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CLASSIFICATION OF EPILEPTIC EEG SIGNALS BASED ON FINITE IMPULSE RESPONSE FILTER AND ARTIFICIAL NEURAL NETWORKS TRAINING ALGORITHMS

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Abstract: The electroencephalogram is a powerful tool for understanding the electrical activities of the brain. The automatic and accurate classification of extracranial and intracranial electroencephalogram signals are significant for the evaluation of epilepsy. Electroencephalogram signals contain significant characteristic information about epileptic brain waves. However, the electroencephalogram signals are easily disrupted by the artifacts polluting. This study proposed a clinical decision support system to extract significant epilepsy-related spectral features from the electroencephalogram signal. The artifact-free electroencephalogram signals features were obtained from the Kaiser window based on Finite Impulse Filter. The extracted features were modelled by the Artificial Neural Networks Back Propagation training algorithms which are Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient. The algorithms' classification performances were compared by the accuracy rates. The experiment results show that compared with the Artificial Neural Networks Back Propagation training algorithms, the performance of the Levenberg-Marquardt is better from the point of accuracy rate which achieves a satisfying classification accuracy of 83.01% for extracranial and intracranial electroencephalogram signals.

Keywords: Extracranial and Intracranial Electroencephalogram Signals Classification, Finite Impulse Response Filter, Kaiser Window, Artificial Neural Networks Training Algorithms

Sonlu Dürtü Yanıtı Filtresi ve Yapay Sinir Ağları Eğitim Algoritmaları tabanlı Epileptik EEG Sinyalinin Sınıflandırılması

Öz: Elektroansefalogram beyinin elektriksel aktivitelerini anlamak için güçlü bir araçtır. Ekstrakranial ve intrakranial elektroansefalogram sinyallerinin otomatik ve doğru sınıflandırılması epilepsinin değerlendirilmesi için önemlidir. Elektroansefalogram sinyali, epileptik beyin dalgası hakkında önemli karakteristik bilgi içermektedir. Fakat elektroansefalogram sinyali artefakt kirleticiler tarafından kolaylıkla bozulmaktadır. Bu çalışma, elektroansefalogram sinyalinden epilepsi hakkında önemli spektral özellikleri çıkarmak amacıyla klinik bir karar destek sistemi önermektedir. Artefakttan arındırılmış elektroansefalogram sinyal özellikleri, Kaiser penceresi tabanlı Sonlu Dürtü Yanıtı filtresinden elde edilmiştir. Yapay Sinir Ağları Geri Yayılım eğitim algoritmalarından Levenberg-Marquardt, Bayesian Düzenlenmesi ve Ölçekli Konjugat Gradyan algoritmalarına çıkarılan özellikler uygulanarak modellenmiştir. Algoritmaların sınıflandırma performansları doğruluk oranlarına göre karşılaştırılmıştır.

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Deneysel sonuçlar, Yapay Sinir Ağları Geri Yayılma eğitim algoritmaları ile yapılan deneyler karşılaştırıldığında, Levenberg-Marquardt algoritması ekstrakranial ve intrakranial elektroansefalogram sinyali için %83,01'lik tatmin edici bir sınıflandırma doğruluğu ile diğer algoritmalara göre daha iyi doğruluk oranı verdiğini gösterir.

Anahtar Kelimeler: Ekstrakranial ve İntrakranial Elektroansefalogram Sinyal Sınıflandırması, Sonlu Dürtü Yanıtı Filtresi, Kaiser Penceresi, Yapay Sinir Ağları Eğitim Algoritmaları

1. INTRODUCTION

The most significant feature extraction method is the Finite Impulse Response (FIR) filter that is very widely used in signal processing to calculate the coefficients of time domain filter.

Electroencephalogram (EEG) signals include too much information about brain functions. Therefore, neurology is widely used in observation in the clinics of brain disorders. Epilepsy disease is an important neurological disorder that limits the daily activities of patients and threatens their lives (Shorvon, 2010). Epileptic seizures were systematically classified by International League Against Epilepsy (ILAE) in the late 20th century (Shorvon, 2010; Wieser, 2004). Assessments made by experts' visualization of EEG signal analysis is insufficient for detecting epilepsy. Routine analysis of EEG markers in clinical diagnosis needs automation and computer methods made it compulsory to use. Therefore, an objective EEG signal for evaluation of different methods were analyzed. In the literature, studies have been carried out on the EEG data (wavelet coefficient, entropy, fractal sizing, and statistical features) of epileptic patients and control group (healthy) individuals (Boonyakitanont, et. al. (2020); Rajagurua and Prabhakar (2017); Duque-Muñoz, et. al. (2014); Wang, et. al. (2017); Abhinaya and Thanaraj (2016)). In this study was worked on the dataset of individuals who have been diagnoses with extracranial and intracranial EEG by the effective feature extraction methods in signal processing: the most used filter-FIR. Our approach aims to compare the FIR features with Artificial Neural Networks Back Propagation (ANN-BP) training algorithms classification performances through computation time, training mean squared errors (MSE) and validation accuracy rates.

1.1. Related Works

Various algorithms have been proposed for the classification of epileptic seizures in the literature. Some seminal studies are summarized on Table 1.

In this table, ANFIS is Adaptive Neuro-Fuzzy Inference System, ATFFWT is Analytic Time-Frequency Flexible Wavelet Transform, DWT is Discrete Wavelet Transform, EMD is Empirical Mode Decomposition, FD is Fractal Dimension, GBM is Gradient Boosting Machine, GSO is Grid Search Optimizer, LMBPNN is Levenberg–Marquardt Backpropagation Neural Network, LS-SVM is Least-Squares Support Vector Machine, MODWT is Maximal Overlap Discrete Wavelet Transform, NN is Neural Network, PCA is Principal Component Analysis, RBFNN is Radial Basis Function Neural Network, RF is Radio Frequency, DSTFT is Discrete Short-Time Fourier Transform, SVD is Singular Value Decomposition, TF is Time – Frequency, WPD is Wavelet Packet Decomposition and WT is Wavelet Transform.

Table 1. Literature review

Study	Techniques	Dataset	Maximum Accuracy (%)
Nigam and Graupe (2004)	Nonlinear pre-processing filter-Diagnostic neural network	Z–S	97.2
Srinivasan et. al. (2005)	Time & frequency domain features-Recurrent neural network	Z–S	99.6
Guler and Ubeyli (2005)	WT features + ANFIS	Z–O–N–F–S	97.00
Kannathal et. al. (2005)	Chaotic measures-Surrogate data analysis	Z–S	90
Subasi (2007)	Discrete wavelet transform-Mixture of expert model	Z–S	95
Polat and Gunes (2007)	Fast Fourier transform-Decision tree	Z–S	98.72
Guler and Ubeyli (2007)	WT, Lyapunov exponents + SVM	Z–O–N–F–S	98.36
Ghosh-Dastidar et. al. (2007)	mixed-band wavelet chaos nine parameters + LMBPNN	Z–N–S	98.67
Ghosh-Dastidar et. al. (2008)	principal component analysis + cosine RBFNN	Z–N–S	97.63
Ocak (2009)	Discrete wavelet transform-approximate entropy (ApEn)	Z–N–F–S	96.65
Guo et. al. (2009)	Discrete wavelet transform-relative wavelet energy-MLPNN	Z–S	95.2
Guo et. al. (2010)	DWT and line length, ANN	Z–S	100
Naghsh-Nilchi and Aghashahi (2010)	eigenvector spectral estimation and multi-layer perceptron	Z–N–S	97.8
Gandhi et.al. (2011)	DWT, energy and std, SVM, NN	FNOZ–S	95.4
Nicolaou and Georgiou (2012)	Permutation entropy, SVM	Z–S	93.5
Acharya et. al. (2012)	ApE, samEn, PhaseEntr 1, phase ent 2 + fuzzy classifier	Z–N–S	98.43
Alam and Bhuiyan (2013)	EMD, higher order moments, ANN	O–S, F–S	100
Samiee et. al. (2015)	STFT Spectral coefficients with their statistical, values, Bayes, LR, SVM, KNN, and ANN	Z–S	99.8
Swami et. al. (2016)	DTCWT, energy and std, Shannon entropy features, RNN	Z–S	100
Sharma et. al. (2017)	ATFFWT and FD, LS-SVM	Z–S, O–S	100
Li et. al. (2017)	DWT + neural network ensemble	ZO–NF–S	95.01
Li et. al. (2017b)	MODWT + RF classifier	ZO–NF–S	98.0
Zhang et. al. (2018)	WPD + fuzzy distributed entropy and Kruskal–Wallis variance + KNN classifier	Z–F–S	98.48
Tsipouras (2019)	RF classifier + frequency sub-bands/energy, total energy, fractional energy,entropy	Z–O–N–F–S	90.78
Wang et. al. (2019)	Symlets wavelets, statistical mean energy std and PCA, GBM-GSO, RF, SVM	Z-S, O–S and OZ–S	100
Deriche et. al. (2019)	SVM–RBF kernel + TF histogram features and SVD	Z–O–N–F–S	97.15

When our approach is compared with other studies in the literature, this paper will contribute to the missing part in the literature due to the experimental analyzes applied to the {Z, O, N, F, S} EEG signals.

The remainder of the paper was structured as the follows: The methods of our proposed models were described step by step in Section 2. Basic structures on noise removal and feature extraction with the FIR filter for the preprocessing. ANN-BP training algorithms with Levenberg-

Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient were particularized. Experimental results were presented in Section 3 and the paper was concluded in Section 4.

2. MATERIALS and METHODS

2.1. Dataset

In this paper, the EEG signal in the BONN database Andrzejak, et. al. (2001) that are apart from the different recording electrodes used for electrodes extracranially and intracranially were used. The sampling rate of the data is 173.61 Hz and the spectral band of the dilution system is between 0.5 Hz and 85 Hz. The entire EEG dataset is five sets ({Z, O, N, F, S}), each set includes 100 single-channel EEG signals of 23.6 s. The sets of {Z, O} were obtained from surface EEG records of five healthy volunteers with open eyes and closed eyes. The signals were measured in two groups at seizure intervals from the hippocampal formation of five individuals in the epileptogenic region {F}. The opposite half-sphere of the brain is set of {N}. The set of {S} is selected from all recording areas displaying ictal activity during the seizure. While {Z, O} were called as extracranial and {N, F, S} were called as intracranial.

2.2. Data Normalization

In this study, min-max normalization Jain and Bhandare (2011) is explained for EEG signals as Eq. (1),

$$X = \sqrt{\frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}} \tag{1}$$

where X represents the specifically EEG {Z, O, N, F, S} signals are normalized extracranial and intracranial EEG signals of the 4097-dimensional input vector.

2.3. Feature Extraction

The original dataset consists of EEG {Z, O, N, F, S} signals each with 100 files, with each file representing a single subject/person. We have totally 4097×500 dataset implemented to the FIR filter for feature extraction. The dataset was discussed three different ANN-BP training algorithms.

The FIR filtering method was used for removing of artifacts and noise prior to feature extraction from easily distorted EEG signals. The FIR filtering method is a non-recursive filter with an impulse response of finite duration. $h[n]$ is impulse response and $H[z]$ is transfer function of the FIR filter which is given with Eq. (2). $h[n]$ is usually an interruption of the infinite impulse response $h_\infty[n]$ or a finite time section with a window (Kumar and Kamalraj (2019); Bayrak, et. al. (2019); Ramoser, et. al. (2000)). $x[n]$ applies as input for the FIR filter and $y[n]$ is its output that is described in Eq. (3).

$$H(z) = Y(z)/X(z) = \sum_{n=0}^{N-1} h[n]z^{-n} \tag{2}$$

$$y[n] = \sum_{k=0}^{N-1} h[k]x[n-k] \tag{3}$$

The structure of the FIR filter for preprocessing in this study which is the impulse response 4097-point.

There are lots kinds of FIR filter window methods according to their designing and analyzing aims. Modified Bartlett-Hann window is an origin and asymptotic (Ha and Pearce, 1999;

Oppenheim et. al. (1999)). The Bartlett window has zeros at the first and last ones, while the triangular window is nonzero at these points (Oppenheim et. al. (1999)). Blackman window is made by extending the desired window length through one signal to $N + 1$ (Oppenheim et. al. (1999)). Minimum four-term Blackman-Harris window is N-periodic (Harris, 1978). Bohman window is the convolutional of the two half-duration cosine side. Chebyshev window is in the artifact of the equiripple design method (Digital Signal Processing Committee of the IEEE Acoustics, 1979). Equivalent noise bandwidth window is the width of a rectangle where the area contains the same total power as the window (D'Antona and Ferrero (2006); Gade and Henrik (1987)). Gaussian window is a reciprocal standard deviation that is a showing of the time-frequency uncertainty principle (Hansen, 2014). Hamming window, Hann (Hanning) window, window length is $L = N + 1$ (Oppenheim et. al (1999)). Taylor window makes tradeoffs between the mainside width and the side level, its distribution avoids edge discontinuities (Brookner, 1991; Carrara et. al. (1995)). Nuttall-defined minimum 4-term Blackman-Harris window (Nuttal, 1981), Parzen (de la Vallée Poussin) window, Triangular window, Tukey (tapered cosine) window (Bloomfield, 2000); Percival and Walden (1993)), Discrete prolate spheroidal or Slepian sequence database and Rectangular window are the other types of window methods. As a result of our experimental studies, the best classifying estimation in Levenberg Marquardt, Bayesian Regularization and Scale Conjugate Gradient algorithms have been yielded through Kaiser window on account of the nature of EEG signal dataset. For this reason, Kaiser window has been preferred in the study.

Kaiser window is important about reducing spectral leakage in analyzing EEG signals that concentrate most of the energy in the amplitude. The Kaiser window is almost optimal and depends on β parameter and it controls its form as given in Eq. (4),

$$w[n] = \frac{I_0\left[1-\{(2n/N)-1\}^2\right]}{I_0(\beta)}, 0 \le n \le N \tag{4}$$

where I_0 shows the zero order Bessel function is measured by the power series expansion as below Eq. (5).

$$I_0(x) = 1 + \sum_{k=1}^{\infty}\left\{\frac{(x/2)^k}{k!}\right\}^2 \tag{5}$$

In this study, the Kaiser window was used to reduce the signals artifacts and noise that led to a broader transition region with the ideal filter response.

Table 2. Classification results for the different β values

β value / Algorithms	1	2	3	4	5
Levenberg-Marquardt (%)	82.47	82.43	83.01	82.30	82.15
Bayesian Regularization (%)	80.03	81.15	81.78	80.93	81.28
Scaled Conjugate Gradient (%)	82.01	82.21	82.71	82.60	81.90

During the our experimental studies, the different values (1, 2, 3, 4, and 5) were applied for the β parameter in Bessel function for the classification of the EEG signals with the Levenberg Marquardt, Bayes and Scale Conjugate Gradient algorithms as shown in Table 2. According to Table 2, it has been observed that our experimental results give the most successful classification results for these algorithms when the β parameter is selected as 3.

2.4. ANN-BP Algorithms

ANN-BP training algorithms are the most widely used for having weight-updating strategies (Samli and Yucel (2015); Leonard and Kramer (1990)). Firstly, all the weights (w) are set, biases (b) are adjusted and the min-max normalized EEG dataset $(X = 4097 \times 500)$ is given as an input. The output is extra- and intracranial EEG signals with {Z, O, N, F, S} according to the momentum (μ).

Lastly, the output (y) is calculated using the Eq. (6).

$$y_j = \varphi\left(\sum_{i=1}^{4097} w_{ji}\, x_i + b_j\right) \quad (6)$$

Three ANN-BP training algorithms of Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient were used in this study to show which algorithm gives better classification performances and faster training for the epileptic EEG signals classification. *Levenberg-Marquardt algorithm* is specifically designed to minimize the sum of square error functions and updates the weights involve the inverse Hessian matrix or an approximation for nonlinear networks (Moré, 1978). The other basic BP training algorithm is *Bayesian Regularization* which adjusts the context of average-case analysis and offers a rigorous framework for making all assumptions in a learning problem explicit and comes with a guarantee of average case optimality conditioned on the assumptions. For the learning problem, the entire method is derived as an approximation to applying the single simple principle (Burden and Winkler, 2008). Third is an optimization method *Scaled Conjugate Gradient algorithm* is to minimize function where the weights in the steepest descent direction in which value is orthogonal (Møller, 1993).

3. EXPERIMENTAL RESULTS

In this study, ten hidden layered Multilayer Perceptron (MLP) Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient network architectures were utilized and each layer of the structure is fully connected to the previous layer. The flowchart of our method was implemented in Figure 1.

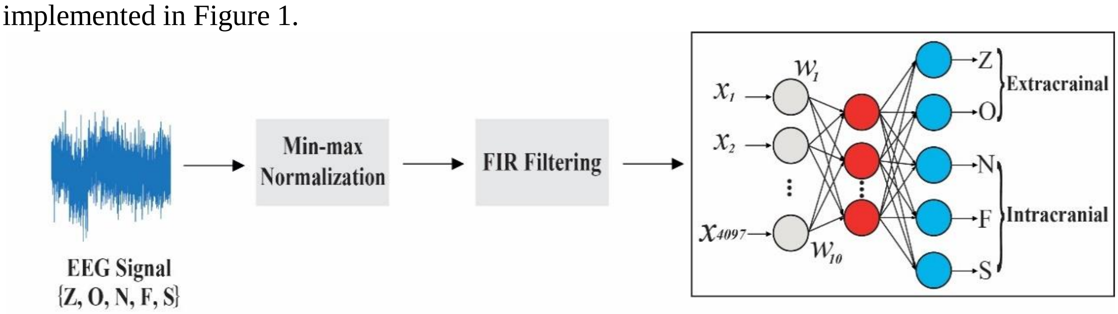

Figure 1:
The flowchart of our method

According to Figure 1, our method is following as:

(1) Min-max normalization for preprocessing phase,

(2) Kaiser window based FIR filter for the extraction of the most significant signals,

(3) ANN-BP training algorithm classification for the most significant signals as extractranially and intracranially.

In Figure 2, the blue line represented min-max normalization EEG signals, and the red line was obtained from the FIR filter.

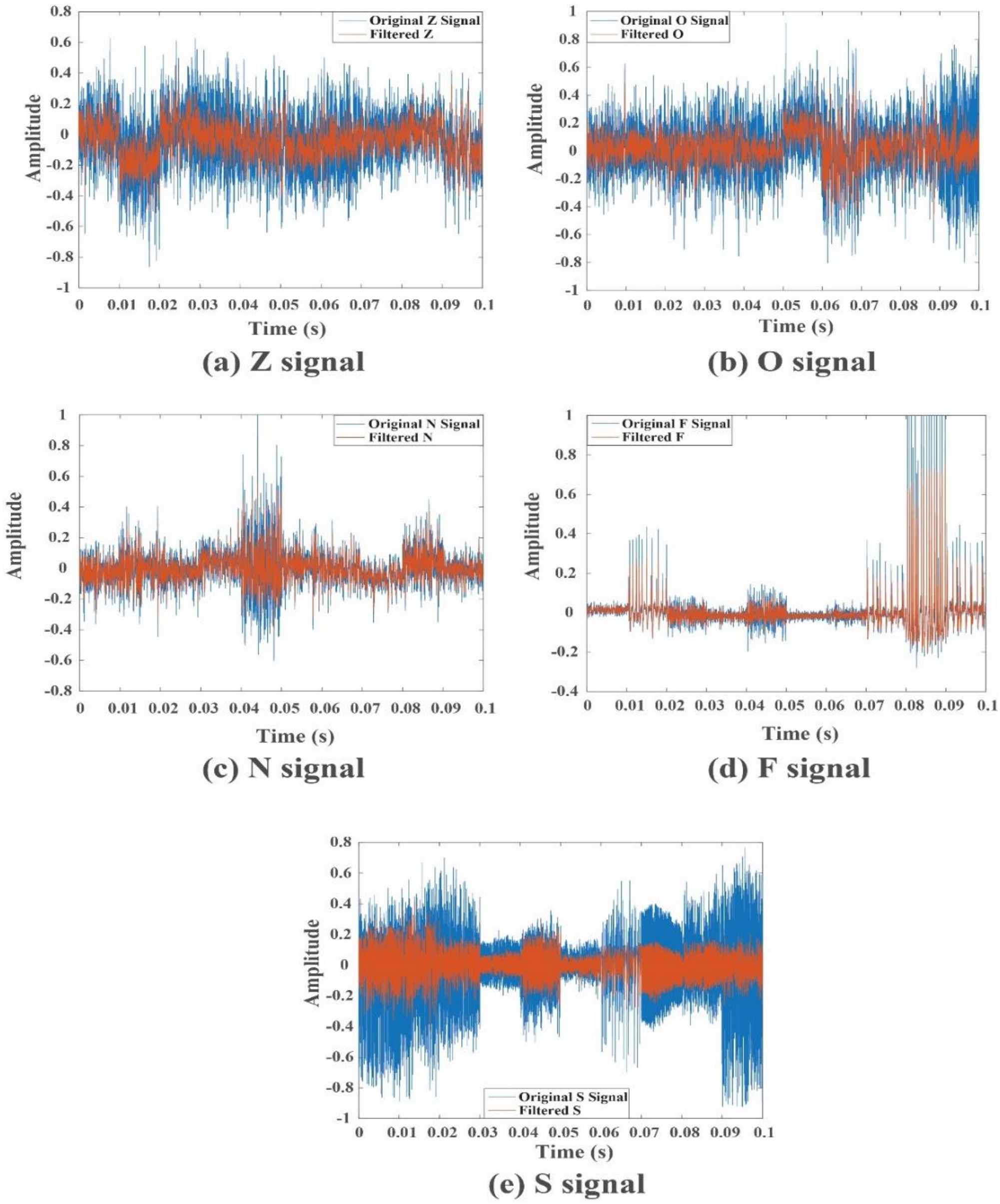

Figure 2:
The results of the FIR filter for EEG signals

The significant EEG features were extracted by Kaiser window-based FIR filter. The EEG dataset (4097 × 500) was classified by having been applied to the FFBP training algorithms, Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient. All the three training algorithms were stopped when any of these conditions occurred:

Step 1: The maximum number of epochs was reached.
Step 2: The maximum amount of time was exceeded.
Step 3: Performance was minimized to the goal.
Step 4: The performance gradient was failed below the minimum gradient.

In this study, optimum Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient training algorithms network architectures were created by ten hidden layered and sigmoid transfer function. The training epoch was set as 1000, the learning rate was chosen as

0.01, and the minimum gradient was set as 1e-05 momentum coefficient was for all three training algorithms. All algorithms' classification performances were compared according to their computation times and their MSE results.

Three ANN-BP algorithms that were Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient modeled by the FIR filter features. The outputs were EEG signals specifically {Z, O, N, F, S}. The FIR filter dataset was (4097×500) and this dataset were randomly divided 70% for training, 15% for testing, and 15% for validation. Figure 3 illustrates the FIR filter features ANN-BP algorithms' classification performances according to the MSE.

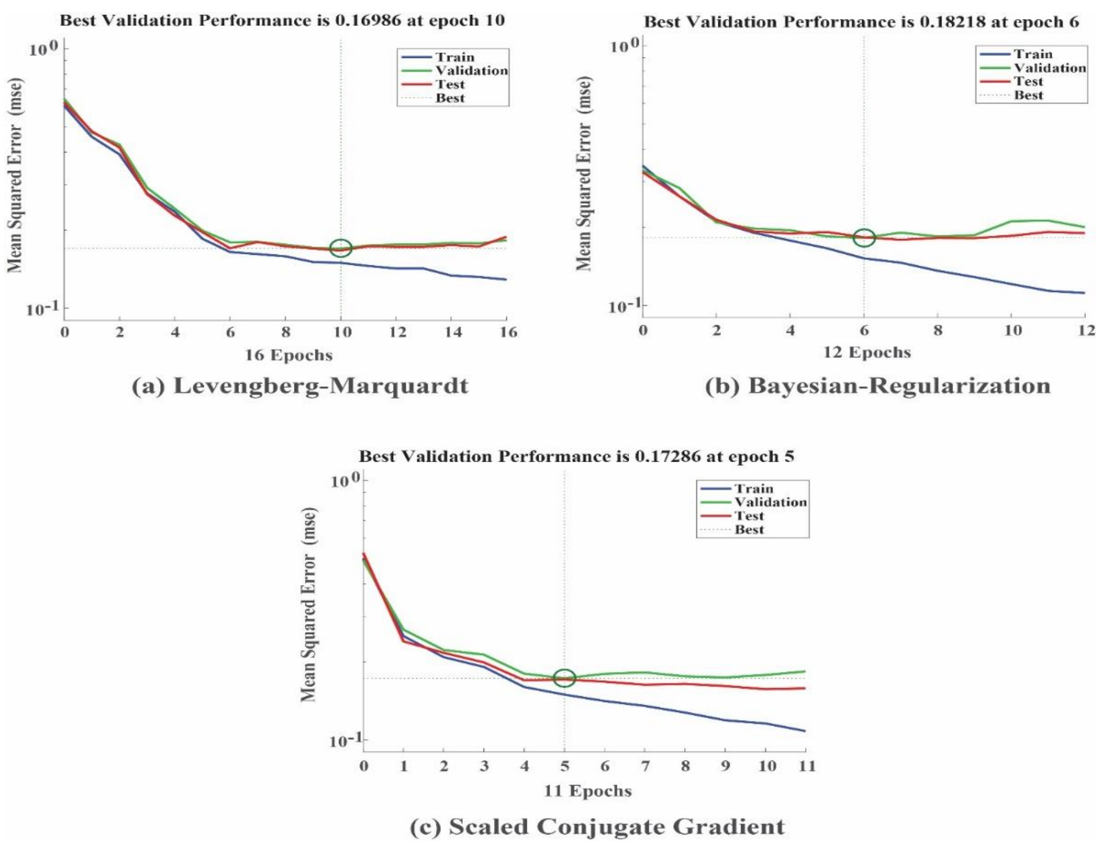

Figure 3:
FIR filter features classification performances

Table 3 was shown, the Levenberg-Marquardt algorithm is the most successful signals classifier compare to Bayesian Regularization and Scaled Conjugate Gradient BP algorithms.

Table 3. Experimental results

Algorithms	**FIR filtered EEG dataset**		
	Computation Time (ms)	*MSE*	*Accuracy Rate (%)*
Levenberg-Marquardt	1021	1.669e-1	83.01
Bayesian Regularization	1199	1.831e-1	81.78
Scaled Conjugate Gradient	1038	1.709e-1	82.71

According to Table 3, comparing the classification models belonging to FIR filtered EEG dataset have been evaluated by the algorithms' computation time, MSE and accuracy rate. Levenberg-Marquardt algorithm is the least time-consuming algorithm in classification to compare the time complexity of algorithms. The least MSE belongs to the Levenberg-Marquardt algorithm. When the classification model accuracy rate is analyzed, the best performances are seen in Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms, respectively.

4. CONCLUSION

The aim of this study is to be able to achieve a classification using FIR filter-based Kaiser window of Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms from the epileptic EEG signals dataset. The achievement of classification model was performed separately for the computation time, MSE and classification accuracy rates. Levenberg-Marquardt was proved to be more effective than the other algorithms because of the β parameter was selected as 3 for the extracted features by the Kaiser window.

In this study, a novel clinical decision support system is developed to epileptic seizures that were identified with extracranially and intracranially. The main contribution of this paper is that it has proposed a computer vision based approach in epileptic individuals' EEG signals significant features were extracted by the FIR filter method.

The results reveal that Levenberg-Marquardt is the most successful signals classifier compare to Bayesian Regularization and Scaled Conjugate Gradient BP algorithms. In the future, (i) other features that may help to extract more efficient epilepsy-related properties can be tested, particularly fractal-related, wavelet-related, entropy-related features can be used, (ii) more EEG data to revalidate novel learning algorithms can be obtained and (iii) other FIR filter window types and other advanced machine learning algorithms can be tested.

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