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Stockwell Transform-based Deep Learning Architecture for the Automated Classification of Obstructive Sleep Apnea from single-lead electrocardiograms

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Abstract

Background: Obstructive Sleep Apnea (OSA) is a severe, chronic sleep disorder that can lead to hypertension and stroke. Traditional diagnosis of OSA is done through polysomnography (PSG), which is expensive, time-consuming, and unpleasant. Previous methods for OSA detection have used time domain and frequency domain features from ECG signals. Earlier methods employed Spectrogram and Scalogram techniques to analyze and visualize the frequency content of ECG signals over time. However, these techniques have limitations such as spectral leakage, compromised time-frequency resolution, susceptibility to cross-terms and interference, and potential computational complexity.
Objectives: To address the limitations of existing techniques for OSA detection using ECG signals and to propose a new approach that combines aspects of Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) for filtering and segmentation as input to a deep learning model.
Methods: The research proposes applying the Stock well transform, a time-frequency analysis method that combines aspects of both STFT and CWT, for filtering and segmentation of ECG signals as input to a deep learning model. A 2D-CNN model is developed for OSA detection using the processed ECG signals.
Statistical Analysis: The performance of the proposed 2D-CNN model is evaluated using metrics such as accuracy, specificity, sensitivity, and recall.
Findings: The proposed 2D-CNN model demonstrates an average accuracy of 91.68%, Specificity of 93.27%, Precision of 95.70%, and recall of 90.72%. The results indicate that the proposed framework outperforms many existing state-of-the-art methodologies for OSA detection using ECG signals.
Applications: The proposed approach can be applied in the development of more accurate and efficient methods for OSA detection, potentially leading to earlier diagnosis and treatment of this sleep disorder.
Improvements: Future developments could focus on further improving the accuracy and computational efficiency of the proposed method, as well as exploring its applicability to other biomedical signal processing tasks.

Keywords: Future developments could focus on further improving the accuracy and computational efficiency of the proposed method, as well as exploring its applicability to other biomedical signal processing tasks.

1. Introduction

OSA is a sleep condition characterized by the obstruction of upper airway passageways, namely in the oropharynx area. This obstruction causes either partial or total collapse of the airway, resulting in a temporary halt of airflow for around 10 seconds during sleep [1]. It is a chronic disease which deprives oxygen and arousal and impacts sleep, also creating breathing problems. Approximately 3% to 7% of the individuals with this condition have disturbed sleep at night [2]. Since the negative intrathoracic pressure collapses the airway during normal inspiration instead of allowing normal airflow, the result is decreased oxygen saturation and activated central nervous system, which in turn results in fragmentation of sleep to reestablish breathing. OSA directly causes unhealthy sleep cycles. As a result of inadequate sleep quality, people experience fatigue, drowsiness, and lack of concentration [4]. OSA is one of the major causes for Hypertension, Cardiovascular illness [3]. It is essential to perform accurate analyses and to treat these complications in a timely manner .

Among clinical sleep apnea diagnosis methods, polysomnography, also known as PSG, is considered the gold standard. An overnight PSG is performed in a sleep laboratory using specialized equipment and a specialized staff. Medical domain experts correlate these recordings to detect sleep apnea in a patient [4]. PSG is a very expensive and painful procedure. Utilising less complicated sleep monitoring has a number of advantages, such as not interfering with sleep, being affordable, and not requiring specialised knowledge [5]. The development of multiple methods for OSA detection is based on various kinds of single-lead signals, including electroencephalograms (EEGs), electrocardiograms (ECGs), snoring, blood oxygen levels, and respiration signals [6]. The proper diagnosis of polysomnography is impeded by its high cost, complexity, time-consuming nature, the need for specialist technicians, signal synthesis and analysis, as well as patient annoyance. Consequently, its use in public health centres is limited. However, for the aforementioned purpose, the ECG signal is the most commonly employed physiological signal.

In [7] authors employed an eight-level wavelet packet analysis technique to distinguish between obstructive sleep apnea (OSA) and central sleep apnea (CSA) using a short-duration (5 s) ECG signal. The incapacity of the brain to provide the right information to the breathing muscles results in CSA. It is distinct from obstructive sleep apnea (OSA), which affects respiration normally but is complicated by an obstruction in the upper airway. In a similar investigation [10], authors distinguished between CSA and OSA using an auto-regressive ANN classifier and wavelet-based ECG features. A classification accuracy of 78.3% was attained. A number of additional time-frequency techniques, such as HHT and DWT, have been implemented in the classification of sleep apnea.

2. Background

First, Researchers are currently concentrating their efforts on detecting obstructive sleep apnea using single-lead electrocardiogram signals [8]. The ability to recognize apnea based on ECG is now highly dependent on deep learning models. Deep Learning (DL) can learn key features from input to produce results with fewer errors than handcrafted ML methods. Automatically extracting and aggregating important features for classification is one of DL's strongest points.An EEG-based method for detecting OSA has been proposed nevertheless, the ECG signal is a straightforward and economical method for detecting apnea episodes [9]. OSA is characterized by deviations in cardiac electrophysiology and autonomic nerve function, which manifest as aberrant ECG variations in pulse energy, amplitude of S-waves, and R-R intervals.

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QRS complex algorithm based the R-R interval using well-localized features for detecting. A framework for diagnosing sleep apnea disorders that utilizes time-domain data has been developed by [10]. The limited features of the 1D CNN render it incapable of extracting useful information from one-dimensional data using time information alone; as a consequence, the CNN performs relatively poorly. To learn feature representations from ECG signals, [11] proposed a Convolutional Neural Network (CNN), followed by a Transformer model with self-attentional components in capturing global temporal context and facilitating classification tasks. The SE-MSCNN system incorporates a channel-wise attention module and a multi-scaled convolutional neural network (CNN) module. This system utilises three sub-neural networks to derive multiple scaled ECG information from adjacent segments of varying durations in order to improve the detection of SA. A channel-wise attention module based on squeeze-to-excitation is additionally utilised to address the issue of locally concentrated feature fusion through adaptive integration of the various scaled features [12].
The technique [13] propose utilizes ResNet18 and ResNet50 deep learning models as a method to categorize obstructive sleep apnea (OSA). When using single-lead ECG signals to detect OSA, To generate scalograms and spectrograms, [14] proposed a model based on continuous wavelet transforms and short time Fourier transforms, respectively. An assessment of the performance of the AlexNet, GoogleNet, and ResNet18 models was conducted, as well as an exploration of the impact of transfer learning on the prediction of OSA events. The continuous wavelet transform was employed in study to transform ECG time-frequency data into Bag-of-Features features. Support vector machine, ensemble learning, and k-nearest neighbour methods were utilised for classification, in conjunction with cross-validation for data analysis.[15] Variational mode decomposition (VMD) reduces the dimensionality of feature vectors using principal component analysis and is used to break down heart rate variability and respiration signals into distinct modes. Spectral entropies, interquartile ranges, and energy can be extracted from these modes and used in the detection of sleep apnea. LeNet-5 CNN is altered and used on neighbouring segments by [16].

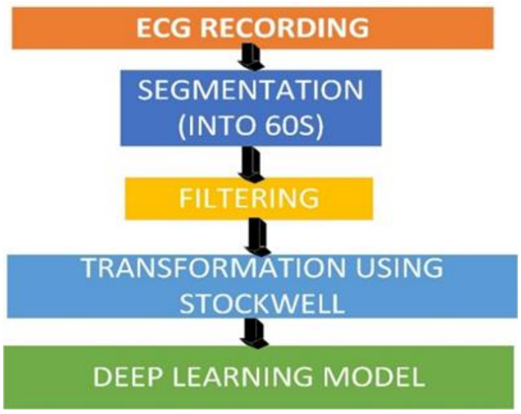

Figure 1. Diagram Illustrating the Proposed Model for Classification of OSA

3. Materials and Methods

In total, three stages comprise the proposed framework. Sixty-second segments are generated from input signals as the initial phase. During the second stage, the stock well transform is employed to convert each fragment from a one-dimensional ECG signal to a two-dimensional T-F Stockwell Spectrogram.

Each 2D image is inputted into the Deep Learning Model during the third stage. Figure 1 depicts the proposed classification of Obstructive Sleep apnea.

Dataset

Our study used data from the PhysioNet database version 1.0.0 containing an apnea ECG database version 1.0.0. developed by Philips University in Marburg, Germany [17]. ECG signals are sampled at 100 Hz is included in this study, containing 70 recordings. It takes an average of about 401 to 508 minutes for each recording to complete. The recordings were categorized into three classes according to the duration of disordered breathing.

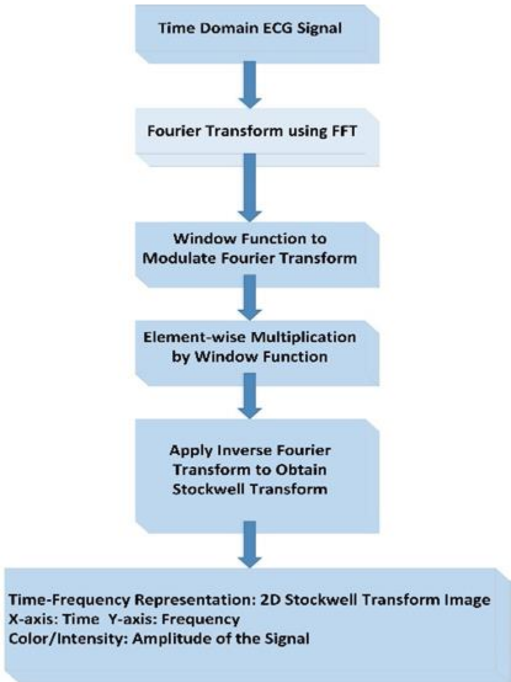

Figure 2. The Stockwell Transform Image Transformation Process in Steps

For example, Class A or apnea includes recordings lasting for more than 100 minutes. An episode of disordered breathing lasting 10 to 96 minutes is classified as Class B, or borderline apnea. There was no disordered breathing within five minutes of recordings in class C. A total of 35 recordings are included in each of the two sets of data.

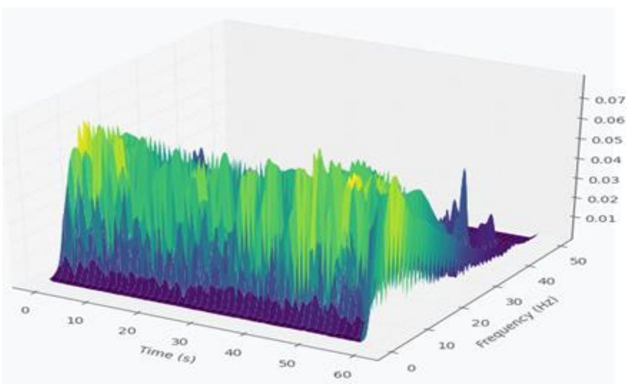

Figure 3. 3D Stockwell Transform of ECG Signal

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Each 60-second data item was annotated by medical experts based on visual examination [4] as either apnea 'A' or non-apnea 'NA' [4]. On the basis of these annotations, one-minute signal segments were extracted.

Preprocessing of the ECG signal

According to the annotations provided in the database, raw ECG signals are first converted into one-minute segments. To remove power line interference and adjust for baseline, ECG signal segments are filtered using a Butterworth band-pass filter with a lower cutoff frequency of 1Hz and an upper cutoff frequency of 45Hz [18].

Stockwell Transform

Stockwell transform when applied on non-stationary signals, such as ECG provides simultaneous localization of time and frequency, adjusting window width to minimize feature blurring and precisely capture transients. Stockwell Transforms (S-transforms) combine elements of Fourier and Wavelet Transforms. Like a spectrogram, the Stockwell Transform represents time-frequency data in a time-frequency manner with improved localization in both time and frequency captured transient features and analysed non-stationary signals [19]. It excels in applications requiring precise timing and improved frequency resolution, offering a comprehensive alternative to traditional time-frequency methods for effective signal analysis as per [20].The decision is based on particular signal properties and analysis objectives, which promotes trial and error to achieve the best outcomes [20].The S transform is obtained by applying phase correction to the continuous wavelet transform using the Gaussian function as the window [21].

$$S_x(t,f) = \int_{-\infty}^{\infty} x(\tau)|f|e^{-\pi(t-\tau)^2 f^2}\, e^{-j2\pi f\tau} d\tau$$

Based on the benefits the Stockwell Transform as mentioned, we used this transform on ECG signal in order to identify significant time-frequency morphological changes in the relevant class with deep learning architecture .There is no need for a separate algorithm for segmentation because the end-to-end system is entirely devoid of R-peak detection approaches.

Proposed Deep Learning Architecture

The Handcrafted features require extensive preprocessing, decomposition, selection, and categorization in traditional machine learning approaches. Even after several trials, the model fails to perform as expected. However deep learning, subset of machine learning field attempts to find representations that are distributed at different levels [22]. Convolutional neural networks (CNNs) provide exceptional classification performance in a range of applications, including signal classification, object identification and segmentation[23].This section describes how each layer functions. Firstly, we pre-process input images by resizing and rescaling them in order to remove the unwanted features from the images obtained and then augmented to enhance generalization of the model. The stock well transformed images are supplied into the CNN after being scaled to (224×224*3) resolution. We propose six feature extraction layers (FE), one flatten layer, and two dense layer for our CNN architecture. First feature extraction layer is followed by three layers of kernels in a 2D convolution layer. Each of the convolutional layer is followed by two max-pooling 2D layer with activation function ‘RELU’. Pooling Layer acts as a sample layer, lowering the size of the feature map and network parameters while preserving vital statistics. It reduces spatial dimensions and features by aggregating neighbouring values across operators to accomplish nonlinear down sampling. By preventing overfitting, this method enhances computing efficiency and translation invariance. In addition to these FE layers, a dense layer with rectifier linear unit (ReLU) activation, and a soft-max layer applied. ReLU is used in this study to improve the output feature maps' nonlinearity. [29], [30].

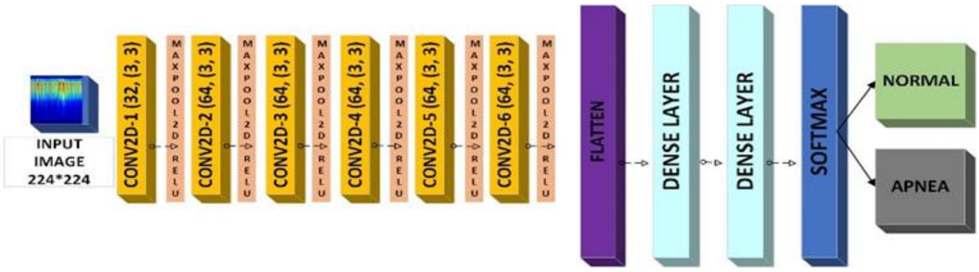

Figure 4. Novel Convolutional Neural Network (CNN) with Attention and Spatial Mechanism

Table 1. Tuneable Parameters and Layers Used in Designed CNN

S.No	Layer	Filters	Kernel Size	Total Tuneable Features
1	Conv2D	32	3,3	896
2	MaxP	-	2,2	
3	Conv2D	64	3,3	18496
4	MaxP	-	2,2	
5	Conv2D	64	3,3	36928
6	MaxP	-	2,2	
7	Conv2D	64	3,3	36928
8	MaxP	-	2,2	
9	Conv2D	64	3,3	36928
10	MaxP	-	2,2	
11	Conv2D	64	3,3	36928
12	MaxP	-	2,2	
13	Dense	128		8320
14	Softmax		NN=2	258

Conv 2D: Two-dimensional convolutional layer, MaxP: Max Pooling, NN: Number of Neurons

4. Experimental Results and Discussion

The main aim of this work was to categorise normal and apnea episodes by using ECG data in order to create a reliable and robust OSA detection system. This is achieved by using the Apnea-ECG database from PhysioNet. This method enables the rapid development and evaluation of the CNN model for ECG applications.

Model Training and Testing

The CNN model is implemented in Python using TensorFlow and Keras. We used Python in Google Colab to convert ECG data into Stockwell transform images. The model is trained and evaluated on a 12th Generation Intel(R) Core (TM) i7-12700H CPU and 16.0 GB of RAM. In the experimental investigations of the study, a total of 10,515 normal images and 6,515 apnea images were utilised. The whole dataset was divided into three sets: training (80%), validation (10%), and testing (10%). The training cum validation phase used a total of 13,632 stock well transform images, while the testing phase was carried out on a set of 1,728 images. The table displays loss curves for testing and training phases. The mean duration per epoch for both validation and training were roughly 121 seconds

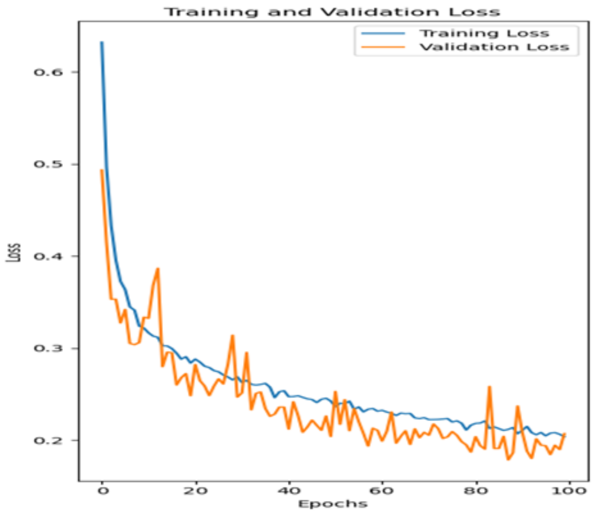

Figure 5. Loss and Accuracy During Testing and Training as a Function of the Number of Epochs

Performance of Classification

Confusion matrix values serve as the foundation for performance measure evaluation, offering insights into the model's accuracy and possible areas for development in terms of differentiating between the normal and apnea classes. The provided confusion matrix displays the categorization results of normal and apnea subjects using CNN on S transform images. Out of 1057 normal photos, the model properly categorised 959 of them. However, it mistakenly recognised 98 stocks well transform images as having apnea. Of the 639 apnea photos, 583 were correctly labelled as such, while 43 were incorrectly classed as normal.

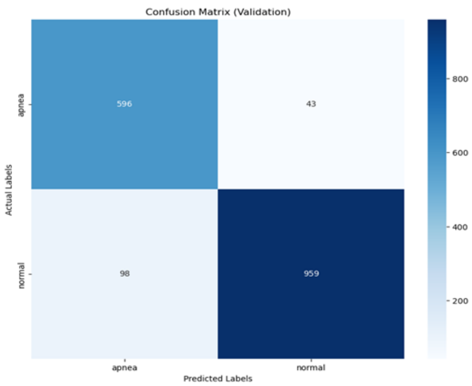

Figure 6. Confusion Matrix

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Performance Metrics

This study's performance indicators include F1-score, sensitivity/recall, specificity, accuracy, and precision. Formulae used to compute the F1-Scoreensitivity/recall, specificity, accuracy, and precision are given below, where TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative.

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

$$\text{Specificity} = \frac{TN}{(TN + FP)}$$

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

$$\text{Recall/Sensitivity} = \frac{TP}{(TP + FN)}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

During training and validation, the CNN model was subjected to 100 epochs with a learning rate of 0.00001 and a batch size of 32. A test dataset evaluation produced results with Accuracy: 91.68 %, Specificity: 93.27 %, Precision: 95.70 %, Recall: 90.72 %.

Table 2. Performance Metrics of the CNN Model

Sl. No	Metric	Value
1	Accuracy	91.68%
2	Specificity	93.27%
3	Precision	95.70%
4	Recall	90.72%

The table provides a thorough summary of the model's efficacy in categorising normal and apnea photos according to the given criteria by summarising many metrics related to its performance.

Comparison with Other Existing Models

Confusion The study describes a method for detecting obstructive sleep apnea (OSA) using single-lead electrocardiogram (ECG) readings, with findings that are in line with previous research.

Table 3. Comparison Table of the Proposed Model with Existing State of the Art Methods

S. No	Author (Year)	Proposed technique	Performance
1	[24] 2018	CAD system with antisymmetric wavelet filter bank	Accuracy= 90.11 Specificity=90.87 Sensitivity=88.88

2	[16] 2019	Modified version of LeNet-5 CNN	Accuracy= 87.60
3	[25] 2020	1D CNN model	Accuracy= 87.90 Specificity=92.00 Sensitivity= 81.10
4	[26] 2021	DWT with particle swarm optimization	Accuracy=89
5	[27] 2022	identifying the sinus atrial (SA) segment by detecting the S peak	Accuracy= 91.13 Specificity= 88.75 Sensitivity= 92.58
6	[13] 2023	Using ResNet Model	Accuracy= 89.00 Specificity= 89.00 Sensitivity= 89.00
7	[18] 2023	ECG beats into images using a constant Q-transform (CQT)	Accuracy= 91.34 Specificity= 90.70 Sensitivity= 90.68
8	Proposed Method 2024	Based on Stockwell Transform	Accuracy= 91.68 Specificity= 93.27

Prior research, including that of [18] (2023), suggested a two-dimensional Convolutional Neural Network (2D-CNN) for frequency domain-based identification and used constant Q-transform (CQT) to turn ECG beats into CQT images.[27] (2022) concentrated on identifying the sinus atrial (SA) segment more accurately by detecting the S peak in a single-lead ECG. For automated OSA diagnosis,[26] (2021) used the wavelet transform, particle swarm optimisation, and a variety of classifiers. For automated OSA diagnosis,[25] (2020) used a 1-D convolutional neural network. used a temporal window artificial neural network in earlier studies.[16] (2019) suggested a altered version of the LeNet-5 CNN that incorporates neighbouring segments. An OSA-CAD system with a biorthogonal antisymmetric wavelet filter bank and a single-channel ECG was presented by [24] (2018). The current study focuses on efficient time-frequency translation to enhance resolution for low-frequency components.
It describes a convolutional neural network with six layers designed for feature extraction and classification. The table presented evaluates the efficacy of the proposed approach in comparison to prior methodologies, emphasizing the innovative advancements and progress made towards attaining precise detection of obstructive sleep apnea (OSA) via enhanced time-frequency resolution and streamlined convolutional neural network architecture.

5. Conclusion

The aim of this study was to use Stockwell Transform images produced from single lead ECG data for classification using a Convolutional Neural Network (CNN) model to diagnose obstructive sleep apnea (OSA). The data was obtained via the PhysioNet apnea-ECG database. Firstly, the signals were separated into segments of one minute, and first-order Butterworth band-pass filtering was used to adjust the baseline. The Stockwell Transform was used to transform the 1D ECG signal processed segments before they were input into the CNN model. When tested on a PhysioNet apnea dataset, the recommended method outperformed previous automated systems in the diagnosis of sleep apnea, with an astounding accuracy of 92%. Due to the model's reliance on a single-lead ECG channel, wearable electronics may be able to include it, making sleep apnea easier to monitor and treat promptly. However, the study notes a number of limitations, such as the model's inability to detect central apnea, mixed apnea, and hypopnea. This may be related to the database only having normal and apnea annotations. The research recommends employing techniques like annotating recordings and including physiological markers to enhance the model's efficacy in order to get around these restrictions. Emphasis is placed on improving relevance and accuracy in a variety of therapeutic contexts. In the end, the CNN model outperforms previous approaches in detecting OSA with remarkable effectiveness. This opens the door for advancements in sleep apnea monitoring and diagnosis.

References

1. C. V. Senaratna et al., "Prevalence of obstructive sleep apnea in the general population: A systematic review," Sleep Medicine Reviews, vol. 34, pp. 70–81, Aug. 2017, doi: 10.1016/j.smrv.2016.07.002.
2. L. Spicuzza, D. Caruso, and G. Di Maria, "Obstructive sleep apnoea syndrome and its management," Ther Adv Chronic Dis, vol. 6, no. 5, pp. 273–285, Sep. 2015, doi: 10.1177/2040622315590318.
3. V. K. Kapur, "Obstructive Sleep Apnea: Diagnosis, Epidemiology, and Economics," RESPIRATORY CARE, vol. 55, no. 9, 2010.
4. B. V. Vaughn and P. Giallanza, "Technical Review of Polysomnography," Chest, vol. 134, no. 6, pp. 1310–1319, Dec. 2008, doi: 10.1378/chest.08-0812.
5. S. A. Stewart, E. Penz, M. Fenton, and R. Skomro, "Investigating Cost Implications of Incorporating Level III At-Home Testing into a Polysomnography Based Sleep Medicine Program Using Administrative Data," Canadian Respiratory Journal, vol. 2017, pp. 1–7, 2017, doi: 10.1155/2017/8939461.
6. J. L. Yu et al., "Influence of apnea vs hypopnea predominance in predicting mean therapeutic positive airway pressures among patients with obstructive sleep apnea," Journal of Clinical Sleep Medicine, vol. 17, no. 11, pp. 2171–2178, Nov. 2021, doi: 10.5664/jcsm.9342.
7. 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, p. 100170, 2019, doi: 10.1016/j.imu.2019.100170.
8. M. Bsoul, H. Minn, and L. Tamil, "Apnea MedAssist: Real-time Sleep Apnea Monitor Using Single-Lead ECG," IEEE Trans. Inform. Technol. Biomed., vol. 15, no. 3, pp. 416–427, May 2011, doi: 10.1109/TITB.2010.2087386.
9. R. Lin, R.-G. Lee, C.-L. Tseng, H.-K. Zhou, C.-F. Chao, and J.-A. Jiang, "A NEW APPROACH FOR IDENTIFYING SLEEP APNEA SYNDROME USING WAVELET TRANSFORM AND NEURAL NETWORKS," Biomed. Eng. Appl. Basis Commun., vol. 18, no. 03, pp. 138–143, Jun. 2006, doi: 10.4015/S1016237206000233.
10. R. V. Sharan, S. Berkovsky, H. Xiong, and E. Coiera, "ECG-Derived Heart Rate Variability Interpolation and 1-D Convolutional Neural Networks for Detecting Sleep Apnea," in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada: IEEE, Jul. 2020, pp. 637–640. doi: 10.1109/EMBC44109.2020.9175998.

11. H. Liu, S. Cui, X. Zhao, and F. Cong, “Detection of obstructive sleep apnea from single-channel ECG signals using a CNN-transformer architecture,” Biomedical Signal Processing and Control, vol. 82, p. 104581, Apr. 2023, doi: 10.1016/j.bspc.2023.104581.
12. X. Chen, Y. Chen, W. Ma, X. Fan, and Y. Li, “Toward sleep apnea detection with lightweight multi-scaled fusion network,” Knowledge-Based Systems, vol. 247, p. 108783, Jul. 2022, doi: 10.1016/j.knosys.2022.108783.
13. C. B. Kumar, A. Bhongade, T. K. Gandhi, and B. K. Panigrahi, “Recognition of Obstructive Sleep Apnea from a Single Lead Electrocardiogram Signal Using a ResNet Model,” in 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India: IEEE, Jul. 2023, pp. 1–5. doi: 10.1109/ICCCNT56998.2023.10308021.
14. H. Nasifoglu and O. Erogul, “Obstructive sleep apnea prediction from electrocardiogram scalograms and spectrograms using convolutional neural networks,” Physiol. Meas., vol. 42, no. 6, p. 065010, Jun. 2021, doi: 10.1088/1361-6579/ac0a9c.
15. H. Sharma and K. K. Sharma, “Sleep apnea detection from ECG using variational mode decomposition,” Biomed. Phys. Eng. Express, vol. 6, no. 1, p. 015026, Jan. 2020, doi: 10.1088/2057-1976/ab68e9.
16. T. Wang, C. Lu, G. Shen, and F. Hong, “Sleep apnea detection from a single-lead ECG signal with automatic feature-extraction through a modified LeNet-5 convolutional neural network,” PeerJ, vol. 7, p. e7731, Sep. 2019, doi: 10.7717/peerj.7731.
17. A. L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals,” Circulation, vol. 101, no. 23, Jun. 2000, doi: 10.1161/01.CIR.101.23.e215.
18. U. R. Kandukuri, A. J. Prakash, K. K. Patro, C. Neelapu, R. Tadeusiewicz, and P. Pławiak, “CONSTANT Q–TRANSFORM–BASED DEEP LEARNING ARCHITECTURE FOR DETECTION OF OBSTRUCTIVE SLEEP APNEA”.
19. A. Nguyen et al., “A computationally efficient crack detection approach based on deep learning assisted by stockwell transform and linear discriminant analysis,” Structures, vol. 45, pp. 1962–1970, Nov. 2022, doi: 10.1016/j.istruc.2022.09.107.
20. S. Sartipi, H. Kalbkhani, P. Ghasemzadeh, and M. G. Shayesteh, “Stockwell transform of time-series of fMRI data for diagnoses of attention deficit hyperactive disorder,” Applied Soft Computing, vol. 86, p. 105905, Jan. 2020, doi: 10.1016/j.asoc.2019.105905.
21. R. G. Stockwell, L. Mansinha, and R. P. Lowe, “Localization of the complex spectrum: the S transform,” IEEE Trans. Signal Process., vol. 44, no. 4, pp. 998–1001, Apr. 1996, doi: 10.1109/78.492555.
22. D. Soydaner, “A Comparison of Optimization Algorithms for Deep Learning,” Int. J. Patt. Recogn. Artif. Intell., vol. 34, no. 13, p. 2052013, Dec. 2020, doi: 10.1142/S0218001420520138.
23. A. Dhillon and G. K. Verma, “Convolutional neural network: a review of models, methodologies and applications to object detection,” Prog Artif Intell, vol. 9, no. 2, pp. 85–112, Jun. 2020, doi: 10.1007/s13748-019-00203-0.

24. M. Sharma, S. Agarwal, and U. R. Acharya, “Application of an optimal class of antisymmetric wavelet filter banks for obstructive sleep apnea diagnosis using ECG signals,” Computers in Biology and Medicine, vol. 100, pp. 100–113, Sep. 2018, doi: 10.1016/j.compbiomed.2018.06.011.
25. H.-Y. Chang, C.-Y. Yeh, C.-T. 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, vol. 20, no. 15, p. 4157, Jul. 2020, doi: 10.3390/s20154157.
26. Kandala. N. V. P. S. Rajesh, R. Dhuli, and T. S. Kumar, “Obstructive sleep apnea detection using discrete wavelet transform-based statistical features,” Computers in Biology and Medicine, vol. 130, p. 104199, Mar. 2021, doi: 10.1016/j.compbiomed.2020.104199.
27. A.-T. Nguyen, T. Nguyen, H.-K. Le, H.-H. Pham, and C. Do, “A novel deep learning-based approach for sleep apnea detection using single-lead ECG signals,” in 2022 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), Chiang Mai, Thailand: IEEE, Nov. 2022, pp. 2046–2052. doi: 10.23919/APSIPAASC55919.2022.9979890.