International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 12 December 2024
Page No: 2802- 2810
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0387

Implementation of Self-Organized Operational Neural Networks for R Peak Detection in Holter ECG

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Abstract
While a number of R-peak detectors have been created, their performance may be significantly impacted when handling noisy, low-quality data from mobile ECG sensors, such as Holter monitors. Even though deep 1-D convolutional neural networks (CNNs) have recently produced state-of-the-art results, their high complexity and need for specialized parallel hardware for real-time processing can limit performance, particularly with compact network configurations. Because CNNs only use one linear neuron model, their learning capacity is limited, leading to this constraint. To tackle this problem, operational neural networks (ONNs) integrate neurons with several types of nonlinear operators in a network architecture that is heterogeneous. The goal of this work is to improve R-peak detection performance in 1-D Self-Organized ONNs (Self-ONNs) while maintaining computing efficiency through the use of generative neurons. Because each generating neuron in a 1-D Self-ONN learns its ideal configuration through adaptation, the Self-Organizing feature eliminates the need for human operator set selection. Our experimental results, utilizing the MIT-BIH Arrhythmia dataset, which contains over a million ECG beats, reveal that 1-D Self-ONNs outperform state-of-the-art deep CNNs in terms of both performance and computational economy.
Keywords: *R-Peak Detection, Holter Monitors, CNNs, ONNs, and MIT-BIH Arrhythmia Dataset.*

1. Introduction
The electrical activity of the heart is recorded by an electrocardiogram (ECG), which also displays the pattern of depolarization and repolarization as well as the beating sequence. The ECG signal's properties, such as ventricles beats and QRS complexes, reveal vital information about the condition of the heart. Though many diagnostic technologies have advanced, the ECG is still the most crucial non-invasive method for clinical assessment and heart monitoring. An essential first step in ECG analysis is R-peak recognition, which forms the foundation for other procedures including beat categorization and cardiac arrhythmia diagnosis [1] [2]. Since the use of traditional Holter monitors is growing and low-cost, low-power mobile ECG sensors have recently been developed, robust, real-time R-peak detection has become highly important. However, ensuring accurate detection is difficult. Current research [3] has demonstrated that performance can drastically decline in the presence of low quality or severely noisy ECG data. Over time, several R-peak identification methods for clinical ECG records have been developed. The algorithm presented by Pan and Tompkins [4] is still one of the most popular and has been a standard for more than thirty years among the innovative techniques. Since then, a number of sophisticated signal processing methods have been developed, such as empirical mode decomposition [8], wavelet transform [5, 6], and Hilbert transform [7]. Examples of combination approaches that blend more contemporary machine learning techniques with conventional signal processing techniques are Hidden Markov Models (HMMs) [10] and Radial Basis Functions (RBFs) [9]. Conventional approaches frequently concentrate on raising the R-peak using signal processing methods like spectral analysis and filter banks prior to peak identification. These approaches are notable for their speed and efficiency but are often tuned for clinical ECG recordings characterized by clear, practically noise-free signals. To evaluate all of these methods, the

benchmark arrhythmia dataset from Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) [16] or other high-quality clinical ECG datasets were employed. Their effectiveness frequently deteriorates dramatically when dealing with poor-quality ECG data [3], making them less useful for transportable ECG sensors with little power. Lack of sufficiently diversified public datasets [11], [12] in this discipline is dealing with noisy ECG signals and ground-truth R-peak positions. Usually, these datasets have size and time restrictions. Even with modern Deep Learning-based peak detection approaches like LSTM networks [13] and CNNs [14], [15], this constraint continues to be a major bottleneck. While both approaches in [13] and [14] aimed to improve resilience, their primary testing was conducted against synthetic additive noise that was injected into ECG recordings from the MIT-BIH dataset. This noise included baseline wander and motion distortions. Therefore, it is unclear how successful they would be in real-world situations where noise is present by nature. Merely adding artificial noise cannot adequately capture the degradations observed in real-world Holter monitoring. In real-world situations, there may be severe and irregular noise levels, intermittent malfunctions, and significant fluctuations in the baseline level. Furthermore, as figure 1 illustrates, the QRS complex's dynamic range is inconsistent. The MIT-BIH dataset has limitations as well; not enough beat variants exist for deep network testing to be done with confidence. This deficiency increases the possibility of bias and overfitting in the outcomes. In a recent article [15], a novel approach utilizing deep 1-D CNNs was used to the Chinna Physiological Signal Challenge (2020) dataset (CPSC). This dataset provides a more comprehensive testing environment with over a million ECG beats. The technique outperforms earlier benchmarks and demonstrates state-of-the-art performance in R-peak detection. However, it has two serious disadvantages: There are two significant computational complexity issues with the 12-layer deep model: 1) Especially when identifying arrhythmia beats, False Positives (FPs) and False Negatives (FNs) are still rather high. The goal of this study is to use a unique network model to address these issues. A significant drawback of convolutional neural networks (CNNs) and traditional multilayer perceptions (MLPs) has been brought to light by recent research [17]–[20]. Both rely on the McCulloch-Pitts [16] neuron model, which is antiquated relative to the complexity of genuine mammalian brain networks. Diverse nonlinear neuron types with unique electrophysiological and metabolic characteristics make up biological neural networks [17], [18]. On the other hand, homogeneous, linear neurons are used by MLPs and CNNs, which makes them appropriate for less complicated, linearly separable issues but insufficient for extremely complex and nonlinear scenarios. To address this restriction, generalized operational perceptions (GOPs) and operational neural networks (ONNs) were created. These models reduce training data and network complexity [17] [20] by utilizing a variety of nonlinear neuron types to tackle complex, multimodal tasks. Operational neurons in GOPs [17] [19] and ONNs [20] are made to resemble real neurons by means of pool (integration in the soma) and nodal (synaptic connections) operators. Combinations of nodal, pool, and activation operators are kept in a pre-established library and make up a "operator set." But ONNs have two significant disadvantages. In this paper, we present 1-D self-organized ONNs (Self-ONNs) for real-time Holter ECG analysis that leverage a generative neuron model to enhance robust R-peak identification. By enabling nodal operators to be produced frequently during backpropagation training, the generative neuron model improves learning performance and fosters self-organization inside Self-ONNs. The ability to produce nonlinear nodal operators boosts flexibility and operational diversity. Therefore, a predefined library of operator sets or an initial search for the best nodal operators are not needed for Self-ONNs. A growing performance gap between ONNs and CNNs has been observed in previous studies on 2-D Self-ONNs, which demonstrate that even with a modest number of neurons, they can beat known techniques in a range of image processing and regression tasks.

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Our primary goal is to improve R-peak detection performance across deep 1-D CNNs while simultaneously drastically reducing network depth and complexity for real-time applications. To provide a thorough validation, we will evaluate our methodology against prior state-of-the-art methodologies in addition to comparisons with deep 1-D CNNs. We shall summarize and highlight the novel and significant contributions made by the paper below.

1.1 Key Contributions of This Study Include

1. **Novelty in Application:** This study is the first to apply 1-D self-ONNs to ECG peak detection, using extensive CPSC (2020) dataset, which includes over one million ECG beats.
2. **Enhanced Learning Capability:** The 1-D self-ONNs with heterogenous structures demonstrate superior peak detection performance, compared to traditional models, needing almost four times fewer neurons and only half the network depth
3. **Improved Accuracy:** Our approach significantly reduces false-negative rates for arrhythmia beats compared to major existing peak detection methods.
4. **Reduced Complexity:** The proposed 1-D Self-ONNs offer superior R-peak detection while markedly decreasing the depth and complexity associated with deep 1-D CNNs [34] models.
5. **Computational Analysis:** This study presents the raw and vectorized backpropagation formulations for 1-D Self-ONNs and includes a detailed computational complexity analysis.

Overall, our work highlights the effectiveness and efficiency of 1-D self-ONNs for real-time ECG peak detection and sets a new benchmark in this domain

2. Existing Method

Numerous R-peak detectors have been created, however their performance typically deteriorates when used with noisy or poor-quality data from portable ECG sensors, such as Holter monitors. Deep 1-D convolutional neural networks (CNNs) have raised the bar in this field. However, real-time processing necessitates the usage of specialized parallel gear due to its complexity. In this section, we first look at how ONNs expand on the 1-D convolution technique. Next, we present the mathematical model of the suggested generative neuron-based 1-D self-ONN.

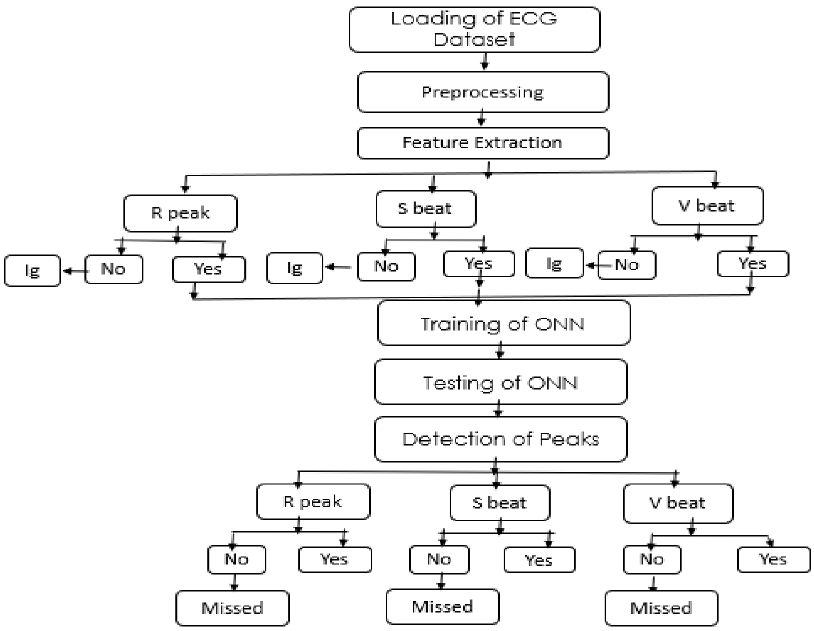

Figure 1 Flow of Existing Method

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Lastly, we introduce a generative neuron variant that enables effective vectorized operations, hence resulting in significant computational savings. Generalized Operator Networks (GOPs) evolved from MLPs to CNNs, with two key distinctions: GOPs are characterized by limited connectivity, while ONNs evolved from MLPs to CNNs. GOPs were created to address the shortcomings of the fundamental linear neuron model that was introduced by McCulloch and Pitts [16] in the 1950s. Recently, extreme learning machines (ELMs) and regular MLPs were surpassed by GOPs [19]. GOPs gave rise to ONNs [20], They have both linear and nonlinear operators and are heterogeneous networks. A more accurate portrayal of biological systems is made possible by this integration. In addition to linear convolutions, ONNs also have pooling and nodal processes, which sets them apart from convolutional neurons. Think about the kth neuron in a 1D CNN's lth layer. For simplicity's sake, let's assume that the convolution method has a unit step and the suitable amount of padding. The following represents this neuron's output:

$$x_k^l = b_k^l + \sum_{i=0}^{Nl-1} x_{ik}^l$$

The output of the $k-th$ neuron in the $l-th$ layer, denoted as b_k^l, is affected by the bias associated with this neuron. The input to this neuron, x_{ik}^l is given by:

$$x_{ik}^l \; conv1D(w_{ik}, y_i^{l-1})$$

In this equation, conv1D represents the 1-D convolution operation, w_{ik} convolutional kernel or weight associated with the neuron, and $y_i^{(l-1)}$ is the output from the previous layer. In this context, $w_{ik} \in R^K$ represents the kernel connecting the ith neuron in the $(l-1)$th layer to the kth neuron in the lth layer. $x_{ik}^l \in R^M$ denotes the input map for the kth neuron in the lth layer, while $y_i^{l-1} \in R^M$ represents the output of the ith neuron in the $(l-1)$th layer. The convolution operation for this neuron can be described as:

$$x_{ik}^l(m) = \sum_{r=0}^{k-1} w_{ik}^l(r) y_i^{l-1}(m+r)$$

In contrast, the core concept behind an operational neuron generalizes this process as follows:

$$x_{ik}^l(m) = P_k^l\left(\psi_k^l(w_{ik}^l(r) y_i^{l-1}(m+r))\right)_{r=0}^{k-1}$$

Where $\psi_k^l(\cdot): R^{M\times k} \to R^k$ and $P_k^l(\cdot): R^k \to R^1$are referred to as The k-th neuron in the l-th layer is responsible for the nodal and pooling functions, respectively. Each neuron in a heterogeneous ONN setup is equipped with unique ψ and P operators, providing the network with the flexibility to apply various nonlinear transformations tailored to specific learning tasks. Manually creating a suitable library of operators and choosing the best one for each neuron can lead to significant overhead. This challenge becomes increasingly complex as the networks size and complexity grow. Convolutional functions may not always be able to represent the optimum operator for a given learning issue. To overcome this constraint, a composite nodal function that can be repeatedly built and improved during backpropagation is necessary. One method for addressing this issue is to employ weighted combination operators from a preset set library, with the weights changed during training. However, this solution may experience stability issues due to the functions' various dynamic ranges, and it still requires human function selection for the operator set library. To solve these issues, we suggest using a Taylor-series-based function approximation to nodal transformation. This solution eliminates the requirement for operator preselection and manual assignment. Equation (11) illustrates the possibility of writing the Self-ONN formulation from (10) as the sum of Q distinct convolutional processes. Additionally, equation (12) demonstrates that a matrix-vector product can be used to define a convolutional process. Instead of describing the transformation in (11) as Q different processes. These two formulations allow us to express it as a single matrix-vector product and, ultimately, as a single convolution operation.

We clarify $y_i^{l-1\,(Q)} \in R^{M\times kQ}$ as:

$$Y_i^{l-1(Q)} = [\,Y_i^{l-1}\,(Y_i^{l-1})^{0^2}\,\ldots..(Y_i^{l-1})^{0^Q}]$$

Where o^n denoting the Hadamard exponentiation operator, the m^{th} row of $Y_i^{l-1(Q)}$ can be expressed

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as follows:

$$Y_i^{l-1(Q)}(m) = \begin{bmatrix} y_i^{l-1}(m) \\ \vdots \\ y_i^{l-1}(m+K-1) \\ \vdots \\ y_i^{l-1}(m)^2 \\ \vdots \\ y_i^{l-1}(m+K-1)^2 \\ \vdots \\ y_i^{l-1}(m)^Q \\ \vdots \\ y_i^{l-1}(m+K-1)^Q \end{bmatrix}^T$$

With this approach, we can reduce the complexity of the nodal transformation to a single matrix-vector product by expressing it as a single convolution operation.

2.1 Disadvantages

- The network`s performance declines when using a more compact configuration.
- The effectiveness of CNNs is restricted by their strictly homogeneous architecture.

3. Proposed Method

Many R-peak detectors have been developed, however when applied to noisy and low-quality data from portable ECG devices, like Holter monitors, their performance usually decreases. Operational Neural Networks (ONNs): These networks combine various nonlinear operators into a heterogeneous design to solve this issue. Using generative neurons in 1-D Self-Organized ONNs (Self-ONNs) to improve peak detection performance while preserving processing efficiency is the aim of this work. One of the main benefits of 1-D Self-Organized ONNs over conventional ONNs is their capacity for self-organization. Therefore, it is no longer necessary to predefine the ideal operator set for every neuron. Every generating neuron, instead, actively chooses the most effective operator throughout the training phase. We will first go over how ONNs enhance the 1-D convolution method in this section. We will next go over the mathematical framework for the suggested 1-D Self-ONN based on generative neurons (Figure 2).

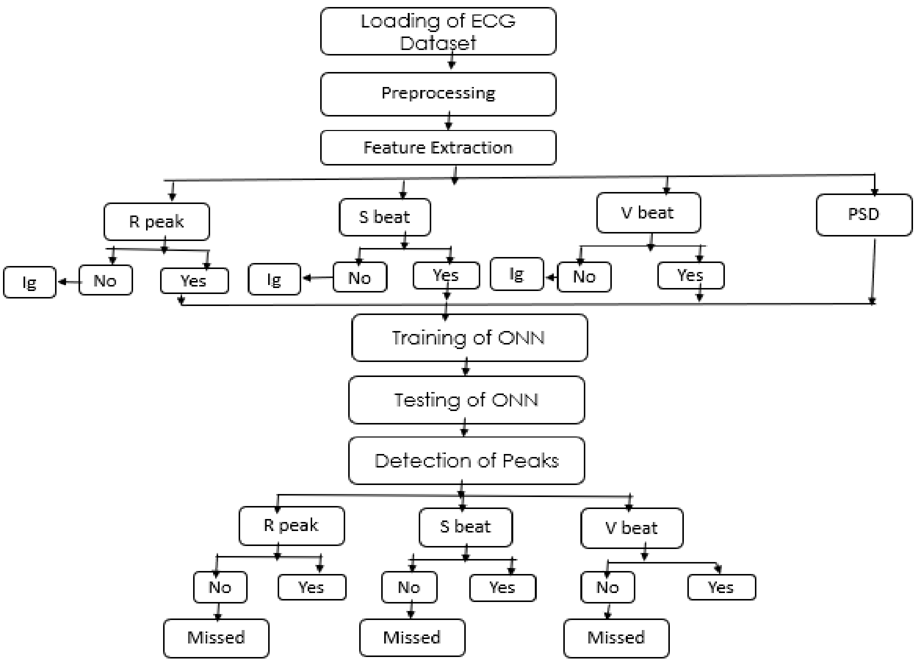

Figure 2 Flow of Proposed Method

In conclusion, we will showcase a generative neuron simplification that significantly lowers computing expenses by enabling effective vectorized operations. On the other hand, ONNs are generated from GOPs with two major limitations: weight sharing and restricted connection, much like CNNs emerge from MLPs. In order to address the well-known drawbacks of Multilayer Perceptions, Generalized Operator Networks [17] were put out as a sophisticated substitute for the fundamental linear neuron model that McCulloch and Pitts [16] first presented in the 1950s. Power Spectral Density (PSD) calculates a signal's power distribution across a range of frequencies. Analyzing the PSD of an ECG signal can be very helpful in locating prominent frequency components, which can help with arrhythmia identification. Extreme Learning Machines (ELMs) have recently been surpassed by Multi-Layer Perceptions (MLPs) and Generalized Operator Networks (GOPs) [19]. Because they are directly descended from GOPs and are heterogeneous networks that integrate both linear and nonlinear operators, Operational Neural Networks (ONNs) [20] are more like biological systems. In conclusion, by combining both nodal and pooling operators, ONNs surpass the linear convolutions utilized in conventional convolutional neurons. Take the k-th neuron in the l-th layer of a 1-D CNN, for instance. The output of this neuron, assuming a typical convolution process with unit stride and sufficient zero padding, can be written as follows:

$$x_k^l = b_k^l + \sum_{1=0}^{N_l-1} x_{ik}^l$$

Where b_k^l is the bias term associated with this neuron and x_{ik}^l is expressed as

$$x_{ik}^l \ \mathrm{conv1D}(w_{ik}, y_i^{l-1})$$

Here, $y_i^{(l-1)} \in R^M$ represents the output of the i-th neuron in the $(l-1)$th layer, and $w_{ik} \in R^K$ denotes the Kernel connecting the i-th neuron of the $(l-1)$-th layer to the $k-th$ neuron of the $l-th$ layer. The input map is given by $x_{ik}^l \in R^M$. The convolution operation can be defined in the following manner:

$$x_{ik}^l(m) = \sum_{r=0}^{k-1} w_{ik}^l(r) y_i^{l-1}(m+r)$$

The core concept of an operational neuron extends the previous approach as follows:

$$\overline{x_{ik}^l}(m) = P_k^l\left(\psi_k^l(w_{ik}^l(r) y_i^{l-1}(m+r))\right)_{r=0}^{k-1}$$

Where the $k-th$ neuron in the $l-th$ layer is assigned a nodal function $\psi_k^l(\cdot): R^{M\times k} \to R^k$ and a pooling function$P_k^l(\cdot): R^k \to R$. Each neuron in a heterogeneous ONN configuration has its own unique set of ψ and P operators. This allows the ONN network to incorporate any nonlinear transformation that is suited to the specific learning problem. The Results are shown in Figure 3 to 6. The burden associated with manually creating an appropriate library of potential operators and finding the best one for every neuron in a network, however, is substantial and increases exponentially with network complexity. Moreover, for the specific learning scenario, it's possible that no ideal operator exists that can be characterized in terms of well-known functions. This important limitation can be overcome by continuously creating and modifying a composite nodal function throughout BP. The operator learns the weights and constructs the library using a weighted combination of each operator in training. Would be a simple way to accomplish this. But since every function has a unique dynamic range, this method might cause instability problems. Furthermore, it would still be dependent on the operator set library being populated manually with appropriate functions. Consequently, we utilize a function approximation based on Taylor series to design a nodal transformation that does away with the requirement for preselection and operator assignment by hand. Equation (11) illustrates how Q separate convolutional procedures can be summarised to produce the Self-ONN formulation (10). Furthermore, a matrix-vector product can be used to represent a convolutional process according to equation (12). Instead of representing the transformation of (11) as Q-separate operations, we currently use these two formulations to indicate it as a single convolution operation, which can be simplified to a single matrix vector product. To

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commence, we present $y_i^{l-1\,(Q)} \in R^{M\times kQ}$ such that

$$y_i^{l-1}(Q) = \quad y_i^{l-1}(y_i^{l-1})^{o2}\cdots(y_i^{l-1})^{oQ}$$

Where o^n denoting the Hadamard exponentiation operator, the m^{th} row of $Y_i^{l-1(Q)}$ can be expressed as follows:

$$Y_i^{l-1^{(Q)}}(m) = \begin{bmatrix} y_i^{l-1}(m) \\ \vdots \\ y_i^{l-1}(m+K-1) \\ \vdots \\ y_i^{l-1}(m)^2 \\ \vdots \\ y_i^{l-1}(m+K-1)^2 \\ \vdots \\ y_i^{l-1}(m)^Q \\ \vdots \\ y_i^{l-1}(m+K-1)^Q \end{bmatrix}^T$$

3.1 Advantage

- Performance remains consistent even when using a compact network configuration.
- Performance of ONNs is not limited even when strictly homogenous configuration is used

3.2 Applications

- Bio-Medical Signal Processing
- Wearables
- Bio-Medical Applications and
- Bio-Medical Diagnosis.

4. Results and Tables

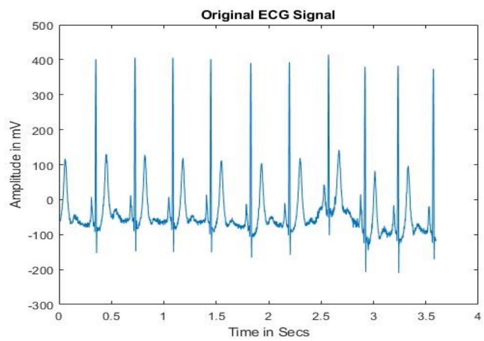

Figure 3 Existing Method

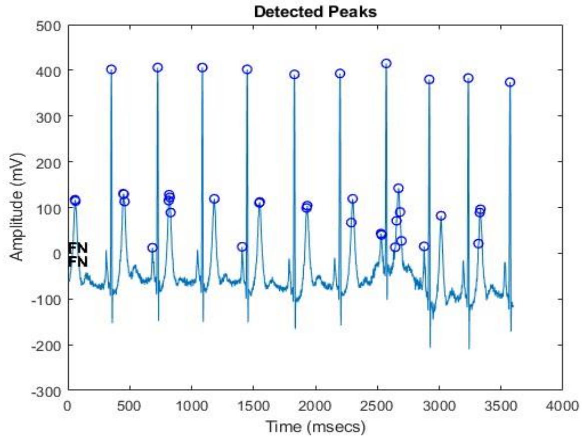

Figure 4 Existing Method

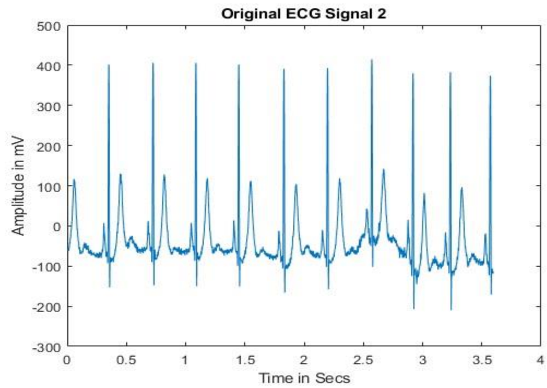

Figure 5 Proposed Method

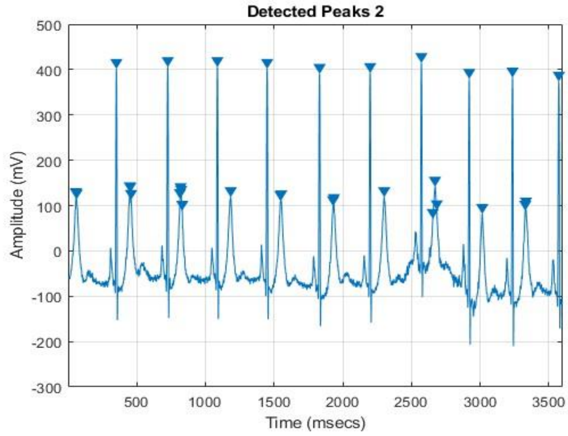

Figure 6 Proposed Method

4.1 Table

Fig 5: As can be seen from the above table, the suggested technique has identified fewer peaks than the current method, indicating a lower false detection rate. The current method has identified more peaks that were not true peaks.

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Page No: 2802- 2810
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https://doi.org/10.47392/IRJAEH.2024.0387

Table 1 Detected Peaks

Detected Peaks							
			S beats			V beats	
	Sample	Detected	Missed	Loss (%)	Detected	Missed	Loss (%)
Existing	100m	4	2	40	4	1	20
	101m	5	2	40	3	1	33
	102m	4	1	20	3	1	33
	103m	4	2	40	5	2	40
	104 m	6	2	40	5	2	40
Proposed	100m	4	0	0	4	1	20
	101m	5	1	20	3	1	33
	102m	4	2	40	3	1	33
	103m	4	1	20	5	2	40
	104 m	6	0	0	5	2	40

Conclusion

After the implementation of PSD for the previous implementation, the detection of R peaks has been improved. Not only it provided better detection rate but it is even easier than the existing methods. The implementation that consists of PSD was more robust than the existing methods.

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