Psychological stress detection with optimally selected EEG channel using Machine Learning techniques

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Abstract

Psychological stress buildup can lead to mental disorders, early mortality, stroke and sudden cardiac arrest and therefore, timely stress detection is important for reducing human suffering. This study aims to present a novel methodology of using reduced channel Electroencephalogram (EEG) signals for cost-effective, convenient, minimally intrusive framework for psychological stress detection. In this study, we investigate the feasibility of using 8-channel EEG configuration consisting of FT9, O1, FC6, Fp2, Oz, F4, T8 and C3 electrodes, selected based on Genetic Algorithm, for psychological stress detection. The dataset of the study comprises 28 healthy subjects (16 males and 12 females, age 23 ± 2 years) and the stressors used are real-life examination stressor and arithmetic stressor. The best results are obtained by classifying the data using machine learning based Support Vector Machines (SVM) classifier achieving highest accuracy 87.50%, sensitivity 81.25%, specificity 92.05% and with wavelet scattering features and SVM achieving highest accuracy 87.50%, sensitivity 82.81%, specificity 90.91%. These methodologies outperformed shallow Convolutional Neural Networks (CNN) based approach that achieved highest accuracy 84.18%, sensitivity 87.5%, specificity 81.76% with mean accuracy of 83.66% using 10-fold cross-validation. This shows the potential of a using only 8 EEG electrodes for reliable psychological stress detection. These results are encouraging for the development of automated stress detection systems for rapid detection in the home or outside the clinic.

Keywords

Psychological stress detection, reduced channel EEG, wavelet scattering, SVM, CNN

1. Introduction

Psychological stress refers to a state where complex dynamic equilibrium of human body, homeostasis, is perceived to be threatened by internal or external adverse or demanding circumstances known as stressors. Stress refers to the organism's total reaction to resource mobilization due to stressors. The previous studies associate stress with early mortality and increased biological age [1], mental disorders [2], sudden cardiac arrest [3,4], stroke and other physical health problems [5]. As per the reports of World Health Organization (WHO), there were around 1 billion people living with a mental disorder in 2019; moreover, depressive and anxiety disorders increased by more than 25% due to pandemic and treatment gap widened owing to disrupted mental healthcare services [6]. A recent study in Norway found that mental disorders are widespread in the student population. About one in three students, meets the formal criteria for a current mental disorder and four out of ten females have a mental disorder [7]. Globally, the high prevalence of mental health issues leads to huge economic burden due to decrease in productivity and associated healthcare costs. The women suffer disproportionately with high prevalence of mental health problems as compared to the male counterparts [8], emphasizing the

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need to timely detect psychological stress in diverse populations. Therefore, unlike previous stress and mental-health male-centric studies [9,10], the present study design involves data acquisition from male and female subjects. Moreover, around 50% of global population lives in countries that has 1 psychiatrist for more than 200000 people [11]. Therefore, it is important to increase reliability and dependance on digital technologies in mental health diagnosis and interventions. A computer-aided automated stress detection system can be useful in pre-screening for reducing burden on already-stressed mental healthcare infrastructure.

Electroencephalography (EEG) signals measure the electrical activity of the brain and are used as an analytical tool for differentiating normal from abnormal brain function. Making an accurate prediction using EEG data requires an extensive expertise, time and effort when done manually. However, with the advancements in Machine Learning (ML) and computational technologies, it is possible to automate this process, resulting in faster more efficient analysis of EEG data. Therefore, this study relies on ML-based classifiers and recently proposed wavelet scattering-based features for psychological stress detection from EEG signals.

Recent works in the field of psychological stress detection using EEG signals include- a study focusing on spectral analysis of frontal lobe EEG signals [12] that used features extracted using Fast Fourier Transform for spectral analysis of frontal lobe EEG signals and reported very good results. An interesting study [13], utilized short-duration EEG signals decomposed using stationary wavelet transform for extracting entropy-based features and used whale optimization algorithm for SVM parameter tuning, reporting the methodology suitable for stress detection. Another study [14] that used images of EEG signals, explored the potential of StressNet for stress detection. The alpha band comprising of 8 – 13 Hz and the frontal alpha asymmetry feature is found suitable for stress detection [15]. A recent comprehensive review covers wide set of methods for stress detection and mental health monitoring using EEG signals [16]. Another review [17] showed that the lack of consistency in procedure, lack of guidelines, varied duration of experiments, different feature extraction techniques and different classifiers may lead to conflicting outcomes. Therefore, despite a large number of studies involving EEG signals and mental stress, there exists no conclusive guidelines about the relevance between EEG features and its extraction methods, filtering, and artifact removal. In addition to this, the optimized minimum number of channels of EEG signals required for stress detection is also a current knowledge gap.

This forms the motivation of this study, as it aims to investigate the feasibility of using reduced channel EEG signals for stress detection application. A drastic reduction to 8 EEG electrodes will be beneficial in designing EEG solutions that are convenient to use, minimally intrusive, cost-efficient, computationally efficient with significantly reduced EEG setup times and will be a step towards making EEG-based systems suitable for homecare environment. In line with this, the present study proposes a methodology for reliable psychological stress detection using 8 electrode EEG configuration.

The sections of the paper are arranged as follows: Section 1 gives an introduction of the problem description, motivation of the study and prior works in the field; Section 2 covers the detailed data acquisition protocol and procedure, the techniques- wavelet scattering, convolutional neural networks and support vector machines classifier; Section 3 of the paper presents the results and discussions of this study and Section 4 is the conclusion of the study.

2. Methodology

2.1. Electrode nomenclature

For EEG analysis, each electrode is assigned a unique name, with the first letter indicating its location on the corresponding area of the brain. The letters translate as follows: Fp/pre-frontal, F/frontal, T/temporal, P/parietal, O/occipital, and C/central. Then, the electrodes are numbered increasingly with the distal direction from the midline sagittal plane of the skull. Even numbers are placed on the right side of the head, while odd numbers are kept on the left. This nomenclature will be further utilized in this study for referring to the electrodes in consideration. The acquired EEG signal consists of the difference in the voltage between the electrode in consideration and a reference electrode and this rhythmic fluctuation of potential difference is recorded.

2.2. Overall methodology

The initial step is to use publicly available SAM 40 EEG dataset [18] for selecting the optimum number of channels, for stress detection. This dataset was recorded from 40 subjects (14 females) with mean age 21.5 years using 32-channel Emotiv Epoc Flex gel kit. The stressors used are- arithmetic test, Stroop color-word test and symmetric mirror image identification. Thereafter, Genetic Algorithm was applied to select most suitable 8-channels for stress detection from these available 32-channels. For this, 15 random channel selections are initialized and each channel subset is described by 8 channels randomly picked from the 32 possible channels. The efficiency of these channels for stress detection is computed. After that, the five best performing channel subsets were selected for crossovers. This signifies making new subsets that inherit channels from the best performing channel subsets. The new subset's first four channels are picked randomly from one subset, and the last four from another. Each of the five channel subsets make one crossover This process is repeated for 10 generations in order to find the best performing channel subset. This procedure is based on [19] and in case of psychological stress detection, this framework is detailed in [20]. The identified 8 most suitable channels for stress detection are- FT9, O1, FC6, Fp2, Oz, F4, T8, C3.

The next step is using these 8 identified EEG channels (FT9, O1, FC6, Fp2, Oz, F4, T8, C3) for data collection from subjects and feasibility of these channels for stress detection is identified using three approaches: firstly, the acquired EEG data is used as an input to ML-based SVM classifier to differentiate stress from non-stressed state in EEG signals. Secondly, from the acquired 8-channel EEG signals, wavelet scattering based features are extracted and these features are used as input to SVM classifier for detecting the stressed and non-stressed state in EEG signals. Thirdly, the acquired dataset is also fed to a Convolutional Neural Network (CNN) and classification in stress and non-stress state is performed. The block diagram of the methodology is depicted in Figure 1 and detailed methodology is presented ahead.

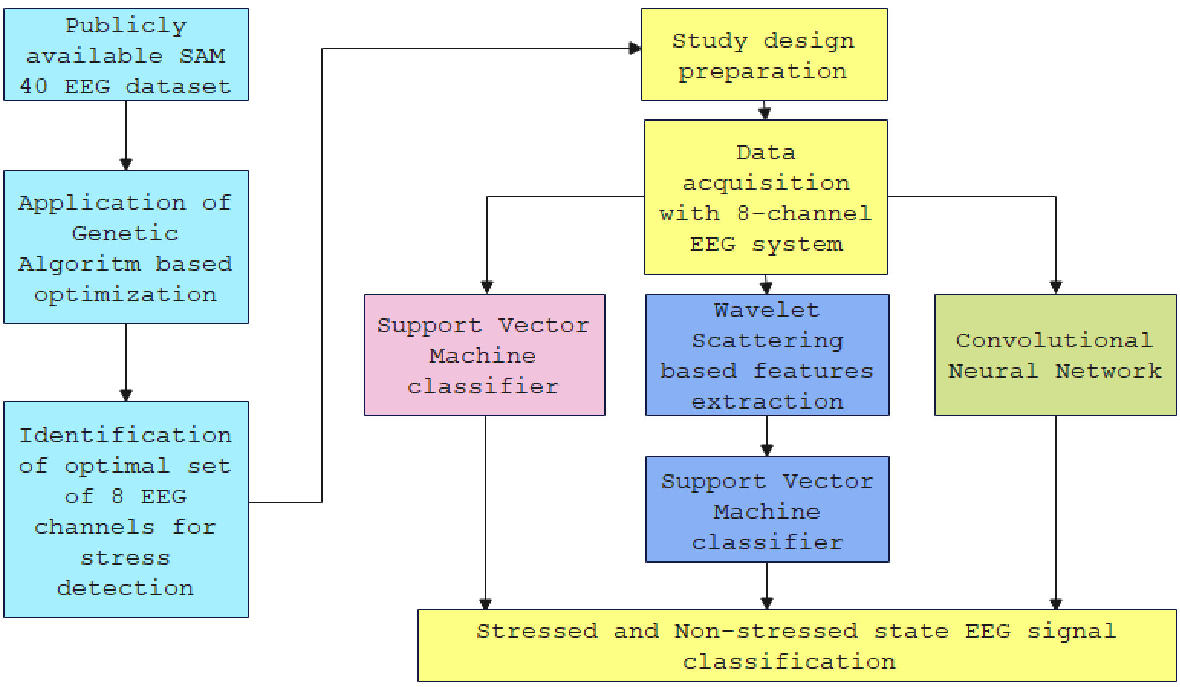


Figure 1: Block diagram depicting proposed methodology of using reduced channel EEG signal configuration for psychological stress detection

2.3. Data acquisition

Data acquisition, in the present study, was done using Mentalab Explore EEG device [21] with sampling frequency of 250 Hz. The EEG data was acquired with the identified optimal 8 channels from 28 healthy subjects (16 male, 12 female) in the age-group 23±2 years, who are students at Norwegian University of Science and Technology, NTNU, Norway. For every subject, 2 sessions (S1 and S2) of EEG recordings were carried out – S1 was before students' institute examination depicting the stressed state and S2 was conducted after Christmas holidays depicting the baseline state. Every session comprised two runs (R1, R2) of five-minute duration each of EEG recordings, where R1 was without arithmetic stressor, where the subjects were in resting state and were not involved in any tasks, whereas for R2 subjects performed an arithmetic test. All the recordings for the study were taken while the subjects were seated in a chair comfortably. The inclusion criteria of the study are presented ahead:

- The subject should be a student of NTNU with examination after S1 recordings
- No cardiovascular, neurological, mental disorder or other disease
- The subject is available to provide S1 and S2 data recordings

The psychological stress in S1 is the primary endpoint of study, and reduced EEG channel-based stress detection is the primary outcome of the present work. The data acquisition protocol for the study is presented ahead:

- The purpose of the study was explained and a written informed consent was taken
- The subject had to fill State Trait Anxiety Inventory (STAI) Y1 questionnaire prior to every recording
- Additionally, subjects also rated perceived stress in the range of 1 to 10 prior to each recording
- The EEG-cap was placed on subject's head
- Electrode location site was cleaned with isopropyl alcohol and a Q-tip.
- Electrical conducting paste was applied to the electrodes to ensure good electrical contact
- The reference electrode was fastened to the right earlobe with skin-friendly medical tape
- Mentalab's software was used to measure electrode impedances and low impedances are essential for quality recordings. The data acquisition setting for the present study is shown in Figure 2.

Figure 2: The data acquisition setting in this study

The subjects were asked to sit in front of a computer monitor at a distance where the arm of the subject can reach the keyboard without excessive body movement. During arithmetic test the students were presented arithmetic statements as presented below:

$$2 + (2/2) + (2x2x2)/2 = 8$$

The subjects had to make calculations in their head, without the use of pen and paper and press "T" if the statement was true and "F" if it was false. Markers were generated when the subject interacted with arithmetic test using a script in Psychopy, and the recordings were synced using Lab Streaming Layer.

It is important to note that although we had 28 subjects enrolled for this study, however a few subjects did not report for the session 2 recordings, which led to the number of recordings to be 103 instead of 112 (28 x 4) in ideal circumstances. As in this study, we are performing inter-subject analysis, this would not affect the findings of this study. However, if this study were to compare every subject's baseline with same subject's stressed state signal (intra-subject analysis), it would have been detrimental to the outcomes of the study due to exclusion of subjects that did not complete two session readings, leading to lesser availability of data. However, this was taken care of in the study design that aimed to conduct inter-subject analysis.

The EEG recordings were acquired with the 8 identified optimal electrodes highlighted in Figure 3 according to 10-20 system of EEG electrode placement. The study has the required approval from Norwegian Center for Research Data with reference number: 968653.

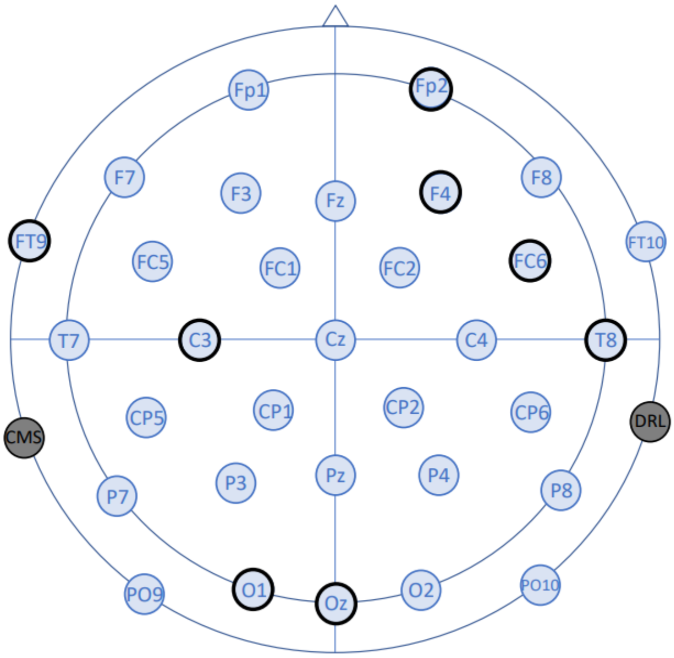


Figure 3: The 8 optimal EEG electrodes used for data acquisition in the study are highlighted

2.4. Data Labeling

The gold-standard used in this study for ascertaining the stress is STAI-Y1 self-report questionnaire. The STAI [22] has two questionnaires: Y1- for state anxiety and Y2- for trait anxiety. As the present study focusses on present psychological state and not the trait of the subjects, STAI-Y1 is used in this study. The subjects also reported perceived stress in Stress Scale (SS) labelling. The STAI questionnaire has shown high reliability when used under psychological stress conditions and has been found suitable in real-life stressful situations including an important examination, dental procedures and job-interviews [22]. The institute examination used in this study is a real-life stressor of moderate intensity and is used in previous studies [23,24]. The studies for stress detection using laboratory-induced stress show increased sympathetic activity and reduced baroreflex gain but their efficacy is limited owing to intrinsic artificiality [23]. The models like public speaking affect respiration due to speaking and may interfere in the interpretation of results [23]. Therefore, real-life exam is used as a stressor and a laboratory-based arithmetic stressor is used in addition to exam-based stressor in order to further increase stress levels. In case of SS scores, it can range from 1-10 and as per instructions to subjects, a low score will indicate that the perceived stress is low and high score will indicate high perceived stress levels. The STAI-Y1 scores of participants can range from 20-80. The subject-wise STAI-Y1 and SS scores of the subjects are shown in Figure 4. In order to convert these scores into labels, we chose specific thresholds. For STAI-Y1, if the score is between 20-37 the subject is non-stressed, and the subject is stressed if the score is between 45-80 [25]. In case of SS, the cut-off was intuitively decided and the subject's recording was labeled as non-stressed if the score is between 1-3, and stressed if SS score is between 7-10. The resulting labels based on these thresholds are presented in Figure 5 of the study where, 1, 2 and 3 stands for non-stressed, moderately stressed and stressed subjects respectively. The two session recordings are considered together for analysis, but are labelled differently according to the procedure described above. The number of records labelled as non-stressed, moderately stressed and stressed are summarized in Table 1.

Figure 4: STAI-Y1 and SS scores of the subjects of the study; missing values represents subject unavailable for session recording

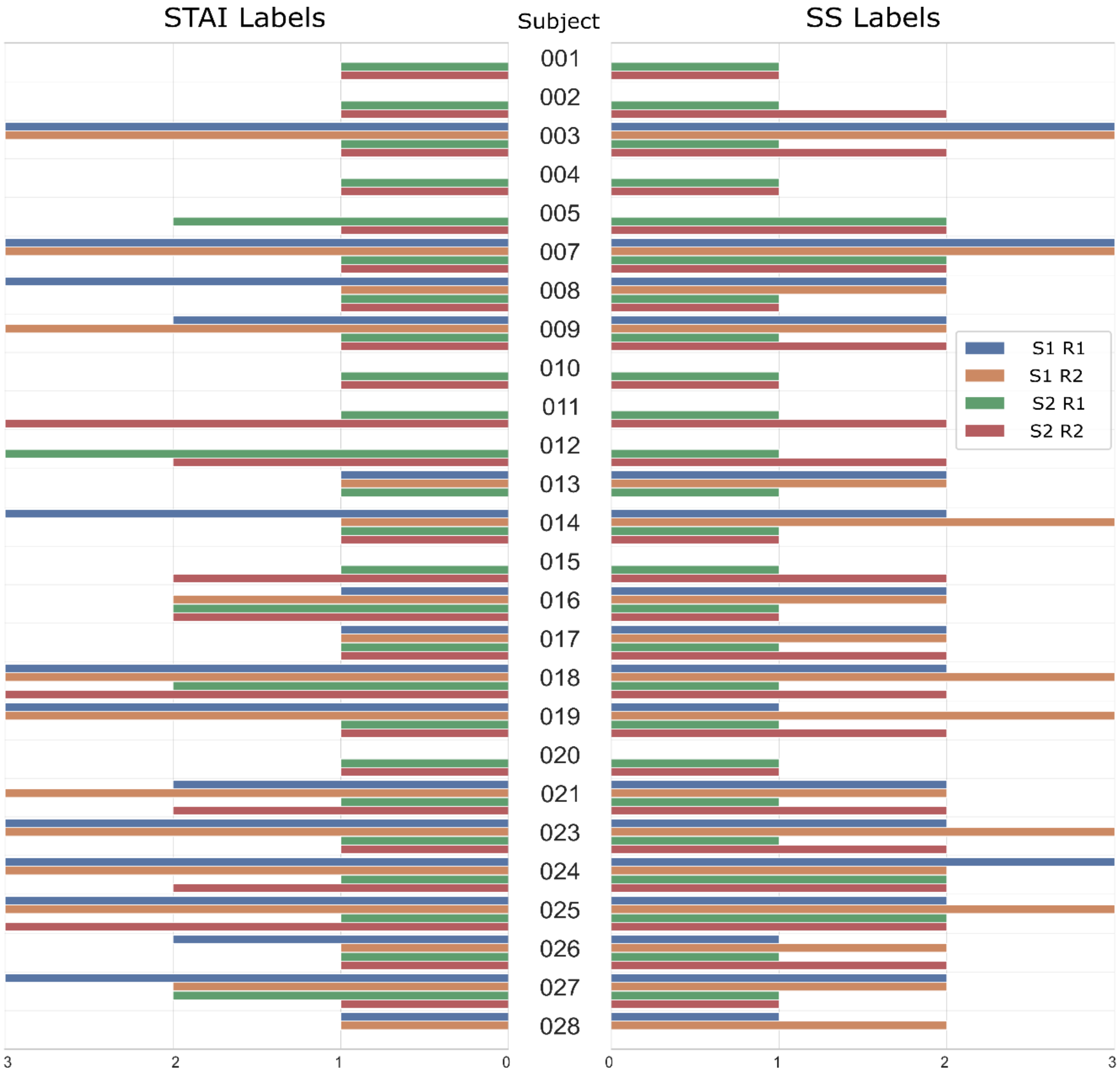


Figure 5: Labels for each participant, where label 1, 2 and 3 represents non-stressed, moderately stressed and stressed subject; missing values represents subject unavailable for session recording

Table 1
Table depicting number of recordings labelled as non-stressed, moderately stressed, stressed

Scale	Non-stressed	Moderately stressed	Stressed
STAI-Y1	47	24	32
SS	39	51	13

In the next step, we eliminated the recordings of the subjects experiencing moderate stress to utilize a binary classification approach as this will enhance the distinction between stressed and non-stressed classes. This results in about half the recordings in SS labels to be categorized as moderately stress as shown in Table 1 of the study. This will lead to a smaller number of recordings for training and testing for reliable model performance, moreover, the new classification will have 25% stressed and 75% non-stressed signals leading to an imbalanced dataset. However, in case of STAI-Y1 labels, the number of moderately stressed signals is small leading to lesser data loss by removing these recordings and the remaining data will comprise of 59.5% non-stressed and 40.5% stressed recordings, thereby, resulting in a comparatively balanced dataset. Therefore, in further analysis, we will consider STAI-Y1 labels for binary classification as stressed and non-stressed EEG signals.

2.5. Wavelet scattering

The Wavelet Scattering Network is used in this study for feature extraction because conventional feature extraction approaches require hand-crafted features to discriminate among classes which is a challenging task that requires expert knowledge. This approach has lesser computational requirements than CNN and does not require large dataset for training that can be challenging in case of biomedical signals that deal with data acquisition from human subjects or animals. Additionally, lack of interpretability of deep neural networks is another problem [26] due to insufficient theoretical foundation and cascaded non-linearities [27]. Therefore, this study uses informative wavelet scattering based features that are shift-invariant and stable to time-warping deformations [26]. It comprises of a cascade of convolution, modulus, and low-pass operators and are equivalent to deep neural networks [26]. The pre-defined filters in wavelet scattering make them faster and reduces computational load as opposed to neural networks that have iteratively trained filters.

In this method, time-invariance scale of the network is $T = 2^J$, where J is number of octaves, filter bank $\wedge_i$ for every layer i of the network is constructed with Q_i wavelets per octave which sets the quality factor. The center frequency of the wavelet in filter bank is ξ and center frequency index is λ, where $\lambda_i \in \wedge_i$.

The zeroth-order scattering coefficients C_o computed by convolving input signal $'a'$ with low-pass filter ϕ is shown as [26]:

$$C_o y(t) = a \star \phi(t) \tag{1}$$

This removes all high frequencies which are recovered by wavelet modulus transform as:

$$|W_1|a = \left(a \star \phi(t), \left|a \star \psi_{\lambda_1}(t)\right|\right)_{t\in\mathbb{R},\, \lambda_1\in\wedge_1} \tag{2}$$

where, wavelets ψ_{λ_1} have octave frequency resolution Q_1 and the first-order scattering coefficients are:

$$C_1 a(t, \lambda_1) = \left|a \star \psi_{\lambda_1}\right| \star \phi(t) \tag{3}$$

On similar lines, second-order wavelet modulus transform are:

$$|W_2|\, \left|a \star \psi_{\lambda_1}\right| = \left(\left|a \star \psi_{\lambda_1}\right| \star \phi,\, \left|\left|a \star \psi_{\lambda_1}\right| \star \psi_{\lambda_2}\right|\right)_{\lambda_2 \in \wedge_2} \tag{4}$$

where, ψ_{λ_2} wavelets have octave resolution Q_2 which is chosen to get a sparse representation for having least number of wavelet coefficients feasible. The second-order scattering coefficients are:

$$C_2 a(t, \lambda_1, \lambda_2) = \left|\left|a \star \psi_{\lambda_1}\right| \star \psi_{\lambda_2}\right| \star \phi(t) \tag{5}$$

The higher-order coefficients can be computed in the similar manner; therefore, n-th order scattering coefficients can be computed as:

$$C_n a = \left|\left|\left|a \star \psi_{\xi_{\lambda_1}}\right| \star \ldots\ldots \right| \star \psi_{\lambda_n}\right| \star \phi(t) \tag{6}$$

where, $\lambda_i \in \wedge_i$ and $\mathrm{i} = 1,2,\ldots,\mathrm{n}$ and ξ is the center frequency of the wavelet in filter bank.

This new technique is reported to have achieved state-of-art classification results [26] in many applications. The scattering-based features are extracted from each layer. This technique is contractive with most of the energy generally concentrated in first two coefficients [26]. This reduces intra-class variability but maintains inter-class variability. This technique has been used in ECG signals-based arrhythmia classification [28], PCG-based normal and abnormal signal classification [29], ground penetrating radar imaging for pipeline identification [30].

The wavelet scattering transform used in this study utilizes the Kymatio implementation [31] which provides the Scattering1D function for 1D signals. This function takes in the hyperparameters J, Q, and T, and for this study, T = 75000 is the length of the full signal, Q =16 and J = 6 is decided based on the performance achieved using these parameters.

2.6. Support Vector Machine (SVM) classifier

The Support Vector Machines (SVM) is a supervised learning algorithm widely employed for classification tasks. Given a labeled dataset, with each sample belonging to one of two categories, the classifier reviews the data and maps each sample as a point in an n-dimensional space, where n represents the number of input features. The objective is to separate the categories by an optimal hyperplane, which maximizes the distance between the categories. The peripheral data points closest to the other category are used as the support vectors, as they significantly influence the configuration of the hyperplane and the margin refers to the area between the decision boundary, which separates the different classes. The distance between the decision boundary and the training data points is street width. The regularization parameter is a hyperparameter that controls the complexity of the model. It determines the trade-off between the size of the street width and the accuracy of the model. A large regularization parameter signifies that the model will have a smaller street width and will try to correctly classify as many of the training data points as possible which can lead to overfitting. A small regularization parameter, on the other hand, allows for a larger street width and is thus open for some misclassification of the training data. This can help to prevent overfitting and can improve the generalization performance of the model. If training set has Q data points $\{a_i, b_i\}_{i=1}^{Q}$, where $a_j \in \mathbb{R}^n$ is ith input pattern and $b_i \in \mathbb{R}$ is ith output pattern, then support vector classifier depicted by [32]:

$$a(b) = sign\left[\sum_{i=1}^{Q} c_i a_i \varphi(b, b_i) + d\right] \tag{7}$$

where, c_i is positive real constant and d is real constant and $\varphi(b, b_i)$ is kernel. The SVM classifier has been used in cancer genomic classification [33], classification of satellite from remotely sensed multispectral data [34], for diagnosing of skin illness [35] and in PCG signals for psychological stress detection [36].

In the present study, SVM iterates through a parameter grid with the regularization parameter either equal to 1e-3, 1e-2, 1e-1, 1, 10, 100, 1e3, 1e4, 1e5 and 1e6 and the kernel function used is linear, polynomial (poly), Radial basis function (rbf) and sigmoid.

2.7. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are neural networks that are widely used for image and video analysis. Unlike traditional neural networks, which process the input data in a linear manner, CNN use convolution to filter the data and identify patterns. The feature maps generated by the convolutional layer are then passed through a series of additional layers, including pooling layers and fully connected layers, to produce the final output. Pooling layers are used to reduce the dimensionality of the feature maps, while fully connected layers use the output of the previous layers to classify the input data. One of the key benefits of CNNs is their ability to learn spatial invariance. This means that CNNs are able to recognize patterns in images, regardless of their position or orientation within the image. This is achieved through the use of pooling layers, which reduce the sensitivity of the network to small variations in the input data. This deep learning technique has capability of automated feature extraction due to convolutional and pooling layers and capability of classification due to fully connected layer [37]. The CNNs are used with EEG signals for epileptic seizures detection [38] and automated Schizophrenia detection [37].

This study utilizes deep and shallow CNN for psychological stress detection using reduced channel EEG signals. The finalized models included a class weight of 1-3 for non-stressed vs. stressed, respectively, epoch length equal to 1 s, and a sigmoid activation function as the last step. The Deep CNN has four convolution max-pooling blocks, where the first one is especially designed to handle EEG input data, the next are three standard convolution max-pooling blocks and a dense softmax classification layer. The exponential linear units are used as the activation function. Whereas, the Shallow CNN used in this study is inspired by Filter Bank Common Spatial Patterns pipeline. The first two layers perform temporal convolution and spatial filtering. Thereafter, a squaring nonlinearity, a mean pooling layer and a logarithmic activation function is performed. The further details of the deep and shallow CNN architecture are provided in [39].

2.8. Performance metrics

The statistic measures used as performance metrics in this study are classification accuracy, sensitivity and specificity and are computed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{9}$$

$$Specificity = \frac{TN}{FP + TN} \tag{10}$$

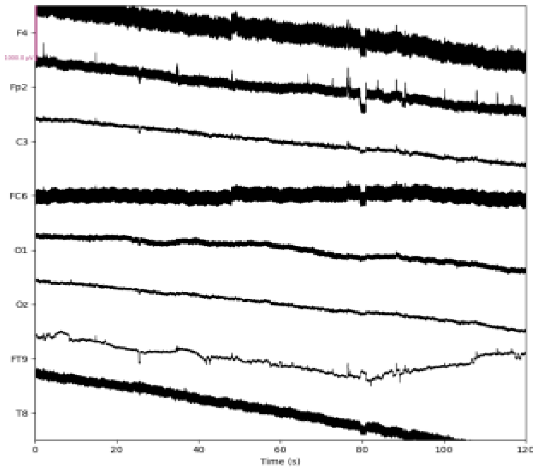
where, TP stands for true positive and depicts number of stressed samples classified as stressed by the algorithm, TN stands for true negative and depicts number of non-stressed samples classified as non-stressed by the algorithm, FP stands for false positive and depicts number of non-stressed samples misclassified as stressed samples by the algorithm and FN stands for false negative and depicts number of stressed samples misclassified as non-stressed by the algorithm.

3. Results and Discussions

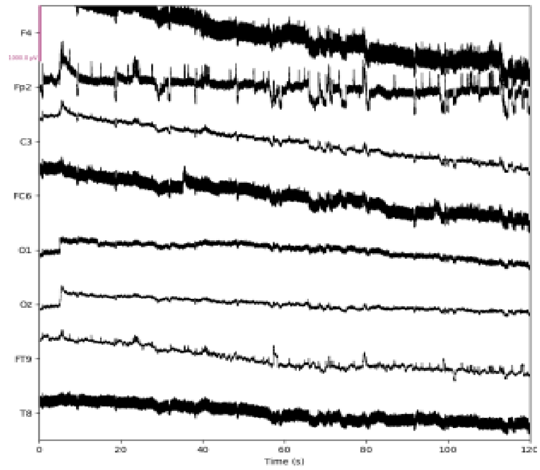
The acquired 8-channel EEG signal, as shown in Figure 6, are used for psychological stress detection in this study. The eight electrodes used for data acquisition are- FT9, O1, FC6, Fp2, Oz, F4, T8 and C3 electrodes as shown in Figure 3 of this study. The experiments are performed on EEG signal recordings from 28 subjects of the study. The STAI-Y1 score labels were chosen to be used in this study since SS labels leads to substantial data loss and extremely imbalanced dataset due to larger number of moderately stressed data and the residual data may not be sufficient for training and testing the model. Therefore, three approaches are used for psychological stress in this study- 1) using SVM classifier on the acquired reduced channel EEG data comprising of 5-minute duration of each recording 2) Wavelet scattering based features acquired from reduced EEG data and use of these features in SVM classifier for classifying stressed and non-stressed state 3) use of Convolutional Neural network- both deep and shallow CNN for classifying stressed and non-stressed state in EEG signals.

In approach 1 of the study, the acquired raw data was directly fed to the SVM classifier. This is due to the fact that the 8 EEG channels used in the study are already optimally selected, in comparison to 32, 64 or 128 EEG channels in prior works. The handcrafted feature selection from this already limited data would further constrict this information and may be detrimental for performance of classifier due to limited information. The Radial Basis Function (RBF) kernel function and C=100 yielded highest accuracy for classifying stressed and non-stressed states as depicted in Table 1 of the study. In approach 2, newly reported wavelet scattering transform is applied and these wavelet scattering features are fed to the SVM as input matrix. The parameters of SVM are the default parameters as depicted in Table 2. In approach 3, the Deep CNN and Shallow CNN, with the architecture explained in Section 2.7 of the study are used. For the purpose of binary classification as stressed and non-stressed data, the moderately stressed signals were removed which led to 47 instances for non-stress and 32 instances of stressed, as shown in Table

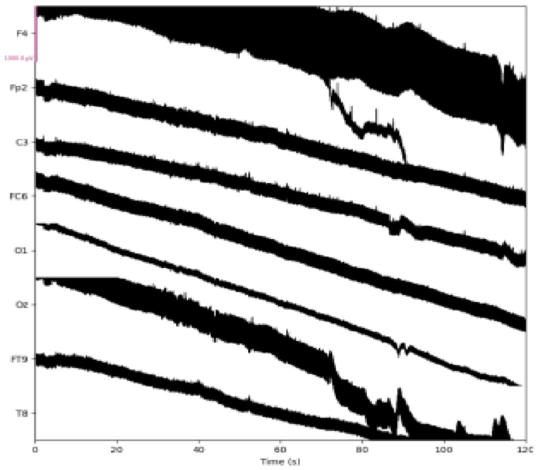
1. These EEG signals were then segmented in epochs of 1 sec, as found suitable in previous EEG-based studies [40,41]. Therefore, the dataset now consisted of 14,100 (47 x 5 x 60) epochs for non-stress and 9,600 (32 x 5 x 60) epochs for stress category signals, which makes it suitable for the application deep learning models. The Shallow CNN provided better performance for classifying stressed and non-stressed state EEG signals, as depicted in Table 2 of the study.



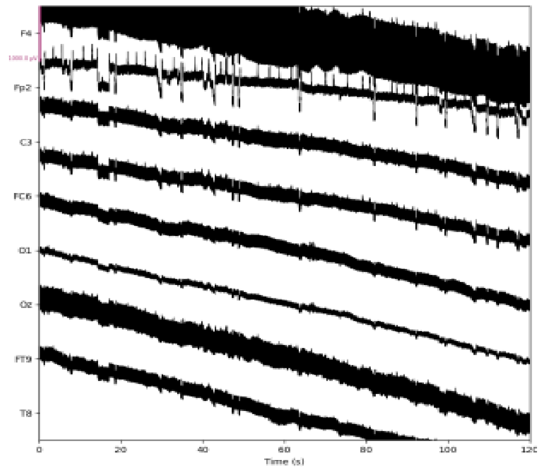
(a) RAW EEG data for Participant 3, Session 1, Run 1.



(b) RAW EEG data for Participant 3, Session 1, Run 2.



(c) RAW EEG data for Participant 3, Session 2, Run 1.



(d) RAW EEG data for Participant 3, Session 2, Run 2.

Figure 6: Acquired raw reduced channel EEG data for a subject, where Session1 is before exam, Session2 is after holidays, Run1 is without arithmetic stressor and Run2 is with arithmetic stressor

In this study, an 80-20 dataset split is used, where 80% of the data was used for training and 20% of the data was utilized for testing purposes. No subject appeared in both the training and testing sets, in order to prevent a bias in reporting the performance metrics. Thereafter, a 10-fold cross validation evaluation strategy was used and the Table 2 reports the best performance achieved in terms of highest classification accuracy achieved. This approach was utilized in all the experiments reported in the study.

Table 2
Table depicting performance metrics achieved using three approaches in the study for psychological stress detection using EEG signals

Approach number	Approach description	Parameters description	Accuracy (%)	Sensitivity (%)	Specificity (%)
1	SVM	C=100, Kernel=rbf	87.5	81.25	92.05
2	Wavelet scattering and SVM	Q=16, J=6, T= 75000 Default	87.5	82.81	90.91
3	CNN	Deep CNN	73.61	87.5	63.52
		Shallow CNN	84.18	87.5	81.76

In this study, the K-NN classifier was also tested which achieved accuracy of 73.03% in classifying stressed and non-stressed state EEG signals, however, the best results were obtained using SVM as classifier. The approach 1 and 2 of the study performed well by achieving high accuracy in classifying stressed and non-stressed states. However, the computational time of approach 2 exceeded the approach 1 due to added computational complexity. The potential of approach 2 should be explored further in future works due to the possibility of scattering parameter tuning that can improve classification accuracy and also due to the power of wavelet scattering in outperforming state-of-art approaches. Regarding the approach 3, the applicability of deep CNN and shallow CNN is tested, the shallow CNN outperformed deep CNN and also achieved a high mean accuracy of 83.66% using 10-fold cross-validation. This provides promising results due to the generalizability of the shallow CNN based model in detecting stress from reduced channel EEG signals.

The results achieved in the present study proves the potential capabilities of drastically reducing number of EEG electrodes to 8 for psychological stress detection application. The advantages of the proposed approach are presented ahead.

3.1. Advantages

The number of electrodes proposed suitable for psychological stress detection in this study is eight electrodes. This is a significant reduction has numerous benefits in comparison to prior studies focusing on use of 32, 64 and 128 EEG electrodes. Firstly, it will make the stress detection systems cost-efficient and suitable for homecare-based environments. Secondly, it will also significantly reduce the setup time due to lesser number of electrodes to be connected and will be a step in the direction of real-time stress monitoring systems. Thirdly, it will be convenient and minimally intrusive in comparison to traditional EEG systems with large number of electrodes. Another advantage is exploring the use of recently developed wavelet scattering transform in reduced channel EEG signal based psychological stress detection. Importantly, gender-inclusive study design and data acquisition protocol are used in this study, which makes the findings of this work generalizable to the diverse population.

3.2. Limitations

The dataset of this study is small and comprise of data acquisition from young adult age group of 23±2 years. The noise reduction step is not included in this study. The STAI-Y1 and SS labelling used in the study can possibly be influenced by subjective understanding of questions or a plausible response bias may exist in psychology-based questionnaires. The difficulty level of examination is also not considered in this study.

3.3. Future Scope

The dataset should be enlarged and include other age-groups and chronic stressors responsible for pathogenesis, in order to investigate the real potential of using reduced channels EEG configuration for psychological stress detection. This will be instrumental in application of the findings to a larger and more heterogenous population. In this way, the optimally reduced channel could lead to a rapid screening of stress that may be possible outside the clinic. The response bias of STAI-Y1 can be managed by adopting the principles stated by Hao *et al.* [42] using cross entropy loss. A customized noise removal system for this application should be designed and incorporated in the methodology to handle the noise captured in the dataset. The hyperparameter and scattering parameter should be further explored in order to increase the classification accuracy of the developed 8-channel EEG stress detection system.

4. Conclusion

This study proposes a novel framework for using reduced channel EEG configuration for psychological stress detection. The highest accuracy of 87.5% is achieved using machine learning-based support vector machine classifier with the wavelet scattering features. The high mean accuracy reported using Convolutional Neural Network and 10-fold cross validation method shows the reliability and robustness of this methodology. These results indicate that there is a clear potential for reducing the number of EEG electrodes required to achieve a reliable stress detection system based on EEG. This reduction in electrodes leads to reduced setup time that was a major drawback of traditional EEG-based stress detection systems. This reduced setup time is also a major step in the direction of wearable EEG-based stress detection system for real-time applications. The significant reduction in number of required EEG electrodes by using optimization opens new possibilities in the field of design of wearable EEG systems as it offers high potential for customized, flexible, less intrusive, and cost-efficient concepts.

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