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The Use of Biosensors to Analyse a Soldier's Stress Level

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Abstract: Currently and increasingly, biosensors are present in our daily lives, even if tendentiously and imperceptibly. As such and given their importance, the scientific community is clearly interested in making progress in this research field. This study is part of the study of biosensors using pre-gelled electrodes and was focused on the analysis of the ability to extract information on the quality of training, emotional state of the military, load and cognitive awareness, as well as the physical condition of the soldier of the future, through their biological signals, extracted and processed by BITalino's biosensors and microcontroller, automatically. This analysis materialized experimentally through the classification of two emotional states, calm and stress, for which up to 98.18% accuracy was achieved.

Keywords: Automatic, Biosensors, Information, Machine Learning, Microcontroller, Militar Applications

Introduction

The evaluation of the condition of military personnel can be a challenging task due to the complex situations where there is no possibility of having a health professional present to assess the military's medical condition and sometimes, when there is, there may be no means of obtaining physiological information to be interpreted by them promptly. Furthermore, in the most critical situations, the time to obtain a diagnosis is relatively limited (Lameirinhas *et al*., 2023; 2022).

Through the new technologies, it is possible to develop models that automatically allow for the detection of physiological and emotional abnormalities. These models make it possible to alert health professionals of the need to carry out screening tests in response to the detection of any anomaly that may occur, intending to reduce the effects of problems being detected lately.

Therefore, the development of solutions using machine learning models to facilitate the work of health professionals has gradually increased. The means currently used to predict physiological abnormalities consist of monitoring situations of high physical exertion by medical teams and blood and urine tests (Lameirinhas *et al*., 2023; 2022; Engana Carmo *et al*., 2021). These methods are insufficient and have proved to be ineffective in preventing the aggravation of health problems, especially in combat training.

The present work deals with the subject of biosensors and the characteristics by which their implementation in the military environment is advantageous, using components from PLUX wireless biosignals S.A.

This study aims to perform a detailed study on the information provided by the sensors of the BITalino (r) evolution plugged kit and to perform an extraction of physiological signals allowing, in an automatic way, to differentiate two distinct emotional states, calm and stress, to conclude the ways to make these systems useful in the military environment. Experimental tests and a theoretical study were conducted to achieve these objectives.

Regarding the development and insertion of this type of technology for military purposes, the member states of the European Union should follow the Stass directive (Gamella, 2017), in order to achieve standardization, interoperability, loading, and portability among all member nations.

Background

The background theoretically addresses the issues on which the present work is based, focusing on the state of the art of biosensors with utility for the soldier of the future and the creation and development of the technology, up to the present day, that allows real-time monitoring of an individual, as well as its various applications.

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Biosensors

Currently, the study and application of biosensors have, more and more, the attention of engineers. beyond the several classical applications in the medical field, a new paradigm has been created that uses an analogy of physical computing, which can be described as physiological computing (O'Sullivan and Igoe, 2004). The new applications of biosensors have become, for this reason, a topic of wide relevance in the engineering community and consequently, there is great evidence that the study of biological signals and their sensors is a growing branch of interest.

The first biosensor was developed, in 1962, by Clark and Lyons which immobilized Glucose Oxidase (GOx), to quantify the glucose concentration of a sample (Sassolas *et al*., 2012; Nambiar and Yeow, 2011). They described how to make better electromechanical sensors (pH, polarographic, potentiometric, or conductometric) by using a single oxygen electrode coupled to a counter electrode.

Biosensors have numerous advantages compared to conventional analysis because they allow the study of an individual's biological signals to be less dependent on laboratory facilities for analysis. For this reason, the cost of processes using biosensors, compared to conventional ones, makes them even more appreciated.

Biosensors have a role with temporally increasing importance in emotion recognition, with emotions being an essential aspect of communication and interaction between people. Although emotions are intuitively known, it is challenging to define "emotion". The Greek philosopher Aristotle described emotions as a stimulus to evaluate experiences based on the potential to generate pain or pleasure. Over the years, other definitions have emerged. However, today, there is still no consensus on these (Horlings *et al*., 2008). To understand these emotions through signals captured by sensors, it is necessary to use classification strategies (Liu *et al*., 2011), such as the dimensional model in Fig. 1.

Despite the difficulty of defining it precisely, emotion is always present and is an essential factor in human life. The emotional state of people strongly influences their way of communicating and also their performance and productivity. Thus, this is a highly relevant theme in the military environment to increase productivity in day-to-day life and in missions on national territory and abroad.

Machine Learning

Machine learning, as a branch of artificial intelligence, in recent years has been playing an increasingly important role in scientific research. Arthur Samuel described it as the field of study that gives computers the ability to learn without being explicitly programmed (Wiederhold and McCarthy, 1992).

Learning algorithms can be divided into several types of models according to the characteristics of the problem in question.

This study uses supervised learning algorithms, which generate a function to relate certain features of a dataset to the desired output. A model is built from data sets to make predictions on new data. Supervised algorithms can be subdivided into classification and regression problems. On one side, in classification problems, the goal is to assign an outcome from among a set of categories, such as stress or calm. On the other side, regression has as its final output a numerical value rather than a category (Ayodele, 2010).

Machine learning models have been used as a problem-solving tool in a broad spectrum of scientific and social areas. In the health field, the concept of interpretability has emerged alongside these models.

That said, interpretability must be balanced with model performance to obtain the best performance while meeting the minimum requirements for interpretability. This task becomes difficult due to the relationship between these two objectives, Fig. 2, the higher the accuracy, the lower the interpretability (Figueiredo, 2022).

Fig. 1: Dimensional model of emotions (Horlings *et al*., 2008)

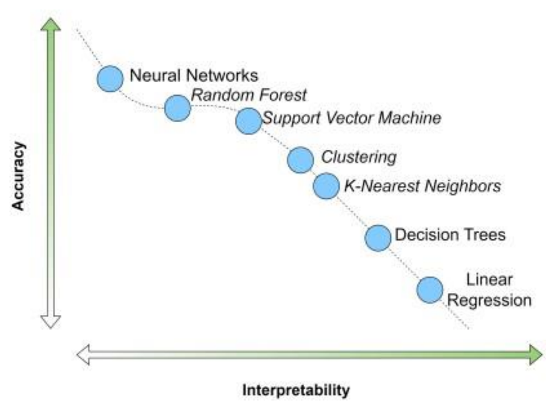

Fig. 2: Balance between interpretability and accuracy (Figueiredo, 2022)

Although this tool has proven helpful in the health area, the interpretability of the models can sometimes impede greater adoption of machine learning in real environments. In this area, only a high performance of the model validation metrics is not enough to have confidence in a machine's decision since this can have direct implications on a person's health.

Interpretability

Society management used to be done solely by human beings, but this may change.

Feature Selection

Feature selection is a pre-processing data strategy. It is characterized to be an effective and efficient way of preparing data, mainly big data. The goal of feature selection is to build more straightforward and more understandable models and make the data cleaner, improving the performance of learning models (Li *et al*., 2017). Feature selection and feature extraction are distinct techniques. Both aim to reduce the number of features in a certain dataset. However, in feature selection including and excluding attributes does not change them, whereas using feature extraction new combinations of attributes are created (Al Nuaimi *et al*., 2020). Feature selection techniques are mainly used when model interpretability is a key requirement.

Methods

The experimental methodology followed the steps presented in the diagram of Fig. 3, which will be described.

Data collection describes the test group, the test performed, and the location and reason for placing the sensors on specific body parts. The data preparation consisted of describing the process of transforming a set of scattered information in .txt files into a working matrix.

Feature selection reduces the working matrix to the most relevant data to obtain a considerably better classification. In learning and classification, are described the methods used, the parameters that optimize them, and the final results. Finally, the certification of the algorithms focuses on developing the best way to validate, through various metrics, the performance of the classification methods on a new dataset.

Data Collection

To extract biological signals for the development of classification processes, a test was conducted with 33 students, 29 from the military academy and 4 from the Air Force academy. This test consisted of watching two videos, with 6 minutes each, having the first one the objective of inducing a calm emotional state, in the green zone of the dimensional model of emotions 1 and the second of stress, in the yellow and red zone of the same model.

These videos were viewed by most of the students through the Pico 2 virtual reality glasses, with only 5 of the students taking the test by watching the videos on a laptop screen.

Figure 4 it is possible to observe the environment of the tests. It should be noted that 5 of the 33 tests were discarded due to errors during the tests, so only 28 were considered.

To obtain relevant biological information, the placement of the electrodes was very important, as it determines both the quality of the signal, as well as the comfort of the individual under test. That said, the electrodes were arranged in Fig. 5.

When performing the Electrocardiogram (ECG) the electrodes were placed, in red in the figure, on the left and right wrists (positive and negative, respectively), because there are parts of the body more accessible and comfortable to place them than the chest (most common place for performing this test) and the decrease in amplitude of the relative signal is not relevant (Němcová *et al*., 2016).

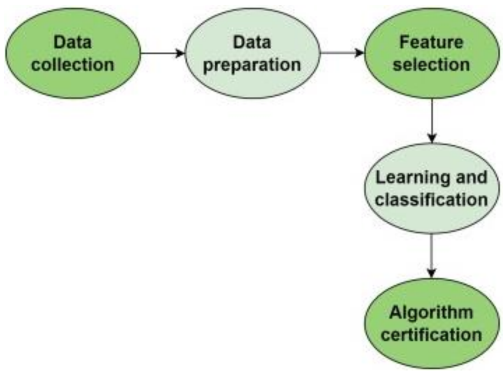

Fig. 3: Methodology of the experimental process adopted

Fig. 4: Student on the test, wearing the Pico 2 virtual reality glasses, with the biological signals, in real-time, on the monitor

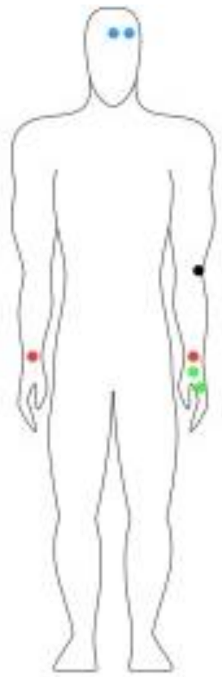

Fig. 5: Electrode placement in the human body

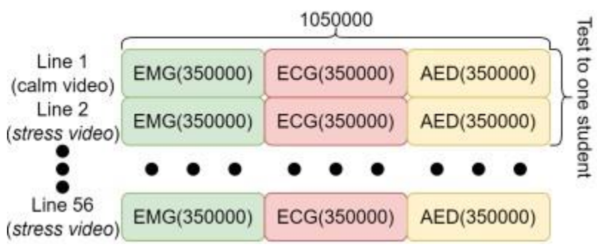

Fig. 6: Representation of the work matrix

Regarding Electromyography (EMG), the electrodes were placed above the eyebrow, blue in the figure, more specifically on the occipitofrontalis and corrugator supercilii muscles of the eyebrow, according to Chen *et al.* (2015). These refer to an old Chinese saying, "Love can be transmitted through the eyebrows", which supports the thesis of the importance of the eyebrows for emotion recognition.

The electrodes of the Electrodermal Activity (EDA), in green in the figure, were arranged on the left palm as the BITalino document indicates (EDA, 2021).

Finally, the reference, in black in the figure, is placed at the elbow because it is a bony area, as indicated in the previous articles mentioned above.

Data Preparation

The tests gave rise to .txt files with several columns, of which three are relevant to the study. The values were taken at a frequency of 1000 Hz by each of the sensors, EMG, ECG and EDA.

The quantity of extracted values was calculated, to use the maximum number of values of each test. In this way, the dimensions of the matrix where the biometric data was later loaded were prepared to develop the machine learning processes.

The average number of lines of the tests was 402141 and the minimum was 370606 and with the minimum, the data to be used was delimited. It was loaded, for the matrix to be used in the machine learning processes, the data from the 10000 line on, due to the existence of initial noise, associated with the individuals' movements at the beginning of the test. The last 15000 lines were removed, due to the movement after the end of the video and the removal of the virtual reality goggles, before the capture of biometric data was stopped.

The limits used were the 10000 and 360000 lines, creating the work matrix exemplified in Fig. 6, with dimensions of 56 lines by 1050000 columns, stored in a .npy file.

The npy files were used to store the data due to their great speed in loading the values, compared to the .txt and .cvs files.

After calculating the times, it was concluded that the .txt files took 4 min and 20 sec to be distributed by the work matrix, while the .npy file was allowed to have the same matrix, ready to use, in 0.18 sec, leading to a significant decrease in the time spent testing new classification algorithms.

Feature Selection

As mentioned above, the dataset comprises a numerical matrix of dimension 56 by 1050000. These dimensions translate into a high model complexity and become an obstacle to achieving good predictions. For this reason, the dimensions of the dataset were reduced, leading to a decline in the learning cost and better predictions with simpler models.

One of the most common feature selection methods is the selection of the *k* best features. This technique can be applied using the library sklearn (Pedregosa *et al*., 2011) library. This method takes each feature from the dataset and compares it to the result. After comparing all the attributes, *k* features are left in the resulting new dataset.

This is one of the simplest methods but should be used before more complex selection methods because it often shows good results. This method works according to a statistical criterion, which should be chosen according to the problem's characteristics. According to Brownlee (2019), given that the work problem has a numerical input and a categorical output, the most appropriate are the Analysis of Variance (ANOVA) and Kendall's.

Since the SelectkBest method, from the sklearn (Pedregosa *et al*., 2011), only supports the ANOVA statistical criterion, this was the one applied. This method allows to evaluation of the dependence of the mathematical expectation or variation of the result on the selected characteristics. Thus, it is possible to assess whether this characteristic is significant in obtaining the result.

Learning and Classification

After the selection of characteristics, several classification algorithms were applied to distinguish the observation of the first video, coded with the logic value 1, from the second video, coded with the logic value 0, corresponding to the calm and stressful emotional state, respectively. In addition, the algorithm parameters that proved to be most suitable for this specific problem were optimized. The algorithms used were linear discriminant analysis, logistic regression, Support Vector Classification (SVC) and ridge classifier.

Linear Discriminant Analysis

Linear discriminant analysis is known as a dimension reduction tool, however, it is also a robust method of classification. It is characterized by being a simple method and by producing good and interpretable results. When real problems are approached to be solved by automatic classification, this is usually one of the first methods used for benchmarking before more complex ones are applied.

This method can be used for supervised classification, considering a generic classification problem with the random variable X of one of the K classes with density $f_k(x)$ in $\mathbb{R}^p$. A discriminant rule tries to divide the information into K regions $\mathbb{R}_1,...,\mathbb{R}_k$ that represent the different classes. Using these regions, the classification done with discriminant analysis consists of allocating X to j, if X is in the region j. That said, it is necessary to know the category in which the X is. To allocate X to a region, this method can follow two rules: The highest likelihood and the Bayesian rule.

In the highest likelihood rule, assuming that each class occurs with equal probability, the X is classified with j if $j = argmax_i f_i(X)$. In the Bayesian rule, knowing the probability of each class, $\pi_i,...,pi_k$, the X is classified with j if $j = argmax_i f_i(X)$ (Xiaozhou, 2020). Whereby, the linear discriminant analysis applied, using the library sklearn (Pedregosa *et al*., 2011), follows the Bayesian rule.

Logistic Regression

Logistic regression is one of the most frequently used linear statistical models within the framework of supervised learning for classification. Linear models consist of one or more independent variables that relate to the dependent variable.

There are three types of logistic regression, the binary, where the dependent variables can only have two possible values, 1 or 0; the ordinal, for variables with ordered categories; and the multinominal, which is used when the dependent variable has three or more unordered categories. Given the characteristics of the problem to be solved, the most appropriate type is the binary (Wibowo *et al*., 2021).

Thus, to improve the final results, the training and testing percentages were changed. These percentages correspond to the amount of data used for learning and, subsequently, for testing the algorithm. By assigning the parameter k, which represents the number of data sets, the values 4-6, the percentages used for training and testing are, respectively, 75 and 25%, 80 and 20%, 83.34 and 16.66%.

In addition, the regularisation parameter, C, was varied logarithmically from 0.1-1000. This parameter can be seen as the classifier's ability to accept misclassifications in the dataset to generalize correctly with the training data, i.e., smaller values of C, translate into greater regularisation.

Support Vector Classification

The main objective of SVC is to create a boundary in a dataset composed of two different classes' elements. It relies on a statistical method based on statistical learning and error minimization in order to obtain the ability to identify the class of a new dataset.

More specifically, through feature vectors, hyperplanes are created, which act as a boundary between classes. Figure 7 is an example of learning the decision boundary (i.e., the hyperplane) by SVC (Kumar and Kolekar, 2014).

The ideal hyperplane is represented by Eq. 1, where X is the feature vector, W is the normal vector to the hyperplane and b is the offset of the hyperplane with origin:

$$W^T X + b = 0 \tag{1}$$

Therefore, in order to improve the final validation values, the training and test percentages were changed, as in the logistic regression 3.4.2. Furthermore, the smoothing parameter C was also varied logarithmically from 0.1-1000, with, as previously mentioned, smaller values of this parameter translating into greater smoothing.

Finally, several kernel functions were tested. This parameter focuses on the choice of hyperplane boundaries between classes and, for this problem, the kernel linear, RBF, sigmoid, and poly.

Ridge Classifier

A regression ridge is a linear regression. A single input variable is considered and then, being its representation a simple line. However, if more dimensions are considered, the relationship is a hyperplane that connects the output variable with the input ones. An optimization process is performed to obtain the model coefficients.

The ridge regressor has a variant classifier, the ridge classifier. This classifier first converts the binary outputs to be classified into {-1, 1} and then the problem is a regression one. Each symbol/class corresponds to the sign of the regressor.

Finally, several solver functions were tested. Each solver tries to find the parameter weights that minimize a cost function, newton-cg, lbfgs, liblinear, sag, and saga were tested.

This model, although not widely used, can lead to quite good validation results. Furthermore, the penalized least squares loss, used by the ridge classifier, allows customizing the method for the problem to be solved with the modification of the solvers (auto, svd, cholesky, lsqr, sparse cg sag, and saga) with distinct computational performance profiles, as well as, with the parameter Alpha that corresponds to $\frac{1}{2C}$, being C the regularization parameter used in other linear models such as logistic regression and linear SVC (Pedregosa *et al*., 2011).

Algorithm Certification

The evaluation of the classifiers is very important in the classification process, it is through the validation methods chosen that the performance of the model is evaluated, allowing its performance to be improved.

There are several ways to evaluate an algorithm, one of the most widely used being the accuracy value. However, on its own, it may not be sufficient to guarantee the effectiveness of the models, in practice or on a new dataset. For this reason, accuracy, sensitivity and F1-score were also used, calculated using the confusion metrics, related to the truth of the dataset and model prediction, where *TP*, *TN*, *FP*, and *FN* denote, respectively, true positive, true negative, false positive and false negative.

The confusion matrix presents the results in the form of a table with two entries, one with the actual classes and the other with the classes predicted by the model, this can be Fig. 8.

In the context of the present dissertation, *TPs* are the instances classified as stress in which the test subject was actually watching the video that induced that emotional state. *FP* are the instances in which the classes are predicted as stress, but in reality, the individual was watching the video that induced the calm emotional state. On the other hand, *TNs* correspond to the cases in which the instances were classified as calm and the video under observation was the corresponding one and *FNs* are the situations in which the classes are identified as calm, but in reality, the video was the one made to induce stress.

The evaluation methods used, calculated through the above-mentioned confusion metrics, are given by expressions 2-5:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 - score = 2\frac{precision \times recall}{precision + recall} \quad (5)$$

In addition to these evaluation methods, the cross-validation technique was used, which consists of dividing the data set into data plots. In turn, these are divided into subsets for estimating the model parameters and for model validation, previously called training and test groups.

The method used to apply this technique was k-fold, this divides the data into k sets of the same size and, from then on, one set is used for testing and the remaining *k*-1 sets are used to estimate the parameters, thereby calculating the model validation metrics. The process is performed k times by alternating the test set, as can be Fig. 9 (Cross-Validation, 2022).

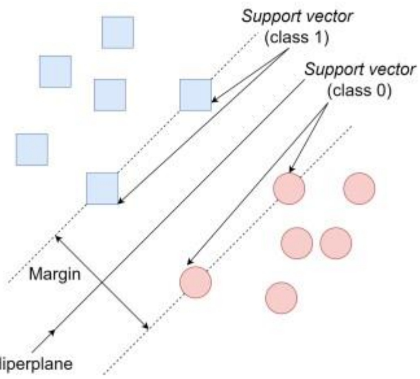

Fig. 7: Representation of a hyperplane example

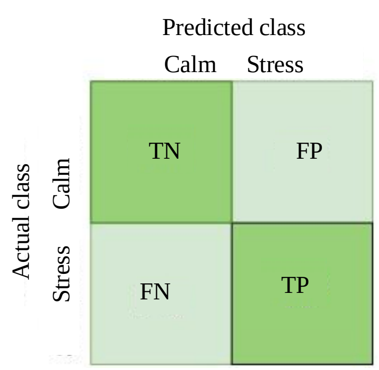

Fig. 8: Representation of the confusion matrix

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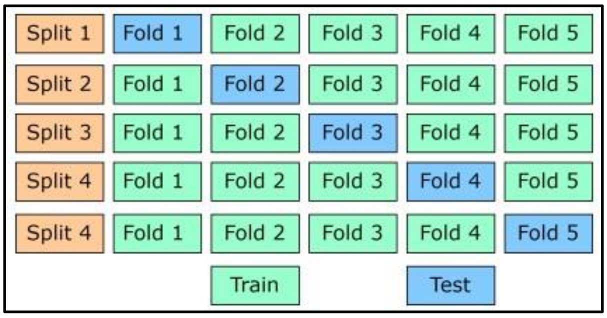

Fig. 9: Scheme of division and execution of the k-fold method with k = 5

Every k time this technique is performed, the validation metrics are calculated. In order to calculate the average of these for each iteration, four vectors were created, corresponding to each metric, in order to store these values to be used at the end of the process.

Results and Discussion

Firstly, the development of the data collection and preparation processes were overcome without too many difficulties, the most important step in these tasks being the decision and optimization of where to place the electrodes. For this reason, they were quickly and successfully completed.

Finally, the validation methods showed that the results were very good, taking into account that in this type of work, all results with accuracy higher than 90% are categorized as very good. These results can be observed in Table 1. Then, at the beginning of the project development, as is common in many machine learning works, no feature selection method was used, which led to long processing times and bad results, being that in this type of work, all the results below 60% accuracy are categorized as bad. By analyzing those results, it can be seen that this step is crucial for obtaining good classification results.

As for the learning and classification methods, several were tested and the five best ones were presented in this dissertation. It was verified that, in spite of the reduced number of tests corresponding to the lines of the work matrix, the extensive amount of features of both the complete matrix, with 10,50000 columns, and the optimized matrix, with 10,0000 columns, led to methods suitable for large amounts of information being more efficient and equally effective.

In this manner it can be concluded that it is possible through these sensors to identify with high accuracy emotional changes and to draw the conclusion that through these sensors we have the ability to detect physical anomalies, being the only obstacle to the noise associated with the movement.

Table 1: Final obtained results, using the experimental methodology

Linear discriminant analysis							
Tol	Splits	Solver	Accuracy	Precision	Recall	F1-score	Time (s)
0.001	5	svd	0.9469	1	0.9142	0.9512	5.15
Logistic regression							
C	Splits	Solver	Accuracy	Precision	Recall	F1-score	Time (s)
1	5	lbfgs	0.9818	0.9714	1	0.9777	10.6247
0,1	5	lbfgs	0.9636	0.9428	1	0.96	11.8165
100	6	liblinear	0.9629	0.9428	1	0.9481	7.53390
Support vector classification							
C	Splits	Kernel	Accuracy	Precision	Recall	F1-score	Time (s)
0,1	5	linear	0.9636	0.9428	1	0.9666	1.8947
0,1	6	linear	0.9629	0.9428	1	0.9686	2.6934
0,1	6	polinomial		0.9629	0.9428	1	0.9686
	2.3256						
Ridge classifier							
Alpha	Splits	Solver	Accuracy	Precision	Recall	F1-score	Time (s)
100	6	auto	0.9629	0.9428	1	0.9686	1.1385
100	6	cholesky	0.9629	0.9428	1	0.9686	1.2957
10	6	svd	0.9629	0.9428	1	0.9686	3.6520

Conclusion

Through the preparation of this study, it was possible to put into practice some of the theoretical and practical knowledge acquired at a military academy and institute superior Tecnico. Furthermore, the contact with the tool's open signals (Opensignals, 2021; Raybaut 2009; Pedregosa *et al*., 2011) was essential for the development of the final product.

The main goal of the work was to explore the ability, through machine learning models, to classify two emotional states using physiological data extracted by biosensors and to optimize this classification to obtain the best validation results in the shortest possible time.

Firstly, the introduction of this study was carried out, framing the theme of biosensors as technologies of interest for military purposes and defining its objectives.

In the second phase, to obtain a theoretical basis, it was studied the state of the art of the topics covered in the remaining dissertation, namely, biosensors, machine learning, interpretability, and, finally, feature selection. These contents are largely deepened and the study of biosensors is mostly directed to the medical and sports fields, being, in this way, easily transposed to its application in the Soldier of the future and, consequently, in the military environment.

Finally, it was necessary to collect data through tests performed on 33 students in order to develop classification processes. To optimize the predictions obtained, several classification models were used and these were carefully analyzed through validation metrics to verify the best solution for the problem in question.

Having finished the work, it is possible to state that all the pre-proposed objectives were fulfilled and the "incorporation of Biosensors in the soldier of the future" is a relevant and very current theme.

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Author's Contributions

José Miguel Martinho Silva: Conceptualization, software, methodology, formal analysis, written original drafted.

Ricardo A. Marques Lameirinhas: Conceptualization, investigation.

João Paulo N. Torres: Conceptualization, software, methodology, investigation, formal analysis and supervision.

Maria João Marques Martins: Conceptualization, software, methodology, investigation, formal analysis and supervision.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and that no ethical issues are involved.

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