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AUTOMATIC CLASSIFICATION OF ECG AND PCG SIGNALS USING CONVOLUTION NEURAL NETWORK FOR DETECTING CARDIOVASCULAR DISEASE

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ABSTRACT

Cardiovascular disease increasing deaths worldwide effecting young age people at their early stage. Heartbeat analysis of a person can be normal or abnormal heart sounds which can be detected only through trained physician. To reduce the dependency on trained physicians for heart sound detection, proposed system focuses on automatic classification of ECG(Electrocardiogram) and PCG (Phonocardiogram) signals after removal of unwanted signals and noise can be eliminated through filters. Convolution Neural Networks to eliminate manual extraction of the features of ECG and PCG signals. Classification of heart disease to detect heart rate by combining signals of ECG and PCG of electrical and mechanical activity to analyse signals effectively this paper proposes R peak detection using convolution method which is a mathematical way of combining two signals to form into new signal in digital signal processing is an efficient technique to detect heart rate through ECG and PCG signals for cardiac disease. The main moto of proposed work is to make use of both the ECG and PCG signals to detect R peaks from both the combined signals of ECG and PCG to detect heart rate abnormality. Thus, the proposed system helps the physicians for automatic classification to diagnose the heart rate in an efficient manner.

Keywords: *Cardiovascular, Electrocardiogram, Phonocardiogram, Convolution Neural Networks, Arrhythmia*

1. INTRODUCTION

Heart disease is the major cause of death in today's era, cardiac cycle heartbeat vary from person to person depending on their body functionality of electrical depolarization -repolarization patterns. Heart disease is the heart's abnormal activity caused due to many reasons, regular monitoring and taking precaution at early stage can prevent from life risk situations. To detect earlier signs of heart disease, signals of ECG and PCG play vital role in diagnostic tool where R peaks can be detected based on the abnormality.

Cardiac health can be monitored through ECG and PCG by Cardiologists as well as medical practitioners to detect abnormality in heart rate. One-third of the deaths worldwide[1] are due to cardiovascular disease whose heartbeats are uneven which can be fatal in some cases. As a consequence, precise and inexpensive diagnosis of arrhythmias is highly desirable [2].

Cardiovascular diseases are a major global burden, according to the World Health Organization, accounting for 30 percent of all deaths [3]. It is therefore essential to detect risk patients early and to understand the mechanism of the disease. In hospitals and clinics, electrocardiograms (ECGs) and MRIs are often used for intervention in these disorders. However, some equipment is prohibitively expensive and of poor health quality and is not portable. Heart sound capture sensors, like a digital stethoscope, are, by contrast, cheap and can detect cardiac disorders as PCG-signals before the symptoms appear[4].

Many literature studies explored the problems posed by manual analysis of ECG and PCG signals using machine learning techniques to accurately detect signal defects. [5] and [6], respectively. Preprocessing is used for signal preparation in most of these methods. The manufactured characteristics of these signals are then extracted & used for advanced investigation for the absolute classification job, which are usually statistical summaries of the signal windows. The inference engine utilizes support for vector machinery, multi-layer perceptrons, decision-making bodies and other traditional ECG analysis machines.

Recent machine learning studies have shown that automatic extraction & illustration systems are more scalable & more accurate forecasts. These handmade features give us an acceptable signal representation. The machine can learn the most appropriate functionality using a deep learning end-to-end framework. This method allows additional precise illustration of the ECG signal that allows the machine to race with human cardiologist for signal analysis [7]. Deep learning methods, in contrast, have a huge number of variables and entails enormous data training.

The concept of the transfer of knowledge between tasks is one way to address the need for a large amount of data. The Image Net dataset was used in computer vision for example for the transfer of knowledge between different tasks of image understanding with state-of-the-art profound learning models[8]. Another example is that participants in various sentence categorization tasks demonstrated a significant understanding of the sentence [9]. On the other hand, the use of transfer learning in health computing is limited. In deteriorating conditions, Alabam and xin.[10] use the constraints of Gaussian method that had been used on patients with secure circumstances.

To detect heart disease effectively, a variety of techniques developed in earlier research but those techniques depend on limited data, to overcome that limitation this system proposes method to make use of both the signals of ECG as well as PCG through convolution function. The literature review specified the limitations of each method when used with ECG and PCG dataset as well as problems that come across manual analysis of those signals are described in specified references.

We propose a new framework for the categorization of ECG & PCG signals in this article, which can be applied to signal transmissions across tasks. To accomplish this, we illustrate a deep neural network architecture with a significant learning capability. Because this network has been trained to detect rhythms, it is reasonable to assume that it is aware of the majority of the ECG and PCG signal's shape-related features. For this task, we also have a lot of labeled data, so training a system with a lot of considerations which is simple.

2. DEEP LEARNING METHODS

Deep Learning (DL) pass on to research on knowledge mining, prediction and smart decision making or, to put it differently, to the recognition of complex patterns by means of a set of records known as training information[11]. The DNNs are more scalable than conventional learning techniques, since the size of instruction dataset usually increases the level of precision. Simple knowledge forms known as decision trees and SVMs, were unproductive for numerous contemporary applications because they need a huge quantity of annotations to generalize & require a major amount of human effort to clearly define earlier awareness for the model.

To improve the precision of various learning assignments, many models proposed including Multilayer Perception(MLP), RNN, CNN, Long Short Term Memory(LSTM) and Deep Belief Network (DBN) [12]. The developing neural organization is a variation of the deferred neural organization, which was brought into the setting of learning hypothesis as of date. While the concept of Convolution neural network is suitable to life sciences, particularly cyclical signals and signal processing.

(i)Multilayer Perception (MLP)

MLPs are the mainly useful in supervised neural networks and are effective at learning complex systems[13]. The architecture of the MLP varies, but it typically contains multiple levels of neurons that are associated to one another. After a non-linear function is processed, every neuron is a subjective addition of its contributions.

(ii)Convolution Neural Network (CNN)

CNN, a trendy DNN structural design, is trained using a grade optimization algorithm. A CNN is composed of a series of continuous levels that are related feed-forward. Four primary layers are revolutionary, standardization, pooling, & completely linked[14]. The first three levels are accountable for feature extraction, while the completely linked layers are responsible for categorization[15]. Fig. 1 illustrates the common architecture of the CNN for categorization.

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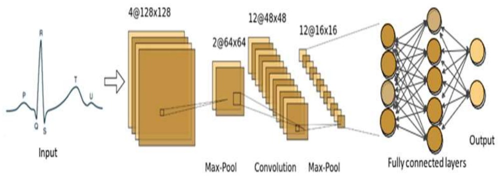

Figure 1: Convolution Neural Network (CNN) Design.

RBM 1

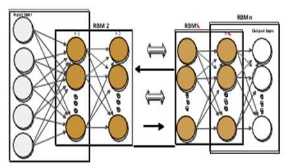

Figure 2: Deep Belief Network (Dbn) Design

iii)Deep Belief Network (DBN)

Hilberg anticipated the multi-layered Boltzmann Restricted DBNs in 2006 (RBMs). DBN is an extremely powerful model for learning to model time-varying random variables[16]. The DBN layers consist of RBMs, as shown in Figure 2. Each RBM receives the previous layer input within a single level and supply the RBM into next level. DBN workouts are performed by RBM workouts from top to bottom level by level.

In 1979, RBM was proposed. RBM is a random random binary variables model that is used in binary data modeling efficiently. A baultemen mechanism is a random field that consists of a symmetrical network of random binary units[17]. Each RBM has two unit layers: a visible layer that represents the data and a hidden layer that can indicate features & capture advanced relationships. As shown in the below figure, weighted links connect the two layers and no connection is available within a layer.

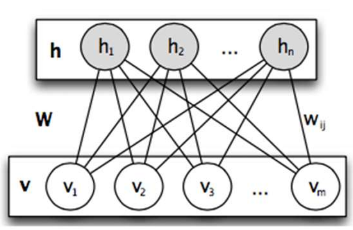

Figure 3: Rbm Architecture

(iv)Recurrent Neural Network (RNN)

RNN is a sort of Artificial Neural Network (ANN) in which loads are shared after some time. Since it takes care of back criticism and current qualities to the organization, RNN is the most suitable model for learning successive information and time arrangement information characterization, and the yield contains the memory expansion of qualities. This is the most proper learning model for learning consecutive information and time arrangement information grouping[18] . The RNN gets information, refreshes its secret state, and makes a forecast at each time step. Gradient Descent Algorithm used to train the weights of RNN and architecture is depicted as shown in Figure 4. RNNs having dynamic behavior due to nonlinear activation functions used at hidden units.

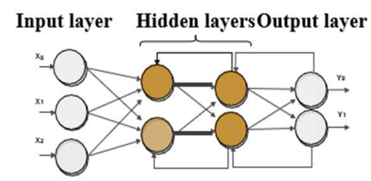

Figure 4: Deep Belief Network Architecture

(v)Long Short-Term Memory (LSTM)

The LSTM is a kind of RNN that was created with sequential & long series dependences in mind. Rather than using plain RNN entities, LSTM employs memory chunks, all of which control a set of memory cells with a couple of multiplication gates as key & production[19]. Based on input & output gates, a memory chunk keeps & revises data over instances. The flow of data into and out of a memory cell is controlled by the doors.

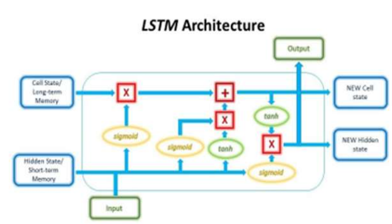

Figure 5: (A) The Long Short-Term Memory (LSTM) Architecture.

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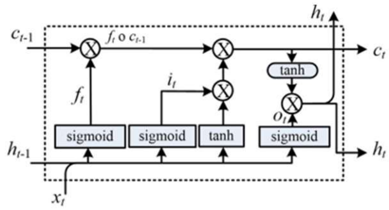

Figure 5: (b) LSTM functionality

(vi) Bidirectional Recurrent Neural Network (BRNN)

By associating two secret layers with inverse headings to a similar yield, the essential objective of BRNN is to get data about a succession's past and future states at the same time. Non-linear units can be replaced as shown in Fig. 6 with LSTM blocks, LSTM-BRNN can be effectively accomplished.

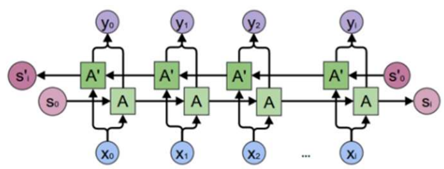

Figure 6: Bidirectional Recurrent Neural Network Architecture

(vii)Gated Recurrent Unit (GRU)

Gated Recurrent Unit is an enhanced description of LSTM that allows for closer training. It is easier to use than LSTM and has a lower computational complexity. GRU is made up of gates that work together to balance the information flow within the units. The update gate is created by combining the input gate and the forget gate to create a new gating unit. The update gate's primary function is to maintain a balance between the states of previous and candidate activations.

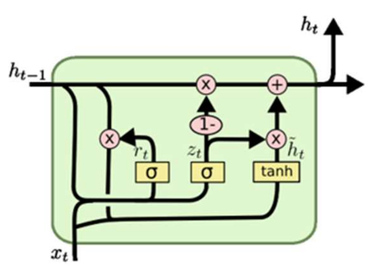

Figure 7: Gated Recurrent Unit's Architecture (GRU)

3. DATA SETS

To generate labeled ECG and PCG records, researchers used the Physio Net MIT-BIH Arrhythmia & the PTB Diagnostic ECG & PCG Databases and association for the Advancement of Medical Instrumentation's (AAMI) EC57 standard [20]

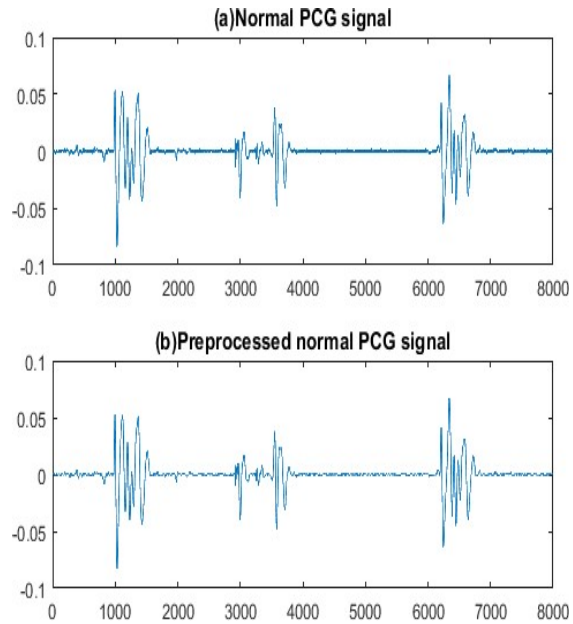

Fig. 8: ECG Window Before & After Processing

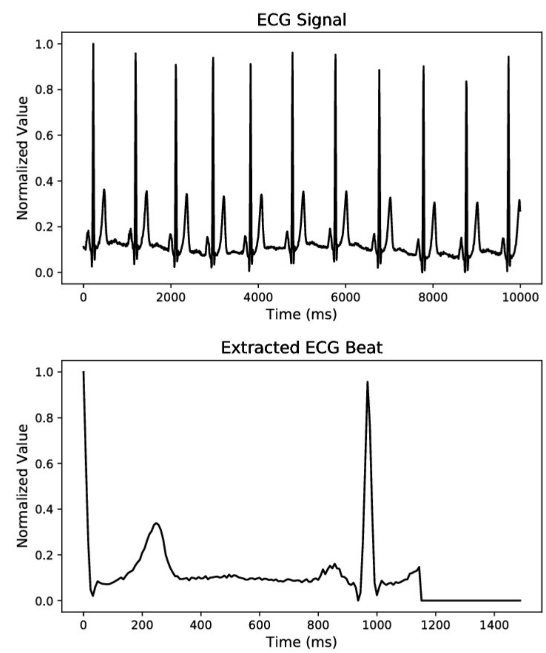

Fig. 9. Normal PCG Signal Before & After Processing

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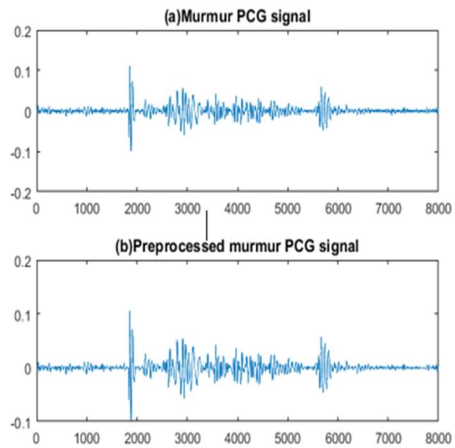

Fig. 10. Murmur PCG Signal (A) Before (B) After Processing

4. METHODOLOGY

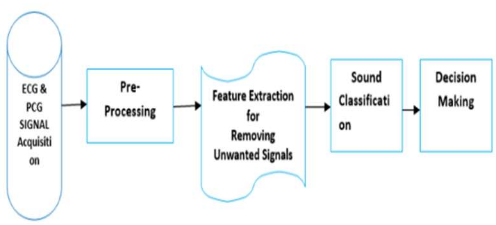

Fig11.Architecture Of The Proposed System

A. SIGNAL ACQUISITION

The PCG and ECG signals have been obtained from a freely available database[21]. The dataset contains normal sounds, murmur sounds, extra heart sounds in the original dataset, which are divided into four categories. Only normal and murmuring signals have been taken into account in this study.

There are standard, solid heart sounds in the typical class, which may contain an assortment of background noises, for example, irregular sounds related with breathing or the receiver brushing against dress or skin. Remembered for the examination are information from kids and grown-ups in quiet and energized states, with cardiovascular rates going from 40 to 140 beats each moment or higher.

A whooshing, turbulent fluid noise roaring characterizes a heart murmur, which can be systolic or diastolic in nature. These sounds might be consequence of a variety of heart conditions. However, it may also contains lub-dub patterns. Identifying the exact location of murmurs is difficult for non-medically trained people requires trained physician to monitor those sounds. Figures 8, 9, and 10 depict PCG and ECG signals that correspond to these two classes. The amplitudes and frequencies of the PCG and ECG vary in normal and pathologic conditions, respectively, as shown in these graphs.

B. PREPROCESSING

Typically, PCG signals are jittery. Random noise equivalent to inhalation or brushing the microphone touching clothing or skin may be present in normal PCG signals. Murmur signals, on the other hand, are characterized by whooshing, roaring, and turbulent fluid noises. Noise and artifacts were reduced to the bare minimum prior to feature extraction. Because PCG signals vary in length, all signals were standardized to a 7-second length from the beginning to account for the problem's importance. To eliminate the microphone effect, DC section of signal is detached. A 900 Hz zero-phase low-pass filter is used to reduce the PCG signal's high frequency noise because the heartbeat components are below 1000 Hz. A median filter has moreover used to remove spontaneous clatter. To improve computational efficiency, the initial sample rate (22.36 KHz) has been condensed to 3 KHz. High pass and Low pass filters are used to remove the noise and unwanted signals and convolution method is a mathematical way of combining two signals to form a new signal from it.

Feature Extraction

A crucial step in the classification of signal events is the extraction of appropriate and discriminatory features. In a variety of applications, time, frequency, & joint time-frequency elements were used. As a result of trial and error, each PCG signal is alienated into numerous divisions, each of which is 5000 samples wide. In our research, we looked at the following characteristics.

Statistical Features (SF): Signal nature data could be useful for detecting various abnormalities in PCG signals. Because higher-order data like skewness & kurtosis are believed to have non-linear active property, they were used, but the results were mixed. As a result, we derived two simple statistical parameters for signal intensities in our research: mean and standard deviation.

C. Classification

For each class of ECG and PCG signals, a mean and covariance matrix are calculated. The posterior probabilities for experimental signals were calculated by means of the trained model for every group. Through Low pass and High pass filters, noise and unwanted signals can be eliminated to increase the accuracy and for detecting the R Peak

$$\mu_x = \frac{1}{n}\sum_{i=1}^{n} x_i \quad \rightarrow (1)$$

$$\sigma_x = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)^2} \quad \rightarrow (2)$$

$$\varepsilon_x = -\sum_i x_i^2 \log(x_i^2) \quad \rightarrow (3)$$

Power Spectral Density (PS): The signal power distribution across the frequency is referred to as the spectral power density. It's essentially the square magnitude of a discrete signal's Fourier's discrete transformation with a suitable scaling procedure. The power sharing of standard & muttered PCG signals over different frequencies can be distinguishing characteristics between these two classes. To extort the PS characteristic from the PCG signal, the term "period gram" was used in this study. **Fraction Dimension (FD):** The difficulty of auto comparable models of signal is measured by the fractal length, which is a guide. The ratio between detail and scale change can be used to define this complexity. Because heart murmur sounds are high frequency mechanisms & self-like prototypes, similar to fractals, the FD is another important characteristic for signal classification. We used Katz's FD measures in this study, which are described in this report

$$D = \frac{log_{10}(L)}{log_{10}(d)} \quad \rightarrow (4)$$

DT: The structure of decision tree is flowchart whose interior hub addresses a property test, branch addresses the test outcome and leaf hub addresses a class mark. In a tree, the root hub is the most elevated hub[22]. There are various minor departures from the essential choice tree calculation.

KNN: This is the most notable non-parametric strategy for characterizing PCG signals that we have utilized. Decisions in favor of a test object are dictated by recognizing the K nearest points of highlight that can contain preparing tests from the ordinary and murmured classes (for example include point)[23].

5. Decision Making and Evaluation:

Make the best decision and evaluate your performance. In the first place, the ECG and PCG are stratified in five parts during five minutes. Each part of a five-minute recording is then cut down to 20 to 15 seconds. This ensures that the signal segments used in the training and validation phases are from completely different sources, resulting in a more realistic evaluation. The average of five cross validations produces the final classification result. After that, five iterations are carried out.

Convolution method used to combine two different signals to analyze the heart rate of heart sounds through ECG and PCG signal during preprocessing to automatically distinguish between normal sounds and abnormal sounds to detect the heart rhythm through corresponding filters to remove the noise and unwanted signals. Average heart rate is detected by evaluating minimum distance between two peaks in the signal during preprocessing.

In this study, standard metrics such as accuracy (Acc), sensitivity (Sen), and specificity (Spe) were used to evaluate classification performance[24]. The G-mean is also used to measure a learning model's balanced performance, which is important given the class imbalance in the figures. These measurements are calculated by using the following equations:

$$\text{ACC} = \frac{TP+TN}{TP+TN+FP+FN} \quad \rightarrow (5)$$

$$\text{Sen} = \frac{TP}{TP+FN} \quad \rightarrow (6)$$

$$\text{Spe} = \frac{TN}{TN+FP} \quad \rightarrow (7)$$

$$\text{G-mean} = \sqrt{sen * Spe} \quad \rightarrow (8)$$

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The numeral of true positives, true negatives, false positives, and false negatives is represented by TP, TN, FP, and FN, respectively.

5.1 RESULTS OF FEATURE SELECTION & CLASSIFICATION

Cross validation is performed by means of the fully associated model, as shown in Figure12 shows the Processed ECG and PCG signals and R Peak Detection. The scatters are used to represent the metrics' true values G-mean[25].

As shown in Figure 12, the proportion of the quantity of chose highlights to the quantity of unique highlights is figured for every area to additionally decide the component areas that add to grouping. In Preprocessing stages of ECG and PCG signal, the Original signals can be processed through First Pass and Second Pass filters to reduce the noise and remove unwanted signals from original signals as shown in below figure. Convolution method to form new signal from two different signals using conv function.

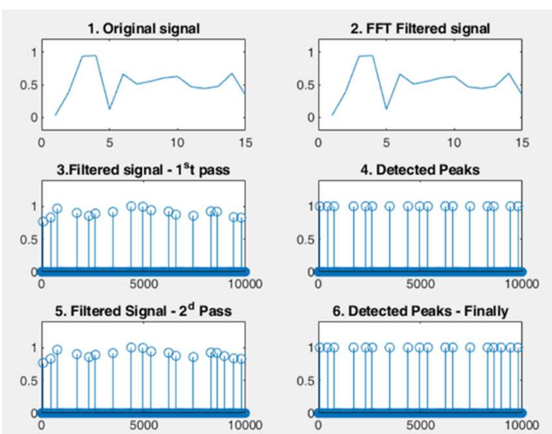

Figure 12: (A)Sample1-Processing Stages

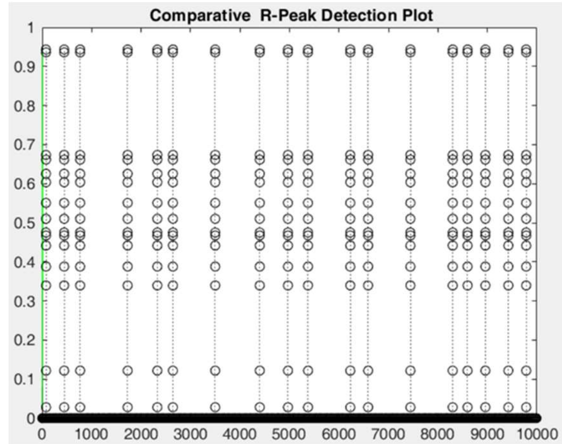

Figure 12: (B)Sample1- Result

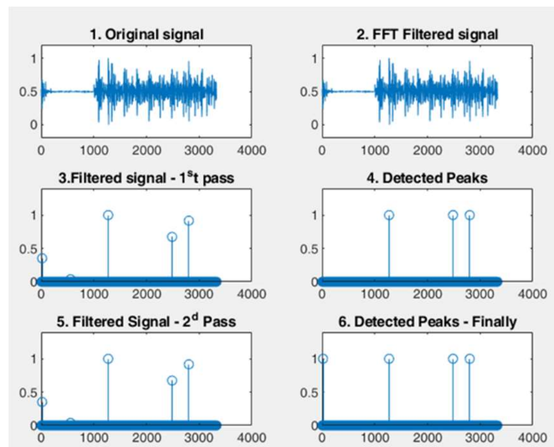

Figure 12: (c)Sample2-Processing Stages

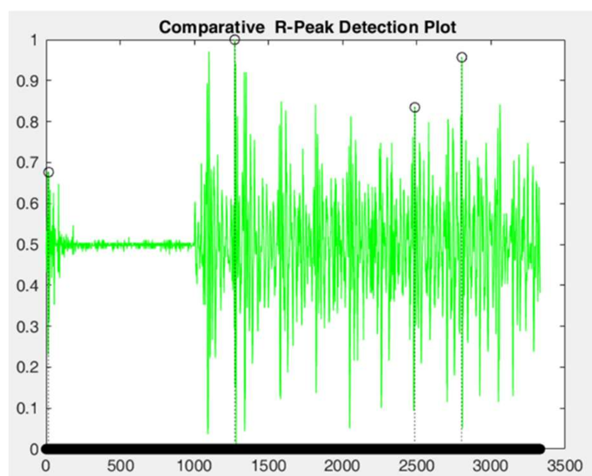

Figure 12: (D) Sample2- Result

6. CONCLUSION

In this study, proposed system presented a convolution technique based on a transferable

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representation for ECG and PCG heartbeats for R peak detection. Processing stages of ECG signals and PCG signals displayed after normalization of the signals using filters as shown in section 5.1. Existing systems trained with limited data leads to inefficient preprocessing steps in detection of R peaks, which can be overcome with the proposed technique. The results showed that the Proposed method is capable for efficient processed signal and detection of R peaks through removal of noise and unwanted signals using filters to detect the accuracy in heartbeat through combination of signals with ECG and PCG. The future scope is to detect efficient techniques in determining various types of heart diseases due to abnormality in the heartbeat of the signals.

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