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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

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Abstract

Mental stress has been recognized the foremost contributing aspect that tends to diverse diseases like stroke and heart attack. To circumvent this, stress quantification is extremelysignificant for clinical involvement and disease avoidance. In this experimentation, we examine the probability of utilizing Electro-encephalography (EEG) signals to distinguishrest state from stress state. The aim of this work is to categorize stress individualsowingto EEG signal withFuzzy-Multilayer Support Vector Machine (F-MSVM). At first, the EEG signal is pre-processed to eradicate two types of noise like ocular artefacts and power line noise to haul out proficientfeaturesthrough theelliptic band pass filter. Subsequently, powerful statistical features are hauled out todevelop the classification accuracy, the features are consistent. Finally, the stress level is considered as high, medium and low with F-MSVM. If high stress, subsequent mantras are chant or hear and this statistical assessment is discussed the performance examination. The experimental resultsdisplays that the probableF-MSVM accomplished greater performance with respect tosensitivity of 91.45%, accuracy of 91.12%, and specificity of 94.86%compared to the prevailing stress detection and classification proceduresby EEG signal.

Key Words: Human brain, stress detection, mantras, statistical features, F-SVM classification.

1. Introduction

People experience stress in their everyday life. Stress hasbeen distinct as “the non-specific reaction of the body to several stipulate for change”. Stress can vary the sensitivity of central-peripheral regulatory schemes portrait them less effectual in assisting health. It has been renowned as merely the major factors influencing to chronic abnormalities and efficiency loses. It manipulates the need towork, recital at work and approach toward life. Chronicstress has been associated to a series of health crisis [1]. Prevailing examination have revealed a correlation among long term disclosure to stress and hazard factors like Cardio vascular diseases [2].

Stress response can be estimated from behavioural, perceptual, and physical reactions to mental stress task. Assessment of perceptual reactions to stress comprises subjective evaluations and perceptions. Self-report survey are significantly generally utilized techniques to calculate an individual’s stress level. Nonetheless, estimating the stress by means of surveys is subjective technique [3]. Consequently, clinicians estimates the stress by computing α-amylase and cortisol levels [4]. Stress response comprises the activation sympathetic nervous system (SNS) and of hypothalamus-pituitary-adrenocortical axis (HPA) causing an enlargement in the cortisol/glucocorticoid secretion in the adrenal cortex.

Next to the release of cortisol, stress can be enumerated from human bio-signals [5]. Investigation have obtained an connection among physiological and salivary cortisol levels variables modifications like skin temperature (ST), heart rate variability (HRV), and blood pressure (BP). Heart rate variability point outs to the beat-to-beat changes in heart beat intervals. Stress roots a reduce in the high frequency elements of the heart beat interval and a raise in thelow frequency elements of that heart beat interval signals correspondingly. Therefore, heart rate variability examination has been recognized as an immediate quantitative computation ofANS activity related with mental stress. Skin conductivity differs with the modification in skin moisturelevel instructing the modifications in sympathetic nervoussystem. Skin conductivity has been accounted to amplify stressful task and can be obtained concurrently with galvanic skin response (GSR) [6].

Moreover, the modifications in ANS can be efficiently signified by electro encephalography (EEG) signals [7]. Electro encephalogram (EEG) is the most general sources of data utilized to examine brain functions and circumstances. It is an extremely multi faceted signal and can be accounted non-invasively by means of surface electrodes from the scalp. EEG is the mainly investigated non-invasive brain imaging device owing to its first-rate temporal resolution, low setup cost and ease of use. In addition, EEG profits from its greater temporal resolution, facilitate it to determine the variations in cognitive activity inside millisecond scale [8]. EEG signals are considered as frequency bands; Theta (4-

8Hz), Delta (0.5-4 Hz), Alpha (8-13 Hz) and Beta (14-30 Hz). Every frequency band signifies a condition of an individual. An enlargement of EEG power spectra in the Beta frequency band relatedwith raise in the attentiveness and arousal; Alpha amplifies with relaxation and Theta takes placeall through thesleep state [9].

EEG signals in prior utilized in the evaluationof variation in the individuals state throughout cognitive tasks. In contrast HRV and blood pressure, EEG provides higher information regarding alertness condition and relaxation [8, 10]. In state of the art, both reduced and enlarged in alpha and beta power have been set up as a mark of mental stress [11]. EEG has effectively categorized stress from the in [12] with an average precision of 85.55% by means ofYule Walker and in [13] average categorization rate of 90%.

The main intention of this investigation is to differentiate the rest state from the stress levels using the EEG signals assorted while performing arithmetic tasks mentally. With the use of F-MSVM method, the stress level has been classified and the religional mantras are used to reduce stress level. Then, the effectual classification method has been spotlights for effectual statistical features extraction. At last, the stressed and the non-stressed people has been classified based on the classification scheme. The proposed F-MSVM method provides enhanced performance in contrast to the existing methods, thus shown in the simulation outcomes.

The remaining works are divided as follows: section 2 elaborates certain prevailing researches grounded on EEG signal stress classification. Section 3 illustrates the anticipatedsystem and the performance outcomes are demonstrated in section 4. At last, this effort is concluded.

2. Related Works

AStress is distinct as an organism’s complete reaction to an environmental stipulation or stimulus, also recognized as a stressor. Stress usually illustrates a negative state that can have a significance on an organism’s mental and physical comfort. The react or stress response may fluctuatefrom one people to other people. The reason for that is the social factors like cultures, ages, races, education background, family background, etc. Those issues may influence the manner their responds to the specific stressenvironment. In last decades, several researches/studies have been executed to recognize the stress respond to the body systemby means of physiological signals. These efforts are primarilyadjusting physiological signals to compute stress like Galvanic Skin Response (GSR), skin temperature (ST), Electroencephalography (EEG), Electrocardiography (ECG), Plethysmography, Pupil diameter (PD), etc.

Certain examinations have merged EEG signal with numerous physiological signals to examine mental stress. Heart rate variability, Skin conductance and EEG signals merges tocategorize stress in [14] outcome with average accuracy of 84.1%with psychological signals and 82.7% with the EEG signals. Skin conductance, Blood pressure, heart rate variability and EEG signals in [15] replicate the stress with greater classificationrate of 95% by means of all physiological signals and 91%with EEG signals.

Based on the previous examination no stress levels has been examined yet. Stoop colour word test [16], mental arithmetic task [17], public speaking [18], cold pressor [19], computer work [20] and videos [21] are used as stress stimuli successfully in the prevailing works.

EEG signal comprises of four major frequency band termed as theta (θ), delta (δ), beta (β) and alpha (α). EEG has been displayed to have a first-rate indicator whilst the procedure of power spectral ratio $(\alpha + \theta)/\beta$ exposed a huge enlargement for fatigue detection [23].

Discrete Wavelet Transform (DWT) was utilized to haul out features from EEG signalsprior to feeding to k-NN to categorize human with respect to happy, surprise, disgust, fear and neutral with classificationprecision of 83.26% [24].

Sulaimanet have makes use of agrouping of spectral centroids techniques and EEG Asymmetry as a feature to sensesolepattern of human stress[25]. Seyyedet have exploited Higher Order Spectra (HOS) to haul out the features prior to feeding Support Vector Machine (SVM) to categorize emotional stress rate with classification precision of 82%[26].

Verona et al. have described the beta performance in frontal hemisphere is higher along with stress subject in contrast to non-stress individual [27]. Likewise, Hayashi et al. have showed that the brain functioning in the right frontal moderately higher contrast to theleft side for people beneathstress [28]. Owing to the prioranalysis, it can be decided that EEG signal is competent to evaluate human stress level as the signals are produced in the brain owing to the transformation of the cognitive condition.

Investigational protocol to draw out the mental stress is a fundamental task. Stressor kinds has also a vitalresponsibility on the outcomes.

The investigators utilized several modes of stress elicitation such as natural stressor by means of real examination segment, Questionnaire [14],public Stroop Test [29], speaking task [29], driving simulator [30], and Mental Arithmetic Task [31–33]. Nevertheless, mental arithmetic task is extensively utilized to draw out stress in mental stress investigations.

3. Proposed Methodology

Fuzzy-Multilayer Support Vector Machine (F-MSVM)

This section provides a powerful F-MSVM sourced stress classification. As well, the step by step procedure has been described.

System Overview

The architecture of the proposed method is illustrated in figure 1. The foremost significance of the proposed method is to reduce the stress of the human by sensing stress using EEG signals. The primary aim of this investigation is to identify the stress rate of an individual and precisely to approximate human stress level. The EEG characteristics has been investigated to evaluate the stress level of the human i.e., relaxed mode or stress level has been projected by F-MSVM method. By main purpose of this method is to decrease the stress level by providing the mantras in a human, along with the statistical approximation of stress level investigation to reduce the stress. In the proposed technique, a significant method is utilized to decrease human stress, hence, the individual may perform effectually in this progression.

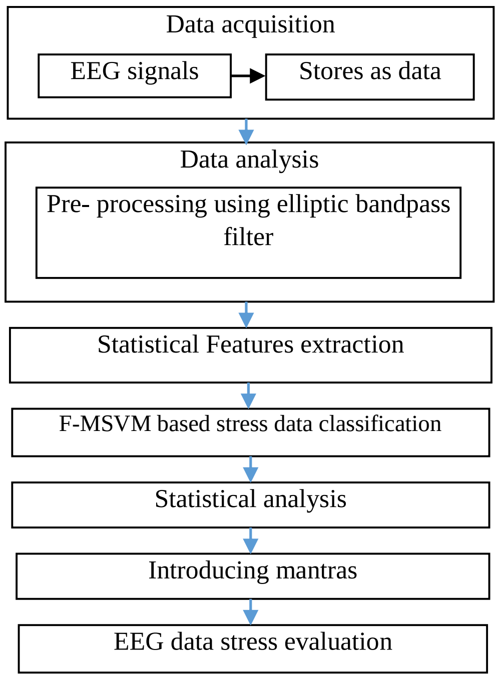

Figure 1: Procedure of Proposed FSVM based Stress Classification and Reduction

Pre-Processing

For performing various tasks, the pre-processed and feature extraction was done in the EEG signals. Uncontaminated non-cerebral artifacts are the substantial problem acquired in a clean data on the cerebral activity. An obstacle has been generated in the process of decision making system, while occurrences of artefacts are sensed in the EEGsignals. Eye blink and body movements or certain sources like electrical interferences are generated by the subject during data acquisition process. In this examination, the greatest output obtained is set as 80μV. As the corresponding signal to the eye blink artefact is 100μV> thus the eye blink has been eradicated from the EEG output signal. The elliptic bandpass filter is utilized to filter the raw signals. The filtered data was provided into theta (4-7 Hz), delta (0.5-4 Hz),alpha (7-13 Hz) andbeta (13-30 Hz) individually as depicted in the figure 2.

Statistical Feature Extraction

For every lobe wise channels [34], five features of EEG signals has been extracted here. The EEG signals of the non-stress subjects and the stresssubjects' comparison provides the better accuracy based on the behavioural change. The features such as standard deviation, least significant value, Variance, Kurtosis, Max, Skewness and mean is hauled out in this scheme.

Mean: The mean value of the data set is obtained by dividing the number of values and adding all values, and specified as the arithmetic average of theelements. The mean frequency distribution of data can be distinct as below when the frequency distribution of the data is provided

$$Mean\ \mu = \frac{1}{n}\sum_{i=1}^{n} f_i x_i$$

Where, f_i specifies the population size and x_i specifies randomly produced frequency signals.

Variance: The arithmetic average of squareddifferences among the mean is known as the variance of data set. Yet again, the summarized data set in the variance offrequency distribution and frequency distribution, is provided by,

$$variance\ \sigma^2 = \frac{1}{n}\sum_{i=1}^{n} f_i(x_i - \mu)$$

Standard Deviation: A frequency distribution of a data set with respect to Standard Deviation (SD) can be distinct as the equation,

$$SD = \sqrt{\sigma^2}$$

Least significant value: In the given data set, it is the minimum value. Thelowest possible value at minimum point of the function in a provided data set is known as least significant value.

Max: The most significant value or highest possible value or a given data set is termed as maximum value (MAX).

Kurtosis: The second measure of potential values ofpeaked distributions, along with activity values in every trial is known as Kurtosis.

Skewness: The measure of similarity or asymmetric distribution is defined as skewness. It can be positive and negative.

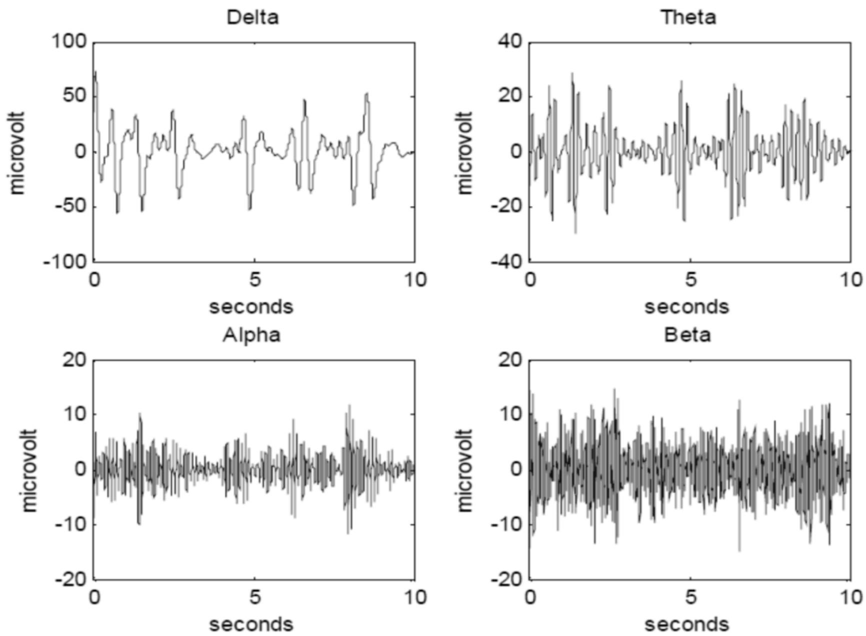

Figure 2: Filtered Signal Into four Sub-Bands Like Delta, Theta, Alpha and Beta

F-MSVM for Stress Level Classification

Information classification is the process of classifying and sorting the information into different kinds, classes and distinct forms. To generate a diverse objective, the classification and the partitioning is facilitated by the data classification in accordance to the data points. To differentiate whether the subject is in tranquil mode or stress mode, data classification has been executed. For accumulating information and different techniques, data classification is an engrossed method to be assorted. To classify the stress level in this unit, F-MSVM method has been utilized. At this point, fuzzy rule optimizes the MSVM parameters to enhance the MSVM performance.

SVM Classifier

An extensive study based on regression and classification has been made by Vapnik in the proposed SVM method [35]. To identify classes a SVM classifier uses discriminanthyperplane. The margins are maximized by using the hyper plane i.e., the distance calculated from the nearest training points. The generalization capability is increased by maximizing the margins. The SVM training is a quadratic optimization problem.

The hyper plane construction is defined below.

$$wTx + b = 0$$

Here, W signifies the weight vector, b specifies offset parameter, therefore the margin amongst the nearest point and the hyper plane was maximized. To create a trade-off amongst the maximization margin and the misclassification amount was controlled by SVM as the only one free parameter is C.

The nonlinear decision function was provided as

$$f(x) = sign[D(x)]$$

Where $D(x) = \sum_{i=1}^{sv} \alpha_i y_i (x, x_i^{sv}) + b$, D(x) to evaluate the classification confidence owing to the signed distance function, i specifies nonnegative Lagrange multipliers, b specifiesoffsetparameter and SV specifies the amount of support vectors. The $x_i^{sv}$is a data points corresponding to i > 0 of the support vectors. A nonlinear mapping x→(x) can implicitly computed based on the kernel function$K(x, x_i^{sv})$. The scalar multiplication˚$\Phi(x)^T\Phi(x_i^{sv})$ is mapped in one step space.

An efficient tool for classification is presented by SVM flexibly, by means of suitable kernels alone with a highly nonlinear decision boundary. The SVM makes use of Radial Basis Function (RBF) kernel and it is distinct as

$$K(x, x_i) = \exp(\frac{||x - x_i||^2}{2\sigma^2})$$

The kernel parameter and the free parameter C are the two parameters that has been selected by the SVM using RBF kernel. In a conventional means, the performance of the optimal generalization is calculated using n-fold cross-validation or an independent test set. Thus the suggested parameters are acquired by optimizing theupper bound of generalization error merely owing to training data. The support vectors fraction i.e., the quotient amongst all training samples and thenumeral of support vectors, provides an upper bound on leave-one-out error estimation as the resultant decision function has been modified while the support vectors were eliminated. Henceforth, for the process of parameter selection [35], a low fraction of supportvectors could be utilized.

A small portion ofdata points are obtained depended on the optimal hyper plane in a SVM i.e., SV. This is significantly sensitive to outliers or noises in the training data. To resolve this crisis, fuzzy memberships of data points are introduced by the F-MSVM classifier. The maximization of the margin is performed by the F-MSVM classifier such as the traditional SVM classifier. To generate a narrow margin, lower margin fuzzy membership and the less significant outliers or noises are provided to prevent noisy data points. The F-MSVM classifier has the ability to equip the training data with outliers or noises by means of lower fuzzy memberships and these noises or outliers are considered to have higher probability [36, 37] data points. With the F-MSVM classifier, the stress level has been identified. To decrease the stress level, the mantras has been chanted if a subject is encountered to have average stress or higher stress rate. This is examined by the statistical examination. To accomplish low stress rate, the component is subjected to certain mantras initially first. The subject's current stress indices value, has been manipulated based on the novel information provided by the EEG information of patient. New Stress indices are utilized to assess the older stress indices value to compute the patients stress rate is lower or higher.

4. Results and Discussion

With the use of EEG signal, the performance i.e. stress classification of the proposed F-MSVM method is compared with the prevailing methods such as K-Nearest Neighbour (K-NN), KELM, Support Vector Machine (SVM) and Extreme Learning Machine (ELM). For analysing the EEG signals, primarily stress indices values have been measured. With respect to the sensitivity, specificity and classification accuracy the performance of the proposed F-MSVM method is analysed.

Database

Certain subject's primary data is recorded in the database. With the use of religional mantras tool, the mantras has been produced. The significant primary data of the subjects 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	muhamadali	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

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 behaviour of subject's, EEG data of the subject is varied. Henceforth, to compute the individual stress level, it is essential to compute the individual's threshold value.

Stress Rate Performance Comparison

With respect to the EEG signal base time the stress rate value is demonstrated in figure 3, 4 and 5. 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 focusses mainly on reducing the stress by mantras.

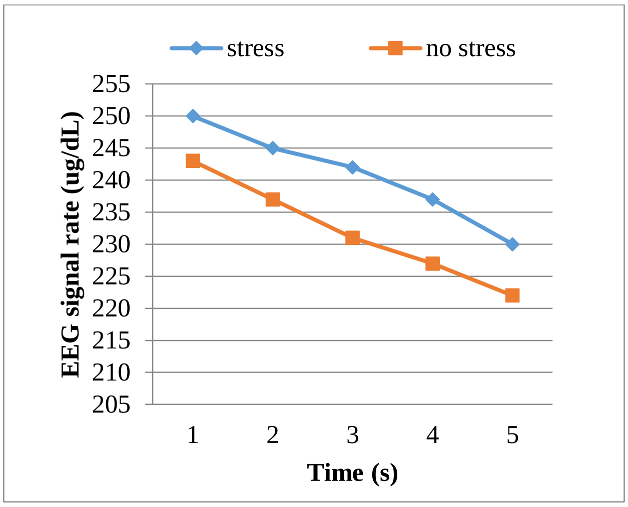

Figure 3: Stress rate comparison by using EEG signal to hearing noise

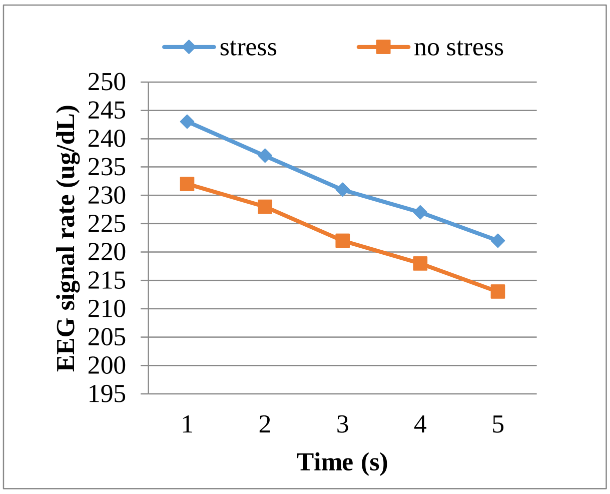

Figure 4: Stress Rate Comparison by using EEG Signal to Hearing Mantras

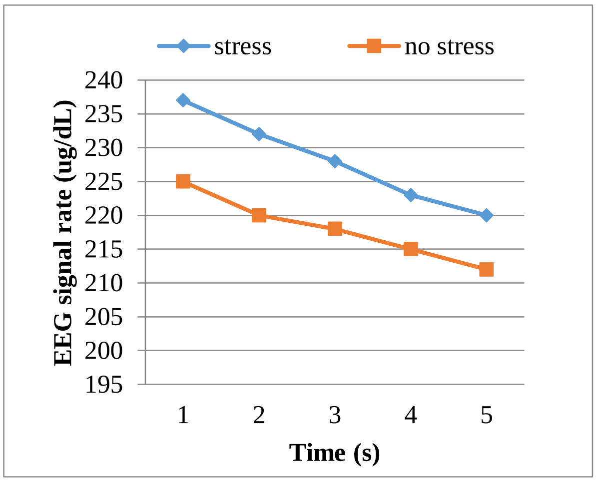

Figure 5: Stress Rate Comparison by using EEG Signal to Chanting Mantras

Accuracy, Sensitivity and Specificity Comparison

The complete performance analysis for comparing the sensitivity, specificity and accuracy of the anticipated F-MSVM and prevailing KELM, K-NN, SVM and ELM is shown in figure 6. The classification accuracy of the anticipated scheme is higher when compared to the existing schemes, owing to the efficient classification and efficient preprocessing with the fuzzy membership function. Due to the less false negative errors, the sensitivity evaluation of the proposed F-MSVM is comparatively higher than that of the existing methods as well specificity is also encountered to be higher in F-MSVM 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 F-MSVM method. The evaluation of the proposed scheme is shown numerically in Table 2.

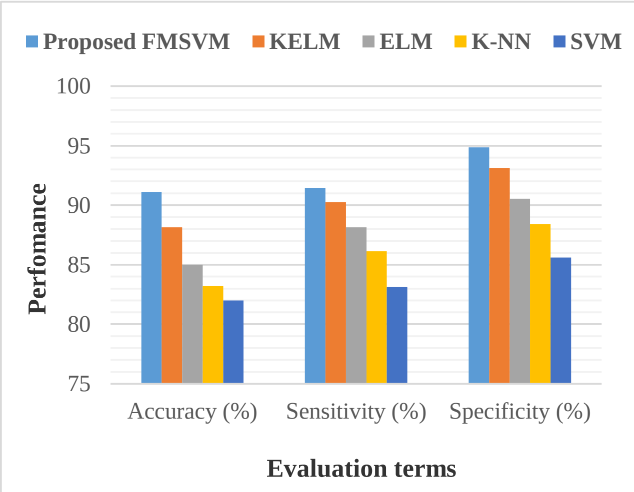

Figure 6: Overall Performance for Various Classification Schemes

Table 2: Overall Performance of Numerical Evaluation for all Classifiers

Evaluation terms	Proposed FMSVM	KELM	ELM	K-NN	SVM
Accuracy (%)	91.12	88.14	85	83.2	82
Sensitivity (%)	91.45	90.25	88.15	86.14	83.12
Specificity (%)	94.86	93.14	90.54	88.41	85.6

5. Conclusion

This research work offered a novel application of F-MSVM classifier for categorizing EEG based stress level categorization. In this examination, the EEG input signals are primarily pre-processed by means of elliptic band pass filter for enhancing the accuracy of classification. Thereby, the efficient features are being extracted and these features are classified by F-MSVM. At last, by means of mantras the highly stressed people are analysed statistically. So as to find the support vectors during the process of training SVM, significant computational efforts are made by solving the quadratic programming crisis. The amount of available parameters in F-MSVM is comparatively equal to the amount of training data points whereas in case of C there is merely one free parameter. Owing to the extra parameters the subsequent difficulty encountered in the experimentation is the training time of the F-MSVM was higher in contrast to the SVM. In terms of accuracy 91.12%, sensitivity 91.45% and specificity 94.86%, the proposed method shows better outcomes in simulation when compared to the prevailing techniques. The future work can be extended by using some other independent component analysis supported features and wavelet along with the neural network supported classification and other machine learning to enhance the classification accuracy.

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