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A Review on Epilepsy Seizure Detection Using Machine Learning and Deep Learning Techniques

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ABSTRACT: A neurological condition known as epilepsy affects millions of individuals worldwide. One of the main challenges in epilepsy management is the accurate and timely detection of seizures. Deep learning and machine learning methods have shown promising results in epilepsy detection and classification. In this study, the aim is to compare the performance of various ML and DL models for the detection of epilepsy. ML models like logistic regression, support vector machines (SVM), random forest, extra trees, decision trees, stochastic gradient descent, naïve Bayes, and XGBoost, as well as DL models like convolutional neural networks (CNN), long short-term memory (LSTM), recurrent neural networks (RNN), and others, were evaluated in a literature review. The results show that, when compared to other approaches, DL's CNN model demonstrates the highest accuracy. The review study offers useful insights for scholars and practitioners in the field by providing a thorough examination of ML and DL algorithms in epileptic seizure identification.

KEYWORDS: Machine Learning, Deep Learning, Convolution Neural Network.

I. INTRODUCTION

Epilepsy can have a significant impact on an individual's daily life, as it can affect their ability to perform everyday tasks, participate in social activities, and maintain employment. The severity and frequency of seizures vary greatly, and some individuals may experience only occasional seizures, while others may have multiple seizures per day. Seizures can also cause injuries, such as falls and burns, which can further limit an individual's independence and mobility. In this, the physical limitations caused by seizures, and epilepsy can also have a significant psychosocial impact on individuals and their families. This epilepsy can lead to feelings of isolation, shame, and discrimination, which can further exacerbate the psychological impact of the disorder.

Measurements are made of the brain's electrical activity and recorded by a non-invasive medical test called an electroencephalogram (EEG). Small electrodes are affixed to the scalp in order to detect and magnify the electrical impulses coming from the brain. These signals, sometimes referred to as brain waves, represent the interaction and operation of several brain regions. Brain traumas, epilepsy, sleep disorders, and other neurological illnesses are all often diagnosed and monitored with EEGs. EEG signals are split into intracranial and scalp EEG categories. The international standard 10-20 technique is used to affix electrodes to the scalp in order to record the scalp EEG. During intracranial electroencephalography, electrodes are placed directly on the exposed surface of the brain to capture electrical activity from the cerebral cortex. Specialists routinely utilize EEG data to identify individuals with epilepsy. Scalp and intracranial EEG signals are separated into several groups.

The review paper's investigation and comparison of several ML and DL approaches for effective seizure detection are its main objectives. It investigates ML methods including logistic regression, SVM, random forest, and others before looking at DL methods like CNN, LSTM, RNN, and others. This paper includes a thorough review of methodologies and findings.

II. RELATED WORK

This section will discuss a literature review of works that have been done by various authors in the fields of machine learning and deep learning for the detection of epileptic seizures. These techniques include SVM, CNN, Random Forest, Decision tree, RNN, Extra tree, and XGBoost.

[1] Atef Hashem Attia et.al, conducted a study on using machine learning classifiers to detect epileptic seizures accurately and quickly using EEG signals. They compared various classifiers such as random forests, K-nearest neighbors, decision trees, SVM, logistic regression, and naïve Bayes. The study used performance metrics like accuracy, (ROC), mean absolute error (MAE), root-mean-square error (RMSE), and detection time. The Bonn University dataset was used for the classification of epileptic seizures. Machine learning algorithms showed promise in accurately analyzing noisy EEG signals and detecting seizures. characteristics and most importantly detection time for each algorithm.

[2] Fauzia P. Lestari et.al., compared naive Bayes, random forest, and K-nearest neighbor (KNN) algorithms for epilepsy detection. They pre-processed raw EEG data, performing feature extraction, and trained the classifiers. KNN achieved the highest accuracy (92.7%) and precision (82.5%), while naive Bayes had the best sensitivity (80.3%). KNN also had the highest specificity (96.7%). Training time was shortest for naive Bayes (0.166030 sec) and longest for KNN (4.789 sec). Overall, KNN outperformed the other classifiers in epilepsy detection.

[3] Lijun Yao et.al., collected data from 287 epilepsy patients and used machine learning algorithms to predict treatment outcomes. XGBoost achieved the best performance, accurately predicting remission vs. never remission with an F1 score of 0.947 and AUC of 0.979. A higher number of seizures before treatment (N3) was the most discriminative factor. XGBoost also accurately predicted early vs. late remission with an F1 score of 0.836 and AUC of 0.918. Multiple seizure types were highly associated with the remission categories. The XGBoost-based classifier can help guide counseling and improve treatment strategies.

[4] Kemal Akyol et.al., conducted a study on classifying electroencephalogram (EEG) signals for epileptic seizure prediction. They evaluated the performance of machine learning algorithms using a dataset extracted from EEG signals. The dataset consists of brain activities from 500 individuals over 23.5 seconds, resulting in a total of 11,500 data points. The goal was to develop a model to predict epileptic seizures, transforming the problem into a two-class classification. To address the class imbalance issue, Random Under Sampling and Random Over Sampling methods were applied. The datasets were split into training and test sets in ratios of 60/40, 70/30, and 80/20. The findings demonstrated that, in all cases, the Random Forest algorithm performed better than other algorithms in terms of accuracy, sensitivity, and specificity.

[5] Raveendra Kumar T.H. et al., developed a modified XGBoost classifier technique to increase classification precision and speed up seizure detection. They employed a focal loss function to minimize training and testing sample mismatch, enhancing the efficiency of the classification model. The CHB-MIT SCALP EEG dataset was used to test the proposed model on data from 24 patients. The performance of the proposed model was compared against other state-of-the-art seizure classification models. The cross-validation experiments showed high average sensitivity and average specificity, with nearly 100% for both metrics. In terms of average sensitivity and average specificity, the suggested modified XGBoost classifier fared better than previous seizure detection methods.

[6] NasminJiwani et.al., have suggested a model to identify seizures that combines long short-term memory (LSTM) and convolutional neural networks (CNN). By fusing CNN and LSTM models, it focuses on extracting temporal and spatial data. The benefit of this automated system is that it accurately extracts spatial and temporal characteristics from EEG signals while requiring fewer trainable parameters. This qualifies the system for applications requiring real-time processing. It has achieved a maximum of 100% accuracy, 100% sensitivity, and 100% specificity to distinguish between healthy and seizure patients.

[7] DhoushaSagga et.al., proposed diverse scientific methods to reliably detect epileptic seizures due to EEG Signals. In this analysis, deep learning based on CNN 1D convolutional neural networks was developed, and used as models for DL, VGGNET, and ResNet. The tests were conducted using standard data sets. The proposed method was exercised on 23 subjects of the CHBMIT dataset, which successfully achieved an average accuracy of 97.60% and 97.32%



respectively for ResNet and VGGNET. The results obtained suggest the effectiveness of the use of ResNet in epileptic seizure detection.

[8] Xilin Liu et.al., developed and optimized three deep learning models (DNN, CNN, and LSTM) for seizure detection at the edge. The models were trained using scalp EEG data and classified into different seizure phases. A sliding window-based weighted majority voting algorithm was used for seizure detection. The models were compressed and quantized for deployment on a microcontroller, reducing power and memory requirements while maintaining accuracy. The LSTM model performed the best overall but had higher power consumption. The DNN model had the shortest execution time, and the CNN model achieved a balance between performance and resource requirements. Compression and quantization led to significant power and memory savings with minimal accuracy loss.

[9] Gaowei Xu et al., proposed a 1D CNN-LSTM model for EEG signal analysis-based automatic epileptic seizure detection. This model preprocesses and normalizes the raw EEG data, applies a 1D CNN for feature extraction, utilizes LSTM layers for temporal feature extraction, and uses fully connected layers for seizure recognition. The model achieved high accuracies of 99.39% and 82.00% on binary and five-class seizure recognition tasks, respectively, outperforming traditional machine learning methods and other deep learning approaches. The study validated the effectiveness of the proposed method using the UCI epileptic seizure recognition dataset.

[10] Xiaoshuang Wang et.al., proposed a novel iEEG-based deep-learning method for effective seizure prediction. They merged channel increment theory with one-dimensional convolutional neural networks (1D-CNN). EEG signals were segmented into 4-second sliding windows without overlap, and progressively increasing numbers of channels were fed into the 1D-CNN model. Patient-specific models were trained for classification, and the channel case with the best classification rate was selected for each patient. The method was tested on the Freiburg iEEG database, achieving high sensitivity, specificity, and accuracy at both segment- and event-based levels. This method obtained an accuracy of 99.73% in 1D-CNN when compared with 2D-CNN which produced 99.3 % accuracy.

Sl no:	Paper Title	Year	Author	Technique	Results
1.	Brain seizures detection using ML classifiers based on EEG signals	2022	Atef Hashem Attia, AshrafMahroos	Random forests, K-nearest neighbors (K-NN), decision trees, support vector machine (SVM), logistic regression and naive Bayes.	Obtained Accuracy of Random Forest: 97%, KNN: 95.2%, Logistic regression: 82%, Decision Tree : 93.9%, SVM: 97.17%, Naïve Bayes: 95.9%
2.	Epileptic Seizure Detection in EEGs by Using Random Tree Forest, Naïve Bayes and KNN Classification	2020	Fauzia P. Lestari, Mohammad Haekal, Rizki Edmi Edison, Fikry Ravi Fauzy, Siti Nurul Khotimah and Freddy Haryanto	KNN, Random forest, naïve bayes	Obtained Accuracy of KNN classifier :92.7%, random tree forest 86.6% and naïve bayes classifier: 55.6%
3.	Prediction of anti-epileptic drug treatment outcomes of patients with newly diagnosed epilepsy by machine learning	2019	Lijun Yao ,Mengting Cai, Yang Chen, Chunhong Shen, Lei Shi, Yi Guo	Decision Tree, Random Forest, Support Vector Machine, XGBoost, and Logistic Regression	Obtained accuracy of Decision Tree 89.5%, Random Forest: 91.8%, SVM: 78.5%, Logistic Regression: 78.12%, and XGBoost: 94.73%



4.	The effects of under-sampling and over-sampling on conventional ML algorithms for seizure detection are compared.	2020	Kemal Akyol, ÜmitAtıla	Random Forest, Logistic Regression, and SVM	Obtained Accuracy Random Forest:98.8%, LogisticRegression:62.5% and SVM:98.7%
5.	XG Boost Classifier Model for Detection of Seizures and Non-Seizures: A Modified Approach	2022	Raveendra Kumar T. H, Narayanappa C. K, Raghavendra S, Poornima G. R	Xtreme Gradient boosting	Obtained Accuracy of:99.98%
6.	A CNN Model for Epileptic Seizures Detection using EEG Signal	2022	NasminJiwani, Ketan Gupta, Md Haris Uddin Sharif	Convolutional Neural Network (CNN)	Obtained accuracy of CNN : 99.5%
7.	Epileptic Seizure Detection using EEG Signals based on 1D-CNN Approach	2020	DhouhaSagga; Amira Eghtiou; Rafik Khemakhem; Mohamed Ghorbel	1D-CNN models (ResNet and VGGNET)	Obtained accuracy ResNet: 97.60 % and VGGNET: 97.32%
8.	Edge deep learning for neural implants: a case study of seizure detection and prediction	2021	Xilin Liu1,Andrew G Richardson	LSTM (long short-term memory), CNN (Convolutional Neural Network) ,DNN(Deep Neural Network)	LSTM: 90.94%, CNN : 89.21%, DNN:64.55%
9.	A One-Dimensional CNN-LSTM Model for Epilepsy Seizure Recognition Using EEG Signal Analysis	2020	Gaowei Xu, Tianhe Ren, Yu Chen and Wenliang Che	1D CNN (1D Convolutional Neural Network), LSTM(long short-term memory)	Obtained accuracy of 1D CNN :99.39% , LSTM:82%
10.	Using long-term scalp and intracranial EEG, one-dimensional convolutional neural networks for seizure onset detection	2021	Xiaoshuang Wang, Xiulin Wang, Wenya Liu, Zheng Chang, TommiKärkkäinen, Fengyu Cong	1D Convolutional Neural Network	Obtained accuracy of 1D CNN:99.73%

Table 1: Summary table of literature survey

III.METHODOLOGY

In this section, we define machine learning and deep learning are the flow of the methods employed for the detection and classification of epilepsy seizures by using the EEG dataset based on our literature survey did previously. We will explore both machine learning and deep learning approaches.

MACHINE LEARNING FLOW

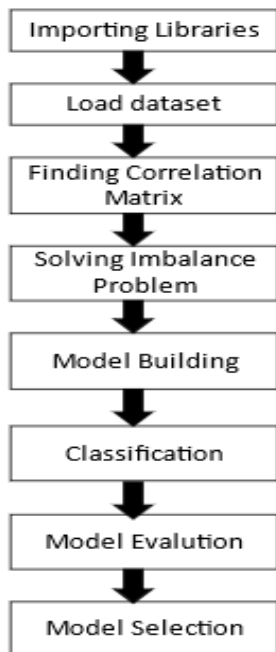


Fig.1: Flow of Machine Learning

DEEP LEARNING FLOW

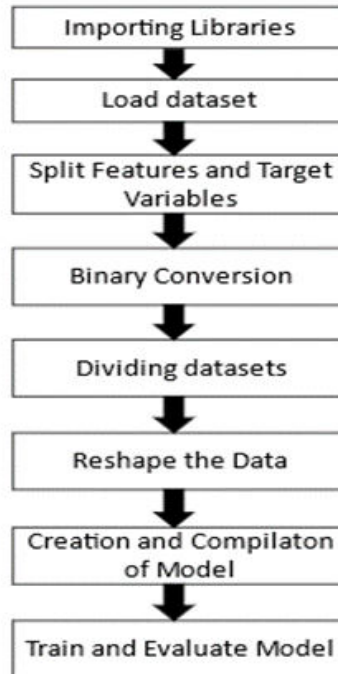


Fig.2: Flow of Deep Learning

The above flow diagrams show the best suitable methodology flow for machine learning and deep learning technique. This investigation shows that the choice of approach has a significant impact on how well seizure detection algorithms work. Different methods were used in ML models, including Logistic Regression, Support Vector Machines (SVM), Random Forests, Extra Trees, and others. These models use classic statistical algorithms and feature engineering techniques to extract discriminative characteristics and classify seizures. These ML models have been useful in understanding how to detect epilepsy, but their effectiveness is constrained by the necessity for manual feature selection and their inability to recognize intricate nonlinear correlations in the data.

However, Deep learning models, in particular Convolutional Neural Networks (CNNs), have become a potent seizure detection method. Automatic feature learning for DL models is accomplished using numerous layers of convolutions, pooling, and non-linear activations. The model is able to extract useful features from the EEG signals' raw data without the requirement for manual feature engineering. The improved performance of CNNs in seizure detection is a result of their capacity to recognize spatial relationships and learn hierarchical representations.

Recurrent neural networks, including Long Short-Term Memory and Recurrent Neural Networks, are also included in DL models, which makes it possible to capture the temporal relationships in the EEG signals. The model's capacity to analyze sequential patterns and long-term interdependence is improved by the use of temporal modeling.

IV. PERFORMANCE PARAMETERS

Several important performance criteria are frequently used to assess the efficacy of models in the seizure detection field. These measures reveal how accurately the model can distinguish between seizure and non-seizure occurrences. The main performance indicators in this situation are as follows:

Accuracy: By measuring the proportion of examples that were correctly classified to all instances, accuracy assesses how accurate the model's predictions are overall. It offers a broad evaluation of the model's effectiveness.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision: The fraction of real positive predictions (seizures) among all positive forecasts is known as precision. It demonstrates the model's capacity to reliably detect seizure occurrences and reduce false positives.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Recall: Recall, also referred to as sensitivity or true positive rate, gauges the percentage of actual seizure occurrences that the model accurately recognized. It evaluates the model's capacity to identify every episode of a seizure while avoiding false negatives.

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

F1 Score: The harmonic mean of recall and precision is the F1 score. It offers a balanced measurement that incorporates recall and precision. In cases where the dataset is unbalanced, it is especially helpful.

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

Sensitivity: The model's capacity to accurately detect positive occurrences (seizure events) among all actually positive cases is represented by sensitivity, also known as the true positive rate. It measures how well the model can account for most seizure cases.

$$\text{Sensitivity} = \text{TP} / (\text{TP} + \text{FN})$$

Specificity: Specificity assesses how well a model can distinguish between genuine negative instances and non-seizure instances. It evaluates how well the model can categorize cases that are not seizures.

$$\text{Specificity} = \text{TN} / (\text{TN} + \text{FP})$$

V. CONCLUSION

This review paper explored a number of machine learning (ML) and deep learning (DL) methods for detecting epilepsy seizures. Through a thorough review of the literature and a comparative analysis of 20 pertinent publications, we were able to determine the advantages and disadvantages of various ML and DL models for correctly identifying and categorising seizures. The optimum methodological flow for both ML and DL models in the context of epileptic seizure detection was our main goal. Our data clearly demonstrate that deep learning (DL) models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in seizure detection. High accuracy, precision, recall, F1 score, sensitivity, and specificity were consistently attained by the CNN-based models, demonstrating their efficacy in properly identifying cases of seizures and non-seizures. CNNs perform better because of their powerful feature extraction abilities and their capacity to recognize spatial correlations in EEG signals.

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