REAL-TIME ASSESSMENT OF OBSTRUCTIVE SLEEP APNEA USING DEEP LEARNING

by

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THESIS

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The University of Texas at Dallas, 2021

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Sleep quality assessments provide various measures to gauge the severity of Sleep Apnea. In the present, sleep quality testing is inconvenient for the patients in terms of both money and a comfortable environment. Evaluation methods like the Polysomnography test require many sensing resources. Our research proposes an inexpensive and an automated system based on Single-lead Electrocardiogram (ECG) signal and a one-dimensional Convolutional Neural Network classifier (CNN). We use only a single-channel ECG to measure the heart signal and deliver them to an 1D-CNN to classify for apneic events. This method provides an alternative to the cumbersome and expensive Polysomnography (PSG) and scoring by Rechtschaffen and Kales visual method. In addition to this, we propose an Android application that uses a Deep Neural Network model that we have trained to use in real assessment of Obstructive Sleep Apnea.

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CHAPTER 1

INTRODUCTION

In this chapter, first, we will briefly discuss information about sleep and why sleep is necessary. Second, we will discuss what sleep apnea is, especially Obstructive Sleep Apnea (OSA), and know how it prevents sleep quality. Third, we will discuss the standardized tool for diagnosing OSA, named the Polysomnography test. Finally, we see the problems the user face during this test thus motivating us to do this study.

1.1 Sleep

Sleep is a natural state of mind that limits our consciousness and all our voluntary muscle activities. It helps to charge ourselves by detaching us from day-to-day interactions with our surroundings. Usually, the night is preferred to be the time for sleep, although night shift workers sleep during the day. Whatever the time a person sleeps, our body requires rest to fuel up where all our muscles and organs start repairing themselves.

Researchers have performed many studies to understand the sleep in humans. However, we are still far from knowing 100% of all about the core functionality of sleep. But we do know that resting helps to reorganize our mood and memory. Also, it helps to maintain our cognitive function. This rejuvenation is possible because sleep restores our immune, memory, and nervous systems. These systems are vital, and they collaborate to help us perform our activities in all professional or social settings.

There are two essential parameters to attain the restoration. First, maintaining the minimum hours of sleep. According to the center for disease control and prevention [39], keeping rest for 10 to 16 hours per night at an earlier age of human life is recommended. As we progress in our human development, the recommended hours reduce, and at our later age a minimum of 7 hours of sleep should be maintained. Another parameter of concern is the quality of sleep. Just maintaining minimum hours of sleep is not good enough and the quality of sleep is crucial. The better the quality of sleep, the better we can manage our cognitive functions. Unfortunately, not everyone can get the best quality of sleep because of sleep disorders like insomnia, hypersomnia, or sleepwalking. Sleep Apnea is also a sleep disorder.

Sleep Apnea is considered a potentially dangerous disorder. It affects the oxygen saturation in the blood due to intermittent breathing. Sudden drops in oxygen levels, increase blood pressure and strain in our cardiovascular system, leading to severe complications like hypertension and heart problems. Other complications include daytime fatigue, type-2 diabetes, and liver problems. The sleep apnea can be classified into three types, Obstructive, Central, and Complex sleep apnea. In Central Sleep Apnea (CSA), the brain forgets to send a signal to our muscles responsible for breathing, leading to oxygen desaturation. This epoch is very short, but the person will have a difficult time sleeping. Complex Sleep Apnea is the combination of Central Sleep Apnea and Obstructive Sleep Apnea. These two are rare cases and are not in the scope of this study. On the other hand, Obstructive Sleep Apnea (OSA) is very common.

1.2 Obstructive Sleep Apnea

According to an article published in Respirology [40], almost 1 billion people worldwide are suffering from OSA. The USA contributes 14.5%, i.e., 24 million people in the USA are suffering from OSA, which is considerable. Obstructive Sleep Apnea, as the name suggests, cause blockage in the airway. During sleep, the muscle behind the throat relaxes, which causes the blockage of intake of oxygen in the body. As soon as the brain realizes the low oxygen level in the blood, it sends a signal to the muscle that rouses the person to open the airway. The blockage period is normally minimal, and the person would not recognize it while sleeping. However, one can encounter100-200 such episodes per night, depending upon the severity of OSA. Thus, we see a hindrance in the quality of sleep. Because of this interference in sleep, a person undergoes daytime fatigue, remains inactive, and cannot concentrate the next day. Road accidents are also one of the dangerous outcomes of the bad quality of sleep.

Various treatments for sleep apnea are available and are prescribed according to the severity of OSA. The minor OSA conditions can be resolved by weight reductions or change of sleep position. Moderate OSA patients use continuous positive air pressure (CPAP), where continuous supply of air is maintained by controlled pressure using an overhead device. Another treatment for sleep apnea is surgery which is rare but prescribed for severe OSA. In order to get a prescription for treatment, the patient should get diagnosed first. The current diagnosis test for sleep apnea is a Polysomnography test. It is good to take the Polysomnography test if awaken by choking many times in the middle of the night or gasping while sleeping because they are OSA symptoms. Another symptom is loud snoring. Sometimes people will neglect these symptoms by considering it as a normal thing. It should also be noted that it does not mean that every person who snores would have OSA.

1.2.1 Polysomnography

Polysomnography test is the traditional method available to get diagnosed for sleep apnea. This test requires various bio-signal sensing devices to examine the patient. Hence, the test is done in a well-equipped lab or sleep center in hospitals. The test records bio-signals like brain waves, blood oxygen level, body posture, heart rate, breathing rate, and eye and leg movements. The doctor then uses these recorded signals to evaluate the patient's sleep pattern. It is a comprehensive test for OSA assessment; however, the doctor will also recommend this test for suspected periodic limb movement disorder. To perform this test, the user needs to be present at night in the sleep center. For night shift workers, who habitually sleep during the day, the hospitals will make the accommodation accordingly. The test is run the whole night to understand and record the sleep patterns of the user. Thus, specialized personnel are required to be present to examine the whole process. This staff member helps the user to get connected with all the electrodes and signal collection devices and create a calm environment that helps the user to get sleep. The staff will also examine the user's body posture during sleep and records any outlier.

1.3 Motivation

Though Polysomnography is a standardized tool for accurate assessment of OSA, it has its own significant disadvantages. In order to access all the bio-signals, it is necessary to attach multiple electrodes for each signal on the user's body, as shown in Figure 1.1. A minimum of 14 electrodes are needed to be attached to record signals for the evaluation of the patient. This creates anxiety for the patient. In addition to this, the test as a whole is a very uncomfortable experience. The patient has to attach all the electrodes to the body and sleep at night away from home. Furthermore, it is possible to have a minor skin infection because of the adhesive used to fasten electrodes. Besides all of this, the Polysomnography test is expensive. The average cost is around $1000 - $2000 per night study. Moreover, it is labor intensive, and is prone to error. As mentioned earlier, expert staff is required to attend to the test and to monitor the evaluation process. This motivates the necessity to formulate an alternative method that is simpler to evaluate the user. In this thesis, we have proposed a 1D-CNN model and a mobile application that will help to ease the difficulties faced in Polysomnography. We have developed an 1D-CNN model for the Apnea prediction and used the pre-trained weights of this model in our proposed mobile application. This application will support the real-time assessment of Obstructive Sleep Apnea.

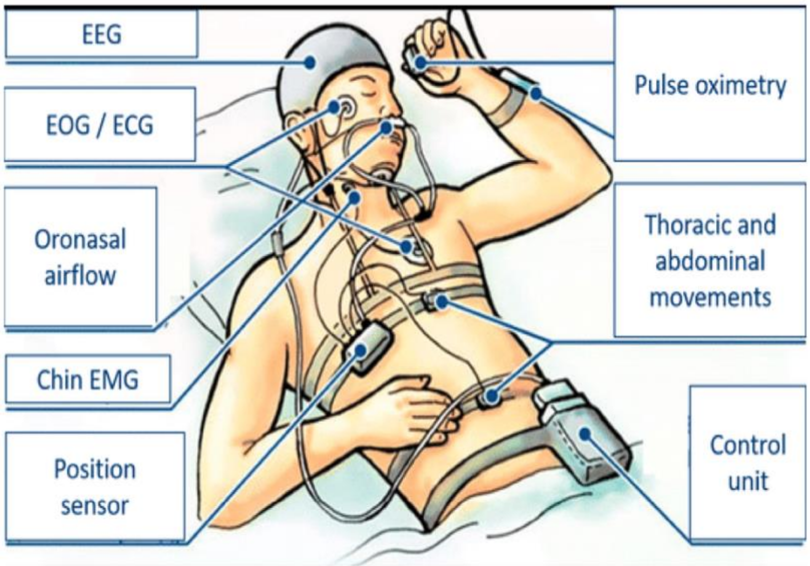

Figure 1.1. Polysomnography test recording

CHAPTER 2

RELATED WORK

This chapter provides a review of the existing literature in the automated assessment of Obstructive Sleep Apnea. We will review techniques that are based on Machine Learning and Deep Learning methods.

2.1 Machine Learning based methods

To minimize the number of channels required to access bio-signals, researchers have performed various studies. The researchers have selected one bio-signal and tried to find some features that will help to classify the apneic events. Various signals chosen by the researchers are ECG [3-5], SpO2 [3, 6, 7], respiration [3, 8], and snoring [3, 9, 10]. Signals like ECG [3-5] and SpO2 [3, 6, 7] are favorable because of more relevant features. In addition to this, there is an indirect effect of sympathetic and parasympathetic tone. These studies used feature reduction/selection routines, such as PCA analysis or other statistical evaluation procedures, to minimize the number of features. After the required preprocessing steps, the chosen features are then used in a machine learning algorithm to discriminate between apneic and non-apneic events.

2.1.1 Support Vector Machine

Support Vector Machine (SVM) is one of the machine learning algorithms used in OSA classification. Many researchers used this technique in their studies.

In the study [29], researchers used the Sleep Heart Health Study database, which contains 50 OSA and 50 regular patient data. They have selected respiratory signals, heart rate variability and oxygen saturation and extracted features from these signals. [29]. Then used the SVM algorithm to discriminate OSA and regular events by using linear and second-order kernels [29].

The study reported in [31] used the Apnea-ECG dataset from the Physionet database [16]. This study uses ECG signals and decomposes the signals into six wavelet sub-bands. They proposed an optimal biorthogonal antisymmetric wavelet filter bank (BAWFB) to perform this breakdown. Furthermore, the study uses these sub-bands to extract features from the fuzzy-entropy and log-energy domains. Finally, this study uses the least squares support vector machine (LS-SVM) algorithm with Gaussian, quadratic, and cubic kernel functions to perform the classification.

In a study reported in [17], they used the Physionet Apnea ECG dataset [16]. Using ECG signal, the study extracted features from the time and the spectral domain for both the RR intervals and the ECG-derived respiration (EDR) signal [17]. Wavelet Transform (WT) decomposition and Fast-Fourier Transform (FFT) are the two spectral analysis methods used in this study. Overall, 111 features were extracted from both the domain. These extracted features for subject-dependent and subject independent cases were used to do automatic OSA assessment using SVM with RBF, Linear, Poly, MLP kernels.

2.1.2 Ensemble learning methods

Ensemble methods like Boosting and Bagging are another class of machine learning techniques used in OSA classification.

In a study described in [30], researchers used the St. Vincent's University Hospital/University College Dublin's Sleep Apnea Database (UCD database) [42], which is available in the Physionet database. They selected the ECG and SpO2 signals for their study, both individually and in the combined form. The study used the same feature extractions technique used in [17] for the ECG signal. Furthermore, they also extracted features from SpO2 signals. Then, used ten machine learning algorithms for evaluation and proposed combinations of algorithms for OSA analysis. The combinations included AdaBoost with Decision Stump, Bagging with REPTree, and either kNN or Decision Table [30].

The study in [32] used the Apnea-ECG dataset described in [16] and the St. Vincent's University Hospital/University College Dublin's Sleep Apnea Database (UCD database) [42]; both are available in the Physionet database. This study selected the ECG signal and used tunable-Q factor wavelet transform (TQWT) for decomposition. After this, the study extracted three statistical features from this wavelet sub-bands. Finally, the researchers used a random under-sampling boosting (RUSBoost) algorithm for the classification task [32].

2.2 Deep Learning methods

In the recent time, we see outstanding results from Deep Learning algorithms in multiple domains. Their inherent nature of extracting relevant features from the data makes them popular in studies like OSA assessment. So, many research teams proposed deep learning-based methods for automatic OSA classification.

2.2.1 Convolutional Neural Network

In a study in [27], the researchers used the Apnea-ECG dataset. The study proposed a 1D-CNN-based method for automating the OSA estimation using a single-lead ECG signal. Since the CNN will automatically extract the features, there is no external feature extraction formulation required in this study.

Similarly, studies in [3] and [11] used the single-lead ECG signal recorded from the Embla N7000 amplifier system (Embla Systems Inc., USA) located at the Sleep Center of Samsung Medical Center (Seoul, Korea). This dataset is not publicly available, according to our knowledge. These studies used 1D-CNN architecture for OSA evaluation. Although the study in [11] also proposed a 2D-CNN-based classification model,] it used short-time Fourier transformation to convert the 1D ECG signal into 2D spectrogram images [11].

2.2.2 Recurrent Neural Network

Recurrent Neural Network is again an excellent deep learning model for the analysis of time-series data. The memory units present in this architecture make them popular for sequential data.

The study in [11] also evaluated the single-lead ECG signal using their proposed RNN architectures by using the data recorded from the Sleep Center of Samsung Medical Center (Seoul, Korea) [11]. This study used the Long short-term memory (LSTM) and Gated-recurrent memory (GRU) architectures for automatic OSA estimation.

2.3 Contribution

From the above review of literature, it seems like, to use machine learning algorithms we need to perform feature extraction and reduction to improve the model's overall performance. However, extracting every relevant feature sometimes is not possible. In addition to this, feature extraction is a labor-intensive task, and it is prone to errors. Also, it requires a significant amount of domain knowledge.

On the other hand, deep learning architectures like 1D-CNN can remove the issues of feature extraction. Furthermore, 1D-CNN has less inference time than RNN, which makes them favorable in a real-time system. The RNN structures take a longer time due to gathering the temporal knowledge from their memory units. Although from the study [11], GRU architecture will provide comparable results to the CNN architecture. Nevertheless, the main essence of early inferencing makes CNN more favorable.

In this study, based on the previous CNN models that various research teams have experimented, we propose our 1D-CNN architecture that will use a single-lead ECG signal and Apnea-ECG dataset available in Physionet Database [16] for model training. In addition to this, we propose a mobile application that uses our pre-trained model to create a real-time assessment of Obstructive Sleep Apnea. This can resolve issues like anxiety, discomfort, and higher cost that are faced with traditional Polysomnography.

CHAPTER 3

REAL-TIME ASSESSMENT OF OBSTRUCTIVE SLEEP APNEA USING SINGLE LEAD ECG AND 1D-CNN

3.1 Abstract

Sleep quality assessment tools provide various measures to gauge the severity of Sleep Apnea. In the present, sleep quality tools are inconvenient for the patients in terms of money and a favorable environment. Evaluation methods like the Polysomnography test require many sensing resources. In our research, we proposed an inexpensive and an automated system for sleep apnea assessment. The system is based on Electrocardiogram (ECG) measurements and a Convolutional Neural Network classifier (CNN). We use only single-channel ECG to measure bio-signals and deliver them to 1D-CNN to classify apneic events. This method provides an alternative to the laborious and expensive Polysomnography (PSG) and scoring by Rechtschaffen and Kales visual method. In addition to this, we propose an Android application that uses our trained model to provide a real-time Sleep Apnea assessment.

3.2 Introduction

Sleep a natural state of mind that helps to rejuvenate the energy required to stay active in life. Center for disease control and prevention recommends having five to eight hours of sleep to be focused and active in daily life. However, having continuous sleep is sometimes impossible because of many sleep disorders. One of them is Sleep Apnea (SA), which affects the respiratory process during sleep. It includes apnea and hypopnea and is caused by recurrent episodes of reduced or absent respiratory airflow caused by upper airway collapse or another airway obstruction [11]. Depending on the cause of oxygen desaturations, the SA gets divided into two main types, Obstructive or Central Sleep Apnea. Central Sleep Apnea occurs when the brain does not send proper signals to the muscles that control breathing [1], which leads to the decrement of oxygen in the body. Obstructive Sleep Apnea (OSA) is a common form and occurs when throat muscles relax.

According to American Sleep Apnea Association, almost 22 million Americans suffer from sleep apnea, with 80% [36] from OSA. Another study from ResMed shows that nearly 1 Billion people worldwide suffer from sleep apnea. Family history, excess weight, a narrowed airway, use of alcohol and smoking, are some factors that increase the risk of OSA. Loud snoring, gasping for air during sleep, morning headaches are some of the common symptoms. OSA is a serious medical condition, and proper treatment is necessary. Handling OSA carelessly will cause major issues like high blood pressure, type 2 diabetes, liver problem, daytime fatigue. Various treatments are available for different levels of severity, like for mild OSA, change of lifestyle is needed, which includes losing weight or quitting smoking. For severe levels, recommended therapies are Continuous positive air pressure (CPAP), oral appliances, and supplemental oxygen. Recommendation of these treatments depends upon the evaluation of overnight sleep of a patient in a specialized lab. In medical terms, this process is called Polysomnography.

Polysomnography is a comprehensive test to study sleep disorders. The test is usually done in a hospital with a specially designed lab. While the hospitals performed this test at night, Polysomnography is occasionally done during the day to accommodate shift workers who habitually sleep during the day [2]. During this process, the patient is attached with electrodes to the body to record various signals. The signals include brain waves, blood oxygen level, heart rate, breathing pattern, and eye and leg movements during the study [2]. To record all these body signals, a minimum of 14 channels are required to sense these signals from the patient body. In addition to this, specialized personal is needed to be present in the lab for proctoring the entire process.

Being a standardized tool for accurate diagnosis of OSA, Polysomnography is expensive. It may cost from $600 to $5,000 (or more) for each night; the average is typically around $1,000 to $2,000 per night [37]. The patients are required to compromise with both the budget and the comforts. Sleeping with many electrodes attached to the body in an environment outside of the home in a sleep center is uncomfortable and may cause anxiety about the experience. Although the test is safe, common side effects such as skin irritation might be possible due to the adhesive used to attach test sensors. Apart from this, it is a labor-intensive test that requires the presence of a sleep specialist. The result must be interpreted by a specialist, which is very time-consuming and prone to errors [3]. Therefore, it is necessary to develop a reliable alternative to ease the entire diagnosing process of OSA.

Various studies proposed different methods to minimize the bio-signals required to detect OSA. These studies were based on signals such as an electrocardiogram (ECG) [3–5], SpO2 [3, 6, 7], respiratory [3, 8], and snoring [3, 9, 10] signals. The sympathetic and parasympathetic tone to the heart rate and systolic blood pressure [11] increases to respond to the SA event. Hence it creates an indirect effect on ECG and SpO2 signals which make them popular in various studies. The methods include extracting features from the temporal, spatial, and frequency domain from these signals. Then these features are pre-processed by principal component analysis, statistical evaluation, and wrapper methods to reduce the dimension of the feature space [11]. These studies then use state-of-the-art machine learning algorithms to work on feature space and classify the OSA episodes.

Extracting features is a labor-intensive and it requires domain knowledge. Recently we have seen the increasing popularity of deep learning due to its ability to automate the extraction of relevant features and merge the process with the classification procedure [3]. Many deep-learning algorithms have shown a performance improvement in applications related to image and speech recognition [3, 12, 13], natural language processing [3, 14], and biomedical engineering [3, 15]. Convolutional Neural Networks (CNNs) are designed to proceed input data, such as two-dimensional images with RGB color channels [3, 26] and one-dimensional (1D) biological signals with single-channel vital signs [3, 27] as multidimensional arrays. In addition to this, studies like [3],[11], and [27] proposed a method to use CNN for the assessment of SA. Based on these studies, our research advances these 1D-CNN-based methods by using a single channel ECG recorder and a mobile application for real-time OSA assessment.

The rest of this paper is assembled as follows. Section 3.3 provides brief information about the database used in this study. Section 3.4 describes the data pre-processing steps used before feeding to the proposed CNN model. Detailed information about the proposed CNN architecture is described in section 3.5. Sections 3.6 and 3.7 express the system specifications and the performance analysis methods used for training the model respectively. Section 3.8 discusses the results. The proposed real-time application advancement is explained in section 3.9. Finally, section 3.10 provides the conclusion of this study.

3.3 Database

In this study, we used the Apnea-ECG dataset, available in the Physionet database, to study the performance. The dataset consists of 70 recordings, divided equally into learning and test set, of digitalized ECG signals with a varying time length of 7-10 hours. These digitalized signals have 16 bits per sample, the least significant byte first in each pair, 100 samples per second, sampled at 100Hzs, nominally 200 A/D units per millivolt [16]. Each signal is annotated for sleep apnea/hypopnea events by an expert visually. The labeling is done based on respiration and oxygen on a per-minute basis. The subjects' recordings (30 men, five women) were arranged into three groups: Group A recordings (20 subjects) with the clear occurrence of sleep apnea (100 min or more, AHI ≥ 15), Group B (borderline) recordings (5 subjects) with some degree of sleep apnea (between 5 and 99 min, 5 ≤ AHI < 15) and Group C (control) recordings (10 subjects) of healthy subjects with no sleep apnea (fewer than 5 min, AHI < 5) [17]. Table 3.1. shows the dataset statistics in detail [17].

Table 3.1. Statistical measures of data used.

	Length (min)	Non-Apnea (min)	Apnea (min)	Apnea (hours)	AHI	Age	Height (cm)	Weight (kg)
Max	578	535	534	10	82.4	63	184	135
Min	43	20	0	0	0	27	168	56
Avg	489.5	303.2	186.1	5.17	28.6	46.5	177	87.2
Std	± 32	± 158.6	± 173.1	± 3.98	± 27.3	± 10.1	± 4.4	± 20.2

3.4 Data preprocessing

The single-lead ECG signals are accessed and filtered using a FIR Bandpass filter of 11Hz bandwidth to remove any noise and baseline drift. The dataset consists of highly unbalanced apneic events and non-apneic events. The data was segmented with under-sampling to handle these imbalanced events. Non-overlapping segmentations of 30 secs are applied to the ECG signals to match the event-based classification. The data were normalized to maintain the same scale of the features and split into training and testing sets. The training data comprised of a balanced number of events of 15674 apneic events and 15674 non-apneic events. The testing set comprising of 10450 apneic events and 10450 non-apneic events were used to evaluate the performance of our CNN model.

3.5 CNN architecture

The inspiration for CNN comes from the cognitive neuroscience model developed based on a cat's visual cortex [3]. The CNNs regularize taking advantage of hierarchical patterns and assembles smaller and simpler patterns in the filter to create complex patterns. The layers in CNN include convolution, pooling, and a fully connected layer. Convolution-layer extract features by applying convolution operations [38] to the input data, and the pooling layer draws out salient features from the extracted features. Final discrimination of the input data is conducted in the classification layer [3, 12, 23]. Many classification layers are present in our proposed CNN model. Table 3.2. and Figure 3.1 shows details of the architecture of our deep neural network model. The description of layers in our proposed model are as follows:

Input: The input is a 1D time-series raw single-lead ECG signal, segmented in 10sec epochs. Each epoch is a matrix of 1x3000.

Convolution layer: As discussed above, this layer extracts features. We used 1D convolution to extract features from the input signal. The 1D convolution can be expressed by

$$x_k^l = b_k^l + \sum_{i=1}^{N} w_k^{l-1} * y_i^{l-1} \quad (1)$$

Where x_k^l denotes the *k*th feature in layer *l*, b_k^l is the bias of the *k*th feature in layer *l*, y_i^{l-1} represents the *i*th feature in layer *l–1*, w_k^{l-1} is the *k*th convolutional kernel from all features in layer *l–1* to the *k*th feature map in layer *l*, *N* denotes the total number of features in the layer *l–1*, and (*) denotes vector convolution [3, 24].

Pooling layer: It usually follows the convolution layer. The pooling layer reduces the dimension space of feature maps by extracting the key features. The most widely used pooling strategy is Max Polling. This function divides the input data into a set of non-overlapping rectangles and outputs the maximum value of each of these subsets [3, 24].

Fully Connected Layers: These are neural network layers present right after the convolutional layers. It is known that this layer performs the classification task, whereas the earlier layers perform feature learning. Although gradient-based backpropagation is favored for network updating, one can also choose other types of updating algorithms.

Apart from these layers, we used a Dropout technique between some layers as a way of regularizing the network to reduce overfitting and to retain the network generalization. In this technique, node connections are randomly ignored or dropped in each training epoch. Once the training is complete, all node connections are used for the classification process [3].

Table 3.2. Architecture detail.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d_0 (Conv1D)	(None, 2951, 16)	816
re_lu_ (ReLU)	(None, 2951, 16)	0
max_pooling1d_24 (MaxPooling	(None, 1475, 16)	0
conv1d_1 (Conv1D)	(None, 1446, 64)	30784
max_pooling1d_1 (MaxPooling	(None, 723, 64)	0
dropout_1 (Dropout)	(None, 723, 64)	0
conv1d_2 (Conv1D)	(None, 723, 64)	122944
max_pooling1d_2 (MaxPooling	(None, 361, 64)	0
dropout_2 (Dropout)	(None, 361, 64)	0
conv1d_3 (Conv1D)	(None, 361, 32)	20512
max_pooling1d_3 (MaxPooling	(None, 180, 32)	0
conv1d_4 (Conv1D)	(None, 180, 32)	10272
max_pooling1d_4 (MaxPooling	(None, 90, 32)	0
dropout_3 (Dropout)	(None, 90, 32)	0
conv1d_5 (Conv1D)	(None, 81, 16)	5136
max_pooling1d_5 (MaxPooling	(None, 40, 16)	0
flatten_6 (Flatten)	(None, 640)	0
dense_7 (Dense)	(None, 64)	41024
dense_8 (Dense)	(None, 2)	130

Total params: 231,618

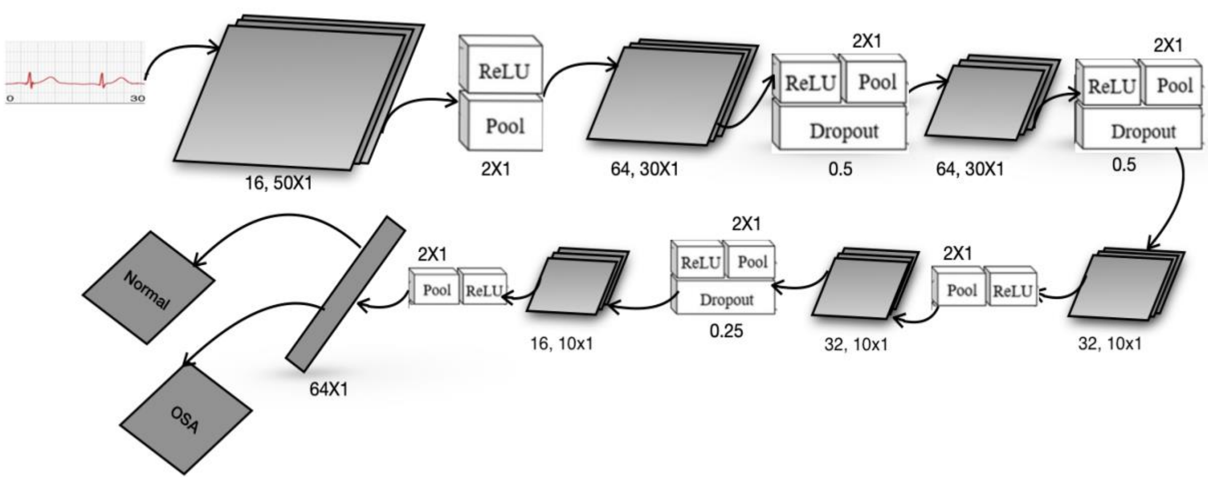

Figure 3.1. Proposed deep neural network

3.6 Implementation

The proposed 1D-CNN model was implemented with Python 3.7 and developed on Keras framework [18][3], a lightweight library used to build and train deep-learning algorithms, with TensorFlow [19][3] background. The model was built in Google Collaboratory, which provides Intel® Xeon® CPU @ 2.20GHz service. It uses a 12GB NVIDIA Tesla K80 GPU with 2 GPU core and 64 GB of memory space.

Training of a 1D-CNN model was done in a fully supervised manner, and the gradients were backpropagated from the SoftMax layer to the convolution layers [20][3]. Adam's updating rule [21] minimizes the cross-entropy function to optimize the network parameter with a learning rate of 0.0001and a decay rate of 0.9. For the optimization, during both training and testing, the data was segmented into mini batches, each containing 256 data segments [22].

3.7 Performance analysis

Various measures are available to evaluate the performance of a CNN model. We used the following standard performance metrics:

$$accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (2)$$

$$precision = TP/(TP + FP) \quad (3)$$

$$recall = TP/(TP + FN) \quad (4)$$

Where true positive (TP), true negative (TN), false positive (FP), and false-negative (FN) refer to the numbers of events in which normal is classified as normal, abnormal is classified as abnormal, abnormal is classified as normal, and normal is classified as abnormal, respectively [3].

$$F_1 = \sum_i 2 \cdot w_i \ \frac{precision_i \cdot recall_i}{precision_i + recall_i} \quad (5)$$

Where i is the class index and $w_i = n_i/N$ is the proportion of the number of samples in the ith class, n_i, and the total number of samples, N [3].

3.8 Results

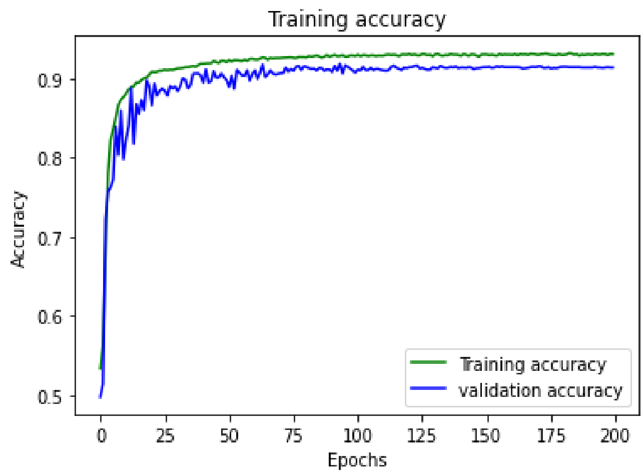

Figure 3.2. Accuracy plot of the 6-layer model

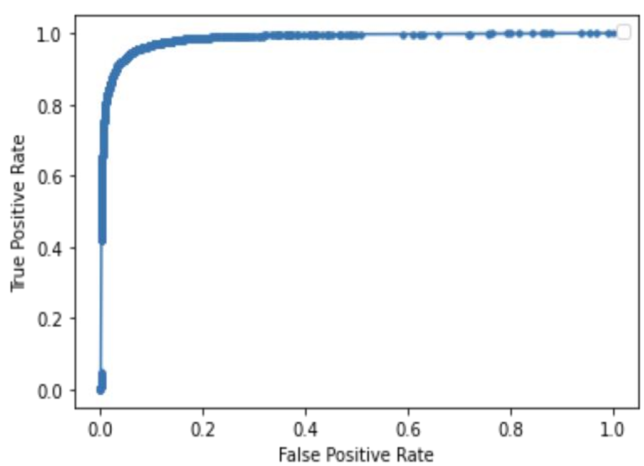

Figure 3.3. ROC curve of the 6-layer model

Table 3.3. Comparison of different architectures

Layers	**Training time (s)**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
5 layers	2	89.59	84.82	95.84
6 layers	3	92.92	94.99	91.03
7 layers	3	91.20	92.03	90.38

We used the Apnea-ECG dataset for the performance evaluation of the proposed 1D-CNN model. Also, we performed the data preprocessing as described in section 3.4. It is necessary to have an optimized architecture to execute a real-time OSA assessment. In addition to this, the inferencing time should be less. To achieve this, we carried out several experiments to select the best-optimized architecture. For the selection criteria, we examined the inferencing time and various other statistical measures. The hyperparameter conditions of the activation function, dropout rate [3], and optimizer function were also considered. Table 3.3. shows the results of the discussed experiment.

We see that the depth of the architecture is approximately proportional to the inferencing time. The inferencing time is less for the five-layer architecture, but still, the model is not optimized. The seven-layer architecture starts overfitting the data, but the six-layer architecture has less inferencing time and also has well-optimized parameters. Figure 3.2. and Figure 3.3 shows the learning of the model in terms of accuracy and degree of separability with different thresholds respectively. The area under this Receiver Operating Characteristics (ROC) curve, which is the Area Under the Curve (AUC) score, is 98.0%. The selected architecture used the Adam [21] optimizer function (lr = 0.0001) with the ReLU [26] activation function. The Dropout [28] techniques with rates (p = 0.25 or 0.5) were applied to minimize the model overfitting.

Before training, the apneic event is set as [1,0], and non-apneic event is set as [0,1]. The softmax activation function in the output layer of the network normalizes the inference into a probability distribution. So, during the testing phase, we used the max function to map the output class. For example, if the Softmax function provides probabilities as [0.76, 0.24], then the max function maps this distribution to apneic class [1,0].

Table 3.4. Compares the results of the proposed model and with other models available in the literature. Our model achieves an accuracy of 92.29%, a sensitivity of 94.99%, a specificity of 91.03%, and an F-1 score of 92.75%. Another study [31] that used the LS-SVM method obtained an accuracy of 90.1%, a sensitivity of 90.8%, and a specificity of 88.8%. The study [27] has attained an accuracy of 98.9%, a sensitivity of 97.8%, and a specificity of 99.2% on 50% of Apnea-ECG data. Also, studies referenced in [17] and [32] used 35 subjects of the same dataset used in this study and achieved an accuracy, sensitivity, and specificity of 91.0%, 88.8% and 90.0% respectively in one case and 87.6%, 91.7% and 91.4% respectively for the other case.

The studies marked with '*' used different datasets for their model evaluation. The study [29]* used the Sleep Heart Health Study (SHHS) data and has 82.4% accuracy, 69.9% sensitivity, and 91.4% specificity. The study in Ref. [30]* has 87.0% accuracy, 85.8% sensitivity, and 84.4% specificity on the St. Vincent's University Hospital/University College Dublin Sleep Apnea Database (UCD database) [16].

Table 3.5. shows the performance results of other 1D-CNN-based studies that have done model evaluation based on proprietary data. They used the polysomnography data that were acquired

Table 3.4. Performance results of our model compared with other models

Author	Method	Acc (%)	Sen (%)	Spe (%)
A-Angari [29]*	SVM	82.4	69.9	91.4
Xie [30]*	Adaboost, Bagging REPTree	87.0	85.8	84.4
Sharma [31]	LS-SVM	90.1	90.8	88.8
Bsoul [17]	SVM	91.0	90.0	91.7
Hassan [32]	TQWT and RUSBoostsures	88.8	87.58	91.4
Debangshu [27]	1D-CNN	98.9	97.8	99.2
Our Model	1D-CNN	92.9	94.9	91.0

Table 3.5. Performance results of another 1D-CNN-based model

Urtnasan [3]	1D-CNN	96.0	96.0	96.0
Urtnasan [11]	1D-CNN	98.5	99.0	99.0

using an Embla N7000 amplifier system (Embla Systems Inc., USA) located at the Sleep Center of Samsung Medical Center (Seoul, Korea) [3, 11]. With this dataset, they have conducted two studies, one yielding an accuracy of 96%, a sensitivity of 96% and a specificity of 96% and the second study yielding an accuracy of 98.5%, a sensitivity of 99% and a specificity of 99%.

From tables 3.4. and 3.5, we can see that our proposed method is showing comparable results when compared to other published methods. Although, a fair comparison is not possible because of the different training datasets and different test datasets used in each study. The results of our 1D-CNN model and the other non 1D-CNN methods that we have listed in Table 3.4 are comparable. However, the added functional requirements of feature extraction and feature selection make the non 1D-CNN models as unfavorable candidates to use in real-time assessment. On the other hand, the inbuilt nature of the automatic feature extraction and selection in 1D-CNN is an attractive candidate for use in real time OSA assessment.

3.9 Mobile application

In the current era, we are experiencing a trend in mobile devices. They are becoming more intelligent than ever because their processors and operating systems are so capable that they can handle multiple tasks simultaneously without interfering with each other. The high computing power and the simple user interface made them a handy device that can handle numerous applications and services without overloading the computing resources. The open-source application development functionality of these operating systems helps us leverage the provided computing power to develop applications, popular as apps today, that can be useful for all the users. One such open-source application is TensorFlow Lite, a deep learning framework for on-device inference [33]. It is a set of tools to help developers run TensorFlow models on mobile, embedded, and IoT devices [34]. It enables on-device machine learning inferencing with low latency and small binary size [34].

To provide an affordable and a comfortable system to assess OSA, we proposed an Android application that detects apneic events in real-time. For this, we are using the VivaLNK [35] Continues ECG Recorder, which uses Bluetooth Low Energy (LE) wireless technology (IEEE 802.15.1, managed by Bluetooth Special Interest Group now) to transfer data between the ECG Recorder and the mobile application built over the VivaLNK SDK [35]. Also, we used our pre-trained TensorFlow model of the 1D-CNN architecture discussed in the previous section and deployed this model into our proposed mobile application by converting it into a TensorFlow Lite version. Either we can deploy the deep-learning model by an Application Programming Interface (API) in a cloud or adding directly in the App as an external asset. In the API part, the model is available on the web or cloud server, and we provide an interface to our application to use it. We chose to go with the App as it requires no Internet or Cloud resources for operation.

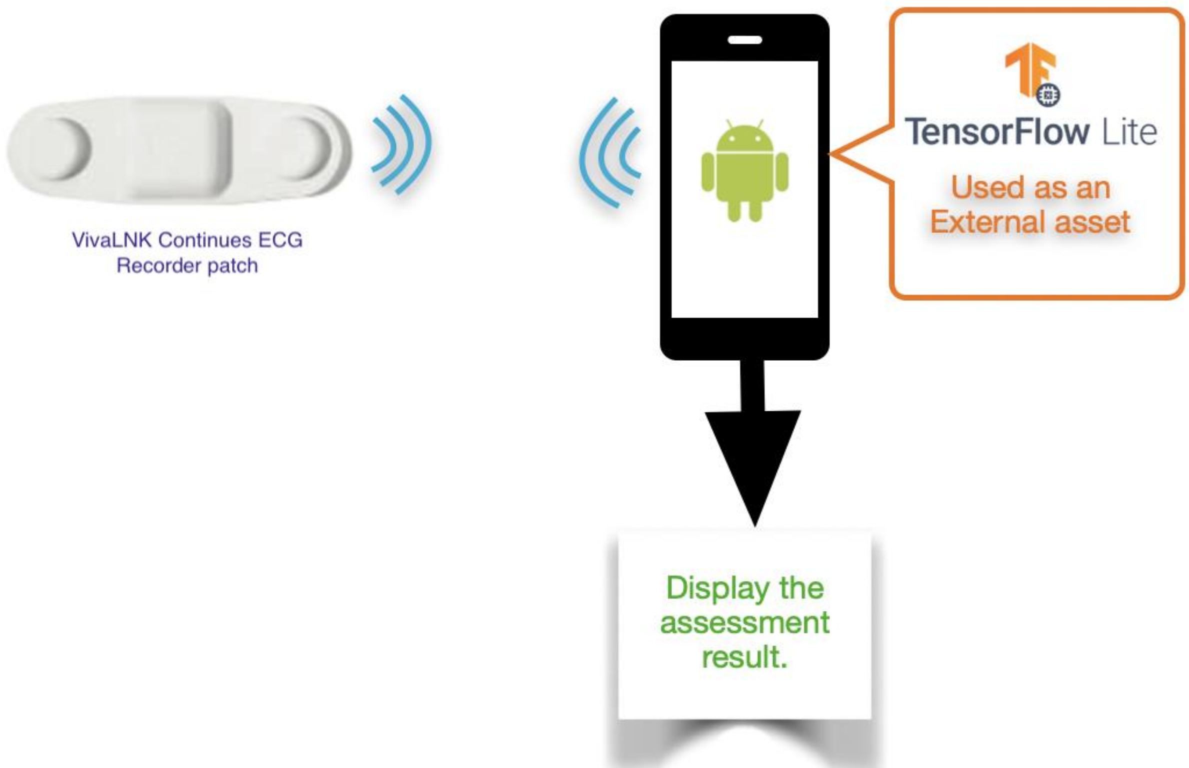

Figure 3.4. Real-time OSA assessment architecture for proposed Mobile application

3.9.1 Sequence of Operations of the proposed application

First, the user will open the mobile application and provide the necessary permission of the location and Bluetooth connectivity to connect and work with the ECG Recorder, shown in Figure 3.4. After the conditions get completed, the application will then search for the VivaLNK [35] Continues ECG Recorder and then send the request to connect via Bluetooth channel. The

Recorder then accepts the request and sends the acknowledgment to get paired with the mobile application. Once the connection gets established, the user will then get redirected to the home page of our application.

On the homepage, the user can invoke the execute (device, command, callback) method by pressing the 'Predict' button to start sampling and classifying the OSA episodes. After pressed, the execute (device, startSampling, callback) command will trigger, which requests the ECGrecorder to send data. For this, the patch needs to be attached to the chest. The patch then starts sending the continuous recording of the ECG to the application. In order to avoid data loss and latency in reception, we created a buffer that stores the ongoing raw ECG data signals for 30 seconds. After 30 seconds or when the buffer is complete, the application will pass the stored data to the pre-processing module. This module converts the raw signal into the required input format for the CNN model described in the data preprocessing section. After the pre-processing, the application passes the new data to the TensorFlow Lite model.

Once the model receives the new data, it starts classifying the apnea/non-apnea episodes every 30 seconds and displays the result. To continuously predict the ongoing data, we developed a database that stores the classified results of every 30 seconds of data. The results get stored till the user executes the stop sampling or removes the patch. The application will display the ongoing as well as the hourly results from the database.

When the execute(device, stopSampling, callback) routine gets trigger by a user, the patch receives the stop request. All the data received finally is passed to the TensorFlow Lite, and the

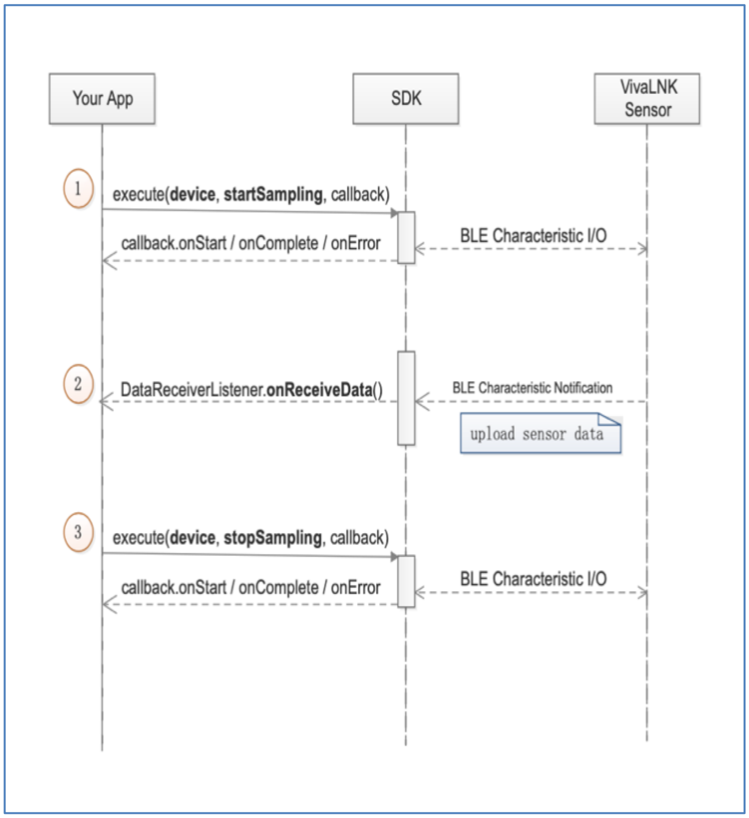

Figure 3.5. Sequence of Operations

result makes the registry on the database. The patch then stops sending the raw ECG data, and the application finally displays the report of the last ongoing inferences made by the core Lite model.

Thus, by using this android application, the user can assess Obstructive Sleep Apnea within the comforts of their home just by attaching a small single-lead ECG patch. The patch requires charging, but it can continuously run for up to four hours between charges.

3.10 Conclusion

This study proposed a 1D-CNN-based method to provide an Obstructive Sleep Apnea (OSA) assessment. It uses a single-channel ECG reading and discriminates between apneic and non-apneic events with an accuracy of 92.92%. Furthermore, our proposed method reduces the laborious and erroneous task of feature extractions because CNN does that job for us.

In addition to this, we developed an Android App for real-time OSA assessment. We use our trained model as an external asset in the Android application, which takes raw ECG signals from the VivaLnk patch and classifies every 30s of ECG signal as apnea or non-apnea event. The application can also generate a detailed report of the assessment. This application would help doctors understand the patient's Apnea-Hypopnea Index Overall, the Android application would reduce the expense of OSA assessment compared to Polysomnography test. Also, our proposed tool helps the patient to complete the test in the comforts of his or her home.

CHAPTER 4

CONCLUSION AND FUTURE WORK

This study contributes to the development of an1D-CNN model for predicting Apnea/Non-Apnea events using a single-lead ECG device. The model was built using the Apnea-ECG dataset available in the Physionet Database. Our model can successfully achieve an accuracy of 92.92% on this dataset. The 1D-CNN method requires no extraction of explicit features which is complex and requires domain knowledge.

We also proposed a mobile application, a step towards developing a tool for real-time assessment of Obstructive Sleep Apnea. The mobile App uses a pre-trained 1D-CNN model for the classification tasks. This tool can reduce the cost of sleep apnea testing and can be done in the comfort of home.

In future studies, one can build a cloud structure where users can use our machine learning model to perform their sleep apnea tests. Furthermore, can create an environment where users' reports will be directly available to their family doctors with the help of the cloud. This method will help users remotely evaluate sleep apnea in the comfort of their homes.

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BIOGRAPHICAL SKETCH

Akshay Bhagwan Sonawane was born in Maharashtra, India. After completing his work at New English High School and Junior college, he entered Savitribai Phule Pune University (SPPU) in Maharashtra, India. He received his Bachelor of Engineering in Computer Engineering from SPPU. During his time in SPPU, he published three research papers based on assisting devices for blind individuals and automated wireless charging with IEEE. In August 2019, he entered the computer science graduate program at The University of Texas at Dallas. His area of research includes machine learning and its application to healthcare, machine learning, and statistical learning theory, incremental or lifelong learning.

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COMPUTER SKILLS

Languages	: C++, Python, Java.
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PUBLICATIONS

Piyush Patil; Akshay Sonawane, Environment sniffing smart portable assistive device for visually impaired individuals, 2017 International Conference on Trends in Electronics and Informatics (ICEI) IEEE.

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PROJECTS

Electrouter **B.E.Project** **June 2017 - May 2018**
Design and developed a smart wireless charging system to charge electronic devices in public areas with 14% and 85% charging extremes with a mobile application for authorization, limitation, energy efficiency and protection from harmful charging hazards.

Email Classification **Machine Learning** **Aug 2019 – Sept 2019**
Worked on the Text Classification problem using Naïve Bayes (Multinomial and Discrete) and MCAP Logistic Regression models on each BOW and Bernoulli data representation. And amplified the accuracies from 80%- 89% to 90%-98%.

Recommendation System **Machine Learning** **Sep 2019 – Oct 2019**
Trained a memory-based Collaborative Filtering algorithm on the movie rating data from the Netflix Prize. Handled data of 28978 unique users and 1821 unique movies and provides RMSE as 0.69 along with MAE as 0.80.

Random Forest **Machine Learning** **Oct 2019 – Nov 2019**
Implemented Random Forest of Chow-Liu tree Bayesian networks. Achieved mean log-likelihood scoresfrom - 9.39 to -139.86 for 10 different datasets by running 10 times each.

AWARDS & HONORS

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AWARDS & HONORS

Indian Students Association UTD(ISA), Member **Aug 2019-Current**.

The Institute of Engineering Pune (IE club), Member **Aug 2014-May 2018**