Machine Learning Techniques for Automatic Classification of Patients with Fibromyalgia and Arthritis

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Abstract — *The ADABoost classifier is a very powerful tool for helping to diagnose multiple diseases. With some critical features related to the pathology, the classifier can automatically perform the subjects classification. In this way, the automatic classification is a useful aid for the doctor to make the diagnosis. In this manuscript, the authors have achieved a specific classification for fibromyalgia and rheumatoid arthritis using medico-social and psychopathological features obtained from specific questionnaires. It has obtained success rate above 89%, reaching a 97.8596% in the best case. With these results, it can avoid the innumerable and uncomfortable medical tests to diagnose the pathology, saving time and money.*

Keywords— *AdaBoost, classification, Fibromyalgia, arthritis.*

I. Introduction

'Machine Learning' [1], [2] techniques are a way to classify samples according to features of the samples. The algorithms can perform a categorization based on the defined features.

The classification involves the fact of performing multiple tests to get a reliable diagnosis in some cases. Existing classification techniques help that taking certain characteristics of pathology, to obtain a subject's classification, giving the doctor a basis to offer the final diagnosis.

Fibromyalgia (FM) [3], [4] is a disorder of unknown etiology characterized by widespread pain, abnormal pain processing, sleep disturbance, fatigue and it is often accompanied by psychological distress [5]. It affects 2-3% of the general population and 90% of patients are women [6].

Rheumatoid arthritis (RA) [7] is another type of painful musculoskeletal disease. It is an autoimmune condition with chronic inflammation that affects various joints of the body. RA has a worldwide prevalence of 0.5–1% and tends to affect three times as many women than men [7].

Rheumatoid arthritis (RA) is diagnosed through the presence of symptoms and results of a physical exam revealing swollen and painful joints, and sometimes laboratory exams detecting the presence of Rheumatoid factor in the blood [8]. In contrast physicians diagnose FM based on the level of tenderness on some spots of the body when pressure is applied, the duration of the presence of the symptoms, level of fatigue, and cognitive difficulties [8], [9].

For this manuscript, author's classified subjects which suffer arthritis and fibromyalgia, through medical, social and psychopathology parameters, is intended to understand the importance of psychopathological assessment in the diagnosis of two similar chronic pain disorders.

The doctor can use results of classification to guide his clinical decision making regarding a differential diagnosis in relation with arthritis and fibromyalgia. Using a classification algorithm the doctor has the ability to understand the probably of the disease given certain features.

Boosting [10] is a very important supervised learning methodology. The performance of these types of algorithms is high thanks to the weighting iterations allowed in each input data. Being a semi-supervised method allows not all samples are previously tagged for training [11], which facilitates the work of training to big data sets.

Moreover, to make optimal classification, it used 'cross-validation' technique [12]; to ensure that the results of the classification are completely independent samples of training and the validation matrix to introduce in the classifier.

II. Material and Methods

A. Participants

53 women with FM and 74 women with RA were recruited from ambulatory centers in Neiva, Colombia between January 2013 and January 2015. All individuals were diagnosed according to the American College of Rheumatology/European League Against Rheumatism (ACR/EULAR) criteria, were aged 18 to 79, and cognitively able to participate. Exclusion criteria were: currently hospitalized, comorbid neurological or psychiatric disorders interfering with independent decision making, terminal illness, or history of alcohol or other drug abuse.

Patients were assessed by a rheumatologist or internal medicine specialist to determine eligibility. After signing an informed consent, a trained research assistant met to obtain demographic and medical information and complete the self-report scales. This study received ethics committee approval.

B. Features

The psychopathologic features included in the study are the Symptom Checklist-90-R [13], and total scales like Global Severity Index (GSI), Positive Symptom Distress Index (PSDI), and Positive Symptom Total (PST). Higher scores indicate more symptoms and/or more distress.

The medical-social features included are the social stratum of the participants, age, Visual Analog Scale

(VAS), occupation, years in school, years with disease, average family income per month and their medication.

C. ADABoost Classifier

AdaBoost is a machine learning algorithm, formulated by Yoav Freund and Robert Schapire [9]. This is a meta-algorithm, and can be used in conjunction with many other learning algorithms to improve performance. AdaBoost classifier is adaptive in the sense that the classifiers built conform to improve subsequent instances misclassified by previous.

This classifier is sensitive to data noise and outliers. In some cases, however, it may be less susceptible to overfitting problem that most learning algorithm. The classifiers used may be weak (i.e., show a rate considerable error), but its performance is slightly better than random (ie, the error rate is less than 0.5 for binary classification), improving the final model. Even classifiers with an error rate higher than would be expected from a random sorter will be useful, as they will have negative coefficients in the final linear combination classifiers and therefore behave as their inverses.

AdaBoost generates and calls a new weak in each of a series of rounds classifier. For each call, a weight distribution is updated indicating the importance of samples in the data set for classification. In each round, the weights of each sample misclassified increase, and the weights of each sample correctly classified are reduced, so the new classification focuses on examples that have so far eluded the correct classification.

Thanks to this classifier, is combined through several iterations of a same algorithm base predictions made adaptively. These adaptive changes in the sample and assigning a weight to each predictor intermediary, more efficient final classifier is obtained.

AdaBoost uses decision trees as base models, originally designed for binary classification. In each iteration, following certain distribution, a tree is built and forecasts on all this data sample is observed. Those bad data classifiers are assigned a higher weight; influencing distribution data of the next stage, forcing predictor take this bad data classifier with greater importance.

The final predictor is the response of a result or a weighted average of the predictors of different stages. By focusing on the misclassified examples, empirical risk decreases rapidly. Thus it is found that instead of contributing to over-learning on the data used, the generalization error decreases. Thus it is determined that this classifier has good performance.

The algorithm of this classifier is described in the following development (binary classification).

Considering a set of samples, initializing the weights of the characteristics thereof with (1).

$$w_1(i) = \frac{1}{n};\ for\ all\ i = 1, \ldots, n \qquad (1)$$

From the samples and weights $w_m(i)$, it is built a g_m classifier that minimizes the overall error (2).

$$\epsilon_m = \sum_i^n w_m(i) 1_{\{g_m(x_i \neq y_i)\}} \qquad (2)$$

It is also estimated (3), and the weights are updated (4).

$$\propto_m = \log\left(\frac{1-\epsilon_m}{\epsilon_m}\right) \qquad (3)$$

$$w_{m+1}(i) = w_m(i) * e^{\propto_m 1_{\{g_m(x_i \neq y_i)\}}};\ i = 1, \ldots, n \qquad (4)$$

So the final classifier is as follows:

$$f(x) = Arg\ max_y \sum_{m=1}^{M} \propto_m 1_{(g_m(x)=y)} = sign\left(\sum_{m=1}^{M} \propto_m * g_m(x)\right) \qquad (5)$$

Furthermore, if the ε_m mistake, the sum of the weights of misclassified features is greater than ½, the algorithm stops, making sure that ranks better than a random classification.

III.RESULTS(SIZE 10 & BOLD)

A. Psychopathology Features

The success rate introducing psychopathology features in ADABoost classifier is 96.5965%

The sensitivity rate is 95.83%, meaning it has a very good capacity for detecting positive cases.

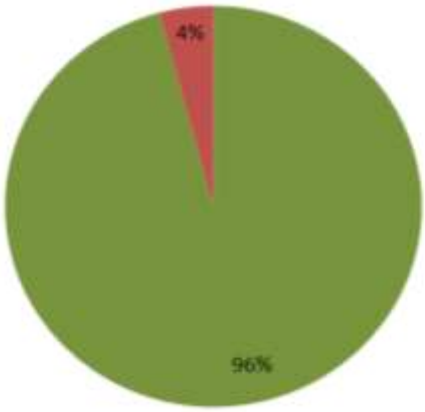

Figure 1. Sensitivity for psychopathology features.

96.97% was obtained for the specificity; it's also having a very good capacity for detecting negative cases.

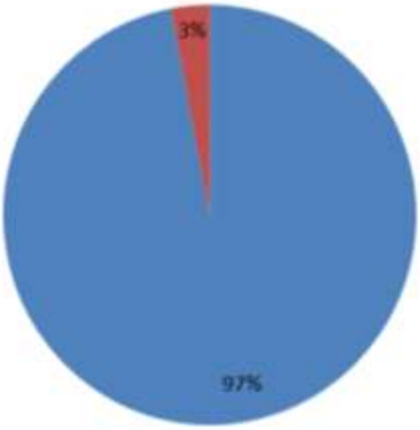

Figure 2. Specificity for psychopathology features.

B. Medico-Social Features

We once again calculate all the previous parameters, but only modifying the characteristic matrix used for classification purposes, including only medico-social characteristics.

From the SVM classifier we obtain a good success rate of 89.9474%.

In this case, certain rates below 88% are obtained.

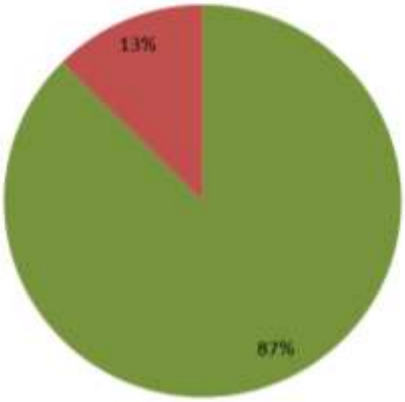

Figure 3. Sensitivity for medico-social features.

For the sensitivity the percentage is 87.5% and for the specificity 87.88%.

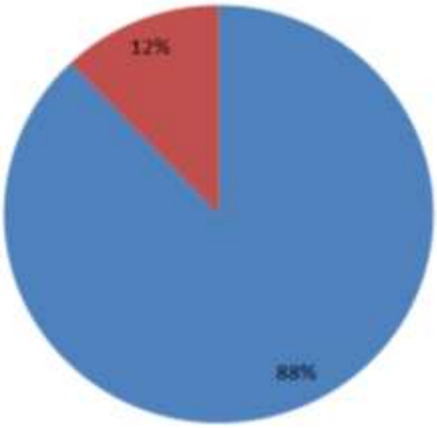

Figure 4. Specificity for medico-social features.

C. Psychopathology + Medico-Social Features

The psychopathological and medico-social characteristics were combined: 22 medico-social and 25 psychopathological characteristics were selected.

The ADABoost classifier was obtained a 97.8596% success rate.

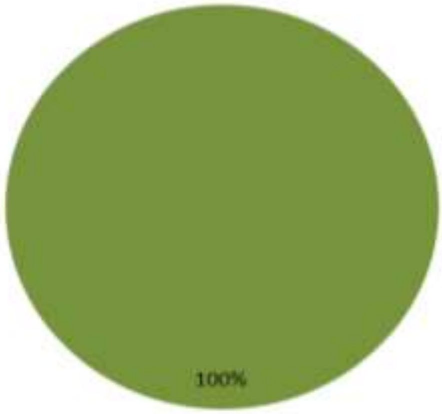

Figure 5. Sensitivity for Psychopathology + Medico-Social Features

Therefore, with this score we can see that the sensitivity (100%) and specificity (94.12%) rates are very good – over 94% in both cases, which suggests that the classifier is a very efficient one.

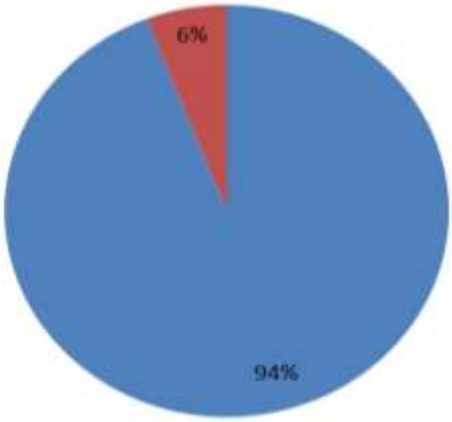

Figure 6. Specificity for Psychopathology + Medico-Social Features.

IV. DISCUSSION & CONCLUSSIONS

In all cases percentages over 89.9474% were obtained for each of the cases using the SVM classifier: psychopathological characteristics (96.5965%), medico-social characteristics (89.9474%) and a combination of the two (97.8596%).

Although the AdaBoost classifier be focused for the classification of face recognition or to classify Alzheimer's disease [14] based on MRI images. It is a classifier which comprises a classifiers chain, in which each iteration corrects the error of the previous iteration, achieving more efficient the classifier.

Therefore, the innovation of classifying patients suffering RA and FM, and with the economic savings advantages, only just to complete the questionnaires by the patient.

It obtained the previous results, it is confirmed that AdaBoost algorithm performs an efficient work to classify patients with FM and RA [15], depending on the features medical-social and psychopathological obtained by the questionnaires. Only with medical-social features, 89.9474% accuracy is achieved. For psychopathology features the success rate is 96.4035%, and joining the two types of features is achieved the 95.8246%.

It can be concluded that the psychopathological features are critical to the correct classification, but also with the medical and social it achieves high percentage of classification. As can be seen in the success rate including all features, medical-social features confuse the classifier.

The results obtained with this only classifier should be explored further, including a classifiers comparison. In addition, if it increases the number of samples may increase the accuracy of the classifier.

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