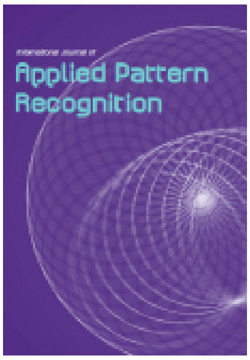

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LSTM-based electroencephalography analysis for sleep disorder subjects

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LSTM-based electroencephalography analysis for sleep disorder subjects

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Abstract: Electroencephalogram (EEG) is a complex, nonlinear signal which requires extensive training for detection of changes due to sleep disorder. Most of the traditional machine learning algorithms has been used in the past for detection of sleep disorder subjects. Recently deep learning has demonstrated a very promising approach for sensing EEG signals as it has excellent capacity of extracting features from raw signals. The proposed work aims to differentiate sleep disorder subjects from normal subjects using a deep learning-based model. To examine this, open-source EEG dataset from ten different electrodes of six sleep disorder subjects and six normal subjects is used here. Long short-term memory (LSTM) model, a class of recurrent neural network (RNN) is proposed for detection of sleep disorder subjects. Finally, in Table 3, accuracies are compared which are obtained in various models applied on same dataset. It is clearly predicted that the offered LSTM based technique gives classification performance of 70.75% accuracy as compared to other techniques in literature survey. Along with accuracy, recall of 88.34%, precision of 65.35% and specificity of 53.17% is evaluated for proposed LSTM model.

Keywords: electroencephalogram; EEG; deep learning; long short term memory; LSTM; recurrent neural network; RNN; recall.

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1 Introduction

Sleep is vital for the proper functioning of human body. Quality of sleep can be determined by sleep experts by connecting sensors to distinct regions of the body. Different types of signals received from these sensing elements are named as polysomnogram (PSG) which consists of an electroencephalogram (EEG), an electromyogram (EMG), an electrooculogram (EOG), and an electrocardiogram (ECG). The process is named sleep stage classification. Sleep scoring or sleep stage classification plays an important role to understand sleep and its disorders (Supratak et al., 2017). Sleep scoring is a tiresome and laborious task; therefore, automatic sleep scoring methods are used.

In order to detect sleep disorders, EEG is an important tool. For this, several algorithmic approaches are reported in literature. Typical steps involved are signal acquiring, pre-processing, feature extraction and classification. This can also be executed by applying machine learning algorithms. As artificial neural networks (ANN) is being used for prediction of sleep disorder, there is no need to explicitly extract the features. ANNs are inherently capable of understanding the underlying patterns in the data.

Since past few years, traditional machine learning based methods are used for detection of sleep disorder. Very few researchers have studied recurrent neural networks (RNNs) for recording of sleep stages. RNNs can qualify outputs with respect to former inputs. If the later outputs in the sequences are dependent on earlier inputs, it becomes very difficult for RNNs for back propagation. Simple RNNs can't take care of long-term dependencies. If a later output depends a lot on earlier input, long short-term memory (LSTM) model is used. LSTM, a type of RNN, adapts long term dependencies. A new model is introduced by Supratak et al. (2017) to score the sleep stages automatically by using EEG signal taken from single channel. Among the major trends that emerged, Roy et al. (2019) analysed that deep learning was chiefly applied for distinguishing EEG in various fields for instance brain computer interface, sleep, epilepsy, empirical and emotive monitoring. LSTM based deep learning method is used for classifying alcoholic subjects by using raw EEG signals as stated by Farsi et al. (2021). Temporal sleep stage identification by applying multivariate and multimodal PSG signals is done by Chambon et al. (2018) using deep learning method. Convolutional neural network (CNN) architecture using VGG-16 by deep transfer method is discussed for brain signal categorisation by Xu et al. (2019). Widasari et al. (2020) worked on automatic sleep disorder classification using Electrocardiography signals instead of high-cost Polysomnography recordings. Feature extraction is done by calculating PSD using Welch method and sleep stage classification is done by applying support vector machine using decision tree. Classification of sleep disorder is done by applying ensemble of bagged tree classifier. The results obtained Shahin et al. (2017) manifest that deep learning can be utilised to diagnose sleep disorders such as insomnia. According to the survey done by Rim et al. (2020) approaching deep learning is fruitful to a greater extent than conventional machine learning for execution.

The execution of EEG classification is improved by using two layered LSTM and four layered improved neural network deep learning algorithm (Nagabushanam et al., 2019). Deep CNN and encoder decoder network using bidirectional RNN is used as a building block for implementation (Mousavi et al., 2019a). Specific loss calculation approaches implemented in this work by Mousavi et al. (2019a) dilute the result of class imbalance problem. Work submitted by Mallikarjun and Suresh (2014) discussed anticipation of depression using the same dataset. Features are extracted by calculating log power spectral density of EEG band. In paper by Arce-Santana et al. (2020) proposed annotation type for sleep stages called Sleep EEGNet. In this method, EEG Signal is automatically recorded using only one channel. Log spectrogram of EEG signal is used as an input for CNN for identifying A-phases during non-rapid eye movement (NREM) sleep data. EEG signals are compared between normal and insomnia subjects by measuring PSD using ROC-LOC channel by Siddiqui et al. (2016). For identification of sleep stages, EEG signal with an output from single channel is processed by using deep convolution neural network by Mousavi et al. (2019b). For automatic detection of sleep disorder, effective multiclass classification algorithms are used. Analysis is done using support vector machine by David et al. (2018).

From the literature review discussed, it can be found that majority of the methods used for detection of sleep disorder using EEG signals are focused on deep learning methods than machine learning algorithms viz. SVM, KNN, XGB, NB and traditional hand-crafted feature extraction methods like Wavelet Transform, Fourier Transform, PCA and Entropy. Extracting distinguished characteristics from various internal layers is inadequate with present feature extraction methods (Farsi et al., 2021). Selection of suitable and efficient feature extraction methods for distinct EEG signals is very difficult with present methods. Nowadays, due to the use of various deep learning methods sensing of EEG signals and extracting features from raw signals has become possible. This work introduces a deep learning based RNN algorithm called LSTM to identify subjects with sleep disorganisation from normal whereas the EEG signals are right away employed as a stimulus to LSTM network model.

The organisation of the remaining part of the paper can be stated as: Section 2 discovers about data and methodology utilised in offered work with the suggested method. Section 3 discloses the results, and Section 4 brings out the conclusion of the work.

2 Data and methodology

2.1 Data and data preprocessing

For proposed work sleep scoring Polysomnographic signals are used from openly accessible database: physionet.org/physiobank/database (Goldberger et al., 2000). Out of 21 data available from only 10 electrodes, which are common in all subjects, are used. For some electrodes like SPO2 & SAO2 dataset is combined in some cases. HR, PLETH, STAT & MIC electrodes are also removed as in some subjects; there is no data for them. Finally, the sleep scoring signals of six sleep disorder subjects and six control subjects are used in this work. The data from 10 different electrodes namely FP2-F4: Prefrontal to frontal electrode, measured from front to back side, F4-C4: frontal electrode, C4-P4: frontal parietal electrode, P4-O2: parietal- occipital electrode, C4-A1: frontal electrode, ROC-LOC: EOG placement, EMG1-EMG2: EMG placement, ECG1-ECG2: ECG placement, DX1-DX2: Drive electrode, SX1-SX2: Sense electrode with 5120 samples per each electrode are considered for proposed work.

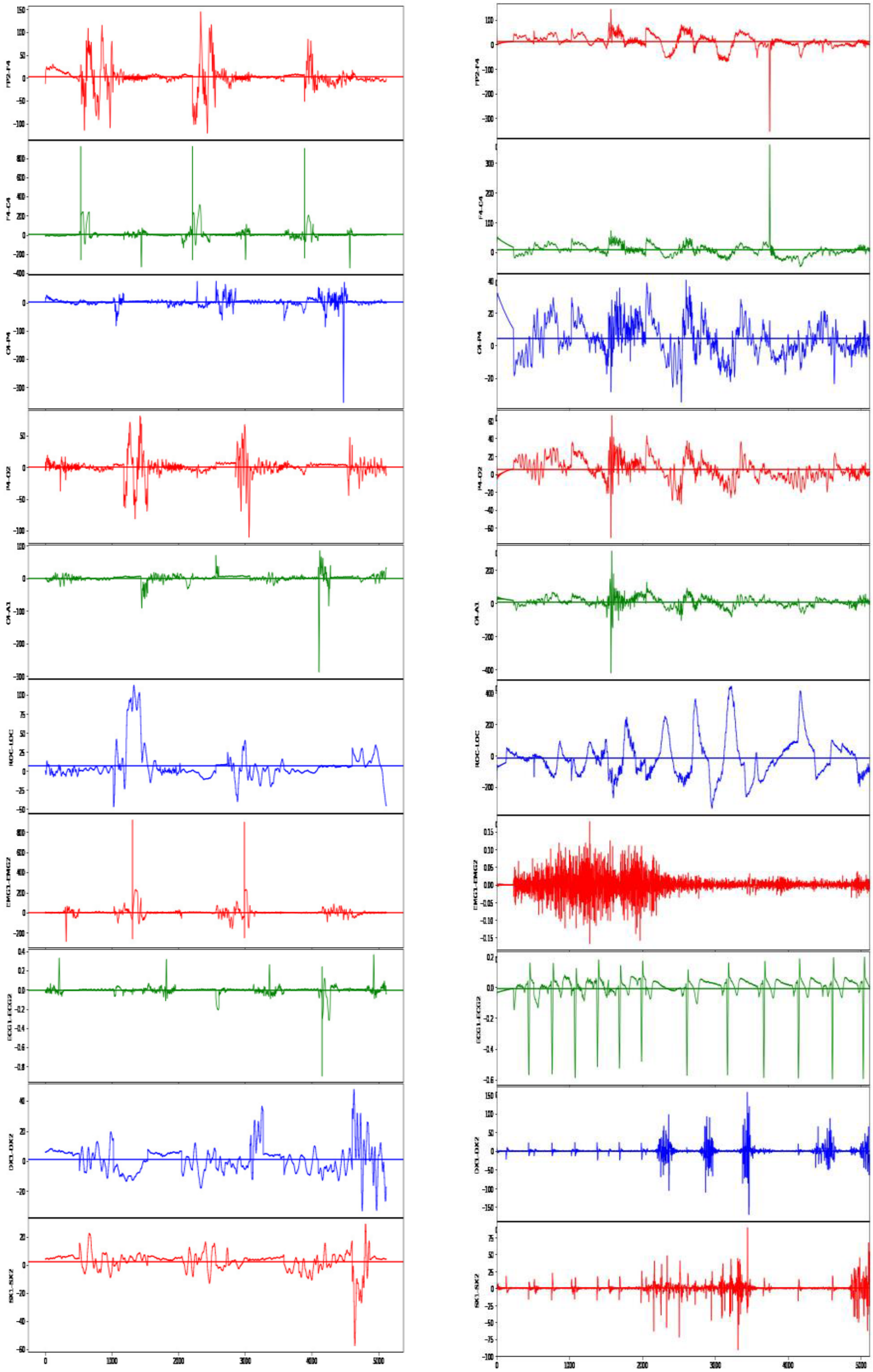
Preprocessing is done with data normalisation. The '.csv' file is created for all the datasets. Extra columns for 'SUBJECT', 'SAMPLE' and 'SLEEP' are added to this file. In the Sleep column class label is marked as '0' and '1' for normal and sleep disorder respectively. A 3D Numpy array with overlapping windows of varied size from 16 to 256 is created and the batch formation is used with a batch size of 256to train the model .This trained model is then used to correctly distinguish a subject with sleep disorder from control. Figure 1 shows raw data for sleep disorder and control subject. In each waveform, a different coloured horizontal line indicates the meaning of that signal and y axis indicates the name of electrode. From the figure, it is clear that, data is quite noisy due to sudden deviation from the mean. In a waveform of sleep disorder subject, the sharp waves show epileptiform discharges which can be associated with some type of jerks or seizures.

Increased frontal slow activity in frontal electrodes is a dominant feature marked on sleep disorder EEG and it indicates that frontal regions are more receptive to sleep deprivation effects than any other regions in the brain (Ogunrinde and Yue 2017) whereas normal EEG waveforms are showing some fixed pattern of occurrences.

2.2 Proposed methodology

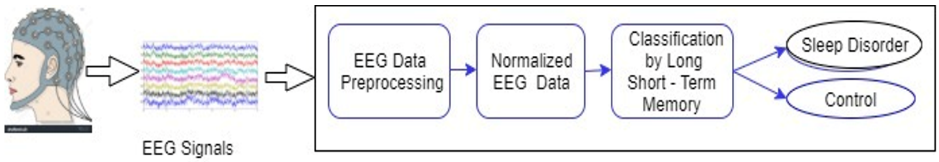
The work proposes a deep learning method for identification of sleep disorder EEG signals. RNN based LSTM algorithm is applied for this work. Figure 2 presents a diagram describing interconnections between the components of suggested deep learning algorithm. With the help of 10-20 electrode system, raw EEG signals are captured and applied for pre-processing. Normalised and pre-processed signals are the inputs of LSTM model where sleep disorder and normal EEG signals are classified.

Figure 1 Data sample for (a) sleep disorder subject (b) control subject (see online version for colours)



(a) (b)

Figure 2 Block diagram of suggested deep learning method (see online version for colours)



In above mentioned method, the normalised EEG signals are applied as an input to the suggested deep learning model. The detailed description of the aimed method with implementation process is described below.

- *Splitting dataset into training and validation sets*

  For implementation of the work, data is split into train and test set. 25% is used for validation and 75% is used for training. The proposed LSTM model learns on training dataset only. (75% data is used for training and remaining 25% untrained data is used for testing)

- *Loss computation*

  Output layer performs the calculation of loss or error. The contrast between real value and the projected value is calculated using the loss function. Various loss functions are accessible in deep learning models. Binary cross entropy loss function is applied for implementation. For binary classification, the typical loss function is binary cross entropy or log loss. To evaluate how good or bad are the predicted probabilities induces the whole purpose of loss function and entropy measures the uncertainty associated with a given distribution. It should return low values for good prediction.

- *LSTM model*

  A RNN is a case of multilayer neural network, applied for prediction of sequential data for example DNA protein sequence, speech recognition; etc. The algorithm is mainly dependent on feedback loop and weighted memory.

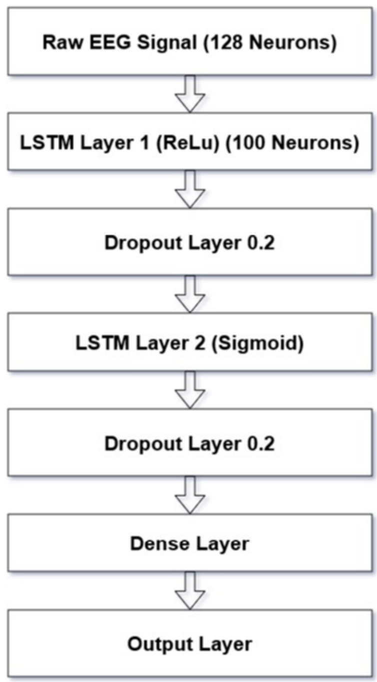
  LSTM method is a particular form of RNN, adequate to learn long term dependencies. The methodology was invented by Hochreiter and Schmidhuber (1997). LSTM method is a type of RNN working powerfully when used for time series dataset of EEG signals. The inspiration for using LSTM in present work is the ability of the model to save significant details regarding former states and tap the time dependencies from information employing memory cell. The power of LSTM to recollect former information made this network perfect for EEG analysis. The LSTM is a productive class of RNN as it defeats the vanishing gradient and overfitting problems and can be widely used.

  The LSTM memory section determines the details that are to be saved in the memory and the ones to be forgotten before sending to the next cell. In this work, LSTM architecture is finalised by testing several parameters like change in number of layers, change in loss function, drop out values and batch size, etc. (Farsi et al., 2021).

- *Execution of the LSTM algorithm*

  In proposed work deep learning using LSTM is enforced to normalised EEG dataset of 12 subjects to identify if the signals are suffering from sleep disorder. Every subject is described with data and label. Figure 3 describes the proposed LSTM model. The design comprises of two fully connected LSTM layers, two dropout layers and a dense layer.

Figure 3 Proposed LSTM model



The first step in LSTM is to decide which information is to be retained in cell state with the help of sigmoid layer called 'forget gate layer'. The next step is to decide what new information should be added to the cell state called as 'input gate layer'. Finally, updating of old cell state to new cell state by deciding how the output is generated with current cell state and current stage input called 'output gate'. With these internal stages, dropout is a simple way to keep neural network away from overfitting. In this technique, some of the layer outputs are ignored randomly. They are temporarily removed from the network along with all their interconnections.

The LSTM and dropout layers are applied to grasp 128 characteristics from EEG waveforms and final classification is done with the help of dense layer. Final deep learning keras LSTM sequential neural network model is shown in Figure 4.

The data of each subject is taken from 10 different channels for 10 seconds. The network arrangement of various layers includes input layer of EEG signal, LSTM layer 1, a dropout layer with a dropout rate of 0.2, LSTM layer 2, second dropout layer and a dense layer for classification is indicated in Figure 4. The LSTM design is developed with 75% of the dataset, applying 20 epochs and validated on 25% of the EEG dataset.

ADAM optimiser is applied for offered implementation whose learning rate is of 0.0001. Tensorflow/Keras library is applied to train the model.

Figure 4 Keras LSTM sequential neural network model

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
lstm_12 (LSTM)              (None, 48, 100)           44400

dropout_12 (Dropout)        (None, 48, 100)           0

lstm_13 (LSTM)              (None, 50)                30200

dropout_13 (Dropout)        (None, 50)                0

dense_6 (Dense)             (None, 1)                 51

=================================================================
Total params: 74,651
Trainable params: 74,651
Non-trainable params: 0
_________________________________________________________________
```

3 Results and discussion

For presented work, CAP Sleep dataset is used from publicly available physionet bank from 12 different subjects (Goldberger et al., 2000). The model of deep learning is developed with training dataset and execution is measured with the validation dataset for different hyper-parameters settings.

3.1 Evaluation metrics for classification performance

The proposed deep learning model is estimated by calculating recall, accuracy, precision and specificity with various hyperparameters required to tune the model. These hyperparameters include learning rate, activation function, number of layers, number of neurons in a layer, score of epochs for training the model, batch size and dropout rate.

3.2 Activation function

The proposed deep learning model can perform linear transformations, but for handling complex operations, it needs to introduce activation function in the model. There are various activation functions like tanh, sigmoid, binary step function and ReLu. Most of the time sigmoid or tanh is used as a nonlinear activation function. For proposed work, ReLu is used as an activation function as it is computationally more efficient. It converges faster than the other two.

3.3 Number of neurons in each layers and number of layers

This parameter determines the complexity of each layer. The complexity of the network should be proportional to the size of the database to avoid underfitting or over-fitting. For the perfect fitting of the model, the number of neurons used in each layer and number of layers is very important. Processing of complex data requires a large number of neurons in every layer. If too many neurons are used the model may lead to overfit. An optimum number of neurons are decided after some experimentation.

3.4 Experimental results

LSTM is trained with 100 hidden units. Binary cross entropy loss function and Adam function for optimisation is utilised for implementation with learning rate of 0.0001. All experiments were performed using the Pythonon GPU provided by Google colab (Geron, 2017).

Table 1 presents the best results obtained for the proposed LSTM model. In this study the best recall obtained is 83.34% EEG datasets are generally very heavy data sets with complicated structure; various factors such as learning rate, epoch score, network depth, and batch size can affect the implementation period.

Table 1 LSTM sequential model results

Proposed model	*No. of layers*	*Recall*	*Loss function error*	*Execution time*	*Epoch*
LSTM	5	88.34	0.63	83 Seconds	20

It is seen from Table 2 showing hyper-parameters of LSTM design that both ReLu and Sigmoid activation function perform well with Adam optimiser having a learning rate of 0.0001.

Table 2 Hyper-parameters of LSTM design

Proposed model	*Optimiser*	*Batch size*	*Loss function*	*Dropout rate*	*Learning rate*	*Activation function*
LSTM	Adam	256	Binary cross entropy	0.2	0.0001	Relu, Sigmoid

Figure 5 shows the advancement of accuracy and loss function during epoch iteration. The recall of the model starts from 51.4% in epoch 1 and reaches 88.34% at the end of the iteration. From Figure 5, it can be observed that LSTM algorithm is best suitable for detection of sleep disorder.

Table 3 explains the comparative report for suggested technique with other implemented methods. In literature review, the previous work done by other authors on similar dataset or some different dataset for identifying sleep disorder subject is discussed. In Table 3 accuracies are compared which are obtained in various models applied on same dataset. It is clearly predicted that the offered LSTM based technique gives better classification performance (70.75%).

Figure 5 Recall and Loss for proposed LSTM model (see online version for colours)

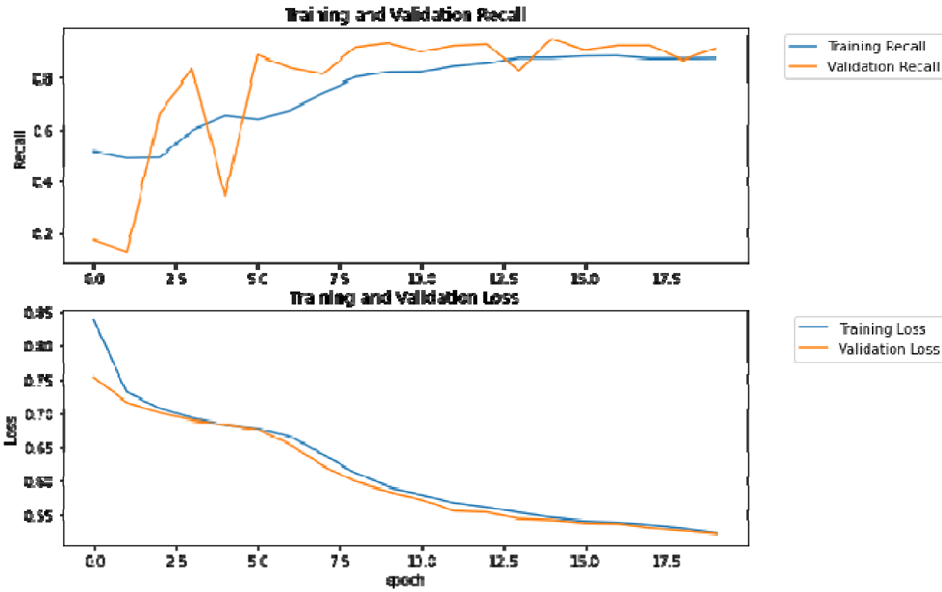


Table 3 Comparative report for suggested method with other implemented methods

Authors	*Methods*	*Described accuracy*
Arce-Santana et al. (2020)	Deep CNN using log spectrogram	88.09%
Widasari et al. (2020)	Ensemble of bagged tree, sleep quality	86.27%
David et al. (2018)	PSD estimation	85%
	PCA, and PLS, with SVM classifier	
Mousavi et al. (2019a)	CNN + RNN	84.26
Mousavi et al. (2019b)	CNN	94.91
Perslev et al. (2019)	U Time	67.8%
	CNN + LSTM	65.2%
Proposed LSTM method	*Long short-term memory based deep learning algorithm*	*70.75%*

Table 4 Comparative results by changing sequence length (n_past)

Hyperparameters → *Statistical parameters* ↓	*n_past = 256*	*n_past = 128*	*n_past = 64*	*n_past = 48*	*n_past = 32*	*n_past = 16*
Recall	1	99	85.86	88.34	91.51	84.26
Accuracy	57.3	68.69	68.94	70.75	70.13	67.84
Precision	53.93	61.63	64.16	65.35	64.1	63.42
Specificity	14.6	38.38	52.04	53.17	48.76	51.41

Table 4 focuses on comparative results of various statistical parameters by changing sequence length. For proposed model recall, accuracy, precision, and specificity are calculated. The best performance is given by considering sequence length of 48. Recall measures the model's ability to detect positive samples and the value for proposed model is 88.34%. Positive predicted value i.e., precision is 65.35% in prescribed model. Specificity measures the ability to predict true negative values of each class. In proposed model the value of specificity is coming as 53.17%.

4 Conclusions

The proposed work intends to describe an effective technique to categorise EEG dataset into two classes: sleep disorder and normal. The performance of the proposed algorithm is assessed on CAP sleep physionet dataset in terms of recall, accuracy, precision and specificity. For implementation of the proposed algorithm, data from ten different electrodes is selected with 5120 samples from each electrode. With a batch size of 256 and 20 epochs, RNN based LSTM method outperformed with 88.34% recall, 70.75% accuracy, 65.35% precision and 53.17% specificity with run time of 83 seconds only. This study suggests selection of hyperparameters in deep learning deployment.

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