



Low Power IoT Sensor with Embedded AI for Healthcare Monitoring

Abstract

This proposal addresses the high-power consumption issue of wearable devices for CVD patients. Power consumption is too high due to continuous RF transmission of data. The idea is to process the physiological signals locally at the sensor using machine learning techniques to detect potential arrhythmias or health conditions. Wireless transmission can be enabled only when deemed necessary by the processing techniques to save power. Existing machine learning (ML) algorithms are not "light" enough to be implemented in IoT devices. This project aims to develop Edge/Near-Sensor computing techniques in IoT devices to opportunistically disable RF transmission.

Introduction:

To address the above-mentioned issues, we are developing a new algorithm where instead of looking for individual arrhythmias, only anomalies in the data are identified. Anytime an anomaly is detected, the wireless transmission can be enabled for real-time streaming, so that a more comprehensive analysis can be done in a cloud server or manually by a clinician. This solves the problem of computational complexity, personalisation and still achieves the power reduction in the sensor.

We aim to develop distributed ML algorithms for IoT devices in which

- A *light* first stage which makes binary decisions to be implemented in an IoT device.
- A second stage which makes a more comprehensive classification on a gateway device.



- Research distributed machine learning techniques with 2 stages.
 - Develop binary stage 1 classifiers to be implemented in the IoT
 - Develop stage 2 algorithm for comprehensive analysis

- Test the detection accuracy of the techniques at Stage 1 and Stage 2 using public datasets
- Develop a sensor prototype and implement the algorithms in firmware and measure improvements.

Algorithm Development:

LSTM based classifiers have been developed in Matlab from scratch. The algorithm is tested with free and open database. The binary classification accuracy in floating point is ~97%. SMOTE algorithm was used for data augmentation to deal with class imbalances. The accuracy with the SMOTE algorithm for floating point is 96%. A fixed-point version of the same algorithm for embedded implementation achieved 96% classification accuracy as well. For stage 2, we developed a CNN algorithm which achieved an accuracy of 98%.

| LSTM/PCA MLP/RR | | REC | TN | FN | ТР | FP | Total | Acc |
|--|----|---------------|------|-----|------|-----|-------|------|
| | 1 | 1 100 | 1857 | 4 | 26 | 13 | 1,900 | 99% |
| concat | 2 | 3 103 | 1725 | 1 | 1 | 1 | 1,728 | 1009 |
| MLP | 3 | 4 105 | 1975 | 8 | 26 | 145 | 2,154 | 93% |
| TOULARY | 4 | 8 111 | 1765 | 0 | 1 | 9 | 1,775 | 99% |
| Output [1:N, 2:A] | 5 | 10 113 | 1498 | 0 | 5 | 2 | 1,505 | 1009 |
| (a) Holistic View | 6 | 14 117 | 1282 | 0 | 1 | 0 | 1,283 | 1009 |
| C | 7 | 17 121 | 1434 | 0 | 2 | 123 | 1,559 | 92% |
| | 8 | 19 123 | 1261 | 0 | 3 | 3 | 1,267 | 1009 |
| | 9 | 21 200 | 1413 | 50 | 680 | 24 | 2,167 | 97% |
| | 10 | 23 202 | 1671 | 22 | 49 | 128 | 1,870 | 92% |
| | 11 | 29 210 | 1964 | 60 | 133 | 44 | 2,201 | 95% |
| $f_t i_t c_t o_t f_t i_t c_t o_t f_t f_t $ | 12 | 30 212 | 2283 | 0 | 0 | 1 | 2,284 | 100% |
| | 13 | 31 213 | 2099 | 151 | 339 | 109 | 2,698 | 90% |
| n_n_x) | 14 | 32 214 | 1510 | 7 | 208 | 152 | 1,877 | 92% |
| ייייייייייייייייייייייייייייייייייייי | 15 | 34 219 | 1710 | 17 | 41 | 4 | 1,772 | 99% |
| $\mathbf{x}_0 = \mathbf{x}_0 + \mathbf{x}_0$ | 16 | 36 221 | 1668 | 15 | 301 | 35 | 2,019 | 98% |
| and the second se | 17 | 37 222 | 1626 | 49 | 160 | 279 | 2,114 | 84% |
| $ \bullet \bullet \bullet \circ \circ \circ \circ \circ $ | 18 | 39 228 | 1392 | 4 | 301 | 5 | 1,702 | 99% |
| Feature Extraction Layer | 19 | 41 231 | 1264 | 0 | 0 | 10 | 1,274 | 99% |
| (\mathbb{N}) | 20 | 42 232 | 298 | 39 | 1127 | 20 | 1,484 | 96% |
| Classification Layer | 21 | 43 233 | 1781 | 63 | 639 | 75 | 2,558 | 95% |
| (b) LSTM Cell Pipelinee | 22 | 44 234 | 2151 | 30 | 23 | 85 | 2,289 | 95% |

For the experiment we have considered first 20 records in the MIT-BIH Arrythmia database consisting of more than 40 thousand beats. Less than 7,000 beats among the first 1,000 beats of each records (from 20,000 beats) were selected for training the neural network.

The development of version 1 of the prototype sensor is completed. Currently the algorithm is being converted to embedded software to be ported into the IoT device. A second algorithm using a simple rule-based classifier is also being developed.



Fig. 4: Training Summary of the proposed Neural Network on DS1 (100 - 124) and DS2 (200 - 234)

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