Emotion and Lie Recognition from EEG signals using Deep Learning

Vanshika Mittal
Department of Computer Science and Engineering
Jaypee Institute of Information Technology
Sector – 62, Noida
mvanshika25@gmail.com

Tushar Jain
Department of Computer Science and Engineering
Jaypee Institute of Information Technology
Sector – 62, Noida
tjainq@gmail.com

Abhishek Verma
Department of Computer Science and Engineering
Jaypee Institute of Information Technology
Sector – 62, Noida
abhishekverma1610@gmail.com

Dr. Suma Dawn
Department of Computer Science and Engineering
Jaypee Institute of Information Technology
Sector – 62, Noida
Suma.dawn@jiit.ac.in

ABSTRACT: This work examines the use of various algorithms and techniques regarding emotion and lie recognition from EEG signals using Deep Learning. Many researchers use electroencephalograms (EEGs) to study brain activity in the context of seizures, epilepsy, and lie detection. It is desirable to eliminate EEG artifacts to improve signal collection. At first, EEG features were extracted based on literature review. Then, a computational framework is proposed using machine learning techniques, performing feature selection and classification into two at a time emotional states. In recent years, there are many great successes in using deep architectures for unsupervised feature learning from data, especially for images and speech.

Keywords: Emotion recognition; EEG; feature selection; classification; machine learning.

I. INTRODUCTION

Emotion plays an important role in human daily life, it reflects human feelings of things. The mental health status even influences human interpersonal interaction and decision making. In medical fields of psychiatry and neurology, the detected emotional states of patients can be adopted as an indicator of the certain functional emotional disorders, such as post traumatic stress disorder and major depression. Most recently, researchers analyzed the emotional characteristics of a smartphone overuse group and a healthy group through EEG signals.

Human emotions can be detected by facial expressions, speech, eye blinking and physiological signals. However, the first three approaches are susceptible to subjective influences of the participants, that is, participants can deliberately disguise their emotions.

There already exists extensive studies using machine learning to identify emotion states with EEG signals. Traditional machine learning based methods have shown effective in classifying emotional states, while the shortage of these kinds of approaches is that the researchers must devote numerous efforts to find and design various emotion-related features from origin noisy signals. And the computation of these features is time consuming. In recent years, deep learning has drawn wide attention due to its great success in the visual field. Some deep learning based approaches have also achieved competitive accuracy in EEG-based recognition task.

II. BACKGROUND STUDY

People communicate and exchange information with each other using language and nonverbal communication. In addition to human-to-human communication, communication between humans and machines or computer agents has become more common. Emotion recognition in humans is an increasingly important research subject in this area. EEG signals are well known in the measurement of brain activity, and have been studied for various purposes. Among the approaches to emotion recognition, methods based on electroencephalogram (EEG) signals are more reliable because of its high accuracy and objective evaluation compared to other external appearance such as facial expression and gesture. However due to the low signal to noise ratio (SNR), it is often very hard to analyze EEG signals 'by hand' even for neurophysiologists. Recent developing deep learning in machine learning community allows automated feature extraction and feature selection and eliminates the limitation of hand-crafted feature.

Most EEGs are done to diagnose and monitor seizure disorders. EEGs also can identify causes of other problems, such as sleep disorders and changes in behaviour. They're used to evaluate brain activity after a severe head injury or before/after a heart or liver transplant. Emotions like arousal (heightened senses like anger and fear) and valence (intrinsic attractiveness/"good"-ness or averseness/"bad"-ness) can be classified using the EEG signals. These will help us greatly in healthcare sector for paralysed patients, babies, children as well as in entertainment and gaming industry to track emotions experienced by the viewers/gamers. Human emotions can be detected by facial expressions, speech, eye blinking and physiological signals and these approaches are susceptible to be deliberately disguised. Physiological signals like electroencephalograms (EEG), electrooculography (EOG), blood volume pressure (BVP) are produced spontaneously by human body.

Consequently, the physiological signals are more objective and reliable in capturing real emotional states. Of all of these physiological signals, the EEG signal comes directly from human brain, which means changes in EEG signals can directly reflect changes in human emotional states. This technology thus can surely be used for lie detection (people can fool the polygraph systems which work on heart beats). Being non-invasive BCI's (Brain Computer Interface) they hold an advantage over invasive BCI's and even MRI's as EEG sensor caps are portable, cost-effective, and without any health hazards (no magnetic rays). They can have further applications in home automation (setting lighting, fragrances in rooms as a consequence of the emotions user in going through).

A. Literature Review

Yilong Yang, Qingfeng Wu, Ming Qiu, Yingdong Wang, Xiaowei Chen [1] indicated rise in accuracy with adequate pre-processing and apply hybrid CNN and RNN Deep Neural Network to classify human emotion states by effectively learning compositional spatial-temporal representation of raw EEG streams. In this paper, baseline signals are considered and a simple but effective pre-processing method has been proposed to improve the recognition accuracy. Meanwhile, a hybrid neural network which combines 'Convolutional Neural Network (CNN)' and 'Recurrent Neural Network (RNN)' has been applied to classify human emotion states by effectively learning compositional spatial-temporal representation of raw EEG streams. The CNN module is used to mine the inter-channel correlation among physically adjacent EEG signals by converting the chain-like EEG sequence into 2D-like frame sequence. The LSTM module is adopted to mine contextual information. Experiments are carried out in a segment-level emotion identification task, on the DEAP benchmarking dataset. Our experimental results indicate that the proposed pre-processing method can increase emotion recognition accuracy by 32% approximately and the model achieves a high performance with a mean accuracy of 90.80% and 91.03% on valence and arousal classification task respectively. the baseline signals were taken into account and a simple, computation cheap pre-processing method has been proposed to improve recognition accuracy. In addition, they applied a hybrid neural network to classify human emotion states by effectively learning compositional spatial-temporal representation of raw EEG streams. At last, the public DEAP dataset was used to evaluate the proposed pre-processing method and neural network model. Experimental results have shown that the pre-processing approach can improve the accuracy by 32% and the model could achieve a high accuracy around 90.80% and 91.03% for valence and arousal classification task, respectively.

M. Sreeshakthy, J. Preethi, A. Dhilipan [2] analysed the human emotions from EEG Signal (Electroencephalogram) with different kinds of situations. Emotions are very important in different activity and decision making. Various feature extraction techniques like discrete wavelet transform, Higher Order crossings, Independent component analysis is used to extract the particular features. Those features are used to classify the emotions with different groups like arousal and valence level using different classification techniques like Neural networks, Support vector machine etc.. Based on these emotion groups analyze the performance and accuracy for the classification are determined.

EXTRACT METHOD	CLASSIFY METHOD	ACCURACY
DWT	K-NN	83.26
Dynamic and PCA Features	SVM	64.7 to 82.91
WT	SVM	82.38
HOC	SVM	82.33
STFT	SVM	80
HOC	NN	80.5
PCA Features	RBF	84.6
DWT	LDA	75.21
HOC	QDA	62.30

An Emotion can be identified by extracting the different kind of feature from the signal. For extracting the features from the signal Wavelet Transform will give the highest accuracy, after preprocessing the signal it has to be smoothed and optimized for the particular feature, using different optimization techniques like GA, PSO, etc. After getting the optimized result apply the RBF and SVM it will provide the high accuracy of emotions in any situation. These emotions will used for Human Computer Interaction, Affective Computing and Robotics etc.

Karim Ansari-Asl, Guillaume Chanel, Thierry Pun [3], focused to deal with the very large number of features to be classified using synchronization likelihood as a new channel selection method. When assessing human emotions using EEG classification, one of the critical problems is to deal with the very large number of features to be classified. In this paper, the authors address this problem using synchronization likelihood as a new channel selection method. Applying this method, they could significantly reduce the number of EEG channels to be used in emotion assessment, with only slight (if any) loss of classification performance depending on the used feature. They report and compare the results obtained by employing a linear classifier on different features extracted either from all channels or from the selected subset of channels. These features include synchronization likelihood, Hjorth parameters, and fractal dimension.

Table 1 – Classification accuracy (%) of LDA for all channels. Used features are SL, activity (Act.), mobility (Mob.), complexity (Com.), Hjorth as concatenation of three preceding features, and FD.

Classes	SL	Act.	Mob.	Com.	Hjorth	FD	Mean
C_1, C_2, C_3	49.3	42	50.3	45.7	51.7	49.3	48.6
C_1, C_2	58	60.5	63	61	63	62.5	61.3
C_2, C_3	68	61.5	66.5	60	67.5	67.5	65.2
C_1, C_3	66	59.5	66	58.5	67.5	63	63.4
$C_2, [C_1, C_3]$	59.7	58	63.7	60	63.3	64.3	61.5
Mean	60.2	56.7	61.9	57	62.6	61.3	60

Table 2 – Classification accuracy (%) of LDA for five selected channels. Used features are SL, activity (Act.), mobility (Mob.), complexity (Com.), Hjorth as concatenation of three preceding features, and FD.

Classes	SL	Act.	Mob.	Com.	Hjorth	FD	Mean
C_1, C_2, C_3	55.3	39.7	43.7	43	48	48	46.3
C_1, C_2	64.5	57.5	50.5	61	61	53.5	58
C_2, C_3	74	57	67.5	56.5	64.5	66	64.3
C_1, C_3	64.5	56	66.5	56.5	64.5	68	62.7
$C_2, [C_1, C_3]$	68.7	56.7	57.3	59.3	60.3	62.7	60.8
Mean	65.4	53.4	57.1	55.2	59.7	59.6	58.4

Emotion assessment is of importance from different point of views, such as emotion integration into HCI systems. Different physical and physiological cues including brain activity are used for emotion assessment. In EEG classification, one of the major problems is the huge number of features to be classified. In the present paper, they report the result of the application of synchronization likelihood as a channel selection method to alleviate “the curse of dimensionality” in EEG classification. Using SL, we could reduce the number of EEG channels from 64 to 5 for EEG classification in emotion assessment. To evaluate the performance of SL in channel reduction, they have used different kinds of features (SL, Hjorth parameters, and fractal dimension) anddifferent classifiers (such as the LDA, the linear support vector machine [SVM], and the SVM using radial basis functions [RBF] as kernel); to be short we report here only the results of a linear classifier, LDA. Results showed that the channel reduction leads only to a slight (if any) loss of classification accuracy rate. Reducing the number of channels contributes to a significant decrease in computation time for emotion assessment. This decrease is of great interest for systems with low computational capabilities such as ambulatory real-time HCI Systems.

Leena Y. Bhole, Maya Ingle [4], provided comprehensive review of existing EEG based emotion recognition techniques along with some insights related to challenges in future research and development issues. An emotional state of user has garnered increasing attention over the last few years in the research areas of Human Computer Interaction (HCI) and Brain Computer Interface (BCI). Emotions include cognitive as well as perspective process. Various modalities contribute to recognize human emotions using machine, out of which EEG is one of the prominent and convenient modality to recognize human emotions. This paper provides a comprehensive review of existing EEG based emotion recognition techniques along with some insights related to

challenges in future research and development issues. It also includes comparison based on different proposed parameters for EEG based emotion recognition.
This field of research has received a great deal of attention because it can help to analyze the human emotion not only from the external part of the body of human being but also its internal feelings. It will help to recognize the real feeling and not the posed emotions. This study provides the review of available ways to recognize the emotions from brain waves captured in the form of EEG signals. EEG signals are associated with alpha (8-12 Hz), beta (13-30 Hz), theta (4-7 Hz) and gamma (31-100Hz) frequency bands. From these bands decreased power in alpha band was found to be associated with emotional state. Above all this, one may find the characteristics of all remaining bands for emotion detection. The comparison of feature extraction and classification methods by different researchers shows that the statistical features for feature extraction and design of some kind of neural network gives higher accuracy, however it may depend on the procedure of recording the EEG data, emotion elicitation process and the dataset size.

Viet Hoang Anh, Manh Ngo Van, Bang Ban Ha, Thang Huynh Quyet [5], demonstrated emotion recognition based on the Russell's circumplex model, Higuchi Fractal Dimension algorithm, and Support Vector Machine as a classifier. Recently, there has been a significant amount of work on the recognition of human emotions. The results of the work can be applied in real applications, for example in market survey or neuro-marketing. This interesting problem requires to recognize naturally human emotions which come from our mind but ignore the external expressions fully controlled by a subject. A popular approach uses key information from electroencephalography (EEG) signals to identify human emotions. In this paper, we proposed an emotion recognition model based on the Russell's circumplex model, Higuchi Fractal Dimension (HFD) algorithm and Support Vector Machine (SVM) as a classifier. Moreover, we also proposed a method to determine an emotion label of a series of EEG signals. The author's model includes two main approaches in machine learning step.
In a first approach, machine learning was utilized for all EEG signals from numerous subjects while another used machine learning for each particular subject. They extensively implemented our model in several test data. The experimental results showed that the first approach is impossible to apply in practical applications because EEG signal of each subject has individual characteristic. In addition, in the second, the model can recognize five basic states of human emotion in real-time with average accuracy 70.5%.

In this paper, they proposed the model with two approaches for emotion recognition based on the Russell's circumplex model, Higuchi Fractal Dimension algorithm, and Support Vector Machine as a classifier. Additionally, the method to determine an emotion label of series of EEG signals was
also proposed. In this paper, efficiency of our model with each approach was considered from the experiments. The experimental results showed that our model should be only used for recognizing emotions of each particular subject from the training to testing step. It is implied that EEG signals of each subject own individual characteristic. In addition, their model can recognize five basic human emotions in realtime with

average accuracy 70.5% from the experiments. However, the accuracy and the number of emotions are still small for real applications. The model clearly needs to be improved.

Ning Zhuang, Ying Zeng, Li Tong, Chi Zhang, Hanming Zhang, and Bin Yan [6], showed feature extraction and emotion recognition system which is based on Empirical Mode Decomposition (EMD) using EEG signals from multimodal EEG benchmark dataset, DEAP (Database for Emotion Analysis Using Physiological Signals). This paper introduces a new method for feature extraction and emotion recognition system which is based on Empirical Mode Decomposition (EMD) using EEG signals from multimodal EEG benchmark dataset, DEAP (Database for Emotion Analysis Using Physiological Signals). EMD is a technique which is suitable for the analysis of nonlinear and nonstationary signals such as brain signals and used for decomposing the signal into a set of elemental signals known as Intrinsic Mode Functions (IMFs). These intrinsic functions represents the multiple frequency components of the original signal with band-limited characteristics. To get the instantaneous phase information of IMF, the Hilbert Transform can be applied. The high frequency component from IMF has the significant effect on the different emotion states. The multidimensional information of these functions are utilized for features. This study shows that the three main features: first difference of timeseries, the first difference of phase, and the normalized energy are effective for recognizing emotions from EEG Signals. In this study, a feature vector with these three features were fed to the SVM Classifier for the classification of emotions. Also the informative channels based on EMD strategy are investigated and 8 channels, namely, FP1, FP2, F7, F8, T7, T8, P7, and P8, are selected for feature extraction.

Wei-Long Zheng, and Bao-Liang Lu [7], showed that the DBNs were trained using Differential Entropy (DE) features from the multichannel EEG dataset which were extracted from 15 Subjects. The reduced electrode set positions are identified using some statistical approaches such as correlation coefficient, F-Score and accuracy rate. Instead of these statistical approaches, the critical frequency bands and channels were investigated by examining the weights of the trained DBNs. An optimal reduction of electrode set position has been investigated which is computationally faster, more feasible and outperforms the original set of channels. The four profiles of EEG channels (4, 6, 9 and 12) were selected among the original 62 channels of EEG, which were relatively stable with the best accuracy of 86.65% than the original 62 channels. The neural signatures which are associated with different emotions were investigated according to the weight distributions obtained from the trained deep neural networks. This study shows the comparison between the deep learning models with shallow models such as DBNs and SVM, K-NN, LR-L2 respectively.
In the emotion experiments, the EEG data has been extracted from fifteen subjects and each subject has done the experiments twice at intervals of about one week. There are totally 30 experiments evaluated in this study. The training data and the test data are from different sessions of the same experiment. The training data contains

nine sessions of data while the test data contains other six sessions of data from the same experiment. The mean accuracies and standard deviations
(%) of SVM and DNN for different kinds of features and five frequency bands were presented. Using the DE features from five frequency bands as inputs, the means and standard deviations of accuracies of, K-NN, LR, SVM, and DBN are 72.60%/13.16%, 82.70%/10.38%, 83.9%/9.72%, 86.08%/8.34%, respectively. The results show that the DBN models outperform over other models with higher mean accuracy and lower standard deviations.

Wei-Long Zheng, Jia-Yi Zhu, and Bao Liang Lu [8], investigated the stable-neural patterns of Electroencephalogram (EEG) with emotion elicitation over time, which are related to the activities of critical areas of brain and frequency bands.
The machine learning technique known as Discriminative Graph Regularized Extreme Learning Machine (GELM) has been adopted for identifying these patterns. The main issues for recognizing the emotions using EEG such as How to discriminate between different emotions based on EEG signals, which patterns of neural oscillations of EEG signals are identifying the emotions in the brain, and to check the performance of models based on machine learning techniques were addressed in this paper. For evaluating these patterns, the new dataset based on SEED (SJTU Emotion EEG Dataset),has been developed in this study. Also a systematic comparison and qualitative evaluation for feature extraction, selection and smoothing and pattern classification were carried out on the DEAP and SEED dataset.

For dimensionality reduction, the minimal redundancy maximal relevance (MRMR) algorithm has been used. This algorithm uses mutual information as the relevance measure with the max-dependency criterion and minimal redundancy criterion. Max-Relevance searches for features satisfying with the mean value of all the mutual information values between the individual feature x and class c. The three conventional classifiers (K-NN, SVM, and Logistic Regression) and a newly developed classifier Discriminative Graph Regularized Extreme Learning Machine (GELM) were used to build the Emotion Recognition System. The discriminative Graph regularized Extreme Learning Machine (GELM) based on the idea that similar samples should share similar properties. GELM yields a much better performance in comparison with other models for face recognition and emotion classification. From the experimental results, the GELM with the differential entropy features outperforms other methods. The best average achieved classification accuracies of 69.67% and 91.07% on the DEAP and SEED datasets, respectively.

Dalin Zhang, Lina Yao, Xiang Zhang, Sen Wang, Weitong Chen, Robert Boots [9], introduced both cascade and parallel convolutional recurrent neural network models for precisely identifying human intended movements by effectively learning compositional spatio-temporal representations of raw EEG streams.
The proposed models grasp the spatial correlations between physically neighbouring EEG signals by converting the chain-like EEG sequences into 2D mesh-like hierarchy. A LSTM based recurrent network is able to extract the subtle temporal dependencies of EEG

data streams. Extensive experiments on a large scale MI-EEG dataset (108 subjects, 3,145,160 EEG records) have demonstrated that both models achieve high accuracy near 98.3% and outperform a set of baseline methods and most recent deep learning based EEG recognition models, yielding a significant accuracy increase of 18% in the cross-subject validation scenario.
In this paper, they propose the use of spatio-temporal representations to enhance EEG-based intention recognition in a more practical scenario of cross-subject and multi-class, and develop two unified end-to-end trainable deep learning models for movement intention recognition. A large-scale dataset of 108 participants on five categories is used to evaluate the proposed models. The experimental results show that both the cascade and parallel architectures could achieve very competitive accuracy around 98.3%, considerably superior to the state-of-the-art methods. Moreover, we build a set of baseline models to investigate the influence of both spatial and temporal information on brain intention recognition, andstudy the key variant architectures of the proposed frame-works. It is demonstrated that the performance improvement is largely due to the spatial and temporal information used in intention recognition process. Our model is also robust where sensor data is missing.

Vipin Gupta, Mayur Dahyabhai Chopda, and Ram Bilas Pachori [10], focused on advanced signal processing techniques to extract the hidden information of emotions from EEG signals. Due to poor generalizability of features from EEG signals across subjects, recognizing cross-subject emotion has been difficult. Thus, our aim is to comprehensively investigate the channel specific nature of EEG signals and to provide an effective method based on flexible analytic wavelet transform (FAWT) for recognition of emotion. FAWT decomposes the EEG signal
into different sub-band signals. Further, we applied information potential (IP) to extract the features from the decomposed sub-band signals of EEG signal. The extracted feature values were smoothed and fed to the random forest and support vector machine (SVM) classifiers that classified the emotions. The proposed method is applied to two different publicly available databases which are SJTU emotion EEG dataset (SEED) and database for emotion analysis using physiological signal (DEAP). The proposed method has shown better performance for human emotion classification as compared to the existing method. Moreover, it yields channel specific subject classification of emotion EEG signals when exposed to same stimuli.
The classification accuracies achieved with random forest classifier are higher than SVM classifier. It has been shown that our method achieves higher classification accuracies in
comparison to existing method for cross-subject channel specific classification of emotion EEG signals. Cross-subject classification using channel specific nature can provide an insight to the emotional sensitivity of different persons across brain regions when the similar stimuli are presented.

Xiang Li, Dawei Song, Peng Zhang, Guangliang Yu, Yuexian Hou, Bin Hu [11], proposed a preprocessing method that encapsulates the multi-channel neurophysiological signals into grid-like

frames through wavelet and scalogram transform. We further design a hybrid deep learning model that combines the 'Convolutional Neural Network (CNN)' and 'Recurrent Neural Network (RNN)', for extracting task-related features, mining inter-channel correlation and incorporating contextual information from those frames. Experiments are carried out, in a trial-level emotion recognition task, on the DEAP benchmarking dataset. Our results demonstrate the effectiveness of the proposed methods, with respect to the emotional dimensions of Valence and Arousal.
In this paper, they have proposed a hybid deep learning model, C-RNN, which integrates CNN and RNN , for emotion recognition based on multi-channel EEG signals. Specifically, the CNN component has the ability in mining inter-channel or cross-modal correlation information. On the
other hand, the RNN (i.e., LSTM) based model structure can learn long- term dependencies and contextual information from sequences. Practically, instead of manually designing task related features as in traditional approaches, we propose a novel pre-processing method that transforms the multi-channel EEG data into a 2D frame representation. The proposed method has been shown effective in the trial-level emotion recognition task. It also has a potential in giving predictions not only for an entire trial but also for each time step, which is very important in real time emotion monitoring scenarios. One problem that we need to address in the future is the influence of insufficient training data on the performance of our hybrid DL model.

Hao Tang, Wei Liu, Wei-Long Zheng and Bao-Liang Lu [12], demonstrated change of emotions is a temporal dependent process. In this paper, a Bimodal-LSTM model is introduced to take temporal information into account for emotion recognition with multimodal signals. They extend the implementation of denoising autoencoders and adopt the Bimodal Deep Denoising AutoEncoder modal. Both models are evaluated on a public dataset, SEED, using EEG features and eye movement features as inputs. Our experimental results indicate that the Bimodal-LSTM model outperforms other state-of-the-art methods with a mean accuracy of 93.97%. The Bimodal-LSTM model is also examined on DEAP dataset with EEG and peripheral physiological signals, and it achieves the state-of-the-art results with a mean accuracy of 83.53%. In this paper, they have introduced two models to predict emotions based on EEG features and features from other modalities. The first is an extension of denoising autoencoders, called BDDAE, and the second is the Bimodal-LSTM model, which can use both the temporal information and frequency-domain information of features. Compared with other existing methods, the Bimodal-LSTM model has achieved the best performance with a mean accuracy of 93.97% on SEED dataset. For DEAP dataset, the Bimodal-LSTM model has achieved the state- of-the-art results with mean accuracies of 83.23% and 83.83% for arousal and valence classification tasks, respectively.

Julie Anne Onton, Christian Andreas Kothe and Scott Makeig [13], aims to correctly predict, given a short EEG segment, whether the participant was imagining a positive respectively negative-valence emotional scenario during the given segment using a predictive model learned via machine learning. The challenge lies in generalizing to novel (i.e., previously unseen) emotion episodes from a wide variety of scenarios including love, awe, frustration, anger, etc. based purely on spontaneous oscillatory EEG activity without stimulus event-locked responses. This paper presents an analysis of a 12-subject electroencephalographic (EEG) data set in which participants were asked to engage in prolonged, self-paced episodes of guided emotion imagination with eyes closed. EEG data were collected from 250 gel-based scalp electrodes, plus four infraocular and two electrocardiographic (ECG) placements using a BioSemi ActiveTwo (Biosemi, NL) amplifier with 24-bit resolution. Caps with a custom wholehead montage that covered most of the skull, forehead, and lateral face surface were used, omitting chin and fleshy cheek areas. Locations of the electrodes and skull landmarks for each participant were digitized (Polhemus). To predict the valence of the emotion experienced by the participant from single EEG segments, they employ a predictive model that estimates, from a given short EEG segment the probability that the subject experienced a positive or negative valence emotion during that period a binary classification. The key result of this analysis is, first, that emotion valence can be classified in this task at better-than-chance level, and second that the level of accuracy may be considered almost practical for real-time neurofeedback or emotion-based interface control. Furthermore, since the emotional scenarios used in the test blocks were distinct from those in the training blocks (for example, awe vs. love), the results quantify to what extent the learned classifiers could generalize to unseen conditions. A rigorous analysis of these data produced strong evidence that a key aspect of emotional state – emotional valence – can be classified from a few seconds of spontaneous EEG data. Because of the inclusion of informative muscular activity in the EEG data for most subjects (possibly related to “tensing up” during some emotion states), they were not able to conclusively determine from these results to what extent brainsource EEG activity alone would allow for emotion classification (though this should be possible with further analysis of these results). At the core of the analysis is an easy-to-implement method to learn and classify informative spectral power changes across standard frequency bands that may be useful for further investigation of emotion recognition from ongoing EEG data.

Katerina Giannakaki, Giorgos Giannakakis, Christina Farmaki and Vangelis Sakkalis [14], described in this paper investigates and assess the effectiveness of selection and classification techniques providing improved classification accuracy. The purpose of this paper is the investigation, evaluation and comparison of advanced feature selection and classification methods providing the most appropriate of them to address effectively the problem of discrimination between calm, exciting positive and exciting negative emotional states.

The study investigates the discrimination between calm, exciting positive and exciting negative emotional states using EEG signals. Towards this direction, a publicly available dataset from eNTERFACE Workshop 2006 was used having as stimuli emotionally evocative images. At first, EEG features were extracted based on literature review. Then, a computational framework is proposed using machine learning techniques, performing feature selection and classification into two at a time emotional states. The proposed methodology is able to obtain accuracy of 75.12% in classifying the two emotional states comparing with similar studies using the same dataset. The experimental procedure included 3 phases, each of them having 30 trials. Each trial started with a 3-second appearance of a dark screen with a cross in the center, followed by 5 images (block), each lasting 2.5 seconds, that all belonged to the same emotional class and then again a black screen was presented for 10 seconds. The session ended with participants assessing the images they had previously seen with a rating for each of the arousal-valence axes. The order of the blocks was random, but all three emotional classes were represented by the same number of trials in each session, namely 10 trials for each class. The last two submodules contain machine learning techniques that were evaluated and compared, in order to determine the best combination of methods and tuning parameters that could more accurately discriminate among the emotional states. In this study, several features were extracted from EEG signals: Signal power in bands , Frontal alpha asymmetry , Peak frequency in alpha band, Hjorth parameters and Cross-correlation of frequency band powers. This paper investigated various selection and classification schemes for the discrimination among emotional states. The analysis presented, showed that the best classification scheme achieved accuracies of 75.59%, 75.06% and 75.12% for the three pairs of classes clam/exciting negative (C-EN), calm/exciting positive (C-EP), exciting positive/exciting negative (EP-EN) respectively. These results are improved as compared to other studies using the same dataset and objective.

Omid Bazgir, Zeynab Mohammadi and Seyed Amir Hassan Habibi [15], shows better performance compared to existing algorithms applied to the "DEAP" dataset. To design an emotion recognition system using EEG signals, effective feature extraction and optimal classification are the main challenges. EEG signals are non-linear, non-stationary, buried into various sources of noise and are random in nature. Thus, handling and extracting meaningful features from EEG signals plays a crucial role in an effective designing of an emotion recognition system.

In this research, an emotion recognition system is developed based on valence/arousal model using electroencephalography (EEG) signals. EEG signals are decomposed into the gamma, beta, alpha and theta frequency bands using discrete wavelet transform (DWT), and spectral features are extracted from each frequency band. Principle component analysis (PCA) is applied to the extracted features by preserving the same dimensionality, as a transform, to make the features mutually uncorrelated. Support vector machine (SVM), K-nearest neighbor (KNN) and artificial neural network (ANN) are used to classify emotional states. The cross-validated SVM with radial basis function (RBF) kernel using extracted features of 10 EEG channels, performs with 91.3% accuracy for arousal and 91.1% accuracy for valence, both in the beta frequency band. In this paper, an emotion recognition system is developed based on the valence-arousal model. The application of wavelet transform on EEG signals, then energy and entropy were extracted from 4 different decomposed frequency bands. PCA was used to make the attributes uncorrelated. SVM, KNN and ANN are utilized for emotional states classification into arousal/valence dimension. In this research, EEG signals from the DEAP dataset are windowed into 2- and 4-seconds windows with 50% overlap, then, decomposed into 5 frequency bands; gamma, beta, alpha, theta and noise. Spectral features, entropy, and energy of each window within the pre-specified frequency band are extracted. To reduce the electronic amplifier, power line and external interference noise, the average mean reference (AMR) method was utilized. Afterwards, the PCA is applied as a transform preserving the input dimensionality to produce uncorrelated attributes. The ANN, KNN and SVM are trained with attributes from different frequency bands, and different pair of channels, by eight-fold cross validation. PCA made the extracted features uncorrelated. In addition, picking appropriate kernel (RBF), greatly increased the cross-validated accuracy.

Wei-Long Zheng, Jia-Yi Zhu, Yong Peng, and Bao-Liang Lu [16], introduced a recent advanced deep learning models to classify two emotional categories (positive and negative) from EEG data. They train a deep belief network (DBN) with differential entropy features extracted from multichannel EEG as input. A hidden markov model (HMM) is integrated to accurately capture a more reliable emotional stage switching. The paper also compares the performance of the deep models to KNN, SVM and Graph regularized Extreme Learning Machine (GELM). The experimental results show that the DBN and DBN-HMM models improve the accuracy of EEG based emotion classification in comparison with the state-of the-art methods. In this paper, they introduce recent advanced deep learning models to EEG-based emotion classification. The main contributions of this paper are as follows: First, find that neural signatures associated with positive and negative emotions in beta and gamma frequency bands do exist. Second, show that differential entropy (DE) features extracted from EEG data possess accurate and stable information for emotion classification. Finally, the paper compares the results between deep modals and shallow models like KNN, SVM and GELM. Moreover, DBN-HMM performs well when compared with the state-of-the-art classification methods. Differential entropy extends the idea of Shannon entropy and is used to measure the complexity of a continuous random variable. The best accuracy of all frequency-band features is achieved with the DBN-HMM, followed by DBN, GELM, SVM and lastly KNN. The results show that DBN-HMM and DBN models outperform over other models with higher mean accuracy and lower standard deviations. The DBN model achieves 2.83% higher accuracy and 2.04% lower standard deviation than SVM. DBN-HMM model achieves 3.54% higher accuracy and 2.18% lower standard deviation than SVM. DBN-HMM perform slightly better than DBN. While GELM sometimes can achieve best performance for some trials, the results of GELM fluctuate more between subjects than DBN and DBN-HMM. It also showed that the DBN and DBN-HMM methods obtained higher accuracy and lower standard deviation than GELM, SVM and KNN. The reliability of classifications achieved suggests that such neural signatures associated with positive methods obtained higher accuracy and lower standard deviation than GELM, SVM and KNN. The reliability of classifications achieved suggests that such neural signatures associated with positive or negative emotions do exist.

Kwang-Eun Ko, Hyun-Chang Yang, and Kwee-Bo Sim [17], propose an emotion recognition system for human brain signals using EEG signals. They measure EEG signals relating to emotion, divide them into five frequency ranges on the basis of power spectrum density, and eliminate low frequencies from 0 to 4 Hz to eliminate EEG artifacts. The resulting calculations of the frequency ranges are based on the percentage of the selected range relative to the total range. The calculated values are then compared to standard values from a Bayesian network, calculated from databases. In this study, they recognized human emotion using an EEG signal with relative power values and a Bayesian network. Their results are shown using text and a human face avatar representing human emotion. In their first analysis, measured EEG signals were transformed into a power spectrum using fast
Fourier transforms (FFTs). The transformed EEG signals were divided into five parts which were displayed in different colors. They constructed a network and used it for computer-based diagnosis and prediction. For example, consider a case in a database consisting of a set of faulty behaviors, as well as the fault determined to have caused those behaviors. The calculated relative power values were compared with the database for emotion recognition. The resulting values clearly differed by individual. They estimated emotions using probability inference in order to account for the differences. When they compared the results with the database, the mean values of the database were the standards of the value judgements. If a measured value was higher than the mean, the value was allocated a positive binary number. The binary values were used to calculate probability inference using a Bayesian network. In this study, human brainwaves are classified according to the emotions and the results are compared. They used audio and visual pictures to induce emotions, and the brainwaves were transformed into power spectrum values using a FFT. It also removed the signals in the low frequency range to eliminate artifacts of brainwaves and the remaining signals which are selected frequency ranges were calculated with relative power values. Because human emotions cannot be measured accurately, they used probability inference and a Bayesian network. In comparing results, many emotions showed different probability values, but “anger” and “sadness” show similar probability values.

Chung, Seong Youb, and Hyun Joong Yoon [18], proposes an affective classification method(2 or 3 classes in Valence and Arousal dimensions) using EEG signals from multimodal EEG benchmark dataset, DEAP
(Database for Emotion Analysis Using Physiological Signals). The two main machine learning approaches: Bayes Classifier and supervised Learning technique were used. Instead of using the posterior function or likelihood function with Bayes classifier they have introduced a new function known as

weighted-log-posterior function. This function is represented as the sum of likelihood function of each feature and the bias factor under the assumption of feature independence. The weights and the bias factors keep computed using supervisory technique such as perceptron convergence algorithm. The maximum value of this function is used by the Bayesian Classifier to classify the affective state. For 2 classes the achieved accuracies are 66.6% and 66.4% and for 3 classes the achieved accuracies are 53.4% and 51.0% for Valence and Arousal respectively. The Bayes Classifier is simple and intuitive but there has not been successful applications yet as compared to other machine learning techniques such as Support Vector Machine.

Ruo-Nan Duan, Jia-Yi Zhu and Bao-Liang Lu [19], proposed a new EEG based feature called Differential Entropy (DE) were used to represent the characteristics that are associated with emotional states. The combination of this feature on symmetrical electrodes (DASM and RASM) were compared with the Energy Spectrum (ES) feature of the frequency domain. Using these features (DE, DASM, RASM, and ES) on EEG data, the classification accuracies are 84.22%, 80.96%, 83.28%, and 76.56%, respectively. Therefore DE feature is well suited for the recognition of emotions as compared to the traditional frequency domain feature, ES. It is also confirmed that EEG signals on frequency band Gamma relates to emotional states more closely than other frequency bands. Feature smoothing method linear dynamical system (LDS), and feature selection algorithm - the principal component analysis (PCA) and the minimal redundancy maximal relevance (MRMR) algorithm to reduce the feature dimension, to save the storage space and speed up the classification procedure.

A 512-point short-time Fourier transform with a non-overlapped Hanning window of 1s was used to calculate the frequency domain features. Four kinds of features were compared, which were ES, DE, DASM, and RASM. Two kinds of classifiers were employed, which were linear-kernel support

vector machine (SVM) and k-nearest neighbors (K-NN) algorithm. All the features used in this study had been smoothed by LDS, and SVM models were applied as classifiers. The result confirms that the emotional states related to EEG in Gamma frequency band more closely than other frequency bands. It can be implied from this result that DE is more suited for EEG-based

emotion classification than traditional ES features.

Li-Chen Shi, Ying-Ying Jiao and Bao-Liang Lu [20], the Differential Entropy (DE) feature has been used for the vigilance estimation based on EEG signals. A physical interpretation of logarithmic form of spectrum feature in EEG signal analysis and a new feature: differential entropy has been presented. Differential entropy is proposed to characterize the level of vigilance, as a complexity measure for continuous EEG signals. For the analysis of EEG signals, the entropy measure has been widely used. From the perspective of information theory, it is defined as the amount of information stores in a more general probability distribution. This paper represents that the Differential Entropy (DE) feature outperforms other features such as Energy Spectrum (ES),

auto-regressive (AR) parameters, fractal dimension and sample entropy.
As human brain is highly non-stationary, the EEG signals which are extracted from the human brain are asymmetric and non-stationary in nature. Analysing these signals are challenging and a crucial task in the area of affective computing and require specific domain knowledge such as channels and frequency bands that are very important for understanding brain response. In the field of affective neuroscience, we should know how to discriminate the neural activities of EEG signals between different types of emotions, how to analyse stability of EEG patterns which reflects the emotions elicited in the human brain, and how deep learning and shallow learning techniques affect the performance of developing models. Also we should evaluate the performance of different popular methods for feature extraction, feature selection, feature smoothing and pattern classification for emotion recognition on different datasets. The human brain is a very complicated, and mysterious information processing system, so we need to know how to analyze neurocognitive data efficiently.

Dan Nie, Xiao-Wei Wang, Li-Chen Shi, and Bao-Liang Lu [21], aims at finding the relationship between EEG signals and human
emotions. EEG signals are used to classify two kinds of emotions, positive and negative. First, author extracted features from original EEG data and used a linear dynamic system approach to smooth these features. An average test accuracy of 87.53% was obtained by using all of the features together with a support vector machine. Next, author reduced the dimension of features through correlation coefficients. The top 100 and top 50 subject-independent features were achieved, with average test accuracies of 89.22% and 84.94%, respectively. Finally, a manifold model was applied to find the trajectory of emotion changes.
So, to conclude author designed an experiment with movie clips as stimuli and SAM as label. Two classes of emotion, positive and negative were mainly concerned about. First author averaged the EEG data into delta, theta, alpha, beta and gamma bands, and computed the log energy of each
sample. Next a LDS based approach was applied to smooth the original features. Last a linear-SVM was used to work on the training and testing set. The average test accuracy with all the features was 87.53%. For the purpose of practicability, author reduced the dimension of features using correlation coefficients and found the top 100 subject-independent features with an average test accuracy of 89.22%. When reducing the dimension further to 50, results were stable for most subjects. The average test accuracy with these 50 features was 84.94%, not much less than that of all the features. With these subject-independent features, author found the brain regions and frequency bands most relevant to emotion. At the end of the study, author used an unsupervised manifold model to draw the trajectory of emotion changes and the trajectory was almost consistent with the true changes.

Ahmad Tauseef Sohaib, Shahnawaz Qureshi, Olle Hilborn, and Petar [22], author focus on emotion detection using EEG. Various machine learning techniques can be used on the recorded EEG data to classify emotional states. K-Nearest Neighbor (KNN), Bayesian Network (BN), Artificial Neural Network

(ANN) and Support Vector Machine (SVM) are some machine learning techniques that previously have been used to classify EEG data in various experiments. Five different machine learning techniques were evaluated in this paper, classifying EEG data associated with specific affective/emotional states. The emotions were elicited in the subjects using pictures from the International Affective Picture System (IAPS) database. The results from all 15 participants was in the best case 56.10%. When dividing the subset into three parts with five subjects each the accuracy rose to 77.78%. In both cases SVM was the best classifier with KNN slightly behind. The results from classifying data from single subjects showed an accuracy of 83.33% for KNN. Interesting is that SVM only showed an accuracy of 50.00% on single subjects.

Yuan-Pin Lin, Chi-Hong Wang , Tien-Lin Wu , Shyh-Kang Jeng and Jyh-Horng Chen [23], focused on the approach for recognizing music-induced emotional responses from brain activity. A comparative study was conducted to testify the feasibility of using hierarchical binary classifiers to improve the classification performance as compared with nonhierarchical schemes.
In this study, author testified the feasibility of classification solution that decomposes multi-class classification into hierarchical binary classifiers for achieving better performance in EEG classification problem. He not only adopted two types of multi-class SVM schemes from nonhierarchical scheme such as all-together to hierarchical scheme such as one-against-one, but constructed a model-based scheme based on the structure of 2D emotion model. From the obtained results, we found that one-against-one scheme of multi-class SVM classifier yielded a best performance in distinguishing four emotion classes.

Zhenqi Li, Xiang Tian, Lin Shu, Xiangmin Xu, and Bin Hu [24], proposes a new approach which extracts RASM as the feature to describe the frequency-space domain characteristics of EEG signals and constructs a LSTM network as the classifier to explore the temporal correlations of EEG signals.
A new method using RASM and LSTM is proposed in this sector, which represents the frequency and spatial characteristics and explores temporal correlations of EEG signals. It utilizes the comprehensive characteristics of EEG signals in temporal, frequency and spatial domains to achieve automatic emotion recognition with a high accuracy. For EEG-based emotion recognition, RASM is a considerable feature and LSTM is a suitable classifier. As the new approach focuses on the trial-oriented recognition, which is limited with a minute-level time resolution. It might not perform well in short time recognition. We then tested our approach in segment-oriented emotion recognition, where the data had the second-level time resolution, and the trial labels were used as the segment labels. Then we got a mean accuracy of 71.96%, which was lower than the trial-oriented recognition, as the emotion labels in the database were set for the trials instead of the segments.

Seyyed Abed Hosseini, Mohammad Bagher Naghibi-Sistani [25], proposes an emotion recognition system using EEG signals, therefore a new approach to emotion state analysis by approximate (ApEn) and wavelet entropy (WE) is described. We have used EEG signals recorded during emotion in five channels (FP1, FP2, T3, T4 and Pz), under pictures induction environment (calm-neutral and negative excited) for participants.

After a brief introduction to the concept, the ApEn and WE were extracted from two different EEG time series. The results showed that, the classification accuracy in two emotion states was 73.25% using the support vector machine (SVM) classifier. The simulations showed that the classification accuracy is good and the proposed methods are effective. During an emotion, the EEG is less complex compared to the normal, indicating reduction in active neuronal process in the brain.

The study shows clear difference in dynamical properties of electrical activity of the brain in subjects, during emotion state. Classically, the electroencephalogram has been the most utilized signal to assess brain function owing to its excellent time resolution. In this research, we propose an

approach to classify emotion in the two categories (calm vs. negative exited) by using brain signals.

This paper, the application of nonlinear time series analysis to EEG signals offers insight into the dynamical nature and variability of the brain signals. The reason we have chosen the EEG signals over the pure psychophysiological signals is the fact that EEG signals represent behavior directly from their source but the psychophysiological signals are secondary manifestations of the autonomic nervous system in response to emotion.

Ma Li, Quek Chai, Teo Kaixiang, Abdul Wahab and Hu ¨seyin Abut [26], proposes an emotion recognition system based on time domain analysis of the bio-signals for emotion features extraction. Three different types of emotions (happy, relax and sad) are classified and results are compared using five different algorithms based on RVM, MLP, DT, SVM and Bayesian techniques. Experimental results show the potential of using the time domain analysis for real-time application.

This chapter proposes an emotion recognition system from EEG signals in time domain. Three emotions, happy, relaxed and sad, were conducted in this experiment. In order to compare the accuracy results, five different models. EEG emotion recognition results in Emotion class

Accuracy (%)
Joy 58.3
Anger 33.4
Sadness 25.0
Fear 41.7
Relaxed 50.0

were used and they are relevance vector machine (RVM), multi layer perception (MLP), decision tree (DT), support vector machine (SVM) and Bayes network. Based on the experiments, RVM and MLP both gave the highest accuracies, with relatively similar results. However, it was concluded that RVM is a better choice over MLP, the reason being the training time of the RVM is 1.5 times faster. RVM also generated the relative importance of features, which identifies eight important features. The experiment was rerun again with these eight selected features to verify the accuracy. The average accuracy is 97.82% for the 24 original features, while the average accuracy for the 8 selected features is 94.27%. It was also observed that the training time for the latter is almost 4.5 times faster than the other one. Considering the trade-off from the accuracy for the increase in speed of the training time, the experimental results were satisfying.

Rendi E. J. Yohanes, Student Member, IEEE, Wee Ser [27], propose to use DWT coefficients as features for emotion recognition from EEG signals. Previous feature extraction methods used power spectra density values dervied from Fourier Transform or sub-band energy and entropy derived from Wavelet Transform. These feature extraction methods eliminate temporal information which are essential for
analyzing EEG signals. The DWT coefficients represent the degree of correlation between the analyzed signal and the wavelet function at different instances of time; therefore, DWT coefficients contain temporal information of the analyzed signal. The proposed feature extraction method fully
utilizes the simultaneous time-frequency analysis of DWT by preserving the temporal information in the DWT coefficients. Visual stimuli from International Affective Picture System (IAPS) were used to induce two emotions: happy and sad. Two classifiers were used: Extreme Learning Machine (ELM) and Support Vector Machine (SVM). Experimental results confirmed that the proposed DWT coefficients method showed improvement of performance compared to previous methods.
In this paper, the performance of two classifiers are considered: Extreme Learning Machine (ELM) and Support Vector Machine (SVM). Based on the assumption that individuals respond differently to emotional stimuli, the classifiers were trained separately for different subjects. The EEG signals obtained from the two electrodes, Fp1 and Fp2, were used separately. To fully utilize the EEG signals, the classifiers were trained using three-fold cross validation method. Firstly, the 30 feature vectors derived from the EEG signals were divided into 3 sets with equal number of happy and sad samples. Secondly, the classifiers were trained using 2 sets and tested using 1 set. Lastly, the first and second steps were repeated two more times using different combinations of the training and testing sets.

Yongbin Gaol, Hyo Jong Lee, Raja Majid Mehmood [28], propose a deep learning algorithm to simultaneously learn the features and classify the emotions of EEG signals. It differs from the conventional methods as we apply deep learning on the raw signal without explicit hand-crafted feature extraction. Because the EEG signal has subject dependency, it is better to train the emotion model subject-wise, while there is not much epochs available for each subject. Deep learning algorithm provides a solution with a pre-training way using three layers of restricted Boltzmann machines (RBMs). Thus, we can use epochs of all subjects to pre-training the deep network, and use back- propagation to fine tuning the network subject by subject. A deep learning architecture is proposed to learn and classify the emotions of EEG signal. It differs from the conventional methods as we apply deep learning on the raw signal without hand-crafted feature extraction. Deep learning algorithm provides us a solution with a pre-training way using three layers of restricted Boltzmann machines(RBMs). Thus, we can use epochs of all subjects to pre-training the deep network, and use back-propagation to fme tuning the network subject by subject. Experiment results verify that emotion recognition of EEG signal is subject dependent, and our subject tied implementation of deep learning achieves better recognition accuracy than conventional algorithms.

Suwicha Jirayucharoensak, Setha PanNgum, and Pasin Israsena [29], detected emotion from nonstationary EEG signals, a sophisticated learning algorithm that can represent high-level abstraction.

Automatic emotion recognition is one of the most challenging tasks. To detect emotion from nonstationary EEG signals, a sophisticated learning algorithm that can represent high-level abstraction is required. This study proposes the utilization of a deep learning network (DLN) to discover unknown feature correlation between input signals that is crucial for the learning task. The DLN is implemented with a stacked autoencoder (SAE) using hierarchical feature learning approach. Input features of the network are power spectral densities of 32-channel EEG signals from 32 subjects. To alleviate overfitting problem, principal component analysis (PCA) is applied to extract the most important components of initial input features. Furthermore, covariate shift adaptation of the principal components is implemented to minimize the nonstationary effect of EEG signals. Experimental results show that the DLN is capable of classifying three different levels of valence and arousal with accuracy of 49.52% and 46.03%, respectively. Principal component based covariate shift adaptation enhances the respective classification accuracy by 5.55% and 6.53%. Moreover, DLN provides better performance compared to SVM and naive Bayes classifiers.

The proposed EEG-based emotion recognition is implemented with a deep learning network and then enhanced with covariate shift adaptation of the principal components. The deep learning network is constituted of a stack of three autoencoders and two softmax classifiers for valence and arousal state classifications. The purpose of PCA is to reduce dimension of input features. The CSA handles the nonstationary effect of EEG signals. The classification accuracy of the DLN with PCA+CSA is 53.42% and 52.05% to classify three levels of valence states and three levels of arousal states. The DLN provides better accuracy performance compared to SVM and naive Bayes classifier. One of the major limitations for performing EEG-based emotion recognition algorithm is dealing with the problem of intersubject variations in their EEG signals. The common features of transferable nonstationary information can be investigated to alleviate the intersubject variation problems.

Noppadon Jatupaiboon, Setha Pan-ngum, and Pasin Israsena [30], proposed to use real-time EEG signal to classify happy and unhappy emotions elicited by pictures and classical music. We use PSD as a feature and SVM as a classifier. The average accuracies of subject-dependent model and subject-independent model are approximately 75.62% and 65.12%, respectively. Considering each pair of channels, temporal pair of channels (T7 and T8) gives a better result than the other area. Considering different frequency bands, high-frequency bands (Beta and Gamma) give a better result than low-

frequency bands. Considering different time durations for emotion elicitation, that result from 30 seconds does not have significant difference compared with the result from 60 seconds. From all of these results, he implemented real-time EEG-based happiness detection system using only one pair of channels. Furthermore, developed
games based on the happiness detection system to help user recognize and control the happiness.

In this research the author proposed to use real-time EEG signal to classify happy and unhappy emotions elicited by pictures and classical music. Considering each pair of channels and different frequency bands, temporal pair of channels gives a better result than the other area does, and high frequency bands give a better result than low frequency bands do. All of these are beneficial to the development of emotion classification system using minimal EEG channels in real time. From these results, we implement real-time happiness detection system using only one pair of channels.

Furthermore, we develop games to help users recognize and control the happy emotion to be what they want. In the future, we will use other physiological signals such as Galvanic Skin Response (GSR), Electrocardiogram (ECG), and Skin Temperature (ST) combined with EEG to enhance the performance of emotion recognition in the aspect of accuracy and number of emotions.

Samarth Tripathi, Shrinivas Acharya, Ranti Dev Sharma, Sudhanshi Mittal, and Samit
Bhattacharya, [31], two types of neural networks(Deep Neural Network and Convolutional Neural networks) were used for the classification of emotions (Valence and Arousal dimensions) using EEG signals from multimodal EEG benchmark dataset, DEAP (Database for Emotion Analysis Using Physiological Signals).The technique called Dropout is an advanced machine learning technique which has been used in this study. Emotions plays an important role in cognitive processes, so in order to extract these emotions from the human brain instead of using facial, speech or text, EEG (Electroencephalography) signals are used. Extracting emotions using EEG are affordable, non-invasive and promote ubiquitous adoption in industries. A standardised DEAP dataset of human affective states contains the physiological signals of 32 subjects using 32 EEG Channels and with sampling rate of 512Hz.These signals were extracted by using the emotional
stimulus of 40 music videos, which were watched by each subject for one-minute in terms of levels of like/dislike, valence, arousal, dominance, and familiarity. Valence (Inactive to Active) and Arousal (Unpleasant to Pleasant) scale was developed by Russel for describing human emotions.

There were 40 experiments for each 32 participants and a labels array which contains the valence, arousal, dominance and liking ratings.

Wei Liu1, Wei-Long Zheng1, and Bao-Liang Lu [32], author aims to enhance the performance of affective models and reduce the cost of acquiring physiological signals for
real-world applications, he adopts multimodal deep learning approach to construct effective models with SEED and DEAP datasets to recognize different kinds of emotions.

To enhance the performance of effective models and reduce the cost of acquiring physiological signals for real-world applications, we adopt multimodal deep learning approach to construct effective models with SEED and DEAP datasets to recognize different kinds of emotions. We demonstrate that high level representation features extracted by the Bimodal Deep AutoEncoder (BDAE) are effective for emotion recognition. With the BDAE network, we achieve mean accuracies of 91.01 % and 83.25 % on SEED and DEAP datasets, respectively, which are much superior to those of the state-of-the-art approaches. By analysing the confusing matrices, we found that EEG and eye features contain complementary information and the BDAE network could fully take advantage of this complement property to enhance emotion recognition.

This paper has shown that the shared representations extracted from the BDAE model are good features to discriminate different emotions. Compared with other existing feature extraction strategies, the BDAE model is the best with accuracy of 91.01 % on SEED dataset. For DEAP dataset, the BDAE network largely improves recognition accuracies on all four binary classification tasks. We analysed the confusing matrices of different methods and found that EEG features and eye features contain complementary information. The BDAE framework could fully take advantage of the complementary property between EEG and eye features to improve emotion recognition accuracies.

Xiang Li , Peng Zhang , Dawei Song, Guangliang Yu , Yuexian Hou , Bin Hu [33], the author presented work on using Deep Belief Network (DBN) to automatically extract high level features from raw EEG signals.

Capturing user’s emotional state is an emerging way for implicit relevance feedback in information retrieval (IR). Recently, EEG-based emotion recognition has drawn increasing attention. However, a key challenge is effective learning of useful features from EEG signals. In this paper, we present our on-going work on using Deep Belief Network (DBN) to automatically extract high- level features from raw EEG signals. Our preliminary experiment on the DEAP dataset shows that the learned features perform comparably to the use of manually generated features for emotion recognition.

This paper investigates on an unsupervised deep feature learning approach in an EEG-based emotion recognition task. The experimental results presented in Section 3.3 show that it is feasible to learn useful affective features from raw EEG data through a deep feature learning framework and its effectiveness is comparable to manually extracted features. In the future, we will further refine the model. Furthermore, the subjects’ ambiguity in self rating after each trial and critical EEG channel selection for feature reduction should be taken into consideration. Finally, we aim to apply the real-time EEG analysis in the IR setting. For example, the users’ affective responses to the retrieval results can be detected and used as affective features to train a personalized relevance model with the user tagged/clicked documents. Then the trained model can be used to predict the topical relevance of other documents. User’s personalized profile get enriched and updated in this process.

Mohammad Soleymani, Maja Pantic, and Thierry Pun [34], presents a user-independent emotion recognition method with the goal of recovering affective tags for videos using electroencephalogram (EEG), pupillary response and gaze distance. We first selected 20 video clips with extrinsic emotional content from movies and online resources. Then, EEG responses and eye gaze data were recorded from 24 participants while watching emotional video clips. Ground truth was defined based on the median arousal and valence scores given to clips in a preliminary study using an online questionnaire. Based on the participants' responses, three classes for each dimension were defined. The arousal classes were calm, medium aroused, and activated and the valence classes were unpleasant, neutral, and pleasant. One of the three affective labels of either valence or arousal was determined by classification of bodily responses. A one-participant-out cross validation was employed to investigate the classification performance in a user-independent approach. The best classification accuracies of 68.5 percent for three labels of valence and 76.4 percent for three labels of arousal were obtained using a modality fusion strategy and a support vector machine. The results over a population of 24 participants demonstrate that user-independent emotion recognition can outperform individual self-reports for arousal assessments and do not underperform for valence assessments.

Valery A. Petrushin, [35], explores how well both people and computers in recognizing emotions in speech. The project is motivated by the question of how recognition of emotions in speech could be used for business. One potential application is the detection of the emotional state in telephone call center conversations, and providing feedback to an operator or a supervisor for monitoring purposes. Another application is sorting voice mail messages according to the emotions expressed by the caller.
Each subject has recorded 20 or 40 utterances, yielding a corpus containing 700 utterances with 140 utterances per emotional state. Each utterance was recorded using a close-talk microphone; the first 100 utterances were recorded at 22-kHz/8 bit and the rest 600 utterances at 22-kHz/16 bit. To recognize emotions in speech author tried the following approaches: K nearest neighbors, neural networks, ensembles of neural network classifiers, and set of experts and then the comparison of results is done.

Theerawit Wilaiprasitporn, Apiwat Ditthapron, Karis Matchaparn, Tanaboon Tongbuasirilai, Nannapas Banluesombatkul and Ekapol Chuangsuwanich [36], proposed another method for performing Person Identification (PI). Due to the nature of the EEG signals, EEG-based PI is typically done while a person is performing a mental task such as motor control. However, few studies used EEG-based PI while the person is in different mental states (affective EEG). The aim of this study is to improve the performance of affective EEG-based PI using a deep learning approach. Author proposed a cascade of deep learning using a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). CNNs are used to handle the spatial information from the EEG while RNNs extract the temporal information. We evaluated two types of RNNs, namely, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). The proposed method is evaluated on the state-of-the-art affective dataset DEAP. The results indicate that

CNN-GRU and CNN-LSTM can perform PI from different affective states and reach up to 99.90–100% mean Correct Recognition Rate. This significantly outperformed a support vector machine baseline system that used power spectral density features. Notably, the 100% mean CRR came from 32 subjects in DEAP dataset. Even after the reduction of the number of EEG electrodes from thirty-two to five for more practical applications, the model could still maintain an optimal result
obtained from the frontal region, reaching up to 99.17%. Amongst the two deep learning models, we found that CNN-GRU and CNN-LSTM performed similarly while CNN-GRU expended faster training time. In conclusion, the studied DL approaches overcame the influence of affective states in EEG-Based PI reported in the previous works.

B. Dataset

DEAP Dataset as an effective pre-processing method has been proposed to improve the recognition accuracy. Meanwhile, we used a hybrid neural network which combines 'Convolutional Neural Network (CNN)' and 'Recurrent Neural Network (RNN)' has been
applied to classify human emotion states by effectively learning compositional spatial-temporal representation of raw EEG streams.

C. Summary

As a challenging pattern recognition task, automatic real-time emotion recognition based on multi-channel EEG signals is becoming an important computer-aided method for emotion disorder diagnose in neurology and psychiatry. Traditional machine learning approaches require to design and extract various features from single or multiple channels based on comprehensive domain knowledge. Consequently, these approaches may be an obstacle for non-domain experts. On the contrast, deep learning approaches have been used successfully in many recent literatures to learn features and classify different types of data. Baseline signals are considered and a simple but effective pre-processing can work wonders to improve the recognition accuracy. A hybrid neural network which combines 'Convolutional Neural Network (CNN)' and 'Recurrent Neural Network (RNN)' has been successfully applied to classify human emotion states by effectively learning compositional spatial-temporal representation of raw EEG streams. The CNN module is used to mine the inter-channel correlation among physically adjacent EEG signals by converting the chain-like EEG sequence into 2D-like frame sequence. The LSTM module is adopted to mine contextual information. Experiments are carried out in a segment-level emotion identification task, on the DEAP benchmarking dataset. The experimental results indicate that the proposed pre-processing method can increase emotion recognition accuracy by a lot and the model achieves a high performance with state of the art accuracies on valence and arousal classification task respectively. We will have applied similar algorithms to produce results for valence, arousal, dominance, liking and familiarity emotions.

As human brain is highly non-stationary, the EEG signals which are extracted from the humanbrain are asymmetric and non-stationary in nature. Analysing these signals are challenging and a crucial task in the area of affective computing and require specific domain knowledge such as channels and frequency bands that are very important for understanding brain response. In the field of affective neuroscience, we should know how to discriminate the neural activities of EEG signals between different types of emotions, how to analyse stability of EEG patterns which reflects the emotions elicited in the human brain, and how deep learning and shallow learning techniques affect the performance of developing models. Also we should evaluate the performance of different popular methods for feature extraction, feature selection, feature smoothing and pattern classification for emotion recognition on different datasets. The human brain is a very complicated, and mysterious information processing system, so we need to know how to analyze neurocognitive data efficiently.

There already exists extensive studies using machine learning to identify emotion states with EEG signals. Traditional machine learning based methods have shown effective in classifying emotional states, while the shortage of these kinds of approaches is that the researchers must devote numerous efforts to find and design various emotion-related features from origin noisy signals. And the computation of these features is time consuming.

A variety of feature extraction methods are proposed in recent years . While the most commonly used methods are Fourier Transform (FT), Power Spectral Density(PSD) and Wavelet Transform (WT) Chen and Zhang compared two different feature extraction approaches and four different machine learning classifiers and found that nonlinear dynamic features lead to higher accuracy . Yin et al. proposed a transfer recursive feature elimination (T-RFE) approach that selects features of EEG to determine the optimal feature subset regarding a cross subject emotion classification issue optimal feature subset regarding a cross subject emotion classification issue.

In recent years, deep learning has drawn wide attention due to its great success in the visual field. Some deep learning based approaches have also achieved competitive accuracy in EEG-based recognition task. In CNN was used to extract time, frequency and location information features of EEG and Stacked Auto Encoders (SAE) was employed to improve the classification accuracy.

Zhang et al. proposed both cascade and parallel convolutional recurrent neural network for EEG based movement intention recognition and achieved a perfect performance. Li et al. proposed a pre-processing method that transforms the multi-channel EEG data into 2D frame representation and integrates CNN and RNN to recognition emotion states in the trial-level. Li et al. extracted Power Spectral Density from different EEG channels and mapped it to two-dimensional plane to construct the EEG Multidimensional Feature Image (EEG MFI), then CNN was adopted to learn temporary image patterns from EEG MFI sequences, while the LSTM RNN was used to classify human emotion. Tang et al. used Bimodal Deep Denoising Auto Encoder and Bimodal-LSTM to classify emotion states and achieved the state-of-the art performance.

III. **REFERENCES**

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