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Original Article

KACZMAR SPATIO Temporal Nelder Mead Multilayer Perceptrons for Stress Detection Using EEG Signals

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Abstract - *Stress is an emotion that people encounter when they are extremely loaded and encounter trials and tribulations while carrying out day-to-day chores. Stress influences individual health seriously, like soaring blood pressure, heart disease, cardiovascular disease, and even lead to stroke. As a result, early stress detection becomes helpful to keep an eye on health-related issues caused by stress. Electro Encephalography (EEG) signal based system assists in identifying the different disorders and disabilities. Hence, there is a requirement for early stress detection using EEG signals that are accurate, precise, and reliable. This is resolved in the proposed method by introducing Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP) that can accurately classify and detect the stress level. In this KST-NMMP method, deep learning using multilayer perceptrons is employed for early stress detection. It is split into four layers, i.e., one input layer, two hidden layers, and one output layer. The input EEG signals obtained from the subjects are provided in the input layer. Next, in the first hidden layer, the artifacts present in the raw EEG signals are filtered out; thus, the stress detection time can be reduced. After noise reduction, the spatial and temporal domain features are extracted from EEG signals; thus, stress detection overhead can be reduced significantly. Finally, stress level classification and detection at an early stage are performed in the second hidden layer employing spatial and temporal features using the Nelder Mead activation function. This proposed KST-NMMP method ensures accurate classification outcome which leads to improvement both in terms of precision and recall significantly. The overall implementation is performed in the Matlab programming language. Finally, the performance is evaluated and compared with the conventional method in terms of precision, recall, stress detection time, and stress detection overhead.*

Keywords **-** *Stress Detection, Electro Encephalo Graphy, Finite Impulse, Kernel Smoother, Kaczmarz Spatio Temporal, Nelder Mead, Deep Neural Activation.*

1. Introduction

One of the ongoing research areas conducted by both psychologists and engineers is the detection of stress faced by human beings in all walks of life. Numerous materials and methods have been designed in recent years for human stress detection. Stress is said to be detected from human bio-signals like, Electroencephalography (EEG), Blood Pressure (BP), Skin Temperature (ST), respiration and so on. Also, human physiological features are used to measure the stress level using physiological signals. A Symmetric Deep Convolutional Adversarial Network (SDCAN) was proposed in [1] stress classification based on EEG signals obtained as input. First, an inference of an adversarial nature was introduced with the purpose of acquiring invariant and discriminative features in an automatic manner from raw EEG signals. This, in turn, resulted in the improvement of classification accuracy. Despite improvement in classification accuracy, the overhead incurred during classification was not analyzed. A stress detection with deep learning method was presented in [2] by employing dataflow infrastructure for monitoring research on humans. In this work, a binary classification of stress was made, and a comparison was made with three distinct machine-learning models. Meta data features were extracted, following which ground-truth stress levels were provided as information via questionnaires. Finally, the classification of stress was made using Electro-Dermal Activity (EDA) and Blood Volume Pulse (BVP) signals, therefore ensuring considerable improvement in the F1-score. Though significant improvement in the F1-score was ensured, however, the time incurred in the classification of stress was not focused.EEG has been utilized to study and identify biomarkers. Despite successful prediction of stress using these bio-markers,[3], however, performance was found to be suboptimal for different conditions of stress, therefore increasing the overhead considerably. To overcome this issue, a latent-based representation of bio-markers to improve EEG performance was presented in [4]. A systematic review of the diagnosis of depression using deep learning was discussed in [5]. In [6], a subject-independent emotion recognition method was proposed from EEG signals by employing Variation Mode Decomposition (VMD) as a feature extraction technique and Deep Neural Network as the classifier. With this type of classifier, they resulted in the improvement of emotion recognition rate in a significant manner. Nevertheless, the time and overhead incurred in emotion recognition were not analyzed. Stress is said to be triggered due to several reasons, like changes in the body's emotional response to different circumstances, like depression, anger, grief, sorrow and so on. According to the emotion, responses are said to be categorized as either positive stress or negative stress. Issues concerning stress are increasing in an exponential manner globally. Hence, early detection and classification of stress is therefore considered of the utmost importance. To differentiate between micronap and non-micronap states, Deep Neural Network (DNN) techniques using different types of EEG signals as input were employed [7].

With this DNN design not only ensured improved precision but also resulted in considerable recall improvement. However, the overhead factor was not analyzed. Long short-term memory was applied in [8] for accurate stress classification. Each deep learning and machine learning algorithm has got its prospective and drawbacks in handling significant classification. In [4], four different deep learning frameworks and two distinct machine learning techniques were applied with the purpose of tracking mental depression from EEG signals. Motivated by the above issues, like precision, recall, and time consumed in stress detection, in this work, a stress detection method using Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP) is proposed. The major contributions of this work are listed below.

- To design an effective method for predicting stress detection using the Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP) method.
- To find computationally efficient and relevant features, the Finite Impulse Kernel and Kaczmarz Spatio Temporal feature extraction algorithm is applied to the pre-processed EEG signals.
- To get better precision and recall rate with minimum time and overhead by selecting the unique and computationally efficient EEG sparse features using Nelder Mead Deep Neural Activation for stress detection.
- To propose a new deep learning-based Multilayer Perceptrons to detect stress as either low stress, high stress, moderate or neutral.
- Finally, the performance of the proposed KST-NMMP-based stress detection method is compared with the state-of-the-art methods.

The structure of the paper is as follows. In Section 2, related papers involving stress detection are reviewed. In Section 3, we introduce the Finite Impulse Kernel and Kaczmarz Spatio Temporal feature extraction, and Nelder Mead Deep Neural Activation for stress detection is proposed. Section 4 describes the experimental setting and discusses the results and analysis of the proposed KST-NMMP method used in stress detection is presented in Section 5. Finally, Section 6 concludes the study.

2. Related Works

Stress is the response of a person manifested by exceptional anxiety when overlooked by a demanding issue. On the other hand, stress can also be perceived as a psycho-physiological state of ultimate ache and anguish for an individual that can be deduced to critical mental health issues like depression or anxiety attacks. Given that anxiety chaos is one of the most prevalent multi-chronic conditions in youth with Autism Spectrum Disorder (ASD), this population is specifically susceptible to mental stress. To ward off this early stress, Machine Learning (ML) was applied [10], wherein non-pharmacological interferences were identified for early detection. A systematic review of depression diagnosis employing deep learning was investigated in [5]. However, another work on stress detection applied in line with sensory devices like wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG) was proposed in [12]. Over the recent few years, deep learning algorithms have been designed swiftly and they are also becoming a significant tool as far as biomedical engineering is concerned. Specifically, there has been a growing interest in the utilization of deep learning techniques for decoding the physiological status of the brain from EEG. An overview of the application of deep learning algorithms in several EEG decoders was presented in [13]. However, another comprehensive review on stress recognition using machine learning was investigated in [14]. Humans have the potential to model distinct expressions in comparison to the emotional state of mind. Hence, it becomes both laborious and cumbersome to judge real emotional states just by physical appearance judgments. In [15], human emotions were first classified using machine learning, and discrete wavelets were employed for extracting from EEG.

This type of design not only resulted in accuracy but also reduced time considerably. Negative stress denotes a serious issue as far as advanced societies are concerned. Several research works have concentrated on stress detection using EEG. To this respect, a hybrid method integrating regularity-based quadratic sample entropy (QSampEn) and symbolic Amplitude-Aware Permutation Entropy (AAPE) has found a significant place in stress recognition. In [16], Dispersion Entropy (DispEn) was introduced to address stress-related issues. An innovative method to perform sampling employing affinity propagation and stratified sampling-based clustering algorithm was designed in [17]. This sampling method determined the different numbers of representative samples in an automatic manner upon comparison with the existing methods. A comprehensive review of emotions from EEG signals was investigated in [14].

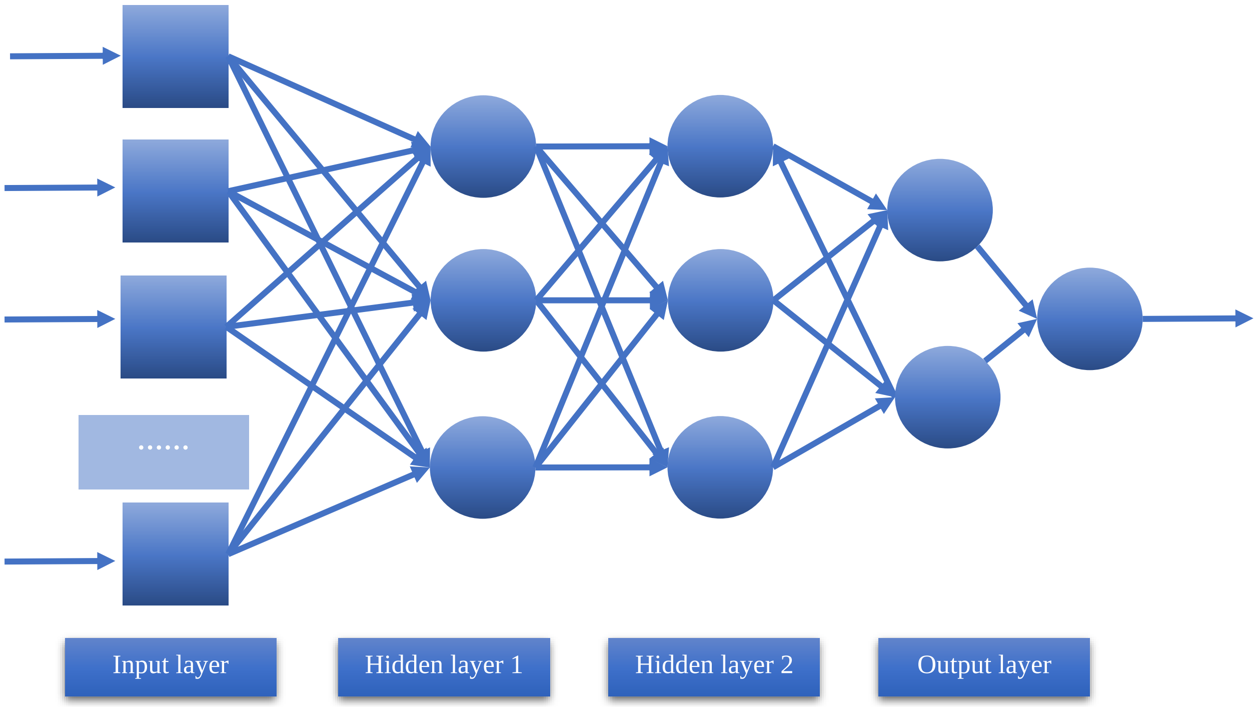


Fig. 1 Structure of kaczmar spatio temporal nelder mead multilayer perceptrons for early stress detection

3. Overview of the Proposed Method

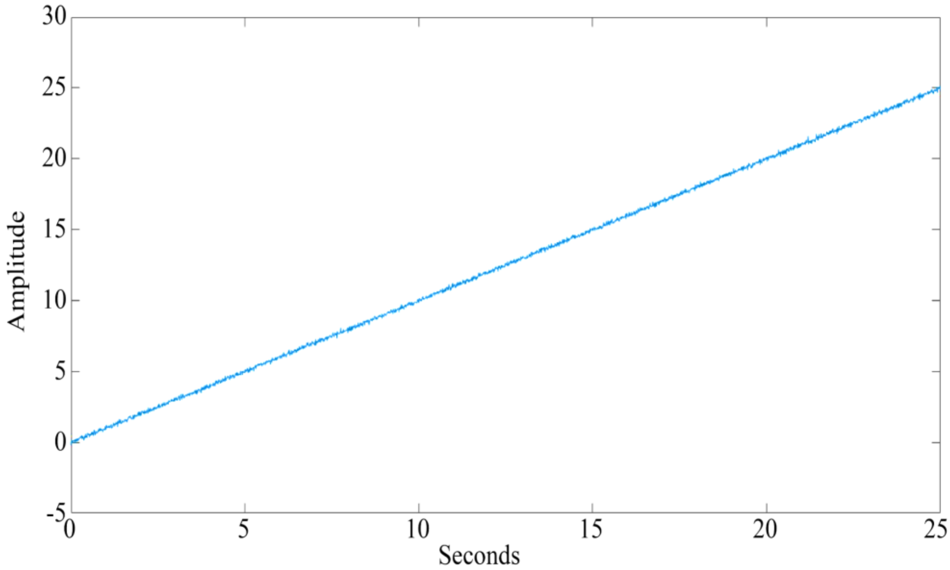
In this section, the proposed method for stress detection employing multilayer perceptrons is presented. Owing to their fast nature and ease of implementation, Multilayer Perceptrons are used extensively. In this work, a method called Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons for early stress detection is proposed. Figure 1 shows the structure of Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons for early stress detection.

A review of mental stress assessment methods employing machine learning and deep learning techniques was presented in [11]. A meticulous review of the state-of-the-art emotion recognition methods, printed in present-day literature, recapitulated prevailing emotion recognition was also designed in [9]. Motivated by the above materials, in this work, a deep learning-based early stress detection method called Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP) is proposed in the following sections.

As shown in the figure, the proposed method consists of four layers, namely, an input layer, two hidden layers and an output layer. The EEG signals are fed to the input layer that comprises neurons equivalent to the number of features in the input data or the EEG signals. The neurons in the input layer propagate the weighted inputs and randomly selected bias through hidden layers. In the very first step, the collected dataset is inserted into the input image. Next, the hidden layer processes information from the input layer, which is said to be accomplished by associating weights and biases with input features. In our work, two processes, i.e., pre-processing and feature extraction, are performed separately in two hidden layers. The input EEG signal goes through the pre-processing modeling of the first hidden layer, and this model helps to reduce the noise by means of a filter and improve the image quality. The main function of the pre-processing model using Finite Impulse Kernel Smoother based filtering helps to identify the artifacts and eliminate them. The feature extraction process is performed in the second hidden layer using Kaczmarz Spatio Temporal, which aids in reducing the dimensionality and, therefore, extracting the most relevant feature for stress detection by taking into consideration the inter-class and intra-class similarity, therefore aiding in different levels of stress detection. Next, in the second hidden layer, the Nelder Mead Deep Neural Activation function is applied for stress detection. Finally, a net sum of hidden nodes is evaluated to obtain output via the activation function. An elaborate description of the proposed method is provided in the following sections.

3.1. Data Collection

This SAM40 dataset comprises a collection of Electro Encephalographic (EEG) data acquired from 40 subjects, out of which 14 were female and the other 26 subjects were male with a mean age of 21.5 years. The experiment was performed to monitor stress while performing several tasks like, the Stoop Color Word Test (SCWT), arithmetic question solving, relaxation and symmetric mirror image identification. The three distinct tasks were performed for 25 seconds following, while three trials were recorded separately for 40 subjects. The EEG was recorded with 32 channel Emotive Epoch Flex gel kit. Also the EEG data were segmented into non-overlapping epochs of 25 seconds and were processed with the purpose of removing drifts. Figure 2 given below shows the subject 1 EEG signals for performing four different tasks: solving arithmetic questions, identification of symmetric mirror images, state of relaxation and stroop color word test, respectively.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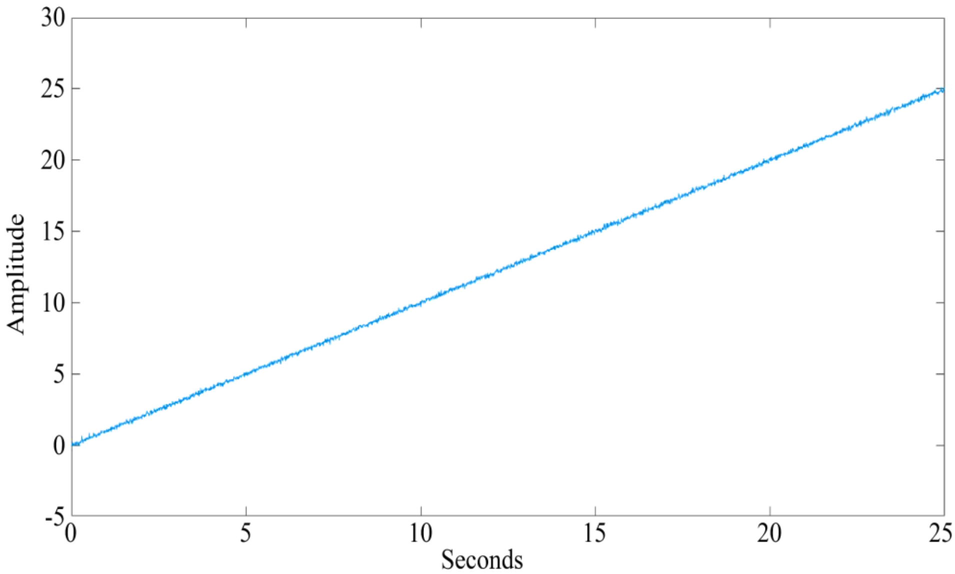
(a)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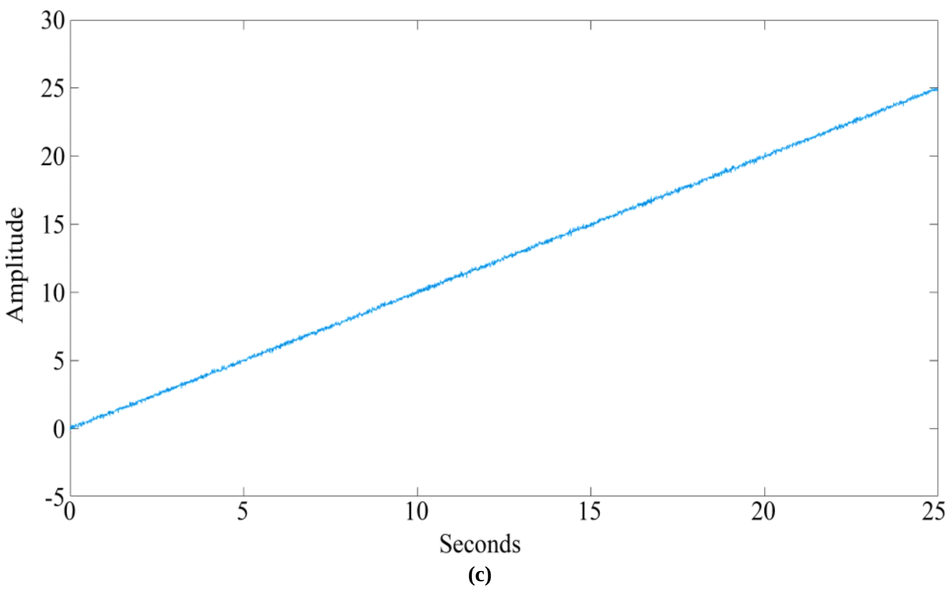
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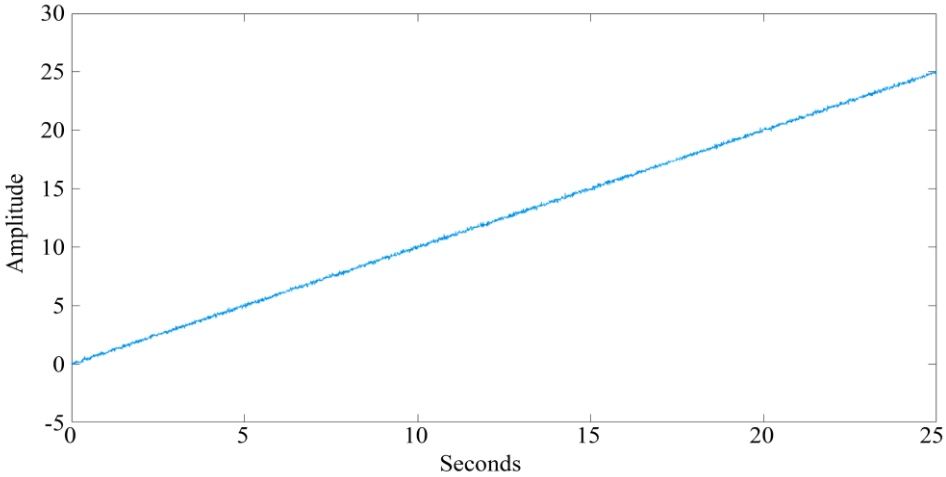
(c)



(d)

Fig. 2 Sample EEG signals (a) Arithmetic solving (b) Symmetric mirror images (c) state of relaxation (d) Stroop test

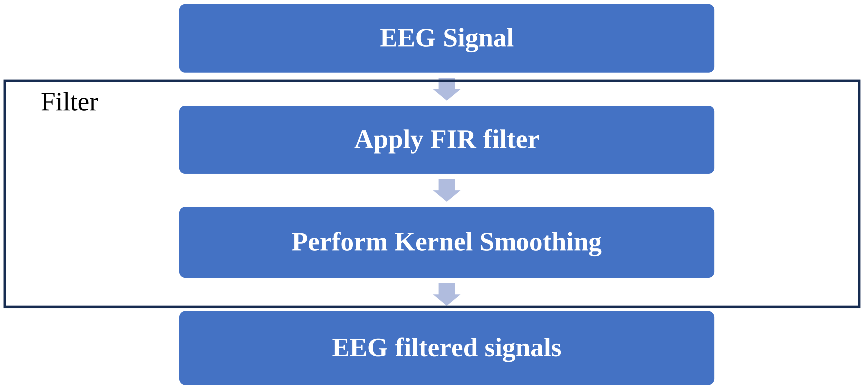


Fig. 3 Structure of finite impulse kernel smoother-based filtering model

As given in the above figure, a sample subject EEG signals have been obtained. Similarly, 40 subjects' EEG signals were obtained for detecting stress.

3.2. Finite Impulse Kernel and Kaczmarz Spatio Temporal Feature Extraction

The first step in early stress detection is the pre-processing. Raw EEG signals captured from the devices contain numerous amounts of noise that are not of interest to stress detection. Hence, the raw EEG signals have to be filtered to obtain relevant data. Pre-processing involves the removal of noisy data that are not of interest to stress detection. In this work, components containing artifacts from the input raw EEG signals are identified and eliminated using a combination of Finite Impulse Response and Kernel Smoother in the first hidden layer. Figure 3 shows the structure of the Finite Impulse Kernel Smoother-based filtering model. As shown in the above figure, with the raw EEG signals obtained as input, two different functions are applied, namely filtering and smoothing. Artifacts are signals caused by eye movements that corrupt the original EEG signal. Finite Impulse Response filters are used to attenuate noisy signals. The Finite Impulse Response (FIR) filters in each input impulse EEG signal in a finite response. To be more specific, the FIR filter sums a finite range of input-weighted signals and is mathematically stated as given below.

$$Q(n) = \sum IR(n-m)P(m) \tag{1}$$

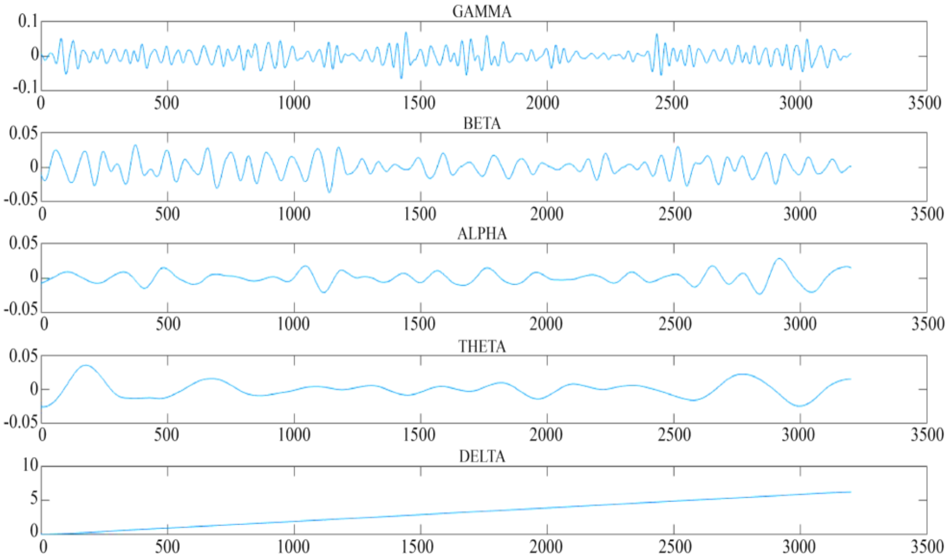
From the above equation (1), '$P(m)$' represents the input EEG signal, with an impulse response of '$IR(n-m)$', therefore producing an output signal '$Q(n)$' respectively. In this work, we designed an FIR filter with a Kernel Smoothing window function. The equation given below describes the window function utilized.

$$K_{Rad}(P_0 - P) = fun\left(\frac{|P-P_0|}{Rad(P_0)}\right) \tag{2}$$

From the above equation (2), 'P_0', 'P' belongs to the input EEG signal set (i.e., $P, P_0 \in P$), with a kernel radius of 'Rad', real value function 'fun', whose value is said to decrease with the increase in the distance between 'P' and 'P_0' respectively. Following which, the smoother function is applied to arrive at the finally processed EEG signals, as given below.

$$PS = N(P_0) = \frac{\sum_{i=1}^{n} Rad(P_0,P_i)N(P_i)}{\sum_{i=1}^{n} Rad(P_0,P_i)} \tag{3}$$

From the above equation (3), 'n' represents the number of observations or the sample subjects involved in the simulation (i.e., in our work, it is 40), whereas '$N(P_i)$' denotes the number of observations at 'P_0' points respectively. Figure 4, given below, shows the results of the pre-processed EEG signals of one subject corresponding to four different tasks: arithmetic solving, symmetric mirror images, state of relaxation and Stroop test, respectively.


GAMMA
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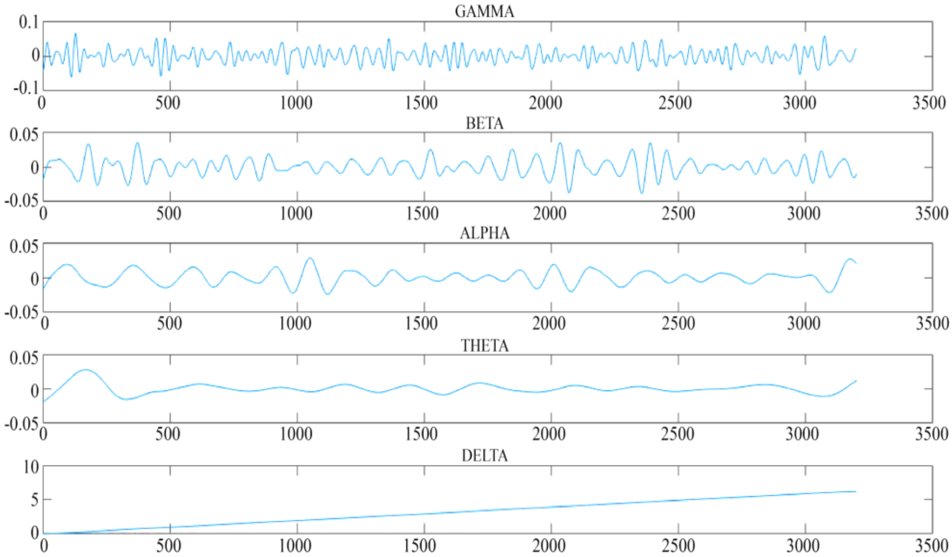
(a)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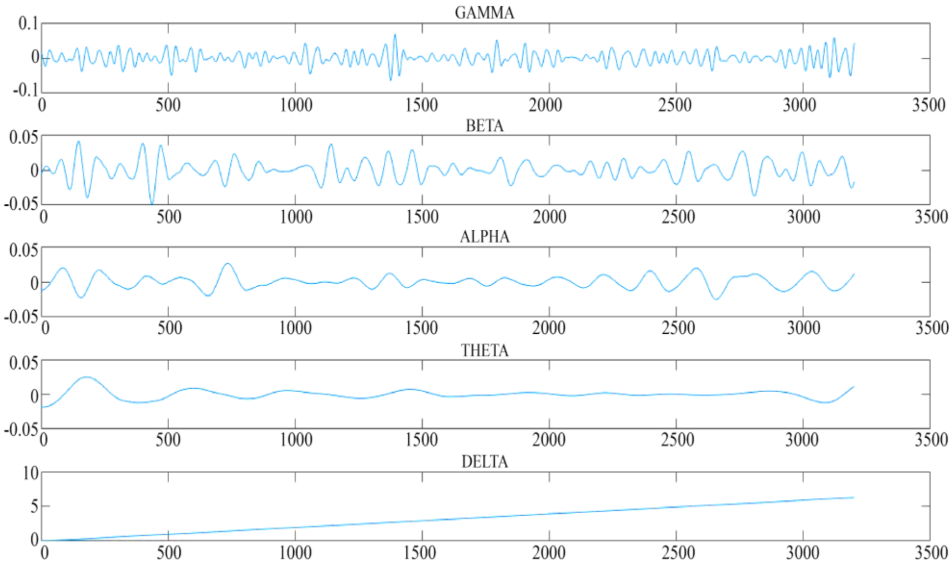
(b)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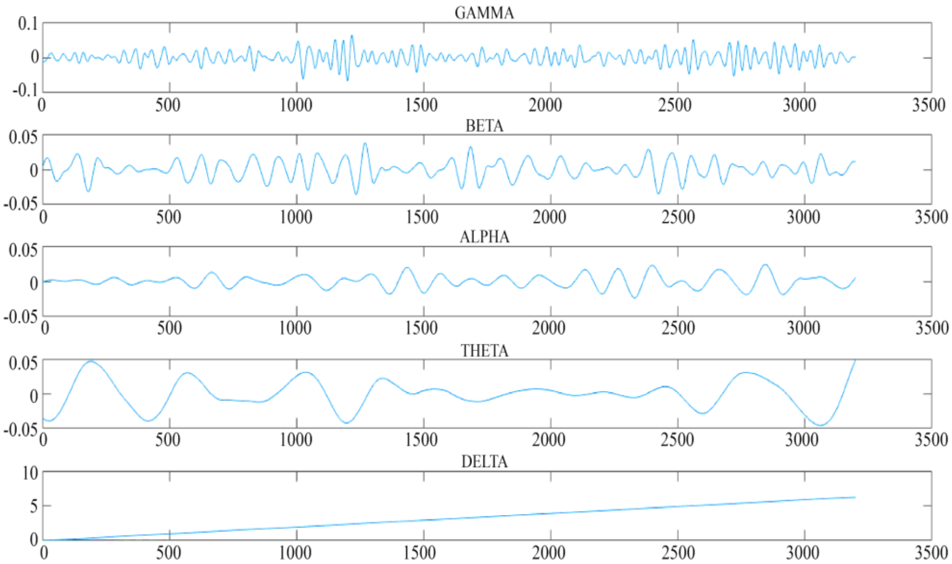
(c)



(d)

Fig. 4 Pre-processed EEG signals (a) Arithmetic solving (b) Symmetric mirror images (c) State of relaxation (d) Stroop test

To enhance the stress recognition rate, it is mandatory to split the signal into distinct frequency bands, extract feature information from each band, and associate it with entire frequency bands to produce more accurate features. The spatio-temporal features in mental stress play a vital role. In some cases, the spatiotemporal transition-based feature is able to distinguish several levels of mental stress in an individual. The Finite Impulse Kernel and Kaczmarz Spatio Temporal feature extraction algorithm applied is applied in our work in the first hidden layer that provides a better extraction of the processed EEG signals or data and reduces the dimensional quality of the image.

Let '$DS = \{PS_n, Q_n\}_{n=1}^{N}$' be the processed EEG training sample, where 'N' represents the number of the training samples with 'n' denoting the sample index, 'PS_n' forming the input processed EEG training sample and 'Q_n' representing the corresponding output or class label. In addition to that, let us define two samples '$NS(PS_n)$' and '$ND(PS_n)$', with '$NS(PS_n)$' representing the most similar sample to 'PS_n' with the same class (i.e., in our work, four classes are said to exist, class 1 for SCWT, class 2 for arithmetic question solving, class 3 for relaxation and class 4 for symmetric mirror image identification respectively) whereas '$ND(PS_n)$' denoting the most similar sample to 'PS_n' with the other class respectively. The objective behind this type of design remains to allocate weight to each feature to denote its significance so as to maximize inter-class distance and minimize intra-class distance. For sample 'PS_n', let us define '$V(PS_n|W)$' as the variation between the intra-class distance and inter-class distance when weighing the significance of each EEG spatial-temporal feature and is mathematically formulated as given below.

$$V(PS_n|W) = W^2[PS_n - NS(PS_n)] - W^2[PS_n - ND(PS_n)] \quad (4)$$

From the above equation (4) results, the larger '$V(PS_n|W)$'is, the more probably that 'PS_n' is correctly classified.

Also, we approach distance '$W^2[PS_n - NS(PS_n)]$'and $W^2[PS_n - ND(PS_n)]$', between similar samples, both with the same and different classes, in a probabilistic manner to acquire the results. Then, the expectation maximum likelihood results for the above probabilistic distribution function are formulated as given below.

$$EML[V(PS_n|W)] = EML\left[W^2\left(PS_n - NS(PS_n)\right) - W^2\left(PS_n - ND(PS_n)\right)\right] \quad (5)$$

$$EML[V(PS_n|W)] = W^2 \sum_{i=1}^{n} Prob(P_i = NS(PS_n)|W)|PS_n - PS_i| - \sum_{i=1}^{n} Prob(PS_i = ND(PS_n)|W)|PS_n - PS_i| \quad (6)$$

From the above equations (5) and (6), 'NS' represents the set of EEG spatio temporal samples with same class as 'PS_n', 'ND' represents the set of EEG spatio temporal samples with the different class as 'PS_n', with '$Prob(P_i = NS(PS_n)|W)$' and '$Prob(P_i = ND(PS_n)|W)$' denoting the probabilistic distribution functions of '$NS(PS_n)$' and '$ND(PS_n)$' respectively.

Finally, with the objective of making the weight sparser, we add complex conjugation 'PS_i'' on 'PS_i' so that the spatio temporal samples with different classes and same class results are stored in real part and imaginary part, therefore reducing the overall dimensionality. The weight value is obtained by solving optimization using the Kaczmarz function, as given below.

$$FE = W^{l+1} = W^l + \frac{PS_j - (PS_i, W^l)}{(PS_i)^2} PS_i' \quad (7)$$

Upon termination of the iteration at the optimal solution, the significance of EEG spatio temporal features is finally represented by the learned weight vector 'W', with spatio temporal samples with different class results are stored in real part '$Q = PS_1 + iPS_2$' and spatio temporal samples with same class results are stored in imaginary part '$Q = PS_1 - iPS_2$' respectively. Figure 5 given below, shows the results of the extracted features relevant for stress detection.

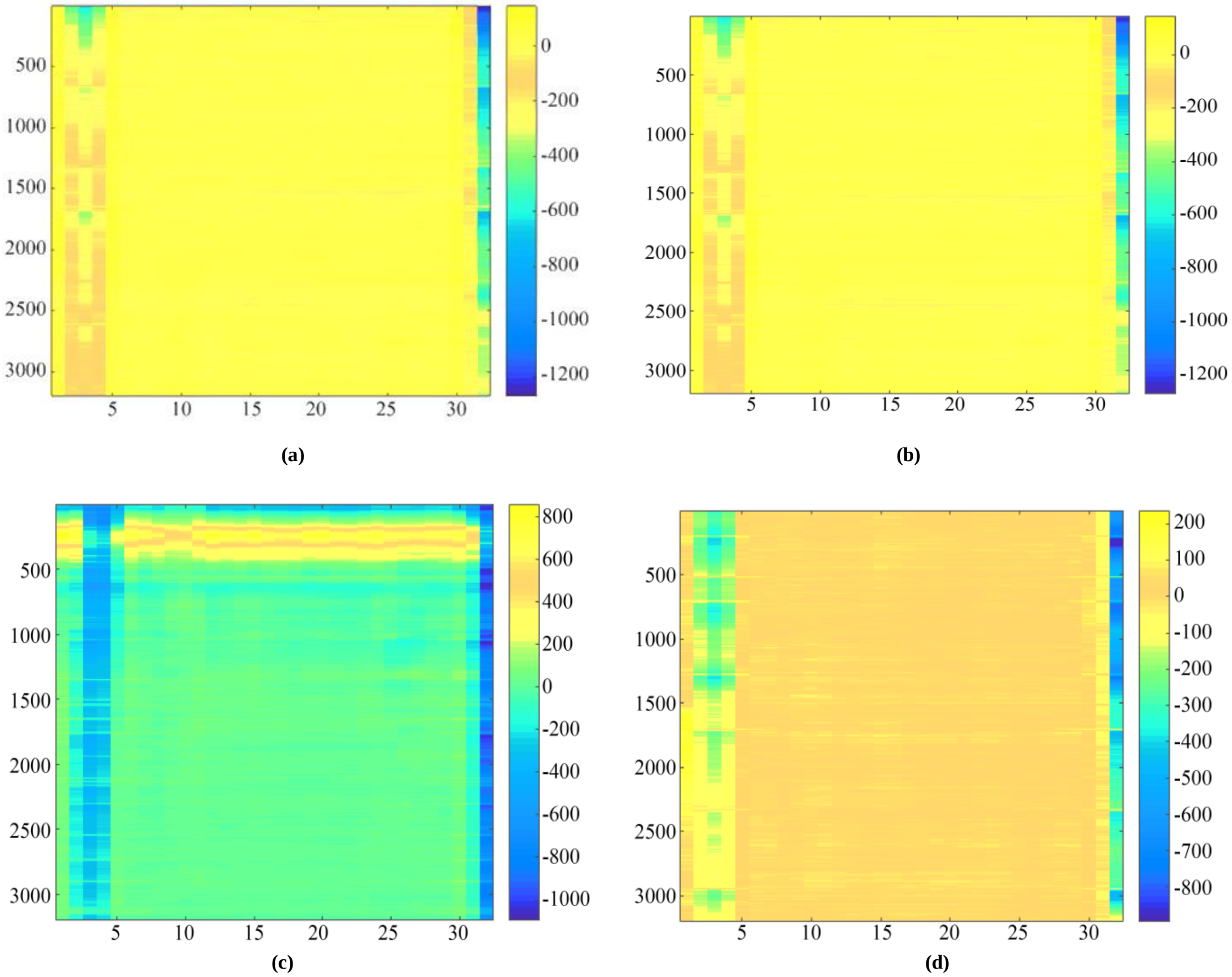


Fig. 5 Spatio temporal feature extraction for processed EEG signals (a) Arithmetic solving (b) Symmetric mirror images (c) state of relaxation (d) Stroop test

The pseudo code representation of Finite Impulse Kernel and Kaczmarz Spatio Temporal feature extraction is given below.

Algorithm 1. Finite impulse kernel and kaczmarz spatio temporal feature extraction

Input: Dataset 'DS', raw input EEG signals 'P'

Output: Dimensionality-reduced robust feature extraction

Initialize subjects
Begin
For each Dataset 'DS' with raw input EEG signals 'P'
//Pre-processing EEG signals
Evaluate Finite Impulse Response (FIR) filters in each input impulse EEG signal as given in (1)
Apply kernel function to FIR as given in (2)
Perform the Kernel Smoothing window function as given in (3)
Return EEG filtered signals 'PS'
End for
//Feature extraction
For each Dataset 'DS' with EEG filtered signals 'PS'
Formulate variation between the intra-class distance and inter-class distance as given in (4) for each sample
Evaluate expectation maximum likelihood results for probabilistic distribution function as given in (5) and (6)
Evaluate optimize weight value as given in (7)
Return spatio temporal features 'FE' (i.e., features extracted)
End for
End

As given in the above algorithm with the objective of obtaining computationally efficient features (i.e., both in terms of time and overhead), first, the input EEG signals are subjected to a Finite Impulse Kernel Smoother-based filtering model. Here, the artifacts present in the input EEG signals that solve for no purpose are eliminated; also, by employing a Finite Impulse Response (FIR) filter with a Kernel Smoothing window function, applying a smoother function results in obtaining the processed signals with minimum overhead. Second, with the processed EEG signals as input, spatio temporal features required for detecting different levels of stress are obtained by fine-tuning the weight and optimizing the same using the Kaczmarz function. Here, by employing complex conjugation, spatio-temporal samples with different classes are stored in the real part, and spatio-temporal samples with the same class are stored in the imaginary part, therefore reducing the overall dimensionality.

3.3. Nelder Mead Deep Neural Activation for Stress Detection

Finally, in this section, with the EEG filtered signals 'PS' and spatio temporal features 'FE' obtained as input, the objective remains in classifying them for accurate and precise stress detection. In this work, a model called Nelder Mead Deep Neural Activation for stress detection is presented. Let us consider the 'PS_m' processed signals with 'FE_n' extracted features formulated as a matrix given below (8).

$$\begin{bmatrix} PS_1FE_1 & PS_1FE_2 & PS_1FE_3 & \dots & PS_1FE_n \\ PS_2FE_1 & PS_2FE_2 & PS_2FE_3 & \dots & PS_2FE_n \\ \dots & \dots & \dots & \dots & \dots \\ PS_mFE_1 & PS_mFE_2 & PS_mFE_3 & \dots & PS_mFE_n \end{bmatrix} \quad (8)$$

As the multilayer perceptron employed in our work has a linear activation function that maps weighted inputs to the output of each neuron, then, the activation function equivalent to the above input matrix for classification is mathematically represented as given below in (9).

$$y(PS_mFE_n) = \tanh(PS_mFE_n) \quad (9)$$

As already mentioned, with multilayer perceptrons being fully connected, each node (i.e., each EEG-filtered signal with corresponding spatio temporal features) in one layer is associated with a certain amount of weight 'W_{ij}' to the other nodes in the following layer.

Here, learning is said to occur in the perceptron by updating weights followed by the filtered samples being processed on the basis of the error that occurred upon comparison to the expected result. The node weights are updated on the basis of the corrections that reduce the error based on the Nelder Mead function. The Nelder Mead function maintains a simplex that is are approximation of an optimal point (i.e., neither relating to high stress nor associated with low stress and lies between high stress and low stress, scale value of 5). The vertices (i.e., the scale value of each subject conducted for a specific trial) are sorted according to the objective function values (i.e., to detect stress). With this type of heuristic optimization, faster convergence is said to exist, therefore resulting in earlier stress detection. Figure 6 shows the structure of Nelder Mead Deep Neural Activation for stress detection. As illustrated in the above figure, to detect the amount of stress induced by the subjects (i.e., 40 different subjects including both male and female) on various tasks (i.e., Stroop color-word test, solving arithmetic questions, identification of sym-metric mirror images, and a state of relaxation) Nelder Mead Deep Neural Activation function is designed. This Nelder Mead Deep Neural Activation function is modeled by correlating the ratings on a scale of 1–10 depending on the extent of stress evoked while performing various mental tasks based on three states of operations, reflection, expansion and contraction of the Nelder Mead function and applying the same to the Activation function to detect the level of stress of each subject. Let us consider the current test points (i.e., EEG-filtered signals). '$PS_1, PS_2, \dots, PS_{n+1}$' of each subject conducted on a trial and order them as given below.

$$Test\ samples \rightarrow f(PS_1), f(PS_2), \dots, f(PS_{n+1}) \quad (10)$$

With the above set of ordered current test points as given in (10), obtain the centroid of EEG filtered signals to which simulation is to be performed.

$$PS_C = \left(\frac{PS_0+PS_1+PS_2}{3}, \frac{Y_0+Y_1+Y_2}{3}\right) \quad (11)$$

With the above-obtained centroid value 'PS_C' of the EEG filtered signals'PS' to detect the level of stress experienced during different tasks (i.e., four different types of tasks) taken on a scale of 1 to 10, the corresponding three operations are performed to reflect the corresponding output. The three distinct operations performed are reflection 'PS_R' (12), expansion 'PS_E' (13) and contraction '$PS_{Con}(l+1), PS_{Con}(l-1),$ ' (14), (15) respectively.

$$PS_R = [PS_C + \alpha\ (PS_0 - PS_{n+1}), Scale], where\ Scale = 1 \quad (12)$$

$$PS_E = [PS_C + \beta(PS_R - PS_C), Scale], where\ Scale = 0 \quad (13)$$

$$PS_{Con}(l+1) = [PS_C + \gamma(PS_R - PS_C), Scale], where\ 2 \leq Scale \leq 5 \quad (14)$$

$$PS_{Con}(l-1) = [PS_C + \gamma(PS_{n+1} - PS_C), Scale], where\ 6 \leq Scale \leq 9 \quad (15)$$

From the above set of three operations, reflection refers to the change in the direction of action at an interface between two different media (i.e., neither increase in stress nor decrease in stress) so that the action returns to the medium from which it originated, expand referring to the increase in size (i.e., high stress) and contract referring to the reduction in size (i.e., low stress) respectively. With this basis, different levels of stress experienced during different tasks taken on a scale of 1 to 10 are measured for three different trials. Moreover, the scores have been taken to correlate the EEG data to the extent of stress experienced by the sample subjects. With this, a rating of 10 on the scale denotes a high level of stress on a specific subject, and a rating of 1 denotes a minimal level of stress on the subjects. Figure 7 shows the classified results.

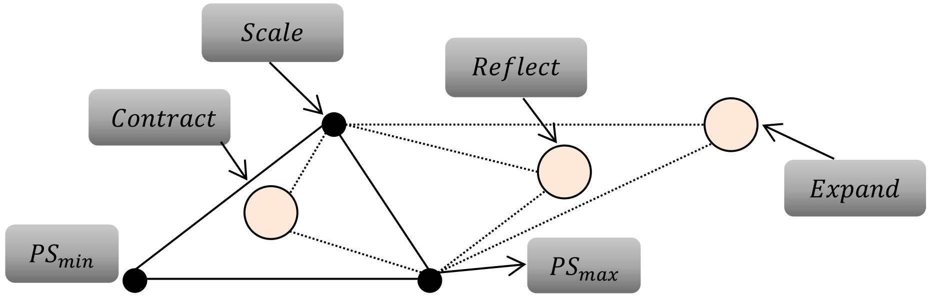


Fig. 6 Structure of nelder mead deep neural activation for stress detection

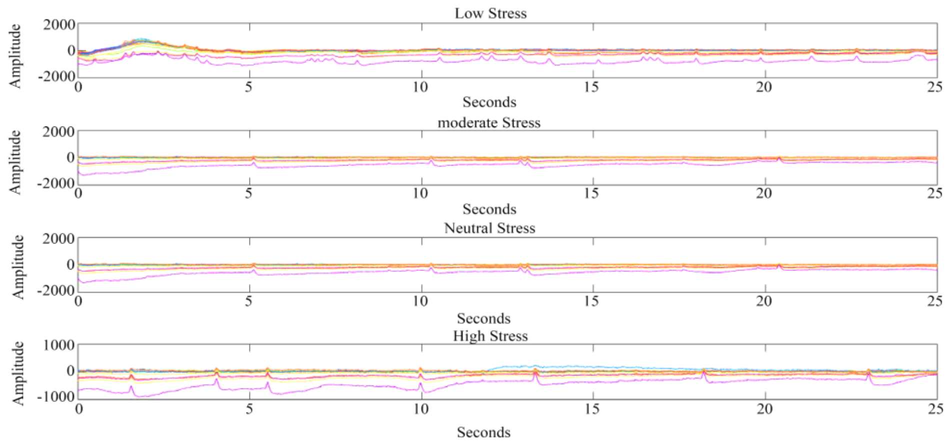


Fig. 7 Classified results (with the sample given for four different tasks)

Algorithm 2. Nelder mead deep neural activation for stress detection

Input: Dataset 'DS', subject
Output: Precise and early stress detection
1: **Initialize** EEG filtered signals 'PS', spatio temporal features 'FE', trials 'T_1', 'T_2', 'T_3', Scale 'S' 2: **Initialize** '$\alpha > 0$', '$\beta > 1$', '$\gamma = 0.5$' 3: **Begin** 4: **For** each Dataset 'DS' with EEG filtered signals 'PS', trials and spatio temporal features 'FE' 5: Formulate input vector matrix as given in (8) 6: Formulate activation function as given in (9) **//classification for stress detection** 7: Obtain test samples and order as given in (10) and obtain scale value for each trial **//Reflection** 8: **If** '$Scale = 1$' 9: Measure the reflected point as given in (12) 10: Samples with EEG filtered signals 'PS' detected with moderate stress 11: Return '$low\ stress$' 12: **End if** **//Expansion** 13: **If** '$Scale = 10$' 14: Measure the expansion point as given in (13) 15: Samples with EEG filtered signals 'PS' detected with neutral stress 16: Return '$high\ stress$' 17: **End if** **//Contraction** 18: **If** '$2 \leq Scale \leq 5$ ' 19: Measure the contracted point on the inside as given in (14) 20: **End if** 21: **If** '$6 \leq Scale \leq 9$' 22: Measure the contract point on the outside as given in (15) 23: **End if** 24: Return stress detected results 25: **End for** 26: **End**

As illustrated in the above figure, with four subjects, EEG signals were acquired as input, the final classified results with the subject in the state of relaxation was identified with low stress, symmetric mirror images subject was identified with moderate stress, arithmetic solving subject was identified with neutral stress and finally, the stroop test subject was identified with high stress respectively. The pseudo code representation of Nelder Mead Deep Neural Activation for stress detection is given below.

As given in the above algorithm, with the objective of improving stress detection performance or stress detection rate, in this work, first, EEG filtered signals of the respective subjects conducted with respect to different trials and tasks based on extracted spatio temporal features are first obtained as input. This specific task of stress detection is performed in the second hidden layer, and the corresponding output (i.e., stress detected) is provided in the output layer.

Three different operations, namely, reflection, expansion and contraction, are performed individually to measure the level of stress. With the convergence rate being high as distinct operations being performed with different levels of stress, detection is not only made at an early stage but also in an improved manner with minimum overhead.

4. Experimental Setup

In this section, we discuss the performance of the proposed stress recognition method using Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP). In this study, experiments are carried out in a subject-dependent manner, where the stress state model is trained for 40 different subjects, and the stress state is classified. The precision and recall for each subject are then calculated using 10-fold cross-validation, and the final precision and recall for one stress dimension is the average of all subjects' values.

The 10-fold cross-validation evaluation refers to that 90% of the EEG signals were trained randomly whereas the remaining 10% were used for testing, and this procedure was iterated ten times or for 10 distinct simulation runs. Ten sets of results were finally averaged.

Furthermore, extensive experiments were conducted on two different existing methods, Symmetric Deep Convolutional Adversarial Network (SDCAN) [1] and stress detection with deep learning [2], to validate the superiority of the proposed KST-NMMP method.

5. Performance Measure

We have applied three different deep learning methods, namely Symmetric Deep Convolutional Adversarial Network (SDCAN) [1], stress detection with deep learning [2] and proposed Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP)on the same SAM40 dataset, to investigate and compare the performance of these methods to detect stress from EEG signals. Matlab multi-paradigm programming language has been applied to implement different methods.

The following performance measures have been identified to evaluate the efficiency of the stress detection method, i.e., the total of true positive cases represented by 'TP', the total of true negative cases represented by 'TN'. In a similar manner, false positive cases are represented with 'FP' and false negatives are represented with 'FN' respectively.

Precision: the objective of measuring precision is to identify the total number of correct positive predictions from the total number of positive predictions using the formula as given below.

$$Precision = \frac{TP}{TP+FP} \quad (16)$$

From the above equation (16), the precision results '$Precision$' is arrived at based on the true positive rate 'TP' (i.e., the method correctly predicts the positive class) and the false positive rate 'FP' (i.e., the method incorrectly predicts the positive class) respectively.

Recall: the objective of measuring recall is to identify the number of samples correctly classified as being stressed. Mathematically, it is evaluated as given below.

$$Recall = \frac{TP}{TP+FN} \quad (17)$$

From the above equation (17), the recall results '$Recall$' is obtained on the basis of the true positive rate 'TP' and the false negative rate 'FN' (i.e., the method incorrectly predicts the negative class) respectively. Stress detection time refers to the time consumed in detecting stress.

A significant amount of time is said to be consumed during the stress detection process, and this is referred to as the stress detection time. This is mathematically stated as given below.

$$SDT = \sum EEG\ Patterns * Time\ (SD) \quad (18)$$

From the above equation (18), the stress detection time 'SDT' is measured based on the four different EEG patterns (i.e., delta [1 – 3 Hz], theta [4 – 7 Hz], alpha [8 – 12 Hz] and beta [13 – 30 Hz]) '$EEG\ Patterns$' and the corresponding time involved in stress detection '$Time\ (SD)$' for the respective subjects of consideration.

Stress detection overhead refers to the memory consumed during the process of stress detection. While performing stress detection, the intermediate results of EEG filtered signals, spatio-temporal features extracted, and the scale value of each subject conducted for a specific trial has to be stored in the stack, therefore consuming a portion of memory. This is referred to as the stress detection overhead and is measured as given below.

$$SDO = \sum EEG\ Patterns * Mem\ (SD) \quad (19)$$

From the above equation (19), the stress detection overhead 'SDO' is measured based on the four different EEG patterns (i.e., delta [1 – 3 Hz], theta [4 – 7 Hz], alpha [8 – 12 Hz] and beta [13 – 30 Hz]) '$EEG\ Patterns$' and the memory consumed in detecting stress '$Mem\ (SD)$' for different subjects.

Table 1. Tabulation for precision and recall with pre-processing and without pre-processing

Methods – 30 subjects (male)	With pre-processing		Without pre-processing	
	Precision	Recall	Precision	Recall
KST-NMMP	0.86	0.9	0.9	0.95
SDCAN	0.81	0.85	0.86	0.9
stress detection with deep learning	0.77	0.8	0.81	0.85

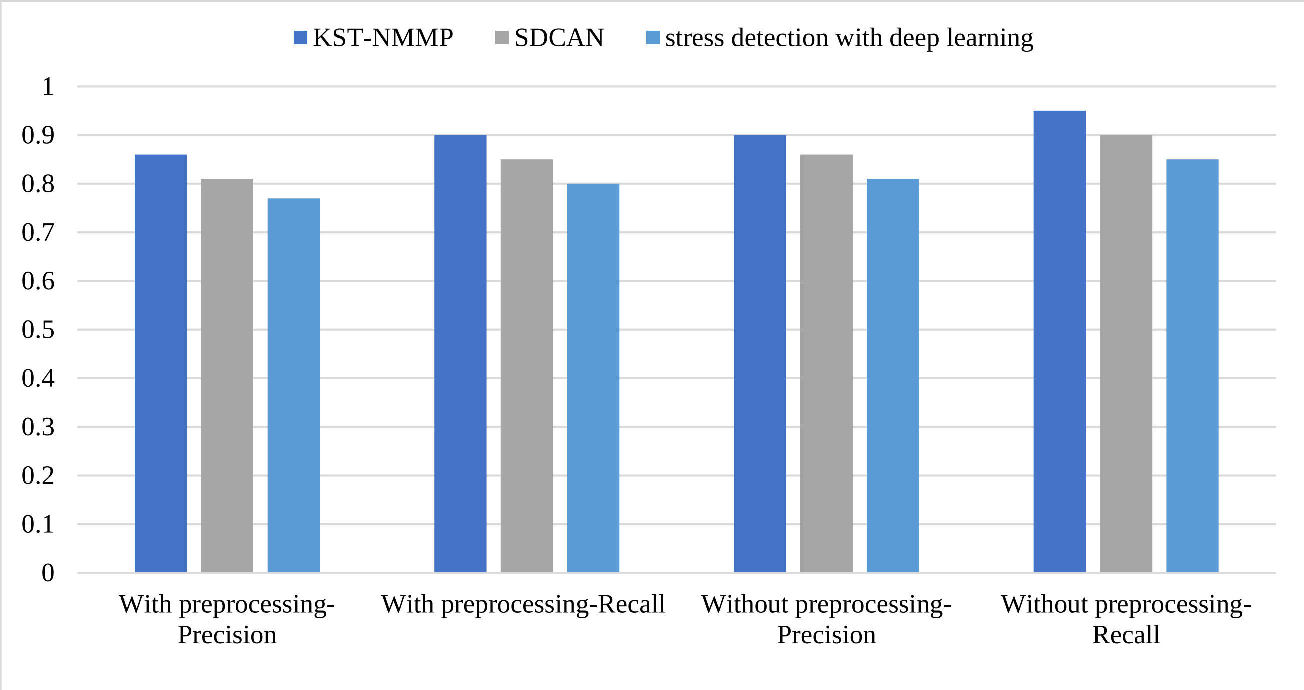


Fig. 8 Graphical representations of precision and recall

5.1. Performance Analysis of Precision and Recall

In this section, the analysis of precision and recall with respect to 30 distinct subjects (i.e., 20 male and 10 female) is made. Table 1 shows the comparative analysis of the precision and recall rate performed both with pre-processing and without pre-processing.

Figure 8 shows the graphical representation of precision and recall. At the same time, precision refers to the ratio of relevant instances among the retrieved instances, whereas recall denotes the ratio of relevant instances that were retrieved. Therefore, both the precision and recall rates are based on relevance factors.

With 30 samples taken for implementation, 8 subjects were observed with no stress and 22 subjects were observed with stress, the true positive rate and the false positive rate using the proposed KST-NMMP observed to be 20, 2, 19, 3 using [1] and 18, 4 using [2] respectively. With this, the overall precision rate with pre-processing using the three methods was found to be 0.86, 0.81 and 0.77, respectively.

Similarly, the true positive rate and the false negative rate using the proposed KST-NMMP method were observed to be 20, 1, 19, 2 using [1] and 18, 3 using [2]. The overall recall rate with pre-processing was observed to be 0.95, 0.90 and 0.85 using the three methods. In a similar manner, the precision and recall rate for 30 subjects without pre-processing was measured. From the above figure, the precision and recall rate with pre-processing was found to be better than without pre-processing. Also, the precision and recall using the KST-NMMP method were found to be better than [1] and [2]. The reason behind the improvement was due to the Nelder Mead Deep Neural Activation for stress detection in the second hidden layer. By applying this activation function, each subject for different trials for distinct tasks was measured separately according to the scale value using three operations: reflection, expansion and contraction. This in turn, assisted in improving the true positive and true negative rate significantly. With this, the precision and recall rate of stress detection, when applied with pre-processing, was found to be improved using the KST-NMMP method by 11% compared to [1] and 12% compared to [2]. In a similar manner, the precision and recall without pre-processing were found to be enhanced using the KST-NMMP method by 11% compared to [1] and [2].

5.2. Performance Analysis of Stress Detection Time

In this section, the stress detection time is measured. One of the important performance metrics as far as stress detection is concerned is the stress detection time. This is due to the reason that early detection was more efficient; the method is said to be in identifying the defects to the general public in measuring the stress; accordingly remedial actions can also be taken. Table 2 shows the comparative analysis of the stress detection time performed for 10 different subjects, with 1 representing subject 1, 2 representing subject 2 and so on.

Table 2. Tabulation for stress detection time

Method	Stress detection time (ms)									
	Subjects									
	1	2	3	4	5	6	7	8	9	10
KST-NMMP	1.35	2.25	5	6.25	8	7.45	9	12	11	10
SDCAN	1.85	3	5.85	7	9.15	9	9.85	14.15	12.45	11.35
stress detection with deep learning	3	3.55	7	8.35	12	10.35	11	15	15	13

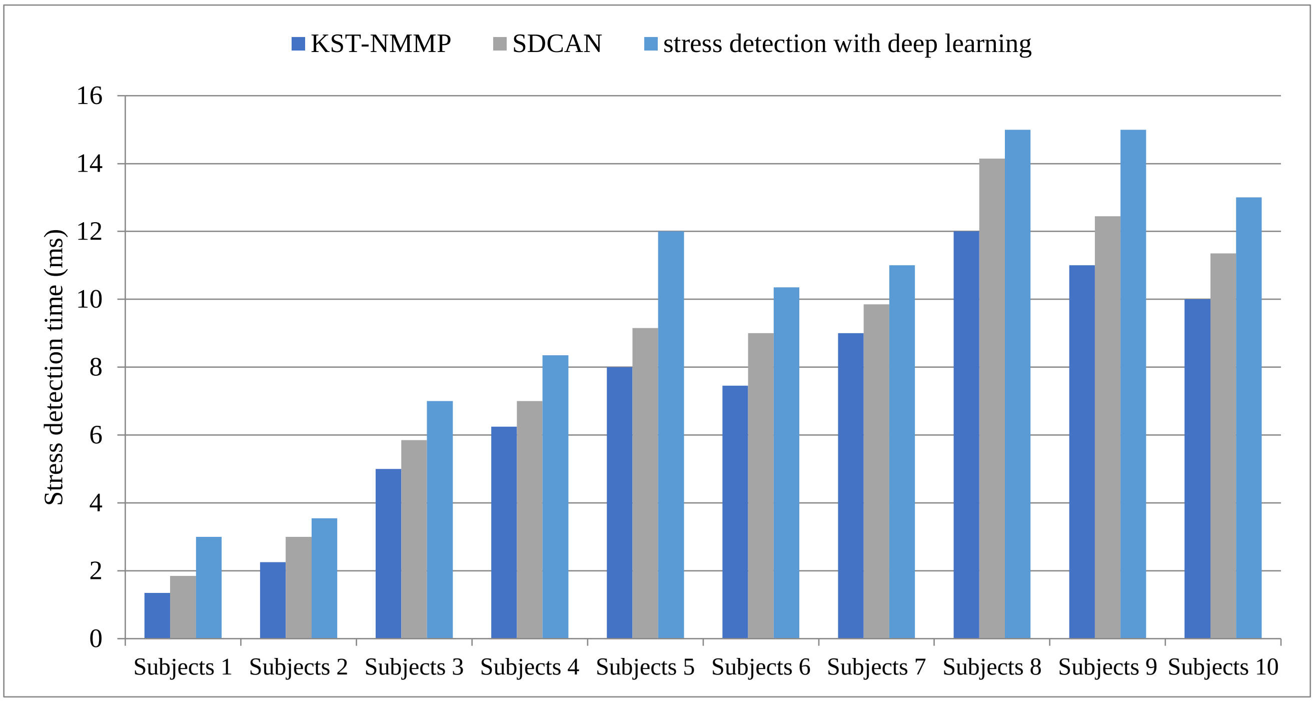


Fig. 9 Graphical representation of stress detection time

Figure 9, given above, shows the stress detection time observed for 10 different subjects with respect to trial 1. The stress detection time is found to be different for 10 different subjects. This is because of different levels of stress induced by the respective tasks. For example, the time consumed in obtaining the EEG patterns using the KST-NMMP method was found to be 0.035ms, 0.065ms using [1] and 0.085ms using [2]. Similarly, the stress detection using the three methods was observed to be 38.56ms, 28.46ms and 35.29ms, respectively. With this, the overall stress detection time was found to be 1.35ms, 1.85ms using [1] and 3ms using [2], respectively. As a result, the stress detection time using the KST-NMMP method was significantly better in detecting stress than [1] and [2]. The reason behind the improvement was owing to the application of the Finite Impulse Kernel Smoother based filtering model to the raw EEG signals. By applying this, the artifacts present in input EEG signals that were of no use were eliminated. Moreover, by means of a Finite Impulse Response (FIR) filter with Kernel Smoothing window smoother results were obtained, therefore reducing the overall stress detection time efficiently.

5.3. Performance Analysis of Stress Detection Overhead

In this section, the stress detection overhead is measured. Another significant performance metric of importance is the stress detection overhead. A small portion of overhead is said to be consumed while storing the intermittent results for stress detection and is referred to as the stress detection overhead. Table 3 shows the comparative analysis of the stress detection overhead performed for 10 different subjects, with 1 representing subject 1, 2 representing subject 2 and so on. Finally, figure 10 shows the graphical representation of stress detection overhead with respect to 10 different subjects. As each subject's EEG pattern generation overhead is different, as the scale obtained is different for each trial, the stress detection overhead is also found to be distinct. However, comparative analysis shows better results using the KST-NMMP method upon comparison with [1] and [2]. The reason behind the improvement was due to the application of Finite Impulse Kernel and Kaczmarz Spatio Temporal feature extraction algorithm. By applying this algorithm, spatio temporal features were obtained for different levels of stress by fine-tuning weight and optimizing using the Kaczmarz function.

Also, with the application of complex conjugation, spatio temporal samples with different classes were stored in the real part, and spatio temporal samples with the same class were stored in the imaginary part, therefore reducing the overall dimensionality. Due to this, the stress detection overhead using the KST-NMMP method was found to be comparatively better than [1] and [2].

Table 3. Tabulation of stress detection overhead

Method	Stress detection overhead (KB)									
	Subjects									
	1	2	3	4	5	6	7	8	9	10
KST-NMMP	2.22	3.15	2.55	4	5.25	4.55	3.85	4	8	7.15
SDCAN	3.02	4	3.15	4.85	6	5.85	5.25	5.55	8.35	8
stress detection with deep learning	3.89	4.85	5	6	6.85	7.15	7	7	10	9.25

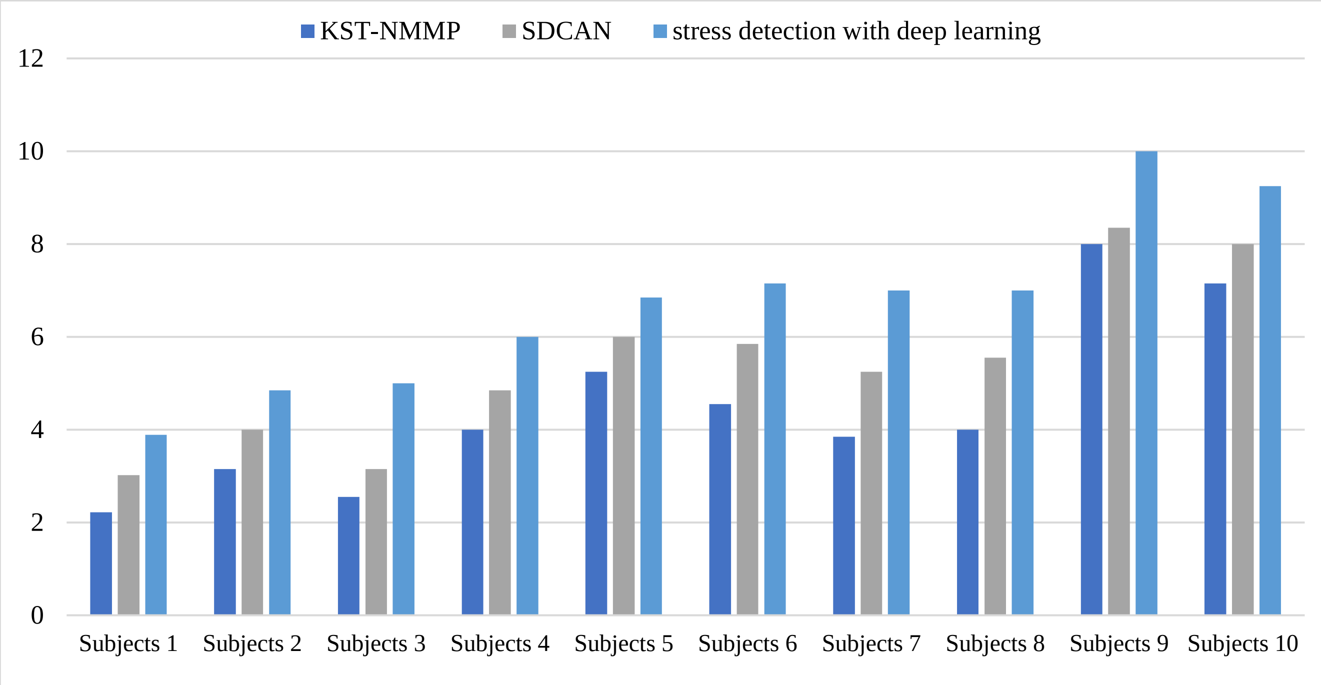


Fig. 10 Graphical representation of stress detection overhead

6. Conclusion

Accurate mental stress detection based on physiological parameters using EEG signals aids in detecting abnormalities in brain waves, and seizing emotional experiences helps in monitoring a significant part of humans. Hence, early and accurate prediction of stress can be carried out, and in certain cases even disease can also be cured. In this work, a method called Kaczmar Spatio Temporal Nelder Mead Multilayer Perceptrons (KST-NMMP) is proposed. Initially, artifacts present in the raw EEG signals are filtered out using the Finite Impulse Kernel Smoother-based filtering model. After noise reduction, spatial and temporal features are extracted from the EEG signals by using Finite Impulse Kernel and Kaczmarz Spatio Temporal feature extraction; thus, the stress detection time and overhead are said to be improved considerably. Finally, stress level classification using spatio temporal features is done by using Nelder Mead Deep Neural Activation for stress detection. The proposed KST-NMMP method is a simulation using Matlab with the aid of an EEG brainwave dataset. The simulation consequences validated that the KST-NMMP method provides better results in performance metrics like, precision, recall, stress detection time and overhead compared to thess state-of-the-art methods.

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