Assessing Neural Patterns of Anxiety Using Deep Learning: An EEG Study

Hamidreza Ghonchi[1], Tom Foulsham[2], Saideh Ferdowsi[1]

***Abstract*—Anxiety can have a profound effect on our lives. People may experience different levels of anxiety ranging from mild to severe, and psychologists and psychiatrists mainly rely on self-report questionnaires to measure this. However, new computer-aided technologies and neuroimaging techniques could significantly help them to verify their diagnosis. In this paper, a novel deep learning model is designed to precisely screen electroencephalogram (EEG) signals to characterise the neural patterns associated with anxiety. Our deep learning model integrates a convolutional neural network, an attention module and a recurrent neural network to effectively estimate the EEG features signifying normal and anxious emotions. In order to improve the performance of the model, we adopted a data transformation approach to generate a spatio-temporal representation of EEG data. We evaluated the performance of our proposed model using a publicly available EEG data set acquired from 23 subjects who reported feeling normal or anxious. Anxiety was further categorised into four sub-groups based on the level of anxiety. The model achieved a classification accuracy of 94.24% and 92.58% for binary (i.e normal and anxious) and multi-class (i.e normal, light, moderate and severe anxiety) scenarios, respectively. The obtained results indicated the success of our proposed model in learning EEG patterns across various levels of anxiety. Additionally, comparing the obtained results with previously published studies demonstrated considerable superiority of our method.**

***Index Terms*—Electroencephalogram, Anxiety Detection, Deep Learning, Mental Health, DASPS**

I. Introduction

ANXIETY is a pervasive mental health issue that is intricately linked with stress. Although stress and anxiety can be considered natural brain responses to various conditions, they may have negative and dangerous effects on people's lives if they remain untreated.

Identifying anxiety in its early stages plays a crucial role in mitigating potential long-term consequences [1], [2].

Neural signals such as EEG can significantly help in diagnosing stress and anxiety by capturing brain and body excitability levels [3]. While traditional questionnaire-based approaches have limitations, modern methods such as neuroimaging and machine learning offer sustainable solutions for anxiety detection [1]. EEG emerges as a pivotal tool in investigating mental disorders like anxiety, offering high temporal resolution and revealing power spectral density (PSD) modulations associated with generalized anxiety disorder (GAD) [4].

Several attempts have been made to identify anxiety and its level using EEG. The DASPS data set, which is publicly available, provides a great opportunity for researchers to investigate the application of machine learning methods in this context. DASPS stands for "A Database for Anxious States based on Psychological Stimulation" [5]. In this dataset, two main labels, "normal" and "anxious", were used to categorise the trials into groups. In addition, four labels comprising "severe anxiety", "moderate anxiety", "light anxiety", and "normal anxiety" were provided to divide the anxious category into four subclasses, based on subject self report. In a recent study, Chatterjee et al. [6] used DASPS to detect and classify anxiety. They used labels provided by the dataset to classify EEG trials into 2 (normal and anxious) and 4 (normal, light, moderate, and severe anxiety) classes using time and frequency domain features. Support vector machine (SVM), K-nearest neighbour (KNN), random forest (RF), decision tree (DT) and gaussian naive Bayes (GNB) were employed in this work for classification. The results indicated that KNN had the highest accuracy of 83.8% for both binary and multi-class classifications. In another study, Daneshmand et al. [7] introduced a technique based on the Chebyshev chaotic map for anxiety classification using the DASPS dataset. They used DT and KNN as classifiers. The results showed that KNN achieved 93.75% and 100% accuracy for binary and four class classification respectively. A study by Muhammad et al. [8] proposed an anxiety assessment framework using frequency domain features to assess different levels of anxiety measured by the DASPS dataset. They used several classifiers and achieved the highest accuracy by random forest 94.90% 92.74% for 2 and 4 classes respectively.

Compared to the above methods that relied on traditional machine learning approaches, deep learning (DL) has also shown promising performance in EEG analysis [9]–[11]. The main benefit of deep learning is its ability to learn complex EEG patterns with no need for feature estimation methods which gives DL-based methods more independence and adaptability. Maheshwari et al. [9] employed diverse EEG datasets to detect various types of emotions. Their work involved developing a rhythm-specific multi-channel convolutional neural network (CNN). They trained their model using five different EEG frequency bands (i.e. delta, theta, alpha, beta, and gamma). Their proposed model achieved 53.45% for classifying DASPS trials into normal and anxious classes. Similarly, Agarwal et al. [10] utilized a $1D$ convolutional long short-term memory (LSTM) network and several datasets to classify emotions using EEG signals. They also investigated how the accuracy of the classification is distributed across different scalp regions. Their results indicated that deep learning can successfully classify different emotional states observed by EEG. The obtained accuracies for DASPS data set were 71.93% and 71.63% for binary and four class classification respectively. In another study, Shikha [11] employed a stacked sparse autoencoder to classify anxiety using EEG signals collected by DASPS dataset. They extracted features

[1]School of Mathematics, Statistics and Actuarial Science, University of Essex, Colchester, UK. hg23552@essex.ac.uk

[2]Department of Psychology, University of Essex, Colchester, UK.

from different domains, including time, frequency, and time-frequency. Their deep learning model achieved an accuracy of 83.93% for classifying normal and anxious trials.

The current paper introduces a novel deep learning model designed to detect and classify anxiety states collected by the DASPS data set. We used the labels suggested by [5] to classify EEG trials into two and four classes. Our proposed deep learning model autonomously extracts optimal features directly from raw data, eliminating the need for manual feature extraction. While traditional pre-processing steps are essential for noise reduction, they can introduce biases and limitations. By eliminating pre-processing and feature extraction, the methodology preserves raw EEG integrity and facilitates a direct analysis of neural dynamics. As a consequence, the method would be more adaptable across diverse datasets. The subsequent sections describe the details of the proposed method. Section III presents the obtained results and section IV concludes the paper.

II. Material and Methods

A. Dataset

The dataset utilized in this paper is DASPS dataset and is provided by IEEE DataPort[1] [5]. This dataset introduces an innovative methodology by capturing Electroencephalogram (EEG) signals from 23 participants during the induction of anxiety through face-to-face psychological tasks. The experimental design of the DASPS dataset includes six trials for each subject, with each trial comprising two main phases, each lasting 15 seconds. In the first phase of each trial, the participant listens to an emotional scenario described by a psychotherapist. In the second phase of each trial, the participant tries to recall the scenario received in phase one. After completing each trial, the participant is asked to rate the feeling using the Self Assessment Manikin (SAM) which assesses both valence and arousal. According to the measured levels of valence and arousal, the trials were labelled as normal or anxious. Categorising the trials by two labels led to obtaining 67 normal and 71 anxious trials. Additionally in another labelling attempt, the anxious trials were categorised into four groups including normal, light, moderate and severe. In the second labelling attempt, 65 trials were identified as normal, 43 trials were identified as light anxiety, 15 trials were labelled as moderate anxiety and 15 trials were identified as severe anxiety. More details about this data set can be found in [5].

B. Data Analysis

Our proposed data analysis pipeline consists of four major steps: *i*) filtering *ii*) scalp maps generation *iii*) windowing and *iv*) training and classification. The main novel part of the data analysis pipeline is the proposed deep learning model that has been used in step *iv*.

1) Filtering: this stage was performed using a band-pass filter with cut-off frequencies 12 Hz and 25 Hz to extract beta-waves from collected EEG signals. Employing a band-pass filter enhances the quality of EEG signals by removing irrelevant components such as muscle activity, slow drifts and environmental noise. Additionally, it aids the identification and analysis of the brainwave patterns that are associated with cognitive states representing emotional processing in the brain [6], [12], [13].

[1]https://ieee-dataport.org/open-access/dasps-database

TABLE I
The conversion function used in our study to transfer the EEG potentials recorded by 14 electrodes at time t to a 2D spatial map. The conversion is performed by replacing the name of each electrode in the table with the recorded potential.

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	AF3	0	AF4	0	0	0	0
0	F7	0	F3	0	0	0	F4	0	F8	0
0	0	FC5	0	0	0	0	0	FC6	0	0
T7	0	0	0	0	0	0	0	0	0	T8
0	0	0	0	0	0	0	0	0	0	0
0	P7	0	0	0	0	0	0	0	P8	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	O1	0	O2	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

The extracted beta waves were then normalised using a z-score for further analysis. After filtering, we assigned labels to the trials according to the procedure presented in [5].

2) scalp maps generation: The EEG signals collected from each participant at each trial can be represented by a $M \times N$ matrix, where M and N represent the number of electrodes and time samples respectively. However, this representation does not provide any spatial information about the data. To address this limitation, we generated a spatial scalp map illustrating the spatial relationship of electrodes in two-dimensional space. To achieve this purpose, we used the conversion function outlined in Table I to transfer the EEG potentials recorded at each time sample t across the scalp to a 11×11 spatial map. This function is constructed based on the positions of the electrodes in the standard $10-20$ EEG system. Since 14 electrodes were used by this dataset, the conversion function includes the spatial information of these electrodes. A similar procedure was employed in relevant studies such as [14], [15]. At the end of this stage, N scalp maps, each has 11×11 spatial resolution, are obtained for each participant.

3) Windowing: The sliding window is one of the best feature extraction techniques that can be used in combination with deep neural networks. It can improve the accuracy by providing a more descriptive presentation of EEG temporal dynamics. Additionally, a sliding window helps to increase the quantity of the training data which significantly affects deep learning performance. Selecting the appropriate size for the sliding window is a challenging task and may lead to different outcomes. In this paper, various sliding windows whose sizes are changed within $100ms - 3s$ were used to identify the optimal size. It should be noted that there was no overlap between the adjacent windows. Using this approach, each trial's phase is divided into several segments each includes a sequence of scalp maps. We call this sequence a data clip. On the other hand, using the conversion function and sliding window in a cascade form leads to achieving a spatio-temporal representation of data that can be beneficial in the exploration of the temporal dynamics of anxiety states using EEG and deep learning.

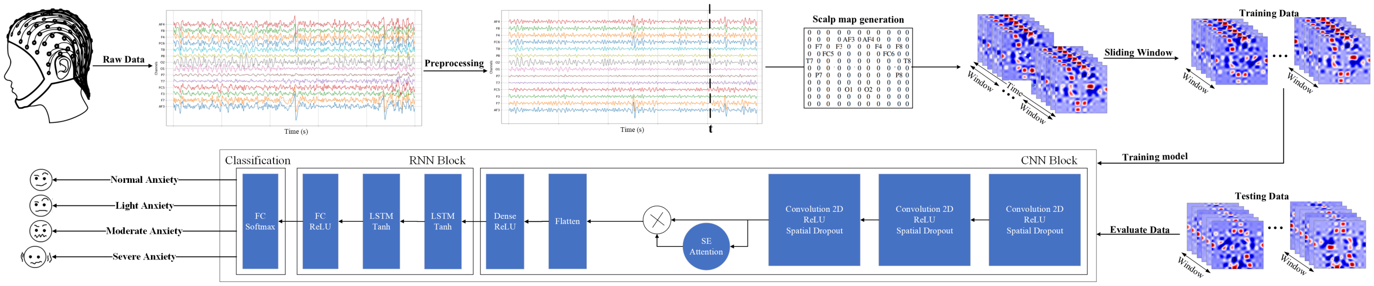

Fig. 1. Overall procedure of the proposed anxiety detection and classification using the proposed deep learning method.

C. Proposed Deep Learning Model

In this section, our novel deep learning architecture is described. This model is proposed to address the challenging task of anxiety detection and classification using EEG signals. Our proposed model integrates convolutional and LSTM layers to extract spatial and temporal features, respectively. The attention module was also added to the model to dynamically focus on salient brain signals' patterns. The deep learning architecture proposed in this paper comprises of three distinct blocks, as shown in Figure 1. The initial block includes three consecutive convolutional layers used for spatial pattern recognition. All three layers within the first block, operate as two-dimensional convolutional layers and play pivotal roles in extracting spatial features from the scalp maps using various filters and kernels. The first two convolutional layers are equipped with F_1 filters and a 3×3 kernel. As a result of employing the Rectified Linear Unit (ReLU) activation functions for each filter, this layer delves into the intricacies of spatial patterns, enabling the network to discern and understand diverse local features of input data. The third two-dimensional convolutional layer further refines the model's understanding of the features extracted by the preceding layers. To this aim, F_2 filters which represents twice the quantity utilized in the preceding layer, and a 3×3 kernel were used by this layer to capture more detailed spatial patterns. To mitigate overfitting, three types of regularizers were implemented on each convolutional layer. These include kernel regularization using $L1$ and $L2$ methods, bias regularization, and activity regularization using $L2$ method. Additionally, to further enhance regularization, each layer is supplemented by a Spatial Dropout layer with dropout rates of D_1, D_1, and D_2, respectively. This comprehensive regularization strategy aids in stabilizing the training process. Moreover, it improves the model's generalization performance by preventing the network from relying on specific features and patterns of the data. The last convolutional layer is followed by a SE Attention Module. This module is used to further enhance the important spatial features by adaptively selecting relevant features before moving to the next stage. The flatten layer prepares the multi-dimensional feature maps for further processing and keeps the temporal dimension. The dense layer with F_3 neurons and Relu activation function serves as a feature transformation step which refines the extracted spatial features before they proceed to the next block. This layered approach enriches the model's understanding of spatial information within the data. It also facilitates the extraction of intricate spatial features that are crucial for accurate analysis. The incorporation of ReLU activation functions at each layer ensures non-linearity by enabling the model to capture complex relationships and nuances within the spatial data representations.

The uniqueness of this architecture lies in the squeeze-and-excitation (SE) attention module which dynamically recalibrates feature maps. This module emphasizes vital spatial information while suppressing less relevant details. In the initial step, global information is extracted across spatial features. This process involves performing average pooling on each extracted feature using convolutional layers. The recalibration is achieved using channel-specific weights estimated by the sigmoid activation functions and enhances the discrimination among EEG features associated with different classes. This strengthens the contribution of informative features while attenuating the impact of uninformative ones [16].

The second block focuses on temporal features by employing LSTM Layers utilising tangent hyperbolic activation functions. The first LSTM Layer with C_1 units captures temporal dependencies within salient spatial feature maps that enable the model to understand sequential patterns. The second LSTM Layer with C_2 units further refines the temporal features and enables the model to extract more complex temporal relationships. The subsequent dense layer with F_3 neurons integrates the temporal information into a more compact representation. Combining CNN and LSTM blocks in our model leads to obtaining a feature vector that includes both temporal and spatial features of brain activity when it is processing different anxiety states.

The classifier block includes a Dense Layer with 2 or 4 neurons and a softmax activation function. 2 refers to normal and anxious classes and 4 refers to normal, light, moderate and severe anxiety classes.

III. Experimental Results

In this section, the performance of the proposed model to detect and classify different anxiety levels using the DASPS dataset is evaluated. We also compare our results with existing methods used on this data set to demonstrate the effectiveness of our model. A summary of all parameters and setups used in this study is presented in Table II. For the model setup, we employed binary cross-entropy as the loss function and the RMSProp optimizer. We trained the model over 300 epochs and utilized k-fold cross-validation with $k = 5$. This approach ensures robust evaluation and enhances the reliability of our findings in classifying anxiety levels. To evaluate

TABLE II
PARAMETERS AND SETUPS USED FOR TRAINING MODEL.

	Parameter Name	Value
Data preparation	Band-pass filter	12-25 Hz
	Normalization	Z-score algorithm
	Window size (seconds)	$0.1, 0.25, 0.5, 1, 2, 3$
Proposed Model	F_1	25
	F_2	50
	Convolution kernels	3×3
	Convolution activations	ReLU
	D_1	50%
	D_2	30%
	F_3	256
	LSTM activations	Tanh
	C_1	64
	C_2	32
	Classifier	Softmax
	Loss	Binary Cross Entropy
	Optimizer	RMSProp
	Epochs	300
	Batch size	32
	K-fold	5

TABLE III
THE COMPARISON OF ACCURACY WHEN SEVERAL WINDOW SIZES WERE USED FOR GENERATING DATA CLIPS.

Window size	2 classes ($acc \pm std$)	4 classes ($acc \pm std$)
15 samples (100 ms)	$93.39\% \pm 0.72\%$	$92.15\% \pm 0.40\%$
26 samples (200 ms)	**94.24%** $\pm 0.33\%$	**92.58%** $\pm 0.52\%$
32 samples (250 ms)	$94.04\% \pm 0.24\%$	$92.52\% \pm 0.28\%$
64 samples (500 ms)	$93.38\% \pm 0.62\%$	$90.77\% \pm 1.47\%$
128 samples (1 s)	$89.38\% \pm 2.22\%$	$83.76\% \pm 2.99\%$
256 samples (2 s)	$70.58\% \pm 2.21\%$	$60.34\% \pm 2.09\%$
384 samples (3 s)	$62.84\% \pm 1.47\%$	$55.58\% \pm 2.11\%$

the performance of the proposed deep learning model, we conducted several experiments using various sliding windows whose sizes change within $[100ms - 3s]$. As described in section II-B, the sliding window technique is used to generate scalp map clips representing a spatio-temporal visualisation of EEG dynamics. Various window sizes lead to obtain scalp map clips whose temporal dimensions are different. The main objective of evaluating the model's performance using data clips with different temporal sizes is to identify the most optimal window size. Table III presents the accuracy rates obtained for 2 classes and 4 classes classification associated with different window sizes. The reported results are the average accuracy rates across all five folds.

The results revealed that the best accuracy is obtained when the size of the sliding window is $200ms$. The proposed model achieved 94.24% accuracy for classifying normal and anxious conditions and 92.58% accuracy for classifying four anxiety levels (i.e. normal, light, moderate and severe). Our findings suggest that smaller window sizes may yield superior results. Several factors contribute to this phenomenon. Firstly, a smaller window size results in a larger number of scalp map clips that are used to train the model. Additionally, with a smaller window size, such as 100, 200, or $250ms$, the number of scalp maps included in each clip decreases, which enables the capture of rapid fluctuations in beta oscillations, leading to simplified training by reducing the complexity of the learning process. However, as the results show, decreasing the size of the sliding window to $100ms$ presents the model with a challenge. One notable issue is the potential loss of temporal content when using smaller window sizes, which may hinder the model's ability to capture long-term dependencies and subtle temporal dynamics within the EEG signals. In contrast, with larger window sizes such as 1, 2, or $3s$, multiple beta oscillations can fit within each window. This capacity to encompass multiple oscillations may inadvertently smooth over rapid changes, resulting in a loss of temporal resolution. Consequently, this smoothing effect can pose challenges for the model in discerning complex patterns within the data.

As evident from Table III, the accuracy of categorising four classes is lower compared to that of two classes. This discrepancy can be attributed to several factors related to the pattern of EEG signals assosiated with these conditions. As discussed in Section II-B3, in the case of two classes, distinguishing between the anxious and normal states represents a clear binary classification task. However, in the context of four classes, the anxious state is subdivided into four distinct categories, each representing different levels of anxiety. Consequently, these classes exhibit greater similarity to each other, resulting in more difficulty for the model to accurately distinguish them. Moreover, the increased number of classes introduces additional complexity to the classification task, requiring the model to identify subtle differences between the various anxious states, which may contribute to the observed decreased accuracy. Additionally, the presence of more classes may lead to increased class imbalance, further complicating the classification process. We had a balanced classification in the 2 class implementation due to having 67 and 71 normal and anxious trials. However, the 4 class implementation faced the challenge of dealing with imbalanced data. We tackled this issue by ensuring that sufficient data from each class is included in both training and testing rounds. Importantly, our results revealed that the proposed deep learning model can learn the pattern of data effectively.

We also compared the performance of our proposed model with methods previously used with the DASPS data set for anxiety classification. Table IV provides a summary of all methods used this data set. Upon review of the table, it becomes evident that many previous studies on this dataset have predominantly utilized feature extraction methods and traditional machine learning algorithms. Muhammad et al. [8] and daneshmand et al. [7] achieved the highest accuracy among the researchers who focused on traditional machine learning approaches. Notably, two references ([9], [10]) opted to directly feed raw data into their deep learning models for anxiety classification, albeit after applying varying preprocessing steps to the data. However, their performance was considerably weaker than traditional machine learning-based studies. This diversity in methodologies underscores the ongoing exploration of diverse approaches in the field, aiming to enhance the accuracy and reliability of anxiety classification models.

Comparing the results indicated that our proposed model achieves promising accuracy in both two and four classes. Unlike traditional approaches relying on feature extraction, our method focuses on data representation and utilizes $200ms$ segments for anxiety classification. This is a major benefit because feature extraction is a labour-intensive process which

TABLE IV
THE COMPARISON OF DIFFERENT METHODS.

State-of-the-arts	# Classes	Features	Classifier	Accuracy
Baghdadi et al. [5]	2 classes 4 classes	Time, Frequency, and Time-Frequency features	Stacked Sparse Autoencoder	83.50% 74.60%
Maheshwari et al. [9]	2 Classes	No features	CNN	53.45%
Agarwal et al. [10]	2 classes: Valence 2 classes: Arousal	No features	1D CNN-LSTM	71.93% 71.63%
Chatterjee et al. [6]	2 classes 4 classes	Hjorth parameters and 4 EEG band powers	KNN	83.8% 83.8%
Shikha et al. [11]	2 classes	Time, Frequency, and Time-Frequency features	Stacked Sparse Autoencoder	83.98%
Jin et al. [12]	2 classes 4 classes	Time-Domain and Frequency-Domain analysis	Random Forest	78.34% 70.45%
Daneshmand et al. [7]	2 classes 4 classes	Innovative Chebyshev chaotic map-based features	KNN	93.75% 100%
Muhammad et al. [8]	2 classes 4 classes	Asymmetry index, rational index, and mean power	Random Forest	94.90% 92.74%
Proposed method Proposed method	2 classes 4 classes	No features	2D CNN-LSTM	94.24% 92.58%

needs necessary specialized expertise. In contrast, our deep learning model autonomously identifies and extracts optimal features from the data, enabling it to effectively distinguish between two or four anxiety classes without the need for human intervention in feature selection. Additionally, this capability gives an excellent adaptability to our method to be applied to different data sets.

IV. CONCLUSION

This study proposed a novel deep learning approach to address the challenge of detecting anxiety and identifying its levels based on EEG. Here, we used a data analysis pipeline including filtering, data preparation, model training and classification. In the first stage, a bandpass filter was used to extract the beta rhythms from raw data. Then a spatio-temporal conversion approach was used to generate the training data set. Not only did this conversion incorporate the spatial information of EEG recording into data, but also it increased the volume of training data which significantly improved the effectiveness of our model. The performance of the proposed method was examined using a $5-$fold cross validation approach. The obtained results indicated that our proposed model notably outperforms the previously published deep learning methods. It should be noted that although our method competes with traditional machine learning techniques, it may be preferable due to being independent of extensive preprocessing and feature extraction procedures.

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