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Efficient Human Stress Level Prediction and Prevention Using Neural Network Learning Through EEG Signals

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Abstract

Stress analysis becomes the most concerned research scenario in the real world which affects the day to day activities of human beings. Detection stress level needs to be done with more concern where the higher stress level would increase the blood pressure that might affect the human lives. In this research work human stress level prediction is done, so that, human with more stress level can be made to hear mantras thus stress can be reduced. In our previous research work Fuzzy-Support Vector Machine is introduced for the stress prediction where it doesn't focus on ElectroOculoGraphy (EOG). Artifacts present in the EEG signals that will reduce the stress level prediction accuracy. This is resolved in the proposed research method by introducing EOG considered Artificial Neural Network Learning (EOG-ANN) technique which can accurately classify the stress level. In this research method, initially EOG artifacts present in the raw EEG signals are filtered out, thus the classification error can be reduced. After noise reduction, time domain features are extracted from the EEG signals thus the classification accuracy can be increased considerably. Finally stress level classification using time domain features are done by using Artificial Neural Network approach. This proposed method ensures the accurate classification outcome which leads to efficient human life saving. If high stress is predicted, then mantras are listened or chanted and statistical examination is conversed, in the course of the performance analysis. The overall implementation is done in the matlab simulation environment from which it can be proved that the proposed method EOG-ANN can ensure the increased accuracy than the existing research methods.

Keywords: Stress level, EEG signals, EOG artifacts, mantras, Time domain features

I. INTRODUCTION

Growing technological facilities lead to increased level of stress in humans which is unavoidable one [1]. Mostly stress occurs due to increased work pressure which might occur in any form [2]. The higher level of stress happening on humans would cause serious effects such as give up self control due to feelings like frustration or helpless. It occurs due to increased stress level which affects the pace of life [3]. There are various analysis have been conducted by various researchers to find the main source of stress. Many scientists conclude that the human brain is the main source of increased stress level [4]. Thus the stress level can be easily recognized by processing the brain signals based on variation. Many research works focused on capturing EEG signals to detect and analyze the stress level of humans [5].

Human stress is mainly categorized into two types. Those are "Acute and chronic" [6]. Here acute stress is found to be short term stress which is frequently found in the humans [7]. Chronic stress is the long term stress which occurs during increased frustration [8]. Here acute stress is found in more humans than chronic stress. However chronic stress is the more serious threat which might affect the normal living of humans. It would be hard for the humans from get relieving from the chronic stress [9].

Electroencephalograph (EEG) signal plays an important role in more researches which can be utilized to detect the human stress level and relaxation state [10]. EEG signals are captured from the central nervous system by using some electrodes [11]. EEG measures the human brain activity by measuring the electrical activity happening on the human brain from cerebral cortex. These activities are mainly generated by the neurons of brain which would vary based on human emotions [12]. Capturing these EEG signals is complex in nature which can be done by using two methods. Those are invasive and non invasive. The nerve cells activities happening on the brain can be captured by fixing the electrodes on scalp surface, thus the accurate recording can be ensured. This process is both cost effective and free of side effects.

From these signals stress level can be identified. There are three processes performed on EEG signals to predict the stress level. Those are [13]: Preprocessing, feature extraction and classification. In the preprocessing stage, unwanted noises present the captured EEG signals would be removed by using various filters. After preprocessing features extraction would be done to reflect the characteristics or behaviour of EEG signals. Finally these features are classified in order to predict the stress level. The overall view of the processed happening on the EEG signal processing is shown in the figure 1.

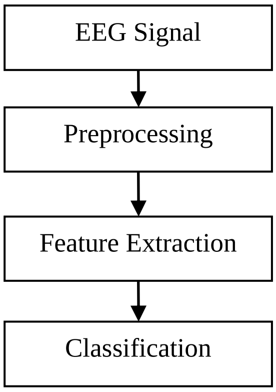

Figure. 1 Stress Analysis

In this research method, initially EOG artifacts present in the raw EEG signals are filtered out, thus the classification error can be reduced. After noise reduction, time domain features are extracted from the EEG signals thus the classification accuracy can be increased considerably. Finally stress level classification using time domain features are done by using Artificial Neural Network approach. This proposed method ensures the accurate classification outcome which leads to efficient human life saving. If high stress, next mantras are listened or chanted and statistical examination is conversed, in the course of the performance analysis.

The overall organization of the research method is given as follows. In this section, general introduction about the stress level and their effects on humans is given. In section 2, various related research methodologies that attempts to perform the stress level analysis has been given. In section 3, proposed research method has been discussed in detailed with suitable examples and explanation. In section 4, experimental evaluation of the proposed research techniques has been given in detail with suitable example and explanation. Finally in section 5, overall conclusion of the research method is given based on simulation outcome obtained.

II. RELATED WORKS

Subhani et al. [14]gathered EEG signals from the different humans with stress and without stress. Here the humans are injected with different emotional audios and videos which can stimulate their neurons. This is done with the help of International Affective Pictures and System (IAPS). Here Kernel Density Estimation (KDE) features were retrieved from the EEG signals and Multi-layer Perceptron (MLP) is applied to predict the human's emotions. There are four emotion categories are considered namely happy, calm, sad and fear. This is implemented and evaluated which proved that this research method is improved in its performance by showing 76% increased accuracy rate than its previous method heterogeneous blind test.

Ulrich-Lai & Herman[15] analyzed and stated that the brain is the center of controlling point in human body. Brain controls the actions carried out in human body and it is responsible for the stress occurrence too. Detecting the stress happening on the humans through brain analysis is a complex task and also it is very difficult to predict whether stress happened is negative stress or positive stress. It can be easily categorized by using neural communication which made it easier. The main parts in the brain in which stress can be processed are listed as follows: hippocampus, amygdala and prefrontal cortex.

Drolet et al.,[16] analysed and proved that the severe stress can affect the functioning of brain cells. In detail it can be said that chronic psychological stress would affect the normal regulatory system function of central peripheral. This would be affecting the health level of humans which needs to be balanced well to avoid the serious threats. Friedman [17] and Hughes [18] identified and proved that the chronic stress is mostly happening on the autonomic nervous system (ANS)function.

Papoušeket al., [19], authors concluded that the continuous stress level happening humans are related to the hemisphere asymmetries which can be modified and processed based on ANS functions. This can be processed and evaluated by altering the functions of ANS modules. Hosseini & Khalilzadeh[20], authors proved that the EEG signal plays greater role in the emotional stress assessment. Authors introduced a classification approach based on higher order spectra (HOS) to classify the emotions.

Kim et al.,[21], authors introduced and analyzed the technique for emotional stress state characterization based on physiological responses. Authors have captured the EEG signals from the brain through central nervous system and characters are categorized into multiple emotional states. American psychologist Ekman performed human emotion characterization based on six emotions that are listed as follows: Anger, happiness, disgust, surprise, sadness and fear. Kim et al.,[22], authors introduced and explained about the method based on multiple dimension space to categorize the emotions based on different factors.

III. HUMAN STRESS LEVEL PREDICTION AND PREVENTION SYSTEM

In this research method, initially EOG artifacts present in the raw EEG signals are filtered out, thus the classification error can be reduced. After noise reduction, time domain features are extracted from the EEG signals thus the classification accuracy can be increased considerably. Finally stress level classification using time domain features are done by using Artificial Neural Network approach. This proposed method ensures the accurate classification outcome which leads to efficient human live saving. If high stress, next mantras are hear or chant and this statistical examination is conversed, in the course of the performance analysis. The overall view of the proposed method is shown in the following figure 2.

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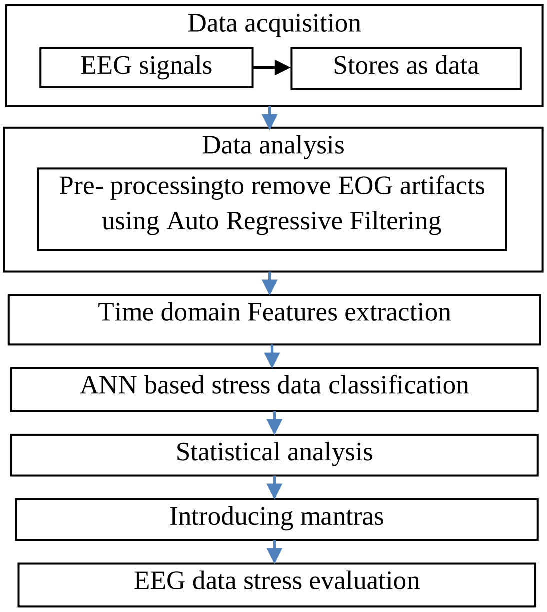

Figure 2. Overall view of the proposed system

In figure 2, overall flow of the proposed research method is shown. The detailed explanation of the proposed research method is given in the following sub sections.

3.1. EOG ARTIFACT REMOVAL

EOG noises are genearated due to continous eye movements and blinks happened while recording the EEG signals. In technical, EOG noises are low frequency and high amplitude signals that affects the original quality of the EEG signal which is recorded. There are two steps performed to remove the EOG noises present in the EEG signals. First is EOG noise detection and EOG noise correction. EOG noise detection is performed by using Auto regression model for the different time domains. The inverse filteirng method for varuing time domain is used to detect the EOG noise which is denoted in Eq.1

$$\begin{cases} y'_t = \sum_{i=1}^{p} a_i . y_{t-1} \\ v_t = y_t - y'_t \end{cases} \tag{1}$$

Where y_t → EEG signal recorded at time t

y'_t→Estimated EEG signal at time t

v_t → variance between y_t and y'_t.

The vairance v_t of the measured EEG signal decides the presence of the EOG artifacts in the measures signal. The variance above the threshold indicates that the EOG noises are detected at recorded EEG signal. Thus the elimination of EOG noise from the EEG signal would lead to obtian the EEG signal without noise. In eq.2 process of subtraction of EOG noise from the EEG signal that results with the impure EEG signal is shown.

$$EEG_{nc}(t, ch) = EEG_{ac}(t, ch) - kEOG_{nc}(t, ch) \tag{2}$$

From Eq. 1 and Eq.2 EOG correction model can be build and represented as like given in Eq.3

$$\begin{cases} EEG_{nc}(t, ch) = EEG_{ac}(t, ch) - kEOG_{nc}(t, ch') \\ EOG_{nc}(t, ch') = EOG_{ac}(t, ch') - pEEG_{nc}(t, ch) \end{cases} \tag{3}$$

Where $EEG_{ac}(t,ch)$ →captured EOG contained impure EEG signal from channel ch

$EEG_{nc}(t,ch)$ → Pure EEG signal

$EOG_{ac}(t,ch')$ → Impure EEG signal recorded in channel ch'

$EOG_{nc}(t,ch')$→non-contaminated EOG signal

In Eq. 3, K and Q values are found by using linear regression method which is an automatic correction method. The calculation procedure of K and P parameters are shown in the followin Eq. (4) which is calculated in the iterative way

$$\begin{cases} k_n = (EEG_{aco} . EOG^T_{ncn}) . (EOG_{ncn} . EOG^T_{ncn})^{-1} \\ q_n = (EOG_{aco} . EEG^T_{ncn}) . (EEG_{ncn} . EEG^T_{ncn})^{-1} \\ EEG_{ncn} = EEG_{aco} - k_{n-1} . EOG_{ncn-1} \\ EOG_{ncn} = EOG_{aco} - q_n . EEG_{ncn} \end{cases} \tag{4}$$

Where $EEG_{ac0}$is the recorded EEG data and $EOG_{ac0}$is the recorded EOG data. We assume that the $EEG_{nc}(t,ch)$ and $EOG_{nc}(t,ch')$ are uncorrelated.

3.2. TIME DOMAIN FEATURE EXTRACTION

After preprocessing, feature extraction from the pure EEG signals is done which can be utilzed to characterize the stress level accurately. Here the preproessed EEG signal would be segmented into five equal frames with constant duration. By doing so, stress level changes can be accurately predicted and can be differentiated for the multiple persons. This is ensured in this research method by introducing the time domain based feature extraction whih can differentiate the feature values accurately. This work considers the 4 time domain features for the accurate classification rate. Those are, simple square integral (SSI), integrated EMG (IEMG), waveform length (WL) and difference of absolute standard deviation value (DASDV). The definition and calculation procedure of these features are shown below with sutiable equation.

Simple square integral (SSI):

A summation of sqaure values of the EMG signal amplitude. Integral square uses energy of the EMG signal as a feature. Generallly, this parameter is defined as energy index.

$$SSI = \sum_{i=1}^{N} X_i^2 \tag{5}$$

Integrated EMG (IEMG):

A summation of abolute values of the EMG signal amplitude. Normally used as an onset detection index in EMG non-pattern recognition and in clinical application. It is related to the EMG signal sequence firing point.

$$\mathrm{IEMG} = \sum_{i=1}^{N} |X_i| \tag{6}$$

Waveform Length (WL):

Cumulative length of the EMG waveform over the time segment. A measure of complexity of the EMG signal. Some literatures called this feature as wavelength (WAVE)

$$\mathrm{WL} = \sum_{i=1}^{N-1} |X_{i+1} - X_i| \tag{7}$$

Difference Absolute Standard Deviation value (DASDV):

A standard deviation value of the wavelength. Look like root mean square (RMS) feature.

$$\mathrm{DASDV} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} (X_{i+1} - X_i)^2} \tag{8}$$

Where N = the length of the EMG signal

X_i = EMG signal in a segment i

3.3. STRESS LEVEL CLASSIFICATION USING ANN

The classification is user independent which means data gathered from all participants are used for training the classifier. The feature vector obtained all the way through HTT is classified into neutral or three stages of stress (stress-low, stress-medium and stress-high). In this work, we adapted Artificial neural network algorithm for the stress level classification.

ANN is a multifaceted adaptive system which can alter its domesticarrangement based on the information pass through it. It is achieved by adjusting the weight of association. Each link has a weight coupled with it. A weight is a number that organize the signal amid two neurons. Weights are attuned to get better the result.

Artificial neural network is an example of supervised learning. Artificial neural network acquired the knowledge in the form of connected network unit. It is difficult for human to extract this knowledge. This factor has motivated in extracting the rule for classification in data mining. The procedure of classification is starts with dataset. The data set is divided into two parts: training sample and test sample. Training sample is used for learning of network while test sample is used for measuring the accuracy of classifier. The division of data set can be done by various method like hold-out method, cross validation, random sampling. In general learning steps of neural network is as follows:

- Network structure is defined with a fixed number of nodes in input, output and hidden layer.
- An algorithm is used for learning process.

The ability of neural network to make adjustment in structure of network and its learning ability by altering the weight make it useful in the field of artificial intelligence.

Algorithm 1: Learning of ANN

Input: dataset D, learning rate, network.

Output: a trained neural network.

Step1: receive the input.

Step2: weight the input. Each input sent to network must be weighted i.e. multiplied by some random value between -1 and +1.

Step3: sum all the weighted input.

Step4: generate output: the output of network is produced by passing that sum through the activation function

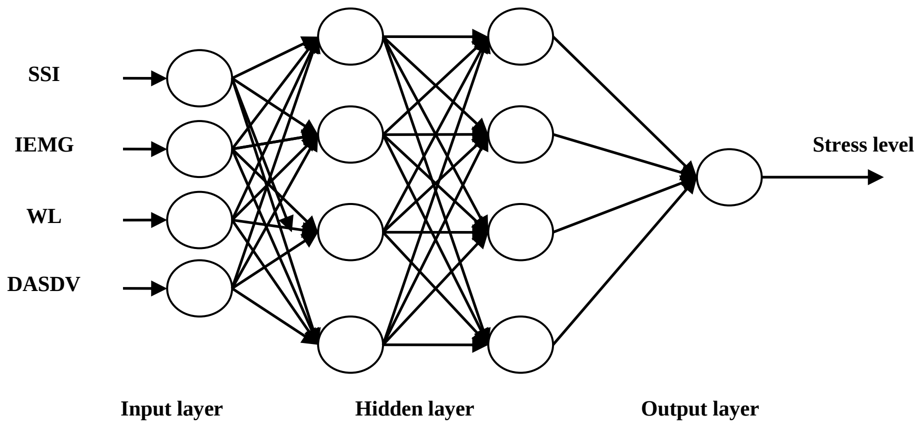

Figure 3. ANN architecture

In the ANN model given in figure 3, the input variables are deformation time domain feature values extracte from the signal namely Simple square integral (SSI), Integrated EMG (IEMG), Waveform Length (WL), Difference Absolute Standard Deviation value (DASDV), while the output variable is stress level (σ). The experimental data obtained from the human with both stress and non stress were used to train and test the model. All the data were divided into two sets: 82% data points were selected as training dataset for training the ANN model and the remaining 18% data points were used as testing dataset for evaluating the performance of the ANN model.

IV. RESULTS AND DISCUSSION

With the use of EEG signal, the performance i.e. stress classification of the proposed EOG considered Artificial Neural Network Learning (EOG-ANN) technique is compared with the prevailing methods such as Fuzzy Support Vector Machine, K-Nearest Neighbour (K-NN), kernel Extreme Learning Machine (KELM), Support Vector Machine (SVM) and Extreme Learning Machine (ELM). For analyzing the EEG signals, primarily stress indices values has been measured. With respect to the sensitivity, specificity and classification accuracy the performance of the proposed FSVM method is analyzed. The proposed method is implemented in matlab simulation environment and it is compared with existing methods to prove the efficiency

4.1. DATABASE PREPARATION

Certain subject's primary data is recorded in the database. With the use of religion mantras tool, the mantras has 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

SL no	Name	Age	Gender	Mantras
2001	harsha	27	female	Gayathri mantra
2002	shyju	39	male	Gayathri mantra/ ohm sarvebhavathesugia/ mahamurthiyenjaya mantra
2003	muhama dali	40	male	Rabbanaatina.../thakbeer/ adham etc.
2004	sajith	37	male	Gayathri mantra/ ohm sarvebhavathesugia/ mahamurthiyenjaya mantra
2005	rabeesh	35	male	Gayathri mantra/ ohm sarvebhavathesugia/ mahamurthiyenjaya mantra
2006	ajay	30	male	Gayathri mantra/ ohm sarvebhavathesugia/ mahamurthiyenjaya mantra

4.2. STRESS LEVEL

Initially, the subject is intended to calculate the stress indices within the system. The physical data and the cognitive data is used to calculate stress indices value, on collecting the data significantly. The threshold value is taken from the subjects stress indices value. Based on the subject's behaviour , EEG data of the subject is varied. Henceforth, to compute the individual stress level, it is essential to compute the individual's threshold value.

4.3. STRESS RATE PERFORMANCE COMPARISON

With respect to the EEG signal base time the stress rate value is demonstrated in figure 4, 5 and 6. While listening to noise and mantras, the stress rate is predicted to be lesser by using EEG signals. As well, while humming the mantras the stress level is measured. It shows that there is a drastic decrease in stress level while chanting and hearing mantras. There is no response in stress level when hearing noise. Therefore, the anticipated system focuses mainly on reducing the stress by mantras.

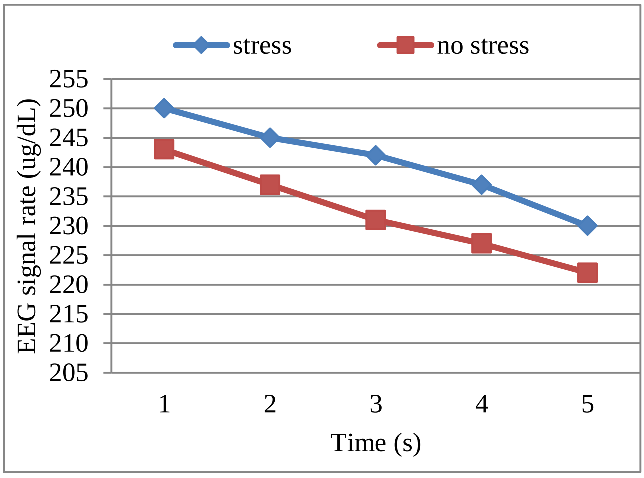

Figure 4: Stress rate comparison by using EEG signal to hearing noise

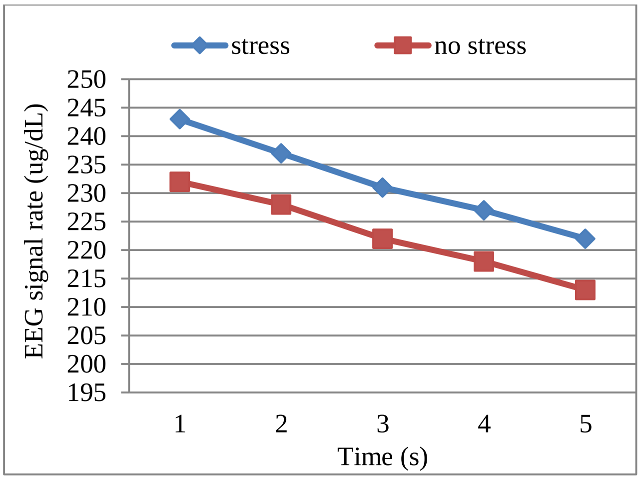

Figure 5: Stress rate comparison by using EEG signal to hearing gayathri mantras

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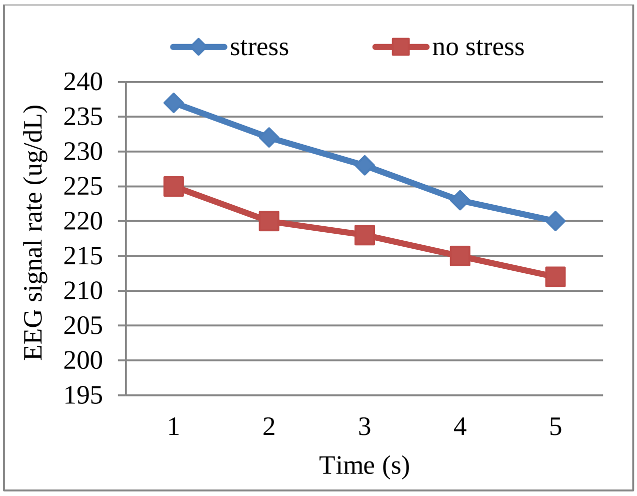

Figure 6: Stress rate comparison by using EEG signal to chanting mantras

4.4. ACCURACY, SENSITIVITY AND SPECIFICITY COMPARISON

The complete performance analysis for comparing the sensitivity, specificity and accuracy of the anticipated EOG-ANN, FSVM and prevailing KELM, K-NN, SVM and ELM is shown in figure 7. The classification accuracy of the anticipated scheme is higher when compared to the existing schemes, owing to the efficient classification and efficient preprocessing. Due to the less false negative errors, the sensitivity evaluation of the proposed FSVM is comparatively higher than that of the existing method, as well specificity is also encountered to be higher in FSVM due to its high true positive rate compared to the existing methods. When there is increased amount of subjects, the performance of the proposed method is also significantly increased, the accuracy is 91.12%, Specificity is 94.86% and sensitivity is 91.45% for the proposed EOG-ANN method. The evaluation of the proposed scheme is shown numerically in Table 2.

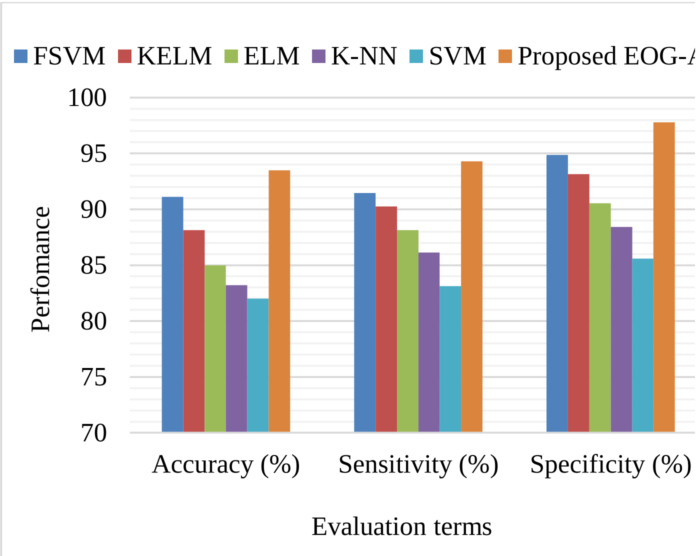

Figure 7: Overall performance for various classification schemes

Table 2: Overall performance of numerical evaluation for all classifiers

Evaluation terms	Proposed EOG-ANN	FSVM [23]	KELM [24]	ELM [25]	K-NN [26]	SVM [27]
Accuracy (%)	93.5	91.12	88.14	85	83.2	82
Sensitivity (%)	94.3	91.45	90.25	88.15	86.14	83.12
Specificity (%)	97.8	94.86	93.14	90.54	88.41	85.6

V. CONCLUSION

In this research method, initially EOG artifacts present in the raw EEG signals are filtered out, thus the classification error can be reduced. After noise reduction, time domain features are extracted from the EEG signals thus the classification accuracy can be increased considerably. Finally stress level classification using time domain features are done by using Artificial Neural Network approach. This proposed method ensures the accurate classification outcome which leads to efficient human live saving. If high stress, next mantras are hear or chant and this statistical examination is conversed, in the course of the performance analysis. The overall implementation of the research method is done in the matlab simulation environment from which it can be proved that the proposed method EOG-ANN can ensure the increased accuracy than the existing research methods.

REFERENCE

[1] Mantri, S. T., Agrawal, P., Patil, D. D., &Wadhai, V. M. (2013). Depression Analysis using ECG Signal. International Journal of Computers & Technology, 11(7).

[2] Lloyd, J., Bond, F. W., & Flaxman, P. E. (2017). Work-related self-efficacy as a moderator of the impact of a worksite stress management training intervention: Intrinsic work motivation as a higher order condition of effect. Journal of occupational health psychology, 22(1), 115.

[3] Koolhaas, J. M., De Boer, S. F., Buwalda, B., &Meerlo, P. (2017). Social stress models in rodents: towards enhanced validity. Neurobiology of stress, 6, 104-112.

[4] Varela, F. J., Thompson, E., &Rosch, E. (2017). The embodied mind: Cognitive science and human experience. MIT press.

[5] Jebelli, H., Hwang, S., & Lee, S. (2017). EEG Signal-Processing Framework to Obtain High-Quality Brain Waves from an Off-the-Shelf Wearable EEG Device. Journal of Computing in Civil Engineering, 32(1), 04017070.

[6] Jang, S., Kim, S. J., Kim, Y. J., Suh, I. Y., Song, C., Oh, H. K., ...& Kim, J. (2017). Levels of Clinical Practice Stress and Coping Strategies according to

Nursing Students' Personality/Behavior Types. Perspectives in Nursing Science, 14(2), 81-89.

[7] Marsland, A. L., Walsh, C., Lockwood, K., & John-Henderson, N. A. (2017). The effects of acute psychological stress on circulating and stimulated inflammatory markers: a systematic review and meta-analysis. Brain, behavior, and immunity, 64, 208-219.

[8] McEwen, B. S. (2017). Neurobiological and systemic effects of chronic stress. Chronic Stress, 1, 2470547017692328.

[9] Sheth, C., McGlade, E., &Yurgelun-Todd, D. (2017). Chronic Stress in Adolescents and Its Neurobiological and Psychopathological Consequences: An RDoC Perspective. Chronic Stress, 1, 2470547017715645.

[10] Runnova, A. E., Zhuravlev, M. O., Koronovskiy, A. A., &Hramov, A. E. (2017, April). Mathematical approach to recover EEG brain signals with artifacts by means of Gram-Schmidt transform. In Saratov Fall Meeting 2016: Laser Physics and Photonics XVII; and Computational Biophysics and Analysis of Biomedical Data III (Vol. 10337, p. 103370Y). International Society for Optics and Photonics.

[11] Dalmau, J., Geis, C., &Graus, F. (2017). Autoantibodies to synaptic receptors and neuronal cell surface proteins in autoimmune diseases of the central nervous system. *Physiological reviews*, *97*(2), 839-887.

[12] Azhar, M., Ahmed, I., Iqbal, S. T., Jahangir, M., Shah, N. A., &Siddiqui, I. (2017). Feature Extraction Using Independent Component Analysis Method from Non-Invasive Recordings of Electroencephalography (EEG) Brain Signals. *Journal of Basic and Applied Sciences*, *13*, 259-267.

[13] Ahirwal, M. K., Kumar, A., & Suri, J. (2017). Soft Computing and Machine Learning: EEG Signal Processing Perspectives.

[14] Subhani, A. R., Mumtaz, W., Saad, M. N. B. M., Kamel, N., & Malik, A. S. (2017). Machine Learning Framework for the Detection of Mental Stress at Multiple Levels. *IEEE Access*, *5*, 13545-13556.

[15] Ulrich-Lai, Y. M., & Herman, J. P. (2009). Neural regulation of endocrine and autonomic stress responses. *Nature Reviews Neuroscience*, *10*(6), 397.

[16] Drolet, G., Dumont, É. C., Gosselin, I., Kinkead, R., Laforest, S., &Trottier, J. F. (2001). Role of endogenous opioid system in the regulation of the stress response. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *25*(4), 729-741.

[17] Friedman, B. H. (2007). An autonomic flexibility–neurovisceral integration model of anxiety and cardiac vagal tone. *Biological psychology*, *74*(2), 185-199.

[18] Hughes, J. W., &Stoney, C. M. (2000). Depressed mood is related to high-frequency heart rate variability during stressors. *Psychosomatic medicine*, *62*(6), 796-803.

[19] Papoušek, M., Papoušek, H., &Symmes, D. (1991). The meanings of melodies in motherese in tone and stress languages. *Infant behavior and development*, *14*(4), 415-440.

[20] Hosseini, S. A., &Khalilzadeh, M. A. (2010, April). Emotional stress recognition system using EEG and psychophysiological signals: Using new labelling process of EEG signals in emotional stress state. In *Biomedical Engineering and Computer Science (ICBECS), 2010 International Conference on* (pp. 1-6). IEEE.

[21] Kim, K. H., Bang, S. W., & Kim, S. R. (2004). Emotion recognition system using short-term monitoring of physiological signals. *Medical and biological engineering and computing*, *42*(3), 419-427.

[22] Kim, K. S., Zhao, Y., Jang, H., Lee, S. Y., Kim, J. M., Kim, K. S., ... & Hong, B. H. (2009). Large-scale pattern growth of graphene films for stretchable transparent electrodes. *nature*, *457*(7230), 706.

[23] B.S. Jawharali and M. Mohanapriya (2017).An Effectual Fuzzy Multilayer Support Vector Machine Based Classification Scheme for Detection of Stress Level from EEG Signals and Reduction of Stress Using Various Mantras. International Journal of Pure and Applied Mathematics, Volume 117 No. 20 2017, 627-642

[24] B.S. Jawharali and M. Mohanapriya (2017).An Efficient Kernel Extreme Learning Machine Scheme for Detection and Reduction of Stress Using Various Mantras through EEG Signal Analysis. Journal of advanced research in dynamical and control systems, **Issue:** 13-Special Issue, 445-457

[25] Liang, N. Y., Saratchandran, P., Huang, G. B., &Sundararajan, N. (2006). Classification of mental tasks from EEG signals using extreme learning machine. International journal of neural systems, 16(01), 29-38

[26] Pandiyan, P. M., &Yaacob, S. (2013). Mental stress level classification using eigenvector features and principal component analysis. *Communications in Information Science and Management Engineering*, *3*(5), 254.

[27] Vanitha, V., and P. Krishnan. "Real time stress detection system based on EEG signals." Biomedical Research 2016)