Low Complexity Algorithms for Arrhythmia Detection from ECG Signals

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17.9 million people died from CVDs in 2019

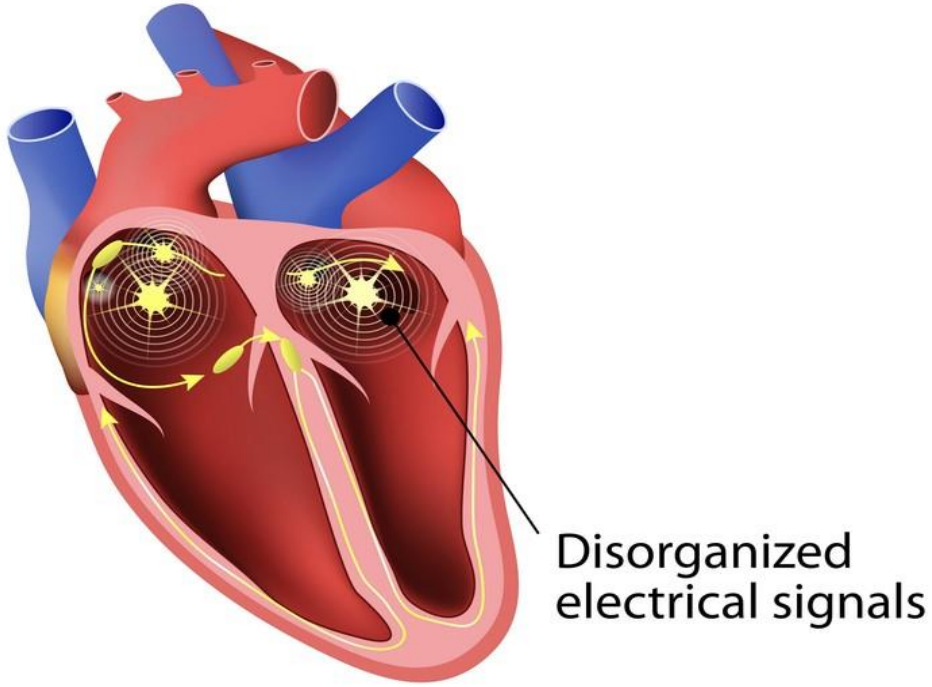
32% of all global deaths

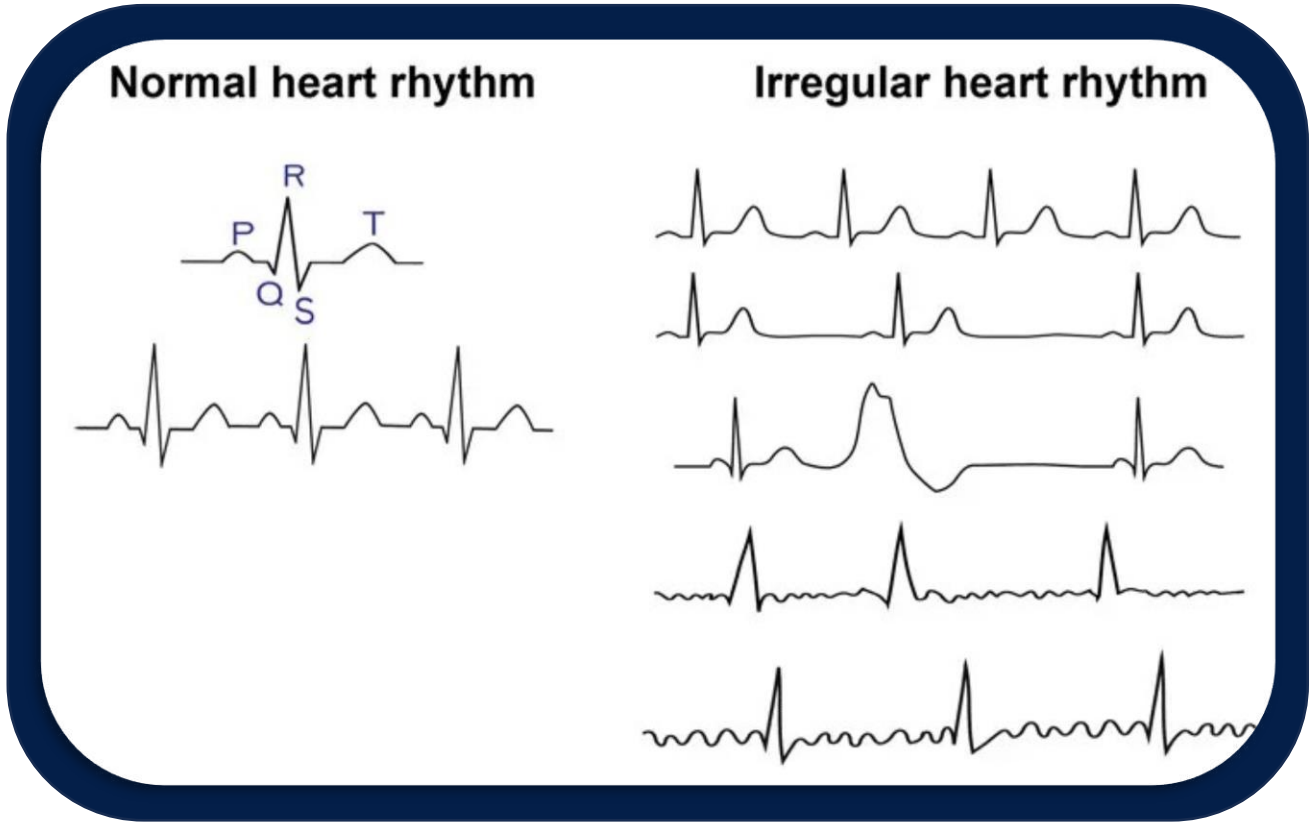
85% were due to heart attack and stroke

Increased to 20.5 million in 2021

Arrhythmia

An arrhythmia is an abnormal heart rhythm





Arrhythmia Detection

Evolved from **stationary** ECG monitoring systems to **wearable** devices

Current methods are not addressing the null power consumption environment

There are no off-the-shelf packages that can be deployed on microcontrollers

Low complexity Real-time Arrhythmia Detection Software

Pre-packaged arrhythmia detection software

Compatible with resource-limited microcontrollers (<2kB SRAM, 1-8 MHz clock frequency)

Low-complexity algorithm to detect different arrhythmia conditions from ECG signals

Low complexity Real-time Arrhythmia Detection Software

R-peak Detection

Beat Classification

ECG Compression

Low complexity Real-time Arrhythmia Detection Software

R-peak Detection

Beat Classification

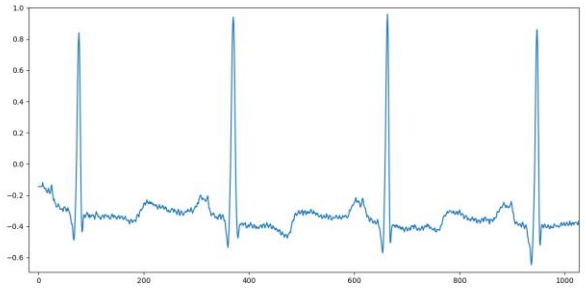
ECG Compression

Progress: R-peak Detection

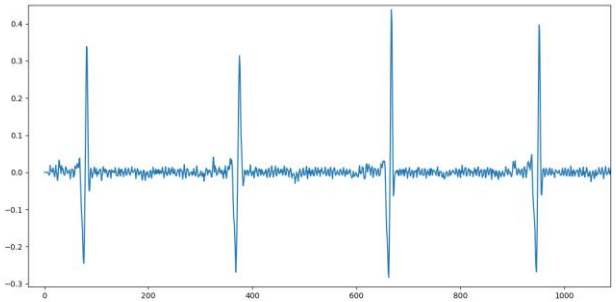
Rule Based R-peak Detection

Leaky Boundary Based R-peak Detection

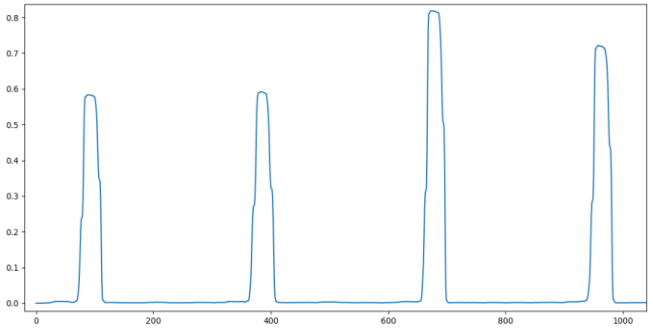
Progress: Rule Based R-peak Detection



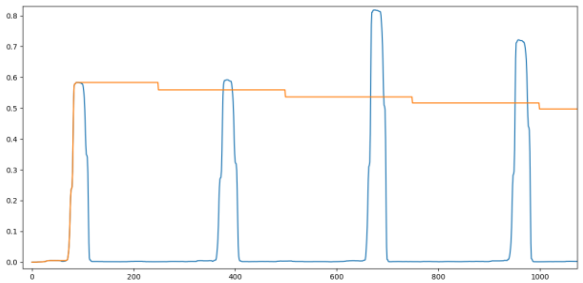
ECG Signal



High-pass filter
(Moving average)



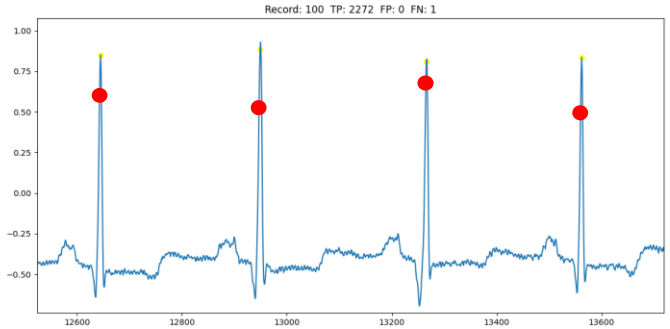
Squaring and moving window summation



Thresholding

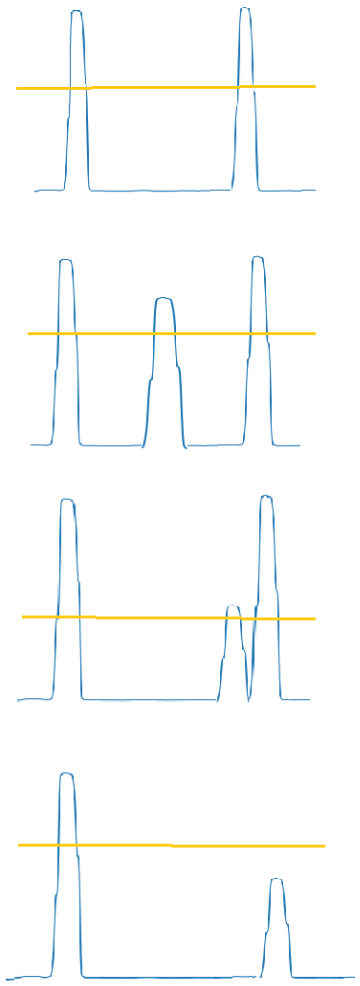
Rule base

- Height
- Heart-rate



Detected R-Peaks

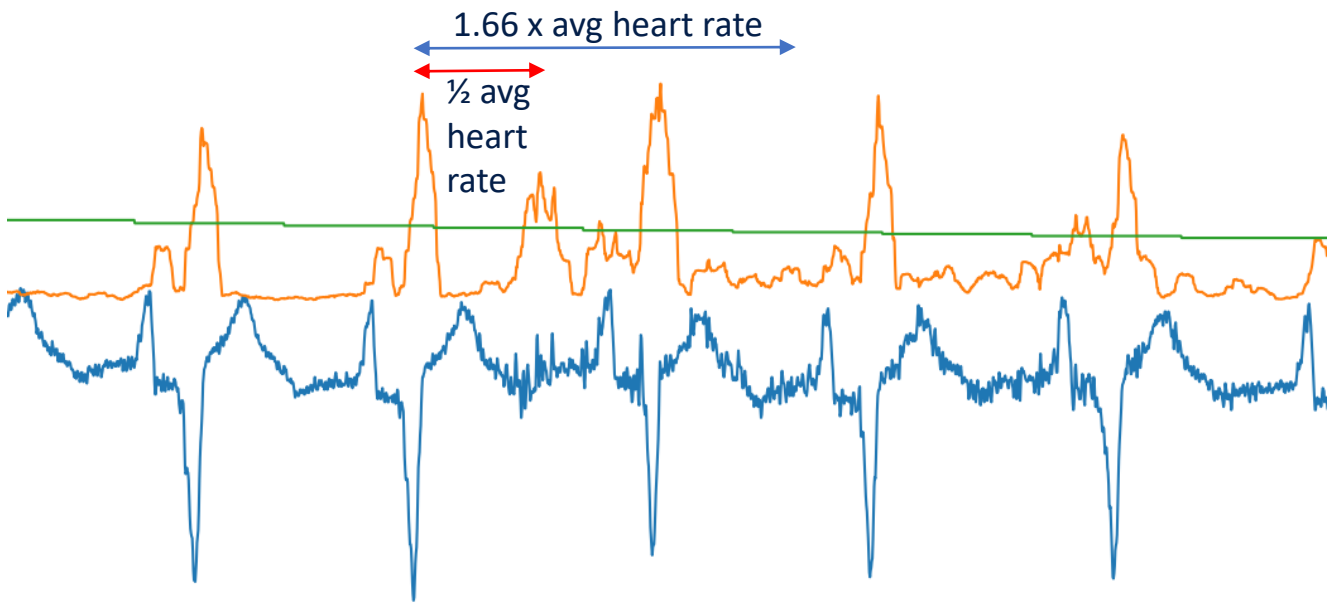
Progress: Rule Base



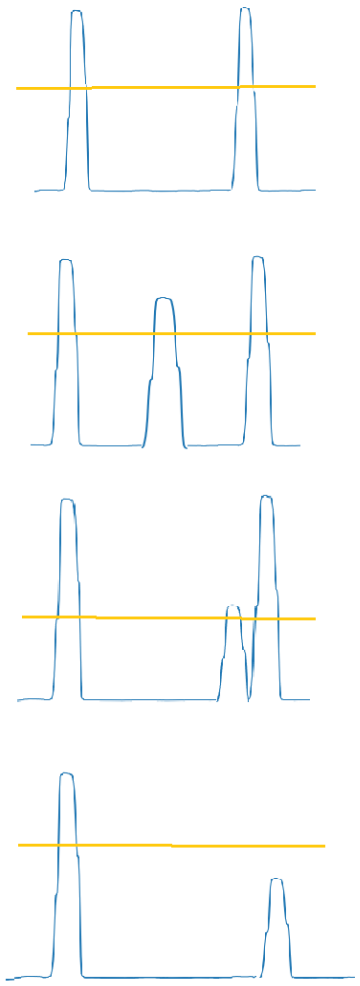
Mark as R-peak if:

1. $\text{distance} > \frac{\text{heart rate}}{2}$ and filter peak height $> 0.75 \times$ prev filter peak height
2. $\text{distance} < \frac{\text{heart rate}}{2}$ and ecg peak height $> 0.75 \times$ prev ecg peak height
3. $\text{distance} < \frac{\text{heart rate}}{4}$ then get maximum height peak as $\text{R} - \text{peak}$

4. If peak not detected until 1.66 $*$heart rate, then get the maximum heigh peak between $[0.25 * \text{heart rate}, 1.25 * \text{heart rate}]$



Progress: Rule Base



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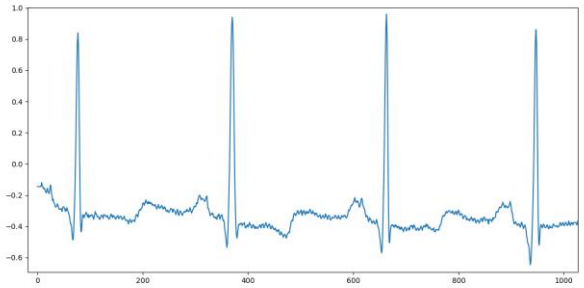
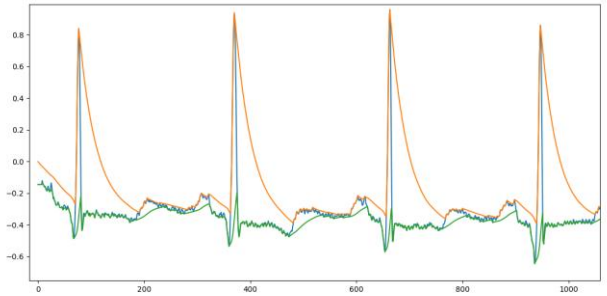
	Sensitivity	Accuracy	Precision
Before Rule Base	98.985	96.476	97.216
After Rule Base	99.244	98.225	98.940

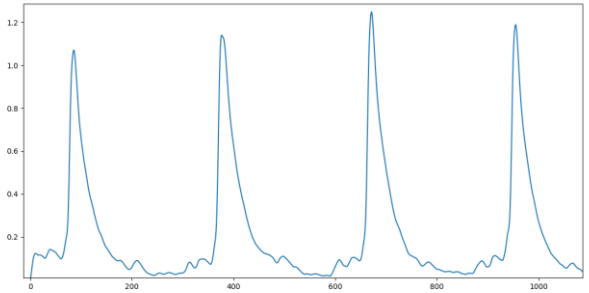
Progress: Leaky Boundary Based R-peak Detection



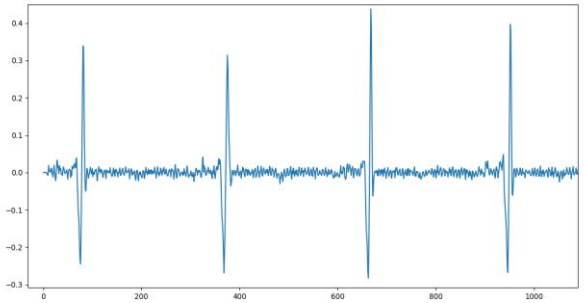
ECG Signal



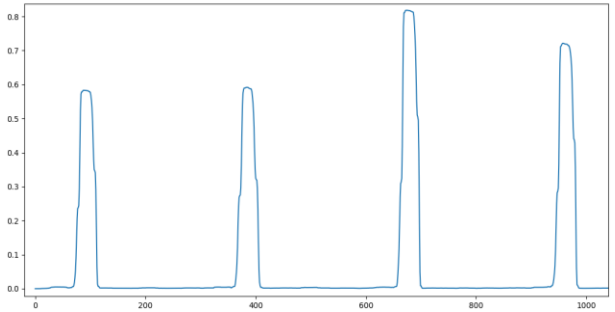
Boundary of the ECG



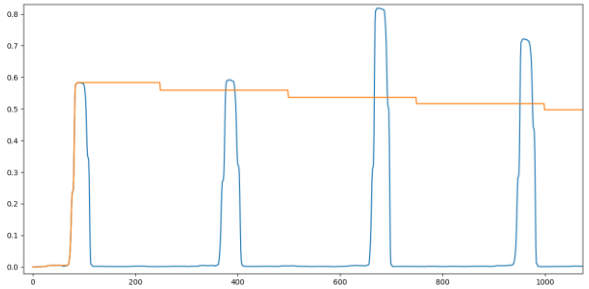
Low-pass filter to the boundary difference



High pass filter
(Moving average)



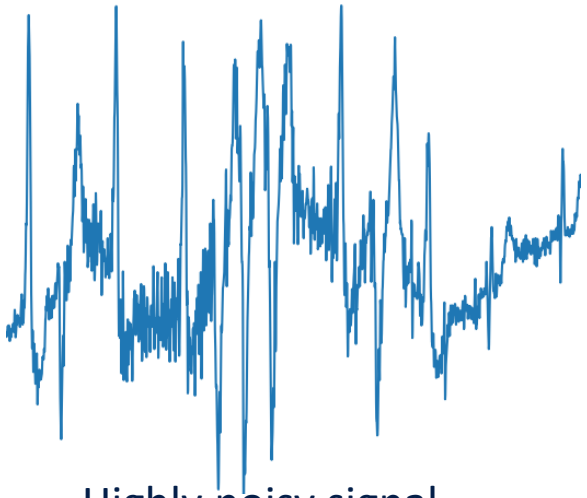
Squaring and moving window summation



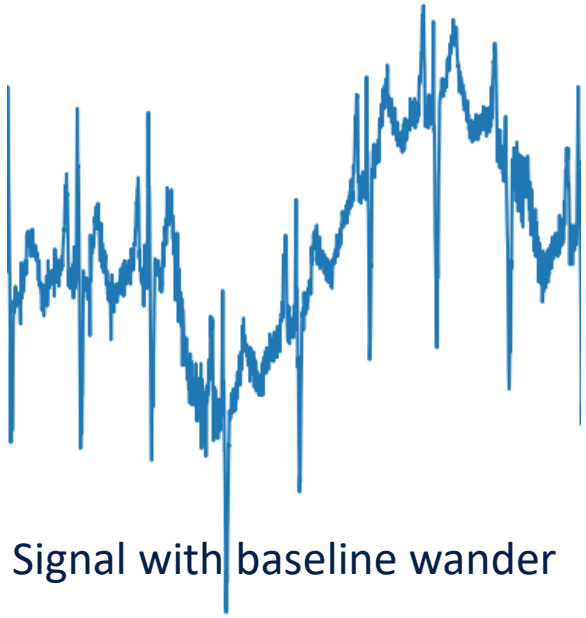
Thresholding

Progress: R-peak Detection Result

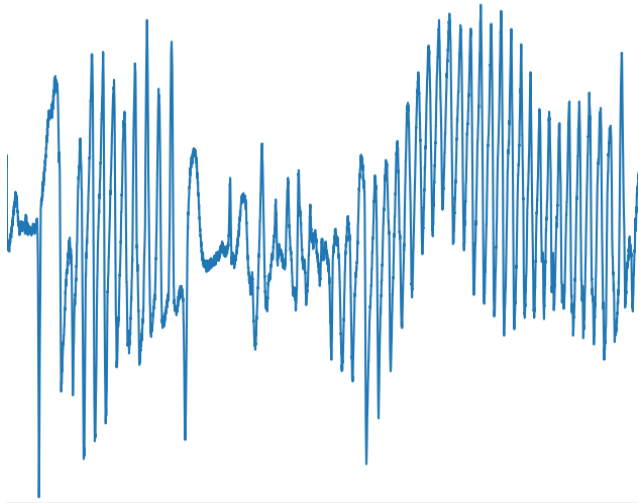
	Sensitivity	Accuracy	Precision
Rule based R-peak detection	99.244	98.225	98.940
Leaky boundary-based R-peak detection	99.548	98.847	99.279



Highly noisy signal

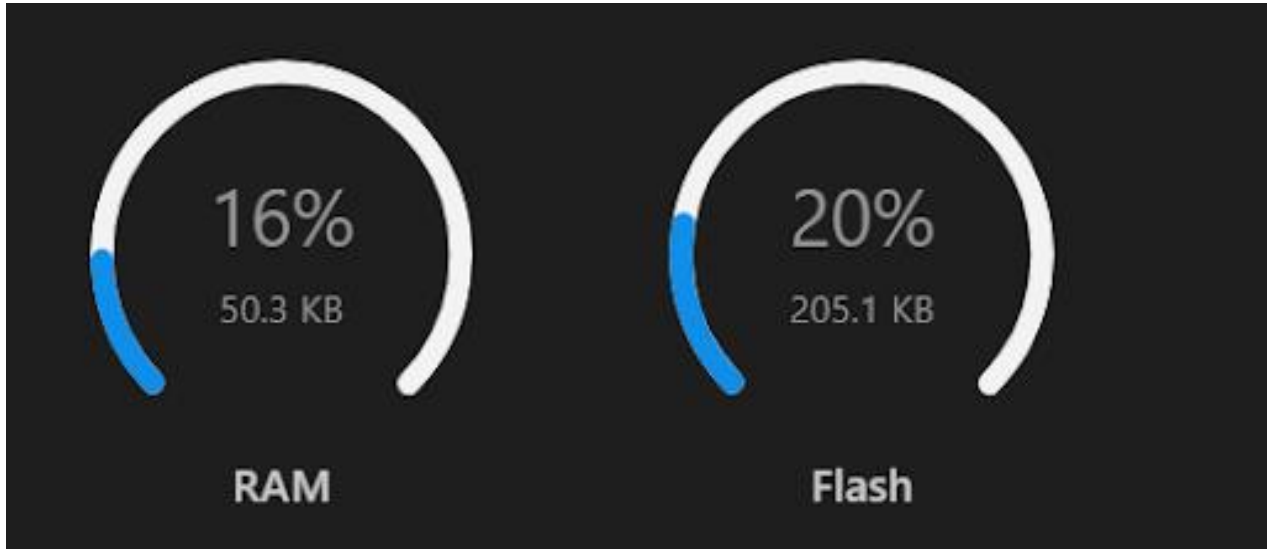


Signal with baseline wander

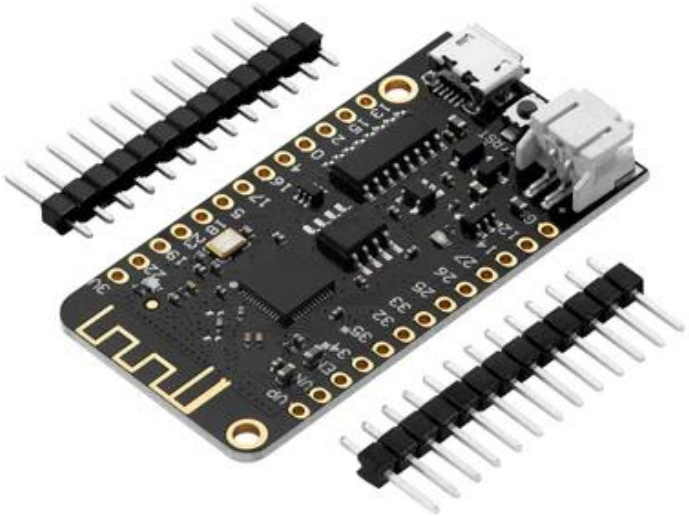


Pacemakers with no R-peaks

Progress: Testing on Hardware



LOLIN32 LITE v1.0.0 with ESP32



- Algorithm rewritten to carry out the QRS detection using a moving average window with total buffer allocation of ~ **37 x 4 bytes**

- Sensor data is serially transmitted to the MCU via UART module, and QRS detection algorithm is run for each sensor data point received

Next Step: Try Different Databases

Test the algorithms on multiple microcontrollers (ESP32, Arduino Leonardo) and calculate power and memory consumptions

Experiment with various arrhythmia databases to test the accuracy

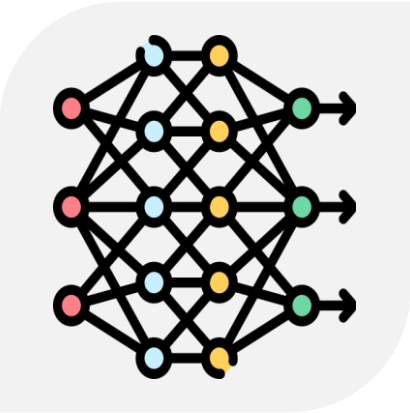
Low complexity Real-time Arrhythmia Detection Software

R-peak Detection

Beat Classification

ECG Compression

Progress: Beat Classification



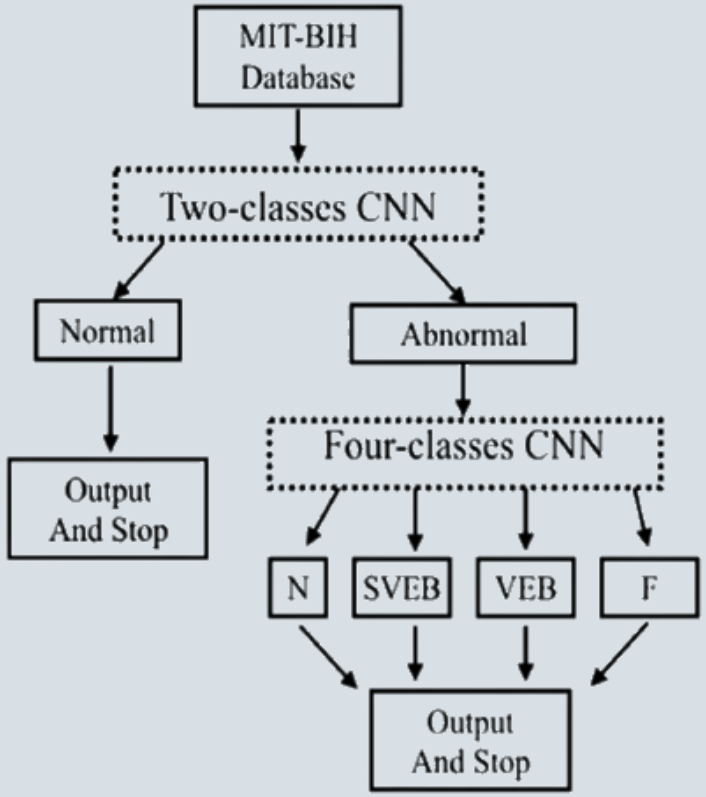
Convolution Neural Network

Spiking Neural Network

Rule Based Classification

Progress: Optimizing Beat Classification

Power optimization using a two-stage CNN



Two-class CNN (4 layers)	Precision	Recall	F1-Score
Normal	0.95	0.97	0.96
Abnormal	0.72	0.58	0.64

Overall Accuracy 93%

Four-class CNN (18 layers)	Precision	Recall	F1-Score
N	0.96	0.80	0.87
SVEB	0.15	0.19	0.17
VEB	0.64	0.85	0.73
F	0.01	0.21	0.03

Overall Accuracy 80%

Progress: Optimizing Beat Classification

Power optimization using a four-class SNN

Multiple beat ECG segment

↓

Input Layer
(500 Spiking Neurons)

Hidden Layer
(100 Spiking Neurons)

Output Layer
(4 Spiking Neurons)

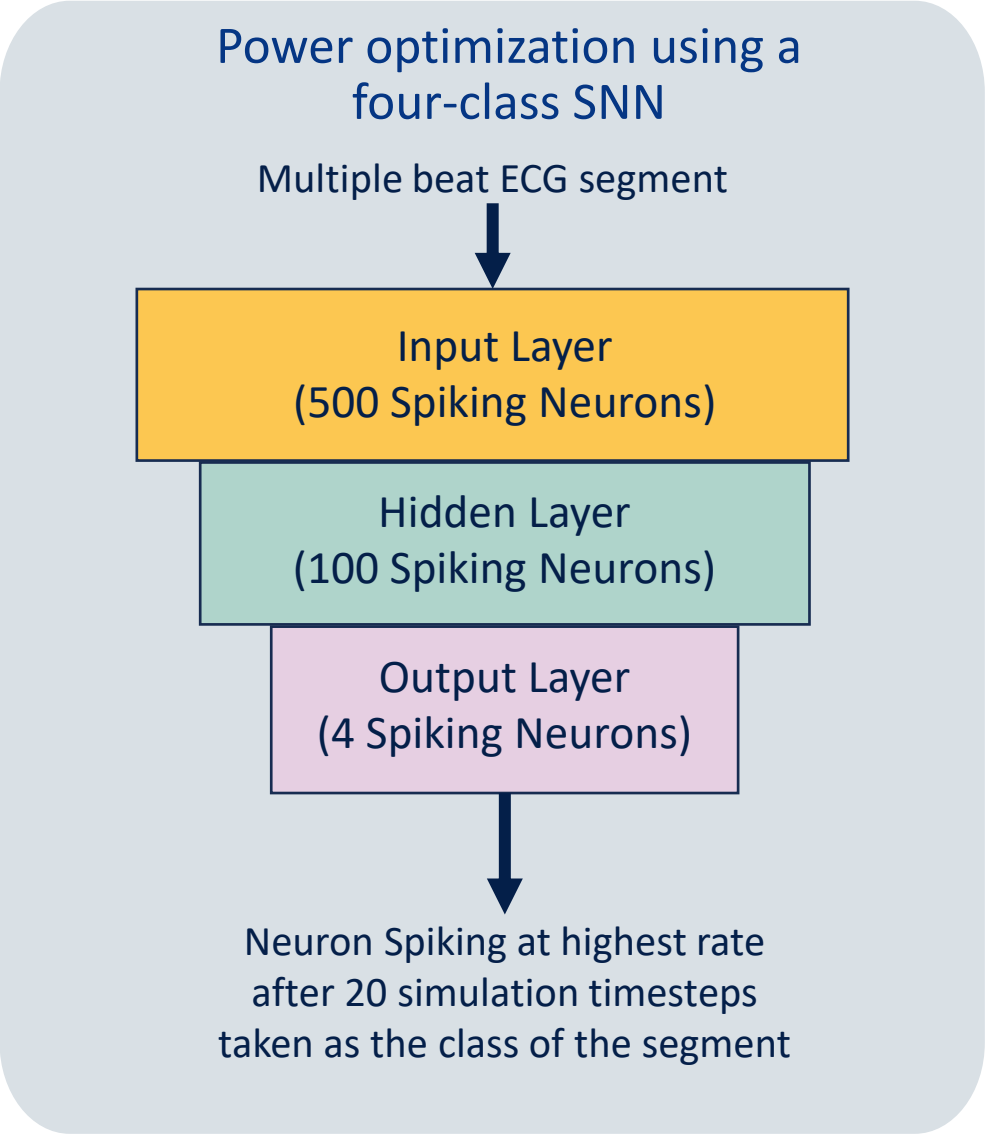
↓

Neuron Spiking at highest rate after 20 simulation timesteps taken as the class of the segment

Four-class SNN (3 layers)	Precision	Recall	F1-Score
N	0.95	0.83	0.88
SVEB	0.04	0.06	0.05
VEB	0.38	0.81	0.52
F	0.02	0.10	0.04

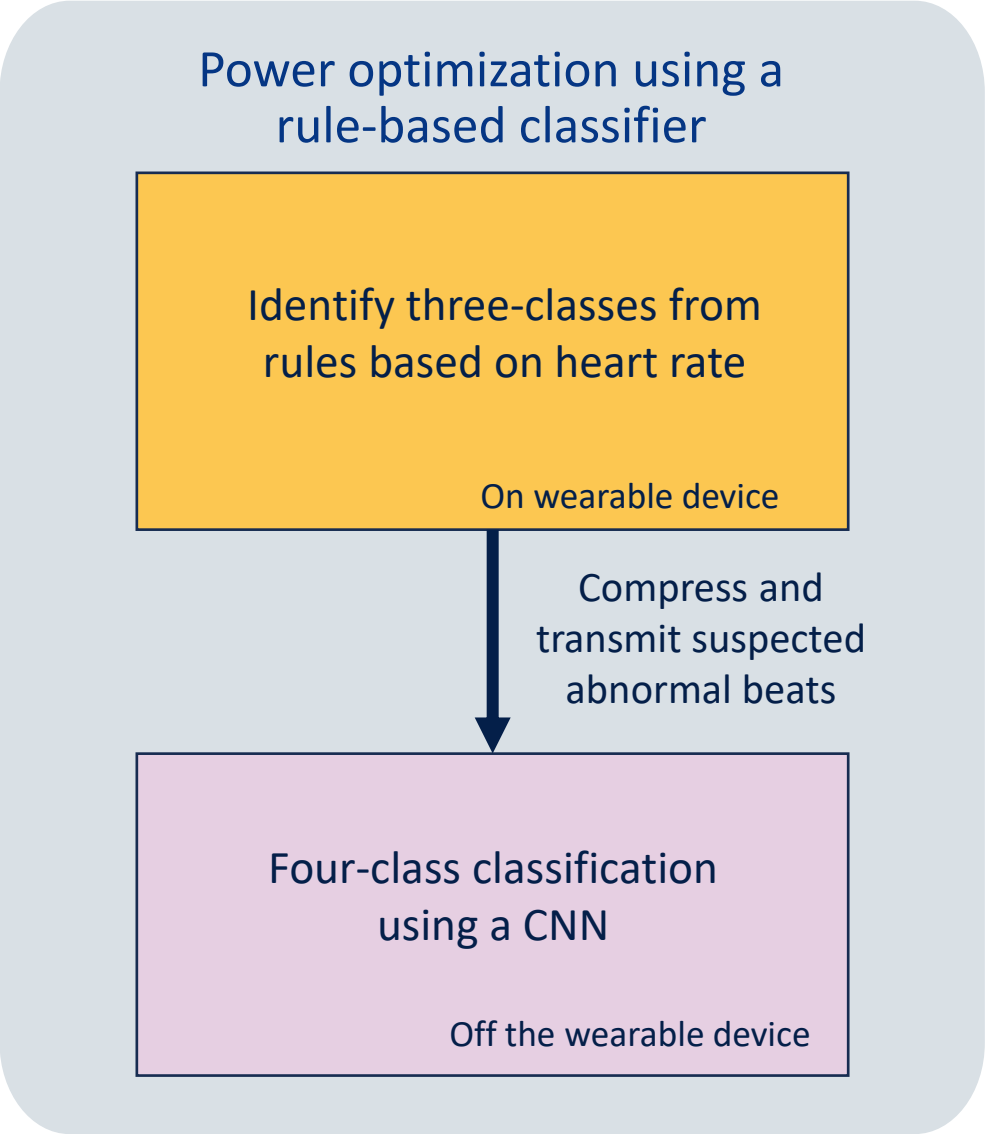
Overall Accuracy
79%

Next Step: Optimizing Beat Classification



- Hyperparameter Optimization to increase accuracy (Threshold voltages, number of neurons, number of layers)
- Test power consumption, memory utilization by implementing on different hardware platforms

Next Step: Optimizing Beat Classification



Rule 1: Normal(N) Vs. Abnormal (SVEB, VEB, F) filtering

If (R-R distance ~ 0.6 to 1.0 seconds) → Normal
else → abnormal

Rule 2: SVEB/F Vs. VEB filtering

If (R-R distance ~ 0.24 to 0.4 seconds) → SVEB or F
else → VEB

Rule 3: For SVEB detection

- Rate > 150-250 bpm
- QRS complex is narrow < 120 ms

Rule 4: For VEB detection

- **Abnormal morphology**
- QRS complex is broad > 120 ms
- Premature broad QRS occurs in between normal QRS patterns

Rule 5: For F detection

- **Abnormal morphology**
- QRS complex is a combination of normal and broad QRS

Progress: Segmentation

Segmentation with optimal buffer size

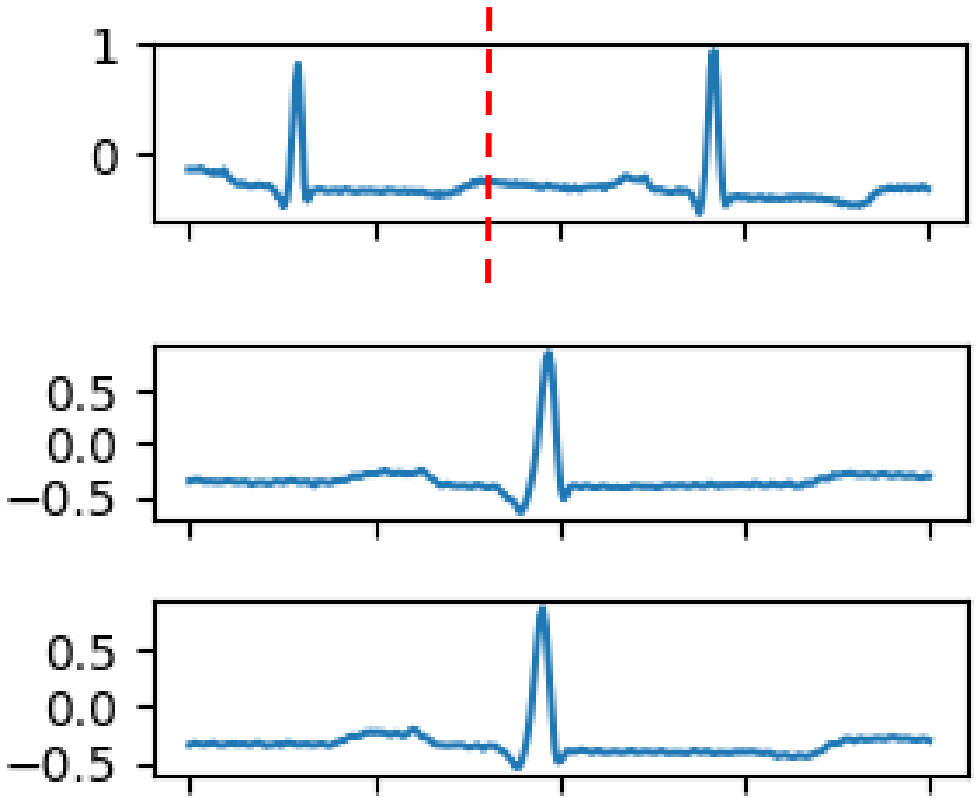
ECG

When R-peak is detected save the ECG until one more R peaks are detected

Divide the data points from the middle to generate two beats

Rescale each beat to a fixed number of data points (e.g., 250)

QRS Segments



Low complexity Real-time Arrhythmia Detection Software

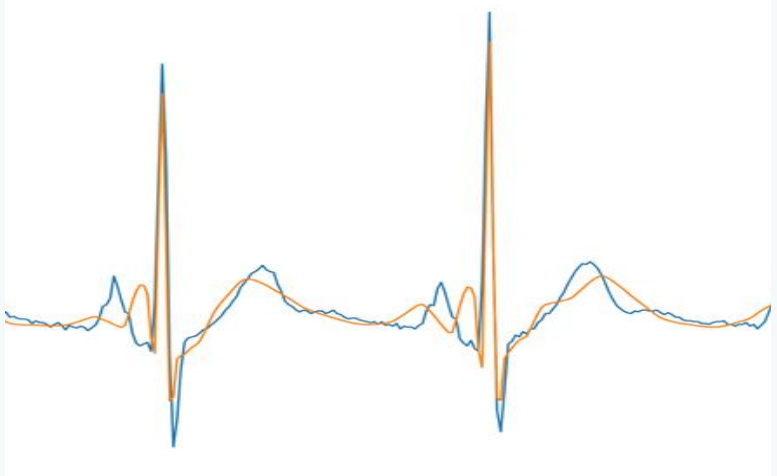
R-peak Detection

Beat Classification

ECG Compression

Progress: Issues in Current Compression Techniques

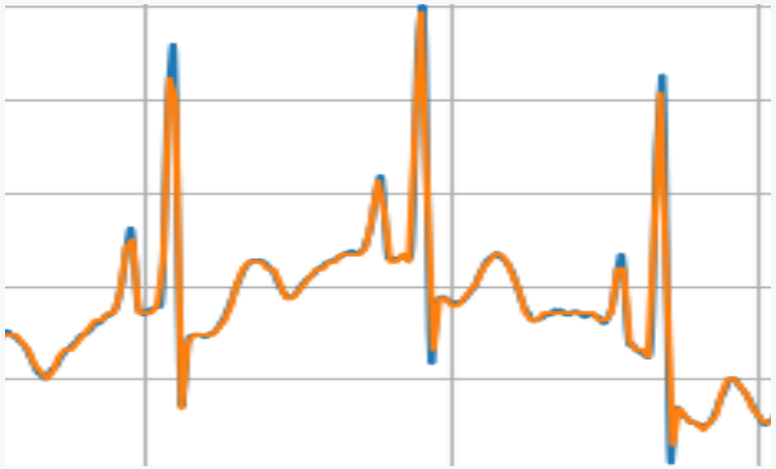
Wavelet transforms and variable run-length encoding



Complexity is high

Lossy reconstruction possible

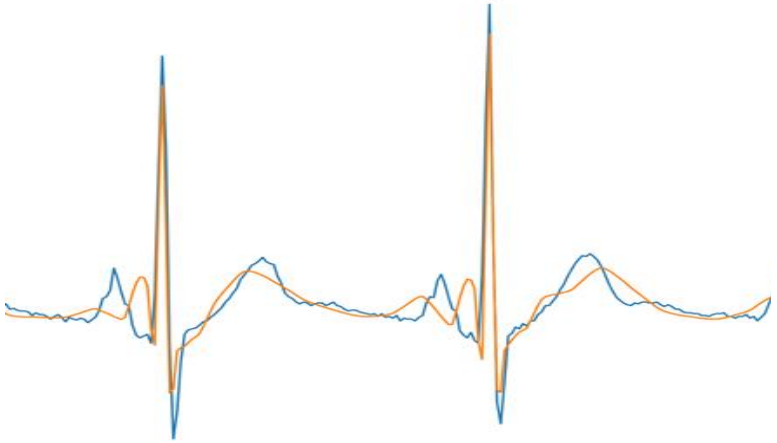
Re-sampling and quantization



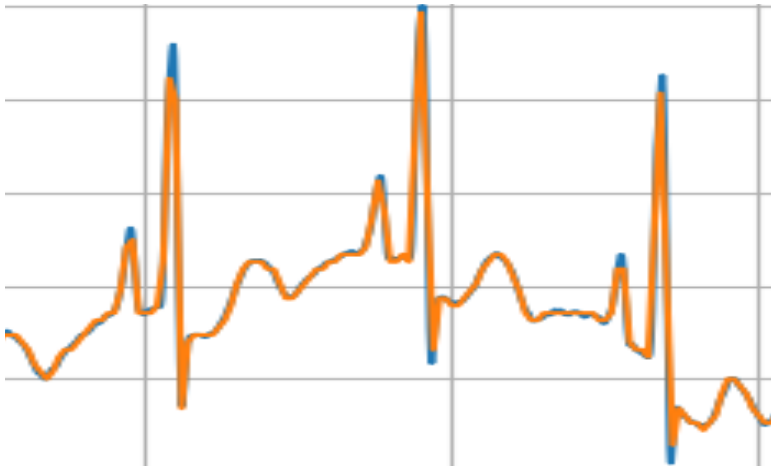
Need higher resolution to preserve important features

Progress: Issues in Current Compression Techniques

Wavelet transforms and variable run-length encoding



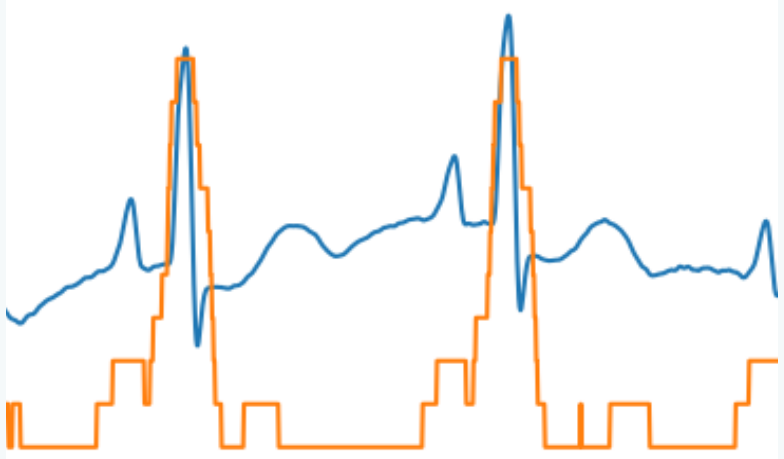
Re-sampling and quantization



Filter and store features based on derivative

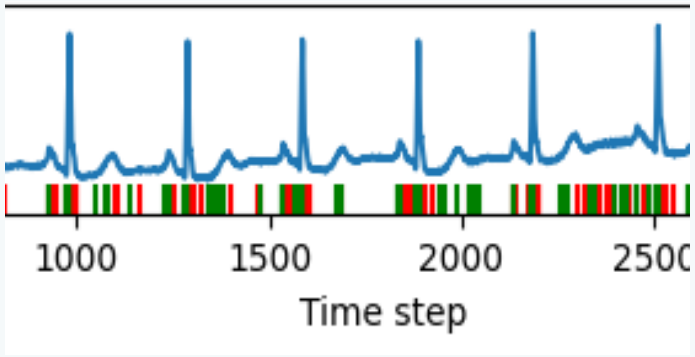
Loss of important features

Cannot reconstruct



Delta modulation for sparse, event-stream encoding

Sensitive to the threshold used for event generation

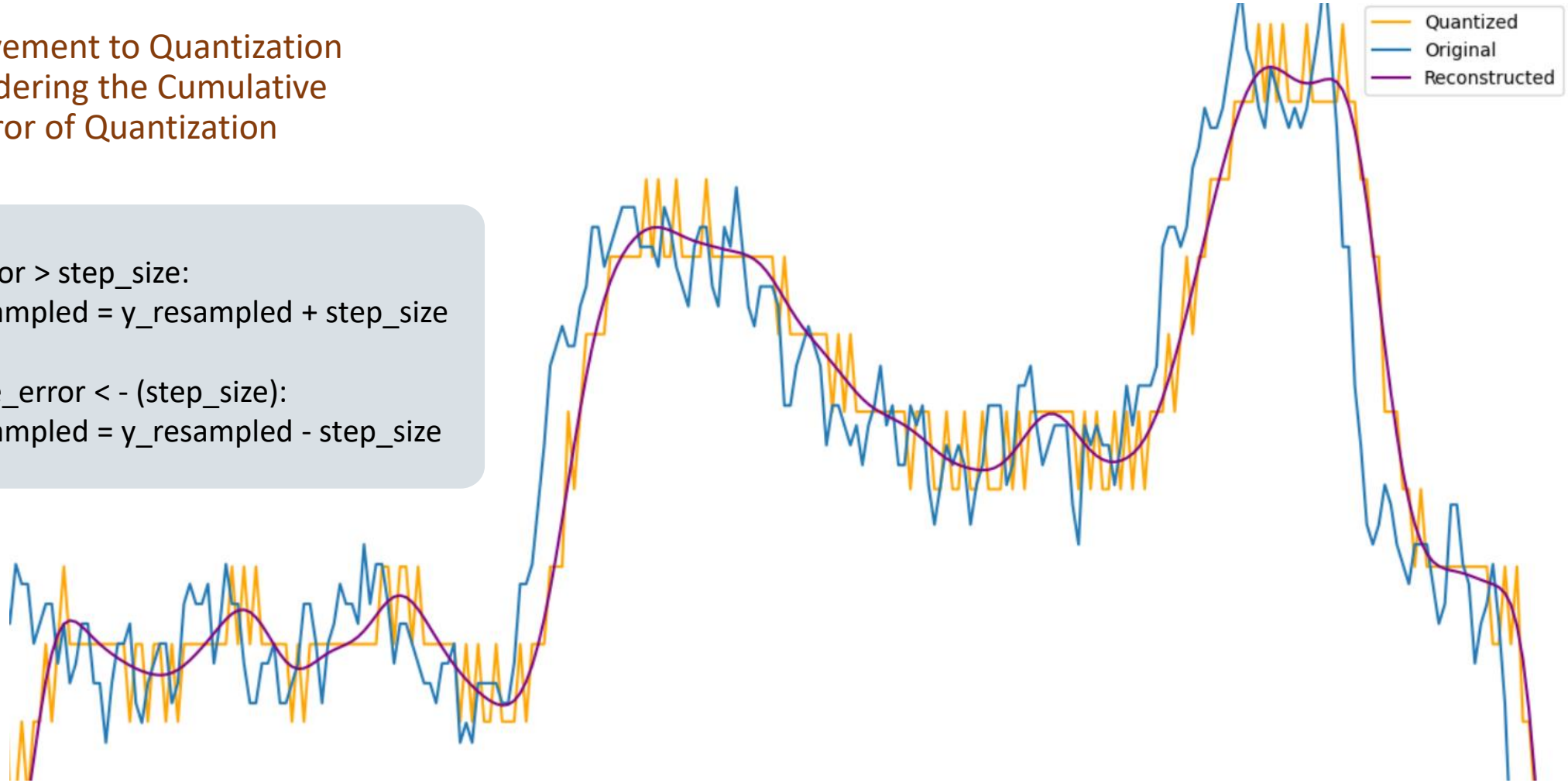


Progress: Novel Compression Technique

Improvement to Quantization
Considering the Cumulative
Error of Quantization

```
If cumulative_error > step_size:
        y_resampled = y_resampled + step_size

else if cumulative_error < - (step_size):
        y_resampled = y_resampled - step_size
```



Progress: Novel Compression Technique

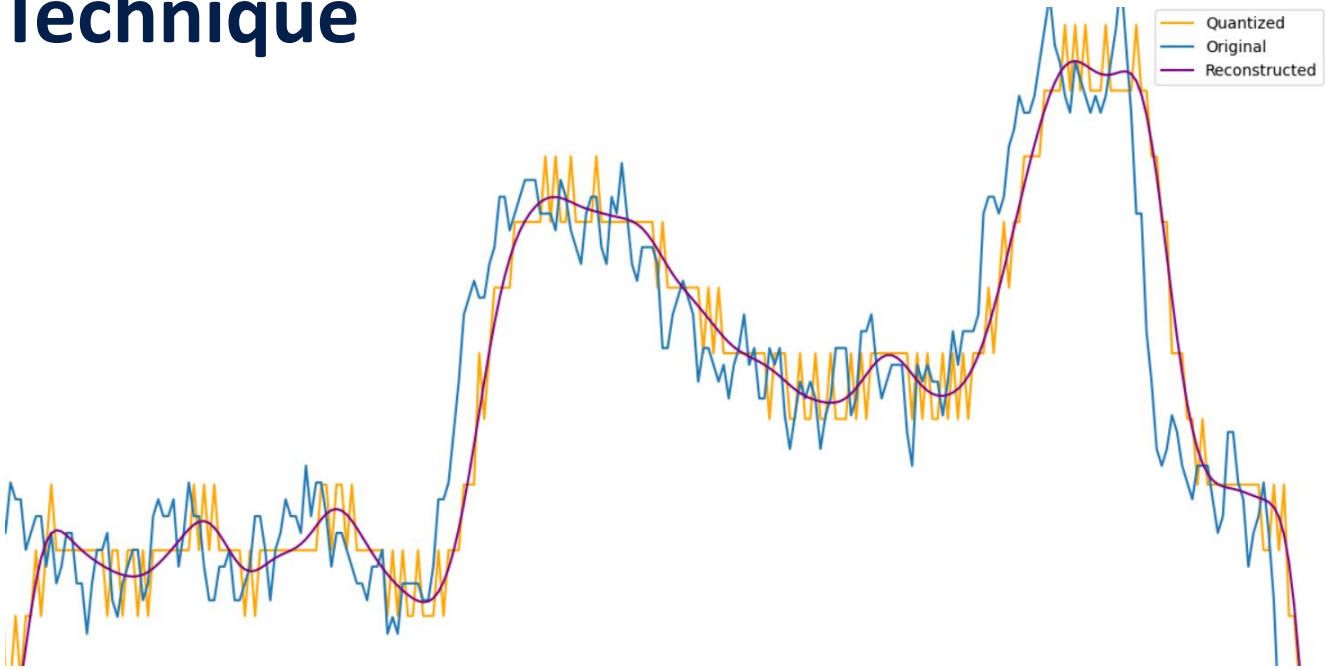
Improvement to Quantization Considering the Cumulative Error of Quantization

2048 levels (11 bits) → 16 levels (4 bits)

37.50 MB

86%

5.06 MB



Number of bits	Recall	Accuracy	Precision	Compressed File size (MB)
2	95.38	86.46	88.48	3.28
3	97.71	95.89	97.76	4.11
4	98.12	97.49	99.35	5.06
5	98.14	97.60	99.44	6.37
11	99.54	98.84	99.28	37.50

Problems Encountered

Optimizing the R-peak detection algorithm

- Buffer overflows when implementing the algorithms in the microcontroller
- Filters added significant delays to the signal, making them not suitable for real time applications

- Optimize the algorithm further to reduce the buffer utilization
- Define filter parameters such that both delay and changes in morphology are minimized

Problems Encountered

Optimizing the automatic arrhythmia classification

- High variance in the dataset when the ECGs are incorrectly segmented into beats
- High class imbalance in the dataset
- The SNN failing to train properly due to vanishing spike information

- Identify two segmentation methods to reduce variance:
  1. Segmentation centering R-peaks
  2. Segmentations containing multiple peaks to classify highest severity beat in the segment
- Use moving window technique and shifting for segment generation
- Reduce the number of spiking neurons (trial and error)
- Reduce the threshold values of the spiking neurons

Next Step: Publishing the Findings

Publish the research findings by writing **three research papers** with the findings in terms of R-peak detection, classification, and compression

Deploy the arrhythmia detection software containing functions for R-peak detection, signal compression, and heart-beat classification as an **open-source package**

Low Complexity Algorithm for Real-time QRS Peak Detection

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I. Introduction

Arrhythmias or irregular heart rhythms are a significant component of cardiovascular diseases (CVD), a leading cause of global mortality. The electrocardiogram (ECG) is a vital tool widely used among healthcare professionals to diagnose and monitor these abnormalities. While the manual inspection of ECG signals in an acute condition is a difficult task, long-term monitoring of the electrical activity of the heart for early detection of transient or infrequent arrhythmias is also challenging without computer-aided diagnosis methods.

Computer-aided arrhythmia classification (CAAC) has become a well-researched topic with the development of public ECG databases. Over time, many sophisticated devices, from portable ECG monitoring devices to automated external defibrillators (AED) that can analyze the heart's rhythm, identify the irregularities, and generate an electrical shock if necessary to help the heart re-establish the normal rhythm have been developed with the help of CAAC.

Furthermore, with the introduction of wearable ECG devices, the possibility of real-time heart disease detection is now made available. For instance, such an edge device can be configured to immediately detect and store a suspected abnormal beat of the ECG for subsequent transmission to a central station for in-depth analysis, either automatically by a machine learning algorithm or manually by a physician. As the QRS complex is a prominent feature used for beat segmentation of an ECG, accurate detection of QRS complexes is essential for such a wearable device.

False QRS detection may result in incorrect segmentations, unnecessary data transmission, and ultimately inaccurate detection of arrhythmia. Detecting QRS accurately is inherently difficult due to physiological variations in the complexes

aiming for swift and precise QRS detection with minimal memory and time consumption is even more challenging. In this paper, we propose a low-complexity algorithm for real-time detection of the QRS peaks in an ECG signal that can be implemented in severely resource-constrained environments.

The two main stages that can be identified in all QRS detection algorithms introduced over the years are the denoising stage using a combination of filters (e.g. highpass and lowpass, or bandpass) to detect the prominent features of the QRS complex such as amplitude and width and the decision making stage to detect the R-peaks using a threshold. The proposed algorithm optimizes this workflow by eliminating the redundant memory utilization and complexity introduced by filters in the feature extraction stage. It employs a simple peak-to-peak envelope detection technique to derive the signal's height feature, ensuring immunity to disturbances like baseline wander and minimum latency. Furthermore, it employs a rule-based approach to eliminate false detections considering the dynamic variation of the heart rate of the ECG signal. This work also utilizes a dynamic threshold sensitive to the height of the R-peaks with high robustness to noise. The proposed work was evaluated for noise robustness, low resource consumption (memory and computational power), and low latency for real-time detection on 3 public databases.

As this optimized solution demonstrates improved performances compared to other existing methods, it can be utilized to develop affordable wearable devices for real-time cardiac health assessments for a broader population.

II. Related Works

The most difficult challenge for QRS detectors is accurately spotting heartbeats when there are noise and unwanted signals. This detection process usually involves two main steps: first,

Work plan

Semester 8									
	1-6	7	8	9	10	11	12	13	14
R-Peak Detection	Algorithm implemented on the hardware	Working on the paper		Check the possibility to further optimization			Finalizing the paper		
ECG Compression	Design compression algorithm with minimum data loss	Analytical comparison of the proposed compression method with already SOTA		Finalizing the paper					
Arrythmia Classification	Building a four-class SNN and simple rules for classification	Hyperparameter optimization of the SNN		Implementing the rule-based classification		Testing the performance on different databases	Finalizing the paper		

Thank You !

Q & A