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Epileptic seizure Classification- A Deep Learning approach

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***Abstract*— Recurrent seizures are a feature of epileptic seizure disorder, a brain ailment. An aberrant brain activity known as a seizure frequently causes changes in sensations, movements, or consciousness. Modified Convolutional Neural Networks (i.e. Feedforward Neural Network) is the deep learning technique utilized for seizure detection and classification, consisting of batch normalization, dense layer with ReLU activation function and a dropout layer. Due to the model's flexible architecture, it captures complex patterns in the EEG signals and the presence of dropout layer helps preventing the overfitting, batch normalization helps in stable and accelerated training, however of its high accuracy, the model may have memorized the data rather than learning the patterns, which could lead to poor performance on a new dataset. The model's output indicates a Testing classification accuracy of 98%, with validation accuracy of 97% and a validation loss of 3.89%.**

Index Terms: Feedforward Neural Network, Binary Classification, Epileptic Seizure detection and classification

I. Introduction

Epileptic seizures are a type of brain illness characterized by frequent seizures. Our brain generates electromagnetic impulses in a predictable way. Neurotransmitters are chemical messengers that allow impulses to move throughout the body via the complex network of nerve cells in the brain. Recurrent seizures are caused by imbalances in the electrical rhythms of the brain. These alterations in brain activity, as mentioned in the abstract, are known as Epileptiform Brain Activity (EBA). There are persons who have Epileptiform Brain Activity even when they do not appear to be having a seizure; in such circumstances, EEG can be used. This test comprises deep breathing to assure the induction of epileptiform brain activity. The remaining part involves a review of the literature survey, dataset details used for the analysis, approach used for the creating the model and the results. Convolutional neural network (CNN) is well recognized for its use in image processing, such as MRI and X-rays; also, deep learning tools are quick. Mount Sinai Ichan School of Medicine researchers have created a deep neural network capable of identifying critical neurological diseases like stroke 150 times faster than a regular human radiologist. Deep learning technologies can detect irregularities in brain activity, which allows doctors to diagnose patients' diseases. Deep Learning Reconstructions (DLR) has developed a new technique that is employed in the image reconstruction process of MRI, which is a critical procedure in the generation of MR images. With its great accuracy, deep learning has also become a significant technique for ultrasonic image recognition, which improves diagnostic accuracy. Deep learning demonstrated superior performance in image processing tasks such as feature extraction and classification. To diagnose brain tumors, CNN models such as AlexNet, VGGNet, and GoogleNet with an SVM model were used. Medical imaging tasks are critical for illness analysis and diagnosis. As a result, it can be justified by diverse ways employed all over the world. CNN is the most effective Deep Learning concept for use in the health field.

II. Literature Survey

Many studies have been conducted on the detection and classification of epileptic seizures, and a large number of research articles have been published on the subject. We refer to certain studies in this study to support our proposed model. The research [1] explores seizure type identification from EEG data using resampling, Fast Fourier Transform, and a variety of machine learning techniques, including k-Nearest Neighbors, Stochastic Gradient Descent, XGBoost, and Convolutional Neural Networks (CNN) with ResNet50. Using the TUSZ seizure corpus (v1.5.2), the project attempts to construct a patient-specific cross-validation baseline. However, a thorough analysis and comparison of existing approaches is inadequate, making it difficult to understand the suggested methodology's uniqueness in the field. The study in [2] focuses on epileptic seizure detection from EEG signals, using a four-step approach that includes dataset description, feature extraction using Discrete Wavelet Transform, feature selection based on correlation factors, and training a classification model using both machine learning (SVM, KNN, RF, DT) and deep learning (LSTM) algorithms. The evaluation measures are accuracy, precision, recall, and f1-score, with precise equations provided. The classification model is evaluated on a variety of datasets, including both seizure and non-seizure signals. The approach in [3] introduces a spectrogram-based feature descriptor that uses the Short-Time Fourier Transform (STFT) to represent EEG data efficiently. This descriptor, using Mean of Magnitude Value (MMV), is input into a CNN model that includes convolutional layers, max-pooling layers, fully connected layers, and a softmax output layer. The process entails extracting a 3D tensor feature descriptor from the spectrogram, improving high-level feature learning, and aiding in epileptic seizure detection and prediction. The epilepsy seizure detection system in [4] uses machine learning techniques such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Gated Recurrent Units (GRU). The technology combines 1-dimensional convolutional neural networks (Conv1D) with GRUs, with Inception Modules used to capture representations at various layers. In addition, dense connections are provided to improve gradient flow and alleviate learning degradation issues. The work from [5] focuses on creating a Human Action Recognition (HAR) system that uses EEG signal data to detect epileptic seizures, which is critical for correct neurological condition diagnosis. For time-series classification, the system makes use of cutting-edge deep learning networks, notably a hybrid residual network known as Inception-ResNet. The Inception-ResNet model is intended for binary classification of epileptic activities in order to improve recognition performance.

The majority of the time, pattern feature learning in deep learning networks is unusable due to the black box issue [6]. For this kind of technique, it will be preferable to use a convolutional neural network, or CNN, as CNNs have numerous hidden convolution layers. In order to find the influence of network learned features to obtain the classifications, the paper [6] first designs its layers to bias the learned filters toward common signal processing computations, such as frequency bands and spatial filtering. Secondly, it learns and adjusts the weight at each layer of the neural network to obtain the features that are most likely to attain the desired, multi-signal EEG is fed to the CNN model dividing the signal into distinct layers in order to determine the likelihood of a multi-signal EEG [7]. Seiznet, a CNN model that uses the least channel EEG signals to detect seizures, is one example of a CNN model that performs better than the traditional CNN model. The VGG16 is a sixteen-layer convolutional neural network that has thirteen 3x3 convolutional layers and three fully connected layers [8]. In this investigation, the combined use of EEG and rsf-MRI provides additional information about the dynamic functional characteristics. Convolutional neural network (CNN) is able to recognize critical features in diagnostic imaging studies with an accuracy comparable to that of human diagnosticians [9]. The technique for recognizing epileptic seizures from EEG data is presented in the paper. To increase detection accuracy, it uses a deep learning system that automatically extracts features from the EEG data. The method provides a more effective and dependable seizure diagnosis tool by greatly reducing the need for manual feature extraction and expert intervention. The outcomes show that the suggested deep learning model performs more accurately and robustly than conventional techniques [10].

The study suggests a productive method for classifying seizure types and extracting features using CNN. It uses the Gramian Angular Summation Field (GASF) transformation to create two-dimensional visuals from one-dimensional EEG inputs. Convolutions, batch normalization, max-pooling, fully-connected, dropout, and an output layer are among the layers utilized in CNN architecture [11]. From the EEG data, thirteen time-domain parameters were retrieved, such as variance, mean absolute value, and waveform length. Seven chosen time-domain features were used to train an ANN model, which produced an overall accuracy of 96% [12]. ConvGru-CNN network, which combines GRU layers with recurrent neural networks (RNNs) for EEG signal categorization, was employed in this work. Because GRUs are sequential, they have been utilized to model temporal dependencies. The ConvGru-CNN model classifies seven different types of epileptic seizures with an accuracy of 88.38% [13]. In this research, a deep C-LSTM model for tumor and seizure detection is presented. Five states of the brain can be classified by it, including two seizure-free states, open and closed eyes, and seizure activity. Within a second, the model seeks to produce predictions. The classification performance of the models is evaluated by the paper using evaluation criteria such as sensitivity, F1-score, and total accuracy [14]. This paper describes a unique method for identifying brain tumors and epileptic seizures from high-dimensional electroencephalogram (EEG) information. The paper presents a deep Convolutional Long Short-Term Memory (C-LSTM) neural network that combines the sequence modeling strength of LSTM layers with the feature extraction capabilities of convolutional layers. This algorithm improves the accuracy of diagnosing brain tumors and epileptic seizures by efficiently capturing both spatial and temporal characteristics from EEG data. The suggested technique outperforms conventional machine learning techniques in terms of performance [15].

Among the several deep learning models discussed in the literature, we believe that a feedforward neural network is the most straightforward, efficient in terms of computation, and simple to train. Choosing a simplified method, the feedforward neural network efficiently classifies epileptic seizures by balancing model complexity and performance. It is also a great option for medical applications due to its low risk of overfitting and good generalization with little data. This guarantees dependable and uniform performance, which is essential for actual clinical settings. Moreover, its very modest computational requirements allow for deployment on edge devices, improving usability and accessibility across a range of healthcare contexts.

III. Overview of Dataset

There are 500 people in all, and each person's brain activity is monitored for 23.6 seconds. 4097 data points are sampled from the time series data. The recorded EEG value at each distinct time point is represented by a data point. There are 500 people in all, and for every 23.6 seconds, 4097 data points are logged for each of them. Out of 500 individuals, 4097 data points are separated and scrambled into 23 chunks, each containing 178 data points for one second. The data is then distributed among the 23 chunks for each individual.

The label y {1,2,3,4,5} is displayed as a column, and the total will be 23x500=11500 pieces of information represented in row. The response is expressed as y, more precisely as {X1, X2, X3……, X178}. The EEG recordings are categorized as follows: 1, 2, 3, 4, 5. 1 indicates seizure activity recording, 2 indicates EEG recording in the presence of a tumor, 3 indicates EEG activity recording in the healthy brain region other than the tumor affected area, 4 indicates EEG recordings made with the eyes closed, and 5 indicates EEG recordings made with the eyes open. Only class 1 has epileptic seizures, while classes 2, 3, and 5 are all non-seizure categories.

IV. Model Details

A modified CNN model shown in Fig 1 was taken into consideration for the seizure classification in the proposed strategy. As previously indicated, the 500 participants in the EEG dataset are divided into two categories: 80% are utilized for training and 20% are used for testing. Dense layers and batch normalization are features of the CNN model. By levelling the inputs of each layer, batch normalization is a strategy to improve neural network training. The process of altering the input data to make it more suited for neural network training is known as "normalizing the inputs." Generally, the idea modifies the input feature's value to have a mean of 0 and a standard deviation of 1. To compute this, subtract the input batch mean and divide the result by the standard deviation. The advantages of normalizing the input data include disappearing the gradient problem by keeping the activations within a specific numerical range and increasing the training process's convergence, which speeds up the model's learning. For improved outcomes, three output layers are taken into consideration following batch normalization. There were three layers: 256, 512, and 1024. This indicates that every neuron in the dense layer takes in information from 178 characteristics and generates a 256-sized output; the same is true for the 512 and 1024 output layers. The model was trained using Nvidia RTX A6000 GPU available at makerspace at university [16].

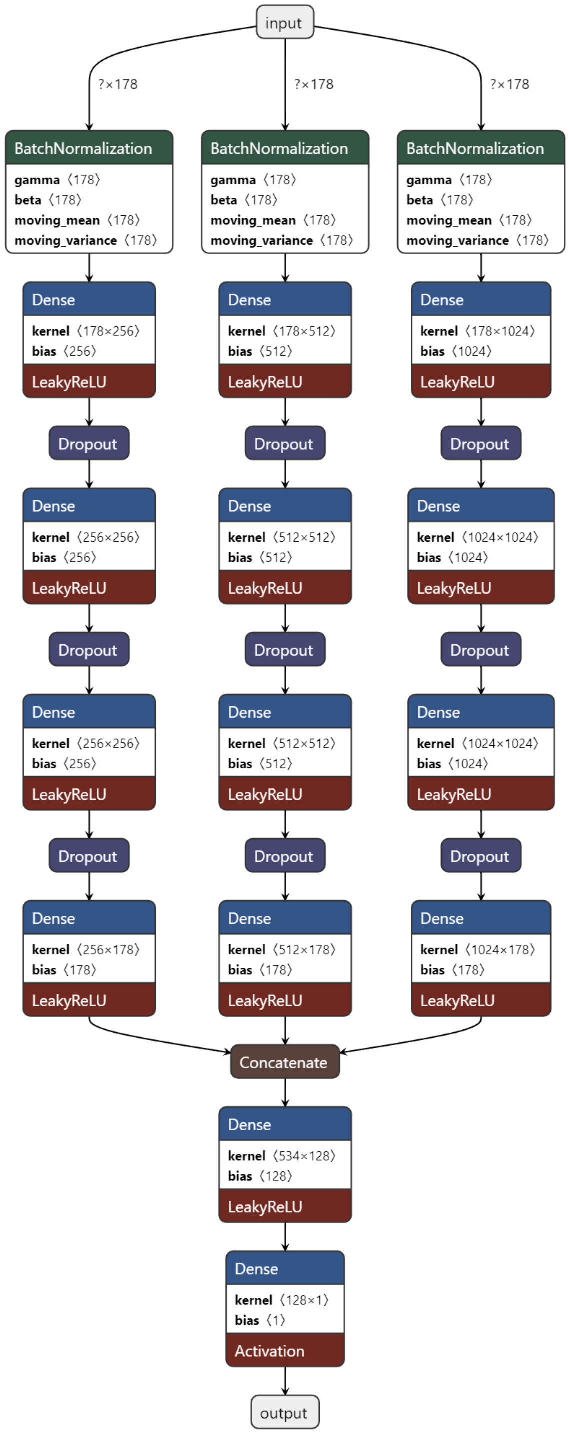

Fig 1. CNN Model Architecture

V. Methodology

The below Fig1 illustrates the workflow for detecting epileptic seizures using EEG data. The process begins with data preprocessing, which includes data normalization and balancing using oversampling methods to ensure a representative dataset. The preprocessed data is then split into training (80%) and testing (20%) sets. Features are extracted from the data, which are then used to train a Convolutional Neural Network (CNN) model. Finally, the trained model undergoes binary classification during testing and validation to distinguish between seizure and non-seizure events.

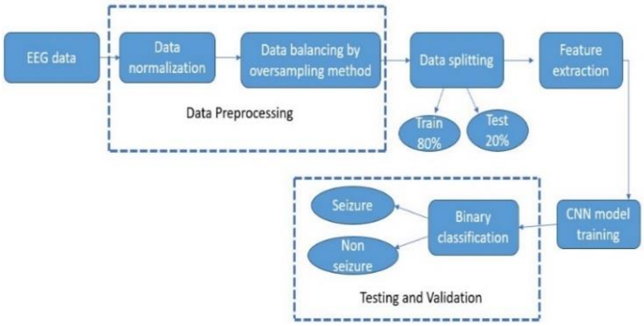

Fig 2. Design flow of model

The above flow diagram has the clear picture of working this Seizure classification CCN model.

A. Normalisation of data

This pre-processed dataset, which contains the EEG data of 500 individuals, is sampled into feature (X) and Label (Y), as previously mentioned in the dataset details. First, the data is normalized because it is easier to process because data points lie between lower and higher levels; in machine learning, normalization is the process of translating data into the range from 0 to 1, or more simply, data transformation onto the unit sphere.

More non-seizures-labelled data and less seizure-labeled data are included in our dataset; that is, label 1 indicates a seizure, while labels 2, 3, 4, and 5 do not.Thus, the majority class is more favourably impacted by our CNN approach.So, some of the machine learning methods should be used to balance the data for each class. Fig 3 represents the imbalanced counts before oversampling.

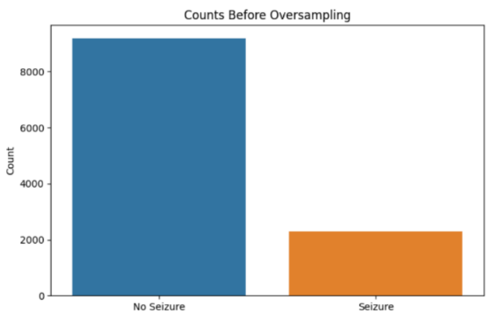

Fig 3. Counts before oversampling

B. Oversampling

There are various ways to perform data oversampling, which is a technique used to balance an imbalanced dataset by increasing the data from minority groups and making all the classes equal. In this case, the random oversampling method is used to first identify the minority class, then randomly select examples from that class, and then duplicate those instances. Fig 4 represents the balanced counts after oversampling.

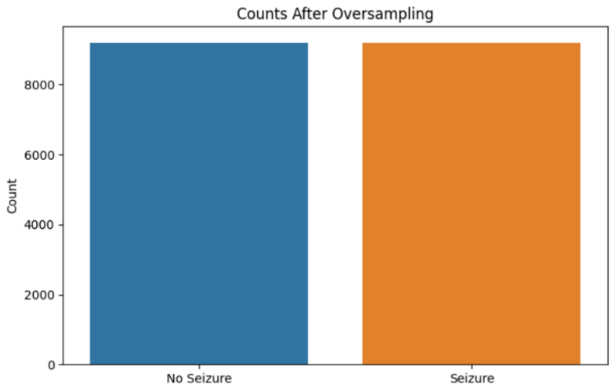

Fig 4. After Oversampling

C. Data splitting into train and test

Prior to oversampling the data, there were 9200 non-seizure occurrences and 2300 seizure occurrences. Following oversampling, the data for each class is equal, with 9200 occurrences in the seizure class and 2300 in the non-seizure class. Following that, 80% of the data is split for training and 20% is used for testing.

D. Model training

A modified CNN model is employed to classify epileptic seizures. As previously indicated, the dataset was subjected to normalization and binary classification using equation 1, with 80% of the data designated for training and 20% for the testing of the dataset. The model referred in fig 1 has three distinct output layers: 256, 512, and 1024, as was previously described. The neural network receives input from 178 features. To improve neural network training, batch normalization is applied to each layer of the input. Three batches—each with 256, 512, and 1024 layers—are used. The network processes each batch of input samples, and the normalization is applied to each batch with distinct layers. This helps to stabilize and speed up the training process. Concatenate is the procedure used to combine the normalized output of several batches so that the seizure is recognized and classified. The layers of each batch began extracting distinct aspects of the EEG signal when the input was supplied to the model. along with, Concatenate is the method used to merge the normalized output of several batches in order to identify and categorize seizures. achieving a validation classification accuracy of 98%. The binary cross entropy loss function (eq 1) is employed to quantify the discrepancy between the model's prediction and what should have been anticipated. When using Binary Classification, it yields results of either 0 or 1

$$\text{Log loss} = 1/N * \Sigma [- (Y_i * \log (P_i) + (1 - Y_i) * \log (1 - P_i))] \quad (1)$$

L is the loss due to cross-entropy.
Y is the ground truth, or true label, and it can be either 0 or 1.
the expected probability (P) instance is a member of class 1 is given.

VI. RESULTS

The analysis involved recording brain activity for 23.6 seconds on a dataset of 500 patients.Each patient's data set consists of 4097 data points, which are subsequently divided into 23 sections.Then, before resampling, each data set included 11500 rows; this gives us 18400 rows of data after resampling. Table 1 includes Each data labeled from 1-5, The EEG recordings were categorized into five conditions: 5 for eyes open, 4 for eyes closed, 3 for healthy brain region activity post-tumor localization, 2 for tumor site recordings, and 1 for seizure activity. These classifications enabled a comprehensive analysis of EEG signals in different states, offering insights into varied brain activities and responses.

Table 1. Seizure Classes

groups	Healthy/seizure	conditions
label1	Seizure	Recording of seizure activity
label2	Healthy normal	They recorder the EEG from the area where the tumor was located
label3	Healthy normal	Yes they identify where the region of the tumor was in the brain and recording the EEG activity from the healthy brain area
label4	Healthy normal	eyes closed, means when they were recording the EEG signal the patient had their eyes closed
label5	Healthy normal	eyes open, means when they were recording the EEG signal of the brain the patient had their eyes open

The proposed modified Convolutional Neural Network receives good training accuracy after using this data; both are close to 98%.

A. Confusion Matrix

Fig 5 reveals a robust performance of the model. With 1865 true positives (TP) and merely 13 false negatives (FN), the model demonstrates a high sensitivity in accurately identifying seizure instances. Additionally, the 1775 true negatives (TN) signify a strong capability to correctly classify non-seizure instances. The presence of 27 false positives (FP) indicates a minor rate of misclassification, emphasizing the need for ongoing refinement but overall affirming the model's effectiveness in seizure detection.

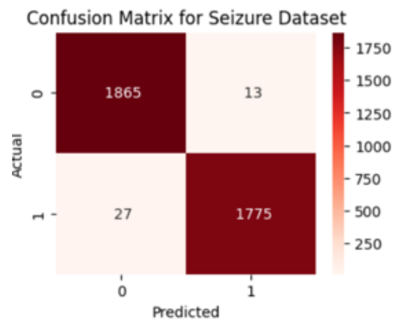

Fig 5. Confusion matrix

B. Evaluation Matrix

Table 2. Evaluation matrix data

	Precision	Recall	F1-score
Non seizure	0.98	0.97	0.97
Seizure	0.98	0.97	0.97
Accuracy	0.97	0.97	0.98
Macro average	0.97	0.98	0.97
Weighted average	0.97	0.98	0.97

Table 2 provides precision, recall, and F1-score metrics for the classification of seizure and non-seizure events, alongside overall accuracy, macro average, and weighted average values. The high scores across all metrics indicate that the model performs well in distinguishing between seizure and non-seizure instances, demonstrating robust classification capabilities.

C. Accuracy and Loss Graphs

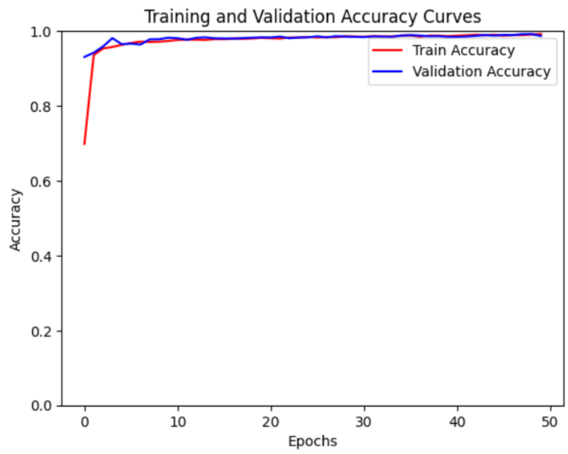

Fig 6. Accuracy Graph

In Fig 6, the performance of an epileptic seizure detection model is depicted based on EEG signals. Following 50 training epochs, the model demonstrated effectiveness, achieving a high accuracy of 98%. This result underscores the model's robust capability in accurately identifying and classifying seizures, as evidenced by both the training and validation curves displayed in the accuracy graph.

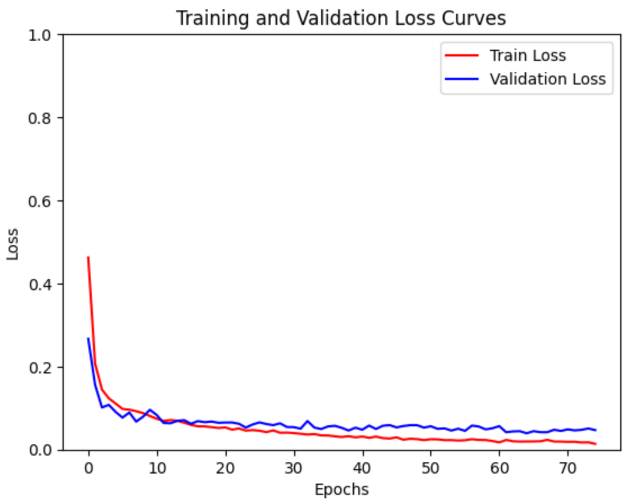

Fig 7. Loss graph

In Fig 7, the performance of an epileptic seizure detection model using EEG signals is depicted, focusing on the loss graph. After 50 training epochs, the model exhibited a train loss curve of 0.45 and a validation loss curve of 0.3. This suggests effective learning and generalization, with the model demonstrating a balanced reduction in loss on both the training and validation sets. Highlights the corresponding loss values for each curve

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