Int. J. Appl. Math. Comput. Sci., 2023, Vol. 33, No. 3, 493–506
DOI: 10.34768/amcs-2023-0036

CONSTANT Q–TRANSFORM–BASED DEEP LEARNING ARCHITECTURE FOR DETECTION OF OBSTRUCTIVE SLEEP APNEA

USHA RANI KANDUKURI[a], ALLAM JAYA PRAKASH[b], KIRAN KUMAR PATRO[c], BALA CHAKRAVARTHY NEELAPU[a], RYSZARD TADEUSIEWICZ[d], PAWEŁ PŁAWIAK[e,f,*]

[a] Department of Biotechnology and Medical Engineering
National Institute of Technology
Sector-1, Rourkela, Odisha, 769008, India

[b] School of Computing Science and Engineering (SCOPE)
VIT Vellore
Tiruvalam Road, Katpadi, Vellore, Tamil Nadu, 632014, India

[c] Department of Electronics and Communication Engineering
Aditya Institute of Technology and Management
Main Street, Tekkali, Andhra Pradesh, 532201, India

[d] Department of Biocybernetics and Biomedical Engineering
AGH University of Science and Technology
al. A. Mickiewicza 30, 30-059 Cracow, Poland

[e] Department of Computer Science
Cracow University of Technology
ul. Warszawska 24, 31-155 Cracow, Poland
e-mail: pawel.plawiak@pk.edu.pl

[f] Institute of Theoretical and Applied Informatics
Polish Academy of Sciences
ul. Bałtycka 5, 44-100 Gliwice, Poland

Obstructive sleep apnea (OSA) is a long-term sleep disorder that causes temporary disruption in breathing while sleeping. Polysomnography (PSG) is the technique for monitoring different signals during the patient's sleep cycle, including electroencephalogram (EEG), electromyography (EMG), electrocardiogram (ECG), and oxygen saturation (SpO2). Due to the high cost and inconvenience of polysomnography, the usefulness of ECG signals in detecting OSA is explored in this work, which proposes a two-dimensional convolutional neural network (2D-CNN) model for detecting OSA using ECG signals. A publicly available apnea ECG database from PhysioNet is used for experimentation. Further, a constant Q-transform (CQT) is applied for segmentation, filtering, and conversion of ECG beats into images. The proposed CNN model demonstrates an average accuracy, sensitivity and specificity of 91.34%, 90.68% and 90.70%, respectively. The findings obtained using the proposed approach are comparable to those of many other existing methods for automatic detection of OSA.

Keywords: apnea, convolutional neural network, constant Q-transform, deep learning, single-lead ECG signals, non-apnea, obstructive sleep apnea.

1. Introduction

Quality of sleep affects the social, physical as well as mental health of a person. People suffering from sleep apnea experience poor quality of sleep and other health abnormalities associated with notable mortality and morbidity rate (Ramar and Guilleminault, 2008). Sleep apnea is a condition that causes irregular or interrupted breathing during sleep. According to the American Academy of Sleep Medicine (AASM), if the cessation in the respiratory flow during the sleep is greater than 10

*Corresponding author

seconds, it can be termed as apnea. The duration of these interruptions might range between 10 and 30 seconds (Zarei and Asl, 2020).

Based on the cause of interrupted breathing, sleep apnea is classified into three types: central, obstructive, and mixed. Among these, obstructive sleep apnea (OSA) is the most commonly observed type (Fatimah *et al.*, 2020). As mentioned, the disruptions in the airflow in OSA occur mainly due to the collapse of upper airway at the level of oropharynx. People with OSA generally have improper neuronal activation of respiratory muscles and diaphragm. As a result, the negative intrathoracic pressure during normal inspiration results in the collapse of the airway rather than normal airflow (Penzel *et al.*, 2000). This leads to a decrease in the oxygen saturation and activation of the central nervous system, which in turn leads to sleep fragmentation to re-establish the respiration. Unhealthy sleep cycles are a direct effect of OSA. The hampered sleep quality leads to fatigue, drowsiness, lack of concentration, etc. In severe cases, this can also result in cardiovascular diseases like heart, stroke, hypertension and even sudden death (Erdenebayar *et al.*, 2019). This emphasizes the importance of sleep apnea screening and treatment at the earliest possible stages.

Polysomnography (PSG) is used as a standard method to diagnose sleep apnea. A polysomnography (PSG) signal is made up of 16 different physiological signals that are recorded overnight, such as electroencephalograms (EEG), electrocardiograms (ECG), electrooculograms (EOGs), electromyograms (EMG), oxygen saturation in the blood (SpO2), respiratory effort, airflow signals, and so on (Wang *et al.*, 2019a; Jackowska-Zduniak, 2022). Based on these signals, the AHI (apnea-hypoapnea index) is evaluated by the professionals for clinical diagnosis of OSA, i.e., an AHI < 5 events/hr is normal, an AHI between 5 and 15 events/hr is considered as mild OSA, an AHI between 15 and 30 events/hr is moderate OSA and an AHI greater than 30 events/hr is regarded as severe OSA (Ramar and Guilleminault, 2008). However, the process could be more patient-friendly, as one needs to attach all electrodes and wires to the patient's body. It must be implemented in sophisticated surroundings, such as sleep laboratories, under the observation of medical professionals during the patient's sleep cycle (Dey *et al.*, 2018). This method is inconvenient and more expensive and might change how well you sleep. Hence, using lesser or single lead signals like ECG, oxygen saturation (SpO2), EEG, etc. to detect OSA became of interest (Mashrur *et al.*, 2021; Shen *et al.*, 2021).

Nocturnal pulse oximetry can address the desaturations occurring in REM sleep due to apnea but the movement artefacts could mislead the reading, producing false alarms and in children with OSA, the desaturations does not always occur with the apnea events (Nixon and Brouillette, 2002). Hence, this method alone cannot serve as an alternative diagnosis for OSA. Lin *et al.* (2006) proposed a new approach for detection of OSA using EEG signals. Bsoul *et al.* (2010) observed in the research on the real-time sleep apnea monitor using Single-Lead ECG that the ECG signal has a potential impact in the detection of OSA. According to some studies, there are variations in the S-wave amplitude (Khalil and Rifaie, 1998), prolonged QRS duration (Gupta *et al.*, 2012), R-R interval, and ECG pulse energy (Khandoker *et al.*, 2009) due to OSA's aberrant effects on cardiac electrophysiology and altered autonomic nerve functions. As a result of these findings, research interest began more towards identification of OSA using single lead ECG signals as an alternative to conventional PSG measurement.

Diagnosing sleep apnea manually with an ECG can sometimes be laborious, monotonous, and inaccurate. This describes the requirement for automatic identification of alterations in ECG in the presence of OSA.

The paper is organised as follows. Section 2 briefly reviews the literature, discusses motivations and characterizes the contribution of the work. The materials and methods applied are explained in Section 3. Experimental results are discussed briefly in Section 4 along with limitations, advantages and future research in Section 4.5.1 and conclusions included in Section 5.

2. Literature survey and contributions

The use of atrificial intelligence based models (Patro *et al.*, 2023; Baygin *et al.*, 2023) for the early detection and accurate diagnosis of medical conditions is currently receiving a lot of interest. The application of deep learning models on various bio-signals such as EMG (Dogan and Tuncer, 2021), ECG (Prakash *et al.*, 2022), and EEG (Dogan *et al.*, 2021; Aydemir *et al.*, 2020) will lead to superior medical diagnosis outcomes. Recent studies show that deep learning models play a very important role in classifying ECG arrhythmias (Hammad *et al.*, 2022; 2020) and myocardial infarction (Hammad *et al.*, 2020). At present, a lot of scientific effort is directed towards detecting obstructive sleep apnea using single-lead electrocardiogram signals.

The following section will discuss several machine learning and deep learning methodologies based on OSA detection methods using the apnea ECG database. For instance, Mashrur *et al.* (2021) developed a method for identifying OSA using scalograms. The continuous wavelet transform (CWT) was used on the processed and pre-processed signals to make conventional and hybrid scalograms. They fed these into a convolutional neural network (CNN) trained to diagnose OSA, and the network correctly labelled one-minute segments from

Table 1. Recent literature on OSA detection using ECG signals.

Literature	Feature extraction technique (or) pre-processing method followed	Classifier	Accuracy sensitivity (in %)	Remarks/limitations
Fatimah *et al.*, 2020	Fourier decomposition method (FDM)	Support vector machine (SVM) with Gaussian kernel	92.59 89.70	The performance of the proposed method is significantly dependent on only the optimal FIFB number, manual feature extraction, selection and the type of classifier used.
Nishad *et al.*, 2018	Tunable-Q wavelet transform	Random forest	88.95 90.95	The random forest classifier can train fast on the feature set but is unproductive and quite slow when it comes to real-time predictions, thus increasing the computational burden.
Wang *et al.*, 2019a	ECG signal time based segments	Time window multilayer perceptron (TW-MLP)	86.10 85.30	Manual feature extraction and selection methods based on previous studies were used. In such cases, the efficiency of the method tends to incline towards the understanding and experience of the researchers.
Mashrur *et al.*, 2021	Continuous wavelet transform (CWT) and scalograms	Convolutional neural network (CNN)	94.30 93.11	The model performance is high only when trained with a combination of conventional and hybrid scalograms.
Shen *et al.*, 2021	R-R intervals	Multiscale dilation attention convolutional neural network (MSDA-CNN) model for feature extraction with weighted-loss time dependent (WLTD) classification model	89.40 89.80	R-R interval sequences (RRIS) are used to extract the features for OSA detection but not the whole single-lead ECG signals.
Chang *et al.*, 2020	Z-score normalization	1D deep CNN model	89.70 81.11	1-D CNN is used to classify apnea and normal ECG segments. The sensitivity in per-segment classification is low (81.1%), which is very significant in medical applications.
Almutairi *et al.*, 2021	R-R intervals and R peaks	CNN and long short term memory (LSTM) with SVM	90.92 88.56	A hybrid network combining CNN and LSTM was proposed in this study. LSTM networks require sequential computation. Hence these networks may take more time and memory to train.

the apnea ECG database. In the work of Shen *et al.* (2021), a multiscale dilation attention one-dimensional convolutional neural network (MSDA-1D CNN) and a weighted-loss time-dependent (WLTD) model are used to detect OSA. The authors could balance the parameter and performance relations by introducing dilated convolution. Using the hidden Markov model and a weighted cross-entropy loss function, they attained an accuracy of 89.4%, a sensitivity of 89.80%, and a specificity of 89.10%, respectively, in per-segment classification.

For detecting OSA using single-lead ECG signals, Chang *et al.* (2020) designed a 1D CNN model in which they used a Butterworth fourth-order band pass filter to filter the raw and noisy signals followed by a Z-Score normalization. These signals are fed into the designed model, which has ten similar feature extraction layers and four classification layers. Using this model, they could achieve an accuracy of 87.90%, sensitivity and specificity of 81.10% and 92.00%, respectively, in per-segment classification. Wang *et al.* (2019b) suggested a revised design of the LeNet-5 model to detect OSA using ECG signals based on the concept of classical deep learning algorithms. They fed R-R intervals and amplitudes into the model they developed. To compare the performance of the suggested model, the authors also used different machine learning approaches such as support vector machines (SVMs), K-nearest neighbour classifiers (KNNs) and multi layer perceptrons (MLPs). The improved model could produce 87.60% accuracy, 90.30% specificity, and 83.10% sensitivity. Investigators claimed that their model with automated feature extraction outperformed the other feature engineering methods employed in their research.

Singh and Majumder (2019) proposed a modified pre-trained AlexNet model along with the transfer learning approach to detect apnea from ECG signals. It was done as a comparative study. Along with the modified pre-trained model, decision fusion models, i.e., by integrating the fully connected layers of the proposed model with conventional classifiers like SVM, LDA, KNN, etc., were used in the performance analysis. First, they used CWT to turn one-minute ECG segments into two-dimensional (2D) scalogram images, which were then fed into the models. Out of all the considered models, the modified pre-trained AlexNet model could yield a better accuracy of 86.22%, a sensitivity of 90.00% and a specificity of 83.82%. Almutairi *et al.* (2021) developed a hybrid model to detect apnea using ECG signals. They used CNN in combination with long short-term memory (LSTM). The designed deep convolution model automatically extracts the ECG features and classifies the signals with a testing accuracy of 90.92%.

Applying the wavelet transform on a single lead ECG signal, Zarei and Asl (2018) proposed a method of automatic detection of OSA. They used entropy-based features to obtain the confidential information from the ECG signals. They were able to classify 60-second signal segments from the apnea ECG database (PhysioNet) using an SVM and achieved 94.63% accuracy. Hassan and Haque (2017) proposed a method that detects OSA using TQWT and random under sampling boosting (RUSBoost). In this work, the signals were decomposed using TQWT. They extracted three statistical features as inputs to the RUSBoost algorithm for classification and attained an accuracy of 88.88% on the ECG apnea database. In order to identify OSA using single-lead ECG signals, Kumar and Kanhangad (2018) suggested employing Gabor filters-based 1D local phase descriptors. Initially, using a bank of Gabor filters, the ECG signals were decomposed into band-limited signals, and with the phase information from these signals, phase descriptor-based histogram features were computed and integrated into one histogram, which is then given to LS-SVM (least-squares support vector machine) for classification. Table 1 presents a summary of the latest studies on detecting OSA using machine learning and deep learning approaches.

The primary aim of this work is to study the efficacy of a constant Q-transform (CQT) in identifying apnea using ECG data. We may achieve equivalent results with existing deep learning and machine learning approaches to identify OSA with a single lead ECG signals. The primary contributions of the proposed work as follows:

- The consistent window size for all frequencies causes issues during mapping frequency on a logarithmic scale. Specifically, the lower peaks are quite broad (sometimes up to a half octave) and lack clarity. A CQT is proposed to resolve this issue by raising the window size for lower frequencies and reducing the window size for high frequencies to alleviate some of the computational strain.

- A novel contribution is proposed based on the advantage of the CQT as above; the ECG signal is transformed to CQT based spectrograms to detect the important time-frequency morphological changes in the respective class using a deep learning architecture.

- A new approach to the signal-to-image conversion method with a deep learning technique is developed in the area of sleep apnea detection.

- The end-to-end system is completely free from the R-peak detection techniques, and there is no separate segmentation of the beat algorithm required.

- The proposed deep learning architecture is designed with a zero-padding technique, which lets us keep the original size of the input.

- A comprehensive empirical experimentation has been carried out to prove the efficacy of the proposed method.

3. Materials and methods

The workflow of the proposed method for detecting OSA using a convolutional neural network is depicted in Fig. 1. First, the raw ECG signals are obtained from the PhysioNet apnea ECG database. One-minute signal segments were constructed from these signals and then filtered to remove the power line interference. Further, the noisy segments are removed using a threshold-based technique. These one-minute segments are then transformed into time-frequency-amplitude plots/images using the suggested constant Q-transform, and they are fed to the proposed CNN network. Signal pre-processing and transformation processes are discussed here. The next few paragraphs will go into depth on the structure of the CNN network and the findings achieved by utilising this model to categorisze ECG signals as apnea or non-apnea.

3.1. Database. In the current study, we used data from the apnea ECG database version 1.0.0, that is available within the PhysioNet database. The signals contained in this database were generated by Philips University in Marburg, Germany (Goldberger *et al.*, 2000; Penzel *et al.*, 2000). This is the most used database for sleep apnea investigations utilizing ECG signals. It consists of a total of 70 sleep ECG recordings, sampled at 100 Hz. On an average, each recording length lasts for about 401 to 508 minutes. Based on the time length of disordered breathing, the recordings were labelled as three classes i.e., Class A or apnea consists of recordings with 100 minutes or more of disordered breathing. Recordings with 10 to 96 minutes of disordered breathing are labelled as Class B or the borderline apnea group. Class C or the control group has recordings with less than 5 minutes of disordered breathing (Penzel *et al.*, 2000). This data set is released in two sets, 35 recordings each. Through visual examination of this disordered breathing during the sleep, medical experts annotated each 60 second data item as either apnea ‘A’ or non-apnea ‘NA’ (Penzel *et al.*, 2000). Based on these annotations, signal segments of one minute were extracted.

3.2. ECG data preprocessing. First, the collected raw ECG signals are converted into one-minute segments depending on the annotations provided in the database. Then, using a first-order Butterworth band-pass filter with a lower frequency of 1 Hz and a higher cut-off frequency of 45 Hz, these ECG signal segments are filtered using baseline correction and removing any power line interference shown in Fig. 2.

Further, to remove the noisy segments from the data set, we adopted a similar method of threshold based noisy segment removal proposed by Mashrur *et al.* (2021). In this noisy segment reduction method, one-minute segments (X) are subdivided into six 10-second sub-segments ($x1$, $x2$, $x3$, $x4$, $x5$, and $x6$). Then from each sub segment, we obtained maximum ($y1$) and minimum ($y2$) values forming a set. Now the median (Z) of the maximum and minimum values is calculated. These median values are used as the threshold values to remove the noisy segments from the data set, i.e., if any value in any sub-segment is greater than doubled the maximum median ($Z1$) or less than doubled the minimum median ($Z2$), then that respective segment is deleted from the data set. Figure 3 presents a flowchart that outlines the comprehensive preprocessing of ECG signals.

3.3. Constant Q-transform. The constant Q transform, often known as CQT, was first suggested by Brown (1991) for music signal processing. It is a type of discrete Fourier transform (DFT) that belongs to the wavelet transform category. CQT is a bank of filters, analogous to DFT, except that it in this case it has geometrically spaced frequency centers (Bo *et al.*, 2014). The size of the DFT application window remains consistent regardless of the frequency types present. Consequently, the signal’s low-frequency components lack adequate detail. CQT offers a detailed analysis of the frequency components present in the signal as the count of the window increases in the presence of lower frequency components. The ratio of the center frequency to resolution must be a constant ratio Q, which results in a logarithmic frequency resolution of the transform. CQT has an advantage over other transforms as it provides better frequency resolution at low frequencies and better time resolution at high frequencies (Bo *et al.*, 2014) and has a flexible temporal window for a wider variety of frequencies (Mateo and Talavera, 2020).

The CQT of a finite length sequence is given by

$$x^{cq}(k) = \frac{1}{N_k} \sum_{n=0}^{N_k-1} x(n) w_{N_k}(n) e^{(-jn)\frac{2\pi Q}{N_k}}, \tag{1}$$

where N_k is the window length of the k-th frequency, $\omega(N_k)$ stands for the window function of N_k, Q means the constant factor of CQT, k signifies the index of the CQT frequency.

This transform is widely used in processing the music signals as its representation is similar to the human perception (Balim *et al.*, 2021). As ECG and speech signals are analogous in nature since they are both nonstationary and time-varying signals, this transform can be applied for ECG signal analysis. In the case of apnea, there are some variations in ECG low frequency components like changes in the s-wave duration and

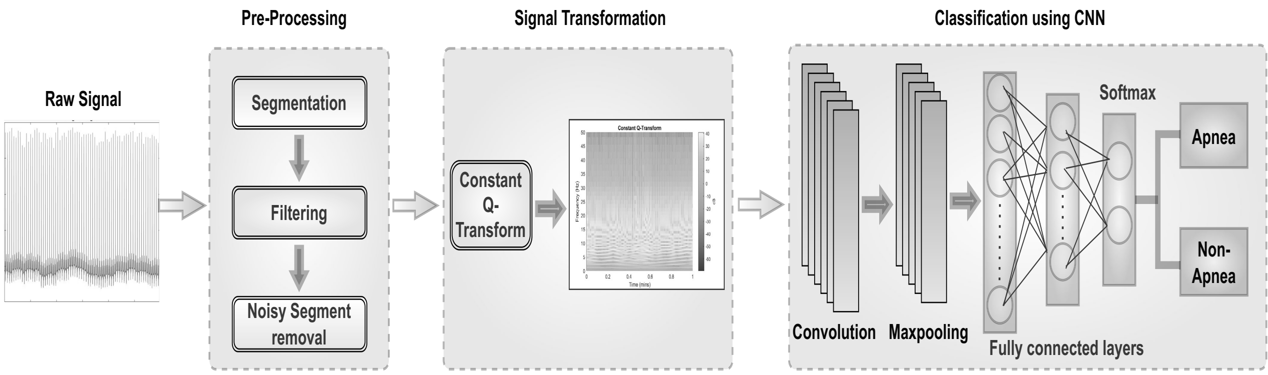

Fig. 1. Workflow of the method proposed to detect apnea from single lead ECG signals.

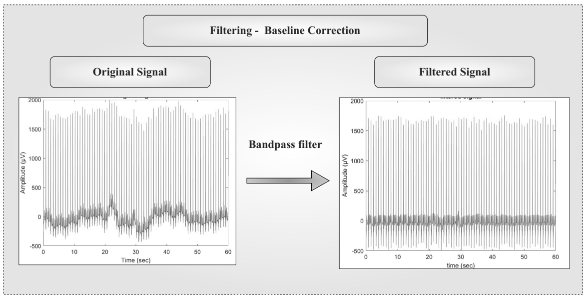

Fig. 2. Filtering of the ECG signal for baseline correction.

amplitude, QRS durations, etc. As it offers better frequency resolution for low frequencies, CQT might be a promising technique for ECG signal analysis for detecting obstructive sleep apnea. Hence, in this work the efficiency of the CQT algorithm in detecting apnea using single-lead ECG signals is explored. Some of the advantages and disadvantages of the CQT are given below.

The advantages of the CQT are as follows:

- Unlike the other transforms like STFT, CQT offers flexibility in varying the window length (N_k) and center frequencies corresponding to changing frequency values.
- In CQT there is no trade-off between time and frequency resolution as seen in other transforms.
- It provides improved low-frequency band resolution in frequency domain.
- It provides a constant Q resolution, i.e., each frequency bin has a constant ratio of center frequency to bandwidth.
- It is more robust to noise and interference compared with other time-frequency transformation techniques.

The disadvantages of CQT are the following:

- Implementation of CQT is computationally more complex compared with other transformation techniques.
- The choice of parameters for the CQT such as the number of frequency bins and the Q-factor can affect the performance of the transform.
- The interpretation of the CQT coefficients can be difficult, as they represent the distribution of energy across different frequency scales.

For the one-minute ECG segment of data (Chen *et al.*, 2014) we utilized the 'cqt' function to obtain CQT images of the ECG signal. A total of 12,993 apnea events and 20,861 non-apnea events are obtained from the apnea ECG database. After noisy segment removal and application of constant-Q transform, the data set was formed of 19,894 non-apnea images and 12,460 apnea images. Figure 4 shows the CQT image of non-apnea ECG, whereas the CQT image of the apnea ECG shown in Fig. 5. We used MATLAB R2020b for preprocessing and transformation of signals into CQT images.

3.4. Proposed deep learning architecture for detection of obstructive sleep apnea. The proposed CNN architecture in this study includes five feature extraction (FE) layers, one flatten layer, and two dense layers, as shown in Fig. 6. First, the images obtained are trimmed to remove the unwanted features. Now images are resized (224×224) and fed to the proposed network. In the first FE layer, 3×3 zero padding is implemented followed by a 2D convolutional layer of 3×3-kernel and batch normalization layer. A second and third FE layers consist of convolutional and batch normalization layers, followed by a 2×2-max-pooling layer with stride 2. The fourth and fifth FE layers are similar to the second and third except they include additional dropouts of 30% and 60%, respectively. These FE layers are followed by a flatten layer and a dense layer with rectifier linear unit (ReLU)

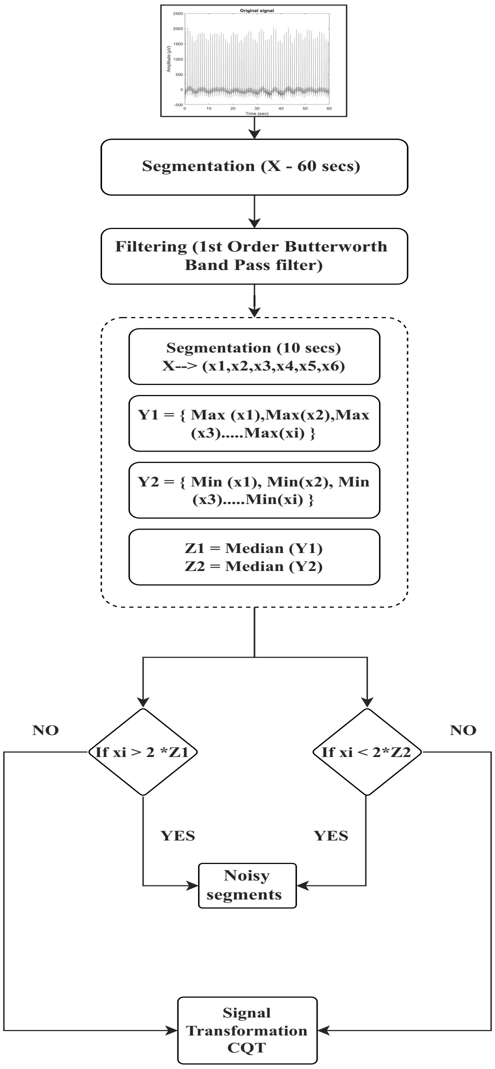

Fig. 3. Preprocessing of ECG signals from the apnea ECG database.

activation and a soft-max layer (Kowal *et al.*, 2021; Jayaraman and Chinnusamy, 2022).

4. Experimental results

The architecture of the CNN model proposed was implemented in Python 3 using the TensorFlow and Keras libraries. We transformed ECG signals to CQT images using MATLAB. The acquired image data set is split into three sets, namely training, validation, and testing sets, in the ratios of 70%, 15%, and 15%, respectively. Training, validation, and testing were conducted on an Intel(R) Core(TM) 2.90 GHz (*i*7-10700) processor with 32 GB RAM and a GPU (NVIDIA GeForce RTX 3060 with 11GB RAM).

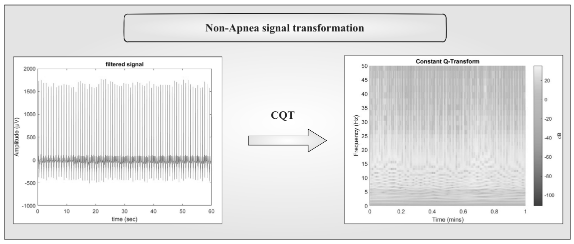

Fig. 4. Filtered non-apnea ECG signal and the respective CQT.

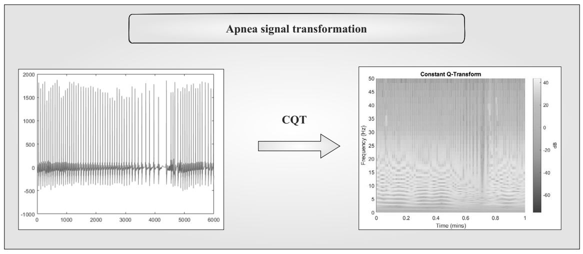

Fig. 5. Filtered apnea ECG signal and the respective CQT.

4.1. Model training and testing. In this work, the experimentation is carried out on 19,894 non-apnea images and 12,460 apnea images. As mentioned above, the overall image data set was further split into three sets, including 70% training, 15% validation, and 15% testing portions. For training cum validation, 27,501 CQT images were utilized, while testing was conducted on 4,853 images. Different tests were run throughout the training phase, and better classification performance was achieved by adjusting the hyperparameters. The hyperparameters used for this analysis are listed in Table 2.

Figure 7 shows the training and testing accuracies in relation to the number of epochs. The accuracy of the training was close to 1.0, whereas the accuracy of the testing was close to 0.91. The loss curves for the model during testing and training are depicted in Fig. 8. The average time taken for validation and training the model was about 336 s for each epoch.

4.2. Classification performance. Here, to represent the classification results of the CNN model proposed in this work, we used a confusion matrix. Figure 9 illustrates the confusion matrix, in which each row denotes a prediction class and each column denotes an actual class. The model properly categorized 2792 out of 2984 non-apnea images and incorrectly classified 192 CQT images as the apnea class. In addition, out of a total of 1869 apnea images, 1641 were correctly categorized as apnea while 228 were misclassified as non-apnea. On the basis of these confusion matrix values, performance

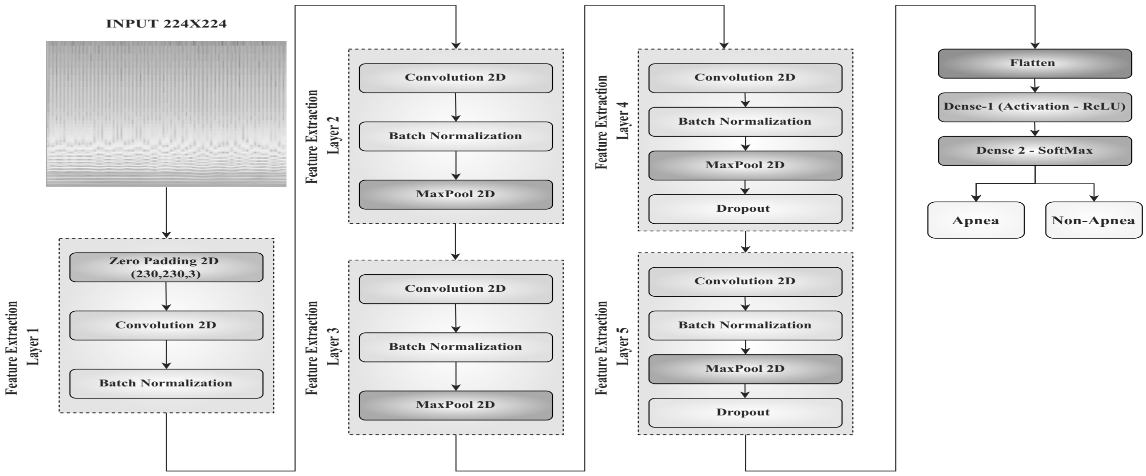

Fig. 6. Proposed deep learning architecture for apnea detection.

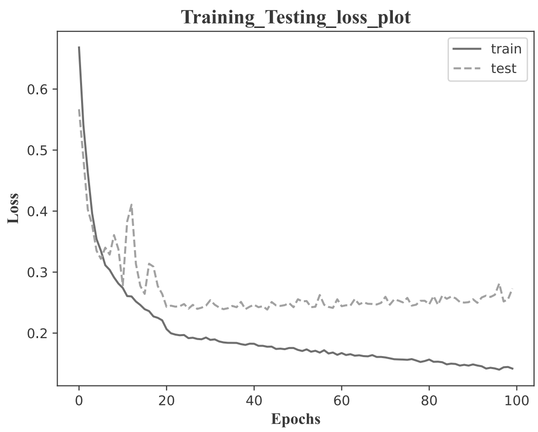

Fig. 7. Training and testing accuracy plots of the CNN model proposed in this work.

Fig. 8. Training and testing loss curves of the CNN model proposed in this work.

measures are evaluated.

4.3. Performance metrics. In this work, accuracy, precision, sensitivity/recall, specificity, and F1-score are taken into consideration to determine the effectiveness of the proposed model (Patro and Prakash, 2022). These metrics are

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}, \tag{2}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{3}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{5}$$

$$\text{F1-Score} = \frac{2 \times \text{Precsion} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{6}$$

where TP = true positive, TN = true negative, FP = false positive, and FN = false negative.

The designed CNN model was trained for 100 epochs at a learning rate of 0.00001 and a batch size of 32 using the training and validation data sets. A test data set was used to evaluate performance measures. With this model, we were able to get a sensitivity of 90.68%, a specificity of 90.68%, and an accuracy of 91.34%. Table 4.1 lists different metrics relating to the designed model's performance.

4.4. Comparison with other existing models. The proposed approach in this study for detecting OSA using single-lead ECG signals was able to produce results comparable with the existing literature. Up

Table 2. Hyperparameters used in this work.

Parameter	Value/method
Optimizer	ADAM
Loss function	Binary cross entropy
Batch size	32
Input size	224×224
Epochs	100
Learning rate	1×10^{-5}
Stride	1
Avg. training time	336 s

Table 3. Performance metrics of the CNN model.

Sl. No	Metric	Value
1	accuracy	91.34 %
2	sensitivity	90.68 %
3	specificity	90.68 %
4	precision	90.98 %
5	F1-score	90.82 %

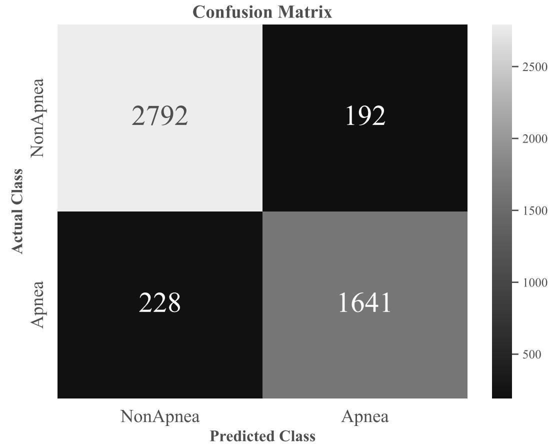

Fig. 9. Confusion matrix of the CNN model proposed in this work.

to date, different approaches and techniques were developed for efficient detection of obstructive sleep apnea. Wang *et al.* (2019a) used time window artificial neural network to detect the time dependencies of OSA. Singh and Majumder (2019) generated 2-D scalograms using continuous wavelet transform in combination with AlexNet. The automated OSA detection method proposed by Chang *et al.* (2020) used a 1-D convolutional neural network for automated feature extraction and classification. Almutairi *et al.* (2021) presented a hybrid network based on a combination of CNN and LSTM networks. Based on the concept of heart rate variability due to OSA, Shen *et al.* (2021) proposed a new approach to detect OSA using the RRIS (R-R Interval sequences) and multiscale dilation attention 1-D CNN. Present work concentrated on the efficient time-frequency transformation technique in order to achieve better resolution for low frequency components for visualizing the changes even at minute level. It also proposed a simple 5-layer convolutional neural network for effective feature extraction and classification. Table 4 provides a comparison of the effectiveness of our suggested method to that of other methods that are currently in use.

4.5. Uncertainty quantification. In medical applications, uncertainty quantification (UQ) methods are critical for ensuring the reliability and robustness of models used for diagnosis, treatment planning, and drug development (Abdar *et al.*, 2022). By accounting for uncertainty, UQ methods can help improve the accuracy and effectiveness of medical models, ultimately leading to better patient outcomes (Psaros *et al.*, 2023). Standard machine learning, as well as deep learning algorithms are used for a broad range of healthcare applications, including analysis of medical image data, with impressive results in terms of accuracy even with very small sample sizes (Kompa *et al.*, 2021). Moreover, deep learning requires large data to fine-tune learnable parameters.

Limited training images may frequently cause epistemic uncertainty and leads to a failure in real-time applications (Abdar *et al.*, 2021). Inaccurate conclusions from these models can be catastrophic for at-risk patients. As a result, accurate uncertainty estimations are crucial for enhancing ML models' efficacy and establishing their credibility and reliability. Valid uncertainty estimates help with clinical decision making and give doctors useful information about the accuracy of their findings (Abdar *et al.*, 2023).There are several methods available for uncertainty quantification, which can broadly be categorized into three main categories (Abdar *et al.*, 2022):

1. *Statistical methods.* These methods use statistical techniques to estimate the uncertainties in model predictions based on the variability in input parameters. Examples of statistical methods include Monte Carlo methods, Latin hypercube sampling, and Bayesian inference.

2. *Interval methods.* Interval methods use interval analysis to define ranges of possible values for model predictions. These methods are particularly useful for handling uncertainties arising from imprecise or incomplete data.

3. *Non-intrusive methods.* Non-intrusive methods involve modifying the model code to propagate uncertainties. These methods do not require any knowledge of the internal structure of the model,

Table 4. Comparison of the proposed method with recent state-of-the-art techniques.

Author	Algorithm used	Dataset and splitting	Classifier	Acc. (%)	Sen. (%)	Spe. (%)	Pre. (%)	F1-Scr. (%)
Wang *et al.*, 2019b	R-R intervals and amplitudes	PhysioNet apnea ECG database (90% train and 10% test)	Modified LeNet-5	87.60	83.10	90.30	–	–
Singh and Majumder, 2019	Continuous wavelet transform with 2D-scalogram	PhysioNet apnea ECG database. Data equally divided for train (released set) & test (withheld set)	Modified AlexNet	86.22	90.00	83.80	–	–
Chang *et al.*, 2020	Z-score normalization	PhysioNet apnea ECG database. Data equally divided for train (released set) & test (withheld set)	1D Deep CNN model	87.10	81.10	92.0	–	–
Almutairi *et al.*, 2021	R-R intervals and R peaks	PhysioNet apnea ECG database. Data equally divided for train (released set) & test (withheld set)	CNN+LSTM with SVM	90.92	91.24	90.36	–	92.76
Shen *et al.*, 2021	R-R intervals	PhysioNet apnea ECG database. Data equally divided for train (released set) & test (withheld set)	MSDA-1D-CNN	89.40	89.80	89.10	83.60	86.60
Proposed CNN model*	**Constant Q transform images (CQT)**	PhysioNet apnea ECG database (70% train, 15% validation and 15% for test)	**2D-CNN**	**91.34**	**90.68**	**90.70**	**90.98**	**90.82**

making them useful for complex models. Examples of non-intrusive methods include polynomial chaos expansion and stochastic collocation.

Our model does not explicitly quantify uncertainty; we believe it has potential for use in applications where uncertainty is a critical factor. We acknowledge that there are several uncertainty quantification methods available, and incorporating such methods into our model could further enhance its usefulness in these domains.

4.5.1. Limitations and future scope. The current work on obstructive sleep apnea detection using CQT-based deep learning has the following advantages:

- (i) an automatic feature extraction approach which reduces the complexity associated with manual feature extraction and selection algorithms;
- (ii) the constant Q-transform approach provides a good time-frequency solution contributing to higher efficiency in OSA detection;
- (iii) CQT is more robust to noise and interference compared other time-frequency transformation techniques so that the system works more accurately.

However, there are also some limitations of the present work that need to be addressed:

- (i) the data used in this work to train the model was limited to the apnea ECG database from PhysioNet;
- (ii) the computational complexity of implementing CQT is higher than that of other transformation methods.

In the future we plan to continue our research using different data sets to improve the model efficiency. The average training and validation time required for a single epoch is comparatively higher. This can be addressed using different input image sizes without compromising the solution. We can further simplify the CNN structure to decrease the computational complexity. Our ultimate goal is to develop a detection model that can accurately diagnoze OSA utilizing a CQT-based deep CNN. Future research could focus more on creating a virtual model to help clinicians diagnose OSA.

5. Conclusion

In this study, we proposed a CNN model to classify CQT images of apnea and non-apnea signals for OSA detection using single lead ECG data. The investigation was conducted on ECG signals from the apnea-ECG database, which is accessible via PhysioNet. Each signal length varies between 401 and 508 minutes and is annotated with apnea (A) or non-apnea (NA) for each 60 seconds. First, the signals were separated into one-minute segments. Further, they were filtered using a first order Butterworth band-pass filter for baseline correction. These filtered segments are transformed into time/frequency plots using constant Q-transform and provided as input to the designed CNN model. The model is trained for 100 epochs on the training and validation sets. The proposed method attained an impressive accuracy of 91.34% for the testing set. The results obtained suggest that our proposed strategy is a credible technique for assisting clinicians in diagnosing sleep apnea.

References

Abdar, M., Fahami, M.A., Rundo, L., Radeva, P., Frangi, A.F., Acharya, U.R., Khosravi, A., Lam, H.-K., Jung, A. and Nahavandi, S. (2022). Hercules: Deep hierarchical attentive multilevel fusion model with uncertainty quantification for medical image classification, *IEEE Transactions on Industrial Informatics* **19**(1): 274–285.

Abdar, M., Khosravi, A., Islam, S.M.S., Acharya, U.R. and Vasilakos, A.V. (2022). The need for quantification of uncertainty in artificial intelligence for clinical data analysis: Increasing the level of trust in the decision-making process, *IEEE Systems, Man, and Cybernetics Magazine* **8**(3): 28–40.

Abdar, M., Pourpanah, F., Hussain, S., Rezazadegan, D., Liu, L., Ghavamzadeh, M., Fieguth, P., Cao, X., Khosravi, A., Acharya, U.R., Makarenkov, V. and Nahavandi, S. (2021). A review of uncertainty quantification in deep learning: Techniques, applications and challenges, *Information Fusion* **76**: 243–297.

Abdar, M., Salari, S., Qahremani, S., Lam, H.-K., Karray, F., Hussain, S., Khosravi, A., Acharya, U.R., Makarenkov, V. and Nahavandi, S. (2023). UncertaintyFuseNet: Robust uncertainty-aware hierarchical feature fusion model with ensemble Monte Carlo dropout for COVID-19 detection, *Information Fusion* **90**: 364–381.

Almutairi, H., Hassan, G.M. and Datta, A. (2021). Classification of obstructive sleep apnea from single-lead ECG signals using convolutional neural and long short term memory networks, *Biomedical Signal Processing and Control* **69**: 102906.

Aydemir, E., Tuncer, T. and Dogan, S. (2020). A tunable-Q wavelet transform and quadruple symmetric pattern based EEG signal classification method, *Medical Hypotheses* **134**: 109519.

Balim, M.A., Hanilçi, C. and Acir, N. (2021). Motor imagery signal classification using constant-Q transform for BCI applications, *29th European Signal Processing Conference (EUSIPCO), Dublin, Ireland*, pp. 1306–1310.

Baygin, M., Barua, P.D., Chakraborty, S., Tuncer, I., Dogan, S., Palmer, E.E., Tuncer, T., Kamath, A.P., Ciaccio, E.J. and Acharya, U.R. (2023). CCPNet136: Automated detection of schizophrenia using carbon chain pattern and iterative TQWT technique with EEG signals, *Physiological Measurement* **44**(3): 035008–035018.

Bo, H., Li, H., Ma, L. and Yu, B. (2014). A constant q transform based approach for robust EEG spectral analysis, *2014 International Conference on Audio, Language and Image Processing, Shanghai, China*, pp. 58–63.

Brown, J.C. (1991). Calculation of a constant Q spectral transform, *The Journal of the Acoustical Society of America* **89**(1): 425–434.

Bsoul, M., Minn, H. and Tamil, L. (2010). Apnea MedAssist: Real-time sleep apnea monitor using single-lead ECG, *IEEE Transactions on Information Technology in Biomedicine* **15**(3): 416–427.

Chang, H.-Y., Yeh, C.-Y., Lee, C.-T. and Lin, C.-C. (2020). A sleep apnea detection system based on a one-dimensional deep convolution neural network model using single-lead electrocardiogram, *Sensors* **20**(15): 4157.

Chen, L., Zhang, X. and Song, C. (2014). An automatic screening approach for obstructive sleep apnea diagnosis based on single-lead electrocardiogram, *IEEE Transactions on Automation Science and Engineering* **12**(1): 106–115.

Dey, D., Chaudhuri, S. and Munshi, S. (2018). Obstructive sleep apnea detection using convolutional neural network based deep learning framework, *Biomedical Engineering Letters* **8**(1): 95–100.

Dogan, A., Akay, M., Barua, P.D., Baygin, M., Dogan, S., Tuncer, T., Dogru, A.H. and Acharya, U.R. (2021). PrimePatNet87: Prime pattern and tunable Q-factor wavelet transform techniques for automated accurate EEG emotion recognition, *Computers in Biology and Medicine* **138**: 104867.

Dogan, S. and Tuncer, T. (2021). A novel statistical decimal pattern-based surface electromyogram signal classification method using tunable Q-factor wavelet transform, *Soft Computing* **25**: 1085–1098.

Erdenebayar, U., Kim, Y.J., Park, J.-U., Joo, E.Y. and Lee, K.-J. (2019). Deep learning approaches for automatic detection of sleep apnea events from an electrocardiogram, *Computer Methods and Programs in Biomedicine* **180**: 105001.

Fatimah, B., Singh, P., Singhal, A. and Pachori, R.B. (2020). Detection of apnea events from ECG segments using Fourier decomposition method, *Biomedical Signal Processing and Control* **61**: 102005.

Goldberger, A.L., Amaral, L.A., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.-K. and Stanley, H.E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals, *Circulation* **101**(23): e215–e220.

Gupta, S., Cepeda-Valery, B., Romero-Corral, A., Shamsuzzaman, A., Somers, V.K. and Pressman, G.S. (2012). Association between QRS duration and obstructive sleep apnea, *Journal of Clinical Sleep Medicine* **8**(6): 649–654.

Hammad, M., Abd El-Latif, A.A., Hussain, A., Abd El-Samie, F.E., Gupta, B.B., Ugail, H. and Sedik, A. (2022). Deep learning models for arrhythmia detection in IoT healthcare applications, *Computers and Electrical Engineering* **100**: 108011.

Hammad, M., Iliyasu, A.M., Subasi, A., Ho, E.S. and Abd El-Latif, A.A. (2020). A multitier deep learning model for arrhythmia detection, *IEEE Transactions on Instrumentation and Measurement* **70**: 1–9.

Hassan, A.R. and Haque, M.A. (2017). An expert system for automated identification of obstructive sleep apnea from single-lead ECG using random under sampling boosting, *Neurocomputing* **235**: 122–130.

Jackowska-Zduniak, B. (2022). Stochastic models of the slow/fast type of atrioventricular nodal reentrant tachycardia and tachycardia with conduction aberration, *International Journal of Applied Mathematics and Computer Science* **32**(3): 429–440, DOI: 10.34768/amcs-2022-0031.

Jayaraman, T. and Chinnusamy, G.S. (2022). Performance analysis of a dual stage deep rain streak removal convolution neural network module with a modified deep residual dense network, *International Journal of Applied Mathematics and Computer Science* **32**(1): 111–123, DOI: 10.34768/amcs-2022-0009.

Khalil, M. and Rifaie, O. (1998). Electrocardiographic changes in obstructive sleep apnoea syndrome, *Respiratory Medicine* **92**(1): 25–27.

Khandoker, A.H., Gubbi, J. and Palaniswami, M. (2009). Automated scoring of obstructive sleep apnea and hypopnea events using short-term electrocardiogram recordings, *IEEE Transactions on Information Technology in Biomedicine* **13**(6): 1057–1067.

Kompa, B., Snoek, J. and Beam, A.L. (2021). Second opinion needed: Communicating uncertainty in medical machine learning, *NPJ Digital Medicine* **4**(1): 4.

Kowal, M., Skobel, M., Gramacki, A. and Korbicz, J. (2021). Breast cancer nuclei segmentation and classification based on a deep learning approach, *International Journal of Applied Mathematics and Computer Science* **31**(1): 85–106, DOI: 10.34768/amcs-2021-0007.

Kumar, T.S. and Kanhangad, V. (2018). Gabor filter-based one-dimensional local phase descriptors for obstructive sleep apnea detection using single-lead ECG, *IEEE Sensors Letters* **2**(1): 1–4.

Lin, R., Lee, R.-G., Tseng, C.-L., Zhou, H.-K., Chao, C.-F. and Jiang, J.-A. (2006). A new approach for identifying sleep apnea syndrome using wavelet transform and neural networks, *Biomedical Engineering: Applications, Basis and Communications* **18**(03): 138–143.

Mateo, C., and Talavera, J.A. (2020). Bridging the gap between the short-time Fourier transform (STFT), wavelets, the constant-Q transform and multi-resolution STFT, *Signal, Image and Video Processing* **14**(8): 1535–1543.

Mashrur, F.R., Islam, M.S., Saha, D.K., Islam, S.R. and Moni, M.A. (2021). SCNN: Scalogram-based convolutional neural network to detect obstructive sleep apnea using single-lead electrocardiogram signals, *Computers in Biology and Medicine* **134**: 104532.

Nishad, A., Pachori, R.B. and Acharya, U.R. (2018). Application of TQWT based filter-bank for sleep apnea screening using ECG signals, *Journal of Ambient Intelligence and Humanized Computing*, DOI: 10.1007/s12652-018-0867-3.

Nixon, G.M. and Brouillette, R.T. (2002). Diagnostic techniques for obstructive sleep apnea: Is polysomnography necessary?, *Paediatric Respiratory Reviews* **3**(1): 18–24.

Patro, K.K., Allam, J.P., Hammad, M., Tadeusiewicz, R. and Pławiak, P. (2023). SCovNet: A skip connection-based feature union deep learning technique with statistical approach analysis for the detection of COVID-19, *Biocybernetics and Biomedical Engineering* **43**(1): 352–368.

Patro, K.K., Prakash, A.J., Samantray, S., Pławiak, J., Tadeusiewicz, R. and Pławiak, P. (2022). A hybrid approach of a deep learning technique for real-time ECG beat detection, *International Journal of Applied Mathematics and Computer Science* **32**(3): 455–465, DOI: 10.34768/amcs-2022-0033.

Penzel, T., Moody, G.B., Mark, R.G., Goldberger, A.L. and Peter, J.H. (2000). The apnea-ECG database, *Computers in Cardiology 2000, Cambridge, USA,* Vol. 27, pp. 255–258.

Prakash, A.J., Patro, K.K., Hammad, M., Tadeusiewicz, R. and Pławiak, P. (2022). BAED: A secured biometric authentication system using ECG signal based on deep learning techniques, *Biocybernetics and Biomedical Engineering* **42**(4): 1081–1093.

Psaros, A.F., Meng, X., Zou, Z., Guo, L. and Karniadakis, G.E. (2023). Uncertainty quantification in scientific machine learning: Methods, metrics, and comparisons, *Journal of Computational Physics* **477**: 111902.

Ramar, K. and Guilleminault, C. (2008). Sleep apnea (central and obstructive), *in* H.R. Smith *et al.* (Eds), *Sleep Medicine*, Cambridge University Press, Cambridge, pp. 129–156.

Shen, Q., Qin, H., Wei, K. and Liu, G. (2021). Multiscale deep neural network for obstructive sleep apnea detection using RR interval from single-lead ECG signal, *IEEE Transactions on Instrumentation and Measurement* **70**: 1–13.

Singh, S.A. and Majumder, S. (2019). A novel approach OSA detection using single-lead ECG scalogram based on deep neural network, *Journal of Mechanics in Medicine and Biology* **19**(04): 1950026.

Wang, T., Lu, C. and Shen, G. (2019a). Detection of sleep apnea from single-lead ECG signal using a time window artificial neural network, *BioMed Research International* **2019**: 9768072.

Wang, T., Lu, C., Shen, G. and Hong, F. (2019b). Sleep apnea detection from a single-lead ECG signal with automatic feature-extraction through a modified LeNet-5 convolutional neural network, *PeerJ* **7**: e7731.

Zarei, A. and Asl, B.M. (2018). Automatic detection of obstructive sleep apnea using wavelet transform and entropy-based features from single-lead ECG signal, *IEEE Journal of Biomedical and Health Informatics* **23**(3): 1011–1021.

Zarei, A. and Asl, B.M. (2020). Performance evaluation of the spectral autocorrelation function and autoregressive models for automated sleep apnea detection using single-lead ECG signal, *Computer Methods and Programs in Biomedicine* **195**: 105626.

Usha Rani Kandukuri graduated in biomedical engineering from the University College of Engineering, Osmania University, Hyderabad, Telangana, in 2019. She is currently pursuing a master's degree in biomedical engineering at the National Institute of Technology, Rourkela. She worked as a research fellow at the National Institute of Indian Medical Heritage (NIIMH), Hyderabad, in 2019–2021. Her research interests include biomedical signal and image processing, deep learning and biomedical instrumentation.

Allam Jaya Prakash was born in Venkampeta (Village), Parvatipuram (District), Andhra Pradesh, India, in 1988. After finishing his primary (2003) and intermediate schooling (2005), he received a BTech degree in electronics and communication engineering from GITAS, Piridi, affiliated to Jawaharlal Nehru Technological University Kakinada (JNTUK), India, in 2009, and an MTech degree in digital electronics and communication systems from the GMRIT, Rajam, affiliated to Jawaharlal Nehru Technological University Kakinada (JNTUK), in 2012. Presently he is working as an assistant professor in the School of Computing Science and Engineering (SCOPE), VIT Vellore, India. His current area of research includes biomedical signal processing, machine learning, and deep learning techniques. He can be contacted at `allamjayaprakash@gmail.com`.

Kiran Kumar Patro holds ME and PhD degrees from the Department of Electronics and Communication Engineering, Andhra University, Visakhapatnam, India. He first worked as a UGC junior research fellow (Govt. of India) for 2 years and then as a senior research fellow for 3 years at Andhra University. His research interests include biomedical signal processing, image processing, pattern recognition and machine learning. He currently works as an assistant professor in the Department of Electronics and Communication Engineering, Aditya Institute of Technology and Management. He has published more than 21 papers in refereed international journals.

Bala Chakravarthy Neelapu received his BTech in electronics and communication engineering from JNTU Hyderabad in 2008, an MTech in electronics and communication engineering from JNTU Kakinada in 2011, and a PhD in engineering from AcSIR (Academy of Scientific and Innovative Research) at the CSIR—Central Scientific Instruments Organisation, Chandigarh, in 2018. Currently, he works as an assistant professor in the Department of Biotechnology and Medical Engineering of the National Institute of Technology, Rourkela, India. He has authored 10 articles in SCI-indexed journals and conferences.

Ryszard Tadeusiewicz has pursued research in the areas of biomedical engineering, biocybernetics, automatic control engineering, computer science and artificial intelligence since 1971. In 1975 and 1981 he was awarded the PhD and DSc degrees, respectively. In 1986 he became an associate professor and in 1991 a full professor at the AGH University of Science and Technology. In his career he has been elected three times as the rector of AGH and three times as the president of the Cracow Branch of the Polish Academy of Sciences. He was the first researcher in Poland to develop artificial intelligence methods based on the use of artificial neural networks. His main scientific achievements are related to the creation of automatic medical image understanding systems. He has contributed significantly to the development of scientific staff, having promoted 76 doctoral students, most of whom are now professors. He has authored over 1900 scientific papers, published in prestigious Polish and foreign scientific journals. He holds honorary doctorates from 14 Polish and foreign universities. Detailed and most up-to-date information is available at `www.Tadeusiewicz.pl`.

Paweł Pławiak was born in Ostrowiec, Poland, in 1984. He holds BEng and MSc degrees in electronics and telecommunications, a PhD (honors) in biocybernetics and biomedical engineering from the AGH University of Science and Technology, Cracow, Poland, and a DSc degree in technical computer science and telecommunications from Silesian Technical University, Gliwice, Poland. He has published more than 70 papers in refereed international SCI-IF journals. His research interests include machine learning and computational intelligence (e.g., artificial neural networks, genetic algorithms, fuzzy systems, support vector machines, k-nearest neighbours, and hybrid systems), ensemble learning, deep learning, evolutionary computation, classification, pattern recognition, signal processing and analysis, data analysis and data mining, sensor techniques, medicine, biocybernetics, biomedical engineering and telecommunications.

Received: 24 November 2022
Revised: 3 April 2023
Accepted: 18 May 2023