Detection of Mental Stress using EEG signals

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Abstract:
Stress is defined as a state of mental or psychological strain or tension resulting from unpleasant or demanding circumstances. These circumstances can be psychological or social. Electroencephalogram (EEG) is a tool to record the electrical activity over the scalp. This technique is widely used in clinical and research setting. In clinical setting, the EEG signal is used to diagnose the disease related to brain. In research setting, the EEG signals are used in rehabilitation; mental stress study. In this paper, detection of stress and identifying of stress levels using electroencephalogram (EEG) analysis in MATLAB using Machine Learning framework is proposed. We discuss several methods that can be used to investigate EEG signals. The features can be obtained via Discrete Cosine Transform and Discrete Wave Transform. The different classifiers that can be used are – Support Vector Machine, Linear Discriminant Analysis, K-Nearest Neighbour, Artificial Neural Network, Naïve Bayes.

Keywords **— Electroencephalography (EEG), MATLAB, Mental Stress, Machine Learning.**

1. Introduction

Stress contributes to sustained feeling of low-energy and depression. Stress causes inefficiency during routine work which makes it a social cause. Chronic stress can negatively affect people causing anxiety and bipolar djmlisorders. Mental stress can also take a toll on our physical health. As per the recent survey 526,000 workers suffering from work-related stress, depression or anxiety (new or long-standing) in 2016/2017 [1]. Mental health care has become a demand. People are seeking for effective mental health care approaches [2]. Conventional counselling demands an individual to be willing to express himself frankly and many who need counselling may not consider it. In this set of circumstances, the study of brain activity and state of brain is essential which is provided using electroencephalogram(EEG) signals.

2. Literature Survey

In **Mental Stress Level Classification : A Review[28]**, Radhika Deshmukh and Manjusha Deshmukh have performed EEG signal processing in three steps - preprocessing, feature extraction and Classification. From the EEG signals, the PSD values and the features wereextracted. The behavior of the signal is extracted and several classifiers for classification. There were four experiments conducted to investigate the performance of the classifiers. Mental stress level classification using Principal Component Analysis(PCA), Artificial Neural Network, Discrete Wave Transform and Spectral Centroids Technique. It was observed that Principal Component Analysis has the highest classification accuracy, 98.33% [29] whereas ANN has 90% accuracy [30], DWT yields 96.3% [31], and SCT results 88.9% according to [19]. Therefore, concluding that PCA is a better method when compared from other methods.

In **Automatic Stress Assessment System for Elderly People**[32] by means of EEG Signals, it is proposed that the there is a correlation with mental stress and EEG in terms of suppression of alpha waves and improvement of theta waves. Under stressful conditions, the power of the Alpha waves fall down and the Theta power increases. Alternatively, under no stress condition, the Alpha waves are dominant. Power line noise is eliminated in the pre-processing stage. Short Time Fourier transform (STFT) is used as a feature extraction technique from which power, amplitude and frequency are extracted and Support Vector Machine(SVM) is used as a classifier to maximize the marginal distance. SVM is chosen due to its simplicity and accuracy of results.

In **Centre for Intelligent Signal and Imaging Research[33]** they discuss the concepts of stress from its origin to detection. Neurophysiological methods such as electroencephalography (EEG), Functional magnetic resonance imaging (fMRI), and magnetoencephalography (MEG) are non-invasive. MEG and EEG have higher temporal resolution than fMRI. EEG shows a good correlation with the mental stress in terms of suppression of alpha waves and improvement of theta waves. Various artefact removal methods are rejection, subtraction, min-max, joint and ICA. Signal's statistical properties are used for feature selection. Short time Fourier transform (STFT) is a feature extraction technique in which separation of stationary signals is performed into small fragments. In STFT a narrow window length can increase the time. Wavelet transform solves the problem. For classification, a discussion based on hyperplane is done, SVM maximizes the marginal distance but has linear decision boundaries, NN acts as a black box and has no inside information, Bayes has simple calculation but requires complete information of the basic probability distribution, and LDA has low computational requirements. In this survey different techniques are reviewed, EEG signals have nonlinear behavior, and hence NN is a better solution than LDA and SVM but doesn't contain internal processing units.

In **Analysis of Single-Electrode EEG Rhythms Using MATLAB to Elicit Correlation with Cognitive Stress[10]** its demonstrated analysis of EEG using MATLAB. In MATLAB issues like artefacts, noise, and interference are tackled. There are three main stages: data gathering where Stroop Color-Word Interference Test is implemented by using Inquisit Lab software, data preprocessing DCT is used to convert signal from time-domain to frequency-domain, and data classification where data collected from 25 subjects was classified using either ANN, LDA, or KNN, then evaluated performance using the leave-one-out cross-validation (LOOCV) and k-fold cross-validation. Classification was performed using ANN, LDA, and KNN where misclassification rate (MR) and mean absolute error (MAE) was found. KNN had lowest MAE but ANN had lowest MR. Classifiers were later trained using the scaled target class, and cross-validated using LOOCV. KNN achieved 72% accuracy, which was better than LDA (60%) and ANN (44%). With k-fold validation (k: no of partition samples) say k=25, with 80:20 ratio (80% as test set and 20%as train set) KNN had 72% accuracy.

In **Stress and EEG [34]** different ways of assessing levels of stress such as psychological assessment, physical assessment that includes biochemical response, heart rate variability and EEG are shown. Biofeedback is a therapeutic approach in which variables like heart rate, blood pressure, and temperature are regulated. Neurofeedback is biofeedback that uses brain waves and has applications for brain diseases and associated symptoms. It has two components, synchronised alpha, and beta waves. 33 healthy participants had volunteered aged 30-40 years old. SRI was used to assess stress, and SAM was used to assess emotional response. Visual stimuli was used to evoke emotional responses. Saliva was taken from participants to determine cortisol levels. EEG was recorded in four conditions: eyes-closed, eyes-open, pleasant images, and unpleasant images. The results showed that salivary cortisol was negatively correlated with SDNN and SDNN and SRI had no significant relationship. Correlation between SDNN and relative high beta power was negative. Correlation between the cortisol level and relative high beta power was positive.

In **Mental Stress Level Classification Using Eigenvector Features and Principal**

Component Analysis [35] This paper presented the efficiency of modified covariance (Eigenvector features) in extracting mental stress features. Brain Computer Interfaces (BCI) has been developed over the last two decades with the goal of extracting internal human brain activity. Physiological signals of the body are used to identify the stress reflex works like Electroencephalography (EEG), Electrocardiography (ECG), Plethysmography, Galvanic Skin Response (GSR), Pupil diameter (PD), skin temperature (ST), etc. The power of spectral density using Fast Fourier Transform (FFT) is used to determine fatigue while EEG signals with four main frequency band namely delta, theta, beta and alpha which is a good indicator of fatigue. Discrete Wavelet Transform (DWT) is developed to classify human information and extract features from EEG signals. Beta activities in frontal hemisphere in larger among stress subject while brain activity in the right frontal is greater compared to left side for people under stress. EEG Asymmetry and Spectral Centroids technique is used to measure pattern of human stress while High Order Spectra (HOS) is used to extract the features before feeding the extracts to Support Vector Machine (SVM) for classification of emotional stress. Public speaking, driving stimulator, Stroop test, and questionnaire are few modes of stress elicitation. This paper introduces the application of Auto Regressive modelling- Modified Covariance on Spectral Analysis. It classified mental stress level from EEG signals using statistical features and Principal Component Analysis (PCA), implemented to reduce the dimension of features. In this work, eigenvector features by modified covariance method on alpha band frequency with conventional statistical features were proposed to extract features that carry information on stress level behaviour and it was observed that classification accuracy increased by 20% when the extracted principal component was used for classification.

In **Mental Stress Quantification using EEG signals** [36] This paper investigated the feasibility of using Electroencephalography (EEG) signals to discriminate stress state from that of rest in mental arithmetic tasks. EEG is one of the most common sources of information used to study brain functions and conditions, non-invasively using surface electrodes from the scalp. EEG enables to measure the changes in cognitive activity with milliseconds due to its high temporal resolution. Compared to blood pressure EEG gives more information about relaxation and alertness condition. Wavelet Transform (WT) has the ability to deal with stationary and non-stationary signals. As EEG signals are non-stationary they provide good classification. EEG signals has four main frequency band namely delta, theta, beta and alpha. The paper demonstrated that alpha rhythm decreased from rest condition to stress condition. In this work, support vector machine (SVM) with 10- fold cross validation was used to classify stress from rest state where only power values extracted from alpha band were used for classification of EEG. It has successfully classified stress from the rest state with an average accuracy of 85.55% using Yule Walker. Other physiological signal such as Skin Conductance, heart rate variability are combined with EEG signals for classification between stress and rest state. e. The study reported a significant difference between the tasks (control and stress) as measured by the two-sample t-test with mean p-values of 0.03, 0.042, and 0.05 for level one ,two and three of arithmetic tasks respectively. The study revealed dominance of right pre-fontal cortex to mental stress.

In **Real time stress detection system based on EEG signals [37]** the authors have shown an EEG based framework for stress detection for scholars. The authors have used MATLAB 8.4 as their environment. The data was collected by making participants undergo a series of test. After collection of EEG data preprocessing was done. In preprocessing of data noises like power line noise and ocular artefact removal was carried. In this study for feature extraction Hilbert hang transform(HHT) was used to get required features in time frequency domain. Hierarchical SVM was used as classifier in this study. The authors have chosen SVM classifier because it is immune to over fitting problem and its high level of accuracy with lesser training data set. Since the training sample was small a 10 fold cross validation was used. From the paper we can infer that the authors had relative success with SVM as it had 89.07 % accuracy rate which was comparatively higher than LDA (70.166%), QDA(76.833%) , KNN(72.667%).

In **Detection of stress/anxiety state from EEG features during video watching [38]** the researchers have taken DEAP data which comprised of people watching videos of 1 minute length. The EEG data was preprocessed with band pass filter and down sampled to 128 Hz. EEG features in this paper included asymmetry, coherence, brain load index and spectral centroid frequency. The main concept was that asymmetry reduction occurs during stress as compared to when relaxed . Discrimination of states in inter hemispheric location was done

using coherence analysis. The BLI was higher during stress state and even the spectral centroids showed increased centroid frequency during stress. Feature selection was performed using sequential forward selection(SFS) and sequential backward selection(SBS). It was found that using SFS was better because it was able to minimise objective function comparing with SBS. The limitations of the project were basically that there was no proper definition of stress to map to . The dataset also seemed to be small . To conclude this study gives features and a way for dataset reduction which can be used to detect stress efficiently using EEG.

In **Machine Learning Framework for the Detection of Mental Stress at Multiple Levels[21]** the authors of the paper have basically given a framework for detection of stress at different levels using EEG . The participants underwent a test which was based on MSIT that induced four levels of stress with time constraint. after data was acquired the EEG data was preprocessed to remove dc artefacts and line noise. The pre -processing was carried out in Net Station 4.43. Feature extraction was then carried out, for feature extraction various features were extracted like absolute and relative power, coherence, phase lag and amplitude asymmetry. Z score standardisation was then carried out to standardise the data. The feature selection process was rank based and the following methods were used: t – test, ROC, Bhattacharya distance were used . Finally, LR, Naïve Bayes and SVM classifier were used for classification. The classifiers were implemented in MATLAB. Classification validation was achieved by using 10 fold cross validation. The study showed that the detection of stress level 1-3 the best performance was given by relative power with t test and NB in level 1 an accuracy of 94.0% was achieved. Similarly with t test and SVM in level 2 produced 93.9% accuracy and t test and NB in level 3 produced accuracy of 94.6%. now surprisingly for level 4, t test and NB along with amplitude symmetry produced the best accuracy of 91.7%. overall the suggested framework helped detect stress with accuracy of 94.6% between 2 levels of stress and control , 83.43% between stress and the other levels of stress. The study basically shows the reliable identification of stress levels can be made through EEG signals, but many level of stress need deeper validation and analysis.

3. Proposed System

The objective of this paper is to detect stress in individuals, to determine what features will help us yielding the required results, to determine what classifier gives us the best results to determine stress, To determine the level of stress to take appropriate measures in helping an individual to overcome one's stress. From the proposed system a computer-sided diagnostic tool could be developed which help in early diagnosis of stress in individuals and take appropriate measures to reduce the stress and its affects.

In the proposed system, feature extraction, feature selection and classification of EEG signals were included. The proposed system framework can potentially classify stress into different levels. The proposed system includes comparison of various feature extraction methods (Discrete Cosine Transform, Discrete Wave Transform and EEG Data Matrix and Z-Score Standardisation) and classification algorithms (K-Nearest Neighbour, Linear Discriminant Analysis, Naive Bayes, Support Vector Machine (SVM)).

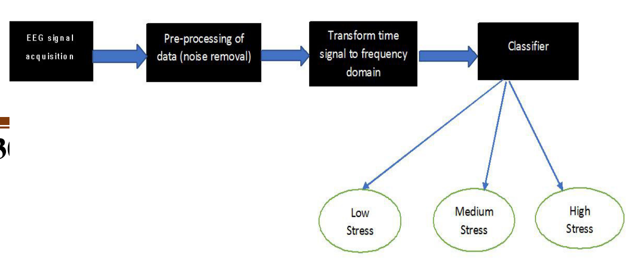

Figure 1 : Proposed System

4. Proposed System

4.1 Pre-Processing of Raw Data The amount of raw data required for classification is impractical for most machine learning algorithms. Hence we need to perform various feature extraction techniques for successful classification of data. Pre-processing of data includes transformation of EEG signals from time domain to frequency domain and removal of noise and artefacts. The typical extraction methods that exists are Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT).

4.1.1 Discrete Cosine Transform (DCT)

Under this method time series signals are converted into frequency components. In the context of Brain Computer Interface [26], maximum, minimum and mean values of EEG signals are calculated using DCT[8]. The one-dimensional DCT for a list of N real numbers is expressed as:

$$(\ ) = '\ \frac{-}{2}(\ ) + \overset{567}{\underset{89:}{}}(\ )\cos\left(\frac{(2\ +1)}{2}\right)$$

Where

$$(\ ) = \sqrt{\frac{7}{=}} \qquad = 0$$

$$(\ ) = 1 \qquad \neq 0$$

On a input of a set of N data values (EEG samples) output of a set of N DCT transform coefficients Y(u) is produced. The first coefficient Y(0) is called the DC coefficient and it holds the average signal value. All the other coefficients are referred to as the AC coefficients. Concentrated signals are produced in DCT where the energy is reduced into fewer coefficients. This compression of data results in truncated size of input vector for applying Machine Learning algorithms and hence less time is required for learning with the feature extraction of DCT.

4.1.2 Discrete Wavelet Transform (DWT)

Under this method any general function can be expressed as an infinite series of wavelets. The main idea is to express a signal as a linear combination of a particular set of functions by shifting and expanding the original wavelets. This decomposition of wavelets results into a set of coefficients called wavelet coefficients and using these weighted coefficients a signal can be rebuilt as a linear combination of the wavelet functions. These wavelets have a feature in which most of their energy is restricted to a finite time interval. Such phenomenon is known as time-frequency localisation which provides good frequency localisation at low frequencies and good time localisation at higher frequencies[8]. Time-frequency plane is segmented which is suitable for most physical signals. This method when applied to an EEG signal will reveal the features that are transient in nature.

Discrete wavelet transform has two parameters Low Pass Filter ‘g’ and a High Pass Filter ‘h’. Waveletφ function $_{i,l}$(k) and Scale function are defined as :

$\varphi_{i,l}(k) = 2^{i/2}\, g_i(k-2^i l)$

$\psi_{i,l}(k) = 2^{i/2}\, h_i(k-2^i l)x$

where the factor $2^{\,i/2}$ is an inner product normalisation, i is the scale parameter and l is the translation parameter. The DWT decomposition can be described as:

$a_{(i)}(l)=x(\varphi i,l(k))*$

$d_{(i)}(l)=x(\psi i,l(k))^*$

where $a_{(i)}(l)$ is the approximation coefficient and $d_{(i)}(l)$ is the detail coefficient at resolution i. Consecutive high-pass and lowpass filtering of the time domain signal results in decomposition of the input signal into different frequency bands[8]. This is shown in the Figure 2 where x[n] is the mother wavelet, h[n] is the high pass filter and g[n] is the low pass filter. The final relevant wavelet decomposition will be obtained at level A5.

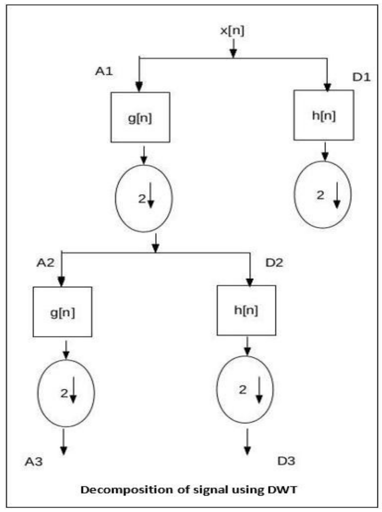

Figure 2 : Decomposition of signal

4.2 Classifier

Once the EEG data has been collected we then need to classify the data using classifiers . [11] MATLAB gives a lot of freedom to choose from a variety of classifiers namely ANN , LDA,KNN to name a few. [12] Performance optimisation maybe done by evaluating all the classifiers various validation such as k fold cross validation.

4.2.1 Types Of Classifiers

i. Artificial neural network

Ann contain hidden neurons which each have a weight attached to them which varieties according to the data set[13]. Ann is a type of supervised learning. Basically, the network learns the relationship between input and output by the adaptation of the weight of each neuron depending on the data set. It can be deduced that if the data set is small then the precision is hindered as the fluctuation of validation error is huge. [14] MATLAB provides the facility of neural tool box but due to memory restriction it is not possible to train an Ann with large variables (>45000) [15]. [16] Thus to reduce the variable size we require feature extraction techniques, namely using existing DCT function in MATLAB on the data collected.

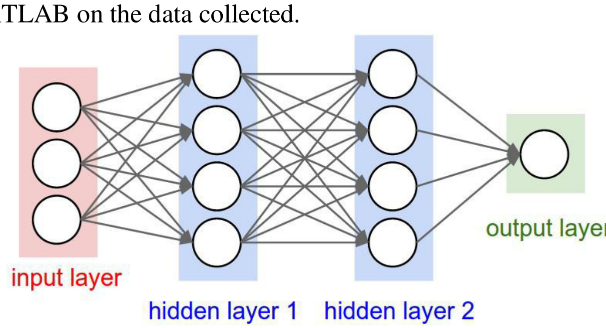

Figure 3 : Ann topology[28]

ii. Linear Discriminant Analysis

LDA is another[11] widely used machine learning algorithm. [17]Linear discriminant analysis (LDA) is a generalisation of Fisher's linear discriminant, a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterises or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification. LDA is popular with BCIA application. LDA linearly converts data from high dimension space to low dimension space. LDA is very simple to implement basically classes of samples are distinguished using a linear combination of features[18] .MATLAB provides statistics toolbox which can be used to implement LDA.

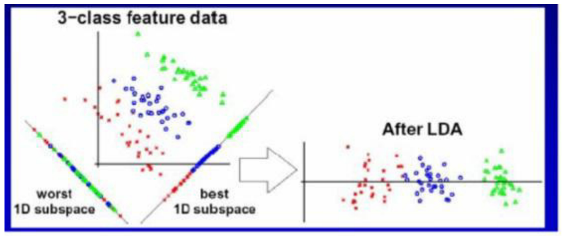

Figure 4 : Example Of LDA[27]

iii. KNN

K nearest neighbour classifier is a simple, lazy , instance based supervised learning algorithm. [19] It basically functions by evaluating both training data and test data based on its nearest value. K denotes the number of nearest value to be considered before taking a decision on output class .for example if k=5 then five nearest point between training and test data will be considered and the final output belong to the training data's class with maximum nearest points[20]. Euclidean distance is normally used to find the distance metric. [22] Euclidian distance between two points is given by

$$(7, =) = E+(1 - 2)^{=} \quad G \quad H97$$

where, x1i and x2i represents the training and testing data respectively . Basically following the feature extraction process the electroencephalogram training data and test data is sent to the classifier. Then Euclidean distance is then determined between every single EEG training sample and testing data . KNN has given a higher accuracy level compared to other classifiers in classifying human stress[21].

iv. Naive Bayes

Naïve Bayes classifiers is basically a conditional probability model where there is the use of Bayes' theorem with addition to independence assumptions between features [23]. Bayes theorem is

$$(\,|\,) = \frac{(\,|\,)\,(\,)}{(\,)}$$

Since the data generated from eeg signals are continuous , a regular presumption is made that the continuous values related with each class are distributed according to a Gaussian distribution. For example, let the training data be continuous .First the data is segmented by class and then in each class the mean and variance of x is computed . [24]Let *U* be the mean of the values in x associated with class C_k, andσc^2letbe the variance of the values in x associated with class C_k. Suppose we have collected some observation value v. Then, the probability distribution of v given a class C_k , p(x= v | C_k) can be computed by

$$(\; = \; |\, P) = \frac{1}{Q2 \; P^{=}} \; 6^{\frac{(T6UV)^{W}}{=XV^{W}}}$$

v. Support Vector Machine

Commonly also called supper vector machines they are supervised learning models with associated learning algorithm [25]. The SVM is a high efficiency classifier model and is used for comparison purposes. With the help of SVM based on high -dimensional space a linear decision boundary can be found. SVM helps in reducing the overall complexity of the model

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and also decrease the probability of over fitting of data . SVM classifier basically can help us to make a hyperplane to gain maximum classification accuracy.

5. Conclusion and Future Enhancement

5.1 Conclusion

It is essential to get accurate and reliable identification of stress and it requires a valid analysis and experimental methodology framework. The main contribution of the paper is developing an experimental model for successfully identifying stress at multiple levels. Our research suggest EEG signals have the potential to reliably to detect stress. However, to quantify stress into different levels it requires further analysis and validation.

5.2 Future Work

- Testing on real time data.
- To help doctors, counsellors, therapists to identify and detect stress in patients using the framework
- To relive working professionals of stress by identifying it at an early stage

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