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EEG Signal Analysis Using Fuzzy Approximate Analysis towards Epileptic Seizure Detection

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ABSTRACT: Electroencephalogram (EEG) is recording of electrical activity of the brain which can be used to detect Epileptic Seizures. Group of Neurons when misfiring produce abnormal electrical discharge which produces seizure. Epilepsy is tendency to have recurrent and unprovoked seizure. It is common brain disorder that affects about 1% of the world population. A wavelet based fuzzy approximate entropy (fApEn) method is presented for the classification of electroencephalogram (EEG) signals into healthy/interictal versus ictal EEGs. Discrete wavelet transform is used to decompose the EEG signals into different sub bands. The fuzzy approximate entropy of different sub-bands is used as feature vector for the classifier. In this work it is observed that the quantitative value of fuzzy approximate entropy drops during the ictal period which proves that the epileptic EEG signal is more ordered than the EEG signal of a normal subject. The fApEn values of different sub-bands of all the data sets are used to form feature vectors and these vectors are used as inputs to Convolutional Neural Network (CNN) classifier. The fApEn feature of different sub-bands (D1–D5, A5) and classifiers is desired to correctly discriminate between three types of EEGs. It is revealed that the highest classification than earlier results published. Classification accuracy of 98% is obtained while classifying normal and epileptic subjects while 97% is obtained while classifying normal and interictal subjects. The results are discussed quite in detail towards the last section of the present paper.

KEYWORDS: EEG, DWT, CNN, Fuzzy Approximate Entropy.

I. INTRODUCTION

EEG measures electrical activity of the brain. EEG is non-invasive technique of medical procedures which is more convenient to the patients. It is Complex, Non-linear and Non-stationary (statistical properties change with the time) in nature. The brain waves are divided into different frequency ranges which are delta [0.5-4 Hz], theta [4-4.75 Hz],alpha [8-13 Hz], beta[14-30 Hz] and gamma [30-45 Hz].EEG is used to discover diseases or abnormalities related to the activity of brain such as sleep disorders, epilepsy and mental disorders[2].

When group of neurons misfire Seizure occurs and Epilepsy is due to occurrence of recurrent Seizure. As compared to the normal state of the brain, the brain activity during seizure differs significantly when frequency and neural firing pattern is accounted for [1].
Epilepsy is brain disorder affecting many people in the world. Due to Epilepsy person becomes unconscious and can have spasms, strange sensations. Epileptic seizure results in the lapse of attention or the whole body convulsions [3].EEG signals from an epileptic patient can be divided into five periods or stages. Non - Seizure period (no Epileptic Syndrome is visible), Ictal period (actual Seizure period), Preictal period, Post Ictal period, Interictal period (Period between post Ictal period to pre Ictal period) [4].Common method of analysis of EEG signals are based on manual

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observation of EEG signals. However, this type of visual analysis of the EEG data is likely to have the judgmental error and it is time consuming [3].

II. RELATED WORK

Various methods like spike detection frequency domain analysis, wavelet analysis and non-linear methods are used currently for the detection and prediction of the elliptic seizure. According to Adeli et al.; instead of entire EEG Signal features selected from individual frequency sub-bands using wavelet transform can provide more information. Non-linear features such as time lag (TL), embedding dimension (ED), co-relation dimension (CD) are selected from each sub-band of EEG which act as a feature vector to detect epileptic seizure [7].

Worrell et al. claimed that seizure onset frequencies are in the range of gamma frequencies, i.e., high frequency band (30 Hz to 100 Hz). Also frequency range of seizure onset can be varied based on brain location, seizure type patient and hospital settings. Also it was observed signal has larger spikes that is high amplitude in the ictal (seizure period) compared to interictal period. [6].

Pincus explained that approximate entropy is a suitable feature to characterize the EEGs as it value drop suddenly during epileptic activity due to excessive discharge of neurons [8].

Pachori decomposed EEG signals into intrinsic mode function (IMS) using EMD and then computed mean frequency for EEG for each IMF by Fourier Bessel expansion to differentiate between seizure and non-seizure EEG Signals [9].

In the current work Discrete Wavelet Transform is employed to decompose EEGsignals intosix EEG sub-bands namelyD1–D5 andA5 using 6^{th} level decomposition [1].

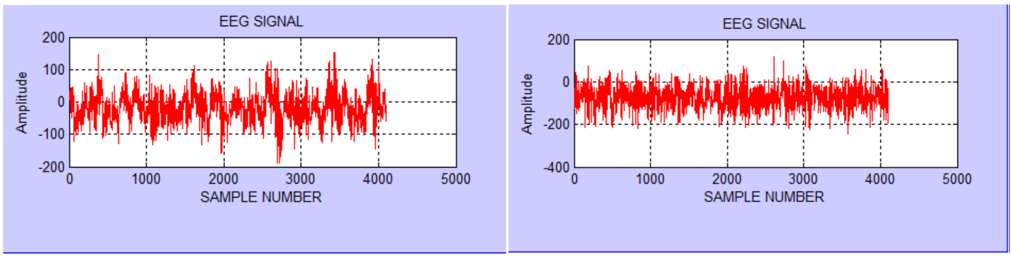
Using these EEG sub-bands Non-linear features like Fuzzy Approximate Entropy are used to detect Epileptic Seizure using Convolutional Neural Network(CNN)classifier[1].

The paper is organized as follows. In Section 2, EEG data collection and Recording is described. Section 3 discusses the proposed methodology. In Section 4 the evaluation procedure and the experimental results are presented which are concluded in Section 5.

III. EEG DATASET

The dataset are collected from University of Bonn, Germany comprising of five sets. There are 100 single channel EEG segments of duration 23.6 sec in each Set. The data segments are selected so that Eye and Muscle movement artifact are absent and free from noise.

The Data set A and B indicate Healthy patient with Eyes open and Eyes closed respectively. The dataset C and D indicates Interictal state and Dataset E indicates Ictal activities (during seizure activity) from Epileptic Patients. The sampling rate of data acquisition system is 173.61 Hz [1].



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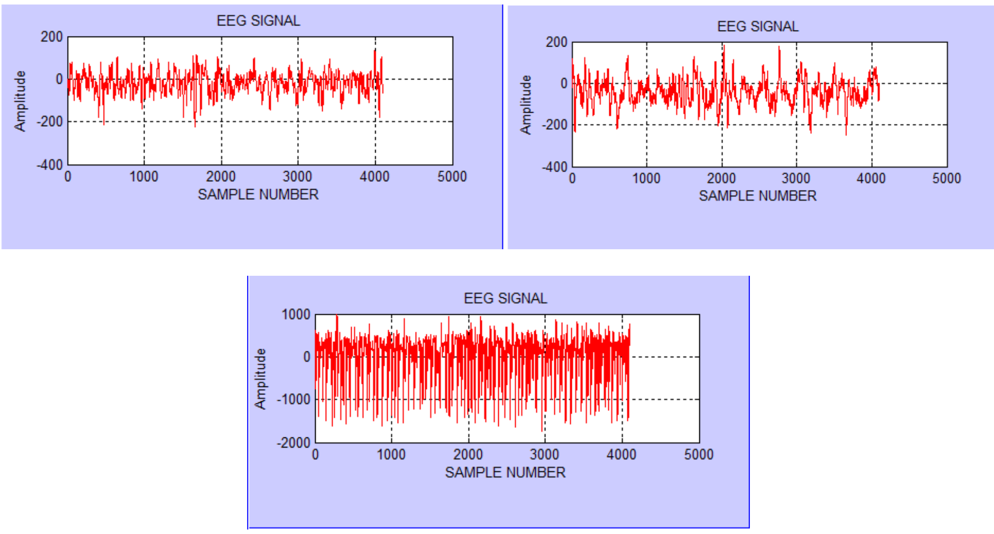
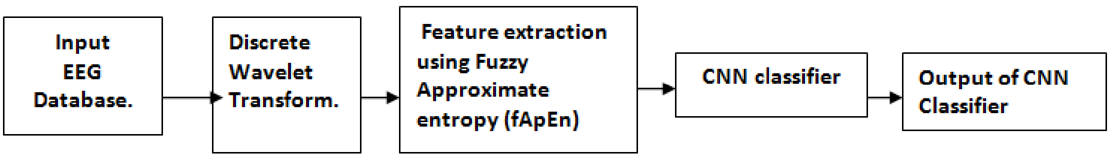


Fig 1.EEG Signal from five available dataset

IV. METHODOLOGY

EEG datasets (A,B,C,D,E) are decomposed using Discrete wavelet transform into six sub-bands. Fifth level decomposition is used for Discrete Wavelet Transform. Features vectors are extracted from these sub-bands using fuzzy approximate entropy method. Feature vector is given as input to Convolutional Neural Network classifier for classifying Healthy, Interictal and Ictal subjects. The Block Diagram shows the following approach.

BLOCK DIAGRAM OF PROPOSED APPROACH



A. DISCRETE WAVELET TRANSFORM

Wavelet transform gives time - frequency representation of Signals and are used in the field of Biomedical areas. And it allows to use variable size of windows and thus is very convenient approach.

DWT is defined as:

$$\text{DWT}(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(t)\Psi\left(\frac{t-2^j k}{2^j}\right) dt$$

In DWT scaling and shifting parameters are converted to the powers of two called dyadic scales and positions.

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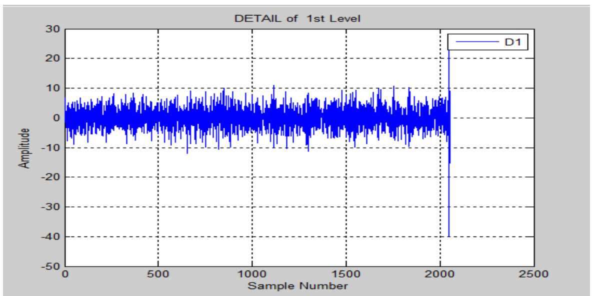
Discrete wavelet Transform is powerful tool for the analysis of Non-stationary signals like EEG. DWT decomposes signal into different frequency bands using wavelet function and scaling.DWT decomposes EEG signal into set of Sub-bands using time domain High pass and Low pass filtering technique.High Pass filter gives detail coefficients and Low pass filter gives approximate coefficients. The cut off frequency of low pass and High Pass filter is one fourth of the sampling frequency.The output signals with frequency bandwidth equal to half of the original signal can be down sampled by the factor of two

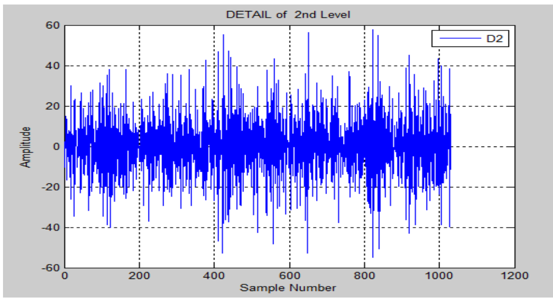
The down-sampled outputs of the first low pass (g) and high-pass filters (h) supply the approximation *A1* and detail *D1*, respectively at first level of decomposition. The first approximation *A1* is furtherdecomposed and the procedure is continuedto get next level – approximate and detailed coefficients.

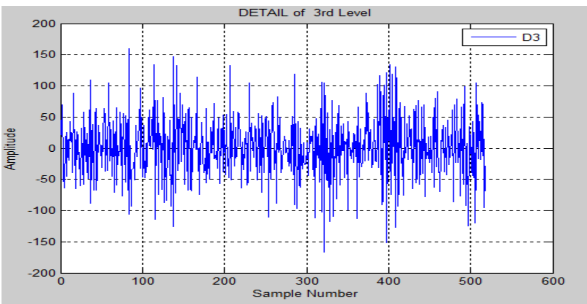
For DWT two factors play a very important role first the number of decomposition levels and second the selection of wavelet function. The frequency components above 40 Hz. In EEG Signal may not have useful information therefore in this work number of decomposition levels is selected to five. Also Daubechies order – 4 (db4) is utilized for implementation due to its orthogonalityproperty[5].

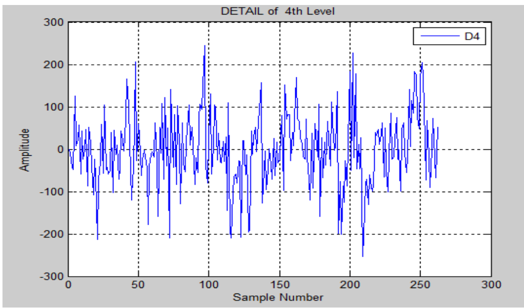
Figure illustrates the DWT process coefficients A1, D1, A2, D2, A3, D3, A4, D4, A5, D5 represent frequency content

Frequency content of the original EEG signal within the bands 0 – fs/4, fs/4 – fs/s, 0 – fs/8, fs/8 – fs/4, 0 – fs/16, fs/16 – fs/8, 0 – fs/32, fs/32 – fs/16, 0 – fs/64 and fs/64 – fs/32 respectively where ‘fs’ is sampling frequency of the original signal.









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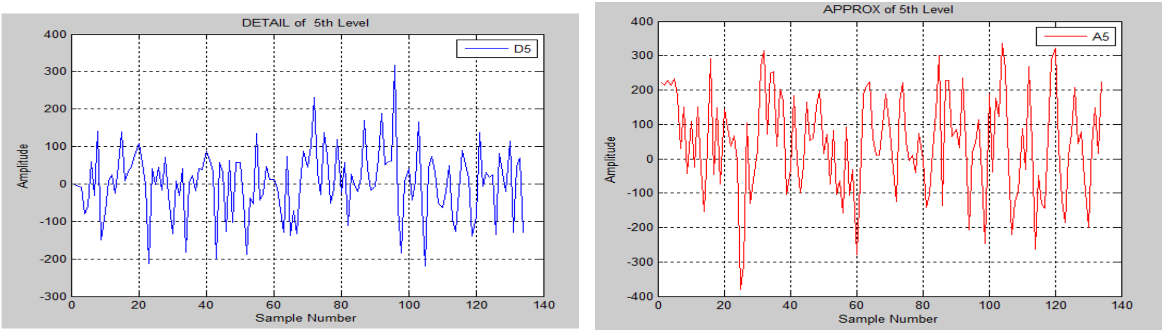

Fig.2. DWT Output of Healthy Subject showing approximate and detail co-efficients(A dataset)

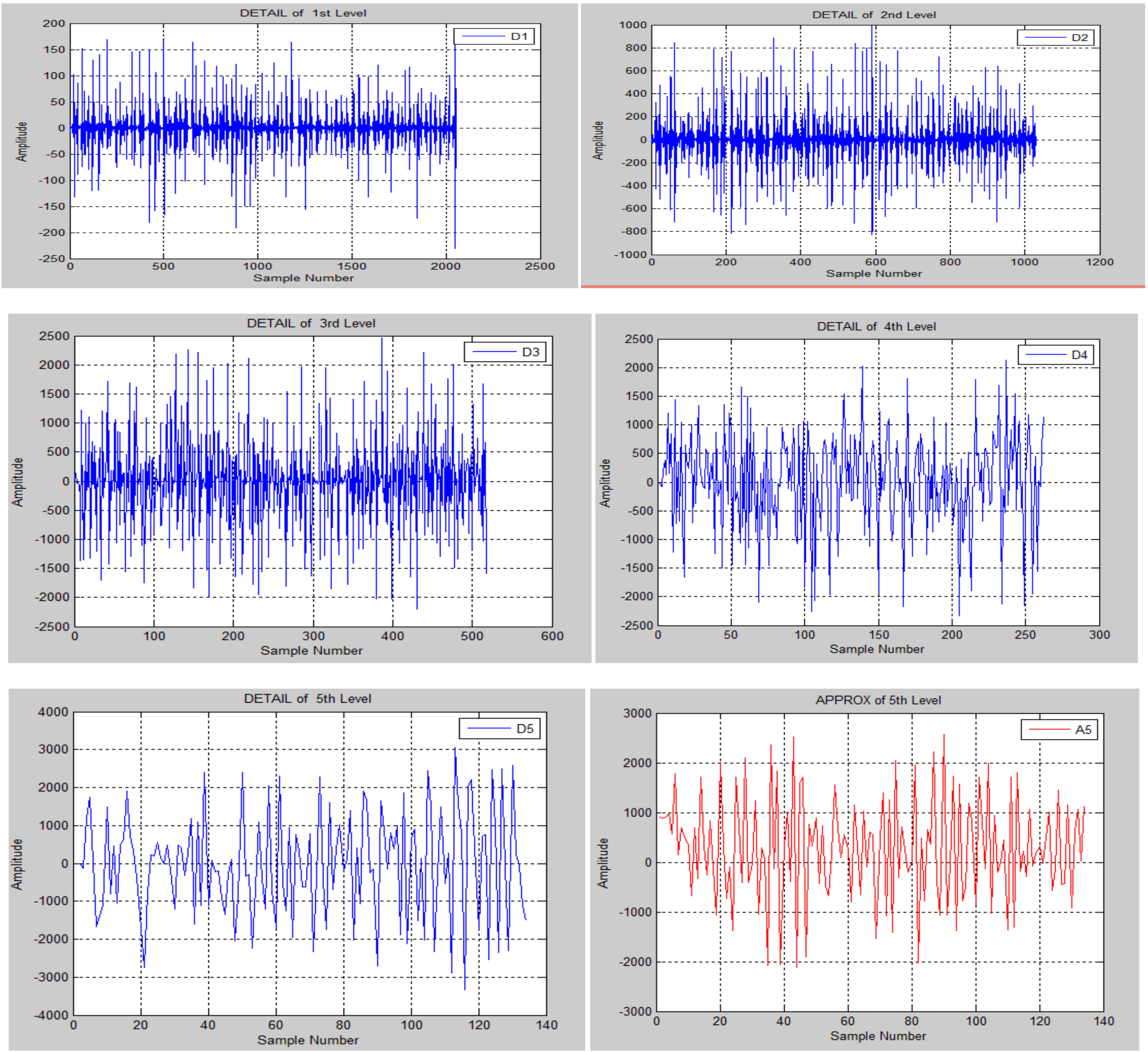

Fig3 DWT output of Seizure Subject showing Detail and approximate co-efficients.

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Frequency band (Hz)	Sub-band signal	Decomposition level
43.4–86.8	D1	1
21.7–43.4	D2	2
10.8–21.7	D3	3
5.4–10.8	D4	4
2.7–5.5	D5	5
0.0–2.7	A5	5

A range of various frequency bands are shown in Table 1. Five different levels of approximation and detail coefficients of an EEG signal are taken from the healthy and epileptic subjects.

B. FUZZY APPROXIMATE ENTROPY

In the real world examples it is difficult to have crisp boundaries that is 0 and 1 in such cases fuzzy logic plays an important role which can have intermediate values for classification. Fuzzy system has many applications in the field of pattern recognition and classification, fuzzy clustering, fuzzy systems for prediction, image and speech processing, etc [1].

Fuzzy Logic was initiated in 1965 by Dr. Lotfi A. Zadeh which is a multi-valued logic that allows intermediate values to be defined as compared to classical set theory [1].

A fuzzy set is any set that allows its members to have different grades of membership (membership functions) in the interval [0,1] [1].

The fuzzy approximate entropy can be performed in following steps:

First; we compose the patterns, second; we compute the number of patters whose distance is less than tolerance and finally we average the natural logarithm of all the relative frequencies.

ALGORITHM

The following vector sequence can be formed from the time series, containing *N* Data points *u(i)= u(1), u(2)….u(N)*, for finding the fuzzy approximate entropy.

X_i^m = {u(i), u(i+1),……u(i+m-1)} – u_0(i) for I = 1,2….N – m + 1

Where u_0(i) is baseline value:

$$u_0(i) = \frac{1}{m}\sum_{j=0}^{m-1} u(i + j)$$

Distance d_{ij}^m between the two vectors X_i^m and X_j^m is defined as:

d_{ij}^m = d [X_i^m, X_j^m]

= max | u(i+k) - u_0(i) – u(j+k) - u_0(j) | where; k ∈ (0,m-1)

i,j = 1 ~ N-m+1, j ≠ i

For a given ‘r’ the similarity degree D_{ij}^m between X_i^m and X_j^m is determined by fuzzy membership function. u (d_{ij}^m, r)

D_{ij}^m = u (d_{ij}^m, r)

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Membership function used is Gaussian function.

u (d_{ij}^m, r) = exp (-d_{ij}^2 / r)

Determine the function: φ^m(r) as

C_r^m(i) = $\frac{1}{N-m+1}\sum_{j=1 j\neq i}^{N-m+1} D_{ij}^m$

φ^m(r) = $\frac{1}{N-m+1}\sum_{i=1}^{N-m+1} \ln [C_r^m(i)]$

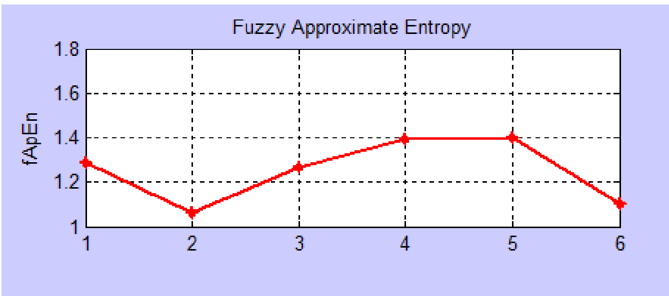
In the same way X_i^{m+1} vector sequence can be formed and φ^{m+1}(r) can be calculated:

$\int ApEn(m,r) = \lim_{n\to\infty}[\ \varphi^m(r) - \varphi^{m+1}(r)]$

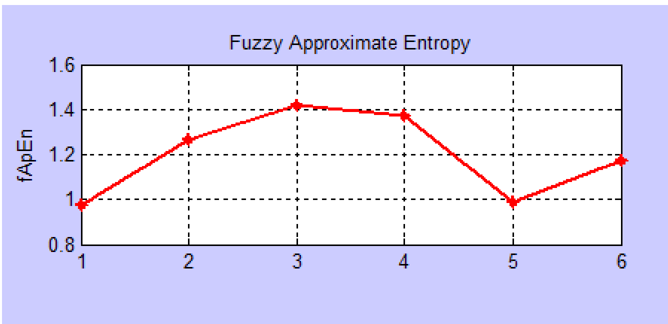
Now $\int ApEn$ can be computed from the finite series:

$\int ApEn(m,r,N) = \varphi^m(r) - \varphi^{m+1}(r)$

The value of 'm' is set to 2.The values of 'r' can be taken between 0.1 and 0.25 times standard deviation (SD) of data.



Fuzzy Entropy values of different sub-bands of Healthy subject



Fuzzy Entropy values of different sub-bands of Epileptic subject

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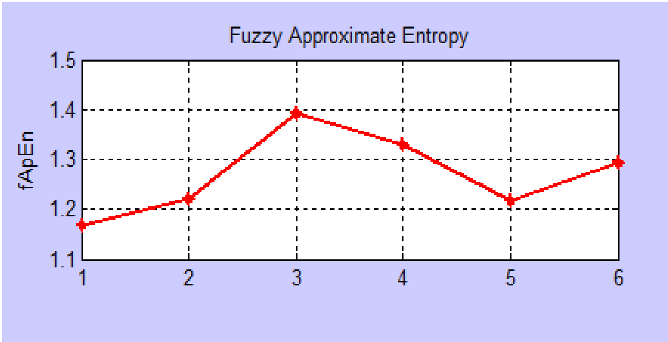

Fuzzy Entropy values of different sub-bands of Interictal subject

Table 2
Average fApEn values of different sub-bands for A–E data sets.

Data set	D1	D2	D3	D4	D5	A5
A	1.463148	1.043947	0.610288	0.361968	0.148678	0.019373
B	1.472347	1.053749	0.570979	0.389287	0.15001	0.022606
C	1.387919	1.059863	0.593303	0.314192	0.135008	0.025094
D	1.271224	0.924724	0.524144	0.300964	0.13823	0.027896
E	0.877076	0.776221	0.524451	0.326328	0.170469	0.039747

Average fApEn values of different sub-bands for A–E data sets.

C. Convolutional Neural Network

In machine learning, a convolutional neural network (CNN, or ConvNet) is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex. Individual cortical neurons respond to stimuli in a restricted region of space known as the *receptive field.* The receptive fields of different neurons partially overlap such that they tile the visual field.The response of an individual neuron to stimuli within its receptive field can be approximated mathematically by a convolution operation. Convolutional networks were inspired by biological processes and are variations of multilayer perceptrons designed to use minimal amounts of preprocessing. They have wide applications in image and video recognition, recommender systems and natural language processing. Convolutional neural networks (CNNs) consist of multiple layers of receptive fields. These are small neuron collections which process portions of the input image. The outputs of these collections are then tiled so that their input regions overlap, to obtain a higher-resolution representation of the original image; this is repeated for every such layer. Tiling allows CNNs to tolerate translation of the input image.

Convolutional networks may include local or global pooling layers, which combine the outputs of neuron clusters. They also consist of various combinations of convolutional and fully connected layers, with pointwise nonlinearity applied at the end of or after each layer.A convolution operation on small regions of input is introduced to reduce the number of free parameters and improve generalization. One major advantage of networks is the use of shared weight in convolutional layers, which means that the same filter (weights bank) is used for each pixel in the layer; this both reduces memory footprint and improves performance

The performance of CNN classifier is evaluated by using three parameters namely, sensitivity, specificity and classification accuracy.These parameters are discussed as follows

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$$\text{Sensitivity(SEN)}=\frac{\text{True Positive}}{[\text{True Positive}+\text{False Negative}]}*100\%$$

$$\text{Specificity(SPE)}= \frac{\text{True Negative}}{\text{True Negative}+\text{False Positive}}*100\%$$

$$\text{Classification accuracy (CA)} = \frac{\text{Correct classified patterns}}{\text{Total Patterns}}*100\%$$

V. RESULTS AND DISCUSSION

All the 500 epochs normal, interictal and epileptic EEG data set are decomposed into different sub-bands using DWT. Frequecncy range of these sub-bands are as follows: A1(0-43.4Hz),A2(0-21.7),A3(0-10.85),A4(0-5.43Hz),A5(0-2.70 Hz),D1(43.4-86.8Hz),D2(21.7-43.4 Hz),D3 (10.85-21.7Hz),D4(5.43-10.85 Hz) and D5(2.70-5.43 Hz).
Approximate and detail co-efficients are plotted in figure 2 and 3 for normal and ictal subject respectively.
fApEn values are calculated from these sub-bands for which graphs are shown in fig 4,5,6 for normal, interictal and epileptic subject respectively.
Results show that fApEn values are more ordered for epileptic subjects.These 6 features are used as input for classifier to classify normal, interictal and epileptic subject respectively.

VI. CONCLUSION

From the manual observation of long time EEG Recording for the detection of the Epileptic Seizure is time consuming, costly and may have judgemental errors. In the proposed work fuzzy approximate entropy is utilized for automatic Seizure detection. It is observed that fApEn value drops during the Seizure interval. After EEG Signal is decomposed into different sub-bands using DWT then detail wavelet coefficients (D1 to D5) and approximate wavelet coefficient (A5) are obtained. The fApEn features are calculated by using Wavelet coefficients D1 to D5 and A5 which provide best detection rate using CNN Classifier. After comparing the performance of this system with those given by other researchers it can be concluded that using DWT based fApEn achieves more satisfactory results such as accuracy of 98 %.

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