International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 05, May-2020

Automated Classification of Multiple Cardiovascular Diseases from ECG Signal

Raj Abhinandan
Dept of Electronics and Communication Engineering
R V College of Engineering
Bengaluru, India

Nirmal Dogra
Dept of Electronics and Communication Engineering
R V College of Engineering
Bengaluru, India

Shantanu Shobhit
Dept of Electronics and Communication Engineering
R V College of Engineering
Bengaluru, India

Dr. Veena Devi
Assistant Professor
Dept of Electronics and Communication Engineering
R V College of Engineering
Bengaluru, India

***Abstract*— CVDs are problems of the heart and veins and incorporate coronary illness, cerebrovascular sickness, rheumatic coronary illness and different conditions. Cardiovascular infections (CVDs)are the number 1 reason for death internationally, taking an expected 17.9 million lives every year. In this work there is identification of three significant cardiovascular illnesses to be specific Arrhythmia, congestive cardiovascular breakdown and typical sinus arrhythmia. The preprocessing of the crude ECG signal is finished utilizing Observational deterioration to get 12 Intermediate modal functions (IMFs) which are symmetrical in nature. Denoised Altered sign is acquired by adding the mix of IMFs which will be the most ideal situation with least clamor and twisting. The adjusted sign is utilized in as contribution to prepare the CNN model. In this manner, prepared CNN model is tried by utilizing the ideal ECG information contribution for the order of Cardiovascular Ailment.**

Keywords*— *Cardiovascular Diseases, Electrocardiogram, Empirical Mode Decomposition, Convolution Neural Networks.

I. INTRODUCTION

An mportant diagnostic tool in identifying chronic and acute heart rhythm irregularities (cardiac arrhythmia's)is the electrocardiogram (ECG), which measures electrical heart activity via electrodes placed on a patient's skin. ECGs are ubiquitous in intensive care units (ICUs), diagnostic labs as well as a monitoring device, where clinicians must be able to make critical care decisions quickly and accurately. The ability to correctly distinguish various arrhythmias from each other is crucial for patient well-being; in many cases, the wave morphologies of benign and lethal arrhythmias can be difficult to distinguish. Existing monitoring systems for ECGs record a myriad of vital signs and also utilize algorithms to determine changes in cardiac rhythm[1].However, accurate identification of arrhythmias is known to be challenging even for medical professionals, and requires considerable medical expertise. A study investigating diagnostic accuracy for licensed general practitioners showed a specificity of 92% and sensitivity of only 80% in distinguishing atrial fibrillation from healthy sinus rhythms[2]. Hence there needs to be better pre-processing techniques as well as more efficient Neural Networks model.

II. LITERATURE REVIEW

Every ECG signal is first decomposed through EMD and higher request IMFs are consolidated to shape an adjusted ECG signal. It is accepted that the utilization of EMD would give a more extensive scope of data and can give denoising execution. This prepared signal is given as input into the CNN that orders the record as per cardiovascular illnesses utilizing SoftMax regressor toward the finish of the system. It is seen that the CNN design learns the intrinsic highlights of the altered ECG signal better in examination with than unprocessed ECG signal. The strategy is applied on three openly accessible ECG databases and it is seen as better than different methodologies regarding arrangement exactness [1].

Past investigations of QRS recurrence content and talk about our novel technique for the conjoint examination of the ECG signal in six measurements: in the area of three measurements, in time, space, and in recurrence area. Orbital recurrence of QRS circle is presented as a six-dimensional trait of ventricular conduction, which assisted with uncovering of obvious ventricular conduction, and to describe electro physiological substrate. [2]

The most recent improvement of the computer aided supported heart sound recognition procedures throughout the most recent five years have been looked into. There are for the most part the accompanying perspectives: the hypotheses of heart signals and the connection between heart signals and cardiovascular ailments; the key advances utilized in the handling and examination of heart sound signs, including denoising, division, highlight extraction and arrangement; with accentuation, the utilizations of profound learning calculation in heart sound preparing. At last, a few zones for future research in PC supported heart sound discovery strategies are investigated.[3]

This offers a proficient way to deal with measure all pieces of P-QRS-T waveform so as to give a right choice of heart functionality. The executed methodology including any means; preprocessing, pattern process, highlight extraction and analysis. The acquired outcome demonstrated a satisfactory acknowledgment rate to check the heart functionality [4].

An overview of a technique for discovery and confinement of myocardial infraction (MI) from the diminished MECG

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 05, May-2020

tensor. The support vector machine was utilized as the arranging method. Exploratory outcomes indicated that the proposed strategy guaranteed an identification precision of 95.30 [5].

In the first place, the division of ECG signals into beats is performed. At that point, FAWT is applied to every ECG, which breaks them into sub band signals. Accomplished most noteworthy arrangement precision of 99.31 [6].

The system is tried on one patient and prepared on rest of the patients. Investigated the separating quality of the highlights features by the convolutional layers by methods for geometric distinctness file and Euclidean separation and contrasted it with the benchmark model.[7]

Presents the recurrence quantification analysis (RQA) of VCG flags in different wavelet scales for the distinguishing proof of cardiovascular issue. The direct order model utilizing multiscale RQA highlights were shown to identify MI with a average sensitivity of 96.5 average specificity of 75 [8].

Presents a review and examination of Experimental Wavelet Change with Exact Mode Decay. Delineation shows the examination of these techniques on one dimensional sign. [9]

Presents another ECG grouping technique dependent on Deep Convolutional Neural Systems (DCNN) and online choice combination. Unique in relation to past strategies which use hand-created includes or take in highlights from the first sign space, the proposed DCNN based strategy takes in highlights and classifiers from the time-recurrence area in a start to finish manner.10]

Proposes the utilization of Discrete Wavelet Change (DWT) to distinguish the QRS (ECG is described by an intermittent wave grouping of P, QRS and T-wave) of an electrocardiogram (ECG) signal. Wavelet Change gives restriction in both time and recurrence. In preprocessing stage, DWT is utilized to evacuate the standard meander in the ECG signal. The exhibition of the calculation of QRS location is assessed against the standard Arrhythmia database. The normal QRS edifices identification pace of 98.1[11]

Examination of current QRS identification calculations dependent on three appraisal models: strength to clamor, parameter decision and numerical proficiency, in order to focus on all inclusive quick powerful detector. [12]

A few sorts of indent channels (simple and advanced) were actualized for assessment of the twisting caused on ECG signals. These channels were applied to ECGs of people and rodents and afterward bending gauges were figured from their subsequent signals.[13]

The denoising signal handling methods are assessed utilizing mean square blunder and sign to commotion proportion. What's more, ECG signal is utilized for individual validation. The proposed paper centers around the investigation of various strategies of denoising and a recognizable proof of individual through an ECG signal.[14]

III. SYSTEM DEVELOPMENT

Methodology

Existing advances for distinguishing Different Cardiovascular ailments were examined and their outcomes were broken down [3]. These were utilized for imperative signs and calculations to decide changes in heart functioning while in certain strategies the arrangement was a significant.

The crude ECG signal informational index was taken from physio net and changed over to the necessary arrangement. So as to get a denoised signal Exact mode disintegration is done as a preprocessing venture to isolate the raw signal into 12 Natural Mode Capacities (IMFs) [5]. The initial three IMFs are added to acquire the altered sign. This adjusted sign thus acquired is utilized as the contribution to the CNN model to build up an exhibition framework and get the outcomes.

Experimental Details

The block diagram, appeared in the Fig.1, proclamations the significant succession of the system the crude ECG signal is Empirically Mode Decomposed[6][7]and initial three IMF signals are added to develop an altered ECG signal appeared in Fig. 2. Blend of initial three IMFs after EMD evacuates the majority clamor and rarities and builds a denoised ECG signal as present in Fig2.

The procedure flow of system is shown in fig. 3. Information for three diseases is download from phisionet.org and afterward changed over into MATLAB arrangement that is in .m expansion. ECG information utilized comprises of 7680 example esteems. The quantity of patient's information for Arrhythmia, Congestive Cardiovascular breakdown and Ordinary Sinus Arrhythmia are 54, 56 and 52 individually.

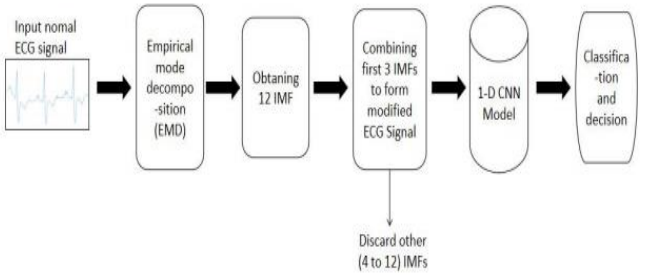


Fig 1 *Block diagram of methodology*

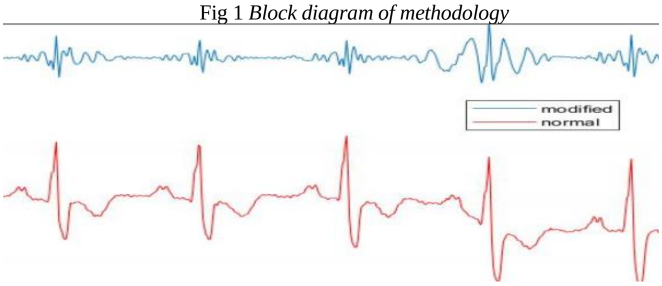


Fig 2 *Normal and Modifies ECG Signal*

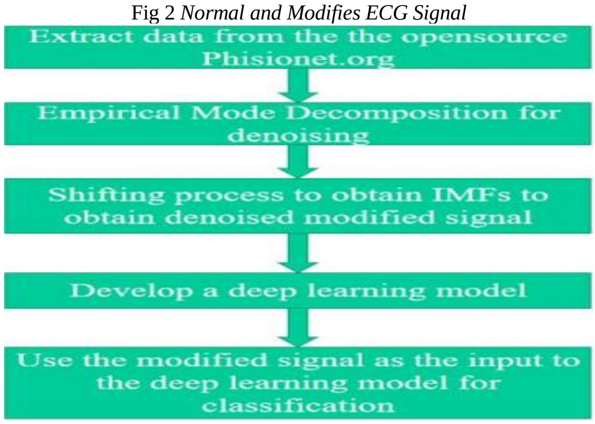


Fig3. *Flow chart of the process*

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 05, May-2020

Empirical mode function is utilized for EMD decay of each example and afterward 12 IMFs are acquired for every dataset. These IMFs are utilized for the preparation neural system, yet various IMFs and their mixes give diverse precision. Along these lines, initial three IMFs are consolidated and utilized for preparing as they contain signal highlights which are essential for arrangement, so they should give better grouping precision. The Convolutional Neural Network (CNN) is intended to deal with one-dimensional information and all the convolution tasks in the convolutional layers are performed on the 1-D grouping [8]. The portion size in each layer is changed to be applied on the 1-D sequence.[9] The initial five layers of the system are convolutional layers.

IV. RESULTS AND DISCUSSION

In this section the database used in the experiment, denoising performance of the modified ECG, classification results of different training approaches, comparison among the training methods and the learning procedures are described in detail. The first three IMFs are shown in figure 4.

Training Process

Individual IMF obtained after EMD are trained separately to find out the performance of each IMF in the classification of ECG signals. The resultant testing accuracies corresponding to each IMF reported that the higher order IMFs (IMF 1, IMF 2, IMF 3) provide better results than the lower order IMFs. Based on the observation, we realized that the higher order IMFs are comprised of signal features that are crucial for the classification of ECG signals and it is expected that the combination of these higher order IMFs might boost the classification accuracy rather than the individual performances. This leads us to consider a modified ECG by combining the first three IMF signals the signal is expecting better results. Hence, the modified ECG signal is fed into the CNN model for training process. The training process validation is shown in fig. 5. As the Epoch increments the best fit line (represented by dotted line in fig. 5) representing accuracy, reaches 100 percent. This shows validation of

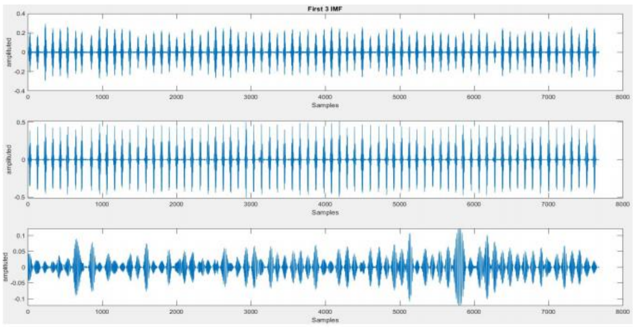


Fig 4 *The First three IMFs*

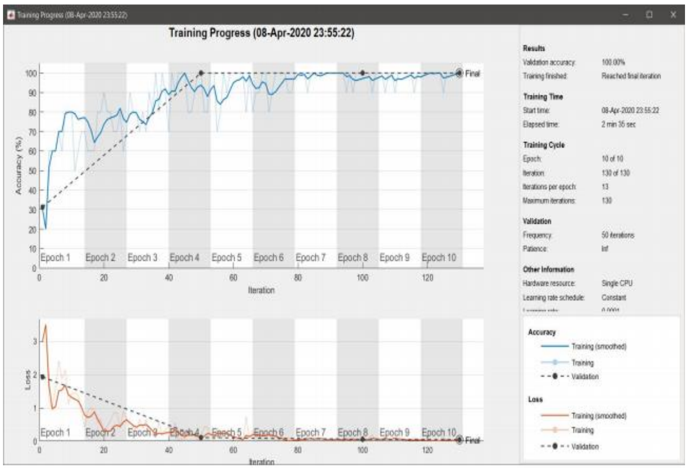
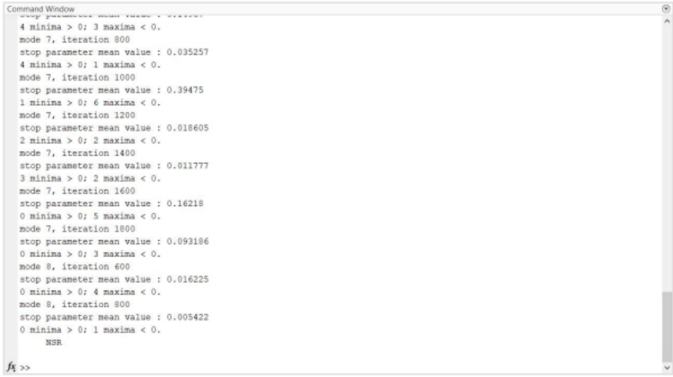
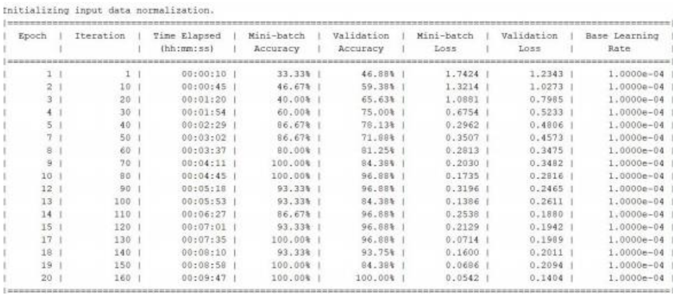


Fig 5 *Model verification the best fit line*



```
Command Window
4 minima > 0; 3 maxima < 0.
mode 7, iteration 800
stop parameter mean value : 0.035257
4 minima > 0; 1 maxima < 0.
mode 7, iteration 1000
stop parameter mean value : 0.39475
1 minima > 0; 6 maxima < 0.
mode 7, iteration 1200
stop parameter mean value : 0.018605
2 minima > 0; 2 maxima < 0.
mode 7, iteration 1400
stop parameter mean value : 0.011777
3 minima > 0; 2 maxima < 0.
mode 7, iteration 1600
stop parameter mean value : 0.16218
0 minima > 0; 5 maxima < 0.
mode 7, iteration 1800
stop parameter mean value : 0.093186
0 minima > 0; 3 maxima < 0.
mode 8, iteration 600
stop parameter mean value : 0.016225
0 minima > 0; 4 maxima < 0.
mode 8, iteration 800
stop parameter mean value : 0.005422
0 minima > 0; 1 maxima < 0.
     NSR
fx >>
```

Fig 6 *Matlab console showing classification*



Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:10	33.33%	46.88%	1.7424	1.2343	1.0000e-04
2	10	00:00:45	46.67%	59.38%	1.3214	1.0273	1.0000e-04
3	20	00:01:20	40.00%	65.63%	1.0881	0.7985	1.0000e-04
4	30	00:01:54	60.00%	75.00%	0.6754	0.5233	1.0000e-04
5	40	00:02:29	86.67%	78.13%	0.2962	0.4806	1.0000e-04
7	50	00:03:02	86.67%	71.88%	0.3507	0.4573	1.0000e-04
8	60	00:03:37	80.00%	81.25%	0.2813	0.3475	1.0000e-04
9	70	00:04:11	100.00%	84.38%	0.2030	0.3482	1.0000e-04
10	80	00:04:45	100.00%	96.88%	0.1735	0.2816	1.0000e-04
12	90	00:05:18	93.33%	96.88%	0.3196	0.2465	1.0000e-04
13	100	00:05:53	93.33%	84.38%	0.1386	0.2611	1.0000e-04
14	110	00:06:27	86.67%	96.88%	0.2538	0.1880	1.0000e-04
15	120	00:07:01	93.33%	96.88%	0.2129	0.1942	1.0000e-04
17	130	00:07:35	100.00%	96.88%	0.0714	0.1989	1.0000e-04
18	140	00:08:10	93.33%	93.75%	0.1600	0.2011	1.0000e-04
19	150	00:08:58	100.00%	84.38%	0.0686	0.2094	1.0000e-04
20	160	00:09:47	100.00%	100.00%	0.0542	0.1404	1.0000e-04

Fig 7 *Table for trained model validation*

the learning process of the model. It is shown in tabular form in Fig 7.

After training the model, testing is done by using the saved model. Raw ECG signal which is to be tested is again modified to provide input to the trained model and then classification process is completed as shown in figure 6. As in figure 6, test function loads raw ECG signal data (file name: 103m.mat) and processes it for modification and then classification happens which in this case is Normal Sinus Arrhythmia (NSR).

V. FUTURE SCOPE

The project has achieved the 100% efficiency in classification of the three diseases that were chosen as based on the frequency of cases in them. Though there are still deaths because of other cardiovascular diseases. Hence by adding more layers to the CNN model and making the system more

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 05, May-2020

interactive as well as getting access to larger data set there can be perfect classification of almost all the diseases. This can be useful in future ease in the medical field hence reducing the chances of human errors in classification as well as making the whole process of curing can be made faster.

VI. CONCLUSION

In conventional multiple heart disease classification schemes, the raw ECG signal is employed in feature learning and classification [12][13]. A modified ECG signal is formed using EMD analysis and then forwarded to the classification task. First, the modified ECG is formed by summing the first three IMF signal is obtained through EMD analysis and it is shown that the modified ECG has better denoising property. Next, a one-dimensional CNN network is developed to learn the features of the modified signal for classification purpose.[14] Apart from this, the proposed method is compared with other approaches to training with different combinations of IMF signals[15].It has been shown The proposed approach is has evaluated and classified the three diseases with better success rate than the work that was previously carried out with modification in preprocessing and CNN architecture.

ACKNOWLEDGMENT

We would like to thank our project mentor Dr. Veena Devi for guiding us in successfully completing this project. She helped us with her valuable suggestions on techniques and methods to be used in completion for the project. We would also like to thanks to our college and the Head of Department Dr. K.S. Geetha for allowing us to choose this topic.

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