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Research Article

An Efficient Approach to Mental Sentiment Classification with EEG-based Signals Using LSTM Neural Network

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Abstract. This research explores the prominent signals and presents an effective approach to identify emotional experiences and mental states based on EEG signals. First, PCA is used to reduce the data's dimensionality from 2K and 1K down to 10 and 15 while improving the performance. Then, regarding the insufficient high-quality training data for building EEG-based recognition methods, a multi-generator conditional GAN is presented for the generation of high-quality artificial data that covers a more complete distribution of actual data by utilizing different generators. Finally, to perform classification, a new hybrid LSTM-SVM model is introduced. The proposed hybrid network attained overall accuracy of 99.43% in EEG emotion state classification and showed an outstanding performance in identifying the mental states with accuracy of 99.27%. The introduced approach successfully combines two prominent targets of machine learning: high accuracy and small feature size, and demonstrates a great potential to be utilized in future classification tasks.

Keywords. EEG, GANs, LSTM Networks, Biomedical signal processing, Deep learning.

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1 Introduction

Emotion has been considered as an indispensable element, and as a kind of physiological and psychological state of mankind, which plays a prominent role in our daily activities specially in the human-computer interaction field, such as interaction, communication, learning, etc. Recognizing the emotional state of individuals can be considered as a challenging task [32]-[39]. Human emotions are diverse and complicated but in general they can be classified into positive and negative categories. Positive emotions can exert beneficial effects on work efficiency and enhance the level of communication with others, whereas, the negative ones can have harmful implications on physical and mental health. Automatic identification of emotions comes with broad functionality. For example, in the area of Human–Computer Interaction (HCI), it is beneficial for systems to understand human emotions and have transparent communication [14, 38, 47]. In addition, identification of emotional state can contribute to the area of medical sciences, for example, it can be employed as a vital computer-aided system for the diagnosis of emotional disorders [4, 14, 33].

Emotion identification approaches can be categorized into non-physiological signals based, such as facial expression, body gesture and speech and physiological signals based, such as electroencephalogram (EEG), galvanic skin response (GSR), electrocardiogram (ECG) and respiration rate (RR) [11]-[48]. Recent physiological researches demonstrate that variation in physiological signals show more similarity to people's real emotion than speech, body gesture or facial expression [10, 12]. Contrary to other physiological signals, EEG can be captured from the brain cortex, which according to different psychophysiological studies, it has proven to be related to human emotions [14, 37].

In recent years, concerning the accelerated growth of battery technology, the acquisition of EEG is more convenient [14, 20]. The bound in between EEG signals and emotional state, has been examined to a large extend [21]-[43]. EEG signals are broadly utilized for emotion analysis since it can discover various details regarding to the emotions from frequency band, electrode position, and temporal information [3]-[43].

Machine learning algorithms have performed a prominent role in pattern detection and classification problems, especially in electroencephalography and facial expression, and according to this, emotional state recognition has attained noticeable classification results [34]-[40]. In general, a wide variety of EEG emotion detection approaches start by extracting features from EEG signals and apply classifiers to categorize the emotion features. For example, in [10], time-domain features were compared. In their research, a deep convolutional neural network based on temporal features, frequential features, and their combinations of EEG signals in DEAP dataset was presented. In the research of Alhagry et al. [3], a new LSTM-based deep recursive neural network (RNN) was proposed. Their proposed approach is able to automatically learn features from the original EEG signals and then perform classification on these learned features.

Li et al. [31], proposed a new hierarchical spatial-temporal neural network for the purpose of learning discriminative spatial-temporal EEG features. In order to learn the spatial features, they employed a bidirectional LSTM neural network which was able to consider the intrinsic spatial relationships of EEG electrodes within brain regions.

Regarding the different brain regions, they proposed a new region attention layer into their model which was able to strengthen or weaken set of weights based on the contribution of brain regions. In [45], for capturing a temporal information of EEG, a deep Simple Recurrent Units (SRU) was employed. Their proposed approach managed to process sequence data and tackled the problem of long-term dependencies occurrence in typical Recurrent Neural Network (RNN). They employed Dual-tree Complex Wavelet Transform (DT-CWT) for decomposing the primary EEG signals into five constituent sub-bands, and then extracting the features using frequency, time and nonlinear analysis.

Al Zoubi et al., [5] presented Liquid State Machines (LSM) for automatic extraction of features and prediction based on raw EEG signals. In [44], a new LSTM architecture was introduced to consider extracted features such as time and frequency domain features, between EEG channels cross correlation and graph theoretic features for the prediction of epileptic seizures based on EEG signals. In the research of Hassouneh et al., [22], a strategy based on convolutional neural network (CNN) and LSTM classifiers was presented to classify physically disabled individuals and Autism children's emotional expressions using facial landmarks and EEG signals. In the research conducted by Cui et al., [14], for considering spatial information from adjacent channels and symmetric channels, an end-to-end regional-asymmetric convolutional neural network was proposed. For considering time frequency demonstration, they used one dimensional convolutional layers, and for regional information, they employed two 2D convolutional layers. An asymmetric differential layer was introduced regarding the discriminative information in between both hemispheres of the brain.

In this study, a new hybrid approach is proposed for the effective identification of mental state. To address the slow training and convergence problem, mean normalization was used to reduce the large disparity in features quantity. The PCA approach was used to reduce the data's dimensionality, retaining the data's variance while removing redundant information. Regarding the insufficient high-quality training data for building EEG-based recognition methods, the artificial generation of high-quality data is an effective approach for overcoming this problem. In the proposed framework, a multi-generator conditional GAN method is presented for the generation of high-quality artificial data that covers a more complete distribution of actual data by utilizing different generators. Finally, for performing classification, a new hybrid LSTM-SVM model was introduced. The main questions that we are going to examine in this research are:

1. Can using PCA as feature extractor be useful in EGG signal categorization?
2. Can using a multi-generator conditional GAN model improve the performance in EGG signal categorization?
3. Can using a new hybrid LSTM-SVM model increase the classification performance compared to previous researches?

The rest of the paper has been organized as follows. The detailed description of the selected datasets and the proposed methods are presented in Section 2. Section 3 devoted to the hybrid architecture of the proposed method. The evaluation parameters used in this study are described in Section 4. Section 5 gives information about the implementation environments. Section 6 shows the experimental results, and provides a comprehensive evaluation and discusses the key findings.

2 Methodology

2.1 Description of the data

In the current research, we used two separate datasets. One was EEG brainwave data for emotional state classification provided by Bird et al., [7]. This dataset was obtained for three minutes from two individuals (1 male, 1 female) in each state of positive, neutral, and negative. EEG brainwave records were captured using a Muse EEG headband with dry electrodes to monitor the TP9, AF7, AF8, and TP10 EEG placements. There is also six minutes of resting neutral data is captured. The second dataset was a collection of EEG brainwave data provided by Bird et al., [8]. The EEG brainwave records were obtained from four individuals (two men and two women) for 60 seconds in each state (relaxation, concentration, and neutral). Similar to the first dataset, a Muse EEG headband was also used for recording EEG placements.

Table 1: Characteristics of datasets

Name	No. Features	No. Records
EEG Emotion state	2548	2132
EEG Mental state	988	2479

2.2 Data pre-processing

Data pre-processing was carried out after the datasets were collected. Cleaning and analysis were the two steps of this process. Identification, filing, and elimination of missing, incorrect, or unclear data can be viewed as data cleaning. Having examined the nature of the datasets, it can be seen all of the records are complete and integers and real values. The datasets were then subjected to mean normalization. To fix the issue of a large gap in feature quantity causing slow training and convergence, the datasets were normalized into a range of 0-1 using mean normalization. The following equation was used to normalize the data column by column (1):

$$Normalized\ Data = \frac{X - mean(x)}{stdev(x)}. \tag{1}$$

PCA's aim is to project the data into a low-dimensional subspace and find the best definition of the data's distribution [48]. Particularly, PCA tries to retain the data's variance while reducing the redundant information. PCA is a popular technique for dimensionality reduction. If we acknowledge the $x_i \in IR^{d*1}$ to be a sample, and consider $t_i \in IR^{r*1}$ as its counterpart projected on the subspace, $i = 1, 2, \cdots, n$. Consider $\overline{m}$ and $\overline{t}$ to be the means of x_i and t_i, respectively. Let $P = [P_1\ P_2 \ldots P_r] \in IR^{d*r}$ be the projection matrix. Therefore, $t_i = P^T x_i$. The model of PCA is to maximize the optimization problem (2):

$$\max_{P^T P=I} \sum_{i=1}^{n} \|t_i - \overline{t}\|^2 = \max_{P^T P=I} Tr \left\{ P^T \left[\sum_{i=1}^{n} (x_i - \overline{m})(x_i - \overline{m})^T \right] P \right\}. \tag{2}$$

Here, $\sum_{i=1}^{n} (x_i - \overline{m})(x_i - \overline{m})^T$ is the total scatter matrix of the data.

The PCA technique was first applied to EEG brain waves for emotion categorization, and the dimensions were reduced from 2548 to 10. The same procedure was employed on EEG brain wave for mental state categorization and the dimension was reduced from 2100 to 15 features. Figure 1 shows the amount of explained variance for the selected features. For a fast and efficient training procedure the PCA was employed before using cGANs for augmentation of the data.

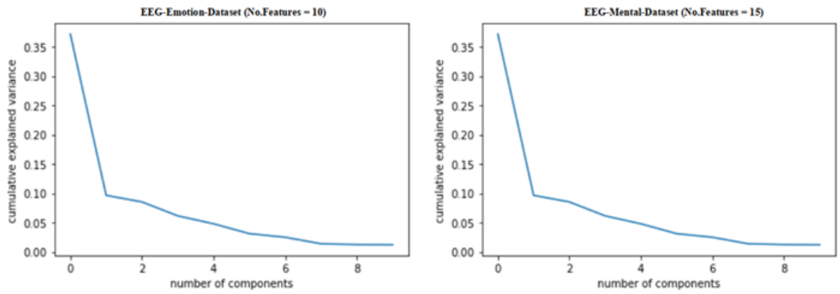

Figure 1: The amount of explained variance by the selected features in each dataset.

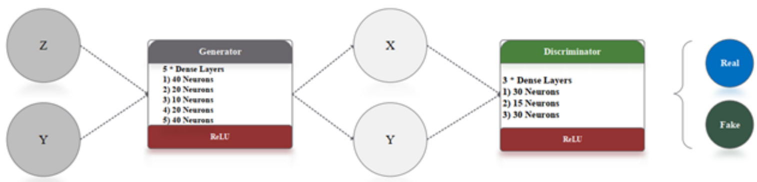

Figure 2: Architecture of the proposed conditional generative adversarial net.

3 The Proposed Hybrid Architecture

3.1 Generative adversarial networks (GANs)

Goodfellow et al. [19] suggested GAN in their seminal work as an alternative generative method for artificial data creation using adversarial self-play. GANs have drawn the interest of researchers since their invention and have shown effectiveness as a generative model in variety of applications [16]-[15].

GANs are constructed of using two different neural networks: the generator (G) and the discriminator (D). The concept is based on game theory, in which two players compete to win. In GANs, G is in charge of producing artificial instances, while D is in charge of deciding which instances are real and which are fake. G's aim is to trick the discriminator to the point that the discriminator is able to distinguish the difference between the real and produced samples. Equation (1) is used to formulate this adversarial optimization issue (3):

$$\min_{G}\ \max_{D}\ F(D,\ G) = E_{X_r'\ P_r}[\log(D(x_r\ ))] + E_{X_g'\ P_g}\left[\log(1 - D(x_g\ ))\right]. \tag{3}$$

Here, g, d, x_r and x_g are G parameters, D parameters, real samples, and generated samples, respectively. *D(x)* is considered as the probability of that x belongs to either the real or the generated data distributions. The G network generates the artificial sample x_g from a stochastic noise input z by (4):

$$x_g = G(z). \tag{4}$$

The two networks D and G are continuously trained to improve D's efficiency in assigning true labels to both actual and generated samples $\log(D(x))$, and to reduce $log(1 - D(x_g))$.

In the current research, an arbitrary condition y for generation is defined to add a conditioning functionality to this structure and produce data points for particular groups of data. This technique limits the generator's output as well as the discriminator's desired input. For this purpose, the generator model can be defined as $G\ :(Z\ \times Y) \to X$, which takes noise data zZ with an embedding yY as an input and it generates an example xX. Regarding the discriminator, the model can be described as $D\ :(X\ \times Y) \to [0,1]$, which takes an example x and a specific y condition (label) and outputs the probability based on the condition y which x came from the empirical data distribution rather than from the generator model. The two-player minimax game's goal function is as follows (see (5)) [36]:

$$\min_{G}\ \max_{D}\ V(D,\ G) = \left(E|_{X\sim\ P_{data}}[\log D(X|Y\ )] + E|_{Z\sim P_Z(Z)}[\log(1 - \ \ D(G(z|y\ )))]\right). \tag{5}$$

For the chosen datasets, we developed a conditional adversarial net dependent on their class labels. In the proposed generator model, a noise prior z with dimensionality 100 was drawn from a uniform distribution. The class labels y were represented by dense vectors of size 10 in which each of the classes for the selected datasets (0 or 1) will map to a different 10-element vector representation. Then, using the Rectified Linear Unit (ReLU) activation function, both z and y are mapped to hidden layers. Layers 40, 20, 10, 20 and 40 neurons, respectively. Finally, for producing the feature size dimensional instances, we used a sigmoid unit layer as our output. Similarly, in the proposed discriminator model, the class labels were represented by dense vectors of 10 in which each of classes will map to a different 10-element vector representation. It will then be mapped to a hidden layer with the features' sizes. The x and y would then be combined into a single vector and mapped to hidden layers with 30, 15, and 30, respectively. A sigmoid unit was utilized for obtaining the final probability of the model. Figure 2 demonstrates the architecture of the proposed conditional generative adversarial net.

We have used the Adam optimizer to train the model on a total of 1200 epochs with mini-batches of size 128. The following cross entropy loss function was considered in (6):

$$L(p,\ y) = -\sum_{i=1}^{k} y_i \log(p_i)\ . \tag{6}$$

The initial values for the learning rate and momentum were set to 0.0002 and 0.5, respectively.

3.2 Long Short-Term memory neural network (LSTM)

After employment of conditional generative adversarial network for producing new instances, a network with feedback and storage capacities was used to take advantage of the data's time-dependent property. The Long-Short Term Memory Neural Network is one such network. A powerful classifier, Support Vector Machine (SVM), was trained to boost and improve the LSTM network's classification and efficiency.

LSTM networks have recently been used in experiments on other aspects of EEG analysis. LSTM was proposed by Hochreiter and Schmidhuber in 1997 [24]. LSTM is a special variant of RNN (Recurrent Neural Networks). It works by memorizing and can store, transfer and process data streams through cell unit in the model architecture represented in Figure 3. In comparison with RNN, data can be memorized in LSTM because each cell unit in it comprises three logic gates based on sigmoid neural network layer, including input gate, output gate, and forgetting gate, in which data can be selectively transferred or processed. To represent the number of data segments that can pass through each unit, each network layer can produce a number ranging from 0 to 1. If it is shown as 0, no data is permitted to pass through, and if it is shown as 1, all data is allowed to pass through [41].

Forgetting gate: produces data in the range of 0 to 1, with 1 denoting "fully reserved" and 0 denoting "completely ignored".

Storage gate: is constructed by a sigmoid layer (input gate) and layer, is utilized to select new data to be stored in the cell. The sigmoid layer points out the values that need to be adjusted, and the layer produces vectors containing new candidate values, which are then added to the cell unit state.

Input gate: generates new value by combining the cell unit status value, filtered value, and added value. Figure 3 illustrates the structure of LSTM cell.

The following formulas represent the mathematical model of the LSTM neural network (see Equations (7)-(11)):

$$i_t = \sigma\left(W_i\left[h_{t-1},\ x_t\right] + b_i\right), \tag{7}$$

$$f_t = \sigma\left(W_f\left[h_{t-1},\ x_t\right] + b_f\right), \tag{8}$$

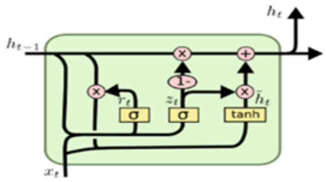

Figure 3: Model structure of LSTM.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \tag{9}$$
$$c_t = f_t c_{t-1} + i_t \, tanh(W_c[h_{t-1}, x_t] + b_c), \tag{10}$$
$$h_t = o_t \, tanh(c_t). \tag{11}$$

Here, i, f, o and c respectively represent input gates, forgetting gate, output gates and cell status, and W and b respectively represent corresponding weight coefficient matrices and offset terms; σ and $tanh$ are the sigmoid and hyperbolic tangent activation functions respectively.

3.3 Model architecture

The proposed model is constructed with four LSTM layers with 128, 64 and 32 neurons respectively. All of the LSTM layers are activated by the ReLU activation function. In the proposed model we implemented Dropout regularization, one of the remarkably effective regularization methods for the purpose of reducing the overfitting and improving the generalization error. Dropout was implemented per-layer in the proposed architecture. The dropout probability was considered 0.2 at each of these layers. Figure 4 shows the proposed LSTM network architecture.

Figure 4: The proposed LSTM network architecture

3.4 Support vector machine (SVM)

Support Vector Machine is an efficient supervised classifier for classifying two or more classes. It distinguishes between two classes by drawing a division boundary between them using data belonging to each class. The SVM algorithm's objective is to find a hyperplane in an N-dimensional space (N is the number of features) that categorizes the data point clearly. It works towards minimizing the expected error's maximum value.

4 Statistical Methods

In the current analysis, the performance classification of model in terms of precision, sensitivity (Recall), F-score (F-measure), Loss and Accuracy was investigated. These criteria are formulated based on the number of true classified positive samples (TPs), the number of true classified negative samples (TNs), the number of false classified positive samples (FPs), and the number of false classified negative samples (FNs).

Precision: Precision indicates how precise/accurate your model is out of those predicted positive $(TP+FP)$ (see (12)).

$$Precision = TP/(TP+FP). \tag{12}$$

Sensitivity: our model's sensitivity/recall determines how much of the Actual Positives it captures when marking it as Positive (True Positive). See (13).

$$Sensitivity = TP/(TP+FN). \tag{13}$$

F-score: F measurement is the harmonic mean of Precision and Recall, and it provides a more accurate measure of the inaccurately classified cases and is defined based on the formula (14):

$$F1-score = (2*Precision*Recall)/(Precision*Recall). \tag{14}$$

Accuracy: Classification accuracy will be determined by the number of accurate predictions as a proportion of all predictions made. This is the most commonly used assessment criterion for classification problems [16] (see (15)).

$$Accuracy \ = (TP+TN)/(TP+FN+FP+TN). \tag{15}$$

5 Implementation Environment

The experiments were implemented on a computer running a windows operating system equipped with Intel Core i7 and accelerated by NVIDIA K80 GPUs. The proposed model was developed using Python programing language on the Anaconda distribution.

6 Results and Discussion

6.1 Experimental results

Because of the structure of the hybrid approach, two sets of experiments were performed. At first in order to show the reliability of generated EEG-based records, the performance of the proposed classification approach was investigated both without and with the usage of cGAN. The cGAN was investigated during the training procedure.

6.1.1 LSTM-SVM model performance evaluation without cGANs

At first, in order to illustrate the positive effect of using cGAN network in the proposed methodology, the first set of experiments were conducted on the original data.

In the EEG mental state dataset, of 2479 records, 496 records were randomly selected as holdout (test) set for the final evaluation of the proposed LSTM-SVM model. Out of 1983 remaining samples, 1586 records were considered for training set and the rest (397 records) for validation set. Similarly, the same procedure was conducted on EEG emotion state dataset, out of 2132 samples, 427 records were randomly considered as holdout set and the rest of the samples were divided into training and validation sets with 1364 and 341 samples, respectively.

To demonstrate our method's reliability, the proposed model's performance is evaluated using 10-fold cross-validation technique. The conducted experiments are repeated four times. The proposed model was trained at total of 200 epochs. According to experimental results, the proposed LSTM-SVM model achieved the accuracy of 92.74% in classifying emotional state, and attained similar result (93.14%) for mental state classification. Regarding the other criteria, the introduced model reached to approximately 93% in terms of sensitivity, precision, f1-score in both of the classification tasks. Table 2 demonstrates the results of applying LSTM-SVM model in mental state and emotional state datasets without using cGAN for augmenting the data. Figure 5 and Figure 6 show the attained confusion matrix of proposed model in EEG emotion state and EEG mental state test set, respectively.

Table 2: Sensitivity, specificity, precision, F1-score, and accuracy values obtained from holdout and validation data set of the proposed model

Classes	**Performance Metrics (%)**			
	Sensitivity	**Precision**	**F1-score**	**Accuracy**
EEG Emotion Dataset				
Test Set (External)				
Positive (1)	89%	91%	90%	
Negative (2)	98%	88%	92%	
Neutral (0)	93%	100%	96%	
Average	93.33%	93%	92.66%	92.74%
EEG Mental state Dataset				
Test Set (External)				
Concentrating (0)	94%	92%	93%	
Neutral (1)	86%	93%	89%	
Relaxed (2)	100%	94%	97%	
Average	99.33%	93%	93%	93.14%

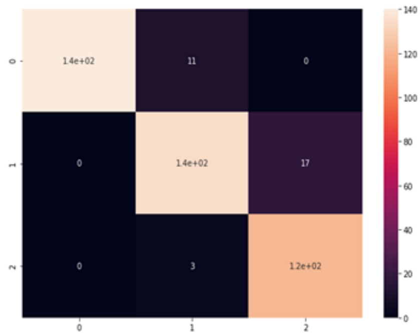

Figure 5: Confusion matrix of the proposed model on EEG emotion test set.

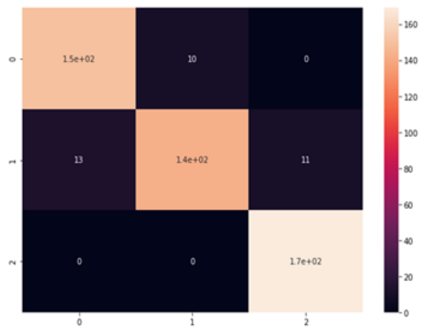

Figure 6: Confusion matrix of the proposed model on EEG mental state test set.

6.1.2 LSTM-SVM model performance evaluation with cGANs

In the second part of the experiment, the performance of LSTM-SVM model was investigated through applying cGANs for augmentation of the data to illustrate the benefits of using cGANs.

In training GANs, achieving the training stability is important. The loss of the networks over the iterations is a strong measure of how well the training is going. According to the previous researches, for a strong GAN training process, it is expected to see a continuous decline in the generator loss and convergence to steady values for both networks. A careful hyperparameter adjustment in the GANs architecture can lead to an effective and stable training.

In order to demonstrate the reliability of the proposed LSTM-SVM network and the quality of the generated data, test sets were randomly selected from the original records before augmenting the data using cGAN.

In the EEG emotion state dataset, of 2132 records, 427 records were selected randomly as holdout (test) set for the final evaluation of the proposed model. The rest of this dataset was used as input to cGAN for generating identical EEG brainwave data. After stabilizing the proposed cGAN model, 20000 new records were generated. Finally, using the generated records, 21705 recordings were considered for the training and validation procedure. The same procedure was implemented on the EEG mental state dataset, in which, out of 2479 recordings, 495 records were selected randomly for holdout set. Similarly, with help of cGAN a set of 20000 new records was generated and 21984 recordings were used for training and validation set. The experimental results were examined under two categories: emotion and mental state classification. The experiments were performed for classifying records based on EEG signals for each dataset.

In the emotion classification problem, the proposed model attained the accuracy of 99.29% mark. In the terms of precision, recall, and f1-score, the proposed model demonstrated a noticeable performance and reached the overall results of 99%. Regarding the mental state EEG brain wave experiment, the proposed architecture achieved overall accuracy of 98.99%. In terms of other selected criteria, the proposed model showed similar results. The attained results for precision, f1-score were almost identical at approximately about 99%. In terms of sensitivity the proposed model showed a substantial superiority and achieved to 99% mark (Table 3). Figure 7 and Figure 8 show the attained confusion matrices of proposed model in EEG emotion state and EEG mental state test set after applying cGAN, respectively.

Table 3: Sensitivity, specificity, precision, F1-score, and accuracy values obtained from holdout and validation data set of the proposed model

Classes	**Performance Metrics (%)**			
	Sensitivity	**Precision**	**F1-score**	**Accuracy**
EEG Emotion Dataset				
Test Set (External)				
Positive (1)	99%	99%	99%	
Negative (2)	99%	100%	100%	
Neutral (0)	99%	99%	99%	
Average	99%	99%	99%	99.29%
EEG Mental state Dataset				
Test Set (External)				
Concentrating	99%	99%	99%	
Neutral	98%	99%	98%	
Relaxed	99%	99%	99%	
Average	99%	99%	99%	98.99%

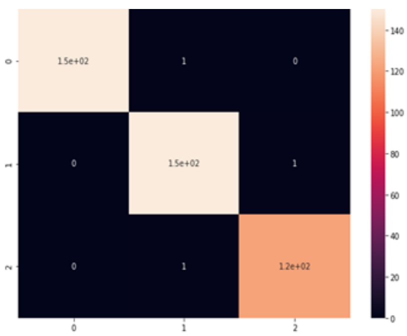

Figure 7: Confusion matrix of the proposed model on EEG emotion test set after applying cGAN.

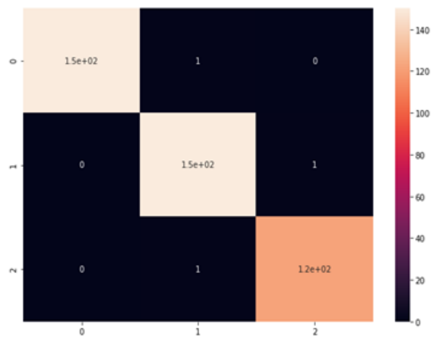

Figure 8: Confusion matrix of the proposed model on EEG mental state test set after applying cGAN.

6.2 Discussion

The hybrid approach we present here successfully combines two prominent targets of machine learning: high accuracy and small feature number. This also implies faster computation time and lower resource consumption, which both are becoming increasingly relevant. We came to the conclusion that reducing the size of the feature vector from 2K as reduced from PCA to 3 and 15 in the selected datasets while improving performance at the same time can be considered a successful improvement of deep learning approach. Our results agree with other related work which the proposed approach showed noticeable superiority in comparison to top-performing models for the classification task. Table 4 illustrates a comparison of the proposed method with other approaches.

Table 4: Comparison of the proposed model with other approaches.

Research	Method	Accuracy
Bos, et al. [9]	Fisher's Discriminant	94.9%
Li, et al. [29]	Common Spatial Patterns	93.5%
Li, et al. [29]	Linear SVM	93%
Zheng, et al. [49]	Deep Belief Network	87.62%
Koelstra, et al. [28]	Common Spatial Patterns	58.8%
Bird, et al. [8]	InfoGain, RandomForest	97.89%
Bird, et al. [8]	InfoGain, MLP	94.89%
The proposed approach	**PCA-GAN-LSTM-SVM**	***99.29%***

As can be seen in the experimental results, our proposed approach attained the highest performance in terms of selected criteria compared to other techniques.

7 Conclusion and Future Work

In the current research, we presented and compared multiple state-of-the-art approaches for mental state classification based on EEG-based signals. We examined the use of conditional GANs regarding the insufficient high-quality training data for building EEG-based recognition methods, and regarding the attained results, employing a multi-generator GAN architecture that could cover a more comprehensive distribution of actual data by utilizing different generators, could be considered as a strong data augmentation technique in comparison to other methods. Compared to previous approaches, using a hybrid LSTM-SVM approach in addition to PCA technique for classification and dimensionality reduction shows great potential for complex classification tasks, which might otherwise require days to train a model or producing inaccurate model. Furthermore, this approach can save power and resource consumption while at the same time boosting performance. Moreover, it is not necessarily the case that deeper models perform better, as is evident from our research. Instead, choosing the model architecture that best fits the problem can positively affect performance.

Given that the usage of deep learning methods in classification of data is a recurring trend, in future work, we will try to, by adjusting the number of neurons and changing the structure of the model, including adding layers and strengthening the data preprocessing step, apply the introduced technique in other area of signal processing tasks.

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