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Recurrence Quantification Analysis and Neural Networks for Emotional EEG Classification

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Abstract

Purpose: There are many benefits for emotion recognition and classification in human-computer interaction, social communications, gaming industries, and entertainment. Therefore, physiological responses of emotions have been receiving a significant attention. However, the assumption of nonlinear characteristics of physiological signals is usually disregarded. *Basic methods:* In the current study, a novel approach for classification of emotional states is presented using electroencephalogram (EEG) signals and nonlinear methodology. Applying 3 channels of EEG from eNTERFACE06_EMOBRAIN database, some measures of recurrence quantification analysis (RQA) (including: recurrence rate, deterministic, average line length of diagonal lines, entropy, laminarity, and trapping time) are calculated in 3 emotional states (exciting negative, neutral and exciting positive). These features are considered as inputs of the multilayer perceptron, time delay neural network, and probabilistic neural network (PNN) classifiers. *Main results:* Based on the RQA measures and PNN, the emotion detection system outlined here is potentially capable of classifying 3 emotional categories. The accuracy rate of 99.96% is attained which is comparable to the results achieved by others. *Conclusions:* The results show that the proposed methodology can be used as an appropriate tool for emotion recognition.

Keywords: Classification; Electroencephalogram; Emotion; Neural Networks; Recurrence Quantification Analysis

Introduction

As a pioneering work to define human emotions, Ekman [1] proposed a basic emotional model in which some discrete feelings such as fear, anger, happiness, sadness, disgust and surprise are introduced. A continuous representation of emotions was proposed [2] where each emotional state is displayed over 2 dimensions: valence and arousal.

Emotional assessment can be realized by different techniques. Traditional approaches have focused only on self-reports [3]. Thanks to affective computing, different modalities such as speech [4], facial expressions [5,6], postures and gestures [7], and physiological signals [8,9] can be served for studying emotional experiences. The benefit of monitoring physiological signals is that these measures can represent changes which cannot be determined by other means [10]. In addition, they are more reliable in the representation of emotional state because the subject cannot conceal them easily.

During emotional episodes some physiological changes occur. The evaluation of the emotional responses can be done through monitoring pulse rate, blood pressure, skin conductance, electrocardiograph (ECG), and electroencephalogram (EEG) readings. A review of different researches on the behalf of autonomic nervous system activity and the emotional states can be found in [9].

Automatic emotion recognition and classification is growing quickly with the technological developments of digital signal processing and various feature extraction methods. Nowadays, emotion recognition and classification can be considered an essential part of human-computer interaction and many other prospective applications such as social communications, gaming industries and entertainment.

Different classifiers have been evaluated to detect emotional classes of interest. Chanel et al. [11] assessed EEG, galvanic skin response (GSR), blood volume pressure (BVP), respiration, and finger temperature features to classify emotional arousals using Naïve-Bayes classifier. Applying sequential analysis and auto-associative networks, the emotion detection system is proposed by Leon et al. [12], and Sakata et al. [13] applied linear discriminant analysis (LDA) to differentiate 6 emotional EEGs and heart rate responses triggered by pictures. Murugappan et al. [14] proposed a system for human emotion recognition applying EEG and discrete wavelet transform. For this purpose, K-Nearest Neighbor (KNN) and LDA are examined. Recently, researchers [8,15] proposed a method using adaptive neuro-fuzzy inference system to predict the emotional status perceived by a natural scene. The recommended feature space comprises visual information and EEG signals.

It has been shown that the physiological systems have nonlinear and chaotic behavior [16]. Although some efforts have been made on the problem of classification, the assumption of nonlinear characteristics of physiological signals is usually ignored. Using physiological signal processing, this study provides confirmation for studying affective states. It demonstrates that emotional states in response to visual stimuli can be differentiated by applying neural networks and nonlinear features. More specifically, the goal of this article was to evaluate the performance of nonlinear features (due to chaotic behavior of bio signals) in combination with the neural networks to propose a robust emotion recognition system with high accuracy.

The rest of this research is organized as follows. In the following sections, an overview of the set of the EEG data used in this study is given and the method of feature extraction is introduced. In addition, the neural networks applied for classification of affective EEGs are presented. Next, the experimental results are reported. Finally, conclusions are offered.

Material and Method

Data Selection

In the current study, EEG signals from the eNTERFACE06_EMOBRAIN database are examined [17]. Five right-handed men (age range: 22-38) contributed to the data collection process. Applying images from the IAPS (International Affective Picture System [18]), the emotions were elicited in subjects. Three categories of emotion are considered: exciting positive, exciting negative and neutral. Each person participated in three different sessions.

To monitor the consistency of emotion across participants, they are also asked to self-assess their emotions. 3 channels of EEG time series (Fz, Cz, and Pz) available in the eNTERFACE06_EMOBRAIN database are applied in this study. All EEG signals were recorded using the Biosemi Active 2 device with 64 EEG channels and the peripheral measuring device. The sampling rate was 1024 Hz except the first session of participant 1 that was recorded at 256 Hz. In [17] the detailed protocol of data acquisition is provided.

Recurrence Quantification Analysis (RQA)

A quantification of the obtained structures from recurrence plots (RPs) is necessary for an objective investigation of the considered system. In order to have more detail about the visual impression yielded by RPs, several measures of complexity have been presented [19-21] to quantify the small-scale structures in RPs. These measures are known as recurrence quantification analysis (RQA) which is based on the recurrence point density and the diagonal and vertical line structures of the RP. Recently, some researchers examined the application of recurrence measures in the analysis of biological systems [22,23].

Consider a series of a trajectory ($\{\vec{x}_i\}_{i=1}^{N}$) of a system in its phase space. Then, the following recurrence matrix can be achieved:

$$R_{i,j} = \begin{cases} 1 & \vec{x}_i \approx \vec{x}_j \\ 0 & \vec{x}_i \neq \vec{x}_j \end{cases} \quad i, j = 1, \ldots, N$$

where N is the number of states and $\vec{x}_i \approx \vec{x}_j$ refers equality up to a distance ε. As a result, recurrence quantification measures can be defined as follows.

Recurrence Rate. The recurrence rate (RR) or per cent recurrences is 1 of the simplest quantity of the RQA

$$RR(\varepsilon) = \frac{1}{N^2} \sum_{i,j=1}^{N} R_{i,j}(\varepsilon) \tag{1}$$

which offers the recurrence point densities of the RPs.

Deterministic. Based on the histogram $P(\varepsilon, l)$ of diagonal lines with the length of l, the determinist is calculated.

$$P(\varepsilon, l) = \sum_{i,j=1}^{N} (1 - R_{i-1,j-1}(\varepsilon))(1 - R_{i+1,j+1}(\varepsilon)) \prod_{k=0}^{l-1} R_{i+k,j+k}(\varepsilon) \tag{2}$$

In order to simplify the equation, the symbol ε can be omitted from the RQA measures (i.e. $P(l) = P(\varepsilon, l)$. The proportion of the diagonal structures of recurrence points to all points is known as a measure for identifying the predictability of the system, which is known as determinism.

$$DET = \frac{\sum_{l=l_{\min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)} \tag{3}$$

By the threshold $l_{\min}$, the diagonal lines which are shaped by the tangential motion of the phase space trajectory are excluded.

The Average Diagonal Line Length

The average time that 2 parts of trajectory locates near each other is reflected in L. This measure can be understood as the average prediction interval.

$$L = \frac{\sum_{l=l_{\min}}^{N} lP(l)}{\sum_{l=l_{\min}}^{N} P(l)} \tag{4}$$

Entropy. Entropy measure refers to the Shannon entropy with the probability of p(l) = P(l)/Nl to allocate a diagonal line with the precisely length of l in the RP.

$$ENTR = -\sum_{l=l_{\min}}^{N} P(l) \ln p(l) \tag{5}$$

This measure reflects the complexity of the RPs in respect of the diagonal lines.

Laminarity. Laminarity can be presented by the ratio between the vertical structures and the entire set of recurrence points:

$$LAM = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)} \tag{6}$$

where, P(v) represents the total number of vertical lines of the length v:

$$P(v) = \sum_{i,j=1}^{N} (1 - R_{i,j})(1 - R_{i,j+v}) \prod_{k=0}^{v-1} R_{i,j+k}$$

The occurrence of laminar states in the system is introduced by LAM. However, this measure does not describe the length of these laminar phases.

Trapping Time. Trapping time calculates the average length of vertical structures. Therefore, similar to LAM measure, the minimal length v_{min} is considered in the formula.

$$TT = \frac{\sum_{v=v_{\min}}^{N} vP(v)}{\sum_{v=v_{\min}}^{N} P(v)} \tag{7}$$

Finally, TT can estimate the average time in which the structure will remain at a particular state or the period that it will be trapped.

In the present study, RQA is done, using MATLAB Toolbox [24]. In addition, to evaluate whether the difference between the extracted features is significant, the t-test ($p < 0.05$) is performed.

Classification

To evaluate the effectiveness of different classification schemes on discrimination of emotional EEG states, the multilayer perceptron (MLP), time delay neural network (TDNN) and probabilistic neural network (PNN) are used.

In comparison with TDNN, PNN is simpler to implement [25]. Both MLP and PNN networks have feed-forward structures and can be implemented as general-purpose classifiers [25]. No derivatives are calculated in PNN and the training process is accomplished in only 1 forward direction. Therefore PNN has a faster training process than TDNN. Furthermore, the weights between the input and pattern layers of PNN are directly estimated from the training data. Additionally, the central processing unit (CPU) time of training of the network is generally a few seconds. Details of each classifier are provided in the following sections.

Multilayer Perceptron. The most common neural network, which is used in the classification problems, is probably the multilayer perceptron network (MLPN). MLPNN is a nonparametric technique for performing a wide variety of detection and estimation tasks [26,27]. MLP is a feed-forward artificial neural network that maps input data onto proper outputs. MLPNN comprises of multiple layers of nodes in a directed path while each layer entirely connected to the next one. In this network, excluding the input nodes, each node is a neuron with a nonlinear activation function. For the training process of the network, a supervised learning technique called back-propagation is utilized. It has been confirmed that if the training features are linearly separable, the perceptron network will converge to an achievable solution of the weight vector within a restricted number of iterations. On the other hand, the network will not converge with a fixed, nonzero value of the learning rate if the training features are not linearly separable [28]. MLPNN is a modification of the standard linear perceptron.

Time Delay Neural Networks (TDNN). The training process of TDNN performs iteratively. By considering the network weights, 1 or more forward-propagations, and 1 back-propagation is included in each cycle to achieve the derivatives of the cost function [25]. Depends on different applications, the number of iterations varies from 10s to several 1000s. If the training is in the batch mode, the iterations should be repeated in every cycle for all the training patterns. In TDNNs, the number of training patterns and the size of the network are 2 important factors in the training speed.

A typical TDNN consists of input, hidden and output layers. Applying TDNN, time delays were inserted on the input vectors in a parallel fashion [29]. TDNNs are usually dependent on a tap delay line which is a special kind of memory where the latest input data are buffered at various points of time. To provide additional memory for the network, such delay lines are required between hidden nodes and output layer. In other words, applying delay lines the inputs arrived to hidden layers at various time intervals. Therefore, they held long enough to support successive inputs.

The response of TDNNs in time t is recognized by the inputs in the previous times (t-1), (t-2),

…, (t-D). A mapping executed by the TDNN, produces an output y(t) at time t as (8):

$$y(t) = f\left(x(t), x(t-1), \ldots, x(t-d)\right) \tag{8}$$

where an input data at time t shown by x(t), and the maximum time-delay is reflected in d. Despite all the connections in the TDNN are in a forward direction [28], which is similar to MLP neural network, the inputs of any unit in the network architecture consist of the output of the previous step. At any time step, the activation of the unit f is calculated as follows:

$$y_i^t = f\left(\sum_{j=1}^{i-1}\sum_{k=0}^{d} y_i^{t-k}.\omega_{ijk}\right) \tag{9}$$

where y_i^t is the output of i[th] node at time t, and ω_{ijk} is the weight of the node i from the output of node j at time t-k [30].

Probabilistic Neural Networks. A PNN can be applied in classification issues [31]. When an input is applied into the PNN, the first layer calculates the closeness between the points of input vector and the points of the training input vectors [32].

The second layer will add measures to each class of input data and construct output vector. Finally, the highest probabilities of the second layer assigned into a transfer function named compete layer. Consequently, it causes 1 for that class and 0 for the other classes [32].

In the training process of PNN, the determination of the smoothing parameter, called sigma, is essential. The spread of the RBF function is determined by the sigma. In this procedure, an optimum sigma value is established by trial and error.

Similar to other networks, the application of PNN has some benefits and drawbacks. PNNs can be used for classification issues. PNN design is straightforward and does not depend on the training process. Above mentioned network is assured to meet a Bayesian classifier as long as enough training data are provided. This network has a good generalization. However, since this network uses more computation, its function approximation or classification is slower to operate in comparison with other kinds of networks.

Support Vector Machine (SVM). For the first time, SVM was proposed by Vapnik [33] to solve a binary classification problem. This algorithm attempts to find out the maximum margin in a hyper plane that categorizes and separates different classes of data. Different versions of SVM have been proposed by reformulation of the standard SVM. Least Squares Support Vector Machines (LS-SVM) is a typical one that employs a kernel-based learning approach [34]. In addition, rather than using quadratic programming (QP) for solving convex problem in a conventional SVM, it employs a set of linear equations.

In the current study, the LS-SVM has been applied.

Results

In order to study the brain dynamics during different emotional states (happiness, disgust, and neutral) the RQA measures (recurrence rate, deterministic, average line length of diagonal lines, entropy, laminarity, and trapping time) are calculated in Fz, Cz, and Pz channels using MATLAB Toolbox [24]. The delay and window length for calculating this measure is selected as 1 and 128, respectively. Statistical analysis confirms that there is a significant difference in RQA measures of the emotional EEG signals. The extracted features are used as inputs of the SVM, MLP, TDNN and PNN classifiers. For this purpose, features were randomly allocated into 2 sets: a training set (2/3 of the data) and a test set (the rest of 1/3 of the data). 3 classes of emotions were considered in the study, including: happy, disgust and neutral states. First, the performance of SVM in discriminating each pair of affective states has been evaluated. For the rest of classifiers, the number of output is 3 with target outputs of happy, disgust and neutral states. Table 1 demonstrates the SVM correct rate for 10 times run.

Table 1. The SVM classification rates in discriminating each pair of emotions for ten times run

Iteration	N vs. H	N vs. D	H vs. D
1	74.85	74.99	74.83
2	74.65	75	74.8
3	74.73	75	74.82
4	74.72	75	74.73
5	74.85	75	74.78
6	74.74	74.99	74.75
7	74.79	75	74.78
8	74.86	74.99	74.76
9	74.81	75	74.76
10	74.78	75	74.84
Mean (±std)	74.778 ± 0.069	74.997 ± 0.005	74.785 ± 0.037

Note: H: happy, D: disgust, N: neutral

As shown in Table 1, using SVM each pair of affects discriminated by the rate of about 75%.

In this application, the sigmoidal and linear functions are applied as an activation function in the hidden and output layers of MLPNN, respectively. Training of the MLPNN is performed by Levenberg–Marquardt and Gradient Descents algorithms.

The values of classification rates in train and test data with different network architectures (number of hidden neurons) are presented in Table 2. Applying different training algorithms and network structures, desirable performance is not achieved by MLPNN.

Table 2. The values of the classification rate of the MLPNN classifier trained with the Levenberg-Marquardt and Gradient Descent algorithms

	Neurons in hidden layer	Classification Rate (%)			
		Levenberg-Marquardt		Gradient Descent	
		Training	Test	Training	Test
Multilayer Perceptron *Classifier*	3	35.03	36	35.51	35.03
	4	35.20	35.64	35.26	35.53
	6	35.54	34.98	35.76	34.56
	8	35.09	35.91	35.16	35.74
	13	32.25	35.55	35.12	35.81

In this study, TDNN is also examined. Hyperbolic tangent sigmoid and linear transfer functions are used as activation functions in the hidden and output layers of TDNN, respectively. In order to examine different architectures of TDNN, 3 different delay vectors are applied. The adjusted delays for the first and second layers are given in Table 3. The values of the classification rate and CPU times of training for TDNN classifier with different delays are presented in Table 3.

According to Table 3, although different network structures with different delays in the first and second layers are tested, the TDNN did not converge to a good result. In addition, the CPU time of training is increased as the number of delays in the 2 above mentioned layers increased.

As mentioned before, to examine the performance of the PNN, the same feature vectors are applied as an input.

Systemic testing of different sigma values is evaluated in PNN. The effect of sigma parameter on the accuracy rate of the classifier is demonstrated in Table 4 and Figure 1. The classification rate for different sigma values are evaluated for 10 trials and the mean and standard deviations of them are summarized in Table 4.

Table 3. The values of the classification rate and Elapsed time of training of the TDNN classifier with different delays

	Delay	Neurons in hidden layer	Classification Rate (%)		Elapsed time (s)
			Training	Test	
Time Delay Neural Network	First layer: 0-5 Second layer: 0-3	3	35.46	35.31	0.922
		4	35.24	35.57	0.914
		6	35.12	35.83	0.900
		8	35.36	35.36	0.913
		13	35.67	34.75	0.931
	First layer: 0-10 Second layer: 0-10	3	35.30	35.48	2.851
		4	35.59	34.86	2.815
		6	35.40	35.24	2.894
		8	35.56	34.96	2.736
		13	34.94	36.19	3.006
	First layer: 0-20 Second layer: 0-20	3	35.37	35.31	14.990
		4	35.82	34.44	15.087
		6	34.97	36.12	15.164
		8	35.77	34.51	13.351
		13	34.91	36.26	15.159

Table 4. Mean and standard deviation values of the classification rate and CPU times of training in the 10 times run of PNN classifier with different sigma values

	Sigma	Classification Rate (%)		Elapsed time (s) Mean±Std
		Train Mean±Std	Test Mean±Std	
Probabilistic Neural Network	0.01	100	$99.96\pm3.24\times10^{-4}$	63.03±7.89
	0.1	$99.6\pm5.49\times10^{-4}$	$99.51\pm5.46\times10^{-4}$	69.35±1.47
	0.2	90.3±0.0045	90.48±0.007	81.32±1.89
	0.3	82.41±0.0045	82.44±0.0089	69.14±0.64
	0.4	79.62±0.0053	79.34±0.0096	68.93±1.19
	0.5	77.19±0.0038	76.98±0.012	69.89±2.21
	0.6	75.39±0.0036	75.42±0.0062	69.23±0.68
	0.7	74.31±0.0038	74.09±0.0062	70.45±2.3
	0.8	73.02±0.0058	73.64±0.0099	68.42±1.40
	0.9	70.01±0.018	70.01±0.0221	68.59±1.001
	1	67.30±0.015	67.66±0.0209	80.41±1.66

According with Table 4, the best recognition rate is attained by sigma < 0.1 in train and test. Furthermore, with sigma = 0.01 the classification rate is $99.96 \pm 3.24\times10^{-4}$ for 10 trails of the network, which shows a robust result. It is noted that in this case the elapsed time is lower than that of other sigma. In addition, with sigma = 0.2 CPU times of training are higher than that of other sigma values.

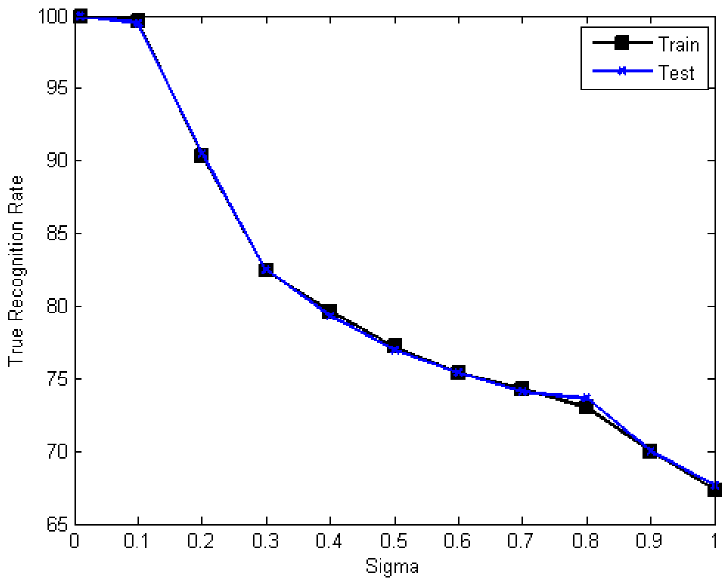

Figure 1. Examination of different sigma values on the recognition rates

Discussion

One of the most challenging issues in the problem of classification that is usually not considered by researchers is that they repetitively forget to assume the nonlinear characteristics of physiological signals. In other words, the assumption of stationarity in the signal is often found in literature. Therefore, the feature vector is often constructed by linear approaches. In this article, nonlinear time series analysis method, i.e. RQA was performed to investigate the effects of emotions on brain activity. Specifically, in this paper, neural network classifiers for the detection of human emotions were presented using 6 RQA indices in 3 EEG channels. Performing statistical analysis, it has shown that RQA parameters can discriminate different affective states of the brain ($p < 0.05$).

Recurrence measures can demonstrate subtle features of dynamic systems which cannot easily perceive by other methods [22]. The advantage of this method is that it can be practical for measuring the dynamics of a signal without demanding stationarity, length or noise [35,36]. In addition, RQA can deal with both linear and non-linear time series, to measure the activity of a system, irrespective of the quantity or dynamical nature of the different foundations [35]. Another advantage of RQA, and the basis of its widespread applicability, is its simplicity. RQA does not require any mathematical assumptions, and only necessitates counting similar events in an embedded space [36].

In order to evaluate the learning and classification performance of the system, 2/3 of feature vector is randomly assigned to train set and the rest is considered as a test. Different classifiers (MLP, PNN and TDNN) with various structures (number of hidden layer neurons, different delays and different sigma) were examined. Using EEG RQA features, the obtained accuracy for the MLP, TDNN and PNN is about 36%, 36% and 99.96%, respectively. Comparison of results obtained using MLP, PNN or TDNN confirms the interest of using PNN to assess emotional conditions.

The experiments show that the PNN is sensitive to the choice of sigma; the smaller the sigma, the higher the accuracy rate. In other words, applying small sigma values (0.01 and 0.1) guarantees the improvement of the classification rates. The capabilities of this classifier were confirmed by recognizing emotional states of 5 subjects with the accuracy rate of 99.96 (with sigma = 0.01).

Previously, Chanel et al. [11] applied Naïve – Bayes on the features of the EEG, GSR, BVP, respiration, and finger temperature. The emotions elicited by images from IAPS. In the proposed approach, the total accuracy of 72% and 58% were achieved for discriminating 2 levels of arousal (low and high) and 3 levels of arousal (low, medium, high), respectively. In another study, Bayes classifier applied on Fast Fourier transform features to distinguish two- and three-level classes of valence and arousal dimensions [37]. For the former, the average accuracy of the valence and arousal estimations was 70.9% and 70.1%, respectively. For the latter, the accuracy rates were decreased into the 55.4% and 55.2%, correspondingly.

Leon et al. [12] described a method for emotion classification using auto associative neural network combining with some features of heart rate, GSR, blood volume pressure. They reached 71% accuracy rate for discrimination of negative, positive, and neutral emotions. Using LDA for identifying 6 emotions, only the accuracy rate of 29% is achieved [13]. Murugappan et al. [14] examined KNN and LDA using discrete wavelet analysis to discriminate emotional EEG states. The maximum accuracy of 83.26% for KNN and 75.21% for LDA was obtained.

Recently, several studies have been conducted in emotion classification by means of Support Vector Machine (SVM). A system based on wavelet decomposition approach in combination with the Principal Component Analysis (PCA) and the SVM proposed in [38]. By remembering an unpleasant odor, the subjects were asked to induce disgust by themselves. The classification results with the average percentage of 90% were encouraging. To classify each of the six emotional states in Parkinson's patients and healthy subjects, the performance of the higher order spectra based features and SVM were evaluated [39]. The algorithm resulted in the accuracy rate of 86.89% ± 1.74% and 94.76% ± 2.28% for patients and healthy subjects, respectively. A multi-modal fusion approach [40] was proposed to recognize 13 emotions from EEG, GSR, blood volume pressure, respiration pattern, skin temperature, electromyogram, and electro-oculogram signals. The maximum correct rate of 85% was reported using SVM. Despite a significant performance of SVM, the recognition rates have been usually reported for each affective state [39] or applied on the huge amount of data [40] which make the system more complex and cost consuming.

More recently, other classification approaches have been evaluated in the literature. Peng and Lu [41] used a discriminative manifold extreme learning machine to classify neutral, negative, and positive states of 6 participants. The average accuracy of 81.01% was accomplished; however, they claimed that better recognition is achieved for positive and neutral categories. By combining mutual information based feature selection approaches and kernel classifiers [42], researchers attempted to categorize 2, 3, and 5 classes per valence and arousal dimensions. The model was capable of recognizing arousal (valence) with rates of 73.06% (73.14%), 60.7% (62.33%), and 46.69% (45.32%) for 2, 3, and 5 classes, respectively.

Figure 2 and Table 5provide a summary of the relevant studies.

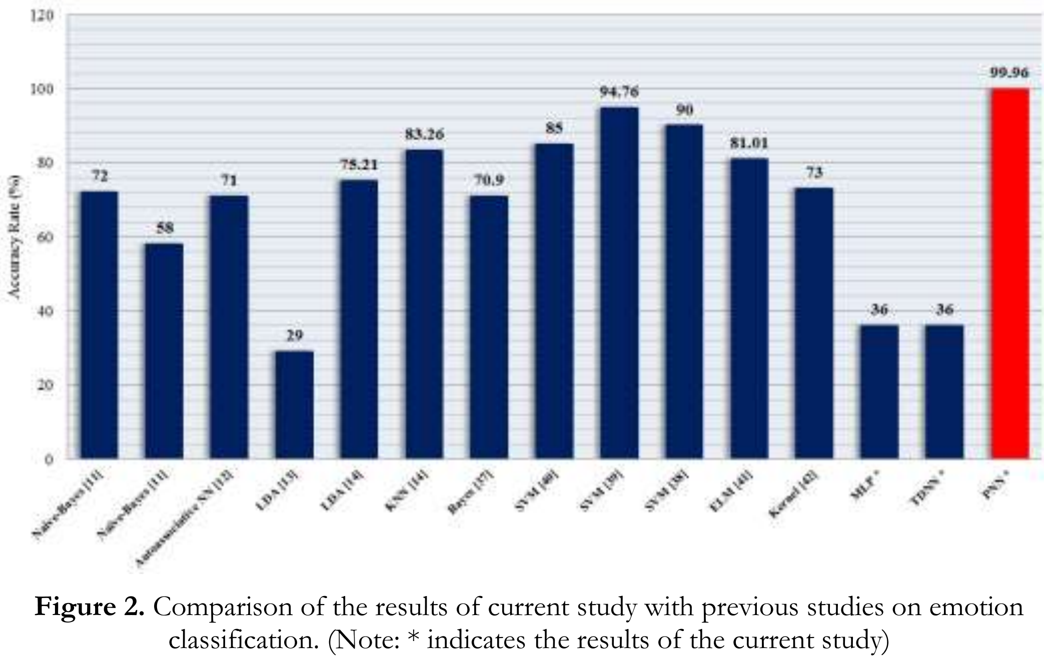

Figure 2. Comparison of the results of current study with previous studies on emotion classification. (Note: * indicates the results of the current study)

Table 5. Accuracy rate of some methods for emotion classification

Study	No. of Subjects	Emotions	Classifier	Result (%)
Chanel et al. (2006)	4	(low, high) arousal	Naïve-Bayes	72
		(low, medium, high) arousal	Naïve-Bayes	58
Leon et al. (2007)	9	neutral, negative, positive	Autoassociative Neural Network	71
Sakata et al. (2007)	16	6 emotional states	LDA	29
Murugappan et al. (2010)	20	5 emotional states	LDA KNN	75.21 83.26
Yoon and Chung (2013)	32	2-level classes in valence and arousal 3-level classes in valence and arousal	Bayes classifier	70.9 and 70.1 55.4 and 55.2
Verma and Tiwary (2014)	32	13 emotions	SVM	Maximum: 85
Yuvaraj et al. (2014)	20	6 emotional states	SVM	94.76% ± 2.28
Iacoviello et al. (2015)	10	disgust	SVM	90
Peng and Lu (2016)	6	neutral, negative, positive	Extreme learning machine	81.01±12.24
Atkinson and Campos (2016)	90 100	arousal valence	kernel classifier	73.06 73.14
Current study	5	neutral, negative, positive	MLP	36
			TDNN	36
			PNN	**99.96**

In conclusion, the accuracy of PNN performed in this study is better than that of previous studies using physiological signals and emotional classes (Table 5 and Figure 2).

Conflict of Interest

The authors declare that they have no conflict of interest.

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