Chapter 5

Experimental results

This chapter reports the experimental results of proposed model MRW-FFWNN and several architectures implemented for the classification of three classes of EEG signals, Ictal, Interictal and Healthy. As it was explained in section 3.5, we used two criteria for decomposition and feature extraction of EEG signals. Each EEG signal was represented by a feature vector of six components, built using the mean, absolute median and variance of both delta (δ) and alpha (α) sub-bands. Therefore, the feature vectors obtained by two criteria are considered as inputs for the classifiers described in this work: FF-ANN, Elman, FFWNN, MRW-FFWNN (proposed model), SRWNN and MRW-SRWNN.

5.1 Performance evaluation

To evaluate the performance of each classifier, we execute several experiments testing each one with K-fold validation; it is a method of the most popular, due to its ability to provide a good statistical estimation of the performance of each classifier [KOH95]. In K-fold validation, the original sample is randomly partitioned into K equal sized subsamples. Of the K subsamples, a single subsample is retained as the validation data for testing the model, and the remaining $K-1$ subsamples are used as training data. The validation process is then repeated K times (the folds), with each of the K subsamples used exactly once as the validation data. The K results from the folds can then be averaged to produce a single estimation. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once [KOH95]. The selection of a value for K depends upon the number of samples available for training and testing the system. Here, we used a 3-fold validation to test each structure reported here.

The results are evaluated in terms of classification accuracy. Accuracy is used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. That is, accuracy is referred to as the degree of correct identification of EEG signals in each class. The accuracy (see Equation 5.1) is the proportion of true results (both true positives or correctly identified, and true negatives or correctly rejected) in the population [ALA14].

$$Accuracy = \frac{\text{number of correct classified samples}}{\text{total of samples}} \tag{5.1}$$

5.2 Training and testing sets

For the classifiers FF-ANN and Elman network, a total of 297 samples (99 of each class) were used in each experiment as input, 198 samples (66 of each class) were used for training and 99 (33 of each class) samples were used for testing (see Table 5.1). Whereas, for the classifiers based on binary-tree strategies and OVO decomposition strategies, a total of 200 samples as input were used in each experiment, 140 samples were used for training and 60 samples for testing. For the case of ictal binary classifier based on structures WNN, 70 samples of ictal EEG signals, 35 samples of inter-ictal EEG signals and 35 samples of healthy EEG signals were used for training; whereas 30 samples of ictal EEG signals, 15 samples of interictal EEG signals and 15

Table 5.1: Class distributions of the samples in the training and testing data sets for classifiers FFANN and Elman Network.

Class	Training set	Testing set	Total
Ictal	66	33	99
Interictal	66	33	99
Healthy	66	33	99
Total	198	99	297

Table 5.2: Class distributions of the samples in the training and testing data sets for ictal binary classifier based on WNN.

Class	Training set	Testing set	Total
Ictal	70	30	100
Interictal	35	15	50
Healthy	35	15	50
Total	140	60	200

samples of healthy EEG signals were used for testing (see Table 5.2). Similar class distributions samples of EEG signals are used for the inter-ictal and healthy binary classifiers. The training and testing data sets were built selecting samples randomly, with the same number of samples for each class. All classifiers were trained using the sets Z (healthy), F (interictal) and S (ictal) of the EEG signals from database of University of Bonn [BON16], [AND01].

In order to obtain the most suitable input features to each classifier, we tested different combinations of filters (Chebyshev, Elliptic, Equiripple and Least squares) and wavelets transforms (DWT and MODWT) using two criteria for the decomposition and feature extraction of EEG signals. For the criterion 1, considering the average highest of the correlation coefficients between the wavelet and each class of EEG signal, the feature extraction was done with Coif3, Coif5 and Db6 for Ictal, Interictal and Healthy EEG signals, respectively. The criterion 2 consisted in choosing the wavelet that provides the highest number of times that such wavelet gotten the best correlation coefficient, therefore the feature extraction was done with Coif3, Sym8 and Db6 for Ictal, Interictal and Healthy EEG signals, respectively. Finally, each EEG signal was represented by a feature vector of six components, built using the mean, absolute median and variance of delta (δ) and alpha (α) sub-bands. Therefore, the feature vectors obtained by the two criteria are considered as inputs for the classifiers described in this work.

5.3 Results: FFANN and Elman classifiers

Tables 5.3 and 5.4 show the best results obtained using the FF-ANN and Elman classifiers to identify EEG signals, with features calculated by criterion 1 and criterion 2, respectively. The experimental results reported here were obtained using 6, 9, 12, 15, 16, 18, 21 and 24 nodes in the hidden layer in each network; a learning rate of 0.05, a MSE_{max} of 0.01 and N_{Epochs} of 1000, due to that these parameters gave the best effectiveness of the classifiers. The best result in each case are bolded. The best result obtained in the classification of EEG signals by the criterion 1 was of 93.00 % of accuracy, using features calculated with a Least squares filter and by MODWT as inputs for a FF-ANN classifier with 12 nodes in the hidden layer and sigmoid as activation function. The best result obtained by the criterion 2 was of 94.33 % of accuracy, using features calculated with an Equiripple filter and by DWT as inputs for a FF-ANN classifier with 21 nodes in the hidden layer and hyperbolic tangent as activation function. In these tables column headed as "Accuracy" refers to percentage of the number of correct classified samples with respect to total of samples of the three classes of EEG signals. Results of all combinations of filters (Chebyshev, Elliptic, Equiripple and Least squares), wavelets transforms (DWT and MODWT) and activation functions used as inputs to FF-ANN and Elman classifiers by the criterion 1, can be found in Tables A.1 and A.2 of the Appendix A; and by the criterion 2, in Tables B.1 and B.2 of the Appendix B.

Table 5.3: Results obtained using the FF-ANN and Elman classifiers with wavelet decomposition to identify EEG signals by criterion 1.

Classifier (hidden nodes)	Features extraction	Activation Function	Accuracy (%)
(1) FF-ANN (12)	**Least Squares - MODWT**	**Sigmoid**	**93.00%**
(1) FF-ANN (15)	Elliptic - DWT	Hyperbolic tangent	92.66%
(2) Elman Network (21)	Least Squares - MODWT	Sigmoid	81.33%
(2) Elman Network (15)	Chebyshev II - MODWT	Hyperbolic tangent	86.00%

Table 5.4: Results obtained using the FF-ANN and Elman classifiers with wavelet decomposition to identify EEG signals by criterion 2.

Classifier (hidden nodes)	Features extraction	Activation Function	Accuracy (%)
(1) FF-ANN (24)	Equiripple - DWT	Sigmoid	93.00%
(1) FF-ANN (21)	**Equiripple - DWT**	**Hyperbolic tangent**	**94.33%**
(2) Elman Network (24)	Least Squares - MODWT	Sigmoid	87.66%
(2) Elman Network (15)	Chebyshev II - MODWT	Hyperbolic tangent	82.33%

5.4 Results: Binary tree classifier

With respect to the classifiers based on WNN, we have executed experiments testing each one of the structures of classification with decision trees: Ic-In-H, Ic-H-In, In-Ic-H, In-H-Ic, H-Ic-In and H-In-Ic. The experimental results were obtained using 60 neurons in the layer 2 in each classifier; a learning rate of 0.001, a MSE_{max} of 0.01, N_{Epochs} of 100 and Mexican hat as activation function, due to that these parameters gave the best effectiveness of the classifiers. The best results using features obtained by criteria 1 and 2 for each one of the classifiers: FFWNN. MRW-FFWNN (proposed model), SRWNN and MRW-SRWNN in terms of accuracy are shown in Tables 5.5 and 5.6, the best result in each case are bolded. In these tables, column headed as "Indeter" refers to percentage of EEGs are not classified in any of the three classes of EEG signals, which are referred to as indeterminate EEGs. The best result obtained in the classification of EEG signals of each one of the structures with decision tree, by the criterion 1 was of 96.67 % of accuracy, using features calculated with a Elliptic filter and by MODWT as inputs for a structure Ic-In-H with MRW-FFWNN as classifier. The best result obtained by the criterion 2 also was of 96.67 % of accuracy, using features calculated with a Equiripple filter and by MODWT as inputs for a structure H-In-Ic with MRW-FFWNN as classifier. Results of all combinations of filters (Chebyshev, Elliptic, Equiripple and Least squares) and wavelets transforms (DWT and MODWT) obtained by criteria 1 and 2, and used as inputs for each one of the structures of classification with decision trees: Ic-In-H, Ic-H-In, In-Ic-H, In-H-Ic, H-Ic-In and H-In-Ic, using FFWNN, MRW-FFWNN, SRWNN and MRW-SRWNN as classifiers can be found in Appendix A (see Tables A.3 - A.8) and Appendix B (see Tables B.3 - B.8), respectively.

5.5 Results: OVO Decomposition

Tables 5.7 and 5.8 show the best results obtained of the classification of EEG signals with binary classifiers by the Voting (VOTE) and Weighted voting (WV) strategies using as inputs the features obtained by the criteria 1 and 2, respectively. Both strategies were executed using a OVO decomposition scheme. The experimental results were obtained using 60 neurons in the layer 2 in each classifier; a learning rate of 0.001, a MSE_{max} of 0.01, N_{Epochs} of 100 and Mexican hat as activation function, due to that these parameters gave the best effectiveness of the classifiers. The best result in each case are bolded. The best result obtained in the classification of EEG signals for the OVO decomposition by the criterion 1 was of 81.67 % of accuracy, using features calculated with a Least squares and by DWT as inputs for a VOTE strategy with MRW-FFWNN as classifier. The best result obtained by criterion 2 also was of 88.83 % of accuracy, using features calculated with a Equiripple filter and by MODWT as inputs for a VOTE strategy with MRW-FFWNN as classifier. Results of all combinations of filters (Chebyshev, Elliptic, Equiripple and Least squares) and wavelets transforms (DWT and MODWT) obtained by criteria 1 and 2, which were used as inputs for each one of the methods Voting (VOTE) and Weighted voting

Table 5.5: Best results of the classification of EEGs based on WNN using binary-tree structures with wavelet decomposition by criterion 1.

Structure	**Classifier**	**Feature extraction**	**Accuracy (%)** Ictal	Inter	Healthy	Indeter	Total
Ic-In-H	(3) FFWNN	**Elliptic - MODWT**	69.48	50.12	64.54	8.00	63.00
	(4) MRW-FFWNN		**100.00**	**95.42**	**91.84**	**0.00**	**96.67**
	(5) SRWNN		71.14	51.05	62.19	9.33	63.00
	(6) MRW-SRWNN		76.70	79.91	30.44	9.00	65.00
Ic-H-In	(3) FFWNN	Least squares - MODWT	69.06	34.53	86.45	9.67	64.67
	(4) MRW-FFWNN		98.02	80.76	100.00	1.00	94.00
	(5) SRWNN		68.75	40.46	82.68	6.67	64.67
	(6) MRW-SRWNN		76.40	38.84	86.65	8.33	69.33
In-Ic-H	(3) FFWNN	Equiripple - MODWT	59.66	55.64	71.51	9.33	60.00
	(4) MRW-FFWNN		92.10	94.21	98.67	0.33	95.00
	(5) SRWNN		62.24	59.25	63.58	10.67	60.33
	(6) MRW-SRWNN		74.86	84.90	49.11	3.67	73.33
In-H-Ic	(3) FFWNN	Equiripple - MODWT	59.01	63.19	45.45	10.67	58.00
	(4) MRW-FFWNN		92.70	92.29	100.00	0.00	94.33
	(5) SRWNN		55.67	61.77	43.64	12.33	56.00
	(6) MRW-SRWNN		82.23	70.33	56.67	8.00	69.67
H-Ic-In	(3) FFWNN	Elliptic - MODWT	62.10	36.56	91.02	10.33	68.33
	(4) MRW-FFWNN		97.01	84.88	100.0	0.00	95.00
	(5) SRWNN		60.45	41.98	95.75	5.33	70.67
	(6) MRW-SRWNN		72.17	41.00	93.18	5.67	72.33
H-In-Ic	(3) FFWNN	Equiripple - MODWT	54.56	36.07	90.72	8.33	67.67
	(4) MRW-FFWNN		92.65	86.84	100.00	0.00	94.67
	(5) SRWNN		57.38	35.98	94.58	6.67	70.00
	(6) MRW-SRWNN		67.87	56.81	97.00	2.00	79.00

Table 5.6: Best results of the classification of EEGs based on WNN using binary-tree structures with wavelet decomposition by criterion 2.

Structure	Classifier	Feature extraction	Accuracy (%)				
			Ictal	Inter	Healthy	Indeter	Total
Ic-In-H	(3) FFWNN	Least squares - MODWT	72.83	59.47	51.68	13.10	63.81
	(4) MRW-FFWNN		100.00	89.81	92.81	0.00	95.71
	(5) SRWNN		77.20	56.67	52.49	13.10	65.24
	(6) MRW-SRWNN		79.56	75.28	39.01	7.38	68.10
Ic-H-In	(3) FFWNN	Least squares - MODWT	68.02	27.64	66.45	22.62	58.33
	(4) MRW-FFWNN		99.10	85.90	100.00	0.95	96.43
	(5) SRWNN		72.89	26.59	64.00	21.90	60.48
	(6) MRW-SRWNN		74.45	22.46	75.79	12.62	63.33
In-Ic-H	(3) FFWNN	Elliptic - MODWT	61.60	64.44	66.80	13.67	64.00
	(4) MRW-FFWNN		94.58	96.86	87.80	0.00	94.00
	(5) SRWNN		70.76	61.48	64.15	9.67	65.00
	(6) MRW-SRWNN		78.36	79.28	33.35	8.00	68.33
In-H-Ic	(3) FFWNN	Chebyshev II - MODWT	63.43	55.42	59.47	14.67	57.83
	(4) MRW-FFWNN		89.26	94.91	85.65	0.67	91.33
	(5) SRWNN		61.78	54.42	63.20	14.17	57.83
	(6) MRW-SRWNN		71.18	74.15	43.81	6.50	65.33
H-Ic-In	(3) FFWNN	Least squares - MODWT	72.00	32.48	84.16	9.67	67.33
	(4) MRW-FFWNN		100.00	83.68	100.00	0.33	96.00
	(5) SRWNN		72.52	29.73	84.48	10.67	67.33
	(6) MRW-SRWNN		71.90	41.49	88.15	8.00	72.00
H-In-Ic	(3) FFWNN	**Equiripple - MODWT**	58.44	32.53	81.79	5.67	64.67
	(4) MRW-FFWNN		**99.00**	**85.79**	**100.00**	**0.00**	**96.67**
	(5) SRWNN		63.99	23.42	86.74	9.00	66.33
	(6) MRW-SRWNN		68.73	32.93	95.38	3.33	74.33

Table 5.7: Results of the classification of EEGs based on WNN using VOTE and WV strategies in a OVO decomposition scheme with wavelet decomposition by criterion 1.

Strategy	Classifier	Feature extraction	Accuracy (%) Ictal	Inter	Healthy	Total
VOTE	(3) FFWNN	**Least squares - DWT**	95.06	25.20	96.94	71.00
	(4) MRW-FFWNN		**80.00**	**69.57**	**95.45**	**81.67**
	(5) SRWNN		75.47	31.21	92.18	65.67
	(6) MRW-SRWNN		89.91	81.77	22.86	64.67
WV	(3) FFWNN	**Elliptic - MODWT**	90.11	44.33	94.94	75.33
	(4) MRW-FFWNN		**100.00**	**100.00**	**15.33**	**78.67**
	(5) SRWNN		80.55	37.71	99.05	70.33
	(6) MRW-SRWNN		81.40	99.00	11.90	67.33

(WV), using FFWNN, MRW-FFWNN, SRWNN and MRW-SRWNN as classifiers, can be found in Appendix A (see Tables A.9 and A.10) and Appendix B (see Tables B.9 and B.10), respectively.

5.6 Discussion

In this chapter, we present the results obtained for the classification of three classes of EEG signals: Ictal, Interictal and Healthy, with our proposed model MRW-FFWNN using different structures of binary-tree and VOTE and WV strategies in a OVO decomposition scheme. Also, we present results obtained with other classifiers: FF-ANN, Elman network, FFWNN, SRWNN and MRW-SRWNN for comparison purposes. We used two criteria for decomposition and feature extraction of EEG signals, and we built a vector of six components composed by the mean, absolute median and variance of δ and α sub-band of each EEG signal, these features are used as input for each classifier. As we stated before, three-fold validation was applied to obtain all of accuracy results. The experimental results were done in three parts, the first contained the results obtained by the FF-ANN and Elman classifiers. The second

Table 5.8: Results of the classification of EEGs based on WNN using VOTE and WV strategies in a OVO decomposition scheme with wavelet decomposition by criterion 2.

Strategy	**Classifier**	**Feature extraction**	**Accuracy (%)**			
			Ictal	**Inter**	**Healthy**	**Total**
VOTE	(3) FFWNN	**Equiripple - MODWT**	97.24	49.05	100.00	81.67
	(4) MRW-FFWNN		**100.00**	**100.00**	**66.67**	**88.83**
	(5) SRWNN		94.59	47.00	100.00	79.67
	(6) MRW-SRWNN		95.82	100.00	4.71	68.00
WV	(3) FFWNN	**Least squares - MODWT**	91.94	50.70	100.00	80.33
	(4) MRW-FFWNN		**96.15**	**100.00**	**14.29**	**78.67**
	(5) SRWNN		69.18	9.79	96.67	57.00
	(6) MRW-SRWNN		86.42	99.00	4.29	66.33

and third parts contained the results obtained by the classifier based on WNN with binary-tree strategy, and with VOTE and WV strategies in a OVO decomposition scheme, respectively. Then, we can summarizes the best results obtained as follows:

- The best result obtained considering the FF-ANN and Elman classifiers was of 94.33 % of accuracy using features calculated by the criterion 2, with an Equiripple filter and by DWT as inputs for a FF-ANN classifier with 21 nodes in the hidden layer and hyperbolic tangent as activation function.

- With respect to the classifiers based on WNN with a binary-tree strategy, the best result obtained was of 96.67 % of accuracy using features calculated by both criteria, 1 and 2. The best result by the criterion 1 was obtained using features calculated by an Elliptic filter and by MODWT as inputs for a Ic-In-H structure. Whereas, for the criterion 2, the best result was obtained using features calculated by an Equiripple-MODWT as inputs for a H-In-Ic.

- Considering the classifiers based on WNN with VOTE and WV strategies in a OVO decomposition scheme, the best result obtained was of 88.63 % of accuracy using features calculated by the criterion 2, with an Equiripple filter and by MODWT as inputs for a VOTE strategy in a OVO decomposition scheme.

The binary-tree strategy works better than OVO decomposition in the classification of EEG signals. It is because to the aggregation methods (VOTE and WV) used in OVO decomposition are the simplest cases to make a final decision based on the binary classifiers.

With respect to the results obtained in the classification of EEG signals using features calculated with different combinations of filters and wavelets, the best results were obtained with the FIR filters, Equiripple and Least squares, and by the MODWT for decomposition. It is because the FIR filters do not require feedback, they are inherently stables and can easily be designed to be linear phase [PRO07]. In addition, the MODWT introduces redundancy across time that can be put to good use in analyzing certain time series [PER00]. The combination of the characteristics of FIR filters and MODWT provides good results.

Finally, we present a summary of the results obtained about of classification of three classes of EEG signals using same database reported in this work (see Table 5.9). We can observe that our best result obtained (96.67 %) is better than the result by Martis et. al [MAR12], where the authors uses a binary-tree strategy; and our best result is similar to other works reported in the state-of-the-art algorithms in the classification to epilepsy-related stages. Therefore, our model can be considered as an alternative for the classification of EEG signals.

Table 5.9: Studies reporting automated detection of three classes of EEG signals using (Z, F, S) same database reported in this work.

Authors	**Type classifier**	**Number of features**	**Feature extraction**	**Accuracy %**
Wang Y. et al. [WAN13]	SVM	6	Fractal features	97.13
Sheng-Fu et al. [SHE10]	PCA and GAs	16	Power spectral	98.67
Ghosh et al. [GHO07]	FF-ANN	9	DWT Db4	96.7
Martis et al. [MAR12]	C4.5 Decision tree	7	–	95.3
Duque et al. [DUQ14]	K-NN	4	Short-time rhythms	98.12
Proposed approach	**MRW-FFWNN (Binary-tree classifier)**	**6**	**MODWT (Criterion 1 and 2)**	**96.67**