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Automatic detection of epilepsy seizure in EEG using entropy features and CNN classifier: A deep learning approach

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Abstract

Discrete wavelet Transform (DWT) is a powerful tool that is beaing widely used in signal analysis like electroencephalography(EEG) for detetcion of epilepsy seizures. EEG is a non invasive and continuous time signal that is recorded by placing the electrodes over the scalp. EEG signals are contaminted with unwanted noise, artifacts, etc hence, the signals need to be filtered before analysis to avoide complication. This research work proposes a novel approach for epilepsy seizure detection using a combination of Discrete Wavelet Transform (DWT) and Convolutional Neural Network (CNN) model. Electroencephalogram (EEG) signals are preprocessed using DWT to obtain multi-resolution coefficients, which capture both time and frequency domain information. Extracted features from DWT are elelction using feature selection by random forest algorithm and further coefficients are fed into a CNN. Experimental results demonstrate the effectiveness of the proposed method, showcasing high accuracy in seizure detection. The DWT-CNN model offers a promising solution for real-time and accurate epilepsy seizure detection, holding significant potential for clinical applications. Analysis of the presented algorithm is performed on the benchmark Bonn EEG dataset. The proposed model achieves an accuracy of 99.9%, a sensitivity of 100%, a precision of 99.81%, and a specificity of 99.8%.

Key Words: Discrete Wavelet transform, epilepsy, Neural Network, Convolutional Neural Network.

Introduction

Epilepsy is a neurological condition characterized by abnormal neural activity in the brain, affecting approximately 1% of the global population in the absence of medical care and resources. The prevalence of epilepsy is estimated to be between 5 to 10 per 1000 people, with around 6 million individuals worldwide receiving treatment for the disease annually. Epilepsy seizures are a defining feature of this disorder and can lead to damage to neurons due to their sudden onset.

Electroencephalogram (EEG) signals are used to study overall brain activity, and their examination plays a crucial role in diagnosing epilepsy and identifying its underlying causes. However, visually analyzing EEG signals is a time-consuming and labor-intensive task that requires expertise. Neurologists' efficiency in analyzing EEG signals is often reduced, leading to potential misdiagnosis.

To address these challenges and improve diagnosis accuracy, EEG recordings are utilized to detect and measure brain potentials by attaching electrodes to the scalp, using the 10-20 international system. EEG signals consist of five major frequency bands: delta, theta, alpha, beta, and gamma. This painless test records brain signals through small sensors, which are then analyzed by a computer or medical expert.

Despite containing valuable brain information, EEG signals are frequently contaminated with artifacts, making accurate analysis for proper diagnosis difficult. To overcome these efficiency issues, a novel method is proposed, involving the decomposition of EEG signals using DWT (Discrete Wavelet Transform), extraction of meaningful statistical features, and classification using deep learning models such as convolution neural networks.

This innovative approach holds promise in enhancing the detection, diagnosis, and treatment of epilepsy, ultimately improving the lives of individuals affected by this challenging neurological condition.

Epileptic EEG Signal and Electrode Placement:
The word epliepsy is derived from greek known as ‘epilepsia’ which means ‘seize upon’. The background of epilepsy is found in Babylonian. Epilepsy is a serious concequence of brain disease detected by analyzing brain signals generated by neurons. These neurons are complex in nature and help to communicate with human organs and generate informative signals. Epileptic signals are irregular electrical signal activity in brain that may

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manifest as seizures. These signals are generated by the electrical activity of neurons with in the brain. It is measured using electroencephalography. EEG signals are recorded by placing electrodes on the scalp to measure voltage fluctuations in brain. Resulting signals then can be analyzed to detect seizures and other abnormal activities in the brain. Epileptic seizures can have a wide range of symptoms, from mild staring spells to severe convulsions, and which are caused by a variety of factors such as brain injury, infection, genetic predisposition, and abnormal brain development. Understanding the characteristics of epileptic signals is crucial for the diagnosis and management of epilepsy, as well as for the development of new treatments for this condition.The electrodes are typically placed in a standardized array as per International 10-20 system[1]. which ensures that the electrodes are placed in specific locations on the scalp to accurately measure activity in different regions of the brain. The signals picked up by the electrodes are then amplified and filtered to remove noise to male detection smoother and efficient.

EEG signal acquisition, a non-invasive and painless method, provides useful insight into brain function. It helps in the diagnosis and management of neurological conditions such as epilepsy, brain tumors and traumatic brain injury. The quality of the EEG signal dependents on the quality of the electrodes and the technique used to place them on the scalp as well as the amplifier and filter settings used during the acquisition process.The EEG signal is composed of different frequency bands, which is associated with definite brain functions and states. Key frequency bands in EEG signals are summarized below.

Delta (0.5-4 Hz): This is the slowest frequency band and is associated with deep sleep.
Theta (4-8 Hz): This frequency band is related with drowsiness and light sleep. It is also seen in brain disorders such as ADHD.

Alpha (8-12 Hz): This frequency band is associated with relaxed wakefulness and the absence of mental activity.
Beta (12-30 Hz): This frequency band is associated with active mental processes such as attention, memory and problem solving.
Gamma (30-50 Hz): This is the fastest frequency band and is associated with high-level cognitive processes such as perception, memory and consciousness.

Research Significance

Research significance in epilepsy seizure detection is paramount to improving the lives of individuals with epilepsy. Advancements in this field have the potential to lead to early intervention, personalized treatment plans, improved quality of life, seizure prediction, wearable devices, valuable research insights, advancements in AI, and reduced healthcare costs. The exploration of epilepsy detection holds great significance for several reasons. One primary rationale is the early identification of epilepsy, enabling prompt treatment for individuals in better health. Moreover, research in epilepsy detection has prompted the development of novel investigative tools and techniques, resulting in improved accuracy and reliability in epilepsy diagnosis. Furthermore, this field of study can identify new targets for the development of innovative epilepsy treatments, ultimately enhancing the quality of life for affected individuals. In summary, epilepsy detection is a crucial area of investigation that can pave the way for significant advancements in comprehending, diagnosing, and treating this condition.The part of the paper is as follows. Section II describes related work. Section III methodology & data collection. Section IV describes results and discussion and finnaly section V conclusion.

Related Work

Epilepsy is a neurological disorder characterized by recurrent and unprovoked seizures, affecting millions of people worldwide. Early and accurate detection of epileptic seizures is crucial for timely medical intervention and effective management of the condition. Over the years, advances in medical technology and the growing availability of large-scale data have paved the way for the application of artificial intelligence (AI) and machine learning techniques in healthcare, particularly in epilepsy detection. Epileptic seizures can happen anytime and cause a loss of consciousness, leading to injuries and even death. Generally, there are two main types of seizures, generalized and partial, depending on whether the seizures affect some part or all of the brain region. In generalized seizures, all brain sections are affected for partial seizures, only an area of the brain is affected[19]

Manual visual inspection and analysis of epileptic electroencephalogram (EEG) signals are traditional methods of detection and classification by experts, which tends to be timeconsuming, tedious, and prone to errors. Therefore, investigation of automatic modes that employ artificial intelligence (AI) is paramount to overcome the problem associated with visual inspection and traditional machine learning techniques. Various traditional and machine learning methods have been developed,such as using time, frequency, time–frequency, and nonlinear methods[20].

H. Vavadi et al[28] proposed a wavelet-approximation entropy based study for seizure detection. The study is evaluated by statistical analysis by using t-test for different pair of groups acheiveing a accuracy of 99.98%.
Yongxin Sun and Xiaojuan Chen[29] proposes an automatic seizure detection model using multifusion features and CNN. The sample entropy, permutation entropy and fuzzy entropy were extracted. Combined features were taken as input to classifier. The study was carried out on different dataset like THUG dataset and CHBMIT dataset. The results shows that multifeature fusion and CNN achieves excellent results compared to single feature analysis.

EEG signals features are usually divided into time,frequency , time-frequency and non linear features which are used in signal classification.

G. R Kiranmari et. Al[21] proposed a model for seizure detection using entropy based features obtained from EEG sub bands. Aung ST et. al,[22], presented a method using distributed entropy for epilepsy detection by showing advantages of fuzzy entropy for which a classification of 92% accuracy is achieved.

M. G. Bellemare et al[23] A combined approach of pyramidal one-dimensional convolutional neural network (P-1-D-CNN) was employed in the identification of epileptic disorders. However, the approach proved ineffective when using a large number of learning parameters.

Zhang S et al[24] proposed a light weight solution on the CHB-MIT scalp EEG dataset. The experimental study was done in two phases, for phase one Pearson correlation coefficient is calculated to obtain the correlation matrices. For phase two, the correlation matrices are classified to distinguish the preictal states from the interictal ones with a simple CNN mode. Using the proposed method 89.98% prediction accuracy was achieved.
Aayesha et al.[25] Suggested a fuzzy-based seizure detection model that incorporates a novel feature extraction and selection method. For the binary classification problem of interictal and ictal periods, the classification accuracy rate of 96.67% was achieved..

Rishabh Bajpai et al.[26] employed the spectrum to transform EEG signals into the image domain. The spectral images were subsequently fed into CNN to acquire robust features, enabling the automated detection of pathological and normal EEG signals with experimental accuracy, sensitivity, and specificity of 96.65%, 90.48%, and 100%, respectively.

Zhao W, Wang[27] ,proposed a CNN model for robust detection of seizure using EEG. Neural network is used to extract the features. Convolution neural network is employed to extract feature from single channel and these features were fed to Softmax layer for classification. The method was evaluated using Bonndatset with 10 cross fold validation. The accuarcy of 98.5% and97.0% of sensitivity was achieved.

Lu Y, Ma Y, Chen C, Wang Y[30], conveys the idea that the three mentioned features (Kraskov entropy based on HHT, instantaneous area of the analytical eigenmode function of EEG signals, and Kraskov entropy applied to the tunable Q wavelet transform) were brought together or unified to create a comprehensive set of features for the purpose of classifying EEG signals for seizure detection. The classification process is then performed using the LS-SVM classifier on this combined feature set.

This paper proposes a technique to enhance the identification of epileptic seizures through the utilization of entropy-driven characteristics like fuzzy entropy and feature selection by random forest. This is done by thresholding method using wavelet and classifying using machine learning and deep learning techniques. This proposed classification model provide high rate of accuracy of 99.9% and additionally support physicians in the early identification of seizures.

Methodology

Data Set Collection

The epilepsy EEG dataset from the University of Bonn, Germany 33, includes EEG signals collected from both healthy subjects and epilepsy patients. The dataset consists of single-channel EEG signals divided into five subsets (Set A ~ Set E). Each subset contains 100 data segments, each with 4097 EEG time series. The duration of each data segment is 23.6 seconds, sampled at a frequency of 173.61 Hz, and pre-processed to remove artifacts in the frequency range of 0.53 to 40 Hz. Set A and Set B subsets represent EEG data from 5 healthy

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subjects with their eyes open and closed, respectively. Set C and Set D subsets contain EEG data from 5 epilepsy patients in the interictal period, with the electrode positions located in the contralateral region of the lesion for Set C and in the lesion area for Set D. Lastly, Set E represents EEG data from 5 epilepsy patients during the ictal period, with the electrode position located in the lesion area.The summary of dataset is shown in table 1.

Table 1. Sample clinical dataset

Settings	SET A	SET B	SETC	SET D	SET E
Subjects	5 Healthy	5 Healthy	5 Epileptic	5 Epileptic	5 Epileptic
Type of Electrode	Surface	Surface	Intracranial	Intracranial	Intracranial
Placement of Electrode	International 10-20 system	International 10-20 system	Hippocampal	Epileptogenic	Epileptogenic zone
Subject condition	Awake, Eyes open	A wake , Eyes	Seizure-free	Seizure-free	Seizure (Ictal)
Number of epochs/ Epoch duration (s)	23	23	23.6	23.6	23.6

Research methods used

The proposed study is divided into three steps shown in figure 1. Firstly, it will be preprocessed, where it is filtered through bandpass filter to remove unwanted noise caused during signal aquistion. The DWT is used to decompose and reconstruct the wavelet to realize wavelet denoising. In decomposition, Five EEG subbands are obtained that is delta(0-4Hz), theta(4-8Hz), alpha(8-6Hz),beta(16-32Hz) and gamma(32-64Hz) as shown in figure 2. Secondly, feature extraction is performed, In the present study, wavelet thresholding is carriedout as denoising method with level 4th order Daubechies wavelet which has better local approximated performance for non stationary signals. Further, feature selection and classification is done using different classifier which includes Support vector machine (SVM) & Convolution neural network(CNN) .

Preprocessing of EEG Signal

Medical signal processing and analysis are essential for extracting valuable information from EEG signals. To achieve meaningful insights, denoising methods are necessary to remove noise and distortions. The wavelet threshold method has proven to be effective in suppressing noise in non-stationary EEG signals by exploiting time-frequency domain analysis. Its ability to preserve critical signal features while removing unwanted noise makes it a valuable tool for EEG

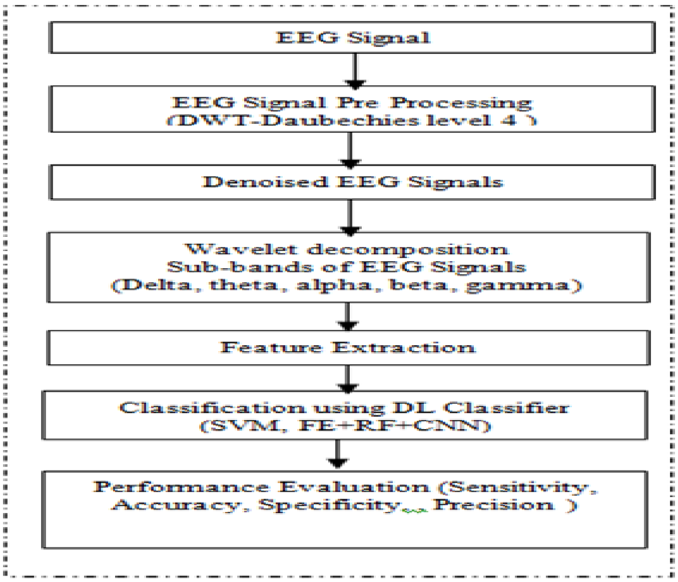

Figure 1: Proposed Classification Model

signal processing in clinical and research settings. The wavelet thresholding fucntion is given by

$\lambda = \sigma\sqrt{2\log N}$ (1)

Where λ represents wavelet threshold, σ represents standard deviation of noise, and N represents length of sample signals.

In this study, the input signal is first passed through a lowpass filter and a high-pass filter both with a cutoff frequency set at one-quarter of the sampling frequency. The initial step of DWT (Discrete Wavelet Transform) decomposition yields the low-frequency approximation coefficient A1 and the detail coefficient D1. Next, the output A1 is then processed by another quadrature mirror filter. This process is repeated to obtain the approximation and detail coefficients for subsequent levels. To ensure that the frequency band above 80 Hz, which may not contain the eigenwaves of epileptic EEG, is excluded, the researchers utilized the "db4" wavelet basis function to perform a 4-level decomposition of the EEG signals. The resulting 4-level decomposition of EEG signals is illustrated in figure 4.3. The subband frequencies for each level of decomposition are as follows: A1: 0 ~ fs/4;D1: fs/4 ~ fs/2;A2: 0 ~ fs/8;D2: fs/8 ~ fs/4;A3: 0 ~ fs/16;D3: fs/16 ~ fs/8 A4: 0 ~ fs/32;D4: fs/32 ~ fs/16 Here, fs represents the sampling frequency of the used data set, which is stated to be 173.61 Hz.Time(1/173.61sec)

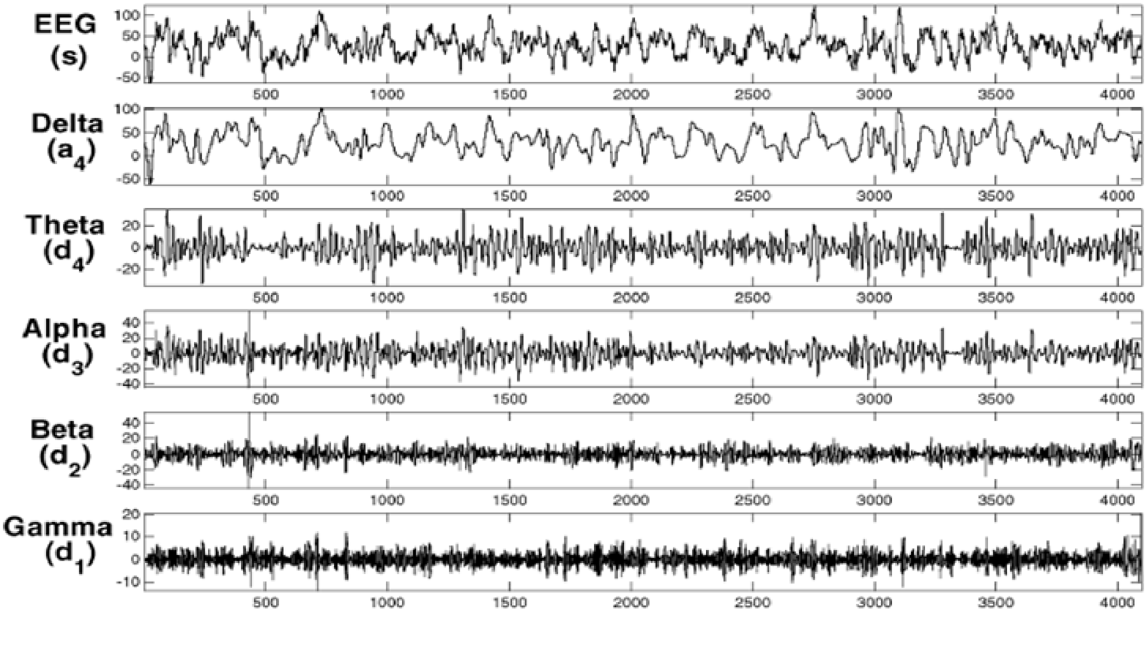

Figure 2: 4 level decomposition of band-limited EEG signal using Daubechie wavelet.

Feature Extraction and selection.
Initially, Discrete Wavelet Transform (DWT) wavelet decomposition is carried out on the filtered denoised EEG signals. The "db4" wavelet was chosen as the basis function, and a 4-stage decomposition was applied to generate five subbands: D1, D2, D3, D4, and A4. Subsequently, various features including SampEn (Sample Entropy), FuzzyEn (Fuzzy Entropy), and DstEn (Distribution Entropy) were extracted from the EEG signals in each of the aforementioned subbands[14-19]. Amongst these entropies, fuzzy and distribution entropy shows potential results16. In this study, non linear features like fuzzy entropy have been implemented.

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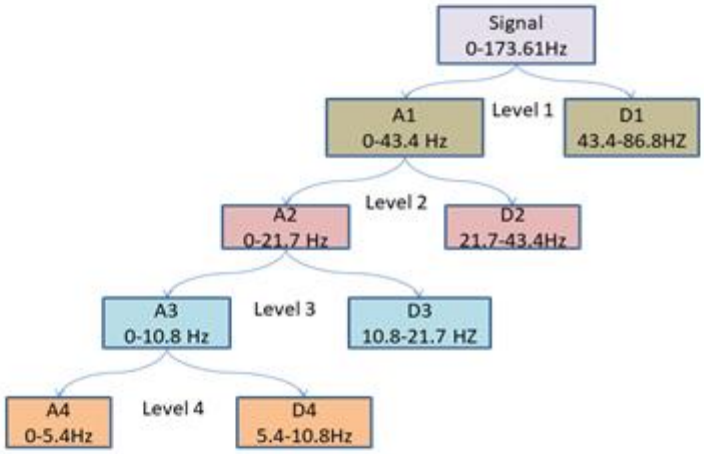

Figure 3: 4 level decomposition of EEG signal from five sub-bands. Shaded color indicates five sub-bands. Nonlinear Features

Given a comprehensive comprehension of EEG signals, it is widely acknowledged that human EEG signals exhibit nonlinearity and randomness in the domain of bioelectric signals, and these nonlinear features provide a better characterization of EEG signals. Entropy serves as a physical measure that can effectively characterize the complexity of EEG signals.

Research has demonstrated that EEG signals during the ictal phase show reduced uncertainty, making it essential to utilize entropy-based methods to characterize EEG features. One such method is Approximate Entropy (ApEn), which was developed on the foundation of Kolmogorov-Sinai entropy and was introduced by Pincus[12] .ApEn predicts the future signal amplitude based on known signal amplitudes, allowing it to describe the uncertainty or randomness present in the signal.

Another entropy measure is Sample Entropy (SampEn), proposed by Richman et al. SampEn shares similar physical meaning with ApEn, but it overcomes three specific shortcomings of ApEn. Firstly, SampEn removes the self-match from the data. Secondly, it determines the total number of well-matched templates before performing the logarithmic operation. Finally, when dimension m is embedded, the reconstructed time series in SampEn consists of N-m rows instead of N-m + 1 rows found in ApEn, ensuring that the number of patterns in embedding dimensions m and m + 1 are equal.

Furthermore, FuzzyEn characterizes the occurrence probability of new patterns, with higher measured values indicating greater occurrence probability and consequently increased complexity of the sequence.

Fuzzy entropy is a complexity measure that quantifies the irregularity and complexity of a time series. It is particularly useful for characterizing EEG signals and can be used in epilepsy seizure detection. The mathematical model for fuzzy entropy is as follows:

Phase Space Reconstruction:
An EEG time series signal denoted by x(i), where i = 1, 2, ..., N, and N is the length of the time series.
Choose two parameters:

Embedding dimension (m): It determines the number of data points used to reconstruct a phase space vector.
Tolerance threshold (r): It determines the similarity criterion between vectors.
Now, create phase space vectors (also called m-dimensional vectors) for the time series as follows:
For each time step i, construct a vector v(i) = [x(i), x(i+1), ..., x(i+m-1)].
Membership Function: The membership function u(i, j) that represents the degree of similarity between two vectors v(i) and v(j). It takes values between 0 and 1, where 0 indicates no similarity, and 1 indicates a perfect match. The membership function can be defined using a Gaussian kernel as follows:
u(i, j) = exp(-D^2(i, j) / r^2) (2)
where D^2(i, j) is the squared Euclidean distance between the vectors v(i) and v(j).
Fuzzy Entropy Calculation:
Fuzzy entropy for a given embedding dimension (m) and tolerance threshold (r) is calculated as follows:

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Fuzzy Entropy(m, r) = - Σ[u(i, j) * ln(u(i, j))] / (N - m + 1) (3)

where the summation is taken over all pairs of vectors v(i) and v(j) with j ≠ i, and ln denotes the natural logarithm.

Thresholding: Once the fuzzy entropy value is calculated, compare it with a predetermined threshold. If the fuzzy entropy value exceeds the threshold, it indicates a higher complexity in the EEG signal, suggesting a possible seizure activity.

Optimization: Optimize the parameters m and r to achieve the best performance for epilepsy seizure detection. This can be done through cross-validation.

Feature selection using Random forest algorithm:

Random Forest is a machine learning ensemble technique that combines the predictive power of multiple decision trees to make robust and accurate predictions. In the context of EEG analysis, it can be used not only for classification tasks but also as a feature selection tool. Feature selection is crucial because not all features extracted from EEG data are equally relevant for distinguishing different brain states or conditions. As an ensemble learning method, Random Forests (RF) employs decision trees as the fundamental component. These decision trees are incorporated within the RF framework through Bagging, which represents an enhanced iteration of the Bagging technique.

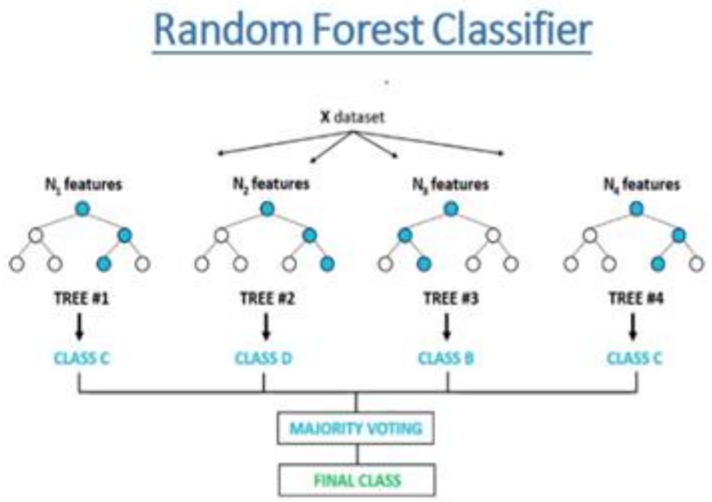

Figure4: RF model.

Classification techniques

A suitable and pertinent dataset is required to train and categorize EEG epileptic signals using DL models. This raw input data can extract significant features and then be utilized as input or directly fed into the network without the need for feature extraction. Seizure detection between normal and epileptic patients is done through classifier model like as SVM and CNN classifier. A brief description of these models is described below.

Support Vector Machine (SVM): It is the most successful machine learning algorithm. SVM is the classification tool used in detection of any abnormalities in biomedical signals and considered as best method for diagnosis. It handles non linear data very efficiently. The SVM classifier segregates the two classes i.e hyper plane and line. Successful application of SVMs is used in detecting epilepsy from EEG signals.

Convolutional Neural Networks (CNNs): has proven to be a powerful tool in various applications of image and signal processing, including medical diagnosis. In the context of epilepsy seizure detection, CNNs play a crucial role in automating the process of identifying seizures from EEG (electroencephalogram) signals. CNNs are a class of deep learning models designed to process grid-like data, such as images or in this case, time-series data like EEG signals. They consist of layers such as convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters (kernels) to extract local features from the input data, while pooling layers downsample and retain the most salient information. The extracted features are then fed into fully connected layers for classification.

Results and discussion:

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The estimatimation of classification of the presented framework is assessed through statistical parametric evaluation metrics by sensitivity (SEN), specificity (SPE), accuracy (ACC) and Precision (PRE). Then is given as follows:

Sensitivity=TP/(TP+FN)*100% **(4)**

Specificity=(TN)/(TN+FP)*100% **(5)**

Accuracy=(TP+TN)/(TP+FN+TN+FP)*100% **(6)**

Precision=TP/(TP+FP)*100% **(7)**

Where, True Positive (TP) represents true normal detected events, True negative (TN) represent true seizure events detected, false positive (FP) indicates total number of erroneously normal events and false negative (FN) defines erroneously seizure events. Classification performance is achieved through unbiased estimation using N-fold cross-validation. This data is divided equally into N equal parts randomly and feature selection is done by N-1 parts and also classifier training and testing the classification by remaining parts8 .This process is repeated N times with system measured by average result of all testing parts. A 10 fold cross-validation is performed. Hence, it produces robust classifications and detection. The figure 5 below shows the input original signal for all dataset which is sampled at 173.6 Hz.

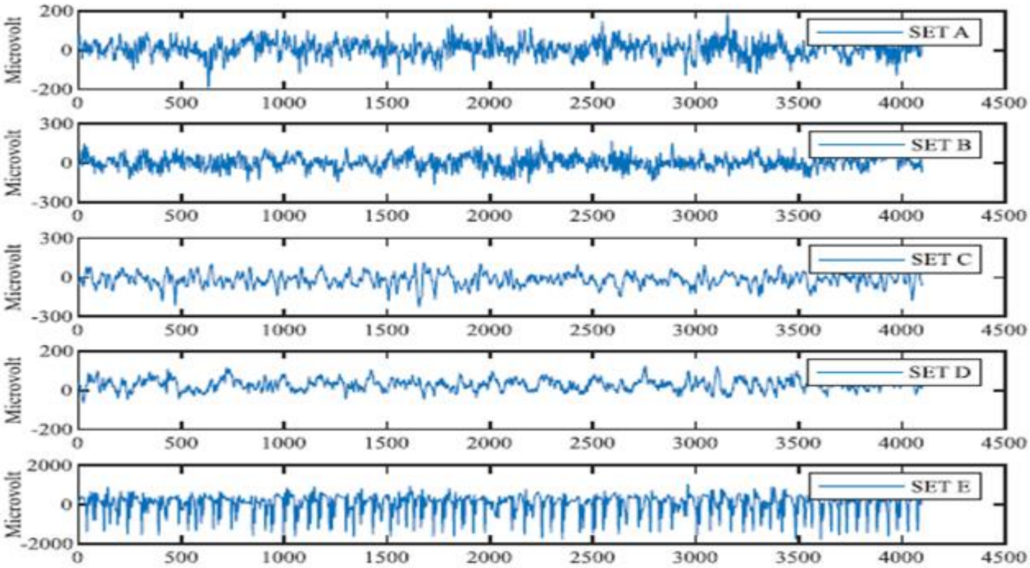

Figure 5: Original signal in time domain

This study makes use of case C-E subject for anaylsis & employs discrete wavelet transform (DWT) to reduce noise in time-frequency domain. The extracted detail and approximated DWT coefficients are shown in figure 7 & 8. A four level (dB4)daubechie wavelet decompostion is used in the process and is shown in figure 6

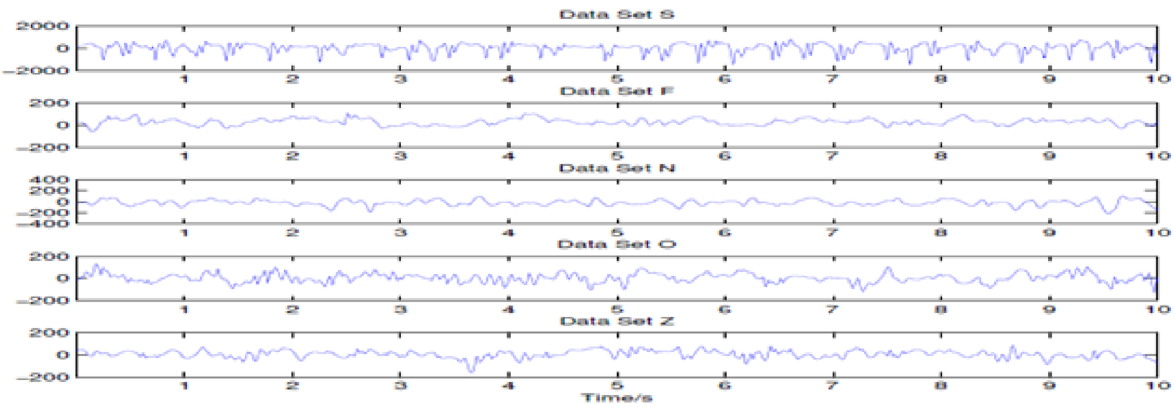

Figure 6: Wavelet thresholding of preprocessed signal in time domain

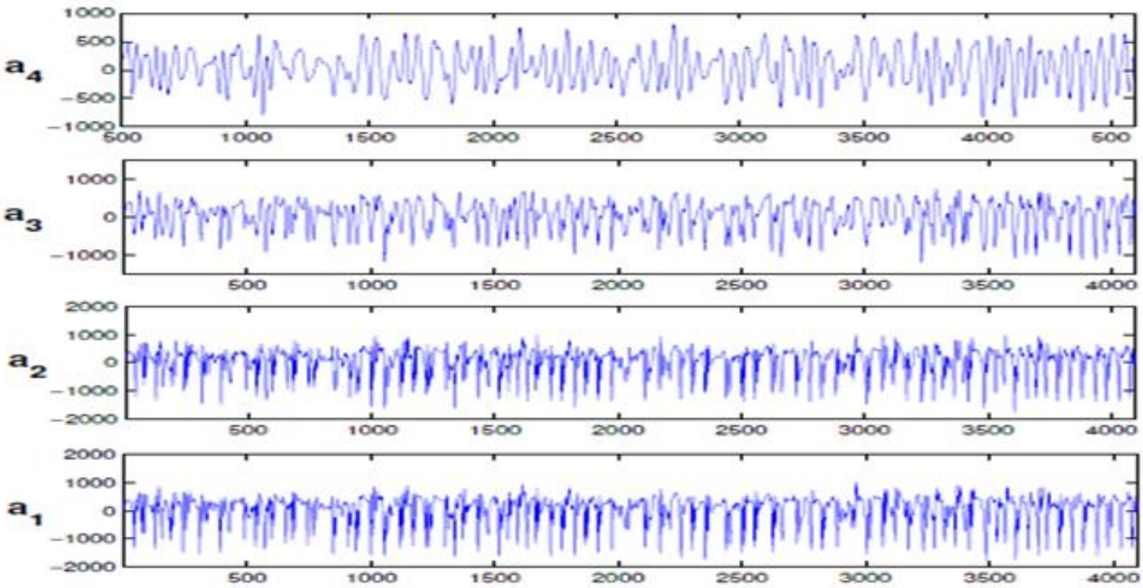

Figure 7: Approximation values of Sub-bands of original Signal after Db4 decomposition from (a1 to a4)

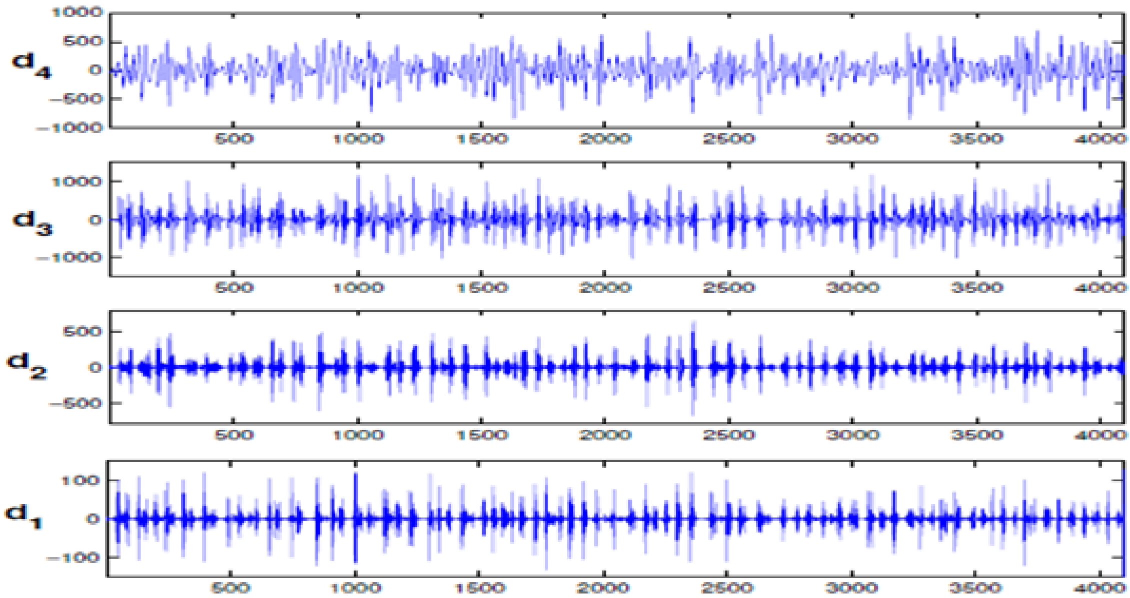

Figure 8: Detail values of sub-bands of original Signal after dB4 decomposition from (d1 to d4)

Table 2: Summary of works that used deep learning in detecting and classifying EEG epileptic seizures

Author	Year	Method used	Accuracy in %	Database
Johansen et al.[35]	2016	CNN	94.7	Bonn University
Lin et al.[36]	2016	SSAE	96.0	Bonn University
Golmohammadi et al.[37]	2017	CNN RNN	95.0	THUG Database
Fisher, R[19]	2017	e ILAE 2017	93.0	NA
Yuan et al.[38]	2017	SSDA	93.0	Children's Hospital Boston
Park et al.[39]	2018	1D-CNN, 2D-CNN	90.5	Children's Hospital Boston
Acharya et al.[40]	2018	1D-CNN	86.7	Bonn University
Gasparini et al.[41]	2018	SAE	86.5	Regional Epilepsy Centre, Italy
RaviPrakash et al.[42]	2019	CNN-LSTM	89.7	AdventHealth Orlando, Orlando, United States
Martis et al.[34]	2013	SampEn-DT	95.7	Bonn University
Jaoude et al.[43]	2020	CNN-BP	98.0	NA

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Bajpai R et. Al[26]	2021	SeizureNet-SVM	96.65	THUG Database
Aayesha, et al[25]	2022	FESD	98.0	Bonn University
Sun Y et al.[29]	2022	CNN	92.26	CHB-MIT and TUH datasets
Loukas Ilias et al.[45]	2023	CNN-STFT	95.33	Bonn University
Xuyang Zhao[44]	2023	RCO MODEL(Image)	93.6	Juntendo University Hospital
Proposed model	2023	Fuzzy Entropy+RF+CNN	99.9	Bonn University(case C-E)

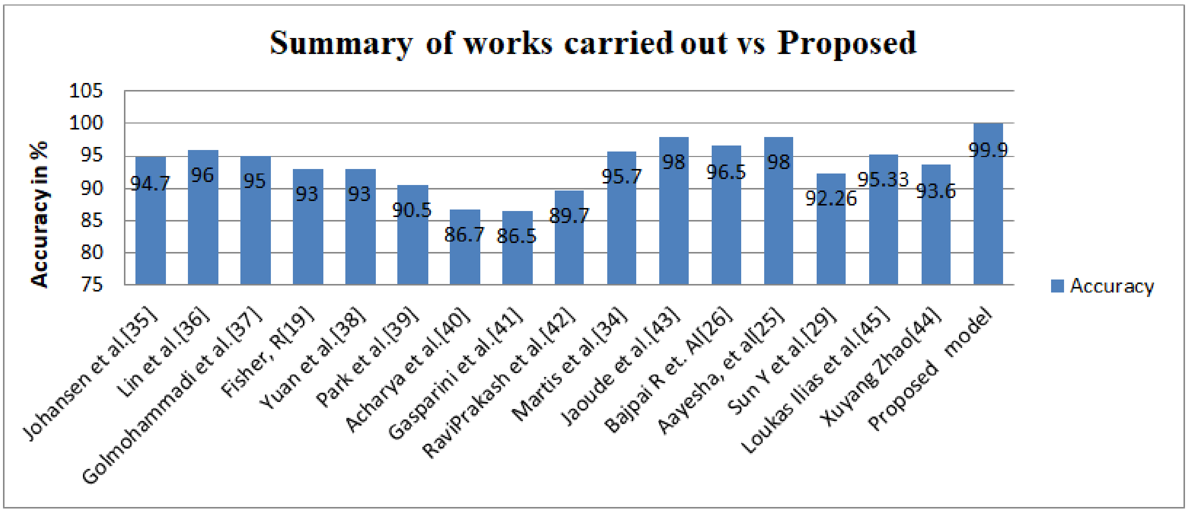

Figure 9: Summary of works carried out in literature for accuracy vs proposed

Table 3. The Performance Evaluation using Machine Learning and Deep learning techniques

Method	**SVM**	**RF+CNN**	**FE+RF+CNN**
% in Accuracy	**99**	**99.5**	**99.9**
% Specificity	**98.5**	**99**	**99.8**
% Sensitivity	**97.6**	**98**	**100**
% Precision	**98.3**	**99.5**	**99.81**

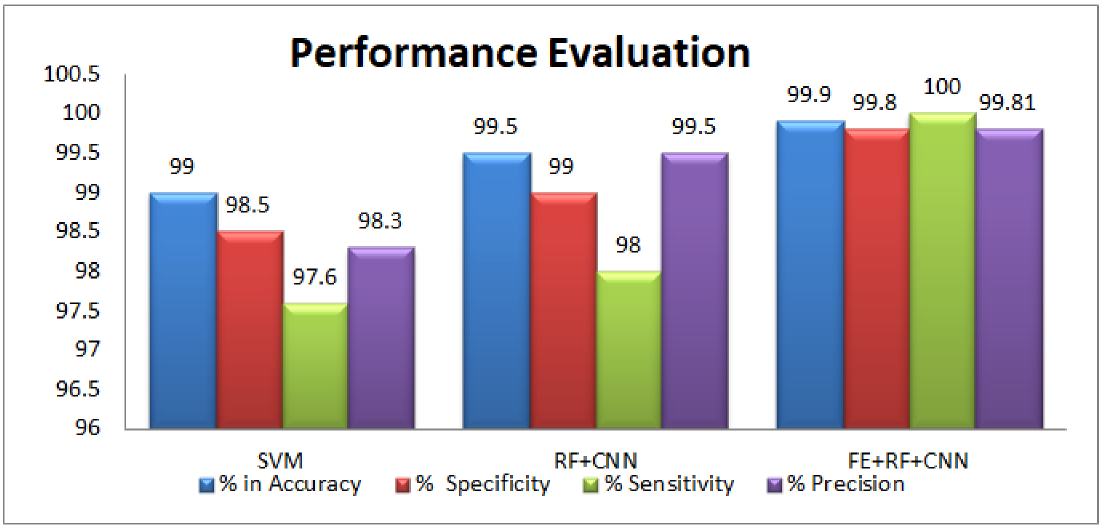

Figure 10: Performance evaluation of case(C-E data set) using ML & DL models

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Conclusion

Precise classification may reduce the damage caused by seizures. In this paper, we propose a novel epileptic EEG signal classification methodology using a of combination of RF and CNN to classify different epileptic states (i.e., nonictal, preictal, interictal, and ictal). The proposed EEG signal classification method outperforms other benchmark models in classifying different epileptic states; for the C-E case, the proposed model achieves a classification accuracy of 99.9%, a sensitivity of 100%, a specificity of 99.80%, and a precision of 99.81%. The suggested EEG classification method holds significant practical importance for the diagnosis and treatment of epilepsy. Hence, this research tackles a crucial obstacle of precisely categorizing epileptic states using multi-feature EEG signals.Furthur, the work can be extended with large datasets and can be implemented with deep learning model as future work.

Availability of data and materials

Publicly available dataset was analyzed in this study and the dataset can be freely accessed. The datasets we used in our work can be found in the below link https://www.ukbonn.de/epileptologie/arbeitsgruppen/ag-lehnertz-neurophysik/downloads/

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