An Energy-Efficient Stress Monitoring System Using Physiological Data

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***Abstract*— Anxiety is your body's natural response to stress. People with anxiety disorders frequently have intense, excessive and persistent worry and fear about everyday situations. As we know stress is the main cause of long-term health disorder, Stress management is so necessary to maintain an individual's stress levels keep down and able to reduce health risks. In this article, we are finding out some measures and methods through which we employ low-cost wearable sensors collection of data and machine learning algorithms to predict an individual's stress level so as to manage his stress level. Researchers have found out that stress levels can also be detected using physiological tests such as pulse rate, heart rate amplitude and skin infections or skin diseases. This research paper' main aim is to offer a necessary analysis of various kinds of stress detection and to find out different methods to overcome it as well as a reliable checklist for more effective stress detection.**

Keywords*—Anxiety detection, feature extraction, physiological measures, wearable sensors, machine learning.

I. INTRODUCTION

Traumatic stress is very normal in today's fast-paced society. Stress may be induced by circumstances or activities that place strain on a person's mind and body. Everyone's reaction to stress is unique, as is their ability to cope with difficult or demanding conditions. Some conditions can cause stress in one person while causing no stress in another. Furthermore, all stress is not harmful to health because it will make people more conscious of their surroundings, keep them warier of risks, and keep them focused on their target. A stressor is an occurrence that creates stress in a person. Many people experience stress as a result of the stressors mentioned 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.

The American Psychological Association (APA) classifies stress into three types: acute stress, episodic acute stress, and chronic stress. Acute stress is the least harmful form of stress as compared to the other two. It can be beneficial at times because it enables the body in dealing with the situation. When a person experiences acute stress on a regular basis, he or she is suffering from episodic acute stress. Chronic stress is the most dangerous form of stress, and if left unchecked for an extended period of time, it will affect a person's physical and mental health. Chronic stress exerts long-term pressure on the body and mind, resulting in a variety of symptoms and an increased chance of contracting such diseases.

People who are at high risk of being depressed should be constantly watched to spot any stress symptoms in order to prevent health complications. Wearable devices make it possible to track stress and warn people of their stress levels, which can be helpful in reducing stress until it causes severe health issues. Since physical and mental wellbeing are inextricably linked, tracking and assessing physiological and physical changes may be used to identify human stress levels.

Functional and biochemical tests of the body may be used to track stress. Pulse rhythm, skin temperature, humidity, blood pressure, and respiration rate are examples of physical indicators, while physiological data include heart rate variation, heart rate variability, and skin conductance. These can be assessed using wearable devices made of low-cost sensors, but machine learning algorithms can be used to classify and forecast an individual's stress level.

Any previous approaches to automated stress recognition systems that used sensors and machine learning are explored in detail in this article. Physiological evidence was collected from people using stressor measures in these studies. Arithmetic equations, questionnaires, mental exercises, and

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working out in the gym are some typical stressor tests. There are several machine learning algorithms that are suitable for stress detection. The most popular are Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbor, Decision Tree, and Random Forest. We summaries the numerous machine learning algorithms available in the literature that attempt to detect the state of stress in this study.

The remaining part of the paper is separated into two sections. Section II describes several strategies for detecting and classifying stress levels. Section III concludes the article and discusses the findings of the literature review.

II. RELATED WORK

In this section, we summarized a report of some approaches of stress detection. These methods differ in the kinds of stress-related factors and procedures used. The initiatives in this methods are physical measures, physiological signals, answering queries, mathematical test, videos, blogging, and other techniques, etc.

A. Stress Detection using Wearable Sensors and IOT Devices

At present days, sensors play a very important role in medical applications. These sensors are mostly used for identifying the disease and measuring its level. Stress is one of the most leading factors in health problems. So, people having a high risk of getting stressed again and again should take precautions for stress problems before it causes some serious health issues to them. So many advanced technologies have been developed which can help people to measure their stress with the help of their mobile phones and wearable belts remoted with mobiles. It is possible that it records the day to day basis physical and mental reports and measures stress 24*7. Most wearable devices like smart bands [3], Chest belts [3] etc. are used for the collection of data. Some of the researchers used hardware and software devices to collect data based on health through some devices like sensors and stress detection. Some software and platforms are being developed to detect stress levels of individual person by continuously monitoring them. A Holster unit used with LI-PO battery and PC USB Client software is one of the examples for detecting stress [2]. Also, there was a platform named Stress aware has been developed in [7] using SVM for stress detection. This kind of real-time software can help an individual to detect stress by continuously monitoring them by some bands or belts wearable devices Which are connected to their mobile phones and collects data related to it and upload on the web where doctors or family members can get access to that information [3]. The summary of few studies is discussed in table 2 which shows stressors, subjects, sensors, best accuracy achieved, the classifiers and methods used by some 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	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) is the process of measuring the electrical activity of the heart by using electrodes placed on the skin. Heart Rate Variability (HRV) is derived from ECG signals, is measured by the variation in the beat-to-beat interval, for detecting mental stress where it is divided into Time Domain and Frequency Domain for further investigation [9], [11]. In [10], ECG signals were pre-processed where baseline drift and noise were removed without disturbing ECG waveform characteristics. The discrete wavelet transform method is used for featuring waveform. The classification was done using a Support vector machine, Artificial Neural Network, Bayesian network and decision tree on real-time data of 20 subjects for getting more accurate results. SVM provides the best results to determine whether the person is suffering from stress or not. [11] has developed a stress detection system evaluating 24 participants and 11 tasks where research protocol can perform for 45 minutes. In this whole system, the best performance came from HRV parameters which were extracted from ECG signals 84.4% accuracy by using SVM in a 10-fold approach. the minimum Redundancy Maximum Relevance (mRMR) selection algorithm was used to select the useful features. The main focus of the scientific community on the usage of only one ECG channel makes these methods more suitable, as they can be easily accessible through wearable devices in daily routine.

2) Stress detection using Electroencephalography (EEG)

Stress is a disorder that can alter brain function by altering its natural state. Electroencephalography (EEG) is a technique used to assess cognitive change in the brain. Since it is reasonable, compact, and appropriate for online projects, the Emotiv Epoc system is commonly used for EEG-related analysis to collect raw EEG data [12] [13]. Stress can be detected by variations in the EEG Alpha and Theta bands. When a human is stressed, the power of alpha waves decreases, while the power of theta waves increases [12]. Guo Jun and Smitha K.G [13] created an automatic EEG-based stress recognition method that included Stroop color-word test and mental arithmetic test stressors. They connected an Emotiv Epoc system to a relevant C# framework created in Microsoft Visual Studio. The relative bandpower values of the high frequency variable (β) compared to the low frequency components (α and θ) are the three main features used here. They examined bandpower features in EEG signals and used SVM as a classifier, yielding a three-level stress recognition system with 75% accuracy and a two-level stress system with 88% and 96% accuracy for the two stressors, respectively.

Typically, conventional EEG systems employ sensors placed on the scalp. However, in [14], the authors suggested a brain-computer interface-driven stress recognition scheme based on a single electrode EEG headset unit called the NeuroSky Mindwave Mobile. They gathered PSS-14 questionnaire responses from 64 students and determined the target class of the training package. Bandpower ratios of the alpha, beta, delta, and theta bands were used to remove features. Using the K-NN algorithm instead of the SVM, the method achieved the best overall classification accuracy of 74.43 %. This method discovered a connection between bandpower ratios of various bands derived from EEG signals from the frontal region of the brain.

3) Stress detection using wearable Photoplethysmography (PPG) device

Wearable PPG sensors are used for stress assessment by collecting Heart Rate variability data [16][17], since it is the most accurate stress predictor [16]. Electrocardiograms (ECG) are often used to collect HRV results, but they are costly and cumbersome due to limited environment and use period (usually conducted in Hospitals). As a result, PPG is better suited for HRV data collection because it allows for continuous HRV tracking. [17] developed a model to assess the feasibility of using wrist-based PPG instead of chest-based ECG for HRV research. They tested six subjects by assessing PPG from their wrists and ECG from their chests, revealing ten HRV parameters with noticeable variations between stress and non-stress states. When using 3 and 5-minute window sizes, green light performs significantly better than IR and ECG. In terms of stress condition designation, the system achieves an average Leave-One-Participant-Out F1 score of 80 % in the PPG dataset vs 79.7 % in the ECG dataset, indicating that PPG is better at recognizing mental stress than ECG. Muhammad Zubair and Changwoo Yoon [18] created a multilevel stress monitoring device that makes use of a low-cost wearable PPG sensor. Mental arithmetic tasks with various distractive and stress-inducing elements such as time limit, performance feedback, and stressful commentary were used to stress 14 graduate students, and calculation of beat-to-beat interval sequence from a sixty-second long section of PPG signal was performed. In the Poincare storey, a new feature set was added that has the ability to measure temporal information at the point-to-point stage. A Sequential Forward Floating Selection (SFFS) algorithm was also used to transition issues between features such as irrelevancy and redundancy. Quadratic discriminant analysis (QDA) and Support Vector Machine (SVM) classifiers were used in this study, with SVM providing the highest precision of 94.33 % for identifying five levels of mental stress.

C) Stress Detection Using Microblogs

Traditional psychological stress diagnosis is normally based on active involvement, which raises the identification expense and labor requirements. People are more likely to express their moods through microblogs due to the rapid growth of social networks. Person stress can be detected by researching and analyzing their microblog. [19] developed a three-level architecture for automated stress detection using cross-media microblog data. They derived middle-level depictions of psychological and art ideas from tweets after collecting low-level elements. To learn the stress categories, a Deep Sparse Neural Network was combined with different features from microblog results. They created a cross-modal auto-encoder (CAE) that outperforms the SVM classifier and is also very feasible and effective. [20] created a model to identify a teen's most stressful times by gathering information about potential stressors. Using 122 planned traumatic study-related activities data from a high school, they checked their approach on 124 students' microblog entries. The self-cognition domain derived the most leading stressor cases, followed by the school life domain. They use four different types of features to train a 70-class maximum entropy classifier. Their system outperformed conventional statistic-based big life event detection approaches in accuracy, memory, and F1-measure by 13.72 %, 19.18 %, and 16.50 %, respectively. This approach shows that depression has a high association with inner cognition disorders in teenagers.

D) Stress Detection Using Videos

Since most laptops now have built-in cameras, using video data to monitor stress levels can be a more cost-effective alternative to wearable technology. [21] devised a system for detecting tension levels based on facial expressions. Five subjects were videotaped for one hour while doing activities such as texting, being subjected to a stressor, and sleeping. From each film, 17 separate facial action units (AUs) were extracted. They used random forest, LDA, Gaussian Naive Bayes, and decision tree as basic classifiers for subject-wise classification. Using a random forest classifier, this approach achieved a subject independent classification accuracy of up to 74% and subject-based classification accuracy of 91%. The findings revealed that the AUs best suited for stress detection were not uniformly the same across all five subjects. Choubeila Maaoui and Alan Pruski [22] created an unsupervised comparative analysis strategy for detecting tension from physiological signals using a low-cost webcam. They measured the instantaneous pulse rate (PR) on human faces using a webcam and photoplethysmography to obtain physiological signals. They tested three classifiers, K-means, the Gaussian mixture model, and the self-organized diagram, on data from 12 subjects to find the best one. K-means clustering based on cosine distance has the highest level of precision 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 common work-related health conditions worldwide [23]. Daily office job tension always entails solving challenges under time constraints and working as a team, all while attempting to beat competitors and work deadlines. [23] used 30 subjects ranging in age from 19 to 53 to assess a system for long-term, real-time, and constant control of tension in office-like circumstances. Wearable sensors were used to remove 19 characteristics from the upper trapezius muscle, including ECG, respiration, skin conductance, and surface electromyogram (sEMG). Physiological results were collected from both participants during three separate stress tests. They used Generalized Estimating Equations to classify the data into stress and rest conditions, with an average classification accuracy of 74.5 %.

Sriramprakash [24] created a stress detector model to improve the generalization potential of stress identification in workers. ECG and GSR data were collected using a wearable tracker called the Kinect 3D sensor. Twenty-five participants were tested under stressors such as relaxation, email disruption, and time constraints. The 17 extracted functions, 4 from GSR and the rest from ECG, were classified using a support vector machine and a K-Nearest Neighbor classifier. The classification results demonstrated that the time and frequency domain features of HR, HRV, and GSR are adequate for stress prediction. [25] describes the creation and testing of an interconnected system of wearable sensors (ECG, EDA, and EEG) and biological markers (salivary samples). The Maastricht Acute Stress Test (MAST) was used to gather data from 15 participants. The SVM classifier was used, which has an accuracy of 86 %. Data from sensors and salivary samples were correlated and developed, yielding a correlation of R2=0.714. The association study revealed that changes in anatomical characteristics corresponded to changes in salivary cortisol levels.

2) Stress detection in Academics

Students are mainly stressed by assignments, grades, exams, and rivalry, all of which influence them directly or indirectly. Early diagnosis of depression in students will boost their health and potential, helping them to do well in school and have a happier life. [26] created a system for detecting emotional fatigue using linear and non-linear HRV functions. They used a three-minute recording of ECG extracts from 42 students in two conditions: oral review (a stress condition) and rest during a vacation. The derived 18 HRV features were statistically and data miningly analysed using validated software methods. The C4.5 tree algorithm, which graded stress and rests with 78 % sensitivity, 80 % precision, and 79 % accuracy, was the best performing machine learning tool.

The authors of [27] conducted various stress-inducing studies in the lab on 9 college students who were outfitted with several body sensors and a commercial android smartwatch, a smartwatch with GSR sensor, a heart sensor (chest-based), and a finger-based GSR sensor. The participants completed nine tasks, and all data was gathered at a 5Hz sampling rate with the exception of the Polar H7 (1Hz), which was later up-sampled to 5Hz to synchronize with the others. On all collected results, statistical features on one-minute fixed time sub-division and correlation-based function subset collection were used. The Naive Bayes, SVM, Logistic Regression, and random forest algorithms were used here, with the random forest algorithm providing the highest accuracy of 88.8 % F-measure in the identification of tension. Ravinder Ahuja and Alisha Banga [28] measured and analysed students' mental stress one week before exams and when using the internet.

They investigated how test pressure or recruitment stress influences a student's mind, as well as how time spent on the internet is linked to stress. They used sensitivity, precision, and accuracy parameters to apply Random Forest, Naive Bayes, Support Vector Machine, and K-Nearest Neighbor algorithms to a dataset of 206 students. Because of its geometric classification method, Support vector machine has a high accuracy (85.71 %).

3) *Stress detection while driving*

Don't drive in stress. Driving in stressful condition may cause harm to you, it may take such events like staying in speed limit or driving in unsafe weather. And though it can cause road traffic violation and car accidents due to lack of alertness because of stress. It is necessary to solve the problem of automatic detection of the stress of the car driver as it has a direct impact on the health and safety of the people. Some researchers had developed some method for stress detection which will help an individual to get information about how to access an individual's pychological as well Physical both condition, so that he/ she can take the necessary precautions. [29] has developed a method which can help to detect stress of driver's by fixing a wearable ECG sensor in car or automobile drivers under various levels of environmental stress which can caused under such driving conditions. MIT-BIH PhysioNet Multi-parameter Database has obtained a dataset of 17 drivers. By using NetBeans Java Platform, 14 different features to detect stress were extracted from ECG signal. This method has achieved 88.24% accuracy in detecting three levels of stress i.e high, medium and low by using machine learning algorithms.

In [30], two devices are use to detect stress which is present in car driver's, that are EDA and ECG signals, where three wearable devices are used to collect data. EDA device is used on each hand for Skin Potential Response (SPR) signals and ECG used on chest for protection. An experiments was done by some of the researchers and made a setup which will recreate movements and accelerations consisting in professional car driving. This experiment setup was like going through a highway by driving where some unforeseen or some drastically events are happening at various places. Support Vector Machine and Artificial Neural

Network has balanced accuracy of 79.58% and 79.94% respectively for the considered events [3], has developed a system software of stress detection having features RR interval, QT interval and EDR using ECG signal. They also did an experiment in which they used 5 minutes of ECG signal on 15 healthy people for testing and driving in heavy traffic which are considered as non-stressed and stressed conditions respectively.

The system has also verified some of the SVM model types by changing their feature number and kernel type. As Cubic SVM has showed an accuracy level of 98.6% with Guassian kernel function and all features, it was considered to be the best model to detect stress. This method has proved that if we use more features then it can increase the accuracy of model.

4) Stress detection in firefighters

And after a tough assignment, firefighters are continually subjected to very challenging conditions. Although a well-trained firefighter faces numerous decision-making uncertainties during a rescue operation due to a variety of situations. As a result, researchers devised several strategies for detecting stress levels in real-time and accurately in order to improve workplace safety. Virginia Sandulescu and Radu Dobrescu [32] created a portable shirt with embedded e-textiles technology to help firefighters avoid discomfort in emergency situations by detecting heat and mental stress using physiological and speech features. Six participants were subjected to the Trier Social Stress Test (TSST) at 40 degrees Celsius in two work conditions: no cooling and body cooling. Of the multiple extracted features from the results, only pulse and voice features were included. For classification, a support vector machine was used, which produces the best results in terms of accuracy, precision, and recall when the Gaussian kernel function is used. This device included a microphone, which enabled contact with the manager and other team members.

A movement tracker was also added to the firefighters' shirts to detect their movements during falls and deadlock conditions. As thermal stress approached a certain amount, alarms were activated, and a warning message was shown to firefighters via a smartphone. The authors of [33] suggested and compared a system for feature selection based on Heart Beat Morphology (HBM) to the standard Window-derived Heart Rate Variability (W-HRV) method commonly used for stress detection. They performed TSST tests on 13 firefighters while monitoring their ECG, actigraphy, and psychological measures using a VitalJacket, a wearable vest.

The effectiveness of HRM and W-HRV functionality was evaluated using Linear Support Vector Machine (SVM), Kernel Support Vector Machine (K-SVM), K-NN, and random forest classifiers. The precision, time resolution, and numerical rapidity of each process were all evaluated, with random forest coming out on top. For stress detection, the authors concluded that HRM methods needed less computation and produced better results than W-HRV. [34] established a stress detector system in which 26 participants' HRV data was obtained using a Polar H7 Chest strap sensor while subjected to physical, psychological, and cumulative stress. Following that, they used machine learning algorithms to classify the various stress types and understand the relationship with HRV results. With a 1-minute time frame, the C5 decision tree model identifies the tension form with 88 percent accuracy.

III. DISCUSSION AND CONCLUSION

Because of today's demanding and aggressive lifestyle, emotional fatigue is very normal in all age groups. Early identification of depression can be very helpful in taking more steps and it can impair both an individual's emotional and physical health. Some researchers gathered physiological data signals to quantify tension using self-made wearable devices (using low-cost sensors) in the methods discussed above, whereas others depend on commercial devices. The physiological signal necessary for detecting stress level was obtained by subjecting them to one or more stressors.

All of the built systems extracted features using different algorithms before employing machine learning algorithms to construct classification models. It has been discovered that features derived from heart rate, heart rate variability, and skin conductance are more efficient in predicting an individual's stress level, while the most powerful classification algorithms are support vector machine, random forest, and K-Nearest Neighbor. This demonstrates that physiological signals can be used to detect stress in a person using wearable sensors and machine learning algorithms that are both accurate and inexpensive. The study's drawback is that many participants used different features that were associated with each other, which increased computation time. In addition, some of them used expensive commercial instruments to capture physiological signals while low-cost sensors should have been used.

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