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Optimization in channel selection for EEG signal analysis of Sleep Disorder subjects

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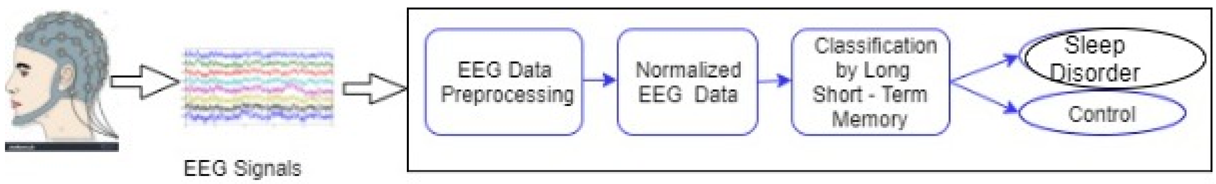
ABSTRACT



Deep learning, a branch of artificial intelligence (AI), is establishing a very promising approach for electroencephalogram (EEG) signals to sense and extract features from raw signals. The presented work here focuses on optimization in channel selection and batch size for EEG signals to identify sleep disorder subjects from normal ones with the deep learning-based model. It is observed that the data from several electrodes reduced recall obtained also starts reducing. To implement this work, an openly available Physionet EEG dataset from various ten electrodes is used. The long short-term memory (LSTM) method from a class of Recurrent Neural Networks (RNN) is nominated for the detection of sleep disorder subjects. The suggested method can achieve a recall of 99.8% on the test dataset.

Keywords: Electroencephalogram (EEG), Deep Learning, Long short term memory (LSTM), Recurrent Neural Network

INTRODUCTION

Artificial intelligence (AI) is one of the newest disciplines in today's research. Learning more about ourselves is possible due to AI.[1] AI can be used for automatic sleep scoring & discovering new insights from sleep data. Sleep is a vital aspect of the physical health the of human being. Sleep is involved in healing and repairing of human heart & blood vessels. Sleep deficiency may cause the risk of heart disease, high blood pressure, diabetes, and stroke.

Sleep can prevent weight gain and boost our immune system. Recent techniques in AI have established the ability in advanced diagnosis and treatment for sleep disorder. By connecting different electrodes to various parts of the body quality of sleep can be determined by various sleep experts. Different types of signals received from these electrodes are named Polysomnogram (PSG) which consists of an electroencephalogram (EEG), an Electromyogram (EMG), an Electrooculogram (EOG), and an Electrocardiogram (ECG). The procedure is known as sleep stage classification. Sleep scoring or sleep stage classification acts important role in understanding sleep and its disorders.[2] The proposed work is concentrated on minimization of number of electrodes and decision of perfect batch size due to which portability can be increased and complexity can be decreased.

EEG is a very effective tool for detection of sleep disorder. Various algorithmic advances are discussed in the literature survey for this. Signal acquisition, preprocessing, feature extraction and classification are the general steps followed for its implementation. As Artificial Neural Network (ANN) is excellently applied for identification of sleep disorder, there is no need for explicit feature extraction. ANNs are inherently capable of understanding the underlying patterns in the data. The values of the recall calculated are nothing but the overall combination of readings taken at respective electrodes. It changes as the data varies from different electrodes. Nowadays, the work is progressing in the optimization of the number of electrodes by selecting the best feature selection methods.

Channel selection helps to decrease the computational cost of feature selection & classification. For detecting and predicting of EEG seizure, statistical parameters like entropy and variance are

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used for channel selection as per the work done by Duun-Henriksen in his work.[3] Epileptic seizure classification is done using a multi-objective optimization method for EEG channel selection using genetic algorithm.[4] Particle Swarm Optimization for classification can achieve high classification accuracy by using less number of channels. As per the work done by Alejandro Gonzalez et. al, in [5] number of channels useful for classification can be effectively decreased without dealing the classification accuracy. Authors Lei Zhang and Qingguo Wei proposed a channel selection algorithm called binary quantum behaved particle swam optimization (BQPSO) executed in a wrapping manner. Here algorithm is used for motor imagery classification. By using proper channel selection algorithm, time of computation can be reduced.[6]

Channel selection for emotion classification is done by authors, Aleksandra Dura & Agnieszka Wosiak by selecting band of frequencies by examining average frequency for each second of trial in their work. . It is found that deep learning approach with optimum electrodes improves the classification of emotion and remarkably reduces the learning time.[7] Sleep stage classification becoming most popular area in researchers nowadays. Perfect selection of channels leads to robust classification results. Deep learning grounded approach by incorporating attention mechanism and bidirectional long short-termm memory method (AT-BiLSTM) using EEG signals is used to identify wakefulness; rapid eye movement (REM) sleep and non-REM sleep stages. AT-BiLSTM method obtained higher accuracy over existing traditional feature extraction methods. Excellent performance achieved by this method is with frontal EEG electrodes than with the electrodes placed at central, occipita, and parietal positions.[8] EEG signal analysis is done using power spectral density (PSD) by using ROC-LOC single-channelel data to classify normal subjects from Insomnia.[9] A new approach for automatic sleep stage classification is proposed in work.[10] In this work, raw EEG signals are directly applied the to deep convolutional neural network without feature extraction step. As per the work discussed by Sandeep Bavkar et. al, a latest approach leads fast recognition of alcoholism by applying EEG signals. The presented work utilizes complete gamma band power for feature extraction and ensemble subspace K-NN used as a classifier to classify alcoholic subjects from normal one. An improved Binary Search Algorithm (IBGSA) is described as a perfect method for selecting the minimum electrodes for detection of alcoholism rapidly.[11]

By using concrete selector layer optimization of EEG channel selection and network parameters is done. The deep learning-based Gumbel- softmax technique is used for end-to-end selection process.[12] Meta heuristics and evolutionary algorithms are used for the optimization of channel selection using Brain Computer Interphase.[13] A new method Exponentially Damped Sinusoidal model (EDS) is introduced by authors in, [14] for selection of EEG channels correlated with epileptic seizures by EEG rhythm extraction. A novel method is used for detection of motor imagery of walking for the rehabilitation of stroke patients using EEG signals. To avoid interference between electrodes, the Laplacian Derivative of power features for selected elelectrodes is used .[15]

In case of BCI systems, patterns of EEG vary from the first session to the second session. Author Arvanesh et al. implemented the Robust EEG Channel Selection technique across sessions in BCI for the Stroke patients.[16] Authors suggested a robust sparse common spatial pattern (RSCSP) model for optimal EEG channel selection for various sessions. Generally in the Brain Computer Interface, multichannel EEG signals are used for processing while performance of BCI can be improved by selecting relevant channels. Optimization in channel selection and classification accuracy is done in EEG BCI systems by authors .[17] By considering the growth in the field of BCI, a recent technique named a Modified Gray Wolf Optimizer (MGWO) is used for EEG channel selection. In this technique, optimum channels can be selected which helps in machine learning classification.[18] Artificial Neural Network (ANN) is well technique for BCI research and have various applications. ANN-based Genetic Neural Mathematic Method (GNMM), is used for selection and classification of EEG signals.[19]

In proposed work, Recurrent Neural Network (RNN) based long short term method (LSTM) is applied for classification of sleep disorder subjects from normal subjects with ten different electrodes. An extra tree classifier is used for channel selection.

DATA AND METHODOLOGY

Data and its pre-processing

For the work discussed here sleep recording Polysomnographic signals are practiced from openly approachable database: physionet.org/physiobank/database. The sleep recording signals of six sleep disorder subjects and six control subjects are utilized in this work. The data from various ten electrodes viz. FP2-F4, F4-C4, C4-P4, P4-O2, C4-A1, ROC-LOC, EMG1-EMG2, ECG1-ECG2, DX1-DX2 and SX1-SX2 are considered for implementation.

Data normalization is done under preprocessing. By increasing one column, in normalized data frame, named the ‘SLEEP’, a ‘0’ class label is assigned for control and a ‘1’ class label for sleep disorder.

Suggested Method

Nowadays, deep learning (DL), a branch of machine learning (ML) and artificial intelligence (AI) become a key technology for today’s researchers. In this technology, the model can take information directly frome the data, with no need for feature extraction seperately. As DL emerged from an artificial neural network (ANN) and, has graced the technique of computing, classification and analysis.[1,20,21] In the work submitted here, the deep learning method is used the for classification of sleep disorder EEG signals from normal signals. The LSTM algorithm based on RNN is employed for the work. The LSTM is a special case of RNN appropriate to learn long-term dependency. The method was innovated by S Hochreiter and J Schmidhuber.[22] In the suggested work, the LSTM method is finalized after testing various parameters like change in the number of layers, change in the loss function, dropout values and batch size, etc.[23]

Implementation of the LSTM Method

In applied work, deep learning-based LSTM model is employed to classify sleep disorder signals from normal signals with an input of normalized EEG signals of 12 different subjects. Each subject is identified with data and labels. A recall is measured by reducing the number of electrodes one by one. Also checked the performance of the model by changing the batch size.

The dataset used for implementation is used from ten different electrodes for 10 seconds from each subject. The training of the LSTM model is done with 75% of the dataset with 20 epochs and validated on 25% of the EEG dataset. ADAM optimizer is used for the proposed implementation with a learning rate of 0.0001. Tensorflow / Keras library is applied to train the model.

Result and Discussion

For offered work the CAP Sleep dataset is used from publicly available Physionet bank from 12 different subjects.[24] Various hyperparameters settings are used to train the deep learning model.

Evaluation Metrics for Performing Classification

The inferred deep learning model is judged by calculating the recall and other hyperparameters expected to tune the model. These hyperparameters include learning rate, activation function, number of layers, number of neurons in a layer, the score of epochs for training the model, batch size & dropout rate.

Activation Function

ReLu is used as an activation function in the proposed model from various activation functions like tanh, Sigmoid, and Binary step. ReLu is computationally more efficient and converges faster than the other two.

Number of neurons in each layer & number of layers

The complexity of each layer is decided by this parameter. The complexity of the network should be proportional to the size of the database to avoid underfitting or overfitting.

Table 1. Effects of LSTM Sequential Model

Proposed Model	No. of layers	Recall	Loss Function error	Execution Time	Epoch
LSTM	5	99.8	0.63	83 Seconds	20

Table 2. Design of Hyper-parameters of LSTM model

Proposed Model	Optimizer	Batch Size	Loss Function	Drop out rate	Learning rate	Activation Function
LSTM	Adam	256	Binary Cross entropy	0.2	0.0001	Relu, Sigmoid

Experimentation done with Python on GPU is provided by Google Colab.

Table 1 shows the best effects obtained for the suggested LSTM model. The best Recall Found is 99.8% with 256 batch size.

EEG datasets are generally very heavy data sets with complicated structures; various parameters such as learning rate, epoch score, network depth, and batch size can affect the implementation period.

It is observed from **Table 2** describing hyperparameters of LSTM design that both ReLu and Sigmoid activation functions perform excellently with Adam optimizer with a learning rate of 0.0001.

Table 3 indicates the optimization in the selection of batch formation. It is observed that there is a decrease in the performance of the test recall with the reduced batch size. The selected batch size for the proposed work (256) is perfect as it draws maximum test recall.

Table 3: Optimization in selection of batch formation

Batch Size	Test Recall
512	97.5
256	99.8
128	98.68
64	92.23
32	92.90

Table 4: Results obtained with number of selected electrodes

No of the elected electrodes	Recall obtained
10	99.8
9	100
8	99.48
7	98.14
6	84.91
5	83.95

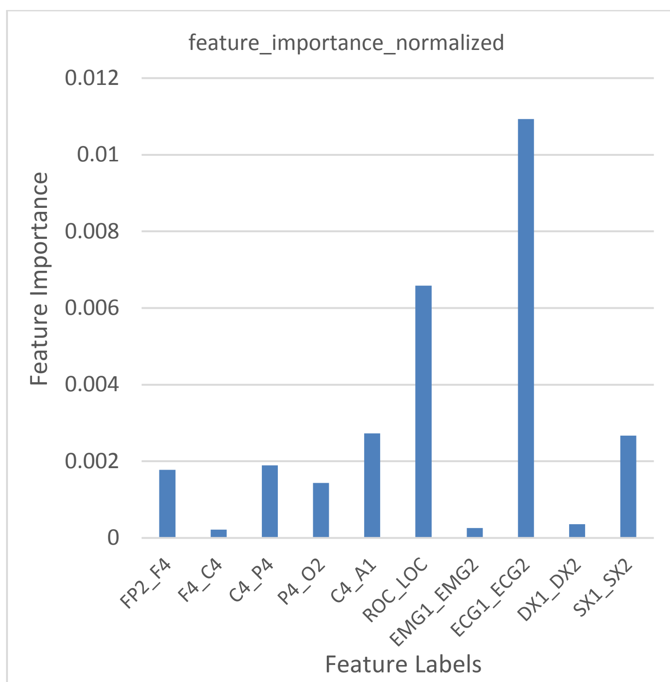

Figure 1 Optimization in the selection of electrodes

In the presented work, best-performing features are studied by using an extra tree classifier. It's a method of ensemble learning technique that combines the result of different de-correlated decision trees to produce output as a classification result. Figure 1 shows the graphical representation of best-performing features. Out of ten different features, ECG1-ECG2 & ROC-LOC electrode's data gives the best feature importance. **Table 4** indicates the results calculated with the number of selected electrodes and recall obtained for that. Table 4 indicates that as the selection in the number of electrodes is reduced, the percentage recall gets decreased.

Conclusion

The presented work aims to discover an effective technique to distinguish EEG signals into two different categories: sleep disorder and normal. The execution of the suggested method is evaluated on the CAP sleep Physionet dataset in terms of recall. For evaluation of the suggested algorithm, data from ten different channels are selected with 5120 samples from each channel. RNN-based LSTM model outperformed using a batch size of 256 and 20 epochs with 99.8% recall with a run time of 83 seconds only. Optimization in the selection of batch formation and selection of electrodes proves the perfection in the selection of hyperparameters in deep learning deployment in the proposed work.

Conflicts of Interest

All authors have participated in drafting the article or revising it critically for important intellectual content; and approval of the final version. This manuscript has not been submitted to, nor is it under review at, another journal or other publishing venue. The authors have no conflicts of interest to declare regarding the publication of this paper.

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