Automatic Stress Detection Using Wearable Sensors and Machine Learning: A Review

Shruti Gedam
Dept. of Computer Science & Engg.
Birla Institute of Technology, Mesra
Ranchi, India
shrutgedam@gmail.com

Sanchita Paul
Dept. of Computer Science & Engg.
Birla Institute of Technology, Mesra
Ranchi, India
sanchita07@gmail.com

***Abstract*— Stress is a feeling of being under abnormal pressure which comes from different aspects of our day to day life. Stress management is important during this modern era to keep up one's stress level low and reduce health risks as stress is one of the primary cause leading to major chronic health disorders. In this paper, we examine and review various stress detection approaches who uses low-cost wearable sensors for data collection and machine learning algorithms for predicting stress level of an individual. Researchers have found that stress level can be detected through some physiological measures like heart rate, heart rate variability and skin conductance. This paper aims to provide a comprehensive review on various stress detection techniques and gives a reliable guideline towards more efficient detection of stress.**

Keywords*—*Stress detection, feature extraction, physiological measures, wearable sensing, machine learning.

I. Introduction

In today's fast-paced world, mental stress is very common. Stress can be caused due to situations or events that put pressure on mind and body of a person. Reaction to stress is different for everyone as the capacity of dealing with tough or demanding situations vary for person to person. Some situations may cause stress to one person, while no stress to one altogether. Also, all stress is not bad for health as it can make people more aware of things around them and keep them more cautious about dangers and focused on their goal. A stressor is an event which causes stress to an individual. Many people usually faces stress due to these stressors described in table 1.

TABLE 1. Stressor Type And Its Examples

Type of stressor	Description and Examples
Physical	Strain on a body Ex: Injury, illness, pain, travel, infection, excess alcohol
Psychological	Anything interpreted as threatening or challenging for mind Ex: Money problem, exams, loss of employment, excessive worrying
Environmental	Associated with surrounding Ex: Noise, crowd, air quality, light, insects, temperature variation, war and disaster.
Psychosocial	Associated with social situation Ex: Divorce, unwanted change of residence, prolonged illness, highly competitive work situation.

According to American Psychological Association (APA),there are mainly three types of stress which are acute stress, episodic acute stress and chronic stress. Acute stress is short term stress which is least damaging type as compared to the other two. It can be good sometimes as this helps body to deal with the situation. When acute stress occurs frequently then an individual is affected with episodic acute stress. Chronic stress is the most harmful type of stress, if left untreated over a long period of time can damage physical and mental health of a person. Chronic stress puts pressure on the body and mind for an extended period which can cause a range of symptoms and increase the risk of developing certain diseases.

To avoid health problems, people with high risk of getting stressed should be continuously monitored to detect any stress signs. Wearable sensors provide opportunities to monitor stress and can inform people about their stress level which can be useful in order to minimize stress balance before it results into serious health problems. Physical health and mental health are closely connected, hence monitoring and measuring of physiological and physical changes can be used for detecting human stress level.

Stress can be detected using physical and physiological measures of body. Physical measures include pulse rate, skin temperature, humidity, Blood pressure and respiration rate whereas physiological measures can be heart rate, heart rate variability, skin conductance. These can be measured using wearable devices made from low-cost sensors although machine learning algorithms can be used to classify and predict stress level of an individual.

In this paper, some previous approaches of automatic stress recognition systems who used sensors and machine learning are discussed in detail. In these, physiological data is extracted using some stressor tests on the people. Some common stressor tests includes arithmetic calculations, questionnaire, mental tasks and working out in gym. There are a diversity of machine learning algorithms which are appropriate for stress detection. Among them Support Vector Machines (SVM), Logistic regression, K-Nearest Neighbor, Decision tree and Random forest are most common. In this review, we summarize the various machine learning algorithms available in the literature that aim at detecting state of stress.

The remaining paper is divided into two sections. In Section II, we describe some methods to detect and classify the stress levels. In Section III, we conclude the paper and discuss the results of this literature review.

II. Related Work

In this section, we briefly summarize some approaches of stress detection. These approaches vary according to the various stress related factors and measures used. The measures used in this includes physical measures, physiological signals, answering questionnaire, mathematical test, videos, microblog and other techniques, etc. Also, stress detection in various environments is described below.

A) Stress Detection using Wearable Sensors and IOT Devices

Nowadays, sensors plays a vital role in medical applications. These are generally used for detection and measurement of various diseases and its levels. Stress is usually recognized as one of the major factors leading to various health problems. Therefore, people with high risk of getting stressed should be continuously monitored for detection of any stress signs before it causes health problems[8]. Advances in wearable sensors and mobile computing make it possible to record a variety of physical and physiological signals on a twenty-four hour basis which helps in detection of stress level. Mostly wearable sensor devices like smart band[3], Chest belts[2] are used for data collection. Some researchers used hardware and software for collection of data through sensors and detection of stress level respectively. A Holster unit was used with LI-PO battery and PC USB Client software for detection of stress[2]. An Amulet wearable platform named StressAware was developed in [7] using SVM. This real time applications classifies the stress level of individuals by continuously monitoring HR and HRV data. Some smart bands can collect and transmit data to users smart phone via Bluetooth and even uploaded to web where it can be accessible by doctor or family members[3]. The overview of few studies are discussed in table 2 which shows stressors, subjects, sensors, best accuracy achieved, the classifiers and methods used by various researchers.

TABLE 2. Overview Of Stress Detection Using Sensors Studies In Chronological Orders, Their Details And Best Accuracy Achieved

Studies	Stressors	Population (Subjects)	Sensors	Classifiers/Algorithms/Models	Best Accuracy Achieved
Jacqueline Wijsman et al. (2011) [1]	Questionnaire, Mathematical Tasks	30	EMG ECG Respiration Skin Conductance	Linear Bayes Normal Classifier Quadratic Bayes Normal Classifier K-Nearest Neighbor Classifier Fisher's Least Square Linear Classifier	80%
Jongyoon Choi et al.(2012) [2]	Some Tests, Breathing exercise	10	EDA EMG Respiration Heart Rate	Stress Prediction Model Logistic Regression Model	81%
Muhammad Zubair et al.(2015) [3]	Tracking	12	Skin Conductance	Logistic Regression Model	91.66%
Anthonette D. Cantara et al. (2016) [4]	Interviews	21	Heart Rate Galvanic Skin Response	Fuzzy Logic Algorithm	72%
Purnendu Shekhar Pandey(2017) [5]	Age, Working out in Gym	318	Pulse Sensor Heart Rate	Logistic Regression Model Support Vector Machine Classifier	68%
Rachmad Setiawan et al.(2019) [6]	Tense and calm conditions	15	Temperature Galvanic Skin Response Heart Rate	Fuzzy Logic Algorithm	80%
Jorge Rodriguez-Arce et al.(2020) [15]	STAI self-report Questionnaire	21	Heart Rate Skin Temperature Galvanic Skin Response Pulse oximeter Breath-rate sensor	Support Vector Machine Classifier K-Nearest Neighbor Classifier Random Forest Classifier Logistic Regression Model	95.98%

B) Stress Detection through Physiological Signals

1) Stress detection using Electrocardiogram(ECG)

Electrocardiogram (ECG) measures the electrical activity of the heartbeat. Mostly Heart Rate Variability (HRV) parameters are derived from ECG signals for detecting mental stress where it is divided into Time domain and Frequency domain for further investigation[9][11]. In [10], the ECG signals were pre-processed where baseline drift and noise were removed without disturbing ECG waveform characteristics. Feature exaction was done using discrete wavelet transform method. And classification was done using Support vector machine, Artificial Neuron Network, Bayesian network and decision tree on real-time data of 20 subjects for getting more accurate results based on accuracy. SVM gives best results among all which is helpful to determine whether person is in stress or not. Giorgos Giannakakis [11] proposed a stress recognition system evaluated on 24 participants and 11 tasks where a research protocol can perform till 45 minutes. The best performance achieved in this system by only utilizing HRV parameters which are extracted from ECG signals was 84.4% classification accuracy by using SVM in a 10-fold approach. The useful features were selected using the minimum Redundancy Maximum Relevance (mRMR) selection algorithm. The concentration of the scientific community on the usage of only one ECG channel makes these methods suitable, as they can be easily used through wearable devices in daily routine.

2) Stress detection using Electroencephalography(EEG)

Stress is a condition which can effects the brain activity by changing its normal state. Electroencephalography(EEG) is used to measure cognitive change in the brain. Emotiv Epoc device is widely used for EEG related research to obtain raw EEG data as it is reasonable, portable and suitable for online projects[12][13]. The stress can be identified through changes of EEG Alpha and Theta band. The brain is under stress when power of alpha waves decreases whereas theta waves increases when the person is under stress[12]. Guo Jun and Smitha K.G [13] designed an automated EEG based stress recognition system with Stroop colour-word test and mental arithmetic test stressors. They interfaced a relevant C# application developed in Microsoft Visual Studio with Emotiv Epoc device. Three key features used here are relative bandpower values of high frequency component (β) compared to the low frequency components (α and θ). They analysed bandpower features from EEG signals and used SVM as classifier which give a three-level of stress recognition system with 75% accuracy and two-level stress system gives 88% and 96% accuracy for the two stressors respectively.

Generally traditional EEG devices use sensors exhibited over scalp. But in [14], authors proposed a design of brain-computer interface based stress identification system using a single electrode EEG headset device named NeuroSky Mindwave Mobile. They collected PSS-14 questionnaire response from 64 students and calculated training set's target class. Features were extracted from bandpower ratios of alpha, beta, delta and theta bands. The system achieved highest average classification accuracy of 74.43% using K-NN algorithm over SVM. This system observed a correlation of bandpower ratios of different bands which are obtained from EEG signals from frontal area of brain.

3) Stress detection using wearable Photoplethysmography (PPG) device

Wearable PPG sensor is used for measurement of stress obtaining Heart Rate variability data[16][17], as it is the most reliable indicator of stress [16]. Mostly electrocardiograms (ECG) are used to obtain HRV data but they are expensive and inconvenient because of limited environment and its usage time (usually conducted in Hospitals). Hence PPG is more suitable for HRV data collection as it provides the possibility of 24/7 HRV monitoring. Chonyan Chen et al. [17] made a model to compare the possibility of using wrist-based PPG over the chest-based ECG for HRV analysis. They experimented with 6 subjects measuring PPG from their wrist and ECG from their chest which shows ten HRV parameters with significant differences between stress and non-stress states. The green light is slightly better than IR and ECG when using 3 and 5 minutes window size. In stress state classification, the method achieves an overall Leave-One-Participant-Out F1 score of 80% in PPG dataset while 79.7% in ECG, which shows that PPG is better to recognize the mental stress than ECG. Muhammad Zubair and Changwoo Yoon [18] developed a multilevel stress detection system using low cost wearable PPG sensor. Mental arithmetic tasks with different distractive and stress evoking elements like time constraint, performance feedback and stressful comments was used as a stressor to 14 graduate students and estimation of beat-to-beat interval series from sixty seconds long segment of PPG signal was carried out. A new feature set was introduced which have the potential to quantify the temporal information at point-to-point level in the Poincare plot. Also a Sequential Forward Floating Selection (SFFS) algorithm was used to migrate the issues among features like irrelevancy and redundancy. Quadratic discriminant analysis (QDA) and Support Vector Machine (SVM) classifiers were used here, among them SVM gives best accuracy of 94.33% for five-level mental stress identification.

C. Stress Detection Using Microblogs

Traditional psychological stress detection usually depends on active participation making the detection cost and labour consuming. Due to speedy development of social networks people become more willing to share moods via microblogs. Stress can be detected from studying and observing microblog of individual. Huijie Lin et al. [19] constructed a three level framework for automatic stress detection method from cross-media microblog data. They collected low level features from the tweets and then extracted middle-level representations of psychological and art theories. A deep Sparse Neural Network was combined with incorporate different features from microblog data to learn the stress categories. They developed a cross-model auto-encoder (CAE) which gives better results than SVM classifier and also gives quite feasible and efficient results. Qi Li et al. [20] developed a model to discover teen's most stressful periods by extracting details of probable stressors causing stress. By taking 122 scheduled stressful study-related events data of a high school they tested their method on microblog posts of 124 students. The most leading stressor events extracted were self-cognition domain followed by the school life domain. They train a 70-class maximum entropy classifier using four types of features. Their method was 13.72% higher in precision, 19.18% higher in recall and 16.50% higher in F1-measure than the traditional statistic-based major life event detection methods. This method confirms that stress in teen's has a high correlation with their inner cognition problems.

D. Stress Detection Using Videos

Nowadays most laptops have inbuilt cameras hence using video data could be more affordable alternative to wearable devices for tracking of stress levels. Carla Viegas et al.[21] developed a method to detect the stress state using facial expressions. Five participants were recorded via webcam for 1 hour while performing some tasks like typing, exposed to a stressor and resting. 17 different facial action units (AUs) were extracted from each video. They used different simple classifiers for subject wise classification which are random forest, LDA, Gaussian Naïve Bayes and decision tree. This method achieved an accuracy of up to 74% in subject independent classification and 91% in subject dependent classification using random forest classifier. The results specified that the AUs most suitable for stress detection were not consistently same for all 5 subjects. Choubeila Maaoui and Alan Pruski [22] developed a comparative analysis based unsupervised technique to detect stress from physiological signals using low-cost webcam. They assessed the instantaneous pulse rate (PR) remotely by observing photoplethysmography on human faces using webcam to get physiological signals. They applied this approach on data obtained from 12 subjects and tested three classifiers K-means, the mixture of Gaussians model and self-organized map to find the best one. The K-means clustering based on cosine distance gives best accuracy for stress detection.

E. Stress Detection in Various Environments using Wearable Sensors

1. Stress detection in working environment

Anxiety, Stress and depression are the most frequently occurring work-related health issues in the world [23]. Regular office work stress often involves solving problems under time pressure and working in a team, trying to beat competitors and work deadlines. In [23], 30 subjects aged 19-53 were used to test a method which can be used for long-term, real-time and continuous monitoring of stress in office like situations. 19 features were extracted using ECG, respiration, skin conductance and surface electromyogram (sEMG) of the upper trapezius muscle with the help of wearable devices. Physiological data were measured during three different stress test given by all subjects. They used Generalized Estimating Equations to classify the data into stress and rest conditions giving 74.5% average classification accuracy.

Sriramprakash.S et al. [24] designed a stress detector model to enhance the generalization ability for stress detection in working people. A wearable device named Kinect 3D sensor was used to get ECG and GSR data. 25 people were tested under relaxation, email interruption and time pressure stressors. Support vector machine and K-Nearest Neighbor classifiers were used to classify the 17 extracted features, 4 from GSR and remaining from ECG. The classification results proved that the time and frequency domain features of HR, HRV and GSR are sufficient to predict the stress. In [25], authors developed and tested an integrated system of wearable sensors (ECG, EDA and EEG) and biological marker(salivary samples). Maastricht Acute Stress Test (MAST) was used for data collection where 15 people were involved. SVM classifier was used which gives 86% accuracy. The data gained from sensors and salivary samples compared and established, producing a correlation of R^2= 0.714. The correlation analysis showed that the changes in physiological features were consistent with the salivary cortisol level.

2. Stress detection in Academics

Students primarily feel stress from homework, grades, exam and competition which directly or indirectly affects them. Health and the future can be improved by early detection of stress in students, allowing them to achieve better performance in studies and improving their life. R.Castaldo et al.[26] developed a method to detect mental stress using linear and non-linear HRV features. They used ultra-short (3 min) recording of ECG excerpts of 42 students in two conditions: oral examination (stress condition) and at a rest after a vacation. Statistical and data mining analysis were done on the extracted 18 HRV features after using validated software tools. The best performing machine learning method was C4.5 tree algorithm which classified stress and rest with 78% sensitivity, 80% specificity and 79% accuracy.

In [27], authors performed some varying stress inducing experiments in lab on 9 college students equipped with multiple body sensors and a commercial android smartwatch, a smartwatch with GSR sensor, a heart sensor (chest-based) and a finger-based GSR sensor. Nine tasks were performed by the subjects and all data was collected at a 5Hz sampling rate except Polar H7 (1Hz) which later up-sampled to 5Hz to synchronize with other. Statistical features on one-minute fixed time sub-division and correlation-based feature subset selection was applied on all collected data. Naïve Bayes, SVM, Logistic Regression and random forest algorithm was applied here where random forest gives best accuracy of 88.8% F-measure in the detection of stress. Ravinder Ahuja and Alisha Banga [28] calculated and analysed the mental stress of students one week before exams and during the usage of the internet. They analysed how the exam pressure or recruitment stress affects the mind of a student and how time spent on the internet is also correlated to stress. They applied Random Forest, Naïve Bayes, Support Vector Machine and K-Nearest Neighbour algorithms on dataset of 206 students using sensitivity, specificity and accuracy parameter. Among them Support vector machine give high accuracy (85.71%) due to its geometric way of classification.

3. *Stress detection while driving*

Driving in stressful events such as staying in speed limit, driving in unsafe weather may cause road traffic violation and car accidents due to lack of alertness of driver. The problem of automatic detection of car driver's stress level has increasingly significant as it directly effect on people's security and health. Researchers developed some stress detection methods which can help an individual to assess one's psychological as well as physical condition, such that he/she will be able to take necessary precaution. N. Keshan et al. [29] developed a method to detect stress from wearable ECG sensor in automobile drivers under different levels of environmental stress caused by driving conditions. A dataset of 17 drivers was obtained from MIT-BIH PhysioNet Multi-parameter Database. 14 different features were extracted from ECG signal using NetBeans Java Platform. Using machine learning algorithms this method achieved 88.24% accuracy in detecting three classes of stress low, medium and high.

In [30], EDA and ECG signals were used to detect stress presence in car drivers, where three wearable devices were used for the data collection, a EDA device on each hand for Skin Potential Response (SPR) signals and ECG on the chest. The experimental setup consisted a professional car driving simulator which recreates movements and accelerations of the car. The stressor test involved driving through a highway where some unforeseen events were happening at some positions. A balanced accuracy of Support Vector Machine and Artificial Neural Network were 79.58% and 79.94% respectively for the considered events. Md Fahim Rizwan et al.[31], developed a stress detection system using ECG signal with features RR interval, QT interval and EDR. They had used 5 minutes of ECG signal on 15 healthy subjects for both resting and driving in heavy traffic conditions which were considered as non-stressed and stressed conditions respectively. System verified several SVM model types by changing the feature number and kernel type. Cubic SVM was the best model to detect stress as it showed an accuracy level of 98.6% with Gaussian kernel function and all features. This methods proved that using more features can increased the accuracy of model.

4. *Stress detection in firefighters*

Firefighters are constantly exposed to extreme stressful situations even after a difficult mission. Even a well-trained firefighter has to deal with many decision-taking uncertainties during a rescue mission because of many circumstances. Hence researchers developed some methods to detect the stress level timely and reliably to improve their work safety. Virginia Sandulescu and Radu Dobrescu [32] designed a wearable shirt with integrated e-textiles technology to prevent stress in emergency situations for firefighters by determining heat and mental stress from physiological and voice features. A stressor test named Trier Social Stress Test (TSST) was conducted on 6 participants at 40 degree temperature in two work conditions: no cooling and body cooling. Only pulse and voice features were used among many extracted features from the data. Support vector machine was used for classification which give best results in terms of accuracy, precision and recall by using Gaussian kernel function. This system integrated a microphone allowing communication with the manager and other team members. Also a movement sensor was attached in shirt to monitor the movements of the firefighters during falls and deadlock situations. Alarms were triggered when thermal stress reached a certain level and an alert message was displayed to firefighter through a smartphone.

In [33], authors proposed and compared a method using HeartBeat Morphology (HBM) for feature selection with traditional Window-derived Heart Rate Variability (W-HRV) method generally used for stress detection. They conducted TSST test on 13 firefighters while recording their ECG, actigraphy and psychological measures through a wearable jacket named VitalJacket. Linear Support Vector Machine (SVM), Kernel Support Vector Machine (K-SVM), K-NN and random forest classifiers were compared to evaluate effectiveness of HRM features and W-HRV features. The evaluation include accuracy, time resolution and computational rapidity of each method, where random forest was best among all. Authors concluded that HRM methods required less computation and give best results than W-HRV for stress detection. U. Pluntke et al. [34] developed a method for stress detection where 26 participant's HRV data was collected using a Polar H7 Chest strap sensor when exposed to physical, psychological and combined stress. After that they applied some machine learning algorithms to identify the different stress types and understand the relationship with HRV data. C5 decision tree model gives 88% accuracy in identifying the stress type with 1-minute time window.

III. Discussion and Conclusion

Nowadays, mental stress is very common in all age groups due to constantly challenging and competitive life. Early detection of stress can be very useful to take further actions as it can affect individuals mental as well as physical health. In the above discussed approaches, some researchers collected physiological data signal to measure stress using self-made wearable devices (using low-cost sensors) while others depend on commercial devices. The physiological signal required for detection of stress level was obtained by applying one or more stressors on the subjects. All the developed system first extracted the features using various algorithms and they applied machine learning algorithms to build classification model. It is found that features extracted using Heart rate, Heart rate variability and skin conductance are more useful in prediction of stress level of an individual while Support vector machine, Random forest and K-Nearest Neighbor are the most effective classification algorithms. This shows that physiological signals can be used to detect stress of an individual with the help of wearable sensors and machine learning algorithms are effective and affordable. The limitation of this study is many researchers used multiple features correlated with each other which results in increased computation time. Also some of them used costly commercial devices for physiological signal collection where low-cost sensors can be used.

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