Emotion Recognition And Classification Using Eeg: A Review

Nandini K. Bhandari, Manish Jain

Abstract: Emotions result in physical and physiological changes which affect human intelligence and the world around us. Emotions which indicates inner feelings of a person is represented by EEG as a direct brain response to a stimuli. EEG-based emotion recognition is widely used in affect computing to improve communication between machines and human. In this paper we provide a comprehensive overview of methods proposed for emotion recognition using EEG published in last ten years. Our analysis is focused on feature extraction, selection and classification of EEG for emotion recognition. This survey will be a mile stone for researchers in enhancing the development of emotion recognition using EEG.

Index Terms: DEAP, CNN, EEG, Electroencephalograph, EMD, emotion recognition, neural network, SVM.

1 INTRODUCTION

Emotions play a vital role in our daily life because they affect human cognition, perception, interaction, decision making ability along with human intelligence [1]. However, they were ignored by human computer interaction (HCI) systems till last decade. The HCI systems along with digital media, find potential applications in biomedical engineering, neuroscience, neuromarketing and other alternate areas of life, which are mainly affected by emotions. Hence, with increasing demand of HCI, automatic human emotion recognition is gaining the attention of researchers. The emotion recognition can be done with the help of text, speech, gesture movements and facial expressions [2] but electroencephalogram (EEG) gives better outcome as it directly measures true feelings. EEG is non-invasive and have high temporal resolution [3]. A rapid development in new wearable, handy, low cost wireless headsets measuring EEG and classification of EEG signals without trained professionals has enormously increased its use in other areas like, sleep management, e-learning, video games, cyber world, healing etc. This literature survey has covered recent methods used in EEG based emotion recognition, which will be helpful to researchers working in this field. The remaining paper is organized as follows. Section II describes emotions, characteristics of EEG signals and basic steps used in emotion recognition. Section III describes about database used in most of the papers. Section IV deals about preprocessing methods used on raw EEG signals. Section V contains information about various processes used in feature extraction and classification. Section VI discusses about the various aspects related to review and section VII gives conclusions extracted from this survey.

2 EMOTIONS AND EEG

An emotion is complex physiological state which involves a person's experience, a physiological response and behavioral change.

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A person's inner emotional state may become apparent by subjective experiences (how the person feels), internal/ inward expressions (physiological signals), and external/ outward expressions (audio/visual signals) [4]. These are temporary signals, having short duration and intensity variation. According to Paul Ekman and Friesen [5], there are six universal emotions, independent of various cultures in the world. They are happiness, fear, anger, sadness, disgust and surprise. Plutchik has considered eight emotions: anger, fear, sad, disgust, surprise, curious, acceptance and joy [6]. These emotions are highly complex in nature, varying from person to person. This complexity makes emotion recognition a challenging task. The studies of emotion recognition use different types of emotions techniques for classification: a. Discrete emotions: Happiness, fear, anger, sadness, disgust and surprise. Researchers may take single emotion or opposite emotions for detection. One may use four emotions namely happy, sad, fear and anger.

b. Two emotions: Positive and negative.

c. Valance arousal model: Valance means from very positive to very negative, arousal means sleepy to exited and dominance gives strength of emotion [7].

EEG (Electroencephalogram)

The human cortex is divided into frontal (F), temporal (T), central (C), parietal (P) and occipital (O) lobes. EEG signal is the voltage fluctuation obtained by ionic current flow with synaptic connections of neuron. In an adult, EEG signal measured from scalp is a sinusoidal signal of range 10-100µV. Useful information from brain is divided in five frequency bands namely, delta (0-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (30-70Hz) [8]. Delta waves are obtained during deep sleep. Theta waves are associated with subconscious mind activities like sleeping and dreaming. Alpha waves occur during relaxed state and are more prominent in parietal and occipital lobe. Beta waves occur during focused mental activity. Gamma waves occur during hyper brain activity [9]. International 10/20 system [10] as shown in figure 1, is used for placing electrodes on skull to get EEG signals. The numbers 10 and 20 suggests, distance between neighboring electrodes (10% or 20% of total front-back or right-left distance of skull).

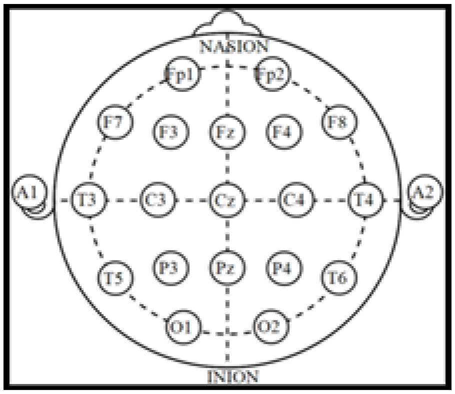

Fig. 1: *The international 10/20 system.*

Alpha wave power change and asymmetric variation in frontal lobe EEG signal indicates the valance state. A valance state is also obtained by beta waves. Alpha waves from pre-frontal asymmetry and gamma waves from temporal asymmetry are useful in arousal recognition. Gamma waves changes or decrease in alpha wave in temporal lobes gives happiness or sadness. In general, we can summarize that maximum information about emotions is obtained from frontal and parietal lobes. The study of emotions show that men have individuality in EEG patterns where as women have more similarity in EEG patterns. The basic steps in emotion recognition process, as shown in figure 2 are as follows:

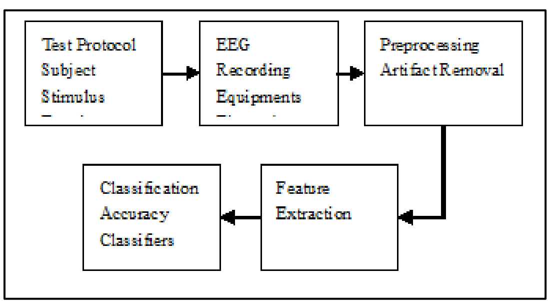

***Fig. 2**. Process of Emotion recognition.*

a. Stimuli: User is exposed to stimulus like images, audio, audio-visual clips, games etc.

b. EEG recorder: Record the variation in voltage occurred in brain with the help of sensors or brain computer interface.

c. Preprocessing: Remove the artifacts and various noises, in the recorded EEG.

d. Feature extraction: Analyze the signal and extract the relevant features.

e. Classification: Use a training data, to train the classifier such that using those computed features one can predict the EEG signal.

3 DATABASE

A number of datasets are available on internet, which can be used for EEG emotion recognition. Some of them are listed below:

i. SEED: This database [11] collected EEG data from 64 electrodes when each subject was watching 15 Chinese clips having emotions positive, negative and neutral. Eight females and seven males were participated for the three sessions, such that dataset contains 45 trials of EEG data for each subject. A feedback was taken from each subject while watching clip, to guarantee the observed emotion.

ii. DREAMER: This database [12], collected EEG data from 23 subjects (9 females and 14 males) using 14 electrodes. 18 clips were used having nine different emotions, i. e. anger, disgust, amusement, excitement, fear, sadness, happiness, calmness and surprise. Self assessment manikins were used for subjective assessment of valance, arousal and dominance.

iii. DEAP: EEG of 32 subjects [13] were recorded from 32 electrodes when each one was watching, forty one minute music videos. These subjects rated videos as valance, arousal, dominance like/dislike and familiarity. Some authors have used some other database, while some of them have created their own database using brain computer interface (BCI) system.

4 PREPROCESSING THE EEG SIGNAL

To get only brain activity signals from raw EEG preprocessing of EEG signal is required. This process includes line noise removal, bad channel elimination and artifact removal. A multi-taper decomposition is used for line noise removal, where a shot sliding window is passed over EEG signal to transform it into frequency bands. Bad channel is detected by finding a correlation of a single channel with others. Artifact removal is one of the prime step in emotion recognition. Artifacts are generated by internal factors like eye movement, muscles contraction, electrical activities of heart and external factors like environment, electrode attachment, cable and recorder. We describe some commonly used methods in artifact removal:

i: Linear regression: In linear regression [14], EEG signal is assumed to be sum of brain signal and artifact, and artifact is removed by subtracting regressed portion from contaminated EEG.

ii. PCA: Principal component analysis [15], orthogonally transforms correlated EEG data to uncorrelated principal components preserving variance of EEG data.

iii: ICA: Independent component analysis removes artifacts with assumptions that there is statistical independence between EEG and artifacts [16] and EEG signal remain stationary during analysis. Physiological and non-biological artifacts related independent components can be removed from EEG using automatic identification ICA algorithm.

iv. CCA i.e. canonical correlation analysis [17] removes artifacts by finding linear relation between EEG and its temporarily delayed version.

v. EMD: Empirical mode decomposition [18], decomposes signal into basic functions called intrinsic mode functions (IF). These IFs are computed using Hilbert transform to get Hilbert spectrum. EMD work well on non-stationary signals like EEG where signal and artifacts are represented by one or more IFs. Ensemble EMD gives more robust results.

5 FEATURE EXTRACTION AND CLASSIFICATION

Features are extracted from processed EEG signal. These features can be found using statistical, time domain, frequency domain or time frequency domain methods. A subset of features which can give best classification accuracy is selected. These features are further classified using machine learning or neural network methods such that similar features are grouped in one class. Various feature extraction and classification methods are discussed in this section.

a. Machine Learning based methods

Machine learning is a part of computational learning in artificial intelligence. The aim of machine learning algorithms is to train themselves on available data and then accurately estimate the unseen tasks. These methods learn from small dataset. In the following paragraphs we have discussed some machine learning methods used in emotion recognition. In [19] low amplitude EEG signals generated because of self induced stimulus of subject while remembering an unpleasant event, were used for emotion classification. Wavelet was used to remove artifacts and get useful features which were further reduced by PCA. SVM classifier [20] was used for classification. This method had helped in detection of frequency bands affected by particular stimulus. Further it was observed, that channel T8 connected to right hemisphere was predominant in revealing the stimulus. R. Du et al [21] calculated Hjorth parameters for different frequency ranges from processed EEG signal. Optimal features were selected by applying balanced one way analysis of variance (ANOVA) on extracted features with p-value <0.05. Emotion classification was done on optimal features using SVM, LDA, deep learning, kNN and ensemble methods using WEKA software [22]. Outstanding results were obtained using voting ensemble algorithm. Group sparse canonical correlation analysis (GSCCA) algorithm [23] was proposed for automatic selection of EEG channels and emotion recognition. In this CCA method was modified to regularized weighted reduced rank regression model [24] using binary weights. A raw EEG signal used for processing had helped group sparse learning process to select channels. The results had signified that both frontal and side lobes of brain play an important role in emotion recognition. 80% accuracy was obtained with four channels, when features from all the frequency bands were used. A real time movie-induced emotion recognition method was developed in [25] to identify individual's emotions using brain waves. Using short time Fourier transform and spatial-temporal method, energy and power related features indicating brain activity were extracted and number of features were reduced using sparse linear discriminate analysis. A multiclass SVM classifier, LIBSVM [26], was used to classify eight emotions. Average classification accuracy for positive emotions was 86% and negative emotions was 65%.In [27], correlation based subset selection system was used for selection specific channels. Useful statistical features were extracted from selected channels. As the output variable of each emotion class was different, linear discriminate analysis (LDA) [28] was used for classification. In [29], fractal dimension features were obtained from EEG signal using higuchi algorithm. A SVM classifier with radial basis kernel function was used for emotion classification. In [30], channels were selected using stepwise discriminant analysis (SDA) of EEG signals. Differential entropy features from five frequency bands δ, θ, α, β and γ were extracted from EEG. Wilks Lambda score was used in SDA, to obtain optimal channels. LDA classifier was used for classification of emotions. 99.85% classification accuracy was achieved with 16 channels. In [31] EMD was used for signal decomposition and sample entropy was applied on first four components. Using black hole algorithm [32] for optimization, suitable SVM features were obtained for classification. The results on MAHNOB HCI tagging database [33] gave accuracy up to 90%.In [34], two stage correlation and instantaneous frequency filtering was used for feature extraction. Non linear features were extracted from EEG after removing unwanted frequency components using variational mode decomposition (VMD). FP1-F7 bipolar channel features were chosen using F score and fed to multi class least square SVM classifier for emotion classification in BCI systems. P. Li et al [35] had established networks in brain, using phase locking value. They had combined information patterns and activation pattern for emotion recognition. Activation patterns were obtained from spectral power differences generated in various regions of brain, while watching emotional clip. The results had shown that, an efficient HCI system can be developed for real world applications. In [36], flexible analytic wavelet transform (FAWT) was used for disintegrating the EEG signal. The sub-bands obtained had provided flexibility in parameter selection (fractional sampling, quality factor, dilation and redundancy). Feature extraction from dissimilar channel sub-bands was done by information potential (IP) estimator. The feature values after smoothening were given to random forest and SVM classifier independently, for emotion classification. This channel explicit cross subject classification is helpful in understanding the emotional sensitivity in brains of different people for same stimuli. In [37] Soft voting strategy was used to design classifier which used series of independent classifiers namely decision tree, Random forest and kNN. Classification was predicted according to argmax of sum of predicted probabilities. Activation emotion curve was drawn from classification results, using two emotion coefficients namely, correlation coefficients and entropy coefficients to understand emotion activation mechanism. Weighted coefficients drawn from correlation coefficients and entropy coefficients, were helpful in improving accuracy of emotion recognition. In [38] an emotion state was defined in continuous space and gradual emotion changes were observed. Linear dynamic system was applied to filter unwanted features and smoothen the desired features. PCA and minimal redundancy maximum relevance (MAMR) [39] algorithms were used for feature dimensions reduction. Discriminative graph regularized extreme machine learning technique for differential entropy gave best results.

Table 1: *Machine learning methods used in emotion recognition*

Classifier used	*Feature extracted*	*No. of channels used*	*Classification accuracy*	*Advantages of classifier*	*Disadvantages of classifier*
SVM (used for two, four or eight emotions)	*Wavelet and PCA*	*1 or 8*	*59%*	*1. Good results on unstructured data 2. Better sealing of high dimensional data*	*1. Long training time for large dataset*
	Hijorth parameter	*14*	*53%*		
	Frequency features	*4*	*80%*		
	Fractal Dimension	*14*	*60%*		
	Differential entropy	*32*	*70%*		
	EMD	*32*	*90%*		
kNN (used for two emotions)	*Hijorth parameter*	*14*	*70%*	*1. simple to implement and understand 2. Good classification for large data*	*1. Sensitive to irrelevant features 2. Selection of k is difficult*
	Differential entropy	*32*	*60%*		
LDA (used for two or four emotions)	*Hijorth parameter*	*14*	*51%*	*1.Simple implementation 2.Reduces high dimensional data to low dimensional data*	*1. fail to discriminate variety of features 2.Fail to work on variance*
	Differential entropy	*16*	*99.85%*		
	Statistical features	*4*	*80%*		

b. Neural network based methods:

Neural network is a parallel distributed processor built with simple processing units [40]. It has capacity to store experimental knowledge which is available whenever required for use. It has resemblance with brain in two aspects

i. Knowledge is obtained by the network from its surrounding through learning process.

ii. Inter neuron connections are used to store the obtained knowledge.

The neural networks are non-linear, adaptable, fault tolerant and have input output mapping. Hence, they can encode complex behaviour of non-linear EEG signals. In the following paragraphs we discuss emotion recognition and classification methods based on neural network. In [41], deep learning network (DLN) [42], was used to find correlation between unknown features of input signal. A DLN was composed of three stacked autoencoders and two softmax classifiers, to classify valance and arousal states. Power spectral densities obtained from 32 channel EEG, were given as input to the DLN. To extract salient components of input PCA was used. Additionally, covariate shift adaption of PCA was used to diminish non-stationary outcome of EEG. Classification accuracy 52 to 53% was obtained. In [43], critical frequency bands and critical channels for effective EEG based emotion classification, were obtained using deep belief network (DBN) [44]. The three emotions classified were positive, neutral and negative. Differential entropy was obtained from multichannel EEG data to train DBN. After obtaining weight distributions from DBN, different setups for frequency bands and channels were chosen and number of electrodes were reduced. It was observed that, properly selected four channels gave the same accuracy as 64 channels. In DBN, training is the main limitation of the system. Generally a large feature space is generated, when most relevant features among all the subjects is chosen. To overcome this issue and to get low dimensional feature space from EEG an Echo state network (ESN) model was suggested in [45]. The dynamic nature of ESNs had eased the learning process of deep neural autoencoder (DNA), working in time domain. A new approach of extraction of equilibrium states, based on intrinsic plasticity (IP) [46] adaption, had maximized the model capacity. Depending on IP trained ESN, favorable combinations of equilibrium states were used for emotion classification and accuracy as high as 95% was achieved. In [47], circular back propagation neural network (CBPN) and deep Kohonen neural network (DKNN) were used to reduce computational complexity and improve accuracy of emotion classification. The circular arrangement of layers in CBPN had helped the input and output layer, to be in close proximity with one another and reduced number of mathematical calculations required for training. In DKNN available dataset was grouped into fewer classes with the help of abstract layer. These classes were further used in emotion classification. In [4] a new physiological model called deep physiological affect network (DPAN) [48] was developed. The model had supported ConvLSTM (convolution long and short term memory) [49] and loss function derived from temporal margin. The developed model had reduced gap between low level physiological sensor photoplethysmogram (PPG) signals and high level EEG signals, which are dependent on circumstances for emotions. The spatiotemporal features were extracted from bipolar EEG and PPG signals. The system had improved accuracy in identifying a specific feeling, based on two dimensional emotion model. In [50], EMD was applied to fixed size EEG signal, whose noise was suppressed by ICA. An approximate entropy [51] was calculated from first four intrinsic mode functions of disintegrated signal. Appropriate combination of attributes were selected and their entropy was fed to Deep belief network [44] for feature extraction. These features were classified using SVM classifier. The results had shown that gamma band signals from frontal and temporal lobes were mainly responsible for emotion recognition. Average accuracy obtained was 83.34%.In [52], a 3D convolution neural network 3DCNN [53] was developed for extraction of spatiotemporal features of EEG signal. Time domain raw EEG was used in construction of frames for feature learning. Data from different channels was taken as input to the network and correlation between their positions was found, for emotion recognition. The model had captured association between dimensional emotions and converted them into discrete emotions. The shallow network had saved processing time. In [54], for getting the localized spatial information from electrodes, differential entropy (DE) features from EEG were mapped as 2D. The electrodes were placed at different locations on the brain. Sparsity was applied, to get sparse DE maps. Hierarchical convolution neural network (HCNN) [55] was applied to transfer input DE maps from input layer to output layer. Each layer had projected the input into another space. These transformations were used in the last fully connected layer to recognize emotions. In HCNN, at each layer the output became more global and abstract, which had resembled the working of human visual cortex. The activation function along with pooling operation of HCNN had enhanced the non linear feature transformation giving better accuracy. In [56] dynamical graph convolution neural network (DGCNN) was proposed for studying nonlinear discriminative EEG features and functional relationship between channels. A graph was used to provide most discriminative features required for emotion recognition. DGCNN had adaptively learned intrinsic relationship between channels by training a neural network to develop an adjacency matrix which can be updated with changes in the graph model. A non-linear mapping in the network was realized by Relu activation function to get non-negative graph output. Diagonal elements in adjacency matrix had indicated the benefaction of EEG channels in emotion classification. Accuracy of 90% was achieved with SEED dataset by combining differential entropies of five frequency bands. In broad learning system (BLS) [57], inputs mapped in feature mode were enlarged in enhancement mode. Using the random mapping ability of BLS, a broad dynamical graph learning system (BDGLS) [58] was designed. Features extracted by DGCNN from irregular EEG signals were used in BDGLS for generating graphs, which were then expanded in broad space using enhancement nodes to get appropriate features for emotion recognition. In [59] emotionally salient regions called hotspots were defined using qualitative agreement (QA) [60] method, which had searched trends across continuous time evaluation for valance and arousal states. A group of bidirectional long short term memory regressors were trained for individual emotional traces and then combined for automatic emotion hotspot detection. Accuracy of 60.9% for arousal and 50.4% was obtained on RECOLA dataset [61]. In [62] hierarchical network with subnetwork nodes, was used for emotion recognition. Each subnetwork node [63] had hundreds of hidden nodes and each node worked as independent local feature extractor and classifier. The top layer of hierarchical network, similar to brain cortex, combined the features obtained from subnetwork nodes. The network had modified these features into mapping space, to have better learning of emotions. This NN based method had shown favorable results with single and multiple modality. According to neuroscience left and right hemisphere of human brain, show asymmetrical response to emotions. Right hemisphere recognizes negative emotions better than left one and left hemisphere understands positive emotions better [64]. A Bi-hemispheres domain adversarial neural network (BiDANN) [65], was used for emotion recognition. In BiDANN [66], two local and one global discriminator was designed in such a way that they worked adversarially with classifier to learn distinguished emotion features from the two hemispheres. This had reduced the difference between source and target domains on each hemisphere and gave better recognition model. The model had three parts viz. feature extractor, classifier and domain discriminator. Feature extractor was used for getting discriminative deep features from the two hemispheres' EEG. Classifier had classified emotions from deep EEG features. Domain discriminator was used for reduction of domain differences improving the performance of recognition. In [67], frequency, time and a combination of time and frequency domain was used for EEG features extraction. A whole frequency band (4-45)Hz was used to obtain frequency feature called power spectral density. A deep (DCNN) convolution neural network having capacity to extract deep and abstract input information, was used for automatic learning of dynamics of EEG signal. The method had performed robust emotion classification. The method had overcome the traditional approach of manual feature extraction and selection, before applying the machine learning classifier. It had improved accuracy and stability of EEG based emotion recognition, giving high performance of brain computer interface systems. A combination of EEG signals and eye movements was used in development of Emotion meter [68]. A wearable headset of six electrodes was used for measuring EEG signal and eye tracking glasses were used to measure eye movement. From the eye movements and complementary characteristics of EEG, emotions were recognized. Emotion meter performance was further enhanced with multi-model deep neural network. A mean accuracy of 85% was achieved. A hierarchical bidirectional consciousness enhanced gated recurrent unit (HBGRUN) network [69], evolved from hierarchical attention network [70] was developed for cross subject emotion classification. It was made up of bidirectional GRU network [71], sample encoder, attenuation based sample aggregation, epoch encoder, attention based epoch aggregation and a series classifier. The constructed model had reflected the hierarchical structure of EEG. Consciousness mechanism was used, at two layers of EEG samples and epoch. The first layer in the system had encoded the local correlation between the samples in the epoch and the second layer had encoded temporal correlation among the EEG epoch in the sequence. By paying discrete levels of attention to content with different priority, model had drawn more significant features of EEG, giving better classification. According to neuroscience different brain regions generate different responses for different emotions. A R2G-STNN (regional to global spatial and temporal neural network) was proposed in [72], which had integrated spatial-temporal data of local and global regions of brain into EEG features, to enhance emotion recognition. The feature extractor of R2G-STNN was used to learn spatial and temporal features of EEG by applying bidirectional long short term memory (BiLSTM) [73] network on each brain region and among different brain regions. As different brain regions generate different emotion signals, a region attention layer was introduced for learning set of weights specifying contribution of brain regions. Classifier was used for predicting emotions from extracted features and also guided the NN learning to generate more discriminative features. A gradient reverse layer was used in discriminator to reduce domain shift between source and subject data, enabling hierarchical feature learning process for emotion classification. A regularized graph neural network (RGNN) was proposed in [74], where each channel was considered as a node in graph. A biologically assisted sparse adjacency matrix was used for capturing local and global inter channel relations. A node-wise domain adversarial training [75] (NodeDAT) was provided to regularize subject independent classification. Thus regularization had improved with minimum domain discrepancies, among source and target domains of each channel. An emotion aware distribution learning (EmotionDL) algorithm was proposed to deal noisy labels in dataset to improve accuracy. In [76], EEG phase space was reconstructed for each channel and then modified in angle space (AS). Non linear features obtained from AS had given valuable information about emotions. Most significant extracted features were given to two classifiers namely multilayer perception and Bayes to recognize emotions. The posterior probabilities of the two classifiers fed to Dempster-Shafer theory [77] were combined, to improve classification accuracy. In [78], a bi-hemisphere discrepancy model (BiHDM) was developed to understand asymmetric differences obtained in the output of two hemispheres, to classify emotions. Four recurrent neural networks (RNN) were engaged on spatial orientations of signal, to travel across the two hemispheres. The RNNs had enabled algorithm to find deep features of EEG, keeping spatial dependency inherent. A pair wise sub-network was implemented to get discrepancy data between two hemispheres and higher level attributes were extracted for classification. For dominant shift reduction between trained and test data, domain discriminator module generating domain invariant features was introduced. The overall algorithm performance was improved with domain discriminator. In [79], depending on spatiotemporal features and inbuilt information provided by functional connections of data, a multichannel EEG recognition algorithm based on phase locking value (PLV) graph convolution neural network (P-GCNN) was developed. It had used PLV [80] based brain matrix to evaluate multi channel EEG features as graphical signal. This P-GCNN had used PLV connectivity to find emotion related functional connectivity which was further used to determine intrinsic relationship between channels for different emotions. The network was trained to locate emotion effective features and classification accuracy about 77% was obtained. In [81] spatial-temporal recurrent neural network (STRNN) was proposed for obtaining features from spatial and temporal information of EEG. Traversal of spatial regions for each temporal slice in different directions, was used by multidirectional recurrent neural network (RNN) layer to get spatially co-occurant variations features. A bi-directional temporal RNN [82] was used to get discriminative features from temporal dependencies and these features were used for emotion recognition. It is observed that negative news on social media has increased mental illness among people. In [83], early recognition of negative emotion, while consuming negative news was done to overcome this problem . Eight symmetrical temporal channels were used for EEG recording. Seven features were extracted from EEG using Fourier and wavelet transform. SVM and multilayer perception (MLP) algorithm was used for emotion classification. MLP was a three layer neural network having three layers as input, hidden and output layer. MLP with power spectral density as feature input had given highest accuracy of 94%.

Table 2: *Neural network based emotion recognition methods*

Classifier	*Feature extracted*	*No. of channels used*	*Remark*
DLN [41]	*Differential Entropy*	*32*	*Accuracy 52-53%*
DBN [43]	*Differential Entropy*	*4, 6,9, 12*	*Accuracy 86% but more training is required to DBN*
DNA [45]	*Temporal features*	*21*	*Accuracy 95%, Detect asymmetric difference obtained in output of two lobes*
DKNN [47] CBPN	*Time, Frequency, Wavelet*	*32*	*Accuracy 95-98%, No. of mathematical calculations are reduced, Dataset grouping in fewer classes*
DPAN [4]	*Spatiotemporal features*	*32*	*Can identify specific feelings Accurately*
DBN [50]	*Approximate entropy*	*16*	*Accuracy 83%. Gamma band is most suitable for emotion recognition*
3DCNN [52]	*Spatiotemporal features*	*32*	*Accuracy 87%, finds correlation between valance and arousal states*
HCNN [54]	*Differential Entropy*	*62*	*On beta waves accuracy is 86% and on gamma waves accuracy is 88%*
DGCNN [56]	*Differential entropy*	*62 and 14*	*Accuracy on SEED dataset 90% and DREAMER 84%*
BiDNN [65]	*Discriminative features*	*62*	*Accuracy 92%,cross subject emotion classification is possible*
DCNN [67]	*Time and frequency*	*32*	*Accuracy 85%, worked on two emotions*
HBGRUN [69]	*Raw EEG*	*32*	*Accuracy 66%*
R2GSTNN [72]	*Spatial features*	*62*	*Subject dependent accuracy 93% and subject independent accuracy 86%*
P-GCNN [79]	*Spatiotemporal features*	*32 and 64*	*Accuracy 77%, PLV used to find inter channel relation*
STRNN [81]	*Spatiotemporal features*	*62*	*Accuracy 89%, Effective hierarchical structure of STRNN*
MLP [83]	*Power spectral density*	*8*	*Accuracy 94%, Used in finding effect of negative news on person*

6 DISCUSSION AND FUTUTRE DIRECTION

EEG is a non invasive signal with strength about 10-100 μV and it is contaminated with noise. ICA based methods can remove all types artifacts when source signals are independent. Researchers have used one of the artifacts removal methods which are discussed in the paper but it is difficult to remove artifact using single method. In future one can combine traditional method with machine learning to get automatic artifact removal. SEED or DEEP database are commonly used by 70% researchers, which have used 64 or 32 electrodes. If exact number of channels required for emotion recognition are found then number of electrodes can be reduced in practical BCI systems. Machine learning techniques like LDA, kNN are simple to implement but the accuracy obtained by these techniques is about 55% for two state emotions. With SVM we can get emotion classification accuracy up to 70% for two class which has been reduced when user has used multiclass SVM for six emotions except [34]. Though neural network and deep learning has increased the performance of emotion recognition, technical and usability challenges are still in existence. It is observed that DBN have good classification ability. We recommend to use power spectral density or differential entropy features for DBN for better results. CNN architecture has capability to extract complex features of data at each layer to determine output. There is no limit on number of channels to be used in CNN as they are capable of handling large data. In future, CNN can be used as fundamental tool for feature learning and classification. In RNN connections between nodes form a directed graph along the temporal sequence. This is helpful in predicting temporal dynamic behavior. Most RNN studies have used two LSTM layers and one or two fully connected layers for classification. In future, one can vary the number of fully connected layers and find accuracy. It is observed that accuracy has increased above 80% with deep learning. Hybrid models have given promising results for EEG classification but further research is required to check the effectiveness of them. In the experimentation, number of subjects having variation in ages, gender should be increased such that, from training more features are obtained giving better classification accuracy during testing. For a deep neural network to do a good job, create a network and proceed it to optimize its architecture such that we get best solution for a particular problem.

7 CONCLUSION

In this paper we have surveyed the methods of emotion recognition using EEG. We have concentrated on machine learning and neural network methods. We summarize EEG signals, their preprocessing techniques, feature extraction and classification techniques used for emotion recognition. It is observed that deep learning methods are predominant in getting high level features automatically from non-invasive EEG signal and are less dependent on manually created features. Finally, we recommend more in depth research on deep learning network design for emotion recognition. A comparison of designed model for interpretation of raw versus de-noised EEG for emotion recognition can be done which is not yet done.

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