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A Deep Convolutional Neural Network Model to Classify Heartbeats

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ABSTRACT

The electrocardiogram (ECG) is a standard test used to monitor the activity of the heart. Many cardiac abnormalities will be manifested in the ECG including arrhythmia which is a general term that refers to an abnormal heart rhythm. The basis of arrhythmia diagnosis is the identification of normal versus abnormal individual heart beats, and their correct classification into different diagnoses, based on ECG morphology. Heartbeats can be sub-divided into five categories namely non-ectopic, supraventricular ectopic, ventricular ectopic, fusion, and unknown beats. It is challenging and time-consuming to distinguish these heartbeats on ECG as these signals are typically corrupted by noise. We developed a 9-layer deep convolutional neural network (CNN) to automatically identify 5 different categories of heartbeats in ECG signals. Our experiment was conducted in original and noise attenuated sets of ECG signals derived from a publicly available database. This set was artificially augmented to even out the number of instances the 5 classes of heartbeats and filtered to remove high-frequency noise. The CNN was trained using the augmented data and achieved an accuracy of 94.03% and 93.47% in the diagnostic classification of heartbeats in original and noise free ECGs, respectively. When the CNN was trained with highly imbalanced data (original dataset), the accuracy of the CNN reduced to 89.07%% and 89.3% in noisy and noise-free ECGs. When properly trained, the proposed CNN model can serve as a tool for screening of ECG to quickly identify different types and frequency of arrhythmic heartbeats.

Keywords – heartbeat, arrhythmia, cardiovascular diseases, convolutional neural network, deep learning, electrocardiogram signals, PhysioBank MIT-BIH arrhythmia database.

1. Introduction

Cardiovascular diseases (CVDs) are the top cause of mortality worldwide [1]. According to the world health organization (WHO), approximately 17.7 million people died from CVDs in 2015. Generally, there are 3 broad groups of CVDs – electrical (arrhythmia, or abnormal heartbeats due to dysfunctional electrical system of the heart), circulatory (blood vessels disorder), and structural (diseases of the heart muscle) [2]. In this work, we focused on arrhythmias - the electrical disorders of the heart [3].

Arrhythmias can be represented by a slow, fast, or irregular heartbeat, and can be grouped into life-threatening and non-life-threatening [4,5]. The diagnosis of arrhythmia is predicated on the identification normal versus abnormal individual heartbeats on electrocardiogram (ECG), and their accurate annotation based on ECG morphology. According to the Association for the Advancement of Medical Instrumentation (AAMI) [6], the non-life-threatening arrhythmias can be divided into 5 main classes namely: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). The ECG is a common way to monitor the rate and rhythm of the heart [7] and can be used to detect many abnormalities and malfunctions of the heart's electrical system. Table 1 shows different types of ECG heartbeats categorized accordingly into these five classes. Each ECG class has a different implication and requires different treatment [8]. Therefore, it is of utmost importance for cardiologists to correctly identify the type of abnormal ECG event before any treatment is administered.

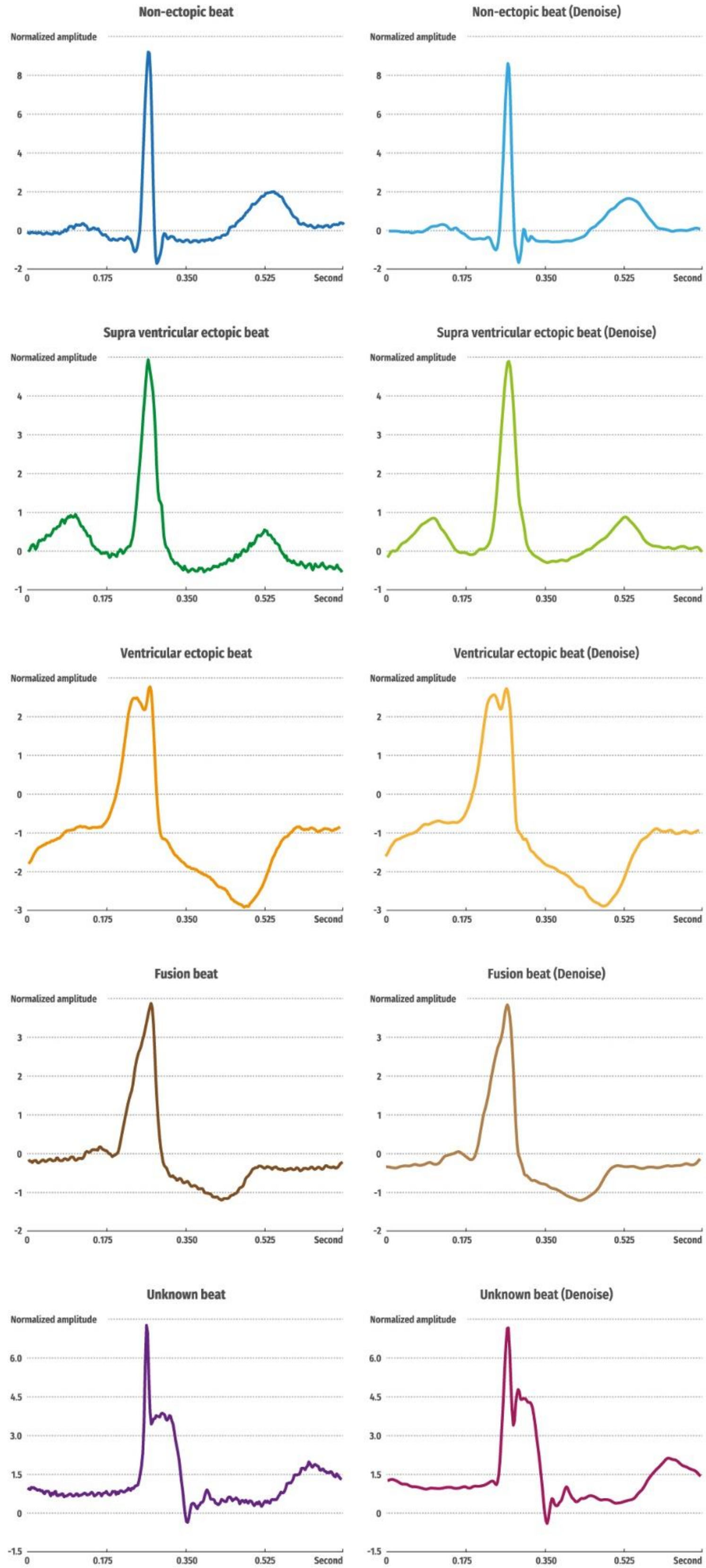
Non-ectopic beat
Normalized amplitude
8
6
4
2
0
-2
0
0.175
0.350
0.525
Second
Non-ectopic beat (Denoise)
Normalized amplitude
8
6
4
2
0
-2
0
0.175
0.350
0.525
Second
Supra ventricular ectopic beat
Normalized amplitude
4
3
2
1
0
-1
0
0.175
0.350
0.525
Second
Supra ventricular ectopic beat (Denoise)
Normalized amplitude
4
3
2
1
0
-1
0
0.175
0.350
0.525
Second
Ventricular ectopic beat
Normalized amplitude
2
1
0
-1
-2
-3
0
0.175
0.350
0.525
Second
Ventricular ectopic beat (Denoise)
Normalized amplitude
2
1
0
-1
-2
-3
0
0.175
0.350
0.525
Second
Fusion beat
Normalized amplitude
3
2
1
0
-1
-2
0
0.175
0.350
0.525
Second
Fusion beat (Denoise)
Normalized amplitude
3
2
1
0
-1
-2
0
0.175
0.350
0.525
Second
Unknown beat
Normalized amplitude
6.0
4.5
3.0
1.5
0
-1.5
0
0.175
0.350
0.525
Second
Unknown beat (Denoise)
Normalized amplitude
6.0
4.5
3.0
1.5
0
-1.5
0
0.175
0.350
0.525
Second

Figure 1
Example ECG events with different categories of heartbeats. Original signals (right column), signals with attenuated noise (left column).

Table 1
A summary table of ECG beats categorized as per ANSI/AAMI EC57; 2012 standard.

N	S	V	F	Q
• Normal	• Atrial premature	• Premature ventricular contraction	• Fusion of ventricular and normal	• Paced
• Left bundle branch block	• Aberrant atrial premature	• Ventricular escape		• Fusion of paced and normal
• Right bundle branch block	• Nodal (junctional) premature			• Unclassifiable
• Atrial escape	• Supra-ventricular premature			
• Nodal (junctional) escape				

From Figure 1, one can glean that the characteristics and patterns of the ECG signals are different for the different heart conditions discussed in this paper. Due to this vast difference in morphology, it is difficult to accurately identify ECG components. Furthermore, the visual assessment which is the current standard of care might result in subjective interpretation and inter-observer biases [8]. To address the drawbacks of visual and manual interpretations of ECG, researchers pursue the development of a computer-aided diagnosis (CAD) systems to automatically diagnose ECG [8]. Much of the work in this area has been done by incorporating machine learning approaches for an accurate assessment of ECG and to distinguish life-threatening from non-threatening events including arrhythmias. Table 7 shows a summary of selected state-of-the-art studies towards this goal. In most of these studies, the authors concentrated on the conventional machine learning approaches. These approaches involve (i) preprocessing, (ii) feature extraction, (iii) feature reduction, and (iv) feature classification. Although these methods demonstrated favourable ECG heartbeat classification performance, they have numerous disadvantages. For instance, the conventional methods require designing of a feature extractor to extract predicting features from the raw ECG signals and then organize them into a set of optimal features that can be fed into the classifier. Moreover, CAD models designed and tested using the above workflow often suffer from overfitting and show lower performance when validated on a separate dataset. Unlike the conventional approaches, deep learning-based approaches possess the capacity to self-learn useful features from the input ECG signals [9]. Hence, with the deep learning, the essential steps that are required in the conventional approaches namely feature extraction, feature selection, and classification can be developed, yet they do not need to be explicitly defined. In fact, they are embedded in the model through self-learning from the data. Numerous papers have shown that the deep learning architectures surpass hand-crafted feature extractors assembled with commonly known classifiers in terms of classification accuracy and speed. The development of deep learning based solutions is also heavily supported by information technology industry[10].

Hence, in this work, a deep learning approach to identify the five different classes of abnormal ECG heartbeats is proposed. The proposed solution is in line with our previous publications where we demonstrated the application of convolutional neural networks (CNN) to automatically detect arrhythmias [11], coronary artery disease [12], and myocardial infarction [13] in ECG signals.

1.1 ECG Database

The ECG heartbeat signals are obtained from the open-source PhysioBank MIT-BIH Arrhythmia database [14]. This database consists of a 48-half-hour long ECG recording from 47 subjects obtained with Lead II ECG signal. Each signal is sampled at 360Hz, and each ECG beat is 260 samples long. Furthermore, these recordings were interpreted and validated by at least two cardiologists. A total of 109,449 ECG beats are extracted for this work (see Table 2). This set of original beats is somewhat noisy and was subjected to a noise removal. Therefore, the first set of original data (set A) consists of original ECG signals without noise removed, whereas the second set (set B) consists of ECG signals that passed through a noise attenuating digital filter.

Table 2
A summary table with the breakdown of the 5 classes of beat subtypes.

Type	Number of Beats
N	90,592
S	2,781
V	7,235
F	802
Q	8,039
Total	**109,449**

2. Methodology

This work presents a novel approach to automatically detect N, S, V, F, and Q classes of ECG heartbeats. A CNN model is trained with set A and then set B, to assess its performance. Furthermore, synthetic data are introduced to even out the number of samples shown in Table 2.

2.1 Pre-processing

The acquired ECG signals are preprocessed as follows:

(1) **Removal of noise**: Denoising and baseline removal of all ECG signals was performed with Daubechies wavelet 6 filters [15]. This step is to obtain denoised signals for the set B.

(2) **ECG heartbeat segmentation**: Signals in seta A and B are segmented into beats and sorted according to the annotations given by cardiologists, This process is followed by R-peak detection is using Pan-Tompkins [16] algorithm. All ECG signals are segmented into segments which are 260 samples long and centred around the detected R-peaks. Subsequently, each segment is normalized using Z-score normalization to address the problem of amplitude scaling and eliminate the offset effect before feeding into the CNN network for training and testing.

2.2 Generation of Synthetic Data

Synthetic data is used to overcome the imbalance in the number of ECG heartbeats in the five (N, S, V, F, Q) classes. The samples of synthetic data are generated after preprocessing by varying the standard deviation and mean of Z-score calculated from the original normalized ECG signals. Segments in the N class remain unchanged because they are the most abundant. The number of the remaining types of segments is increased to match the number of segments of the N class. After augmentation, the total number of segments in including N, S, V, F, and Q classes has increased to 452,960 beats.

2.3 Convolutional Neural Network

CNN is one of the most commonly used types of artificial neural networks [17]. Conceptually, a CNN resembles a multilayer perceptron (MLP). Every single neuron in the MLP has an activation function that maps the weighted inputs to the output. An MLP becomes a deep MLP when more than one hidden layer is added to the network. Similarly, the CNN is considered as MLP with a special structure. This special structure allows CNN to be both translation and rotation invariant due to the architecture of the model [18]. There are 3 basic layers– convolutional layer, pooling layer, and fully-connected layer [19] with a rectified linear activation function in a CNN architecture [9].

2.4 The Architecture

Table 3 summarizes the architecture of the proposed CNN model. There are 9 layers in this network including 3 convolution layers, 3 max-pooling layers, and 3 fully-connected layers (see Figure 2).

For every convolution layer (layer 1, 3, and 5), the layers are convolved with their respective kernel size (3, 4, and 4) using Equation (1). After every convolution layer, a max-pooling operation is applied to the feature maps. The purpose of max-pooling is to reduce the size of the feature map. The parameters for the kernel (filter) size in this work is obtained through brute force technique whereas the stride for convolution and max-pooling operation is set at 1 and 2 respectively. The leaky rectifier linear unit (LeakyRelu) [20] is used as an activation function for layers 1, 3, 5, 7, and 8. The fully-connected layers consist of respectively 30 and 20 and 5 output neurons win the final layer (layer 9). The softmax function is used to separately output each class namely N, S, V, F, and Q.

The convolution operation is computed by the below equation.

$$x_n = \sum_{k=0}^{N-1} y_k f_{n-k} \tag{1}$$

where y, f, and N are the signal, filter, and the number of elements in y respectively. The output vector is represented by x.

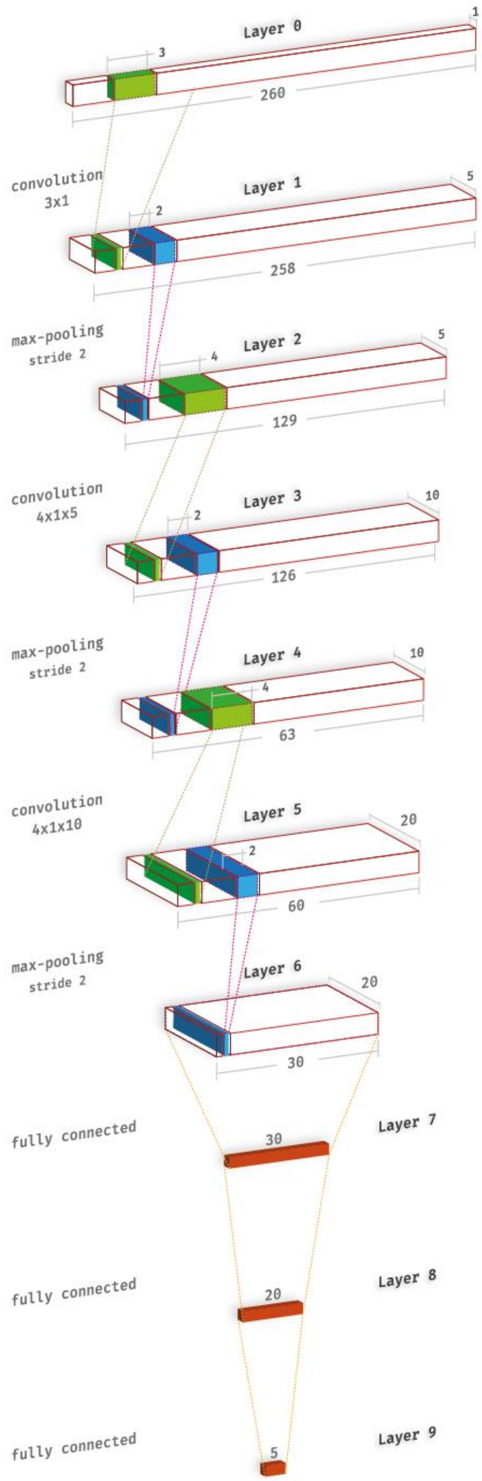

Figure 2
The architecture for the proposed CNN model.

Table 3
A summary table of the proposed CNN model for this work.

Layers	Type	No. of Neurons (Output Layer)	Kernel Size for Each Output Feature Map	Stride
0-1	Convolution	258 x 5	3	1
1-2	Max-pooling	129x 5	2	2
2-3	Convolution	126 x 10	4	1
3-4	Max-pooling	63 x 10	2	2
4-5	Convolution	60 x 20	4	1
5-6	Max-pooling	30 x 20	2	2
6-7	Fully-connected	30	-	-
7-8	Fully-connected	20	-	-
8-9	Fully-connected	5	-	-

This CNN model was trained through the backpropagation [21] technique with a sample size of 10. The hyperparameters are set as follows: the regularization (**λ**), learning rate, and momentum parameters are set at 0.2, 3x10^{-3}, and 0.7 respectively. They impede overfitting of the data, assist the convergence of the data, and control the speed of learning during training. The parameters are adjusted accordingly by brute force technique to achieve optimal performance. Also, the biases and weights are updated through equation (2) and equation (3).

$$\Delta W_l(t+1) = -\frac{x_\lambda}{r} W_l - \frac{x}{n}\frac{\partial C}{\partial W_l} + m\Delta W_l(t) \tag{2}$$

$$\Delta B_l(t+1) = -\frac{x}{n}\frac{\partial C}{\partial B_l} + m\Delta B_l(t) \tag{3}$$

where W, B, l, λ, x, n, m, t, and C denotes the weight, bias, layer number, regularization parameter, learning rate, total number of training samples, momentum, updating step, and cost function respectively.

Training and testing of the algorithm were done in 20 epochs. The validation was performed after every epoch. $\frac{7}{10}$ of the training data ($\frac{9}{10}$) is used for testing of the algorithm.

In addition, a ten-fold cross-validation [22] approach is employed. Hence, after the generation of synthetic ECG heartbeats, the ECG heartbeats are randomly divided into 10 equal parts. $\frac{9}{10}$ parts of the ECG heartbeats are used for training and $\frac{1}{10}$ parts of the ECG heartbeats are used for testing of the proposed model. This method is repeated 10 times by rotating the test data. Then, the performance measure (specificity, sensitivity, and accuracy) is evaluated in each round. Finally, the overall performance measure is obtained by averaging the performances recorded in all 10 rounds.

3. Results and Discussion

The proposed CNN algorithm was trained on a PC workstation with two Intel Xeon 2.40 GHz (E5620) processors and 24 GB of RAM. It took approximately 9573.2 seconds and 9586.7 seconds to complete one training epoch for set A (ECG heartbeats without noise removal) and set B (ECG heartbeats with noise removal) respectively. The CNN algorithm was developed in MATLAB (Matlab, Natick, MA USA) software.

Tables 4 and 5 present a confusion matrix of ECG heartbeats for set A and set B respectively across all folds. According to Table 4, less than 12% of the ECG heartbeats are wrongly classified. Likewise, for set B less than 10% of the ECG heartbeats are wrongly assigned. The minimal PPVs recorded for both sets are attributed to the detection of class N and are respectively 85% and 87%. The overall average classification performance (accuracy, ppv, sensitivity, and specificity) [5, 23–25] for set A and set B are collected in Table 6.

Table 4
A confusion matrix of ECG heartbeats for set A across all ten-folds.

		Predicted								
		N	**S**	**V**	**F**	**Q**	*acc* (%)	*ppv* (%)	*sen* (%)	*spec* (%)
Original	**N**	83,018	3,294	1,600	2,051	629	95.14	85.17	91.64	96.01
	S	8,365	80,663	801	386	377	96.82	94.76	89.04	98.77
	V	2,019	737	85,218	2,307	311	97.84	95.08	94.07	98.74
	F	2,496	146	1,588	86,251	111	97.97	94.69	95.21	98.67
	Q	1,575	280	414	93	88,230	99.16	98.40	97.39	99.61

acc = accuracy, *ppv* = positive predictive value, *sen* = sensitivity, *spec* = specificity

Table 5
A confusion matrix of ECG heartbeats for set B across all ten-folds.

		Predicted								
		N	**S**	**V**	**F**	**Q**	*acc* (%)	*ppv* (%)	*sen* (%)	*spec* (%)

Original	**N**	82,926	3,615	1,548	2,100	403	95.68	87.43	91.54	96.71
	S	7,151	82,066	637	346	392	97.02	94.30	90.59	98.63
	V	1,855	845	85,353	2,250	289	97.91	95.30	94.22	98.84
	F	1,610	252	1,654	87,024	52	98.15	94.76	96.06	98.67
	Q	1,305	246	370	113	88,558	99.30	98.73	97.75	99.69

acc = accuracy, *ppv* = positive predictive value, *sen* = sensitivity, *spec* = specificity

Table 6
The overall average classification performance across all ten-folds.

Beats Type	***tp***	***tn***	***fp***	***fn***	***acc* (%)**	***ppv* (%)**	***sen* (%)**	***spec* (%)**
Set A	347,913	83,018	7,574	14,455	93.47	97.87	96.01	91.64
Set B	350,447	82,926	7,666	11,921	94.03	97.86	96.71	91.54

tp = true positive, *tn* = true negative, *fp* = false positive, *fn* = false negative
acc = accuracy, *ppv* = positive predictive value, *sen* = sensitivity, *spec* = specificity

Skewed (imbalanced) data sets can negatively affect the overall performance of conventional and CNN-based classification systems. In order to alleviate this issue, synthetic data was generated to ensure that the number of samples in each class is proportional. The CNN model trained with well-balanced class data outperformed the model that was trained with a dataset that had a class imbalance as large as 112-fold (the ratio of events between N and F classes). The CNN that was trained using the imbalanced set had reduced *ppv* and *acc* for F class by as much as 34.64% and 5% respectively (with noise removal performed). Furthermore, a confusion matrix for set A and set B is computed for the imbalanced set (see Table A1 and Table A2). It is noted that the highly skewed data indeed produce a *ppv* which is highly skewed towards the class with the highest number of segments. The *ppv* recorded for class S and F for set A is 31.25% and 17.80% respectively and set B is 35.91% and 15.97% respectively whereas the *ppv* for class N in set A and set B is 99.04%. This experiment confirmed that balancing classes in the dataset can improve the classification of ECG events through the CNN. Our results in this aspect are in line with results reported previously [26].

Recent advances in the arrhythmias detection collected in Table 7 yield highly accurate classification results. However, the implementation of CNNs can further improve the analysis of ECG by faster signal processing and learning filters that are robust to noise. Classifications performed on sets A and set B revealed that CNN's performance for set A is close to that for set B even though no noise removal was implemented. This suggests that the proposed model can detect noisy ECG heartbeats reasonably well because the algorithm learns necessary filters and therefore self-remove the unwanted noise present in the ECG signals.

The benefits of this proposed CNN model are as follows:

i. Fully automatic, hence no additional feature extraction, selection, or classification is required.
ii. The approach is insensitive to the ECG signal quality.
iii. Ten-fold cross-validation strategy is implemented in this proposed CNN model, thus boosting the robustness of the model.

The drawbacks of this proposed CNN model are as follows:

i. Requires long training hours, specialized hardware to efficiently train (GPU), and is the training is computationally expensive.
ii. A very large number of images is required to train the model that can reliably recognize multiple patterns.

However, once the training of the ECG signals is completed, the classification of ECG heartbeat signals is fast. Furthermore, the proposed system can be deployed in clinical settings to assist cardiologists in an objective diagnosis of the ECG heartbeat signals. It can also be used in intensive care units (ICUs) and in rural areas where medical care is not easily available.

Table 7
Selected works done on the automated categorization of ECG beats acquired from the database of MIT-BIH.

Author	Year	Approach	Performance
		Two-class	
Inan et al. [27]	2006	• *Conventional machine learning approach:* → D_yWT → NN classifier	acc: 95.16%
Sayadi et al. [28]	2010	• Kalman filter • Bayesian filtering	acc: 99.10% sen: 98.77% spec: 97.47%
Martis et al. [29]	2011	• *Conventional machine learning approach:* → HOS → WPD → SVM classifier	acc: 98.40% sen: 98.90% spec: 98%
Martis et al. [30]	2013	• *Conventional machine learning approach:* → ICA → GMM classifier	acc: 99.42% sen: 100% spec: 99%
		Three-class	
Prasad et al. [31]	2013	• *Conventional machine learning approach:*	acc: 97.65% sen: 98.75% spec: 99.53%

		→ HOS → ICA → KNN classifier	
Martis et al. [32]	2013	• *Conventional machine learning approach:* → Cumulant + ICA → Bispectrum + ICA → KNN classifier	Cumulant+ICA: acc: 99.50% sen: 100% spec: 99.22%
Martis et al. [33]	2014	• *Conventional machine learning approach:* → PC + DWT → IC + DWT → PC + DCT → IC + DCT → KNN classifier	IC+DCT: acc: 99.45% sen: 99.61% spec: 100%
Five-class			
Martis et al. [34]	2012	• *Conventional machine learning approach:* → PCA → LPC + PCA → DWT + PCA	PCA: acc: 98.11% sen: 99.90% spec: 99.10%
Martis et al. [35]	2013	• *Conventional machine learning approach:* → HOS → PCA → LS-SVM classifier	acc: 93.48% sen: 99.27% spec: 98.31%
Martis et al. [36]	2013	• *Conventional machine learning approach:* → Cumulant + PCA → NN classifier → DWT + Cumulant + PCA → LS-SVM classifier	Cumulant + PCA: acc: 94.52% sen: 98.61% spec: 98.41% DWT+Cumulant+PCA acc: 93.76% sen: 99.46% spec: 97.36%
Martis et al. [37]	2013	• *Conventional machine learning approach:* → DWT + ICA → PNN classifier	acc: 99.28% sen: 99.97% spec: 99.83%
Martis et al. [38]	2013	• *Conventional machine learning approach:* → DCT → PCA	acc: 99.58% sen: 98.69% spec: 99.91%

		→ PNN classifier	
Li et al. [39]	2016	• *Conventional machine learning approach:* → WPD + RR → WPE → WPE + RR → RF classifier	WPE+RR: acc: 94.61%
This work	**2017**	• **9-layer deep convolutional neural network** • **Two sets of experiment (with and without noise removal)** • **Generation of synthetic data**	**Set A:** **acc: 93.47%** **sen: 96.01%** **spec: 91.64%** **Set B:** **acc: 94.03%** **sen: 96.71%** **spec: 91.54%**

acc: accuracy, sen: sensitivity, spec: specificity

DCT: Discrete Cosine Transform, DWT: Discrete Wavelet Transform, D_yWT: Dyadic Wavelet Transform, HOS: Higher Order Statistics, IC: Independent Component, ICA: Independent Component Analysis, LPC: Linear Prediction Component, PC: Principal Component, PCA: Principal Component Analysis, RR: RR intervals, WPD: Wavelet Packet Decomposition, WPE: Wavelet Packet Entropy

GMM: Gaussian Mixture Model, KNN: K-Nearest Neighbor, LS-SVM: Least Square-Support Vector Machine, NN: Neural Network, PNN: Probabilistic Neural Network, RF: Random Forest, SVM: Support Vector Machine

4. Conclusion

A deep learning approach is presented in this study to automatically identify and classify the different types of ECG heartbeats, which are crucial for diagnosis of cardiac arrhythmia. The CNN that we developed can classify 5 different ECG heartbeat types and thus, can be implemented into a CAD ECG system to perform a quick and reliable diagnosis. The proposed model has the potential to be introduced into clinical settings as an adjunct tool to aid the cardiologists in the reading of ECG heartbeat signals. Implementing such model in polyclinics to online and off-line screen large amounts of ECG recordings would reduce the patient waiting time, lessen the workload of cardiologists and reduce the cost of ECG signal processing in the hospitals.

In the future studies, the authors would like to extend the proposed model by training a CNN to recognize temporal sequences of ECG heartbeat signals. The occurrence, sequential patterns and persistence of the five classes (N, S, V, F, and Q) of ECG heartbeats considered in this work can be grouped under three main categories of green, yellow, and red, which represents normal, abnormal, and potentially life-threatening conditions of heart electrical activity, respectively. The authors plan to discuss the performance of the CNN model using de-skewed data and data with added different level of noise in the future studies.

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6. Appendix

Table A1
A confusion matrix of ECG heartbeats for set A across all ten-folds (imbalance data set).

		Predicted								
		N	**S**	**V**	**F**	**Q**	***acc* (%)**	***ppv* (%)**	***sen* (%)**	***spec* (%)**
	N	80,034	5,053	1,771	3,021	713	89.65	99.04	88.35	95.90

	S	309	2,371	58	25	18	94.86	31.25	85.26	95.11
	V	177	113	6,705	205	35	97.75	77.62	92.67	98.11
	F	45	7	38	707	5	96.93	17.80	88.15	96.99
	Q	242	43	66	15	7,673	98.96	90.87	95.45	99.24

acc = accuracy, *ppv* = positive predictive value, *sen* = sensitivity, *spec* = specificity

Table A2
A confusion matrix of ECG heartbeats for set B across all ten-folds (imbalanced set).

		Predicted								
		N	**S**	**V**	**F**	**Q**	***acc* (%)**	***ppv* (%)**	***sen* (%)**	***spec* (%)**
Original	**N**	80,073	4,055	2,197	3,425	842	89.68	99.04	88.39	95.90
	S	316	2,342	62	28	33	95.78	35.91	84.21	96.08
	V	193	85	6,632	272	53	97.27	73.54	91.67	97.67
	F	37	9	43	710	3	96.50	15.97	88.53	96.56
	Q	227	30	84	10	7,688	98.83	89.20	95.63	99.08

acc = accuracy, *ppv* = positive predictive value, *sen* = sensitivity, *spec* = specificity

Table A3
The overall average classification performance across all ten-folds (imbalanced set).

Beats Type	***tp***	***tn***	***fp***	***fn***	***acc* (%)**	***ppv* (%)**	***sen* (%)**	***spec* (%)**
Set A	18,084	80,034	10,558	773	89.07	63.14	95.90	88.35
Set B	18,084	80,073	10,519	773	89.03	63.22	95.90	88.39

tp = true positive, *tn* = true negative, *fp* = false positive, *fn* = false negative
acc = accuracy, *ppv* = positive predictive value, *sen* = sensitivity, *spec* = specificity