Title: Feature Extraction with Stacked Autoencoders for EEG Channel Reduction in Emotion Recognition

Running Title: Channel Reduction with SAEs

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Abstract-

Emotion recognition by EEG signals is one of the complex methods because the extraction and recognition of the features that are hidden in the signal are sophisticated and require a significant number of EEG channels. Presenting a method for feature analysis and an algorithm for reducing the number of EEG channels fulfills the needs for research in this field. Therefore, this study has investigated the possibility of utilizing deep learning to reduce the number of channels while maintaining the quality of the EEG signal. Stacked autoencoder network (SAEs) is used to extract optimal features for the classification of emotion in valence and arousal dimensions. Autoencoder networks have the ability to extract complex features to provide linear and non-linear features which are a good representative of the signal. The accuracy of conventional emotion recognition classifier (SVM) using feature extracted from SAEs was obtained 75.7% for valence and 74.4% for arousal dimensions, respectively. Further analysis also illustrates that valence dimension detection with reduced EEG channels has a different composition of EEG channels compared to arousal dimension. In addition, the number of channels is reduced from 32 to 12, which is an excellent development to design a small size EEG device by applying these optimal features.

Keywords: Deep learning, Stacked auto-encoder (SAE), Channel reduction, EEG analysis, Emotion

1) INTRODUCTION

Emotions are recognized as one of the most important parameters in daily human activities. The most important effect of this parameter is creation a healthy relationship in social environments [1]. Identifying emotion is the first step to discover the effective human connection in the face of the environment, which has become one of the most up-to-date subjects in order to control the positive and negative states of human beings [2]. Emotions can be identified qualitatively by assessing facial expressions [3]. The study of brain signals is a quantitative method that BCI systems have successfully achieved a high level of classification of emotional states through machine learning applications.

Brain signals are produced by the central neuron system [4]. These signals are performed non-invasively on the surface of the skull with measuring devices such as electroencephalograms (EEG). An electroencephalograph is a device that measures the pulses produced in the center of the head [5]. It has high temporal resolution that can reflect the strength and position of brain activity. The signals are measured by electrodes mounted on the scalp based on the 10-20 electrode system. A channel is obtained from the voltage difference between two electrodes, and the set of channels together create the EEG recording. The EEG signal is recorded [6] by a number of channels that depending on the accuracy of the measurement, the number of channels can be selected 24, 32, 64, 128 and 256. Identification of emotions from EEG signals requires several important factors, including the features and number of channels that is used during recording. [6] As the number of channels increases, the accuracy of the measurement increases; however, a large number of channels on the head can delay the signal recording process, which is inconvenient for both the physician and the patient. In addition, with increasing the number of channels, the costs of signal recording increase. Therefore, reducing the data record time and its costs would be possible by decreasing the number of channels and maintaining the quality of the record result. In the article of Jana at al. depicted an efficient seizure prediction technique using a Convolutional Neural Network with optimizing the EEG channels [7].

Features which are extracted for emotion recognition are the most important steps in the EEG signal processing. These steps consist of EEG signal preprocessing, including artifacts of EMG and EOG signals. Many scientists are interested in automated feature learning that deep learning neural networks provide acceptable results. Deep learning networks are one of the up-to-date topics in the field of machine learning in EEG signal analysis. Deep networks are an unsupervised and supervised learning method. These networks have provided acceptable results in reducing the input space of large databases, such as brain signal data [8]. Stacked autoencoder networks are one of the deep learning methods that can automatically extract the complex nonlinear abstracted features from signal. Jose at al. [9]developed the structure of stacked autoencoders to extract low-level and high-level features in deep layers. These features are a good representation of signal, which is considered as good indication to evaluate the importance of the presence or absence of channels [6] [8]. Therefore, stacked autoencoder network can be effective in reducing the number of channels based on feature fusion. In order to EEG channels reduction, Candra at al applied the WEAVE feature to classify emotion and they achieved 76.8% accuracy for valence and 74.3% for arousal emotion, respectively [6].

In this study, the optimal features of EEG signal are extracted using stacked auto encoder networks. Indeed, a deep learning method is proposed to emotion recognition for important feature extraction from EEG signals. The linear or nonlinear combination of temporal, frequency and linear features is extracted with SAEs. a channel reduction method is also used to improve an emotion classification in order to classification in two dimensions arousal and valance. It means that a combination of features by SAEs is proposed as an EEG-emotion feature to classify low/high state of valence and arousal dimensions. The evaluation determines the importance of each channel based on the characteristics obtained from the SAE networks. This approach can reduce the number of channels and time to prepare the process of recording and during signal recording that this proposed method is described in next section.

This study consists of four sections which are explained below. In Section 2, the structure of the autoencoder neural network is completely described. In the third section, it discusses methods for classifying EEG data based on standard EEG features related to emotion recognition according to two dimensions, arousal and valance, as well as features extracted from the auto encoder network are discussed. Results and discussion sections are presented in Section 4 and 5 that the results of the experiments are reported in these parts. The results of channel reduction algorithm on classification applying support vector machine (SVM) algorithm were discussed along with channel location that is related to valence and arousal dimensions.

2) MATERIALS AND METHODS

This section of the paper has five main parts. In the first part, the database which is used in this study has been explained. After that, EEG data processing, including pre-processing and processing, is mentioned. The third part has described the stacked autoencoders (SAEs) network and then the technique of reducing the number of channels is stated. In the end, the performance evaluation criteria that can assess the performance of the proposed method is mentioned.

2-1) DEAP DATABASE

In this study, the DEAP physiological database has been used, which were collected by Koelstra et al. in 2012 to analysis emotion states. One of the recorded electrophysiological signals in the database is the EEG signal which consists of 32 electrodes according to the international 10–20 electrodes placement system. The EEG signal was recorded from 32 participants with a mean age of 28 years, 16 of whom were female and this data were not gender biased. Emotional stimuli, which induced 4 types of emotion for each subject, were done with 40 types of one-minute music videos and after that asking them to rate their emotions with emotional labels using the Self-assessment Mankins questionnaire on valence and arousal dimensions. The selection of videos was based on 4 classes of emotion: high arousal-high valence, high arousal-low valence, low arousal-high valence, and low arousal-low valence. The sampling frequency at the time of EEG signal recording was 256 Hz, which was then reduced to 128 Hz by the down sampling method. A baseline 5-minute signal was recorded for each participant, with a 3-second interval between each video to relieve the individual's emotional state. [10] The model of Arousal and valence dimension is illustrated in Figure 1.

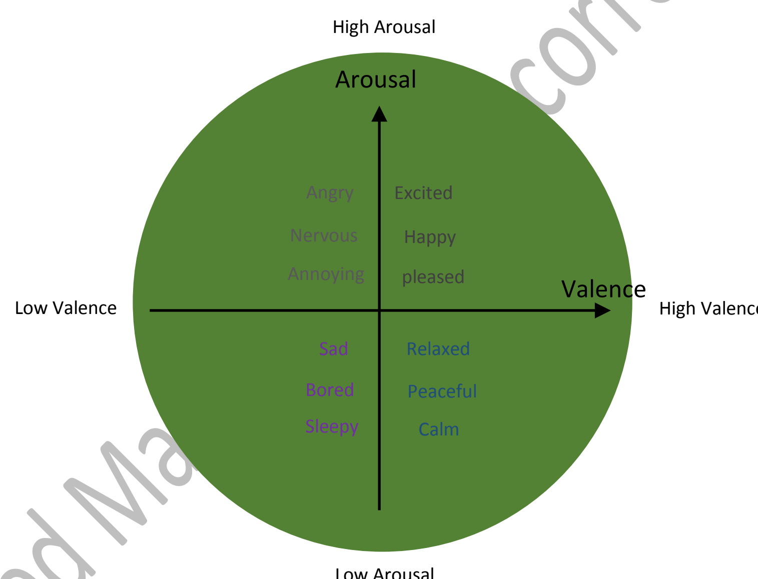

Figure 1 *Arousal and valence-based emotion model*

2-2) EEG DATA PROCESSING

Classification of human emotions and emotional states is the main purpose of this study. Artifacts and noises, including EMG and EOG signals are removed by independent component analysis (ICA) method [11]. Based on previous study in emotion recognition, EEG signal has three main feature categories that are categorized into time, frequency and time-frequency features that are considered in this study [12]. The most common features that used in emotion recognition studies are power, mean, standard deviation, zero-crossing rate, entropy, fractal dimension and correlation dimension that are shown in Table ۱ [13] [14]. We used these features to train the SAEs with a 1-second, 2-second, 4-second and 8-second windows with 50% overlap (w). All features are normalized between zero and one. These features are the inputs of stacked autoencoders that they are combined to represent the best abstracted features. The sampling frequency was 128 Hz; therefore, the EEG signal consists of 128 samples in one second. Considering “m” the duration of the signal based on seconds, 10 features (based on Table ۱) and 32 channels, the size of input is equal n=(32×10×m×50%)/w, n is the dimension of the extracted features in input.

***Table* ۱** *feature extracted from EEG channels*

Selected Features	Rules
EEG power of Sub-bands**:** theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), gamma (30–45 Hz)	$\mathbf{P} = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i^2 \rvert$ $\mathbf{x_i}$ **is the matrix of data**
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$ $\mathbf{x_i}$ **is the matrix of data**
Standard deviation	$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu)^2$ $\mathbf{x_i}$ **is the matrix of data**
Zero-crossing rate	$ZCR = \frac{1}{2N}\lvert sgn[x(n)] - sgn[x(n-1)]\rvert$ $\mathbf{x_i}$ **is the matrix of data**
Fractal dimension	$log_{\varepsilon}N = \frac{\log N}{\log \varepsilon} = -D.$
Approximate entropy	$C_i^m(r) = (number\ of\,(x_j)\,such\ that\ d\lvert x_i - x_j\rvert \le r)/(N-m+1)$ $\varphi^m(r) = (N-m+1)^{-1}\sum_{i=1}^{=(N-m+1)}\log(C_i^m(r))$ **ApEn=**$\varphi^m(r) - \varphi^{m+1}(r)$ $\mathbf{x_i}$ **is the matrix of data**
Correlation dimension	$C(\epsilon) = \lim_{n\to\infty}\left(\frac{g}{N^2}\right)^n$

2-3) STACKED AUTOENCODER FOR FEATURE EXTRACTION

The autoencoder networks are one of the deep learning methods that the structural of them is symmetrical. There are three layers including input layer, hidden layer, output layer that are named encoder and decoder parts. The output of the first encoder acts as the input of the second AE network that this process will be continued to make a stacked auto encoder. The features that are extracted from DEAP database are the extension of the stacked autoencoder. The network in SAEs level uses unlabeled data based on an unsupervised approach [15]. The flowchart of the proposed method that we applied is illustrated in Figure 2. The last decoder is removed and the weights and biases are our final abstracted features that we need. Fine-tuning function when classifying of emotion that set SAE parameters is the most important part in emotion classification. This stage is trained with labeled data to train all layers at one time [8].

$$h = \sigma(\mathrm{x}.\mathrm{W} + \mathrm{b}) \qquad (1)$$

$$\sigma(\mathrm{z}) = \frac{1}{(1 + e^{-z})} \qquad (2)$$

$$\mathrm{x}' = \sigma(\mathrm{h}.\mathrm{W}^T + \mathrm{c}) = \sigma[\sigma(\mathrm{x}.\mathrm{W} + \mathrm{b}).\mathrm{W}^T + c] \qquad (3)$$

$$\mathrm{E} = \sum_{k=0}^{l} (x - x')^2 \qquad (4)$$

In Equation (1), $\mathrm{x} \in \mathrm{R}^n$ is the vector of the input (feature selected from raw EEG) and $\mathrm{h} \in \mathrm{R}^p$ is the vector of the hidden layer, P is the dimension of abstracted features. σ is sigmoid function and $W \in R^{p \times n}$ is a weight matrix, $b \in R^p$ is a bias vector that is shown in Equation (2). In Equation (3), $\mathrm{x}' \in R^n$ is the next layer that the dimension of x' is equal x. The weights of the hidden layer reconstruct output or x'. The square error cost function in Equation (4) is E that the E is minimized when the input and the reconstructed input are the most similar. The weights and biases of the last hidden layer are the features extracted from the SAE network that is calculated with fine-tuning method by minimizing the reconstruction loss.

2-4) CLASSIFICATION

The features obtained from the stacked autoencoder networks are used to classify emotion classes. KNN (K Nearest Neighbor Classifier), BN (Naive Bayesian Classifier) and SVM (Support Vector Machines) classifiers are considered because these classifiers are widely used in the field of emotion recognition [16]. An architecture of presented model is illustrated in the Figure 2, including the extraction of primary features from the raw data of EEG signal, applying SAEs to obtain abstracted features and emotion classifiers from optimal features.

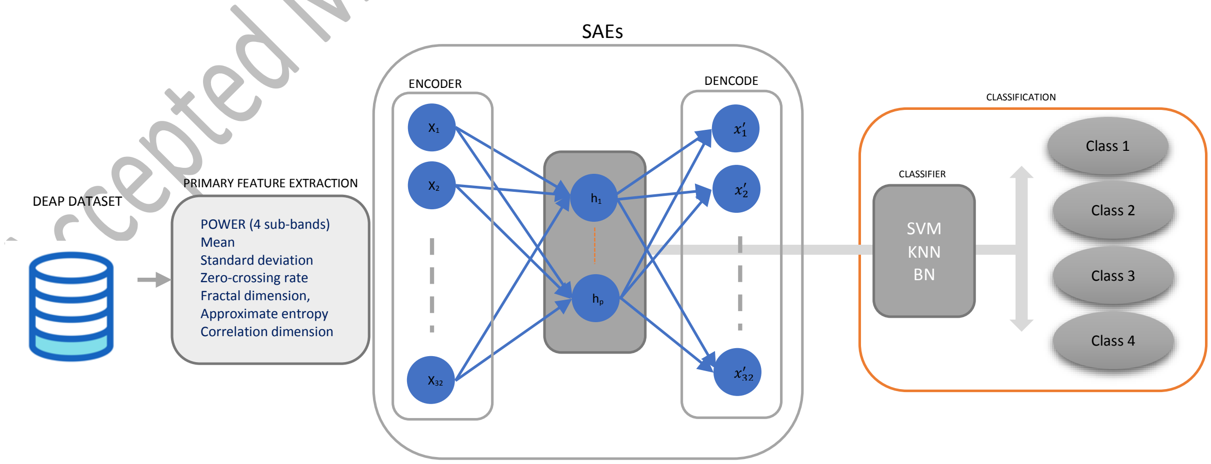

Figure 2 *The architecture of feature extraction and classification*

2-5) CHANNEL REDUCTION

In many studies, all the channels of EEG signals are used for emotion recognition. However, some of them are indicated that all channels have no significance [6]. As we know, using all 32 channels is not comfortable for doctors and patients during EEG signals recording. Therefore, the emotion recognition that are using a minimum number of channels has many advantages, for example, reducing the computational time and increasing the time efficiency. The requirement of a channel reduction method is seen for the development of emotion classification trend.

In proposed method, each channel is important and the importance of all of them evaluates individually based on the accuracy of the classifier in the absence of that channel. Indeed, the accuracy of emotion classification when all 32 channels are used has been calculated. Then, each channel is ignored and the average of the network is recalculated with the remaining channels. Therefore, when the average of the accuracy is not decreased, the ignored channel is unimportant and execution of the method continues. The Table 2 illustrates a channel reduction algorithm.

Table 2 *Algorithm for channel reduction*

channel select ⇐ 32 channels
channel reduction ⇐ True
While *channel reduction == True* do
channel reduction ⇐ False
new channel select ⇐ channel select
average accuracy ⇐ accuracy (channel select)
for *channel* in *channel select* **do**
new average accuracy ⇐ accuracy (channel select - channels)
if *new average accuracy>= average accuracy* **then**
new channel select ⇐ (new channel select - channel)
channel reduction ⇐ True
end
end
channel select ⇐ new channel select
end

2-6) PERFORMANCE EVALUATION METRICS

There are criteria for evaluating the performance of the method provided. These criteria must be able to properly evaluate the presence or absence of each channel. Classification accuracy, sensitivity, specificity and false-positive rate (FPR) criteria are considered as the methods are calculated using in equation (1), (2), (3) and (4), respectively in which TP stands for true positive, FP is false positive, FN stands for a false negative and TN is true negative [17].

$$\text{Classification accuracy} = \frac{(TN + TP)}{(TN + FN + TP + FP)} \tag{1}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{2}$$

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{3}$$

$$\text{FPR} = \frac{FP}{FP + TN} \tag{4}$$

3) RESULTS

In this study, an emotion recognition method using EEG signals is proposed. SAE network is one of most practical the deep learning techniques, which is used for important feature extraction and feature fusion hidden in raw EEG signals for the classification. Recording brain signals with an EEG system using 32 channels cannot be very comfortable for doctors and patients. Thus, A channel reduction technique with maintaining the quality of signal recording and main feature of brain signals is needed to reduce the number of channels for emotion recognition.

In this section, the results obtained from the network are presented in the form of classification accuracy, sensitivity, specificity, and FPR. The 1-second, 2-second, 4-second, and 8-second windows with 32 channels are considered for extracting features and training the SAEs. Based on results, the accuracy of classification has been enhanced when the network uses 8-second window to train data. Therefore, the optimal duration is considered 8-second window as shown in Table 3.

Table 3 *The mean accuracy of classification for 32 participants (SVM, BN, KNN) using different length (1-second, 2-second, 4-second and 8-second) in valence and arousal dimensions*

The mean of accuracy ± SD				
Valence				
classification	**1-second**	**2-second**	**4-second**	**8-second**
SVM	0.8101±0.003	0.8175±0.021	0.8102±0.001	0.8255±0.081
BN	0.7101±0.011	0.7285±0.015	0.7681±0.005	0.7862±0.016
KNN	0.6958±0.061	0.7137±0.008	0.7315±0.014	0.7471±0.002
Arousal				
SVM	0.7361±0.026	0.7602±0.009	0.7729±0.004	0.8163±0.026
BN	0. 6883±0.071	0.6932±0.041	0.7412±0.062	0.7948±0.006
KNN	0.7172±0.001	0.7202±0.012	0.7296±0.016	0.7393±0.059

According to the method, 10 channels including Fp1, Fp2, Af3, F8, F4, Fz, Cp5, Pz, Po3 and Po4 channels in valence dimension and Af4, F7, Fc1, C3, Cp5, Cp2, P3, P4, Po4 and O1 channels in arousal dimension have been reduced when the network is in the first iteration. Hence, only 22 significant channels are remained. In the next time, 4 channels Af4, F7, Fc6 and P8 in valence dimension and Fp1, Fz, T7 and Cp6 in arousal dimension have been reduced and only 18 channels are available. In the third iteration, 6 channels Fc5, Fc2, T7, Cz, Cp6 and Oz in valence dimension and F4, Fc5, Fc2, C4, Cp1 and Po3 in arousal dimension have been reduced and only F3, FC1, C3, C4, T8, CP1, CP2, P7, P3, P4, O1, O2 channels in valence dimension and Fp2, AF3, F8, F3, FC6, Cz, T8, P7, Pz, P8, O2, Oz channels in arousal dimension are considered as the 12 most important channels. In the fourth iteration, when each channel is reduced, the accuracy is significantly decreased as shown in Table 4. Therefore, based on the calculated accuracy in ultimate stage, the channel reduction process is ended and only 12 channels are named F3, FC1, C3, C4, T8, CP1, CP2, P7, P3, P4, O1, O2 channels in valence dimension and Fp2, AF3, F8, F3, FC6, Cz, T8, P7, Pz, P8, O2, Oz channels in arousal dimension are used to emotion classification. SVM classifier has obtained higher accuracy than other classifiers. The achieved SVM classification accuracy, sensitivity, specificity, and FPR are 75.7%, 89 %, 76.33 %, 0.1475 in valence dimension and 74.4%, 84 %, 73.65 %, 0.1348 in arousal dimension respectively using the sample duration of 8-s EEG data with 6 channels.

***Table 4** The mean accuracy of classification for 32 participants (SVM, BN, KNN) using different number of channels (32 channels, 22 channels, 18 channels and 12 channels) in valence and arousal dimensions*

The mean of accuracy				
classification	**32 channels**	**22 channels**	**18 channels**	**12 channels**
SVM	0.8255±0.081	0.7959±0.090	0.7850±0.005	0.7578±0.026
BN	0.7862±0.016	0.7581±0.021	0.7384±0.004	0.7051±0.058
KNN	0.7471±0.002	0.7332±0.093	0. 6995±0.017	0. 6536±0.063
Arousal				
SVM	0.8163±0.026	0.7798±0.009	0.7606±0.004	0.7445±0.026
BN	0.7948±0.006	0.7566±0.041	0.7203±0.062	0.7004±0.006
KNN	0.7393±0.059	0.7035±0.012	0.6808±0.016	0.6501±0.059

The accuracy value of maximum and minimum in valence dimension with a steeper graph is greater than arousal dimension as shown in Figure 3. Among the classifiers selected in this study, SVM network has reported the highest accuracy in two dimensions, arousal and valence. In valance dimension, the accuracy of the SVM classification starts from 0.8255±0.081 and stops algorithm with the accuracy of 0.7578±0.026, and in the arousal dimension, it starts from 0.8163±0.026 and stops with the accuracy of 0.7445±0.026.

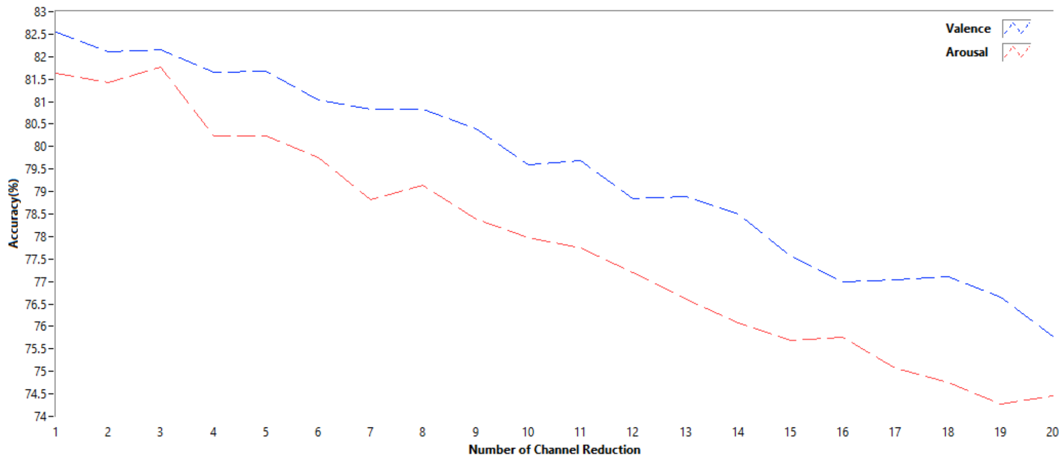

Figure 3 *The accuracy of SVM classification before and after channel reduction in Valence an arousal dimensions*

The locations of the 12 EEG channels obtained from valence and arousal dimensions before and after channel reduction are shown in Figure 4, as we can see, valence and arousal dimensions involve a different combination of EEG channels. In valence dimension, channels F3, FC1, C3, C4, T8, CP1, CP2, P7, P3, P4, O1, O2 have remained. These channels are more related to the middle left and right hemispheres. Although, in valence dimension, channels Fp2, AF3, F8, F3, FC6, Cz, T8, P7, Pz, P8, O2, Oz is considered which involve frontal and parietal lobes of the brain.

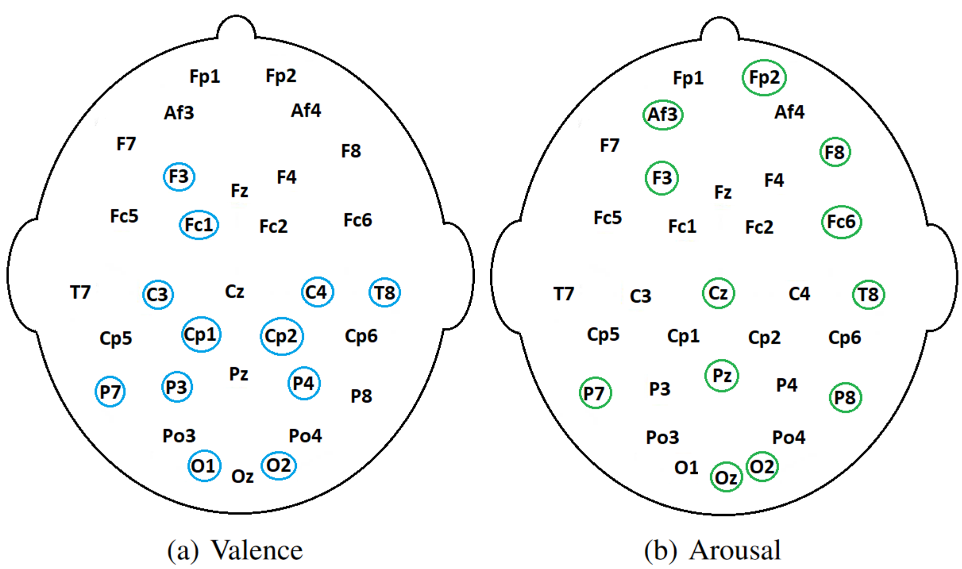

Figure 4 *The location of 12 EEG channels in a)valence and b)arousal dimension*

The result of accuracy comparison SVM, KNN, BN classifiers and feature extraction methods, PCA(Principal component analysis) and NPCA(nonlinear- Principal component analysis) with 8-second windows is shown in Table 5. The results illustrate that the feature extraction method by the stacked autoencoder has reported the highest accuracy compared with BN and KNN for 12 channels.

***Table 5** accuracy of SVM, BN and KNN classifiers and PCA and NPCA feature extraction methods with 8-second windows and 12 channels*

valence			
Accuracy	**Feature extraction method**		
	PCA	NPCA	SAE
SVM	0.6035±0.011	0.6601±0.001	0.7578±0.026
BN	0.5230±0.016	0.5923±0.006	0.7051±0.058
KNN	0.5531±0.012	0.5642±0.059	0. 6536±0.063
arousal			
Accuracy	**Feature extraction method**		
	PCA	NPCA	SAE
SVM	0.5942±0.002	0.6501±0.021	0.7445±0.026
BN	0.5191±0.021	0.5810±0.003	0.7004±0.006
KNN	0.5390±0.001	0.5598±0.025	0.6501±0.059

4) DISCUSSION

This paper proposes an efficient emotion recognition method using EEG signals, which can classify emotional states. Deep learning network is used in this study to extract complex linear and nonlinear features from EEG data. A channel reduction technique is applied to emotion recognition using the minimum number of channels of the EEG signal. This algorithm provides a non-invasive easy-use method to diagnostic emotion states. The SVM classifier has reported the highest accuracy compared to BN and KNN classifiers. EEG emotion recognition using SAE feature selection method has been demonstrated with accuracy of 75.7% for valence and 74.4% for arousal. SAE has the advantage of the ability to extract low-level features from the input layer and high-level features in deep layers [9].

The limitations of this study include primary feature selection, detection of various cognitive disorders and investigation of EEG feature category separately. In future studies, this method can be used to classify other medical data. Moreover, the primary extracted features can be automatically extracted by neural networks.

By using SAE networks, the EEG channels can be reduced from 32 to 12 with less than 9% reduction in accuracy in both valence and arousal dimensions. This process can reduce the number of channels and simplify the process of recording the signal so that the important parameters in the EEG signal are completely preserved. The proposed method emotion recognition using EEG signals of 12 channels only. although, channel selection algorithms are in general based on features extracted from the EEG signals, this approach could report most efficient results among the state-of-the-art emotion recognition methods.

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