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Detection of Neurological Disorder Epileptic Seizures Using Various Approaches: A Review

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Abstract: Epilepsy is a serious, persistent neurological disorder that may be detected via brain signals generated by brain neurons. The abnormalities in the brain that cause epileptic seizures can have a negative impact on a patient's health. It appears all of sudden and shows no symptoms, that further increases the death rate of people. Nearly 1% of people worldwide experience epileptic seizures. Over the years, a number of techniques have been researched, put forth, and created. For the purpose of signal transmission and internal organ communication, neurons are closely coupled to one another. Electrocorticography (ECoG) and electroencephalography (EEG) media are typically accustomed to discover these brain impulses. These signals generate a large amount of data and are complicated, noisy, non-linear, and non-stationary. These restrictions on automated interictal spike and epileptic seizure identification, a crucial tool for closely reviewing and analyzing the EEG data, are recommended. These limitations draw our attention to a study of automated methods that may classify signals into epileptic and nonepileptic categories for neurologists. This paper presents a review on the primary difficulties that are observed during the implementation of epilepsy prediction algorithms, the paper also provides various feature selection and classification techniques.

Keywords: Neurological Disorder, Epilepsy, Seizure Detection, Machine Learning, Deep Learning.

1. INTRODUCTION

Diseases affecting the central and peripheral nerve systems are referred to as with mental conditions. Muscle twitching, seizures, trembling, and paralysis, clumsiness, along with lack of consciousness are some of the typical symptoms. The nerve system is affected by more than 600 disorders. The terms "epilepsy" which is derived from the Roman and Greek words "epilepsia" and signify "seizure" or "to seize upon." Seizures are frequently recurrent due to this severe neurological illness, which has recognisable characteristics. Epilepsy is discussed in the more than three-thousand-year old Babylonian treatise on medicine. In addition to humans, this disease also affects rats, dogs, and cats as well as other animal species.

One of the most complex acute no communicable brain illnesses, epilepsy can afflict anybody at any age, irrespective of gender or ethnicity, and seizures can occur in people of any age. People with epilepsy have several difficulties in their normal everyday lives. They must exercise the appropriate level of care given this disease. A patient may suffer injury or perhaps be put in danger of dying when they experience a seizure, especially if they work with heavy machinery or operate automobiles. Nearly 1% of the global total suffers with epilepsy, and even in affluent nations, 80 out of every 100,000 individuals are newly diagnosed with the condition each year [4], [6]. Epilepsy may severely affect a person's life in some way for psychological and social concerns. It occurs more frequently in grownups and young children. Males are somewhat more likely than females to experience it. Although epilepsy cannot be cured, it can be managed with medicine and other methods.

Multiple seizures experienced by a patient are the major sign of epilepsy. It causes a sudden breakdown or unusual brain activity that causes a patient's behavior, feelings, and momentary loss of consciousness to shift uncontrollably. Aura-less seizures can happen at any time and can last

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anywhere from a few seconds to a few minutes. Burns, fractures, and occasionally even mortality are brought on by this, among other serious traumas.

A abrupt aberrant, A self-sustaining electrical discharge that happens in the cerebral networks and normally lasts for less than a few minutes is what epileptic seizures are known for (ES).ES Attacks are challenging to foresee, and neither their severity nor length can be predicted. Patients and their families are therefore extremely concerned about the events' injuries and safety concerns. Early epilepsy event detection is therefore crucial for preventing and reducing its detrimental effects. The section of the publication that discusses these terms in further detail [4].

Depending on the symptoms, neurologists categorize seizures into the generalized and partial groups depicted in Fig. 1. Sometimes called a "focal seizure," a partial seizure involves only a portion of the brain only impacts one side of the brain. A partial seizure can be of two different types: simple-partial and complex-partial. A patient in the simple-partial is conscious but unable to talk coherently. A "focal impaired awareness seizure" occurs when a person has a complex-partial, they start acting strangely, like chewing and muttering, and they get disoriented about their surroundings. Generalized seizures, in contrast, quickly damage every part of the brain and dismantle whole brain networks. Despite the fact that generalized seizures come in a variety of forms, they may typically be categorized into two groups: convulsive and non-convulsive.

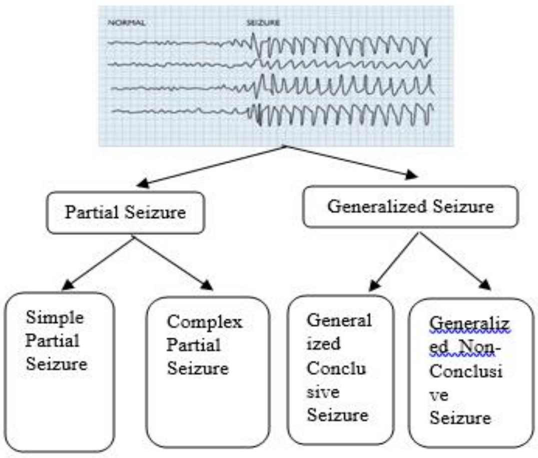

Fig 1: An illustration of seizure types and their subtypes

In epilepsy research, electroencephalogram (EEG) data are mostly utilised to track abnormalities in the brain caused by seizures. An electroencephalogram is a useful, unobtrusive method that is frequently used to evaluate brain activity and analyse epilepsy. Either a human or automatic process can be used to complete this. It is difficult and time-consuming to identify an expert's seizure also seizure length in an EEG recording. To evaluate an EEG recording for a single seizure victim, one frequently requires hours or even days of data. It can take less time for clinicians to examine EEG data and make an offline diagnosis if an automated seizure detection technology is available. So, it is very important to have automated seizure activity detection. Multiple sophisticated tests that demand time and effort are required for epilepsy identification from an input EEG signal.

Among the most typical and severe brain disorders, epilepsy impacts about 70 million people globally. [1]. It has an impact on 1% of people under the age of 20 as well as 3% of those over the age of 75 [2]. Epilepsy sufferers are constantly a little afraid of having an episode in public. They have anxiety when driving, travelling alone, or engaging in any activity that might personally harm them. They also feel restricted in their ability to live their lives freely. Some treatments are required for epileptic patients in order to better their condition and protect them from any harm. Over the last few decades, machine learning (ML) has spread across a variety of study fields by employing statistical approaches to discover patterns in massive datasets. For healthcare researchers, a fresh page is being opened with the accessibility of substantial amounts of biological data. The improvement of machine learning algorithms and data analysis approaches are essential for the development of useful medical solutions. As medical data's complicated nature makes manual representation identification difficult, ML is widely used in healthcare for disease diagnosis [7]

The study provides a brief overview of techniques that have been suggested and used to identify seizures in EEG recorded data. The paper was divided into many pieces; in Section 1, a fundamental overview of the issue and its causes were covered. A brief review of the literature on various methods is provided in Section 2. Multiple publicly accessible datasets for study are described in Section 3 along with their descriptions. The comparative analysis and difficulties of the current system are covered in Part 4 and 5 along with future developments and directives in Section 6, and concluding observations in Section 7. The final section contains several references.

2. LITERATURE SURVEY

Researchers are working to implement artificial intelligence as well as machine learning approaches for improving clinical practice as these technologies improve. Early illness diagnosis and prediction are important goals in healthcare to be able to offer timely preventative measures. This is particularly accurate with epilepsy, which is characterised by unexpected and repeated episodes. If epileptic seizures could be foreseen in any way, patients would be spared the negative effects that they would otherwise experience. Seizure prediction is still a challenge despite decades of research. Due to the insufficient quantity of data available to address the issue, this is expected to continue, at least in part. early and precise epileptic seizure prediction may undergo a cognitive shift as a result of fascinating brand-new innovations in machine learning-based algorithms. In this, K. Rasheed et al. [4] offer a thorough analysis of contemporary ML methods for early seizure prediction utilising EEG inputs.

In this investigation, Marzieh Savadkoohi et al. [5] look at the characteristics of the electrical activity in the brain in various physiological conditions and recording areas for seizure detection. The findings will be helpful to neurophysiologists in the prompt and precise identification of epileptic seizures in their patients. The signals in this study were extracted from 23.6 s segments of 100 single-channel surface EEG recordings produced at a sampling rate of 173.61 Hz. Five healthy volunteers recorded their signals with their eyes closed and open, while five epilepsy patients recorded their intracranial EEGs during both seizure-free periods and epileptic episodes.

In the design suggested by Michele Lo Giudice et al. [6], a CNN is used to conduct an EEG time-frequency transformation along with a classification step. With 94.4% accuracy, As a result of CNN distinguish between participants with ES also subjects with PNES in their EEG data. Comparing CNN to conventional learning algorithms, it demonstrated strong performance in the given binary classification (multi-layer perceptron, support vector machine, linear discriminant analysis and quadratic discriminant analysis). Information theoretical investigation was done to comprehend how CNN accomplished this performance. In particular, the two classes' feature maps' permutation entropy (PE) was assessed and compared. Although preliminary, the results obtained support making advantage of these cutting-edge methods to assist neurologists in making early diagnosis.

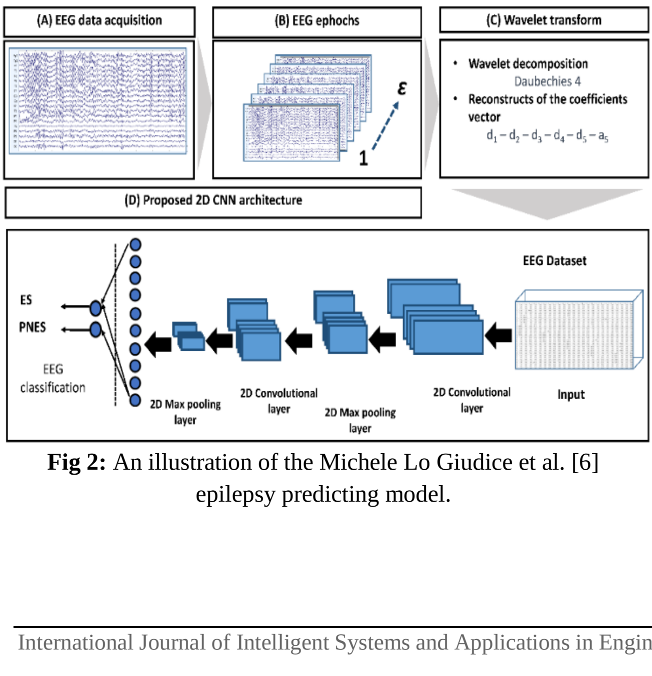

Fig 2: An illustration of the Michele Lo Giudice et al. [6] epilepsy predicting model.

One of the most essential targets in healthcare is to identify as well as to forecast disease early so that preventative therapies may be given when they are most effective. This is particularly true when it comes to epilepsy, which is characterised by recurrent and unpredictable seizure activity. If epileptic seizures could be predicted beforehand, patients may be saved from the numerous negative effects of them. Despite years of study, seizure prediction is still a problem. This is possible to continue, at least in part, since there isn't enough information to solve the issue. A rush of recent advancements in machine learning-based algorithms has the potential to revolutionise the industry's paradigm. The authors of this study, Andhale Praveen, and Dr. Varsha [7], looked at both machine learning methods for predicting epileptic seizures and the body of existing research on epileptic seizures. In EEG analysis, feature selection, ES detection as well as prediction, and thus the assessment of prediction or detection approaches, ES prediction is a vast issue. In contrast to what this study's results show, the bulk of earlier review articles concentrated mainly on EEG analysis, with just a small number including the development of prediction algorithms.

To identify ictal, preictal, and interictal segments for epileptic seizure identification, Mengni Zhou et al. [8] used a convolutional neural network utilizing raw EEG signals as opposed to manual feature extraction. In order to examine the potential of these parameters, authors contrasted the results of time and frequency domain signals in the identification of epileptic signals using the intracranial Freiburg and scalp CHB-MIT databases. The viability of this strategy was investigated using three different types of trials with two binary classification issues (interictal vs. preictal and interictal vs. ictal) and one three-class problem (interictal vs. preictal vs. ictal). Average detection accuracies for the three trials were 96.7, 95.4, and 92.3% for frequency domain signals in the Freiburg database while they were 95.6, 97.5, and 93% for detection in the CHB-MIT database. The average accuracies in the three studies employing time domain signals from the Freiburg database were 91.1, 83.8, and 85.1%, however the corresponding values for the CHB-MIT database were only 59.5, 62.3, and 47.9%. These findings demonstrate that frequency domain signals may be used to efficiently detect the three scenarios. Only a few patients, however, are able to successfully identify the three situations utilising time domain signals as input samples. Ultimately, the author asserts that In contrast to signals in the temporal domain, frequency domain signals have substantially better classification accuracy.

While drugs can control widespread epileptic seizures, surgery is the preferred treatment for people with focal epilepsy. The failure of these drugs to prevent epileptic seizures has been documented to occur in more than 30% of instances, resulting in mishaps and a shorter life expectancy for the patient. The prediction of seizures with increasing accuracy remains a difficulty, despite the fact that several researchers have suggested approaches that employ machine and/or deep learning methodologies a way to anticipate epileptic seizures applying scalp EEG information. As a result, Muhammad Haseeb Aslam et al. [9] suggest a three-step procedure. It incorporates scalp EEG data preparation using the PREP pipeline, a more complex option than straightforward notch filtering. This strategy classifies interictal state and preictal state segments employing LSTM in order to anticipate seizures, then employs a regression-based strategy to increase the SNR. It combines manually created statistical characteristics such temporal mean, variance, and skewness with automatically generated features utilizing CNN. On the CHB-MIT scalp EEG dataset, the suggested approach achieves accuracy of 94%, sensitivity of 93.8%, also specificity of 91.2%.

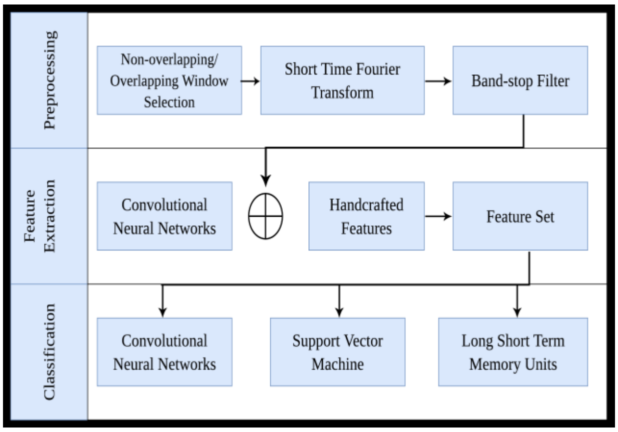

Fig 3: Schematic representation of the Muhammad Haseeb Aslam et al. [9] epilepsy predictive model.

To create the best characteristics for seizure forecast, Pinto et al. [10] constructed a particular (patient-oriented) predictive model with an optimization method using additional data from patients who had temporal lobe seizures that had been recorded. This study serves as a proof-of-concept for the use of EA in seizure prediction. By taking into account the synergy between characteristics and every stage of the pipeline, performance beyond the level of chance was attained for a sizeable portion of patients (32%) while retaining interpretability. It was feasible to construct a number of executions for 89% of patients for all investigated pre-ictal periods, those were statistically significant, which offers us optimism in this technique even if in each of the three pre-ictal stages, only 32% of patient models outperformed the chance level. The real-time application of this methodology is light and straightforward: light pre-processing and feature extraction processes are proceeded by the use of a logistic regression. Just the most recent 4 h preceding each seizure were used because the training phase of this technology could be computationally costly. However, the suggested technique is performed better from other methodologies employing data from the same database in regards of FPR/h and sensitivity, which may point to the need for more complicated models. For a total of 710 hours and 49 seizures of continuous process recording, logistic regression-based classifiers were tested and thoroughly confirmed. According to the findings, seizure occurs in the signal, which may assist the acceptance of changes in brain signal processing and, eventually, result in seizure prediction algorithms

By converting one-dimensional EEG data into two-dimensional EEG pictures using ResNet-50, a subtype of convolutional neural networks, George et al. [11] introduced an automatic seizure detection system that classifies the EEG data into ultimately ictal, nonictal, and preictal categories. The current model predicts an upcoming seizure using this pioneering strategy with a 94.98% accuracy rate. This illustrates that using a deep neural network to analyse EEG data and forecast an epileptic seizure is an effective strategy.

In order to detect seizures in ten paediatric patients at least thirty seconds before they begin, M. Dedeo and M. Garg [12] developed amethod for locating important preictal sites and their associated frequencies in the high gamma range of 30 to 100 Hz utilising data from the MIT Physionet EEG database gathered at the Children's Hospital Boston. The next step is to assess the potential predictive power of event-related potential analysis in this high gamma band, to offer evidence that detection algorithms should take a patient's frequent frequency extremes' variable strengths into consideration, as well as offering evidence that patient-specific machine learning algorithms may be more beneficial in the detection of juvenile seizures given that they are harder to detect than adult seizures. By implementing high gamma band signal processing at the places suggested by this approach, it may be feasible to significantly increase the effectiveness of machine learning detection algorithms on paediatric patient data, which is susceptible to issues caused by algorithmic limits.

It is important to take into account because of preictal along with interictal patterns might differ significantly between patients as well as within the same patient, from one seizure to the next and from hour to hour. Therefore, seizure detection techniques tailored to the needs of the patient function better. The findings of this study also demonstrate that the issues mentioned above are unimportant because the patients' EEGs were analysed using sophisticated signal processing techniques, and evidence of preictal seizure activity was found in all 50 preictal epochs in nine out of ten patientsWe must handle a drop in EEG scalp electrode channels as well as a decrease in processing resources to train the time-series signal if a seizure prediction system is to become a workable option. Anibal Romney and V. Manian [13] present Model Agnostic Meta-Learning (MAML) applied to a Deep Neural Network as an improved patient-specific channel reduction for seizure prediction. Each patient's channel count in the CHB-MIT Dataset, which includes 23 patients were chosen and optimised by the authors. Employing Ensemble Empirical Mode Decomposition also Sequential Feature Selection, the feature vectors are retrieved (SFS). To categorise the limited EEG data produced from the fewer subject-dependent electrodes, we utilised the MAML model. The findings of the experiment show that sensitivity and specificity are, on average, 91% and 90%, respectively. Using only a few EEG scalp electrodes, our study reveals that MAML is a potential method for learning EEG patterns to anticipate epileptic episodes.

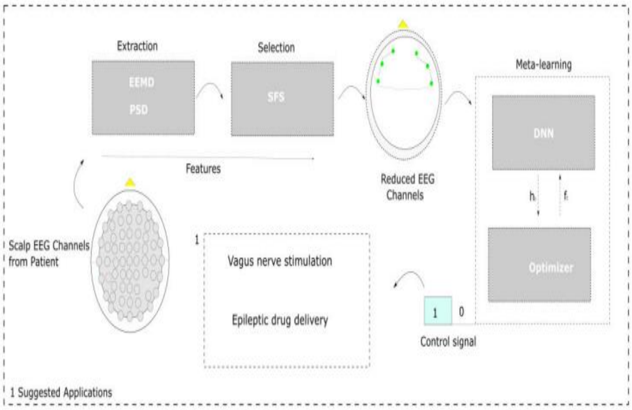

Fig.4 Romney And V. Manian [13] suggested model implemented on each of the 23 patient EEG recordings.

An innovative deep-learning method for identifying seizures in paediatric patients is proposed by Ahmed Abdelhameed and Magdy Bayoumi [14] and is predicated on the categorization of raw multichannel EEG signal recordings that have undergone little processing. In order to achieve the highest classification accuracy over the ictal and interictal brain state data, the unique technique integrates a two-dimensional deep convolution autoencoder (2D-DCAE) with a neural network-based classifier. Two prototypes were constructed and evaluated for testing and assessing our method utilising three distinct EEG data segment lengths and a 10-fold cross-validation procedure.

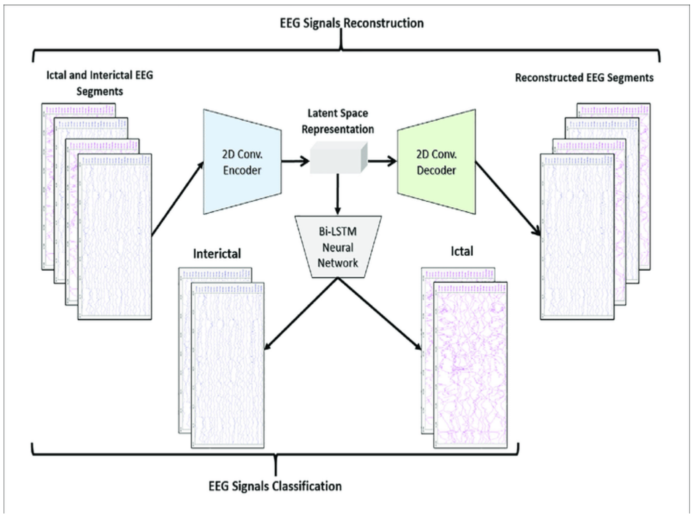

Fig 5: Schematic representation of Abdelhameed and Magdy Bayoumi [14] the two-dimensional deep convolutional neural network-based seizure detection systems

A supervised deep convolutional autoencoder model with a bidirectional long short-term memory based classifier and an EEG segment length of 4 s had the greatest performance based on five assessment measures. This model has 98.79 0.53% accuracy, 98.72 0.77% sensitivity, 98.86 0.53% specificity, 98.86 0.53% precision, and an F1-score of 98.79 0.53% using the public dataset gathered from the Children's Hospital Boston as well as the Massachusetts Institute of Technology. According to these findings, the suggested method was able to offer one of the most successful seizure detection techniques when contrasted to other state-of-the-art techniques already in use when applied to the same dataset.

In their work, Rasheed et al. [15] used transfer-learning (TL) to assess how well four renowned deep learning (DL) frameworks performed at predicting epileptic seizures. Methods: An approach that generates synthetic data using DCGAN trained on actual EEG data in a patient-specific manner was proposed by RASHEED et al. We use convolutional epileptic seizure prediction and one-class SVM to evaluate the quality of the generated data (CESP). Using an average of 10 minutes between accurate prediction and seizure onset samples, we assess the effectiveness of the VGG16, VGG19, ResNet50, and Inceptionv3 trained on augmented data using TL. Results: For training on synthetic datasets and testing on real Epilepsy ecosystem and CHB-MIT datasets, the CESP model obtains sensitivity of 78.11% and 88.21%, and false prediction rates of 0.27/h and 0.14/h, respectively. Inceptionv3 achieved the maximum accuracy with TL and enhanced data, with a sensitivity of 90.03% and 0.03 FPR/h. Inceptionv3 and CESP model prediction outcomes improved by 4-5% using the suggested data augmentation method compared to state-of-the-art augmentation strategies. The results of CESP demonstrate how well synthetic data acquired associations between features and labels, and how well CESP predicted for both datasets using enhanced data. Relevance: The suggested DCGAN can be utilised to produce synthetic data to improve prediction accuracy and get around the lack of high-quality data problem.

The goal of Xinwu Yang et al. [16] research is to explore the time-frequency correlation of characteristics derived from multi-channel EEG signals in order to provide a general strategy for forecasting seizures in specific patients. By using the short-time Fourier transform (STFT), the authors transform the raw EEG data into spectrograms that represent time-frequency properties. For the first time, Xinwu Yang et al. propose a dual self-attention residual network (RDANet) that combines a channel attention module that exploits the interdependence between channel mappings with a spectrum attention module that integrates local features with global features to improve forecasting performance. For 13 patients from the public CHB-MIT scalp EEG dataset, the suggested method had a sensitivity of 89.33%, a specificity of 93.02%, an AUC of 91.26%, and an accuracy of 92.07%. Longer or shorter EEG signal prediction segments have a considerable impact on prediction accuracy, according to the author's research.

A fully defined model for automated seizure prediction is put out by Ines Assalia et al. [17] based on stability state analysis and autoregressive multivariate modelling from actual and simulated electroencephalography (EEG) data. This method creates a stability index whose content analysis allows for the crisis to be predicted. The neuro-computer platform TVB (The Virtual Brain: www.thevirtualbrain.org), This records 29 crises for 8 individuals from a freely accessible database using Epileptor as a mass neural model for white matter and the "John Doe" matrix as grey matter. Along with 14 virtual patients are used to validate this method. According to early research by Ines Assalia et al., the eight true cases had an average forecast time of 237.21s, a detection accuracy of 97.87%, and a sensitivity of 100%.

The CHB-MIT dataset (all 24 cases) used by Dorsa EPMoghaddam et al. [18] comprises scalp EEG recordings. The suggested approach is grounded in the idea of random matrices. After denoising the data with wavelet decomposition, analyse the spatial coherence of the epileptic recordings by looking at the width of the covariance matrix Eigen value distribution at different time and frequency bins. Main effects. Support vector machine classifiers that are patient-specific have been trained to distinguish among interictal and preictal data exhibiting excellent results with a false prediction rate as minimal as 0.09 h1. The suggested method obtains average values of 99.05% accuracy, 93.56% specificity, 99.09% sensitivity, and 0.99 for the area under the curve. According to the author, the suggested technique has a low percentage of incorrect predictions while outperforming cutting edge research with regards of sensitivity. Furthermore, suggested technique offers great sensitivity without impacting interpretability, in contrast to neural networks, which may attain high performance.

An electroencephalogram (EEG)-based seizure detection system using the discrete wavelet transform, Hjorth parameters, statistical characteristics, as well as a machine learning classifier is proposed by Md Abu Sayeed et al. [19] inside the IoT framework. Two steps go into the seizure detecting process. The DWT decomposes EEG signals into sub-bands in the first step, and characteristics (activity, signal complexity, and standard deviation) are retrieved from each of these sub-bands. The EEG data is categorised using a deep neural network (DNN) classifier in the second stage. The hardware-in-the-loop technique was used to implement a prototype of the suggested neuro-detect. The findings show a substantial difference among interictal and ictal EEG in terms of HP values, with ictal EEG being less complicated than interictal EEG. This method claims 98.6% accuracy for classifying normal and interictal EEG as opposed to ictal EEG and 100% accuracy for classifying normal vs ictal EEG.

The proper interpretation of an electroencephalogram (EEG) signal might take considerable years of training due to its complexity. Deep learning (DL), which has the ability to create effective feature representations from unstructured data, has recently demonstrated considerable promise in aiding in the understanding of EEG signals. However, it is yet unclear if DL actually offers advantages over more conventional EEG processing techniques. Yannick Roy et al. [20] assess 156 publications that use DL to analyse EEG in this study. These papers span a variety of application fields, including epilepsy, sleep, brain-computer interface, and cognitive and emotional monitoring, and were published during January 2010 and July 2018. For the purpose of guiding future research and formulating suggestions, the author seeks to identify trends and highlight intriguing ideas. For each investigation, many pieces of information were retrieved about the 1) data, 2) pre-processing technique, 3) DL design options, 4) outcomes, and 5) repeatability of the trials. Thousands of hours to fewer than 10 minutes' worth of EEG data were used throughout research, according to our findings. Convolutional neural networks as well as recurrent neural networks, both of which typically have 3 to 10 layers, were utilised in 40% of the studies' models, respectively. Additionally, almost half of the research used raw or previously processed EEG time data to train their models. Therefore, across all pertinent trials, the median accuracy improvement from DL techniques over baselines from conventional methods was 5.4%. But more crucially, they discovered that research frequently suffer from poor reproducibility: the majority of articles would be difficult or impossible to repeat given the lack of access to their data and source code. In order to advance the area, a list of suggestions for more research was supplied. Additionally, a summary table of articles on DL and EEG was made accessible, and the community was encouraged to participate.

In-depth reviews of approaches to machine learning for seizure detection have been provided under this study. Mohammad Khubeb et al. [21] come to the conclusion that decision forests (an ensemble of decision trees) are the most efficient "non-black-box" classifiers. This is due to the fact that it may generate several logical rules that are clear and explain situations well. Additionally, it can aid in learning about crucial facts including seizure kinds and seizure localisation.

This investigation's objective is to evaluate the effectiveness of many well-known machine learning algorithms for predicting epileptic seizures in relation to the impacts of imbalance and balancing datasets. Kemal Akyol et al. [22] employed RUS and ROS algorithms on the original dataset to obtain balanced datasets in order to achieve this goal. In order to equalise the class distribution, the ROS approach randomly replicates data from minority classes. For certain machine learning algorithms, the danger of overfitting is increased by this process. The RUS technique, on the other hand, equalises class distribution by randomly removing the dataset's samples from the dominant class. Overall tests revealed that due to the dataset not being overfit, RF and SVM techniques on the ROS used dataset got good accuracy. With the exception of RF, the RUS technique resulted in information loss and lower performance of other algorithms. Despite RUS reducing the amount of samples in the dataset utilised for this investigation, the RF method performed effectively.

3. ACCESSIBLE DATASETS

The study dataset is challenging and important for assessing how well the intended strategy is working. Multiple electrodes are arranged in a certain way to collect the brain impulses used in the seizure/epileptic stroke detection procedure, known as the EEG. These collected signals are utilised to locate the seizure and are vital in accurately determining the patient's status. A publicly accessible dataset serves as a good standard for evaluating and contrasting the outcomes. An overview of several publicly accessible datasets is given in this section for researchers.

3.1 CHB-MIT

The physionet server website (CHBMIT) hosts and provides access to the Children's Hospital Boston dataset. The physionet server is used in conjunction with Cygwin utilities to swiftly collect data. This dataset includes EEG recordings that have been precisely categorised as "seizure" and "seizure free." There are 23 patients in all, 17 females and 5 boys between the ages of 1 and 19. Every patient has a unique recording of their seizures and nonseizures in the.edf file format. These signals all have a 1D size and are captured at a sampling rate of 256 Hz.

3.2 THE FREIBURG

There are 21 individuals in this dataset of EEG recordings, eight of whom are men between the ages of 13 and 47 and thirteen of whom are women between the ages of 10 and 50 who suffer from physically focused epilepsy. Before the epilepsy check itself, it was observed by certain medical observations at the Freiburg Hospital's Epilepsy Checking Center.

3.3 BONN DATASET

It is divided into five pieces, each denoted by a letter from A to E. Each segment has 100 single-channel footages, each of which is 23.6 seconds long and was recorded using the universal 10-20 electrode positioning framework. Using a comparable 128-channel amplifier arrangement, signals are recorded.

4. RESEARCH FINDINGS

Study Overview						
Sr.No	Study	Dataset	Classifier	Sensitivity	Specificity	Accuracy
1.	Michele Lo Giudice et al. [6]	CHB-MIT	CNN	-	-	94.4%
2.	Mengni Zhou et al. [8]	CHB-MIT	CNN	95.6%	97.5%	93%
		Freiburg	CNN	96.7%	95.4%	92.3%
3.	Muhammad Haseeb Aslam et al. [9]	CHB-MIT	LSTM,CNN	93.8%	91.2%	94%
4.	George et al. [11]	CHB-MIT	ResNet-50	-	-	94.98%
5.	Anibal Romney And V. Manian [13]	CHB-MIT	DNN	91%	90%	-
6.	A.Abdelhameed and M.Bayoumi [14]	CHB-MIT	Bi-LSTM	98.72%	98.86%	98.79%
7.	Rasheed et al. [15]	CHB-MIT	DCGAN	78.11%	-	90.03%
8.	Xinwu Yang et at. [16]	CHB-MIT	CNN, ResNet	89.33%	93.02%	92.07%
9.	Ines Assalia et at. [17]	CHB-MIT	Autoregressive multivariate modelling	100%	-	97.87%
10.	EPMoghaddam et al. [18]	CHB-MIT	SVM, KNN	99.09%	93.56%	99.05%

5. CHALLENGES

Despite recent advancements in the identification and categorization of epileptic seizures, there are still obstacles that prevent further study, including, among others, the accompanying:

- The dataset used for investing epileptic seizures are collected from different sources and they are available but merging these dataset is challenging for researchers so as to merge many datasets to produce a substantial dataset for training the model since each has a multiple sampling frequency, a varied number of electrodes, plus variable characteristics.

- Clinical datasets are typically not made accessible to the public, and many datasets only include chosen EEG signal segments, making them unsuitable for real-world applications in which detection must always be performed from real-time signals.
- Frequently, feature values may vary depending on how the brain is acting. Therefore, it is difficult to choose the right characteristics and do the appropriate computations for identifying seizure no seizure and preseizure.
- To implement real-world applications in a clinical setting, real-time data must be employed for detection and classification; However, it is difficult to capture real time data.
- Another issue that makes it challenging to compare algorithms with similar performance is the absence of uniformity across the produced algorithms.
- The lack of long-term EEG data is a major challenge in the ES prediction and analysis studies.

6. FUTURE DIRECTIONS

This survey paper offers a thorough analysis of methods for identifying and detecting epileptic seizures. From classical methods to the more current deep learning application, there has been great improvement over the years. To effectively integrate and enhance these generated models, various problems have been found and raised, which have led to some intriguing research issues that still need to be answered. Here are some recommendations for advancing future research.

- The epileptic seizure datasets are huge and have a high dimension; therefore, it is necessary to further research dimensional reduction approaches that may minimize the dataset dimension while preserving the important signal information.
- It is recommended to take into account suitable characteristics that reduce the computational complexity and processing time of the classifier. Application of the right classifier and the right feature selection can achieve the desired results.
- Convolutional neural networks can be used to identify epileptic seizures since they integrate feature extraction and classification, speeding up the process and lowering computational complexity in the process.
- There should be a lot more research towards hybrid deep learning algorithms.

7. CONCLUSION

This study looked at and reviewed a number of automated EEG seizure detection and classification methods. It is important to note that previous researchers have put a lot of work into finding the best characteristics that are helpful for correct classification. Each electrode placed to the skull produces various numerical measurements, thus it is extremely important also challenging to pick the efficient as well as appropriate features. In contrast side, to achieve high accuracy of seizure categorization, several studies have combined two or more characteristics. Since choosing the best classifier is difficult, they are tested and assessed using a variety of datasets, which brings us to our final point regarding classifier selection. According to the literature, prior researchers employed SVM, KNN, CNN, and ANN among other approaches. A random forest classifier, moreover, produces findings for seizure detection that are very accurate, according to the research. Additionally, we have highlighted research challenges that need more study as well as future work directions.

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