International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 18 August 2023 **Revised:** 20 September 2023 **Accepted:** 10 October 2023*

On the Development of Machine Learning Based Real-Time Stress Monitoring : A Pilot Study

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Abstract— During specific environmental changes, the human body regulates itself through emotional, physical or mental responses. One such response is stress. The psychological and physical stability of an individual may be affected by recurrent occurrences of acute stress. This often leads to anxiety disorder, other psychological illnesses, hypertension, and other physiological disorders. The work performance of the individual is also negatively affected due to long-term stress. Across various age groups, the global population is primarily influenced by anxiety, depression and psychological stress. The long-term adverse effects of stress can be mitigated by effectively monitoring and managing stress through a cost-efficient and reliable stress detection system. This paper mainly focuses on stress detection using a machine-learning approach. Wearable sensor data from electroencephalogram (EEG) and electrocardiogram (ECG) are considered during exposure to stress and the level of stress undergone by the participant is further analyzed. This approach helps in stress detection, analysis and mitigation, which in turn improves the quality life of people. Machining Learning technique k-means clustering algorithm is used after removal of artifacts to obtain case-specific clusters that segregate features pointing to non-stress and stress periods. The results of the proposed K-means clustering algorithm are compared to state-of-the-art techniques such as Artificial Neural Network (ANN), Decision Tree (DT), Random Forest (RF) and Support Vector Machine (SVM). From the results, it was concluded that the proposed algorithm outperformed the other with an accuracy of 96% in the overall analysis.

Keywords- Machine learning, EEG, ECG, EDA, stress detection, wearable devices.

I. Introduction

Stress is one of the top ten causes of health issues. Occupational safety & health administration, American Psychological Association, World Health Organization and several such organizations are increasing awareness among the general public towards the negative impacts of stress on human health and how it affects society. Several diseases, such as coronary artery disease and hypertension, are caused due to long-term exposure to stress despite the benefits of short-term stress responses [1]. Burnout, anxiety disorders, depression and other mental illnesses may be caused due to prolonged exposure to stress. It is crucial to take necessary actions to be aware of stressful conditions and cope with the adverse effects of stress [2]. This can be achieved through a biofeedback system that can perform timely detection of stress and notify the user to take effective action to mitigate stress. Various stress-related health issues can be overcome efficiently using sensors that can detect stress levels and machine learning classifiers [3]. The conventional studies related to psychophysiology often show no correlation between anxiety levels and physiological parameters. However, modern research involving machine learning techniques has proven that it is possible to recognize anxiety through physiological analysis [4]. Along with lowering healthcare expenditure, mortality and morbidity, the well-being of the users is the key focus area in health research to create novel technologies that can overcome these inconsistencies and challenges. Electroencephalography (EEG), electrodermal response (EDA), photoplethysmography (PPG), electrocardiogram (ECG) and respiration (RSP) are some of the commonly used biomarkers for the detection of anxiety, stress and their related physiological responses [5].

EEG is used for recording the electrical activity of the neurons in the brain from the scalp or cerebral cortex [6]. The cognitive and electrophysiological states of the human brain can be analyzed ideally using EEG as it offers a quick assessment of the underlying neural activity with a nominal temporal resolution of a few milliseconds. A single photodiode can be used to obtain the optical measurement of arterial volume, which helps measure the PPG or EEG signals for analyzing mental stress. Heart rate variability (HRV) and heart rate (HR) parameters can be extracted from the PPG and ECG signals [7].

However, compared to ECG, PPG offers a more convenient way of measuring the HRV. This is because respiration is a crucial factor in evaluating HRV. ECG recordings shorter than five minutes or longer than 24 hours are used for short-term and long-term HRV analysis, respectively. Within 24 hours, it is possible to represent the general physiological regulations of an individual. Hence, this analysis is considered to have a high degree of accuracy [8]. Despite the high dependency on the processed ECG signal and its window length makes short-term HRV analysis a more practical option. Anxiety is determined using ultra-short HRV that ranges for less than five minutes in [9]. Compared to the standard techniques, the ultra-short HRV uses a considerably shorter recording time for quick data generation and is most suited for mobile applications [10]. Anxiety and psychological stress can often be indicated by the RSP parameter, which is often influenced by emotional events. The number of breathing cycles per minute is termed as respiration rate. This parameter increases with worry or tension, leading to hyperventilation in severe conditions [11]. Sweat generation is used for measuring the electrical conductance of skin using EDA sensors. Skin conduction response and skin conduction level is measured using this sensor to indicate anxiety and stress.

Further, various researchers have used functional magnetic resonance imaging (fMRI), written texts and audio signals to detect anxiety. The task frameworks of other modalities and their associated disadvantages are eliminated using the fMRI mechanism [12]. The fMRI is expensive when compared to other modalities. The data is sensitive to head movements and has a low temporal resolution. Machine learning algorithms make use of EDA, RSP, EEG, ECG and other such biomarkers as inputs for the identification and classification of stress levels [13]. Sequential feature selection, phase lag index (PLI) algorithms and probabilistic distributional clustering (PDC) are some commonly used feature selection algorithms. With advanced machine learning techniques, such as support vector machine, random forest, one-vs-one (OVO), long short-term memory (LSTM) and convolutional neural network (CNN), stress assessment can be performed with finer granularity where fine-grained labels such as high, medium, low and no stress are be used for labeling the outputs of the stress tests [14]. This paper utilizes various machine learning classifiers to determine the most effective physiological features for stress detection and prediction using a large dataset. Wearable devices are used to obtain physiological data such as EEG, ECG and EDA to train and test the model.

II. RELATED WORK

Several researchers have been working on an automatic stress detection system in the recent past. The stress level of the user is detected through data by the built-in accelerometer in the smartphone [15]. The working environment is another significant domain in which stress sensing is used. The face temperature of individuals is detected through the thermal infrared camera, and the stress level is analyzed [16]. Physiological data such as skin conductance and ECG, computer logging, facial expression, body posture is used to examine working conditions with mental stress through automatic classifiers [17].

A. Machine learning techniques for stress monitoring

The relationship between the physiological signals obtained by the sensors and the corresponding stress levels are analyzed using the features from the physiological signals. Classification of stress are made by machine learning models based on these features. The common features extracted from respiration, EEG, GSR and ECG signals are shown in Table 1.

TABLE I. FEATURES USED FOR STRESS DETECTION

Input Data Parameters	Features
Respiration	Mean respiration, spectral power density of the signal in four different energy bands-EB1 - 0-0.1 Hz, EB2- 0.1-0.2 Hz, EB3- 0.2-0.3 Hz, and EB4 - 0.3-0.4 Hz
EEG	Alpha, beta, theta, gamma, delta, variance, mean, median, zero-cross rating, kurtosis, skewness, standard deviation, complexity, activity, peak amplitude, mobility, instantaneous frequency, wave duration, number of waves
GSR	Skin conductance
ECG	SD1, SD2, SD1/SD2, LF, HF, LF/HF, pNN20, pNN50, SDSD, RMSSD, HR, SDRR

The combination of physiological signals is processed and classified using CNN and other neural network algorithms. One-dimensional (1D) CNN is used for most signals, whereas two-dimensional (2D) CNN is used while working with EEG signals [18]. Several convolution-pooling layers are used in the multilayer perceptron and its output consists of fully connected layers. In the convolution layer, multiple-dimensional filters are used for convolving the input features. In the pooling layer, the output of the convolution layer is sub-sampled, and a smaller scale of features is produced [19]. The error classification is minimized through the back-propagation algorithm, which learns the filters and shared network weights in the convolution layer. Several studies make use of predominant algorithms like Random Forest (RF) [20, 21] and Support Vector Machine (SVM) [22, 23]. Several individual decision trees that operate as ensembles are available in the RF algorithm. Every tree produces a class prediction, and the model prediction is chosen based on the class that receives the maximum votes. In RF, a random selection of a subset of features is performed out of the total features. Further, each node in a tree is split by the best split feature in the subset. However, all the features are considered for splitting a node in bagging. A hyperplane is found in SVM that can best divide a dataset into multiple classes.

The research states that K-means and cluster-wise classification are applied to EEG and other physiological signals [24]. The subjects are divided into categories using K-means, and generalized regression neural network (GRNN) which are used for conducting regression analysis on individual clusters based on a training dataset belonging to the recovery and task load stages. A set of K-GRNN models reduces the cluster-wise error. The EEG features are categorized into data points representing stress and non-stress periods with a different cluster using unsupervised learning in [25]. However, in this technique, the classification of anxiety levels is challenging as the classification accuracy is higher when the data is grouped into two rather than three. 10-fold cross-validation, leaving one out, and other validation techniques are also used in many cases. The existing research does not discuss the impact of using various cross-validation techniques.

The EEG signals, a combination of RSP, EDA and ECG, and a combination of EDA and ECG helped to achieve the best performance in the Random Forest algorithm. However, certain contradictions are found in these results among various literature due to the size of the datasets used. The best performance of SVM is achieved while using a combination of EEG and ECG [26], only EEG, and a combination of HR, RSP, EDA and skin temperature (ST) [27]. A variety of ST, PPG and EDA offered the best accuracy for neural networks [28]. A good performance is achieved by combining EMG, EDA, ECG and EEG signals or only EEG signals with an accuracy of up to 85%. In contrast, a combination of RSP, ST and ECG provided a lower accuracy of 77% in [29]. RSP, EDA and ECG signals are commonly used in several researches. Certain researchers also analyzed the influence of anxiety on skin temperature. Aristizabal et al. [30] concluded that skin temperature does not significantly affect stress. Humidity, temperature and other environmental conditions influence the skin conditions, and hence the information on the intensity of stress is not optimal while gathered from the body temperature.

B. *Challenges in existing stress detection systems*

Various combinations of signals have resulted in different accuracy results. Several challenges are faced due to the inconsistency in this breakdown. The causes of this issue are analyzed and the major challenges for detection of stress level lies on various factors such as differences in sample sizes, mental and psychiatric comorbidity and difference in confounding factors, limited data about the mental condition of the patient before the study, limited data on the age and gender of the participants, limited data regarding the exact features used and feature selection, use of different machine learning models and different signal combinations and variation in classification techniques. The proposed paper focusses on designing a real time system to detect and monitor an individual stress level by considering these challenges.

III. PROPOSED WORK

The ECG and EEG signals of the patients are recorded for a period of 15 minutes continuously in a simultaneous manner. Experimental sets are dedicated to acute stress induction. The experimental setup for acquiring the real time signal is developed by which 20 healthy participants within the age group of 25 ± 15 years are recorded and data are collected. Previously, every subject was observed, and 24 features were extracted, including five features for EEG, four signals for ECG and 1 for EDA. The subjects were made to undergo 60 minutes of training, of which 30 minutes corresponded to no-stress activities and 30 minutes to stressful tasks. In this proposed work, a total of 500 healthy participants are considered within the same age group of 25 ± 15 years, such that 250 participants are males and 250 participants are females. The EEG signal and ECG signal are obtained from the participants using Muse S (Gen 2) EEG headset, Savvy ECG sensor, and Shimmer3 GSR sensors.

A. *Experimental Procedure*

There are six steps involved in this work, setting the environment to stimulate stress on the participants. The experiments involved are as follows:

a) A1: The first experiment involves a standard procedure which consists of fundamental questions such as height, weight, date of birth, name, etc. It also contains one question which requests the participant to spell the alphabet and the number from 1 to 30.

b) A2: The second step involves requesting the participant for simple body movements like moving one step forward and one step backwards.

c) A3: For the third step, the patients should close their eyes to compare themselves and relax. Now the participants are asked to solve arithmetic problems within 10 seconds. A timer is also displayed to be seen by the participant and a discouraging phrase when they feel to answer correctly. As the participant progresses, the complexity of the questions will also increase.

d) A4: For the next experiment, the participants were asked to watch and listen to videos and sounds. Participants are questioned in a foreign language as part of the following experiment.

e) A5: The next part involves memory testing for a few seconds. To imbibe pressure on memory skills, the participant is asked to memorize as many objects as possible within a short period.

f) A6: The last step involves the participants' logical thinking with simple questions like identifying the missing numbers in a series.

The entire sequence of the experiment is provided in Table II as part of the acute induced stress test.

TABLE II. SUMMARY ON VARIOUS SEQUENCE OF EXPERIMENTS

Experiment	Time (seconds)	Test
A1	150	General Questions
A2	120	Relaxation Body Movements
A3	30	Simple Arithmetic Test
A4	90	Audio Distractions
A5	30	Memory Testing
A6	30	Logical Solving

However, when classifying EEG signals, there is high disagreement and variability. This is primarily due to the brain frequency sub-bands level, which are difficult to compare. Newson et al. [31] have performed a statistical analysis, which is used in this proposed work to define the frequency bands. The DWT decomposition levels are used to determine the ranges by which stress detection are measured. The EEG channels are decomposed with 4 coefficients using Daubechies wavelet. The EEG signal for N=2000, with 10 s comprises the DWT featuring which is used to decompose the signal to determine the approximation coefficients. A total of 5 levels are procured with Daubechies wavelet "db3". The original signal acts as a low pass filter that helps to secure the sampling frequency by half and it helps to filter components in the frequency range of 500-250 Hz. Incorporating the Mallat algorithm, the approximation frequency band can be expressed as eq (1).

$$(p,\ p+\frac{q-p}{2^p}) \tag{1}$$

Coefficients can be calculated using the frequency band defined by eq (2)

$$(\ p+\frac{q-p}{2^p}, p+\frac{q-p}{2^p}) \tag{2}$$

For each frequency level, a frequency band is formulated and represented in Table III, provided the higher frequency is removed.

TABLE III. FREQUENCY AND BRAIN BAND CLASSIFICATION

Classification	Frequency Band (Hz)	Frequency Brain Band (Hz)
Alpha	7.125-12.8	8-14.99
Beta	12.8-27	15-35
Theta	3.25-7.125	4-7.99
Gamma	27-50	35-40
Delta	1.5-3.25	1-3.99

B. *EEG signal analysis using machine learning method*

The primary contribution of the proposed work is to incorporate k-means cluster-based algorithm to classify stress based on personal necessity. Based on the periods of stress and non-stress, the EEG features are clustered with the help of the K-means clustering methodology. In such cases, similar features are clustered together by sharing cluster data. Therefore, based on the assumption that the individual feature values vary, the k-means algorithm is used to cluster the EEG features during periods of stress and non-stress. A target number of clusters 'k' is used to determine a finite dataset P(a_i,a_2,a_3,..a_N). This methodology is used to determine the optimal partition of data clusters share. A pair-wise Euclidean distance can be defined for (a_i,a_2,a_3,..a_N) in range R using the eqn (3)

$$\left\|(a_i-a_j)^2\right\| \tag{3}$$

The k-means optimization algorithm is used to identify the partition that decreases, considering all clusters such that:

$$\min_{x_1 \cup x_{2,\ldots} \cup x_k = P} \sum_{i=1} \sum_{a \in x_i} \left\| a - \frac{1}{|c_i|} \sum_{a_j \in x_i} a_j \right\|^2 \tag{4}$$

To find the solution for the minimization problem, the k centroid is located amidst the data points. Now each data point is clustered to the nearest means iteratively in order to determine the new mean point.

K-means++ is the k-means optimization algorithm used in this proposed work wherein initialization is performed depending on non-uniform sampling. This methodology involves the following steps to be carried out: The artifacts are removed, and the frequency levels are identified to standardize data. The standardized data is further fed to the k-means clustering algorithm as the input. The data is further sub-categorized into batches with 5 seconds of recording of features holding 1500 points. A matrix [CA, FL, BA, CH] is used to organize the data, namely cases, frequency levels, batches and channels. The standard deviation and energy are calculated for every case as the main features. For the period of non-stress and stress, the tests are executed with 4 clusters such that one cluster is used to categorize data points along with an additional cluster.

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C. ECG signal analysis

The Autonomous Nervous System (ANS) is used to control the rhythm of heart rate (HR) of a human being. The ANS answers meet the requirements of the external and internal stimuli. The external stimuli are preferred over the internal stimuli by the stress response. The HR of human beings is used to understand the body's response to multiple environmental stimuli. An ECG-based HR is a non-invasive mechanism to identify and record psycho-social and emotional stress levels. Moreover, it also serves as a reference to similar events like metabolic changes, hemodynamic changes, physical exercise, breathing etc. Hence these ECG signals should be used as a mechanism to detect stress accurately rather than as an analyzer of stress. The North American society facing electrophysiology and the European society of cardiology task force establishes norms and metrics wherein certain statistical HR measures and some standards can be used for clinical purposes.

In this proposed work, the RR intervals are analyzed to identify variation in stress as per studies made by authors in [32], which suggest a strong correlation between stress undergone and the RR intervals reading. The RR peak distance is calculated using DWT's first approximation coefficient. The distance between consecutive RR peaks is determined with the help of the soft thresholding function. The ECG data obtained from the participants is segmented into 6, according to the period for every test, as shown in Table I. The standard deviation and average for RR intervals are calculated for every participant in every segment, and the result is obtained. For every experiment, the RR intervals are observed and analyzed. Based on the stress level, a stress gradient represents the amount of stress in Figure 1.

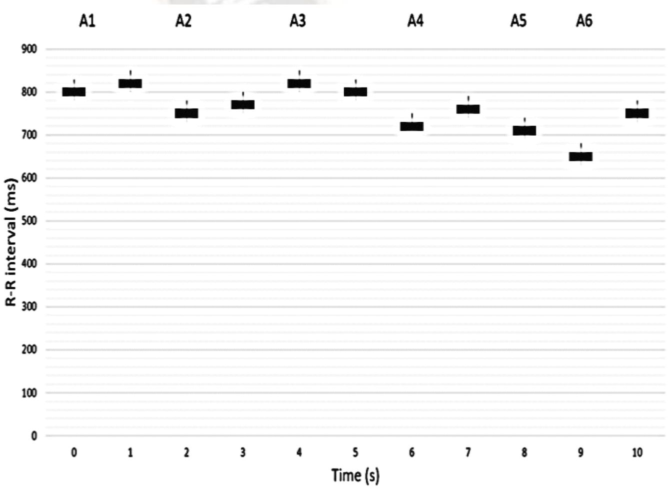

Figure 1. Stress level based on Experiment

In general, the participants are exposed to stress experiments within 15 minutes. In every case, there is a specific pattern in which the RR interval decreases. This is measured with respect to the second experiment, the relaxation experiment. This could be an indicator of stress and is further correlated with the results of EEG metrics. Accordingly, an expression is formulated as equation (5) to calculate the increment of HR concerning the RR interval captured during the relaxation experiment (A2).

$$\mu_{ECG} = \frac{\mu_{R-R_{ref}} - \mu_{R-R_n}}{\mu_{R-R_{ref}}} \tag{5}$$

Such that $\mu_{R-R_{ref}}$ denotes the relaxation period calculated. Here RR represents the interval mean value of the experiment.

IV. RESULTS AND DISCUSSIONS

There are two parts involved in this section. The first part involves the use of ECG and EEG stress analysis figures. An evaluation of the stress levels is carried out based on the subject provided. This data is obtained concerning the participants' health conditions and daily habits. The next part involves the use of Machine learning methodology to perform stress classification. Data processing is performed using Python along with libraries like Keras and scikit-learn.

A. EEG and ECG- based inter-individual stress evaluation

After cleaning the signals, the features are clustered after extraction. The primary objective of the proposed work is to determine how individuals respond to stress experiments, and each response is recorded with the help of biomarkers variation. Based on the ECG and EEG data observation, it is possible to discriminate between the non-stress and stress periods. Some interpretations in the observed reading vary according to the individual. This work uses a quantitative mechanism to evaluate the stress response. Based on the evaluation, it is possible to list out the highly sensitive participants to stress.

The ECG and EEG data are collected to indicate stress discrimination. Here, the clustered outputs are preprocessed using the RR intervals and an encoding mechanism. This is followed by using supervised learning models. A total of five models are compared, namely Artificial Neural Network (ANN), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM) and the proposed K-Means Clustering. The optimal hyperparameters to train every model is performed with the help of a grid search mechanism. For every case, 30% of the data is used for testing and 70% for training. This work aims to build a general framework for stress detection. Figure 2 represents the results of the stress detection with accuracy in the five methodologies carried out.

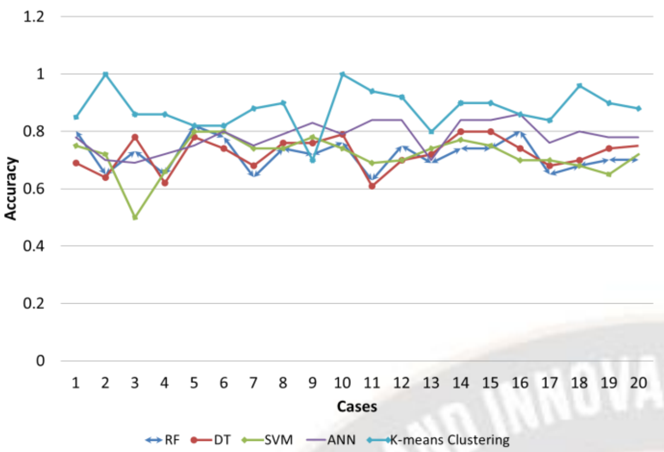

Figure 2. Machine learning methodology comparison

V. CONCLUSIONS

This proposed methodology uses a non-invasive ECG/EEG signal output to obtain multi-sensing data. A group of 500 healthy participants are considered within the same age group of 25 ± 15 years, such that 250 participants are males and 250 participants are females. The EEG signal is obtained from the participants using Muse S (Gen 2) EEG headset, Savvy ECG sensor, and Shimmer3 GSR sensors. The participants are exposed to a control-induced series of stress tests, and their ECG and EEG readings are recorded to be analyzed. Machine Learning technique with K-means clustering algorithm is used after removing artifacts to obtain case-specific clusters that segregate features pointing to non-stress and stress periods. The ECG and EEG signals obtain accurate metrics to analyze the stress sensitivity level. Detection of participants' stress helps an individual to analyze and prevent possible chronic health ailments.

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