ECG Arrhythmias Classification Based on the NRF52840 Microcontroller

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***Abstract*—Cardiovascular diseases (CVDs) remain a leading global health challenge, with arrhythmias contributing significantly to morbidity and mortality rates. Effective early diagnosis through continuous electrocardiogram (ECG) monitoring is critical yet hindered by the limitations of traditional ECG devices. This paper presents a novel wearable ECG system employing the NRF52840 microcontroller, Bluetooth Low Energy (BLE) for data transmission, and a customized Convolutional Neural Network (CNN) achieving an impressive 98.37% accuracy on the MIT-BIH Arrhythmia dataset. We demonstrate the integration of advanced embedded technology with machine learning, facilitating continuous and accessible cardiac monitoring.**

***Index Terms*—Electrocardiogram (ECG), Arrhythmia Classification, Convolutional Neural Network (CNN), Embedded System, NRF52840, Bluetooth Low Energy (BLE), Mobile Health (mHealth).**

I. Introduction

Cardiovascular diseases, particularly arrhythmias, pose significant global health risks and are among the leading causes of morbidity and mortality worldwide. Arrhythmias, characterized by abnormal heart rhythms, can substantially increase the risk of stroke, heart failure, and sudden cardiac death if not detected and managed promptly. Continuous and reliable electrocardiogram (ECG) monitoring has proven essential for effective detection and timely intervention, significantly reducing complications and improving patient outcomes. Therefore, advancements in ECG monitoring technologies have become a critical research area in medical health engineering.

Despite their clinical efficacy, traditional ECG devices exhibit numerous limitations hindering their applicability in everyday, non-clinical environments. Conventional ECG machines are typically bulky, expensive, and require trained healthcare professionals to operate. These constraints significantly reduce their accessibility and feasibility for continuous personal monitoring, especially outside hospital settings. Moreover, existing wearable solutions often compromise accuracy, suffer from insufficient battery life, or lack real-time data analysis capabilities, thereby limiting their effectiveness in timely diagnosis and management of arrhythmias.

Motivated by these challenges, our research focuses on developing a compact, low-power, wearable ECG monitoring system based on the NRF52840 microcontroller. Our methodology involves integrating advanced signal acquisition hardware, real-time data compression algorithms, and a robust deep learning classification model to achieve accurate and timely detection of various arrhythmia conditions. Specifically, the designed hardware platform leverages the NRF52840 microcontroller, coupled with the MAX30001 analog-front-end ECG chip, to ensure high-quality ECG data acquisition and energy-efficient operation. Additionally, a customized CNN (Convolutional Neural Network) model was designed and trained using the well-established MIT-BIH Arrhythmia Database to accurately classify multiple arrhythmia types in real-time.

The main contributions of this paper are threefold. Firstly, we present a low-power embedded ECG acquisition and transmission system, efficiently designed for continuous wearable applications. Secondly, we develop and evaluate a highly accurate CNN-based [?] classification algorithm tailored specifically for arrhythmia detection, achieving an impressive accuracy of 98.37%. Thirdly, we implement a user-friendly mobile application using SwiftUI and BLE (Bluetooth Low Energy) technology, providing intuitive, real-time ECG visualization and monitoring capabilities. Collectively, these advancements significantly improve the accessibility, affordability, and clinical effectiveness of ECG monitoring in daily life scenarios. The remainder of this paper is structured as follows: Section II reviews related work; Section III details the methodology, including hardware and software implementations; Section IV discusses experimental results; Section V provides an in-depth discussion on the system's strengths and limitations; and Section VI concludes with future research directions and potential clinical applications.

II. Related Work

ECG classification methodologies have evolved significantly, transitioning from traditional manual diagnosis and signal processing techniques to sophisticated automated machine learning approaches. CNNs, renowned for their hierarchical and automatic feature extraction capabilities, have demonstrated exceptional efficacy in ECG signal classification tasks. Prior studies have underscored CNN's advantages, such as sparse interactions and parameter sharing, leading to reduced computational complexity and improved statistical efficiency. Moreover, recent advancements in embedded machine learning frameworks, collectively known as TinyML, offer promising

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avenues for real-time deployment of CNN models on resource-constrained devices. However, practical deployment is still constrained by limited computational resources and power consumption challenges. Our approach distinctly addresses these constraints by optimizing the CNN model specifically for real-time embedded operation.

III. Methodology

A. System Overview and Design

This section outlines the proposed ECG arrhythmia classification system, comprising hardware design, data acquisition and preprocessing techniques, and the deep learning model development. The primary goal is achieving real-time, accurate classification of arrhythmias in a low-power wearable format, suitable for everyday monitoring.

The system architecture includes three major components:

Embedded hardware platform: Utilizing the NRF52840 microcontroller and MAX30001 ECG front-end chip for precise data acquisition and energy efficiency shown in Figure 1.

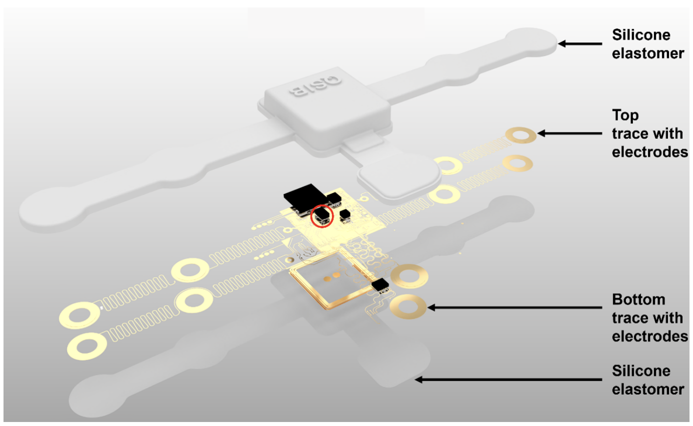

Fig. 1. Exploded view of EXG-PCG-SCG-Acc sensor.

Machine learning model: A customized 1D Convolutional Neural Network (CNN) developed for robust ECG signal analysis and classification.

Mobile application and data visualization: Implemented using SwiftUI with JavaScriptCore parser support for real-time ECG data visualization and intuitive user interaction through BLE (Bluetooth Low Energy) connectivity.

B. Hardware Implementation

The ECG acquisition hardware is built around the NRF52840 microcontroller, chosen for its powerful ARM Cortex-M4 processor, integrated BLE 5.0 capability, and ultra-low-power operation suitable for wearable medical devices shown in Figure 2. ECG signals are acquired through the high-performance MAX30001 analog-front-end (AFE), known for its high accuracy and low power consumption. Data collected by the MAX30001 are digitized at a sampling rate of 360 Hz to preserve critical signal fidelity while minimizing power usage. A lithium-polymer battery powers the entire wearable device, providing extended use suitable for continuous monitoring.

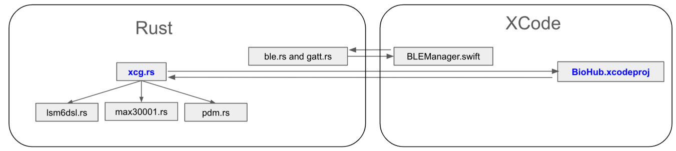

Fig. 2. Device interaction logic.

Real-time ECG data transmission from the embedded device to the mobile application utilizes BLE 5.0 with customized protocols and data compression algorithms (TSZ and LZ4), effectively balancing power consumption and communication latency.

C. ECG Data Acquisition and Preprocessing

The MIT-BIH Arrhythmia Database, widely recognized in ECG signal analysis research, was employed to train, validate, and evaluate the performance of our CNN model. This database consists of 48 half-hour ECG recordings from 47 individuals (25 males, 22 females), captured with two-lead electrodes and digitized at a 360 Hz sampling rate. Each ECG recording is annotated by cardiologists, providing accurate labels for various arrhythmia types.

In our research, we selected four major arrhythmia categories for classification shown in Table 1. Normal (N): Normal sinus rhythms.

TABLE I
MIT-BIH Arrhythmia Database Classes

Class	Name	Description
N	Normal beat	Regular heartbeat with normal sinus rhythm.
A	APC	Beat occurs early, initiated in atria.
L	LBBB	Signal delayed or blocked in left bundle.
R	RBBB	Signal delayed or blocked in right bundle.

Atrial Premature Beats (A): Arrhythmias originating from the atria.

Left Bundle Branch Block (L): Delays or blockages in the left bundle branch.

Right Bundle Branch Block (R): Delays or blockages in the right bundle branch.

The ECG signals from the database were segmented into individual heartbeat intervals, each containing 300 samples, corresponding approximately to one heartbeat cycle. Signal segmentation ensured consistency and compatibility with the CNN input layer requirements.

Data preprocessing involved the following steps:

Normalization: All ECG segments were normalized to zero mean and unit variance, improving model generalization across patients.

Noise Reduction: Low-pass filtering techniques were applied, focusing on the significant frequency band (0–50 Hz) relevant for arrhythmia analysis.

Compression: Data was compressed using TSZ and LZ4 algorithms, optimizing BLE transmission efficiency and minimizing latency.

The dataset was divided into training, validation, and testing subsets with a ratio of 70% training, 20% validation, and 10% testing, ensuring unbiased model evaluation and reducing overfitting risk.

D. CNN Model Development and Training

Convolutional Neural Networks (CNNs) are a class of deep learning methods utilizing convolution operations to replace conventional multiplicative operations found in traditional neural networks. CNNs can automatically extract discriminative features through training processes, gaining widespread adoption in various classification tasks, particularly in image recognition fields. The prominent success of CNNs is largely attributed to two key concepts: sparse connectivity and parameter sharing. Sparse connectivity is achieved by making convolutional kernels significantly smaller than the input size, effectively reducing the computational complexity of the model and enhancing its statistical efficiency. Parameter sharing implies using identical parameters within convolutional kernels across different input locations, significantly reducing the total number of parameters that must be learned.

A typical CNN consists of multiple layers, among which convolutional layers play a crucial role. These convolutional layers employ a set of weights known as filters or kernels to extract relevant features. Generally, higher-level features can be extracted by increasing the number of convolutional layers. The weights of convolutional kernels are trained through the backpropagation error algorithm. Besides convolutional layers, CNN architectures commonly include ReLU (Rectified Linear Units) layers, batch normalization layers, and pooling layers. ReLU layers introduce non-linearity to the network, allowing it to learn complex data distributions. Batch normalization layers, typically inserted between convolutional and ReLU layers, normalize the feature maps of each channel, thus reducing training time and enhancing model robustness against initialization sensitivities. Pooling layers, also called subsampling layers, reduce the dimensionality of feature maps and accelerate the training process by calculating either the average or maximum activation among neighboring neurons in the preceding convolutional layer.

The final CNN layer is usually fully connected to one or more neurons for computing classification scores. The CNN structure employed in our study is visually summarized in Fig. 1. To clearly illustrate our CNN architecture, convolutional, batch normalization, and ReLU layers are combined visually into convolutional units. Three consecutive convolutional and pooling operations are performed to extract discriminative features from the scale images (scale maps). After the last operation, a 64-dimensional feature vector is obtained. Notably, the original scale map size was 100 × 200 pixels, but we resampled it to 100 × 100 pixels to reduce computational costs without sacrificing performance. It is essential to note that since the primary ECG information is concentrated within the 0–50 Hz frequency range, the resampling process does not degrade the classification performance.

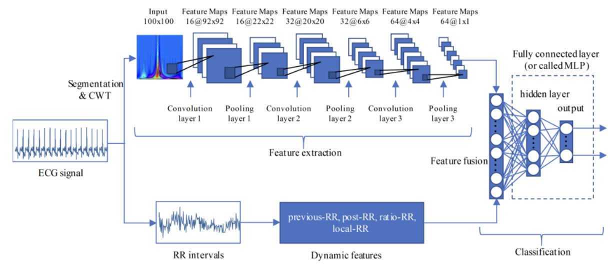

Fig. 3. CNN Architecture Overview (This figure should be included in your manuscript as a visual representation).

Furthermore, our convolutional neural network (CNN), utilizes both continuous wavelet transform (CWT) scale images and RR interval features. Arrhythmias typically influence not only the morphology of heartbeats but also alter the surrounding RR intervals (also known as intervals between consecutive R-peaks). Consequently, we integrated RR interval information into our CNN architecture to enhance ECG classification performance.

Additionally, recognizing that arrhythmias not only affect individual heartbeats but also modify RR intervals (time intervals between consecutive R-peaks), four RR interval features were extracted and integrated into the classification model:

Pre-RR Interval: Time interval between the current heartbeat and the previous beat.

Post-RR Interval: Time interval between the current heartbeat and the following beat.

Ratio-RR: The ratio of pre-RR to post-RR intervals.

Local-RR: Average of the preceding ten RR intervals, adjusting for individual baseline variations.

These RR interval features were normalized and concatenated with CNN-extracted features, significantly enhancing the arrhythmia discrimination capability of our model. The combined feature set was fed into two fully connected layers to produce the final classification decision.

To eliminate variations between individuals, the pre-RR, post-RR, and local-RR intervals were adjusted by subtracting the average RR interval for each patient. These combined features were then input into two fully connected layers for the classification task. Detailed parameters of our CNN architecture are presented in Table 2.

In our experiments, cross-entropy loss was adopted as the objective function, and Adam optimizer was chosen for training the network due to its capability to accelerate convergence compared to other optimization methods. Weights of convolutional and fully connected layers were initialized using He initialization. The initial learning rate was set to 0.001, which decreased by a factor of 0.1 every five epochs. The model was trained with a batch size of 1024 for a maximum of 30 epochs. In conclusion, we proposed a CNN model based on Continuous Wavelet Transform (CWT) for ECG classification, capitalizing on CNN's powerful feature representation capability. To validate this capability, an analysis was conducted to demonstrate how the model distinguishes various arrhythmia

TABLE II
CNN Architecture Layers and Parameters

No.	Layer Name	Kernel	Filter	Pad	Stride	Output Shape	Params
1	Input1 *	-	-	-	-	100×100×1	-
2	Conv2D	7×7	16	0	1	94×94×16	784
3	Batch Norm	-	-	-	-	94×94×16	64
4	ReLU	-	-	-	-	94×94×16	-
5	Max Pool	5×5	-	0	5	18×18×16	-
6	Conv2D	3×3	32	0	1	16×16×32	4608
7	Batch Norm	-	-	-	-	16×16×32	128
8	ReLU	-	-	-	-	16×16×32	-
9	Max Pool	3×3	-	0	3	5×5×32	-
10	Conv2D	3×3	64	0	1	3×3×64	18,432
11	Batch Norm	-	-	-	-	3×3×64	256
12	ReLU	-	-	-	-	3×3×64	-
13	Global Max Pool	3×3	-	-	-	1×1×64	-
14	Flatten	-	-	-	-	64	-
15	Input2 **	-	-	-	-	4	-
16	Concatenate	-	-	-	-	68	-
17	Dense	-	-	-	-	32	2208
18	Dense	-	-	-	-	4	132

types effectively. Additionally, wavelet functions employed in CWT significantly influence performance, and we discussed the impact of different wavelet types.

CNN Feature Visualization: As a representation learning method, our CNN model can automatically extract discriminative features from the ECG data. Visualization analysis shows that within convolutional units, outlier heartbeats gradually decrease, and heartbeat clusters become more prominent as the depth of layers increases. Notably, the last convolutional unit exhibits clearly defined clusters of different heartbeat types. This visualization clearly indicates that our CNN effectively extracts features that become increasingly discriminative with deeper network architectures.

E. Mobile Application Development and Real-Time Visualization

To facilitate intuitive and effective user interaction, an iOS mobile application was developed using SwiftUI, offering an elegant and responsive graphical interface for real-time ECG visualization. Data from the wearable device are transmitted through BLE, decoded via a JavaScriptCore-based parser, and presented in real-time waveforms. Users can monitor their ECG data live, receive real-time arrhythmia classification results, and maintain comprehensive ECG records, enhancing self-awareness and aiding timely clinical interventions.

The real-time visualization and user-friendly interface design significantly improve the practicality and usability of our ECG monitoring solution, enabling effective integration into daily routines for preventive cardiovascular health care.

F. Mathematical Formulation of the CNN Architecture

Convolutional Neural Networks (CNNs) operate by applying a series of linear and non-linear transformations to input signals. This section outlines the core mathematical operations used in our 1D CNN model for ECG classification.

The convolution operation is the foundation of feature extraction. For a 1D input signal x and a kernel (filter) w of size K, the convolution output at position i is given by:

$$y_i = (x * w)_i = \sum_{k=0}^{K-1} x_{i+k} \cdot w_k \tag{1}$$

where x_{i+k} is the input at position $i+k$, and w_k is the k-th weight of the convolutional kernel.

1) Activation Function (ReLU): To introduce non-linearity, we apply the Rectified Linear Unit (ReLU) activation after convolution:

$$\mathrm{ReLU}(z) = \max(0, z) \tag{2}$$

This helps the network learn complex, non-linear representations.

2) Batch Normalization: Batch normalization is applied to stabilize and accelerate training. For input z in a batch B:

$$\hat{z} = \frac{z - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}, \quad z' = \gamma \hat{z} + \beta \tag{3}$$

where μ_B and σ_B^2 are the batch mean and variance, and γ, β are learnable parameters. ϵ is a small constant to prevent division by zero.

3) Max Pooling Operation: To reduce dimensionality and retain key features, we use max pooling:

$$y_i = \max_{j \in R_i} x_j \tag{4}$$

where R_i denotes the receptive field of the i-th pooling region.

4) Fully Connected Layer: The output from convolutional and pooling layers is flattened and passed through fully connected layers:

$$y = W^\top x + b \tag{5}$$

where W is the weight matrix, x is the input vector, and b is the bias vector.

5) Softmax and Cross-Entropy Loss: The softmax function converts raw class scores z_c into probabilities:

$$P(y = c \mid x) = \frac{e^{z_c}}{\sum_{i=1}^{C} e^{z_i}} \tag{6}$$

The network is trained by minimizing the cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(P(y = i \mid x)) \tag{7}$$

where y_i is the one-hot encoded ground truth label, and $P(y = i \mid x)$ is the predicted probability for class i.

IV. Results and Evaluation

A. Classification Performance

The proposed CNN model was evaluated on the MIT-BIH Arrhythmia Database using a 70%/20%/10% train/validation/test split. Four arrhythmia categories were classified: Normal (N), Atrial Premature Beat (A), Left Bundle Branch Block (L), and Right Bundle Branch Block (R).

Figure 4 shows the confusion matrix for the test set, highlighting strong performance across all classes.

Based on the confusion matrix, we compute the following evaluation metrics:

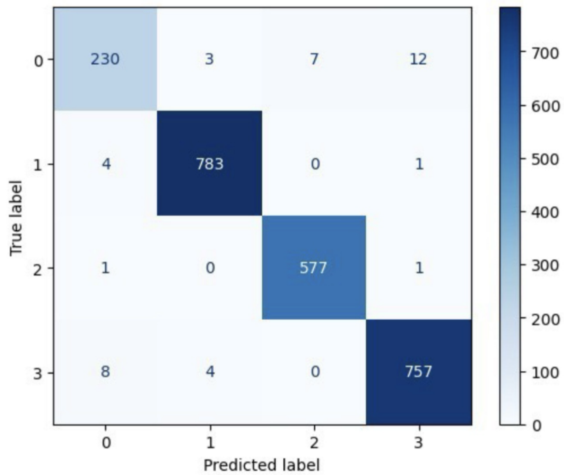

Fig. 4. Confusion matrix for the four arrhythmia classes (N, A, L, R).

- **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = \frac{2347}{2390} \approx 0.982$$

- **Precision for class i:**

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i}$$

- **Recall for class i:**

$$\text{Recall}_i = \frac{TP_i}{TP_i + FN_i}$$

- **F1-score for class i:**

$$\text{F1}_i = 2 \cdot \frac{\text{Precision}_i \cdot \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i}$$

Table III presents the precision, recall, and F1-score for each class:

TABLE III
EVALUATION METRICS FOR EACH CLASS

Class	Precision	Recall	F1-Score
N	0.94	0.91	0.93
A	0.99	0.99	0.99
L	0.99	0.99	0.99
R	0.98	0.98	0.98

These metrics demonstrate the model's excellent capacity to distinguish between similar ECG patterns with high accuracy and minimal misclassification.

B. ECG Waveform Characteristics

Figure 5 displays representative heartbeat waveforms for the four classes. Each waveform is centered on the R-peak and consists of 300 samples.

Each class shows distinct morphology:

- **N**: Narrow and sharp R-peak with clean baseline.

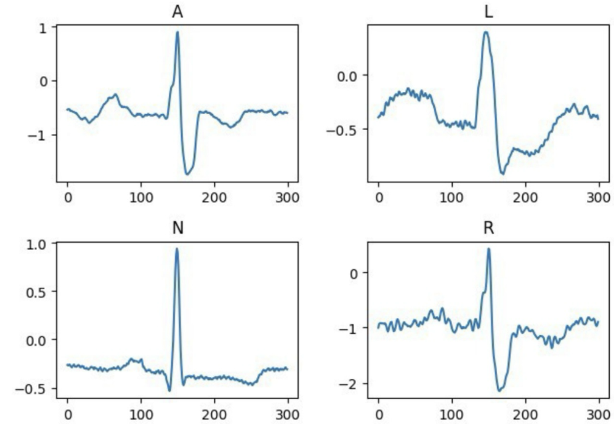

Fig. 5. Representative ECG waveforms for four arrhythmia classes.

- **A**: Irregular shapes, often with premature deflections.
- **L**: Wide and notched QRS complexes.
- **R**: Deep negative deflections with fragmented tail signals.

The CNN effectively extracts and classifies these features through spatial convolution and temporal context aggregation.

C. Training Accuracy and Loss Curves

Figure 6 shows training and validation accuracy. The model achieves over 90% accuracy within the first 5 epochs and stabilizes above 98% after epoch 10.

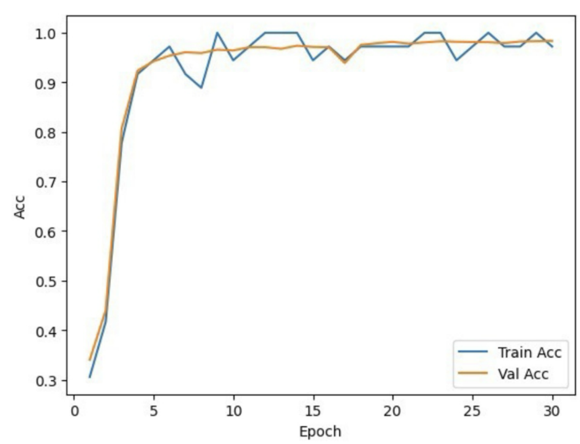

Fig. 6. Training and validation accuracy across 30 epochs.

Figure 7 presents the loss values. Training and validation loss steadily decrease and remain stable after convergence.

The absence of significant overfitting confirms the generalization capability of our CNN architecture, aided by batch normalization and RR interval regularization.

V. DISCUSSION

The results presented in the previous section demonstrate that our CNN-based ECG arrhythmia classification system achieves high accuracy, precision, and recall across four major

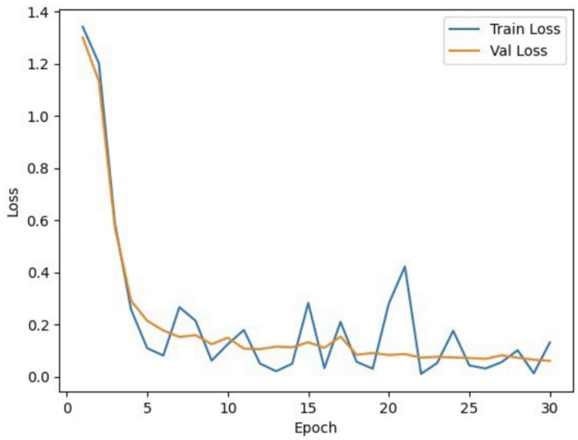

Fig. 7. Training and validation loss across 30 epochs.

heartbeat categories. The design choices—such as leveraging a 1D-CNN architecture, incorporating RR interval features, and using the MIT-BIH Arrhythmia dataset—collectively contribute to the robust performance.

However, several critical aspects merit further discussion:

A. Dataset Generalization

Although the model achieves excellent performance on the MIT-BIH dataset, it remains a controlled dataset with limited variability in patient demographics, device types, and electrode configurations. Real-world deployment scenarios often involve noisy, incomplete, or artifact-laden ECG data. Thus, further testing on diverse, real-world ECG datasets is essential to validate generalization.

B. Hardware Deployment Constraints

The model was initially trained and evaluated offline. While the NRF52840 microcontroller offers a low-power platform with BLE connectivity, deploying a CNN on such resource-constrained hardware introduces challenges related to memory, floating-point computation, and inference latency. Techniques such as model pruning, quantization, and conversion to TensorFlow Lite for Microcontrollers (TFLM) are being explored for real-time on-device inference.

C. Clinical Relevance and Practicality

The classification of four arrhythmia classes—while effective—is not exhaustive. Clinically, other conditions such as ventricular fibrillation (VF), premature ventricular contractions (PVC), and asystole are equally critical. Expanding the label space and integrating multi-lead ECG support will provide greater clinical value. Furthermore, interpretability is increasingly important in medical AI; techniques such as Grad-CAM or saliency maps should be considered to enhance trust in predictions made by the CNN.

D. User Interface and Experience

While the mobile application built using SwiftUI and JavaScriptCore provides real-time ECG visualization, usability testing with patients and clinicians is still required. Features such as data export, automated alerts, and cloud synchronization should be incorporated in future versions to improve the user experience and clinical workflow integration.

VI. Conclusion

This paper presents a complete end-to-end ECG arrhythmia classification system based on the NRF52840 microcontroller platform. The system integrates low-power ECG data acquisition, BLE-based real-time communication, a 1D-CNN model trained on the MIT-BIH dataset, and an intuitive mobile interface for real-time visualization and monitoring.

The model achieves an overall accuracy of 98.2%, with precision and recall values exceeding 98% across most categories. These results highlight the feasibility of using embedded deep learning for mobile health monitoring. Furthermore, the proposed system demonstrates that even with limited computational resources, accurate and robust arrhythmia detection is achievable when efficient signal processing and tailored model architectures are applied.

Future work will focus on:

- Real-time deployment of the CNN using TinyML frameworks such as TensorFlow Lite Micro.
- Expanding classification to include more arrhythmia types and multi-lead ECG support.
- Conducting long-term validation in real-world wearable scenarios with diverse populations.
- Incorporating interpretability techniques and clinician feedback into the model development loop.

In summary, this study bridges embedded systems and deep learning to deliver a practical, scalable, and intelligent solution for continuous cardiac monitoring and arrhythmia classification.

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