Epileptic Detection and Classification Using Convolutional Neural Network with Dual Tree Complex Wavelet Features

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Abstract: *Epilepsy is a kind of brain disease that can be diagnosed by observation of EEG signals. Mostly it occurs within the children. However, some of the cases are observed in adults. It is a challenging task for physicians to detect this disease at an early stage. Authors in this work have classified the Epileptic and normal EEG signal by adopting the deep learning approach. For efficient features, dual tree complex wavelet (DTCWT) is considered. The decomposed wavelet features are used as the input to the convolutional neural network (CNN) classifier. Around 97% classification accuracy is observed by using the proposed approach.*

Keywords:*EEG,Epilepsy,DTCWT,Deeplearning,CNN*

1Introduction

Human brain continuously generate the electrical impulses in a specific order pattern and these impulses travel among the neurons, nerve cells, and throughout the entire body via neurotransmitters. Generally, seizure is a type of brain disorder happens due to the immediate alternation and temporary changes of electrical activity in brain. Epileptic is a brain disorder that happens due to repeated seizures. Machine learning has a major role in biomedical data analysis and classification. Research on machine learning based biomedical data analysis is getting popular since last few decades. Deep learning is a most popular machine learning approach and it has been used in many applications due to its auto feature extraction nature. But sometimes it may omit the useful features from the data and it impact on classification accuracy. For this, a comparison of CNN for classifying the raw and decomposed EEG is shown in the proposed work. Numerous works were done related to epileptic detection and are discussed below.

In [1] the framework for detection of epileptic seizures has been proposed. Discrete wavelet transform (DWT) was considered for analysis of EEG signals and feature extraction. They have considered 14 different combinations to classify the signal with two-class problem. Also the DWT co-efficient were used for eye opening and epileptic cases.5 Datasets have been used for the statical feature extraction from the DWT co-efficient. These features were fed to the KNN classifier and found the accuracy level. In [2] the accuracy of epileptic seizure detection and reduced computational cost has been focused. To improve the detection of accuracy and extract features different Datasets have been used by using 54 DWT Mother Wavelet. These features are reduced by using GA algorithm to select best features. Then it is fed to ANN classifier to perform better in terms of evaluation matrix. In [3] the analysis framework for EEG signal is proposed. DWT was considered in which signals were decomposed into frequency sub-bands .Here statical features were extracted from sub-bands to represent the Wavelet co-efficient. The dimension of features wasreduced by using PCA, ICA and LDA.SVM has been used as a classifier with three features PCA, ICA& LDA. Authors in [4], have considered wavelet neural network (WNN) for the purpose of detecting seizures from long duration EEG signal. Their proposed approach is a hybrid approach that combines conventional neural network with wavelet transform.

By using DWT relative amplitude and relative fluctuation index were extracted, and all features were extracted. At last, the feature vectors were fed into the trained classifier and found the accuracy level. In [5] an effective method for Epileptic seizure was carried out. DWT was used for decomposition of sub-bands. A set of two Datasets were used for normal and seizure patients. Then features can be calculated from each sub band.

2. Proposed Approach

The proposed epileptic classification approach is a three stage model as shown in Figure 1. Physionet is an open source biomedical database from which the EEG data is taken for classification purpose. Relevant features are extracted by applying dual tree complex wavelet transform (DTCWT) in the original EEG. For classification, CNN is used that classifies the features extracted by DTCWT.

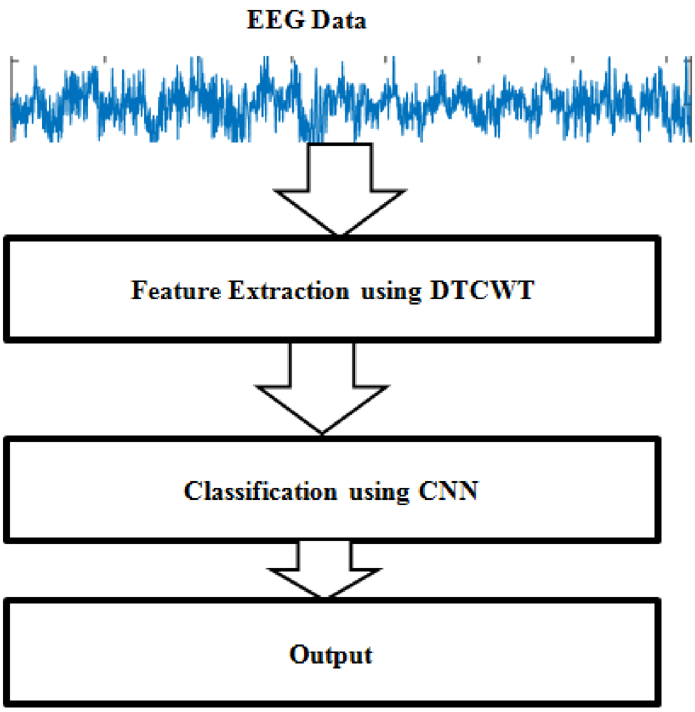

Fig. 2. Proposed classification approach

Feature Extraction

For non-stationary signal analysis, wavelet transform plays an importnat role. It decomposes the input siganl into various levels as presented in Figure 2. Generally it decomposes the signal into detailed and approximiate coefficients that coresponds to the low and high pass filtering. Wavelet transfoem is type of linear transform that filters the original signal to a multi-resolution representation by applying scaled and shifted approach of the mother wavelet. DTCWT is a class of wavelet transform where analytic filters are used for perfroming the wavelet decomposition. The real and imaginary parts are separated by DTCWT into two diffrent trees. Here the signal is decomposed interms of complex shifted and dilated mother wavelet ψ(x), and scaling function φ(x). For a one dimensional input, the real and imaginary parts of the wavelet and scaling function can be derived by

$$\psi_r(t) = \sqrt{2}\sum_n H_a(n)\varphi_r(2t-n)$$

$$\psi_i(t) = \sqrt{2}\sum_n H_b(n)\varphi_i(2t-n)$$

$$\psi_r(t) = \sqrt{2}\sum_n L_a(n)\varphi_r(2t-n)$$

$$\psi_i(t) = \sqrt{2}\sum_n L_b(n)\varphi_{ri}(2t-n) \tag{1}$$

where L and H represents the lowpass and highpass filters. The wavelet functions ψr and ψi produce the complex wavelet function ψc, which is given by $\psi r + j\psi i$ [6].

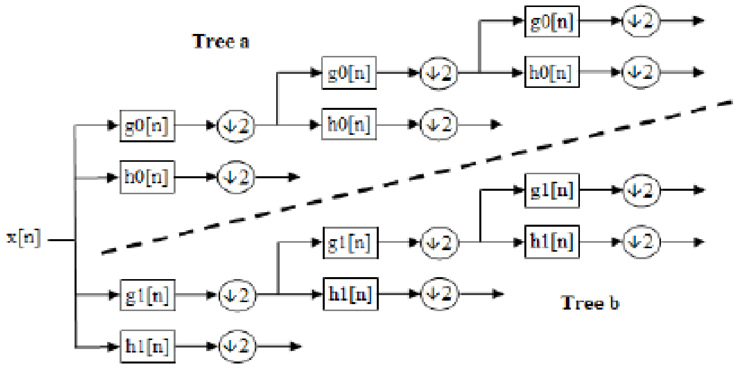

Fig. 2. Structure of DTCWT decomposition process.

Convolutional Neural Network (CNN)

CNN is a class of deep neural network architecture and has been widely used in different types of data analysis and classification. The data may be image, signal, attributes. Generally, a CNN is a neural network type classifier composed with number of convolutional layers. Each convolutional layer is followed by a pooling layer (sub-sampling). Again the pooling layer is followed by one or more fully connected layers. The structure of a CNN is presented in Fig. 3. There are also some certain numbers of neurons presented in both the convolutional and pooling layers. A weight sharing approach exists in between the neurons of both the layers to deal with the overfiting problem.

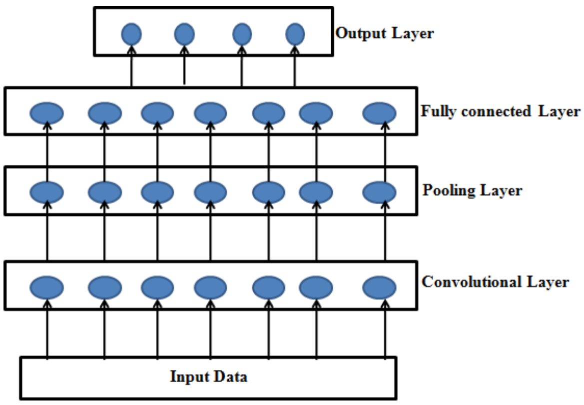

Fig. 3. Structure of the CNN

The convolution process for the input data can be presented as follows:

$$\lambda_j^f = \omega^f n_j + \beta^f \quad (3)$$

$$\alpha_j^f = \frac{1}{1+e^{\lambda_j^f}} \quad (4)$$

where λ_j^f corresponds to the convolutional output result which is associated with j^{th} input data and feature map f .ω^f is the corresponding weight and β^f is the bias for the feature map f. α_j^f is the output for a non-linear activation function which is either sigmoid or tanh. n_j denotes the j^{th} training data. For reducing the dimensionality of the input data and increasing the learning process, maxpooling operation is applied to the hidden layer that is called sub sampling layer. The operation is performed by finding the maximum average of convolved feature among the adjacent neurons presented in preceding convolutional layer. The convolutional and sub sampling layers follow one or more fully connected layers are used whose neurons are connected to all the neurons from the preceding layer. Most of the CNN parameters are interested by the fully connected layer parameters. There are ten layers in the proposed one dimensional CNN classifier including four convolutional layers, four max-pooling layer, and two fully connected layers. The detail summarization of the network structure is presented in Table II. After the convolutional process max pooling is applied for reducing the size of the feature set. Sigmoid activation function is applied in each convolutional layer (1, 3, 5, and 7). The fully connected neural network consists of 256, 128, and 64 neurons. The tanh activation function is used in the network for getting the separate output for each class. The network is trained by using the backpropagation algorithm. The weights and bias values are updated by using adaptive moment estimation (Adam) optimization algorithm This algorithm is a popular optimization algorithm is deep learning because it achieves good results fast [7]. The complete structure of the proposed CNN classification model is presented in Fig. 4.

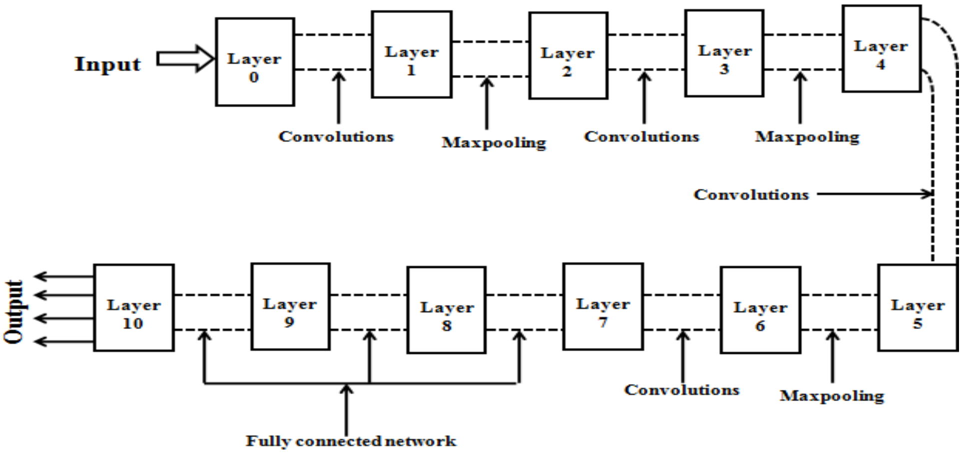

Fig. 4. Proposed CNN structure.

TABLE II Layer summary of the proposed CNN

Layer Type	Layer
Convolutional + Relu	0-1
Max pooling	1-2
Convolutional + Relu	2-3
Max pooling	3-4
Convolutional + Relu	4-5
Max pooling	5-6
Convolutional + Relu	6-7
Fully connected	7-8
Fully connected	8-9
Fully connected	9-10

Results and Discussion

The EEG signal is collected from Physionet open source repository. Normal and epileptic signals are shown in Figure 2 and 3. After collecting the data it is decomposed by wavelet transform. Decomposed signal are shown in Figure 4.

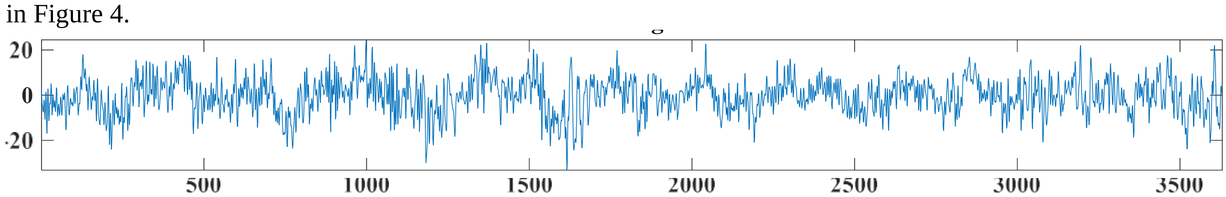

Figure 2: Normal EEG signal

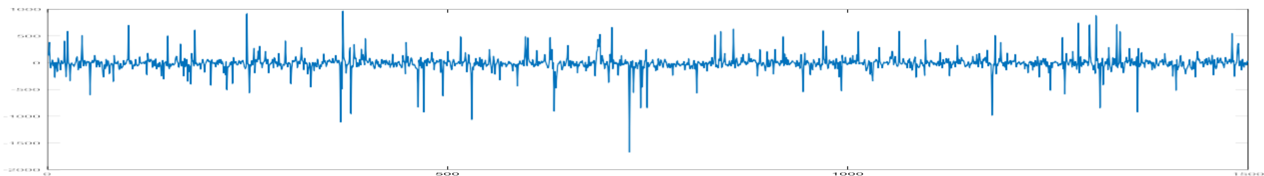

Figure 3: Epileptic EEG signal

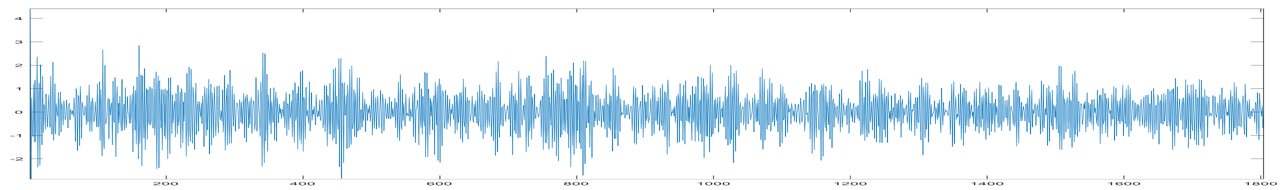

Figure 4: Decomposed EEG signal

The proposed CNN model is designed by using the Tensor flow framework in Python. The simulation process is held in an Intel Core i5 system with 8 GB RAM. The original data set is divided into training and testing set. About 90% (7675 samples) EEG data is considered for training and rest 10% data (853 samples) is taken for testing purpose of the network. CNN is trained with the training data by the backpropagation algorithm. The batch size for training is 275 and categorical cross-entropy is used as the loss function. Classification model is trained using backpropagation algorithm. The classification performance of the CNN classifier with DTCWT feature is presented in Fig. 14. The accuracy is quite better as compared to CNN without DTCWT.

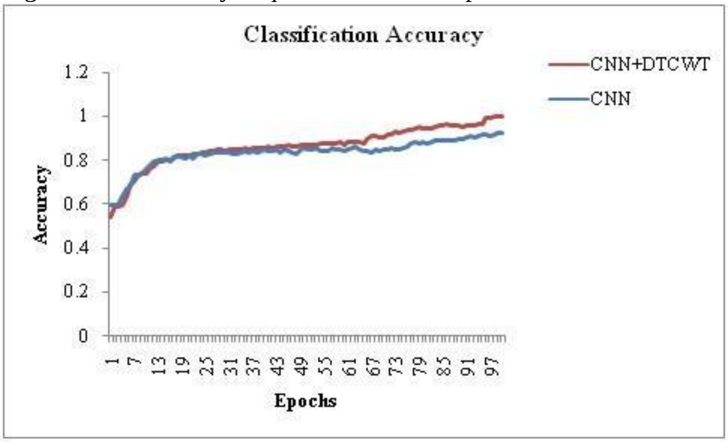

Fig. 14. Classification accuracy archived from CNN

The performance is also measured with different parameters as accuracy, specificity, and sensitivity. Sensitivity is the number of correct positive predictions divided by the total number of positives. Specificity is another performance measuring parameter and can be calculated as the number of correct negative predictions divided by the total number of negatives. Performance of the proposed method is presented in Table III and IV.

TABLE IV CNN+DTCWT classification result for each class.

Class	Sensitivity (%)	Specificity (%)	Accuracy (%)
Normal	99.40	98.27	99.29
Epileptic	96.26	99.87	99.76
Average	97.83	98.57	99.52

Conclusion

Automatic disease classification is one of the most important research in bioinformatic domain. A CNN classifier with DTCWT features is proposed to classify epileptic for early diagnois. It is perfroming efficiently for classifying the EEG signals. The CNN with DTCWT features is performing better as comapred to simple CNN model. A SVM classifier with gaussian kernel is designed for the validation of the result. Further the obtained result is also comapred with some earlier works and it can be confirmed that the proposed method is perfprming effectively for EEG classification. Further the classification accuracy can be improved by optimising the network structurure and that has kept as the future work.

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