Fernando Ortiz-Rodríguez
Sanju Tiwari
Miguel-Angel Sicilia
Anastasija Nikiforova (Eds.)

Communications in Computer and Information Science 1666

# Electronic Governance with Emerging Technologies

First International Conference, EGETC 2022
Tampico, Mexico, September 12–14, 2022
Revised Selected Papers

Springer

EGETC

# Communications in Computer and Information Science 1666

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*Editors*
Fernando Ortiz-Rodríguez
Autonomous University of Tamaulipas
Ciudad Victoria, Mexico

Sanju Tiwari
Autonomous University of Tamaulipas
Ciudad Victoria, Mexico

Miguel-Angel Sicilia
University of Alcalá
Alcalá de Henares, Spain

Anastasija Nikiforova
University of Tartu
Tartu, Estonia

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# Preface

A trend toward improving the public sector has emerged in many countries in recent years. Some demands are adding to the need for efficiency, transparency, and overall better performance, and some are trained by the innovation wave that originated with the adoption of the Internet and web-based services by, and care of, the private sector, boosted by smartphones and tablets. With the potential administrative revolution and feeling the need to reduce the existent gap between the private and public sectors, an increasing number of governments have adopted e-government strategies to support development.

There have been increased efforts to utilize advanced electronic and mobile services for the benefit of all. But fixed and wireless broadband subscriptions have increased unevenly across regions. A major effort is required to ensure universal access to the internet in the least developed countries. Countries in all regions are increasingly utilizing new information and communication technologies to deliver services and engage people in decision-making processes. One of the most important new trends is the advancement of people-driven services - which reflect people's needs and are driven by them. Disparities remain within and among countries. Lack of access to technology, poverty, and unequal society prevents people from fully taking advantage of the potential for information and communications technology (ICT) and e-government for sustainable development.

During the last decade, the role of emerging technologies in governments and public administrations has grown significantly. In addition, online communities and the rise of blockchain networks have resulted in new ideas and forms of governance inside communities with a degree of autonomy and self-organization. Decentralized autonomous organizations (DAOs) are examples of those forms of organization and governance that transcend national and geographical boundaries. As enabled by blockchain, decentralization is the critical element that allows for algorithmic coordination procedures that are the framework of DAOs.

Emerging technologies are enablers for these new forms of governance and novel applications to traditional governance functions. Concretely, artificial intelligence and the processing of large volumes of data are reshaping the knowledge-based economy. The number of experimental and theoretical findings is increasing rapidly due to many successful emerging technologies. The role of those technologies has been witnessed across various domains, including health care, education, tourism, and industry, among others.

This volume contains the main proceedings of the first International Conference on Electronic Governance with Emerging Technologies (EGETC 2022). EGETC has been established as a yearly venue for discussing the latest scientific results and technology innovations related to emerging technologies supporting electronic governance. It aims to provide a forum for academics, scholars, and practitioners to share and exchange recent developments in the domain of e-government and governance of digital organizations and to shed light on the emerging research trends and their applications. The first edition took place in Tampico, Mexico, during September 12–14, 2022.

The main scientific program of the conference comprised 17 papers: 15 full research papers and two short research papers selected out of 54 reviewed submissions, which corresponds to an acceptance rate of 31%.

The General and Program Committee chairs would like to thank the many people involved in making EGETC 2022 a success. First, our thanks go to the four reviewer chairs and the 49 reviewers for ensuring a rigorous and open review process that, with an average of three double-blind reviews per paper, led to an excellent scientific program.

Further, we thank the kind support of the team at Springer. We finally thank our sponsors for their vital support of this edition of EGETC 2022. The editors would like to close the preface with warm thanks for our supporting keynotes and our enthusiastic authors who made this event truly international.

September 2022

Fernando Ortiz-Rodríguez
Sanju Tiwari
Miguel-Angel Sicilia
Anastasija Nikiforova

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# Contents

# Deep Learning Based Obstructive Sleep Apnea Detection for e-health Applications

E. Smily Jeya Jothi[1], J. Anitha[2], Jemima Priyadharshini[3], and D. Jude Hemanth[2](✉)

[1] Avinashilingam Institute for Home Science and Higher Education for Women, Coimbatore, India

[2] Department of ECE, Karunya Institute of Technology and Sciences, Coimbatore, India
judehemanth@karunya.edu

[3] Immanuel Hospital, Chennai, India

**Abstract.** The lack of oxygen caused by constricting of the upper respiratory system causes Obstructive Sleep Apnea (OSA), which mainly manifests as low concentration, sleepiness during the daytime, and irritability. Human lives can be saved and treatment costs can be reduced when OSA is detected early. OSA can be quickly detected by computer-aided diagnosis (CAD) using Electrocardiogram (ECG) and Photoplethysmogram (PPG) signals. Deep Learning (DL) has attracted dramatic attention due to its uses in biomedical applications and its efficiency in classifying OSA events. In this study, Convolutional Neural Networks with Long-Short Term Memory (CNN-LSTM) and Densely Connected Long-Short Term Memory (DC-LSTM) networks are used to detect apneic events using ECG and PPG signals. The study involves 200 recording of ECG signals and PPG signals collected from publically available apnea database. DC-LSTM network achieved accuracy of 98.2%, sensitivity of 97.4%, specificity of 97.5%, and Kappa coefficient of 0.92. In terms of performance, the algorithms employed here are comparable with those that are fully automated. This methodology can be easily incorporated with wearable medical devices, which makes it useful for e-health monitoring of OSA at home.

**Keywords:** OSA · ECG · PPG · LSTM · CNN · Densely connected LSTM

## 1 Introduction

A person is considered to have OSA if their nasal or oral respiratory amplitudes are reduced by 90% or more during sleep, for a period of 10 s or more. The OSA patients suffer from sleep fragmentation and repetitive airflow restriction, which reduce their sleep time and degrade their quality of sleep [1]. Sleep apnea occurs when breathing stops during sleep. It takes about 10–20 s between episodes of apnea. In the end, a reduced heart rate is caused by the inadequate supply of oxygen to the heart. ECG signals, which indicate the amount of oxygen that is carried by the heart, are the easiest way to monitor heart rate performance. When the amount of oxygen in the blood is low, the heart rate will be reduced, since the amount of oxygen is not sufficient to maintain the heartbeat.


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ECG signals can provide information on the oxygen delivered to the heart and are the easiest method for monitoring heart rate performance. An average case of apnea lasts approximately for 10–20 s and there may be more than 15 episodes in a severe case [2].

The ECG signal can be generated by connecting electrodes to the skin, producing an affordable and accurate simulation of heartbeats. Several studies have examined the possibility of detecting apnea by analyzing ECG signals. An ECG signal can be used to determine the performance of a heart condition. ECG signals typically have a low amplitude of 0.5 mV at an offset level of 300 mV, with a frequency range of 0.05 to 100 Hz. An electrocardiogram is a mark of electrical activity in the heart over a time period. Waves (P, Q, R, S, T, U) and intervals (S-T, Q-T, P-R, R-R) make up the complete ECG signal. Heartbeats' duration and amplitude are calculated using intervals in order to process or classify them [3]. Figure 1 illustrates the ECG intervals and waves. Standard ranges of these waves are shown in Table 1 [4, 5].

The PPG device has a number of unique properties that make it a very interesting part of the rapidly evolving and popular field of medical wearable devices, particularly its capacity to capture autonomic nervous system modulations during sleep. In addition to home-based detection of sleep disoriented breathing, long-term monitoring of insomnia, circadian rhythm, sleep disorders, and treated sleep disoriented breathing are all potential medical applications of PPG. Future wearables could benefit from new contact sensor combinations, particularly those that measure brain activity [6].

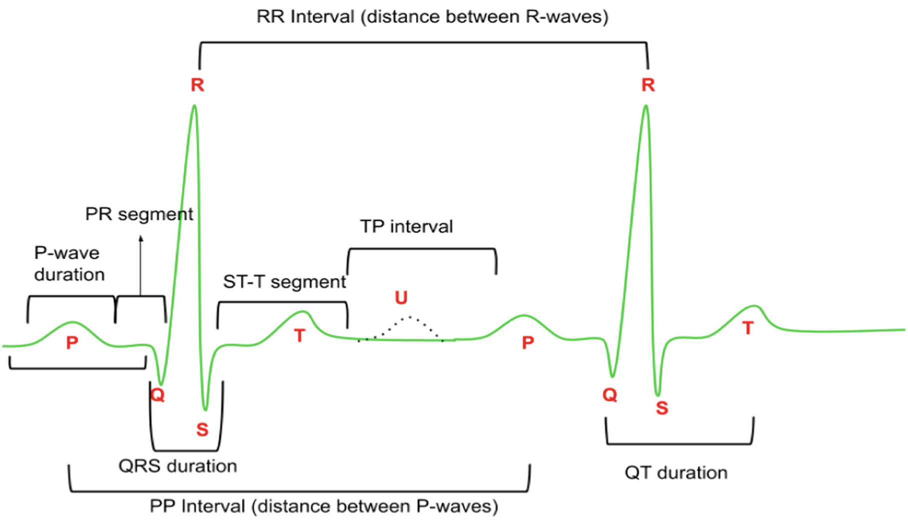


**Fig. 1.** Components of ECG waveform

Photoplethysmography (PPG) is a device that measures numerous physiological functions in an unobtrusive manner. PPG identifies changes in arterial blood pressure and breathing patterns during sleep, as well as abnormal breathing patterns, because sleep follows a common cardiovascular and respiratory pattern. In order to apply these data extraction processes clinically, mathematical models must be tested, trained, and validated before they can be applied to data [7]. Through the recorded ECG and PPG signals from the patients, the proposed system can direct users to distinguish between OSA patients and normal individuals.

**Table 1.** Range of ECG waves

| ECG waves | Duration (s) | Amplitude (mV) |
|---|---|---|
| P wave | 0.08–0.1 | 0.25 |
| T wave | 0.16–0.2 | $>0$ |
| QRS complex | 0.08–0.1 | $Q < 0, R > 0, S < 0$ |
| R-R interval | 0.6–1.2 | – |
| P-R interval | 0.12–0.22 | $R > 0$ |
| S-T interval | 0.2–0.32 | Isoelectric |
| Q-T interval | 0.35–0.45 | – |

The sections in this paper are as follows: Sect. 2 discusses sleep apnea and CAD in relation to each other relating to various research works. The methodology is outlined in Sect. 3. The results and analysis of the obtained results are presented in Sect. 4. Following that is a discussion of the limitations, conclusion and future work.

## 2 Literature Survey

In order to determine the presence of OSA in an individual, the ECG signals are analysed to identify the heart rate and the RR interval. Analyses of the main components of the QRS complex are used to measure the increased sympathetic activity during apnea. The data between the heart rate and respiration are extracted using orthogonal subspace projections. Machine learning algorithms are trained on the extracted features. Researchers concluded that the use of ECG sensor values is sufficient to detect sleep apnea accurately [8].

By acquiring signals from a single-channel ECG, an automated OSA detection method based on CNN is proposed. 82 subjects participated in the study, and the data has been divided into training phase and testing phase [9]. A three-step procedure is used to detect OSA from ECG signals: (i) automatically segmenting the signal instead of using equal-length segmentation rules, (ii) removing RR intervals in the segmented signal using local median filters, and (iii) analyzing the ECG signals based on the severity index for OSA. An average accuracy of 97.41% is achieved using the Physionet Apnea ECG database in this study [10].

During the training of the deep learning network, seventeen features are extracted from airflow signals. The binary classification is originally used with AHI cut-off indices. A cross-validation technique of 10 folds is used, and the accuracy of the proposed method is significant at three different cut-offs −5, 15 and 30 (83.46%, 85.39%, and 92.69%) [11]. An apnea disease diagnosis system based on CAD is developed. The method has been designed in three steps: firstly, notch filters are used to reduce noise in ECG signals, secondly, nine features are extracted from the signal, and thirdly, 13 machine learning algorithms and four deep learning methods are used to classify sleep apnea from ECG data [5]. Deep Neural Network (DNN) is used for sleep apnea detection by analyzing the heart rate variability and respiratory rate variability values of Polysomnography (PSG) signals. Support Vector Machine (SVM) classifiers are fed with samples of segments every 2 min. PSG signals are normalized using Covariance Normalization, which strips away many features without affecting the patient details. The DNN proposed achieved 88% accuracy rate [9].

Two deep learning methods are utilized in order to detect OSA events automatically: a bidirectional long short-term memory (BiLSTM) network and a temporal convolutional network (TCN). In the convolutional layer, three different scaling features are discovered. An ECG signal with a single channel is processed through CNN to detect OSA. LSTM algorithm is used to analyse OSA transition rules. A 10-s sliding window is used to segment the ECG signal for detection of OSA events. A kappa coefficient of 0.92, a specificity of 96.2%, and an accuracy of 96.1% are achieved with the proposed model. A limitation of the study is that the proposed method could not identify hypopnea events, and transition epochs could not be scored accurately [6].

## 3 Methodology

### 3.1 Dataset

**ECG:** ECGs are collected from the human body by using an electrical impulse applied to the heart [11]. The dataset used for this study comes from Physionet's Apnea ECG database [12], which is publicly available. 70 records are in total, divided equally between a learning set and a test set of 35 records. For each patient, the total ECG duration is between [25,200, to 36,000] minutes. Data in this dataset is intended for determining apneic and regular ECG events lasting for one minute, based on which signals have been categorized as normal or OSA-affected. Due to the obstruction of the airflow, the ECG signal with OSA is less stable and consistent than the normal signal. Brain signals to muscles are interrupted when the mind stops sending them, so airflow is reduced. Shortly, the amount of oxygen is lacking, which results in an abnormal heart rate.

**PPG:** Patient-related BIDMC PPG and Respiration Dataset collected from hospitalized critically-ill patients at Beth Israel Deaconess Medical Centre in Boston, Massachusetts, USA, is made publicly available in Physionet [12]. The impedance respiratory signal was manually annotated by two annotators for each recording. 53 recordings in the dataset are each 8 min long, and contain:

- Signs representing bodily functions, such as the PPG, impedance respiratory signal, and electrocardiogram (ECG), which are sampled at a frequency of 125 Hz.
- Heart rate, respiration rate, and blood oxygen saturation level are physiological parameters. These parameters are sampled once per second.
- Fixed variables, like age and gender, can also be recorded at the same time.
- Breaths can be annotated manually (Fig. 2).

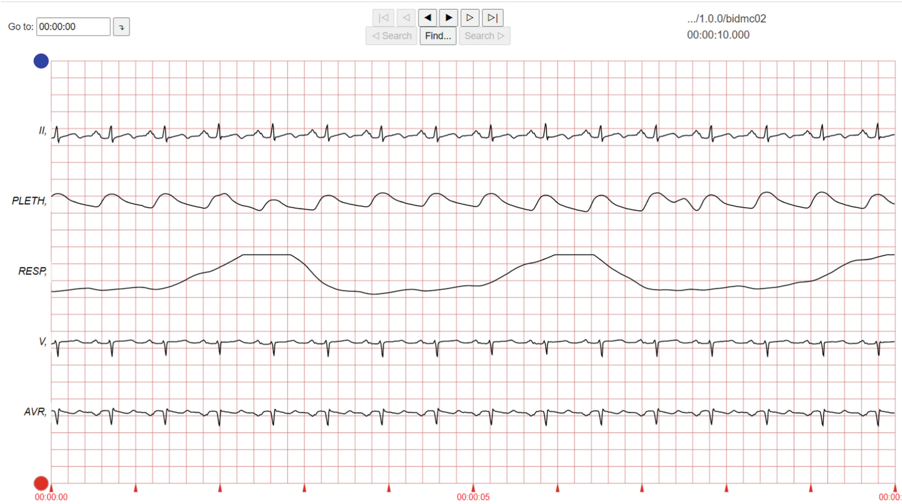


**Fig. 2.** Sample waveform from BIDMC PPG and respiration dataset

### 3.2 CNN-LSTM

In the CNN-LSTM, layers related to Convolution, LSTM, Pooling, SoftMax and Fully Connected (FC) are used. Neuron $j$ net input is defined as follows in layer $l$:

$$Y_j^l = \sum\nolimits_{i \in M_j} w_{j,i}^l * x_i^{l-1} + b_j^l \tag{1}$$

where $M_j$ represents the input map selection, $w_{i,j}$ denotes the filter or weight corresponding to the connection between neurons $j$ and $i$, $x_i^{l-1}$ is the signal output by neuron $i$ in layer $l-1$, $b_j^l$ is the bias of the neuron $j$, and * denotes convolution. The training performance of a rectified linear unit (ReLU) is robust when compared to other activation functions. To achieve the desired output maps, we used ReLU as the activation function. A pooling layer follows the convolutional layer. Using this layer, successive layers can be reduced in dimension, network parameters, and computation cost. By considering the average value or maximum value, specific functions are used to summarize subregions. As a result of the pooling layer, the CNN could also learn scale-invariant features or those that are associated with orientation variations [13–15]. A window is drawn across the previous feature map during the pooling process. The convolutional layer is activated first, followed by max pooling. Finally, a dense layer is fully integrated with the outputs of all previous layers, which typically is used in the final stages of CNN-LSTM analysis.

### 3.3 LSTM

In an LSTM or Long-Short Term Memory network, the cell state is managed by three gates, namely the forget gate, the input gate, and the output gate. The gate units are fed with the output features of the previous dense layer of the CNN network. Each LSTM cell updates its state by activating the gate units, which are controlled by a continuous value between 0 and 1. After each t steps, the hidden state ($h_t$) of the LSTM is updated. As shown in the Eqs. (2)–(4), there are three gates: input, forget, and output.

$$Input\ gate\ = sigmoid(W_i x_t + W_i h_{t-1} + b_i) \tag{2}$$

$$Forget\ gate\ = sigmoid\big(W_f x_t + W_f h_{t-1} + b_f\big) \tag{3}$$

$$Output\ gate\ = sigmoid(W_o x_t + W_o h_{t-1} + b_o) \tag{4}$$

$$Hidden\, state,\ h_t = o_t.\sigma_c(c_t) \tag{5}$$

where $h_t$ is the hidden state, $\sigma_c$ is tanh function, $x_t$ is the input, $h_{t-1}$ is the input from the previous timestep LSTM, $o_t$ is the output of the LSTM, and $c_t$ is the cell state of LSTM network. The weight matrices ($W_i$, $W_f$, $W_o$), and bias ($b_i$, $b_f$, $b_o$) are not time-dependent. By detecting these feature maps, the LSTM layer extracts their temporal information. Such layers are specifically designed for solving dependencies arising over the long term. This skill is less hard than that of RNNs, namely remembering long-term information. In this study, 100 hidden units are used in the LSTM layer.

### 3.4 Densely Connected LSTM (DC-LSTM)

The module consists of multiple LSTM layers as illustrated in Fig. 3. For the first layer of LSTM, the input signal sequence is

$$\{x(w_1), x(w_2), \ldots, x(w_s)\} \tag{6}$$

and the output of the initial layer is

$$y^1 = \left\{y_1^1, y_2^1, \ldots, y_s^1\right\} \tag{7}$$

The input signal sequence is represented by $x$, weights by $w$, the output by $y$ and the last layer of the network as $s$. For the second layer, the concatenated output from the previous layer is taken, formulated as,

$$\left\{\left[e(w_1); y_1^1\right], \left[e(w_2); y_2^1\right], \ldots\ldots, \left[e(w_s); y_s^1\right]\right\} \tag{8}$$

and the output is

$$y^2 = \left\{y_1^2, y_2^2, \ldots, y_s^2\right\} \tag{9}$$

In the third layer, the input is formulated as,

$$\left\{\left[e(w_1); y_1^1; y_1^2\right], \left[e(w_2); y_2^1; y_2^2\right], \ldots\ldots, \left[e(w_s); y_s^1; y_s^2\right]\right\} \tag{10}$$

The rest of the layers process similarly. Considering that there are $L$ dense layers in LSTM network, the average pooling value is formulated as,

$$y^* = average\left(h_1^L, h_2^L, \ldots, h_s^L\right) \tag{11}$$

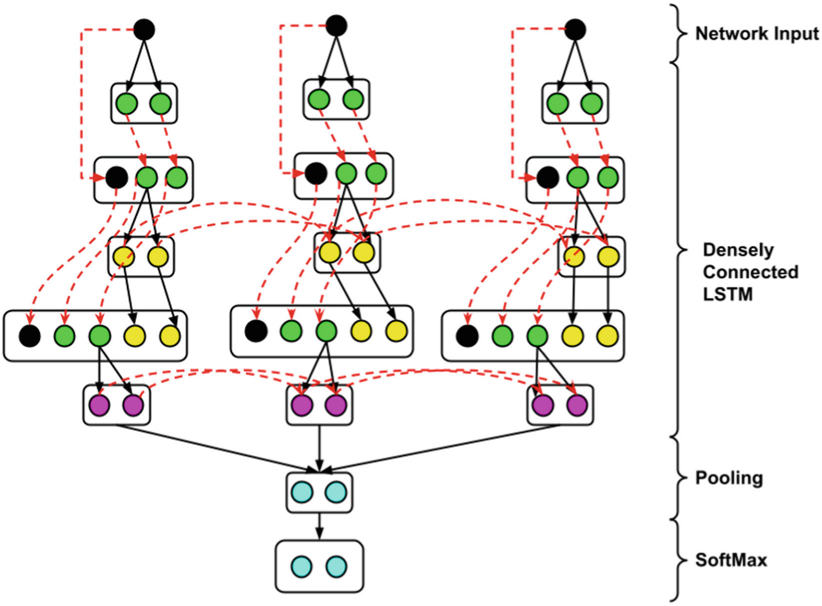


**Fig. 3.** Architecture of DC-LSTM

It consists of a simple soft-max classifier that takes a list of features, $y^*$, as features, and predicts a probability distribution over all labelled sentences.

The advantages of densely connected LSTM are,

- Trainable even with a very deep network. For each RNN layer, the outputs are directly sent to the last RNN layer as inputs, so vanishing gradient is alleviated because there is an implicit deep supervision.
- Better parameter efficiency is achieved. By reading the original input sequence directly, the system does not have to transfer all of the information to the network; it just adds it to the network. This means that the DC-LSTM layers are very thin (10 hidden units per layer).

In Fig. 3, black node denotes the input layer. Yellow-, green- and purple-coloured nodes are the hidden layers, the orange-coloured dotted lines indicate the average pooling between the layers and operation of copying. The blue-coloured node denotes the class. Solid lines represent the connection between layers.

### 3.5 Experimental Parameters

There are 70 ECG signals in the Apnea database, of which 35 are used for training and the rest for testing. Database for PPG signals included impedance respiratory signal, ECG lead II signal, and PPG, as well as heart rate and pulse rate. Signal data for 212 patients is listed along with the patient ID, ventilation status, and recording condition (critical or normal). A total of 282 measurements are taken, with data augmentation being done to increase the sample size for testing and training. Geometric transformation, rotation, and flipping are among the techniques used to enhance the data in this project. Of the total signals considered 80% of the data is taken for training, 15% for testing, and 5% for validation. Table 2 provides details about the learning parameters of the proposed model. There are several factors in this table, including: learning rate, optimizer, hidden units, number of fully connected layers, LSTM units, epochs, and activation function. There are no differences between the models as far as comparison is concerned.

**Table 2.** Deep network parameters

| Parameters | CNN-LSTM | DC-LSTM |
|---|---|---|
| Learning rate | 0.0001 | 0.0001 |
| Optimizer | Adam | Adam |
| Hidden units in LSTM | 100 | 100 |
| No. of fully connected layers | 2 | 2 |
| Dropout | 0.15 | 0.15 |
| No. of LSTM units | 512 | 512 |
| Epochs | 30 | 30 |
| Activation function | ReLU, SoftMax | ReLU, SoftMax |

## 4 Results

The purpose of this study is to compare two deep learning models for classifying sleep apnea with the help of ECG and PPG signals. Using hyper-parameter settings enables the classification method to tune its parameters to reduce error and hold onto the optimal settings for internal parameters. Our method is evaluated by using the Kappa Coefficient (KP), a statistical measure of inter-rater agreement. Further, Accuracy, Sensitivity, Specificity, Positive and Negative Predictive Values, are calculated according to epoch-by-epoch analysis,

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN}\% \tag{12}$$

$$Sensitivity = \frac{TP}{TP + FN}\% \tag{13}$$

$$Specificity = \frac{TN}{TN + FP}\% \tag{14}$$

$$PPV = \frac{TP}{FP + TP}\% \tag{15}$$

$$NPV = \frac{TN}{TN + FN}\% \tag{16}$$

**Table 3.** Performance of the proposed model for detection of OSA

| Study | DL | KP | Acc. (%) | Sen. (%) | Spec. (%) | PPV (%) | NPV (%) | F1 score (%) |
|---|---|---|---|---|---|---|---|---|
| E. Urtnasan et al. 2018 [3] | CNN | – | 96 | 96 | 96 | – | – | 95 |
| L. Chen et al. 2015, [5] | SVM | – | 97.4 | – | – | – | – | – |
| N. Banluesombatul et al. 2018 [7] | CNN | – | 79.45 | 77.6 | 80.1 | – | – | – |
| Sheta A et al. 2021, [8] | CNN-LSTM | 0.89 | 86.25 | – | – | – | – | – |
| Vattamthanam, S et al. 2020, [9] | RNN | | 88.03 | – | – | – | – | – |
| Zhang, J et al. 2021 [10] | CNN | – | 96.1 | 96.1 | 96.2 | – | – | 96.2 |
| Proposed model | DC-LSTM | **0.92** | **98.2** | **97.4** | **97.5** | **98.2** | **93.8** | **97.5** |

True positives, true negatives, false positives, and false negatives are denoted by TP, TN, FP, and FN. The experiment is implemented using MATLAB R2021a. Different datasets, features sets, and classifiers have been used in different studies, making it difficult to compare various methods of automatic OSA detection. Comparing classification performances between existing methodologies and the proposed model is shown in Table 3, so that a fair comparison can be made with existing research. The proposed model performed better than the models in the previous studies, as shown in Table 3. Prior research primarily focused on the PPG or ECG signals; this study combined the two signals. Several factors contribute to the high level of accuracy achieved by the proposed deep learning method based on the table. Further, our method can be used with wearable medical devices, which makes it useful for monitoring OSA from home.

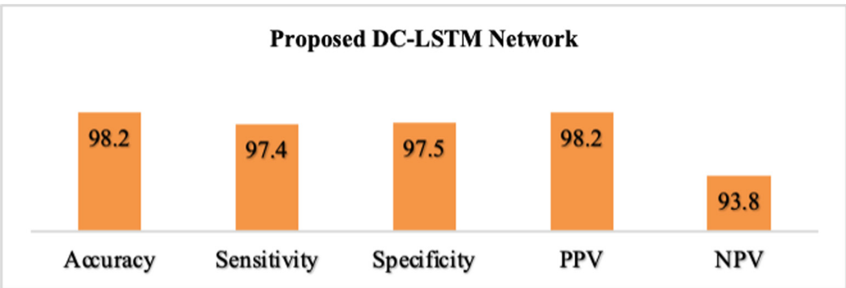


**Fig. 4.** Performance of proposed DC-LSTM model

Using deep learning methods, a CAD-based OSA detection method has been developed in this study. Figure 4 shows the performance of the proposed DC-LSTM network. Sleep apnea can be diagnosed using electrocardiograms and polysomnography recordings. With a sensitivity of 97.4%, specificity of 97.5%, accuracy of 97.3%, and a Kappa coefficient of 0.92, the proposed network model is as good as other research findings in detecting normal and apneic events. Traditional machine-learning methods require researchers to spend a lot of energy on feature extraction in sleep data, but neural networks do a better job in solving these problems. With increasing network depth, a CNN and LSTM are one of the most popular structures in deep learning. Group convolution and LSTMs are used at both levels in the structure, which enables us to maximize feature extraction capabilities, increase memory, and decrease network parameters, resulting in a faster training time for our network.

### 4.1 Limitations of the Study

Learning alone does not provide a complete understanding of output, which involves classifiers. In order to accomplish such tasks, convolutional neural networks are used. Network training is limited by the fact that it takes a longer time. Deep learning networks cannot be selected according to a standard theory. A better understanding of machine learning and deep learning is required for both the training and assessment of the results.

## 5 Conclusion

A lack of sufficient oxygen supply led to a persistent sleep disorder, OSA. Detecting OSA in its early stages can save lives. An innovative Densely Connected LSTM (DC-LSTM) is proposed in this paper for the detection of OSA. With DC-LSTM, vanishing gradients are alleviated, and overfitting can be effectively addressed even when networks have as many layers as dozens. Despite its robustness and automation, the proposed approach can be easily adapted for the analysis and prediction of other physiological signals. Experiments show that the proposed model is significantly better than traditional LSTMs and gets promising performance when compared to state-of-the-art approaches based on ECG and PPG signals.

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