An Optimized Approach to Huntington's Disease Detecting via Audio Signals Processing with Dimensionality Reduction

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***Abstract*—Huntington's disease is a hereditary condition in which brain nerve cells rupture over time. This work proposes a new method for the detection of Huntington's disease using digitised voice signals by diseased and healthy volunteers while they were reading Lithuanian poems. In this approach, the produced features by voice signals suffer a dimensionality reduction to optimize the prediction stage. The performance evaluation regarded 186 speech exams and 24 volunteers, combining twelve audio signal feature extractors with classification models. The results indicate an excellent performance, reaching precision and accuracy over 99 percent with prediction time below 1 second. This approach shows promising results indicating its usability to improve the medical diagnosis via computer-aided diagnosis.**

***Index Terms*—Huntington's Disease, Computer-Aided Diagnosis, Signals Processing, PCA.**

I. Introduction

Huntington's disease is a rare brain disorder that causes the loss of motor, cognitive, and emotional ability, progressive reduction of main brain activities, compromising daily living capacity. This infirmity is classified as a neurodegenerative disease caused by the mutant HTT gene. It is estimated a frequency between 3 and 7 per 100,000 people of European ancestry, is even rarer in Japanese, Chinese, and African descendants [1].

Recent studies investigate the relationship between genetic mutation and the causes of this disease since the HTT gene provides instructions for the synthesis of the huntingtin protein [2]. Early signs of Huntington's disease are small involuntary movements, irritability, depression, and trouble making decisions or learning new information. Some affected individuals may have trouble speaking and swallowing, due to the involuntary movements. There are also alterations of voice and speech in patients afflicted occasioned by brain disorder strongly correlated with this disease [3], [4].

Although there are studies for diagnosing this disease using machine learning models combined with brain images, such as Magnetic Resonance Imaging or Computed Tomography [5], [6], [7], applications using images increase tratament cost reaching expenses of the order of US$1000 per patient [8], [9]. Thus, approaches with simpler equipment as a voice recorders are interesting alternatives especially for large-scale applications such as those focused on public health [10], [11], [12].

According to the alterations of voice and speech caused by Huntington's disease, in this paper, we propose a new approach of low cost based solely on voice recordings of patients reading Lithuanian poems, written by poet Maironis, to classification between Huntington's disease and healthy patients. Moreover, it is proposed an optimization on the prediction stage through an extracted features dimensionality reduction with no performance loss. To improve the performance evaluation, we evaluated twelve recent signal feature extractors through openSource Media Interpretation by Large feature-space Extraction (openSMILE) [13] combined with machine learning models K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Multilayer perceptron (MLP), Linear Discriminant Analysis (LDA), and Quadratic discriminant analysis (QDA).

The results show that the features extractor IS09 Emotion combined with SVM classifier reached precision, recall, and accuracy indexes over 99% with prediction time below one second. Through Principal component analysis (PCA), were necessary only 40 components, with a reduction of 89.58% of total original features. According to results reached, this approach presents a promising performance indicating its application in the computer-aided diagnosis.

Among the main contributions of this paper, we highlight the low-cost approach to pathology classification, a method for optimization of the extracted features by voice signals,

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and methodology with high precision and accuracy rates for detection Huntington's disease. This paper is structured as follows: Section II gives a brief description of the related works; Section III describes materials and methods and the database preparation. Section IV shows the proposed methodology; Section V and VI present the main results and discussed them. Finally, the conclusion and future works are in Section VII.

II. Related Works

Several papers have been presented in the literature for the classification of neurodegenerative disorders, making it a field of study especially for applications focused on signal processing produced by patients suffering from the disease [14], [15].

Engin et al. [16] proposed an analysis of vibration signals from an accelerometer to identify individuals with Parkinson's disease. In its study, characteristics in the vibrations of the signals were identified and a neural network was used for classification.

On the other hand, some studies focus on diagnosing other types of neurodegenerative diseases, Iram et al. [17] proposes the use of a hybrid system with analysis of multiple signals, combining Bayesian, SVM, K-Nearest Neighbors classification models and correlating the characteristics with patients who suffer from Alzheimer's disease.

Recent works in the literature use classification of symptoms of Huntington's disease via Machine Learning techniques, such as Artificial Neural Networks (ANN), Decision Tree and Random Tree [18]. Some articles also classify Huntington's disease using KNN or SVM [19], but achieve accuracy results in an average of 65%.

The above works do not use dimensionality reduction, making learning and prediction times high, increasing as the size of the database increases. None of the above works suggest a dimensionality reduction to reduce dataset components according to importance degree. In this work, we propose an analysis from Principal Component Analysis (PCA). This approach this can make the learning time considerably shorter, using data maximum verisimilitude. The training stage can be improved through PCA, reducing analysis components while to try maintaining accuracy and precision metrics.

There is some work using the Huntington's disease database but none of the works reached near the results of this paper or extracted the audios using the openSMILE framework and then classified the disease with several classifiers such as KNN, SVM, MLP, LDA and QDA.

III. Materials and methods

In this section, we present a description of materials and methods used for database preparation using dimensionality reduction. Moreover, a description of the classification models and feature extraction is presented. On the final of the section, the evaluation metrics are discussed.

A. Principal component analysis (PCA)

Principal component analysis (PCA) is a method of dimensionality reduction. It is used to reduce the dimensionality of a database and is useful for reducing the number of attributes with minimal information loss, thereby increasing training speed, decreasing the number of attributes and maintaining accuracy of the training data set.

Proposed by Karl Pearson [20], PCA uses two main methods as the basis for estimating the main components: variance and covariance. Variance is a measure of the variability, measuring how spread the dataset is. It is calculated from the average squared deviation from the mean score. Covariance measures the extent to which corresponding elements from two sets of ordered data changing in the same variance sense. With variance and covariance values, PCA calculates eigenvectors and corresponding eigenvalues, sorting the results in decreasing eigenvalues order.

The PCA promotes a transformation in the data, so that the data resulting from this transformation have its most relevant components in the first dimensions, in the main denominated axes. In this way, the PCA becomes very useful for use with large dimensional data. In other words, this method enables the selection of the most relevant features for the solution of the investigated problem.

B. Classification Models

K-Nearest Neighbors (KNN) is a method that analyzes the K nearest samples to determine which class belongs to the central sample, is usually called the lazy classifier because the function returns a local approximation of the defined class, but it is one of the most effective methods for classification of data with a small number of dimensionality, created by Fix and Hodges [21], the classifier it is useful for datasets where there is little or no prior knowledge about the distribution of the data.

Support Vector Machines (SVM) is a supervised classification model, created by Vladimir N. Vapnik et al [22]. The idea of the method is simple, the model creates a boundary at the most extreme points of each class in a N-dimensional space (N is the features number) to create separation, thereby providing support vectors to define each class.

Multilayer perceptron (MLP) is an artificial neural network that can have multiple input, output, neurons in the hidden layer. First develop with Frank Rosenblatt work with perceptrons [23], the MLP uses a non-linear activation function can train each neuron through backpropagation. One of the advantages of MLP is the ability to solve problems stochastically.

Linear Discriminant Analysis (LDA) is a method for separating different classes using matrix or linear combinations of characteristics in a given set of data, usually using covariance matrices and a priori maximum estimation. It assumes that each class has a normal distribution of its data, and the covariance of all the classes is identical.

Quadratic discriminant analysis (QDA), like LDA, tries to model the distribution of the classes. Unlike LDA, however, it

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TABLE I
FEATURES EXTRACTORS AND TOTAL NUMBER OF FEATURES.

Feature Extractor	Number of features
avec2011	1942
avec2013	2268
emo_large	6553
emobase	989
emobase2010	1583
IS09_emotion (IS09_e)	384
IS10_paraling (IS10_p)	1582
IS10_paraling_compat (IS10_pc)	1582
IS11_speaker_state (IS11_st)	4368
IS12_speaker_trait (IS12_st)	5757
IS12_speaker_trait_compat (IS012_stc)	6125
IS13_ComparE (IS09_C)	6373

does not assume that the covariance of each class is identical. Each class has its own covariance matrix on this algorithm.

K-fold is a method of non-exhaustive cross-validation [24]. The sample is randomly partitioned into k different sets. We use $k-1$ sets as the training data and 1 as the validation data. The process is repeated k times, with each set being used exactly once as the validation sample. The final result is the mean of the k results.

C. Features Extraction

In this work, audio signals provided by both patients and healthy people were used, each audio signal was post-processed to extract attributes. The attributes used in this work were produced through the open-Source Media Interpretation by Large feature-space Extraction (openSMILE) [13]. This toolbox offers several feature extractors from audio signals, among the various extractors of audio signal attributes, was chosen 12 extractors for each audio.

Table I describes this features extractors and respective number of features in relation. Below we list some of principal audio features adopted:

- Energy, intensity and loudness;
- Mel Frequency Cepstral Coefficients (MFCC);
- Perceptual Linear Predictive (PLP);
- Perceptual Linear Predictive Cepstral Coefficients (PLP-CC);
- Linear Predictive Coefficients (LPC);
- Line Spectral Pairs (LSP);
- Fundamental frequency;
- Voice quality: Jitter and Shimmer;
- Spectral features;
- Zero and Mean-Crossing rate.

This audio features was selected because it is consolidated features in literature and used in other works with good performance to detect disease from voice signals [11], [14], [25]. Thus, our aim was to evaluate the ability of these audio features assist the detection of Huntington's disease by means of a voice signals.

D. Evaluation Metrics

Accuracy is the number of hits made among all predicted values, given by equation 1

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

Recall is given as the ratio of the correct values among the values that were to be correctly identified, given by equation 2

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Precision is the ratio of correct values among values defined as given by equation 3

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

F1-score is a measure of balancement between Precision and Recall between unbalanced classes, given by equation 4

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

The Matthews Correlation Coefficient metric is a good measure for data with values where the difference in samples in each class differs, so when True positive and True negative values equals zero, the result is one, which is a perfect correlation, even if the classes are unbalanced, as equation 5 shows:

$$MCC = \frac{TP*TN - FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{5}$$

IV. METHODOLOGY

To extract the sample audios and classify the databases, only one computer was used, without any use of its Graphic Processing Unit (GPU). The tests were performed on a environment with AMD Ryzen 7 2700, 3.20GHz with 16GB of RAM and source code was written in programming language Python 3.

Classification tests were performed on 108 files that PCA computation returned in on openSMILE extractor [13], spending 2 days to finish all processing. After PCA is applied to all extraction files to reduce the number of features, we run the classifiers KNN, SVM, MLP, LDA and QDA in sample.

A. Dataset

The database used in this study was obtained by recording the audios of 24 patients, 13 were healthy patients and 11 pathological patients with Huntington's disease. The patients recite two poems written by Maironis, a Lithuanian poet. The poems are Lietuva brangi and Trakų pilis. This poems were record repeated times for each subject. In total, was 120 speech exams record of Healthy subjects and 66 speech exams of subjects with Huntington's disease. Once recorded, the recitations are then converted to WAVEform and MPEG-4 audio format. The information of all the recorded audios was extracted using the openSMILE Toolbox [13]. After the extraction of each audio, twelve different samples were generated, in each sample is the result of the toolbox extractors, as show in Figure 1.

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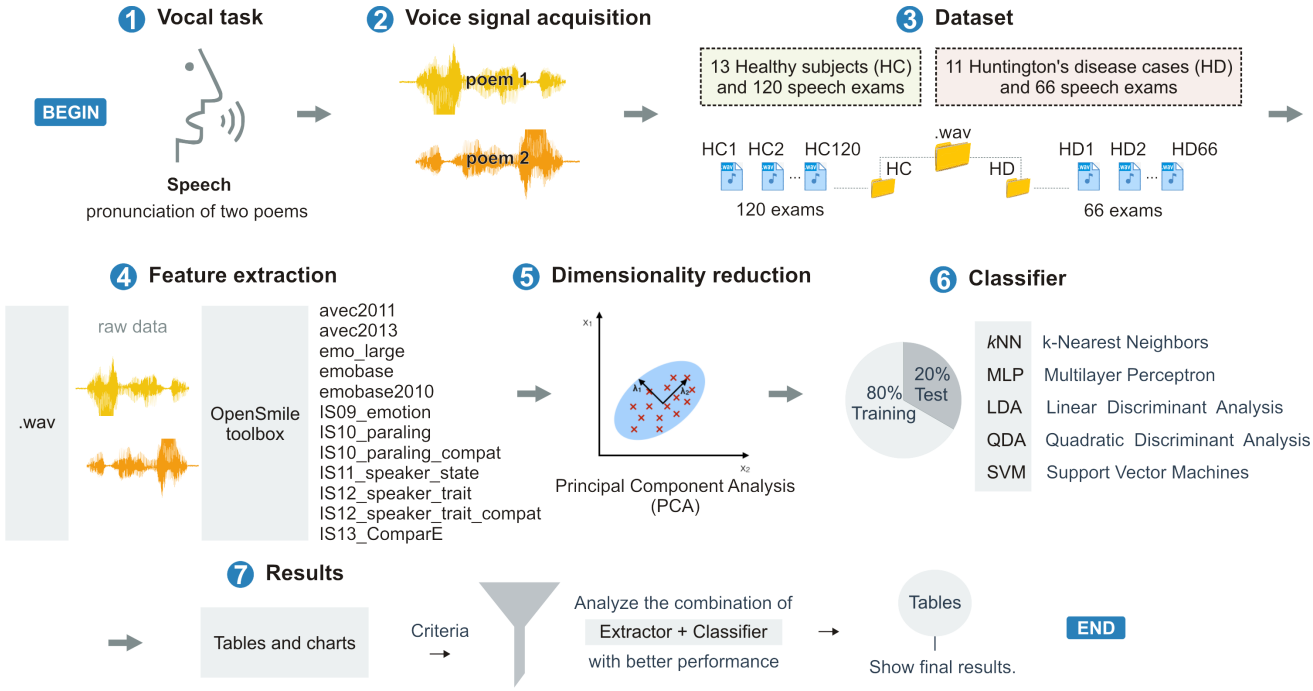

Fig. 1. Fluxogram with steps for Huntington disease classification.

B. Atribute Selection and Dimensionality Reduction

After extraction, all the files were assigned the number of attributes, with the label at the end indicating (HC) Healthy control subject and (PD) for Huntington's disease case. The high number of attributes makes it computationally costly to train several classification models, so the Principal Component Analysis (PCA) method was applied to reduce the dimensionality of the model [26], [27], keep the information generated by the extractors, decrease the amount of processing while maintaining the database fidelity, as show in Figure 1. Creating nine files for each extraction method, with the number of attributes varying from ten to ninety, with step of ten. Thus, resulting in 108 different samples.

After a shuffle in the dataset, to avoid bias, the dataset is divided into two samples, training and test, with 80 percent for training and 20 percent for testing.

C. Hyperparameters Selection

After this, some classifiers are given different hyperparameters to find the best setting for the data set. The Multilayer perceptron will change the number of neurons in the hidden layer, varying its values from 50 to 200. The SVM will change the kernel, varying between Radial Basis Function (RBF) and linear, with gamma values ranging from 2^{-13} to up to 2^{3}, the C-values will be changed from 2^{-5} to 2^{15}. Finally, K of KNN values will be changed from 1 to 50, taking only the odd numbers. The LDA and QDA does not have hyperparameters. To get the best combination of hyperparameters, we test these with grid search.

Grid search is a method of choosing the best hyperparameters for a given model. Given a set of possible hyperparameters, we process each combination, choosing the best, train the model with this configuration and get a result in a validation set. We then repeat this proccess an arbitrary number of times. The algorithm returns the combination of hyperparameters that yielded the best result.

V. Results and Discussion

After processing the data set, all results were analyzed and then several tables were generated for their visualization, such as the best of the extractors according to accuracy and precision each, the best extractor-classifier set and the best extractor according to their number of attributes.

The method reached more than 98% of precision on 8 different extractor versions with KNN, and in 2 of them it also more than 98% of F1-score. The results show that the best hyperparameters for SVM are C = 8, gamma = 0.0625 and linear kernel. For KNN, k = 1, metric = minkowski and uniform weights. For MLP, activation function = ReLU, alpha = 0.0001, epsilon = $1e^{-8}$, hidden layer sizes = 123, and solver = adam.

After the best combination of hyperparameters for each model is found, we now predict the values on the remaining twenty percent test. The values are then evaluated with four different metrics: Accuracy, Recall, Matthews Coefficient, Precision, and F1-score.

For the combination of extractors with classifier IS13_CompareE and SVM, it showed a time of 0.69 seconds, according to Table IV, but reached an accuracy of 89.4737%. On the other hand, the emobase extractor with 50 attributes and MLP classifier reached the value of 99.55 Accuracy but with a time of 14 seconds for training. For

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Fig. 2. Extractors and accuracy relation by different classifiers.

TABLE II
BEST PRECISION RESULTS.

Extractor	PCA	KNN	LDA	MLP	QDA	RFD	SVM
emobase	20	99.8471	99.2222	93.3333	86.6667	92.3077	91.6667
IS10_paraling	40	98.4820	98.3215	85.7143	98.1011	98.8742	91.6667
IS10_paraling	30	98.8897	98.3589	78.5714	98.4855	80.0000	98.2232
emobase2010	10	97.2111	97.3256	90.9091	63.1579	69.2308	80.0000
emobase2010	10	99.4896	99.2335	90.9091	63.1579	69.2308	80.0000
IS10_paraling	50	95.8888	95.6974	80.0000	95.5563	95.2301	91.6667
emobase	30	98.2589	93.7500	88.2353	98.3056	98.2148	98.2189
emobase	50	97.2111	97.3256	99.9997	98.3556	94.2148	95.4587
IS09_emotion	50	85.1278	93.7500	85.3698	85.2398	75.0000	88.2353
avec2013	50	89.2186	93.7500	93.3333	89.3218	89.8975	82.3529

TABLE III
BEST F1-SCORE RESULTS.

Extractor	PCA	KNN	LDA	MLP	QDA	RFD	SVM
emobase	50	47.619	96.7742	99.9842	12.5000	88.8889	93.3333
emobase	40	40.0000	96.7742	96.7742	50.000	89.6552	93.3333
IS09_emotion	40	96.5517	93.7500	93.7500	23.5294	75.0000	99.5899
emobase	30	96.5517	96.7742	93.7500	88.8889	88.8889	88.8889
emobase	20	33.3333	92.8571	93.3333	86.6667	85.7143	81.4815
IPC	30	92.8571	80.000	93.3333	88.8889	64.0000	85.7143
IPC	30	92.8571	80.0000	93.3333	88.8889	64.0000	85.7143
avec2013	50	63.6364	96.7742	93.3333	12.5000	63.6364	87.5000
IS09_emotion	30	50.0000	90.9091	92.8571	88.8889	74.0741	96.7742
IS09_emotion	50	42.1053	96.7742	92.8571	12.5000	66.6667	93.7500

the values of F1-score, IS12_speaker_trait_compact extractor with 90 attributes and SVM classifier reached values of 85%, but with a training time of 0.69 seconds, the same emobase with 50 attributes and MLP classifier reached F1 results of 99.98%.

Figure 2 shows the extractor-accuracy relationship using fewer than 50 attributes, as the best results in Table IV tend to be with small attribute number, the extractors with the best accuracy results were emobase and IS09_e, with values above 95%, the best classifiers for the following extractors were MLP and SVM. The MLP and SVM classifiers also achieved the best results among the other classifiers, with values above the rest of the other five classifiers.

Based on the results of Table II, we can easily see that the best models for this classification problem were KNN and SVM. These two achieved better segmentation time concerning all the other methods considered, performing excellent results of Precision, F1-Score, Recall, in optimal time. In the examples of attributes between 10 and 30, the KNN reached above 99% in precision values and SVM reached above 98%, as show in Table III. KNN yielded good results with small numbers for k, which leads us to conclude that the PCA was able to get a very good separation of the two classes in its transformation. This is also confirmed by SVM's good performance. As show in table VI, the best combination of extractors-classifier for time is IS08_e with SVM and 40 attribute number, witch results in 0.5883 training time with 99.99% accuracy result.

VI. CONCLUSION AND FUTURE WORKS

Concerning the extractors, we can see that emobase reached perfect precision and F1-score on several variations in the number of attributes, the IS10_paraling also showed great results for F1-score. However, the single instance that yielded the best result, reaching 99.99% precision with 3 different classifiers, was IS10_paraling with 10 features. Further testing could be done with these two extractors to determine the optimal one for this type of audio extraction.

Given the great number of different extractors, models and number of features used, we believe the method hereby described would benefit from using an ensemble method. By using bootstrap aggregating, for example, the method could combine the already excellent results it got to get even more robust and trustworthy. We also believe it is important to test this method with a bigger dataset. With the division between training and test, the training test ended up with 38 values, which is a small sample.

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TABLE IV
LIST OF FOUR BETTER RESULTS TO COMBINATIONS OF FEATURE EXTRACTOR AND CLASSIFIER WITH PRINCIPAL COMPONENT NUMBER OF PCA. THE RESULTS ARE DESCENDING ORDER BY THE F1-SCORE METRIC.

Extractor	PCA	CLF	Acc	F1-Score	MCC	Pre	Rec
avec2011	40	LDA	94.7368	93.3333	88.9855	93.3333	93.3333
	50	LDA	92.1053	90.3226	83.7919	87.5000	93.3333
	30	LDA	92.1053	89.6552	83.414	92.8571	86.6667
	30	SVM	92.1053	89.6552	83.414	92.8571	86.6667
avec2013	50	LDA	96.3684	96.7742	94.6963	93.7500	97.0002
	40	SVM	97.3684	96.5517	94.5751	98.4358	93.3333
	60	SVM	94.7368	93.3333	88.9855	93.3333	93.3333
	50	MLP	94.7368	93.3333	88.9855	93.3333	93.3333
emo_large	60	LDA	94.7368	93.7500	89.7567	88.2353	97.8558
	90	MLP	94.7368	92.8571	89.2935	98.7888	86.6667
	40	LDA	92.1053	90.3226	83.7919	87.5000	93.3333
	50	LDA	92.1053	90.3226	83.7919	87.5000	93.3333
emobase	**50**	**MLP**	**99.5517**	**99.9842**	**99.8999**	**99.9997**	**98.5444**
	40	MLP	97.3684	96.7742	94.6963	93.7500	98.7145
	40	LDA	97.3684	96.7742	94.6963	93.7500	98.6596
	30	LDA	97.3684	96.7742	94.6963	93.7500	97.5528
emobase2010	90	KNN	97.3684	96.5517	94.5751	98.4688	93.3333
	60	KNN	97.3684	96.5517	94.5751	98.7221	93.3333
	50	KNN	94.7368	92.8571	89.2935	98.2458	86.6667
	80	KNN	94.7368	92.8571	89.2935	98.7582	86.6667
IS09_emotion	40	SVM	95.8512	99.5899	99.9798	99.9897	98.4599
	30	SVM	97.3684	96.7742	94.6963	93.7500	97.1111
	50	LDA	97.3684	96.7742	94.6963	93.7500	96.2254
	40	KNN	97.3684	96.5517	94.5751	96.2378	93.3333
IS10_paraling	70	SVM	94.7368	92.8571	89.2935	95.8524	86.6667
	20	QDA	92.1053	89.6552	83.414	92.8571	86.6667
	90	SVM	92.1053	88.8889	84.1244	98.4200	80.0000
	70	MLP	92.1053	88.8889	84.1244	98.4242	80.0000
IS10_paraling_compat	40	KNN	97.3684	96.5517	94.5751	97.5282	93.3333
	50	KNN	97.3684	96.5517	94.5751	96.7000	93.3333
	90	KNN	97.3684	96.5517	94.5751	96.7547	93.3333
	60	KNN	97.3684	96.5517	94.5751	96.5852	93.3333
IS11_speaker_state	20	RDF	92.1053	88.8889	84.1244	99.7815	80.0000
	30	QDA	89.4737	84.6154	79.0374	99.1111	73.3333
	70	MLP	89.4737	84.6154	79.0374	97.8256	73.3333
	60	LDA	86.8421	83.871	72.8875	81.2500	86.6667
IS12_speaker_trait	70	LDA	94.7368	93.3333	88.9855	93.3333	93.3333
	80	LDA	92.1053	89.6552	83.4140	92.8571	86.6667
	60	MLP	92.1053	88.8889	84.1244	97.2566	80.0000
	70	SVM	89.4737	86.6667	77.9710	86.6667	86.6667
IS12_speaker_trait_compat	70	LDA	94.7368	93.3333	88.9855	93.3333	93.3333
	90	LDA	92.1053	89.6552	83.4140	92.8571	86.6667
	60	LDA	89.4737	86.6667	77.9710	86.6667	86.6667
	90	SVM	89.4737	85.7143	77.9452	92.3077	80.0000
IS13_ComParE	80	SVM	89.4737	86.6667	77.9710	86.6667	86.6667
	80	SVM	89.4737	86.6667	77.9710	86.6667	86.6667
	30	QDA	89.4737	84.6154	79.0374	96.2138	73.3333
	30	QDA	89.4737	84.6154	79.0374	96.0333	73.3333

TABLE V
LIST OF FIVE BETTER RESULTS TO COMBINATIONS OF SIGNAL FEATURE EXTRACTOR AND CLASSIFIER. THE RESULTS ARE DESCENDING ORDER BY THE F1-SCORE METRIC.

Extractor	PCA	CLF	Acc	F1-Score	MCC	Pre	Rec
emobase	**50**	**MLP**	**99.9988**	**99.9842**	**99.8999**	**99.9997**	**98.5444**
IS09_emotion	40	SVM	95.8512	99.5899	99.9798	99.9897	98.4599
avec2013	50	LDA	96.3684	96.7742	94.6963	93.7500	97.0002
emobase2010	90	KNN	97.3684	96.5517	94.5751	97.4782	93.3333

ETHICAL STATEMENT

The study protocol related to this data set was approved by the Regional Kaunas Bioethics Committee (P2-24 / 2013). Written informed consents were obtained from study participants, patient identifiers were removed to ensure anonymity.

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TABLE VI
LIST OF FIVE BETTER RESULTS TO ALL COMBINATIONS OF FEATURE EXTRACTOR AND CLASSIFIER. THE RESULTS ARE DESCENDING ORDER BY THE F1-SCORE METRIC.

Classifier	Acc	Training Time (s)	Test Time (s)	PCA
avec2011				
LDA	94.7368	0.1199	0.0002	40
SVM	92.1053	0.8095	0.0003	30
LDA	92.1053	0.0329	0.0002	30
LDA	92.1053	0.1566	0.0001	50
avec2013				
SVM	97.3684	0.5962	0.0001	40
LDA	97.3684	1.1054	0.0002	50
MLP	94.7368	13.1836	0.001	80
SVM	94.7368	1.7484	0.0003	60
emo_large				
MLP	94.7368	13.3553	0.0004	90
LDA	94.7368	0.1553	0.0001	60
LDA	92.1053	0.5378	0.0002	50
LDA	92.1053	0.1802	0.0001	70
emobase				
MLP	99.97.0	14.3631	0.0002	50
MLP	97.3684	13.5816	0.0002	40
LDA	97.3684	0.0276	0.0001	30
KNN	97.3684	0.2051	0.0019	30
emobase2010				
KNN	97.3684	1.271	0.005	90
KNN	97.3684	1.2898	0.0011	60
KNN	94.7368	0.1883	0.0008	20
KNN	94.7368	0.4069	0.0014	40
IS09_e				
SVM	**99.99**	**0.5883**	**0.0002**	**40**
LDA	97.3684	0.1287	0.0001	50
KNN	97.3684	1.2694	0.0036	40
SVM	97.3684	0.665	0.0004	30
IS10_p				
SVM	94.7368	0.6348	0.0005	70
SVM	92.1053	1.3442	0.0003	90
LDA	92.1053	1.0323	0.0001	30
MLP	92.1053	15.5117	0.0004	70
IS10_pc				
KNN	97.3684	0.191	0.0046	40
KNN	97.3684	0.1928	0.0048	60
KNN	97.3684	0.2191	0.0023	90
KNN	97.3684	0.2157	0.0045	50
IS11_ss				
LDA	92.1053	3.1848	0.1041	20
MLP	89.4737	12.9344	0.0004	70
QDA	89.4737	0.0216	0.0005	30
SVM	86.8421	0.6348	0.0003	90
IS12_st				
LDA	94.7368	0.5531	0.0002	70
MLP	92.1053	11.4847	0.0002	60
LDA	92.1053	0.1613	0.0001	80
SVM	89.4737	0.7480	0.0002	70
IS12_stc				
LDA	94.7368	0.1437	0.0001	70
LDA	92.1053	0.1669	0.0001	90
SVM	89.4737	0.6906	0.0006	90
LDA	89.4737	0.1715	0.0001	80
IS13_C				
SVM	89.4737	0.6383	0.0002	80
SVM	89.4737	0.6383	0.0002	80
QDA	89.4737	0.0141	0.0004	30
QDA	89.4737	0.0141	0.0004	30

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