Chapter 16 Machine Learning-Based Arrhythmia Classification: A Comprehensive Review

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ABSTRACT

The rising numbers of cardiovascular diseases (CVDs) have become a major health concern. Arrhythmia is a most deadly heart condition in all cardiovascular diseases. Thus, prompt and accurate diagnosis of patients with arrhythmia is important in preventing heart disease and sudden cardiac death. Arrhythmia can be detected by the presence on electrocardiogram (ECG) of an irregular heart electrical activity. The heart's electrical activity is recorded as an ECG signal which contains physiological and pathological information. Classification of the ECG signals is very important to automatically diagnose heart disease. This chapter addresses the various types of learning methods for automatically classifying different types of heart beats. Reported studies demonstrate that the convolutional neural network (CNN) model is supremely suggested for the classification of arrhythmia. The best classification accuracy of 99.88% is achieved by an ensemble of depthwise separable convolutional (DSC) neural networks.

INTRODUCTION

Out of all the causes of death cardiovascular illnesses are prominent ones in humans. The mortality rate of cardiovascular disease (CVD) is at the highest of all death cases today according to the latest World Health Organization (WHO) data. CVDs are responsible for the death of 17.7 million individuals, ac-

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counting for almost 31% of all deaths. Out of these deaths, more than seventy-five percent of these deaths took place in developing countries. High blood pressure, smoking, dyslipidemia, insufficient physical activity, being overweight and unreasonable dietary structure are all common causes of cardiovascular diseases. CVDs also rise in mortality and pervasiveness. Arrhythmia is the most deadly cardiac disease in all cardiovascular diseases (Huang et al., 2019; Zhu et al., 2019).

Abnormal cardiac electrical activity is commonly referred to as Arrhythmia, and is characterized by a fast, sluggish, and irregular heartbeat. Generally, Arrhythmias are two types, one of the arrhythmias is life-threatening like ventricular fibrillation and the other is non-life-threatening like tachycardia. Life-threatening arrhythmias can cause a hemodynamic collapse in the heart, stroke, sudden death and cardiac arrest (Xia et al., 2019). In these conditions, patients need emergency care. Although non-life-threatening arrhythmias do not cause heart failure, prompt treatment is still necessary to prevent further cardiac function deterioration (Zhang et al., 2014). Therefore, to manage and prevent cardiovascular diseases, regular monitoring of the heart's electrical activity becomes a necessary and important issue (Huang et al., 2019).

The heart's electrical activity is reflected in the ECG signal, which carries physiological and pathological information. Prediction of CVDs becomes easier with help of ECG abnormalities in both young and old people (Xia et al., 2018).Thus, an ECG is considered the most effective diagnostic tool to recognize various types of arrhythmias or heart abnormalities. The Association for the Advancement of Medical Instrumentation (AAMI) differentiates the different types of arrhythmias and regulates five types of heartbeat: normal (N), supraventricular (S), ventricular (V), a fusion of normal and ventricular (F), and unknown heartbeat (Q) (Xia et al., 2019). The ECG primarily includes atrial and ventricular depolarization and repolarization. Therefore, ventricular arrhythmias and atrial arrhythmias are known as two primary types of arrhythmias. However, human recognition and diagnosis of arrhythmias is always imprecise and time-consuming. Automatic algorithms supported by computers are therefore highly successful for the diagnosis (Zhu et al., 2019).

The algorithms used for ECG Arrhythmia classification are composed of these common stages: Pre-Processing, Heartbeat Segmentation, Feature Extraction, and Classification. Figure 1 shows common stages of ECG arrhythmia classification. In the first stage, ECG signal denoising is performed where it removes the noises like baseline wandering, and power line interference. Heartbeat segmentation is used to split each P-QRS-T segment from the ECG waveform. In the next stage, features of ECG waveform such as heartbeat interval, amplitude, and duration are extracted for further analysis. Finally, according to AAMI heartbeats are classified into various types (Zhu et al., 2019).

Figure 1. Common stages of ECG arrhythmia classification



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