# LSTM-Based Seizure Detection

A Deep Learning Approach for Predicting Epileptic Seizures

EE523 Advanced Biomedical Signal Processing

Under the supervision of

**Dr. Maheshkumar H.Kolekar**

Associate Professor, EEE


Presented By:

Chandana Deepak Sai 2101EE23

## I. INTRODUCTION

Epilepsy is one of the most common seizure disorders that is caused by abnormal brain activities and result in blank stares, unusual physical movements, and also cause unconsciousness in patients. Epilepsy is known as a seizure disorder and is diagnosed after a person has at least two seizures that are not caused by some known medical conditions. Epileptic patients have a high risk of Sudden Unexpected Death in Epilepsy (SUDEP), a leading cause of death in people with uncontrolled seizures. Most patients also suffer from many other unpredictable comorbidities of epilepsy, such as memory loss, depression, and other psychiatric disorders. According to the World Health Organization (WHO), more than 65 million people worldwide suffer from epilepsy. Therefore, accurate and timely epilepsy detection is crucial for patients to facilitate timely medication and reduce the risk of future epilepsy related complications. Epileptic seizures can be classified into various types based on the location of the seizure in the brain, the physical symptoms, and the occurrence rate.

## II. EEG SIGNALS

Epileptic seizures can be detected using EEG signals by identifying certain abnormal brain activities associated with epileptic seizures, such as sharp spikes. As shown in Figure 1, the EEG signal can be classified into four main categories: preictal, seizure or ictal, postictal, and interictal. Preictal is the time before seizure occurrence, which lasts around fifty minutes to one hour, postictal is the time right after a seizure, interictal is the time between preictal and postictal stages, and ictal refers to the phase when a seizure takes place.

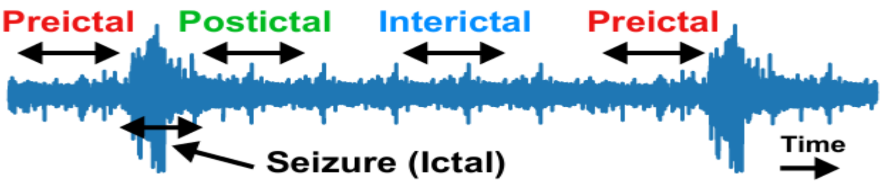



Fig. 1. Various stages of EEG signal in epileptic patients.

There are two types of EEG signals: Scalp EEG (sEEG) and intracranial EEG (iEEG). sEEG is recorded using electrodes that are placed on the scalp of the subject, as shown in Figure 2a. sEEG is noninvasive and easy to place; however, it cannot be used to record data for a long time. sEEG can be contaminated with different types of artifacts, including motion artifacts. Further, sEEG uses a lower number of electrodes compared to iEEG but covers a larger brain surface. iEEG signals are recorded using invasive electrodes placed directly on the brain. As illustrated in Figure 2b, these elec trodes can either be subdural or depth. The first is placed on the brain as grids or strips and covers a larger surface area, whereas the latter is inserted deep into the brain, thereby providing higher accuracy . iEEG provides 20 to 100 times higher signal quality than sEEG, more immune to motion artifacts, and provides better seizure localization.

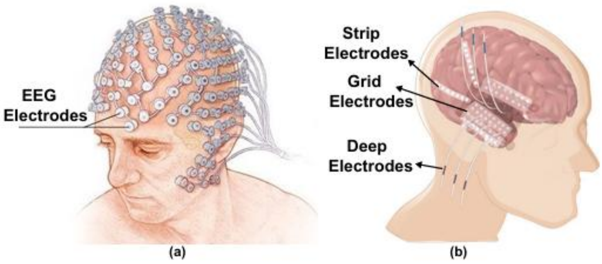
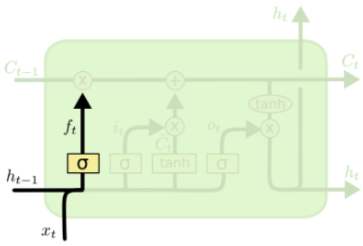



Fig. 2. Placement of electrodes in (a) sEEG and (b) iEEG .

## III. LSTM NETWORKS

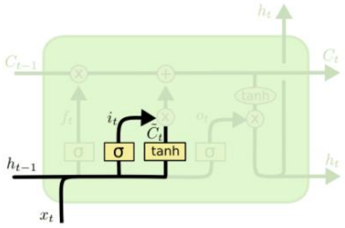
Long Short-Term Memory networks usually just called "LSTMs" are a special kind of RNN, capable of learning long-term dependencies. LSTMs are explicitly designed to avoid the long-term dependency problem. The key to LSTMs is the cell state, the horizontal line running through the top of the diagram. The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. It's very easy for information to just flow along it unchanged. The LSTM does have the ability to remove or add information to the cell state, carefully regulated by structures called gates. Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation.

The first step in our LSTM is to decide what information we're going to throw away from the cell state. This decision is made by a sigmoid layer called the "forget gate layer." It looks at $h_{t-1}$and, $x_t$and outputs a number between 0 and 1 for each number in the cell state $C_{t-1}$. A 1 represents "completely keep this" while a 0 represents "completely get rid of this."



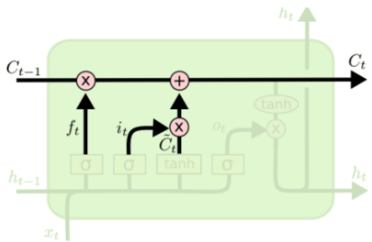

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

The next step is to decide what new information we're going to store in the cell state. This has two parts. First, a sigmoid layer called the "input gate layer" decides which values we'll update. Next, a tanh layer creates a vector of new candidate values, $\tilde{C}_t$, that could be added to the state. In the next step, we'll combine these two to create an update to the state.



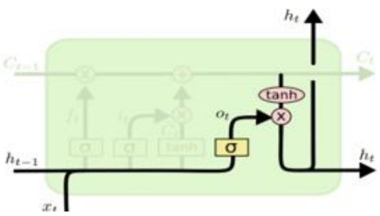
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

It's now time to update the old cell state, $C_{t-1}$ , into the new cell state $C_t$. The previous steps already decided what to do, we just need to actually do it. We multiply the old state by $C_t$., forgetting the things we decided to forget earlier. Then we add $i_t * \tilde{C}_t$ . This is the new candidate values, scaled by how much we decided to update each state value.



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Finally, we need to decide what we're going to output. This output will be based on our cell state but will be a filtered version. First, we run a sigmoid layer which decides what parts of the cell state we're going to output. Then, we put the cell state through tanh (to push the values to be between −1 and 1 and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.



$$o_t = \sigma\left(W_o \ [h_{t-1}, x_t] \ + \ b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

Summing up from the above gates, this forms the LSTM structure. The LSTM network is composed of input, forget, and output gates, each managing different aspects of information flow. Together, these gates allow the LSTM to retain, update, or discard information, making it effective for modelling sequential data like EEG signals.

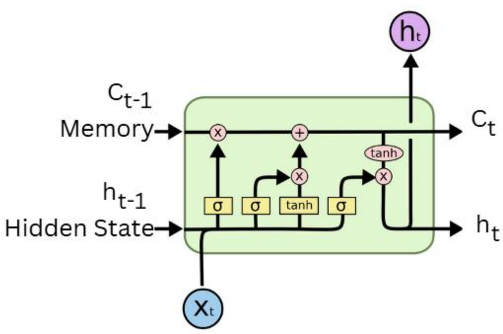
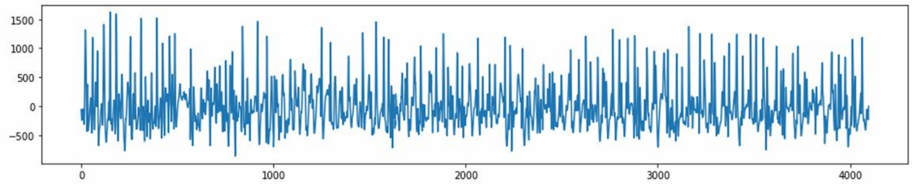


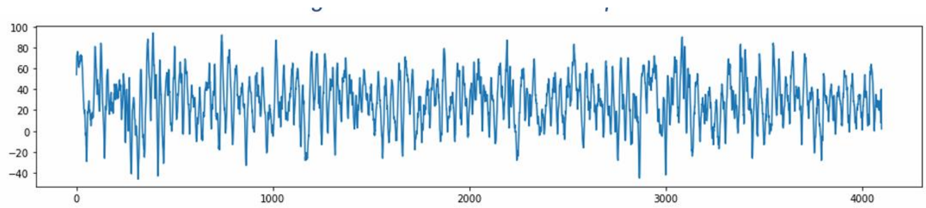

Fig 3. Complete LSTM Architecture

## IV. DATA DESCRIPTION

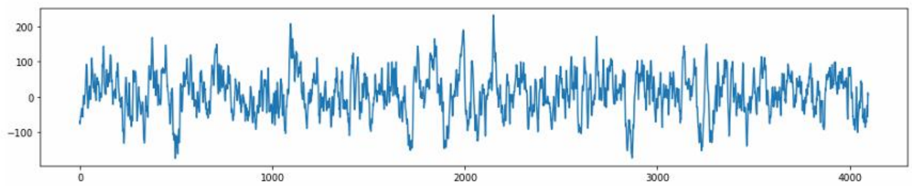
The data, published on Bonn University's Epileptology department website, presents Electroencephalogram (EEG) recording of 500 individuals. For each individual, brain activity was recorded for a duration of 23.5 seconds; these recordings are represented by 4096 evenly spaced, consecutive data points (i.e every 0.0057 seconds). Each row of the dataset, representing an individual's recording, also has a column with the classification of the recording. The five labelled datasets (A, B, C, D, E) are presented along with their corresponding target classes:



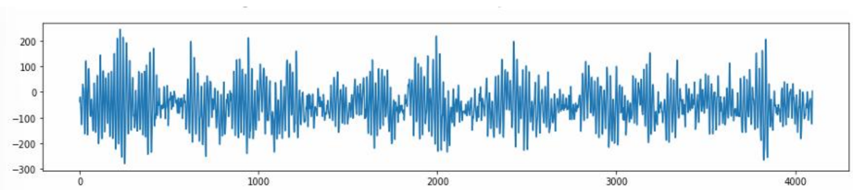

Set A - Class 4: EEG recording of a non-epileptic awake patient with eyes open.



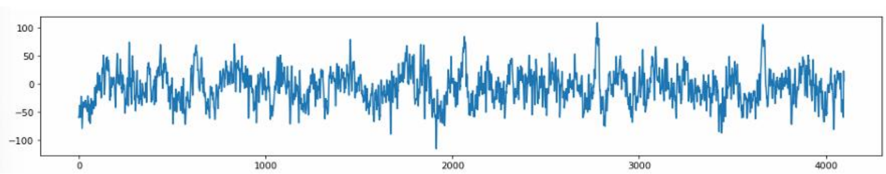

Set B - Class 3: EEG recording of a non-epileptic awake patient with eyes closed.




Set C - Class 2: EEG recording of an epileptic patient during seizure free period using electrodes implanted in the brain epileptogenic zone.



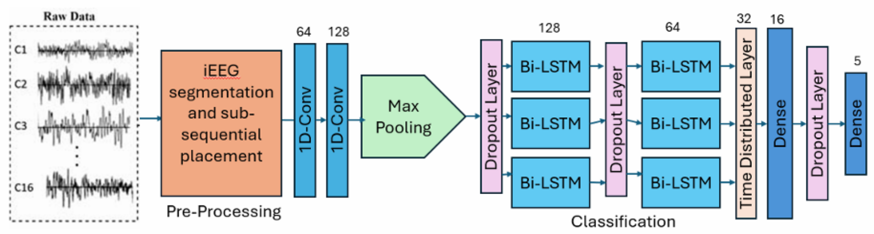

Set D - Class 1: EEG recording of an epileptic patient during seizure free period from the hippocampal formation of the opposite hemisphere of the brain from C.




Set E - Class 0: EEG recording of a patient experiencing an active epileptic stroke.

Our Aim is to classify all five classes, meaning it should be able to distinguish between a patient that is having a seizure, a patient that is between seizures, and a healthy patient. Additionally, it will be able to determine in which part of the brain the recording is made (Sets C & D) and whether the patient's eyes are open or closed (Sets A & B)

## V. PROPOSED MODEL




Architecture of our LSTM Model

Here's a detailed breakdown of the flow in the LSTM-based architecture, using the information in the diagram:

**1. Pre-Processing**

- Input: Raw EEG data channels (e.g., C1, C2, ..., C16) are segmented and placed in a sequential format.
- EEG Segmentation and Sequential Placement: This step processes the EEG signal to create segments. Each segment contains a time window of data, ensuring that the sequence structure of the data is preserved for sequential analysis.

**2. 1D Convolution Layers**

- The segmented EEG data is passed through two 1D convolutional layers with increasing filter sizes (64 and 128, respectively).
- Purpose of 1D Conv: The 1D convolutions help capture spatial patterns in the EEG signal across each time window. Convolution in one dimension focuses on extracting features over time within each segment.
- Equations for 1D Convolution:

$$y(t) = \sum_{k=0}^{K-1} x(t+k) \cdot w_k + b$$

**3. Max Pooling Layer**

- After the 1D convolutions, a Max Pooling layer is applied to reduce the dimensionality of the data and retain only the most prominent features.

- Purpose: Max pooling helps in down-sampling, reducing computation, and controlling overfitting by focusing on the strongest features.
- Equation for Max Pooling:

$$y(t) = \max(x(t), x(t+1), \ldots, x(t+M-1))$$

**4. Bi-Directional LSTM (Bi-LSTM) Layers**

- The features are then passed through a series of Bidirectional LSTM (Bi-LSTM) layers with 128 and 64 units.
- Purpose of Bi-LSTM: The Bi-LSTM layers capture both past and future context by processing the sequence in both forward and backward directions. This is especially useful for capturing complex temporal dependencies in EEG data.

At each time step, the forward and backward LSTM units respectively compute their hidden vectors, denoted as a f$h_t$ and b$h_t$, which are then concatenated to form the final hidden vector for the Bi-LSTM model. The output ht is as follows:

$$h_t = [fh_t, bh_t]$$

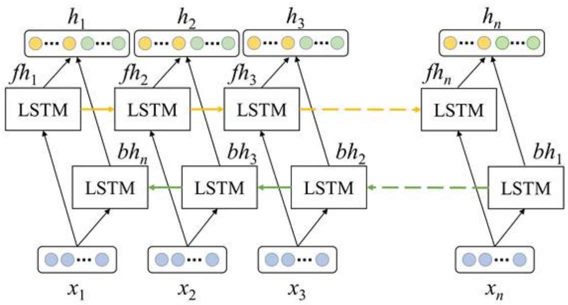



Fig 4. Architecture of Bi-LSTM.

Fig 4 illustrates the basic structure of the Bi-LSTM model, where {x1,x2,..., xn} denote the feature vectors, n is the number of time steps, {fh1, fh2,..., f$h_n$} and {bh1, bh2,..., b$h_n$} denote the forward hidden vector and backward hid den vector, respectively, and $h_n$denotes the vector of size ($n_{sm}$ , $n_{fe}$) connected by f$h_n$ and b$h_n$

**5. Dropout Layers**

- Purpose: Dropout is applied after each Bi-LSTM layer to prevent overfitting by randomly setting some neurons to zero during training.

**6. Time-Distributed Layer**

- The Time-Distributed layer applies a fully connected layer to each timestep individually in the sequence.

- Purpose: This allows the model to handle sequences as input while treating each timestep independently, enabling it to capture temporal patterns for classification.

### 7. Dense Layers and Output

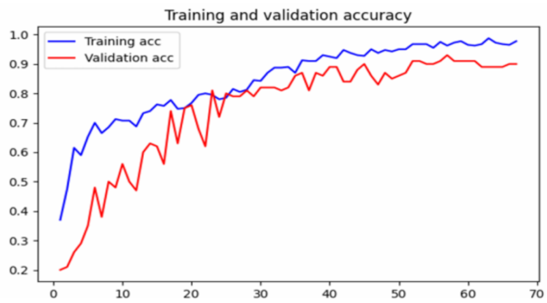
- The output from the Time-Distributed layer is passed through a series of Dense layers (with 32, 16, and 5 units respectively).
- The final Dense layer with 5 units suggests a classification output with 5 possible classes.

Equation for Dense Layer:

$$y = \mathrm{softmax}(W \cdot x + b)$$

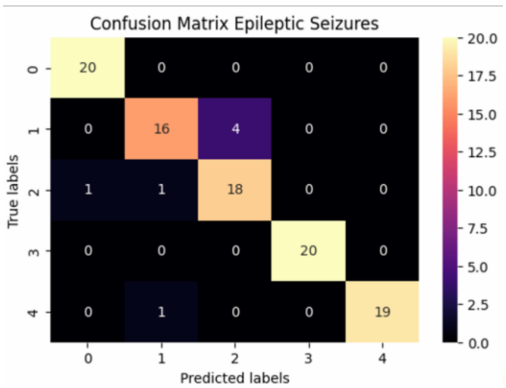
## VI. RESULTS

Our model achieves high accuracy in distinguishing seizure from non-seizure events, demonstrating effective feature extraction and temporal pattern recognition. The combination of Convolution and Bi-LSTM layers enables robust performance, capturing both local and sequential dependencies in the EEG data. This approach outperforms traditional methods, offering reliable classification for clinical applications.




Training and Validation accuracy


Training and Validation Losses

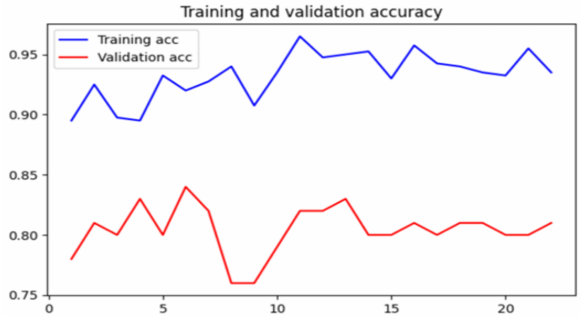



Classification Matrix

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.95 | 1.00 | 0.98 | 20 |
| 1 | 0.89 | 0.80 | 0.84 | 20 |
| 2 | 0.82 | 0.90 | 0.86 | 20 |
| 3 | 1.00 | 1.00 | 1.00 | 20 |
| 4 | 1.00 | 0.95 | 0.97 | 20 |
| accuracy | | | 0.93 | 100 |

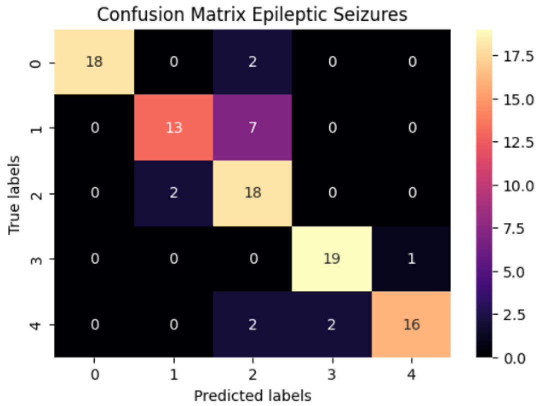
Performance of our Model

## Results Using CNN:




Training and Validation accuracy


Training and Validation Losses

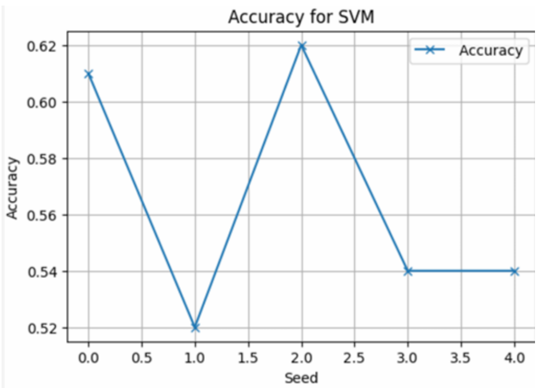



Classification Matrix

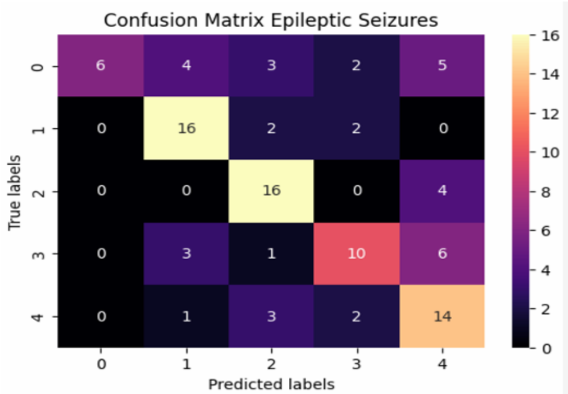
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 1.00 | 1.00 | 20 |
| 1 | 0.64 | 0.70 | 0.67 | 20 |
| 2 | 0.70 | 0.70 | 0.70 | 20 |
| 3 | 1.00 | 0.90 | 0.95 | 20 |
| 4 | 0.95 | 0.95 | 0.95 | 20 |
| accuracy | | | 0.85 | 100 |

Performance of CNN Model

## Results Using SVM




Validation accuracy




Classification Matrix

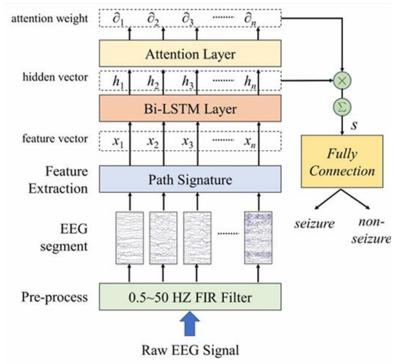
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.30 | 0.46 | 20 |
| 1 | 0.67 | 0.80 | 0.73 | 20 |
| 2 | 0.64 | 0.80 | 0.71 | 20 |
| 3 | 0.62 | 0.50 | 0.56 | 20 |
| 4 | 0.48 | 0.70 | 0.57 | 20 |
| accuracy | | | 0.62 | 100 |

Performance of SVM Model

From the above results, we can conclude that our model performed well compared to CNN and SVM. The hybrid approach of combining Convolution for feature extraction and Bi-LSTM for capturing temporal dependencies allowed for more accurate classification of seizure events. This architecture proved to be more effective in recognizing complex patterns in EEG data, surpassing the performance of traditional CNN and SVM models in terms of accuracy and reliability.

## VII. FURTHER EXTENSION

In addition to our Model having Bi-directional LSTMs (Bi-LSTMs) we can add attention mechanisms and Path Signature offer powerful improvements for seizure prediction




Model Architecture of Bi-LSTM and Attention Mechanism

Path signature is a method for converting paths into feature vectors. A path can be any temporally correlated data stream, which is converted into a multidimensional path by performing an embedding algorithm on the data stream and then calculating the individual terms in the path signature. In this study, the paths are the multichannel scalp EEG signal data.

When segmenting and extracting features from the input signal, some redundant information may be extracted due to the suddenness of seizure onset, inaccurate seizure labelling locations, etc. Therefore, not all feature vectors at each time step contribute equally. To address this issue, we introduce the attention mechanism into the model to adaptively enhance useful information's effect and suppress irrelevant information's effect by assigning them different weights. The hidden vector output $h_n$ from the Bi-LSTM network is fed as input to a simple multi-layer perceptron to obtain a new hidden representation $u_t$. Then a weight vector $u_w$ is randomly initialized and SoftMax normalized to the hidden representation $u_t$ to obtain the probability vector ∂t. Hidden representation is learned together during the training process to characterize feature vectors' importance at different time steps. After that, the output vector s is obtained by weighting $h_t$. The calculation formula is as follows:

$$u_t = \tanh\left(W_w h_t + b_w\right)$$

$$\partial_t = \frac{\exp\left(u_t^T u_w\right)}{\sum_t \exp\left(u_t^T u_w\right)}$$

$$s = \sum_t \partial_t h_t$$

## IX REFERENCES


- S. M. Varnosfaderani *et al.*, "A Two-Layer LSTM Deep Learning Model for Epileptic Seizure Prediction," *2021 IEEE 3rd International Conference on Artificial Intelligence Circuits and Systems (AICAS)*, Washington DC, DC, USA, 2021
- Y. Tang, Q. Wu, H. Mao and L. Guo, "Epileptic Seizure Detection Based on Path Signature and Bi-LSTM Network with Attention Mechanism," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 32, pp. 304-313, 2024
- https://www.ukbonn.de/epileptologie/arbeitsgruppen/ag-lehnertz-neurophysik/downloads/
- P. van Mierlo, Y. Höller, N. K. Focke, and S. Vulliemoz, “Network per spectives on epilepsy using EEG/MEG source connectivity,” Frontiers Neurol., vol. 10, p. 721, Jul. 2019.
- R.Hussein,S.Lee,R.Ward, andM. J.McKeown, “Epilepticseizure prediction:Asemi dilatedconvolutional neural networkarchitecture,” arXivpreprintarXiv:2007.11716,2020
- A. Anuragi, D. S. Sisodia, and R. B. Pachori, “Epileptic-seizure classification using phase-space representation of FBSE-EWT based EEG sub-band signals and ensemble learners,” Biomed. Signal Process. Control, vol. 71, Jan. 2022, Art. no. 103138.
- N. Makaram, N. von Ellenrieder, H. Tanaka, and J. Gotman, “Auto mated classification of five seizure onset patterns from intracranial electroencephalogram signals,” Clin. Neurophysiol., vol. 131, no. 6, pp. 1210–1218, Jun. 2020.
- R. Rahman, S. Maleki Varnosfaderani, O. Makke, N. J. Sarhan, E. Asano, A. Luat, andM. Alhawari, “Comprehensive analysis of EEGdatasetsforepilepticseizureprediction,”2021IEEEInternational SymposiumonCircuitsandSystems(ISCAS),Daegu,Korea,2021.