Project Objective

Abstract:The electrocardiogram (ECG) is one of the most extensively employed signals used in thediagnosis and prediction of cardiovascular diseases (CVDs). The ECG signals can capture the heart'srhythmic irregularities, commonly known as arrhythmias. A careful study of ECG signals is crucialfor precise diagnoses of patients' acute and chronic heart conditions. In this study, we propose atwo-dimensional (2-D) convolutional neural network (CNN) model for the classification of ECGsignals into eight classes; namely, normal beat, premature ventricular contraction beat, paced beat,right bundle branch block beat, left bundle branch block beat, atrial premature contraction beat,ventricular flutter wave beat, and ventricular escape beat. The one-dimensional ECG time seriessignals are transformed into 2-D spectrograms through short-time Fourier transform. The 2-D CNNmodel consisting of four convolutional layers and four pooling layers is designed for extractingrobust features from the input spectrograms. Our proposed methodology is evaluated on a publiclyavailable MIT-BIH arrhythmia dataset. We achieved a state-of-the-art average classification accuracyof 99.11%, which is better than those of recently reported results in classifying similar types ofarrhythmias. The performance is significant in other indices as well, including sensitivity andspecificity, which indicates the success of the proposed method.Keywords: ECG signal; classification; arrhythmia; convolution neural network; deep learning1. IntroductionCardiovascular diseases (CVDs) are the leading cause of human death, with over 17 millionpeople known to lose their lives annually due to CVDs [1]. According to the World Heart Federation,three-fourths of the total CVD deaths are among the middle and low-income segments of the society [2].A classification model to identify CVDs at their early stage could effectively reduce the mortalityrate by providing a timely treatment [3]. One of the common sources of CVDs is cardiac arrhythmia,where heartbeats are known to deviate from their regular beating pattern. A normal heartbeatvaries with age, body size, activity, and emotions. In cases where the heartbeat feels too fast orslow, the condition is known as palpitations. An arrhythmia does not necessarily mean that theheart is beating too fast or slow, it indicates that the heart is following an irregular beating pattern.It could mean that the heart is beating too fast—tachycardia (more than 100 beats per minute (bpm)),Remote Sens. 2020,12, 1685; doi:10.3390/rs12101685 www.mdpi.com/journal/remotesensing

or slow—bradycardia (less than 60 bpm), skipping a beat, or in extreme cases, cardiac arrest. Some othercommon types of abnormal heart rhythms include atrial fibrillation, atrial flutter, and ventricularfibrillation. These deviations could be classified into various subclasses and represent different types ofcardiac arrhythmia. An accurate classification of these types could help in diagnosing and treatment ofheart disease patients. Arrhythmia could either mean a slow or fast beating of heart, or patterns that arenot attributed to a normal heartbeat. An automated detection of such patterns is of great significancein clinical practice. There are certain known characteristics of cardiac arrhythmia, where the detectionrequires expert clinical knowledge.The electrocardiogram (ECG) recordings are widely used for diagnosing and predicting cardiacarrhythmia for diagnosing heart diseases. Towards this end, clinical experts might need to look at ECGrecordings over a longer period of time for detecting cardiac arrhythmia. The ECG is a one-dimensional(1-D) signal representing a time series, which can be analyzed using machine learning techniques forautomated detection of certain abnormalities. Recently, deep learning techniques have been developed,which provide significant performance in radiological image analysis [4,5]. Convolutional neuralnetworks (CNNs) have recently been shown to work for multi-dimensional (1-D, 2-D, and in certaincases, 3-D) inputs but were initially developed for problems dealing with images represented astwo-dimensional inputs [6]. For time series data, 1-D CNNs are proposed but are less versatile whencompared to 2-D CNNs. Hence, representing the time series data in a 2-D format could benefit certainmachine learning tasks [7,8]. Hence, for ECG signals, a 2-D transformation has to be applied to makethe time series suitable for deep learning methods that require 2-D images as input. The short-timeFourier transform (STFT) can convert a 1-D signal into a 2-D spectrogram and encapsulate the time andfrequency information within a single matrix. The 2-D spectrogram is similar to hyper-spectral andmulti-spectral images (MSI), which have diverse applications in remote sensing and clinical diagnosis,including spectral un-mixing, ground cover classification and matching, mineral exploration, medicalimage classification, change detection, synthetic material identification, target detection, activityrecognition, and surveillance [9–15]. The 2-D matrix of spectrogram coefficients could be useful forextracting robust features for representation of a cardiac ECG signal [16]. This representation couldallow the application of CNN architectures (designed to operate on 2-D inputs) for development ofautomated systems related to CVDs.