Development and Evaluation of an Ambulatory Stress Monitor Based on Wearable Sensors

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Abstract

Monitoring stress levels has turn out to be a critical part of healthcare structures for physical and mental illnesses. Continuous stress tracking might help users better understand their stress patterns and offer physicians with greater dependable information for interventions. However, current stress tracking structures have did not acquire private information in an ordinary context. The contemporary country of sensor era permits us to broaden structures measuring the physiological signals, which replicate stress with the aid of using wearable devices. Therefore, we advise a stress tracking device that offers a goal each day healthcare primarily based totally on private physiological signals: electrocardiogram (ECG), photo plethysmogram (PPG), and galvanic skin response (GSR). We use the wearable devices, Shimmer3 ECG, Shimmer3 GSR and Empatica E4 Wristband, to monitor stress ubiquitously. We carry out managed stress experiments on sixteen members and the device effectively detects stress with 92.55% accuracy for 10-fold cross-validation and 83.61% accuracy for subject-wise cross-validation. In everyday settings, the device assesses stress with 82.12% accuracy. We also examine whether movement artifacts have an affect on stress assessment.

Keywords - Mental stress, electrocardiogram, galvanic skin response, physical activity, heart rate variability, support vector machine, stress classifier.

1.INTRODUCTION

Stress at work has become a serious problem affecting many people of different professions, life situations, and age groups. The workplace has changed dramatically due to globalization of the economy, use of new information and communications technologies, growing diversity in the workplace, and increased mental workload. In the 2000 European Working Conditions Survey (EWCS) [9], work-related stress was found to be the second most common work-related health problem across the EU. 62% of Americans say work has a significant impact on stress levels. 54% of employees are concerned about health problems caused by stress. One in four employees has taken a mental health day off from work to cope with stress.

Stress can contribute to illness directly, through its physiological effects, or indirectly, through maladaptive health behaviors (for example, smoking, poor eating habits or lack of sleep) [2]. It is important to motivate people to adjust their behavior and life style and start using appropriate stress coping strategies. So that they achieve a better stress balance far before increased level of stress results in serious health problems.

The avoidance of stress in the everyday working environment is impossible. Still, if people are informed of their stress levels, they become empowered for taking some preemptive actions in order to alleviate stress [10].There are a number of factors that are likely to cause stress at work including but not limited to long work hours, work overload, time pressure, difficult, demanding or complex tasks, high responsibility, lack of breaks, conflicts, under promotion, lack of training, job insecurity, lack of variety, and poor physical work conditions (limited space, inconvenient temperature, limited or inappropriate lighting conditions) [7].

We aim at the automation of the identification of the stress causes of an employee in question, as well as the identification of the common causes of stress for employees within an organization. Figure 1 shows the main ideas of our approach: We aim at making stress and stressors visible by (1) keeping track of the calendar events and daily routine of the worker, (2) measuring stress-related physiological signs from the sensor data, (3) annotating these events with the sensor data and the results of automated analysis of additional information sources, such as sentiment classification of the incoming and outgoing e-mails or social media messages and explicit user feedback, (4) extracting the relationship between event data and sensor data, i.e. relations between the increases and decreases in the stress level with the characteristics of the events of daily lives (what, where, when, with whom, etc.), and (5) using extracted knowledge about this relationship for personalized coaching.

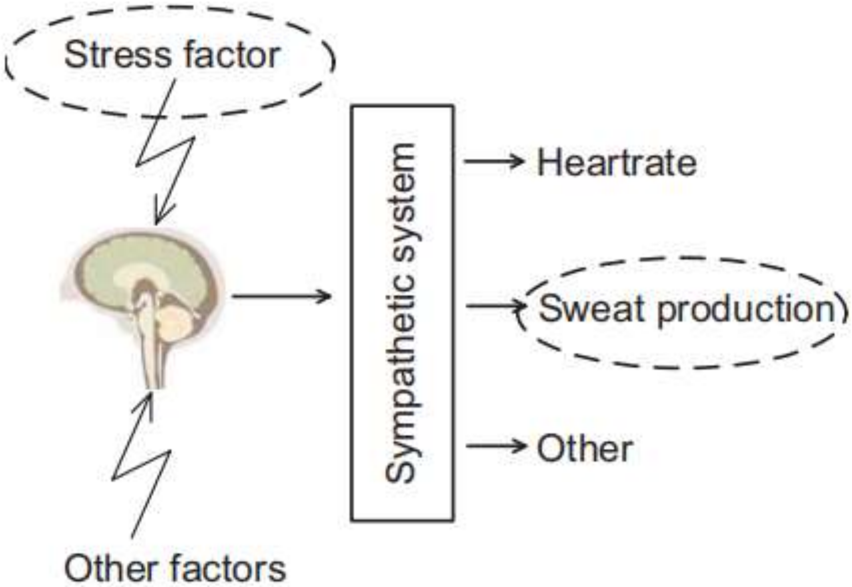


Fig.1 Reaction to stress factors is governed by the autonomous nervous system

In order to find this relationship, a number of subtasks need to be done. One of the main subtasks is detecting stress from the sensor data. Due to modern ICT and sensor technologies, objective measuring of the stress level in on lab settings becomes possible. Such symptoms as voice, heart rate, galvanic skin response (GSR) and facial expressions are known to be highly correlated with the level of stress a person experience [1,3]. In this paper we focus on the use of the GSR data (reflecting sweating) measured by a prototype device worn at a wrist.

The direct use of the GSR measurements obtained is not that straightforward. Partly this is caused by noise and inaccuracies in the collected sensor data, but what is more crucial – the reaction to various stress factors is governed by the autonomous nervous system and this “path” to the symptomatic system is shared with a lot of other mechanisms, such as the mechanism of adaption to the outside temperature and humidity. We have conducted a pilot case study aimed at the identification of likely challenges we need to address to make our approach work in practice. In this paper, we focus only on the problem of detecting changes in the stress level from the GSR sensor data alone. We study the peculiarities of noise and disturbances in the signal and argue the need of the related contextual data for improving the quality of stress detection.

The rest of this paper is organized as follows. In below, we formulate the problem of stress identification and categorization from the sensor data stream mining perspective.

We focus on a sub problem of arousal identification in online settings, which we formulate as a drift detection task. We highlight the major problems of dealing with GSR data, collected from a watch-style stress measurement device in normal (i.e. in non-lab) settings, and propose simple approaches how to deal with them. In Section III we present the results and lessons learnt from the conducted experimental study on real GSR data collected during the recent pilot field study. Finally in Section IV we give conclusions and discuss directions for further work.

2.STRESS IDENTIFICATION

Stress comes in three flavors:

- Acute: stress caused by an acute short-term stress factor.
- Episodic acute: acute stress that occurs more frequently and/or periodically.
- Chronic: stress caused by long-term stress factors and can be very harmful in long run.

Most people experience acute stress during their everyday life. It is a primal flight-or-fight response to immediate stress factors and is not considered harmful. When the frequency of these occurrences increase, physiological symptoms might occur. This type of stress is associated with a very busy and chaotic life and can be considered to be harmful when it occurs over prolonged periods of time. The last type of stress, chronic, is considered to be the most harmful. Prolonged periods of stress could be caused by personal circumstances or other long-term factors.

In our work, we want to prevent people from transferring to the chronic category and therefore, we target the acute and episodic acute stress. Particularly, in this paper we focus on the identification of acute stress in order to facilitate coaching of the episodic acute stress.

2.1 Background

The autonomic nervous system (ANS) regulates the body's major physiological activities, including the heart's electrical activity, gland secretion, blood pressure, and respiration. The ANS has two branches: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS mobilizes the body's resources for action under stressful conditions. In contrast to the SNS, the PNS relaxes the body and stabilizes the body into steady state.

2.2 Heart Rate Variability (HRV) and Stress

Under acute stress, the SNS increases heart rate, respiration activity, sweat gland activity, etc. After the stress has passed, the PNS reverses the stress response [11]. Since the ANS controls the heart, measuring cardiac activity is an ideal, noninvasive means for evaluating the state of the ANS. An ECG is a recorded tracing of the electrical activity generated by the heart.

Figure 2 shows a P wave, a QRS complex, and a T wave in the ECG. The P wave represents atrial depolarization, the QRS represents ventricular depolarization, and the T wave reflects the rapid repolarization of the ventricles [5]. The R-R interval is the time interval between two R peaks and is used to calculate heart rate.

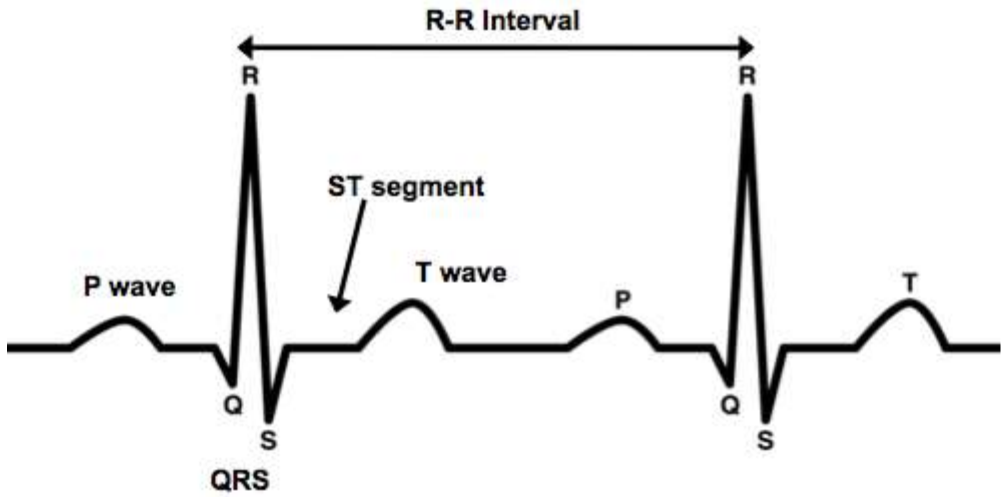


Fig. 2. Electrocardiogram sample

2.3 Heart rate variability (HRV)

Heart rate variability refers to the beat-to-beat variation in the R-R interval. HRV analysis can be categorized into time-domain and spectral-domain analysis.

Several time-domain parameters include:

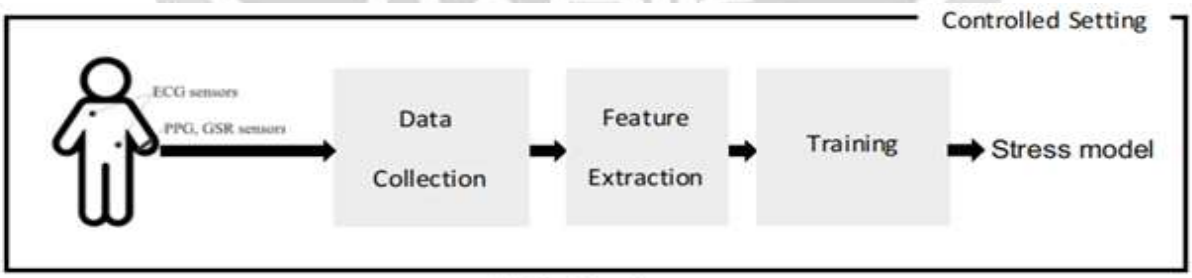
- mean HR: mean heart rate (beats per minute)
- mean RR: mean heartbeat interval (ms)
- SDNN: standard deviation of RR-intervals between normal beats
- RMSSD: root mean square of the difference between successive RR-intervals and
- pNN50: the percentage of heartbeat intervals with a difference in successive heartbeat intervals greater than 50 ms. Three widely used components can be found in HRV power spectrum:
- LF (0.04-0.15 Hz): a low-frequency component that is mediated by both the SNS and PNS
- HF (0.15-0.4Hz): a high-frequency component mediated by the PNS and
- LF/HF: LF to HF ratio that is used as an index of autonomic balance.

2.4 Galvanic Skin Response (GSR) and Stress

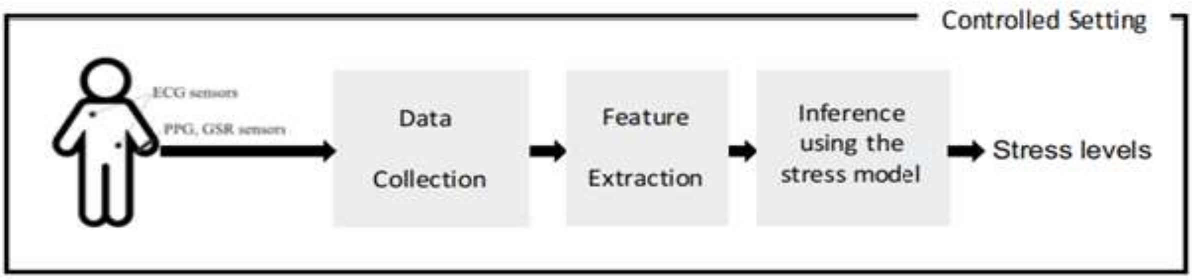
GSR is a measure of the electrical resistance of the skin. A transient increase in skin conductance is proportional to sweat secretion [4]. When an individual is under mental stress, sweat gland activity is activated and increases skin conductance. Since the sweat glands are also controlled by the SNS, skin conductance acts as an indicator for sympathetic activation due to the stress reaction. The hands and feet, where the density of sweat glands is highest, are usually used to measure GSR. There are two major components for GSR analysis. Skin conductance level (SCL) is a slowly changing part of the GSR signal, and it can be computed as the mean value of skin conductance over a window of data. A fast changing part of the GSR signal is called skin conductance response (SCR), which occurs in relation to a single stimulus. Widely used parameters for GSR include the amplitude and latency of SCR and average SCL value.

3.METHODOLOGY

Our stress monitoring system provides an assessment of stress levels using three main physiological signs: ECG, PPG, GSR. Our research has been conducted in two different settings: controlled setting and everyday setting. To find a correlation between stress and physiological signals, we perform offline laboratory-based stress tests to collect bio-signals from wearable devices. We then process the raw signals to extract features, build predictive models using these features, and find the relationship between each feature and stress. We assume that stress is labeled in binary: whether each participant is stressed or not. Figure 3 shows the process overview in a controlled setting. Figure 3a shows the training process to build a predictive stress model. Figure 3b shows the inference process to find the relationship between each feature and stress by the stress model



(a) Training Process



(b) Inference Process

Fig.3 Process overview in the controlled setting

We also collect physiological signals in an everyday setting through wearable devices to find daily stress levels. With everyday data, we perform feature extraction and prediction using the models trained in the controlled setting to get personal stress levels. Figure 4 shows the process overview in the everyday setting.

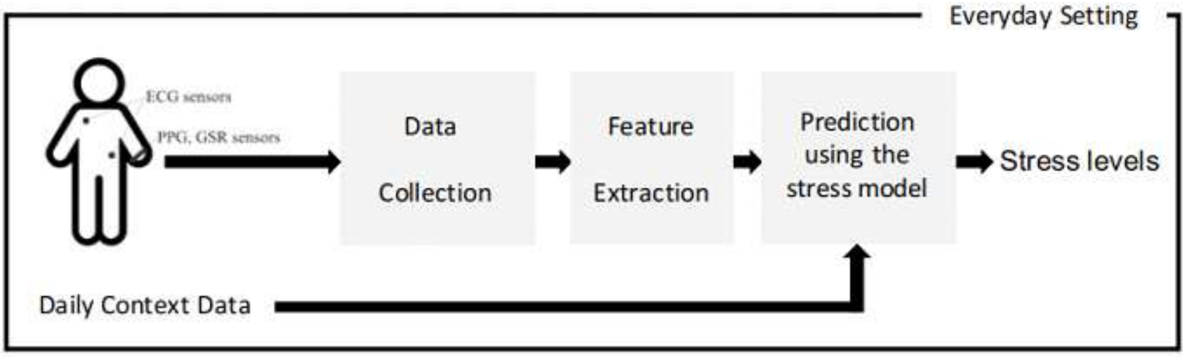


Fig.4 process overview in the everyday setting

3.1 Wireless Sensor Network

We used the SHIMMER platform developed by Intel's Digital Health Group. SHIMMER is a small wireless sensor platform with an integrated 3-axis accelerometer designed to support wearable applications. We also used SHIMMER's ECG and GSR daughter boards for data acquisition. The sensor data from the ECG sensor and accelerometer were sampled at 100 Hz, and the data from the GSR sensor were sampled at 32 Hz. Data were transmitted to a PC via Bluetooth connectivity and saved to binary and comma-separated value files. We used three sensor nodes for the wireless sensor network configuration. The ECG sensor node was strapped to an elastic chest belt and three electrodes were placed on the body to form lead II and lead III1 recording configurations. The GSR sensor was attached on a wrist band. Then, skin conductance was measured at the base of two fingers by measuring the electrical current that flowed as a result of applying a constant voltage.

3.2 Feature Selection

Using all features is not necessarily helpful as they may not help in increasing accuracy. If a feature is not related to stress, having it among related features may increase noise [12]. Computing some loosely correlated features may also not be useful because of the computational complexity. For instance, frequency domain and independent features have non-linear computational complexity. Especially in local implementations in Internet-of-Things [13,14] based systems, these overheads are considerable. Thus, we decide to select features that are more correlated to stress. In order to find the best subset of features, we adopt a greedy stepwise method [15]. This method starts from an empty set. It adds features that increase accuracy and removes features that decrease it. We continue doing these two steps until we reach a set of features in which adding no new feature or removing any selected feature can increase accuracy. To evaluate the accuracy of each subset, we use a 5-nearest-neighbor classifier, correlation-based feature selection method, and information gain. Based on this method, the features are shown in Table 1 in bold are selected.

TABLE 1

EXTRACTED FEATURES FROM SENSORS, SELECTED FEATURES IN BOLD

Sensor	Features
ECG	HR, SDRR, SDSD, RMSSD, **pNN20**, pNN50, LF, HF, LF/HF, SD1, SD2, **SD1/SD2**
PPG	HR, **SDRR**, SDSD, RMSSD, pNN20, pNN50, **LF**, HF, **LF/HF**, **SD1**, SD2, SD1/SD2
GSR	**Skin conductance**

3.3 Machine Learning based Classification

The bias of physiological data can vary by using personal data sets or general data sets [16]. Personal data sets contain data collected from the same person (within), and general data sets contain data from other subjects (between). In order to test the efficiency of our classifier, we test it in both cases. We use several machine learning based classification algorithms such as K-nearest neighbor (kNN) with k {1, 3, 5, 7, 9}, support vector machine (SVM), and Naive Bayes classifier. kNN is a method that uses *k* nearest data-points and does a majority vote to predict the result [17]. SVM finds hyper-planes to divide data-points into different classes [18]. We used the Weka implementation of LIBSVM [19]. Naive Bayes classifiers predict the result based on the probabilities of each feature's probabilistic knowledge [20]. Naive Bayes classifiers act differently based on the distribution of data-points [21].

4.RESULTS AND DISCUSSION

In this section, we present our experimental results in the controlled and everyday settings. First, we validate our developed stress models using three different classification algorithms (i.e., kNN, SVM, and Naive Bayes). We test whether the classifiers generalize across data-points as well as across subjects. We then apply the classifier on everyday data to predict stress, observe and study the contextual factors affecting the results, and analyze techniques to mitigate them. We use everyday self-report stress label as ground truth (i.e., reference point). We also collect context data (e.g., running, walking, eating, etc.) to evaluate the effect of noise such as motion artifacts on the decisions in everyday settings. To examine how a combination of features affects stress detection accuracy, we create four groups of bio-signals: GSR+PPG+ECG, GSR+PPG, GSR+ECG, and only PPG. The rationale to study the PPG only case is the fact that this is the most dominant, cost-effective, and convenient method used in wearable such as smart bands, watches, and rings, making it the most feasible monitoring method for everyday settings.

4.1 Stress Assessment in a Controlled Setting

To objectively assess the stress in a controlled setting, we build a stress model using different classifiers (kNN, SVM, and Naive Bayes). We conducted two different sets of experiments: i) with all features, and ii) with selected features (presented in Section 4.5). In addition, we analyze the data from two different perspectives: data-points vs. subjects. In the data-points view, we treat the data points similarly regardless of the participant they were collected from whereas in the subject wise analysis, we group each individual's data.

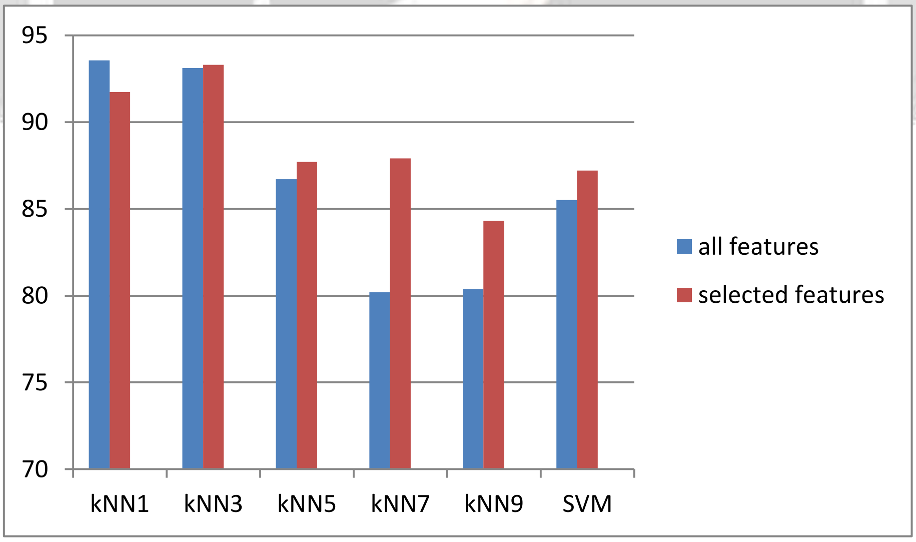


Fig.5 Controlled setting stress assessment accuracy of the different classifiers using the different number of features

4.2 Stress Assessment in the Everyday Setting

We predict the stress level in the everyday setting through the stress model. We split everyday data into minutes, extract the features, and run them through the stress model. To get an accuracy of everyday stress prediction, we use a binary self-described stress level as ground truth. Participants report their self-assessment of stress level every 30 minutes. Since we have the stress model from the controlled setting, we use a majority vote to prevent an unstable prediction for data-points due to its inherent noise cancellation property [22]. We use two-third majority to consider a prediction reliable.

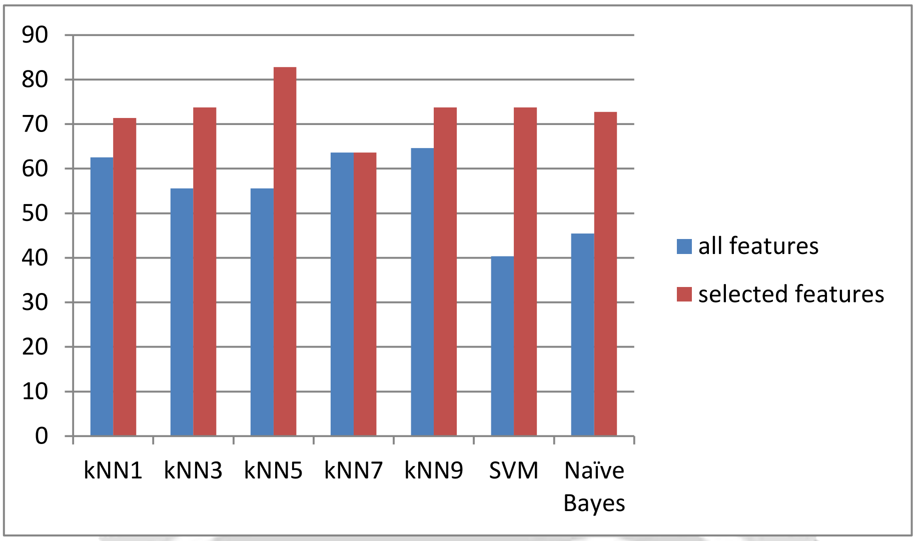


Fig.6 Everyday stress assessment accuracy of the different classifiers using the different number of features

I. CONCLUSION

Previous mental stress investigations were conducted in the laboratory with sedentary subjects. However, the controlled setting in a laboratory is not suitable for mobile mental stress monitoring because physical activity affects the measured physiological signals. The main aim of this investigation was to determine whether activity information can compensate for the interactive effects of intellectual pressure and physical activity, which affect the accuracy of intellectual pressure detection. We proposed a pressure tracking device that turned into examined for everyday pressure evaluation. We designed, implemented, and analyzed the device offering not only high accuracy pressure detection in the controlled setting but also affordable predictions in the everyday setting. We performed controlled pressure evaluation experiments on 17 contributors and everyday setting tracking on 1 volunteer. Our results demonstrate 94.55% accuracy within side the generalized version for pressure detection at the same time as displaying 83.61% accuracy when the classifier generalizes throughout subjects. The accuracy of the device within side the setting is 82.12%. Our device is compared against associated research in terms of the sensors used, accuracy in the generalized version, check units, check period, and check activities.

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