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Article

A Hardware-Aware MLP Inference Framework for Bradyarrhythmia Classification

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Abstract: This paper presents a hardware-accelerated model for bradyarrhythmia classification, which addresses the shortcomings of traditional techniques by the integration of machine learning with hardware to enable power-efficient and accurate classification of bradyarrhythmia, using Butterworth bandpass filter. Common software algorithms for ECG classification find it difficult to maintain performance and efficiency, especially in wearable or portable medical devices. The architecture which is designed helps in improving the accuracy of classification of bradyarrhythmia with MLP and bridging the gap between accuracy and hardware implementation which helps in the development of biomedical signal processing and machine learning.
Keywords: Normal Sinus Rhythm, Bradyarrhythmia, Butterworth Filter, Hardware Acceleration, Multi-Layer Perceptron

1. INTRODUCTION

Cardiovascular diseases contributes majority of the mortality worldwide, with arrhythmias playing a significant role in sudden cardiac events. Bradyarrhythmia, is a condition of slow heart rate, which leads to insufficient blood circulation and complications if neglected. Electrocardiography (ECG) is a non-invasive tool used to monitor and analyse the waves of the heart to diagnose the problems. Figure 1 shows Normal Sinus Rhythm (NSR) and Bradyarrhythmia ECG.

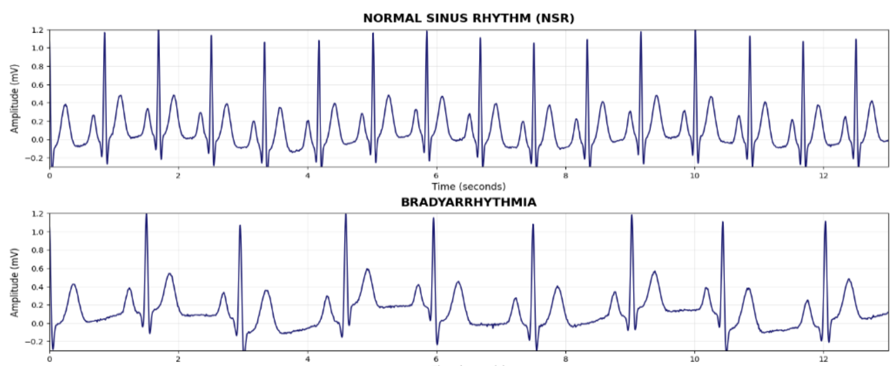


Figure 1: Normal Sinus Rhythm and Bradyarrhythmia

Traditional methods of ECG analysis are too dependent on manual study by clinicians, which consumes more time and susceptible to errors made by humans, especially when the readings are long such as Holter monitor data. ECG waveforms are also affected by noise from muscle activity, low and high frequency, making accurate diagnosis tough. Signal preprocessing techniques like Butterworth filtering are commonly there to improve signal quality to keep the ECG clean.

With machine learning becoming popular, classification of ECG has a major scope to improve from the past. Neural networks, particularly Multi-Layer Perceptron (MLP), have demonstrated strong capability in identifying complex patterns in physiological data, as shown in figure 2. However, software-based implementations may not meet real-time constraints incritical healthcare applications, thereby motivating the need for efficient hardware-accelerated solutions.

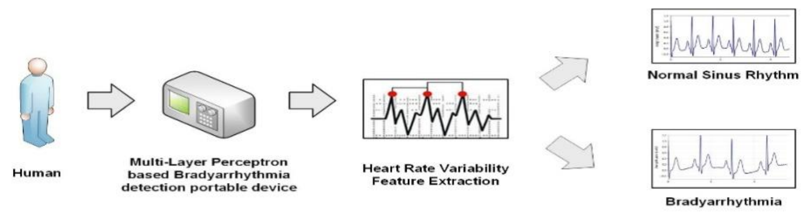


Figure 2: Classification of ECG Signals with portable device based on MLP

2. LITERATURE REVIEW

The examination of ECG signals for the identification of cardiac anomalies has been an active area of research for several decades. With the increasing prevalence of cardiovascular diseases, there is a growing need for accurate and efficient diagnostic systems. Earlier methods mainly depended on doctors to manually examine ECG recordings, which sometimes produce inconsistent results. Because of these limitations, automated ECG analysis techniques have become more widely used in recent years.

Sheng-Yueh Pan, Duc Huy Nguyen, and Paul C.-P. Chao developed a neural network model for the early prediction of sudden cardiac arrest (SCA) based on heart rate variability (HRV) metrics. A Multi-Layer Perceptron model (MLP) with hidden layers are trained and evaluated by calculating accuracy, specificity and sensitivity [1].K. P. Nandini and G. Seshikala proposed an efficient FPGA-based system for real-time arrhythmia detection with machine learning and fiducial windowing. [2].

Sahoo, Dash, Behera and Sabut proposed a research which provides details of different machine learning methodologies applied to categorization of cardiac arrhythmias in ECG signals. It evaluates key processes, including examination of R-peaksfor identifying cardiac irregularities[3].Yanlong Chen, Mattia Orlandi, Pierangelo Maria Rapa, Simone Benatti, Luca Benini and Yawei Li had introduced a wavelet-Transformer model for physiological signal modeling but highlighted hardware-friendly alternatives [4].

ShuennYuh Lee, Ming Yueh Ku, Sing-Yu Pan and Chou Ching Lin had developed a hardware-optimized neural network for ECG analysis on open-source RISC-V platforms. Their research focused on custom instruction extensions that specifically accelerate the matrix-vector multiplications found in MLP[5].AlaaEleyan and Ebrahim Alboghbaish developed a deep-learning-based system that uses Long Short-Term Memory (LSTM) for the categorization of electrocardiogram (ECG) signals[6].

Samson Dauda Yusuf, Ibrahim Umar and Lucas Williams Lumbi proposed an integrated filtering approach combining Butterworth and Savitzky-Golay filters for improved ECG quality. The study showed that their pipeline optimizes signal quality without distorting low-frequency diagnostic features[7].

3. PROPOSED SYSTEM FOR BRADYARRHYTHMIA CLASSIFICATION

The proposed methodology block diagram for hardware-accelerated neural network-based bradyarrhythmia classification is in figure 3.

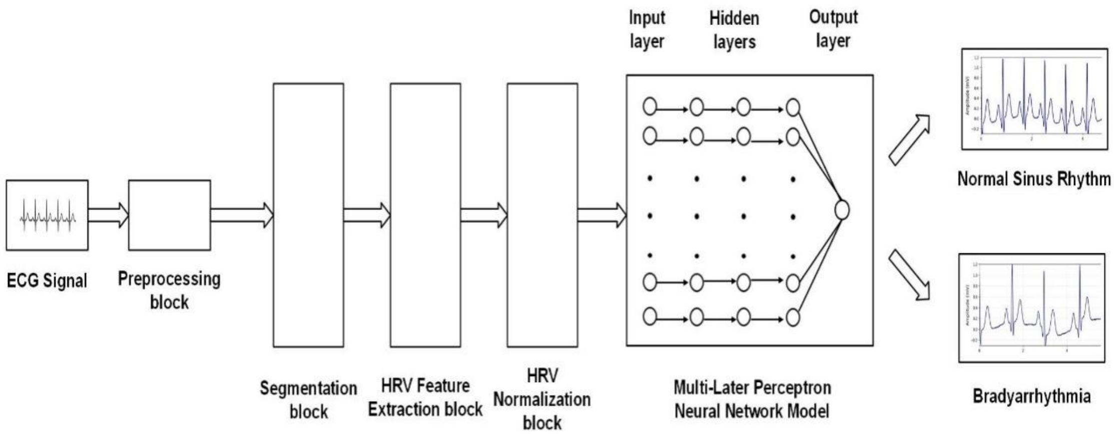


Figure 3: Proposed HRV-MLP Bradyarrhythmia Classification

3.1 ECG data Acquisition

The ECG data was found in PhysioNet repository, which provides high-quality, publicly available ECG databases.NSRdatabase and Arrhythmia database were used and 18 datasets from each were selected.

3.2Preprocessing Block

Preprocessing of ECG signals is a crucial step to improve signal quality before feature extraction or classification. Raw ECG data usually contains unwanted noise such as baseline wander.The Butterworth bandpass filter is typically implemented by cascading a high pass filter (cutoff at 0.5 Hz) and a low pass filter (cutoff at 40 Hz). The magnitude response of an analog Butterworth low-pass filter of order *n* is given by Eq. 1.

$$|H(j\omega)| = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2n}}} \quad (1)$$

where ω_c is the cutoff frequency and n is the filter order, which is 4^{th} order. For a bandpass filter, the transfer function combines both low-cutoff and high-cutoff frequencies.

Performance metrics are found to assess the signal quality. These metrics give evaluation of noise reduction and signal fidelity after filtering.

MSE calculates the average squared difference in the actual and clean ECG. It is expressed as in Eq.2.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \quad (2)$$

Where x_i is the raw signal, y_i is the filtered signal, and *N* is the total sample count.

RMSE is the square root of MSE that gives information the spread of the residual errors. The expression is shown in Eq. 3.

$$RMSE = \sqrt{MSE} \quad (3)$$

Mean Absolute Error or MAE measures how different the raw ECG signal is from the signal on average. Its equation is given in Eq. 4.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \quad (4)$$

SNRmeasures the ratio between original signal power and noise power. It is mentioned in Eq. 5.

$$SNR = 10 \log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (5)$$

where $P_{signal}$is the original power and P_{noise} is noise power.

PSNR measures the ratio of the power of signal and power of noise. It is useful in processing of signal to assess reconstruction or filtering quality in decibels. It is mentioned in Eq. 6.

$$\text{PSNR} = 10\log_{10}\left(\frac{MAX^2}{MSE}\right) \quad (6)$$

where *MAX* is the signal's maximum value.

R² represents how filtered signal explains the change in raw ECG. It varies between 0 and 1., where a value closer to 1 indicates better preservation of signal characteristics. It is shown in Eq. 7.

$$R^2 = 1 - \frac{SS_{res}}{SS_{rot}} \quad (7)$$

where SS_{res} is the sum of squared residuals and $SS_{tot}$is the total sum of squares.

3.3Segmentation

The filtered ECG are segmented into fixed-length windows for consistent feature extraction and classification. Each ECG signal is broken down into 2000 samples. We chose this size because it has RR intervals to get a good idea of the HRV and easy when it comes to the equipment and processing.

3.4 Feature Extraction Block

After detecting the R-peaks from the filtered ECG signal, the RR interval sequence is calculated. Based on this interval series, different HRV features are found from the time-domain, frequency-domain, and nonlinear domains. Figure 4 shows the feature extraction block.

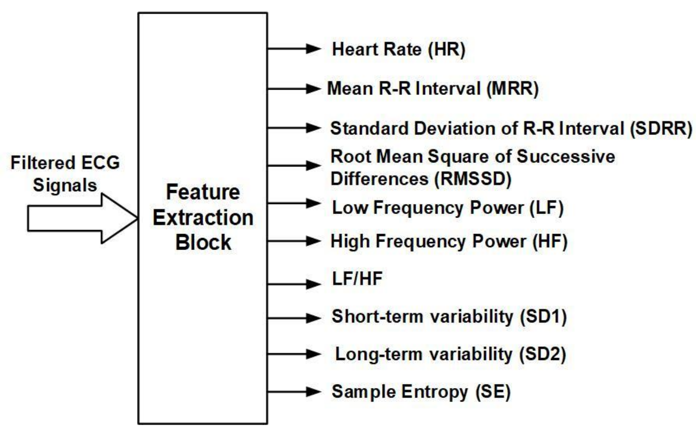


Figure 4:Feature Extraction Block

.**3.4.1 Time-Domain Features**

Time-domain features are the simplest and most widely used methods for analyzing heart rate variability. These features are found from the RR interval.

Heart rate is how many times the heart beats in one minute. It is inversely related to the RR interval and when RR interval is short, heart rate is high and vice versa. It is in Eq. 8.

$$\text{HR} = \frac{60}{\overline{RR}} \quad (8)$$

where $\overline{RR}$is the mean RR interval in seconds.

The mean RR interval is the average time between consecutive R-peaks in an ECG signal and indicates the rhythm of the heart. It is calculated as in Eq. 9.

$$\overline{RR} = \frac{1}{N}\sum_{i=1}^{n} RR_i \quad (9)$$

where RR_i represents individual RR intervals and N is the number of intervals.

SDRR intervalis the overall variation in RR intervals and reflects the combined effect of the sympathetic and parasympathetic nervous systems. It is defined in Eq.10.

$$\text{SDRR} = \sqrt{\frac{1}{N-1}\ \sum(RR_i - MRR)^2} \quad (10)$$

RMSSD measures short-term changes in heart rate by calculating the variation between consecutive RR intervals. It is computed as mentioned in Eq. 11.

$$\text{RMSSD} = \sqrt{\frac{1}{N-1}\ \sum(RR_{i+1} - RR_i)^2} \quad (11)$$

3.4.2 Frequency-Domain features

Frequency-domain HRV features analyze how the signal's power is spread across various frequency bands of the RR interval. LF represents short variations in heart rate by finding the differences between consecutive RR intervals. It is highly sensitive to parasympathetic (vagal) nervous system activity. It is computed as shown in Eq.12.

$$\text{LF}=\int_{0.04}^{0.15} \text{PSD(f)df} \quad (12)$$

where PSD(f) is the power spectral density of the RR signal.

HF power corresponds to the power in the high-frequency band (0.15–0.4 Hz) and is mainly linked to parasympathetic activity and respiratory sinus arrhythmia. It is computed as in Eq. 13.

$$\text{HF}=\int_{0.15}^{0.4} \text{PSD(f)df} \quad (13)$$

The LF/HF ratio is a commonly used index to find the equilibrium between sympathetic and parasympathetic system. It is in Eq. 14.

$$\frac{LF}{HF} \quad (14)$$

3.4.3 Nonlinear features

Nonlinear HRV features obtain heart rate patterns that cannot be fully explained using linear statistical or spectral methods. The cardiovascular system is inherently nonlinear, influenced by multiple interacting physiological processes.

SD1 is a nonlinear HRV measure from the Poincaré plot and represents short-term variability of RR intervals. It is calculated as in Eq. 15.

$$\text{SD1}=\sqrt{\frac{1}{2}}\times\text{RMSSD} \quad (15)$$

SD2 represents long-term changes in the Poincaré plot and reflects both sympathetic and parasympathetic influences. It is given by the Eq. 16.

$$\text{SD2} = \sqrt{\text{2SDRR2} - \ \frac{1}{2}\ \text{RMSSD2}} \quad (16)$$

Sample entropy measures how complex and irregular the RR are. It isin Eq. 17.

$$SampEn(m,r,N) = -ln(\frac{A}{B}) \quad (17)$$

where A is thematched patterns of length m+1, B is the matched patterns of length mmm, r is tolerance, and N is data length.

3.5 Normalization Block

Normalization is done to increase performance and stability of the Multi-Layer Perceptron (MLP) neural network. In this proposed system. Z-score normalization transforms the features for zero mean and standard deviation of one. The Z-score normalization for each HRV feature is mathematically defined in Eq. 18.

$$\text{z} = \frac{x-\mu}{\sigma} \quad (18)$$

where x is the original value, μ is mean and σ is how much it varies.

3.6 Multi-Layer Perceptron Model

A Multi-Layer Perceptron is a type of network that helps with classification. It has layers of neurons including the input layer, hidden layers and output layer. The MLP architecture is in figure 5.

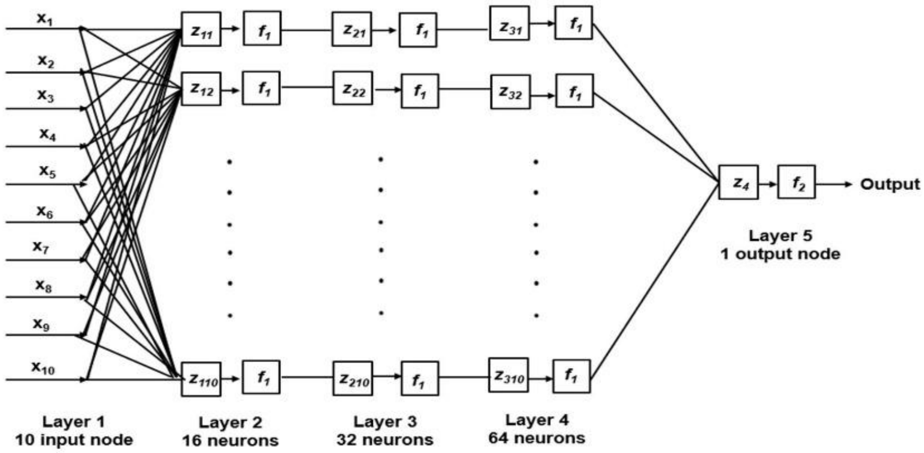


Figure 5:Multi-Layer Perceptron Model Architecture

The weighted sum is the first computational step performed inside every neuron of the MLP. Each input value is scaled by an associated weight, and the resulting products are aggregated along with a bias term.

The weighted sum is mathematically represented as in Eq. 19.

$$z = \sum_{i=1}^{n} w_i x_i + b \quad (19)$$

where x_i represents the input features, w_i represents the weights, b is the bias, and z is the intermediate output.

The Multiply–Accumulate (MAC) unit serves as a fundamental computational block in the hardware realization of MLP. It performs the core mathematical operation required for neural network processing, where each input feature is multiplied by its corresponding weight and results are stored to produce the weighted sum.

Rectified Linear Unit (ReLU) is a widely adopted activation function in neural networks. It is defined in Eq. 20.

$$f_1 = f(x) = \max(0, x) \quad (20)$$

For negative input values, the function generates an output equal to zero and passes positive values unchanged. This simple formulation makes ReLU computationally efficient and easy to implement in both software and hardware-based systems.

The hardware architecture is in figure 6.

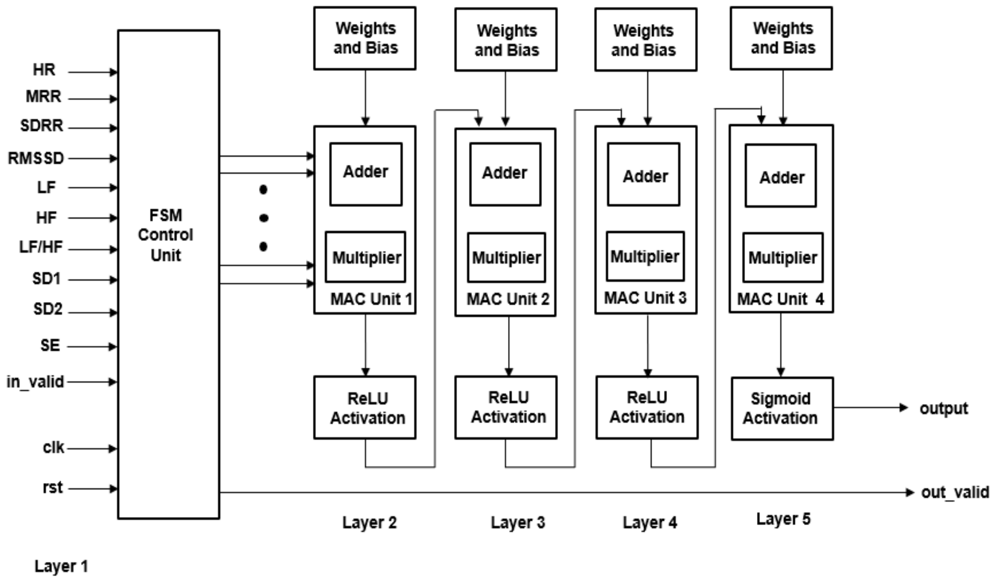


Figure 6: Block Diagram of MLP Hardware Architecture

Sigmoid is often used in the output layer when the model performs binary classification. It is defined in Eq. 21.

$$f_2=f(x) = \frac{1}{1+e^{-x}} \quad (21)$$

It changes any input value into a number between 0 and 1. In ECG classification tasks, for example, the sigmoid function can output the probability of a signal being normal or indicative of bradyarrhythmia.

4. IMPLEMENTATION OF THE BRADYARRHYTHMIA CLASSIFIER

The implementation begins with the acquisition of raw ECG signals. The input ECG signal is first applied to a preprocessing stage, where operations such as bandpass filtering, baseline drift removal, and signal amplification are carried out to improve signal quality. After preprocessing, the filtered ECG signal is passed to the segmentation stage. In this stage, the continuous ECG waveform is divided into individual heartbeats or fixed-length segments using R-peak detection. Proper segmentation helps achieve accurate feature extraction and improves the efficiency of later processing stages. This is carried out in Python 3.10.

In the next stage, the segmented ECG signals are given to the HRV feature extraction block, where time, frequencydomain and nonlinear HRV parameters are found from the RR intervals. After feature extraction, the values are normalized in the HRV normalization stage so that all features lie within a common range. The normalized feature vector is then sent as input to the Multi-Layer Perceptron (MLP) Neural Network Model, consisting of an input, hidden and output layers that classifies the input into Normal Sinus Rhythm or Bradyarrhythmia. The MLP is implemented in Cadence. The flowchart of implementation is shown in figure 7.

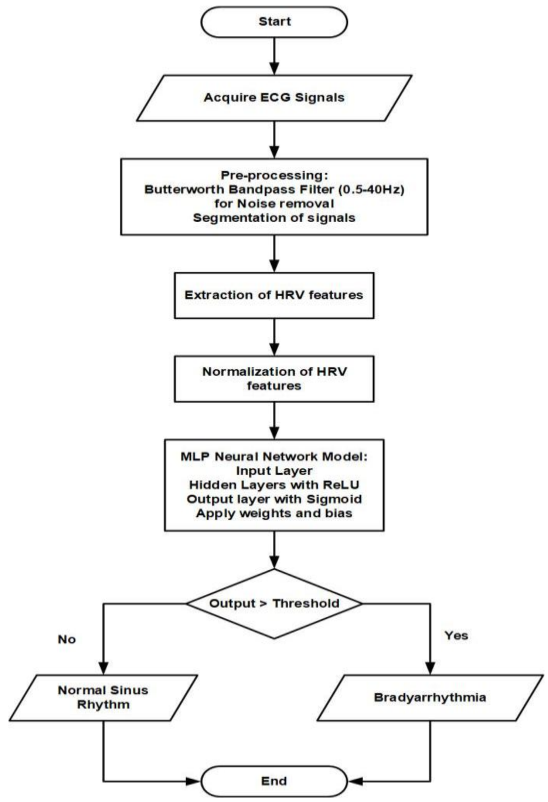


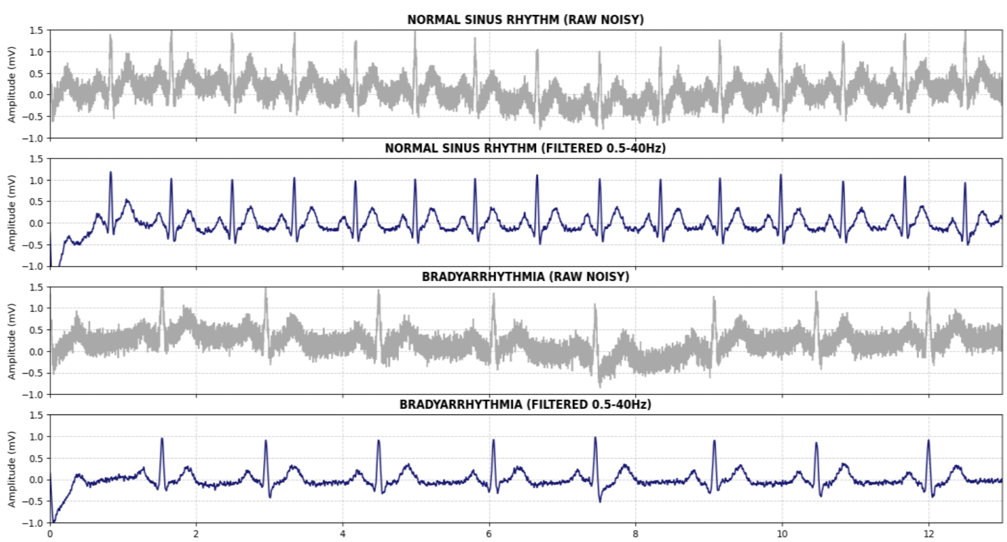
Figure 7: Flowchart of the System

5. RESULTS AND DISCUSSION

The implementation results are in this section.

5.1 Butterworth Filter Results

To improve signal quality, a 4th-order Butterworth bandpass filter is applied in Python using the scipy.signal library.The selected cutoff frequency range of 0.5 Hz to 40 Hz is suitable because most important ECG components such as P wave, QRS complex, and T wave lie within this frequency band. The filtered signal is shown in figure 8.



Time (seconds)

To ensure reliable evaluation across multiple ECG records, mean and standard deviation of all these performance metrics are calculated. The calculated performance metrics of the 4th order Butterworth filter is shown in table 1.

Table 1: Performance Metrics of Butterworth Filter

Metric	Mean	Standard deviation
SNR (dB)	13.0986	2.9509
PSNR (dB)	28.7675	3.0894
MSE	0.0073	0.0057
RMSE	0.0811	0.0267
MAE	0.0648	0.0226
R2	0.9378	0.0392

5.2 Normalization Results

Since these HRV features have different units and numerical ranges, Z-score normalization is applied to standardize the feature values before they are given to the MLP classifier. This method transforms each feature so that it has a mean zero and standard deviation one, ensuring equal contribution of all features during training.

5.3 Multi-Layer Perceptron Model Results

The Multi-Layer Perceptron (MLP) is trained by the extracted and normalized HRV features to differentiate ECG into Normal Sinus Rhythm (NSR) and bradyarrhythmia classes. The six-fold cross validation is a model evaluation used to test the performance of the architecture by dividing the complete dataset into 6 equal parts, called folds. performance and reduces the chances of biased results caused by a train-test split. The performance metrics of the MLP model is shown in table 2.

Table 2: Performance metrics of the Multi-Layer Perceptron Model

<table>
<tr><th colspan="2"></th><th>Training</th><th>Testing</th></tr>
<tr><td rowspan="3">Without Butterworth filter</td><td>Accuracy (%)</td><td>96.96</td><td>95.93</td></tr>
<tr><td>Specificity (%)</td><td>97.25</td><td>95.83</td></tr>
<tr><td>Sensitivity (%)</td><td>97.15</td><td>96.11</td></tr>
<tr><td rowspan="3">With Butterworth filter</td><td>Accuracy (%)</td><td>98.53</td><td>97.52</td></tr>
<tr><td>Specificity (%)</td><td>98.60</td><td>97.65</td></tr>
<tr><td>Sensitivity (%)</td><td>98.54</td><td>97.44</td></tr>
</table>

Increase in accuracy, specificity and sensitivity is obsevered when Butterworth filter is included. This is due to the removal of low and high frequency noise by the bandpass filter. The accuracy increased by 1.59%, specificity increased by 1.82% and sensitivity increased by 1.33%.

5.4 Synthesis Results

Table 3: Synthesis Results

	Without filter	With filter
Area	66913.742	77898.632

Power (W)	1.50409E-03	1.93657E-03
Timing (ps)	11100	11204

The synthesis reports of the proposed model using Cadence Genus is in table 3. The parameters which are used to evaluate are area, power and delay.

It is observed that integration of Butterworth filter leads to slight increase in area, power and delay, which is acceptable for portable devices for classifying bradyarrhythmia. The accuracy, specificity and sensitivity of the model has increased when the Butterworth filter is integrated, which is suitable for portable devices for finding Bradyarrhythmia.

6. Conclusion and Future Scope

The primary aim is to design hardware-accelerated Multi-Layer Perceptron (MLP) for the real-time classification of bradyarrhythmia, and the results demonstrate a successful integration of VLSI design principles with biomedical signal processing. By implementing a 4th-order Butterworth bandpass filter as a preprocessing stage, the system effectively neutralized baseline wander and high-frequency noise, ensuring that the morphological features of the ECG signal remained intact for feature extraction.The performance of the MLP model reached a realistic and robust accuracy during testing, successfully distinguishing normal sinus rhythms from pathological slow heart rates. While the current system provides a robust foundation for bradyarrhythmia classification, several areas exist for enhancing its functionality and integration. The current MLP architecture could be expanded to include a wider variety of cardiac conditions, such as Atrial Fibrillation (AFib) and Tachyarrhythmia.

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