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A Novel Approach to Detect Cardiac Arrhythmia Based on Continuous Wavelet Transform and Convolutional Neural Network

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ABSTRACT

Electrocardiogram (ECG) signal is informative as well as non-invasive clinical tool to diagnose cardiac diseases of human heart. However, the diagnosis requires professionals' clarification and is also time-consuming. To make the diagnosis proficient, a novel convolutional neural network (CNN) has been proposed for automatic arrhythmia detection. In this work, the ECG data collected from the MIT-BIH database have been preprocessed, and segmented in short ECG segments of 60 s. Then, all these segments have been transformed into scalogram images obtained from time-frequency analysis using continuous wavelet transform (CWT). Finally, these scalogram images have been exploited as an input for our designed CNN classifier to classify cardiac arrhythmia. In this approach, the overall accuracy, sensitivity, and specificity are 99.39%, 98.79%, and 100% respectively. Proposed CNN model has significant advantages, and it can be used to differentiate the healthy and arrhythmic patients effectively.

1. INTRODUCTION

The amount of cardiovascular diseases upsurges incredibly and 17.3 million people decease every year conveyed by World Health Organization (WHO) (Mendis, Puska, Norrving, & Organization, 2011). The arrhythmias are most serious among them, and may cause sudden cardiac arrest or stroke (Huikuri, Castellanos, & Myerburg, 2001). Indeed, proper diagnosis of arrhythmias can considerably preclude such sudden cardiac death. ECG comprises complete details about the normality or abnormality of human heart, and various classes of arrhythmias can be diagnosed from it. In (De Bie, Martignani, Massaro, & Diemberger, 2020), short-term samples of 10 s obtained from pediatric and adult patient's ECG signals for atrial fibrillation or other abnormal rhythms detection. Furthermore, various feature extraction approaches such as time-domain and frequency-domain, statistical, and time-frequency analysis have been implemented for arrhythmia detection. Here, the features like heart rate, RR interval, R amplitude, PR interval, QRS duration, P-wave, and T-wave duration (Chen, Wang, & Wang, 2018; De Chazal & Reilly, 2006; Mitra, Mitra, & Chaudhuri, 2006) have been extracted from the time-domain analysis . Moreover, statistical features have been extracted in terms of variance, kurtosis, and skewness (Queiroz, Azoubel, & Barros, 2019; Queiroz, Junior, Lucena, & Barros, 2018). Besides, many literatures implemented wavelet transform to classify ECG arrhythmias in time-frequency analysis (Banerjee & Mitra, 2013; Khorrami & Moavenian, 2010).

In addition, to assist clinicians for detecting and classifying arrhythmias automatically a CNN based approached has been emerged in recent years. The CWT and CNN based approach has been proposed jointly for automatic arrhythmia classification with an overall accuracy of 98.74% (Wang et al., 2021). Here, the 2D-scalograms obtained from CWT while features extraction conducted using CNN from those scalograms. Moreover, different cardiac arrhythmias have been detected after the preprocessing of ECG signals using a 34-layer CNN (Brisk et al., 2019), 1D-CNN of 31-layers (Li, Zhou, Wan, Li, & Mou, 2020), CNN with long short-term memory (LSTM) (Chen et al., 2018), and 11-layer deep CNN (Acharya et al., 2017). Besides, a combination of signal quality index (SQI) algorithm and densed-CNN has been proposed to distinguish atrial fibrillation from short ECG segments (9–60 s) (Rubin, Parvaneh, Rahman, Conroy, & Babaeizadeh, 2018). Additionally, for automatic classification of cardiac arrhythmias various new models such as wavelet transform with 2D-CNN (Mohonta, Motin,

& Kumar, 2022), deep neural network (DNN) models constitutive of residual convolutional modules and bidirectional LSTM (He et al., 2019), and Deep Multi-Scale Convolutional neural network Ensemble (DMSCE) (Prabhakararao & Dandapat, 2021) have been proposed.

In this work, a new CNN model has been proposed to recognize the subjects with arrhythmias, and discriminate them from the healthy one. To expedite this, ECG segments of 60 s have been transformed into RBG scalograms based on CWT method for pattern recognition. Then, these scalograms of ECG segments have been fed into our proposed CNN model for automatic detection of cardiac arrhythmias.

The remainder of the paper is depicted as follows: section 2 describes the materials and methods part. In section 3, a comprehensive results and discussion has been presented based on proposed classifier performance. Finally, the conclusion is in fourth section.

2. MATERIALS AND METHODS

Our proposed method for arrhythmia detection has been divided into six stages containing data acquisition, pre-processing, segmentation, R peak detection, time-frequency transformation, and CNN classifier. The overall layout of our proposed method is shown in Figure 1.

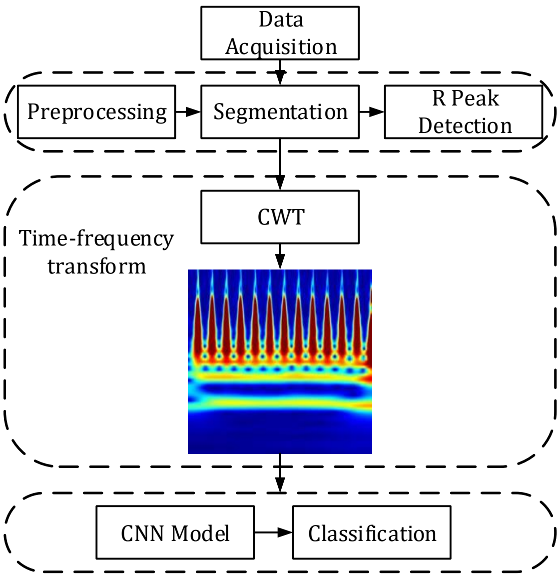

Figure 1: Overall layout for arrhythmia detection

A. Data Acquisition

The ECG data have been separated into two groups: healthy subjects, and the subjects with arrhythmia. The data is considered from the MIT-BIH database, and the duration of ECG recordings of each subject is 30 min. Here, 13 subjects have been grouped as healthy considered from normal sinus rhythm (NSR) database, whether 52 subjects have been considered from arrhythmia (ARR), atrial fibrillation (AFI), supraventricular arrhythmia (SVA) and malignant ventricular ectopy (MVE) database to form arrhythmic group.

B. Pre-processing and Segmentation

In pre-processing, the discrete wavelet transform (DWT) has been considered for eliminating the noise, baseline wander and artefacts from ECG signals. The low and high-frequency components of a signal has been decomposed using DWT, and then the signal has been reconstructed. Here, the ECG signal has been decomposed considering ‘sym4’ wavelet where low-frequency and high-frequency information are carried out by the approximation coefficient, and the first and second level detail coefficients respectively. Therefore, the denoised ECG singals have been reconstructed based on inverse wavelet transform only considering the third and fourth level detail coefficients. After that, each ECG recording has been divided into segments with 60 s duration. The segmented raw and filtered ECG signal of 60 s are shown in Figure 2 and Figure 3 respectively. So, the healthy and arrhythmic group have total 390 and 1560 segments respectively.

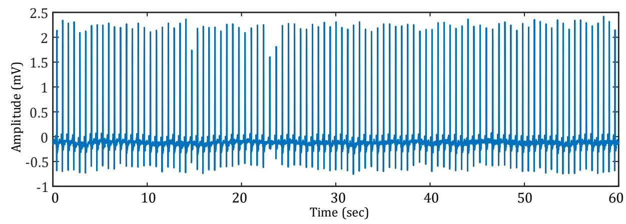

Figure 2: Original ECG signal

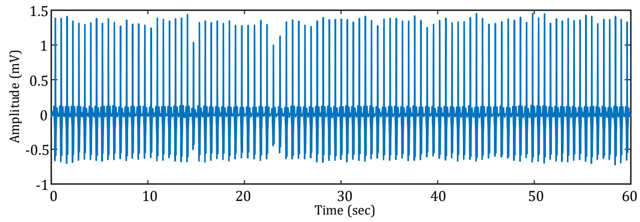

Figure 3: Filtered ECG signal

C. R Peak Detection

In this paper, the R peaks of ECG signal have been detected in three steps: (i) squaring the magnitude of the signal, (ii) finding the average value, and (iii) detecting R peaks. Here, the threshold value for the minimum peak height is the average value, and 0.14 s is considered as minimum peak height. The detected R peaks of a ECG signal is shown in Figure 4.

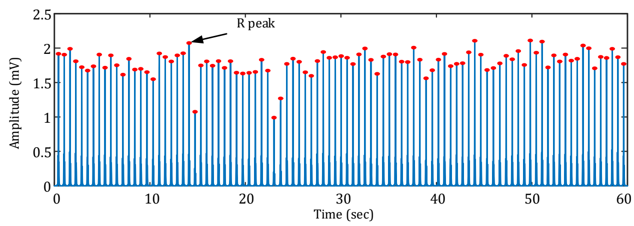

Figure 4: Detection of R peaks

There are a number of segments in healthy, and arrhythmic group which contain abnormal, and normal rhythm respectively. To exclude these undesirable segments, the detected R peaks have been used to compute the average heart rate (AHR) for each segment. After that, the segments which are in normal range ($60\ bpm \leq AHR \leq 100 bpm$), and abnormal range

($60\ bpm > AHR, or\ 100\ bpm < AHR$) have been nominated for the healthy group, and arrhythmic group respectively. In this way, the segment's selection has been conducted, and finally each group contains total 249 ECG segments.

D. Time-Frequency Analysis

In this analysis, ECG signals are represented in time-frequency domain, and has medical importance to diagnose different cardiovascular diseases. Here, all the segments of each group have been converted into scalogram images from using CWT. The CWT Scalograms decompose the information of a signal in spectral patterns.

The CWT for a continuous signal $x(t)$, is defined as follows (Wang et al., 2021)

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

Where, $\psi^*(t)$, t, a, and b are the complex conjugate of the basic wavelet, time shift, scale factor, and location parameter respectively.

E. CNN Model

In this analysis, a CNN network has been proposed to detect arrhythmia from RGB scalogram. It consists of several common layers: convolutional (Conv), Rectified Linear Unit (ReLU), batch normalization (BN), max pooling (MaxPool), fully connected (FC) and softmax. The basic model of proposed CNN is shown in Figure 5.

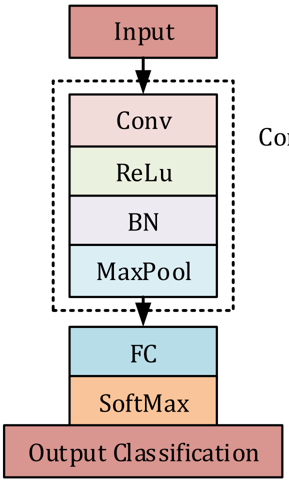

Figure 5: The basic model of proposed CNN

The input of the network is RGB time-frequency scalogram of size 227×227×3. This model has four convolutional block. Every convolutional block contains convolutional layer, batch normalization layer, and a pooling layer. A non-linear activation function, ReLu, is used after the convolutional layer to enhance the approximation ability between each layer of the network. Besides, the function of the batch normalization layer is to batch normalize the activation output of the layer. The parameters of the max pooling layer of every convolutional block are same, and have the Kernel size 3×3 and the stride 2. But, the parameters of convolutional layer in each block are different. Moreover, the fully connected layer shows the classification results and the softmax activation function implies the probability that the input belongs to each class. Finally, 70% of images have been considered to train our model, and rest are used for testing. Table 1 represents the summarization of the proposed CNN model.

Table 1
Summaries the parameters of proposed CNN model

Layer Type	Kernel Size	Stride	Kernel	Padding
Conv_1	11×11	4	64	-
MaxPool_1	3×3	2	-	-
Conv_2	5×5	1	256	2
MaxPool_2	3×3	2	-	-
Conv_3	3×3	1	384	1
MaxPool_3	3×3	2	-	-
Conv_4	3×3	1	256	1
MaxPool_4	3×3	2	-	-
FC	-	-	2	-

3. RESULTS AND DISCUSSION

In this work, our proposed CNN model is a simple one which consists of only four convolutional layers, and one fully connected layers. Here, RGB scalograms of size 227×227×3 of all ECG segments have been obtained from CWT method for arrhythmia detection. After that, the designed CNN model took these scalograms as an input, and differentiate arrhythmic subjects from the healthy ones automatically. Here, total 348 scalograms are used to train the model, while 150 images are considered for testing purpose. In this approach, 6 epochs and 204 iterations have been considered, and it took around 13 min to compete the classification process. The confusion matrix of the proposed CNN model is shown in Figure 6.

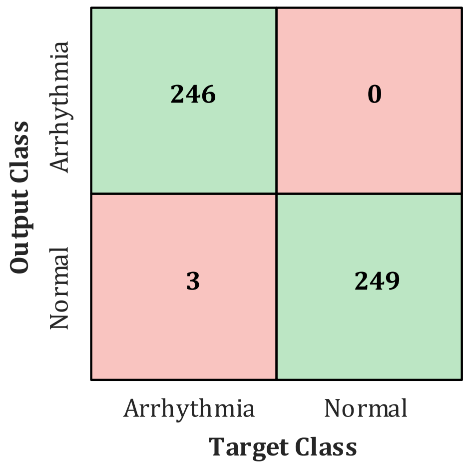

Figure 6: Confusion matrix for proposed CNN model

Here, three statistical parameters have been computed to evaluate the performance of our classifier which are as follows (Queiroz et al., 2019):

$$Se(\%) = \frac{TP}{TP+FN} \times 100 \qquad (2)$$

$$Sp(\%) = \frac{TN}{TN+FP} \times 100 \qquad (3)$$

$$Acc(\%) = \frac{TP+TN}{TP+FP+TN+FN} \times 100 \qquad (4)$$

Where, *Se* is the sensitivity which represents how the technique is effective for detecting arrhythmia, *Sp* is the specificity which denotes how the technique is effective for detecting healthy subjects, and *Acc* is the accuracy which measures the effectiveness of the technique regarding diagnosis. Also, *TP* is the true positive, *TN* is the true negative, *FP* is the false positive, and *FN* is the false negative.

The accuracy and loss curves of our proposed model are shown in Figure 7 and Figure 8 respectively. It is obvious that the network has reached its stable position after approximately 30 iterations.

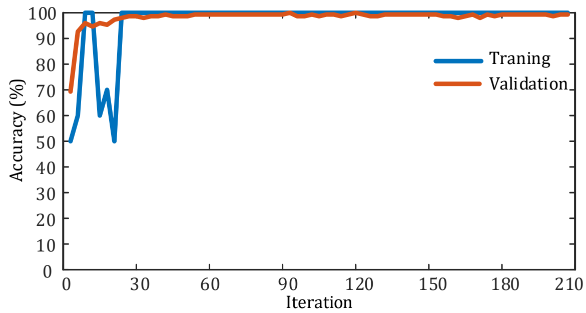

Figure 7: Accuracy of the proposed model

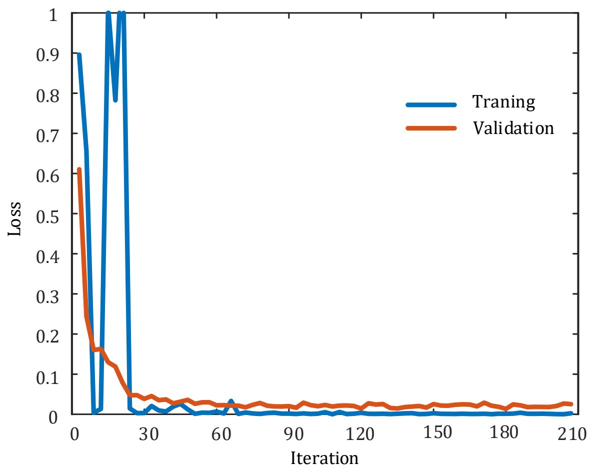

Figure 8: Loss of the proposed model

Table 2
Performance evaluation indicators for proposed CNN model

Sensitivity (*Se*)	Specificity (*Sp*)	Accuracy (*Acc*)
98.79 %	100 %	99.39%

It is apparent from Figure 7 and Figure 8 that the accuracy, and loss are 99.39%, and 0.015 respectively. Besides, the accuracy of the proposed CNN model is better than using a pretrained AlexNet model (Mohonta & Ali, 2021). Besides, the statistical indices such as sensitivity (*Se*), specificity (*Sp*), and accuracy (*Acc*) of this classification are portrayed in Table 2.

The comparison between the performance of our work and other existing methods has been summarized in Table 3. In (Wang et al., 2021), the arrhythmia detection had been performed with a combination of CWT and CNN-based approaches. A deep learning model named ResNet-31 had been used to detect cardiac arrhythmia from single lead ECG signals which showed 99.06% accuracy (Li et al., 2020). Also, a combination of CNN and long short-term memory (LSTM) based model had been proposed for automatic arrhythmia classification, and achieved 98.10% accuracy (Chen et al., 2018). Moreover, accuracy of 94.90% had been achieved for arrhythmia detection using CNN-based approach from ECG segments of 5 s. (Acharya et al., 2017). Arrhythmia has been classified from ECG signal using STFT-based spectrogram and proposed 2D-CNN model, and achieved an overall accuracy of 99.00%.

Table 3
Performance evaluation indicators for proposed CNN model

Reference	Duration of each ECG segment	Notable features	Approach	Overall *Acc*
(Wang et al., 2021)	200 samples (around 0.56 s)	CWT	CNN-18	98.74%
(Li et al., 2020)	300 samples (around 0.83 s)	Deep learning	ResNet-31	99.06%
(Oh, Ng, San Tan, & Acharya, 2018)	1000 samples	Deep learning	CNN and LSTM	98.10%
(Acharya et al., 2017)	5 s	Deep learning	CNN-11	94.90%
(Huang, Chen, Yao, & He, 2019)	10 s	STFT	CNN	99.00%
This study	**60 s**	**CWT**	**CNN**	**99.39%**

In sum, the deep learning model extracts features automatically from CWT scalogram which conveys the time-frequency information of arrhythmia. Actually, the wavelet-based technique decomposes complex information and patterns of an image into elementary forms. Hence, the propounded CNN model has outperformed the other related works, and effectively diagnosed and classified arrhythmic subjects from normal one with an overall accuracy of 99.39%. However, small number of ECG segments has been considered in this analysis. Further analysis could be done with the same approach using large number of segments.

4. CONCLUSIONS

The information of electrical activity of the heart can be epitomized through ECG signal which also helps to diagnose cardiac disorder non-invasively. Here, the detection of arrhythmia from ECG segments has been conducted based on wavelet transform and CNN classifier. In this diagnosis, a novel CNN model has been incorporated for image recognition that investigates the CWT scalograms, and delivers better performance with an overall accuracy of 99.39%. So, the results demonstrate that the proposed approach automatically extracted features from the ECG signal to distinguish arrhythmic subjects from healthy one successfully. Therefore, this approach can be implemented clinically to guide academicians and medical professionals for efficient arrhythmia diagnosis.

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REFERENCES

Acharya, U. R., Fujita, H., Lih, O. S., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. *Information sciences, 405*, 81-90.

Banerjee, S., & Mitra, M. (2013). Application of cross wavelet transform for ECG pattern analysis and classification. *IEEE transactions on instrumentation measurement, 63*(2), 326-333.

Brisk, R., Bond, R., Banks, E., Piadlo, A., Finlay, D., McLaughlin, J., & David, M. (2019). Deep learning to automatically interpret images of the electrocardiogram: Do we need the raw samples? *Journal of electrocardiology, 57*, S65-S69.

Chen, X., Wang, Y., & Wang, L. (2018). Arrhythmia recognition and classification using ECG morphology and segment feature analysis. *IEEE/ACM transactions on computational biology bioinformatics, 16*(1), 131-138.

De Bie, J., Martignani, C., Massaro, G., & Diemberger, I. (2020). Performance of seven ECG interpretation programs in identifying arrhythmia and acute cardiovascular syndrome. *Journal of Electrocardiology, 58*, 143-149.

De Chazal, P., & Reilly, R. B. (2006). A patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features. *IEEE transactions on biomedical engineering, 53*(12), 2535-2543.

He, R., Liu, Y., Wang, K., Zhao, N., Yuan, Y., Li, Q., & Zhang, H. (2019). Automatic cardiac arrhythmia classification using combination of deep residual network and bidirectional LSTM. *IEEE access, 7*, 102119-102135.

Huang, J., Chen, B., Yao, B., & He, W. (2019). ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network. *IEEE access, 7*, 92871-92880.

Huikuri, H. V., Castellanos, A., & Myerburg, R. J. (2001). Sudden death due to cardiac arrhythmias. *New England Journal of Medicine, 345*(20), 1473-1482.

Khorrami, H., & Moavenian, M. (2010). A comparative study of DWT, CWT and DCT transformations in ECG arrhythmias classification. *Expert systems with Applications, 37*(8), 5751-5757.

Li, Z., Zhou, D., Wan, L., Li, J., & Mou, W. (2020). Heartbeat classification using deep residual convolutional neural network from 2-lead electrocardiogram. *Journal of electrocardiology, 58*, 105-112.

Mendis, S., Puska, P., Norrving, B. e., & Organization, W. H. (2011). *Global atlas on cardiovascular disease prevention and control*: World Health Organization.

Mitra, S., Mitra, M., & Chaudhuri, B. B. (2006). A rough-set-based inference engine for ECG classification. *IEEE transactions on instrumentation measurement, 55*(6), 2198-2206.

Mohonta, S. C., & Ali, M. F. (2021). *Cardiac Arrhythmia Diagnosis based on Features Extraction and Convolutional Neural Network from ECG Signals.* Paper presented at the 2021 5th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT).

Mohonta, S. C., Motin, M. A., & Kumar, D. K. (2022). Electrocardiogram based arrhythmia classification using wavelet transform with deep learning model. *Sensing Bio-Sensing Research*, 100502.

Oh, S. L., Ng, E. Y., San Tan, R., & Acharya, U. R. (2018). Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats. *Computers in biology medicine, 102*, 278-287.

Prabhakararao, E., & Dandapat, S. (2021). Multi-Scale Convolutional Neural Network Ensemble for Multi-Class Arrhythmia Classification. *IEEE Journal of Biomedical Health Informatics*.

Queiroz, J. A., Azoubel, L. M. A., & Barros, A. K. (2019). Support system for classification of beat-to-beat arrhythmia based on variability and morphology of electrocardiogram. *EURASIP Journal on Advances in Signal Processing, 2019*(1), 1-9.

Queiroz, J. A., Junior, A., Lucena, F., & Barros, A. K. (2018). Diagnostic decision support systems for atrial fibrillation based on a novel electrocardiogram approach. *Journal of Electrocardiology, 51*(2), 252-259.

Rubin, J., Parvaneh, S., Rahman, A., Conroy, B., & Babaeizadeh, S. (2018). Densely connected convolutional networks for detection of atrial fibrillation from short single-lead ECG recordings. *Journal of electrocardiology, 51*(6), S18-S21.

Wang, T., Lu, C., Sun, Y., Yang, M., Liu, C., & Ou, C. (2021). Automatic ECG classification using continuous wavelet transform and convolutional neural network. *Entropy, 23*(1), 119.