Multi Class Classification of EEG Signal for Epilepsy Disease Detection Using Deep Learning

Qurat ulain
2016-NUST-MS-IT-000000170142

Supervisor
Dr. Muhammad Shahzad
Department of Computing

A thesis submitted in partial fulfillment of the requirements for the degree of Masters in Information Technology (MS IT)

In

School of Electrical Engineering and Computer Science,
National University of Sciences and Technology (NUST), Islamabad,
Pakistan.

(June 2020)

Approval

It is certified that the contents and form of the thesis entitled "Epilepsy disease detection using Deep learning Techniques" submitted by QURAT UL AIN have been found satisfactory for the requirement of the degree

Advisor : Dr. Muhammad Shahzad

Signature: M. Shahzad

Date: 06-Jul-2020

Committee Member 1:Dr. Qaiser Riaz

Signature: Qaiser Riaz

Date: 06-Jul-2020

Committee Member 2: Dr. Muhammad Moazam Fraz

Signature: Moazam Fraz

Date: 07-Jul-2020

Committee Member 3:Dr. Arsalan Ahmad

Signature:

Date: 06-Jul-2020

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS/MPhil thesis entitled "Epilepsy disease detection using Deep learning Techniques " written by QURAT UL AIN, (Registration No 00000170394), of SEECS has been vetted by the undersigned, found complete in all respects as per NUST Statutes/Regulations, is free of plagiarism, errors and mistakes and is accepted as partial fulfillment for award of MS/M Phil degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis.

Signature: M. Shahzad

Name of Advisor: Dr. Muhammad Shahzad

Date: **06-Jul-2020**

Signature (HOD): ______________________

Date: ______________________

Signature (Dean/Principal): ______________________

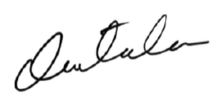
Date: ______________________

Certificate of Originality

I hereby declare the submission of this thesis as my own work and to the best of my knowledge it contains no particular substance previously published or written by another author, nor material which to a substantial extent has been accepted for the award of any degree or diploma at SEECS, NUST or at any other educational institute, except where due acknowledgement has been made in the thesis.

I also declare that the content of this thesis is the product of my own thesis, except for the assistance from others in the project's formulation, conception or in style, presentation and linguistics which has been acknowledged.

Author name: **Qurat ulain**

Signature: 

Acknowledgement

I am grateful to ALLAH who granted me success and it was impossible without His blessings. I would like to give special thanks to my Supervisor Dr. Muhammad Shahzad and GEC members for guiding me throughout this work. I would also like to thank annotators for helping me in this work. I want to thank all my lovely friends and family for supporting throughout the degree. I would like to thank everyone who directly or indirectly contributed in this journey.

Qurat ulain

This dissertation is dedicated to myself; I have worked hard tirelessly for the last 20 years to be where I am today. I appreciate my courage and consistency in the face of struggles. There was no pressure to go faster. I had set my goals at my own pace. Thank you for being me.

Contents

List of Figures

List of Tables

Abstract

This work is related to a real life health issue i.e. Epilepsy. Epilepsy disease is a neurological disorder which causes generation of an abnormal signal in brain causing uncontrollable jerking movements, temporary confusion and loss of awareness and may even cause death. Electroencephalogram (EEG) is used to read brain's behavior by doctors but according to some research EEG fails to detect the epilepsy disease in epileptic patient because it happens due to a sudden generation of abnormal electrical signal so it is difficult to diagnose. Different techniques and approaches have been introduced to overcome this problem which is generally classified into two groups: conventional methods (Machine learning) and Deep learning methods (CNN &LSTMs). From the previous literatures we find that conventional methods achieve remarkable accuracy on seizure dataset so rather than using the same method used previously we researched and analyzed that different stages of epilepsy have never been categorized before specifically the seizures during the non-conscious state and the conscious state. Identification of seizures during NCES is important because comma or absence state causes no focal seizure symptoms hence it cannot be analyzed visually such long term activity in a brain of a coma patient may cause life time brain damage or even cause death. To extract complete information of epilepsy from EEG five stages including convulsive epileptic seizures , Non convulsive epileptic seizures (NCES) , pre-ictal stages and post ictal stages which have never been categorized thus hinders the power to actually understand these signals as different stages of Epilepsy. Keeping in view these different stages of epilepsy might contribute in better understanding of disease and help in inventing treatments that can be effective during any of this stage multi classification is carried out. As time series is complex in nature, and it's difficult to identify the important features out of them because not all of this information contributes towards predicting the outcomes. Through learning the various techniques of feature extraction from literatures we focused on feature minimization and applied entropy based feature extraction approach. We use a single feature named SampEn for Classification. The calculated feature is fed to SVM as an input for classification. The CNN and LSTMs models are trained for classification are highly optimized [both in terms of Accuracy and speed] than the previous state of the art architectures. The error rate calculated on the output our model is compared with the results of previously implemented models and it is noticed that the results of the previously implemented techniques are same or less as resulted by our proposed approaches. Comparative analysis is carried out between all the applied approaches where CNNs performed better and they achieves an accuracy as high as 99.0 ± 0.1 in case of binary classification for all the stages and 87.5 99.0 ± 0.1 in case of multi five class classification. A summary of the experimental approach used in our work is shown in blocked

Chapter 1

1.1. Introduction

Epilepsy is becoming a severe nervous disorder affecting around 50 million people worldwide and around 100 million people gets affected atleast for once in their lives.(Alarcón and Valentín, 2012, WHO, 2016) . This brain disease referred to as convulsion known as Epileptic Seizures. The infected rate of this disease as reported is 0.5-1% but overall in the world the burden of this disease is 1% of the population's infection. (Shafer and Sirven, 2014, WHO, 2005).The most distressful thing about seizures is that they will happen at any time with none prior signs, which will led to some severe injuries including fractures, burns, and sometimes it can cause death (Hannah and Brodie, 1998). As a result, organizations like ILEA the International League of Epilepsy is associated to World Health Organization (WHO) came into being for generating awareness and offering better treatment (Engel et al., 2008, WHO, 2005, 2016) and the International Bureau of Epilepsy (IBE) is also associated with WHO organized for the same purpose.Various seizure detection solutions have been proposed in different research domains specifically data science and machine learning. We've skilled and analyzed several research papers regarding this field and decided to utilize our opportunity to participate in this sector of research with some new approaches. People suffering from nervous disorders such as epilepsy faces hard time in handling the abnormal behaviors, irregular activities and sensations. Detecting epileptic seizures are vital in diagnosis of epilepsy to assist the patients so the better receive the medication, care and even be sure of their medical issues. To disclose the structural and functional information of brain Electroencephalogram (EEG) signal is beneficial it also helps in determining disorders like malfunctions in our brain. Different types of epileptic seizures show different symptoms. From various literature reviews it's clear to us that EEG signals peaks and irregularity helps in determining the seizures. EEG signal analysis along with other techniques including feature extraction, division in time frequency domain, amplitude and wavelet transforms etc. helps in detection and classification of epileptic signals from non-epileptic signals. With this we will differentiate between healthy brain and epilepsy affected brain.

1.1.1. What is epilepsy?

Epilepsy disease is a neurological disorder in which brain activities occurred due to two unprovoked seizures occurs in 24 hours apart with the susceptibility of generating further seizures [39]. Approximately 50 million people around the world are affected with epilepsy [8], but the medical treatments which already exist like surgery and antiepileptic drugs have many other adverse side effects [26]. Seizures, which can also be categorized as unpredictable seizures, not only affect the patient's psychological state but also affect the processes in which our brain coordinates with the other organs and body parts. The signs of seizure and its symptoms may include: [30]

1. Temporary confusion
2. A staring spell
3. Disorderly convulsive movements of limbs.
4. Loss of senses i.e unconsciousness
5. Psychic symptoms includes fear and Anxiety.

Risk factors are which make a person more likely to be effected with the epilepsy. These risk factors may cause the permanent damage to the brain portions and cause it to not develop or work and may even lead to death. Although person is not suffering from epilepsy but one can look at these factors which are also known as triggers and they may precipitate the abnormal signals. These factors directly influence the severity and the number of the seizures so learning about these factors may help them to improve their social and physiological health. Risk factors are categorized as genetic factor and environmental factors.

Genetic factors: Family history and personal health history

Environmental factor: Brain damage, brain infection, developmental disorders or structural changes in the brain

Figure1.1 Risk factors – genetic and environmental

1.1.2. Why epilepsy difficult to diagnose?

An epilepsy diagnosis requires tolerance and manual analysis of EEG data demands for highly trained clinicians and availability rate of new data is always challenging. The amount of information required for seizure detection is time consuming hence it makes the manual interpretation expensive and resource hungry. Single clinical visit is not enough to diagnose this disease. But if you stick with the method, your doctor can find out if the disease is causing you seizures. The physical health, limbs behavior, mental state and EEG signals need to be examined before, during, and after a seizure. Since the doctor probably won't be there once you have seizure attack so it requires a number of clinical visits and inquiries to identify if patient is suffering from epilepsy and the state of criticality. Usually doctor does some or all of following tests which include:

1. A brains test commonly known as EEG (electroencephalogram), is carried out to study the abnormal behavior of the electrical patterns or signals generated in the brain due to epilepsy

2. Blood tests can be used to understand the medical disorders.

3. CT scan (also called CAT scan), brain X-Ray or MRI scan can be used to identify the infectious areas of brain i.e. tumor.

Depending upon the patients' health, other tests are recommended as well, like a spinal puncture which is also known as spinal tap or the EKG (electrocardiogram, which is used to see the heart, or a sleep test. To better understand patient's condition it is important to have basic understanding of seizure types and its stages. Epilepsy points out different sets of anomalies, with different causes, symptoms and clinical expressions. People might experience one or the other sort of seizures. Epileptic seizures are mainly categorized in to 2 main types by neuro-experts; 'partial seizure'- affecting the part of the brain and 'generalized seizure'- affecting the whole brain. The picturing of seizure classification is represented in:

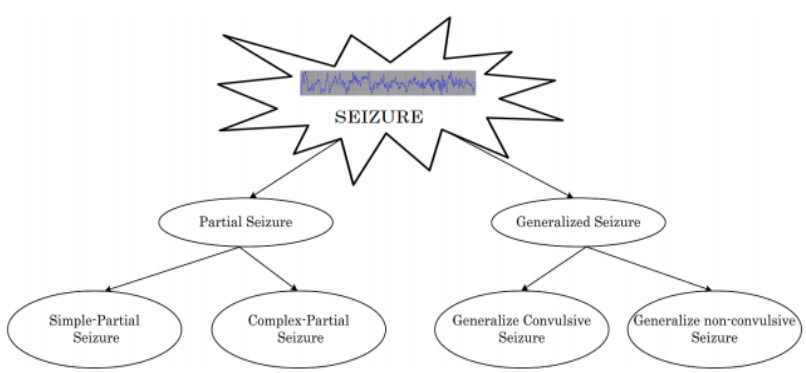


Figure 1.2 Types of seizures.

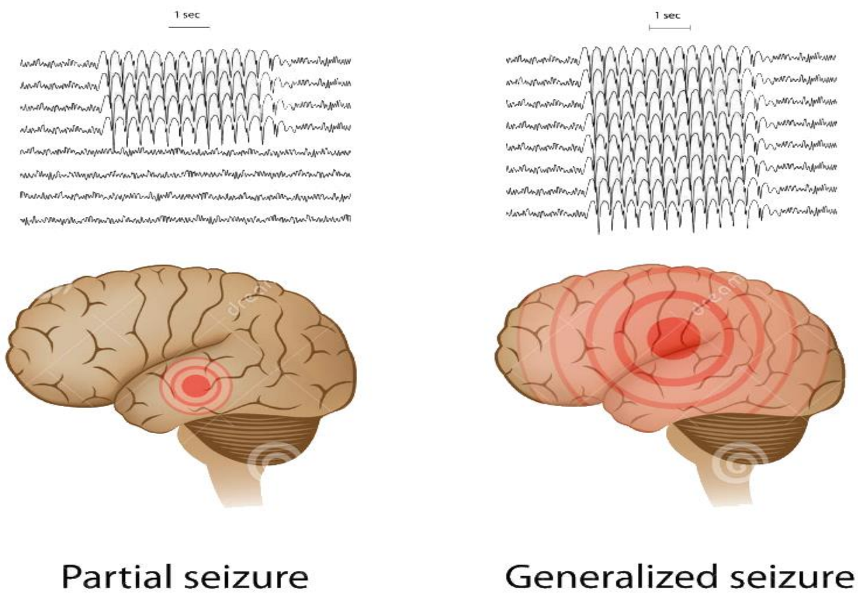


Figure 1.3 Classifications of Epileptic Seizures

Electroencephalogram (EEG) is the most common brain signal recoding technique used to monitor the brain's signal activity. Doctor place sensors on the scalp that record electrical activity of the brain.

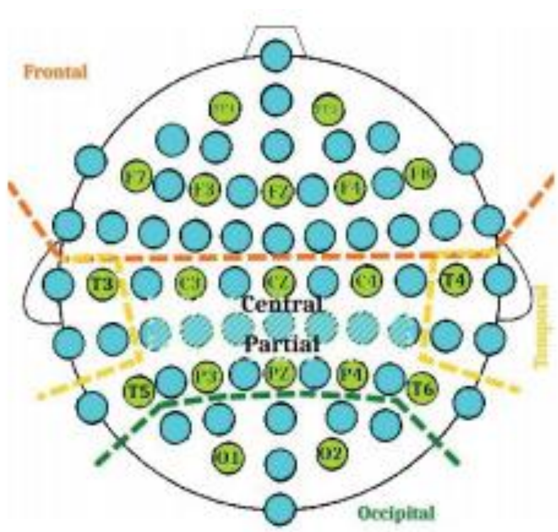


Figure 1.4 Classification of convulsion

A change in the normal brain wave symbols the problem. Many of epileptic patients have abnormal EEGs. It may happen that a person is suffering from epilepsy but its tests appear normal but this normal test result doesn't mean that the patient is normal i.e. epilepsy is not present or seizures aren't real. Therefore much advancement has been made to identify the disease and models are designed which gives an alert before the seizure occurrence and this can help in improving the patient's quality of life. Diagnosis for the neurological disorders demands for future nursing of the patient.

Usually studies rely on electroencephalograms (EEGs) which are the brain signals and are recorded from the different regions of the brain scalp [5], [16], [39], for identification of the disease and capturing physiological measurements of epilepsy. In general symptoms aren't always supposed to be present in EEG data. These signal information is paired with the expertise of a neurologists which finds way out for creation of automated task based systems. Because of this automated task based system the machine learning methods started getting popularity in EEG interpretation in recent years. In Patients usually two types of abnormal activities have been observed in the recordings of EEG:

Ictal activity recorded during a convulsion and inter-ictal considered as an abnormal signal are recorded between epileptic seizures (Fig. 1.5). The EEG's signature for an inter-ictal activity comprises transient waveforms which are occurring occasionally, as sharp wave or a spike wave, as an isolated spike or spike trains. EEG's signature for ictal period (convulsion) comprises of polymorphic waveforms of different frequency and amplitude. It's an endless discharge of such waveforms with spikes and sharp wave complexes. Electro cerebral in activities are observed for a longer duration as compared to inter-ictal periods [37], [46]. The authors who used to analyses the epileptic signals they focused on automated spikes of signals for the disease detection [29].

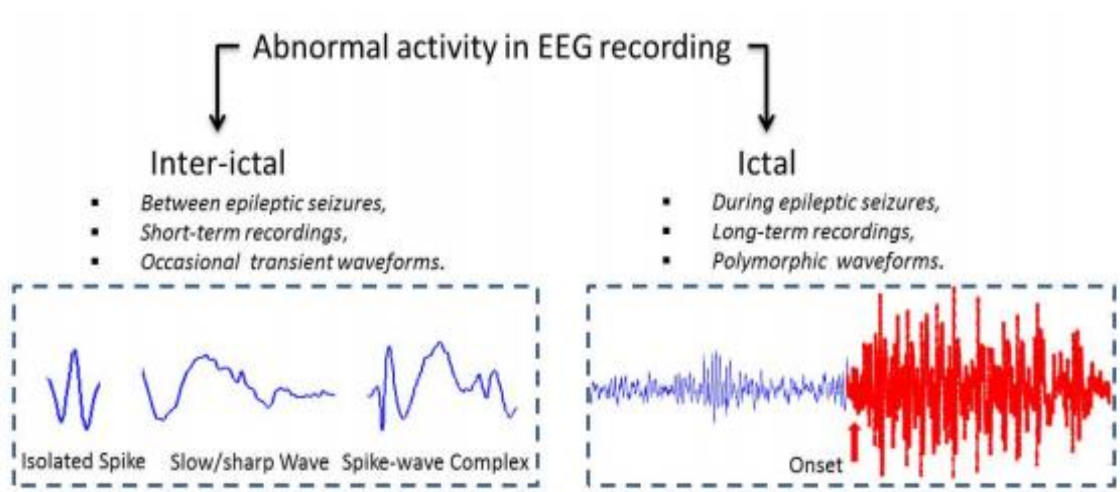


Figure 1.5 Classification of ictal stages

1.2. Motivation:

In the present world human services are being facilitated by artificial intelligence which is not only promoting the socioeconomic development but also improving the quality of life by making advancements in medical science specifically in neurology. This type of work is of great relevance to a developing nation like Pakistan where doctor to patient ratio is very high and epilepsy specialists are numbered. The amount of information required for seizure detection is time consuming hence it makes the manual interpretation expensive and resource hungry. The physical health, limbs behavior, mental state and EEG signals need to be examined before, during, and after a seizure. To better understand patient's condition it is important to have basic understanding of seizure stages. Epilepsy points out different sets of anomalies, with different causes, symptoms and clinical expressions. This research can serve as a base detection technique for level 1 case and reduce dependency on doctors. Successful completion will enable more people to cheap and comprehensive expert help.

1.3. Objective and scope:

This research has been carried out for addressing the problem of EEG signals in epilepsy by employing a new method of feature extraction and comparing the different method of deep learning techniques. For evaluation, 5 clinical problems of seizures detection including Coma stage classification are considered. To make the usefulness of the proposed method in real world practical clinical scenarios, we used an information selected from 5 hundred subjects during different stages of epilepsy for the purpose of training. Hence the main objectives of the proposed methodology are summarized as follows:

1. To adopt a new method of feature extraction rather than conventional methods often applied in time series domain including STFT, DFTS, RSTFT etc.

2. To specifically identify the seizures in comma or absence state because NCES causes no focal seizure symptoms hence it cannot be analyzed visually such long term activity in a brain of a coma patient may cause life time brain damage or even cause death.

3. To extract complete information of epilepsy from EEG five stages including convulsive epileptic seizures , Non convulsive epileptic seizures (NCES) , pre-ictal stages and post ictal stages which have never been categorized thus hinders the power to actually understand these signals as different stages of Epilepsy. However, these different stages of epilepsy can might contribute in better understanding of disease and help in inventing treatments that can be effective during any of these stages.

4. To demonstrate the better performance of formulated feature extraction technique and deep learning models in seizure detection for epileptic and non-epileptic classification in comparison to existing state of the art publications..

5. In future this method of automatic detection of different stages of epilepsy can be integrated for real time applications with devices used for epileptic seizure warning or secure control, to improve the patients social and physical health.

1.4. Novel Contribution:

This thesis has made the following novel contribution in existing research:

1. Binary classification for NCES (Coma state) vs (CES) seizure class is carried out.

2. Multi classification for all the five classes is carried out for the first time in the field of epilepsy disease detection in comparison to previous publications.

3. Sample entropy (SampEn) as a measure of single feature is used to feed in conventional machine learning algorithm rather multiple number of features, for the first.

4. Deep learning models are applied on time series data of EEG comparative analysis and stage wise better model for disease detection ranging from A-E is proposed in terms of complexity and time efficiency.

5. The research is carried out in national interest and will help neurologists /doctors in Pakistan in saving and improving socials and physical health of people.

6. The UNDP sustainable goal for health and well-being is achieved ensuring the good health of Pakistani citizens.

1.4 Thesis Organization:

Thesis comprises of 5 chapters. Chapter 1 gives the overall introduction, motivation, also describes the objectives and novelties of the research. Chapter 2 sheds light on the literature review. Chapter 3 is Implementation and describes all the steps that were involved in this research. Chapter 4 is Results and Analysis, which explains and gives comparisons of all the results. Chapter 5 discusses the Conclusion and Future Work for this research

Chapter 2

Related Work

This chapter discusses and evaluates previous research that has been con-ducted in epilepsy disease detection. The section 2.1 discusses how Machine learning is being used. Then we look into some previous works including, how research has been carried out through the years and what progress has been made. We will discuss different approaches and methods used for disease detection and classification. Discussion about techniques for feature extraction and selections that were used in previous work. Machine learning based classifiers are explained with experiments and limitations in previous research. In the last section, a critical analysis and comparison of the proposed frameworks used in the previous studies has been addressed

2.1 Predications and detection of seizures

The predicition of seziures before the ictal state i.e. the identification of epileptic seizures in pre-ictal state are of great importance because they can contribute in better understanding of disease and help in inventing treatments that can be effective for controlling the further generation of epileptic signal. Moreover there are five different phases which are actually involved in the epileptic seizure as shown below in Fig 2.1 [17], including eye open or in conscious state , eyes closed coma or absence state, there is an ictal state where epileptic seizures are at their peak and there is pre ictal state that occurs before seizure activity and then there is a post ictal state that appears after the completion of seizure activity.During the ictal stage, patients usually experience clear physical symptoms which can be identified and noticed by anyone without any medical attestation and different from other seizures stages.

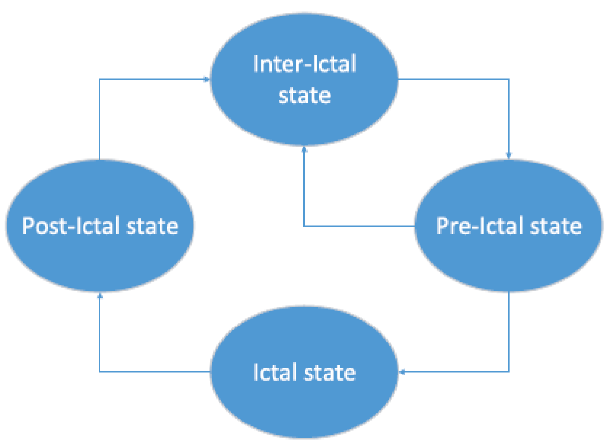


Figure 2.1 Epilepsy state flows.

There is a stage when seizures are at their peak and patient is completely suffering from the epilepsy this stage is named as ictal stage and then there is a stage when the seizures are about to end called post ictal stage in this stage patient is more likely recovering from the abnormal brain signal activity, this post ictal activity is long in time span and usually it remains for hours. It makes very obvious that the predication and classification of the inter ictal stage from the pre ictal stage might help in preemptive therapies which can be used to hinder the transition of pre ictal to inter ictal stage. So if any one succeeds in identifying the pre ictal stage correctly, it can make medical staff capable of give the appropriate medication to the patients to prevent the from ictal stage. But once the patient is driven from pre ictal stage to post ictal stage than there is no option for preemption.

In the researches the problem of epilepsy disease detection is always considered as binary classification where ictal state is labeled as one and non ictal that can be pre ictal , post ictal or ictal free stages are considered as same class and labeled as zero. It is to note that our work is on seizure detection for all the stages of epilepsy

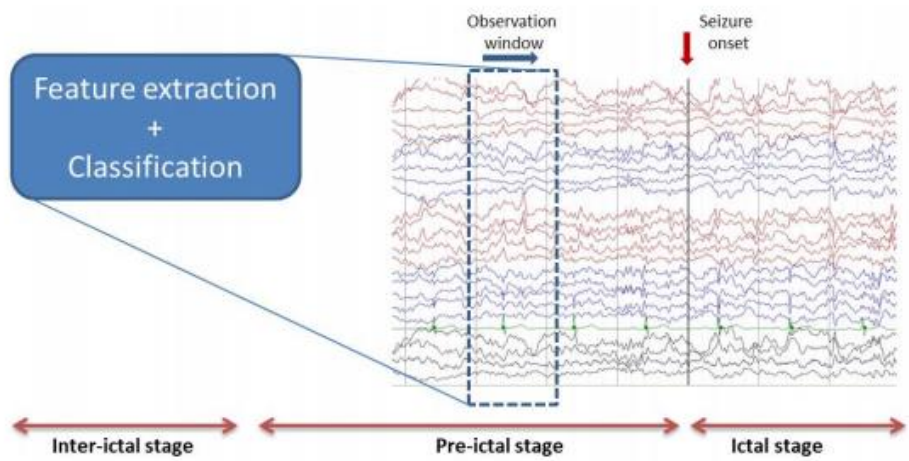


Figure 2.2 Epilepsy signal representation

As discussed the detection of all the stages like pre ictal from ictal is very challenging. Because it includes some level of abnormal signals as well that is present in epileptic state.

It is reviewed from the literatures that the detection of seizure includes two main steps. First step includes the preprocessing of EEG signals and the extraction of useful high level features out of so these features can serve as feature vectors for the representation of EEG signals. And the second step is using machine learning or deep learning models to classify and identify the seizures. A detailed study of previous applications has been carried out in this regard and a pictorial representation of previous work regarding feature extraction techniques and classification types is presented by:

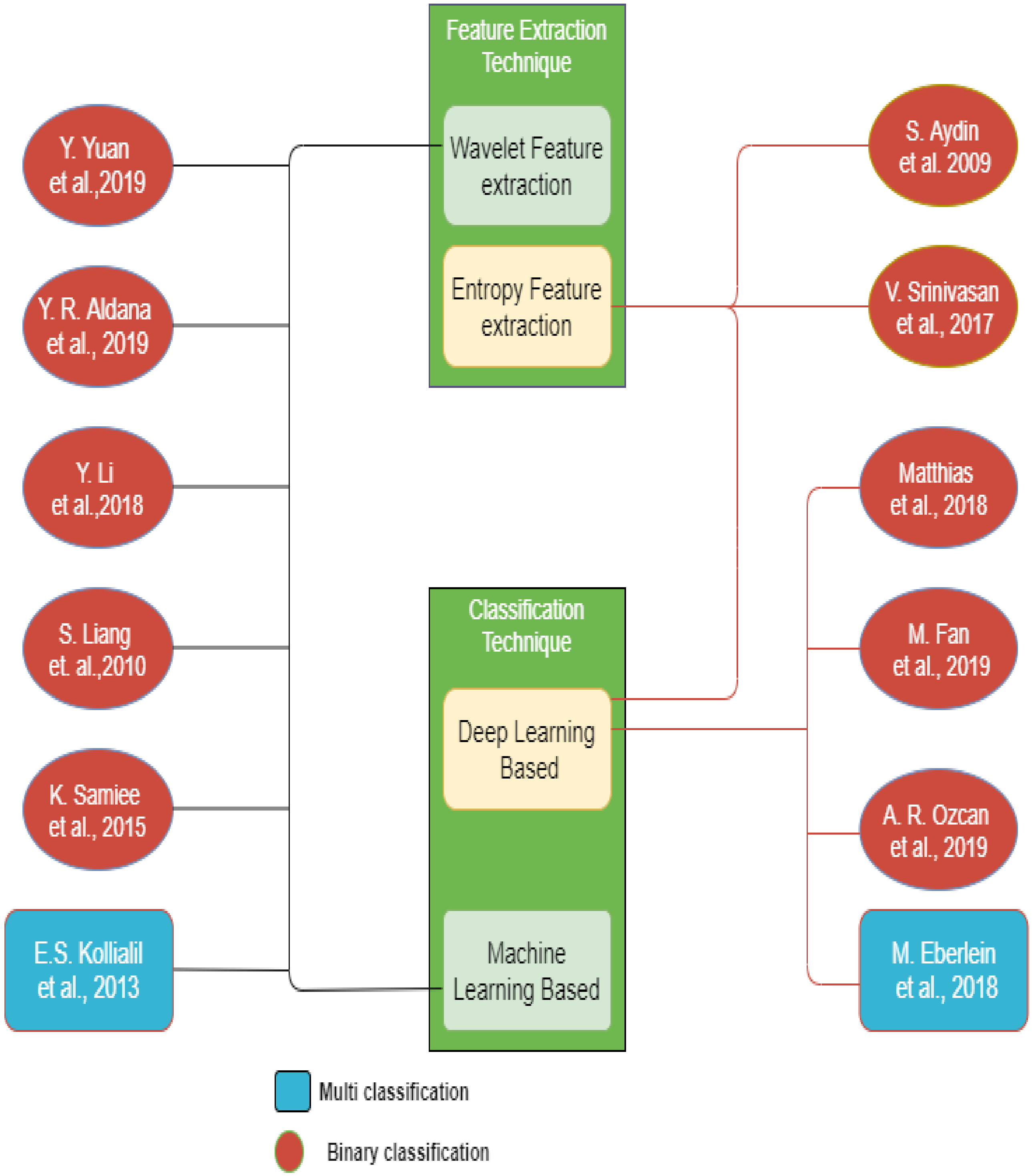


Figure 2.3 Related work flow diagrams

A detailed description of literatures explaining their techniques and technologies proposed for epileptic seizure detection are defined below:

[1] Seizure Prediction in Scalp EEG Using 3D Convolutional Neural Networks with an Image-Based Approach

In this research paper a study is presented which aims at the development of generalized method for seizure-prediction. Solution provided uses CNN for the processing of the input. For the collective evaluation of the temporal and spatial correlation in training data, multi frame 3D-CNN model is presented. By using spectral band power statistical movement and Hjorth parameters, frequency domain and time domain features of the EEG signals are revealed. Variable Weighted learning is presented to counter the negative effects of the fixed-length preictal period. The EEG features are converted to image format by using CNN model. By using variable-weighted learning and normal learning, the performance of 3D CNN Seizure prediction is done. During training, model parameters' convergence is attained by doing optimizations in the cross entropy loss function. Comparison among MLP CNN & 3D CNN is done for performance analysis.

The proposed solution has 85.7% sensitivity, FPR of 0.096/h and time-in-warning of 10.5%. The dataset comprises of the scalp-EEG results of 16 patients. In contrast to the Poisson based random predictor, the proposed solution is statistically significant, at significance level of 0.05. Various duration experiments show that seizure prediction success rate is improved if we determine the accurate lengths of epileptic stages with respect to different patients.

The data set used in the case study is collected from 23 subjects only and training is carried out on randomly selected data. The paper doesn't use LSTM and the proposed model is hardware specific. The training and testing are done on randomly selected data using Kfold Cross Validation and Leave One out Cross Validation (LOOCV). evaluation of Temporal-Correlation was delayed until the LSTM and spatial correlation was evaluated in the very beginning off CNN, from first layer.

[2] Convolutional Neural Networks for Epileptic Seizure Prediction

In this work, for seizure predictions, a new methodology for the classification of Intracranial Electroencephalography (iEEG) is presented. Compared to previous approaches, in this work hand-crafted features are omitted and CNN topology is used to determine suitable signal characterization and the binary classifications. Three models are used on the dataset. The dataset comprises of long-term recordings of three patients and four dogs.

The results validate the feasibility of the solution generally. Limitations and strengths of the proposed methodology are discussed in this paper. Only binary classification is used in this work so the accuracy can be improved by using all 5 classes. Based on the experiments the limitations of this work are very evident. For patient 1 of dataset 2 the experiment totally failed, with unknown reason. It doesn't use LSTM structures which can significantly improve the temporal information

[3] Epileptic Seizure Classification of EEGs Using Time–Frequency Analysis Based Multiscale Radial Basis Functions

In the proposed solution, by using MRBF along with MPSO, time-frequency representation in EEG signals is proposed for the improvement of time-frequency resolution.

MRBF MPSO, which is a novel framework, is proposed for the feature extraction of time frequency regarding epileptic EEG signals. Component analysis algorithm is used to decrease the dimensionality of the features. The features are then provided to SVM classifier with RBF, to differ between seizure-free EEG signals and epileptic seizure EEG.

The Proposed method is then evaluated by using several feature extraction algorithms to assess the Classification performance. Experiments indicated that the given method of classification works better compared the existing solutions and shows the effectiveness of differing among seizure epochs and seizure-free epochs. MRBF-MPSO is compared with RLS, SRBF and standard MRBF under the different classifiers such-as, Linear discriminant analysis, K-nearest neighbor, NB, Logistic, Random Forest and Support Vector Machine (SVM), the proposed solution out performed all of them. The proposed method achieved the accuracy of 100%, 99.8%, 97.6% and 98.73% in four classification problems such as S-N, S-Z respectively.

They don't use all the classes for classification purpose only binary classification is carried out.Accuracy of classification can be improved by using all the classes, using LSTM structures will also help with the better prediction. The classification models have room for improvement, by using multiclass classification the problem can be solved at the classification stage. The data set used wasn't spanning along different spectrums like scalp-EEG etc.

[4] Detecting Abnormal Pattern of Epileptic Seizures via Temporal Synchronization of EEG Signals

In this paper Analysis of spatial-temporal synchronization using spectral graph theoretic features is done. Above that, to detect seizure onsets in real time, an efficient multivariate approach is developed. For this purpose, complex network-model is proposed. It's use is for the recurrence pattern's representation of the EEG signals, and by using spectral-graph, theoretic features the quantification of the temporal synchronization patterns is done. Other than that, in a multivariate EEG system, for the monitoring of the epileptic to normal state transitions, features are extracted by using the application of statistical control chart.CHB-MIT Scalp EEG database of 23 patients is used to test the solution. According to the results, on average, presented the graph theoretic feature gave high sensitivity of ~98% and latency as low as ~6 s. above that in 18 patients the seizure onsets are 100% detected.

Two models are proposed for the representation of the recurrence patterns of multivariate EEG signal. On three different types of data, namely, Original-CHB-MIT-signal, the band-decomposed-signals and the EEG signal with surrogate and white-noise at different levels, the effectiveness is assessed by testing the solution. Sensitivity, latency and false alarm rate are the metrics used for the performance analysis in the tasks of the detection of seizures. In epileptic EEG, increased temporal synchronization is achieved by using this approach and the detection performance is comparable to the previous studies. Using this approach patient specific diagnosis is made possible, Real time seizure detection is made possible by the increase of temporal synchronization in the epileptic EEG.

Their proposed method carries binary classification only and multiple temporal scales are not addressed regarding time-varying dynamics from multiple temporal scales.

[5] Nonconvulsive Epileptic Seizure Detection in Scalp EEG Using Multiway Data Analysis

This research work focuses on a method for the detection of nonconvulsive-seizures. Linear Discriminant Analysis, K-Nearest Neighbor and a Radial Basis SVM classifiers are used to differentiate between normal and a seizure EEG. Block Term Decomposition and Canonical Polyadic Decomposition (CPD) are used to obtain the classifier features. Proposed approach is compared with existing approaches, based on sensitivity accuracy and specificity; it is shown by the results that the proposed solution performs better than all of them. The application of multiway data analysis and HHT has never been done before this. Wavelet or HH transform is used for the expansion of the EEG into tensor. The testing data for the algorithm comprises of a scalp-EEG dataset of around 139 seizures. Based on experimentation, the most appropriate framework for NCES is the CPD analysis and HHT (Hilbert-Huang-Tensor) representation. For sensitivity, specificity, and accuracy, RB-SVM classifier shows the best performance, over 98%.

The drawback in their proposed methodology is small data set from14 patients with 136 seizures signals is used and high number of false negatives are found in results. The given methods are shown as the best NCES methods, based on the results. The proposed solution works in real time with actual field values of the patients. The training strategies could be improved as the number of false negatives in this approach is higher and because of that the disease can undergo serious progressions.

[6] A Multi-View Deep Learning Framework for EEG Seizure Detection

The proposed work comprises of a deep-learning framework which is unified multi-view, for the capturing of seizures which are associated with the abnormalities of the brain, based on scalp EEG signals (multi-channel). End-to-end model is used which is used in the learning of multi-view features from seizure detection using spectrogram which is supervised and multi-channel EEG reconstruction which is unsupervised.

A new autoencoder-based is constructed which is based on multi-view learning model and it uses both intra correlations and inter correlations among the different channels of the EEG signal for full exploitation of the information which is multi-channel. To keep multi-view structure focused on the relevant channels of the EEG, channel-aware seizure detection module is proposed by the addition of competition mechanism during the phase of training. The given solution is validated for its effectiveness by conducting experiments among nine baselines. Conventional deep learning methods and traditional handcrafted feature extraction are used as baselines. To lower the dimensionality of the features PCA is used. The dataset comprised of benchmark scalp EEG is used for the experimentation. Outcomes prove that the given model bumps up the f1-score up to 85.34% and higher average accuracy at 94.37%. Performance of the normal and Semi Supervised detection, cross validation (subject-independent) is carried out based on 5-fold. It outperformed its competitors by a significant margin. SSDA and ConvA auto encoders are deployed for the construction of multi view architecture.

Table.1. Literature Review

Ref	Author	Evaluation Strategy	Performance Metrics	Area Covered	Limitations
[1]	R. Ozcan et. al., 2019	Comparative study Experimentation using test bed	Sensitivity FPR, Time-in-warning proportion, AUC, Significance level	Analysis of EEG based on Frequency /time domain features Studying S-P performance 3D-CNN using variable-weighted and normal learning Epileptic stage length	Test is done on a small dataset (16). Training done on randomly selected data Small dataset of 23 patients
[2]	Eberlein al., 2018	Comparative study Experimentation on test bed	AUC	Using CNN for signal characterization and binary classification	Small data set One clear issue is the failure of the algorithm on Patient 1 Only binary classification is used
[3]	Y. Li et. al., 2019	Comparative study MBRF + MPSO + Principal component analysis algo (PCA)	Time resolution, Frequency resolution, Accuracy, Classification effectiveness	Novel framework for tome-frequency feature extractions using MPSO on top of MBRF SVM with RBF function for the Differentiation among signals with seizure and seizure free signals	All classes not used And only binary classification is carried out.

[4]	M. Fan et. al., 2019	Comparative study Simulation spectral network metrics PCA	Sensitivity, Accuracy Latency, FAR (False-Alarm Rate)	Analysis of spatial-temporal synchronization using spectral-graph-theoretic features Real time seizures Detection.	Multiple temporal scales are not addressed regarding time-varying dynamics
[5]	Y. R. Aldana, et. al., 2019	Comparative Study Experimentation done on Real-time data K-NN RB-SVM\ LDA	Accuracy, Specificity, Sensitivity	Non-convulsive seizure detection CPD used for classifiers Using HHT and multiway data analysis	High number of false negatives Small data set from14 patients with 136 seizures signals.
[6]	Y. Yuan et. al., 2019	Comparative study Simulation PCA	F-Score, Accuracy, AUC-Precision Recall, AUC-Receiver operating characteristic	Using scalp EEG signals (multi-channel) for the capturing of seizures Using auto encoders for the construction of multi view architecture.	Small dataset of 23 patients

For the prevention of a epileptic seizures it is very important to predict it in a timely manner, this can save the patient from undergoing the noxious treatment. Moreover, epilepsy cycle mainly includes five phases as presented in Figure 1 [17], which includes eye in conscious state or open state, eyes in absence state or closed coma state, pre-seizure (the pre-ictal stage), during seizure (the ictal stage), post-seizure (the post ictal stage) and stage between two consecutive seizures (inter-ictal).

During the ictal stage, clear physical symptoms are shown by the patients, making it easier to distinguish it from the other two stages. Subsequently, patients are recovering from the seizure in the post-ictal stage, it usually lasts for hours. when patient is suffering from complete seizures it is known as an Ictal stage. Thus, the classification of the pre-ictal stage and the inter-ictal stage is the goal of the prediction of a seizure, as in the pre-seizure stage, preemptive measures can be used for the prevention of the transition towards ictal-stage. So, if pre-ictal stage is correctly identified, the appropriate treatment can be provided by the medical staff for the prevention of a patients leading to the ictal stage. In comparison, once pre ictal stage transitions into ictal stage, we can’t do preemption any more. Therefore, we can address seizure prediction problem as a binary-classification, in which inter ictal stage is denoted with zero label and pre-ictal stage is represented by label one. It should be Noted that the focus of this research is on the prediction of the seizure and not the detection. The prediction of the seizure is more challenging and it is comparatively more useful than seizure detection, as the prediction of a seizure allows the medical staffs to take appropriate measures to avoid seizures from occurring. Two basic steps are involved in the seizure prediction or detection in most of previous research studies. First step being features extraction from the EEG signals, which can be utilized for feature vectors for the representation of signals of EEG. The second step includes the use of deep learning models or machine learning to identify and classify the seizures. For this purpose, previous applications are studied in detail

Methodology

3.1. Overview:

This work is related to a real life health issue i.e. Epilepsy. Epilepsy disease is a neurological disorder which causes generation of an abnormal signal in brain causing uncontrollable jerking movements, temporary confusion and loss of awareness and may even cause death. Electroencephalogram (EEG) is used to read brain's behavior by doctors but according to some research EEG fails to detect the epilepsy disease in epileptic patient because it happens due to a sudden generation of abnormal electrical signal so it is difficult to diagnose. Different techniques and approaches have been introduced to overcome this problem which is generally classified into two groups: conventional methods (Machine learning) and Deep learning methods (CNN &LSTMs). From the previous literatures we find that conventional methods achieve remarkable accuracy on seizure dataset so rather than using the same method used previously we researched and analyzed that different stages of epilepsy have never been categorized before specifically the seizures during the non-conscious state and the conscious state. Identification of seizures during NCES is important because comma or absence state causes no focal seizure symptoms hence it cannot be analyzed visually such long term activity in a brain of a coma patient may cause life time brain damage or even cause death. To extract complete information of epilepsy from EEG five stages including convulsive epileptic seizures , Non convulsive epileptic seizures (NCES) , pre-ictal stages and post ictal stages which have never been categorized thus hinders the power to actually understand these signals as different stages of Epilepsy. Keeping in view these different stages of epilepsy can might contribute in better understanding of disease and help in inventing treatments that can be effective during any of this stage multi classification is carried out. As time series is complex in nature, and its difficult to identify the important features out of them beacaue not all of this information contributes towards predicting the outcomes. Through learning the various techniques of feature extraction from literatures we focused on feature minimization and applied entropy based feature extraction approach. We use a single feature named SampEn for Classification. The calculated feature is fed to SVM as an input for classification. The CNN and LSTMs models are trained for classification are highly optimized [both in terms of Accuracy and speed] than the previous state of the art architectures. The error rate calculated on the output our model is compared with the results of previously implemented models and it is noticed that the results of the previously implemented techniques are same or less as resulted by our proposed approaches. Comparative analysis is carried out between all the applied approaches where CNNs performed better and they achieves an accuracy as high as 99.0 ± 0.1 in case of binary classification for all the stages and 87.5 99.0 ± 0.1 in case of multi five class classification. A summary of the experimental approch used in our work is shown in block diagram

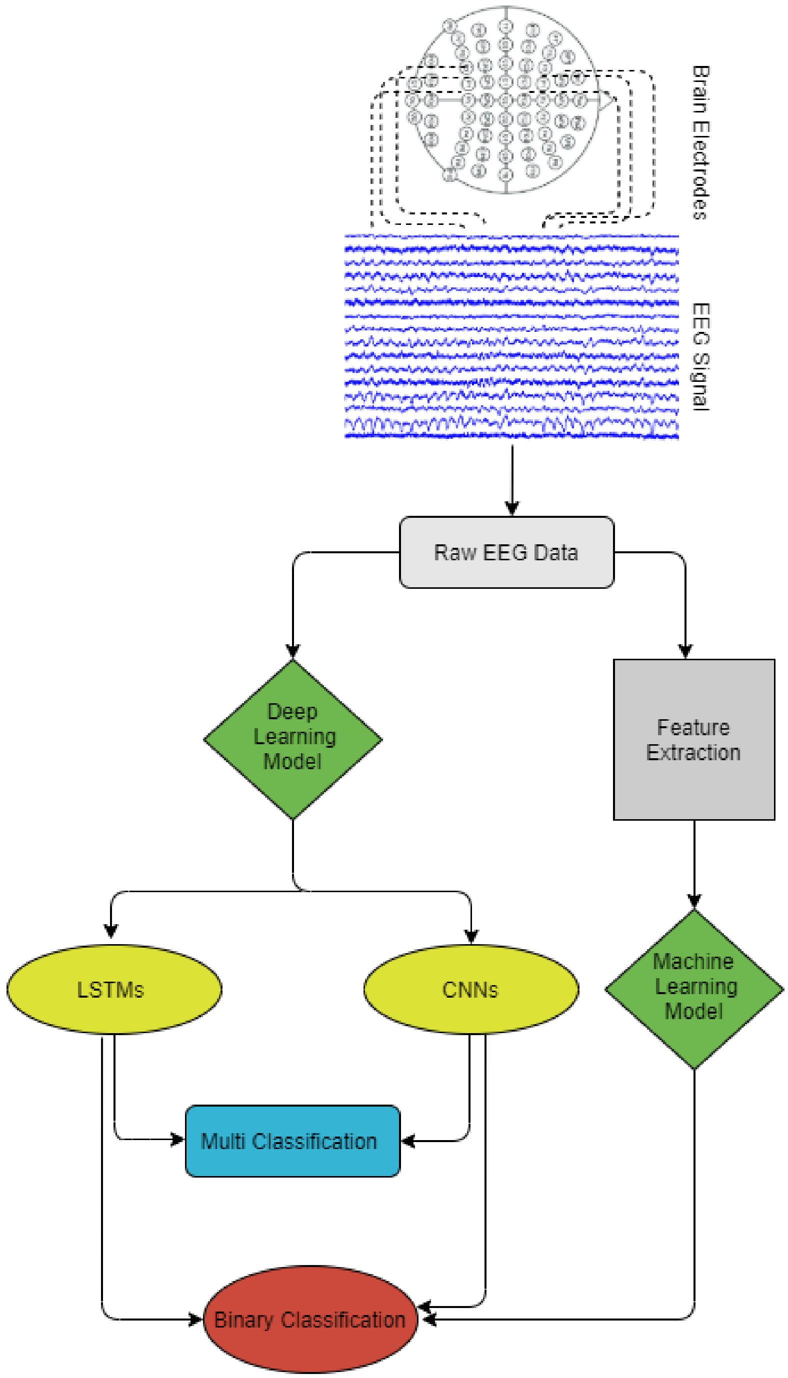


Fig 3.1. Block diagram for proposed methodology

3.2. Data Acquisition:

The dataset used for the analysis is collected by the Epileptology Department of University of Bonn which is publically available and is extensively in different literatures for epilepsy detection. It consists of 500 subsets ranging from A-E. Recordings are made with the help of international 10-20 electrodes. The samples for raw EEG signals from A – E is represented in below picture

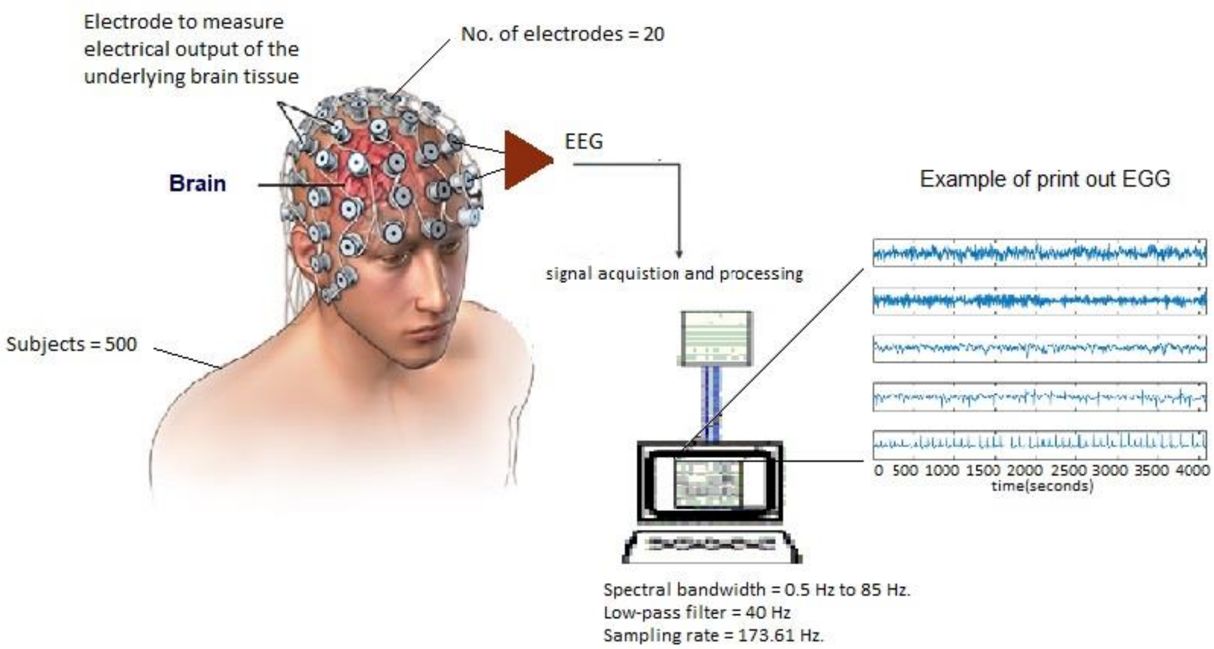


Fig 3.2 University of Bonn epilepsy dataset details

Electrodes are attached on various regions of scalp and EEG signals are recoded at 173.61 Hz with a 12 bit resolution. There are 100 single channel recordings in each subset. A subset is collected from a subjects in CES state , B subset collected from a subjects in NCES state , C subset represents the Pre-ictal state, D representing the post-ictal state and E state is collected during peak of seizure activity. All the five classes of the Epiletotic data set are presented as below :

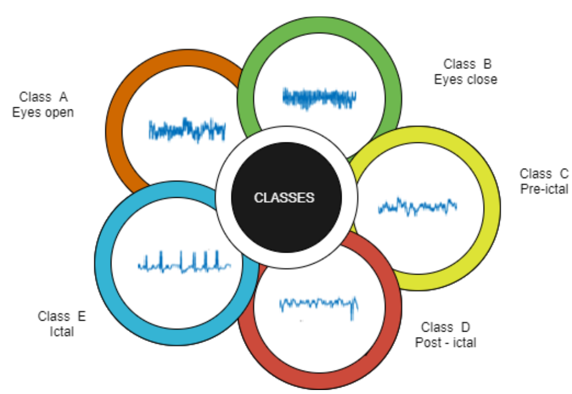


Fig 3.3 Classes in dataset

The data is acquired from 500 subjects and their respective time series are sampled into 4097 data points where every data point represents the value of EEG at that particular time instance. So there are 500 total subjects with each individual having 4097 data points and every 4097 data points of these subjects are shuffled and divided into 23 chunks. Hence each divided chunk containing 178 data points for a single second. So it becomes 23 chunks into 500 subjects i.e. 23 x 500 = 11500 information pieces or rows of data. And each information data or row contains 178 data point i.e. 178 columns. And the last column contains the class label {A,B,C,D,E}

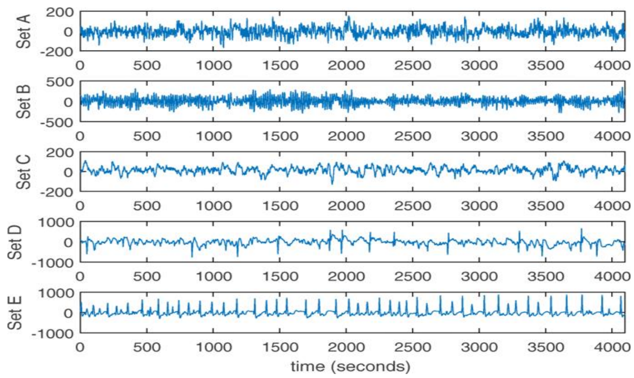


Fig 3.4 Signal representation of classes

3.3. Data preprocessing:

The spectral bandwidth that is used for data collection in the acquisition system is 0.5Hz to 85 Hz. For preprocessing the low pass filter is applied of 40Hz. And the sampling rate used for data is 173.61Hz. There become 178 data points against each subject and further segmentation is carried out on these samples and total 11500 single channels EEG fragments are generated for all the subsets. The dataset used for analysis is complex in nature as it ranges from –ve to +ve values.

	A	B	C	D	E	F	G	H	I	J	K	L
1	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
2	135	190	229	223	192	125	55	-9	-33	-38	-10	35
3	386	382	356	331	320	315	307	272	244	232	237	258
4	-32	-39	-47	-37	-32	-36	-57	-73	-85	-94	-99	-94
5	-105	-101	-96	-92	-89	-95	-102	-100	-87	-79	-72	-68
6	-9	-65	-98	-102	-78	-48	-16	0	-21	-59	-90	-103
7	55	28	18	16	16	19	25	40	52	66	81	98
8	-55	-9	52	111	135	129	103	72	37	0	-38	-77
9	1	-2	-8	-11	-12	-17	-15	-16	-18	-17	-19	-18
10	-278	-246	-215	-191	-177	-167	-157	-139	-118	-92	-63	-39
11	8	15	13	3	-6	-8	-5	4	25	41	48	44
12	-5	15	28	28	9	-29	-41	-19	14	30	22	-6

Fig 3.5 EGG time series signals in data points

3.4. Feature extractions:

As per literatures the automatic detection of epileptic disease has been addressed and catered by various researchers by using different methodologies which can be used for feature extraction for time series data the widely spread feature extraction techniques used in past few years. Y.R. Aldana et al. [47] explain the feature extraction techniques generally used for time series data are mentioned below:

1. Wavelet Transformation [7]–[9], [16]
2. Entropy [10], [11]
3. Non-linear parameters [8], [11], [12].

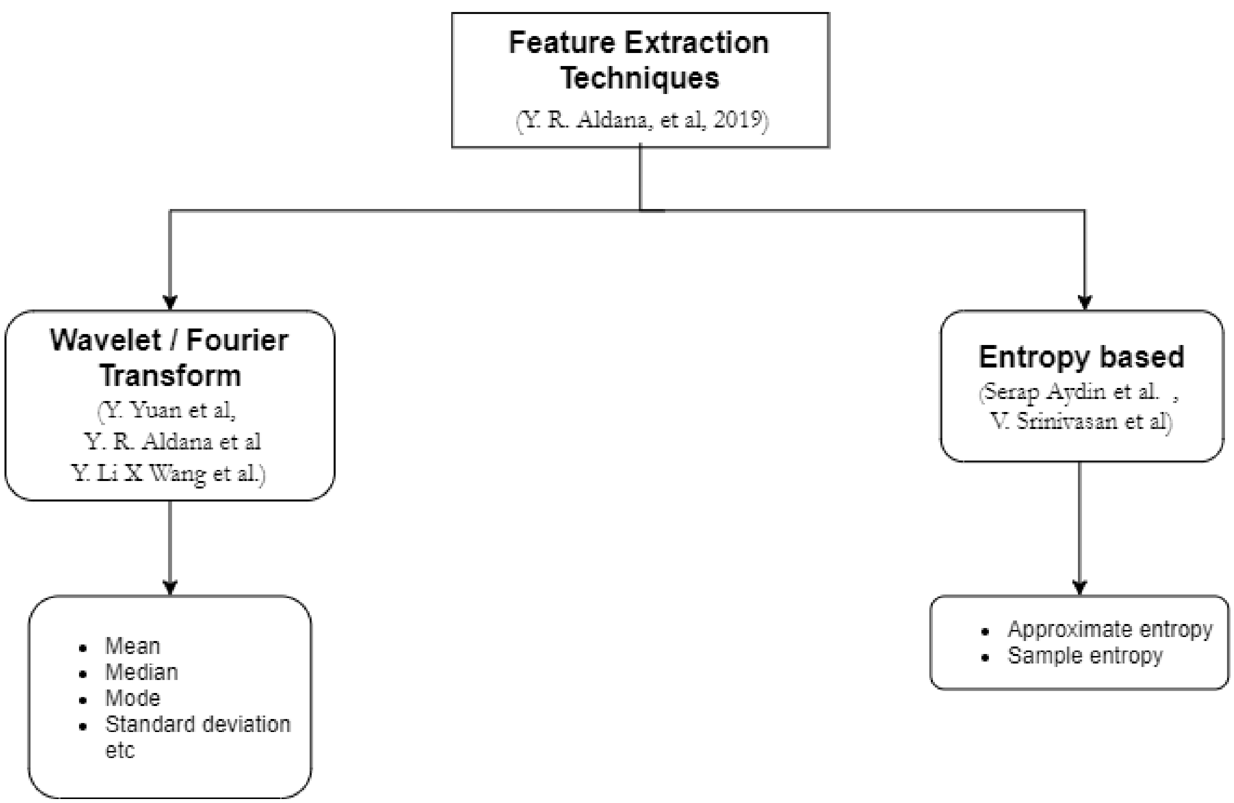


Fig 3.6 Feature extraction techniques proposed in literatures

The time duration and the channel count of epileptic seizures are considered as important and popular criteria for threesholding [9], [14]–[16]. It is difficult to detect seizures if they are too localized like only few channels have been affected by the seizures or the time duration for calculation is too short. The patterns in seizures vary from person to person and even from one seizure activity to another seizure activity. Therefore the threshold that works for one patient may not work for the other patient necessarily. Different time series domains have been described by feature spaces. The computed feature spaces are then classified by using deep learning techniques which includes densely connected neural networks.

Usually the problem which is faced during the large scale classification is the curse of dimensionality which impacts the classifiers performance and systems computation power. In order to overcome these challenges feature selection and reduction method is adopted. Goal is to identify the features with minimum redundancy and maximum relevance. Different feature extractions techniques have been reviewed from literatures.

Popular methods considered for feature extraction includes FFT [3] as Yaun et al. [47] uses SFTF short Fourier Transform for feature extraction and them feed them to classifier. Li et al. [33] uses spike based approach, Shoec et al. [41] reported seizure detection using DFTF discrete Fourier transform and Serap et al.[42] uses entropy based feature extraction and uses approximate entropy as the measure of feature. Many state of the art methods used for feature extraction are wavelet analysis.

3.4.1 Wavelet analysis:

In wavelet analysis the EEGs are decomposed into various frequency sub bands by applying different wavelet techniques like Fourier-based techniques like short-time Fourier Transform and Time-Frequency analysis TFA like Daubechies (db2) wavelet approach [8]. Features extracted like absolute mean value;

1. Absolute median value;
2. Absolute standard deviation;
3. Absolute maximum value;
4. Absolute minimum value of the coefficients etc.

In wavelet analysis they used time –domain for finding rhythmic and periodic discharges of EEG’s in seizures. Fourier Transform is commonly used for analyzing the time series data of EEG signals assuming the fact that the EEG’s are not stationary as well as nonlinear but generally from EEG signals Fourier Transforms do not perform really well in extraction of features because Fourier deals with signals like they are local stationary [6]. But actually the EEG’s are non-stationary so it’s better to use time frequency based analysis like Wavelet Transforms which don’t rely on the concept of EEG signals stationarity. The popular technique used for preprocessing of EEG signals which are non-stationary is their decomposition in time frequency sub bands. Feature extraction and their detection is carried out by these sub bands [7]. Adeli et al. [9] used Daubechies wavelet is another approach that is used for epileptic seizure detection. In 5 sub bands of frequency which are of clinical interests: gamma rhythms (30–50 Hz), beta rhythms (13–30 Hz), alpha rhythms (8–12 Hz), theta rhythms (4–8 Hz), delta rhythms (0–4 Hz). By using such techniques various time frequency based vector features has been extracted consisting of average , mean, variance, maximum , minimum , standard deviation, mode etc. of every sub band's wavelet coefficient [35]-[34].

3.4.2. Entropy-based feature extraction:

Entropy measure is another time domain feature extraction method used to determine the irregularities in a data series on the basis of their existing patterns. There are typically two types of entropies used for time series data:

1. Shannon entropy as Approximate entropy (ApEn)

2. Sample entropy (SampEn)

The basic objective of both the entropies ApEn and SampEn is to identify the extent of randomness in the time series without piror information of the generating source of dataset. This makes their applicability limitless and these algorithms have been used widely in different research fields. The concept of information theory (IT) is the basic matric used in both the entropy measurements, which is a magnitude used to quantify the measure of uncertainity and it is the measure the probabilistic measure of an event.[40]

3.4.3. Why sample entropy is better than approximate entropy?

Time series are examined by entropy methods for similar epochs. Value of approximate entropies will be small if the epochs are more similar and more frequent. If the value of approximate entropy is small it means the degree of regularity is high. Approximate entropy matches each sequence with itself and counts it and this practice is presented in Eckmann and Ruelle's work [91] Eckmann, J. P., & Ruelle, D. (1985). Ergodic theory of chaos and strange attractors in reference to (pp. 273-312) Springer, New York, NY. The theory of chaotic attractors presents that the hyper parameters used in statistical family of entropies are (m , r, N). It is defined as the natural algorithm's negative average is equal to the conditional probability between two sequences which are identical for m points having a tolerance of r with in next point. As approximate entropy measure each sequence with itself it led a discussion of biasness in approximate entropy explained in literatures [22][23][24]

This biasness in approximate entropy causes lackness in two important properties. Because of this biasness ApEn becomes dependent on the length of record and it becomes lower for records which are shorter in length. And the second property it lacks in , relative consistency. Ideally if approximate entropy is higher for one dataset than the other dataset ideally it should remain higher for that particular but actually it doesnot and it remain higher for all the dataset and is tested in the following literature[23][22]. The lacking of approximate entropy in these two properties is very important to keep under consideration as approximate entropy are used for relative measuring in comparing datasets [22][24]. To overcome this shortcoming of approximate entropy another entropy measure named sample entropy has been introduce which doesn't count the matches with itself. Sample entropy is introduced by Grassberger and his fellowmen [52][9][13]. In Sample entropy the conditional probabilities –ve natural logarithm for m points the two sequences which are identical they will remain similar at the next point and in the probability calculation of sample entropy the self matches are not considered. If the value of sample entropy is low it means there are more similarities in self matches of the given sequence of time series data. Sample entropy not only reduces the self matches but also takes approximately half of the time for calculation as used by the approximate and it is independent of the length of the data and is relatively consistent in conditions where approximate entropy fails.

Sample is better over approximate entropy because it eliminates the biasness by ignoring the self matches and for calculating conditional probabilities sample entropy requires a template that find a match of length m+1. Approximate entropy becomes sensitive to outliers if biasness is removed if there is a template that doesn't match any other vector in length m , approximate entropy cannot be calculated in such cases because of presence of ln(0).

3.5. Proposed Technique – Feature extraction

3.5.1. Sample entropy:

In our research a machine learning model is proposed for the detection of epileptic seizure which uses sample entropy (SampEn) for feature extraction [37]. Sample entropy, statistical parameter which is used to measure the probability of current amplitude the values of the EEG signal on the basis of its previous amplitude to reflect the nonlinear behavior of a brain activity. This entropy is a measure of correlation and regularity if the value of sample entropy is low it means the system is more persistent, repetitive and predictive and high entropy value means more independent and less number of repetitive patterns and less randomness. And it works by dividing the series into blocks and them similarity is calculated by comparing them.

The calculation of sample entropy is dependent on 3 parameters naming (m, r, N). N represents the number of data points in a sample; m represents the bracket size which finds a match in the length m+ 1. And r is the filter/tolerance or similarity criteria. This tolerance is used as relative size used as a part of standard deviation of the N amplitudes like r* SD [43].

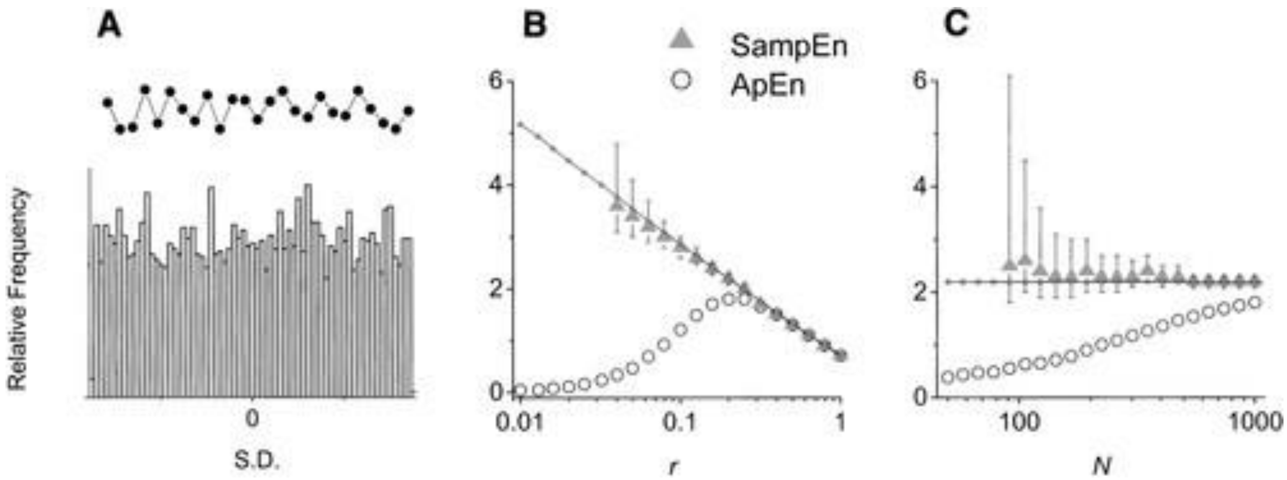


Fig 3.7 Sample entropy hyper parameters

The selection of threshold is very important in the selection of these methods and the shortcomings of these methods are their relation to the arbitrary nature of thresholds which are selected and used for detection. The threshold criteria that most popularly considered is the duration of time during which seizures occurs and channels which are affected by the seizure activity. The detection will be very challenging or possibly cannot be detected if the duration of seizure occurrence is too short or their occurrence is too localized means only few of the channels have seizures.[11].

We finalized our work with values of r = 20% of standard deviation and N=178 and m=2 because studies in different literatures suggest these parameters as best suited points for calculations. Bruce, Eugene N., Margaret C. Bruce, and Swetha Vennelaganti. In clinical neurology journal: in the official publication of Electroencephalographic Society of America 26, no.4 (2009):257. It is stated that the sample entropy helps to track the changes that occur in EEG power spectrum for the sleep states and the aging states of seizures. The hyper parameters for the sample entropy include N. N is the count of the previous predication used to calculate the value of the subsequent (m) while using the different values of r where r is the filter size. And it is also called the noise filter and is used as a part of standard deviation for the value of N amplitude. The analysis we carried out started with the parameters m=2, r=20% of standard deviation for amplitude value and N is 1024 in our case. Because from literature reviews the author (Bruce et al. 2009) mentioned and is determined that these values of m and r are best suited and suggested from time series data of brain signals.. [10,14,15] but we evaluated our system for other values of tolerance ranging from 10% to 30% of standard deviation in a separate step and m values from 1 to 3. Entropy is calculated in R on personal computer according to the following formula. The m vectors defined for sample entropy for x are given by $x_m(i) = [x(i)\ \ x(i+1)\ \ x(m+I-1)]$ where i between 0 to N-m and sample entropy in the case is given by Abel Torres[44] as

$$E_{SampEn}(m, r, N) = -\ln\frac{t^{m+1}(r)}{t^{m}(r)}$$

Where m =2
r = 0.2 * S.D
N= 178

Proposed approach is better than entropies used in previous literatures because entropy measures the rate of information that is produced so the comparison of data with itself is meaningless Grassberger et al. 199 dismissed such self matches.

3.6. Classification:

The EEG signals generated from brain and collected through ambulatory systems are usually very large and complex and their detection for the epilepsy disease activity is time taking and requires experts neurologists. As already described seizure detection for experts in few visits is not possible because these seizures can be generated at any time interval and of any length. So the traditional methods for this disease detection are very tedious and with the advancements in bio medical sciences automated systems have been introduced for disease detection through machine learning algorithms and different techniques of deep learning models have also been used for this purpose. Keeping in view these advancements and literatures we are proposing an automated system of epileptic disease detection using neural networks and machine learning algorithms. S. Liang in 2010 presented EEG-based absence seizure detection by using machine learning algorithm SVM [34]. In 2019 Y. R. Aldana presented non convulsive epileptic seizure detection in scalp EEG using multiway data analysis automated diagnostic systems for epilepsy disease detection using K- nearest neighbors, SVMs and Linear Discriminant Analysis [35]. In 2019 G.C.Jana presented performance analysis of supervised machine learning algorithms for epileptic seizure detection with high variability EEG dataset by using machine learning algorithms like SVM's and liner discriminant analysis LDA [36]. Different machine learning techniques for detection are proposed by different researchers for epilepsy disease detection and they used different number of features like average amplitude, average mean , average median , variation coefficient , average power spectrum etc. As described in above section our work purposes a single time-domain feature named sample entropy for the EEG signal and fed in SVM for classification to reflect the nonlinear behavior of brain signal's activity.

3.6.1. Sample entropy based SVM:

To the best of our knowledge the binary classification using sample entropy in machine learning with SVM as classifier have never reported before as an input. In our work we employed SVM for epilepsy disease detection. In case of binary classification the sample entropy (SamEn) values with respect to the epileptic class of EEG signal and the normal signals are feed into the SVM as an input. SVMs have ability to map the data points of input to the feature space of high dimension by using the transformations of kernels in such a way that data points are linearly separable and decision boundaries have large margins among the classes. There are decision boundaries in SVM and the points which are near to these boundaries are called support vectors. These points are used to maximize the distance. SVMs can also be optimized by using the gradients descent and their derivatives which help to plot a data in n-dimensional space as a point and n represents the number of features being used and the value of a particular coordinate represents the value of feature in the n dimensional space. Polynomial kernel of quadratic equation of second degree is used for classification task. The target values are 0 for seizure free class and 1 for seizure affected or epileptic class of EEG signal. The training of SVM is carried out on 70% of data.

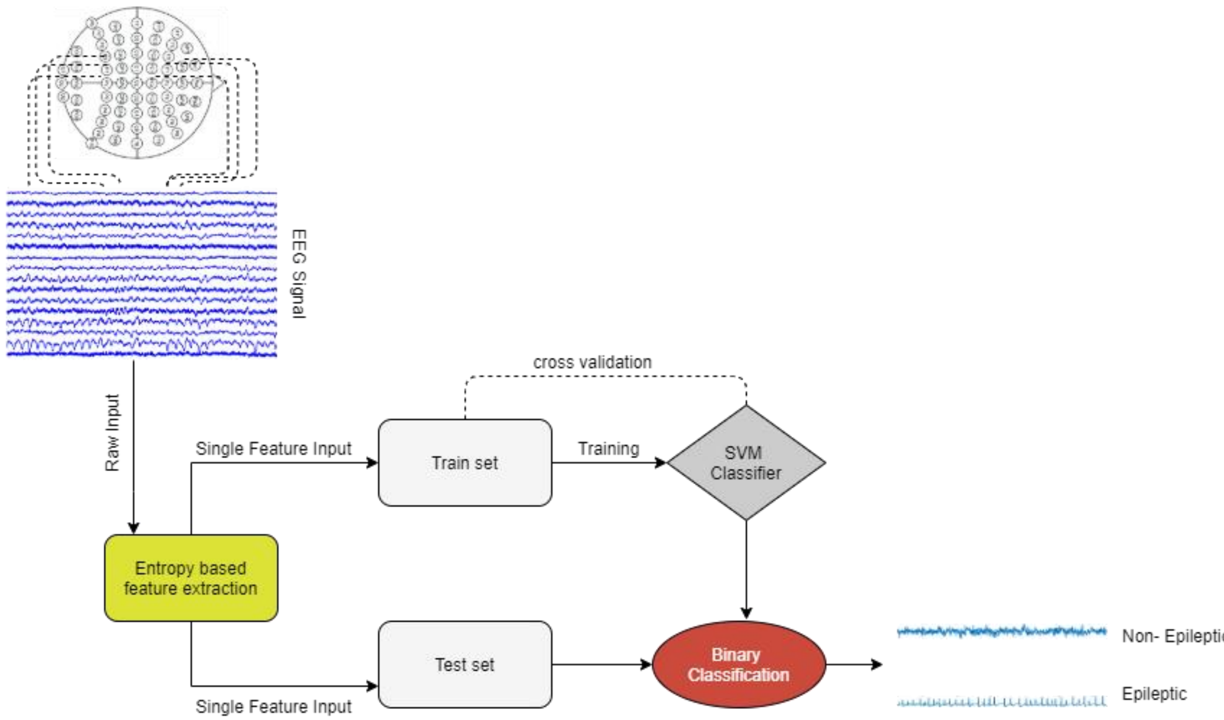


Fig 3.8 Proposed sample entropy based SVM architecture

3.6.1.1. Evaluation results:

In this research for the detection of epileptic signals we employed support vector machine performs well because a computationally low intensive feature based on entropy called sample entropy is used which is robust. The results achieved from the experiments we performed with our proposed technique shows that the accuracy achieved by our system is as high as 99.5%. Its computational burden is low because it is based on a single feature so it is best suited for real world clinical applications used for the detection of epilepsy from the signals collected by the ambulatory recordings.

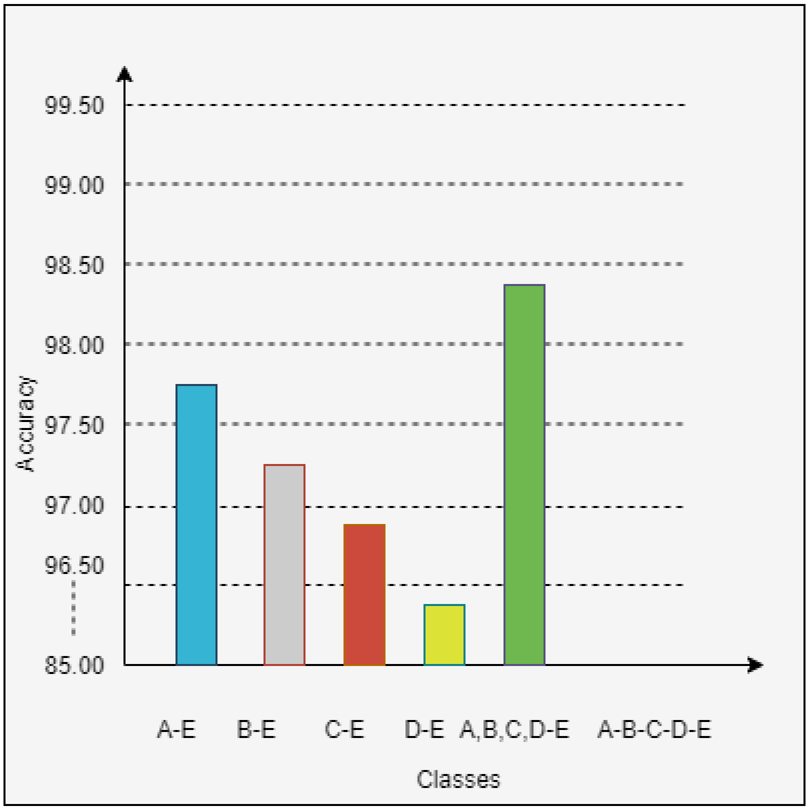


Fig 3.9 SVM binary classification results.

3.6.2. Deep learning Model:

Artificial neural network serves the purpose of classification and performs well because of their inherent features like their adaptive learning nature; their generalization capability distinguishes them from machine learning algorithms and makes them robust. They are useful and perform well in conditions where simpler classification algorithms fail to give good results. Epileptic seizure detection from EEG using different types of ANNs have been reported in several literatures [19]. To the best of our knowledge the multi classification has never been reported before. Inspiring from the successes of the artificial neural networks in time domain we chose to classify EEG for all the classes from conscious, coma, pre-ictal, post-ictal and seizure state using convolutional neural network architecture. The significance of CNN is that it captures the information of neighborhood. To reason for its importance is either in case of images or time series data is the fact that the localization of each point is important.

3.6.2.1. Convolutional Neural Networks:

CNN's ability to learn the important features makes it popular in different domains other than image classification is its ability to learn important features which are spatially invariant. Importance of CNN increases because it captures the information of neighborhood and localization of each point is very important which makes the algorithm capable to identify specific patterns regardless of their point of occurrence inspiring from CNN's localization property we proposed multi classification of time series data with CNN which sets us apart from other literatures where authors used conventional machine learning techniques like K- nearest neighbor, random forests etc. Our work shows that the combination of CNNs and the time series data of EEG eliminate the overhead of handcrafted feature extraction and allows the algorithm to learn the relevant important patterns automatically. For this purpose 1-D CNN model has been used for binary as well as multi classification.

CNN model is fed with the univariate features as an input and CNN classifies the signals for more than two channels. Sliding window is used in CNN model which helps to capture the various temporal patterns and classification is carried out on basis of those captured patterns. Challenge in classifying the EEG signals by CNN is size of sliding window to be chosen which has to extract the important patterns from the temporal data and the selection of the testing and training patterns specifically when data is unbalanced and long term time series. Sliding window size is selected on assumption that the time series data have stationary signals, so the important temporal patterns can be captured accordingly by the sliding window. We carry out a binary and multi classification using classes : ictal , inter ictal, pre ictal , post ictal and seizure period. Binary classifications has been carried out by using CNNs but they mainly focused on two classes only class A conscious state vs class E with seizures our goal is to consider the remaining three classes as well and classifying them with respect to seizure class. Class like class C that is pre-ictal class and post-ictal class have never been treated separately in the best of our knowledge by of the publication as these are the stages a moment before the seizures happen and a moment before seizures end identification of these stages separately will help us to understand epilepsy and its effects at different stages. However, this information might contribute in better understanding of disease and help in inventing treatments that can be effective during any of these stages.

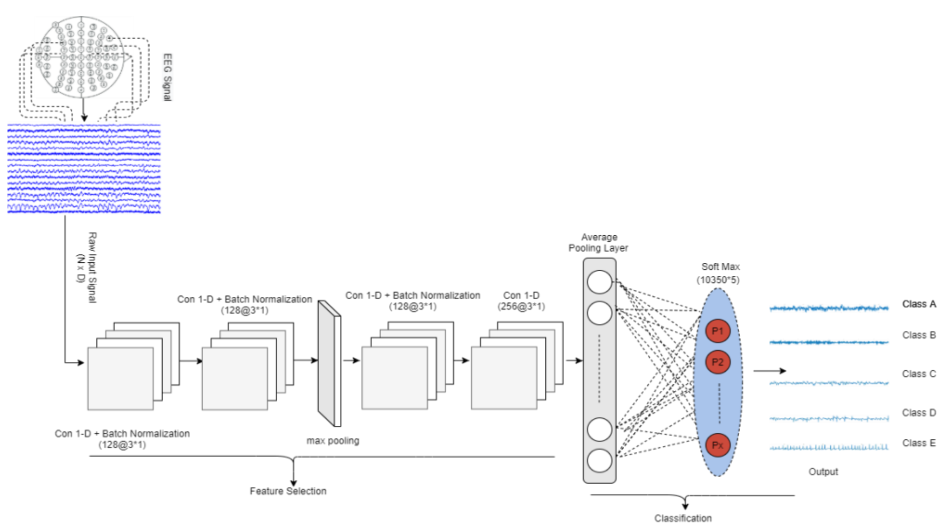


Fig 3.10 Proposed CNN architecture for classification

To carry out this classification we divided the data into testing and training set in 30 and 70 proportion and K-fold cross validation is conducted for training. Proposed CNN architecture comprises 4 sets of convolution layers, 2 sets of pooling and ReLU respectively. The number of filter is 128 and kernel is 3 and there are 5 neurons in the fully connected layer the optimizer used is Adam. Following hyper parameters are used for training which is carried out for 30 to 50 epochs: 1.0 e^-8 learning rate, size of mini batch is 32. In our work a CNN model is trained with 10 cross validations.

```
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 176, 128)          512
_________________________________________________________________
batch_normalization_1 (Batch (None, 176, 128)          512
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 174, 128)          49280
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 58, 128)           0
_________________________________________________________________
batch_normalization_2 (Batch (None, 58, 128)           512
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 56, 256)           98560
_________________________________________________________________
batch_normalization_3 (Batch (None, 56, 256)           1024
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 55, 256)           131328
_________________________________________________________________
global_average_pooling1d_1 ( (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 5)                 1285
=================================================================
Total params: 283,013
Trainable params: 281,989
Non-trainable params: 1,024
```

Fig 3.11. CNN architecture for seizure detection

In case of binary classification CNN models trains well and gives an average accuracy of 98.99% for non-seizure and seizure class.

Table.3.1. Evaluation results for CNN classification

CLASSIFICATION	Accuracy	Precision	Recall
A- E	0.9977	0.9991	0.9923
B-E	99.86%	99.87%	0.9843
C-E	0.9888	0.9992	0.9946
D-E	98.00%	99.89%	98.99%
A,B,C,D- E	99.94%	0.9995	0.9964

But in case of multi classification the accuracies drop down to 83.5% we identified the reason it happens due to vanishing of the gradient and the because of the curse of dimensionality as per knowledge neural networks serves as function approximates and the accuracies increase when the number of layers are increased. But there is a limit to increase the number of layers in any architecture as well as our goal is to propose a model suitable for real time application as the eeg signals generated from brain and collected through ambulatory systems are usually very large and complex and their detection for the epilepsy disease activity in real life is time taking and requires experts neurologists. Keeping in view these hinders we are supposed to propose an automated system of epileptic disease detection using neural networks which is less complex and time efficient increasing number of layers may improves the accuracy of system but it will directly effects the systems complexity in terms of size and time consumption. Also increasing the number of layers will start saturating the accuracy at one point and accuracy will degrade eventually. And it happens not because of over fitting to overcome this skip connections has been introduced by authors like Orhan A.E at.el 2017 and by He, K., Zhang at el. 2016. [17][18].Considering the neural block with input value of x for learning the distribution of H(x). the residual will be denoted as

R(x) = Output — Input

R(x) = H(x) — x

Rearranging to get H(x) be :

H(x) = R(x) + x

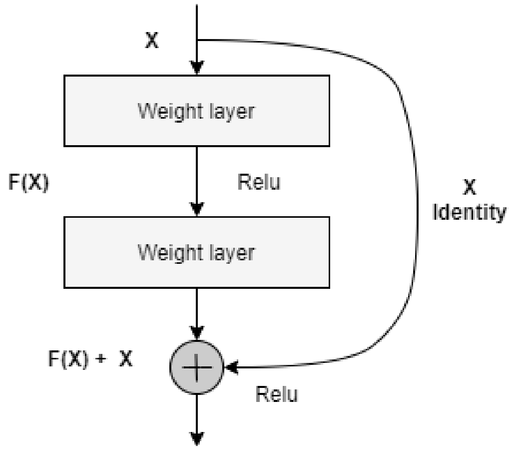


Fig 11 Skip connections introduced in CNN

The idea behind using the skip connections is to keep the flow of gradient uninterrupted and prevents the vanishing of gradient from first layer to the last layer as reported by Long. J at el. 2015 [21]. In traditional neural networks layers are learning the output H(x) actually where in case of skip connection the layers are trying to learn residual R(x). So by applying these skip connections the larger values of gradient are propagated to intial layers and these layers become capable of learning as fast as the final layers were learning which were previously not able to due to vanishing gradient. In the below diagram its represented how skip connections are arranged to make gradient flow optimal and increase accuracy for multi class. By using this our overall accuracy for multi classification improves from 87.53 % to 90.35% .

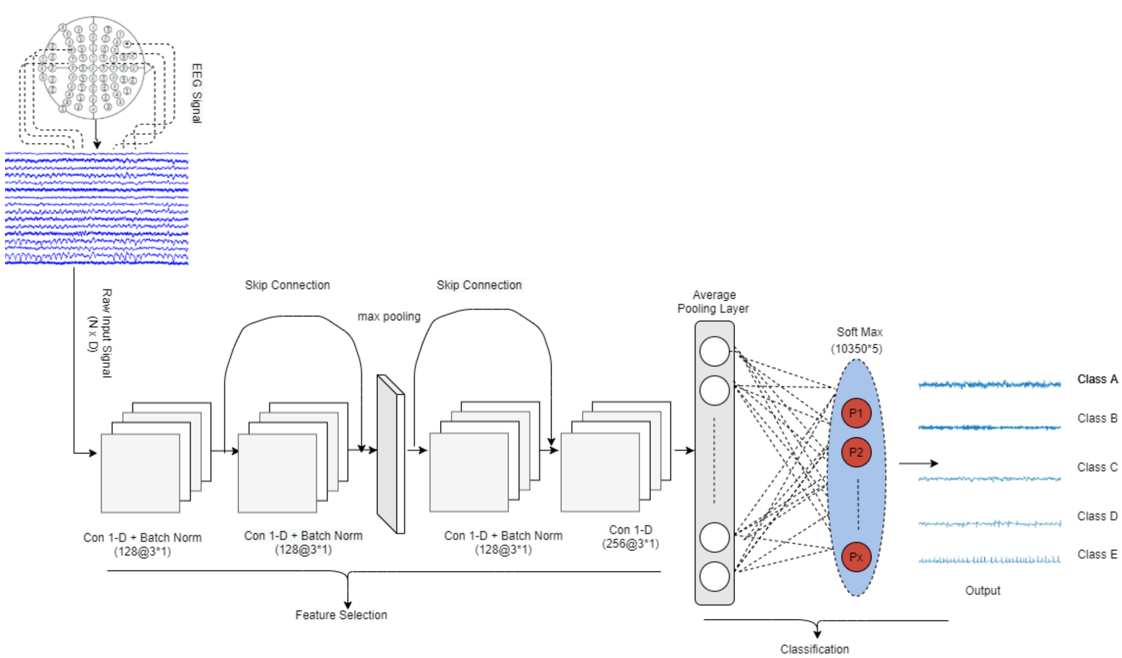


Fig 12Improved CNN architecture

Data split into 30% and 70% for testing and training respectively. The classification accuracy is calculated and analyzed is presented below:

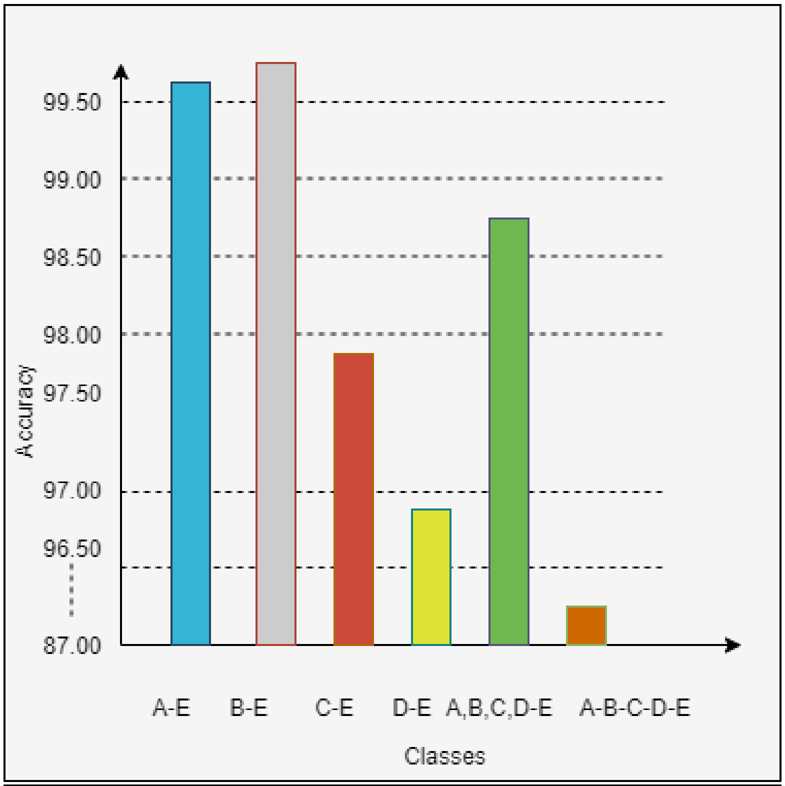


Fig 13. CNN classification Results.

3.6.2.2. Long Short Term Memory LSTMs:

Deep neural networks are extensively used for time series data like Recurrent neural networks (RNN) which are improved by introducing memory gates to them and the evolved networks called LSTMs. These networks are suited for sequential data like time series brain signals. The neurons in LSTMs not only contain the connections called weights in their successive layers but they are also present among themselves. The information provided by the previous inputs are memorized by these connections as they have special kind of gated mechanism in them. The unknown sized long time lags in the important events can be captured by LSTMs as they have an ability to learn and cater long term dependencies present in the sequential data [17].Recurrent neural networks are known as RNN and they named recurrent because their output is dependent on the computations of the previous and the same task has been performed for every element in the sequence. They have additional cells which are used for storing information they capture the information for the computed results and store them in those memory cells. RNNs performance usually drops in case of long sequences because they fail to encounter the problems like gradient explosion and gradient vanish.

LSTMs are proposed to improve the performance of RNNs and they use the gated mechanism for this purpose The gates used in LSTMs are of three types naming input, output and forget gate. The flow of information in the network is controlled by these gates. The information that needs to be allowed to flow is controlled by sigmoid functions and the point wise multiplication functions. The hyper parameters which are used to train a model are {W, Wz,U,Uz,Vz}.The number of layers used in LSTMs is the important hyper parameter that needs to be chose carefully. The single layer in the model indicates the one single output. And in the model where many to one relation it implies that multiple LSTMs input stacks infers the single output. For every pair of class the architecture's performance is considered and model is selected accordingly. For classification the LSTM model is used and we applied different number of hidden units but network succeeds in achieving the best results with 64 hidden units in one single layer and 128 hidden units in two hidden layers. Classification is carried out by using a layer of soft-max function. Complicated signals can be better handled by more complex models but such complicated models will affect their clinical implementation and use in real life applications. To make the model feasible for real life applications light-weight architectures has been proposed with less number of layers and is proved by achieving the best results on the experimental data. The trained model helps to extract the temporal features which lead to predict about different states of brain. The specific structure of the features is learnt and these features help to identify structures which are responsible for triggering specific classification.

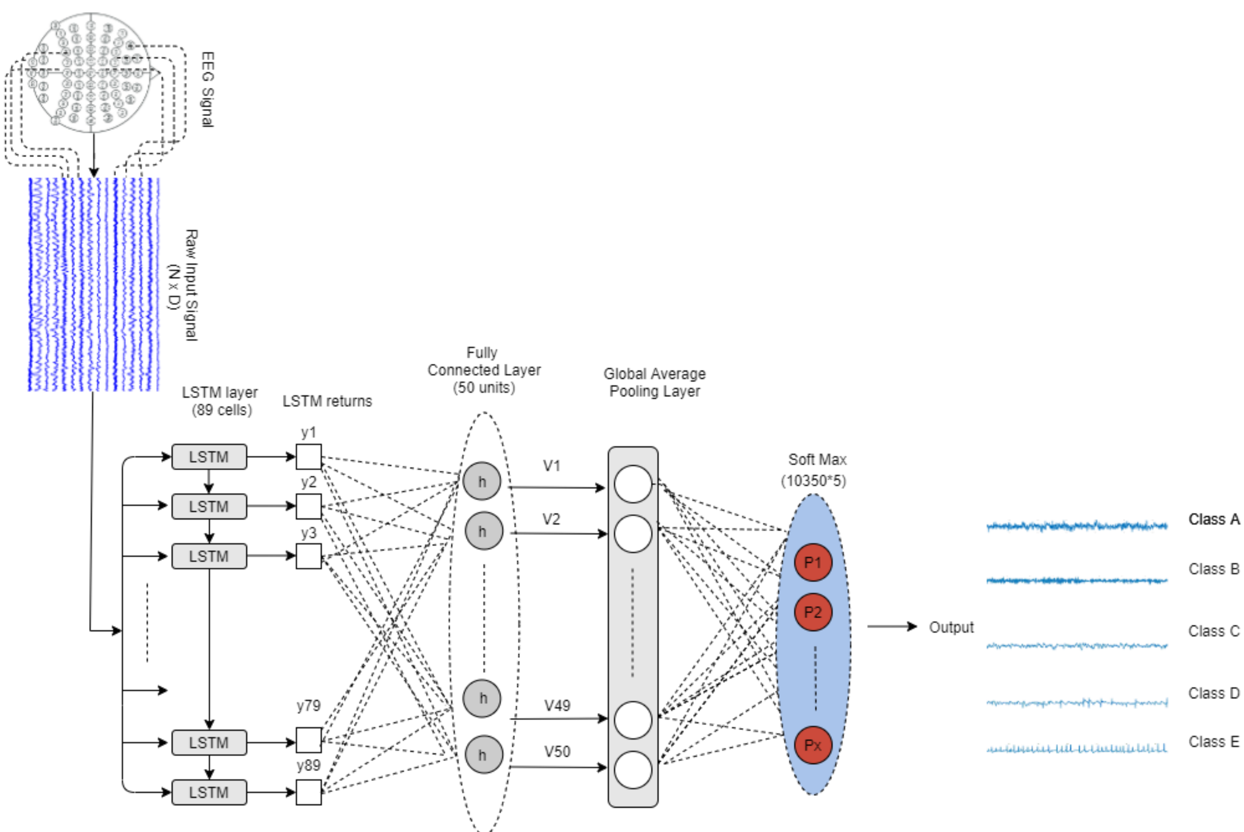


Fig 14. Proposed LSTMs Architecture .

Multi classification for the five sets of EEGs is carried out by the proposed network. All the five sets are presented in fig 3.4. The classification which is carried out for set A and set E differentiates the epileptic signals from the healthy normal signals. The input that is feed into the network is a temporal sequence of shape [10350, 89, 2]. This explains 10350 input rows with 89 time units of dimension 2.

K-fold cross validation has been adopted for the verification of the proposed architecture by checking its generalization and its robustness. The models reliability is confirmed by the cross validations [18] as it allows to verify that the data have not seen during the training process. The data split used is 70% training, 10% test data and 20% validation data and evaluation is carried out by randomly splitting the samples of each set. The validation samples are different from the tests samples in a way that during the model training phase the test samples are not seen. Average performance for each fold is considered as the test and validation accuracy of the proposed framework as we used 10 fold cross validation for this verification. The evaluation matrices used to express the performance of system for multi classification is precision, recall, F-score and confusion matrix.

The optimization of the binary cross-entropy loss function is carried out for the training of the LSTMs networks. The optimizer that is used in our model is ADAM optimizer having a learning rate 10-3 and different decay rates are also tried but system performed well for 0.9 as first momentum and 0.9999 for second momentum. Drop out is used to avoid our model from over fitting in case of small training data and 0.2 probability is used for dropout and batch size that is used is 4. 20 epochs are used for training of model and other parameters used for model training are initialized with default Keras values the weights for the hidden units of LSTMs are initialized by them[19].The input feed into lstm is reshaped into (10350,89,2) and 89 lstms cells called lstm returns are used and the output resulted is (10250,5). Softmax is used which gives the probabilities for five classes and assign the label with max probability.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_5 (LSTM)                (None, 89, 100)           41200
_________________________________________________________________
time_distributed_5 (TimeDist (None, 89, 50)            5050
_________________________________________________________________
global_average_pooling1d_5 ( (None, 50)                0
_________________________________________________________________
dense_10 (Dense)             (None, 5)                 255
=================================================================
Total params: 46,505
Trainable params: 46,505
Non-trainable params: 0
```

Fig 3.11. LSTM architecture for seizure detection

The average performance achieved by the multi fold cross validation is presented in the graph for the results. Our proposed deep learning model achieves an average accuracy of 92.54% for the validation set in all the pairs of classification tasks from A to E. The error rate and the validation accuracy for our training will be discussed in result evaluation respectively. It shows and demonstrates that features which are learnt shows clear difference in the dynamic properties of the electrical signals generated in the different regions of brain during different physiological activities.

3.6.2.3. Experimental Results:

Our proposed deep learning framework succeeds in achieving remarkably better accuracies in binary and multi classification it's architecturally less complex and light weight with a computation cost of 4.5 sec average for training purpose which is comparatively low. The performance of the system stands out among other deep learning models applied on the same data set for classification tasks as reported in [13] where the training purpose the data used is 90% in contrast we used 70% of data for training purpose on the same data set and out performed. Our proposed architecture not only perform well in deep learning but it achieves significantly higher accuracies from previously proposed machine learning models which are trained on powerful extracted features [20] and are serving the purpose of robust classifiers but these methods are relied on manual methods of feature extractions and they used specific expert knowledge which makes them less applicable in real world clinical scenarios. The maximum accuracy achieved in our experiment is for class B-E and the lowest is achieved for C-E and D-E the obtained results are same as per expectation, their dynamic properties from the epileptogenic zone during the seizure activity are more related to the ictal signals as compared to the healthy EEG segments.

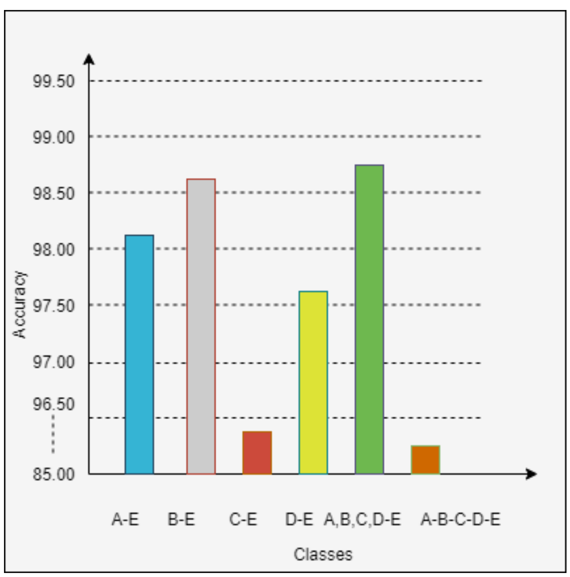


Fig 15. LSTMs classification Results.

Chapter 4

Analysis and Results

First, evaluation measures are discussed in this chapter that will be used through whole chapter for results and experiments evaluation. These evaluation measures are Accuracy, F1 score, Precision, Recall, and two different cross-validation techniques. After discussing evaluation measures, classification results of applied approaches are discussed and compared. The model that out performed is than compared with state of the art implemented models. The results are evaluated on basis on binary classification for not only epilepsy vs non-epilepsy but for NCES and CES as well. For multi classification all the five stages are considered and results are evaluated on its bases. Different evaluation metrics are calculated with best classifier and selected as best classifier. After all evaluation final results are discussed.

4.1. Evaluation Metrics

The assessment of the purposed approaches is carried out by using different evaluation matrices. This work is based on machine learning and data science. Some evaluation metrics are used as standard for this type of work [42]. These metrics are Precision, Recall, Accuracy, and F1 score. Data split into 30% and 70% for testing and training respectively. The classification accuracy is calculated and analyzed by different evaluation matrices which include:

- Confusion matrix
- Precision
- Recall
- Accuracy
- F1 Score

The prediction for each epoch belongs to the following

- True positive (TP): It represents seizure events that are correctly detected by the system(recall)

- True negative (TN): It represents the accuracy of an EEG detection system in differentiation of non-ictal events.
- False positive (FP): It is the probability of missing a seizure event
- False negative (FN): It represent ictal events that are not detected by the system

4.2. Classification Accuracy rate:

Accuracy rate is the representation of relationship between the sensitivity and specificity and is defined as [42]

Acc = sensitivity × prevalence + specificity × (1 − prevalence)

Where prevalence (PV) is the ratio of positive samples in the test population and is given by the formula

P V = TPs + TNs

TPs + FNs + TNs + FPs

Precision: It is also called positive predictive value that indicates the seizure epochs which are correctly predicted as positive by the system [42].

PPV = TPs

TPs + FPs

F1-measure: It is a harmonic mean between recall and precision and is defined as :

F1=2 × precision × recall

In problems like seizure detection for epilepsy the F1 – measure provides better evaluation metric as compared to accuracy for classification's performance because class distributions are imbalanced [42].

4.2.1. Binary classification:

In binary classification on EEG epileptic data we denoted the epochs which are seizure free as 0 and the ictal epochs are classified as class 1 with both positive and negative data samples in them. For binary classification all the possible sets for A-E including the classification of conscious state vs epileptic state, non-conscious state with respect to epileptic state, pre ictal vs ictal and post ictal vs ictal state. Comparison between all the possible states is considered because from literature reviews it's identified those seizures states have never been considered before specifically the non-conscious state and pre- ictal and post-ictal. Seizures have always been categorized as seizure vs non seizure state.

The sets considered for classification are A-E, B-E ,C-E,D-E , A,B,C,D-E from the dataset provided by the University of Bonn EEG. Binary classification is carried out by using a machine learning algorithm SVM and deep learning techniques including CNN and LSTM. The CNN models overall yields an accuracy of 0000 outperforming the LSTM and SVM at 000 and 000 respectively. in case of stage wise classification CES and NCES state the overall accuracy of all the three models outperformed and achieves as accuracy of 99.0+0.1

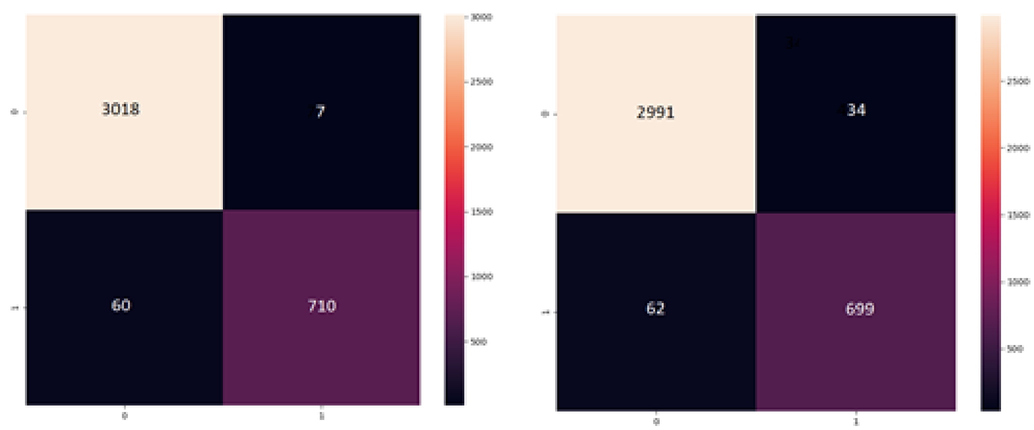


fig 4.1: Confusion metrics for binary classification of LSTM and CNN

The dataset of Bonn University deep learning as well as machine learning classifiers they achieved a perfect score for precision 100% which is highly appreciable and recommended in the their real time medical application. However it can be attributed that the high precision score is achieved due to size of data set that is small. But the good precision score implies that the classifiers performance is highly dependent on its recall.

Table 4.1: Classifier Results for binary classification

Classes	SVM	CNN	LSTM
A-E	97.77	99.77	98.11
B-E	97.39	99.86	98.53
C-E	96.91	97.88	97.02
D-E	96.46	96.63	97.61
A,B,C,D-E	98.45	98.76	98.62

All the three classifiers are used for binary classification and it is analyzed from the results that CNN outperformed for all the classes where LSTMs surpass the accuracy by 0.09% in class of post ictal vs ictal class. For pre ictal and post ictal stage with respect to ictal state overall accuracy of all the three models drops down as expected because the these two stages are highly relevant to the ictal stage and the false positive rate increased in this case.

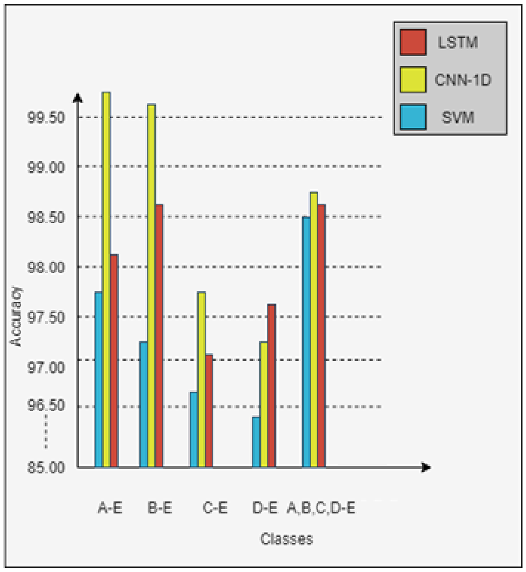


Fig 4.2. Classification Results for applied techniques.

Fig.4.2. shows the results of each model in graphical form for the easier understanding and comparison Since the results does not differ a lot in case of LSTMs and CNNs and the difference noticed is small , the results shows CNN are considered as superior classifier for the problem where they need to classify the ictals pre and post state since LSTMs use back propagation for their training which makes an algorithm iterative where CNN learns and trains faster.

4.2.2. Multi classification:

In multi- classification all the five classes including ictal , post ictal , pre ictal , NCES and CES seizure are considered and classification is carried out by using deep learning models LSTMs and CNNs. The deep learning frameworks become capable in achieving the accuracies on average 87.5% and for CNN and LSTM respectively. The accuracies drop for the pre ictal and post ictal which directly implies that these cases are difficult to diagnose for classification. These cases clearly invites for further investigation. It is notified that the CNN is the only classifier whose performance remains reasonable for all the cases in the dataset. Since the results of both the classifiers in case of multi classification are improved for the dataset provided by the University of Bonn in terms of precision and accuracy which can be observed in the fig4.3 of their confusion matrices that the trained models are prone to over fitting.

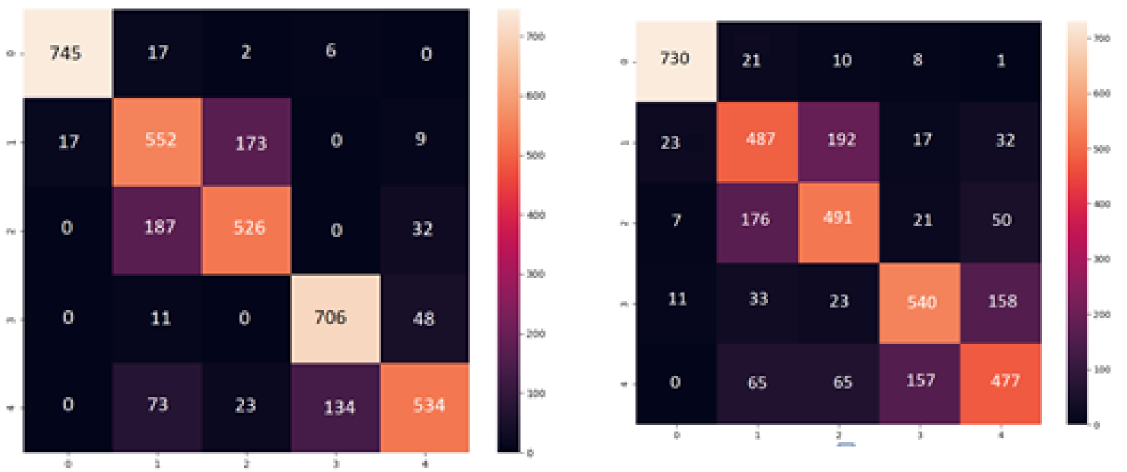


fig 4.3: Confusion metrics for binary classification of LSTM and CNN

Table 4.2: Classifier Results for multi classification

Classes	CNN	LSTM
A-B-C-D-E	88.53%	85.66%

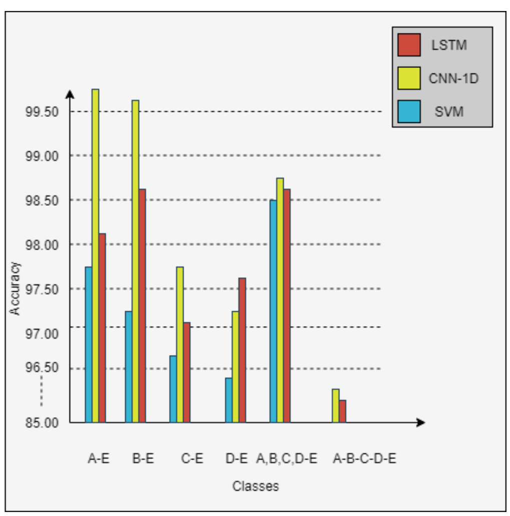


Fig 4.4: Classifier Results for Multi classification

Our applied approaches have been validated by using different tasks of classification. In binary classification all the classes have been classified with respect to E ictal class. In multi classification five classes (A/B/C/D/E) systems have been evaluated over them. the experimental classifications are repeated thrice to emphasize on performance's stability and strength of the systems. The average results of evaluation accuracies of proposed systems in comparison to the state of the art approaches have been presented in table 4.3. The table shows that the proposed systems outperformed and best classification tasks are obtained by using the CNNs in every case. In binary classification tasks, the results reported by the K. Samiee et al. on the same data set by using the discrete wavelet transform for feature extraction and extracted 32 features and applying the for classification they achieved and accuracy of 97.40% for Multilayer perceptron although other machine learning algorithms have also been implemented by them like naive Bayes, support vector machine (SVM), logistic regression, K-nearest neighbors . The V. Srinivasan uses the technique of approximate entropy for feature extraction as single feature input to artificial neural network and achieves an accuracy of 99.90% that surpasses our accuracy in case of LSTMs and SVMs and the author L. Guo uses wavelet energy technique for extraction of features and artificial neural networks are applied for classification and it achieves an accuracy of 95.2% and the author s. Erturk spectral power bands for imaged based CNN classification of EEG signals and achieves an accuracy of 99.54% for binary classification.

The authorC. Fatichah uses discrete wavelet transform for feature extraction and fuzzy neural networks are applied for classification and they achieved an accuracy of 99.5%. For multi classification as the best of our knowledge of the author has ever classified all the five classes of epilepsy this approach of classifying all the five classes is the novel contribution of our research ternary classification has been carried out by authors U. Orhan achieves an accuracy of 96.79% by using multi-layer perceptron's and k-means clustering and classified the three classes by considering classes A/D/E only. The author A. M. Abdelhameed achieves an accuracy of 99.33% for ternary classification by using theone-dimensional deep convolutional auto encoder for feature extraction and applied multi-layer perceptron's and LSTMs for classification. Below table summarizes the result comparison of our applied approaches and the previous works done the same dataset provided by the University of Bonn.

Table 4.3: Classifier Results in comparison to literatures.

Classes	**Accuracy**				
	K. Samiee et al.	S. Erturk et al.	V. Srinivasan et al.	**Our Approach**	
	Acc	Acc	Acc	Acc	Model
A- E	90.00%	99.54%	99.90%	99.77%	CNN
B-E	96.80%	-	-	99.86%	CNN
C-E	96.30%	-	89.30%	97.88%	CNN
D-E	97.70%	-	-	96.63%	LSTM
A,B,C,D- E	97.40%	-	-	98.76%	CNN
A-B-C-D-E	--	--	--	88.53%	CNN
Feature extraction	DSTFT	SPB	AppEn		

4.3. Results and Discussion:

In our research, neural networks of two types mainly, LSTMs and CNNs are implemented for the epileptic seizure detection. Experimental results show that the applied techniques succeed in achieving the significantly high accuracies as compared to the previous approaches specifically in case of multi classification and the overall accuracies as high as 87.53% is achieved by CNN's for multi classification and 99.94% for binary classification. Our proposed machine learning model uses a computationally low and a more robust entropy based single feature which is called SampEn, in our best knowledge which has not been used so far. As in general complexity of the model is increasing exponent with the number of features. As in our research, a single entropy based feature i.e. sample entropy which has never been reported before for EEG time series data used and SVM's binary classification achieved 98.77% accuracy our introduced methodology is based on a single feature which lowers down the computational load on the system and that is why it's more applicable for real-time clinical applications of epileptic seizure detection provided by the ambulatory recordings. Multi classification has been carried out for all the five classes thus different stages of Epilepsy can be detected which might contribute in better understanding of disease and help in inventing treatments that can be effective during any of these stages. On the basis of overall classification accuracy obtained, the efficiency of model and the computational power of system it is found that our proposed approaches achieved more accuracies as compared to the previous state of the art systems for the EEG time series space.

Chapter 5

Conclusion and Future Work

This chapter contains brief explanation about the work, that has been accomplished and how the research objectives were achieved along with brief discussion of the significance of this research has been explained. In the end, limitations and future work has been indicated further improvements.

5.1. Conclusion:

Brain diseases are one of the most commonly spreading diseases in current era. Due to technological advancements in medical science, the survival rate for patients is increasing day by day, but still many people die due to lack of timely diagnosis and detection of disease. To timely detect the various symptoms of epilepsy, variety of research has been carried in the past decade. A large number of researchers have proposed a variety of ways to detect the epilepsy as epileptic and non-epileptic. However detection in different stages of epilepsy including pre ictal , post inctal and especially conscious state seizures and non-conscious stage seizures have been ignored. This research is carried out to specifically identify the seizures in comma or absence state because NCES causes no focal seizure symptoms hence it cannot be analyzed visually such long term activity in a brain of a coma patient may cause life time brain damage or even cause death and to extract complete information of epilepsy from EEG five stages including convulsive epileptic seizures , Non convulsive epileptic seizures (NCES) , pre-ictal stages and post ictal stages which have never been categorized thus hinders the power to actually understand these signals as different stages of Epilepsy. However, these different stages of epilepsy can might contribute in better understanding of disease and help in inventing treatments that can be effective during any of these stages. Different Machine learning and deep learning's CNN played its part in the detection of epilepsy. Various machine learning algorithms such as K-Nearest Neighbors (K-NN), Support Vector Machines (SVM), Decision Trees and Random Forest etc. aid to learn trends available in the signals on manual extraction of features including different techniques like wavelet extractions and entropy based features

As fulfillment of clinical requirements and standards is necessary for the classification and analysis of long-term epileptic EEG records and this is a challenging problem because of that. Firstly, each of the EEG detection system should give high true-positive rate and false alarm rate at minimal. Furthermore, as the availability of annotated data for each patient is which doesn't allow the deployment of advanced supervised machine learning models such as CNNs and LSTMS. Also, due to the high variability of EEG signal patterns and the non-stationary behavior of EEG signals, non-patient and generic specific models may affect the performance. When it comes to machine learning, when the extracted features' dimension is higher in comparison to the number of available samples in the training set, the curse of dimensionality phenomenon can occur. When we talk about binary classification of multi-channel EEG records in which the annotated data is limited, this phenomenon is mostly leads to the over-fitting of the model. Enhancement of the discriminatory power of conventional feature extraction techniques is aided by using a single entropy-based feature of EEG signals, by doing this these problems are investigated and have been addressed. In classification of multi-channel EEG records, the curse of dimensionality problem is addressed in the proposed method [P3], by lowering the number of extracted features from input EEG space. In a patient-specific classification task of epileptic long-term EEG records of BONN data-set, the proposed feature extraction method was examined for its effectiveness by observing a minimal training rate of 25% in the dataset. For the proposed epileptic detection system, a computationally low-intensive and robust feature known as SampEn has been used. With the increasing number of features, the complexity of the model is increasing exponentially. A single entropy-based feature, which has never been reported before for EEG time-series data used in the proposed research and binary classification of SVM achieved 98.77% accuracy. High precision, accuracy and recall obtained by the proposed solution, for the semantical analysis of the irregularity and chaosity of non-icatl and ictal EEG signal patterns for CES and NCES. . A compressed and compact representation of multi-channel EEG records is provided by the proposed feature extraction methods in this thesis, which is suitable for discrimination and classification techniques. Furthermore, the curse of dimensionality phenomena is eradicated and classifier is aided to find each class's distribution by using limited number of extracted features.

5.2. Limitations and Future work:

Raw data is directly given to CNN and other deep learning techniques for additional analysis. Though, in non-epileptic EEG classification problems, the proposed LSTMs method failed to outperform state-of-art results while CNNs succeed and perform better in multi classification. In the classification of the single-channel epileptic EEG time series, the application of such a system can be investigated. Despite the superior classification performance and lower reconstruction MSE of the proposed solution compared to standard STFT, to evaluate the effectiveness of RSTFT in a real-world application with a lower training rate and long-term multi-channel EEG recordings, the research must be conducted further. In multi classification results, the proposed solution out-performed the state-of-art methods. Above that, proposed feature extraction method is evaluated for the robustness and it is demonstrated in classification in which 25% randomly selected data used for training the model. The delay in seizures and its Extensive computational cost are the main drawbacks of these systems. Although the performance of the proposed methods were shown in coma stage and epilepsy detection, in the future, the scope of the application is not limited to those addressed in this thesis and can be extended further for the analysis of other brain activities, such as restoration and rehabilitation, prediction and prevention, wearable devices and on-board diagnostics, BCI, event-related potentials (EPR), media recommendation systems and social interaction.

References:

1. http://www.meb.unibonn.de/epileptologie/science/physik/eegdata.html.
2. K. Samiee, P. Kovács and M. Gabbouj, "Epileptic Seizure Classification of EEG Time-Series Using Rational Discrete Short-Time Fourier Transform," in IEEE Transactions on Biomedical Engineering, vol. 62, no. 2, pp. 541-552, Feb. 2015, doi: 10.1109/TBME.2014.2360101
3. Aydın, Serap, Hamdi Melih Saraoğlu, and Sadık Kara. "Log energy entropy-based EEG classification with multilayer neural networks in seizure." Annals of biomedical engineering 37, no. 12 (2009): 2626.
4. V. Srinivasan, C. Eswaran and N. Sriraam, "Approximate Entropy-Based Epileptic EEG Detection Using Artificial Neural Networks," in IEEE Transactions on Information Technology in Biomedicine, vol. 11, no. 3, pp. 288-295, May 2007, doi: 10.1109/TITB.2006.884369.
5. M. Fan and C. Chou, "Detecting Abnormal Pattern of Epileptic Seizures via Temporal Synchronization of EEG Signals," in IEEE Transactions on Biomedical Engineering, vol. 66, no. 3, pp. 601-608, March 2019, doi: 10.1109/TBME.2018.2850959.
6. R. Ozcan and S. Erturk, "Seizure Prediction in Scalp EEG Using 3D Convolutional Neural Networks With an Image-Based Approach," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 11, pp. 2284-2293, Nov. 2019, doi: 10.1109/TNSRE.2019.2943707
7. Y. Yuan, G. Xun, K. Jia and A. Zhang, "A Multi-View Deep Learning Framework for EEG Seizure Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 1, pp. 83-94, Jan. 2019, doi: 10.1109/JBHI.2018.2871678.
8. P. Xanthopoulos et al., "A novel wavelet based algorithm for spike and wave detection in absence epilepsy", Proc. IEEE Int. Conf. Bioinformat. Bioeng., pp. 14-19, 2010.
9. Grassberger, Peter. "Finite sample corrections to entropy and dimension estimates." Physics Letters A 128, no. 6-7 (1988): 369-373.
10. Pincus SM, Goldberger AL: Physiological time-series analysis: What does regularity quantify? Am J Phsiol 1994, 266:H1643–56Pincus, SM Goldberger, AL
11. E. S. Kollialil, G. K. Gopan, A. Harsha and L. A. Joseph, "Single feature-based non-convulsive epileptic seizure detection using multi-class SVM", Proc. IEEE Int. Conf. Emerg. Trends Commun. Control Signal Process. Comput. Appl., pp. 1-6, 2013.
12. Y. Li, X. Wang, M. Luo, K. Li, X. Yang and Q. Guo, "Epileptic Seizure Classification of EEGs Using Time–Frequency Analysis Based Multiscale Radial Basis Functions," in IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 2, pp. 386-397, March 2018, doi: 10.1109/JBHI.2017.2654479.

13. Ben-Mizrachi, Avraham, Itamar Procaccia, and Peter Grassberger. "Characterization of experimental (noisy) strange attractors." Physical Review A 29, no. 2 (1984): 975.
14. Pincus SM, Gladstone IM, Ehrenkranz RA: A regularity statistic for medical data analysis. J Clin Monit 1991; 7:335–45Pincus, SM Gladstone, IM Ehrenkranz, RA
15. Pincus SM: Approximate entropy as a measure of system complexity. Proc Natl Acad Sci USA 1991; 88:2297–301Pincus, SM
16. P. Sharma, Y. U. Khan, O. Farooq, M. Tripathi and H. Adeli, "A wavelet-statistical features approach for nonconvulsive seizure detection", Clinical EEG Neurosci., vol. 45, no. 4, pp. 274-284, 2014.
17. Orhan, A. E., & Pitkow, X. (2017). Skip connections eliminate singularities. arXiv preprint arXiv:1701.09175.
18. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
19. V. P. Nigam and D. Graupe, "A neural-network-based detection of epilepsy", Neurol. Res., vol. 26, pp. 55-60, 2004.
20. M. K. Kiymik, A. Subasi and H. R. Ozcalik, "Neural networks with periodogram and autoregressive spectral analysis methods in detection of epileptic seizure", J. Med. Syst., vol. 28, pp. 511-522, 2004.
21. Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).
22. Pincus, S. (1995). Approximate entropy (ApEn) as a complexity measure. Chaos: An Interdisciplinary Journal of Nonlinear Science, 5(1), 110-117.
23. Pincus, Steven M. "Quantifying complexity and regularity of neurobiological systems." In Methods in Neurosciences, vol. 28, pp. 336-363. Academic Press, 1995.
24. Pincus, S. M., Cummins, T. R., & Haddad, G. G. (1993). Heart rate control in normal and aborted-SIDS infants. American Journal of Physiology-Regulatory, Integrative and Comparative Physiology, 264(3), R638-R646.
25. Grassberger, Peter, Thomas Schreiber, and Carsten Schaffrath. "Nonlinear time sequence analysis." International Journal of Bifurcation and Chaos 1, no. 03 (1991): 521-547.
26. Eberlein, Matthias, Raphael Hildebrand, Ronald Tetzlaff, Nico Hoffmann, Levin Kuhlmann, Benjamin Brinkmann, and Jens Müller. "Convolutional neural networks for epileptic seizure prediction." In 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2577-2582. IEEE, 2018.
27. M. Eberlein et al., "Convolutional Neural Networks for Epileptic Seizure Prediction," 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Madrid, Spain, 2018, pp. 2577-2582, doi: 10.1109/BIBM.2018.8621225

28. Bruce, Eugene N., Margaret C. Bruce, and Swetha Vennelaganti. "Sample entropy tracks changes in EEG power spectrum with sleep state and aging." Journal of clinical neurophysiology: official publication of the American Electroencephalographic Society 26, no. 4 (2009): 257.
29. R. Dogaru and I. Dogaru, "A Convenient Method for Learning to Classify Biomedical and Other Complex Signals based on Neuronal Boolean Complexity," 2019 11th International Symposium on Advanced Topics in Electrical Engineering (ATEE), Bucharest, Romania, 2019, pp. 1-4.
30. N. Ghassemi, A. Shoeibi, M. Rouhani and H. Hosseini-Nejad, "Epileptic seizures detection in EEG signals using TQWT and ensemble learning," 2019 9th International Conference on Computer and Knowledge Engineering (ICCKE), Mashhad, Iran, 2019, pp. 403-408.
31. M. Z. Abedin, S. Akther and M. S. Hossain, "An Artificial Neural Network Model for Epilepsy Seizure Detection," 2019 5th International Conference on Advances in Electrical Engineering (ICAEE), Dhaka, Bangladesh, 2019, pp. 860-865.
32. G. C. Jana, A. Sabath and A. Agrawal, "Performance Analysis of Supervised Machine Learning Algorithms for Epileptic Seizure Detection with high variability EEG datasets: A Comparative Study," 2019 International Conference on Electrical, Electronics and Computer Engineering (UPCON), ALIGARH, India, 2019, pp. 1-6.
33. S. Ramakrishnan, A. S. Muthanantha Murugav
34. el and P. Saravanan, "Epileptic EEG Signal Classification using Multi-class Convolutional Neural Network," 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), Vellore, India, 2019, pp. 1-5.
35. S. Liang, W. Chang and H. Chiueh, "EEG-based absence seizure detection methods," The 2010 International Joint Conference on Neural Networks (IJCNN), Barcelona, 2010, pp. 1-4, doi: 10.1109/IJCNN.2010.5596856
36. Y. R. Aldana, B. Hunyadi, E. J. M. Reyes, V. R. Rodríguez and S. Van Huffel, "Nonconvulsive Epileptic Seizure Detection in Scalp EEG Using Multiway Data Analysis," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 2, pp. 660-671, March 2019, doi: 10.1109/JBHI.2018.2829877.
37. G. C. Jana, A. Sabath and A. Agrawal, "Performance Analysis of Supervised Machine Learning Algorithms for Epileptic Seizure Detection with high variability EEG datasets: A Comparative Study," 2019 International Conference on Electrical,
38. Electronics and Computer Engineering (UPCON), ALIGARH, India, 2019, pp. 1-6, doi: 10.1109/UPCON47278.2019.8980115.
39. H. Demuth and M. Beale, Neural Network Toolbox, Natick, MA:MathWorks, 2000.
40. V. Srinivasan, C. Eswaran and N. Sriraam, "Approximate Entropy-Based Epileptic EEG Detection Using Artificial Neural Networks," in IEEE Transactions on

Information Technology in Biomedicine, vol. 11, no. 3, pp. 288-295, May 2007, doi: 10.1109/TITB.2006.884369.

41. Cao, Yuzhen, Yixiang Guo, Hui Yu, and Xuyao Yu. "Epileptic seizure auto-detection using deep learning method." In 2017 4th International Conference on Systems and Informatics (ICSAI), pp. 1076-1081. IEEE, 2017.
42. P. Xanthopoulos et al., "A novel wavelet based algorithm for spike and wave detection in absence epilepsy", Proc. IEEE Int. Conf. Bioinformat. Bioeng., pp. 14-19, 2010.
43. http://cs229.stanford.edu/section/evaluationmetrics.pdf.Evaluationmetrics.2018.
44. Delgado-Bonal, Alfonso, and Alexander Marshak. "Approximate entropy and sample entropy: A comprehensive tutorial." Entropy 21, no. 6 (2019): 541.
45. Sarlabous L, Torres A, Fiz JA, Jané R. Evidence towards improved estimation of respiratory muscle effort from diaphragm mechanomyographic signals with cardiac vibration interference using sample entropy with fixed tolerance values. PLoS One.