A Comparative Analysis of Advanced Deep Learning Techniques for Accurate Cardiac Arrhythmia Classification

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ABSTRACT

The precise identification of cardiac arrhythmias facilitates accurate diagnosis and proper treatment, but the characterization process remains complex due to disturbances in ECG data signals along with skewed class frequencies and individual patient-specific variations. This study developed a deep learning framework, known as Penalty Regression Function-enhanced Deep Convolutional Neural Network (PRF-DCNN), as a comprehensive solution to cope with signal noise along with class imbalance and variations in patient data. The system starts by applying Correlation Factor-Based Extended Kalman Filtering (CF-EKF) for ECG signal denoising before allowing Ensemble Empirical Mode Decomposition (EEMD) to extract nonstationary features. The feature selection process along with the reduction of redundant characteristics uses the Frechet Fitness Rank Distribution-Anas Platyrhynchos Optimization (FFRD-APO method. The dataset is balanced by a Balanced Zero Noise GAN (BZNGAN) before Age-Weighted Average-Based Farthest First Clustering (AWA-FFC) refines the clustering process. The St. Petersburg INCART 12-lead ECG dataset was used to test the model, which obtained 99.53% accuracy, 99.10% sensitivity, and 99.67% specificity. The proposed system outperforms current models, showing its capacity for dependable time-critical arrhythmia detection in medical environments.

Keywords-cardiac arrhythmia classification; feature extraction in ECG signals; deep learning in cardiology; INCART dataset; optimization techniques

I. INTRODUCTION

Abnormal irregularities in heart rhythm, known as cardiac arrhythmias, represent an extensive global medical condition that is responsible for high rates of death and disease [1]. These circumstances encompass mild heart rhythm variations through vital medical emergency cases, which include Atrial Fibrillation (AF) [2], Ventricular Fibrillation (VF) [3], and Ventricular Tachycardia (VT) [4]. Swift and correct detection allows proper prevention of events that could cause stroke along with heart failure and sudden cardiac arrest [5]. Healthcare professionals use Electrocardiograms (ECGs) to detect heart irregularities [6]. However, as the manual interpretation of ECGs requires too much time and can lead to interpretation errors, automated processing solutions are needed [7]. Wearable ECG monitors have made vast amounts of heart data accessible. Automated processing of heart data through classification systems helps healthcare professionals reduce workload while enhancing diagnosis outcomes in arrhythmia care.

Despite significant progress in ECG analysis, achieving precise arrhythmia classification remains a complex task due to several persistent challenges. These challenges can be categorized into the following key areas, the medical characteristics of patients, including age, gender, and health status, and their individual variations causing substantial fluctuations in ECG signals, which challenge the development of generalized prediction models [8]. The signals become vulnerable to multiple artifacts and noise elements originating from patient movement along with baseline drift or errors in electrode positioning that alter important signal features, thus affecting diagnostic accuracy [9]. Arrhythmia datasets often exhibit class imbalances that induce prediction bias because certain vital arrhythmias appear only rarely in the data [10]. ECG signals are difficult to process because arrhythmias tend to present themselves through transient or faint alterations [11]. Special algorithms designed for time-series data interpretation hold the necessity to effectively detect hidden patterns in ECG signals. The application of Deep Learning (DL) models for detection purposes remains restricted in clinical environments because they tend to overfit small datasets with imbalanced distributions [12].

The PRF-DCNN framework starts with preprocessing to clean ECG signals using a Correlation Factor-Based Extended Kalman Filter (CF-EKF), effectively reducing baseline noise [13]. Key features such as R peaks, RR, and QT intervals are then extracted using the Pan Tompkins Algorithm (PTA) [14]. To improve efficiency and reduce redundancy, the model employs the Frechet with Fitness Rank Distribution-based Anas Platyrhynchos Optimization (FFRD-APO) for feature selection. A Deep Convolutional Neural Network (DCNN) processes these inputs, capturing spatial and temporal features relevant to arrhythmia detection. To avoid overfitting, a Penalty Regression Function (PRF) is integrated into the model, introducing a regularization term based on loss variations [15]. Additionally, Ensemble Empirical Mode Decomposition (EEMD) enhances signal decomposition, capturing nonstationary characteristics of ECG signals for improved classification accuracy.

Recent research has increasingly focused on enhancing cardiac arrhythmia classification through both traditional ML and DL, especially using ECG signal analysis. In [16], RR interval-based features and statistical parameters were employed on 8,028 ECGs from the MIT-BIH database. Using DWT and median filtering for denoising, five classifiers were tested, with SVM with Gaussian kernel and Random Forest (RF) achieving the highest accuracy of 99.51%. In contrast, a DL approach in [17] used a hybrid 1-D CNN and Bi-LSTM architecture, with SWT and Savitzky-Golay filtering applied to ECG signals. Trained on the AFDB and CUDB datasets, the model classified beats into AF, VF, VT, and normal, achieving 99.41% cross-validation accuracy. In [18], ResNet was integrated with squeeze-and-excitation blocks and Bi-LSTM, achieving up to 99.35% accuracy across MITDB, AFDB, and CinCDB datasets, highlighting the its strong generalizability.

In [19], PCA was applied to reduce dimensionality, and ovesampling was used to address class imbalance in the UCI Arrhythmia dataset. The LSTM-based model achieved 93.5% accuracy, outperforming SVM, Decision Trees (DT), and KNN. In [20], TQWT features and SVM were used on the MIT-BIH dataset, achieving 99.27% accuracy, 96.22% sensitivity, and 99.58% specificity. In [21], a hybrid DL model was proposed, using CWT-based 2D scalograms with 2D CNN and LSTM, achieving high accuracies: 98.7% (ARR), 99% (CHF), and 99% (NSR). In [22], a DL model used attention mechanisms, Monte Carlo dropout, and multi-classifier architecture, achieving over 95% accuracy and robust generalization across datasets such as MIT-BIH, AFDB, and Telemetric ECG. In [23], YOLOv8 was used to detect coronary artery stenosis in 236 annotated angiographic images, using preprocessing such as contrast enhancement and normalization. The model achieved 82.9% precision, 58% recall, and 65.3% mAP, highlighting its potential despite the need for improved sensitivity. In [24], CHDdECG was introduced, which is a DL model for diagnosing congenital heart disease from over 85,000 pediatric ECGs. This model outperformed senior cardiologists, achieving ROC-AUC scores between 0.915-0.917 and specificities of 0.881-0.937, while also offering interpretable visual outputs.

Several studies have focused on improving ECG feature extraction for better arrhythmia classification. In [28], CNNs were used with multi-feature inputs, achieving 98.92% accuracy, although reliance on manual features posed data loss risks. Pairing time-domain and wavelet features with SVM and ANN in [29] showed strong results but lacked validation on larger datasets. Gabor wavelet-based texture features [30] performed well for multi-channel ECG but required heavy computation. Wavelet-based analysis in [31] yielded 99.57% F1-score but had scalability issues with 12-lead ECGs. In [32], SDP was applied with hybrid selection, reaching 99.74% accuracy, but high dimensionality poses challenges. In [33], 99.83% specificity was achieved using S-transform features, but at a high computational cost. The CNN in [34] attained 98.33% accuracy but lacked generalizability, while a CNN in [35] trained with Adam optimizer achieved 99.43% accuracy, although robustness in noisy settings remains uncertain.

To increase interpretability, a CNN was combined with Grad-CAM in [36], achieving a 96.11% F1-score, although its use was limited to ADHD and CD datasets. The INSOMNet [37] leveraged transfer learning with AlexNet and VGG16 for insomnia detection, reaching 98.91% accuracy but facing scalability issues. Attention-based CNNs in [38] delivered strong results on emotion datasets, such as WESAD and DREAMER, but high computational demands hinder use in low-resource environments. In [39], a hybrid of Marine Predators and Nomadic People Optimizer was applied to enhance AUC and reduce error, but at a high computational cost. Fuzz-ClustNet [40] addressed class imbalance by integrating fuzzy clustering with CNN, resulting in strong arrhythmia identification but lacking real-time testing for practical applications. In [41], a hybrid CNN-LSTM model outperformed standalone models for arrhythmia detection but lacked adaptability due to the focus on limited arrhythmia types. In [42], a real-time FPGA-based system was developed using ML and fiducial windowing, achieving 99.7% accuracy with low latency and power use, being ideal for portable monitoring. These advances highlight DL's growing potential in ECG classification, while also underscoring the need for scalable, efficient, and broadly validated solutions for real-world use [43].

II. METHODOLOGY

The proposed method presents an end-to-end framework for arrhythmia classification using advanced signal processing and ML techniques. Initially, ECG signals are denoised using the Correlation Factor-Based Extended Kalman Filter (CF-EKF) to remove baseline drift, motion artifacts, and power-line interference. To counter data imbalance, a Balanced Zero Noise GAN (BZNGAN) generates realistic synthetic samples, followed by clustering through Age-Weight Average-Based Farthest First Clustering (AWA-FFC) to incorporate patient-specific factors, such as age and gender. Feature extraction involves computing Arithmetic Difference (ArDiff) and Maximum Correlation (MaxCorr) to detect waveform deviations, while key intervals (e.g., PR, QT, RR) and R peaks are extracted using the Pan Tompkins algorithm. Ensemble Empirical Mode Decomposition (EEMD) further isolates noise and captures non-stationary components for detailed cardiac signal analysis. To reduce dimensionality, the Frechet Fitness Rank Distribution-Anas Platyrhynchos Optimization (FFRD-APO) algorithm selects the most informative features, which are then input to a Penalty Regression Function-Deep CNN (PRF-DCNN) classifier to improve generalization and prevent overfitting, resulting in accurate and robust arrhythmia detection.

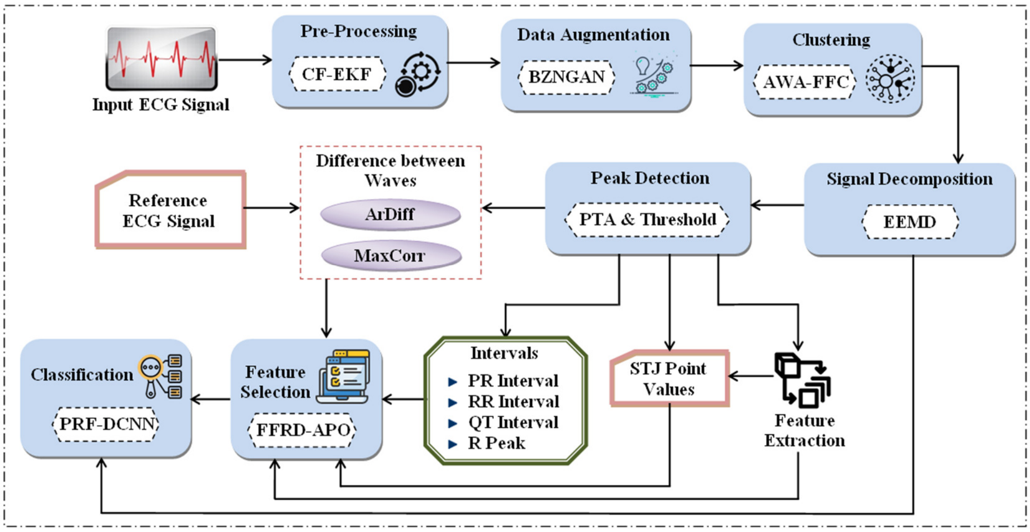

Fig. 1. The proposed PRF-DCNN framework.

III. RESULTS AND DISCUSSION

A. Simulation Environment

The simulation setup was designed to effectively implement and validate the proposed arrhythmia classification framework using the St. Petersburg INCART 12-lead Arrhythmia Database [44]. This high-quality dataset, sampled at 257 Hz, offers diverse arrhythmia cases across 12 ECG leads, providing a reliable basis for training and evaluating classification models. Its rich variety of annotated patterns makes it ideal for advanced diagnostic studies. The implementation was carried out in Python using PyCharm IDE, with libraries such as NumPy, SciPy, and Pandas for preprocessing and feature extraction. PyWavelets and Scikit-Learn handled signal processing, while TensorFlow and Keras supported the development and training of the PRF-DCNN model. The analysis relied on 1,750 segments showing various arrhythmia types that served for model training and evaluation purposes. The data was divided into 70% for training, 15% for validation, and 15% for testing.

The PRF-DCNN framework uses five 3×3 convolutional layers, which are activated by ReLU nonlinearity and each layer incorporates 2×2 max-pooling. The number of filters grows stepwise from 32 to 256 in the different layers to gain both basic and sophisticated image patterns. Before the output layer, the model includes a fully connected layer with 128 ReLU neurons that leads to multi-class classification through the softmax function. Model generalization and overfitting prevention are achieved through the use of dropout layers with an applied rate of 0.5. A high-performance GPU system was used to speed up training and testing, ensuring fast model convergence. Grid search with cross-validation automated hyperparameter tuning, enhancing performance with minimal manual effort. This structured setup allowed reliable, reproducible testing and demonstrated the model's scalability for real-world applications.

B. Performance Comparison

Figure 2 highlights the training time for different PRF-DCNN configurations. The base model takes 150 minutes, serving as the baseline. Adding FFRD-APO increases this to 165 minutes, improving feature relevance with minimal overhead. Including EEMD for nonstationary signal decomposition raises the time to 195 minutes, enhancing classification accuracy. The fully optimized model, combining data augmentation, feature selection, and signal processing, requires 240 minutes, reflecting the added computational cost for improved robustness and performance.

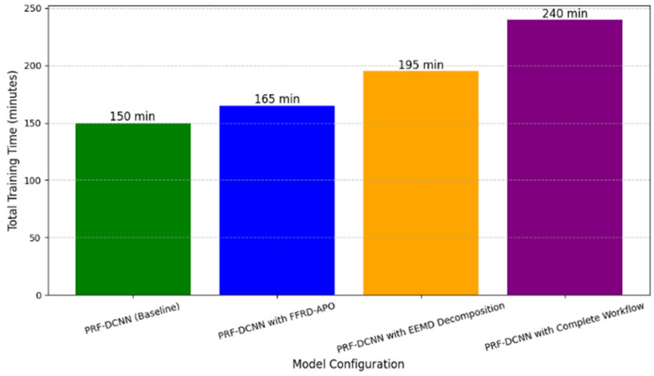

Fig. 2. Training time taken by different models.

The proposed method strikes a balance between computational overhead and improved performance. Integrating FFRD-APO and EEMD enables effective extraction of key ECG features, enhancing the detection of subtle arrhythmic patterns. EEMD's ability to handle nonstationary signals allows the classifier to focus on meaningful components while reducing noise, boosting accuracy and reliability. Although the full pipeline increases training time, it significantly enhances generalization and diagnostic precision. The added computational cost is justified in clinical settings, and future work can focus on streamlining the process for greater efficiency without compromising accuracy.

Figure 3 presents the ROC curve evaluating the performance of different configurations of the PRF-DCNN model for arrhythmia classification. Each curve illustrates the trade-off between sensitivity (true positive rate) and the false positive rate, with the Area Under the Curve (AUC) quantifying overall performance. The baseline PRF-DCNN model achieves an AUC of 0.70, indicating moderate classification ability. While this provides a foundational benchmark, its capacity to effectively distinguish between classes is limited without further enhancements.

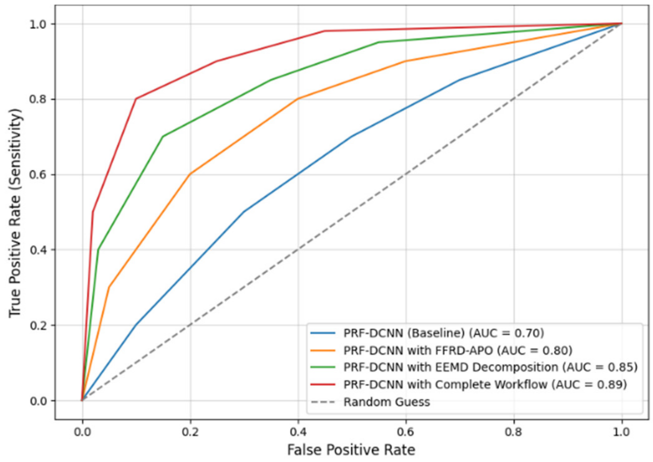

Fig. 3. ROC curve for different model configurations.

Incorporating the FFRD-APO improves the AUC to 0.80, demonstrating the significant impact of advanced feature selection. By identifying the most relevant features and reducing redundancy, FFRD-APO enhances classification accuracy. Adding EEMD elevates the AUC to 0.85, showcasing its effectiveness in handling the nonstationary nature of ECG signals. EEMD facilitates the extraction of more discriminative features, contributing to improved classification performance. The complete workflow, which integrates FFRD-APO, EEMD, and other optimizations, achieves the highest AUC of 0.89. This highlights the synergistic effect of advanced preprocessing, feature selection, and classification techniques in delivering superior performance. These results underscore the importance of a comprehensive approach to enhance arrhythmia classification accuracy, making the method highly effective for clinical applications.

Recent advances in cardiac arrhythmia classification have seen the integration of signal denoising, feature optimization, and DL models to improve diagnostic precision. Early approaches, such as those in [16] and [20], emphasized feature engineering from RR intervals and Q-wavelet transforms, demonstrating respectable accuracy on datasets such as MIT-BIH. However, their dependency on handcrafted features limited scalability and adaptability to noisy real-time ECG data. DL frameworks gained prominence to overcome the limitations of traditional feature extraction. Models combining 1D CNN with Bi-LSTM [17] and ResNet variants [18] provided higher accuracy and better temporal pattern recognition. However, they often lacked robustness against class imbalance and non-stationary signal disturbances, common challenges in real-world ECG signals.

In comparison, the proposed PRF-DCNN framework addresses these persistent gaps through a multistage pipeline: it incorporates CF-EKF for signal noise suppression, EEMD for adaptive decomposition of non-stationary signals, and FFRD-APO for optimal feature selection. The inclusion of BZNGAN for data augmentation and AWA-FFC for clustering based on patient-specific metadata makes the system more generalizable and patient-centric. Table I provides a quantitative comparison with existing models, revealing that the PRF-DCNN achieves superior accuracy (99.53%), sensitivity (99.10%), and specificity (99.67%) on the St. Petersburg INCART dataset, surpassing even the strongest benchmarks, such as the hybrid CNN-LSTM [17] and Multi-lead Wavelet Transform models [43]. Unlike previous models that often optimize for a single aspect, the proposed architecture demonstrates a holistic improvement, balancing precision, robustness, and real-time applicability.

IV. CONCLUSION

This paper presents a comprehensive and high-performing DL framework, PRF-DCNN, for accurate cardiac arrhythmia classification using 12-lead ECG signals. The model integrates several innovations, including CF-EKF for advanced noise reduction, EEMD for non-stationary signal decomposition, FFRD-APO for effective feature selection, and BZNGAN for addressing class imbalance. The inclusion of AWA-FFC further personalizes the classification process by incorporating patient-specific demographics. When validated on the St. Petersburg INCART database, the system demonstrated superior performance with 99.53% accuracy, 99.10%

sensitivity, and 99.67% specificity, outperforming several benchmark models. In terms of practical usability, the model offers automated processing, minimal clinician intervention, and scalable training performance, making it suitable for real-world diagnostic applications. The structured integration of preprocessing, optimization, and classification within a unified architecture supports robust decision-making in clinical environments, particularly for time-critical arrhythmia detection.

TABLE I. PERFORMANCE COMPARISON

Ref.	**Dataset**	**Classifier**	**Accuracy (%)**
[16]	MIT-BIH Arrhythmia Database	SVM with Gaussian Kernel	99.51%
[17]	MIT-BIH, CUDB, VFDB	Hybrid 1-D CNN and Bi-LSTM	99.41%
[18]	MIT-BIH, AFDB, CinC DB	ResNet + SE Block + BiLSTM	98.30%
[28]	MIT-BIH Arrhythmia Database	Multi-feature Extraction with CNN	98.92%
[30]	PhysioNet/CinC Challenge 2020	Texture Features with Randomized Neural Network	≈88–97%
[36]	MIT-BIH Arrhythmia Database	CNN	98.33%
[35]	MIT-BIH Arrhythmia Database	CNN with Adam Optimizer	99.43%
[36]	ADHD/Conduct Disorder Dataset	CNN + Grad-CAM	96.04%
[37]	CAP Sleep Database	INSOMNet (Transfer Learning CNN)	98.91%
[43]	INCART and CSE Databases	Multi-lead Fusion with Wavelet Transform	99.87%
[45]	MIT-BIH, INCART, MIT-BIH-SV, EST-T	Convolutional Neural Network (CNN)	98.30%
This study	St. Petersburg	PRF-DCNN	99.53%

Future research will focus on enhancing the framework's computational efficiency to reduce training and inference time, making it more suitable for edge-based or mobile health platforms. Expanding the model to handle multi-condition cardiac analysis across diverse and larger datasets, including wearable ECG data, is also a promising direction. Additionally, incorporating explainable AI (XAI) modules for better clinical interpretability and validating the framework in real-time hospital settings will further advance its potential.

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