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ORIGINAL RESEARCH

A study on multi-class anxiety detection using wearable EEG headband

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Abstract
In this paper, we present a trait anxiety detection framework using resting-state electroencephalography (EEG) data. Our proposed framework consists of EEG data acquisition, pre-processing, feature extraction and selection, and classification stages. EEG data of 65 participants is recorded in an eye-open state for the duration of two minutes. The trait anxiety scores are gathered using the state-trait anxiety inventory questionnaire, which is used to label the participant's EEG data into two (non-anxious and anxious) and three (non-anxious, low anxious, and highly anxious) classes. Pre-processing of the recorded EEG data is performed using the onboard noise cancellation scheme of the MUSE EEG headband. Channel selection is performed by applying a t-test and analysis of variance on the power spectral densities for two and three classes of anxiety respectively. Five time-domain features are extracted from the selected EEG channels. The wrapper method for feature selection is applied for selecting an optimum subset of features, which are used to classify the trait anxiety. The highest classification accuracy of 87.69% and 83.07% using random forest classifier is achieved for two and three class anxiety classification respectively. Our proposed trait anxiety detection scheme outperforms existing schemes in terms of higher classification accuracy and reduced feature vector length.

Keywords Trait anxiety · Anxiety detection · Wearable sensors · Electroencephalography · Feature extraction · Multi-class classification

1 Introduction

Anxiety is a mental health problem that can adversely affect the daily life of an individual. Anxiety is a long-term mental disorder, which is initiated by stressful situations (Baghdadi et al. 2019). Anxiety does not fade away when the stressful event is over, rather it exists for a prolonged duration and can cause severe social and health problems. Anxiety is a very common mental health disorder in the United States of America affecting around 18% of the population of the society (Association et al. 2013), out of which only 36.9% of the individuals going through anxiety get treated. According to the Anxiety and Depression Association of America (ADAA) report, people suffering from an anxiety disorder are six times more likely to be hospitalized as compared to the normal person (Newman et al. 2013). The anxiety disorder increases the risk of cardiac diseases and researches have shown that anxiety is strongly linked with stroke and heart attack (Emdin et al. 2016; Kollia et al. 2017). Anxiety can be triggered from a variety of real-life situations that seems threatening to a person like a competitive exam (Von der Embse et al. 2018), a social evaluative situation (Leichsenring and Leweke 2017), a painful medical procedure (Bradt and Teague 2018) or chronic life-threatening disease (Reynolds et al. 2017).

Anxiety is measured using subjective as well as objective methods (Caballo et al. 2010; Wiederhold et al. 2018). Subjectively anxiety is measured by the use of questionnaires developed by psychologists. State-Trait Anxiety Inventory (STAI) (Spielberger et al. 2017) is one of the most widely used questionnaires for subjective evaluation of anxiety by psychologists because this questionnaire is available in twelve different languages and it only requires a sixth-grade reading level. On the other hand, objective measures of anxiety include physical and physiological measures. Physical measures include facial cues (Giannakakis et al. 2017) and eye blink (Pinkney et al. 2014), whereas the physiological

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measure requires different sensors to measure the changes occurring in the body. These include heart rate (Khanade and Sasangohar 2017), heart rate variability (Chalmers et al. 2014), brain activity (Harrewijn et al. 2016), electrodermal activity (Rosebrock et al. 2016), and cortisol (Hek et al. 2013). It is a fact that the human brain is more affected by anxiety (EngElS et al. 2010). Electroencephalography (EEG) is a non-invasive method of measuring the cognitive state of a person and has been explored for mental health diagnoses (Zanetti et al. 2019; Harrewijn et al. 2016; Arsalan et al. 2019b; Saeed et al. 2018; Asif et al. 2019).

In literature, several EEG based methods to detect anxiety have been proposed. In Giannakakis et al. (2015), a study to investigate the effects of state anxiety on the EEG signal in response to video clips was presented. It was found that the asymmetry index has reduced during an anxiety state in comparison to a relaxed state. A study to develop the relationship between anxiety and the features extracted from EEG and photoplethysmogram (PPG) signals was presented (Zheng et al. 2016). Alpha and beta band wavelet coefficients were found to be highly correlated with the anxiety level. A study to correlate the mathematical anxiety and the brain activity of the individual was presented (Klados et al. 2015). The experimental result showed that the low mathematical anxiety group had increased cortical activation as compared to the high mathematical anxiety group in fronto-central and centro-parietal brain locations. In Jayakkumar et al. (2017), an EEG based method for anxiety reduction was presented. The study concluded that an increase in the amplitude of the beta band of the EEG signal was associated with the anxiety level of an individual. A study to investigate the activity in a different part of the brain in the patients suffering from generalized anxiety disorder (GAD) using EEG was presented (Wang et al. 2016). Closed eye EEG was recorded and the correlation dimension (CD) feature among the control and GAD patients groups was analyzed. Results indicate that the value of CD was significantly higher in all brain regions as compared to the control group. A study to investigate the EEG and virtual reality (VR) for anxiety reduction was presented in Tarrant et al. (2018). The results indicate that with the use of VR, beta activity in the anterior cingulate cortex was significantly reduced, which supports the evidence that VR can be used for relieving anxiety.

Most of the studies available in the literature aim at the development of the correlation of EEG signals with the anxiety level. The EEG data acquisition in most of the studies was done by using caps and headsets with a dense placement of electrodes resulting in high computational cost for the processing of acquired data, which makes it impractical for use in daily life. Moreover, the existing methods rely on some kind of stimuli, thus making their use difficult for anxiety assessment in daily life. Recently, a machine learning framework to classify anxiety states using brain signals was proposed (Arsalan et al. 2019a). The dataset used for anxiety classification was recorded for 28 users and time-domain features were used to classify two anxiety states. This paper extends that work by increasing the number of users in the experiment and classifies two and three anxiety states. Moreover, the impact of channel and feature selection is also explored to better detect anxiety states. To the best of our knowledge, no EEG data is publicly available to classify trait anxiety levels using resting-state EEG. In the proposed study, STAI (Y-2) questionnaire is filled by the participants and scores are thresholded to label them into two (non-anxious, anxious) and three (non-anxious, low anxious, highly anxious) classes. The significant EEG channels are selected for two and three class problems using the power spectral density of each channel. Five time-domain features are extracted from the selected EEG channels. Wrapper based feature selection algorithm is applied to select optimum features to classify anxiety into two or three classes. The major contributions of this work are,

1. Multi-class classification of trait anxiety is presented based on resting-state EEG recording. The dataset is publicly available for future research.[1]
2. Impact of channel and feature selection on multi-class anxiety classification is presented.

The organization of the remaining parts of the paper is given below. Section 2 explains the methodology of the proposed framework followed by multi-class anxiety detection results in Sect. 3 and the conclusion in Sect. 4.

2 Methodology

Figure 1 shows the proposed anxiety classification mechanism, which consists of four stages named EEG data acquisition, pre-processing and channel selection, feature extraction and selection, and classification. The following sub-sections present the details of each block.

2.1 EEG data acquisition

2.1.1 Participants

A total of 65 participants (33 males and 32 females) were recruited for the experiment. The age of the participants ranges from 18 to 40 years with mean ($\mu = 27.5$) and standard deviation ($\sigma = 5.75$). All participants had a minimum of twelve years of education. The experimental setup was designed according to the declaration of Helsinki.

[1] https://sites.google.com/site/simplrgp/resources.

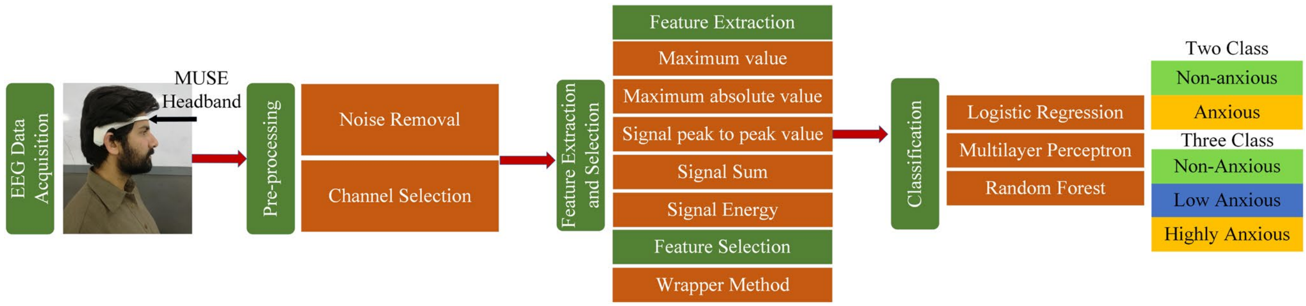

Fig. 1 The proposed framework for anxiety classification using resting state EEG signals

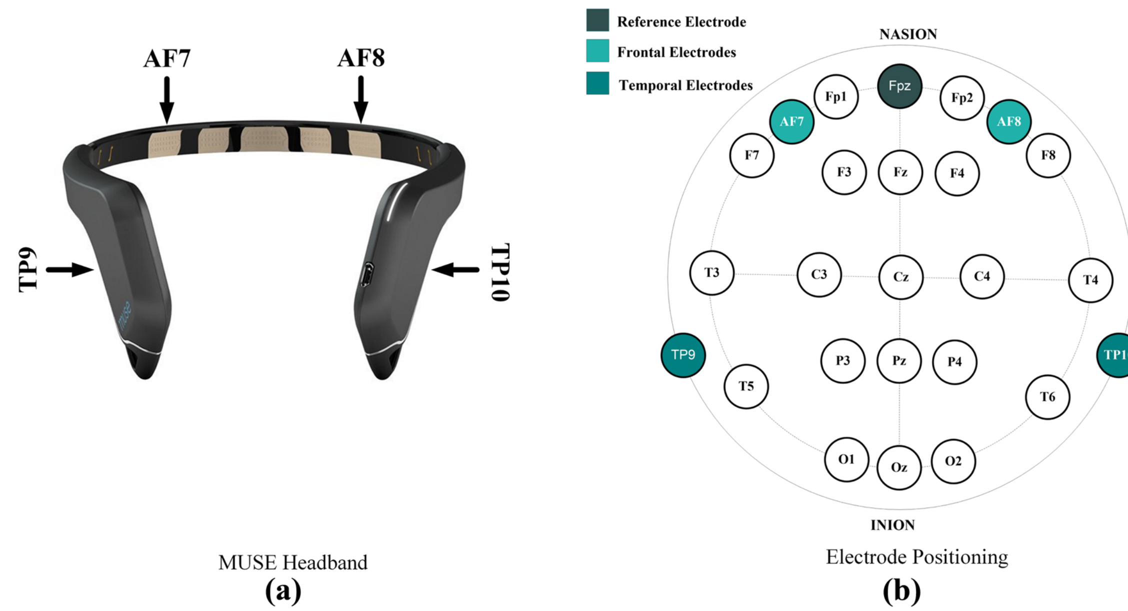

Fig. 2 The equipment used in this study for EEG recordings

2.1.2 Experimental procedure

The participants were guided to a quiet and noise-free room with a good lighting condition where they were thoroughly briefed about the experiment. Written consent to participate in the experiment was obtained. The subject was asked to fill in the demographic details to record the biodata of the participant like age, gender, education, and income. Next, the participants were asked to fill the STAI questionnaire (Spielberger 2010). It is a 40-item questionnaire, which is divided into two parts Y-1 and Y-2 each having 20 questions. Y-1 questionnaire measures the state anxiety of an individual i.e., how a person is feeling about an event right now, and Y-2 measures the trait anxiety i.e., how a person generally feels about typical situations faced in daily routine. In this study, participants were asked to fill the Y-2 questionnaire. Each question can be answered on a scale from 1 to 4, where 1 means that an event never occurs and 4 means that a particular event occurs very frequently. A minimum score of 20 and a maximum score of 80 can be obtained from this questionnaire. The trait anxiety scores are used to label the participants into a non-anxious and anxious state for the two-class problem, and non-anxious, low anxious, and highly anxious for the three-class problem. The participant's EEG data were recorded for the duration of two minutes in open eye condition while sitting on a comfortable chair in a noise-free environment.

2.1.3 Equipment

In this study, EEG data acquisition was performed using a low cost commercially available Interaxon MUSE headband. It consists of 4 dry electrodes at position *TP*9, *AF*7, *AF*8, *TP*10 and a reference electrode at *Fpz* according to 10–20 electrode positioning system. Figure 2 shows the MUSE headband and its electrode placement according to the

10–20 electrode positioning system. The frontal ($AF7$, $AF8$) and temporal ($TP9$, $TP10$) electrodes are made up of silver and silicon rubber material, respectively. MUSE headband records EEG signals at a sampling rate of 256 Hz, which are transferred via a Bluetooth connection with the Muse monitor application for further offline processing.

2.2 Pre-processing

The recorded EEG data was subject to pre-processing before the feature extraction and selection stage. Frontal and the reference electrodes i.e., FPz have a driven right leg (DRL) circuit between them for noise cancellation. DRL circuit ensures that there should be proper contact between the electrodes and the human scalp. Variance, amplitude, and kurtosis of the recorded EEG signal are used for discriminating noisy and clean signal. A statistically significant set of channels is identified by applying a t test (for two-class) and analysis of variance (ANOVA) (for three-class) on the power spectral density of the raw EEG data. Power spectral density is calculated using the Welch method with a 50% overlapping window. The selection of significant channels is based on the p value (p) of t test and ANOVA for two- and three-class problems. The channels are considered significantly different if $p < 0.05$.

2.3 Feature extraction and selection

Five groups of features are extracted from the selected EEG channels, which are found statistically different based on power spectral density. These features include maximum value, maximum absolute value, signal peak-to-peak value, signal sum, and signal energy. Some of these features have been employed in a study to differentiate depression patients and healthy subjects (Kalatzis et al. 2004). Moreover, these features have also been used in different EEG based studies like sleep stage classification (Zhang et al. 2017), motor imagery (Resalat and Saba 2016), eye movement classification (Adam et al. 2014), and epilepsy detection (Omerhodzic et al. 2010). These features have been proved to be useful for the classification of different states, hence are believed to be handy for trait anxiety classification.

The maximum value corresponds to the highest value of the recorded epoch of the EEG signal. The maximum absolute value corresponds to the maximum absolute value of the recorded EEG signal. The signal peak to peak value of the EEG signal is obtained by subtracting the minimum value from the maximum value of the recorded EEG signal. The signal sum is the addition of all the samples of the recorded EEG signal. Energy is computed by calculating the sum of the square of the absolute values of all the samples of the EEG signal. The mathematical representation of the extracted features is given below.

Maximum value:

$$s_{c_{max}} = max\{s_c[n]\}, \tag{1}$$

where $s_{c_{max}}$ is the maximum value of the signal $s_c[n]$ recorded at channel c.

Maximum absolute value:

$$MAV = max\{|s_c[n]|\}. \tag{2}$$

Signal peak-to-peak value:

$$s_{c_{pp}} = s_{c_{max}} - s_{c_{min}}, \tag{3}$$

where $s_{c_{min}}$ is the minimum value of the signal $s_c[n]$.

Signal sum:

$$S_c = \sum_N s_c[n], \tag{4}$$

where N is the total number of samples.

Signal energy:

$$E_c = \sum_N |s_c[n]|^2. \tag{5}$$

Features extracted from the selected channels are concatenated to form a feature vector. This feature vector is subjected to a wrapper method for feature selection to select the optimum subset of features. The wrapper method is a classifier dependent method that selects a different subset of features for each classifier. The selection of an optimum subset of features is treated as a search problem and different subsets of features are evaluated and compared with each other thus selecting the subset of features yielding the highest classification accuracy. The forward selection approach is adopted where the algorithm starts with an empty set and then the addition of features in this set is performed iteratively by populating it with features, which contributes to the improvement in the classification accuracy of the algorithm. This iterative procedure stops when the addition of features to the set does not improve the performance of the algorithm any further.

The features extracted from the selected channels and after applying feature selection for trait anxiety classification are visualized by plotting the distribution of the feature values in terms of non-anxious and anxious groups, which is shown in Fig. 3. The feature extracted from the selected channels yields a partial overlap for two classes i.e., non-anxious and anxious. Applying feature selection further reduces the overlap of the distribution of feature values from non-anxious and anxious groups. This indicates the significance and discriminating nature of the selected features from the selected channels.

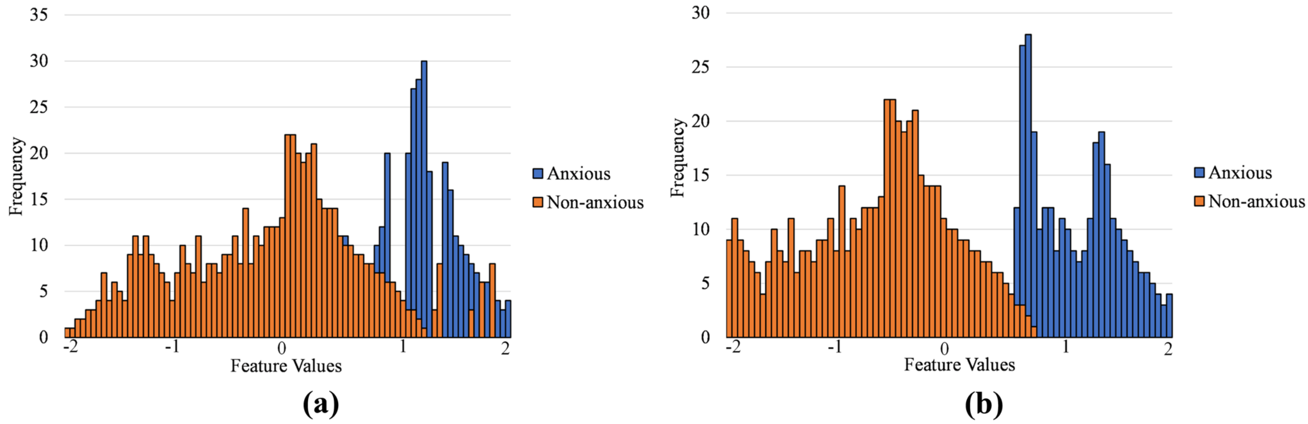

Fig. 3 Feature value distribution of both classes i.e., non-anxious and anxious from **a** selected channels, **b** selected channels and selected features

2.4 Classification

In the current study, three different classification algorithms are used for the trait anxiety classification that includes multilayer perceptron, logistic regression, and random forest. A brief detail of each of the classifiers is given below.

2.4.1 Multilayer perceptron (MLP)

Multilayer perception is the most commonly used type of neural network, which is used for classification tasks (Hastie et al. 2009). The simplest MLP network consists of three layers i.e., input, hidden, and output layer. The input and output of an MLP classifier are connected via a directed graph. A transfer function is applied in the hidden layer to transform the input of the neural network to the output. In this study, a four-layer hidden network with a sigmoid activation function and a learning and momentum rate of 0.3 and 0.2 respectively are used.

2.4.2 Logistic regression (LR)

Logistic regression is a statistical model used for classification problems and is based on a logistic function (Wright 1995). Logistic regression is used in cases where the target variable is categorical. Logistic regression is based on developing a model of prediction based on the probability of a certain class. The transformation function for logistic regression is obtained by plugging the sigmoid function in the linear regression equation. The implementation of logistic regression used in this study is ridge estimator regularization.

2.4.3 Random forest (RF)

Random forest is a supervised machine learning algorithm, which is used for classification as well as regression tasks (Breiman 2001). A random forest algorithm is built using a large number of decision trees. Random forest is an ensemble classifier, which uses feature randomness to build each tree and develop a forest of uncorrelated trees whose prediction is much better than the prediction made by any individual tree. Prediction made by random forest is an average of the predictions made by each of the decision trees included in the forest. The hyperparameter of the random forest is the same as a decision tree or a bagging classifier. The number of decision trees for the RF classifier used in the current study is 100.

3 Experimental results

3.1 Labeling

The subjects are labeled based on the STAI (Y2) score, which is the standard questionnaire designed for the state anxiety (Spielberger 2010). For two-class grouping, the fixed score range i.e., (0–40) for non-anxious and (41–80) for the anxious group have been used (Julian 2011). Similarly, for the three-class problem the fixed score ranges like (0–40) for non-anxious, (41–50) for low anxious, and (51–80) for highly anxious have been used (Kayikcioglu et al. 2017). The division of subjects into two classes of anxiety using the mean value of the obtained STAI scores and three classes of anxiety based on mean and standard deviation values of the obtained STAI scores has also been used (Asif et al. 2019). The main aim of the current study is to develop a framework to classify trait anxiety using EEG signals. Therefore, we

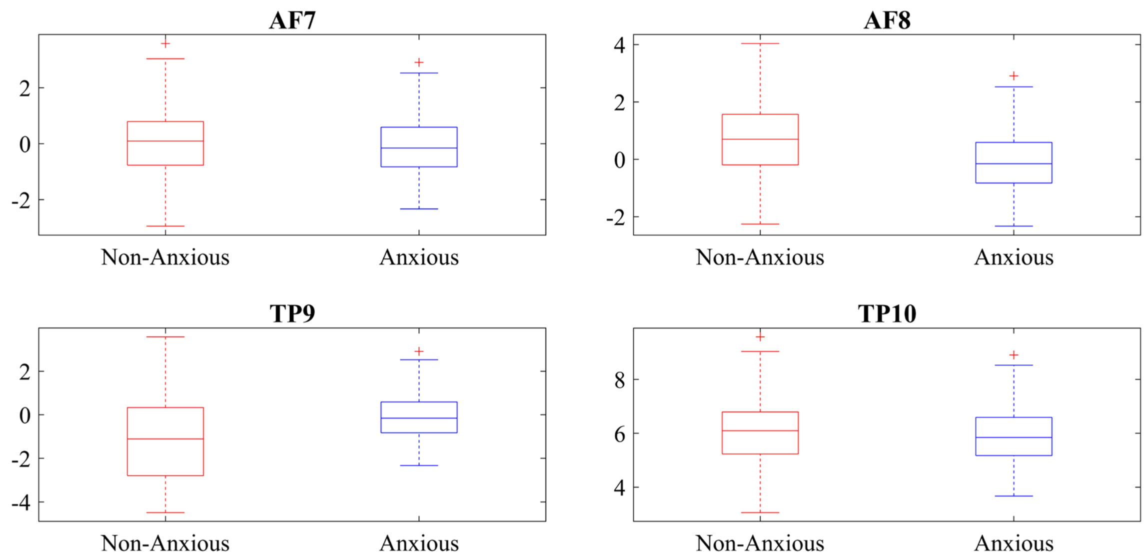

Fig. 4 Boxplot of the power spectral densities for all the channels of the MUSE headband for two class problem i.e., anxious and non-anxious groups

grouped the participants into two and three classes based on the mean and standard deviation of the obtained STAI (Y2) scores.

The mean and variance of STAI (Y2) score is $\mu_{Y2} = 45.37$ and $\sigma_{Y2} = 10.98$. For the two-class problem, participants are divided into two groups based on the mean score. The subjects having scores less than the mean score are considered into the non-anxious group, whereas subjects having scores greater than the mean value are considered in the anxious group. For the three-class problem, participants having the score in range from 0 to $\lceil \mu_{Y2} - \frac{\sigma_{Y2}}{2} \rceil$ i.e., (0 to 40) are labeled as non-anxious group, participants with the score ranging from $\lceil \mu_{Y2} - \frac{\sigma_{Y2}}{2} \rceil + 1$ to $\lceil \mu_{Y2} + \frac{\sigma_{Y2}}{2} \rceil - 1$ i.e., (41–50) are labeled as low anxious group, and participants having the score ranging from $\lceil \mu_{Y2} + \frac{\sigma_{Y2}}{2} \rceil$ to 80 i.e., (51–80) are labeled into highly anxious group. For the two-class problem, 35 participants are labeled as non-anxious participants, whereas 30 participants are labeled as anxious participants. Similarly, for the three-class problem, 27 participants are labeled into a non-anxious group, 17 participants are labeled into a low anxious group, and 21 participants are labeled into a highly anxious group.

3.2 Channel and feature selection

Channel selection is performed by using a t test for two-class and ANOVA for the three-class problem. T-test and ANOVA are applied to the power spectral density calculated from the EEG data of each channel of the MUSE headband. Power spectral density is calculated by using the Welch method with an overlapping window of 50%. The results of the statistical test depict that $AF8$ and $TP9$ channels are significantly different for two (p value of 0.034 and 0.049, respectively) and three (p value of 0.029 and 0.038, respectively) class problem. Whereas the other two channels i.e., $AF7$ and $TP10$ have a p value of 0.14 and 0.28 for two-class labeling and a p value of 0.42 and 0.57 for three class labeling. Figures 4 and 5 show the boxplot of the power spectral densities of EEG data from all the channels of the MUSE headband for two and three class problems respectively. It can be observed that the power spectral densities of the channels $AF8$ and $TP9$ are visually distinct from each other for the non-anxious and anxious subjects for two classes and non-anxious, mildly anxious, and highly anxious subjects for three classes.

Features are extracted from the EEG data of the statistically significant channels i.e., $TP9$ and $AF8$ constituting a feature vector length (FVL) of 10. The number of features corresponding to each of the channels is 5. This feature vector is labeled using the STAI (Y2) score for two as well as three classes, which is fed to the wrapper method for feature selection to select an optimum subset of features. Figure 6 shows the plot of selected features from the statistically significant channels visualized in two dimensions using the t-distributed stochastic neighbor embedding (t-SNE) scheme (Maaten and Hinton 2008) for two and three class problem. t-SNE is a dimensionality reduction technique, which has been widely used for visualizing high dimensional data. It can be observed from the plot that the two-class anxiety classification i.e., non-anxious and anxious is more visually discriminating as compared to three class anxiety classification i.e., non-anxious, low anxious, and highly anxious.

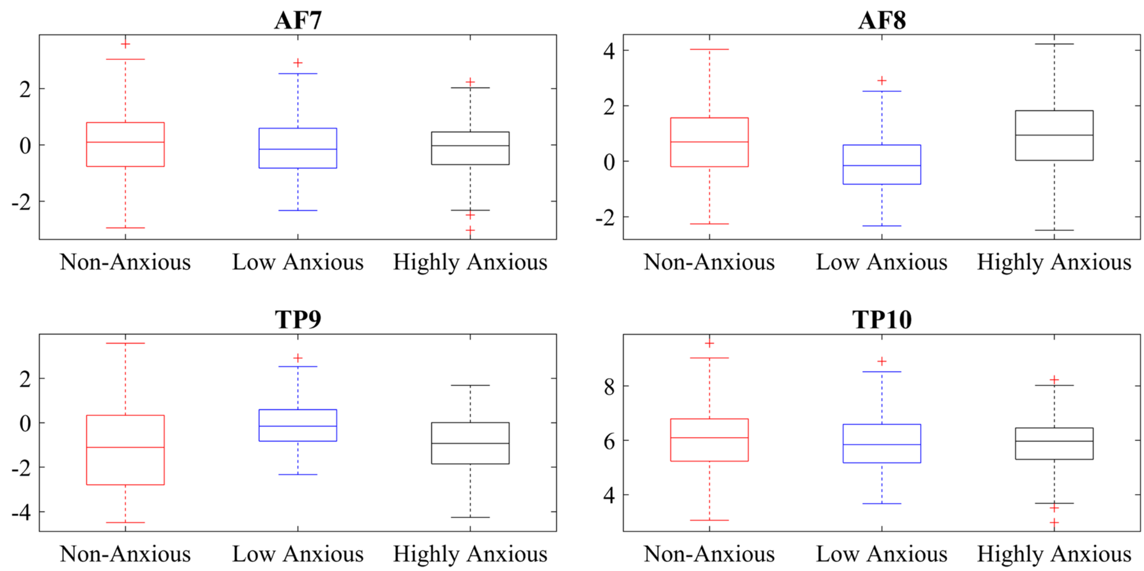

Fig. 5 Boxplot of the power spectral densities for all the channels of the MUSE headband for three class problem i.e., non-anxious, mildly anxious and highly anxious groups

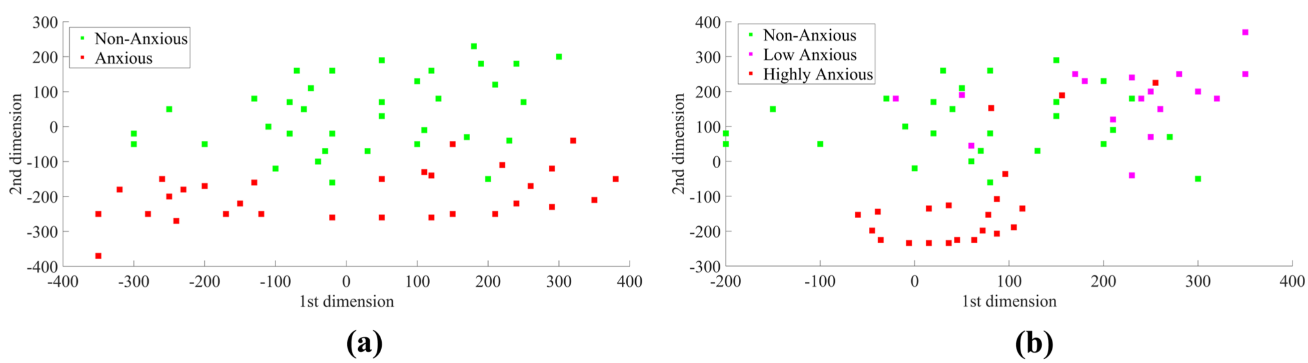

Fig. 6 T-SNE plot for the selected set of features from the significant channels for trait anxiety classification **a** two-class, **b** three-class

3.3 Classification performance

Anxiety classification into two and three classes is performed by using three different classifiers i.e., LR, MLP, and RF. The training and testing of the algorithms are performed using Weka 3.8 tool (Witten et al. 2016). The results are calculated using a 10-fold cross-validation scheme. It is worth mentioning that our proposed scheme is subject independent i.e., the training and testing data do not belong to the same subject. The classification algorithms are evaluated in terms of accuracy (A_{cc}), F-measure (F_m), kappa statistics (K), mean absolute errors (MAE) and root mean square error (RMSE). Accuracy is defined as the correct number of predictions out of the total number of predictions made. F-measure is the weighted harmonic mean of the precision and recall of a classifier. Kappa statistics is the measure of the closeness of the classification results to the ground truth. MAE metric is defined as the average of the prediction error, which is calculated by taking the absolute value of the difference of actual and predicted values. RMSE is calculated by taking the square root of the mean square error, which is defined as the average squared error of our predictions.

Table 1 presents the classification performance of the proposed anxiety classification scheme. The results are calculated in four different combinations of channels and features i.e., all channel (C_{all}) and all features (F_{all}), all channels and selected features using wrapper method (F_{sel}), selected channels using t test (C_{sel}) and all features and selected channels and selected features. It is evident from the results that the highest classification accuracy for two as well as three class is achieved when selected features from selected channels are used with all the classifiers and the highest classification accuracy is achieved with the RF classifier. An accuracy of 87.69% and 83.07% is achieved for two

Table 1 Performance comparison of the proposed trait anxiety classification scheme in terms of classifier used, feature vector length, accuracy, F-measure, kappa statistics, mean absolute error and root mean square error for two class and three class problems

Channels and features	Classes	Classifier	FVL	*Acc* (%)	F_m	K	MAE	RMSE
$C_{all} + F_{all}$	Two	MLP	20	56.92	0.56	0.12	0.46	0.56
		RF	20	46.15	0.46	− 0.08	0.51	0.54
		LR	20	49.23	0.48	− 0.02	0.47	0.62
	Three	MLP	20	41.53	0.38	0.07	0.41	0.51
		RF	20	26.15	0.24	− 0.16	0.46	0.51
		LR	20	38.46	0.38	0.06	0.40	0.55
$C_{all} + F_{sel}$	Two	MLP	8	56.92	0.57	0.14	0.46	0.49
		RF	7	69.23	0.69	0.37	0.35	0.45
		LR	10	56.92	0.56	0.12	0.45	0.51
	Three	MLP	5	46.15	0.43	0.13	0.40	0.47
		RF	6	50.76	0.51	0.25	0.34	0.49
		LR	2	50.76	0.49	0.21	0.40	0.47
$C_{sel} + F_{all}$	Two	MLP	10	72.30	0.71	0.43	0.33	0.44
		RF	10	78.46	0.78	0.56	0.28	0.38
		LR	10	66.15	0.65	0.30	0.38	0.46
	Three	MLP	10	46.15	0.44	0.14	0.35	0.45
		RF	10	69.23	0.69	0.53	0.25	0.37
		LR	10	41.53	0.41	0.10	0.38	0.48
$C_{sel} + F_{sel}$	Two	MLP	6	76.92	0.76	0.52	0.34	0.42
		RF	**2**	**87.69**	**0.87**	**0.75**	**0.21**	**0.32**
		LR	4	70.76	0.70	0.40	0.31	0.43
	Three	MLP	5	56.92	0.53	0.30	0.33	0.41
		RF	**3**	**83.07**	**0.82**	**0.74**	**0.20**	**0.35**
		LR	6	52.30	0.48	0.24	0.39	0.47

Bold values represent the highest accuracies achieved for two- and three-class trait anxiety classification

and three class classification using RF classifier with a feature vector length of 2 and 3, respectively. Moreover an F-measure of 0.87 and 0.82, and kappa values of 0.75 and 0.74 are achieved for two and three-class anxiety classification, respectively. In terms of error parameters, MAE of 0.21 and 0.20, and an RMSE value of 0.32 and 0.35 is achieved for two and three classes, respectively. The selected features using RF classifier for two-class problem include $s_{TP9_{pp}}$ and E_{AF8}, whereas for three class anxiety classification the selected features are $s_{AF8_{pp}}$, E_{TP9} and E_{AF8}.

Tables 2 and 3 present the confusion matrices for two-class and three-class anxiety classification along with the sensitivity and specificity of the classifier, respectively. Sensitivity is defined as the number of actual positive cases, which are predicted positive. Whereas specificity is the number of actual negative cases predicted as negative. The RF classifier has the maximum number of correctly classified instances as compared to MLP and LR classifier. For the two-class case, 32 out of 35 instances are correctly classified for non-anxious class, whereas for anxious class 25 out of 30 instances are correctly classified using RF classifier. Moreover, for the three-class case, 23 out of 27 instances are correctly classified for the non-anxious class, 20 out of 21 instances are correctly classified for the highly anxious class and 11 out of 17 instances are correctly classified for low anxious class. A higher value of sensitivity and specificity is observed for the RF classifier as compared to LR and MLP classifiers for two as well as three class problems. Figure 6 also supports the fact that for two-class problem data points are more clearly distinguishable as compared to the data points of three classes.

Table 2 Confusion matrix for two class anxiety classification using RF, MLP and LR classifier

NA	A	Classified as	Sensitivity	Specificity
(a) RF				
32	5	NA = Non-anxious	0.86	0.91
3	25	A = Anxious	0.89	0.83
(b) MLP				
32	12	NA = Non-anxious	0.72	0.91
3	18	A = Anxious	0.85	0.60
(c) LR				
27	11	NA = Non-anxious	0.71	0.77
8	19	A = Anxious	0.70	0.63

Table 3 Confusion matrix for three class anxiety classification using RF, MLP and LR classifier

NA	HA	LA	Classified as	Sensitivity	Specificity
(a) RF					
23	2	2	NA = Non-anxious	0.85	0.85
1	20	0	HA = Highly anxious	0.80	0.95
3	3	11	LA = Low anxious	0.84	0.64
(b) MLP					
24	2	1	NA = Non-anxious	0.53	0.88
14	5	2	HA = Highly anxious	0.55	0.23
7	2	8	LA = Low anxious	0.72	0.47
(c) LR					
18	6	3	NA = Non-anxious	0.52	0.66
6	14	1	HA = Highly anxious	0.56	0.66
10	5	2	LA = Low anxious	0.33	0.11

Hence, for two classes, the number of data points is less misclassified than the three-class problem.

3.4 Comparison and discussion

This study presents a machine learning approach to classify multilevel trait anxiety using EEG signals recorded from 65 subjects. Table 4 presents a comparative analysis of the proposed scheme with the existing state-of-the-art anxiety classification methods using EEG signals. The methods selected for the comparison either classify trait anxiety (Arsalan et al. 2019a) or state anxiety (Zheng et al. 2016; Baghdadi et al. 2019). To the best of our knowledge, there is only one study available in the literature to classify two states of trait anxiety i.e., non-anxious and anxious using baseline line EEG recordings of 28 subjects (Arsalan et al. 2019a). Classification accuracy of 78.50% is achieved by the selected features from all of the 4 channels using a random forest classifier with a feature vector length of 6. Applying our proposed trait anxiety classification scheme using the channel and feature selection on the same dataset used in Arsalan et al. (2019a) has shown an increase in classification accuracy and reduction in the feature vector length. An accuracy of 89.28% is achieved by the proposed method with a feature vector length of only 3. This increase in classification accuracy and reduction in feature vector length is due to feature extraction and selection only from the selected channels.

An EEG based study for the human state anxiety quantification using wearable EEG and PPG sensors is discussed in Zheng et al. (2016). Wavelet coefficients of the alpha and beta band of EEG signals and mean pulse rate features of PPG signals are highly correlated to the state anxiety level of an individual. The three-level anxiety classification was performed using features from EEG and PPG signals and the accuracy of 62.5% using kNN classifier is achieved with a feature vector length of 9. Another state anxiety classification scheme using EEG signals and face-to-face psychological stimuli is presented in Baghdadi et al. (2019). Two and four-level anxiety detection is performed with a classification accuracy of 83.50% and 74.60% respectively using a stacked sparse autoencoder classifier with a feature vector length of 277. For studies using 14 EEG electrodes, an accuracy of 83.50% and 74.60% is achieved with a feature vector length of 277 for two and four class classification, respectively. In our proposed trait anxiety classification scheme, an accuracy of 87.69% and 83.07% is achieved for two and three class anxiety classification with a feature vector length of 2 and 3, respectively using EEG recording of 65 subjects. The achieved classification accuracy of the proposed framework is higher than all other methods. Similarly, the feature vector length for two and three classes for the proposed trait anxiety classification is smaller than the existing schemes in the literature. Our proposed scheme performs better than the existing anxiety classification schemes in terms of accuracy and feature vector length. We believe that the comparison of the proposed trait anxiety framework with the state anxiety methods is not fair, but this comparison

Table 4 Performance comparison of the proposed scheme with state-of-the-art methods for human anxiety classification using EEG

Method, year	Number of participants	Number of EEG channels	Feature vector length (classes)	Accuracy (classes)	Classifier	Anxiety type
Arsalan et al. (2019a), 2019	28	4	6 (2)	78.50% (2)	RF	Trait anxiety
Proposed, 2020	**28**	**4**	**3 (2)**	**89.28% (2)**	**RF**	**Trait anxiety**
Baghdadi et al. (2019), 2019	23	14	277 (2) 277 (2)	83.50% (2) 74.60% (4)	SSAE	State anxiety
Zheng et al. (2016), 2016	20	1	9 (3)	62.50% (3)	kNN	State anxiety
Proposed, 2020	**65**	**4**	**2 (2)** **3 (3)**	**87.69% (2)** **83.07% (3)**	**RF**	**Trait anxiety**

Bold values represent the result of our proposed method in terms of number of participants, number of EEG channels, feature vector length, accuracy achieved, number of classes, classifier used and anxiety type shows that the proposed technique has significant accuracy in classifying multiple trait anxiety states. The comparison also shows that the classification accuracy can be improved by introducing channel selection before feature extraction and feature selection.

4 Conclusion

In this paper, a two and three-class human trait anxiety classification scheme using baseline EEG signals is proposed. Channel selection is performed by selecting statistically significant channels using a t test for two classes and ANOVA for three class labeling based on power spectral density. $TP9$ and $AF8$ are found to be significantly different channels. Five features that include maximum value, maximum absolute value, signal peak to peak value, signal sum, and signal energy are extracted from the selected EEG channels. The wrapper method for feature selection is applied to select the optimum subset of features. The selected subset of features is given as input to three different classifiers which include MLP, RF, and LR. RF classifier gives the best results for two and three-class trait anxiety classification. An accuracy of 87.69% and 83.07% is achieved for two and three-class anxiety classification using an RF classifier with a feature vector length of 2 and 3 respectively.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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