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The Robust EEG Based Emotion Recognition using Deep Neural Network

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Abstract: This paper focuses on a novel Electroencephalography (EEG) based one dimensional convolution neural network (CNN) to classify emotional states. Differential entropy (DE) is considered as a feature extraction method after pre-processing phase. Besides, feature smoothing-linear dynamic system (LDS) and min-max normalization are used on the DE features before feeding into deep model. We design a one dimensional CNN model with six convolutions and fully connected blocks which gives outstanding performance in six combinations of SEED dataset. The model presented average accuracy of 98.55% and 95.91% in binary and single sessions respectively by using 10 fold cross validation. The proposed results fully demonstrate that our method achieves out of the best performance compare with other EEG based emotion recognition systems. Therefore, this model can be applied to other emotional datasets as a classifier and health care decision support system (DSS) as well.

Keywords: *Brain-Computer Interfaces (BCI), emotion recognition, electroencephalogram (EEG), one-dimensional CNN (1D-CNN)*

1. Introduction

Emotions are the most valuable feature of humans which play an important role in daily activities specially communication and decision making [1]. Humans to take advantage of sound, body gesture or facial expressions can be automatically recognized various emotions [2]. Nowadays, emotional artificial intelligence (AI) most widely used in communication and interaction between human and machine such as detection or treatment of mental disorder and game addiction as well [3].

Brain computer interface (BCI) is a system for acquisition biomedical data. Several BCI methods are employed in emotion recognition. Clinical Electroencephalogram (EEG) is one of the useful BCI technics that was introduced by Hans Berger, a German psychiatrist in 1930s [4]. The EEG signals are non-stationary time series, which are recorded overall brain activity by using electrodes. Physiological signals such as EEG are presented the best performance in contrast with facial expressions or speech in emotion recognition. Due to hiding emotions by humans in various situations, audio and visual based approaches cannot always reflect high accuracy results [5]. Physiological signals not only non-controlled, but also are non-invasive and quick response signals. However, EEG based emotion recognition signal is one of the challenge issues because the raw signals consist of various artifacts and noises which arise from electrooculogram (EOG), electromyogram (EMG) or somebody´s components during the recording phase. Nevertheless extraction meaningful information from EEG signals depends on increase signal-to-noise ratio (SNR) [6]. Removing noise and preprocessing stage are performed prior the classification to increase SNR and extract useful features from raw signals.

In the past decades, researchers proposed well known statistics indicator such as median, standard deviation, kurtosis and etc. as a feature. On the other hand, traditional machine learning (ML) methods cause to increase the cost of the model with respect to the vast number of features. To addresses this challenge, researcher has proposed different feature extraction methods for emotion recognition. These methods divided into three groups: time domain, frequency domain and time-frequency domain approaches. Nowadays power spectral density (PSD) and differential entropy (DE) are commonly used and majors feature extraction technics in emotion detection [7]. Using an entropy measure in EEG signals can be helped to distinguish emotional states. DE is a most efficient feature method that was employed in many research works. The outstand performance of DE specially in EEG based emotion recognition has been shown in [7-10]. Lu et al. [10] Have proposed a dynamic entropy based emotion recognition system with support vector machine (SVM) as a classifier that reached 64.15% and 85.11% accuracies for three and two emotion classes respectively.

In the past few years, researcher applied several classifier algorithms on various data sets in emotion recognition. As already mentioned above EEG signals reveal precise information more than audio signals and facial expressions in emotion detection. Most emotion recognition studies have been classified by using traditional ML approaches such as SVM [10], K nearest neighbors (KNN) [9], principle component analysis (PCA) [11], random forest (RF) [12] and linear discriminant analysis (LDA) [13]. However, these learning methods generally have presented low accuracy in contrast of deep learning (DL) methods. A survey study about using classifiers in emotion recognition was proposed by Mei Li et al. [14]. They focused on classification methods and investigated pipeline of previous studies in terms of classification method. Zheng et al. [9] developed an EEG dataset (SEED) that

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was acquired from 15 subjects within three days. They used asymmetric features (DE, PSD, DASM, RASM and DCAU) for each frequency band as inputs into ML models. Their results showed that DE is a powerful feature in EEG based emotion recognition. Gupta et al. [15] proposed a kernel based non-parametric estimator to extract features from EEG signals then feature smoothing process was applied to the raw features before fed into RF and SVM. Their estimator was called information potential (IP). They used only 12 out of 62 channels of SEED dataset and reported accuracy for each selected channel. Wang et al. [16] have designed a learning system which can randomly generate learning graph space to find suitable features. In this study, the DE method was considered to extract features and it reached a reasonable accuracy (93.66%). Linear discriminant analysis (LDA) has been identified as estimator, dimension redactor and feature extraction method as well. Wei Chen et al. [13] presented a feature set consists both of the DE and LDA. Their best performance of SVM was 85.60%. In the other study, researchers used PCA technic to reduce dimensions of EEG channels from 62 to 5 channels. They have investigated the feasibility of different statistical features by using t-test technique [11].

Deep learning techniques are able to extract features from raw data automatically therefor they are more attractive than other shallow models in EEG based emotion recognition. However, some researchers use feature extraction stage along with DL techniques to increase performance of the models. Hwang et al. [7] have generated image from DE to learn a CNN network with long short term memory (LSTM). They have reported 90.41% accurate for 62 channels with take advantage of feature visualization. Wei et al. [17] proposed a deep simple recurrent model which EEG raw signals were decomposed into 5 sub bands with dual-tree complex wavelet (DT-CWT) after preprocessing stage. Then extracted five kinds of features named MAV, PSD, FD and DE to learn the model. Zheng et al. [18] suggested GELM model by using DE features which were obtained comparative accuracy over other ML algorithms. Their study achieved 91.07% accuracy rate after LDS feature smoothing phase. Fdez et al. [12] have developed a normalization method (stratified normalization) to train deep neural network. This normalization method increased the classification accuracy to 91.6% and 79.6% in two and three emotional classes respectively.

In this study, a novel one-dimensional CNN (1D-CNN) network to classify three emotional states on SEED dataset has been proposed. In order to achieve high accuracy with low standard deviation, DE features is considered as input data forward by preprocessing stage. A feature smoothing technique is applied to the feature vectors before the classification stage. Min-Max is a well known normalization method that is employed followed by smoothing and before fed into the model. To avoid overfitting and achieve the best performance 10 fold cross validation (CV) is employed in train and test deep model. A flowchart for the proposed pipeline is shown in Figure 1. According the figure, our pipeline contains five various steps which start from preprocessing to learning deep model. Three emotional states are end of the diagram that labeled before in the dataset. DE feature vectors with all frequency bands have already provided by SEED dataset.

In the next section, preparation of used dataset (SEED), preprocessing stage, feature extraction, feature smoothing and classification algorithm will be described. In section 3, results of proposed model and comparison with other research works in terms of accuracy and standard deviation will be discussed. Finally, the conclusion of the study will be in the last section.

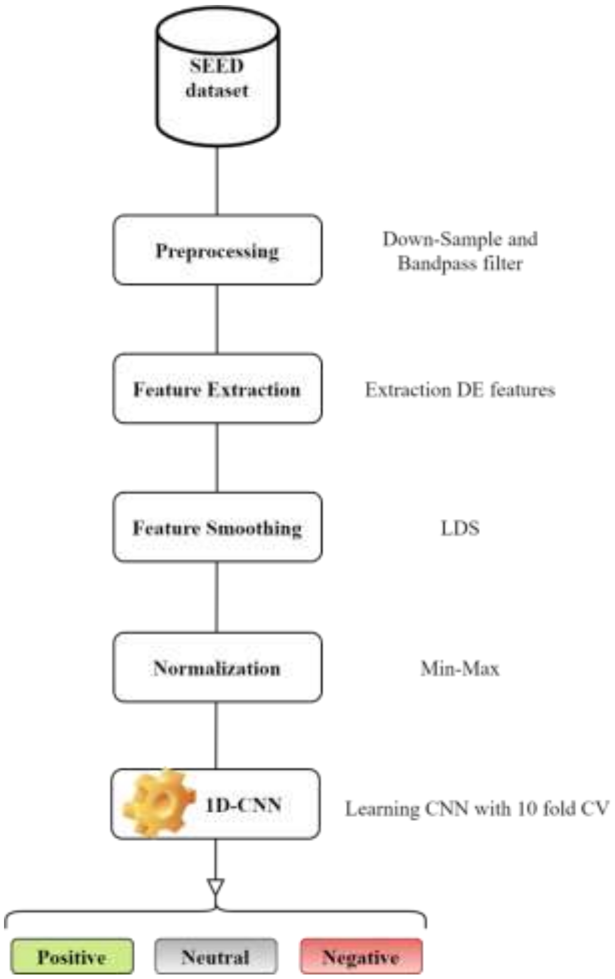

Fig 1. Diagram of proposed pipeline

2. Material and Methodology

2.1. Dataset

In this paper, we conducted our experiment on the SEED dataset [9] that is publicly available for research purposes. The recorded EEG signals were gathered from 15 subjects (7 men and 8 women). There were totally 15 Chinese clips with three different emotional states (positive, neutral and negative) to stimulate subjects. Each emotion contains five clips and each of them lasted approximately 4 min. According to the dataset, recording EEG from all subjects was repeated for three times in three different days. As shown in Figure 2, SEED dataset consists of three days (D1, D2 and D3) and each day includes 15 experiments and each experiment has 15 trials (sessions) within. All the experiments were performed with an interval about one week. In each experiment, the subjects watched the 15 clips with three different labels (positive, neutral, and negative), hence there are totally 3×15= 45 experiments in SEED dataset.

To collect EEG signals, a 62-channel electrode cap with a 10-20 system was used and all data were recorded with a sampling rate of 1000 Hz. During the preprocessing phase, the entire data was sampled at 200 Hz, followed by a 0 to 75 Hz band-pass frequency filter that was used to eliminate noise and artifacts from the raw data set.

The SEED dataset consists of three different days and there are several studies, which had been carried out classification by using only two days out of three days. In general, some researchers [7][16] considered first day (D1) and third day (D3) for classification. Due to the achievement, comprehensive results and investigation into more situations, we provided and regulated six scenarios from the combination of the three existing days. The dataset consists of six selected scenarios that three of them are binary and remain single days. To address overfitting and enhancing the performance model, we implemented train and test with 10 fold CV.

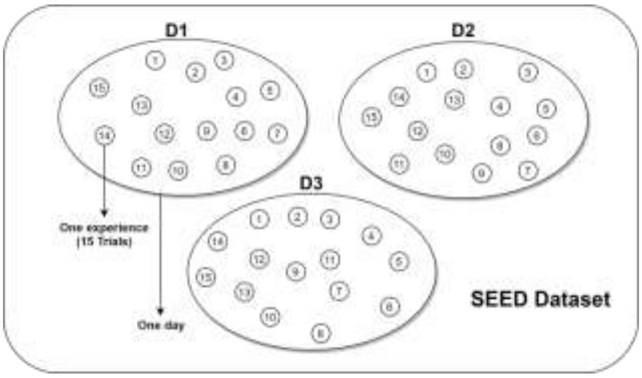

Fig 2. Diagram of SEED dataset

2.2. Feature Extraction

Feature extraction plays one of the vital roles in machine learning techniques and affects the accuracy of the models. As the previously before, DE presents an efficient performance on classification of human emotion as a feature extraction method. Thus, we used DE to measure complexity of the separate EEG signals in terms of high and low energy frequencies.

DE method is adopted by Shannon entropy, which first used by Duan et al. [8] on EEG signals. The DE can be identified by the following formula:

$$h(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx = \frac{1}{2}\log 2\pi e\sigma^2 \quad (1)$$

Where σ is standard deviation and X obeys the Gaussian distribution and x is a variable. The SEED dataset has already provided a bunch of data consist of DE features of EEG signals for five frequency bands (Delta, Theta, Alpha, Beta, Gamma) [9]. In order to extract five frequency bands of EEG signals, they used 256 point Short-Time Fourier Transformation without overlapped Hanning window with 1s. Thus, the DE features were created with 310 dimensions for each sample (62channels×5frequencies = 310). According to each clip`s duration that last about 4 min, there were about 240 non-overlapped windows and about 3300 samples for each trial and experiment respectively.

2.3. Feature Smoothing

In order to remove irrelevant components of feature sequences, we used an EEG based linear dynamic system (LDS) that proposed by Shi et al. [19]. The LDS can be selected parameters directly from EEG signals without labeling process. It has been avoided rapid fluctuation signals in raw extracted feature values and smoothed the signal sequences. Zhang et al. [20] have compared the performance of various classifiers on EEG signals and achieved good accuracy with LDS. The goal of the LDS is an estimation of hidden emotional variables in EEG signals that cause to be smooth signals. We applied LDS on all 5 frequency bands.

2.4. Normalization

Normalization methods are widely used in machine learning algorithms to scale features. The normalization lack leads to reduce the performance of the models. Min-Max is one of the well-known normalization methods which use in EEG based emotion detection [12]. It has a simple calculation mechanism that scales features between 0 and 1. Min-Max can be identified according to the following equation:

$$f(x) = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (2)$$

Where x is original value and $f(x)$ is the normalized value of x. The min (x) and max (x) denoted minimum and maximum values of x respectively. We employed this method on the DE features followed by smoothing phase and before fed into our model.

2.5. Classification

Using a convolutional neural network (CNN) not only present a remarkable performance in EEG based classification problems, but also attract much more attention in recent years [21]. In some research works, the CNN networks used in two dimensional pixel grid or EEG image based [15] however; in this study, we took advantage of one dimension CNN (1D-CNN) for classification of emotional states. The proposed deep network consisted of six blocks, which the first three of them were dedicated to the extraction and training features and remain in the classification process respectively. The extracted DE features were assumed to be input data instead of row signals. Besides, each convolution block includes three layers. The overall CNN architecture employed in this paper is illustrated in Figure 3. Convolutional operation is shown as follows:

$$y_k = \sum_{n=0}^{N-1} x_n h_{k-n} \quad (3)$$

That x in input data, h is filter, and N is the number of elements in the used signals and y is output vector.

In the proposed deep algorithm, leaky rectified linear unit (Leaky ReLU) as activation function was considered. Leaky ReLU is a non-linear activation function and one of the vital hyper parameters in each layer. Leaky ReLU is modification of ReLU function which replaced zero part of the domain in [-∞, 0] by a negative slope (alpha) [22]. Alpha could be considered different numbers for other studies. For example, Acharya et al.[23] defined 0.1 for alpha in EEG based seizure detection, however, we identified this coefficient 0.3 in this paper. The Leaky ReLU can be simply defined as follows:

$$f(x) = \begin{cases} 0.3x & \text{if } x \le 0 \\ x & \text{if } x > 0 \end{cases} \quad (4)$$

Furthermore, the Softmax function in the last fully connected (FC) layer was used as an emotional classifier with three neurons. The detail of structure our model is presented in Table1.

Table 1. The detail of 1D-CNN structure

Block	Type	No of neurons	Kernel size	Stride
Conv 1	Convolution	301×8	10	1
	Leaky ReLU	301×8	-	-
	BN	301×8	-	-
Conv 2	Convolution	294×10	8	1
	Leaky ReLU	294×10	-	-
	Max-pooling	147×10	2	2
Conv 3	Convolution	145×10	3	1
	Leaky ReLU	145×10	-	-
	Max-pooling	72×10	2	2
Flatten	-	720	-	-
FC 1	FC	50	-	-
	Leaky ReLU	50	-	-
	Dropout (r=0.2)	50	-	-
FC 2	FC	10	-	-
	Leaky ReLU	10	-	-
	Dropout (r=0.5)	10	-	-
FC 3	FC	3	-	-
	Softmax	3	-	-

Our experiments have shown that creating large numbers of neurons in FC layers can cause problems in recognition classes and reduce the overall accuracy of the model. For this reason, we regulated dropout rate at 20% and 50% for the first and second FC blocks respectively.

In this model, a BN layer [24] in the first block and one max-pooling layer in each remained convolution blocks was used. In addition, two dropout layers were employed in first two FC blocks after flatten layers, which helped to fast convergence of training phase and cope with overfitting as well.

We utilized an acceptable training and testing method that not only avoid overfitting but also use minimum bias and variance in the dataset. K fold CV was used to train and test phases and K was considered 10. In 10 fold CV, all of the dataset divide into 10 folds which one of them is dedicated to test and remain is used to train model, this is repeated for 10 times [25]. In train process, we utilized a convolution backpropagation (BP) to train our 1D-CNN model. BP calculates gradient of loss function with respect to the weights (kernels). In addition, we used categorical-cross entropy loss function with Adamax optimizer, which is an Adam algorithm based. The overall hyper parameters of the model are given in Table 2.

Table 2. Hyper-parameters configuration

Learning rate	0.001
Epochs	100
Optimization function	Adamax
layer activation function	LReLU
Output activation function	Softmax
Loss function	categorical_crossentropy

The proposed model was implemented in a powerful deep learning library, Keras and runs on R studio program with AMD A10 (2.4 GHz) processor and 16 GB RAM with 10 epochs of training.

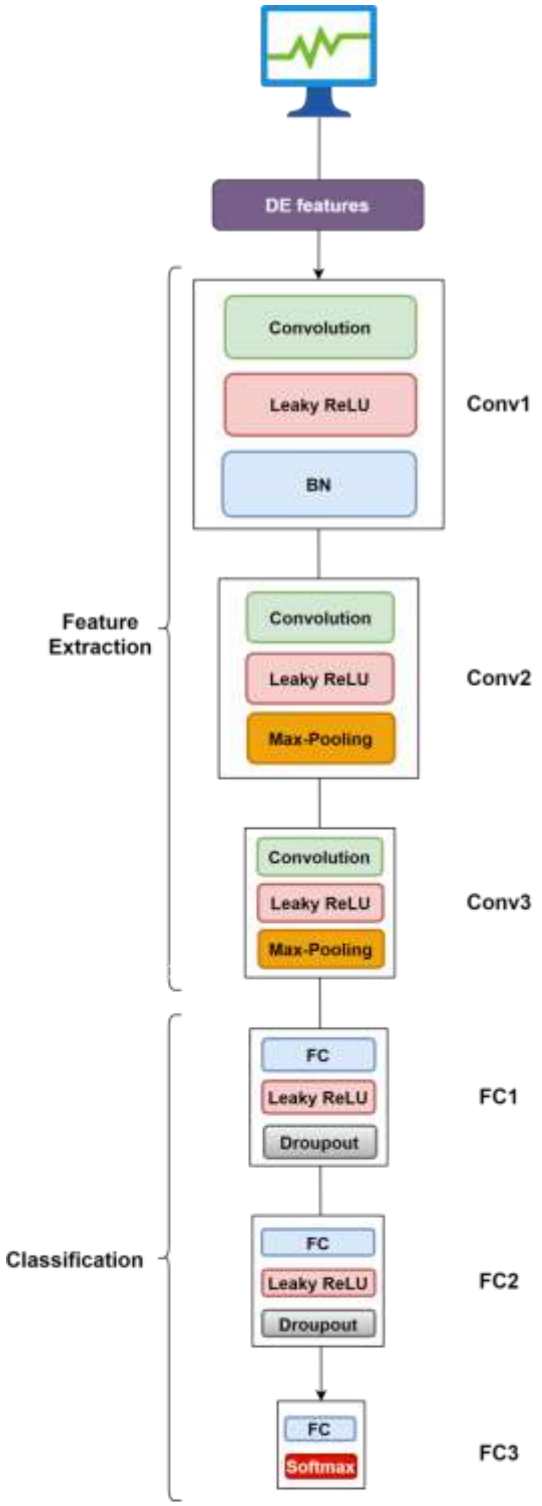

Fig 3. The proposed 1D-CNN architecture

3. Result and Discussion

As mentioned before in the dataset section, each subject repeated the experiment for three times in three different days. According to 15 trials in each experiment, we had 15 experiments in one day (Fig2). In order to have fully investigated, we considered all five frequency bands and all 62 channels. Furthermore, six scenarios from the combination of all days were created. Table 3 shows six scenarios detail and number of samples in each of them.

According to the table, each single day includes 15 corresponding experiments which one experiment consists of 3394 samples. Therefore, there were 3394×15=50910 samples for each single day and 101820 samples belonged to each binary day with 30 experiments.

Table 3. Combinations of three days

Scenario	Experiments	Number of Samples
First day	15	50910
Second day	15	50910
Third day	15	50910
First and second day	30	101820
First and third day	30	101820
Second and third day	30	101820

In this study, we designed a new one-dimensional CNN algorithm that is more suited to EEG-based emotion recognition. Input data were regulated prior entry the model. In order to create feature vectors, we considered all the frequency bands of each channel that were smoothed using the LDS method. As a result, each sample includes of 62×5= 310 DE features.

We investigated the performance of six scenarios of the SEED dataset in three different days, as shown in Table 4. It consists of 10 accuracy folds for each scenario. In addition, the average accuracy, standard deviation and median for convenient comparison are given. According to the table, our model achieved out stands and stable accuracies for all combinations in the full 62 electrodes. The proposed model reached 99.72% as the best performance between all folds and scenarios that was belonged to sixth fold and D1&D3 scenario. Generally, all performances corresponding to the D1&D3 were outperformed in terms of accuracy. The third day (D3) achieve 98.84% accuracy as the best performance between other single days. The last three rows of the table provide valuable and comprehensive information on the performance of the model. Our model achieved the best mean accuracy of 98.55% and the lowest standard deviation of 1.76% in the first and third day (D1&D3) scenario. The second high performance belongs to D3 scenario with 95.91% and 3.09% for accuracy and standard deviation respectively. The median of D1&D3 is also greater than other scenarios.

Table 4. The accuracies of our emotion model

Folds	First day	Second day	Third day	First & Second day	First & Third day	Second & Third day
Fold 1	86.07	87	88.29	76.67	**93.82**	82.55
Fold 2	91.61	94.3	94.38	88.64	**97.68**	86.48
Fold 3	93.42	94.38	97.07	91.49	**98.92**	89.28
Fold 4	93.01	93.62	**98.84**	91.14	98.8	88.7
Fold 5	90.96	91.89	98.09	90.91	**99.64**	87.65
Fold 6	93.75	93.44	97.01	92.78	**99.72**	89.2
Fold 7	90.04	93.16	96.46	92.6	**99.25**	88.61
Fold 8	92.59	93.73	97.7	92.03	**99.39**	86.8
Fold 9	93.05	92.44	97.41	92.11	**99.04**	92.81
Fold 10	92.2	93.71	93.87	92.59	**99.21**	90.3
Mean	91.68	92.77	**95.91**	90.1	**98.55**	88.24
Median	92.4	93.53	97.04	91.76	**99.13**	88.65
Standard Deviation	2.28	2.17	3.09	4.87	**1.76**	2.7

Average accuracy and standard deviation of all scenarios were about 92.87% and 2.81%, respectively, that were outstand performance in EEG based emotion recognition. The low standard deviation rates demonstrated that the model is more convergence on the selected dataset. In our model, low and high standard deviations are 1.76% and 4.87% respectively.

Performances of all existing scenarios as box chart clearly are presented in Figure 4. The horizon axis is in existing scenarios while the vertical axis is corresponds to accuracy. Interval of accuracies is given to the box plot in terms of each scenario. Moreover, the content of the Table 4 is proved by using this figure.

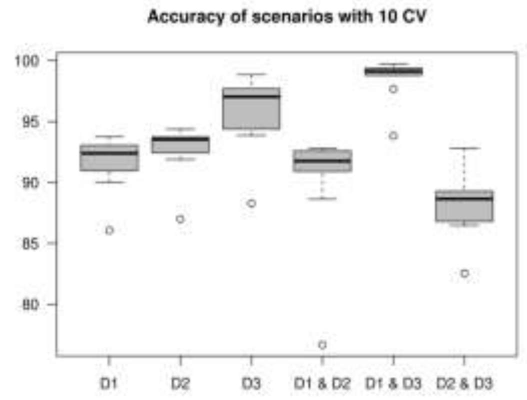

Fig 4. The comparing accuracies of scenarios on box chart

For the convenience perceiving behavior of the model, we presented mean accuracies with folds for each scenario in the Figure5. In this figure, the horizon axis represents the folds and the vertical axis provides the corresponding accuracies. According to figure 5, all scenario performances in the first fold are low. This issue related to train mechanism of CV. As the mentioned before D1&D3 scenario and D2&D3 presented the best and worst results respectively between other scenarios shown in Figure 5.

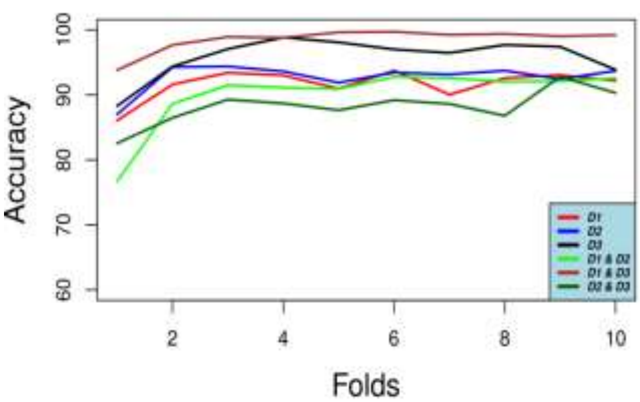

Fig 5. The comparing accuracies of scenarios on linear diagram

In the last years, researchers attempted to classify and recognized emotional states on SEED database. They applied both of the ML and DL methods on the single or binary days and achieved effective accuracies. Table 5 Shows the results of other works and compare them with our proposed model in binary days. Almost all of the previous studies, only D1 and D3 scenarios were considered to train and test, however; we investigated all binary and single scenarios that are given in Table 5 and Table 6 respectively. The tables consist of seven columns that give useful and summary information about the previous study works. Our model classified three state emotions (Positive-Neutral-Negative) on the full 62 channels. Among our model accuracies presented the best performance on D1&D3 dataset (98.55%) and standard deviation (1.76%). The highest accuracy between previous works is 93.66% with a standard deviation of 6.11% [16] that our deep algorithm proposed much better performance than it. Other proposed performances belong to D1&D2 and D2&D3 with accuracies of 90.10% and 88.24% respectively

We proposed performance of all single days and compared with other works in Table 6. The table indicates that, standard deviations for all proposed scenarios are lower than other works that arise from high robustness our proposed model. The best accuracy in single day scenarios belongs to D3 with 95.91% and then D2 with 92.77% also D1 with 91.67%. So far Hwang et al. [7] proposed a high accuracy for D3 (89.14%) however, our accuracy is much higher than it also our model presented comparable results in terms of standard deviation.

Table 5. Comparison of classification accuracies (binary datasets)

Author(s)	Classifier	Channels	Subjects	Classes	Standard Deviation	Accuracy (%)
Zheng et al. [9]	DNN	12	15	3	8.62	86.65
Chen et al. [13]	SVM	62	15	3	3.20	82.50
Rahman et al. [11]	ANN	35	15	3	-	86.57
Bai et al. [26]	LSTM	8	15	3	-	90.1
Zheng et al. [18]	GELM	62	15	3	7.54	91.07
Lu et al. [10]	SVM	62	15	2	11.54	85.11
Wei et al. [17]	SRU	62	15	2	-	83.13
Duan et al. [8]	SVM	62	6	3	-	84.22
Wang et al. [16]	BDGLS	62	15	3	6.11	93.66
Gupta et al. [15]	RF	12	15	3	-	90.48
Hwang et al. [7]	CNN	62	15	3	8.71	90.41
Fdez et al. [12]	ANN	62	15	3	-	79.60
Fdez et al. [12]	ANN	62	15	2	-	91.60
Our method	1D-CNN (D1&D2)	62	15	3	4.87	90.10
	1D-CNN (D1&D3)	62	15	3	**1.76**	**98.55**
	1D-CNN (D2&D3)	62	15	3	2.70	88.24

Table 6. Comparison of classification accuracies (single datasets)

Author(s)	Classifier	Channels	Subjects	Classes	Standard Deviation	Accuracy (%)
Duan et al.[8]	SVM (D1)	62	6	3	-	81.75
	SVM (D2)	62	6	3	-	86.69
Hwang et al.[7]	CNN (D1)	62	15	3	8.46	91.68
	CNN (D3)	62	15	3	8.97	89.14
Zheng et al.[18]	GELM (D1)	62	15	3	8.64	90.83
	GELM (D2)	62	15	3	8.59	88.22
	GELM (D3)	62	15	3	10.97	87.80
Our method	**1D-CNN (D1)**	62	15	3	**2.28**	**91.68**
	1D-CNN (D2)	62	15	3	**2.17**	**92.77**
	1D-CNN (D3)	62	15	3	**3.09**	**95.91**

4. Conclusion

In this paper, an automatic one-dimension CNN model to recognize emotional states was proposed. The model consists of BN and dropout layer contrast with traditional CNN, which led to have more robustness. The DE features followed by a few preprocessing phase were used as input data and fed into the deep model. We conducted our analysis under the six different scenarios from SEED dataset with full 62 channels and 5 frequency bands. The performance of each scenario compared with other paper works in terms of accuracies and standard deviations. Moreover, the performance of all folds presented in table and various charts. The average accuracy of each scenario demonstrated superiority of the method. This model can be applied to other EEG datasets, as a classifier and health care support system.

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