Cardiac Arrhythmia Detection from 2D ECG Images by Using Deep Learning Technique

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***Abstract*—Arrhythmia is irregular changes of normal heart rhythm and effective manual identifying of them require a lot of time and depends on experience of clinicians. This paper proposes deep learning-based novel 2-D convolutional neural network (CNN) approach for accurate classification of five different arrhythmia types. The performance of the proposed architecture is tested on Electrocardiogram (ECG) signals that are taken from MIT-BIH arrhythmia benchmark database. ECG signals was segmented into heartbeats and each of the heartbeats was converted into 2-D grayscale images as an input data for CNN structure. The accuracy of the proposed architecture was found as 97.42% on the training results revealed that the proposed 2-D CNN architecture with transformed 2-D ECG images can achieve highest accuracy without any preprocessing and feature extraction and feature selection stages for ECG signals.**

***Keywords*—Arrhythmia Detection; Convolutional Neural Networks; Deep Learning; ECG Images; Electrocardiogram.**

I. Introduction

Nowadays, arrhythmia-based cardiovascular diseases are main cause of sudden death and heart failure. ECG is a tool that records the electrical activity of myocardium when state of contraction and relaxation. Heartbeat includes the P wave that represented atrial depolarization, QRS wave that represented the ventricular depolarization and T wave that represented the ventricular repolarization in the heart [1]. Arrhythmia is known as abnormal heart rhythm which can be form of irregular heart rhythm or not normal wave morphology [2]. ECG arrhythmia classification means that identification of normal and abnormal (arrhythmic) heartbeats based on heartbeat morphology of ECG signal. In ECG diagnosis, normal state and abnormal state classification of heartbeats plays vital role in medicine. Analyzing duration and identification of heartbeats depends on the clinician experiences which can block the earlier and accurate detection [3]. As a solution, automatic cardiac rhythm detection algorithms and new approaches can be proposed for efficient performances [4, 5].

Current studies mainly focus on the machine learning algorithms and novel approaches deep learning for effective detection of arrhythmic heartbeats. In last decades, machine learning-based ECG signal classification approaches achieve favorable results. Two main topics that affects the success of the these approaches i.e., selection of feature extraction techniques and types of classification algorithms [6].

Ye et al. [7] applied Wavelet transform (WT) and Independent component analysis (ICA) with Support Vector Machine (SVM) for arrhythmia detection which is achieved accuracy of 99.66% on MIT-BIH database.

In recent years deep learning based ECG arrhythmia classification approaches have been proposed due to the novel advances in these studies. Deep learning-based approaches no need to feature extraction step in contrast existing pattern recognition studies [8]. The recent findings show that deep neural networks (DNNs) extract representative features directly from input data and classify them with the aid of hidden layers (convolutional and max-pooling layers). DNNs, convolutional neural networks (CNNs), recurrent neural networks (RNNs) long short-term memory (LSTM) and combinations of these networks and pattern recognition algorithms were used as deep learning approaches on ECG arrhythmic heartbeat classification. DNNs models are sent to ECG signals as 1D data form of features. Yıldırım et al. [9] proposed deep bidirectional LSTMs network-based approach with wavelet-based layers that obtained the frequency sub-bands of ECG signals which is achieved 99.39% for five different arrhythmia classification on MIT-BIH database.

Yao et al. [10] introduced attention-based time-incremental convolutional neural network (ATI-CNN) that preserve both spatial and temporal information of ECG signals with classification accuracy of 81.2% on classification of paroxysmal arrhythmias. Another study [11] proposed that combining of topological data analysis, features and deep learning approach which is achieved 99.00% on MIT-BIH arrhythmia benchmark database. Rahhal et al. [12] proposed a novel approach based on DNNs with using stacked denoising autoencoders (SDA) for ECG signal classification which is obtained high accuracy values on three different databases. Hannun et al. [13] developed a deep neural network (DNN) to arrhythmia detection with accuracy of 83.7%.

CNNs used the data in the form of 1D combinations of features, and 2-D, 3-D images that represented the attributes of the ECG signal. Kiranyaz et al. [14] introduced 1-D CNN model with hand-crafted manual features which is performed high accuracy values on MIT-BIH arrhythmia database. Yıldırım et al. [15] proposed new 1-D CNN architecture for arrhythmia classification with accuracy of 91.33% on MIT-BIH database.

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The studies show that 2-D CNNs which is image-based ECG signal classification structure achieves better performances than 1-D CNNs [16, 17]. Jun et al. [18] proposed deep 2-D CNNs-based ECG arrhythmia classification model with using 2-D grayscale images that are obtained from each ECG beat which is achieved accuracy of 99.05% on MIT-BIH database. He et al. [19] proposed the time-frequency representation of ECG signals by continuous wavelet transform (CWT) as an input data for 2-D CNNs which is achieved accuracy of 99.23% for atrial fibrillation arrhythmia classification on the MIT-BIH database. Huang et al. [17] proposed 2-D deep CNN-based five different arrhythmias classification with using time-frequency spectrograms of heartbeats by short-time Fourier transform which is classified arrhythmias with accuracy of 99.00% on MIT-BIH database. Li et al. [20] used CNN with three different types (Morlet wavelet, Paul wavelet, Gaussian Derivative) of wavelet transform and 2-D time-frequency images were given as input data to classification architecture which is achieved accuracy of 97.96% on MIT-BIH database, 97.36% on American Heart Association (AHA) database respectively.

This paper proposes a deep learning based new method for detection of five different ECG arrhythmia types. 2-D CNN approach tested on ECG signals that were obtained from MIT-BIH database. ECG signals are transformed to ECG beats with segmentation processing. After segmentation, each beat of 1-D ECG signals converted into 2-D grayscale images as an input data on proposed CNN structure. The architecture of proposed model is mimicking the LeNet CNN structure for classification of different arrhythmia types. The results revealed that, this model has achieved high performance measurements for classification of five different types of arrhythmic heartbeats.

II. METHODOLOGY

Extracting ECG beats from the signal is important to identify arrhythmia type of the signal. In order to separate ECG signals into their heartbeats, heartbeat segmentation was applied to the signal. This study is aimed to find accurate arrhythmia detection algorithm based on heartbeat images and deep learning technique. For transforming each beat into 2-D images, image transformation was applied to the signal. After image transformation, 2-D CNN architecture was applied to the images and finally performance measures were evaluated.

A. Database and Segmentation

ECG signals were taken from MIT-BIH arrhythmia database [21]. The database contains different beat types which are obtained from 48 records of 47 volunteers. Each record has 30 minutes duration, 360 Hz sampling rate and bandpass filtered at 0.1– 100 Hz. The records consist of two channel which are modified limb II and one of the modified leads V1, V2, V4 or V5. Modified limb II was selected in this work [22]. All heartbeats of a record were annotated according to their arrhythmia types by independent experts. Advancement of Medical Instrumentation (AAMI) recommends that each heartbeat can be categorized five different types which are non-ectopic beats (N), ventricular ectopic beats (V), fusion (F) beats), supraventricular ectopic beats (S) and unclassifiable beats (Q) [23]. The categorization is demonstrated in Table I. AAMI standards was considered and five arrhythmia types were used in this study. Total number of beats for each arrhythmia types are also shown in Table I. for this study. Each ECG record was segmented into its heartbeats. *WFDB* Toolbox [24] was used to segment heartbeats from the signal. This tool extracts annotated beats by finding QRS structure of beats on the signal. An annotated beat example was shown in Fig. 1.

TABLE I. MAPPING OF MIT-BIH DATABASE TO AAMI ARRHYTHMIA TYPES

AAMI Arrhythmia Type	**MIT-BIH Heartbeat Classes**	**Beat Count**
Non-Ectopic Beats (N)	Normal Beat Left Bundle Branch Block Beat Right Bundle Branch Block Beat Nodal (Junctional) Escape Beat Atrial Escape Beat	8965
Supraventricular Ectopic Beats (S)	Aberrated Atrial Premature Beat Premature or Ectopic Supraventricular Beat Atrial Premature Contraction Nodal (Junctional) Premature Beat	2779
Ventricular Ectopic Beats (V)	Ventricular flutter Wave Ventricular Escape Beat Premature Ventricular Contraction	7236
Fusion Beats (F)	Fusion of Ventricular and Normal Beat	803
Unknown Beats (Q)	Paced Beat Unclassifiable Beat Fusion of Paced and Normal Beat	8006

B. Image Formation

Despite traditional methods, ECG signals were examined with 2-D image formation in this study. After beat segmentation, each heartbeat was converted into 2-D images. Through this conversion, filtering and feature extraction parts were eliminated. Each image was also transformed 128×128 grayscale images due to eliminate *RGB* color effects. Color is not important for differentiate arrhythmia types from the images in this study. Grayscale formation decreases image dimension and this transformation provides easily analyzing of them. 2-D ECG beat images were directly used as an input in deep learning architecture without any preprocessing on the images.

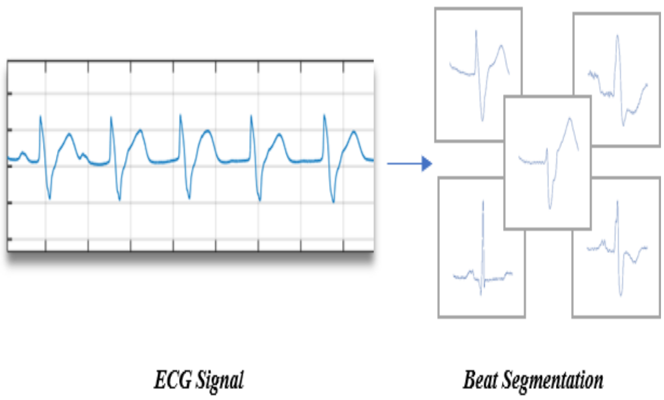

Fig 1. Part of an ECG signal and arrhythmic beat segmentation examples.

C. *CNN Architecture*

Deep learning is a part of artificial neural network structure that has differences from conventional machine learning techniques [25]. It includes more than three layers which has many hidden layers. CNN architecture was used in this study which is one of the popular deep learning architectures. It was selected due to success of 2-D data classification [26]. 2-D ECG images directly used as an input that no need removing noise or extracting features. Proposed CNN architecture includes two convolution layer, two pooling layer and a fully connected layer. Max pooling was used in pooling layer. For activation function, rectified linear units (ReLU) was implemented before pooling layers. Convolution and pooling layers represent feature extraction step and fully connected layers represents classification steps. Pooling layer provides to reduce dimension of input samples with protect effective features [27]. After the fully connected layer, softmax function was applied and categorized output neurons to each arrhythmia types which are N, S, V, F, and Q.

Standard back propagation with a batch size of 64 and learning rate of 0,001 was applied in training stage. 150 epochs were found optimal epoch number after many trying. After finish training stage, the model was tested to find accuracy of experiment. All data was divided two parts for training and testing stage. 80% of data was used for training and 20% was used for testing stage.

III. Results

2-D CNN model was used for differentiate five different arrhythmia types. ECG signals were converted image formation after separating their ECG beats. For training and testing phases of CNN model *Keras* and *TensorFlow* libraries were implemented to the model. All experiments were carried out with Intel I7 8300 CPU. Different epoch numbers and batch sizes were tried to find highest accuracy in this model. 150 epochs and 64 batch sizes gave highest accuracy for proposed model. Accuracy was calculated 97.42% with this epoch and batch sizes. Through this, the study showed great success to differentiate five different arrhythmia types.

In training phase, beat images were separated training and validation parts as 80% of data were selected for training and 20% of data were selected for testing. At the end of the model, training loss was calculated 0.073, training accuracy 97.42%, validation loss 0.08 and validation accuracy 97.25% as demonstrated in Fig. 2.

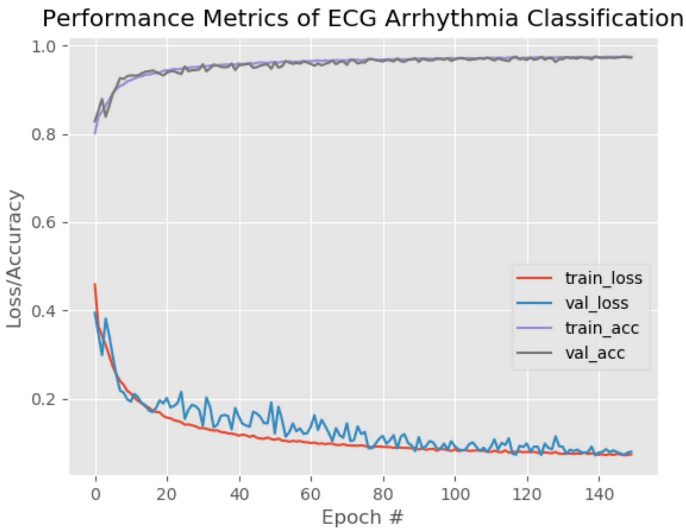

Fig. 2. Performance metrics of proposed architecture.

Fig. 3. shows confusion matrix of the model. According this, dark color represents correct classification of the arrhythmia type. Fig. 2. and Fig. 3. demonstrate that the model is appropriated for differentiate arrhythmia type of an ECG signal.

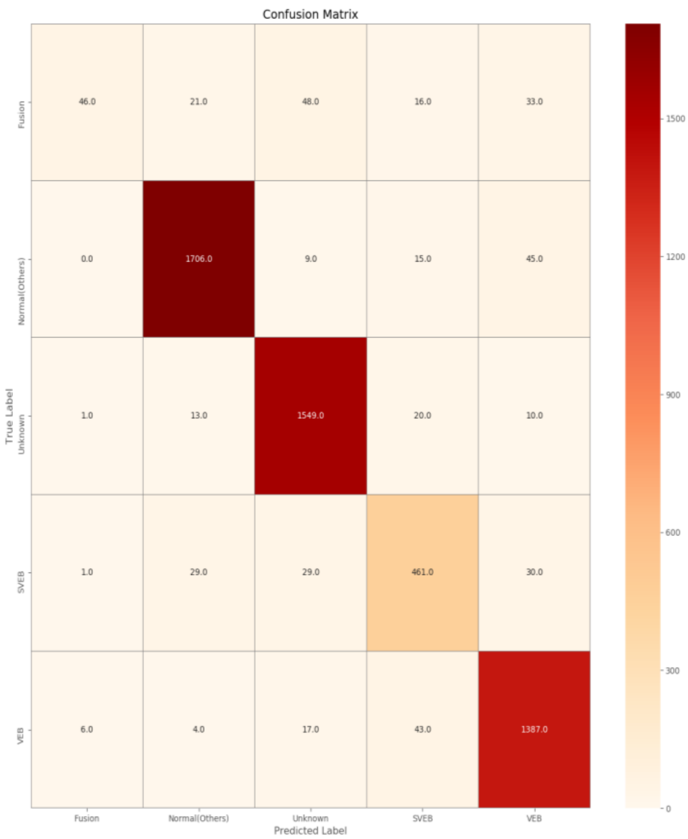

Fig. 3. Confusion matrix of propoesed architecture.

IV. CONCLUSION

In this paper, have been presented a novel approach for classification of 5 different arrhythmia types using deep learning technique. Unlike traditional methods which is used 1D ECG signal input to neural networks, we have been used 2D ECG images as input data. Therefore, there is no need to apply pre-signal processing methods to the input data. Furthermore, the effect of the noise in the signal is minimized. In addition, the obtained ECG images are sent to the networks in a single-color depth, thus, avoiding complex network structures. The deep learning results show that proposed CNN architecture accurate for classification these arrhythmia types.

In addition to all of these results, in this study, the effect of the number distribution in the input data on the success of the deep learning model was observed. As far as the arrhythmia database allows, detection of Fusion arrhythmia, which has fewer beats than the other arrhythmia types that are attempted to be kept equal, has a lower success rate than other arrhythmia types detection. Therefore, when creating a deep learning model, it is recommended to keep the number of data allocated to classes equal.

A deep learning model which is obtaining in this study, with has high success rate and rapid querying can help in the diagnosis of arrhythmia. In addition, this developed deep learning model can quickly and accurately query for real-time arrhythmia diagnosis. In future studies, the deep learning model can be expanded by increasing the types and numbers of arrhythmias.

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