Machine Learning Based Solutions for Real-Time Stress Monitoring

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***Abstract*— Stress may be defined as the reaction of the body to regulate itself to changes within the environment through mental, physical, or emotional responses. Recurrent episodes of acute stress can disturb the physical and mental stability of a person. This subsequently can have a negative effect on work performance and in the long term can increase the risk of physiological disorders like hypertension and psychological illness such as anxiety disorder. Psychological stress is a growing concern for the worldwide population across all age groups. A reliable, cost-efficient, acute stress detection system could enable its users to better monitor and manage their stress to mitigate its long-term negative effects. In this article, we will review and discuss the literature that has used machine learning based approaches for stress detection. We will also review the existing solutions in the literature that have leveraged the concept of edge computing in providing a potential solution in real-time monitoring of stress.**

I. What is Stress?

Stress is defined as the reaction to adverse environmental situations that challenges the typical adaptive capability as perceived by an individual [1]. Although positive stress (eustress) helps the individual to stay focused to deal with adversities, negative stress (distress) causes the activation of the HPA (hypothalamic-pituitary-adrenocortical) axis. Prolonged activation of the HPA axis may cause physiological and psychological disorders [2]. Psychological stress is also found to affect physiological processes and has a negative effect on daily work performance and is thought to affect the national economy [3]. Monitoring negative stress levels can provide useful information for identifying the stressors and provide an opportunity to adopt necessary precautions in preventing resulting disruption.

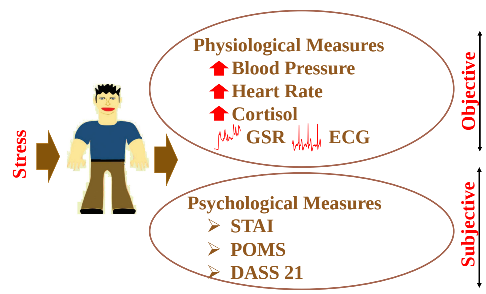

Fig. 1: Examples of objective and subjective measures of stress.

The two distinct effects of negative stress are defined as: (i) physiological or "objective" stress; and (ii) psychological stress or the "subjective" stress also known as the perceived stress. Objective stress is reflected by the change in physiological measures such as elevated blood pressure, increased heart rate, and increased cortisol levels. Subjective stress is the perception of whether or not a situation as stressful by an individual. The most common method of measuring perceived stress is by employing stress questionnaires like DASS 21 (Depression, Anxiety and Stress Scale - 21 Items), STAI (State-Trait Anxiety Inventory), and POMS (Profile of Mood States) (see Figure 1). Two main physiological measures for stress include: (i) Cortisol (stress hormones) and (ii) Physiological signal measurements like GSR (Galvanic Skin Response), ECG (Electrocardiogram), and EEG (Electroencephalogram).

In [4], we have discussed the different physiological measures of stress and the technologies associated with the measurement of stress metrics. Further in [5], we have provided an overview of different sensors and commercially available devices for measuring stress. In this article, we will explore the different machine learning based approaches for stress detection and also study the solutions presented in the literature for facilitating the deployment of a stress detection model for real time monitoring.

II. Physiological Signals for Stress Monitoring

The most common physiological measure for stress detection is Galvanic Skin Response (GSR). GSR is related to physiological and psychological arousal. Arousal in the autonomic nervous system (ANS) increases the activity of the sweat glands resulting in increased skin conductance. Figure 2 shows how GSR is related to the activation of the ANS to aroused state and deactivation from the stressed state to relaxed state [6]. However, detecting stressed states is complicated by several factors influencing the quality of signal, variations in response, etc. Also, using GSR alone has not been able to distinguish between stressed and non-stressed states when attempting to classify stress in more than two levels. For example, better than 99% accuracy was obtained in [7] by using features from both Electrodermal Activity (EDA) and Photoplethysmograph (PPG) signals, contrasted with an 82.8% accuracy reported when using only EDA features [8]. As multi-sensor based approaches works better than a single sensor, stress monitoring devices should have multiple sensors embedded in them to be suitable for more accurate stress detection. Furthermore, wearable sensor frameworks are best suited for real-time monitoring as they enhance convenience and comfort for the user and facilitate unobtrusive monitoring.

Several prototypes and implementation methods of wearable frameworks for stress monitoring have been proposed in the literature. In [9], researchers have developed a stress monitoring patch that is capable of capturing skin temperature, skin conductance, and pulse wave signals. In [10], a glove based sensor to capture EDA signals and pulse wave signals has been proposed. In [11], a physiological signal monitoring and communication system were developed by researchers from MIT Media Lab. A smart sensor capable of capturing heart rate, skin conductance and skin temperature was proposed in [12]. In [13], a stress monitoring system based on a body sensor network has been designed for an ambulatory setting.

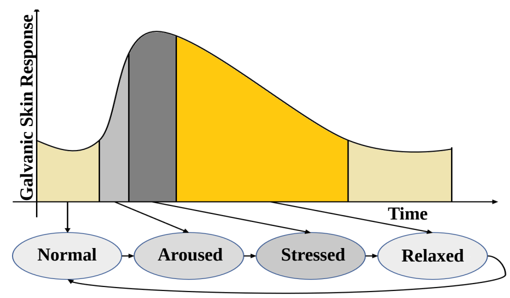

Fig. 2: Variation of GSR with mental stress [6].

However, there are also several commercially available devices and platforms for physiological signal acquisition and recording. Table I lists some popular commercially available devices suitable for data collection and analysis for research in the area of stress detection.

TABLE I: Popular commercially available devices for research.

Brand	Device	Signals	RTI	Ambulant
Empatica	E4 wristband	PPG, GSR, HR, ACC, ST	Yes	Yes
Garmin	Vivosmart	HR, HRV, ACC	Yes	Yes
Zephyr	BioHarness 3.0	HR, HRV, GSR, ACC, ST	Yes	Yes
iMotions	Shimmer 3+ GSR	GSR, PPG	Yes	No
BIOPAC	Mobita Wearable	ECG, EEG, EGG EMG, and EOG	Yes	No

GSR = Galvanic Skin Response, HR = Heart Rate, ACC = Acceleration, ST = Skin Temperature, HRV = Heart Rate Variability, PPG = Photoplethysmograph, RTI = Real Time Implementation

III. Machine Learning Techniques for Stress Monitoring

Features from physiological signals represent the relationship between these physiological signals and corresponding stress levels. These features are the backbone of any machine learning model based on which classifications are made. Figure 3 shows the common features extracted from ECG, GSR, EEG and Resp (Respiration) signals [14].

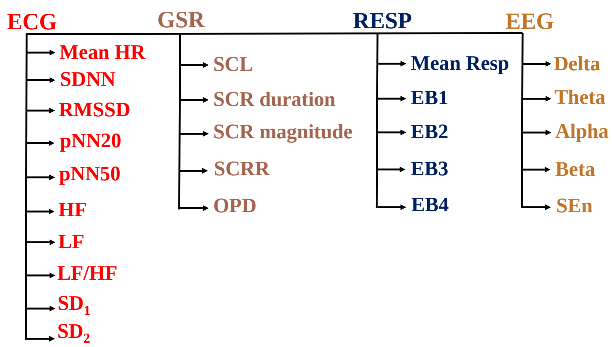

Fig. 3: Common features extracted from ECG, GSR, Respiration and EEG.

Features from ECG signals typically consist of the mean heart rate, SDNN (standard deviation of the R-R peak interval), RMSD (RMS value of the successive differences between R-R peak intervals), pNN20 and pNN50 (percentage of the successive normal sinus R-R intervals which are more than 20ms and 50 ms respectively), HF and LF (high frequency and low frequency components of R-R interval) in the range (0.15-0.4 Hz) for high frequency and (0.04-0.15 Hz) for low frequency and the LF/HF ratio. Finally, SD_1 and SD_2 are the crosswise and lengthwise standard deviations of the Poincaré plots.

GSR is characterized by two components: a slow changing tonic component called Skin Conductance Level (SCL); and a fast-changing phasic component named the Skin Conductance Response (SCR). Features like SCL, duration and magnitude of SCR and SCRR (Skin Conductance Response Rate), and the time duration during which the influence of stimulus persists also called OPD (Ohmic Perturbation Duration) constitute the set of features commonly studied in the context of stress detection.

Mean respiration frequency and the spectral power density of the signal in four different energy bands (0-0.1 Hz), (0.1-0.2 Hz), (0.2-0.3 Hz), and (0.3-0.4 Hz) denoted by EB1, EB2, EB3, and EB4 respectively are the most commonly examined features of respiration signal. Similarly for EEG signal, features from four different frequency range of the EEG signal namely: Delta(0.5-3.5 Hz), Theta (4-7.5 Hz), Alpha (8-13 Hz), and Beta (14-32 Hz). Sample Entropy (SEn) is also used as a feature for distinguishing between the two states.

Table III lists some of the related works in stress detection published during the past eight along with key attributes like number of subjects, physiological signals used, number of features, length of acquisition window, number of stress classes and accuracy.

Figure 4 shows an overview of a typical stress classification framework. The signals from the wearable sensors are preprocessed and subsequently features are extracted from the processed signals are used to train a machine learning model to classify between stressed and normal state. In the context of real time stress monitoring, there are several design challenges associated with traditional cloud computing like latency, energy consumption, cost, security etc. To address these design challenges, several works have used edge computing as a potential solution.

TABLE II: Characteristics of popular machine learning algorithms.

Algorithm	Classification Rule	Training	Testing
SVM	Support Vectors	$O(n^2p+n^3)$	$O(n_{SV}p)$
κ-NN	Distance Criteria	NA	$O(np)$
DT	Decision Tree	$O(n^2p)$	$O(p)$
LDA	Dimension Reduction	NA	$O(npt+t^3)$
NB	Bayes Theorem	$O(np)$	$O(p)$

n = number of samples, p = number of features, n_{SV}=number of support vectors, $t = min(n,p)$,SVM=Support Vector Machine,κ-NN=κ Nearest Neighbor, DT=Decision Tree, LDA=Linear Discriminant Analysis, NB=Naive Bayes

IV. Edge Computing for Stress Monitoring

The idea of edge computing is to migrate some of the computing capacity close to the endpoint where data is collected also known as the edge. When computations are done at the edge, the response time from the system reduces considerably as the data does not need to transmit through a very long distance. Also, techniques like data abstraction reduce the amount of data to be processed which

TABLE III: Related work and attributes.

	Year	Subjects	Signals	ML Algorithm	Features	AW(s)	Classes	Accuracy(%)
Palanisamy et al. [15].	2013	10	ECG	κ-NN	12	32	2	94.58
Muaremi et al. [16]	2014	10	ECG, Resp, ST, EDA, Activity	SVM, κ-NN, ANN, RF	187	NA	2	73
Liapis et al. [17]	2015	31	EDA	LDA	21	NA	2	98.8
Zubair et al. [18]	2015	12	EDA	LR	NA	NA	2	91.66
Sandulescu et al. [19]	2015	5	BVP, HRV, EDA	SVM	NA	0.1	2	80
Ghaderi et al. [20]	2015	7	EDA, EMG, HR, Resp	SVM	16	200	3	98.41
Hovsepian et al. [21]	2015	67	ECG, Resp, Activity	SVM	22	NA	2	72
Castaldo et al. [22]	2016	10	ECG	κ-NN	12	32	2	94.58
Abouelenien et al. [23]	2016	50	HR, Resp, EDA, ST, TF	DT	59	NA	2	89.07
Lee et al. [24]	2016	8	Activity	SVM	14	300	2	83.34
Gjoreski et al. [25]	2016	5	BVP, ST, EDA, HR	RF	63	240	2	76
Mozos et al. [26]	2017	18	EDA, BVP, Speech, Activity	AdaBoost	NA	NA	2	94
Egilmez et al. [27]	2017	7	EDA ,BVP	SVM, LR, RF	110	60	2	88.8
Lee et al. [28]	2017	28	BVP, Activity	SVM	20	NA	2	95
Chen et al. [29]	2017	9	ECG, EDA, Resp	SVM	NA	100	3	99
Betti et al. [30]	2018	12	HRV, EDA, EEG	SVM	15	300	2	86
Rachakonda et al. [31]	2019	NA	Image Inputs	CNN	4	NA	2	97
Rachakonda et al. [32]	2019	NA	EDA, Activity, ST	DNN	NA	NA	2	98.3
Nath et al. [33]	2020	13	EDA, PPG	RF	5	30	2	92

EDA=Electrodermal Activity, EMG=Electromyogram, Resp=Respiration, HR=Heart Rate, ECG=Electrocardiogram, BVP=Blood Volume Pulse, HRV=Heart Rate Variability, ST=Skin Temperature, PD=Pupil Diameter, LDA=Linear Discriminant Analysis, SVM=Support Vector Machine, FDA=Fisher Discriminant Analysis, κ-NN=κ-Nearest Neighbor, LR=Logistic Regression, DT=Decision Tree, ANN=Artificial Neural Network, RF=Random Forest, CNN=Convolutional Neural Network, AW=Acquisition Window, ML=Machine Learning, NA=Not Available

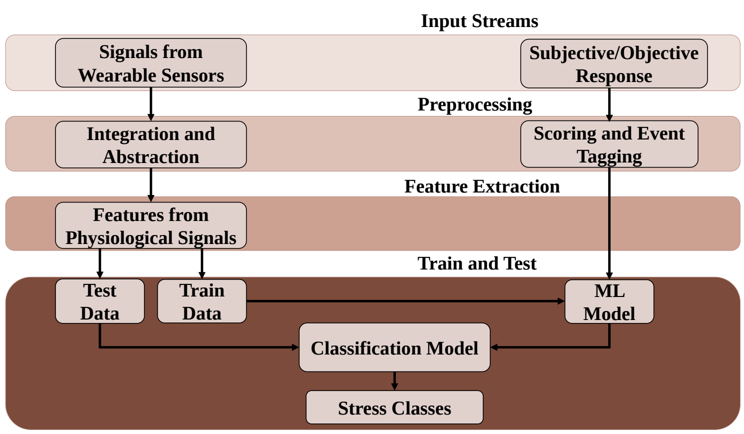

Fig. 4: Overview of a machine learning based stress classification framework [14].

results in decreased energy consumption. There is also additional security with edge computing as less information is transmitted to the cloud and are less vulnerable to external threats. Further computation and storage cost of cloud services will also be reduced if data is processed in the edge itself [37]. Figure 5 shows the general overview of a stress monitoring framework in an edge computing paradigm [34] [35] [32].

In an edge computing framework, preprocessing, feature extraction, and classification happen in the edge layer which is usually very close to the user. The input signal stream from the user gets

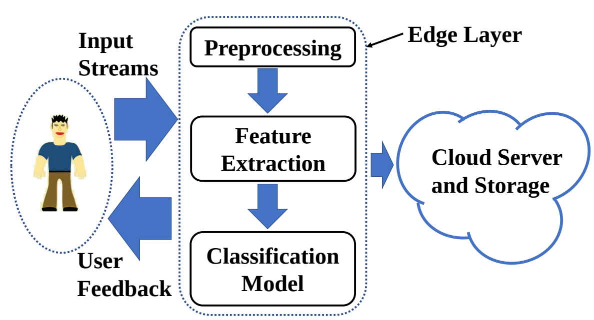

Fig. 5: Overview of a stress monitoring framework for edge computing.

TABLE IV: Related work on stress detection using edge computing.

Work	Use Cases	Input Signals	Edge Platform	Edge Latency (sec)	Edge Power Consumption	Cloud Platform	Cloud Latency (sec)	Cloud Power Consumption
Pace et al. [34]	Worker Stress	ECG	Raspberry Pi3	0.123		Azure	0.244	
			ZOTAC NANO PC	0.152				
	Athlete Stress		Raspberry Pi3	0.120			0.338	
			ZOTAC NANO PC	0.140				
Azar et al. [35]	Driver Stress	ECG, GSR	Polar M600		17%			44%
Rachakonda et al. [32]	Physical Activity	Thermometer Humidity Accelerometer	Single Board Computer	120-240			NA	
Raghav et al. [36]	WSEAD	ECG, GSR EMG, RESP ST, ACC	Raspberry Pi3	0.012			NA	
	SWELL-KW	GSR, ECG	Raspberry Pi3	0.003			NA	
	DREAMER	ECG, EEG	Raspberry Pi3	0.011			NA	

processed and analyzed in the edge and the result is generated in the edge layer itself which can be forwarded back to the user. The abstracted data could also be forwarded to the cloud server for further analyses and research. Table IV shows the related work in stress detection that has leveraged the use of edge computing techniques.

In [34], authors have proposed BodyEdge, which is a three-layer edge framework, namely the IoT layer, edge layer, and the cloud layer. The proposed architecture was implemented to detect high stress levels for workers and athletes from HRV (Heart Rate Variability) features. It can be observed from Table IV, the round trip time delay was significantly lower for the edge-based platforms as compared to a cloud platform. In [32], authors have used accelerometer, humidity and temperature sensor and using Deep Neural Network (DNN) to detect stress levels in an edge computing framework. The round trip delay time was reported to be around 2-4 minutes.

In [35], the author proposed a data compression algorithm to compress the collected data before transmission. The edge prototype was implemented in the memory card of a Polar M600 wearable device. It is reported that the battery life reduced to just 83% after 4 hours when the data compression technique was applied as opposed to 56% when the compression algorithm was not applied. In [36], a deep learning based framework for stress and affect classification was proposed and implemented on Raspberry Pi3. The proposed framework achieved low latency performance in the WSEAD, SWELL-KW, and DREAMER dataset.

V. Conclusion and Future Work

In this article, we have discussed the importance of continuous real-time stress monitoring. We have explored the literature and techniques for stress detection and monitoring. We have also discussed the existing works in the literature that have used edge computing framework for real-time stress monitoring.

Most of the works on stress detection are oriented towards psychological stress detection. Although there have been few works on physiological stress detection, there is further need for research towards detecting physiological stress. Research should be conducted to design robust classification models that can generalize classifications irrespective of the signal acquisition device and configuration. This will ensure the applicability of a framework in any setting irrespective of the type of edge devices and the configuration in which the data is collected.

Another interesting research direction that could be explored is the use of an edge-cloud framework which will distribute the process of preprocessing, feature extraction and classification across different layers of edge and cloud. This might be useful when integrating multiple end users to a single platform. In this context, there are other research scopes such as dealing with the massive amount of data that might be generated at the edge with time. Works are being done in this field to enhance the quality of data storing and retrieval mechanisms in an edge-cloud settings [38]. Ensuring privacy, security, and confidentiality of the data streams generated is also another exciting research direction [37]. Another direction that would be interesting to explore is to study the effectiveness of different intervention mechanisms in mediating acute stress responses. This will be a critical step towards developing a ubiquitous stress detection and management system which has the potential to further develop into a smart health monitoring system. Finally, real-time monitoring of stress can be integrated in a smart home environment [39] to assist older adults and persons with dementia or cognitive impairment.

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