**Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation**

#### **Introduction**

Cardiac disorder may cause a severe warning to public health, and in most cases, some arrhythmias can cause severe damage or death. According to the data provided by World Health Organization (WHO) [1], approximately 25.6 million people died due to cardiovascular disease in 2020. Electrocardiogram (ECG) test is used as a diagnostic tool in healthcare institutes. The electrodes attached to the patients’ body surface can record the heart’s electrical signal over time. Figure [1](https://www.hindawi.com/journals/complexity/2021/9919588/fig1/) shows the ECG leads attached to the human’s body surface to get the heart’s electrical signals.

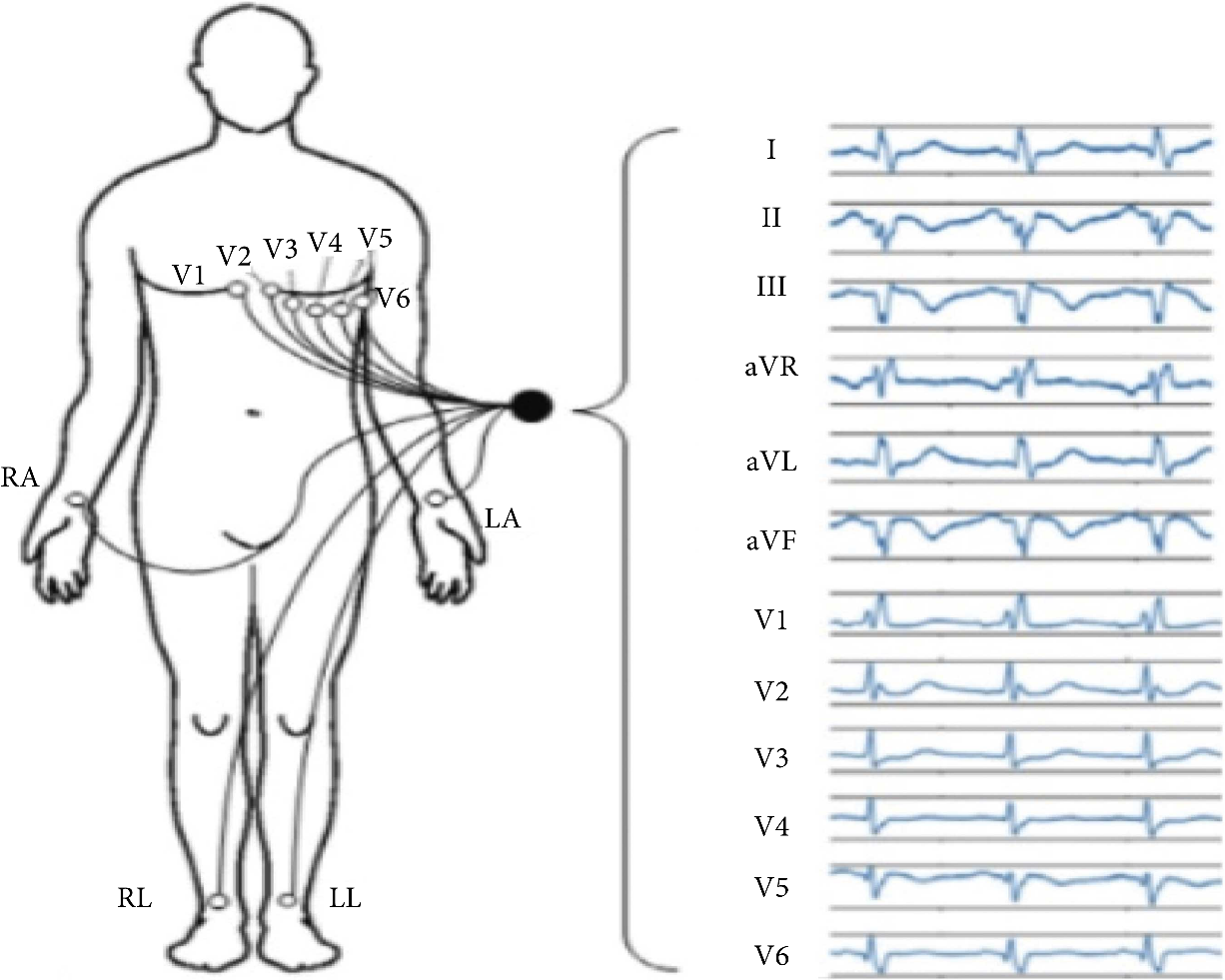


Fig.1.1

The healthcare professionals manually diagnose the patient heart condition by interpreting the ECG image. In the advent of technology, several automatic diagnostic tools are developed for arrhythmias classification and detection to assist doctors. PCGs and ECGs are used to diagnose arrhythmia classification. PCG (also known as heart sound auscultation) is commonly listened to or recorded by practitioners through a stethoscope to identify heart irregularities.

For this reason, heartbeats have been critically studied to make a diagnosis [2–5]. Khan et al. [6] provided a very thorough introduction of related studies in the problem domain and proposed a technique based on DNN, for the classification of three kinds of arrhythmia beats. CNN is considered a state-of-the-art tool for the classification of arrhythmia, and it has been studied with several variations such as 1-dimensional, 2-dimensional, or the combination of both [7, 8]. According to Xiao et al. [7], a novel arrhythmia classification technique comprises three phases: preprocessing, 1-dimensional CNN architecture based on clique blocks with bidirectional connections between layers and transition blocks with attention mechanism, and majority voting to predict the final result. Experiments were performed on PhysioNet/CinC 2016 database.

However, low-frequency noise considerations recorded in arrhythmia beats are ignored, and 2-dimensional acoustical representation requires additional computation, which cannot be accomplished without hyperparameters. Similarly, Noman et al. [8] proposed a framework based on 1-dimensional CNN for direct feature learning from raw arrhythmia beats and 2-dimensional CNN, which takes 2-dimensional time-frequency feature maps.

In the state-of-the-art studies [4–8], automated system which predicts high accuracy results is developed for arrhythmia detection but still not adoptable by healthcare professionals.

The primary concerns which affect the success of the developed arrhythmia detection systems are (i) manual features selection, (ii) techniques used for features extraction, and (iii) algorithm used for classification and the most important is the use of imbalanced data for classification. The automated arrhythmia detection required the feature extraction of ECG images that required domain knowledge.

In the last few years, deep learning-based systems are being recognized as a tool in healthcare institutes that have capabilities to automatically extract high-level abstract features, avoiding laborious manual feature design. A deep neural network is configured in the same fashion as the human brain works. A single neuron understands and recognizes the pattern based on the logical principles among different components. The proposed work’s major concern is to review the recent trends of arrhythmia classification techniques and enlist the limitation and future requirements. This study can help the researcher get a deeper understanding of arrhythmia classification and the deep learning methods used to develop automated systems.

The reminder of the paper is organized into six sections. The methods used in the proposed study are discussed in Section [2](https://www.hindawi.com/journals/complexity/2021/9919588/#sec2), and the research community’s related work in the current field is presented in Section [3](https://www.hindawi.com/journals/complexity/2021/9919588/#sec3) with a close comparison. Recent trends of arrhythmia classification and limitation of the current study are discussed in Sections [4](https://www.hindawi.com/journals/complexity/2021/9919588/#sec4) and [5](https://www.hindawi.com/journals/complexity/2021/9919588/#sec5), respectively. The paper is concluded in Section [6](https://www.hindawi.com/journals/complexity/2021/9919588/#sec6).

1. **Literature survey**

Based on the selection criteria, the fifty technical articles on arrhythmia classification are examined which are published between January 2010 to January 2020. The selected articles are critically examined, and if any selected articles are available on more than one scientific repository or database, it is considered only once.

The different kinds of methodologies, classification algorithms with their accuracy results, and optimization methods used for arrhythmia classification are reviewed from the selected articles. Table [2](https://www.hindawi.com/journals/complexity/2021/9919588/tab2/) shows the literature survey on arrhythmia classification techniques that are used in this study.

The authors present the recent trends for arrhythmia classification, the techniques used for features extraction, and the variation of deep neural networks. The study is beneficial for the scientific community to select the arrhythmia classification techniques as per their desires. Table [3](https://www.hindawi.com/journals/complexity/2021/9919588/tab3/) identified the latest trends from recently proposed studies for arrhythmia classification.

**3.Recent Trends in Arrhythmia Classification**

The primary objective of this study is to present the techniques used in arrhythmia classification with a publicly available ECG database used in deep/machine learning algorithms. The selected state-of-the-art research studies show the most common methods used for arrhythmia classification and their accuracy results. The accuracy results represent the learning algorithm’s success rate that how well the machine was trained to identify the ground truth automatically.

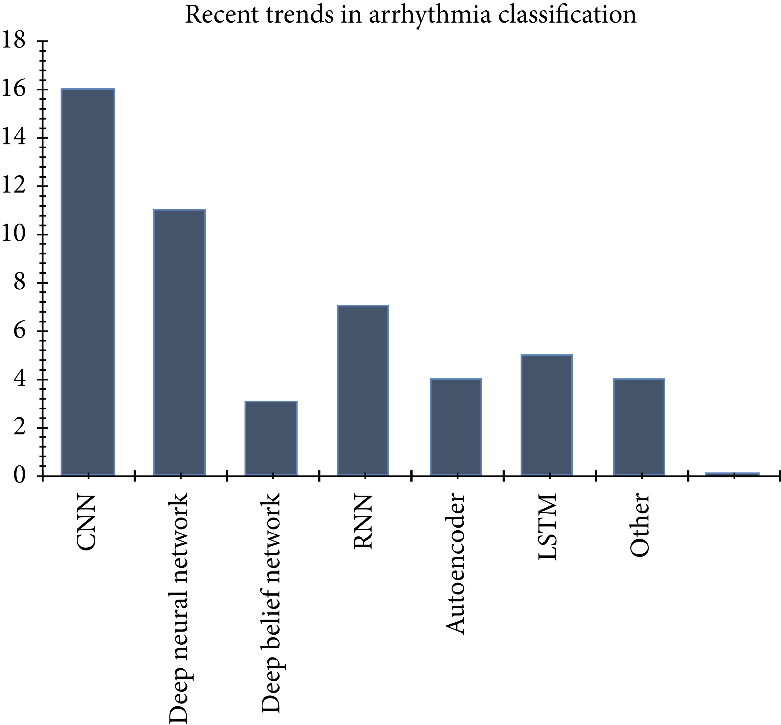


Fig.3.1

The primary objective of this study is to help the scientific community to list the methodologies used in arrhythmia classification with prediction results that researchers can easily select the techniques as per their requirements. Figure [3](https://www.hindawi.com/journals/complexity/2021/9919588/fig3/) shows the statistics of most adopted arrhythmia classification techniques used in selected studies.

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