PROJECT ABSTRACT

ECG Arrhythmia Detection using 1D CNN

A 1D convolutional neural network classifying ECG beats into the five AAMI arrhythmia classes on the MIT-BIH database, with Pan–Tompkins QRS detection, a live monitor demo, training notebook and viva kit. Delivered built-to-order with report, PPT and Q&A.

01. Title

ECG Arrhythmia Detection using 1D CNN

02. Introduction / Background

Automated arrhythmia detection is one of the most cited applications of deep learning in biomedical signal processing: Holter monitors record millions of beats daily that cardiologists cannot review by hand. The MIT-BIH Arrhythmia Database is the standard benchmark — 48 half-hour ambulatory recordings with over 100,000 expert-annotated beats. This project builds the full literature pipeline: raw ECG is cleaned and segmented around R-peaks detected by the classical Pan–Tompkins algorithm, each beat window feeds a 1D CNN, and the network outputs one of the five AAMI beat classes.

03. Problem Statement

Student projects on ECG classification typically shuffle beats into train/test splits, leaking patient-specific morphology into the test set and inflating accuracy, and they rarely implement the QRS-detection front-end that makes the system real. This project addresses both: it uses the inter-patient DS1/DS2 protocol so metrics reflect new patients, implements Pan–Tompkins QRS detection faithfully, and explains every stage — preprocessing, segmentation, architecture and evaluation — in a live demo and a documented notebook.

04. Objectives

- Implement Pan–Tompkins QRS detection and beat segmentation (216-sample windows at 360 Hz).
- Design and train a 1D CNN (Conv1D 32/64, pooling, dense 128, 5-way softmax) on MIT-BIH.
- Evaluate with the inter-patient DS1/DS2 protocol: accuracy, per-class precision/recall, VEB/SVEB sensitivity, confusion matrix.
- Build a live ECG monitor demo streaming real MIT-BIH signal through the actual detection code.
- Deliver the complete student kit: notebook, trained model, demo, report, PPT and viva Q&A.

05. Proposed Methodology

The pipeline has four stages. (1) Signal: MIT-BIH records are loaded at 360 Hz, baseline wander is removed and the Pan–Tompkins detector (bandpass, derivative, squaring, 150 ms moving-window integration) locates R-peaks; 216-sample windows are cut around each peak and labeled into the five AAMI classes. (2) Modelling: the 1D CNN is trained with class weighting against the heavy normal-beat imbalance, split by patient (DS1 train, DS2 test). (3) Evaluation: the held-out patient set is scored once for accuracy, per-class metrics, VEB/SVEB sensitivities and the confusion matrix. (4) Demo: the same preprocessing and detection code runs live on streaming MIT-BIH signal with beat-by-beat analysis.

06. System Architecture / Working

The training notebook produces a serialized 1D CNN plus the preprocessing parameters. The single-file web demo loads a real MIT-BIH excerpt, runs the Pan–Tompkins detector in JavaScript, marks R-peaks live, computes heart rate and beat measurements (RR interval, QRS width estimate), and shows a beat table, an annotated rhythm strip and an RR-interval Poincaré plot. A model-report view documents the CNN architecture, the AAMI class definitions and the design-target metrics.

07. Hardware / Software Requirements

- Python 3, TensorFlow/Keras, NumPy, SciPy, Matplotlib, scikit-learn
- Jupyter Notebook (training & evaluation)
- MIT-BIH Arrhythmia Database via PhysioNet
- HTML5 canvas + JavaScript (live ECG demo)
- Any modern laptop; no GPU required for inference

08. Expected Outcomes

- A trained 1D CNN with design-target accuracy ≥98% on the inter-patient test split.
- Per-class metrics, VEB sensitivity ≥96% and SVEB sensitivity ≥90% (design targets).
- A live ECG monitor demo with beat detection and rhythm analysis.
- A complete report, PPT and viva Q&A on signal processing and 1D CNNs.

09. Applications

- Teaching biomedical signal processing and QRS detection.
- Demonstrating 1D CNNs for time-series classification.
- Academic study of class imbalance and inter-patient evaluation.
- Prototype front-end for Holter-analysis research tools.

10. Future Scope

- Multi-lead ECG fusion for richer morphology.
- Real-time deployment on wearable hardware.
- Semi-supervised learning to exploit unlabelled recordings.
- Explainability overlays showing which waveform segments drive each decision.