Anxiety Detection from EEG Features Using 1-Dimensional Convolutional Neural Network

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Abstract— Anxiety is defined as fear and symptoms of somatic tension experienced when a threat or danger is anticipated. In recent years, biological markers have been explored to detect anxiety noninvasively, one method is Electroencephalography (EEG). Detecting state anxiety using EEG is an intriguing area of research. This study detects the state of anxiety based on an EEG signal using a 1-Dimensional Convolutional Neural Network (1-D CNN). The dataset is provided by the Database for Anxious States based on Psychological Stimulation (DASPS). DASPS is an EEG recording obtained from twenty-three participants for this investigation. The data were analyzed for statistical features, and then a 1-D CNN was employed to classify anxiety levels. The results show that 95.1% of mild and severe anxious conditions can be accurately detected. Furthermore, 94.8% of detection accuracy is achieved when anxiety is classified as normal, mild, moderate, or severe. Overall, this study provides a solid foundation for multi-level anxiety detection by improving accuracy and selecting better features.

Keywords— State Anxiety Detection, Electroencephalogram, 1-D Convolutional Neural Network, Deep Learning

I. INTRODUCTION

Anxiety is defined as an emotion that arises in anticipation of danger or threat, causing a person to feel fear and symptoms of somatic tensions. Even though often used interchangeably, anxiety and fear refer to different mental states. Unlike fear, which has a clear and specific cause, anxiety arises when the cause of the danger is uncertain [1]. Anxiety generally manifests as excessive worry about a situation. However, the extent and reasons for these worries vary. In most cases, those worries are triggered by fear of accidents, worries about loved ones and worry about being the target of shameful attention. The presence of illnesses can also contribute to the onset of anxiety symptoms in patients with endocrine disorders, cardiovascular disorders, respiratory disorders, metabolic disorders, and neurological disorders, as well as other chronic diseases that require intrusive treatment [2].

Anxiety is classified into state anxiety and trait anxiety based on its occurrence. State anxiety refers to temporary reactions to adverse events, whereas trait anxiety refers to a persistent tendency to respond to various situations with concerns, troubles, or worries [3]. In essence, anxiety does not threaten an individual's well-being since it is an adaptation mechanism of the body to deal with potential dangers. This is indicated by the increase in functional connectivity in the temporal and ventral regions of the brain [4]. However, if it persists for an extended period and becomes excessive, it may develop into an anxiety disorder.

An individual who suffers from severe anxiety may have difficulty carrying out daily activities. Research has shown that anxiety negatively affects children and adolescents' social behavior, emotional development, and academic performance [2]. Anxiety may also form comorbidities with other mental and physical illnesses, which can negatively impact a patient's medical and psychological treatment [5], [6]. Thus, early detection of anxiety plays a crucial role in improving the quality of life for individuals suffering from anxiety. Despite this, most cases of mental disorders among children and adolescents remain undiagnosed and untreated until they reach adulthood [7]. The World Mental Health Survey reported that only 27.6% of respondents received treatment for anxiety disorders, while only 9.8% received adequate treatment [8]. Anxiety treatment includes regular screenings to assess the effectiveness of psychological interventions and improve the sensitivity of the diagnostic tools utilized [9], [10].

The commonly used tool to identify anxiety is to use Spielberger's State-Trait Anxiety Model. However, this approach highly depends on participants' abilities and perceptions while filling out the questionnaires. Consequently, scientists began exploring alternative methods for detecting anxiety from physiological changes that have been reported as symptoms of anxiety, such as elevated heart rates, sweating, trembling, flushing, restlessness, agitation, and irritability. Numerous studies have been conducted on electroencephalography (EEG), electrocardiogram (ECG), electrodermal activity (EDA), electromyography (EMG), respiration (RSP), skin temperature (ST), galvanic skin response (GSR), blood volume pulse (BVP) and photoplethysmography (PPG) [11].

Nonetheless, exploring the brain's electrical activity is fascinating for further investigation, as it plays a vital role in regulating emotions. It has been established that there are differences in neuroanatomical and functional characteristics between the two types of anxiety, implying that further study may be beneficial for investigating the early diagnosis or effectiveness of treatment [4]. Research on anxiety detection using EEG signals has typically utilized primary data collected from different EEG devices with different gold standards, environmental conditions, and recording protocols. Consequently, it is difficult to compare the performance of the EEG signal detection method for detecting anxiety states. Hence, the Database for Anxious States based on Psychological Stimulation (DASPS), which provides open-access EEG signal recording data, is a useful resource for the study of anxiety detection methods [12].

Several studies have used this dataset to detect anxiety through various approaches. On the detection of two levels of anxiety using stacked sparse autoencoders (SSAE), an accuracy score of 83.5% was obtained from 277 extracted features [12]. These features include time, frequency, and time-frequency features. Further, another study found a slight improvement in accuracy scores to 83.9% with 318 features [13]. As a comparison, the latest study using random forest classification achieved 94.9% accuracy by utilizing nine frequency features [14].

Those studies prompted the exploration of 1-D CNNs as an alternative classifier to identify state anxiety levels from the DASPS dataset. This is due to CNN's ability to optimize feature training from raw data inputs so less computation is required [15]}. Moreover, many studies report that CNN handles limited data better. The main difference between 1-D CNNs and CNNs commonly used for image processing is the size of the data input, kernel, and feature maps in 1-D arrays instead of 2-D or 3-D. Therefore, this study aims to achieve a higher classification accuracy of state anxiety levels using 1-D CNN. The experiment includes a comparison of classification accuracy using 1-D CNN and random forest.

This paper consists of four sections. With the Introduction in Section I, following are the remaining sections of the paper: Section II explains the experimental procedure as well as the underlying theory, including data preprocessing, feature extraction, and feature classification methods. Section III presents and discusses the results. Finally, Section IV concludes this study.

II. METHOD

Figure 1 illustrates the proposed anxiety detection framework. The scheme consists of four main components: a detailed description of the DASPS dataset, data pre-processing, feature extraction techniques in three different domains (time, frequency, time-frequency), and feature classification techniques using random forests and 1-D CNNs. The subsections below describe each component in more detail.

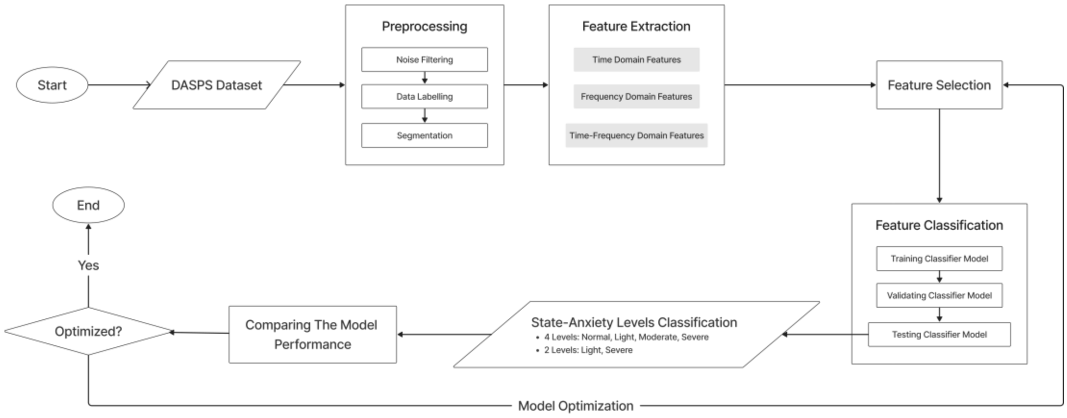

Figure 1. Research Flowchart

A. Dataset Description

The data used in this study was obtained from the DASPS database [16]. This is a free-to-access EEG signal collected from 23 healthy participants, 13 of whom are women and 10 of whom are men with an average age of 30. The EEG signals are recorded using a wireless EEG headset, Emotiv Epoc Neuro, which has 14 channels with a sampling rate of 128 Hz. To stimulate anxiety states, a Flooding protocol is used in conjunction with face-to-face interactions with psychologists to ensure each participant's comfort when being confronted by six traumatic situations. Survey results indicate that loss, family differences, financial difficulties, deadlines, witnessing a fatal accident, and mistreatment caused the most significant level of anxiety among all participants. The anxiety levels of the participants were measured before stimulation using the Hamilton Anxiety Rating Scale (HAM-A). Then, the EEG signal was recorded when the therapist described a situation for 15 seconds and participants were asked to recall for another 15 seconds. Afterward, participants were asked to assess their feelings during stimulation with the Self-Assessment Manikin (SAM). Valence and arousal score results from this method were then utilized to reevaluate participants' HAM-A results to determine their anxiety levels (Chatterjee et al., 2023). An overview of the experimental protocol for EEG recording is shown in Figure 2.

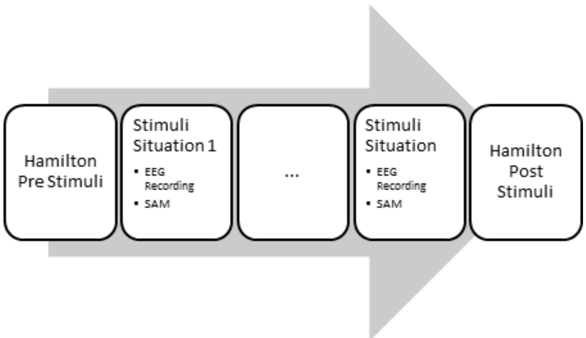

Figure 2. Anxiety Stimulation Experimental Protocol

B. Data Prepocessing

In the pre-processing stage, anxiety levels assessed by psychologists according to Hamilton scores are recategorized into two categories. Normal and light anxiety levels are categorized as mild, while moderate and severe anxiety levels are classified as severe. Consequently, ten participants with mild anxiety levels and 13 participants with severe anxiety levels were obtained from the first classifying, which consisted of four normal, six mild, six moderate, and seven severe participants. Furthermore, raw EEG signals are filtered to eliminate noise from powerlines that typically have a frequency of 50-60 Hz, as well as unwanted physiological signals such as electromyogram (EMG), electrocardiogram (ECG), and artifacts that result from minor movements of the body and the eyes [17]. For that reason, an FIR filter is applied to remove EEG signals with frequencies below 4 Hz and above 45 Hz. Figure 3 shows a sample of the filtered signal.

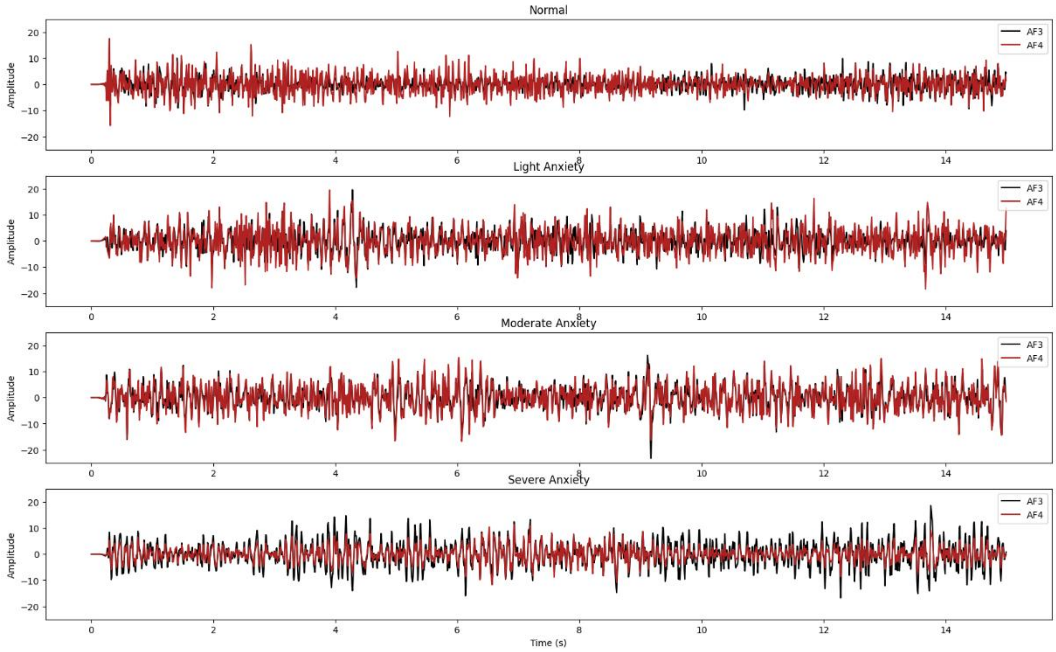

Figure 3. The EEG signals from the AF3 and AF4 channels at normal, light, moderate, and severe state-anxiety levels

Considering the 23 participants involved and six repetitions of the recording, there are 138 sets of 30-second signals available to be processed. Therefore, it is necessary to slice each EEG signal recording into shorter durations to multiply the amount of data for processing. In this study, the EEG signal was divided into 15-second and 1-second segments. Consequently, two data sets, 276 sets and 4140 sets, will be analyzed and compared for their effectiveness in detecting anxiety.

C. Feature Extraction

At the feature extraction stage, the cleaned signal will be analyzed to extract the information that characterizes anxiety severity. As part of this study, time, frequency, and time-frequency domains were extracted [18], [19].

1) *Time-domain Feature*

Time-domain feature extraction is the simplest computational signal analysis technique that observes signal amplitude change over a period of time. It applies a statistical-mathematical method to calculate the amplitude (x) of (N) samples of the EEG signal. The feature extraction techniques used in this study include mean absolute value (MAV), root mean square (RMS), and three Hjorth parameters (activity, mobility, and complexity) [20], [21]. The formula is as follows:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \quad (2)$$

$$activity(x(t)) = \frac{\sum(x_i-\bar{x})^2}{n-1} \quad (3)$$

$$mobility = \sqrt{\frac{activity(\dot{x}(t))}{activity(x(t))}} \quad (4)$$

$$complexity = \sqrt{\frac{mobility(\dot{x}(t))}{mobility(x(t))}} \quad (5)$$

MAV measures the average of the absolute value of a signal's amplitude. RMS measures the square root of the signal's average power for a given period. Activity measures the squared standard deviation of the amplitude, also referred to as the variance or mean power. A Hjorth parameter is the basic properties of EEG signals extracted from the amplitude variance and its derivatives. The variance of amplitude is referred to as activity. Mobility is a time-based feature that represents the average frequency of the signal, while complexity represents its change over time.

2) Frequency-domain Feature

Signal features in the frequency domain are obtained by estimating the power spectral density using Welch's method. Then, the average power frequency, variance, and square mean root are extracted for classification.

3) Time-Frequency Domain Feature

A frequency-time domain feature is extracted by evaluating the strength of the associated signal at a particular frequency-time point. This approach uses the Discrete Wavelet Transform (DWT), which is a discrete implementation of the wavelet transform. Signals are passed through a filter bank consisting of a series of low-pass and high-pass filters of Symlet9 [22]. As a result, several sets of multiresolution coefficients from various filter frequency ranges were obtained. The number of filters used indicates the signal decomposition level. In this study, five levels of decomposition were used, each representing a component of the EEG frequency band, i.e. the ($\delta, < 4\ Hz$), theta ($\theta,\ 4 - 8\ Hz$, alpha ($\alpha,\ 8 - 13\ Hz$), beta ($\beta,\ 13 - 30\ Hz$, and gamma ($\gamma, > 30\ Hz$) waves [23].

D. Anxiety Level Classification

After the signal features are extracted, machine learning models classify anxiety levels based on their features. In this process, 90% of the data is used for training and validation, and the remainder is used for testing. This study utilized Random Forest Classification and a one-dimensional Convolutional Neural Network as classifiers.

1) Random Forest}

Random Forest (RF) is a machine-learning method for classification and regression that is based on ensemble trees. The random forest classifier consists of a large number of decision trees that are randomly distributed and uncorrelated. A random forest makes predictions based on the most popular votes provided by each tree included [24].

2) One-Dimensional Computational Neural Networks}

Computational Neural Networks (CNN) is a learning algorithm composed of interconnected neurons [25]. As a development of the previous model, ANN, this algorithm overcomes complex computations when processing image data. Since it was introduced, CNN has shown excellent performance at recognizing patterns within images. Therefore, researchers are beginning to explore CNNs for processing one-dimensional data, especially in the study of non-stationary signals such as physiological signals [26]. For example, detecting arrhythmias from ECG signals [27], gene-based cancer prediction [28], EEG signals classification [29], etc.

Basically, the architectural components of a 1-D CNN are similar to traditional CNNs, which consist of input, hidden, and output layers. This model differs mainly in the size of the kernel, inputs, and outputs that are in a one-dimensional array. A raw 1D signal enters the model through the input layer and exits through the output layer. The outlet is a multilayer perceptron with the number of neurons equivalent to the number of classes. Three types of layers can be arranged to accomplish classification purposes for hidden layers. Among these are convolutional, pooling, and fully connected layers, each of which serves a different purpose [30]. A convolutional layer is the first layer in the CNN architecture, where input data is convolved into map features using a kernel. A pooling layer is usually used to reduce the dimension of a map feature after a convolutional layer. One strategy is to calculate the average or maximum value among neighbouring samples. The fully connected layer contains 90% of the CNN parameters and works like a traditional neural network. This layer transforms the neural network input into a vector of a predetermined length. In this case, the resulting vector will be used as a feature for classification.

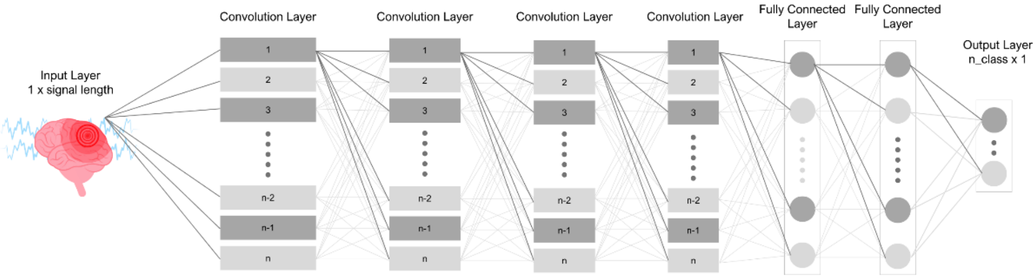

Figure 4. Illustration of 1-D CNN architecture with four convolution and two fully connected layers

In total, 90% of the data will be used for training and validating the classification models. Validation for random forests applies a stratified K-Fold with ten folds to maintain data class proportion. As for CNN, the data for this validation is taken from 10% of the training data which was set aside. Consequently, the remaining 10% of the data is used to test the model.

III. Result and Discussion

This study aimed to develop an alternative framework to detect state anxiety using EEG signals recorded from wearable devices. The data was obtained from A Database for Anxious States based on Psychological Stimulation (DASPS) with anxiety levels classification according to the Hamilton Anxiety Rating Scale (HAM-A) [16]. The dataset includes 138 recordings, including 24 normal conditions, 36 light anxieties, 36 moderate anxieties, and 42 severe anxieties. Due to the small amount of data, each recording was sliced into 1-second lengths to avoid overfitting, resulting in a total of 4140 records. In anticipation of unbalanced proportions in the four data classes, as shown in Figure 4 these anxiety levels were regrouped into two classes. Normal and light anxiety are regrouped together as light anxiety, whereas moderate and severe anxiety are regrouped as severe anxiety.

A comparison of anxiety detection accuracy scores with these two signal durations is provided in Table 1. The results revealed that a 1-second EEG signal performed better than a 15-second signal. The amount of data used affects the performance of the detection model since 3726 data were used for training and 414 data were used for testing. Accordingly, 1-dimensional CNN can be regarded as a suitable classification algorithm for anxiety detection. The model generated high accuracy scores when detecting four and two anxiety levels, with 86.11% and 90.17%, respectively. Despite this, the number of features will be too large for repetitive tasks in the future since 630 features are employed. Therefore, each of these frameworks is further explored by providing feature inputs based on the corresponding domain to achieve the most efficient model.

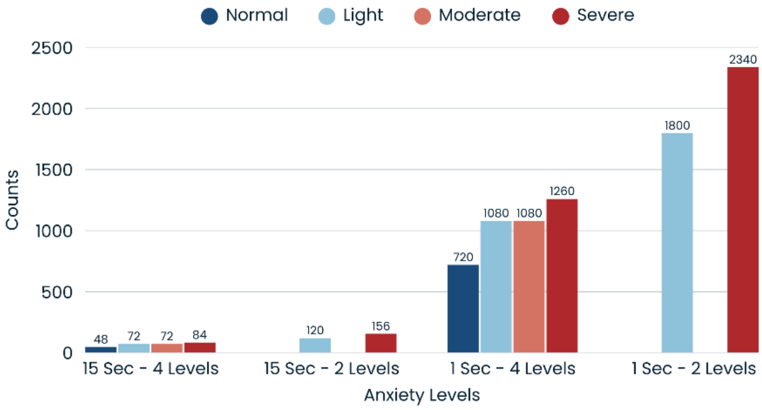

Figure 5. Distribution of anxiety classes at two and four levels based on HAM-A Scores for fifteen and one second ling EEG signal

Table 1.
A Comparison of State Anxiety Detection Results Using Random Forest (RF) and 1-Dimensional Convolutional Neural Network (1-D CNN)

Duration	Anxiety Levels	Model	Accuracy (%)	F-1 Score (%)	Sensitivity (%)	Specificity (%)
1 sec	2 Levels	1-D CNN	90,17	90,21	90,59	89,74
		RF	89,37	89,15	91,02	87,22
	4 Levels	1-D CNN	86,11	86,03	89,81	96,75
		RF	80,07	79,92	82.41	82,41
15 sec	2 Levels	1-D CNN	87,50	87,50	87,50	87,50
		RF	71,43	67,25	93,75	41,67
	4 Levels	1-D CNN	79,41	79,55	100,00	87,50
		RF	75,00	74,91	100,00	75,00

Table 2.
A Comparison of 1-D CNN's Classification Accuracy Based on The Features Selection

Anxiety Levels	Feature	#Features	Accuracy (%)	F-1 Score (%)	Sensitivity (%)	Specificity (%)
2 Levels	All Features	630	90,17	90,21	90,59	89,74
	Frequency	42	89,96	89,95	89,32	90,59
	Time	70	95,09	95,09	95,29	94,87
	Time-Frequency	518	87,61	87,61	86,32	88,88
4 Levels	All Features	630	86,11	86,03	89,81	96,75
	Frequency	42	89,48	89,52	95,00	97,48
	Time	70	94,84	94,84	98,31	99,19
	Time-Frequency	518	87,30	87,27	92,92	97,54

The 630 features consist of 70 time features, 42 frequency features, and 518 time-frequency features. Following this, each group of features is used as input to compare the accuracy of its performance in detecting anxiety. The results of this observation are presented in Table 2. A time feature extracted from 14 EEG channels provides the highest accuracy with an improvement of 5-8% over the number of features that are only 10% of its original. The accuracy score obtained, 94.84% for anxiety detection at the 4-level and 95.09% for anxiety detection at the 2-level, were superior to previous studies using frequency and random forest features [14]. Table 3 presents a comparison between the proposed and prior models.

Table 3.
A Comparison of The Proposed Model's Performance with Other DASPS-based Studies

Ref	Anxiety Levels	Feature (n)	Classifier	Accuracy	F-1 Score (%)	Sensitivity (%)	Specificity (%)
[13]	2 Levels	All Features (318)	SSAE	89,93	#NA	#NA	#NA
	4 Levels	All Features (318)	SSAE	70,25	#NA	#NA	#NA
[14]	2 Levels	Frequency (9)	RF	94,90	93,00	94,00	94,00
	4 Levels	Frequency (10)	RF	92,74	90,00	88,75	96,75
Our	2 Levels	Time (70)	CNN	95,09	95,09	95,29	94,87
	4 Levels	Time (70)	CNN	94,84	94,84	98,31	99,19

Overall, DASPS data is still challenging for researchers when developing models to produce the most accurate performance. In a study conducted by [13], only 83.93% of anxiety levels could be accurately classified by SSAE. Nonetheless, when more levels of anxiety are considered, such as normal, mild, moderate, and severe, this model's accuracy decreases to 70.25%. The following year this accuracy score improved to 92.74% and 94.90% by extracting no more than 10 frequency features from the AF3, AF4, FC5, FC6, P7, and P8 channels. The study applied the Random Forest algorithm to identify anxiety levels. Further, this study improved the accuracy score of a state-anxiety classification model using a one-dimensional CNN algorithm.

The proposed model shows significant improvement when compared to its predecessors in terms of accuracy, F1 score, sensitivity, and specificity. The 1-D CNN model reliably identifies two types of anxiety levels. For both the classification of two and four anxiety levels, the score difference across all metrics is no more than five percent. Further, when compared to the model presented in [14], the proposed model outperforms in identifying mild, moderate, and severe stress conditions, as indicated by its sensitivity scores. Additionally, in terms of specificity—the model's ability to accurately detect non-stress conditions—the proposed model achieves better results with an error margin of less than one percent.

In general, 1-Dimensional Convolutional Neural Network (1-D CNN) is effective in recognizing anxiety levels when compared to Sparse Autoencoder (SSAE) and Random Forest (RF) classifiers. This study provides evidence that adapting the CNN architecture to a one-dimensional format benefits the classification of one-dimensional data, such as EEG signals. This finding supports CNN as a robust algorithm capable of handling cross-domain data classification, whether images or signals. However, regarding efficiency, the RF classifier exhibits higher performance with 85% fewer features required than this study, which was 70 features. Nevertheless, both models need further evaluation to compare their computing efficiency, particularly concerning time and memory usage.

IV. CONCLUSION

The paper presents an analysis of EEG data recorded during exposure therapy and using an Emotiv EPOC headset to develop a two and four levels anxiety classification framework. This study compared the performance of several possible frameworks based on the extraction of signal features from signals with durations of one second and fifteen seconds and classification by random forest and CNN. Results showed that CNN was the most effective algorithm for detecting two levels and four levels of anxiety from 1-second EEG signals with accuracy scores of 90.17% and 86.11%, respectively. This model requires 630 features consisting of time, frequency, and time-frequency features. The model is further explored for classification based on each feature domain to reduce the number of necessary features. According to the results, anxiety detection using their statistical features had the highest accuracy for 2 and 4 anxiety levels, 95.09% and 94.84%, respectively. In the future, the model needs to be tested using data from various EEG devices to ensure its reliability against a wide range of device types.

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