



# Automatic detection of arrhythmia from imbalanced ECG database using CNN model with SMOTE

Saroj Kumar Pandey<sup>1</sup> · Rekha Ram Janghel<sup>1</sup>

Received: 8 January 2019 / Accepted: 29 October 2019  
© Australasian College of Physical Scientists and Engineers in Medicine 2019

## Abstract

Timely prediction of cardiovascular diseases with the help of a computer-aided diagnosis system minimizes the mortality rate of cardiac disease patients. Cardiac arrhythmia detection is one of the most challenging tasks, because the variations of electrocardiogram (ECG) signal are very small, which cannot be detected by human eyes. In this study, an 11-layer deep convolutional neural network model is proposed for classification of the MIT-BIH arrhythmia database into five classes according to the ANSI-AAMI standards. In this CNN model, we designed a complete end-to-end structure of the classification method and applied without the denoising process of the database. The major advantage of the new methodology proposed is that the number of classifications will reduce and also the need to detect, and segment the QRS complexes, obviated. This MIT-BIH database has been artificially oversampled to handle the minority classes, class imbalance problem using SMOTE technique. This new CNN model was trained on the augmented ECG database and tested on the real dataset. The experimental results portray that the developed CNN model has better performance in terms of precision, recall, F-score, and overall accuracy as compared to the work mentioned in the literatures. These results also indicate that the best performance accuracy of 98.30% is obtained in the 70:30 train-test data set.

**Keywords** Arrhythmia · Convolutional Neural Network · Electrocardiogram · Imbalance · Heartbeat

## Introduction

Worldwide millions of people are suffering from cardiovascular diseases [1]. According to the reports of World Health Organization, 30% of the world's deaths are due to cardiovascular diseases [2]. The major cause of the cardiac deaths is cardiac arrhythmia. Cardiac arrhythmia is a condition, where the functioning of the heart is abnormal [3, 4].

Due to arrhythmia, heart rhythm will be either too fast or too slow or irregular from regular rhythm of the heart. Because of arrhythmia, the heart cannot send enough blood to the body parts. Therefore the blood cannot flow in right proportion, due to which the functioning of heart, brain is affected and other parts of the body. Most arrhythmias are harmful to the heart. There are two type of arrhythmia

non-life-threatening and life-threatening. Therefore, continuous monitoring of the activity of heartbeats is inevitable. So, it is very important to ascertain the arrhythmia for proper medical care by detecting heart diseases [5–7]. The best equipment for monitoring and identifying arrhythmia is an electrocardiogram (ECG).

An electrocardiogram is a noninvasive and inexpensive diagnostic device, which is used for monitoring electrical activity of the heart and is also widely applied in several applications [8]. ECG is represented in the form of electrical signals, which shows the electrical activity of the heart over the period and consists of the important physiological data, which is widely used for analysis of heart-beat function. The heart's electric field is generated by placing the electrode on different parts of the body [9]. ECG signals will construct a sequence of three waves: P wave, Q-R-S waves (known as QRS complex), and T wave, which are repeated periodically in time, so it is a periodic signal as shown in Fig. 1.

The ECG signal classification is widely categorized into four phases: data pre-processing, heartbeat peak segmentation [10], feature extraction, and classifiers [11, 12]. The data pre-processing phase emphasizes on noise removal

✉ Saroj Kumar Pandey  
sarojpandey23@gmail.com

Rekha Ram Janghel  
rrjanghel.it@nitrr.ac.in

<sup>1</sup> Department of Information Technology, National Institute of Information Technology, Raipur, India

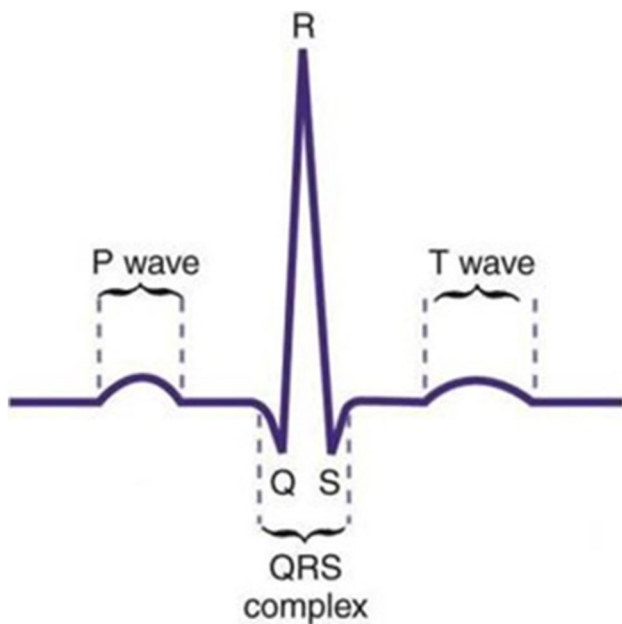


Fig. 1 Electrocardiogram signal [4]

from signal acquisition like power line interference and base-line wander noises [13–15]. Heartbeat peak segmentation phase (i.e. the finding of R peaks and Q-R-S complex in the signal) has been used approximately for the last three decades. In this part, heartbeat frequency information has been used and the signal is split into single or multiple periods of heartbeats [16, 17].

The third phase is feature extraction, which plays an important role throughout the classification process and different techniques have been introduced and validated. So in this section, the different manners of feature extractions have been categorized into two parts: the first one is: manual based feature extraction and the second one is learning-based feature extraction. In this paper learning-based feature extraction is used. For manual based methods, features are extracted from frequency domain such as wavelet transform [18–20], cosine transform [21], and Fourier transform [22, 23] as well as time domain, using the morphological features of the signal that can be directly extracted from the ECG data. The mostly used morphological features are R–R interval, P–R interval, P duration, Q–R–S duration, T duration, and Q–T intervals [24, 25]. Literature [26] has also explored some higher-order statistical features.

The traditional classical features, which were extracted from simple handcraft, cannot provide abundant and inner information. Learning-based feature extraction, also known as fine features and also deeper. Some dimension reduction techniques such as principal component analysis and independent component analysis, have been explored deeper features from the ECG signals [27, 28]. In [29] author applied an S-transform method for feature extraction after that

proposes a learning method, based on supervised regularization-based robust subspace for learning low-dimensional vital feature from the subspace of original features. In [30] authors explored a different kind of features, such as the perspective of visual level feature combinations and view level feature combinations. The best result was obtained when all the visual features were combined.

In these techniques, the principal information may be preserved by projecting a low-dimensional space [31]. Some artificial neural network methods influence the great capacity of the networks, having many layers and several parameters, trained iteratively for extracting the course to learn features hierarchically. The features extracted from ANN are more beneficial than traditional handcrafted features. The traditional CNN has explored significant power for extracting features. Additionally, two methods: feature extraction and classification are integrated into CNN based classifiers [32, 33]. In traditional methods, both are separated. Hence this paper is based on CNN. In the last phase, various ECG signal classification techniques that are generic and fully automatic are used. The classifiers that are widely used for correct class prediction are support vector machine [34–36], Random-forest [37, 38], ANNs, and deep-learning [39–41].

Recently deep learning techniques have been applied [45] successfully for the diagnosis of ECG heartbeats and diseases. The deep-CNN [43], deep-neural network [33], and deep-belief network [44], have become very popular in ECG arrhythmia classifications. In this paper, a new CNN model has been proposed by making considerable modifications to the CNN models in previous works [46, 57, 61]. Similarly the change in number of convolutional layer, convolutional kernel size, stride, number of neurons in fully connected layers and also modify the learning rate of the CNN model can be done. In [46], the CNN model was trained and tested on the over-sampled ECG database, so the result may be biased because validation was performed on the oversampled test dataset. In this paper, validation has been performed on real dataset, while the CNN model has been trained with the oversampled dataset.

Therefore in this paper, we introduced a new model, based on the CNN model for classification of ECG heartbeats into five groups, in order to significantly enhance the efficiency and effectiveness of the classification. The proposed model is highly preferable for the implementation of real-time monitoring of ECG for mobile devices. The overall proposed model consists of four steps, first normalization, second segmentation, third data-augmentation, and finally classification of the ECG signals. Since CNN require large number of data samples for training the model that can reliably detect the multiclass classification problem. So in this study, for data augmentation technique is used which partially fulfill both requirements as class imbalance problem and number of data samples. Augmentation technique also enhance the performance of the CNN model. Once the

network is trained the diagnosis of ECG signal is fast. The rest of the paper is organized as follows: Second section describes the methodology of ECG signal classification. The database used and results are described in section three. Section four describe the discussion. Finally, the conclusion of this article is presented in section five.

## Methodology

The MIT-BIH Arrhythmia database has been taken to analyse the performance of the proposed CNN model. The proposed model involves four main steps such as database normalization, heartbeat segmentation, class imbalance process, and classification. The block diagram of the proposed model is presented in Fig. 2.

### ECG signal normalization

Normalization means scaling the signal at an identical level. All ECG signal values have been normalized by applying the Z-score normalization method. Generally, a Z-score is a value of standard deviation from the mean value of the given samples. This method resolves the problem of amplitude scaling and vanishing the offset effects. The Z-score normalized signal values from dataset are obtained by the following formula [47].

$$\text{signal values} = \frac{\text{signal values} - \text{mean of signal values}}{\text{standard deviation of signal values}} \quad (1)$$

In MIT-BIH arrhythmia database, 48 subjects records are presented. each ECG signal record files are normalized individually. First, calculate the mean and standard deviation of

each record files and then normalized the each sample value of ECG record file according to equation one.

### Heart-beat segmentation

The MIT-BIH arrhythmia database continuously records the signals. To obtain individual heartbeats, ECG signals are segmented and stored using the annotation file information given by the cardiologists. In the segmentation process, firstly find all the peak values from the given annotation file information and then based on the peak values, entire ECG signal sets are divided into segments. The length of each segment is 360 samples long and is centered on the peak locations [48] that are 179 samples taken before the R-peak value and 180 samples have been taken after the R-peak value in each segment according to the given annotation files information.

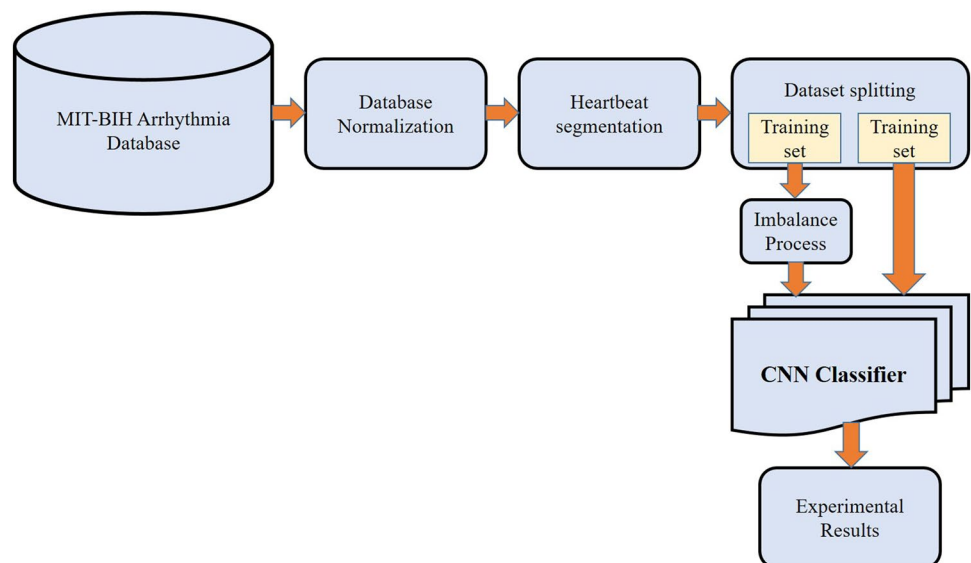
### Imbalance process

The MIT-BIH ECG arrhythmia database is highly a non-uniform distribution of heartbeats in the different classes. There are approximately 80% (According to ANSI-AAMI) hearts beats, that belong to one class and the remaining 20% of the heartbeats belong to the other four classes, so this dataset is referred to as a class imbalance problem because the number of samples in the majority class is a hundred folds higher than that of the minority class samples.

The approaches used for handling the class imbalance problems are as follows:

- Algorithm level
- Data level
- Hybrid of algorithm and data.

**Fig. 2** Block diagram of the proposed model



In this paper, data level approach is applied, namely Synthetic minority oversampling technique (SMOTE) [49].

### Synthetic minority oversampling technique (SMOTE)

It is a most widely used oversampling method introduced by Chawla in 2002 [49]. This method generates new synthetic minority samples without duplicating the samples. The generation of synthetic data is done by the following equation.

$$x^{\text{synthetic}} = x^i + (x^j - x^i) \times \delta \quad (2)$$

where  $x^i$  represents the instance of minority class under consideration,  $x^j$  is a randomly selected instance from the K-nearest neighbours of minority instance  $x^i$ .  $\delta$  is a vector in which every element is a random number from [0, 1]; it is used to generate a synthetic instance in reference to two original instances  $x^i$  and  $x^j$  respectively, which are also known as primary reference instance and assistant reference instance respectively.  $x^{\text{synthetic}}$  is generated along the line between  $x^i$  and  $x^j$  and direction of line joining towards  $x^j$ . It also minimizes the risk of over-fitting.

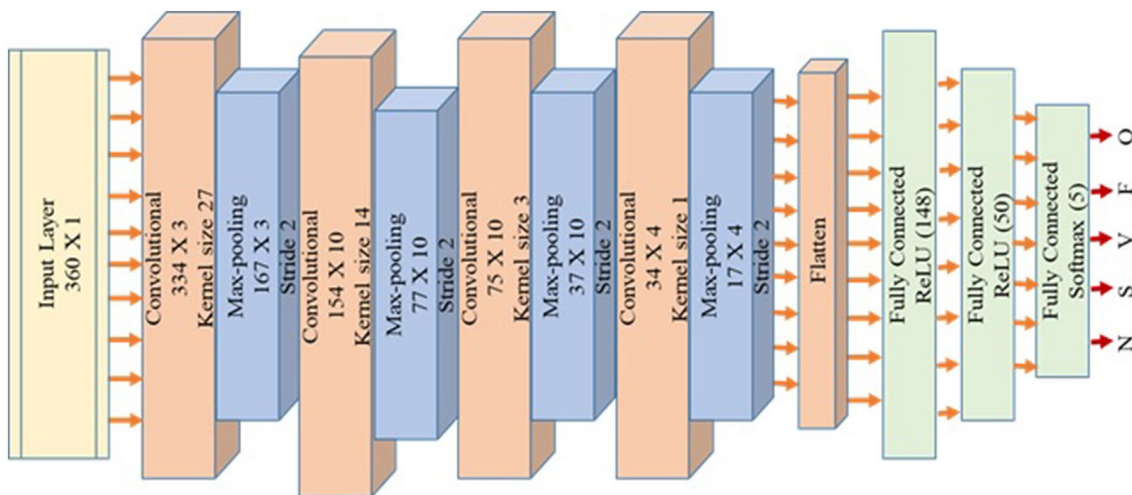
In this way, synthetically created balancing set is formed that contains an equal number of instances in training dataset of each class. According to AAMI standard, ECG signal database is divided into five classes' namely normal, supraventricular, ventricular, fusion, and unknown class. The total samples of class N are not oversampled as they are available in enough quantity. The classes (S, V, F, & Q) are oversampled to increase the number of samples in order to match the total number of samples of class N [50]. Table 1 describes the total number of heart beats before and after synthetic data generation in training dataset.

### Convolutional neural network model

The property of CNN architecture is that it automatically emphasizes and extracts the most suitable features from the input data by applying convolution operation. It keeps more concentration on the local features and its location among the other features. Otherwise, on the same feature maps on CNN, the weights of neurons are the same resulting

**Table 1** A table describe the total number of heart-beats before and after synthetic data generation in training dataset

Heart beat types	Number of heart beats in real dataset	After oversampling, number of heartbeats in training set				
		50%	60%	70%	80%	90%
N	87542	43746	52475	61261	70039	78840
S	2726	43746	52475	61261	70039	78840
V	7221	43746	52475	61261	70039	78840
F	802	43746	52475	61261	70039	78840
Q	3888	43746	52475	61261	70039	78840
Total	102179	218730	262375	306305	350195	394200



**Fig. 3** Architecture of proposed CNN model for classification

in network learning in parallel, which markedly saves the learning time [51]. The proposed architecture of CNN model for heartbeat classification is shown in Fig. 3.

In this paper, four convolutional layers, the first, third, fifth, and seventh are convolved along with filter size 27, 14, 3, and 1 according to the Eq. 3.

$$Y_n = \sum_{i=0}^{N-1} x_i f_{n-i} \quad (3)$$

where Y represents the output vector, x represents the signal values, f denote the filters, and N denotes the number of elements.

After each convolutional layer, a second layer max-polling is used, which aims to diminish the size of the feature map. The Brute force technique is used in this task for the obtained parameter of filter (kernel) size in the layers 1, 3, 5, and 7. The rectifier linear unit (ReLU) [52] activation function is used for layer first, third, fifth, seventh, ninth, and tenth. There are three fully connected layers ninth, tenth, and eleventh consisting of 148, 50, and 5 outputs neurons, respectively. The final layer (11) use the softmax function to classify each output class separately (as N, S, V, F, & Q). In this model, CNN was trained using Adam optimizer technique. The training parameters are set as follows: learning rate is  $1e-3$ , and regularization is 0.01 respectively. The CNN model uses a batch size of 34. The loss parameter is calculated using the categorical cross-entropy function with SMOTE technique used on the database and weighted categorical cross-entropy function without SMOTE technique used on the database. The CNN model has been trained and tested iteratively. The iteration count has been taken are 30. The testing is also performed after every iteration. The proposed CNN model architecture is summarized in Table 2.

**Table 2** The proposed CNN architecture summary for this task

Layers	Layer type	Output neurons	Kernel size	Stride
I	Convolutional	$334 \times 3$	27	1
II	Max-polling	$167 \times 3$	2	2
III	Covolutional	$154 \times 10$	14	1
IV	Max-polling	$77 \times 10$	2	2
V	Covolutional	$75 \times 10$	3	1
VI	Max-polling	$37 \times 10$	2	2
VII	Covolutional	$34 \times 4$	1	1
VIII	Max-polling	$17 \times 4$	2	2
IX	Fully Connected	148	—	—
X	Fully Connected	50	—	—
XI	Fully Connected	5	—	—

## Results

In this work, we have taken ECG signals from the open-source Physio-Bank ATM MIT-BIH Arrhythmia datasets [53]. The Arrhythmia database was composed by gathering data 48 ECG recordings from 47 subjects in which 22 women databases aged between 23 to 89 years old and 25 men database aged between 32 to 89 years old. The dataset specifies 1,09,449 labelled cardiac beats of 15 different heartbeat classes. In accordance with ANSI/AAMI EC 57: 1998 standard, four records 102, 104, 107, 217 contain paced beats. These records are removed from the evaluation database. Further, the heartbeats are categorized into 15 original classes of the MIT-BIH arrhythmia database are rearranged into five categories according to ANSI/AAMI standard.

Performance of heartbeats detection according to ANSI-AAMI standards is compared. Observational results show that the CNN model for heartbeats classification is effective and also analyses the computational complexity. The proposed CNN model is implemented in Win-Python 3.6.6 using Keras libraries. All observations are performed on Dell workstation with dual Intel Xeon E5-2600, 2.4 GHz processor, and 64GB RAM. The average minimum CPU time is 296 and maximum is 489 seconds per epochs in order to complete the training and testing of the ECG database.

The performance of CNN model was evaluated in terms of accuracy (Acc), Recall (Se), Precision (P), and F-score. These parameters are determined by the value of true positive (TP), false positive (FP), false negative (FN), true negative (TN), and the whole instances presented in the database ( $\Sigma$ ) are as follows:

$$\text{Overall Accuracy} = \frac{TP_1 + TP_2 + \dots + TP_N}{\Sigma} \quad (4)$$

$$\text{Recall}(Se) = \frac{TP}{TP + FN} \quad (5)$$

$$\text{Precision}(P) = \frac{TP}{TP + FP} \quad (6)$$

$$F - \text{score} = 2 \frac{P \times Se}{P + Se} \quad (7)$$

In this study, first, the real data is divided into different sets of training and testing dataset. In the first section, 50% of real data was oversampled using SMOTE technique; then this oversampled data was used for training of proposed CNN model. The trained CNN model has then used on 50% real data for testing phase, which that the model had never seen in the learning phase. Similarly, in the second, third,



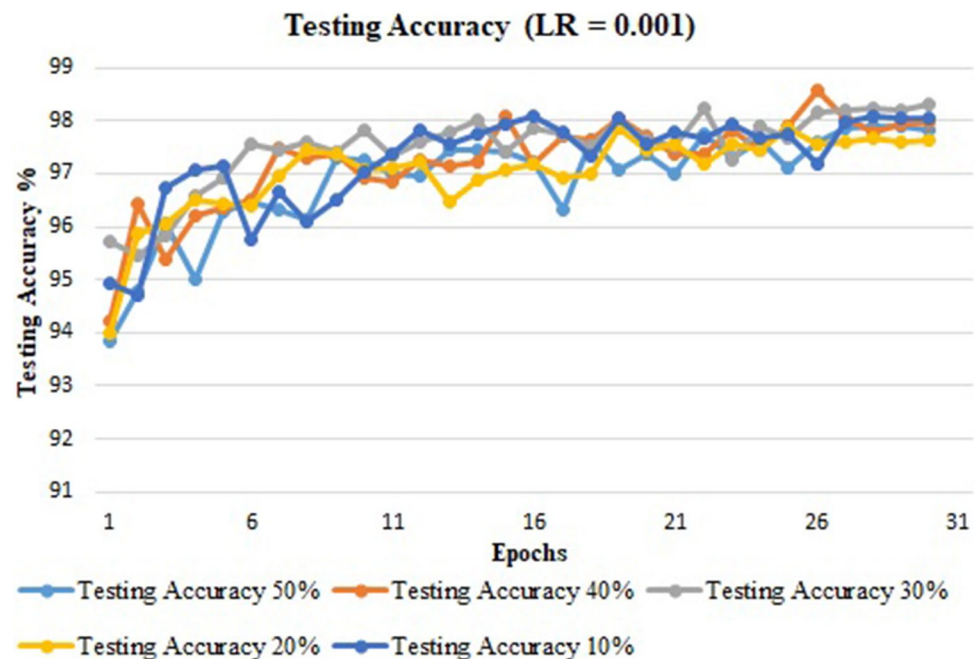
fourth, and fifth section 60%, 70%, 80%, and 90% real data were oversampled using SMOTE technique. Then this over-sampled data were applied for the training of proposed classification CNN model. The trained CNN model used the rest 40%, 30%, 20%, and 10% real data respectively for testing of the model, which had never seen in the learning phase. Figs. 4, 5 shows that the testing accuracy and loss performance graphs used learning rate of 0.001 of the proposed CNN model during 30 iterations for five class's heartbeat classification.

Table 3 tabulates the performance of the CNN model classification on various test datasets such as 50%, 40%,

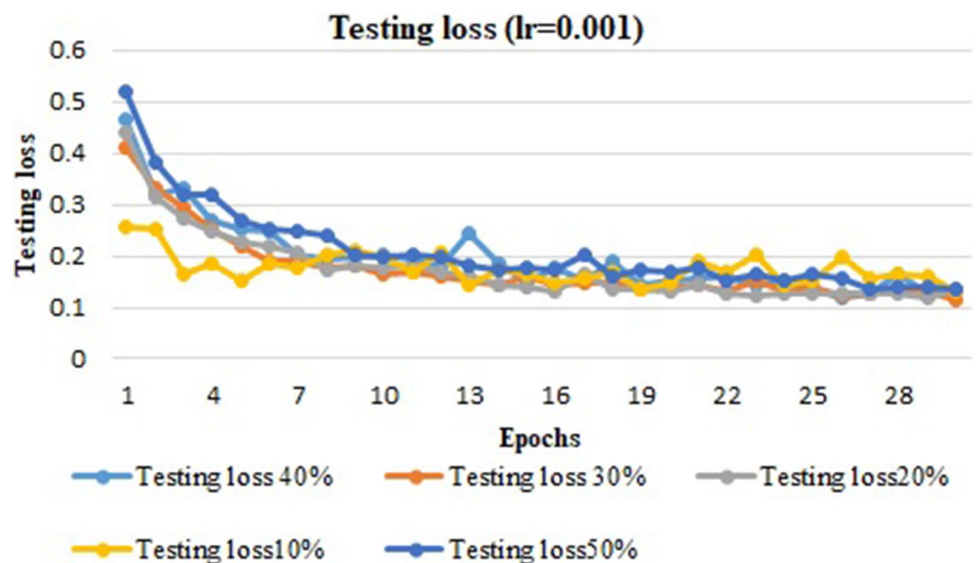
30%, 20%, and 10% respectively. This table specify the average precision, average recall, average F-score and overall accuracy that were calculated for each class analysis based on confusion matrix evaluation according to Eqs. 4 to 7. The overall best testing accuracy of the CNN model for five class classification was 98.30%, which was obtained by using training test ratio 70:30. The training and test dataset were randomly selected while adjusting the hyper parameters of CNN model. The statistical performance shows that the best results are obtained in the model.

The confusion matrix of the 11-layer CNN classifier model has obtained the best overall accuracy using training

**Fig. 4** Testing accuracy performance using learning rate 0.001 with ECG dataset for five classes



**Fig. 5** Testing loss performance using learning rate 0.001 with ECG dataset for five classes



**Table 3** Statistical performance on ECG test dataset with different training-testing ratios in % using proposed CNN model

Train-test ratio	50–50	60–40	70–30	80–20	90–10
Overall accuracy	97.84	98.14	<b>98.3</b>	97.64	98.03
Average Precision	87.19	85.00	86.06	83.13	87.19
Average recall	92.99	94.76	95.51	95.81	92.99
Average F1-Score	89.84	89.08	89.87	88.07	89.84

Bold value indicates the better result compared to other results

test ratio 70:30 and learning rate is 0.001, as shown in the Table 4. It maps the right and wrong identification of heartbeats.

Figure 6 shows the average CPU time is taken to train per heartbeat signals (segment) of the proposed CNN model and to use in Ref. [46, 57].

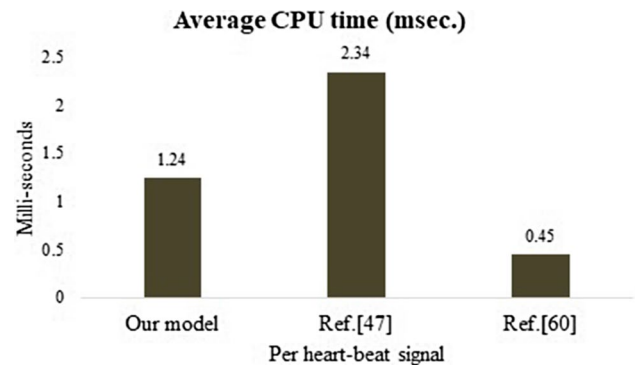
## Discussion

Table 5 summarizes the performance comparison works published in various ECG classification using machine learning and deep learning techniques. Those techniques have obtained highest overall classification performance using the MIT-BIH arrhythmia database. The performance of our 11-layer CNN model was comparable with the best obtained existing work performance, thus validation of the effectiveness of our proposed CNN model in classifying the MIT-BIH arrhythmia database. Kutulu et al. [54], have developed a multistage automatic classification system. In this system, 150 features were extracted with the help of higher-order statistics, wavelet packet decomposition, morphological features, and Fourier transform by applying a combination of 5 K-NN classifiers. This work has achieved an accuracy of 93.49% using 3345 beats of training and 2542 beats of testing set.

In [55], a hybrid approach using segmented and fixed interval wave shape; that switches between those two features resulted in the best multi-way classification performance. In the work [24], four types of heartbeats were classified based on non-normalized and normalized R–R intervals. The classification of the heart beats has been done

**Table 4** Confusion matrix using 30% test data and learning rate is 0.001 of the proposed model

	Predicted					
	HBT	N	S	V	F	Q
Original	N	25917	186	37	132	9
	S	46	717	3	2	1
	V	32	13	2092	29	2
	F	12	0	12	207	0
	Q	2	0	3	0	1187

**Fig. 6** Average CPU time taken per heartbeat signals

with the help of the linear discriminate classifiers and the morphological features were extracted by linear prediction modelling and wavelet analysis. In [59], Hermit function coefficients and R-R intervals have been used as a feature vectors. The block based neural network trained with particle swarm optimization technique was used for optimizing the structure and weights of the neural networks.

In [57], author proposed a 7-layer, 1-Dimensional CNN model for the classification of ECG beats. In this model, the input segment length was 128 samples centered on the R-peak. The learning rate was initially set to 0.001 and has been changed in accordance with the mean square errors. For fair comparison with [57], we have also been trained and tested our model without using SMOTE method, and results are shown in appendix, which gives better overall accuracy. In [61], Kachuee et al. proposed a model based on deep CNN for heartbeat classification. Specifically, the model was trained with residual connections for detecting the heartbeats. In [59], a Principal Component Analysis network has been used by the author for extracting the features based on a raw ECG signal. Targeting at the improvement of classification accuracy, Linear SVM was applied, and then the accuracy achieved is 97.77%. In [46], Acharya et al. has proposed a 9-layer deep CNN model for classifying the heartbeats using synthetic data generation for oversampling of minority classes, while we have used 11-layer deep CNN model using SMOTE method. In this model [46], the convolutional layers have the kernel size 3, 4, and 4 respectively,

**Table 5** Comparison of heart-beat classification performed on the same database

Authors	Year	Proposed classifier	Overall accuracy %
Kutlu et al. [54]	2011	K-NN classifier	93.49
Martis et al. [26]	2013	Neural Network and SVM classifier,	93.48
Chazal et al. [55]	2013	Linear discriminant	92.4
Lin et al. [24]	2014	Linear discriminant	93
Raj et al. [56]	2015	Rule based approach	97.96
Zubair et al. [57]	2016	Deep CNN model	92.7
Li et al. [58]	2016	Random Forest, SVM, DT, PNN, K-NN	94.61
Shadmand et al [59]	2016	Block based neural network	97
Acharya et al [46]	2017	Deep CNN model	94.03
Yang et al [60]	2018	Linear SVM	97.94
Kachuee et al. [61]	2018	Deep CNN	93.4
Proposed method	2019	11-layer CNN model	<b>98.3</b>

Bold value indicates the better result compared to other results

while our model used kernel size 27, 14, 3, and 1 respectively. Heartbeat segment size was 260 samples long, while our's sement size was 360 samples long. The three fully connected layers in [46] have consisted the number of output neurons 30, 20, and 5 respectively, while our model consist of 148, 50, and 5, respectively. In [46], leaky-Relu activation functions with learning rate  $3 \times 1e - 3$  was used while in our model used Relu activation functions with learning rate  $1e - 3$ . The performance results of this paper may be optimistically biased since both the training and validation sets were oversampled using synthetic data generation.

In the methodical literature, the works focus on the classification of heartbeats into five classes. A total number of 44 files in the MIT-BIH database are used for the purpose of performance evaluation. From Table 5, it can be seen that we have obtained the overall best accuracy of 98.30% for recognition of 5-classes heartbeat. Our proposed model has given better results than the works summarized in the above table. We have also implemented categorical cross-entropy loss and weighted categorical cross-entropy loss [62] for imbalanced dataset without using SMOTE method. The results are shown in the “Appendix” section in Tables 6 and 7. In Table 6, the results are poor compared to Table 3 results, but in Table 7 the overall accuracy in little bit improved compared to Table 3, while recall and F-score is not good. Since in healthcare point of view recall plays an important role in correctly identifying disease. Thus compared to Tables 6 and 7, Table 3 shows better recall and F-score of the heartbeat detection in the MIT-BIH arrhythmia database using SMOTE method. This proposed CNN model is easy to use and less complex because in this model, data has been fed without performing the de-noising process and feature extraction, selection, classification were combined into end-to-end CNN model.

## Conclusion

The objective of this paper is to implement a deep learning CNN model that which automatically classifies the ECG heartbeat according to the AAMI standards. The performance of the novel CNN model that correctly classifies heartbeat classes was found to be improved after generating the synthetic data using SMOTE technique and reducing the minority class imbalance problem. This model is fully automatic, hence there is no requirement of an additional system like feature extraction, feature selection, and classification. Once the model is trained, it can be applied to predict ECG signals for arrhythmia patients. By performing experiments on the arrhythmia database (MIT-BIH database), our model shows greater effectiveness and efficiency for ECG signal classification. Due to less computational complexity, the proposed CNN model can be used for classifying long term ECG signals and detecting disease events in real time. It is very much effective for wearable devices.

**Acknowledgements** This study was not funded by any agencies.

## Compliance with ethical standards

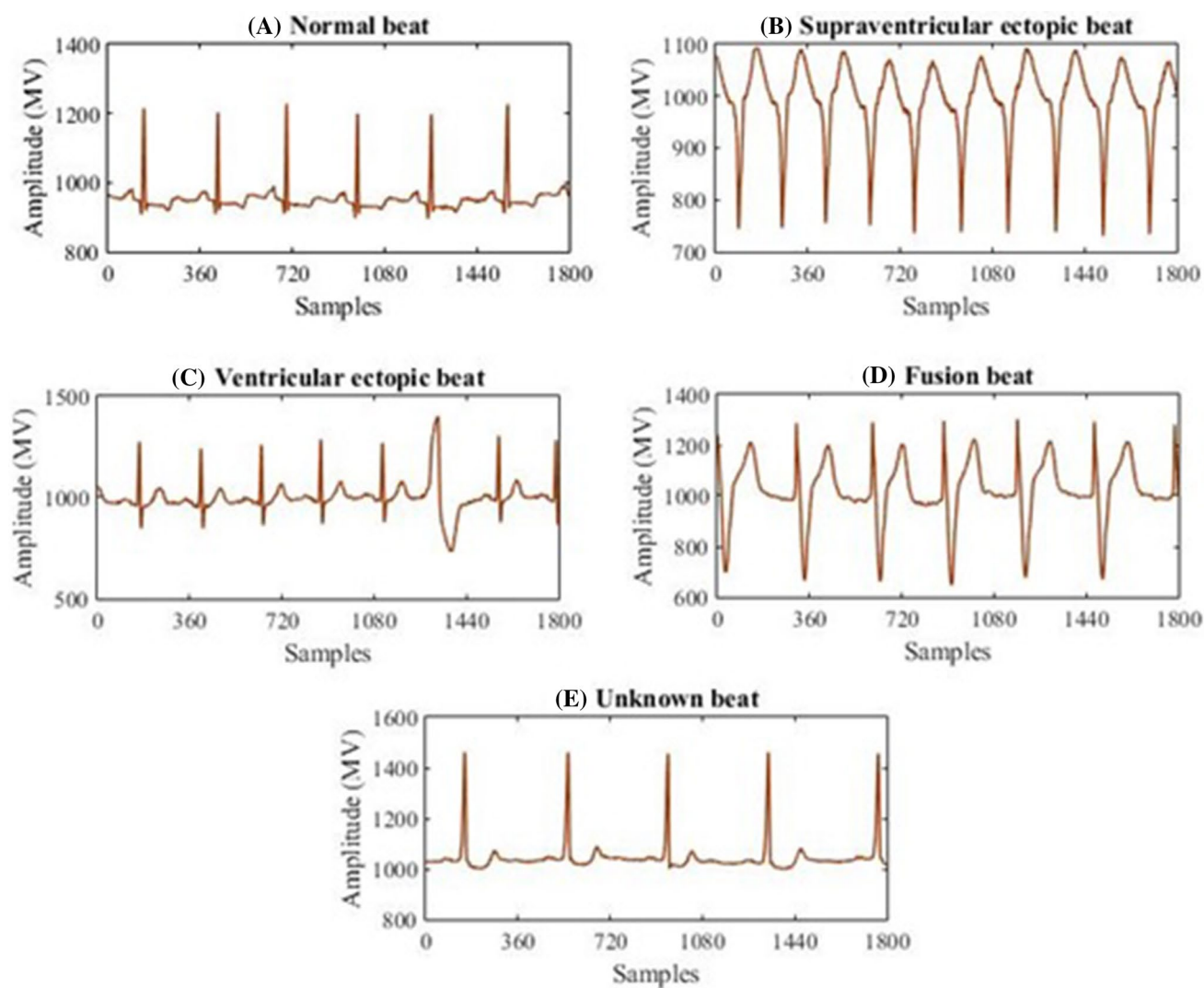
**Conflict of interest** All authors declare that they have no conflict of interest.

**Ethical approval** This article does not contain any studies with human participants or animals performed by any of the authors.

## Appendix

See Figure 7, Tables 6 and 7.





**Fig. 7** Five types of heartbeat signal wave representation according to the ANSI/AAMI standards

**Table 6** Training testing ratio 70:30 without SMOTE technique and using weighted categorical cross-entropy loss function with imbalanced dataset

Heartbeats	Precision	Recall	F1-score	Overall accuracy
N	0.9872	0.9971	0.9971	0.9843
S	0.9340	0.7542	0.7542	
V	0.9626	0.9603	0.9603	
F	0.8819	0.5498	0.5498	
Q	0.9966	0.9773	0.9773	
Average	0.9525	0.8478	0.8478	

**Table 7** Training testing ratio 70:30 without SMOTE technique and using categorical cross-entropy loss function with imbalanced dataset

Heartbeats	Precision	Recall	F1-score	Overall accuracy
N	0.96632	0.993	0.97924	0.9604
S	0.96195	0.592	0.73269	
V	0.87544	0.81	0.84168	
F	0	0	0	
Q	0.96832	0.949	0.95847	
Average	0.7544	0.669	0.7024	

## References

- Mehra R (2007) Global public health problem of sudden cardiac death. *J Electrocardiol* 40(6):S118–S122
- World Health Organization (2017) Noncommunicable diseases: progress monitor 2017
- Hadhoud MM, Eladawy MI, Farag A (2006) “Computer aided diagnosis of cardiac arrhythmias.” *Computer Engineering and Systems, The 2006 International Conference on*. IEEE
- Singh S et al (2018) Classification of ECG arrhythmia using recurrent neural networks. *Proced Comput Sci* 132:1290–1297
- De Chazal P, O’Dwyer M, Reilly RB (2004) Automatic classification of heartbeats using ECG morphology and heartbeat interval features. *IEEE Trans Biomed Eng* 51(7):1196–1206
- Alonso-Atienza F et al (2014) Detection of life-threatening arrhythmias using feature selection and support vector machines. *IEEE Trans Biomed Eng* 61(3):832–840
- Khadra L, Al-Fahoum AS, Al-Nashash H (1997) Detection of life-threatening cardiac arrhythmias using the wavelet transformation. *Med Biol Eng Comput* 35(6):626–632
- Sörnmo L, Laguna P (2005) Bioelectrical signal processing in cardiac and neurological applications, vol 8. Academic Press, Amsterdam
- Melillo P et al (2015) “Wearable technology and ECG processing for fall risk assessment, prevention and detection.” *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. IEEE
- Jain S et al (2017) QRS detection using adaptive filters: a comparative study. *ISA Trans* 66:362–375
- Adam G, Witold P (2011) ECG signal processing, classification and interpretation: a comprehensive framework of computational intelligence. Springer, London
- Singh BN, Tiwari AK (2006) Optimal selection of wavelet basis function applied to ECG signal denoising. *Digital Signal Proc* 16(3):275–287
- Sameni R et al (2007) A nonlinear Bayesian filtering framework for ECG denoising. *IEEE Trans Biomed Eng* 54(12):2172–2185
- Pasolli E, Melgani F (2015) Genetic algorithm-based method for mitigating label noise issue in ECG signal classification. *Biomed Signal Proc Control* 19:130–136
- Roonizi EK, Sassi R (2016) A signal decomposition model-based Bayesian framework for ECG components separation. *IEEE Trans Signal Proc* 64(3):665–674
- da Silva Luz EJ et al (2016) ECG-based heartbeat classification for arrhythmia detection: a survey. *Comput Methods Programs Biomed* 127:144–164
- Pinheiro E, Postolache O, Girão P (2011) “Method for segmentation of cardiac signals based on four parameter sine fitting.” *EUROCON-International Conference on Computer as a Tool (EUROCON), 2011 IEEE*. IEEE
- Ceylan R, Özbay Y (2007) Comparison of FCM, PCA and WT techniques for classification ECG arrhythmias using artificial neural network. *Expert Syst Appl* 33(2):286–295
- Ye C, Coimbra MT, Vijaya Kumar BVK (2010) Arrhythmia detection and classification using morphological and dynamic features of ECG signals. *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*. IEEE
- Kutlu Y, Kuntalp D (2012) Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients. *Comput Methods Progr Biomed* 105(3):257–267
- Shinde AA, Kanjalkar P (2011) The comparison of different transform based methods for ECG data compression. *Signal processing, communication, computing and networking technologies (ICSCCN), 2011 International Conference on IEEE*
- Gu Z, Zhang N, Qian S (2013) Analyzing electrocardiogram signals with multiscale short-time fourier transforms. U.S. Patent No. 8,494,622. 23 Jul
- Uslu E, Bilgin G (2012) Exploiting locality based Fourier transform for ECG signal diagnosis. *Applied Electronics (AE), 2012 International Conference on*. IEEE
- Lin CC, Yang CM (2014) Heartbeat classification using normalized RR intervals and morphological features. *Math Probl Eng*. <https://doi.org/10.1155/2014/712474>
- Ye Can, Vijaya Kumar BVK, Coimbra MT (2012) Heartbeat classification using morphological and dynamic features of ECG signals. *IEEE Trans Biomed Eng* 59(10):2930–2941
- Martis RJ et al (2013) Cardiac decision making using higher order spectra. *Biomed Signal Proc Control* 8(2):193–203
- Chawla MPS (2009) A comparative analysis of principal component and independent component techniques for electrocardiograms. *Neural Comput Appl* 18(6):539–556
- Imah EM et al (2011) A comparative study on Daubechies Wavelet Transformation, Kernel PCA and PCA as feature extractors for arrhythmia detection using SVM.” *TENCON 2011-2011 IEEE Region 10 Conference*. IEEE
- Lu W et al (2018) Wearable computing for internet of things: a discriminant approach for human activity recognition. *IEEE Internet of Things J* 6(2):2749–2759
- Jing P et al (2018) A framework of joint low-rank and sparse regression for image memorability prediction. *IEEE Trans Circuits Syst Video Technol* 29(5):1296–1309
- Wang JS et al (2013) ECG arrhythmia classification using a probabilistic neural network with a feature reduction method. *Neurocomputing* 116:38–45
- Kiranyaz S et al (2015) Convolutional Neural Networks for patient-specific ECG classification. *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. IEEE
- Pourbabae B, Roshtkhari MJ, Khorasani K (2017) Deep convolutional neural networks and learning ecg features for screening paroxysmal atrial fibrillation patients. *IEEE Trans Syst Man Cybern* 99:1–10
- Khalaf AF, Owis MI, Yassine IA (2015) A novel technique for cardiac arrhythmia classification using spectral correlation and support vector machines. *Expert Syst Appl* 42(21):8361–8368
- Varatharajan R, Manogaran G, Priyan MK (2018) A big data classification approach using LDA with an enhanced SVM method for ECG signals in cloud computing. *Multimed Tools Appl* 77(8):10195–10215
- Raj S, Ray KC (2017) ECG signal analysis using DCT-based DOST and PSO optimized SVM. *IEEE Trans Instrum Meas* 66(3):470–478
- Alickovic E, Subasi A (2016) Medical decision support system for diagnosis of heart arrhythmia using DWT and random forests classifier. *J Med Syst* 40(4):108
- Kropf M, Hayn D, Schreier G (2017) ECG classification based on time and frequency domain features using random forests. *Computing* 44:1
- Xiong Z et al (2018) ECG signal classification for the detection of cardiac arrhythmias using a convolutional recurrent neural network. *Physiol Meas* 39(9):094006
- Nurmaini S, Gani A (2018) Cardiac arrhythmias classification using deep neural networks and principle component analysis algorithm. *Int J Adv Soft Comput Appl* 10(2):14–32
- Muthuvel K et al (2015) Classification of ECG signal using hybrid feature extraction and neural network classifier. *New Delhi, power electronics and renewable energy systems*. Springer, New Delhi, pp 1537–1544

42. Acharya UR et al (2017) Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. *Inform Sci* 405:81–90
43. Acharya UR et al (2017) Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. *Inform Sci* 415:190–198
44. Wu Z, Ding X, Zhang G (2016) A novel method for classification of ECG arrhythmias using deep belief networks. *Int J Comput Intell Appl* 15(04):1650021
45. Al Rahhal MM et al (2016) Deep learning approach for active classification of electrocardiogram signals. *Inform Sci* 345:340–354
46. Acharya UR et al (2017) A deep convolutional neural network model to classify heartbeats. *Comput Biol Med* 89:389–396
47. Wikipedia contributors (2018) Feature scaling. Wikipedia, The Free Encyclopedia. Wikipedia, The Free Encyclopedia, 24 Jun 2018. [https://en.wikipedia.org/w/index.php?title=Feature\\_scaling&oldid=847274325](https://en.wikipedia.org/w/index.php?title=Feature_scaling&oldid=847274325)
48. Chen S et al (2017) Heartbeat classification using projected and dynamic features of ECG signal. *Biomed Signal Proc Control* 31:165–173
49. Chawla NV et al (2002) SMOTE: synthetic minority over-sampling technique. *J Artif Intell Res* 16:321–357
50. Prati RC, Batista GEAP, Monard MC (2008) A study with class imbalance and random sampling for a decision tree learning system. *IFIP International Conference on Artificial Intelligence in Theory and Practice*. Springer, Boston
51. Yi Z et al (2014) Time series classification using multi-channels deep convolutional neural networks. *International Conference on Web-Age Information Management*. Springer, Cham
52. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems*
53. Goldberger AL et al (2000) PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. *Circulation* 101(23):e215–e220
54. Kutlu Y, Kuntalp D (2011) A multi-stage automatic arrhythmia recognition and classification system. *Comput Biol Med* 41(1):37–45
55. De Chazal P (2013) A switching feature extraction system for ECG heartbeat classification. *Computing in Cardiology Conference (CinC)*, 2013. IEEE, USA
56. Raj S, Maurya K, Ray KC (2015) A knowledge-based real time embedded platform for arrhythmia beat classification. *Biomed Eng Lett* 5(4):271–280
57. Zubair M, Kim J, Yoon C (2016) An automated ECG beat classification system using convolutional neural networks. *IT Convergence and Security (ICITCS)*, 2016 6th International Conference on. IEEE
58. Li T, Zhou M (2016) ECG classification using wavelet packet entropy and random forests. *Entropy* 18(8):285
59. Shadmand S, Mashoufi B (2016) A new personalized ECG signal classification algorithm using block-based neural network and particle swarm optimization. *Biomed Signal Proc Control* 25:12–23
60. Yang W et al (2018) Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine. *Comput Biol Med* 101:22–32
61. Kachuee M, Fazeli S, Sarrafzadeh M (2018) ECG heartbeat classification: a deep transferable representation. *arXiv preprint [arXiv:1805.00794](https://arxiv.org/abs/1805.00794)*
62. Li J, Chen R (2018) Detection of premature ventricular contractions using densely connected deep convolutional neural network with spatial pyramid pooling layer.” *arXiv preprint [arXiv:1806.04564](https://arxiv.org/abs/1806.04564)*

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.