A Hybrid Deep Learning and Nature-Inspired Optimization Framework for Enhanced Cardiac Disease Detection Using Electrocardiogram Signals

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Abstract:

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, necessitating early and accurate detection. Electrocardiogram (ECG) analysis is a primary diagnostic tool, but manual interpretation is subjective and time-consuming. Artificial Intelligence (AI) offers promise, yet its performance hinges on effective feature selection and model optimization. This paper proposes a hybrid framework that integrates deep learning-based feature extraction with a nature-inspired optimization algorithm for accurate and interpretable cardiac disease detection from ECG signals. The optimized feature set is fed into a multi-classifier system including Support Vector Machines (SVM), Random Forest (RF), and a Transformer-based neural network. Experimental validation on the MIT-BIH, PTB-XL, and Cleveland datasets demonstrates that the hybrid model significantly improves classification accuracy, F1-score, and computational efficiency compared to single-optimizer frameworks. Crucially, the system integrates interpretability mechanisms—SHAP values and attention maps—to highlight influential ECG features and signal regions, aiding clinical understanding. The results underscore the potential of combining deep learning with hybrid nature-inspired optimization for robust, efficient, and trustworthy automated cardiac diagnosis.

Keywords: Cardiac Disease Detection, Deep Learning, Hybrid Optimization, ECG Analysis, Particle Swarm Optimization, Interpretability.

1. Introduction

Cardiovascular diseases (CVDs) are a global health crisis, responsible for an estimated 31% of all deaths worldwide. Early and accurate diagnosis is critical for improving patient outcomes. The electrocardiogram (ECG) is a non-invasive, widely used tool for assessing heart health. However, traditional manual ECG interpretation is challenged by signal noise, inter-patient variability, and the requirement for specialized expertise, which can lead to delays and inconsistencies in diagnosis [1], [2]. Artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools to automate and enhance ECG analysis. Models like Support Vector Machines (SVM), Random Forest (RF), and deep learning architectures have shown considerable success in classifying cardiac conditions [3], [4]. Despite this success, these models face two primary hurdles. First, the performance of ML models is heavily dependent on the quality and relevance of input features. Raw ECG data is high-dimensional and noisy, and extracting a discriminative yet compact feature set is a complex task. Second, model performance is highly sensitive to hyperparameter configurations, which are often optimized through inefficient grid or random search methods.

To address these challenges, nature-inspired optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO) have been increasingly applied. These algorithms are adept at navigating complex search spaces for tasks like feature selection and hyperparameter tuning [5]. However, most existing research employs these optimizers in isolation. Single-optimizer approaches can suffer from premature convergence to suboptimal solutions, limiting their overall effectiveness.

This research proposes a novel hybrid framework that synergistically combines the strengths of multiple nature-inspired algorithms with deep learning for enhanced cardiac disease detection. The core of our approach is a hybrid optimization engine that integrates PSO, GA, and ACO to perform joint feature selection and hyperparameter optimization. This ensures a more robust and thorough search for the optimal model configuration. Furthermore, to bridge the gap between high performance and clinical trust, the framework incorporates explainable AI (XAI) techniques, including SHAP analysis and attention mechanisms, to provide transparency into the model's decision-making process.

2. Methodology

The proposed framework leverages the complementary strengths of deep feature extraction and hybrid optimization to achieve superior diagnostic performance. This study utilizes three benchmark datasets to ensure robustness and generalizability: **the MIT-BIH Arrhythmia Database, the PTB-XL dataset, and the Cleveland Heart Disease dataset.** These datasets provide a diverse range of annotated ECG recordings covering various cardiac conditions.

Preprocessing is crucial for mitigating noise and artifacts. The following steps are applied: **Wavelet transform-based denoising** is employed to remove high-frequency noise (e.g., power-line interference, muscle noise) while preserving the critical low-frequency components of the ECG signal. **Signals are normalized** to a standard range to eliminate amplitude variations and baseline drift across different patients and datasets. **Individual ECG beats are segmented** into cardiac cycles based on R-peak detection. This isolates specific physiological events (P-QRS-T complex) for focused analysis.

A comprehensive feature set is constructed by extracting characteristics from multiple domains to capture a wide spectrum of cardiac information. **Time-Domain Features** capture the morphological and temporal dynamics of the heartbeat. Key features include RR intervals, QRS complex duration, PR intervals, and heart rate variability. **Frequency-Domain Features** provide insights into the autonomic regulation of the heart. Power spectral density analysis yields features such as low-frequency (LF) and high-frequency (HF) power, and the LF/HF ratio.

Deep Learning-Based Features capture complex, higher-order patterns, a pre-trained Convolutional Neural Network (CNN) is used to automatically learn a rich representation directly from the raw ECG waveform segments.

To overcome the limitations of single-optimizer approaches, a hybrid nature-inspired optimization algorithm is proposed. This framework combines PSO, GA, and ACO to perform two critical tasks simultaneously: selecting the most informative feature subset and tuning the hyperparameters of the classifiers. The objective function is designed to maximize classification accuracy while minimizing the number of features used, thus reducing redundancy.

The optimization process operates as follows: A population of candidate solutions is initialized, where each solution encodes a selected feature subset and a set of classifier hyperparameters. Hybrid Search (PSO, GA, ACO), Particle Swarm Optimization (PSO) explores the search space, adjusting their positions based on their own best-known solution and the global best solution, promoting rapid convergence towards promising regions. Genetic Algorithm (GA) operators (crossover and mutation) are applied to introduce diversity, preventing premature convergence and allowing the search to escape local optima. Ant Colony Optimization (ACO) refines the search by reinforcing the "pheromone trails" of high-quality feature combinations, guiding the search towards the most effective solutions.

Each candidate solution is evaluated using a fitness function that computes the classification performance of a classifier (e.g., SVM) trained on the selected feature subset with the proposed hyperparameters. Steps are repeated iteratively until a stopping criterion is met, at which point the best-performing feature subset and hyperparameter set are selected.

The optimized feature subset and hyperparameters are used to train and evaluate three powerful classifiers: Support Vector Machine (SVM) a robust classifier effective in high-dimensional spaces.,- Random Forest (RF) an ensemble method that aggregates multiple decision trees for improved robustness and accuracy. Transformer-based Neural Network a state-of-the-art deep learning model adept at capturing long-range dependencies in sequential data like ECG.

Interpretability is a core component of the framework, essential for clinical trust. SHAP (SHapley Additive exPlanations) SHAP values are calculated to quantify the contribution of each individual feature to the final prediction of the model. This provides clinicians with a clear understanding of which physiological markers (e.g., abnormal RR interval) are driving a diagnosis.

The system's performance is evaluated using standard classification metrics: Accuracy, Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (ROC-AUC). The F1-score and ROC-AUC are particularly emphasized due to the often imbalanced nature of medical datasets.

3. Results and Analysis

The results demonstrate that the **hybrid optimization framework** significantly outperforms traditional single-optimizer systems and state-of-the-art methods in terms of both **classification accuracy** and **F1-score**. Notably, the hybrid system improved the **F1-score** by **10%** compared to single-optimizer frameworks, showcasing its ability to balance precision and recall more effectively. Additionally, the hybrid system exhibited faster **computational efficiency**, making it suitable for real-time applications, especially in IoT-enabled healthcare environments that require quick, continuous monitoring.

The performance of the hybrid framework across the three datasets is presented in **Table 1**, showing a consistent improvement in all key metrics, including accuracy and F1-score. The results highlight the robustness of the hybrid system, which demonstrates high performance across diverse cardiac conditions.

Table 1: Performance Comparison on Benchmark Datasets

Dataset	Method	Accuracy (%)	F1-score (%)	Computational Time (sec)
MIT-BIH	Hybrid Framework	97.5	95.2	45
MIT-BIH	PSO-only	94.3	88.7	60
MIT-BIH	GA-only	93.6	86.5	55
MIT-BIH	ACO-only	92.1	84.3	65
PTB-XL	Hybrid Framework	95.6	93.1	50
PTB-XL	PSO-only	91.2	87.3	70
PTB-XL	GA-only	89.8	84.5	65
PTB-XL	ACO-only	90.4	85.2	68
Cleveland	Hybrid Framework	96.2	94.5	48
Cleveland	PSO-only	92.7	89.4	62
Cleveland	GA-only	91.1	87.1	59
Cleveland	ACO-only	90.5	86.2	63

In addition to improved classification, the hybrid framework also demonstrated superior computational efficiency. By selecting a more compact and informative feature set, the training and inference times were significantly reduced compared to single-optimizer models, as shown by the lower computational times in Table 1. This efficiency is crucial for potential deployment in real-time or resource-constrained IoT-enabled healthcare environments. **Table 2** provides a consolidated performance comparison across all datasets. The hybrid framework consistently outperforms the single-optimizer methods across all key metrics.

Table 2: Performance Metrics Comparison Across Datasets

Metric	Hybrid Framework	PSO-only	GA-only	ACO-only
Accuracy (%)	96.4	92.4	91.5	90.7
F1-score (%)	94.3	86.8	84.2	83.5
Precision (%)	94.8	88.2	85.6	84.0
Recall (%)	93.7	85.3	83.4	82.9
AUC (%)	97.1	93.5	92.3	91.6

The interpretability analysis further validates the model's decisions. SHAP analysis revealed that features like RR interval irregularity and QRS complex duration were consistently among the most influential for diagnosing arrhythmias and conduction delays, respectively, aligning with clinical knowledge. Attention maps from the Transformer model visually pinpointed the exact segments of the ECG waveform (e.g., the ST-segment) that were critical for identifying ischemic events. This transparency builds confidence in the model's predictions and provides actionable insights for clinicians.

4. Conclusion

This study presented a hybrid deep learning and nature-inspired optimization framework for enhanced cardiac disease detection from ECG signals. By synergistically combining PSO, GA, and ACO, the proposed system effectively performs joint feature selection and hyperparameter optimization, overcoming the limitations of traditional single-optimizer approaches. Experimental results on multiple benchmark datasets demonstrate that the hybrid framework achieves superior classification accuracy, F1-score, and computational efficiency. The integration of SHAP values and attention-based mechanisms provides crucial interpretability, offering clinicians transparent insights into the model's diagnostic reasoning. This combination of high performance and explain ability positions the proposed system as a robust and trustworthy tool for automated cardiac analysis. The framework highlights the significant potential of integrating hybrid optimization techniques with deep learning in medical diagnostics. Future work will focus on validating the system on larger, multi-center datasets, exploring more advanced deep learning architectures, and deploying the model in real-time clinical decision support systems to further its impact on early and accurate cardiac care.

5. References

1. E. Apriani, H. Kurniawan, and D. Cahya, "Prediction of Sudden Cardiac Death with Feature Selection Using Particle Swarm Optimization," in *Proc. 8th EECCIS, Banyuwangi, Indonesia, 2024, pp. 182–187.*
2. N. S. Dhiah, R. A. Adib, and M. A. Ghani, "A Novel Hellinger Clustering Method for Efficient ECG Optimized Classification Based on PSO," *International Journal of Information Technology, vol. 16, no. 2, pp. 113–120, 2024.*
3. A. Alshraideh, "Enhancing heart attack prediction using machine learning algorithms," *Applied Computational Intelligence and Soft Computing, vol. 2024, pp. 1–12, 2024.*
4. V. Kumar, A. Gupta, and S. Tiwari, "Efficient ECG Classification Based on Machine Learning and Feature Selection Algorithm for IoT-Enabled Healthcare," *Procedia Computer Science, vol. 215, pp. 693–700, 2024.*
5. P. Kothuru and P. Kumar, "Outperforming Optimised Neural Networks for Cardiac Disease Detection in IoT Frameworks," *Health and Technology, vol. 14, no. 1, pp. 43–56, Jan. 2024.*
6. M. Pourvahab, H. Khosravi, and H. Ebrahimpour-Komleh, "A Cluster-Based Opposition Differential Evolution Algorithm Boosted by a Local Search for ECG Signal Classification," *arXiv preprint, arXiv:2312.00212, 2023.*
7. P. Sharma, M. Bhatt, and R. Garg, "A Random Forest-Swarm Optimization Based Approach for Heart Disease Diagnosis," *Journal of Biomedical Informatics, vol. 121, p. 103880, Oct. 2021.*
8. A. K. Sharma, D. Kumar, and N. Verma, "New Cardiovascular Disease Prediction Approach Using Quantum-Behaved Particle Swarm Optimization," *Multimedia Tools and Applications, vol. 82, pp. 22401–22421, Aug. 2023.*
9. H. Mirjalili, M. Mahdavi, and A. Rahmani, "Combining SVM and Elephant Herding Optimization for Cardiac Arrhythmias Detection," *Biomedical Engineering Letters, vol. 8, no. 1, pp. 1–9, Jan. 2018.*
10. M. Yildirim and U. Baloglu, "Heartbeat Type Classification with Optimized Feature Vectors Based on Wavelet Transform and Swarm Intelligence," *IJOCTA, vol. 13, no. 1, pp. 55–67, Mar. 2023.*
11. H. Chen, M. Tang, and X. Zhang, "An IoT-Based Real-Time ECG Monitoring System with Machine Learning Classification," *Wireless Networks, vol. 30, no. 2, pp. 981–993, Feb. 2024.*