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Departamento de Engenharia Electrónica e Telecomunicações e de Computadores

Intelligent Sports Weights

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Introduction

The growth of Neural Networks studies has increased significantly and it is becoming popular not only among researchers but also product developers. This development is driven by the technologies such as sensors, Bluetooth and continuous improvements with faster more compact embedded systems. These technological advances have, in turn, resulted to high adaptability for movement detection applications. The reach of this application goes beyond regular security scenarios that resemble playing sports where secure and seamless access control is crucial for a good user experience. This report presents the initial work carried out for the conception of a system for recognizing movements in physical exercise, it also be explained how to start to transform sensor collected signals into movement that can be analysed and worked in order to fulfill the project goal.

1.1 Motivation

In a world that more and more often is import to have a healthy lifestyle and healthy well-being and with the widespread aging of the population. Exercise plays an important role in this evolution. Not always the rhythm of this busy days allow us to have the right expertise with us, so multiple people uses the online applications to exercise. However, many exercises performed without supervision or knowledge can lead to disabling injuries, undermining the purpose of exercising in the first place. The concern of this project relies in the possible problem that performing fitness exercises not executed correctly can lead to injury. With the emergence of embedded systems with very compact sensor capabilities and extremely low power consumption (uA / nA), there is the possibility of equipping gym equipment to provide feedback on the correctness of exercise movements.

1.2 Objectives

The main objective of this work is to develop an embedded system capable of collecting motion data, in particular using IMU for accelerometer readings and show the user in a user-friendly way in the exercise is being well performed .The system is intended to be integrated into gym equipment with the following key requirements:

- Autonomy, should operate autonomously for over 8 hours, ensuring prolonged usage without the need for frequent recharging.
- Compact Design, must be compact and lightweight facilitating ease of use during exercise routines.
- Real-time Data Acquisition: It should possess the capability to collect motion data in real-time and communicate this information wirelessly to a host device using BLE (bluetooth low energy) technology.
- User Feedback, provide meaningful feedback to the user based on a predefined training dataset. This feedback may include the evaluation of exercise movements as either well or poorly executed, assessment of movement speed, and determination of trajectory correctness. Also some count how many where done and the how many where correctly done.
- Validation, validate the movement via a Neural Network The work to be performed consists of:
    1. Extracting data from the sensor via Bluetooth
    2. Dataset generation
    3. Selection and training of the most suitable neural network
    4. Program an application to present different exercises (challenges) to the user
    5. Keep tracking of the user's performance (score)

Keywords: Neural Networks · Embedded Systems · BLE · Motion classification

1.3 Report Overview

First it's described and introduction how the system work and it's objectives. In Chapter 2 it's highlighted the neural networks for movement recognition, explaining the existing **neural network** types. In Chapter 3 can be found the related works and explanation of the tests that where made to examples, to better understand the state of the art. In Chapter 4 it's talked about the related technologies, explaining BLE technology and micro-controllers summary. In Chapter 5, describes the proposed solution for a automatic movement recognition, showing the high level architecture and some initial implementation. In Chapter 6, it's described the progress made so far, the challenges encountered and how we plan to address them. Finally in Chapter 7, a work plan is presented.

2

Background on Neural Networks for Movement Recognition

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Speak about the neural networks for movement/pattern recognition ver link wikipedia

2.1 Convolutional Neural Network - CNN

https://www.geeksforgeeks.org/introduction-convolution-neural-network/

2.2 Long Short-Term Memory - LSTM

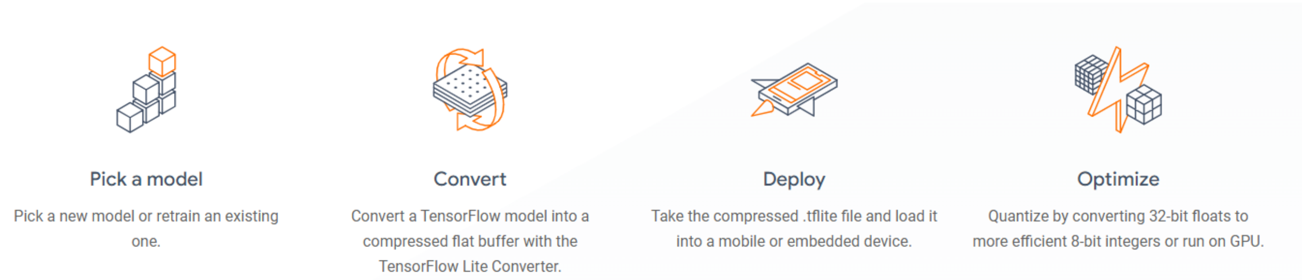
ver video - extraido de features e não de videos

DNN (deep)? tinyML livro pag 143 e 243

2.3 Conclusions

[8] book

Figure 2.1: TensorFlow Lite: Flow



3

Related Works

As stated in study "Activity recognition in beach volleyball using a deep convolutional neural network" [17] the potential automation of recognising human movements, commonly referred to as human activity recognition (HAR), can be achieved through machine or deep learning model approaches [5]. Sensor-based activity recognition in gym activities is not covered extensively in the literature, but there are multiple references to sports that can be apply to the same field of work, following the same purpose of this project. In "Application of a tri-axial accelerometer to estimate jump frequency in volleyball"[1] attempted to determine the jump frequency in volleyball in order to understand and prevent patellar tendinopathy. Using an accelerometer to estimate jump frequency it was concluded that differences in these parameters were not sufficient for distinguishing between jumping and non-jumping movements. IMU-based Trick Classification in Skateboarding [18] used inertial-magnetic measurement units (IMUs), using wearable sensors detect the tricks done by a skateboard, using the IMU signal processing methods to detect or classify specific activities, [2] used it in skiing. Also a Binary Classification of Running Fatigue using a Single Inertial Measurement Unit [19] used gyroscopes and acceleration sensors on runners to distinguish between two different states: runner's non-fatigued and fatigued state. They concluded that such a differentiation may be possible. IMUs have also been used for activity recognition in various other sports, e.g., in skiing, golf, skateboarding, etc. They have also been employed for the recognition of daily life activities like gesture recognition [7]. Inertial measurement units (IMU) are small, low power[3], low cost, non-stationary and wireless so that they facilitate fully integrated or wearable systems. In most of the aforementioned publications, classification was based on a set of generic features that were calculated from the sensor data. These features were the input to a classifier that was trained to discriminate between different classes. Neural Networks - Deep Learning represents an alternative to these classical classification approach based on hand-crafted features. The most important advantage of Neural Network is the automatic extraction of features, also known as representation learning. In this study [5] it was used a Deep Neural Networks (DNNs) on resourced-constrained MCUs and the experimental results show that without incurring heavy overhead on memory and run-time latency, the compressed DNNs could maintain the original accuracy or run with moderate accuracy loss. Machine learning classifiers modelled with generic hand-crafted features, were compared against a CNN for classifying nine beach volleyball actions using IMUs [18]. Investigation of deep learning methods in comparison to conventional machine learning algorithms would be of particular interest to evaluate if the trend of superior performances is beneficial for sport-specific movement recognition. The usability of CNNs and/or DCNNs for sports activity or even gym exercises recognition remains to be investigated in more deep. Moreover, the performance of CNNs and DCNNs in sensor-based activity recognition needs to be compared systematically to other state-of-the-art activity recognition approaches. The purpose of this paper is to describe an automatic system for gesture recognition in gym exercises. To this end, we explore the applicability of Neural Networks for sensor-based activity classification and try compare it to other state-of-the-art classification methods, while Common data inputs are obtained from inertial measurement units (IMUs).

4

Related Technologies

4.1 Ultra-Low Power Embedded Systems for Motion Acquisition

Ultra-low power embedded systems for motion recognition are designed to in a very efficient way read and process motion-related data while consuming minimal energy. These type of systems are crucial in applications where battery life is a critical factor. IMUs are small, low power, low cost and wireless, for the purpose of the project, the electronic device chosen has to measure and report acceleration, orientation, angular rates, and other gravitational forces ofor that is essencial to have accelerometers and gyroscopes incorporated. A comparison was made between 4 different micro-controllers, energy-efficient was also something that was taken into account to chose the best fit for the project.

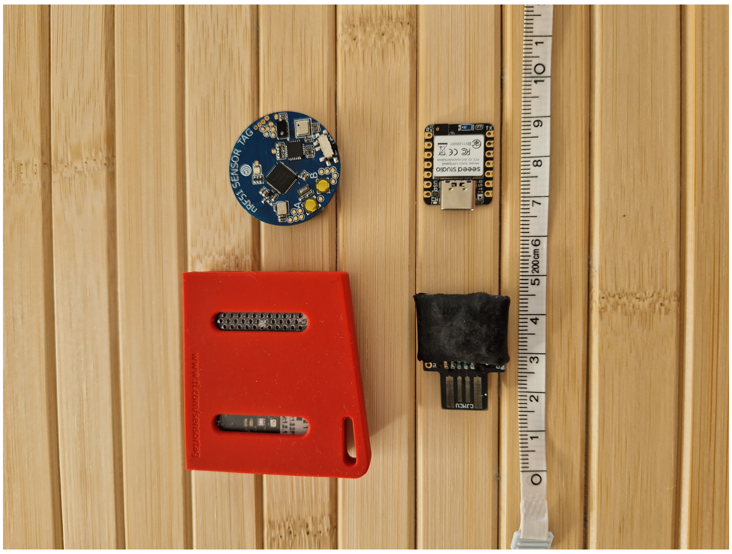
4.2 BLE

Bluetooth Low Energy is a wireless, low-power personal area network. Its goal is to connect devices over a relatively short range. BLE was created with IoT applications in mind, IoT devices tend to be constrained and require extended battery use, so BLE favors low power consumption over continuous data transfer. BLE is attractive to consumer electronics and Internet-connected machine manufacturers because of its low cost, long battery life, and ease of deployment. From thermometers and heart rate monitors to smart watches and proximity sensors, Bluetooth LE facilitates infrequent short-range wireless data communication between devices, powered by nothing more than a dime-sized battery. In this project it's the perfect tool needed to use to communicate from the device to the host.

4.3 The micro-controller

A few micro-controllers where investigated, analysed and tested, before making the choice of the one that fit better with the goals of the work.

Figure 4.1: Tested Micro controllers



FALTA COLOCAR LEGENDA E NUMERAÇÃO NA IMAGEM

Feature	NRF51 Sensor Tag	Seeed Studio XIAO nRF52840 Sense	CJMCU Beetle	Texas Instruments TIDC-CC2650STK-SENSORTAG
Price	€15.36	€22.20	€8.73	59€
Micro-controller	nRF51822	nRF52840	ATmega32U4	CC2640R2F
Processor	32-bit industry standard ARM Cortex-M4F processor	Nordic nRF52840 ARM® Cortex®-M4 with FPU runs up to 64 MHz	Atmel AVR 8-bit microcontroller family	CC2650
On-chip Memory	192 kB flash and 24 kB RAM	1 MB flash and 256 kB RAM	32 KB flash	20 KB of SRAM
Onboard Memory	6 KB to 256 KB or more	2 MB QSPI flash	SRAM: 2.5 KB	128 KB of Flash memory
Interface	UART (RTS/CTS)	1xUART, 1xIIC, 1xSPI, 1xNFC, 1xSWD, 11xGPIO(PWM), 6xADC	UART, I2C, and SPI Interfaces	1 x UART , 1 x SPI, 1 x I2C, GPIO, ADC
Dimensions	Diameter 25mm	21 x 17.5mm	30x20mm	55x50mm
Power	Battery (non rechargeable) - CR2032	Lithium Polymer battery Standby power consumption: <5A	Battery (non rechargeable)	Battery (non rechargeable)
Wireless Communication	BLE	BLE	BLE	BLE
Bluetooth Version	BT 4.1	BLE 5.0	BT 4.0	BT 4.2
USB Port	No	Included	No	No
Development Platform	Nordic Semiconductor SDK	Arduino IDE	Arduino IDE	Texas Instruments Code Composer Studio
Portable	Yes	Yes	Yes	Yes
Sensors Included	Yes	Yes	Yes	Yes
Sensors	temperature, humidity, accelerometer, gyroscope, magnetometer	6 IMU temperature, humidity, accelerometer, gyroscope	accelerometer, gyroscope, magnetometer, pressure	Supports 10 Low-Power Sensors: temperature, humidity, accelerometer, gyroscope, magnetometer, pressure, etc
Led included	Yes	Yes	Yes	Yes
Arduino library	No	Yes	Yes	No
Advantages	Low cost 3 axis Accelerometer Sensor RF 2.4Ghz BLE5.0 Low Power Consumption Bluetooth PCBA Module Indoor Positioning NRF52810	Low cost, Low Power, BLE5, Great documentation, not expensive, easy to start use and program, IMU with etra capabilities - like pedometer, etc	Low-power, extended-range capabilities	Advanced debugging and profiling tools

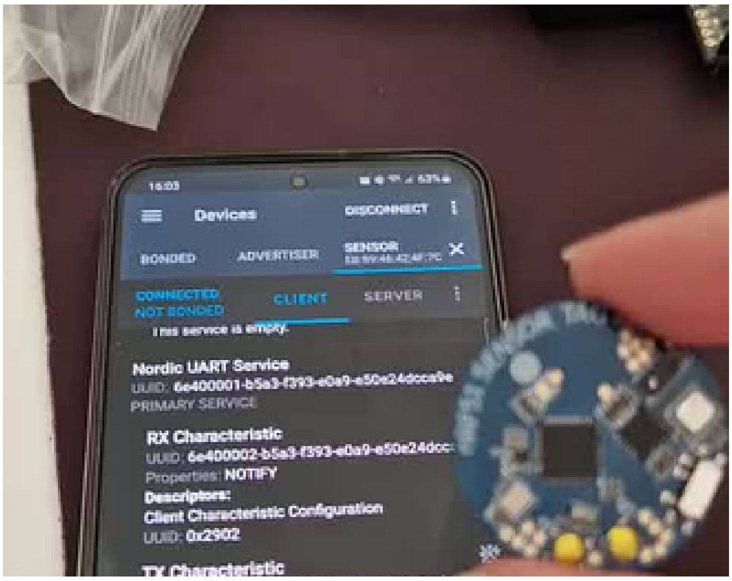
Table 4.1: Micro-controllers - Comparison Table

4.3.1 NRF51 Sensor Tag

The first micro-controller tested was the nRF51822, with the following main characteristics:

1. Adopt nRF51822 Bluetooth-Compatible 4.0 BLE SOC
2. ARM CORTEX-M0
3. 3-axis acceleration 3-axis gyroscope chip MPU6050
4. Adopt BMP180 temperature atmospheric pressure sensor chip
5. Sensing pressure range: 300-1100 hPa; Temperature range: -40- +85 Celsius
6. Ambient light proximity sensor chip AP3216
7. With power switch
8. Support CR2032 button battery to supply power
9. Size:30mm*30mm

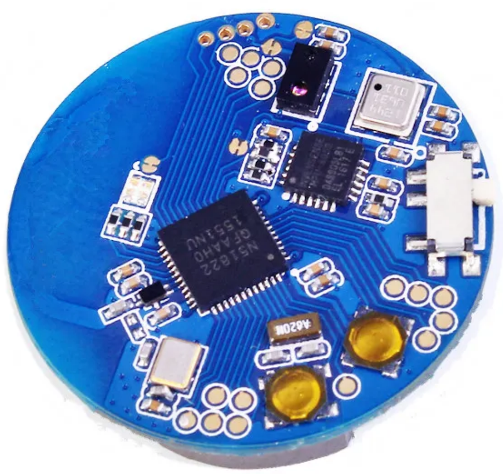
Figure 4.2: Example of a Mobile App used



Several tries were made, using apps in a mobile phone. Apps used: LightBlue, BLE Scanner, nRF Connect, EFR Connect.

It was excluded due to the lack of examples and public documentation. No data-sheet available, making it very difficult to use and experiment.

Figure 4.3: NRF51 Sensor Tag



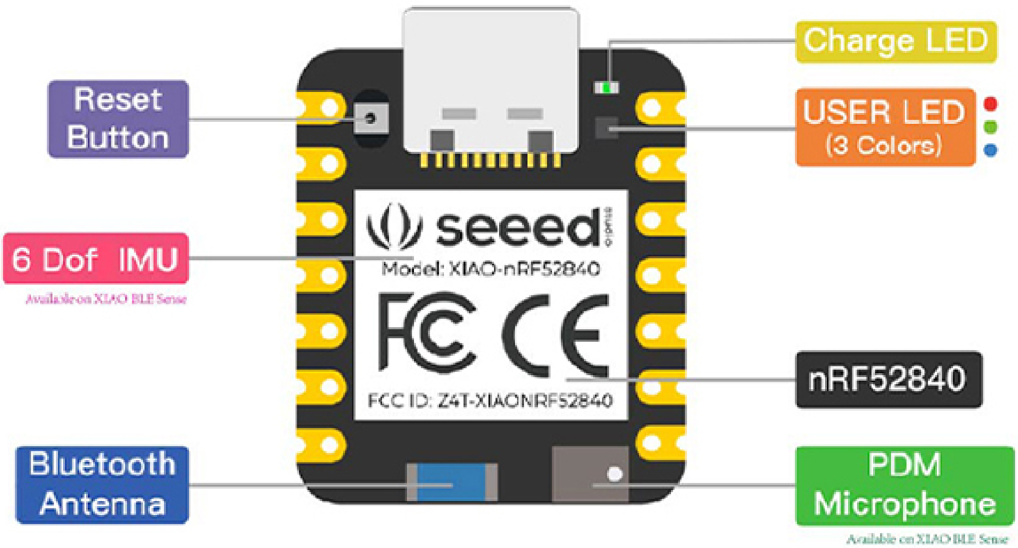
4.3.2 XIAO nRF52840 Sense

XIAO is a combination of compactness, capability, and user-friendly design. XIAO nRF52840 Sense features an onboard microphone and 3-axis IMU, suitable for the TinyML AI+IOT project, making it an ideal option for TinyML AI project. With:

- Onboard digital microphone for real-time audio recognition
- 6-aix IMU for gesture recognition
- Sensing, Processing, Communication in 1 Node

This micro-controller was chosen due to multiple features: it's small, works with a rechargeable battery,

Figure 4.4: XIAO nRF52840 Sense: Hardware overview

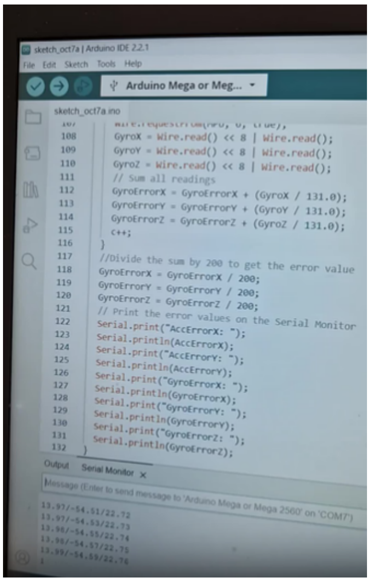


4.3.3 Texas Instruments BLE-1721

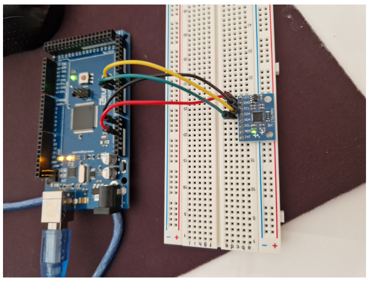
Excluded due to the size, price and the learning curve of the software, no extra tests were made with this micro-controller.

4.3.4 MPU6050

MPU6050 is a three-axis accelerometer and three-axis gyroscope Micro Electro-mechanical system (MEMS). It aids in the measurement of velocity, orientation, acceleration, displacement, and other motion-related features. It was not considered or compared because of the size.



(a) Arduino IDE: Testing MPU6050



(b) Hardware: Testing MPU6050

Figure 4.5: MPU6050: Experiment

4.4 Accelerometer and Gyroscope

Accelerometers detect linear acceleration of devices, that is, the acceleration along an axis. Gyroscopes, on the other hand, work with the Coriolis Effect instead of acceleration, and it detects the angular velocity, i.e, how fast the body is turning. In this project we will use Machine Learning to detect which gesture the person is performing by means of the accelerometer and gyroscope data coming from an IMU (Inertia Measurement Unit) sensor. To collect the data that will be trained and used in the model, the Accelerometer and Gyroscope are the ones that are used. It's important to understand the limitations or possible corrections to do to this data.

5

Proposed Solution for Automatic Movement Recognition

5.1 System Architecture Overview

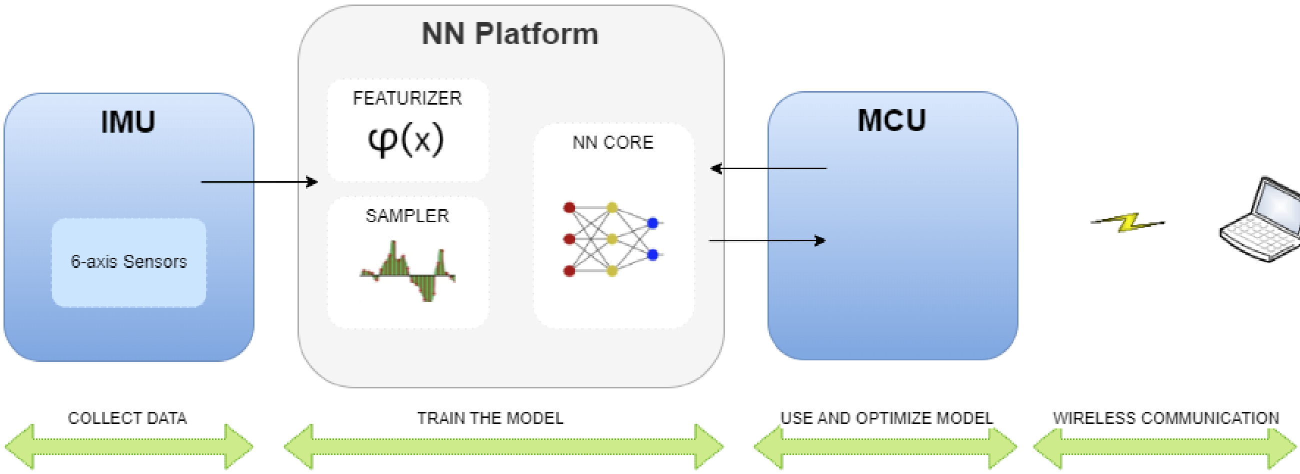
Building this embedded system for real-time motion recognition involves integrating an Inertial Measurement Unit (IMU), Micro-controller Unit (MCU), and an OLED display.

The system collects motion data through the IMUs accelerometer. The MCU, equipped with a Neural Network (NN) implementation, analyzes the motion data on-the-fly, categorizing movements as well or poorly executed, fast or slow, and correct or incorrect trajectory. This information will be display using a LED and an OLED display, depending on the equipment being used and the movement.

For training the NN, raw sensor data is transmitted to a computer - the host - via Bluetooth Low Energy (BLE). The approach follows a bottom-up methodology, starting with the platform selection, leveraging the accelerometer for precise data capture, conducting trials for diverse datasets, and implementing the neural network within the MCU to achieve accurate real-time motion analysis with low power consumption.

It's important to note that sample datasets were used to test some MCU and some parts of the system, but the goal is to build this datasets with live data, training the network.

Figure 5.1: System Architecture



5.2 Candidate Neural Network

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5.3 Initial Implementation

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How the micro controller and ML work together

começar a olhar para os dados recolhidos do acelerometro. - qual o ritmo de amostragem? 1 amostra (de cada eixo) por segundo? milisegundo? - qual a resolução da medida? quantos bits? - quando recebe os dados, pode usar o grafico do arduino para fazer um plot. vai observar a influência da força gravitica (existe sempre!). Como vamos compensar/remover esse efeito para ficarmos apenas com o movimento/deslocamento? Com a direcção da força gravitica tb sabemos para onde o peso está voltado/inclinado.

Falar do edge impulse? eu abro o website do edge impulse e há lá 1001 coisas disponíveis nos menus. referir apenas tool do edge impulse não diz o que está a fazer... é preciso dizer, escolheu o dataset XPTO que se encontra em www.abcd.com/xpto, depois usou ZZZ de www.zzz.com e obteve YYY, e por aí fora. se nao, ninguem consegue repetir essas experiencias

Edge impulse Build datasets, train models, and optimize libraries to run on any edge device, from extremely low-power MCUs to efficient Linux CPU targets and GPUs. Edge Impulse provides a range of neural network architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and fully connected networks.

6

Evaluation Methodology and Preliminary Results

In this chapter it's possible to see the preliminary tests that were done. First to understand how to collect the data, afterwards to start understanding how to work with that data. Creating the first datasets to be analysed and in the future improved, also testing the first draft of Models and tools. So far, the selection of the material seems to be nearing a final decision. However, during testing, as mentioned earlier, some of the materials were changed

There is still a few challenges to overcome:

- optimize power consumption through efficient sensor sampling rates, low-power modes, and smart algorithms to minimize the impact on device battery life.
- Real-time processing is crucial for immediate feedback in sports applications.
- Wearable devices need to be comfortable, small, light for users during various sports activities.
- Use the best Option for training the model

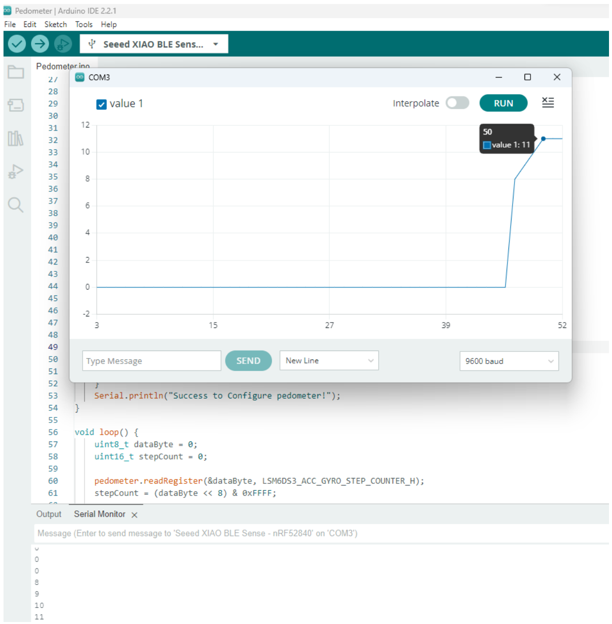
6.1 Pedometer Experience

A demonstration of how to collect the data from the sensor, and using the potential of it's libraries. In this case, to show number of steps walked thought time, just by using a simple count.

Material used:

1. Seeed Studio XIAO nRF52840 Sense
2. Arduino IDE

Figure 6.1: Serial Plotter with number of Steps: 11 in this case



6.2 Tiny-ML Magic Wand Experience

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Material used:

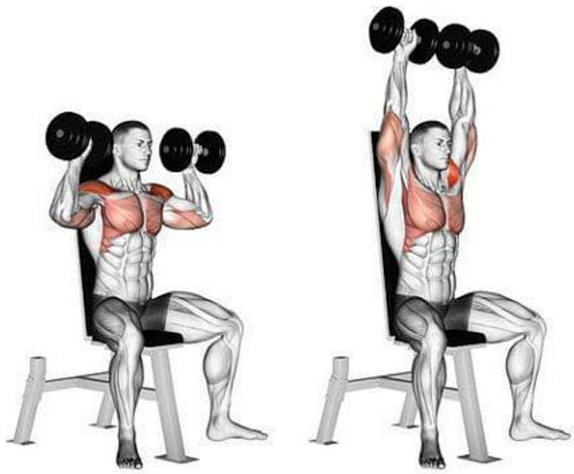
1. XXXXX Micro-controller
2. Arduino IDE

Figure 6.2: Magic Wand Material

6.3 IMU classifier with TensorFlow Lite Experience

In this example, it was used TensorFlow Lite on Seeed Studio XIAO nRF52840 Sense and detect gestures such as punching and flexing using the on-board accelerometer.

Figure 6.3: Flex exercise

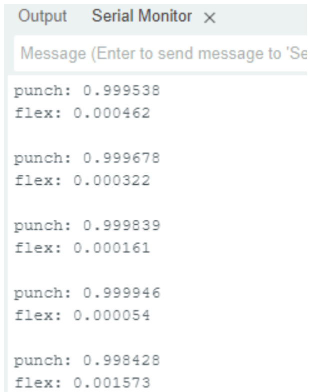


Material used:

1. Seeed Studio XIAO nRF52840 Sense
2. Arduino IDE
3. Pre-built model (dataset)
4. TensorFlow Lite Library

In the serial monitor, the following results could be observed.By monitoring and performing a flexing action, it can be seen that will give a result close to 1 next to flex. By monitoring and performing a punching action, it can be seen that will give a result close to 1 next to punch.

(a) Flex result



(b) Punch result

Figure 6.4: IMU classifier with TensorFlow Lite: Results

6.4 IMU classifier with TensorFlow Lite using Edge Impulse Experience

Seeed Studio XIAO nRF52840 Sense Edge Impulse Getting Started

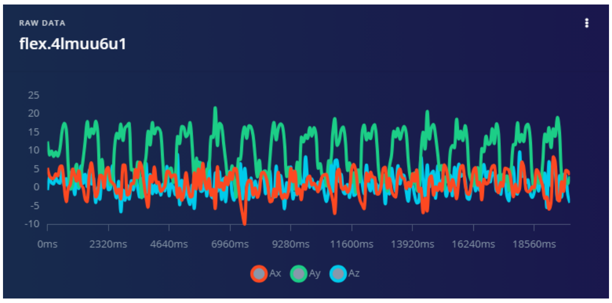
- **Data Collection:** Collect data directly to edge impulse
- **Train the model:** Create and train a model in Edge Impulse

  Spectral Analysis *- Great for analyzing repetitive motion, such as data from accelerometers. Extracts the frequency and power characteristics of a signal over time.* ***Classification*** *- Learns patterns from data, and can apply these to new data. Great for categorizing movement or recognizing audio.*
- **Test Results:** Upload the library, TensorFlow lite and model to the micro-controller

In this case, it was used the following material:

1. Seeed Studio XIAO nRF52840 Sense
2. Edge impulse platform (uses tensor flow lite)
3. Arduino IDE

Figure 6.5: MU classifier with TensorFlow Lite using Edge Impulse: Raw data graph



Results:

Figure 6.6: MU classifier with TensorFlow Lite using Edge Impulse: Model

Figure 6.7: MU classifier with TensorFlow Lite using Edge Impulse - Result: Flex

```
Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 24 ms., Classification: 0 ms., Anomaly: 0 ms.):
    flex: 0.99609
    punch: 0.00391
```

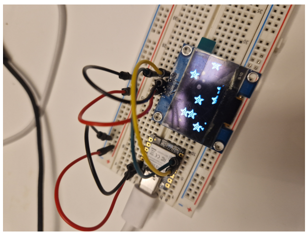
Figure 6.8: MU classifier with TensorFlow Lite using Edge Impulse - Result: Punch

```
Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 24 ms., Classification: 0 ms., Anomaly: 0 ms.):
    flex: 0.01562
    punch: 0.98438
```

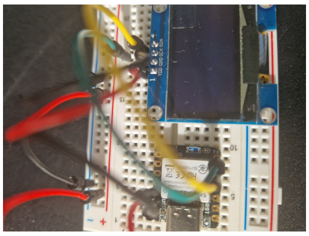
6.5 Stars - OLED experience

In this case,the following material was used :

1. Seeed Studio XIAO nRF52840 Sense
2. OLED XFP1116
3. Breadboard
4. Breadboard jumper wire



(a) OLED Display



(b) Breadboard with the components to perform the Experience

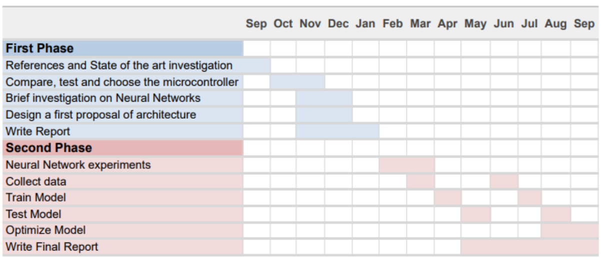
Figure 6.9: OLED Experiment

7

Work Plan

The project reach now a state, that is possible to have a vision of the future planning and what needs to be done. This plan can be checked in figure 7.1.

Figure 7.1: Gantt chart project plan



There are already some modifications to the objectives based on the results obtained so far, regarding the proposed micro-controller, another one was found and seems to be a better choice to the project.

8

Conclusions

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Partial Conclusions:

Summarise the key points achieved so far.

Highlight any necessary adjustments to the original objectives or approach.

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