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# Cardiac Arrhythmia Screening System

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## Abstract

Cardiac arrhythmia can lead to a sudden cardiac death. Hand-engineered features based arrhythmia classification systems are usually time consuming. In this paper, we propose an efficient automatic cardiac arrhythmia classification system based on single-lead Electrocardiogram (ECG) signals to classify normal and abnormal beats. Beats are extracted from 1-minute ECG records duration of MIT-BIH database, each beat is 281 samples long around R peaks. The proposed system uses one-dimensional convolution neural network (1D-CNN) that acts as an end-to-end model and involves fewer numbers of learnable parameters compared to traditional CNN models, which improve model generalization. We performed pre-processing to remove ECG recording artifacts before feeding beats into 1D-CNN. In addition, we used data augmentation to overcome lack of data; the model performance was validated by testing it on a new data set. The model achieved 99.45%, 99.2%, and 98.8% of accuracy, specificity and sensitivity, respectively evaluated using 10-fold cross-validation. The results demonstrate that with an appropriate choice of 1D-CNN architecture, 1D-CNN can achieve high classification performance in handling arrhythmia diagnosis problem. The proposed system demonstrated competitive classification accuracy in classifying normal and abnormal beats comparing to other deep learning-based methods researches. Furthermore, employing deep learning based methods outperformed traditional hand-engineered feature extracted methods in-terms of time-consuming and classification accuracy, 1D-CNN could be useful for medical image analysis.

**Keywords**: *Arrhythmia, Convolutional Neural Network, Deep learning*.

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## 1. Introduction

Heart diseases are one of major causes of sudden cardiac death. According to the World Health Organization, 17.7 million people died from heart diseases in 2015 (*Cardiovascular Diseases ({CVD}s) World Health Organaization*, n.d.), (*About Arrhythmia*, 2019). An early detection of heart abnormalities will reduce the opportunity of sudden cardiac death. Electrocardiogram signal represents the electrical behavior of heartbeats over time, it is recorded by placing electrodes on skin, ECG signals contain information about heart morphology, so ECG extracted features can be used to detect and classify different arrhythmia types. However, in some cases, it is impossible to extract ECG features due to the presence of noise; also analyzing ECG segment is time consuming. Many automatic arrhythmia classification systems have been suggested to detect and classify different types of arrhythmia (De Chazal et al., 2004), (Luz et al., 2016), (Arjona Barrionuevo et al., 2002), (Padmavathi & Ramakrishna, 2015) .

In developing these automatic systems, two main phases are performed: feature extraction phase and classification phase. In feature extraction phase, traditional hand-engineered methods are usually used to extract domain features, then these features will be used to detect and classify different arrhythmia types using classification algorithms (Khazaee, 2013), (Tsipouras & Fotiadis, 2004), (Acharya et al., 2003), (Jovic & Jovic, 2017), (Jovic & Bogunovic, 2012), (Asl et al., 2008), (Dalvi et al., 2016). In systems based on ECG signal, morphological and timing ECG domain features have been extracted and analyzed for arrhythmia classification, several detection and classification methods have been used such as, support vector machine, neural network with radial basis function, wavelet transform and rule-based methods.

Since ECG is a noise sensitive signal, it is sometimes in feasible to extract ECG features such as P waves to be used in arrhythmia classification. HRV is non-invasive, valuable and robust tool to analyze and classify different types of arrhythmia, it is less sensitive to noise than ECG signal, and it can detect only some types of arrhythmia. Few number of automatic arrhythmia classification systems are based on photo plethysmography (PPG) signal, PPG signal represents the blood volume. Wavelet transforms and support vector machine are used in this research field (Owis et al., 2002), (Jadhav et al., 2010), (Galen et al., 2015). Recently, deep learning has become state-of-the-art trend in artificial intelligent, where learning algorithms are used to search the domain space for deep architectures that represent high level of abstractions. The deep learning methods act as end-to-end model that fuses feature extraction and classification in a single step, they have outperformed traditional classification algorithm in various applications (Mostafa & Fung, 2017), (Naderi & Nasersharif, 2017), (Yaman et al., 2017), (Cengil et al., 2017).

Many deep learning methods have been used in developing ECG classification systems to detect different arrhythmia types. Some of the developed systems used hybrid model that consists of a combination of more than one deep learning method to take the advantages of the involved methods. While these systems have achieved a competitive accuracy in classifying different arrhythmia types, there is an extra overhead and complexity in adjusting the parameters of hybrid model and training it. Recurrent neural networks have also been used in developing automatic cardiac detection systems and they performed well, but they require more memory space as they used it to process inputs (Singh et al., 2018), (Faust et al., 2018). CNN have shown increased performance in image classification problems, 1D-CNN has been used in many automatic classification systems to classify different arrhythmia types and achieved competitive performance. The major bottleneck is lack of data necessary for training, most systems based on 1D-CNN used unbalanced set of input data which affects the performance of models (Acharya et al., 2018), (Hsieh et al., 2020).

We developed a deep learning system based on 1D-CNN; our system accepts one-dimensional input of ECG single lead signal. We performed segmentation to classify normal and abnormal beats, each beat of size 281 samples long. We introduced a novel data augmentation scheme to obtain balanced data set. This system has outperformed hand-engineered systems and achieved competitive ECG signals classification performance in terms of accuracy, sensitivity and specificity compared to deep learning methods, making our system a highly recommended option in clinical diagnosis to save time and effort. In this paper, we tested the performance of the model on a MIT-BIH dataset. Additionally, the model is validated using 10-fold cross validation. We tested the performance of the model on a new dataset. We can summarize the main highlights of our work as follow:

1. An end-to-end model that does not require extracting ECG features, the ECG segment is used as input to 1D-CNN. The network learns to extract features automatically from ECG segments and map to different arrhythmia types; it outperforms related literature results, reached an accuracy of 99.45%.

2. 1D-CNN model architecture that consists of four combinations of two convolution layers followed by a max-pooling layer, the dimension of the generated feature map has not been reduced immediately after each convolution layer. Also, the number of kernels are reduced as we go deep through the network, which reduce the number of learn able parameters and avoid the risk of over-fitting.

3. It introduces a novel augmentation approach to overcome data lack and thus, avoid over-fitting based on taking a weight for each sample in a beat type and adding it to a weighted corresponding sample in a similar beat type to generate a new one. Additionally the model performance is validated using 10-fold cross validation.

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The organization of our paper is as follow: In Section 2, we will review some related works. Then in Section 3, we will discuss the proposed method. In Section 4, we present evaluation protocols. Finally, we present our results in Section 5 and give discussion and conclusions in Section 6 and 7 respectively.

## 2. Related Works

Many automatic arrhythmia detection and classification systems have been proposed to detect and classify different cardiac arrhythmia, the common main purpose of these systems is to reduce the opportunity of the sudden cardiac death. These systems used different signals such as ECG signal (Arjona Barrionuevo et al., 2002), (Padmavathi & Ramakrishna, 2015), (Khazaee, 2013), (Osowski & Linh, 2001), heart rate variability (Tsipouras & Fotiadis, 2004), (Acharya et al., 2003), (Jovic & Bogunovic, 2012), (Asl et al., 2008), (Akhter et al., 2015) and some systems are based on both signals to classify different arrhythmia types. Also, systems differ in the data used for training and testing process, while some partition the whole data-set into training and testing set known as class- based systems, others use a set of data for training and leave some data for testing without using it in training process, known as subject-based systems (Andersen et al., 2019). Since the main process of classification arrhythmia types is feature extraction process, automatic classification systems can be classified based on feature extraction methods into two main categories: traditional hand-engineered methods and deep learning-based methods.

In this section, we will provide an overview of the related state-of the-art systems, which use different feature extraction and classification methods for discriminating different types of arrhythmia based on ECG signals. ECG signal is noise sensitive but it contains information about heart morphology and it is widely used for developing automatic cardiac arrhythmia classifications systems. Ma et al.,(Ma et al., 2020) proposed a robust and low computational cost model to detect Atrial Fibrillation (AF) episodes of ECG signal, extracted RR-intervals and used as input to ANN

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
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www.mecsj.com

classifier, the classification model obtained sensitivity of 99.3%, specificity of 97.4%, and accuracy of 98.3%, Dokur et al., (Dokur & Ölmez, 2001) determined ECG features from eight high dimensional feature spaces of ECG Fourier and ECG wavelet transform, used dynamic programming with divergence value, then the authors applied a genetic algorithm to train hybrid neural network, the model classified ten beats of MIT-BIH database and real time ECG measurement system with accuracy of 96%. Osowski et al., (Osowski & Linh, 2001) used Q-R-S complexes extracted features as inputs to fuzzy sub-network that connected to a final multi-layer perceptron classifier and obtained an accuracy of 96.06%. Ashtiyani et al., (Ashtiyani et al., 2018) proposed a method to classify two arrhythmia types and normal rhythm. In this method, HRV signal is transformed to discrete wavelet transform (DWT), four features (entropy, mean, variance, kurtosis and spectral component) are selected from DWT by genetic algorithm (GA), and are deployed by support vector machine for classification. They obtained accuracy of 97.14%, sensitivity of 96.9%, and specificity of 97.54%. In (Ebrahimzadeh et al., 2016), the authors used Hermit features of Q-R-S complex and three timing interval feature as inputs to multi-layer perceptron (MLP) to classify three ECG beats, i.e., normal, premature ventricular arrhythmia (v) and other arrhythmia. They reported an accuracy of 98.02%. Anderson et al.,(Andersen et al., 2017) proposed a method to classify AF and normal rhythm, they extracted five time-domain features from the inter beat intervals and used support vector machine (SVM) as classifier. This method obtained an accuracy of 96.9%. In (Desai et al., 2016), Recurrence Quantification Analysis (RQA) features were used for classifying four different ECG beats namely normal (N), atrial fibrillation , atrial utter (AFL) and ventricular fibrillation (VF) using Rotation Forest. Results reported an accuracy of 98.3%. Authors in (Acharya et al., 2016) used Decision Tree (DT) and K-Nearest Neighbor (KNN) for the automated detection of three serious arrhythmia types, i.e., AF, AFL and VF, in addition to normal rhythm. The authors extracted non-liner ECG features and used them as inputs to DT and KNN. DT classifier with fourteen non-liners features yielded 96.3% accuracy, and the KNN classifier achieved an accuracy of 93.3% using twelve non-liners ECG features. A new novel ECG representation called temporal vector-cardiogram (TVCG) based on vector cardiogram (VCG) was defined in (Garcia et al., 2017) to extract ECG features, and then discriminative features were selected by optimization algorithm. The authors employed SVM to classify supraventricular beat (S), ventricular beat and normal beat. Results indicate that this method obtained an accuracy of 92.4%. Authors in (Sahoo et al., 2017) proposed automatic diagnosis for four cardiac arrhythmia: normal, left bundle branch block (LBBB), right bundle branch block (RBBB), Paced beats (P). They used multiresolution wavelet transform of ECG signal to extract Q-R-S complex features; the extracted features were fed into neural network (NN) and support vector machines. The proposed method is evaluated on 48 records of MIT-BIH and achieved an accuracy of 98.39%, 96.67% for SVM and NN respectively. A global recurrent neural network (GRRN) was adopted in (Wang et al., 2019) to explore ECG beats based on temporal and morphological features; an active learning method was used to select ECG beats. The model classified four different arrhythmia types with an accuracy of 99.2%. Authors in (Yang et al., 2018) identified five types of ECG signals in MIT-BIH arrhythmia database by employing SVM on extracted features of ECG domain, obtained by principal component analysis network, and yielded accuracy of 97.77%. In (Khazaee, 2013), a method was proposed to detect and classify heart beats into three classes: premature ventricular contractions beats, normal beats and other beats based on ECG signal morphological features and HRV signal timing features. The authors used seven files of MIT-BIH and applied radial basis function neural network. The best value of redial basis function neural was chosen by using a genetic algorithm, the proposed technique achieved classification accuracy of 95.83%. Most of the previous developed systems are based on hand-engineered features to detect and classify different arrhythmia types, which require a prior human knowledge of the desired domain. In addition, the extracted features may be not useful as a predictor of different arrhythmia types, which degrade model generalization.

The current state-of-the-art trend in artificial intelligence is deep learning, where learning algorithm searches for deep architectures that represent data. Many automatic cardiac arrhythmia classifications have turned forward deep learning. Authors in (Andersen et al., 2019) proposed a model that used a combination of convolutional and Recurrent Neural Networks (RNN) to classify segments of RR intervals as AF or normal sinus rhythm, the proposed model achieved a sensitivity of 98.98% and specificity of 96.95%. In (Singh et al., 2018), three layers of Long Short-Term Memory (LSTM) neural network was used for classifying normal and abnormal beats in ECG signal, and achieved results of 88.1%, 92.4%, and 83.35% for accuracy, sensitivity and specificity, respectively. In (Faust et al., 2018), deep learning system based on LSTM neural network was used to detect AF beats in Heart Rate signals, a window of size 100 beats is fed as input to the network. The proposed system achieved accuracy of 98.51%. In (Acharya et al., 2017), three arrhythmia types, in addition to normal sign rhythm using were classified using an eleven-layer deep CNN with an output layer of four neurons, ECG signals of five and two seconds were extracted from three data-bases and used as input to CNN. Results indicate that the proposed method achieved an accuracy, sensitivity, and specificity of 92.50%, 98.09%, and 93.13% respectively for two seconds ECG segments and accuracy of 94.90%, sensitivity of 99.13%, and specificity of 81.44% for five seconds ECG segments.

Many of the proposed systems use hand-engineered features, which require a prior knowledge of domain. Also, the performance of these systems is affected by the quality of extracted features and their representation of domain. Deep learning methods are used to avoid hand-engineered features process and therefore saving time and effort where deep learning methods act as an end-to-end model.

The overview of deep learning methods indicates that ECG segments were used as an input to RNN or CNN or combination of both to classify different types of arrhythmia. CNN has outperformed RNN in-terms of saving hardware consumption. Using hybrid model increases the overhead of setting model parameters. ECG segments can be either long ECG duration or single beats; beat-classification can be used to classify long duration and fragments of ECG signal by taking a specific threshold of beats number.

The main bottleneck of using deep learning methods is lack of data where unbalanced data-set was used with suggested models that affect system's performance. We felt motivated to propose a model that uses balanced data-set and can act as a basis of classifying different types of arrhythmia, ECG signal is 1D. We used 1D-CNN that outperforms other deep learning method in this area. Our model classifies normal and abnormal beats using balanced set of data, we applied data augmentation scheme to obtain our balanced data set. As far as we know, 1D-CNN is not used to classify normal and abnormal beats of MIH-BIH database, where abnormal beats contain various types of arrhythmia.

## 3. Proposed Method

Deep learned features systems have outperformed hand-engineered features methods by eliminating the need of prior knowledge of domain. Convolutional Neural Networks (CNNs) have been so effective than other artificial neural networks in applications of image data input, they can develop an internal representation of any image data. As an ECG signal is 1D signal, 1D-CNNs have been used in developing many automatic arrhythmia classification systems and they have achieved competitive performance compared with other DL methods. The main bottleneck of applying 1D-CNN is requiring large amount of data to avoid the risk of over-fitting. Most systems used unbalanced long duration of ECG segments data set, which affected the performance of the suggested models [42], [43]. Also, the presence of noise and artifact in data degrades the performance of classification process [44]. We felt motivated to employ 1D-CNN with small number of learnable parameters for developing an automatic classification system that uses balanced and clean data-set to classify normal and abnormal beats. ECG signals consist of beats; each beat refers to a cardiac cycle. Arrhythmia can be indicated when there is a change in the morphological pattern of ECG signal. For example, atrial fibrillation can be indicated when there is over irregular beats in 1 minute ECG signal [45], different arrhythmia types can be indicated

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based on beat-classification [44], hence we will apply beat classification that can be used to classify long duration and fragments of ECG signal by taking a specific threshold of beats number.

Arrhythmia classification framework automatically maps each ECG beat to a class label. We have developed an efficient and robust intelligent system without any needs of prior knowledge of domain by suing 1D-CNN with small number of parameters and achieved an accuracy that is near human expert. Our method consists of three main stages:

1. Preprocessing: Remove artifacts such as motion artifacts, baseline wanders and power-line interference, which affect the diagnosis of arrhythmia types and thus reduce classification accuracy.

2. Segmentation: Extract individual beats to perform beat-classification.

3. Classification: Map each beat type to a specific class label.

Our proposed 1D-CNN is applied to MIT-BIH database. We extracted 1-minute duration of ECG signals, and then we performed pre-processing to remove noise and articraft that degrade classification performance. Segmentation was performed to obtain beats, each of size 281 samples long, we applied a novel data augmentation method to overcome lack of data and obtain balanced dataset. Finally, we chose an appropriate 1D-CN model architecture to build robust automatic cardiac arrhythmia classification system.

An overview of the proposed method is shown in Figure 1.

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Issues (60) 2022
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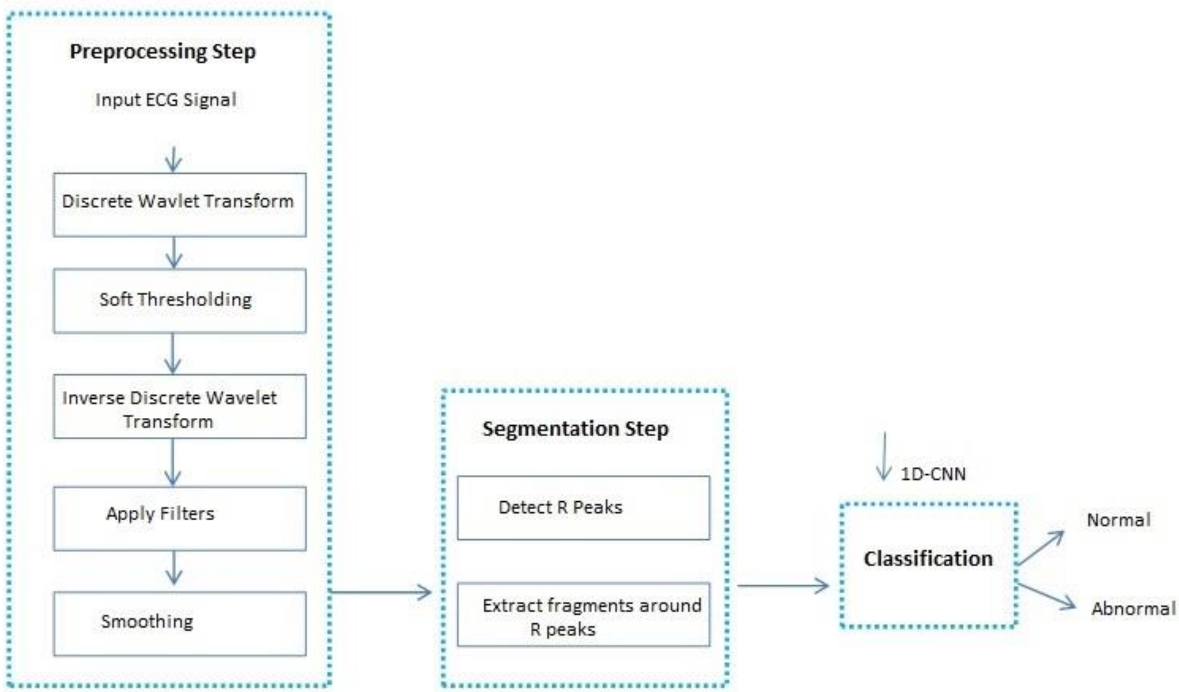


Figure 1: The proposed method.

### 3.1 ECG Data

We acquired benchmark data sets, which are available in public domain such as MIT-BIH arrhythmia database. MIT-BIH arrhythmia database is the most common database that was developed to act as an objective evaluation tool for different arrhythmia classification systems, it consists of 48 records of ECG data, each record is 30 minutes long, 23 records of the 48 records were chosen randomly from a large set of long-term ECG Holter recordings to represent variations of ECG data, while the remaining records were chosen specifically to represent complex arrhythmia such as supra-ventricular arrhythmia that may encounter arrhythmia classification systems.

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Issues (60) 2022

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The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Each ECG record contains two lead, each lead is recorded by placing electrodes on different places on the skin. MIT-BIH data set was pre-processed and digitized, a set of rhythm labels and beat labels were added to each record, during the early usage of the data set, some of these labels were revised and corrected several times [2].

### 3.2 Preprocessing

ECG is widely used for arrhythmia classification problem; good quality of ECG is utilized by cardiologists to identify different arrhythmia types. However, real ECG recordings are often corrupted by artifacts, which will lead to an inaccurate diagnosis of arrhythmia types. There are two main ECG recording artifacts:

- Baseline wanders due to the motion of medical instruments or patients during recording.
- High- frequency noise due to power line interference, or mechanical forces affecting the electrodes.

Artifacts types reduce classification accuracy, so there is a need to remove these types of artifacts before making any classification. Baseline drift is a low frequency noise. Setting the coefficients corresponding to this noise component to zero and subsequently reconstructing the signal by inverse transform will eliminate baseline wander [46]. Adaptive band-pass filtering and adaptive band-stop filtering are important fundamental techniques for detection and suppression of unknown narrowband signals immersed in a broadband signal [47]. High-frequency noise can be removed using low-pass filters. Based on these observations some related preprocessing methods [48], the following combinations of methods have been performed for the pre-processing stage:

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Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

As a first step, baseline wander is eliminated, to accomplish this task, ECG signal is transformed into discrete wavelet transform with wavelet db8, and then the discrete wavelet transform coefficients are threshold with soft threshold of value of 4.33. Minimax threshold selection rules are used because they are more conservative and would be more convenient when small details of the signal lie near the noise range, after that the original ECG signal are reconstructed using inverse discrete wavelet transform (IDWT). Secondly, to suppress power-line interference, an adaptive band stop filter (BSF) with stop band corner frequency of 55 Hz is applied to the reconstructed signal. Thirdly low-pass Butter-worth filter (LPBF) with attenuation pass band corner frequency, pass band ripple, stop band corner frequency, attenuation in the stop band of 40hz, 0.1 db,50hz and 30db respectively is applied, the processed signal is smoothed to obtain the final processed signal. The steps of Pre-processing are shown in Algorithm 1. Also, an overview of input and output of Pre-processing phase is shown in Figure 2 and Figure 3.

| **Algorithm 1**: Preprocessing Algorithm | |
|---|---|
| **Input :** | **ECG signal** |
| **Output:** | **Preprocessing Algorithm** |
| E1 | DWT (E,db8) |
| E2 | Soft (E1,4.9) |
| E3 | IDWT (E2) |
| E4 | BSF (E3,50) |
| E5 | LPBF (E4,40,0.1) |
| P | Smoothing (E5,5) |

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Issues (60) 2022
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www.mecsj.com

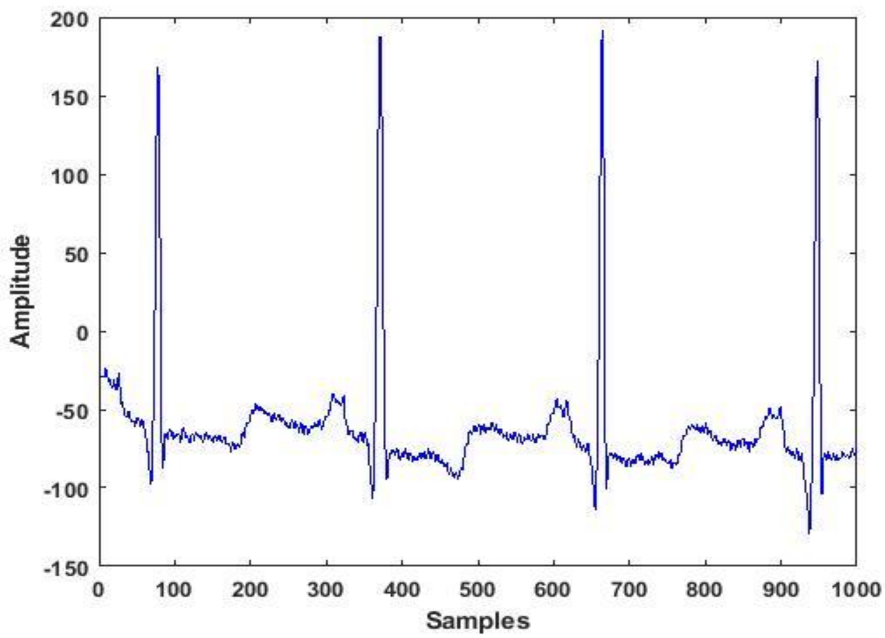


Figure 2: Original ECG signal.

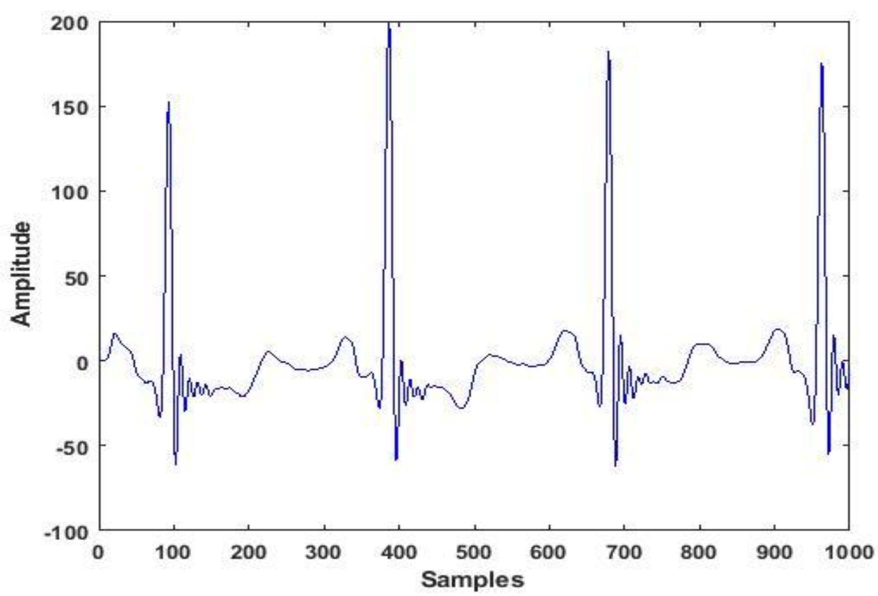


Figure 3: Processed ECG signal.

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
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### 3.3 ECG Segmentation

After prepossessing step, we performed ECG segmentation, each cardiac cycle in ECG signal consists of the PQRST waves, where P is the atrial systole contraction pulse, Q is a downward defection immediately preceding the ventricular contraction, R is the peak of the ventricular contraction, S is the downward defection immediately after the ventricular contraction, and T is the recovery of the ventricles. The duration, morphology, and amplitude of the QRS complex contain useful information about beat type and thus can be used in arrhythmia classification process, we performed our segmentation process around R peak [44], each ECG segment contains 140 samples to the left of the R peak and 140 samples to the right of the heartbeat. So, each segment is 281 samples long including R peak, we used these 281 samples, which form a single beat for two-classification problem. Figure 4 shows Segmentation Phase.

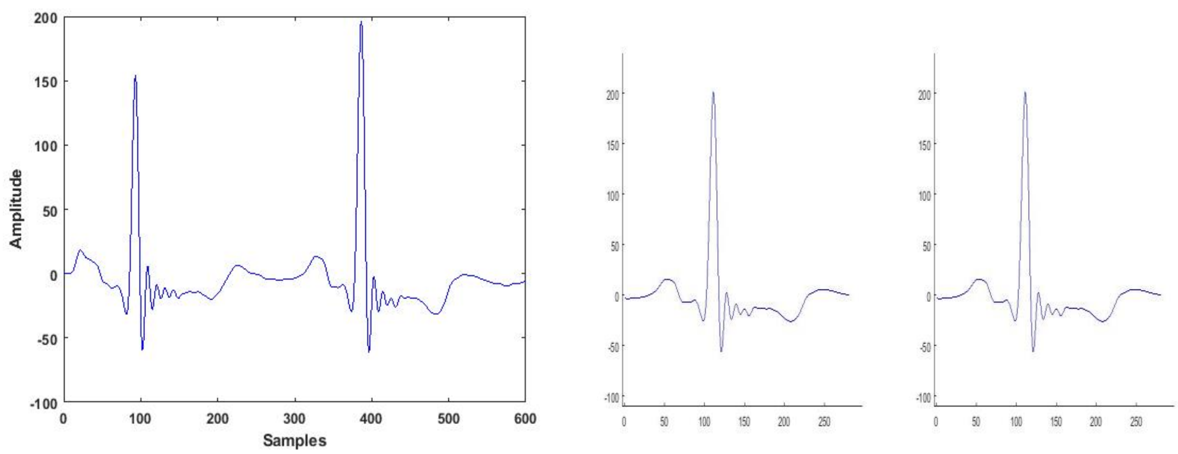


Figure 4: Segmentation Phase.

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
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## 3.4 Classification of Beats using 1D-CNN model

Since ECG beats are 1D, we will apply 1D-CNN. A deep CNN learns features from data regardless location of features and acts as an end-to-end classification system, which is different from traditional hand-engineered method where features are extracted and selected based on prior domain knowledge and then passed to a classifier. CNN contains main operation, namely convolution. The convolution operation uses filter with predefined size that moves along the data to extract features and produce feature map. The filter performs convolution operation with a fixed field of input data. Multiple feature maps can be generated using multiple filters. At each hidden layer the nodes have to learn filter weights that are shared by all neurons, this reduces the number of learned parameter at each layer. Convolutional networks may include pooling to reduce the dimensions of data by combining neurons at the prior layer into a single neuron in the next layer. There are three main types of pooling: max, min, and average. Max-pooling chooses the maximum value of neurons at one layer as a value of neuron in the next layer, average pooling uses the average value of neurons at prior layer and min-pooling chooses the minimum value of neurons at one layer as a value of neuron in the next layer. At the end of CNN, there is one or more fully connected layer that passes the output to a classification layer to make the final decision.

### 3.4.1 Architecture of the 1D-CNN model

We will apply deep learning by using 1D-CNN, which requires a large amount of training data. The main bottleneck still arise during the design of such a model is the small number of ECG signal segments that are necessary to set CNN large parameters as it goes deeper. We handled this issue by using a novel data augmentation method. Our model is 1D-CNN that acts as end-to-end model and it is shown in Table 2. Unlike traditional CNN models, it does not reduce feature map after each convolution layer, instead it used two consecutive convolution layers followed by max pooling layer to extract more discriminative features before reducing map. Also, it uses decreasing

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
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www.mecsj.com

number of kernels, where low-level layers have small number of filters and high-level layers have large number of filters. This structure reduces the number of learnable parameters.

A Block diagram of the model layers is seen in Figure 5

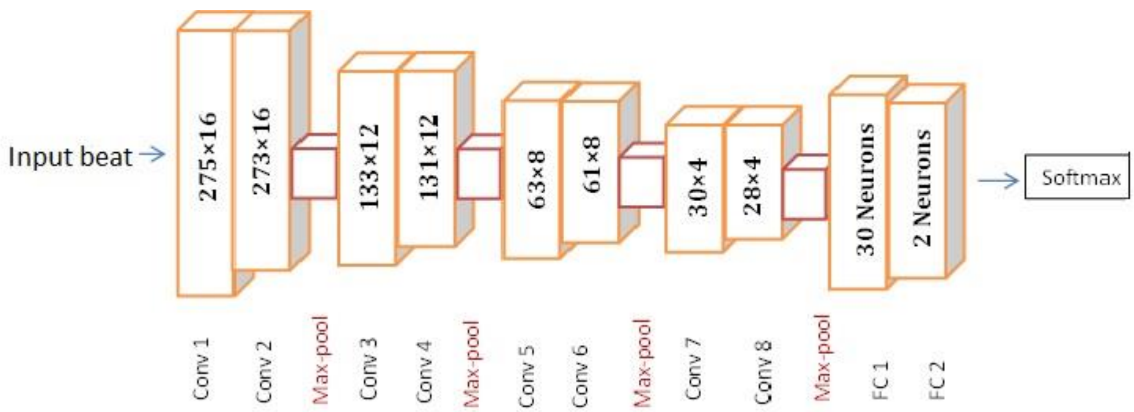


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Figure 5: Block diagram for the proposed 1D-CNN model.

**Model selection**: To prove the performance of our model, Table 1 shows four models with different configuration along with the number of learnable parameters in each model. Model 1 and model 2 use increasing number of kernels as we go deeper within the network, where low-level layers have small number of filters and high-level layers have large number of filters but with different number of neurons at fully connected layer. Model 1 and model 2 in Table 1 contain eight convolutional layers with 4, 4, 8, 8, 12, 12, 16 and 16 kernels, respectively. While the other two-models using decreasing number of kernels, where low-level layers have large number of filters and high-level layers have small number of filters. Model 3 and model 4 are specified in Table 1, they contain eight convolutional layers with 16, 16, 12, 12, 8, 8, 4 and 4 kernels, respectively. All models have batch normalization layer that is added after every convolution layer and fully-connected layer to solve internal covariate shift and speed up training process. We added dropout

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

Layer after fully-connected-layer with probability =0.3 to drop some hidden neurons and to overcome over-fitting problem.

We run each model ten times and computed the accuracy values using 10-fold Cross validation. The details of 10-fold Cross validation for the models are shown in Table 3. Model 3 and Model 4 shows better results than Model 1 and Model 2 and they have less number of learnable parameters than Model 1 and Model 2. We used Wilcoxon rank with sum test to choose the final Model among model 3 and model 4 and we got p value of 0.35 that is greater than our significance level of 0.05. This indicates that there is no difference between Model 3 and Model 4, and the difference is not significant at 50%. So we can select any model, we selected model 3 since it has less number of learnable parameters than Model 4. Our 1D-CNN consists of four combinations of two convolutions layers, followed by max pooling layer, and at the end, two fully connected layers. We did not reduce feature map immediately after each convolution layer (Conv), we used two consecutive convolution layers in hope to extract more abstract features, and then the feature maps were reduced. Also, we used a large number of filters at the beginning and reduced the number as we go deep through the network; our model has the least number of learnable parameters as can be seen in Table 2. The convolution layers are convoluted with their respective filter size to produce ECG feature map, the input layer is convolved with a kernel size of 7 to produce features maps that are convolved also with a kernel size of 7. A max-pooling of size 3 is applied to every feature map. The features maps are convolved with a kernel size of 3, then the produced features maps are convolved with a kernel size of 3. A max-pooling of size 3 is applied to every feature map. The process of two consecutive operation followed by max- pooling operation is repeated twice but with different features maps sizes.

A batch normalization layer is added after every convolution layer and fully connected layer to solve internal covariate shift and speed up training process, we also added dropout Layer after fully- connected-layer with probability =0.3 to drop some hidden neurons and to overcome over-

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

fitting problem and enhance model generalization, the soft max function is used at the of model to output classes.

Table 1: The conceptual architecture of 4 1D-CNN models.

| Layers /model | | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|---|
| Conv | n | 4 | 4 | 16 | 16 |
| | s | 7 | 7 | 7 | 7 |
| Conv | n | 4 | 4 | 16 | 16 |
| | s | 7 | 7 | 7 | 7 |
| Max-pooling | n | 3 | 3 | 3 | 3 |
| Conv | n | 8 | 8 | 12 | 12 |
| | s | 3 | 3 | 3 | 3 |
| Conv | n | 8 | 8 | 12 | 12 |
| | s | 3 | 3 | 3 | 3 |
| Max-pooling | n | 3 | 3 | 3 | 3 |
| Conv | n | 12 | 12 | 8 | 8 |
| | s | 3 | 3 | 3 | 3 |
| Conv | n | 12 | 12 | 8 | 8 |
| | s | 3 | 3 | 3 | 3 |
| Max-pooling | n | 3 | 3 | 3 | 3 |
| Conv | n | 16 | 16 | 4 | 4 |
| | s | 3 | 3 | 3 | 3 |
| Conv | n | 16 | 16 | 4 | 4 |
| | s | 3 | 3 | 3 | 3 |
| Max-pooling | n | 3 | 3 | 3 | 3 |
| Fully-connected | N | 30 | 35 | 30 | 35 |
| Fully-connected | N | 2 | 2 | 2 | 2 |
| Number of Learnable parameters | | 33,929 | 33935 | 11573 | 11601 |

* n: number of filter, s: size of filter

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Issues (60) 2022
ISSN: 2616-9185
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Table 2: Model Architecture.

| layer | Type | Activation Function | Number of filters | Size of filter | Number of neurons | Stride |
|---|---|---|---|---|---|---|
| 0-1 | Convolution | ReLU | 16 | 1*7 | | 1 |
| 1-2 | Convolution | ReLU | 16 | 1*7 | | 1 |
| 2-3 | Max-Pooling | | | 1*3 | | 2 |
| 3-4 | Convolution | ReLU | 12 | 1*3 | | |
| 4-5 | Convolution | ReLU | 12 | 1*3 | | |
| 5-6 | Max-Pooling | | | 1*3 | | 2 |
| 6-7 | Convolution | ReLU | 8 | 1*3 | | 1 |
| 7-8 | Convolution | ReLU | 8 | 1*3 | | 1 |
| 8-9 | Max-Pooling | | | 1*3 | | 2 |
| 9-10 | Convolution | ReLU | 4 | 1*3 | | 1 |
| 10-11 | Convolution | ReLU | 4 | 1*3 | | 1 |
| 11-12 | Max-Pooling | | | 1*3 | | 1 |
| 12-13 | Max-Pooling | | | 1*3 | | 1 |
| 13-14 | Fully-connected | | | | 30 | |
| 14-15 | Fully-connected | | | | 2 | |

Table 3: The proposed four models and their mean performance using 10-fold cross-validation

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| | | **Data augmentation** | | |
| Accuracy + std | 96.84 + 0.03 | 97.12+ 0.02 | 98.41 + 0.02 | 97.64 + 0.02 |
| Specificity + std | 96.33+ 0.02 | 97.02+ 0.01 | 98.66 +0.01 | 98.84+ 0.02 |
| Sensitivity +std | 96.45 + 0.03 | 96.82+ 0.04 | 97.23+0.01 | 97.54 + 0.01 |
| ***Std :standard deviation** | | | | |

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
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**3.4.2 Data augmentation.**

We will apply deep learning, which requires a large amount of training data. The main bottleneck is a small number of ECG signal segments that will cause over-fitting. In this situation, data augmentation if applied correctly, it will enhance training performance. We will extract beats from MIT-BIH database 1-minute time duration, which has not the enough number of beats to train a deep and balanced network, so we suggested a novel data augmentation scheme.

The augmentation method based on taking a weight for each sample in a beat and adding it to weighted corresponding sample in a similar beat type. The weight (t) can be any value from zero to one. And the corresponding generated beat x is extracted as in the following Equation $x = tx_1 + (1 - t)x_2$. Where $x_1$ and $x_2$ are two beats of same type.

A key challenge for data augmentation is to generate new data that maintains the correct label, if data augmentation results in the loss of label information; it will reduce the performance of the model.

*3.4.3 Training and testing of 1D-CNN model*

For training our model performance, we constructed two data sets:

- Patient independent set where Beats are created independent of patients, and divided into training, validation and testing sets.

- Patient-out set where the patients are divided into training, validation, and test sets. The beats from each set are extracted and used for training, validation and testing.

For patient independent case we extracted 2500 beats from 39 records (patients) of MIT-BIH database: 1250 normal beats and 1250 abnormal beats. For training process, we used 500 beats

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

(250 normal beats and 250 abnormal beats) and applied data augmentation to generate 62,250 beats, for testing process we used 2000 beats. The details of data used in training and testing process appear in Table 4.

Table 4: ECG Data-set 1

| Beat type | ECG duration | Number of patients | Training beats | Testing beats | Total number |
|---|---|---|---|---|---|
| Normal Beats | 1 min | 19 | 62250 | 1000 | 63500 |
| Abnormal Beats | 1 min | 20 | 62250 | 1000 | 63500 |

For patient-independent case, we extracted 250 normal and 250 abnormal from 10 patients, also we extracted the same number of beats for validation process from 10 different patients, for testing process we extracted 1400 beats 425 from 20 patients. We performed data augmentation on both training and validation test to obtain 62,250 beats for both training and validation. The details of data used in training and testing patient-independent case appear in Table 5.

Table 5: ECG Data-set 2.

| Data set | ECG duration | Number of patients | Normal beats | Abnormal beats | Total number |
|---|---|---|---|---|---|
| Training | 1 min | 10 | 31125 | 31125 | 62250 |
| Validation | 1 min | 10 | 31125 | 31125 | 62250 |
| Testing | 1min | 10 | 700 | 700 | 1400 |

We used ten-fold cross validation to derive an accurate estimation of model prediction performance. We used Adam optimizer that has shown good results in many similar applications [49]. It has been widely used in deep learning application and became a popular optimizing algorithm in deep learning based methods. We used it with an initial learning rate of 0.0003 to avoid local minima problem that may happen when using Adam optimizer, We used the default value for Squared Gradient Decay Factor which is 0.99 mini, batch sizes of 64, and 30 epochs, .

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
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The convolution layers are convolved with their respective filter size to produce ECG feature maps, which are reduced by max-pooling layer, the number of filters are decreased as we going deeper through the network, the soft max function is used at the of model to output classes, the parameters are learned from data during training process. We obtained validation accuracy of 98.143% and an accuracy of 99.45% for Patient independent set, while the accuracy of patient-out set does not exceed 95%, we adapted Patient independent set for our model.

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## 4. Evaluation protocol

To obtain valid results and to enhance model generalization, we used 10-fold cross validation. The training data set is randomly spitted into ten parts, in each turn, nine of data are hold as training set and the rest as a test set, and then we computed results average over the 10 turns that acts as training classification performance. We used three metric to measure our model effectiveness. They are Accuracy, sensitivity and specificity. The definitions of these measures are given as follow:

$$Sensitivity\ (Sn) = TP/(FN + TP)$$

$$Accuracy(Acc) = TP + TN/TotalSamplesNumber$$

$$Specificity\ (Spe) = TN\ /(TN + FP)$$

Where, True Positive ($TP$) which is the number of abnormal beats correctly classified, True Negative ($TP$) which is the number of normal beats correctly classified, False Positive ($FP$) which is the number of normal beats incorrectly classified as abnormal and False Negative ($FN$) which is the number of abnormal beats incorrectly classified as normal. In addition, we used statistical method to compare the performance of different models, it is Wilcoxon test. The definition of this measure is given below:

Wilcoxon test: is a non-parametric statistical test that compares two paired groups. The tests essentially calculate the difference between sets of pairs and analyze these differences to establish if they are statistically significantly different from one another.

## 5. Results

We used our model to test unseen data, the average accuracy of 10-fold cross-validation reached 98.143%. The 10-fold cross-validation results and the confusion matrix are shown in Table 6and Table 7 respectively.

Table 6: The % accuracy of 10-fold cross validation.

| Fold Number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Accuracy | 97.81 | 98.26 | 98.36 | 98.21 | 98.10 | 98.22 | 98.43 | 98.21 | 98.30 | 97.53 | 98.143 |

Table 7: Confusion Matrix.

| Beat type | Normal | abnormal |
|---|---|---|
| Normal Beats | 996 | 4 |
| abnormal Beats | 7 | 993 |

It can be seen that 99.6% ECG beats are correctly classified as normal 465 beats. 99.3% of ECG beats are correctly classified as abnormal, also the model achieved accuracy of 99.45%, specificity of 99.6% and sensitivity of 99.3%, to analyze our results in more details, and Figure 6 presents the box-plots of normal and abnormal 30 features after activation of fully connected layer. Box-plots takes up less space in representing data, which is useful when comparing datasets, but since we

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Issues (60) 2022
ISSN: 2616-9185
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have 30 features for each type, training features were reduced to two-dimension space using T-distributed Stochastic Neighbor Embedding (t-SNE), t-SNE is a dimensional reduction method used to visualize data in high-dimensional space in a low-dimensional space of two or three dimensions, it aggregates neighboring points as similar objects, and dissimilar objects are formed with aggregating distant points. The obtained two-dimensional feature is shown in Figure 7.

The scatter plot provides insights into how the model makes the classification decision process. Low level layers extract huge number of microstructures; higher layers combine them into features of higher level. A good classification model should produce a small intra-class variance and a large inter-class variance. It shows that our model is able to obtain discriminative features. There is a clear separation between normal and abnormal beats.

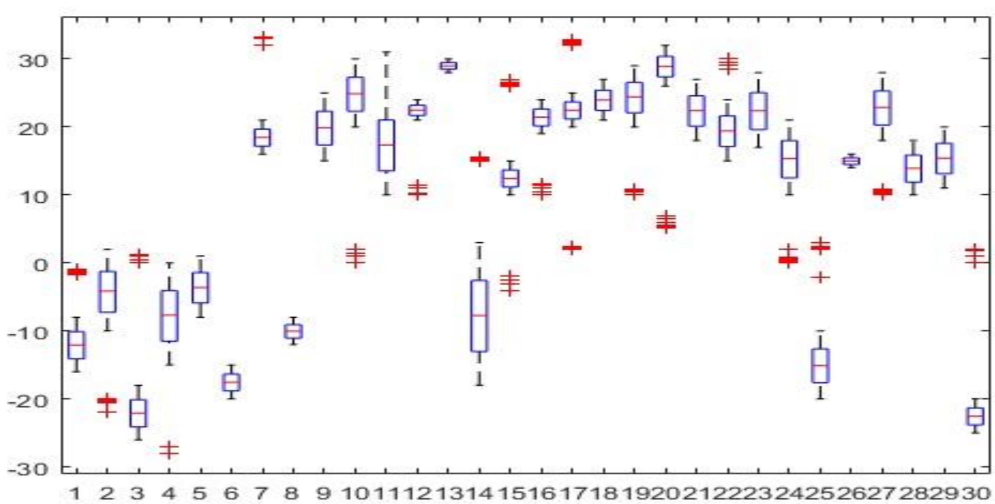


Figure 6: Boxplot of normal and abnormal after FC layer.

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

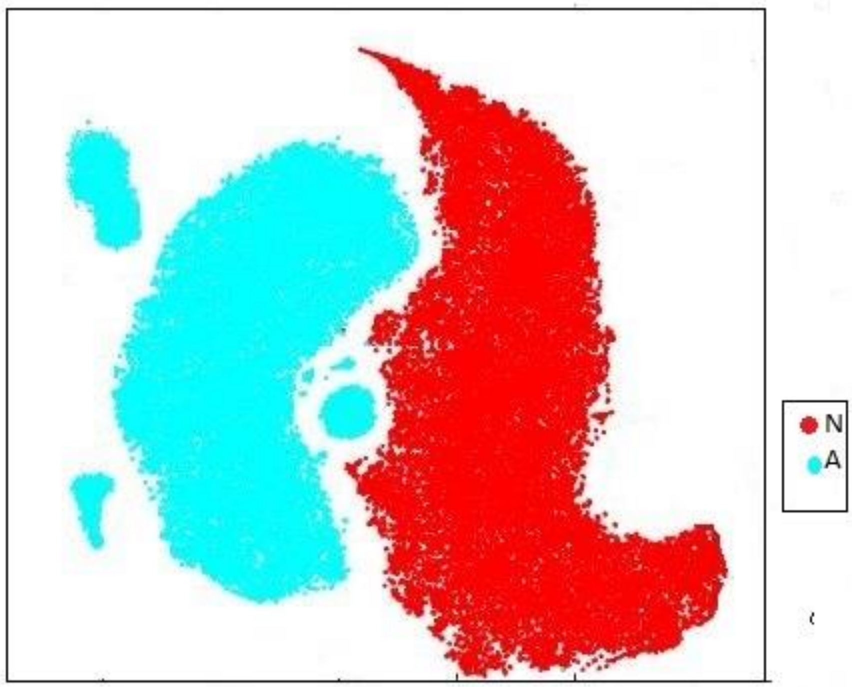


Figure 7: The scatter plots of two-dimensional features of training data at the output of FC layer. The normal and abnormal beats are well separated.

## 6. Discussion

Many automatic systems have been proposed to classify different types of arrhythmia. To visualize the performance of our schemes we used confusion matrix and we computed some common performance measures to facilitate making fair comparison between some similar related methods. The scatter plots of two-dimensional features of training data at the output of FC layer. The normal and abnormal beats are well separated systems classify normal and abnormal segments while other classified normal segment and single type of arrhythmia such as atrial fibrillation.

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

Our model achieved an accuracy of 99.45%, specificity of 99.6%, sensitivity of 99.3%, which is a competitive classification performance comparing to other related works. Sannino et al.,(Sannino & De Pietro, 2018) proposed a method based on DNN classifier, the proposed classifier composed of seven hidden layers, with 5, 10, 30, 50, 30, 10 and 5 neurons, respectively. The DNN Classifier created all the neuron layers, based on the ReLU (Rectified Linear Unit) activation function. Peaks are detected to extract temporal features. Four temporal features were extracted; they include pre-R, Post-RR, Local-RR, Global RR. These four features along with 50 samples representing the beat were fed into DNN classifier; they used 2712 beats for training and 1864 beats for testing and achieved an accuracy of 99.68%. In (Andersen et al., 2017), the authors extracted five time-domain features from the Inter Beat Intervals (IBI) and used (SVM) to classify normal and AF beats, they reached an accuracy of 96.9%. It is worth to observe that (Sannino & De Pietro, 2018) and (Andersen et al., 2017) used totally different extracted features to represent the domain, which give an indicator that the performance of these systems depend on data and do not generalize well. The main difference between our method and there is that they are based on hand-engineered features while our CNN model does not require any hand-engineered features. Although their approach is faster than our suggested one in training process, it is much slower at test time. Authors in (Singh et al., 2018) used RNN-LSTM to classify normal and abnormal beat, and obtained an accuracy of 88.1%. Our system achieved 11.35% higher accuracy i.e., 99.54%. Also, it needs less memory space.

Rasmus et al., (Andersen et al., 2019) used a hybrid model of CNN and RNN to classify normal and atrial segments; they achieved sensitivity and specificity of 98.98% and 96.95% respectively. We used a single deep learning method with less memory overhead and complexity; our results also have outperformed their performance. Some existing systems are based on hand-engineered features, where features are extracted based on a prior knowledge of domain to extract representative features. They do not learn internal representation of data, so they do not generalize well. Also, feature extraction process is time-consuming and errors-prone. In contrast, our proposed system is an end-to-end model, which eliminates the need of hand-engineered features, and learns features from internal structures of data by combining small features. Our model gives results immediately and can be used in real-time application.

Some other systems based on deep learning methods such as RNN or CNN or combination of both. We have used a single model of 1D-CNN, which reduces the overhead, and complexity of using a hybrid model. Also, it involves lowest number of parameters compared to three similar standard CNN models, which generalize model well, avoid the risk of over-fitting and reduces memory overheated. We used a balanced data set during training process by introducing a novel data scheme, which improves the performance of our model.

Our model represents a true alternative to conventional methods; it can also be used to improve the results of classifying different types of arrhythmia. Also, it performed beat classification, which can act a basis to classify different arrhythmia types by taking threshold of beats types. In addition, we can use our 1D-CNN model as a base estimator in an ensemble model for classifying different types of arrhythmias.

Multi-Knowledge Electronic Comprehensive Journal For Education And Science Publications ( MECSJ )
Issues (60) 2022
ISSN: 2616-9185
www.mecsj.com

## 7. Conclusion

We have performed normal and abnormal beats classification problem and achieved a competitive classification performance comparing to other related works. As far as we know, we Did not find research depends on 1D- CNN to classify normal and abnormal beats, also most of deep learning-based methods classify normal beat and a single type of arrhythmia such as atrial fibrillation.

The main benefits of our proposed model for two arrhythmia types are:

1. Fully automatic model that act an end-to-end model.

2. Classified normal beats and abnormal beats, where abnormal beats set contains a variety of beats that is similar to normal rhythm such as atrial fibrillation beat, left bundle branch block and right bundle branch block. Achieved competitive performance measures in terms of accuracy, sensitivity and specificity when compared to related works.

3. It represents a true alternative to conventional methods. The proposed model can also be used to improve the results of classifying different types of arrhythmia.

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