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# Emotion recognition in EEG signals using deep learning methods: A review

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A R T I C L E I N F O

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A B S T R A C T

Emotions are a critical aspect of daily life and serve a crucial role in human decision-making, planning, reasoning, and other mental states. As a result, they are considered a significant factor in human interactions. Human emotions can be identified through various sources, such as facial expressions, speech, behavior (gesture/position), or physiological signals. The use of physiological signals can enhance the objectivity and reliability of emotion detection. Compared with peripheral physiological signals, electroencephalogram (EEG) recordings are directly generated by the central nervous system and are closely related to human emotions. EEG signals have the great spatial resolution that facilitates the evaluation of brain functions, making them a popular modality in emotion recognition studies. Emotion recognition using EEG signals presents several challenges, including signal variability due to electrode positioning, individual differences in signal morphology, and lack of a universal standard for EEG signal processing. Moreover, identifying the appropriate features for emotion recognition from EEG data requires further research. Finally, there is a need to develop more robust artificial intelligence (AI) including conventional machine learning (ML) and deep learning (DL) methods to handle the complex and diverse EEG signals associated with emotional states. This paper examines the application of DL techniques in emotion recognition from EEG signals and provides a detailed discussion of relevant articles. The paper explores the significant challenges in emotion recognition using EEG signals, highlights the potential of DL techniques in addressing these challenges, and suggests the scope for future research in emotion recognition using DL techniques. The paper concludes with a summary of its findings.

## 1. Introduction

Emotions are a complex mental state that manifests in physical behaviors and physiological activities. They are automatic mental and physical reactions that arise when the organism perceives a situation that requires such a reaction. Emotions affect not only people's health, but also their decision-making [1,2]. The presence of harmful emotions can have serious implications on a person's psychological and physiological well-being, leading to various challenges, such as the risk of mental conditions like schizophrenia (SZ) [1] and depression [2]. SZ is a mental disorder that presents symptoms such as delusions, hallucinations, and disordered thinking, which are attributed to the distorted perception of reality [1]. Recent studies have suggested that excessive exposure to negative emotions can increase the probability of developing psychotic symptoms, which are characteristic features of SZ. Additionally, depression has been linked to the persistent elevation of stress hormones, which are released during prolonged periods of negative emotions [2]. To mitigate the impact of such adverse emotions, researchers in psychology are exploring innovative approaches to regulating emotions in numerous environments [3]. Categorizing emotions into clear-cut categories is a daunting task for psychological sciences and requires a considerable level of expertise. In psychology, the two major models employed in the study of emotions are emotion-based and multidimensional theories [4].

Emotions are intricate and can be difficult to classify 205,206. There may be overlap or uncertainty among different categories, and some emotions may not belong to any category. While many psychologists endorse the theory of basic emotions, there is no consensus on the exact

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number of basic emotions. For instance, Ekman initially proposed six basic emotions, which are fear, anger, joy, sadness, disgust and surprise, each of which is associated with distinct facial expressions [207]. Later, Ekman expanded his list to include other basic emotions such as embarrassment, pride, excitement, shame, contempt, satisfaction, and amusement. Tomkins identified interest-excitement, enjoyment-joy, anger-rage, distress-anguish, fear-terror, surprise-startle, shame-humiliation, and contempt-disgust as the most basic emotions [208]. Robert Plutchik developed a theory of emotions based on evolutionary principles, suggesting that eight primary emotions form the basis of all emotions: anger, fear, sadness, disgust, surprise, anticipation, trust, and joy. He also created a visual model of these emotions called the Emotion Wheel, which illustrates how they can be combined to create more complex emotions [209]. Additionally, Russell proposed sixteen emotions, and these emotions can be plotted on a two-dimensional plane of arousal (from pleasant state to unpleasant state) and valence (from a calm state to an excited state) [210]. Figure (1) shows the Russell for emotion recognition.

Currently, there is significant research being conducted in the field of emotion recognition, which has gained the attention of researchers. Emotion recognition can be classified into two categories based on the types of signals used: non-physiological and physiological [207, 211–215]. Non-physiological signals include voice intonation, body posture, movement, facial expression, and other similar signals [19–26, 28,187–204,216–293]. These signals can be controlled and concealed subjectively, often leading to incorrect diagnoses by the classifier [294]. In contrast, physiological signals include Electroencephalogram (EEG) [211], temperature (T) [212], electrocardiogram (ECG) [213], electromyogram (EMG) [214], galvanic skin response (GSR) [215], and respiration (RSP).

The human heart is profoundly impacted by different emotional states, with fear, sadness, and happiness being some of those states [295, 296]. ECG is a non-invasive method of recording the electrical activity of the heart accurately, efficiently, and reliably for emotion recognition research. The changes in emotions are readily discernible by the heart's electrical currents. This test involves recording ECG signals via cutaneous electrodes, which account for changes in the heart rate per second [295,296]. However, ECG signals also have some disadvantages. ECG signals may have a lower signal-to-noise ratio when recorded under noisy conditions. Moreover, the interpretation of ECG signals requires specialized expertise and may be difficult to comprehend for non-experts [295,296].

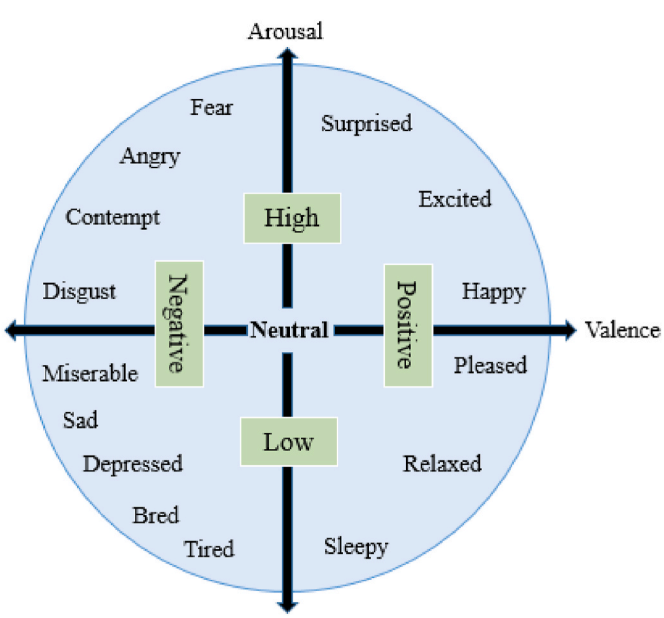


**Fig. 1.** Details of emotion recognition classes based on Russell approach.

Electromyography (EMG) recording is a non-invasive technique used to assess the state of muscles and motor nerves [297,298]. The frequency response of EMG signals corresponds directly to body muscle movements. As emotions govern facial muscles, the brain controls them [297, 298]. Thus, EMG recording is an efficient approach to recognizing emotions. The brain sends electrical impulses to the muscles for expressing emotions, and muscle electrical activity resulting from the manifestation of emotions is recorded by EMG [297,298]. The use of EMG for recognizing emotions is still at an early stage, and there are several challenges that researchers face. One major challenge is the variability in muscle activation, as different individuals can show varying patterns of muscle contraction for the same emotion [297,298].

Galvanic skin response (GSR) is a biofeedback method used for recognizing emotions that involve measuring changes in skin conductance [299,300]. The method can be used for the assessment of skin's electrical properties, such as resistance or conductivity, as a result of the activity of the sweat glands in the fingers and palms of the subject. GSR is a reliable indicator of physiological arousal and is often considered a reflection of emotional arousal and stress. The use of GSR for emotion recognition is subject to several challenges. For example, the GSR signal can be influenced by various external factors, including temperature, humidity, and skin contact pressure, potentially leading to inaccurate emotion recognition [299,300]. Moreover, there is often substantial variability in GSR data among different individuals [299,300].

The EEG is a non-invasive physiological signal that directly measures brain electrical activity during emotional states [301,302]. Compared with other methods, EEG signals have several advantages, including better time resolution, faster data collection and transmission, and lower cost. Moreover, EEG is a spontaneous and non-subjective physiological signal that can reflect human emotional states in an unbiased manner [301,302]. While EEG signals have several advantages that make them a useful modality for emotion recognition, they also have several limitations [301,302]. One of the significant challenges with using EEG signals for emotion recognition is the presence of different noises [301,302]. Another disadvantage of EEG signals is that they have a limited spatial resolution. This can make it difficult to detect the specific fields of the brain that are activated during emotional states accurately [301,302].

Recognizing emotions from EEG signals is a challenging and demanding task, primarily because EEG signals are recorded through various channels, and the process of obtaining them is often time-consuming [303]. Additionally, EEG signals are susceptible to both internal and external noises, making it arduous for psychologists to accurately detect emotions from them. Conventional machine learning (ML) and DL techniques are the main approaches taken to extend EEG-based emotion recognition methods [304,305]. These techniques involve extracting time, frequency, time-frequency, and non-linear features from preprocessed EEG signals [306–309]. However, selecting the most suitable models for this purpose requires a significant amount of specialized knowledge, limiting their effectiveness and the capability of EEG recognition. ML approaches involve four key stages: preprocessing, feature extraction, feature selection (dimension reduction), and classification [173,310]. The feature extraction and feature selection steps in ML are performed through trial and error [173,310]]. Finally, the extracted features are categorized using ML methods to achieve the desired emotion classification resul [173,310]].

In emotion recognition techniques that utilize DL, the stages of feature extraction and feature selection are executed by deep layers, thereby requiring fewer implementation steps in the process of emotion recognition [311,312]. Additionally, DL techniques possess the advantage of sustaining their performance accuracy regardless of complex and vast input data, which is not the case with ML methods [311,312]. However, the challenges witnessed in emotion recognition are centered around creating a unified and integrated classification method of temporal and spatial features, as well as developing methods that utilize spatial information provided by various electrode channels to improve the precision of emotion recognition in DL. Given the inherently unpredictable nature of emotions and their changes over time, the role of temporal dependence becomes more significant when evaluating emotional states [313].

In this paper, a comprehensive review was conducted on studies that utilized deep learning (DL) techniques for emotion recognition from EEG signals. The review provides insights into related challenges and optimal approaches for future research directions. The literature review is presented in Section (2) and includes studies that applied various AI methods for emotion recognition from biological signals such as EEG, with publications spanning from 2017 to 2023. The search strategy was based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines [314], as discussed in Section (3). Section (4) examines key components of the reviewed papers, including EEG datasets, pre-processing methods, and DL techniques. In addition, Table 4 provides a summary of emotion recognition studies that utilized EEG signals and DL models. Section (5) delves into challenges associated with emotion recognition papers. Section (6) presents our discussion about emotion recognition research using DL methods. In addition, future directions, conclusions, and findings are presented in sections (7) and (8), respectively. Overall, this review paper provides an in-depth analysis of DL techniques' applications to emotion recognition from EEG signals, and the diverse insights provided herein offer valuable guidance for future research in the field.

## 2. Emotion recognition using AI methods

The researchers in recent studies utilized various ML and DL techniques for emotion recognition from biological data such as EEG signals. This section evaluated review papers that utilized numerous AI methods for identifying emotions from EEG biological signals. The publications by authors in Refs. [5–7] concentrated on utilizing ML techniques for emotion recognition from EEG signals. Additionally, researchers in Refs. [8,9] applied DL techniques to recognize emotions from EEG signals. Some of the review papers discussed the use of both ML and DL methods in identifying emotions [11–16]. A detailed overview of the reviewed papers, including the information on the journal, year of publication, citations, the AI technique employed, and modality, can be found in Table 1.

**Table 1**
Review papers published in emotion recognition using biological signals with AI methods.

| Work | Publisher | Year | Number of Citations | Methods | Modalities |
|---|---|---|---|---|---|
| [5] | Computational intelligence and neuroscience | 2020 | 110 | ML | EEG |
| [6] | International Clinical Neuroscience Journal (ICNSJ) | 2017 | 61 | ML | EEG |
| [7] | Springer | 2018 | 54 | ML | Physiological signals |
| [8] | Elsevier | 2021 | 33 | ML | EEG |
| [9] | Frontiers | 2020 | 36 | DL | EEG |
| [10] | Journal of Applied Science and Technology Trends (JASTT) | 2021 | 97 | DL | Different Modalities |
| [11] | ACM | 2022 | 12 | DL, ML | EEG |
| [12] | Springer | 2022 | 11 | DL, ML | EEG |
| [13] | Elsevier | 2022 | – | DL, ML | EEG |
| [14] | IEEE | 2021 | 38 | DL, ML | EEG |
| [15] | Elsevier | 2020 | 234 | DL, ML | EEG, Multi-modal physiological signals |
| [16] | Sensors | 2018 | 479 | DL, ML | EEG and other Physiological Signals |
| [17] | International Journal of Scientific & Technology Research (IJSTR) | 2020 | 9 | DL, ML | EEG |
| [18] | Journal of Computational and Theoretical Nanoscience (JCTN) | 2018 | 14 | DL, ML | EEG |

## 3. Search strategy based on PRISMA guidelines

In this section, PRISMA guidelines were used to search for relevant articles in the literature [314]. Papers applying DL techniques to emotion recognition from EEG signals were published between 2016 and 2023. The proposed guidelines comprise three stages: First, 251 articles applying AI techniques to emotion recognition from EEG signals were gathered. Initially, 23 out-of-scope articles were removed. Then, 19 articles were filtered as they did not use DL techniques and had inauthentic citations. Third, 34 articles that did not use EEG signals for emotion recognition were filtered and removed, and finally, 175 articles were used for analysis. Figure (2) represents the proposed three-level PRISMA guidelines [314] for emotion recognition from EEG signals using DL techniques. Table 2 presents the inclusion and exclusion criteria used in this study.

## 4. Computer-aided diagnosis system

This section delves into the steps involved in utilizing DL techniques to recognize emotions from EEG signals. Recent research has highlighted the importance of managing emotions for both physical and mental well-being [1,2]. Neglecting one's emotional state is a common cause of depression [2]. Various methods, including biological signals, have been used for emotion recognition [7]. However, due to the different types of emotions and their varying intensities, recognizing emotions is a complex and challenging task for psychologists and experts. To alleviate this challenge, researchers have suggested employing a Computer-Aided Diagnosis System (CADS) based on EEG signals [9]. AI techniques, such as ML and DL, are employed to implement CADS in emotion recognition research. The use of DL architecture for emotion recognition has grown significantly in recent years due to its greater efficiency compared to ML techniques. The main components of a CADS for emotion recognition include EEG datasets, pre-processing algorithms, and DL models. The pre-processing step eliminates various artifacts present in EEG signals. Following that, DL models are used for feature extraction and classifying EEG signals. Finally, specific criteria are used to evaluate the efficiency of DL architectures in recognizing emotions. Figure (3) depicts the block diagram of CADS for emotion recognition utilizing DL techniques.

### *4.1. Dataset*

Developing highly efficient emotion recognition algorithms based on AI techniques requires large datasets with a considerable number of subjects. Therefore, datasets play a crucial role in emotion recognition research. There are several datasets available for this purpose, including the SJTU emotion EEG dataset (SEED) [19], SEED-IV [20], the database for the analysis of affective interaction between EEG and facial expression (DAI-EF) [21], the database for emotion analysis using physiological signals (DEAP) [22], the Loughborough University Multimodal Emotion Dataset (LUMED) [23], MAHNOB-HCI [24], DREAMER [25], AMIGOS [26], SDEA [27], and the Multi-Modal Physiological Emotion Database (MPED) [28]. Each EEG dataset is briefly explained below. More information can be found in Table 3 at the end of this section.

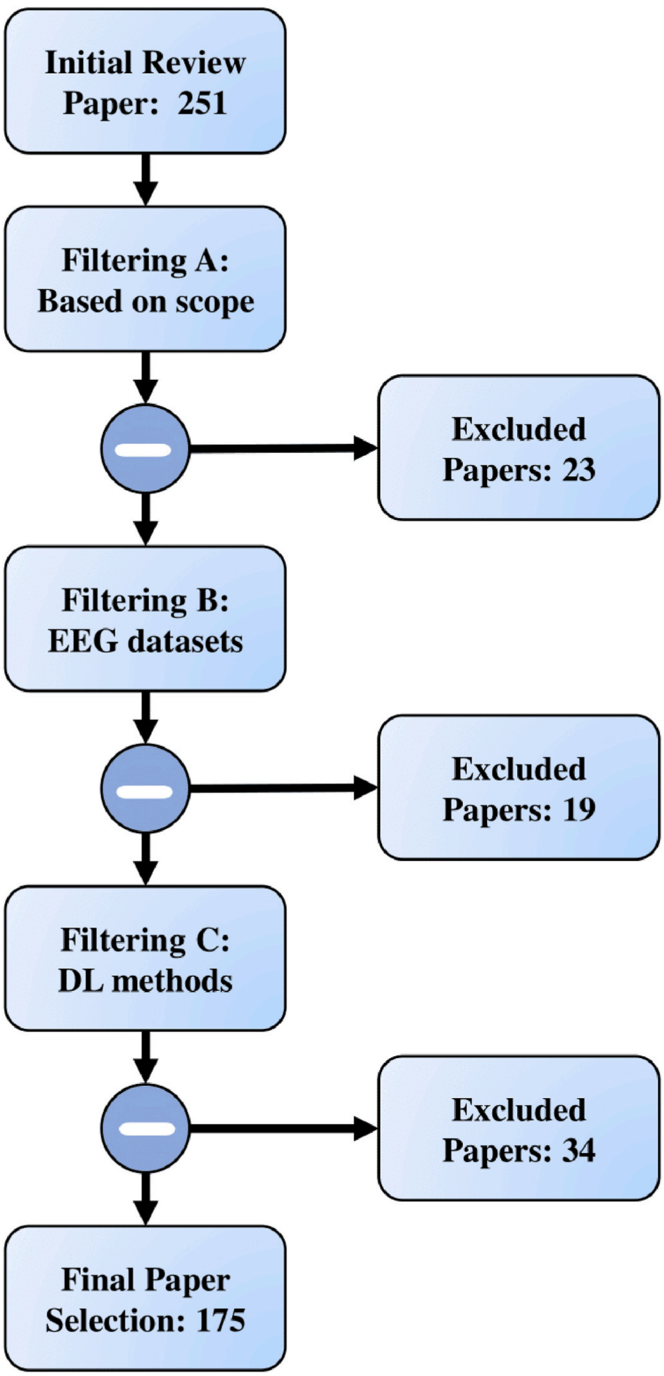


**Fig. 2.** Proposed PRISMA block diagram used for emotion recognition from EEG signals.

**Table 2**
Exclusion and inclusion criteria used for emotion recognition using EEG signals.

| Inclusion | Exclusion |
|---|---|
| EEG Signals | 1. Treatment of Brain Diseases based on Emotion Recognition |
| 3. Emotion Recognition | 2. Clinical methods for Brain Diseases treatment |
| 3. Emotion Models | 3. Brain-Computer Interface Based on Emotion Recognition |
| 4. Deep Learning Models | |

#### 4.1.1. SEED

SEED dataset has been developed at the Brain-like Computing and Machine Intelligence Center for Brain-like Computing and Machine Intelligence (BCMI), Shanghai Jiao Tong University [19]. The dataset includes eye movement and EEG signals obtained from 15 subjects while watching videos. The recordings were conducted over three days, with each video lasting about 4 min and eliciting three types of emotions: positive, negative, and neutral. There was a gap of about a week or more between the two experimental sessions in the SEED dataset [19]. The dataset comprised three sessions per experiment, with EEG data collected from 15 participants in each session. The EEG data were recorded using a 62-channel ESI NeuroScan device at a sampling rate of 1 KHz [19]. The sampling frequency was then reduced to 200 Hz, and a band-pass filter at 0–75 Hz was employed to eliminate any artifacts in the EEG signal data [19].

#### 4.1.2. SEED-IV: an evolution of the original SEED dataset

The SEED-IV dataset includes four distinct emotions: happy, sad, fear, and neutral. A total of 15 subjects participated in this study and their EEG signals were recorded during three separate experiment sessions [20]. Each session involved exposure to 24 different 2-min video clips, with 6 clips corresponding to each emotion category [20]. During the observation process, participants received a 5-s hint before viewing the 2-min film clip, followed by a 45-s self-assessment period. Data was collected using a 62-channel ESI NeuroScan device and SMI eye-tracking glasses, with band-pass filtering applied within the 1–70 Hz frequency range after EEG sampling at a reduced frequency of 200 Hz [20].

#### 4.1.3. DAI-EF

The DAI-EF dataset is composed of EEG signals and facial expressions, collected to facilitate emotion recognition. The dataset determines emotions using both physiological and behavioral responses to video clips [21]. The EEG signals were captured using a 64-channel Biosemi ActiveTwo device. The dataset also collects GSR, respiration, eye movement, and facial video signals. The data recorded in this dataset was obtained from 100 videos designed to evoke emotional and neutral states in subjects during a pilot study [21]. These videos have a duration of 1–2 min and include popular commercial ads and user-generated videos. Subsequently, the 20 participants in Amazon Mechanical Turk offered 40 annotated video clips on a 7-point Likert scale based on six basic emotions. These specific clips contain content most likely to induce the six basic emotions, namely anger, disgust, fear, joy, sadness, and surprise [21].

#### 4.1.4. DEAP

The DEAP dataset comprises EEG and peripheral physiological signals from 32 subjects, collected using a Biosemi ActiveTwo device [22]. EEG signals were recorded based on an international 10–20 electrode system while the subjects viewed 40 1-min music videos. Following each video presentation, the participants were queried on their self-assessed ratings for arousal, valence, like/dislike, dominance, and familiarity [22]. The sampling frequency was decreased from 512 Hz to 128 Hz, followed by the application of a band-pass filter of 4.0–45 Hz to cancel out noise in the EEG signal data [22].

#### 4.1.5. LUMED

The LUMED-2 dataset is a multi-modal dataset created through the joint efforts of Loughborough University in the UK and Hacettepe University in Turkey [23]. This dataset recorded the EEG signals of 13 subjects while they were exposed to audio and visual stimuli. All stimuli had a total duration of 8 min and 50 s, with video clips selected from the internet specifically to evoke certain emotions. Between each video clip, a 20-s grey screen was presented to give participants a chance to rest. Following each session, participants were requested to indicate their emotional state based on the categories of happy, sad, or neutral. Additionally, the subjects' facial expressions were captured using a 640

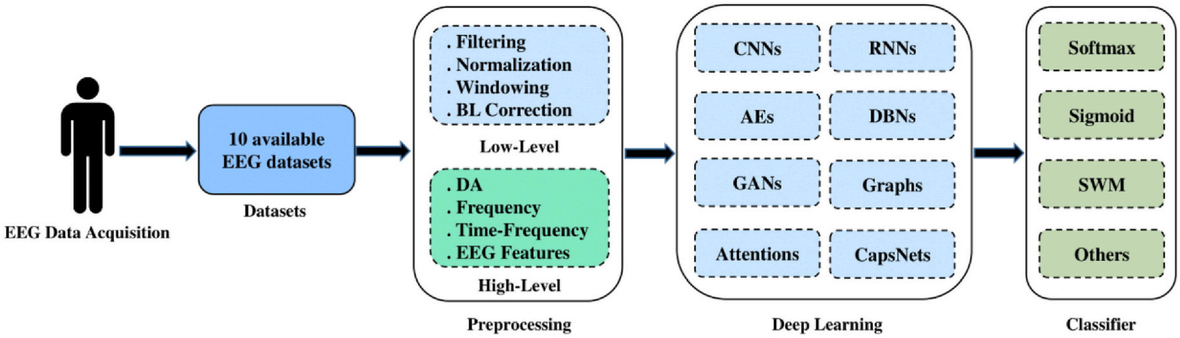


**Fig. 3.** Illustration of the block diagram used for emotion recognition using DL methods.

**Table 3**
Available EEG datasets for emotion recognition.

| Dataset | Number of Subjects | FS (Hz) | Number of Channels | Data Modality | EEG Device | Quantification of Emotion |
|---|---|---|---|---|---|---|
| SEED [19] | 15 (7 male, 8 female) | 1000 | 62 | EEG, Peripheral physiological signals (Electromyography, Electro-Oculogram), Face video | ESI NeuroScan | Discrete type (Arousal-negative, Arousal-neutral, Arousal-positive) |
| SEED-IV [20] | 15 (7 male, 8 female) | 1000 | 62 | EEG, Eye-tracking data | ESI NeuroScan | Discrete type (happy, sad, fear, and neutral) |
| DAI-EF [21] | 60 (31 male) | – | 64 | EEG, GSR, EOG and EMG signals from zygomaticus major respiratory effort, eye gaze and face video | Biosemi ActiveTwo | Discrete type (anger, disgust, fear, happiness, sadness and surprise) |
| DEAP [22] | 32 (16 male, 16 female) | 512 | 32 | EEG, GSR, Respiration Amplitude, Skin Temperature, Blood Volume, Electromyogram and Electrooculogram | Biosemi ActiveTwo | Continuous type (Arousal, Valence, Dominance, Liking) |
| LUMED [23] | 13 (7 male, 6 female) | 500 | 8 | EEG, Peripheral physiological signals (Galvanic Skin Response( | ENOBIO | Discrete type (happy, sad, and neutral) |
| MAHNOB-HCI [24] | 27 (11 male, 16 female) | 256 | 32 | EEG, Visual, Audio, Eye Gaze, ECG, GSR, Respiration Amplitude, Skin temperature | Biosemi ActiveTwo | Discrete type (9 types), continuous type (Arousal, Valence, Dominance) |
| DREAMER [25] | 25 (14 male, 11 female) | 128 | 14 | EEG, Peripheral physiological signals (Electrocardiogram) | Emotiv EPOC | Continuous type (Arousal, Valence, Dominance) |
| AMIGOS [26] | 40 | 128 | 14 EEG +3 Peripheral physiological signals | Audio, Visual, Depth, EEG, GSR and ECG | Emotiv EPOC | Discrete type (familiarity, like/dislike, and basic emotions), continuous type (Arousal, Valence, Dominance) |
| SDEA [27] | 30 (13 male, 17 female) | 1000 | 16 | EEG | NeuroScan | Discrete type (neutrality, funny and angry) |
| MPED [28] | 23 (10 male, 13 female) | 1000 | 62 | EEG, Peripheral physiological signals (Electrocardiogram, Respiration, Galvanic Skin Response( | ESINeuroScan | Discrete type (joy, funny, anger, fear, disgust, sad and neutrality) |

× 480 webcam recording at 30 frames per second. The EEG signals were recorded using an 8-channel ENOBIO device at a sampling rate of 500 Hz, followed by pre-processing via a band-pass filter at the 0–75 Hz range [23].

#### *4.1.6. MAHNOB-HCI*

The MAHNOB-HCI dataset was compiled to identify emotional states through a multi-modal approach, which involves the synchronized recording of facial videos, audio and EEG signals, as well as peripheral/central nervous system physiological signals [24]. Within this dataset, EEG signals were captured through a 32-channel headset at a sampling frequency of 256 Hz from 27 participants during their viewing of 20 brief clips (over two separate experiments). These clips varied in duration from 35 to 117 s. During the first experiment, subjects viewed 20 emotionally evocative videos and reported their experienced emotions. In the second experiment, short videos and images were shown initially without any accompanying tags, and then again with correct and incorrect tags [24]. Participants were required to judge and provide feedback on these tags, resulting in recorded videos and bodily responses being divided and stored in a database. Additional detail about the MAHNOB-HCI dataset can be accessed in Ref. [24].

#### *4.1.7. DREAMER*

The DREAMER dataset is an example of a multi-modal dataset that includes EEG and ECG signals collected from 23 subjects. These signals were captured via 14 EEG electrodes, at a sampling frequency of 128 Hz [315]. The EEG data were collected while the subjects watched 18 video clips, with each clip designed to induce one out of nine basic emotions, namely calmness, amusement, anger, sadness, happiness, disgust, excitement, surprise, and fear [25]. The clips were played without interruption for a duration of 65–393 s, considered sufficient time to evoke an emotion. Participants self-evaluated their arousal, valence, and dominance levels on a scale of 1–5 [25]. Each participant's dataset was divided into three parts: 1) 18 baseline signal segments pertaining to calmness, 2) empirical signal segments, and 3) 18 related (tags) labels [25].

#### *4.1.8. AMIGOS*

The AMIGOS dataset includes a 14-channel EEG and three peripheral physiological signal channels were recorded in two laboratory environments [26]. The first stage of the experiment involved 40 subjects who were asked to watch 16 emotional clips of short duration. In the second stage, the subjects watched four longer clips either alone or in groups while wearable sensors recorded ECG, EEG, and GSR signals [26]. The experiment also included HD frontal and RGB full-body and depth videos for further analysis. Following the video clips, the subjects rated their self-assessment for arousal, valence, like, and dominance on a scale ranging from 1 to 9 [26]. During pre-processing, the EEG signals were downsampled to 128 Hz, and a band-pass filter at 4.0–45 Hz was applied to remove the background noise before data analysis [26].

#### 4.1.9. SDEA

The SDEA dataset comprises EEG signals obtained from 30 subjects, consisting of 13 males and 17 females, with an average age of 20 years [27]. The EEG data were recorded after the participants watched 12 Chinese video clips aimed at eliciting three emotions - neutrality, humor, and anger. To induce targeted emotional states, the MPED stimulus was utilized, which has been validated through psychological methods [27]. Before collecting the EEG signals, subjective self-assessment was conducted to ensure that the participants' emotional states aligned with the stimulus material. The data was recorded using a 16-channel NeuroScan device at a sampling frequency of 1 kHz [27].

#### 4.1.10. MPED

The MPED dataset consists of model physiological signals such as EEG, respiration (RSP), and ECG. The experiment involved 23 subjects, comprising 10 males and 13 females who were exposed to 28 videos [28]. These videos stimulated the participants to experience seven different emotions, namely joy, humor, anger, disgust, fear, sadness, and neutrality [28]. Before the experiment, all the elicitation materials were accurately labeled and assessed via psychological methods to ensure the expected level of emotion was achieved. The EEG signals were recorded using a 62-channel ESI NeuroScan device at a sampling frequency of 1 kHz. During pre-processing, to eliminate electrooculogram (EOG) and EMG artifacts, the raw EEG signals were manually filtered [28].

### 4.2. Preprocessing

Pre-processing is a crucial stage employed in the development of a CADS-based emotion recognition system using EEG signals. EEG signals are susceptible to both external and internal artifacts, making emotion recognition a challenging task. To overcome these challenges, different pre-processing techniques have been proposed. These techniques can be broadly categorized into two groups: low-level and high-level techniques. Table 4 presents several low and high-level pre-processing techniques used in these studies to enhance the quality of EEG data before analysis. In the following subsections, we have discussed these low and high-level pre-processing techniques in detail.

#### 4.2.1. Low level

This section introduces low-level preprocessing techniques in papers on emotion recognition from EEG signals. According to Table 4, noise removal, windowing, normalization and baseline correction are among the most important low-level preprocessing methods for EEG signals [316,317]. EEG signals are susceptible to various types of noise, such as electrical interference, muscle activity and movement artifacts. These noises are commonly removed by different filters such as band-pass, low-pass and high-pass in the low-level preprocessing stage. *Windowing* is another low-level preprocessing step in EEG signals. At this stage, the EEG signals are segmented into smaller time intervals for more accurate processing [316]. This leads to an increase in the resolution of the information used for emotion recognition through AI techniques. Additionally, the amplitude of EEG signals may vary across multiple recording sessions or for each subject. To overcome this challenge, normalization techniques such as z-score or baseline correction are employed [39–44]. From Table 4, it is evident that various low-level preprocessing techniques have been employed by researchers in their work on emotion recognition. Filtering, normalization, and segmentation methods are the most frequently used low-level preprocessing techniques in these studies.

#### 4.2.2. High level

In deep learning applications, high-level pre-processing techniques for EEG signals can lead to improved performance of CADS. Table 4 outlines the successful high-level pre-processing techniques used for emotion recognition from EEG signals. Data augmentation (DA) [318] is a popular high-level pre-processing technique that involves increasing artificial input data for DL models. This strategy helps to prevent overfitting and enhances the accuracy of emotion recognition using DL models. Researchers have also implemented other high-level pre-processing techniques such as discrete wavelet transform (DWT) [172], continuous wavelet transform (CWT) [40], and empirical mode decomposition (EMD) [122] to remove noise and break down EEG signals into different frequency bands. Independent component analysis (ICA) was applied as a high-level pre-processing technique for emotion recognition with promising results [125]. Additionally, in another research, the short-time Fourier transform (STFT) [39], fast Fourier transform (FFT) [178], and connectivity methods [46] were used to convert 1D EEG signals into 2D images as part of high-level pre-processing. The resulting 2D images were applied as inputs to 2D DL models.

### 4.3. Deep learning models

DL models have shown promising results in diverse applications, including medical fields where CADS are used to increase efficiency. In recent years, many studies have successfully utilized DL models for emotion recognition from EEG signals. This section highlights the key DL models used for this purpose, including convolutional neural networks (CNNs) [319,320], generative adversarial networks (GANs) [321, 315], recurrent neural networks (RNNs) [319,320], autoencoders (AEs) [319,320], and Graph models [322,323]. The section starts with CNNs, which come in 1D, 2D, and pre-trained models that can identify emotions from EEG signals with high accuracy. These DL architectures are briefly explained below.

#### 4.3.1. CNNs

In recent years, the use of DL architectures has led to significant results in various fields, such as emotion recognition [319,320]. CNNs are the most successful DL models. In that regard, researchers particularly try to introduce new models based on these architectures [319, 320]. AlexNet was the first evolution of CNN architecture that won the ImageNet challenge. There are three main types of layers in a CNN: convolutional layers, pooling layers, and fully connected (FC) layers 319,320,324. The convolutional layer does feature extraction, and the pooling layer reduces dimensionality [319,320]. Finally, the FC layer classifies input data or detected features. CNN models employ spatial patterns to create a robust representation of existing data [319,320]. Thus, CNN architectures are implementable on 1D, 2D, and 3D data. CNN can be divided into 1D, 2D, 3D, and pre-trained models. The following lines explain CNN architectures for EEG-based emotion recognition [319,320].

*4.3.1.1. 1D-CNNs.* CNN models have the ability to learn complex patterns from medical data, making them suitable for diverse applications, provided they are trained on datasets with a large number of subjects [319,320]. This unique feature has made CNNs a popular choice for processing 1D and 2D medical data. In emotion recognition research, EEG signals are typically 1D signals and can be processed using the convolutional layers of 1D CNN architectures. The convolutional layers play a critical role in identifying patterns in EEG signals for emotion recognition. Additionally, pooling and fully connected (FC) layers are utilized for dimensionality reduction and signal classification, respectively. Compared to 2D CNN architectures, 1D CNN architectures have fewer hyperparameters, making them easier to implement on hardware with limited resources. Figure (4) illustrates a typical 1D CNN

**Table 4**
Summary of DL methods used for emotion recognition using EEG signals.

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| [29] | 2018 | SEED | 15 Subjects | DE | HCNN | NA | MATLAB | Acc (Beta) = 86.2<br>Acc(Gamma) = 88.2 |
| [30] | 2021 | SEED, **DEAP** | 15 (SEED),<br>32 (DEAP) | CWT | 2D-CNN | Softmax | MATLAB | Acc = 49.12 (3-class)<br>Acc = 54 (2-class) |
| [31] | 2023 | DEAP | 32 Subjects | time, frequency and time-frequency features | 2D-CNN | NA | PyTorch | Acc-val = 98.36<br>Acc-aro = 98.27<br>Acc = 98.38(4-class) |
| [32] | 2022 | DEAP | 32 Subjects | 3D spatial-spectral features | DBCN | Softmax | NA | Acc-val = 90.93 (subject-dependent)<br>Acc-aro = 89.67 (subject-dependent)<br>Acc-val = 83.98 (subject-independent)<br>Acc-aro = 79.45 (subject-independent) |
| [33] | 2018 | DEAP | 32 Subjects | Down sampling, STFT | 2D-CNN | Softmax | TensorFlow | Acc-aro = 76.56<br>Acc-val = 80.46 |
| [34] | 2019 | DEAP | 32 Subjects | MFM | CapsNet | NA | TensorFlow | Acc-aro = 68.28<br>Acc-val = 66.73<br>Acc-dom = 67.25 |
| [35] | 2019 | DEAP, **SEED** | 15 (SEED),<br>32 (DEAP) | Spectrogram, BoDF | AlexNet | **SVM** | NA | Acc = 93.8 |
| [36] | 2019 | DREAMER, **AMIGOS**, MAHNOB-HCI, DEAP | Different Subjects | Frequency filters, DE, PSE, RGB heat-map, PCA | VGG16 for feature extraction, LSTM | ELM | NA | Acc = 81.05 |
| [37] | 2020 | DEAP | 32 Subjects | 3D multiscale sample entropy matrix | 2D-CNN | HMM | TensorFlow | Acc-val = 79.77<br>Acc-aro = 83.09<br>Acc-dom = 81.83 |
| [38] | 2021 | DEAP, SEED, **DREAMER**, AMIGOS | 32 Subjects | Topographic and holographic feature maps | 2D-CNN | SVM | MATLAB | Acc = 89.31 |
| [39] | 2021 | DEAP | 32 Subjects | STFT, DA algorithm Borderline-SMOTE | 1D-CNN | Softmax | NA | Acc-val = 97.47<br>Acc-aro = 97.76 |
| [40] | 2021 | SEED | 15 Subjects | CWT, DE | 2D-CNN | Softmax | Python | Acc = 91.45 |
| [41] | 2019 | DEAP | 32 Subjects | Normalization, PSD | 2D-CNN | Softmax | NA | Acc = 88.76 |
| [42] | 2020 | Clinical | Different Subjects | ICA | 1D-CNN | Softmax | NA | Acc = 92.44 |
| [43] | 2019 | DEAP | 32 Subjects | k-means | ECNNs | Plurality voting | NA | Acc = 82.92 |
| [44] | 2020 | DEAP | 32 Subjects | 3D EEG stream representation based on spatio-temporal information | 3D-CNN | NA | PyTorch | Acc-val = 99.11(2-class)<br>Acc-aro = 99.74(2-class)<br>Acc = 99.73(4-class) |
| [45] | **2018** | **SEED**, DREAMER | 15 (SEED),<br>23 (DREAMER) | Adjacency matrix, Different features | DGCNN | Softmax | NA | Acc = 79.95(subject independent)<br>Acc = 90.4(subject dependent) |
| [46] | **2019** | **SEED**, DEAP | 15 (SEED),<br>32 (DEAP) | DE, PLV connectivity | GCCN | Softmax | NA | Acc = 84.35 |
| [47] | 2019 | **SEED**, DREAMER | 15 (SEED),<br>23 (DREAMER) | DE, PSD, DASM, RASM, DCAU, LDS, BLS | GCB-net | Softmax | NA | Acc = 94.24 |
| [48] | 2019 | DEAP | 32 Subjects | Normalization | Multi-column CNN | Voting | Pytorch | Acc-val = 90.01<br>Acc-aro = 90.65 |
| [49] | 2020 | DEAP | 32 Subjects | Brain connectivity, PCC, PLV, TE | 2D-CNN | Softmax | PyTorch. | Different Results |
| [50] | 2021 | DEAP | 32 Subjects | Multi-spectral topology maps | 2D-CNN, LSTM | Softmax | NA | Acc-val = 90.62<br>Acc-aro = 86.13<br>Acc-dom = 88.48 |
| [51] | **2020** | **DEAP**, DREAMER | 32 (DEAP), 23 (DREAMER) | Baseline processing | MLF-CapsNet | NA | TensorFlow | Acc-val = 97.97<br>Acc-aro = 98.31<br>Acc-dom = 98.32 |
| [52] | **2020** | **DEAP**, SEED | 32 (DEAP),<br>15 (SEED) | Windowing, DE | CDCN | Softmax | Keras | Acc-val = 92.24<br>Acc-aro = 92.92 |
| [53] | 2021 | DEAP | 32 Subjects | WPD, entropy, energy, 1D concatenated data representation, 2D interpolated data representation | 2D-CNN | Softmax | NA | Acc-val = 91.85<br>Acc-aro = 91.06 |
| [54] | 2021 | Clinical | 12 Subjects | ICA, PSD | 2D-CNN, 3D-CNN | Softmax | NA | Acc-val = 73.34<br>Acc-aro = 56.58 |
| [55] | 2021 | SEED | 15 Subjects | PSD | 2D-CNN | Softmax | NA | Acc = 94.63 |

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**Table 4** (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| [56] | **2021** | **DEAP**, DREAMER, DASPS | 32 (DEAP), 23 (DREAMER), 23 (DASPS) | ICA | 1D-CNN | Softmax | NA | Acc = 96.39 |
| [27] | 2021 | SEED, **DREAMER**, SDEA, MPED | 15 (SEED), 23(DREAMER), 30 (SDEA), 23 (MPED) | DE, PSD | GECNN | NA | TensorFlow | Acc = 94.26 |
| [57] | 2022 | DEAP, **DREAMER**, SEED, AMIGOS | 32 (DEAP), 23 (DREAMER), 15 (SEED), 40 (AMIGOS) | Relief F, NCA, holographic feature maps | 2D-CNN | SVM | NA | Acc-val = 90.76 Acc-aro = 92.92 Acc-dom = 92.97 |
| [58] | 2020 | DEAP, **SEED**, LUMED | 32 (DEAP), 15 (SEED), 11 (LUMED) | – | InceptionResnetV2 | Softmax | TensorFlow | Acc = 86.56 |
| [59] | 2020 | Clinical | 20 Subjects | SPWVD | 2D-CNN | Softmax | NA | Acc = 93.01 Pre = 93.26 F1-score = 0.9326 |
| [60] | 2021 | SEED | 15 Subjects | – | ResNet18 | Softmax | NA | Acc = 93.42(3-class) |
| [61] | 2022 | DEAP | 32 Subjects | DE, sample entropy, Hjorth parameter, PSD | CNN + inception structure | SVM | PaddlePaddle | Acc-val = 80.52 Acc-aro = 75.22 |
| [62] | 2022 | DEAP, **MAHNOB-HCI** | 32 (DEAP), 20 (MAHNOB-HCI) | effective connectivity maps | **ResNet-50** | Softmax | NA | Acc = 99.4 F1-score = 99.42 |
| [63] | 2022 | DEAP, MAHNOB-HCI, **DREAMER** | 32 (DEAP), 20 (MAHNOB-HCI) | Effective connectivity maps | **ResNet-18** | Softmax | NA | Acc = 96 |
| [64] | 2022 | DEAP | 32 Subjects | MVMD, multivariate time-frequency image | ResNet-18 | Softmax | MATLAB | Acc-val = 97.75 Acc-aro = 99.03 Acc-dom = 97.59 |
| [65] | 2018 | SEED | 15 Subjects | Spatio-temporal patterns, DE | STRNN | Softmax | NA | Acc = 89.5 |
| [66] | **2020** | **SEED**, SEED-IV, MPED | 15 (SEED, SEED-IV), 30 (MPED) | DE (SEED, SEED-IV), STFT (MPED), Horizontal and vertival streams | Two directional RNNs | Softmax | TensorFlow | Acc = 93.12 |
| [67] | 2018 | Clinical | 20 Subjects | RQA | CFCNN | Softmax | Keras | Acc = 92.24 |
| [68] | **2020** | **SEED**, VIG | 15(SEED), 21(VIG) | STFT, DE, interpolation methods | CNN-LSTM | Softmax | PyTorch | Acc = 90.41 |
| [69] | 2019 | DEAP | 32 Subjects | ICA, DA, STFT | CNN-LSTM | Softmax | NA | Acc = 84.922 ± 4.697 |
| [70] | 2019 | DEAP | 32 Subjects | ICA, frequency filters | CNN-LSTM, CNN-GRU | Softmax | NA | CRR = 99.90–100 |
| [71] | 2020 | Clinical | 20 Subjects | ICA | CNN-LSTM | Softmax | NA | Acc = 71.61(early fusion) |
| [72] | 2020 | DEAP, **SEED** | 32(DEAP), 15 (SEED) | DE | 4D-CRNN | Softmax | Keras | Acc = 94.74 |
| [73] | 2020 | DEAP | 32 Subjects | PSD, 2D mesh matrix | **Cascaded CNN-LSTM** | Softmax | TensorFlow | Acc-val = 93.64 Acc-aro = 93.26 |
| [74] | **2020** | **DEAP**, DREAMER | 32 (DEAP), (DREAMER) | spatial encoding | RACNN | Softmax | NA | Acc-val = 96.65 Acc-aro = 97.11 |
| [75] | 2022 | DEAP, **SEED** | 32 (DEAP), 15 (SEED) | DE | Ensemble of 2D-CNN, LSTM, 2D–CNN–LSTM models | Softmax | NA | Acc = 97.16 |
| [76] | 2022 | SEED | 15 Subjects | DE, PSD, 4D spatial-spectral-temporal representations | Attention-based CNN–Bi-LSTM | Softmax | NA | Acc = 95.39 (DE),90.49(PSD) |
| [77] | 2022 | DEAP | 32 Subjects | WPD, statistical features, Hurst exponent, BGWO | Bi-LSTM | Softmax | MATLAB | Different Results |
| [78] | 2021 | DEAP | 32 Subjects | DE | Fusion of GCNN and LSTM | NA | NA | Acc-val = 90.45 (subject-dependent) Acc-aro = 90.60 (subject-dependent) Acc-val = 84.81 (subject-independent) Acc-aro = 85.27 (subject-independent) |
| [79] | 2020 | SEED | 15 Subjects | DT-CWT, time, frequency and nonlinear analysis | SRU models | MV | Keras, TensorFlow | Acc = 83.13 pre = 82.24 Sen = 81.53 |
| [80] | 2020 | DEAP, **SEED** | 32 (DEAP), 15 (SEED) | DWT, third-order cumulants, PSO | Bi-LSTM | Softmax | NA | Acc = 90.81(3-class) |
| [81] | 2019 | DEAP | 32 Subjects | SAE for signal decomposition,PSD, PCC | LSTM | Sigmoid | NA | Acc-val = 81.1 Acc-aro = 74.38 |
| [82] | 2020 | DEAP | 32 Subjects | – | LSTM + Attention + CNN | Softmax (3classes), Sigmoid (2classes) | Keras | Acc-val = 90.1(2-class) Acc-aro = 88.3(2-class) Acc-val = 86.95(3-class) |

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**Table 4** (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Acc-aro- = 84.1(3-class) |
| [83] | 2021 | DEAP | 32 Subjects | – | 2D-CNN with soft attention + ConvLSTM | Softmax | TensorFlow | Acc-val = 87.84 Acc-aro = 87.69 |
| [84] | **2021** | **DEAP**, SEED | 32 (DEAP), 15 (SEED) | spatial channel distribution | CNN-LSTM | Softmax | NA | Acc-val = 97.41 Acc-aro = 97.39 Acc-dom = 97.68 |
| [85] | **2022** | **SEED**, DEAP, CHB-MIT | 32 (DEAP), 15 (SEED), 23(CHB-MIT) | – | Attention based CNN + LSTM | Softmax | TensorFlow | ACC = 76.7 |
| [86] | 2018 | DEAP | 32 Subjects | – | Ensemble of DBN-GC + discriminative RBM | NA | NA | Acc-aro = 75.92, Acc-val = 76.83, |
| [87] | 2022 | BED | 21 Subjects | Spectral features, ARRC, MFCC, M3GP | Separable 1-D CNN | Softmax | TensorFlow, Keras | Acc = 92.1 |
| [88] | **2022** | **DREAMER**, DEAP | 23 (DREAMER) 32 (DEAP) | DE, STFT, Feature smoothing and scaling | AD-TCN | Softmax | NA | Acc-val = 65.66 Acc-aro = 63.69 |
| [89] | 2022 | DEAP | 32 Subjects | Spatio-temporal features, 2D matrix mapping | CapsNet | Softmax | NA | Cross subject inference Acc-val = 48.219 Acc-aro = 58.525 |
| [90] | 2022 | DEAP | 32 Subjects | Few-shot model | 3-D CNN–Bi-LSTM | NA | NA | Acc-val = 69.92 Acc-aro = 68.89 |
| [91] | 2022 | DEAP | 32 Subjects | PSD features, power topographic maps, temporal statistics | 2D-CNN + TFLN + Feature Fusion Network (2 Bi-LSTM units) | Sigmoid | Pytorch | Acc-aro = 86.16 (Subject-dependent) Acc-val = 85.42 (Subject-dependent) |
| [92] | 2022 | DEAP, **SEED** | 32 (DEAP), 15 (SEED) | Connectivity features (PCC, PLV, PLI), decomposition | MSRN | Softmax | Pytorch | Acc = 87.05 |
| [93] | 2022 | DEAP, SEED, IDEA | 32 (DEAP), 15 (SEED), IDEA (14) | PSD, Hjorth parameters, DE, LF-DE | Deep Bi-LSTM | **Softmax**, SVM, k-NN | NA | Acc = 59 (SEED training-DEAP testing) |
| [94] | **2022** | **DEAP**, DREAMER | 32 (DEAP), 23 (DREAMER) | Down-sampling, Artifact subspace reconstruction method | MTCA- CapsNet | Softmax | NA | Acc-val = 97.41 Acc-aro = 97.25 Acc-dom = 98.35 |
| [95] | 2022 | SEED, **SEED-IV** | 15 (SEED), 15 (SEED-IV) | PCA, SSM, similarity SNF, NE, STFT, DE, PSD | GCN | NA | NA | 5.30% of SEED and 7.20% of SEED-IV as labeled samples: Min Acc improvement = 13.14 |
| [96] | 2022 | DEAP | 32 Subjects | Down-sampling, filtering | 2D-CNN | Softmax | NA | Acc-val = 99.98 Acc-aro = 99.99 |
| [97] | 2022 | Clinical, **SEED**, DEAP | 16 (Clinical),15 (SEED), 32 (DEAP) | Mapping using Bernoulli–Laplace-based Bayesian model, Weighted graph adjacency matrix | DGCNN | Softmax | Tensorflow | Acc = 99.25 (Subject-dependent) Acc = 98.51 (Subject-independent) |
| [98] | **2022** | **DEAP**, SEED | 32 (DEAP), 15 (SEED) | DE | CNN-BiLSTM | Softmax | NA | Acc-val = 94.02 Acc-aro = 94.86 |
| [99] | 2022 | SEED | 15 Subjects | MEMD | Pre-trained CNNs | Softmax | TensorFlow | Acc = 100 (AutoKeras) Acc = 99 (transfer learning) |
| [100] | **2022** | **SEED**, SEED-IV, DEAP | 15 (SEED),15 (SEED-IV), 32 (DEAP) | Frontal, temporal, parietal, and occipital lobes features | HVF2N-DBR | Softmax | Keras | Acc = 89.33 |
| [101] | 2022 | Clinical | 49 Subjects | DA | MBCNN | Sigmoid | NA | Acc-val = 67.8 Acc-aro = 77 |
| [102] | 2020 | DEAP, **DREAMER** | 32 (DEAP), 23 (DREAMER) | – | ACRNN | Softmax | TensorFlow | Acc-val = 97.79 Acc-aro = 97.98 Acc-dom = 97.67 |
| [103] | 2018 | DEAP | 32 Subjects | – | Parallel CNN-LSTM | Softmax | Tensorflow | Acc-val = 90.8 Acc-aro = 91.03 |
| [104] | 2020 | DEAP | 32 Subjects | WPD, DT-based feature selection | BDAE | LIBSVM | MATLAB | Acc = 85.71 |
| [105] | 2020 | DEAP, SEED, **CMEED** | 32 (DEAP), 15 (SEED) | Down-sampling, STFT, and DE features | ATDD-LSTM | Sigmoid | NA | Acc-val = 94.21 Acc-aro = 88.03 |
| [106] | 2019 | SEED | 15 Subjects | Handcarft feature matrix, regional handcraft feature | Bi-LSTM | Softmax | NA | Acc = 93.38 |
| [107] | 2018 | DEAP | 32 Subjects | DE | 2D-CNN | Softmax | Tensorflow | Acc-val = 89.45 Acc-aro = 90.24 |
| [108] | 2018 | DEAP | 32 Subjects | Brain connectivity features, PSD features | 2D-CNN | Sigmoid | NA | Acc = 99.72 (CNN-5 with PLV matrices formed with the dist2 method) |
| [109] | 2020 | DEAP | 32 Subjects | Statistical features | 2D-CNN | Softmax, SVM | TensorFlow | Different Results |
| [110] | 2022 | SEED | 15 Subjects | DE features, STFT | DCOT | Softmax | NA | Acc = 93.83 (subject-dependent) |

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**Table 4** (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Acc = 93.03 (subject-independent) |
| [111] | 2018 | DEAP | 32 Subjects | FFT, LFCC features | ResNets (feature extraction) | **KNN** | NA | Acc-val = 90.39<br>Acc-aro = 89.06 |
| [112] | 2020 | University of Tabriz | 14 Subjects | – | 1D–CNN–LSTM | Softmax | Python | Acc = 97.42 (2-class)<br>Acc = 96.78 (3-class) |
| [113] | 2019 | SEED V | 16 Subjects | DE features, thirty-three-dimension features, Rescaling | ResNet-LSTM, BDAE | SVM | NA | Acc = 79.63 |
| [114] | 2020 | DEAP, **SEED-IV** | 32 (DEAP), 15 (SEED-IV) | DE features smoothed by LDS, DE features smoothed by moving average | RODAN(including Bi-GRU + FC + Domain adversarial network) | NA | NA | (SUBJECT-BIASED)<br>Acc = 98.15 ± 0.2 |
| [115] | 2021 | DEAP | 32 Subjects | PSD, DE, DASM, RASM, ASM and DCAU features | HGCN | Softmax | NA | Acc-val = 90.56<br>Acc-aro = 88.79 |
| [116] | 2021 | SEED | 15 Subjects | DE, PSD features, Adjacency matrix | LR-GCN | NA | NA | Subject-dependent<br>Acc = 94.72 (DE), 85.24 (PSD) |
| [117] | **2021** | **SEED**, SEED-IV | 15 (SEED), 15 (SEED-IV) | DE features | SOGNN | Softmax | PyTorch | Acc = 86.81/5.79 |
| [118] | 2020 | DEAP, **AMIGOS** | 32 (DEAP), 40 (AMIGOS) | – | 3D-CNN | NA | TensorFlow | Acc-val = 96.96(2-class)<br>Acc-aro = 97.52(2-class)<br>Acc = 95.86(4-class) |
| [119] | 2020 | DEAP | 32 Subjects | PSD features | LSTM | **Sigmoid** | Keras with TensorFlow backend | Subject-dependent<br>Acc-val = 94.69<br>Acc-aro = 93.13 |
| [120] | 2019 | Clinical | 20 Subjects | Filtering, ICA | 2D-CNN | NA | NA | Acc-val = 86.87<br>Acc-aro = 81.54 |
| [121] | 2020 | DEAP | 32 Subjects | PSD features | LSTM | **Sigmoid** | NA | Acc-val = 94.69<br>Acc-aro = 93.13 |
| [122] | 2021 | Clinical | 20 Subjects | Different Preprocessing Steps | Bi-LSTM | Softmax | NA | Acc-val = 85.38<br>Acc-aro = 77.52<br>AUC-val = 78.29<br>AUC-aro = 68.16 |
| [123] | 2021 | DEAP | 32(EEG), 22 (Video) | Eye and EOG artifacts removal, filtering, Resizing, DA, Mask-RCNN | 3D-CNN | Voting | NA | Acc-val = 96.13<br>Acc-aro = 96.79 |
| [124] | 2019 | DEAP, **SEED** | 32 (DEAP), 15 (SEED) | NA | VAE | NA | NA | Acc = 84.29 |
| [125] | 2022 | DEAP | 32 Subjects | Local and global brain regions, PCA | NRDNN, AConvNet | NA | NA | Acc = 72.97<br>F1-score = 71.66<br>AUC = 60.37 |
| [126] | 2019 | DEAP | 32 Subjects | – | MM-ResLSTM | Softmax | TensorFlow | Acc-aro = 92.87,<br>Acc-val = 92.30 |
| [127] | 2021 | DEAP | 32 Subjects | Data division, Fusion of wavelet energy ratio, WE, and approximate entropy features | 3D-CNN | Softmax | NA | Acc-val = 93.61 (subject-dependent)<br>Acc-aro = 94.04 (subject-dependent)<br>Acc-val = 83.83 (subject-independent)<br>Acc-aro = 84.53 (subject-independent) |
| [128] | 2020 | GAMEEMO | 28 Subjects | Spectral entropy features | Bi-LSTM | Sigmoid | NA | Acc = 76.93<br>ROC = 90 |
| [129] | **2019** | **DEED**, MPED | 15 (DEED), 23 (MPED) | Hjorth, HOC, PSD, STFT and HHS features | SGA-LSTM | NA | NA | Acc = 90.38 (HOC feature + subject-dependent),<br>Acc = 72.14 (STFT feature + subject-independent) |
| [130] | 2019 | DEAP | 32 Subjects | STFT, DE, Feature smooth | TCN | Softmax | NA | Acc-val = 74.4<br>Acc-aro = 71.4 |
| [131] | 2022 | DEAP | 32 Subjects | Data division, PSD feature, Adjacency matrix | CR-GCN | Softmax | PyTorch | Acc-val = 94.69 (subject-dependent)<br>Acc-aro = 93.95 (subject-dependent)<br>Acc-val = 94.78 (subject-independent)<br>Acc-aro = 93.46 (subject-independent) |
| [132] | **2022** | **SEED**, DREAMER | 15 (SEED), 23 (DREAMER) | PSD, DE, DCAU, RASM, and DASM features | GCB-Res | Softmax | NA | Acc = 94.56 |
| [133] | **2021** | **SEED-IV**, MPED | 15 (SEED-IV), 30 (MPED) | DE features, STFT, Dynamic and static graph | PGCN | Softmax | TensorFlow | Acc = 77.08 (subject-independent) |

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**Table 4** (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| | | | | representations, Graph FT | | | | |
| [134] | **2021** | **SEED**, MPED | 15 (SEED), 23 (MPED) | DE features, STFT | IAG | Softmax | TensorFlow | Acc = 69.44 (subject-independent) Acc = 95.44 (Subject-dependent) Acc = 86.30 (Subject independent) |
| [135] | **2019** | **SEED**, DEAP | 32 (DEAP), 15 (SEED) | DE, PSD, DASM and DCAU features, PLV matrices | P-GCNN | Softmax | NA | Acc = 84.35 |
| [136] | 2021 | SEED, SDEA, **DREAMER**, MPED | 15 (SEED), 30 (SDEA), 32(DREAMER), 23 (MPED) | DE, PSD and HHS features | GECNN | NA | TensorFlow | Acc-val = 95.73 (Subject-dependent) Acc-aro = 92.79 (Subject-dependent) |
| [137] | **2022** | **SEED**, SEED-IV | 15 (SEED), 15 (SEED-IV) | Granger causality matrix, (DE, PSD, DASM, RASM and DCAU) features | CGCNN | Softmax | NA | Acc = 93.36 (SEED) |
| [138] | 2021 | NA | 25 Subjects | ICA, Decomposition, Statistical Features | **Bi-LSTM** | NA | NA | Acc = 96.41 (MAV) |
| [139] | **2020** | **SEED**, SEED-IV | 15 (SEED), 15 (SEED-IV) | Sparse adjacency matrix | RGNN | Softmax | NA | Acc = 94.24 (Subject-dependent) Acc = 85.30 (Subject-independent) |
| [140] | 2021 | DEAP | 32 Subjects | Data calibration, Data division, DE | Fusion of GCNN and LSTM | Sigmoid | NA | Different Results |
| [141] | 2018 | DREAMER | 15 (SEED), 23 (DREAMER) | Adjacency matrix, (DE, PSD, DASM, RASM and DCAU) features | DGCNN | Softmax | NA | Acc = 90.4(Subject-dependent) Acc = 79.95(Subject independent) |
| [142] | 2021 | SEED | 15 Subjects | DE, PSD features, Adjacency matrix, Laplacian matrix | LR-GCN | NA | NA | Subject-dependent Acc = 94.72 (DE),85.24 (PSD) |
| [143] | 2021 | Tianjin University | 25 Subjects | Adjacency matrix, re-referencing | ASTGCN | Softmax | Pytorch | Acc = 90.6 ± 3.4 |
| [144] | 2022 | SEED, **DEAP** | 15 (SEED), 32 (DEAP) | (DE,PSD, RASM and DASM) features, Adjacency matrix | EEG-GCN | Softmax | NA | Acc-val = 81.77 (Subject-dependent) Acc-aro = 81.95 (Subject-dependent) |
| [145] | **2021** | **SEED**, DEAP, DREAMER, CMEED | 15 (SEED), 32 (DEAP), 23 (DREAMER), 37 (CMEED) | (DE, PSD, DASM, RASM, ASM and DCAU) features, Adjacency matrix | SparseDGCNN | Softmax | NA | Subject-dependent Acc = 99.01(PSD + DE) Subject-independent Acc = 88.67 (PSD + DE) |
| [146] | **2019** | **SEED**, DREAMER | 15 (SEED), 23 (DREAMER) | DE, PSD, DASM, RASM and DCAU features | Graph GCB-Net | Softmax | NA | Acc = 94.2 (DE) |
| [147] | 2021 | SEED | 15 Subjects | Spatio-temporal features | 3DCANN | Softmax | TensorFlow | Acc = 96.37(Subject-independent) Acc = 97.35(Subject-dependent) |
| [148] | 2020 | SEED | 15 Subjects | DDE features, Using ICC algorithm for decomposition | 2D-CNN | Softmax | TensorFlow, MATLAB | Acc = 97.56 Sen = 98.67 Spe = 96.44 |
| [149] | 2018 | SEED | 15 Subjects | DE features, Using LSTM for feature extraction | BiDANN | Softmax | NA | Acc = 92.38/07.04 Subject-independent Acc = 96.37 |
| [150] | 2021 | DEAP, MAHNOB-HCI, **SEED** | 32 (DEAP), 30 MAHNOB-HCI, 15 (SEED) | NA | EEGFuseNet (Hybrid CNN-RNN-GAN) | Sigmoid | Pytorch | Subject-independent Acc = 80.83(2-Class) F1-Score = 82.03(2-Class) |
| [151] | 2022 | DEAP | 32 Subjects | Sliding window | GANSER | Softmax | PyTorch | Mean Acc-val = 93.52 (2-Class) Mean Acc-aro = 94.21 (2-Class) Mean Acc = 89.74 (4-Class) |
| [152] | **2022** | **SEED**, MPED | 32 (DEAP), (MPED) | ICA, DE and HOC features | GRU-MCC | Softmax | Pytorch | **SEED** |
| [153] | **2022** | **SEED**,SEED-IV | 15 (SEED), 15 (SEED-IV) | DE features smoothed by LDS | Siam-GCAN | Softmax | NA | Acc = 94.78/05.97 |
| [154] | **2022** | **SEED**, DEAP | 15 (SEED), 32 (DEAP) | Noise removal, DE features | CNN-BiLSTM | Softmax | NA | Acc = 81.54 |
| [155] | 2022 | DEAP, **MAHNOB-HCI**, SEED | 32 (DEAP), 25 MAHNOB-HCI, 15 (SEED) | Short-term continuity modeling | Hierarchical self-attention network | NA | NA | Acc-val = 79.9 Acc-aro = 81.37 |

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**Table 4** (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| [156] | 2021 | SEED, MPED, **DREAMER** | 15 (SEED), 23 (MPED), 23 (DREAMER) | Energy features | V-IAG | Softmax | TensorFlow | Acc-val = 92.82<br>Acc-aro = 93.09 |
| [157] | **2021** | **DEAP**, DREAMER | 32 (DEAP), 23 (DREAMER) | DE features, Cross-band feature rearrangement and construction | DFCN | Softmax | TensorFlow | Acc-val = 94.59<br>Acc-aro = 95.32<br>Acc-dom = 94.78 |
| [158] | 2022 | DEAP, **DREAMER** | 32 (DEAP), 23 (DREAMER) | Covariance Matrix, Single-link hierarchical clustering based on Riemann metrics, Spatial and temporal features | SSTD | Softmax | NA | Acc-val = 76.81<br>Acc-aro = 81.64<br>Rec-val = 87.7<br>Rec-aro = 95.12<br>Pre-val = 76.67<br>Pre-aro = 81.21 |
| [159] | 2022 | DEAP, **SEED**, SEED-IV | 32(DEAP), 15 (SEED), 15(SEED-IV) | PCC, Adjacency matrix | ST-GCLSTM | Softmax | MATLAB, PyTorch | Acc = 96.72 |
| [160] | 2023 | DEAP, **SEED** | 32(DEAP), 15 (SEED) | DE feature, FC feature | STFCGAT | Softmax | TensorFlow | Acc = 99.11 (Subject-dependent)<br>Acc = 94.83 (Subject-independent) |
| [161] | 2022 | DEAP | 32 Subjects | VMD and EMD to obtain IMF, Peak value of PSD and First difference of the signal features | DNN | Softmax | TensorFlow | Acc-val = 62.5<br>Acc-aro = 61.25 |
| [162] | **2021** | **WeDea**, DREAMER, DEAP, SEED | 30(WeDea), 32 (DEAP), 23 (DREAMER), 15 (SEED) | Filtering, wICA, WPT, (PSD, STFT, DE, FD, and SM) features | LSTM | NA | NA | Acc = 86.9 |
| [163] | 2022 | DEAP**, SEED** | 32 (DEAP), 15 (SEED) | (**LF-DE**, PSD, DE, RASM, DASM, Hjorth parameters) features | **BiLSTM**, MLP | Softmax | NA | Acc = 80.64 |
| [164] | **2022** | **DEAP**, DREAMER | 32 (DEAP), 23 (DREAMER) | DE features, Z-score normalization | SFCSAN | Softmax | TensorFlow | Acc-val = 95.15<br>Acc-aro = 95.76<br>Acc-dom = 95.64<br>Acc-lik = 95.86 |
| [165] | 2022 | DEAP | 32 Subjects | 3D feature space, Channel attention block | 2D-CNN | Softmax | NA | Acc-val = 97.06<br>Acc-aro = 97.4 |
| [166] | 2018 | Clinical | 15 Subjects | (RASM, DASM, DCAU, PSD and DE) features, LDS | DBN | Sigmoid | MATLAB | Acc = 86.08 |
| [167] | 2021 | DEAP, **DREAMER** | 32 (DEAP), 23 (DREAMER) | STF, STFT, PSD, (**RASP**, DE, RADE) features | Bi-LSTM | Softmax | MATLAB, Python | Acc-val = 63.10<br>Acc-aro = 72.38 |
| [168] | **2022** | **SEED**, SEED-IV | 15 (SEED), 15(SEED-IV) | PSD, DE features, Smoothing using LDS | 3D-DenseNet | Softmax | Keras, TensorFlow, PyTorch | Results for Fine-Tuning or Meta-Transfer<br>Acc = 77.52 |
| [169] | 2020 | DEAP | 32 Subjects | DA using RCE, BNF, Z-score normalization | PSCP-Net | Softmax | NA | Acc-val = 96.16 (Subject-dependent)<br>Acc-aro = 95.89 (Subject-dependent) |
| [170] | 2021 | SEED, **DEAP**, DREAMER | 15 (SEED), 5 (DEAP), 10 (DREAMER) | ET-MCSP feature extraction | LSTM | Softmax | NA | Acc = 82.7 |
| [171] | 2021 | DEAP | 32 Subjects | Noise removal, WT, CWT | PreTrained Models | SVM | NA | **MobilNetv2**<br>Acc = 98.93(Delta rhythm with channel C3) |
| [172] | 2021 | DEAP, **SEED** | 32 (DEAP), 15 (SEED) | 1D-DWT, Channel selection | SLGU-ENet | **SVN**, KNN, NB | MATLAB | Acc = 94.7<br>Pre = 92 |
| [173] | 2023 | SEED | 15 Subjects | TQWT, TQWT-DE features, TFBS | HCRNN | Softmax | Keras | Acc = 95.33 (MAV-TFBSs)<br>Acc = 94.95 (DE-TFBSs) |
| [174] | **2023** | **Clinical**, SEED, SEED-IV | 8(Clinical), 15 (SEED), 15(SEED-IV) | ICA, CWT | Double way DNN (residual module + attention modules + CNN) | Sigmoid | NA | Acc = 94.57 ± 1.86 |
| [175] | **2023** | **DEAP**, DREAMER | 32(DEAP), 23 (DREAMER) | CWT | TC-Net | Softmax | PyTorch | Acc-val = 98.76<br>Acc-aro = 98.81<br>Acc-dom = 98.82 |
| [176] | 2020 | DEAP | 32 DEAP | Using wavelet soft threshold algorithm for artifacts removal, Spectral energy | Hierarchical LSTM | Softmax | NA | Acc = 85.9 |
| [177] | 2022 | Clinical (Tianjin University of Technology), SEED | 15(Clinical), 15 (SEED) | ICA, DE features, Discriminative channel selection, spatial feature | EDANN (3DLSTM-ConvNET+ Label Classifier + Domain Discriminator) | LogSoftmax | NA | Subject-dependent<br>Acc = 98.4<br>Subject-independent<br>Acc = 67.9 |

(*continued on next page*)

Table 4 (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| | | | | matrix, Continuous time spatial feature matrix | | | | **SEED** Acc = 97.4 |
| [178] | **2022** | **SEED**,SEED-IV, DEAP | 15 (SEED), 15(SEED-IV), 32 (DEAP) | IFFT and STFT, DE and PSD features | DBGC-ATFFNet-AFTL | Softmax | NA | Acc = 97.31 F1-Score = 97.2 AUC = 99.3 |
| [179] | **2022** | **DEAP**, DREAMER | 32(DEAP), 23 (DREAMER) | Segmentation | ECNN-C | NA | PyTorch | Acc-val = 98.35 Acc-aro = 98.51 Acc-dom = 98.55 |
| [180] | 2023 | DEAP, **SEED**, SEED-IV, HIED | 32(DEAP), 15 (SEED), 15(SEED-IV), 15 (HIED) | ICA, (PSM, SDM, SQM, DEM) features | RFP and S2D | NA | PyTorch | Acc = 96.84(3-class) |
| [181] | **2023** | **DEAP**, SEED | 32(DEAP), 15 (SEED) | Dynamic adjacency matrix, DE features | DGGN | Softmax | PyTorch | Acc-val = 96.98 (Subject-dependent) Acc-aro = 97.19 (Subject-dependent) Acc-val = 94.87 (Subject-independent) Acc-aro = 94.42 (Subject-independent) |
| [182] | **2023** | **SEED**, SEED-IV | 15(SEED), 15(SEED-IV) | Spatial mapping, Interpolation, DE features | MFBPST-3D-DRLF | Softmax | PyTorch | Acc = 96.67 |
| [183] | 2023 | Clinical | 30 Subjects | ASR, ICA | MTL, CNNs Models (**ShallowConvNet**, EEGNet, DeepConvNet) | Softmax, LDA, SVM | Keras, TensorFlow | **ShallowConvNet** Acc = 72 **SVM** Acc = 69.6 |
| [184] | 2023 | SEED | 15 Subjects | – | SEER-net | Softmax | Keras, TensorFlow | Acc = 90.73 |
| [185] | 2023 | DEAP-Twente, **DEAP-Geneva**, SEED | 32(DEAP-Twente + DEAP-Geneva), (SEED) | DE feature, PLI adjacency matrix | CSGNN | Softmax | NA | Acc = 91 |
| [186] | 2021 | SEED, SEED-IV, SEED-V, DEAP, **DREAMER** | 15(SEED), 15 (SEED-IV), 16 (SEED-V), 32 (DEAP), 23 (DREAMER) | DE features | DCCA, BDAE | SVM, Softmax | NA | Acc-aro = 89 (DCCA) Acc-val = 90.6 (DCCA) Acc-dom = 90.7 (DCCA) Acc-aro = 88.6 (BDAE) Acc-val = 86.6 (BDAE) Acc-dom = 89.5 (BDAE) |
| [187] | 2023 | EEG-ImageNet | 6 Subjects | Functional Connectivity, Adjacency matrix | FC-GDN | Softmax | NA | Acc = 98.4 Pre = 98.56 Rec = 98.56 |
| [188] | 2023 | DEAP | 32 Subjects | AEP, BiCubic interpolation | FPN-LSTM | Softmax | NA | Acc-val = 90.05 Acc-aro = 90.84 |
| [189] | 2023 | **SEED**, SEED-IV | 15(SEED), 15 (SEED-IV), | Down-sampling, Filtering, DE feature | SMCD (2D-CNN+2 Classifiers) | 2 Classifiers | PyTorch | Acc = 96.36 **(**Subject-dependent) Acc = 88.75 (Subject-independent) |
| [190] | 2023 | **SEED**, SEED-IV, SEED-V | 15(SEED), 15 (SEED-IV), 15 (SEED-V) | Adjacency matrix, | PGCN | NA | PyTorch | Acc = 84.59 ± 8.68 |
| [191] | 2023 | Clinical | 12 Subjects | STFT, Wavelet Entropy, Hjorth and Statistical) Features | GRUER | Softmax | Keras | Acc = 98 |
| [192] | 2023 | Kaggle | 2 Subjects | PCA | DNA-RCNN | M-RF | NA | Acc = 98 Pre = 98 Rec = 96 |
| [193] | 2023 | DEAP | 32 Subjects | Coordinate Attention | AP-CapsNet, MobileNet | Softmax | NA | Acc-val = 93.89 Acc-aro = 95.04 Acc-dom = 95.08 |
| [194] | 2023 | **SEED**, DEAP | 15(SEED), 32 (DEAP) | DE feature | 2D-CNN, LSTM, CNN-LSTM | Ensemble model | NA | Acc = 97.16 ± 1.08 |
| [195] | 2023 | **SEED**, SEED-IV | 15(SEED), 15 (SEED-IV), | Causal, functional and topological graph construction, (DE, DASM and DCAU) features | FGCN | Softmax | NA | Acc = 78.67 (DASM) |
| [196] | 2023 | **SEED**, DEAP | 15(SEED), 32 (DEAP) | (DE and PSD) features, Denoising, Smoothing using MA and LDS | TMLP + SRDANN | Softmax | NA | Acc = 81.04 |
| [197] | 2023 | **MAHNOB-HCI**, CK+, EMO-DB | 24 MAHNOB-HCI | WT, PSD feature | GhostNet, tLSTM, LFCNN | Score decision fusion | NA | Acc-val = 81.3 Acc-aro = 94.5 |

(*continued on next page*)

**Table 4** (*continued*)

| Works | Year | Dataset | Number of Cases | Preprocessing | DL Model | Classifier | Toolbox | Performance Ceria (%) |
|---|---|---|---|---|---|---|---|---|
| [198] | 2023 | DEAP, **SEED** | 32(DEAP), 15(SE, ED) | Biharmonic spline interpolation method, (PE, DE, PSD, WE) features | Residual Network | Softmax | NA | Acc = 90.04 (PE(DE)) |
| [199] | 2023 | DEAP, **SEED** | 32(DEAP), 15(SEED) | Raw multiband matrix | GRU-Conv | Softmax | PyTorch | Acc = 87.04 |
| [200] | 2023 | DEAP, SEED | 32(DEAP), 15(SEED) | Functional connectivity matrix, Electrode reduction, DE feature | **SITCN**, STCN | AM-softmax | Keras, TensorFlow | **DEAP** Acc-val = 95.02 (without DE) Acc-aro = 95.29 (without DE) |
| [201] | 2023 | DEAP | 32 Subjects | Z-score normalization, DA | LP-1D-CNN | Softmax | TensorFlow | Acc-val = 98.43 (HV vs. LV) Acc-aro = 97.65 (HA vs. LA) |
| [202] | 2023 | **DEAP**, SEED-IV | 32(DEAP), 15(SEED-IV) | DWT, (Statistical, Spectral and DE) features | DCNN | Softmax | MATLAB | Acc = 97.12 Spe = 96.52 Sen = 98.92 |
| [203] | 2023 | DEAP | 32 Subjects | 1D sequences to 2D frames, ICA | Temporal relative (TR) encoding | Softmax | NA | Acc-val = 95.18 Acc-aro = 95.58 |
| [204] | 2023 | DEAP, **SEED** | 32(DEAP), 15(SEED) | STFT, BoHDF, OMTLBP_SMC texture-based features | GoogLeNet DNN | KNN | NA | Acc = 96.95 |

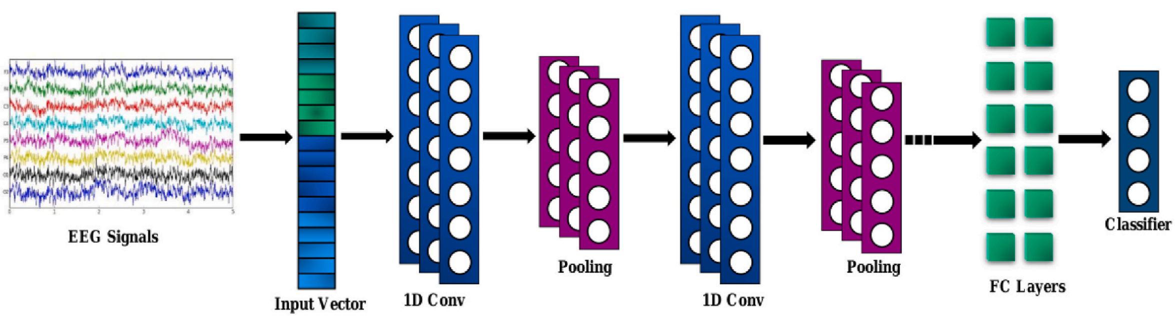


**Fig. 4.** A typical 1D-CNN model used for emotion recognition using EEG signals.

architecture used for EEG-based emotion recognition. 1D-CNNs can be implemented on hardware with limited resources. However, one of their main disadvantages is that they may not perform as well as other models when faced with complex and highly varied data [319,320].

*4.3.1.2. 2D-CNNs.* 2D CNN architectures are highly popular in various medical applications [325–327]. They are designed based on convolutional, pooling, and FC layers, similar to 1D-CNN architecture [319, 320]. As 2D-CNN architectures are the default architecture for CNNs, they are widely used for segmenting and classifying medical data, allowing for the extraction of spatial characteristics and aiding in diagnostic procedures [328–331]. 2D-CNN architectures have also been successfully implemented in some emotion recognition studies, where 1D EEG signals are first converted into 2D images using high-level pre-processing techniques. In the subsequent step, the 2D-CNN architecture extracts features and classifies the 2D images based on EEG signals. Figure (5) provides a general overview of the 2D-CNN architecture used for EEG-based emotion recognition. 2D-CNNs have several advantages in emotion recognition from EEG signals. They excel at identifying spatial patterns and can effectively capture complex relationships in medical data, making them highly suitable for emotion recognition. However, 2D-CNNs are computationally expensive and require more training time and processing power than ML methods.

*4.3.1.3. Pre-trained models.* Access to large-scale medical datasets poses a significant challenge in using DL models [328,329]. Researchers usually work with limited medical data containing a vast number of subjects, which makes use of DL architectures for medical applications challenging [331,332]. To overcome this challenge, researchers have developed various pre-trained models. These networks were initially

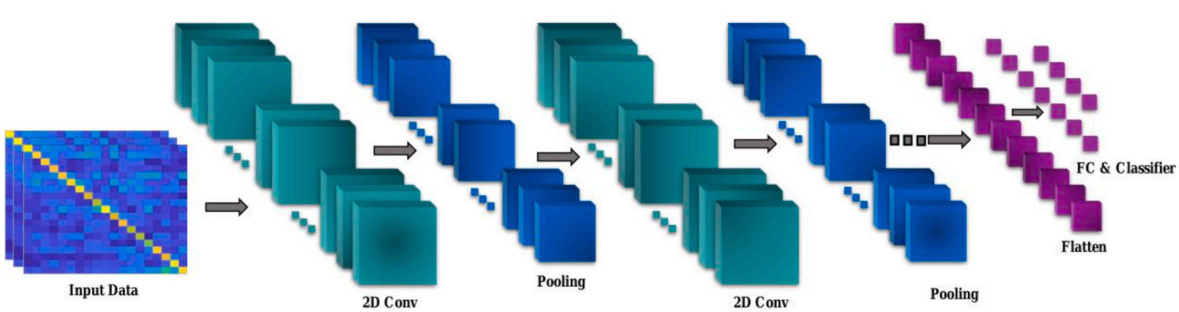


**Fig. 5.** A typical 2D-CNN model used for emotion recognition using EEG signals.

inspired by CNN architectures [331–333] and were first trained on the ImageNet dataset before storing their new weights. To adapt to the intended application, the pre-trained models were fine-tuned using the stored weights on the specific dataset. Among the most widely used pre-trained architectures are GoogleNet, VGG, and AlexNet [331,332]. A handful of pre-trained models have shown promising results in emotion recognition [58]. Figure (6) presents a general block diagram of pre-trained architectures utilized in emotion recognition. Pre-trained models help to overcome the challenges of limited medical data, enabling researchers to fine-tune models on smaller datasets. However, pre-trained models may not always generalize to new medical domains, and they may not be effective when the source and target tasks are significantly different.

#### 4.3.2. GANs

At the beginning of this section, the challenge of insufficient access to large datasets was highlighted [321,315]. To address this challenge, pre-trained architectures were proposed as a solution. In contrast, overcoming data deficits in DL models is approached differently through the use of data augmentation (DA) techniques. An essential set of DA methods are Generative Adversarial Networks (GAN) architectures [333,334], which were first introduced by Goodfellow in 2016. GAN architectures consist of two parts, a generator and a discriminator network, which use an adversarial approach to increase each other's losses. The generator creates realistic data while the discriminator distinguishes between generated and original data [333,334]. GAN architectures can be applied to various data types, such as signals and images, and have produced significant results in medical research by addressing the limited number of samples in datasets [333,334]. However, GANs are computationally expensive, and their training can be unstable. Additionally, generated data must be evaluated to ensure that the generated data is plausible and representative of the medical data to prevent any issues in clinical applications [333,334].

#### 4.3.3. Graph CNNs

The CNNs are restricted to processing structured-flat data and are not well-suited to deal with irregular and non-Euclidean domain data that is graph-structured. The solution to this problem is the Graph CNNs (GCNNs) which integrates CNNs and spectrum theory to excel in processing such types of data [322,323,335,336]. The GCNN is particularly useful in extracting distinctive features of signals in the discrete spatial domain. In recent years, they have been getting more attention in the field of EEG research due to their ability to analyze the symmetrical connections of brain regions. GCNNs offer several advantages over CNN in signal processing and can consider relationships between EEG channels to extract spatial features of nodes [322,323,335,336]. Existing GCNN methods can be classified into two main categories depending on the procedure used for adjacency matrix construction, either based on functional connectivity between channels or the physical relationship between channels. A block diagram of a GCNN architecture designed for emotion recognition is displayed in Figure (7). One disadvantage of GCNNs in the classification of EEG is that creating an adjacency matrix for complex medical data is challenging, and the process can be time-consuming. Furthermore, the choice of adjacency matrix construction method can significantly impact the accuracy of the model.

#### 4.3.4. RNNs

Recurrent neural networks (RNNs) are an important class of deep learning models commonly employed for time series analysis. These models are trained using unsupervised learning techniques [319,320], where time series of varying lengths are fed into RNN architectures. However, it can be particularly challenging for RNNs to identify suitable patterns in such datasets. The major RNN architectures are Simple RNN, Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) [319,320]. RNNs have also been successfully applied to emotion recognition from EEG signals, with some combining RNNs with CNNs to extract complex spatiotemporal features in emotion recognition tasks. The fusion of CNN and RNN models has led to promising results in EEG-based emotion recognition research [85]. A block diagram of an RNN architecture for emotion recognition is presented in Figure (8). A key limitation of RNNs for EEG signal classification is their vulnerability to vanishing gradient issues that can occur during training. As EEG signals frequently contain intricate temporal dependencies, such limitations of RNNs can lead to the decreased overall performance of the model in EEG signal classification tasks.

#### 4.3.5. AEs

Autoencoders (AEs) belong to a group of DL models that incorporate both encoders and decoders in their architecture [319,320]. These models are based on unsupervised learning and are widely utilized for various purposes such as data representation, feature extraction, dimension reduction, and compression. AE models work by encoding high-dimensional input data to generate a lower-dimensional latent (hidden) space [319,320]. In the decoder section, the data is deconstructed and restored to its original form through reverse processing. Some of the most essential AE architectures include Sparse AEs (SpAEs) [337], denoising AEs (DAEs) [338], Stacked AEs (SAEs) [339], and convolutional AEs (CAEs) [340]. These models have been extensively explored in the diagnosis of diseases from EEG signals [341,29]. As an example, researchers in Ref. [81] successfully applied AEs architectures in emotion recognition from EEG signals. Figure (9) depicts the block diagram of an AE architecture used for emotion recognition. While AEs have shown promise in feature extraction from EEG signals, there are also two potential disadvantages. One of the limitations of AE models is the difficulty in interpreting the resulting features extracted from the latent space. Moreover, AE models might struggle with the high variability and complexity of EEG signals, which may result in the loss of some important information during the feature extraction process.

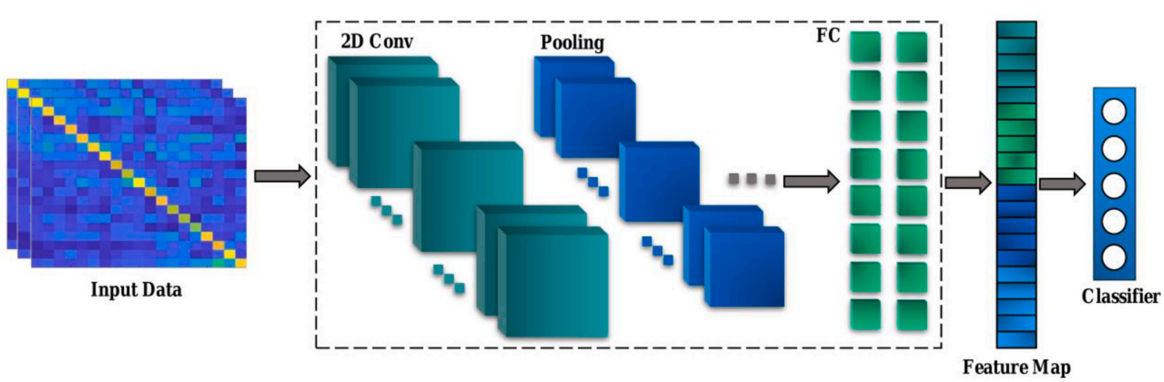


**Fig. 6.** A typical pretrained model used for emotion recognition using EEG signals.

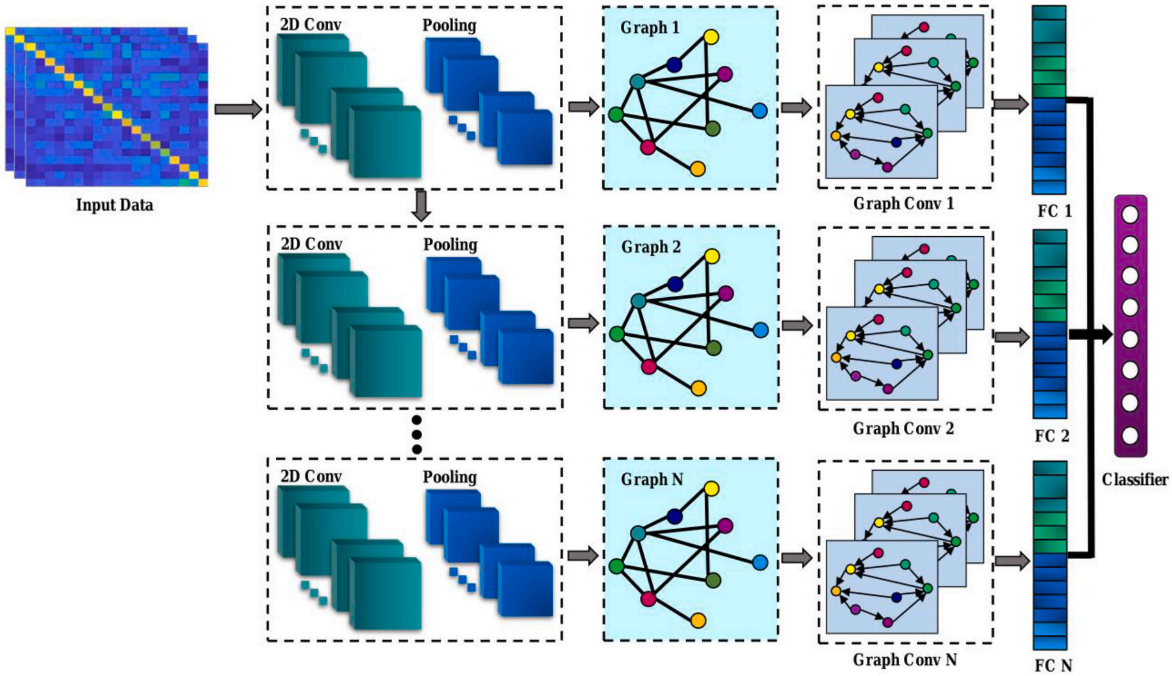


**Fig. 7.** A typical GCNN model used for emotion recognition using EEG signals.

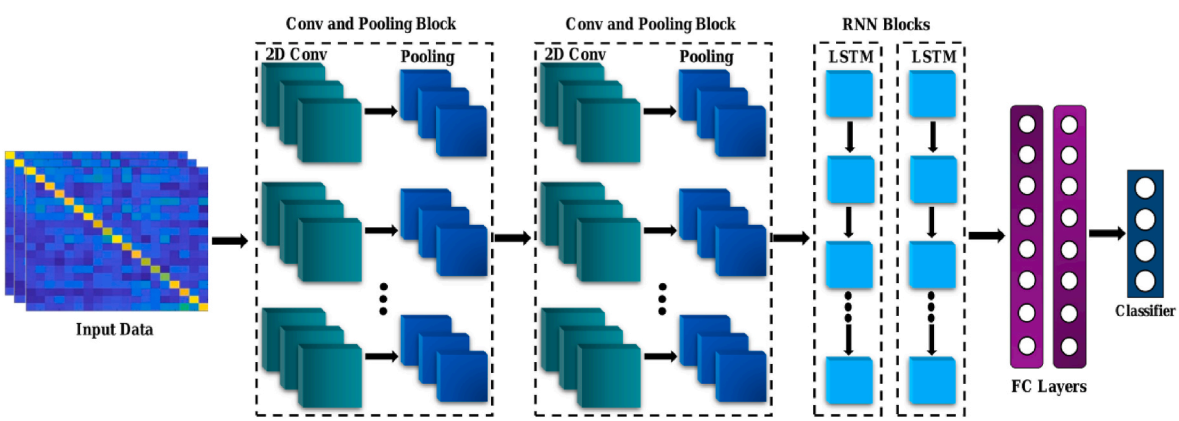


**Fig. 8.** A typical CNN-RNN model used for emotion recognition using EEG signals.

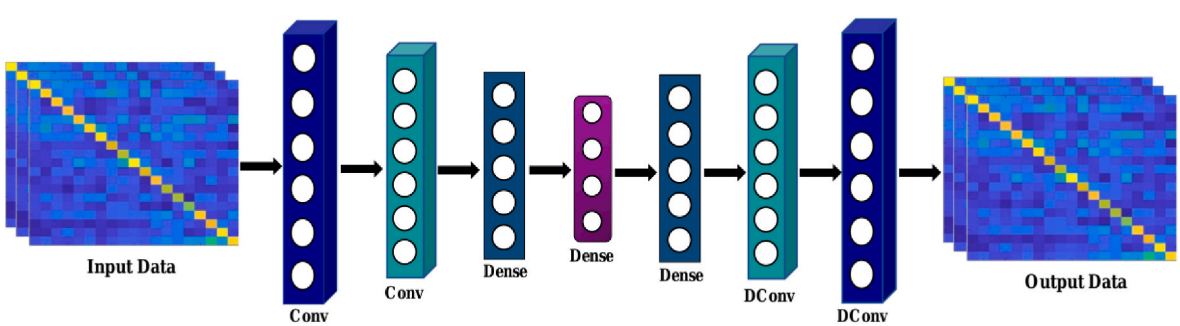


**Fig. 9.** A typical CNN-AE model used for emotion recognition using EEG signals.

## 5. Challenges

In the previous sections, we briefly touched on the challenges associated with emotion recognition using DL techniques. However, this section provides more comprehensive details on these obstacles faced. Emotion recognition researchers encountered several challenges to obtaining high classification performances such as the unavailability of EEG datasets containing a large number of subjects, multimodal datasets, emotion datasets for brain disorder diagnostics, EEG data imbalance, explainable artificial intelligence (XAI), DL models, and hardware resources. Each challenge is explained briefly in the subsequent paragraphs. Overcoming these challenges can aid in both the development and application of advanced DL models in emotion recognition research.

### 5.1. Dataset

Datasets are an integral part of CADS for emotion recognition. Access to suitable datasets in various medical fields has always posed a significant challenge [217–220]. While several EEG datasets exist for emotion recognition research, the lack of datasets is regarded as the primary hurdle for emotion recognition research using DL techniques. This is because recording EEG sequences is more expensive compared to audio-visual datasets. Section 4.1 highlights the EEG datasets available for emotion recognition. However, these datasets have challenges, including a low number of subjects, inadequate data, noise and biased coverage. These constraints create difficulty when applying advanced DL models in emotion recognition research. As indicated in Table 3, many emotion recognition researchers have employed the available EEG data. Unfortunately, these datasets are few, noise-free and challenging to evaluate. Consequently, the availability of EEG modality datasets with a larger number of subjects can facilitate extensive research in this field.

### 5.2. Multimodal dataset

In emotion recognition, various biological sensors are used to capture data from different parts of the human body [221–223]. The most vital signals are facial expressions and EEG signals, heart rate, and GSR, along with text, audio, and video [189–199]. Compared to using individual patterns, multimodal data may provide essential information that can enhance emotion recognition if appropriately extracted. The high performance in emotion recognition has been propelled using multimodal datasets in this research. However, a prominent challenge is the scarcity of available multimodal datasets for emotion recognition researchers, resulting in limited research on emotion recognition using DL techniques. The availability of multimodality datasets with a larger number of subjects can serve as a starting point for emotion recognition.

### 5.3. Datasets for diagnosis of brain disorders

As previously mentioned, uncontrolled emotions have a significant impact on the incidence of various brain disorders, including Parkinson's disease (PD) [224], SZ [225], and depression [226]. Examining emotions over extended periods can aid in the prevention of such brain disorders. Unfortunately, humans often neglect emotions, contributing to the development of these disorders. Researchers have explored PD and SZ pathology based on emotion recognition [224–226]. The use of emotion recognition to diagnose brain disorders has become a crucial field of interest for medical researchers [224–226]. However, no emotion-based EEG datasets have been introduced to date, posing a significant challenge in this field. Multimodality datasets with a large number of subjects can pave the way for applied research on emotion recognition.

### 5.4. Imbalanced data

In medical applications, datasets are characterized by multiple classes that do not necessarily have an equal number of data samples [227–229]. In AI, this imbalance in data across different classes is referred to as data imbalance [227–229]. Table 3 displays the EEG datasets utilized for emotion recognition, revealing that classes within the datasets contain differing amounts of data. Unbalanced EEG datasets present another challenge to emotion recognition studies that use DL techniques, leading to overfitting in emotion recognition DL networks. The lack of balance in data also results in varying sizes of subjects across classes, necessitating a reduction in data size for other classes to address this issue. In emotion recognition, this can lead to the loss of a few EEG signals in each class [227–229].

### 5.5. Explainable AI

DL architectures are typically nonlinear and are commonly viewed as black box models because they lack information about the factors that could enhance the efficiency of DL models [230,231]. In medical applications, developing methods for visualizing, explaining, and interpreting DL models has garnered significant attention recently [232]. The XAI has produced a suite of ML techniques that generate more explainable models while maintaining a high level of accuracy, enabling human users to understand, trust, and effectively manage the emerging generation of AI partners [232,233]. Table (4) indicates that XAI methods have not been implemented in emotion recognition along with DL techniques. The use of XAI models in emotion recognition based on EEG signals holds great promise and presents an exciting avenue for future research. On the other hand, XAI techniques still face challenges when it comes to interpreting biological signals like EEG. XAI methods are typically used for image interpretation, and their techniques are not well-suited for time series data such as biological signals [342,343]. Review papers in the field of XAI for medical applications [344,345] show that most of the methods, such as Grad-Cam [346], have been designed for medical imaging analysis applications. Therefore, the limited availability of XAI techniques for analyzing biological signals like EEG is another challenge for emotion recognition.

### 5.6. Deep learning

This section examines the challenges of DL models in emotion recognition from EEG signals. According to Table 4, most researchers have employed CNNs in emotion recognition due to the 1D raw EEG signals. Although 1D DL architectures are commonly used, significant results have also been obtained using 2D DL models. The advantage of 2D-CNN models is that they can extract crucial features from EEG signals [234,235]. However, using these models requires substantial computational power and high-end hardware resources due to the numerous hyperparameters. Additionally, it is worth noting that emotion prediction from EEG signals is a critical issue that has not received much attention. Developing DL models for emotion prediction from EEG signals is a promising field that can be explored further.

### 5.7. Hardware resources

In the previous section, the challenges of using DL techniques in emotion recognition have been explained. As mentioned, DL models such as two-dimensional CNN architectures with emotion recognition applications require advanced hardware resources [236,237]. Therefore, the hardware resource limitations for the research of emotion recognition from EEG signals are one of the main challenges for training and implementing complex DL models. These networks require a large amount of computational power and memory to process data and perform complex calculations. GPU is the most common hardware utilized to train DL architectures. However, GPUs are expensive and not accessible to everyone. Moreover, EEG datasets also pose more maintenance and processing challenges compared to conventional systems because they require significant memory storage. There is no research on overcoming hardware limitations using cloud computing [238]. Although Google and Amazon servers provide enough memory space and hardware resources, they are not suitable for real research with real-world applications.

## 6. Discussion

In this section, we delve into the specifics of articles that utilized DL models for emotion recognition from EEG signals. Table 4 demonstrates the details of studies on emotion recognition from EEG signals, including dataset, EEG modality, pre-processing techniques, DL models employed, classifier algorithms, and evaluation parameters. Moreover, we aim to compare our work with previous studies conducted in a graphical format, highlighting the strengths and advantages of our review article over previous research efforts. Additionally, we conducted a detailed analysis on emotion recognition research, providing a more thorough understanding of the methodologies implemented in DL models using EEG signals for automated emotion recognition.

### 6.1. Comparison of our work with other review papers

Over the past few years, the field of emotion recognition using biological signals has gained increasing significance using ML and DL techniques. The primary objective of these research studies is to develop AI-based emotion recognition systems to investigate and analyze brain activity during emotional experiences, which is of great interest to medical researchers. So far, various review papers have been introduced in the field of emotion recognition from EEG signals using different AI techniques. For instance, researchers in Refs. [5,6] presented review articles on emotion recognition using ML techniques. These papers first reviewed the existing literature in the field and then briefly outlined its challenges. In other studies, some researchers conducted a review of papers on emotion recognition from physiological signals using DL techniques. These studies surveyed the literature on emotion recognition using EEG [9] and biological signals [10] with DL techniques. In Refs. [11–14,17,18], review papers on emotion recognition from EEG signals using ML and DL techniques are reported. Additionally, researchers in Refs. [15,16] reviewed papers on emotion recognition using both ML and DL techniques from EEG and biological signals. According to Refs. [11–16], the primary aim of these researchers was to highlight the significance of using EEG signals in emotion recognition. Furthermore, these review papers serve as useful references for comparing research in the field of emotion recognition using ML and DL techniques.

However, unlike prior reviewed articles, we have exclusively studied the most crucial papers on emotion recognition from EEG signals specifically using DL techniques. To begin with, we comprehensively examined the most significant EEG signal-based emotion recognition datasets. Previous reviews have neglected this crucial step. Additionally, another salient advantage of our research is providing a detailed table that precisely scrutinizes emotion recognition literature. This is significant as other review articles have not reported the specifics of each research analyzed. Our review paper features a section titled "Challenges," where we delve into the most significant challenges in the field, such as dataset, DL techniques, hardware constraints, and more. Notably, this section is a unique contribution that has not been explored in other review papers. Furthermore, we present the most important future research directions for emotion recognition from EEG signals using DL techniques in a separate section, which is another novelty of our paper as it has not been extensively addressed in other review papers. Figure (10) displays a comparison between our work and other review papers, highlighting the various novelties presented in our paper, which we have described in this paragraph.

### 6.2. Dataset

The dataset is an essential part of DL-based CADS in emotion

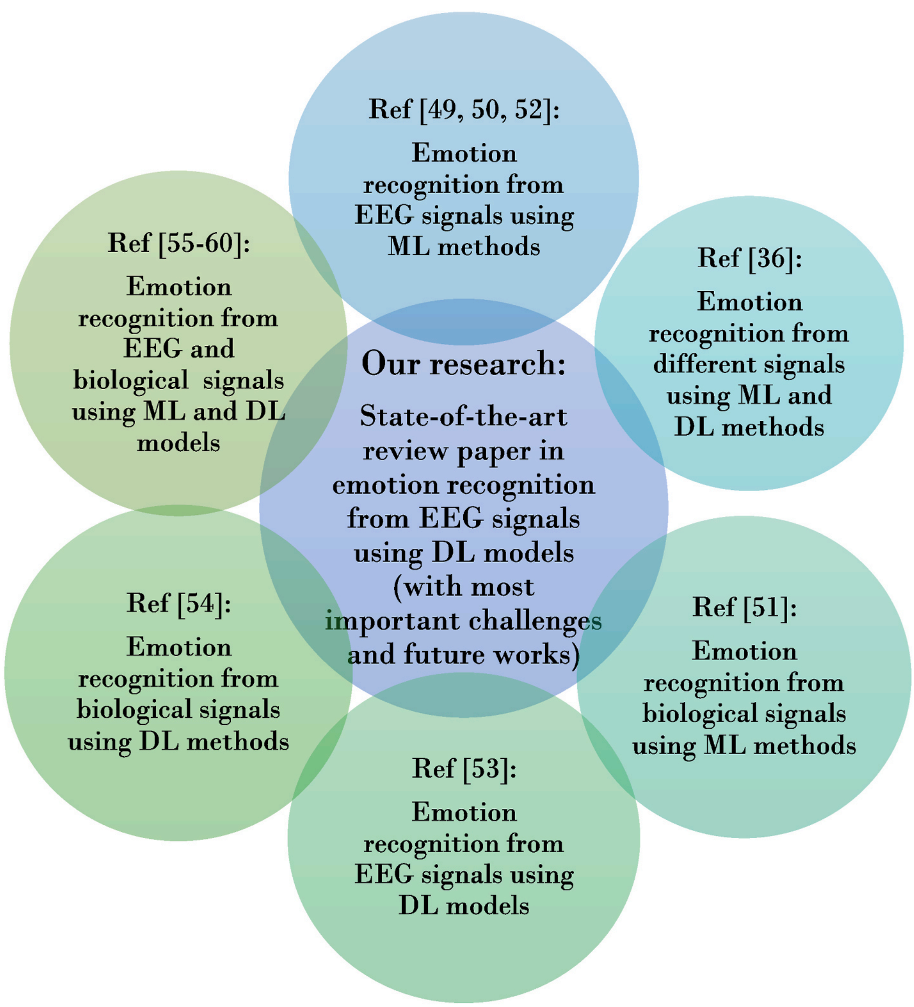


**Fig. 10.** Comparison of our study with other review papers published for automated emotion recognition.

recognition. Section 4.1 indicates the available EEG modality datasets used for emotion recognition. Table 3 specifies the details of each dataset, including the number of subjects, sampling frequency, and task type. These datasets are widely popular in emotion recognition research using DL techniques. Part of Table 4 shows the EEG datasets used in emotion recognition research using DL techniques. Figure (11) displays the number of EEG datasets used in emotion recognition research. Figure (11) and Table 4 indicate that the DEAP dataset is the most widely used in emotion recognition research. This dataset used a large number of subjects and diverse tasks. Hence, it is the most popular dataset used for emotion recognition researchers.

### 6.3. Deep learning models

This article review primarily delves into DL-based emotion recognition models. Numerous DL models have been tried and tested in emotion recognition research (Table 4). Among these models, CNNs, RNNs, AEs, graphs, and GANs have been widely used in emotion recognition from EEG signals, as indicated in Table 4. Figure (12) presents the number of DL networks in emotion recognition from EEG signals, revealing that CNN models are the most prevalent choice. The diversity and effectiveness of CNN architectures - 1D-CNNs, 2D CNNs, and GCNNs - have paved the way for their significant use in EEG signal-based emotion recognition. As previously discussed, their versatility and efficiency make CNN models the most widely used in this field.

### 6.4. Deep learning tools

There is a multitude of tools available for implementing various DL architectures. Popular DL libraries include Keras, TensorFlow, and PyTorch, among others. These libraries serve as a framework for building, training, and evaluating DL. TensorFlow is known for its ease of use and simplicity, making it an excellent choice for beginners. Figure (13) indicates the abundance of DL tools utilized within emotion recognition research. The TensorFlow library is heavily favored due to its consistent updates, versatility, and ease-of-use in implementing the CADS for emotion recognition. The information from Figure (13) shows that the TensorFlow toolbox is the predominant choice for emotion recognition research utilizing DL techniques.

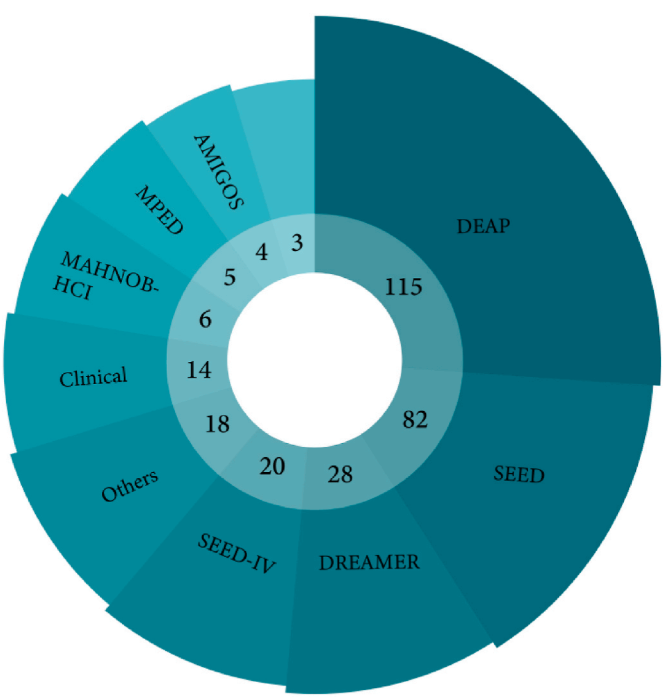


**Fig. 11.** Number of times datasets used for automated emotion recognition using DL models.

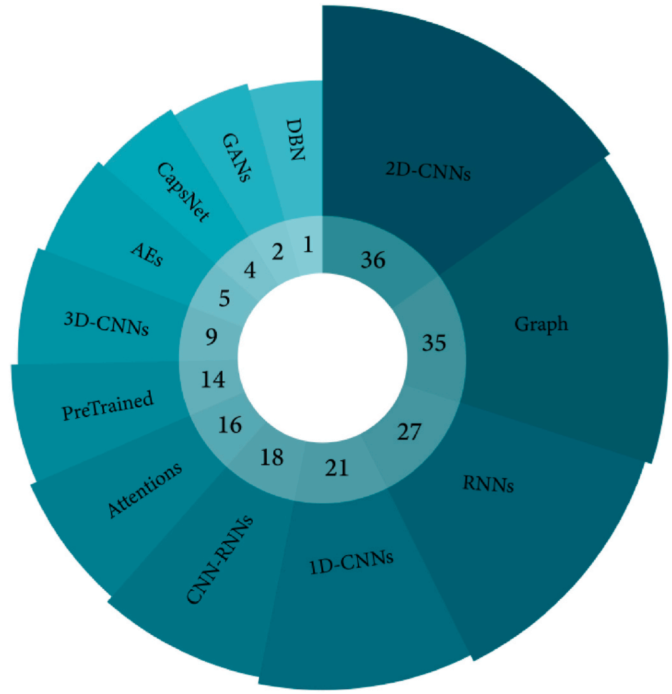


**Fig. 12.** Number of times each DL model used for emotion recognition.

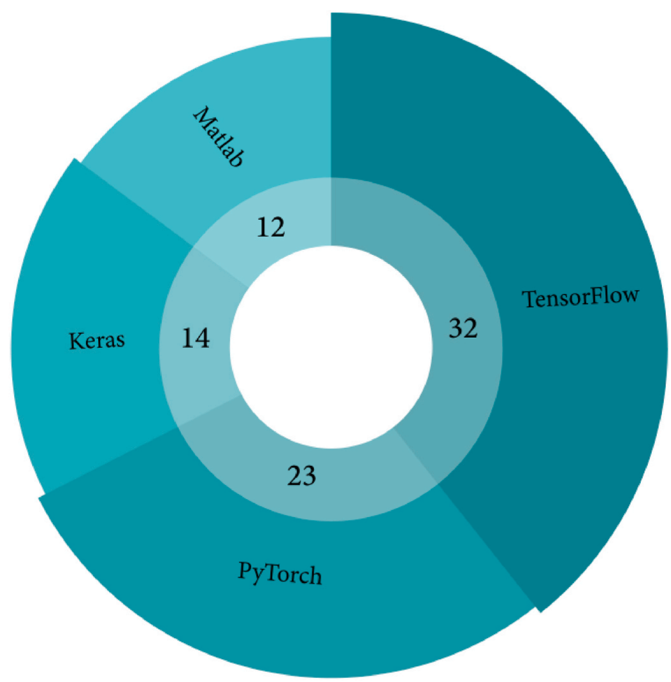


**Fig. 13.** Number of times each DL tool used for emotion recognition.

### 6.5. Classifiers

In DL models, classification typically is in the final layer as an activation function or method. This section focuses on the classification algorithms utilized in DL techniques for emotion recognition from EEG signals. Table 4 includes a section on the classification algorithms in emotion recognition and classification. Figure (14) displays

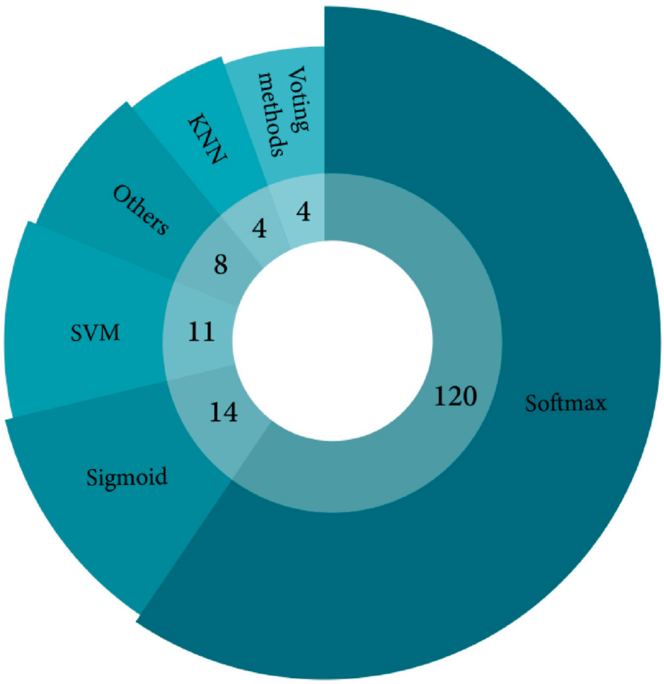


**Fig. 14.** Number of times each classifier used for automated emotion recognition research using DL models.

classification algorithms for emotion recognition, based on Table 4. According to Figure (14) and Table 4, the Softmax algorithm is the most commonly used for data classification, proving to be efficient and accurate in recent years. Softmax is a popular DL classification algorithm used in various applications. Simplicity, probabilistic Interpretation, handling multiple classes, regularization, and gradient-based optimization are the most advantages of the softmax classifier. Emotion recognition research results also confirm its superior performance compared to other classification algorithms.

## 7. Future works

This section describes future works on emotion recognition using DL techniques. Table (4) lists the different studies that have utilized DL techniques for emotion recognition from EEG signals. These tables show the potential for future research to explore new methods and techniques in various fields. The recommendations put forth in this section are of great significance for practical research on emotion recognition in the near future. Some of the future research on emotion recognition include datasets, DL techniques, XAI, hardware resources, and uncertainty. By focusing on these future works, we can pave the way for more successful outcomes in studying and understanding human emotions through DL techniques.

### *7.1. Datasets*

Section 4.1 introduced EEG datasets for emotion recognition applications. Also, Table 3 presented the details of each dataset, including the number of subjects, modality, and tasks. It indicates that the available datasets have a limited number of subjects. The datasets with large subjects can lead to valuable results in emotion recognition research. Accordingly, future studies should be provided with EEG datasets with a large number of subjects. Table 3 shows various types of EEG signal recording tasks in each dataset. Additionally, future studies can broaden the scope of emotion recognition research by designing various tasks while recording EEG signals.

### *7.2. Multimodal datasets*

Emotion recognition researchers commonly utilize several medical signals and images for their studies. The popular medical data are EEG, ECG [239], functional near-infrared spectroscopy (fNIRS) [240], and magnetic resonance imaging (MRI) [241]. Authors in Ref. [242], employed multimodal data for emotion recognition. Researchers in this field also utilized EEG-fNIRS, EEG-MEG, and EEG-fMRI data to improve emotion recognition accuracy. However, as mentioned in the previous section, a principal challenge to emotion recognition research is utilizing DL techniques with limited multi-modal datasets. Large-scale multi-modal datasets with a substantial number of subjects could pave the way for remarkable advancements in this field.

### *7.3. DL models*

In this section, we will introduce and evaluate the current DL architectures that are utilized in emotion recognition. Table 4 highlights the significant research conducted in this field, with a focus on DL techniques. We can observe from Table 4 that some researchers implemented standard DL models such as CNNs, RNNs, or AEs, while others attempted a combination of these models to improve emotion recognition accuracy. Recently, researchers have adopted and applied new DL models such as attention and graph CNNs, which have displayed remarkable results. In the subsequent subsections, we will further discuss various new DL models that can be utilized for future emotion recognition research using EEG signals, such as transformers [273–276], graph CNNs [277–280], self-supervised [19,281–283], and multi-task learning [20–23].

#### *7.3.1. Transformer models*

Transformer models are a recent addition to the family of DL architectures that have garnered attention from medical researchers, particularly those studying biological signals such as EEG. These models are based on the encoder-decoder structure, with attention layers playing a crucial role [243,244]. Transformers are primarily used for medical data segmentation or classification, with vision transformer (ViT) being a popular choice due to its basic structure, designed based on self-attention [245,246]. In comparison to CNNs models, transformer architectures have been successfully applied in medical research. Future studies can explore the use of transformer models to analyze emotion recognition from EEG signals. One potential approach could involve converting the EEG signals into 2D data during the pre-processing stage, followed by applying transformer models such as ViT [259], graph [260], or Recurrent Spatial Transformer [261].

#### *7.3.2. Graph CNN models*

Graph theory is a vast field in AI with numerous potential applications in the medical field [247]. In recent years, it has been integrated into DL architectures to enhance their efficiency. Graph-based DL architectures are generally divided into two categories - graph neural networks (GNN) and GCNN [247–250]. GNN models process graph data and are a straightforward solution for predictive tasks at the node, edge, and graph levels [247–250]. On the other hand, GCNN architectures are commonly used for classifying EEG signals and producing valuable results. Different GCNN architectures have been implemented successfully for emotion recognition from EEG signals [146]. In future works, researchers can adopt new approaches such as attention graphs [262] and semi-supervised attention graphs [263] to produce more valuable findings in emotion recognition. These architectures can be used to explore emotion recognition from a different perspective, leading to novel insights and improved accuracy in the field.

#### *7.3.3. Semi-supervised learning*

Different emotions are experienced at various levels by individuals, and as a result, EEG signals are classified into various classes for emotion recognition. However, this poses a challenging task for labeling EEG signals. Additionally, the labeling process is further complicated due to lengthy EEG signals. One solution to overcome these challenges is to adopt semi-supervised learning (SSL) models [251–254]. Several latest SSL models, such as Contrastive SSL [264], SSL Attention [265], and SSL Graph [263], have been used successfully to diagnose medical conditions based on EEG signals. SSL architectures can also be used in the future for emotion recognition from EEG signals and potentially yield valuable results.

#### 7.3.4. Multi-task learning

In recent years, multi-task learning architectures based on DL have emerged for various applications. These models are highly flexible and outperform standard DL models [255–258]. Authors in Ref. [257] evaluated the performance of multi-task learning architectures in classifying EEG signals and found them to be extremely effective due to their high efficiency and accuracy. A promising avenue for future research is to apply multi-task models to emotion recognition from EEG signals. Furthermore, end-to-end multi-task learning could be a promising approach in future studies on emotion recognition using EEG signals. Other multi-task models based on RNNs [266], AEs [267], attention mechanisms [268], etc. could also be used in this field.

### 7.4. Explainable AI

In recent years, XAI has emerged as a practical field in medical research using physiological signals and medical images [269,270]. These methods have been employed as a post-processing step in various medical applications, offering valuable insights into the data to clinicians and researchers. Integration of XAI techniques with DL models is a promising avenue for future research in emotion recognition. This approach can enhance the trust of psychologists in emotion recognition systems based on EEG signals and DL techniques, as the XAI components can provide relevant information and insights into the decisions made by the DL models. To date, several XAI methods have been utilized along with DL techniques to accurately analyze biological signals. The t-SNE technique, for instance, has been extensively employed as an XAI method for diagnosing brain diseases from EEG signals, which has significantly enhanced doctors' confidence in using DL techniques for such diagnoses [347,348]. As a future work direction, the application of XAI techniques such as t-SNE may yield intriguing outcomes in emotion recognition from EEG signals. Additionally, as mentioned in the challenges section, limited XAI methods have been provided to interpret EEG signals. Therefore, as another potential area for future research is the development of novel XAI methods based on biological signals.

### 7.5. Hardware resources

The increased complexity of DL models has led to an equally heightened demand for computational power, resulting in new obstacles to face. One possible solution to this issue is utilizing cloud services, by Google and Amazon [271,272]. However, there are still challenges associated with running DL models on these cloud computing servers. Recent advancements in quantization techniques show promise in resolving this challenge, as they enable significant reductions in required hardware resources [273–275]. This method could be employed in future DL model research [273–275]. Another potential approach involves the utilization of deep compact CNNs which can be implemented on systems with limited hardware resources [276]. Among the most noteworthy compact-size, CNN techniques are FBNetV3 [277], MnasNet [278], TinyNet [279], and MobileNet [280]. Furthermore, utilizing deep compact-size CNNs can also be beneficial for emotion recognition from EEG signals.

### 7.6. Uncertainty

Recently, uncertainty quantification (UQ) techniques have been employed for DL models, whose primary objective is to evaluate the performance of these networks [284]. Several studies have demonstrated that the use of uncertainty quantification methods has yielded valuable outcomes in various fields [285–288]. Although DL architectures are highly capable in prediction applications based on complex data, they often exhibit poor performance when confronted with different data [286,287]. Uncertainty in DL architectures involves model uncertainty, data uncertainty, and parameter uncertainty [286–288]. The implementing uncertainty in the DL models can help to use the model even in a home-based environment by evaluating the UQ and taking care to counter it.

## 8. Conclusion and finding

In recent years, extensive research has been focused on emotion recognition from EEG signals using different DL models [349–353,281,282]. Emotions are experienced differently by individuals, and the variation in these experiences can impact nerves, behavior, thoughts, and relationships [281,282]. The classification of emotions is typically divided into six main categories: Joy, Sadness, Fear, Surprise, Anger, and Disgust [354–359,281,282]. Additional emotions can arise through a combination of these categories. Unchecked emotions can lead to psychological afflictions such as PD [224], SZ [225], and depression [226]. Among the several emotion recognition strategies introduced thus far, the recording of biological signals has proven to be the most crucial. EEG, ECG [239], fNIRS [240], and MRI [241] are among the most important approaches used for emotion recognition with physiological signals.

Recording EEG signal data is more popular in emotion recognition than recording other biological signals [34–39]. EEG signals are preferred as there are no negative side effects on the subject during recording. Furthermore, EEG signal recording is comparatively easier, economical, user-friendly and portable [34–39]. In addition to this, EEG signals provide data with high temporal and frequency resolution, while being recorded across various channels that offer essential information from multiple fields of the brain for accurate emotion recognition [34–39]. Despite these advantages, EEG recording is associated with certain challenges. The primary obstacles associated with EEG modality include internal and external artifacts, complex data interpretation due to various channels, and data recording for long durations.

Comprehensive research is currently being conducted on emotion recognition from EEG signals using AI techniques to identify individual emotions and prevent conditions such as depression and SZ [15–18]. Initially, emotion recognition research was focused on utilizing ML techniques. Various feature extraction and classification techniques were employed in ML research to improve the accuracy of emotion recognition. However, ML approaches tend to struggle when dealing with large amounts of data and typically require a trial-and-error approach [6–8]. To address these shortcomings, DL techniques have emerged as a potential solution for emotion recognition from EEG signals [16–18]. This paper provides a review of articles that have used DL techniques for this purpose.

The introduction of the paper initially covers the classification of emotions and the techniques used to identify them. Subsequently, the advantages and limitations of several methods used for recording signals, including EEG [211], temperature [212], ECG [213], EMG [214], and GSR [215], were reviewed. The importance of EEG signals, as well as the challenges associated with using them to recognize emotions, were then discussed. Finally, the paper expounds on the advantages of DL techniques in comparison to ML techniques for emotion recognition from EEG signals.

Section (2) reviews the articles on emotion recognition from EEG signals based on DL techniques. The reviewed papers were published between 2016 and 2023. In this section, Table 2 summarizes the details of the reviewed literature. This section presents the latest research developments on EEG-based emotion recognition. This section also compares our review article with other works.

In Section (3), we described the search strategy utilized during the literature review, which followed the PRISMA guidelines. Our focus was on gathering articles that explored emotion recognition through DL techniques between 2017 and 2023. We followed the PRISMA guidelines [314] in three stages to examine the relevant studies. To facilitate the selection of the articles, we have also included a proposed PRISMA block diagram and a table, which outlines the inclusion and exclusion criteria. These measures were put in place to simplify the selection process and ensure the quality of the reviewed papers.

Section (4) discusses the CADS developed for emotion recognition from EEG signals using DL models. This section reviewed the important steps of CADS used for emotion recognition, including pre-processing and DL models. First, the available EEG datasets for emotion recognition were presented. Then, the most critical low- and high-level techniques used for pre-processing of EEG signals were briefly introduced. Then, the most important DL techniques used in emotion recognition: CNNs, pre-trained architectures, AEs, RNNs, graphs, and GANs were discussed. Table (4) summarizes the studies conducted in this field.

Section (5) deals with the challenges faced during emotion recognition using DL techniques. The most important challenges are multimodal datasets, *imbalanced* datasets, XAI, DL techniques, and limited hardware resources. This section separately discussed each challenge in detail. Overcoming these challenges can pave the way for further applied research on emotion recognition using DL techniques.

Section (6) and its subsections focus on emotion recognition studies conducted. Table 4 presents the studies conducted on emotion recognition from EEG signals using DL techniques. This section examined the information presented in Table 4, including datasets, DL models, and classification algorithms. Also, we have compared our review paper with other review papers published on this same topic to highlight the novelty of our work.

Section (7) outlines the most important suggestions for future research on emotion recognition. These suggestions include datasets, DL techniques, XAI, hardware resources, and uncertainty. The most important future works regarding the subsections of DL models include the application of architectures transformers, GCNNs, SSLs, and Deep Multi-Task Learning (DMTL) in emotion recognition from EEG signals. This section is a source of inspiration for the latest ideas in this field. According to Table 4, it can be seen that some researchers have utilized graph and attention mechanism models in their studies on emotion recognition from EEG signals and have achieved successful results. However, new methods in these techniques have been introduced, providing researchers with further possibilities to explore in future studies.

The research findings suggest that it may be feasible to develop a practical tool for emotion recognition from EEG signals in the future. For example, the medical industry, including the Internet of Medical Things (IoMT) [283,19], is rapidly expanding through the utilization of AI techniques. IOMT systems possess significant storage capacity for information and are equipped with high-powered hardware units for information processing [360,361]. Consequently, investigating the potential use of IOMT systems for emotion recognition represents an intriguing research field, as it may lead to practical implementation of DL algorithms for real-time emotion recognition. Another section of the paper covers hardware challenges and their potential future work. One promising direction for future research involves utilizing systems-on-chips (SoCs) based on field programmable gate array (FPGA) [362] and application-specific integrated circuit (ASIC) [363] chips for emotion recognition from EEG signals. The proposed DL algorithm can be implemented and trained on these chips, allowing for the rapid and real-time detection of emotions from EEG signals containing various emotions. As noted previously, emotions impact various parts of the human body, and therefore, detecting emotions may involve utilizing different biological signals such as EEG, ECG, EMG, and others. Therefore, an emotion recognition system that employs multiple DL techniques to detect emotions from all biological signals represents a crucial area for future research. Such a system has the potential to produce accurate and reliable results in emotion recognition.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. : Abbreviations

| A | |
|---|---|
| Accuracy | Acc |
| Adaptive spatiotemporal graph convolutional network | ASTGCN |
| Additional Margin softmax loss | AM-softmax |
| Adversarial discriminative-temporal convolutional network | AD-TCN |
| Auto-encoder | AE |
| Area under ROC curve | AUC |
| Arousal | Aro |
| Artifact subspace reconstruction | ASR |
| Attention-based convolutional recurrent neural network | ACRNN |
| Attention-based LSTM with Domain Discriminator | ATDD-LSTM |
| Autoregression reflection coefficients | ARRC |
| Azimuth Equidistant Projection | AEP |
| B | |
| Bag of deep features | BoDF |
| Bag-of-hybrid-deep-features | BoHDF |
| Baseline noise _ltering | BNF |
| Bimodal Deep AutoEncoder | BDAE |
| Binary grey wolf optimization | BGWO |
| Broad learning system | BLS |
| C | |
| Causal Graph Convolutional Neural Network | CGCNN |
| Channel frequency convolutional neural network | CFCNN |
| Channel-fused dense convolutional network | CDCN |
| Channel-Relationships-Based Graph Convolutional Network | CR-GCN |

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| A | |
|---|---|
| Channel selection graph neural network | CSGNN |
| Convolutional Neural Network | CNN |
| Continuous Wavelet transform | CWT |
| Correct Recognition Rate | CRR |
| D | |
| Data Augmentation | DA |
| 4D convolutional recurrent neural network | 4D-CRNN |
| Deep belief network | DBN |
| DE matrix | DEM |
| Deep canonical correlation analysis | DCCA |
| Deep Neural Network | DNN |
| Deep Normalized Attention-based Residual Convolutional Neural Network | DNA-RCNN |
| Depthwise convolution and Transformer encoders | DCOT |
| Differential entropy | DE |
| Dilated fully convolutional network | DFCN |
| Decision Tree | DT |
| Deep belief network with glia chain | DBN-GC |
| Differential asymmetry | DASM |
| Differential causality | DCAU |
| Dilated bottleneck-based CNN | DBCN |
| Discrete wavelet transform | DWT |
| Domain Generative Graph Network | DGGN |
| Dominance | DOM |
| Dual-tree Complex Wavelet Transform | DT-CWT |
| Dual-branch dynamic graph convolution-based adaptive transformer feature fusion network with adapter-finetuned transfer learning | DBGC-ATFFNet-AFTL |
| Dynamic graph CNN | DGCNN |
| Dynamic differential entropy | DDE |
| Dynamic empirical convolutional neural network | DECNN |
| E | |
| Efficient CNN and contrastive learning | ECNN-C |
| Electrocardiogram | ECG |
| Electroencephalogram | EEG |
| Empirical Mode Decomposition | EMD |
| Energy Threshold-Based Multicommon Spatial Pattern | ET-MCSP |
| F | |
| Fast Fourier transform | FFT |
| Feature Pyramid Networks | FPN |
| Fourier transform | FT |
| Fully Convolutional Neural Network | FCN |
| Functional connectivity | FuC |
| Functional connectivity-based geometric deep network | FC-GDN |
| Fully-connected | FC |
| Fusion graph convolutional network | FGCN |
| G | |
| Gated Recurrent Unit Emotion Recognizer | GRUER |
| Gated Recurrent Unit-Minimum Class Confusion | GRU-MCC |
| Generative Adversarial Network-based Self-Supervised Data Augmentation | GANSER |
| Gradient-priority particle swarm optimization | GPSO |
| Graph Convolutional Broad Network | GCB-net |
| Graph-embedded convolutional neural network | GECNN |
| Graph Convolutional Neural Network | GCNN |
| Graph-embedded CNN | GECNN |
| H | |
| Heart rate | HR |
| Heart rate variability | HRV |
| Hierarchical convolutional neural network | HCNN |
| Hierarchy graph convolution network | HGCN |
| Higher order crossings | HOC |
| Hilbert-Huang transform spectrum | HHS |
| Hybrid Convolutional Recurrent Neural Network | HCRNN |
| I | |
| Independent component analysis | ICA |
| Instance-Adaptive Graph | IAG |
| Intrinsic mode functions | IMF |
| J | |
| K | |
| K-nearest neighbor | KNN |
| L | |
| learnable electrode relations graph convolutional network | LR-GCN |
| Least the Absolute Shrinkage and Selection Operator | LASSO |
| Lightweight pyramidal 1D CNN | LP-1D-CNN |
| Linear discriminant analysis | LDA |
| Linear dynamic system | LDS |
| Linear Formulation of Differential Entropy | LF-DfE |
| Linear-frequency cepstral coefficients | LFCC |
| M | |

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| A | |
|---|---|
| Mean Absolute Value | MAV |
| Mel-frequency cepstral | MFCC |
| Modified-random forest | M-RF |
| Multiband feature matrix | MFM |
| Multi-branch convolutional neural networks | MBCNN |
| Multiclass genetic programming with multidimensional population | M3GP |
| Multi-Layer Perceptron | MLP |
| Multi-level features guided capsule network | MLF-CapsNet |
| Multimodal residual LSTM | MM-ResLSTM |
| Multiple frequency bands parallel spatial–temporal 3D deep residual learning framework | MFBPST-3D-DRLF |
| Multi-scale residual network | MSRN |
| Multi-task learning | MTL |
| Multi-task channel attention CapsNet | MTCA- CapsNet |
| Multi-variate empirical mode decomposition | MEMD |
| Multivariate variational mode decomposition | MVMD |
| N | |
| Neighborhood Component Analysis | NCA |
| Network Enhancement | NE |
| Nuclear norm regularized deep neural network framework | NRDNN |
| O | |
| P | |
| Parallel sequence-channel projection convolutional neural network | (PSCP-Net) |
| Particle swarm optimization | PSO |
| Pearson correlation coefficient | PCC |
| Phase lag index | PLI |
| Phase lock value | PLV |
| Phase-locking value graph convolutional neural networks | P-GCNN |
| Principal component analysis | PCA |
| Precision | Pre |
| Preprocessed signal matrix | PSM |
| Progressive graph convolution network | (PGCN) |
| Power spectral density | PSD |
| Power spectral entropy | PSP |
| Pyramidal graph convolutional network | PGCN |
| Q | |
| R | |
| Random channels exchange | RCE |
| Random Forests | RF |
| Rational asymmetry | RASM |
| Recall | Re |
| Recurrence plot | RP |
| Recurrence quantification analysis | RQA |
| Regional-Asymmetric CNN | RACNN |
| Regionally-Operated Domain Adversarial Network | RODAN |
| Regularized graph neural network | RGNN |
| Residual Graph Convolutional Broad Network | GCB-Res |
| Residual feature pyramid network | RFPN |
| Restricted Boltzmann machine | RBM |
| S | |
| Sample-by-sample Similarity Matrix | SSM |
| Sample-Reweighted Domain Adaptation Neural Network | SRDANN |
| Self-organized graph neural network | SOGNN |
| Self-training Maximum Classifier Discrepancy | SMCD |
| Semi-skipping Layered Gated Unit Efficient Network | SLGU -ENet |
| Sensitivity | Sen |
| Short-Time Fourier Transform | STFT |
| Simple ElectroEncephalographic-based Recognition Network | SEER-net |
| Sing-link end-to-end spatio-temporal demographic network | SSTD |
| Siamese graph convolutional attention network | Siam-GCAN |
| Similarity network fusion | SNF |
| Simple recurrent units | SRU |
| Smoothed pseudo-Wigner–Ville distribution | SPWVD |
| Space to-depth | S2D |
| Spatial-temporal feature fused convolutional graph attention network | STFCGAT |
| Spatio-Temporal Field | STF |
| Spatial-temporal graph convolutional LSTM network | ST-GCLSTM |
| Sparse graphic attention long short-term memory | SGA-LSTM |
| Spatio-temporal RNN | STRNN |
| Spatial-Frequency Convolutional Self-Attention Network | SFCSAN |
| Specificity | Spe |
| Stacked Autoencoder | SAE |
| Standard Deviation | SD |
| Support Vector Machine | SVM |
| Symmetric difference matrix | SDM |
| Symmetric quotient matrix | SQM |
| T | |

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| A | |
|---|---|
| Temporal Convolutional Network | TCN |
| Temporal Feature Learning Network | TFLN |
| Three-dimension convolution attention neural network | 3DCANN |
| Transfer entropy | TE |
| Transformer Capsule Network | TC-Net |
| Transposition Multi-Layer Perceptron | TMLP |
| Tree-like LSTM | tLSTM |
| True Negative | TN |
| True Positive | TP |
| Tunable Q-factor Wavelet Transform | TQWT |
| TQWT-Feature Block Sequences | TFBS |
| U | |
| V | |
| Valence | Val |
| Variational instance adaptive graph | V-IAG |
| Variational Mode Decomposition | VMD |
| W | |
| Wavelet Entropy | WE |
| Wavelet packet decomposition | WPD |
| Wavelet-independent component analysis | wICA |
| Wavelet packet transform | WPT |
| Wireless-based eeg Data for emotion analysis | WeDea |
| X | |
| Y | |
| Z | |

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