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An Improved Elman Neural Network based Stress Detection from EEG Signals and Reduction of Stress Using Music

C. Ranjith[1] and Dr. B. Arunkumar[2]

[1]Research Scholar, Department of CSE, Karpagam Academy of Higher Education, Coimbatore, India

[2]Associate Professor, Karpagam Academy of Higher Education, Coimbatore, India.

Abstract

Stress or depression can be seen as a physiological response to everyday emotional, mental and physical challenges. A long-term exposure to stress situations can have negative health consequences, such as increased risk of cardiovascular diseases and immune system disorder. Therefore, timely stress detection can lead to systems for better management and prevention in future occurrences. In this research analysis, a novel classification scheme is introduced to find the serious cause and effects mental stress or depression. This is done by analysing the Electroencephalogram (EEG) signals in which feature extraction and classification would be carried out. These EEG signals have been gathered from the multiple persons to predict the mental work load stress or depression variation. Anticipating higher performance with reduced error rate and improved accuracy, this analysis has been carried out by using Improved Elman Neural Network (IENN).Before prediction, EEG signals would be pre-processed to improve the quality of the signals obtained. In pre-processing stage power line noise and ocular artifacts would be removed by using match filter.Then, the Power Spectral Entropy (PSE) and Gray Level Different Statistics (GLDS) based features are extracted to improve the classification accuracy. At last, the stress level is categorized as low, medium and high by IENN. In ENN, the weight values are optimized by using Dragonfly Algorithm (DA) and hence named as IENN. In this classification, if high stress is detected, then subjects are allowed to hear music and this statistical examination is conversed in the course of the performance analysis. The experimental outcomes demonstrate that the anticipated IENN accomplished higher performances compared to the existing stress or depression detection and classification algorithms with EEG signal.

Keywords: Human brain, stress detection and reduction, music, GLCM, statistical, Elman neural network, dragonfly.

1. INTRODUCTION

Depression or Stress is generally considered to be a state in which an individual is expected to be more stress, in which he / she can only cope with some of the demands. These demands may be psychological or social. It is known that mental health stress is present in everyday life because of carelessness in living standards; mental health and physical health are deteriorating [1]. Psychological stress is a major factor in many psychological illnesses. For example, it increases depression [2], heart attack and heart failure [3]-[6].

The stress reduction should first measure the size. Clinically, stress is identified through questions and interviews and these are subjective methods. Alternatively, stress/depression-related physical and physiological changes are used as indicators of stress/depression. [7] For example, physically, depression changes the student expressions [8], irregular ratio [9] and face gestures [10]. On the other hand, depression creates changes in the Autonomic Nervous System (ANS) [11]. Therefore, physiological biologists of stress from ANS are at Heart Rate (HR) and Heart Rate Variation (HRV) [12], respiration [13] and skin conductance [14]. According to recent neuroscience, human brain is the main target of depression [15] because the human brain's senses determine whether the situation is threatening and stress/depressionful. Stress and electroencephalography (EEG) are the most appropriate methods for measuring brain functional changes to obtain non-infiltration neuro-science systems. Importantly, AIGs typically have implications with other stress signs, such as HR and HRV [16] and are especially stress/depressionful [17].

When evaluating stress from EEG signals, the classification mechanisms that have worked with maximum accuracy with 96% higher accuracy for classification between two types of depression, [18] extracting multiple electrolytic properties from the EEG signal. These findings, the EEG, are a possible assessment tool for stress/depression. Recent studies have shown that the EMEG may differ due to depression in attachment operations such as complete power and mutual information. [19] Similarly, the imbalance in EEG alpha energy has been shown to be affected by HRV biological feedback during stress treatment [20].

Another study discussed EEG Alpha asymmetry, revealing stress/depression-related disorders in a virtual reality environment [21]. EEG Eigen value decomposition was used for depression level classification [22]. Another study posed an EEG-based brainstorming index to assess the profound assessment of university students in their study [23]. The time frame of psychological stress has been studied by the possibilities of the event in a successfully designed stress/depression-disorder model [24]. This study indicates that stresshas occurred in the early stages of cognitive processes. An assistant vector machine [25], [26], K-nearest neighbor (KNN) [22], [27], artificial neurological networks

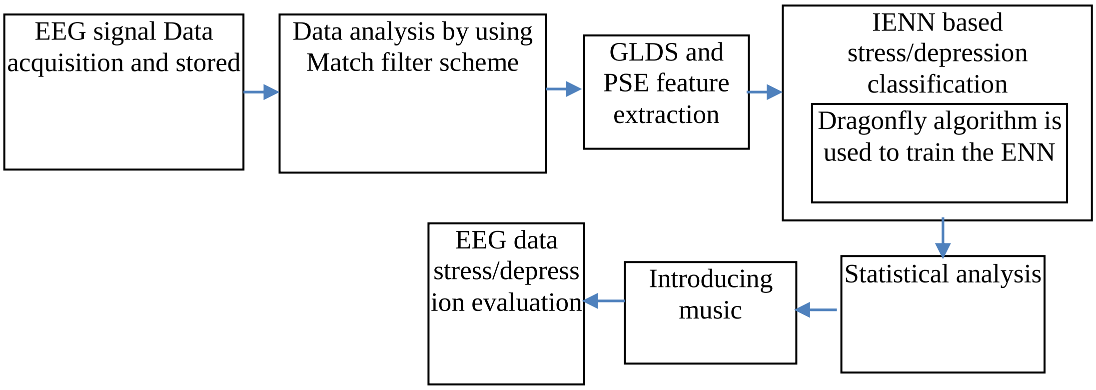

Figure 1: Proposed IENN based stress classification architecture

(ANNs) [28], in the context of identifying and distinguishing depression from other conditions using EEG-based guidelines [28], [29] and random forests [30]. Not only is depression found to be diagnosed by EEG signals, EEG signals combine with other procedures to identify skin stress [30], intracellular spectroscopy (FNIRS) [25] and electrolytic (ECG) [31] near the function.In existing work, three type of algorithms like Feed Forward Neural Network with Particle Swarm Optimization (FFNN-PSO)[32], Relevance Vector Machine (RVM) [33], Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) are tested for predicting the stress and reduction through music.From the above researches, still the accurate stress detection and reduction is more difficult. So, in this paper, the stress reduction is mainly focused by using music.

The main contribution of this paper is the introduction of the mental health ethical system, which is evaluated for its efficacy to assess stress/depression. In this work, first, EEG signal acquired brain function. Late rmeasured EEG signals are activated prior to increasing the quality of electrical signal operations without loss of confirmed information by introducing matched filter. After that, the features of the GLDS and PSE are extracted. Finally, IENN is used to find a different level of stress and rest state by processing EEG signals collected from various sources. Depending on the use of IENN, the state of stress is categorized and the stress is determined to solve stress/depression. This classification scheme classifies people with stress and dependency. The proposed method concludes that the proposed IENN has achieved great efficiency compared to existing methods. The following sections have been organized with the following sections: The proposed ENN-based classification and analysis results are discussed in Section 3 and 4, finally, this work is completed.

2. PROPOSED METHODOLOGY

In this section, the anticipated IENN classification scheme for stress detection has been discussed.

System overview

Figure 1shows the design of presented scheme. The objective of this presented scheme is to reduce the human stress by using EEG signals. The main aim of this scheme is to examine accurately estimated the human stress and classify the human stress level. The stress has been evaluated by using the EEG characteristics and stress level of human (i.e. stress or relaxed mode). This stress levels are classified by using IENN classification scheme. If high stress is monitored, then next music of subject's choice is played and this statistical examination is conversed in the course of the performance analysis. The step by step process has been discussed in given below subsections.

EEG data acquisition

Here spectral power density is utilized to calculate the mean power of EEG signals and hamming window distance is calculated by using the power spectral density. Here window size is fixed as 256 with 50% overlapping and then FFT length is fixed as 1024. The situation that are considered while measuring EEG signals are listed as follows:

- Relax: Signals are measured when the subject is sitting in the relaxation mode. It was done for two minutes (i.e. 30sec x 4 trails)
- Music's: The signals are measured when subject is sitting in the relaxation mode and hearing songs of his/her choice. This was also done for two minutes (i.e. 30sec x 4 trails).
- Stress signal: Here signals are measured when subject provided with unpleasant noisy music. Noises are varied during examination. It is also done for two minutes (i.e. 30sec x 4 trails)

Pre-processing using Match filter

In this study we applied matched-filtering for the purpose to eliminate artifacts, commonly seen in scalp EEG, by eliminating the matched-filtered signals from the original signals. The match filter [32], also referred to as the coherent detector, is a quasi-optimum linear filter h(t) which maximizes the output Signal-to-Noise Ratio (SNR) and thus improves the detection of a known signal. It is not frequency band-specific but instead is used to extract a particular waveform from signals polluted and corrupted by noise signal.

Feature extraction

Feature extraction is the most important step in a Computer Aided Diagnosis scheme. The predictable method hauls out two different well-known kinds offeatures from every EEG signal.

PSE feature extraction

PSE is information entropy, which is able to quantify the spectral complexity of an uncertain system. It is defined in [33]. For an uncertain system, let's assume a random variable X as states of the system, the value of X is considered as $X = \{x_1, x_2, \ldots, x_n\}$

The corresponding probability is

$$P = \{p_1, p_2, \ldots, p_n\} 0 \leq p_i \leq 1, i = 1,2,\ldots,n \quad (1)$$

Under constraints $\sum_{i=1}^{n} p_i = 1$

Therefore, the information entropy of the system canbe expressed as

$$H = -\sum_{i=1}^{n} p_i \, ln p_i \quad (2)$$

The time-series signals become power spectrum byFFT transform, and the information entropy of powerspectrum is called power spectral entropy. Thealgorithm can be summarized as:

1) The Discrete Fourier Transform $X(\omega_i)$ of signalcan be obtained by FFT; where ω_i is the frequencypoint of the number i.

2) Calculate its power spectral density (PSD)

$$\hat{P}(\omega_i) = \frac{1}{N} |X(\omega_i)|^2 \quad (3)$$

3) Normalize$\hat{P}(\omega_i)$, and obtain power spectraldensity distribution function

$$p_i = \frac{\hat{P}(\omega_i)}{\sum_i \hat{P}(\omega_i)} \quad (4)$$

4) Using equation (4), the PSE can be worked out.PSE can be interpreted as a measurement of the time uncertainty in frequency domain. In power spectrum of EEG signals, when the spectrum peak is narrow, it's entropy value is small. It indicates that the signal has an obvious concussive rhythm, that is to say, if wave is orderliness, its complexity is small; whereas, the spectrum peak is more smoothness, and its entropyvalue is more greatness. Therefore, the PSE can reflect the spectra structure of EEG signals.

Gray Level Different Statistics (GLDS)

The GLDS method is supported on the statement that functional texture information can be haul out by means of first order statistics from an EEG signal.

The algorithm is based on the evaluation of the likelihood density of signal pairs at a specified distance $\delta = \Delta x, \Delta y$ encompassing a definite complete gray level difference value. For fine texture signals, inter signal gray level values have large dissimilarity whereas in coarse texture signals havelesser values. To distinguish the four sets of EEG signals we utilized entropy (ENT) and Angular Second Moment (ASM) of GLDS.

$$ENT = -\sum P_\delta(i) \log(P_\delta(i)) \quad (5)$$

$$ASM = \sum P_\delta(i)^2 \quad (6)$$

Where P_δ→the individual probabilities.The ENT and ASM were approximated for the subsequentdistances $\delta = (d, 0), (d, d), (-d, d), (0, d)$consequently the instance mean and standard deviation were approximated.

Classification by using Improved Elman neural network

Elman neural network is a kind of feedback neural network; based on back propagation(BP) neural network hidden layer adds an context layer, as the delay operator, the purpose of memory, so that the network system has ability to adapt to the time-varying dynamic characteristics and has strong global stability. Figure 2 shows Elman neural network structure.

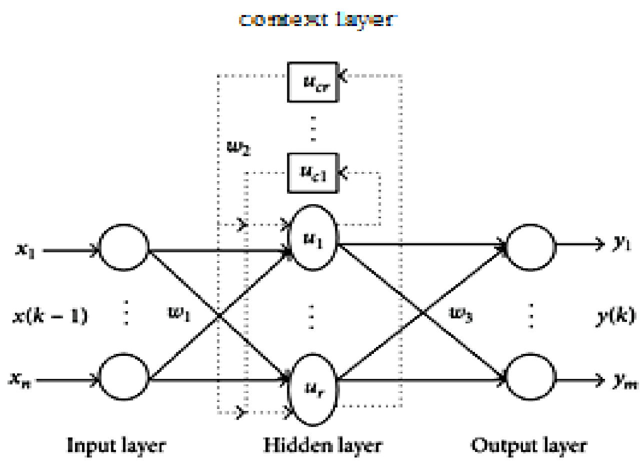

Figure 2: ENN architecture

The topology is generally divided into four layers: input layer, hidden layer, context layer, and output layer. Context layer is used to remember the output of hidden layer, which can be seen as a step delay operator. Based on Back Propagation (BP) network, the output of hidden associates with its input through the delay and storage of context layer. This method of relationship is sensitive to historical data, and internal feedback network can increase the ability of handing dynamic information. Remembering the internal state makes it have dynamic mapping function, which makes the system have the ability to adapt to time-varying characteristics.

Suppose with n input, m output, the number of hidden and context neurons are r, the weight of input layer to hidden layer is w_1, the weight of context layer to hidden layer is w_2, the weight of hidden layer to output layer is w_3;$u(k-1)$ is the input of neural network, $x(k)$ is the output of hidden layer, $x_c(k)$ is the output of context layer, and $y(k)$is the output of neural network; then

$$x(k) = f\left(w_2 x_c(k) + w_1\big(u(k-1)\big)\right) \tag{7}$$

Where $x_c(k) = x(k-1)$

f is the hidden layer transfer function, which is commonlyused in S-type function; that is,

$$f(x) = (1 + e^{-x})^{-1} \tag{8}$$

g is the transfer function of output layer, which is often alinear function; that is,

$$y(k) = g\big(w_3 x(k)\big) \tag{9}$$

Elman neural network uses BP algorithm to revise weights; the error of network is

$$E = \sum_{k=1}^{m} (t_k - y_k)^2 \tag{10}$$

Wheretk is the output vector of object. To improve the ENN prediction accuracy, the weight value of ENN is optimized by using Dragonfly Algorithm (DA)

Optimal weight of ENN selection by using Dragonfly Algorithm (DA)

To increase stress detection accuracy, the weight of ENN is optimized by DA. Generally, Dragonflies have an exclusive swarming characteristic with definite two functions: hunting (static feeding scheme) and migration (dynamic migratory scheme) [34]. As recognized that an optimization by means of meta-heuristic has two foremost stages (exploration and exploitation), for dragon-flies, the hunting and migration characteristics are extremely alike to these stages.

Based on the two above schemes, in this paper, the optimal weight has been selected. Here, the dragonflies are considered as weights and optimal food source are the high weight values. The objective of this process is to select height weight value among all weight value of feature inputs.

To replicate the characteristics of dragonflies swarming, three primitive standards of swarming are exploited separation (S), alignment (A) and cohesion (C), as well as considering two novel ideas, attraction in the direction of food sources (F) and distraction external enemies (E) to accomplish the survival point of the swarm. Mathematical facts of modelling the five characteristics for revising the location of individuals in swarm are illustrated in [34].

Two vectors (i.e. step and position vectors) are measured for the method of revised dragonfly's (i.e. weight values of input features) location in search space and their movement' simitation. The course of dragonfly'sprogress is illustrated by the step vector, which distinct as revealed in equation (11).

$$X_{t+1} = (sS_i + aA_i + cC_i + fE_i + eE_i) + w\Delta X_t \tag{11}$$

Where s defines separation weight, S_i specifies the separation of the i − th individual, a displays the alignment weight, A_i is defined as an alignment of i−th individual, c is the cohesion weight, C_i is specifies the cohesion of the i − th individual, f is the food factor (i.e. effectual weight), Fi→the food source of the i −th individual, e →the enemy factor, E_i→the enemy location of the i − th individual, w→ the inertia weight, and t→the iteration counter.

The position vectors are considered as exposed in equation (12)

$$\Delta X_{t+1} = X_t + \Delta X_{t+1} \tag{12}$$

Where t is the sum of present iteration.

Hence, throughout optimization (i.e. optimal weight selection), with adaptively tuning the swarming parameters, diverse explorative and exploitative characteristics can be accomplished. As well, a neighbourhood with a definite radius is supposed around every artificial dragonfly. The neighbourhood region is amplified in addition whereby the swarm turn out to be one cluster at the ultimate phase of optimization to unite to the global optimum. Based on the above procedures, the stress and non-stress is classified in effective manner.

2. RESULTS AND DISCUSSION

Based on the distinctiveness of the dataset, two foremost parameters should be measured when choosing the classifier is curse of dimensionality and bias variance substitution. Curse of dimensionality is that the amount of training information desirable to present high-quality outcomes rises exponentially with the aspect of the feature vectors, while bias-variance substitution is distinctiveness of classifier towards elevated bias with low variance .Here, the proposed stress classification method of IENN presentation has been evaluated and the results are compared with state-of-the-methods like FFNN-PSO, RVM, SVM and LDA by using EEG signal. Initially, stress indices value has been evaluated for analysis the EEG signal. Then, the performance are analysed in terms of classification accuracy, sensitivity and specificity.

Dataset preparation

Certain subject's primary data is recorded in the database. With the use of music hearing tool, the songs have been produced. The significant primary data of the subject's are recorded in the below given table 1.

Table 1: Sample subjects for proposed scheme evaluation

Year	Name	Age	Gender	Music's
2001	harsha	27	female	melody's
2002	shyju	39	male	Carnatic
2003	muhamadali	40	male	Western songs
2004	sajith	37	male	melody's
2005	rabeesh	35	male	Carnatic
2006	ajay	30	male	Western songs

StressLevel

In the stress recognition system, initial step is to measure and find the index value of subject's stress level. It would be the first completion of data gathering process. Once the data is gathered, stress indices of individual subjects would be identified. This would be measured for both cognitive data and the physical data. This value would be taken as threshold value for further processing of stress prediction. This is calculated because each volunteer would have varying EEG signal frequency based on their health impacts. This can be adapted by calculating the threshold stress index for individual subject. This research work measures individual stress indices (SI) for the finding the stress level of individual subjects. Here graph construction procedure is used for the analysis process of gathered data. This graph would indicate stress level individual volunteer.

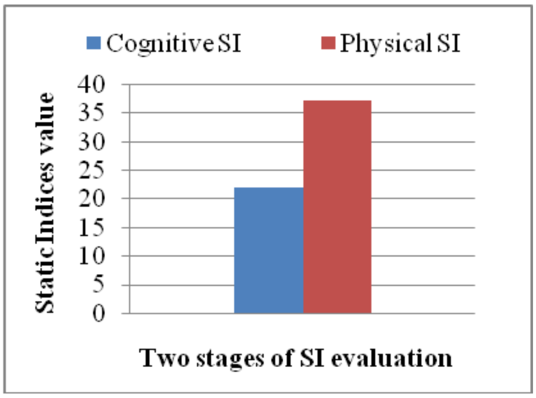

Figure 3: Stress indices values for two stages

In figure 3, stress index value comparison has been given in two stages. It is used to indicate the variation present between different stress indices value. This graph represents the stress level before noise and after noise. It can be proved that the stress would be higher in case of presence of noise in the environment.

After prediction of stress level of humans, it is required to update the stress index value based on the previous stress index values. This can be used to know the variation between the stress levels in different stages.

In figure 4, Stress index value is compared in the graphical format in three stages. Those stages are before task load, after task load, and after recovery. From this comparison it can be concluded that the stress index value after recovery would be lesser than other stages.

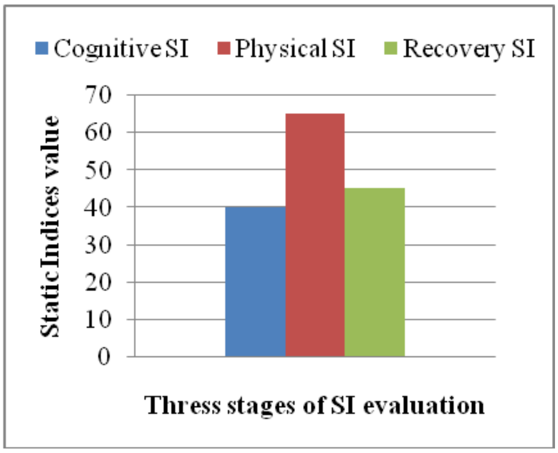

Figure 4: Stress indices for three stages

Stress rate performance comparison

Music (of any genre like traditional or classic) is a kind of technique which can give relief to human from high stress by relaxing their mood. It would help more for the aged people by relaxing their mind. Different music based on their behaviour can made use in stress level reduction process. Figure 5, 6 and 7 shows the stress rate value by using EEG signal based on time. These all predicts the stress and no stress rate by using EEG signal, when hearing noise and music. As well as, when chanting the music, the stress level is measured. It clearly shows, the stress level is less, when hearing and chanting music compared than to hearing noise. So, only the presented system has been focused to reduce the stress by using music's (i.e. traditional or classic).

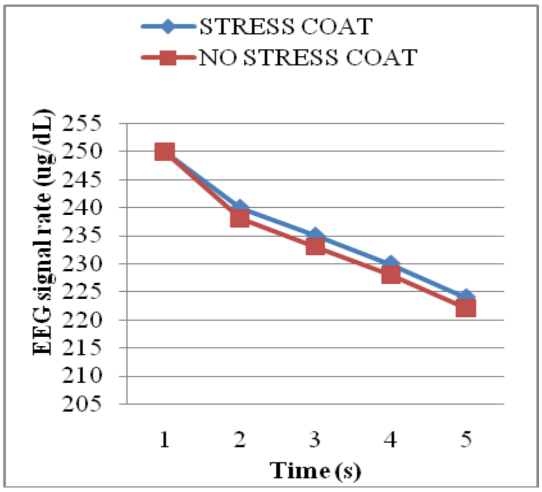

Figure 5: Stress coat on listening to noise

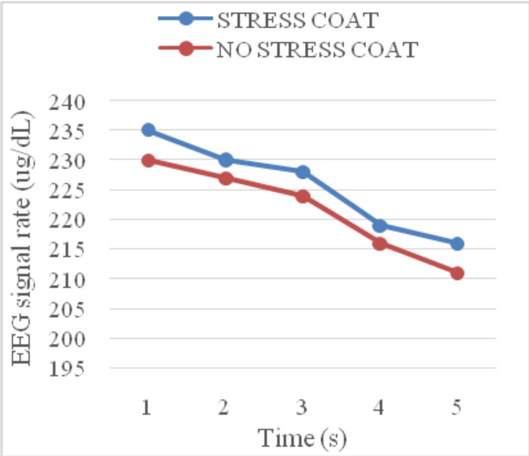

Figure 6: Stresscoat on listening to traditional or classical music

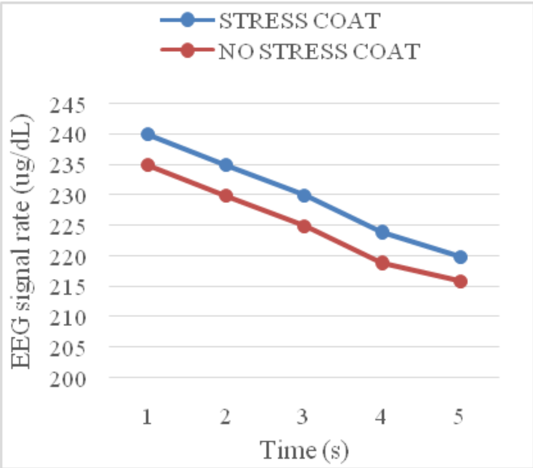

Figure 7: Stress coat on listening to heavy metal music

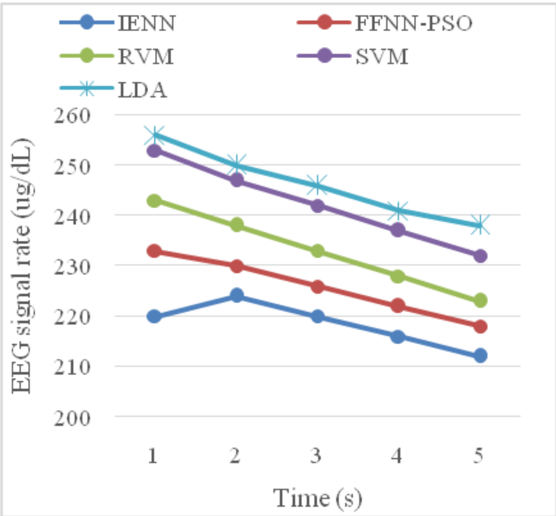

Figure 8: Stress Rate analysis between classification schemes

Figure 8 shows the stress level among various classification schemes. It shows the proposed IENN attained less stress compared than existing FFNN-PSO, RVM, SVM and LDA schemes due to efficient weight optimization and hearing and chanting music.

Accuracy, sensitivity and specificity comparison

Figure 9 shows the overall performance comparison of accuracy, sensitivity and specificity for proposed IENN and existing FFNN-PSO, RVM, SVM and LDA. It shows the classification accuracy of proposed scheme attained high compared than existing schemes, due to the efficient pre-processing and effectual classification by using IENN. Then, the sensitivity of proposed IENN attained high compared than others, due to less false negative errors, as well as the specificity is also high compared than others, due to the high true positive rate. When, the number of subjects increased means, the performance of proposed also increased. The proposed IENN attained accuracy of 94.12%, sensitivity of 93.25%, and specificity of 98.23%. The numerical evaluation is showed in table 1.

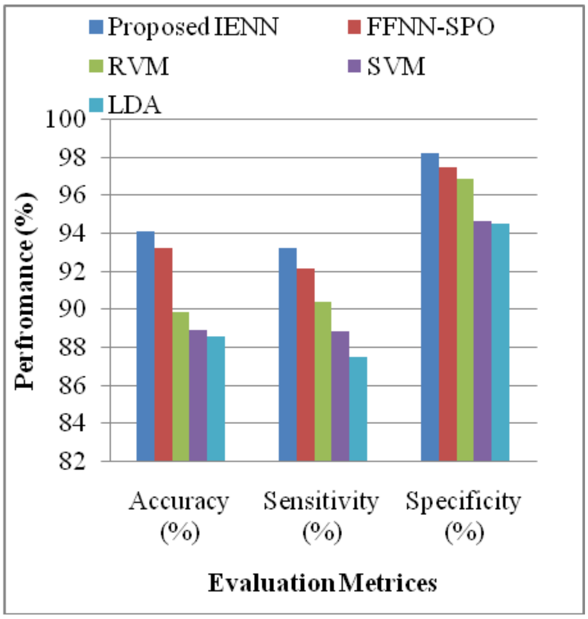

Figure 9: overall performance comparisons among all classifications schemes

Table 1: Precision, sensitivity and specificity performance comparison for all classifiers

Classifiers	Precision	Sensitivity	Specificity
Proposed IENN	94.12%	93.25%	98.23%
FFNN-PSO [32]	93.25%	92.14%	97.52%
RVM [33]	89.87%	90.38%	96.87%
SVM [33]	88.90%	88.84%	94.68%
LDA [33]	88.56%	87.51%	94.54%

3. CONCLUSIONS

In this work, Improved Elman Neural Network (IENN) based classification scheme has been presented for stresslevel classification and music introduced for reducing the stresslevel. In this process, at first, the EEG signal has been acquired and then pre-processed by using a digital band-pass filter for improving the image quality. Then, the PSD based features has been extracted for improving the classification performance. Finally, the features are classified by IENN. In ENN process, to attain minimum error the DA is applied. The experimental outcomes demonstrate that the presented IENN accomplished higher performance in terms of accuracy of 94.12%, sensitivity of 93.25%, and specificity of 98.23%contrast to the existing stressdetection and classification algorithms with EEG signal due to the effectual feature extraction and classification. In future, the proposed scheme applied for real time data.

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