Machine learning approaches for the prediction and detection of epilepsy

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Abstract:

The one of the most difficult factors associated with epilepsy is the unanticipated nature of seizures triggered by epilepsy. The techniques which can identify tremors before several minutes of its occurrence, may be helpful in reducing the harmful effects of seizure and even can reduce the sudden death rate. Thus, early detection of seizures can enhance the quality of life of an epileptic patient.EEG has been utilized for forecasting seizures by employing contemporary computer tools, artificial intelligence, and deep learning techniques. despite this, ambient noise can contaminate EEG readings, and artefacts like flickers of the eye and contractions of the muscles can cause "bumps" in the signal that result in electromagnetic interference that is difficult to see for more-duration recordings. These restrictions on computerized interictal peak and epileptic attack identification, a crucial tool for closely studying and analyzing the EEG data, are recommended. The deep learning models in this research aim to enhance epileptic seizure detection using a Field Programmable Gate Array (FPGA) implementation of the quick Fourier transform interfere with.For detection of seizures, the following steps have been taken: (1) time-frequency evaluation of EEG portions using STFT; (2) collection of spectrum bands and characteristics that are of interest; and (3) seizure identification by using a convolutional neural network, and bilateral transient-term memory with long-term retention. This brief overview also makes suggestions for how neurological doctors should actively work to achieve advancements in EEG-based ML seizure detection.

Keywords: Electroencephalography, artificial intelligence (AI), Epilepsy and machine learning (ML), seizure onset zone (SOZ).

Introduction:

People with epilepsy experience seizures that aretriggered by an abnormality in brain activity[1].The third most prevalent type of brain illness is epilepsy [2]. A genetic mutation, which produces abnormal neuronal behavior or neuronal migration, is one of the many potential causes of epilepsy.Despite the fact that epilepsy's underlying origin is still unknown, early detection can aid in treatment. Medication or surgery are two therapy options for epilepsy patients. [3] If epileptic seizures are anticipated early, there will be ample time to administer medicine to avoid them. The preictal state, the ictal state (which starts after the postictal phase of an early seizure and ends before the beginning of the ictal phase of a subsequent seizure), the ictal phase (which starts after the postictal phase of the early seizure), and the postictal state (which begins after the ictal state and all conditions that occur before the seizure begins) are the four main phases of epileptic convulsions [4].

Seizure Prognosis:

It is the method of distinguishing between the pre-ictal and inter-ictal stages in detection of seizure. It is also referred to as anticipating seizures.Epileptic seizures may be anticipated by studying the onset of a preictal phase. Epileptic convulsion forecasting uses artificial intelligence learning methods. These replicates comprise the gathering of EEG data, pre-screening, function, and types of convulsive phase. Threshold-based methods looks at a high/low variance in the levels of a specific spotlight over the pre-ictal stage to predict seizures.

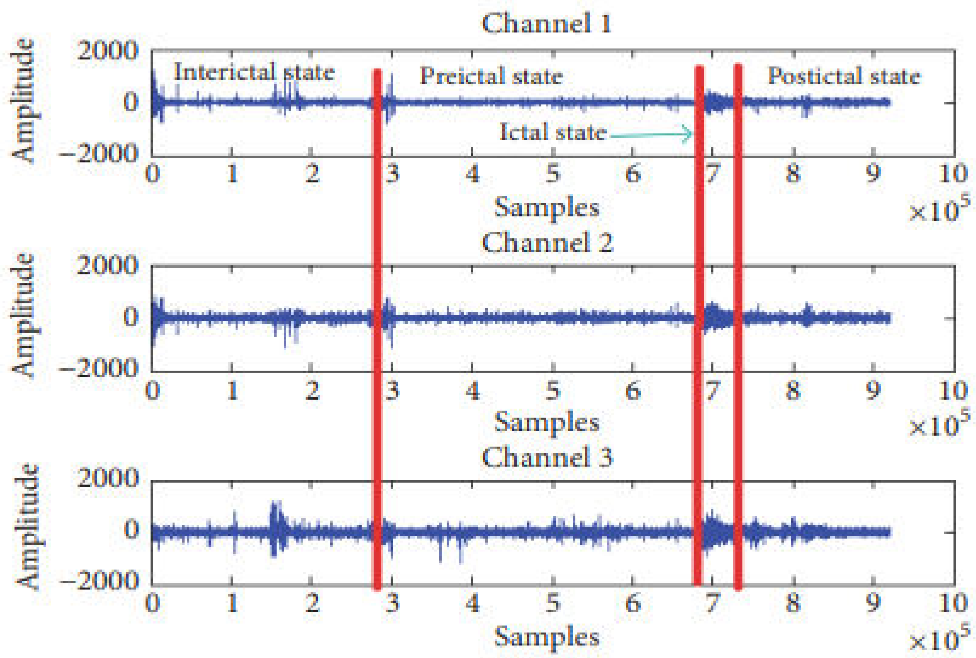

FIGURE 1: States of epileptic seizure.

(Usman Syed et.al;2017, States of epileptic seizure) [51]

EEG signal's raw data can also be used to perform the classification procedure. The threshold value of the attributes affects the seizure's prognosis. An alert is sounded to warn of an impending seizure if the estimated characteristics' value exceeds the activation value (pre-ictal value).[5] The prediction and management of epileptic seizures frequently use modern machine learning techniques or deep learning methodologies. Researchers frequently employ both SVM and the Adaptive Neural Network (ANN) [5,7,8,9]. These systems classify the EEG signal data based on attributes that are obtainedfrom the EEG recordinganalysis. Thepostictal and ictal phases are typically not included in the research by deep knowledge procedure that is used in therapeutic imaging and signal screening because they are inefficient for seizure prediction [6,5,7,8,9,10,11]. The main factors are powerful computing and vast amounts of data, which frequently have a significant impact and importance. Convolutional Neural Network (CNN), which performs better in the field of image processing, can be used to anticipate seizures [8]. Not only are the seizure prediction algorithms reliable, but they may also be used in real-time. Enhancing true positive rates and forecast times requires pre-screening and features obtained from EEG signals.Pre-processing of the EEG signal removes the noise and unwanted components.A major advantage of pre-screening EEG signals is the improvement of Signal-to-Noise Ratio (SNR). The Common Spatial Pattern (CSP) and a large Laplacian filter are just two of the filters that researchers use to pre-process the EEG data. Some machine learning methods, such as the discrete cosine transform (DCT), fast fourier transform (FFT), and plot theory, are done for the functional extraction procedure. Using classifiers like SVM and Least Squares SVM (LS-SVM), the EEG signal was studied to find a seizure signal [12].

These artificial intelligence techniques include EEG data capture, categorization, feature extraction from the waveforms, and signal preprocessing [13]. Neuroimaging methods includeelectroencephalography (EEG), electrocorticography (ECoG), single-photon emission computerized tomography (SPECT), functional magnetic resonance imaging (fMRI),resting state functional magnetic resonance imaging (Rs-fMRI) positron emission tomography (PET), functional near-infrared spectroscopy (fNIRS) andmagnetoencephalography (MEG) [14,18]. Additionally, simple-partial and complex-partial partial seizures fall into two main categories. In the simple-partial, the patient is usually able to communicate and looks to be cognizant, cause in the complex-biased, person act erratically, become confused, and constantly chew and mutter. There are also two primary components to a generalised seizure. Nonconclusive seizures can be distinguished from conclusive seizures by their clear motor symptoms, whereas epileptic seizures are difficult to detect since they have absence of motor signals [19,20].

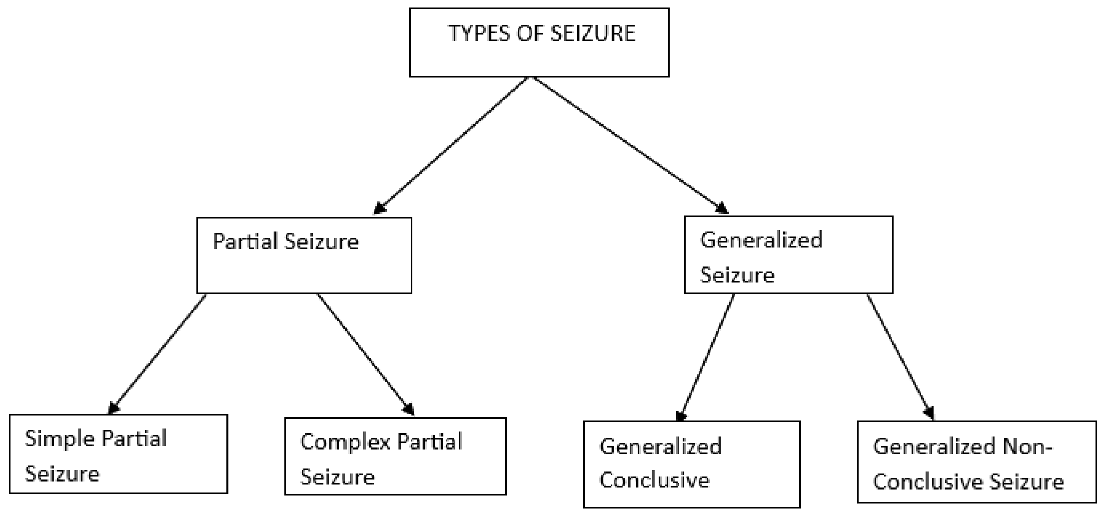

Figure 1: The illustration of seizure types and their subtypes.

Description of the suggested approach:

We propound a deep knowledge-based strategy in prediction of epileptic seizures. Our propound methodology includes interictal state and preictal state classification, substantial feature extraction, and preprocessing of EEG signals. Figure 2 depicts the suggested method for predicting epileptic episodes. The initial step involved preprocessing EEG signals to reduce background noise and improve SNR. In the preprocessing stage, noise artefacts are eliminated using empirical mode decomposition.The bandpass Butterworth filter is used to reduce the disturbance after the Fourier transform,EEG signals have been used to covert thetime domain to rhythm.To decrease the issue of class imbalance, Artificial preictal EEG segments were created using useful adversarial signalsafter the noise was eliminated. Both manually constructed and automatically generated characteristics have been recovered for all channels of preictal and interictal EEG data after the preprocessing. To decrease the effects of the "curse of dimensionality," strongly correlationfunctions have been eliminated from the functional set and cross relation between functions has been obtained by using Pearson Correlation Coefficient (PCC). Then Particle Swarm Optimisation (PSO) is used to choose the best functional set. In order to categorise preictal and interictal states, ModelAgnostic Meta-Learning (MAML) was given the output probabilities of SVM, LSTM, and.CNN.

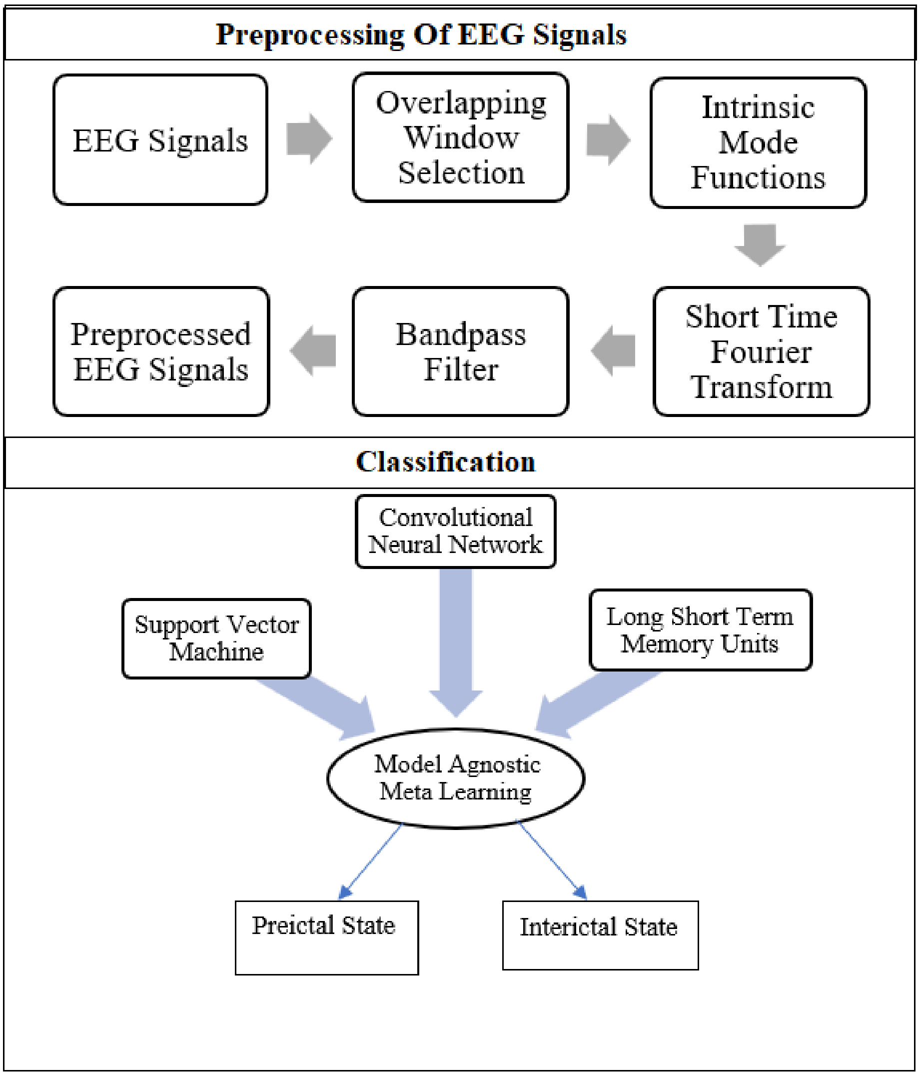

Fig. 2. Flow diagram of proposed methodology for epileptic seizure prediction.

Pre-screening of EEG signals:

EEG signals are susceptible to interference from other electrodes, power line noise, and movement-related cortical potentials., and ECG. The Signal to Noise Ratio (SNR) of an EEG signal decreases under all these circumstances, which reduces the signal's capacity to distinguish among interictal and preictal states. As a result, pre-screening techniques have been developed that comprise reducing noise, such as inter-electrode interference ,power line noiseand noise added because of other distortions. Another issue is the preictal to interictal samples ratio, or the fact that the interictal state is far more common in the datasets that are currently available than the preictal condition.As a result, the classification process is hindered by an issue with class imbalance. Artificial data have been produced for the preictal class in the suggested approach to decrease the impact of the issue of disturbance between preictal and interictal classes. EEG signals ARE collected from the patient's scalp in order to improve the signal-to-noise ratio. For forecasting convulsive episodes, signals with higher SNR are more noise-resistant. Using the suggested technique, which made use of a sliding/overlapping window with a time window of 30 s and a 15 s overlap, the EEG recordings were divided into fixed-length segments Fig. 3 displays thrice time phases of the intersecting window of 30 s [21].

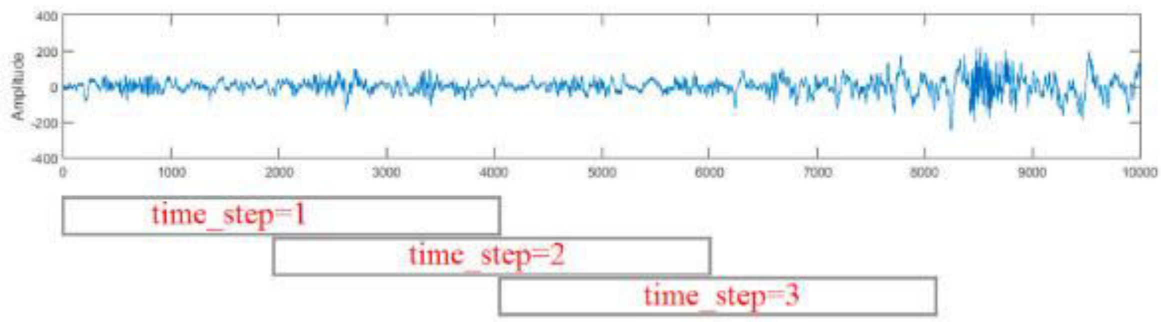

Fig. 3. Overlapping window selection for EEG Signals with time step representing each window.

(Usman Syed et.al; 2021, Overlapping window selection for EEG Signals with time step representing each window) [52]

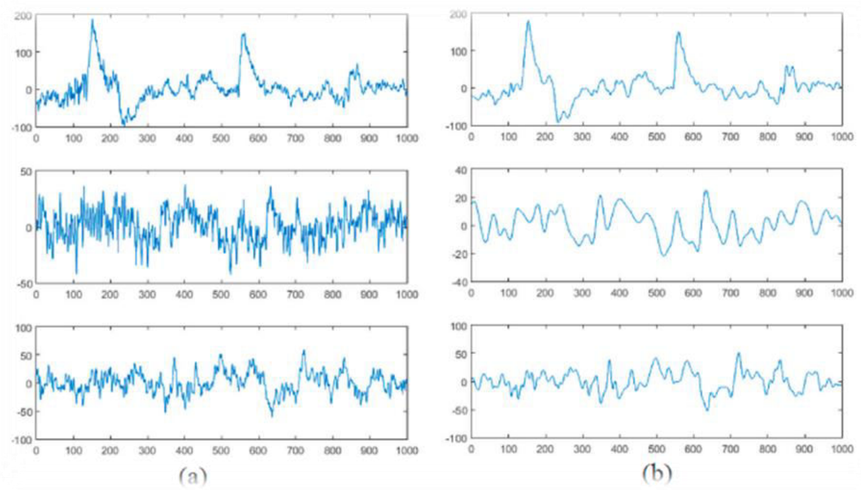

Fig.3.1Three-time phases of the 30 s overlapping window are shown in Fig. 3.

(Usman Syed et.al; 2021, Three-time phases of the 30s overlapping window are shown in Fig.3) [53]

Epilepsy Detection and Classification Process:

The following is a description of the process for classifying and detecting epileptic seizures:

A Seizure Detection Framework:

Using an EEG seizure dataset, we present a framework for seizure identification in this scenario. Data collection, feature extraction, feature selection, and seizure classification using machine/deep learning techniques are the four processes in the seizure detection process. The general framework for epileptic convulsions detection is shown in Fig. 4.

Data Assortment:

The first and major prior step in convulsion detection is data gathering. It can be done by method of EEG monitoring machine to record the brain's electrical activity. The EEG evaluating device applies the EEG cap to the scalp using 10–20 international units. [22]. The observational equipment detects the electrical impulses generated by various electrodes or channels that are linked to the cellulite's surface with topological information and changeable voltage [23]. The neuroexpert has also meticulously investigated and tracked these chaotic EEG signals, classifying them into "seizure" and "non-seizure" states.

Data transformation:

The difficult process of data transformation turns the raw EEG signal data into a 2-Dtabular data after data Collection. This pertinent data, however, is insufficient for analysis to detect seizures. To provide accurate information regarding a seizure, a variety of features are applied, and modalities are used for creation of the dataset. The preprocessing data phase comes after the dataset has undergone a successful transformation (data transformation procedure). It is a data mining technique that cleans, reduces, and removes null values from EEG seizure records to create meaningful and intelligible formats [24].

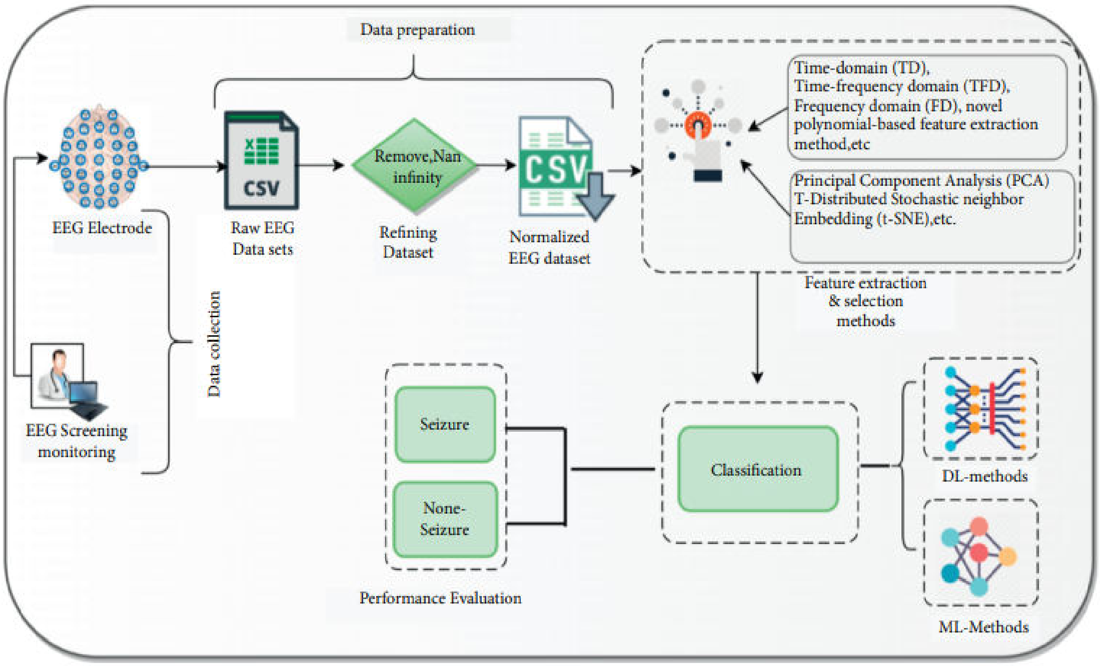

FIGURE 4: A block diagram of epileptic seizure detection using EEG signals and machine/deep learning techniques.

(Ahmad Ijaz et.al; 2022, A block diagram of epileptic seizure detection using EEG signals and machine/deep learning techniques)[54]

Methodology:

The brain waves that were detected at the surface of the skull had a very low amplitude (between 0-100 microvolts and 0.5-100 Hz). The following five categories can be used to group the brain waves based on their frequency: Gamma (12-15Hz),(12-35Hz),Delta (0.5–4 Hz), and Alpha (8–12 Hz) [25, 26]. As a consequence, we got rid of the unnecessary characteristics and kept the most significant and relevant ones[27,28]. Fig. 5 displays the architectural diagram of the suggested replica. Features were obtained by using mean, variance, skewness, and kurtosis statistics, the time, frequency, and time-frequency-time domains were examined [29]. The numerical meanings of skewness, kurtosis, variance, and meaning are shown in Eq. (1-4).

$$Mean: E(x) = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

$$Variance: Var(x) = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - E(x))^2 \quad (2)$$

$$Skewness: S(x) = E\left[\left(\frac{x - E(x)}{\sqrt{Var(x)}}\right)\right]^3 \quad (3)$$

$$Kurtosis: K(x) = E\left[\left(\frac{x - E(x)}{\sqrt{Var(x)}}\right)\right]^4 \quad (4)$$

The expected value, E, for the symmetry or asymmetry of the distribution function is measured by the skewness, S(x), and the anticipated value, E, for the height or intensity of a data distribution's peaking is represented by the kurtosis, K(x). In the equations above, the mean, E(x), denotes the average of the data points[30].

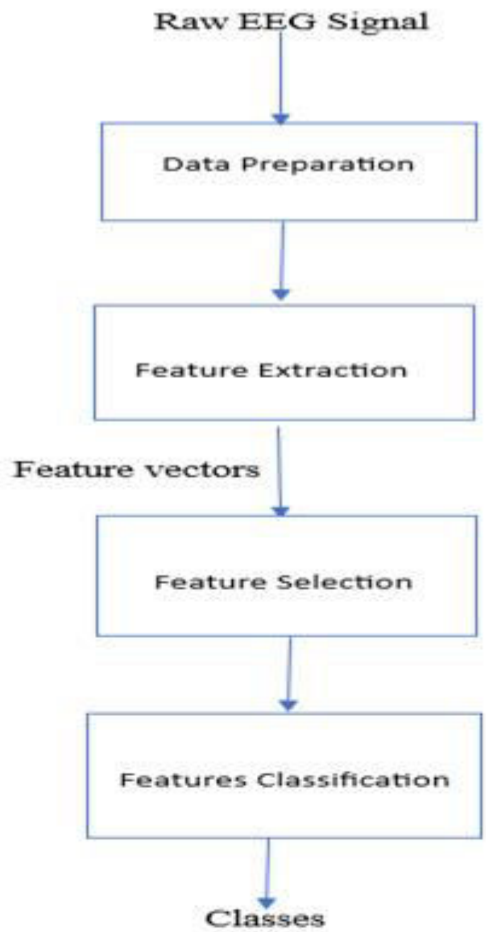

Fig. 5 The proposed EEG signal's structural arrangement classifiers.

ML application for epilepsy EEG signals:

Recognition of seizures automatically ("Seizure detection") refers to the practise of identifying seizures either just before or immediately after they begin. EEG abnormalities are typically defined and detected bydirect visual test. However, labelling EEG signals manually takes time, and some mistakes are inevitable.

Kharbouch et al. used ML approaches to develop a technique for instantly detecting seizures using intracranial transducers. [31].

Shoeb et al. created support vector machines (SVM, linear and nonlinear) to differentiate between a person's convulsive and nonconvulsive activity in order to take use of the spectrum energy (37 Hz) of intracranial EEG to detect the convulsion start[32].

Temko et al. reviewed the metrics for EEG-based neonatal seizures and propound an SVM-based convulsion detection system [33].

Fergus et al. employed the Kclass nearest neighbour classifier, which has a sensitivity and specificity of 93% and 94%, to identify seizures using scalp EEG [34].

Hassan and Subasi used full array method of empirical mode decomposition with frequency adjustmentto breakdown a single-channel EEG data in order to precisely categorise epileptic episodes [35]. They then created a linear programming boosting technique for ensemble learning.

There is evidence that the improved neonatal seizure detector developed by Ansari et al. [36]—which employs an SVM technique with radial basis kernel function—can be used to other neonatal seizure detectors.

Jaiswal et al. proposed two effective methods for extracting EEG characteristics in addition to SVM for automated seizure detection: cross-sub pattern correlation-based PCA and sub pattern-based PCA. [37].

In order to detect epileptic episodes, Hussain tested many machine learning techniques (SVM, K-nearest neighbour classification [KNN], decision tree, and ensembled learning by extracting various features from time and frequency domain data. He discovered that SVM and KNN had the highest overall accuracy [38].By combining linear elimination of dimensionality and categorization, Sendi et al. developed a Spark-based ML technique (SVM-based) to address the epilepsy diagnosis problem. All patients combined (N = 24) yielded an average proficiency of 99.32%, a precision of 99.41%, and selectivity of 95.25. The recognition of seizures technique had an average delay of roughly 0.38 ms [39].

Newly, most modern machine learning ways have been made public. Wei et al. demonstrated advantages over 2D CNN and traditional methods by using a 3D convolutional neural networks (CNN) architecture to detect convulsions using an EEG with almost 90% accuracy, 88.9% sensibility, and 93.8% uniqueness. [40].

Akut presented a wavelet-based advanced learning strategy that was effective on modest datasets and didn't require feature extraction [41].

Epileptogenic zone diagnose:

The area of the brain where epileptic discharge is highly synchronized during the onset of convulsions is referred to as the seizure onset zone (SOZ) or epileptic zone[42]. Correct SOZ identification by trustworthy protocols is essential to get ready for epilepsy surgery. Since seizure electric activity can occur suddenly and spread across numerous cortical regions at once, locating the primary epileptogenic zone can be difficult. The signals produced by high-resolution intracranial electrodes are the most effective for studying the SOZ. In contrast to low-frequency discharges, one of these, high frequency oscillation (HFO), is known as SOZ related biomarkers in epilepsy and transmits information. Prior studies have looked at several related characteristics or elements using intracranial electrodes instance with subdural electrocorticography [ECoG], stereotactically implanted intracranial EEG [SEEG], etc. Since convulsive onset is a complicated portent made up of numerous spatiotemporal components, a single function cannot be evaluated in isolation. We therefore thought that ML approaches could address those issues. To identify a "fingerprint" that successfully distinguishedregions of propagation's time-frequency SOZ patterns,An SVM-based learning approach was developed by Grinenko et al[43]. Using the IEEG from six patients undergoing resection surgery, Dian et al. trained a method for recognizing the SOZ. The recommended method makes use of machine learning (ML) methods, such as the SVM classifier, extracted features for seizure identification, such as high- and low-frequency oscillations, and suitably chosen zones for excision from a patient [44].Elahian et al. employed ML methods based on phase locking values between low frequency cycles (4–30 Hz) and high gamma activity (80–150 Hz)to successfully identify SOZ from ECoG [45]. In order to study anatomoelectroclinical relation to anatomical localization of the epileptogenic network, AhmedtAristizabal et al. integrated deep learning semiological, brain electrical, and anatomical features [46]. For the detection and location of interictal epileptiform discharges (IED), Baud et al. used unsupervised learning [47]. In order to investigate structural (functional connectivity) and recurrent patterns, the suggested method, which is based on non-negative matrix factorization, made use of spatiotemporal properties present across all channels and all time points. The study proposed a practical method for automated IED detection and identification. In order to localise SOZs from functionally important brain regions for the investigation of sick HFO, Liu et al. developed a unique technique [48]. The theory of chaotic dynamics is said to display better prediction than linear measures because preictal EEG is dynamic [49]. greater than one-variate measurements (such spectral power), bivariate and multivariate metrics have been demonstrated to have advantages[50].

Conclusion and future work:

The ability to foresee epileptic seizures can be highly helpful in controlling seizures that cannot be controlled by medication or surgery.Due to a variety of problems, including insufficient pre-screening of the EEG signals, class disturbance issues, it is still challenging to predict a reduced false-positive rate and higher sensitivity epileptic convulsions. In this work, we suggest a technique that lessens the effects of these issuesand more reliable and with a smaller proportion of false positives predicts epileptic episodes. The propound way to reduce the impact of classdisturbance by creating artificial preictal class data using GANs and increasing SNR with EMD.Combining data has resulted in the extraction of a complete feature setmanually made and automatically generated CNN-based features, then selecting the best features using PCC and PSO. There has been a suggested array classifierin this study to distinguish between preictal and interictal states. The suggested ideashave been applied to scalp and intracranial EEG datasets. The novel strategy works better than the existing oneaccording to particularity, sensitivity, and typical expectation time for both datasets when the results are compared to those from the existing methods. In order to predict epileptic episodes, microelectrodes are implanted inside the brain tissues during deep brain electroencephalogram recordings. This work uses EEG data from the scalp and inside the head to predict epileptic episodes. In near future it may be possible to predict focal seizures using deep learning on brain EEG data, which also produce EEG recordings with a high signal to noise ratio. Because the heart rate changes before and during epileptic seizures, heart rate variability can also be used in addition to EEG signals to predict them..The detection of preictal states can be done via short-term heart rate measurements. It will be possible to improve an epileptic seizure prediction system in the future by integrating the EEG data and heart rate variability.

Declaration of conflicting objectives:

We want to reiterate that there are no known disputes of interest pertaining to this publication and that no sizable financial support has been provided that could have impacted the research's findings. We certify that all authors listed on the article have read, reviewed, and approved it; we deny any involvement from anyone who satisfies the criteria for authorship but is not listed. We again reiterate that the writers' order as it appears in the text was accepted by all of us.

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