Machine Learning Approaches to Automatic Stress Detection: A Review

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***Abstract*—People experience mental stress on a daily basis from a variety of different reasons, including environmental reasons (traffic, noise, or bad weather), social reasons (family issues, friends, and financial problems), or from events such as wedding planning or giving a presentation in front of large audience. A manageable amount of stress is healthy and can motivate a person; however, a large amount of continuous stress or a strong response to stress can be harmful. For this reason, the detection of mental stress, as well as its prediction, has become a significant area of research. In this paper, we review and summarize various approaches found in the literature for stress detection using machine learning and suggest directions for future research and interventions.**

***Index Terms*—stress detection, features extraction, wearable sensing, machine learning, biosignal processing**

I. Introduction

Our current lifestyle is becoming more complex, comfortable, and highly technological. Along with the comfort that technology has brought, it also promotes unhealthy lifestyle habits such as negative eating habits, less exercise and lack of sleep. These habits can negatively influence a person's life. Stress describes the tension level caused by daily demands as well as many other factors such as family, work, and social problems. Statistically, work-related stress costs the healthcare system in the United States (US) $190 billion a year [1].

There are three types of stress depending on the time period in which stress occurs, and these types are: chronic stress, episodic acute stress, and acute stress. Whereas chronic stress stays for an extended period of time, acute stress disappears quickly [2]. The human body needs a reasonable amount of stress to stay healthy and ensure the efficiency of its organs. However, unmanageable stress can harm human health and increase the risk for serious long-term problems. Chronic stress can lead to obesity, heart attacks, type 2 diabetes, stomach aches, body aches, infection of men prostate, and disruption of a womans menstrual cycle [3], [4]. Thus, self-awareness and applying proper coping skills to deal with stressors have become essential to sustain a healthy, stressfree life. If the human body feels stressed, it generates a "fight or flight" response to survive various threats. In this response, adrenaline and cortisol hormones are discharged into the bloodstream to ask the body to react quickly. Furthermore, significant amounts of oxygenated blood reach the muscles for energy metabolism, which leads to a decrease in abdominal blood flow, and an increase in blood pressure. The body will remain in a defensive mode until the stressor ends, after which the body returns to a homeostasis condition. In chronic stress, the body cells become desensitized to cortisol, which causes inflammation and leads to brain cell and blood vessel damage [5]. Accordingly, the development of an automated stress detection approach capable of accurately detecting stress bio-markers and informing the user has great value in the ability of identify stressors and help with the management of stress. This research has been investigated in the literature. Some of the available approaches depend on the use of questionnaires, which are often not accurate because of individual differences. Other approaches include the use of measuring devices such as mobile, remote, or wearable sensing devices to collect physiological signals such as electrocardiogram (ECG) and electrodermal activity (EDA). Valuable features can be extracted from these signals and analyzed in an attempt to identify stressed and non-stressed states. Medical signal processing usually is a complex task, especially for long-term signal recordings. Several signal processing techniques are applied to find out relevant characteristics of the signal. The values of the extracted features are used directly as an input to a supervised classifier or cluster analysis. Classification of these bio-signals can help doctors interpret the signals efficiently and provide appropriate treatment [6]. In the machine learning domain, computers learn from experience by using computational methods to learn information from data without being explicitly programmed or without any dependency on a predefined equation. The machine relies on two learning techniques to learn information; unsupervised and supervised learning. In unsupervised learning, the machine finds a pattern in the input data, where the input data is not labeled. An example technique of this type is clustering, which analyzes input data and finds the hidden patterns and groups the similar classes. In supervised learning, the machine develops and trains the predictive model by using labeled data to predict future output by learning from a known set of input and output data. Two techniques are used in this type of machine learning approach; the regression technique, which is used to predict future continuous values; and the classification technique, to predict discrete, categorical values such as determining whether the email is spam or not.

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Selecting an optimal machine learning algorithm to train the model is not a simple task; thus, many cases use trial and error as a method to obtain the optimal algorithm. Developing the machine learning algorithm starts by cleaning the data and applying various preprocessing steps that enhance the data. This step ensures better performance of the algorithm. The next step is feature extraction, in which the descriptice feater are extracted from the data and inputted into the machine learning algorithm [7].

There are a variety of machine learning algorithms that are suitable for stress detection. Among them are support vector machines (SVM) and logistic regression (LR) [8], all of which are used in the approaches that will be discussed in this paper. In this review, we summarize the various approaches available in the literature that aim at detecting states of stress.

The remainder of this paper is divided into two sections. In Section II, we describe several approaches to detect and classify the stressed state. In Section III, we conclude the paper and discuss the outcomes of this literature review.

II. Literature Review

In this section, we briefly summarize some approaches to detecting stress level. These approaches vary according to the measurements used. The measurements used in the below literature review include facial movements, biological signals, nasal skin temperature or conductance, blood volume pulse (BVP), answering the questionnaire, monitoring keyboard interactions, collecting data ECG, EDA, mobile usage, and the human voice. The below approaches explore several features in order to select the most efficient ones and calculate the stress level with considerable accuracy.

A. Driver Fatigue, Attention States and Stress Levels

Car drivers are usually involved in cognitive tasks or stressful events such as staying within the speed limit, driving in unsafe weather, and sometimes they become distracted while trying to multi-task texting, music playing, or talking with others in the car while driving. Therefore, it is necessary to develop awareness mechanisms that detect the stress level of drivers. In [9], to determine the stress level of the driver, researchers designed a thermal-imaging based system to track facial area in order to measure the temperature of the driver's blood using a driving simulator under different levels of workload. Their experiment demonstrates that there is a relation between workload increment and thermal emissions; however, more investigation is required to find the relation with stress level classification. The authors in [10] collect ECG signals for 17 automobile drivers to extract different features such as the interval average of RR, QQ, SS, QR, RS and average beats. Next, they apply naive bayes, logistics regression, sequential minimal optimization (SMO), multilayer perceptron, instance-based IB, ZeroR, random forest, J48, and random tree algorithms to categorize the stress levels in one of three classes; 1)"high stress - driving in the city", 2)"low stress-rest state," and 3)"moderate stress - driving on the highway." By considering the difference in the average heart rate between rest and high-stress state, they were able to detect high-stress level with 100 % accuracy. Adding twave related features and other signals to their analysis need to be tested. Authors of [11] use time segmented physiological signals (GSR, foot GSR, EMG, HR and Respiration) for 17 drivers from PHYSIONET database to extract 78 features for each segment by finding values of root mean square (RMS), mean normalization, average power (0.01 to 0.1 Hz 0.2 Hz, F1 to F2 Hz), ratio low/high band, interquartile range, and sum of local peaks. After that, all features were ranked by SVM and classifier. Finally, the best features were selected, and SVM and KNN classifiers were applied to classify the stress level of the drivers. In [12], the authors use driver self-reports and skin conductance to detect stress levels. A camera is used to record facial images of the driver and a wearable glove with signal processing and sensor module units collect GSR signals. This data is sent to a mobile device through bluetooth for further processing. The authors extract time-domain, frequency-domain, and phase-domain features from the IMU sensor. The accuracy of detecting stress levels by using motion sensors and SVM classifier is 94.78%. More investigation is required to study the relation between events such as stopping at traffic lights and stress the level of the driver.

B. Detecting Stress while Working or Studying

High levels of stress reduce students ability to concentrate on their studies and sometimes influence forgetfulness, restlessness, and weakness. Stressful academic situations such as high study demands can have a negative impact on students emotion, behavior, and mood. Such situations may also affect the performance of students and prevent them from successfully achieving the academic goals. Furthermore, stress in the workplace leads to disengagement and less productive employees. Therefore, the detection of stress in early stage is important to reduce the psychological and physical damages. In [13], an application was developed to collect smart-phones accelerometer data to identify the stress behavior of 30 subjects in daily working environments. The user scores his stress on a 5 point scale three times during office hours. A score of 4 to 5 indicates high-stress level, 3 shows a medium level, while a score of 1 and 2 indicate low-stress levels. The authors set the sampling rate at 5Hz to recognize subject physical activities with high accuracy and to optimize battery life. The authors extract 34 features from accelerometer raw data and use forward feature selection method to select features that increase the classifier's accuracy. For classification, the authors use Naive Bayes, decision trees classifiers where the overall classification accuracy reached 71% by using user-specific models and 60% by using the similar-users model.

In [14], the authors used "StudentLife" data [1] which consists of sensing data from campus students smart-phones, such as call log, accelerometers, audio (noise, conversation, silence), and stress level questionnaires data. They propose a stress detection model to classify the students' perceived stress level

[1] http://studentlife.cs.dartmouth.edu/

as “stressed,” “slightly stressed” or “not stressed.” The authors extract short-term, date-time, relative epoch features - e.g., the ratios of stationary, silence, voice, noise, days until midterm, answering epoch, conversation duration, epoch period and deviation of voice, activity, silence, noise. The authors apply classification algorithms such as random forest, and SVM and compare the results with the answers to the questionnaire. The student-specific model achieved around 60% accuracy with random forest classifier which out performed the baseline.

C. Measuring Nasal Skin Temperature to Detect Stress

In [15], the authors use temperature sensors to measure the nasal skin temperature. Nasal skin temperature has been shown to decrease with elevated stress levels due to the reduction of blood flow caused b shrunken blood vessels. The author developed an application which analyzes the collected data (temperatures and acceleration data) and specifies the time when the user felt stressed. The authors use the accelerometer to measure users motion with three small temperature sensors attached to users glass. The experiments showed that the f-measure was 66.7%, 93.3%, 100% for the factors stress, motion, and environmental temperature, respectively. For future work, they suggested collecting daily life data by their system.

D. Automatic Stress Detection from Videos

In [16], the authors ask external workers from Crowdflower platform to annotate the stress state for 44 individuals in video files. Moreover, they use the facial features which are found in the video with the derived annotation labels to detect stress. The aggregated label is assigned non-stressed if 50% of the workers answer “N.” Behavioral features such as hand and head movement, self-touching, activation intensity are extracted from the skeleton and video data. The authors adopt four machine learning algorithms for automatic stress detection: random forest, neural networks (NN), neural decision forests (NDF), and SVM with the three kernel functions: linear, radial Basis Function and polynomial. The work in [16] found that the votes (annotations) help valuable information for prediction or classification and that is why the authors suggested applying this framework to measure depression and engagement in future research. In [17], body language features are extracted from video files to detect stress. The authors developed software which provides a mental arithmetic test which consists of six steps of increasing difficulty. The subject stands three meters far from the screen which has a camera and Microsoft Kinect attached to it to record videos of the whole body. The subject is then asked to fill out a stress self-assessment questionnaire after watching his/her videos. From the recorded videos, they extracted a set of body activity features and facial features. Their study showed that raw features (such as PCC, FFT2, AU9-std, AU4-std, AU4 mean) and person-specific features (e.g., FFT1, HAPC, FFT7, HAPMV, PCC) were considered useful to detect stress with high accuracy. Their model detected stress with 77% accuracy when using SVM.

E. Emotional Arousal Detection using Physiological Signals

In [18], physiological data is collected from EEG, ECG, GSR, photoplethysmography (PPG) and electrooculography (EOG). The authors apply machine learning algorithms to detect emotional arousal and identify stimulus type (e.g., games, music, videos). Through the physiological bio-signals, they determine the low and high emotional states of the individual and the stimuli behind each state. Their supervised learning approach starts with asking subject to watch relaxing and exciting videos and music while keeping his/her eyes closed. In the second stage, subjects were asked to play computer games such as Tetris using touchpad and keyboard. The experiment involves playing a 35-second clip of a flowing creek between each video and music file to return the individual to the neutral state. The authors placed electrodes on the middle and index fingers from the left hand of the subject to GSR biosignals. In addition, wrist electrodes are used to measure ECG signal and EEG electrodes are placed on the F4 spot (frontal lobe) to measure brain activity. To collect the blood flow data (PPG), a pulse oximeter attached to the index finger is used. The participants were asked questions about the emotion strength after each stimulus, and how confident they felt. Ninety eight features including frequency and time domain were extracted from five signal channels to train the models. These features were reduced to 26 in order to classify the stimulus, 21 features to classify arousal, and nine were shared between them. To classify both stimulus and arousal, they found that power in the delta band was useful. They applied four classification algorithms: bagged and complex tree [2], medium KNN, and medium Gaussian SVM. The accuracy of stimulus classification was 80.6%, and 88.9% for arousal classification. In [19], the authors measure GSR, BVP, skin temperature, and pupil diameter to calculate the stress level of the computer user. From these signals, 11 features are extracted : L/H ratio, BV amplitude, response no, GSR mean value, response amplitude, response rising time, response energy, the slope of ST and PD mean value. SVM was applied to distinguish between the stressed and relaxed user’s state. The experiment showed that pupil diameter was the most efficient signal compared to the other three signals. The result showed a correlation between collected physiological signals and emotional stress detection. Moreover, SVM classifier performed better in stress states identification than other classifiers such as decision tree and naive bayes classifiers. The accuracy of the classification is 90.10% (under controlled conditions). In [20], a classifier was proposed to detect stress automatically from nonlinear features of short-term heart rate variability (HRV) extracted from ECG of students during and after oral examinations. Based on approximate entropy and poincare plot measures, the classifier achieved 90% classification accuracy, 95% specificity rate, and 86% sensitivity, respectively. The result shows that detection of stress might be effective with the use of short-term ECG. In [21], the authors use data from GSR, ECG and

[2]https://towardsdatascience.com/decision-tree-ensembles-bagging-and-boosting-266a8ba60fd9

accelerometer to detect mental stress states of 20 participants while walking, sitting and standing. To train the classification model, they used HRV spectral domain and time domain features in addition to GSR features such as the sum of response duration, magnitude, a total number of startle response, and standard deviation and mean of skin conductance level. The proposed model achieves 92.4% classification accuracy with the help of accelerometer data.

F. Stress Discovery through Blinking Detection

In [22], a computer vision based methodology was proposed to detect stress via auto patterns detection for eyes blinking in video recorded conversations. Their approach uses face tracker to identify eye region and normalize the color appearance of these areas. It also uses offset features, Shannons entropy, and in-between blinking time lapses. The proposed system shows a correlation between the eye blink patterns and the perceived stress.

G. Stress Detection through Typing Behavior

In [23], the proposed approach monitors keyboard interactions to detect changes in physical and cognitive status in older adults in addition to distinguishing between stressed and relaxed conditions. The participants in this study type a sample text after completing physical and cognitive challenge tasks. The approach analyzes keystroke and text features of the generated text. A step-wise logistic regression technique was used with three-fold cross-validation. Z-scores normalized the data before applying machine learning. The accuracy for classifying cognitive and physical stress versus the control conditions is 75% and 66%, respectively.

H. Stress Discovery using Wearable Sensors and Mobile Phones

In [24], a wrist device is used to detect stress events. Accelerometer data were used by activity recognition classifier to recognize users activities and distinguishes between stress and other situations that cause similar physiological arousal. A web application was developed to collect laboratory data where the participants need to solve mental arithmetic tasks within the specific time interval to induce pressure. In [25], authors collect data from three sources: (i) mobile usage (message, location, calls), (ii) skin conductance and accelerometer data from wrist sensor, (iii) survey (general health, mood, stress). The classification determines if the individual is stressed or not. The experiment starts with filling three surveys. A wearable sensor records accelerometer data and skin conductance. The method showed 75% accuracy of stress recognition and indicated that both wearable sensors and mobile phones data include useful features to detect stress. These features are mean and standard deviation of mobility radius. The authors will collect bigger data-set to understand the dynamic effect of the long-term data. In [26], the authors collects body temperature, GSR, and RR interval of the subjects while solving tower of Hanoi to detect mental stress in real time. The collected data was validated by the outcomes of the questioners which were filled by the subjects before and after the experiments. The author extracted 27 features from the collected signals while 10 of them with the highest mutual information were used to train KNN classifier. The accuracy of stress prediction is 89.8%. In [27], the authors designed the smart band to predict whether the individual is under stress or not. It consists of two electrodes, skin conductance sensor, 3-axis accelerometer, blue-tooth, and a micro-controller to analyze the collected skin conductance and other pentameters of 12 subjects. The electrodes pass small electrical current to the skin. The collected data is sent to a smart-phone through bluetooth to show the user his stress level. Moreover, the data is uploaded to the web so that doctors can use these data for better treatment. The authors used logistic regression to predict the probability of stress state of the subject. The accuracy with regularization is 91.66% and 100% without it.

I. Stress Detection from Human Voice

In [28], an android smartphone is used to recognize stress from the human voice in real-time. Voice data from 14 participants were collected by Google Nexus One phone during an indoor job interview which includes 8 questions and an outdoor marketing tasks (stressed scenarios). The participants were also asked to read simple stories indoor and outdoor (no stress). A program in the background to collect GPS and accelerometer data was also used. Also, skin conductance data were collected through GSR sensors which were embedded in a wristband called Affectiva. The GSR reading showed an increment in the marketing and job interviews while a decrement was noted in neutral scenarios. A smartphone is attached to a participants waist and another phone is placed on his/her shoulder for speaker segmentation. The StressSense uses Gaussian mixture models with the diagonal covariance matrix. The classifier StressSense scored 81% accuracy for indoor environment, and 76% for outdoors. In [29], a classification method to determine acute stress period of a subject based on his GSR and Speech was proposed. Facial expressions, GSR, and speech are collected by using HD handy-cam camcorders. The model uses decision tree, K-means clustering, SVM classifiers. By using speech and GSR features, SVM achieved 92% and 70% accuracy respectively. GSR signal varies on a daily basis for the same person. In [30], the authors use a deep learning model with 7 hidden layers and RelU activation function to predict stress state of the subject while listening to the music using EEG signal. The proposed model predicts 80% of the subjects' stress states.

III. Discussion and Conclusion

From the above discussed approaches, it is clear that physiological sensor signals can be used to detect stress level of the individual where physiological sensing devices are used to collect these signals. To select useful features from the gathered signals, signal pre-processing must be implemented. Once the features are determined, the machine learning algorithms can then applied to build the classification model. The accelerometer data are considered as significant measure to recognize physical activities and detect movements. Galvanic skin response, heart rate variability and skin temperature can reflect autonomic nervous system activity, thus their features are useful in predicting the stress level of individual. Random forest, support vector machine and decision trees are examples of effective classification algorithms for mental stress detection. In addition, thermal imaging technology as well as wearable sensors can be used for stress detection. Using deep learning to predict individual stress level becomes a promising techniques.

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TABLE I
APPROACHES SUMMARY

Approach	Data Sources	Features	Machine Learning Algorithms	Performance	Device/Application
[10]	ECG Signals "MIT-BIH PhysioNet Multi-parameter Database"	RR, QQ, SS, QR, RS, Average Difference Beats, Average Beats	Naive Bayes, Logistics, SMO Multilayer Perceptron, IB1, IBk, ZeroR, Random Forest Random Tree J48	100% Diff. Average rate 98% All 8 Features	-
[11]	Hand GSR,Foot GSR, EMG ,HR,Respiration "PHYSIONET"	Average Power, Ratio low/high Band, Inter-quartile Range Peak 2 Peak Number- Sum- local peak	SVM, KNN	98.42% 100,200 sec 99% 300 sec	-
[12]	GSR, Questioners Facial Expressions "PHYSIONET"	PSD, FFT, PPF, MNF,MED, VAR, STD, AVG, ENG	SVM	94.78%	Wearable Glove Stress Monitoring System
[13]	Smart-phone Accelerometer, Survey Answers	Mean/StdDev/Variance for x- y- z- axis , 3 axes- (variance,mean,max, min,SrdDev,absolute value, median,range), variance Sum, entropy, Energy, other features	Naive Bayes , Decision Trees	71% User Specific Model), 60% Similar Users Model	Mobile Application Samsung Galaxy SIII Mini
[14]	Smart-phone Sensing Data Survey Answers "StudentLife"	Short-term, Date-Time, Relative Epoch	Random Forest, SVM, Bagging, j48	60% (Student Specific Model)	-
[17]	Body Activity, Facial, Questioners	PCC, FFT2, AU9-std, AU4-std, AU4 mean, FFT1, HAPC, FFT7, HAPMV, PCC	SVM - RBF	77%	Mental Arithmetic Test Software
[18]	EEG, ECG, GSR, PPG, EOG, Questioners	21(Arousal Classification) 26(Stimulus Classification) 9(Shared)	Bagged &Complex Tree, Medium KNN, Medium Gaussian SVM	80.6% Stimulus Classification 88.9% Arousal Classification	-
[19]	BVP, ST, GSR, PD	L/H Ratio, Mean IBI, IB STd, BV Amplitude, Response No.- Aplitude- Rising Time-, , GSR Mean Value, Slope of ST, PD Mean Value	Nave Bayes Decision Tree SVM	90.10% Under controlled conditions	Customized Paced Stroop Test
[20]	ECG	SD1, SD2, En(0.2)	Linear Classifier	90% Classification Accuracy	In-House Software
[21]	GSR, ECG Accelerometer	HRV Spectral & Time domain Features GSR Features	J48, Decision Tree, Bayes Net, SVM	92.4% Classification Accuracy	Customized Paced Stroop Test
[25]	Mobile Usage, Accelerometer Questioners Skin Conductance	Mean of SD and total mobility radius	PCA +SVM (RBF, Linear), KNN	75%	Mobile Phone Survey
[26]	Body Temperature, GSR, RR, Questioners	$\mathrm{P}LF$, $\mathrm{P}HF$, $\mathrm{P}TB$, RR_{mean}, GSR_{mean}, GSR_{std}, DGSR_{mean}, DGSR_{std}, BT_{mean}, BT_{max}	KNN	89.8%	-
[27]	Skin Conductance Activities Tracking, Sleep Quality	R_s, V_o, V_{cc}	Logistic Regression	91.66% With Regularization 100% Without Regularization	Smart Band Mobile Application
[29]	GSR, Speech Facial Expressions	Smooth Energy, MFCCs RASTA-PLP Peak Hight,Mean std,min,max	K-means,SVM,GMM	92% using Speech features 70% with GSR features	-