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ECG Arrhythmia Classification Using Faster R-CNN

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Abstract:- Electrocardiogram (ECG) demonstrates the electrical activities in the heart, and is the most important physiological parameter that gives the proper analysis regarding the functioning of the heart. In this work, an automatic and powerful deep feature learning process is used. By using it a convolution neural network (CNN) is exert to study pristine features from the raw ECG data to achieve disease identification without any complex feature engineering process. An Electrocardiogram (ECG) is the primary diagnostic tool for recording and interpreting ECG signals. These signals holds details regarding different kinds of arrhythmias, ECG signals are complex and non-linear in nature so that it is tough to analyse these signals manually. Furthermore, the exposition of ECG signals is subjective and may vary from expert to expert. Therefore, a computer aided diagnosis (CAD) system has been proposed, which guarantees that the evaluation of ECG signals is objective and reliable. In proposed system, a convolution neural network (CNN) technology is used to automatically detect different ECG segments. An efficient electrocardiogram (ECG) arrhythmia classification technique with deep 11 layer convolution neural network (CNN) is used in this system. In which every ECG signal will transform into a 2D gray-scale image as an input to the CNN classifier. Batch normalization, Xavier initialization, data augmentation and dropout are different deep learning techniques which are used for CNN optimization.

Keywords: Arrhythmia, Atrial fibrillation, Atrial flutter, Convolution neural network, Deep Learning, Electrocardiogram signals, Ventricular fibrillation.

1. INTRODUCTION

The heart diseases are the common reason for the human death. Every year, around 7.4 million demises are due to heart diseases out of which, 52% of demises due to strokes and 47% demises due to coronary heart diseases. So, it is necessary to identify different heart disease at an initial stage to protect heart-related deaths [15].

Heart is the most crucial organ of human body. According to record of World Health Organization (WHO) cardiovascular disease (CVD) is the main disease [20]. In India among all the diseases, cardiovascular diseases are the main reason, which cause more people to die every year [17]. We know that heart attack occurs suddenly without any indication but the disturbances in heart activities may found before it. As we grow, the cardiovascular system weakens and become more subjective to disease [7].

An arrhythmia depicts an irregularity in heartbeat - the heart pulses may too slowly, too fast, or randomly. Arrhythmias occur once the electrical signals to heart that manage heart pulses are not operating properly. Sometimes, we observe random heart pulses, which may feel like a racing heart or fluttering. Several heart arrhythmias are not dangerous; but, if they're notably unusual, or occur from a weak or broken heart, arrhythmias will cause serious and even doubtless fatal symptoms. Heart pulse rate of healthy person lies between 60 to 100 bpm when resting. A healthy person can seldom suffer from long cardiopathy unless they have an external trigger, such as drug misuse or an electric shock. There are several types of arrhythmia from them Atrial fibrillation (Afib), Atrial flutter (Afl) and Ventricular fibrillation (Vfib) are the common occurring types of arrhythmia [6].

Here, we mainly concentrate the object-centred scenario. To enhance the nature of ROIs and recoup the picture without obscuring curios, we propose to encode the main regions alongside some background features, i.e., quantized shading histogram and nearby descriptors. With that, we always try to maintain visual quality of that object region. Then again, the bit-rate utilization can be additionally diminished with encoded quantized background features. In proposed methodology, we select a set of available images as prior and try to achieve background synthesis without semantic distortion.

Atrial fibrillation is a random and mostly fast heart pulses that can increase the risk of stroke, heart failure and other heart-related diseases. During this, the heart's two upper chambers known as the atria beats asynchronously with the two lower chambers known as the ventricles of the heart[1]. The symptoms of it usually involve heart vibrations, diminishing of breath and asthenia. It is common and mainly affects older patients. In atrial fibrillation heart may beat from 100 to 175 beats per minute. It includes an abnormal R-R interval, irregular and rapid ventricular contraction, and there is absence of P wave in the ECG signal [7].

A. Objectives

There are many objectives and applications of this technique in health care system.

1. To develop a technique for automatically detection of various ECG segments.
2. To speed up existing classification process by using Faster RCNN.
3. To test system performance on available datasets.

2. LITERATURE SURVEY

In traditional machine learning algorithm, there are only input, output and one hidden layer is used. But, in "Deep Learning" there are many hidden layers are present with the input and output [5]. Due to the use of various hidden layer it is able to recognize the more complex features. This feature of DNN enables it to manage big, high-dimensional data with a large number of features. The deep learning network ends with an output layer: a logistic or softmax classifier that sets a probability to a particular result or label [5]. Different methods for automatic recognition of ECG arrhythmia depending upon signal feature extraction have been recently proposed, such as Discrete wavelet transform (DWT) [12,13], support vector machine (SVM) [21,22], regression neural network (RNN) [14], feed forward neural network (FFN) [11], back propagation neural network (BPNN) [8], learning vector quantization (LVQ) [18,23]. When a number of data sets are available, the use of deep learning is good practice and usually exceeds the human protocol rate [11].

In 2016 I. S. Rao et al. proposed the system to improve the Performance Identification of different Heart Diseases which is based on neural network classification [6]. In some research, KNN is used for classification of heart beat into different type [17]. CNN is used for the automatic recognition of coronary artery disease, and it is found that CNN remains robust [1], although shift and scale invariance make it advantageous. In some research, the authors offer strong methods to recognize heart disease by using CNN and Multilayer Perceptron (MLP). CNN is used for distinguishing normal and abnormal heart beats recording with 82% accuracy which is credible for large datasets [9]. In paper [10] the deep learning methodology for single-image super-resolution (SR) with CNN method has been developed which gives the outstanding results than the state-of-the-art method. U. Rajendra Acharya et al. proposed the ECG based diseases diagnosis techniques without QRS recognition [1]. In that, Feature extraction, feature selection, and classification steps are merged in the CNN algorithm. He used ten-fold cross validation to evaluate performance of CNN.

In 2017 at PhysioBank competition, Fernando et al. introduced a new algorithm which gave 83% accuracy on test data. In that algorithm he used CNN for the classification of four types of arrhythmia from ECG recordings [2]. In same PhysioBank competition, Ghiasi et al. used the feature based algorithm with deep CNN to detect atrial fibrillation which results in 80% of accuracy on training datasets [3].

3. SYSTEM ARCHITECTURE

A. Problem Statement

To design and develop automatic and robust deep feature learning process using a Faster Regional Convolution Neural Network (R-CNN) and to learn inherent features from the raw ECG signal to perform disease detection without having any complex feature engineering process.

B. System Overview

Our CNN based ECG arrhythmia classification consists following steps: ECG data pre-processing, and the ECG arrhythmia classifier.

In proposed system, for training and testing of CNN model we are going to use the arrhythmia database. This model handles two-dimensional image as an input data. ECG signals are converted into ECG images for the ECG data pre-processing. In CNN classifier step the classification of ECG types are take place. Following Fig Shows overall working of propose architecture.

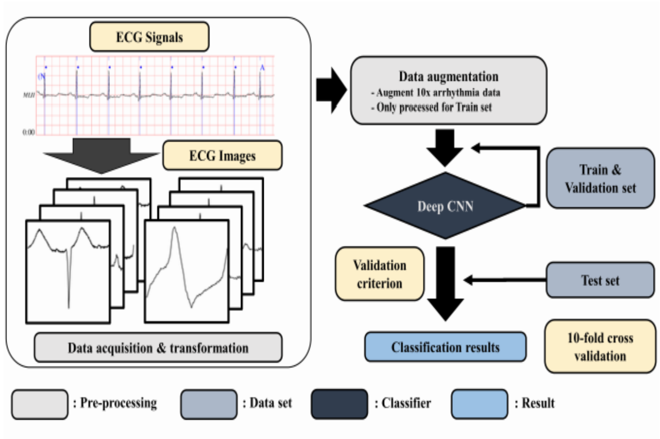

Fig. 1. System Architecture

- *ECG data pre-processing*

Image is the input data for Two-dimensional CNN. So that, we convert ECG signals into ECG images by plotting every ECG beat into individual 128 x 128 grayscale image.

- *ECG arrhythmia classifier*

We adopted CNN/FR as the ECG arrhythmia classifier. The previous feed-forward neural network was not appropriate for image classification since there is an exponential growth of numerous free parameters due to the unripe image is directly processed without considering the topology of the image. With the emergence of the CNN model, correlation of spatially adjacent pixels can be extracted by applying a nonlinear filter and by applying multiple filters, it is possible to extract various local features of the image. The reason we applied Faster RCNN is that we first convert the ECG signal into ECG image form. As a result, higher ECG arrhythmia classification accuracy can be obtained.

4. METHODOLOGY

A. Data flow

Proposed system includes following steps: ECG data pre-processing, and the ECG arrhythmia classifier. In this system, For training and testing of CNN model we used the MIT-BIH arrhythmia database. During ECG data pre-processing step, ECG signal is converted into 2D ECG image, and this image is used for classification of ECG types which is carried out in CNN classifier step. Following Fig Shows overall working of propose architecture.

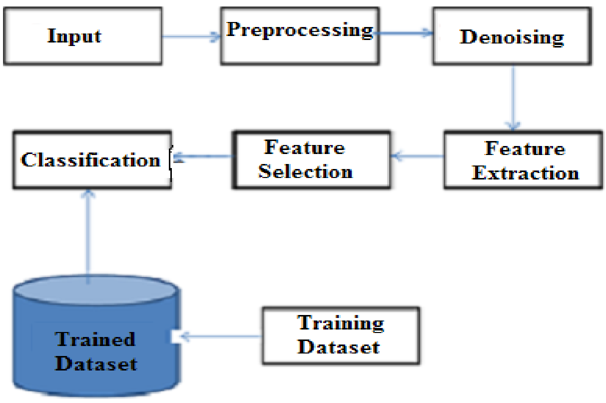

Fig. 2. Workflow of system

1. *Preprocessing:*

The raw ECG data sr(n) is separated to emphasize the QRS segment, which is distinguished by a excessive slope. The distinct cardiogram signal is acquired by creating subtraction between adjacent samples.

2. *DE noising:*

Because of preprocessing, signals are polished and made ready for actual processing. Removal of unwanted noise is one of the preprocessing units. The Power-line causes electromagnetic fields which are said to be common noise source for an ECG Signal. These are characterized by the sinusoidal interference of 50-60 Hz accompanied with a various harmonics.

3. *Segmentation:*

The ECG signals are fragmented and classified according to cardiac conditions of heart, and the prescribed annotations are retrieved from a public database. We classify the four types of ECG signals into net A and net B without any wave identification. Using Z-score normalization each segment is normalized to solve the issues of amplitude scaling. The offset effect is eliminated and then feed the ECG segment to the 1-dimensional deep learning CNN.

4. *Feature Extraction:*

In this process different features of an ECG signal are extracted. This process is followed by feature selection to select only important features for classification process. We did not follow the traditional process of automated CAD systems.

5. *Classification*:

Convolutional Neural Networks (CNNs) is advancement to neural networks in which convolutional layers replace with sub-sampling layers, redolent of simple and complicated cells in the human cortical area, that are frequently utilized for the purpose of "deep learning" like object recognition in large image archives during achieving the modern performances.

B. Algorithm

The algorithm used for proposed framework is Faster R-CNN. The main motivation behind use of this technique is that instead of running a CNN 2,000 times per image, we can run it just once per image and get all the regions of interest (regions containing some object).

Faster R-CNN mainly used for object detection instead of pattern matching. It is the updated version of Fast R-CNN. The fundamental distinction between both of them is that Fast RCNN uses selective search for generating different Regions of Interest, while Faster RCNN uses "Region Proposal Network" (RPN) to generate different Regions Of Interest. The input to RPN is image feature maps and output of it is a collection of object proposals with an object-ness score. Faster R-CNN has two networks:

1. Region Proposal Network (RPN) used for generating region proposals
2. Network which is used to detect object using above generated proposals.

Following Figure shows the structure of Faster R-CNN.

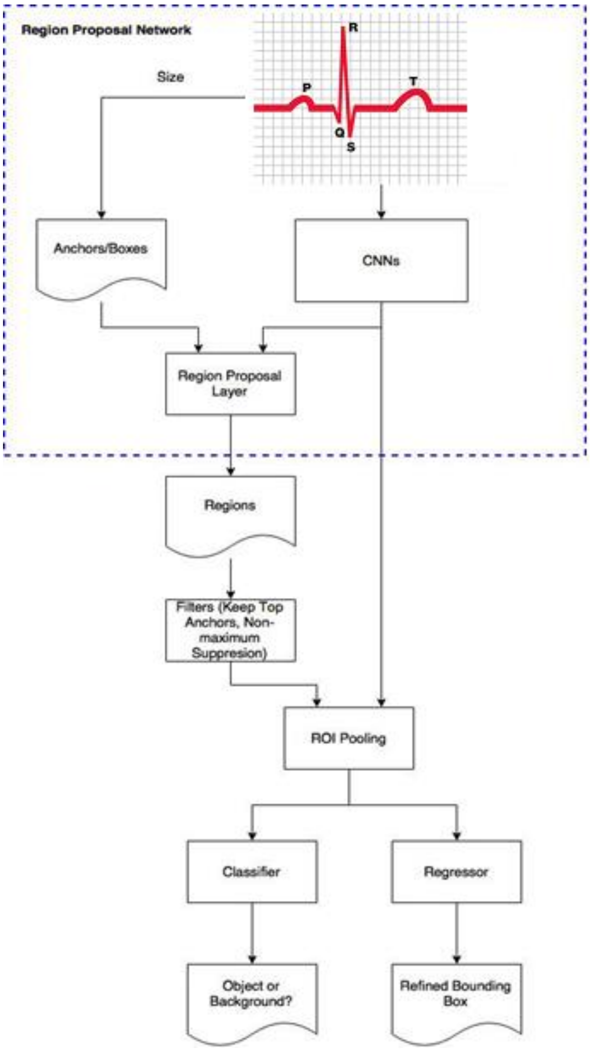

Fig. 3. Working of Faster R-CNN

1. Faster R-CNN Algorithm Steps:

1. Take the per-trained Convolution Neural Networks (CNN).
2. Retrained this model by training the last layer of the network based on the number of classes that need to be identified.
3. Pass input image to the retrained trained convolutional neural network. It will return the feature map for input image.
4. Apply the Region proposal network on these feature maps. This gives the object proposals with their score of object-ness.
5. Apply a RoI pooling layer on these proposals to make all the proposals to the equal size.
6. Finally, pass the proposals to a fully connected layer which has two layer one is softmax layer and other is linear regression layer at its top, to classify and output the bounding boxes for objects.

5. PROBLEM FORMULATION

A. Mathematical Model

Let the system be described by S,

S= {I, F, O}

Where,

I= I is the set of input to system, I= {I 1, I2 }

Input to system is the file containing ECG signal.

F= F is the set of different function that system will do, F= {F1 , F2 , F3 , F4,…Fn }

Following are the different functions that are used in system.

F1: Signal Processing.

F2: DE noising.

F3: Segmentation

F4: Feature Extraction.

F5: Feature Selection

F6: Classification

O=O is the set of output, O={O1, O2, O3,…On}

Output is the class of arrhythmia.

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