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Abstract

Pain is a health problem that affects people physically and emotionally. To determine the pain experimented, a survey is carried out, which implies self-evaluation, honesty, and verbal or facial communication capability. In this paper, we present a comparison of two computational algorithms for two classifiers: the first classifier discriminates between pain and no pain, and the second one classifies three levels of pain. The algorithms employed were the support vector machine (SVM) and a quadratic discriminant analysis method (QDA). Acute pain was induced in fifteen participants by electrostimulation, during the experiment we assessed electromyography (EMG), electrocardiography (ECG), electrodermal activity (EDA), and electroencephalography (EEG), as well we asked the participants to report their pain perception using the visual analog scale. Subsequently, we extracted features related to pain assessment from the acquired signals. Three analyses were performed, binary classifications with multiple features, binary classifications with one feature, and three-level classifications with various features. We compared the SVM and the QDA algorithms using the confusion matrix, and the computational cost. For the binary classification, the SVM algorithm accuracy was 88.02% and the QDA algorithm accuracy was 70.78%, with a computational cost of 9.587 s and 3.023 s, respectively.

Keywords: Electrophysiological signals; Pain assessment; Feature extraction; Support vector machine; Quadratic discriminant analysis

Inteligencia computacional para la medición de presencia de dolor mediante el uso de señales electrofisiológicas

Resumen

El dolor es un problema de salud que afecta a las personas física y emocionalmente. Para determinar el nivel de dolor experimentado, se realiza una encuesta que implica autoevaluación por parte del paciente y capacidades de comunicación verbal o facial. En este artículo, se presenta la comparación de los resultados de dos algoritmos computacionales para dos tipos de clasificación: el primero discrimina entre dolor y no dolor, el segundo clasifica tres niveles de dolor. Los algoritmos empleados fueron Máquina de Soporte Vectorial (SVM) y el método de Análisis de Discriminante Cuadrático (QDA). Se indujo dolor agudo a 15 participantes por electroestimulación, se evaluó electromiografía (EMG), electrocardiografía (ECG), actividad electrodérmica (EDA), y electroencefalografía (EEG), y se le pidió a los participantes reportar el dolor percibido mediante la escala análoga visual. Posteriormente se adquirieron características de las señales asociadas al dolor. Se realizaron tres análisis: clasificación binaria con múltiples variables, binaria con una característica y clasificación de tres niveles con varias características. Se compararon los algoritmos SVM y QDA utilizando la matriz de confusión y el costo computacional. Para la clasificación binaria la exactitud del SVM fue del 88,02% y del QDA del 70,78%, con un costo computacional de 9,587s y 3,023s respectivamente.

Palabras clave: Señales electrofisiológicas; Medición de dolor; Extracción de características; Máquina de soporte vectorial; Análisis de Discriminante Cuadrático.

1. Introduction

Pain is defined as a subjective and unpleasant sensation in which perception is affected by factors such as gender, race, beliefs, and experiences, amongst others. All the population suffers from this unpleasant sensation. For example, it is present in 52.9% of the 65-year-old population in the United States (Siqueira et al., 2020). Also, a study showed a prevalence of chronic pain in children from 10 to 14 years old of 46% of this population (Stahlschmidt et al., 2018). Pain can become a health problem when it seriously affects the individual, as it affects their physical functionality, emotional health, interpersonal relationships, and quality of life DIA (2011). It also represents a social problem related to the cost associated with medical consultations and work absenteeism. Each year 15-20 percent of the total population experience acute pain, while chronic pain is twice as common (Medrano Garcıa et al., 2010). Pain diagnosis

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is relevant to evaluate possible illnesses, injuries, or specific health situations. It also helps to select a therapy, define the use of medications, evaluate a treatment progression, or control and reduce the pain considerably. Vanderbilt University physicians demonstrated the continued realization of verbal pain perception in mature people, which allows for the proper administration of pain management medications, which significantly improves the health condition (Monroe et al., 2015). Pain is usually treated with pharmacological products (Nisbet and Sehgal, 2019). Nevertheless, the incorrect administration of medicines can lead to other problems, such as addiction to painkillers, depression, or impairment of the individual's social behavior (Lusher et al., 2006; Monroe et al., 2015; Jollant et al., 2019). In the United States addiction to painkillers is increasing (Codeine, Darvocet, or Morphine), and prescription of opioids became the second most prevalent type of abused drug (4.5 million abusers; 1.37% of the population) (Van et al, 2015). Painkillers abuse is an important health problem, mainly because it could be the beginning of new drug addiction or can even cause death. By 2002, death certificates listed opioid analgesic poisoning as a cause of death more commonly than heroin or cocaine (Nora, 2014). Conventional techniques to estimate pain are based on the patient's self-report. Some of them are the visual analog scale (VAS) (Breau, 2010), the numerical classification scales (NRS); and the verbal classification scale (Petrovic et al., 2000; Briggs and Closs, 1999). Other methods related to pain assessment are based on surveys that evaluate other aspects such as feelings and relationships, as well as the evaluation behaviors related to the presence of pain, such as anger and anxiousness. Nevertheless, some people are not able to express their pain perception, such as those with cognitive or language disabilities or babies (Jollant et al., 2019). Other methods are based on computational analysis, where some characteristics related to facial and corporal patterns can be evaluated (Egede et al., 2020; Hassan et al., 2021). For example, the Facial Action Coding System helps to evaluate micro-facial expressions related to feelings like anger, fear, happiness, or sadness. There are micro-expressions related to pain such as lower eyebrows or forehead, raising cheekbones and tightening eyelids, wrinkling the nose, raising the upper lip and closing the eyes, winking, raising the edge of the lips, and chin lift, among others. The combination of micro-expressions enables the assessment of pain and its intensity of it. For newborns or children, it is employed the Child Facial Coding System (Rojo et al., 2015). To characterize the micro-expressions, some techniques are employed such as the principal components analysis (PCA), Gabor filters (Roy et al., 2016), Thin Plate Spline (Rathee and Ganotra, 2015), the Hankel

matrix (Lo Presti and La Cascia, 2017), those techniques enable feature extraction that subsequently is evaluated by classifiers such as neural networks (Rodriguez et al., 2022), convolutional neural networks (CNN) (Pikulkaew and Chouvatut, 2021), Support Vector Machine (SVM) (Rathee and Ganotra, 2015; Roy et al., 2016), Extreme Learning Machines (ELM) (Rupenga and Vadapalli, 2016) to define pain level. Several methods of pain characterization are focused on using the use of electrophysiological signals. For example, in Hadjileontiadis (2018) authors record electroencephalography signals (EEG) data during a cold pressor test experiment and analyze them using the wavelet higher-order spectral (WHOS) features to distinguish between pain or non-pain. They found that WHOS features help to differentiate relaxation from pain with an accuracy of 75%. In Hadjileontiadis (2015) authors also use the EEG signal by employing the wavelet higher-order spectral to extract features from EEG and using the quadratic discriminant analysis to classify pain. The authors obtained an accuracy of 71.31% employing the alpha waves. In Subramaniam and Dass (2021) authors use the features related to the electrodermal activity (EDA) and ECG using CNN long/short term memory (LSTM), they evaluated the classification between pain and no-pain, distinguished between males and females obtaining an accuracy of 95.79%, and 70.59% respectively. In Nir et al. (2010) authors investigate how the peak alpha frequency (PAF) is associated with the perception of pain. They used an RM-ANOVA analysis and found a statistically significant change in PAFs between conditions (resting-state, innocuous, and noxious) at the temporal electrodes ipsilateral (P=0.028) and contralateral (P=0.015) to the applied stimulation. A different approach is the analysis of pain based on the use of electromyography, for example, in Hung et al. (2014) the authors classify low back pain during lifting loadings, using features such as the root means square of the signal (RMS) and the means power spectrum density, they obtained and accuracy of 89%. On Hung et al. (2014), the authors use electromyography signals (EMG) with principal component analysis neural network (PCA) to classify LBP based on lifting capacity. The method has more than 80% of accuracy in distinguishing between healthy and back pain subjects. Finally, in Susam et al. (2018) authors use machine learning and electrodermal activity data, using timescale decomposition as the feature extraction method, and linear support vector machine as the classifier algorithm to assess pain. The authors obtained an average accuracy of 65.94%. Other works employ different signals and information, for example, Wang et al. (2020) used skin conductance, ECG, and EMG for pain recognition using Hybrid RNN-ANN Based Deep Physiological Network, where they obtained with deep

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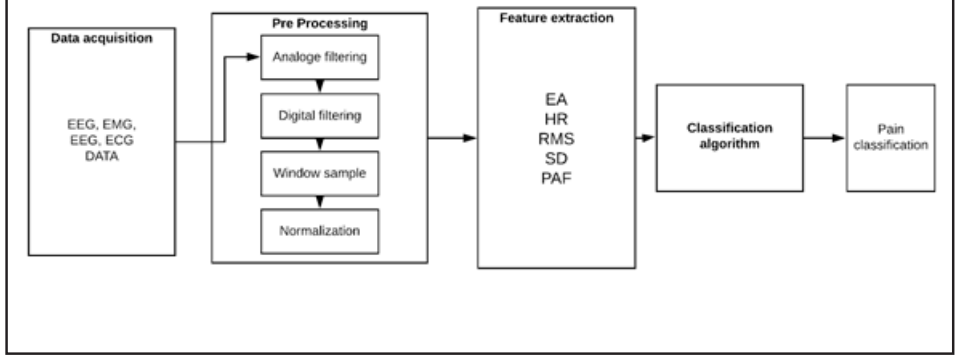
recurrent neural network accuracy of 82.7% and with Hybrid RNN – ANN an accuracy of 83.3%. This in comparison with the previous studies demonstrates an increase in the accuracy of binary pain recognition. In Erdogan and Ogul (2020), the authors assess pain based on eight vital signs: the Glasgow Coma Scale (GCS-eye opening), heart rate, oxygen saturation, pupil size (left and right), respiration rate, skin temperature, and urine color. They use four different machine learning algorithms, obtaining the best result with the Random Forest algorithm, with an accuracy of 76.1%. Despite the use of more features than other studies, the accuracy is similar to or lower than that obtained with one electrophysiological signal. In Thiam et al. (2021) the authors pre-process the signals (ECG, EDA, and EMG) with a multi-modal deep denoising convolutional auto-encoder to improve the obtained data. Afterward, they use the self-supervised learning algorithm to classify between pain and no pain. As result, they reach an average accuracy of 77.58%. This method implies a higher computational cost. On Bellmann and Schwenker (2020) authors combine ECG, EMG, and EDA features, training the algorithms with a personalized classification model using SVM and decision tree as classifiers, obtaining an average accuracy of 80.54%. Authors on Pouromran et al. (2021) compared the difference between the use of features from one or different electrophysiological signals. Using features extracted from EDA, ECG, and EMG signals with Extreme Gradient Boosting Regression and Random Forest, they concluded that EDA is the best signal for pain intensity estimation with an accuracy of 83.30%, the same accuracy that they reached using the three signals. Other authors combine electrophysiological sensors with another kind of data, such as in Yang et al. (2019), where authors used ECG and EDA with wearable sensors that recorded linear acceleration and angular velocity from the wrist-worn based on regression models. The result from the combination of features associated with the three information sources was an average accuracy of 75.80%. In Susam et al. (2022) authors combine electrodermal activity with video information. From the evaluation of features from the EDA signal and facial action unit from the video taken during post-surgery in children, the authors use Support Vector Machine and kernel density estimation to estimate pain, obtaining an accuracy of 90.91%, which implies an improvement in pain classification at a high computational cost. In this paper, we use two different methods of computational intelligence (Support Vector Machine (SVM) and Quadratic Discriminant Analysis (QDA)) to evaluate two cases: the first is the classification between pain and no pain, and the second one is the classification among three level of pain. The algorithms are based on the analysis of characteristics

related to EEG, ECG, EDA, and EMG, and their comparison to the self-reported pain using the visual analog scale (VAS) during an experiment where we induced acute pain. We compared the results, performance, and computational cost for both methods, and we expose a brief comparison with the results reached by other authors.

2. Methodology

This section presents the methodology to classify pain, and no pain, based on the analysis of electrophysiological signals. The development of the classification algorithms begins with an experiment to induce acute pain, where the EEG, ECG, EDA, and EMG electrophysiological signals were acquired. The process was divided into three main aspects (see figure 1): the signals' pre-processing, the feature extraction associated with pain, and the development of the classification algorithms, which are detailed here. Finally, this section presents the validation process to evaluate two classification algorithms.

Figure 1. Block diagram of the proposed algorithm for pain and no-pain classification



2.1. Experiment and data acquisition

The experiment was based on an acute pain induction test using electrostimulation. The device to do this was a Cadwell® brand electrodiagnostic equipment reference Sierra Summit with two channels. The population for the experiment was composed of seven women, and eight men, with ages between 17 and 45. Participants signed an informed consent once the procedure has been explained. The exclusion criteria to participate in the experiment included the presence of chronic diseases that involve sensory injuries such as

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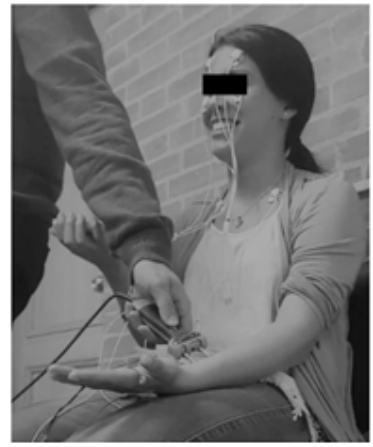
diabetes, polyneuropathy, traumatic injuries, cognitive impairment, and the use of pacemakers. An external electric stimulus was induced for the study on the motor median nerve in the participant's non-dominant hand. The active electrode is located between the tendons of the flexor carpi radialis and flexor carpi ulnaris, using a ground pole located on the back of the hand. The other active electrode is located on the point of the abductor pollicis brevis and the first metacarpal joint. During the experiment, the current increased every 30 seconds from 10 mA to a maximum of 100 mA. During the last minute, the electrical impulse was given every 2 seconds. The maximum time of the experiment was 4 minutes or until the participant required the finalization of the test.

The EDA, ECG, EMG, and EEG electrophysiological signals were collected through all the experiments using the Bitalino Board (BITalino (r)evolution Board Kit BT), with a sampling frequency of fsE = 1 KHz. The ECG signal active electrodes were placed on the clavicles and the reference in the iliac crest. The electrodermal activity (EDA) was registered between the index-middle finger and the index-third finger. The EMGs was assessed by locating the active electrodes bilaterally in the belly of the Orbicularis Oris muscle, and the reference on the nasal bridge. Finally, the electrodes for the EEG signal were placed on the 10-20 system in Fpz and Oz 1-2 (see figure 2). Additionally, the pain perceived by each participant was evaluated verbally every 20 seconds by using the visual analog scale (VAS).

2.2. Pre-processing

The Bitalino board has analog and digital processing according to the acquired signal. Later, a digital filter was used for each signal. For the ECG signal, a Butterworth band pass filter was used with cutoff frequencies (fc) between 0.1 Hz and 250 Hz, with an order of fifty. In the case of the EMG, a Butterworth high pass filter was used, with a cutoff frequency of fc = 20Hz of twenty-five order. For the EEG signal, a Butterworth band pass filter was used with cutoff frequencies of fc1 = 2Hz, and fc2 = 8Hz of order fifty. Finally, for the EDA signal, we employed a Butterworth high pass filter with a cutoff frequency of fc = 0.4Hz twenty-fifth order.

Figure 2. Electrodes location.



2.3. Feature Extraction

Some characteristics of the electrophysiological signals are related to pain as was studied in the introduction. Usually, works evaluate different characteristics associated with one electrophysiological signal. In this work, we evaluate the more relevant characteristics according to the literature for the EEG, ECG, EDA, and EMG signals. To do this, we used a window of 20000 samples to evaluate the features related to each signal, and each final feature was selected as the mean found every 20 seconds, that is the time when the VAS was assessed.

2.3.1. Feature extraction for the ECG signal

For ECG we used the heart rate (HR) characteristic. According to Padmanabhan and Sindhu.G (2014), Hautala et al. (2016) HR increases after a new stimulus that causes pain. To calculate the HR it is necessary to find the R peaks of the QRS complex. For this purpose, the double-level method was used to detect the R-peak. The HR is calculated on (1) based on the difference in seconds of two R-peaks, tp_{i-1} and tp_i. To locate the R-peak it is used a threshold value L, which is calculated in (2), where a is a fixed value typically used as 0.6, when a value exceeds the threshold L the time is saved in t_1, and t_2 is calculated as the time where the next value cross down the threshold, therefore and the R-peak is located in (3).

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$$HR = \frac{1}{tp_{i-1} - tp_i} \qquad (1)$$

$$L = a * max|ECG(t)| \qquad (2)$$

$$tp = \frac{t_1 + t_2}{2} \qquad (3)$$

2.3.2. Feature extraction for the EEG signal

For the EEG signal, the feature selected is the peak alpha frequency (PAF) assessed by exploring the source-level power spectra using a Fast Fourier Transform (FFT). According to Kostyunina and Kulikov (1996), Christie et al. (2017), and Nir et al. (2010), the PAF reflects the emotional and autonomic states. When the PAF increases, it reflects joy and anger, otherwise, when PAF decreases, it is related to fear and sorrow, the authors in Nir et al. (2010) found that a small decrease exists in the magnitude of PAF when pain is experienced. The PAF is calculated as the higher activation magnitude for the FFT.

2.3.3. Feature extraction for the EMG signal

The electromyographic activity (EA) and root mean square (RMS) was used in Hung et al. (2014) to evaluate the muscle force. In previous studies, it was demonstrated that subjects with pain produced significantly lower force values than those without pain. The EA is calculated on (4), where sEMG is the data of the EMG signal after the pre-processing, and T is a constant period, which is established as the time to take one sample of the VAS (20 sec). Finally, the root mean square (RMS) follows (5).

$$EA = \frac{\int_t^{t+T} sEMG(t)dt}{T} \qquad (4)$$

$$RMS = \sqrt{\frac{\int_t^{t+T} sEMG(t)^2 dt}{T}} \qquad (5)$$

2.3.4. Feature extraction for the EDA signal

Related to the EDA signal, the standard deviation (SD) as TSD metric (timescale decomposition) was selected as a statistical feature extraction methodology based on the results obtained by the authors in Susam et al. (2018). The TSD on SD allows us to collect statistical information and changes over the signal. The purpose of the statistical analysis is to eliminate variability caused for issues such as response delays. Therefore, this is calculated on (6), where μ is the mean of the signal and α is the SD, and N is the length of the signal that is analyzed.

$$\alpha = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(EDA(i) - \mu)} \qquad (6)$$

2.4. Pain classification algorithms.

We selected as classifiers the Gaussian Support Vector Machine and the Quadratic Discriminant Analysis, to classify between pain and no pain, based on the literature review. According to the VAS, reported by the participants, two tests were performed. The first test classified the data between pain and no pain with all the features and the second one used only the PAF, according to the VAS reported, the system classifies no pain from 0 to 3, and pain for the other values. The third test consisted in classifying data into 3 levels of pain: 0 - 3 for low pain, 4 - 7 for medium pain, and 8 - 10 for high pain. Data were divided into two different sets: the first set of data, composed of 70% of the total dataset was used to train the algorithms applying k-fold cross-validation to avoid overfitting. The second set, composed of 30% of the total data, was used to validate both algorithms.

2.4.1. Support vector machine

The support vector machine is a supervised machine-learning algorithm. The main idea of the SVM is to find the optimal hyperplane, which separates data into two classes. For our purpose, the hyperplane separates data between pain and no pain. The inputs for the algorithm are the electrophysiological features and the

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corresponding VAS binary value. Data are fixed on an optimal hyper-plane, which differentiates each category (class 1 has an output Y (i) = 1 for pain, and class 2 has an output Y (i) = 0 for no pain). The hyper-plane is defined according to the cost function 1 (see (7)), and the cost function 2 (see (8)).

$$Y(i) = 1 \leftrightarrow \theta^T * f \geq 1 \quad (7)$$

$$Y(i) = 0 \leftrightarrow \theta^T * f \leq 1 \quad (8)$$

$$min_\theta C * \sum_{i=1}^{m} y^i * cost1\left(\theta^T * f^i\right) + \left(1 - y^i\right) * cost2\left(\theta^T * f^i\right) \quad (9)$$

The SVM finds the optimal hyper-plane by minimizing $\Theta \epsilon R_m+1$, which represents the vector parameter of the hyper-plane, where m is the size of the training set, and f εRm+1 is a new feature vector given by a Gaussian Kernel. It is calculated the similarity of a landmark li and the original features Xi, where i is the dimension of the data or the number of characteristics, and σ refers to the spread of the normal distribution.

$$f^i = e^{\left(-\frac{\|X - l^i\|^2}{\sigma^2}\right)} \quad (10)$$

$$l^1 = X^1, l^2 = X^2, \ldots, l^m = X^m \quad (11)$$

2.4.2. Quadratic discriminant analysis

The quadratic discriminant analysis is the general form of the Fisher Linear Discriminant, it is a statistical method used in pattern recognition and machine learning to find a quadratic combination of features that separates two or more labels. This method is based on Bayes Law given by equation 12.

$$P(Y = x|X = x) = \frac{PIk * fk(x)}{\sum PIl * fl(x)} \quad (12)$$

In (12) the probability of the output y with each class k is estimated. In this case, we have two classes (pain, and no pain). Additionally, x is defined as the vector of the signals' features, and PIk refers to the base probability of each class k, trained with the training data. For the QDA algorithm, it is assumed that each input is conditionally independent. The equation that represents the QDA algorithm is given by (13), where the Cst constant refers to the probability that the input takes some value.

$$logP(y = k|x) = logP(x|y = k) + logP(y = k) + Cst \qquad (13)$$

2.5. Algorithms training

To train the algorithms, the k- fold cross-validation algorithm was used. This is used in machine learning models to protect against over-fitting in predictions. The method divides the data into fixed numbers of partitions or folds to run the training process Wong and Yeh (2020). This method follows the below algorithm:

(1) Choose a K number of folds (in our case, we selected K = 2).

(2) Divide the data randomly into K subsets with equal size.

(3) Train the model with K − 1 folds and test it with the Kth fold.

(4) Repeat the process with each fold until using all the folds for training and testing.

(5) Calculate accuracy per iteration, and the average of all accuracies is the performance metric.

2.6. Validation

To evaluate the algorithms' performance, we used the confusion matrix, which allows the analysis of aspects such as accuracy, precision, sensitivity, and specificity. The confusion matrix (see table 1) is based on the evaluation of the following values: TP (true positive) represents the amount of correct prediction of class 1; TN (true negative) represents the amount of correct prediction of the class 0, FP (false positive) represents the wrong prediction of class 1, and FN (false negative) represents the wrong prediction of class 0.

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Table 1: Confusion Matrix

	Predicted: No (0)	**Predicted: Yes (1)**
Real: Yes (1)	FN	TP
Real: No (0)	TN	FP

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \quad (14)$$

$$Precision = \frac{TP}{TP + FP} \quad (15)$$

$$Specificity = \frac{TN}{TN + FP} \quad (16)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (17)$$

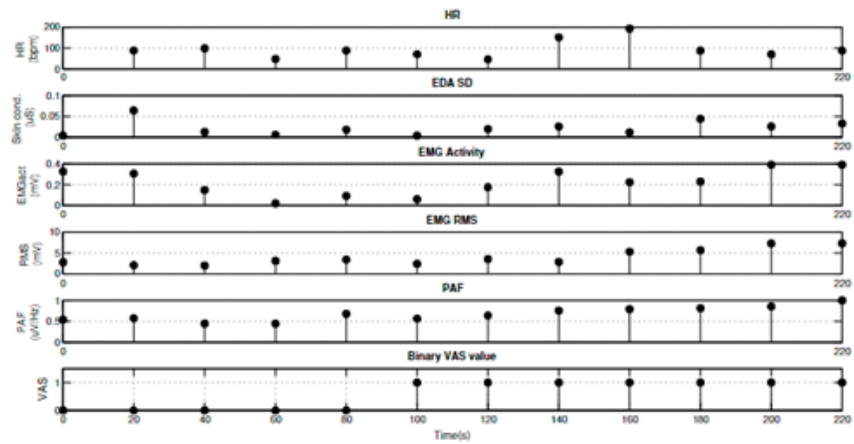
Finally, we evaluated the computational cost, which is measured as the convergence time required to complete the training process.

3. Results

In this section, we present the principal results obtained, using the SVM and QDA algorithms, for two tests: i) a binary classification between pain and no pain, and ii) a classification between no pain, moderate pain, and severe pain. As well, we compare the performance of the algorithms using several features related to different electrophysiological signals and the results by employing one characteristic, which is what works presented in the literature review do. Here, we show some graphical examples of the results obtained and the final parameters to evaluate the algorithms' performance. Figure 3 shows the values of the different features used,

contrasted to the VAS binary value for one of the participants. As can be seen, PAF, RMS, and EMG Activity or EA are the features that present more changes after 100 seconds, the time when the users start to report pain. Features as the HR presents an increment at 100 seconds, but after a while, the HR returns to a typical value. The SD shows a small increment in comparison to the other features. It is important to correctly select the signals' features to classify them properly. The data was divided into two sets: 70% of the data was used to train the algorithms, and the 30% remainder was used to test the algorithms.

Figure 3. Parallel between the features and the respective value of VAS for one subject, each feature is used for training and testing the classification models.



For the binary classification, the accuracy for the training set was ACC = 85.66% for the QDA, and ACC = 96.634% for the SVM algorithm with a Gaussian kernel, by employing all the features assessed. Figure 4 shows the classification using the SVM and the QDA algorithms compared to the VAS binary output for data employed from the test set, in the case of one of the participants. Table 2 shows the results obtained for the test set, including precision, accuracy, sensibility, specificity, and computational cost to compare the SVM and the QDA algorithms.

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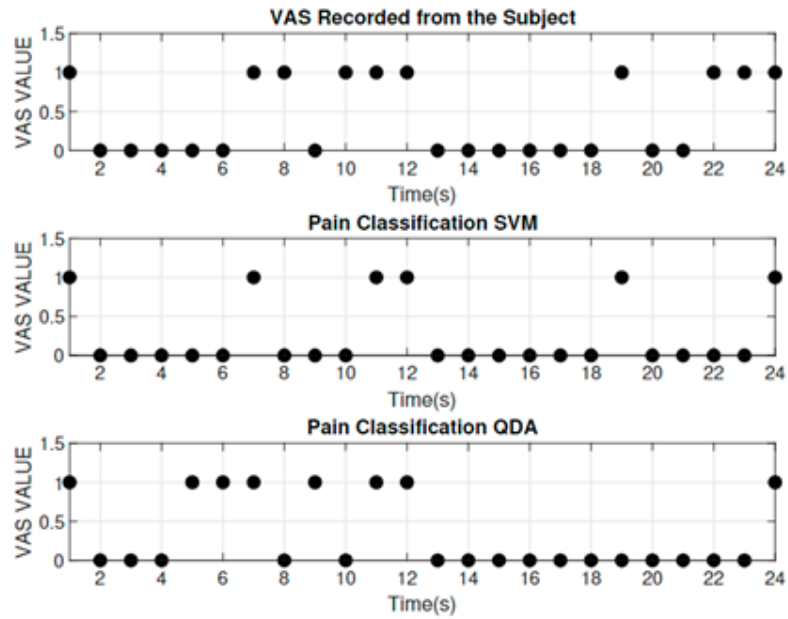
Table 2. Algorithm's results using all the features

Metrics	SVM	QDA
Accuracy (%)	88.02	70.28
Precision (%)	90.4	62.5
Sensitivity (%)	95	78.75
Specificity (%)	85.71	57.14
Computational cost (s)	9.587	3.023

Figure 4. Classification obtained with QDA and SVM contrasted with the binary VAS.



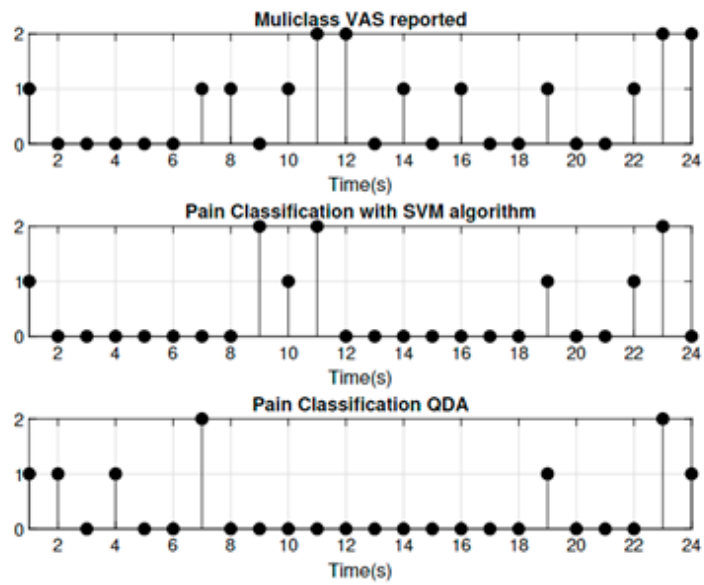
For the binary classification, a second test was performed using the same algorithms but evaluating only one of the features (for this case, we selected the peak alpha frequency (PAF). Table 3 shows the results of the classification for the test set. As can be seen, the algorithms' performance is lower than using more features related to different electrophysiological signals. For the third test, with three levels of pain and employing all the features evaluated, the QDA obtained an accuracy ACC = 68.6% for the training set, and the SVM with a Gaussian kernel an ACC = 95.2%. Figure 5. shows the classification using the SVM and the QDA algorithms compared to the VAS reported as no pain, moderate and severe pain from the test

set, in the case of one of the participants. Table 5 shows the results obtained for the test set, including precision, accuracy, sensibility, specificity, and computational cost to compare the SVM and the QDA algorithms.

Table 3. Algorithm's results using PAF

Metrics	SVM	QDA
Accuracy (%)	60.95	60.00
Precision (%)	59.09	57.89
Sensitivity (%)	85.00	86.67
Specificity (%)	28.89	24.44
Computational cost (s)	1.293	0.808

Figure 5. Classification obtained with QDA and SVM contrasted with the multi-class VAS.



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4. Discussion

The use of all the features shows better results for both algorithms employed, even if it implies a higher computational cost. Additionally, the SVM algorithm surpasses the QDA algorithm reflected in greater accuracy, precision, sensitivity, and specificity. Accuracy is related to the number of cases correctly predicted for both classes in contrast to all the predicted data. Precision refers to the right prediction of pain contrasted to the total prediction of this class between the well and wrong classification of pain. Specificity indicates the correct classification of no-pain, related to the adequate and incorrect classification for this class. Sensitivity symbolizes the relationship between the number of cases where the pain was classified properly, against the sum of the number of cases where the pain was properly classified and the cases where the pain was misclassified. The principal problem of the QDA algorithm is that it predicts no pain where there is pain, this can be seen in the small value of the specificity, which means that it can correctly predict class 0 in around half of the new data. On the other hand, the specificity, related to the SVM algorithm, shows a correct classification in the case of no pain. The sensitivity obtained shows that both models correctly classify pain, but SVM has better performance at a rate of almost 16% better than QDA by evaluating the new data. According to the particular case presented in figure 4, the QDA has an accuracy of 58.34%, and the SVM of 83.33%. As was said above, the SVM is a better classifier than the QDA, it has better accuracy values in training and test sets. The last is because the SVM optimally separates the hyper-plane solving an optimization problem while the QDA has an analytical solution that depends on the covariance matrix of all the data to maximize the separability of the classes, at the moment to present new data for QDA that was not part of the training process it has more problems to classify. Nevertheless, according to the accuracy, it is worth mentioning that both algorithms are good classifiers due to they reach an accuracy higher than 70% with the new data.

Table 4. Multiple classification results

Metrics	SVM	QDA
Accuracy (%)	78.90	63.16
Precision (%)	100	50.00
Sensitivity (%)	50.00	28.57
Specificity (%)	100	83.33
Computational cost (s)	6.29	1.24

When one feature is employed, as was expected the absences of other features affect the performance of the classifiers. It is worth saying that these classifiers present a similar or even better value of sensitivity, which means that both have a desirable prediction of class 1, contrary to specificity, which means that classifiers cannot predict more than the 70% of class 0. The last parameters are related to the accuracy and precision obtained for both algorithms, which are considerably lower than the results presented when we employed more features assessed from the different electrophysiological signals.

Table 5: Comparison with other works.

Reference	Signals acquired	Algorithms	Accuracy (%)
Subramaniam and Dass (2021)	EDA, ECG	Multilayer perceptron	70.59
Wang et al. (2021)	Skin conductance ECG, EMG	Hybrid RNN-ANN	82.70
Thiam et al. (2021)	ECG, EDA, EMG	Self-supervised	77.58
Yang et al. (2019)	ECG, EDA, wrist-worn mov.	Decision Tree	80.54
Susan et al. (2022)	EDA, EMG and face video	SVM	90.91
Our approach (single feature)	EEG	SVM, QDA	60.95
Our approach (binary class)	ECG, EDA, EMG, EEG	SVM, QDA	88.02
Our approach (multiple class)	ECG, EDA, EMG, EEG	SVM, QDA	78.90

On the other hand, when we perform the third test, using multiple classes for classification. Initially, the accuracy obtained from the models on the training set is slightly different in the SVM with a decrease of 1.43%, however, for the QDA the reduction of the performance is highly different, with a 17.2% difference between the experiments. Nevertheless, when the comparison is done with the test set, the difference between the models improves compared to the training set, where we obtained a difference of 9.12% for SVM and 7.68% for QDA. Therefore, the results obtained in this

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experiment allow establishing a different way to classify pain, having three several classes sacrificing the accuracy of less than 10%. The main difference between the experiments lies in the sensitivity, having a 50% for SVM and 28.57% for QDA, this means that the models have trouble identifying the true class, taking into consideration that having an additional class increases the difficulty for the classification. However, this low value in the sensitivity is compensated by having high precision and specificity for the SVM and high specificity for the QDA. According to the accuracy, the SVM continues reaching an accuracy higher than 70% with the test data. The computational cost, when we classify between pain and no pain, is around three times bigger for the SVM than the QDA algorithm, and twice when just one characteristic is used. When we classify three different levels of pain employing all the features, the computational cost remains higher for the SVM, but lower than in the first experiment. The reason is that the processes were run using a computer with a solid-state drive. Comparing the results obtained from previous works, we can find that the SVM and QDA algorithms on the first experiment have better results in the classification when they are trained with features from different electrophysiological signals than the results reached when only one signal was used. In Susam et al. (2018) authors use the SVM classifier employing the EDA signal's features, reaching an accuracy of 71.61% in one of the analyses presented and 77.66% in the second analysis. In Hadjileontiadis (2015), the authors used QDA and SVM employing the data from EEG, and they obtained different classification performances evaluated with the classification accuracy (CA). According to the analyses realized, where the CA found was between 80% and 90%. Authors in Hung et al. (2014) use surface electromyography to classify low back pain, obtaining a sensitivity of 90%, a specificity of 88%, and an accuracy of 89%. Similarly, the results obtained are in most cases better, compared to those presented in the literature review. The idea to use different electrophysiological signals is to improve the classification process, taking into account that some parameters can change for reasons distinct from pain. For example, HR can be affected by aspects such as the use of medicines. In this paper, a second experiment was performed using only one feature to train the classifiers. The results, as expected, are better when using more characteristics from the different signals. Therefore, this work shows that the use of attributes related to the different signals improves the classification rates, comparing the results obtained against previous works where one electrophysiological signal was employed. For the classification between three levels of pain, the results for the SVM are similar

comparing the above articles. It is important to mention that having an extra class, gives more information for real applications such as pain management. In Table 5 we present our results and the most recent works that use more than one electrophysiological signal to classify pain. The first conclusion is that all the works reach better results using several electrophysiological signals than the one that we present in which we used just the features of the EEG signal to classify pain. It is important to have in mind that the features of one electrophysiological signal can be affected by other aspects different than pain, such as the use of medications. On the other hand, when we compare the results reached by the authors with our binary classification approach, it can be seen that we got better results than those presented on Subramaniam and Dass (2021). On the other hand, authors in Wang et al. (2020) use Deep Recurrent Neural Network, obtaining an accuracy of 82.7% for multilevel pain assessment. They got a better result with a difference of 3.8%. Nevertheless, the computational cost of this kind of algorithm is higher than the algorithms that we employed. Further, in multiple-level classification, we reach better results than those presented on Thiam et al. (2021). Finally, in Susam et al. (2022) authors evaluate the accuracy in the assessment of pain using EDA features reaching an accuracy of 68.18%. When they used the features associated with the video records they reached an accuracy of 77.27%. Then they combined features of both sources of information reaching an accuracy of 90.91%. Even if the results are better than the ones obtained here, the data processing implies a higher computational cost. It is important to highlight that for real-time applications, the computational cost is a valuable parameter that can affect the performance of a system whose dynamics are based on the assessment of pain, such as applications of pain relief with virtual reality scenarios.

5. Conclusion

The present study aims to explore the relationship between the EMG, ECG, EEG, and EDA signals' features, and pain. The idea was to explore if pain assessment can be improved when using features from different electrophysiological signals in comparison to the use of characteristics related to just one electrophysiological signal, which is usually what previous works did. Moreover, we evaluate and compare the different results obtained using binary pain classification and three labels of classification (low pain, medium pain, and high pain). Two different classifiers were used, the Support Vector Machine

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and Quadratic Discriminant Analysis in an experiment where acute pain was induced in healthy participants. To validate the performance of each algorithm the classification of the new data was compared to the VAS reported by the participants to determine the confusion matrix. As a result, we found that the classification by using the SVM algorithm has a better performance than the QDA algorithm obtaining an accuracy of 88.02% and 70.78% in the test data, respectively when using all the electrophysiological signals, also these results are better than those reached by using the PAF characteristic with the same classification algorithms. Furthermore, the results for multiple class classification the SVM has the same behavior as the binary classification, with better performance than QDA with an accuracy of 78.90% for SVM and 63.16% for QDA. Even though the accuracy for SVM multiple classification y is 10% lower than SVM with binary classification, with multiple classifications we have more detailed information on the pain that can be useful for medical applications. The results are better compared to the performance of previous studies in which similar classifiers were used using characteristics of just one electrophysiological signal. Future work of this study includes the analysis of chronic pain.

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