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Assessment of a Coordinated Arrangement of Wearable Physiological Sensors for Stress Checking in Work Spaces by Utilizing Organic Markers

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Abstract:- The objectives of this investigation were to create and evaluate a wearable physiological sensor system for detecting human stress using ECG, EDA, and EEG data, as well as to see if the changes in physiological indicators were correlated levels. The main elements of the study are listed below. This study included 15 healthy volunteers with an average age of 40.8 years, comprising seven men and six women. They underwent the well-known Maastricht Intense Stress Test, a procedure that is known to cause significant physical and psychological stress, while wearing three commercial sensors have been employed to keep track of their physiologic responses.Throughout salivary samples were taken at various points. The use of a Salivary concentrations of cortisol were correlated with the obtained physiological indicators using an algorithm called the Support Vector Machine (SVM) segmentation technique were both part of the statistical analysis. A significant ability to discriminate between stress and relaxation was shown by fifteen features obtained from measurements including heart rate variability, electro dermal activity, and electroencephalography signals. Based on these important features, the classification system produced results with an accuracy rate of 86% that was satisfactory.Furthermore, the correlation analysis revealed, with an R-squared value of 0.714, a considerable consistency between changes in physiological characteristics and the trends in salivary cortisol levels. The study successfully showed that the wearable sensor system's implementation caught human stress levels and measured the state of stress with accuracy. The design of adaptable and controllable systems, such as medical devices, targeted at inducing interventions to stop stress-related effects, is particularly affected by these findings.

Keywords: *Stress detection, Physiological sensors, Machine learning, Cortisol, Work environments.*

Introduction

In today's context, stress is defined as a situation where the demands placed on individuals do not align with the resources available or fail to address their specific needs and motivation. It results when the workload exceeds an individual's capacity in terms of both strength and time. Similarly, tasks that are repetitive and unstimulating, not making use of an individual's expected skills and experience, can induce stress [1]. Numerous recent studies have emphasized the increasing role of stress and its consequences in culture [2]. Psychological Association, 75% of population reports experiencing stress-related symptoms in the past year. Additionally, 25% of individuals believe that there is a lot of tension significantly impacts their physical well-being. Furthermore, a survey by the European Commission [3] found that over 22% of workers in the EU believe that their occupations put their health and in danger, with percentages even higher for older workers, those in jobs with high public- and private-risk exposure and those with erratic work schedules. In general, the global economy and society as a whole are significantly impacted by the rising incidence of stress and anxiety as well as losses in personal wellbeing. For instance, work-related stress costs the UK £12 billion annually in lost productivity due to the failure of over 13 million working days [4]. This problem is particularly evident in occupations that demand a lot of physical and mental energy, such as those in transportation healthcare the military, civil defense, and office work. Another study found that a sizable percentage of people confess to never having used techniques or activities to lessen and manage their stress levels [10]. Consequently, there is an urgent need for efficient stress management in the workplace, ideally including reliable techniques for automatic and continuous observation of an individual's level of stress.Employers should therefore look for ways to keep their employees happy, healthy, and productive while also assuring their safety. This is especially important given ongoing demographic changes that are causing an ageing workforce and increasing the need for initiatives to help individuals work longer and more safely. Designing, developing, testing, and assessing a wearable physiological sensor system as a whole for strain monitoring in work situations utilizing biological indicators is the main goal of this article in this context.

Objectives

Definition and evaluation of stress

According to nature, life is consisting of a constant exchange of information, energy and surroundings, all while adhering to a delicate known as "homeostasis". Stress is a term used in biology to describe a genuine or possible threat to physiological integrity as well as an existing or predicted breakdown of this homeostasis [12].Key limbic brain cortex evaluates any event's potential to upset homeostasis before it happens. A general alert response is elicited if the event doesn't match mental representations created in response to prior emotional experiences [11]. The degree to which each of these components is displayed depends significantly on an individual's sensitivity and resilience. This response entails psychological changes like anxiety, fear, increased attention, vigilance, and preparation. Stressful situations trigger two main physiological reactions. The sympathy-adrenal-medullary (SAM) axis is activated as the primary and most immediate reaction. This happens simultaneously activated and the parasympathetic branch of the ANS is temporarily suppressed [13]. As a result, the release of noradrenaline from sympathetic nerve ends and the adrenal medulla is increased, as well as the release of adrenaline and noradrenaline from the adrenal medulla. Such changes cause a sharp rise in heart rate, heart contractility, blood pressure, vascular constriction, bronchial dilatation, and respiratory rate. All of these changes get the person ready for a difficult endeavor. During this process, the hypothalamus releases corticotrophin-releasing hormone (CRH), which encourages the pituitary gland to release adrenocorticotropic hormone (ACTH). As a result of ACTH, the adrenal cortex then releases cortisol [11, 13].

Blood glucose levels rise as a result of elevated cortisol levels, giving the body a powerful energy source to fulfil the needs of a demanding endeavor. In contrast to the SAM axis, the HPA axis's stress response can linger for up to an hour after a single stressful incident [14]. These historically old stress responses gave living species a huge advantage, especially the "fight or flight" reaction, mainly focused on ensuring individual survival. However, these evolutionarily advantageous responses could possibly evolve into negative.Severe cardiovascular cardiovascular disease, stroke, high blood pressure, and tachycardia may indeed be caused by abrupt fluctuations in catecholamine levels, whereas elevated by a factor in the development of conditions like cancer, colitis with ulceration, and stomach ulcers [18].In particular, in those who are weaker and less resilient when repeatedly exposed to stressful events without proper intervals of recovery, physiological responses to stress have an impact on mental and social behavior. This repeated exposure frequently results in hampered perception, insufficient focus, incomplete and errors in judgement [19, 20, 21], all of which can have serious repercussions, especially in a professional setting. Heart rate variability (HRV), an electroencephalogram (EEG), and electrodermal activity (EDA) were utilised in this investigation to assess the physiological reactions to stress. This decision is consistent with Sharma's ranking of physiological and physical indications for detecting stress, which placed HRV, EDA, and EEG as the top three indicators, respectively. The accuracy of the stress measurement was validated and evaluated using salivary cortisol.

Methods

In previous decades, emotional and subjective methods, such as psychometric scales and instruments that rely on subjects' self-reports of their uncomfortable, have been used to measure stress and anxiety [23, 24]. These questions can be completed by the respondent themselves or by a trained expert [25, 26]. The results of psychometric tests can be influenced by a person's own skewed view of their stress levels, and people frequently fail to appropriately communicate their emotional states [27]. This kind of evaluation is also characterised by a lack of objectivity and does not allow for ongoing monitoring.Since they are less vulnerable to subjectivity and variability than traditional psychometric tools, physiological indicators have been used to measure stress in recent years. Conventional diagnostic equipment have a number of common drawbacks, including their weight, rigidity, and excessive intrusiveness and brainwave patterns are commonly used in the literature to gauge how stressed people are while performing different jobs [22]. Skin conductance changes as a result of increased sweat gland activity brought on by psychological stress. Previous research hasutilized EDA as a measure of sympathetic arousal to look into anxiety in people using computers, driving, and engaging in other activities [34, 35, 36]. These studies have used EDA either alone [33] or in combination with other physiological measurements. The impact of the autonomic nervous system (ANS) on cardiac activity has also been examined in a number of research. Analyzing Heart Rate Variability (HRV) in both temporal and frequency domains is crucial for comprehending the effects of both sympathetic and parasympathetic activity, particularly with regard to the Electrocardiogram (ECG) signal. In numerous investigations. In reaction to both mental and physical stimuli, the frontal cortex's development can also vary. EEG signals are divided into a number of psychological conditions. EEG evaluation has been used to categories performance during a variety of demanding jobs and to look into the anxiety levels of computer gamers [22]. Although physiological measures have been used in the past to gauge participants' levels of anxiety during various activities, changes in physiological signals can be impacted by a variety of variables, including bodily posture, proactive tasks, and the surroundings. In order to increase the precision of stress detection, numerous researches have recognized the need to use a mix of physiological and motion sensors. This sensor fusion approach enables the investigation of the most efficient sensor pairings and, as a result, the determination of the most trustworthy data processing approaches. For particular types of regulated learning, sensors like electrocardiography (ECG), electro dermal activity (EDA), and oxygen saturation (SpO2) are frequently combined. There are additional cases where breathing rate, electromyography (EMG) and extra EEG data are included. To the best of our knowledge, the overall accuracy for differentiating stress levels using various combination or single-sensor techniques ranges from 0.79 to 0.95. Accuracy typically suffers when data processing attempts to distinguish between three levels of stress.

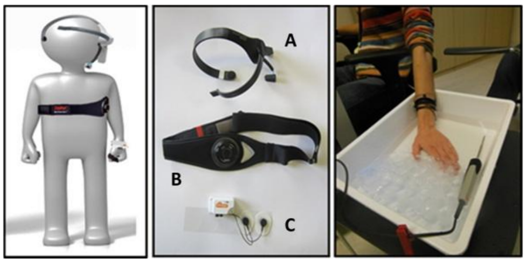

Fig. 1's left and center panels show the specific way that wearable sensors for acquiring physiological signals should be worn.The Zephyr BioHarnessTM3 (BH3) chest belt, the Mind Wave Mobile EEG headset, and the Shimmer Sensor.Right panel: Illustration showing how the cold pressure test was conducted.

A. Participants

The Fondazione Wear Gnocchi (FDG) in Florence, Italy, employed a total of 15 healthy individuals, with an average chronological age of 40.8 years (9.5) and a gender split of 8 men and 7 women. A medical expert evaluated their eligibility by looking over their medical histories and performing physical exams to find any possible exclusion factors. These requirements covered ailments such heart cardiac arrhythmias, uncontrolled diabetes or hypertension, chronic heart failure, coronary artery disease, acrocyanosis, Raynaud's disease, frequent drinking, and substance abuse misuse, or the use of drugs that are known to have an impact on stress responses. People with disorders of the salivary glands or oral lesions were also disqualified from the study.

B. Instruments

Those that make up the wireless sensor system that was used to gather data throughout the experimental trials are described in this section. A well-designed multimodal sensor framework was necessary to detect changes in physiological signals. The system in use was made up of three distinct wearable sensors and an interface-specific computer. Three primary factors—the nature of the observed signals (heart rate variability, electrodermal activity, and electroencephalogram), measurement accuracy, and sensor unobtrusiveness—were taken into consideration while choosing wearable sensor devices for the study. With this in mind, the point of view. The BioHarnessTM3 Sensor (Breeze, Maryland, USA) was developed for this purpose. The Breeze BioHarness TM3 (BH3) is a Bluetooth-enabled chest belt made to record 250 Hz sample rates of ECG-derived signals including heart rate (HR) and inter-beat interval (IBI). The Sparkle is a wearable sensor for EDA monitoring made out of two specialized finger electrodes and a central unit that can send data to a computer via Bluetooth at a sampling rate of 51.2 Hz. The Mind Wave EEG headset is a Bluetooth gadget that can record single-channel EEG raw data at 512 Hz sampling rate and give a measurement of the user's concentration and meditation using frequency power spectral density (sampling rate 1 Hz). Through a USB Bluetooth 2.1+EDR Dongle, the three wearable sensors were each Bluetooth-enabled to a PC. The BH3 sensor sent out two different kinds of messages: (I) the 136-byte ECG message payload and (II) the 40-byte IBI message payload. While the ECG signals were transmitted at a rate of 4 Hz, The person's heart rate determined the IBI message rate, which was roughly one message every two seconds. The MindWave sensor sent the EEG wave power EEG index with 35 bytes at 1 Hz and the EEG raw data with a 1-byte payload at 500 Hz. The Sparkle sensor transmitted a single sort of communication, a 10-byte GSR signal, at a frequency of 51.2 Hz. The device's entire data payload was 1600 bytes per second, or nearly 50% of the maximum rate that could have been transferred.

C. Experimental Protocol

The Pole test, a quick and safe evaluation meant to cause both physical and elicit strong autonomic was administered to the participants. Smeets has provided a detailed explanation of the Pole exam, which was created and validated by Maastricht University in the Netherlands [13]. In this research, the original Pole protocol was divided into four separate stages: Relaxation, Stress, Recovery1, and Recovery2. Wearable sensors and the collection of physiological data were easily integrated into these stages. After getting the baseline saliva sample, the relaxation phase started. Participants in this stage wore the array of sensors and sat still in a room for 10 minutes. They were careful not to use their phones, listen to music, be exposed to outside noise, or engage in any other external activities.Following this time, a quick presentation explaining the forthcoming activities was given for 5 minutes to the participants. After this educational session, the Stress phase began, which combined two different stressors: Four sessions of mental arithmetic exercises were interspersed with five cycles of immersion in cold water. For the length of each cold water immersion session, the non-dominant hand was submerged in ice-cold water (5°C) (Fig. 1). As quickly and accurately as they could, participants were instructed to mentally count backwards from 2043 in steps of 17. during the stress induction phase, a complete presentation that trained the subjects both orally and visually.

D. Analysis of Physiological Data

Data were segmented into three distinct phases: Relaxation and 10 minutes of recovery. For each phase, distinct datasets encompassing data were produced. Then, a collection of pertinent features were extracted from these datasets through processing. Offline analysis of the link between the physiological data and the sequence of characteristics was conducted using Matlab® R2012a (Math Works, Massachusetts, USA)..There was 38 different parameters in the final dataset. Galvanic skin conductance (SC), which includes both quick phasic activity with brief peaks or surges lasting 1 to 5 seconds, and slow-changing tonic activity, is the output of the Gleam sensor. To extract GSR characteristics, these phasic activities were used. Other associated sweating actions take place over a longer period of time during the tonic phase. The SC signal's frequency range is limited to 2 Hz. Since Gleam samples at 51.2 Hz, components unrelated to the SC signal were removed using a fourth-order Butterworth low-pass filter with a cutoff frequency of 2 Hz The phasic signal was then removed using a moving average filter with a 5-second window, allowing the tonic signal to be recovered and processed using a unique peak detection and feature extraction approach. Peak-to-peak detection was used to identify alerts, which were then quantified using the following metrics: The HRV data from the BH3 gadget shows the interval between successive heartbeats in time. The analysis of cardiovascular signals included both time-domain and frequency-domain research projects. Based on IBI data, an algorithm was created to extract significant propertiesEctopic beats, which are abnormal cardiac rhythms caused by premature heartbeats, were found and treated.

The average of five consecutive IBI intervals with the ectopic beat as their centre. was used to replace intervals that diverged by more than 20% from the preceding one. The interbeat (RR) interval sequence was converted into a Normal-to-Normal (NN) interval sequence suited for HRV analysis by correcting the ectopic rhythm. According to Mali et al., the equally sampled NN interval sequence at 4 Hz was subjected to Fourier-based power spectral density (PSD) calculations. The power distribution in the three main was described by these PSD estimates. The frequency domain was used to extract a total of 10 HRV parameters, which are listed in the text. These parameters were calculated using a 16-order parametric autoregressive (AR) model, with the Burg technique used to determine the coefficients.

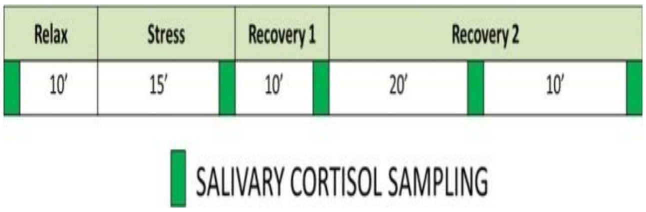

Fig.2. The order, length (in minutes), and details of each stage of the experimental protocol.

E. Data Analysis for Salivary Cortisol

To get rid of any particles, saliva samples that were gathered in Salivette containers, warmed up, blended, and centrifuged for 10 minutes at 3000 g. Only saliva samples that were clean and clear were used. A total volume of 600–800 l was recovered for each sample after centrifugation. Using a commercially available immunoassay (Cortisol ELISA, RE 52611, IBL International Hamburg, Germany), the cortisol levels in 50 l of saliva were twice tested. To ensure the assay's quality before the trial began, various tests were run. Two saliva samples were used to analyse the within-run variability, and the results showed a variance of less than 10% for both CK1 and CK2: 1.64 and 0.03 g/dL (n = 5 replicate tests, respectively; and 5%, respectively). The detection range of the cortisol ELISA is 0.015–4 g/dL..The between-run variability of a singly repeated sample (1.45 0.1 g/dL, CV = 3.2%) was analysed, and it revealed a fluctuation of less than 5%. The accuracy of the device was evaluated in accordance with the manufacturer's recommendations using dilution experiments with a linear response using dilutions of 50 to 6.125 L of saliva. Each cycle included the analysis of two control samples. Saliva samples' Each sample's cortisol levels were calculated using optical densities (OD), which were measured at 450 nm and calibrated against a standard curve. Luminex PONENT software with a Multiplex analyzer (MILLIPLEXTM Analyst, Merck Millipore Corporation, D, and Luminex Corporation, USA) was used to fit the dose-response curves using a five-parameter logistic equation (log scale). After the ANOVA, differences between several independent groups were examined using the Fisher's test. We carried out using the SAS programme, version 5.0.1 (SAS Institute Inc., SAS Campus Drive, Cary, NC, USA).

F. Correlation between both cortisol and physiological

In order to evaluate the study investigated the link between the salivary cortisol concentration curve and the selected set of relevant metrics in order to determine the capacity of the physiological monitoring system in capturing various stress situations. The objective definition of the subjects' stress reaction provided by the cortisol concentration curve served as the baseline for comparison. The physiological response can be thought of as immediate, although hormonal responses typically show a delay and frequently take place around 20 minutes after exposure to the stimuli [30]. This information was used to interpolate and fourth-degree polynomial fitting for each subject. The new data points were synchronised with the physiological monitoring windows' time points the 20-minute delay can be attributed to (Relax, Stress, Recovery1). This made it possible to examine how closely physiological and biological data actually matched. Cortisol levels were compared to a network of physiological indicators using (confidence significance threshold of 0.05). Figure 3 depicts the full procedure of data collecting.

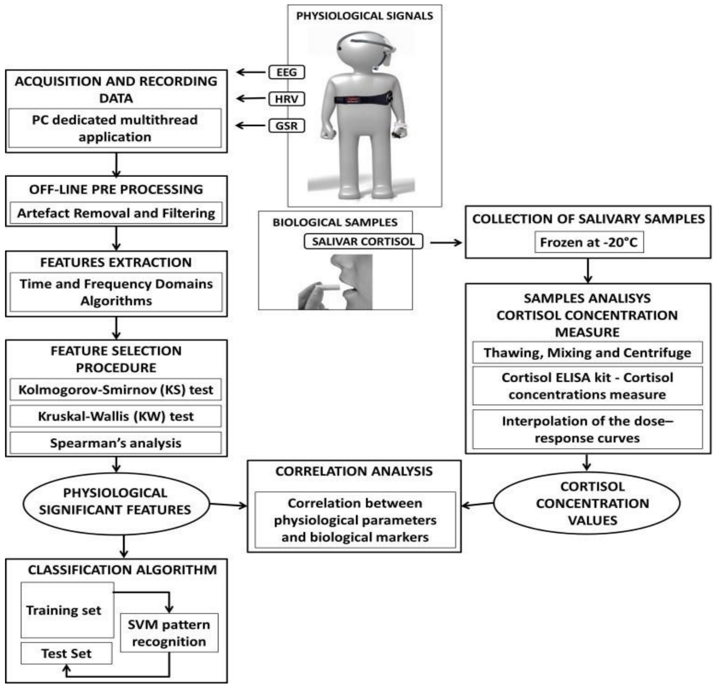

Fig. 3. Reiterative scheme about the entire process of acquisition, processing and analysis of physiological and biological data

Results

The results from biological data analysis and glandular sample analysis are presented in this section. Additionally, it investigates the relationship between the level of salivary cortisol and the features that were derived from the signals.

A. Relationship between physiology and cortisol

38 features that the results comprise data that were extracted, with mean values and standard deviations displayed on line. Moreover, for non-parametric data obtained using the Kruskal-Wallis (KW) test are shown. The p-values index, which is created using, features extracted both during the relaxation and stress periods, sheds light on potential variations that could be statistically significant between the two experimental situations. 22 of the 38 traits show notable differences in physiological reactions to the Pole test. Further dataset reduction was judged necessary eliminate data redundancy and increase the precision of stress detection. The duplicated data could make it difficult to identify stress, and several features had a strong correlation with one another. Specifically, five heart activity-related characteristics .These characteristics come from five HRV, five EDA, and five EEG signals. IBI Heart activity is represented by Mean in the time and frequency domains for SDNN, VLF Power,%VLF, and %HF. Startle Amp, Rise Time, #Startle, SD Startle RMS, and Phasic Value are all connected with skin conductance.. Finally, there is a connection between brain activity and attention, meditation, alpha1, alpha2, and beta1. The data from the relaxation and stress stages were subjected to Principal Component Analysis (PCA). In the PC environment, the two independent groups were split and visualised. According to the PCA analysis, the top 7 main components explained more than 80% of the variance in the entire set of data. In order to categorise subjects as stressed or not, a algorithm was trained and evaluated on these 7 uncorrelated parameters. To assess the system's performance in terms of sensitivity, specificity, and overall accuracy, training and testing datasets were randomly selected and contrasted using (k = 5).The difference in cortisol levels before and after is shown in Figure 4. Different coloured lines on the graph represent distinct data points and trends:

- Red: These data points show the actual cortisol concentrations measured in samples taken at start of relaxation phase, the end of the stress period, as well as the beginning and end of Recovery2

- Blue: To construct a smoothed curve from the original cortisol samples, a suitable polynomial of degree four was performed to the blue line.
- Green: Taking into consideration the 20-minute hormonal response delay to a stressor, this line shows the resampled cortisol value associated with the relaxation phase.

Similarly, taking into account the 20-minute delay in the hormonal reaction to a stressor, the violet line shows the resampled cortisol value associated with the stress phase.

- Grey: To account for the 20-minute delay in the hormonal reaction to a stressor, the grey line reflects the resampled cortisol value for the Recovery1phase.

This graph illustrates the dynamics of the cortisol system by displaying how levels change over time in response to stress and recovery.

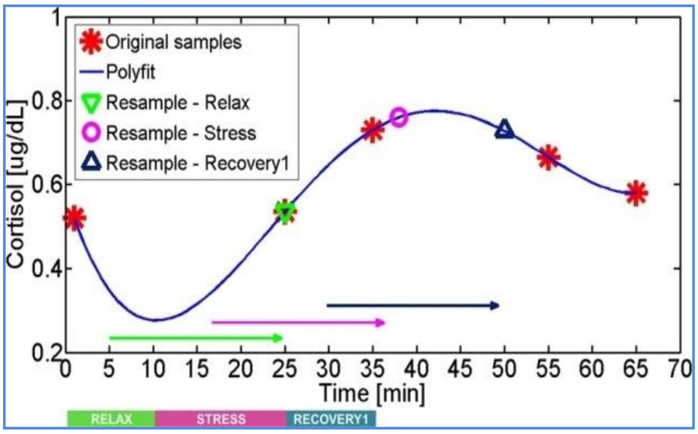

Figure 4: The difference in cortisol.

Regarding the periods of relaxation and stress, see Fig. 5. To promote better comprehension and convenience of seeing, the data arrangement is displayed on a plan made up of the two primary PCs. The SVM k-fold cross-validation approach is demonstrated in one specific iteration.

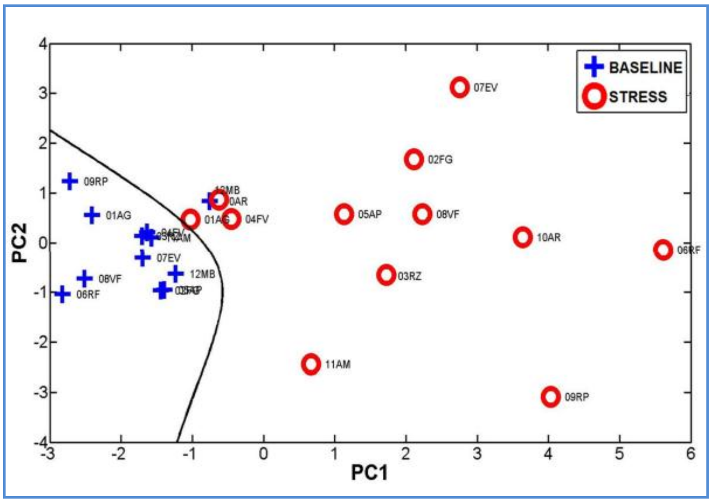

Figure 5: The periods of relaxation and stress.

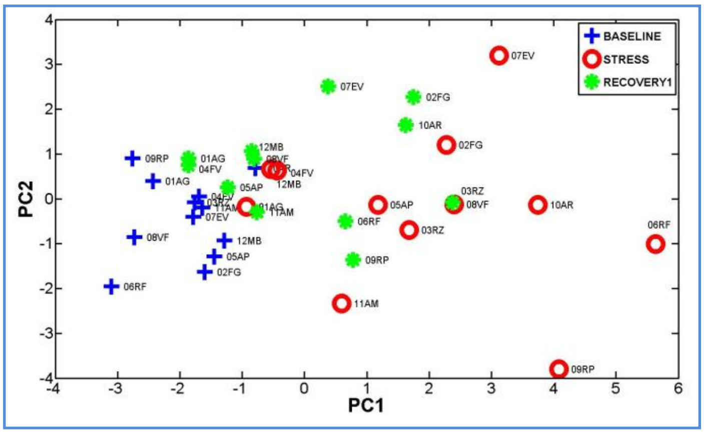

Figure 6: PCA for the periods of recovery, stress, and relaxation

Figure 6 shows the PCA for the periods of recovery, stress, and relaxation. The two main PCs were employedto simplify viewing and offer a better understanding. The Recovery1 phase resulted in a position that was halfway between, which lengthen the real period in which the individual returns to the initial conditions.

B. Results Salivary Cortisol

A measurement of a cortisol levels in saliva served a dual purpose. First, it aimed to confirm the effectiveness of our Pole protocol and experimental setup in inducing stress. Second, it aimed to obtain a biological stress marker that could be used to compare against the physiological data collected during the experiment. This comparison helps in understanding the relationship between physiological responses and cortisol levels, providing insights into the body's stress response.

C. Correlation Results

The dataset used for the SVM classification, which included HRV, EDA, and EEG features, was also subjected to a correlation analysis with salivary cortisol levels. Specifically, this analysis aimed to examine the relationship between a dataset with 15 physiological characteristics and a vector containing cortisol values skin conductance-related parameters (Frighten Startle RMS, Phasic Value), and brain activity (Attention, Meditation, Alpha1, Alpha2, Beta1) were just a few of the aspects represented by these features. Both the physiological characteristics and cortisol levels were standardized in proportion to their baseline values to aid in the correlation analysis. The analysis's findings showed a strong association between the cortisol pattern and the physiological characteristics.

Discussion

A main element is to design and assess the application of a wearable sensor device for identifying strain brought on by both physical and psychological stresses. Three wearable gadgets for HRV, artificial intelligence (EDA and measurements of EEG were used to keep an eye on participants throughout the experimental trial. It was possible to derive parameters from the examination of these physiological signals that were closely related to alterations in a range of emotional and physical states. The data collected led to satisfactory results, demonstrating the viability of the technology. Actually, this research was able to distinguish between the various phases of the experiment that the patients underwent using both quantitative (SVM) and qualitative (PCA) methods. The ability to identify characteristics between tension and relaxation stages, accordance with previous literature, was made possible by the precision of wearable sensors and the selection of analyzed data. The key novel aspect this study provides evidence that these alterations are, in fact, linked to variations in stress levels.The efficiency the stress detection method is confirmed, a proven marker for stress and the physiological indications of choice. The separate cluster in the PCA analysis from the Recovery1 stage, which did the stage, was another stage that was looked at in this study. The possibility of quantifying various stress levels is made possible by the presence of this third cluster.Users can receive alerts before stress reaches a crucial threshold because to the capacity to identify transitory stress levels. The dual nature of the Pole protocol may be the cause of the pronounced disparity between the Relax and Recovery phases. The real time it takes for the subject to return to their original conditions is increased by the interaction of their physical and mental elements. In an earlier experiment, Smeets had shown that the Pole technique may create tension. Our 12 participants' cortisol concentration curve pattern was similar to that mentioned by Smeets Despite some modifications, such as raising the water temperature from 2°C to 5°C to account for different cold tolerances in the Italian population compared. Due to its intricacy and the lengthy processing times associated with biological materials, the trial only included a small number of subjects, but this similarity validates the test's propensity to cause participants to become stressed.

The goal of this study was to show that a system capable of successfully detecting stress responses in people who have undergone the Pole test, a quick and non-invasive procedure that is known to cause strong sympathetic and glucocorticoid stress reactions, could be created by integrating commercial and wearable sensors. The study coupled the evaluation of salivary cortisol, a proven biological stress marker, with the use of physiological wearable sensors. This study's data processing enabled the discovery of a more comprehensive set of physiological markers capable of detecting stress. Results from the examination of sensor and salivary sample data were very intriguing. Participants in the Pole test experienced a detectable stress reaction that could be identified and described by a number of important physiological indicators. The robust marker cortisol, which is used as a standard for stress assessment, consistently represented this reaction. There was a physiological reactions and cortisol levels.

The participants' recovery state was likewise mirrored by the wearable sensors and physiological characteristics, demonstrating that the observed fluctuations were in fact connected to the participants' degrees of physical and mental stress. Given the system's demonstrated capacity for stress detection and the satisfactory correlation with a reliable biological marker, future research will focus on developing feature extraction and classification algorithms as well as conducting additional tests to validate more precise stress models in practical contexts. The algorithms will also be converted into a suitable language for use on portable devices, providing real-time feedback on stress in useful applications. This will enable the development of a system capable of continuously monitoring strain and associated outcomes.

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