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A novel solution of enhanced loss function using deep learning in sleep stage classification: predict and diagnose patients with sleep disorders

Ereena Rajbhandari[1] · Abeer Alsadoon[1] · P. W. C. Prasad[1] · Indra Seher[1] · Tran Quoc Vinh Nguyen[2] · Duong Thu Hang Pham[2]

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Abstract

Sleep stage classification is important to accurately predict and diagnose patients with sleep disorders. Though various deep learning approaches have been implemented to classify sleep classes, these consist limitations that impact the accuracy and processing time of the classification model. The aim of this research is to enhance the accuracy and minimize the training time of the deep learning classification model. The proposed system consists of One Dimensional Convolutional Neural Network (CNN) with enhanced loss function to improve the accuracy of scoring of five different sleep classes. Preprocessing, Feature Extraction and Classification are the main components of the proposed system. Initially, EEG signals are fed to an adaptive filter for preprocessing, in order to remove any noise in signal. Thereafter, feature is extracted through multiple convolutional and pooling layers, and finally the classification is done by fully connected layer using softmax activation with enhanced loss function. The proposed solution is tested on data samples from multiple datasets with five classes of Sleep classification. Based on the obtained results, the proposed solution has found to achieve an accuracy of 96.26% which is almost 4.2% higher than the state-of-the-art solution which is 92.76%. Furthermore, the processing time has been reduced by 11 milliseconds against the state-of-the-art solution. The proposed system focused on classifying sleep stages in five classes using EEG signals with deep learning approach. It enhances the loss function in order to minimize errors in the prediction of sleep classes and improves the accuracy of the model. Furthermore, the training speed of the model has also been reduced by applying batch normalization techniques inside the model. In the future, larger datasets of different sleep disorder patients with varying features can be used for training and implementing the proposed solution. The datasets can also be pre-processed using additional techniques to refine the data before feeding to the neural network model.

✉ Abeer Alsadoon
alsadoon.abeer@gmail.com

Extended author information available on the last page of the article

Keywords Deep learning · Sleep stages classification · Convolutional neural network (CNN) · Loss function · Batch normalization · Adaptive filtering

1 Introduction

Sleeping is a crucial part of human life. An average person spends one third of his life in sleeping. Sleeping is important for human in order to perform normal activities when they are awake. In this modern era, sleep disorders have been widespread due to the competitive lifestyle [22]. Sleep disorder not only causes abnormalities during human awake state, but also can cause long lasting health issues that can result even to death. To analyze sleep disorder of a person, a recording called Polysomnography is commonly used. These records consist of signals such as electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), and electromyogram (EMG) [22]. Classifying these records is done manually by experts by visually observing the signal images. These techniques involve a minimum of two experts where one of the experts observes the signals and labels them, which is then observed by the second expert for an agreement [13]. In the past, manual human inter-rater agreement technique was used to classify the sleep stage which has very lower accuracy, since some of the slight variations in the signals might not be visible to human eye, but they might be important factors to consider. In addition, an agreement between two experts alone is not enough to confirm the labels on sleep stages [29]. Therefore, many deep learning techniques have been developed and implemented to analyze various sleep datasets in order to automate the sleep stage scoring [25].

Developments in machine learning have made it to be widely used in the prediction, detection, and classification of diseases in the health sector. Deep learning is playing a vital role in the analysis of medical data for the prediction and detection of diseases earlier than their occurrence [26]. Scoring of sleep stages can also be done using deep learning. There has been a lot of past works done on using neural networks to score sleep stages of the polysomnography signals in which the most common one is the Convolutional Neural Network (CNN). This was mainly due to CNNs work with sparse data [27] and are able to do both feature extraction and classification [25]. CNN is used in training images and image classification which are two-dimensional. But, it has much more features in classifying data like EEG which are one dimensional data [4]. CNN provides more accurate classification of sleep stages compared to the manual technique that needs experts. But, accuracy of the CNN model depends on various factors: number of layers, loss function, training datasets, activation function, and so on [15]. The important factor that affects the accuracy of this model is the loss function, and hence to improve it, both regression and classification loss of the model need to be addressed.

Current studies done on CNN feature extraction and classification for sleep stage scoring use different techniques and methods to increase the accuracy and performance of the classification model [4]. ReLU has been used in state of the art as an activation function with multiple convolution layers to increase the accuracy of the model to 90.76% [25]. The classification accuracy of CNN model is better than the human inter-rater. However, accuracy of the classification depends on various factors of the model such as the model layers, regularization, data preprocessing, and prediction errors. Therefore, accuracy can further be improved in the current state of the art.

Next section of this paper looks into the literature to identify the existing deep learning based models that have been developed and implemented to analyze various sleep datasets in order to automate the sleep stage scoring. But it is possible to provide more accurate classification of the sleep stages using these techniques while reducing overall processing time. The important factor that affects the accuracy is the loss function, and hence to improve it, a modified loss function combining both cross entropy loss and mean square loss is used in the proposed model and is discussed in the paper. Furthermore, the state-of-the-art solution does not consider any filtering techniques to remove the noise in the image which is important for better performance. Hence, an adaptive filter based on LMS is used in the proposed model during the pre-processing stage to remove unwanted noise from the raw EEG signal. The state of the art does not consider internal covariate shift in inputs in their model, and batch normalization is carried out in the proposed model after the pooling layer in order to reduce the covariate shift in input inside the network to maximize the training speed.

2 Literature review

Literature is reviewed to research and analyze existing techniques and methods, in order to find out a way to improve the current models. It also provides knowledge on various algorithms and methods used by other researchers in the same area.

2.1 Convolutional neural network

Yildirim, et al. [25] improved the accuracy of One-dimensional Convolutional Neural Network (1D-CNN) by adding dropout regularization as a layer for sleep stage classification. Using multiple convolution layer with Rectified Linear Unit as an activation function for feature extraction has enhanced the performance of the model and provided multi-class classification. The overall accuracy of this network for five sleep class stages was 90.76% which is comparatively higher than the existing models [4]. Also, a larger number of unfiltered datasets (sleep-edf and sleep-edfx) were used to train the model. However, this solution has not addressed the training time of the model and did not focus on the loss function that gives the error of the predicted data. For further work, the model can be improved by focusing on the prediction error and training speed. Similar concept of Convolutional Network has been used by Mousavi, et al. [14]. They successfully implemented deep Convolutional Network model with batch normalization for improving training speed of the model. While extracting the feature in convolution layer, down sampling and normalization have been implemented to enhance the performance of the model. The model consists of two fully connected layers to reduce the prediction error and ultimately maximizing classification accuracy of the sleep stages. Further, they also implemented an overlapping technique for data augmentation for preprocessing the datasets to reduce computational complexity which also been implemented in the previous researches [6]. The system provides an accuracy of 90% and Cohen's Kappa coefficient of 0.9 for five sleep class stages. However, the model has been trained using only healthy datasets and the loss function used for the model can further be improved to maximize the accuracy of the model.

Sokolovsky, et al. [21] have also applied Deep Convolutional Neural Network Model Architecture, but with seven level of convolutional layer to improve the performance of the sleep stage classification model. The solution focused on increasing the accuracy based on network depth, rather than the multiple channel signal similar to the research done by Jeon, et al. [11]. The model also implemented batch normalization to maximize the training speed of the model. Accuracy of this solution was 81%. Even though the accuracy of the solution is lower than the other methods, error calculation of the predicted data in this model, which is mean square error, is of interest for the proposed system as it has addressed the regression error of the model. On the other hand, Phan, et al. [15] represented sleep stage classification as a joint classification problem to address the shortcomings of common classification models. They proposed a CNN framework with multi-task CNN with softmax activation, and loss function for combined classification of sleep stages. Further, additive and multiplicative voting probabilistic aggregation was used in the evaluation for ensembling multi-view decision of the model's prediction. This model yields an overall classification accuracy of 83.6% and 82.3% for Montreal Archive of Sleep Studies (MASS) and sleep-edfx datasets respectively, which is higher compared to the machine learning model [12]. The CNN framework proposed in this solution is of interest for the proposed system which automates both feature extraction and classification.

Similarly, Sors, et al. [22] improved performance of the model for sleep scoring by using Deep learning technology. They proposed a deep Convolutional Neural Network based on single channel EEG signal, rather than multiple channel signals. This model provided an overall accuracy of 87% with macro Cohen's Kappa of 0.81 for Sleep Heart Health Study (SHHS) datasets. However, the model needs to address the class imbalance problem with a better solution than the cost-sensitive learning or oversampling [23]. They added visualization method to analyze class-wise patterns that are learned by the model which could be an area of interest for the proposed system. In the same domain, [27] has improved the performance of classification of unlabeled data using an unsupervised algorithm. The author has proposed a model that is based on the complex-valued input CNN for automated feature extraction and classification, and unsupervised k-means algorithm for training unlabeled dataset. The model proposed by this research achieved a total accuracy of 87%. It is of interest for the proposed system, since CNN is used to train the unlabeled dataset.

2.2 Recurrent neural network

Phan, et al. [16] improved the accuracy in classifying sleep stages by implementing hierarchical Recurrent Neural Network (RNN) and named it as SeqSleepNet with GRU blocks.. A recurrent layer based on attention was used for short term sequential modeling, and another recurrent layer was used to learn epochwise features for long term sequential modelling. Training of the model was done in an end to end fashion using dynamic folding and unfolding of input sequence which is an area of interest for the proposed system. This model achieved an overall accuracy, macro F1-score, and Cohen's kappa of 87.1%, 83.3%, and 0.815 respectively on MASS datasets. Aboalayon et al. [1] introduced a Cascaded LSTM recurrent neural network to automate Neuro Cognitive Performance assessment by scoring sleep stages of patients. They implemented a 4-class LSTM and a 2-class LSTM RNN models to score the sleep classes using selected parameters. The features extracted from the signal were selected using two methods, Principal Component analysis (PCA) and Minimum Redundancy Maximum Relevance (mRMR). The overall percentage of correct classification (PCC) of this solution is 86.74%. Using LSTM in RNN, they solved the gradient varying and exploding problem, but it made training the data harder because of memory-bandwidth-bound computation which limits the full realization of neural network model [7]. Hence, the solution provided for gradient exploding problem is of interest, but it might not be a suitable model of neural network for the implementation and is hence of no further interest.

2.3 Mixed neural network

Mousavi, et al. [13] designed a model by combining both Convolutional and Recurrent Neural Network to perform an automated classification of sleep classes. The model is named SleepEEGNet which consists of convolutional layer to extract features from the input, sleep data, and sequence to sequence bidirectional RNN to obtain long short-term context dependencies between sleep epochs. This model improved the accuracy by using a novel loss function to minimize the class imbalance problem which might be of interest to improve the accuracy of the proposed system. An overall accuracy of 84.26%, a macro F1-score of 79.66%, and Cohen's kappa of 0.79 were achieved by this model. Similar technology was used by Phan, et al. [15] to combine convolutional layer and recurrent layer to classify the PSG data by treating it as a sequential spectrogram. Convolutional layer evaluated the co-occurrence of signal pattern and the recurrent layer was used to evaluate temporal relationship in the input data. The model presented an overall accuracy of 87%, and Cohen's Kappa Coefficient of 0.76 in the classification of sleep stages. Further, this research applied different data pre-processing methods to analyze the impact of reducing noise to improve the accuracy of the model which is an area of interest for the proposed system since input data pre-processing methods would be needed to implement the developed model.

In addition, Biswal, et al. [3] enhanced the accuracy of sleep staging by implementing the deep neural network model that combines Recurrent and Convolutional Neural Network (RCNN) for classifying the raw PSG signal into five classes of sleep stages. They used one dimensional CNN (1D-CNN) for feature extraction and Bi-directional Recurrent Neural Network (Bi-RNN) for classification. This model achieved accuracies of 87.6%, 88.2%, and 84.7% for sleep staging, sleep apnea, and limb movements respectively.

Research by Bresch, et al. [5] is yet another work done on this concept. They enhanced the performance of classification of sleep classes with the addition of demographic information such as age and gender by using a deep learning model based on Long short-term Memory (LSTM). The author has proposed a deep neural network model based on Convolutional Neural Network and Recurrent LSTM Neural Network in order to improve the performance and to automate the sleep staging process. Long short-term Memory (LSTM) layer has been used to remove the dense layer by disabling memory cell functionality and enabling the softmax function. This reduces the computational burden on the network. However, optimization technique of loss function can further be addressed to express the loss in each layer which can improve the performance of the proposed system. The Cohen's Kappa Coefficient of the proposed system is 0.75 which is higher than the human inter-rater agreement [5, 24]. Malafeev et al. [19] improved the performance of Convolutional Neural Network Long Short-term Memory (CNN-LSTM) model by using Residual Network in order to prevent the gradient vanishing problem. They implemented residual network approach in CNN-LSTM model that prevented gradient loss problem suffered by networks with large number of layers which also improved the training of the model and classification performance. It achieved a Cohen kappa of 0.82 and 0.8 for CNN-LSTM model and LSTM model respectively. However, binary classification sigmoid and tanh activation function have been used which can be improved by using multi-class classification as in ReLU [17].

Dong, et al. [8] implemented the mixed neural network which is different from the previous literature with combined multi-layer perception with RNN. They enhanced the accuracy of sleep stage classification by improving recognition of temporal relationship. The authors proposed a mixed neural network model composed of multi-layer perception Rectifier Neural Network and Long short-term Memory RNN. They used a Rectifier network to obtain hierarchical features from the input, LSTM RNN to train the model on sequential data, and the softmax layer for classification. It improved the limitation on classic RNN by using LSTM architecture that is capable of training on long term dependencies data [28]. The mixed network proposed by Dong, et al. [8] achieved an overall accuracy of 85.92%, and macro F1 Score of 80.50%. Even though the concept is an area of interest, it might not be useful for the proposed system and hence is not of further interest. Pillay et al. [10] improved the classification of sleep stages of term babies by applying generative modelling approach. They implemented the model using Gaussian mixture model (GMM) and Hidden Markov Model (HMM), compared kappa coefficient of both classifiers, and concluded that HMM outperforms the GMM Classifier. The model involved experts to label the acquired data, and extracts and selects features followed by using classifiers to classify sleep stages based on the selected features. This model included personalized scaling of a feature after the extraction of the feature and before the selection of the feature. Scaling has improved the classification performance by 0.1 (Cohen's kappa) when model was implemented without scaling [2]; [12]. The proposed model with HMM classifier achieved a mean kappa of 0.62(±0.16), and GMM classifier achieved a mean kappa of 0.56(±0.18). Hence, it was concluded as the HMM classifier has outperformed the GMM classifier. However, this is not of interest for the proposed system for adaptation, but personalized scaling of feature might be of interest.

After all the literature reviews, the solution provided by Yildirim, et al. [25] has been chosen as the best solution or state of the art for its higher accuracy performance than the other researches. The solution proposed a convolution neural network with one dimensional convolution layer to handle one dimensional EEG signal. The solution has successfully handled over-fitting problem by using drop out layer and ReLU activation has been used for multiclass Classification [9, 18, 20].

2.4 State of the art

This part presents features of state-of-the-art model system (highlighted inside blue broken line in Fig. 1) and its limitations (highlighted inside red broken line in Fig. 1). Yildirim, et al. [25] proposed a one-dimensional Convolutional Neural Network (1D-CNN) to improve the accuracy of the classification of sleep stages. Only normalization was done on the raw polysomnogram (PSG) signal which was then segmented into 30s epoch. The raw signal is directly fed into the Convolutional layer for feature extraction and learning, and later dense layer of CNN with softmax activation performed the classification task. The solution provides an accuracy of 90.76% in sleep stage classification which is quite high compared to the human rater and some other deep network based classification such as SeqSleepNet and DeepSleepNet with accuracy of 87% and 85% respectively. This model consists of three major stages- Pre-processing, Feature Extraction, and Classification as shown in the figure below.

Pre-processing Pre-processing starts from acquiring the PSG signal data sets from the selected database. Sleep-edf and Sleep-edfx public databases are used to get the data to feed

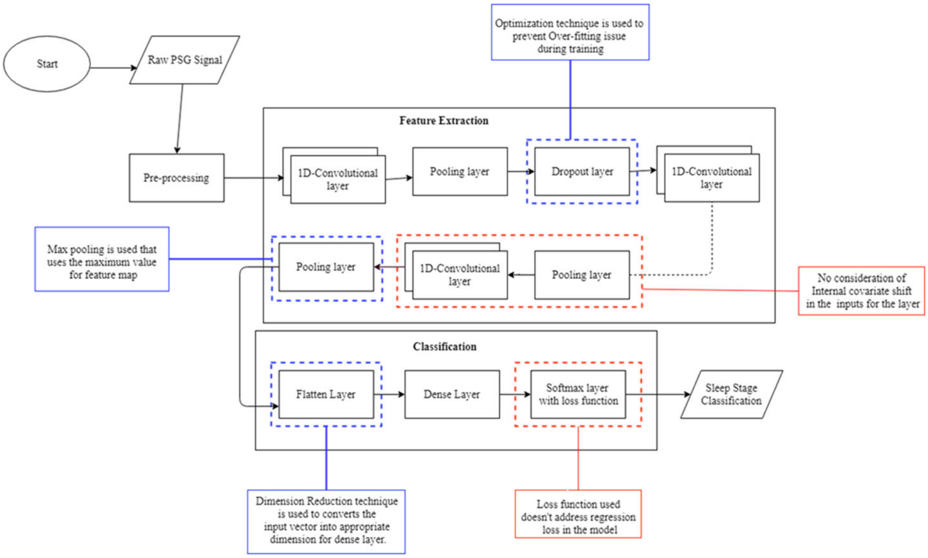

Fig. 1 Block diagram of state-of-the-art system [Feature of the state of the art is shown using blue boxes and limitation are shown using red boxes]

the classifier network. The raw PSG signal is then segmented to obtain 30s segment called epoch from Hypnogram of the PSG signal. After segmenting the signal, pre-processing is done for standardization and normalization of the signals in the range of zero to one.

Feature extraction and learning For Feature Extraction stage, raw segmented signal from the dataset is fed into the one-dimensional Convolution layer which performs convolutional operation on the input signal. Each convolution layer consists of Rectifier Linear Unit (ReLU) to overcome vanishing gradient problem. The output of the convolutional layer i.e. feature map is sub-sampled in the pooling layer. Max pooling is used in the pooling layer which uses the maximum value from the cluster of neurons of the previous layer, unlike the average pooling which uses the average value. Dropout layer is placed after every 2 convolutional layers to prevent overfitting. However, batch normalization is not accompanied with the dropout function which affects the training process. It is important to regularize the model and maximize the training speed of the model.

Classification Classification is done by the final layer of the Convolutional Neural Network which is fully connected dense layer with softmax activation function. Softmax function is used since it is capable of multi classification, unlike sigmoid and tanh that can only do binary classification. Flatten layer is placed before the dense layer in order to convert the input vector of the dense layer into appropriate dimensions. Softmax layer used for the classification has only considered cross entropy loss function which is not enough for addressing both classification and regression loss. Hence, further enhancement of the loss function can be done to increase the accuracy of the sleep stage scoring model.

In this model, only the classification loss or error has been considered by calculating cross entropy loss function, which has limited the accuracy of the model. In order to improve the accuracy of the model, we also need to consider regression loss such as mean square error

(MSE). Furthermore, this model has no consideration about covariance shift that exist inside the classification network inputs. Covariate shift is the change or shift that occurs in the input value. Batch Normalization is used to normalize the data inside the network. It makes sure that the distribution of data has not gone too high or too low. It also has regularization effect that reduces over-fitting problem to some extent. According to Mousavi, et al. [14], batch normalization alone cannot solve the over-fitting problem, but implementing it with dropout method improves the performance of the deep Neural Network. The state of the art sleep stage classification model presented an overall accuracy of 90.76%, sensitivity of 0.8, and F1 Score of 0.81 (Tables 1, 2 and 3).

The One-dimensional Convolutional Neural Network is implemented to improve the accuracy of classification of the sleep stages as shown in eq. 1 [25]. However, considering batch normalization while training the model can regularize the network and improve the performance of the model. The output of the convolution layer of the model is

$$O_n^l = \left(S_{|W(i,j)} * W(i,j)\right)_n \tag{1}$$

where,

$$S_{|W(i,j)} = \sum_{i=1}^{|W|} W(i)S(i+n-1) \tag{2}$$

S is input signal
W is kernel weight
N is number of training sample.
i is i^{th} neuron layer
j is j^{th} neuron layer

Table 1 Sleep stage classification deep learning Algorithm

Algorithm: One dimensional Convolutional Neural Network Input: Raw PSG Signal Output: classification probability of sleep stages.

BEGIN
 	
Step 1: Data Pre-processing
1.1 Segment raw PSG signal into 30s segment epoch
1.2 Normalize the EEG signal to 120 Hz
Step 2: Feature Extraction
2.1 For i = 1 to n //n is the number of convolutional layer unit, conduct following operation in each convolution layer.
$(S*W)_n = \sum_{i=1}^{\lvert W\rvert} W(i)S(i+n-1)$
2.2 Extract feature map
Feature map = convolve-input (Filters)// Convolve input features with filters
2.3 Pooling layer
Pooled(feature) = max-pooling(features) // max- pooling
2.4 Dropout layer
Randomly select some neurons and throw them out i.e. ignore them during training to prevent the problem of over-fitting.
Step 3: Classification
3.1 Flatten Layer: to convert the input vector for dense layer into appropriate dimension
3.2 Dense layer: Soft-max activation function with cross entropy loss function
3.3 Predicted sleep class stage is generated
3.4 Calculate Loss Function (prediction error).

Table 2 Sleep stage classification deep learning Algorithm

Algorithm: Convolutional layer with modified loss function and batch normalization. **Input:** Filtered EEG spectrogram **Output:** classification probability of sleep stage.
BEGIN Step 1: Input raw EEG signal Step 2: Perform Adaptive filtering 2.1. Apply Finite Impulse filter 2.2. Apply optimization criterion using LMS Step 3: Initialize all layers Step 4: Convolution layer 4.1 Initialize ReLU activation function 4.2 Apply convolution operation 4.3 Apply drop out method Step 5: Pooling layer 5.1. Conduct max-pooling for down-sampling Step 6: Apply Batch Normalization Step 7: Fully connected (Dense) layer 7.1. Initialize softmax activation function 7.2. Classification of feature map Step 8: Loss Function 8.1 Calculate modified loss function 8.2 Back propagate error through the network to update parameter.

3 Proposed system

After reviewing deep learning Neural Network methods for sleep stage classification, the advantages and disadvantages of each method are evaluated. Based on the analysis, it is found that the loss function is an important factor for the accuracy of the system, and batch normalization with drop out method speeds up the training time in neural network. Nevertheless, noise removal in the raw data improves both training and performance of the system.

After analyzing all the factors in each reviewed paper, the solution provided by Yildirim, et al. [25] is selected as the best solution and used as state-of-the-art solution for the proposed solution. The main reason for selecting Yildirim, et al. [25]'s solution is because it has proposed One-dimensional Convolution Neural Network with ReLU activated Convolutional layer. Rectifier Linear Unit (ReLU) has been used to overcome vanishing gradient problem. Another reason is the implementation of the Drop out method to solve the over fitting problem that exist in multi-layer neural network. Moreover, the classification accuracy of [25] the model is better, compared to other deep learning techniques used for sleep stage classification. However, there is still some limitations with the solution presented by Yildirim, et al. [25]. It has missed to consider internal covariate shift in inputs of each layer inside the network, which drastically affects the processing time (training time) in the model. Furthermore, softmax

Table 3 Statistics of dataset

Dataset name	Dataset type	Number of subjects	Total number of samples	Number of samples used
Sleep-edf	Sleep Cassette (SC) and Sleep Telemetry (ST)	8	15,188	3000
Sleep-edfx	Sleep Cassette (SC) and Sleep Telemetry (ST).	61	127,512	3000
ISRUC-Sleep	Three channel Overnight Sleep Recording	118	N/A	3000

activation is used with the loss function that can still be modified to get better performance, and accuracy of the classification of the model has improved the training time of the model by applying Batch Normalization after each pooling layer. New modified loss function can be introduced to increase the accuracy of the classification model. Also, it has not considered filtering the raw EEG data for noise removal, which can cause increase in learning time later for the network, and affects the accuracy the performance of the model.

The proposed model is composed of three major components (Fig. 2) named: Pre-processing, Feature Extraction and Classification.

Pre-processing The EEG data obtained from the public PSG signal database is pre-processed using the adaptive filter based on Least Mean Square (LMS) algorithm to remove the noises from the signal [21]. Adaptive filtering involves two steps wehre Finite Impulse filter is used for filtering due to its linear characteristics, and then optimization criterion LMS is used to filter out the noises such as Power line interference, Ocular artifacts, Cardiac artifacts, and muscle disturbances. These are necessary to be done since some of the common noises present in the PSG signal can affect the performance of the model. After filtering interference signals from the dataset, features can be extracted in the feature extraction stage.

Feature extraction For Feature Extraction stage, the pre-processed EEG signal is fed into the one-dimensional Convolution layer. Each convolution layer has Rectifier Linear Unit (ReLU) which overcomes the vanishing gradient problem. The output of the convolutional layer i.e. feature map is then sub-sampled in the pooling layer. Max pooling is used in the pooling layer that uses maximum value from the cluster of neurons of the previous layer unlike average pooling which uses average value. This improves the efficiency of the network by reducing the network's susceptibility of over-fitting. Dropout layer is placed after each convolution layer to handle over-fitting, and batch normalization is done after every pooling layer in order to remove the internal covariate shift. This will normalize the output of each layer and removes any covariate shift before it is fed to the next layer.

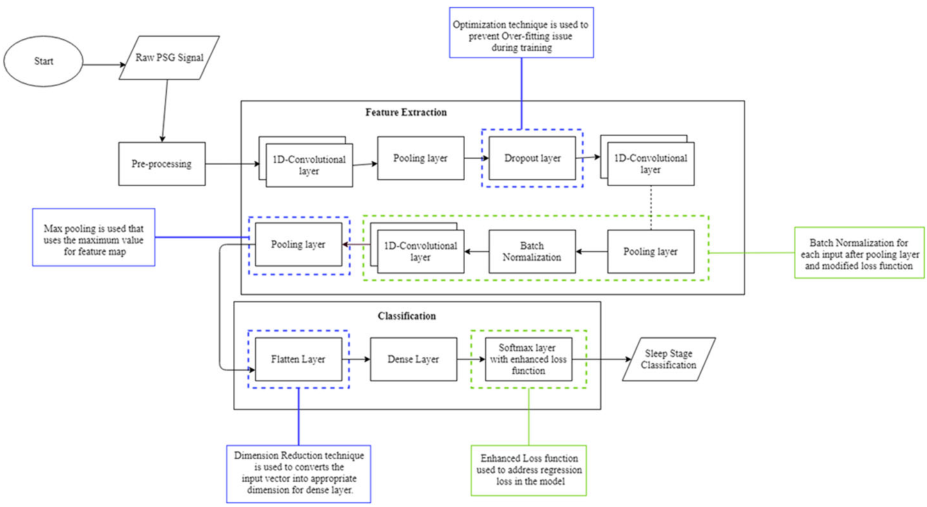

Fig. 2 Proposed solution for sleep stage classification [Feature of the proposed solution is shown using green boxes and feature of state-of-the art solution is shown using blue boxes]

Classification Classification is done by the final layer of the Convolutional Neural Network which is Fully connected dense layer with softmax activation function. Softmax function is used since it is capable of multi classification unlike sigmoid and tanh that can only do binary classification. Flatten layer is placed before the dense layer in order to convert the input vector for dense layer into appropriate dimension. Modified loss function combining both modified cross entropy loss and mean square error is calculated to minimize the error of the model and maximize the accuracy of the classification.

3.1 Proposed equation

In the proposed system, combined loss function with modified cross entropy loss function and mean square loss function have been implemented to improve the accuracy of the classification of the convolution model, and batch normalization has been considered to improve the training speed of the model. Modified loss function is combined with the softmax prediction in fully connected layer and ReLU activation in convolution layer in order to address both classification error and regression error.

Yildirim, et al. [25] has provided cross entropy loss function as:

$$L = -\frac{1}{n}\sum_{i=0}^{n}\left[y_i \ln\left(\widehat{y_i}\right)\right) - (1-y_i)\Big)\ \left(1-\ln\left(\widehat{y_i}\right)\right)\Big] \tag{3}$$

where,

L is Cross Entropy loss function.
y is actual output.
$\widehat{y}$ is the predicted output.
n is number of samples.
i is i^{th} neuron layer.
j is j^{th} neuron layer.

Loss function in eq. 3 was modified as eq. 4 to reduce the error for the prediction of sleep stage.

$$ML = -\sum_{i=0}^{n}\left[y_i \ln\left(\widehat{y_i}\right)\right) - (1-y_i)\Big)\ \left(1-\ln\left(\widehat{y_i}\right)\right)\Big] \tag{4}$$

where,

ML is modified Cross Entropy loss function.
y is actual output.
$\widehat{y}$ is the predicted output.
n is number of training sample.

Mousavi, et al. [14] has provided Mean Square Error (MSE) as eq. 5 below. This equation is used to address regression error of the model which was not address in the state-of-the-art solution.

$$MSE = \frac{1}{n}\sum_{i=0}^{n}\left(y_i - \widehat{y_i}\right)^2 \tag{5}$$

where,

n is number of training sample
y is actual output.
$\widehat{y}$ is the predicted output.

Enhanced loss function is obtained for our proposed solution as eq. 6 by combining eq. 4 and eq. 5 as:

$$EL = ML + MSE \tag{6}$$

The equation can be written as the following:

$$EL = -\sum_{i=0}^{n}\left[y_i \ln\left(\widehat{y_i}\right)\right) - (1-y_i)\Big)\ \left(1-\ln\left(\widehat{y_i}\right)\right)\Big] + \frac{1}{n}\ \sum_{i=0}^{n}\left(y_i - \widehat{y_i}\right)^2 \tag{7}$$

where,

EL is Enhanced loss function.
y is actual output.
$\widehat{y}$ is the predicted output.
n is number of training sample.

Yildirim, et al. [25] has provided a general formula for output of convolutional neural network as:

$$O_n^l = \left(S_{|W(i,j)} * W(i,j)\right)_n$$

where,

S is input signal
W is kernel weight
N is number of training sample.

Sokolovsky, et al. [21] has provided Batch Normalization formula as eq. 8. This equation will address the internal covariate shift in the inputs inside the model and help minimize the training time.

$$z_l = \widehat{y_{l-1} y_i} + \beta_l \tag{8}$$

where,

$\widehat{y_{i-1}}$ is input to Batch normalization layer

$$\widehat{y_{i-1}} = \frac{y_{l-1} - \mu_B}{\sqrt{\sigma_B^2 - \varepsilon}} \tag{9}$$

l: present neuron layer

$$\mu_B = E[y_{l-1}]$$

$$\sigma_B^2 = var\left[y_{l-1}\right]$$

ε is a constant for numerical stability
y_l is parameter of scale
β_l is shift in input learned during training.

Now, the output of batch normalization layer for the proposed system is obtained by combining eqs. 1 and 8 as:

$$Ez_l = O_n^l + \beta_l \tag{10}$$

Finally, the output matrix of the proposed convolution model can be obtained from the enhanced loss function (eq. 6) and batch normalized vector (eq. 10) as below:

$$EO = Mz_l + ML' \tag{11}$$

3.2 Area of improvement

The state-of-the-art solution has not considered internal covariate shift in inputs of each layer inside the network, and it has only considered the cross-entropy loss function [25]. This solution proposes batch normalization of the inputs after each pooling layer in order to address the covariate shift in the inputs and a modified loss function that combines modified cross entropy loss and mean square error [14] to minimize error (loss) of the model. Batch normalization will increase the training speed (processing time) by a significant amount [21], while modified loss function will increase the accuracy of classification by minimizing the prediction error [14]. Moreover, using adaptive filter during pre-processing the public EEG dataset will remove any unwanted noise that can affect model training and classification performance [14].

The proposed solution for sleep stage classification consists of Convolutional Neural Network with convolutional layer, pooling layer, and dense or fully connected layer. The proposed solution has improved the performance of the model by improving the loss function and adding batch normalization after pooling layer and before the next convolutional layer. Batch Normalization is important to apply in a neural network with large number of layers in order to address internal covariate shift. Covariate shift is the change in distribution in input inside the network in a deep network. This can directly affect the training or learning time of the model since input in each layer is affected by the parameters in each input layer. Solution for this issue is to batch normalize the inputs before feeding it into another layer.

Loss function is important to apply on a deep neural network since it measures the inconsistency between predicted class and actual label which can be used to improve the accuracy of the model. The state-of-the-art solution uses only the cross-entropy loss function which is not enough to estimate the error of each network layer. Therefore, modified loss function has been used in the proposed system that combines cross entropy loss and mean square loss to improve the loss detection and calculation. The proposed modified loss function can identify both regression and classification loss. This will improve the accuracy of the model by back propagating the error and changing the parameter in the hidden layer to minimize the classification error.

4 Results and discussion

Python 3.7 with TensorFlow and Keras are used for the implementation of the proposed Convolution Neural Network model. Three publicly available datasets of sleep study are used for training and testing of the proposed model. Sleep-edf, exdended sleep-edf (sleep-edfx), and ISRUC-Sleep database from Institute of Robotics of Coimbra University, Portugal are used which have records from 8 subjects with 15,188 samples, 61 subjects with 127,512 samples and 118 subjects with large volume of samples respectively. Only few datasets are chosen for our work. The selected records are each divided into 30-s segment and thus total sample of 3000 from each dataset are used. The samples are divided into two parts as 70% and 30% for training and testing of the proposed model. The test data consists of new samples and is conducted on the trained model. The model is trained using Adam Optimizer with a learning rate of 0.2, a filter size of 3, 4, 5 respectively, a hidden unit of 150, a batch size of 50, and a dropout rate of 0.7 for the implementation of the model, a computer with 2.3 GHz of Intel core i5 5th generation processor with 4.0 GB RAM is used. The first database is quite small and has samples only with R&K scoring, while the second database sleep-edfx has bigger number of samples and contains both AASM and R&K scoring. The model classified the labeled data samples into five different sleep classes that are Wake, Stage 1(S1), Stage 2(S2), Slow Wave Spindles(SWS) and Rapid Eye Movement(REM). A detailed experiment is performed for five sleep class stages and results all classes are shown using Tables and Graphs.

During the Feature Extraction Stage, CNN model is implemented to automatically extract features and train the model from the labelled datasets for all the above samples. The feature map extracted from the convolution layer is input to the max-pooling layer. The down sampled output of the pooling layer is batch normalized before it can be fed to another convolution layer. Once all the layers of convolution and pooling layer are completed, the output is fed into flatten layer to convert the dimension of the input vector of dense layer. The fully connected dense layer provides sleep classification using the softmax activation. Once the model is trained with the selected datasets, it is evaluated with different testing or validation datasets. Accuracy of Sleep-edf database at training stage for state of the art and the proposed system is shown in Fig. 3. Both solutions showed different accuracy performances. It shows that our proposed solution has improved the classification accuracy performance by 4.2% than the state-of-the-art solution. Also, the proposed system has achieved the maximum accuracy at shorter time than the state-of-the-art which indicates that the training time has also been improved in the proposed solution.

The classification accuracy and processing time of all three datasets during the training and testing has been provided in Table 4 which is further explained and visualized in graphs below (Figs. 4 and 5). It shows that accuracy of the proposed solution has improved compared to that of state of the art, and also processing time has been reduced using proposed solution.

The results of proposed system are compared with the state-of-the-art solution using tables and bar graphs. The results are compared using two different methods: 1) comparison of accuracy and processing time of training and validation for all three different datasets and 2) comparison of accuracy of five sleep stages (i.e. Wake, S1, S2, SWS, and REM). The results for all three datasets are evaluated in terms of accuracy and processing time. Moreover, accuracy is calculated based on percentage of correctly predicted output to labelled input. And processing time is calculated based on prediction time in seconds.

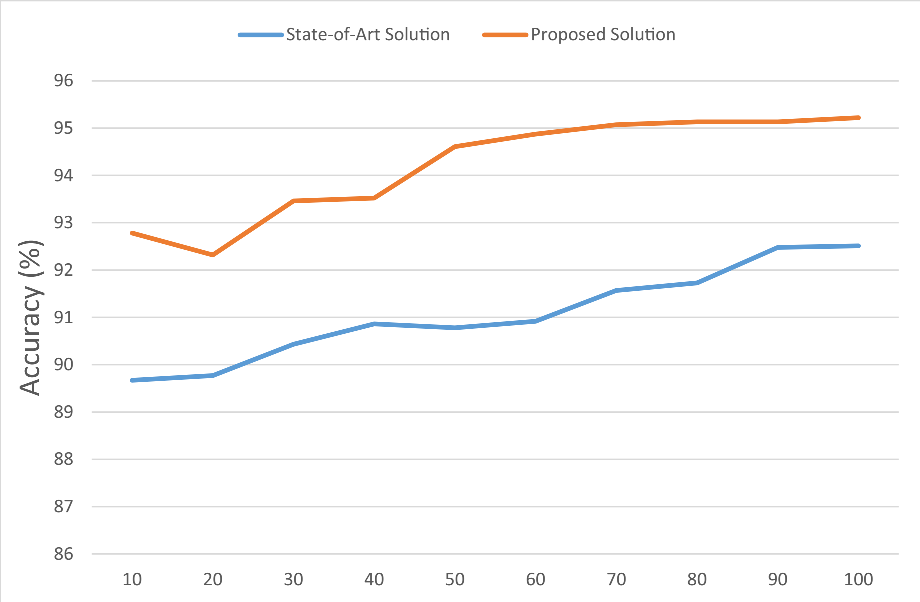

Fig. 3 Average sleep stage classification accuracy on sleep-EDF dataset for state of the art and the proposed solution. **a** The blue line shows the classification accuracy of state-of-the-art solution. **b** The orange line shows the classification accuracy of proposed solution

Table 5 provides the accuracy and processing time of state of the art and the proposed solution for all five (Wake, S1, S2, SWS and REM) sleep stages on sleep-edf datasets which is then represented and compared in graphs (Figs. 6 and 7) below.

Table 6 provides the accuracy and processing time of state of the art and the proposed solution for all five (Wake, S1, S2, SWS and REM) sleep stages on Sleep-edfx which is then represented and compared in graphs (Figs. 8 and 9) below.

Table 7 provides the accuracy and processing time of state of the art and the proposed solution for all five (Wake, S1, S2, SWS and REM) sleep stages on ISRUC-Sleep datasets which is then represented and compared in graphs (Figs. 10 and 11) below.

The results of the proposed algorithm showed improvement in classification accuracy and processing time to that of state-of-the-art solution which is based on Convolution Neural

Table 4 Average accuracy and processing time of state of the art and proposed system on all three datasets at training and validation

S.N.	Dataset Name	Stage	State of the art		Proposed Solution	
			Accuracy (%)	Processing Time (milliseconds)	Accuracy (%)	Processing Time (milliseconds)
1.	Sleep-edf	Training	92.06	46	96.28	37
		Validation	91.83	41	95.11	31
2.	Sleep-edfx	Training	91.95	42	95.02	30
		Validation	91.29	40	94.98	32
3.	ISRUC-Sleep	Training	92.10	45	95.19	36
		Validation	91.75	41	94.89	34

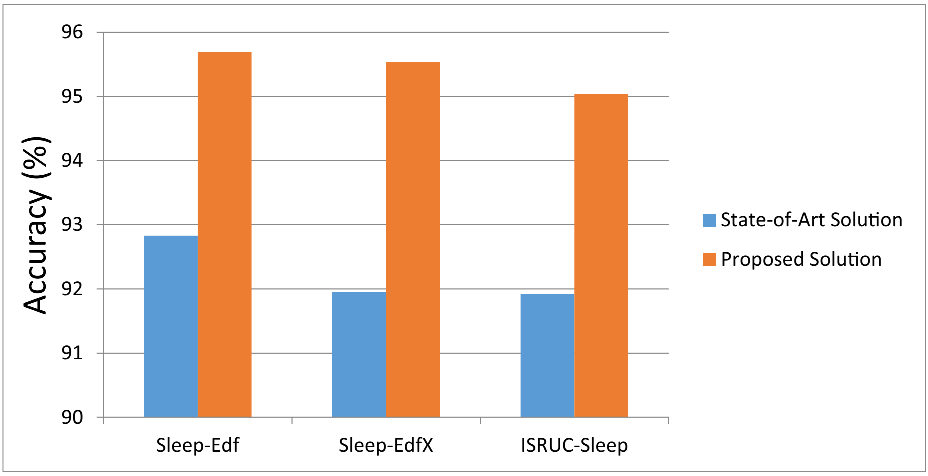

Fig. 4 Classification accuracy of state of the art and proposed system for all three datasets. The blue color shows accuracy of Proposed solution while orange color shows accuracy of State-of-the-Art solution. **a** The first bar graph is accuracy comparison on Sleep-edf data samples. **b** The first bar graph is accuracy comparison on Sleep-edfx data samples. **c** The first bar graph is accuracy comparison on ISRUC-Sleep data samples

Network. The classification accuracy and processing time are calculated by using built-in functions in Python called evaluate() and now() respectively. These functions are included in Keras package. The evaluate() function is used for accuracy, which initially computes the True Predicted Value using predicted output of the given input and label of the sample. For processing time, now() function is used which returns the time at that instance so that the start time and end time are obtained and the difference is calculated. Our proposed solution improves the classification accuracy by 4.2%, and processing time is reduced by 11 milliseconds. The overall classification accuracy is calculated from probability score of the dataset in

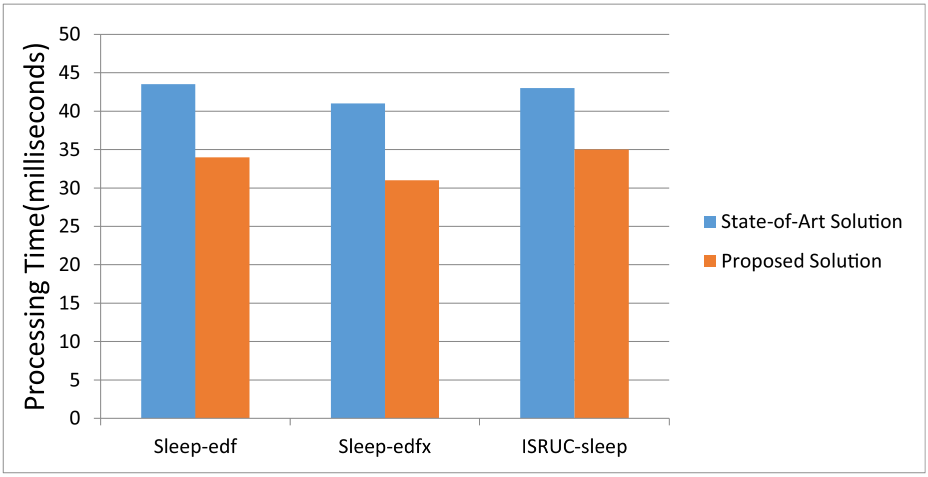

Fig. 5 Processing time of state-of-the-art and proposed system for all three datasets. The blue color shows accuracy of proposed solution while orange color shows processing of State-of-the-Art solution. **a** The first bar graph is accuracy comparison on Sleep-edf data samples. **b** The first bar graph is accuracy comparison on Sleep-edfx data samples. **c** The first bar graph is accuracy comparison on ISRUC-Sleep data samples

Table 5 Comparison of classification accuracy for five sleep stages on sleep-edf datasets of state of the art and the proposed system

Dataset name	Stage	State-of-art		Proposed solution	
		Accuracy (%)	Processing time (milliseconds)	Accuracy (%)	Processing time (milliseconds)
Sleep-edf	Wake	95.43	46	96.89	37
	S1	76.35	48	79.01	38
	S2	86.89	42	88.65	31
	SWS	87.00	44	89.10	35
	REM	87.09	40	89.25	30

each sleep classes, while processing time is the actual execution time in Python. The amount of improvement in accuracy and processing time of Sleep stage classification is evaluated by executing state of the art and the proposed solution and comparing them.

Softmax activation with modified loss used in fully connected layer of CNN model has improved the performance in the proposed system. The use of modified loss function is applied on a deep neural network to measure the inconsistency between predicted class and the actual label which improved the classification accuracy of the model. Enhanced loss function has been used in the proposed system that combines cross entropy loss and mean square loss in order to improve the loss detection and calculation. The proposed enhanced loss function identified both regression and classification losses using modified loss function and added mean square loss function. This improved the accuracy of the model by back propagating the error and changing the parameter in the hidden layer to minimize the classification error. Moreover, Batch Normalization is applied to address internal covariate shift. This directly improved the training time since input in each layer is affected by the parameters in each input layer which ultimately improved the processing time of the model. Thus, using

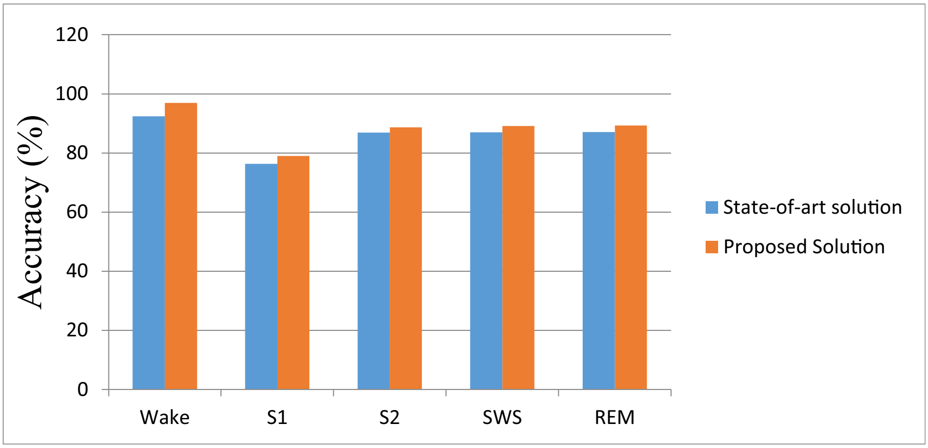

Fig. 6 Classification accuracy for five sleep stages on sleep-edf datasets of state-of-the-art and proposed system. The blue color shows accuracy of State-of-the-Art solution while orange color shows accuracy of proposed solution. **a** The first bar graph shows average accuracy of classification of Wake Sleep Stage. **b** The second bar graph shows average accuracy of classification of S1 Sleep Stage. **c** The third bar graph shows average accuracy of classification of S2 Sleep Stage. **d** The fourth bar graph shows average accuracy of classification of SWS Sleep Stage. **e** The fifth bar graph shows average accuracy of classification of REM Sleep Stage

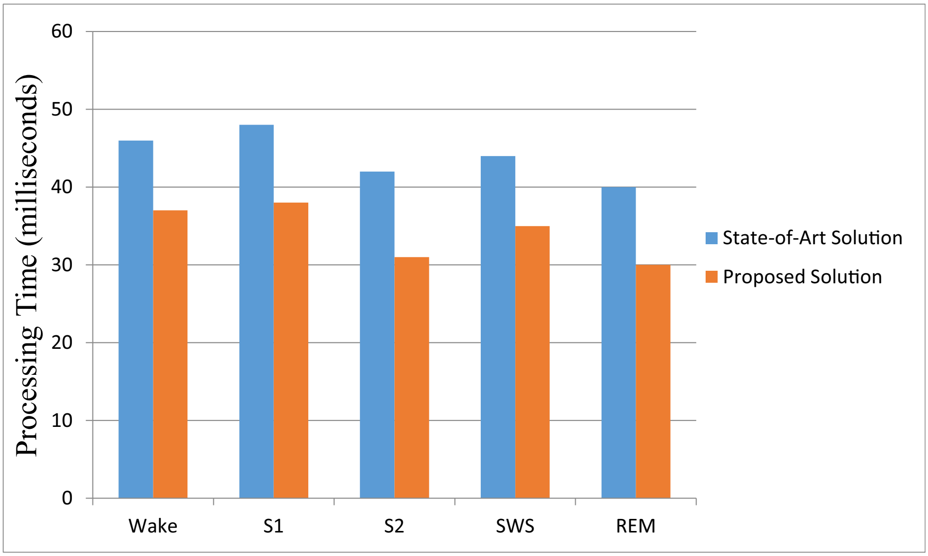

Fig. 7 Processing time for five sleep stages on ISRUC-sleep datasets of state of the art and the proposed system. The blue color shows processing time of State-of-the-Art solution while orange color shows of proposed solution. **a** The first bar graph shows average processing time of classification of Wake Sleep Stage. **b** The second bar graph shows average processing time of classification of S1 Sleep Stage. **c** The third bar graph shows average processing time of classification of S2 Sleep Stage. **d** The fourth bar graph shows average processing time of classification of SWS Sleep Stage. **e** The fifth bar graph shows average processing time of classification of REM Sleep Stage

enhanced loss function and batch normalization, classification accuracy is improved by 4.2% and processing time is decreased by 12 s.

All datasets are pre-processed using adaptive filter in the proposed system before inserting it into the model for feature extraction which improved the training time. The limitations in the state of the art has been improved in the proposed solution to obtain an accuracy of 96.28% against 92.06% and reduced processing time by 11 milliseconds. The use of modified cross entropy loss function and added mean square loss function minimized the prediction error and resulted in high accuracy of the model. On the other hand applying batch normalization after convolution and pooling layer, training speed is increased which in overall reduced the processing time of the model. In comparison to state-of-the-art solution, the proposed solution

Table 6 Comparison of classification accuracy for five sleep stages on sleep-edfx datasets of state-of-art and proposed system

Dataset name	Stage	State-of-Art		Proposed Solution	
		Accuracy (%)	Processing time (milliseconds)	Accuracy (%)	Processing time (milliseconds)
Sleep-edfx	Wake	94.23	41	96.76	38
	S1	74.69	47	76.92	35
	S2	86.17	45	87.57	33
	SWS	85.43	44	87.04	37
	REM	89.05	46	90.09	30

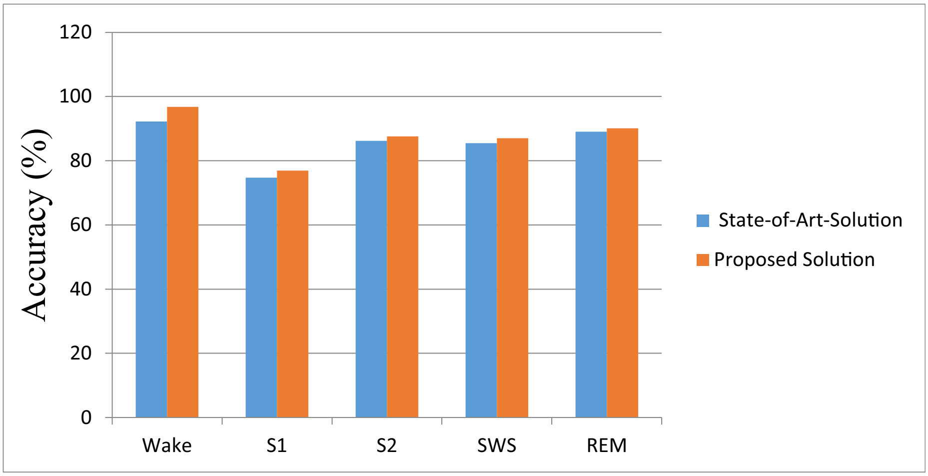

Fig. 8 Classification accuracy for five sleep stages on sleep-edfx datasets of state of the art and proposed system. The blue color shows accuracy of State-of-the-Art solution while orange color shows accuracy of proposed solution. **a** The first bar graph shows average accuracy of classification of Wake Sleep Stage. **b** The second bar graph shows average accuracy of classification of S1 Sleep Stage. **c** The third bar graph shows average accuracy of classification of S2 Sleep Stage. **d** The fourth bar graph shows average accuracy of classification of SWS Sleep Stage. **e** The fifth bar graph shows average accuracy of classification of REM Sleep Stage

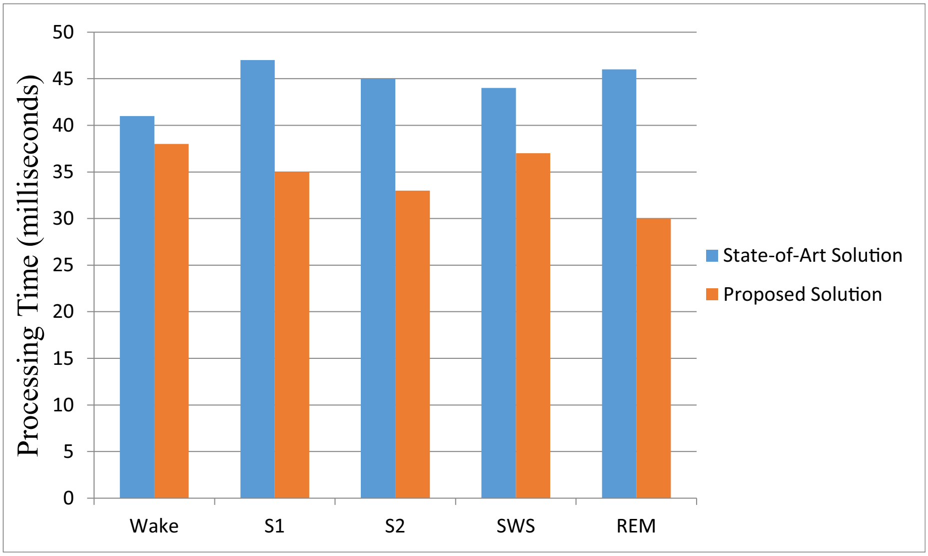

Fig. 9 Processing time for five sleep stages on ISRUC-sleep datasets of state of the art and proposed system. The blue color shows processing time of State-of-the-Art solution while orange color shows of proposed solution. **a** The first bar graph shows average processing time of classification of Wake Sleep Stage. **b** The second bar graph shows average processing time of classification of S1 Sleep Stage. **c** The third bar graph shows average processing time of classification of S2 Sleep Stage. **d** The fourth bar graph shows average processing time of classification of SWS Sleep Stage. **e** The fifth bar graph shows average processing time of classification of REM Sleep Stage

Table 7 Comparison of classification accuracy for five sleep stages on sleep-edfx datasets of state-of-art and proposed system

Dataset Name	Stage	State-of-Art		Proposed Solution	
		Accuracy (%)	Processing Time (milliseconds)	Accuracy (%)	Processing Time (milliseconds)
ISRUC-Sleep	Wake	92.86	47	96.65	38
	S1	71.32	41	74.38	36
	S2	81.18	47	85.69	37
	SWS	85.96	46	88.17	32
	REM	86.29	43	88.92	30

has achieved higher accuracy and reduced processing time while classifying different sleep class stages.

Table 8 shows the comparison of the state of art and our proposed solution.

5 Conclusion and future work

Sleep stage classification is crucial to get information about a patient's sleep condition so that medical personnel can perform an appropriate diagnosis for the patient. Several deep learning based classification models have been implemented to precisely classify the sleep stages in supervised environments. Each of these solutions consists some limitations that impact the accuracy and processing time of the classification model. The main aim of our research is to enhance the accuracy of sleep stage classification while reducing the overall processing time. To improve the accuracy of classification of the sleep stages, we have implemented an

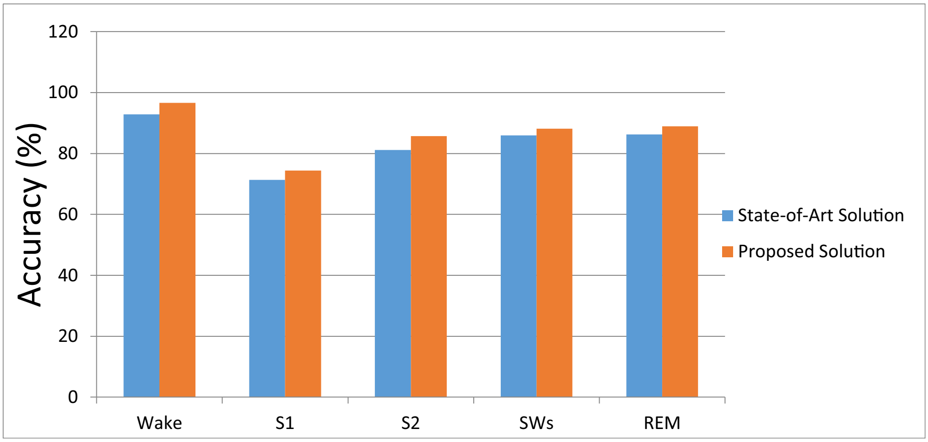

Fig. 10 Classification accuracy for five sleep stages on ISRUC-Sleep datasets of state of the art and the Proposed System. The blue color shows accuracy of State-of-the-Art solution while orange color shows accuracy of the proposed solution. **a** The first bar graph shows average accuracy of classification of Wake Sleep Stage. **b** The second bar graph shows average accuracy of classification of S1 Sleep Stage. **c** The third bar graph shows average accuracy of classification of S2 Sleep Stage. **d** The fourth bar graph shows average accuracy of classification of SWS Sleep Stage. **e** The fifth bar graph shows average accuracy of classification of REM Sleep Stage

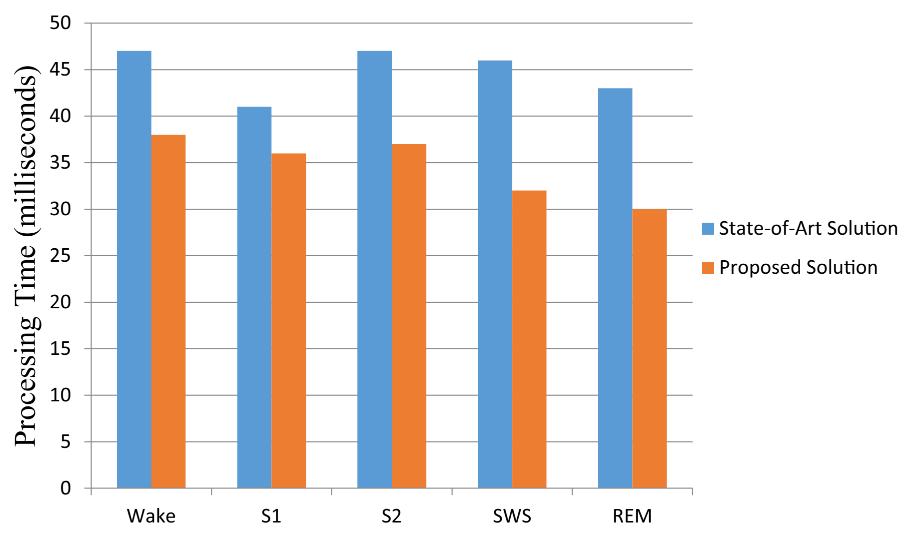

Fig. 11 Processing time for five sleep stages on ISRUC-Sleep datasets of state of the art and the Proposed System. The blue color shows processing time of State-of-the-Art solution while orange color shows of proposed solution. **a** The first bar graph shows average processing time of classification of Wake Sleep Stage. **b** The second bar graph shows average processing time of classification of S1 Sleep Stage. **c** The third bar graph shows average processing time of classification of S2 Sleep Stage. **d** The fourth bar graph shows average processing time of classification of SWS Sleep Stage. **e** The fifth bar graph shows average processing time of classification of REM Sleep Stage

enhanced loss function that has been derived by combining the mean squared error rate with cross entropy loss function to address both regression and classification loss in network to minimize error in the network. As opposed to the state of art, batch normalization is done after

Table 8 Comparison table between proposed solution and state-of-the-art solution

	Proposed solution	State-of-the-art technique
Name of the Solution	Enhanced Loss Function for Sleep stage Classification	One dimensional Convolutional Neural Network for Sleep stage classification.
Accuracy	96.28%	92.06%
Processing Time	33 milliseconds	45 milliseconds
Proposed Equation	$z_l = \widehat{y}_{l-1}\, y_i + \beta_l$	$Ez_l = O_n^l + \beta_l$
Contribution 1	Modified loss function combining both cross entropy loss and mean square loss is used to address both regression and classification loss in network to minimize error in network. This will improve the accuracy of classification of sleep stages.	The state of art solution only considers cross entropy loss.
Contribution 2	Batch normalization is done after the pooling layer to reduce the covariate shift in input inside the network to maximize the training speed.	The state of the art does not consider internal covariate shift in inputs in their model.
Contribution 3	Adaptive filter based on LMS is used during the pre-processing stage to remove un-wanted noise from the raw EEG signal for better performance of the model.	The state-of-the-art solution does not consider any filtering techniques to remove the noise in the image.

the pooling layer to reduce the covariate shift in input inside the network to maximize the training speed. The state-of-the-art solution does not consider any filtering techniques to remove the noise in the image. However, in the proposed system, an adaptive filter based on LMS is used during the pre-processing stage to remove unwanted noise from the raw EEG signal for better performance of the model. The test results show that the accuracy has been improved by almost 4.2% while the processing time has been reduced by 11 milliseconds compared to state-of-the-art solution. In the future, larger datasets of different sleep disorder patients with varying features can be used for training and implementing the proposed solution. The datasets used can be pre-processed using better techniques to further aid in refining the dataset before feeding it to the neural network model (Table 9).

Appendix

Table 9 Abbreviation table

Abbreviation	Full form
SWS	Sleep Wave Spindles
REM	Rapid Eye Movement
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short Term Memory
ReLU	Reticfied Linear Unit
LMS	Least Mean Square
GMM	Gaussian Mixture model
HMM	Hidden Markov Model
MSE	Mean Square Error
Edf (Sleep-edf)	European data format
PCA	Principal Component analysis
mRMR	Minimum Redundancy Maximum Relevance
MASS	Montreal Archive of Sleep Studies
EEG	Electroencephalogram
ECG	Electrocardiogram
EMG	Electromyogram
EOG	Electrooculogram

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Affiliations

Ereena Rajbhandari[1] • Abeer Alsadoon[1] • P. W. C. Prasad[1] • Indra Seher[1] • Tran Quoc Vinh Nguyen[2] • Duong Thu Hang Pham[2]

[1] School of Computing and Mathematics, Charles Sturt University, Sydney, Australia

[2] The University of Da Nang – University of Science and Education, Faculty of Information Technology, 459 Tôn Đức Thắng, Hoà Khánh Nam, Liên Chiểu, Đà Nẵng 550000, Vietnam