



Sleep Apnea Events Detection Using Deep Learning Techniques

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Abstract

This research underlines an automated approach for detecting sleep apnea events from sleep studies. The Polysomnogram test is the gold standard for diagnosing sleep apnea. Unfortunately, it is expensive, time-consuming, and uncomfortable for patients. We selected signals that can be simply obtained by using a portable fingertip pulse oximeter and hexoskin smart shirt. Hence, the cost of polysomnography will be reduced by utilizing less equipment and sufficient at the same time. Therefore, the scientific value of this research is to simplify the used ways by other sleep experts in this field. Two sleep apnea databases were used to train and test four deep learning models. Three physiological signals were combined to form one window of 60 seconds in size. Deep learning approaches were proved to be sufficient in detecting apnea events depending on data quality and the neural network architecture. The hybrid model outperformed other models with 97% and 92% of accuracy.

Keywords: Sleep apnea; Polysomnography; Deep learning

Introduction

Sleep apnea is a respiratory-related disease where breathing pauses and repeatedly starts during sleep. It occurs when either the airway collapses or the brain cannot successfully send the signal to the breathing muscles. There are two main cases for sleep apnea; Obstructive Sleep Apnea (OSA) and Central Sleep Apnea (CSA), which in no air comes in or out of the lung for few seconds to minutes and can, happen about 30 times or more per hour [1]. Hypopnea is a partial blockage of the airway with at least a 30% decrease in airflow enduring at least 10 seconds and with 3% oxygen desaturation [2]. Neglecting the treatment of sleep apnea leads to severe diseases, such as high blood pressure and heart attack [3].

Polysomnography (PSG) is used to diagnose the patient who spends an entire night or more in a sleep laboratory. PSG is often ambulatory, so patient can sleep at home. However, sleeping in the lab may occur

uncomfortable because of the connection of the electrodes with different positions of the body [4]. Physiological signals are divided into two categories: Simple signals measured by sensors that are integrated into smart wearable devices and complex signals obtained by professional tools while transferred to user devices. The simple signals are the heartbeat and snoring, whereas the complex ones include Electrocardiography (ECG), Electroencephalography (EEG), Electromyography (EMG), Electrooculography (EOG), Oxygen Saturation (SpO₂), Nasal airflow, and blood pressure. sleep experts' diagnose this disease by monitoring and analyzing these signals during the total time of sleep. The current treatment is the titration of continuous positive Airway Pressure (CPAP), Bilevel Positive Airway Pressure (BiPAP) and Adaptive Servo Ventilation (ASV). They control the airway and keep it open continuously [5]. This study aims at determining whether deep learning can detect sleep apnea events from any PSG. This will add value to future researches.

Literature review

Many researchers conducted studies on sleep apnea events detection differently. Some of them used feature engineering with traditional machine learning methods whereas others adapted deep learning techniques [6]. Demonstrated Long Short-Term Memory (LSTM) with a single ECG signal. The apnea diagnosis was carried out on the characteristics derived from the Heart Rate Variability (HRV) tests. Long Short-Term Memory (LSTM) was chosen to report the time based dependency in HRV data, as one of the critical aids of LSTM is the capability to use the prior situation Suggested using LSTM to detect the OSA severity by using one feature Instantaneous Heart Rate (IHR) alone [7]. Then, by adding an extra feature, which is the SpO₂. Many physicians applied this technique to their patients [8-10]. Reported Convolutional Neural Network (CNN) architecture to detect apnea with different trials. First, they used the nasal airway signal to equate CNN to Support Vector Machine (SVM). Later, the 2D spectrogram images of the nasal airflow signal with the raw 1D nasal airway signal were used to apply a different strategy. Their results adapted using three separate signals; nasal airflow, abdominal and thoracic. Urtnasan used a single ECG signal with CNN, LSTM, and Gated Recurrent Unit (GRU) techniques. They recorded high performance [11,12]. However, they could have proved that by using multisignal generalized the study by training the RCNN model on MGH data and testing it on SHHS data, though this approach lacked accuracy. Li proposed a novel approach for improving accuracy by integrating the Hidden Markov Model (HMM) with Deep Neural Network (DNN), while adopting the fusion decision algorithm to boost overall performance [13]. Nesaragi proposed an LSTM model consisting of two stages while neglecting the SpO₂ signal [14]. They discovered the strong point of using instantaneous frequency and spectral entropy features for the detection of arousals. Islam proposed another way of detecting sleep apnea using 3D scans while using predefined models in transfer learning to beat the limitation of the small data set. Their results illustrated the connection between facial morphology and OSA. Wang developed an improved LeNet-5 convolutional neural network with ECG segments for sleep apnea detection [15]. The use of transfer learning models has proved useful and promised. Mahmud referred to low performance caused by the data's lack. They used EEG signals composed of only seven different apnea patients [16].

Material and Methods

This part illustrated the utilized sleep apnea databases and the used deep learning algorithms with the performance metrics of this study.

Sleep apnea databases

Two sleep apnea databases from PhysioNet are used for this study [17]. These datasets are "You Snooze You Win Database" was a target at the PhysioNet/Computing in cardiology challenge 2018 is provided by the Massachusetts General Hospital (MGH) Computational Clinical Neurophysiology Laboratory (CCNL) and the Clinical Data Animation Center (CDAC) [18]. It includes 1,985 patients for the detection of sleep disorders obtained in an MGH sleep laboratory. They split the database into 994 folders as a training set and 989 folders as a test set. Certified sleep technologists at the MGH labeled the database according to the existence of arousals. These derived arousals were either classified as: Respiratory Effort-Related Arousals (RERA), spontaneous arousals, hypoventilation, bruxism, hypopneas, apneas (central, obstructive, and mixed), vocalizations, snores, periodic leg movements, breathing cheyne stokes or partial airway obstructions [19]. The database includes two directories (training and test). Each directory contains one sub-folder per patient. Every subfolder includes signal, header, and arousal files. Test sets are unlabeled. Therefore, we were unable to use them in the testing. Records in the database were taken from different persons in both sex and age.

This challenge's database "Apnea-ECG Database (Challenge 2000)" includes 70 records, divided into two equal parts, 35 records as a training set (a01-a20, b01-b05, and c01-c10), and 35 records as a test set (x01-x35) [20]. Only the learning sets were annotated. Each record includes signals, headers, and other data. Besides, eight records (a01, b01, c01, a02, c02, a03, c03, and a04) are followed by four additional signals (CHEST, ABD, Nasal Airflow, and SpO2). Three of them were used for further testing [21]. Figure 1 shows the approach of sleep apnea events detection.

Deep learning techniques

Long Short-Term Memory (LSTM): Hochreiter and Schmidhuber initially suggested Long Short-Term Memory (LSTM) expression in 1997 [22]. LSTM is a kind of Recurrent Neural Network (RNNs), and it became very popular in recent years due to its significant performance and in solving the vanishing gradient problem. LSTM overcomes that by imposing fixed error flow. It clearly learns when to save the information and when to retrieve it using gradient descent. LSTM has distinct elements in the recurrent hidden layer, called memory blocks. These blocks provide memory cells with self-connections to preserve the network's time based state as well as different multiplicative units called gates to alter information flow [23].

Each memory block within the interior architecture consists of three types of gates, as shown in Figure 2, which are specifically:

Input gate: It dominates the quantities that go into the cell of the new value.

Output gate: It considers the input at time t, the prior hidden state, and the present value of the cell.

Forget gate: It dominates the ex-cell value quantities that go into the present cell value.

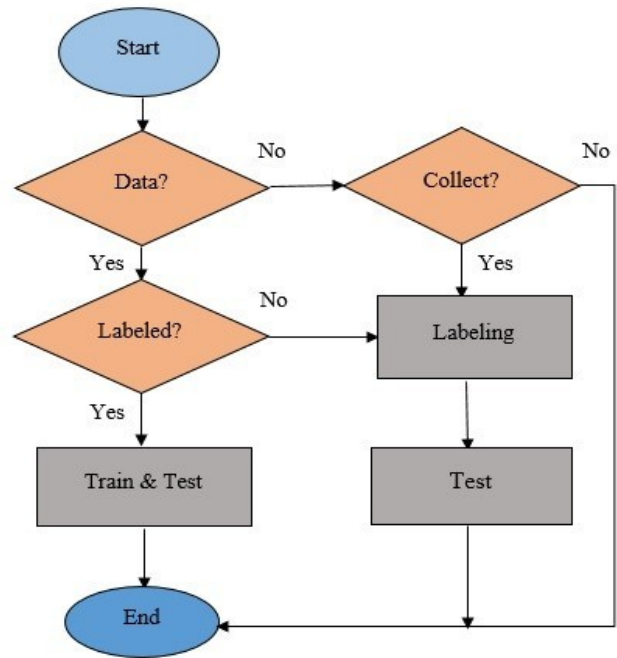


Figure 1: Sleep apnea events detection approach.

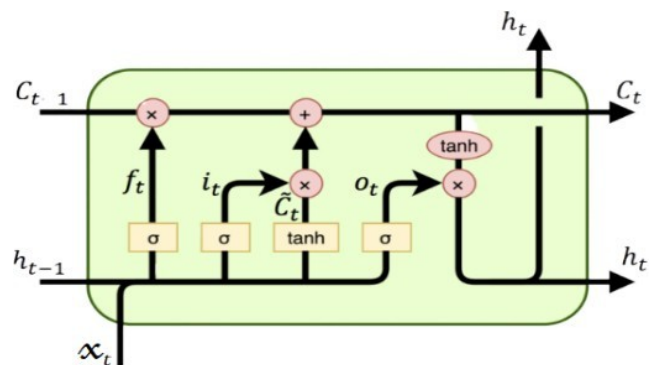


Figure 2: LSTM memory block, where f_t , i_t , and o_t represent the forget, input, and output gates, respectively. c_{t-1} and c_t represent the memory cell and the content of the new memory cell.

The memory cell in an LSTM network works as a single unit within the hidden layer of traditional networks. The formulas are given in the following equations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \dots\dots\dots (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \dots\dots\dots (2)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \dots\dots\dots (3)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \dots\dots\dots (4)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \dots\dots\dots (5)$$

$$h_t = o_t * \tanh(C_t) \dots\dots\dots (6)$$

Gated Recurrent Unit (GRU): Many similar concepts, but it has a much smaller set of parameters so that it can be trained more quickly at a sustained hidden layer size. Some researches illustrated that the accuracy between LSTM and GRU is comparable and even better with the GRU in some cases. GRU includes the same internal structure of LSTM, but the memory cell consists of two gates rather than three, as shown in Figure 3, which are namely:

Update gate: It also compares how much of the hidden value of the previous candidate and how much of the hidden value of the current candidate combines to get the new hidden value.

Reset gate: It controls how much of the previous hidden state is considered when the new candidate hidden value is created. In other words, it can “reset” the hidden value.

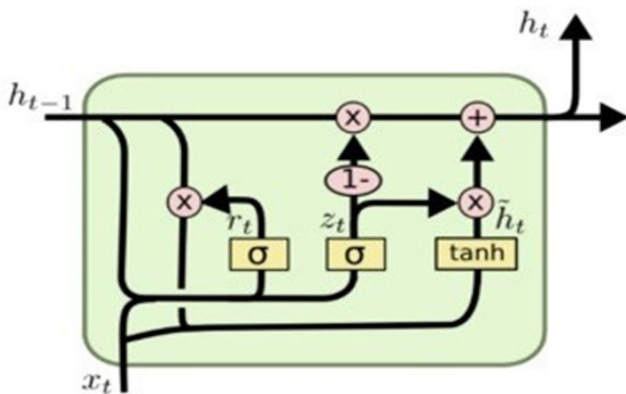


Figure 3: GRU memory block, where r_t and z_t denote the reset and update gates, and h_t and \tilde{h}_t denote the activation and the candidate activation.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \dots \dots \dots (7)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \dots \dots \dots (8)$$

$$\tilde{h}_t = \tanh(W_h \cdot [r_t * h_{t-1}, x_t] + b_h) \dots \dots \dots (9)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \dots \dots \dots (10)$$

Residual Network (ResNet): Residual Network (ResNet) is a pretrained deep neural network model used in many tasks like prediction and feature extraction, or being fine-tune to a specific case. Transfer learning is wisely using the knowledge acquired earlier from different missions or issues to mitigate new problems quicker [24]. ResNet50 model was used as the pre-trained model for sleep apnea events detection by eliminating the predicting layer and substituted it with our binary predicting layer. Weights of the first few layers were untouched or updated during the training because they save general information like curves and edges. Instead, we made the network to emphasis on learning specific features in the subsequent layers [25].

Hybrid model: It consists of the ResNet50 architecture with two RNN layers. One GRU layer comes after the input layer, and one bidirectional LSTM layer comes before the output layer.

Performance assessments: The test set includes samples that have never been seen before by the algorithm. Therefore, if the model

performs well in predicting, it can be assumed that it is generalizing well. We used the following metrics for assessing the classification model:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \dots \dots \dots (11)$$

$$Precision = \frac{TP}{(TP+FP)} \dots \dots \dots (12)$$

$$Recall = \frac{TP}{(TP+FN)} \dots \dots \dots (13)$$

$$F1 - score = \frac{(2 * Recall * Precision)}{(Recall + Precision)} \dots \dots \dots (14)$$

Results

Some standard python packages were used to access physionet. They were also used to display and prepare signals for apnea events detection. We used the WFDB API package for remote access instead of downloading the training set for data preprocessing [26]. We obtained 13 physiological signals in each PSG. Signals were measured in microvolts, excluding oxygen saturation (SpO2), which was measured as a percentage. We selected three signals (ABD, CHEST, and SpO2) and dropped the rest from our estimations. ABD and CHEST refer to abdominal and thoracic belts, respectively. An apnea events dictionary was created, containing only apnea labels [27]. All labels for apnea/stages were pulled from PhysioNet and combined with those three signals. They were loaded into a data frame, and then the apnea events dictionary that we created was mapped with the same data frame. Hence, other unused labels (sleep stages) in that dictionary were shown as missing values. Therefore, they were replaced by zero [28]. Labels are finally encoded into the one-hot array.

We used google collaborator as a free cloud service based on jupyter notebooks for implementing this task. Colab gives 12 GB of RAM and increases it up to 25 GB after runtime if required [29]. We downloaded the training set of the YSYW database directly, but in multistages to avoid RAM crashing. The figures illustrate the CHEST signal annotated by an obstructive apnea and the raw targeted signals before preprocessing (Figures 4-7).

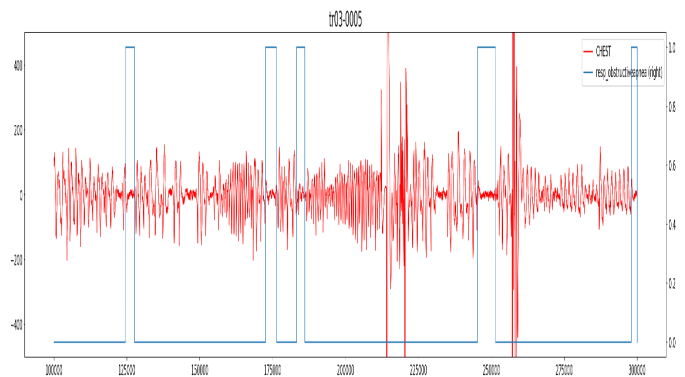


Figure 4: CHEST signal of patient tr03-005 annotated by an obstructive apnea. **Note:** — CHEST; — resp_obstructive apnea (right).

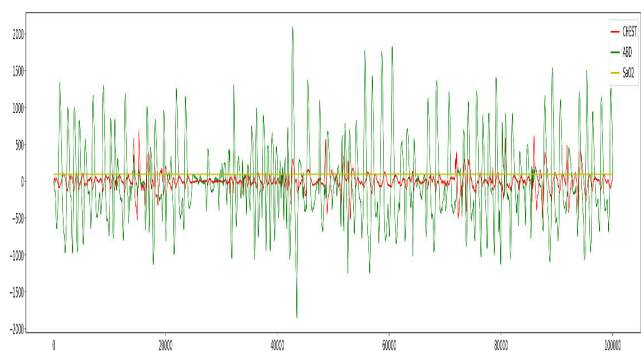


Figure 5: Signals (before preprocessing). **Note:** — CHEST; — ABD; — SaO₂

Signals where SpO₂ is below 50% were removed because there is a possibility that the connection with devices would be lost [30]. The sampling frequency was resampled to 100 Hz because 100 samples per second are enough to use. The imbalanced problem between apnea and normal classes was fixed by under sampling. Finally, we reshaped signals into intervals with a fixed length [31]. We applied the minimum-maximum method to scale data between 0 and 1 for normalization according to equation 15. Figure 6 shows the final shape of signals before using them for the task of apnea events detection (Table 1) [32].

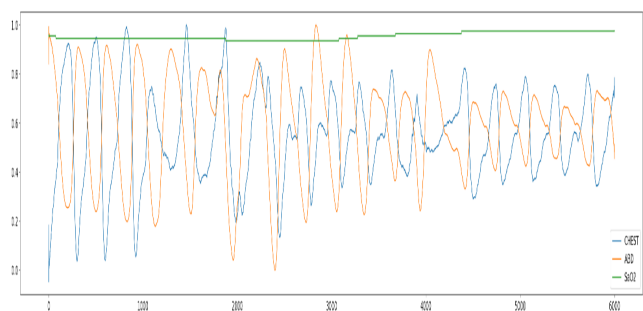


Figure 6: Scaled signals (after preprocessing). **Note:** — CHEST; — ABD; — SaO₂

Several techniques were chosen for comparison according to their performances. LSTM and GRU models included four LSTM and GRU

layers, respectively. Each has 30, 60, 120, or 200 memory cells followed by batch normalization and dropouts to avoid over fitting. For classification, we used one fully connected layer at the output layer. ResNet50 model included 48 convolution layers, one maxpool layer, and one average pool layer. Convolution layers related to different kernel size and activation functions. An average pool layer followed by a fully connected layer containing 1000 nodes with softmax function at the end.

We extracted 39209 windows from the test set of the YSYW database, which represents the last 91 patients of the training set. Besides, we also extracted 2849 windows from the test set of the Apnea-ECG database, which represent only eight patients who have signals of ABD, CHEST, and SpO₂. These windows were gathered from every patient's data. Each window was formatted as a 1×6000 . The mathematical meaning of this representation is that the size of the sampling window, which is 60 seconds, was multiplied by the size of the sampling frequency. The amplitude of the signals was normalized between 0 and 1. In the training phase, we divided the PSG data of each patient into short intervals and shifted these intervals for data augmentation. The best validation accuracy started to be stable beyond 700 epochs of training [33]. The batch size was taken as 32 because a big batch size would lead to poor generalization and lower test accuracy. We applied more than one deep learning model in order to compare the prediction and generalization performance with other methods. According to Tables 1 and 2 it can be concluded that the hybrid model gives the best results in both databases with an overall accuracy of 97% and 92%. GRU model comes next with an overall accuracy of 92% and 91%.

Discussion

Considering the results that we obtained in this study; we could say that deep learning has given high performance in this task. The four deep learning techniques, including LSTM, GRU, ResNet-50, and the hybrid model, were structured and evaluated according to several metrics. In practice, we found that models obtained by using only one signal from the PSG study cannot be generalized for further use because the symptoms are likely to vary based on the physical variations in patients. Consequently, it was discovered that using more than one signal gives the chance to catch a higher number of abnormal events. We used the per window method in generating

Databases	Models	True positive	True negative	False positive	False negative
YSYW	LSTM	8507	25473	2715	2514
Apnea-ECG	LSTM	1402	1065	209	173
YSYW	GRU	9507	26622	1715	1365
Apnea-ECG	GRU	1195	1410	155	89
YSYW	ResNet50	9067	23906	2980	3247
Apnea-ECG	ResNet50	1219	1183	257	190
YSYW	Hybrid	10433	27433	1004	329
Apnea-ECG	Hybrid	1440	1193	174	42

Table 1: Confusion matrices parameters of our models applied to the YSYW and Apnea-ECG databases. Note: 0: Normal and 1: Apnea.

Databases	Signals	Models	Train Subjects	Test Subjects	Accuracy (%)	Precis (%)	Rioencall (%)	F1-score (%)
YSYW	ABD CHEST Spo ₂	LSTM	900	91	87	76	77	76
pnea-ECG	ABD CHEST Spo ₂	LSTM	-	8	87	87	89	88
YSYW	ABD CHEST Spo ₂	GRU	900	91	92	85	87	86
Apnea-ECG	ABD CHEST Spo ₂	GRU	-	8	91	89	93	91
YSYW	ABD CHEST Spo ₂	ResNet50	900	91	84	75	75	75
Apnea-ECG	ABD CHEST Spo ₂	ResNet50	-	8	84	83	87	85
YSYW	ABD CHEST Spo ₂	Hybrid	900	91	97	91	97	94
Apnea-ECG	ABD CHEST Spo ₂	Hybrid	-	8	92	89	97	93

Table 2: Results of comparison between different deep learning models in sleep apnea events detection.

signals and detection of apnea events. Some researchers used the per-record method. They computed the Apnea Hypopnea Index (AHI) for some windows in order to obtain a record that is classified as having normal, mild, moderate, or severe apnea. Nesaragi also used the YSYW database in a different way of us [25]. First, they focused on arousal and non-arousal events. EEG signals must be used to detect arousal events. Hypopnea and arousal events can only be distinguished with EEG signals. Second, the evaluation was not based on precision or accuracy. They opted for AUROC instead and obtained low performance. They did not discuss the internal architecture of the LSTM model [34]. They trained two layers of Quadratic Discriminants (QD), which were connected to several LSTMs. Then, the output of the trained QD layers was averaged to get the final prediction. The YSYW database was not used previously for apnea events detection, which reflects our novelty and uniqueness of the results. Also, none of previous researches make use of the same group of signals that are used. However, most previous researchers preferred to use the Apnea-ECG database. Another new point of this study, learning parameters of trained models is transferred directly instead of training from scratch [35]. Finally, the window's size, which represents the input data, is a vital feature for increasing or decreasing the performance of the system. A window of size 30 seconds might give better results because more than one apnea might occur during one minute. That is what Pomprapa emphasized in their paper [36].

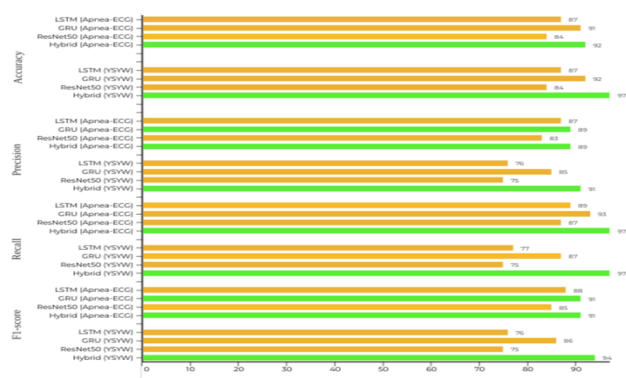


Figure 7: Evaluation metrics of our models applied to the YSYW and Apnea-ECG databases.

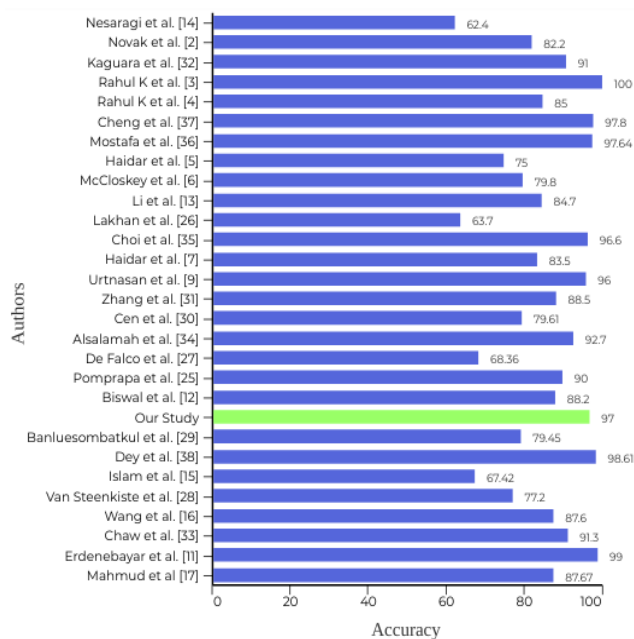


Figure 8: Comparison between our study's results and other results of relevant studies in accuracy.

Conclusion

Sleep apnea syndrome is a serious disease with complaints that cannot be relieved without treatment. The cost and time of diagnosis are exorbitant. Hence, deep learning techniques can be used in this field to provide the necessary solutions. The trained model of this study can be reused in a sleep lab or home test. The patient can collect the same data by using sensors, which can be easily obtained. On the other hand, sleep technologists can also compare their diagnosis with the predicted diagnosis to improve accuracy. The classification of sleep stages is very important for researchers. Sleep stages are obtained by analyzing EEG signals that illustrate brain activity, considering its importance in diagnosing other diseases like epilepsy. EEG can determine whether a person is asleep or awake during the sleep apnea test. Collecting labeled patient's data is a critical problem that faced

researchers in this field because one PSG needs one day to be labeled by a sleep technician.

Compliance with Ethical Standards

This type of study does not require informed consent.

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