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Artificial Intelligence-Driven Sleep Apnea Detection using Deep Neural Networks

Minakshi Subhash Dhole[1] and Dr. Amit Jain[2]

Research Scholar, Department of Electronics & Telecommunication Engineering[1]

Research Guide, Department of Electronics & Telecommunication Engineering[2]

Sunrise University, Alwar, Rajasthan, India

Abstract*: Sleep apnea is a sort of breathing condition when breathing pauses while you're sleeping and lasts for at least 10 seconds. Type 4 sleep research, which emphasizes mobility and signal reduction, is used in the suggested model. Compared to type 4 sleep research, the primary drawbacks of type 1 full night polysomnography are its time commitment and the amount of space needed for sleep recording, such as a sleep lab. A viable substitute for successful polysomnography, the deep convolutional neural network model based on the SPO2 sensor is portable and reasonably priced for the identification of sleep apnea. In all, 180,000 samples from 50 patients' SPO2 sensors were utilized in this investigation. Using a deep convolutional neural network and a cross entropy cost function, the overall accuracy of sleep apnea diagnosis is 91.3085% with a loss rate of 2.3.*

Keywords: Deep learning, deep convolutional neural network, continuous single bio-parameter recording

I. INTRODUCTION

Type 4 sleep studies, also known as continuous single bio-parameter or dual-bio-parameter recording, are the kind of research that our system uses. One or two channels, such as oxygen saturation and airflow, are the bare minimum of signals that may be used in these type 4 research [3-6, 12-30]. Sleep cannot be scored because type 4 investigations often lack EEG and EMG findings. During sleep, it may be utilized to detect respiratory sleep disorders. An additional option to type 4 sleep investigations is the use of tracheal sound and oxygen saturation using acoustic sensors. Learning model parameters or features from the training dataset is the main goal of using the deep convolutional neural network model for sleep apnea diagnosis [7]. To ascertain whether or not there are sleep apnea events in the signal sample, the model's performance is correlated with the learnt parameters [7-9]. Finding the correlation between the deep convolutional model's performance and the interpretability of its many parameters is a difficult problem for sleep apnea identification. Although a wide range of convolutional neural networks may be used to image classification tasks, only a smaller proportion of them are utilized for signal processing or sound wave recognition. Because of the inner workings of the CNN model, creating and evaluating a decent model is like trying to solve a black box problem and requires a significant amount of trial and error [9]. The deep learning model pays close attention to how the sensor's signals are represented. The suggested approach draws inspiration from picture classification, where the amplitude of the sensor wave data is represented as digit vector figures that may be factorized or matrix vectorized into any dimensional structure. The primary difficulty in detecting sleep apnea is the continuous nature of the high frequency respiratory signal waves, which makes the signal representation unclear. To bridge the gap between the continuous nature of the biological signal from the sensors and the nature of deep learning, the biological signal is being proposed to the deep learning model. A reasonable and appropriate way to decipher and understand the time series character of the high frequency SPO2 signal is to use a convolutional neural network model [30–32]. The results of five empirical tests that were conducted to validate and evaluate the identification of sleep apnea indicate that it may provide healthcare professionals relevant interpretation. The following succinctly describes the paper's main contribution:

- The accuracy and loss rate of SPO2 signal are compared with other methods of sleep apnea detection using SPO2 signal.
- A deep learning approach utilizing convolutional neural networks is proposed for the detection of sleep apnea in order to explore the segment of the time series data whether apnea occurs or not.

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This is how the remainder of the paper is structured. Section 2 provides illustrations of the deep learning processes, which include data collection, data preparation and segmentation, deep learning model selection, training, testing, hyper-parameter tweaking, and prediction. Section 2 also displays the deep learning model's system architecture. Section 3 discusses our system's performance assessment findings based on five empirical investigations that used 50 patients as subjects. 190,000 samples of individuals with sleep apnea are included in the investigations. In contrast, the severity of sleep apnea varies from patient to patient based on the AHI score and conditions. Section 4 wraps up and discusses the possible avenues for further study in the identification of sleep apnea.

Deep Learning Steps

The suggested deep learning model using convolutional neural networks is inspired by the biological neural network of human brain decision making [7, 9, 31, 32]. It is predicated on a single input, which is necessary for decision-making and involves several neurons transmitting information via an electrochemical mechanism. In the actual world, individuals suffering from sleep apnea would benefit from the deep learning method's ability to identify and forecast the condition [1]. To depict the characteristics of the data and its trends, the deep learning model enables learning from the features. In deep learning, supervised learning—where training data comprises both input and the intended output—and unsupervised learning—where training data contains input but not the intended output—are two different tendencies [31]. The whole deep learning process, including data collection, preparation, and segmentation, as well as the creation of deep learning models such deep convolutional neural networks, training, testing, hyper-parameter tweaking, and prediction, is shown in Fig. 1.

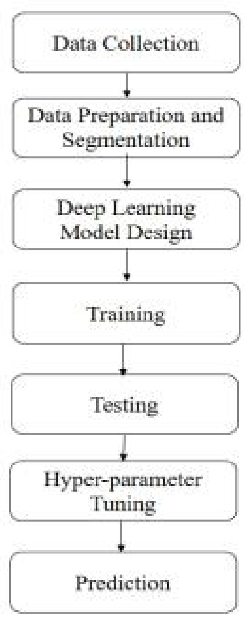

Figure 1 Deep learning steps for apnea detection

System Design

The design of the detection of sleep apnea can be seen in three layers in which the first layer, second layer and third layer are data collection layer, analysis layer and diagnosis layer respectively and can be seen in Fig. 2.

In order to identify sleep apnea, the first layer gathers information on the patient's oxygen saturation. The analysis of sleep apnea detection takes place in the second layer. The frequency of sleep apnea episodes and the severity of the patients' sleep breathing condition may be determined in the third diagnostic layer. The third layer, referred to as the diagnostic layer, is where medical professionals determine whether or not sleep apnea has been correctly diagnosed.

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Figure 2 System Design of Sleep Apnea Detection

Prior to being inserted into the system, the segmented signal for the one-dimensional feature vector, as seen in Figure 3, will be labeled. For instance, Xa = {x1, x2, x3,…, xn}, where n = sampling rate * one epoch (30 sec), xn ∈ Xa, and Xa ∈ X, where x is a random variable that represents the signal data every second. This is assuming that X is a single segmented SPO2 signal. Each split signal is saved in the feature vector as follows before being entered into the deep learning model.

X_1	X_2	X_3	………	X_{n-1}	X_n	Apnea/ Not Apnea

Figure 3 Data Vector of SPO2 Sensor

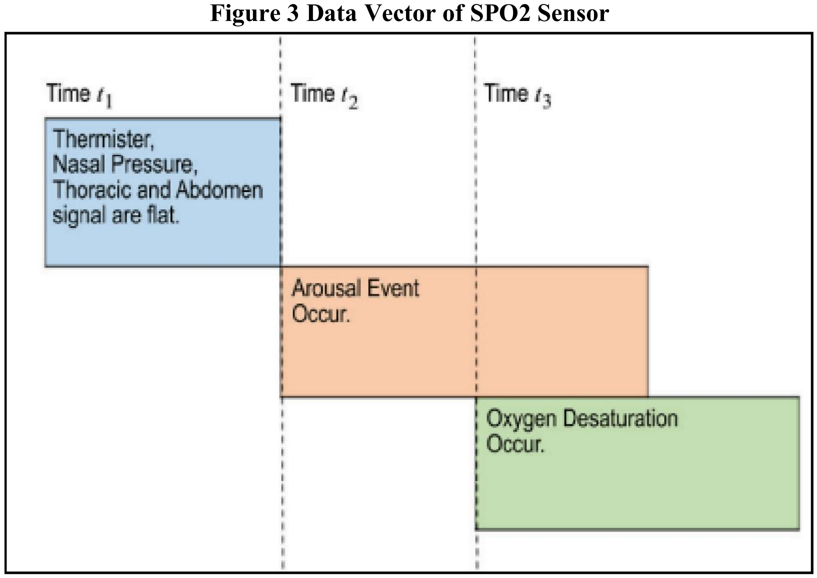

Figure 4 Three consecutive events when sleep apnea occurs

According to Fig. 4, the figure illustrates how the sleep apnea event occur. There are three consecutive time events known as t1, t2, and t3. When breathing stops, the brain sends some signals to the muscle in order to do breathing. This kind of arousal event can be seen in the EEG electrodes' signal that are attached to the patients' head. This event can be seen and is marked in t2 time segment. The arousal event from the EEG electrode, respiratory signals flat event can be seen in the following Fig. 5 and Fig. 6.

As for the event relating to the time t1 from Fig. 4, it is significant that the signals coming from the nasal pressure, thermistor, thoracic and abdomen decreased and the signals become flat compared to the normal trend line. This kind of event can be seen in Fig. 5. In other words, these four signals drop significantly compared to the normal breathing condition. The first four signals highlighted in blue are thermistor, nasal pressure, thoracic and abdominal signal. After occurrence of the signal drop in these four signals, the oxygen desaturation occurs in SPO2 signal highlighted in red.

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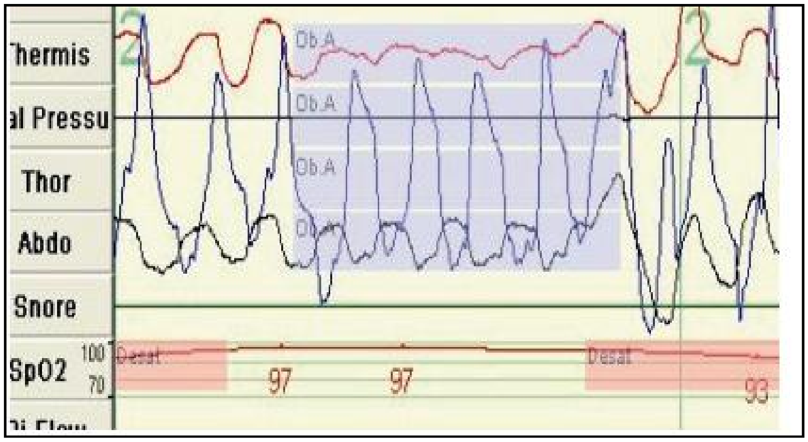

Figure 5 Hermiston, nasal pressure, thoracic and abdominal signals drop event relating to time event.

The abrupt shift of the brain signal from the electrodes with the frequency of less than 16% which does not include spindle and it can last for at least 3 sec. When the sleep apnea occurs, this event is highlighted using green and a red box in Fig. 6.

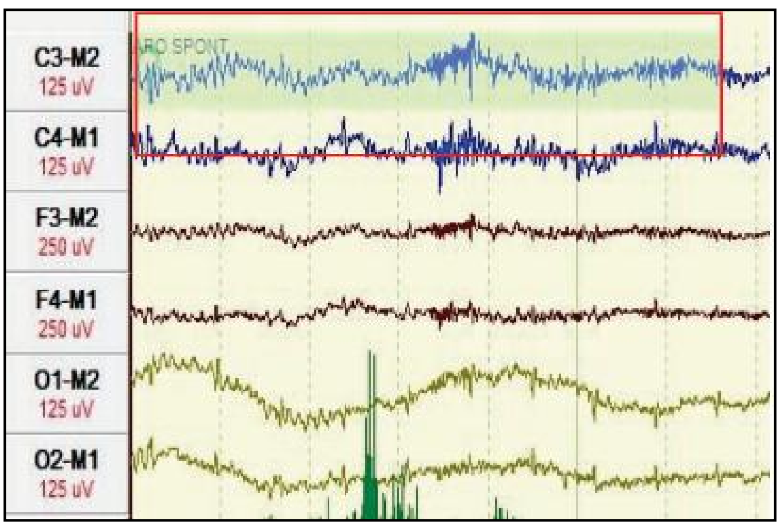

Figure 6 Arousal event relating to time event t1

The t3 time event of SPO2 signals associated with Fig. 6 shows the occurrences of oxygen desaturation as a consequence of the lung stopping breathing. The C3-M2 indicates that the right pre-auricular electrode, which is located close to the right ear, is the reference point for the central electrode on the left side of the brain. The C4-M1 indicates that the left pre-auricular electrode, which is located close to the left ear, is the reference point for the central electrode on the right side of the brain. The F3-M2 indicates that the right pre-auricular electrode, which is located close to the right ear, is the reference point for the frontal electrode on the left front side of the brain. The F4-M1 indicates that the left preauricular electrode, which is close to the left ear, is the reference point for the frontal electrode on the right side of the brain. The O1-M2 indicates that the right pre-auricular electrode, which is located close to the right ear, is the reference point for the occipital electrode on the left front side of the brain. The O2-M1 indicates that the left pre-auricular electrode, which is located close to the left ear, is the reference point for the occipital electrode on the right side of the brain. One of the conclusions is that after the oxygen desaturation event at time t3, the heart rate started to rise.

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Apnea/Hypopnea Event Detection

The flat signals do not mean that the signal is very flat because the up and down can be seen according to minute, second and our view. The baseline amplitude for the apnea is the preceding 3 to 6 breaths in which time segment before and after the event is represented as t1 and t3 respectively, and the amplitude before and after the apnea event is represented as A1 and A2 respectively in which t1 < t2 < t3. If the maximum relative amplitude for the apnea threshold is set to 10 percent, it means that A2 divided by A1 should be less than 10 percent and the apnea event is detected if the amplitude of the event is twenty percent or below of preceding data according to Fig, 7. For the hypopnea event the maximum threshold is less than 70 percent according to AASM manual scoring 2017.

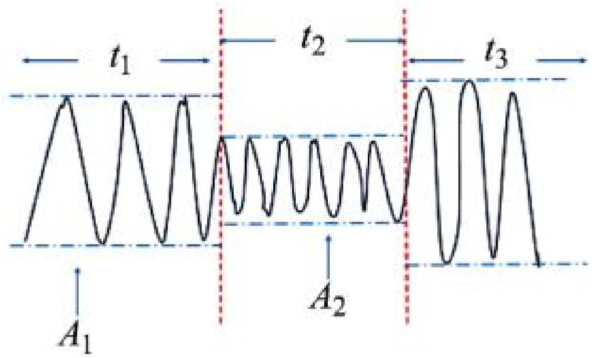
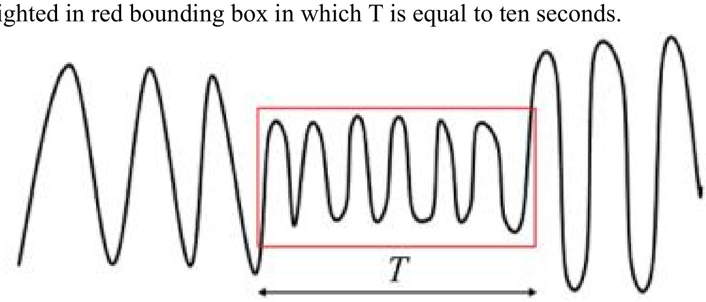


Figure 7 Amplitude Threshold Apnea Event.

The following Fig. 8, illustrates that the minimum duration of the event that can be identified as apnea or hypopnea is ten seconds. It is highlighted in red bounding box in which T is equal to ten seconds.



Deep Convolutional Neural Network

The simplified version of the convolutional neural network is portrayed in Fig. 9 in which the first layer is the input layer, the last layer is the output layer which can be identified whether certain segment from the sensor has apnea or not, and the layers between the first and last layer are the hidden layers.

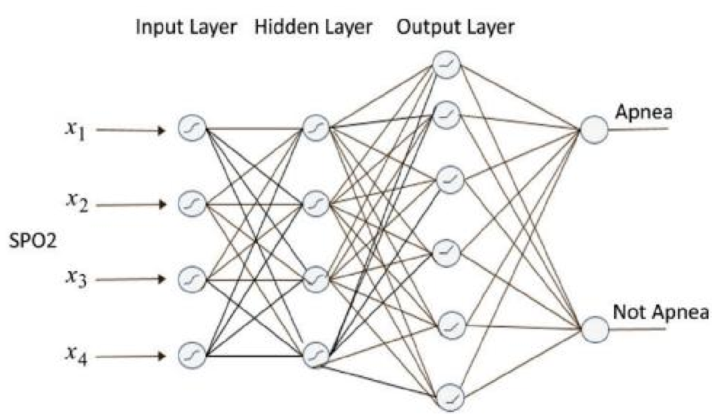


Figure 9 A simple representation of CNN for SPO2

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The design of the deep convolutional neural network, which uses 10 layers, is summarized in the following Tab 1. Additionally, it has three max pooling layers and three two-dimensional convolutional layers. 32,614 trainable parameters will be available for the convolutional neural network once each empirical study's deep convolutional neural network model has been performed. 794 samples are used for training, and 3,178 samples are utilized for testing. Every sample contains 484 SPO2 signal data points at a frequency of 16 Hz. The flatten layer, dense layer, dropout layer, pooling, and two-dimensional convolutional layers are all included in the suggested model. The first convolutional layer has 320 parameters; the second convolutional layer has 9,248 parameters; and the third convolutional layer has 18,496 parameters. Furthermore, the first dense layer has 4,160 parameters, whereas the third dense layer has 390 parameters. The convolutional layer's function is to learn the unique characteristics of the input signal and extract features. The model's dimensionality is decreased without sacrificing its features or patterns by the pooling layer that accepts the largest value. Furthermore, the dense layer—also referred to as the completely linked layer—can be used as a last layer for prediction.

Table 1 Deep Convolutional Neural Network Design

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 20, 20, 32)	320
max_pooling2d_1	(MaxPooling2(None,10,10,32)	0
conv2d_2 (Conv2D)	(None, 8, 8, 32)	9248
max_pooling2d_2	(MaxPooling2(None,4,4,32)	0
conv2d_3 (Conv2D)	(None, 2, 2, 64)	18496
max_pooling2d_3	MaxPooling2 (None, 1, 1, 64)	0
flatten_1 (Flatten)	(None, 64)	0
dense_1 (Dense)	(None, 64)	4160
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 2)	390
Total params: 32,614		
Trainable params: 32,614		
Non-trainable params: 0		
Train on 794 samples, validate on 3178 samples		

PERFORMANCE EVALUATION

The accuracy metrics of the suggested deep convolutional neural network model are used in five empirical tests with fifty patients, each of which has 3,700–4,000 sample data from 10 patients. Two figures—one for accuracy and one for loss—illustrate each empirical investigation. The loss rate is computed using the cross entropy. The suggested model's total performance is 91.3085 percent. This performance assessment section also includes a comparison of the suggested convolutional neural network model with the other models. It compares several classifiers, including the suggested convolutional neural network of the deep learning model, bagging representation tree, support vector machine (SVM), linear discriminant analysis (LDA), and artificial neural network utilizing SPO2 signal. Figure 10 summarizes the comparison of five empirical investigations with respect to training accuracy. Orange, red, green, purple, and blue trend lines, respectively, are used to depict scenarios 1, 2, 3, 4, and 5. Ten patients with varying ages, weights, BMIs, and AHI indices are included in each scenario. Between 1 percent and 20 iterations, all of the trend lines varied and grew progressively. After 20 cycles, the accuracy percentage begins to settle; after 40 iterations, it stabilizes even more, reaching around 90% accuracy. We may infer that between 40 and 100 iterations is the steady condition for training the data.

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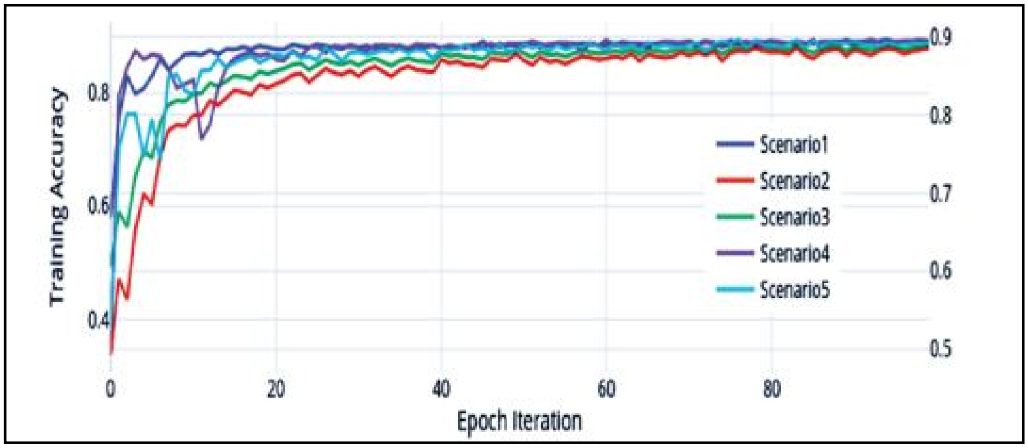

Figure 10 Comparison of training accuracy for five empirical studies

The summary of the comparison of five empirical studies regarding training prediction loss can be seen in Fig. 11 in which scenario 1, scenario 2, scenario 3, scenario 4 and scenario 5 are illustrated using blue, orange, green, purple and cyan trend line respectively. In this paper, the total number of patients that participated in the detection of sleep apnea is fifty patients and subject specific scenario validation is used with the split rate of 0.2. Each of the scenarios had ten different patients of different age, BMI, weight, AHI index. All of the trend lines relating to training loss were going down until the number of twenty iterations and at the same time, they fluctuated and were unstable until twenty iterations. They became more stable after 20 iterations. The stable condition for training prediction loss was between 20 iterations to 100 iterations.

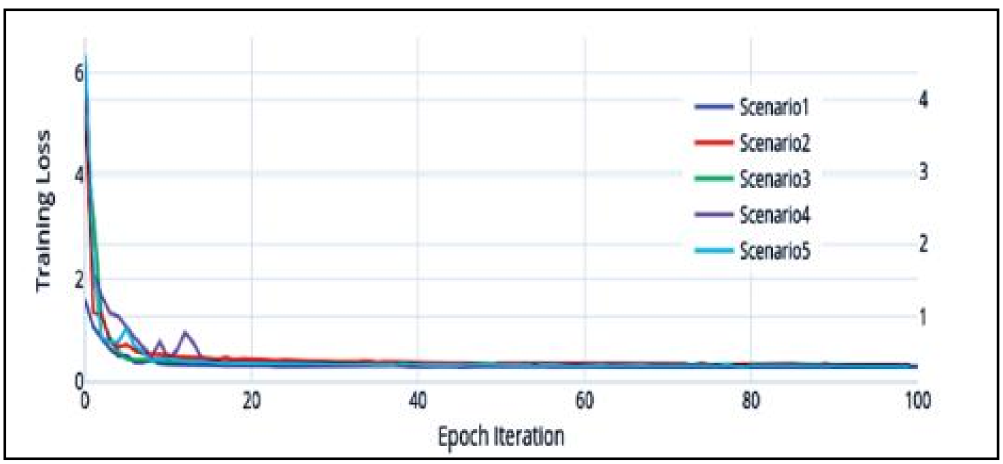

Figure 11 Comparison of training prediction loss for five empirical studies

The SPO2 signals are utilized to compare the suggested model with other classifiers, as shown in Tab. 2. With an accuracy of 91.3085 percent and a split rate of 0.2, the suggested model fared better than the others. It uses 80 percent testing data (3178 data samples) and 20 percent training data (794 samples). The comparison of several classifier types, including LDA, SVM, bagging representation trees, and artificial neural networks for sleep apnea diagnosis, is shown in Tab. 2 below. As can be shown, the accuracy of the deep convolutional neural network is 91.3085 percent. In other words, out of 100,0000 data, the model can make highly accurate predictions for 913085 data. The other model uses a large amount of data for training and just a small percentage for testing. However, in order to prevent overfitting in the suggested model for sleep apnea diagnosis, 20% of the data are utilized for training and 80% are used for testing. Since each patient records sleep for eight hours, the twenty percent utilized for training is really too little for the suggested model. These five empirical studies include fifty patients.

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Table 2 Comparison between different types of classifier for sleep apnea detection.

Ref	Type of Classifier	Split Rate	Training Data	Testing Data	Accuracy
[29]	LDA	0.5	50%	50%	86.5
[30]	SVM	0.3	70%	30%	90
[31]	Bagging Rep Tree	0.1	90%	10%	84.80
[32]	Artificial Neural Network	0.17	83%	17%	90.3
Proposed Model	CNN	0.2	20%	80%	91.3085

The suggested model utilizes its own database after gathering data from fifty patients with sleep apnea with the assistance of medical specialists from the sleep lab, while the other model uses the standard database with a little quantity of data.

II. CONCLUSION

In conclusion, a critical step before feeding into deep learning is the preparation and segmentation of the data model. To prevent overfitting, the deep learning experiment using the deep CNN (convolutional neural network) model is evaluated using SPO2 with subject validation and a split rate of 0.2.

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