# Seizure Detection Using Time Delay Neural Networks and LSTMs

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**Abstract— Automatic detection of seizures from EEG signals is an important problem of interest for clinical institutions. EEG is a temporal signal collected from multiple spatial sources around the scalp. Efficient modeling of both temporal and spatial information is important to identify the seizures using EEG. In this paper, we propose a neural network system using the time-delay neural network to model temporal information (TDNN) and long short term memory (LSTM) layer to model spatial information. On the development subset of Temple University seizure dataset, the proposed system achieved a sensitivity of 23.32% with 11.13 false alarms in 24 hours.**

## I. Introduction

Epilepsy is a neurological disorder affecting about 50 million people worldwide [1]. Numerous epileptic symptoms include psychological disorders like staring spells, anxiety, fear, temporary confusion, uncontrollable jerking movements of body parts, and loss of consciousness. It is characterized by a prolonged peculiar burst of neuronal activity within different regions of the brain [2]. These signatures can be captured efficiently by the scalp EEG signals. Trained neurologists are currently required to detect the seizure from the scalp EEG recordings. Using machine learning models to identify and annotate seizures can bring down the clinical processing time. The objective of the Neureka 2020 epilepsy challenge is to benchmark various machine learning algorithms detecting seizures from EEG signals. In this paper, we propose a novel model using time-delay neural networks (TDNNs) and long short term memory (LSTM) to detect the seizures.

In the literature, various approaches have been proposed to detect seizures from EEG signals. Some of the inceptive models were based on SVM (Support Vector Machine) without any temporal modeling [3–6]. Later, hidden Markov model-based systems [7, 8] that model temporal information were proposed for seizure detection. However, for modeling different channels in EEG, either the features from different sensors were concatenated [9] or a second stage fusion method was used [8]. Recently deep learning models that use convolutional neural networks (CNNs) [10–13], recurrent neural networks (RNNs) [14], and LSTMs [13] have been proposed to detect seizure. 2D CNNs that convolve across time and channels [12] are used to model both temporal and spatial information. The system proposed in this paper first models the temporal patterns using TDNNs. The spatial signatures are then modeled using an LSTM layer on the channel-wise outputs of the TDNN layers. The proposed system was ranked $6^{th}$ in the N20E challenge.

The rest of the paper is organized as follows. Section II provides the details of the proposed system and the baseline systems. Section III provides the experimental setup that was used to train and evaluate the proposed system. Section IV discusses the results of the proposed system. Finally, Section V concludes the paper.

## II. Proposed Seizure Detection System

Figure 1 shows a diagrammatic representation of the proposed TDNN-LSTM system. The model takes as input features of shape $d \times T$ from each channel $C$; $d$ is the feature vector dimension; $T$ is the number of time steps or frames. In this paper, linear frequency cepstral coefficients (LFCC) computed for each channel is used as the feature (see Section III-A). The first three layers of the network operate at frame level for all the channels using TDNNs (see Section II-A).

The fourth layer averages the hidden representation for each channel across the input time frames. This average pooling gives a single vector representation for every input channel. Hence the fourth layer operates at the channel level. In the fifth layer, the representations from different channels are combined using an LSTM layer. In this layer, the proposed network converts the given EEG input of any duration into a fixed length vector representation. The sixth and seventh layers are simple feed-forward layers, and the final output layer performs softmax over two nodes, one for seizure and the other for background signal. The proposed TDNN seizure detection system is a modified version of the TDNN based DNN system used for EEG subject identification in [15]. In Section II-A and II-B, we explain in detail how the TDNN and LSTM layers are used to model temporal and sequence information, respectively.

### *II-A. TDNN for modeling temporal dependency*

TDNN layer does contextual modeling for each segment of the EEG signal by convolving across time. TDNN layers are 1D convolution layers, where the context can be interleaved. This interleaved convolution allows the TDNNs to model longer context with fewer parameters compared to traditional CNNs. In the proposed model TDNN is used to model the temporal dependency in seizure signals, irrespective of the channel.

### *II-B. LSTM for modeling spatial dependency*

Given a input sequence of vectors, LSTM provide a non-linear representation of the sequence by retaining information from relevant vectors. In this paper, LSTM layer is used to model a non-linear representation of relevant TDNN embeddings form different channels to detect seizure. We use a random sequence of channels embedding (fixed across training and inference), as input to the LSTM layer. Given, this input, our result show that, the LSTM layer is able to encode details of seizure segments from relavent channels in the EEG and forget the insignificant ones.

The detailed configuration of the number of hidden layers and the temporal and spatial context used in each layer is given in Table 1. The proposed network takes as input the features extracted from a multi-channel EEG segment and outputs a probability of the corresponding segment having a seizure. Owing to the average pooling across time in the fourth layer, the model can process EEG segments of variable lengths. The model is trained using an equal number of examples from both the seizure and the background class. A moving window with a shift of one frame is used to detect the seizures from a continuous recording of EEG. This moving window produces a probability for each frame having a seizure. These probabilities are post-processed and used to get the final transcription of epileptic seizures present in the recording. The experiment specific details of how this system was trained and evaluated on N20E challenge data is detailed in Section III.

Table 1. Layer-wise configuration of the proposed TDNN-LSTM system. The input to the network is $C$ matrices of shape $d \times T$. $C$ is the number of channels, $d$ is dimension of feature vector and $T$ is number of frames. Layers $1-4$ operate for every channel. The output of layer 4 from each channel is combined and given as input to layer 5.

| Layer No | Layer Type | TDNN Filter | Temporal Context | Spatial Context | Input Size | Output Size |
|---|---|---|---|---|---|---|
| 1 | TDNN | {t-2,t,t+2} | 5 | 0 | d x T | 256 x T |
| 2 | TDNN | {t-4,t-2,t, t-2,t-4} | 13 | 0 | 256 x T | 256 x T |
| 3 | TDNN | {t} | 13 | 0 | 256 x T | 256 x T |
| 4 | Average Pooling | - | T | 0 | 256 x T | 256 x 1 |
| 5 | LSTM | - | T | C | 256 x C | 128 x 11 |
| 6 | FF | - | T | C | 128 x 1 | 32 x 1 |
| 7 | FF | - | T | C | 32 x 1 | 32 x 1 |
| 8 | Output | - | T | C | 32 x 1 | 2 x 1 |

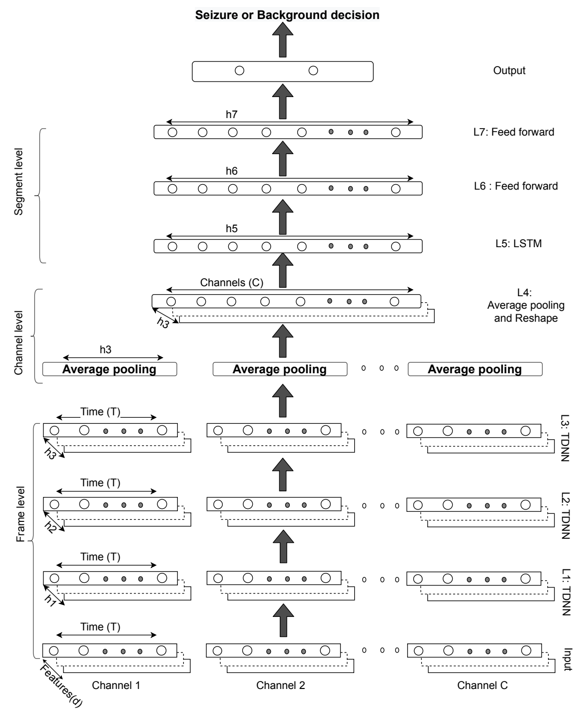


Figure 1. Diagrammatic representation of proposed TDNN-LSTM network for seizure classification

## III. Experimental Setup

### *III-A. Features*

To accurately detect seizures, the raw EEG signals are first converted to features that retain the seizure's signatures. In the literature many features have been used, which include, wavelet transform [3], fast-Fourier transform spectrum (FFT) [4] and spectrogram extracted using short-time Fourier transform (STFT) [16]. Linear frequency cepstral coefficients (LFCC) computed by applying DCT on linear filterbank energies have also been used widely as features for detecting seizures [8, 17, 18]. In this paper, we have experimented with LFCC features computed using a window size and a shift of 300 and 150 milliseconds, respectively. A total of 15 coefficients computed between 0 Hz to 60 Hz were used to train the proposed system.

### *III-B. Channels*

The proposed seizure detection system has been experimented with three different sets of EEG channels. The first system used all the 19 channels shown in Figure 2-A. These 19 channels were present in all the recordings of the TUH-EEG seizure dataset. Further, to test the proposed system with a reduced number of channels, we developed a 9 channel and 4 channel system, as shown in Figure 2-B and 2-C, respectively. These channels were chosen such that they sample the different regions of the scalp uniformly.

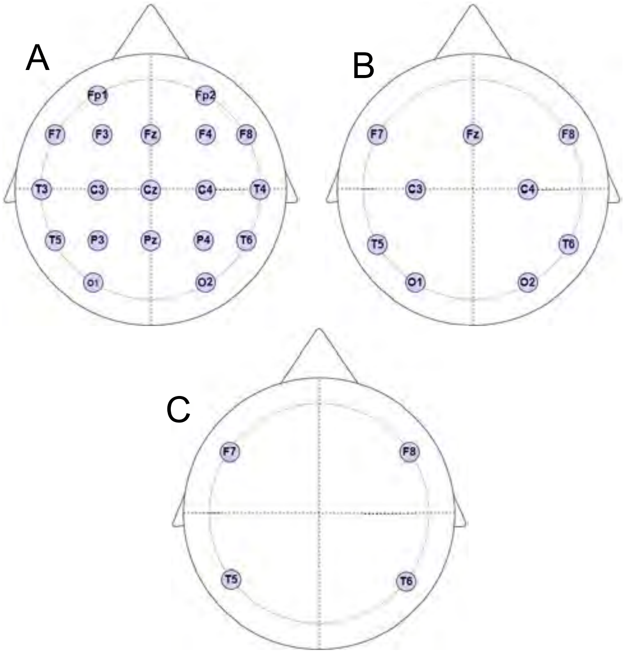


Figure 2. EEG channel configuration used for seizure detection

### III-C. Training

The seizure detection system proposed in this paper is trained using the TUH-EEG seizure dataset [19] (v.1.5.1). The training subset of this dataset consists of a total of 592 subjects having about 47 hours of seizure events. The further details of this dataset is given in Table 2. It is to be noted that, in this dataset, the subjects used for train, development, and evaluation are mutually independent.

As discussed in Section II, the proposed system is a classification network that accepts variable-length inputs. To augment the available data for seizures, the EEG recordings were split into segments of size 20, 30, and 40 seconds. The network was trained using all three segment sizes. The number of examples available for seizure and background EEG segments was equalized by randomly sampling the latter.

### III-D. Evaluation

The evaluation of the proposed system is done using the development subset of the TUH EEG seizure dataset (v1.5.1). In addition to the development subset, the prediction of seizures on the evaluation subset were submitted to the N20E challenge. Unlike the development subset, the ground truth of the evaluation seizure subset is not public and was evaluated by the challenge organizers.

Moving windows of duration 20, 30, and 40 seconds (similar to training phase) with a shift of one frame was used to transcribe the EEG. For each frame, this step gives three probabilities of the frame having a seizure (one for each window size). These probabilities are averaged to calculate the final score. The final seizure segments are extracted using a threshold on this score and post-processing to reduce false alarms.

Table 2. Details of TUH EEG Seizure dataset (v1.5.1)

| Description | Train | Development | Evaluation |
|---|---|---|---|
| Patients | 592 | 50 | 53 |
| Sessions | 1185 | 238 | 152 |
| Files | 4597 | 1013 | 1023 |
| No of Seizure events | 2370 | 673 | |
| Seizure(secs) | 168,139.23 | 58,445.11 | |
| Non-Seizures(secs) | 2,540,144.77 | 554,786.89 | |
| Total(secs) | 2,708,284.00 | 613,232.00 | |

### III-E. Evaluation Metrics

The predicted seizures were evaluated using a popular scoring method in the seizure detection community, called the Any-Overlap method (OVLP) scoring [20]. In addition to OVLP, Time Aligned Event Scoring (TAES) was also used. TAES is similar to OVLP, but it considers the percentage overlap between the ground truth and the hypothesis to weight the errors. The details of these scoring methods can be found in [18]. Sensitivity, precision, and the number of false alarms in 24 hours, calculated using OVLP and TAES, are used as scoring metrics to evaluate the proposed system.

## IV. Results and Discussion

The proposed TDNN-LSTM system outputs the score of each frame having a seizure (see Section III-D). A threshold score is used to determine the final traces of seizures. As discussed in Section III-B, the proposed seizure detection system was built using three configurations with different number of channels. Section IV-B discusses the results of all the three systems using different thresholds on the development set. In Section IV-C, the best system is selected and evaluated on the evaluation set. In Section IV-D, we present preliminary results on how our model performs for different types of seizures.

### IV-A. Sensitivity and precision at different thresholds

In pattern recognition, a binary prediction system is evaluated using sensitivity (or recall) and precision. For an ideal system, both sensitivity and precision should be high. In Figures 3 and 4, the sensitivity and precision are plotted for various thresholds, respectively. The precision and sensitivity values were calculated using the OVLP method.

The model detects many seizures when the threshold is low, leading to poor precision. As the threshold is increased, the precision improves, reducing the sensitivity. In Figure 3, it can be observed that the 9 channels system has consistently given the best sensitivity.

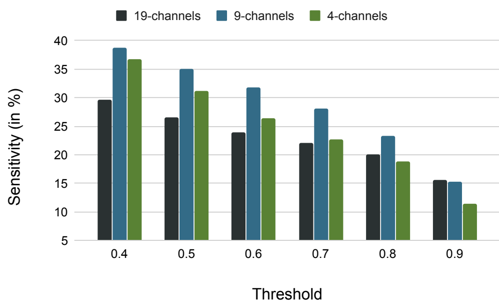


Figure 3. Sensitivity of the proposed systems at different thresholds

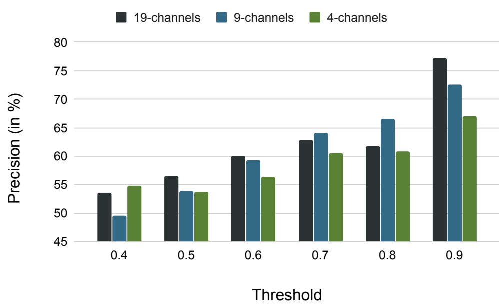


Figure 4. Precision of the proposed systems at different thresholds

Compared to this in Figure 4, with 19 channels, the system that has consistently given higher precision. The performance of the 4 channel system compared with that of the 9 or 19 channel system suggests that 4 channels are adequate for seizure detection.

### *IV-B. Sensitivity vs false alarms*

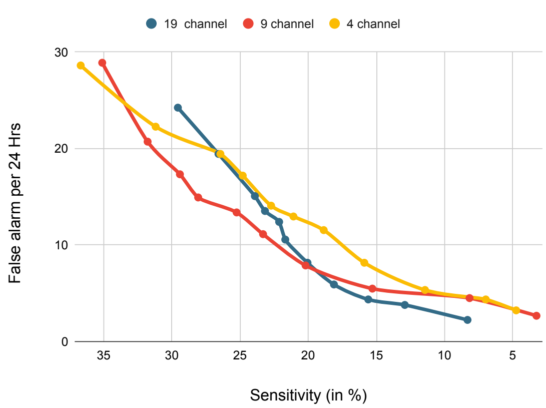


Figure 5. Sensitivity vs false alarm for systems using differnt number of channels

The results in Figures 3 and 4 were calculated using different thresholds. As the threshold is increased, it is observed that sensitivity drops and precision increases. In the literature on EEG seizure detection, sensitivity, and the number of false alarms in 24 hours is widely used to evaluate systems [8, 17]. The best system should give high sensitivity and low false alarms. Hence in Figure 5, the false alarms per 24 hours at various sensitivity levels are plotted for all the three systems.

Human performance on seizure detection is at 65% sensitivity with 12 false alarms in 24 hours [21]. From Figure 5, it can be clearly seen that the 9 channel system has the highest sensitivity of 23.32% with 11.13 false alarms in 24 hrs. This result shows that the proposed model is able to generalize better just using 9 channels rather than all the channels.

### *IV-C. System submitted to N20E challenge*

The N20E challenge was ranked by sensitivity, false alarms, and the number of channels. Hence for the final system, we fixed the threshold such that systems with all the three configurations of channels gave about 11.13 false alarms in 24 hours (Figure 5). The results of these systems can be found in Tables 3. In addition to OVLP, the TAES algorithm was also used to evaluate the final system. The results of the corresponding final system evaluated using TAES is given in Table 4.

Table 3. Result of proposed system using OVLP scoring method

| | Sensitivity | FA per 24 hrs |
|---|---|---|
| 4-channel | 18.87 | 11.55 |
| 9-channel | 23.32 | 11.13 |
| 19-channel | 21.69 | 10.56 |

Table 4. Results of proposed system using TAES scoring method

| | Sensitivity | FA per 24 hrs |
|---|---|---|
| 4-channel | 10.55 | 17.72 |
| 9-channel | 11.96 | 17.17 |
| 19-channel | 10.60 | 15.98 |

From both Tables 3 and 4, it can be seen that the 9 channels system has given better sensitivity at lower FA per 24 hours. Further, the N20E challenge was ranked by the number of channels used in addition to sensitivity, false alarms; hence, the 9 channels system was chosen as the best. This system scored a sensitivity of 16% with 16 false alarm per 24 hours (using the TAES method) on the held-out evaluation set and secured a rank of 6 out of 14 teams.

### *IV-D. Focal and Generalized seizures*

In general, seizures can be classified as focal seizures (FS) and generalized seizures (GS). Focal seizures are the one which affects specific areas of the brain and generalized seizures affect all the regions of the brain.

On analysing the TUH-EEG dataset, we see that the training data comprises of 78.56% of FS and 20.59% of GS, and the dev data consists of 57.8% of FS and 35.8% of GS. In this section, we report the sensitivity of FS and GS separately on the development set using the 9 channel system. From Figure 6, it is observed that

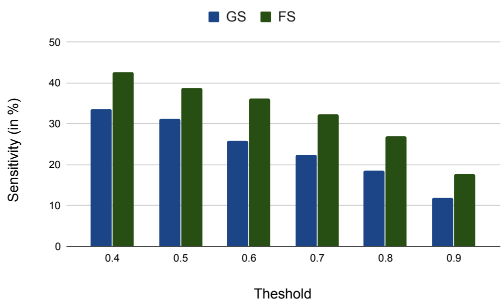


Figure 6. Sensitivity vs threshold for focal, generalized and combined seizures

FS has consistently achieved better sensitivity than GS for different thresholds. These results clearly indicate that focal seizures are modeled more robustly than generalized seizures. This is due to the imbalance in the training data.

## V. Conclusion

In this paper, we proposed a novel DNN model using TDNNs and LSTMs to detect seizures. It is an end-to-end model that takes features from multiple channels and provides a probability of input signal containing a seizure. The proposed model first models the temporal information using TDNNs and then models the spatial data using LSTMs. Using just 9 channels, the proposed model achieves a sensitivity of 23.32% with 11.13 FAs in 24 hours. Reducing the number of channels to 4, the model's sensitivity gracefully dropped to 18% with the same amount of FAs in 24 hours.

## Code Availability

The implementation of the proposed TDNN-LSTM system for seizure deduction is available at: https://github.com/mariganeshkumar/eeg_seizure

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