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A CNN-LSTM Model for Sleep Stage Scoring Using EEG Signals

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***Abstract*—This paper proposes a deep-learning model for automated sleep stage scoring with single-channel EEG recordings that combines CNN and LSTM. Several of the methods in use today rely on qualities that have been hand-engineered. However, only a few techniques retrieve the temporal data necessary for determining the phases of sleep. The extraction of time-invariant features will be possible using convolutional neural networks, and LSTM will be able to learn the transition rules. The model was trained and tested using the Sleep-EDF-v1 dataset, which is publicly available. We used single-channel Fpz-Cz EEGs and scored them in accordance with the AASM standard. 83.38% accuracy was achieved overall.**

Keywords— Sleep stage scoring, EEG, CNN, LSTM

I. INTRODUCTION

It is a known fact that humans need proper sleep for their well-functioning. Without good sleep, it will be difficult to concentrate on our day-to-day tasks. Various studies conducted in this field show that good quality of sleep translates to better health. Sleep deficiency can increase the chances of medical conditions like obesity, diabetes and cancer developing in the humans [1]. The effects of loss of sleep will be detrimental when it is on a daily basis. The negative impacts could be anything like reduced productivity in work, decrease in appetite, deteriorating memory and complications like hypertension [2]. Studies show that sleep promotes consolidation of memory [3]. The high frequency of sleep disorders, therefore calls for extensive assessments of sleep patterns [4].

Sleep stage classification is to analyze the quality of sleep [5]. The "American Academy of Sleep Medicine" (AASM) standard [6] defines the features for distinct sleep stages as five stages. The next sections go into great depth on the various stages of sleep.

Polysomnography (PSG), by definition, is the simultaneous recording of physiological signals during sleep. It is viewed as the highest standard for sleep evaluation and sleep disorder diagnosis [7]. PSGs are recorded in sleep laboratories. The recordings include physiological signals obtained throughout the course of a full night of sleep. Each recording may contain biological signals such as electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG) and electrocardiogram (ECG) [8]. Sleep stages are then scored manually by sleep experts. This scoring and analyzing of PSG recordings are performed in small time windows called epochs [9]. This is a time-consuming process and the low reliability and difference among scorers lead to the need for an automatic sleep stage scoring system. The most often utilized PSG signal for determining the stage of sleep is EEG data since wearable technology makes it simple to collect. Due to the unpredictable and chaotic character of EEG data, it is challenging to display it, which further underlines the necessity for an automated sleep stage grading system. [10]. Due to its automatic feature extraction capability from raw signals, deep learning is being extensively used in sleep stage scoring [11]. Convolutional neural networks (CNNs) or recurrent neural networks (RNNs) or the combination of both are generally used in deep learning methods. The ability to learn shift-invariant features makes CNNs useful for many deep learning applications [12]. In addition, CNNs can take the place of artificial design feature engineering and previous knowledge [13]. RNNs are often used when the problem involves the dimension of time [12]. RNNs like Long-Short Term Memory (LSTM) preserve the contextual information when time sequence data are analyzed [13]. Table I shows the current trends of the sleep stage scoring problem.

TABLE I: CURRENT TRENDS OF SLEEP STAGE SCORING PROBLEM

Dataset	System	Accuracy
Sleep EDF-v1	XSleepNet [21]	86.3
	IITNet [18]	83.9
	SeqSleepNet [23]	82.2
	Multitask CNN [24]	81.9
	Deep convolutional network [20]	81
	DeepSleepNet [14]	80.8
	Auto-encoder [25]	78.9

We propose a deep learning model for the automated scoring of sleep stages in this study. The primary contribution of this work includes developing an efficient model architecture based on CNN-LSTM combination to score EEG epochs. The proposed model is used to classify sleep stages by using the publicly available Sleep EDF-v1 dataset. An evaluation with other state-of-the-art methods is also performed to show that the proposed model is comparable with the already existing methods.

The paper is organised as follows. In Section II, EEG signals and sleep stages are described and the proposed method is explained in detail. The dataset and evaluation metrics are also explained and in Section III, the results obtained from evaluation of the proposed method is compared with the results of the other studies in the same field. A conclusion of the study with future scope is given in Section IV.

II. Methods

A. EEG Signals and Sleep Stages

The primary organ in charge of directing and regulating the human's conscious and thought processes is the brain. The EEG readings represent the electrical processes of the brain. The most crucial component of the nervous system controlling the body movement is the cerebral cortex, which controls the brain's cognitive and emotional functions. Different human activities and perceptions can be linked to the different areas of the cerebral cortex, where each area serves a unique purpose. The highly developed cerebral cortex's neuron cells allow humans to perform complicated functions. Each neuron cell communicates with another neuron through dendritic connections in order for complicated behaviours to occur, which opens up a world of possibilities for human activity [23].

According to scientific research, a significant number of neuronal cells combine to create an EEG signal. It consists of several cells mixed together in a non-linear fashion and also coupled non-linearly. An intricate non-linear dynamic system makes up the human brain. Low signal and high noise, complex signal aspects, prominent frequency features, non-linearity, and non-stationarity are some of the properties of the EEG signal [15].

The cerebral cortex's neurons' reaction to electrical activity is the main source of EEG. Electrodes placed on the scalp are used to collect signals produced by potential activity of the nerve cells. As like most signals, several characteristics can be seen in the amplitude, frequency, and phase in the EEG. EEG has a frequency range of 0.5 to 100 Hz, and clinical medicine only takes into account spontaneous EEG in the 0.5 to 30 Hz range. It may be classified into non-basic waves and the four major rhythm waveforms based on the features of the frequency. There are regular and irregular waves, the regular waves are rhythm waves. The four different types of rhythm waves are δ wave, θ wave, α wave and β wave, in the order of increasing frequency and decreasing amplitude. δ wave are more common in new-borns or persons with intellectual impairments than in awake, healthy adults. However, adults can show this wave when they are extremely exhausted, deep asleep, or under deep anaesthesia. θ wave is predominantly found in adolescents aged 10 to 17 years. It is primarily seen in the parietal and temporal regions. It only occurs when the brain nerve is drowsy, sad, or frustrated, similar to the wave. The human ability to reason logically and creatively, which is not shared by other creatures, is symbolised by the α wave. β waves are most prevalent in the frontal and central areas of the brain and is the fastest rhythmic wave there is. They may be used to explain how a brain wakes and are seen when individuals move, think, read, etc [15].

There are waves other than the four rhythm waves. With no well-defined frequency range, K-complex waves are formed of spikes both positive and negative in nature. The transient time being less than 0.5s, the negative spikes are observed first and then the positive ones. Sawtooth wave is seen at frequencies between 2 and 7 Hz. The waveform has a sawtooth-like appearance and therefore its name. Usually during the beginning of a dream, especially when the person is in a mild sleep condition or when dreaming, sawtooth waves can be seen. Spindle wave has a considerable amplitude and is found between 12 and 14 Hz. It is the most dynamic in the EEG. It begins at the lowest point and gradually rises to its highest position in the centre before descending to its lowest point. This sort of wave is a common waveform during light sleep [15].

According to AASM standard, sleep stages are divided into five stages, each of which are briefly discussed below:

W: Adults typically spend roughly two-thirds of their waking hours awake. The frequent blinking of the eye is apparent, which is a characteristic of this sleep stage. The EEG displays a continuous alpha wave between a frequency of 8 to 13 Hz and amplitude 20 to 100 μV in the waking stage [15].

N1: This stage, which typically makes up between 5% and 10% of the total period of sleep, occurs as the waking state transitions into some other sleep stages or if there is greater movement during sleeping, takes place. Each incident only lasts a few minutes. The content of the α wave declines (by about 50%), and that of θ wave increases slowly [15].

N2: This phase, which typically makes up around 50% of the total sleep period, lasts longer than N1 phase throughout the whole night. Two novel EEG signal features, the sleep spindle wave and the K-complex wave, gradually begin to appear during this time. At this point, the θ waves intensify and simultaneously appear with the δ wave [15].

N3: In this stage, the human body is at deep sleep stage. The healing mechanisms are at their peak in this stage. At this time, the "biological waste" that is essential for controlling mood, refuelling energy, and modifying mental state will be routinely removed from the brain by the cerebrospinal fluid. [ref]. N3 stage corresponds to almost 20% of the total sleep duration. EEG signals of frequency range is 0.5 to 2 Hz are observed and δ waves gradually increase which make up more than one-fifth of the waves [15].

REM: Rapid Eye Movement (REM) comprises of about 20 to 40% of the sleep cycle. Identical to the signal observed in the N1 phase, its most prominent characteristic is the rapid eye movement. At this point, the α waves grow but have an erratic pattern, and there is also a lot of eye movement [15].

B. Proposed Method

The proposed model classifies the sleep stages of single channel EEG epochs. To put it mathematically, from a single channel EEG, if there are N epochs, the model predicts the sleep stages for each of the epochs yielding predictions for each epoch from one of the K sleep stages. The predicted stage of each epoch corresponds to W, N1, N2, N3 and REM respectively. This is as per the AASM convention. Our model is a based on both CNN and LSTM, taking motivation from the methods proposed in [14].

The network close to the input layers is a convolutional neural network. A kind of neural network called a convolutional neural network mimics the biological visual perception system, thereby carrying out both supervised and unsupervised learnings. Convolutional neural networks,

which are widely used in the processing of discrete signals and images.

The most important layer in a CNN is the convolutional layer, which efficiently extracts higher dimensional information from the input layer's data. The inter-layer connections and kernel settings in the hidden layers enable CNNs to learn the features with less computation. The features of the input data are extracted by the convolutional layer, which contains multiple convolutional kernels with weight coefficient and bias vector. Throughout each calculation, the kernel window is translated in the input layer at the set step length until the convolution process uses all of the input. The feature map is created by adding non-linear components to the activation function. The result of computation is also referred to as feature mapping [15].

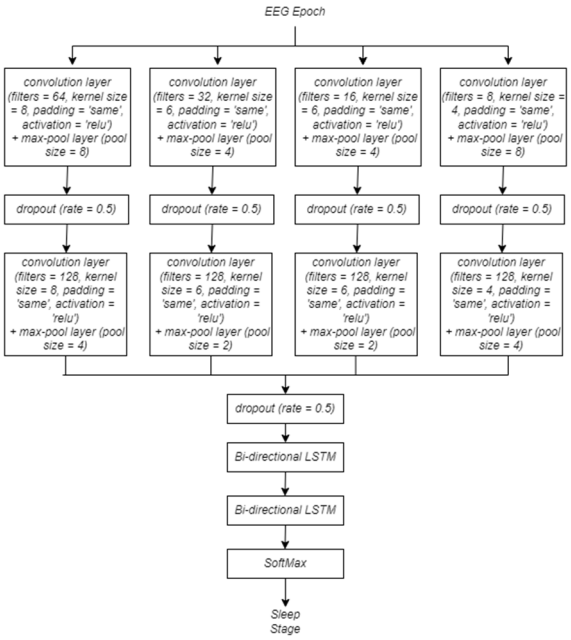

Fig. 1. Overview of the proposed architecture.

The convolution operation's features include sparse connections and parameter sharing. Each input and output cell are integrated and combined in networks that connect every layer with a fully connected layer, creating difficulties like as exploding and vanishing gradients and over-fitting. Convolution kernels are both physically and numerically much smaller than input nerve cells. They may have sparse weight characteristics and drastically minimise the amount of weight parameters [15].

In order to minimise the feature map matrix, To lessen the amount of processing, a pooling layer can be added following the convolutional layer. The pooling layer processes the output of the preceding layer using functions such as maximum, L2 norm, and so on. The original feature map is subjected to further feature localization processing, and it is then mapped into a separate feature space while fully accounting for each point's neighbour value in the output of the preceding layer. To improve the network's computational efficiency, the pooling layer may efficiently lower the amount of the features while retaining their output in the final layer.

The completely linked layer maps the output from the preceding levels. The effect of spatial position on item detection is diminished by a fully connected layer, which transforms the feature map generated by earlier layers into a feature vector. Dropout layers are utilised to decrease feature redundancy since fully linked layers are prone to overfitting [15]. Dropout is often employed to make the fully connected layer more sparse and minimise feature redundancy across neurons since the dense matrix operation, on which the fully connected layer is based, has a low processing efficiency and is highly conducive to over-fitting.

The CNN part used in the representation learning step is comprised of four CNNs. From the unprocessed EEG data, CNNs are employed to extract the time-invariant characteristics. The proposed architecture is shown in Fig. 1. Four parallel branches of CNNs were taken to capture features with different scales in a balanced manner. The parallel branches will help to extract spatial features with different levels in a stabilised way. The kernel sizes for each of the convolution layers in each branch is 8, 6, 6 and 4 respectively. The filter size is 128 for each of the convolution layers. The kernel size is an indication of the complexity of the model. In the CNN-LSTM model, CNN will be used for feature extraction and LSTM for long-time sequence data processing. The LSTM model, which comprises of two parallel bi-directional LSTM layers, is added to the CNN model's output to get the desired result. The pre-processed input (output of the CNN model) is fed as input to the LSTM model. The activity feature vector is obtained after the convolution operation. The dimensionality of the feature vector is reduced using the maximum pooling method. As an extension of the recurrent neural network, LSTM may be able to more efficiently tackle the problem of heavy data dependency in time sequence.

A RNN is mainly used for processing sequence data which may contain the time dimension. The proposed method uses RNNs to teach the temporal information included in EEG data. This is particularly useful in learning the transition of sleep stages where the sleep stages might be based on the previous sleep stages. RNNs process a sequence of features ai after processing a_{i-1}, using h_{i-1} and c_{i-1} where h_i and c_i represent the hidden and cell states [15]. LSTM uses memory cells that can basically hold data for extended periods of time to store long-term dependencies. In order to correctly identify the activities, the LSTM calculates the preservation of cell state in line with the control between its various gates, maintaining the link between the data with strong correlations, and corrects issues with long-term dependencies. The input layer neuron creates the output with the help of activation function. The final expression is calculated using the SoftMax activation function, to obtain the probabilities of various sleep stages.

The decision as to whether a particular information is to be retained or forgotten is dependent on the interaction among different gates of the LSTM model. The cycle is repeated and the accuracy is calculated accordingly.

For our model to learn the temporal information, such as sleep transition rules, we used bi-directional LSTM. This is helpful in those instances, for example, a person is in the N2 sleep stage, and the AASM manual states that even in the absence of K-complexes or sleep spindles, epochs with low amplitude and mixed frequencies can be classified as N2. When this occurs, LSTMs might recall seeing the N2 stage

and continue to rank epochs as N2 if comparable activity is observed [16]. Bi-directional LSTM process the forward and backward sequence independently, thereby, being able to use information from past and future.

This model has three operations for each convolution layer: convolution, batch normalisation, and activation function non-linearization. In the last layer following the convolution process, batch normalisation modifies the output distribution. Time sequence features are extracted using LSTM, deep local correlation data is obtained using parallel CNN architecture, time sequence features and convolution features are combined into a fully connected layer, and the Softmax layer produces the multi-classification result. In our work, the batch processing size is set at 64. Rectified linear activation unit (ReLU), a piecewise linear function with unilateral inhibition is chosen as the activation function and causes the neurons to have sparse activation, accelerating convergence. The SoftMax layer converts the result into one of the five sleep stages.

C. Dataset and Evaluation Metrics

Our model was evaluated using the Sleep-EDF-20 public dataset [16]. The dataset is obtained from the PhysioBank [17]. The dataset contains data files for 20 subjects, who were involved in the Sleep Cassette (SC* files) study. The study, which involved healthy participants between the ages of 25 and 101, provides insights on the impact of age on sleep. At a sample rate of 100 Hz, each PSG file has two EEG channels (Fpz-Cz and Pz-Oz), one EOG channel, and one EMG channel. We used the single channel Fpz-Cz channel from the SC study as the input to our model, following previous studies [16,18,19]. From 20 participants in this study, 39 PSG recordings were obtained. As they didn't fit into any of the five stages of sleep, the movement artefacts that were marked as MOVEMENT or UNKNOWN were eliminated. The Rechtschaffen & Kales (R&K) documentation was used to score the dataset first. To confirm with the AASM standard, the stages N3 and N4 were combined. In order to concentrate more on the stages of sleep, waking intervals that lasted just 30 minutes before and after the sleep were only added. We used the pre-processed Sleep-EDF-20 dataset by [16] in our work. Table II summarises the distribution of sleep stages.

TABLE II: DISTRIBUTION OF VARIOUS SLEEP STAGES

Dataset	Ns	W	N1	N2	N3	REM
Sleep-EDF-v1	20	8026	2804	17799	5703	7717

Overall accuracy and F1 score were used to evaluate our model's performance to accurately categorise different stages of sleep. The overall accuracy of the model is calculated as

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Where the terms "true positives", "true negatives", "false positives", and "false negatives" respectively stand for TP, TN, FP and FN. The F1 score is calculated as

$$F1 = \frac{2 * PR * RE}{PR + RE} \qquad (2)$$

Where PR and RE denote precision and recall respectively.

The recall value of a class denotes how well the model was able to predict the true instances of a particular class. It is also called as sensitivity. Precision, on the other hand, gives us what proportion of sleep stages identified as a particular class actually belong to that class. Sensitivity and Precision are calculated as

$$Recall/Sensitivity = \frac{TP}{TP + FN} \qquad (3)$$

$$Precision = \frac{TP}{TP + FP} \qquad (4)$$

D. Experimental Setting

To assess the training model, we divided one-tenth of the training set into a validation set. The distribution of training, validation and testing sets are 81%, 9% and 10% respectively. The details of data files in each set are given in Table III. The learning rate for the Adam optimizer was set at 0.0001. The mini-batch size used was 64. The model was compiled using the categorical cross entropy loss function. This type of loss function is generally used when there is a classification problem which predicts the data belongs to one class or the other. In this case, the data is being classified to one of the sleep stages. Since this a classification problem as mentioned already, SoftMax activation function was used in the output layer. There is a chance that the model might overfit, therefore, dropout layer with rate 0.5 was used to prevent overfitting of the model.

TABLE III: DISTRIBUTION OF DATASET

Dataset	Distribution (No. of samples)		
	Training	*Validation*	*Test*
Sleep-EDF-v1	34060	3784	4201

III. Results & Discussion

The performance of the model was evaluated using precision (PR), recall (RE) or sensitivity, specificity, F1 score (F1) and overall accuracy (ACC). Our method achieved an overall accuracy of 83.38% on the Sleep-EDF-v1 dataset. Table IV shows the classification report obtained.

TABLE IV: CLASSIFICATION REPORT

Sleep Stage	Precision	Recall/Sensitivity	F1 Score
W	0.92	0.89	0.90
N1	0.55	0.28	0.37
N2	0.85	0.92	0.88
N3	0.99	0.68	0.81
REM	0.71	0.90	0.79

Other state-of-the-art methods by [11, 14, 18, 20, 21], who employed CNN-LSTM combinations have achieved an accuracy in the range 80-90%. The comparison is shown in Table V. The metrics used for comparing the performance of different models that use CNN-LSTM architecture are accuracy and macro-averaging F1 score. The table illustrates that our method performed similarly to the other methods tested on the same EEG channels. The performance can also be linked to the scores of different sleep stages, the model has been able to differentiate and score the different sleep stages well. The same is evident from the classification report given in Table IV. The F1 scores of all the sleep stages except N1 is

above 80%, which is actually good. The F1 score for the stage N1 is less compared to other stages. N1 stage is difficult to classify, it is because the inter reliability of N1 stage is less compared to other sleep stages. It could also be due to the smaller number of N1 samples in the dataset.

The Sleep-EDF-v1 dataset comprises of signals from different EEG channels. The channel used in this study was the Fpz-Cz channel. This channel captures most of the frequencies. Delta activity, K-complexes and other low frequency spindles are also captured which are significant for scoring of sleep stages. It may also be noted that the dataset is imbalanced. The dataset may be expanded by means of data augmentation techniques ensuring a balanced dataset. However, our model has achieved good accuracy even though the dataset is imbalanced.

Sleep stage scoring is based on the information which is sequential in nature. This means that each sleep stage has some relationship with the stages that precedes and succeeds the current sleep stage. Hence, the need for employing a deep-learning model which works well on sequence data like LSTM arises.

Our model was trained and tested only using the Sleep-EDF-v1 dataset, unlike some other models where they were first pre-trained on other large datasets. Data Augmentation techniques could be employed to help synthesis new patterns of data and also to generate new data so that training will be more efficient. As future work, this method could be further applied to other sleep datasets like Sleep-EDF and Montreal

TABLE V: COMPARISON OF PROPOSED METHODS WITH OTHER METHODS THAT UTILIZE CNN-LSTM ARCHITECTURE

Dataset	System	EEG Channel	Fs	Epochs (sec)	Test Epochs	ACC	MF1
SleepEDF-20	Proposed Method	Fpz-Cz	100	30	42045	**83.38**	**75**
SleepEDF-20	Deep convolutional network [20]	Pz-Oz	100	30	18815	81.0	73.6
SleepEDF-20	XSleepNet [21]	Fpz-Cz	100	30	-	**86.3**	**80.6**
SleepEDF-20	DeepSleepNet [14]	Fpz-Cz	100	30	41950	82.0	76.9
SleepEDF-20	DeepSleepNet [14]	Pz-Oz	100	30	41950	79.8	73.1
SleepEDF-20	IITNet [18]	Fpz-Cz	100	30	42308	83.6	76.5
SleepEDF-20	TinySleepNet [11]	Fpz-Cz	100	30	44220	85.4	80.5

Archive of Sleep Studies (MASS). Further studies on reducing the complexity and thereby the training time are also potential areas for further research. Also, other physiological factors like electrocardiogram, electro-oculogram, breath, etc should also be considered as these have an impact on the complexity of the sleep. New factors or parameters have to be identified for better and more efficient sleep stage scoring. Data from multiple channels could be used. A thorough analysis of different stages of sleep from data of different channels will bring new insights.

IV. Conclusion

A CNN-LSTM based architecture is proposed in this study for the scoring of sleep stages. The manual scoring of sleep stages using PSG recordings by sleep experts is a tedious process. Sleep is a very complex process, making it challenging to stage events with great precision using automated approaches. The EEG signals from a single channel is used, thereby simplifying the monitoring of sleep stages. The proposed method leverages the ability of CNNs and RNNs to sleep stage scoring and an accuracy of 83.38% was obtained. LSTM, to learn the transition rules, was employed particularly to learn the transition of sleep stages from one stage to another. The model performance was also analysed using F1 score. The proposed model requires improvement, particularly in the scoring of N1 stage. The model can be used for different biomedical applications like epilepsy detection. The proposed model can be used in clinical applications to identify sleep patterns which can further help to identify sleep disorders like sleep apnea. The model should be tested with external data for that. To improve the generalization of the model, transfer learning techniques can be employed [12]. Also, the model can be tested with datasets that contain sleep data of subjects with sleep problems. In this study, we have only considered EEG signals, but other signals like EOG, ECG, etc also play a role in determining the sleep stages. As future work, the impact of such factors will be studied and more investigation on how these factors can be included in the deep-learning model will also be done.

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