Automatic Pain Intensity Estimation based on Electrocardiogram and Demographic Factors

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Abstract: Automatic pain intensity estimation possess significant importance for reliable and complete pain management. The accurate and continuous monitoring is essential in order to attain objective insight about the condition of the patient. In this work, we elaborate physiological signals in order to estimate the pain intensity and investigate the impact of demographic factors. Specifically, we exploit electrocardiography signals, adopting the Pan-Tompkins algorithm to extract important features and apply well-validated classification methods, while we explore the correlation of gender and age with the pain manifestation.

1 INTRODUCTION

Pain according to the most accepted definition is ”an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage” (Merskey et al., 1979). The two main types of pain are acute and chronic, where their main difference is related to the duration; in the case of acute pain the sensation is momentary, whereas in chronic lasts longer than a few months. Pain is a major issue in humans' lifetime, since every day people of all ages experience pain, either due to an accident or due to an illness or even during a treatment. A large percentage of people who have been treated for serious illnesses, even if they have overcome them, may suffer from persistent pain (Lynch, 2011). Since pain is a situation with physical and psychological dimensions, it affects people in a major degree provoking a plethora of daily life challenges, and especially in chronic pain condition, it often leads to depression, sleep problems, and anorexia (Lopez-Martinez and Picard, 2017). Pain constitutes an incumbrance in health care systems, since more than 50% of those who are in a hospital are experience the phenomenon of pain (Cordell et al., 2002). Large resources of medical and nursing staff are consumed for the therapy of chronic pain, exceeding the cost of diseases such as cardio-vascular and neoplasms (Gaskin and Richard, 2012). A considerable body of research indicates divergence on pain expression and sensation among individuals with different gender or age. In the study of Bartley and Fillingim (2013) conducting a psychological review research, concluded that females experience greater discomfort and pain in more areas of the body than males, and generally are more sensitive. Similarly, in the research (Toomey, 2008) also discovered that females had lower thresholds evaluating equal stimuli as more intense and painful compared to men, while Hadjistavropoulos and Craig (2002) refereed that elders present important alterations in pain perception, compared to younger people.

Self-report is the common approach in clinical practice used for determining the presence and the severity of pain, by rating scales or questionnaires. This process is time consuming and challenging especially for patients with communicational abnormalities, intellectual disabilities, people with serious illness or infants, and moreover, the continuous pain monitoring is unfeasible with the absence of computer systems (Werner et al., 2014). Adequate and objective pain assessment is required, in order to provide the necessary care to people who are suffering, since inappropriate management of pain can lead to additional serious health problems.

The process of recognizing pain, is based on analysis of behavioural and physiological responses;

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the behavioural reaction is related with facial expressions, vocalizations and body-head movements, while the physiological are the interactions from the neural structures which lead to the sympathetic outflow being affected and increased, something that can be observed in the physiological signals (Stewart and Panickar, 2013), such as electroencephalography (EEG), electrodermal activity (EDA), electromyography (EMG) and electrocardiography (ECG).

This study elaborates a pain estimation procedure, exploiting ECG signals and investigates the differences on various demographic groups, related to gender and age. In particular, we scrutinize the variation in pain manifestation among males and females, we examine the pain diversities across age groups, and furthermore we combine the factor of age with the gender. The remaining of this paper is organised as follows: in Section 2 we present the related work on automatic pain estimation, Section 3 describes the methodology for the feature extraction approach and the machine learning methods, in Section 4 we present the conducted experiments and results and the paper is concluded in Section 5.

2 RELATED WORK

A significant number of published research efforts (Wang et al., 2020; Mamontov et al., 2019), were based on biosignals to interpret the pain sensation, since in many cases the video modalities e.g. facial expression are relatively difficult to elaborate, especially in clinical settings where the patient rotates or due to facial occlusions from medical support devices or the patient's hands. Additionally, there are circumstances where the individuals pretend facial expression in order to elicit personal interest (Rohling et al., 1995). The correlation among pain and physiological signals like heart rate variability, electrodermal activity, brain function, and respiration rate have been examined in plethora of studies (Werner et al., 2019).

According to a study done by Chu et al. (2017) linear discriminant analysis was utilized based on data of six healthy participants, to categorize the pain into five distinct levels, based on ECG and EDA employing Genetic Algorithms and Principal Component Analysis. Kächele et al. (2016) exploited EDA, ECG and EMG, extracting several features such as skewness, standard deviation and QRS complexes. Applying Random Forest (RF) conducted multi-classification on five pain levels, while Lopez-Martinez and Picard (2017) designed a multitask neural network for personalized pain recognition using ECG and EDA signals. Similarly, in their work Amirian et al. (2016) explored the continuous and discrete pain estimation exploiting ECG, EMG and EDA. Time domain (e.g. Willison amplitude), frequency domain and entropy features (e.g. Shannon) were extracted and a Radial Basis Function (RBF) Neural Network was designed achieving accepted performances.

Recently, Deep Learning (DL) approaches have been studied for their application in pain estimation, after their success in different scientific areas. The research of Thiam et al. (2019) investigated DL models for pain categorization. They applied 1D Convolutional Neural Networks (CNN) on galvanic skin response signals improving the binary classification between no pain and the highest pain intensity. Yu et al. (2020) studied three levels of pain based on EEG, developing a framework that consisted of several convolutional modules, each one related to different frequency range, while Lopez-Martinez and Picard (2018) proposed a Recurrent Neural Network (RNN) for determining the severity of the pain, based on the deconvolved signals, extracting tonic-phasic components from EDA and R peaks as well as interbeat intervlas (IBIs) from ECG.

Furthermore, to the best of our knowledge there exist two studies which investigate demographic factors. In the study of Hinduja et al. (2020) the authors exploited several physiological signals (e.g. diastolic blood pressure, respiration rate, EDA), facial action units and the combination of them as well, revealing the existence of significant differences among men and women in pain sense, on both unimodal and multimodal approaches. Similarly, Subramaniam and Dass (2021) conducted experiments through ECG and EDA adopting Convolutional Neural Networks (CNN) disclosed performance variations between the gender.

3 METHODOLOGY

The employed pain database, the electrocardiography processing algorithm, as well as the extraction method of features and classification algorithms will be described in this section.

3.1 BioVid Heat Pain Dataset

In this study we utilized the publicly available *"BioVid Heat Pain Database"* (Walter et al., 2013), which comprises facial videos, and biosignals (ECG, EMG, EDA) from 87 subjects (44 males and 43 females, age 20-65), and currently is the only publicly available dataset which includes the subjects'

age and gender. Data were collected by subjecting heat stimulus on the right arm by a thermode. Before the data recording was started, for each subject the pain threshold (the temperature for which the participant's sensing changes from heat to pain) and pain tolerance (the temperature at which the pain becomes intolerable) were determined. The specific thresholds utilized as the temperatures for lowest and highest pain levels, and addition two intermediate levels were included, resulting to 5 pain conditions: No pain (NP), mild pain (P1), moderate pain (P2), severe pain (P3), very severe pain (P4). The participants were stimulated 20 times for every intensity, thus generating 100 samples for each of the four modalities. We employed *Part A* of the *BioVid*, specifically the pre-processed ECG samples with a Butterworth bandpass filter ($87 \times 100 = 8700$).

3.2 ECG Signal Processing and Analysis

An ECG signal reflects the electrical activity of the heart over a period of time. A normal ECG consist of a series of waves, namely P, Q, R, S, T and sometimes U. These waves and their intervals give important information regarding the heart's function. The P wave signs atrial depolarization. The QRS complex represents ventricular depolarization and contraction, while the T wave represents repolarization of ventricles. Therefore, each heartbeat is represented by the PQRST complex (see Figure 1). The accurate and reliable detection of the R wave in the QRS complex is of high importance since it is the most prevalent peak in the complex. By accurately detecting the R wave we can compute the heart rate (HR) and the heart rate variability (HRV), which is related with the time interval between consecutive R waves, called R-R interval or Interbeat interval.

One the most widely used real time QRS detection algorithm is the Pan-Tompkins Algorithm (Pan and Tompkins, 1985). Over the past decades the original Pan-Tompkins algorithm and several modifications have been evaluated, with the results to support its efficiency even in noisy and low-quality data (Fariha et al., 2020; Liu et al., 2017). The performance of the Pan-Tompkins Algorithm has been repeatedly evaluated and therefore considered to be one of the state-of-the-art algorithms for QRS detection, used also for performance comparison in new approaches (Zhao et al., 2021). In this study we adopted the original Pan-Tompkins Algorithm for the detection of the QRS complex. The integration of the algorithm emerged in two stages: the preprocessing and the decision. The preprocessing is an essential procedure to prepare the ECG, removing the noise and artefacts,

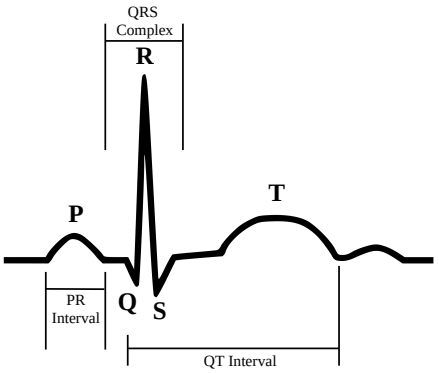

Figure 1: The PQRST complex.

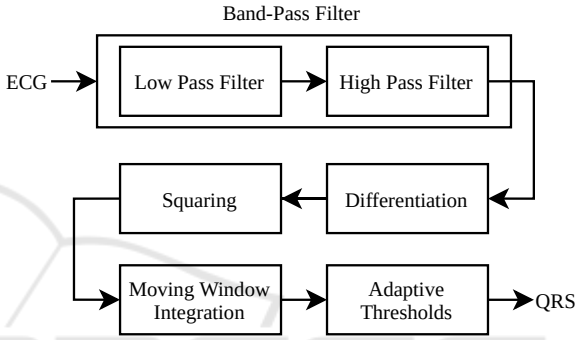

Figure 2: The flow diagram of the pre-processing procedure of the Pan-Tompkins algorithm.

smoothing the signal, and increasing the QRS slope. The flow diagram of the preprocessing procedure of the Pan-Tompkins algorithm is shown on Figure 2.

3.3 Feature Extraction

The succeeding phase is the extraction of specific features based on the inter-beat intervals (IBIs). In our work, the mean of IBIs, the root mean square of successive differences (RMSSD), the standard deviation of IBIs (SDNN), the slope of the linear regression of IBIs, the ratio of SDNN to RMSSD, and the heart beat rate, were calculated as follows:

1. Mean of IBIs
$$\mu = \frac{1}{n}\sum_{i=1}^{n}(RR_{i+1} - RR_i) \quad (1)$$
where *RR* are consecutive *R* peaks.
2. Root mean square of successive differences
$$RMSSD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n-1}(RR_{i+1} - RR_i)^2} \quad (2)$$
3. Standard deviation of IBIs
$$SDNN = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(RR_i - \mu)^2} \quad (3)$$

4. Slope of the linear regression of IBIs

$$A^T Ax = A^T b \tag{4}$$

based on the least-square approximation, where b is the vector of *RR* peak intervals and A is the corresponding time series.

5. Ratio of SDNN to RMSSD

$$SR = \frac{SDNN}{RMSSD} \tag{5}$$

6. Heart beat rate

$$HR = \frac{60 \cdot FS}{\mu} \tag{6}$$

where FS is the frequency of ECG recording and is equal to 512 Hz. Figure 3 shows the raw ECG signal and the applied algorithm's steps as well.

3.4 Classification Methods

For the classification phase, three well known classifiers were deployed: Linear Discriminant Analysis (LDA), the Support Vector Machine (SVM) with linear kernel, and the SVM with Radial Basis Function (RBF) kernel. Furthermore, all the conducted experiments repeated threefold with identical settings, utilizing a particular classifier in every repetition in order to compare their performances, founded on the leave-one-subject-out (LOSO) cross validation, employing all the available subjects and ECG samples, and as evaluation performance we adopted the metric of accuracy.

1. Linear Discriminant Analysis

$$P(X|y=k) = \frac{exp\Big(-\frac{1}{2}(X-\mu_k)^t \Sigma_k^{-1}(X-\mu_k)^t\Big)}{(2\pi)^{d/2}|\Sigma_k|^{1/2}} \tag{7}$$

where P is the probability density function of features X given the target y and class k.

2. SVM with linear kernel

$$K(x_1, x_2) = x_1^T x_2 \tag{8}$$

where x_1, x_2 are features from two distinct classes.

3. SVM with Radial Basis Function (RBF) kernel

$$K(x_1, x_2) = exp\left(-\frac{||x_1 - x_2||^2}{2\sigma^2}\right) \tag{9}$$

where σ is the width of the kernel.

4 EXPERIMENTS & RESULTS

Utilizing the aforementioned classification algorithms, we conducted several experiments with the objective of pain recognition and it's relation with demographic factors. The classification tasks were based on the pain conditions and implemented in a multi-class classification manner, as well as binary classification. Specifically five distinct experiments were performed: (1) multi-class pain classification, (2) NP vs P1, (3) NP vs P2, (4) NP vs P3, (5) NP vs P4. In (1) the purpose is to classify an ECG signal in one of the five pain conditions, while in (2)-(5) to classify it in one of the two pain conditions, i.e. no pain and the corresponding pain level. In addition, taking into consideration the gender and the age of subjects, we developed four different schemes; (1) the basic scheme where we employed the whole dataset, (2) the gender scheme where the data were divided based on the gender of subjects i.e. males-females, (3) the age scheme based on the age of subjects, creating three groups i.e. *'20-35'*, *'36-50'*, *'51-65'*, and finally (4) the gender-age scheme was in accordance to gender and age combined, creating six different subjects groups i.e. *'males 20-35'*, *'females 20-35'*, *'males 36-50'*, *'females 36-50'*, *'males 51-65'*, *'females 51-65'*. The best classification results are presented in Figures 4-5 for every corresponding task and the utilized classification method, while the Tables 1-5 enclose every individual experiment.

Table 1 presents the results utilizing the whole dataset, where for the multi-class pain classification we achieved 23.79%, and the performance scores increased as much as the pain intensity raise, reaching 58.62% on NP vs P4, indicating the challenges to detect the low magnitude of pain severity. Regarding the classification algorithms, the SVM (linear) performed ameliorative, besides the last task related to the higher level of pain, while the SVM (RBF) exhibited inferiorly. On the gender scheme (see Table 2), we observe differences among males and females. Females in total presented 1.12% variation from males, where in task NP vs P4 attained 60.69% accuracy over 56.07%, where the 4.62% increase indicates that women are more sensitive in higher pain levels than men. Curiously, in NP vs P1 and NP vs P2 the males outperformed by 1.16% and 1.78%, respectively, and similarly to the first scheme, the SVM (linear) obtained greater results in most of the tasks. Figure 4 depict the gender differences, based on the classification accuracy.

On the age scheme (see Table 3), the group *'20-35'* presented 25.06% in multi-level classification over 23.27% and 22.35% from the groups *'36-50'*and

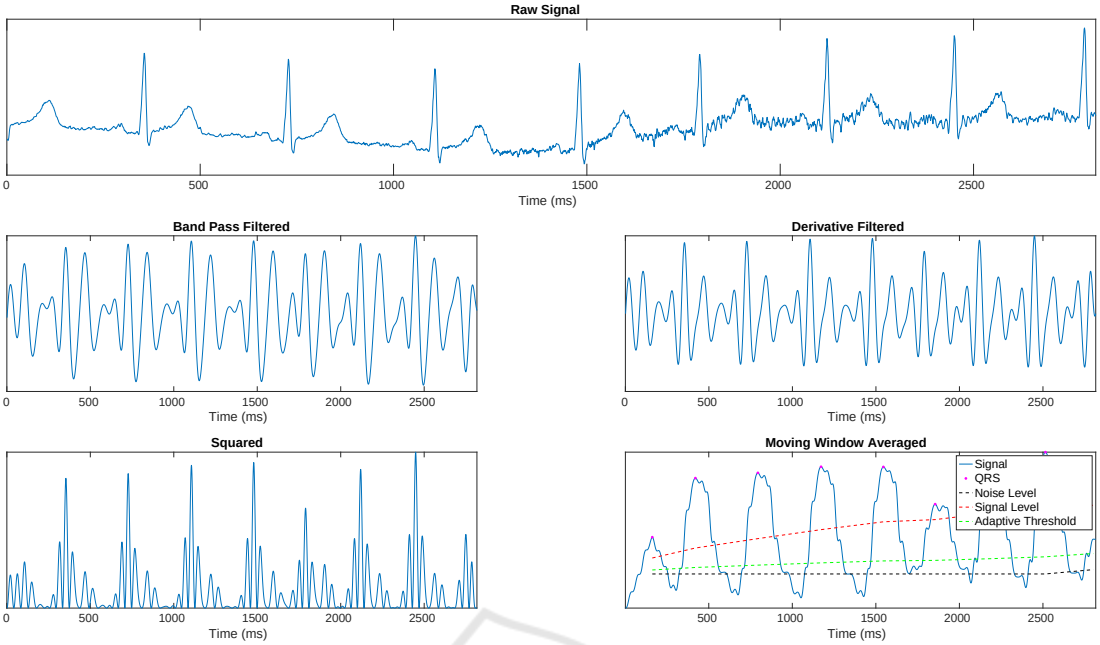

Figure 3: The signal pre-processing with Pan-Tompkins algorithm.

Table 1: Classification results of the Basic Scheme, reported on % accuracy.

Group	Task	Algorithm		
		LDA	SVM LN	SVM RBF
All	MC	23.72	23.79	22.77
	NP vs P1	50.97	52.38	49.97
	NP vs P2	52.55	52.78	52.70
	NP vs P3	55.20	55.37	53.87
	NP vs P4	58.62	58.39	57.41

MC: multi-classification NP: no pain P1: mild pain P2: moderate pain P3: severe pain P4: very severe pain LDA: Linear Discriminant Analysis LN:Linear RBF: Radial Basis Function

Table 2: Classification results of the Gender Scheme, reported on % accuracy.

Group	Task	Algorithm		
		LDA	SVM LN	SVM RBF
Males	MC	22.13	22.25	20.70
	NP vs P1	51.53	52.61	47.72
	NP vs P2	53.12	53.69	52.15
	NP vs P3	54.94	54.71	51.36
	NP vs P4	55.28	56.07	51.36
Females	MC	25.11	24.41	23.41
	NP vs P1	50.23	51.45	49.06
	NP vs P2	51.62	51.86	51.91
	NP vs P3	55.98	55.87	55.29
	NP vs P4	60.17	60.69	59.82

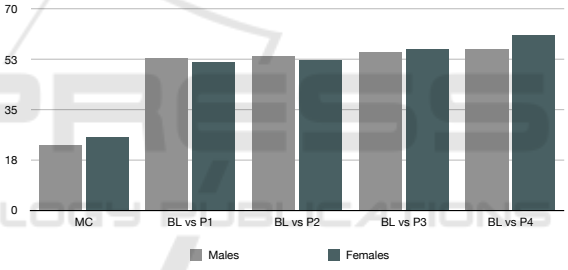

Figure 4: Classification results on the Gender Scheme.

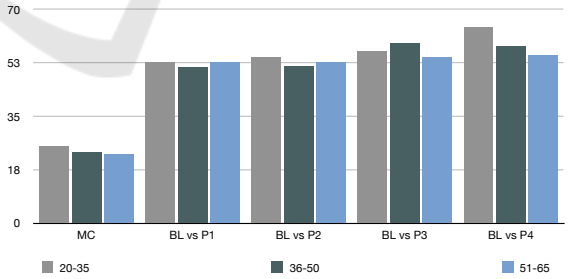

Figure 5: Classification results on the Age Scheme.

'51-65' respectively, revealing that age is a factor which influences the pain sensation. Especially, in NP vs P4 demonstrated a difference nearly 9% between the youngest and the oldest group. Analogously to the gender scheme, in low pain intensities there exist slight differences among the groups, which increased as the pain escalates. Specifically, the variance (σ^2) between the three groups in NP vs P1 was 1.38% while in the remaining tasks was

2.44%, 6.35% and 20.42% respectively, revealing that in order to identify the differences of pain perception among the groups, is essential for pain to increase to a high intensity. On the basis of classification accuracy, the group *'20-35'* described with the highest sensitivity followed by the group *'36-50'* and *'51-65'*. Additionally, relating to the classification methods, the SVM (RBF) in group *'51-65'* performed superior in almost every task, while in group *'20-35'* completely underperformed, indicating that is the finest choice for difficult separable classes. In Figure 5 illustrated the results of Age scheme.

In the last scheme, we studied in a more precisely manner the subjects, in order to obtain a better insight about the correlation of pain and the demographic factors of gender and age. In Tables 4-5 we observe that in the multi-class pain classification the higher accuracy achieved by *'females 20-35'* with 24.80% accuracy, while in NP vs P1 the *'females 51-65'* reached 55.38%, disclosing again that the female gender characterized by a elevated sensitivity. Likewise, the highest performance in NP vs P2 achieved by the *'females 51-65'* followed by the *'males 51-65'*, although in NP vs P3 the *'females 36-50'* exceeded by 3.5% from the second best group *'males 20-35'*. Finally, in the last task of NP vs P4 the *'females 20-35'* outperformed attaining 67%, where the minimal performance observed on *'males 51-65'* with 54.50%, where the particular groups are the uttermost and the minor sensitive group respectively. We report that in some cases the classification accuracy is lower than others, despite the fact the pain level is increased (e.g. *'Females 36-50')*. An explanation could be related to the recording procedure of biosignals, where the subjects may get accustomed to the stimulation thenceforwards.

In Figure 6 we visualize the classification performances of the six groups in the Gender-Age scheme. Additionally, in Table 6 we compare ours accomplished results with related studies which utlized the ECG signals from *BioVid* database and followed the same evaluation protocol, in order to have objective and fair comparison. We are able to achieve the best classification performance in the multi-class setting, as well as in NP vs P1 and NP vs P2. In the the remaining binary classification tasks we obtain acceptable results.

Table 3: Classification results of the Age Scheme, reported on % accuracy.

Group	Task	Algorithm		
		LDA	SVM LN	SVM RBF
20-35	MC	25.06	24.73	21.96
	NP vs P1	52.83	52.83	49.90
	NP vs P2	54.33	53.75	52.75
	NP vs P3	55.58	56.16	54.66
	NP vs P4	63.83	63.41	60.75
36-50	MC	23.27	22.06	23.03
	NP vs P1	50.34	48.36	50.68
	NP vs P2	49.13	51.20	50.17
	NP vs P3	58.10	58.70	58.27
	NP vs P4	58.10	57.75	55.94
51-65	MC	21.89	22.07	22.35
	NP vs P1	52.23	51.87	52.58
	NP vs P2	52.14	51.69	52.76
	NP vs P3	53.66	53.39	54.10
	NP vs P4	54.46	54.19	54.91

Table 4: Classification results of the Gender-Age Scheme (Males), reported on % accuracy.

Group	Task	Algorithm		
		LDA	SVM LN	SVM RBF
Males 20-35	MC	23.13	23.20	18.73
	NP vs P1	52.50	52.83	45.83
	NP vs P2	54.00	53.50	53.16
	NP vs P3	56.33	56.50	54.83
	NP vs P4	60.00	59.00	53.66
Males 36-50	MC	23.21	22.21	20.92
	NP vs P1	50.53	50.53	46.42
	NP vs P2	50.00	51.78	47.50
	NP vs P3	54.64	56.25	47.32
	NP vs P4	55.53	56.25	51.96
Males 51-65	MC	20.06	21.60	19.60
	NP vs P1	52.66	51.66	50.66
	NP vs P2	54.00	54.66	51.50
	NP vs P3	53.00	54.66	51.50
	NP vs P4	53.33	54.50	49.83

5 CONCLUSION

Automatic pain intensity estimation possess great value in effective pain management. This paper studied the ECG biosignals, utilizing the Pan-Tompkins algorithm for the detection of QRS complexes extracting features related to the inter-beat intervals. Additionally, we experimented with three machine learning methods, comparing them in tasks of multi-class and binary pain classification of different pain intensities. Furthermore, we scrutinized the effect of gender and age in pain manifestation, revealing that they

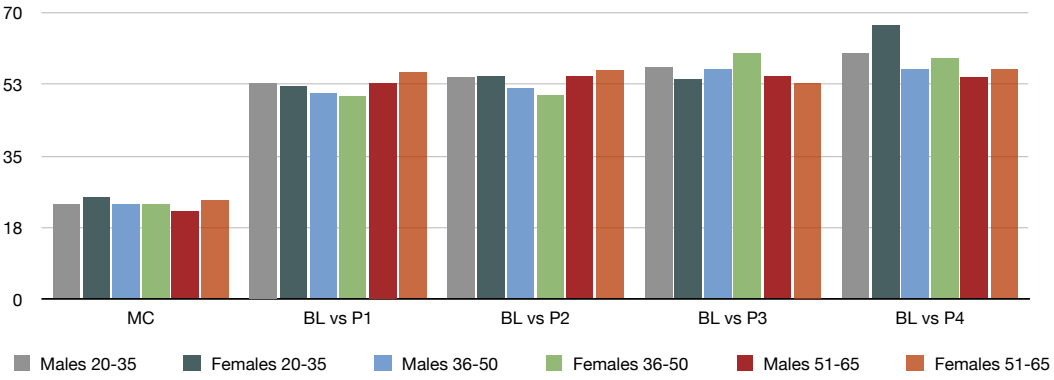

Figure 6: Classification results on the Gender-Age Scheme.

Table 5: Classification results of the Gender-Age Scheme (Females), reported on % accuracy.

Group	Task	Algorithm		
		LDA	SVM LN	SVM RBF
Females 20-35	MC	24.73	24.80	23.26
	NP vs P1	49.83	51.50	52.00
	NP vs P2	54.50	53.66	46.50
	NP vs P3	53.50	52.83	49.00
	NP vs P4	65.83	67.00	62.16
Females 36-50	MC	23.06	22.73	21.93
	NP vs P1	48.16	49.33	48.33
	NP vs P2	48.66	49.83	47.83
	NP vs P3	57.50	60.00	55.00
	NP vs P4	59.00	58.83	56.16
Females 51-65	MC	21.23	21.84	23.92
	NP vs P1	48.84	49.80	55.38
	NP vs P2	51.15	48.65	55.96
	NP vs P3	53.07	53.07	50.96
	NP vs P4	52.69	55.00	56.34

Table 6: Comparison of studies which utilized *BioVid*, ECG signals and LOSO cross validation, reported on % accuracy.

Method	Task	Results
Lopez-Martinez and Picard (2018)	NP vs P4	57.69
Werner et al. (2014)	NP vs P1	48.70
	NP vs P2	51.60
	NP vs P3	56.50
	NP vs P4	62.00
Thiam et al. (2019)	MC	23.23
	NP vs P1	49.71
	NP vs P2	50.72
	NP vs P3	52.87
	NP vs P4	57.04
Ours	MC	23.79
	NP vs P1	52.38
	NP vs P2	52.78
	NP vs P3	55.37
	NP vs P4	58.62

are major factors directly related to pain perception. The conducted experiments exhibited great variation among the genders where the males presented lower sensitivity, especially in high pain intensities. Regarding to age factor, significant variations demonstrated as well, disclosed that as long the age increases the pain sensation is diminished, and as consequent the increased risk for further injury. In particular demographic groups the difference is over 12%, indicating the divergence of pain sensation among people. We suggest that clinical pain assessment tools, need to be specifically designed for certain groups related to the particular demographic factors considering the unique pain manifestation' characteristics. Furthermore, we indicate to researchers who will involve in the creation of new pain databases, the necessity for the integration of demographic factors, as well as information about the social context and the psychological conditions of subjects. Our future work will explore the utilization of the remaining biosignals of *BioVid*, either in unimodal or in a multimodal approach as well.

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