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Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model

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ABSTRACT

High-risk patients of cardiovascular disease can be provided with computerized electrocardiogram (ECG) devices to detect Arrhythmia. These require long segments of quality ECG which however can lead to missing the episode. To overcome this, we have proposed a deep-learning approach, where the scalogram obtained by continuous wavelet transform (CWT) is classified by the network based on the signature corresponding to arrhythmia. The CWT of the recordings is obtained and used to train the 2D convolutional neural network (CNN) for automatic arrhythmia detection. The proposed model is trained and tested to identify five types of heartbeats such as normal, left bundle branch block, right bundle branch block, atrial premature, and premature ventricular contraction. The model shows an average sensitivity, specificity, and accuracy to be 98.87%, 99.85%, and 99.65%, respectively. The result shows that the proposed model can detect arrhythmia effectively from short segments of ECG and has the potential for being used for personalised and digital healthcare.

1. Introduction

Arrhythmia, irregularity in the heartbeat rhythm, is a life-threatening cardiac fault that can cause cardiac arrest and death [1]. Electrocardiogram (ECG) is a non-invasive recording of the electrical activity of the heart and is widely used for diagnosis and monitoring cardiovascular disease. Episodes of arrhythmia can be identified from ECG recordings and number of computerized methods for analysis of ECG have been developed [2]. There are several machine learning techniques with handcrafted features that have been developed for ECG-based arrhythmia detection. In [3], support vector machine (SVM), neural network (NN), and probabilistic neural network (PNN) classifiers were applied to ECG discrete wavelet transform features for classification to detect five types of arrhythmia beats. In [4], morphological along with dynamic time warping features of ECG were incorporated into an SVM classifier. In [5], statistical features such as variance, skewness, and kurtosis were computed from segmented ECG beats to distinguish the abnormal heartbeats from normal ones using LDA, SVM, and KNN classifiers. Most of these above-mentioned algorithms involve hand-crafted feature selection.

To improve the performance and eliminate the features computation selection process, several deep learning (DL) models have been proposed. In [6–10], CNN based models were designed to analyse ECG time-series signals for classifying cardiac arrhythmia. In these CNN based models, without any pre-processing one dimensional (1D) raw ECG signal was fed to train the network. The segment duration of ECG used in these studies ranged over a wide range; from 5 s to 5 min. Additionally, recurrent neural network (RNN) and long short-term memory (LSTM) have been integrated with CNN to improve the model performance [11–18]. The length of the segment used to generate these models ranged from 9 to 60s. Besides, a deep residual CNN [19], and hybrid models based on modified version of Marine Predators algorithm (MPA) and CNN [20] have been proposed to achieve improved classification accuracy in automatic arrhythmia detection. Moreover, CNN models were applied to extract features to train the classical machine learning models [10]. In [10], CNN was applied to extract features from an ECG segment of 5 min duration (38,400 samples) and KNN, SVM, and multilayer perceptrons were trained to identify the patients with paroxysmal atrial fibrillation from a healthy control. In the case of 1D time series, longer segments preserve higher temporal information. Most of the 1D ECG time series based deep learning models require longer segment to tune its hyperparameter to improve the classification accuracy. Since more information can be extracted from the time-frequency domain rather than only the time domain, different time-frequency

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Table 1
ECG dataset collected from MIT-BIH arrhythmia database.

Arrhythmia types	MIT-BIH records	Number of segments
Normal beat (N)	100, 101, 103, 113, 115	1500
Left bundle branch block beat (L)	109, 111, 207, 214	1500
Right bundle branch block beat (R)	118, 124, 212, 231	1500
Atrial premature beat (A)	209, 220, 222, 223, 232	1500
Premature ventricular contraction beat (V)	106, 119, 200, 208, 233	1500

conversion techniques were applied to raw ECG signals before being fed into DL models to identify arrhythmic beats [21–26]. Moreover, a 2D-CNN model has been utilized which automatically eliminated noise and converted 2D spectrograms from ECG signal for arrhythmia classification [27].

DL methods have been shown to be effective, but require large segments of the recording, and the presence of any artefact in the duration can result in erroneous results [28]. The aim of this work was to overcome this limitation with improved arrhythmia classification. One approach which has been reported here is to use the spectral representation of small segments of ECG recording and implement CNN based model for its classification. In this work, CWT with a 2D CNN-based model has been proposed for the identification and classification of arrhythmic beats using short-length ECG signals. The ECG recordings were segmented automatically and mapped into four types of images using FFT, CWT grayscale, STFT, and CWT RGB techniques. The segmented images have been fed into our proposed 2D-CNN model for training which extracts features from the images to classify five types of arrhythmic rhythms automatically including normal sinus rhythm. The performances of the proposed model were compared with the existing state-of-art techniques in the literature. Compared to the existing alternatives in the literature, the proposed model shows excellent results in detecting arrhythmias from short length ECG signals. The remaining of this paper has been arranged as below. Section 2 describes the methodology used for arrhythmic beats classification, including ECG data acquisition, beat segmentation, and CNN classifier. The results and discussions have been delineated in section 3. Lastly, the conclusion has been reported in section 4.

2. Materials and methods

2.1. Data acquisition

In this work, ECG recordings with five types of arrhythmic beats (normal, left bundle branch block, right bundle branch block, atrial premature, premature ventricular contraction) have been obtained from the MIT-BIH arrhythmia database [29]. The duration of each recording is of 30 min, and the sampling rate is 360 Hz. Here, the segments or epochs of 81 samples each have been considered from each type of ECG recording without any pre-processing. The normal (N), left bundle branch block (L), right bundle branch block (R), atrial premature (A), and premature ventricular contraction (V) classes have been obtained from 23 recordings. The recordings have been selected randomly [25] and there are 7500 segments in total. A five-fold cross validation has been employed to evaluate the performance of our model. The detailed information of subjects and the number of segments of each class are depicted in Table 1.

2.2. Methods

This work proposes a novel 2D-CNN model using the scalogram-based deep learning technique to classify five types of arrhythmias using ECG signals. The ECG time series was mapped into images using four different ways such as FFT, CWT-grey, STFT, and CWT-RGB to feed and train the deep learning model. For simplicity, the deep learning model fed with FFT, CWT-grey, STFT, and CWT-RGB is referred to as TN1, TN2, TN3, and TN4, respectively.

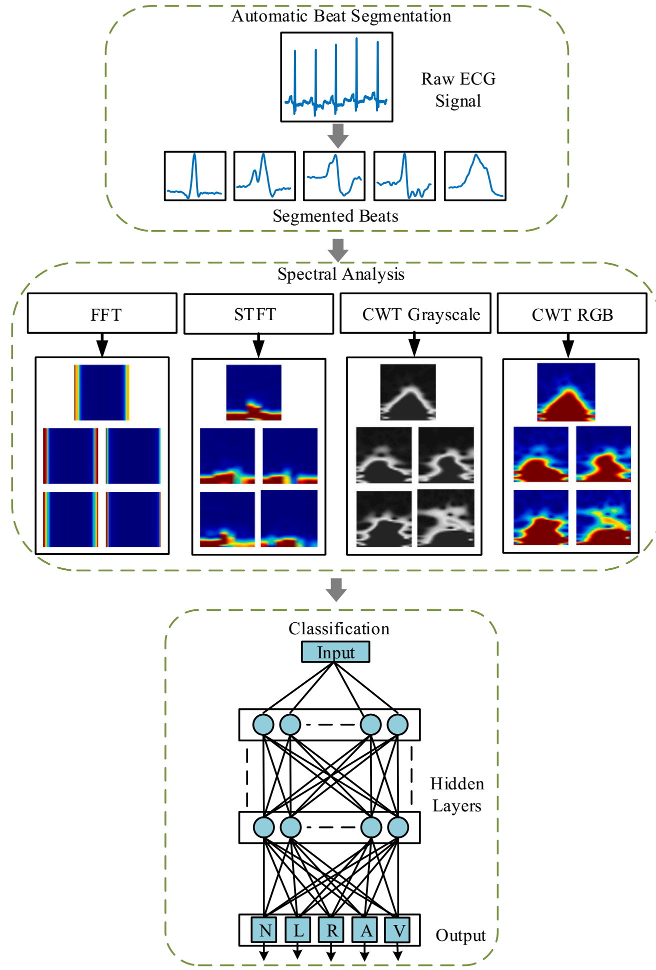


Fig. 1. Block diagram of proposed ECG based automated arrhythmia detection. The top, middle and bottom block represent ECG beat segmentation, spectral transformation, and deep learning-based classification.

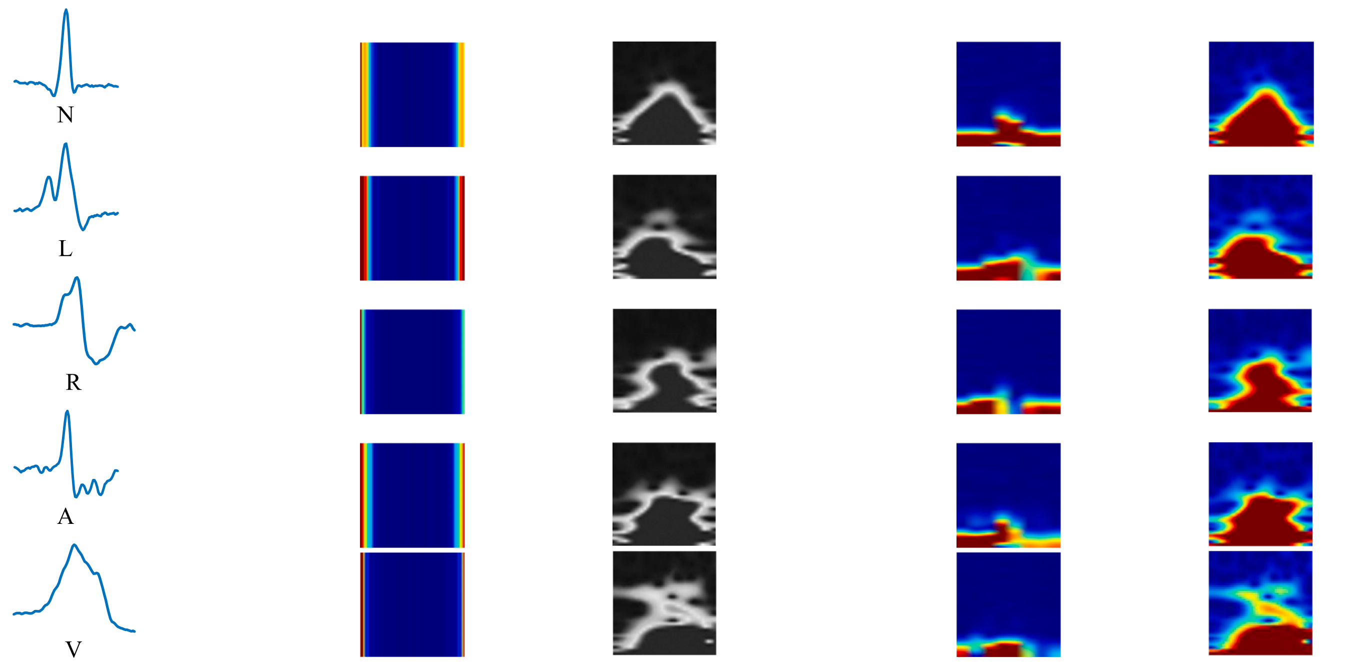
The block diagram of the proposed hybrid model for arrhythmia classification is shown in Fig. 1. The model consists of three parts i) automatic beat segmentation, ii) spectral transformation, and iii) CNN based deep learning model for beat classification. Firstly, each ECG signals were sliced into segments comprises of 81 samples (duration of 0.225 s). Secondly, each segment has been converted into images using four different transformation techniques such as FFT, CWT with grayscale, STFT, and CWT with RGB. Finally, a proposed CNN model was trained using images derived from above mentioned four different techniques to classify five different ECG beats i.e., N, L, R, A, and V. The detailed procedure of each section has been delineated below step by step.

2.2.1. Automated beat segmentation

We have applied the Pan Tompkins algorithm for ECG R peak detection [30]. These R peaks have been used as a reference to segment the raw ECG signal automatically into epochs. We have considered 40 samples before and after the R peak. Hence, each beat segment consists of 81 samples with a duration of 0.225 s. The reference of each heartbeat was annotated according to their arrhythmia types manually by the independent cardiologists. The following equation has accomplished this beat segmentation:

Table 2
An example of spectral image of five types of segmented beats.

Waveform of ECG segment	FFT	CWT Grayscale Scalogram	STFT	CWT RGB Scalogram



$$B\left(R_{peak}(i)-40\right) \leq B(i) \leq B\left(R_{peak}(i)+40\right) \tag{1}$$

where, $B(i)$ and $R_{peak}(i)$ are the *ith* number of beat and location of R peak of *ith* beat respectively and $i = 1, 2, 3,$ …………etc.

2.2.2. Spectral transformation

In this study, we have mapped the segmented time series into images using four different ways such as fast Fourier transform, and short-time Fourier transform, continuous wavelet transform (CWT) with grayscale, and CWT with RGB. The equation for FFT of any time series x is defined as:

$$Y_{p+1,q+1} = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} \omega_m^{jp} \omega_n^{kp} X_{j+1,k+1} \tag{2}$$

where, $\omega_m = e^{-2\pi i/m}$ and $\omega_n = e^{-2\pi i/n}$ are the complex roots of unity, i is the imaginary unity, p and j are indices that run from 0 to m– 1, and q and k are indices that run from 0 to n-1.

The equation for STFT of any time series x is defined as [25]:

$$STFT\{x[n]\} = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-j\omega n} \tag{3}$$

where, $x[n]$ denotes the ECG signal which sampling frequency is 360 Hz, and $w[n]$ is the window function which is given as

$$w[n] = \begin{cases} 0.5[1-cos(2\pi n/(M-1))], & 0 \leq n \leq M-1 \\ 0, & otherwise \end{cases} \tag{4}$$

The CWT for a continuous signal $x(t)$, is defined as follows [26]:

$$CWT_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(at)\psi^*\left(\frac{t-b}{a}\right)dt \tag{5}$$

where, $\psi^*(t)$ denotes the function of wavelet, a, b and t are the scale factor, location parameter, and a time shift respectively.Morse wavelet has been used as mother wavelet and the generalized Morse wavelet is defined as [31]:

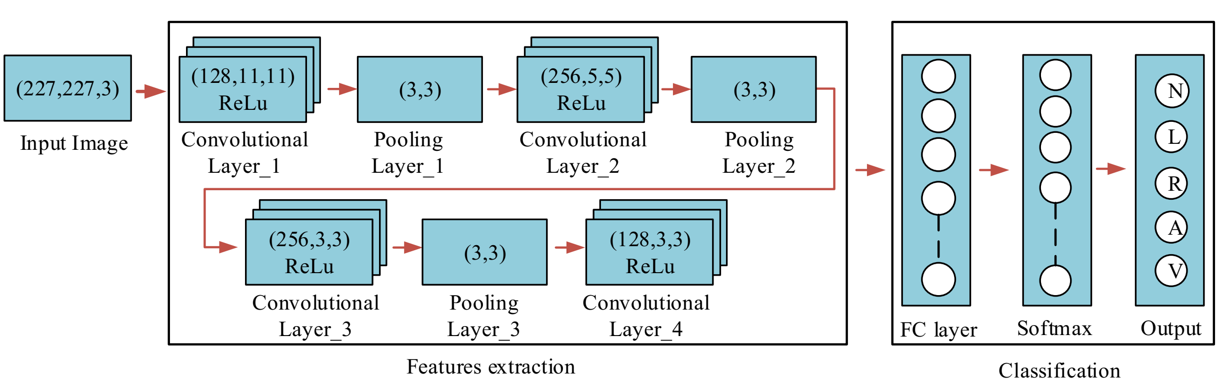


Fig. 2. Schematic arrangement of our 2D-CNN Model.

Table 3
Parameters of proposed 2D-CNN model.

Layer type	No. kernel	Kernel size	Region size	Stride	Activation function	Padding
Conv2D	128	11 × 11	–	4	ReLU	–
BatchNorm	–	–	–	–	–	–
MaxPool	128	–	3 × 3	2	–	–
Conv2D	256	5 × 5	–	1	ReLU	2
BatchNorm	–	–	–	–	–	–
MaxPool	256	–	3 × 3	2	–	–
Conv2D	256	3 × 3	–	1	ReLU	1
BatchNorm	–	–	–	–	–	–
MaxPool	256	–	3 × 3	2	–	–
Conv2D	128	3 × 3	–	1	ReLU	1
BatchNorm	–	–	–	–	–	–
Fully connected	5	–	–	–	Softmax	–

$$\psi_{\beta,\gamma}(\omega) = \int_{-\infty}^{\infty} \psi_{\beta,\gamma}(t) e^{-j\omega t} dt = U(\omega)\alpha_{\beta,\gamma}\omega^{\beta} e^{-\omega\gamma} \tag{6}$$

where, $\alpha_{\beta,\ \gamma}$ and $U(\omega)$ are the normalization constant and unit step function respectively, and the parameters β and γ control the wavelet form.

In case of CWT analysis, both grayscale and RGB scalogram were generated from ECG time series. Finally, the spectral conversion of ECG segments into scalogram using FFT, CWT-grayscale, STFT and CWT-RGB have been illustrated in Table 2.

2.2.3. CNN model

In this work, spectral images derived from four different techniques were applied separately to train our CNN-based deep learning model resulting in four trained models. Here, 80% of total scalograms from each technique have been considered for training purpose and rest for the testing. Fig. 2 depicts the schematic arrangement of our 2D-CNN model, which consists of four convolution layers, three pooling layers and one fully connected layer.

Firstly, the segmented ECG recording has been transformed into spectrum images of size 227 × 227. The first and fourth convolutional layers have same convolutional kernel of size 128, but the size of kernels are 11 × 11 and 3 × 3 respectively. Similarly, second and third

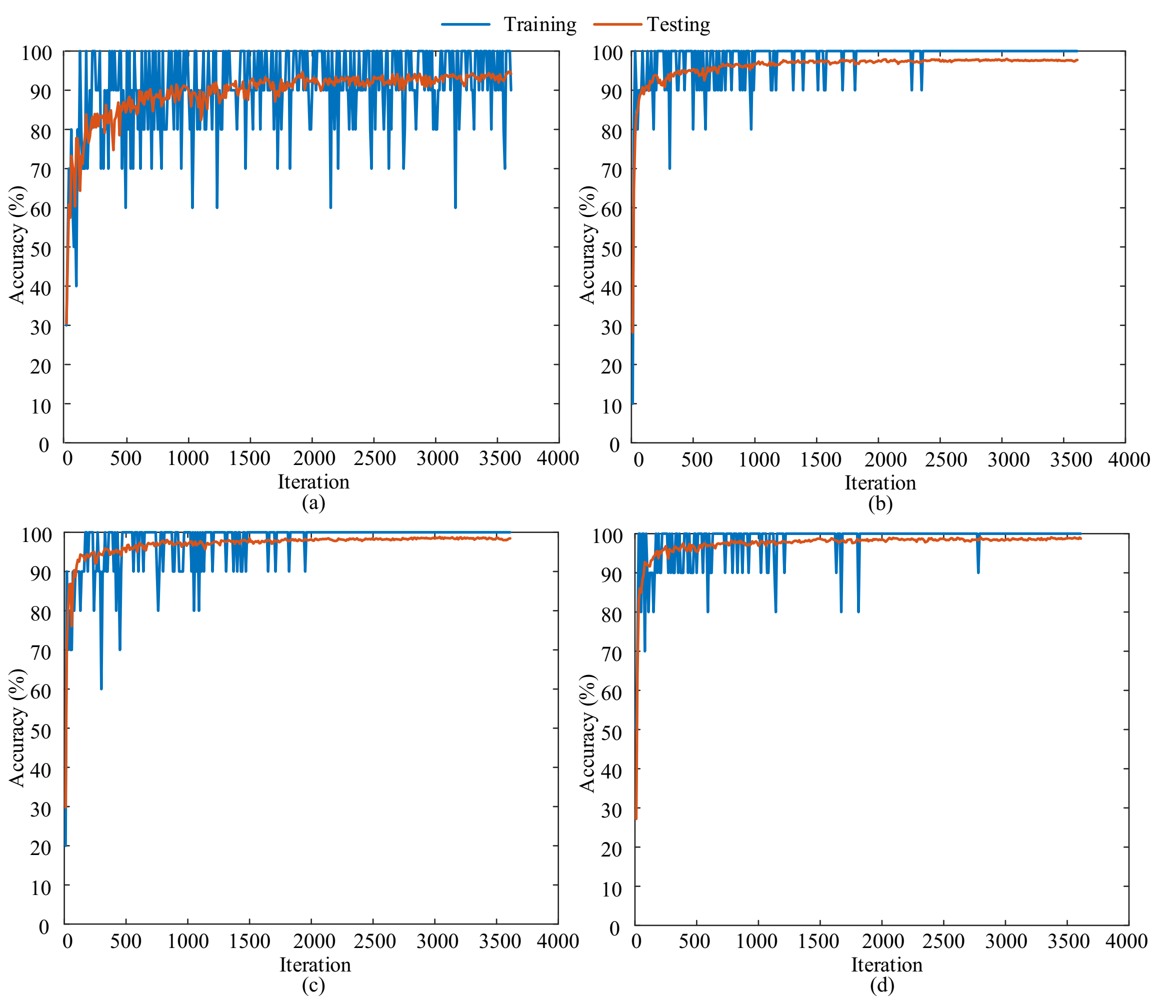


Fig. 3. Accuracy curve for model (a) TN1, (b) TN2, (c) TN3, (d) TN4.

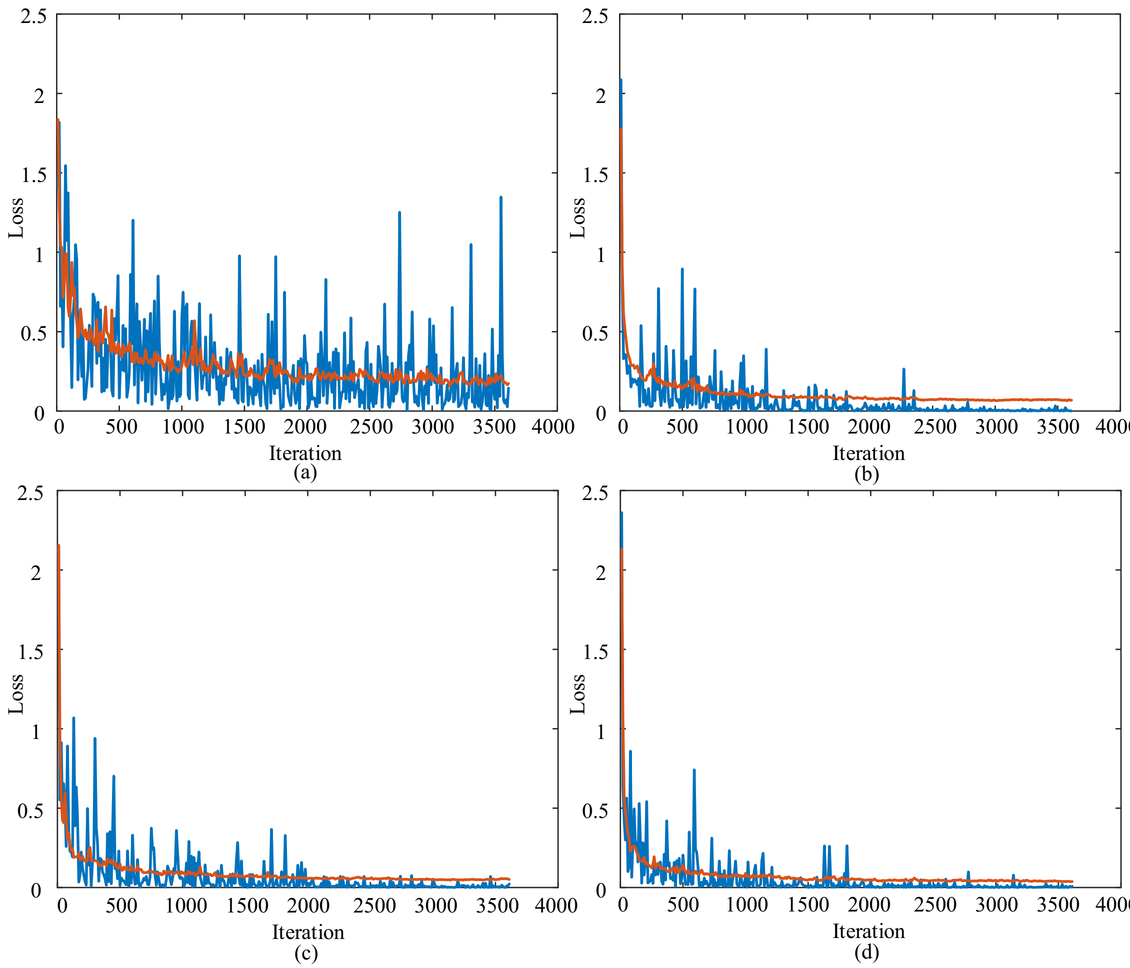


Fig. 4. Loss curve for model (a) TN1, (b) TN2, (c) TN3, (d) TN4.

convolutional layers have been organized with 256 convolutional kernels while the kernel size are different i.e., 5 × 5 and 3 × 3 respectively. After each convolutional layer except fourth, maxpooling layer of size 3 × 3 has been utilized to diminish the dimension of feature maps. Finally, the classification output is obtained from fully connected (FC) layer along with softmax activation function.

A rectified linear unit (ReLU) based nonlinear activation function follows each convolutional layer. The ReLU activation function is defined as:

$$ReLu(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{7}$$

Furthermore, a batch normalization layer normalizes the feature activations and is used after ReLU function. The batch normalization is defined as follows [32]:

$$\widehat{x_i} = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{8}$$

$$y_i = \gamma \widehat{x_i} + \beta \tag{9}$$

where, B, μ_B and σ_B^2 represent the mini-batch, mean and variance respectively. Also, ε is a constant whereas γ and β are the scale and shift parameters respectively. The parameters associated with proposed 2D-CNN model are given in Table 3.

Finally, stochastic gradient descent with momentum has been used as a solver to train the network. A mini-batch size of 10 images is used to train the model and the learning rate is 0.0001. All the computation was performed in MATLAB 2021a using Intel(R) Core (TM) i5-4200U CPU with 16 GB RAM and it took 37 min to classify.

2.3. Performance metrics

We have used three metrics to measure the performance of our proposed model, i.e. sensitivity, specificity, and accuracy, which are described below.

$$Sensitivity(\%) = \frac{TP}{TP + FN} \times 100$$

$$Specificity(\%) = \frac{TN}{TN + FP} \times 100$$

$$Accuracy(\%) = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

where, TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative respectively. TP, TN, FP, and FN indicate the number of correct predictions of positive classes as positive, negative classes as negative, negative classes as positive, and positive classes as negative respectively.

3. Results and discussions

The average accuracies for models TN1, TN2, TN3, and TN4 are 97.92%, 99.04%, 99.39%, and 99.65%, respectively. The accuracy and loss curves of each model are shown in Fig. 3, and Fig. 4, respectively.

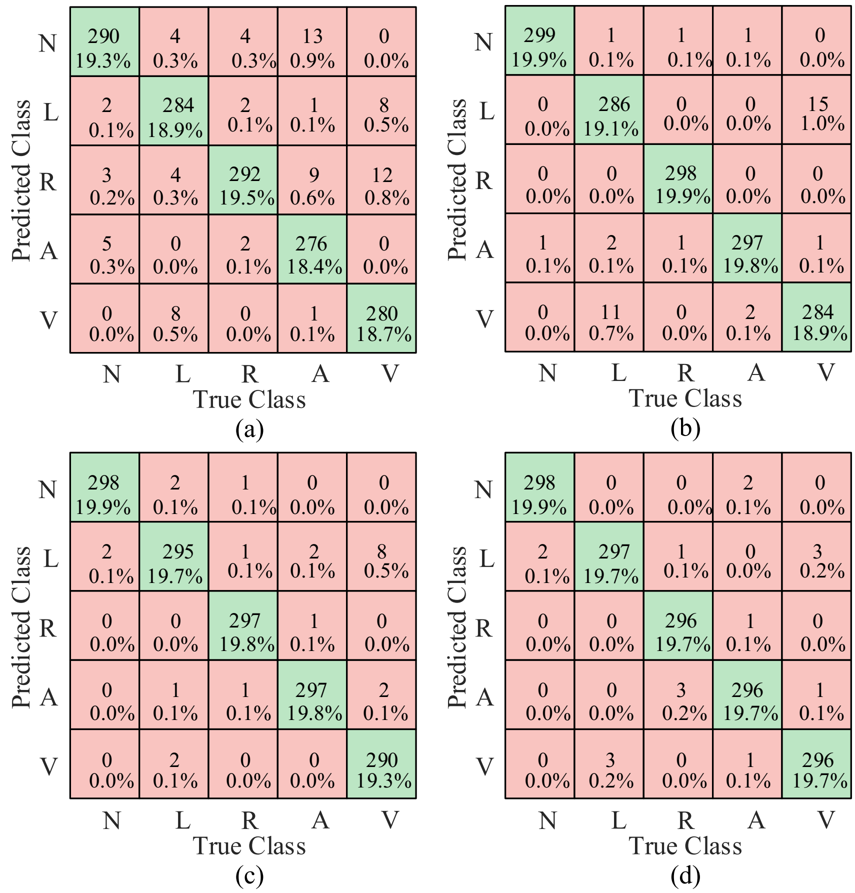


Fig. 5. Confusion matrices for model (a) TN1, (b) TN2, (c) TN3, (d) TN4.

Table 4
Performance measures for five types of beats.

Beat Classes	Sensitivity (%)				Specificity (%)				Accuracy (%)			
	TN1	TN2	TN3	**TN4**	TN1	TN2	TN3	**TN4**	TN1	TN2	TN3	**TN4**
N	96.67	99.67	99.33	**99.33**	98.25	99.75	99.75	**100**	97.93	99.73	99.67	**99.87**
L	94.67	95.33	98.33	**99.00**	98.92	98.75	98.92	**99.75**	98.07	98.07	98.80	**99.60**
R	97.33	99.33	99.00	**98.67**	97.67	100	99.92	**100**	97.60	99.87	99.73	**99.73**
A	92.00	99.00	99.00	**98.67**	99.42	99.58	99.67	**99.75**	97.93	99.47	99.53	**99.53**
V	93.33	94.67	96.67	**98.67**	99.25	98.92	99.83	**99.75**	98.07	98.07	99.20	**99.53**

Table 5
Classification performance for four types of training approach.

Models	Average Sensitivity (%)	Average Specificity (%)	Average Accuracy (%)
TN1	94.80	98.70	97.92
TN2	97.60	99.40	99.04
TN3	98.47	99.62	99.39
TN4	**98.87**	**99.85**	**99.65**

For model TN1, the accuracy becomes consistent after 3000 iterations, while for the other three models TN2, TN3, and TN4, it took approximately 1500 iterations. Since the number of iterations of TN1 is higher than TN2, TN3, and TN4, the time to adjust the parameters of the loss function is longer.

The confusion matrices of the four models are illustrated in Fig. 5. The sensitivity, specificity, accuracy of these models to detect the five types of beats are shown in Tables 4 and 5. In terms of classification, TN2, TN3, and TN4 exhibited consistent performance in terms of

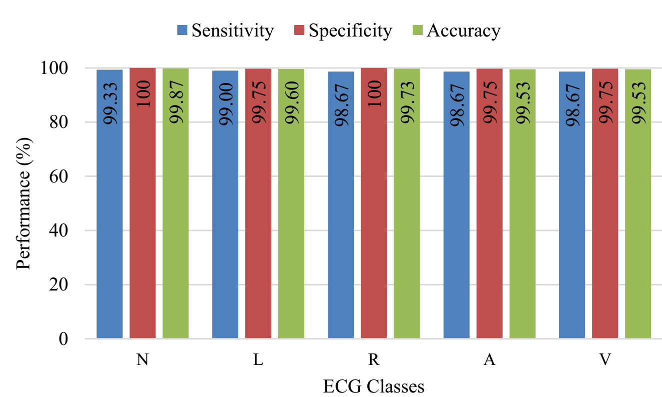


Fig. 6. Graphical representation of the three performance parameters for TN4 for five class classification.

Table 6
Comparison of the proposed model with the exiting models in the literature.

Reference	Duration of each ECG segment	ECG segment transformation	Approach	No. of Class	Beat Segment	Accuracy
Oh et al. [15]	1000 samples (2.78 s)	Deep learning	CNN and LSTM	5	16,499	98.10%
Izci et al. [21]	–	Grayscale image	2D-CNN	5	27,789	97.42%
Zheng et al. [22]	185 samples (0.51 s)	Grayscale image	CNN and LSTM	8	107,620	99.01%
Isin et al. [23]	200 samples (0.56 s)	Binary image	AlexNet	3	416	92.00%
Huang et al. [25]	3600 samples (10 s)	STFT spectrogram	2D-CNN	5	2520	99.00%
Wang et al. [35]	200 samples (0.56 s)	CWT scalogram	CNN-18	4	49,661	98.74%
This study	**81 samples (0.225 s)**	**CWT RGB scalogram**	**2D-CNN**	**5**	**7500**	**99.65%**

sensitivity, specificity, accuracy, while TN1 showed poor performance in classifying those beats, as shown in Table 4. Since TN1 involves FFT-based mapping, it completely lost the temporal information, as shown in Table 2. On the other hand, TN2, TN3, and TN4 models involve time-frequency mapping capable of extracting both time and frequency domain information. That is why TN2, TN3, and TN4 showed consistent performance than TN1.

Among the four different models, TN4 outperformed the other three models in terms of average sensitivity, specificity, and accuracy, followed by TN3, TN2, and TN1. The performance parameters achieved by the TN4 model for all the different classes are shown in Fig. 6. Although the STFT alleviates the shortcoming of Fourier transform by preserving both time and frequency information [33] for a shorter period which is reflected in the model performance, both of them decomposes fixed lengths short segments of the signal in sine and cosine wave which results in error, more pronounced at the lower frequency range [34]. On the other hand, wavelet transform performs multi-resolution decomposition because of which there is no biased error.

The performance comparison of the proposed model with the existing alternatives in the literature has been portrayed in Table 5. Most of the algorithms listed in Table 5 used CNN-based deep learning model, and their performance varies from 92% to 99%. The duration of ECG segment used to train the model varies from 185 to 3600 samples or 0.51 to 10 s. Compared to these methods, our approach uses only 81 samples (0.225 s) which makes our model faster. Additionally, the signature of arrhythmia is more evident in CWT than FFT or STFT (Table 2) since it carries the detail information, and the multi-resolution analysis by wavelet transform overcomes the baseline issue due to movement artefacts does not affect the signature corresponding to the arrhythmia. In terms of average accuracy, our model is comparable to the existing models and outperforms the listed models in Table 6.

In a sum, here we have proposed a 2D-CNN approach with CWT to classify the five types of arrhythmic beats. The scalograms obtained from short length ECG segments (0.225 s) using CWT have been exploited to train our 2D-CNN based model. Our model improves the classification accuracy compared to other approaches as mentioned in Table 6. Additionally, the smaller sample on data length makes the proposed model computationally less complex compared to the existing alternatives. Hence, this proposed approach can be applied for automatic arrhythmia classification to assist clinicians. Besides, the patient's ECG can be monitored in the mobile devices to facilitate the application such as real-time signal processing [7]. However, further investigation could be done with a large dataset and a wide range of arrhythmia classes.

4. Conclusion

This paper proposes a deep learning model with different time-frequency representations of short length (0.225 s) ECG segment to identify arrhythmia accurately. CWT-RGB with proposed 2D-CNN model shows the highest classification performance in terms of average sensitivity, specificity and accuracy of 98.87%, 99.85% and 99.65%, respectively. Moreover, the use of smaller segments makes the model computationally simpler and faster without compromising the model performance. These findings can be a template for the automated detection of arrhythmias for future personalised and digital cardiac health monitoring.

CRediT authorship contribution statement

Shadhon Chandra Mohonta: Methodology, Software, Data curation, Writing – original draft, Writing – review & editing. **Mohammod Abdul Motin:** Conceptualization, Supervision, Data curation, Validation, Writing – review & editing. **Dinesh Kant Kumar:** Visualization, Investigation, Writing – review & editing.

Declaration of Competing Interest

Declaration statement by co-authors for the manuscript, " Electrocardiogram Based Arrhythmia Classification Using Wavelet Transform with Deep Learning Model".

We declare the following:

1. Data: The public database from MIT has been used in this study.
2. Ethics: The research protocol was approved by Rajashahi University of Engineering & Technology, Bangladesh.
3. Conflict of Interest: Nothing to declare.
4. Financial support: Nothing to declare.

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