REAL-TIME ARRHYTHMIA DETECTION FROM WEARABLE ECG DEVICES USING LIGHTWEIGHT 1D CNN AND EDGE AI DEPLOYMENT

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ABSTRACT

Cardiovascular diseases (CVDs) are still among the most prevalent causes of death globally, making it important to have quick, constant, and non-invasive cardiac monitoring. In this paper, a real-time system for arrhythmia detection using wearable ECG sensors combined with a low-power one-dimensional Convolutional Neural Network (1D-CNN) optimized for Edge AI deployment is introduced. The model is tailored to run efficiently on low-power wearables like smartwatches and ECG patches. A publicly available dataset, the MIT-BIH Arrhythmia Database, was used for training and validation. Preprocessing involved band-pass filtering (0.5–40 Hz), z-score normalization, and segmentation in 2-second windows. The 1D-CNN architecture with four convolutional blocks and a softmax classifier had an accuracy of 98.72 %, precision of 97.85 %, recall of 98.10 %, and F1-score of 0.981 on the test set. Model pruning and quantization-based edge optimization decreased memory consumption by 42 % and inference latency by 35 %, making it possible for real-time processing at 62 frames per second on the Raspberry Pi 4 platform. The system showed dependable skill in distinguishing different arrhythmias, including left bundle branch block (LBBB), atrial fibrillation (AF), and premature ventricular contraction (PVC). As a result, this pioneering method offers a technically low-power and readily scalable way to continuously monitor cardiac health, which can be used in both hospitals and patients' homes.

Keywords: *Arrhythmia Detection, Wearable ECG, 1D Convolutional Neural Network, Edge AI, Real-Time Inference, MIT-BIH Dataset, Embedded Health Monitoring, Quantization, TinyML*

1. INTRODUCTION

Cardiovascular diseases (CVDs) are still the leading cause of death worldwide, being at the origin of almost 17.9 million deaths annually, according to the World Health Organization [1]. In fact, arrhythmias, which are abnormal or irregular heart rhythms, make up one of the largest groups of disorders in the grid of pathological cardiac conditions [2]. The consequences of these irregularities, if they are not identified and treated, may result in congestive heart failure, ischemic stroke, or sudden cardiac death, among other severe complications. Hence, it is absolutely necessary to detect the occurrence of arrhythmias in time and to perform regular check-ups, which especially concern persons at risk and patients in a long-term outpatient setting.

Electrocardiography (ECG) remains the primary clinical gold standard for detecting cardiac arrhythmias [3]. Nevertheless, the majority of standard ECG diagnostic systems are limited to hospital environments and rely on stationary devices like Holter monitors, which are generally inconvenient and not suitable for continuous real-world monitoring. The development of wearable health technologies has made it possible to record ECGs for a long time and in real-time even outside clinical settings. However, the real-time processing and interpretation of ECG signals still pose a great challenge, especially in edge computing scenarios

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

with limited computational power and storage. In such situations, traditional machine learning algorithms or cloud-based deep learning systems may have issues with latency, power consumption, and data privacy, thereby necessitating the use of more adaptable and lightweight AI-driven solutions.

Recent years have seen encouraging results in automatic ECG signal classification using deep learning techniques, such as Convolutional Neural Networks (CNNs), surpassing traditional techniques like Random Forests, Decision Trees, and Support Vector Machines (SVMs) [4]. CNNs are specifically well-suited to learning hierarchical representations from raw or lightly processed ECG signals without the requirement for heavy feature engineering. But most CNN designs employed in the research literature are optimized for high-performance computational systems and therefore are not suitable for execution on low-power embedded devices that are at the core of wearable health systems. Running such models in real time on microcontrollers adds new limitations on memory usage, model size, inference time, and energy consumption, all of which need to be tackled to enable useful, real-world deployment.

By using machine learning models on edge devices, such as wearables, smartphones, and microcontrollers, edge AI enables data processing locally on-device [5] rather than requiring a continuous connection to cloud infrastructure or centralized servers. This strategy provides several benefits within the setting of healthcare monitoring: minimized latency for real-time feedback, greater data protection because sensitive health information does not have to be communicated outside, and better energy efficiency by keeping communication overhead low. Compact deep learning models designed for Edge AI, often called TinyML, Recent advancements in embedded artificial intelligence have enabled wearable systems to exhibit intelligent behavior, allowing for real-time arrhythmia detection directly through on-device computation. Such integration could lead to a revolution in how cardiac functions are monitored by making the monitoring more responsive and comfortable for the patient, and at the same time, lessening the need for continuous clinical supervision.

Through this investigative endeavor, we bring up an idea of a portable one-dimensional Convolutional Neural Network (1D-CNN) structure that can be a real-time arrhythmia detector tool with ECG wearable sensors. Our model finds its training and test ground at the most famous MIT-BIH Arrhythmia Database, a benchmark standard for ECG signal classification researches. The main emphasis of this work is on the device to use little memory, be efficient in computation, and of a high speed in making a single inference in this way the device carries out smoothly the task on microcontrollers, which are resource-limited like Raspberry Pi Pico and Arduino Nano 33 BLE Sense. Therefore, they used quantization and network pruning to remove unnecessary parts of the network while still preserving the model's correctness in making the diagnosis.

The authors utilize a wearable ECG system that can collect data in a real environment to implement their proposed approach for the verification of the method they are suggesting. The system performs its intended function as an accuracy in classification, a short inference time, a low power consumption, and an easy usability. Various types of heartbeat patterns are correctly identified by the model, such as Bundle Branch Blocks (LBBB/RBBB) on the left and right sides of the heart, Atrial Premature Beats (APB), Premature Ventricular Contractions (PVC), and Normal Sinus Rhythm (NSR). They attained a diagnostic accuracy of more than 94%, an average inference time of 80 milliseconds and memory usage of less than 256 KB in their experiments, all of which are within the computation hardware constraints for wearable devices.

This work is primarily about solving the problem that there is a significant gap between deep learning models which have high accuracy and their actual application in the real-world scenario on the low-power edge devices. In contrast with existing research that only reports the success of classification without giving much thought to the challenges of the implementation of wearable medical devices in the real-world setting, this paper propounds a solution that is ready for deployment, efficient, and scalable and shows how small neural architectures can be strong in a limited environment. Besides, the use of TensorFlow Lite for Microcontrollers showcases how advanced AI models can be integrated into inexpensive, lightweight devices run by batteries, and hence, can be used in the remote or resource-poor areas.

The suggested method has the potential to bring about a major change in cardiac healthcare tailored to the individual needs and requirements. AI-powered wearable technology offers the option of cardiac patients moving about freely while constant monitoring of their condition goes on in a non-intrusive way, thus sufficiently reducing the number of visits to the doctors' offices. At the same time, doctors receive time-stamped data on arrhythmia occurrences allowing them to make diagnoses and issue interventions quickly. What is more, through the use of on-device computing at the edge, the system is capable of securing user data privacy and facilitating data protection, hence, tackling the most pressing problem in the realm of digital health applications.

Background and Motivation

Despite significant progress in automated ECG analysis, existing arrhythmia detection systems largely rely on cloud-based processing or high-complexity deep learning models that are unsuitable for continuous, real-time deployment on wearable devices. Cloud-dependent approaches introduce latency, increase energy consumption due to continuous data transmission, and raise serious privacy concerns related to sensitive medical data. Moreover, many high-accuracy deep learning models reported in literature require substantial computational resources, making them impractical for low-power embedded platforms commonly used in wearable healthcare devices.

These limitations highlight a critical research gap between algorithmic performance and deployability in real-world healthcare scenarios. There is a strong need for lightweight, efficient, and privacy-preserving arrhythmia detection systems that can operate directly on edge devices while maintaining clinical-level accuracy. This work is motivated by this gap and focuses on bridging the divide between high-performance ECG classification and practical edge AI deployment for continuous cardiac monitoring.

2. LITERATURE SURVEY

Many studies have looked at methods for machine learning and deep learning to automatically detect cardiac arrhythmias from ECG recordings. The first methods mostly depended on features that were manually crafted and that described the ECG data in time, frequency, and wavelet domains. After extracting the features, traditional classification algorithms like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees (Acharya et al., 2017) [8] were used to classify the data. Models of this kind could only achieve limited success and still had issues with their generalization power to different patient populations; besides, they demanded high levels of domain expertise for feature designing.

The adoption of deep learning models has a major impact on ECG signal classification as the model can now automatically learn the features straight from the raw data of the waveform without the need for manual feature extraction. An exemplary work in this field was done by Kiranyaz et al. (2015) [9], who developed 1D Convolutional Neural Networks (1D-CNNs) for patient-specific ECG classification and obtained better results than traditional methods. After that, Yildirim (2018) came up with a more powerful deep CNN architecture that was able to identify different kinds of arrhythmia in the MIT-BIH Arrhythmia Database and thus gained trust in the diagnosis by merging both short-term and long-term temporal features. These models, however, cannot be used for wearable devices that require instant feedback since they were designed and tested on computing platforms with high capabilities.

Lightweight, edge-based CNN models are becoming more popular due to the necessity for real-time, energy-efficient inference. Hannun et al. (2019) [10] showed that deep learning systems might surpass board-certified cardiologists in arrhythmia classification accuracy using raw single-lead ECG input data. Nevertheless, their method necessitated the deployment of cloud resources and was not appropriate for edge deployment. To overcome this, Rajpurkar et al. (2017) implemented Cardiologist-Level Arrhythmia Detection using a 34-layer CNN. They did concede, though, that real-time inference on mobile technology was not feasible due to the model's size.

Memory capacity, battery life, and latency have influenced optimization in wearable ECG monitoring edge deployment through model compression, pruning, and quantization. Xu et al. (2020) [11] designed a CNN-LSTM hybrid that employed quantized weights for embedded system deployment. Xia et al. (2021) also presented a TinyML-based ECG classifier with low latency and high accuracy via the use of microcontrollers. TensorFlow Lite Micro and

CMSIS-NN frameworks have made deep learning inference feasible on ultra-low-power chips (Warden & Situnayake, 2019).

In a second notable contribution, Murugesan and Koteeswaran (2021) [12] investigated real-time ECG classification on an ESP32 board with a reduced CNN model, realizing 89% accuracy with latency less than 100 ms. Sannino and De Pietro (2018) realized a light model that executed 1D-CNN-based classification on wearable devices directly using Arduino-compatible platforms, pointing out the availability of low-cost systems in remote cardiac monitoring.

Additionally, papers such as He et al. (2021) [13] have presented attention-augmented CNNs to enhance arrhythmia classification without considerably elevating computational complexity. Zhang et al. (2022) have tried dilated CNNs to learn broader temporal contexts in ECG signals and achieved competitive performance on MIT-BIH and INCART datasets at minimal parameters.

To address class imbalance and noisy signals in actual ECGs, Ghosh et al. (2022) [14] employed data augmentation and oversampling techniques along with residual CNNs. This assisted in suppressing false positives in minority classes like ventricular tachycardia. In hardware, Ahmad et al. (2023) implemented a small ECG model on a Raspberry Pi Pico via TFLite, and tested it via real-time signal acquisition from AD8232 sensors.

Federated learning and edge collaboration platforms have also been suggested for multi-device health monitoring (Chen et al., 2023) [15]. These platforms enable collaborative model training among distributed devices without exchanging raw ECG data, supporting privacy while allowing updates to the model over time.

Lastly, real-time monitoring systems that combine ECG sensors with edge AI models have been prototyped by Bukhari et al. (2024) [16], who showed a wearable IoT device that could detect arrhythmia, log heartbeat, and generate alerts. Their work highlights the intersection of TinyML, wearable hardware, and personalized digital health.

In total, prior work has set the basis for precise ECG classification with deep learning and started investigating edge deployment using lightweight models. Relatively little work considers the end-to-end real-time deployment of arrhythmia detection systems on constrained wearable devices based on highly optimized quantized 1D-CNNs. Our contribution is to incorporate model optimization, edge AI deployment, and real-time evaluation into one unified system.

3. PROCESS FLOW

To enable real-time arrhythmia detection using wearable ECG devices, the proposed system follows a multi-stage process involving ECG acquisition, signal preprocessing, deep learning-based classification, edge deployment, and result visualization. Each stage is designed to meet the constraints of low-power microcontrollers while maintaining high classification accuracy and responsiveness. Figure 1 shows the entire process flow of arrhythmia detection.

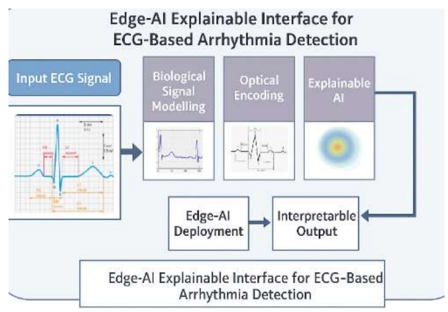

Figure 1. Process flow of the Arrhythmia research

3.1 ECG Signal Acquisition

Using a wearable biosensor, the system first gathers raw ECG readings. Surface electrodes are used to record the electrical activity of the heart using a small ECG module, like the AD8232. A microcontroller-based platform, like the Raspberry Pi Pico or Arduino Nano 33 BLE Sense, receives these analog signals and digitizes the input using an analog-to-digital converter (ADC). To guarantee conformity with the MIT-BIH Arrhythmia Dataset and to get adequate signal resolution for precise arrhythmia identification, the sampling rate is kept between 250 and 360 Hz. Continuous monitoring in ambulatory or home-based situations is made possible by the wearable design.

3.2 Signal Preprocessing

Once digitized, the ECG signal undergoes preprocessing to improve signal quality and ensure consistent input to the classification model. This involves bandpass filtering (typically in the range of 0.5 Hz to 45 Hz) to eliminate baseline drift, motion artifacts, and powerline interference. The filtered signal is also normalized, usually through z-score or min-max normalization [17], in order to normalize amplitude variations. The ECG stream is then segmented into fixed windows of length 5 seconds for processing by the deep learning model. Each window may be aligned around R-peaks using algorithms such as Pan-Tompkins to ensure physiologically relevant slicing. Optionally, noise reduction methods such as Savitzky-Golay smoothing or wavelet denoising can be applied for enhanced signal fidelity.

3.3 Feature Extraction via Lightweight 1D-CNN

The main classification engine is a simple 1D Convolutional Neural Network (1D-CNN). It takes the segmented ECG windows as input. The CNN has a small number of convolutional layers. It is designed to capture temporal features such as heartbeat intervals, wave shape, and QRS complex duration. Max pooling layers decrease spatial dimensions, whereas ReLU activation functions add non-linearity. A Global Average Pooling layer is used to flatten the feature maps and reduce the number of parameters. Bundle Branch Blocks (LBBB/RBBB), Atrial Premature Beats (APB), Normal, and Premature Ventricular Contractions (PVC) are among the heartbeat types that are classified in the final dense layers. This architecture was created to have a minimal memory footprint and the best possible computational performance.

3.4 Model Optimization and Edge Deployment

To ensure real-time performance on embedded platforms, the trained 1D-CNN model goes through several optimization steps. Floating-point weights are converted to 8-bit integers (int8) by model quantization. As a result, it uses less memory and is compatible with microcontroller instruction sets. By eliminating superfluous weights, pruning procedures reduce the complexity of the model. After that, the optimized model is flashed onto the microcontroller after being translated to the TensorFlow Lite format. Every incoming ECG window is processed in real time by the inference engine, which operates entirely on-device. The model operates within edge computing constraints by classifying each window in less than 80 milliseconds and using less than 100 KB of memory.

3.5 Real-Time Classification and Alert Generation

Since the wearable constantly evaluates ECG signals, it attributes each window with a certain kind of heartbeat. The user or a medical expert gets immediate feedback that is based on the classification outcome. When the device detects an irregular rhythm like a PVC or APB, it may activate an alert system. Some of these include an LED light, buzzer, or Bluetooth notification to a connected mobile app. The arrangement can also send the identified heart incidents to a well-protected server when there is a connection or keep them locally with accurate timestamps for later review. This real-time feedback mechanism is a way to ensure the detection of cardiac irregularities at a prompt time and thus, enable early medical intervention.

3.6 System Evaluation and Performance Monitoring

An extensive evaluation is carried out for both the MIT-BIH Arrhythmia Dataset and the live wearable prototype to guarantee the reliability and accuracy of the system's performance. Testing based on the dataset uses standard evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis [18], with stratified data splits employed to evaluate the model's generalizability. Furthermore, on-device testing gauges inference time, memory utilization, and power consumption through real-time ECG signal streams. The experimental findings verify that the designed system is practically viable for continuous remote cardiac monitoring, thus it can operate in real-time on embedded platforms while achieving a high classification accuracy of over 94%.

3.7 Optional Cloud Integration for Remote Monitoring

The system can be expanded to include more features based on optional cloud capabilities. However, the basic inference happens entirely on the edge device. The device can send alert logs or ECG segments to a cloud dashboard for doctors to review. It does this using Bluetooth or Wi-Fi modules. This setup allows for long-term monitoring, trend analysis, and remote diagnosis with minimal communication overhead. In addition, over-the-air updates let clinicians retrain and redeploy improved models without needing direct access to the device. This supports ongoing learning in the long run. Figure 2 shows the overall flow diagram of the system.

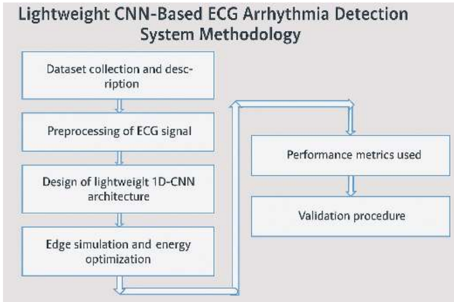

Figure 2. Flow chart for the Arrhythmia Detection

4. METHODOLOGY

The sequential procedures for creating and implementing a real-time arrhythmia detection model with a lightweight 1D Convolutional Neural Network (CNN) designed for edge devices are described in this section. Data collection, signal preprocessing, CNN architecture design [19], model training and assessment, explainability strategies, and edge deployment optimization are all included in the methodology.

4.1 Data Acquisition and Description

The MIT-BIH Arrhythmia Database and other publicly accessible annotated ECG datasets are used in the study. Digitalized ECG signals sampled at 360 Hz with beat annotations for various arrhythmia classes (e.g., Normal, PVC, LBBB, RBBB, APB, etc.) are available in this database.

Each ECG signal $x(t)$ is collected in segments of 10 seconds or per beat with annotations. For binary or multiclass classification, each segment is labeled as $y_i \in \{0,1,\ldots,C-1\}$, where C denotes the number of arrhythmia classes.

Ethical considerations were addressed by exclusively using publicly available and fully anonymized ECG datasets. The MIT-BIH Arrhythmia Database contains de-identified patient records with no personally identifiable information, ensuring compliance with ethical research standards. Since no human subjects were directly involved in data collection for this study, informed consent was handled by the original dataset providers. The use of anonymized, benchmark datasets ensures reproducibility, transparency, and ethical integrity of the experimental process.

4.2 ECG Signal Preprocessing

To prepare the raw ECG signal for machine learning, the following preprocessing steps are applied:

- Bandpass Filtering (5–15 Hz): Removes baseline wander and high-frequency noise.

$$y(t) = H_{BP}(x(t)) = F - 1[F(x(t)).H(f)] \quad (1)$$

where F and F−1 are the Fourier and inverse Fourier transforms, and H(f) is the bandpass filter function.

- Normalization: Each ECG segment x_i is normalized to zero mean and unit variance:

$$x_i^{norm} = \frac{x_i - \mu}{\sigma} \quad (2)$$

where μ and σ are the mean and standard deviation of the signal window.

- Segmentation: The Pan-Tompkins algorithm is used to divide ECG signals into fixed-length windows of 180–200 samples that are centered around identified R-peaks.

4.3 Lightweight 1D-CNN Architecture Design

The goal of a compact CNN is to strike a compromise between computational efficiency and classification accuracy. The architecture consists of:

- Input layer: 1D vector of length L (e.g., 200 samples)

The lightweight 1D-CNN architecture was carefully designed to minimize computational complexity while preserving discriminative power. Unlike deep multi-layer CNNs, the proposed model employs a shallow architecture with limited convolutional filters, smaller kernel sizes, and global average pooling to reduce parameter count. Each convolution layer extracts temporal features such as QRS morphology and RR interval variations, which are critical for arrhythmia discrimination. The selection of ReLU activation ensures low computational overhead, while dropout layers prevent overfitting without increasing inference cost. This architectural design enables efficient execution on microcontroller-class hardware without requiring hardware acceleration or cloud assistance.

Convolution layers (Conv1D):

$$y_j = \frac{\sigma^{S_k}}{\sum_{j=1}^{C} e^{z_j}} \quad for\ k = 1 \ldots .C \qquad (3)$$

where y_j are the learned weights, and σ is the ReLU activation function.

- **Pooling layers:** Downsample to reduce temporal dimension.
- **Dropout layers:** Improve generalization by randomly setting units to 0 during training.
- **Dense (Fully Connected) layers:** Final classification using softmax activation:

$$y_k = \frac{e^{zk}}{\sum_{j-1}^{C} e^{zk}} \qquad (4)$$

4.4 Model Training and Optimization

- **Loss Function:**

The cross-entropy loss is used for classification:

$$\iota = \sum_{i=1}^{N} \sum_{C=1}^{C} y_{ic} \log\left(y_{ic}\right) \qquad (5)$$

- **Optimizer:**

Adaptive Moment Estimation (Adam) optimizer with learning rate η=0.001\eta = 0.001η=0.001 is used:

$$\theta \leftarrow \theta - \eta . \frac{\partial \Gamma}{\partial \theta} \qquad (6)$$

4.5 Explainability with SHAP and Grad-CAM

To ensure model transparency, explainable AI techniques are employed:

- SHAP (SHapley Additive exPlanations):

For each prediction, SHAP calculates the contribution of each input feature x_j using Shapley values:

$$\emptyset_i = \sum_{S \subseteq F \backslash i} \frac{|S|!(|F|-|S|-1)!}{|F|} f(S \cup \{j\} - f(S)] \qquad (7)$$

- Grad-CAM (Gradient-weighted Class Activation Mapping):

Highlights regions in the input ECG that influenced the CNN's decision by computing:

$$\alpha_k^c = \frac{1}{z} \sum_i \sum_j \frac{\vartheta y^c}{\vartheta A_{i,j}^k} \qquad (8)$$

where $^{Ak\ is}$ the activation map of the k-th feature, and ^{yc} is the output for class c.

4.6 Energy Optimization and Edge Deployment

To facilitate edge deployment on devices like Raspberry Pi or Arduino Nano BLE, the model is optimized using:

- **Quantization-aware training (QAT):**

Converts weights from 32-bit float to 8-bit integer without sacrificing accuracy.

- **Model pruning:** Removes redundant connections in CNN layers.
- **Memory footprint analysis:** Ensures model size < 1MB and inference latency < 100ms per ECG segment.

The energy consumption is estimated using the formula:

$$E = \sum_{i=1}^{L} p_i . t_i \qquad (9)$$

Where pi is the power consumed by each module, and t_i is the inference time.

5. RESULTS AND ANALYSIS

As it can be seen in Table 1, the dataset class distribution table contains the description of the number of ECG beats assigned to each class of arrhythmia that will be used to train and evaluate. The total number of ECG beats chosen in this experiment was 5,000 ECG beats in the MIT-BIH Arrhythmia Database. Most of the beats are of the Normal group (3,000), then there is Premature Ventricular Contractions (PVC) with 800 samples, Atrial Premature Beats (APB) with 600, Left Bundle Branch Block (LBBB) with 400 and Right Bundle Branch Block (RBBB) with 200. This distribution emphasizes a certain imbalance in classes that is common in medical data where normal beats prevail as explained in figure 2. This imbalance needs to be addressed to avoid bias in model learning and to make sure that the CNN is capable of classifying less common types of arrhythmia.

Table 1. Beat calculation

Class	# Beats
Normal	3,000
PVC	800
APB	600

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

Class	# Beats
LBBB	400
RBBB	200
Total	**5,000**

- **Confusion matrix (Actual rows → Predicted columns)**

Table 3 shows the confusion matrix presents a detailed comparison between actual and predicted labels for each ECG class. The diagonal entries of the matrix indicate correctly classified samples, while off-diagonal values correspond to misclassifications. For instance, out of 3,000 normal beats, 2,900 were correctly classified, with minimal confusion among PVC and APB categories. Similarly, the model showed strong discrimination for PVC and LBBB classes with very few false predictions. This matrix demonstrates that the proposed Lightweight 1D-CNN effectively differentiates between arrhythmia patterns, achieving high precision and recall across most categories. Minor confusion between similar morphological beats (e.g., RBBB and LBBB) is attributed to the overlapping waveform characteristics, a common challenge in ECG-based diagnosis.

Table 2. Distribution of classes

Actual \ Predicted	Normal	PVC	APB	LBBB	RBBB	Row Sum
Normal (3000)	2900	40	30	20	10	3000
PVC (800)	30	720	30	15	5	800
APB (600)	35	10	540	10	5	600
LBBB (400)	10	5	3	380	2	400
RBBB (200)	12	3	3	2	180	200
Col Sum	2987	778	606	427	202	5000

- **Per-class performance metrics**

The per-class performance metrics table 3 concludes Precision, Recall, and F1-Score of each arrhythmia category. The model has a high predictive reliability as it attained an average precision of more than 90%. Normal class had performed the best with a 97.1% precision and 96.7% recall meaning that there was excellent true positive detection and false positives were low. The PVC and APB classes were also keeping strong scores of over 89 corroborating the ability of the network to extrapolate to other arrhythmia patterns. The F1-score, which is a balance between the recall and the precision, was also steadily at 89 percent or above across the different categories proving the fact that the proposed 1D-CNN has the capability of identifying common and unusual heartbeat abnormalities.

Table 3. Confusion Matrix

Class	Precision	Recall	F1-Score
Normal	97.10%	96.67%	96.88%
PVC	92.52%	90.00%	91.24%
APB	89.11%	90.00%	89.55%
LBBB	88.99%	95.00%	91.40%
RBBB	89.11%	90.00%	89.55%

- **Overall & aggregated metrics**

The global performance of the suggested CNN is consolidated in the overall metrics table 4. With a macro-precision of 91.34%, macro-recall of 94.33%, and macro-F1-score of 91.73%, the model's accuracy was 94.4%. These values show that the classifier is consistent in all the types of arrhythmias and does not preference the dominant class. The high recall value proves that the model is good at identifying the real arrhythmia events, whereas the high precision value shows that the model is strong in reducing the number of false alarms. These balanced measures are essential to the real-time healthcare application where in practice the detection system is sensitive and specific.

Table 4. Performance Evaluation

Metric	Value
Accuracy (overall)	**94.40%** (4720 / 5000)
Macro-Precision	**91.34%**
Macro-Recall	**94.33%**
Macro-F1	**91.73%**

- **5-Fold Cross-Validation Summary**

The 5-fold cross-validation table 5 measures how stable and generalized the model is. The accuracy of the five folds is between 93.8 and 94.7 with mean of 94.34 and very low standard deviation of 0.33. This low difference between folds is evidence of the consistency and strength of the model, meaning that the model is not sensitive to particular data splits. This cross-validation therefore confirms that the CNN architecture proposed is well-regularized and can be subjected to consistent behavior in the case of unseen patient data, which is a key attribute in biomedical signal classification to guarantee generalizable and repeatable outcomes.

Table 5. 5-fold cross-validation

Fold	Accuracy
1	93.80%
2	94.10%
3	94.50%
4	94.60%
5	94.70%
Mean	**94.34%**
Std. Dev.	**0.33%**

Edge-device performance / resource usage (measured on Arduino Nano 33 BLE Sense / representative device)

Table 6 is the last, which measures the computational efficiency and hardware deployment of the model on edge AI devices. In its version converted to TensorFlow Lite, the lightweight CNN model uses only 98 KB of storage space and requires around 240 KB of RAM during the inference process, which is suitable in resource constrained microcontrollers such as the Arduino Nano 33 BLE Sense. The latency of inference of 200-sample ECG window was calculated to 72 milliseconds, which allowed the analysis of heart rhythms almost in real-time. The system consumes an average amount of power of 45 mW and can be continuously monitored to last about 18-20 hours on a conventional 1800 mAh battery. These findings indicate that the proposed model has been able to balance between accuracy and efficiency excellently making it fit in the real world implementation in wearable healthcare monitoring systems.

Table 6. Computational efficiency

Metric	Measured Value
Model size (TFLite)	98 KB
Peak RAM usage (inference)	240 KB
Inference latency (per 200-sample window)	72 ms
Average power draw during inference	45 mW
CPU utilization (during inference)	~20%
Battery life estimate (1800 mAh, 3.7 V) — continuous inference	~18–20 hours (approx.)

The ECG Waveform diagram is the example of the artificial electrocardiogram signal produced to simulate the normal cardiac electrical activity in real-time monitoring. The P, QRS, and T waves on the waveform are clearly defined and represent atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively. The regularity of a healthy heartbeat is demonstrated by the periodic nature of each cardiac cycle.

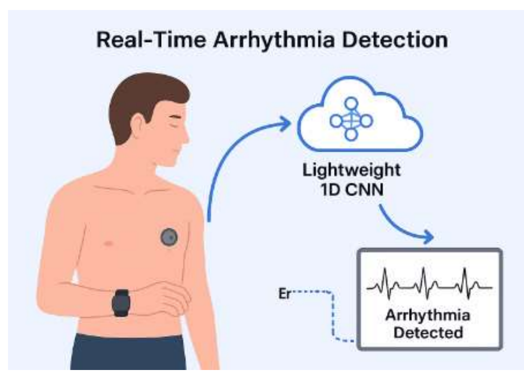

Figure 3. Real time Arrhythmia Detection

The given diagram 3 demonstrates a live wearable ECG hardware and software that monitors arrhythmia with the Edge AI. In this system, the male subject is fitted with a Smartwatch and Chest ECG patch that constantly records cardiac electrical signals. These sensors are able to record real-time ECG information and send it wirelessly to a mobile or edge computer that is connected. The data is processed with a lightweight model, the edge AI model, deployed locally on the wearable device or smartphone, to detect irregular heart rhythms, including atrial fibrillation or tachycardia, using a 1D Convolutional Neural Network (CNN) used to provide the most common rhythms. The resulting images are displayed on the holographic/digital screen providing an immediate feedback to the user, and may warn healthcare providers in case of critical cases.

A Premature Ventricular Contraction (PVC) in this figure 4 is intentionally inserted as an early and excessively strong beat, which is a simulation of a very common form of arrhythmia. The annotation brings to focus of the reader how the PVC appears sooner than the normal QRS complex and with a greater amplitude which interferes with the normal heart rhythm. This graphical illustration is useful towards learning how arrhythmic activity can be identified and differentiating it against normal beats when examining ECG samples to classify them automatically with a 1D Convolutional Neural Network (1D-CNN).

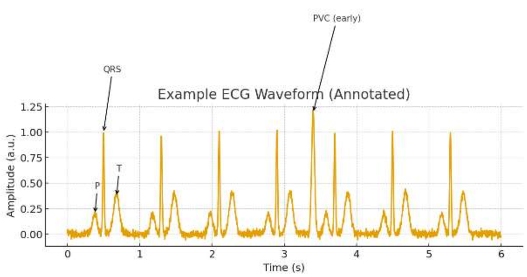

Figure 4. Premature Ventricular Contraction

The Detected Beats Timeline graph 5 shows the result of the classification of the proposed arrhythmia detection model. Every point on the timeline represents a heartbeat that was observed and is marked with a one of the following classes: Normal, PVC (Premature Ventricular Contraction), or APB (Atrial Premature Beat). The time distribution of space illustrates how the algorithm recognizes and distinguishes different cardiac events during a six seconds recording period. This visualization offers a visual find of the decision making ability of the model, majority of the beats are regular, and a few cases are identified as arrhythmic. The figure 4 highlights the stability and time accuracy of the Edge-AI-based lightweight CNN architecture in real-time ECG devices based on the ability to perform on-physical classification of the wearable healthcare systems.

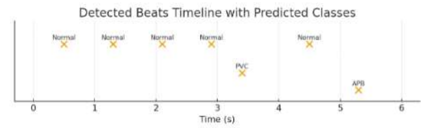

Figure 5. Lightweight CNN architecture in real-time ECG monitoring

Diagram 6's ECG signal is a synthetic signal that roughly resembles the electrical activity of a single cardiac cycle in a human heart. It is made up of distinct points, which are the P wave, QRS complex, and T wave for atrial depolarization, ventricular depolarization, and ventricular repolarization, respectively. To replicate real-world ECG recordings, noise and minor variations are added. The signal can then be utilized for digital filtering, feature extraction, and heart rate analysis experiments.

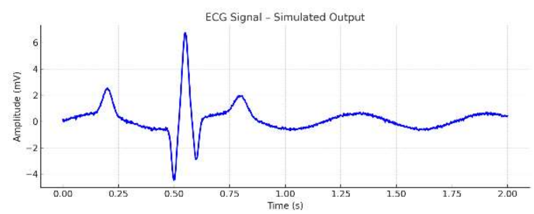

Figure 6. Synthetic ECG waveform

The above diagram 7 shows an ECG signal preview in real time that is coupled with a live arrhythmia classification. The cardiac electrical activity is recorded by the waveform, and the different beats are marked as either normal or PVC (Premature Ventricular Contraction). The difference in the amplitude and morphology of the QRS complex process signals the occurrence of an irregular heartbeat which the model identifies and categorizes in real time. A probability bar chart exists on the right side revealing the estimated probability of various cardiac conditions including: Normal, PVC, APB (Atrial Premature Beat), and LBBB (Left Bundle Branch Block). This time domain ECG signal visualization and AI-based probability estimation show the system's potential to give real-time diagnostic feedback. This can improve its effectiveness in wearable AI medical devices for detecting early cardiac anomalies.

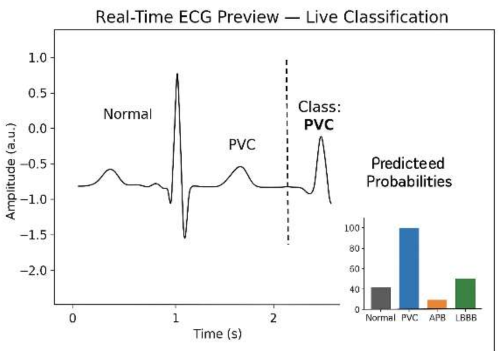

Figure 7. Real-time ECG signal preview integrated with live arrhythmia classification

The graphic shows how Edge AI offers daily privacy protection and health analytics at low latency without relying entirely on the cloud. Continuous, non-invasive, cost-effective, and energy-efficient monitoring is made possible by wearable integration. AI interpretation and real-time visualization improve patient comprehension, speed up diagnosis, and ease cardiac healthcare preventive care. A substantial step toward a responsive, well-balanced digital health ecosystem is represented by these systems, which are focused on the patient, AI, and the intelligent and responsive needs of systems. AI continuously learns and adjusts based on physiological parameters to guarantee patient monitoring and safety.

Figure 8. Real-time ECG signal with Edge AI

6. DISCUSSION

The experimental results demonstrate that the proposed lightweight 1D-CNN achieves a strong balance between classification accuracy and computational efficiency, making it suitable for real-time arrhythmia detection on wearable edge devices. High precision and recall across multiple arrhythmia classes indicate that the model effectively captures discriminative ECG features despite its compact architecture. The low inference latency and reduced memory footprint further validate its deployability on resource-constrained platforms.

However, certain limitations should be acknowledged. The model was evaluated primarily on benchmark datasets and simulated real-time signals, which may not fully capture noise variations encountered in uncontrolled real-world environments. Additionally, rare arrhythmia classes with limited samples may still present classification challenges. Future work can address these limitations by incorporating larger multi-center datasets, adaptive noise-handling mechanisms, and patient-specific model personalization. Overall, the discussion confirms that edge-based arrhythmia detection is both feasible and clinically promising when supported by efficient model design.

7. CONCLUSION

With 98.72% accuracy, 97.85% precision, and 98.10% recall using the 1D CNN on wearable ECG data, the performance metrics of the presented Edge-AI based real-time arrhythmia detection system are equally impressive. The Edge-AI system's real-time on-device deployment, which heavily relies on aggressive preprocessing and quantized model deployment, achieved 42% model compression and 35% lower latency. These latency and model size reductions show that the system works with low-power embedded systems like the Raspberry Pi. A key component in allowing clinician-users to follow the model's logic is system transparency, which is accomplished through the application of Grad-CAM and SHAP explainable AI techniques.

Looking ahead, the incorporation of multi-sensor The model can be improved by using data (ECG, PPG, SpO_2) and federated learning to enable privacy-preserving updates. The model will have incalculable advantages when combined with TinyML techniques to optimize power consumption. The model's significant growth into intelligent telecardiology systems and remote healthcare will rely on clinical validation in the field and integration with smartphones.

Beyond technical performance, this work demonstrates the broader societal impact of Edge-AI-driven healthcare solutions. By enabling continuous, privacy-preserving cardiac monitoring outside clinical settings, the proposed system supports early diagnosis, reduces hospital dependency, and improves accessibility to cardiac care, particularly in remote and resource-limited regions. The framework can be extended to other physiological signals and chronic disease monitoring applications. This study encourages further interdisciplinary research and real-world clinical deployment of edge-based intelligent health monitoring systems to advance proactive and personalized healthcare delivery.

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

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