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Novel algorithm for detection of cognitive dysfunction using neural networks

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ABSTRACT

According to the World Health Organization (WHO), the number of cases of neurodegenerative diseases will double by 2030 and triple by 2050, becoming an alarming problem for the health systems. Cognitive dysfunction is one of the first symptoms of neurodegenerative diseases, so cognitive dysfunction detection contributes to the early detection of these diseases. On the other hand, the electroencephalogram (EEG) is a non-invasive test that records the electrical activity of the brain and has a wide field of applications in the medical field, one of which is the detection of cognitive dysfunction. The combination of signal processing tools, feature extraction, and artificial intelligence applied to EEG information allows the creation of helpful tools for the automatic detection of cognitive dysfunction. This work aimed to implement an efficient and robust computational system focused on processing EEG signals through Wavelets and the automatic classification of cognitive dysfunction using neural networks. The proposed method achieved an efficiency of 97.5% and an F1 of 98.42% using 10 electrodes for EEG recording.

1. Introduction

Cognitive dysfunction is a condition that can occur at any stage of development and has specific characteristics that also depend on its etiology. Cognitive dysfunction refers to a condition with self-reported cognitive complaints as well as objective cognitive difficulties observed on neuropsychological tests [1,2]. Cognitive dysfunction can be assessed using psychometric tests such as the Montreal Cognitive Assessment Test (MoCA). It constitutes a valid tool to evaluate cognitive functioning. The MoCA is a brief, 10-minute cognitive screening tool that detects, cognitive dysfunction in various conditions including mild cognitive impairment, etc. [3–6]. It is easy to administer and interpret and is also easy to discuss with other clinicians and colleagues [7]. The MoCA has been found to have greater diagnostic accuracy than the Mini-Mental State Examination (MMSE) and to access memory impairments better [8,9]. It test covers more cognitive domains than the MMSE. Cognitive dysfunction according to MOCA is defined as a cutoff point below 26 points [10]. It is considered before neurodegenerative diseases, the most common cause of disability and dependency among the elderly; due to the increase in cases in recent years and the trends for 2030, it has become a growing challenge for public health and health systems [11]. The importance of the detection of cognitive dysfunction lies in allowing timely treatment in the event of pathologies, since with early cognitive stimulation the decline of higher functions can be slowed down and the appearance of behavioral disorders reduced, improving quality of life not only of the person who suffers it but also of their relatives [12]. Cognitive dysfunction can be detected using the electroencephalogram (EEG), this tool has wide application in the clinical area in the detection, monitoring, and even prediction of brain diseases [13,14]. EEG is the recording of the electrical activity of the brain [15]. It is a non-invasive and fast application that has been shown to offer clinically relevant information [16]. On the other hand, processing techniques such as Wavelet Transform (WT) or Fourier Transform (FT) are used to remove noise and extract relevant information from the EEG, contributing to the identification of biomarkers/patterns [17]. WT is a mathematical technique for processing non-stationary and fast transient signals. It was developed in the early 80 s and consists of decomposing the signal into scaled and displaced versions of the mother Wavelet to achieve a timescale representation while preserving the temporal aspect. The Mother Wavelets are the families of basis functions with finite energy that are defined in space and are used as an analysis function to examine the function of interest in the time-frequency domain. Some examples of functions are Symlets, Mexican Hat, Daubechies, Morlet,

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Table 1
Comparison of characteristics and results of methodologies focused on biopotential processing and automatic detection of brain diseases.

Year	Pathology	Processing technique	Electrodes	Public dataset (size)	Efficiency
2013 [21]	Mild Cognitive Impairment (MCI)	Independent Component Analysis (ICA)	18	Not Reported (NR)	91.76%
2017 [22]	Parkinson's disease (PD)	Hilbert transform	4	(40)	88–92%
2017 [23]	Alzheimer disease (AD)	Discrete Wavelet Transform (DWT)	10	(42)	92.86%
2018 [24]	Huntington	Fast Fourier Transform (FFT)	19	(51)	83.00%
2018 [25]	AD with Lewy and PD	FFT	128	(52)	89.85%
2018 [26]	AD and MCI	FFT, Wavelet Transform	19	(86)	79%–92%
2019 [4]	MCI with epilepsy	Combination of connectivity metrics	19–32	(51)	85%
2020 [5]	MCI	Permutation entropy and autoregressive	19	(27)	98%
2021 [6]	AD and MCI	DWT and Burg method	19	(35)	96.89%
2021 [7]	Cognitive dysfunction and Human Immunodeficiency Virus (HIV)	Event-related potentials	9	(102)	Correlation = 0.56
2022 [9]	Schizophrenia	Variational mode decomposition and an optimized extreme learning machine classifier	19	✓(NR)	93.71%
2023 [27]	MCI	Fourier transform and bidirectional long short-term memory	19	(20)	Only accuracy 97.20%
2023 [28]	MCI	Dual fusion of feature and decision layers	19	(79)	Only accuracy 96.30%
2023 [29]	MCI	Transformer architecture	64	(118)	76%

and Biorthogonals. In this research work, the Biorthogonal Mother Wavelet was used, characterized by symmetry and compact support. The WT improves the analysis of non-stationary signals compared to the Fourier Transform and its derived techniques, because more detailed information in time and frequency can be obtained, thanks to the mapping of the information in time scale [17,18]. After obtaining the EEG signals, and applying the processing technique(s), the classification stage follows. Classification and/or prediction of diseases is one of the applications of Neural Networks (NNs). They are simplified models that emulate how the human brain processes information [19,20]. NNs have various applications ranging from facial recognition, social networks, market prediction, aerospace, and healthcare.

The junction of EEG information, processing signals, and automatic classification made up a system focused on the detection of cognitive dysfunction. A large number of investigations focused on this area have been reported in the literature. Jianga et al. applied two tests to detect this pathology. The first is used to assess attention, memory, language, and spatial orientation. The second study was the EEG considering 32 electrodes; the recording was made while watching a movie and only the results of the patients who answered the questions about the movie correctly were taken into account. They used analysis of variance techniques to evaluate the performance of the proposed method and found a significant difference in frontal-central brain electrical activity between patients and controls [30].

The main symptom of most neurodegenerative diseases is cognitive impairment associated with memory loss. Reddy et al. work to detect Creutzfeldt-Jakob disease, where the main symptom is memory loss and personality changes. Detection is achieved through the use of various clinical studies: EEG, MRI, and cerebrospinal fluid studies [31,32]. Fiscón et al. managed to distinguish patients affected by mild cognitive impairment from control cases with an efficiency close to 92%. They used a monopolar montage EEG with 19 channels and a sampling time frequency of 256 Hz. As processing techniques, tests were performed using the FFT and WT, considering five levels of decomposition. The mother Wavelets used were the Daubechies and the Symlet [26].

Table 1 describes a summary of the research carried out to develop EEG-based tools for brain disease detection with a focus on the early detection of neurodegenerative diseases. It is observed that the average size of subjects in the database ranges between 23–52 participants where more than 50% of the articles do not mention the details of the database and 90% of the databases are not public. In addition, they use the 10–20 system distribution with 19 to 32 electrodes. The smaller the number of electrodes used, the lower the costs, signal processing time, setup time for data acquisition, and percentage of failures during the recording. The most used processing techniques are the Fourier variants, these are widely used for their ease of implementation and interpretation, however, they present problems with non-stationary signals in the time-frequency domain. Classification techniques using AI are the most used and the classification efficiency is between 85%–93%. For a system focused on the detection of pathology to be used as an auxiliary tool in the clinical area, it is necessary to meet specific standards that include efficiency levels greater than or equal to 97% [33].

This work aims to develop an efficient, robust, and reliable methodology for detecting cognitive dysfunction, using the least amount of EEG electrodes, signal processing techniques, and artificial intelligence classification techniques. In addition, it identifies the areas of the brain that show more pronounced differences in obtaining features and that allow a more efficient classification. The databases used were added to a public repository and will contribute to other techniques being compared with this methodology.

The document is organized as follows: Methods 2 contains the description of the developed algorithm. Results 3 includes data analysis and discussion of evaluation metrics. Finally, conclusions 4 show the article's contributions and future work on EEG systems for automatically detecting cognitive dysfunction.

2. Methods

The proposed methodology is divided into database identification, data decoding, mother wavelet identification, descriptor evaluation, data splitting, channel selection, and classification using a Multilayer Perceptron (MLP), Fig. 1. The last step is to evaluate the performance with the test data and the identified model for classification.

2.1. Databases

The database is made up of two EEG research centers. The final database contains 27 control cases and 20 cases of cognitive dysfunction and HIV [34]. Table 2 describes the characteristics of each data group.

In addition to identifying the data in the Table 2, it was verified that the acquisition protocols and projects for data acquisition passed through the ethics committee of the respective institution. The identification of cases with cognitive dysfunction was through age, schooling, gender, and group, the global average cognitive score obtained in the

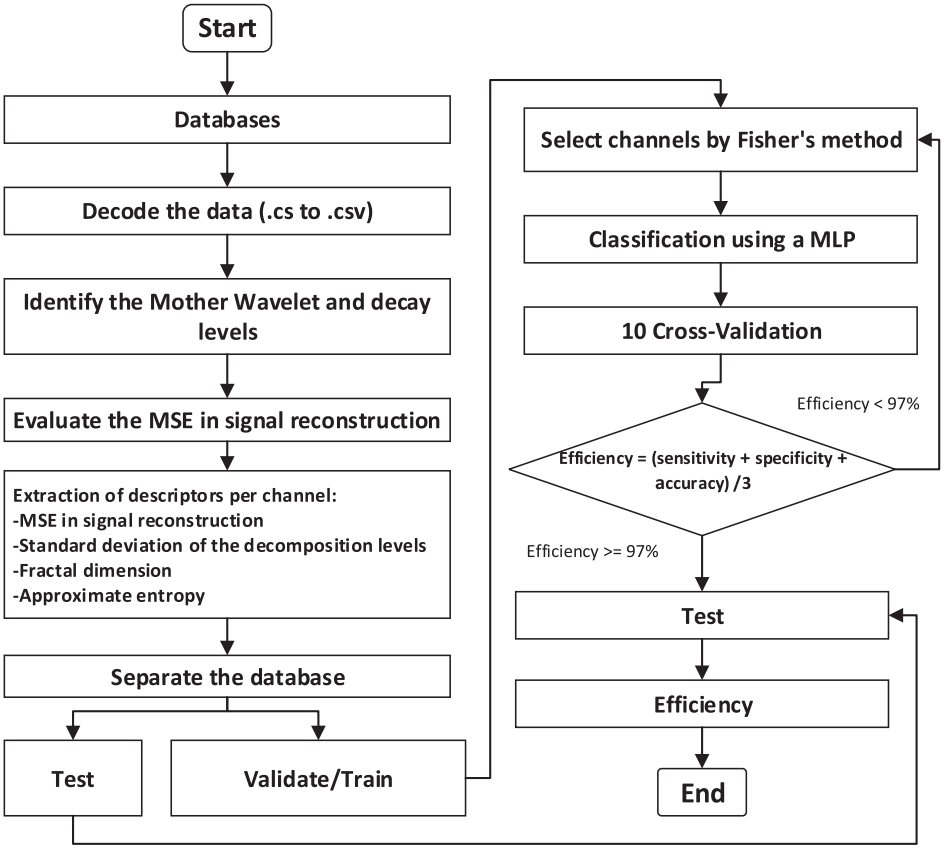

Fig. 1. Flowchart of the proposed methodology for the automatic detection of cognitive dysfunction using EEG information.

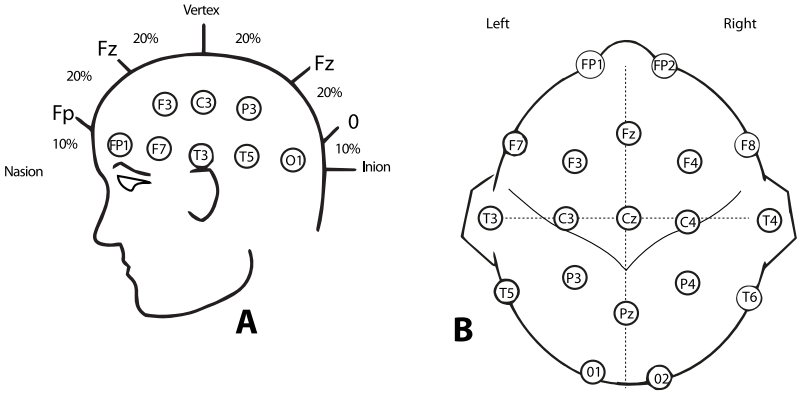

Fig. 2. Electrode distribution using the 10–20 system.

Table 2
Characteristics of the database.

Data	Control cases	Cases with cognitive dysfunction
Age range	26–58	27–59
Average age (DesvEstand)	35 (6.55)	39 (8.22)
Number of participants	27	20
Electrodes	19	19

cognitive, as well as the average obtained by the cognitive domain. The global average cognitive score was obtained with the cognitive tests Stroop test, Verbal Fluency test, Hopkins Learning Verbal test- Revised, and Wisconsin Sorting Card test. For all cases, EEG recording was taken with eyes closed during the resting state with 16–21 min duration. Participants remained comfortably seated with eyes closed in a room with no light.

EEG was collected through 19 leads of the international 10–20 system (FP1, FP2, F7, F8, F3, F4, T3, T4, C3, C4, T5, T6, P3, P4, O1, O2, FZ, CZ, and PZ), Fig. 2, with an electrode cap (Electro-cap International Inc., Eaton, Ohio, USA) referred to linked mastoids. Electrophysiological data were acquired with a 19-channel Neuronic Medicid electroencephalograph (Neuronic Mexicana®). The sampling frequency was 240 Hz, with a 16-bit resolution, a low-frequency filter of 0.5 Hz, a high-frequency filter of 30 Hz, and a 50/60 Hz notch filter. Subtraction of the global scale factor was applied to AP measures in all bands to decrease nonphysiological variability [35].

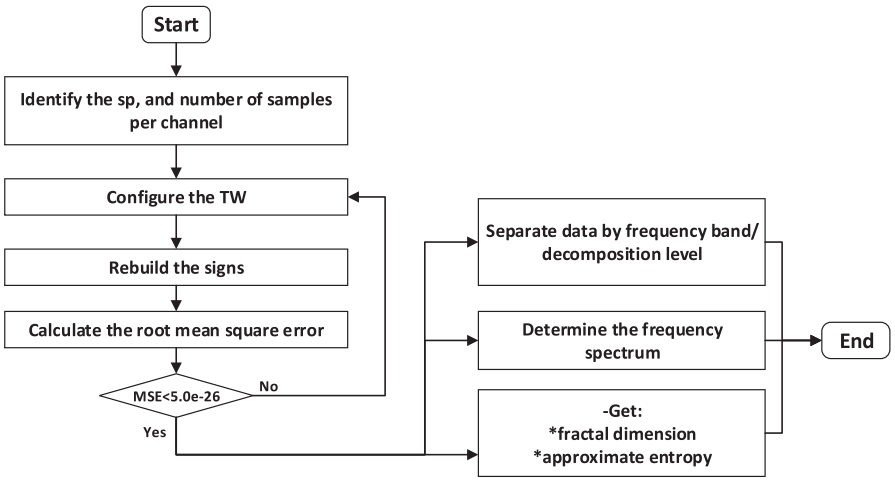

Fig. 3. Processing and extraction of features from EEG information.

2.2. Data decoding

Data decoding consists of exporting the original format (cdc, mrk, pat, plg, win) to a csv file where each line contains the information of a channel. After data conversion is complete, the file is read identifying each channel, scale, sample time, and record time. With the above information, a copy of the information used in the descriptor processing and extraction stage is made.

2.3. Feature extraction

This step consists of applying the DWT with different Mother Wavelets and different amount of decomposition levels. The Mean Square Error (MSE) in signal reconstruction is quantified for each combination of features and at the end, the combination with the least error is selected. This process is important because most of the characteristics are obtained in the frequency domain, and also because the user is provided with graphs per channel of the behavior of the signals in the time-frequency domain. 150 combinations are tested, including the Mother Wavelets: Haar, Daubechies, Symlets, Coiflets, Biorthogonal, Reverse, Discrete FIR, Gaussian, Mexican hat, Morlet, Complex Gaussian, Shannon, Frequency B-Spline, and Complex Morlet. The Eq. (1) represents the biorthogonal mother wavelet, where b: translation parameter, a: scale parameter, $f(x)$: signal to be analyzed, $\frac{1}{\sqrt{a}}$: normalization constant, $\overline{\psi(\frac{x-b}{a})}$: Mother Wavelet. This wavelet achieved the best results (see Fig. 3).

$$W_\psi f(a,b) = \int_{\mathbb{R}} f(x) \frac{1}{\sqrt{a}} \overline{\psi(\frac{x-b}{a})} dx \tag{1}$$

Once the Mother Wavelet and the decomposition levels are selected, the frequency spectrum, standard deviation (StandDesv) of the decomposition levels, the fractal dimension (FD), and the approximate entropy (WE) are obtained. These features were previously selected from a set of features that included the frequency and time domain, such as max, min, mean, median, 1st quartile, 2nd quartile, variation, kurtosis, mode, range, standard deviation, skewness, among others. The selection was made using statistical methods, ANOVA.

The StandDesv for each decay level obtained from the application of the Biorthogonal Mother Wavelet with seven decay levels is descriptor one and is applied to all channels. The FD is descriptor two, it has values between 1 and 2, and it serves to quantify the degree of irregularity (complexity of the neuronal profiles), for which it is expected that the results of the cases with cognitive dysfunction are greater than the cases of control. This descriptor is calculated in the time domain by the Higuchi method and the procedure is repeated for each channel.

The WE serves to quantify the degree of order, that is, the relative energy; is descriptor three and is responsible for evaluating behavior that is inversely proportional to the FD, which is why the results of the control cases are expected to be greater than the results with cognitive dysfunction. The WE is calculated in the frequency domain, from the wavelet coefficients (2), the relative energy definition (3), and finally the approximate entropy (4) [23,36–38]. The procedure is repeated for each channel.

$$c_i\psi = \langle x, \phi_i \rangle \tag{2}$$

where x is the signal, ϕ_i is the wavelet family and $i = 1, 2, \ldots, N$ represents the decomposition levels.

$$p_i = c_i^2 / \sum_{i=1}^{N} c_i^2 \tag{3}$$

$$WE = \sum_{i=1}^{N} p_i log(p_i) \tag{4}$$

The last descriptor is the MSE since the value of the MSE turned out to be higher for the cognitive dysfunction cases than for the control cases. Algorithm 1 describes the flow in the process of decoding and extraction of descriptors, it also illustrates the type of output expected in each descriptor.

Algorithm 1 Pseudocode of algorithm

Require: Initialization of the initial parameters: cases, scale, sample time, and record time
Require: Decoding(Data .cs to .csv)
  while conditions for completion are not met **do**
    Select Mother Wavelet and decomposition levels
    Determine the MSE of the reconstruction of the EEG signals
  Output: WM_t, levels
  Evaluate the MSE: WM_t, levels
  Output: MSE by channel
  Evaluate the DesvStand: WM_t, levels
  Output: $DesvStand$ of the 7 levels of decomposition per channel
  Evaluate the FD: WM_t, levels
  Output: FD by channel
  Evaluate the WE: WM_t, levels
  Output: WE by channel

2.4. Channel selection

Channel selection is made by applying Fisher's test and the t-student test. These tests are useful for selecting the set of channels that provides

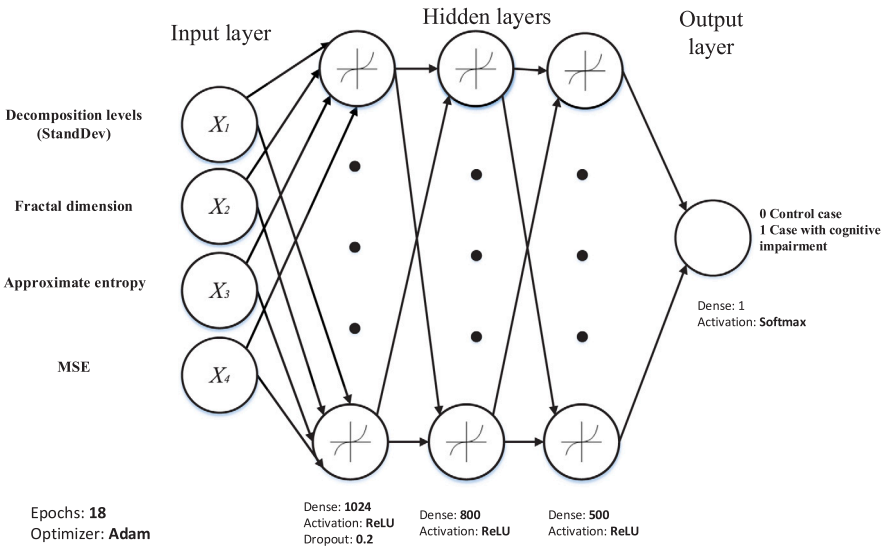

Fig. 4. Architecture of the neural network used for the classification of cognitive dysfunction.

the most relevant information to achieve the classification with greater efficiency and fewer channels.

Fisher's test is a statistical method to compare the variances of data groups, the 19 channels are the independent variable and the variances of the descriptors in each channel are compared. When the ratio of the variances is close to 1, there is little evidence to indicate that the variances are not equal. On the other hand, the higher the value of the variances ratio result, provides evidence of a difference in the variances of the groups. Considering the size of the data for each group and a p-value of 0.03, i.e., a 97% reliability, an F = 2.12 is considered. Combinatorial tests were carried out taking from 1 channel to the group of 19 channels to identify the group that achieved the best performance.

2.5. Neural network architecture for cognitive dysfunction classification

The neural network performs the function of the automatic classifier. An MLP is used as the main method for classification. MLP is a neural network composed of an input layer, an output layer, and multiple hidden layers that can solve linearly inseparable problems. As a comparative method, several tests are performed with Support Vector Machine (SVM) using different datasets and kernels. SVM is a machine learning supervised learning model for classification and regression, the algorithm is based on the concept of the hyperplane, it seeks to find a hyperplane that separates the data groups in the best possible way. In the previous subsections, the descriptors of each channel and the selection of channels that provide the information that helps a more efficient classification are defined. The information of the descriptors performs the input function for the network, the internal layers are defined from the size of the data and in behavior analysis in relation to its efficiency. The output of the network is a binary response corresponding to whether or not the analyzed case has cognitive dysfunction (see Fig. 4).

2.6. Performance evaluation metrics

In this step, the performance evaluation will be carried out to determine metrics and cross-validation will be used. Cross-validation, *k-fold*, consists of taking the data set and creating from it two separate sets: a training set and a validation set. Subsequently, the training set is divided into ten subsets and, at the time of training, each subset is taken as a test set of the model, while the rest of the data is considered a training set [39].

This process is repeated ten times, and in each iteration, a different test set will be selected, while the remaining data will be used as the

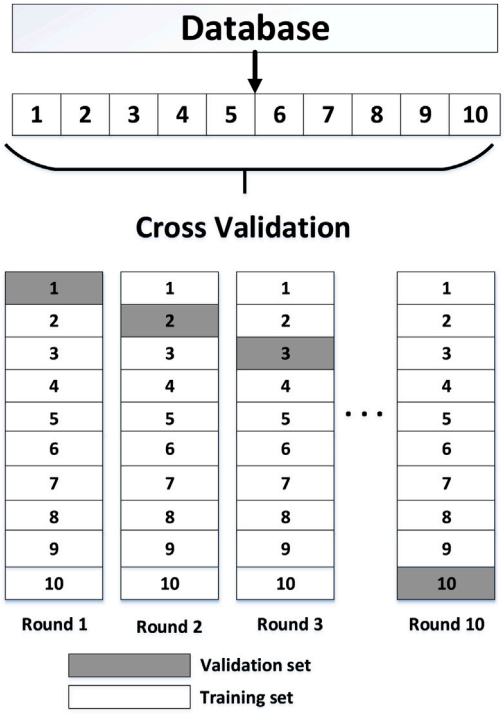

Fig. 5. Tools for processing EEG signals that allow evaluating parameters associated with dementia diseases.

training set. During each iteration, a quantification of false positive and false negative cases will be calculated, from these values the precision (5), specificity (6), sensitivity (7) and efficiency (8) are determined, where TN are true negative cases, FN are false negative cases, TP are true positive cases, and FP are false positive and negative cases [40].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Specificity(Recall) = \frac{TP}{TP + FN} \tag{6}$$

$$Sensitivity = \frac{TN}{TN + FP} \tag{7}$$

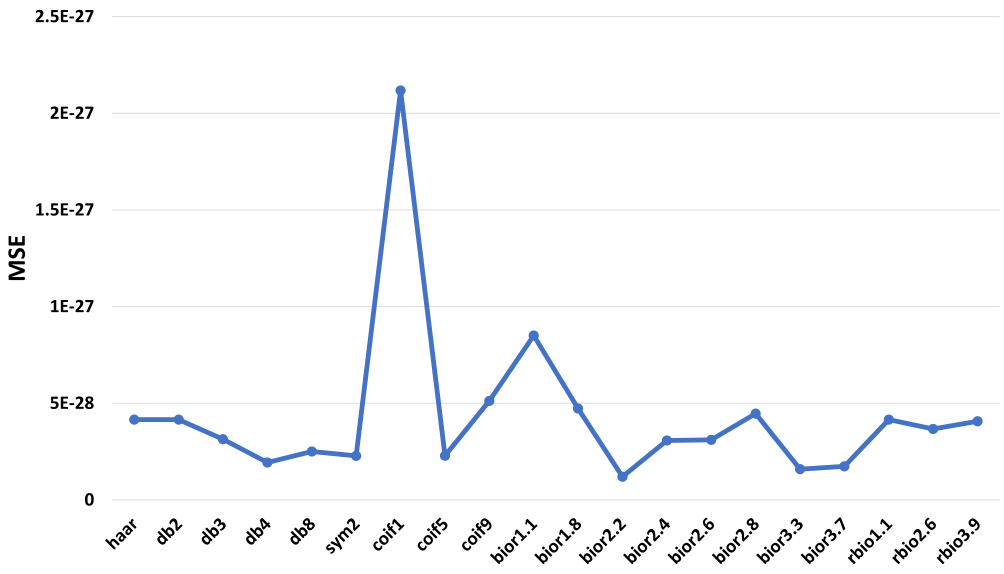

Fig. 6. Error in signal reconstruction using different mother Wavelets.

$$Efficiency = \frac{Sensitivity + specificity + Accuracy}{3} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$F_1 = \frac{2 \times Precisión \times Recall}{Precisión + Recall} \tag{10}$$

Once the iterations are completed, the efficiency and the error of each of the models produced are calculated. The average of the 10 trained models is calculated to obtain the efficiency and the final error. Fig. 5 illustrates the process used for cross-validation. In addition to the efficiency, the precision, confusion matrix, and F1, a harmonic measure of recall rate and precision, are determined.

3. Results and discussion

The 20 best results of using different Wavelets and decomposition levels for the selection of Wavelet features are shown in Fig. 6. The set of results using the Biorthogonal Wavelet showed the lowest errors, which is why it was selected for feature extraction. The Mother Wavelets that obtained the largest error values are Coiflets, Gaussian, and Morlet. The results of the MSE were included as a descriptor for the neural network due to the differences found between each data set.

Fig. 7 shows the results for the MSE, marking the control data group and the group with cognitive dysfunction with different colors. The results suggest that, although the biorthogonal Mother Wavelet achieved the smallest error for the reconstruction of the signals from the database, it more accurately represents the waveform for the signals belonging to the control cases. Even a line separating each group of results could be added, which will be of great help for the classification step. This parameter corresponds to the first input descriptor in the neural network. For each descriptor, the channels that show the greatest difference between each group of results were identified. For the MSE, the channels that show the greatest difference are T3, Pz, and Fz. For all the figures of results of the descriptors, each point corresponds to the average of the data.

Fig. 8 corresponds to the results for the WE, the objective of this characteristic is to quantify the degree of order. Therefore, the results of the group of control cases obtain higher amplitudes than the group with cognitive dysfunction. It is not expected that all the channels have the same behavior as they are located in different locations on the scalp and therefore in areas with different purposes. For the WE, the channels that show the greatest difference are C3, P4, and F4.

Fig. 9 corresponds to the results for the fractal dimension, the results of the data group with cognitive dysfunction achieve a greater amplitude in several channels since what is evaluated with this descriptor is the degree of irregularity, i.e., this is opposite to WE. Its descriptor corresponds to the third input of the neural network. For FD, the channels that show the greatest difference are C4, O1, C3, and O2.

Fig. 10 shows the channels that showed a greater difference in the calculation of the standard deviation for each level of decomposition, considering 7 decomposition levels and a biorthogonal mother wavelet, T3, F8, T4, P3, P4, 02. In general, the behavior in all channels is very similar, with some more abrupt changes for certain channels. Starting at decomposition level 3, the curves are separated, achieving the greatest difference at decomposition level 7, that is, the differences between both groups are concentrated in the slowest frequencies (theta and delta frequency band).

According to the results of the Fisher test and considering the minor overlaps in the identification of ranges by data group, the 10 channels that showed the greatest difference in the quantification of the descriptors are F4, C3, C4, P3, P4, T3, O1, O2, FZ, and PZ, Fig. 12. The descriptors of this group of channels are used with different architectures of the neural network and perform the function of input elements. The graph 11 shows the results ordered from lowest to highest, marked with a dotted orange line from which electrode will be used for the classification stage.

Table 3 shows the results of the tests with different MLP architectures, the architectures that achieved the highest efficiency are highlighted in bold (4-110-1 and 4-1024-800-500-1).

Separate tests were also performed on all channels, the results are shown in Fig. 13, the channels that achieve the best performance individually are F4, T3, F4, C4, and T5.

Fig. 14 shows the performance of the network using only one descriptor for each channel. The descriptors that achieve the best performance are the decomposition levels and the MSE. When reviewing the behavior of these descriptors in the different channels, it is observed that they are the ones that present the most abrupt differences between each data group.

The results obtained from the MLP were compared with other AI tools, an algorithm for SVM was implemented. Tests were carried out using a degree = 3, gamma = scale y kernel = linear/polynomial with the polynomial kernel the best results and the shortest execution time were achieved. Table 4 shows the results of tests with SVM using a polynomial kernel and different amounts of data.

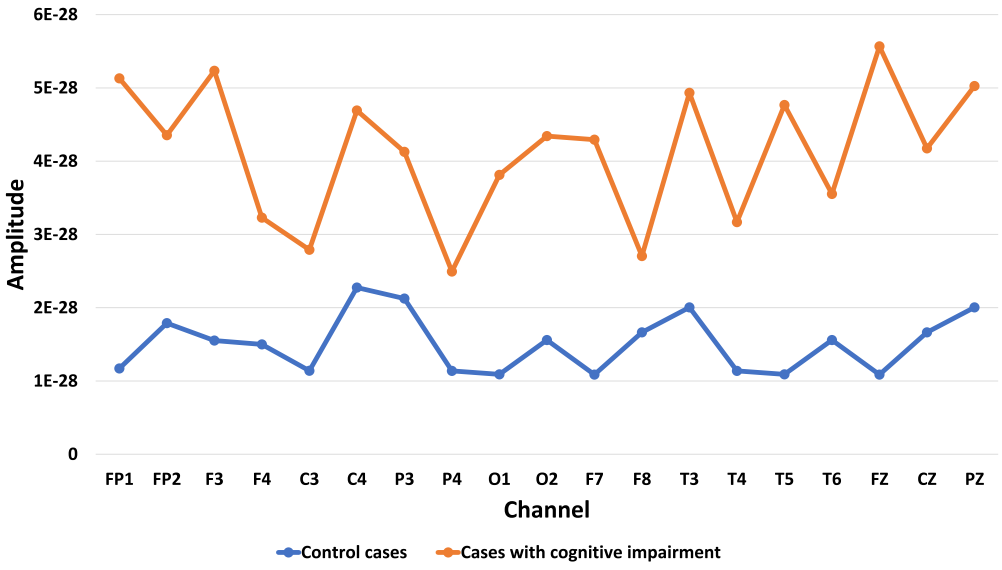

Fig. 7. MSE results by the data set. Each point represents the average of all results for the specific channel and group.

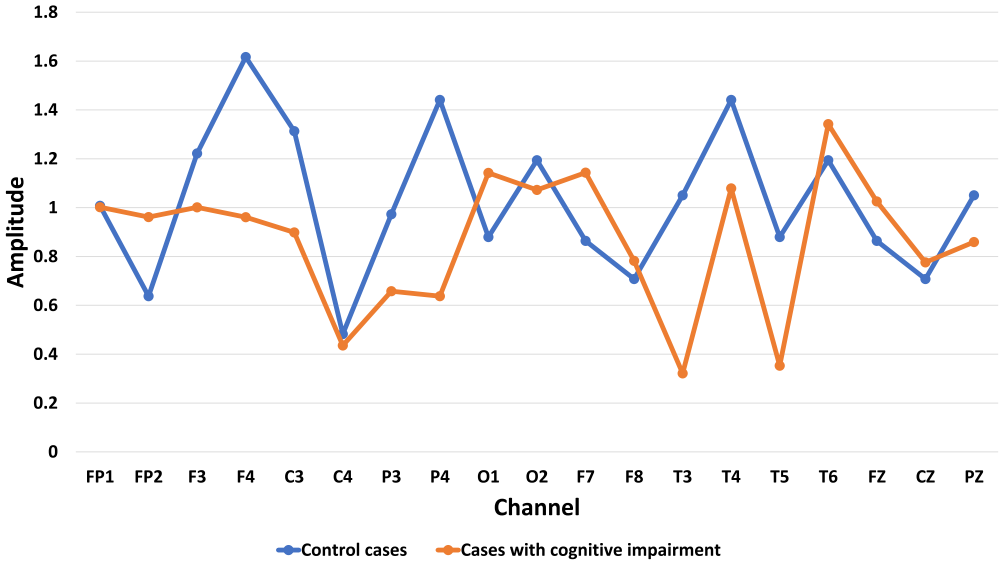

Fig. 8. WE result by the data set. Each point represents the average of all results for the specific channel and group.

Table 3
Efficiency obtained using different MLP architectures.

MLP architecture	Efficiency [%]
4-8-1	66.11
4-16-1	78.87
4-32-1	95.19
4-64-1	95.55
4-110-1	**97.00**
4-256-1	96.74
4-1024-1	96.64
4-32-32-1	68.72
4-256-256-1	89.07
4-1024-1024-1	93.86
4-1024-800-500-1	**97.5**
4-1024-500-500-1	90.11
4-128-128-128-1	81.42
4-1024-1024-1024-1	88.60

Table 4
Efficiency obtained using different SVM architectures.

Data	Execution time	Kernel	Efficiency [%]
All 19 channels	>1 week	Linear	NR
All 19 channels	1 day	Polynomial	92.2%
1 channel	1 h	Polynomial	56.1%
10 channels	1 day	Polynomial	94.0%

Table 5 shows the evaluation metrics results for three methodologies from the literature against the proposed method, using the same database. In the three metrics, the proposed method achieves the best results, 0.61% more efficient, 0.4% more precise, and 2.02% higher F1 than the method [6], which is the closest of the compared methods.

4. Conclusions

According to the results of classification efficiency, the use of biorthogonal wavelets in combination with neural networks allows achieving efficiency levels equal to or greater than 97%. The MLP architectures that achieved the highest efficiency were 4-110-1 and 4-1024-800-500-1. The first achieves an efficiency of 97% and the second

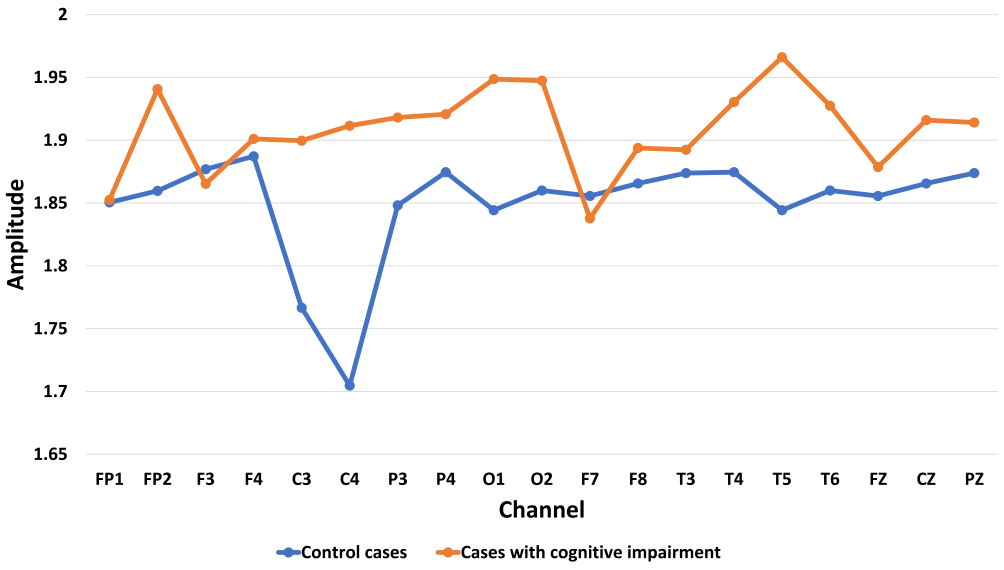

Fig. 9. FD results by data group. Each point represents the average of all results for the specific channel and group.

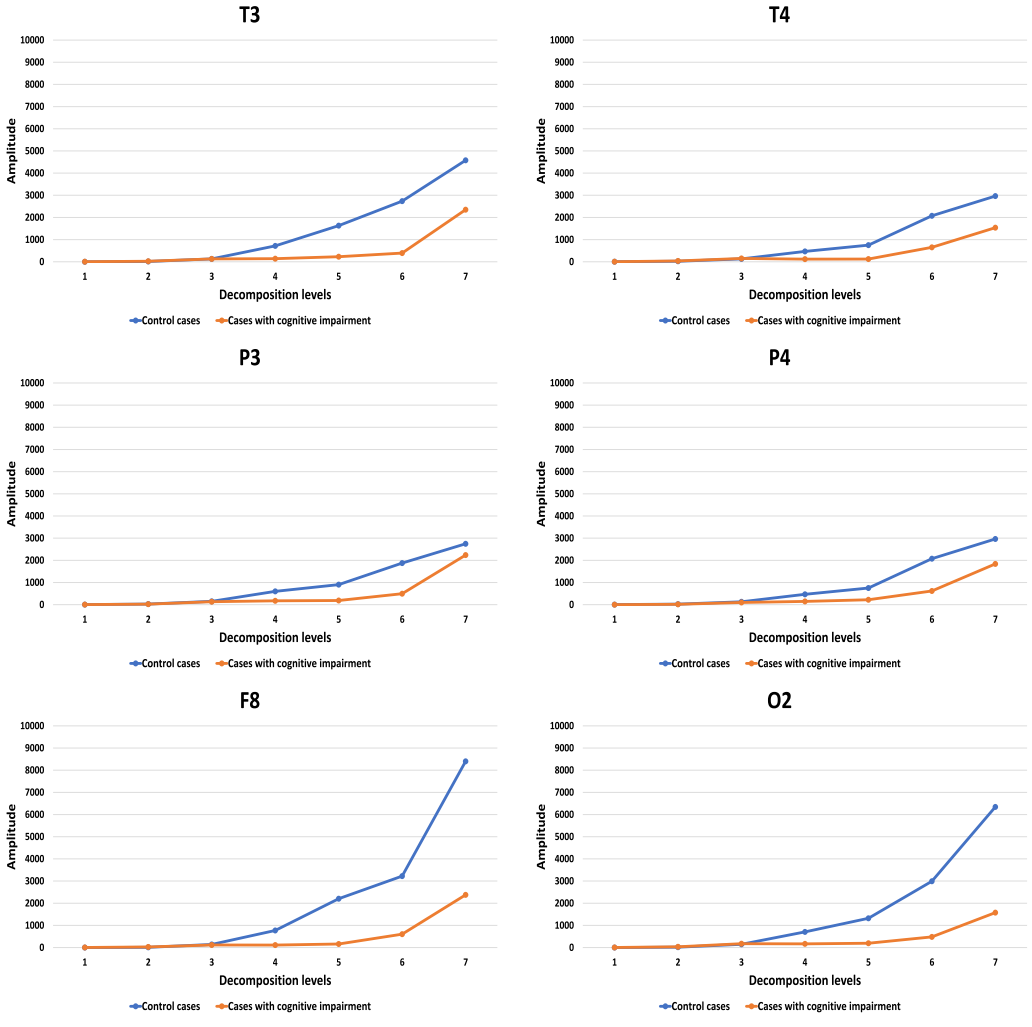

Fig. 10. Standard deviation results for each decomposition level using the Biorthogonal Wavelet. Each point represents the average of all results for the specific channel and group.

97.5% according to cross-validation. The comparative results between the MLP and the SVM show that the training time of the SVM is 2400 times slower than that of the MLP, both have close efficiency results, although the highest efficiency is achieved with the MLP.

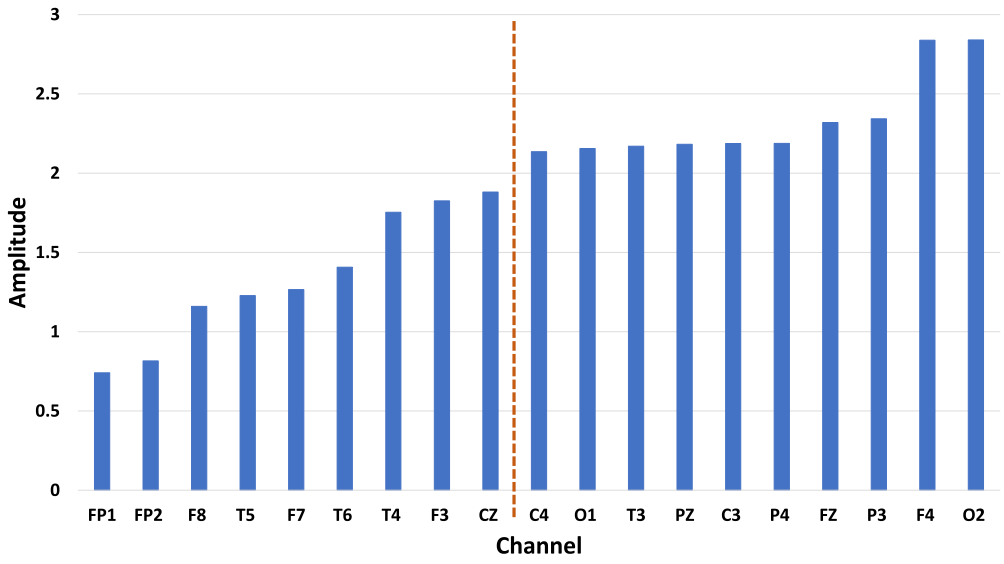

Fig. 11. Channel selection using the ratio of variances of the quantitative results of the describers.

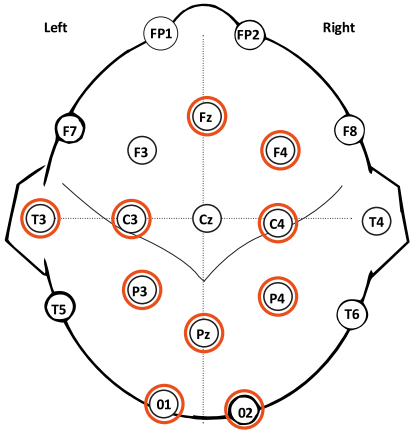

Fig. 12. Selected channels of system distribution 10–20.

Table 5
Comparison of evaluation metrics.

Method	Efficiency [%]	Accuracy [%]	F1 [%]
[6]	96.89%	96.50%	96.40%
[40]	90.66%	92.00%	88.00%
[8]	91.63%	91.80%	91.70%
Proposed	97.50%	96.90%	98.42%

The combination of the following descriptors is innovative and allows clinically acceptable classification levels to be achieved: MSE on signal reconstruction, standard deviation of wavelet decomposition levels, fractal dimension, and approximate entropy. The descriptors that contribute the most are the quantification of the standard deviation of the decomposition levels of the Wavelet and the MSE on signal reconstruction, these are characteristics where more abrupt differences are observed between the two groups of cases. The MSE on signal reconstruction is used for the first time as a descriptor in the classification of cognitive dysfunction, the values obtained for this characteristic indicate that a better reconstruction of the signal is achieved for the control cases than for the cases with cognitive dysfunction, this using the biorthogonal Wavelet with 7 decomposition levels.

On the other hand, the channels that contribute the most to increasing efficiency levels are C4, O1, T3, PZ, C3, P4, FZ, P3, F4, and O2. These channels relate to the brain areas focused on activities to memory, movement control, and visual activities. In addition, this group of electrodes forms a symmetrical position, that is, the electrodes selected from the right hemisphere are the same as the left hemisphere.

The development of this research work allowed the development of scalable, modular software architectures with high levels of efficiency focused on the processing of biopotentials and the automatic identification of patterns. Furthermore, making the databases used in this methodology public contributed so that it could be compared in detail with future methodologies.

The identification of biopotentials still has many areas of improvement such as the cleaning of signals in acquisition systems or the efficient and robust classification of multiple brain diseases with the same device. In future research, a multiclassification will be sought, that is, classify cognitive dysfunction, control cases, and at least one type of neurodegenerative disease. In addition, the number of participants will increase for each group.

CRediT authorship contribution statement

Luz-María Sánchez-Reyes: Conceptualization, Methodology, Formal analysis. **Juvenal Rodríguez-Reséndiz:** Conceptualization, Methodology, Resources. **Gloria Nélida Avecilla-Ramírez:** Conceptualization, Investigation. **María-Luisa García-Gomar:** Conceptualization, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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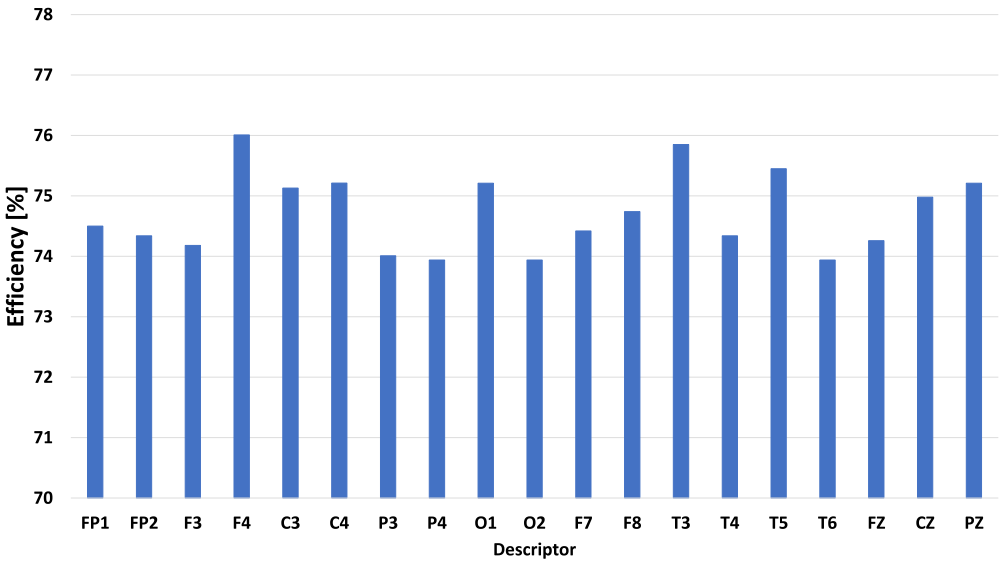

Fig. 13. Performance per channel using the MLP.

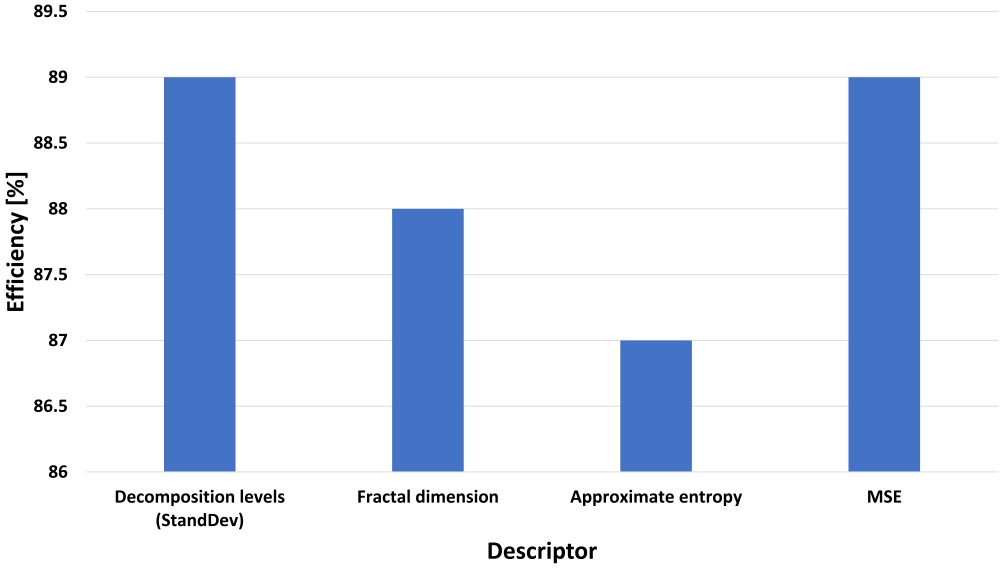

Fig. 14. Performance by feature using the MLP.

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