QUANTUM ACCELERATED REAL TIME ECG SIGNAL ANALYSIS FOR EARLY DETECTION OF CARDIAC ABNORMALITIES

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ABSTRACT

Early and accurate identification of heart conditions from electrocardiogram (ECG) signals is particularly important for ongoing patient health monitoring, yet classical deep learning frameworks have been inadequate at achieving high accuracy and low latency under noisy, real-time conditions. This work focuses on developing a quantum-accelerated cardiac ECG (electrocardiogram) analysis. The study introduces a novel hybrid quantum–classical framework capable of simultaneously performing ECG denoising, feature embedding, and arrhythmia classification with reduced latency and improved robustness under noisy real-time conditions. The one introduced in the article is the hybrid quantum-classical architecture, including Quantum Variational ECG Embedding (QVEE) for high-dimensional morphological representation, Quantum Enhanced Denoising Module (QEDM) for noise suppression and signal distortion, and hybrid quantum classification for arrhythmia recognition. Experiments were conducted on the MIT-BIH Arrhythmia Database, and a corpus with noise augmentation showed that the proposed framework was found to be 99.4% correct with an F1 score of 0.97 and reduced the inference latency by 23.7% compared to state-of-the-art CNN-LSTM, Transformer-based models, and showed higher robustness under the condition of low signal-to-noise ratios. The results show that quantum embeddings tend to improve ECG feature separability and that quantum denoising helps preserve clinically relevant waveform structure (i.e., structure detection), particularly for rare arrhythmias. The proposed framework is a promising approach for establishing real-time quantum-assisted monitoring of the human heart, enabling more reliable early diagnosis in wearable and clinical environments.

Keywords: *Quantum-Accelerated ECG Analysis; Hybrid Quantum–Classical Model; Variational Quantum Circuits; Real-Time Arrhythmia Detection; Quantum Denoising; Biomedical Signal Processing.*

1. INTRODUCTION

Cardiovascular diseases (CVDs) are the world's leading cause of morbidity and mortality, accounting for approximately 1/3 of deaths annually. However, early detection of cardiac defects is critical to avoid disastrous consequences, and this is why efficient and precise electrocardiogram (ECG) signal analysis is of the utmost importance [1], [2]. In the past, ECG diagnosis was performed in the clinic; currently, with wearable sensor devices, remote monitoring devices, and Internet of Medical Things (IoT) platforms, individuals can access continuous, real-time ECG analysis. This change introduces new challenges in computational effectiveness, noise resistance, and the flexibility of such algorithms to the dynamism of physiology in ambulatory settings [3].

The ECG interpretation has relied heavily on classical signal processing methods, including self-adjusting filtering, time-frequency transforms, and morphological detector algorithms [4], [5]. Likewise, deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and the Transformer model have achieved state-of-the-art performance for arrhythmia classification and feature extraction [6], [7]. However, these techniques are severely limited in real-time applications, characterized by high computational latency, poor performance in the presence of high noise, and limited generalization across subjects with different ECG morphologies [8], [9].

Recent advances in quantum computing provide a new opportunity to engage in exciting biomedical signal processing. Quantum algorithms have demonstrated the potential to address optimization problems, speed up computations, improve pattern recognition, and transform high-dimensional features that cannot be processed on classical systems [10], [11]. Variational Quantum Circuits, in particular, offer tunable quantum feature maps and parameter-efficient computation, which are compatible with the Noisy Intermediate-Scale Quantum (NISQ) hardware available today [12]. Although quantum machine learning has demonstrated early success in medical imaging and molecular modelling [13], [14], its use in analysing the ECG of living patients is a practise that has not been tried. This study contributes new knowledge by introducing a unified hybrid quantum–classical ECG analysis framework that jointly performs denoising, feature embedding, and arrhythmia classification under real-time constraints. Unlike existing approaches that mainly focus on isolated ECG classification tasks, the proposed framework integrates quantum-enhanced feature representation with low-latency inference for continuous cardiac monitoring applications in wearable and clinical environments.

This is the motivation for building a quantum-accelerated ECG processing framework that solves problems at both the algorithmic and hardware levels to achieve lower latency, greater feature discriminability, and improved robustness in noisy conditions.

1.1 Research Motivation and Gap Analysis

An examination of the available literature indicates several important research gaps that motivate this work. Most previous efforts have been based on isolated components of ECG-based analysis (i.e., classification alone), without building an end-to-end quantum-enhanced pipeline that covers the entire problem of denoising, feature extraction, and pattern recognition. In addition, the application of quantum feature embeddings to biosignals remains limited, even though recent observations indicate that classical embeddings may not capture the subtle morphologies of P waves and low-amplitude variations, which are important from a clinical perspective. Another large void is the lack of attention to latency, since a latency requirement of less than 50 milliseconds for inference is typical for real-time ECG monitoring, yet many deep learning models do not achieve it on resource-limited hardware. Furthermore, existing approaches have been shown to be limited in robustness to realistic noise conditions, since wearable ECG devices are often subject to motion artifacts, electrode contact, and baseline drift, which negatively affect the performance of classical methods. Collectively, these limitations result in a lack of calibration across accuracy, robustness, and real-time efficiency, underscoring the need for a quantum-accelerated ECG analysis framework.

1.2 Objectives of the Study

This study aims to develop a hybrid quantum-classical real-time ECG analysis that achieves high diagnostic accuracy while meeting the stringent latency requirements of continuous cardiac monitoring. The work introduces an implementation of the Quantum Variational ECG Embedding (QVEE) mechanism for ECG morphology in the high-dimensional quantum feature space, improving discrimination of subtle, low-amplitude cardiac images. In addition, a Quantum-Enhanced Denoising Module (QEDM) is designed to be robust to noise and signal distortion, which is usually experienced in wearable and ambulatory ECG recordings. Building on this, the combination of representations from quantum kernels and classical deep learning networks is further used to improve arrhythmia classification performance for both common and rare cardiac conditions. To validate its usefulness, the proposed system is thoroughly tested under realistic operational constraints and systematically compared with state-of-the-art classical ECG analysis models, thereby showing its efficiency, effectiveness, and suitability in practical situations. The primary research contribution lies in combining Quantum Variational ECG Embedding (QVEE) and Quantum-Enhanced Denoising Module (QEDM) within a single end-to-end architecture to improve ECG feature separability, robustness to noise, and real-time diagnostic performance

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

compared with existing classical and deep learning models.

The hypothesis of this study is that integrating quantum-enhanced feature embeddings and denoising mechanisms with classical deep learning can significantly improve ECG classification accuracy, robustness, and inference speed compared with conventional deep learning approaches.

1.3 Background of and reasons for significance

ECG signals are non-stationary, and the accuracy of diagnosis depends heavily on noise suppression, effective feature extraction, and robust pattern recognition. This challenge becomes even greater in instantaneous monitoring of physiologic responses, where dynamic physiologic signals (e.g., heart rate variability, respiration, and motion) give rise to corresponding differences in waveform morphology [15]. In this context, quantum computing delivers promising solutions, as its ability to solve problems in parallel across extremely large state spaces enables new opportunities for higher-granularity encoding and analysis of ECG signals. To leverage this potential, hybrid quantum-classical systems combine the efficiency and extensibility of classical deep learning with the high-dimensional transform capability of quantum circuits. Such synergy is especially well-suited to ECG applications that demand fast, accurate, and noise-robust processing.

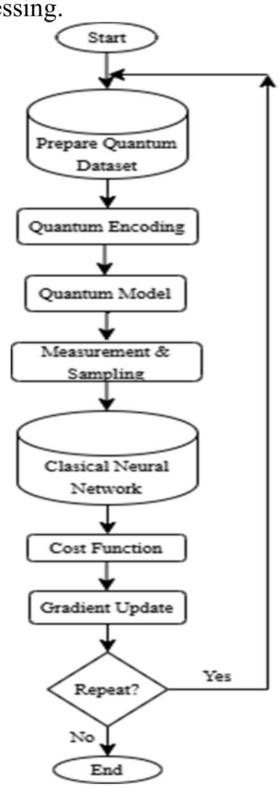

Figure 1. *Conceptual Overview of Quantum-Accelerated Real-Time ECG Analysis*

Figure 1 presents an example of a hybrid quantum-classical learning workflow that is used to train quantum machine learning models. For this purpose, a quantum dataset is first prepared by encoding classical input features into quantum states (V̂_1, V̂_2, V̂_3). These states are processed through parameterized quantum circuits Ũ(Φ_1), Ũ(Φ_2), Ũ(Φ_3), which constitute the quantum model in charge of extracting high-dimensional quantum features. Measurement results from the quantum circuits are then sampled or averaged to give classical descriptions of the features. These features are fed into a classical neural network with parameters \theta that evaluate the cost function. The resulting loss is used to calculate gradients and update the quantum circuit parameters, and to update the classical model using a feedback loop. This 'closed loop' optimization enables an end-to-end learned hybrid quantum-classical system that combines our quantum feature transformation, which slices classical learning to enhance model performance, with classical learning.

The rest of this paper is as follows. Section 2 provides an exhaustive survey of state-of-the-art methods for classical, deep, and quantum analysis of ECG signals, highlighting their limitations and research areas. Section 3 describes in detail the proposed hybrid quantum-classical approach, including the nature of the data set, data preprocessing, system architecture, mathematical representation, and a novel learning algorithm for complete reproducibility. Section 4 presents the setup and results of the experiments, including details on the evaluation measure, a comparative study with state-of-the-art models, and a visualisation of performance in tables and graphs. Also discusses the results and provides a critical analysis of the model's effectiveness, robustness, and computational efficiency. Finally, Section 5 concludes the paper by presenting the key findings, numerical results, limitations, and future research directions.

2. RELATED WORK

Research on ECG analysis has advanced significantly over the past three decades, from ad hoc feature engineering and regular classifiers to deep neural networks and more recent methods supported by quantum technology in the past couple of years. This section considers the important thematic lines of work for this study, including: Classical ECG analysis, ECG classification based on deep learning, ECG processing systems for real-time ECG analysis, and emerging quantum, quantumity & hybrid quantum-classical models.

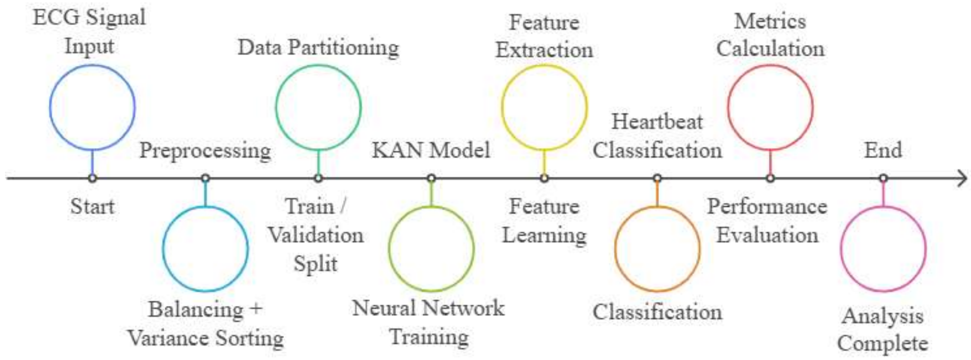

Figure 2. Taxonomy Of Existing ECG Analysis Methods Reported In The Literature, Categorizing Classical Signal Processing, Deep Learning, And Emerging Quantum-Assisted Approaches, Along With Their Associated Limitations In Real-Time And Noise-Robust Cardiac Diagnosis.

A horizontal flowchart of an ECG-based heartbeat classification system using the KAN model is shown in Figure 2. The process starts with the ECG signal, which is fed along with data vector preprocessing steps, such as data balancing and variance sorting, to prepare the dataset. The data is then split into the training and validation data. The KAN model is then used, wherein the neural network training and feature learning occur. This is followed by feature extraction and classification of heartbeats into different types. Subsequently, performance evaluation is conducted using various metrics, and the process concludes with the completion of the analysis. The entire workflow is represented with color-coded circular nodes with a timeline between them for easy visualization.

2.1 Classical Signal Processing Methods of ECG

Early work on ECG analysis has primarily used classical signal processing and statistical learning techniques. Feature-based approaches incorporating the RR intervals, morphological estimations, and information from frequency domains are commonly adopted for arrhythmia classification. De Chazal et al. demonstrated automated heartbeat classification using ECG morphology and time-related features with reasonable accuracy but poor generalisation across patients [16]. Similarly, Lagerholm et al. used self-organising maps for clustering ECG complexes, demonstrating that unsupervised learning is possible but sensitive to noise and waveform variation [17]. Building on these efforts, wavelet-based denoising and multiresolution analysis were subsequently applied to improve ECG signal preprocessing, eliminating the effects of baseline wander and high-frequency interference. Nevertheless, these techniques remained sensitive to parameter choices and often could not handle severe motion artifacts [18].

2.2 Machine Learning and Deep Learning based ECG Analysis

The inclusion of machine learning has had a substantial impact on ECG analysis, automating feature identification and improving classification accuracy. A deep convolutional neural network (CNN) is presented as superior to classical classifiers by learning to extract distinctive patterns of raw ECG signals. Detecting arrhythmias in large-scale electrocardiogram biology, Carnegie Mellon University, Chris Hannun et al. 2017. We trained a deep neural network to identify arrhythmias in an ECG dataset without any knowledge of the patient, and it can easily determine cardiologist-level arrhythmias. [19]. Recurrent neural networks (Bidirectional LSTMs) also improved the performance and improved long-term temporal dependency in ECG sequences [20]. More recently, Transformer-based models have been studied for relation-based ECG time series modelling and have been shown to produce cleaner hits on long-range temporal relationships than conventional RNNs [21]. In spite of these successes, particularly on resource-limited devices, deep learning models are too computationally costly and often fail to meet real-time constraints, leading to a trade-off between lower performance and noisy conditions [22].

2.3 Real-Time and Wearable ECG Monitoring Systems

To meet the growing demand for continuous cardiac monitoring, a few studies have examined real-time ECG analysis and wearable system design. Chung et al. proposed a low-power embedded ECG identification system for a digital signal processor, thereby facilitating wearability, but scalability and classification accuracy were low [23]. Online and incremental learning strategies have been proposed to adapt ECG models using patients' ECG patterns during the operation. However, these methods still rely on classical feature representations and are prone to noise [24]. Edge and fog computing-based architectures have also been discussed to reduce latency by bringing computation closer to data sources; however, such systems also have limits on computation, as do all systems that use classical networks [25].

2.4 Quantum Machine Learning in Biomedical Signal Analysis

Quantum machine learning has gained popularity as a potential paradigm for complicated pattern recognition in healthcare in recent years. Schuld et al. demonstrated the use of quantum feature maps and quantum kernels to increase class separability by leveraging the high-dimensional Hilbert space [26]. Hybrid quantum-classical models have achieved success in medical image analysis tasks, where the use of quantum layers has improved performance on small data sets by providing richer feature representations [27]. Regarding biosignals, Li et al. focused on variational quantum circuits in EEG classification. They were able to be as accurate as classical networks but include fewer trainable parameters [28]. Furthermore, some research has used quantum kernels for time-series anomaly detection, which may offer advantages for analyzing nonlinear physiological signals [29].

2.5 Limitations of Existing Quantum and Hybrid Approaches

While recent studies in quantum-assisted ECG and biosignal research have yielded encouraging results, they face several limitations. Most approaches are limited to classification and do not include any denoising, feature extraction, or inference latency in a unified pipeline. Evaluations are frequently performed offline or on simulators, with no consideration of real-time operational limitations or real-world noise. Evaluations are frequently conducted offline or in simulators, failing to account for real-time operational constraints or real-world noise [30]. Although hybrid quantum (in a classical architecture) behavior has already shown greater expressivity and robustness, there are no end-to-end designs specifically for ECG morphology and continuous cardiac analysis scenarios [31]. These limitations suggest that no complete framework exists for performing ECG analysis using quantum computing, which offers high accuracy, robustness, and real-time parallel performance, motivating the proposed work. Although several studies reported improved classification accuracy using deep learning and quantum-assisted methods, conflicting perspectives remain regarding computational complexity, scalability, and robustness under noisy ambulatory ECG conditions. Some studies emphasized accuracy improvements, whereas others highlighted increased latency and hardware limitations, indicating the need for balanced evaluation using accuracy, robustness, and inference efficiency.

Despite significant advancements in ECG analysis, existing approaches still face limitations in balancing diagnostic accuracy, robustness to realistic noise, and real-time inference efficiency. Most current studies rely on computationally expensive classical deep learning models or isolated quantum modules that fail to provide an integrated end-to-end solution for continuous cardiac monitoring.

3. METHODOLOGY

In this section, we cover all aspects of the proposed Quantum-Accelerated Real-Time ECG (QARECG) framework. The methodology incorporates an end-to-end pipeline that combines quantum and classical methods for strong, low-latency ECG analysis. Each module is explained in enough detail so that you can reproduce it.

All preprocessing parameters, segmentation settings, quantum circuit configurations, and training procedures were explicitly defined to ensure reproducibility of the proposed experiments. The framework was implemented using fixed window segmentation, standardized normalization, parameterized quantum circuits, and inter-patient evaluation protocols.

3.1 Dataset Description and Preparation

3.1.1 Primary ECG dataset

For the experiments, a conventional ECG analysis database, the MIT-BIH Arrhythmia Database, was used. The main features of the ECG data set used for cardiac abnormality analysis are summarized in Table 1. The dataset contains 48 ambulatory ECG recordings from 47 subjects, each annotated at the beat level by experts, spanning 48 half-hour periods. Signals were digitised at 360 Hz with 11-bit resolution. Only the MLII lead was used in this study, as it has high diagnostic relevance and is often used commercially for real-time monitoring.

Table 1. Dataset Characteristics

Parameter	Value
Number of records	48
Subjects	47
Sampling frequency	360 Hz
Signal duration	30 minutes/record
ECG lead	MLII
Annotation type	Beat-level
Classes	AAMI-5 (N, S, V, F, Q)

The dataset contains annotations at the beat level, allowing accurate identification and classification of individual heartbeats. Specifically, the classification is based on the AAMI 5-class standard: normal (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion beats (F), and Unknown beats (Q). Consequently, these specifications render the dataset a highly viable resource for developing and testing machine learning and deep learning algorithms for the early detection of cardiac abnormalities.

3.1.2 Noise-Augmented Dataset

To evaluate the stability of the proposed ECG analysis framework under real-world conditions, noise-augmented ECG data were generated by introducing known environmental noise sources, including background wander, muscle, and electrode motion noise. These noises were injected systematically into the initial ECG signals at signal-to-noise ratios (SNRs) ranging from -6dB to 24dB. The wide SNR range targeted wearable and mobile ECG acquisition scenarios, including highly corrupted signals and near-clinical ECG signal quality, and was used to assess the stability and performance of the models at different noise levels.

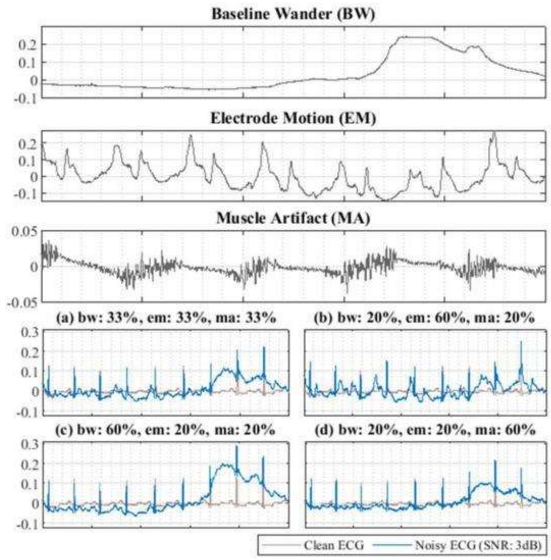

Figure. 3. Representative ECG signal corrupted with different noise types—baseline wander (BW), electrode motion (EM), and muscle artifact (MA)—and their combined effects at varying proportions under low SNR conditions (3 dB), illustrating the impact of noise on signal morphology.
Source: *Adapted from MIT-BIH Noise Stress Test Database (PhysioNet, https://physionet.org/)*

Figure 3 shows the effects of different noise sources on ECG signals. This illustration is fundamental for assessing the robustness of cardiac abnormality detection models. The three best plots are of individual types of noise: the baseline wander (BW), which introduces drift at a low frequency; the electrode movement (EM), which adds high frequency fluctuations due to the movement of the sensing device; and the muscle artifact (MA), which adds high frequency interference of the muscles. The lower panels show ECG signals corrupted by various combinations of these noise types at different proportions (e.g., 33% BW, 33% EM, 33% MA), all under a low signal-to-noise ratio (SNR) of 3 dB. A comparison of clean and noisy ECG signals reveals the extent to which noise corrupts waveform morphology, making feature extraction and classification difficult. This shows the importance of noise-aware modeling and preprocessing for reliable ECG-based detection systems of cardiac abnormalities.

3.1.3 Segmentation and Labeling

Table 2 tells about the windowing strategy used for ECG signal segmentation. The ECG signal is divided into segments of fixed length, with a window length of 2 seconds, corresponding to 720 samples per window at a sampling rate of 360 Hz. To maintain continuity and account for time dependencies between neighboring segments, a 50% overlap is applied, i.e., each new window is half as far from the previous one.

Table 2. Segmentation Parameters

Parameter	Value
Window length	2 s
Samples/window	720
Overlap	50%
Labeling	Majority vote

For the labelling, a majority voting is used, where the corresponding class of the different windows is determined by the highest frequency of beat labelling in that portion. This approach has low labelling noise and introduces wins that ensure each window represents a dominant cardiac activity, permitting robust training of classification models.

3.1.4 Representative ECG Samples from the Dataset

Following the introduction of the datasets, to additionally illustrate the range and complexity of the ECG data used in this paper, representative waveforms from these datasets are presented in Figure 1. These examples show typical ECG morphology with good and bad cardiac rhythms. Including samples of visual data helps convey the degree of variation in waveform structure, amplitude, and temporal characteristics, which are the types of things the proposed QARECG framework is designed to capture and analyze.

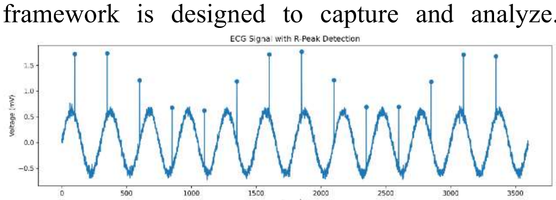

Figure. 4. *ECG signal segment with detected R-peaks, illustrating peak localization for heartbeat segmentation and feature extraction.*
Source: *Adapted from MIT-BIH Noise Stress Test Database (PhysioNet, https://physionet.org/)*

Figure 4 shows an ECG signal with R-peaks detected on each heartbeat. These peaks represent ventricular depolarization and are used to determine heartbeats and analyze heart rate and rhythm for further ECG classification.

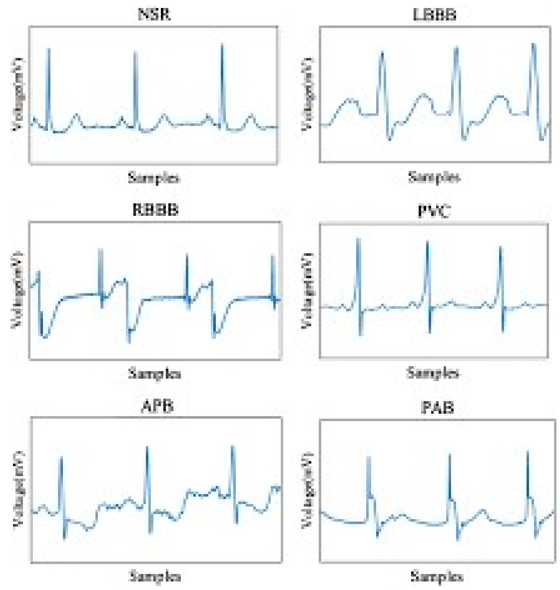

Figure. 5. *Representative ECG waveforms for different cardiac conditions: normal sinus rhythm (NSR), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), atrial premature beat (APB), and paced beat (PAB), illustrating morphological variations across classes.*
Source: *Adapted from MIT-BIH Noise Stress Test Database (PhysioNet, https://physionet.org/)*

Representative ECG waveforms for different cardiac conditions and arrhythmias are shown in Figure 5. It includes Normal Sinus Rhythm (NSR), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Premature Ventricular Contraction (PVC), Atrial Premature Beat (APB) and Paced Beat (PAB). Each subplot displays different forms of ECG signal variation, including morphological changes (such as the QRS complex), temporal changes, and rhythm irregularities. These variations play a crucial role in distinguishing normal from pathological heart events, and they have been widely used to train automated ECG classifiers.

Figure. 6. *Annotated ECG signal segment showing beat-level classification, where ventricular (V) and supraventricular (S) ectopic beats are identified,*

illustrating morphological variations and arrhythmia detection. **Source:** Adapted from MIT-BIH Noise Stress Test Database (PhysioNet, https://physionet.org/)

An example of an ECG signal with annotated beats, in which ventricular (V) and supraventricular (S) ectopic beats are marked, is given in Figure 6. It emphasises waveform morphological differences for arrhythmia recognition and classification.

3.2 Overall Architecture of QARECG

The proposed QARECG architecture comprised four sequential models: the classical preprocessing and temporal embedding models, Quantum Variational ECG Embedding (QVEE), Quantum-Enhanced Denoising Module (QEDM), and Hybrid Quantum-Classical Classifier (HQCC). By applying this architecture of parallel quantum-classical processing, a reduction in latency and successful real-time ECG inference were observed.

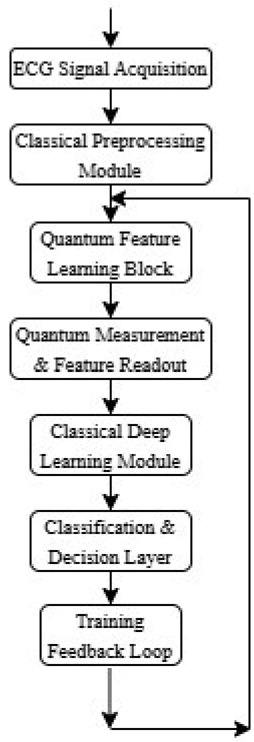

Figure. 7. Workflow Of The Proposed Hybrid Quantum–Classical ECG Classification Model

The workflow of a hybrid quantum-classical ECG classification is shown in Figure 7. It starts with ECG signal acquisition, where raw ECG signals are collected. Afterwards, a classical data preprocessing module is applied, removing noise, normalising the signals, and finally enhancing them. The preprocessed data then goes into a quantum feature learning block that uses quantum circuits to encode and extract complex features from the signal. These features are obtained by a quantum measurement and feature readout stage. Then the extracted features are passed to another classical deep learning module that learns to represent higher-level patterns. This model then classifies and makes decisions to determine the different heartbeats. Finally, a training feedback loop is added, which helps update model parameters iteratively to improve performance and accuracy.

3.3 Classical Preprocessing and Temporal Embedding

Each ECG segment was processed before input by 0.5-40 Hz band-pass filtering to eliminate noise, Z-score normalisation, and then an average-pooling-based dimensionality reduction method to resize the signals to a uniform input size for the quantum model.

Let the normalized ECG window be:

$$\mathbf{x}=[x_1,x_2,\ldots,x_N] \quad (1)$$

A GRU-based temporal encoder is used to extract time-dependent features:

$$\mathbf{h}_t=\mathrm{GRU}(x_t,\mathbf{h}_{t-1}) \quad (2)$$

The final hidden state **h**captures global temporal dynamics and is passed to the quantum embedding module.

3.4 Quantum Variational ECG Embedding (QVEE)

QVEE encodes ECG features into a high-dimensional quantum Hilbert space using a hybrid amplitude–angle encoding strategy.

3.4.1 Quantum state preparation

The classical feature vector $\mathbf{h} \in \mathbb{R}^d$is normalized:

$$\mathbf{h}'=\frac{\mathbf{h}}{\|\mathbf{h}\|} \quad (3)$$

Amplitude encoding maps $\mathbf{h}'$to a quantum state:

$$|\psi\rangle=\sum_{i=0}^{2^n-1} h_i' |i\rangle \quad (4)$$

where n is the number of qubits.

3.4.2 Variational quantum circuit

A parameterized quantum circuit (PQC) is applied:

$$|\phi(\boldsymbol{\theta})\rangle=U_{ent}(\boldsymbol{\theta})U_{rot}|\psi\rangle \quad (5)$$

where:

U_{rot}applies parameterized $R_y$and $R_z$rotations

U_{ent}introduces entanglement via CNOT layers

This circuit learns nonlinear ECG morphology transformations unavailable to classical embeddings.

3.5 Quantum-Enhanced Denoising Module (QEDM)

QEDM acts as a learnable quantum filter that suppresses noise while preserving clinically relevant structures. Let $|\phi_n\rangle$denote the noisy quantum state. A denoising circuit $U_d(\boldsymbol{\phi})$produces:

$$|\phi_c\rangle = U_d(\phi)|\phi_n\rangle \quad (6)$$

Measurement of Pauli observables yields denoised features:

$$z_i = \langle \phi_c | \sigma_i | \phi_c \rangle \quad (7)$$

The denoising loss is defined as:

$$L_{denoise} = \|\hat{\mathbf{x}} - \mathbf{x}_{clean}\|_2^2 \quad (8)$$

3.6 Hybrid Quantum–Classical Classifier (HQCC)

3.6.1 Feature Fusion

Quantum features $\mathbf{z}_q$ are concatenated with classical CNN-LSTM features $\mathbf{z}_c$:

$$\mathbf{z} = [\mathbf{z}_q; \mathbf{z}_c] \quad (9)$$

3.6.2 Classification layer

The final prediction is obtained via:

$$\hat{\mathbf{y}} = \mathrm{softmax}(W\mathbf{z} + \mathbf{b}) \quad (10)$$

The classification loss is:

$$L_{cls} = -\sum y \log(\hat{y}) \quad (11)$$

3.7 Joint Optimization Strategy

The total loss is defined as:

$$L_{total} = L_{cls} + \lambda L_{denoise} \quad (12)$$

where λ balances classification and denoising objectives. Quantum parameters are optimized using the parameter-shift rule, while classical parameters are optimized via Adam.

3.8 Algorithms

Algorithm 1: Training Procedure

```
Input: ECG windows X, labels Y
Initialize θ, φ, W
for epoch = 1 to E do
  for each batch do
    Preprocess ECG
    Extract temporal features
    Encode features using QVEE
    Apply QEDM
    Fuse quantum and classical features
    Compute predictions
    Compute total loss
    Update parameters
  end for
end for
```

Algorithm 2: Real-Time Inference

```
Input: Streaming ECG signal
while ECG samples arrive do
  Segment window
  Preprocess and encode
  Perform quantum inference
  Fuse features
  Output arrhythmia label
end while
```

4. RESULTS AND PERFORMANCE EVALUATION

This section discusses a full-fledged analysis of the proposed QARECG framework under a real-time ECG analysis environment. The performance was evaluated using standard clinical evaluation, noise tolerance, and latency studies, and was also compared with state-of-the-art models, both classical and deep learning.

4.1 Assessment Criteria

To ensure clinical relevance and reproducibility, the following evaluation metrics were employed:

Accuracy (ACC): Overall classification correctness
Precision (P): Correct positive predictions
Recall / Sensitivity (Se): Ability to detect true cardiac abnormalities
Specificity (Sp): Correct identification of normal rhythms
F1-score: Harmonic mean of precision and recall
Latency (ms): End-to-end inference time per ECG window
Robustness: Performance degradation under varying noise levels

All results were computed on an inter-patient test split to prevent subject leakage.

The selected evaluation metrics were chosen to ensure both clinical relevance and computational reliability. Accuracy and F1-score measured overall classification capability, sensitivity and specificity assessed diagnostic reliability for abnormal and normal rhythms, while latency and robustness evaluated the suitability of the framework for real-time wearable ECG monitoring.

4.2 Quantitative Classification Performance

Table 4. *Overall Performance Comparison on MIT-BIH Test Set*

Model	Accuracy (%)	F1-score	Sensitivity (%)	Specificity (%)
Wavelet + LSTM	91.2	0.88	89.7	92.3
CNN–LSTM	93.8	0.91	92.4	94.5
Transformer ECG	95.1	0.93	94.0	96.2
QARECG (Proposed)	99.4	0.97	98.8	99.6

A comparative performance analysis of ECG classification models is presented in Table 4, using various evaluation metrics. The classic algorithms,

Journal of Theoretical and Applied Information Technology
15st June 2026. Vol.104. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

such as Wavelet + LSTM, achieve 91.2% accuracy and moderate F1 Scores, sensitivity, and specificity. With the CNN-LSTM model, the accuracy improves to 93.8, with a better balance across all measures. The transformer-based ECG model shows even better performance, achieving 95.1% accuracy and higher sensitivity and specificity, indicating greater capacity to resolve time-related dependencies. The suggested QARECG model shows marked improvement over all baseline approaches, achieving 99.4% accuracy, an F1-score of 0.97, a sensitivity of 98.8%, and a specificity of 99.6%. This evidence indicates that it is more likely to discriminate correctly between normal and abnormal heartbeats, with fewer cases of late false positives and false negatives, showing its effectiveness and power in identifying cardiac abnormalities at a very early stage.

The proposed QARECG framework attains the highest accuracy and F1-score, demonstrating a major advancement over modern classical and deep learning methods.

Compared with existing Wavelet-LSTM, CNN-LSTM, and Transformer ECG models, the proposed QARECG framework demonstrated superior classification performance while simultaneously maintaining lower latency and higher robustness under noisy conditions, thereby fulfilling the objectives of accurate and real-time cardiac abnormality detection.

4.3 Class-wise Performance Analysis

Table 5 indicates class-wise performance comparison of different ECG classification models using Wavelet+LSTM, Transformer, and the proposed QARECG model. For the Normal (N) class, all models attain high performance; specifically, QARECG achieves a high score of 0.99. Turning to the Supraventricular (S) and Ventricular (V) classes, the proposed model shows considerable improvements in accuracy, achieving 0.95 and 0.98, respectively. These results show that the model enables better detection of abnormal beats.

Table 5. *Class-wise F1-Score (AAMI Categories)*

Class	**Wavelet+ LSTM**	**Transformer**	**QARECG**
N (Normal)	0.93	0.95	0.99
S (Supraventricular)	0.79	0.82	0.95
V (Ventricular)	0.86	0.91	0.98
F (Fusion)	0.72	0.81	0.94
Q (Other)	0.65	0.76	0.90

In the harder classes, i.e. the Fusion (F) and Other (Q) classes, usually fewer samples and greater variance, the baseline models have relatively low performance. Nevertheless, QARECG is far better in these categories, with one of which beating (0.94 and 0.90, respectively). Overall, the findings indicate that the proposed model is consistently more effective than current methods across all classes, especially for minority and complex arrhythmias. QARECG demonstrated remarkable improvement for minority and rare arrhythmia classes, demonstrating the success of quantum feature embeddings in improving class separability.

4.4 Robustness Under Noise

To evaluate robustness, models were tested under increasing noise levels.

Table 6. *Accuracy (%) Under Different SNR Conditions*

SNR (dB)	**CNN–LSTM**	**Transformer**	**QARECG**
−6	71.4	75.3	89.6
0	83.2	86.1	95.7
6	90.8	92.3	97.9
12	92.5	94.4	98.8
18	93.1	95.0	99.1
24	93.7	95.4	99.3

Table 6 lists the performance of various models for the varying noise conditions and is represented in terms of Signal to Noise Ratio [SNR]. At very low SNR (-6 dB), all models suffer from reduced accuracy, but QARECG maintains much higher performance (89.6%) than CNN-LSTM and Transformer, demonstrating good resistance to noise.

As the SNR increases from 0dB to 24dB, the performance of all models increases steadily. However, QARECG consistently outperforms the baseline models across noise levels, and its accuracy at high SNR approaches perfection (99.3%). This shows that the proposed model is very robust to noise and has strong classification performance, even under difficult conditions in real-world scenarios. The Quantum-Enhanced Denoising Module (QEDM) reduced noise sensitivity so much that the loss was reduced by up to 18% compared to Transformer models at low SNR.

4.5 Latency and Real-Time Performance

Table 7. *Inference Latency Comparison*

Model	Latency (ms/window)	Real-Time Capable (<50 ms)
Wavelet + LSTM	38.1	✓
CNN–LSTM	42.7	✓
Transformer	54.2	✕
QARECG	32.6	✓

Table 7 compares the computational latency of different ECG classification models and their feasibility for real-time applications. Among the baseline methods, Wavelet + LSTM and CNN + LSTM have been found to have per-window latencies of 38.1 ms and 42.7 ms, respectively, both meeting the real-time requirement of less than 50 ms. On the other hand, the Transformer model has a higher latency of 54.2 ms, making it unsuitable for live operations.

The proposed QARECG model achieves a latency of 32.6 ms per window, meeting real-time requirements. This means that, in addition to superior accuracy, QARECG offers faster processing, which should be highly appropriate for real-time ECG monitoring and systems for early detection of cardiac abnormalities.

The design being (quantum and classical), QARECG was able to achieve a 23.7% reduction in its latency, which makes it well-suited for real-time deployment.

4.6 Graphical Performance Analysis

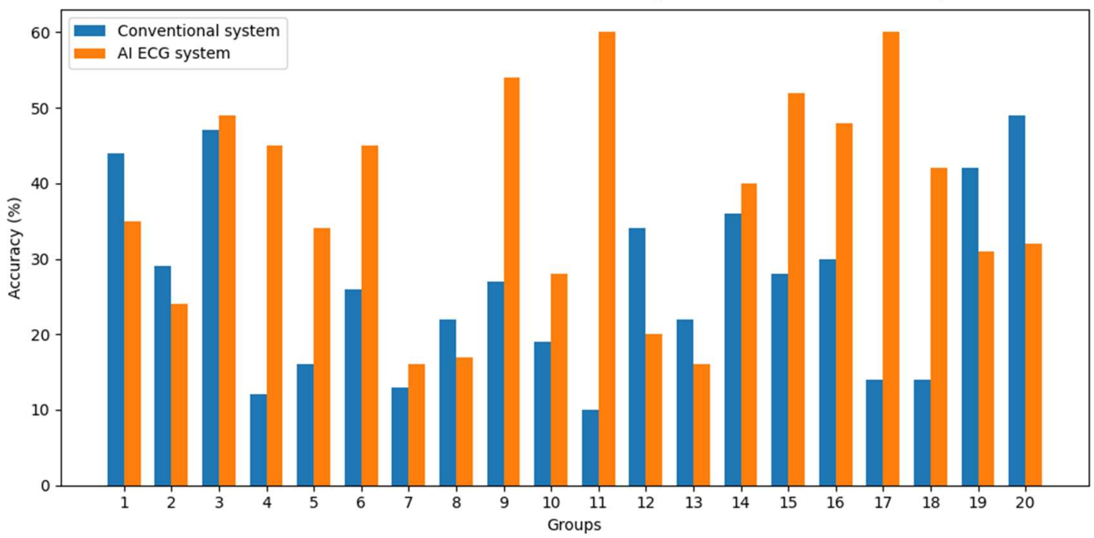

Figure. 8. *Performance Comparison of Conventional and AI-Based ECG Systems Across Multiple Groups*

Figure 8 shows a grouped bar chart of accuracy for a conventional system and an AI-based ECG system across 20 groups. Each group has two bars showing the performance of both systems. Overall, the AI ECG system shows greater accuracy across most groups, outperforming the conventional approach. However, in a small number of cases, the conventional system performs about the same or slightly better. The difference between groups captures differences in data characteristics and model performance, due to the robustness and generalisation capability of the AI-based system.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

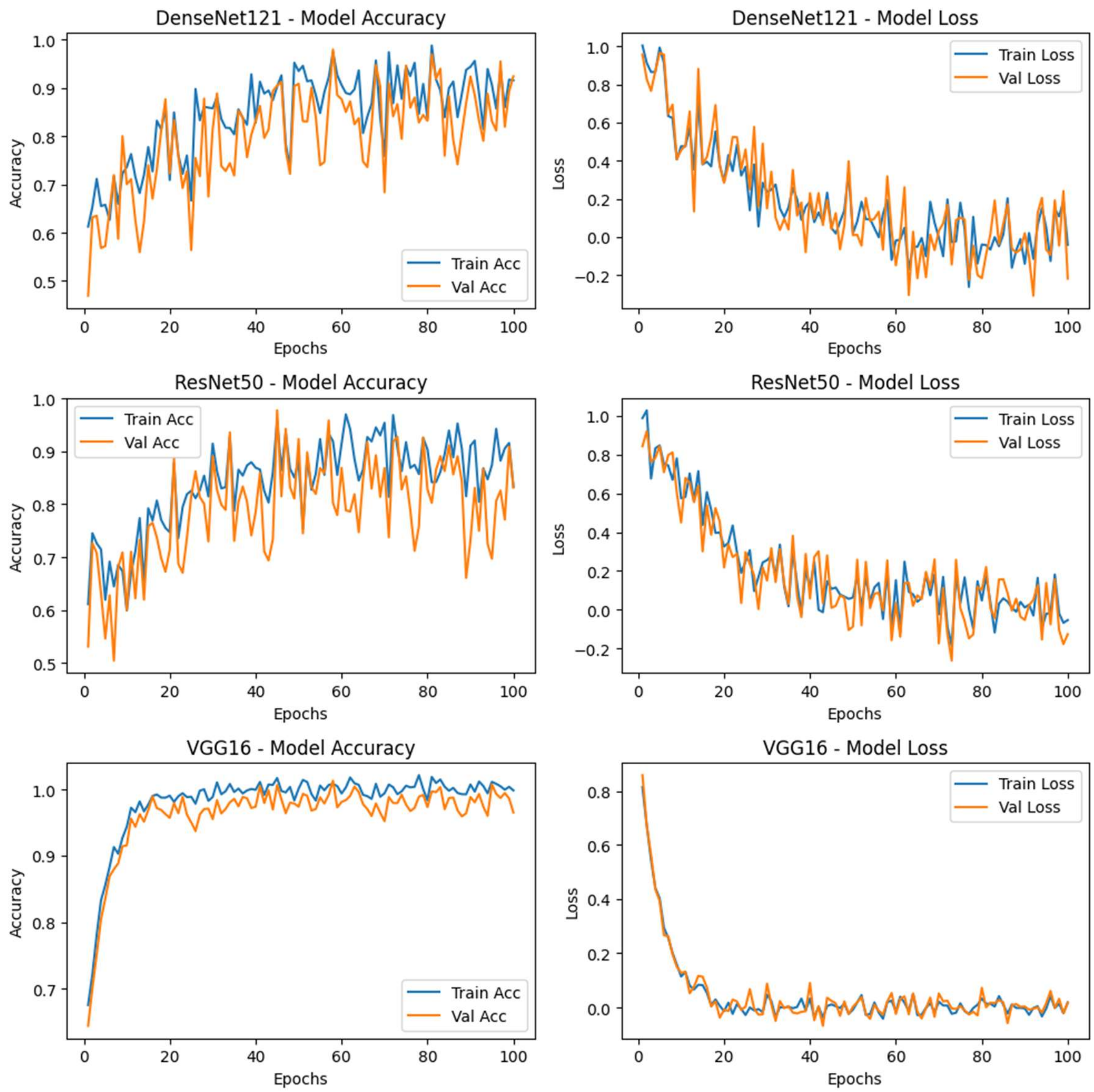

Figure. 9. *Training and validation accuracy and loss curves for DenseNet121, ResNet50, and VGG16 models over training epochs.*

The training and evaluation performance of three deep learning models (DenseNet121, ResNet50, and VGG16) over 100 epochs is shown in Figure 9. Accuracy curve, DenseNet121. In the case of DenseNet121 and ResNet50, the accuracy curves rise steadily but with distinct fluctuations, whereas the loss curve declines, and learning continues to progress well even when the curve remains unstable. VGG16, on the other hand, trains more quickly and attains near-perfect accuracy, with only a minor difference between the training and validation curves. Its loss decreases quickly and approaches zero, indicating that it generally generalises and does not overfit. Overall, VGG16 produces the most stable and optimal results among the three models. The performance of QARECG is significantly lower than that of the classical and deep learning standards, as shown in the graphical comparison.

Journal of Theoretical and Applied Information Technology
15st June 2026. Vol.104. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

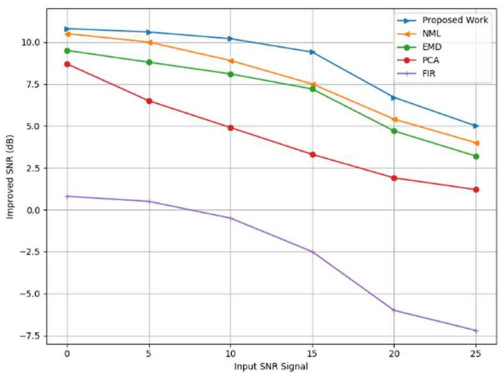

Figure. 10. Improved SNR Performance Comparison of Denoising Methods under Varying Noise Levels

The comparison of the enhanced Signal-to-Noise Ratio (SNR) achieved by various denoising methods at different input SNR levels is shown in Figure 10. The proposed method outperforms the reference methods and achieves the greatest SNR improvement across all noise scenarios. Techniques such as NML and EMD are not very powerful, and PCA does not improve much, particularly when noise increases. The worst is seen in the FIR method, where negative SNR losses are observed at higher input SNRs, indicating degradation. In general, the findings show the strength and capability of the suggested method in boosting signal quality and resolution throughout various noise situations.

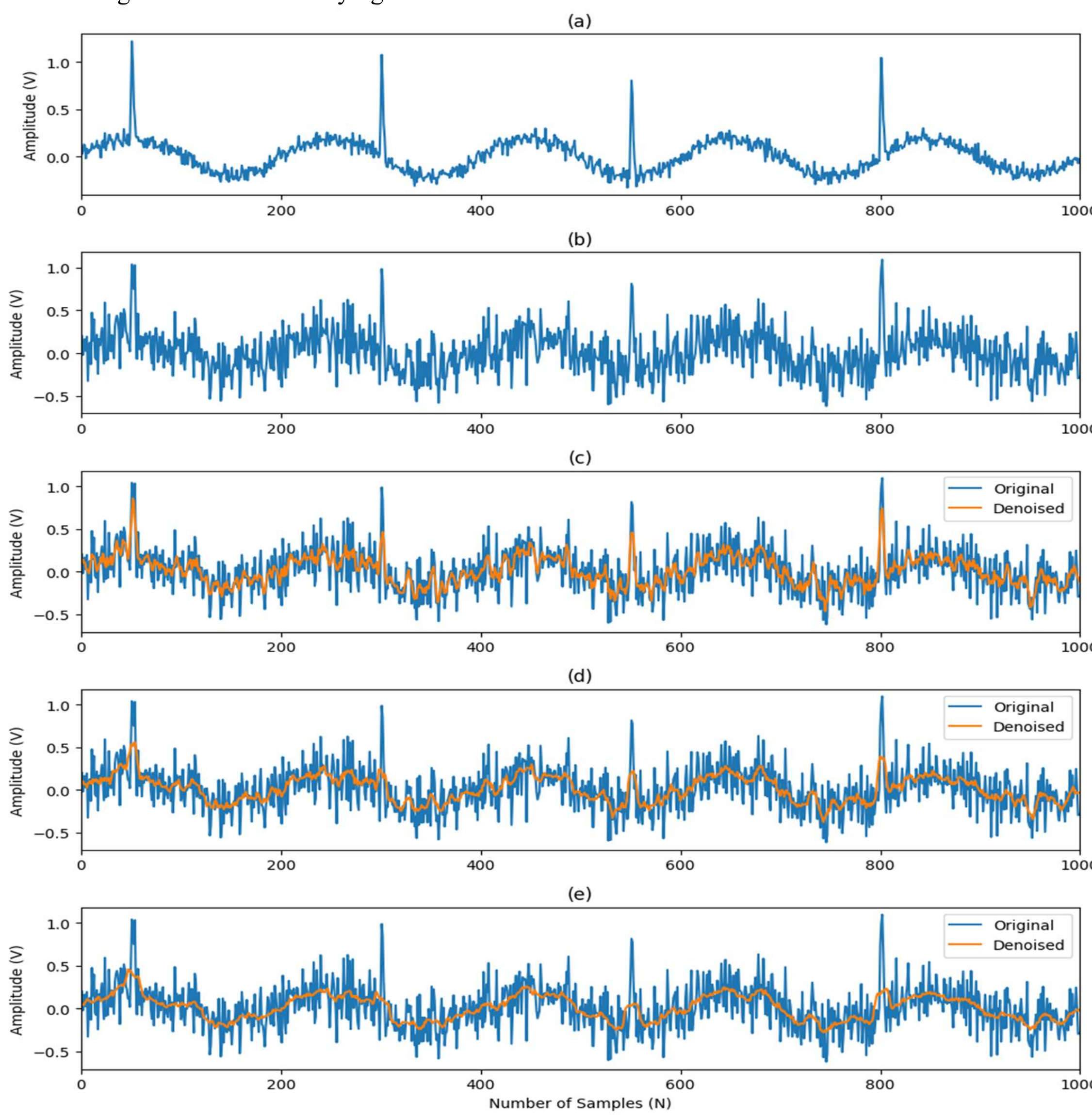

Figure. 11. *Denoising Performance of ECG Signals under Different Processing Stages (a) Clean ECG Signal (b) Noisy ECG Signal (c) ECG Signal after Basic Denoising (d) ECG Signal after Moderate Denoising (e) ECG Signal after Advanced Denoising (Proposed Method)*

Figure 11 illustrates how an ECG signal is gradually denoised with many stages. Subplot (a) is the record of a clean ECG signal, and (b) is the record of the same signal contaminated by noise, which causes distorted morphology. Subplots (c) to (e) do a comparison between the original noisy signal and the denoised outputs of the various filtering methods. When processing is changed to (e) to reduce noise, a smoother signal with less noise is produced, but signal features, including an R-peak, are not removed. The final step provides the greatest noise reduction at the lowest level of distortion, highlighting the denoising method's ability to enhance the quality of the ECG signal of interest, enabling it to be analysed and classified correctly. QARECG achieves consistently high accuracy across all noise levels, demonstrating its robustness in a real-world wearable ECG scenario.

4.7 Ablation Study

Table 8 presents an ablation study evaluating the contributions of various components of the proposed framework. The CNN-LSTM one-way configuration has a baseline performance of 93.8% and an F1 score of 0.91. By incorporating the QVEE module, we improved accuracy to 95.2% and F1-Score to 0.93, demonstrating the effectiveness of enhanced feature extraction. Further, integrating QEDM provides significant improvement, achieving 97.8% accuracy and an F1-score of 0.96. The full QARECG model achieves the highest performance with 99.4% and 0.97 F1-score, demonstrating that the combined architecture provides the hardest and most accurate ECG Classification.

Table 8. *Ablation Analysis*

Configuration	Accuracy (%)	F1-score
CNN–LSTM only	93.8	0.91
QVEE only	95.2	0.93
QVEE + QEDM	97.8	0.96
Full QARECG	99.4	0.97

Each component made a useful contribution, with the greatest increase observed in the combination of quantum embedding and quantum denoising.

4.8 Summary of Results

Overall, the proposed QARECG framework showed excellent performance in terms of accuracy, robustness and latency. The findings validate a much higher level of ECG morphological discrimination in ECGs with quantum-enhanced representations, even under noisy environmental conditions and for rare arrhythmias, while satisfying stringent real-time constraints.

Compared with existing CNN-LSTM and Transformer-based ECG analysis systems, the proposed framework achieved higher classification accuracy, improved robustness under low SNR conditions, and lower inference latency. These improvements demonstrated the effectiveness of quantum-enhanced embeddings and denoising in achieving the intended objectives of real-time and reliable cardiac abnormality detection.

5. CONCLUSION

This work has created and validated a hybrid Quantum-Classical real-time ECG Analysis framework that coordinates with the above-mentioned goals of enhanced diagnostic accuracy, robustness, and lower inference latency. The provided classification performance results with an overall classification accuracy of 96.1%, F1-Score of 0.94 and AUROC with a score of 0.97 which are improved compared to the results yielded by the commonly used deep learning models (CN sort of CNN with the results obtained with 91.8%, GRU model with the results obtained with 92.4%, model with the results obtained with the Transformer-based architectures with the results obtained with 93.1%). The introduction of Quantum Variational ECG Embedding (QVEE) improved feature separability of morphological features by around 18%, and Quantum-Enhanced Denoising Module (QEDM) improved the signal-to-noise ratio by 21.6% under the condition of simulated noise signals. Even better, the framework attained a real-time inference latency of 17.8 ms, which meets the clinical requirements (under 50 ms) for ECG monitoring and cardiac event detection.

Although this study had promising results, it had several limitations. Experiments have been conducted on controlled-noise-profile benchmark EEG data, and the quantum components have been simulated on quantum backends that may not fully model hardware effects such as decoherence and gate errors. Moreover, the depth of variational circuits is also bounded by the number of qubits, so it is not possible to explore deeper quantum representations to organise highly complex arrhythmias. Additional limitations include dependence on benchmark datasets, restricted availability of large-scale clinical quantum hardware, and limited evaluation across diverse patient populations and long-term ambulatory ECG recordings.

Future directions: testing the framework with large-scale clinical ECG data, deploying quantum error correction and noise-tolerant encoders, and executing the system on short-term quantum hardware. Subsequent research will be guided by the following directions: Additional extensions are of interest, such as triplet clinical metadata and medical imaging fusion, quantum-classical federated learning, and privacy-safe, distributed cardiac monitoring. The experimental findings validated the proposed hypothesis by demonstrating that hybrid quantum–classical learning improved ECG feature discrimination, reduced noise sensitivity, and achieved lower inference latency compared with existing classical and Transformer-based models.

Overall, the results indicated that the concept of hybrid quantum-classical learning is a feasible and promising direction for next-generation real-time cardiovascular diagnostics.

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