EEG Forecasting With Univariate and Multivariate Time Series Using Windowing and Baseline Method

Thara D. K., Department of ISE, Channabasaveshwara Institute of Technology, Visvesvaraya Technological University, India

Premasudha B. G., Department of MCA, Siddaganga Institute of Technology, India

Murthy T. V., Siddaganga Hospital and Research Center, India

Syed Ahmad Chan Bukhari, Collins College of Professional Studies, St. Johns University, USA

ABSTRACT

People suffering from epilepsy disorder are very much in need for precautionary measures. The only way to provide precaution to such people is to find some methods which help them to know in advance the occurrence of seizures. Using Electroencephalogram, the authors have worked on developing a forecasting method using simple LSTM with windowing technique. The window length was set to five time steps; step by step the length was increased by 1 time step. The number of correct predictions increased with the window length. When the length reached to 20 time steps, the model gave impressive results in predicting the future EEG value. Past 20 time steps are learnt by the neural network to forecast the future EEG in two stages; in univariate method, only one attribute is used as the basis to predict the future value. In multivariate method, 42 features were used to predict the future EEG. Multivariate is more powerful and provides the prediction which is almost equal to the actual target value. In case of univariate the accuracy achieved was about 70%, whereas in case of multivariate method it was 90%.

KEYWORDS

EEG, Epilepsy, Forecasting, LSTM, Multivariate, Seizure, Univariate, Windowing

INTRODUCTION

For the people with epilepsy disorder, the moment the seizure occurs will be very dangerous and challenging. Nearly 1% of the population suffers from epilepsy even today. The seizure begins with a sudden unexpected storm of electrical signal in some region of the brain. The signal may be emitted in one or two regions of the brain and may also spread to other regions. This causes convulsions and loss of consciousness in case if the seizure is very severe. Such situations become very terrible for the patient and people around him to handle. This disrupts the daily activity and lifestyle of the

DOI: 10.4018/IJEHMC.315731

person suffering from epilepsy. Though neurologists provide best available anti-epileptic drugs to the patients, patients continue to suffer seizure at times. The fear of unexpected seizures makes patients to consume excessive medicines and suffer side effects. Therefore, forecasting epileptic seizures is a good attempt which can improve the treatment and in turn the life of the epilepsy patients to a far extent (Brinkmann, 2015) (Javier, 2017). A precise prediction could help them to avoid risky activities, handle the anxiety levels and avoid unnecessary medications. Alternate method followed by the neurologists is to go with a surgery and remove the part of the tissue from the brain which is found to be causing seizures. Still one more method identified was to implant a neurostimulator device. These devices keep track of the electrical pulses in the nervous system and prevent the sudden emission of high energy signals. This prevents sudden unexpected seizures. But too many electrical pulses could not be controlled by the device and hence this cannot be the best solution. Therefore, it is necessary to study the electrical patterns of the seizures in the brain in order to predict them.

Many different algorithms, machine learning approaches are used so far by the researchers to perform forecasting of EEG signals (Nguyen, 2020) (Iwok, 2016) (Kulkarni, 2020). Deep learning technique: long short-term memory is a best technique for the analysis of time series data sets. Since EEG recordings are collected along with the time steps continuously, LSTM is the best method for analysis.

In this paper we perform EEG forecasting in two parts; once using univariate time series and second time using multivariate time series (Kim, 2013). In case of univariate time series forecasting, the prediction of the next time steps is performed only based on the earlier time steps of a single attribute. The response variable i.e. the target variable is influenced by only one factor (Aqsa Shakeel, 2020). Whereas, in case of multivariate time series forecasting; the prediction of the future time step value is performed based on multiple time dependent attributes (JD Peter, 2019). Each attribute will have dependency not only on the earlier time steps of its own but also on the earlier time steps of the other attributes(K J Blinowska,1991)(R. Ranjan, 2017). Thus the response variable is influenced by multiple factors. Because of this reason multivariate time series forecasting is considered to be more accurate than univariate time series.

The remaining portion of this section presents the related work. Section 2 describes the proposed method in which we cover the details of the dataset, pseudo code of the proposed method. Section 3 discusses the results followed by the conclusion.

RELATED WORK

Brinkmann et al., 2015, carried out work for forecasting seizures using machine learning technique, support vector machine and intracranial EEG signals for canines. The authors tried to identify a preictal state in the epileptic canine continuous long EEG signals using SVM. For the study they used 16-channel EEG recording device. The device was implanted for dogs on an average of 380 days out of which 220 days of EEG recording which were recorded at 40Hz were considered for the study. The recordings consisted of approximately 51 seizures out of which 35 seizures were preceded by at least 4hrs of non-seizure signals. The EEG recordings were stratified into 11 contiguous frequency bands and were binned for analysis. The classification performance of SV was evaluated on the basis of 5 fold cross validation. Window size was set to 90 minutes. Cross validation process was repeated for a range of preictal windows to do the comparison between the results of each time. All 5 dogs were analyzed with a better prediction performance compared to time-matched Poisson random predictor but the method developed in this work was patient specific.

Muñoz-Almaraz (2017) applied supervised filters on EEG signals for forecasting naturally occurring epilepsy. The authors proposed an approach for preprocessing EEG signals using supervised filters. The filters are used with k-nearest neighbour algorithm for improving the performance of the prediction. The detailed analysis of the proposed preprocessing method is described in terms of receiver operating systems and area under curve. The results of the study show significant improvement in the results compared to power band filtering approach. The authors illustrated that, supervised filters give better results even for the dataset with large number of attributes and long duration time lengths. Thus the method demonstrated good results with machine learning approach in predicting epileptic EEG signal. The dataset was collected from Mayo Clinic.

Nguyen et al. (2020) have worked on predicting the features of EEG signals. The authors say that electroencephalogram is the best tool for understanding the brain because of its capability in recording every tiny voltage exchanged between the neurons inside the brain. The data can be stored and reproduced by the models built using machine learning neural networks. The authors have proposed a complex networks model composed of weakly connected dynamical systems. The model was recognized as Collective Almost Synchronization. Two topologies of the network were used in this work; random and small world consisting of 1000 neurons. This model was able to successfully generate both epileptic and non-epileptic EEG signals. The author's main contribution in the work was predicting some of the features like Hurst exponent, and the power spectrum. The prediction was done 5.76s earlier. An average error was observed to be 9.22%. For the work the authors used both healthy and epileptic EEG signals.

Shakeel et al. (2020) have developed an algorithm for EEG forecasting using least mean squared algorithm. The authors worked on two prediction lengths; one was prediction of 128ms and the other one was prediction of 256ms. The autoregressive model gave good results for short data segments with 128ms prediction duration. Least mean square based autoregressive model gave good results for long data segments with 256ms length. Though this work was not on epilepsy prediction, the method used in this work for the prediction of future oscillations of EEG signals helped us to understand one of the methods to forecast EEG signals. The least mean square with low computational cost helps in forecasting the apha oscillations of the EEG signals which is used to study many nervous system disorders.

Kuasuriya et al. (2011) carried out EEG based epileptic seizure forecasting using wavelet Transform and artificial neural network. The forecasting process was done in two stages. In the first stage EEG signal features are extracted using wavelet transform and in the second stage artificial neural network was used for classification purpose. The performance of the model was evaluated on the basis of sensitivity, specificity and accuracy. For the study the authors used free online data from Freiberg EEG data repository. They also collected data from local hospitals in Sri Lanka. In total the dataset consisted of 105 multichannel EEG signals. The dataset was divided into two sets; Set A and Set B. Set A consisted of 53 healthy EEG signals. And Set B consisted of 52 inter-ictal EEG signals.

In the related work discussed above, the forecasting of EEG is performed by classifying preictal EEG from the ictal and inter-ictal EEG using machine learning algorithms like support vector machines and k nearest neighbour. Kuasuriya et al. (2011) have used artificial neural network. In these experiments the feature extraction of the input EEG is taken as a separate task. The features obtained are used for identifying preictal EEG. In our study since we used long short term memory for forecasting the future value of the EEG we do not perform feature extraction. The network learns the features automatically and predicts the future value. And in this study we do not perform classification of the preictal EEG from the other states of the EEG; instead we use univariate and multivariate methods to predict the future value.

PROPOSED METHOD FOR EEG FORECASTING

Dataset

The dataset used for the work was a freely available data from Bonn university Germany. It consists of 5 folders in total. Each folder consisted of 100 files. Each of these 100 files consisted of 4097 data points. This dataset was a combination of both intracranial EEG and extracranial EEG. It included both healthy EEG signals and also unhealthy i.e., epileptic EEG signals. It also included ictal, inter-ictal and also pre-ictal stages of EEG signal. The recording was done at a frequency of rate of 176.61Hz.

Each EEG signal was 23.6 s long. This dataset consisting of data from 500 individuals was restructured and was presented in the form of a matrix with 11500 rows and 178 columns. A glimpse of the data with 178 columns is shown in the figure below. The 179th column is a class label. We used two class labels in the dataset. All the instances belonged to either to class label 1 and to class label 0. Class label 1 is a seizure event and class label 0 is a non-seizure event.

Pseudo Code of the Proposed Method

The steps used in the proposed method for univariate time series prediction is shown in the pseudo code in Algorithm 1. The entire data consisting of 11500 rows with 178 columns is divided into two sets. One set with 8000 rows for training purpose and remaining 3000 rows were used for validation purpose. The seed was set to 13 using tf.random.set_seed () function. The random seed sets the starting point for generating a random number sequence. The purpose of using seed is to get the same patterns of numbers when we are training a neural network. Because when the same number is passed to two instances of the neural network they generate same sequence of results. As described earlier the forecasting is done both using univariate and multivariate time series data. In the first stage we used univariate forecasting. During this we used an attribute labelled X2 for predicting the target value. Before using the attribute X2 for prediction the dataset has to be standardized to get better results. For standardizing the dataset we computed mean and standard deviation for the training dataset. Standardization is done using the formula given below:

$$x_i = \frac{\left(x_d - mean\right)}{std}$$

- x_i is the new value obtained for a particular training instance.

Figure 1. A glance of the dataset with 178 attributes

A glance at the data.

```
[ ] df.head()
```

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X25	X26
0	52	40	32	36	36	32	34	30	38	47	63	56	33	30	29	27	23	29	25	27	28	35	47	55	61	53
1	-134	-126	-119	-127	-106	-93	-86	-70	-66	-100	-147	-145	-133	-118	-88	-62	-58	-60	-46	-48	-65	-74	-77	-92	-83	-51
2	6	4	11	1	-23	-50	-60	-51	-21	16	49	72	79	77	57	52	60	74	70	51	21	-20	-43	-45	-20	8
3	-73	-75	-80	-85	-87	-85	-82	-82	-80	-81	-80	-84	-86	-91	-85	-79	-77	-75	-71	-73	-77	-86	-93	-101	-108	-115
4	-99	-110	-118	-126	-128	-131	-129	-126	-127	-127	-128	-122	-114	-107	-99	-95	-89	-83	-69	-62	-53	-48	-39	-36	-38	-38

5 rows × 179 columns

X27	X28	X29	X30	X31	X32	X33	X34	X35	X36	X37	X38	X39	X40	...	X140	X141	X142	X143	X144	X145	X146	X147	X148	X149
53	33	22	-11	-9	-5	4	17	22	36	53	70	77	72	...	50	72	87	98	95	83	53	25	14	14
-42	-42	-48	-44	-66	-79	-87	-110	-133	-119	-89	-94	-68	-27	...	-115	-114	-128	-144	-129	-108	-73	-28	5	19
35	47	41	40	43	46	44	43	38	27	17	12	14	17	...	-62	-84	-89	-82	-67	-42	-13	-5	-4	-10
-111	-100	-86	-76	-74	-73	-68	-63	-51	-41	-36	-28	-26	-29	...	-55	-51	-43	-40	-35	-30	-36	-42	-42	-42
-39	-32	-23	-7	10	24	37	43	44	42	39	30	33	47	...	-11	-1	8	18	13	8	12	18	30	35

X150	X151	X152	X153	X154	X155	X156	X157	X158	X159	X160	X161	X162	X163	X164	X165	X166	X167	X168	X169	X170	X171	X172	X173	X174	X175	X176	X177	X178	OUTPUT_LABEL
19	11	17	36	43	43	44	57	65	72	76	75	65	58	43	27	11	19	29	37	52	59	72	81	88	82	78	79	80	0
26	22	-6	-37	-37	-18	-29	-63	-88	-104	-125	-133	-133	-147	-117	-64	-47	-52	-67	-93	-128	-124	-101	-81	-67	-46	-27	-35	-45	0
-7	14	47	79	81	55	16	-23	-49	-52	-51	-55	-64	65	87	84	57	23	-17	-25	-18	-1	0	-4	-21	-35	-32	-21	-9	0
-40	-41	-37	-36	-35	-21	-16	-7	-1	-1	10	20	29	35	35	31	35	39	45	39	35	25	21	20	8	0	-11	-12	-16	0
32	29	28	34	45	57	68	80	89	103	106	104	86	76	72	61	64	60	62	65	59	52	41	29	12	-12	-22	-30	-27	0

- x_d is the original value in the data set.
- $mean$ and std are the mean and standard deviation of the training dataset.

Windowing is the method used for setting the length of the time steps to be used as a history for forecasting the future value (Ranjan, 2017)(Geva, 1998). More on windowing is described in the next section. Now previous 20s seconds duration of EEG signals are used to predict the future EEG signal strength. The results of the forecasting are viewed in the form of graphs. The historical data is plotted in blue in the graph. The real future value and the predicted value are represented using green dot and Red Cross mark respectively. The batch size was set to 256 time steps and the buffer size was set to 10000. The sequential model was built using 8 LSTM units. The layer was followed by dense layer consisting of 1 unit. The EEG data was given as input to LSTM model. The model was compiled with the optimizer "adam" and the loss using "mean absolute error"(Kulasuriya, 2011). The model was trained using the training data set. Evaluation was done using validation data. During evaluation, the evaluation step was set to 200 and epochs to 10. The architecture of the proposed work is given in figure 2. Due to the large size of the dataset (Kose, 2017) (Peter, 2019), in the interest of saving time, each epoch will only run for 200 steps, instead of the complete training data as normally done. The graphs plotted were plotted for 10 different trails. For every 10 trail we obtained at least 7 accurate predictions. The plotted graphs are presented under results section.

Algorithm: Pseudocode univariate timeseries forecasting

```
Step 1:   Input = X, Target value = Y
        X = {x1, x2, x3, ……., x11500}
Step 2:   X_Train = 70% of X
X_Val = 30% of X
Step 3: Set seed using set_seed() method using random module
Step 4: The attribute X2 used for forecasting in univariate
method.
Step 5: Standardize input data using standard scalar technique.
        Compute mean and standard deviation and standardize each
and every value in the input data using the formula
Step 6: Apply windowing method to set the historical EEG data
```

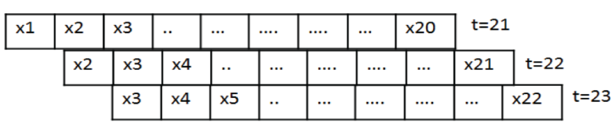
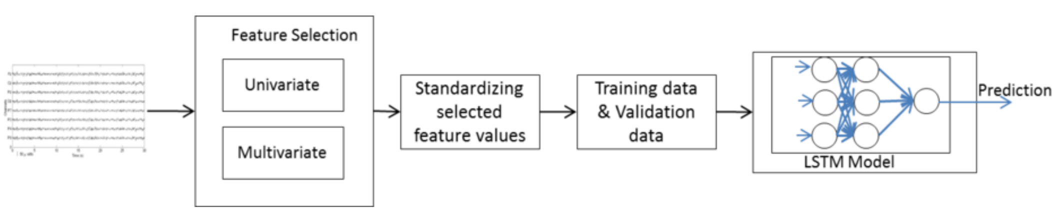


Figure 2. Architecture of the proposed work



```
Step 7: Plot the predictions
          show_plot(historical time_steps, true_value, predicted_
value)
Step 8: Set Batch size=256
           [x1,x2,x3..x256][x2,x3,x4,….x257]
Step 9: Build LSTM model, compile with the optimizer 'adam' and
compute loss with 'mae'
Step 10: train the LSTM model with X_Train
Step 11: Validate the model with X_Val
Step 12: Plot predictions
Step 13: Repeat the same procedure for multivariate time series
forecasting.
```

As a next step we continued forecasting using multivariate time series. In this case out of 178 attributes we used 42 attributes to perform EEG forecasting shown in table 1. The features considered for multivariate analysis are shown below.

As in the univariate case, the features considered for prediction are first standardized using mean and standard deviation (Arunkumar, 2017). The start index and the end index are set based on the window size. The window size gives the number of time steps used as the history data for the future prediction (Mansouri, 2017). Batch size and Buffer size are kept same as it was for univariate time series forecasting. A neural network model was built using sequential layer (Thara, 2019) as the first layer, then followed by long short-term memory layer after which we added dense output layer. The model was compiled using root mean square optimizer and mean absolute error for loss calculation. Then the model was trained using the training data and validated using validation data set. Number of epochs was set to 10 and each epoch executed for 200 steps. The forecasting trails were repeatedly taken. For every 10 trails nearly 9 trails were observed to be close to the actual values. The results were plotted using Matplotlib (Rajinikanth, 2017)(Thara, 2019). The history data was presented in blue line, Actual future value was shown with Red Cross mark and the model prediction in green dot. The graphs plotted are shown under results section. For the forecasting study we used baseline (Ansari, 2018) and windowing method (Arunkumar, 2017) and the same are described in the next section.

RESULTS AND DISCUSSIONS

The experiments were conducted using python programming language in jupyter notebook using the standard library packages; Keras, TensorFlow, Numpy, Pandas. Time series EEG data can is framed as a supervised learning problem. It consists of data with 178 attributes. Each instance of the dataset consists of an output variable which says whether the instance of that particular time step is a seizure event or a non-seizure event. The goal here is that when we provide the input the mapping should be done in such a way that we should be able to predict the output value. This supervised learning can be further split into classification and regression problem. In this study we are moving into regression analysis. In case of classification, the output variable also called the class label is categorical. But in our case, we are aiming at forecasting the future value of the EEG using the given old previous time steps of about 20 seconds. Regression is performed when the output variable is a continuous value. To achieve this we are using windowing method. The size of the window was set to 20 time steps. The

Table 1. Features considered in Multivariate time series forecasting

features_considered = ['X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8', 'X9', 'X10', 'X11', 'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18', 'X19', 'X20', 'X21', 'X22', 'X23', 'X24', 'X25', 'X26', 'X27', 'X28', 'X29', 'X30', 'X31', 'X32', 'X33', 'X34', 'X35', 'X36', 'X37', 'X38', 'X39', 'X40', 'X41', 'X42']

dataset is restructured such that the every 20 time steps are used as the input variables and the next time step as the output variable. The previous 20 time steps are used to predict the next time step. The order of the previous time step observations and the next time step observations are preserved. This method of using previous time steps to forecast the future value is called sliding window forecasting. The figure 3 shows the window of length 6 time steps. According to this the previous 6 time steps are used as the historical data to predict the future time step value. In our study we use window of length 20 time steps to predict the EEG value of the future time step. Figure 4 shows a single window of past 20 observations and also the true target amplitude value to predict.

Once the window size is set, the next thing we need to work is number of attributes we use for prediction. If we use only one attribute at each time step for prediction then we call that as univariate time series forecasting. If we use multiple attributes of the dataset at each time step for prediction then

Figure 3. Window of length 6 time steps

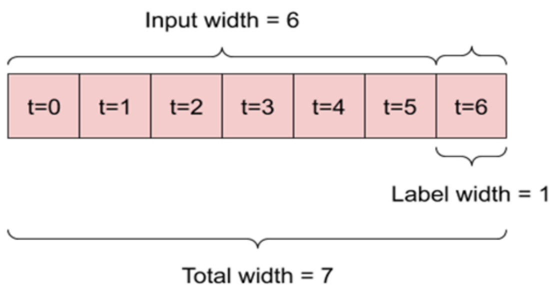


Figure 4. Single window with 20 time steps of past history

```
print ('Single window of past history')
print (x_train_uni[0])
print ('\n Target apmlitude to predict')
print (y_train_uni[0])


Single window of past observations
[[ 2.910476]
 [-6.634105]
 [ 8.405671]
 [-3.701733]
 [-5.714145]
 [-6.289120]
 [-4.243773]
 [-1.215386]
 [-2.609281]
 [ 4.002928]
 [ 3.625901]
 [ 6.105772]
 [ 2.507994]
 [ 3.082968]
 [-9.418546]
 [-3.388791]
 [-6.543673]
 [-5.196668]
 [-2.189503]
 [ 7.255721]]

Target amplitude to predict

-0.341424
```

we call that as multivariate time series forecasting. Multivariate time series analysis is complicated compared to univariate.

EEG Forecasting Using Univariate Time Series

In this case only one attribute is kept under observation by the neural network at each time step. We used the attribute X2 for observation for 20 time steps; the LSTM neural network based on the observed knowledge predicts the future time step value. A graph is plotted to represent the prediction made by the neural network. Twenty time step values will be used as the historical data. These values are printed as a line graph. The actual future value is presented in Red Cross mark and the model prediction in green dot. Figures 5 to 7 shows the plots of the predictions of the LSTM neural network. From figure 5 we can observe that out of 10 predictions, 4 predictions of the neural network are very close to the target value. Figure 6 shows that 3 predicted amplitude values of the EEG signals out of 10 are exactly equal to the actual amplitude value of the future EEG signal. And figure 7 shows that 3 predictions out of 10 are very far from the actual amplitude values. Which means; there is a large difference between the actual amplitude and the predicted amplitude of the EEG signal. So from this we can conclude that in univariate time series forecasting, 70% of the predictions are matching with the actual target values.

EEG Forecasting Using Multivariate Time Series

In case of multivariate multiple attributes are kept under observation continuously to predict the future EEG value (Thara D.K, 2019). In our study we used attributes from X1 to X42 i.e. totally 42

Figure 5. Univariate Forecasting; predicted values very close to true value

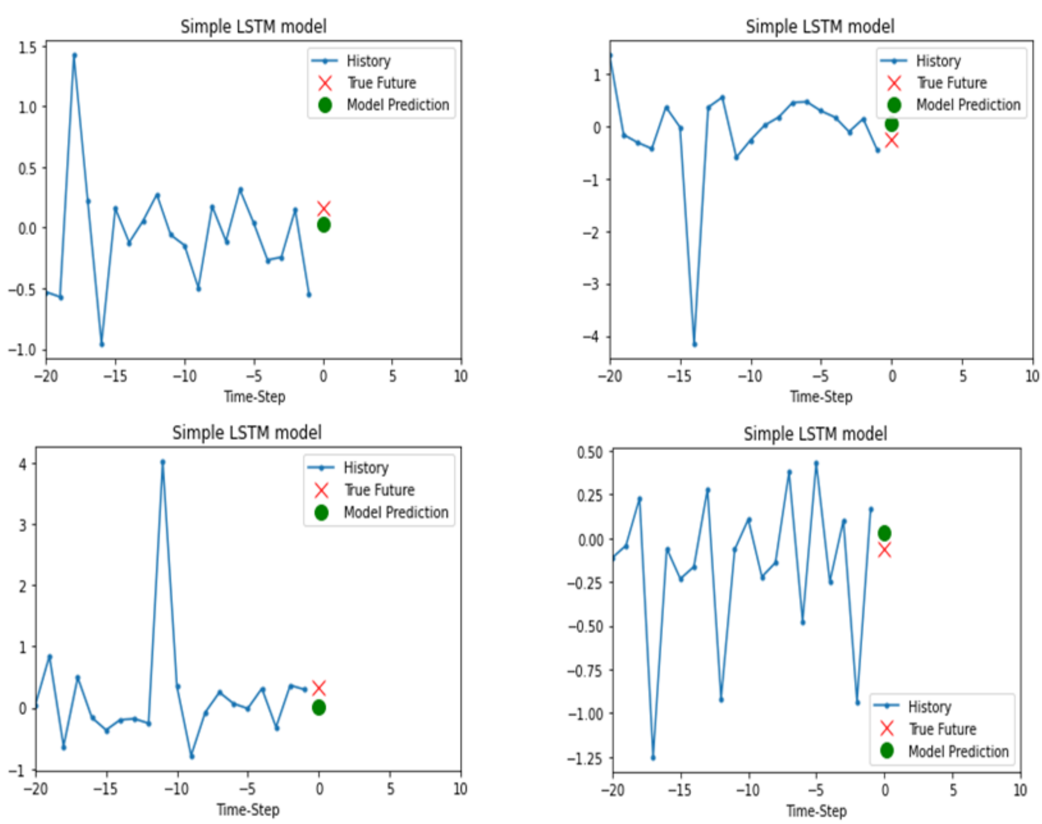


Figure 6. Univariate Forecasting; Predicted value exactly same as true value

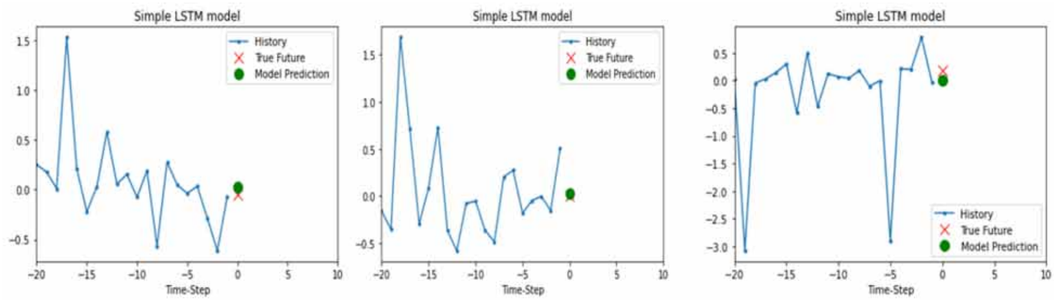
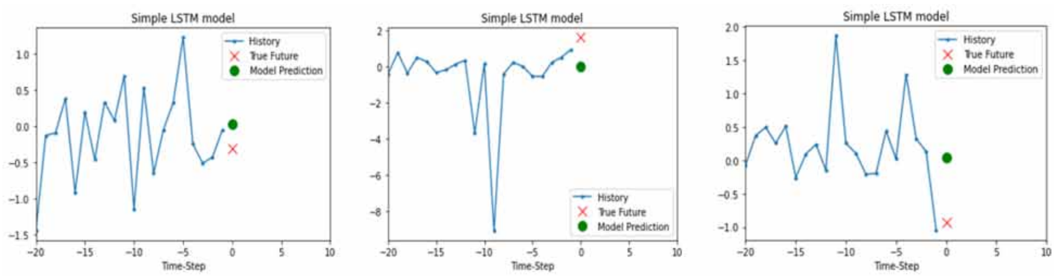


Figure 7. Univariate Forecasting; large difference between the predicted value and the true value



variables were used for forecasting purpose. The prediction graphs are plotted in the same manner as we did for univariate method. The observations made in multivariate prediction are as follows: out of 10 predictions 6 predictions are exactly matching with the actual target values. This can be observed in figure 8. Similarly figure 9 shows three predictions which are very close to the target value. And from figure 10 we can observe there is only one prediction which is showing large difference with the actual target value. So, out of 10 predictions made 9 are matching with the target value and only one prediction is having large difference compared to actual target value. From this we can conclude that 90% of the predictions are correct predictions when done with multivariate time series. The Comparison of the proposed approach with the results of the existing works is shown in table 2.

CONCLUSION AND FUTURE SCOPE

In the view of developing some method which could be helpful to epilepsy patients so that they can get a clue in prior about the occurrence of seizure so that they can avoid dangerous activities like swimming, driving and save their lives we have developed an EEG forecasting method using a deep learning technique LSTM. We used publicly available dataset from Bonn University for the study. The study consisted of two stages, once using univariate and second stage using multivariate method. In each stage we tried 20 trails using different instances. The future value of the EEG signal is predicted. For the study we used windowing method. We tried the window size of different lengths. Starting from 5 time steps, length of the window was slowly increased. For the window of length 20 time steps the prediction rate was increased to 90%. We observed that for every 10 trails made, in case of multivariate 9 trails gave good accuracy. Thus in this study we conclude that multivariate time series forecasting using LSTM gives outstanding results compared to univariate time series analysis. In future the multivariate method can be used for programming the alarm devices which can be used to forecast the seizure event occurrence in epilepsy patients. This helps the patients to take extra care

Figure 8. Multivariate Forecasting; Predicted value exactly same as true value

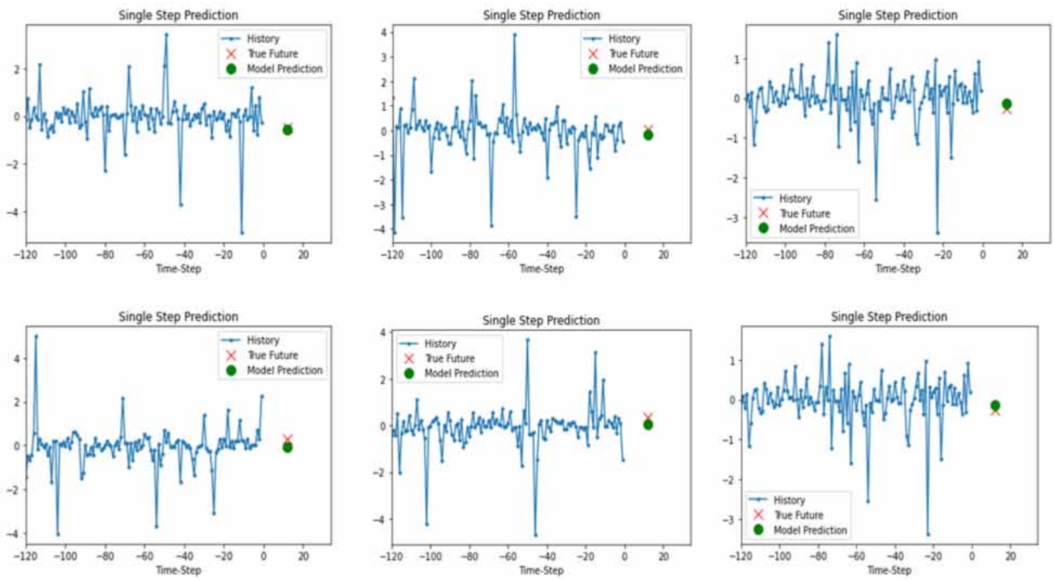


Figure 9. Multivariate Forecasting; Very slight difference between the predicted value and the true value

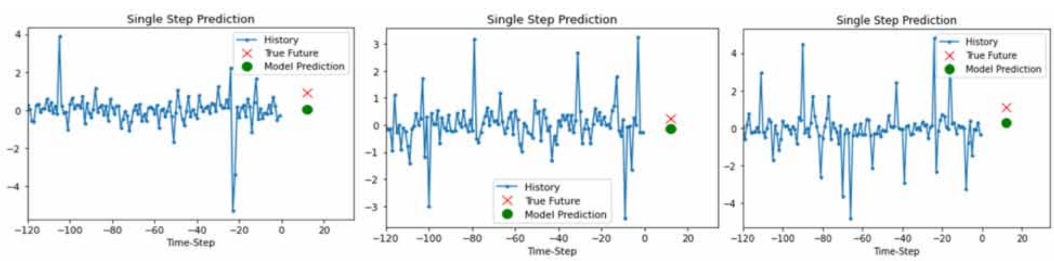


Figure 10. Multivariate Forecasting; Large difference between the predicted value and true value

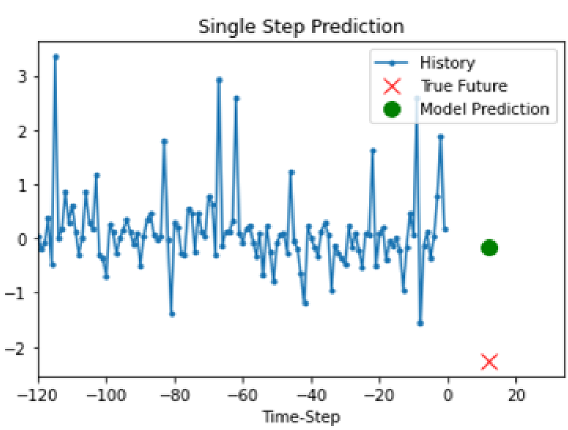


Table 2. Comparison of the proposed approach with the results of the existing works

	Technique	Method	Accuracy
Benjamin H. Brinkmann et al (2015)	SVM	Windowing	85.7%
Proposed approach	Long short term memory	Windowing (univariate, multivariate)	70% 90%

about themselves by avoiding any dangerous activities. They can be made to lie down and rest. This will defintely improve the life of epilepsy patients.

ACKNOWLEDGMENT

I sincerely thank my supervisor for her immense support and coordination in successful conduction of the experiment.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

FUNDING AGENCY

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Amir, B. Geva, M., & Kerem, D. (1998). Forecasting Generalized Epileptic Seizures from the EEG Signal by Wavelet Analysis and Dynamic Unsupervised Fuzzy Clustering. IEEE Transactions On Biomedical Engineering, 45(10).

Ansari, G. J., Shah, J. H., Yasmin, M., Sharif, M., & Fernandes, S. L. (2018). A novel machine learning approach for scene text extraction. *Future Generation Computer Systems*, *87*, 328–340.

Arunkumar, N, Ramkumar, K., & Venkatraman, V., Abdulhay, E., Fernandes, S., Kadry, S., & Segal, S. (2017). Classification of focal and non-focal EEG using entropies. *Pattern Recognition Letters*, *94*, 112–117.

Arunkumar, N., Ramkumar, K., Venkatraman, V., Abdulhay, E., Fernandes, S. L., Kadry, S., & Segal, S. (2017). Classification of focal and non-focal EEG using entropies. *Pattern Recognition Letters*, *94*, 112–117.

Benjamin, H., Patterson, E., Vite, C., Vasoli, V., Crepeau, D., Stead, M., Howbert, J., Cherkassky, V., Wagenaar, J., Litt, B., & Worrell, G. (2015, August 4). Forecasting Seizures Using Intracranial EEG Measures and SVM in Naturally Occurring Canine Epilepsy. *PLoS One*, *10*(8), e0133900. doi:10.1371/journal.pone.0133900

Blinowska, K. J., & Malinowski, M. (1991). *Non-linear and linear forecasting of the EEG time series. Biological Cybernatics*. Springer.

Ibagon & Gabriel. (2018). Forecasting the Neural Time Series: Deep Neural Networks for Predicting Event-Related EEG Responses. [Thesis, UC San Diego, USA]. https://escholarship.org/uc/item/5tg8k05h

I. A. Iwok and A. S. Okpe, (2016). A Comparative Study between Univariate and Multivariate Linear Stationary Time Series Models. *American Journal of Mathematics and Statistics*. doi:. 10.5923/j.ajms.20160605.02

Kim, S.-H., Faloutsos, C., & Yang, H.-J. (2013). *Coercively Adjusted Auto Regression Model for Forecasting in Epilepsy EEG*. Hindawi Publishing Corporation Computational and Mathematical Methods in Medicine Volume. doi:10.1155/2013/545613

Kose, U., & Arslan, A. (n.d) Forecasting Chaotic Time Series Via Anfis Supported by Vortex Optimization Algorithm: Applications on Electroencephalogram Time Series. *Arabian Journal for Science and Engineering*. doi: doi:10.1007/s13369-016-2279-z

Kulasuriya, K. A. & Perera, M. (2011). *Forecasting Epileptic Seizures Using EEG Signals, Wavelet Transform and Artificial Neural Networks.* IEEE.

Kulkarni, S.A., Gurupur, V.P., & Fernandes, S.L. (August 17, 2020), Introduction to IoT with Machine Learning and Image Processing using Raspberry Pi. *Chapman and Hall/CRC*

Ljubomir,, I., Aftanas, N., Lotova, V., Koshkarov, I., Popov, S., & Makhnev, V. (1997). Nonlinear Forecasting Measurements of the Human EEG During Evoked Emotions. *Brain Topography*, *10*.

Mansouri, F., Dunlop, K., Giacobbe, P., Downar, J., & Zariffa, J. (2017). A Fast EEG Forecasting Algorithm for Phase-Locked Transcranial Electrical Stimulation of the Human Brain. Frontiers in Neuroscience. doi:. 10.3389/fnins.2017.00401

Muñoz-Almaraz, F. J., Zamora-Martínez, F., Botella-Rocamora, P., & Pardo, J.Muñoz-Almaraz, F. J. (2017, June 20). Supervised filters for EEG signal in naturally occurring epilepsy forecasting. *PLoS One*, *12*(6), e0178808. doi:10.1371/journal.pone.0178808

Nguyen, P., Hayashi, Y., Da Silva Baptista, M., & Kondo, T. (2020). Collective almost synchronization-based model to extract and predict features of EEG signals. *Scientific Reports, nature search*.

Peter, J.D., Fernandes, S. L., & Thomaz, C. (November 12, 2019) *Advances in Computerized Analysis in Clinical and Medical Imaging.* Chapman and Hall/CRC.

Peter, J. D., Fernandes, S. L., Thomaz, C. E., & Viriri, S. (2019). *Computer aided intervention and diagnostics in clinical and medical images*. Springer International Publishing.

Rajinikanth, V., Raja, N., Satapathy, S., & Fernandes, S. (2017). Otsu's Multi-thresholding and Active Contour Snake Model to Segment Dermoscopy Images, *Journal of Medical Imaging and Health Informatics, 7*(8), pp. 1837-1840.

Ranjan, R., Arya, R., Fernandes, S. L., Sravya, E., & Jain, V. (2017). *A fuzzy neural network ap- proach for automatic K-Complex detection in sleep eeg signal. Pattern Recognition Letters*. Elsevier.

Aqsa Shakeel, Toshihisa Tanaka and Keiichi Kitajo. (May 2020). Time-Series Prediction of the Oscillatory Phase of EEG Signals Using the Least Mean Square Algorithm-Based AR Model. *Applied Science, MDPI*.

Shakeel, A., Tanaka, T., & Kitajo, K. (2020). Time-Series Prediction of the Oscillatory Phase of EEG Signals Using the Least Mean Square Algorithm-Based AR Model. *Appl. Sci.*, *3616*. doi: doi:10.3390/app10103616

Thara, D. K. PremaSudha B.G and Fan Xiong. (2019a). Auto-detection of epileptic seizure events using deep neural network with different feature scaling techniques. *Pattern Recognition Letters, 128,* 544-550. 10.1016/j.patrec

Thara, D. K., Sudha, B.G., & Xiong, F. (2019b). Epileptic seizure detection and prediction using stacked bidirectional long short term memory. *Pattern Recognition Letters, 128*, 529-535. 10.1016/j.patrec.2019.10.034

Thara, D. K., Premasudha, B. G., & Nayak, R., Murthy, T.V., Prabhu A., & Hanoon, N. (2020). Electroencephalogram for epileptic seizure detection using stacked bidirectional LSTM_GAP neural network. *Evolutionary Intelligence*. Springer. 10.1007/s12065-020-00459-9

Thara D K graduated from Sri Siddhartha Institute of Technology with a Bachelor's degree in the branch of Computer Science & Engineering. She secured post-graduation with Master of Technology from AMC College Bangalore in the branch of Computer Science & Engineering. She is pursuing Ph.D. in the field of Machine Learning and Deep Learning. She is also serving as an Assistant Professor in the department of Information Science & Engineering in Channabasaveshwara Institute of Technology, Tumkur, Karnataka, India and has got 13 years of teaching experience. She has published articles and book chapters in various national and international journals indexed in ACM, Scopus and Web of Science. Her research interests include data mining, data analytics, machine learning and deep learning.

B G Premasudha secured her Master of Technology in CSE from JNTU, and Bachelor of Engineering in E &C and Master of Computer Applications from Bangalore University; she bagged Doctorate of Philosophy from MGR University. Currently she is working as a Professor in the department of Master of Computer Applications and also serving as a research guide in Siddaganga Institute of Technology, Tumkur, Karnataka, India. She has more than 30 years of teaching experience. She has published articles and book chapters in various national and international journals indexed in Scopus, SCI, ACM and Web of Science. She has delivered technical talk in various organizations and chaired the technical sessions in several conferences. She has worked on various funded projects and received grants from VGST, GKVK Bangalore, University of Agricultural and Horticultural Sciences (UAHS), Shivamoga and ICT Skill Development Society, Karnataka. She received travel grants to present paper in the conference held at Dubai. She was awarded with "Distinguished Educator" award from National Foundation for Entrepreneurship Development. She has developed and released a Mobile app titled "Krishiganaka" for andriod phones and it is available for Tumkur district farmers to obtain their soil heath card to know the fertilizer recommendations to their lands. Her research interests include Cloud Computing, Artificial Intelligence, Wireless Sensor Networks, MANET and VANET, Location Based Services, Spatial Data Analysis, Geographic Information Systems, Data Analytics, Image processing, Machine Learning and Deep Learning.

Murthy T V, MBBS, MD - Medicine, DM – Neurology. He is a Neurologist in Siddaganga Hospital & Research Center, Tumakuru, Karnataka, India. He Has got 19 years of experience in the field of Neurology. He also practices at Seshadri Neuro Centre - Gandinagar Tumkur.

Syed Ahmad Chan Bukhari is a Biomedical Knowledge Engineer and Data Scientist in Yale University, New Haven. His research interests include Biomedical and Health informatics, Semantic Web, Patient Centered Outcomes Research Machine Learning, Information Retrieval. He has taught courses like Software Design Methods, Operating Systems, Data Base Management Systems, Medical & Health Informatics, Intro Healthcare Informatics, Healthcare Info & Data Mgt, Data Standards/Vocab In Hlthcr And Healthcare Database Mgt Sys. His research focuses on devising techniques to semantically annotate and federate heterogeneous biomedical data to derive meaningful information and to improve the experimental reproducibility.