Wearable Stress Detection Device

Wearable Technologies 867H1

Felipe Martin CandNo: 260774

May 19, 2023

UNIVERSITY
OF SUSSEX

Contents

1 Introduction

Stress has become a significant health issue in modern society. With the advancements in technology, wearable stress detection devices offer the potential to monitor stress levels and provide biofeedback to help individuals manage stress. These devices often utilize heart rate variability (HVR) and skin conductance sensors to detect stress, and machine learning models to process the data.

This project provides a comprehensive feasibility analysis of wearable stress detection devices using HVR and skin conductance sensors, exploring various aspects such as socio-economic factors, hardware, software, and machine learning models.

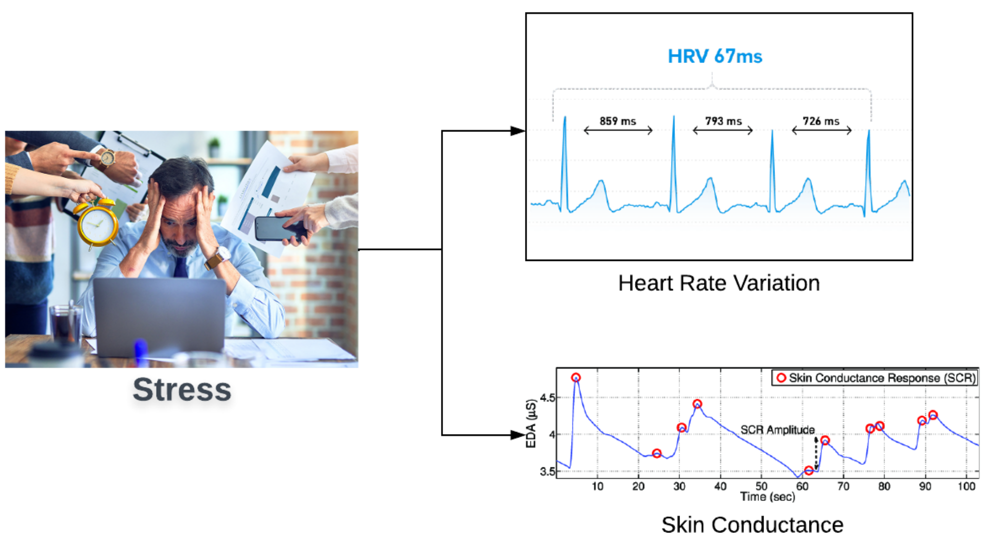
2 Heart Rate Variation

Heart rate variation (HVR) is the variation in time between heartbeats, which can provide insights into the autonomic nervous system activity and stress levels [1]. When a person is under stress, their sympathetic nervous system is activated, leading to an increase in heart rate and a decrease in heart rate variability [1][2]. A decrease in HRV has been linked to increased stress levels and may be an indicator of various health problems, including anxiety, depression, and cardiovascular diseases. Several studies have demonstrated the potential of HRV as a reliable indicator of stress levels, including in real-life situations and under different stressors [3][4].

In summary, heart rate variation can be used as an indicator of stress levels, with decreases in HRV often associated with increased stress. Wearable devices and dedicated apps can monitor heart rate and HRV to detect changes in stress levels and provide feedback to help users manage their stress.

3 Skin Conductance

Skin conductance sensors, on the other hand, measure the electrical conductivity of the skin, which can be an indicator of emotional arousal. Emotional arousal is associated with increased sweating and hence increased skin conductance. Skin conductance sensors are non-invasive and can provide continuous and real-time measurements of emotional arousal, making them an ideal tool for stress detection in wearable devices. Several studies have demonstrated the potential of skin conductance sensors as reliable indicators of stress levels, including in laboratory settings and under different stressors [5][6].

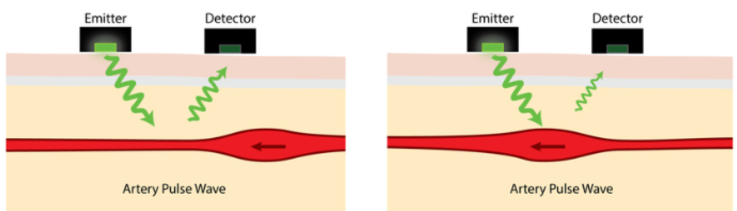


4 Feasibility analysis

Wearable stress detection devices are becoming increasingly popular due to their ability to monitor stress levels in real-time. The devices use various sensors and prediction models to detect stress levels in individuals. This feasibility analysis will focus on the use of HRV and skin conductance sensors in wearable stress detection devices.

4.1 Hardware Feasibility

The availability and suitability of sensors for measuring heart rate variability (HRV) and skin conductance are crucial considerations when designing wearable technologies. For HRV measurement, the photoplethysmography (PPG) sensor is often chosen due to its reliability and accuracy in capturing heart rate-related signals. PPG sensors utilize light-based technology to detect changes in blood volume, providing insights into HRV [7]. These sensors, commonly found in wrist-worn wearables like the Apple Watch [8], offer a compact form factor and have been validated for HRV analysis [9].



In terms of skin conductance measurement, an appropriate sensor is the electrodermal activity (EDA) sensor, also known as a galvanic skin response (GSR) sensor. EDA sensors measure the electrical conductance of the skin, which is influenced by sweat gland activity, reflecting changes in sympathetic nervous system activity and emotional arousal. Various EDA sensor options are available, including wearable electrodes or wristbands that measure skin conductance levels [10]. These sensors have been utilized in studies related to stress monitoring, emotional states, and cognitive load assessment [11].

When choosing sensors for HRV and skin conductance measurement, it is essential to consider factors such as sensor size, power consumption, compatibility with wearable devices, and the ability to obtain real-time data. PPG sensors, commonly integrated into wrist-worn wearables, offer a convenient and unobtrusive form factor for continuous HRV monitoring [8]. EDA sensors should be selected based on their compatibility with wearable devices and the ability to capture skin conductance data accurately in real-time.

To ensure the reliability and accuracy of the chosen sensors, it is advisable to refer to scientific studies that have evaluated their performance. Validated PPG sensors have demonstrated accurate HRV measurements in various research contexts [9]. Similarly, EDA sensors with proven validity and reliability in skin conductance assessment contribute to the credibility of the collected data [11].

In conclusion, the hardware feasibility of wearable stress detection devices relies heavily on the accuracy and reliability of the sensors used. HRV and skin conductance sensors are among the most commonly used sensors in stress detection devices due to their small size, portability, and non-invasiveness. These sensors have demonstrated potential as reliable indicators of stress levels, and further research is needed to optimize their performance in wearable devices.

4.2 Software Feasibility

The software feasibility of wearable technologies utilizing HRV and skin conductance sensors can be enhanced by leveraging Python programming language, adopting a cloud-based approach, incorporating wireless connectivity, utilizing machine learning techniques for stress/no stress classification, and utilizing Power BI for data visualization. These factors contribute to the development of robust and intelligent software systems for data acquisition, processing, analysis, classification, and visualization.

Data Acquisition: The software, programmed in Python, should establish wireless connectivity with the HRV and skin conductance sensors. Python provides a range of libraries for wireless communication protocols, allowing seamless data acquisition from the sensors using Bluetooth or Wi-Fi [12]. This wireless connectivity ensures mobility and convenience for the users.

Cloud-Based Approach: Adopting a cloud-based approach using Python enables scalable and secure storage and processing of physiological data. Python-based cloud platforms, such as AWS or Azure, provide infrastructure for handling large volumes of data. By utilizing cloud services, the software offloads resource-intensive tasks to remote servers, allowing real-time data synchronization and access from multiple devices [13].

Signal Processing and Analysis: Python's extensive ecosystem includes libraries such as SciPy, NumPy, and Pandas, which provide efficient algorithms for signal processing and analysis of HRV and skin conductance data. These libraries enable noise removal, feature extraction, and statistical analysis, preparing the data for subsequent classification using machine learning algorithms [14].

Machine Learning for Classification: Python's machine learning libraries, including scikit-learn and TensorFlow, can be utilized for stress/no stress classification based on HRV and skin conductance data. The software can train and deploy classification models, such as support vector machines (SVM), random forests, or neural networks, to classify physiological data into stress and no-stress categories. Machine learning techniques enhance the software's intelligence and enable personalized stress monitoring and interventions.

Data Visualization with Power BI: Power BI, a powerful data visualization tool, can be integrated with the software to create interactive and visually appealing dashboards and reports. Python provides libraries and APIs to connect to Power BI and transfer the analyzed data for visualization purposes. Power BI's rich set of visualization options and interactive features enable users to explore and understand their stress patterns and trends intuitively.

Real-Time Analysis and Feedback: Python's versatility allows for real-time analysis of physiological data. The software can perform real-time classification using machine learning models to provide immediate feedback to the users regarding their stress levels. Real-time analysis enables timely interventions or actions based on stress levels, promoting stress management and well-being.

By leveraging Python programming language, adopting a cloud-based approach, incorporating wireless connectivity, utilizing machine learning for stress/no stress classification, and utilizing Power BI for data visualization, the software for wearable technologies can achieve reliable data acquisition, efficient signal processing, real-time analysis, intelligent stress classification, and interactive data visualization, providing users with personalized stress monitoring, support, and actionable insights.

4.3 Socio/Economic Feasibility

The socio-economic feasibility of wearable stress detection devices depends on several factors, including the cost, accessibility, and acceptability of the devices. While there are several commercially available wearable stress detection devices that use HRV and skin conductance sensors, their high cost can limit their accessibility to certain socio-economic groups.

For example, the Fitbit Sense, a wearable device that includes stress detection features, costs around $300 USD as of May 2023. Similarly, the Apple Watch Series 7, which also includes stress detection features, costs around $400 USD. These prices may be prohibitively expensive for some individuals, particularly those in low-income households or developing countries.

Additionally, there may be concerns about privacy and data security that could affect the acceptability of wearable stress detection devices. Users may be hesitant to share their personal health data with third-party companies, and there may be concerns about the potential misuse of this data. These concerns may be more prevalent in certain socio-economic groups or cultures.

Despite these challenges, there is growing interest in developing affordable and accessible wearable stress detection devices. For example, researchers are exploring the use of low-cost sensors, such as photoplethysmography (PPG) sensors, to detect stress. PPG sensors measure the changes in blood flow through the skin, which can be an indicator of stress levels. These sensors can be integrated into wearable devices such as smartwatches or fitness trackers and could potentially reduce the cost of stress detection devices.

Moreover, wearable stress detection devices could have significant socio-economic benefits if they can be made more accessible and affordable. For instance, these devices could help individuals manage stress more effectively, potentially reducing the risk of stress-related illnesses. Additionally, employers could use wearable stress detection devices to monitor and manage workplace stress, which could improve employee health and productivity.

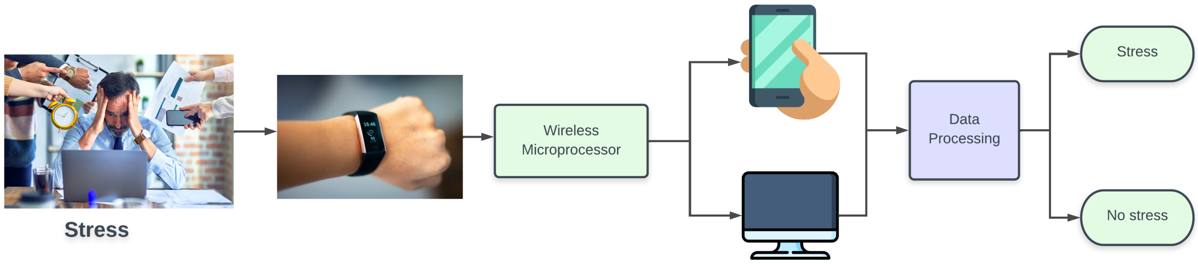
In conclusion, while the high cost and privacy concerns associated with wearable stress detection devices may limit their accessibility and acceptability, researchers and developers are exploring ways to make these devices more affordable and accessible. As these devices become more affordable and widely available, they could have significant socio-economic benefits by helping individuals and organizations manage stress more effectively.

4.4 Wearable stress detection devices in the market

- Fitbit Sense: This device measures heart rate variability and skin temperature to determine stress levels. It also includes an electrodermal activity sensor to measure sweat response. Additionally, it offers stress management tools such as guided breathing exercises and mindfulness activities. Its limitations include a high price point and limited battery life. [15]
- Garmin Vivosmart 4: This device measures heart rate variability, stress, and sleep. It also includes a relaxation breathing timer and activity tracking. Its limitations include limited accuracy for stress measurements and a small display size. [15]
- Apple Watch Series 6: This device measures heart rate variability and offers stress tracking through its Health app. It also includes a blood oxygen sensor and electrocardiogram feature. Its limitations include a high price point and limited battery life. [15]
- Samsung Galaxy Watch Active 2: This device measures heart rate variability, stress, and sleep. It also includes guided breathing exercises and activity tracking. Its limitations include limited accuracy for stress measurements and a relatively high price point. [15]
- Spire Health Tag: This device is a small, adhesive sensor that can be attached to clothing to measure heart rate variability, breathing, and activity. It also includes stress management tools such as guided breathing exercises and meditation prompts. Its limitations include limited accuracy for stress measurements and a relatively high price point. [16]

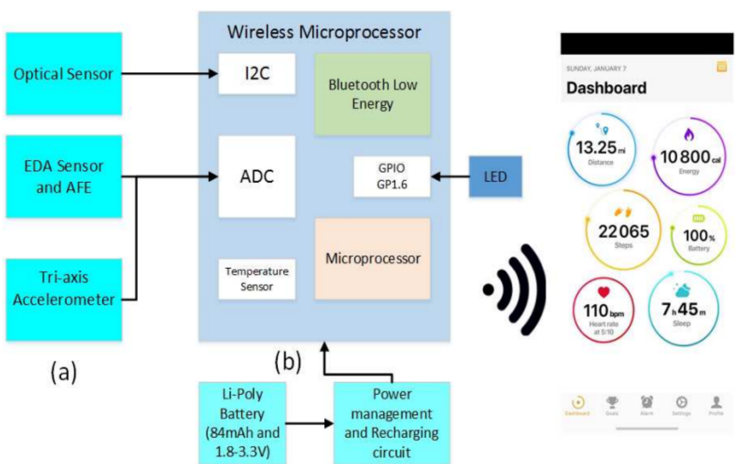
5 Conceptual Design

The conceptual hardware design will be based on the prototype of [17]. The general flowchart is shown below.



The technical characteristics of the prototype are as follows:

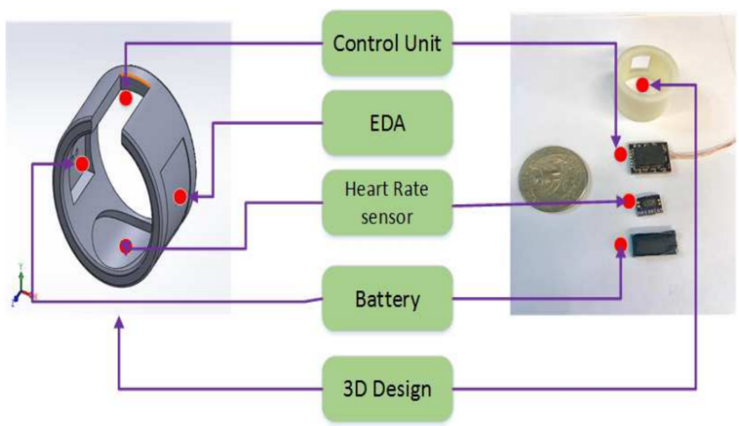
Wireless System: The wireless system is based on Bluetooth Low Energy (BLE) technology, which enables efficient and low power consumption communication between the device and other compatible devices, such as mobile phones or computers. It uses a Bluetooth Low Energy transceiver radio module that has a range of up to 30 metres and low latency. This module uses the Gazell or GZLL protocol technology, developed by Nordic Semiconductor, to establish the connection and communication.



Heart Rate Sensor: The heart rate sensor used in the device is the MAX30105 from Maxim Integrated Inc. This sensor is extremely small in size (6x3x2 mm) and communicates via I2C interface. The sensor has red, green and infrared LEDs, photodiodes and optical electronics. It uses the principle of pulsing the different LEDs and capturing the reflected signal to detect changes in blood volume and measure heart rate. The MAX30105 sensor has high ambient light rejection and is capable of operating on a supply voltage of 1.8V to 5V.

Skin Conductance Sensor (EDA): The skin conductance sensor used in the device is based on flexible silver electrodes. These electrodes are placed on the device in a suitable location to measure skin conductance. The electrodes are designed with a flexible, skin-friendly silver material. They are placed on areas of the body with a high density of sweat glands, such as the forehead, armpits, feet or fingers. The design of the device allows precise placement of the electrodes for optimal skin conductance measurement.

In short, the wireless system uses Bluetooth Low Energy technology for communication. The heart rate sensor (MAX30105) communicates via the I2C interface and uses LEDs and photodiodes to measure heart rate. The skin conductance sensor uses flexible silver electrodes placed on the device to measure skin conductance, which is an indicator of stress. These sensors and the wireless system enable the acquisition and transmission of physiological data for health monitoring and stress detection.



5.1 Classification Algorithm

In order to classify the data obtained from the sensors into stress or non stress we will use a KNN classification algorithm. This is because it was the one that obtained the best accuracy in the tests with the dataset compared to Random Forest, Decision Trees and Support Vector Machine. Below is the comparison table between the different models.

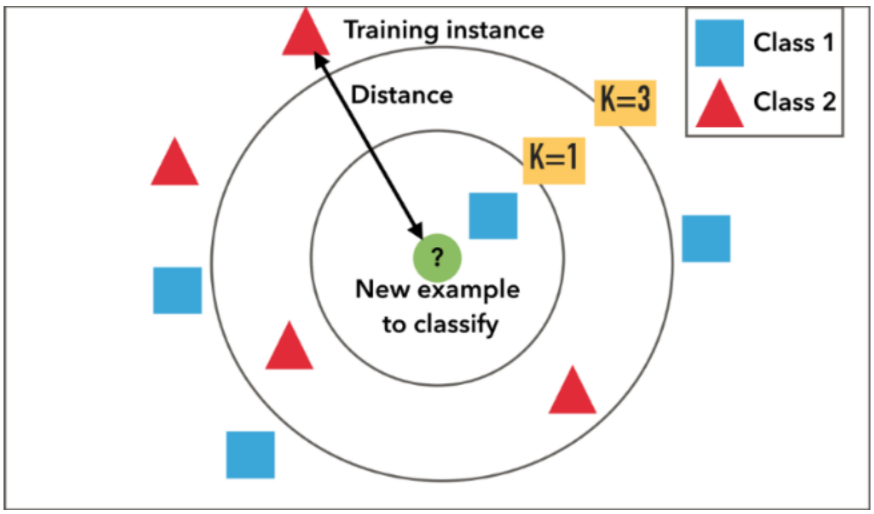
Classifier	Accuracy	Precision	Recall	F1
Decision Tree	0.668213	0.668206	0.668213	0.668206
Random Forest	0.714617	0.714779	0.714617	0.714510
KNN	0.714617	0.721531	0.714617	0.712077
SVM	0.621810	0.622096	0.621810	0.621386

5.1.1 K-Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) algorithm tries to find the points closest to a given point in order to infer its value. This algorithm can be used for both classification and regression problems.

Although simple, it is used in the resolution of a multitude of problems, such as in recommendation systems, semantic search and anomaly detection.

Its pros are that it is easy to learn and implement. Its disadvantages are that it uses the entire dataset to train "each point" and therefore requires the use of a lot of memory and processing resources (CPU). For these reasons kNN tends to work better on small datasets and without a huge amount of features.



How does KNN work?

- Calculate the distance between the point to be classified and the rest of the points in the training dataset.
- Select the "k" closest elements (with smaller distance, depending on the function used).
- Perform a "majority vote" among the k points: those of a class/label that dominate will decide their final ranking.
- Considering point 3, we will see that in order to decide the class of a point, the value of k is very important, as it will almost end up defining to which group the points will belong, especially in the "borders" between groups.

The most popular ways of measuring the closeness between points are the Euclidean distance or the Cosine Similarity (it measures the angle of the vectors, the smaller they are, the more similar they are). Recall that this algorithm - and virtually all algorithms in ML - work best with several features from which we take data (the columns of our dataset). What we understand as "distance" in real life, will remain abstract to many dimensions that we cannot easily "visualise" (as for example on a map).

6 Proof of Concept

Once the conceptual design is established, we will perform a proof of concept by focusing on the classification model that the device will use to process the data. For this, we work with a real dataset with HRV and Skin coductance measurements [18].

The full python code with data analysis, cleaning, training of the machine learning model and evaluation can be found at the following link: Github Repository

6.1 Dataset

The SWELL-KW dataset was created by researchers at Radboud University and consists of data collected from 25 subjects performing office work under different stress conditions [18]. The data includes computer logging, facial expression, body postures, ECG signal, and skin conductance and HRV. Participants went through three working conditions: no stress, time pressure, and interruptions [18] .

In the study, physiological data were collected using body sensors, specifically ECG (electrocardiogram) and skin conductance data. For the ECG, filters were applied to remove large fluctuations in the signal and obtain a filtered signal with clear peaks. A peak detection algorithm was used to count the peaks found per minute and calculate the distance between the peaks (R-R). Heart rate variability was also calculated using the root mean square of the inter-peak distances (RMSSD). One-minute intervals in which more than one unusual peak distance was found were excluded, as too large or too small distances were considered as indicators of erroneous detections. The resulting heart rate and heart rate variability data were included in the feature set. In addition, raw skin conductance data were provided. The average skin conductance level was calculated by averaging the raw signal [18].

6.1.1 Procedure and features

The experiment consisted of three blocks representing different stressor conditions, each lasting approximately one hour. Each block started with an 8-minute relaxation phase, during which a nature film clip was shown. Participants then received instructions for the tasks they needed to work on. In each block, participants were given two randomly selected topics out of six, ensuring that an opinion topic was combined with an information topic. They were asked to write two reports, one for each topic, and give a presentation on one of the topics (participants could choose). To avoid learning effects, different topics were provided in each block. Participants were given a count-down clock to track the remaining time in both stressor conditions.

After completing the tasks in each block, participants were asked to fill out a questionnaire regarding that specific block. This relaxation-tasks-execution-questionnaire procedure was repeated for blocks 2 and 3. Short breaks were allowed between the conditions, and the entire experiment lasted approximately 3 hours. Participants were debriefed after the experiment.

The feature dataset is annotated with the conditions under which the data was collected. Per participant three times 6 minutes relaxation data are included, ca. 45 minutes of working under normal conditions, ca. 45 minutes working with email interruptions and ca. 30 minutes working under time pressure. The labels in the dataset corresponding to each situation are: Rest, no stress, time pressure and interruption.

The following table is a sample of the dataset:

	Unnamed: 0	PP	C	timestamp	HR	RMSSD	SCL	date	subject	label	Condition	ElapsedTime
0	0	PP1	1	20120918T131600000	NaN	NaN	80.239727	2012-09-18 13:16:00	p1	rest	R	0
1	1	PP1	1	20120918T131700000	61.0	0.061420	77.365127	2012-09-18 13:17:00	p1	rest	R	1
2	2	PP1	1	20120918T131800000	64.0	0.049663	77.359559	2012-09-18 13:18:00	p1	rest	R	2
3	3	PP1	1	20120918T131900000	60.0	0.052487	76.728772	2012-09-18 13:19:00	p1	rest	R	3
4	4	PP1	1	20120918T132000000	61.0	0.051189	76.512877	2012-09-18 13:20:00	p1	rest	R	4
...	...	...	...	...	...	...	...	...	...	...	...	...
123	3135	PP25	3	20121107T161500000	NaN	NaN	NaN	2012-11-07 16:15:00	p25	time pressure	T	170
124	3136	PP25	3	20121107T161600000	NaN	NaN	NaN	2012-11-07 16:16:00	p25	time pressure	T	171
125	3137	PP25	3	20121107T161700000	NaN	NaN	NaN	2012-11-07 16:17:00	p25	time pressure	T	172
126	3138	PP25	3	20121107T161800000	NaN	NaN	NaN	2012-11-07 16:18:00	p25	time pressure	T	173
127	3139	PP25	3	20121107T161900000	NaN	NaN	NaN	2012-11-07 16:19:00	p25	time pressure	T	174

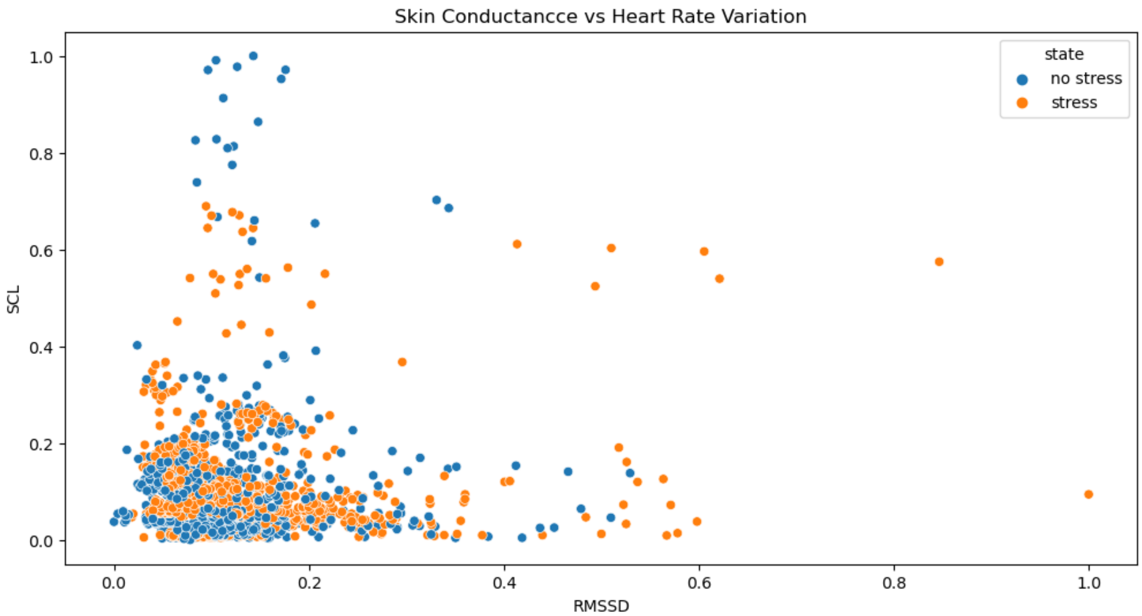
6.1.2 Cleaning data and preprocess

We perform a data cleaning process where we remove null values, duplicates and erroneous data. Then, we perform the preprocessing which consists of normalising the data. Data normalisation is a process used to scale the values of variables in a specific range. The objective of normalisation is to make variables comparable to each other and to avoid that a variable with higher or lower values has more weight in the analysis than other variables. To perform the normalisation, we use the MinMaxScaler function of sklearn.preprocessing, which contains tools for preparing and preprocessing data before using it in machine learning algorithms. The MinMaxScaler function normalises the data to a range of [0,1].

Finally, we transform the labels of the data set into stress or non-stress only. Rest and no stress were labelled as no stress and time pressure and interruption as stress. The final distribution of the data categorised into Stress and no stress is shown in the graph below.

As can be seen in the graph above, the data is balanced, which will avoid bias from one of the classes in particular.

We then plot the skin conductance vs HRV and observe that there is a different pattern of behaviour between the stress class and the non-stress class, so it is feasible to apply a classification model to obtain a prediction.



6.2 KNN model

The code utilizes the K-nearest neighbors (KNN) classification algorithm through the scikit-learn library in Python. Firstly, the KNeighborsClassifier class is imported from the sklearn.neighbors module. Then, a KNN model named KNN is created with 21 nearest neighbors. Next, the model is trained using the training data. Finally, predictions are made using the trained model on the test data, and the results are stored in a variable.

7 Evaluation

The K-Nearest Neighbors (KNN) model was evaluated using four common evaluation metrics: accuracy, precision, recall, and F1-score. Here's a description of each evaluation metric and how they are calculated in the given code:

Accuracy: Accuracy measures the proportion of correctly predicted instances over the total number of instances. It provides an overall assessment of the model's correctness. Calculation: The accuracy_score function compares the predicted labels with the true labels and returns the accuracy score.

Precision: Precision measures the proportion of true positive predictions (correctly predicted positive instances) over the total number of positive predictions (true positives + false positives). It indicates how well the model predicts positive instances accurately. Calculation: The precision_score function calculates the precision score by comparing the predicted labels with the true labels. The average='weighted' parameter indicates that precision scores are calculated for each class and then averaged based on the support of each class.

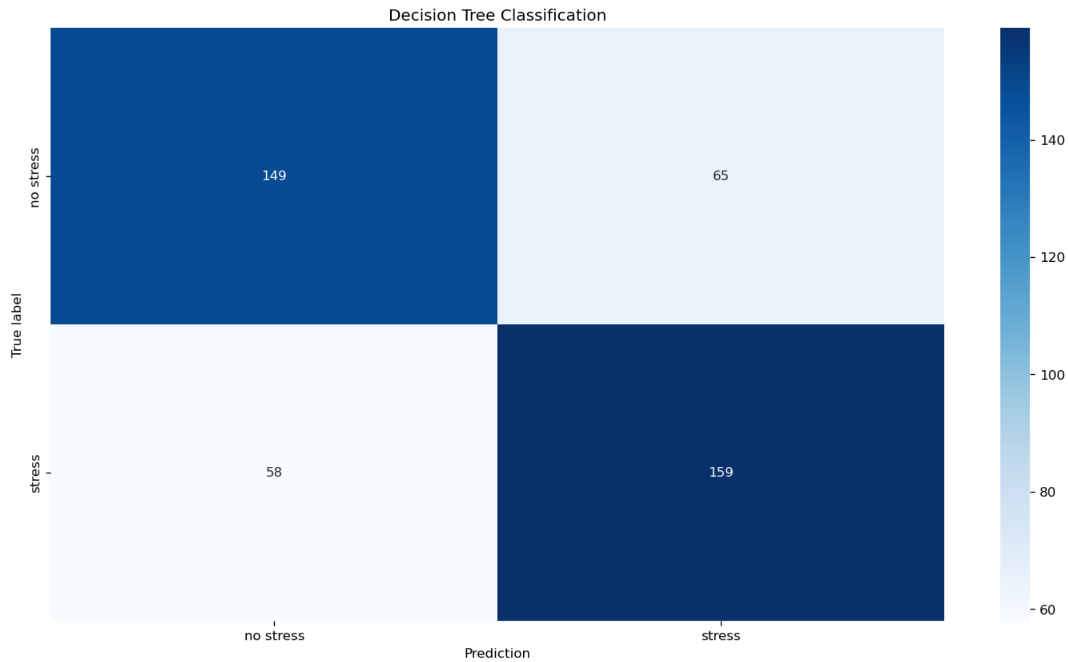
Recall: Recall (also known as sensitivity or true positive rate) measures the proportion of true positive predictions over the total number of actual positive instances (true positives + false negatives). It indicates how well the model captures positive instances. Calculation: The recall_score function calculates the recall score by comparing the predicted labels with the true labels. Similar to precision, the average='weighted' parameter indicates weighted averaging based on the support of each class.

F1-score: The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of the model's accuracy and completeness. Calculation: The f1_score function calculates the F1-score by comparing the predicted labels with the true labels. The average='weighted' parameter indicates weighted averaging based on the support of each class.

7.1 Results

The following table shows the classification matrix of the model which allows us to see the behaviour of the different metrics, and the graph shows the confusion matrix, which allows us to see where the model is failing in order to implement future improvements.

	precision	recall	f1-score	support
0	0.76	0.62	0.68	214
1	0.68	0.81	0.74	217
accuracy			0.71	431
macro avg	0.72	0.71	0.71	431
weighted avg	0.72	0.71	0.71	431



Based on the provided metrics, the KNN model shows moderate performance in classifying stress and no stress instances. Here are some general observations:

The precision of 72% indicates that out of all instances predicted as stress, approximately 72% are correct. This means there is a reasonable level of accuracy in identifying true stress instances.

The recall of 71% suggests that the model is able to capture around 71% of the actual stress instances. This indicates that the model has some ability to correctly identify stress instances, but there may be some false negatives.

The F1 score, which is the harmonic mean of precision and recall, is 71%. This indicates a balance between precision and recall. It suggests that the model is providing a reasonable trade-off between correctly identifying stress instances and minimizing false positives and false negatives.

The accuracy of 71% indicates the overall percentage of correct predictions made by the model.

In summary, the KNN model demonstrates moderate performance in classifying stress and no stress instances, with reasonable precision, recall, F1 score, and accuracy.

8 Conclusions

The evaluation of the stress detection system, including its feasibility, proof of concept, and conceptual design, provides several key conclusions. Firstly, the system demonstrates its technical feasibility by successfully collecting physiological data from body sensors, processing it, and applying machine learning techniques like the KNN algorithm for stress detection. This indicates that the system is technically viable.

Secondly, the system serves as a proof of concept by effectively capturing physiological responses related to stress through the collection of raw and preprocessed data, such as ECG and skin conductance. The successful implementation of the KNN algorithm further supports the concept by showcasing the system's ability to classify and detect stress based on the collected data.

Finally, The conceptual design of the stress detection system involves the integration of body sensors, data pre-processing techniques, and machine learning algorithms to detect and classify stress based on physiological responses. After evaluating the system as a whole, it can be concluded that it presents a promising approach for stress detection in real-world applications. However, further work is required to enhance the accuracy of the model. This can be achieved by improving the quality and representativeness of the training data, as well as increasing the volume of data to ensure a more diverse population is covered. These steps will contribute to refining the model and optimizing its performance in capturing and accurately identifying stress levels.

9 References

[**1**] Pham, T. et al. (2021) Heart rate variability in psychology: A review of HRV Indices and an analysis tutorial, Sensors (Basel, Switzerland).
Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8230044/ .

[**2**] What affects your heart rate variability? WebMD. Available at: https://www.webmd.com/heart/what-is-heart-rate-variability .

[**3**] Shaffer, F., Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. Frontiers in public health, 5, 258.

[**4**] Laborde, S., Mosley, E., Thayer, J. F. (2017). Heart rate variability and cardiac vagal tone in psychophysiological research–recommendations for experiment planning, data analysis, and data reporting. Frontiers in psychology, 8, 213.

[**5**] Boucsein, W. (2012). Electrodermal activity. Springer Science Business Media.

[**6**] Benedek, M., Kaernbach, C., Detenber, B. H. (2010). Psychophysiology in practice: A review of methodological issues in recording electrodermal activity. Humana Press.

[**7**] Allen, J. (2007). Photoplethysmography and its application in clinical physiological measurement. Physiological Measurement, 28(3), R1-R39. doi: 10.1088/0967-3334/28/3/R01.

[**8**] Apple. (n.d.). Apple Watch - Health. Retrieved from https://www.apple.com/health/

[**9**] Hernando, D., et al. (2018). Wearable Photoplethysmography Devices. In Wearable Sensors: Fundamentals, Implementation and Applications. Academic Press.

[**10**] Boucsein, W. (2012). Electrodermal Activity. In Electrodermal Activity (2nd ed.). Springer.

[**11**] Greco, A., et al. (2016). Assessment of Electrodermal Activity During Cognitive Load Using Task-Evoked Pupillary Response. International Journal of Psychophysiology, 109, 1-8. doi: 10.1016/j.ijpsycho.2016.08.011.

[12] Python Software Foundation. Python for Wireless Networks.
Retrieved from https://wiki.python.org/moin/Wireless

[13] Amazon Web Services. Python on AWS. Retrieved from https://aws.amazon.com/python/

[14] Van Rossum, G., Drake, F. L. (2011). Python 3 Reference Manual.

[15] Stress wearables: Best devices that monitor stress and how they work
Available at: https://www.wareable.com/health-and-wellbeing/stress-monitoring-wearables-explained-7969 .

[16] Spire Health Tag Review. Available at: https://www.wareable.com/wearable-tech/spire-health-tag-review-6541 (Accessed: 18 May 2023).

[17] An integrated wearable sensor for unobtrusive, continuous ... - IEEE xplore. Available at: https://ieeexplore.ieee.org/ielaam/6488907/8651406/8453031-aam.pdf .

[18] The swell knowledge work dataset for stress and User Modeling Research
Available at: http://cs.ru.nl/ skoldijk/SWELL-KW/Dataset.html .