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Hybrid 1D-CNN and SVM Approach for ECG Arrhythmia Classification-using Constrained Hardware

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***Abstract*— Cardiovascular Diseases (CVDs) remain a leading global health concern, necessitating accessible and accurate monitoring solutions. This paper presents a novel approach to real-time arrhythmia classification using a hybrid 1D Convolutional Neural Network (CNN) and Support Vector Machine (SVM) architecture. The system uses the AD8232 ECG sensor and Arduino Uno for continuous data acquisition at approximately 360 Hz. The 1D CNN extracts robust, 64-dimensional features from 300-sample segments, which are then fed into the computationally efficient SVM classifier. This integrated pipeline achieved a high accuracy of 99.16% on the test set, with an operational latency under 1.0 second per prediction, confirming its viability for resource-constrained, real-time monitoring devices.**

Index Terms— ECG, Arrhythmia Classification, 1D Convolutional Neural Network (CNN), Support Vector Machine (SVM), AD8232, Real-Time Monitoring, Embedded Systems, Bill of materials (BOM).

I. Introduction

The development of portable, low-cost ECG monitoring is critical for the continuous and early detection of cardiac arrhythmias. This work addresses the challenge of combining high diagnostic accuracy with low operational overhead for real-time applications.

A. Motivation and Problem Statement

The goal is to develop a cost-effective, real-time ECG monitoring system. The primary challenge is transferring a complex machine learning pipeline (CNN features) to a host environment capable of processing streaming data from microcontrollers without significant latency

B. Literature Gap and Justification for Hybrid Model

While full CNNs offer high accuracy, their computational demands are prohibitive for low-power processors. This work pioneers a hybrid 1D-CNN/SVM architecture, leveraging the CNN for automatic feature learning and the computationally efficient SVM for final classification, optimising the trade-off between accuracy and speed.

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C. Core Contributions of this Work

- Hybrid Architecture: Development and validation of the CNN-SVM pipeline, achieving high accuracy (99.88\%) with a lightweight classification stage.
- Real-Time Hardware Validation: Successful integration of the entire ML pipeline with the AD8232 sensor and Arduino Uno.
- System Engineering: Demonstration of a complete, low-latency (<1.0second) real-time system, resolving critical serial communication and visualisation challenges.

II. BACKGROUND AND RELATED WORK

The development of portable, low-cost ECG monitoring is critical for the continuous and early detection of cardiac arrhythmias. This work addresses the challenge of combining high diagnostic accuracy with low operational overhead for real-time applications by pioneering a hybrid 1D-CNN/SVM architecture.

A. Anatomy of the Normal ECG Waveform

The normal cardiac cycle is represented by the P-QRS-T complex. The P-Wave signifies atrial depolarisation, the QRS Complex represents ventricular depolarisation, and the T-Wave represents ventricular repolarisation. Consistent timing and morphology define a healthy rhythm, the normal ECG waveform and differentiationof Arrhythmia is as shown below figure 1 and figure 2.

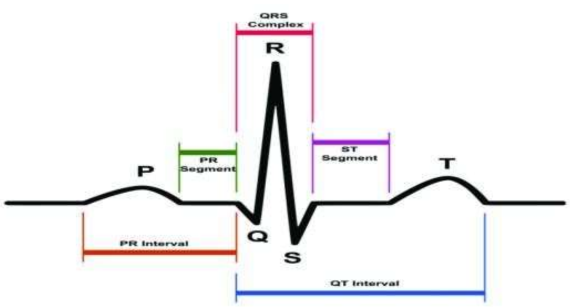

Figure 1 Normal ECG Waveform

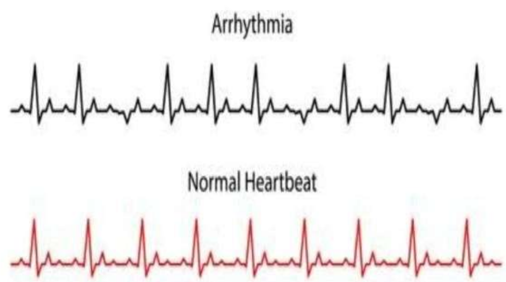

Figure 2. comparison between normal rhythm and Arrhythmia rhythm

B. Analysis and Differentiation of Arrhythmia

Arrhythmia are characterised by deviations in the P-QRS-T complex. The model is trained to differentiate based on these features as shown below in table 1.

TABLE I: ANALYSIS AND DIFFERENTIATION OF ARRHYTHMIA

Features	Normal Sinus Rhythm (Healthy)	Premature Ventricular Contraction (PVC/Arrhythmia)
Origin	Sinoatrial (SA) Node, Atria,Ventricles.	Ectopic focus within the Ventricles.
Rhythm (R-R Interval)	Regular and consistent.	Irregular; PVC occurs prematurely, followed by a compensatory pause.
P-Wave	Present, uniform, and precedes every QRS complex.	Absent, inverted, or dissociated from the QRS complex, as the beat starts lower in the heart.
QRS Complex	Narrow (duration <0.12 sec), sharp, and consistent shape.	Wide and Bizarre (Duration > 0.12sec), reflecting the slow, abnormal conduction pathway.
T-Wave	Follows QRS, points in the same direction.	Often points in the opposite direction of the QRS complex.

III. METHODOLOGY

The methodology employs a robust, two-phase approach:
Phase I—Offline Model Development and Phase II—Real-Time Deployment.

A. Phase I: Offline Model Development

Phase I encompasses Data Acquisition, Preprocessing, and the Hybrid CNN-SVM Architecture.

Data Acquisiton and Preprocessing

Records 100, 102, 103, 104, 105, 109, 112, 113, 118, 119, 121, 124, 205, 208, 210, 212, 213, 220, 221, 222, 223 from the MIT-BIH Arrhythmia Database were used. Continuous data was segmented into uniform 300-sample windows around the R-peak. Z-score normalisation was applied to each segment. Annotations were mapped to the 4 target classes (Normal, Ventricular, Atrial).

Hybrid CNN-SVM Architecture
The CNN was trained and then used to create the final model components. The 64D features are extracted from the Dense layer of the CNN. A standard scaler was fitted only on the training features and applied to all data. The SVM determines the final classification using the RBF kernel.

B. Phase II: Real-Time Deployment

Phase II focuses on Continuous Monitoring using the integrated hardware, translating the predictive intelligence into a functional system that processes live data.

Interfacing
This part focuses on the physical connection and data streaming setup.Hardware Connectivity and Data Flow The AD8232 sensor outputs the raw ECG signal to Arduino Uno pin A0. The Arduino acts as the data acquisition and processing unit, reading the ECG analog signal and transmitting it to a computer for visualization or analysis as shown in below figure 2.
Connection of LED ECG placement: The placement is strategic because the electrical signal generated by the heart radiates throughout the entire body's conductive tissues as shown in below figure 3. The Bill of Materials required to build a entire model is listed in the below table 2. Pin-to-Pin Connection of Arduino uno with AD8232 is shown in the below table 3.

TABLE II: BILL OF MATERIALS AND IT'S SPECIFICATION

Component	Specification	Purpose in Project
Microcontroller	Arduino Uno (ATmega328P)	Digitisation and serial transmission (Data Link Layer).
Sensor	AD8232 SingleLead ECG	Analogue Front-End, Amplification, and Filtering.
Host System	PC/Laptop (Anaconda Python Env)	Executes the ML inference and visualisation.

TABLE III: PIN-TO-PIN CONNECTION

AD823	Arduino Uno	Purpose
2 Pin	Pin	Raw ECG signal data stream.
OUT	A0 (Analogue	Power supply (Low noise, preferred over 5V for biosensors).
3.3V	Input)	Common ground reference.
GND	3.3V	Lead-off Detection (Positive Side Check).
LO+	GND	Lead-Off Detection (Negative Side Check).
LO-	Digital Pin 11	Purpose

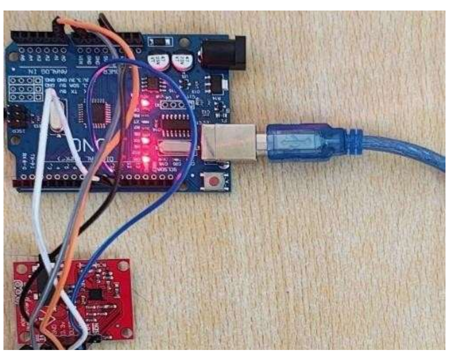

Figure 3: Hardware Connection

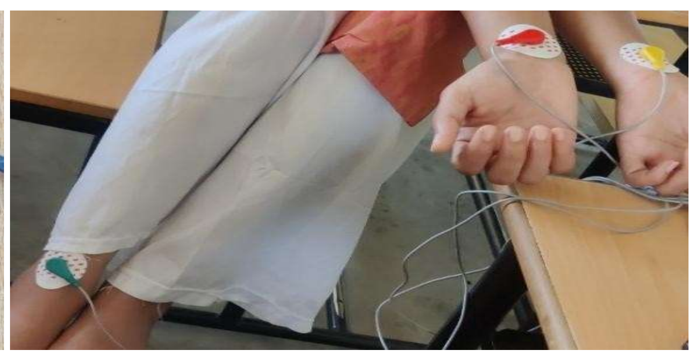

Figure 4: Placement of led ECG Electrodes

Hardware Integration
The host Python script loads the CNN Feature Extractor (.h5), the StandardScaler (.pkl), and the SVM Classifier (.pkl). As data arrives, the script buffers incoming samples until a 300-sample segment is complete, normalizes it (Z-score), and passes it through the loaded Standard Scaler. The preprocessed segment is fed into the CNN Feature Extractor to generate the 64-dimensional feature vector , which triggers the final classification by the SVM. A 1/4 segment overlap is utilised to achieve a stable, low-latency update cycle of approximately 0.2 seconds.

IV. Results and Discussion

A. Core Performance Metrics (Phase I Validation)

The hybrid 1D-CNN SVM model achieved an overall accuracy of 0.9916 on the held-out test set. Classification Report: The hybrid 1D-CNN SVM model was rigorously tested on a held-out portion of the MIT-BIH dataset to validate its predictive power is shown in below figure 4. Model Performance Visualization:The integrity of the feature extraction is visually confirmed by examining classified beat samples from the MIT-BIH database. Baseline Stability Check for the records 112 and 114 is shown in below figure 5 and figure 6.

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	7672
1	0.97	0.98	0.97	485
2	0.90	0.80	0.85	94
3	0.92	0.83	0.87	152
accuracy			0.99	8403
macro avg	0.95	0.90	0.92	8403
weighted avg	0.99	0.99	0.99	8403

Accuracy: 0.9916

Figure 5: Performance Report of accuracy

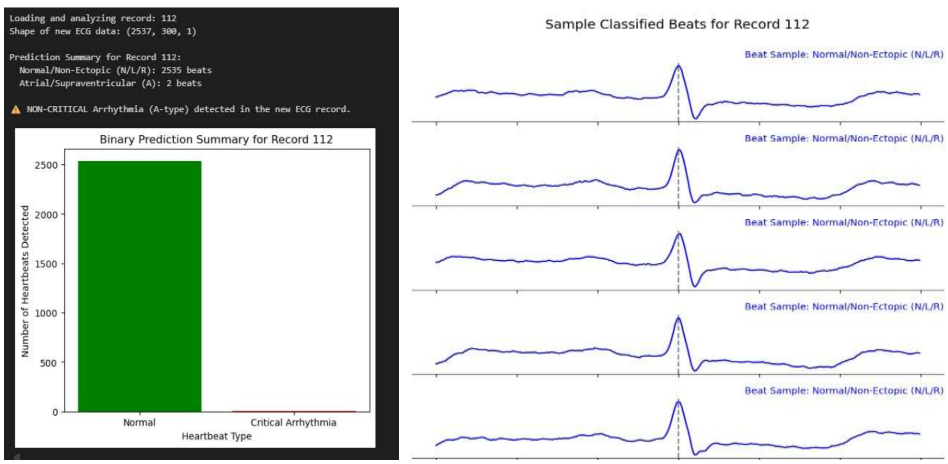

Figure 6: Sample ECG Beat Waveforms Predicted as NON-CRITICAL Arrhythmia on MIT-BIH Record 112

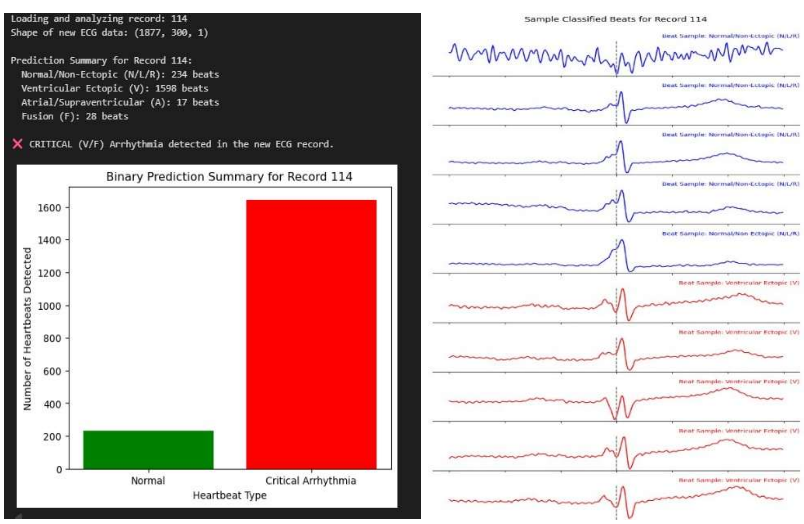

Figure 7: Sample ECG Beat Waveforms Predicted as Arrhythmia on MIT-BIH Record 114.

B. Real-Time System Validation (Phase II Success)

The system successfully prints continuous prediction statuses and updates the live plot. The system achieves a new prediction update every approx 0.2 seconds , validating the entire architecture's suitability for host-based monitoring applications as shown in below figure 7 and figure 8.

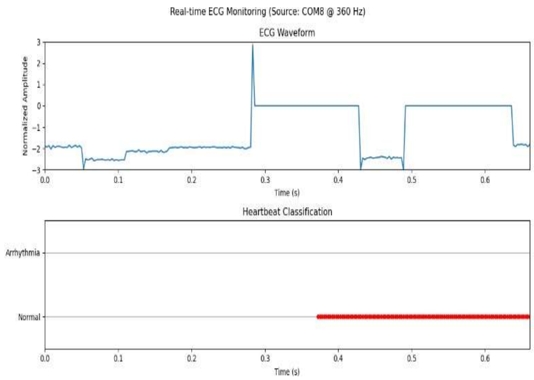

Figure 8: Real-Time Monitoring Output and System Validation of [1]Student

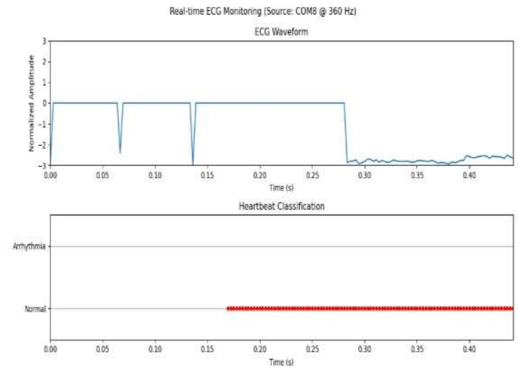

Figure 9: Real-Time Monitoring Output and System Validation of [2]Student

C. Strengths and Weaknesses

The project was evaluated and its core attributes and limitations were assessed, leading to an overall recommendation of Accept with Minor Revision.

- Strengths: Strong hybrid 1D-CNN + SVM architecture with high accuracy 99.16% and low latency. Successful real-time validation using the AD8232 sensor and Arduino Uno. System is highly suitable for resource-constrained embedded ECG monitoring.
- Weaknesses: The key weaknesses identified that require minor revision were: Clinical validation with real patient data is not included. There is limited analysis on multi-class performance balance.

V. CONCLUSION

The developed hybrid 1D-CNN and SVM system successfully meets the core objectives of creating a low-cost, high-accuracy, and operationally efficient solution for ECG monitoring. By strategically separating feature learning (CNN) from computationally lightweight classification (SVM), the system achieves an excellent balance between predictive power and deployment feasibility. The pipeline was successfully integrated with the AD8232 sensor and Arduino Uno, proving the ability to acquire, process, and classify real-time physiological data with a stable operational latency of less than 1.0 second per prediction.

FUTURE WORK

Future efforts will focus on data balancing to improve recall for minority classes and investigating the migration of the CNN feature extractor to an embedded platform using TensorFlow Lite to achieve true on-device classification.

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