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A Review on Emotion Recognition with Machine Learning using EEG Signals

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Emotions are critical in people's daily lives since their decision-making, interaction, intelligence, and perception are all influenced by the emotions they display. Emotion recognition with machine learning based on EEG signals has been an exciting topic and employed in several areas such as health care, social security, and safe driving. In this paper, a review on emotion recognition using EEG signals employing machine learning is carried out based on various factors such as the stimulus used, equipment, modalities, filters, features, classifiers, and detected emotions, along with the limitations. This paper identifies the basic methodology used in the emotion recognition process with various tools and technologies utilized in it. Finally, it gives the issues and challenges for future research directions.

Introduction

Emotions play a vital role in daily life of human beings as decision-making, interaction, intelligence and perception of a person is directly dependent on the emotions expressed by him (1). Emotion is a multifaceted psychological phenomenon that begins with a stimulus (external/internal) and is short-lived, consistent in response and discrete in nature. It includes three distinct components that are i) subjective experience- defining feelings of a person, ii) physiological response-internal/inward expression, and iii) behavioral or expressive response-audio/visual expression. They are a series of coordinated responses that include behavioural, linguistic, physiological, and neurological mechanisms (2)-(3). Humans express emotions differently and in order to recognize emotions, these need to be measured quantitatively. Researchers use two techniques in order to model the emotions, the first one is to establish emotions as set of basic discrete, measurable and physiology-related. According to Ekman et al. (4), emotions can be categorized into six basic emotions namely happiness, sadness, surprise, fear, anger and disgust, that has evolved through natural selection. Rest of the emotions can be formed by these basic ones like disappointment is composed of sadness and surprise. Emotions are mapped onto the Valence, Arousal, and Dominance (VAD) dimensions in the second technique. Valence ranges from very positive pleasant feelings to very negative unpleasant feelings, arousal ranges from sleepy or tranquil to agitated, and dominance is related to the strength of the emotion (5). The Circumplex Model of Affect, on the other hand, just uses two dimensions of valence and arousal (6). Emotion recognition has been used in a variety of applications, including safe driving, healthcare, particularly mental health monitoring, and social security (7)-(10) (62)-(64). In the field of Human-Computer Interaction (HCI), emotions have been largely ignored. Therefore, in order to fulfill this gap a new study has been emerged called as Affective Computing (AC) that converges technology-and-emotions into HCI in order to model emotional-interaction between a person (subject) and a system (11). Emotional state becomes apparent by internal and external expression that generates physiological and audio/visual signals respectively. The physiological signals generate the human's underlying response that corresponds to the central and autonomic nervous system. These signals can be utilised to better recognise the emotions expressed by the subject during the time of observation. Electromyography (EMG)-frequency of muscle tension- is a common signal used to detect emotions. It is connected with unpleasant emotions. Heart rate (HR) rises linearly in response to unpleasant emotions like dread. The Galvanic Skin Response (GSR) grows linearly with arousal, the Respiration Rate (RR) becomes irregular with more aroused emotions like rage, and the Electroencephalography (EEG) - emotions felt from observation recorded over the brain (12), and these EEG signals support the links that has been discovered between emotional state and brain activity (13). EEG is a recording of the electrical activity of active nerve cells of brain, as shown in Figure 1, via electrodes placed on the scalp (14). It measures the voltage fluctuations from the ionic current flows

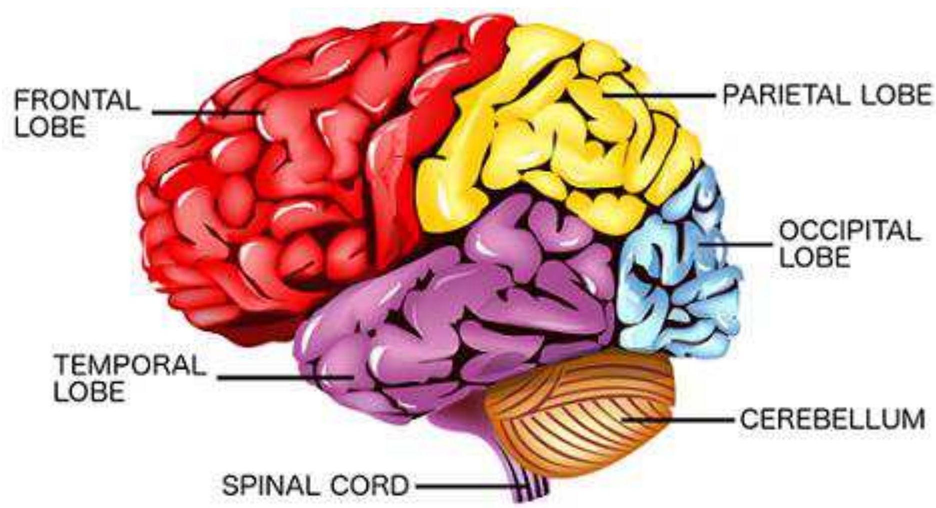

Figure 1. The human brain cortex is divided into frontal, temporal, parietal, and occipital lobes. The frontal lobe is in charge of conscious thought, the temporal lobe is in charge of the senses of smell and sound, as well as the processing of complex stimuli like faces and scenes, the parietal lobe is in charge of integrating sensory information from various senses, as well as object manipulation, and the occipital lobe is in charge of vision.

during excitation of neurons within the brain. In order to record the EEG signals, International 10/20 system (IS) is followed that have standardized the sets of locations for electrodes on the skull as shown in Figure 2 (15)-(16). This system is established on the connection between the location of any electrode and the underlying area of cerebral cortex. The EEG is a non-stationary signal with low amplitude that was first measured by Hans Berger in 1924 in human beings (17). Typical EEG signal in adults, ranges from 10-100 μV when measured from scalp, and contains the information of interest between 0.1 Hz to 100 Hz frequency domain range (18). This range can be categorized into five frequency bands namely the delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (> 30 Hz), depending upon the level of frequency (see Figure 3) (19). Delta waves are related with the subconscious mind and are produced during deep sleep.

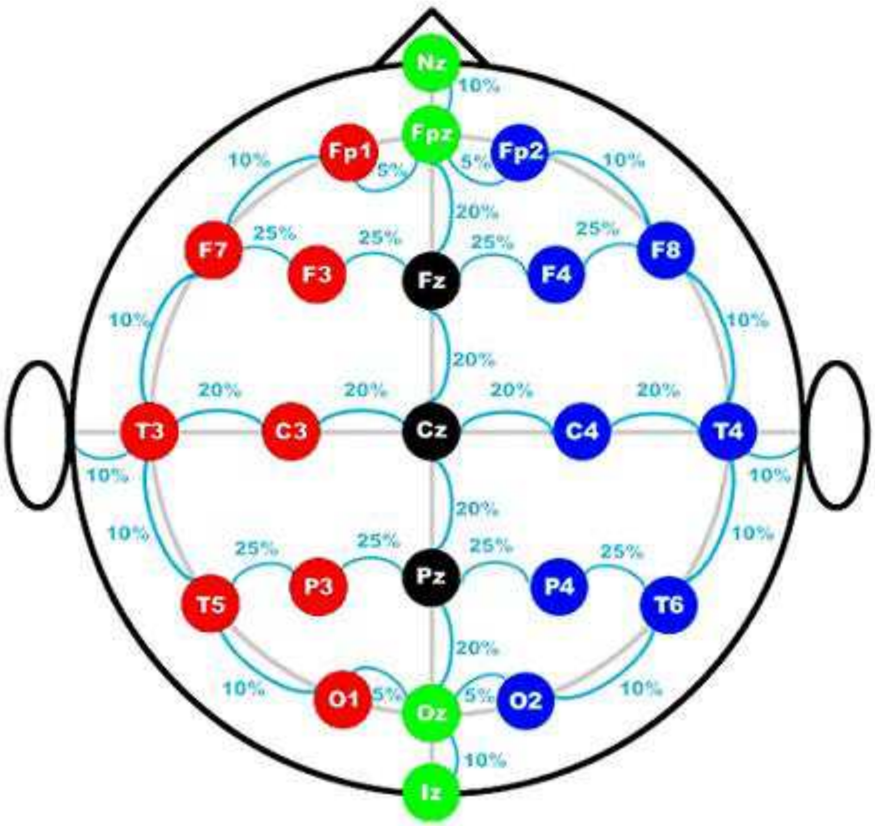

Figure 2. EEG electrode placement on scalp: The International 10/20 system.

These waves were also discovered during profound meditation and some tasks requiring constant focus. Sleeping, drowsiness, fantasizing, and dreaming are all related with theta waves, which are associated with the subconscious mind. Alpha waves are related with a relaxed mental state, tranquility, awareness, and increased visibility over the occipital and parietal areas. Beta waves are more dominant in the frontal brain and are associated with the awake, conscious mind that people use to function and perform daily tasks. Finally, gamma waves are linked to increased brain activity (20). The signals generated in the brain can be evaluated and subsequently perceived by various model such as Sensory Evoked Potentials (21), Event-Related-Potentials (22), and Event-Related-De/Synchronizations (23). EEG signals contains abundant information about psychological and physiological state of human body. Its use is non–invasive, fast and inexpensive, and is very important tool for recognizing emotions, clinical diagnosis, healthcare and research. EEG signals are also employed in Brain Computer Interface (BCI). BCI is a powerful communication tool where the EEG signals directly goes from the brain to the computer and does not require any muscle movement to issue command to complete the interaction (24). It helps in development of biomedical applications, resulting in making of assistive devices for disabled people, physically challenged, motor disabilities, neuromuscular injuries and neurodegenerative diseases. Its scope has been expanded to include non-medical applications to bring and facilitate ease of comfort to human beings (25)-(26).

This paper is organized into eight sections. Section 2 provides motivation behind the research. Section 3 gives an overview of the most recent work in the field of emotion recognition. Section 3.1 presents the present start of art in this field, followed by section 5

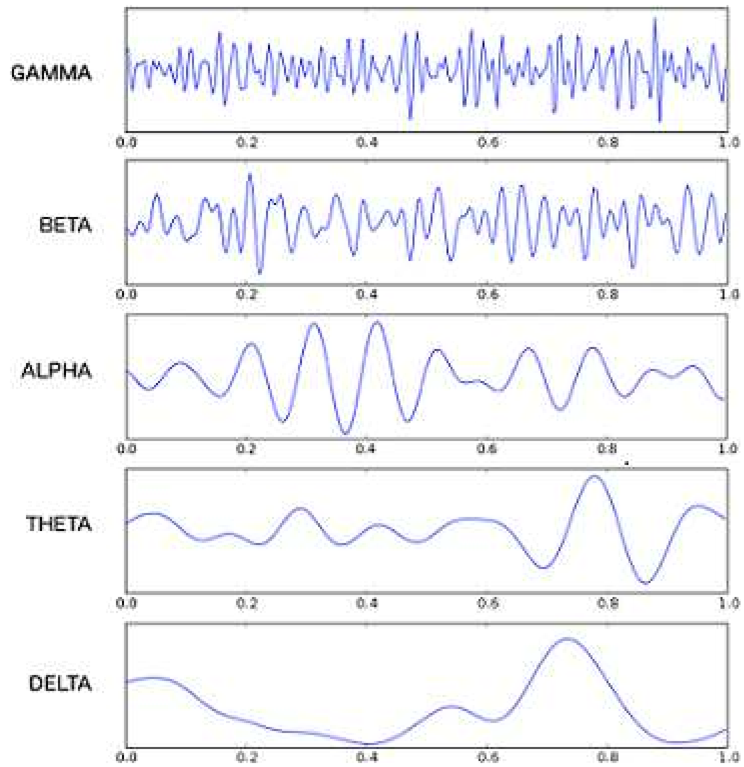

Figure 3. Five brain waves: delta, theta, alpha, and gamma.

which presents the issues and challenges. Then the detailed description of tools and technologies are given in section 6. Section 7 describes the methodology used in emotion recognition. Finally, conclusion is drawn in section 8.

Motivation of Research

According to WHO, suicide is the second leading cause of death worldwide because of negative emotions such as stress and anxiety. This leads to problems in our society, such as the people who are suffering from mental health problems which can provoke them to commit suicide (29). Thus, emotion recognition system will help them to cope with negative affects like anger, sadness and stress in the context of their well beingness. Also, emotions are also being explored not only to improve HCI but also to learn more about what goes on in a human mind during vital operations. It is critical to provide a methodology for moving participants from a high-arousal state of mind to a low-arousal state of mind. Emotion identification from many modalities, such as face, speech, and others, is not only time intensive, but also difficult to capture a sufficient amount of data, and can be less accurate than EEG. To become natural communication between human and machine, emotion recognition is necessary.

Disability is another a major worldwide social issue with more than 650 million people having disabilities all around the world (27). According to a report provided by the Ministry of Statistics and Programme Implementation of the Government of India based on Census 2011, roughly 2.68 crore people in India are disabled, accounting for 2.21 percent of the total population (28). Emotion recognition techniques provides aid to these disabled persons to communicate their felling and interact with the surrounding people and caretakers for their well beingness and to improve their quality of life.

Literature Studied

In this section a literature survey is conducted which contains the review of papers presented in Table 1. It includes the information about the stimulus and databases used for elicitation of emotion, equipments used to record signals, modalities used for emotion recognition, filters used for processing, feature extracted, emotions recognized, classifiers used and summary.

Present State of Art in Emotion Recognition

Alarcao et al. (11) undertook a review of neurophysiological research from 2009 to 2016, offering a detailed assessment of the available work on emotion identification based on EEG signals. They focused their efforts on evaluating and comparing the critical components of the recognition process (e.g., subjects, features extracted, classifiers). The authors developed a set of best practices for producing consistent, reproducible, well-validated, and high-quality emotion identification results using EEG data based on their findings.

Correa et al. (30) presented a dataset, AMIGOS, for multimodal research of affect, personality traits and mood on individuals and groups, collected from 40 subjects. The dataset allows the multimodal study of affective responses, by means of neuro-physiological signals, and their relation with personality, mood, social context and stimuli duration. They recorded physiological signals, namely, EEG, ECG and GSR, and visual modality of subjects. Further, they classified affects on valence and arousal dimension and personality traits, PANAS and social contexts, over positive and negative class for all signal modalities using Gaussian Naive Bayes classifier. In addition to it, they used linear-SVM to classify visual modality. Consistent significant results were obtained for affect, personality and mood using all the modalities.

Huang et al. (9) suggested an EEG-based BCI system for recognizing emotions in patients with DOCs like coma, vegetative state, minimally conscious state, and emerging minimally aware state. These patients have motor deficits and are unable to communicate their emotions appropriately. The study included ten healthy people and eight DOC patients. The SVM classifier was used to train the system, which achieved a high average online accuracy of 91.5 percent 6.34 percent for healthy participants and 58.5 percent for DOC subjects.

Dehzangi et al. (34) designed a portable BCI system for ICU communications (BCI4ICU) optimized to operate effectively in an ICU environment for consistent and effective communication by using subject dependent SSVEP. This system includes Android-based openGL paradigm stimuli generation module via user interface on the mobile device, custom designed Android based wireless data acquisition and processing

TABLE I. Literature survey related to Emotion Recognition on EEG signals

Ref.	Stimulus	Equipment	Modalities	Filters	Features (methods)	Classifiers	Emotions	Summary
(7)	Angry conditions	Biography Infiniti system, EEG recording system	EEG, GSR	N/A	Delta, beta, SC, BVP	HNB	Angry	Simulation and on-road experiments were conducted to induce and detect angry driving. This system achieved an accuracy of 85%. Angry driving warning products can be developed for safe driving.
(8)	Sleep and alert deprived conditions	Multi-channel amplifier (g.HIamp, g.tec Medical Engineering GmbH)	EEG, EOG, Contextual information	Bandpass filter (0.5-60Hz), Butterworth, Notch filter	Delta, theta, alpha, beta, gamma, blink duration, (SWP PSD, KSS)	k-NN, SVM, CBR, RF	Sleepiness	A high-fidelity driving simulator was used to construct an automated driver tiredness detection system in which 30 drivers drove in both alert and sleep-deprived conditions. Using four classifiers, the evaluation was conducted on binary and multi-class classification. SVM achieved accuracy of 79 percent (multi-class) and 93 percent (binary).
(9)	Video clips	SynAmps2 amplifier (32 channel)	EEG	FIR bandpass (0.1-70Hz), Notch filter	Delta-, theta-, alpha-, beta-, gamma- (STFT, PSD)	SVM	Positive, negative	BCI system based on EEG signals was developed to recognize the emotion. It was used to detect emotional state in patients with DOC. Average accuracy of 91.5% was achieved on 10 healthy subjects and in patients, it was 58.5%.

(30)	Video clips	Emotiv EPOC (14 channel), JVC GY-HM150E camera, Shimmer 2R	EEG, ECG, GSR and Visual	Bandpass filter, BSS	Time and frequency domain (PSD, PCA, LDA)	SVM, GNB	Valence, arousal, personalit y and mood	Dataset for recognition of affect, personality and mood in individual and social context was proposed, acquired from 40 subjects. Classification of valence and arousal using single and combination of modalities was done. For personality and mood, binary classification of positive and negative class was implemented. Significant results were achieved on each dimension in different scenarios.
(31)	Work load	Emotiv EPOC+ (14 channels)	EEG	Bandpass filter (0.5-64Hz), Notch filter, ICA	Time and frequency domain (Wrapper, Correlation)	k-NN, SVM, GDA	Stress	Worker's stress at real construction sites was recognized automatically. Data was labelled into two classes of low and high stress. Highest classification accuracy of 80.32% was achieved using SVM.
(32)	Mental tasks	Emotiv EPOC+ (16 channel), Empatica E4 wristband	EEG, EDA, BVP	N/A	Delta, theta, alpha 1, alpha 2, beta, gamma, HR, SC, mean (FFT, PSD)	RF	Cognitive load	The valuation of cognitive load in visually impaired individuals in real time was done to help them in navigations. The experiment was conducted in unfamiliar indoor and outdoor environments. AUROC weighted results were obtained

								which showed 83-87% prediction rates in multimodal classification.
(33)	Stressful condition	Emotiv EPOC+ (14 channel)	EEG	Bandpass filter (0.5-64Hz), Notch filter, ICA	Time and frequency domain (Wrapper, PSD)	OMTL	Stress	EEG-based stress recognition framework was developed that takes into account brain patterns which continuously change under same stressors. It trains the stress recognition algorithm and gives new input signals in real time. The OMTL resulted in the best prediction accuracy of 71.14% in lab environment and 77.61% in field.
(34)	SSVEP	Cognionics EEG device (8 channel)	EEG	Butterworth bandpass, Notch filter	Time and frequency domain (CCA, PSD)	GMM, SVM	Feeling pain, discomfort	Gaussian Mixture Model based training and adaptation algorithm for BCI system was proposed for ICU patients, to communicate with their caregivers. This model attained 98.7% of identification accuracy for effective communication for 10 healthy subjects. For 8 DOC patient, average accuracy obtained was 58.5%.
(35)	Stressful conditions	Emotiv EPOC+ (14 channel), Empatica	EEG, EDA, HR, BVP	Bandpass, Notch filter	Time and frequency domain (FFT, SVD, PSD)	RF	Stress	Authors proposed Mobility aids capable of adapting to cognitive-emotional load for visually impaired people when

		E4 wristband						navigating in stressful environment. Significant results were achieved by classification experiments with accuracy 81-93%
(36)	Movie clips	Sensors	EEG, ECG, GSR and Visual	N/A	Time and frequency domain	SVM, NB	Valence, arousal, liking, familiarity	The researchers presented a multimodal database for implicit personality and affect identification, which includes physiological responses from 58 users acquired using commercial and wearable sensors.
(37)	AMIGOS	Shimmer 2R	ECG, GSR	Bandpass filter ECG (0.5-15Hz) and GSR (0.05-19Hz)	Time and frequency domain, Statistical and non linear	DCNN	Valence, arousal	Deep learning approach was used for emotion detection on AMIGOS dataset. DCNN performed better than SVM and GNB classification.
(38)	Images	Flexcom Infiniti biofeedback	EEG, SC, RR PPG	Bandpass filter (0.5-35Hz)	Time and frequency domain (GA)	EEN	Calm-neutral, negative-excited	The cognitive model of the brain under emotional stress was applied by employing the stimulus of photographs induction environment to create an emotional stress recognition system using multi-modal bio-signals (calm-neutral and negative-excited). On two emotional states, 82.7 percent accuracy was reached.

(39)	Audio-visual	Brainmarker BV	EEG	Bandpass filter (4-32 Hz)	Time and frequency domain (PSD, DWT)	k-NN, SVM	Stress, positive, negative	An investigation on recognition of emotional stimulus in a stressful environment was conducted in four states of negative and positive emotions, calm and highly exited emotions. The results obtained were very significant and the average accuracy of 80% was obtained.
(40)	IAPS	Geodesic EEG Systems 300 (128 channel)	EEG	Bandpass filter (1-45Hz), Sliding window cross - correlation	Delta-, theta-, alpha-, beta-, gamma-, (PSD)	k-NN	Valence-, arousal	22 healthy volunteers were emotionally stimulated using affective pictures in an EEG-based study to determine brain dynamics in response to happy and unpleasant stimuli. The findings revealed that functional connectivity in the highest frequency bands (i.e. > 30Hz) was the most responsive to arousal modulation, with automatic valence classification achieving an accuracy of up to 86.37 percent.
(41)	Audio music	Neurosky EEG headset (1 channel)	EEG	Bandpass filter (1-50Hz)	Time, frequency, and wavelet domain	MLP, KNN, SVM	Happy, sad, love and anger	Human emotions were recognized using audio music as stimulus, as it considered a powerful method to elicit emotions like sad, happy, love and anger. Main objective was

								to determine the effect of different genres of music. The average classification accuracy attained was 78.11 % for MLP, 72.80% for k-NN and 75.52 for SVM.
(42)	IAPS	Biosemi Active Two (54 channel)	EEG, GSR, BP, RR	Bandpass filter (4-45Hz), laplacian reference	Theta-, alpha-, beta-, gamma-Statistical, GP	QDA	Calm-, positively-excited, negatively - excited	For emotion identification, the authors developed a multimodal integration of brain and peripheral inputs. EEG signals appear to function better than other physiological signals, with an accuracy of 76.6 percent.
(43)	Music Videos	Biosemi Active Two (32 channel)	EEG, EMG, EOG	Bandpass filter (0.5 35Hz) (CAR, BSS)	Time and frequency domain (PSD)	SVM	Valence, arousal	The authors proposed a training linear SVM classifier for single trial classification using both EEG and peripheral physiological inputs, reaching an accuracy of 58.8% on valence and 55.7 percent on arousal. The information was gathered from six people.
(44)	Video	EEG device (32 channel)	EEG	N/A	Delta, alpha, theta, gamma (CSP, ASP, FBCSP)	NB	Valence, arousal	Recognition of emotions on valence and arousal by employing Naive Bayes (NB) classifier on the training set data of EEG signals that was extracted using the stimulus of videos (30 sec) on 4 subjects. The accuracy of the classifier

								was >80% on arousal and >65% on valence.
(45)	IADS	Emotiv (14 channel)	EEG	Bandpass filter (4-45Hz), Notch filter, CAR, BSS	Statistical, HFD	SVM	Valence, arousal, domin-ancc	Real-time EEG-based subject-dependent valence level recognition algorithm was proposed that was tested on EGG signals form DEAP dataset to recognize valence, arousal and dominance giving an accuracy of 76.51% on arousal/dominance and 50.80% on valence.
(46)	IAPS	EEG NeuroScan (64)	EEG	N/A	Theta, low-beta (13-20Hz), alpha, high-beta (20-30Hz), gamma- (DFT)	Adaptive SVM	Valence, arousal	Authors improved the classification accuracy on valence and arousal, using EEG signals extracted from 7 subjects while using IAPS images to induct emotions. They implemented adaptive SVM classifier to get the accuracy of 73.57% on arousal and 73.42 on valence.
(47)	DEAP	Biosemi Active Two (18 channel)	EEG	AMR and normalizati on	Delta, alpha, beta, and gamma (DWT)	k-NN	Valence, arousal	Authors proposed wavelet-based emotion recognition system to classify emotions on valence and arousal using EEG signals from DEAP dataset. They implemented k-Nearest Neighbors (k=3) algorithm to get the classification accuracy

								of 84% on arousal and 86.75% on valence.
(48)	Video	Biosemi Active Two (32 channel)	EEG	Bandpass filter (4-45Hz), CAR	Delta, alpha, beta, theta, gamma (AI, PSD)	SVM	Valence, arousal	Authors collected the multimodal database, using stimulus videos (1 to 2 min) on 27 subjects. They used EEG signals to classify emotions on valence and arousal by training RBF kernel SVM classifier on the training data that gives accuracy of 62.10% on arousal and 50.50% on valence.
(49)	DEAP	Biosemi Active Two (32 channel)	EEG	Bandpass filter (4-45Hz), BSS	Theta, alpha, and gamma	NB	Valence, arousal	Authors addresses the emotion recognition problem from EEG signals to classify emotions on valence and arousal dimension. They used DEAP dataset and classified emotional state using two and three classes. By training NB classifier, they had 70.9 percent valence, 70.1 percent arousal classification accuracy on two classes and 55.4 percent valence, 55.2 percent arousal classification accuracy on three classes.
(50)	DEAP	Biosemi Active Two (32 channel)	EEG	Bandpass filter (4-45Hz), BSS	FFT	k-NN	Valence, arousal	Authors proposed emotion recognition using autoregressive (AR) model, sequential forward feature selection (SFS) and K-nearest

								neighbor (KNN) classifier and EEG signals. They got the accuracy of 72.33% valence, 74.20% arousal for 2 classes and 61.10% valence, 65.16% arousal for 3 classes.
(51)	DEAP	Biosemi Active Two (14 channel)	EEG	Bandpass filter (4-45Hz), automatic removal of ocular artifacts	Theta-, low-alpha (8-10Hz), alpha-, beta-, gamma-	SVM RBF	Valence, arousal	Based on novel features, the authors suggested an emotion identification model for EEG-based Brain–Computer Interfaces. They trained kernel SVM classifier using training data from DEAP dataset and got the accuracy of 73.06% arousal; 73.14% valence for 2 classes and 60.7% arousal, 62.33% valence for 3 classes.
(52)	DEAP	Biosemi Active Two (2 channel)	EEG	Bandpass filter (4-45Hz), BSS	Theta, alpha, and beta (HOC)	SVM	Valence, arousal	The authors use EEG signals to investigate derived aspects of bi-spectrum for emotion quantification using a Valence-Arousal emotion model. Implementing Least-squares SVM with kernel function RBF classifier on the DEAP dataset yielding 60.9 percent low arousal, 68.8% high arousal, 59.4% low valence, and 62.5 percent high valence accuracies.

(53)	Music	Waveguard EEG (12 channel)	EEG	Bandpass filter (0.5-60Hz), Notch filter, ICA	Delta, alpha, theta, beta and gamma (PSD, DWT, HFD)	DBN	Valence, arousal	Authors presented an improvement in emotion recognition in music listening by applying an early study of DBNs where emotions were annotated continuously in time by subjects. The EEG data was extracted on 15 subjects by stimulus of music (73 to 147 sec) and DBN classifier was trained to get the trained model. They obtained the accuracy of 82.24% on valence and 82.59% on arousal.
(54)	Music videos	Biosemi Active Two (32 electrodes)	EEG	Bandpass filter	Delta, theta, alpha, beta and gamma (PSD)	GNB	Arousal, valence, like/dislike, dominance, and familiarity	A multimodal data set was offered for the investigation of human affective states. While watching 40 one-minute long music video clips, 32 participants' EEG and peripheral physiological signals were obtained.

Filter: ICA: Independent Component Analysis, S-Golay: Savitzky-Golay, CAR: Common Average Reference, ASP: Asymmetric Spatial Pattern, CSP: Common Spatial Patterns, FBCSP: Filter Bank Common Spatial Pattern, AMR: Average Mean Reference, BSS: Blind Source Separation

Features: Wavelet Transform (WT), PCA: Principal Component Analysis, LDA: Linear Discriminate Analysis, SWP: Sleep/Wake Predictor, KSS: Karolinska Sleepiness Scale, SVD: Singular Value Decomposition, CCA: Canonical Correlation Analysis, GA: Genetic Algorithm, GP: Grassberger and Procaccia, HFD: Higuchi Fractal Dimension, AI: Asymmetry Index, HOC: Higher Order Crossing, FFT: Fast Fourier Transform, STFT: Short-time Fourier Transform, PSD: Power Spectral Density

Classifiers: k-NN: k-Nearest Neighbors, LDA: Linear Discriminant Analysis, NB: Naive Bayes, NN Neural Network, Radial Basis Function SVM: Support Vector Machines, MLP: Multi-layer Perceptron, CBR: Case Base Reasoning, RF: Random Forest, GDA: Gaussian Discriminant Analysis, GNB: Gaussian Naive Bayes, HNB: Hidden Naive Bayes, Gaussian Mixture Model, DCNN: Deep Convolution Neural Network, ENN: Elman Neural Network, QDA: Quadratic Discriminant Analysis, DBN: Deep Belief Network platform app, and novel subject-specific Gaussian Mixture Model- (GMM-) based algorithm was used for training and adaptation in real time that achieved 98.7% average identification-accuracy.

Using EEG signals, Jebelli et al. (31) proposed a system for automatically recognizing workers' stress in construction sites. The authors gathered EEG data from seven construction workers on the job. Workers' salivary cortisol, a stress hormone, was also collected to determine if they were under or over stress while on the job. EEG signals were analyzed for time and frequency domain characteristics. The researchers used numerous supervised learning algorithms to detect workers' stress while on the job. The fixed windowing technique with the Gaussian Support Vector Machine (SVM) gave the maximum classification accuracy of 80.32 percent, according to the data. The results showed that the fixed windowing approach and the Gaussian Support Vector Machine (SVM) yielded the highest classification accuracy of 80.32%.

Issues and Challenges

Based on the literature survey following are the research gaps extracted:

Emotion Recognition on VAD dimension

EEG signals from AMIGOS dataset (30) were used to recognize emotions only on valence and arousal dimension, but not on dominance scale. Therefore, the emotion identification and strength of emotions can be known by recognizing the emotions on VAD dimension. Further, the use of different feature extraction and selection methods such as deep belief network may also improve the accuracy of emotion recognition. In addition to this, different classification algorithm techniques may also be employed to enhance the accuracy of emotion recognition system.

Diversity in Emotion Recognition

An EEG based emotion recognition system by Huang et al. (9) showed moderate performance of 58.5% for patients with DOC that too on two classes of emotions (positive and negative) only. For some of the patients, the system showed good performance while for others it showed very poor performance. Further, the authors tested and validated the system not only with very a smaller number of subjects (8 DOC patients) but also used same stimulus for each type of patient. Therefore, the reliability and the performance of the system must be validated on a greater number of subjects with DOC. Also, the recognition performance in patients with DOC may be improved by eliciting the emotion using different stimulus for each type of DOC patients. Further, wide range of emotions such as surprise, fear and disgust should be considered for better recognition system.

Emotion Recognition for Disable Persons

Dehzangi et al. (34) designed SSVEP and EEG based subject orientated BCI system for patients in ICU environment to consistently and effectively convey their emotions and thoughts. The patients are required to gaze on one of the icons (representing different needs/services) flickering at different frequencies to convey the kind of help they need to doctors, nurses, and caregivers. However, this communication model cannot work for patients with visual impairment. Therefore, self-induced emotion signals or motor imagination/movement tasks signals can be used to elicit the brain signals instead of SSVEP. The system can be further extended to add more input communications icons such as intensive care physicians and critical care nurses.

Emotion Recognition System for Stress Detection

Jebelli et al. (32) developed a stress recognition method using EEG signals for early recognition of worker's stress at construction sites in order to enhance their safety, wellbeing and productivity. Authors have classified the stress into two class (low and high) only, which is not discrete but fuzzy in nature. Thus, fuzzy classification may be applied for enhancing stress recognition accuracy. In addition to this, more number of subjects can be considered to test the reliability of this method.

Tools and Technologies

This section includes the most significant hardware, software and the methodology that is used for research in the area of emotion recognition.

Hardware

There are many non-invasive, efficient, wired and wireless EEG equipments available in the market. The most commonly used equipments are Emotiv EPOC headset (https://emotiv.com), Biosemi Active Two (http://www.biosemi.com/products.htm), neuroSKY Mindwave (http://compumedicsneuroscan.com) and g.MOBIlab (http://www.gtec.at/Products).

Emotiv EPOC. The Emotiv EPOC is a multi-channel, high-resolution wireless neuroheadset. The EPOC detects the user's thoughts, feelings, and expressions in real time by using a set of 14 sensors plus two references to capture electric impulses produced by the brain. The electrodes are always placed in accordance with the international 10/20 scheme.

Biosemi Active Two. A Biosemi Active Two system measures potential differences on the human body surface. This system can be used to record signals originating from the brain. It can also be used to capture ECG signals from heart and EMG from muscles. In addition, it can acquire signals from variety of additional sensors in order to measure factors like body temperature, muscle force etc. (55).

NeuroSKY Mindwave. This headset is a wearable device which measures some physiological signals by using EEG, ECG, EOG and blood pressure. The headset measures brainwave signals and helps in monitoring physiological factors like mediation and attention levels (56).

g.MOBIlab. It's a program that lets you capture multimodal bio signal data on a regular PC or notebook. This aids in the study of brain, heart, and muscle activity, as well as eye movement, respiration rate, galvanic skin response, pulse, and other bodily signals. It comes in two flavors: an 8-channel EEG and a multi-purpose version (57).

Software

MATLAB. It is an interactive software system which performs numerical computations, and implementations and validations of machine learning algorithms. It also has a user-friendly Graphical User Interface (GUI) that allows users to openly and interactively route their high-density EEG dataset. MATLAB provides signal processing and signal conditioning for a variety of biomedical signals, as well as precise data collecting, when used in conjunction with Simulink. It has user-selectable multichannel modules that allow EEG, ECG, EMG, and EOG data to be recoded in simultaneously (58).

Python. It's a sophisticated programming language with features including array and matrix multiplications, image processing, digital signal processing, and visualization. Python has been used to create a number of popular data exploration and visualization tools. As Python framework also exhibit data analysis functionality, this way it provides an easy way of changing analyses on-the-fly using multiple implementations from user-created specifications to robust, compiled libraries. Having the property of Interpreted languages, Python provides a solid foundation for the development of the powerful and flexible data analysis tools (59).

Methodology

The general approach used to recognize the valence and arousal level of emotion comprising several phases that includes data acquisition, signal processing, feature extraction and reduction, and classification is shown in Figure 4.

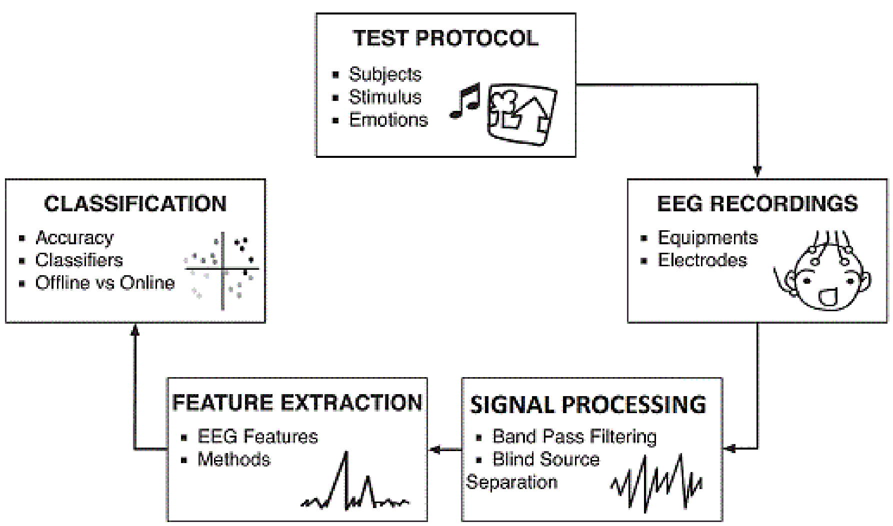

Figure 4. Methodology for recognition of valence and arousal of emotion.

Test Protocol

The information regarding the subject and stimulation is contained in this phase. The subject is the person who participates in the experiment or whose physiological data will be used for future research analysis. The stimulus is what causes a person to feel something. Subject and event-elicited elicitation are the two most common methods for eliciting emotions. In the first, participants are asked to recall some former emotional experiences from their lives that helped them produce an emotion. Second, diverse modalities such as video, audio, and visual stimulus are used in event elicitation.

EEG Recording

EEG equipments are used to read the brain signals from the scalp of head. They contains multiple electrodes which are placed against the head to record the voltage changes in the brain. International 10/20 Standard System is used for the proper electrode placement on the head.

Signal Processing

The signal recordings captured through an EEG are usually contaminated by some noise or artefacts which are not generated from the brain itself such as like muscle movements, eye-blink, and cardiac activity. These noisy signals degrade the quality of the recorded data, and thus the use of de-nosing methods such as filtering and artifacts removal become a necessary part of the recognition procedure. Artifacts removal techniques such as BSS, ICA, Notch filter and CAR are used for processing process. According to the survey done by Soraia M. Alnrcao ct a1. (2019), 24% of the works removed various types of artefacts associated to the subject manually. Their names and usage in percentage are Blind BSS (19.3%) and ICA (8.8%). Around 30% of the works used approaches like CAR (58.9%), Laplacian (23.60%), and AMR to re-reference the electrodes (5.9 percent). Because not all of the frequencies recorded are suitable for the emotion recognition problem, bandpass filters were utilised in about 84 percent of the studies. The Notch filter was used in 16.58 percent of the works, mostly at frequencies of 50 and 60 Hz. Finally, 43.9 percent of the works sampled their original EEG signals at a lower frequency: 52 percent at l28Hz. 160 percent at 206 Hz, 12 percent at 256 Hz, 4% at 512 Hz, and 4% at 500 Hz. 4% at 250 Hz and 4% at 32 Hz.

Feature Extraction

The main task of this stage is to extract the salient features which can relate the EEG data into their respective emotional states (60). Generally, EEG features are extracted in time domain, frequency domain, and time-frequency domain. Time domain features figures about the EEG signals synchronization measured from various electrodes which gives the idea of similarity between the signals. Its features are amplitude related such as energy, power, mean, and variability. It also includes ERP and Hjorth Features (61). Frequency domain features from EEG include power features from different frequency bands such as delta rhythm (0.5M Hz), theta rhythm (4-8Hz), alpha rhythm (8-13 Hz), beta rhythm (13-30 Hz) and gamma rhythm (30-50 Hz). Time-frequency analysis comprises those techniques that studies a signal in both the time and frequency domains simultaneously, using various time-frequency representations. According to a recent survey, the most popular methods for feature extraction include Fourier Transform (STFT or DFT) (25.4%), statistical (23.8%), PSD (22.2%), WT (19.1%), Entropy (AE), DE, SE, or Wavelet Entropy (WE) (15.9%), HOC (9.5%), Common Spatial Patterns (CSP) (7.9%), Fracta (7.9%), and Asymmetry Index (AI) (4.8%). (4.8 percent).

Classification

The final and most significant stage is classification, which employs a huge number of classifier families to distinguish between different emotion categories. Bayesian, SVM, and Decision trees are among the most often utilised. SVM was employed by a number of researchers with various kernels, including RBF, Linear, Polynomial, Gaussian, and Pearson. Some of the works additionally employ adaptive SVM, Multi-class Support Vector Machine (ML-SVM), or Least Squares Support Vector Machine (LS-SVM). Most of the studies employ the k-Nearest Neighbors (k-NN) algorithm, with k ranging from 2 to 8. Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naive Bayes (NB), and Multi-Layer Perception Back Propagation are also used by some writers (MLP-BP).

Conclusion

The present paper is focused on the recognition of emotions in human beings based on EEG signals. A review of research articles was conducted that revealed the information about the stimulus, equipments, filters, features and classifiers used for emotion recognition. Since the previous few years, the field of affect recognition has gotten a lot of attention. It has branched out into numerous domains that aid with human well-being, safety, health, and growth. Previously, this discipline was restricted to the study of emotions and feelings, but it is currently focusing on real-time applications. For instance, in the areas of healthcare, e-learning, neuro-science, entertainment, behavior prediction etc. where the researchers are working. Further, the best results can be obtained using different combination of multiple tools and techniques, and various processing techniques.

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