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Multi-class Epileptic Seizure Classification Using Different Deep Learning Techniques- A Comparative Study

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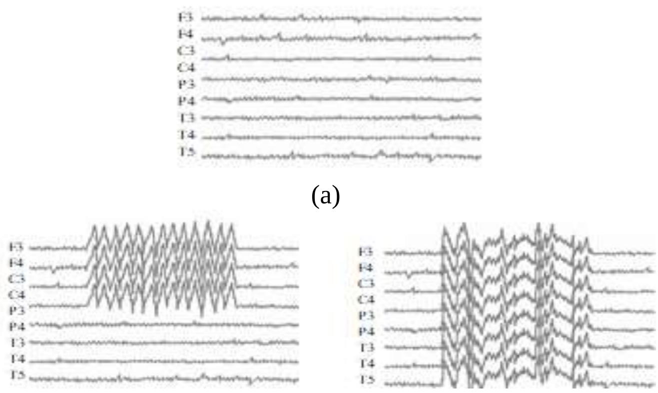
Abstract - Epileptic seizure classification is a very popular research topic worldwide. With the advent of Deep Learning, the classification accuracy has increased and given hope to aid diagnosis in real-time. Epilepsy is one of the oldest and the most common neurological disorders, but diagnosing the type of seizure is still not very easy. It requires expert doctors as it is difficult to distinguish the type of seizure from the EEG due to artifact, noise, and other disturbances. Its treatment depends on the seizure type and based on which Anti-Epileptic Drugs (AEDs) are prescribed by clinicians. But AEDs have severe side effects. Thus, it is necessary to diagnose the type of seizure correctly. In this paper, multi-class epileptic seizure classification was performed with different Deep Learning techniques, using time-domain pre-processing. Different classifiers have been compared based on their misclassification cost, prediction time, training time, and accuracy using the MATLAB environment.

Index Terms - EEG, Epileptic seizure, LSTM, Deep learning, TUHEEG.

INTRODUCTION

Epilepsy is a neurological disorder marked by disturbed electrical rhythms known as seizures in the central nervous system. It is the most common neurological issue and its description was found in the oldest (400 BC) system of medicine in the world. It is popularly known as fits. Despite many decades of research worldwide, there has been no significant breakthrough in its diagnostic or therapeutic aspects. Although many Anti-Epileptic Drugs (AEDs) are available for different types of seizures, but, they come with severe side effects. So, it's very important to diagnose the type of seizure [1]-[3] accurately. Many mathematical models, algorithms, and procedures have been applied to increase the accuracy of type detection from the electroencephalogram (EEG) signals (which is the most used electrophysiological method in the clinical diagnosis of epilepsy). With the advent of Deep Learning, researchers are trying different analyses of the EEG recordings for automatic type detection.

Some of the most common Deep Learning techniques used to classify seizures include 1D- Convolutional Neural Networks(CNNs), 2D-CNNs, Recurrent Neural Networks (RNN), Long Short Term Memory(LSTM) networks, Pretaied networks like ResNet, VGGNet, GoogleNet, SAEs, etc. [4]-[20] Seizures are the main symptoms of epilepsy. Recent study shows presence of 20 different types of epileptic seizures, which are broadly classified into partial epileptic, generalized epileptic, febrile epileptic, and unclassified types, and they are further subdivided into other types based on symptoms, the effects of which are also observed in the EEG recording. Partial seizures affect only a certain part of the brain, while generalized seizures affect the whole brain. Fig. 1 (a) shows EEG reading of healthy person whereas Fig. 1 (b) and 1 (c) show the EEG recording of partial epileptic and generalized epileptic seizure occurrences.



(a)

(b) (c)

FIGURE 1
EEG SIGNAL OF FEW CHANNELS
(A) HEALTHY PERSON'S READING, (B) PARTIAL EPILEPTIC. (C) GENERALISED EPILEPTIC.

This paper discusses multi-class epileptic seizure type detection using various Deep Learning techniques that use time-domain pre-processing. The methods are compared based on their respective misclassification cost, prediction time, training time, and accuracy. The networks were modeled and tested in MATLAB [21]}. The paper describes the database used, data pre-processing technique adopted, the Deep Learning implementation, finally by the results and conclusion in the following segments.

DATASET

TABLE 1
DESCRIPTION OF THE DATA-SETS USED

Seizure Type	Description	Number of Patients	Seizure Events	Duration (sec)	Version used
FNSZ	Focal seizures which cannot be specified by its type	14	132	17090.7556	v1.5.0
GNSZ	Generalized seizures which cannot be further classified into one of the groups	10	71	2000.182	v1.5.0
TNSZ	Stiffening of body during seizure (EEG effects disappear)	3	112	2060.506	v1.5.0 and v1.4.0
CPSZ	Partial seizures during unconsciousness. Type specified by clinical signs only.	12	76	9516.3219	v1.5.1

Temple University EEG Corpus (TUH EEG Corpus) [22] is a huge collection of clinical EEG data collected over more than a decade. The data is stored in the form of EDF (European Data Format) files, and consists of 24 to 36 channels of signal data, sampled at 250 Hz, with 16 bits per sample. Selected data follows the average reference configuration (AR), while the annotations follow the TCP channel configuration. Each EDF file is accompanied by an anonymized report given by a neurologist, including patient's medial history like symptoms during seizure, medication details, along with that age, gender and frequency of seizure occurrence. It also includes clinician's findings and analysis on seizure event . Files were taken from version 1.5.0, released in March 2019, and also from version 1.4.0. The corpus consists of 10 types of seizures: Focal Non-Specific Seizure (FNSZ), Generalized Non-Specific (GNSZ), Simple Partial Seizure (SPSZ), Complex Partial Seizure (CPSZ), Absence Seizure (ABSZ), Tonic Seizure (TNSZ), Clonic Seizure (CNSZ), Tonic-Clonic Seizure (TCSZ), ATSZ (Atonic Seizure) and MYSZ (Myoclonic Seizure). A four-class classification problem is being analyzed- using the Generalized (GNSZ), Focal Non-Specific (FNSZ), Tonic (TNSZ), and Complex Partial(CPSZ) classes-with 71, 132, 112, and 76 recordings respectively. From the collected data, the total seizure duration extracted is 30667.7655 seconds.

PRE-PROCESSING OF DATA

The EDF files were downloaded from the TUH corpus for seizure types GNSZ, FNSZ, TNSZ and CPSZ. Using the start and stop duration of seizures provided by the corpus, each signal has been segmented to seizure event areas,and the same has been converted to CSV format. Each row in these CSV files represented a channel and the This CSV files then pre-processed before inputting to any model. The last few channels in the signals generally correspond to background signals and the data had a differing number of channels across all the files, so a common value of 26 channels was chosen. The files were then labeled as 0, 1, 2, and 3 for FNSZ, GNSZ, TNSZ, and CPSZ respectively. In addition to this, around 79 columns were found to be empty and therefore removed. The length of the samples was found to be unequal. From Fig. 1 (b) and Fig. 1(c), it can observe that the type of seizure depends on the pattern of occurrence in the channels and not on the number of seizure occurrences in the same channel. To equalize the lengths while avoiding loss of frequency information, the signals were repeated to a length of 16384 samples. An additional label column was added to the seizure types, resulting in a 10166x16384 matrix. Final data was then put into a matrix of size 10166 x 16385, with the last column for labels.

METHODOLOGY AND IMPLEMENTATION

In this paper, the LSTM model has been tried out to start with/without pre-processing in the time domain. then, after time domain pre-processing different deep learning models are trained as except LSTM, all other classifiers require equal size of the sequences, feed in. The basics of all the models are discussed as follows:

I. Long Short Term Memory (LSTM)

LSTMs follow an artificial Recurrent Neural Networks architecture, which has both feedforward and feedback connections. They can process an entire sequence of data at a time. One of the most important advantages is, they can also work with sequences of different lengths, which makes them very popular in the field of Deep Learning. Fig. 2 shows the architecture of an LSTM network and equations (1) to (6) describes its mathematical model.

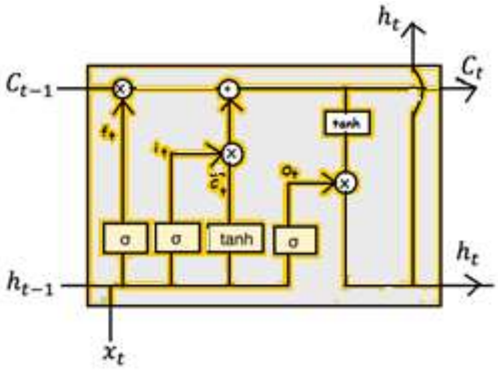


FIGURE 2
ARCHITECTURE OF LSTM NETWORKS

Let us consider:
C_t , h_t : hidden layer vectors.
x_t: input vector.
b_f , b_i , b_c, b_o : bias vector.
W_f ,W_i , W_c, W_o : parameter matrices.
σ, tanh : activation functions.

$$f_t=\sigma(W_f . [h_{t-1} , x_t]+ b_f) \quad (1)$$
$$i_t=\sigma(W_i . [h_{t-1} , x_t]+ b_i) \quad (2)$$
$$o_t=\sigma(W_o . [h_{t-1} , x_t]+ b_o) \quad (3)$$
$$\tilde{C}_t=\tanh(W_c . [h_{t-1} , x_t]+ b_c) \quad (4)$$
$$C_t= f_t \odot C_{t-1} + i_t \odot \tilde{C} \quad (5)$$
$$h_t = o_t \odot \tanh(C_t) \quad (6)$$

The LSTM network is used to classify the sequence data which inputs a sequence of data into a network and makes predictions based on the individual time steps of the sequence data. No time-domain preprocessing done for this network. The input to the network was a cell array containing 391 sequences of varying lengths and the output or the target is a categorical vector of labels 0,1,2,3 for FNSZ, GNSZ, TNSZ, CPSZ respectively. The input data was split with a training ratio of 80 percent and the model was tested on the remaining 20 percent, The training data with 312 sequences was split into several mini-batches and the resulting sequences were padded to have the same length. Too much padding can sometimes have a negative impact on the training, hence, it was avoided by sorting the data according to the sequence length and applying a mini-batch with a similar length. This padded input sequence was then fed to the LSTM architecture with 100 hidden units and the output layer as the classification layer. The mini-batch size chosen was 27. The output of the network was then tested with the test data consisting of 79 sequences. The test data was sorted in the same way as the train data i.e. based on the sequence length. The longest sequence length was chosen to maintain the padding length across all sequences. The accuracy of the predicted classification data was calculated against the test data.

II. Nearest Neighbour Classifiers

Nearest Neighbour Classifiers achieve consistently high performance in supervised pattern recognition as they do not assume distributions of the training examples a priori. A test sample is classified by calculating distances to the nearest training samples and assigning the class of the majority to the test. The Euclidean Distance between two points is calculated as shown in equation (7) below.

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (7)$$

Where (x_1, y_1) and (x_2, y_2) are the points in consideration.

Neural Network Classifiers

Neural Network Models mimic the human brain. They consist of multiple units called neurons, forming layers, that take in vectors as input, apply an activation function, and pass the output to neurons in the next layer with added weights and biases (as in equation (7)). These weights and biases are tuned to optimize the model accuracy. The pre-activation function in terms of the input vector x is given by equation (8).

$$y' = w^T x + b \quad (8)$$

Where w^T is the transposed weight vector and b is the bias. Most common activation function is the sigmoidal activation applied on the preactivation function.

$$y = \frac{1}{1+e^{-y'}} \quad (9)$$

III. Support Vector Machine

SVM stands for Support Vector Machines, a supervised learning algorithm that can efficiently map features into higher dimensions with the help of kernals. The distance between the hyperplane and classes (known as margin) is maximized while making the hyperplane lie in the center of the margin. SVM Hyperplane equation in 'M' dimensions is given by equation (10).

$$y = \omega^T \phi(x) + b \qquad (10)$$

Where $\phi(x)$ is the fixed feature-space transformation, b is the bias parameter and ω^T is the weight vector.

RESULTS AND DISCUSSION

In this paper, two types of training were discussed- one using a LSTM network without time-domain data pre-processing, and the other using various classifiers after time-domain data pre-processing.

The accuracy obtained in the first method was 74.36\%, where sequence input had 26 dimensions. The network consisted of a BiLSTM layer with 150 hidden units, and 4 fully connected layers.

The hardware resource used was a single CPU, with a constant learning rate of 0.001. The training time was 725 min 14 sec. It was run for 50 epochs, with 11 iterations in each epoch.Fig.3 and Fig.4 show the iteration vs. accuracy graph and the iteration vs. loss graph of LSTMs.

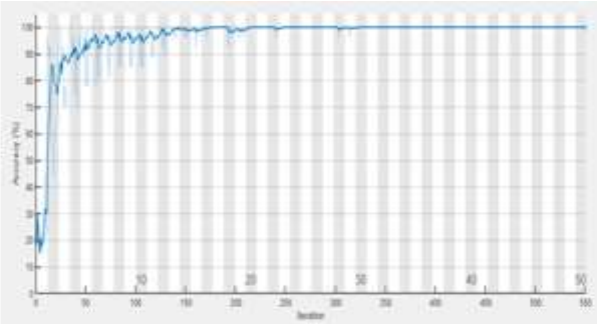


Fig 3
Iteration Vs Accuracy in % in LSTM

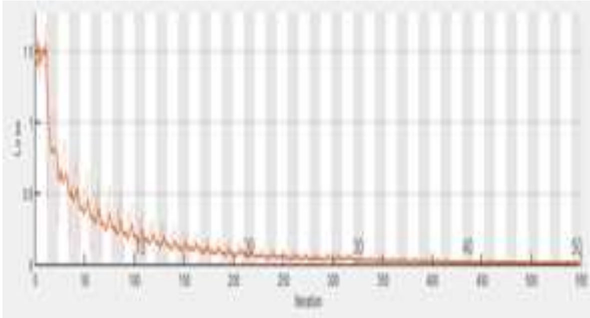


Fig 4
Iteration Vs Loss in LSTM

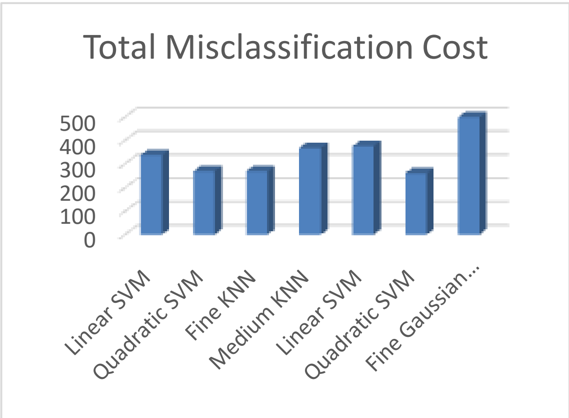


FIG 5
TOTAL MISCLASSIFICATION IN VARIOUS CLASSIFIERS

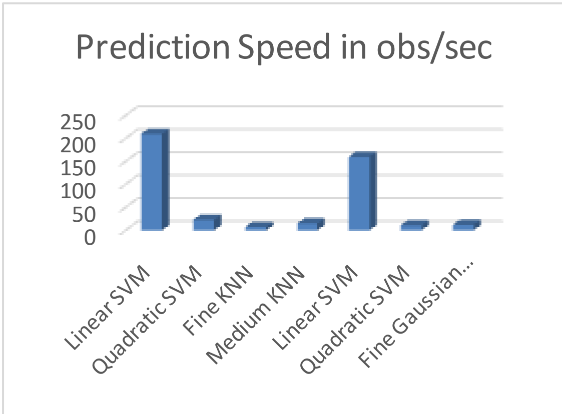


FIG 6
PREDICTION SPEED IN VARIOUS CLASSIFIER

FIG 7
TRAINING TIME IN VARIOUS CLASSIFIER

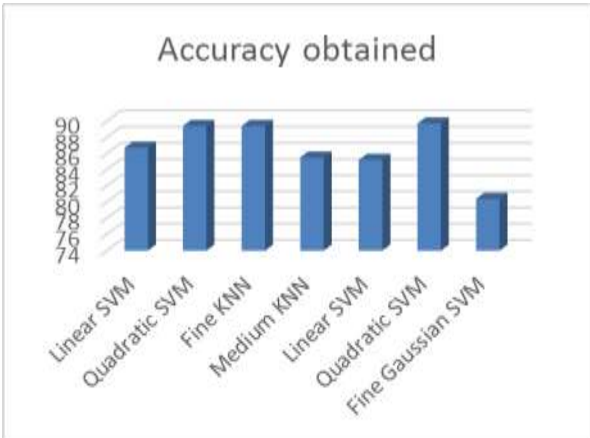


FIG 8
ACCURACY IN % IN VARIOUS CLASSIFIER

Table 2
PERFORMANCE DETAILS OF ALL THE CLASSIFIERS

Sl.No.	Network	Total Misclassification Cost	Prediction Speed in obs/sec	Training Time in sec	Hyperparameter tuning/ model options	Accuracy obtained
1	Linear SVM	338	~210	1018.1	Box constraint level-2	86.7
2	Quadratic SVM	269	~23	1110.5	Box constraint level-2	89.4
3	Fine KNN	269	~7.2	1206.8	3-nearest neighbours	89.4
4	Medium KNN	368	~15	3306.7	-	85.5
6	Linear SVM	376	~160	2087.8	-	85.2
7	Quadratic SVM	261	~11	3670.5	-	89.7
9	Fine Gaussian SVM	499	~12	1860.6	Box constraint level 2	80.4

In the second method, the data was pre-processed in the time domain and passed through various classifiers with or without hyperparameter tuning/ changes in the model options, as shown in Table II. Fig.5 shows the total misclassification cost and Fig.6 shows the prediction speed of each classifier. Fig.7 shows the training time taken and Fig. 8 shows the accuracy of various classifiers. From these figures, the variations in different classifiers in different criteria has been observed. For instance, a medium KNN classifier had a total misclassification cost of 368 and accuracy 85.5\%, with a low prediction speed of 15 obs/sec, and a comparatively high training time 3306.7 seconds.

CONCLUSION

From the study, it is observed that the accuracy increases from 74.36\% (in the case of the LSTM) to 89.7\% (in the case of the Quadratic SVM) with time-domain preprocessing, whereas, the training time drastically reduces from 725 minutes 14 seconds i.e. 43,514 secs to 3670.5 secs and further less in the other classifiers used. Both with and without pre-processing, there is quite a bit of difference in all aspects. Comparison between the classifiers after pre-processing is shown in Table II. The Quadratic SVM performs the best for the chosen criteria.

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