



INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X

Impact Factor: 6.078

(Volume 12, Issue 5 - V12I5-1185)

Available online at: <https://www.ijariit.com>

Wearable ECG Monitoring with Embedded Deep Learning for Real-Time Arrhythmia Detection

Ms. Subha P S

subhaps.ec@marian.ac.in

Marian Engineering College

ABSTRACT

Cardiovascular diseases remain a leading cause of death worldwide, and arrhythmia, an irregularity in heart rhythm, demands timely detection. Conventional ECG monitoring is bulky, hospital-bound and computationally heavy, which limits continuous monitoring in everyday settings. This paper presents an IoT-based arrhythmia detection system that combines a low-cost wearable ECG front end with a lightweight deep learning model running directly on the sensor node. Biopotentials are acquired with ECG electrodes, conditioned by an AD8232 analog front end, digitised and processed by an ESP32 microcontroller, and classified by a one-dimensional convolutional neural network (DL-LAC) into five heartbeat classes: Normal (N), Supraventricular (S), Ventricular (V), Fusion (F) and Paced (P). Because the network learns features directly from raw single-lead ECG, no manual feature engineering is required. The model, trained on the MIT-BIH Arrhythmia Database, reaches approximately 96.2% overall accuracy, with on-device inference latency of about 80 ms per window and a memory footprint below 500 KB. Duty cycling reduces power consumption by about 40%, extending battery life from four to over six hours. The results indicate that on-device deep learning is a practical route to continuous, low-latency and privacy-preserving cardiac monitoring.

Keywords: Arrhythmia Detection, ECG, Internet of Things, Edge Computing, Convolutional Neural Network, ESP32, AD8232

1. INTRODUCTION

Cardiovascular diseases (CVDs) account for nearly 31% of annual deaths globally [1]. Among them, arrhythmia requires prompt diagnosis, which traditionally relies on continuous electrocardiogram (ECG) monitoring using large, power-hungry and costly equipment.

The Internet of Things (IoT) is shifting healthcare from reactive treatment to proactive, preventive care. Wearable sensors can continuously capture ECG and other vital signs and transmit them wirelessly to clinicians. However, most ECG analysis pipelines require extensive noise removal and manual

feature extraction, which makes them unsuitable for ultra-edge IoT sensors with limited energy and computational capacity.

This work integrates a lightweight one-dimensional convolutional neural network (1D-CNN) with a low-power IoT sensing platform so that arrhythmia classification runs at the sensor node. This removes the dependence on cloud processing and reduces latency, cost and bandwidth. The main contributions are:

- 1) an end-to-end wearable design using ECG electrodes, an AD8232 analog front end and an ESP32 microcontroller;
- 2) on-device classification of heartbeats into five classes using a lightweight 1D-CNN that needs no manual feature extraction; and
- 3) hardware and software optimisation (duty cycling, pruning, quantisation and burst transmission) that supports continuous ambulatory use.

2. RELATED WORK

Deep learning has been widely applied to ECG arrhythmia classification. Yao et al. proposed an attention-based time-incremental

CNN for multi-class detection from 12-lead, varied-length ECG[2]. For wearable deployment, Saadatnejad et al. presented an LSTM-based classifier designed for continuous monitoring on personal devices [3]. Earlier work, such as the ventricular fibrillation detector of Greenwald [4], relied on hand-designed detection algorithms.

The closest work to ours is the DL-LAC method of Sakib et al.[5], which classifies heartbeats from single-lead ECG using a 1D-CNN without noise filtering or manual feature extraction, and which was reported to outperform K-nearest neighbour (KNN) and random forest (RF) baselines. Our system adopts this model family and focuses on its integration into a complete, battery-powered ESP32 wearable with on-device alerting.

3. SYSTEM ARCHITECTURE

3.1 Overview

3.2 Deep Learning Model

The DL-LAC model is a 1D-CNN that operates on raw

Fig. 1 shows the system. ECG signals from wearable electrodes are amplified and filtered by the AD8232, digitised by the ESP32, pre-processed and segmented, classified by the 1D-CNN, and passed to decision logic that raises alerts. Results are sent over Wi-Fi or Bluetooth to a mobile or web dashboard, and optionally to the cloud for long-term storage and trend analysis.

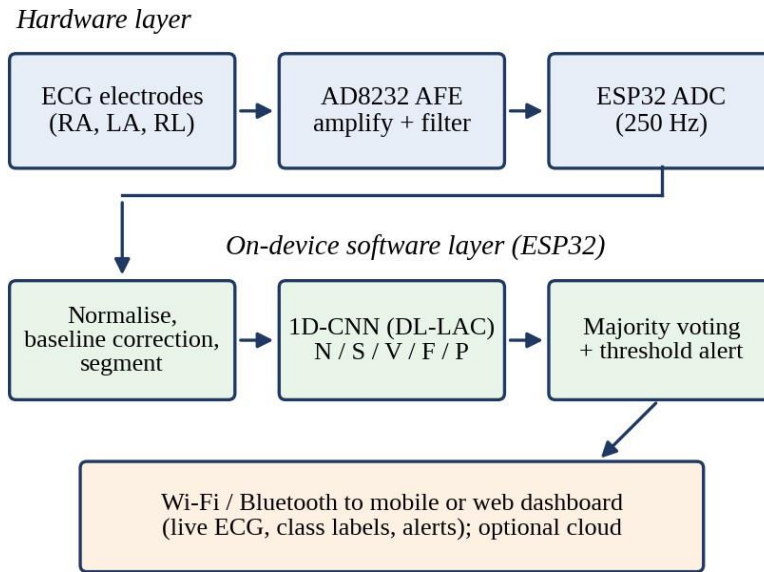
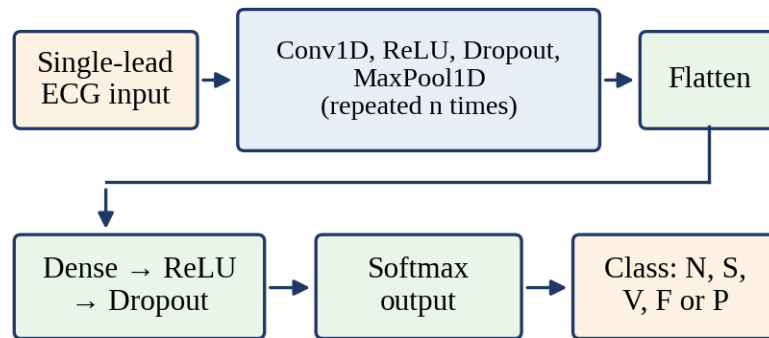


Figure -1: Block diagram of the proposed IoT arrhythmia detection system.

3.3 Hardware

ECG electrodes: Three electrodes (right arm, left arm and right leg/reference) are placed on the chest or wrists in a Lead-I single-lead ECG treated as a time series, normalised so that it generalises across patients. Fig. 2 shows the structure, which has an automated feature-extraction stage followed by a classification stage.



Automated feature extraction (top) | classification (bottom)

Figure -2: Structure of the 1D-CNN classifier.

Convolution layers slide learned filters across the waveform to detect morphological patterns such as the P-wave, QRS complex and T-wave[8]. A ReLU activation adds non-linearity. *Dropout* deactivates random neurons during training to prevent overfitting.

Max-pooling keeps the strongest responses and reduces dimensionality and computation, which is important on edge hardware. The resulting feature maps are flattened and passed to *dense layers* that learn the relationship between features and rhythm class.

Finally, a softmax layer gives the class probabilities:

configuration. The signals are in the millivolt range (about 0.5–

$$P(y=k|x) = e^{-\sum_{j=1}^n z_j} \quad (1)$$

2 mV), so good skin contact is important to limit noise and motion artifacts.

AD8232 analog front end: The AD8232 is a compact front end for biopotential measurement. It amplifies the electrode signal, applies built-in high-pass and low-pass filtering to isolate the QRS complex, suppresses baseline drift and motion artifacts, and uses a right-leg drive circuit to improve common-mode rejection. Its clean analog output feeds the ESP32 ADC.

ESP32 microcontroller: The ESP32 digitises the signal, runs the pre-processing and CNN inference, and provides Wi-Fi and Bluetooth connectivity. Its low power consumption and processing capability make it suitable for wearable healthcare devices.

Power: A rechargeable Li-ion/Li-Po cell with charging, over-charge protection and voltage regulation supplies the node, making it suitable for home-based and ambulatory monitoring.

3.4 Software Pipeline

On the ESP32, the raw samples are normalised, baseline-corrected and low-pass filtered, then split into fixed windows or beat-wise segments. Each segment is classified independently. A majority-voting stage over consecutive predictions, together with confidence thresholds, reduces false positives before an alert is issued to the dashboard.

where z is the vector of dense-layer outputs and the five classes are N, S, V, F and P. The class with the highest probability is selected as the label for the segment.

4. IMPLEMENTATION AND OPTIMISATION

4.1 Data and Training

The model was trained and evaluated on the MIT-BIH Arrhythmia Database [6], obtained from PhysioNet [7]. Preprocessing comprised normalisation, noise filtering and segmentation into time-series samples, using NumPy, Pandas and SciPy. Accuracy, recall and F1-score were used as evaluation metrics. KNN and RF classifiers were implemented as traditional baselines.

4.2 Edge Deployment

The trained network was converted to a lightweight format and deployed on the ESP32 for local inference. Model pruning, quantisation and low-power configuration were applied to speed up processing on the microcontroller.

4.3 Power and Communication Optimisation

The ESP32 low-power modes and duty cycling allow the device to alternate between active monitoring and standby, reducing power consumption by about 40% and extending battery life from four to over six hours per charge. The ECG sampling rate was set to 250 Hz, which gives sufficient

resolution for heartbeat analysis without unnecessary computation. Data are compressed, buffered and sent in short bursts rather than a continuous stream, which lowers communication energy and improves responsiveness.

5. RESULTS AND DISCUSSION

Table I summarises the reported results. The CNN converged quickly; training accuracy rose steadily while validation loss fell, and dropout kept performance stable on unseen samples. On the test set the model reached approximately 96.2% overall accuracy, and its per-class precision, recall and F1-score were consistent despite the class imbalance typical of ECG data.

Table -1: Summary of reported system performance

Parameter	Reported value
Overall test accuracy (MIT-BIH)	≈96.2 %
Inference latency(ESP32)	≈80 ms/window
Model memory footprint	<500 KB
ECG sampling rate	250 Hz
Power reduction (duty cycling)	≈40 %
Battery life per charge	4 h to >6 h

Compared with KNN and RF, the CNN performed better in accuracy, processing time and memory efficiency. Traditional methods need manual feature extraction, whereas the CNN learns directly from raw ECG, which reduces pre-processing effort and computational complexity. On the ESP32, inference took about 80 ms per window with memory use below 500 KB, and alerts were generated immediately when abnormal rhythms were detected. This shows that real-time classification is feasible on low-power hardware without cloud computation.

Running inference at the edge also reduces transmission latency, bandwidth use and privacy risk, since raw ECG need not leave the device. The 1D-CNN can capture P-wave, QRS and T-wave morphology end to end, avoiding handcrafted features such as wavelet transforms or R-R interval analysis, and this supports adaptability across diverse patients.

6. CONCLUSION AND FUTURE WORK

This paper presented a wearable IoT system that detects arrhythmia on the sensor node using an AD8232 front end, an ESP32 microcontroller and a lightweight 1D-CNN. The system classifies five heartbeat types with about 96.2% accuracy and about 80 ms latency, and its power management supports several hours of continuous use. The results indicate that edge AI can make continuous, low-cost and portable cardiac monitoring practical.

Future work includes reporting per-class metrics and confusion matrices, cross-dataset and real-patient validation, a quantitative

comparison with the KNN and RF baselines, and a clinical evaluation of alert reliability.

REFERENCES

- [1] World Health Organization, “Cardiovascular diseases (CVDs),” Fact sheet. [Online]. Available: [https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-\(cvds\)](https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds))
- [2] Q. Yao, R. Wang, X. Fan, J. Liu, and Y. Li, “Multi-class arrhythmia detection from 12-lead varied-length ECG using attention-based time-incremental convolutional neural network,” *Inf. Fusion*, vol. 53, pp. 174–182, Jan. 2020, doi: 10.1016/j.inffus.2019.06.024.
- [3] S. Saadatnejad, M. Oveisi, and M. Hashemi, “LSTM-based ECG classification for continuous monitoring on personal wearable devices,” *IEEE J. Biomed. Health Informat.*, vol. 24, no. 2, pp. 515–523, Feb. 2020, doi: 10.1109/JBHI.2019.2911367.
- [4] S. D. Greenwald, “The development and analysis of a ventricular fibrillation detector,” Ph.D. dissertation, Massachusetts Inst. Technol., Cambridge, MA, USA, 1986.
- [5] S. Sakib, M.M. Fouda, Z.M. Fadlullah, N. Nasser, and W. Alasmay, “A proof-of-concept of ultra-edge smart IoT sensor: A continuous and lightweight arrhythmia monitoring approach,” *IEEE Access*, vol. 9, pp. 26093–26106, 2021, doi: 10.1109/ACCESS.2021.3056509.
- [6] G. B. Moody and R. G. Mark, “The impact of the MIT-BIH arrhythmia database,” *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 3, pp. 45–50, May/Jun. 2001.
- [7] A. L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000.
- [8] Z.J. Wang, R. Turko, O. Shaikh, H. Park, N. Das, F. Hohman, M. Kahng, and D. H. Chau, “CNN Explainer: Learning convolutional neural networks with interactive visualization,” Aug. 2020, arXiv:2004.15004. [Online]. Available: <http://arxiv.org/abs/2004.15004>