Lab 2 - Gesture or Motion Classification

Introduction

In this lab, we will ask you to create a fully-functioning embedded machine learning system. The process will include collecting data, performing feature extraction, training a model, and deploying that model to an embedded system.

We will classify the motion and vibration data made by you (as in the class example) or from a machine of your choice. This is to mimic using embedded machine learning in an industrial environment. We want to be able to determine if a machine is off, on, low, high, anomaly, etc.

Required Hardware

You may use the TinyML Kit based on [Arduino Nano 33 BLE Sense] to complete the project. You will also need some tape (recommended: electrical tape) to secure your Kit to the machine (If you prefer, use only the Nano-33 instead the complete Kit.

Setup

Before we start collecting data, we must first figure out what we want to monitor! In the class, we constructed a demo that classified person-made hand movements. In this project, we will work preferably with machines to classify operating modes and look for anomalies (As a minimum task, you can repeat the class example).

To begin, choose a machine in your home that produces some kind of vibration data that you wish to monitor and classify. Here are some ideas of things you may want to monitor:

- Washing machine
- Blender
- Air compressor
- Refrigerator
- Air conditioner
- Keyboard (typing)
- Ceiling fan

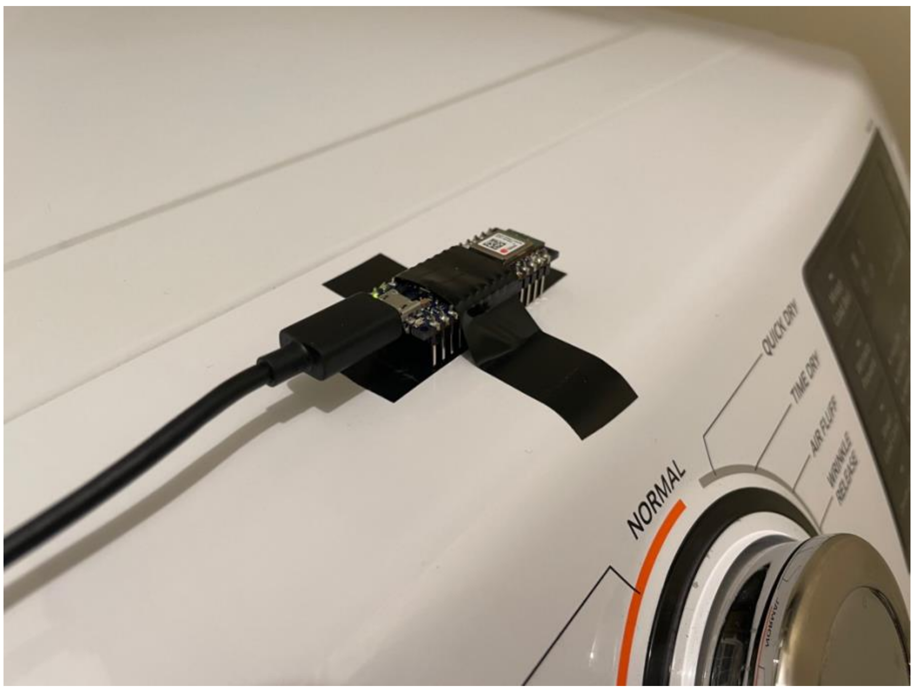
Connect Device to Edge Impulse

Create a new project on Edge Impulse. Give the project a name, such as “IESTI01-industrial-motion-classifier.”

Attach Device

Use some tape to adhere your Arduino board (or Kit) to your chosen device.

WARNING: If the device is metal, put a layer of tape down as a barrier to prevent the Arduino’s pins from shorting together.



Note that you will need to connect your Arduino board to your computer. Connect your Arduino to your computer using a USB cable.


SAMSUNG
SAMSUNG


Oster
0
Off
Pulse
7 8 9 10 11 12
1 2 3 4 5 6

Data Collection

Head to the **Data acquisition** page in your Edge Impulse project. Your device (if connected) should show up on the right side of the window. If not, follow the steps showed on class to connect a device to your project.

You will need to choose a few classes for your model to be able to predict. For example, on the above "Blender project", was tried to capture the motion on a 12 Speed Blender (with a pulse button).

The classes were:

1. Off (motor off, with eventual movent of the blender)
2. Low_Empty (Speed 1, Empty Jar)
3. Low_Water (Speed 1, Jar with 500ml of water)
4. High_Water (Speed 12, Jar with 500ml of water)

For the Washing Machine project, the model was able to identify when the dryer was in one of the following states:

- Off
- Light load
- Heavy load

Collect at least 2 minutes of accelerometer data for each class. When you're done, you should see the collected data filled out with samples. Don't forget to label your class before you start collecting data!

When you're done, repeat the process for the test data. However, you only need to collect about 30 seconds of data for each class.

Feature Extraction

Head to the **Impulse design** page in your project. Add a **Spectral Analysis** processing block. Add a **Neural Network** block and a **K-means Anomaly Detection** block to the learning blocks section.

Head to the **Spectral Features** page and click **Generate features**. Take a look at the *Feature explorer*. What patterns do you see in the samples? Can your classes be easily separated?

Try changing the *X Axis*, *Y Axis*, and *Z Axis* parameters in the *Feature explorer*. Which features offer the best separation among the groupings of labels? In our class example, RMS offered decent separation. Write down which set of features offers the best separation. You will want to select these features in the Anomaly Detection section.

Model Training

Head to the **NN Classifier** page in your project. Click **Start training**. After a few minutes, the model should be done training.

Scroll down and take a look at your confusion matrix. You should see good accuracy for not just the whole model but within each class.

If you're not happy with the results, try changing some of the hyperparameters and train again! For example, change the training cycles (epochs), add another neural network layer, change the nodes in each layer, learning rate, etc.

Be careful of overfitting! If you see that the validation loss is much higher than the training loss (look carefully at the training output), your model may be overfit. In that case, try reducing the number of nodes or layers in your model and try again.

The ultimate goal is to find the smallest neural network (smallest number of nodes and layers) that meets your needs. As you increase the number of nodes and layers, you increase the computational complexity of the model, which requires more resources in your microcontroller.

Ideally, you want your validation accuracy to be in the 80-95% range, depending on your application).

Go to the **Anomaly detection** page of your project. Select the features that you wrote down in the previous section (these will most likely be the RMS values for the X, Y, and Z axes). Click **Start training**. When that's done, you should see your features with their clusters in the *Anomaly explorer*.

Model Testing

Go to the **Model testing** page in your project. Click the checkbox next to *Sample Name* to select all of your test samples. Click **Classify**. After a few moments, your test set should be classified using the model you trained.

If you see something less than about 65% accuracy, your model may be overfit or underfit. Try collecting more data and adjusting some of the hyperparameters.

Be careful! Each time you update your model's hyperparameters because of some new information from the test set, you then begin introducing bias into your model, such that it may overfit the test set as well. At this point, your test set is no longer a test set, but rather a secondary validation set.

I recommend gathering new test data if you plan to adjust the hyperparameters and re-train the model at this point. You can move your test samples to the training set if you wish (in *Data acquisition* > *Test data*). Also, if you go to the *Dashboard* for your project, you can click *Rebalance dataset* to have Edge Impulse automatically group your training and test datasets together and then randomly split them up again into training and test sets.

Deployment

Make sure that your Arduino board is in the same spot as when you collected data! If you move it, you could affect the accelerometer readings.

Head to the **Deployment** page in your Edge Impulse project. Click on **Arduino library**, scroll down, and click **Build**.

Once your project has been downloaded, open the Arduino IDE. Go to **Sketch > Include Library > Add .ZIP library**. Select your downloaded .ZIP file from Edge Impulse. Go to **File > Examples > <your-project> > nano_ble33_sense_accelerometer**.

Click **Upload** to compile and send the program to your Arduino board. This may take over 10 minutes to compile and upload.

When it's done, open a serial monitor. Run your machine in the various modes to see if your Arduino can correctly classify the mode.

Challenge:

Try flashing the Arduino's onboard LED whenever either a particular class or anomaly value is above a threshold. What threshold you choose is up to you. I recommend starting with 0.6 if you're using a class label or 0.3 if you're using the anomaly score.

For example, in the blender project, the Arduino code was changed to include the Nano LEDs, following the logic:

- High_Water ==> Red ON
- Low_Empty: ==> Green ON
- Low_Water: ==> Blue ON
- Off: ==> All OFF

If the anomaly score was positive, the internal LED was also ON

- Anomaly ==> LED_BUILTIN ON

Low_Empty (green)	Low_Water (blue)	High_Water (red)	Anomaly
High_Water: 0.00000 Low_Empty: 0.75391 Low_Water: 0.19531 Off: 0.05078 Prediction: Low_Empty	High_Water: 0.20703 Low_Empty: 0.00000 Low_Water: 0.79297 Off: 0.00000 Prediction: Low_Water	High_Water: 0.70312 Low_Empty: 0.11719 Low_Water: 0.18359 Off: 0.00000 Prediction: High_Water	High_Water: 0.00000 Low_Empty: 0.99609 Low_Water: 0.00000 Off: 0.00000 Prediction: Low_Empty anomaly score: 0.181