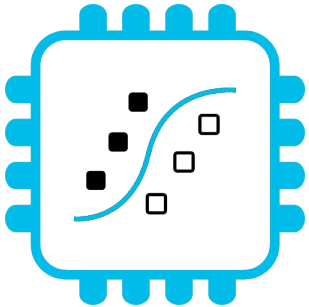
emlearn

6 years of TinyML



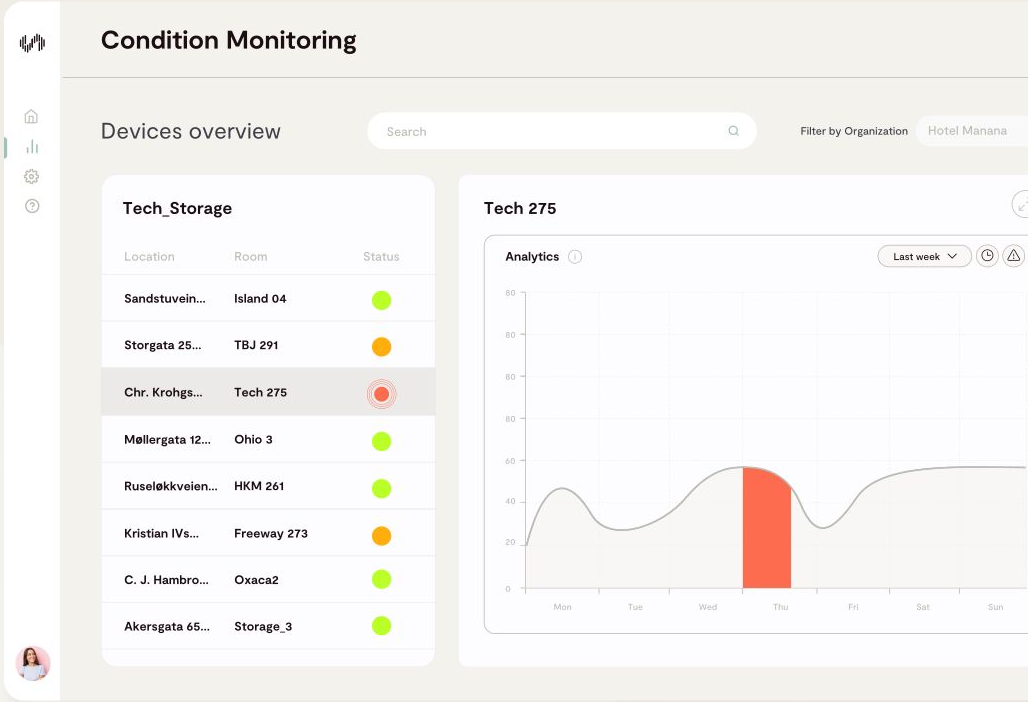
"scikit-learn for microcontrollers"

https://github.com/emlearn/emlearn

Jon Nordby jononor@gmail.com

We utilise sound and vibration analysis to detect and warn you of upcoming errors in your technical infrastructure before they happen.

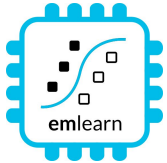
soundsensing



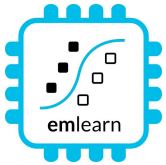
Trusted by Nordic market leaders

anthon eiendom · RAGDE EIENDOM · NORDR · SELVAAG · AF EIENDOM · OBOS · THON EIENDOM · EIENDOMSSPAR · Oslo · WÄRTSILÄ · ASPELIN RAMM · MALLING & CO · STATSBYGG

Outline / agenda

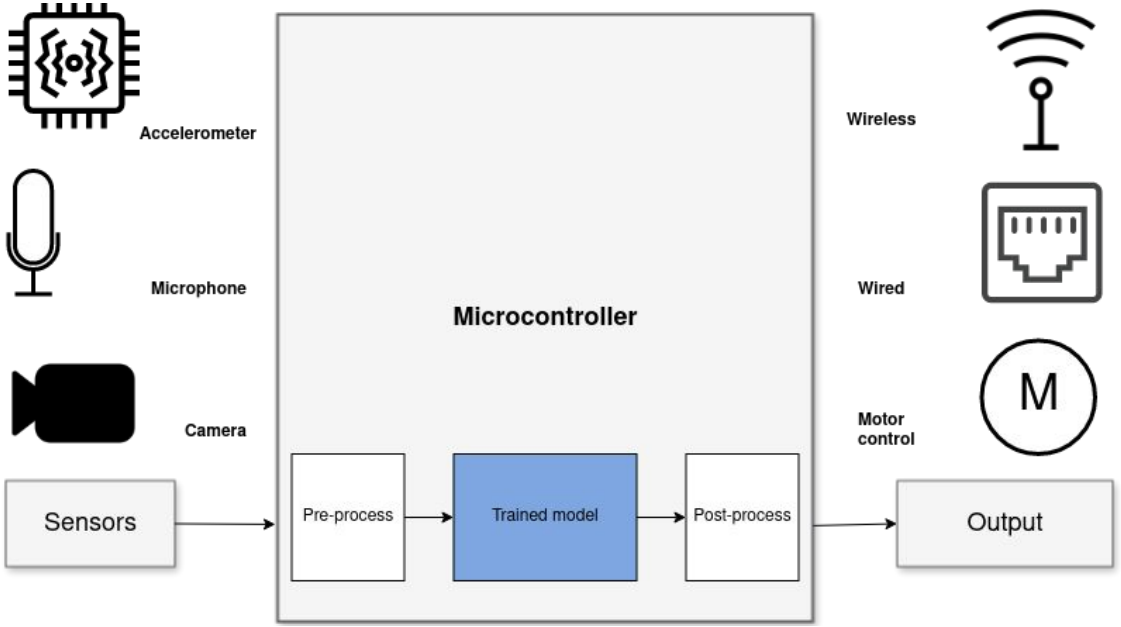


1. **Introduction** to emlearn project
2. Model spotlight: **Tree-based ensembles**
3. **Projects** made with emlearn
4. TinyML using Python with **emlearn + MicroPython**



Introduction

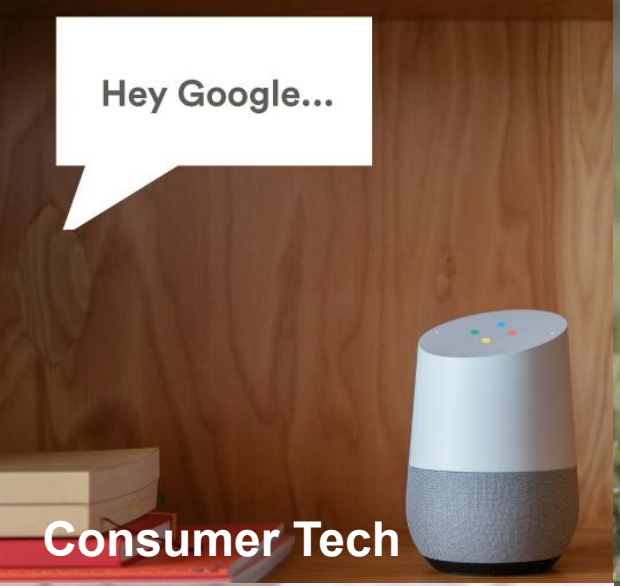
Sensor data analysis with Machine Learning



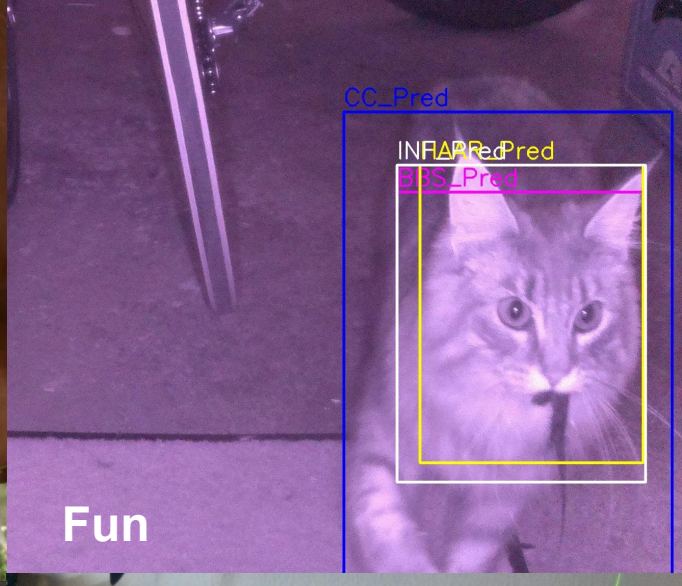
System diagram for “TinyML” solution

Benefits vs sending data to cloud

- Stand-alone
- Low latency
- Power efficiency
- Privacy
- Low cost

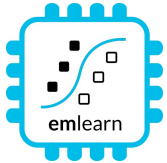

Hey Google...
Consumer Tech


Industrial


CC_Pred
INFRARed_Pred
BBS_Pred
Fun


15:34
Heart Rate
52
62
06:45
00:45 AM
75%

emlearn
- Machine Learning for microcontrollers



https://github.com/emlearn/emlearn/

Convenient training

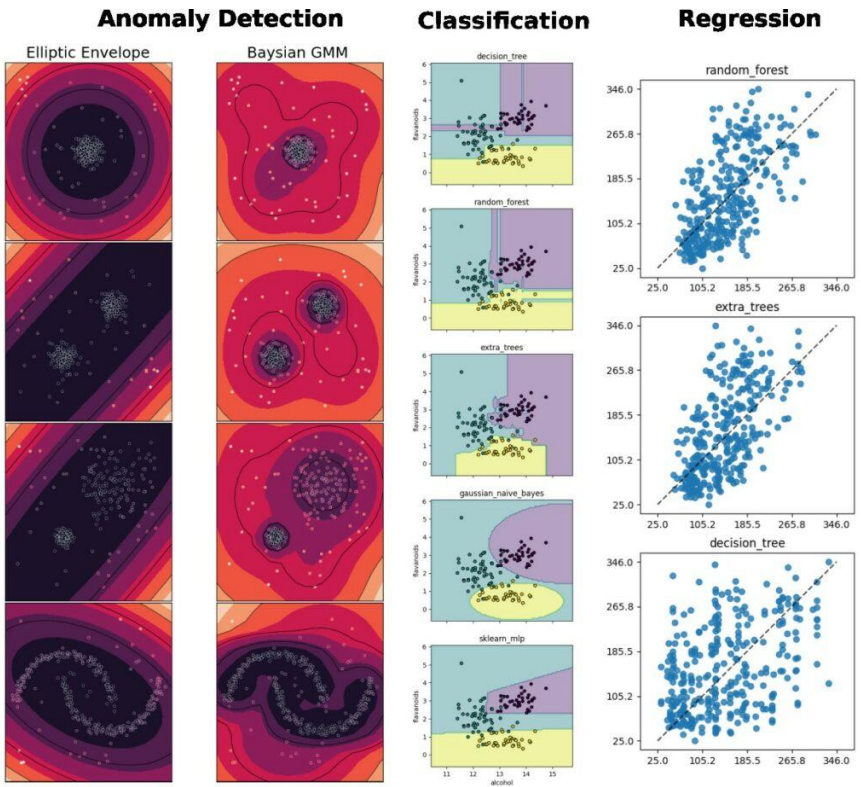
- Model creation **in Python**
- **Use standard libraries**
  a. scikit-learn
  b. Keras
- One-line to **export to C**
- Verification tools included

Embedded Friendly C code

- **Portable C99** code
- No dynamic allocations
- **Header-only**
- High **test coverage**
- Integer/**fixed-point** math *
- **Small**. 2 kB+ FLASH

* Only some models

Supported tasks



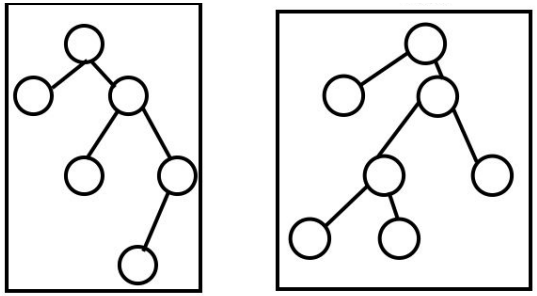
Supports the most common tasks for embedded
& sensor data use cases.

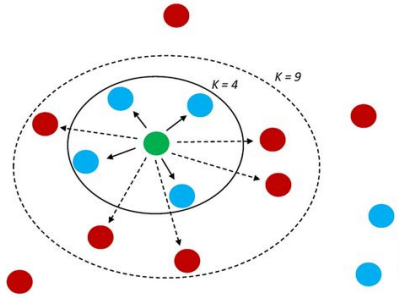
- Classification
- Regression
- Anomaly Detection

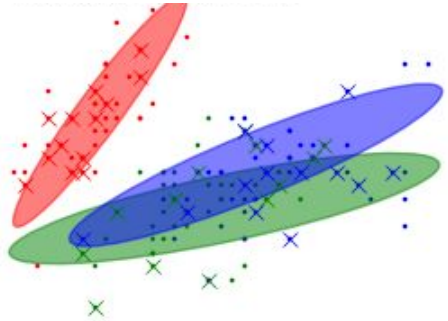
Supported models

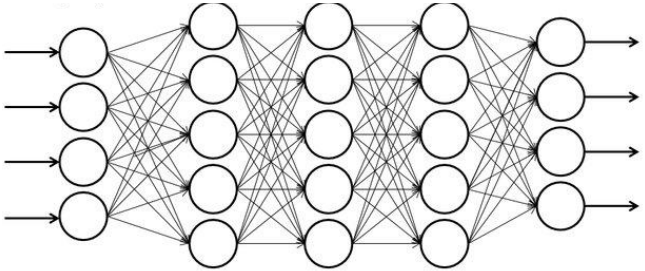
Selection of simple & effective embedded-friendly models

- Decision Trees (DT)
- Random Forest (RF)
- K Nearest Neighbors (KNN)
- Gaussian Mixture Models (GMM)
- Multi-Layer-Perceptron (MLP)

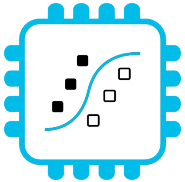








How to use emlearn



0. Install the library

1. Train model in Python

2. Convert model to C code

3. Use the C code

0. Install

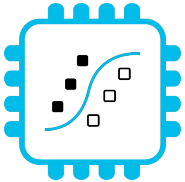
As Python package (PyPI)

```
pip install emlearn
```

As git submodule

```
git submodule add \
  https://github.com/emlearn/emlearn/
```

Train and export a model



1. Train using standard Python ML libraries.

```
from keras import …

model = Sequential([
    Dense(16, input_dim=n_features, activation='relu'),
    Dense(8, activation='relu'),
    Dense(1, activation='sigmoid'),
])
model.compile(....)
model.fit(X_train, Y_train, epochs=1, batch_size=10)
```

A) keras neural network

```
from sklearn.neural_network import MLPClassifier
model = MLPClassifier(hidden_layer_sizes=(100,50,25))

model.fit(X_train, Y_train)
```

B) scikit-learn neural network

2. Use **emlearn.convert()** and **.save()**

```
import emlearn

cmodel = emlearn.convert(model, method='inline')

cmodel.save(file=mynet_model.h', name='mynet')
```

```
#include <eml_net.h>

static const float mynet_layer_0_biases[8] = { -0.015587f, -0.005395f, -0.010957f, 0.015883f ….
static const float mynet_layer_0_weights[24] = { -0.256981f, 0.041887f, 0.063659f, 0.011013f, …
static const float mynet_layer_1_biases[4] = { 0.001242f, 0.010440f, -0.005309f, -0.006540f };
static const float mynet_layer_1_weights[32] = { -0.577215f, -0.674633f, -0.376140f, 0.646900f, …
static float mynet_buf1[8];
static float mynet_buf2[8];
static const EmlNetLayer mynet_layers[2] = {
{ 8, 3, mynet_layer_0_weights, mynet_layer_0_biases, EmlNetActivationRelu },
{ 4, 8, mynet_layer_1_weights, mynet_layer_1_biases, EmlNetActivationSoftmax }
};
static EmlNet mynet = { 2, mynet_layers, mynet_buf1, mynet_buf2, 8 };

    int32_t
    mynet_predict(const float *features, int32_t n_features)
    {
        return eml_net_predict(&mynet, features, n_features);
    }
.....
```

Example of generated code

Using the C code

3. **#include** and call **predict()**

```
// Include the generated model code
#include "mynet_model.h"

// index for the class we are
detecting
#define MYNET_VOICE 1

// Buffers for input data
#define N_FEATURES 6
float features[N_FEATURES];

#define DATA_LENGTH 128
int16_t
sensor_data[DATA_LENGTH];
```

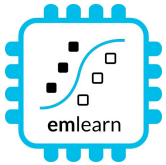
setup

```
// Get data and pre-process it
read_microphone(sensor_data, DATA_LENGTH);
preprocess_data(sensor_data, features);

// Run the model
out = mynet_predict(features, N_FEATURES);

// Do something with results
if (out == MYNET_VOICE) {
    set_display("voice detected");
} else {
    set_display("");
}
```

loop



Tree-based ensembles

Random Forest / Decision Tree

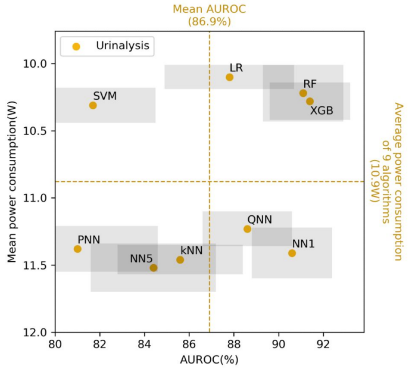
The most popular model in emlearn

Trees - relevant across the task complexity range

Low

Go-to for tabular data

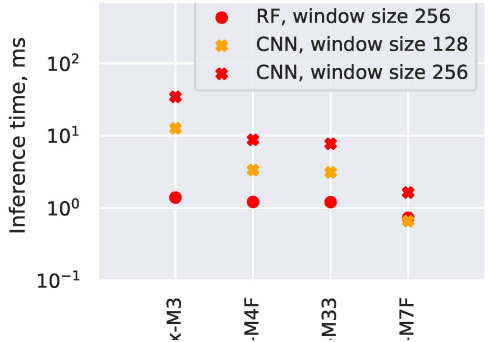
Very easy to get good performance, with minimal tweaking.



Medium

Alternative to deep learning

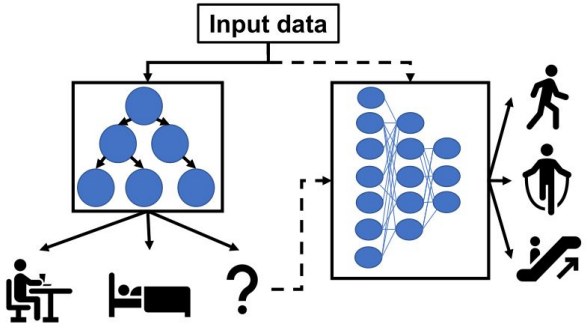
Elsts et.al [1] showed performance matching a deep-learning approach, at 10x to 100x better resource usage



High

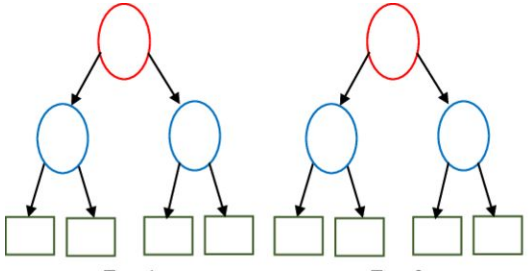
Combine with neural network

Daghero et.al [2] showed up to 67.7% energy saving using two-stage approach



1. *"Are Microcontrollers Ready for Deep Learning-Based Human Activity Recognition?"*
   Atis Elsts, Ryan McConville (2021) https://www.mdpi.com/2079-9292/10/21/2640
2. *"Two-stage Human Activity Recognition on Microcontrollers with Decision Trees and CNNs".*
   Francesco Daghero, Daniele Jahier Pagliari, Massimo Poncino (2022) https://arxiv.org/abs/2206.07652
3. *"Energy Efficiency of Inference Algorithms for Clinical Laboratory Data Sets: Green Artificial Intelligence Study"*
   Jia-Ruei Yu et. al (2022) https://www.jmir.org/2022/1/e28036/

emlearn trees: Leaf compression

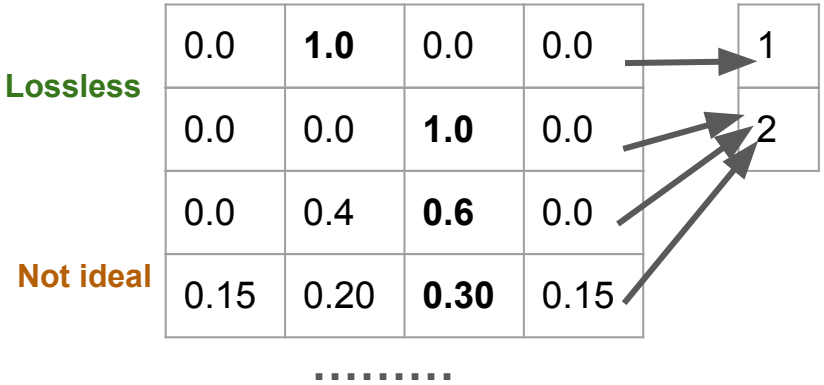


scikit-learn decision trees store class probabilities in leaf-nodes. Size: n_leaves * n_classes * 4 bytes
Consequence: Leaves take a large amount of space

emlearn (since 2019) does **hard majority voting** instead
And does **leaf-node de-duplication** *across* all trees

Size: n_classes * 1 * 1 byte
Saving 50-80% of space

Tradeoff: May read to reduced predictive performance with some leaf values



emlearn trees: Inference modes

Data structure (“loadable”)

+ Can be loaded at runtime
- Only supports float

```
static const EmlTreesNode xor_model_nodes[14] = {
  { 1, 0.197349f, 1, 2 },
  .........
  { 0, 0.421164f, -2, -1 }
};
EmlTrees xor_model = {  14,  xor_model_nodes,  ……  };

static int32_t
eml_trees_predict_tree(const EmlTrees *f, int32_t tree_root,
                       const float *features, int8_t features_length) {
    int32_t n = tree_root;
    while (n >= 0) {
        const float value = f[forest->nodes[node_idx].feature];
        const float point = forest->nodes[node_idx].value;
        const int16_t child = (value < point) ?
                    f->nodes[n].left : f->nodes[n].right;
        …..
    }
    return leaf;
}
```

Code generation (“inline”)

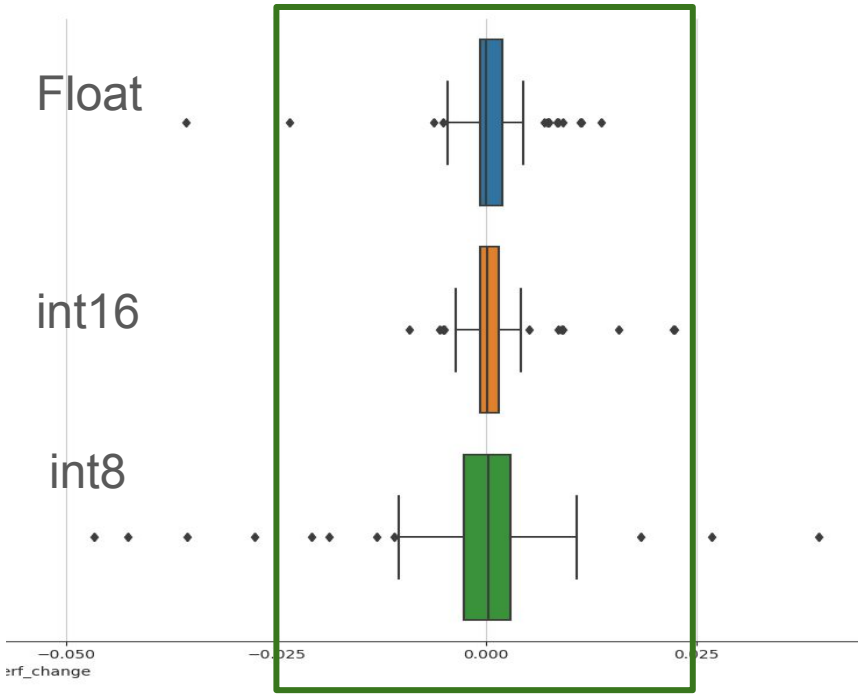
+ Supports int8/int16/int32 and float

```
static inline int32_t
xor_model_tree_0(const float *features, int32_t
features_length)
{
    if (features[1] < 0.197349f) {
        if (features[0] < 0.466316f) {
            return 0;
        } else {
            return 1;
        }
    } else {
        if (features[1] < 0.256702f) {
            if (features[0] < 0.464752f) {
                return 0;
            } else {
                return 1;
            }
        } else {
....
}
```

emlearn trees: Upcoming optimizations

Fixed point for loadable

int16 instead of float
12 bytes -> 8 bytes per node



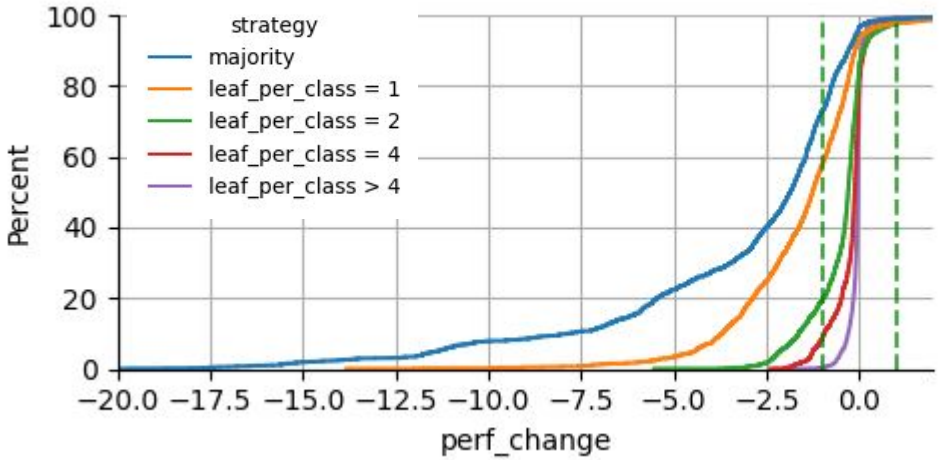
-0.025 to +0.025
Change in AUC ROC
= practically lossless

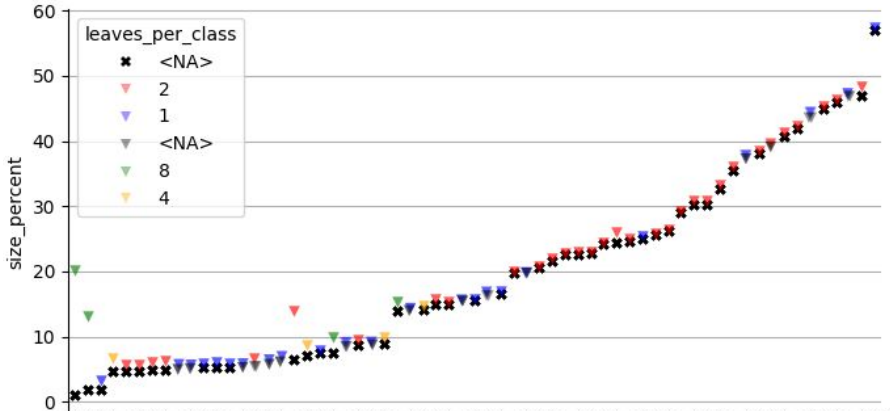
Evaluated on 48 datasets from OpenML CC18 suite

emlearn trees: K-means clustering for leaf de-duplication

Optimizing for: Small model size
Constraint: Under 1 percentage point drop in AUC ROC
Evaluating on 48 datasets from OpenML CC18 suite

Preliminary results
- paper to follow

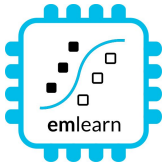




Hard majority
sometimes bad:
Failed perf constraint on 75% of datasets

Clustering with
N leaves per class
Allows adaptable size/perf tradeoff

2-8 leaves per class sufficient
0% of datasets failed performance constraint
High model size compression 50-90%



Projects using emlearn

Real-world uses across the globe

Referred in 40+ publications

Health monitoring for cattle

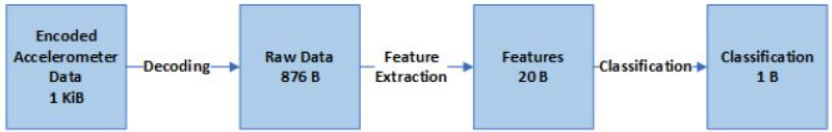
Accelerometer data
used to **detect abnormal behavior**.
Can indicate **health issues** or other problems

Classified using a **Decision Tree**
lying/walking/standing/grazing/ruminating

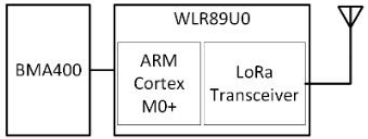
Activity is transmitted using **LoRaWAN**

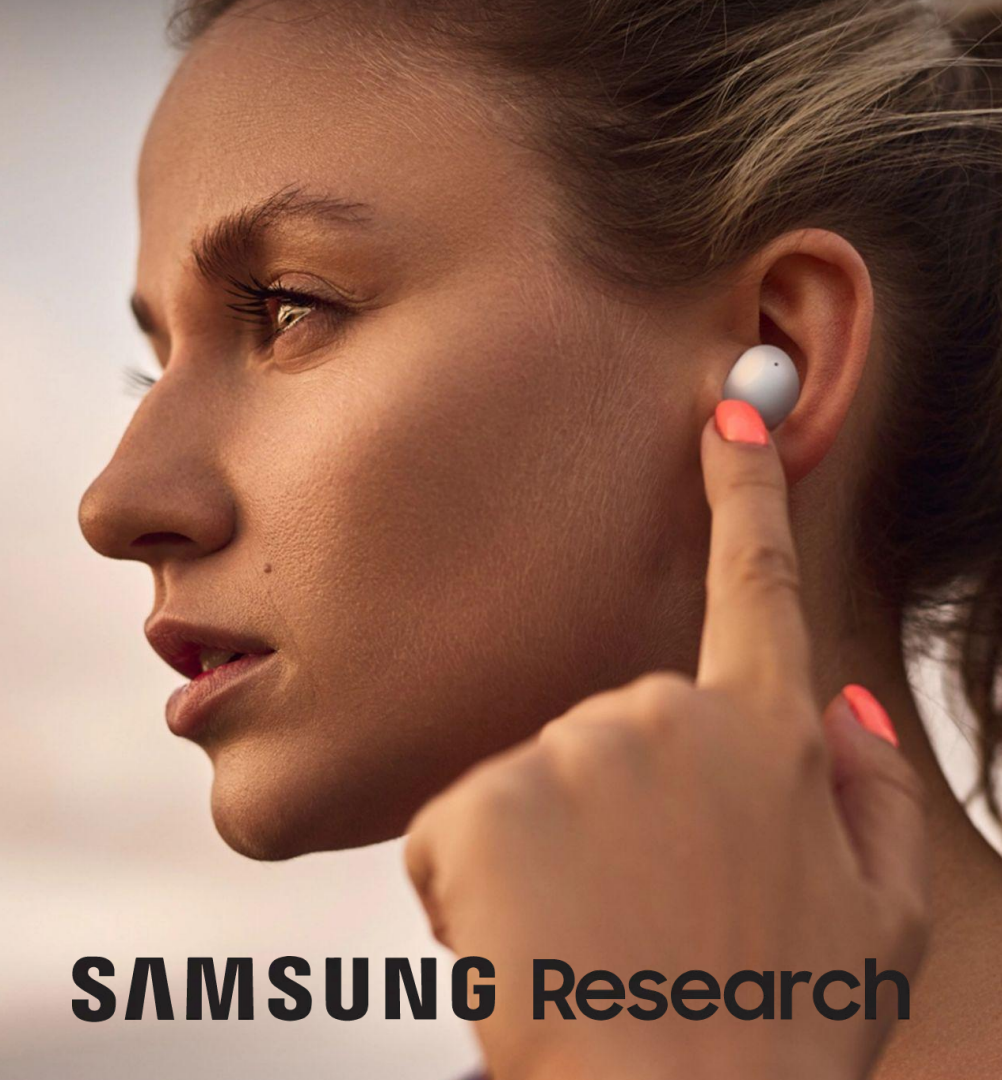
Running ML on-sensor: **under 1 mW**

50 times lower power than sending raw data



Power Efficient Wireless Sensor Node through Edge Intelligence
Abhishek Damle (2022)



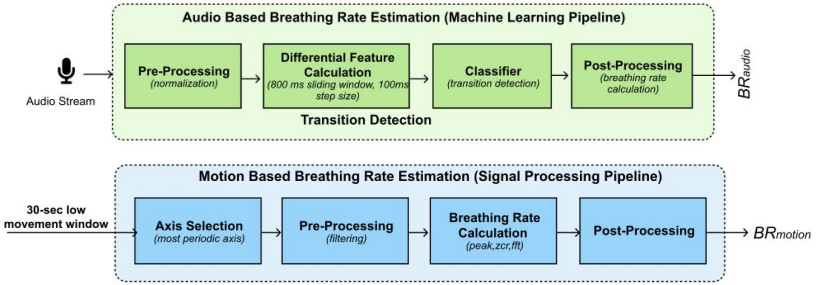


Health monitoring earable

Breathing rate is critical to monitor for persons with **respiratory health problems**.

Monitoring **for every-day use**, not just in clinical context. Using earable to replace specialized devices.

Random Forest classifier for audio.



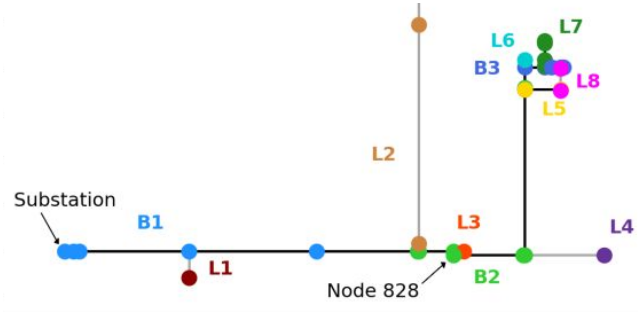
Remote Breathing Rate Tracking in Stationary Position Using the Motion and Acoustic Sensors of Earables
Tousif Ahmed et.al (2023)

Electric grid monitoring

Detect and localize faults in the electric grid.

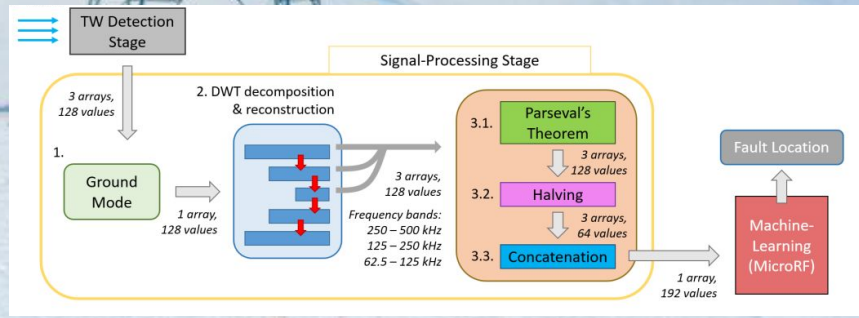
Analyzes the voltage signals at a single location. Able to detect where the fault originated.

Runs on a DSP board from Texas Instruments.



Micro Random Forest: A Local, High-Speed Implementation of a Machine-Learning Fault Location Method for Distribution Power Systems
Tousif Ahmed et.al (2023)

Sandia National Laboratories



1 dollar TinyML

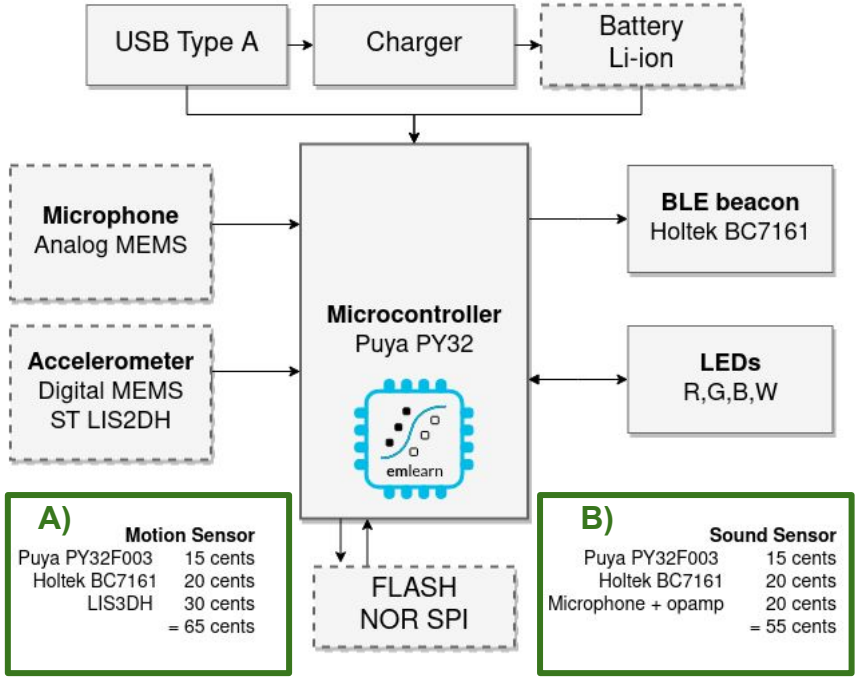
https://hackaday.io/project/194511-1-dollar-tinyml

Research project.

Question:
Can we make a useful TinyML system
<1 USD in total component cost (BOM)?

Preliminary answer:
Either motion (accelerometer)
or sound sensor (microphone)

Challenge:
4 kB RAM / 32 kB FLASH



1 dollar TinyML

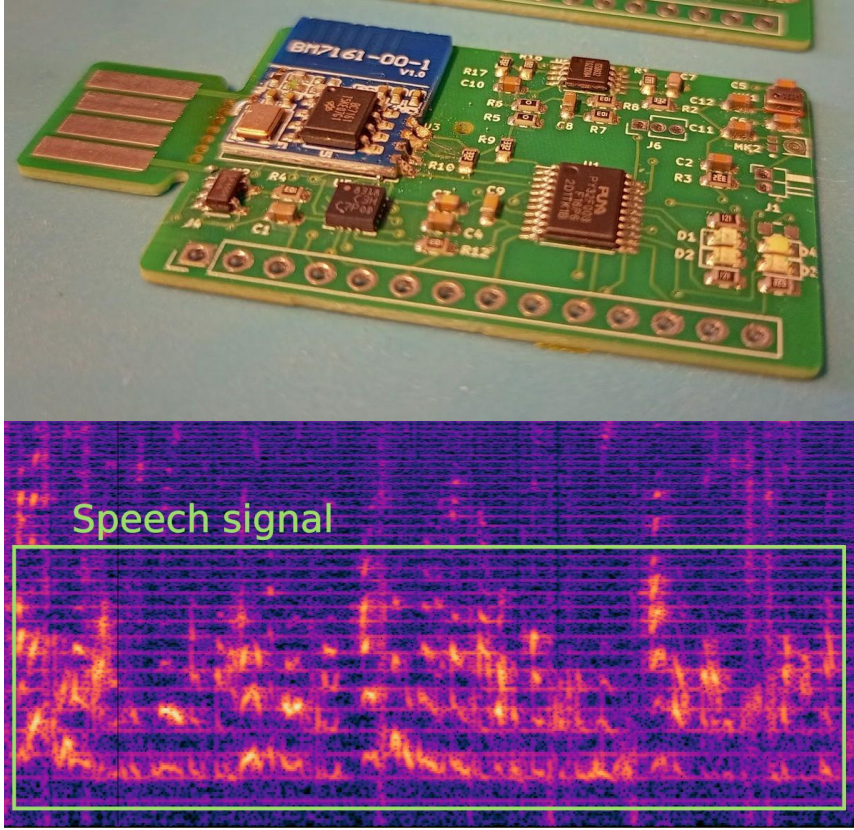
https://hackaday.io/project/194511-1-dollar-tinyml

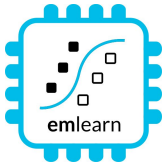
Status

- Basic hardware checks OK
- 8 kHz audio sampling OK
- FFT spectrogram compute OK
  - 1 second window
  - 32 frequency bins
  - 32 ms time resolution

TODO

- Fit ML model in
  800 bytes RAM // 10 kB FLASH
- Implement BLE transmission





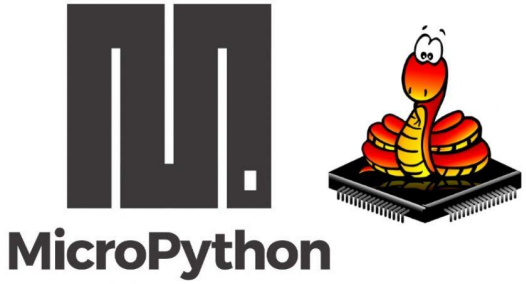
emlearn for MicroPython

Python is the lingua franca
for Machine Learning

How can we enable people to build
TinyML solution also using Python?

For easier learning and prototyping

MicroPython - Introduction



Implements a subset of Python 3.x

For devices with 16 kB+ RAM
Supports 8+ microcontroller families

As compatible with CPython as possible, within constraints.

No CFFI or C module compatibility!
TLDR: Small scripts will mostly work with minor mods. But not PyData stack

Package manager “**mip install**”
Can load C modules at runtime!

RP2040

More info: https://micropython.org

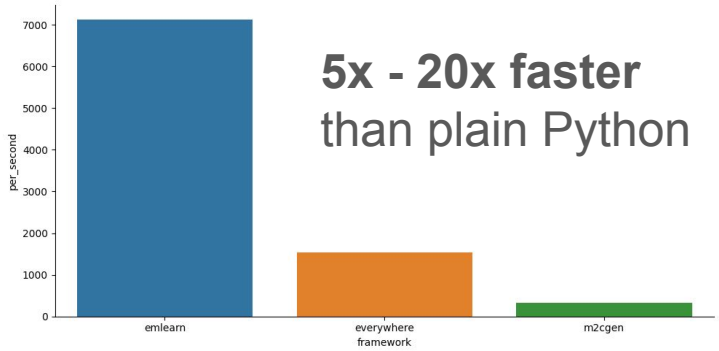
emlearn-micropython:
MicroPython bindings for emlearn

https://github.com/emlearn/emlearn-micropython/

Combine the **convenience, familiarity and productivity of Python** - with the **speed of C**

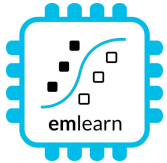
Modules installable at runtime (.mpy)

- Random Forest (RF) / Decision Trees (DT)
- K Nearest Neighbors (KNN)
- Infinite Impulse Response filters (IIR)
- Fast Fourier transform (FFT)
- Convolutional Neural Networks - via TinyMaix (CNN)



5x - 20x faster
than plain Python

emlearn-micropython: Install & Export model



Export model on PC

```
import emlearn

estimator = train_model()
converted = emlearn.convert(estimator)
converted.save(name='gesture', format='csv', file='gesture_model.csv')
```

Copy model to device

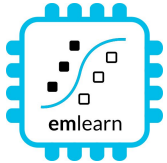
mpremote fs cp **gesture_model.csv** :

Download and copy MicroPython library to device

*curl https://emlearn.github.io/...../**xtensawin_6.2**/emltrees.mpy*
mpremote fs cp emltrees.mpy :

Prebuilt binary
No need to setup
C toolchain and SDK

emlearn-micropython: Load model & run




```
import emltrees
# Instantiate model. Capacity for trees, decision nodes, classes
model = emltrees.new(20, 200, 10)

# Load model "weights"
with open('gesture_model.csv') as f:
    emltrees.load_model(model, f)
```

Load model on device

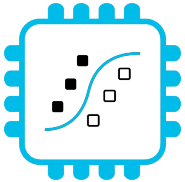
```
# Read sensor data
sensor.fifo_read(samples)

# Preprocess features
preprocessor.run(samples, features)

# Run model
out = model.predict(features)
```

Run inference

Summary



1. emlearn is an open-source project
   implements classical ML models for embedded systems

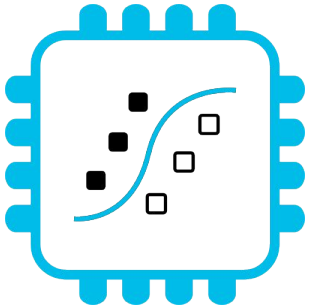
2. Tree-based models are very useful in TinyML applications.
   emlearn has a good implementation for microcontrollers.

3. Can build TinyML applications in Python only
   using MicroPyton + emlearn

More information: https://emlearn.org

emlearn

6 years of TinyML



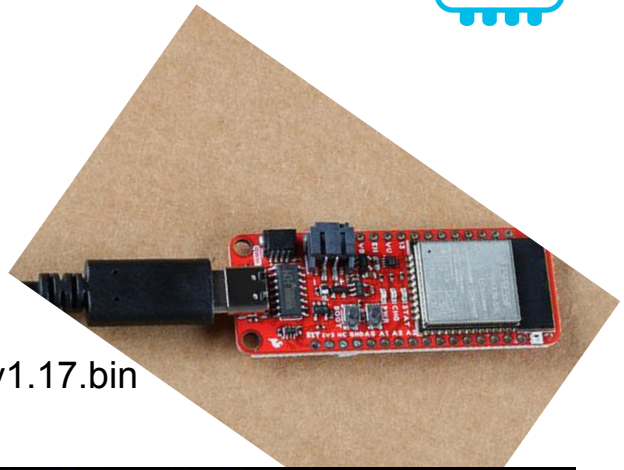
"scikit-learn for microcontrollers"

https://github.com/emlearn/emlearn

Jon Nordby jononor@gmail.com

Bonus

MicroPython - Installing



Download prebuilt firmware

https://micropython.org/download/?port=esp32

Flash firmware to device

pip install esptool

esptool.py --chip esp32 --port … erase_flash
esptool.py --chip esp32 --port … write_flash -z 0 micropython-v1.17.bin

Connect to device

pip install mpremote

mpremote repl

```
MicroPython v1.8.3-24-g095e43a on 2016-08-16; ESP module
Type "help()" for more information.
>>> print('Hello world!')
Hello world!
>>>
```

IDE (optional): Thonny, VS Code, et.c.

TinyML for MicroPython - comparisons

Project	Deployment	Models	Program size	Compute time
emlearn	Easy. Native mod .mpy	DT, RF, KNN, CNN	Good	Good
everywhereml	Easy. Pure Python .py	DT, RF, SVM, KNN,	High with large models	Poor
m2cgen	Easy. Pure Python .py	DT, RF, SVM, KNN, MLP	High with large models	Poor
OpenMV.tf	Hard. Custom Fork	CNN	High initial size	Good
ulab	Hard. User C module	(build-your-own) Using ndarray primitives	High initial size	Unknown (assume good)

Microcontroller - tiny programmable chip

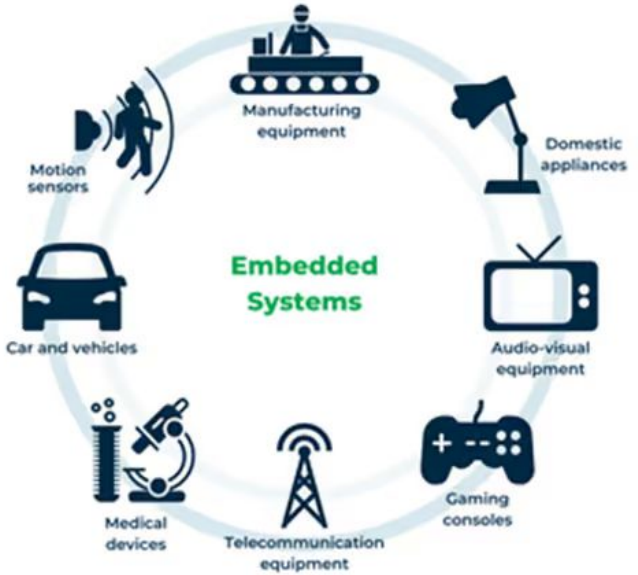
Compute power: 1 / 1000x of a smartphone

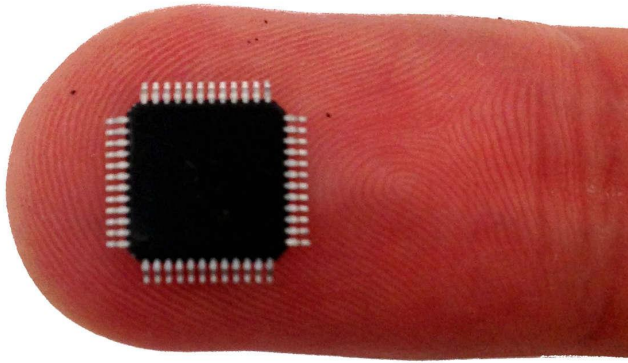
- **RAM:** **0.10 - 1 000 kB**
- **Program space:** **1.0 - 10 000 kB**
- **Compute** **10 - 1000 DMIPS**
- **Price:** **0.10 - 10 USD**

Over 20 *billions* shipped *per year*!

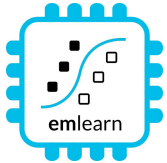
Increasingly accessible for hobbyists

2010: Arduino Uno
2014: MicroPython
2019: MicroPython 1.10 - ESP32 PSRAM





Training a RandomForest model

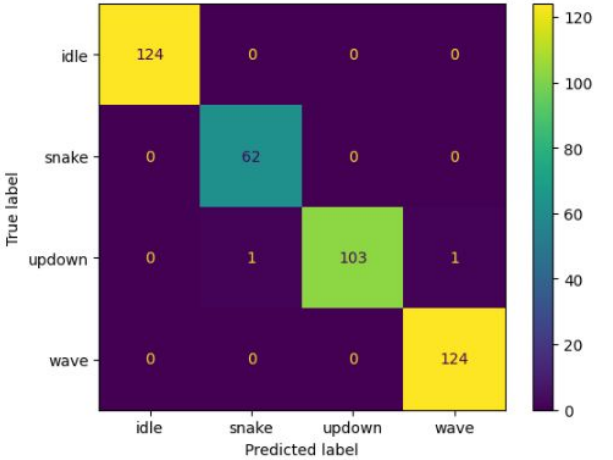


Standard process - familiar to anyone who has used scikit-learn.
But - Make sure model size is not huge.

```
# preprocess data
windows = train.groupby(....).apply(create_windows,
        length=int(2000/15), hop=int(260/16))
features = windows.groupby(...).apply(spectral_features)

# train model
from sklearn.ensemble import RandomForestClassifier
est = RandomForestClassifier(n_estimators=10, max_depth=5)
est.fit(features, features.reset_index()['class'])

# evalutate on test set
…
```



Task feasibility versus microcontroller type

	RAM (kB)	**FLASH** (kB)	**CPU** (CoreMark)		**IMU** 100 hz 5 s	**Sound** 16 kHz 1 s	**Image** 64x64 px 1 fps
Arduino Uno ATMega 328 @ 16 Mhz	2	32	4.0		✓	❌	❌
Arduino Nano BLE 33 NRF52840 ARM Cortex M4F @ 64 Mhz	256	1 000	215		✓	✓	❌
Arduino Nano ESP32 ESP32-S3 @ 240 Mhz	8 000	16 000	613 (per core)		✓	✓	✓
Teensy 4.0 ARM Cortex M7 @ 600 Mhz	1 000	2 000	2313 (per core)		✓	✓	✓