Cardiac anomaly detection models for wearable devices

Aaptha B V* , Ankith B V*, Aryan Sharma*, Dr Madhura Purnaprajna**
*Department of Computer Science and Engineering
** Department of Electronics and Communications Engineering
**Centre for Heterogeneous and Intelligent Processing Systems Research Centre
*PES University, Bangalore, India

***Abstract*—Sudden Cardiac Arrest (SCA) is a devastating heart abnormality which leads to millions of casualties per year. Thus, early detection or prediction of SCA could save human lives in a greater scale. In this work, we aimed to predict SCA before its occurrence and significant results has been obtained using the proposed signal processing methodology. Models were trained using a CNN, CNN + Long Short Term Memory (LSTM) model and a Random Forest Classifier on the MIT-BIH Arrhythmia dataset. Taking these models to an embedded device is the main purpose of this work. The CNN models were compressed using int8 quantisation. Our early results indicated 96% on accuracy with approximately 33.16% reduction in size. We propose to apply variable width quantisation and retraining to further improve compression.**

***Index Terms*—Cardiac Anomaly, Deep learning, Healthcare, Machine learning, 2-lead ECG readings, waveform, time series data, Full integer quantisation.**

I. Introduction

In recent years, high performance computing has played an increasingly important role in scientific and engineering applications. One such application is the detection of cardiac anomalies. There are a few cardiac anomalies which, if detected early, can be treated successfully to save a person's life. But there are very few healthcare devices that prove to be efficient and convenient to use at the same time. Our solution is inclined towards helping people who are prone to getting cardiac arrests. By using ECG data, various machine learning and deep learning algorithms can be used to detect anomalous patterns. Many models regarding the same topic are not size-aware even though there are several available. The model size increases due to the full-precision arithmetic used and data being sparse. In this paper, we propose different lightweight models that prove to be computationally less intensive and energy efficient.

II. Methodology

The objective of this study is to make light and computationally inexpensive models which can be run on a wearble to detect abnormalities in ECG data. This study also examines whether Machine Learning models can detect abnormalities in ECG data more effectively than Deep Learning models. We seek to determine whether the loss in accuracy is worth the tradeoff for a lighter and less computationally intensive model .We have used PhysioNet's MIT-BIH Arrhythmia dataset [10] for our experiment. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings. An Arrhythmia dataset is enough to check for irregularities in a person's heart beat. Since we are not classifying the beats with respect to it's annotations, we did not check which abnormality occurs. The MIT-BIH dataset contains Electrocardiogram waveform data. We used the wfdb package [12] to read the data from Physionet Database.

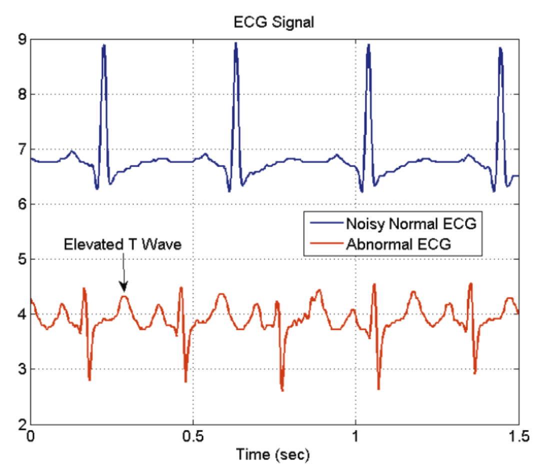

Fig. 1. Normal ECG Vs Abnormal ECG reading [13].

First, we take a look into the Physiobank Beat annotations and classify them as normal and abnormal beats.We then extracted the label information using the specified package(wfdb) and split the hour long excerpts into smaller chunks. The splitting of ECG data is done in order to get more training data. The dataset contains approximately 82,873 inputs after pre-processing. To detect these abnormalities, we came up with 3 solutions:

- Forest Classifier
- CNN model
- CNN+LSTM model

We chose to use Random forest as it is often used for time series forecasting. Since it is an ensemble method, it provides a good accuracy and handles outliers as well. A random forest handles these outliers by essentially binning them. As CNNs feature parameter sharing and dimensionality reduction, we chose them for the experiment. In addition to the CNN, we added an LSTM layer since it is capable of learning long-term dependencies.

III. Experimental Setup

A. Convolutional Neural Network

We made a lightweight two layered convolutional neural network. The model inputs the ECG data and outputs the beat type (normal or abnormal). The network consists of a convolutional layer and a Dense layer including a flatten layer and dropout of 0.5. The accuracy of this model was approximately 96.19% with a validation accuracy of 81.43%.
FLOPS is a measure of computaional performance of processors. Using Tensorflow libraries [14] we calculated the Floating Operations Per Second (FLOPS) of our model, it had 17,315 FLOPS. A model of this computational capacity can be run on a micro-controller.

B. Random Forest Classifier

Deep learning approaches are not always necessary. While they are more accurate on time series data, they are quite large in size compared to small machine learning algorithms. One such example is a Random Forest Classifier.
Random Forest is an ensemble machine learning algorithm which uses a combination of decision trees and is generally used on structured data such as tabular data. But they can also be used to classify time series data. To apply Random Forests algorithm on time series data, we transform it into a supervised learning problem. To do so, we do the pre-processing mentioned in previous section, but instead of feeding these inputs into a neural network, we input these values into a csv file. The random forest classifier was then implemented on it. We achieved a cross-validation accuracy of 85.8%.

C. CNN + LSTM model

LSTMs can handle sequential data more efficiently than CNNs, which are small and efficient, but not as efficient during processing. Our results could be confirmed by using a combination of convolutional neural network and a recurrent neural network architecture called Long Short Term Memory (LSTM) to determine whether they corresponded to our data more closely. We used one convolutional layer, a dense layer and a LSTM layer of 2 inputs in a TimeDistributed architecture to obtain our model. The accuracy of LSTM model was approximately 98.49% with a validation accuracy of 80.81%. We had around 51 thousand parameters with 86,621 FLOPS.

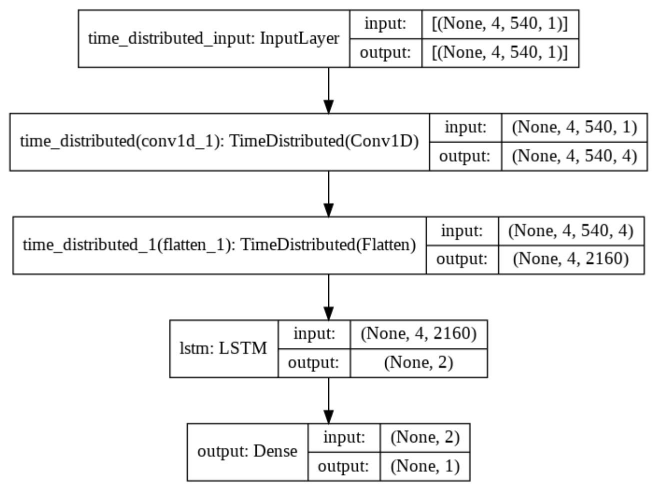

Fig. 2. CNN + LSTM model architecture.

Originally our model was 202.86 KB. But after changing the filter and kernel size, our model size dropped down to 67.67 KB. We did full integer quantisation on this model and the size reduced by 4 times, speedup increased by 3 times. This quantisation is the most essential method in order to make a model work on a microcontroller. Our model size became 16.92 KB. Post-training quantisation is a conversion technique that can reduce model size while also improving CPU and hardware accelerator latency, with little degradation in model accuracy. We obtained an accuracy of 97.96%. The difference between the accuracy's of both the models was merely 0.53%.

IV. Experiment Results

As shown in Table I, we quantised the performance of all the models on the MIT-BIH Arrhythmia dataset and tabulated its accuracy. We checked whether the models were overfitting by comparing the performance on training, testing, and validation datasets. The accuracy on training data was high when compared to the test and cross-validation accuracy. To avoid this we increased the dropout rate by 0.2. The accuracy on the validation set increased by 9.26%. However, the random forest classifier did not overfit the dataset.

TABLE I
Accuracy scores of methods on the MIT-BIT Arrhythmia Dataset

Architecture	Acc. [%]	Val. Acc. [%]	Param #	FLOPS
CNN	96.19	81.43	17,321	17,315
CNN + LSTM	98.49	80.81	51,932	86,621
CNN (Q)	96.13	86.42	17,321	17,315
CNN + LSTM (Q)	97.96	83.16	51,888	69,299
Random Forest	85.8	85.8	-	-

Note: Q is a quantised model

Quantisation aware training on the models increased the speedup by 3 times. We can further improve the usability of these models in real life situations by combining the Arrhythmia dataset with other potential datasets such as an atrial fibrillation dataset. This is because atrial fibrillation can cause serious harm and may result in brain strokes.

Conclusion and Related Work

This paper presents lightweight neural network and machine learning architectures that can be implemented on embedded devices. While other implementations of the same exist [1] [2], our primary objectives were to minimize the memory footprint and propose a computationally less intensive approach to detect cardiac anomalies. Using CNN models and a Random Forest classifier presented the desired results. We observe that Random Forest classifiers can be considered in the detection of cardiac anomalies. If ever there is a bottleneck in performance, switching to a machine learning model to detect anomalies in ECG data is a viable option. This opens up the possibility of using Machine Learning models over Deep Learning models.

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