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Edge-AI for Power reduction: Application to accelerometer sensors

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ABSTRACT: Edge-AI is the use of AI algorithms directly embedded on a device contrary to a remote AI which makes use of an AI on a cloud or remote server for prediction. Recent improvements in microcontroller computing capabilities along with deep learning algorithms conversion frameworks made it easier to run small models directly on microcontroller units. In this paper, we present how an embedded deep convolutional neural network can be used for real-time human activity recognition with +98% accuracy and extending battery life. Experiments conducted on an Arm Cortex-M4 showed that average power can be reduced up to 10% when inferences are run on edge vs using a remote server.

Keywords: Internet of things (IoT), Deep Convolutional Neural Networks (DCNN), Human Activity Recognition (HAR), Wearable sensors, Edge-AI

1 INTRODUCTION

There is a growing interest in IoT devices in all fields as a primary or complementary source of information for a better understanding and interface with the physical world.

IoT devices are used for surveillance i.e. environment, healthcare, and many more applications to provide a response to an external variable but also in more complex settings where there is a need for fast and autonomous reaction.

The combination of IoT devices and artificial intelligence brought a new type of intelligent device capable of learning and interacting with its surrounding using past information. This is possible due to the improved capabilities of microcontrollers but also the effort was done in reducing the memory and energy footprint of deep learning algorithms.

In this paper we use a deep convolutional neural network to classify human activities from an accelerometer sensor and transmit the prediction over Bluetooth low energy, this will reduce the number of transmissions done compared to sending raw accelerometer data. In this approach, we hope to reduce the overall power consumption of the device without compromising its accuracy.

The rest of the paper is organized as follows. Section 2 presents materials and methods; it provides a brief description of the dataset used and deep learning model architecture. A comparison of energy consumption of methods using off-device AI (cloud) for processing vs embedded model directly on MCU is then presented in section 3.

2 METHODS AND MATERIALS

In this section, we present the proposed Deep Convolutional Neural Network (DCNN) model architecture and the dataset used for the initial training.

2.1 Proposed model architecture

CNNs are traditionally used for image classification but lately, they have also been used with time-series data, to automatically extract features with minimal preprocessing. In this paper, we use a modified architecture of the DCNN model proposed by Mhalla et al. [1] as illustrated in Figure 1.

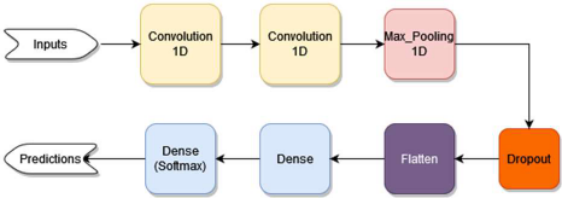

Figure 1: Proposed DCNN model Architecture

2.2 Data training and testing

We used a public dataset to train and evaluate our model. The "Sensor's activity dataset" presented in [2] is part of UTWENTE datasets.

This dataset contains labeled accelerometer, gyroscope, and magnetometer data collected from 10 different participants. The participants performed 7 basic activities labeled as follows:

- Walking
- Jogging
- Upstairs
- Downstairs
- Sitting
- Biking
- Standing

Data were collected using a smartphone from 5 different body positions.

In this paper we only focused on accelerometer data, since previous studies [2], [3] showed that magnetometer data does not improve accuracy. Moreover, in order to limit energy consumption, gyroscope is intentionally omitted as it is the most energy-consuming sensor on an inertial measurement unit (IMU). We then use only data from *the jeans pockets* position.

DCNN model is then trained on 80% of the dataset, the remaining 20% is used for testing. The performance of the model is measured in terms of accuracy and precision.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

To limit the dependence on sensor direction the model uses the absolute values of the 3-axis accelerometer sensor data and its magnitude vector.

Figure 2 shows the model accuracy on test data. We can notice that the model performs very well especially on static activities, i.e., *sitting, and standing*. The overall accuracy of the model is above 98%.

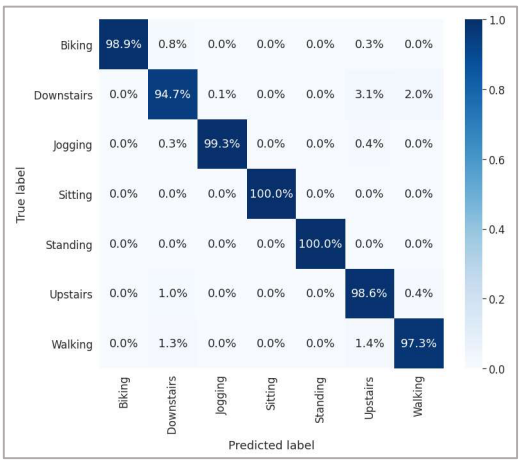

Figure 2: Test Results

3 POWER CONSUMPTION

In this section we compare the energy consumption of a microcontroller in two different scenarios:

- Microcontroller transmitting raw accelerometer data to a remote server over Bluetooth for processing on remote AI
- Embedded DCNN model on the microcontroller, detection is done directly on board and only the predicted activity code is sent over Bluetooth.

For this evaluation, we use an Arduino Nano 33 BLE. It is a Cortex-M4 development board with Bluetooth Low-Energy capabilities and an IMU on board (LSM9DS1).

Using the previously developed DCNN model directly on the Arduino board must be converted first into a C-array. Tensorflow provides a Python API for this purpose and a compatible C library. Each layer is then converted to its equivalent in Tensorflow Lite Micro [4]. After conversion, the model is halved in size and is less than 217kB, which is small enough to fit on the board's flash memory.

Table 1 shows the average current and power consumption of the Arduino in both scenarios. We can notice that with a voltage supply of 3.3V, the Arduino consumes 2.45 mW less with the model embedded on board.

Table 1. Average Current and Power consumption

Scenario	Avg Current (mA)	Avg Power (mW)
Remote AI	7.078	23.357
Embedded AI	6.335	20.905

In terms of memory usage, the predicted activity can be coded using only 3 bits whereas raw accelerometer data represents 4 floating numbers (128-bits in total). Considering that our model requires 100 samples per inference run, the total size of data transmitted to the remote AI is 1.6 kB.

4 CONCLUSION AND FUTURE WORK

We presented how deep convolutional neural networks can be used for human activity recognition and handle data from different sources other than the one initially trained on i.e., smartphones. The experiments done on microcontrollers demonstrated that deep learning algorithms can be used not only to improve recognition accuracy but also to increase the battery life of IoT sensors.

In this work we were able to run inferences directly on MCU using an embedded pre-trained model and were able to confirm the accuracy of recognition and power reduction, in future work, we will increase the number of activities, adding more complex gestures and run inference on multiple sensors forming a body area network.

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