IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 25, 2021, accepted June 14, 2021, date of publication June 22, 2021, date of current version July 9, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3091487

Emotion Recognition From EEG Signal Focusing on Deep Learning and Shallow Learning Techniques

MD. RABIUL ISLAM[1], (Member, IEEE), MOHAMMAD ALI MONI[2,*], MD. MILON ISLAM[3], MD. RASHED-AL-MAHFUZ[4], (Member, IEEE), MD. SAIFUL ISLAM[5], MD. KAMRUL HASAN[6], MD. SABIR HOSSAIN[7], (Member, IEEE), MOHIUDDIN AHMAD[6], (Member, IEEE), SHAHADAT UDDIN[8], AKM AZAD[9], SALEM A. ALYAMI[10], (Member, IEEE), MD. ATIQUR RAHMAN AHAD[11], (Senior Member, IEEE), AND PIETRO LIÓ[12]

[1]Department of Electrical and Electronic Engineering, Bangladesh Army University of Engineering & Technology, Natore 6431, Bangladesh
[2]UNSW Digital Health, WHO Center for eHealth, Faculty of Medicine, The University of New South Wales, Sydney, NSW 2052, Australia
[3]Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna 9203, Bangladesh
[4]Department of Computer Science and Engineering, University of Rajshahi, Rajshahi 6205, Bangladesh
[5]School of Information and Communication Technology, Griffith University, Gold Coast, Southport, QLD 4222, Australia
[6]Department of Electrical and Electronic Engineering, Khulna University of Engineering & Technology, Khulna 9203, Bangladesh
[7]Department of Computer Science and Engineering, Chittagong University of Engineering & Technology, Chittagong 4349, Bangladesh
[8]Complex Systems Research Group, Faculty of Engineering, The University of Sydney, Darlington, NSW 2008, Australia
[9]iThree Institute, Faculty of Science, University of Technology Sydney, Ultimo NSW 2007, Australia
[10]Department of Mathematics and Statistics, Faculty of Science, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh 13318, Saudi Arabia
[11]Department of Media Intelligent, Osaka University, Ibaraki 567-0047, Japan
[12]Computer Laboratory, University of Cambridge, Cambridge CB3 0FD, U.K.

Corresponding author: *Mohammad Ali Moni (m.moni@unsw.edu.au)

ABSTRACT Recently, electroencephalogram-based emotion recognition has become crucial in enabling the Human-Computer Interaction (HCI) system to become more intelligent. Due to the outstanding applications of emotion recognition, e.g., person-based decision making, mind-machine interfacing, cognitive interaction, affect detection, feeling detection, etc., emotion recognition has become successful in attracting the recent hype of AI-empowered research. Therefore, numerous studies have been conducted driven by a range of approaches, which demand a systematic review of methodologies used for this task with their feature sets and techniques. It will facilitate the beginners as guidance towards composing an effective emotion recognition system. In this article, we have conducted a rigorous review on the state-of-the-art emotion recognition systems, published in recent literature, and summarized some of the common emotion recognition steps with relevant definitions, theories, and analyses to provide key knowledge to develop a proper framework. Moreover, studies included here were dichotomized based on two categories: i) deep learning-based, and ii) shallow machine learning-based emotion recognition systems. The reviewed systems were compared based on methods, classifier, the number of classified emotions, accuracy, and dataset used. An informative comparison, recent research trends, and some recommendations are also provided for future research directions.

INDEX TERMS Emotion, electroencephalogram, human-computer interaction, deep learning, shallow learning.

NOMENCLATURE

Acronym	Full Form
AI	Artificial Intelligence
BDAE	Bimodal Deep Auto Encoder
CFS	Correlation-based Feature Selector
CNN	Convolutional Neural Network
CNS	Central Nervous System
CV-CNN	CNN model used for Computer Vision
CWT	Continuous Wavelet Transform
DASM	Differential Asymmetry
DBN	Deep Belief Network
DCAU	Differential Causality
DCT	Discrete Cosine Transform

The associate editor coordinating the review of this manuscript and approving it for publication was Gang Wang.

DE	Differential Entropy
DEAP	Database for Emotion Analysis using Physiological Signals
DE-CNN	Dynamic Empirical Convolutional Neural Network
DNN	Deep Neural Network
DT	Decision Tree
DWT	Discrete Wavelet Transform
EEG	Electroencephalogram
EMD	Empirical Mode Decomposition
EOG	Electrooculogram
FFT	Fast Fourier Transform
FG-SVM	Fine Gaussian Support Vector Machine
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GPU	Graphical Processing Unit
HCI	Human-Computer Interaction
HCNN	Hierarchical Convolutional Neural Network
HHT	Hilbert-Huang Transform
HOC	Higher-Order Crossing
ICA	Independent Component Analysis
kNN	k Nearest Neighbor
LDA	Linear Discriminant Analysis
LS-SVM	Least Square Support Vector Machine
MC-CNN	Multi-Column Convolutional Neural Network
MCSVM	Multi-Class Support Vector Machine
MLP	Multi -Layer Perceptron
mRMR	Minimum Redundancy Maximum Relevance
NB	Naïve Bayes
PANA	Positive Activation Negative Activation
PCA	Principal Component Analysis
PCC	Pearson Correlation Coefficients
PC-RNN	Parallel Convolutional Recurrent Neural Network
PSD	Power Spectral Density
PSO	Particle Swarm Optimization
RA-CNN	Regional Asymmetric Convolutional Neural Network
RASM	Rational Asymmetry
RF	Random Forest
RGNN	Regularized Graph Neural Network
RNN	Recurrent Neural Network
SEED	SJTU Emotion EEG Dataset
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
VEn	Voting Ensembles
WT	Wavelet Transform
ZC	Zero Crossing

I. INTRODUCTION

Emotion recognition is the process of comprehending and extracting the current human mental state or the modes of mind. A significant amount of research has been conducted about emotion recognition from brain signals in recent years [1]–[7]. With the advancement of Artificial Intelligence (AI) technologies, emotion recognition has become an indispensable part of research in the field of neuroscience, computer science, cognitive science, and medical science [8]–[11]. Although the expression of the human face [12]–[17], body movement [18]–[20], gesture [21], [22], etc. also express one's emotional condition, it is significant to extract original emotion from spontaneous brain Electroencephalogram (EEG) signal. And that is because any type of thought, imagination, dream, and plan of human beings have a meaningful and indicative impact on the formation of brain signals [23]–[25]. Moreover, subjects have no way to control the automatically generated EEG signal. Besides, emotion recognition from voice, gesture, and posture becomes impossible for the inarticulate or physically handicapped people who cannot speak or express their emotions through gesture or posture. Therefore, it can be said that EEG is a suitable means of extracting human emotion and is already devoted to understanding human emotion in many studies.

Emotion recognition using EEG has become an exciting and fast-growing area of research [26], [27]. As a result, the number of publications per year is increasing continuously as shown in Fig. 1. The data of several published articles were collected from the 'PubMed' website by searching 'Emotion recognition from EEG'.

However, EEG is the signal of very small amplitude; therefore, recognizing emotion from EEG is a very challenging task. Nevertheless, numerous researchers have attempted to alleviate this problem by adopting sophisticated techniques, including deep learning-based [28]–[33] or shallow machine learning-based [34]–[39] approaches on either raw signals or combined extracted features to recognize exact emotion.

In this paper, many emotion recognition systems are analyzed. Basically, the whole system of emotion recognition from EEG can be classified into two major groups i) Deep machine learning-based system, ii) Shallow machine learning-based system. Deep learning-based systems including CNN, DNN, DBN, RNN, BDAE, VEn, etc. are used as classifiers. On the other hand, shallow learning-based systems including SVM, kNN, RF, DT, ANN, PNN, MLP, etc. are used as classifiers. This study also showed the overall performance of both types of systems along with some background information. The schematic diagram of our study is shown in Fig. 2.

For this review, the literature search was conducted by following the strategy of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) as shown in Fig. 3. Firstly, in the identification step, a search was carried out by querying 'Google Scholar' and 'PubMed' with the term 'Emotion recognition from EEG' year range of 2015 to 2020. Here, 762 articles were identified. Next, in the screening step, the articles of non-English language and the review, database, or letter type articles were excluded. Later the article title and abstract were screened one by one, and 169 articles were found that had irrelevant research objectives and 48 articles methods were not matched. Afterward,

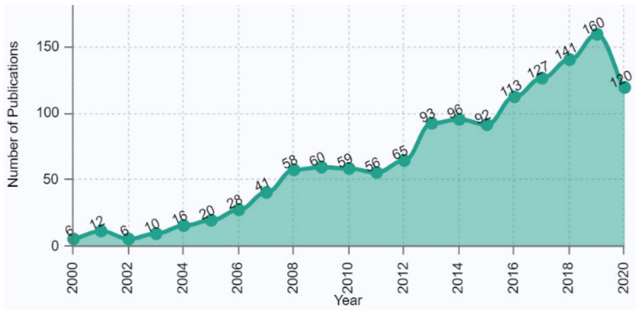


FIGURE 1. The number of publications per year on emotion recognition from EEG is increasing continuously. The number of publications in 2020 has declined may be due to COVID-19 pandemic.

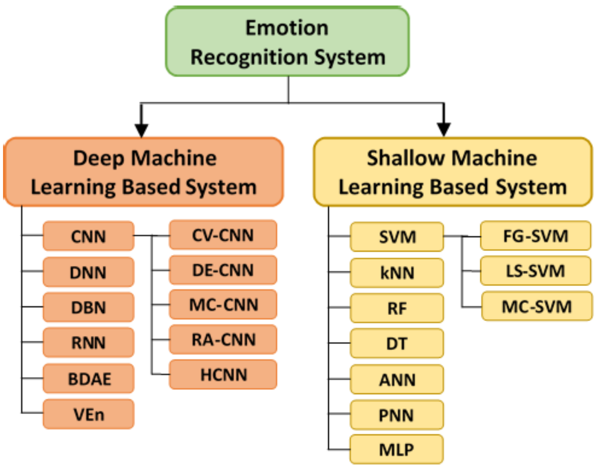


FIGURE 2. The categorization of general emotion recognition systems.

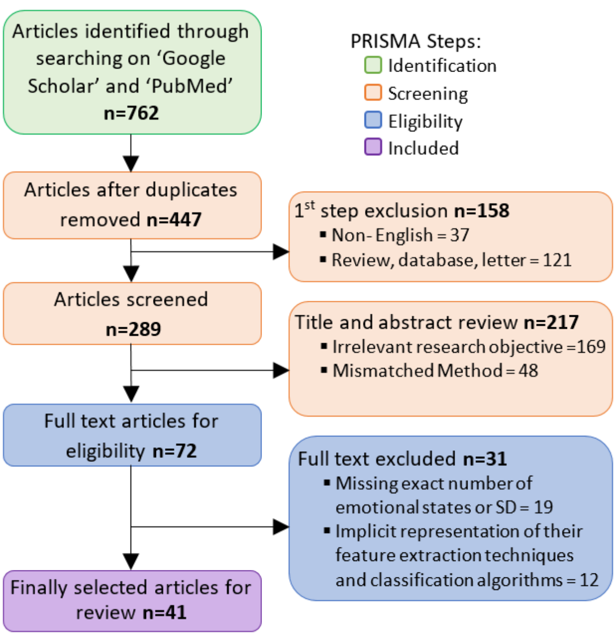


FIGURE 3. The PRISMA technique-based article search strategy including the reasons for inclusion and exclusion.

72 articles were remained that were checked in detail. At last, 31 articles were excluded because these did not mention the exact number of emotional states and some articles (12) did not represent the feature extraction methods or classification algorithms explicitly. Through the sequential process of identification, screening, and eligibility testing finally, 41 papers were included to conduct this review process.

This review article will be cooperative for the following contexts:

1) Introductory information regarding emotion, EEG signal analysis, necessary software, available datasets, popular features, and classifiers are described thoroughly, which provides useful domain knowledge to the new researchers.
2) Performance comparison based on features of deep learning and shallow machine learning-based classification algorithms is thoroughly presented that may assist the researchers of intermediate level in finding out advanced research direction.
3) A summary of a list of highly-relevant articles with their limitations and recommendations are also provided, which may facilitate expert-level researchers their way-forward to design a perfect emotion recognition system for real-world applications.

The arrangement of this paper is stated below. A short note on emotion, EEG, EEG data acquisition techniques, and analyzing software are narrated in the "Overview" section. The step-by-step procedure, feature, and classifier, etc., are described in the section named "General Framework for Emotion Recognition". Next, a performance comparison of deep learning and shallow learning-based recognition systems is presented in the "Discussion" section. Finally, after presenting the "Observations and Recommendations" section, the paper was concluded.

II. OVERVIEW

A. EMOTION

Emotion is a spontaneous feeling that implies how we act for a particular instance. For different situations, a person may have a different feeling like happiness, fear, anger, boredom, etc. A person's character indicates the present mental states, behavior, and thought, which can be simply termed as emotion [40], [41], its accurate quantification is uncountable. However, according to recent research articles, very common types of human emotional states are amusement, boredom, disgust, excitement, joy, satisfaction, sympathy, romance, horror, entrancement, confusion, awe, nostalgia, fear, empathetic, calmness, anxiety, admiration, awkwardness, triumph, sadness, nostalgia, interest, envy, craving, adoration, etc. [42]–[44]. To classify or organize emotions, many psychologists proposed numerous models that are summarized in Table 1. Among them, Russel's Circumplex 2D model [45] is a popular one.

According to dimensionality, the emotion model can also be categorized into two types, namely the 2D (Two-Dimensional) Model and the 3D (Three-Dimensional) Model. The 2D model classifies emotions based on two-dimensional data consisting of valence and arousal value

TABLE 1. The notable models of emotion with the name of the inventor and types of emotional states in ascending chronological order.

SN	Model Name	Inventor	Year	Emotional States / Details
1.	Paul Ekman [49]	Paul Ekman	1972	Happiness, anger, fear, surprise, sadness, and disgust
2.	PAD (Pleasure, Arousal and Dominance) Model [50]	Albert Mehrabian and James A. Russell	1974	3D model based on pleasure, arousal, and dominance
3.	Russell's Circumplex Model [45]	James Russell	1980	2D, Many states categorized by HVHA, HVLA, LVHA, LVLA
4.	Plutchik's Model [51]	Robert Plutchik	1980	Anger, fear, sadness, disgust, surprise, anticipation, trust, and joy
5.	Positive Activation Negative Activation (PANA) Model [52]	Watson and Tellegen	1985	2D model where the vertical axis represents low to high positive affect and the horizontal axis represents low to high negative affect
6.	Vector Model [53]	Bradley, M. M.	1992	Arousal data with a vector for valence
7.	Parrott, W. G [54]	Parrott, W. G	2000	Joy, anger, sadness, fear, love, surprise

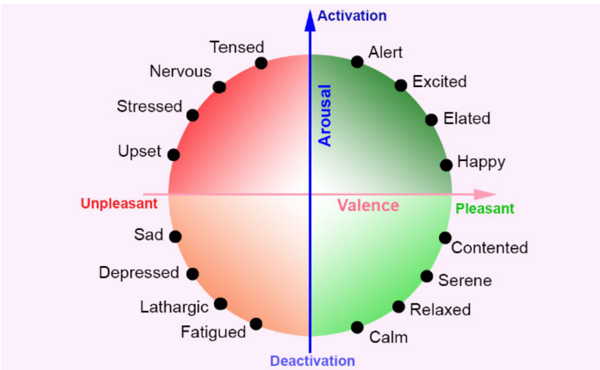


FIGURE 4. The 2D model of emotion consists of the dimensions named valence and arousal.

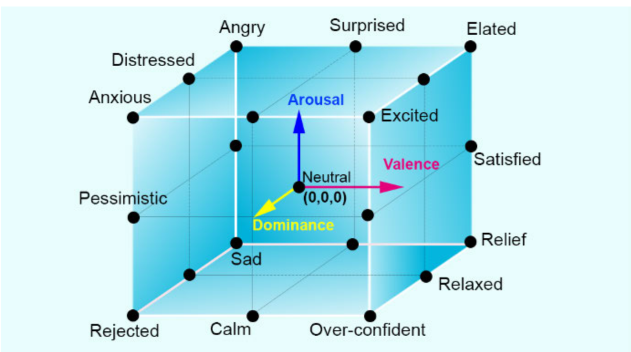


FIGURE 5. The 3D model of emotion consists of the dimensions named valence, arousal and dominance.

Fig. 4. On the contrary, the 3D model, shown in Fig. 5, deals with valence, arousal, and dominance. The term 'Valence' indicates the level of pleasure, whereas the 'Arousal' and the 'Dominance' indicate the level of excitation and the controlling/dominating nature of emotion, respectively.

B. ELECTROENCEPHALOGRAM (EEG)

The Electroencephalogram is a waveform recording system that records the brain electrical activity from the scalp of humans over a period of time. It measures the fluctuation of voltage (in the range of microvolt) generated from the ionic current flowing through the brain's neurons [46]. For

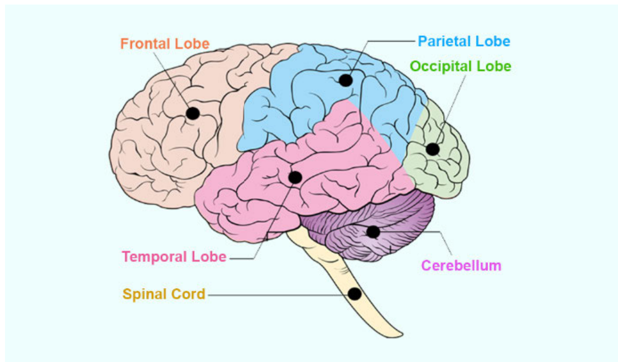


FIGURE 6. The main parts of the human brain indicate the Frontal, Parietal, Temporal and Occipital lobe. Accessed on: Jan. 27, 2021. [Online]. Available at: https://www.albert.io/blog/ultimate-brain-guide-for-ap-psychology/.

recording proper and significant EEG data, one has to know about the brain anatomy of humans. The brain that is considered as the core of the Central Nervous System (CNS), consists of three integral parts: *cerebrum, cerebellum,* and *brainstem*. Among the three, the cerebrum is the largest and composed of the right and left hemispheres. However, the cerebrum hemisphere is also composed of four different lobes, namely frontal, parietal, temporal, and occipital, as shown in Fig. 6. EEG signals can be treated as a composition of 5 sub-bands signals, namely delta, theta, alpha, beta, and gamma [47], [48], where every sub-band is linked with various mental states and conditions. The name and corresponding location, frequency range, and brain activity of different sub-bands are shown in Table 2.

C. EEG DATA ACQUISITION TECHNIQUES

For recording EEG data, some standard acquisition systems are Biosemi ActiveTwo [43], [55], Emotiv Epoc+ headset [56]–[58], Brain Vision LLC, EEG module of Neuroscan, Mobita 32-channel wireless EEG system, etc. Among these, the Biosemi ActiveTwo system is more familiar and quite popular. Moreover, in about 16.1% of the cases, the Emotiv Epoc+ headset is used for data acquisition [59] as it is wearable, portable, wireless, and of low cost, which makes it attractive to practitioners recently.

TABLE 2. Relationship of mental state and activity with EEG sub-bands and the different lobe of the human brain.

Sub-bands	Range of frequency	Location on brain	Mental state and activity
Delta wave	(0-4) Hz	Frontal	Deep Sleep, Unconscious, Continuous attention (for babies)
Theta wave	(4-12) Hz	Midline, Temporal	Drowsiness, Imaginary, Enthusiastic, Fantasy
Alpha wave	(8-12) Hz	Frontal, Occipital	Closing the eye, Relaxed, Calm
Beta Wave	(12-30) Hz	Frontal, symmetrically distributed on both sides	Calm to intense to stressed, Aware of surroundings, Anxious, Thinking, Start to alert
Gamma Wave	>30 Hz	Frontal, Central, Somatosensory cortex	Cross-modal sensory processing, Alertness, Agitation, Short term memory for matching objects
Mu Wave	(8-10) Hz	Sensorimotor cortex	Rest state motor neuron indication

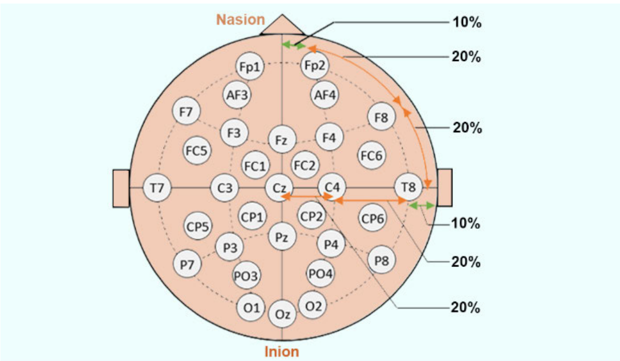


FIGURE 7. The top view of the human head where electrodes are placed by following the international 10/20 electrode placement system. The reason for naming 10/20 is also provided with a clear indication.

The process of EEG data acquisition is characterized by several varying factors, i.e. the number of electrodes (i.e. channels), electrode placement system on the scalp, types of stimuli, frequency of recording, and the device of signal acquisition. The International 10/20 electrode placement system is very commonly practiced for emotion recognition, as shown in Fig. 7. Emotional photos [60], audio [61]–[63], video [57], [64], audio-visual film clips [43], [58], [65]–[67], or any other emotional task or event [68] are used as stimuli during the recording of the EEG signal. Audio-visual film or movie clips are the best choices as stimuli for emotion-related study.

D. SOFTWARE FOR EEG SIGNAL ANALYSIS

Researches-based on the EEG signal is becoming more attractive day by day. However, a beginner-level researcher has to spend much effort in finding the EEG signal analyzing software packages or tools. Therefore a list of several well-known software packages or tools is provided in the following Table 3.

TABLE 3. List of popular software/toolbox for EEG signal analysis, (major part was adopted from iMotions).

Name of the software	Additional Information
BESA Research	BESA GmbH
BIOPAC ACQKnowledge	BIOPAC Inc.
Brainstorm	University of Southern California, Los Angeles, CA
BrainVision analyzer	Brain Products GmbH
BrainVoyager	Brain Innovation B.V.
Cartool Software	Biomedical Imaging Center Lausanne, Geneve.
Curry 7	Compumedics Limited
EEGLAB	Swartz Center for Computational Neuroscience, UCSD
LORETA	A key Institute of Brain-Min Research, Zurich
MATLAB	A platform of programming and numeric computing
Anaconda	Distribution of programming languages for scientific computing
FieldTrip	A MATLAB software toolbox for MEG, EEG and iEEG analysis, Radboud University
SPM12	An academic software toolkit for the analysis of functional imaging data

III. GENERAL FRAMEWORK FOR EMOTION RECOGNITION

This section demonstrates the overall architecture of emotion recognition from the EEG signal, which comprises the processes of data management, preprocessing, feature extraction, feature selection, and classification algorithms, etc. These processes are depicted in a step-by-step manner in Fig. 8.

Within our selected 41 articles, in 85% of articles (35/41), the publicly open dataset was used, and in the rest 15% of articles (6/41), the self-generated dataset was used. Among the 85% articles conducted by publicly open dataset, 61%, 7%, 2%, and 15% of the articles used DEAP, SEED, MAHNOB and other datasets, respectively. For feature, 25% of papers (10/41) used time-domain feature, 51% papers (21/41) used frequency-domain feature, 10% papers (4/41) used time-frequency domain feature, and other features were used in the rest 14% papers (6/41). Sometimes both features are used by the same scholar; however, only the leading features were considered for statistics.

To extract the feature, the Short-Time Fourier Transform (STFT) was used in 5 works, and the wavelet transform, Discrete Cosine Transform (DCT), Higher-Order Crossing (HOC), Hilbert-Huang Transform (HHT), and other methods were used on 2, 1, 3, 2, 6 papers respectively. Some authors

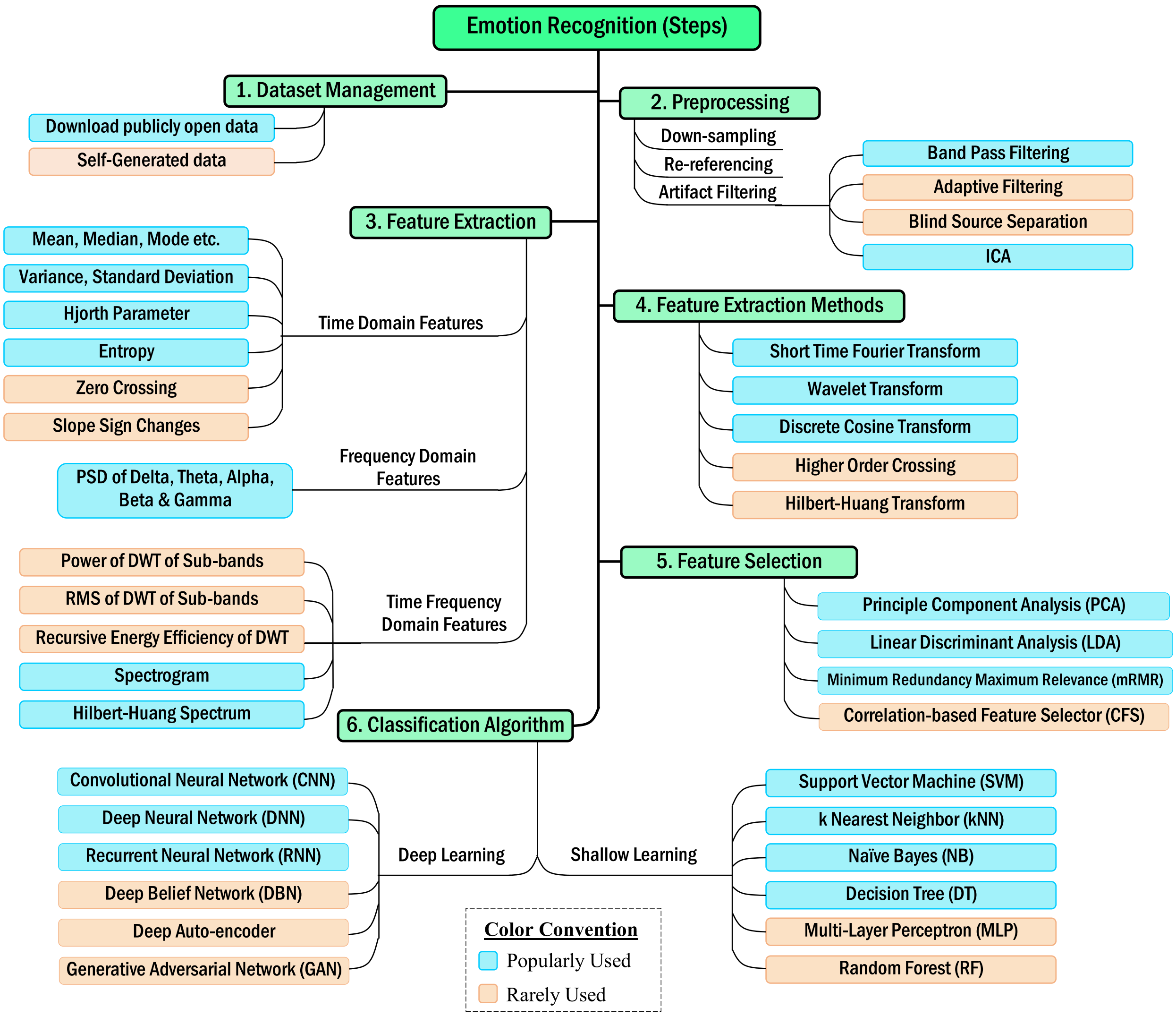


FIGURE 8. Emotion recognition procedure showing step by step. Each step consists of the relevant options or examples or methods. Popularly used options and rarely used options are represented by using two different colors.

used a simple calculation or did not specify properly. Lastly, 44% of the authors (18/41) used deep learning, and 56% of the authors (23/41) used shallow learning techniques as a classification algorithm. Within the 44% deep learning classifier; the CNN, DNN, DBN, and others were used on 24%, 5%, 3%, and 12% works respectively. Among the 56% shallow learning classifier; the SVM, kNN, DT, MPL and others were used on 34%, 7%, 3%, 2%, and 10% works correspondingly. The round figure of percentages of different categories and subcategories was presented clearly by multilevel pie charts of Fig. 9.

A. EEG DATASET MANAGEMENT

Human emotion can be extracted in the following two ways:

(i) with the help of stimuli like images, audio, video, audio-visual, tactile, odor, etc., and (ii) subjects are asked about any past emotional state or event of life they faced. Recently, most of the researchers are using the first way. Inside the first method, about 26% used the images as stimuli, 23.8% used video, 17.5% used audio, 22.2% used the existing dataset that consists of a combination of physiological and emotional data [59]. The rest of the 10.5% works exploited the emotional data related to emotional games, or live performances, or life events.

For emotion recognition, the first requirement is to collect or record the EEG data. Whenever some research is conducted using the same raw data, then the research's performance or accuracy can be compared. As a result, some scholars built research-level data and made those available for all without any cost. Among them, some common and popular datasets are enlisted in Table 4.

B. PREPROCESSING

Preprocessing occurs between the data collection and analysis by performing transformations and/or reorganizing the EEG data. Preprocessing of EEG can be done without

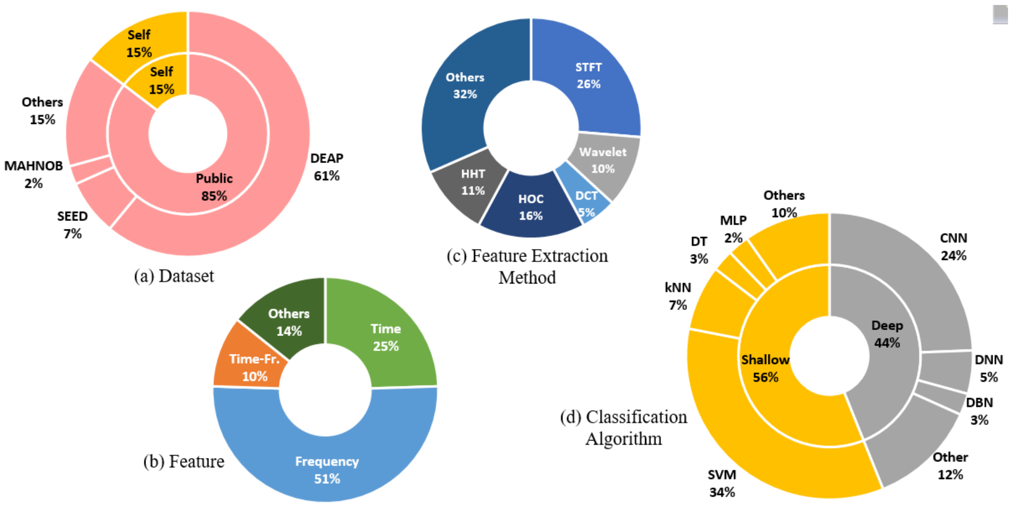


FIGURE 9. The percentage of different categories and subcategories of the dataset, feature, feature extraction method, and classification algorithm appeared in our analyzed 41 articles.

changing any data if the data is only organized or extracting a portion of the data for further analysis. Removal of bad channels, another form of preprocessing step, is done based on visual inspection of artifacts in EEG. Some other widely used preprocessing methods, namely spatial transformations and temporal filtering, are as follows:

1) DOWN-SAMPLING

By down-sampling, the size of the EEG data may be reduced [69], [70]. For example, in the DEAP dataset [43], EEG data is firstly recorded at 512 Hz; later, it is down-sampled at 128 Hz. For multiple time processing, storing, or wireless transmission, the reduced-size data by down-sampling is preferable.

2) RE-REFERENCING

The EEG electrode voltage is relative to the other one electrode or the average of some electrodes. By changing the reference, the EEG signal shape will be varied [71]. Therefore, it is important to re-referencing when initial data is not recorded following proper reference. The mastoid, Cz, an average of two earlobes, or an average of all electrodes, etc., are some common choices for referencing.

3) ARTIFACTS FILTERING

Generally, raw EEG signals are disturbed by two types of artifacts, such as internal artifacts and external artifacts. Eye blinking, eyeball movement, facial muscle movement, heart pumping, respiration, etc., are categorized as internal artifacts. On the other hand, external artifacts include cable frequency, head movement, electrode displacement, etc. In the frequency perspective, the noise by power line frequency may be 50 Hz or 60 Hz, the noise generated by muscle movement is higher than 40 Hz, and the noise caused by the rest of the internal artifacts is below 4Hz.

a: BANDPASS FILTERING

The artifacts that have the frequency out of the range of the selected frequency of the original EEG signal can be removed by using a proper bandpass filter. The human eye blink after (2-10) seconds interval, which means a frequency ranges of (0.5-0.1) Hz. A normal adult's heartbeat ranges from 60-100 beats per minute (1-1.67) Hz. The normal range of respiration rate is 12-20 breaths per minute that indicate the frequency range (0.2-0.33) Hz. However, the artifacts generated by just the facial muscle movement or EOG cover the frequency range from (0-200) Hz and mainly affect EEG up to 20 Hz. As a result, it is clear that except for the EOG artifact, all the internal type artifacts can be removed by using the bandpass filtering technique. The different researchers [69], [73] used a different range of bandpass filters, and among them, (4-45) Hz is predominantly used. The range (1-100) Hz is used moderately, and ranges like (8-30) Hz, (4-45) Hz, (2-42) Hz, (2-50) Hz, etc., are applied rarely.

b: ADAPTIVE FILTERING

As EOG (0Hz-200Hz) is not out of the range of actual EEG (4Hz-45Hz) signal, some researchers [74]–[76] used to apply adaptive filtering to remove this type of artifacts. However, to apply adaptive filtering, additional EOG recording is required. Normally an adaptive filter takes both EEG (with artifacts like EOG) and EOG as input and then calculates the original frequency of the EOG artifact to subtract the artifact from the raw EEG signal [76]. Some scholars use the notch filter mainly at 50Hz and 60 Hz.

c: BLIND SOURCE SEPARATION

The Blind Source Separation algorithm is used to remove the artifacts and to extract the original neural signals from raw EEG data [77]. The algorithm includes Independent

TABLE 4. Publicly available datasets for Emotion Recognition in descending chronological order (2020-2007).

Dataset	Year	Stimuli	Number of Subjects (M/F)	Age Range	EEG Acquisition Device	Rating Scale	Recorded Signals	Annotation
GAMEEMO [56]	2020	Video by emotional Game	28	20-27	14 channel Emotiv EPOC+	Arousal and valence (funny, boring, horror and calm)	EEG	Data for 4 different emotional states during 5 minutes of playing the emotional game.
K-EmoCon [64]	2020	Video footage of the debate	32 (20/12)	19-36	NeuroSky Mind Wave Headset	Valence, arousal and (cheerful, happy, angry, nervous, sad)	Videos (face, gesture), Speech audio, accelerometer, biosignals (EEG, ECG, BVP, EDA, skin temp.)	Multi-perspective emotional data through social interaction based on valence and arousal value during the time of showing video footage of debates on social issues.
SEED [65]	2017	Audiovisual (film clips)	15 (7/8)	N/A	N/A	Positive, negative and neutral	EEG	A dataset collection for various purposes using EEG signals
AMIGOS [57]	2017	Video	40 (27/13)	21-40	Emotiv EPOC neu-roheadset	Valence and arousal	EEG, ECG, and GSR	Multimodal Dataset for Affect, Personality and Mood
ASCERTAIN [66]	2016	Video (36 movie clips)	58 (37/21)	Mean 30	Dry electrode EEG device	Arousal, valence, engagement, liking, familiarity	ECG, GSR, frontal EEG, facial features	First database to connect personality traits and emotional states via physiological responses
DREAMER [58]	2015	Audiovisual (movie clips)	25 (14/11)	22-33	Emotiv EPOC EEG headset, SHIMMER ECG sensor	Valence, arousal, dominance	14 channel 128 Hz EEG, 256 Hz ECG	Wireless Low-cost EEG and ECG dataset
CREMA-D [72]	2014	Audiovisual	91 (48/43)	20-74	N/A*	Happy, sad, anger, fear, disgust, and neutral	N/A*	Consists of facial and vocal emotional expression in sentences spoken
DEAP [43]	2012	Video	32 (16/16)	19-37	Biosemi ActiveTwo	Valence, arousal, dominance, liking, familiarity	32 channel 512 Hz EEG; physiological signals; face video (no. 22)	A multimodal dataset consists of EEG and peripheral physiological signal
Belfast Database [68]	2012	Laboratory-based emotion induction tasks	Set 1: 114 (70/44) ; Set 2: 82 (37/45); Set 3: 60 (30/30)	N/A	N/A*	Frustration, disgust, fear, surprise, amusement, anger, sadness	Emotion*	Dataset to recognize emotion from facial and vocal signals regarding the emotional task.
MAHNOB-HCI [55]	2011	Video, image	27 (11/16)	19-40	Biosemi ActiveTwo	Emotional keyword, arousal, valence, dominance, predictability	EEG (32 channels), ECG, peripheral physiological signal, face and body video, eye gaze, audio	A multimodal database where eye gaze, video, audio peripheral, and physiological signals are synchronized.
IAPS [60]	2008	Color photos	N/A	N/A	N/A*	Pleasure, arousal, dominance	N/A*	Provides emotional stimuli for emotion and attention
IADS [61]	2007	Sound	N/A	N/A	N/A*	Pleasure, arousal, dominance	N/A*	Provides ratings for acoustic stimuli

*These datasets do not directly record the EEG signal. Rather, they store the audio, visual or audio-visual elements that can create different emotions in the human brain. N/A = Not Appropriately defined.

TABLE 5. Various explored features of the EEG signal.

Domain	Features	Pros and Cons
Time domain	Maximum, minimum, mean, median, mode, Root Mean Square, variance, standard deviation, skewness, kurtosis, first difference, normalized first difference, Hjorth index (activity, mobility, complexity), non-stationary index, entropy, Higher-Order Crossing (HOC), Slope Sign Changes (SSC), Zero Crossing (ZC), Waveform Length (WL)	The time domain features are sensitive for a time but not worked accurately in an anti-noise platform. EEG is a non-stationary type signal, so time domain features are not so meaningful. So, the performance of time domain features is not satisfactory at all.
Frequency domain	Band power of Power Spectral Density of EEG subbands (delta, theta, alpha, beta, gamma)	The main advantage of the frequency domain is that it has comparatively high anti-noise ability. In addition, the computational complexity is comparatively higher and not cost-effective.
Time-frequency domain	Power of DWT of sub-bands, RMS of DWT of subbands, the recursive energy efficiency of DWT, spectrogram, Hilbert-Huang Spectrum	Frequency domain features have comparatively good performance in anti-noise ability, but joint time-frequency domain features perform more than this.

Component Analysis (ICA), Algorithms for Multiple Unknown Signals extraction (AMUSE), Second-Order Blind Identification (SOBI), Joint Approximate Diagonalizations of Eigenmatrices (JADE), etc. These techniques are used to remove internal and external artifacts from the EEG signal

d: INDEPENDENT COMPONENT ANALYSIS

The ICA technique extracts the statistically independent components of a mixed-signal like raw EEG [70], [71]. From these several independent components, the artifact-relevant components are eliminated and again remixed the other components to achieve original data. As ICA normally considers that the raw EEG signal is a combination of sources that are less than or equal to the number of the channel connected, it can only separate those number of sources. The fast ICA [78] algorithm is commonly used to artifact removal to increase the signal-to-noise ratio [79], [80].

C. FEATURE EXTRACTION

The most fundamental and challenging task to recognize human emotion is to find out the most relevant features that vary with the changes of emotional state. Features can be primarily categorized as time domain, frequency domain, and time-frequency domain features. These types of features and their advantages and disadvantages are expressed briefly in Table 5. In emotion recognition, the extracted features for shallow and deep learning-based emotion recognition methods are summarized in Tables 7 and 8 respectively.

1) TIME DOMAIN FEATURES

Time domain features include statistical features such as mean, median, standard deviation, mode, variance, minimum, maximum, etc. A few researchers [1], [37] used these features along with other features or feature sets.

2) FREQUENCY DOMAIN FEATURES

The frequency domain feature contains more relevant information for this type of signal. In the frequency domain, the popular methods are Power Spectral Density (PSD), Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT) [81], [82], etc. In emotion recognition, the spectrum analysis is also a popular analysis using Fourier transform [83]. Some scholars tried to classify emotion using the Eigenvector method, which is suitable for transient and stationary signals [84]. A few types of research [85], [86] are also available, which covers the autoregressive model, which gives good frequency resolution, but spectral estimation is difficult. The autoregressive analysis is perfect for this type of signal which has sharp spectral features [84].

3) TIME-FREQUENCY DOMAIN FEATURES

According to the research in [84], the Fast Fourier Transform and Auto-Regressive model fall victim to slow computing and inability to analyze the non-stationary type signal. The joint time-frequency domain consists of the wavelet transform [87], [88]. Basically, EEG is a signal whose type is non-stationary and non-linear. The analysis of this type of signal is challenging and complicated. Recently, the wavelet transform has become a very popular method of analysis due to its good performance both in the time and frequency domain [88]. Wavelet transform can be classified into two types: (i) Continuous Wavelet Transform [89], and (ii) Discrete Wavelet Transform.

The mathematical expressions of some common features are shown in Table 6.

D. FEATURES AND FEATURE EXTRACTION METHODS

Numerous methods can extract the different features of the EEG signal. Some important methods of feature extraction along with parameters are illustrated here briefly with mathematical expression if necessary.

1) SHORT TIME FOURIER TRANSFORM (STFT)

The time domain EEG can be easily transmitted into the frequency domain using the Fourier transform. Numerous scholars [82], [90]–[92] used this method to extract EEG features. To evaluate the Power Spectral Density feature (PSD) feature the Short-Time Fourier Transform (STFT) method

TABLE 6. The mathematical expression of some popularly used features for emotion recognition.

Feature Name	Mathematical Expression	Comments
Mean	$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$	$X(n)=\{x_1, x_2, \ldots, x_n\}$ and μ_x= arithmetic mean value.
Mean of the absolute value of 1st difference	$\delta_x = \frac{1}{N-1}\sum_{i=1}^{N}\lvert x_{i+1}-x_i\rvert \quad (2)$	$X(n)=\{x_1, x_2, \ldots, x_n\}$ and δ_x= mean of the absolute value of 1st difference
Mean of the absolute value of 1st difference of standardized signal	$\bar{\delta}_x = \frac{1}{N-1}\sum_{i=1}^{N}\lvert \bar{x}_{i+1}-\bar{x}_i\rvert = \frac{\delta_x}{\sigma_x} \quad (3)$ Where $\bar{X}(n) = \frac{X(n)-\mu_x}{\sigma_x}$	$\bar{X}(n) = \{\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n\}$ is the standardized signal.
Mean of the absolute value of 2nd difference	$\gamma_x = \frac{1}{N-2}\sum_{i=1}^{N}\lvert x_{i+2}-x_i\rvert \quad (4)$	$X(n)=\{x_1, x_2, \ldots, x_n\}$ and γ_x= mean of the absolute value of 2nd difference
Mean of the absolute value of 2nd difference of standardized signal	$\bar{\gamma}_x = \frac{1}{N-2}\sum_{i=1}^{N}\lvert \bar{x}_{i+2}-\bar{x}_i\rvert \quad (5)$	$X(n)=\{x_1, x_2, \ldots, x_n\}$ and $\bar{\gamma}_x$= mean of the absolute value of 2nd difference of standardized signal.
Median	$m_{(N\to odd)} = x_{ord}\left(\frac{N+1}{2}\right) \quad (6)$ $m_{(N\to even)} = \frac{1}{2}\left[x_{ord}\left(\frac{N}{2}\right) + x_{ord}\left(\frac{N}{2}+1\right)\right] \quad (7)$	x_{ord} = ordered dataset of $x(n)$, where data are arranged by following the order from low value to high value.
Mode	-	Most frequent value of a dataset
Standard Deviation	$\sigma_x = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu_x)^2} \quad (8)$	Standard deviation (σ_x) indicates the data distribution from its mean value. Here, the denominator is N, not $N-1$; as the signal has a discrete random value of the same probability.
Variance	$\sigma_x^{\,2} = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu_x)^2$	The Square of standard deviation is variance. For time-series signal it represents the average power.
Power Spectral Density (PSD)	$P(f) = \left\lvert \int_{-\infty}^{+\infty} x(\tau)e^{-j2\pi f\tau}\,d\tau \right\rvert^2 \quad (9)$	PSD is the average energy of different frequency bands. Here $P(f)$ = Energy of frequency band. The logarithm of PSD can be used as a feature for emotion recognition.
Power	$P = \sum \frac{X^2}{L(x)} \quad (10)$	The strength of a signal can be measured by power. To calculate power Fast Fourier Transform is used.
Wavelet Energy	$E(l) = \sum_n \lvert C_l[n]\rvert^2 \quad (11)$	Here, $E(l)$=wavelet energy at level l, $C_l[n]$=wavelet coefficient at level l.
Relative Wavelet Energy	$p(l) = \frac{E(l)}{\sum_{m=1}^{M} E(m)} \quad (12)$	$p(l)$=relative wavelet energy at level l, m=number of the wavelet decomposition.
Wavelet Entropy	$T(l) = -\frac{E(l)}{\sum_{m=1}^{M} E(m)} \log\left(\frac{E(l)}{\sum_{m=1}^{M} E(m)}\right) \quad (13)$	Entropy is the indication of the measure of asymmetric, unbalance, and uncertainty.
Skewness	$b_1 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^3}{\sqrt[3]{\frac{1}{n-1}\sum_{i=1}(x_i-\bar{x})^2}} \quad (14)$	Skewness is the measure of the asymmetry of the probability distribution of a random variable.
Kurtosis	$g_2 = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right]^2} - 3 \quad (15)$	Kurtosis is the measure of tiredness of the probability distribution of a random variable.
Relative Entropy	$d_{pq} = \sum_k p_k \log_2\left(\frac{p_k}{q_k}\right) \quad (16)$	Here, p_k=probability function of discrete distribution, q_k=probability function of 2nd discrete distribution, d_{pq}= relative entropy of p concerning q.

can be used. By using the popular STFT, a window can be slid along the time series data to perform Discrete Fourier Transform (DFT) on a certain time segment. The Fast Fourier Transform (FFT) algorithm computes the DFT of a sequence by the following formula,

$$X_k = \sum_{n=0}^{N-1} x_n e^{-2jnk/N}, \ where\ k = 0, \ldots\ldots N-1 \quad (17)$$

where $x_0, x_1, \ldots, x_{N-1}$ are the complex numbers and $e^{i2\pi/N}$ is a primitive N^{th} root of *1*.

It may be noted that FFT is an algorithm to perform DFT, on the other hand, STFT is a method of sliding window on time series data to perform DFT on that data. The STFT can be expressed mathematically as

$$X_{STFT} = \int [x(t)w^*(t-f)e^{-j2\pi ft}]dt \quad (18)$$

where $w(t)$ is the window function.

2) DISCRETE COSINE TRANSFORM (DCT)

The Discrete Cosine Transform (DCT) converts a time domain signal into basic frequency components [93], [94]. The output of DCT of an N point time domain signal consists of N number coefficients where the low-frequency components are concentrated on the left, and the components of high frequency are on the right side.

As the coefficients for high-frequency components are close to zero by ignoring these, only the first few coefficients are considered as EEG features for emotion recognition. Thus DCT enables us to compress data, remove the necessity of high-frequency filtering, and reduce the computational complexity in terms of time and space during the classification algorithm. The DCT coefficients of an N point EEG data can be calculated by the following formula.

$$Y(u) = \sqrt{\frac{2}{N}}\alpha(u)\sum_{x=0}^{N-1} f(x)\cos\left[\frac{\pi(2x+1)}{2N}\right] \quad (19)$$

where $u = 0, 1, \ldots, N\text{-}1$ and $\alpha(u) = [1/\sqrt{2}$ (when $u = 0$); 1 (when $u \neq 0$)]

3) WAVELET TRANSFORM (WT)

For a non-stationary signal like EEG, wavelet transform is the most suitable method for extracting the features. Wavelet transform provides more accurate frequency information at low frequencies and more accurate time information at high frequencies. It generates a multi-resolution time-frequency plane by the successful transmission of a signal through a low pass and high pass filter [95], [96]. There remain two types of wavelet transform: (i) Continuous Wavelet Transform (CWT), and (ii) Discrete Wavelet Transform (DWT).

In the field of emotion recognition from EEG, the DWT is popularly used. The DWT is used to remove noise and to decompose the EEG signal into sub-bands signals such as delta, theta, alpha, beta, and gamma. Using DWT, the main EEG signal can be split into approximate coefficients and detail coefficients. A time domain signal can be decomposed by using DWT by following the formula.

$$\gamma(t) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{2^a}}\psi\left(\frac{t-b\times 2^a}{2^a}\right)dt \quad (20)$$

where, $\Upsilon(t)$ = DWT of any time-domain signal $x(t)$; $\psi(t)$ = mother wavelet, a and b are the scale parameter and shift parameter respectfully;

The approximate and detail coefficients can also be calculated by following formulas

$$x_{app} = \sum_{k=-\infty}^{\infty} x[b]g[2n-b] \quad (21)$$

$$x_{\det} = \sum_{k=-\infty}^{\infty} x[b]h[2n-b] \quad (22)$$

4) HIGHER-ORDER CROSSING (HOC)

Higher-Order Crossing consists of the number of zero-crossing of a finite zero means time-series data. 'How many times does a signal cross the zero level?' this has to be calculated for extracting HOC. When a filter is applied to a time-series signal, the number of zero-crossing changed. Consequently, for a set of filters applied, a set of numbers can be generated. This is called the HOC sequence for the set of filters. Different types of HOC sequences can be calculated by appropriate filter design, and this HOC is used to generate a feature vector [37], [121], [125], [127], [128]. Later the features can be used for the classification of emotion from EEG. The HOC feature vector can be calculated by the following equation for a specific value of k,

$$D_k = NZC\{\Im_k(Z_t)\}; \quad k = 1,2,3,\ldots; \ t = 1,\ldots,T \quad (23)$$

where, NZC is for the estimation of the Number of Zero Crossing.

$$\nabla Z_t \equiv Z_t - Z_{t-1} \quad (24)$$

$$\Im_k \equiv \nabla^{k-1}; \quad k = 1,2,3\ldots \quad (25)$$

Here, Z_t represents finite zero means series data, ∇ is the high pass filter, and $\Im_k$ is the sequence of high pass filter.

5) HJORTH PARAMETER

The Hjorth parameters, introduced by Bo Hjorth in 1970, indicate the statistical properties and are popularly used to extract features from the EEG signal [5], [10], [122]. The parameters include activity, mobility and complexity. For a time domain EEG signal x(t) the parameters can be calculated by the following formulas

$$\text{Activity},\ A = \text{var}(x(t)) = \frac{1}{N}\sum_{n=1}^{N}[x(t)-\mu_x]^2 \quad (26)$$

$$\text{Mobility}\ M = \sqrt{\frac{\text{var}(\frac{d(x(t))}{dt})}{\text{var}(x(t))}} \quad (27)$$

TABLE 7. Features and features extraction techniques of deep learning-based emotion recognition systems.

Author, Year	Features	Feature Extraction Techniques
Liu et al., 2020 [97]	Dynamic Differential Entropy (DDE)	-
Cimtay and Ekmekcioglu, 2020 [98]	Raw EEG data	Windowing, pre-adjustments, and normalization
Khare and Bajaj, 2020 [99]	2D images from 1D EEG	Pseudo Wigner–Ville distribution
Wang et al., 2020 [100]	Electrode-Frequency Distribution Maps (EFDMs)	Residual block-based deep Convolutional Neural Network (CNN)
Cui et al., 2020 [101]	Temporal feature, regional feature, asymmetric feature	N/A
Hassan et al., 2019 [33]	Electro-Dermal Activity (EDA), Photoplethysmogram (PPG) and Zygomaticus Electromyography (zEMG)	-
Islam and Ahmad, 2019 [102]	Pearson's Correlation Coefficients (PCC)	-
Pandey and Seeja, 2019 [103]	Peak value of Power Spectral Density (PSD) and the first difference of Intrinsic Mode Functions (IMF) signal	Variational Mode Decomposition (VMD)
Chen et al., 2019 [29]	Power Spectral Density (PSD)	Fast Fourier algorithm
Yang et al., 2019 [104]	Deep neural network-based feature	-
Chao et al., 2019 [105]	Multiband Feature Matrix (MFM) with frequency domain	-
Moon et al., 2018 [106]	Power Spectral Density (PSD), Pearson's Correlation Coefficients (PCC), phase-locking value (PLV), and Phase Lag Index (PLI)	Welch's method for Power Spectral Density (PSD)
Li et al., 2018 [90]	Differential Entropy (DE)	Short-Time Fourier Transform (STFT)
Yang et al., 2018 [107]	Spatial and temporal feature vectors	Convolutional Neural Network (CNN) (for spatial feature vector), Recurrent Neural Network (RNN) (for temporal feature vector)
Mehmood et al., 2017 [10]	Hjorth parameter	-
Alhagry et al., 2017 [31]	Raw EEG signal	Long Short-Term Memory (LSTM) recurrent neural network
Liu et al., 2016 [108]	Power Spectral Density (PSD) and Differential Entropy (DE)	-
Zheng and Lu, 2015 [91]	Differential Entropy (DE)	Short-Time Fourier Transform (STFT) with a non-overlapped Hanning window

Note: N/A = Not appropriately defined; hyphen sign (-) indicates no addition/remarkable technique is needed for feature extraction.

$$\text{Complexity},\ C = \frac{Mobility(\frac{d(x(t))}{dt})}{Mobility(x(t))} \tag{28}$$

The activity, mobility, and complexity represent the signal power, mean frequency, and frequency change, respectively. Autoregression [129]–[131], PCA [132], [133], ICA, etc. methods are also used for extracting a feature from the EEG signal to recognize emotion. However, as these are rarely used and as we want to optimize the length of the article, these are not described here. No one fixed feature or feature set can be treated as the best feature considering all perspectives. Therefore many researchers tried to find out the superior features that are more related to emotion recognition. In Table 7, the summary of extracted features and corresponding feature extraction methods is presented using various deep learning-based emotion recognition methods. The features and feature extraction methods of shallow machine learning-based emotion recognition systems are demonstrated in Table 8.

The Power Spectral Density (PSD) [29], [39], [105], [108], [110], [116], [118] and Differential Entropy (DE) [93], [99], [110], [116], [117] features were applied commonly among the reviewed emotion recognition works. Many researchers used statistical features [94], [122], [126], [129]. Menezes *et al.*, 2017 [121] and Lan *et al.*, 2016 [125] used the HOC feature. Zhong *et al.*, 2020 [110] used the sparse adjacency matrix. The author Cui *et al.*, 2020 used temporal, regional and asymmetric features [101]. Mehmood *et al.*, 2017 [10] and Atkinson and Campos, 2016 [124] used the Hjorth parameter. Pearson's Correlation Coefficients (PCC) is used by some scholars [102], [106]. Cimtay and Ekmekcioglu, 2020 used Raw EEG data as feature [98]. These applied techniques are illustrated in Table 7 and 8; later, their performances based on accuracy along with other factors are shown in Table 10 and 11. It may be noted that there is no exact single solution of the question: which feature is best fitted for emotion recognition from EEG? The best feature of one system may not be best for another as it varies upon some factors like the number of classified emotions, the number of channels, type of dataset, level of complexity, choice of algorithm, the model of emotion, etc.

E. FEATURE SELECTION

Feature selection methods aim to generate a subset of features that consist of a reduced number of highly significant features. They help to extract the appropriate features that have a deep relationship between the input variable to the target variable. Based on the procedure of the combination of selection algorithm, features selection methods are mainly three

TABLE 8. Features and features extraction techniques of shallow learning-based emotion recognition systems.

Author, Year	Features	Feature Extraction Techniques
Soroush et al., 2020 [109]	Numbers of intersections of Poincare Planes (PPs)	Phase Space (PS) and Angle space (AS)
Zhong et al., 2020 [110]	Sparse adjacency matrix	Graph analysis
Vijayakumar et al., 2020 [111]	Covariance matrix and eigenvectors	Principle Component Analysis (PCA)
Qing et al., 2019 [112]	Correlation coefficients and entropy coefficients	-
Islam and Ahmad, 2019 [87]	Wavelet energy, wavelet entropy	Discrete Wavelet Transform (DWT)
Li et al., 2019 [113]	Feature sets from activation, connection, and fusion patterns	Optimal feature groups by F-score
Yang et al., 2018 [114]	Differential Entropy (DE), Power Spectral Density (PSD), Differential Asymmetry (DASM), Rational Asymmetry (RASM), Differential Causality (DCAU)	-
Zhuang et al., 2018 [115]	Differential Entropy (DE), the first difference of Intrinsic Mode Functions (IMFs)	Differential Entropy (DE) based on Short-time Fourier Transform (STFT) and first difference of Intrinsic Mode Functions (IMFs) based on Empirical Mode Decomposition (EMD); Minimum Redundancy Maximum Relevance (mRMR) algorithm for dimensionality reduction
Li et al., 2018 [116]	Time and frequency domain features (mean, variance, Hjorth parameter, power spectral density, etc.) and non-linear dynamical system features (approximate entropy, correlation, Lyapunov exponent, etc.)	Sliding window-based method
Li et al., 2018 [38]	Entropy and energy	Discrete Wavelet Transform (DWT)
Alazrai et al., 2018 [117]	Time-frequency domain features	Quadratic Time-Frequency Distribution (QTFD)
Degirmenci et al., 2018 [5]	Intrinsic Mode Functions (IMFs)'s power, entropy, correlation, Hjorth parameter, etc.	Multivariate Empirical Mode Decomposition (MEMD)
Luo, 2018 [118]	Differential Entropy (DE)	-
Nakisa et al., 2018 [119]	Time, frequency, and time-frequency domain features	Evolutionary Computation (EC) algorithm for feature selection
Liu et al., 2018 [39]	Power Spectral Density (PSD) and asymmetry features	Short-Time Fourier Transform (STFT)
Zhong and Jianhua, 2017 [120]	Time and frequency domain features	Transfer Recursive Feature Elimination (T-REE)
Menezes et al., 2017 [121]	Statistical features, power band and Higher-Order Crossing (HOC)	-
Ackermann et al., 2016 [92]	Statistical features	Short-time Fourier Transform (STFT), Higher-Order Crossing (HOC) and Hilbert-Huang Spectrum (HHS)
Hu et al., 2016 [122]	Time domain, Hjorth parameters, frequency domain, Approximate Entropy (ApEn), Kolmogorov entropy, largest Lyapunov exponent, spectral entropy, complex, correlation dimension (D2) and Singular Value Decomposition entropy (SVDen)	-
Zhang et al., 2016 [86]	Entropy	-
Kumar et al., 2016 [123]	Entropy, squared entropy, mean-magnitude of bispectrum, 1st order spectral moment, 2nd order spectral moment	Fast Fourier Transform (FFT)
Atkinson and Campos, 2016 [124]	Statistical features (including median, standard deviation, kurtosis coefficient, etc.), band power for different frequencies, Hjorth parameters, and Fractal Dimension (FD) for each channel	Minimum Redundancy Maximum Relevance (mRMR) algorithm for dimensionality reduction
Lan et al., 2016 [125]	Fractal dimension, power, statistical feature, Higher-Order Crossings (HOC)	A Higuchi algorithm [126] was used to compute the FD feature

Note: hyphen sign (-) indicates no addition/remarkable technique is needed for feature extraction.

types, namely filter method, wrapper method, and embedded method. Numerous scholars practiced using different algorithms under these methods. Finding out the proper feature selection algorithm for EEG-based emotion recognition is challenging. However, as in the task of emotion recognition from EEG deals with the numerical input variable and categorical output variable, the correlation-based Analysis of Variance (ANOVA) and Kendall's rank coefficient are commonly used.

Nowadays, many learning algorithms perform feature selection tasks internally. For instance, sparse regression and LASSO use L1 regularization techniques for feature selection. Moreover, the stochastic searching algorithm does the same by finding out global minima. As an updated learning algorithm done the feature selection internally, a few researchers use feature selection algorithm separately for emoting recognition. Some notable feature selection algorithms are the Particle Swarm Optimization

TABLE 9. Short notes including important features of some familiar classifiers used in emotion recognition systems.

Classifier	Short Notes on Classifier
Convolutional Neural Network (CNN)	As emotion recognition is nothing but pattern recognition, CNN is highly preferred in recent years as a classifier. CNN is a deep architecture-based method that automatically extracts the significant features from its training data to classify. It is a feed-forward neural network that can provide state-of-the-art accuracy in classification tasks like emotion recognition.
Recurrent Neural Networks (RNN)	RNN considers the output of the previous step to make a decision for the present state. Unlike a traditional feedforward neural network, RNN learns from the prior input while generating new output. Here different output may appear for the same input based on the previous input in the series.
Support Vector Machine (SVM)	SVM can be used for classification and regression tasks. It finds out the hyperplane that distinctly classifies the data points. The main objective is to discover such a plane that has the maximum distance between the points of both classes. Although designing the perfect kernel is difficult, SVM is highly preferred because of its higher accuracy with less computation. In emotion recognition, more than 55% of the work used the SVM technique as a classifier. The Radial Basis Function (RBF) is popularly used as the kernel. Also, linear, polynomial, Gaussian, and person kernels are used as a kernel of SVM.
k Nearest Neighbor (kNN)	kNN is a simple machine learning algorithm that can be used for classification and regression tasks. Here, "k" is the (generally odd) number of nearest neighbors that acts as the main deciding factor for a new data point. To calculate k, as all the training data is required simultaneously, it requires high memory. The kNN is non-parametric in type. As it has no or a little training phase, it can be considered as a lazy learning algorithm.
Linear Discriminant Analysis (LDA)	LDA is popularly used to reduce the dimensionality of the features. This method generates one or some optimum hyperplane following minimum variance to reduce the dimension for classification. It may be noted that this analysis is also used as a classification algorithm in many works.
Naïve Bayes (NB)	The word 'Naïve' means simple and 'Bayes' comes from the statistician Thomas Bayes (1702-1761). Naïve Bayes algorithm is a probabilistic machine learning technique that is used for classification. The features are considered independent, that is why the presence of one particular feature does not affect the other. For this reason, it is called simple or 'Naive'.
Random Forest (RF)	Random Forest algorithm is rarely used in emotion recognition. It generates decision trees on randomly selected data then gets a prediction from each tree; thus provides the best result through the voting method.

(PSO) [119], [134]–[136], Genetic Algorithm (GA) [137]–[139], Minimum Redundancy Maximum Relevance (mRMR), Ant Colony (AC), Correlation Feature Selection (CFS), Simulated Annealing (SA) algorithm, Sequential Forward Selection (SFS), Welch's t-test, etc.

F. CLASSIFICATION ALGORITHMS

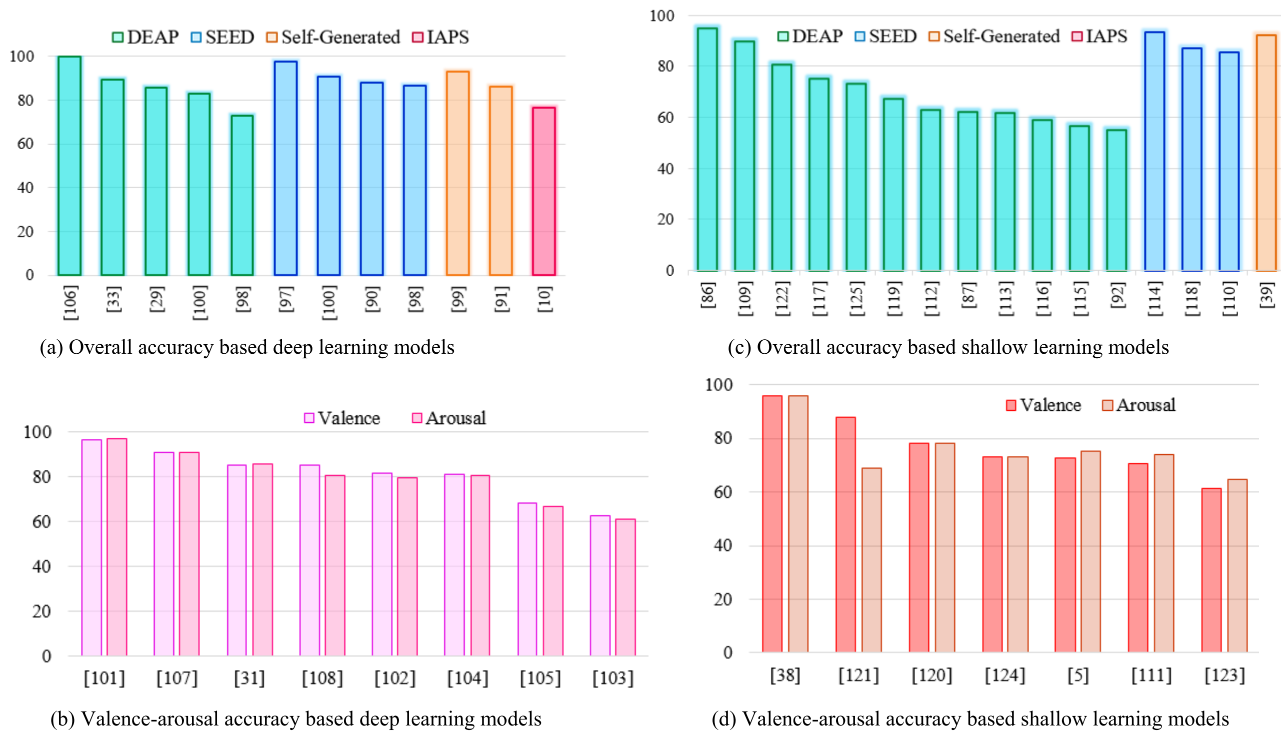
Numerous classification algorithms are being used by many scholars. Among them, some common algorithms are stated with annotation on the following Table 9.

IV. DISCUSSION

Many researchers published review articles on Emotion Recognition using EEG [42], [59], [140], [141]. In [42], the authors reviewed the application and classification of emotion recognition from EEG. Here, the field of application was described elaborately, but there is a lack of information regarding accurate system development, including practical features, feature extraction methods, comparison of performance, etc. In the systematic review of [140], the researchers described feature and classifier-wise advantages, disadvantages, and percentage of articles that used the specific feature, which is good. However, there is no observation and recommendation at a glance that will carry directive information for future researchers. In [141], a VR stimuli-based survey was conducted, whereas in our review, we compared the systems of audio, video, audio-visual, picture type stimuli based emotion recognition systems. In [59], they depicted a descriptive survey, but most articles (above 90%) followed only shallow machine learning-based classifiers. However, we discussed shallow and deep learning-based systems with a proper comparison, including the application of recently developed novel deep learning models. After all, we conducted a review that comprises 12 recent sources of the dataset with eight information features of each, features along with equation, deep and shallow learning methods with a comparison of performance, observation and recommendation table, etc., that gives the latest and valuable information for the future research.

This paper summarizes the performance, methods, and techniques associated with emotion recognition focusing on deep and shallow machine learning-based techniques.

Among many deep machine learning-based reviewed systems, most of the systems are developed either direct CNN based [98]–[100], [102], [106] or by modified CNN based system. The modified CNN methods are like DE-CNN [97], HCNN [90], MC-CNN [104], PCRNN [107], RA-CNN [101]. A few scholars [10], [29], [90], [91] compared the deep machine learning-based system performance with the system based on other classification algorithms like SVM, LR, kNN, etc. Most of the research was conducted by 'DEAP'[12], [29], [31], [33], [102]–[106] some are by 'SEED' [90], [97], [98], [100], [108] and a little is by 'Self-Generated' [91], [99] dataset. A noticeable point is that using the same recognition system with the same number of classified emotions, the accuracy for 'DEAP' data is lower than any other dataset like 'SEED' or 'MAHNOB' of self-generated. It is clear from the data stated Table 10 for authors [98], [100] and from Table 11 for author [112], [113], [116], [119].



(a) Overall accuracy based deep learning models

(b) Valence-arousal accuracy based deep learning models

(c) Overall accuracy based shallow learning models

(d) Valence-arousal accuracy based shallow learning models

FIGURE 10. **The percentage of accuracy of reviewed deep and shallow learning-based emotion recognition systems. Higher accuracy is placed on the left position compared to lower. (a) Overall accuracies of reviewed deep learning-based emotion recognition systems conducted with DEAP, SEED, Self-Generated and IAPS dataset. (b) Accuracies based on valence and arousal classification of reviewed deep learning-based emotion recognition systems conducted with the DEAP dataset. (c) Overall accuracies of reviewed shallow learning-based emotion recognition systems conducted with DEAP, SEED and Self-Generated dataset. (d) Accuracies based on valence and arousal classification of reviewed shallow learning-based emotion recognition systems conducted with the DEAP dataset.**

In emotion recognition, scholars classify emotion either directly or indirectly with the level of valence and arousal. For direct classification, the overall accuracy is achieved and for indirect classification, the accuracy of valence and arousal can be found. The overall accuracy of the various reviewed deep learning-based system is graphically represented in an order of higher accuracy in Fig. 10(a). From the graph, it is clear that the majority of the system[29], [33], [90], [91], [98]–[100], [106] has an accuracy of more than 80%. The highest overall accuracy, 99.72%, is achieved by the scholar [106] that is excellent. Fig. 10(b) shows the accuracy of the indirect emotion recognition system based on the level of valence and arousal. Among the systems [101] achieved the highest accuracies on valence (96.65%) and arousal (97.11%) using the RA-CNN classifier for 2 class classification on the DEAP dataset. On the other hand, a scholar [103] has used the DNN classifier and achieved only 62.5% and 61.25% accuracies on valence and arousal, respectively, which was lowest here. 'Highest accuracy indicates good system and lowers one means system is not so good' this message is true when all the factors of two systems remain equal. In [103], the output class is 4, not 2 like [101]; hence the same category of the system shows lower accuracy for 4 class classification.

The shallow machine learning-based emotion recognition systems and their accuracy with relevant information are represented in the Table 11. From the Table, it is clear that the majority of scholars (65.2% 15 here, out of 23) uses SVM [39], [86], [124], [125], [92], [111], [113], [115]–[118], [121] or modified SVM like LSSVM [120], [123], MCSVM [109] techniques as classifier, etc. Some scholars used the Decision Tree [112], Genetic Algorithms [124], k Nearest Neighbor [38], [87], Multi-Layer Perceptron [109], Probabilistic Neural Network [119], Random Forest [92], regularized Graph Neural Network [110] classification algorithms. The author in [122] used CFS and kNN simultaneously and attained 80.8% accuracy. In [114] a hierarchical network scheme with subnetwork nodes was presented with 93.26% accuracy for positive, negative, and neutral emotion classification. Binary classification is very common. Moreover, some system has three [5], [92], [110], [112], [114], [118], [122], [124]; four [86], [87], [109], [117], [119]; five [110], [117], [124] or even six [115] number of output class. The overall accuracies of shallow machine learning-based reviewed systems are represented in Fig. 10(c). From this figure, it is clear that most of the scholars used the DEAP dataset [5], [38], [123]–[125], [86], [87], [92], [109], [111], [117], [120], [121]. In addition, for SEED [110], [114], [118] and self-generated [39] data, the accuracy is higher compared to DEAP. As accuracy is just a factor for system evaluation, indicates the overall performance

TABLE 10. The percentage of accuracy along with relevant dataset, number of extracted emotions, classifier of different deep learning-based emotion recognition systems sorted by ascending chronological order (2020-2015).

Author, Year	Dataset	Number of Extracted Emotions (Type / Scale)	Classifier	Accuracy (%) Dataset: Accuracy±SD (# class)
Liu et al., 2020 [97]	SEED	2 (P, N)	DE-CNN	97.56
Cimtay and Ekmekcioglu, 2020 [98]	SEED, DEAP, LUMED	2,3-SEED; 2-DEAP; 2-LUMED	CNN	SEED: 86.56 (2), 78.34 (3) ; DEAP: 72.81 ; LUMED: 81.8
Khare and Bajaj, 2020 [99]	Self-Generated	4[a]	CNN	93.01
Wang et al., 2020 [100]	SEED, DEAP	3 (P, N, Neu)	CNN	SEED: 90.59; DEAP: 82.84
Cui et al., 2020 [101]	DEAP, DREAMER	2	RA-CNN	DEAP: Val: 96.65 Aro: 97.11 ; DREAMER: Val: 95.55, Aro: 97.01
Hassan et al., 2019 [33]	DEAP	5[b]	FC-SVM	89.53
Islam and Ahmad, 2019 [102]	DEAP	2 (P, N); 4	CNN	Val: 81.51 Aro: 79.42 (2) Val: 71.67 Aro: 70.18 (4)
Pandey and Seeja, 2019 [103]	DEAP	4[c]	DNN	Val: 62.5 Aro: 61.25
Chen et al., 2019 [29]	DEAP	2	CV-CNN[1]	85.57
Yang et al., 2019 [104]	DEAP	2[d]	MC-CNN	Val: 81.4 Aro: 80.5
Chao et al., 2019 [105]	DEAP	2	CDL	Val: 68.28, Aro: 66.73, Dom: 67.25
Moon et al., 2018 [106]	DEAP	2	CNN	99.72
Li et al., 2018 [90]	SEED	3 (P, Neu, N)	HCNN[2]	88.2
Yang et al., 2018 [107]	DEAP	2 (Val, Aro)	PCRNN	Val: 90.80, Aro: 91.03
Mehmood et al., 2017 [10]	IAPS	4[e]	VEn[3]	76.6
Alhagry et al., 2017 [31]	DEAP	3 (Val, Aro, Lik)	DNN	Val: 85.45, Aro: 85.65, Lik: 87.99
Liu et al., 2016 [108]	DEAP, SEED	4 (Val, Aro, Dom, Lik)	BDAE	Val: 85.2, Aro: 80.5, Dom: 84.9, Lik: 82.4
Zheng and Lu, 2015 [91]	Self-Generated	3 (P, N, Neu)	DBNs[4]	86.08

Note: Number of extracted emotions: Positive (P), Negative (N), Neutral (Neu), Valence (Val), Arousal (Aro), Dominance (Dom), liking (Lik); **Name of the classifier:** Bimodal Deep Auto Encoder (BDAE), Capsule-Network-Based Deep Learning Model (CDL), CNN model used for Computer Vision (CV-CNN), Deep Belief Networks (DBNs), Deep Neural Network (DNN), Dynamic Empirical Convolutional Neural Network (DE-CNN), Fine Gaussian SVM (FC-SVM), Hierarchical Convolutional Neural Network (HCNN), Multi-Column Convolutional Neural Network (MC-CNN), Parallel Convolutional Recurrent Neural Network (PCRNN), Regional-Asymmetric Convolutional Neural Network (RA-CNN), Voting Ensembles method (VEn); **Number of extracted emotion:** [a]Fear, happy, relax, and sad; [b]Happy, relaxed, disgust, sad and neutral; [c]Happy angry sad calm; [d]Any two among (excited, happy, pleased, peaceful, calm, gloomy, sad, fear and suspense); [e]Happy, calm, sad, and scared; **Note on classifier:** [1]Compared with BT, BLDA, SVM, LDA, CV-CNN, GSCNN, STCNN; [2]Compared with LDA, kNN, SVM, naïve-Bayes, random forest, deep-learning; [3]Compared with SVM, kNN, SAE; [4]Compared with SVM, LR, and kNN

as there remains precision, recall, AUC, number of output class, etc. and so many factors. The performance of valence and arousal based emotion recognition systems [5], [38], [111], [120], [123], [124] are presented graphically in Fig. 10(d). From the data of Table 10 and 11 the average accuracy of deep and shallow learning-based emotion recognition systems for the six consecutive years (2020-2015) are 87.23%, 87.55%, 99.72%, 82.40%, 85.20%, 86.08% and 87.53%, 62.46 %, 69.66%, 76.49%, 76.93%, 73.10% respectively. These data are plotted in Fig. 11. From these representations, it is obvious that deep machine learning-based system performance is comparatively higher than the shallow machine learning-based system.

V. OBSERVATIONS AND RECOMMENDATIONS

After the systematic review, some issues regarding classifier, feature extraction, dataset, etc. have appeared. The observation regarding some important issues and corresponding recommendations are summarized in the following Table 12. In addition, we have investigated some findings that should be concerned in the future. The significant points that we found are:

1) Many researchers considered only the emotionally aroused EEG data without subtracting the considering baseline EEG data. Baseline EEG signals generate the spontaneous EEG data of human beings. Some researchers [142], [143] calculated the difference

TABLE 11. The percentage of accuracy along with relevant dataset, number of extracted emotions, classifier of different shallow learning-based emotion recognition systems sorted by ascending chronological order (2020-2015).

Author, Year	Dataset	Number of Extracted Emotions (Type / Scale)	Classifier	Accuracy (%) Dataset: Accuracy±SD (# class)
Soroush et al., 2020 [109]	DEAP	4[a]	MLP, kNN, MCSVM	89.76 ± 1.9
Zhong et al., 2020 [110]	SEED, SEED-IV,	SEED: 3 (P, Neu, N) SEED-IV: 5[b]	RGNN	Subject-dependent: SEED: 94.24±05.95 SEED-IV: 79.37±10.54 Subject-independent: SEED: 85.30±06.72 SEED-IV: 73.84±08.02
Vijayakumar et al., 2020 [111]	DEAP	2	SVM[1]	Val: 70.41 Aro: 73.75
Qing et al., 2019 [112]	DEAP, SEED	3 (N, Calm, P)	DT[2]	DEAP: 63.09 ; SEED: 75
Islam and Ahmad, 2019 [87]	DEAP	4[c]	kNN	62.3±1.1
Li et al., 2019 [113]	MAHNOB, SEED, DEAP	3 (P, Neu, N)	SVM	MAHNOB: 68±0.07 SEED: 88±0.06 DEAP: 62±0.09
Yang et al., 2018 [114]	SEED	3 (P, Neu, N)	New[3]	93.26
Zhuang et al., 2018 [115]	Self-Generated	6[d]	SVM	56.65
Li et al., 2018 [116]	DEAP, SEED	DEAP: 2 (HV, LV)); SEED: 3 (P, Neu, N)	SVM[4]	DEAP: 59.06 (AUC =0.605) SEED: 83.33 (AUC =0.904)
Li et al., 2018 [38]	DEAP	N/A	KNN	Val: 95.70 ± 0.62 Aro: 95.69 ± 0.21
Alazrai et al., 2018 [117]	DEAP	4, 5	SVM	75.1 (4), 73.8 (5)
Degirmenci et al., 2018 [5]	DEAP	2 (V, A)	ANN	Val: 72.87 Aro: 75
Luo, 2018 [118]	DEAP, SEED	DEAP: 2 SEED: 3(P, N, Neu)	SVM	SEED: 86.96±9.72 DEAP: Val: 78.17±9.58 , Aro: 73.79±10.82
Nakisa et al., 2018 [119]	DEAP, MAHNOB, Self-Generated	4 (HA-P, HA-N, LA-P, LA-N)	PNN	DEAP: 67.4±3.4 MAHNOB: 96.9±1.9 Self-Generated: 65±3.2
Liu et al., 2018 [39]	Self-Generated	2 (Other, Neu), 2 (P, N)	SVM	92.26; 86.63
Zhong and Jianhua, 2017 [120]	DEAP	2 (Val, Aro)	LSSVM	Val: 78 Aro: 78
Menezes et al., 2017 [121]	DEAP	2 (N, P)	SVM	Val: 88 Aro: 69
Ackermann et al., 2016 [92]	DEAP	3	SVM, RF	55
Hu et al., 2016 [122]	Self-Generated	3	CFS+kNN	80.8±3
Zhang et al., 2016 [86]	DEAP	2, 4[a]	SVM	94.98 (2) 93.20 (4)
Kumar et al., 2016 [123]	DEAP	2 (High, Low)	LSSVM[5]	Val: 61.17, Aro: 64.84
Atkinson and Campos, 2016 [124]	DEAP	2, 3, 5	GA, SVM	Val: 73.06, Aro: 73.14 (2) Val: 60.7, Aro: 62.33 (3) Val: 46.69, Aro: 45.32 (5)
Lan et al., 2016 [125]	DEAP	2 (P, N), 2 (other), 4[e]	SVM	73.10 (2); 71.75 (2); 49.63 (4)

Note: Number of extracted emotions: Positive (P), Negative (N), Neutral (Neu), High Arousal (HA), Low Arousal (LA), High Valence (HV), Low Valence (LV), Valence (Val), Arousal (Aro), Not Appropriately defined (N/A); **Name of the classifier:** Decision Tree (DT), Genetic Algorithms (GA), k Nearest Neighbor (kNN), Least Square Support Vector Machine (LSSVM), Multi-Layer Perceptron (MLP), Multi- Class Support Vector Machine (MCSVM), Probabilistic Neural Network (PNN), Random Forest (RF), Regularized Graph Neural Network (RGNN); **Note on the number of extracted emotion:** [a]HAHV, HALV, LALV and LAHV; [b]Neutral, sad, fear, and happy; [c]Happy, angry, sad, relaxed; [d]Joy, neural, sad, disgust, anger, fear; [e]Pleasant, happy, frightened and angry; **Note on classifier:** [1]Compared with kNN, LDA, LR, DT; [2]Compared with kNN, and random forest with soft voting; [3]Compared with LR, kNN, SVM, ELM, H-ELM DBNs; [4]System with "leave-one-subject-out" verification strategy; [5]Compared with back-propagation ANN.

between an emotionally aroused EEG signal and a spontaneous EEG signal. Next, considering it as a feature, they may show a far better result.

2) The best feature or feature extraction method is difficult to suggest as emotion is a complex physiological phenomenon. However, the wavelet transform, PCA, ICA,

TABLE 12. Synopsis of the shortcomings of the general emotion recognition system and relevant recommendations.

Issues	Observations	Recommendations
Data processing and classification algorithms	A deep learning-based emotion recognition system requires a Graphical Processing Unit (GPU) for active operation, therefore it is stiffer to develop for practical use.	A cloud-based GPU system may be considered for usage in the real world.
	The systems based on CPU are time-consuming, whereas GPU-based are costly that creates a dilemma.	Based on the level of necessity and economic capability, GPU or CPU systems have to be selected.
	Many times the information of specific classifiers, parameters, kernel information, loss function, objective function, etc. is not provided explicitly and completely.	Future researchers should insert all the relevant information without any obscurity.
	Systems including an imbalanced number of data for the same class of emotion tend to generate an unexpected result.	Oversampling, undersampling, data augmentation, data reduction, etc. techniques may be used to make balanced data for each class.
Feature Extraction	The features having no relation with the human emotional state will cause the system to be heavy, time-consuming.	Only those features that vary with emotion have to be considered.
The logic for emotional state classification	The voluminous researcher only classifies the level of valence and arousal but does not provide the proper relation with emotion or decision-making logic exactly how he/she decides emotional state with the output level of valence and arousal.	How emotional states like happy, angry, sad, relaxed, etc. are linked with the level of valence, arousal, and/or dominance, should be clearly stated in every publication. Is it based on Russell's Circumplex model or any other model or how?
Subject and culture dependency	In many research, it is not clearly stated whether the emotion recognition system is subject dependent or independent.	Subject dependency status should be provided. However, the subject independent emotion recognition system is more significant compared to a person-specific system.
	Emotion varies slightly with a different culture. However yet rare or almost no research is yet found that considers the cultural effects.	To recognize emotion accurately, the culture of a nation should be considered in the future to develop an emotion recognition system for the people of a certain culture.
Dataset	EEG signal acquisition is taken place in a laboratory environment that may not be similar to practical real emotion.	Efforts have to be increased to collect real-life emotional data-based EEG signals.
	The effect of emotion on the human brain signal has remained present in a very short time. Therefore, EEG recordings of long duration are insignificant.	The subject should spend a long time reaching a real emotional state, however, the researchers should consider only the recording of the exact time of emotional state.

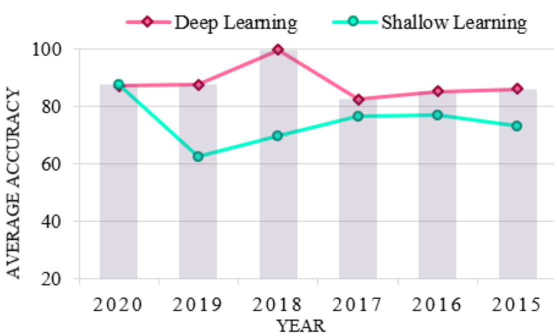


FIGURE 11. Comparison of the average accuracies of deep and shallow machine learning-based emotion recognition systems of six (2020-2015) consecutive years.

Hjorth parameters, etc., perform well, which have been proved in publication.

3) Among a wide range of algorithms, deep learning techniques like CNN, DBN, RNN, etc. are more effective algorithms compared to shallow learning-based algorithms like kNN, NB, and RF. However, it may be noted that the SVM performs well in EEG-based emotion extraction among the shallow learning techniques.
4) Whenever portability and simplicity are not required, the multimodal data incorporating the ECG, EOG, EMG, fMRI, and other physiological signals can significantly improve the performance of the emotion recognition system.

It may be noted that recently EEG microstates are being analyzed to determine their relationship with information processing and brain activities like cognition of the human brain [144], [145]. However, more research is needed on these phenomena in the future.

VI. CONCLUSION

The review summarizes the features, features extraction techniques, system performance, algorithms already used by numerous researchers for emotion recognition. The revision is done by following two main categories, deep machine learning-based emotion recognition systems and shallow machine learning-based systems. Hopefully, the enthusiasm will be helped by showing the comparison table, performance graph, and by knowing the information of publicly available datasets and the name of the analyzing software or tools. The recommendations also may be a perfect direction for future researchers to build up effective emotion recognition system using machine learning for real-life applications.

REFERENCES

[1] J. Shukla, M. Barreda-Angeles, J. Oliver, G. C. Nandi, and D. Puig, "Feature extraction and selection for emotion recognition from electrodermal activity," *IEEE Trans. Affect. Comput.*, vol. 5, no. 3, pp. 327–339, Feb. 2019, doi: 10.1109/TAFFC.2019.2901673.

[2] N. Zhuang, Y. Zeng, L. Tong, C. Zhang, H. Zhang, and B. Yan, "Emotion recognition from EEG signals using multidimensional information in EMD domain," *BioMed Res. Int.*, vol. 2017, pp. 1–9, Aug. 2017, doi: 10.1155/2017/8317357.

[3] J. Marín-Morales, J. L. Higuera-Trujillo, A. Greco, J. Guixeres, C. Llinares, E. P. Scilingo, M. Alcañiz, and G. Valenza, "Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics using wearable sensors," *Sci. Rep.*, vol. 8, no. 1, pp. 1–15, Dec. 2018.

[4] X.-H. Wang, T. Zhang, X.-M. Xu, L. Chen, X.-F. Xing, and C. L. P. Chen, "EEG emotion recognition using dynamical graph convolutional neural networks and broad learning system," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2018, pp. 1240–1244, doi: 10.1109/BIBM.2018.8621147.

[5] M. Degirmenci, M. A. Özdemir, R. Sadighzadeh, and A. Akan, "Emotion recognition from EEG signals by using empirical mode decomposition," in *Proc. Med. Technol. Nat. Congr. TIPTEKNO*, 2018, vol. 21, no. 1, pp. 81–89, doi: 10.1109/TIPTEKNO.2018.8597061.

[6] R. Mahajan, "Emotion recognition via EEG using neural network classifier," in *Soft Computing: Theories and Applications* (Advances in Intelligent Systems and Computing), vol. 583. Singapore: Springer, 2018, pp. 429–438.

[7] W. Zheng, "Multichannel EEG-based emotion recognition via group sparse canonical correlation analysis," *IEEE Trans. Cognit. Develop. Syst.*, vol. 9, no. 3, pp. 281–290, Sep. 2017, doi: 10.1109/TCDS.2016.2587290.

[8] M. Z. Soroush, K. Maghooli, S. K. Setarehdan, and A. M. Nasrabadi, "A review on EEG signals based emotion recognition," *Int. Clin. Neurosci. J.*, vol. 4, no. 4, pp. 118–129, Oct. 2017, doi: 10.15171/icnj.2017.01.

[9] A. Mikuckas, I. Mikuckiene, A. Venckauskas, E. Kazanavicius, R. Lukas, and I. Plauska, "Emotion recognition in human computer interaction systems," *Elektronika Elektrotechnika*, vol. 20, no. 10, pp. 51–56, Dec. 2014, doi: 10.5755/j01.eee.20.10.8878.

[10] R. M. Mehmood, R. Du, and H. J. Lee, "Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors," *IEEE Access*, vol. 5, pp. 14797–14806, 2017, doi: 10.1109/ACCESS.2017.2724555.

[11] N. Sebe and I. Cohen, "Multimodal approaches for emotion recognition: A survey," *Proc. SPIE*, vol. 5670, pp. 56–67, Jan. 2005. [Online]. Available: http://proceedings.spiedigitallibrary.org/proceeding.aspx?articleid=857894

[12] D. Yang, A. Alsadoon, P. W. C. Prasad, A. K. Singh, and A. Elchouemi, "An emotion recognition model based on facial recognition in virtual learning environment," *Procedia Comput. Sci.*, vol. 125, pp. 2–10, Jan. 2018, doi: 10.1016/j.procs.2017.12.003.

[13] S.-H. Wang, P. Phillips, Z.-C. Dong, and Y.-D. Zhang, "Intelligent facial emotion recognition based on stationary wavelet entropy and Jaya algorithm," *Neurocomputing*, vol. 272, pp. 668–676, Jan. 2018, doi: 10.1016/j.neucom.2017.08.015.

[14] Z. Yu and C. Zhang, "Image based static facial expression recognition with multiple deep network learning," in *Proc. ACM Int. Conf. Multimodal Interact.*, Nov. 2015, pp. 435–442, doi: 10.1145/2818346.2830595.

[15] Y. Zhou, H. Xue, and X. Geng, "Emotion distribution recognition from facial expressions," in *Proc. 23rd ACM Int. Conf. Multimedia*, Oct. 2015, pp. 1247–1250, doi: 10.1145/2733373.2806328.

[16] S. Siddharth, T.-P. Jung, and T. J. Sejnowski, "Impact of affective multimedia content on the electroencephalogram and facial expressions," *Sci. Rep.*, vol. 9, no. 1, pp. 1–10, Dec. 2019.

[17] G. Muhammad and M. S. Hossain, "Emotion recognition for cognitive edge computing using deep learning," *IEEE Internet Things J.*, early access, Feb. 10, 2021, doi: 10.1109/JIOT.2021.3058587.

[18] G. Castellano, L. Kessous, and G. Caridakis, "Emotion recognition through multiple modalities: Face, body gesture, speech," in *Affect and Emotion in Human-Computer Interaction* (Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 4868. Berlin, Germany: Springer, 2008, pp. 92–103.

[19] G. Castellano, S. D. Villalba, and A. Camurri, "Recognising human emotions from body movement and gesture dynamics," in *Proc. Int. Conf. Affect. Comput. Intell. Interact.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 4738, 2007, pp. 71–82, doi: 10.1007/978-3-540-74889-2_7.

[20] H. Gunes and M. Piccardi, "Bi-modal emotion recognition from expressive face and body gestures," *J. Netw. Comput. Appl.*, vol. 30, no. 4, pp. 1334–1345, Nov. 2007, doi: 10.1016/j.jnca.2006.09.007.

[21] F. Noroozi, C. A. Corneanu, D. Kaminska, T. Sapinski, S. Escalera, and G. Anbarjafari, "Survey on emotional body gesture recognition," *IEEE Trans. Affect. Comput.*, vol. 12, no. 2, pp. 505–523, Apr. 2021, doi: 10.1109/TAFFC.2018.2874986.

[22] S. Piana, A. Staglianó, F. Odone, and A. Camurri, "Adaptive body gesture representation for automatic emotion recognition," *ACM Trans. Interact. Intell. Syst.*, vol. 6, no. 1, pp. 1–31, May 2016, doi: 10.1145/2818740.

[23] E. Fox, *Emotion Science: Cognitive and Neuroscientific Approaches to Understanding Human Emotions*, vol. 46, no. 10. London, U.K.: Palgrave Macmillan, 2009.

[24] M. B. B. Heyat, F. Akhtar, A. Khan, A. Noor, B. Benjdira, Y. Qamar, S. J. Abbas, and D. Lai, "A novel hybrid machine learning classification for the detection of bruxism patients using physiological signals," *Appl. Sci.*, vol. 10, no. 21, p. 7410, Oct. 2020.

[25] M. B. B. Heyat, F. Akhtar, M. A. Ansari, A. Khan, F. Alkahtani, H. Khan, and D. Lai, "Progress in detection of insomnia sleep disorder: A comprehensive review," *Current Drug Targets*, vol. 22, no. 6, pp. 672–684, Apr. 2021.

[26] Y. Yin, X. Zheng, B. Hu, Y. Zhang, and X. Cui, "EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM," *Appl. Soft Comput.*, vol. 100, Mar. 2021, Art. no. 106954.

[27] C. Tan, M. Šarlija, and N. Kasabov, "NeuroSense: Short-term emotion recognition and understanding based on spiking neural network modelling of spatio-temporal EEG patterns," *Neurocomputing*, vol. 434, pp. 137–148, Apr. 2021.

[28] H. Tang, W. Liu, W. L. Zheng, and B. L. Lu, "Multimodal emotion recognition using deep neural networks," in *Proc. Int. Conf. Neural Inf. Process.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 10637, 2017, pp. 811–819, doi: 10.1007/978-3-319-70093-9_86.

[29] J. X. Chen, P. W. Zhang, Z. J. Mao, Y. F. Huang, D. M. Jiang, and Y. N. Zhang, "Accurate EEG-based emotion recognition on combined features using deep convolutional neural networks," *IEEE Access*, vol. 7, pp. 44317–44328, 2019, doi: 10.1109/ACCESS.2019.2908285.

[30] P. Keelawat, N. Thammasan, B. Kijsirikul, and M. Numao, "Subject-independent emotion recognition during music listening based on EEG using deep convolutional neural networks," in *Proc. IEEE 15th Int. Colloq. Signal Process. Appl. (CSPA)*, Mar. 2019, pp. 21–26, doi: 10.1109/CSPA.2019.8696054.

[31] S. Alhagry, A. Aly, and R. A. El-Khoribi, "Emotion recognition based on EEG using LSTM recurrent neural network," *Int. J. Adv. Comput. Sci. Appl.*, vol. 8, no. 10, pp. 355–358, 2017, doi: 10.14569/ijacsa.2017.081046.

[32] S. Tripathi, S. Acharya, R. D. Sharma, S. Mittal, and S. Bhattacharya, "Using deep and convolutional neural networks for accurate emotion classification on DEAP dataset," in *Proc. 31st AAAI Conf. Artif. Intell.*, 2017, pp. 4746–4752. [Online]. Available: https://www.aaai.org/ocs/index.php/IAAI/IAAI17/paper/view/15007/13731

[33] M. M. Hassan, M. G. R. Alam, M. Z. Uddin, S. Huda, A. Almogren, and G. Fortino, "Human emotion recognition using deep belief network architecture," *Inf. Fusion*, vol. 51, pp. 10–18, Nov. 2019, doi: 10.1016/j.inffus.2018.10.009.

[34] O. Sourina and Y. Liu, "A fractal-based algorithm of emotion recognition from EEG using arousal-valence model," in *Proc. Int. Conf. Bio-Inspired Syst. Signal Process. (BIOSIGNALS)*, vol. 2, 2011, pp. 209–214.

[35] K. C. Tseng, B.-S. Lin, C.-M. Han, and P.-S. Wang, "Emotion recognition of EEG underlying favourite music by support vector machine," in *Proc. 1st Int. Conf. Orange Technol. (ICOT)*, Mar. 2013, pp. 155–158, doi: 10.1109/ICOT.2013.6521181.

[36] Y.-H. Liu, C.-T. Wu, Y.-H. Kao, and Y.-T. Chen, "Single-trial EEG-based emotion recognition using kernel Eigen-emotion pattern and adaptive support vector machine," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 4306–4309, doi: 10.1109/EMBC.2013.6610498.

[37] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 186–197, Mar. 2010, doi: 10.1109/TITB.2009.2034649.

[38] M. Li, H. Xu, X. Liu, and S. Lu, "Emotion recognition from multichannel EEG signals using K-nearest neighbor classification," *Technol. Health Care*, vol. 26, pp. 509–519, Jul. 2018, doi: 10.3233/THC-174836.

[39] Y.-J. Liu, M. Yu, G. Zhao, J. Song, Y. Ge, and Y. Shi, "Real-time movie-induced discrete emotion recognition from EEG signals," *IEEE Trans. Affect. Comput.*, vol. 9, no. 4, pp. 550–562, Oct. 2018, doi: 10.1109/TAFFC.2017.2660485.
[40] S. Marsella and J. Gratch, "Computationally modeling human emotion," *Commun. ACM*, vol. 57, no. 12, pp. 56–67, Nov. 2014, doi: 10.1145/2631912.
[41] K. R. Scherer, "What are emotions? And how can they be measured?" *Social Sci. Inf.*, vol. 44, no. 4, pp. 695–729, Dec. 2005, doi: 10.1177/0539018405058216.
[42] A. Al-Nafjan, M. Hosny, Y. Al-Ohali, and A. Al-Wabil, "Review and classification of emotion recognition based on EEG brain-computer interface system research: A systematic review," *Appl. Sci.*, vol. 7, no. 12, p. 1239, Dec. 2017, doi: 10.3390/app7121239.
[43] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "DEAP: A database for emotion analysis; using physiological signals," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 18–31, Jan. 2012, doi: 10.1109/T-AFFC.2011.15.
[44] R. A. Calvo, S. D'Mello, J. M. Gratch, and A. Kappas, *The Oxford Handbook of Affective Computing*. London, U.K.: Oxford Univ. Press, 2015.
[45] J. A. Russell, "A circumplex model of affect," *J. Personality Social Psychol.*, vol. 39, no. 6, pp. 1161–1178, 1980, doi: 10.1037/h0077714.
[46] M. Teplan, "Fundamentals of EEG measurement," *Meas. Sci. Technol.*, vol. 2, no. 2, pp. 1–11, 2002.
[47] D. P. Subha, P. K. Joseph, R. U. Acharya, and C. M. Lim, "EEG signal analysis: A survey," *J. Med. Syst.*, vol. 34, no. 2, pp. 195–212, Apr. 2010, doi: 10.1007/s10916-008-9231-z.
[48] A. Subasi and M. I. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8659–8666, Dec. 2010, doi: 10.1016/j.eswa.2010.06.065.
[49] P. Ekman, "Expressions of emotion," in *Proc. Nebraska Symp. Motivat.*, vol. 19, 1972, p. 207.
[50] A. Mehrabian and J. A. Russell, "A measure of arousal seeking tendency," *Environ. Behav.*, vol. 5, no. 3, pp. 315–333, 1973, doi: 10.1177/001391657300500303.
[51] R. Plutchik, "The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice," *Amer. Sci.*, vol. 89, no. 4, pp. 344–350, 2001. [Online]. Available: http://www.jstor.org/stable/27857503
[52] D. Watson, L. A. Clark, and A. Tellegen, "Development and validation of brief measures of positive and negative affect: The PANAS scales," *J. Personality Social Psychol.*, vol. 54, no. 6, pp. 1063–1070, 1988, doi: 10.1037/0022-3514.54.6.1063.
[53] A. Keil, M. M. Bradley, O. Hauk, B. Rockstroh, T. Elbert, and P. J. Lang, "Large-scale neural correlates of affective picture processing," *Psychophysiology*, vol. 39, no. 5, pp. 641–649, Sep. 2002, doi: 10.1111/1469-8986.3950641.
[54] W. G. Parrott, *Emotions in Social Psychology: Key Readings* (Key Readings in Social Psychology), 1st ed., A. A. Edwards, Ed. Psychology Press, Nov. 2000, pp. 34–40. [Online]. Available: http://www.amazon.com/Emotions-Social-Psychology-Key-Readings/dp/0863776833
[55] M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic, "A multimodal database for affect recognition and implicit tagging," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 42–55, Jan. 2012, doi: 10.1109/T-AFFC.2011.25.
[56] T. B. Alakus, M. Gonen, and I. Turkoglu, "Database for an emotion recognition system based on EEG signals and various computer games—GAMEEMO," *Biomed. Signal Process. Control*, vol. 60, Jul. 2020, Art. no. 101951, doi: 10.1016/j.bspc.2020.101951.
[57] J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras, "AMIGOS: A dataset for affect, personality and mood research on individuals and groups," 2017, *arXiv:1702.02510*. [Online]. Available: http://arxiv.org/abs/1702.02510
[58] S. Katsigiannis and N. Ramzan, "DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 1, pp. 98–107, Jan. 2018, doi: 10.1109/JBHI.2017.2688239.
[59] S. M. Alarcao and M. J. Fonseca, "Emotions recognition using EEG signals: A survey," *IEEE Trans. Affect. Comput.*, vol. 10, no. 3, pp. 374–393, Jul. 2019, doi: 10.1109/TAFFC.2017.2714671.
[60] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, "International affective picture system (IAPS): Affective ratings of pictures and instruction manual," Univ. Florida, Gainesville, FL, USA, Tech. Rep. A-8, 2008.
[61] M. M. Bradley and P. J. Lang, "The international affective digitized sounds affective ratings of sounds and instruction manual," Univ. Florida, Gainesville, FL, USA, Tech. Rep. B-3, 2007, pp. 29–46. [Online]. Available: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:The+International+Affective+Digitized+Sounds+Affective+Ratings+of+Sounds+and+Instruction+Manual#1
[62] I. Daly, D. Williams, F. Hwang, A. Kirke, E. R. Miranda, and S. J. Nasuto, "Electroencephalography reflects the activity of sub-cortical brain regions during approach-withdrawal behaviour while listening to music," *Sci. Rep.*, vol. 9, no. 1, pp. 1–22, Dec. 2019.
[63] K. Scherer, "Vocal communication of emotion: A review of research paradigms," *Speech Commun.*, vol. 40, nos. 1–2, pp. 227–256, Apr. 2003.
[64] C. Y. Park, N. Cha, S. Kang, A. Kim, A. H. Khandoker, L. Hadjileontiadis, A. Oh, Y. Jeong, and U. Lee, "K-EmoCon, a multimodal sensor dataset for continuous emotion recognition in naturalistic conversations," *Sci. Data*, vol. 7, no. 1, pp. 1–16, Dec. 2020, doi: 10.1038/s41597-020-00630-y.
[65] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, "Differential entropy feature for EEG-based emotion classification," in *Proc. 6th Int. IEEE/EMBS Conf. Neural Eng. (NER)*, Nov. 2013, pp. 81–84, doi: 10.1109/NER.2013.6695876.
[66] R. Subramanian, J. Wache, M. K. Abadi, R. L. Vieriu, S. Winkler, and N. Sebe, "ASCERTAIN: Emotion and personality recognition using commercial sensors," *IEEE Trans. Affect. Comput.*, vol. 9, no. 2, pp. 147–160, Apr. 2018, doi: 10.1109/TAFFC.2016.2625250.
[67] M. S. Hossain and G. Muhammad, "Emotion recognition using deep learning approach from audio-visual emotional big data," *Inf. Fusion*, vol. 49, pp. 69–78, Sep. 2019, doi: 10.1016/j.inffus.2018.09.008.
[68] I. Sneddon, M. McRorie, G. McKeown, and J. Hanratty, "The belfast induced natural emotion database," *IEEE Trans. Affect. Comput.*, vol. 3, no. 1, pp. 32–41, Jan. 2012, doi: 10.1109/T-AFFC.2011.26.
[69] M. Lakshmi, D. Prasad, and D. Prakash, "Survey on EEG signal processing methods," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 4, no. 1, pp. 1–8, 2014.
[70] F. Lotte, "A tutorial on EEG signal-processing techniques for mental-state recognition in brain-computer interfaces," in *Guide to Brain-Computer Music Interfacing*. London, U.K.: Springer, 2014, pp. 133–161.
[71] S. Michelmann, M. S. Treder, B. Griffiths, C. Kerrén, F. Roux, M. Wimber, D. Rollings, V. Sawlani, R. Chelvarajah, S. Gollwitzer, G. Kreiselmeyer, H. Hamer, H. Bowman, B. Staresina, and S. Hanslmayr, "Data-driven re-referencing of intracranial EEG based on independent component analysis (ICA)," *J. Neurosci. Methods*, vol. 307, pp. 125–137, Sep. 2018, doi: 10.1016/j.jneumeth.2018.06.021.
[72] H. Cao, D. G. Cooper, M. K. Keutmann, R. C. Gur, A. Nenkova, and R. Verma, "CREMA-D: Crowd-sourced emotional multimodal actors dataset," *IEEE Trans. Affect. Comput.*, vol. 5, no. 4, pp. 377–390, Oct. 2014, doi: 10.1109/TAFFC.2014.2336244.
[73] E. M. Whitham, K. J. Pope, S. P. Fitzgibbon, T. Lewis, C. R. Clark, S. Loveless, M. Broberg, A. Wallace, D. DeLosAngeles, P. Lillie, A. Hardy, R. Fronsko, A. Pulbrook, and J. O. Willoughby, "Scalp electrical recording during paralysis: Quantitative evidence that EEG frequencies above 20 Hz are contaminated by EMG," *Clin. Neurophysiol.*, vol. 118, no. 8, pp. 1877–1888, Aug. 2007, doi: 10.1016/j.clinph.2007.04.027.
[74] A. Jafarifarmand and M. A. Badamchizadeh, "Artifacts removal in EEG signal using a new neural network enhanced adaptive filter," *Neurocomputing*, vol. 103, pp. 222–231, Mar. 2013, doi: 10.1016/j.neucom.2012.09.024.
[75] H.-L. Chan, Y.-T. Tsai, L.-F. Meng, and T. Wu, "The removal of ocular artifacts from EEG signals using adaptive filters based on ocular source components," *Ann. Biomed. Eng.*, vol. 38, no. 11, pp. 3489–3499, Nov. 2010, doi: 10.1007/s10439-010-0087-2.
[76] C. Guerrero-Mosquera and A. Navia-Vázquez, "Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data," *IET Signal Process.*, vol. 6, no. 2, pp. 99–106, Apr. 2012, doi: 10.1049/iet-spr.2010.0135.
[77] N. Oosugi, K. Kitajo, N. Hasegawa, Y. Nagasaka, K. Okanoya, and N. Fujii, "A new method for quantifying the performance of EEG blind source separation algorithms by referencing a simultaneously recorded ECoG signal," *Neural Netw.*, vol. 93, pp. 1–6, Sep. 2017, doi: 10.1016/j.neunet.2017.01.005.

[78] L. De Lathauwer, B. De Moor, and J. Vandewalle, "An introduction to independent component analysis," *J. Chemometrics*, vol. 14, no. 3, pp. 123–149, 2000, doi: 10.1002/1099-128X(200005/06)14:3<123::AID-CEM589>3.0.CO;2-1.

[79] P. Tichavský, Z. Koldovský, and E. Oja, "Performance analysis of the FastICA algorithm and Cramér–Rao bounds for linear independent component analysis," *IEEE Trans. Signal Process.*, vol. 54, no. 4, pp. 1189–1203, Apr. 2006, doi: 10.1109/TSP.2006.870561.

[80] A. Dermoune and T. Wei, "FastICA algorithm: Five criteria for the optimal choice of the nonlinearity function," *IEEE Trans. Signal Process.*, vol. 61, no. 8, pp. 2078–2087, Apr. 2013, doi: 10.1109/TSP.2013.2243440.

[81] S. Chaudhary, S. Taran, V. Bajaj, and A. Sengur, "Convolutional neural network based approach towards motor imagery tasks EEG signals classification," *IEEE Sensors J.*, vol. 19, no. 12, pp. 4494–4500, Jun. 2019, doi: 10.1109/JSEN.2019.2899645.

[82] G. Lee, M. Kwon, S. K. Sri, and M. Lee, "Emotion recognition based on 3D fuzzy visual and EEG features in movie clips," *Neurocomputing*, vol. 144, pp. 560–568, Nov. 2014, doi: 10.1016/j.neucom.2014.04.008.

[83] K. Schaaff and T. Schultz, "Towards emotion recognition from electroencephalographic signals," in *Proc. 3rd Int. Conf. Affect. Comput. Intell. Interact. Workshops (ACII)*, Sep. 2009, pp. 1–6, doi: 10.1109/ACII.2009.5349316.

[84] A. S. Al-Fahoum and A. A. Al-Fraihat, "Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains," *ISRN Neurosci.*, vol. 2014, pp. 1–7, Feb. 2014, doi: 10.1155/2014/730218.

[85] S. Hatamikia, K. Maghooli, and A. M. Nasrabadi, "The emotion recognition system based on autoregressive model and sequential forward feature selection of electroencephalogram signals," *J. Med. Signals Sens.*, vol. 4, no. 3, pp. 194–201, 2014, doi: 10.4103/2228-7477.137777.

[86] Y. Zhang, X. Ji, and S. Zhang, "An approach to EEG-based emotion recognition using combined feature extraction method," *Neurosci. Lett.*, vol. 633, pp. 152–157, Oct. 2016, doi: 10.1016/j.neulet.2016.09.037.

[87] M. R. Islam and M. Ahmad, "Wavelet analysis based classification of emotion from EEG signal," in *Proc. Int. Conf. Electr., Comput. Commun. Eng. (ECCE)*, Feb. 2019, pp. 1–6, doi: 10.1109/ECACE.2019.8679156.

[88] Z. Mohammadi, J. Frounchi, and M. Amiri, "Wavelet-based emotion recognition system using EEG signal," *Neural Comput. Appl.*, vol. 28, no. 8, pp. 1985–1990, Aug. 2017, doi: 10.1007/s00521-015-2149-8.

[89] V. Bostanov and B. Kotchoubey, "Recognition of affective prosody: Continuous wavelet measures of event-related brain potentials to emotional exclamations," *Psychophysiology*, vol. 41, no. 2, pp. 259–268, Mar. 2004, doi: 10.1111/j.1469-8986.2003.00142.x.

[90] J. Li, Z. Zhang, and H. He, "Hierarchical convolutional neural networks for EEG-based emotion recognition," *Cognit. Comput.*, vol. 10, no. 2, pp. 368–380, Apr. 2018, doi: 10.1007/s12559-017-9533-x.

[91] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks," *IEEE Trans. Auton. Mental Develop.*, vol. 7, no. 3, pp. 162–175, Sep. 2015, doi: 10.1109/TAMD.2015.2431497.

[92] P. Ackermann, C. Kohlschein, J. A. Bitsch, K. Wehrle, and S. Jeschke, "EEG-based automatic emotion recognition: Feature extraction, selection and classification methods," in *Proc. IEEE 18th Int. Conf. e-Health Netw., Appl. Services (Healthcom)*, Sep. 2016, pp. 1–6, doi: 10.1109/HealthCom.2016.7749447.

[93] D. Birvinskas, V. Jusas, I. Martisius, and R. Damasevicius, "EEG dataset reduction and feature extraction using discrete cosine transform," in *Proc. 6th UKSim/AMSS Eur. Symp. Comput. Modelling Simulation (EMS)*, Nov. 2012, pp. 199–204, doi: 10.1109/EMS.2012.88.

[94] G. M. Bairy, S. Bhat, L. W. J. Eugene, U. C. Niranjan, S. D. Puthankattil, and P. K. Joseph, "Automated classification of depression electroencephalographic signals using discrete cosine transform and nonlinear dynamics," *J. Med. Imag. Health Informat.*, vol. 5, no. 3, pp. 635–640, Jun. 2015, doi: 10.1166/jmihi.2015.1418.

[95] R. E. J. Yohanes, W. Ser, and G.-B. Huang, "Discrete wavelet transform coefficients for emotion recognition from EEG signals," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, Aug. 2012, pp. 2251–2254, doi: 10.1109/EMBC.2012.6346410.

[96] M. Akin, "Comparison of wavelet transform and FFT methods in the analysis of EEG signals," *J. Med. Syst.*, vol. 26, no. 3, pp. 241–247, 2002, doi: 10.1023/A:1015075101937.

[97] S. Liu, X. Wang, L. Zhao, J. Zhao, Q. Xin, and S. Wang, "Subject-independent emotion recognition of EEG signals based on dynamic empirical convolutional neural network," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, early access, Aug. 24, 2020, doi: 10.1109/tcbb.2020.3018137.

[98] Y. Cimtay and E. Ekmekcioglu, "Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEG emotion recognition," *Sensors*, vol. 20, no. 7, p. 2034, Apr. 2020, doi: 10.3390/s20072034.

[99] S. K. Khare and V. Bajaj, "Time-frequency representation and convolutional neural network-based emotion recognition," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Jan. 31, 2020, doi: 10.1109/tnnls.2020.3008938.

[100] F. Wang, S. Wu, W. Zhang, Z. Xu, Y. Zhang, C. Wu, and S. Coleman, "Emotion recognition with convolutional neural network and EEG-based EFDMs," *Neuropsychologia*, vol. 146, Sep. 2020, Art. no. 107506, doi: 10.1016/j.neuropsychologia.2020.107506.

[101] H. Cui, A. Liu, X. Zhang, X. Chen, K. Wang, and X. Chen, "EEG-based emotion recognition using an end-to-end regional-asymmetric convolutional neural network," *Knowl.-Based Syst.*, vol. 205, Oct. 2020, Art. no. 106243, doi: 10.1016/j.knosys.2020.106243.

[102] M. R. Islam and M. Ahmad, "Virtual image from EEG to recognize appropriate emotion using convolutional neural network," in *Proc. 1st Int. Conf. Adv. Sci., Eng. Robot. Technol. (ICASERT)*, May 2019, pp. 1–4, doi: 10.1109/ICASERT.2019.8934760.

[103] P. Pandey and K. R. Seeja, "Subject independent emotion recognition from EEG using VMD and deep learning," *J. King Saud Univ.-Comput. Inf. Sci.*, Nov. 2019, doi: 10.1016/j.jksuci.2019.11.003.

[104] H. Yang, J. Han, and K. Min, "A multi-column CNN model for emotion recognition from EEG signals," *Sensors*, vol. 19, no. 21, p. 4736, Oct. 2019, doi: 10.3390/s19214736.

[105] H. Chao, L. Dong, Y. Liu, and B. Lu, "Emotion recognition from multiband EEG signals using CapsNet," *Sensors*, vol. 19, no. 9, p. 2212, May 2019, doi: 10.3390/s19092212.

[106] S.-E. Moon, S. Jang, and J.-S. Lee, "Convolutional neural network approach for EEG-based emotion recognition using brain connectivity and its spatial information," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Apr. 2018, pp. 2556–2560, doi: 10.1109/ICASSP.2018.8461315.

[107] Y. Yang, Q. Wu, M. Qiu, Y. Wang, and X. Chen, "Emotion recognition from multi-channel EEG through parallel convolutional recurrent neural network," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2018, pp. 1–7, doi: 10.1109/IJCNN.2018.8489331.

[108] W. Liu, W. L. Zheng, and B. L. Lu, "Emotion recognition using multimodal deep learning," in *Proc. Int. Conf. Neural Inf. Process.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 9948, 2016, pp. 521–529, doi: 10.1007/978-3-319-46672-9_58.

[109] M. Z. Soroush, K. Maghooli, S. K. Setarehdan, and A. M. Nasrabadi, "Emotion recognition using EEG phase space dynamics and poincare intersections," *Biomed. Signal Process. Control*, vol. 59, May 2020, Art. no. 101918, doi: 10.1016/j.bspc.2020.101918.

[110] P. Zhong, D. Wang, and C. Miao, "EEG-based emotion recognition using regularized graph neural networks," *IEEE Trans. Affect. Comput.*, early access, May 11, 2020, doi: 10.1109/taffc.2020.2994159.

[111] S. Vijayakumar, R. Flynn, and N. Murray, "A comparative study of machine learning techniques for emotion recognition from peripheral physiological signals," in *Proc. 31st Irish Signals Syst. Conf. (ISSC)*, Jun. 2020, vol. 7, no. 1, pp. 1–21, doi: 10.1109/ISSC49989.2020.9180193.

[112] C. Qing, R. Qiao, X. Xu, and Y. Cheng, "Interpretable emotion recognition using EEG signals," *IEEE Access*, vol. 7, pp. 94160–94170, 2019, doi: 10.1109/ACCESS.2019.2928691.

[113] P. Li, H. Liu, Y. Si, C. Li, F. Li, X. Zhu, X. Huang, Y. Zeng, D. Yao, Y. Zhang, and P. Xu, "EEG based emotion recognition by combining functional connectivity network and local activations," *IEEE Trans. Biomed. Eng.*, vol. 66, no. 10, pp. 2869–2881, Oct. 2019, doi: 10.1109/TBME.2019.2897651.

[114] Y. Yang, Q. M. J. Wu, W.-L. Zheng, and B.-L. Lu, "EEG-based emotion recognition using hierarchical network with subnetwork nodes," *IEEE Trans. Cognit. Develop. Syst.*, vol. 10, no. 2, pp. 408–419, Jun. 2018, doi: 10.1109/TCDS.2017.2685338.

[115] N. Zhuang, Y. Zeng, K. Yang, C. Zhang, L. Tong, and B. Yan, "Investigating patterns for self-induced emotion recognition from EEG signals," *Sensors*, vol. 18, no. 3, p. 841, Mar. 2018, doi: 10.3390/s18030841.

[116] X. Li, D. Song, P. Zhang, Y. Zhang, Y. Hou, and B. Hu, "Exploring EEG features in cross-subject emotion recognition," *Frontiers Neurosci.*, vol. 12, p. 162, Mar. 2018, doi: 10.3389/fnins.2018.00162.

[117] R. Alazrai, R. Homoud, H. Alwanni, and M. Daoud, "EEG-based emotion recognition using quadratic time-frequency distribution," *Sensors*, vol. 18, no. 8, p. 2739, Aug. 2018, doi: 10.3390/s18082739.

[118] Y. Luo and B.-L. Lu, "EEG data augmentation for emotion recognition using a conditional wasserstein GAN," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 2535–2538, doi: 10.1109/EMBC.2018.8512865.

[119] B. Nakisa, M. N. Rastgoo, D. Tjondronegoro, and V. Chandran, "Evolutionary computation algorithms for feature selection of EEG-based emotion recognition using mobile sensors," *Expert Syst. Appl.*, vol. 93, pp. 143–155, Mar. 2018, doi: 10.1016/j.eswa.2017.09.062.

[120] Y. Zhong and Z. Jianhua, "Subject-generic EEG feature selection for emotion classification via transfer recursive feature elimination," in *Proc. 36th Chin. Control Conf. (CCC)*, vol. 11, Jul. 2017, pp. 11005–11010, doi: 10.23919/ChiCC.2017.8029114.

[121] M. L. R. Menezes, A. Samara, L. Galway, A. Sant'Anna, A. Verikas, F. Alonso-Fernandez, H. Wang, and R. Bond, "Towards emotion recognition for virtual environments: An evaluation of eeg features on benchmark dataset," *Pers. Ubiquitous Comput.*, vol. 21, no. 6, pp. 1003–1013, Dec. 2017, doi: 10.1007/s00779-017-1072-7.

[122] B. Hu, X. Li, S. Sun, and M. Ratcliffe, "Attention recognition in EEG-based affective learning research using CFS+KNN algorithm," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 15, no. 1, pp. 38–45, Jan. 2018, doi: 10.1109/TCBB.2016.2616395.

[123] N. Kumar, K. Khaund, and S. M. Hazarika, "Bispectral analysis of EEG for emotion recognition," *Procedia Comput. Sci.*, vol. 84, pp. 31–35, Jan. 2016, doi: 10.1016/j.procs.2016.04.062.

[124] J. Atkinson and D. Campos, "Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers," *Expert Syst. Appl.*, vol. 47, pp. 35–41, Apr. 2016, doi: 10.1016/j.eswa.2015.10.049.

[125] Z. Lan, O. Sourina, L. Wang, and Y. Liu, "Real-time EEG-based emotion monitoring using stable features," *Vis. Comput.*, vol. 32, no. 3, pp. 347–358, Mar. 2016, doi: 10.1007/s00371-015-1183-y.

[126] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Phys. D, Nonlinear Phenom.*, vol. 31, no. 2, pp. 277–283, 1988, doi: 10.1016/0167-2789(88)90081-4.

[127] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from brain signals using hybrid adaptive filtering and higher order crossings analysis," *IEEE Trans. Affect. Comput.*, vol. 1, no. 2, pp. 81–97, Jul. 2010, doi: 10.1109/T-AFFC.2010.7.

[128] A. Patil, C. Deshmukh, and A. R. Panat, "Feature extraction of EEG for emotion recognition using Hjorth features and higher order crossings," in *Proc. Conf. Adv. Signal Process. (CASP)*, Jun. 2016, pp. 429–434, doi: 10.1109/CASP.2016.7746209.

[129] A. E. Vijayan, D. Sen, and A. P. Sudheer, "EEG-based emotion recognition using statistical measures and auto-regressive modeling," in *Proc. IEEE Int. Conf. Comput. Intell. Commun. Technol. (CICT)*, Feb. 2015, pp. 587–591, doi: 10.1109/CICT.2015.24.

[130] Y. Zhang, S. Zhang, and X. Ji, "EEG-based classification of emotions using empirical mode decomposition and autoregressive model," *Multimedia Tools Appl.*, vol. 77, no. 20, pp. 26697–26710, Oct. 2018, doi: 10.1007/s11042-018-5885-9.

[131] X. Li, X. Sun, X. Wang, C. Shi, J. Kang, and Y. Hou, "Research on electroencephalogram emotion recognition based on the feature fusion algorithm of auto regressive model and wavelet packet entropy," *Sheng Wu Yi Xue Gong Cheng Xue Za Zhi*, vol. 34, no. 6, pp. 831–836, 2018, doi: 10.7507/1001-5515.201610047.

[132] M. A. Rahman, M. F. Hossain, M. Hossain, and R. Ahmmed, "Employing PCA and T-statistical approach for feature extraction and classification of emotion from multichannel EEG signal," *Egyptian Informat. J.*, vol. 21, no. 1, pp. 23–35, Mar. 2020, doi: 10.1016/j.eij.2019.10.002.

[133] S. Jirayucharoensak, S. Pan-Ngum, and P. Israsena, "EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation," *Sci. World J.*, vol. 2014, pp. 1–10, Sep. 2014, doi: 10.1155/2014/627892.

[134] W. M. Wong, A. W. C. Tan, C. K. Loo, and W. S. Liew, "PSO optimization of synergetic neural classifier for multichannel emotion recognition," in *Proc. 2nd World Congr. Nature Biologically Inspired Comput. (NaBIC)*, Dec. 2010, pp. 316–321, doi: 10.1109/NABIC.2010.5716292.

[135] R. Nivedha, M. Brinda, D. Vasanth, M. Anvitha, and K. V. Suma, "EEG based emotion recognition using SVM and PSO," in *Proc. Int. Conf. Intell. Comput., Instrum. Control Technol. (ICICICT)*, Jul. 2017, pp. 1597–1600.

[136] M. Sreeshakthy and J. Preethi, "Classification of emotion from EEG using hybrid radial basis function networks with elitist PSO," in *Proc. IEEE 9th Int. Conf. Intell. Syst. Control (ISCO)*, Jan. 2015, pp. 1–4, doi: 10.1109/ISCO.2015.7282340.

[137] A. S. Rodionov and A. A. L'vov, "Comparison of linear, nonlinear and feature selection methods for EEG signal classification," in *Proc. Int. Conf. Actual Problems Electron Devices Eng. (APEDE)*, 2004, vol. 11, no. 2, pp. 436–439, doi: 10.1109/apede.2004.1393604.

[138] D. Shon, K. Im, J.-H. Park, D.-S. Lim, B. Jang, and J.-M. Kim, "Emotional stress state detection using genetic algorithm-based feature selection on EEG signals," *Int. J. Environ. Res. Public Health*, vol. 15, no. 11, p. 2461, Nov. 2018, doi: 10.3390/ijerph15112461.

[139] M. Leon, J. Ballesteros, J. Tidare, N. Xiong, and E. Astrand, "Feature selection of EEG oscillatory activity related to motor imagery using a hierarchical genetic algorithm," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jun. 2019, pp. 87–94, doi: 10.1109/CEC.2019.8789948.

[140] E. P. Torres, E. A. Torres, M. Hernández-Álvarez, and S. G. Yoo, "EEG-based BCI emotion recognition: A survey," *Sensors*, vol. 20, no. 18, p. 5083, Sep. 2020.

[141] N. S. Suhaimi, J. Mountstephens, and J. Teo, "EEG-based emotion recognition: A state-of-the-art review of current trends and opportunities," *Comput. Intell. Neurosci.*, vol. 2020, pp. 1–19, Sep. 2020.

[142] P. Chen and J. Zhang, "Performance comparison of machine learning algorithms for EEG-signal-based emotion recognition," in *Proc. Int. Conf. Artif. Neural Netw.*, 2017, pp. 208–216.

[143] J. Zhang, Z. Yin, P. Chen, and S. Nichele, "Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review," *Inf. Fusion*, vol. 59, pp. 103–126, Jul. 2020.

[144] K. Zhang, W. Shi, C. Wang, Y. Li, Z. Liu, T. Liu, J. Li, X. Yan, Q. Wang, Z. Cao, and G. Wang, "Reliability of EEG microstate analysis at different electrode densities during propofol-induced transitions of brain states," *NeuroImage*, vol. 231, May 2021, Art. no. 117861.

[145] Y. Li, W. Shi, Z. Liu, J. Li, Q. Wang, X. Yan, Z. Cao, and G. Wang, "Effective brain state estimation during propofol-induced sedation using advanced EEG microstate spectral analysis," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 4, pp. 978–987, Apr. 2021.

MD. RABIUL ISLAM (Member, IEEE) received the M.Sc. degree in electrical and electronic engineering (EEE) from the Khulna University of Engineering & Technology (KUET), Bangladesh, in 2019. He joined North Western University Khulna, as a Lecturer, in 2016. Since 2020, he has been working as an Assistant Professor in the Department of EEE, Bangladesh Army University of Engineering & Technology (BAUET). He has published several research articles in peer-reviewed journals and conferences. His research interests include machine learning, pattern recognition, signal processing, intelligent system design, and human–computer interfacing.

MOHAMMAD ALI MONI received the Ph.D. degree in artificial intelligence and Bioinformatics from the University of Cambridge, U.K., in 2014. From 2015 to 2017, he was a Postdoctoral Research Fellow with the Garvan Institute of Medical Research, Sydney. He was also an Associate Lecturer with the University of New South Wales, Australia. At the end of 2017, he was awarded a USyd Fellowship at The University of Sydney. He is currently working as a Research Fellow and a Conjoint-Lecturer with the University of New South Wales, Australia. His research interests include artificial intelligence, machine learning, data science, and clinical bioinformatics.

MD. MILON ISLAM received the B.Sc. and M.Sc. degrees in computer science and engineering (CSE) from the Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh, in 2016 and 2019, respectively. He joined the CSE Department, KUET, as a Lecturer, in 2017. He is currently working as an Assistant Professor with the CSE department, KUET. He has published several research articles in peer-reviewed high-impact journals, book chapters, and conferences. His research interests include machine learning and its application, deep learning, intelligent systems design, health informatics, the Internet of Things (IoT), and to solve real-life problems with the concept of computer science. He is also a program committee member of several prestigious conferences. In addition, he is a reviewer of several reputed journals and conferences.

MD. RASHED-AL-MAHFUZ (Member, IEEE) received the B.Sc. and M.Sc. degrees in computer science and engineering from the University of Rajshahi, Rajshahi, Bangladesh. He joined the Pabna University of Science and Technology, as a Lecturer of computer science and engineering, in January 2011. Then, he moved to the University of Rajshahi, as a Lecturer of computer science and engineering, where he is currently an Assistant Professor. His research interests include machine learning, big data analysis, signal and image processing, social cognition, and bioinformatics.

MD. SAIFUL ISLAM received the B.Sc. (Hons.) and M.S. degrees in computer science and engineering from the University of Dhaka, Bangladesh, in 2005 and 2007, respectively, and the Ph.D. degree in computer science and software engineering from the Swinburne University of Technology, Australia, in February 2014. He is currently a Lecturer with the School of Information and Communication Technology, Griffith University, Australia. His current research interests include database usability, spatial data management, artificial intelligence, and big data analytics.

MD. KAMRUL HASAN received the B.Sc. and M.Sc. degrees in electrical and electronic engineering (EEE) from the Khulna University of Engineering & Technology (KUET), in 2014 and 2017, respectively, and the M.Sc. degree in medical imaging and application (MAIA) from the University of Burgundy, France, the University of Cassino and Southern Lazio, Italy, and the University of Girona, Spain, as an Erasmus Scholar, in 2019. He is currently working as an Assistant Professor with the EEE Department, KUET. He is supervising several undergraduate students for the classification, segmentation, and registration of medical images with different modalities. He has already published many research articles on medical image and signal processing in different international journals and conferences. His research interests include medical image and data analysis, machine learning, deep convolutional neural networks, medical image reconstruction, and surgical robotics in minimally invasive surgery.

MD. SABIR HOSSAIN (Member, IEEE) received the bachelor's and master's degrees in computer science and engineering from the Chittagong University of Engineering and Technology. He is currently working as a Faculty Member (Assistant Professor) with the Chittagong University of Engineering and Technology. Besides teaching and research activities, he also works as an independent freelancer. His research interests include algorithmic complexity analysis, data mining, machine learning, big data, and information visualization.

MOHIUDDIN AHMAD (Member, IEEE) received the B.S. degree (Hons.) in electrical and electronic engineering (EEE) from the Chittagong University of Engineering and Technology (CUET), Bangladesh, in 1994, the M.S. degree in electronics and information science (major—biomedical engineering) from the Kyoto Institute of Technology of Japan, in 2001, and the Ph.D. degree in computer science and engineering (CSE) from Korea University, South Korea, in 2008. From November 1994 to August 1995, he worked as a part-time Lecturer with the Department of Electrical and Electronic Engineering, CUET, Bangladesh. From August 1995 to October 1998, he worked as a Lecturer with the Department of EEE, Khulna University of Engineering & Technology (KUET), Bangladesh, where he joined as an Assistant Professor, in June 2001, and as an Associate Professor, in May 2009, he is currently a Full Professor. He had been working as the Head of the Department of BME and EEE. His research interests include signal and image processing for disease diagnosis, computer vision and pattern recognition, clinical engineering, and modern healthcare. He is a Life Fellow of IEB.

SHAHADAT UDDIN is currently a Senior Lecturer with the Faculty of Engineering, The University of Sydney, Australia. His research interests include health informatics, complex networks, data science, artificial intelligence, and project analytics. He has published several international and multi-disciplinary journals, including *Expert Systems with Applications*, *Complexity*, *International Journal of Medical Informatics*, *Scientific Reports*, and *Journal of Informetrics*. He has been awarded many academic awards for his outstanding research excellence, including the Top Researcher Award (Bangladesh University of Engineering & Technology Alumni Australia, 2020), the Campus Director Leadership Award (Central Queensland University 2006), the Certificate for Research Excellence (University of Sydney 2010), and the Dean's Research Award (University of Sydney, 2014).

AKM AZAD received the Ph.D. degree in computational systems biology and biostatistics from Monash University, Australia, in 2017. He did his first Postdoctoral Fellowship with the Faculty of IT, Monash University. He was a Postdoctoral Research Associate with the AI Laboratory, School of BABS, UNSW Sydney, contributing/leading multiple bioinformatics, and computational biology projects. Recently, he has joined the University of Technology Sydney, as a Research Fellow for developing cutting-edge methodologies and tools for online inference of phylogenetic trees from COVID-19 sequences. His research interests include AI/ML/DL, Bayesian statistics, MCMC, Bayesian networks, bioinformatics, and computational biology.

SALEM A. ALYAMI (Member, IEEE) received the Ph.D. degree in bio-statistics from Monash University, Australia, in 2017. Since 2017, he has been an Assistant Professor with the School of Mathematics and Statistics, Faculty of Science, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia, contributing/leading several grants in biostatistics projects. Recently, he has appointed as the Dean of the Deanship of Scientific Research with IMSIU. His research interests include Bayesian networks, neural networks, Bayesian statistics, MCMC methods, and applications of statistics in biology and medicine.

MD. ATIQUR RAHMAN AHAD (Senior Member, IEEE) He is currently a Professor with the University of Dhaka (DU). He is also a Specially Appointed Associate Professor with Osaka University. He studied at the University of Dhaka, University of New South Wales, and Kyushu Institute of Technology. He authored/edited ten books in Springer, published ∼160 journal articles/conference papers/ chapters, ∼100 keynote/invited talks, and ∼35 awards/recognitions. He is a member of OSA, ACM, and IAPR. He is an Editorial Board Member of *Scientific Reports* (Nature), an Associate Editor of *Frontiers in Computer Science*, an Editor of *International Journal of Affective Engineering*, the Editor-in-Chief of *International Journal of Computer Vision and Signal Processing (IJCVSP)*, the General Chair of the 10th ICIEV (http://cennser.org/ICIEV), the 5th IVPR (http://cennser.org/IVPR), the 3rd ABC (https://abc-research.github.io), and a Guest-Editor of *Pattern Recognition Letters* (Elsevier), *JMUI* (Springer), *JHE* (Hindawi), and *IJICIC*. More details can be found at: http://ahadVisionLab.com.

PIETRO LIÓ received the M.A. degree from the University of Cambridge, the Ph.D. degree in complex systems and non-linear dynamics from the Department of Engineering, School of Informatics, University of Firenze, Italy, and the Ph.D. degree in (theoretical) genetics from the University of Pavia, Italy. He is currently a Full Professor of computational biology with the Computer Laboratory, University of Cambridge, and a member of the Artificial Intelligence Group. His research interests include bioinformatics, computational biology modeling, and machine learning to integrate various types of data (molecular and clinical, drugs, social and lifestyle) across different spatial and temporal scales of biological complexity to address personalized and precision medicine.