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Arrhythmia Recognition and Classification Using ECG Morphology and Segment Feature Analysis Using DCNN Classifier

Amirthavarshini A, Thulasi Mani J, Harishma S, Selvaraj M, Subetya M

B.E Student, Dept. of Electronics and Communication Engineering SRM Valliammai Engineering College Chennai-603 203, India
B.E Student, Dept. of Electronics and Communication Engineering SRM Valliammai Engineering College Chennai-603 203, India
B.E Student, Dept. of Electronics and Communication Engineering SRM Valliammai Engineering College Chennai-603 203, India
Assistant Professor, Dept. of Medical Electronics SRM Valliammai Engineering College Chennai-603 203, India
Student, Dept. of Electronics and Communication Engineering SRM Valliammai Engineering College Chennai-603 203, India

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ABSTRACT—Correct detection and classification of ventricular fibrillation (VF) and ventricular tachycardia (VT) is decisive for the success of defibrillation therapy in automatic external defibrillators and patient monitoring. A huge variety of algorithms have been proposed based on temporal, spectral, and time-frequency parameters extracted from the surface ECG signal by considering those parameters individually. A life-threatening arrhythmias detection algorithm combining 14 ECG parameters on a different domain using a machine learning algorithm has been used to improve detection efficiency and accuracy. The main objective of this project is to propose a Machine learning algorithm such as the Deep Convolution Neural Network (DCNN) algorithm along with feature selection techniques that are used to increase the accuracy in detecting and discriminating between regular and irregular heartbeat.

Keywords—ECG signal, classification, machine learning, DCNN, heart rate.

I. INTRODUCTION

The total number of cardiovascular diseases (CVD) increases tremendously, according to the 2014 China Cardiovascular Report, and the number of CVD in the next decennium is supposed to continue growing frequently. Currently, CVD is the major cause of the total death of Chinese residents: 44.8% in rural areas, and 41.9% in the city[1]. The common causes of CVD include smoking, high blood pressure, overweight, lack of physical activity, and irrational dietary structure. The growing number of CVD has become a crucial public health problem. In all CVD, arrhythmias are the most fatal cardiac diseases. Hence, diagnosis of arrhythmia patients timely and accurately is of great significance for the prevention of heart disease and sudden cardiac death. provided. The electrocardiogram (ECG) is used for recording electrical activity and describes the main direction of electrical impulses throughout the heart. Arrhythmia will appear with the existence of abnormal heart electrical activity on ECG. ECG mainly contains repolarization and depolarization of atrial and ventricular. So, two main types are identified atrial arrhythmias and ventricular arrhythmias. However, arrhythmias recognition and diagnosis by humans are time- consuming and always inaccurate. Therefore, an automatic computer-assisted algorithm is a high-efficient way to diagnose. Long-term monitoring is necessary for reporting acute arrhythmia and controlling chronic disease progressions, such as ventricular premature, atrial premature, and myocardial infractions. The appearance of some ectopic beats might provide

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indicators for the detection of chronic arrhythmia. Therefore, identifying abnormal cardiac beats from normal ECG data is an imperative task. In this work, we mainly concentrate on the recognition of chronic arrhythmia and the detection of ectopic beats.

II. IMAGE PROCESSING

Image processing is a form of signal processing in which the input is an image, maybe a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the input image. Most of the image-processing techniques involve treating the image as a dimensional signal and applying standard signal-processing techniques to it. Image processing normally refers to digital image processing in which optical and analog image processing is also possible. The acquisition of images is referred to as imaging in which it is an action of retrieving an image from an external source for further processing. Image processing allows one to enhance image features of the input while attenuating the detail irrelevant to the given application, and then extract useful information from the enhanced image.

A. Image Enhancement.

Image enhancement is the improvement of the digital image quality wanted for visual examination or for machine analysis, without any knowledge about the origin of degradation. If the source of degradation is known, then this is said to be the process of image restoration. Both are iconical processes, namely input and output are images.

B. Image Restoration

The purpose of image restoration is to check the defects that degrade an image. Degradation is of many forms such as motion blur, noise, and misfocus of image. In cases of motion blur, it is possible to come up with a very good estimate of the actual blurring function and undo the blur to restore the original image. If the image is corrupted by noise, the best way to do this is to compensate for the degradation it caused. In this project, we will introduce and implement several methods used in the image processing world to restore images.

C. Image Segmentation

Image segmentation is the process of segregating a digital image into multiple segments that are a set of pixels, also known as superpixels. The goal of segmentation helps in reducing the complexity of the image to make further processing or analysis of the image simpler. It is typically used to locate objects, lines, and curves present within the boundaries of an image. More precisely, image segmentation is the process of assigning a label to every pixel in a given image such that pixels with the same label share certain characteristics.

D. Feature Extraction

In image processing, feature extraction begins from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the successive learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction which is the process of isolating the most consistent, non- redundant, and relevant features to use in model construction.

E. Image Classification

Image classification refers to the task of extracting information and labeling groups of pixels or vectors within an image based on specific rules. It uses the spectral information constituted by the digital numbers in one or more spectral bands and seeks to classify each individual pixel based on this spectral information related to the image.

III. DEEP LEARNING

In deep learning, a convolutional neural network (CNN, or ConvNet) is a kind of deep neural network, most commonly applied to inspect visual imagery.

A. Convolution

The main layer of CNN is the convolutional layer. Convolution is a mathematical operation or a type of artificial neural network, which is widely used for image/object recognition and classification. In our case, the convolution is applied to the input data using a convolution filter to produce the result of the applied filters to an input image.

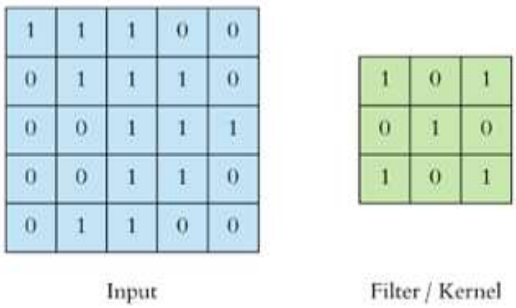

Figure 1: Input of the convolution layer and Kernel

B. Stride and Padding

Stride denotes how many steps we move the convolution filter in each step. We can observe that the size of the output is smaller than the input. To maintain the proportion of output as in input, we use padding. Padding is a process of adding zeros to the input matrix symmetrically. The gray area around the input is known as the padding.

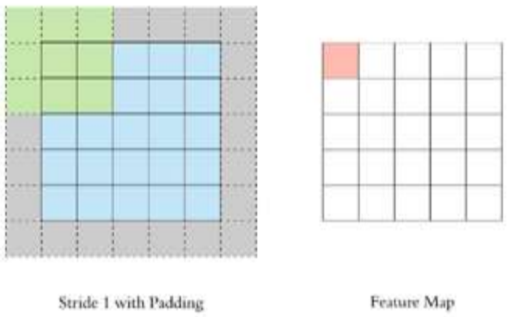

Figure 2: Stride and Padding

C. Pooling

Pooling layers sample each feature map independently, reducing the height and width, and keeping the depth undamaged. The most common type of pooling is max pooling which just selects the maximum element from the region of the feature map covered by the filter. Clashing with the convolution operation, pooling has no parameters. It slides a window over its input and merely takes the max value in the window. Similar to a convolution, we describe the window size and stride.

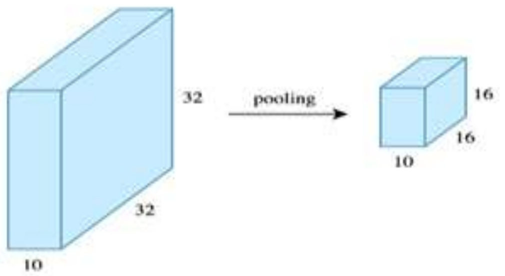

Figure 3: Pooling

D. Fully Connected

After the convolution + pooling layers we add a couple of fully connected layers to enfold the CNN architecture. This is the same as the fully connected ANN architecture. Be sure that the output of both convolution and pooling layers are 3D volumes, but a fully connected layer expects a 1D vector of numbers. So, we flatten the output of the ultimate pooling layer to a vector and that becomes the input to the fully connected layer. Flattening is simply converting the data into a 1-dimensional array for inserting it into the next layer. The output of the convolutional layers is flattened to create a single feature vector and this long feature vector is connected to the final classification model, called a fully-connected layer.

IV. EXISTING SYSTEM

The existing system uses an eigenvector which allows us to "reduce" a linear operation to separate, simpler, problems. Independent component analysis is a machine learning technique to separate independent sources from a mixed input signal that is different from the principal component analysis which focuses on maximizing the variance of the data points. Wavelet transform is a scattering network that helps you to obtain low-variance features from signals and images used in machine learning and deep learning applications. Linear Prediction is a mathematical operation where future values of a discrete-time signal are estimated as a linear function of previous samples. In digital signal processing, linear prediction is often called linear predictive coding (LPC) and can be viewed as a subset of filter theory.

V. PROPOSED SYSTEM

Our proposed system uses the DCNN algorithm to detect and classify the ECG signal which is particularly used to ensure accuracy. The noise in the input signal is removed by the filter and is further processed to attain feature selection of the signal. The output from the extraction of the signal is compared to the dataset in the trained model. The signal that is classified is transmitted to the individual through GSM.

VI. METHODOLOGY

ECG signal needs to be generated for processing and analyzing the noise present in the signal. Input signal needed to be pre-processed before going to process of feature extraction of the signal. Here there are many processes for preprocessing steps prescribed that as mean subtraction, moving average filtering, high-pass filtering, and low-pass filtering. With this methods noise, low-quality signals, and flatline will be removed. After completion of the noise removal process in the ECG signal, need to extract the feature parameters from the previous image.

- Temporal/Morphological Parameters: are defined in the time domain.
- Spectral parameters: are calculated in the frequency domain.
- Complexity parameters: provide different measures of the complexity of the ECG signal.

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VII.MIT-BIH ARRHYTHMIA DATABASE

The MIT-BIH arrhythmia database is an openly available dataset that provides standard inspection material for the detection of heart arrhythmia. Since 1980, it is used for purpose of fundamental research and medical device development on cardiac rhythm and other related diseases. The dataset from this source is given to the trained model in which the input ECG signal is compared.

ECG signal 101.dat

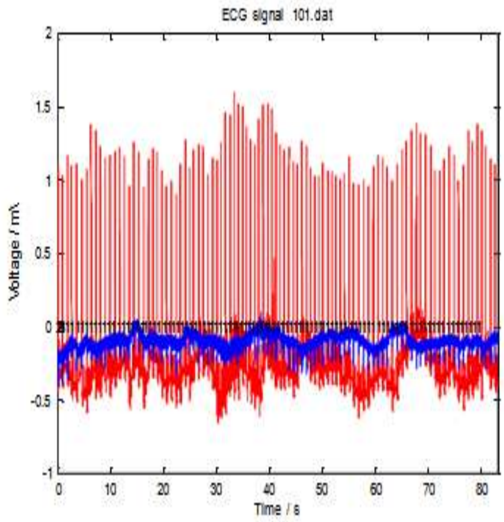


Figure 4: MIT-BIH Arrhythmia Database

VIII. BLOCK DIAGRAM

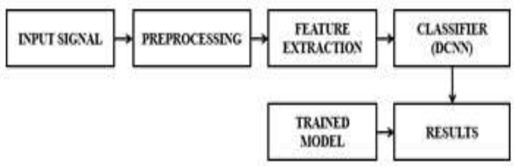


Figure 5: Block Diagram of the system

IX. HARDWARE AND SOFTWARE REQUIREMENTS HARDWARE:

- Arduino is an open-source electronics platform based on user-friendly hardware and software. Arduino boards are able to read inputs - light on a sensor, a finger on a button, or a Twitter message - and turn it into an output - activating a motor, turning an LED on, publishing something online.
- GSM stands for Global System for Mobile communication which is a digital mobile network that is primarily used with mobile phones all over the world. The technique uses narrowband time division multiple access (TDMA) which is capable of carrying 64 kbps to 120 Mbps of data rates.
- Serial Port is used which acts as an interface between Arduino and GSM module.

Software:

MATLAB is a high-performance language for technical computing which fuses computation, visualization, and programming in a user-friendly environment where problems and solutions are exhibited in amicable mathematical notation.

X. CIRCUIT CONNECTION

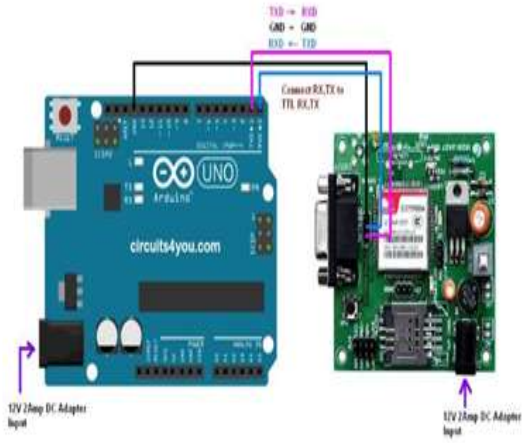


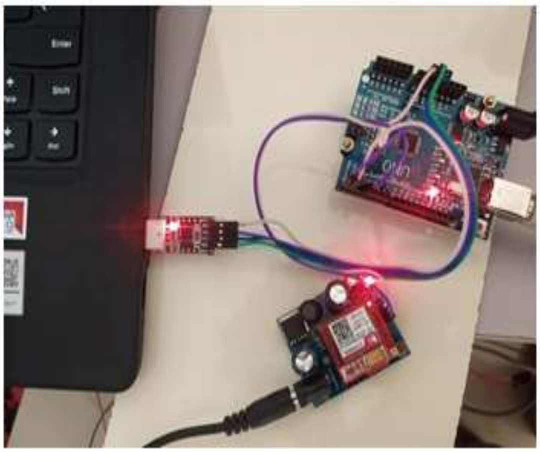
Figure 6: Circuit connection of GSM with Arduino

XI. PROGRAM CODE

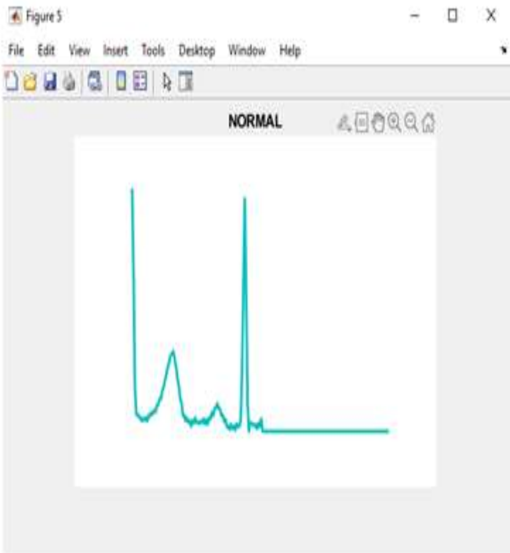
https://drive.google.com/drive/folders/1sQMv07D1ZPjUKf gYWoTOOL5fCdamqcK0?usp=sharing

XII. RESULT

HARDWARE IMPLEMENTATION



SOFTWARE IMPLEMENTATION



XIII. CONCLUSION

In this project, we presented a study on ECG-based emotion recognition. Our experimental results indicate that it is feasible to identify four emotional states normal and abnormal mental states, and average test accuracy is obtained by combining ECG frequency domain features and Deep Learning. In addition, the experimental results show that the frontal and parietal ECG signals were more informative about the emotional states. Therefore, the result analysis of the patient is transmitted to the individual through GSM.

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