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Review on Epilepsy Detection with Explainable Artificial Intelligence

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***Abstract*—Epilepsy is a neurological disorder and it is growing day by day. Electroencephalogram (EEG) signals are used to diagnose this brain related disorder. These signals are recorded from patient and classified as epileptic and normal EEG signals. Many machine learning and other techniques are used for performing this classification. Convolutional neural network is widely used for identification of these signals. Lots of improvement is done in machine learning techniques and its performance. At the same time these machine learning models are getting more and more complex. It is very difficult to understand their operations and how they arrive at particular decision. They are becoming black boxes. Because of this it is difficult to adopt them in medical domain. In epilepsy detection the results are very sensitive. Explainable Artificial Intelligence (XAI) is a growing field which provides new methods that explains and interprets the results produced by machine learning models. This paper provides review of neural network based epileptic seizure detection methods. It also gives an overview of various XAI methods which are helpful in interpreting the decisions of machine learning models. These methods can be used with neural network-based epilepsy detection system. XAI methods describe why particular signal is classified as epileptic or non-epileptic. They highlight the features which are important in making decisions. These methods help medical practitioners to trust the decision made by machine learning models and to accept these models and their results in medical domain such as epilepsy detection.**

Keywords— Explainable Artificial Intelligence (XAI), epilepsy detection, Electroencephalogram (EEG), transfer learning, Convolutional Neural Network (CNN), Deep Neural Network (DNN).

I. INTRODUCTION

Epilepsy is a neurological disorder. It can be found that around 65 million people all over the world are suffering from this disorder. When a person suffers from this disorder, his brain activities become abnormal. His behavior changes. He may feel different sensations. His brain loses control on his body. EEG signals obtained from brain of a person are used to detect epilepsy. Human brain generates some electrical signals. EEG is used to measure these signals of brain. It measures voltage fluctuation occurring in the brain. These signals are recorded using some specific device. These signals are classified as epileptic and non-epileptic signals using some machine learning techniques. Various models such as Artificial Neural Network (ANN), Long Short Term Memory (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Support Vector Machine (SVM) are used for epilepsy detection. In literature various methods are reported to identify preictal, interictal and ictal signals. Identification of preictal signals can be helpful in preventing the person from getting injured during seizure attack. XAI methods can be applied to understand what goes inside the network when it classifies the signal into specific class. It can be used to explain and debug black-box machine learning models. These methods can increase the trust in machine learning models and helps them to get easily adopted in medical domain.

Lots of research is done on EEG signal classification for epilepsy and other brain related disorders. In case of epilepsy, researchers tried to classify epileptic signals from single and multiple channels. Research is done on binary classification like epileptic and non-epileptic signals, pre-ictal and ictal signals. Some research is done on multiclass classification like non-epileptic, pre-ictal, inter-ictal and ictal signals. Now a days there is an increase in use of machine learning techniques for EEG signal classification for detecting epileptic seizure. Also, different feature extraction techniques are use with raw EEG data. This section presents related work in this domain.

DNN and CNN based methods are used in [1-5] with various feature extraction techniques. RNN based approach is used in [6, 7]. Transfer learning approaches are also used by various researchers [8-16]. It can be observed that many neural network-based methods exist to detect epileptic seizures which are reviewed in this paper. Summary of this review is given in table I which provides details of dataset used by these methods and their performance estimation. Section II describe the need of XAI methods in neural network-based epilepsy detection systems. Various XAI methods are also discussed in section III of this paper which can improve the design of these neural network-based models for epilepsy detection. These XAI methods can be used to explain the results generated by these models.

II. NEED FOR XAI IN EPILEPSY DETECTION

From review report given in table I, it is found that machine learning techniques are used to a large extent for epileptic signal detection. Deep neural networks are giving good accuracy in epileptic and non-epileptic signal classification. Use of transfer learning approaches is also increased which used pretrained CNN model for epileptic signal identification. Transfer learning approaches reduce the amount of time and number of training samples needed to train the CNN model. This improvement in performance and

TABLE I. NEURAL NETWORK BASED EPILEPTIC SEIZURE DETECTION METHODS

Ref. No.	Dataset	Method	Performance Estimation
[3]	Bonn University, Germany	DNN	Accuracy: 97.21%
[17]	Bonn University, Germany	E-GCN	Accuracy: 98.35%
[18]	Freiburg EEG dataset	CNN	Sensitivity: 90.8%
[19]	Bonn University, Germany	ANN, PNN and SVM	Accuracy: 87.5%, 89.3%, 91.2%
[2]	CHB-MIT scalp EEG database	LMD + Bi-LSTM	Sensitivity: 93.61%, Specificity: 91.85%
[20]	Bonn University, Germany	Bayesian optimization-based Bi-LSTM model	Accuracy: 94.00%
[8]	Bonn University, Germany	Generalized Hidden-Mapping Transductive Transfer Learning (GHM-TTL)	Accuracy: 98.30%
[9]	American Epilepsy Society Seizure Prediction Challenge	CNN (transfer learning)	-
[10]	CHB-MIT scalp EEG database	MLP, DCNN + MLP, DCNN+ Bi-LSTM, DCAE + Bi-LSTM and DCAE +Bi-LSTM + CS (transfer learning)	Accuracy: 99.66%
[11]	CHB-MIT scalp EEG database	Autoencoder + Bi-LSTM (transfer learning)	Sensitivity: 94.6%
[12]	CHB-MIT scalp EEG database	Resnet152, Inception-v3 and Inception-Resnet-v2 (transfer learning)	Accuracy: 92.77%
[13]	CHB-MIT scalp EEG database	DCNN (transfer learning)	Accuracy: 92.60%
[14]	Temple University Hospital (TUH) EEG database	Pretrained network + SVM (transfer learning)	Accuracy: 88.30%
[15]	Bonn University, Germany	Alexnet + SVM (transfer learning)	Accuracy: 95.00%
[16]	CHB-MIT scalp EEG database + iNeuro database	Pretrained network + HNN (transfer learning)	Accuracy: 98.97%, 92.04%
[21]	Bonn University, Germany	CNN	Accuracy: 95.8%
[22]	Bonn University, Germany	ANN	Accuracy: 97.33%
[23]	Bonn University, Germany	Complex-Valued Neural Network (CVANN)	Accuracy: 98.28%
[24]	Temple University Hospital (TUH) EEG database	LSTM	Weighted-F1 score: 0.945
[25]	Freiburg Hospital dataset + CHB-MIT scalp EEG database	CNN	AUCs Above: 92%, 96%
[26]	Data recorded from epilepsy patient	RNN	Least computational cost
[27]	Data recorded from epilepsy patient	CNN	Accuracy: 89.01%
[28]	Bonn University, Germany + CHB-MIT scalp EEG database	DNN	Accuracy: 98.53%
[29]	public EEG database	DNN	Accuracy: 100.00%
[30]	CHB-MIT + SNUH scalp EEG database	DNN	Sensitivity: 89.4% and 97%

accuracy comes at the cost of increased complexity of the model. It becomes difficult to understand the operation of the model and how it has arrived at particular decision [31]. In medical domain like epilepsy detection and others, the results are very sensitive and small mistakes may cause serious effects. So, despite the outstanding performance and good accuracy of deep learning models, it becomes difficult for medical practitioners to use these models in their day-to-day work. XAI is a field that provides new methods to explain and interpret the results produced by machine learning models [32].

For epilepsy detection, EEG signals are recorded from brain of a person using some specific device. These signals are recorded during seizure attack and in normal condition. These signals are preprocessed to remove artifacts. Various transformation techniques like Continuous Wavelet Transform (CWT), Short-Time Fourier Transform (STFT) and Discrete Cosine Transform (DCT) are applied on signals and they are converted into images. These images are given to deep neural network for epilepsy detection which provides more accurate results in less time [14-16]. But as mentioned earlier there should be some methods to verify correctness of these results as wrong prediction could be life threatening. XAI methods provide the way to understand the working principle of the model and explains why system is arrived at specific decision [32]. It helps to build trust in these models and increases the chances of their acceptance in healthcare.

XAI algorithms follow three principles - transparency, interpretability and explanability. The process extracts the model parameter from training dataset. Then it generates labels from test dataset. System designer should describe this process. This is called transparency. When AI system arrive at some specific decision, then there is some reason behind that decision. Interpretability represents the basis for taking that decision. It is represented in human understandable form. If the system is more interpretable then it becomes easier to identify the relationship of cause and effect between input and output of a system. Explanability is the collection of features of the interpretable domain that have contributed in arriving at particular decision. It helps to explain internal logic of a system and its working mechanism [31].

XAI methods can justify the decisions of model in human understandable form and thus improve transparency and fairness of the model. Transparency is important to assess the quality of decisions given by model. If one model produces sub-optimal decision but with full scientific explanation or logical reasoning and other model produce highly confident decision but without any explanation, the first model is preferred over the other. Another point to consider is trustability which is the measure of confidence in the decision of deep learning models. Explanations of the prediction made by classifier is important to build up the trust in the model.

Another problem associated with model is biasing. There can be biases while collecting the data for implementing particular system. Also, machine learning algorithms may contain some deficiencies. Because of this reason model has inclination towards some specific portion of data. XAI methods help to understand model behavior for different data distribution. These methods can give better understanding of skewness and biases in the input data. This helps to create fairer model by using bias mitigation methods. Model is fair if it provides impartial decision without favoring any specific population of input data. The AI model can evolve more with the use of XAI methods. These methods help to improve overall design of the model and reduce human bias [32, 33].

These XAI methods can be used to create white box interpretable models or explain black box complex models. A deep learning model is considered as white box model if model parameter and architecture information of the model is known. A model is considered as black box model if model parameter and architecture information of the model is hidden from end user. Some of these XAI methods are applicable to specific model while others are applicable to all models. Some of these methods provide explanation for single data instance or particular prediction while other provide explanation for entire model. It is important to choose right XAI method for explanation [31].

III. Overview of XAI Methods

Table I describe the work done on classification of epilepsy data using neural networks. From review report in table I it can be found that many methods use transfer learning approach and classify EEG signals as epileptic and non-epileptic. In this approach existing pretrained CNNs are used. These CNNs are trained on already existed datasets and only outer layers are used to learn the features of new EEG data corresponding to epileptic and non-epileptic signals. Some XAI methods can be used for interpreting the results of such black box machine learning models. It can be used to explain why specific signal is classified as epileptic or non-epileptic. Some of these methods are described below which can be used for interpretation of results of epileptic signal classification.

A. Gradients

It is a gradient-based attribution method. It specifies by what amount the prediction will change for a change in input dimension. This method highlights those areas of the image which play a major role in classifying the image into given class [31, 32].

B. Integrated Gradients

Integrated Gradients visualize the input features which are important in making the predictions for the output class. This method is applicable to image, text and structured data and models like regression and classification models. In this method original neural network is not modified. Sensitivity and implementation invariance are two fundamental axioms that must be satisfied by the integrated gradients. It helps to improve the accuracy of a model. This method shows positive attributions and negative attributions of the feature inputs. Positive attributions are the features that influence the model positively in making particular decision. Negative attributions are the features that have negative influence on the model in making particular decision [34].

C. LRP

LRP stands for layer wise relevance propagation. It is one of the most important methods in XAI. It provides an explanation of any neural network output. It consists of two passes - forward and backward. First pass is the forward pass in which activations are computed for each layer of the network. The activation score at the output layer of the network is used for making predictions. Second pass is the backward pass. In this pass the output scores are propagated in reverse direction until the input layer is reached. At input layer it focuses on the pixels which are important in making decision. It marks the pixels which classify the input in specific class. The magnitude of the contribution of each pixel in making prediction is called relevance value R. First the relevance values are calculated for each input layer. These relevance values can be sorted that determine which factor is playing a major role in making the prediction [35].

In LRP, the redistribution process is conservative. It means that using backpropagation process the magnitude of output is conserved. The output value is given by the sum of input layer's relevance map. This property is applicable to any two consecutive layers. It is also applicable to input and output layers with the help of transitivity property. LRP is used to explain decisions of CNN as well as LSTM provided that the network should contain only ReLU activation function [35].

D. DeepLIFT

DeepLIFT stands for Deep Learning Important FeaTures. It backpropagates contribution of each neuron to every feature of the input. Positive and negative contributions can be considered separately. DeepLIFT finds importance in terms of differences from reference state. Reference state for the input is the neutral input that do not have specific property. Similarly reference state for the neuron in the network is its activation value given the reference input. For the output of the network reference state is the computed output for the reference input. It compares the activation of each neuron with 'reference activation' and assigns contribution scores accordingly. There can be some dependencies which may be missed by other approaches and revealed by DeepLIFT. To calculate importance of each feature, it takes only one backward pass. Therefore, this method is fast [36].

E. LIME

LIME is one of the most popular XAI method which stands for Local Interpretable Model-agnostic Explanations that can handle almost any model. It can provide explanation for any supervised model which will be treated as black box model. It assumes that every complex model is linear on a local scale. It uses simple model to explain the prediction of more complex model. It tries to understand how the predictions changes by perturbing the input of data samples. It works with an input which has human understandable representation. i.e., an image. LIME explains how much each feature contributes in the prediction. Small perturbations are created on the original instance. Interpretable models are trained on this data. The interpretable models can be linear models or decision trees. This method has some pitfalls. Only small region is considered around the data sample and linear model can approximate local behavior only for this small region. Linear model cannot work if this region is expanded. Also, bias may get introduced into the explanations of model because of perturbations [37].

F. SHAP

SHapley Additive exPlanations (SHAP) is derived from the Shapley values of the game theory. Shapley value is a solution concept in game theory. Like LIME it can provide explanation for any model which is treated as black box. This method identifies contribution of each feature in a particular prediction. Average marginal contribution is taken for all possible combinations of a feature value. This is Shapley value. To obtain the Shapley value for particular feature, prediction made by model is calculated with feature and without feature and for all the subsets. This method has some limitations. Computation time increases with increase in number of features. Change in order of features selected changes the Shapley value. SHAP is slower than LIME as time is required to compute Shapley values. SHAP gives better local accuracy and consistency than LIME because it considers all possible combinations of input [38].

G. CAM

CAM stands for class activation map. This method generates heatmap of an image which shows important region of an image in terms of making particular prediction. Sometimes these heatmaps are also used for object localization. Network contains multiple convolutional layers. Global average pooling is performed just before final output layer. This output is given to fully connected layer. This layer generates desired output. Identification of the image region is required which is playing important role in prediction. It is done by projecting the weights of the output layer in backward direction. These weights are projected on convolutional feature maps which is obtained from the last convolution layer. This technique is known as class activation map. Class activation map method has some limitations. This method requires the presence of global average pooling layer in the architecture. If this layer is not present, then it is not possible to apply this method. It is used to visualize only final layer heatmap and no other layers. These limitations are addressed in Grad-CAM method which is an improvement over the existing method. Different variations of this method are described below [31, 32].

1) Grad-CAM: This method does not require the presence of global average pooling layer in the architecture. It can create heatmaps by visualizing any layer in the network. Grad-CAM is applicable to any CNN-based architecture. It can be applicable to CNNs with fully connected layers. Some CNNs are used for structured outputs. Also, some CNNs are used in tasks which takes multimodal inputs. Grad-CAM is applicable to all these CNNs. It does not require to change or retrain the architecture [31, 32].

2) Guided Grad-CAM: Grad-CAM cannot highlight fine-grained details. In guided backpropagation when backpropagating through ReLU layers, negative gradients are suppressed. It captures pixels which are detected by neurons. It does not capture the pixels that suppress neurons. In guided Grad-CAM, guided backpropagation is fused with Grad-CAM visualizations. Element-wise multiplication is used for making fusion. Similar results can be achieved with deconvolution. Difference between guided backpropagation and deconvolution is that guided backpropagation is less noisy and deconvolution visualizations contains artifacts [31, 32].

3) Grad-CAM++: Grad-CAM++, as the name suggest, is an extension of the Grad-CAM method. CNN model predictions are represented with better visual explanations using this method. This method is good for multi-label classification problems. It assigns different weights to each pixel. Importance of each pixel is captured separately. Each pixel in feature map has some importance in overall decision of CNN which is represented by this method. This method is computationally equivalent to previous gradient-based methods [31, 32].

These are few XAI methods discussed here. Various other XAI methods which can be applicable to deep learning models for epilepsy detection are given in Table II [39].

IV. CONCLUSION

In this paper neural network based epileptic seizure detection methods are reviewed which are summarize in table I. Also overview of various explainable artificial intelligence methods is given which can be used with these neural network-based models to interpret and explain the results generated by them. Now a days lots of research is done on use of transfer learning approach for detecting epileptic signals. This approach directly uses pretrain network. System designer do not need to understand architecture and working of CNN model in detail. These pretrain models give good accuracy and performance. In this situation it is difficult to understand why system has classified particular signal as epileptic or non-epileptic. So, it becomes difficult for medical practitioner to trust the results generated by these models and accept them in their day-to-day work despite their good accuracy and performance. Here XAI comes into picture. XAI methods explain the results generated by these models and helps them to get accepted in healthcare. Yet XAI methods are not used with epilepsy detection systems. This review paper can encourage the readers to use these methods which can improve system design and increase trust in them.

TABLE II. XAI METHODS WHICH CAN BE APPLICABLE TO DEEP LEARNING MODELS FOR EPILEPSY DETECTION [39]

Method	**Method**
Anchors	Layer-wise Relevance Propagation
ApproShapley (Shapley Value Sampling)	LRP (Composite strategy)
AClass Activation Mapping	LRP (Specific variants)
Contextual Prediction Difference Analysis	Local Interpretable Model-agnostic Explanations
DeconvNet	Meaningful Perturbation
DeepLIFT	NeuronConductance
DeepLIFT (Rescale)	NeuronGuidedBackprop
DeepLIFT SHAP	NeuronIntegratedGradients
Deep Taylor Decomposition	Occlusion Analysis
ExcitationBackprop	PatternAttribution
ExtremalPerturbation	PatternNet
GNNExplainer	Prediction Difference Analysis
GNN-LRP	Randomized Input Sampling for Explanation
GradCAM	Saliency Analysis / Gradient
Gradient SHAP	SHapley Additive exPlanations
Gradient X Input	SHAP Interaction Index
GuidedBackprop	SmoothGrad
Guided GradCAM	SmoothGrad2
Integrated Gradients	Spectral Relevance Analysis
Internal Influence	TreeExplainer
Kernel SHAP	VarGrad
LayerConductance	Testing with Concept Activation Vectors
Local Rule-based Explanations	TotalConductance

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