An embedded system for the classification of sleep disorders using ECG signals

Lavu Venkata Rajani Kumari, Babishamili Daravath, Yarlagadda Padma Sai
Department of ECE, VNR Vignana Jyothi Institute of Engineering and Technology, Telangana, India

Article Info

Article history:

Received Jul 19, 2024
Revised Nov 1, 2024
Accepted Nov 11, 2024

Keywords:

Deep learning
Deep LSTM
Electrocardiogram
Sleep apnea
Time-series data

ABSTRACT

Sleep apnea (SA) is a well-known sleep disorder. It predominantly appears due to lack of oxygen in humans. Identifying SA at an early stage can help early diagnosis. The primary motto of our research is to identify SA using electrocardiogram (ECG) signals. Here, three classes are considered for classification. One is normal (N), and the other two are SA classes obstructive sleep apnea (OA) and central sleep apnea (CA). ECG signals are accumulated for MIT-BIH polysomnographic dataset. The ECG data divided into ECG segments and labelled using annotation file. The proposed deep long short-term memory (LSTM) model is then trained using ECG segments and further tested. The model is then finetuned and optimized to obtain the best accuracy. An accuracy of 98.51% is obtained. In addition, performance measures like precision, sensitivity, specificity, F-score are also evaluated. The model is then deployed on NVIDIA's Jetson nano board to build a prototype. Our model is effective, promising and outperformed existing state of art techniques.

Corresponding Author:

Lavu Venkata Rajani Kumari
Department of ECE, VNR Vignana Jyothi Institute of Engineering and Technology
Telangana, India
Email: rajanikumari_lv@vnrvjiet.in

1. INTRODUCTION

Sleep apnea (SA) becomes a major problem while human breathing is interrupted [1]. Persons with SA often feels tired even after having a proper sleep. SA is mainly categorized as obstructive sleep apnea (OA) and central sleep apnea (CA) [2]. Obstructive apnea occurs when the upper airway is repeatedly blocked during sleep, leading to a decrease or cessation of airflow. CA occurs when the brain does not send breathing signals, which makes it difficult for a person to breathe. The standard way to diagnose SA is polysomnography (PSG), which needs analyzing the patients' physiological data while sleeping. Collecting data using PSG is costly and time-consuming. Several cost-effective methods have been proposed to detect SA [3]-[6]. Some researchers contend that SA constitutes a predictable risk factor for stroke, leading to individuals affected by SA having an approximate twofold increased risk of stroke when contrasted with those unaffected by the condition [7]. It is evident that SA poses a significant risk to the overall physical and mental well-being of individuals worldwide, as approximately 936 million adults between age 30-69 experience mild to severe OA while 425 million adults in the same age group endure moderate to severe OA [8]. High prevalence of SA, it is crucial to conduct screenings for individuals with this disorder and implement prompt interventions. The significance of our research is to detect SA using electrocardiogram (ECG) signals. The dataset used in this study is MIT-BIH polysomnographic dataset [9].

Collection of ECG data is highly cost effective [10], [11]. Hence, the models developed using ECG data are lowest cost models that can identify SA over a period. Various academic studies have examined the efficacy of identifying SA through the analysis of ECG signals [11]-[25]. Kaya and Yilmaz [12] tried find the relation between SA and ECG signals. The relationship between sleep apnea and ventricular re-polarization was examined. The significance of examining the ECG signals to detect the occurrence of SA [12] was noted. Xie and Minn [14] used an adaptive boosted decision tree algorithm [13] along with decision stump to identify sleep apnea. Rodrigues *et al*. [16] examined various classification models for predicting apnea-hypopnea index (AHI). Nishad *et al*. [17] offers a straightforward method for detecting sleep apnea in adult patients, with the ability to discern its presence through visual examination of ECG using filterbanks. Chen *et al*. [18] considered bidirectional gated recurrent units (Bi-GRUs) as building blocks of the model. Novel model was proposed by adding Bi-GRU layer to 1-D CNN. Uznańska *et al*. [19] identified a strong association between sleep apnea and cardiovascular illness. Liu *et al*. [20] considered the pretrained EfficientNet model as backbone and utilized XGboost to update the sample weights. Varon *et al*. [21] introduced an innovative automated approach for detecting sleep apnea using wide neural networks. In their study, for decomposition of nonstationary data, non parametized techniques were used. Li *et al*. [22] introduced a novel approach combining neural networks and hidden markov models (HMM) to identify SA. Chang *et al*. [23] developed one dimensional CNN for detecting sleep apnea using ECG signal. Sheta *et al*. [24] considered time series data to develop a DL model. An long short-term memory (LSTM) layer along with CNN was used. Mashrur *et al*. [25] proposed an end to end approach using wavelet transforms and empirical mode decomposition (EMD) along with 2-D CNN. ECG segments were converted into scalograms and considered as input.

Various hardware boards with integrated CPU along with graphic cards can be found for prototyping needs, including Jetson Nano/AGX/ TX1/TX2/Xavier, Raspberry Pi, Beagle Board, and Asus Tinker Board [10]. The NVIDIA Jetson platforms, exhibit superior functioning capabilities attributed to their high-speed GPUs. As a result, the Jetson series stands at the forefront of single-board computing within the realm of deep learning applications by providing developer kits with diverse features. The use of the Nvidia Jetson Nano developer kit in the creation of a prototype exemplifies its efficacy in facilitating innovative projects and technological advancements. Hence, in this research jetson nano kit is used to build hardware prototype.

The intent of this study is to develop a deep LSTM model using LSTM blocks. Three classes normal (N), OA and CA are considered for classification. This work mainly emphases on detecting SA using time-series data. ECG Signals are collected from MIT-BIH polysomnography dataset and segmented to obtain ECG segments. These segments are labelled via annotations file given in database. Deep networks are developed using LSTM building blocks with 300 hidden unit. This developed network is trained and optimized. Then it is tested for detecting SA using NVIDIA jetson board.

The remaining part of the paper is structured as follows. Section 2 depicts our proposed approach, including the details on dataset, segmentation and deep learning framework. Section 3 describes the experimental setup used for classification. In section 4, investigative findings are detailed and compared with literature. Section 5 describes the conclusion of our research.

2. METHOD

The objective of our research is to identify SA from ECG signals. The Data is collected from MIT-BIH polysomnographic dataset and segmented into ECG segments. These ECG segments are labelled using the annotations mentioned in database. The labelled dataset is considered for training and testing the proposed DeepLSTM model. Figure 1 signifies the proposed methodology.

2.1. MIT-BIH Polysomnographic dataset

MIT-BIH polysomnographic dataset [8] contains 18 records. Dataset considered in this research is an imbalance dataset. To consider balanced data, we have considered 7 records-Slp01am, Slp01bm, Slp04m, Slp16m, Slp37m, Slp60m, Slp67xm in this research. The segments in these records are labelled as per the annotions given in dataset. The remaining records have a majority of normal signals and only few apnea signals. Hence, the remaining signals are ignored. The summary of beats considered is shown in Table 1.

The Normal class is noted as ‘N’, obstructive sleep apnea class is notes as ‘OA’, and central sleep apnea class is noted as ‘CA’. These three considered classes are shown in Figure 2. The labelled data is further divided into training, testing and validation data. Summary of beats considered for training, testing, and validation is given in Table 2.

2.2. Deep LSTM framework

LSTM is a type of recurrent network used for processing time-series data. In this study we have considered LSTM blocks to build a LSTM layer. 300 hidden LSTM blocks are used to develop a LSTM layer. Labelled ECG segments are given as inputs to designed LSTM layer. The output is connected to fully connected layer followed by SoftMax activation. The layered architecture of proposed DeepLSTM framework is displayed in Figure 3.

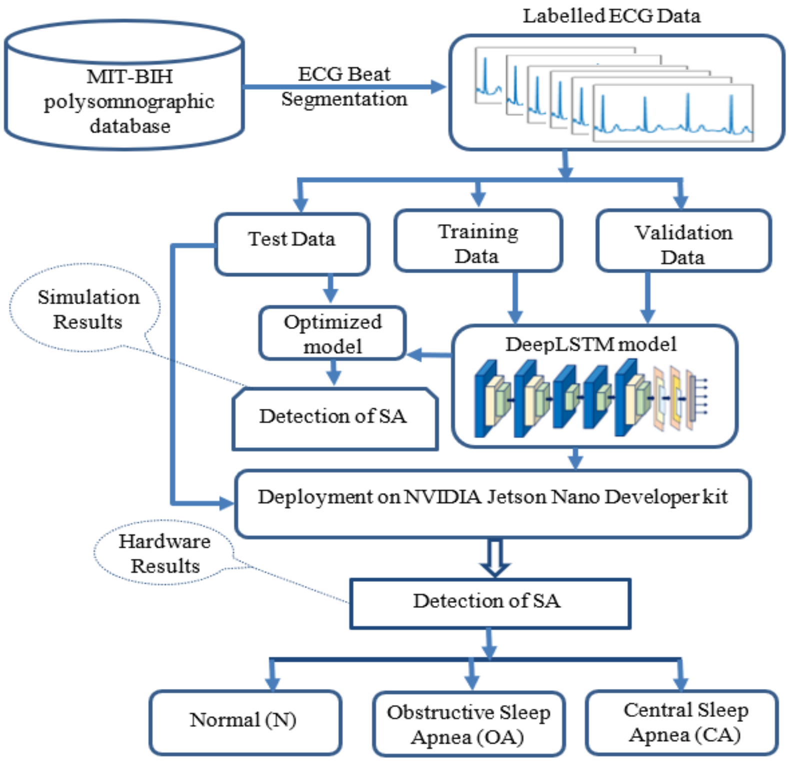
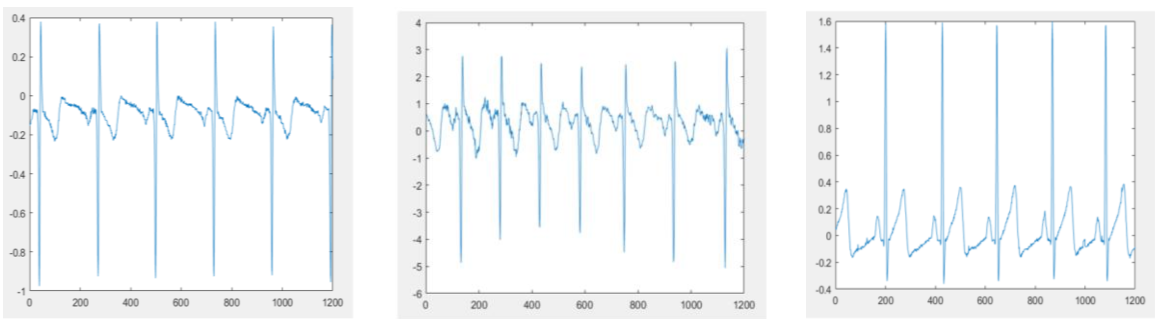


Figure 1. Proposed methodology

Table 1. Details of considered ECG segments form dataset

Record	Normal (N)	Obstructive sleep apnea (OA)	Central sleep Apnea (CA)
Slp01am	564	-	-
Slp01bm	336	-	-
Slp04m	-	165	-
Slp16m	-	210	-
Slp37m	-	525	-
Slp60m	-	-	147
Slp67xm	-	-	753
Total	900	900	900



(a) (b) (c)

Figure 2. ECG signals considered from dataset, (a) normal ECG, (b) obstructive sleep apnea class, and (c) central sleep apnea class

Table 2. Details of ECG segments considered for training, validation and testing

Class	Training	Validation	Testing	Total
N	630	90	180	900
OA	630	90	180	900
CA	630	90	180	900
Total	1890	270	540	2700

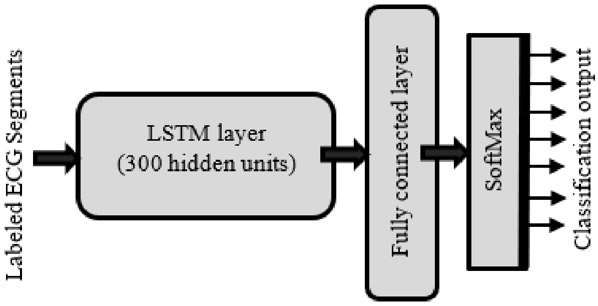


Figure 3. Layered architecture of proposed DeepLSTM framework

3. RESULTS AND DISCUSSIONS

NVIDIA Jetson nano board is utilized for developing hardware prototype. Its functionality affords us the opportunity to conduct the training of a designated DNN with a power consumption limited to 5 watts. This board is equipped with a 64- bit quad-core Arm CortexA57 CPU operated at 1.43 Gigahertz, paired with a NVIDIA Maxwell GPU containing 128 CUDA cores capable of 472 GFLOPs (FP16), and is supported by 4 GB of 64-bit LPDDR4 RAM. Tegrastats was utilized for the purpose of performance analysis and training Deep Neural Networks. It is a tool offered by NVIDIA for collecting data on hardware utilization, memory usage, and power consumption of both the CPU and GPU. NVIDIA Jetson nano developer kit is shown in Figure 4.

A total of 2700 ECG segments as given in Table 1 are considered for training, testing and validation. The step-by-step evaluation of the result obtains during the training process is shown in Figure 5. Once the training is completed, build the executable file. Initialize the libraries CuDNN, TensorRT along with nvcc path and check CUDA availability. Now, launch the executable file on target. Figure 6 shows the results when the executable file is launched on hardware and tested with test data. The confusion matrix obtained when tested with 540 ECG segments is shown in Figure 6. It is observed that for Class 'N', all the 180 ECG segments are correctly classified as class 'N'. Out of 180 'OA'. 174 segments are correctly classified as 'OA' and 6 segments are misclassified as 'CA'. Similarly, among 180 'CA' segments 178 are correctly identified as 'CA' and 2 segments are misclassified as 'OA'.

To verify the efficacy of developed model, precision, specificity, sensitivity, F-score, and accuracy are evaluated using formulae listed [26]-[28].

$$Precision = \frac{Tp}{Tp+Fp} \tag{1}$$

$$Recall = \frac{Tp}{Tp+Fn} \tag{2}$$

$$Specificity = \frac{Tn}{Fp+Tn} \tag{3}$$

$$F - Score = \frac{Tp}{Tp+0.5(Fp+Fn)} \tag{4}$$

$$Accuracy = \frac{Tp+Tn}{Tp+Fp+Fn+Tn} \tag{5}$$

Where Tp-True positives, Tn -True negatives, Fp -False positives and Fn -False negatives. The performance parmeters of our proposed DeepLSTM framework is summarized in Table 3. It can be observed that there is no misclassification of 'N' type segments. All of the misclassified segments are from 'OA' and 'CA' type ECG segments.

Numerous findings observed by researchers are listed in Table 4. Kaya and Yilmaz [12] developed a ML algorithm using decision tree and used ensemble method adaboost to improve the performance. An accuracy of 82% was obtained. Uznańska *et al.* [19] performed HRV analysis considering ECG signals and an accuracy of 85% was obtained. Liu *et al*. [20] achieved an accuracy of 85% using a hybrid model which includes DL and HMM. Varon *et al*. [21] implemented a DL model using 1D CNN and achieved an accuracy of 87.9%. Li *et al*. [22] added LSTM layer along with CNN and achieved an accuracy of 86.25%. Our proposed DeepLSTM outperformed existing methodologies with an accuracy of 98.51%.

Figure 4. NVIDIA Jetson nano developer kit

```
Number of training images: 1890
Number of validation images: 270


Initializing input data normalization.
```

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:00	26.67%	59.38%	4.6580	1.4526	0.0010
2	30	00:10:01	73.33%	59.38%	0.9057	0.9468	0.0010
3	60	00:20:03	66.67%	62.50%	1.0064	1.0275	0.0010
4	90	00:30:04	66.67%	59.38%	0.7693	0.8893	0.0010
5	120	00:40:05	33.33%	59.38%	1.0207	0.7603	0.0010
7	150	00:50:07	86.67%	78.12%	0.5593	0.6586	0.0010
8	180	01:00:08	86.67%	81.25%	0.3727	0.5614	0.0010
9	210	01:10:09	86.67%	78.12%	0.3077	0.5213	0.0010
10	240	01:20:11	80.00%	75.00%	0.5895	0.5206	0.0010
12	270	01:30:12	73.33%	84.38%	0.4651	0.4970	0.0010
13	300	01:40:13	86.67%	78.12%	0.2746	0.5063	0.0010
14	330	01:50:15	86.67%	81.25%	0.2943	0.6244	0.0010
15	360	02:00:16	100.00%	78.12%	0.2102	0.4025	0.0010
17	390	02:10:17	93.33%	91.25%	0.2943	0.6244	0.0010
18	420	02:20:19	100.00%	98.12%	0.2746	0.5063	0.0010
19	450	02:30:20	100.00%	98.12%	0.2102	0.4025	0.0010
20	465	02:40:21	100.00%	99.62%	0.0017	0.0315	0.0010

```
Total training time: 02hh 40mm 32ss

accuracy =

    0.9962

Trained network size: 2982.32 kB
Test prediction time (number of tests: 270)... Average prediction time (execution environment: gpu): 8.95e-03 sec
```

Figure 5. Step by step evaluation

```
### Launching the executable on the target...
Executable launched successfully with process ID 13812.
Displaying the simple runtime log for the executable...
Note: For the complete log, run the following command in the MATLAB command window:
system(hwobj,'C/Users/Documents/MATLAB//R2023b//NVIDIAJetson/model_predict_ecg.log')
Fetch time = 1.908e+01 sec
tPred = 1.955e+01 sec

         CA     OA     W

   CA    178    2      0
   OA    6      174    0
   W     0      0      180

accuracy =
    0.985185
```

Figure 6. Hardware results

Table 3. Performance measures

Class	Precision (%)	Sensitivity (%)	Specificity (%)	F-score (%)
N	100	100	100	100
OA	96.667	98.864	98.352	97.753
CA	98.889	96.739	99.438	97.802
Overall Test accuracy: 98.51%				

Table 4. Comparison of our approach with state-of-the-art models

Authors	Method	Performance (%)
Xie and Minn *et al*. [14]	Decision tree with Adaboost	82
Varon *et al*. [21]	Wide neural networks (WNN)	96.60
Li *et al*. [22]	DL+HMM hybrid model	85
Chang *et al*. [23]	1D CNN model	87.9
Sheta *et al*. [24]	CNN+LSTM	86.25
Mashrur *et al*. [25]	CWT+EMD	94.3
Our proposed model	DeepLSTM	98.51

4. CONCLUSION

DeepLSTM model has been proposed to detect SA from ECG signal. The data has been collected from MIT-BIH polysomnographic database. ECG signals are then segmented into ECG segments. These segments are labelled using the annotation file mentioned in database. The proposed model is then trained considering various hyperparameters. Further, model is saved with best hyperparameters and then tested. Our model recorded the best accuracy of 98.51% compared to existing literature. It is concluded that sleep disorders can be identified using sleep quality features from a 30-second epoch of the ECG signal. This method has proven to be reliable for modeling sleep disorders without the need for a multichannel PSG signal. Additionally, it is straightforward to implement on embedded hardware devices. Our proposed system is portable and customizable, making it an ideal solution for continuous sleep apnea monitoring.

REFERENCES

[1] I. Umbro, V. Fabiani, M. Fabiani, F. Angelico, and M. Del Ben, "A systematic review on the association between obstructive sleep apnea and chronic kidney disease," *Sleep Medicine Reviews*, vol. 53, 2020, doi: 10.1016/j.smrv.2020.101337.

[2] M. Sharma, M. Raval, and U. R. Acharya, "A new approach to identify obstructive sleep apnea using an optimal orthogonal wavelet filter bank with ECG signals," *Informatics in Medicine Unlocked*, vol. 16, 2019, doi: 10.1016/j.imu.2019.100170.

[3] S. Yook, D. Kim, C. Gupte, E. Y. Joo, and H. Kim, "Deep learning of sleep apnea-hypopnea events for accurate classification of obstructive sleep apnea and determination of clinical severity," *Sleep Medicine*, vol. 114, pp. 211–219, 2024, doi: 10.1016/j.sleep.2024.01.015.

[4] P. Fonseca *et al.*, "Estimating the Severity of Obstructive Sleep Apnea Using ECG, Respiratory Effort and Neural Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 7, pp. 3895–3906, 2024, doi: 10.1109/JBHI.2024.3383240.

[5] A. Thommandram, J. M. Eklund, and C. McGregor, "Detection of apnoea from respiratory time series data using clinically recognizable features and kNN classification," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, pp. 5013–5016, 2013, doi: 10.1109/EMBC.2013.6610674.

[6] S. Kim *et al.*, "A Comprehensive Study on a Deep-Learning-Based Electrocardiography Analysis for Estimating the Apnea-Hypopnea Index," *Diagnostics*, vol. 14, no. 11, 2024, doi: 10.3390/diagnostics14111134.

[7] O. D. Lyons and C. M. Ryan, "Sleep Apnea and Stroke," *Canadian Journal of Cardiology*, vol. 31, no. 7, pp. 918–927, Jul. 2015, doi: 10.1016/j.cjca.2015.03.014.

[8] A. V. Benjafield *et al.*, "Estimation of the global prevalence and burden of obstructive sleep apnoea: a literature-based analysis," *The Lancet Respiratory Medicine*, vol. 7, no. 8, pp. 687–698, 2019, doi: 10.1016/S2213-2600(19)30198-5.

[9] Goldberger A. *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," *Circulation [Online]*, vol. 101, no. 23, pp. E215–E220, 2021.

[10] Mohebbanaaz, Y. Padma Sai, and L. V. Rajani Kumari, "Cognitive assistant DeepNet model for detection of cardiac arrhythmia," *Biomedical Signal Processing and Control*, vol. 71, 2022, doi: 10.1016/j.bspc.2021.103221.

[11] Mohebbanaaz, Y. Padma Sai, and L. V. Rajani Kumari, "A Review on Arrhythmia Classification Using ECG Signals," *2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science, SCEECS 2020*, 2020, doi: 10.1109/SCEECS48394.2020.9.

[12] K. A. Kaya and B. Yilmaz, "A new tool for QT interval analysis during sleep in healthy and obstructive sleep apnea subjects: A study on women," *Turkish Journal of Electrical Engineering and Computer* Sciences, vol. 21, no. 5, pp. 1504–1513, 2013, doi: 10.3906/elk-1203-62.

[13] O. Faust, U. R. Acharya, E. Y. K. Ng, and H. Fujita, "A review of ECG-Based diagnosis support systems for obstructive sleep apnea," *Journal of Mechanics in Medicine and Biology*, vol. 16, no. 1, 2016, doi: 10.1142/S0219519416400042.

[14] B. Xie and H. Minn, "Real-time sleep apnea detection by classifier combination," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 3, pp. 469–477, 2012, doi: 10.1109/TITB.2012.2188299.

[15] L. V Kumari, Y. P. Sai, and others, "Classification of ECG beats using optimized decision tree and adaptive boosted optimized decision tree," *Signal, Image and Video Processing*, vol. 16, no. 3, pp. 695–703, 2022.

[16] J. F. Rodrigues, J. L. Pepin, L. Goeuriot, and S. Amer-Yahia, "An Extensive Investigation of Machine Learning Techniques for Sleep Apnea Screening," *International Conference on Information and Knowledge Management, Proceedings*, pp. 2709–2716, 2020, doi: 10.1145/3340531.3412686.

[17] A. Nishad, R. B. Pachori, and U. R. Acharya, "Application of TQWT based filter-bank for sleep apnea screening using ECG signals," *Journal of Ambient Intelligence and Humanized Computing*, vol. 15, no. 1, pp. 893–904, 2024, doi: 10.1007/s12652-018-0867-3.

[18] J. Chen, M. Shen, W. Ma, and W. Zheng, "A spatio-temporal learning-based model for sleep apnea detection using single-lead ECG signals," *Frontiers in Neuroscience*, vol. 16, 2022, doi: 10.3389/fnins.2022.972581.

[19] B. Uznańska, E. Trzos, T. Rechciński, J. D. Kasprzak, and M. Kurpesa, "Repeatability of sleep apnea detection in 48-hour holter ECG monitoring," *Annals of Noninvasive Electrocardiology*, vol. 15, no. 3, pp. 218–222, 2010, doi: 10.1111/j.1542-474X.2010.00367.x.

[20] M. H. Liu *et al.*, "EfficientNet-based machine learning architecture for sleep apnea identification in clinical single-lead ECG signal data sets," *BioMedical Engineering Online*, vol. 23, no. 1, 2024, doi: 10.1186/s12938-024-01252-w.

[21] C. Varon, A. Caicedo, D. Testelmans, B. Buyse, and S. Van Huffel, "A Novel Algorithm for the Automatic Detection of Sleep Apnea from Single-Lead ECG," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 9, pp. 2269–2278, 2015, doi: 10.1109/TBME.2015.2422378.

[22] K. Li, W. Pan, Y. Li, Q. Jiang, and G. Liu, "A method to detect sleep apnea based on deep neural network and hidden Markov model using single-lead ECG signal," *Neurocomputing*, vol. 294, pp. 94–101, 2018, doi: 10.1016/j.neucom.2018.03.011.

[23] H. Y. Chang, C. Y. Yeh, C. Te Lee, and C. C. Lin, "A sleep apnea detection system based on a one-dimensional deep convolution neural network model using single-lead electrocardiogram," *Sensors (Switzerland)*, vol. 20, no. 15, pp. 1–15, 2020, doi: 10.3390/s20154157.

[24] A. Sheta *et al.*, "Diagnosis of obstructive sleep apnea from ECG signals using machine learning and deep learning classifiers," *Applied Sciences (Switzerland)*, vol. 11, no. 14, 2021, doi: 10.3390/app11146622.

[25] F. R. Mashrur, M. S. Islam, D. K. Saha, S. M. R. Islam, and M. A. Moni, "SCNN: Scalogram-based convolutional neural network to detect obstructive sleep apnea using single-lead electrocardiogram signals," *Computers in Biology and Medicine*, vol. 134, 2021, doi: 10.1016/j.compbiomed.2021.104532.

[26] L. V. Rajani Kumari and Y. Chalapathi Rao, "ECG beat classification using proposed pattern adaptive wavelet-based hybrid classifiers," *Signal, Image and Video Processing*, vol. 17, no. 6, pp. 2827–2835, 2023, doi: 10.1007/s11760-023-02501-6.

[27] L. V. R. Kumari, A. Lohitha, A. Kavya, and N. Tarakeswar, "Automated sleep apnea classification based on statistical and spectral analysis of electrocardiogram signals," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, pp. 1450–1457, 2022, doi: 10.11591/ijeecs.v25.i3.pp1450-1457.

[28] Mohebbanaaz, Y. Padma Sai, and L. V. Rajani Kumari, "Detection of cardiac arrhythmia using deep CNN and optimized SVM," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 24, no. 1, pp. 217–225, 2021, doi: 10.11591/ijeecs.v24.i1.pp217-225.

BIOGRAPHIES OF AUTHORS

Lavu Venkata Rajani Kumari Hyderabad has completed BTech in ECE, MTech in Embedded Systems, and PhD degree in biomedical signal processing from JNTUH. She has presented 45 research papers in international journals/conferences and three patents. She is a Senior member of IEEE, Life member of ISTE and Member of IETE. Her areas of research interest are Bio-Medical, Signal and Image Processing, Embedded systems, IOT, Machine Learning and deep learning to create societal impact. She has received an AICTE-RPS with an amount of 8.25 lakhs. She is the Coordinator of QS and UGC and actively involved in NBA, NAAC and JNTUH works at institute level. She can be contacted at email: rajanikumari_lv@vnrvjiet.in.

Babishamili Daravath Hyderabad completed B.Tech in ECE. She is presently pursuing M.Tech in VNR VJIET, Hyderabad. She can be contacted at email: babydaravath06@gmail.com.

Yarlagadda Padma Sai is professor and Dean-Student Progression ECE, VNRVJIET, Hyderabad has received Ph.D. in Bio-medical Signal processing from Osmania University. She is a senior member of IEEE, Life member of ISTE, ISOI, ASCI and Fellow of IETE, IEI, Chairman for WIE Affinity Group IEEE Hyderabad Section. She has presented and published 80 research papers in National and International Conferences/Journals. One of the inventors of the patent and published by Indian Patent office Titled a Method and System for Analyzing Risk Associated with Respiratory Sounds. She has received 2 awards (one Gold and special prize) from Korea International Women Invention Exposition (KIWIE-2019) as women entrepreneur of Salcit Technologies Private Limited. She can be contacted at email: padmasai_y@vnrvjiet.in.