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Mental Stress Detection and Classification using SVM Classifier: A Pilot Study

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***Abstract*—Human stress brings changes in both physical and mental health which leads to chronic illness or injury, hypertension, cardiac arrest. It also causes emotional problems such as anxiety, depression, anger, grief, guilt, low self-esteem which affects normal healthy life. This paper presents the design, development and testing of a biomedical measurement system for detecting human mental stress using machine learning approach. This paper investigates the measure of heart rate variability from am ECG signal for detecting human stress by using Support Vector Machine (SVM) classifier technique and ultra-short term HRV analysis method. MIT-BIH multi-parameter database is also used in this paper to load ECG signals for extracting the time domain features for detection of human mental stress. The different experiments have been carried out with 60 segments of RR interval in both normal state and stress state condition by ultra-short term HRV analysis method. The implementation of SVM classifier with RBF kernel provides the accurate detection of mental stress level. The measurement result indicates that the proposed techniques achieve the mental stress classification accuracy of 91%. From the results, it was concluded that the proposed methodology provides a promising way to detect mental stress in an individual.**

Keywords— Mental stress, SVM classifier, ECG Signal, Feature Extraction, Machine Learning.

I. Introduction

The development of biomedical measurement system in healthcare network for measurement of human physiological parameters has been growing due to the rapid increasing the nature of many diseases and working life behaviours of an individual. The smart system with flexible approaches for detecting the diseases becomes very essential in modern world for early detection. The advanced signal processing methods and techniques provides a wide range of design principles for measuring and detecting many diseases. The non-invasive devices play a vital role to measure the physiological signals from human body which leads to identify the important vital parameter in biomedical research. Human mental stress is the reaction of mind that develops when a person feels threatened or tense as a result of a variety of situations. It has the potential to limit one's personal freedom which also degrades happiness and individual productivity. Nowadays, depression has become the most common issue in human life which has the potential to develop chronic diseases. To avoid many health-related problems, it is desired to detect an individual's stress level at an early stage. It would be possible to avoid the negative effects of stress on human lives. Stress has various response to a mix of external and internal stressors that cause an organism to become stressed. The body's coping technique in reaction to any external pressure or threat is known as stress. The Sympathetic Nervous System (SNS) releases stress hormones like cortisol in response to a stressful situation, which leads to an increase in available energy sources via a chain of events. This massive amount of energy is used to fuel a variety of physiological functions, such as increasing metabolic rate, increasing heart rate, and encouraging blood vessel dilatation in the heart and other muscles, as well as reducing immune system and digestion. The brain activates the parasympathetic nervous system (PSN), which is responsible for restoring biological homeostasis, when stresses are no longer a threat to the body. If the PSN does not attain equilibrium, chronic stress can develop, resulting in a continuous and extended activation of the stress response.

There are several methods for detecting stress level, tensions which includes questioning, evaluations, attitude observation. The different researchers have been investigated to detect the stress level from brain signals such as EEG. In the current scenario, there is a huge need for developing a biomedical measurement system to detect mental stress automatically due to critical situations. This paper proposed to develop a biomedical measurement system to detect human mental stress from an ECG signal. The most promising feature called RR interval is extracted from the signal for detection of mental stress. In the Autonomic Nervous System, the analysis of RR interval signals in terms of Heart Rate Variability (HRV) is widespread. The sympathetic and parasympathetic branches of the autonomic nervous system regulate the sino atrial node, which generates ECG variability signals.

The methods used in this paper mainly focused on analysing the heart rate variability and classifying the stress level. HRV is also described as differences between consecutive heartbeats. There are a number of studies that show that mental stress has an impact on HRV [1-5]. This paper also provides the implementation of advanced signal processing methodology for extraction of features from an ECG signal and develops a support vector machine-based classification algorithm for stress level classification. The proposed paper extracting the necessary information on various ECG signal and measures the stress level. This will become a promising method to support the public to measure their stress level in advance and understand the situation very efficiently. The measurement of an ECG signal produces the information on the nature of electrical activity which can be recorded using bioelectrodes. There are different features can be extracted from the acquired ECG signals. The features such as RR interval, heart rate, time domain features and heart rate variability become very necessary for detection of mental stress level [6-7]. The research reported that the measurement of time domain features provides the robust way in stress detection as compared to others [8]. Many researchers have investigated the method for stress detection by measuring heart rate variability. The nature of HRV has close correlation with autonomic nervous system which further a promising key role for detection of mental stress. The characteristics of heart rate variability provides the accurate measurement of stress level conditions because the mental and physical state change caused by variation in HRV. Also, the literature paper reported that the state of mental, physical stress is greatly aligned with the nature of HRV parameters [9-10]. From the outcome of literature papers, it was observed that the mental stress level detection and monitoring can be possible by measuring individual ECG signal. The advanced signal processing approach is integrated with ECG measurement for accurate measurement of heart rate variability for detection of stress level. The organization of this paper is structured as follows: Section 2 presents detail information on various methods involved for stress measurement. Section 3 provides the system architecture and the implantation of machine learning algorithms. Section 4 highlights the measurement results and concludes the paper.

II. Stress Masurement Techniques

The literature papers which are collected form scientific publishing environment highlight the methods and techniques for measuring the stress level. The ultimate purpose of this paper is to provide the methodology and effective measures on stress level detection and classification through physiological signals.

A. The Psychological Approach

The different methods for assessing mental stress traditionally has been done using psychological techniques. The most popular method used by the researchers includes preparing set of interviews and obtaining the necessary inputs from an individual through questionnaires [3-5]. These traditional method of detecting mental stress becomes an effective solution to detect personal stress level. The methods such as Perceived Stress Scale (PSS), Life Events and Coping Inventory (LECI) and Stress Response Inventory (SRI) are greatly used in clinical practice and psychological studies to assess individual stress [3-4].

B. Behavioural and Physical approach

From the literature papers, it was noticed that the method to calculate an individual's stress level based on the behavioural approach [11, 12]. The facial recognition approach also used by the investigator for detecting mental stress [13]. The approaches used by the behavioral approach provides an effective feature based on the individual characteristics. Researchers also utilised a new physical way to evaluate stress levels, which comprises a characteristic of central-autonomic physiological processes and chemical reactions in the body as a result of changes in the immune systems [14].

C. Physiological methods

Mental stress could be detected directly due to the nature of physiological responses. The physiological responses obtained from an individual are properly trained and able to detect mental stress. The real time data from the biosignals provides a clear perspective view to design a real time system for measuring stress level. The different methods focused on the objective techniques that have real-time data for detecting stress level [5]. There are many physiological parameters are used to construct the real time system for predicting mental stress level. These parameters are extracted from the signal acquired from human body. The most vital parameters are heart rate, respiration rate, blood volume, RR interval from an ECG signal, Galvanic Skin Response, Body temperature, EMG, blood pressure, SpO2 and eye movement used to evaluate a person's stress level. Further, the classifier algorithm is used in conjunction with signal processing and feature extraction algorithms to determine an individual's stress level. There have been several recent studies that looked at a variety of methodology for stress detection which includes soft computing techniques and statistical signal processing methods [15], Fuzzy, k-NN [16] SVM and Bayes classifier [17].

III. System Architecture

The proposed system architecture is shown in Fig 1. The different modules involved in the proposed system consists of analog front-end unit for signal acquisition. This work focused on the acquisition of ECG signal and collection of database signals to extract the desired features for stress measurement. The processing unit is designed for collecting and processing the signals. By assessing heart rate variability, this module's functional work produced the appropriate time domain and frequency domain information from an ECG signal (HRV). Further, the heart rate variability features are trained with machine learning approach for detection of stress level. The use of a self-organizing map and a support vector machine approach to identify and classify stress levels was proposed in this paper.

The large number of ECG data are collected from an ECG sensor attached to human body. MIT-BIH multi-parameter database is used for collecting ECG signals to detect the stress level. The measurement of ECG has been taken with various driving situations. The driving is set up in such a way that the subject experiences each of the four stress levels over the course of an hour. The four different categories of stress level such as no stress, low stress, medium stress and high stress-based signals are collected from the database and recorded.

The heart rate variability by measuring RR interval is calculated from ECG data. The examination of heart rate variability (HRV) is a valuable and important tool for determining cardiac autonomic function. The research says that HRV is the change in heart rate from beat to beat which are measured by wearable sensor and considered as an important feature linked to mental stress [18]. The time domain research of HRV includes time domain variables such as the mean and standard deviation of RR intervals. The power of HRV's respiratory-dependent high frequency and low frequency components are the frequency domain properties. Many researches have investigated and analyzed the signal irregularities which are correlated with stress [19]. It has been found that the frequency domain features are highly correlated with mental stress by analyzing the frequency component of HRV [20]. The process of extracting the features are carried out on measuring HRV.These features are further used for training the system to detect mental stress [21-31].

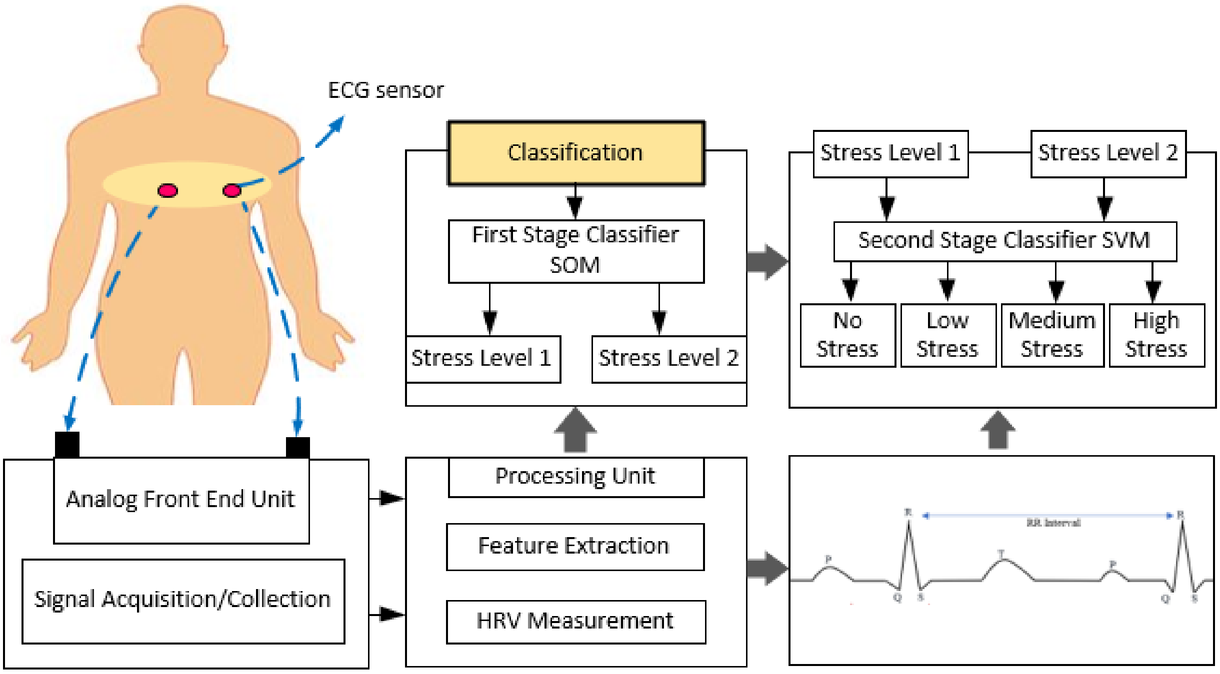

Fig. 1: System Architecture for detection of mental stress level

IV. Results and Discussions

The real time signals and MIT-BIH database signals are used to develop a system to detect mental stress. The statistical signal processing methods have been applied on input ECG signal. The characteristics of an ECG signal is analyzed using LabVIEW software environment. The feature extraction algorithm is implemented and RR interval is estimated from an ECG signals. The large number of database signals are further used to extract the desired features which could be used to train the system. This paper consists of a database signals with stressed signals and baseline segments and total number of 700 signals are considered in the system for analysis. The experimental set up consists of ECG sensor for acquiring an ECG signal. The representation of an acquired ECG signal is shown in Fig3. The filtering techniques are used to remove the noises from an input signal. The bandpass filter is used in this paper to remove baseline wandering and the output response is shown in Fig 4. The filtered signals are further used to analyse the heart rate variability. The advanced signal processing methods have been applied to extract the desired features for the detection of stress level. The extracted data are used as input to SVM classifier to detect an individual stress level.

This paper proposed two stage classification approach for stress measurement. The four different level of stress are considered and the proposed system is trained with no stress, low stress, medium stress, and high stress datas . The features retrieved from the HRV signals are first fed into the SOM, which divides the stress levels into two categories: stress level 1 and stress level 2. The same seven features are fed into the SVM classifier in the second step, with stress level 1 containing data linked to no stress and low stress, and stress level 2 containing data related to low stress and high stress. The integration of SOM with SVM classification approach delivers the accurate classification of stress level. The Self-Organizing Map does not require supervision. They try to match their weights to the data provided and keep the intended characteristics of the applied data. The algorithm for self-organizing map set the weights randomly for each node. The weights of each node in the network are compared to the input vector to determine which ones are the most similar and given a name called best matching node. The radius of the best matching node neighborhood is estimated and any nodes discovered within the best matching node radius are modified to obtain the same input vector. The weights of a node change as it gets closer to the best matching node. The following equation is used to update the weight vector:

$$wj = wj + \eta.h(j, i(x)).\,(x - wj) \tag{1}$$

Where, wj -Weight vector, x- input vector, η-learning rate and h(j, i(x)) - neighborhood of the function best matching node. For efficient SOM classification, the best matching node neighbourhood radius and learning rate are initially set to a big number and then gradually reduced to a smaller one. The implementation of self-organizing map algorithm is shown in Fig 2.

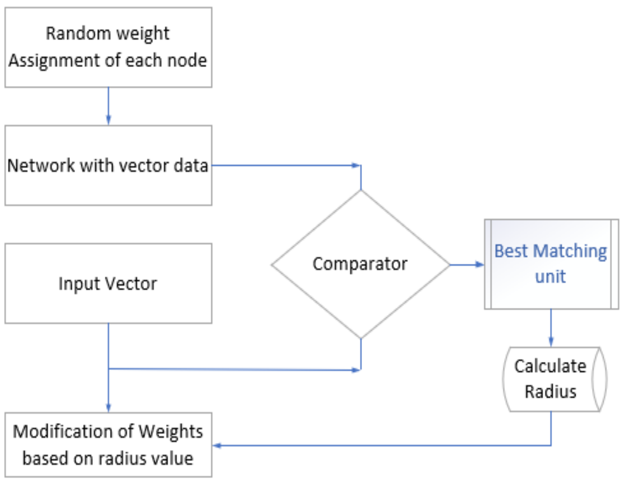

Fig. 2: Steps involved for implementation of self-organizing map algorithm

TABLE I: ECG Feature extracted for detection of stress level and statistical evaluation of SVM classifiers at different stress levels

Subject	**Features Extracted**						**Stress Detection**
	mRR	**HR**	**nVLF**	**nLF**	**nHF**	**SVI**	
Subject 1	934.6652877	69.49	1868.532	570.6431	2.993254	190.6431	No stress
Subject 2	817.0623804	64.36	568.7428	1553.972	39.69485	39.14794	Low stress
Subject 3	876.7620224	67.45	2101.871	655.1759	14.53688	45.06992	Low stress
Subject 4	1038.640693	68.809	5757.544	592.913	7.093235	83.58852	No stress
Subject 5	774.5485079	74.565	964.6963	374.9395	33.46883	11.20265	Medium stress
Subject 6	767.3769938	81.342	960.7083	414.7542	22.92733	18.08995	Low stress
Subject 7	752.588898	62.0950	1275.418	2882.461	131.0936	21.9878	Low stress
Subject 8	1317.768589	85.8577	4649.302	125.0966	3.595002	34.79737	Low stress
Subject 9	733.9800071	74.588	1214.158	374.41	25.4943	14.68603	Low stress
Subject 10	759.3673249	62.726	1220.239	386.0325	24.48046	15.76901	Low stress

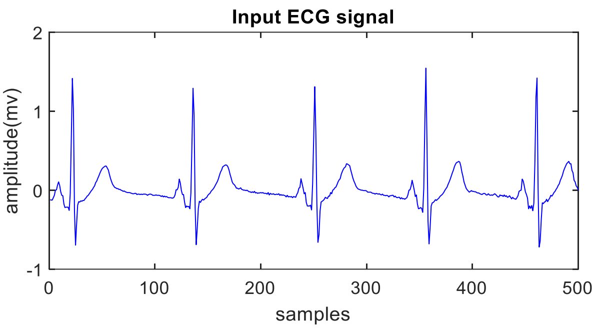

Fig. 3: Real time ECG signal collected from sensor

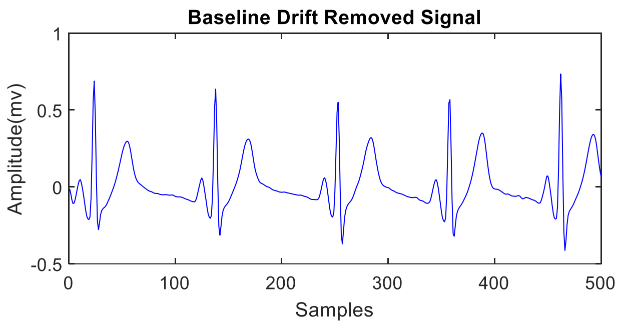

Fig. 4: Baseline wandering removed ECG signal

One-minute slices of an ECG signal are used to extract time domain and frequency domain characteristics. The data comprises of various attributes taken from ECG signals for different individuals with different heart rates. This research uses the frequency domain properties listed below to determine stress levels. The major metrics are the power spectrum of very low frequency (VLF) between 0.0033 and 0.04Hz, low frequency (LF) between 0.04 and 0.15 Hz, and high frequency (HF) between 0.15 and 0.4 Hz [32]. The normalized power spectrum of normalized very low frequency (nVLF), normalized low frequency (nLF), normalised high frequency (nHF), and Symphatovagal balance index (SVI) are efficient metrics derived from the ECG signal to classify stress levels. The python and matlab programming environment are used to test the algorithm for detection of stress level. Table 1 shows the features extracted from an ECG signal and statistical evaluation of SVM classifier to classify the condition of stress level of each subject. From the results, it was noticed that SVM classifier could be an efficient approach and promising way to detect the stress level from an ECG signal.

V. Conclusions

This paper presents the development of software-based stress detection and classification model using support vector machine-based classification algorithm. Detecting stress level becomes the most important for predicting many health-related issues. The biomedical signals from body provides an efficient vital information about the status of human health conditions. This paper proposed the measurement of stress level through an ECG signal. The database signals are collected and analyzed with different health conditions. The four different level of the signals are recorded and grouped in the categories of no stress, low stress, medium stress and high stress. The heart rate variability is estimated from the recorded ECG signals. The advanced signal processing techniques are implemented to extract the desired features and analyzed the HRV. The statistical features are applied as inputs to SVM classifier to perform the stress level classification. As compared to other existing techniques, SVM classifier gives the accuracy of 91%. The results show that the proposed methodology provides an effective solution to measure individual stress level in a working environment.

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