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Automated detection of cyclic alternating pattern and classification of sleep stages using deep neural network

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Abstract

The visual sleep stages scoring by human experts is the current gold standard for sleep analysis. However, this method is tedious, time-consuming, prone to human errors, and unable to detect microstructure of sleep such as cyclic alternating pattern (CAP) which is an important diagnostic factor for the detection of sleep disorders such as insomnia and obstructive sleep apnea (OSA). The CAP is only observed as subtle changes in the electroencephalogram (EEG) signals during non-rapid eye movement (NREM) sleep, making it very difficult for human experts to discern. Hence, it is important to have an automated system developed using artificial intelligence for accurate and robust detection of CAP and sleep stages classification. In this study, a deep learning model based on 1-dimensional convolutional neural network (1D-CNN) is proposed for CAP detection and homogenous 3-class sleep stages classification, namely wakefulness (W), rapid eye movement (REM) and NREM sleep. The proposed model is developed using standardized EEG recordings. Our developed CNN network achieved good model performance for 3-class sleep stages classification with a classification accuracy of 90.46%. Our proposed model also yielded a classification accuracy of 73.64% using balanced CAP dataset, and sensitivity of 92.06% with unbalanced CAP dataset. Our proposed model correctly identified majority of A-phases which comprised of only 12.6% in the unbalanced dataset. The performance of the developed prototype is ready to be tested with more data before clinical application.

Keywords Sleep stages · Cyclic alternating pattern (CAP) · Classification · Electroencephalogram (EEG) · Deep learning · CAPSLPDB · CNN

1 Introduction

Sleep is often taken for granted, but it is crucial for our physical and mental health [1]. Approximately 50 to 70 million Americans are reported to have sleep disorders [2] and at least 25 million Americans have obstructive sleep apnea (OSA) [3]. Also, 30% of the adults in the United States of America are diagnosed with insomnia [4]. Sleep disorders like OSA and insomnia are also associated with numerous health problems such as stroke [5], cardiovascular disease [6], and obesity [7]. However, sleep problem is a global issue that is not just unique to America. In 2012, Stranges et al. [8] investigated the prevalence of sleep problem from 8 countries across Asia and Africa, using two publicly available datasets: International Network for the Demographic Evaluation of Populations and Their Health (INDEPTH) and the World Health Organization Study on Global Ageing and Adult Health (WHO-SAGE). They reported that 16.6% of the adults (≈150 million) included in their study had sleep problems and this number is expected to exceed 260 million by 2030

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because adults, especially in low-income settings, are ignorant of the detrimental health effect of sleep problems. Another global sleep problem study by Konayagi et al. [9] had analyzed data from the World Health Organization's World Health Survey (WHS) across 70 countries. They reported that the odds of having sleep problems for an individual with a known psychotic symptom is 2.41 (p value <0.001); more than two times increase in the risk of having sleep problems. Hence, sleep problem is becoming a serious public health issue on a global scale and an accurate diagnostic tool of sleep disorder is needed [10, 11].

Sleep stages are also known as the macrostructure of sleep and there are initially six stages according to Rechtschaffen and Kales (R&K) rules [12]: Wakefulness (W), Rapid Eye Movement (REM), and Non-REM which is divided into 4 stages (NREM S1- S4). Later, the American Academy of Sleep Medicine (AASM) guidelines [13] classified NREM S3 and NREM S4 together as Slow Wave Sleep (SWS) due to similarity in their characteristics, resulting in a total of five sleep stages. The five sleep stages can be described with electroencephalogram (EEG) characteristic rhythm and other physiological changes as follows:

- **Wakefulness**: The brain activity is in the most active stage and is represented by high frequency alpha rhythms and occasional beta rhythms [14].
- **NREM S1**: In this stage, an individual proceeds to fall asleep and alpha rhythms disappear while theta rhythms make their appearances [14]. This is the lightest sleep stage where individuals are easily awakened by disruptive noises [2]. Heart rate and breathing begin to slow down and muscle starts to relax as well [15].
- **NREM S2**: Sleep spindles and K-complex will occasionally appear for approximately 1 to 2 s [14]. High density sleep spindles are also observed in individuals who learn new tasks before sleep, hence indicating its relation to memory consolidation [16]. Body temperature begins to drop, and eye movement ceases at this stage [15].
- **SWS (NREM S3 and S4)**: Low frequency delta rhythms will appear intermittently in NREM S3 and eventually dominates in NREM S4 [14]. An optimal amount of SWS allows individuals to feel refreshed when they wake up. Heart rate and breathing are the slowest at this stage and muscles are fully relaxed. This is the deepest sleep stage where individuals usually find it hard to wake up [15].
- **REM**: Proceeds immediately after SWS and it is represented by theta rhythms and flattening of EEG signals, accompanied by loss of muscle tone of the body core [14, 17]. Breathing patterns are fast and irregular during REM sleep and heart rate increases to near waking levels. Dreams are known to occur in this stage and REM sleep is accompanied by the loss of muscle tone to prevent individuals from acting out of their dreams [15].

Currently, the visual sleep stages scoring by human experts is the gold standard for sleep analysis [18]. According to the AASM guidelines [13], overnight polysomnogram (PSG) recordings are first segmented into 30s fragments (epochs). Next, each epoch is scored into different sleep stages. It is very often that an epoch may contain two or more sleep stages. Thus, human experts score each epoch based on the sleep stages, which appears predominantly. For instance, an epoch comprises 45% NREM S1 and 55% NREM S2 will be classified as NREM S2 sleep. However, this method results in heterogenous sleep stages scoring [18]. In fact, NREM S3 and S4 are heterogeneously combined as SWS for ease of classification because human experts are incapable of adapting to slow background EEG changes which makes the classification of NREM S3 and S4 challenging, as counting the delta rhythm occurrence is difficult [12, 18]. To address the limitation of heterogenous sleep stages scoring, Kemp et al. [19] and Pardey et al. [20] suggested that NREM sleep should be represented as a continuous function, rather than subdivisions of NREM sleep.

Another challenge regarding the current sleep stages scoring approach is the exclusion of microstructure of sleep which only appears for a few seconds, significantly shorter than an epoch of 30s duration [18]. The microstructure of sleep includes cyclic alternating pattern (CAP), elementary arousal (K-complexes) and micro-arousal [18, 21]. In particular, arousal instability is more evident in the CAP sequence rather than in micro-arousal events. Hence, CAP provides a global framework to measure sleep instability [21]. CAP only appears in periodic EEG activity of the NREM sleep and it is associated with sleep events such as falling asleep, transition in sleep stage, and awakenings [22, 23]. Thus, if there is an appearance of CAP in REM sleep, it could be a prognostic element of sleep disorder [24].

CAP can be described as recurrent transient electrocortical events that consist of two distinct phases: A-phase and B-phase [23]. A-phase is a transient phenomenon that has known association with brain activation [24, 25] and it is further broken down into three subtypes described as follows [24, 25]:

- **A1-phase** can be identified by an increase in amplitude to 3 times that of normal background activity and they are usually delta rhythms, K-complexes, and bursts.
- **A2-phase** is a combination of A1 and A3 phase, characterized by a mixture of slow and fast rhythms. This phase also indicated a drop in sleep stability.
- **A3-phase** can be identified by an increase in frequency compared to background activity and they are usually alpha and beta rhythms.

Hence, A-phase is characterized by having either low frequency with high amplitude EEG signals (A1-phase) or high frequency with low amplitude EEG signals (A3-phase) or a

combination of these two phenomena (A2-phase) [25]. A-phases can be distinguished from B-phases which are background EEG activities as shown in Fig. 1 [11].

A CAP cycle is formed when B-phase immediately follows after A-phase, otherwise, the A-phase is considered to be isolated [24]. A CAP sequence is formed when two or more CAP cycles occur in a sequence. The duration of each CAP phase can vary from 2 s to 60s and normally, young adults have a mean duration of two and half minutes of CAP sequence, which consists of six CAP cycles [24, 26]. On the other hand, individuals with sleep disorders such as OSA are found to have higher CAP rate, cycles, and duration. This phenomenon is evident when OSA patients are accompanied by excessive sleepiness as well [27]. Abnormal CAP rates are found in epilepsy [28], insomnia [29], obstructive sleep apnea (OSA) [27], and coma patients [30]. Therefore, CAP is an important marker for unstable sleep that is, unfortunately, not included in visual sleep analysis [18, 26].

As such, there is a need to resolve the limitations of visual sleep analysis, which are heterogenous sleep stages scoring and exclusion of CAP. This can be achieved with the aid of a computer aided diagnostic (CAD) tool that is superior to human counterparts in detecting the subtle changes in background EEG related to microstructure of sleep like CAP that is commonly left out in sleep stages scoring by human experts [18, 31–33]. Studies have also shown that CAD performed equally well, if not better, in sleep stages scoring as compared to the human experts [34–36]. In the recent past, numerous studies have attempted to develop CAD tools based on machine learning and deep learning methodology for automated classification of sleep stages and detection of CAP separately. Rahman et al. [37] used EEG signals from the expanded sleep-EDF database in their study for 3-class sleep stages classification (W, NREM & REM) and achieved an accuracy of 94.1% with discrete wavelet transform (DWT) and support vector machine (SVM). Likewise, Yildirim et al. [38] proposed a 1-Dimensional Convolutional Neural Network (1D-CNN) model for 3-class sleep stages classification and achieved an overall accuracy of 94.2% using EEG signals in both Sleep-EDF and expanded sleep-EDF database. As for CAP detection, Mendez et al. [39] proposed k-nearest neighbor (KNN) classifier to distinguish A-phases in CAP and achieved 80% accuracy. Hartmann et al. [40] proposed long short-term memory (LSTM) model for A-phase detection in CAP and achieved an accuracy of 82.4%.

In this work, we have attempted to address the limitation of traditional sleep stages scoring and automatic CAP detection using a deep learning model based on 1-Dimensional Convolutional Neural Network (1D-CNN). To the best of our knowledge, this is the first automated model developed for both sleep stages classification and CAP detection. The main contributions of this work are given below:

- The proposed model is compatible for the classification of both macrostructure and microstructure of sleep.
- For CAP detection, the proposed model can be trained with a smaller dataset (Table 4: balanced CAP dataset) and evaluated with a bigger dataset (Table 3: unbalanced CAP dataset). Hence, higher classification efficiency is obtained with shorter training time.
- The proposed model has the potential to be further developed into a CAD tool for clinical applications.

2 Materials & methods

Section 2.1 describes the data preparation and preprocessing methods, Section 2.2 outlines the experiment setup of this

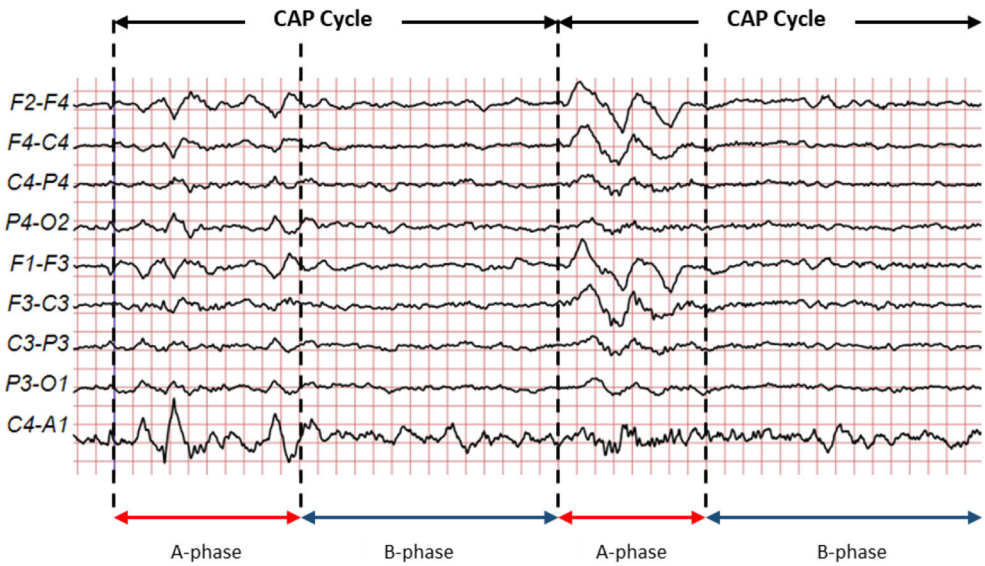

Fig. 1 CAP waveform recorded from different EEG electrodes in CAPSLPDB, healthy subject N1

work, and Section 2.3 elaborates the architecture of the proposed 1D-CNN model.

2.1 Data acquisition

In this paper, we considered a publicly available CAP sleep database (CAPSLPDB), which was acquired from PhysioNet [23, 41]. The PSG recordings in CAPSLPDB were obtained from an experiment conducted in the Sleep Disorder Center of the Ospedale Maggiore of Parma, Italy [23]. A total of 108 overnight PSG recordings were collected from 16 healthy and 92 pathological subjects, for a duration of 9–10 h. The PSG recordings included at least 3 EEG channels, 2 EOG channels, 2 EMG channels, ECG, and respiratory signals, which were sampled over a range of sampling frequencies (100 Hz, 128 Hz, 200 Hz, and 512 Hz.).

In this paper, we used single-channel EEG recordings (C4-A1 or C3-A2) from 6 healthy subjects that were sampled at 512 Hz sampling frequency. For sleep stages classification, the dataset was prepared by first segmenting the EEG recordings into segments of 30 s duration. Then, the substages of NREM sleep (S1, S2, and SWS) were combined to obtain a single sleep stage, as shown in Table 1. Considering the minimum possible duration of occurrence of CAP, the EEG signals were segmented into segments of 2 s duration for CAP detection. Then, the subphases of A-phase were combined to obtain a single phase. However, there are two types of datasets created for CAP detection: unbalanced CAP dataset (Table 2), and balanced CAP dataset (Table 3). In the unbalanced dataset, all samples were considered, while in the balanced dataset, we have ensured equal number of samples in each CAP phase. This means that the number of samples is the same across the subphases of A-phases in Table 3, before ensuring that the number of samples are equal for A- & B-phases. The samples in the balanced datasets were chosen at random for consistency purposes [25].

Table 2 Summary of the total number of samples for unbalanced CAP dataset

Subject	A1	A2	A3	A-phase	B-phase	Total
N1	1013	354	548	1915	12,915	14,830
N2	550	327	597	1474	10,560	12,034
N3	285	284	494	1063	10,110	11,173
N5	1307	157	377	1841	11,460	13,301
N10	703	159	445	1307	8550	9857
N11	796	270	386	1452	9210	10,662
Total	4654	1551	2847	9052	62,805	**71,857**

2.2 Experiment setup

The workflow of the experimental setup is shown in Fig. 2. After segmentation of the raw EEG recordings, the dataset was preprocessed by standardization of EEG signals to mean

Table 1 Summary of the total number of samples in sleep dataset for (a) 5-classes and (b) 3 -classes

(a)

Subjects	W	S1	S2	SWS	REM	Total
N1	39	35	513	321	239	1147
N2	143	141	369	197	151	1001
N3	136	50	350	280	188	1004
N5	10	50	413	305	232	1010
N10	67	2	262	313	215	859
N11	56	6	266	346	380	1054
Total	451	284	2173	1762	1405	**6075**

(b)

Subjects	W	NREM	REM	Total
N1	39	869	239	1147
N2	143	707	151	1001
N3	136	680	188	1004
N5	10	768	232	1010
N10	67	577	215	859
N11	56	618	380	1054
Total	451	4219	1405	**6075**

t3.1 **Table 3** Summary of the total number of samples for balanced CAP dataset

t3.2 Subject	A1	A2	A3	A-phase	B-phase	Total
t3.3 N1	354	354	354	1062	1062	2124
t3.4 N2	327	327	327	981	981	1962
t3.5 N3	284	284	284	852	852	1704
t3.6 N5	157	157	157	471	471	942
t3.7 N10	159	159	159	477	477	954
t3.8 N11	270	270	270	810	810	1620
t3.9 Total	1551	1551	1551	4653	4653	**9306**

of 0 and standard deviation of 1. Subsequently, the dataset was split into training set (70%), validation set (15%) and test set (15%). Training and validation were initially used during hyperparameter optimization to determine the layer parameters of proposed model. Once the model architecture was fixed, the proposed model was trained 50 times with the training set, and the best model was saved at highest validation accuracy obtained during model training. The test set was then used to evaluate the performance of the saved best model.

However, an exception was applied for unbalanced CAP dataset; the unbalanced CAP dataset was not used to train the model, hence it was not split into the respective train, validation, and test sets. Instead, the proposed model was trained with the training set of balanced CAP dataset, while the performance of the model was evaluated twice using the test set of balanced datasets and the entire unbalanced CAP dataset. In other words, the unbalanced CAP datasets served as a secondary test set to evaluate model performance for CAP detection.

2.3 Proposed deep learning model (1D-CNN)

A typical 1D-CNN model consists of convolutional and pooling layers that are responsible for feature extraction and the operation of the convolutional layer can be described by the following formula [38]:

$$(S*W)_n = \sum_{i=1}^{|W|} W(i)S(i+n-1) \quad (1)$$

where S, W and $*$ represent the 1D input signal, kernel and discrete convolution operation. The dimension of

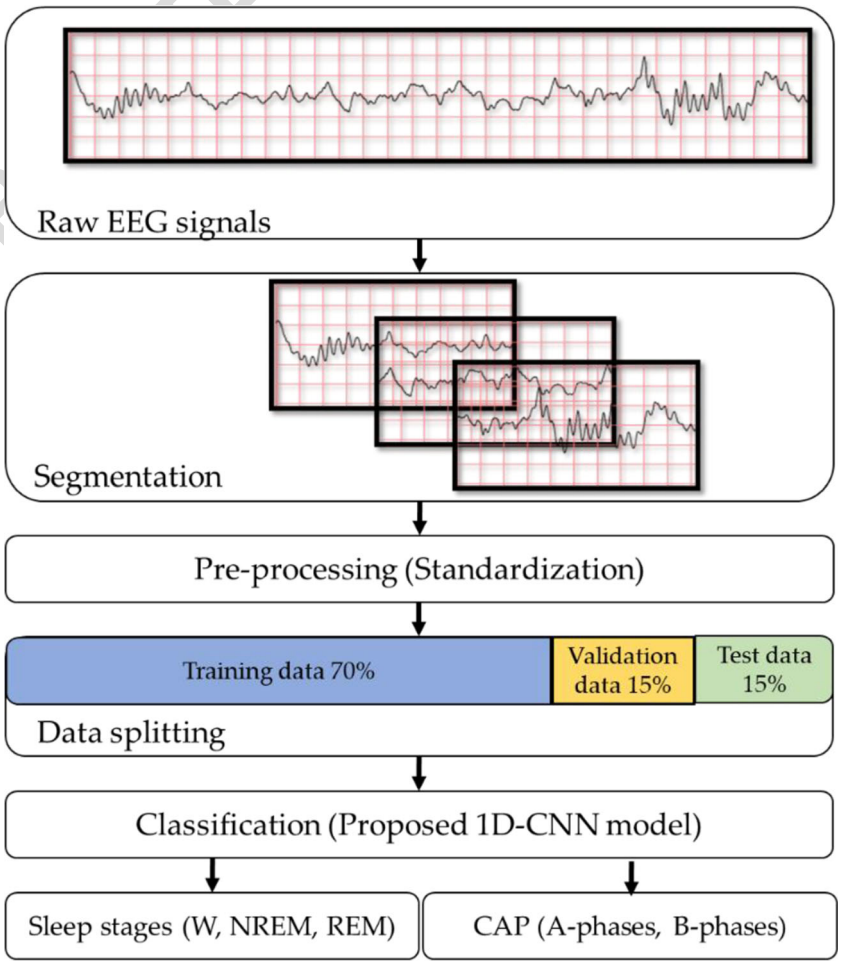

Fig. 2 Workflow of experimental setup

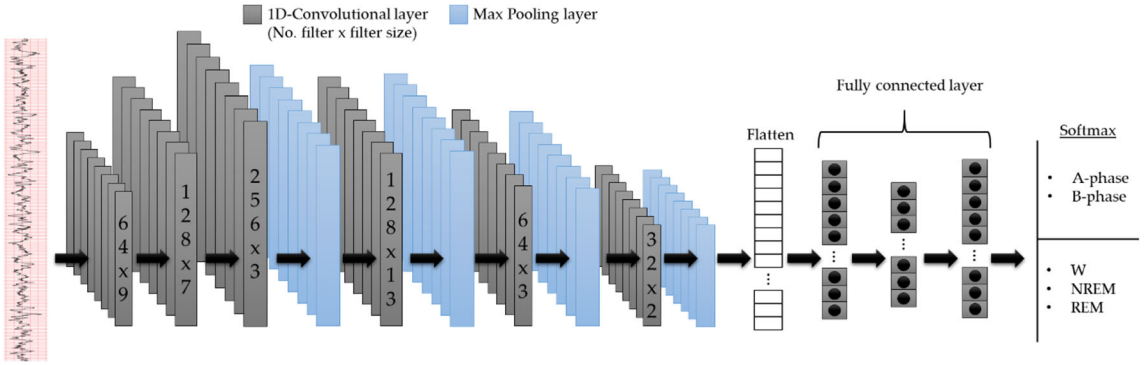

Fig. 3 Proposed 1D-CNN model architecture

the kernel in 2D-CNN is denoted as $W(i,j)$ but for 1D-CNN, only $W(i)$ is concerned. The kernel (W) is also the weights in any CNN model and the weights are updated every time the kernel slides over the input signals. The kernel output the feature maps once it runs through the input signals.

The output feature map (O) can be described by the following formula:

$$O_n^l = \left(S_{W(i)} * W(i)\right)_n \tag{2}$$

The features maps are further processed by multiple convolutional and pooling layers to make the features more distinct, thereby increasing the recognition and classification ability of 1D-CNN models. The processed feature maps are then flattened into single list vectors before entering the fully connected layers where classification takes place. The model architecture for the proposed model is based on 1D-CNN and is illustrated in Fig. 3. The details of the layer parameters and hyperparameters are provided in Tables 4 and 5, respectively. The proposed model starts

Table 4 Detail of layers in proposed 1D-CNN model

No.	Layer	No. filter	Kernel size	Unit size	Parameter	Output (CAP)	Output (Sleep)
1	1DConv1	64	9	–	ReLu, Stride=3	64×339	64×5118
2	BatchNorm	–	–	–	–	64×339	64×5118
3	1DConv2	128	7	–	ReLu, Stride=1	128×333	128×5112
4	BatchNorm	–	–	–	–	128×333	128×5112
5	1DConv3	256	3	–	ReLu, Stride=1	256×331	256×5110
6	BatchNorm	–	–	–	–	256×331	256×5110
7	MaxPool	–	–	2	Stride=2	256×165	256×2555
8	1DConv4	128	13	–	ReLu, Stride=1	128×153	128×2543
9	BatchNorm	–	–	–	–	128×153	128×2543
10	MaxPool	–	–	2	Stride=2	128×76	128×1271
11	1DConv5	64	3	–	ReLu, Stride=1	64×74	64×1269
12	BatchNorm	–	–	–	–	64×74	64×1269
13	MaxPool	–	–	2	Stride=2	64×37	64×634
14	1DConv6	32	2	–	ReLu, Stride=1	32×36	32×633
15	BatchNorm	–	–	–	–	32×36	32×633
16	MaxPool	–	–	2	Stride=2	32×18	32×316
17	Dropout	–	–	–	Rate=0.7	32×18	32×316
18	Flatten	–	–	–	–	1×576	1×10,112
19	Dense	–	–	64	ReLu	1×64	1×64
20	Dropout	–	–	–	Rate=0.2	1×64	1×64
21	Dense	–	–	16	ReLu	1×16	1×16
22	Dropout	–	–	–	Rate=0.2	1×16	1×16
23	Dense	–	–	64	ReLu	1×64	1×64
24	Dense	–	–	num_class	Softmax	1 x num_class	1 x num_class

Table 5 Details of hyperparameters in proposed 1D-CNN model

Hyperparameters	
Batch size	64
Kernel regularizer (l2)	0.005
Optimizer	Adam
Learning rate	0.001
Decay rate	0.01
Loss function	Categorical crossentropy

with a series of 3 convolutional layers followed by another 3 convolutional layers with 4 pooling layers placed in between them. Consider the example of CAP detection, the input segment duration of 2 s with 1024 timesteps are convoluted into 64 feature maps with the length of 339 in the first convolutional layer. The example of the resulting feature maps generated by 6 convolutional layers in the proposed model, is illustrated in Fig. 4. By the time it reaches the last pooling layer, 32 feature maps with the length of 18 is generated. The flatten layer converts the 32 feature maps from the last pooling layer into single-list vectors with the length of 576, which is used to train the neurons in the fully connected layers.

To prevent overfitting of the proposed model, batch normalization is done after every convolutional layer and the regularizer (l2) of each kernel is set to 0.005. Dropout layers are also introduced in between the fully connected layers to prevent overfitting. Finally, the last layer of the proposed model is a SoftMax classifier which contains the same number of neurons as the number of classes for sleep stages (3 classes) and CAP (2 classes) respectively. SoftMax classifier generates probability scores which indicate the likelihood in which the single list vectors are classified into. For instance, a single list vector may have a probability score of 0.85 for A-phase and 0.15 for B-phase, respectively. The sum of the probability score for all the classes will always equate to 1.0. Adam optimizer with 0.001 learning rate and 0.01 decay rate is used in the proposed model.

Table 6 Training time of proposed 1D-CNN model in each respective sleep and CAP dataset

Datasets (*EEG signals*)	Training time (hh:mm:ss)
Sleep dataset	05:40:02
Balanced CAP dataset	00:23:24

The proposed model is created using Keras (v2.3.1) with Tensorflow (v1.14.0) backend, and both are deep learning tools from Python programming language. The specification of the computer used to train and evaluate the model is as follows: Intel Core i7–10875H CPU, RTX 2070 Super 8GB, 32GB RAM, and 500GB NVMe SSD. The training time for each dataset is shown in Table 6.

The parameters in Tables 4 and 5 are decided through numerous trials and errors. An example of layer parameters and hyperparameters optimization is shown in Fig. 5, where the parameters of 64, 128, and 256 filter number for the 2nd convolutional layer is tested. For each filter number, the model is trained and evaluated for 5 rounds with training and validation set respectively. The box and whiskers plot summarizing the mean, median, and standard deviation for each parameter is summarised in Fig. 5. From the plot in Fig. 5, the filter number of 128 is chosen for the 2nd convolutional layer because it has the highest overall accuracy and lowest standard deviation.

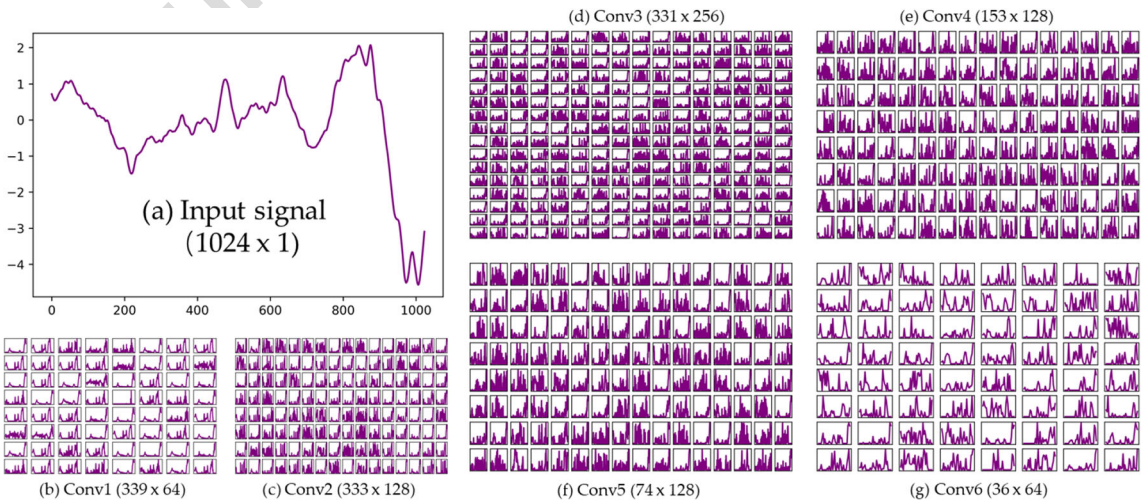

Fig. 4 Feature maps obtained from the convolutional layers in the proposed model during model training for CAP detection. **a** Input EEG signal, and feature map of the **b** 1st convolutional layer, **c** 2nd convolutional layer, **d** 3rd convolutional layer, **e** 4th convolutional layer, **f** 5th convolutional layer, and **g** 6th convolutional layer

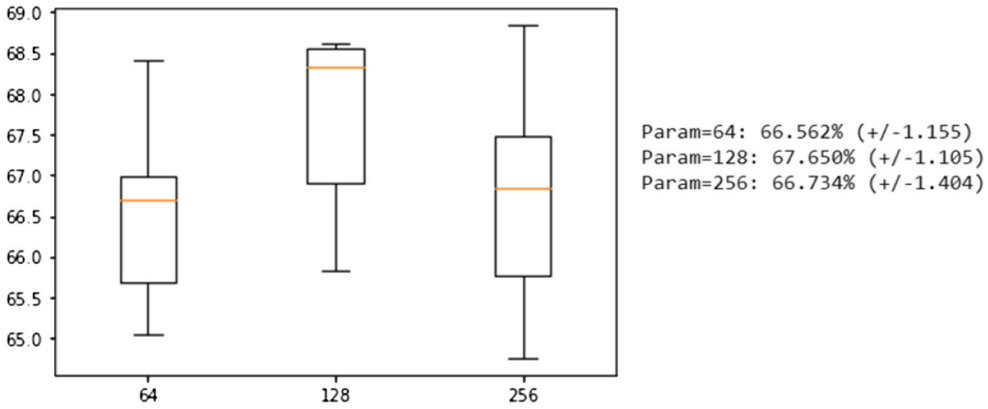

Fig. 5 Hyperparameter optimization for the 2nd convolutional layer in Table 4

3 Results

This section reports the major findings of the experiment. The experimental results for sleep stages classification is presented in Section 3.1. CAP detection results are described in Sections 3.2 and 3.3 summarizes the major findings of this work.

3.1 Sleep stages classification

The sleep dataset was split into training, validation, and test set with the ratio of 70:15:15, respectively. The proposed model was trained with training set for 50 epochs and the 'best model' was saved when highest validation accuracy is obtained during model training. The test set is unknown to the proposed model and was used to evaluate the performance of the 'best model'.

The 'best model' was saved at validation accuracy of 90.34%, and the resulting test accuracy and performance parameters are shown in Table 7. It can be noted that the proposed model achieved high precision rate of 97.11% and sensitivity of 95.73% for NREM and REM sleep, respectively. Higher precision rate indicates that the proposed model can correctly predict NREM sleep more than the other two sleep stages. This can be observed from the confusion matrix in Fig. 6, where the proposed model correctly predicted 571 NREM sleep samples compared to W stage (52 samples) and REM sleep (202 samples). However, this is within expectation since NREM sleep has the largest number of samples compared to the other two sleep stages. On the other hand, higher sensitivity indicates that the proposed model can correctly predict the majority of REM sleep within the same class. This can also be seen from the confusion matrix in Fig. 6, where the proposed model misclassified 9 out of 211 REM sleep samples, while the other sleep stages have large number of misclassifications.

3.2 CAP detection

The experiment for CAP detection differs from sleep stages classification as there are two different datasets: unbalanced and balanced CAP dataset. Likewise, the balanced CAP dataset is split into training, validation, and test set with the ratio of 70:15:15. However, the performance of the proposed model is evaluated twice with the test set of balanced CAP dataset and the entire unbalanced CAP dataset. Similarly, the 'best model' for CAP detection was obtained with validation accuracy of 74.43%, and the resulting performance parameters are shown in Table 8.

Unlike multiclass problem in sleep stages classification, CAP detection is a binary classification problem. The precision of the model is the ability to refrain from classifying the negative samples (B-phases) as positive samples (A-phases) [42]. The sensitivity of the model is the ability to correctly identify A-phases, while specificity of the model focuses on the ability to correctly identify B-phases [42]. From Table 8, high model sensitivity is observed in balanced CAP dataset (80.29%), hence highlighting the ability of the proposed model to identify A-phases. The model sensitivity was also consistently high when evaluated with unbalanced CAP dataset (92.06%). This is crucial because A-phases occupy only

Table 7 Model accuracies (%) and various performance values (%) for sleep stages classification. Performance values corresponds to test accuracy

Accuracy		Sleep stages	Precision	Sensitivity	F1	Samples
Training	98.71	W	75.34	76.46	75.91	68
Validation	90.34	NREM	97.11	90.21	93.53	633
Test	**90.46**	REM	79.22	95.73	86.70	211

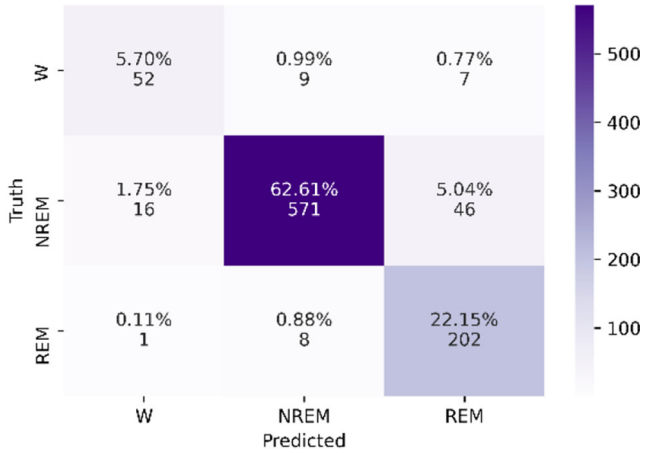

Fig. 6 Confusion matrix sleep stages classification

12.6% of the unbalanced CAP dataset; from the confusion matrix in Fig. 7, the proposed model is able to detect 8333 out of 9052 A-phase samples correctly.

However, the remaining B-phases occupy 87.4% of the unbalanced dataset generated large data noise that hindered the ability of the model to correctly distinguish B-phases from A-phase. Hence, the other performance parameters such as classification accuracy, precision, and specificity were compromised (Table 8).

3.3 Summary of results

The results for sleep stages classification and CAP detection are summarized in Table 9. The performance parameters obtained for sleep stages classification is shown in Table 9 are the average performance values of all three sleep stages presented in Table 7. Generally, there is a trade-off between model precision and sensitivity [43]; high sensitivity of 92.06% and low precision of 20.13% is obtained when the proposed model is evaluated with the unbalanced CAP dataset (Table 9). Hence, F1-score can be used to assess the ability of the model to achieve balance between precision and sensitivity [43]. F1-score is commonly used to evaluate unbalanced datasets due to the non-uniform distribution of class labels [43].

For sleep stages classification, the proposed model achieved high average F1-score of 85.38% (Table 9), indicating that the proposed model has managed to achieve equilibrium between precision and sensitivity. Hence, the model can effectively capture the EEG characteristics rhythms for the three sleep stages. As for CAP detection, F1-score was moderately high in balanced CAP dataset (75.34%), however, low F1-score of 33.04% is observed when proposed model is evaluated with unbalanced CAP dataset (Table 9). This indicates that the proposed model was affected due to the presence of noise from the B-phases which comprised of 87.4% of the dataset.

The performance graph for sleep stages classification and CAP detection is shown in Fig. 8. Smaller gap between training and validation accuracy is observed for CAP detection as compared to sleep stages classification, indicating that the proposed model is more prone overfitting problem when training to classify sleep stages. This is may be due to the use of smaller dataset (6075 samples) for sleep stages classification. Nonetheless, the gap between training and validation accuracy for sleep stages classification remained the same and validation accuracy was stable at around 90%. Hence, the proposed model may be slightly overfitted for sleep stages classification without much compromising on the model performance.

4 Discussion

Many 3-class sleep stages classification studies have been reported based on machine learning and deep learning methods using two popular sleep databases: Sleep-EDF and Sleep-EDFX [19, 41]. To the best of our knowledge, this is the first study to use CAPSLPDB for 3-class sleep stages classification. Table 10 shows the novelty of this work compared to the other sleep stages classification studies. In this study 6075 samples of EEG signals were used which was lower than other reported studies using sleep-EDF database. However, it may be noted that the studies conducted using Sleep-EDF and Sleep-EDFX databases obtained the classification accuracy between 92% to 95%, while the classification accuracy obtained in this study for 3-class sleep stages classification was 90.46%. This might be due to the high sampling frequency (512 Hz) of the EEG signals used in this study which is five times higher than the other studies (100 Hz). Another reason may be the number of samples; 6075 samples were used in this study while other studies used 14,963 to 127,512 samples. Nonetheless, our proposed model was able to recognize the EEG characteristic rhythm of three sleep stages using EEG

Table 8 Model accuracies (%) and various performance values (%) for CAP detection. Performance values corresponds to test accuracy

	Accuracy (%)			Performance parameter (%)			
Dataset	Train	Validation	Test	Precision	Sensitivity	F1	Specificity
Balanced	75.93	74.43	73.64	70.96	80.29	75.34	66.95
Unbalanced	–	–	52.99	20.13	92.06	33.04	47.36

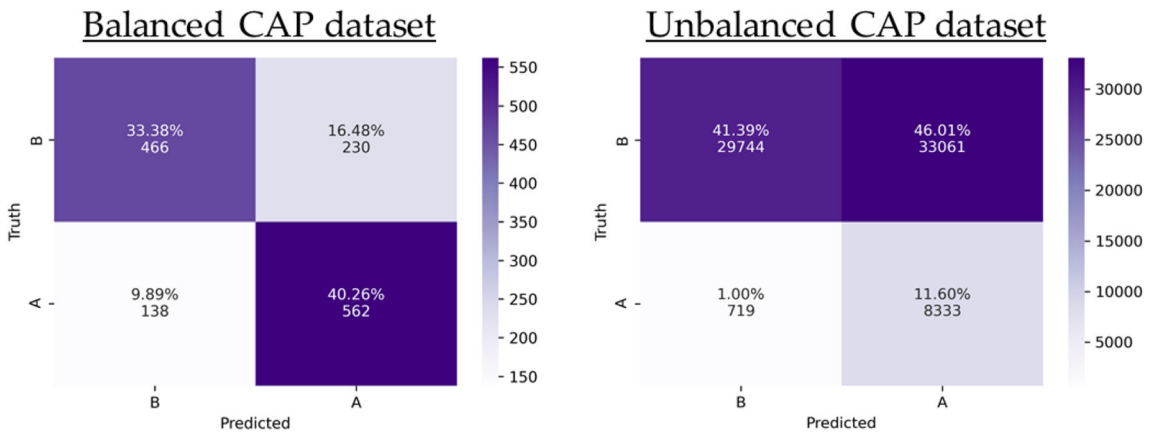

Fig. 7 Confusion matrix for test set of balanced CAP dataset and complete unbalanced CAP dataset

t9.1 **Table 9** Summary of results (%) obtained from sleep stages classification and CAP detection

t9.2 Classifications	Dataset	Accuracy	Precision	Sensitivity	F1	Samples
t9.3 Sleep stages	–	90.46	83.90	87.47	85.38	912
t9.4 CAP	Balanced	73.64	70.96	80.29	75.34	1369
t9.5	Unbalanced	52.99	20.13	92.06	33.04	71,857

signals of higher sampling frequency (512 Hz) and achieved high model performance.

There are also numerous CAP detection studies which utilized EEG signals from CAPSLPDB, and they are summarized in Table 11. Our study used the same sampling frequency (512 Hz) and epoch duration (2 s) as Dhok et al. [25]. Hence, we have the same number of samples; 71,862 and 9306 for unbalanced and balanced data, respectively, as Dhok et al. [25]. Our proposed model performed marginally better in balanced dataset as compared to Dhok et al. [25]; our proposed model obtained classification accuracy of 73.64% and sensitivity of 80.29% while their proposed conventional machine learning model yielded the classification accuracy of 72.53% and sensitivity of 76.76%. However, developed model yielded higher classification accuracy of 87.45% using unbalanced dataset, as compared to our proposed deep learning model (52.99%). Despite having lower model accuracy, our proposed model obtained the highest sensitivity score of 92.06% using standardized EEG signals with unbalanced dataset. Our proposed model correctly identified the minority A-phases (12.6% of unbalanced dataset) better than the other studies as shown in Table 11.

To date, only Hartmann et al. [40] have proposed deep learning model based on LSTM using EEG signals sampled at 128 Hz sampling frequency. Hence, this study is the first to employ deep learning model based on 1D-CNN for

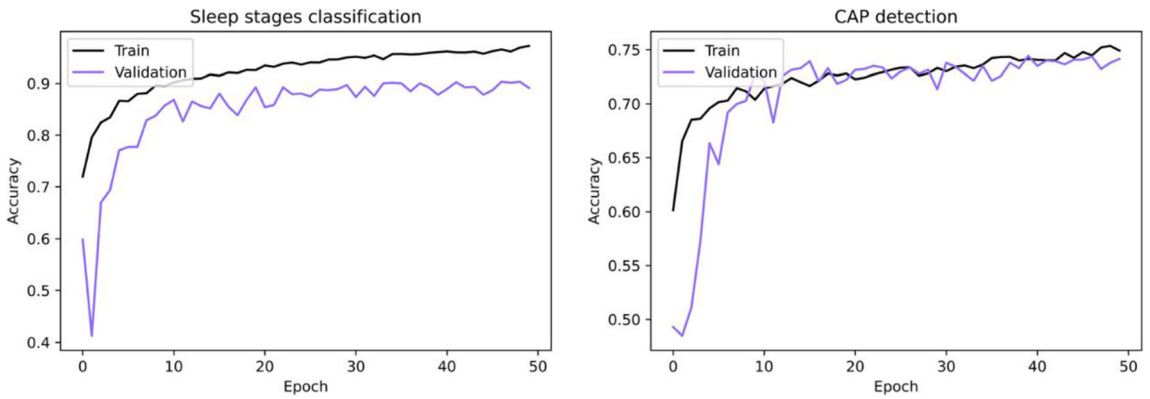

Fig. 8 Performance graph (model accuracy) of sleep stages classification and CAP detection during model training

Table 10 Summary of automated sleep stages classification studies that uses 3 classes (W, NREM, and REM)

Author	Database	Sampling frequency	Approach	No. of samples	Accuracy (%)
da Silveira et al. [44]	Sleep-EDFX	100 Hz	DWT+RF	106,376	93.90
Yildirim et al. [38]	Sleep-EDFX	100 Hz	1D-CNN	127,512	94.23
Hassan et al. [45]	Sleep-EDF	100 Hz	EEMD+RUSBoost	15,188	94.23
Hassan et al. [46]	Sleep-EDF	100 Hz	CEEMDAN+ Bagging	15,188	94.10
Zhu et al. [47]	Sleep-EDF	100 Hz	HVG+SVM	14,963	92.60
Sharma et al. [48]	Sleep-EDF	100 Hz	Wavelet filter+SVM	15,139	93.50
Yildirim et al. [38]	Sleep-EDF	100 Hz	1D-CNN	15,188	94.20
This work	CAPSLPDB	512 Hz	1D-CNN	6075	90.46

CAP detection using EEG signals of 512 Hz sampling frequency.

In addition, conventional machine learning models require features to be extracted from the PSG recordings, and the model may overfit if high dimensional PSG recordings are used to train the model [53, 54]. However, feature extraction may result in information loss as PSG recordings are converted to a lower-dimensional feature vector [53]. Also, the feature extraction procedure is done manually which is more tedious, subjective and laborious [55]. Therefore, our proposed deep learning model successfully addressed these limitations by eliminating the need for feature extraction.

The notable aspects of our proposed model are given as follows:

- The same layer parameters and hyperparameters were used for both 3-class sleep stages classification and CAP detection, and high model performance was achieved.
- The proposed model was able to capture the EEG characteristic rhythms of three sleep stages and CAP.
- The multifunctional CAD tool comprised of two stages. The first stage separates sleep EEG recordings into three sleep stages (W, NREM and REM) and acts as a filter to simultaneously remove W stage. Subsequently, the second stage detects CAP in NREM and REM sleep to obtain CAP rate, cycle and duration for sleep analysis.
- A completely automated system was successfully generated, thus removing the need for manual feature extraction.
- Large amount of data could be handled with minimal information loss [56].
- To the best of our knowledge, this is the first automated 3-class sleep stages classification study developed using EEG signals obtained from CAPSLPDB dataset. Furthermore, most of the automated CAP detection studies were done using lower sampling frequency as shown in Table 11. Hence, this is the first study to propose a deep learning model for both sleep stages classification and CAP detection using high sampling frequency of 512 Hz. There are no related papers in

Table 11 Summary of CAP detection studies using CAPSLPDB database

Author	Approach	Sampling frequency	Datasets	Performance parameter (%)		
				Accuracy	Specificity	Sensitivity
Mendez et al. [39]	KNN classifier	100 Hz	Unbalanced	80.00	80.00	70.00
Navona et al. [49]	Thresholding	128 Hz	Unbalanced	77.00	90.00	84.00
Mariani et al. [50]	ANN classifier	100 Hz	Unbalanced 240,429	87.19	90.49	69.55
Mariani et al. [51]	SVM, LDA, AdaBoost and ANN	100 Hz	Unbalanced	84.90	86.60	72.50
Mendonça et al. [52]	Feed Forward Neural Network with Finite State Machine	–	Unbalanced (≈ 50,000)	79.00	80.00	76.00
Hartmann et al. [40]	Variable LSTM	128 Hz	Balanced and unbalanced	82.42	83.90	75.28
Dhok et al. [25]	Wigner-Ville based entropy features	512 Hz	Balanced A-phases: 4653 B-phases: 4653	72.53	69.19	76.76
			Unbalanced 71,862	87.45	52.09	87.75
This work	1D-CNN	512 Hz	Balanced A-phases: 700 B-phases: 696	73.64	66.95	80.29
			Tested with unbalanced data (71862)	52.99	47.36	92.06

this topic for us to do a fair comparison with due to the novelty of our work.

The limitations of this study are as follows:

- Elimination of noise is extremely challenging, especially in unbalanced CAP dataset as B-phases comprise of 87.4% of the dataset. For this reason, the proposed model was not trained with unbalanced CAP dataset because of the overwhelming number of samples in B-phases had generated data noise that causes our proposed model to predict every sample as B-phases, thus hindering the detection of A-phases.

5 Future work

Our proposed work can be extended in the following ways:

- Consider other physiological signals like electrooculogram (EOG) and electromyogram (EMG) recordings for 3-class sleep stages classification.
- Develop hybrid deep learning models such as the combination of CNN and LSTM for CAP detection since LSTM is known for its ability to learn and predict patterns in sequence.
- Build a cloud-compatible deep learning system so that the CAD tool can conveniently access the required data and apply it immediately.
- Real-time PSG recordings will also be considered for wearable devices that use real time data to track sleep.

6 Conclusion

In this study, we proposed a deep learning model based on 1D-CNN for 3-class sleep stages and CAP detection, using EEG recordings of a high sampling frequency (512 Hz). The proposed model consists of multiple 1D-convolutional and pooling layers which will extract the salient features from EEG signals of various sleep stages and CAP. Subsequently, the extracted features are used to train the neurons in the fully connected layers for the classification of sleep stages and CAP detection. The developed model achieved good model performance for sleep stages classification, yielding an accuracy of 90.46%, precision of 83.90%, sensitivity of 87.47, and F1-score of 85.38%. The model yielded the classification accuracy of 73.64% for balanced CAP dataset, and 52.99% for unbalanced CAP dataset. Our proposed system obtained a sensitivity score of 92.06% using unbalanced CAP dataset due to its ability to identify 11.6% out of 12.6% of A-phases in the entire unbalanced CAP dataset. Hence, the proposed two-stage model is sensitive to the EEG characteristic rhythms of both macro-and micro signatures of sleep EEG signals. The first stage breaks down sleep EEG signals into 3 sleep stages and the second stage respective sleep stages are identified automatically. However, the proposed model need to be tested with more data before the clinical application. In future, we intend to improve the model performance by using electrooculogram (EOG) and electromyogram (EMG) recordings for sleep stages classification.

Author contributions All authors contributed to this article. The idea for the article was provided by HWL and URA. SGD provided MATLAB code for data preparation. HWL developed and the model and drafted the first manuscript. Subsequently, CPO, SGD, MS, AAB, and URA edited the manuscript and provided suggestions to improve the manuscript.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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AUTHOR QUERIES

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Q1. Biography and photo are desired. Please provide if necessary.
Q2. Please check if the provided cities are correct and presented correctly.
Q3. Please check if all tables are correctly presented.