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Extended Reality For DisasteR management And Media planning

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D3.7

Sensor data analysis for situation awareness v2

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Abstract

The current deliverable describes the main algorithms used for stress detection based on the sensor data received from the smart vest, including the experiments performed for the training of the algorithm and the results from the Vicenza pilot.

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History

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Author list

Organization	Name	Contact Information
CERTH	Vasilis Xefteris	vxefteris@iti.gr
CERTH	Stamatis Samaras	sstamatis@iti.gr
CERTH	Stefanos Vrochidis	stefanos@iti.gr
STX	Maria Pacelli	m.pacelli@smartex.it

Executive Summary

This deliverable explains the analysis of physiological sensors employed in XR4DRAMA. These sensors are embedded in a smart vest and are used in the disaster management scenario to predict the stress levels of first responders. The physiological sensors are suitable for stress detection. The main method includes extracting features from the physiological sensors, selecting the subset of features that performs better, and then feeding it to a machine-learning algorithm for the final detection of stress levels. In the deliverable, we describe the training of the machine-learning algorithm based on data collected for this cause along with results from the disaster management pilot in Vicenza.

Abbreviations and Acronyms

ECG	Electrocardiogram
GA	Genetic Algorithm
HRV	Heart Rate Variability
IMU	Inertial Measurement Unit
kNN	k-Nearest Neighbors
MSE	Mean Square Error
PCA	Principal Component Analysis
RF	Random Forest
RFE	Recursive Feature Elimination
RSP	Respiration
SVM	Support Vector Machines
XGB	eXtreme Gradient Boosting

Table of Contents

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

The sensor data analysis module of xR4DRAMA, developed in T3.1 of WP3, is responsible for analyzing the data received from the smart sensor input, as also described in D3.1.

The sensor data analysis module receives data from the smart vest worn by the first responders. The smart vest is equipped with sensors capable of monitoring the users' electrocardiograph, respiration data, and inertial measurement unit data. The outcome of this analysis is the prediction of the stress of the first responders wearing the smart vest during the disaster management use case. Stress detection is also performed using voice recordings of the first responders as described in D3.10. The two different stress level detection modules' results are combined into a unique stress level through the fusion module, also described in D3.10.

In Figure 1 the position of the sensor data analysis module in the xR4DRAMA architecture can be seen. The sensor data analysis module receives data from the smart sensor inputs, predicts stress levels based on the received data, and feeds these results to the multimodal information fusion and semantic representation component of the xR4DRAMA architecture.

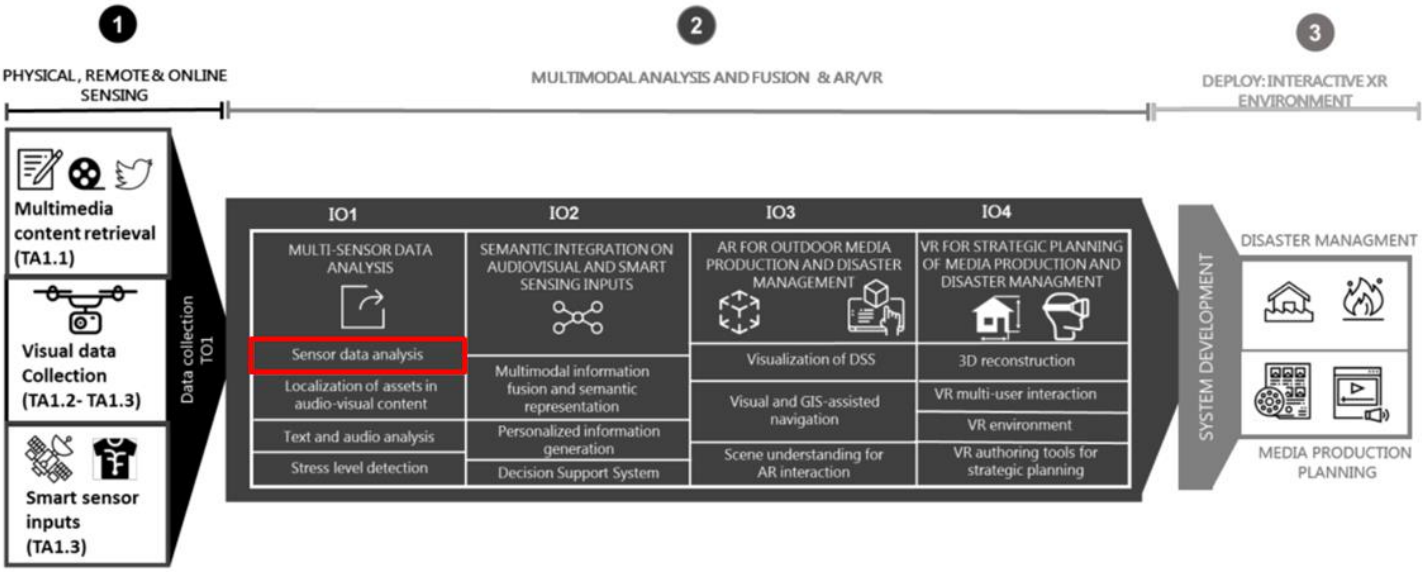

Figure 1. The position of the sensor data analysis component in the xR4DRAMA architecture.

In this deliverable, the final version of the sensor data analysis module is described. In Section 2 we describe the training of the module including feature extraction and different fusion and feature selection methods. In Section 3 the results of the training of the module are presented along with the deployment of the final model and the results from the Vicenza pilot.

2 SENSOR DATA ANALYSIS

In this Section, we describe the training of the final sensor-based stress level detection module, including the feature extraction and the different fusion and feature selection methods tested.

2.1 Training of version 2 of sensor-based stress detection

The sensor-based stress level detection is based on analyzing the data received from the smart vest described in D2.4 in order to predict the stress level of the user wearing the smart vest. The data includes electrocardiographic (ECG) data, respiration measurement (RSP) data, and inertial measurement unit (IMU) data, including a 3-axis accelerometer, gyroscope, magnetometer, and quaternion measurements. Examples of these data can be seen in Figure 2.

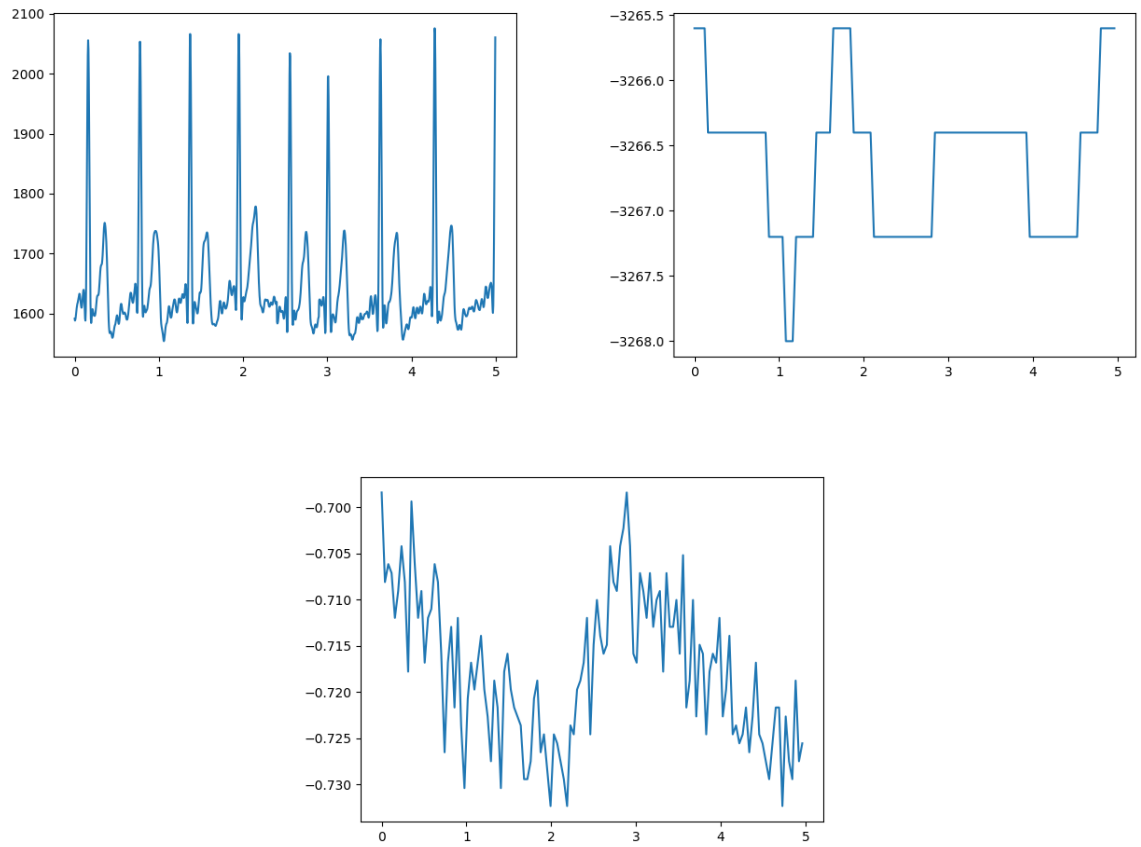

Figure 2. Examples of data collected from the smart vest. Figure 2a includes ECG data from the smart vest. Figure 2b includes RSP data from the smart vest. Figure 2c includes single-axis accelerometer data of the IMU from the smart vest.

These data are first processed in order to extract features from them and are fed into a pre-trained model for stress level detection. In the following subsections, we describe the main methods for feature extraction and the different model tested along with the fusion and feature selection methods used.

2.1.1 Feature extraction from sensor data

After receiving the data from the smart vest, preprocessing is necessary in order to transform the data into a more exploitable form. This preprocessing includes simple transformation by multiplying the signals with certain weights. After being preprocessed, the signals from the different modalities are further analyzed in order to extract useful features from them. According to the type of modality, a different feature set was extracted.

From the ECG data, statistical and frequency domain features regarding the signal, the R-R[1] intervals, and the heart rate variability (HRV) were extracted. For the extraction of these features, we made use of the hrv-analysis toolbox[2] and the neurokit2 toolbox (Makowski, 2021) for Python. The RSP feature set includes statistical and frequency features of the signal, breathing rate, respiratory rate variability, and breath-to-breath intervals. The respiration features were also extracted using the neurokit toolbox (Makowski, 2021) for Python.

The quaternion data from the IMU modality were transformed into Euler angles or roll pitch and yaw angles; roll is rotation around x in radians (counterclockwise), pitch is rotation around y in radians (counterclockwise), and yaw is rotation around z in radians (counterclockwise). For the IMU feature set, we extracted simple time and frequency domain statistical features for each one of the single-axis IMU signals. These features are: *mean, median, standard deviation, variance, maximum value, minimum value, interquartile range, skewness, kurtosis, entropy, energy, and 5 dominant frequencies*.

The feature extraction process was performed using a 60-second moving window with a 50% overlap for the evaluation process. The total number of features is 314 features; 94 ECG features, 28 RSP features, and 192 (16 per single-axis data * 12 single-axis signals) IMU features. A detailed description of the features extracted can be seen in Appendix A.

2.1.2 Fusion methods

Since there are three different modalities deployed in the smart vest, a fusion scheme of the different modalities should be implemented. By fusing the different modalities the system can learn more insights regarding the user's state, thus improving its stress level detection performance. For this cause, we tested different fusion methods, including both early- and late-level fusion methods. For early-level fusion, we tested simple concatenation between all pairs of modalities along with all three of them. For late-level fusion, we tested two different methods; mean and median of the predicted stress level of every single modality alone.

2.1.3 Feature selection methods

Apart from different fusion methods we also tested different feature selection methods to improve the performance of the stress level detection module. Feature selection is a procedure for reducing the input feature set length, by only keeping the most useful features, thus removing all the redundant information from the feature set. In our case,

[1] The physiological phenomenon of variation in the time interval between heartbeats

[2] https://pypi.org/project/hrv-analysis/

since we performed a massive feature extraction with a total of 314 features, feature selection can benefit the system by reducing the volume of the features. Three different methods were tested for feature selection; Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and Genetic Algorithm (GA).

RFE is a feature selection method based on the importance of each feature which is computed by the model. After the model is fitted with the feature set, the features with the smallest feature importance are removed so that the performance of the model increases. To find the optimal number of features cross-validation is used with RFE to score different feature subsets and select the best-scoring collection of features. PCA computes the variation of the input data and then gives scores to all features regarding how much of that variation they describe. In our case, we keep the top 20 features that describe most of the total variation of the whole feature set.

Finally, GA is an optimization method based on natural selection. It is a recursive procedure based on biological evolution. In each iteration, a number of individuals (chromosomes) from a population is selected to be parents over the next generation which is produced via mutation. Over successive generations, the population "evolves" toward an optimal solution. The way to assess which solution is better, a fitness function is used. In our case, the fitness function is the performance of the model. The steps followed in a GA procedure are as follows:

1. Initialization of the population of chromosomes.
2. Selection of the part of the population that survive using the fitness function as a criterion.
3. Creation of a new generation of chromosomes through a combination of genetic operators: crossover and mutation.
    - The crossover is a genetic operation used to combine two parents to create a new chromosome.
    - The mutation is a genetic operation used to maintain diversity from one generation to the next.
4. Repetition of steps 2 and 3 until a termination condition is reached.

Following these steps, the algorithm removes features from the feature set until the performance of the stress level detection model is maximized.

3 EXPERIMENTAL RESULTS

In this Section, the main results of the training experiments of the sensor-based stress level detection module are presented. We also present the result of the Vicenza disaster management pilot, including the training of the stress level detection model, the deployment of the module to the system, and the results from the collected data from the first responders.

3.1 Results from training

In this subsection, we describe the main results of the training evaluation protocol. Before presenting the results of the different feature and decision level fusion methods and the different feature selection methods, we provide a short description of the experimental protocol of the data collection for the training of the sensor-based stress level detection module.

3.1.1 Experimental protocol

The experimental protocol of the data collection for the training of the sensor-based stress level detection module is described in detail in D3.4. It is based on inducing stress in the users by performing certain challenges of high stress (stressors) followed by challenges of relaxation. This process results in alternations between high and low levels of stress during the whole experimental procedure. The users during the whole experiment were wearing the smart vest in order to record their physiological signals. After each challenge was completed the users were asked to report their stress level on a scale of 0-100.

These self-reported stress level values refer to the whole challenge that was completed, nevertheless, the utilized features were extracted using a 60-seconds time window with 50% overlap. Therefore, we assigned each 60-second window with the self-reported stress level that corresponds to this time window. The ground truth values were normalized on a scale of 0-1.

In all cases of feature- and decision-level fusion methods and feature selection methods, we tested four different machine learning algorithms. These algorithms are the Support Vector Machines (SVM) algorithm, the k-Nearest Neighbors (kNN) algorithm, the Random Forest (RF) algorithm, and the eXtreme Gradient Boosting (XGB) algorithm. All of these algorithms were used with continuous ground truth values, and all of these algorithms were used as regression models for the detection of stress levels.

3.1.2 Fusion methods results

The results of the different fusion methods tested during the training of the sensor-based stress level detection module are presented in Table 1. The different fusion methods include four different feature-level fusion methods and two different decision-level fusion methods. The results also include the performance of each modality alone.

From the different results presented in Table 1, it can be seen that the IMU modality performs better than the other two modalities when its modality is utilized alone. This can also be seen from the fusion methods where only two modalities are combined, where

combinations including the IMU modality achieve lower Mean Square Error (MSE) results than the combination of ECG and RSP.

The best-performing fusion scheme is the concatenation of all the different modalities using all different machine learning algorithms. The two different decision-level fusion methods do not perform better than the concatenation of all features using either one of the four different machine-learning algorithms. The best-performing machine learning algorithm in almost all cases is the XGB algorithm. The best-performing combination of the fusion method and machine learning algorithm is the concatenation of all features with the XGB regression algorithm achieving an MSE score of 0.073.

Table 1: MSE results of the different feature and decision-level fusion methods of the training evaluation protocol.

	ECG	RSP	IMU	ECG + RSP	ECG + IMU	RSP + IMU	HR + RSP + IMU	Late mean	Late median
SVM	0.1709	0.1530	0.1305	0.1723	0.1306	0.1305	0.1305	0.1412	0.1363
kNN	0.1439	0.1553	0.1107	0.1285	0.1106	0.1106	0.1107	0.1170	0.1125
RF	0.1113	0.1280	0.0918	0.1073	0.0916	0.0871	0.0886	0.0984	0.1025
XGB	0.1237	0.1307	0.0844	0.1092	0.0835	0.0858	**0.0730**	0.0958	0.1006

3.1.3 Feature selection methods results

Apart from the different feature and decision-level fusion methods tested during the training phase of the sensor-based stress level detection module, three different feature selection methods were also tested. Since the best-performing feature set with all different machine learning algorithms is the concatenated feature set of all different modalities, we applied the different feature selection methods to the concatenated feature set. The three different methods are RFE, PCA, and GA feature selection algorithms.

The results of the three different feature selection algorithms are presented in Table 2. From the Table, it can be seen that the best-performing method depends on the machine learning algorithm utilized. Nevertheless, the PCA feature selection method is the worst-performing method in all cases. The best-performing combination of the feature selection method and machine learning algorithm is the XGB algorithm with the use of the GA-based feature selection method, achieving an MSE score of 0.0567.

Table 2: MSE results of the different feature selection methods of the training evaluation protocol.

	RFE	PCA	GA
SVM	0.1052	0.1201	0.1305
kNN	0.1023	0.1106	0.1106
RF	0.0790	0.1044	0.0742
XGB	0.0772	0.0953	**0.0567**

Comparative results of the fusion and feature selection methods show that the GA-based feature selection method outperforms the concatenation of all features from all modalities reducing the MSE by 0.0163. In both of the cases of fusion and feature selection methods, the best-performing machine learning algorithm is the XGB algorithm using features from all the different modalities. In Figure 3 we present comparative results of the XGB machine learning using concatenation and GA-based feature selection methods along with the ground truth values. From the Figure, it can be seen that the GA-based feature selection method improves the overall performance by reducing the error between the predicted stress level and ground truth values in many cases. Apart from the improvement in the performance of the sensor-based stress detection module, the utilization of the GA-based feature selection method also reduces the volume of the incoming data, since the feature sets length is reduced from 314 to 162 features.

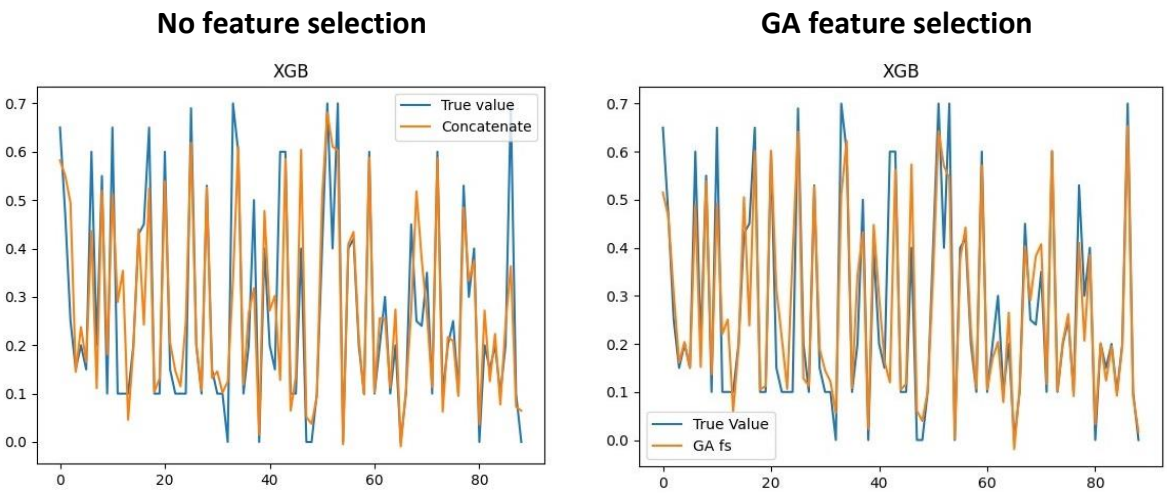

Figure 3. Plot of the ground truth stress levels reported versus the predicted stress levels using the XGB regressor with and without the use of GA feature selection technique.

3.2 Results from pilot

In this subsection, we describe the main results from the Vicenza pilot regarding sensor-based stress level detection. At first, we describe briefly the disaster management pilot scenario of Vicenza and then we delve into the sensor-based stress level detection module, focusing on its training, deployment, and results from the gathered data from the pilot.

3.2.1 Pilot data collection description

The disaster management pilot that took place in Vicenza is described in detail in D6.3. In this deliverable the whole pilot is described including the structure, context, and organization, giving a detailed picture of the actions that participants were asked to perform during the pilot scenario. In the context of this deliverable, it is important to summarize the main actions that include the first responders since they were wearing the smart vest that monitored their physiological signals which were used for sensor-based stress level

detection. The pilot includes two main phases; the pre-emergency phase and the emergency phase, and three different roles for the participants, those being the roles of control room operators, first responders, and citizens.

The pre-emergency phase focuses on the forecasting of flood incidences. In more detail, the storyline starts with the reception of an official warning message by the municipality of Vicenza, dealing with the worsening of safety conditions along the Bacchiglione river. Since the stress level detection module of the xR4DRAMA platform is not involved in this phase there is no need for further analyzing the design of the certain phase.

During the emergency phase, the first responders were asked to perform certain tasks from the control room. These tasks include sending incident reports to signal the authorities that there were flooding events in various areas of the city center. For the whole time of the emergency phase, the first responders were wearing the smart vest to monitor their stress levels in real time. There was no simulation of flood events during the disaster management pilot scenario, thus the first responders did not experience any certain stressor that could induce high levels of stress.

3.2.2 Deployment of the stress level detection module

Since the best performing combination of method and machine learning algorithm is the XGB algorithm with the GA-based feature selection method we trained an XGB model using the subset of features that the GA-based feature selection method resulted in, using the full training dataset. After training the sensor-based stress level detection model, we deployed it to the system in order to acquire data retrieved from the smart vest in real time and perform the stress level detection.

The sensor-based stress level detection module operates with 60-second long input signals. However, the received signals from the smart vest are packed in 5-seconds packages. Therefore the sensor-based stress detection module has to stack 12 5-seconds long packages together to result in a 60-seconds long package of signals to process. Each time the sensor-based stress level detection module receives a new 5-second long package it appends it to the previous stack and discards the first one, like having a 60-seconds long moving window with a step of 5 seconds. After the data from the smart vest are received and stacked, feature extraction, feature selection, and stress level detection are taking place. The full procedure can be seen in Figure 4.

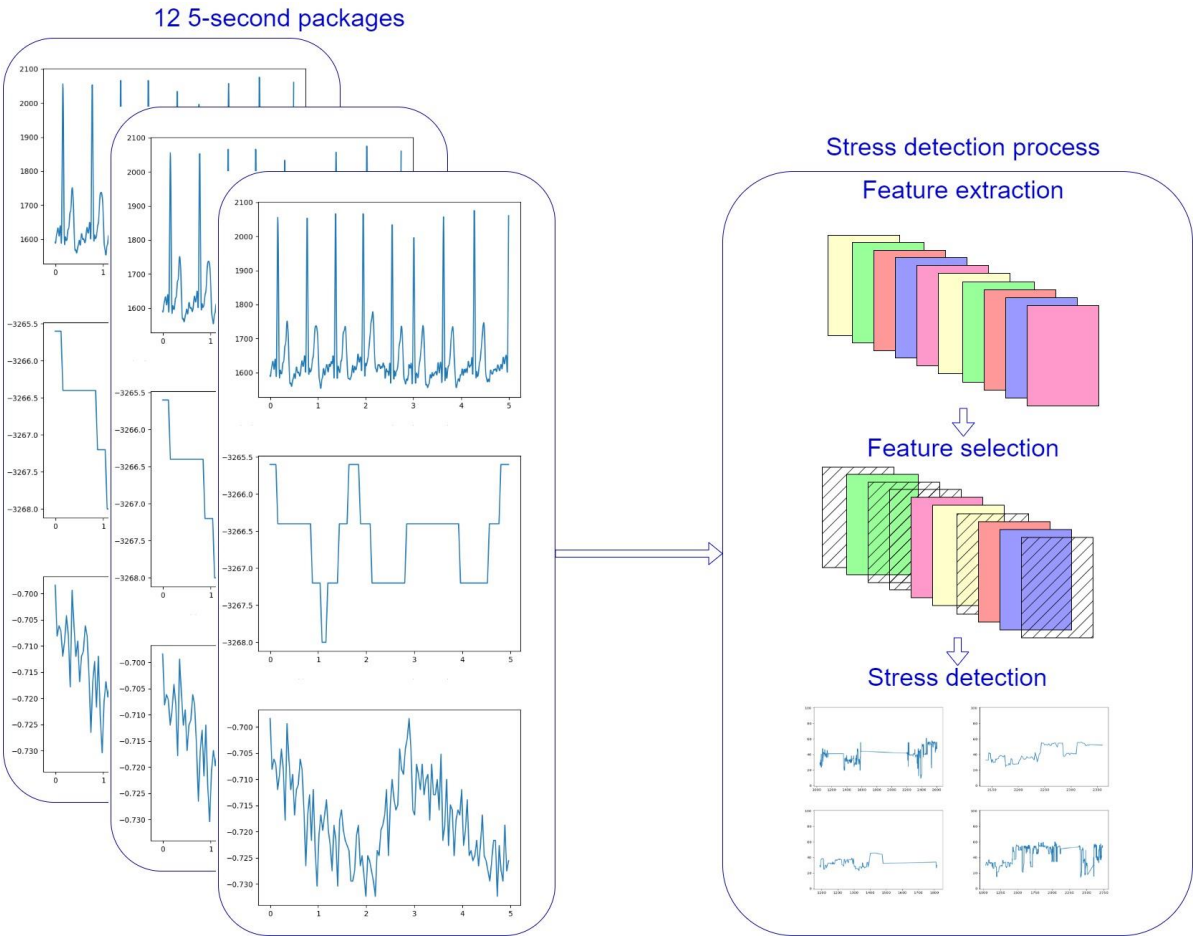

Figure 4. Workflow of the sensor-based stress level detection module during the disaster management pilot in Vicenza

The trained algorithm used for the sensor-based stress level detection along with the whole feature extraction and feature selection procedure has been implemented in Python[3], using the xgboost package[4] for the machine-learning algorithm, and the neurokit2[5] and hrv-analysis[6] packages for the feature extraction, and is deployed using a virtual environment. The stress level detection results from the sensor-based stress level detection module are accessible through the swagger found in **https://xr4drama.iti.gr:5201/**, where there are endpoints to retrieve results based on the user id, the project id, and the timestamp, or a combination of the previous.

[3] **https://www.python.org/**

[4] **https://xgboost.readthedocs.io/en/stable/python/**

[5] **https://pypi.org/project/neurokit2/**

[6] **https://pypi.org/project/hrv-analysis/**

3.2.3 Stress detection module results from pilot

The results of the sensor-based stress level detection module from the disaster management pilot can be seen in Figure 5. In the Figure the stress level of four participants during the whole experiment can be seen; each sub-figure depicts the stress levels of a different participant during the whole experiment. Since as mentioned before there was no stressor to induce high levels of stress during the experiment, the expected values of stress levels are in the range of 40 to 60, which can be described as a medium stress level. From the Figure it can be seen that in all cases the stress levels of the participants, as predicted by the sensor-based stress level detection module, are in the same range of 40 to 60, indicating that the sensor-based stress level detection module performs reasonably in terms of its precision. In terms of its process time, the sensor-based stress level detection module performs in near real-time, having a processing time of up to 1 second.

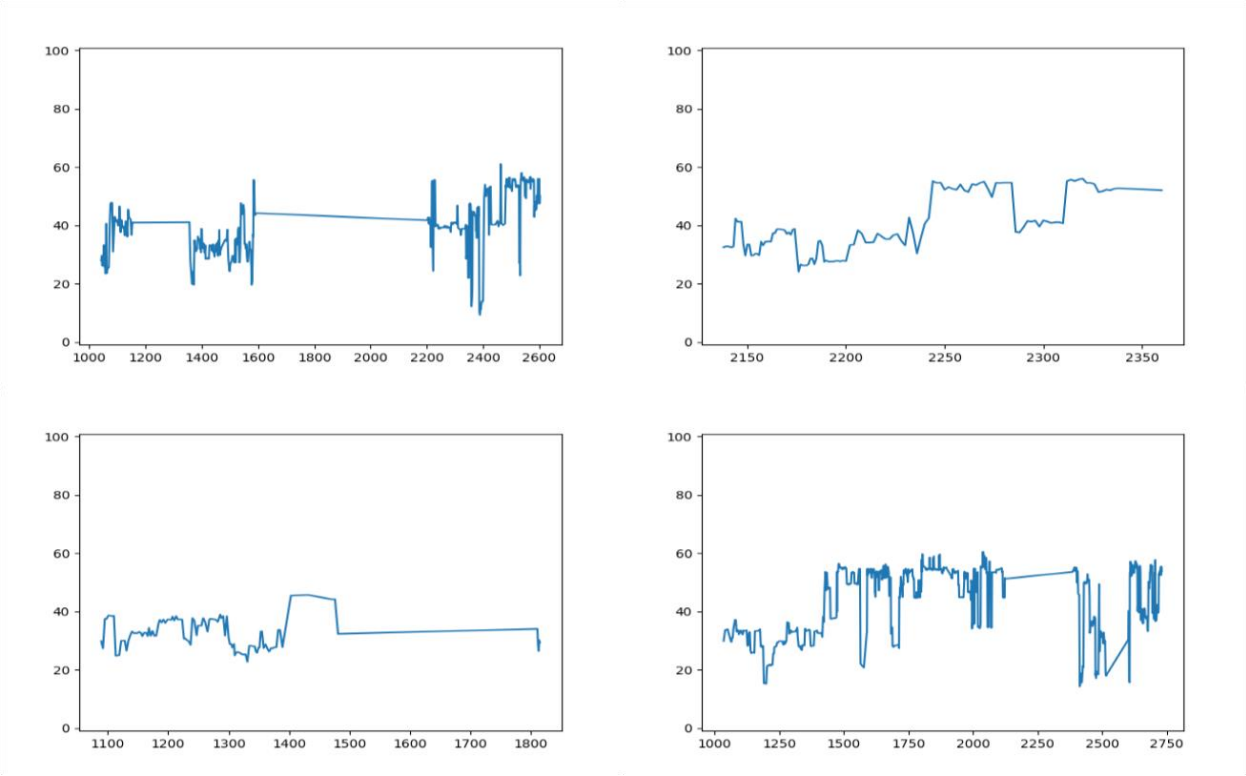

Figure 5. Stress level results of the stress detection module from data from the pilot over time. Each one of the four different plots depicts the results of a different subject.

4 CONCLUSIONS

In the current deliverable, we presented the algorithms used for the analysis of sensor data aiming to detect stress levels, along with the results from the data collection experiment and the disaster management pilot in Vicenza. The algorithm makes use of features extracted from ECG, RSP, and IMU sensors and then applies a feature selection method before feeding the remaining feature subset to a machine-learning algorithm. Results from the training of the module revealed that the XGB machine-learning algorithm along with the GA-based feature selection method achieve the best performance, with an MSE score of 0.0567. Results from the Vicenza pilot reveal that the module is able to perform in real-time and the stress levels predicted were at reasonable levels.

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A Appendix

A.1. Appendix heading

A.1.1 Appendix subheading

In Table 3 the description of the extracted features from the deployed sensors of the smart vest used for the sensor-based stress level detection are presented, separated according to the modality.

Table 3. Description of features extracted from each modality of the smart vest

Modality	Feature description
ECG	• Mean, max, min, and standard deviation of heart rate • Mean, standard deviation, median, max, min, mean absolute deviation, interquartile range, 20 and 80 percentile of the R-R intervals • Standard deviation of average R-R intervals of 1, 2, and 5 minutes data • Mean of standard deviation of R-R intervals of 1, 2, and 5 minutes data • RMS and standard deviation of successive differences between R-R intervals. • Root mean square of successive differences divided by the mean of the R-R intervals. • Standard deviation of the R-R intervals divided by the mean of the R-R intervals. • Median absolute deviation of the R-R intervals divided by the median of the R-R intervals. • Spectral power of HRV of ultra low frequencies (0 to 0.0033 Hz), very low frequencies (0 .0033 to 0.04 Hz), low frequencies (0 .04 to 0.15 Hz), high frequencies (0 .15 to 0.4 Hz) and very high frequencies (0 .4 to 0.5 Hz). • Ratio of low frequency spectral power to high frequency spectral power of HRV. • Normalized low frequency spectral power and high frequency spectral power of HRV, divided by the total spectral power of HRV. • Log transformed high frequency spectral power of HRV. • The proportion of R-R intervals greater than 20ms and 50ms, out of the total number of R-R intervals. • The baseline width of the R-R intervals distribution obtained by triangular interpolation. • The HRV triangular index, measuring the total number of R-R intervals divided by the height of the RR intervals histogram. • Standard deviation perpendicular (SD1) and along the identity line (SD2), their ratio SD1/SD2, and the area of ellipse described by SD1 and SD2 • Cardiac sympathetic index (Toichi, 1997), modified cardiac sympathetic index (Jeppesen, 2014), and cardiac vagal index (Toichi, 1997) • Percentage of inflection points of the RR intervals series. (Costa, 2017) • Inverse of the average length of the acceleration/deceleration segments. (Costa, 2017)

	• Percentage of short segments. (Costa, 2017) • Percentage of R-R intervals in alternation segments. (Costa, 2017) • Guzik's Index, Slope Index, Area Index, and Area Index of Heart Rate Asymmetry (Yan, 2017). • Short-term, long-term, and total variance of contributions of decelerations (prolongations of R-R intervals) and accelerations (shortenings of R-R intervals) (Piskorski, 2011). • Contributions of heart rate decelerations and accelerations to short-term, long-term, and total HRV (Piskorski, 2011). • Approximate, Sample, Shannon, Fuzzy, Multiscale, Composite Multiscale (Wu, 2013), and Refined Composite Multiscale (Wu, 2014) entropy of HRV. • Correlation dimension, Higuchi's fractal dimension (Higuchi, 1988), Katz's fractal dimension (Katz, 1988), and Lempel-Ziv complexity (Lempel and Ziv, 1976) of HRV • The monofractal detrended fluctuation analysis of the HR signal, corresponding to short-term and long-term correlations. • Widht, peak, mean, max, distance between minimum and maximum singularity exponents, asymmetry ratio (Orozco-Duque et al., 2015), h-Fluctuation index (Orozco-Duque et al., 2015), and cumulative function of the squared increments (Faini et al., 2021) of Multifractal Detrended Fluctuation Analysis of HRV.
RSP	• Mean respiratory rate and mean respiratory amplitude • Average and variance of inspiratory and expiratory duration, and inspiratory-to-expiratory time ratio • Mean, median, median absolute deviation, normalized median absolute deviation, standard deviation and normalized standard deviation of breath-to-breath intervals (Respiratory Rate Variability (Soni et al., 2019) • Spectral power density pertaining to very low (0 to 0.04 Hz), low (0.04 to 0.15 Hz), and high (0.15 to 0.4 Hz) frequency bands of Respiratory Rate Variability • Normalized spectral power density pertaining to low and high frequency bands, dividing the low/high frequency power by the total power of Respiratory Rate Variability • The ratio of low frequency power to high frequency power of Respiratory Rate Variability • Approximate entropy and Sample entropy of Respiratory Rate Variability • RMS and standard deviation of successive differences between breath-to-breath intervals. • Root mean square of successive differences divided by the mean of the breath-to-breath intervals. • The spread of breath-to-breath intervals on the Poincaré plot along (SD2) and perpendicular (SD1) to the line of identity, and the ratio between short and long term fluctuations of the breath-to-breath intervals (SD2 divided by SD1)
IMU	• Mean, median, standard deviation, variance, max, min, interquartile range, skewness, kurtosis, entropy, energy, and 5 dominant frequencies of single-

	axis data