CLASSICATIONOFARRYTHMIABYUSINGDEEPLEARNING WITH 2-D ECG SPECTRAL IMAGEREPRESENTATION

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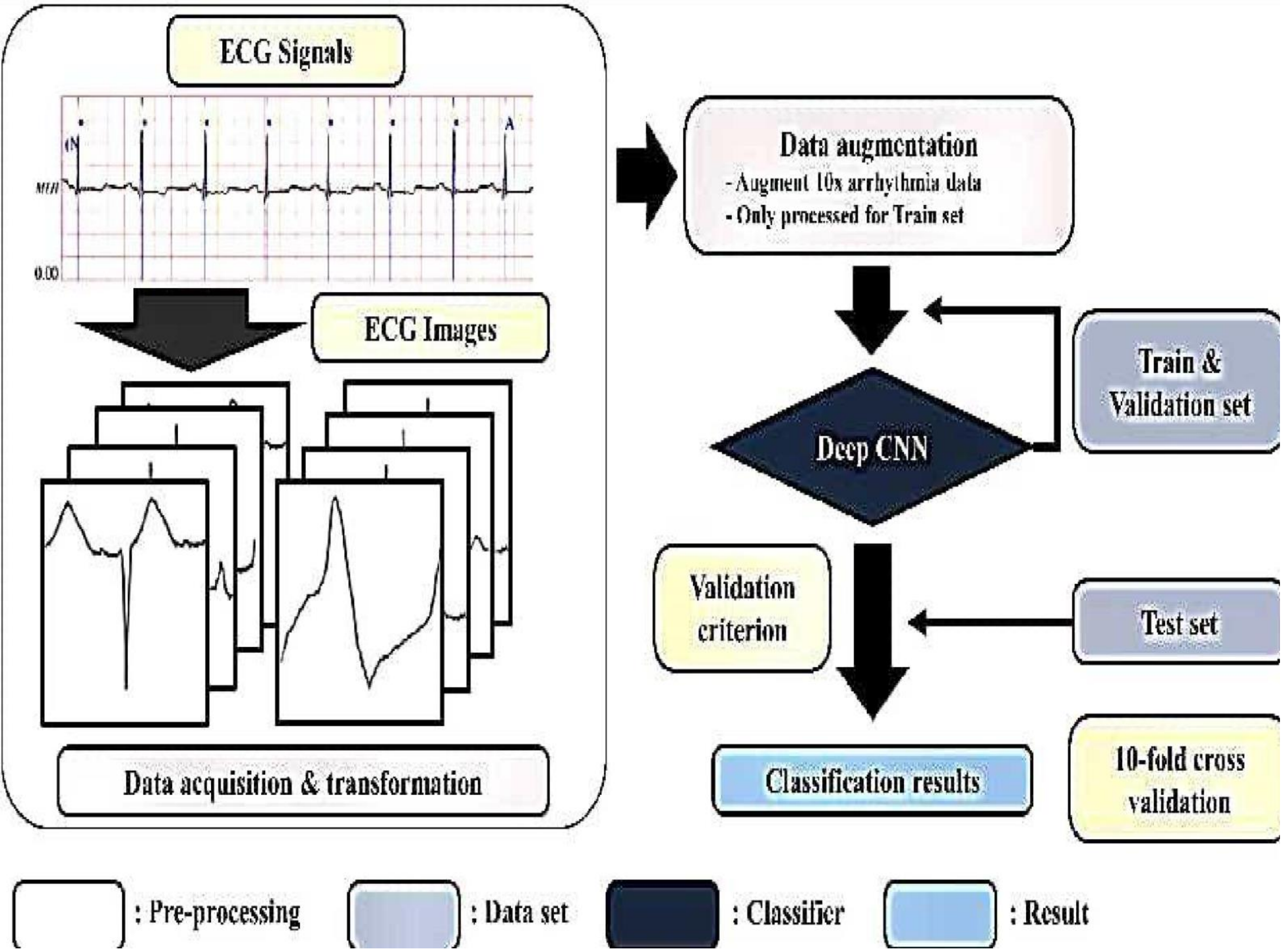

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The studies show that 2-D CNNs which is image-based ECG signal classification structure achieves better performances than 1-D CNNs [16, 17]. Jun et al. [18] proposed deep 2-D CNNs-based ECG arrhythmia classification model with using 2-D grayscale images 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.

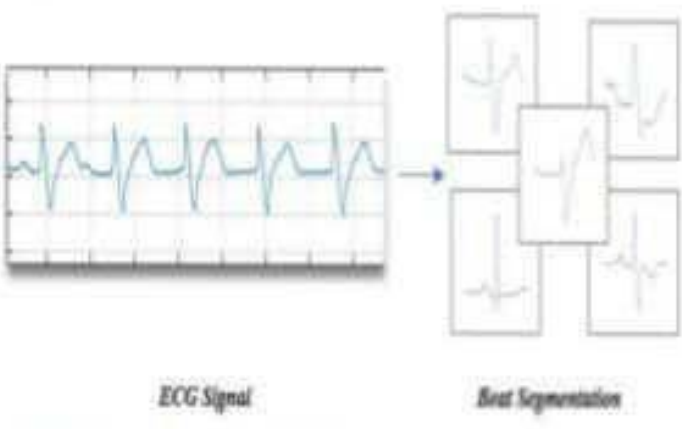

Fig 1. Part of an ECG signal and arrhythmic beat segmentation examples.