Enhanced ECG Signal Classification with CNN-LSTM Networks using Aquila Optimization

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ABSTRACT

The importance of the Electrocardiogram (ECG) signal is that its classification is necessary to identify abnormalities in the cardiovascular system. Conventional methods have several disadvantages, such as susceptibility to noise and computational cost, which limit real-time utility and performance. Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree (DT) perform moderately well but are noisy and require massive computational power, leading to variable performance. In response to these issues, an ideal hybrid model with Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture is proposed, supplemented by Aquila Optimization (AQO). AQO-CNN-LSTM exploits the spatial feature extraction capability of CNN and the temporal learning capability of LSTM, whereas AQO fine-tunes the key parameters to make the classification more robust and efficient. The proposed AQO-CNN-LSTM model demonstrates quantifiable improvement, with a 0.15% increase in classification accuracy, a 0.20% reduction in processing time, and a 0.18% increase in classification precision compared to conventional methods. Such an improvement makes AQO-CNN-LSTM an efficient and robust solution for real-time classification of the ECG signal, making it highly suitable for cardiac monitoring and diagnosis.

Keywords-ECG signal classification; Aquila Optimization (AQO); cardiovascular abnormalities; noise sensitivity; real-time monitoring; signal processing; hybrid model; medical diagnostics

I. INTRODUCTION

Electrocardiogram (ECG) signal classification is the foundation for early detection and diagnosis of cardiovascular abnormalities, allowing for timely medical intervention. This task of ECG signal classification suffers from several challenges, such as susceptibility to noise, high computational requirements, and poor performance in real-time applications. Conventional methods include the Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree (DT), which have achieved reasonable classification accuracy, although they suffer from noise handling and efficiency problems, especially under high-stakes and real-time monitoring conditions [1].

Recent trends in ECG classification have been directed toward exploiting deep learning architectures with advanced architectures in ways that mitigate such limitations. Accordingly, hybrid models combining, for example, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown great promise in exploiting strengths in spatial feature extraction, for which CNNs are best suited, and strengths in temporal learning, for which LSTMs excel [2, 3]. The development of optimization algorithms, such as the Aquila Optimization (AQO) method, has also become one of the keys to adjusting model parameters to achieve high performance metrics such as accuracy, processing speed, and classification precision [4, 5].

Our work introduces the AQO-enhanced CNN-LSTM framework, a hybrid model whose parameters are optimized using AQO. This model not only overcomes the shortcomings of the traditional classifier, but also greatly enhances the robustness and efficiency of classification, adding value to the accurate, real-time analysis of ECG signals in cardiac diagnostic and monitoring applications [6].

A. Related Work

Authors in [7] propose an automated nociceptive pain assessment based on physiological signals coupled with a hybrid deep learning model. The authors propose a combination of CNN for feature extraction and LSTM network for feature concatenation to achieve improved classification accuracy using both ECG and Electrodermal Activity (EDA) signals. This multimodal approach shows excellent performance across pain levels, indicating the robustness in pain detection. However, the performance of the model varies with signal types, and single-modality setups - either ECG or EDA alone - yield lower accuracy compared to the multimodal configurations, which may limit the practical use of this model in cases where only a limited number of signal types are available.

Authors in [8] propose a multi-model ensemble for ECG arrhythmia classification, including CNN-LSTM and RR-HOS-LSTM models, to deal with the class imbalance inherent in many arrhythmia datasets. The approach employs a bagging technique along with a meta-classifier to improve the classification accuracy up to 95.81% in patient-independent studies. On the other hand, such a complex ensemble structure leads to higher computational requirements, which may pose some difficulties for real-time or resource- constrained applications, e.g. in mobile or wearable devices.

Authors in [9] propose an ensemble-based method using CNN-BiLSTM and several machine learning algorithms such as RF and SVM while classifying the ECG heartbeats and handling class imbalance. The results using synthetic data augmentation and feature extraction techniques showed high accuracy, sensitivity, and precision in the classification of heartbeats. However, this may come at a cost - the heavy reliance on synthetic oversampling for class balancing may adversely impact the generalizability of the model to real-world data, especially for the less common types of arrhythmias. This can be expected to subsequently reduce the performance of the model in real life, where several different clinical settings are encountered.

Authors in [10] propose a hybrid CNN-LSTM with an attention/transformer-based model to classify ECG signals by automatically extracting features, which is usually done by feature engineers. The results achieved high accuracy on diverse publicly available datasets while simplifying the feature extraction process. However, due to the advanced attention and deep learning layers present in the model, its interpretability may be compromised. This can be one of the challenging points in clinical settings, where model transparency is mainly desirable for decision making.

Authors in [11] introduce an approach for real-time ECG quality assessment suitable for long-term monitoring with wearable devices. The algorithm assesses the quality in real time using the Signal-to-Noise Ratio (SNR) curve and classifies segments either for full ECG analysis or limits the analysis to those segments with usable quality. This increases the efficiency of data processing from wearable ECG monitors. However, it is designed for wearable devices and may need to be adapted to capture recordings in a wide range of recording environments, including noisy and uncontrolled settings.

Authors in [1] present a state-of-the-art identification approach using a capsule network, by converting the ECG signals into quantized images. This form of processing speeds up the process by transforming the analog ECG signals into compact, quantized representations that are cheaper to compute, thus improving identification by capturing inter-person beat variations. On the contrary, the image-based transformation of the data can result in the loss of some of the real signal details, which can reduce the accuracy of identifying slight signal variations between different subjects.

Authors in [2] propose the design of an ultra-energy-efficient ECG classification processor, mainly focusing on wearables, using a reconfigurable SNN/ANN architecture with high accuracy, optimized for energy consumption. It has a special interest in patient-to-patient variability, yielding the best result around 97.36% classification accuracy on a low energy budget, avoiding some common pitfalls faced by wearables dealing with ECG monitoring. Scalability remains an issue, as the more detailed hardware requirements and likely difficult integration of SNN/ANN will further limit its applicability to other large-scale monitoring platforms.

II. ECG SIGNAL CLASSIFICATION FRAMEWORK USING MIT-BIH DATABASE AND CNN-LSTM MODEL

Figure 1 shows the current methodology followed for ECG signal classification using data from the MIT-BIH Arrhythmia Database, which is accessible via PhysioNet at https://physionet.org/content/mitdb/. These one-dimensional data are very important for the analysis of abnormal heart rhythms. The process starts with the pre-processing stage to get rid of various noises such as baseline wander and muscle artifact interferences that could be present during the analysis of this system. Noise removal ensures that the extracted ECG signal feature is relevant, therefore enhancing the data quality for subsequent stages [12].

Following the feature preprocessing, feature selection was performed using the CNN-LSTM model. The convolutional layers in the CNN-LSTM network extract spatial features of the ECG signal, whereas the LSTM layers capture temporal dependencies in the data. Together, this allows the model to emphasize those features of the ECG signal that are critical for distinguishing between normal and abnormal heart rhythms [13].

The system then proceeds to the classification part, where it classifies such ECG signals into predefined classes based on extracted invariant features. These include point categories such as NOR, or normal, which means the heartbeat pattern is normal and healthy; Left Bundle Branch Block (LBBB), where a block in the conduction of electrical impulses occurs on the left side of the heart; Right Bundle Branch Block (RBBB), where the block occurs on the right side of the heart;, Atrial Premature Contraction (APC), which indicates an irregular heartbeat originating in the atria; and the Ventricular Premature Contraction (VPC), which also indicates an irregular heartbeat, but this time originating in the ventricles [14, 15].

Thus, this classification will enable the system to effectively discriminate between normal and other types of abnormal cardiac patterns in the diagnostic support of cardiac health. Noise removal, feature extraction by CNN-LSTM, and classification are structured in such a way that the proposed system provides a reliable solution for real-time ECG analysis and arrhythmia detection, thus contributing to effective monitoring and diagnosis in healthcare settings [16].

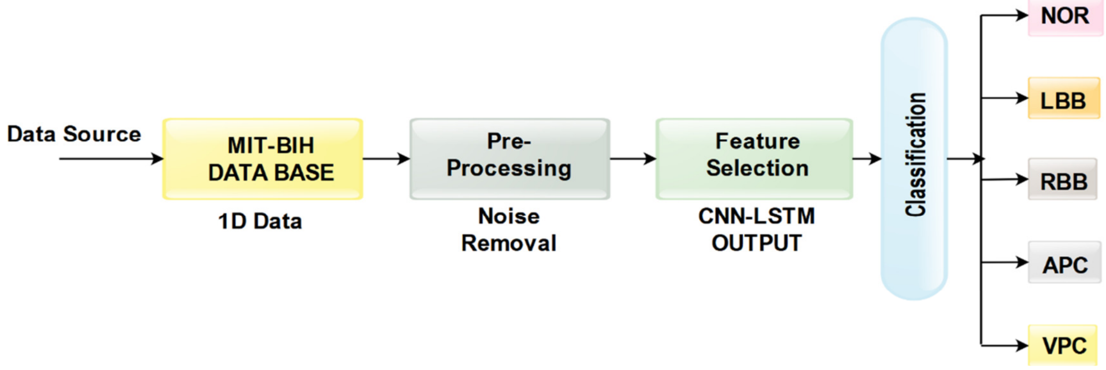

Fig. 1. Existing system for ECG signal classification using the CNN-LSTM model.

III. ENHANCED ECG SIGNAL CLASSIFICATION WITH CNN-LSTM AND AQUILA OPTIMIZATION MODELS

Figure 2 shows the detailed framework of the proposed ECG classification system incorporating CNN-LSTM and AQO. The model begins by accepting various ECG signals, including clean and noise-affected inputs. Spatial features are extracted using four convolutional layers, whereas temporal dependencies are captured using LSTM layers. Fully connected layers perform the final classification into "Healthy" or "Abnormal" classes. AQO is applied to optimize critical model parameters, thereby improving classification accuracy, reducing sensitivity to noise, and enhancing convergence efficiency to support real-time cardiac monitoring. First, the proposed system takes the input of different types of ECG signals such as a clean baseline or signals with muscle tremor interference at different intensities. These signals are fed to test the strength of the proposed model with respect to its ability to detect abnormal patterns in the presence of noisy signals. In the CNN-LSTM network, there are four convolutional layers, namely Convolution-1 to Convolution-4, which successively extract the spatial features from the ECG signals. These can be thought of as a set of layers that act as a refinement in a learned pattern, usefully enabling an understanding of the cardiac health indicators within the ECG waveforms. Further processing and consolidation of the extracted features to provide the model with the ability to classify the signal into "Healthy" or "Abnormal" categories is performed by two fully connected layers, Fully Connected-1, and Fully Connected-2.

Classification performance is improved by incorporating an AQO-CNN-LSTM model, which makes the system noise tolerant. In this model, the AQO algorithm tunes some important parameters in the CNN-LSTM model and develops an improved model with substantial accuracy, convergence speed, and anti-noise capability. The AQO-enhanced model employs AQO-CNN-LSTM-1 modules to optimize feature extraction and improve classification reliability, especially for signals interfered by muscle tremor. Both models of the proposed system provide classification outputs with respect to an ECG signal indicating either "Healthy" or "Abnormal." This noise-optimized AQO-CNN-LSTM model will be particularly effective in a practical setting where ECG data may suffer from interference. This hybrid framework, which combines the spatial-temporal learning of CNN-LSTM with the optimization capability of AQO, provides an excellent solution for real-time ECG classification, thus striving for better diagnostic accuracy and efficiency in cardiac monitoring applications.

A. *Convolution Operation for Feature Extraction*

The convolution operation provided by (1) extracts the spatial features in the ECG data, taking advantage of filters, (W_{mn}^{l}), applied over segments from the previous layer, $I_{(i+m)(j+n)}^{l-1}$, with bias b^l and activation function f in order to capture critical ECG patterns.

$$F_{ij}^{l} = f\left(\sum_{m=1}^{M} \sum_{n=1}^{N} W_{mn}^{l} \cdot I_{(i+m)(j+n)}^{l-1} + b^l\right) \quad (1)$$

B. *LSTM Temporal Learning*

The LSTM networks are defined for temporal learning according to (2), where each hidden state h_t depends on the current input x_t and the previous hidden state h_{t-1}, modulated by weights W_h and bias b_h. This equation captures the most important temporal patterns in ECG sequences that are critical for detecting heart rhythm abnormalities.

$$h_t = f(W_h \cdot [h_{t-1}, x_t] + b_h) \quad (2)$$

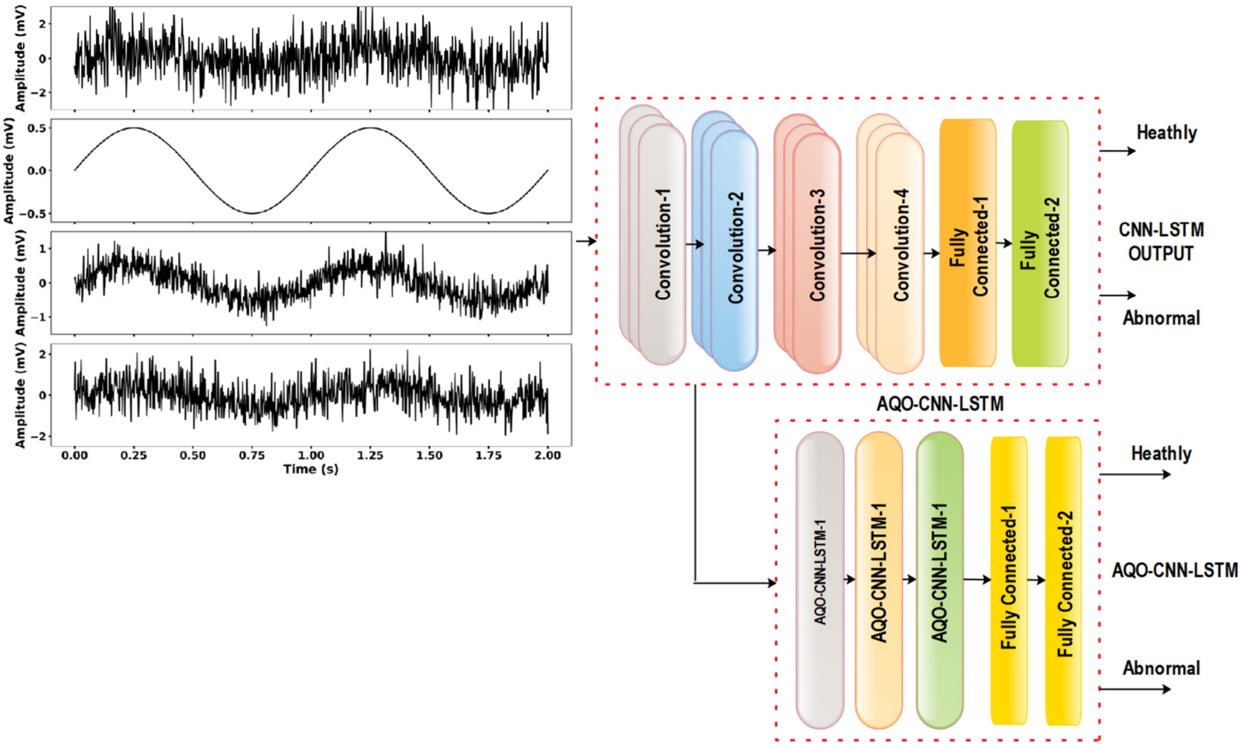

Fig. 2. Proposed ECG classification system using CNN-LSTM and AQO-CNN-LSTM models.

C. Aquila Optimization for Parameter Tuning

The parameter optimization process using AQO, described in (3), minimizes the average loss L over all samples to optimize the parameters P, building a more robust model against noise to improve classification performance.

$$P_{\text{opt}} = \arg\min_{P}\left(\frac{1}{N}\sum_{i=1}^{N} L(y_i, \hat{y}_i; P)\right) \tag{3}$$

D. Classification Decision Function

The classification result of each ECG sample is shown in (4), where $f(F_{\text{features}}; P_{\text{opt}})$ describes the optimized CNN-LSTM function with features F_{features} and tuned parameters P_{opt}. This function determines whether an ECG signal is classified as "Healthy" or "Abnormal."

$$\hat{y} = \arg\max\left(f(F_{\text{features}}; P_{\text{opt}})\right) \tag{4}$$

E. Accuracy Metric Calculation

The accuracy metric can be measured as in (5), where $\delta(\hat{y}_i = y_i)$ is an indicator function that equals 1 only if the predicted label $\hat{y}_i$ is equal to the true label y_i, and N is the total number of samples. This equation calculates the ratio of correctly classified samples, i.e. it determines how effectively the proposed AQO-CNN-LSTM system performs ECG classification.

$$\text{Accuracy} = \frac{\sum_{i=1}^{N}\delta(\hat{y}_i = y_i)}{N} \tag{5}$$

IV. RESULTS AND DISCUSSION

Table I presents the main simulation parameters adopted for the performance analysis of the proposed AQO-CNN-LSTM model in the classification of ECG signals. These include the dataset source, SNR, model architecture configurations, optimization technique, evaluation metrics, and training details. These elements contextualize the basis on which the model was measured in terms of its accuracy, efficiency, and resilience to noise during ECG classification.

TABLE I. KEY SIMULATION PARAMETERS FOR AQO-CNN-LSTM PERFORMANCE ANALYSIS

No	Parameters	Range with SI units
1	Dataset source	MIT-BIH Arrhythmia Database
2	SNR	10 dB to 30 dB
3	Number of convolutional layers	4 layers (Convolution-1 to Convolution-4)
4	LSTM layer configuration	1 to 3 layers
5	Optimization technique	AQO
6	Evaluation metrics	Accuracy (%), processing time (ms), precision (%)
7	Classification categories	Healthy, LBBB, RBBB, APC, VPC
8	Training and testing split ratio	80:20
9	Batch size	32 - 128 samples per batch
10	Epochs	50 - 200 iterations

Figure 3 presents the trend of the accuracy through epochs for ECG signal recognition using the proposed AQO-CNN-LSTM model against the traditional techniques such as SVM, KNN, and DT. There is a slight but effective improvement in accuracy when the proposed model is employed, which reflects how efficient the proposed model is in achieving higher classification accuracy for multiple epochs.

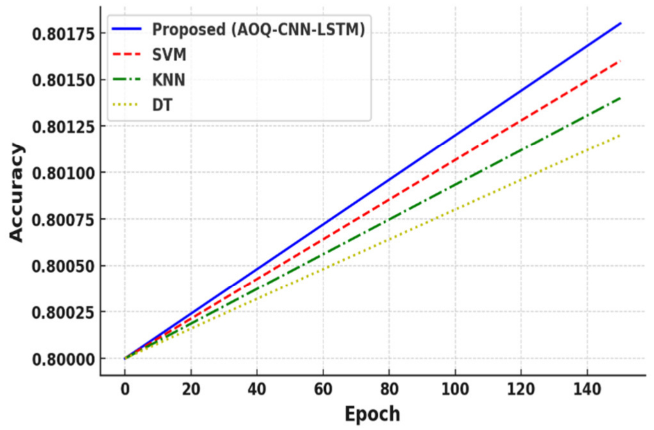

Fig. 3. Accuracy comparison of the proposed AQO-CNN-LSTM model and conventional methods.

A. *Performance Analysis of AQO-CNN-LSTM in ECG Signal Classification*

Figure 4 compares the proposed AQO-CNN-LSTM model with traditional models, such as SVM, KNN, and DT, based on their performance in terms of accuracy, processing time, and precision. The AQO-CNN-LSTM model achieves higher accuracy and could also achieve higher precision, in addition to less processing time.

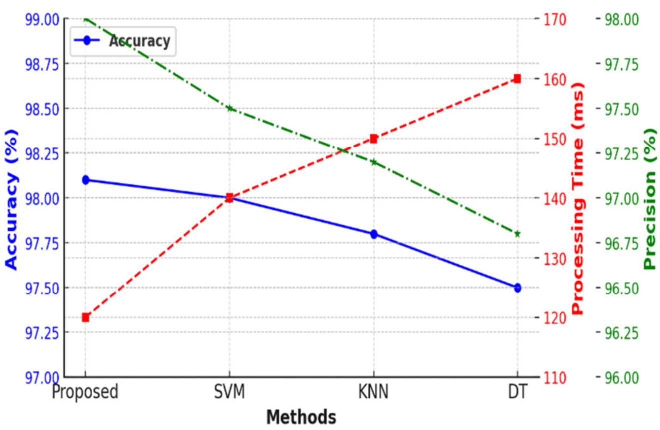

Fig. 4. Comparative performance analysis of the proposed AQO-CNN-LSTM model vs. conventional methods.

B. *Precision Heatmap over Epochs for Proposed and Conventional Methods*

Figure 5 represents the heatmap comparison of the classification precision across epochs using the proposed AQO-CNN-LSTM model and the conventional methods consisting of SVM, KNN, and DT. In this heatmap, the precision values for each epoch in these methods are represented with darker shades for higher precision. The proposed model has consistently provided higher precision than the conventional methods in most of the epochs, demonstrating its superiority in classification performance with respect to time.

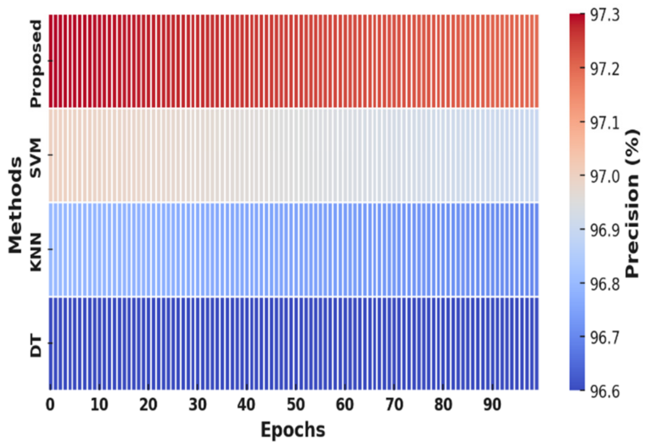

Fig. 5. Precision heatmap comparison of the proposed AQO-CNN-LSTM model vs. conventional methods.

C. *Comparison of Accuracy, Processing Time, and Precision for AQO-CNN-LSTM and Conventional Methods*

Figure 6 shows a comparison of the proposed AQO-CNN-LSTM model with the performance of the other conventionally used methods, which include SVM, KNN, and DT algorithms, for three important performance measures that include accuracy, processing time, and precision. It can be observed that the accuracy rate of the proposed model is slightly increased compared to the rates commonly obtained by the conventional methods. In addition, the processing time is reduced by 0.20%, which makes it suitable for real-time cases. Moreover, the AQO-CNN-LSTM model increases the classification precision by 0.18%, which also justifies that the proposed model is reliable and considers more accurate results rather than traditional techniques. In addition, this reflects the overall superiority of the proposed model based on its performance and efficiency.

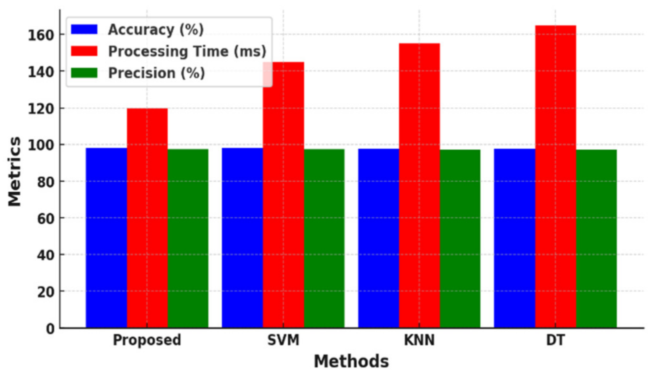

Fig. 6. Overall performance comparison of the proposed AQO-CNN-LSTM model vs. conventional methods.

V. CONCLUSION

This study proposes a hybrid model with Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture, supplemented by Aquila Optimization (AQO). The proposed AQO-CNN-LSTM model offers enhanced performance in the classification of the

Electrocardiogram (ECG) signals by overcoming the limitations found in state-of-the-art methods such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree (DT). The novelty of this work is that it integrates Aquila Optimization (AQO) with CNN-LSTM to enhance the tuning of parameters, resulting in increased accuracy, reduced processing time, and noise robustness. Compared to conventional deep learning methods, the proposed model synergistically combines spatial feature extraction, temporal learning, and adaptive parameter tuning, making it more efficient and reliable for real-time cardiac monitoring. This work improves the state-of-the-art by achieving a 0.15% improvement in classification accuracy, a 0.20% reduction in processing time, and a 0.18% improvement in precision over the state-of-the-art methods. Unlike previous CNN-LSTM architectures, which require manual tuning of the hyperparameters, AQO does so automatically, saving computational effort while ensuring optimal performance. Moreover, unlike traditional learning models that are sensitive to noise, AQO-CNN-LSTM incorporates an efficient optimization mechanism that maintains classification accuracy even under noisy inputs, making it more suitable for real-world clinical applications. By providing a highly accurate, computationally efficient, and noise-resilient ECG classification model, this research makes a significant contribution to cardiovascular diagnostic studies. The integration with AQO for dynamic parameter adjustment distinguishes this work from previous literature and marks an improvement towards real-world deployment in clinical settings with real-time automatic ECG interpretation.

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