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EEG signal analysis for detection of Abnormalities with CWT and SVM Technique

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ABSTRACT

Background: Epilepsy is the most common neurological disorder in humans after stroke or brain attack, is when poor blood flow to the brain. Recurrent attack is the main characteristic of the epilepsy. Electroencephalogram (EEG) is the recording of electrical activity of the brain and it contains valuable information related to the different physiological states of the brain. Thus, EEG is considered an indispensable tool for diagnosing epilepsy in clinical applications. Since epileptic occur irregularly and unpredictably, automatic seizure detection in EEG recordings is highly required. Complex Wavelet Transform (CWT) is used in this work for feature extraction which has the properties such as scaling orthogonal, symmetry and short support simultaneous characteristics, etc. With these properties, recently CWT has become promising in signal processing applications. Approximate entropy is a measure that quantifies the complexity or irregularity of the signal. This paper presents a novel method for automatic epileptic seizure detection, which uses approximate entropy features derived from Complex Wavelet Transform and combines with an (Approximate Entropy)ApEn to extract the EEG signals regarding the existence or absence of seizure. After that the ApEn features are applied to (Support Vector Machine)SVM which improves the performance. The high accuracy obtained for classification problems verified the success of the method.

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INTRODUCTION

R The electroencephalogram (EEG) was first considered in humans by German psychiatrist name Hans Berger in 1929 and it is a recording of the electrical activity of the brain from the scalp as discussed by Ghafar *et al* (2008). EEG recordings are noninvasive, painless, are relatively low-cost and measure voltage-difference at the scalp in the microvolt range as given by Sifuzzaman *et al* and Makeiga *et al*. EEG signal has been a valuable clinical tool to assess human brain activities as discussed by Serruyaa and Kahana (2008). The frequency range of EEG signals is 1-60 Hz. In most cases, identification of the epileptic EEG signal is done manually by skilled professionals, who are less in number and it is a time consuming method as given by Golovko *et al* (2007). Chang and Moura have been given about automatic detection of epileptic seizures is an important part in the diagnosis of the disease. The millisecond time-based resolution of EEG helps experts to verify the EEG activity of the subject samples and to differentiate between functional inhibitory and excitatory actions. This procedure required the EEG to be recorded in a few days. A few series of an epilepsy attack need to be scrutinized for confirmation purpose before surgical treatment AlMejrad *et al* (2010).

Today's EEG technology can accurately detect brain activity at a resolution of a single millisecond Ahirwal and Dlondhe (2012). The EEG records variable potential difference between two electrodes placed on the scalp in bipolar recording and mono polar recording and each pair of electrodes is connected to an amplifying system as discussed by Adamczak *et al* (2010) and Chana *et al* (2008). The potential difference is then displayed on an ink-writing oscillograph or on an electronic oscilloscope. It is therefore a non-invasive procedure that allows researcher's clear access to a healthy human brain. EEG has two clear advantages for brain research Chana *et al* (2008). The first is characteristic of any electrical recording system-high precision time measurements. Changes in the brain's electrical

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activity occur very quickly, and extremely high time resolution is required to determine the precise moments at which these electrical events take place Sheikhani *et al* (2008) and Guler *et al* . In an EEG, electrodes are placed at the head skin to make a good contact with the scalp and register the electrical potentials due to neuronal activity. EEG shows a good correlation with the mental stress in terms of suppression of alpha waves and improvement of theta waves. Alpha waves are more active in occipital and frontal regions of the brain as discussed by Ibrahimy (2010). These waves are associated with idleness of the brain. So in no stress condition, when the brain is doing no activity, alpha waves are dominant. In stressful situations, the power of alpha waves falls down showing the change in response under stress as given by Ampil (1998). Beta waves show varying behaviour in different frequencies in different parts of the brain and power in theta waves increases under stress or mental tasks Ekuakille *et al* (2013).

Any activity which does not correlate with the age and state of the patient called abnormal EEG, it could be of the following two main types of activity, first one is non epileptiform abnormal pattern and the second one is epileptiform pattern, Non epileptiform abnormal pattern consists slow waves and asymmetry Price (2005) and Abdulla (2011). Now slow waves are further divided into two types, namely focal slowing and diffuse slowing, focal slowing means if slowing is restricted to only one hemisphere or specific region and most prominent focal slowing is delta activity which ranges 0.5 to 3.5 Hz, it may be continuous or intermittent Filligoi (2011). Diffuse slowing means synchronous and symmetrical slowing that appears in the whole background throughout the recording which indicates the involvement of both hemispheres of the brain or cerebral dysfunction. While identifying diffuse slowing the age, state and medications of the patients must be known Williams and Li (2011).

2. Literature Survey:

Rajendra Acharya *et al* (2013) have proposed manual interpretation and detection of normal and abnormal activities in the EEG signals. Here, it was implemented to a Computer Aided Diagnostic (CAD) system to automatically identify the normal and abnormal activities using minimum number of highly discriminating features in the classifiers. In this method, the author captured the complex physiological phenomena such as abrupt transitions and chaotic behaviour in the EEG signals. In this method, they discussed various feature extraction methods and the results of different automated epilepsy stage detection techniques are discussed in detail.

Omerhodzic *et al* have proposed a wavelet-based neural network (WNN) classifier for recognizing EEG signals for implementation and testing under three sets EEG signals. First, the Discrete Wavelet Transform (DWT) with the Multi-Resolution Analysis (MRA) was applied to decompose the EEG signal at resolution levels of the components of the EEG signal (δ, θ, α, βand γ) and the Parseval's theorem were employed to extract the percentage distribution of energy features of the EEG signal at different resolution levels. Second, the neural network (NN) classifies these extracted features to identify the EEGs type according to the percentage distribution of energy features. The performance of the proposed algorithm has been evaluated using in total 300 EEG signals. Here, the final results showed that the classifier has the ability of recognizing and classifying EEG signals efficiently.

Gandhi *et al* (2013] hav proposed a technique wavelet function among the existing members of the wavelet families for electroencephalogram signal (EEG) analysis. The EEGs considered for this study belong to both normal as well as abnormal signals like epileptic EEG. Important features such as energy, entropy and standard deviation at different sub-bands were computed using the wavelet functions- Haar, Daubechies, Coiflets, and Biorthogonal. Feature vectors were used to model and train the Probabilistic Neural Network (PNN) and the classification accuracies were evaluated for each case. The results obtained from PNN classifier were compared with Support Vector Machine (SVM) classifier. In this proposed method, they had attempted to improve the computing efficiency as it selects the most suitable wavelet function that can be used for EEG signal processing efficiently and accurately with lesser computational time.

Orhan *et al* (2011) has proposed multilayer perceptron neural network (MLPNN) based classification model as a diagnostic decision support mechanism in the epilepsy treatment. EEG signals were decomposed into frequency sub-bands using discrete wavelet transform (DWT). The wavelet coefficients were clustered using the K-means algorithm for each frequency sub-band. The probability distributions were computed according to the distribution of wavelet coefficients to the clusters, and then used as inputs to the MLPNN model. They conducted five different experiments to evaluate the performance of the proposed model in the classifications of different mixtures of healthy segments, epileptic seizure free segments and epileptic seizure segments.

Williams *et al* (2011) have discussed Wavelet Transform method which made to deny EEG signals. Because of the distance between the skull and the brain and their different resistivity's,EEG recordings on a machine was usually mixed with the activities generated within the area called noise. EEG signals have been used to diagnose major brain diseases such as Epilepsy, narcolepsy and dementia. Dancing was often done with Independent Component Analysis algorithms, but of late Wavelet Transform has been utilized. In this proposed method, using of ICA algorithms Radical and evaluated the performance measures Mean Square Error (MSE), Percentage Root Mean Square Difference (PRD) and Signal to Noise Ratio (SNR). The experimental results indicated that it performed superior to the ICA algorithms producing cleaner EEG signals which could influence diagnosis as well as clinical studies of the brain.

The various limitations are observed from the literature using the EEG signals. In this paper, a novel method CWT is used to extract the feature in the filtered EEG signal and also open features .Real and imagery signal with absolute value is considered to study the performance of classifier technique. This gives the fast response and better feature extraction. The rest of the paper is organized as follows. Section 3 describes the proposed method. Section 4 discusses about the implementation results, and Section 5 concludes the paper.

3. Proposed Model :

In this work, a novel epileptic seizure detection method is proposed. The method consists of three steps. Initially, CWT is used to decompose the EEG signal to several sub signals. Then, the approximate entropy feature is extracted from each sub-signal. Finally, the extracted features are used as input to an SVM, which discriminates the EEGs according to the specified classification problems.

The proposed method uses CWT and SVM to classify the EEG signal for epilepsy seizure detection. Fig 1. Shows the flow chart of the proposed algorithm. The first stage is the pre-processing stage, including four levels of data processing which are signal filtering, sample selection, applying CWT, and finally dimensionality reduction with ApEn. The other stages are a classification of EEG signal with abnormality of Epilepsy.

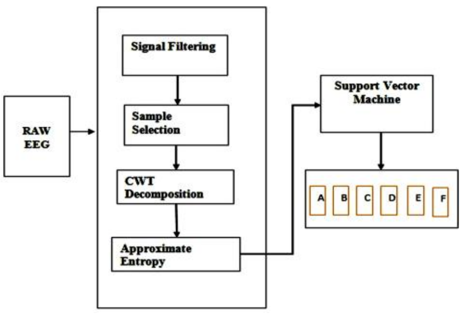

Fig. 1: Proposed architecture of abnormal detection with EEG.

3.1. Signal Filtering:

In this step, a method of signal filtering is presented. This is applied to remove the baseline wandering of the EEG signal. The raw EEG signal of records 500 from Andrzejak *et al*. (2001) database, which has baseline peripatetic, is used in this work. It is obvious that the baseline wandering has been removed, leading to a better performance in the SVM classifier. Baseline wandering is a low frequency component in the EEG signal known as noise. It is produced due to the improper electrode connection and movement of subject (patient).So the raw EEG data contains noises and to remove this noise suitable filter is required. Practically band pass, low pass and high pass filters are not enough since these filters may remove the required information from the EEG. FIR filters can be used, but it has the limitation of fixed step size. The adaptive filter is used based on optimization theory. Here the error can be minimized by adjusting the filter. So in this proposed method adaptive filter is used to remove the noise from EEG.

The input signal x(n) is fed into the adaptive filter and computes output signal y(n) at time n. The output signal is compared to a second signal d(n), called the desired response signal, by subtracting the two samples at time n. This difference signal given by

$$e(n) = d(n) - y(n) \quad (1)$$

is known as the error signal. The error signal is fed back to the filter to adjust the parameters from time n to n+1 by using the adaptive algorithm defined in the filter structure.

$$y(n)=\sum_{1=1}^{N} a_i(n)y(n-i) + \sum_{j=0}^{N} b_j(n)x(n-j) \quad (2)$$

Using the vector notation as:

$$y(n) = W^T(n)U(n) \quad (3)$$

Where WT(n) is the weight vector

The selection of the analysing function in wavelet transforms, which is called the mother wavelet, has a significant effect on the result of analysis and should be selected carefully based on the nature of the signal. The most important factor to select a mother wavelet in this study refers to the simplicity of the computed CWT coefficients, while having the appropriate and sufficient data about the EEG signal. In this proposed method, CWT has been selected for feature extraction also. The analysis shows that extracted features from EEG signal by using the CWT would be suitable and appropriate for the data classification and the computed coefficients can represent morphological differences very well.

3.2. CWT (Complex Wavelet Transform):

Classical DWT has some limitations while using non stationary signals. The DWT analysis does not keep the phase information, but the phase information describes the behavior of any non stationary signal. Another problem is shift invariance. A small time shift in the input signal will be reflected in each sub band of DWT .Also the DWT has poor directional selectivity.

The DWT has spatial orientations in vertical, horizontal and diagonal directions only.

To overcome these limitations, complex wavelet transform is used in this work. The CWT has the features of shift invariance. Also it keeps the phase information detail of non stationary signal and is strongly oriented to the directins at angle of +-150,+-450 and +-750

When we consider the conventional DWT with 1 D

$$\psi_1(x,y) = \phi(x)\ \psi(y) \quad (4)$$

$$\psi_2(x,y) = \psi(x)\ \phi(y) \quad (5)$$

$$\psi_3(x,y) = \psi(x)\ \psi(y) \quad (6)$$

The CWT is derived by kingsburry (1990) named as dual tree complex wavelets are used in this work. The CWT can be obtained from a complex scaling function and complex wavelet function.

$$\phi_s(x) = \phi_r(x) + j\phi_i(x) \quad (7)$$

$$\psi_c(x) = \psi_r(x) + j\ \psi_i(x) \quad (8)$$

r and i denotes the real and imaginary part

The 2 D CWT is achieved by the separable filter bank along with rows and columns and the 2D CWT produces six sub bands

$$\psi_{1,1}(x,y) = \phi_h(x)\ \psi_h(y) \quad (9)$$

$$\psi_{1,2}(x,y) = \psi_h(x)\phi_h(x) \quad (10)$$

$$\psi_{1,3}(x,y) = \psi_h(x)\psi_h(y) \quad (11)$$

$$\psi_{2,1}(x,y) = \phi_g(x)\ \psi_g(y) \quad (12)$$

$$\psi_{1,2}(x,y) = \psi_g(x)\phi_g(x) \quad (13)$$

$$\psi_{1,3}(x,y) = \psi_g(x)\psi\ g(y) \quad (14)$$

Here the wavelets are defined as:

$$\psi_i(x,y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x.y) + \psi_{2,i}(x.y)) \quad (15)$$

$$\psi_i(x,y) = \frac{1}{\sqrt{2}}(\psi_{1,i}(x.y) - \psi_{2,i}(x.y)) \quad (16)$$

For i=1,2,3. $\frac{1}{\sqrt{2}}$ is the normalization value

If we only consider the complex part of complex wavelets the 2D frequency plane is same as that of the real part

$$\psi_{3,1}(x,y) = \phi_g(x)\ \psi_h(y) \quad (17)$$

$$\psi_{3,2}(x,y) = \psi_g(x)\phi_h(x) \quad (18)$$

$$\psi_{3,3}(x,y) = \psi_g(x)\psi_h(y) \quad (19)$$

$$\psi_{4,1}(x,y) = \phi_g(x)\ \psi_g(y) \quad (20)$$

$$\psi_{4,2}(x,y) = \psi_h(x)\phi_g(x) \quad (21)$$

$$\psi_{4,3}(x,y) = \psi_h(x)\psi_g(y) \quad (22)$$

$$\psi_i(x,y) = \frac{1}{\sqrt{2}}(\psi_{3,i}(x.y) + \psi_{4,i}(x.y)) \quad (23)$$

$$\psi_{i+3}(x,y) = \frac{1}{\sqrt{2}}(\psi_{3,i}(x.y) - \psi_{4,i}(x.y)) \quad (24)$$

The real and imaginary part of the CWT is implemented using dual tree structure. A CWT produces three sub bands in each of spectral quadrants 1 and 2, giving six sub bands of complex coefficients at each level, which are strongly oriented $\pm 15^o$, $\pm 45^o$, $\pm 75^o$ directions.

3.3. Approximate Entropy (ApEn):

Approximate entropy is a time domain feature of EEG which gives the nonlinear dynamics of brain activity. The irregularities of signal depend on ApEn value. A low ApEn value indicates the EEG recording is regular and a high ApEn value indicates the EEG as irregular. ApEn value defined in terms of the unpredictability of subsequent sampled depends on the previous smples.

The ApEn value can be calculated by the formulae derived by Steven (1990) as

$$\textbf{ApEn (m,r)} = \lim_{N\to\infty} [\phi^m(r) - \phi^{m+1}(r)] \quad (25)$$

where The number of subsequent samples taken as vector 'm' and the 'r' is the tolerance coefficient.

$$\phi^m(r) = (N+m-1)^{-1} \sum_{i=1}^{N-m+1} In\, C_i^m(r) \quad (26)$$

Equation (26)is the function of predictability

$C_i^m(r)$ is the matching rate of vector comparison.

The irregularities of signal depend on the ApEn value. These ApEn values are then applied as input to the SVM and the training dataset is generated. Approximate entropy is a statistical parameter that measures the regularity or predictability of a specific time series. It is also known that ApEn possesses good characteristics such as robustness in the characterization of the epileptic patterns. Therefore, in current study ApEn is chosen to discriminate EEGs. ApEn value for each sub-signal of the EEG data decomposed with CWT is calculated to form a feature vector. Before computing ApEn, two important parameters, which are embedding dimension (m) and tolerance (r), have to be defined.

After the ApEn values were obtained for 10 sub-signals derived from CWT of the EEG, they construct a feature vector that is used as input to an SVM for classifying EEG.

3.4. Classification with SVM algorithms:

The SVM is one of the most popular supervised learning algorithms for solving classification problems. While using Artificial Neural Network (ANN) the known examples are used to train the neural network to collect the knowledge about any problem. Also the selection of learning rate in ANN is a crucial part. Since the performance of ANN algorithm is highly sensitive and depend on the learning rate. The classical Multilayer perceptron neural network (MLPNN) has multiple local minima. The training time of the MLP also high. The basic of SVM involves the adoption of a nonlinear kernel function to transform input data into a high dimensional feature space, which is easier to separate data rather than at the original input space. Thus, depending on input data, the iterative learning process of SVM will finally devise optimal hyper planes with the maximal margin between each class in a high dimensional feature space. Hence, the maximum-margin hyper planes will be the decision boundaries for distinguishing different data clusters. Therefore, the larger distance between hyper planes and group data will result in better classification performance.

Input: Reconstructed signal from CWT
Output: Mean Value of signal
// Calculate N data points from single
Step 1: $n = [n_{(1)}, n_{(2)}, n_{(3)}, ... n_{(N)}]$
// Select windows length
Step 2: $m = [m_{(1)}, m_{(2)}, m_{(3)}, ... m_{(N)}]$
Step 3: Select tolerance (R)
If SL n=1:N
Then
m =n
else
select n=n(1)
m=m(1) D= (m(1)-n(1)) // Calculate distance

Step 4: Increment n=n+1 and m=m+1
Calculate
D Select D_{max}=DIf Increment Calculate distance
Step 5: If windows length value
m=1: D_{max}
Then,
check $D_{max} \geq Tolerance(r)$
End
Step 6:Calculate ApE
$$\text{ApEn} = \frac{\text{TL}}{\text{TW}}$$

A suitable training algorithm has a short training process, while achieving better accuracy. One of the most common training algorithms is Bayesian regularization back-propagation, which is also used in the current work. This algorithm updates the weight and bias values according to Levenberg–Marquardt optimization. It minimizes a combination of squared errors and weights and then determines the correct combination so as to produce a network that generalizes well.

4. Data sets used:

The data described by Andrzejak *et al*. (2001)is used in the current work. The whole dataset consists of five sets (denoted as Z, O, N, F and S), each containing 100 single-channel EEG segments of 65.6s duration, with a sampling rate of 160.6 Hz. These segments were selected and cut out from continuous EEG recordings after visual inspection for artifacts. Sets Z and O consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized signal. Volunteers were relaxed in an awake state with eyes open (Z) and eyes closed (O), respectively. Sets N, F and S originated from an EEG archive of presurgical diagnosis. Segments in set F were recorded from the epileptogenic zone, and those in se N from the hippocampal formation of the opposite hemisphere of the brain. While sets N and F contained only activity measured during seizure free intervals, set S only contained seizure activity. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12-bit resolution and they have the spectral bandwidth of the acquisition system, which varies from 0.5 Hz to 85 Hz.

In this work, two different classification problems are created from the above dataset in order to verify the performance of the proposed method. In the first problem, two sets are examined, normal and seizure, the normal class available in set Z while the seizure class available in the set S. The notation of the problem is simplified as Z–S. In the second problem, all the EEGs from the data set are used and they are normal and abnormal.

5. Result:

The waveform in figure 2(a) shows the actual signal .After applying the adaptive filter CWT is applied and the signal is decomposed into sub signal. From each sub signal ApEn feature is extracted and given as input to SVM. By applying ICWT the signal is constructed and the difference also plotted.

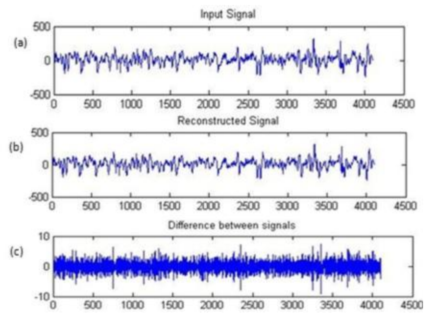

Fig. 2: (a)Raw EEG signal/Input signal(b)ICWT signal (C)Difference between ICWT and RAW EEG/input signal.

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5.1 Statistical parameters:

The evaluation of the proposed method on classification problems is determined by computing the statistical parameters of sensitivity, specificity and classification accuracy. The definitions of these parameters are as:

Sensitivity:

Number of correctly detected positive patterns/total number of actual positive patterns. A positive pattern indicates detected seizure**.**

Specificity:

Number of correctly detected negative patterns/total number of actual negative patterns. A negative pattern indicates detected non-seizure.

Classification accuracy:

Number of correctly classified patterns/total number of patterns. A pattern indicates both seizure/ non-seizure

Table 1: Comparison of classifier performances on Andrzejak *et al*. (2001)database.

	Z	O	N	F	Sum
TP	49	50	49	48	196
TN	50	49	50	50	199
FP	1	1	0	1	3
FN	0	0	0	1	2
Sensitivity	100	100	99	100	100%
Specificity	98.039	97.679	99.791	98.91	98.03%
Accuracy	99	98	99	99	99%

Statistical parameters are compared with the proposed method and the chart shows the comparison.

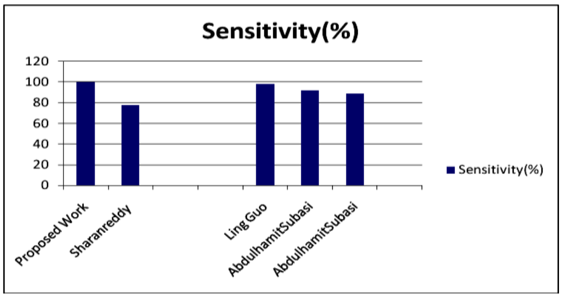

Fig. (a): Sensitivity comparison of Proposed and Existing Methods.

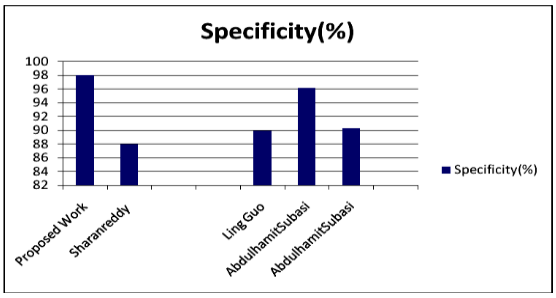

Fig. (b): Specificity comparison of Proposed and Existing Methods.

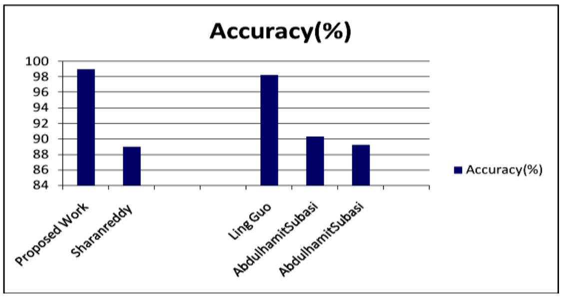

Fig. (c): Accuracy comparison of Proposed and Existing Methods.

Fig. 3(a)(b)(c): shows the chart of sensitivity, specificity and accuracy compared to other existing methods.

Table 2: Comparison of several classifier performances.

Methods and parameters	Feature extraction	Classi fication	Sensit ivity (%)	Speci ficity (%)	Accu racy (%)
Proposed Work	Approxi mate entropy	SVM	99.01	98.039	99
Sharanreddy *et al. (2012)*	Multi Wavelets and Approximate Entropy	ANN	78	88	89
Ling Guo *et al.* (2010)	Approximate entropy	ANN	98.02	89.91	98.27
AbdulhamitSubasi *et al.*(2005)	AR and MLE	ANN	92.3	96.2	90.3
AbdulhamitSubasi *et al.*(2005)	Logistic regression	MPNN	89	90.3	89.2

Discussion&Conclucsion:

In this work, we have testified the feasibility of classification solution that decomposes multi-class classification into hierarchical binary classifiers for achieving better performance in EEG classification problem. In this study, Several stages of pre-processing have been used in order to prepare the most appropriate input vector for the VM classifier. The main advantage of this proposed work is that, by using 10 scales in computing CWT of signals, the morphological differences between several types of EEG signal are highlighted and the extracted features show the differences more clearly. Another advantage of this study is that the reduction of the dimension of data leads to the most appropriate input vector for classifier which improved the performance of the SVM classifier significantly. Also, this work can be extended by applying an appropriate preprocessing algorithm with EEG signal for the noise removal can promise more efficiency.

REFERENCES

AbdulhamitSubasi and Ergun Ercelebi, 2011. "Classification of EEG signals using neural network and logistic regression", Computer Methods and Programs in Biomedicine, 78: 87-99, 2005.

AbdulhamitSubasi, M., Kemal Kiymik, AhmetAlkan and EtemKoklukaya, 2005. "Neural Network Classification of Eeg Signals by Using AR With MLE Preprocessing For Epileptic Seizure Detection", Mathematical and Computational Applications, 10(1): 57-70.

Ali Sheikhani, Hamid Behnam, Mohammad Reza Mohammadi, Maryam Noroozian and PariGolabi, 2008. "Connectivity analysis of quantitative Electroencephalogram background activityin Autism disorders with short time Fourier transform and Coherence values", Congress onImage and Signal Processing, 207-212.

Ali, S., AlMejrad, 2010. "Human Emotions Detection using Brain Wave Signals: A Challenging",European Journal of Scientific Research, 44(4): 640-659.

Ampil, 1998. "Primer for EEG Signal Processing in Anesthesia", American Society of Anesthesiologists, 89(4): 980-1002.

Arnaud Jacquin, Elvir Causevic, Roy John, Jelena Kovacevic, 2005. "Adaptive Complex wavelet-based filtering of EEG for extraction of Evoked potential responses" 0-7803-8874-7/05/$20.00 ©2005 IEEE V - 393 ICASSP.

Fasano, A., V. VillaniL. Vollero, 2011. "Baseline Wander Estimation and Removal by Quadratic Variation Reduction" 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, 30-3.

Filligoi, G., 2011. "Chaos Theory and Semg", Journals in Science and Technology, 9-16.

Guruva, A., Reddy and Srilatha Narava, 2013. "Artifact Removal from EEG Signal" International Journal of Computer Applications77(13): 17-19. Published by Foundation of Computer Science, New York, USA

Hsun-Hsien Chang and Jos´ M.F. Moura, 2010. "Biomedical Signal Processing", 2nd Edition of In Biomedical Engineerng and Design Handbook,McGraw Hill, 1(22): 559-579.

Inan Guler, ElifDerya and Ubeyli, 2005. "Adaptive neuro-fuzzy inference system for classificationof EEG signals using wavelet coefficients",Journal of Neuroscience Methods, 148(2): 113–121.

Janett Walters-Williams and Yan Li, 2011. "Using Invariant Translation to Denoise Electroencephalogram Signals", American Journal of Applied Sciences, 8(11): 1122-1130.

Janett Walters-Williams and Yan Li, 2011. "Using Invariant Translation to Denoise Electroencephalogram Signals", American Journal of Applied Sciences, 8(11): 1122-1130.

Lay-Ekuakille, A., P. Vergallo, A. Trabacca, M. De Rinaldis, F. Angelillo, F. Conversano and S. Casciaro, 2013. "Low-frequency detection in ECG signals and joint EEG-Ergospirometricmeasurements for precautionary diagnosis", Measurement, 46: 97–107.

Ling Guo, Daniel Rivero, Alejandro Pazos, 2010. "Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks", Journal of Neuroscience Methods, 193(1): 30, Pages 156–163.

Marie Chana, Daniel Estèvea, Christophe Escribaa, Eric Campo, 2008. "A review of smart homes-Present state and future challenges", Computer Methods and Programs in Biomedicine,. 91(1): 55–81.

MijailDemianSerruyaa and Michael J. Kahana, 2008. “Techniques and devices to restorecognition”, Behavioural Brain Research, 192(2): 149–165.

Mitul Kumar Ahirwal and NarendraDlondhe, 2012. “Power Spectrum Analysis of EEG Signalsfor Estimating Visual Attention”, International Journal of Computer Applications, 42(15): 22-25.

Muhammad IbnIbrahimy, 2010. “Biomedical Signal Processing and Applications”, International Conference on Industrial Engineering and Operations Management, Dhaka, Bangladesh.

Newton Price, Charles, J. de SobralCintra, Renato, T. Westwick, David and Mintchev, 2005. Martin,“Classification Of Biomedical Signals Using The DynamicsOf The False Nearest Neighbours (DFNN) Algorithm”, International Journal "Information Theories & Applications", 12(1): 18-24.

Nick Kingsbury, 2001. “Complex Wavelets for Shift Invariant Analysis and Filtering of Signals”, Applied and Computational Harmonic Analysis, 10: 234–253.

Omerhodzic, I., S. Avdakovic, A. Nuhanovic and K. Dizdarevic, 2010. “Energy Distribution of EEG Signals: EEG Signal Wavelet-Neural Network Classifier”, International Journal of Biological and Life Sciences, 6(4): 210-215.

Podgorelec, V., 2012. “Analyzing EEG Signals with Machine Learning for Diagnosing Alzheimer’s Disease”, ElektronikaIrElektrotechnika,. 18(8): 61-64.

Rajendra Acharya, U., S. VinithaSree, G. Swapna, Roshan Joy Martis and Jasjit S. Suri, 2013. “Automated EEG analysis of epilepsy: A review”, Knowledge-Based Systems, 45: 147–165.

Rosniwati Ghafar, AiniHussain, Salina Abdul Samad and Nooritawati Md Tahir, 2008. “Umace Filter for Detection of Abnormal Changes In EEG: A Report of 6 Cases”, World Applied Sciences Journal, 5(3): 295-301.

Scott Makeiga, Klaus Gramanna, Tzyy-Ping Junga, Terrence J. Sejnowskib and HowardPoiznerb, 2009. “Linking brain, mind and behavior”, International Journal of Psychophysiology, 73(2): 95–100.

Sharanreddy, P.K., Kulkarni, 2012. “Multi-Wavelet Transform Based Epilepsy Seizure Detection”, IEEE EMBS International Conference on Biomedical Engineering and Sciences I Langkawi I 17th - 19th.

Sifuzzaman, M., M.R. Islam and M.Z. Ali, 2009. “Application of Wavelet Transform and its Advantages Compared to Fourier Transform”, Journal of Physical Sciences, 13: 121-134.

StanisławAdamczak, 2010. WłodzimierzMakieła, Krzysztof Stępień,“Investigating Advantages and Disadvantages of the Analysis of A Geometrical Surface Structure with the Use of Fourier And Wavelet Transform”, Metrol. Meas. Syst., XVII(2): 233-244.

Steven, M., Pincus, 1991. “Approximate entropy as a measure of system complexity” Proc. Nati. Acad. Sci. USA, 88: 2297-2301.

Tajik, J. and S. Nazifi, 2011. A Study of Correlation of Serum Leptin with Trace Elements in Water Buffalo (Bubalus bubalis). Australian Journal of Basic and Applied Sciences, 31: 231-234.

Tapan Gandhi, BijayKetanPanigrahi and SnehAnand, 2011. “A comparative study of wavelet families for EEG signal classification”, Neurocomputing, 74(17): 3051–3057.

Tomovska, J., S. Presilski, N. Gjorgievski, N. Tomovska, M.S. Qureshi and N.P. Bozinovska, 2013. Development of a spectrophotometric method for monitoring angiotensin-converting enzyme in dairy products. Pak Vet J, 33(1): 14-18.

UmutOrhan, MahmutHekim and MahmutOzer, 2011. “EEG signals classification using theK-means clustering and a multilayerperceptron neural network model”, Expert Systems with Applications, 38: 13475–13481.

Vairavan Srinivasan, Chikkannan Eswaran, Natarajan Sriraam, 2007. “Approximate Entropy-Based Epileptic EEG Detection Using Artificial Neural Networks ” IEEE Transactions On Information Technology In Biomedicine, 11-3

Vladimir, A., Golovko, Svetlana V. Bezobrazova, Sergei V. Bezobrazov, Uladzimir S. Rubanau, 2007. “Application of Neural Networks to the Electroencephalogram Analysis for Epilepsy Detection”, Proceedings of International Joint Conference on Neural Networks, Orlando, Florida, USA, 12-17.

Waleed Abdulla, Lisa Wong, 2011.“Neonatal EEG signal characteristics using time frequency analysis”, Physica A, 390: 1096–1110.

Yang, H., C. Guan, K.S. Chua, S.S. Chok, C.C. Wang, P.K. Soon, C.K. Tang, K.K. Ang, 2014. “Detection of motor imagery of swallow EEG signals based on the dual-tree complex wavelet transform and adaptive model selection. ” J Neural Eng., 11(3): 035016. doi: 10.1088/1741-2560/11/3/035016. Epub, 19.

Yuan-Pin Lin, Chi-Hong Wang, Tien-Lin Wu,Shyh-Kang Jeng and Jyh-Horng Chen, 2009. “EEG-based emotion recognition in music listening: A comparison of schemes for multiclass support vector machine”, IEEE International Conference on Acoustics, Speech and Signal Processing, Taipei, 489 – 492.

Yuan-Pin Lin, Chi-Hong Wang, Tzyy-Ping Jung, Tien-Lin Wu, Shyh-Kang Jeng, Jeng-RenDuann and Jyh-Horng Chen, 2010. “EEG-Based Emotion Recognition in Music Listening”, IEEE Transactions on Biomedical Engineering, 57(7): 1798 – 1806.