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A New Intelligent Approach for Automatic Stress Levels Assessment based on Multiple Physiological Parameters Monitoring

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***Abstract*—Stress is a natural feeling of not being able to cope with specific demands and events, and it may even worsen a person's health, especially in chronic disease patients. Stress questionnaires are inefficient and time-consuming. Several models for stress estimation are based on facial analysis, voice recognition, Thermography, Electrocardiography, and Photoplethysmography, but they are not practical for patients. More robust systems with multiple parameters use devices that are incompatible in the same ecosystem. Machine learning techniques can also be used, but most studies only detect stress, few classify it, and none quantify it. The latest developments in health state monitoring present Photoplethysmography as the leading solution. Since it's non-invasive and can be integrated into wearable devices, it's more user-friendly and could be used in smart environments.** **Since it's non-invasive and can be integrated into wearable devices, it's more user-friendly and could be used in smart environments.** **The proposed work introduces novelty regarding Photoplethysmography signal processing algorithms to extract multiple physiological parameters simultaneously. In terms of innovations, a multi-channel detection system with a distributed computing platform is considered, which, besides containing the algorithms, also includes the introduction of new physiological parameters and the proposal of a model for estimating stress levels based on Fuzzy Logic, classifying stress into 5 levels. To validate the results, experimental protocols were created to induce thermal stress in volunteers, which yielded excellent system efficiency and accuracy indicators. The health status monitoring results and estimations are presented using a mobile application that was also developed.**

***Index Terms*—Blood Oxygen Saturation, Digital Signal Processing, Embedded Systems, Fuzzy Logic, Galvanic Skin Response, Heart Rate, Heart Rate Variability, Mobile Application, Photoplethysmography, Respiratory Rate Estimation, Stress Levels Classification.**

I. INTRODUCTION

STRESS is a serious health problem that affects a large percentage of society, regardless of age, environment, social status, and other aspects. The fact that it is common and that the term "stress" is generalized, causes people to neglect this condition.

According to the Labour Force Survey (LFS) in 2019/2020, about 51% of work-related illnesses were a direct consequence of stress [1]. These consequences do not only translate into the feeling of fatigue but may even contribute to the aggravation of several chronic diseases in long term. Therefore, it is extremely important to monitor stress at an early stage, not only in a work environment, but throughout the daily routine.

Technology plays a key role in our society, in order to try to solve existing problems, and as such, within the scope of stress assessment, several proposals have emerged, mostly making use of smartphones, smartwatches and smart bands, in order to acquire relevant physiological parameters, such as Heart Rate (HR), Heart Rate Variability (HRV), Galvanic Skin Response (GSR) or also called Electrodermal Activity (EDA), Body Temperature (BT), among others. A robust system for the acquisition of multiple parameters has not yet been proposed, as there are numerous obstacles, including battery life, the inability to collect data in multiple situations, noise artefacts, device compatibility, system mobility, system parameter relevance, user acceptance, and accuracy, among others. In addition, most of the suggested research merely differentiate between states of stress and relaxation, which is not reflective of the vast array of conceivable details that determine the classification of stress levels.

The main objective of this work is to study the impact of stress on people's health conditions, through real-time monitoring of relevant physiological parameters. As such, in this work we present a multichannel sensory system, based on the acquisition and processing of Photoplethysmography (PPG) signals, to which was added the acquisition of GSR data, a parameter strongly related to stress. This system also includes the implementation of intelligent algorithms for physiologic parameters estimation, and machine learning for the

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classification of stress levels. Through the mobile application developed, each user can monitor his/her health status, which includes detailed information related to the multiple vital signs acquired and stress levels monitoring.

This work represents a compromise between methods reliability and mobility/practicality of the system. Our goal was to develop a system with high levels of reliability, accuracy but also usability.

In terms of novelty, this work introduces a multichannel system capable of acquiring up to six physiological parameters in real time, with HR, HRV, Respiratory Rate (RR) and Blood Oxygen Saturation (SpO2) being estimated based on PPG signal processing, to which BT and GSR were also added, making it possible not only to monitor the user´s health status, but also to classify in real time the stress levels in a more accurate manner and adapted to a great diversity of users. Furthermore, this system differs from others, also betting on mobility, and although it is not an ultra-small device, it is a robust and autonomous system, which guarantees the safety and reliability of data, non-invasive and easy to use, not requiring any placement of sensors/devices, working only based on user's touch. Another aspect to mention in terms of novelty was the development of a mobile application from which users can consult all the collected data, providing real-time values, daily averages and monthly averages, as well as the arrangement of information in graphs for better perception, classification of each physiological parameter according to the values tabulated by the World Health Organization, giving advices based on that classification, and estimation and classification of stress levels, also including important tips for their good management.

In terms of innovation, this work introduces improvements to the algorithms previously developed in [2] for the extraction of physiological parameters based on PPG signal acquisition and processing, with particular emphasis on the algorithms for RR and HRV estimation. In the case of RR, this parameter lacks models for its estimation that do not involve counting the number of breaths per minute manually, which is a frequent practice in hospitals, or more complex approaches based on Electrocardiography (ECG) or Thermography. Thus, we improved the proposed model for estimating RR [2] based on the mathematical analysis of several PPG signal components. In the case of HRV, most proposed methods are based on a period for data acquisition (usually 5 minutes), after which the processing is performed, and an estimation is obtained. Nevertheless, in this research we propose a new technique based on ultra-short intervals with a 10-second periodicity. Another important aspect in terms of innovation is the intelligent algorithm proposed for the stress levels estimation based on Fuzzy Logic. In this model, each physiological parameter is classified, from which its Membership Function is extracted. These Membership Functions are then utilized to establish five rules, from which the coefficients allow to classify the stress in 5 levels, something completely new.

It is also important to mention that the work proposed in this paper is an extension of the MeMeA 2022 conference paper [2], developed by the same authors, and as such, the efficiency of the previously proposed methods has been enhanced. Furthermore, this work also combines the use of mobile interfaces for stress monitoring [3].

This paper is organized as follows. Section II portrays the background related to health monitoring and stress assessment, and a review of literature related to the topic, both for a better theoretical framework. Section III discusses the methodology adopted, that is, the work that was performed and the material used. Section IV presents the discussion of the results obtained from the experimental procedures performed. Conclusion and future work follow.

II. Related Work

This section discusses the relation between stress and health status, considering the stress assessment solutions including the acquisition of physiological parameters that can be related to the stress levels.

A. Stress and Health

When confronted with a stressor, the human body generates an autonomous response, that is, the autonomic nervous system triggers hormonal reactions, among them the release of cortisol (typically known as the stress hormone) into the bloodstream, thus leading to changes in several physiological parameters, such as HR, RR, SpO2, Muscle Tension, among others. This autonomous response depends on the duration for which the stressor is active. If a person is subjected to stress for long periods, he/she becomes more susceptible to develop serious health problems, such as Cardiovascular Diseases, Respiratory Diseases, Mental Illnesses, Diabetes, Sleep disorders, Immune System Degradation, Cancer, Anxiety, Depression, among others [4].

Beyond that, when stressful experiences are repeated without proper recovery intervals, the physiologic responses to stress alter cognitive-behavioural processes in usually sensitive and robust individuals. Imperfect perception, insufficient attention, inadequate or delayed information processing, and mistakes of judgment are all common side effects of repeated exposure to stressful situations, and they can have major repercussions, especially in the working environments [5].

Given that everyone is susceptible to stress, determining which types of stressors will influence everyone is highly subjective, especially given the wide variety of stressors, including thermal stressors, neurological stressors, environmental stressors, psychological stressors, physiological stressors, among others. Through contact with physicians and psychologists, it was possible to identify environmental and physiological stressors as the primary sources of stress for all individuals. Variations in temperature (extreme heat or cold), the effect of certain noises (various audible frequencies), the impact of light beams (bright light, glaring light, insufficient light, flash, etc.), and even the influence of music (dissonant, irregular rhythms, impactful, etc.) are examples of stressors. From the standpoint of detection and classification of stress levels, the type of stressors used is clinically irrelevant, so long as it is ensured that the induction of stress is effective for the intended purpose and does not exceed certain limits, thereby ensuring the physical integrity of the patients. However, given that the general population is more susceptible to environmental conditions in their daily lives and that many professions involve exposure to indoor or outdoor thermal environments that can affect work capacity and, ultimately, health, thermal stressors were considered [6,7].

B. Stress Assessment

Currently, the monitoring of stress levels is not objective because it is primarily based on self-assessment questionnaires, such as the Perceived Stress Scale (PSS) [8], or even through the monitoring of brain activity via Electroencephalogram (EEG) [9], which is performed in controlled environments, such as laboratories, thereby limiting the applicability of these techniques in everyday life.

There have also been reports of face recognition-based stress monitoring [10,11], employing the capabilities of mobile devices such as smartphones and tablets [12,13]. For example, face recognition seeks to assess a person's emotional state by comparing the captured facial expression to a database containing samples of facial expressions with a specified meaning.

TABLE I
RECENT RELATED WORKS ON STRESS ASSESSMENT

Article	Stress Signal Base	Method	Classification	Sample Size	Accuracy [%]	Environment
[4] (2017)	ECG, GSR, Respiration, Blood Pressure, SpO2	Support Vector Machine, k-Nearest Neighbours	Stressed, Relaxed	32 subjects	95,80%	Real Life
[9] (2016)	EEG	Support Vector Machine	Neutral, Medium, Low, High	6 subjects	89,07%	Laboratory
[12] (2020)	HRV, GSR	Random Forest, Support Vector Machine, k-Nearest Neighbours	Baseline, Cognitive Load, Stressed	32 subjects	92,15%	Real Life
[13] (2018)	Mobile Application	Support Vector Machine, Artificial Neural Network, k-Nearest Neighbours	Stressed, Baseline	13 subjects	70,00%	Real Life
[14] (2019)	PPG, GSR	MATLAB, WEKA Toolkit	Stress, No Stress	21 subjects	90,40%	Laboratory
[16] (2017)	GSR, PPG	Support Vector Machine, Logistic Regression, Random Forest	Stressed, Relaxed	9 subjects	88,88%	Laboratory
[18] (2016)	Empatica Wrist Device	Activity Recognition Classifier, Device Stress Detector	Stress, No Stress	21 subjects	92,00%	Laboratory, Real Life
[51] (2012)	GSR	MATLAB, WEKA Toolkit	Relaxed, Nervous	15 subjects	76,56%	Laboratory
[19] (2021)	PPG, Inter-beat Interval, Blood Volume Pulse	Convolutional Neural Network, Average Pixel Intensity with Trees Classifier	Baseline, Stress, Amusement	6 subjects	99,18%	Laboratory
[20] (2018)	EEG, GSR	Data Fusion, Linear Regression, Keystroke Analysis	Low Stress, High Stress	22 subjects	77,25%	Laboratory
[21] (2019)	EEG, GSR, PPG	Support Vector Machine, Naïve Bayes, Multi-layer Perceptron	Stress, No Stress	28 subjects	75,00%	Laboratory
[22] (2018)	HRV, GSR, EEG, Salivar Cortisol	Support Vector Machine, Correlation Analysis	Baseline, Stress	15 subjects	86,00%	Laboratory
[23] (2021)	HRV	Principal Component Analysis, Random Forest Algorithm	Stress, No Stress	30 subjects	74,51%	Laboratory
[24] (2016)	PPG, GSR, Respiration, Thermal Cam	Decision Tree	Stressed, Relaxed	50 subjects	73,00%	Real Life
[27] (2017)	HRV, GSR	F-State Machine	Low, High Stress, High Alert	166 subjects	98,40%	Laboratory

Unfortunately, in terms of continuous monitoring in the real world, where solutions characterized by higher autonomy, mobility, and unobtrusively are preferred, facial recognition presents some limitations that made it less applied in real life. Using image recognition for stress detection presents practical limitations from a user experience, healthcare, and data viability perspective. Interpreting stress from images is subjective and context-dependent, making the development of a universally applicable model challenging. Continuous image monitoring raises privacy concerns and can affect user acceptance. Acquiring diverse and representative datasets for training is difficult, impacting the reliability of stress detection. Cultural and gender variations in stress expressions introduce complexities. To enhance accuracy, integrating image recognition with other data sources is necessary. Technical challenges, such as lighting and image quality, can influence the precision of stress detection. These limitations highlight the importance of adopting a comprehensive and user-centric approach when implementing image recognition for stress detection in healthcare and user-oriented applications, making them too complex for wearable solutions or mobile healthcare systems.

In the case of smartphone use, and more specifically their built-in equipment, it is common to attempt to extract the PPG signal through the camera and using the flash, although the reliability of the resulting signal is questionable.

As shown in Table I, the most recent works with promising results typically address physiological stress, using vital signs monitoring, from a variety of methods. Something to highlight is the fact that a parameter always present in these works is the GSR. Although there is a substantial association between GSR and stress, this measure alone is insufficient to quantify stress properly. The GSR fluctuates with sweat production, which means the more sweat is produced, the greater the GSR value will be. Intense physical activity or disorders such as Hyperhidrosis (excess sweat production) have a direct effect on the GSR, and as a result, it is impossible to tell whether an individual has exerted effort or is stressed. Thus, there are studies that propose the correlation of GSR with several physiological parameters such as HRV [11,27], Blood Pressure (BP) [4,19], Respiration [4,25], among others, or even combining GSR with techniques such as PPG [13,16], ECG [4,18], EEG [20-22] or Electromyography (EMG) [25], however, most of them only detect the presence of stress and there is no classification or quantification of stress levels.

Techniques such as the EEG, which is used to analyse brain activity, and the EMG, which is used to evaluate the health of muscles and nerve cells, are commonly used in medical diagnoses. However, these techniques are performed in controlled environments and require specialised equipment that is not exactly practical. In the specific case of the EEG, it is a common mistake to attempt to combine this signal with physiological parameters such as GSR [20,21] or HRV [22], as they have different natures, i.e., the EEG is something related to the brain, human emotions, and psychological lining, and as such, it only contributes to monitoring psychological stress. Thus, it is not feasible to utilise EEG to validate models for assessing stress based on physiological parameters.

Techniques such as ECG and PPG, which are used to monitor different aspects of cardiological activity, are more useful in systems designed to estimate stress because they enable the extraction of relevant physiological parameters from signal processing [4, 22]. However, many proposed works do not make the most of this potential, extracting only HRV or SpO2 [4, 22].

C. Acquisition of Stress-related Physiological Parameters

As was seen in the previous subsection, the most promising works in the field of stress assessment explore physiological parameters, however the robustness of these models is questionable, not in terms of methods efficacy or accuracy, but rather in the origin of everything, i.e., in the acquisition of the data that feeds these systems, and there is a shortage of relevant physiological parameters. In the few studies that explore multiple physiological parameters, the system itself lacks mobility and practicality, as it involves several devices, which often do not allow a complete integration, and that make their use unappealing to users. Thus, one of the challenges in this research field is to implement a system capable of acquiring multiple physiological parameters, but which at the same time bets on simplicity for the user, something that can be achieved through innovations related to physiological parameters acquisition methods.

In terms of proposed methods for the acquisition of physiological parameters related to stress, the ECG technique is a gold standard, however, PPG has shown great potential, and through data analysis, it is possible to estimate essential physiological parameters such as HR [28-30], HRV [29,30], RR [28,31,32], SpO2 [33,34], among others.

In recent years, new wearable device solutions have been introduced to the market. The work to developed increasingly efficient wearable devices, small, with high connectivity and mobility, is followed by different research groups. Multi-functional sensing platform that provides HR, HRV, RR, SpO2 and BP, are still on prototype level. Thus, different authors are reporting results on systems for multi-parameter monitoring, however, the solutions are characterized by several sensors or complex methods characterized by high computational load, which consequently affects aspects such as mobility or autonomy [28,29,31].

In more complex systems, the ECG approach is often adopted, which is based on monitoring the electrical activity of the heart, however, this technique is not quite practical, since it requires the placement of electrodes on certain areas of the torso and the patient's immobility [35]. Thus, the PPG approach has been a strong contender to replace the use of ECG in a numerous applications, as it is based on monitoring changes in blood flow through the emission of a light beam and its detection, requiring only that the patient approach a part of his/her body, and as such, in addition to being more practical and less expensive than ECG, PPG is a non-invasive technique [35,36].

Regarding PPG sensors placement, fingers are typically used, or as alternative the wrist region. It is important to note that choice between finger and wrist sensors depends on the application and specific requirements. While PPG wrist sensors are more discrete and do not cause much obstruction or discomfort, finger sensors offer important advantages, such as more accurate readings (finger has a higher density of blood vessels closer to the skin surface, allowing for better detection of blood flow changes), better signal quality (sharper and clearer wave, facilitating the extraction of precise physiological information), and reduced movement artefacts (finger regions are less prone to movement artefacts).

Regarding PPG sensors operation, there are several types available on the market, and as a result, it is crucial to select the sensor that is most suitable for the intended purpose of the work. These sensors can be classified based on their signal acquisition mode, LED emitter configuration, and LED emitter type. PPG sensors may be Transmissive (using light transmitted through tissues) or Reflective (using light reflected by tissues). They can also be classified according to the arrangement and colour of the emitting LEDs: one emitting LED (green) and one photodetector LED, or two emitting LEDs (one infrared and one red) with one photodetector LED. PPG sensors employing a single green LED are resistant to movement artefacts but have a limited penetrating depth. They can be used to monitor Heart Rate (HR). PPG sensors with a red LED provide superior light penetration and are useful for collecting additional data, such as Heart Rate Variability (HRV) and Respiratory Rate (RR). A PPG sensor with two LED emitters (red and infrared) is required to measure Blood Oxygen Saturation (SpO2). The choice of PPG sensor should align with the specific physiological parameters to be measured, as discussed in more detail in the preceding paper [2].

The scientific literature reports the acquisition of physiological parameters such as HR, HRV, RR and SpO2, and the presented solutions are varying from author to author. Thus, different PPG specifications and noise artifacts must be considered, requiring a pre-processing and filtering procedure for the PPG signal, which may require the implementation of different types of filters [28,32-34]. In the case of using a PPG sensor based on IR and RED, both signals must be filtered.

In general, obtaining HR from the PPG signal, requires determining the time elapsed between two consecutive maximum peaks, a time that serves to estimate the number of Beats Per Minute (BPM) [18,30].

In the case of obtaining the RR from the PPG signal, several methods have been proposed over the years, such as the development of machine learning algorithms based on the correlation of data present in medical databases, as is the case of MIMIC-III [28]. The problem with these approaches, is that they become dependent on the reliability of the data, and if the data is contaminated, the entire process can be called into question. Another issue is the context in which the data were collected and if they can be replicated, such as during specific physical activities or the experience of specific emotions or stress levels. In addition to the above-mentioned method for the acquisition of RR from the PPG signal, it is important to note other approaches based on the amplitude and frequency modulation of the PPG signal, from which the maximum and minimum peaks of the signal are obtained and correlated to estimate RR [32,40,41].

As mentioned previously, a PPG sensor coupled with an IR LED and a RED LED is required to extract the SpO2 from the PPG signal. This measurement is based on the variation of values relating to light absorption by body tissues.

III. Methodology

In this section, the proposed system for health status monitoring is presented, which also has a user interface based on a mobile application. The data acquired from measurement channels related with physiological parameter monitoring is used to implement the Fuzzy Logic classification algorithm for induced stress.

The proposed system was initially designed with the purpose of performing stress monitoring in chronically ill people during their daily life, however, the system can be used for general purposes, being very useful for anyone who wants to monitor their health status, and particularly the assessment of their stress levels. Compared to other works previously proposed and mentioned, our work presents innovation in terms of offering more to the users and everything compact in a system of considered small dimension, and with autonomy to be used anywhere. The purpose of the design lies in the fact that users interact with the system through simple touch, having only to approach their hand, without the need for great complexity and placement of equipment.

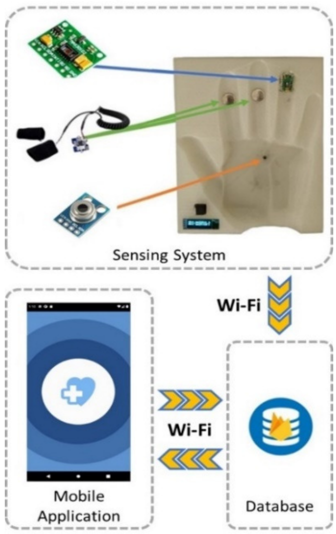

Fig. 1. System Architecture. The proposed system presents 3 layers, being the Sensing System, Database and User Interface (Mobile Application). All communication between the layers is done via Wi-Fi.

In this section, the experimental procedure carried out to monitor the human body's response to induced thermal stress is also described, thus allowing the implementation of an accurate algorithm for stress classification.

Stress can be represented in several ways, depending on the type of stressor in question, such as, Pathophysiological Stress (associated with unusual oscillations in body temperature), Neurological Stress (associated with the overloading of neurons and consequent increase in the brain's electrical activity), Chronic Stress (associated with chronic diseases such as Hypertension, Type 2 Diabetes, weight gain, Dyslipidaemia), Psychological Stress (associated with emotions), and in our case, Thermal Stress (associated with temperature variation outside the individual). Note that the aim of this work is to propose a new model for stress levels monitoring. Any of the stress types mentioned is present in people's everyday life, and as such, any one of them could be induced to validate the proposed system. The choice of Thermal Stress resided in the fact that it is more accessible compared to other types of stress, also opening future perspectives for the introduction of Thermography.

A. Sensing System

The proposed sensing system for health status monitoring, is composed by two ESP32 microcontrollers, an OLED LCD display (SSD1306), a microSD memory card reader/writer module, a Real Time Clock (RTC), a Radio Frequency Identifier (RFID), a PPG sensor (MAX30102), a GSR sensor (Grove - GSR sensor - Seeed), an Infrared Temperature Sensor (GY-906 Infrared Temperature Sensor Module MLX90614) and two Li-Po batteries (3.7V, 850mAh). The main system components communicate with the system microcontrollers using either the Inter-Integrated Circuit (I2C) or Serial Peripheral Interface (SPI) protocols.

The usage of SSD1306 allows the real-time display of the acquired data. The RTC and microSD memory card reader/writer modules, are used to ensure that the acquired data are stored for future analysis tasks. If the microcontrollers establish a Wi-Fi connection successfully, the data is remotely stored in the database. The inclusion of an RFID reader into the sensorial system enables user identification, associating the unique RFID identifier of each user with each acquired data. Also related to the user's identification, when creating an account in the developed mobile application, users must also associate the number of their RFID identifier.

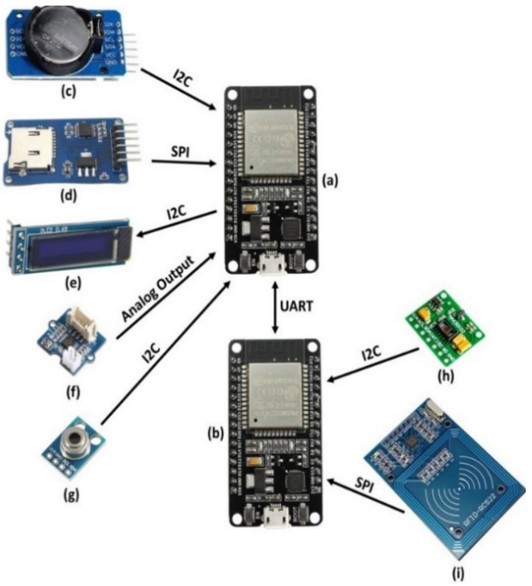

Fig. 2. Sensing System Architecture. (a) ESP32 Microcontroller 2. (b) ESP32 Microcontroller 1. (c) Real Time Clock. (d) MicroSD Memory Card Reader/Writer Module. (e) OLED LCD Display. (f) GSR Sensor. (g) Infrared Temperature Sensor. (h) PPG Sensor. (i) Radio Frequency Identifier Reader.

The ESP32 microcontrollers used in the sensing system are characterised by Dual-Core 32-bit CPU, maximum Clock of 240 MHz, ROM memory of 448 Kbytes, RAM capacity of 520 Kbytes, and Flash memory of 4 MB.

The first microcontroller (Micro1) is responsible for users' authentication through RFID identifier, data acquisition from the PPG sensor, and the embedded Digital Signal Processing (DSP). The embedded DSP includes PPG maximum, minimum and average values calculation, followed by HR, HRV, RR and SpO2 estimation. The PPG sensor will be discussed in more detail in the following "1) Data Acquisition" subsection.

The communication between both microcontrollers is done through Universal Asynchronous Transmitter Receiver (UART). Since this connection is asynchronous, steps were taken to synchronize both microcontrollers by implementing locking algorithms, widely used in Concurrent and Distributed Programming. In this way, Micro1 sends to the second microcontroller (Micro2) the user RFID identifier number along with the data extracted from the PPG signal processing.

In turn, Micro2 is responsible for data acquisition from GSR and infrared temperature sensors, and storing the PPG, GSR and Temperature data locally, through SD memory card, or remotely via Wi-Fi connection with database. GSR and infrared temperature sensors will be discussed in more detail in the following "1) Data Acquisition" subsection. The system includes two microcontrollers that achieves functioning reliability without compromising its efficiency.

The next subsections will cover in more detail the different stages of the sensory system, such as data acquisition and processing, physiological parameter estimation, and data storage.

1) **Data Acquisition**

The GSR sensor is responsible for galvanic skin response evolution in the induced stress context. High level of stress may stimulate the nervous system, resulting in increased sweat secreted by the sweat glands. This sensor contains two electrodes that are designed to be placed on two fingers of the same hand. This sensor's conditioning module operates as an analog-to-digital converter, enabling us to extract the GSR value in resistance (Ohm).

The Infrared temperature sensor enables systems to acquire temperature data with or without direct object contact. In the proposed sensory system, this sensor is used to acquire the user's body temperature. This sensor has a measurement range between -70 and +380ºC with an accuracy of 0.5ºC. The sensor itself has an operational temperature range between -40 and +125ºC.

The MAX30102 sensor was used as PPG sensor. It allows the acquisition of the IR component of the PPG signal, necessary to estimate the HR, HRV and RR, but also the acquisition of the RED component necessary to estimate the SpO2. This sensor uses the I2C communication protocol, thus featuring four connections, being the 5-volt power supply, Ground (GND), Serial Data Line (DAS) and Serial Clock Line (SCL). According with the experimental obtained signals the noise and artifacts level requires the filter implementation to increase the SNR. It is important to point out that the MAX30102 sensor presents an Analog Digital Converter (ADC) with a resolution of 14 bits, that is, the maximum value acquired by this sensor can go up to 16383 bits. In this way, to visualize the data acquired by MAX30102, it was necessary to make a conversion from bits to voltage, through Equation 1.

$$Analog\ Voltage = \frac{ADC_{readings} * Sensor_{voltage}}{ADC_{resolution}} \quad (1)$$

2) **PPG Signal Pre-processing and Feature Extraction**

In the work preceding this one [2], the extraction of multi-parameters from PPG signal processing was presented, along with a significant module for signal filtering that accounted for the substantial amount of noise associated with motion artefacts. All filter selection and design stages were outlined in [2], and a first-order low-pass filter with a cutoff frequency of 30 Hz and a sampling frequency of 300 Hz was used, resulting in the Continuous Time Transfer Function (H) represented in Equation 2, and in the Discrete Time Transfer Function (Hd) represented in Equation 3. Based on Equation 3, it was possible to determine the final equation for the digital filter, represented in Equation 4. To filter the IR signal and the RED signal, this equation was implemented in the microcontroller. Note that in Equation 4, "x" represents the original signal samples acquired by the MAX30102 sensor prior to filtering, whereas "y" represents the signal samples obtained following filtering. The result of filtering the IR component of the PPG signal can be seen in Fig. 3. bellow.

$$H(s) = \frac{188.5}{s+188.5} \quad (2)$$

$$Hd(z) = \frac{0.4665}{z-0.5335} \quad (3)$$

$$y(n) = 0.5335 * y(n-1) + 0.4665 * x(n) \quad (4)$$

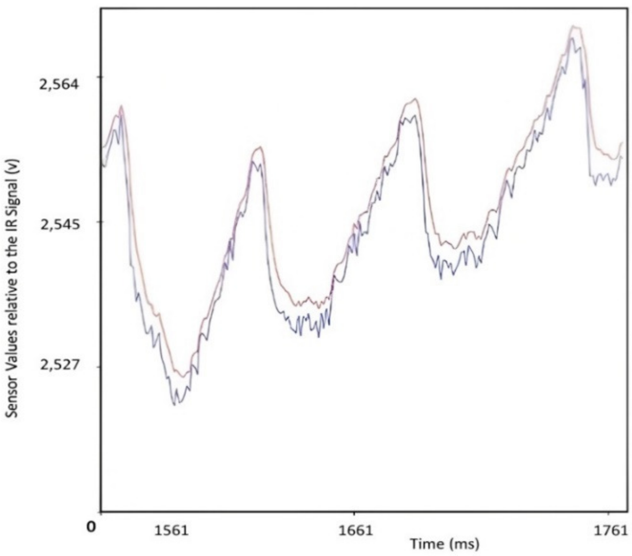

Fig. 3. IR Component of the Filtered PPG Signal. Note that in blue is the plot of values relative to the IR component of the unfiltered PPG signal, and in red is the plot of values relative to the IR component of the filtered PPG signal.

3) **Physiological Data Extraction from PPG Signal**

In this stage, the filtered PPG signal was processed to extract the maximum, minimum and mean values, as presented in [2], from which several physiological parameters were extracted, such as HR, HRV, RR, SpO2.

For the HR estimation, the peak values of the IR component of the PPG are used. Thus, the HR values is obtained in real-time considering the time interval between two consecutive maximum peaks. This time interval is commonly named as Pulse-to-Pulse Interval (PPI). Each cycle of the PPG signal corresponds to one beat, and as such, by determining the time elapsed between two consecutive maximum peaks, it is possible to estimate how many beats per minute one would have. The estimated HR is given by Equation 5 and expressed in BPM.

$$HR = \frac{60}{(PPI_i - PPI_{i+1})} \quad (5)$$

In the case of HRV estimation, typically named Pulse Rate Variability (PRV) in the context of PPG, once again the maximum values of the PPG signal are fundamental, since HRV is determined based on the time difference between two consecutive heartbeats.

There are several methods for estimating HRV, depending on the microcontroller characteristics and time duration for data acquisition [43]. For this work, the method developed for PRV estimation was based on the Root Mean Square of Successive Differences (RMSSD) between heartbeats, expressed in milliseconds. This method suggests an acquisition interval of 60 seconds.

As such, the estimation of HRV is based on the summation of the square of the difference between the Inter Beat Interval (IBI) at time t and the IBI at time t+1, where t varies from 0 to 60 seconds. Thus, the RMSSD is given by the square root of the mean of the summation. An important aspect to be considered, is that from the system user's point of view, a 60 second acquisition period is too long, while from the clinical point of view, the recommended acquisition interval is 5 minutes. Thus, the methodology proposed for HRV (PRV) estimation applies the RMSSD method to acquisition intervals of 60, 30, 20 and 10 seconds, then compared with the values obtained in an acquisition interval of 5 minutes. Based on the results obtained in [2], the final algorithm proposed for HRV estimation considers which interval is more appropriate and is also capable of apply variable acquisition intervals according to the acquisition phase. Additionally, this methodology implements multiple timeslots with a 5-second interval between them to increase the periodicity of the values update.

In the case of RR estimation, the PPG signal is analysed in real-time to identify maximum values. These values are then used to create the so-called respiration wave. Each time this wave reaches a maximum, a breath is counted. At each microcontroller clock cycle, the system checks the number of breaths in the counter (bCounter) and depending on the time elapsed since the beginning of the acquisition (bTime), estimates the RR, as shown in Equation 6 and expressed in Breaths Per Minute (BPM').

$$RR = \frac{(bCounter * 60)}{(bTime)} \quad (6)$$

For SpO2 estimation, the data related to the IR component and the RED component, both from the PPG signal, were correlated. For this purpose, the coefficients AC (difference between maximum and minimum peak) and DC (mean value between maximum and minimum peak) of both components were determined. The importance of determining these coefficients lies in the need to calculate the perfusion index (division of the AC coefficient by the DC coefficient) of each component, from which the Ratio (R) is calculated using Equation 7 [45]. However, depending on the specifications of the type of sensor used, empirical coefficients must be defined for sensor calibration [34,39]. In the case of the sensor in use, the estimation of SpO2 is given according to Equation 8 and expressed in percentage (%).

$$HR = \frac{(AC_{RED} * DC_{IR})}{(DC_{RED} * AC_{IR})} \quad (7)$$

$$HR = 110 - 25 * R - 1 \quad (8)$$

4) **Remote Data Storage**

Intelligent systems are increasingly dependent on technologies capable of processing data quickly and automatically, such as Machine Learning techniques, Neural Networks, Deep Learning, and Data Mining. To fulfil their functions effectively and precisely, these tools require huge amounts of data stored in databases. Thus, selecting the best suitable database for a system is essential.

For NoSQL database implementation, the Google "Firebase" database was chosen, considering its advantages for mobile and web application development, offering compatibility with IOS, Android, Web, Unity, and C++. Firebase not only allows fast real-time access, but also provides a high level of integration with cloud storage, the usage use of machine learning techniques as so as the fast and secure authentication methods [46].

B. Mobile User Interface

The system' user interface is based on Android mobile application. The mobile application allows users to perform the real-time monitoring of their physiological parameters. Additionally, daily averages, monthly averages and classification results can be visualized, to help users for better manage their health condition.

In addition to physiological parameters monitoring, the application is also responsible for the assessment of stress levels, through the implementation of Fuzzy Logic. To implement the Fuzzy Logic, we defined for each physiological parameter its reference values (HR [47], HRV [48], RR [49], SpO2 [50] and GSR [51]), the classification and the type of Membership Function, according to Table II.

Fig. 4. Different Mobile Application Layouts.

TABLE II
PHYSIOLOGICAL PARAMETERS TREATMENT

Parameter	Classification based on Parameter Reference Values				
	Very Low	Low	Normal	High	Very High
HR [BPM]	0 – 50	50 – 60	60 – 90	90 – 100	100 – 200
HRV [ms]	9 – 19	19 – 32	32 – 77	77 – 107	107 – 160
RR [BPM']	0 – 10	10 – 12	12 – 18	18 – 22	22 – 30
SpO2 [%]	85 – 90	90 – 95	95 – 97	97 – 99	100
GSR [KOhm]	10 – 20	20 – 30	30 – 50	50 – 70	70 – 100

A Membership function for a Fuzzy set A on the universe of discourse X is defined as $\mu A:X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set A.

Based on previous Table II, the Membership Functions used in the proposed model are categorised as Trapezoidal Function Type R for "Very Low", defined in Equation 9, Trapezoidal Function Type L for "Very High", defined in Equation 10, and Triangular Function for "Low", "Normal" and "High", defined in Equation 11. According to physiological parameter classification based on the reference value ranges, the minimum value is "a", the maximum value is "b", and the average value is defined as "c".

To define the Fuzzy Logic, 5 rules were also created, one for each classification of stress levels. These rules are presented below in Table III. The quantification of stress is then given by Equation 12.

TABLE III
CLASSIFICATION OF STRESS LEVELS ACCORDING TO THE FUZZY LOGIC ALGORITHM

Stress	Rules (R)	Stress Level (S)
Very Calm	VeryLow(HR) ∧ VeryLow(HRV) ∧ VeryLow(RR) ∧ VeryHigh(SpO2) ∧ VeryHigh(GSR)	$S1 = R * 1$
Calm	Low(HR) ∧ Low(HRV) ∧ Low(RR) ∧ High(SpO2) ∧ High(GSR)	$S2 = R * 2$
Normal	Normal(HR) ∧ Normal(HRV) ∧ Normal(RR) ∧ Normal(SpO2) ∧ Normal(GSR)	$S3 = R * 3$
Stressed	High(HR) ∧ High(HRV) ∧ High(RR) ∧ Low(SpO2) ∧ Low(GSR)	$S4 = R * 4$
Very Stressed	VeryHigh(HR) ∧ VeryHigh(HRV) ∧ VeryHigh(RR) ∧ VeryLow(SpO2) ∧ VeryLow(GSR)	$S5 = R * 5$

$$\text{Trapezoidal\_Type\_R} = \begin{cases} 0 & ,x > b \\ \frac{b-x}{b-a} & ,a \leq x \leq b \\ 1 & ,x < a \end{cases} \tag{9}$$

$$\text{Trapezoidal\_Type\_L} = \begin{cases} 0 & ,x < a \\ \frac{x-a}{b-a} & ,a \leq x \leq b \\ 1 & ,x > b \end{cases} \tag{10}$$

$$\text{Triangular\_Function} = \begin{cases} 0 & ,x \leq a \\ \frac{x-a}{c-a} & ,a < x \leq c \\ \frac{b-x}{b-c} & ,c < x < b \\ 0 & ,x \geq b \end{cases} \tag{11}$$

$$Stress = \frac{S1+S2+S3+S4+S5}{R1+R2+R3+R4+R5} \tag{12}$$

C. Experimental Procedure

In the scope of this work, experiments were carried out, with 16 volunteers. Specific biometric information for the volunteers is presented in Table IV below. All participants were informed about the experiments and gave their verbal consent. None of the participants reported any mental, cardiac, respiratory, or other disturbances. However, due to the poor quality of some physiological signs obtained, data from 2 participants were excluded from the analysis.

TABLE IV
VOLUNTEERS SPECIFIC BIOMETRIC INFORMATION

-	Male Gender	Female Gender	Total
Participants	12	4	16
Age Range	16 – 91	26 – 71	16 – 91
Average Age	44	45	44
Standard Deviation of Ages	23	16	22

Previous research [2] validated proposed models for estimating HR, HRV, RR, and SpO2 from PPG signal acquisition and processing. However, the architecture of the sensory system was updated, including the replacement of the PPG MAX30100 sensor with the PPG MAX30102 sensor, which opened the possibility of enhancing the accuracy of the methods.

Bearing this in mind, the goal these experiments was to evaluate the response of the human body to induced thermal stress. To this end, the experiments were conducted at room temperature in a controlled environment. The participants remained seated and at rest during the entirety of the experiments. Participants were instructed to use their right hand to engage with the sensory system to collect physiological parameters (HR, HRV, RR, SpO2), and their left hand as the target of thermal stress induction (hot and cold). Limits were established to guarantee the participants physical integrity, and as such, it was defined as low temperature 20ºC [52] and high temperature 40ºC [53].

Regarding the experimental material, the sensory system developed, two containers with water (one with cold water and the other with hot water), ice (temperature adjustment), and a food thermometer were used.

The experiments had the following 5 phases:

- **Phase 1 - Rest Period:** this phase lasted 5 minutes, in which the physiological parameters were acquired, thus intended to establish a baseline for each participant.
- **Phase 2 - Induction of Thermal Stress with Cold:** this phase took place immediately after Phase 1 and lasted 1 minute, in which the participants physiological parameters were monitored when in contact with cold. This phase did not exceed 1 minute, so as not to endanger the participants physical integrity.
- **Phase 3 - Recovery Period:** based on specialized advice in the Thermography research field, this phase lasted 10 minutes, the period necessary for the human body to recover from contact with cold. This phase took place immediately after Phase 3, that is, the participants removed their hands from the cold and kept them at room temperature, that is, without any kind of heating, thus serving to monitor the participants recovery capability.
- **Phase 4 - Induction of Thermal Stress with Heat:** this phase took place immediately after Phase 3 and lasted 1 minute, with the participants' physiological parameters being monitored when in contact with heat. This phase did not exceed 1 minute, so as not to endanger the participants physical integrity.
- **Phase 5 - Recovery Period:** as in Phase 3, a duration of 10 minutes was also defined, the period necessary for the human body to recover from the contact with the heat. This phase took place immediately after Phase 4, that is, the participants removed their hands from the heat and kept them at room temperature, that is, without any type of cooling, thus serving to monitor the participants recovery capability.

At the end of each phase, each participant was asked to assess stress level on a scale from 1 to 5, which served as reference values for the validation of the Fuzzy Logic technique's results.

As previously stated, the sensory system acquires samples of each physiological parameter every 10 seconds, for a total of 30 samples every minute. Thus, given the total duration of the experiments (27 minutes), a total of 810 samples were acquired, consisting of 162 samples per each physiological parameter.

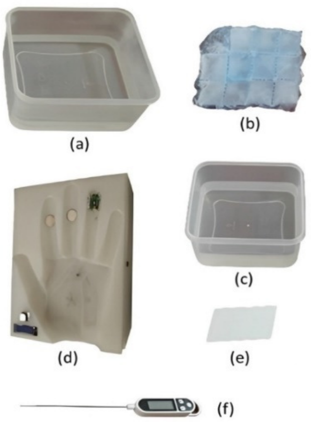

Fig. 5. Experimental Setup. (a) Container with hot water. (b) Ice. (c) Container with cold water. (d) Sensing System (measured HR, HRV, RR, SpO2 and GSR. (e) RFID identifier. (f) Food Thermometer.

IV. Results and Discussion

This section discusses the outcomes of the described experimental procedures in terms of enhancing the performance of the proposed models for estimating physiological parameters, as well as the study regarding thermal stress induction and validation of stress levels classification. Furthermore, final issues regarding the system's viability, both from a technical and user standpoint, are addressed.

A. Accuracy Enhancement of Physiological Parameter Estimation

Regarding the methods for estimating HR, HRV, RR, and SpO2 previously presented in [2], the use of a new PPG sensor made it possible to improve the developed algorithms to achieve higher accuracy. The analysis of these methods was carried out in the same way and replicating the same conditions as in [2], with statistical analyses being carried out in accordance with the measurement of type A uncertainties, i.e., data collected from a series of observations and evaluated using statistical methods, namely relative error. The reference values were obtained using equipment such as the Medlab P-OX100 medical metre (HR and SpO2 measurement), methods such as RMSSD (HRV measurement), or devices like the one developed and validated in [54] (RR measurement).

Compared to the results previously obtained in [2], the maximum relative error in obtaining HR improved from 2.78% to 1.47%, while the maximum relative error in obtaining SpO2 remained at 1.02%. Maximum relative error in RR estimation remained at 9.09%.

As described in [2], HRV estimation relies on varying acquisition periods of 60, 30, and 10 seconds. In the case of the 60-second period, the maximum relative error improved from 7.41% to 1.45%, while the maximum relative error for the 30-second period improved from 12.23% to 4.35%. In the 10-second period, the maximum relative error improved from 18.52% to 7.25%. In [2] there was still a 20-second period, but this was eliminated from the algorithm due to the significant maximum relative error of 55.56%, which, although improved to 21.73%, was still not satisfactory enough to be considered.

B. Thermal Stress Induction and Validation of Stress Level Classification

The main goal of this experiment was to investigate the effects of temperature stressors on physiological parameters. In this instance, HR, HRV, RR, SpO2 and GSR are considered.

The behaviour of the acquired physiological parameters follows a pattern, in the sense that, thermal stress induction leads to significant increase in physiological parameters values. In contrast, during the recovery phases, the values of physiological parameters tend to decrease. To simplify the data analysis, the averages of each physiological parameter collected throughout the entire experiment were calculated. As an example, the HRV averages for each participant are shown in Fig. 6. Note that for the purpose of improving data exposure, we chose not to represent all participants.

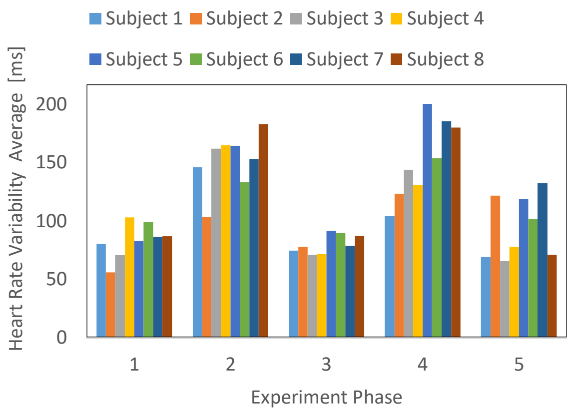

Fig. 6. HRV Averages for each Participant during each Testing Phase.

In the specific case of the GSR, after the first cold perturbation, there is a noticeable increase in the values, but in the recovery period, a large decrease in the values is not observed, as is the case with the other physiological parameters, leading us to believe that due to the strong connection between GSR and stress, it is affected longer by the stressor. Another interesting aspect concerning the GSR is that the hot disturbance serves to help relax the participants rather than as a stressful factor, as can be seen in Fig. 7.

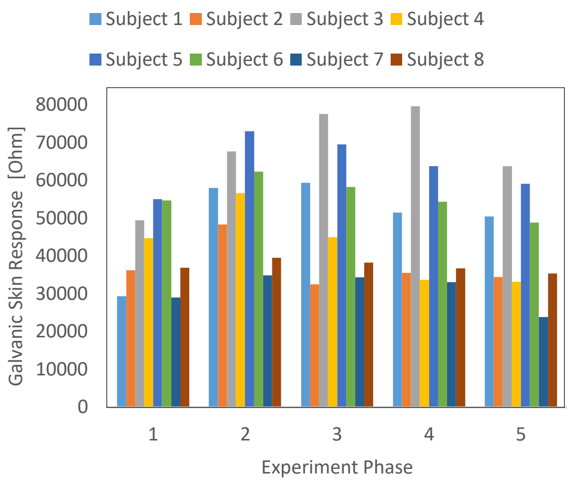

Fig. 7. GSR averages for each participant during each testing phase.

Another important thing to mention is that the participants age also influences how the human body reacts to the stressor. In the case of participants over the age of 65, the time it takes their bodies to recover is longer than that of younger participants. Furthermore, the reaction time to the stressor itself is longer. This is illustrated in Fig. 8 by comparing one of the young, randomly selected participants (age criteria ranged from 16 to 30 years) with an older, equally randomly selected participant (age criteria ranged from 60 to 91 years). In addition, the choice also had gender as a criterion, with males to be chosen (larger number of participants).

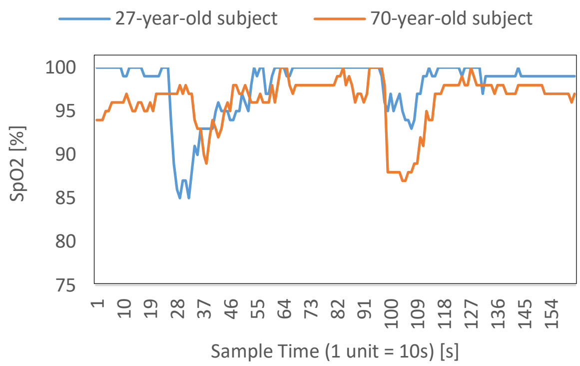

Fig. 8. Comparison between the SpO2 Values obtained by a 27-year-old Participant (highlighted in blue) and a 70-year-old Participant (highlighted in orange) throughout the duration of experiment 2 (Thermal Stress Induction).

To validate the model for estimating stress levels using Fuzzy Logic, participants were given a slider button and asked to estimate their level of stress on a scale of 1 to 5. After the experiments, the data was analysed in detail and the Fuzzy Logic methodology was applied. This resulted in a classification of stress levels from 1 to 5, which was compared to the self-classification performed by the participants. The performance of this model was evaluated using a multi-class confusion matrix presented below in Fig.9, based on which performance evaluation metrics including sensitivity, specificity, and accuracy were calculated and presented below in Table V.

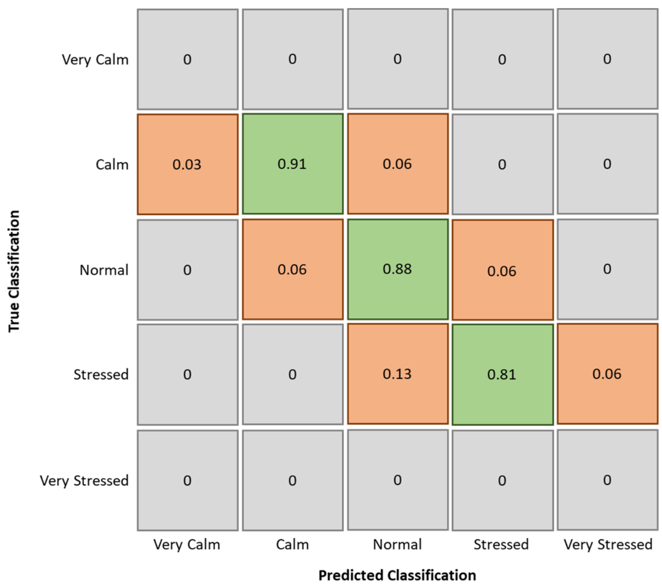

Fig. 9. Multi-class Confusion Matrix for Stress Classification Model.

TABLE V
EVALUATION METRICS DERIVED FROM CONFUSION MATRIX

Metric	Classification of Stress Levels According to the Model				
	Very Low	*Low*	*Normal*	*High*	*Very High*
Sensitivity	-	0.94	0.87	0.75	-
Specificity	1	0.92	0.90	0.97	1
Accuracy	1	0.93	0.89	0.93	0.99

In terms of results, the proposed Fuzzy Logic methodology presents satisfactory results in terms of sensitivity, specificity, and accuracy. No big discrepancy of results was found between the self-classification performed by the participants and the classification generated by Fuzzy Logic model. To further validate the model, more stress induction tests should be done in extreme settings where volunteers may report "very calm" and "very stressed" stress scores. In addition to increase the number of participants, noise or light stressors could be also considered for the stress induction.

C. Final Considerations

Volunteers proved the system's viability in real-world scenarios. All participants felt comfortable with the system's sensing component as well as the mobile application that was developed. Usability characteristics such as "intuitive" and "easy to comprehend" were underlined for all age groups. Positive comments were also provided on the system's usability. Moreover, the dynamic format for placing the human hand in the system allowed the participants to feel no discomfort while ensuring accurate data acquisition, which is often a problem because the contact between the person and the equipment is not always optimal, thereby compromising the accuracy of the acquired data.

The viability of the system's application outside of a laboratory context was also demonstrated. As previously stated in the experimental protocol, the experiments were conducted in a controlled environment and under the same conditions, however, there were situations in which participants were asked to repeat the same experimental protocol, but in different locations, to determine its impact on the obtained results. If the conditions were similar, such as room temperature and an environment unfavourable to external disturbances, among others, the acquired data were unaffected. This demonstrated the system's viability in the real world, outside of a laboratory setting. In contrast, if we consider daily activities, it is evident that the experiments could not be conducted under these conditions owing to the system's limitations, such as its size and the immobilisation of the user hand, among others. Yet, the goal was to assess the system as a solution for stress assessment, and as such, any action outside the context might affect the acquired data. Now that the system has been validated under more controlled conditions, it is possible to perform multiple activities simultaneously using the system, however, there are still some limitations in terms of movement, so a new wearable version of the system is being considered to improve the level of usability and enable the assessment of stress in daily life.

Two potential solutions are being considered for the new wearable version of the system. One of the solutions is to distribute the sensing system in a glove. Can be also considered a second design that closely resembles smartwatches. In this case, the size of the system is reduced, but a special measuring technique is required, considering the position of the sensors that requires voluntary actions of the user. The architecture may also be modified by moving the authentication part of the sensory system to the user interface, hence reducing the size of this new version significantly. In terms of characteristics and acquired physiological parameters will remain the same, however, the addition of other sensors may be considered.

V. CONCLUSION AND FUTURE WORK

Stress is a chronic condition that affects a large part of the world's population. New practical solutions that contribute positively to improving daily life are ongoing work. The new approach presented was successfully implemented, introducing a multi-channel sensory system capable of acquiring multiple physiological parameters, primarily based on Photoplethysmography, and resorting to the implementation of intelligent algorithms, which presented satisfactory results not only in the monitoring of health status, but also in the detection and classification of stress levels. The proposed method for estimating HRV, represents one of the main contributions of this work, being based on a known method, such as RMSSD, but adding a more dynamic behaviour, betting on a greater speed in presenting the results, but never compromising its accuracy. Another important contribution was the methodology adopted for the classification of stress levels based on Fuzzy Logic, which presented very satisfactory results.

As future work, one of the challenges is to make the system more robust, with the possible addition of new mechanisms and improvements. The replacement of the Fuzzy Logic technique by other more robust machine learning techniques is also part of the goals. In addition to what has already been mentioned, a first wearable prototype for real time monitoring during daily life is under development.

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