# Stress Detector System Using IoT and Artificial Intelligence


Areej Mustafa
*Dept. of Elec. and Comp. Eng.*
*University of Sharjah*
Sharjah, UAE
areejyousefm@gmail.com

Maitha Alahmed
*Dept. of Elec. and Comp. Eng.*
*University of Sharjah*
Sharjah, UAE
maitha19977@gmail.com

Aysha Alhammadi
*Dept. of Elec. and Comp. Eng.*
*University of Sharjah*
Sharjah, UAE
ayshayj.3@gmail.com

Bassel Soudan
*Dept. of Elec. and Comp. Eng.*
*University of Sharjah*
Sharjah, UAE
bsoudan@sharjah.ac.ae



***Abstract*— This work presents the design and implementation of an IoT stress detection and classification system. Three sensors, a skin conductance sensor, an ECG sensor, and a simple skin temperature sensor are integrated into a wearable device for measurement of physiological features. The measurements are communicated to a cloud server through the user's mobile phone. On the cloud, Artificial Intelligence algorithms analyze the sensor data and determine the user's current state of stress. The predicted state is fed back to the user's mobile for display and suggestion of stress-relieving activities. In case of emergency stress levels, a message is forwarded to the physician who can access the data through the cloud server's interface. The system is able to achieve 97.6% accuracy binary classification based on real-time sensor data.**



***Keywords—Stress Detection, Skin Conductance Sensor, Electrodermal Activity Sensor, IOT, Artificial Intelligence, Wearable.***


## I. Introduction

### A. Motivation

In modern life, stress has become a common problem, as it has a major negative effect on people's health and performance. Research consistently shows that stress raises the risk of serious heart problems [1]. This has motivated the design of a device that detects a person's stress level and suggests solutions to reduce the stress level through a mobile application. Different AI methods were implemented in this project to identify a person's stress level with the highest accuracy possible.

A number of designs have been previously attempted for similar purposes. In [2], electrodermal activity (EDA) electrodes were integrated in a wristband to make it lightweight and easier for use in daily life. The system however only measures skin conductance changes from the wrist; which has been shown to be less accurate. The system also only takes measurements and does not perform any analysis to detect stress level.

In [3], a wearable wireless multi-sensor device was implemented that uses a photoplethysmograph (PPG), an EDA sensor, a 3-axis accelerometer, and a temperature sensor. These sensors are integrated in a wristband to make it comfortable and lightweight. The system has a software application that sends the data to a desktop computer using Bluetooth. This system is intended only for research as it only measures the values but does not perform analysis or provide user feedback.

In [4], an EDA sensor was integrated into a sock in an attempt to increase user comfort. Hence the EDA measurement will be taken from the sole of the foot. An experiment was done to see the difference between the data collected on the hand and on the foot, and it was concluded that skin conductance response work slightly better at hand than at foot. This system only measures the values but does not perform analysis or provide feedback.

A galvanic skin response device is used to detect the conductance of the skin of the user to be able to determine whether the user is under stress or not [5]. The two electrodes of the GSR are placed on the fingers to measure the skin conductance. The device sends the data it collects to the coordinator through Zigbee, and the coordinator sends the information to the computer. This system does not provide feedback to the user.

A handheld wireless skin conductance sensor has been integrated into a device used for applications such as gaming, tutoring systems, and experimental data collection [6]. The device communicates the measurements to a computer over a Bluetooth connection. The sensor's electrodes are not situated on the device itself, which helps in reducing the motion artefacts in the EDA signal. This system also simply measures the conductance value and does not provide feedback to the user.

Previous research has indicated that stress can be detected using different physiological indicators. However, it has also been shown that heart rate variability, skin conductance and skin temperature are the best indicators to detect stress. In this work, a method is being proposed to identify a person's state of stress based on changes in skin conductance, skin temperature, and heart rate variability (HRV). A wearable device implementation is proposed that combines a skin conductance sensor for detecting changes in skin electricity, an ECG sensor to detect variations in heart rate associated with stress, and a skin temperature sensor to detect the reduction in temperature on the extremities that occur when the person is stressed. Measurements taken by these sensors will be analysed in real-time through a cloud-based artificial intelligence implementation to determine the stress level of the user. Based on the results, corrective measures will be suggested through a mobile application, and in case of emergency, the user's physician may be notified.

## II. Background

When a person becomes stressed, the excretion of adrenaline and cortisol hormones increases, and the body goes into fight-or-flight response. Elevated levels of these hormones cause discernible changes in some externally measurable physiological indicators. Researchers have been using these factors to identify when a certain subject is under stress.

Some of these indicators are changes in the heartrate and redirection of blood flow towards the brain and other major internal organs. As the heartrate increases, there will also be noticeable changes in the heart rate variability (HRV), which is a measure of the variation in time between each heartbeat. This variation is controlled by a part of the nervous system called the autonomic nervous system (ANS), a low HRV leads to an increased risk of death [7]. HRV is typically higher when the heart beats are slow and gets lower as the heart beats increases. Hence, there is an inverse dependence relationship between the heart rate and HRV [8]. It can be concluded that HRV decreases under stressful conditions. In addition, sweat glands controlled by the Sympathetic Nervous System (SNS) will increase secretion of sweat, which leads to an increment in the skin conductivity [2]. Additionally, the redirection of the blood flow to the major organs causes changes in body temperature, especially at the extremities.

A previous research study examined a number of physiological signals with the aim of identifying externally discernible signals that can be used as indicators of different stress states. The data were analyzed using MATLAB in order to observe signals whose values showed significant correlation with different stress states. The study concluded that the signals in Table 1 showed strong correlation with the subject being under stress.

While the features in Table 1 showed strong correlation with stress, no closed form formula can be identified that connects specific feature values to stress state. Therefore, an Artificial Intelligence (AI) system needs to be trained on existing control data to identify stress state from real-time sensor readings. An obvious choice here was to use a supervised learning AI implementation since the problem requires classification of the input to match specific parameters.

TABLE I. PHYSIOLOGICAL SIGNALS SHOWING STRONG CORRELATION WITH STRESS

| Feature name | Description |
|---|---|
| Sum_RiseTime (s) | Sum of the rise duration of the stressors |
| Decay_Rate (lS/s) | Mean value of the decrease duration of the stressors |
| Mean_GSR (lS) | Mean value of Galvanic Skin Response (GSR) signal |
| IBI_mean (s) | Mean of inter-beat-interval corresponding to R-to-R interval |
| HR_mean (bpm) | Mean of heart rate |
| SDHR (bpm) | Standard deviation of the heart rate |
| RMSSD (s) | Square root of the mean of the squared differences between adjacent normal RR intervals |
| pNN50 (%) | Percentage of differences between adjacent normal RR intervals exceeding 50 ms |
| Peak VLF (Hz) | Frequency peak in very low frequency (VLF) range (0.04–0.15 Hz) |
| %VLF (%) | Percentage of signal power in the VLF respect to the total signal power |
| Peak LF (Hz) | Frequency peak in low frequency (LF) range (0.04–0.15 Hz) |

The WESAD database obtained from the University of California was used for training the AI system [9]. It contains 60 million samples for 15 different subjects. Each sample contains outputs from a skin conductance sensor, an ECG sensor and a skin temperature sensor. The database also contains a classification of the user's stress state. The states were identified as baseline, stressed, amusement, and meditation. The sensor sampling frequency was 700 Hz.

## III. PROPOSED DESIGN

The aim of this work was to design a wearable device that integrates three sensors: skin conductance sensor, ECG sensor and skin temperature sensor. The device will take measurements from the three sensors and transmit the data over a short distance wireless connection to the user's mobile. The mobile then forwards the readings using an internet connection a cloud-based database. The AI software running on the cloud server analyzes the readings based on learned historical parameters and identifies the user's current stress state. The results of the analysis are stored back in the database and forwarded to the user's mobile phone. At the same time, if the stress level is deemed to be at an "*emergency level*", a message is forwarded to the physician. A mobile application receives the results from the cloud server, displays the stress level to the user and suggests one of a number of solutions aimed at lowering the stress level. The physician is given access to the data on the cloud server and can assess the case and may intervene if deemed necessary. The diagram in Fig. 1 below summarizes the interaction between the major components of the system.

The system can be coarsely divided into a group of hardware components controlled by a number of software components. The following sections describe these different subsystems and their interaction.

### A. *Overview of the Hardware*

The hardware subsystem consists mainly of the wearable device and its subcomponents. The wearable device needs to be comprised of sensors, a microcontroller and an appropriate short-range wireless communication mechanism.

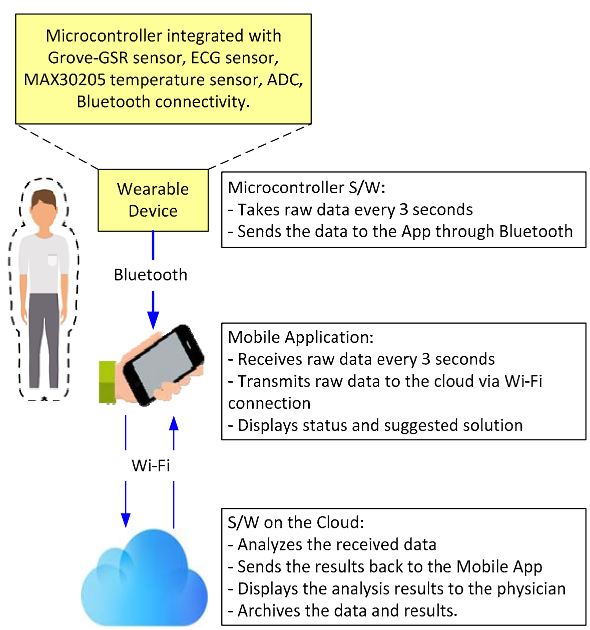


Fig. 1. High-level Conceptual Design.

Based on the previous research mentioned earlier, it was determined that three sensors are needed to measure the physiological changes associated with change in stress level. These sensors are a skin conductance sensor, a skin temperature sensor and ECG sensor. A microcontroller is needed to sample the sensor readings at specified intervals, convert their analog readings into appropriate digital format, and then transmit the values over a standard wireless communication mechanism.

The driving criteria in selecting the system components is the target of having an accurate, unobtrusive, lightweight, and reasonably inexpensive system. A byproduct of this criteria was an additional requirement of low power consumption to ensure a reasonably long use period before the need to recharge the power supply. Finally, market availability also played an important factor in the selection.

*1. ECG Sensor*

The most accurate method for measuring Heart Rate Variability (HRV) is using an ECG sensor. The ECG sensor utilizes three electrodes placed at different points on the human body as shown in Fig. 2 [9]. The readily available AD8232 ECG sensor was selected based on the criteria mentioned earlier [10]. It requires a supply voltage of 2.0 to 3.5 V and integrates a low pass filter and an ultralow power analog-to-digital convertor (ADC).

*2. Skin conductance sensor*

A skin conductance or EDA sensor uses two electrodes to measure fluctuations in current flow through the skin that can be attributed to changes in sweat gland activity affecting the skin's electrical properties. An EDA sensor's accuracy may vary significantly based on location of measurement (e.g., fingers, palm and wrist). The most accurate position has been determined to be between index and ring finger on the same hand (as shown in Fig. 3). The SA9309M EDA sensor was selected [11].

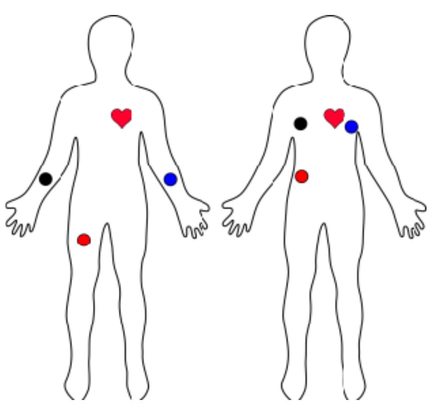

Fig. 2. ECG Sensor Placement [10].

Fig. 3. Skin Conductance Sensor Placement.

*3. Skin temperature sensor*

The normal body temperature is approximately 37°C and may fluctuate based on the subject's stress state. The plots in Fig. 4 show that the fluctuation varies in intensity depending on where on the body the measurement is taken [5]. It is observed from the insets in the figure that stress causes a more noticeable decrease in skin temperature when measured at the fingertips. The MAX30205 sensor was chosen for its accuracy ($\pm 0.1°C$) and low power consumption (about 3 mW) [12]. It is also small enough to fit easily on a user's fingertip.

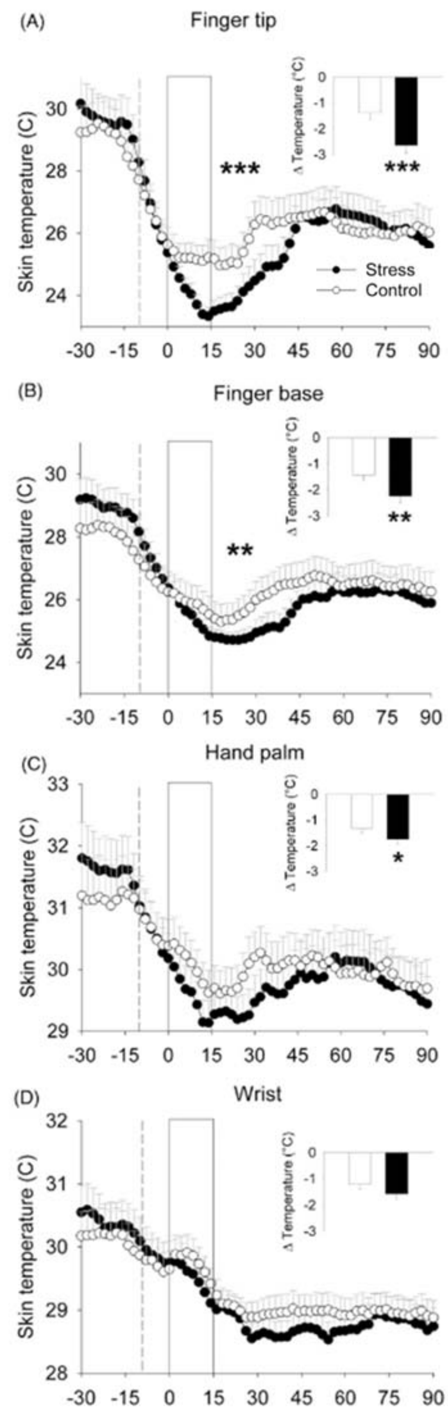


Fig. 4. Temperature Changes at Different Locations of the Human Body as a Result of Stress [5].

*4. Wireless communication between wearble and mobile*

A low power wireless communication mechanism is needed between the wearable and the user's mobile. Long distance support is not a requirement given the typical close proximity of mobile phones to their users. Bluetooth 5.0 was selected for its high data rate and a reasonably wide range of 200 meters.

*5. Microcontroller*

A microcontroller is needed as part of the wearable device for capturing readings from different sensors, converting them to digital before transmission over the Bluetooth connection. After considering a number of options, the Arduino Uno R3 was chosen as it presents adequate performance, provides enough memory space and has a suitable number of analog pins to connect the sensors. The Arduino R3 has lower power requirements as compared to the other choices.

### *B. Overview of the main software components*

*1. Microcontroller software*

The microcontroller in the wearable is expected to record samples from the three sensors every 3 seconds. The period of 3 seconds was chosen arbitrarily as it presents a reasonable compromise between enter-sample latency and amount of data to process. Once the samples are taken, the microcontroller digitizes the analog values using the onboard analog to digital converter (ADC) before sending the data over Bluetooth to the mobile. Please refer to Fig. 1.

*2. Mobile application*

The software on the mobile is expected to receive digitized sensor data every 3 seconds from the microcontroller through Bluetooth. The mobile application next forwards the data over a secure internet connection (either over WiFi or 3G) to the cloud server.

In the opposite direction the mobile application receives feedback from the cloud server about the stress state of the user. The application displays the stress state and based on the results suggests solutions for stress reduction such as listening to built-in music, meditation exercises, etc. Please refer to Fig. 1 for an illustration of the interaction between the mobile application and the other software components.

*3. Software on the Cloud*

Software on the cloud server can be broken into two main components: the database and the AI system. The digitized sensor data will be transmitted from the mobile to a cloud server over a secure internet connection. Once the real-time sensor data is received on the cloud server, it will be first stored in a database that will be used by the AI system for determining the stress state. The database is also made accessible to the physician in cases of emergency. The other main component of software on the cloud is the AI system that will be implemented in Python. Upon initialization, the WESAD database is used to train the AI system and then the trained system is used to predict the stress state whenever sensor readings are received.

Once the stress state is determined, the software on the cloud returns the information over the same secure connection to the mobile. If the stress state is deemed too elevated, an emergency message is sent to the physician with instructions on accessing the data on the server.

## IV. RESULTS

The wearable device has been implemented and successfully integrated the sensors with the microcontroller and Bluetooth connectivity. The microcontroller takes readings from the three sensors every 3 seconds. The picture in Fig. 5 shows the placement of the different sensors and the wearable device.

The mobile application was developed using the MIT App Inventor development environment. The screenshot in Fig. 6 shows the interface of the mobile application when the system first starts. The mobile application receives the sensor data whenever it is collected on the wearable device.

The mobile application then forwards the data to the cloud where it is first stored in a Firebase database [13]. Firebase was selected for its simplicity and direct connection with Python. The screenshot in Fig. 7 shows the data stored in Firebase on the cloud. This is the same database that the physician will access to check on the status of the user. A future enhancement of the system is a user-friendly dashboard of the data for the physician.

A number of AI algorithms were implemented using Python to determine the most accurate algorithm given the specific data of the sensors. The algorithms that were evaluated were the Artificial Neural Network (ANN), K-Nearest Neighbor (KNN) classifier, the Decision Tree algorithm, and Support Vector Machine (SVM). Other algorithms such as Linear Regression, and Logistic Regression were not considered since they do not directly support non-numeric classifiers.

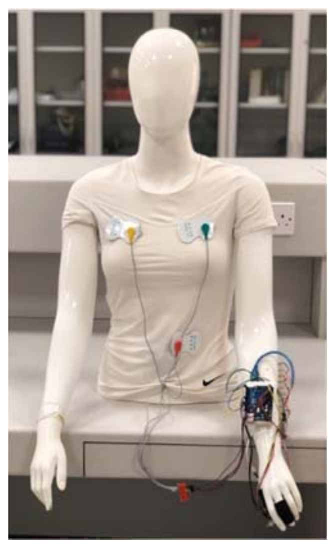

Fig. 5. Hardware Part of the System.

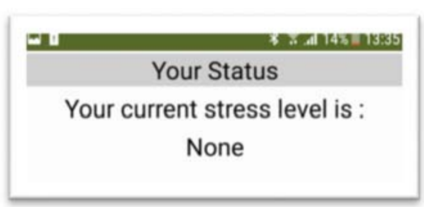


Fig. 6. Interface of the Mobile Application at First Start.

As stated earlier, the WESAD database was used for the training and evaluation of prediction accuracy. The WESAD database contains data categorized under a number of user state categories not related to stress (such as amusement). Therefore, the database was pruned to keep only readings categorized as “baseline” and “stressed”. In addition, the sensor data in the database was sampled at 700 Hz. Given that the stress state of the subject cannot change that quickly the database was down-sampled to 0.2 Hz (equivalent to one reading every 5 seconds). After adjusting the database contents, the training data size is 5148 samples containing the two classifications: baseline and stressed. Ninety percent of the database content was used for training and the remaining 10% were used to test the accuracy of the prediction.

The best accuracy achieved with KNN was when K was set to 3. The achieved accuracy was about 96%. SVM produced a disappointing accuracy of only 65%. It was not possible to get any accuracy better than 0 out of the ANN implementation. The highest accuracy achieved was using Decision Tree which produced an accuracy of 97.6% (as shown in Fig. 8). Based on this, the Decision Tree algorithm was chosen.

After completing the training phase, the system was initiated for a live real-time test. The wearable device was worn by a member of the team and all communications were established seamlessly. Once the hardware was worn by the user in the relaxed stage, it immediately started taking and transmitting sensor readings. The sensor data was automatically added in the database and the AI software analyzed the new samples and rendered a condition prediction. The mobile application displayed the status of the user which at this stage was correctly identified as “relaxed” as shown in Fig. 9.

The test subject then started running at a fast pace on the treadmill and the sensor readings started changing towards the stressed levels. As the pace increased, the readings reached the “stressed” level. The system correctly analyzed the readings and displayed the “stressed” status on the mobile screen with a number of stress reducing suggestions as shown in Fig. 10.

## V. Conclusion

An IoT stress detection and classification system has been implemented using a wearable device that communicates to a cloud server through the user’s mobile phone. Artificial Intelligence algorithms on the cloud server analyzes the real-time sensor data and predicts the current stress state. The system uses three sensors, a skin conductance sensor, an ECG sensor, and a simple skin temperature sensor. The wearable was implemented using inexpensive readily available off-the-shelf hardware. It uses wireless low-power Bluetooth to relay the sensor readings to the mobile. The wearable weighs less

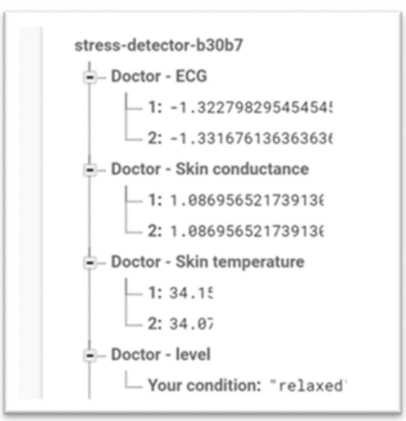


Fig. 7. Sensor Data in Firebase.

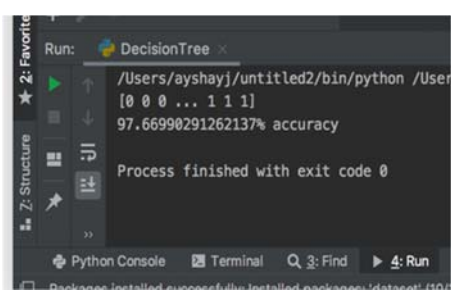


Fig. 8. Accuracy of Prediction using Decision Tree Algorithm.

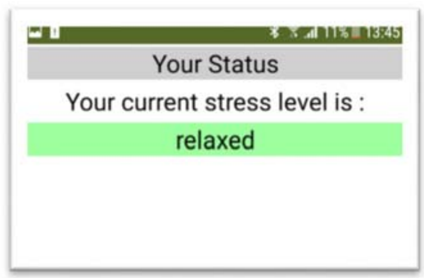


Fig. 9. Mobile Application Indicating “relaxed” State.


Fig. 10. Mobile Application Indicating “stressed” State.

than 400 grams and is powered by a power bank that can support up to 48 hours of continuous operation.

The data is forwarded from the mobile over a secure internet connection to a Firebase cloud database for archiving before being analyzed by the AI system. The AI system achieves 97.6% accuracy binary classification of the stress state. The predicted state is feedback to the user's mobile for display and suggestion of stress-relieving activities.

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