

# Low Power IoT Sensor with Embedded AI for Healthcare Monitoring

## Abstract

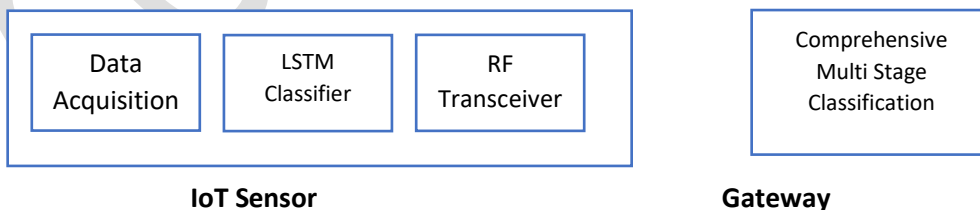
This proposal addresses the high-power consumption issue of wearable devices for CVD patients. Power consumption is too high due to continuous RF transmission of data. The idea is to process the physiological signals locally at the sensor using machine learning techniques to detect potential arrhythmias 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 97%. A fixed-point version of the same algorithm for embedded implementation achieved 97% classification accuracy as well. The power savings of wireless transmission from the proposed algorithm used in an embedded test setup in Fig 8 is shown in Fig 10. For the experiment we have considered first 20 records in the MIT-BIH Arrhythmia database consisting of more than 40 thousand beats. Less than 7,000 beats among the first 1,000 beats of each record (from 20,000 beats) were selected for training the neural network.

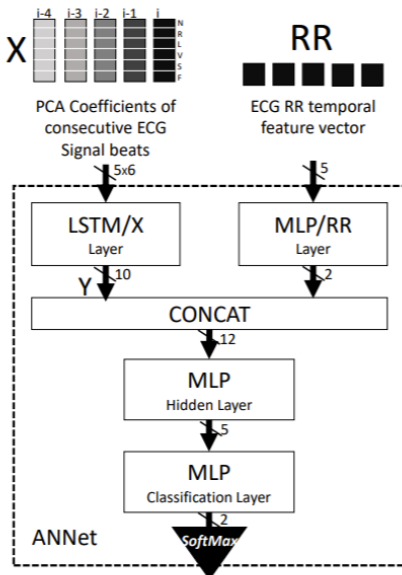


Fig. 3: Top level architecture of ANN

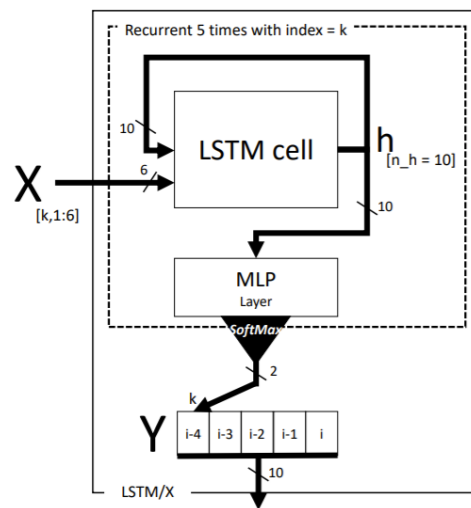


Fig. 2: LSTM Cell Pipeline as part of LSTM/X (Fig.3)

TABLE II: Patient Specific Training summary of floating po network for the DS2: MIT-BIH arrhythmia dataset

Record	TN	FN	TP	FP	Test Acc.
100	1,857	4	26	13	0.99
103	1,725	1	1	1	1.00
105	2,094	6	28	26	0.99
111	1,765	0	1	9	0.99
113	1,498	0	5	2	1.00
117	1,282	0	1	0	1.00
121	1,434	0	2	123	0.92
123	1,261	0	3	3	1.00
200	1,423	27	703	14	0.98
202	1,671	22	49	128	0.92
210	1,964	60	133	44	0.95
212	2,283	0	0	1	1.00
213	2,099	151	339	109	0.90
214	1,621	8	207	41	0.97
219	1,710	17	41	4	0.99
221	1,668	15	301	35	0.98
222	1,626	49	160	279	0.84
228	1,392	4	301	35	0.98
231	1,264	0	0	10	0.99
232	298	39	1,127	20	0.96
233	1,781	63	639	75	0.95
234	2,236	30	23	0	0.99
Gross	35,952	496	4,090	942	0.97

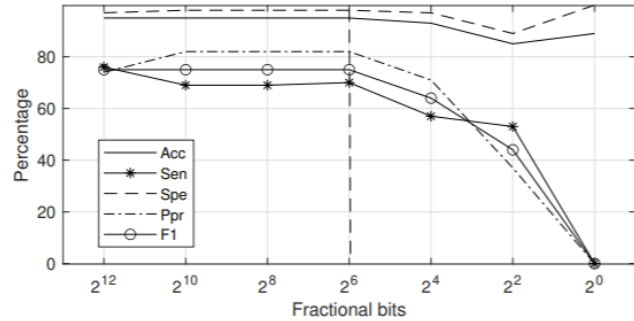


Fig. 5: Global training performance metrics of the proposed network with different level of quantization

The LSTM based classifier is ported into an embedded device running Cortex M4 CPU. The power savings have been verified in an embedded development kit. The flow diagram of implementation of the algorithm on the embedded environment is shown in Fig 9. Average power savings of this technique in wireless transmission using pre-recorded ECG from physionet database is shown in Fig 10.

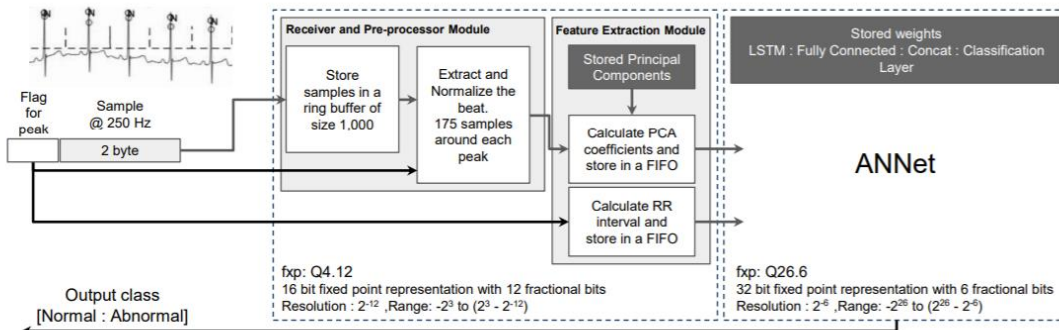


Fig. 9: Flow diagram of the implementation of the algorithm on the embedded environment

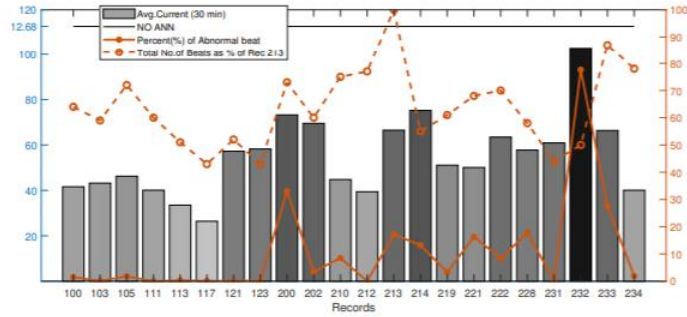


Fig. 10: Average Current Consumption in  $\mu A$  over 30 minutes of DS2 records. We can see that record 213 has the highest average heart beat rate (scaled to 100%). The records with the largest number of abnormal beats (e.g. 232) show the highest current.

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