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# ECG Classification using Machine Learning

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***Abstract:*** ***Recently, the obvious increasing number of cardiovascular disease, the automatic classification research of Electrocardiogram signals (ECG) has been playing a important part in the clinical diagnosis of cardiovascular disease. Convolution neural network (CNN) based method is proposed to classify ECG signals. The proposed CNN model consists of five layers in addition to the input layer and the output layer, i.e., two convolution layers, two down sampling layers and one full connection layer, extracting the effective features from the original data and classifying the features using wavelet .****The classification of* ***ARR (Arrhythmia), CHF (Congestive Heart Failure), and NSR (Normal Sinus Rhythm) signals. The experimental results contains on ARR signals from the MIT-BIH arrhythmia,CHF signals from the BIDMC Congestive Heart Failure and NSR signals from the MIT-BIH Normal Sinus Rhythm Databases show that the proposed method achieves a promising classification accuracy of 90.63%, significantly outperforming several typical ECG classification methods.***

***Keywords: Cardiovascular disease; Convolution neural network; ECG signal classification; Wavelet transform.***

## I. INTRODUCTION

An electrocardiogram (ECG) is therapeutic test recognizes cardiovascular variety from the standard by assessing the electrical activity delivered by the heart. A heart delivers minimal electrical inspirations which spread through the heart muscle. These inspirations can be recognized by an ECG machine. An ECG machine records the electrical development of the heart and introductions this data as a pursue on a paper. ECG finds the purpose behind indications or chest torment and moreover recognizes bizarre heart musicality or cardiovascular (heart) varieties from the standard. Gathering of electrocardiogram information encourages the lead of longitudinal examinations to analyze the relationship of specific ECG variations from the norm to consequent occasions of cardiovascular sickness.

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What's more, information from NHANES III give an interesting chance to comprehend ECG irregularities in high hazard bunches which could upgrade future cardiovascular infection recognition and aversion endeavors. ECG is the chronicle of the electrical property of the pulses and turned out to be one of the most significant apparatuses in the analysis of heart infections.

Because of high death pace of heart infections, early location and exact separation of ECG sign is fundamental for the treatment of patients. Early and exact identification of ECG arrhythmia causes specialists to distinguish different heart maladies.

Arrangement of ECG sign utilizing AI procedures can give generous contribution to specialists to affirm the finding. Arrangement and identification of arrhythmia types can help in recognizing the variation from the norm present in ECG sign of a patient.

Grouping f ECG sign is a difficult issue because of issues associated with characterization process. Serious issues [1, 2] in ECG arrangement are absence of institutionalization of highlights, inconstancy among the ECG highlights, independence of the ECG designs, non presence of ideal characterization rules for ECG grouping.

ECG sign is one of the biomedical sign, which are widely thinks about and connected in facility. A typical ECG waveform is generally made out of P wave, QRS edifices, and T wave, and the exact recognition of them is significant to analyze ECG signal. Be that as it may, in light of the fact that ECG sign is very faint, it is amazingly simple to meddle by the distinctive noises while assembling and recording. Step by step instructions to stifle noises effectively is constantly a significant issue in the location of ECG signal. Recently, wavelet change has been generally utilized in signal and picture preparing because of the time-recurrence localization characteristics.

There are primarily two sorts of wavelet denoising strategies utilized in denoising of ECG signal [3,4,5] one is wavelet change modulus maxima strategy. This strategy can take out commotions and remain the data of the original signal in most extreme simultaneously, however the sum of calculation is extraordinary, and the procedure of computation may beunstable. The other is wavelet thresholding denoising method. Wavelet thresholding denoising strategy bargains with wavelet coefficients utilizing an appropriate edge picked in advance.

## II. METHODOLOGY

This area for the most part presents the techniques for information preparing, standards and applications. Figure 1 portrays the definite procedure of the entire strategy, which has 3

fundamental advances, i.e., information pre-handling, include extraction and arrangement.
Firstly, The default wavelet utilized in the channel bank is the scientific Morse wavelet [6,7] as shown in Figure 4. You can shift the time-data transfer capacity and evenness parameters for the Morse wavelets, to tune the Morse wavelet for your needs. In this way, the split of ECG signals and the decrease of measurement are performed by utilizing of wavelet change.

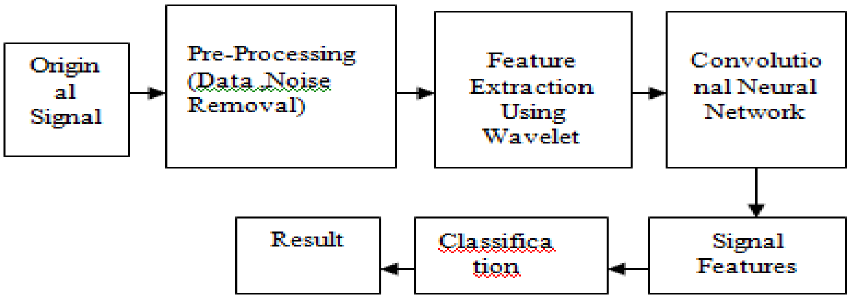


**Figure 1: ECG classification flow diagram**

All ECG information were this document comprises of 162 records are ARR-Arrhythmia, CHF-Congestive Heart Failure, NSR-Normal Sinus Rhythm. The initial 96 columns of 'ARR' are adjusted duplicates of the two ECG chronicles in the 48 information documents contained in the MIT-BIH Arrhythmia Database. The following 30 lines of 'CHF' are adjusted duplicates of the two ECG chronicles in the 15 information documents contained in The BIDMC Congestive Heart Failure Database. The last 36 columns of 'NSR' are altered duplicates of the two ECG chronicles in the 18 information records contained in the MIT-BIH Normal Sinus Rhythm Data base. These are put away in the information document.
Convolution neural system [8] is for the most part made out of two sections, include extraction and arrangement. The segment of highlight extraction is in charge of separating viable highlights from the ECG flag naturally, while the piece of order is accountable for characterizing signals precisely by utilizing the extricated highlights.

## III. RESULTS

In this training process we will take training signals and validation signals to find out the Initializing image normalization as shown in Figure 2.

Number of training signals: 130
Number of validation signals: 32
Initializing image normalization.

Training Process of the Signals:

| Epoch | Iteration | Time Elapsed (hh:mm:ss) | Mini-batch Accuracy | Validation Accuracy | Mini-batch Loss | Validation Loss | Base Learning Rate |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 00:01:37 | 26.67% | 37.50% | 1.1973 | 1.0680 | 1.0000e-04 |
| 2 | 10 | 00:04:27 | 60.00% | 65.63% | 0.8487 | 0.8438 | 1.0000e-04 |
| 3 | 20 | 00:07:23 | 86.67% | 81.25% | 0.4919 | 0.6018 | 1.0000e-04 |
| 4 | 30 | 00:10:10 | 86.67% | 78.13% | 0.6340 | 0.4614 | 1.0000e-04 |
| 5 | 40 | 00:12:57 | 73.33% | 87.50% | 0.5900 | 0.3632 | 1.0000e-04 |
| 7 | 50 | 00:15:46 | 86.67% | 90.63% | 0.3955 | 0.3222 | 1.0000e-04 |
| 8 | 60 | 00:18:43 | 100.00% | 90.63% | 0.1448 | 0.2713 | 1.0000e-04 |
| 9 | 70 | 00:21:59 | 86.67% | 90.63% | 0.2746 | 0.2486 | 1.0000e-04 |
| 10 | 80 | 00:25:31 | 93.33% | 90.63% | 0.2758 | 0.2184 | 1.0000e-04 |
| 12 | 90 | 00:28:26 | 93.33% | 90.63% | 0.1590 | 0.2216 | 1.0000e-04 |
| 13 | 100 | 00:32:04 | 100.00% | 90.63% | 0.0601 | 0.2026 | 1.0000e-04 |
| 14 | 110 | 00:35:25 | 93.33% | 90.63% | 0.2449 | 0.1984 | 1.0000e-04 |
| 15 | 120 | 00:38:14 | 93.33% | 90.63% | 0.1960 | 0.2245 | 1.0000e-04 |
| 17 | 130 | 00:41:03 | 100.00% | 93.75% | 0.1446 | 0.2224 | 1.0000e-04 |
| 18 | 140 | 00:43:46 | 100.00% | 90.63% | 0.0513 | 0.2324 | 1.0000e-04 |
| 19 | 150 | 00:46:25 | 93.33% | 90.63% | 0.1123 | 0.2264 | 1.0000e-04 |
| 20 | 160 | 00:49:03 | 93.33% | 90.63% | 0.0794 | 0.2003 | 1.0000e-04 |

**Figure 2: Accuracy for different iterations**

An electrocardiogram (ECG) might be utilized to analyze arrhythmia(ARR). It is a perusing of pulse and mood. Congestive heart disappointment (CHF) is a clinical disorder wherein the heart neglects to siphon blood at the rate required by the using tissues or in which the heart can do as such just with a height in filling weight. NSR used to mean a particular kind of sinus musicality where every single other estimation on the ECG additionally fall inside assigned ordinary breaking points as shown in Figure 3..

**ARR, CHF and NSR Signals**

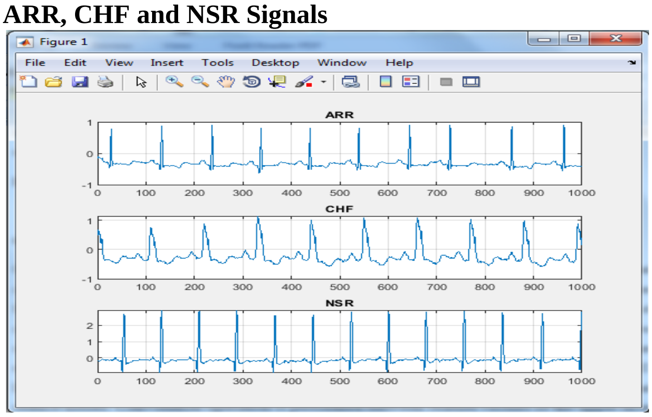


**Figure 3: Arrhythmia, CHF, normal ECG signals**



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### Scalogram of the Signals:

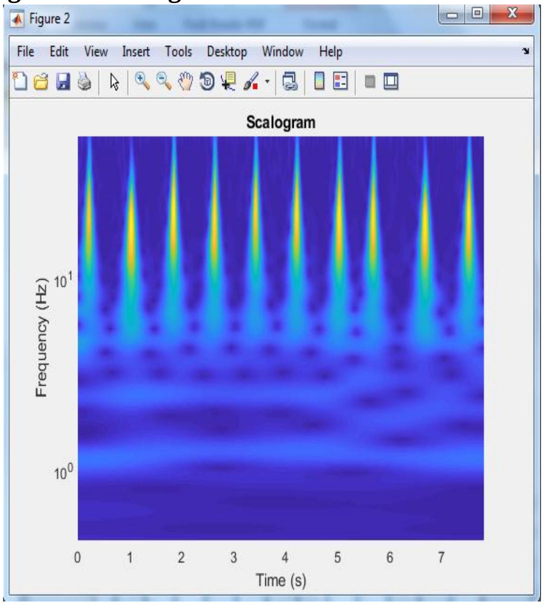


**Figure 4: CWT of ECG signal**

### Training Progress of the Signals:

In this ECG signal training process we know that validation accuracy is 90.63% using Number of training signals 130 Number of validation signals 32 as shown Figure 5.

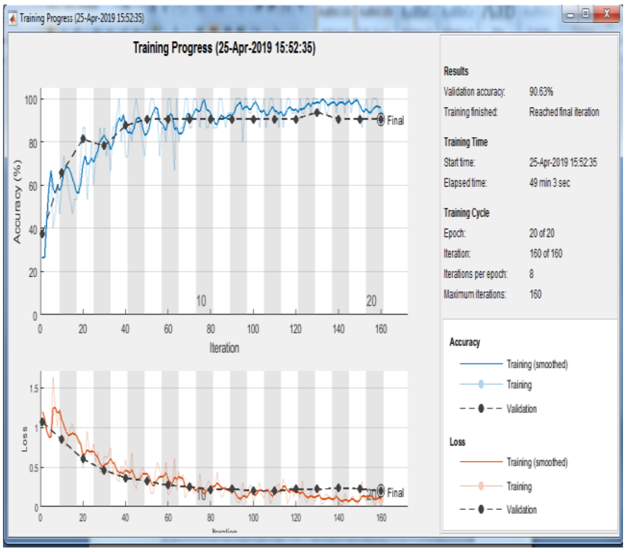


**Figure 5: Training process of CNN**

## IV. CONCLUSION

The characterization of ECG sign is useful to avert and analyze the cardiovascular infection and it is a significant research subject during the time spent combining prescription and PC innovation. So as to acquire higher quality ECG signals, There are utilizing Continuous wavelet change channel bank are utilized in this project. At that point, CNN model is understands the characterization of ARR (Arrhythmia), CHF (Congestive Heart Failure), and NSR (Normal Sinus Rhythm) signals. At last, the upgraded CNN model learns viable highlights and finishes order naturally. A decent grouping exactness of 90.63% is acquired by contrasting and the past work.

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