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RESEARCH

Wavelet based deep learning approach for epilepsy detection

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Abstract

Electroencephalogram (EEG) signal contains vital details regarding electrical actions performed by the brain. Analysis of these signals is important for epilepsy detection. However, analysis of these signals can be tricky in nature and requires human expertise. The human factor can result in subjective and possible erroneous epilepsy detection. To tackle this problem, Machine Learning (ML) algorithms were introduced, to remove the human factor. However, this approach is counterintuitive in nature as it involves using complex features for epilepsy detection. Hence to tackle this problem we have introduced a wavelet based deep learning approach which eliminates the need of feature extraction and also performs significantly better on smaller datasets compared to the present state of the art ML algorithms. To test the robustness of our model we have performed a binary (2-way) and ternary (3-way) classification using our model. It is found that the model is much more accurate than the present state of the art models and since it uses deep learning it also eliminates the need of feature extraction.

Keywords: Convolutional neural network (CNN), Discrete wavelet transform (DWT), Electroencephalogram (EEG), Epilepsy detection, Multi class classification

Introduction

Automatic detection of diseases has been a hot topic of research for a long time now. Researchers have used various computer aided techniques for automated detection of diabetes [1], breast cancer [2], microaneurysms [3] etc. Epilepsy detection is also one of the hot research topics which is researched on a large scale. The epilepsy is detected from Electroencephalography (EEG) signals.

The Electroencephalography (EEG) signals gives details about the electrical brain activity. Traditionally, neurological experts have detected epilepsy by personally inspecting the EEG brain activity. This method is prone to error and is a time-consuming, since it completely depends on the skillset of the expert. To avoid inconsistency in the detection of epilepsy, automatic detection of epilepsy was proposed [4].

The approaches proposed in automatic epilepsy detection involved using complex features to train the Machine Learning algorithms for epilepsy detection. Sharmila et al. [5] used features like Mean and MAV to classify the data. Many researchers have used entropy based classifiers [6–8] which use various features like approximate entropy, fuzzy entropy etc. to classify the epileptic data as accurately as possible. Similarly, Chen et al. focused on extracting Fourier features from Dual Tree Complex Wavelet transform [9]. Taran et al. [10] suggested a new feature extracting technique which used OAS based methods for feature extraction. Most of the researchers until now have focused on either engineering new features or suggested new methods to extract features.

However, there is major flaw in the above mentioned approaches. All of these approaches focus on extracting features to train their models for epilepsy detection which makes the automated epilepsy detection process tedious. These features are complex and not intuitive in nature. Moreover, the designed features might also not be robust in nature. This means that the designed features might prove effective in binary classification but might fail in ternary classification. Therefore, it is necessary to eliminate the need of feature extraction since it is a very tedious and non-intuitive process. Hence to eliminate the need of feature extraction we have used a deep learning

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model known as Convolutional Neural Networks (CNN) for epilepsy classification.

However, the effect of deep learning algorithms on epilepsy detection is not studied much. This is because deep learning algorithms require a large amount of data to prove an effective classifier. It is very time consuming and expensive to generate a large EEG datasets for epilepsy detection. Hence due to limited availability of dataset, traditionally people have preferred Machine Learning techniques that involve feature extraction. Acharya et al. [11] tried to use CNN on small EEG dataset but the accuracy obtained from the model (88.67%) was far from the state of art models.

There are two main problems that we are trying to solve in this paper: (1) simplifying the process of automated epilepsy detection by eliminating the need of feature extraction, (2) improving the accuracy of deep learning models on small EEG datasets. To tackle the above mentioned problems, we have presented a novel wavelet based deep learning model. The model performs very well on small datasets and gives accuracy comparable to the state of the art ML models. We have also tested our proposed model on binary and ternary classification to prove that our model is robust in nature. This test further bolsters our claim of using deep learning for epilepsy detection.

In this paper Sect. 3 gives a brief introduction of dataset. The next section mentions the need for models that successfully perform multiple classifications. After this a brief overview of WT and CNN has been described in Sect. 5. This is followed by a detailed description of the methodology that we have used for training and pre-processing. The final section contains the detailed summarisation of our models performance and a comparative analysis of the model with different state of the art architectures.

Literature survey

The automated epilepsy detection is a complex task and many researchers have contributed novel techniques to detect and classify epilepsy. In this section a brief overview of the state of the art ML and deep learning models which are used for epilepsy detection are described. Most of the papers suggested in this section are specific to the dataset used in this paper.

For a long time researchers have used transforms to pre-process the data. Different transforms like Fourier transform and Short Time Fourier Transform [12, 13] were suggested by many researchers which transferred the EEG signal to frequency domain for analysis. However, the above approaches resulted in loss of information due to certain fundamental flaws in Fourier Transform. Hence to tackle the problems of Fourier transform, Wavelet Transform [14] was proposed. A lot of research has gone in exploring the effect of wavelet transform on EEG data. Researchers have used Discrete Wavelet Transform [5], wavelet chaos theory [15], wavelet power spectrum [16] etc. to improve the accuracy of epilepsy detection. Recently a new variant of Wavelet transform named as Tunable Q-factor wavelet Transform [17] was proposed by Al Ghayab et al. which used the resonance of signal to extract features from the EEG signal. Impressive accuracy of 100% was obtained using this method with a K-NN classifier. Another approach suggested by Al Ghayab et al. [18] was to extract features from FFT or DWT. He used an algorithm named InfoGain which extracted the top features from frequency domain using information gain as the primary selection parameter. He obtained accuracies as high as 100% for a binary classification using LS-SVM classifier. Similarly, Siuly et al. took a different approach and suggested a new transform named Hermite Transform [19] which transferred the EEG data to a new form. The features that were extracted from this form were gave accurate classification results which were comparable to the state of art models.

Many researchers have explored different statistical techniques to extract features. Instead of using a transform to preprocess the EEG signal, some researchers have preferred to employ different statistical techniques. Kabir et al. [20] used a K-means clustering based approach to cluster the EEG signal according to the classes. He extracted the features from the clustered data and classified the data using a classifier. An impressive accuracy of 100% was obtained for binary classification using this method. Supriya et al. used a complex network approach to suggest a new method named edge weight method [21] for visibility graphs. A single feature was extracted from this visible graph. This extracted feature carried information equivalent to multiple features and hence inturn reduced the computation cost. The accuracy obtained by this method was as high as 100% for a binary classification. The edge weight method was further improved by Supriya et al. [22] in another paper where she suggested to use weighted visibility graph to extract new features like modularity and average weighted degree. This method was tested on multiple binary classification sets and the accuracy obtained from this method varies from 91 to 100%.

Contrary to Machine Learning approaches, only a small amount of research has been done to study the effect of deep learning models on epilepsy detection. Acharya et al. [11] tried to use CNN to classify the EEG signal into three classes. However, the accuracy of this method is just 88.67%. Not a lot of emphasis has been laid on using deep learning algorithms on EEG datasets. This might be due to the fact that deep learning models are relatively new and there is a lack of large datasets for epilepsy detection.

The overview of the current state of the art models in automated epilepsy detection suggest that, not a lot of research has been carried out to use deep learning in the field of epilepsy detection. Most of the attention is focused on using Machine learning techniques. One of the main reason, for this is lack of large datasets, to train the deep learning models. Hence, we proposed a Deep learning model whose accuracy is comparable to the state of art ML techniques.

Dataset description

The dataset is accessed from the University of Bonn, Germany. This dataset consists of the EEG recordings of five different patients [23].

The EEG data was recorded for 5 different patients. For every patient the data has been recorded for 23.6 s and this process is repeated 100 times. This means that EEG for every patient has been recorded 100 times (hence 100 segments), each for a duration of 23.6 s. The data, that is every segment has been sampled at 173.61 Hz which accounts for 4097 samples per segment.

The dataset contains 5 sets as mentioned above. The first two sets that is Set A and Set B contain the EEG recording of patients which are non epileptic in nature. Set C and Set D contain EEG recordings between the interval of two seizures (inter-ictal). Finally the last set that is Set E contains EEG recordings of epileptic patients (ictal). The Fig. 1. Gives a graphical representation of EEG signals available in the data. The figure shows data of the first 1024 samples.

We have chosen Bonn dataset because we wanted to test the accuracy of CNN (which is a data heavy model) on smaller datasets and test its performance on smaller datasets. We have used a tenfold cross validation to train CNN over our data and have used CNN to for binary and ternary classification.

Need for multi class classification

The given dataset can be classified in either 2 classes [24] (epileptic and non-epileptic) or in 3 classes (epileptic, inter-ictal, non-epileptic). Both the classification problems serve a different purpose. They are

- Binary classification
  - It gives a normal versus ictal classification result
  - The prediction of the model in this category helps the doctors to identify if the person is undergoing seizure and hence prescribe necessary medication to minimise the effect of seizure.
- Ternary Classification

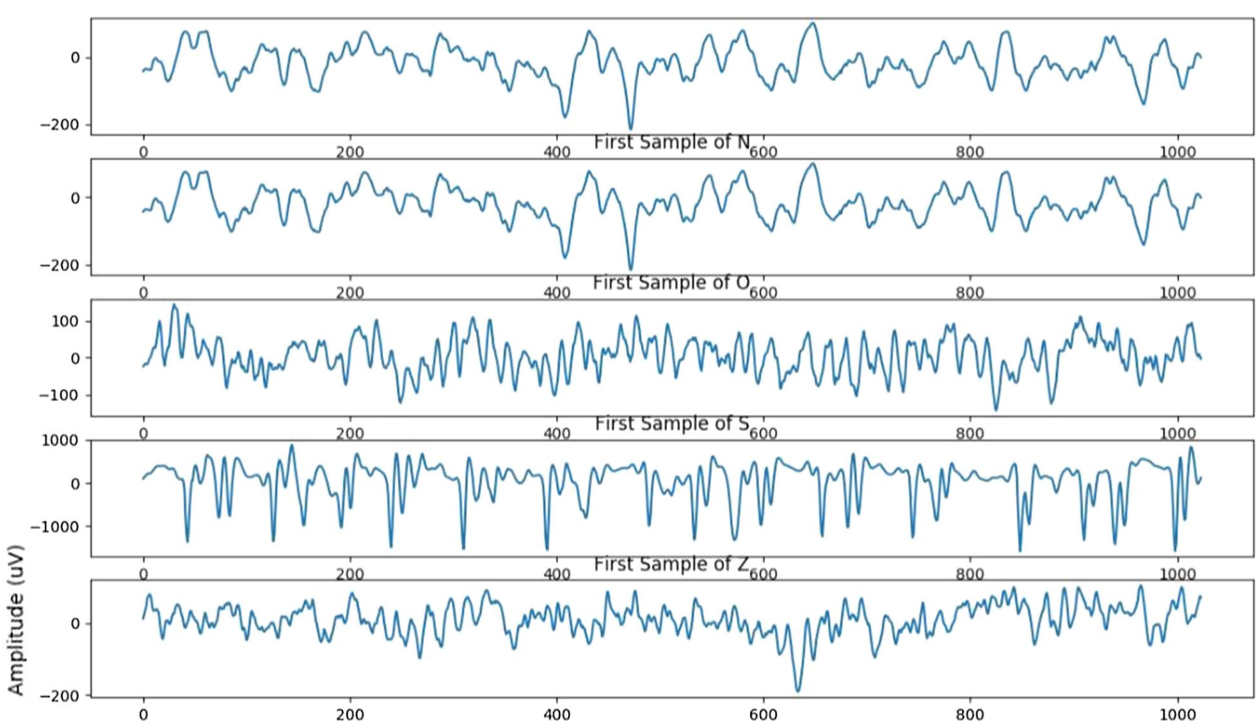

Fig. 1 Graphical representation of dataset

- It gives normal, inter-ictal or ictal as a classification result.
- It is important to determine if the EEG recordings are inter-ictal in nature. Since inter-ictal is an EEG recording between two successive seizures, it gives the doctors a necessary early warning, due to which they can take preventive measures before the onset of next seizure.

For binary classification the paper focuses on ABCD versus E classification. We have chosen this set because of the dataset imbalance problem (400 samples vs. 100 samples). The ternary classification is performed using the sets AB versus CD versus E.

Prerequisites

In this section we have explained the basic theory of Wavelet Transform (WT) and Convolutional Neural Networks and the reason for choosing both of them respectively.

Pre-processing

There has been a lot of research conducted to test different pre-processing techniques for epilepsy detection. There are three main approaches that are used by researchers to pre-process the data. The first is analysing the signal in time domain [25, 26] and extracting crucial time domain information. The second involves frequency domain analysis [12, 13] and the third involves time–frequency domain analysis [14, 15]. Each of the above mentioned approaches has certain pros and cons.

We have chosen Wavelet Transform which belongs to time–frequency domain. This is because

- Even though it is faster to use time domain pre-processing, it generally tends to miss major changes in frequency that are crucial for epilepsy detection.
- In case of frequency domain certain time domain features are missed by the algorithm which leads to misinformed predictions.

Hence we have used Wavelet transform which takes the best of both worlds and uses the time and frequency domains for analysis.

Wavelet transform (WT)

The WT can successfully capture important features at lower frequencies by using long time windows and higher frequencies can be captured by using short time windows. There are two types of WT namely: continuous wavelet transform (CWT) and discrete wavelet transform (DWT)

In CWT coefficient of wavelets are calculated at all possible scales. However, it is computationally expensive to do so. To tackle this problem DWT is used instead of CWT. The scaling and shifting is done in powers of two and as a result, we do not need to calculate all the coefficients. The DWT is defined [27] by Eq. (1)

$$DWT(a,b) = \frac{1}{\sqrt{|2^a|}} \int_{-\infty}^{\infty} \left(z(t)\psi\left(\frac{t-2^a b}{2^a}\right)\right) \mathrm{d}t \tag{1}$$

where x and y are replaced by 2^a and $2^a b$ respectively.

DWT can be implemented effectively by passing it through Low Pass filter and High Pass filter.

Convolutional neural networks

The CNN is a deep learning algorithm which has proven to be extremely influential in classification. In the past work CNN has mostly been used to classify images [28]. The main advantage of CNN is that the algorithm can learn appropriate features on its own and classify the data in different classes. The CNN have been used on large datasets. However, the application of CNN on small time series datasets is a field which is not explored much. In this paper we have used to eliminate the need of feature extraction and classify epilepsy.

However, there are other architectures present like RNN which are more popular for time series classification. However, RNN tend to localise rather than generalise and RNN are useful when the causality property of the data needs to be exploited. In case of epilepsy detection we are mostly focused on recognising the pattern and classify data accordingly, for which CNN seems to do a great job. There are various layers present in CNN namely

Convolutional layers

The convolutional layer is the layer where the appropriate features are learnt by the CNN. The convolution operation is as mentioned in Eq. (2). The convolutional layer consists of filters. These filters are initially initialised with random values and as the CNN is trained over the data the values in these filters goes on changing to detect the appropriate features. The values are adjusted in order to minimise the cost function of CNN. The training of CNN is possible because of back-propagation algorithm [29]. Back-propagation calculates the gradient of loss function, which is needed in order to update the weights of the filters.

$$Z_k = \sum_{i=0}^{n-1} y_i l_{m-i} \tag{2}$$

where y = input signal, n = number of elements in x, z = output vector, l = filter. The subscript k denotes the kth element in vector.

Fully connected layer

In this layer, each neuron in the preceding layer is linked to all the neurons in the next layer. This type of model is common in Artificial Neural Networks. Every neuron is associated with a weight and the value of weight goes on changing as the network trains itself. Similar to convolutional layer the gradients of the loss function are calculated using back-propagation algorithm and the weights are adjusted to minimise the cost function.

Max pooling layer

The max-pooling layer is used after convolutional layer. This layer has two main functions: (1) to down-sample, (2) to generalise.

Activation layer

There are two types of activation functions used in our model

- Rectified linear units (ReLU)
- Softmax function

1. Rectified linear unit (ReLU)

This layer brings a non-linearity in the neural networks. The formula for ReLU is given in Eq. (3)

$$\max(0,x) \tag{3}$$

where x = input function.

The ReLU layer is added after every convolutional and fully connected layer.

2. Softmax function

The Softmax function is assigned in the final layer of the CNN. The function helps to compute the categorical probability distribution of the input data. The addition of all the categorical probabilities comes out to be 1.

Dropout

Dropout is a regularisation technique which is used to prevent the CNN from over-fitting. The dropout is introduced in the Fully Connected Layers of CNN. In dropout random nodes are switched off. This means that the output of these nodes is not considered during forward and backward passes.

Batch normalisation

The Batch Normalisation is used in order to introduce the effect of covariance shift. The batch Normalisation also has a regularisation effect on CNN. This layer helps the CNN to train faster as well as regularises the CNN and prevents it from overfitting.

Methodology

In order to enable CNN learn and classify data accurately on a small dataset, we have first pre-processed the data. The pre-processing is done by using Discrete Wavelet Transform (DWT). This technique ensures that we have collected all the frequencies important for epilepsy detection. This is followed by classification of data using CNN. The graphical representation of the methodology is as mentioned in Fig. 2.

Pre-processing

We have used DWT for pre-processing of the data as mentioned earlier. There are 4097 samples present in every segment (100 such segments for every patient) of the data. We have used a 5 level decomposition using sym24 wavelet [31] to decompose these 4097 samples into different wavelet coefficients.

For ease of use of EEG signal for epilepsy detection the EEG signal is divided into 5 main subbands namely: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz) and gamma (> 30 Hz). Among these 5 sub-bands the frequencies which are used for epilepsy detection lie below 30 Hz [30]. Therefore, we have tried to extract all the lower frequencies and eliminated all the higher frequencies. The decomposition has been done with the help of sym24 wavelet [31]. For extracting the lower frequencies we have done a 5 level decomposition since it is enough to extract the lower frequencies and eliminate the noise (higher frequencies).

The Fig. 3 shows the 5 level decomposition we have employed in this paper. In the figure G(n) represents Low pass filter while H(n) represents a High Pass filter. The D1 and D2 frequencies are eliminated [5] since they represent higher frequencies. The rest of the available coefficients are used by the CNN for classification. The Table 1 gives an overview of the frequencies every wavelet coefficient carries. After elimination of D1 and D2 coefficients

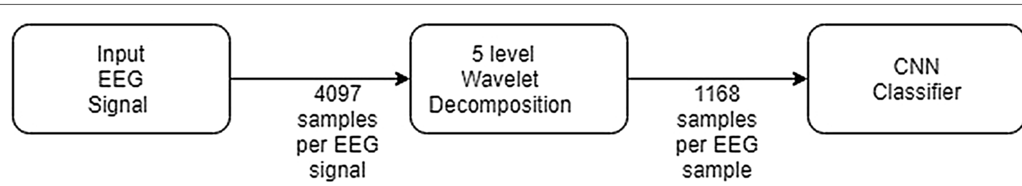

Fig. 2 Representation of methodology

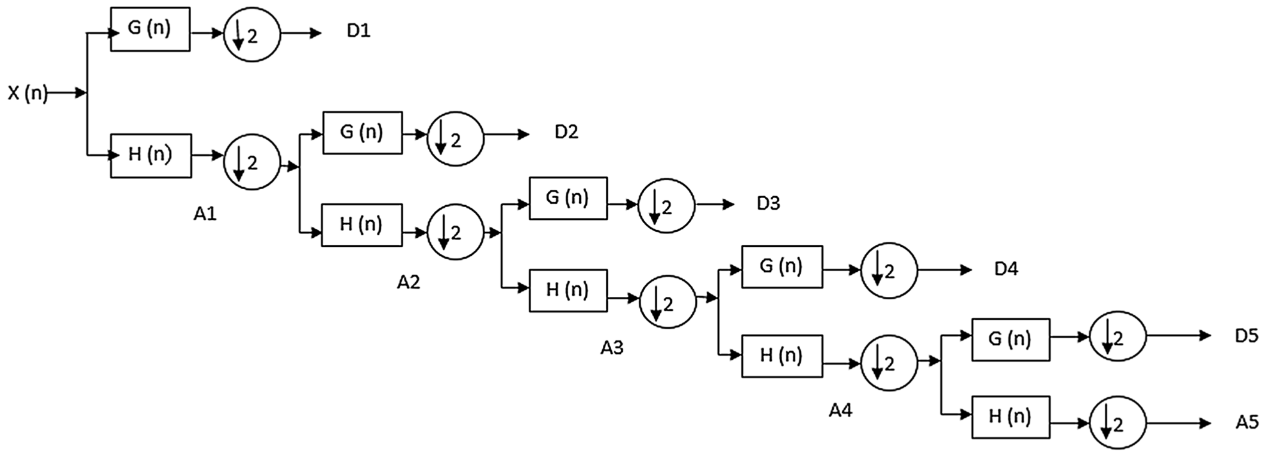

Fig. 3 5 level decomposition using DWT

Table 1 Frequency content in each wavelet coefficient

Band	Coefficient	Frequency (Hz)
Delta	A5	0–2
	D5	2–4
Theta	D4	4–8
Alpha	D3	8–13
Beta	D2	13–30
Gamma	D1	Greater than 30

we are left with 1168 wavelet coefficients which are passed on to classification algorithm.

Convolutional neural networks

The CNN is a deep learning algorithm which has proven to be extremely influential in classification. In the past work CNN has mostly been used to classify images [28]. The main advantage of CNN is that the algorithm can learn appropriate features on its own and classify the data in different classes. The CNN have been used on large datasets. However, the application of CNN on small time-series datasets is a field which is not explored much. In this paper we have used CNN to eliminate the need of feature extraction and classify epilepsy.

Training and testing of CNN model

After preprocessing stage we have gathered all the required wavelet coefficients (1168 to be precise) that are important for epilepsy detection and used this as the final data. These coefficients are supplied as an input to the CNN and the CNN tends to learn the features from this input data.

During training we have assumed that every layer uses VALID padding. We have initialised the dropout to 0.25 in order to prevent overfitting. We have used tenfold validation to train our CNN model. For each fold the CNN model is trained for 150 epochs with a batch size of 5.

The Batch Normalisation is used in order to introduce the effect of covariance shift. The batch Normalisation also has a regularisation effect on CNN. This layer helps the CNN to train faster as well as regularises the CNN and prevents it from overfitting. In case of Max Pooling Layer the size of filter used is 1×2. As a result, the output of Max pooling layer will be half the size of the input given to max pooling layer. The last layer is then passed through a Softmax function to determine the class of data. To prevent overfitting the value of dropout layer is set to 0.25.

The training has been done on Tesla K80 GPU since GPU tend to provide faster computation time. The GPU has 12 GB Memory, 61 GB RAM, 100 GB SSD. The Table 2 gives a detailed architecture that we have used in this paper.

Result

The CNN model is trained for tenfold cross validation. In this section the results obtained for binary and ternary classification are compared with the present state of art models. Since the accuracy of the model is to be tested on smaller datasets every mentioned classifier in this section is trained on Bonn dataset. To make the results more interpretable the result section is divided in two sections: (1) the first analyses the results of binary classification, (2) the second analyses results of ternary classification.

Results for binary classification

In Table 3 accuracy, sensitivity and specificity of the proposed model is compared with the state of art models with respect to 2-way classification. Set ABCD

Table 2 CNN architecture

Layer	Type of layers	Total neurons at O/P of layer	Kernel size of layer	Kernels used per layer
0–1	Convolution	1166 × 32	1 × 3	32
	Batch normalisation			
1–2	Convolution	1163 × 34	1 × 4	34
	Batch normalisation			
2–3	Max pooling	581 × 34	1 × 2	–
3–4	Convolution	579 × 64	1 × 3	64
	Batch normalisation			
4–5	Convolution	576 × 64	1 × 4	64
	Batch normalisation			
5–6	Max pooling	288 × 64	1 × 2	–
6–7	Fully connected layer	550	–	–
	Batch normalisation			
	Dropout			
7–8	Fully connected layer	250	–	–
	Batch normalisation			
	Dropout			
8–9	Fully connected layer	100	–	–
	Batch normalisation			–
	Dropout			
9–10	Fully connected layer	25	–	–
	Batch normalisation			
	Dropout			
10–11	Fully connected layers	2/3 (Depending on classification problem)		

(non-epileptic) is compared with Set E(ictal). It is observed that the proposed model outperforms all the state of art models. Since the accuracy obtained is 100%, the confusion matrix is not mentioned in the paper.

Results for ternary classification

The Table 4 gives a comparison of the proposed model with the state of art machine learning models. It is observed that the proposed model is comparable in terms of accuracy to the current state of art ML models

Table 5 gives a comparison of the proposed model with the state of art deep learning models. It is observed that the current state of the art deep learning models are not very accurate with accuracy of 88.67%. Our model performs much better than the present state of art deep learning models (Table 6).

Our model outperforms the previously mentioned deep learning model in [11] because Acharya et al. directly classified the data into 3 classes without using any pre-processing technique. Since no pre-processing technique was used the frequencies which were unnecessary for epilepsy classification (greater than 13 Hz) were also fed into CNN. This noisy data forced the CNN to learn wrong patterns and hence it gave an accuracy of 88.67%. This problem would have been overcome if the dataset was large. However, for epilepsy detection the dataset generation is time consuming and expensive. Hence due to limited data the CNN model proposed in [11] learnt wrong features which resulted in low classification accuracy. To tackle this issue we have used DWT before CNN, which eliminated the higher frequencies thereby aiding the CNN in learning adequate patterns/features.

Conclusion

In this paper, a wavelet based deep learning model has been proposed for epilepsy detection. Since the proposed model is a deep learning model, the tedious process of feature extraction is completely eliminated. Moreover, the deep learning model performs exceedingly well on small datasets and the accuracy is comparable to the state of the art Machine Learning models. We have also tested the robustness of our model by performing binary and ternary classification in the model. The model is comparable to the current state of art. This proves that a deep learning model eliminates the step of feature extraction and can be a robust and accurate model for epilepsy detection.

Table 3 Comparison of proposed model for 2-way classification (ABCD vs. E)

DataSet	References	Year	Classifier	Sensitivity	Specificity	Accuracy
Bonn	Fu et al. [32]	2015	SVM	–	–	98.80
	Hassan et al. [33]	2016	Decision Tree	99.49	100	99.6
	Samiee et al. [34]	2015	MLPNN	99.20	93.80	98.10
	Perker et al. [24]	2016	CVANN	100	98.01	99.33
	Jaiswal et al. [35]	2017	ANN	98.30	98.82	98.72
	Wang et al. [36]	2017	SVM	97.98	99.56	99.25
	Proposed model	2019	CNN	100	100	100

Table 4 Comparison of proposed model with ML models for set AB–CD–E

DataSet	Author	Year	Classifier	Sensitivity	Specificity	Accuracy
Bonn	Acharya et al. [37]	2012	Fuzzy	100.0	100.0	99.7
	Acharya et al. [38]	2012	GMM	99.0	99.0	99.0
	Gajic et al. [39]	2015	Quadratic classifier	98.6	99.33	98.7
	Hassan et al. [33]	2016	Decision Tree	98.3	98.6	98.4
	Tzimourta et al. [40]	2019	Random Forest	96.04	97.75	95.84
	Proposed model	2019	CNN	98.5	99.45	99.4

Table 5 Comparison of proposed model with Deep Learning models for set AB–CD–E

DataSet	Author	Year	Classifier	Sensitivity	Specificity	Accuracy
Bonn	Acharya et al. [11]	2017	CNN	95.0	90.0	88.67
	Proposed model	2019	CNN	98.5	99.45	99.4

Table 6 Confusion Matrix for AB versus CD versus E

	Non-epileptic	Inter-ictal	Epileptic
Non-epileptic	199	1	0
Preictal	0	200	0
Epileptic	0	4	96

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