising development for identity verification systems [66].
6. **Sports and Performance Enhancement:** Through real-time feedback on their emotional and cognitive states, athletes and performers can optimize their performance with the help of EEG-based monitoring. Brain activity is essential for achieving athletic success, setting winners apart from the rest. Due to its portability, non-invasiveness, and high temporal resolution, advances in neuroimaging techniques, particularly EEG, enable researchers to investigate the neural mechanisms underlying performance. EEG research indicates that athletes demonstrate unique neural adaptations in contrast to non-athletes, implying a neurological advantage. Grasping these connections between brain and behavior aids in the refinement of training strategies, bolstering concentration in high-pressure situations, and

elevating performance levels in both competitive sports and artistic endeavors [67].

7. Social Robotics: by making AI systems more empathetic and responsive, emotion recognition based on EEG can improve human-robot interaction. Originally designed for medical uses, brain-computer interface (BCI) technology has broadened its scope to include fields such as workload monitoring and emotion recognition. In contrast to conventional lab-based BCIs, contemporary non-medical BCIs utilize dry electrodes, need little calibration, and enable portable data collection in real-world environments. Inexpensive, portable EEG devices like those found in the DREAMER database facilitate emotional interactions between humans and robots. In practical use, single-channel EEG devices are favored as they can be easily incorporated into daily routines for real-time emotional tracking [68].
8. Cognitive Research: Emotion recognition based on EEG contributes to the study of cognitive processes associated with emotions, providing insights into the brain's processing of various emotional states. As electronic devices have proliferated, it has become essential for human-computer interaction (HCI) systems to incorporate emotional intelligence in order to improve user experience. The effectiveness of most current systems is limited by their inability to recognize and respond to human emotions. For this to be dealt with, it is necessary for machines to interpret emotional states accurately. For intelligent human-computer interaction, an emotion recognition system that is dependable and flexible is essential. By comprehending the patterns of human communication, computers can produce suitable replies, thereby enhance system efficacy and promote a more organic interaction between humans and machines [69].

5. Conclusion

EEG-based emotion recognition has developed into a potent means of comprehending human emotions, with uses in healthcare, human-computer interaction, marketing, biometric security, and sports performance. This review examined different EEG datasets, classification methods, challenges, and practical implementations. Although EEG offers objective and dependable emotional data, challenges like signal noise, individual variability, and computational complexity persist. With the development of deep learning and enhanced data acquisition methods, these restrictions are being tackled, which renders emotion recognition based on EEG more feasible. Future studies should aim to strengthen model robustness, incorporate multi-modal strategies, and create real-time applications. With advancements in this area, emotion recognition based on EEG could transform many fields, enhancing mental health diagnostics, adaptive AI systems, and tailored user experiences.

Even though there has been a lot of development, there are still a number of issues. In order to enhance accuracy, future studies should concentrate on improving cross-subject generalization, creating lightweight models for real-time applications, and combining EEG with other modalities like voice or facial expressions. Furthermore, developing reliable and inclusive emotion identification algorithms will require growing datasets with increasingly representative and diverse populations. These approaches present encouraging avenues for the field's advancement.

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