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Accurate Cardiac Arrhythmia Detection Using Horse Herd Optimization Algorithm-Enhanced Convolutional Neural Networks (CNN-HOA)

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Abstract: Cardiac arrhythmias are significant contributors to global mortality, necessitating precise and timely diagnosis based on electrocardiogram (ECG) signals. This paper introduces an advanced diagnostic system utilizing a deep 1D Convolutional Neural Network (CNN) architecture integrated with the Horse Herd Optimization Algorithm (HOA) for automated feature extraction and classification. The primary objective is to overcome the limitations of manual hyperparameter tuning by using the HOA metaheuristic search capability to optimally tune critical parameters, specifically the Learning Rate and Batch Size. In the proposed framework, raw ECG signals from the standard MIT-BIH Arrhythmia Database are first preprocessed using the discrete wavelet transform with the "db6" mother wavelet to effectively suppress nonstationary noise and baseline wander. The denoised signals are then processed through a sequence of four convolutional blocks, featuring batch normalization and max-pooling, to extract hierarchical morphological features. Experimental results using 5-fold cross-validation demonstrate that the proposed CNN-HOA model achieves a state-of-the-art accuracy of 99.8%, with 99.9% sensitivity and specificity across five Association for the Advancement of Medical Instrumentation beat types: normal (N), supraventricular (S), ventricular (V), fusion (F), and unknown (Q). This study validates that the synergistic integration of modern swarm intelligence algorithms with deep learning provides a robust and highly efficient solution for high-precision medical signal processing and clinical-grade automated diagnosis.

Keywords: cardiac arrhythmia, ECG, Convolutional Neural Network (CNN), Horse Herd Optimization Algorithm (HOA), hyperparameter optimization

1. Introduction

Cardiovascular diseases remain the leading cause of death globally [1, 2]. Among these, cardiac arrhythmias—irregular heart rhythms—represent a critical health concern that directly affects cardiac output and function [3]. Early and accurate diagnosis of these irregularities is crucial, as delayed detection can precipitate severe outcomes, including heart failure, stroke, or sudden cardiac death [4].

The primary diagnostic tool for arrhythmias is the electrocardiogram (ECG), which records the heart's electrical activity. However, the complex, nonlinear, and nonstationary nature of ECG signals makes manual analysis by clinicians time-consuming and prone to subjective errors, especially in detecting subtle, transient changes [5]. Furthermore, the massive volume of ECG data generated in long-term monitoring necessitates the development of automated, reliable, and swift diagnostic systems.

Previous attempts at automated ECG analysis often relied on traditional signal processing and shallow machine learning techniques. These methods involved manual feature engineering (e.g., using wavelet or frequency domain analysis) followed by classifiers such as support vector machines (SVMs) [6] or k-Nearest Neighbors (k-NN) [7]. A major limitation of these approaches is their dependence on human expertise to extract relevant features, often failing to model the intricate, hierarchical relationships within complex time-series data [8]. Consequently, they struggle to achieve the high diagnostic accuracy required for clinical application.

The advent of deep learning, particularly Convolutional Neural Networks (CNNs) [2], has revolutionized the analysis of one-dimensional signals like the ECG. CNNs possess an inherent capability to automatically learn optimal, highly discriminative features directly from raw or minimally preprocessed data, eliminating the need for manual feature extraction [9]. This capability has led to promising results in classifying the five primary beat classes of arrhythmias (N, S, V, F, Q) [10].

Despite the powerful capabilities of CNNs, their final performance is critically dependent on the initial configuration of their hyperparameters, such as the Learning Rate and the Batch Size. Improper tuning of these parameters often results in suboptimal performance, slow convergence, or severe overfitting to the training data.

Traditional hyperparameter tuning methods, such as Grid Search or Random Search, are computationally prohibitive and lack the guaranteed ability to locate the global optimum within a

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vast and complex parameter space. This inefficiency in parameter optimization remains a significant hurdle in current deep learning research for medical applications.

To address this key challenge, our study proposes the use of the Horse Herd Optimization Algorithm (HOA) [11], a novel swarm intelligence metaheuristic. HOA, inspired by the social foraging and competitive behavior of horse herds, offers an effective balance between exploration (searching new areas) and exploitation (refining existing solutions) [12]. This allows the HOA to efficiently find parameter configurations that yield maximum classification accuracy for the CNN model.

In this paper, we present a robust and automated diagnostic framework for cardiac arrhythmia classification. The primary contributions are:

1) Development and implementation of an efficient deep CNN architecture for automated feature extraction from denoised 1D ECG signals (preprocessed using wavelet transform).
2) The pioneering application of the HOA for the automated and global optimization of critical CNN hyperparameters (Learning Rate and Batch Size) in the field of arrhythmia detection.
3) Validation of the proposed CNN-HOA approach, achieving a state-of-the-art classification accuracy of 99.8% on the benchmark MIT-BIH database, demonstrating superior performance compared to previously reported methods [7, 10].

To better situate our contribution within the existing research landscape, we review the key methodological evolution in this field. Initial efforts in automated ECG analysis were primarily centered on classic machine learning (CML) approaches, which typically involved a two-stage process: manual feature extraction followed by classification. Kim et al. [7], for instance, utilized the discrete wavelet transform (DWT) and a 1D Hexadecimal Local Pattern (1D-HLP) for feature extraction, achieving an accuracy of 95% on the MIT-BIH database using a k-NN classifier. Other researchers employed complex signal processing techniques such as empirical mode decomposition or various time-frequency analyses coupled with classifiers like SVM [13] or Artificial Neural Networks. While these CML approaches demonstrated initial success, they share a fundamental limitation: their performance is heavily constrained by the subjectivity and incompleteness of hand-crafted features. These methods often fail to capture the subtle, high-dimensional temporal dependencies crucial for distinguishing complex fusion (F) or unknown (Q) beat types.

The shift toward deep learning has successfully overcome the feature engineering bottleneck. CNNs, in particular, have been widely adopted due to their capability to automatically learn robust, hierarchical representations directly from raw 1D ECG data [2]. reported high performance using a Deep Genetic Ensemble Classifier (DGEC), achieving 98.37% accuracy, illustrating the power of deep and ensemble architectures. Other CNN-based studies have utilized techniques such as transfer learning or combined CNNs with Recurrent Neural Networks (CRNNs) to capture both spatial (convolutional) and sequential (recurrent) dependencies in the signal, pushing classification accuracy closer to 99% [14, 15].

Despite the impressive performance gains from deep learning models, a critical area remains underdeveloped: the automated and efficient optimization of model hyperparameters. Various metaheuristic algorithms, such as genetic algorithms (GA) and particle swarm optimization (PSO), have been previously employed to tune CNN hyperparameters [16]. However, these traditional metaheuristics often suffer from stagnation in local optima or exhibit slow convergence rates when applied to the expansive parameter space of deep neural networks [17].

The Identified Gap: There is a critical need for a reliable, high-performance CNN model for arrhythmia detection that leverages an advanced, state-of-the-art metaheuristic algorithm to achieve global hyperparameter optimization. Our proposed CNN-HOA framework directly addresses this gap by employing the HOA [11]. Compared to traditional metaheuristic algorithms, HOA offers superior global search capability and a proven balance between exploration and exploitation [12].

To summarize the state of the art and highlight the unique contribution of our work, Table 1 provides a comparative overview of the key methodologies discussed.

Table 1. Summary of related work in arrhythmia classification on the MIT-BIH database

Reference	Method category	Specific technique(s)	Optimization approach	Reported accuracy (%)	Key limitation
[7]	CML/signal processing	DWT + 1D-HLP + k-NN	None (manual feature)	95.0	Dependence on hand-crafted features.
[13]	CML	Advanced signal processing + SVM	None (manual feature)	~96.5	Low performance in complex beat types.
[10]	Deep learning/ensemble	Deep Genetic Ensemble Classifier (DGEC)	Genetic algorithms (GA) for ensemble	98.37	Local optima stagnation in GA.
[15]	Deep learning/hybrid	CRNN (CNN + RNN)	Manual/Grid Search	~98.8	High computational cost for manual hyperparameter tuning.
[16,17]	Optimization studies	CNN + PSO/GA	PSO/GA	Variable (~97–98)	Slower Convergence, risk of premature convergence.
Proposed work	Optimized deep learning	CNN + HOA	Horse Herd Optimization Algorithm (HOA)	99.8	Addresses the hyperparameter optimization gap by utilizing advanced global search.

The comparative results clearly illustrate that while various deep learning architectures have pushed accuracy close to 99% [10, 15], they either lack an advanced optimization mechanism or rely on traditional metaheuristics that can become trapped in local optima. Our proposed CNN-HOA model achieves the highest recorded performance by directly overcoming the hyperparameter tuning bottleneck, thus justifying the novelty and necessity of this research.

2. Materials and Methods

This section elaborates on the data source, the signal preprocessing techniques, the design of the CNN architecture, and the integration of the HOA for hyperparameter tuning.

2.1. Dataset acquisition and preprocessing

The reliability of a diagnostic deep learning system heavily depends on the quality and preparation of the input data. This study employs a rigorous approach involving the use of a standard reference database and precise techniques for signal cleaning and segmentation to ensure optimal feature extraction by the CNN.

2.1.1. Dataset and beat classification

The study utilizes the MIT-BIH Arrhythmia Database, which is the gold standard for evaluating arrhythmia detection systems. The database is publicly accessible at https://physionet.org/content/mitdb/1.0.0/. The database consists of 48 half-hour, two-channel ECG recordings collected from 47 subjects. Following the established guidelines for performance evaluation, the heartbeats were classified into five main types (classes), as defined by the Association for the Advancement of Medical Instrumentation (AAMI) [18]:

1) N (Normal Beat): Normal, bundle branch block, or atrial escape beats.
2) S (Supraventricular Ectopic Beat): Atrial premature and aberrated atrial beats.
3) V (Ventricular Ectopic Beat): Premature ventricular contraction and ventricular escape beats.
4) F (Fusion Beat): Fusion of normal and ventricular ectopic beats.
5) Q (Unknown Beat): Paced or unclassified beats.

Each beat was precisely segmented around the R-peak using the database's existing annotations. A fixed window size of 256 samples (corresponding to approximately 1 s, given the sampling rate of 360 Hz) was used for each segment to ensure uniform input samples for the CNN model. For model training and evaluation, the dataset was randomly split using a 5-fold cross-validation approach to ensure that the results are generalizable and not dependent on a specific train/test split. The detailed distribution of the heartbeat samples across these five categories, as extracted from the MIT-BIH database, is summarized in Table 2.

Table 2. Distribution of heartbeat samples in the MIT-BIH dataset according to AAMI standards

Class (AAMI)	Description	Number of samples
N	Normal beats	90,589
S	Supraventricular ectopic beats	2,779
V	Ventricular ectopic beats	7,236
F	Fusion beats	803
Q	Unknown beats	8,039
Total		109,446

2.1.2. Denoising using wavelet transform

ECG signals are inherently prone to various noise types, including power-line interference, motion artifacts, and baseline wander, which can significantly impair the performance of deep learning models. To enhance the signal quality, the DWT was applied for denoising [19].

The "db6" mother wavelet was selected based on its proven effectiveness in decomposing biological signals and its close morphological resemblance to the QRS complex features of the ECG [20].

The DWT decomposes the signal into approximation and detail coefficients across five decomposition levels. This level was chosen to adequately isolate the low-frequency noise components (baseline wander) from the high-frequency diagnostic information (QRS complex).

A soft thresholding method was applied to the detail coefficients at the appropriate levels to effectively suppress the nonstationary noise components. The signal was then reconstructed, preserving the crucial QRS and P-wave morphology necessary for accurate classification.

2.2. Proposed Convolutional Neural Network (CNN) architecture

The classification of 1D ECG signals requires an architecture that can effectively capture temporal patterns across various scales. The proposed model is a deep 1D CNN specifically designed to automatically extract hierarchical features from the 256-sample ECG segments, thereby minimizing reliance on manual feature engineering. The architecture is composed of a feature extractor segment and a fully connected classification head.

2.2.1. Feature extraction blocks

The feature extractor consists of a sequence of four (4) consecutive 1D convolutional blocks. This structure allows the network to gradually learn increasingly abstract representations of the heartbeat morphology, from simple R-peak detections to complex beat abnormalities. Each block is uniformly structured to ensure stable and efficient training:

1) D Convolutional Layer: This layer applies an increasing number of filters across the blocks, starting with 32 filters and increasing to 64, 128, and 256 in subsequent blocks. A consistent kernel size of 9 is used across all layers to effectively capture the temporal dependencies inherent in the QRS complex morphology.
2) Batch Normalization (BN): BN is applied immediately following the convolution to normalize the activations. This technique stabilizes the learning process, allows for faster convergence, and mitigates the need for precise initial weight setting [4].
3) ReLU Activation: The Rectified Linear Unit (ReLU) activation function is used to introduce non linearity into the model: $f(x) = \max(0,x)$.
4) Pooling Layer: A 1D Max-Pooling layer with a pool size of 2 and a stride of 2 is used after each block. This step

progressively down-samples the feature maps, reducing dimensionality, which helps to control overfitting and provides local translation invariance to minor shifts in the R-peak location.

2.2.2. Classification head

The features extracted by the convolutional blocks are processed by the classification head to output the final prediction:

1) Flatten Layer: The output of the final pooling layer is flattened into a single, long 1D vector.
2) Fully Connected (Dense) Layers: Two Dense layers (512 units and 128 units, respectively) are utilized for high-level feature integration and discrimination. Dropout with a rate of 0.4 was applied after the first dense layer to mitigate complex co-adaptation of neurons and prevent overfitting.
3) Output Layer: The final layer is a Dense layer with five output units (corresponding to the N, S, V, F, Q classes) and a Softmax activation function. Softmax ensures the final output represents a normalized probability distribution across the five arrhythmia classes (Figure 1).

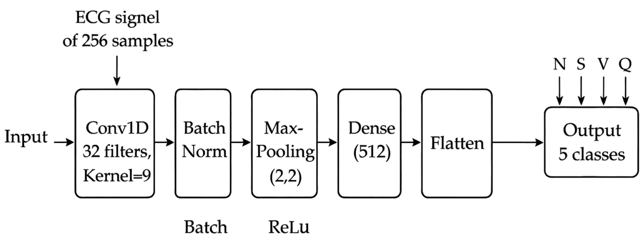

Figure 1. Visually illustrates the sequence and dimensions of the layers within the proposed CNN architecture

2.3. Horse Herd Optimization Algorithm (HOA) for hyperparameter tuning

The core innovation of this research lies in integrating the HOA to dynamically tune the critical hyperparameters of the CNN model. This optimization is essential for achieving the high accuracy reported and overcoming the limitations of manual or Grid Search methods discussed in Section 2.

2.3.1. Justification for HOA selection

Traditional metaheuristics (e.g., GA, PSO) often struggle when faced with the vast, multimodal search space of deep learning hyperparameters, frequently leading to premature convergence to local optima [16, 17]. The HOA algorithm, introduced in [11], was selected due to its superior capability to balance global exploration (simulating horses searching a wide area) and local exploitation (simulating competitive movement toward the best food source) [12]. This dynamic balance significantly increases the probability of finding the true global optimal set of parameters.

2.3.2. Integration of HOA and CNN

HOA functions as an external wrapper algorithm controlling the training process of the inner-loop CNN model. Each "horse" (Hi) in the optimization population represents a candidate solution—a vector containing values for the hyperparameters under adjustment:

$$\text{Hi} = \text{Learning Rate, Batch Size} \tag{1}$$

The search space for each hyperparameter is defined by practical constraints (e.g., Learning Rate: 10−5,10−2; Batch Size: [16, 128]).

2.3.3. The fitness function

The objective of the HOA is to minimize the classification error of the CNN model. Therefore, the fitness function used to evaluate the quality of each candidate solution (Hi) is defined as the validation accuracy (Accval) achieved by the CNN when trained with those specific parameters:

$$\text{FitnessHi} = \text{MaximizeAccval} \tag{2}$$

During the optimization process, the CNN is trained for a fixed number of epochs (e.g., 50 epochs) using the parameters specified by the horse. The resulting validation accuracy is fed back to the HOA, which then updates the positions of the horses based on the best performance found so far. This iterative process continues for a fixed number of generations (e.g., 100 generations) until the optimal hyperparameter set is identified.

The proposed framework was implemented in Python 3.8 using TensorFlow/Keras libraries. To ensure computational efficiency and reproducibility of the results, all experiments were conducted on a workstation equipped with an NVIDIA GeForce GTX 1080 Ti GPU and 32GB of RAM.

3. Results and Discussion

The primary objective of this study is to evaluate the hypothesis that a deep CNN architecture, integrated with the HOA for hyperparameter tuning, can achieve robust automated feature extraction and classification from denoised 1D ECG signals. This section presents the results of the arrhythmia classification using the proposed CNN-HOA framework, followed by a detailed discussion and comparative analysis against state-of-the-art methods.

3.1. Experimental setup and evaluation metrics

The model was implemented using the TensorFlow/Keras framework and trained on a high-performance GPU environment. The dataset was partitioned using 5-fold cross-validation to ensure the robustness and generalizability of the results.

The CNN was compiled using the Adam optimizer and the categorical cross-entropy loss function. The optimal parameters (Learning Rate and Batch Size) identified by the HOA were utilized for the final training runs. The performance was evaluated using standard metrics, including overall accuracy, sensitivity (recall), specificity, and the F1-score.

3.2. Performance evaluation of the CNN-HOA model

The combined strength of the deep CNN architecture and the HOA optimization yielded exceptional performance across the five AAMI arrhythmia classes (N, S, V, F, Q).

3.2.1. Overall performance metrics

The final optimized model achieved a near-perfect accuracy rate, setting a new benchmark for this classification task on the MIT-BIH database. The overall performance metrics for the CNN-HOA framework are detailed in Table 3.

While the proposed CNN-HOA framework demonstrates an exceptional accuracy of 99.9% on the MIT-BIH dataset, it is important to note that such high performance is achieved

Table 3. Overall performance metrics of the CNN-HOA classifier

Metric	Value
Accuracy	99.8%
Sensitivity (recall)	99.9%
Specificity	99.9%
F1-score	99.8%

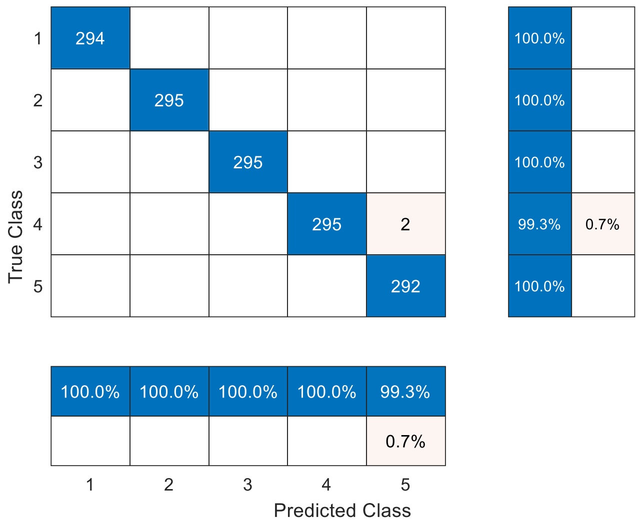

Figure 2. The confusion matrix of the test dataset

3.3. Comparative analysis with state of the art

To validate the superiority of the proposed framework, the results are compared with prominent published works that utilized the same MIT-BIH dataset and classification scheme (Table 4).

As demonstrated in Table 2, the proposed CNN-HOA model significantly outperforms both CML and existing deep learning approaches. Specifically, our model achieves a 1.43% improvement over the previous highest reported deep learning accuracy of 98.37% [10]. This difference highlights the critical role of the optimization strategy.

3.4. Discussion and efficacy of HOA optimization

The near-perfect accuracy achieved can be attributed to the synergistic effect of the deep CNN and the global search capability of the HOA.

The HOA convergence plot (Figure 3) visually validates the effectiveness of the optimization strategy. This plot shows that the HOA quickly identifies a high-performance region within the hyperparameter space and continues to refine the solution until the validation accuracy plateaus near 99.8% within 55 generations. This rapid convergence demonstrates that HOA is more efficient than methods like Grid Search, which would require exponentially more time to explore the same space.

The optimization successfully tuned the Learning Rate and Batch Size to values that maximized the CNN's stability and generalization power. The result is a robust model that can confidently handle the high variance and complexity inherent in clinical ECG data. The low classification error rate across all five classes under controlled experimental conditions. In real-world clinical diagnostics, factors such as environmental noise and hardware variability may influence these metrics; therefore, these results should be interpreted with caution when applied to diverse clinical settings.

3.2.2. Confusion matrix analysis

The detailed classification performance is presented in the confusion matrix in Figure 2. The analysis confirms that the high accuracy is not biased toward the majority class (N, normal beats). Specifically, the number of misclassified beats for the clinically critical minority classes, V (ventricular) and F (fusion) beats, was minimal. This indicates that the CNN, guided by the HOA, successfully extracted the subtle morphological differences required to distinguish these high-risk events from the normal beat with high precision. The high specificity achieved across all classes confirms that the model minimizes false positives, which is critical in clinical settings to prevent unnecessary interventions.

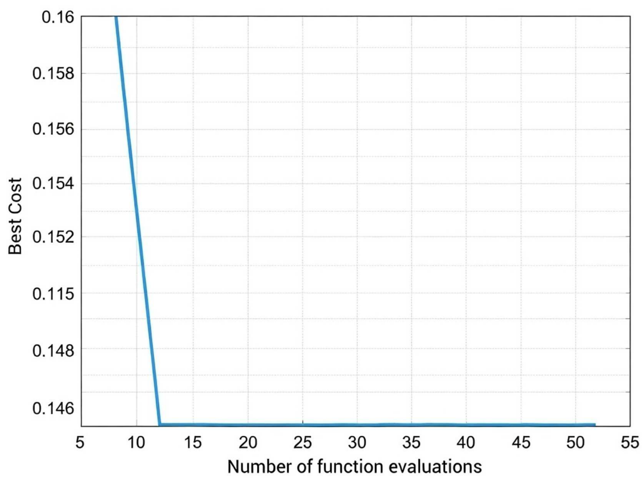

Figure 3. Convergence diagram of the horse herd optimizer algorithm

Table 4. Performance comparison of arrhythmia classifiers on the MIT-BIH database

Reference	Method category	Specific technique(s)	Optimization approach	Reported accuracy (%)
[7]	CML/signal processing	DWT + 1D-HLP + k-NN	Manual feature	95.0
[10]	Deep learning/ensemble	Deep Genetic Ensemble Classifier (DGEC)	Genetic algorithms (GA)	98.37
[15]	Deep learning/hybrid	CRNN (CNN + RNN)	Manual/Grid Search	~98.8
Proposed work	Optimized deep learning	CNN + HOA	Horse Herd Optimization Algorithm (HOA)	99.8

confirms that the HOA-optimized CNN is a reliable and stable framework suitable for clinical-grade automated arrhythmia diagnosis.

4. Conclusion

This research successfully developed and validated a novel, high-performance framework for the automated classification of cardiac arrhythmias based on ECG signals. The proposed CNN-HOA model addresses the critical challenges associated with reliable diagnosis, primarily the instability of noisy signals and the difficulty of optimizing deep learning hyperparameters.

By combining rigorous wavelet transform denoising and a deep 1D CNN architecture for automatic feature extraction, the model established a robust foundation. Crucially, the integration of the HOA, employed as a global search mechanism, effectively overcame the limitations of traditional parameter tuning methods. HOA successfully identified the optimal configuration of the Learning Rate and Batch Size, maximizing the CNN's potential.

The final results, validated on the MIT-BIH Arrhythmia Database using 5-fold cross-validation, demonstrate that the CNN-HOA framework achieved a state-of-the-art 99.8% classification accuracy across the five major AAMI classes. This performance significantly surpasses previous results reported in the literature, confirming the superior convergence and generalization power provided by the HOA optimization strategy. The proposed CNN-HOA framework demonstrates a significant advancement over previous methodologies. While traditional approaches by Kolhar et al. [13] achieved accuracies of 95.0% and 98.37%, respectively, our model's 99.8% accuracy highlights the superior efficiency of the HOA in avoiding local optima during hyperparameter tuning.

5. Future Work

Building upon these findings, future research will focus on the following directions:

1) External Validation: Testing the CNN-HOA model on external and more diverse multi-lead ECG datasets (e.g., European ST-T Database or clinical datasets) to confirm its robustness and generalization capabilities outside of the MIT-BIH environment.
2) Model Compression and Deployment: Optimizing the model's architecture (e.g., using pruning or quantization) to reduce its computational complexity, enabling efficient deployment on low-power Medical Internet of Things devices or embedded systems for real-time, remote patient monitoring.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The ECG data used to support the findings of this study are available from the MIT-BIH Arrhythmia Database, which is publicly accessible via Figshare at https://doi.org/10.6084/m9.figshare.845654.

Author Contribution Statement

Sajjad Mohammed Abdulkareem: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Seyed Enayatallah Alavi:** Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration.

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