EEG-Based Seizure Detection Using Feed- Forward and LSTM Neural Networks Based on a Neonates Dataset

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Abstract

Electroencephalography (EEG) signals are used for the diagnosis of neurological disorders and detection of seizures. Early detection of seizures not only can save the patient's life but also can improve the quality of life. The traditional methods for seizure detection are time-consuming. To combat these problems and further improve the accuracy of seizure detection, the techniques of deep machine learning have been applied to EEG signals. This work develops an EEG-based seizure detection program using deep machine learning to detect seizures using EEG signals. The model is developed using a data set of EEG recordings from 79 human subjects. To this end, a literature review has been conducted to review the latest research related to deep learning algorithms applied to EEG signals for seizure detection. The EEG data has been pre-processed, filtered, and segmented before being fed to the machine learning model. Three models were developed, two models are based on feed-forward neural networks and the third model is based on long-short term memory (LSTM) network. For the feed-forward neural network with 10 hidden neurons, the obtained accuracy was too low (66.1%). For the feed-forward neural network with 100 hidden neurons, the accuracy was slightly improved to 74.3%. The LSTM model showed an accuracy of 87.7%. The model correctly classified 96.4% of normal patients as having no seizures and correctly classified 71.6% of seizure patients as having seizures. The limitations on increasing the accuracy of the models are discussed and possible solutions are suggested. If channel-specific seizure annotations are provided by medical experts, the accuracy of the model is expected to increase significantly.

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ABSTRACT Electroencephalography (EEG) signals are used for the diagnosis of neurological disorders and detection of seizures. Early detection of seizures not only can save the patient's life but also can improve the quality of life. The traditional methods for seizure detection are time-consuming. To combat these problems and further improve the accuracy of seizure detection, the techniques of deep machine learning have been applied to EEG signals. This work develops an EEG-based seizure detection program using deep machine learning to detect seizures using EEG signals. The model is developed using a data set of EEG recordings from 79 human subjects. To this end, a literature review has been conducted to review the latest research related to deep learning algorithms applied to EEG signals for seizure detection. The EEG data has been pre-processed, filtered, and segmented before being fed to the machine learning model. Three models were developed, two models are based on feed-forward neural networks and the third model is based on long-short term memory (LSTM) network. For the feed-forward neural network with 10 hidden neurons, the obtained accuracy was too low (66.1%). For the feed-forward neural network with 100 hidden neurons, the accuracy was slightly improved to 74.3%. The LSTM model showed an accuracy of 87.7%. The model correctly classified 96.4% of normal patients as having no seizures and correctly classified 71.6% of seizure patients as having seizures. The limitations on increasing the accuracy of the models are discussed and possible solutions are suggested. If channel-specific seizure annotations are provided by medical experts, the accuracy of the model is expected to increase significantly.

INDEX TERMS EEG, Seizure detection, Neonatal, Deep machine learning, feed-forward, LSTM.

I. INTRODUCTION

The aim of this work is to develop an EEG-based seizure detection program using deep machine learning. The deep machine learning model will be developed based on a data set of EEG recordings from 79 human subjects. The data was acquired and the seizure events were annotated by medical experts. The details of the data will be explained in detail in the data description section. The developed model should be able to successfully identify seizure events from EEG signals. Before moving to data description and model design, a concise survey of the recent literature related to EEG-based seizure detection using deep machine learning will be presented.

As it is well-known, a seizure is a burst of uncontrolled electrical activity between neurons that results in temporary abnormalities in behavior, sensation, movement, or level of awareness [1]. The condition of having recurring seizures is known as epilepsy [2]. The symptoms as well as types of seizures vary. The two major classes of seizures are focal or partial onset and generalized onset seizures [3]. Focal onset seizures start from one area of the brain and can spread across the brain leading to mild or severe symptoms [4]. Generalized seizures can either begin as focal seizures that spread to the two sides of the brain or can start simultaneously over both sides [4]. Generalized onset seizures usually start in childhood if there is abnormal regulation between parts of the brain [5]. Since seizures are essentially abnormalities in the brain's electrical activity they can be detected and identified by analyzing the Electroencephalogram (EEG) bio-signal of the brain.

When a seizure starts, the normal pattern of brain activity changes and different brain activity can be seen on the EEG reading. In focal seizures, this change is only seen on the EEG electrodes that are on the part of the brain where the seizure is happening, the other electrodes give normal readings [6]. However, in generalized onset seizures, the abnormal activity is seen from all EEG electrodes [6]. However, seizure detection using EEG involves at least two major complications. Firstly, most seizures do not have a typical EEG pattern, they only lead to changes (abnormalities) in the EEG signal but not a fixed pattern. Secondly, some people have abnormal EEG patterns that are not related to seizures or epilepsy. That is why a medical expert is needed to identify seizures based on EEG readings.

Early detection of seizures could be vital in protecting the patient from harms that can happen during a seizure. Early detection of seizures targets the potential time window between the onset of measurable changes in the brain electrical activity and the beginning of disabling clinical symptoms for the patient. If the patient is alarmed, based on their EEG activity, that a seizure is going to happen in few minutes or seconds (referring to its clinical symptoms), they can take several precautions to ensure their safety during the seizure event. Simple precautions such as getting out from crowded places, staying away from traffic, or seeking someone’s attention may prevent the patient from serious injuries that could happen during an unexpected seizure. Moreover, automatic seizure detection can help the medical professionals to diagnose epilepsy [6]. These, among other reasons, resulted in a huge research interest in developing methods of early seizure detection using machine learning techniques based on the analysis of EEG signals.

II. Literature Review

Based on an analysis of prior studies, it is asserted that numerous machine learning methods such as Radom Forest, Support Vector Machine, Lip-Miner, Decision Tree, Neural Network, XGboost, K Nearest Neighbors, and Naïve Bayes etc., have been used in prediction and detection of seizures. Artificial neural networks (ANNs) are widely used in machine learning models and useful tools to handle prediction, classification, clustering, data analysis and pattern recognition. Machine learning has been used for EEG processing and epileptic seizure prediction. The authors of [6] have proposed an architecture for detection model based on fully convolution networks (FCN) to detect the seizure on data from unobserved patient. The FCN has been configured in 3 blocks with 128 layers and convolutional layers to perform the detection task [6]. Based on the experimental results, it has been found that some patients are harder to detect the seizure for, to combat this challenge another cross-patient model has been made for deep learning to evaluate the seizure. The accuracy and precision of seizure detection has been increased when modification is made in seizure detection algorithm. The main advantage of this proposed algorithm is that it requires minimum pre-processing stage from raw EEG signal without filtering and domain transformation. The proposed machine learning algorithm was able to automatically detect epileptic seizure using an imaged-EEG images of brain signal [6].

Another convolution Neural Network based algorithm “SeizNet” has been proposed by [5] for seizure detection. The SeizNet is designed and compared with traditional SVM machine learning machine with additional dropout layers and batch normalization after each convolution layer. The proposed algorithm is an end-to-end solution and has been applied on EEG data of 29 number of patients to verify the accuracy of prediction [5]. The main objective of SeizNet is to develop a detection system by using the least number of channels to accurately detect the seizure possibility. The experimental results are compared with 18-channel and 2-channle CNN & SVM algorithm, it has been found that the SeizNet has increased sensitivity and reduced false alarms in seizure detection. The 2-channles trained SeizNet algorithm is light-weight and an efficient seizure monitoring system in comparison to other algorithms which are using all channels or more than two channels [5]. Finally, based on the literature of CNN machine learning algorithms related to seizure detection it has been concluded that the integration of machine learning is very encouraging in medical field and has the potential to detect the various aspects of seizures in advance of the clinical symptoms.

To better illustrate the methods employed in both papers, a comparison between different parameters of the two studies is summarized in Table I. The salient features of SeizNet are the utilization of a smaller number of channels, light weight, and feasible solution for home-based seizure monitoring which is established on end-to-end approach. The main advantage of FCN is that it does not require any estimation of pre-selected features, has no environment restrictions, and minimum pre-processing requirement for EEG signal. The CNN has been changed into FCN to produce dense predictions per pixels of 2D images obtained from EEG signal. In both detection algorithms, the learning strategy has been transferred to train a model on a database, once the model has been trained by the deep machine learning then the model can be fine-tuned such that it can detect seizures from different data sets. The unique features of SeizNet are that the model can be trained by only 2 channel's data and able to deliver similar performance in comparison to traditional approach trained with full scalp EEG data.

TABLE I
COMPARISON OF DIFFERENT PARAMETERS BETWEEN SIEZNET & FCN

No.	Parameter	SeizNet Detection Algorithm	FCN Detection Algorithm
1	Specifier	BPsvm	CHB-MIT
2	Blocks & Layers	Drop out layer, Batch Normalization,	Pool, FCN layer and SoftMax Layer
3	Filter	56 Filters in 4th Convolution Layer	128 Filters
4	Number of Patient	29	23
5	EEG Recording	25 to 66 Minutes	130 Minutes
6	Sampling Frequency	200 HZ	256 HZ
7	Sensitivity	93.3%	99.6%
8	False Alarms	0.58	0.5

When building a deep learning model three main challenges could be countered. First, EEG data is not stationary and statistical features change and are not the same across different subject and even same subject over time while (machine learning) ML is sensitive to acute variations. Second, EEG counters diverse range of artifacts such as eye-blinks, environmental white noise, and muscle activity. The accuracy of detection drops 10% every time EEG data is corrupted with medium level noise [7]. Finally, it is not efficient to train classical ML with low amount of data.

Usually, artifacts affect negativity the seizure patterns but there are others that help detection accuracy. The three following artifacts are the most vital:

1. Muscle Artifacts: can be seen as random noise that could be filtered with BPF of 20 Hz and 60 Hz cut-off frequencies and multiplied by muscle scalp map [8].
2. Eyes Blinking and Movement: this random noise signal filtered by BPF of 1 Hz and 3 Hz cut-off frequencies.
3. White Noise: are the other environmental electrical noise classified as Gaussian noise.

The usual proposed method to approach this problem in the literature can be summarized in the following points.

1. The EEG data are segmented to create from the non-stationary signal to several pseudo-stationary epochs. This stage is classified as pre-processing step. The major constraint is to have large number of labelled data during machine training, and by segmentation will have more training samples that improve the deep learning model. [8] tested wide range of segmentation and found out as the number of segmentation increased accuracy decreases in logarithmic function.
2. After selecting the algorithm to train the data in deep learning, one could perform two common scenarios to train and test the deep learning model:
   a- Hold-out: Splinting the sampling data 80% for training and 20% for testing.
   b- Cross-validation: usually 5-folds are done. The data is divided into 5 sections, then 1st section is taken out for testing and the rest for training. Next, 2nd section of data taken for testing and rest for training and that will keep going, and every time validation and accuracy is measured and at the end average is calculated.

[9] applied multilevel wavelet transform as feature extraction method and extreme learning machine (EML) as classification model reaching sensitivity of 99.48%. To avoid the three artifacts mentioned before, they used robust deep learning while detecting epileptic seizures. Robust is the capability of our machine model to cope with errors (such as noise) during class prediction. The process of building their model was as follows:

1. The EEG data was divided into time-series data into short-length segmentation since the beginning of the seizure pattern that emerges with random EEG signals.
2. Pre-processing, where the model captures from the segmented data that is temporally correlated with successive EEG sampled data. This segmented data goes through neural network with long short-term memory cells to learn the most robust EEG features for epileptic seizure data.

3. The cross-entropy was calculated between true labels and predicted labels by feeding the selected and trained features into SoftMax classifier layer.
4. The prediction model performance was examined on ideal conditions data, that are eliminated from noise.
5. After testing their model on real life conditions of EEG data, the model maintained high detection accuracy. This proves how robust their model against the three main noises.

III. Data Description and Pre-processing

The data given is a set of 79 multichannel EEG recordings from 79 subjects (human neonates) [10]. The data was collected from neonates admitted to the neonatal intensive care unit (NICU) at the Helsinki University Hospital. The average duration of the recordings is 74 minutes. The data is intended to record and identify neonatal seizures. According to experts' agreement, 22 neonates had no seizure while 39 of them had seizures [10].

Each EEG recording lasted almost one hour; median recording duration was 74 minutes (IQR: 64 to 96 minutes). The EEG signals were recorded with a NicOne EEG amplifier (Natus, USA) with a sampling frequency of 256 Hz, and EEG caps (sintered Ag/AgCl electrodes; Waveguard, ANT-Neuro, Germany) with 19 electrodes positioned as per the international 10–20 standard, including a recording reference at midline [10]. A bipolar montage was generated for annotation according to the standard longitudinal bipolar layout (a.k.a. 'double banana'): Fp2-F4, F4-C4, C4-P4, P4-O2, Fp1-F3, F3-C3, C3-P3, P3-O1, Fp2-F8, F8-T4, T4-T6, T6-O2, Fp1-F7, F7-T3, T3-T5, T5-O1, Fz-Cz, Cz-Pz [10]. This is shown in Figure 1.

The annotations of the seizures were stored in a text file using the start (onset) and duration of each seizure with one second resolution. So, the annotations did not include information on the location or nature of the seizure. Seizures were annotated according to a well-established definition: a distinct, abnormal electrographic event with a clear beginning and end comprising sustained, repetitive evolving spike/sharp waves or rhythmic waveforms. This event was defined as a seizure if it had a duration of over 10 seconds [10]. The experts doing the annotations were blinded to the clinical details of infants, and were only aware that the neonate had clinical suspicion of seizures. The annotations were based on the EEG signal. Annotations were stored in a MAT file and a CSV file [10]. The MAT file contains a cell array of 79 elements, where each element corresponds to a study ID number. Each element of the cell array is an M×N array, where M is the number of experts (M = 3) and N is the

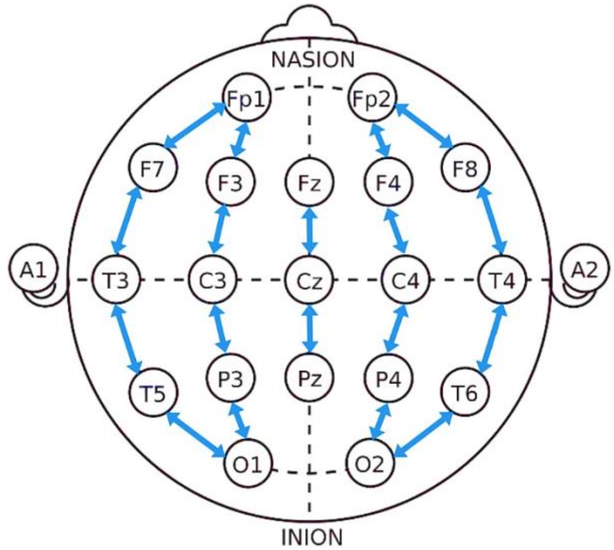


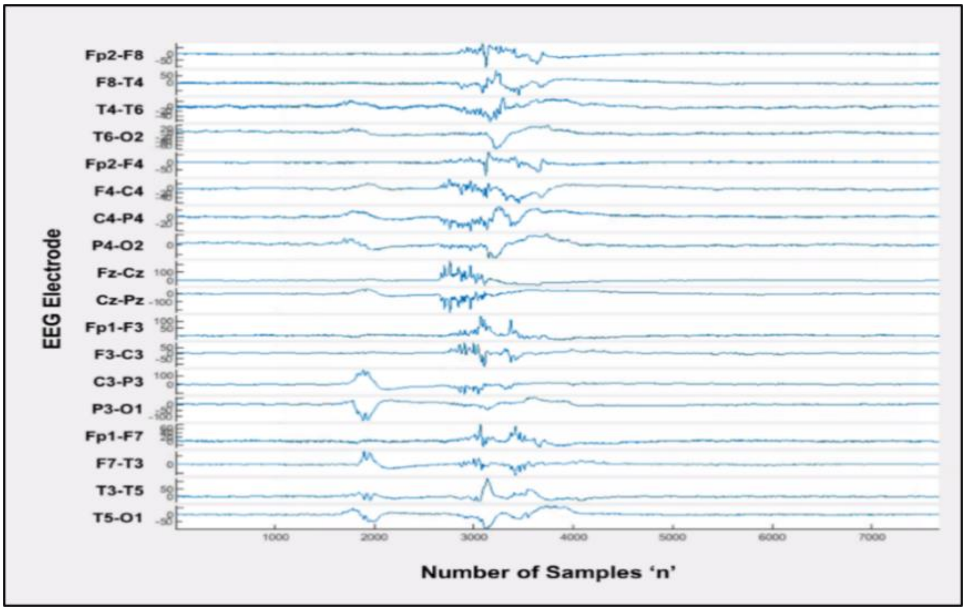
FIGURE 1. **The bipolar EEG montage used by reviewers to annotate the presence of seizures [10].**

duration of the annotation in seconds. Each second is ascribed a 1 (denoting seizure) or 0 (denoting non-seizure) [10].

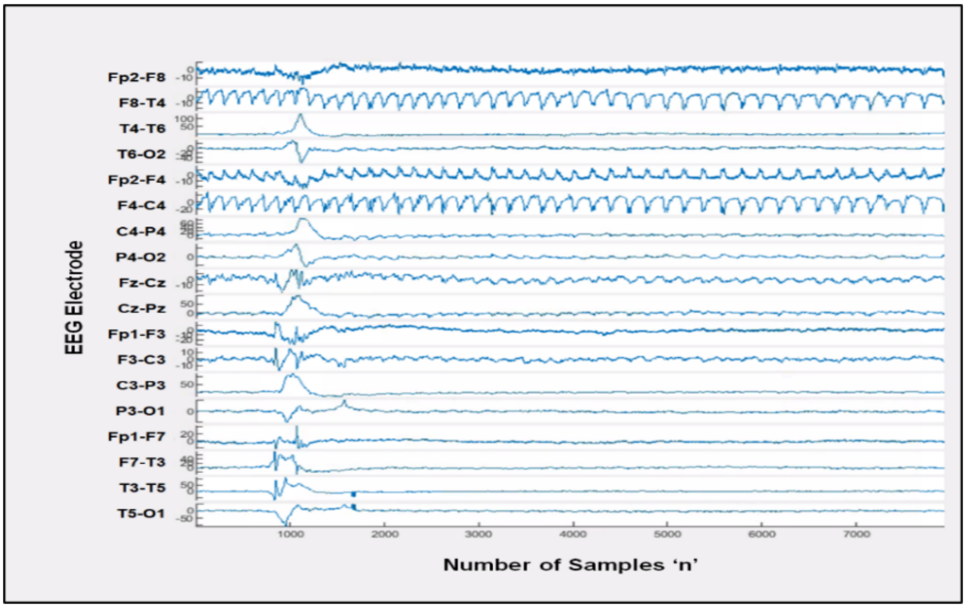
The files in the dataset are:

- EDF files containing the EEG recording using a referential montage from study ID 1-79. EEG units are microvolts, sampled at 256 Hz.
- CSV file (A, B or C) and MAT file containing the annotations of 3 experts for all 79 neonates sampled every second (1 Hz).
- CSV file containing clinical information and data acquired from patient notes as well as information on the general spatial distribution of consensus seizures within the recording (marked only by reviewer A) aligned with EDF file.

In order to visualize the EEG data and visualize the noticeable features of seizures as they appear on EEG signal, part of the EEG signal for patient 1 (EEG1) was plotted for an interval of 30 seconds, once for a seizure-free interval and another for a seizure interval. Patient 1 has seizure by experts' agreement. The EEG signals are in edf file format. EEG1 consists of 6993 seconds for the 19 electrodes as placed in Figure 1. There are 19 columns in the data, one for each electrode. We converted the data from the timetable format to cell format and lastly cell format to matrix format. Having the data in a matrix makes it much easier to handle. After that, we converted the data from unipolar EEG montage to bipolar montage in order to be consistent with the EEG montage that was used by the experts for annotation. The conversation from unipolar montage to bipolar montage is straightforward since all data from the 19 electrodes measured with respect to the common reference was given.



(a)



(b)

FIGURE 2. (a) The normal condition EEG signal of patient 1 in the time interval 0-30 seconds. (b) The seizure event EEG signal of patient 1 in the time interval 370-400 seconds.

Thus, the 18 bipolar EEG channels were obtained as discussed previously in the data description. Figure 2-a is the non-seizure EEG signal while Figure 2-b is the seizure EEG signal. The y-axis is units of mV while the x-axis shows the sample number (sampling frequency is 256 Hz). The 18 EEG channels are clarified on the y-axis. Each plot is 30 seconds long (7680 sample), the first plot illustrates the EEG signal of patient 1 while having no seizure (normal EEG) that lasted from 0-30 seconds, and the second plot illustrates the EEG signal of patient 1 while having a seizure that lasted from 370-400 seconds. As it can be seen, there are larger fluctuations in Figure 2-b compared to Figure 2-a, as Figure 2-b represents the readings of the electrodes from 370 second until 400 second, as in this period the patient had seizure event. These high amplitude and repetitive fluctuations or patterns are caused by the abnormal and intense electrical activity occurring in the brain during the seizure. It is such differences between the EEG of normal brain activity and EEG of seizure activity that will be utilized for teaching the model and developing the machine learning model that can identify seizures based on these unique characteristics.

Since the used EEG is non-invasive then the hair, skin, and skull thickness are affecting the signal amplitude and strength, therefore the signal amplitude falls between 5 to 300μV. With such weak signal there are different types of noises that affect the signal easily and they need to be eliminated. Starting with the DC component in the analog domain creating offset, it can be rejected by high pass filter. Also, it is noted that the average power in the range of 70 Hz to 128 Hz is indicative of noise [10]. Thus, a low pass filter is needed to reject signals with frequencies higher than 70 Hz as they represent noise and not EEG signal.

Consequently, a bandpass filter is required to achieve both requirements for noise rejection. So, we applied 6th order bandpass Butterworth filter with lower cut-off frequency of 0.5 Hz and higher cut-off frequency of 70 Hz and infinity impulse response as shown in Figure 3. Butterworth filter is suitable for biomedical signals because other filters with sharper cut-off frequency will have ripples that are not accepted for biomedical signals, since they can eliminate major information from the signal. Also, a Notch filter was designed with frequency of 50 Hz originating from power line noise and their harmonics that could be eliminated by the notch filter as shown in Figure 4. Notch filter is characterized as very selective filter with a very high rejection for the exact selected band frequency, without attenuating other frequencies. The filters eliminate the high frequency noise. Also, the amplitude of the signal has no sudden high peaks, which were indicators of artifacts, after filtering. So, the resulting signal is free of noise and artifacts and can be accurately used for EEG-based seizure detection.

Regarding data segmentation, we utilized the annotations of the seizures provided by the medical experts to separate the seizure events from the non-seizure events. The EDF files for each patient containing the waveforms for 19 channels were imported, and then converted from EDF file format to timetable format, and lastly converted to matrix format. These conversions were necessary to start manipulating the data stored in each EDF file in order to separate non-seizure from seizure events for each patient. We have developed a code that automatically identifies all patients who have seizures by agreement of experts. Secondly, for each patient, the intervals of seizure are identified by their start and end time in seconds. This was accomplished by using the annotation for each patient. Thirdly, for each patient the seizure intervals were stored in an array.

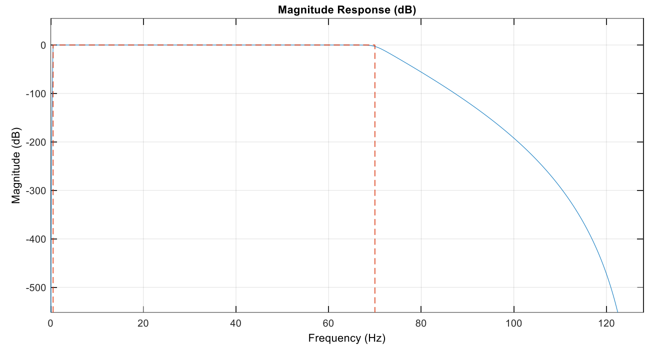


FIGURE 3. **Response of the bandpass Butterworth 6th order filter with cut-off frequencies of 0.5 Hz and 70 Hz.**

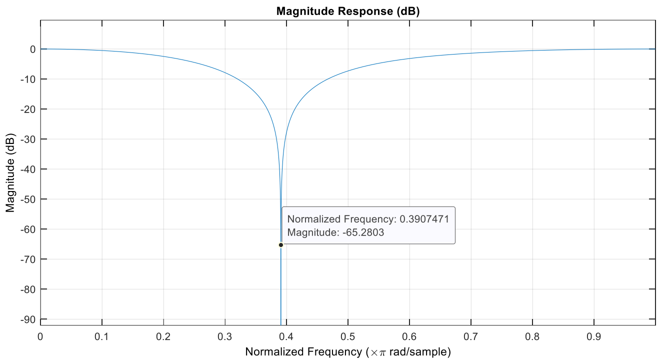


FIGURE 4. **Response of the Notch filter at 50 Hz.**

Each two consecutive numbers in the array represent the start and end time of a given seizure event, respectively. Fourthly, the EEG signal of each patient was separated based on the presence or absence of seizure, and then stored in two new variables. Thus, the final result of the code was the automatic separation of the original EEG signal into two signals; a signal that contains all the non-seizure events and a signal that contains all the seizure events.

After storing all the seizure events of each patient in one matrix and all the non-seizure events in a separate matrix, the data can be segmented into the samples that will be used for developing the machine learning model. Each data segment is around 10 seconds long, because this is the minimum time interval used for defining a seizure. In other words, by having 10 second segments it is ensured that each segment has at least one identifiable seizure event. However, since the non-seizure events are much greater than the seizure events, there is a 50% overlap in segmenting the seizure data. Thus, we can extract a greater number of seizure samples from each patient in order to make the number of seizure samples comparable with the number of non-seizure samples. A code was developed to measure the duration of each EEG signal and calculate the number of segments that can be extracted from that signal. After that, the data is segmented based on the segmentation indices calculated. The segments are then ready to be inputted to the machine learning model.

IV. Deep Machine Learning Model

Before selecting a deep machine learning algorithm to utilize for our data, few common algorithms are explored in terms of their overall architecture and intended application area. The algorithms that will be compared are Convolutional Neural Networks (CNNs), feed-forward neural networks, and Long-short term memory (LSTM) networks.

Convolutional neural networks are a type of neural network that utilizes convolutional reckoning procedures. Convolutional Neural Networks (CNN) is an ordinary neural network that has a figurative insert. Convolutional neural networks are made up of three types of layers (building blocks): convolution, pooling, and fully linked layer [11]. The first two layers acquire features while the third layer is an entirely connected layer; modifies particular characteristics into the ultimate design, particularly for classification. In the field of image processing, CNN is extremely popular and is a practical machine learning technique. CNN is usually used for machine learning on images and visual data.

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) that is employed to foresee data sequences. LSTM can learn long-term dependencies between the time steps of a sequence. An LSTM is different from a CNN as it is generally obtained to examine and formulate forecasts established on data classifications, a CNN, on the other hand, is programmed to alter "spatial similarity" in data and regulates well on images and oration. An LSTM is a neuron unit that integrates data back to itself for the second time phase in a sequel at a fundamental phase. It is a subdivision of the recurrent neural network (RNN), which is a more general kind of neural network [12].

Long short-term memory (LSTM) has long term memory that is referred to for every new prediction done. A sample of this new prediction is saved in the network called forget gate with past accumulated predictions. Also, in this network based on the current prediction it decides what to forget and what to keep. Next network in LSTM is the selecting gate, that votes what prediction to print and what need to stay within the network for next classifications [13]. “Ignoring gate”, after each prediction decides what prediction need to be out of assumption and what could be part of the assumption. LSTM learns and predicts from time steps of sequence data. The problem addressed here is a classification problem, thus the LSTM architecture suits our application. LSTM hidden layers and cell state learn from previous time steps by adding and removing information for the layers, by the previous mentioned gates. LSTM network can work with data with varying sequence lengths, by padding, truncating, or splitting the sequence, like that all sequence in each mini-batch have specified length. By adding dropout layers after LSTM layer overfitting could be prevented.

A feed-forward neural network has a specific number of hidden layers that are preceded by the input and followed by the output. Each hidden layer has a given number of hidden neurons, that number can usually be chosen in the way that results in the most satisfactory performance of the model. An LSTM is a special kind of node within a neural network. It can be put into a feedforward neural network, and it usually is. When that happens, the feedforward neural network is often referred to as an LSTM. Feed-forward neural networks are commonly used for pattern recognition and classification problems. Multi-layer Perceptron uses back-propagation to train the model. Back-propagation measures the error between the output value and the correct value to create pre-defined function [14]. This detected error is fed back to the network, so the algorithm can adjust its weights for each connection which reduces the error function for the next output. This process keeps going during the training process until the network converge to state the error of calculation is small. Usually, weights are adjusted by gradient descent. The network measures the derivation of the error function with respect to the current weight, and then changes the weight such that the error decreases [15]. The main layers of feed-forward neural network are illustrated in Figure 5. They are input layer with the input signal, one hidden layer that can be defined with a specific number of hidden neurons to map the finite input-output problem, and output layer with expected number of classes [16].

Two machine learning algorithms have been used for EEG seizure detection. Firstly, we trained a feed-forward neural network with 10 hidden neurons in the hidden layer. The network has a hidden layer with an adjustable number of hidden neurons and a fixed output layer. Secondly, we trained the same feed-forward network but with 100 hidden neurons in the hidden layer to see the improvement that could be achieved by increasing the number of hidden neurons. The architecture of the feed-forward neural network is shown in Figure 5, for the model with 10 hidden neurons. Thirdly, we trained an LSTM model. The LSTM model has five main layers. First, the sequence input layer which is one-dimensional in this case. Second, the bidirectional LSTM layer with 100 hidden neurons was chosen. Bidirectional LSTM was used as it can look at the dependencies between the time steps of the sequence both in forward and backward directions and thus results in more accurate classification as compared to forward-only LSTM. Third, two classes are specified (for seizure and non-seizure) by including a fully connected layer of size 2. Fourth, there is the SoftMax layer.

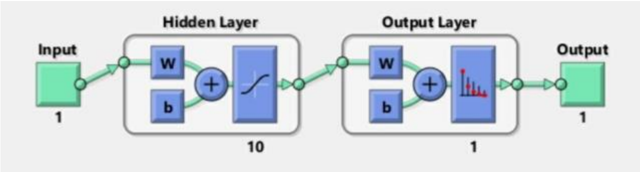


Figure 5. **Feed-forward neural network architecture.**

Fifth, the classification output layer which uses cross entropy measure.

Regarding the feed-forward model, cross-entropy was selected for our algorithm performance. Cross-entropy is used as loss function for classification model. It measures difference between two random set of events probabilities. More information is expected within lower probability events, since it is surprising and less likely to happen. The progress was measured from the gradient, so the higher the gradient the faster the model will learn and change the weights of the neurons regard to the change in error measured. Finally, validation check was used to provide unbiased evaluation about model performance while training and tuning the model hyper-parameters on the training dataset.

Regarding the parameters of LSTM, Adam (adaptive moment estimation) was used as it is a bias-correction that works well in practice and most accepted compare to other optimization methods. Adam's parameters learning rate adapts with first moment (the average of recent magnitudes of gradients for the weight) and second moment (uncentered variance of gradients). The following are the parameters we tuned under Training Options ADAM optimizer to optimize our learning rate in MATLAB. LSTM layers are declared Bi-LSTM layer, an extension of traditional LSTM layer that learns bidirectional between time steps of time series or sequence data from the long-term memory. Bi-LSTM train two instead of one LSTM input sequence. The first input sequence is as normal time steps of time series and second input is the reverse copy of the first input. This improves the model with the sequence classification problem, by resulting in faster and fully learned model. Selected Initial Learn Rate function to select best learning rate of our model. Selecting its value was by trial and error, till we reached highest accuracy. Then, gradient threshold needs to be defined to avoid gradient becoming too small and error gradients accumulate, resulting in unstable network. Maximum epochs is another hyper-parameter that was defined equal to 5. Thus, the network will go through the learning algorithm 5 epochs, and as many iterations as needed within each epoch, while working through the entire training dataset. Inside this loop there is defined nest loop called mini batch that was defined with size 27 samples that is smaller than our training dataset.

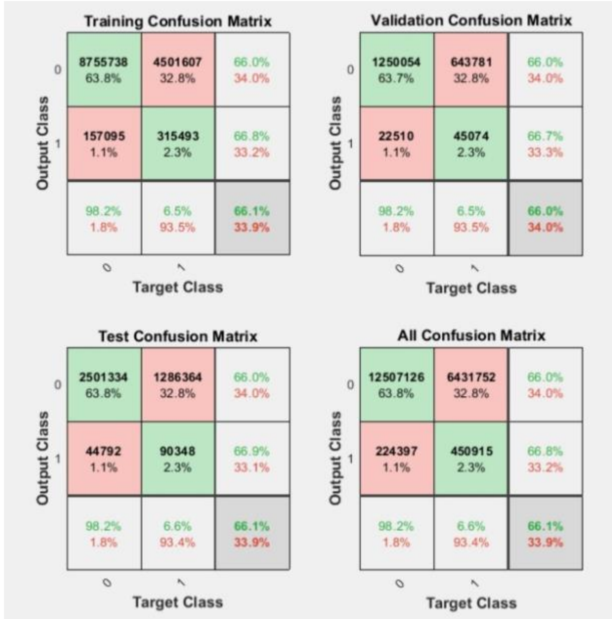


Figure 6. **Confusion matrix for the feed-forward neural network with 10 hidden neurons.**

So, 27 samples will work through by comparing the prediction with the expected-out variable and calculate the error. Then the algorithm will update and improve its model according to the error, until the model error is sufficiently minimized.

For both of the feed-forward neural networks, 70% of the data was used for training, 15% for validation, and 15% for testing. For LSTM, 80% of the data was used for training while 20% was used for validation and testing.

V. Validation and Results

For the feed-forward neural network with 10 hidden neurons, the obtained accuracy was quite low: only 66.1%. The model correctly classified 98.2% of normal patients as normal (no seizure) but was only able to correctly classify 6.6% of seizure patients as having seizure. So, the model had very high sensitivity but very low specificity. The confusion matrix for this model is shown in Figure 6. The explanation of each parameter in the confusion matrix is detailed in the discussion and Figure 14. Figure **7** shows the gradient of the feed-forward network for each epoch and the validation checks each epoch. It is seen that the validation checks reach 6 at epoch 185 causing the training to halt as was specified in the set-up of the model. Figure 8 displays the validation performance of the model for each epoch. Again, the validation performance is measured based on the cross-entropy of the resulting training. It is seen that the best validation performance is reached at epoch 179. Finally, Figure 9 provides the error histogram of the network.

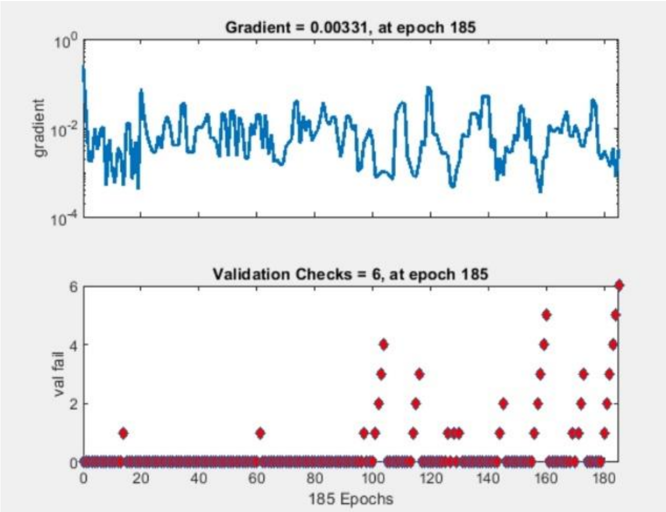


Figure 7. **Plot of the network's gradient and validation checks for each epoch.**

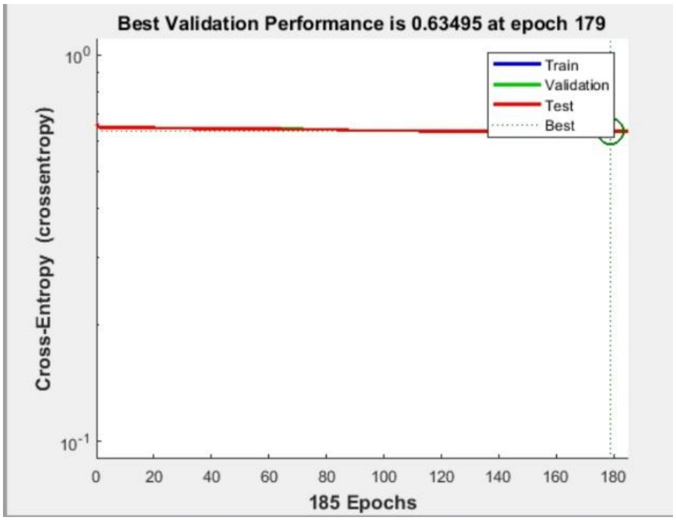


Figure 8. **Plot of the validation performance of the neural network for each epoch.**

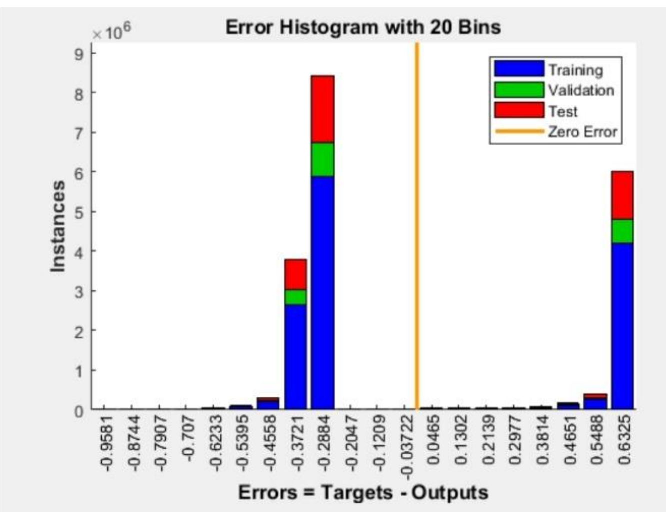


Figure 9. **Error histogram for the feed-forward network for training, validation, and testing data sets.**

The x-axis shows the value of the error defined as the target minus the output of the model. The y-axis shows the instances of occurrence of that particular value of error. Bins are the number of vertical bars that are observed on the graph. The error range is divided into 20 smaller bins. It is seen that there are many instances of error, and this explains the relatively poor performance of the model.

For the feed-forward neural network with 100 hidden neurons, the accuracy was slightly improved to 74.3%. The increase in accuracy is seen not to be significant so there is no point in further increasing the number of hidden neurons and instead a different machine learning model has to be used. The network correctly classified 99.1% of normal patients as normal (no seizure) but was only able to correctly classify 29.1% of seizure patients as having seizure. The feed-forward neural network with 100 hidden neurons had almost the same output figures as the network with 10 hidden neurons. So, it can be concluded that feed-forward neural networks in general are not very suitable for this problem if high accuracy is required. However, the network has superior performance in correctly identifying normal patients, but very poor performance in identifying seizure patients.

For the LSTM model, several attempts were tried using different options to reach the highest accuracy. The most accurate model required 7675 iterations. Figure 10 shows the plot of the accuracy of the model on the training data for each iteration. It is seen that the accuracy varies from as low as 50% to as high as 90%. Figure 11 shows the corresponding training loss for each iteration. The training loss is the cross-entropy loss on each mini-batch. It is value should ideally go to zero. In this case it is seen to go as low as 0.3 and does not exceed 0.9 in any iteration. If the training is not converging, the plots oscillate between values without trending in a certain direction as shown here. The oscillation means that the training accuracy is not significantly improving. Although in other trials the oscillation was absent and the plots quickly converged, those models had overall lower performance compared to the trial shown here. So, it is not possible to get rid of the oscillation and achieve a high accuracy at the same time for this specific classification problem. However, it is possible that the oscillation shown in Figures 10 and 11 seizes but after many more iterations than shown here but the accuracy is unlikely to improve. The LSTM training stage gave an accuracy of 78.2% with a confusion matrix shown in Figure 12. The LSTM model testing gave an accuracy of 87.7%. The model correctly classified 96.4% of normal patients as normal (no seizure) and correctly classified 71.6% of seizure patients as having seizure.

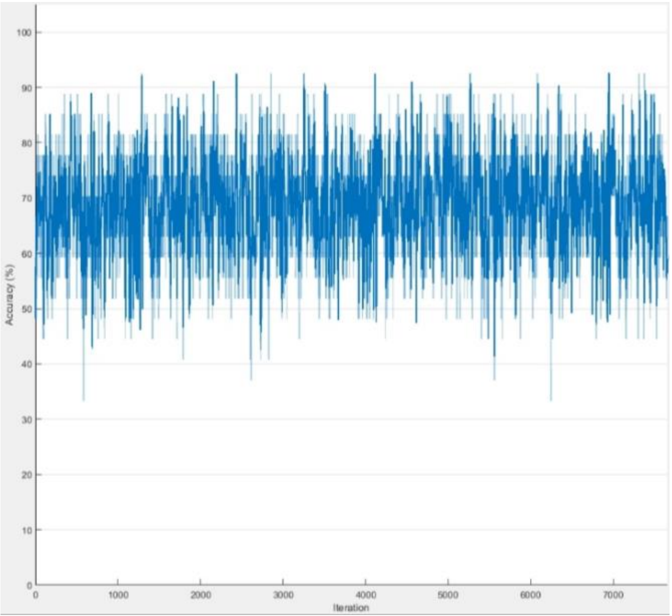


Figure 10. **Plot of the training accuracy of the LSTM model for each iteration.**

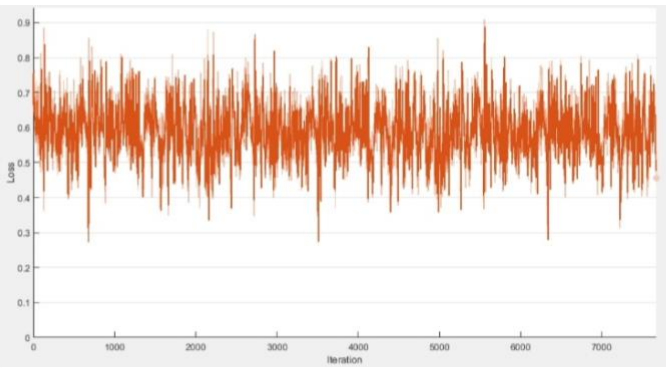


Figure 11. **Plot of the training loss of the LSTM model for each training iteration.**

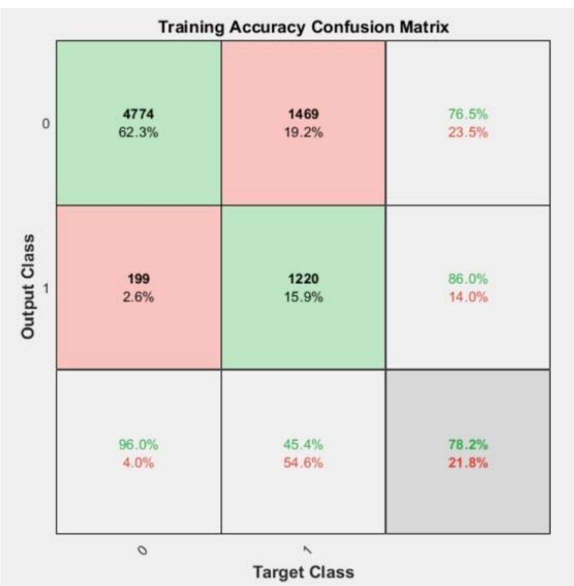


Figure 12. **Training confusion matrix for the LSTM network.**

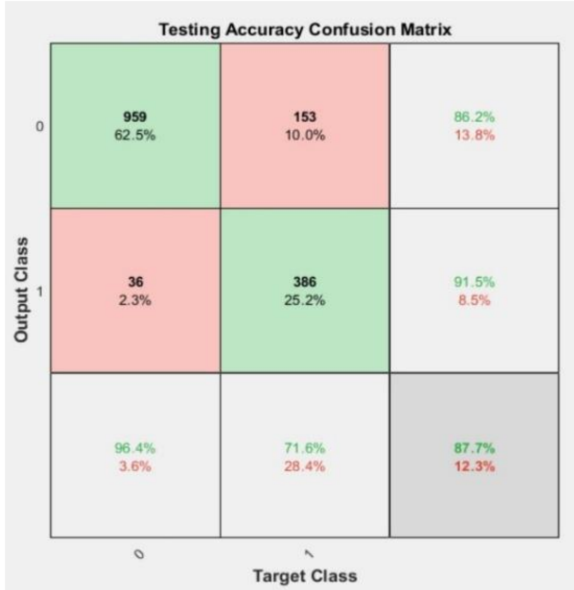


Figure 13. **Testing confusion matrix for the LSTM network.**

The LSTM model testing confusion matrix is shown in Figure 13. Only 12.3% of the patients were miss-classified: 2.3% miss-classified as seizure patients while they are normal and 10.0% miss-classified as normal patients while they have seizure. The model has a sensitivity of 96.4%, a specificity of 71.6%, a precision of 86.2%, and a negative predictive value of 91.5%. It can be seen that the LSTM model gives higher accuracy than the two feed-forward neural network models.

VI. Discussion

The definition of the various parameters of the confusion matrix in the format used above is given in Figure 14 for convenience. Since the annotations provided by the experts associated a seizure event with ‘1’ and a non-seizure event with ‘0’, the model mapped a normal patient as being a “positive” and a seizure patient as being a “negative.” So, “true positive” is the number of correctly classified normal EEG events, “false positive” is the number of seizure events miss-classified as no seizure, “true negative” is the number of correctly classified seizure EEG events, and “false negative” is the number of normal events miss-classified as seizure events.

The sensitivity of the model is the measure of the correct true positive (normal EEG) classifications to all actual normal EEG events. The specificity of the model is the measure of the correct true negative (seizure EEG) classifications to all actual seizure events. The precision of the model is the measure of the correct true positive (normal) classifications to the sum of true positive and false positive classifications; measure of accuracy in correctly identifying normal patients.

True Positive (TP)	False Positive (FP) Type I Error	**Precision** $\frac{TP}{(TP+FP)}$
False Negative (FN) Type II Error	True Negative (TN)	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$
Sensitivity $\frac{TP}{(TP+FN)}$	**Specificity** $\frac{TN}{(TN+FP)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

Figure 14. Definition of the confusion matrix parameters.

The negative predictive value of the model is the measure of the correct true negative (seizure) classifications to the sum of true negative and false negative classifications; measure of accuracy in correctly identifying seizure patients.

It can be observed that the LSTM model has low precision and specificity. However, it has high sensitivity and negative predictive value. In other words, the model can accurately predict that a patient has no seizure (true positive) but it is not very accurate in predicting that a seizure patient does have a seizure. In fact, 10% of the patients who have seizure will be falsely classified as normal patients. But it is highly unlikely that a normal patient will be falsely classified to have a seizure. This could be attributed to the several limitations in the data of the patients with seizure. Firstly, it is difficult to determine whether a patient has seizure even by medical experts. This is evident from the original data set where the three medical experts had disagreements on 18 patients regarding whether they were normal or seizure condition patients. So, even human experts face difficulty in determining seizures. Secondly, the seizure event does not appear on all EEG channels. Since the neonates had different types of seizure and depending on the location of the seizure event in the brain and its type, the seizure event may not be captured by all electrodes. If all channels are used without consideration to the specific channels that actually show seizures, the model will have extremely low accuracy since we would be feeding it false information; claiming seizure in all channels while only few of them actually have seizure. That's why we relied on the work of [17] to choose the specific channel for each patient that actually showed seizure and feed this to the network. In other words, for each patient we selected the specific channel/ channels that showed the seizure events during their occurrence. In this way, the seizure data fed to the network is much more accurate than if all channels were fed blindly. But the accuracy of this work would depend on the accuracy of precise classification of the channels that actually showed seizure events for each patient. This could be improved by the help of medical experts in addition to the machine learning used by [17]. These limitations possibly account for the miss-classifications made by the neural networks and improving the accuracy is not possible without overcoming these limitations in the data set itself and its interpretations by human experts. The main method to improve the accuracy of the model is to get channel-specific seizure annotations by medical experts. In other words, the experts would need to point out which channel/s show the seizure event for each given seizure event of each patient. Having this channel-specific ground truth implies that the data fed to the machine learning model as being seizure data will be accurately and completely showing seizure events.

Another method to improve the accuracy of seizure detection is to apply the machine learning model on each set of channels showing seizures (re-apply the model developed here on other channels separately) and take the decision of seizure detection based on the collective result from each model. However, to do this the channels used must also show considerable seizure events for each patient otherwise they will give the false classification of no seizure event. Given the data, most seizure events are not visible on more than two channels. So, the model can only be re-applied once. As a result, this method may not result in considerable improvement of the seizure detection accuracy.

Given the annotation of seizures for each channel, the following channels were used. Channel 1 used for patients 41 and 73. Channel 2 for patients 7, 50, and 78. Channel 4 for patients 63 and 76. Channel 5 for patients 11, 13, and 16. Channel 6 for patients 1, 67, and 79. Channel 7 for patients 4, 31, 34, 36, 62, and 66. Channel 8 for patient 14. Channel 9 for patients 15, 17, 20, 21, and 25. Channel 12 for patients 38 and 47. Channel 13 for patients 9, 22, 51, 52, 69, and 75. Channel 14 for patients 19, 39, 40, and 77. Channel 15 for patient 44. Channel 16 for patient 5. It must be noted that for some patients with several seizure events, not all the seizure events are visible on the same channel. So, if the specific channel that shows a particular seizure event is used for each of these events, the accuracy of the model will increase as a result of giving the deep learning model more accurate pattern for each single seizure event. However, this requires determination of the appropriate channel not just for each patient but for each seizure event of every patient.

As can be seen, the source of limitations encountered leading to a decreased accuracy of the deep learning model is related to the way the data is structured and the seizures are annotated. Mainly, these problems originate from the uncertainty of the channels that a specific seizure event can be seen on. Unfortunately, the medical experts of this data set did not provide information of the channel that shows the seizure event. The medical experts must not only annotate the seizure events with respect to EEG recording time but also with respect to the EEG channels; seizure annotations must be provided for each channel separately. If this information is given by medical experts, the accuracy of the model is expected to improve significantly.

VII. Conclusion

In this paper, we have reviewed the deep machine learning approaches for seizures detection using EEG data. The multichannel EEG recordings of 79 subjects having 64 to 96 minutes of recording have been utilized to train and test several deep machine learning models. The EEG signals were visualized to demonstrate the difference between EEG pattern of normal and seizure patients. To easily handle the data, the data has been converted from timetable format to cell format and then converted to matrix format. In the next step, 18 bipolar channels have been extracted from unipolar montage which dramatically helps in the differentiation of seizure and non-seizure EEG signals as described in the original data set. The repetitive fluctuations and patterns plotted in the achieved results indicate the seizure activity of the brain, that fluctuated readings can be used for developing the machine learning models. Noise (due to hair, skin, and other artifacts) can affect signals adversely, that noise was eliminated by using a 6^{th} order Butterworth bandpass filter with lower cut-off frequency of 0.5 Hz and higher cut-off frequency of 70 Hz and a notch filter with 50 Hz cut-off frequency to remove mains supply noise. The comparison has been made with feed-forward and LSTM and results show that our approach can learn adaptively and effectively discriminate between the seizures and normal patients. The feed-forward neural network has been utilized with 10 hidden neurons and 100 hidden neurons separately in the hidden layer, to analyze the improvement by increasing the hidden neurons. The results show 66.1% and 74.3% accuracy for 10 hidden layers and 100 hidden neurons respectively. LSTM with five main layers has shown 87.7% accuracy. The LSTM model has correctly classified 96.4% normal patients and 71.6% seizure patients. It has been concluded that the accuracy of the LSTM model is higher than the two feed-forward neural network models. In the discussion, it has been shown that the main limitation on improving the accuracy comes from the lack of channel-specific seizure annotations from medical experts. If this information is provided, the accuracy of the models can be improved significantly.

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