Comprehensive Analysis on Human Emotion Recognition using EEG and Facial Video Clips

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Abstract
Emotion recognition has become an area of research interest in recent years because of its applicability in several domains like neuropathy treatment, online shopping, mental rehabilitation, therapeutic gaming, and drug testing, etc. Many researchers proposed techniques for emotion recognition. This review paper focuses on three critical points in emotion recognition using EEG and facial expressions data. First, the mechanisms for capturing emotions using EEG signals have been highlighted. Secondly, an overview of existing techniques either based on handcrafted features or deep learning has been presented. Thirdly, the description and analysis of the databases that are available to validate the performance of algorithms, de-signed for recognizing certain types of emotions have been presented. We have provided an overview and analysis of the research work on emotion recognition from 2017 to 2022. In recent years, there has been a shift from handcrafted features to deep learning. The techniques based on deep learning and handcrafted features have been compared and their strengths and limitations have been elaborated. Finally, future research directions have been highlighted.
Keywords:
Deep learning methods; EEG signals; Human-Computer Interactions; HCI; Handcrafted methods.

1. Introduction

Currently, there are several applications on human computer interaction (HCI) which focus on emotions. The industry of information technology (IT) provides such a responsive system in which an operator does not have to dictate the process manually. Appliances use the tacit appeal from the operators by recognizing their explicit emotion. For instance, if there is a program being broadcasted on TV, it will automatically set brightness and contrast according to the program. In another example, when the user is playing a game on TV, the device automatically sets a brighter light and higher contrast because the user is in game mode.

Humans are full of emotions and moods in their everyday life and their perception depends upon these emotions such as rational decision-making, insight, interaction among each other, and intelligence [1]. However, they have been overlooked mainly in HCI.

Now a days, IT and HCI are developing in their emotional computing capabilities. Emotional connections among computers and humans are playing an active role in affective computing, given that the user's emotional state has been calculated [2]. We can observe an individual's mood by certain indicators how an individual feels), variations inside a body (bodily signals), and apparent expressions (vocal/visual cues) [3]. A special feeling can offer valued material; however, there are problems with rationality and validation [4]. How the individual feels cannot be precisely known. Perhaps there are other ways to assess human emotions.

Physiological variations replicate the status of a human's behavior. Some types of biological signals and imageries are stored to examine emotions. For example, EEG signals are used to capture brain activities (as shown in Figure 1). Electromyogram (EMG) signals illustrate activities of the muscular system. The respiratory system is monitored using the respiration rate. The functionality of a cardiac system is observed using an electrocardiogram (ECG), heart rate variability (HRV) and blood pressure, etc. and facial image sequences represent facial expressions.

As an important mode of HCI, the facial expressions detection systems are being deployed in different many fields such as medicine, distance education, audio visual games and security [99]. The detection of facial expression is an area of significance for the emotional assessment research. The growing trends of artificial intelligence dictate the ease of interaction between humans and machines. Accordingly, dynamically progressive research in facial expression detection systems is in the greater interest of society as well as the individuals [100]. Recently, there has been a rapid growth in the research of facial expression detection systems and the researchers are intrigued by the applications and societal impact of developing a robust and state of the art facial expression detection system [101]. The current facial expression detection systems involve following areas of research: feature extraction and classification. The feature extraction methods are further divided into geometric and appearance-based methods. The geometric-based feature extraction methods mainly focus on eye, eyebrow, nose, mouth, or other facial components individually while appearance-

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based feature extraction methods consider particular section of the face [102]. Also, the classification methods are focused on classifying several discrete sets of emotions as defined by the researcher. However, there is an increasing trend in the researchers of focusing on deep learning models for feature extraction and classification tasks [102].

For emotion recognition, EEG signals are being employed extensively for emotion analysis in HCI because of its direct dependency on the brain. Also, the concept of transparent EEG [48], a product containing small EEG sensors, wireless-based EEG amplifiers, and smartphone-based signal acquisition and stimulus presentations, provides additional possibilities for research. The smartphone-operated wearable devices for emotion capturing allows getting a real insight into the problem under consideration. However, EEG signals are non-stationary, which is a negative attribute related to them, given that they are measured precisely on the human-friendly interface. The correlation of spontaneous EEG signals causes problems sometimes in terms of time.

EEG signals permit researchers to examine phase variations in terms of emotional stimuli [5]. Therefore, possibilities to study emotion recognition based on EEG are becoming popular in diverse fields such as e-learning, e-healthcare, e-commerce, virtual scenarios, and entertainment, etc. [6]. It can help to perform a task by emotion recognition, for example, online gaming, psychologists, and support therapists [7].

In the literature, research conducted on EEG based emotion recognition mostly considers frequency-dependent information. The frequency-dependent feature extraction method suggests decomposing an EEG signal into several frequency bands, e.g., delta band (1-3Hz), theta band (4-7Hz), alpha band (8-13Hz), beta band (14-30Hz) and gamma band (31-50Hz). The usually exploited features from these bands include the differential entropy (DE) and the power spectral density (PSD) etc. However, the author in [16] proposed automatic feature selection techniques. Five different automated feature selection techniques were considered to extract the most informative EEG features from the whole dataset.

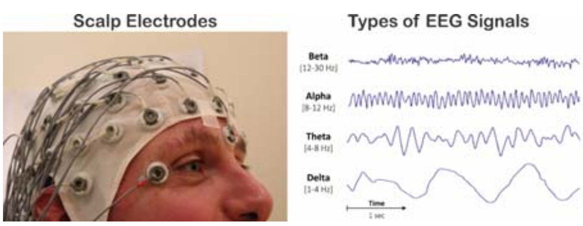

Fig. 1. EEG signals showing brain activity (Photo by Chris Hope, made available by Tim Sheerman-Chase at [49] through CC BY 2.0 license [50]).

Emotions of a human are very hard to detect when it comes to unstable EEG signals because of their susceptibleness to noise. Many authors have put their efforts into being capable of categorizing various features of EEG signals and recognize emotions. To get a general idea of how these authors have collaborated into this field, in [38], the author dis-cussed the prevailing categorization schemes used to categorize the emotion features of EEG signals. Linear and nonlinear approaches were used by the author to make a comparison of categorization schemes. The author in [39] studied the reasons behind the reduction of results while comparing various research on the subject. A study on offline vs. online emotion recognition systems was carried out in [40]. The author concentrated its focus on education on the topic of emotion recognition using EEG signals. In [41], the author reviewed the papers to give an investigation on mutual drawbacks of research on EEG signals and on characteristics like sub-jects, extracted features, algorithms to classify, etc., used in identifying emotions. In the end, the author provided a set of endorsements on top methods to assist researchers. There is no discussion on dataset-based comparison between techniques and results of each dataset considering a different number of emotion types in the literature.

Human emotions can be investigated through different ways. For instance, it is more often to use static pictures containing facial expressions to analyze emotions but certain factors (intensity of light, size of facial portion in the image, background variations etc.) limit the efficiency of emotion recognition. Moreover, it is extremely difficult to evaluate the concealed or unexpressed expressions. On the other hand, sensor-based emotion recognition problems including EEG signals involve extracting actual information from human body. However, EEG signals are very much susceptible to noise [41]. Due to such limitations of single modality-based emotion recognition problems, gradually researchers are convinced to use multiple modalities in analyzing human emotions. In such multiple modality-based methods, two or more types of signals of a single subject are fused together in order to enhance the efficiency of problem under consideration and build more robust systems. Multimodal methods to fuse EEG and facial data are increasingly becoming popular due to their applications in the fields of healthcare and HCI [104]. Several methods including deep learning and handcrafted based feature extraction methods have been investigated for human emotion recognition.

In this work, we reviewed studies that examined how to recognize emotions from EEG signals, facial video clips and their fusion. We considered three critical points to conduct this review: the first one highlights the existing feature extraction techniques either handcrafted or deep learning, second one regarding databases that are used to validate an algorithm designed to recognize different types of emotions and third one distinguishes the methods in terms of stimuli and number of emotional categories. This review examines research papers from 2017 to 2022 because a significant shift from handcrafted to deep learning-based feature extraction techniques was observed during this span. A study conducted by Fonseca et. al. [41] provides details on techniques presented by different authors on emotion recognition till 2016. But it lacks a comparison between the handcrafted and deep learning-based techniques.

This work is arranged in the following order; Section 2 overviews the methodology of this work, Section 3 contains the back ground of EEG based emotion recognition in detail, an overview of the different emotion recognition approaches is provided in Section 4, these approaches are discussed in Section 5, some future recommendations in Section 6 and finally, a conclusion in Section 7.

2. Methodology

Queries initiated on Google Scholar, IEEE Xplore, and Research Gate were used to gather the prevailing re-search articles for this study. After that, we separated the publications between 2017 and 2022 suitable in EEG based emotion recognition collection. Our initial assortment provided 237 papers, which we assembled by the researcher and then removed those that were additional contributions. A final list of 96 articles were selected.

Articles selected were examined further according to three perspectives. First, we reviewed all the papers according to stimuli. Second, we performed a more specific analysis of them. This analysis resulted in the division according to handcrafted and deep learning-based works and furthered the techniques with their performance measure studies in each work. Lastly, we arranged the papers according to the dataset used, types of emotions, and average accuracy.

3. Background

The ways of evoking emotions play a vital role in emotion recognition systems. Some researcher believe that video clips can stimulate human emotions the best while others find music or memories the most effective way. What is clear is that the stronger the stimulation is, the richer the database will be. By using excellent and intense stimulation, emotion recognition is more likely to be performed with better results and higher accuracy.

3.1. Brain Anatomy

In 1970, anthropologist Paul Ekman projected that human creatures qualified six rudimentary sentiments: joy, surprise, anger, sadness, disgust, and fear. Subsequently, researchers have remained undecided on a precise number of emotions - some scholars say there are only four, while others say about 27. Experts likewise argue whether humans acquire these emotions from childhood or it is universal that all humans have the same number of emotions. But emotions stimulated from movement in various sections of the brain are an acknowledged fact.

Neurons in the brain are electrical devices. Many channels are sitting in the cell membrane that allows positive or negative ions to flow into and out of the cell. Normally, the inside of the cell is more negative than the outside because the cell's resting membrane potential is -70 mV. The membrane potential varies according to the inputs coming from the axons of other neurons termed as excitatory and inhibitory inputs. These inputs mean that different types of neurons release different neuro-transmitters which determine its effect

Action potentials are the central units of communication between neurons and occur when the total of all of the excitatory and inhibitory inputs makes the neuron's membrane potential reach around -50 mV called the action potential threshold (see Figure 2).

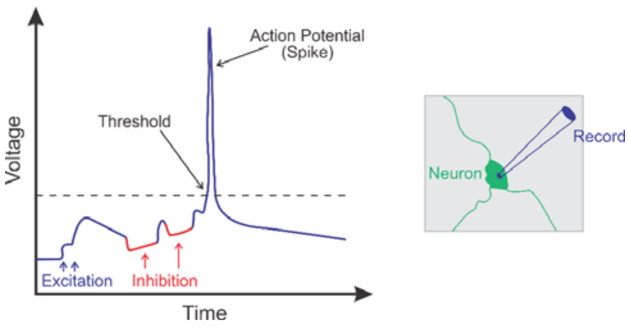

Fig. 2. An example of a neuron's spike.

Neurons talk to each other across synapses. When an action potential reaches the presynaptic terminal, it causes neurotransmitters to be released from the neuron into the synaptic cleft. After traveling across the synaptic cleft, the transmitter will attach to neurotransmitter receptors on the postsynaptic side, and depending on the neurotransmitter released, particularly positive (e.g., Na+, K+, Ca+) or negative ions (e.g., Cl-) will travel through channels that span the membrane. postsynaptic receptor, switching the signal back again into an electrical form, as charged ions flow into or out of the postsynaptic neuron.

Synapses can be thought of as converting an action potential into a chemical signal in the form of neuro-transmitter release, and then, upon binding of the transmitter to the postsynaptic receptor, switching the signal back again into an electrical form, as charged ions flow into or out of the postsynaptic neuron.

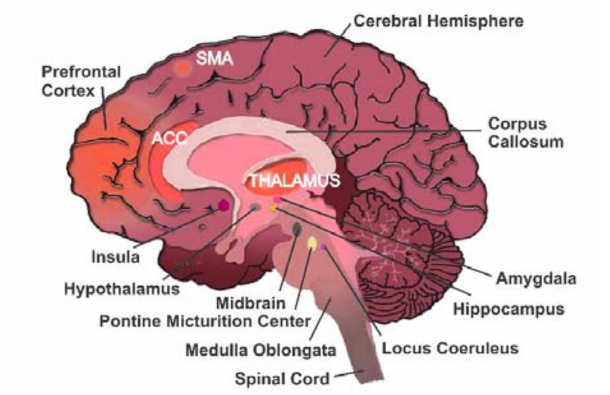

Fig. 3. The Sagittal section of the brain where ACC and SMA stand for Anterior Cingulate Cortex and Supplementary Motor Area respectively.

There is a connection of four brain constructions with emotions: the amygdala, the prefrontal cortex, the insula or insular cortex, and the periaqueductal gray located in the midbrain (see Figure 3). The amygdala, a paired structure inside the brain, assimilates sentiments, emotive conduct, and motivation. It recognizes fear, discrimination among friend and foe, and recognizes societal rewards. Also, the amygdala is significant in conventional training. The prefrontal cortex contributes to both emotion generation and emotion regulation related to fear extermination/conditioning tasks and linked with increased/reduced sympathetic arousal. The insula is the cause of a strongly negative emotion called disgust. Investigations of various magnetic resonance imaging (MRI) have stated that discomfort feelings instigate the insula. Experts have noted that receiving human physical state reports is done by the insula, which produces a link between a particular emotional state which to the inner state, moods, and practical actions. The periaqueductal gray, situated inside the brainstem, is concerned with pain. It comprises of receptors for pain reduction compounds like morphine and oxycodone and can benefit suppress motion in pain identifying nerves. Also, the periaqueductal gray is involved in defensive and reproductive activities, motherly love, and anxiety [42, 43].

3.2. Facial Expressions

Paul Ekman investigated human facial expressions for the first time in 1970 [105]. The author reported in the findings of the study that human facial expressions are universal. The author added in the findings that happiness, sadness, anger, fear, surprise, and disgust are the most common facial expressions of a human being in the category of universal facial expressions. Although, the study suggested that culture and demographics have certain effect on the display of expressions but it was obvious that the categories of facial expressions were unchanged. Later, Ekman and Friesen [106] proposed the Facial Action Coding System (FACS). The FACS was designed to encrypt the facial expressions in terms of action units (AU) represent the variations on the face. Every single AU corresponds to a particular muscular basis on the face and a set of AU makes a facial expression. Also, the implementation of this process takes place manually by following a number of rules which makes the process very time-consuming and laborious. Moreover, Mase [107] proposed optical flow (OF) based algorithm to identify facial expressions and considered to be the founding father to introduce image processing techniques in detecting facial expressions. However, the FACS was the beginning of a new era in the field of facial expressions which instigated the researchers to investigate facial expressions with the help of image processing tools. Recently, several researchers have worked on the recognition of facial expressions to categorize the above-mentioned discrete set of emotions [101-104].

Table 1. Comparison between handcrafted and deep learning methods in terms of strengths and weaknesses.

Method	Strength(s)	Weakness(s)
Handcrafted	• Easy to exploit the algorithm • Suitable for detecting special features • Suitable for small datasets	• Detection accuracy is fair • Detection accuracy may vary according to the database
Deep Learning	• Suitable for large datasets • Can be used to reduce dimensions of a data without dropping the important features	• Requires a large number of training data

3.3. Feature Extraction

When EEG catches signals, it can have various amplitudes (between 10 to 100 μV) and frequencies (between 1 to 100 Hz), which need to be separated based on some criteria. Also, the classification procedure primarily depends on those features. Selecting the features for actual representative the class-specific information is an essential process in such classification. So, there is a requirement of mining more real highlights for the classification task. There are two main ways of extracting features i.e., handcrafted and automatic extraction with the deep learning models. There are numerous handcrafted feature extraction methods in the literature [53]. Moreover, automated feature extraction methods have been reported in the literature with excellent performance [19]. Therefore, to evaluate best methods for emotion recognition using EEG signals, there is a need to make a comparison among handcrafted and deep learning methods used by many researchers. A comparison of handcrafted and deep learning methods in terms of their strengths and weaknesses is provided in Table 1.

3.4. Emotion Illustration

Another problem in emotion recognition studies is the number of elicited emotions and the emotion model. Some studies, according to the discrete model of emotions, consider a specific number of emotions and others, according to valence, arousal, and dominance model suppose more emotions. For example, authors in [11, 12] studied anger, sadness, surprise, happiness, disgust, and fear emotions according to discrete emotion model, while authors in [4, 5, 9, 10] studied emotions according to the valence and arousal model.

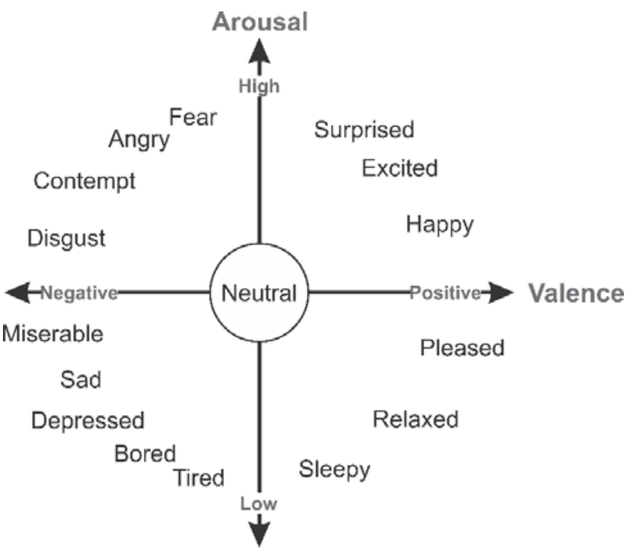

Figure 3. Valence-Arousal based 2-D graph.

3.5. Public Datasets

Researchers can use some public datasets on emotion recognition for free in order to evaluate their proposed techniques. The advantage of public dataset is that researchers do not need any laboratory and specific recording systems, appropriate condition, shield environment, etc. Also, they do not need participants, however, reliable and free datasets are available with appropriate EEG recordings for emotion recognition. The following are the publicly available datasets.

3.5.1. DEAP

In 2012 a multimodal datasets-based investigation for emotion recognition was presented by Koelstra et. al. [8]. This study was done in two laboratories of Geneva and Twente. In these recordings, valence and arousal model was considered in which there were 40 video clips containing various emotions and thirty-two contributors. 32-channel EEG signals, 4-channel EMGs, 4-EOG signals, 2-channel GSR signal, 2-ERG signals, and the temperature in a single channel, single-channel respiration rate, and 1-channel blood volume pressure were recorded. Each individual provided five indexes, including arousal, valence, likes/dislikes, domination, and familiarity, in terms of ratings. Also, out of 32 individuals, 22 participant's facial videos were also recorded. Raw and preprocessed signals are also available in this dataset which can be used on request [8].

3.5.2. SJTU Emotion EEG Dataset (SEED)

In [9] Zheng and Lu presented the SJTU emotion EEG Dataset.15 individuals participated in this research. Chinese video clips were shown to these individuals and their EEG signals were recorded. Three types of emotions i.e., positive, negative and neutral were recorded. Each individual completed a questionnaire after viewing videos. This study was completed in three sessions so that researchers could check the constancy of patterns and neural signatures among members and sessions. The 10-20 international standard system was used to record the EEG signals from each individual. Raw and preprocessed signals with multiple revisions are available on request [9].

3.5.3. MAHNOB-HCI

Soleymani et. al. [54] presented an investigation on a multimodal dataset for emotion recognition using emotional stimuli. The recordings included facial videos, audio signals, eye gaze data and peripheral signals including EEG, ECG, respiration pattern, GSR and skin temperature. These signals were recorded with a synchronized setup. Including 16 females and 11 males, a total of 27 contributors joined in the experiment. The participants were subjected to watch 20 videos of various emotional categories and, afterwards, filled a self-assessment report rating arousal, valence, dominance, and predictability. The data is available on request [54].

3.5.4. DREAMER

Katsigiannis and Ramzan [55] investigated a multimodal dataset containing EEG and ECG signals using video stimuli to elicit emotions. A total of 23 persons including 14 males and 9 females were subjected to watch 18 videos from different categories of emotion and reported self-assessment ratings for valence, arousal, and dominance. The signals were extracted using portable, wearable, wireless, low-cost device according to the International 10-20 system. The data is available on request [55].

3.5.5. Loughborough University Multimodal Emotion Database-2 (LUMED-2)

Ekmekcioglu and CIMTAY [56] proposed a unique multimodal dataset for emotion recognition. The researchers of Loughborough University, UK, and Hacettepe University, Turkey, created this dataset from 7 male and 6 female contributors by making them watch video stimuli containing specific emotional content. Also, at the end of each session, the contributors were asked to label the video from the set of discrete emotional categories. The labeling resulted in three different categories of emotions namely: happy, sad and neutral. The multimodal data consists of facial videos, EEG and GSR. The dataset is available through CC BY 4.0 license [57]. The Table 2 summarizes the common attributes of EEG signals in all public datasets.

Table 2. Attributes of EEG signals in public datasets.

Dataset Title	**No. of Participants**	**No. of Trials**	**Duration of each Trial**	**Number of EEG Channels**	**Sampling Rate of EEG data (Hz)**	**Frames per Second for Facial Recordings**	**Emotion Categories**	**Ratings**
DEAP [8]	32	40	63 seconds	32	512	Yes	Arousal	1-9
							Valence	
							Dominance	
							Liking	
							Familiarity	1-5
SEED [9]	15	15	~4 minutes	62	1000	Yes	Positive Neutral Negative	Discrete
SEED-IV [18]	15	72	~2 minutes	62	1000	Yes	Happy Sad Fear Neutral	Discrete
SEED-V [58]	20	15	2-4 minutes	62	1000	Yes	Happy Sad Neutral Fear Disgust	0-5
MAHNOB-HCI [54]	27	20	34-117 s	32	256	No	Arousal Valence Dominance Predictability	1-9
DREAMER [55]	23	18	65-393 s	14	128	No	Valence Arousal Dominance	1-5
LUMED-2 [56]	13	1	8 minutes 50 s	8	500	No	Happy Sad Neutral	Discrete

4. Literature Review

4.1. Handcrafted Based Methods

A graph regularized sparse linear regression (GRSLR) was presented by Yang et. al. [10]. This study was conducted to Treat the EEG emotion recognition issue. Many experiments were done and a conclusion was made that GRSLR was superior to the classic baseline models.

Tengfei et. al. [11] presented a method named as dynamical graph convolutional neural networks (DGCNN). This method is used to deal with multi-channel EEG features in which a graph is used to perform EEG emotion classification. Accurate variables such as valence, arousal, and dominance classifications are obtained by this method on the DREAMER database scheme outperformed by their competitors. Xiang et. al. [12] considered a leave-one-subject-out verification approach to check emotion recognition execution. The results of this study authenticated the option of discovering robust EEG features in cross-subject emotion credit.

The author of the following research [13] presented a new emotional initiation curve to prove the beginning process of feelings. After feature removal and cataloging, the algorithm constructs novel initiation curves of emotions founded on the classification consequences and two constants i.e., the correlation constants and entropy constants. The emotional beginning device is also elucidated by this study of an algorithm.

Zhuang et. al. [14] presented a process for feature withdrawal and emotion acknowledgment. This research was based on empirical mode decomposition (EMD). By using this method EEG signals are decayed into Intrinsic Mode Functions (IMFs) mechanically. Information from IMF which is multidimensional is utilized as structures. Differences in time series, phase, and normalized energy were calculated in this research. The part of each IMF was queried and it was initiated that high-frequency constituent IMF1 has an important result on the discovery of many emotional states.

Another method included multimodal feeling acknowledgment was presented in [15]. This study was based on convolutional auto-encoder (CAE) [15]. In the first step, a CAE was intended to get the fusion features of multichannel EEG signals and multi-type EP signals. In the second step, a fully linked neural network classifier is built to attain emotion recognition.

Table 3 includes handcrafted methods used by numerous investigators for emotion recognition. A complete description of which method was used and how the performance was measured has been discussed.

Table 3. Hand crafted based methods.

Reference	**Feature Extraction Method**	**Types of Emotions**	**Database**	**Performance**	
				Accuracy	**other**
Feature Extraction from EEG Data					
Kong et. al. [35] – 2021	Forward weighted horizontal visibility graphs Backward weighted horizontal visibility graphs Time-domain features	Valence Arousal	DEAP	98.12%	Sensitivity = 97.98% Specificity = 97.14% Precision = 97.97%
Mokatren et. al. [67] – 2021	Wavelet packet decomposition	Valence Arousal	DEAP SAD	91.85% 92.19%	–
Naser et. al. [68] – 2021	Spectral features Functional connectivity Laterality index Functional connectivity patterns Dual-tree complex wavelet packet transform (DT-CWPT) based features	Arousal Valence Dominance	DEAP	73.90%	Sensitivity = 73.04% Specificity = 74.77% F1 score = 0.74 BER = 0.26
Sarma and Barma[69] – 2021	Power spectral density Continuous wavelet transforms	Positive Negative Arousal Valence	SEED DEAP	95% 86%	–
Asa et. al. [70] – 2021	Tunable Q wavelet transform	Positive Neutral Negative	SEED	93.1%	AUC = 0.983 F1 score = 0.931 Kappa coef. = 0.897
Nawaz et. al. [60] – 2020	Power features Entropy features Fractal dimension features Statistical features Wavelet energy features	Valence Arousal Dominance	DEAP	78.96%	–
Li et. al. [61] – 2020	Time domain features Frequency domain features Time-Frequency domain features	Valence Arousal Positive Negative	DEAP Personal	76.67% 89.50%	–

Gao et. al. [62] - 2020	Power spectrum features Wavelet energy entropy features	Happy Neutral Sad	Personal	89.17%	–
Alakuş et. al. [64] – 2020	Statistical features Chaotic features Time-frequency analysis features	Arousal Valence Positive Negative	Personal	80% 87%	Kappa coef. = 0.664 Kappa coef. = 0.667
Yin et. al. [66] – 2020	Power features Power difference features Power ratio features Temporal statistics features Complexity indicators features	Valence Arousal	DEAP MAHNOB-HCI	67.32% 69.58%	F1 score = 66.89% F1 score = 71.39%
Chen et. al. [10] – 2019	Combined differential entropy and LDA	Positive Neutral Negative	SEED	82.5%	Precision = 80.1% Recall = 80.2% F1 score = 79.9% Kappa coef. = 69.8%
Qing et al. [13] – 2019	Used correlation coefficients and entropy coefficients	Positive Calm Negative	DEAP SEED	75%	–
Pandey et al. [16] - 2019	Empirical mode decomposition Variational Mode Decomposition Power spectral density First difference of intrinsic mode functions	Calm Happy Sad Angry	DEAP	62.50%	–
Ergin et al. [44] - 2019	Intrinsic mode functions	Arousal Valence Dominance	Personal	83.1%	–
Li et al. [12] – 2018	9 different types of Time-frequency domain features 9 different Non-linear dynamical system features	Happy Neutral Sad	DEAP SEED	83.33%	AUC = 0.904
Thejaswini et al. [23] - 2018	Discrete wavelet transforms	Calm Happy Fear Sad	Personal	90.90%	–
Morteza et al. [24] - 2018	Nonlinear time series analysis	Happy sad fear neutral	DEAP	91.83%	Recall = 89.13% Specificity = 91.12% Precision = 89.41%
Liu et al. [25] – 2018	short-time Fourier transform (STFT)	Joy Amusement Tenderness Anger Disgust Fear Sad Neutral	Personal	92.26%	–
Mert et. al. [26] - 2018	Multivariate empirical mode decomposition	Valence Arousal	DEAP	75%	–

Zamanian, and Farsi [63] – 2018	Gabor feature extraction Features based on intrinsic mode functions	Happy Sad Exiting Hate	DEAP	93.86%	–
Zhuang et al. [14] – 2017	Empirical Mode Decomposition	Valence Arousal	DEAP	71.99%	F1 score = 77.69%
Mehmood et al. [32] - 2017	Hjorth parameters	Happy Calm Sad Scared	Personal	76.6%	–
Zhao et al. [59] – 2017	short-time Fourier transform (STFT)	Amusement Joy Tenderness Anger Disgust Fear Sad	Personal	86.11%	–
Feature Extraction from EEG and Facial Data for Fusion					
Tan et. al. [104] – 2021	Power Spectral Density and Differential Entropy for EEG features and Monte Carlo method for decision level fusion	Fear Happy Sad Neutral	SEED-IV	81.67%	–
Li et. al. [116] – 2021	Power Spectral Density for EEG features	Arousal Valence	MAHNOB-HCI DEAP Personal	78.56%	Recall = 69.28%
Li et. al. [30] – 2019	Power spectrum density for EEG facial landmark for facial features LSTM for decision level fusion	Positive Neutral Negative	Personal	–	CCC = 0.631
Huang et. al. [117] – 2019	Power Spectral Density for EEG features and weight fusion and adaboost approach for decision fusion	Arousal Valence	MAHNOB-HCI DEAP Personal	80%	–

* AUC (Area Under the Curve), LDA (Linear Discriminant Analysis), Kappa coef. (Cohen's kappa coefficient), BER (Balance error rate), CCC (Concordance Correlation Coefficient).

4.2. Deep Learning Based Methods

A team of researchers including Pandey and Seeja [16] presented a study. In this research, a deep education method for recognizing emotion from non-stationary EEG signals was presented. They used a Variational Mode Decomposition (VMD) method for feature removal. Deep Neural Network does better in comparison to the state-of-the-art methods in subject-independent emotion gratitude from EEG. Researchers Wenming et. al. [17] used a network of a domain named the bi-hemispheres domain adversarial neural network (BiDANN) to distinguish human emotion from EEG signals. BiDANN maps were used in this study for the EEG data of both left and right hemi-spheres into discriminative feature spaces distinctly. The results of this study showed that the planned model attains a state-of-the-art presentation.

Zheng et al. [18] established a multimodal sentiment acknowledgment context called Emotion Meter that associated brain waves and eye movements EEG and eye movements were used in this research for mixing the internal cognitive states and external subconscious performances of individuals to improve the acknowledgment accuracy of Emotion Meter. Results from this experiment prove the efficiency of Emotion. Deep canonical correlation analysis (DCCA) was presented by Liu et. al. [19]. This model was presented to evaluate multimodal emotion acknowledgment for five multimodal datasets. The simple idea behind DCCA is to alter each instrument distinctly and organize different instruments into hyperspace. Specified canonical correlation analysis constraints were used in this research. Results from this research specified that DCCA had better strength. By imagining feature deliveries with t-SNE and evaluating the mutual material be-tween different instruments before and after using DCCA, they establish a concept that the features distorted by DCCA from different instruments are more similar and discriminative across emotions.

Yang et. al. [20] introduced a CNN method for knowing emotions from many channels of EEG signals. In this study, data was developed in the expansion phase to recover the presentation of their CNN model. They presented DEAP dataset to attain better correctness for valence and stimulation as compared to previous studies. In one research piece presented by Li et. al. [21] a new bi-hemispheric discrepancy model (BiHDM) was presented. The main objective of this study was to learn the unequal changes among two hemispheres for EEG emotion acknowledgment. The researcher evaluated four directed recurrent neural networks (RNNs) which were based on two spatial alignments to cross electrode signals on two separate brain portions. These signals enabled the model to get the deep demonstrations of all the signals of EEG electrodes. Intrinsic spatial dependence remained intact. In the next step, they intended a pairwise subnetwork to detention the inconsistency material between two hemispheres and extract higher-level features for concluding cataloging. They conducted trials on three public EEG emotional datasets. The results of these experiments showed that the new state-of-the-art results can be attained.

A Spatio-temporal recurrent neural network (STRNN) was presented by Liu et. al. [19]. In this study spatio-temporal demonstration of raw EEG signals was used to categorize human emotion by learning of STRNN. Evaluation of spatially co-occurrent differences of human emotions, a multidirectional RNN layer was engaged to capture long-range appropriate signs. This was done by crossing the spatial regions of each temporal slice alongside various directions. Further, a bi-directional temporal RNN sheet was used to evaluate the discriminative features symbolizing the temporal addictions of the sequences, where the spatial RNN layer was used to produce sequences. The results of this research showed that the community emotion datasets of EEG and facial appearance prove the future STRNN method was more modest over those state-of-the-art methods.

The researchers Thejaswini and Kumar [23] used an Artificial Neural Network (ANN) for EEG that was based on sentiment recognition. A modality named Support Vector Machine (SVM) and K- nearest neighbor (KNN) was applied to the removed feature set to grow prediction models. This instrument was also used to classify this into four emotional states like peaceful, pleased, fear and sad. Results showed that they attained better correctness than previous work. Soroush et. al. [24] inspected to excerpt significant nonlinear characteristics from EEGs with the goal of emotion acknowledgment. Methods used in this research were machine learning methods evolutionary feature selection methods and committee machines. These methods were used to improve cataloging performance. The cataloging was achieved by regarding both stimulation and valence issues on to 2 various databases. These databases included individually recorded EEGs and a standard dataset to appraise the suggested method. Success was achieved by this process.

Soroush et. al. [24] inspected to excerpt significant nonlinear characteristics from EEGs with the goal of emotion acknowledgment. Methods used in this re-search were machine learning methods evolutionary feature selection methods and committee machines. These methods were used to improve cataloging performance. The cataloging was achieved by regarding both stimulation and valence issues on to 2 various databases. These databases included individually record-ed EEGs and a standard dataset to appraise the suggested method. Success was achieved by this process.

Liu et. al. [25] presented a method by analyzing brain waves to identify a 10 individual's emotional states by using a real-time movie-induced emotion recognition system. This real-time SVM system attained complete correct-ness of 92.26 % in recognizing high-awakening and 15 valence sentiments from impartiality. Experimental results show 86.63 percent in knowing positive from negative emotions

Degirmenci et. al. [26] examined better possessions of empirical mode decomposition (EMD) for sentiment acknowledgment by using EEG signals. In the research, data was gathered from one directed BIOPAC lab system. EEG signals were gained from graphic suggested abilities of 13 female and 13 male individuals for 12 agreeable and 12 disagreeable pictures. Some instruments named as SVM, LDA, and Naive Bayes classifiers were used for the cataloging which better-quality results.

Yu-Xuan et. al. [27] presented an original channel frequency convolutional neural network (CFCNN), shared with reappearance quantification analysis (RQA), for the vigorous credit of EEG signals collected from different emotional states. They employed movie clips as the stimuli to induce happiness, sadness, and fear emotions and simultaneously measure the corresponding EEG signals. The results indicated that the system can provide a high emotion recognition accuracy of 92.24% and comparatively excellent constancy as well as a reasonable Kappa value of 0.884, version the system chiefly useful for the feeling credit task.

Jinpeng et. al. [28] planned a network named hierarchical convolutional neural network (HCNN). This network was used to categorize the positive, neutral, and negative expressive states. They used three methods i.e., stacked autoencoder (SAE), SVM, and KNN as opposing methods. In the results of this study, HCNN yields showed the highest accuracy, and SAE is marginally mediocre but surely greater to SVM and KNN, in emotion acknowledgment especially on Beta and Gamma waves. Hassan et. al. [29] used unverified deep belief net-work (DBN) for complexity level feature removal from fused comments of Electro-Dermal Activity (EDA), Photoplethysmogram (PPG) and Zygomaticus Electromyography (ZEMG) devices signals. To categorize 5 basic emotions i.e., Happy, Relaxed, Disgust, Sad and Neutral the feature vector was used in this study. Fine Gaussian Support Vector Machine (FGSVM) based model meaningfully augmented the correctness of emotion gratitude rate as likened to the existing state-of-the-art emotion organization methods.

The deep learning methods used by numerous investigators for emotion recognition are summarized in Table 4. A complete description of which method was used and how the performance was measured are discussed.

Table 4. Deep learning-based methods.

Reference	Feature Extraction Method	Types of Emotions	Database	Performance	
				Accuracy	other
Feature Extraction from EEG Data					
Gao et. al. [73] – 2022	CNN inception structure	Arousal Valence	DEAP	80.52%	–
Joshi et. al. [82] – 2022	Deep RNN	Arousal Valence	DEAP SEED	90.17%	–
Arjun et. al. [86] – 2022	LSTM) with channel-attention autoencoder and CNN model	Arousal Valence Positive Neutral Negative	DEAP SEED	69.5% 72.3%	–
Jana et. al. [87] – 2022	CapsNet architecture	Valence Dominance Arousal Liking	DEAP	85.396%	–
Zheng et. al. [31] – 2021	3D feature maps and CNNs	Arousal Valence	DEAP	94.04%	–
Topic and Russo [71] – 2021	CNN	Arousal Valence	DEAP SEED DREAMER AMIGOS	74.91% 73.11% 81.25% 79.54%	–
An et. al. [72] – 2021	Convolutional autoencoder	Arousal Valence	DEAP	90.76%	–
Fdez et. al. [75] – 2021	Multilayer neural network with normalization	Positive Neutral Negative	SEED	91.6%	–
Fang et. al. [76] – 2021	Multi-feature deep forest model	Neutral Angry Sad Happy Pleasant	DEAP	71.05%	–
Ahmad et. al. [77] – 2021	CNN based on ResNet50	Positive Neutral Negative	SEED	94.86%	–
Yin et. al. [80] – 2021	Fusion of graph convolutional neural network (GCNN) and LSTM	Arousal Valence	DEAP	90.60%	–
Garg et. al. [81] – 2021	1D and 2D CNN Combined	Arousal Valence Dominance	AMIGOS	96.63%	–
Guo et. al. [83] – 2021	Deep Multilayer Perceptrons	Positive Neutral Negative	SEED	93.8%	–

Chen et. al. [88] – 2021	Domain-specific Feature Extractor using MLP	3 categories for SEED 4 categories for SEED-IV	SEED SEED-IV	89.63% 61.43%	–
Li et. al. [92] – 2021	Bi-hemisphere domain adversarial neural network	Positive Neutral Negative	SEED	92.38%	–
Hagad et. al. [93] – 2021	Deep Learning model with adversarial training and multi-domain adpatation and Gaussian distribution	Positive Negative Neutral	DEAP SEED	63.52% 63.28%	–
Thinh et. al. [94] – 2021	2D-CNN	Valence Arousal	DEAP	98.36%	–
Demir et. al. [96] – 2021	AlexNet MobilNetv2	Valence Arousal	DEAP	91.07% 98.93%	–
Özdemir et. al. [98] – 2021	Deep recurrent convolutional network	Valence Arousal Dominance	DEAP	90.62%	–
Chao et. al. [33] – 2020	Principal component analysis network (PCANet)	Valence Arousal	DEAP	71.85%	–
Liu et. al. [74] – 2020	CNN combined with Sparse Autoencoder and and Deep Neural Network	Valence Arousal	DEAP SEED	92.86% 96.77%	–
Zhang et. al. [78] – 2020	CNN-LSTM	Valence Arousal	DEAP	94.17%	–
Song et. al. [79] – 2020	Dynamical Graph Convolutional Neural Networks	Valence Arousal Dominance	SEED DREAMER	90.4% 86.23%	–
Zhang et. al. [85] – 2020	Improved radial basis function neural network	Sadness Joy Anger Fear	Personal	82.27%	–
Bao et. al. [91] – 2020	Two-level domain adaptation neural network	Positive Neutral Negative Sadness Anger Fear	SEED Personal	87.9% 87.04%	–
Wei et. al. [95] – 2020	Recurrent Neural Network	Positive Negative Neutral	SEED	83.13%	Precision = 82.24% Recall = 81.53% F1-score = 81.24%
Alnafjan et. al. [97] – 2020	NeuCube-based Spiking neural network	Valence Arousal	DEAP	84.62%	–
Zhou et al. [15] – 2019	Convolutional Auto-Encoder	Valence Arousal	DEAP	92.07%	–
Liu et al. [19] – 2019	Deep canonical correlation analysis	Happy Sad Fear Neutral Disgust	SEED SEED-IV SEED-V DEAP DREAMER	94.58%	–
Yang et al. [20] – 2019	CNN	Happy Calm Sad Fear Suspense	DEAP	90.01%	Recall = 82.87% Precisio = 85.64% F1 score = 84.88%

Yang et al. [21] – 2019	Recurrent neural networks	Funny Neutral Sad Anger Fear Disgust Neutral	SEED SEED-IV MPED	93.12%	–
Mehedi et al. [29] – 2019	Deep belief network architecture	Happy Relaxed Disgust Sad Neutral	DEAP	94.0%	–
Dahua et al. [30] – 2019	LSTM	Positive Negative Neutral	SEED	–	CCC = 0.63
Dong et al. [47] – 2019	Capsule network (CapsNet)	Arousal Valence Dominance	DEAP	68.28%	–
Zhong et al. [84] – 2019	Regularized graph neural network with Node-wise Domain Adversarial Training and Emotion-aware Distribution Learning	Positive Negative Neutral Sad Fear Happy	SEED SEED-IV	94.24% 85.30%	–
Li et al. [90] – 2019	bidirectional BiLSTM with regional to global spatial and temporal neural network to update weights	Positive Neutral Negative	SEED	93.38%	–
Li et. Al. [17] – 2018	Adversarial neural network	Positive Neutral Negative	SEED	83.28%	–
Song et al. [11] – 2018	Dynamical Graph Convolutional Neural Networks	Happy Neutral Sad	SEED, DREAMER	86.23%	–
Zheng et al. [18] – 2019	Deep neural network	Happy sad fear neutral	SEED-IV	85.11%	–
Wang et al. [27] – 2018	CFCNN, combined with RQA	Happiness Sadness Fear	Personal	92.24%	Keppa=88.40%
Jinpeng et al. [28] – 2018	Hierarchical convolutional neural network	Positive Negative Neutral	SEED	86.20%	–
Chao et al. [45] – 2018	Deep belief networks with glia chains based on deep learning framework	Valence Arousal	DEAP	76.83%	F1 score = 70.15%
Tong et al. [22] – 2017	STRNN to integrate the feature learning from both spatial and temporal information	Positive Neutral Negative Anger Contempt Disgust Fear Happiness Sadness Surprise	SEED	95.40%	–
Alhagry et al. [46] – 2017	LSTM	Arousal Valence Dominance	DEAP	87.99%	–

Zheng [89] – 2017	Group sparse canonical correlation analysis	Positive Nuatral Negative	SEED	85.23%	–
Feature Extraction from EEG and Facial Data for Fusion					
Tan et. al. [104] – 2021	CNN model for facial data and Monte Carlo method for decision level fusion	Fear Happy Sad Neutral	Personal	83.33%	–
Song and Kim [108] – 2021	2D-CNN for facial data Stacked LSTM for EEG data Deep learning model for feature level fusion	Fear Happy Sad Disgust	Personal	83.75%	–
Lu et. al. [111] – 2021	VGG-16 model for EEG and facial data and LSTM based decision level fusion method	Anger Disgust Fear Happy Sad Surprise	MAHNOB-HCI	95%	–
Zhaoand Chen [112] – 2021	Bilinear convolution network for EEG and facial data and LSTM based fusion method	Arousal Valence	MAHNOB-HCI DEAP	86.8%	F1 score = 0.739
Aguiñaga et. al. [113] – 2021	Deep neural network for EEG and Facial data	Happy Anger Sad	DEAP	87.4%	AUC = 0.924 F1 = 0.871 Precision = 0.896
Jiang et. al. [114] – 2021	Separate LSTM for facial and EEG data and LSTM-CNN model for fusion	Positive Negative	Personal	93.13%	–
Li et. al. [116] – 2021	CNN model for facial data and Enumeratorand AdaBoost fusion methods	Arousal Valence	MAHNOB-HCI DEAP Personal	78.56%	Recall = 69.28%
Hassouneh et. al. [109] – 2020	CNN model for facial features LSTM model for EEG features and fusion	Anger Disgust Fear Happy Sad Surprise	Personal	99.8%	Precision = 99.8% Sensitivity = 99.0% Specificity = 99.9% F-score = 99.5%
Cimtay et. al. [110] – 2020	Separate CNN model for EEG and Facial data and a hybrid fusion method	Anger Disgust Fear Happy Sad Surprise	LUMED-2 DEAP	91.5%	–
Zhang [115] – 2020	Dual-modal depth automatic encoder (BDAE) for EEG and facial data	Fear Happy Sad Neutral	Personal	85.71%	–
Wu et. al. [118] – 2020	Hirarchical LSTM model	Arousal Valence	DEAP	90%	F1 score = 0.83
Huang et. al. [117] – 2019	CNN model for facial data and weight fusion and adaboost approach for decision fusion	Arousal Valence	MAHNOB-HCI DEAP Personal	80%	

* EDA (Electro-Dermal Activity), DBN (Unsupervised deep belief network), CFCNN (Channel frequency convolutional neural network), RQA (Recurrence Quantification Analysis), MLP (Multi-Layer Perceptron).

4.3. Dataset Based Comparison

In the DEAP dataset, nearly 95% of accuracy has been attained for 3 and 4 types of emotions and 94% performance in terms of accuracy for 5 classes of emotions. Around 98% accuracy is touched for binary class emotions (see Table 4). In SEED dataset, above 96% accuracy has been reported by the researchers and the SEED-IV dataset has provided an accuracy up to 87% on 5 classes of emotions and that of 4 and 7 classes of emotions is reported around 85% and 79% respectively. The SEED V dataset established 83% of accuracy in 5 types of emotions. DREAMER research has achieved a maximum of 86% accuracy in categorizing the emotions. Whereas the research work based on personal experiment for extraction of EEG signals has achieved 92% accuracy for categorizing 3 classes. Also, some of the personal experiment-based results are acquired using online experiment and the accuracy was reduced during online experiment. The poor choice of hyper paraments may been the reason as for as deep learning based online experiments are concerned. Moreover, noise attenuation on EEG signals cannot be ruled out completely which explains that the preprocessing techniques need improvement in such scenarios.

Table 4. The comparison of existing work based on a database.

Dataset Name	Types of Emotions	Results	Ref.
DEAP	Positive, Neutral, Negative	92.36%	[36]
		72%	[37]
		62.50%	[13]
		95%	[69]
		93.1%	[70]
		90.17%	[82]
		63.52%	[93]
		59.06%	[12]
	Neutral, Happy, Sad, Angry	91.83%	[24]
		62.50%	[16]
	Happy, Sad, Fear, Neutral, Disgust	94.0%	[29]
		90.0%	[20]
		85.62%	[19]
	Valence, Arousal	92.07%	[15]
		94.04% 98.12%	[31] [35]
		76.83%	[45]
		71.99%	[14]
		86%	[69]
		76.67%	[61]
		67.32%	[66]
		75%	[26]
		80.52%	[73]
		69.5%	[86]
		74.91%	[71]
		90.76%	[72]
		90.60%	[80]
		98.36%	[94]
		98.93%	[96]
		71.85%	[33]
		92.86%	[74]
		94.17%	[78]
		84.62%	[97]
		86.8%	[112]
		71.00%	[116]

		80%	[117]
		90%	[118]
		91.85%	[67]
	Arousal, Valence, Dominance	87.99%	[46]
		68.28%	[47]
		78.96%	[60]
		90.62%	[98]
		73.90%	[68]
	Arousal, Valence, Dominance, Liking	85.396%	[87]
	Neutral, Pleasant, Angry, Sad, Happy	71.05%	[76]
	Anger, Disgust, Fear, Happy, Sad, Surprise	91.5%	[110]
	, Angry, Sad, Happy	87.4%	[113]
	Happy, Sad, Exiting, Hate	93.86%	[63]
SEED	Positive, Neutral, Negative	82.5%	[10]
		86.20%	[28]
		83.33%	[12]
		83.28%	[17]
		79.95%	[11]
		75%	[13]
		90.17%	[82]
		72.3%	[86]
		91.6%	[75]
		94.86%	[77]
		93.8%	[83]
		89.63%	[88]
		92.38%	[92]
		63.28%	[93]
		96.77%	[74]
		90.4%	[79]
		87.9%	[91]
		83.13%	[95]
		94.24%	[84]
		93.38%	[90]
		85.23%	[89]
		-	[30]
		73.11%	[71]
	Happy, Sad, Fear, Neutral, Disgust	94.58%	[19]
	Funny, Neutral, Sad, Anger, Fear, Disgust, Neutral	93.12%	[21]
		89.50%	[22]
SEED-IV	Happy, Sad, Fear, Neutral	85.11%	[18]
		85.30%	[84]
		61.43%	[88]
	Happy, Sad, Fear, Neutral, Disgust	87.45%	[19]
	Funny, Neutral, Sad, Anger, Fear, Disgust, Neutral	74.35%	[21]
SEED-V	Happy, Sad, Fear, Neutral, Disgust	83.08%	[19]
DREAMER	Happy, Neutral, Sad	86.23%	[11]

	Arousal, Valence, Dominance	86.23%	[79]
	Happy, Sad, Fear, Neutral, Disgust	90.67%	[19]
	Valence, Arousal	81.25%	[71]
MAHNOB-HCI	Valence, Arousal	69.58%	[66]
		78.56%	[116]
		75.63%	[117]
		75.3%	[112]
	Anger, Disgust, Fear, Happy, Sad, Surprise	95%	[111]
LUMED-2	Happy, Sad, Neutral	81.2%	[110]
RCLS	Happy, Neutral, Sad	84.34%	[10]
MPED	Funny, Neutral, Sad, Anger, Fear, Disgust, Neutral	40.34%	[21]
AMIGOS	Arousal, Valence	79.54%	[71]
	Arousal, Valence, Dominance	96.63%	[81]
Personal	Negative, Positive	89.50%	[61]
		93.13%	[114]
		87%	[64]
	Happy, Sad, Fear	92.24%	[27]
	Sad, Joy, Anger, Fear	82.27%	[85]
	Disgust, Happy, Fear, Sad	83.75%	[108]
	Anger, Disgust, Fear, Happy, Sad, Surprise	99.8%	[109]
	Neutral, Happy, Fear, Sad	90.90%	[23]
		87.04%	[91]
		83.33%	[104]
		85.71%	[115]
		76.6%	[32]
	Joy, Amusement, Anger, Tenderness, Disgust, Fear, Sadness, Neutral	92.26%	[25]
		86.11%	[59]
	Arousal, Valence, Dominance	83.1%	[44]
	Arousal, Valence	92.19%	[67]
		68.50%	[116]
		69.75%	[117]
		80%	[64]
	Happy, Neutral, Sad	89.17%	[62]

4.4. Stimuli Based Comparison

There are certain types of stimulations: pictures [1], video clips [2], music [3], memories [4], self-induction [5], environment elicitation like light, humidity and temperature [6], games [7], etc. Some conducts of provoking emotions and persuaded emotions are listed in Table 5.

Table 5. Different Categories of Emotion Stimulation.

Stimulus	Types of Emotions	Ref.
Pictures	Negative, Positive	[19]
	Calm, Happy, Fear, Sad	[36], [32]
	Valence, Arousal, Dominance	[44]
Audio-Visual	Valence, Arousal, Dominance	[68], [60], [19], [20], [46], [47], [81], [98], [79]
	Valence, Arousal	[16], [14], [15], [24], [25], [45], [35], [67], [69], [61], [66], [26], [73], [86], [31], [71], [72], [80],

		[94], [96], [33], [74], [78], [97], [112], [116], [117], [118]
	Negative, Neutral, Positive	[13], [17], [30], [69], [70], [82], [86], [28], [75], [77], [83], [88], [92], [93], [10], [62], [74], [79], [91], [95], [84], [90], [11], [89], [110]
	Happy, Sad, Fear, Neutral	[18], [23], [88], [91], [104], [115]
	Disgust, Sad, Fear, Neutral	[108]
	Arousal, Valence, Dominance, Liking	[87]
	Funny, Neutral, Sad, Anger, Fear, Disgust, Neutral	[21], [59]
	anger, happiness, sad, surprise, contempt, disgust, fear	[22], [109], [111]
	Sad, Joy, Anger, Fear	[85]
	Happy, Calm, Sad, Suspense, Fear	[20], [29]
	Neutral, Pleasant, Angry, Sad, Happy	[76]
	Happy, Sad, Fear	[27], [84]
	Happy, Sad, Anger	[114]
	Positive, Negative	[61], [71], [113]
	Happy, Sad, Exiting, Hate	[63]
Music	Negative, Positive	[19]
	Valence, Arousal, Dominance	[29], [44]

5. Discussion

In this study for evaluating EEG signals, we made a comparison between research which present emotion recognition methods for EEG signals in Tables 2, 3, 4 and 5. While investigators used separate methods, datasets, and measured the performance using different methods, overall results are much evocative.

In the literature, a total of 69 studies are considered for analysis and out of those, about 34% of the studies have been conducted using handcrafted methods while more than 65% of the investigations considered deep learning methods. The researchers show more trust in deep learning techniques in comparison to handcrafted. In handcrafted methods, overall, 85% accuracy was attained given that the publicly obtainable dataset was used in most of them. Also, in some cases, it was observed that the handcrafted method was used to extract the features and neural network was used for further selection of features and classification [15]. In most of the studies, accuracy measure is used to check the performance of the algorithm in hand crafted based methods. Whereas in deep learning techniques, an average accuracy of 92% accuracy on a publicly available dataset and 88% on personal datasets was attained. It was also observed that among others, deep learning-based unsupervised deep belief network (DBN) method for depth level feature extraction by Mehedi et al. [29] gained 94% accuracy. Single classifiers like SVM, KNN, etc. have extensively been studied in the literature for classification. About 90% of the considered articles have used single classifier for classification. Researchers assessed the performance of their deep learning-based techniques using numerous measures like accuracy, recall, f1-score, precision, AUC, and kappa coef., etc.

The information provided in Table 4 suggests that very few researchers have considered increased number of emotion classes regardless of which method/datasets used. Moreover, more than 60% of the studies have been carried on DEAP dataset, around 37% have considered SEED dataset, almost 7% have used SEED-IV dataset and 18% have created their own datasets to validate the proposed algorithm. It can be observed that personal experiment-based findings are less common in this research field although it plays an important role in the future of robotic world and HCI. Additionally, many researchers have presented only EEG signals-based emotion classification. Few authors (3%) have used EEG signals along with other signals with/without fusion method for emotion recognition.

To capture emotions, most of the research work (almost 90%) is based on videos while very few consider pictures or music as stimulus for emotion elicitation to extract EEG signals from human brains (see Table 5). Moreover, different types of emotion shave been considered in the literature of classification but the majority have attempted basic types of emotions to recognize while many researchers focused on valence and arousal to represent their human emotion recognition model's performance.

A necessary step in deep learning to improve accuracy is optimization. It was noticed in the literature that a very few authors have considered optimization techniques like PSO or GA etc. to improve the feature selection process while others have adopted features selection methods such as PCA to improve performance and processing time. Moreover, it is an emerging trend in the researchers to investigate using signals from selected electrodes while neglecting the rest of the signals to improve efficiency of the system specially in terms of equipment and processing time. The deep learning-based feature selection provides an edge over the handcrafted by selecting only those features which can help improve accuracy and neglecting those which are only increasing the processing time but over the cost of amount of data. One can only expect excellent performance from deep learning model if the training data is large enough to suppress overfitting and push the model towards generalization. In this regard, several data augmentation techniques have been proposed by the researchers to overcome the issue of data size.

Additionally, the age group considered for capturing the EEG signals in nearly all the research was of 25+ years of age. The division of the age group to study emotions is not fair.

6. Future Recommendations

Many researchers have used the publicly available datasets to check the performance of their method. It can be challenging for researchers to create a satisfactory environment to elicit emotions, however, a personal dataset can provide an edge to show better performance. The algorithm should also be tested on as many publicly available datasets as possible to validate the performance of an algorithm trained on a personal dataset.

As discussed earlier, emotions can be measured using EEG signals and facial expressions, etc. It can be worthy of analyzing emotions recognized from two or more types of signals combined. There have been a few studies on EEG signals and facial expressions combined for emotion recognition analysis using deep learning techniques.

Moreover, the optimization techniques for feature extraction are useful for not only video datasets but also EEG signals. Better optimization techniques to extract the features can be applied to improve the results. The optimization techniques improve the classification results for a single classifier by removing the noisy parts of the signals.

The extraction of EEG signals differs as the quality and/or sensitivity of the electrodes considered for EEG signal collection is not consistent. Also, the extraction of less noisy EEG signals is subjected to the number of electrodes and their deployment around the scalp while following the standards of 10–20 international system of standards for acquiring EEG signals. It is required to make the equipment, designed to extract the EEG signals, less expensive, standardized and easy to handle so that it should be less complex task for the researchers to conduct online experiments and more general data-based experiments could be conducted. Although literature explains that human emotion elicitation excites the temporal region of the brain but other online experiments have confirmed that other regions of the brain such as the frontal and parietal regions may also be excited and can provide a better efficiency in emotion recognition. Besides, the combination of low and high frequency bands of EEG signals can help in recognition of true human emotions. Moreover, the selection of the electrodes prior to the selection of features has proven to excellent way to improve performance of an emotion recognition model.

Decreasing the electrodes for acquisition of EEG signals can have a positive effect on emotion recognition accuracy because some channels carry irrelevant information [115]. Also, the quality of emotion recognition system using EEG can be improved greatly while decreasing the noise accompanied by the channels with the help of decreasing the quantity of EEG channels [119]. As we all know that considering all the channels of EEG signals to train a neural network may over burden the network [119]. On the other hand, in facial recognition systems, currently all the systems give best efficiency on images carrying front view of the subject but this violates the robustness of the system [92]. The facial expression-based emotion recognition systems lack in efficiency due to non-uniform brightness in the images, size of the facial area of the subject and relatively small areas of eye, nose, mouth due to some shade, discrepancies in poses, etc. [102]. The recent studies on facial expression recognition are unable to identify micro facial expressions related to some human emotion. And that might be due to the variation in facial actions from user to user depending on age, gender, cultural, race and other factors. The databases need to be updated according to these factors and facial actions [101].

A multimodal method with a fusion of facial video clips and EEG signals gives enhanced recognition accuracy [105-109]. Though, it is equally significant to fuse them in appropriate ratio to get maximum performance.

7. Conclusion

This work covers studies on emotion classification. Many scholars have put their efforts to classify the EEG signals and EEG combined with facial video clips. Some of the studies have presented very good results. Though, it remains a challenge to understand EEG signals completely for the sake of emotion classification. It was observed in the literature review that most of the techniques that have been applied for emotion recognition have used deep learning. A few authors have presented handcrafted techniques. Movie clips or audio-visual-based emotion stimuli are wildly trusted among other types of stimuli. Publicly available datasets (offline experiments) are more common in researchers as compared to personal experiment-based datasets (online experiments) for evaluating a unique methodology.

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