

Hardware Architectures for Embedded and Edge Al

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Exercise session 3 – Data collection with Edge Impulse

Requirements

- Chrome web browser
- Arduino CLI
 - Win: https://arduino.github.io/arduino-cli/0.31/installation/#download
 - Lin: https://lindevs.com/install-arduino-cli-on-ubuntu
- Data collection firmware
 - https://cdn.edgeimpulse.com/firmware/arduino-nano-33-ble-sense.zip
- You'll need an account at
 - https://www.edgeimpulse.com/

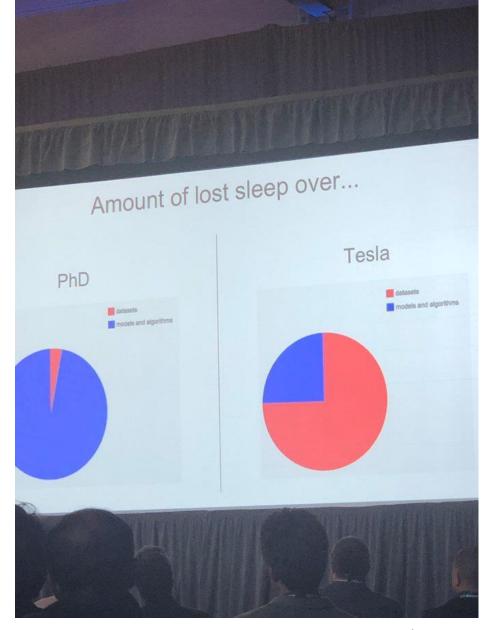
Outline of today

Collect a reasonably dimensioned dataset to perform object detection:

- Data collection
- Data labelling
- Data validation

We'll see the example of object detection/classification.
Is collecting data for object detection/classification a challenging task?

It is, for the same reasons that make object detection a challenging task!



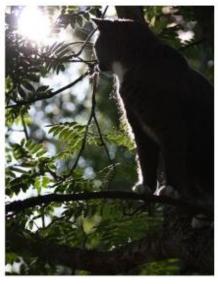
https://petewarden.com/2018/05/28/why-you-need-to-improve-your-training-data-and-how-to-do-it/

Challenges: illumination



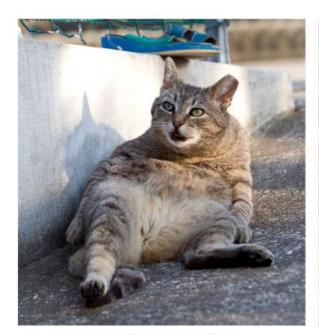






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Challenges: deformation



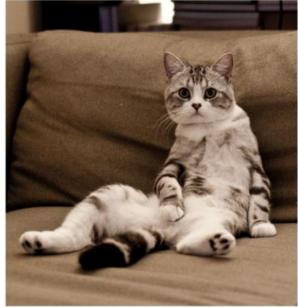
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Challenges: occlusion





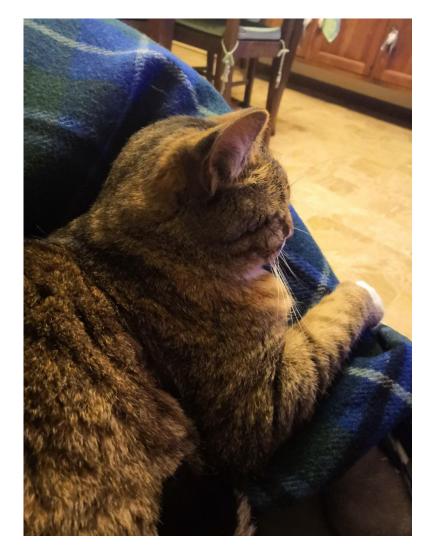


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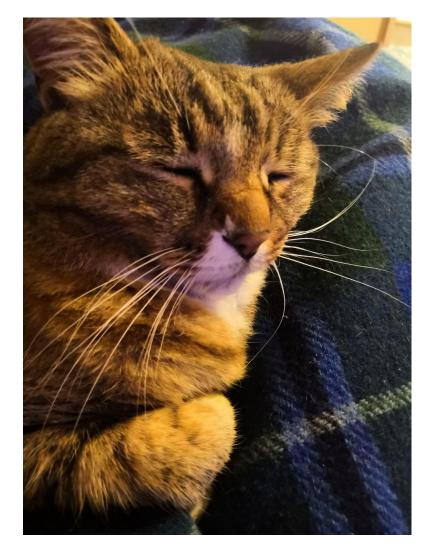
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Challenges: view point change





Camera movement



Challenges: inter-class variability



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Challenges: scale variation



Dataset construction for image detection/classification

- A deep learning algorithm can address all this challenges only if many possible examples of these challenges are present in the dataset.
- Thus, a generic image detection/classification algorithm meant to run in unkown conditions, should be trained on data with:
 - Different illuminations, view points
 - Occluded and deformed targets
 - Examples of different objects of the same class

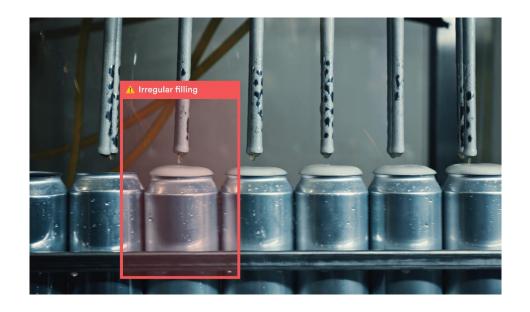
Image classification in the context of tinyML

Very often in the context of tinyML you do not have to deal with all the presented challenges at the same time:

- You can collect (some) data from the sensors that will be used on the device, in the environment in which it will be deployed.
- This can simplify a lot the learning phase for the algorithm.
- It's possible to start from simple conditions, then augment the capabilities of your algorithm by adding new data collected under new conditions.
- In some applications, it may be possible to even make the object that you want to detect more evident (e.g., coloring it, using objects with unusual shapes...)

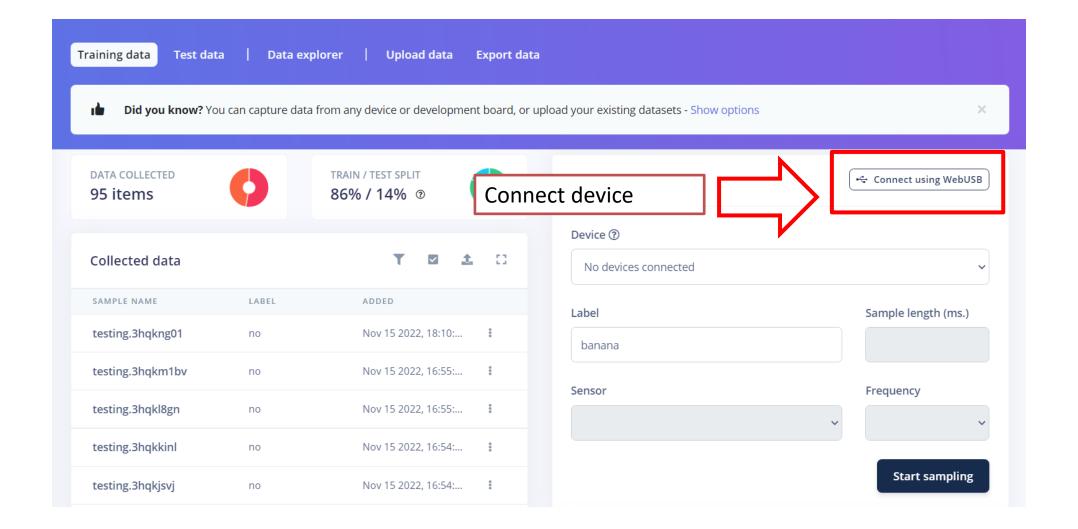
Why this approach

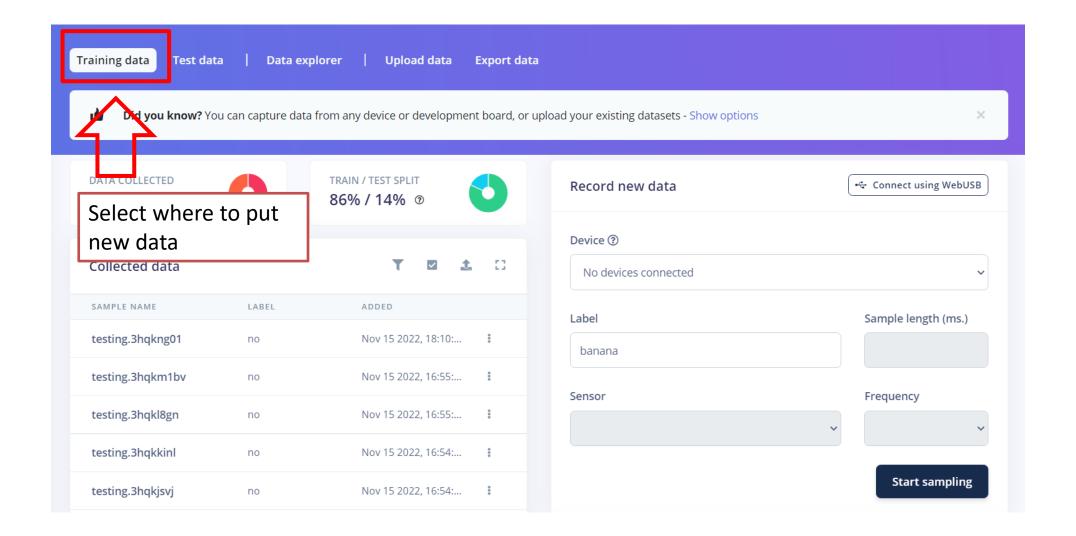
- A complete model that can work in any condition on tasks of arbitrary complexity with reasonable performances may be too memory/energy demanding for our target devices, and difficult to obtain (expecially in the time of an exercise session ☺)
- We can exploit the fact that we are collecting the data with the same device that will run the algorithm, in the same condition
- An algorithm that works in some well defined conditions can still be extremely useful (e.g.: computer vision in the industry, anomaly detection ...)

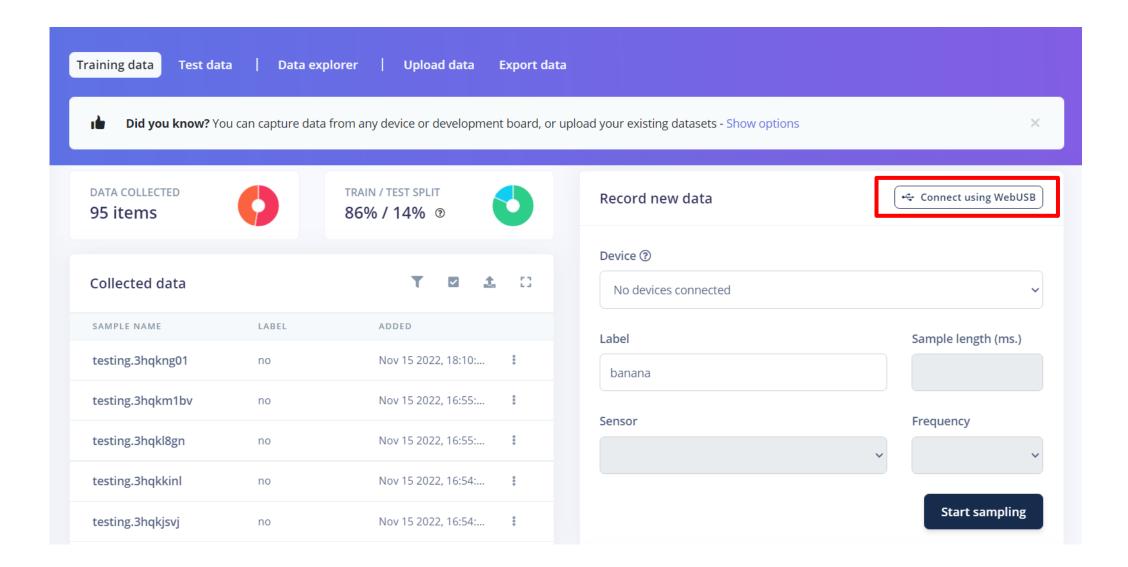


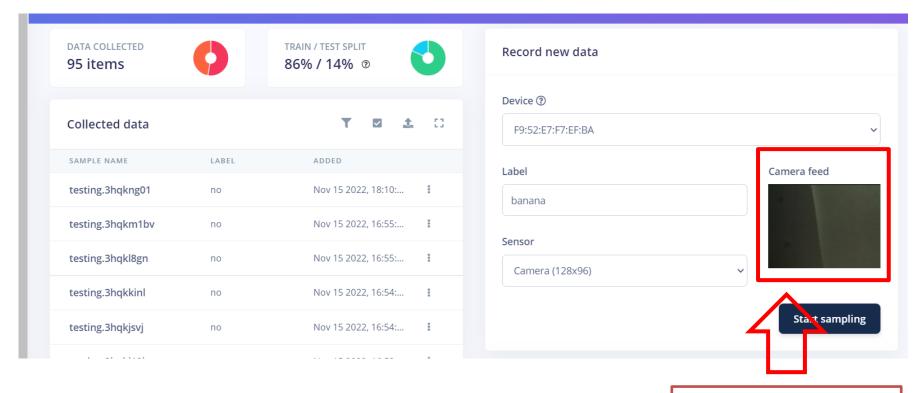


Data collection with edge impulse

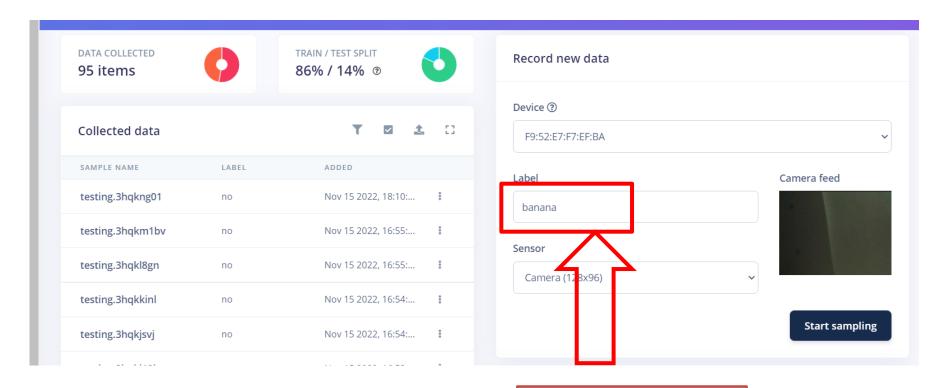






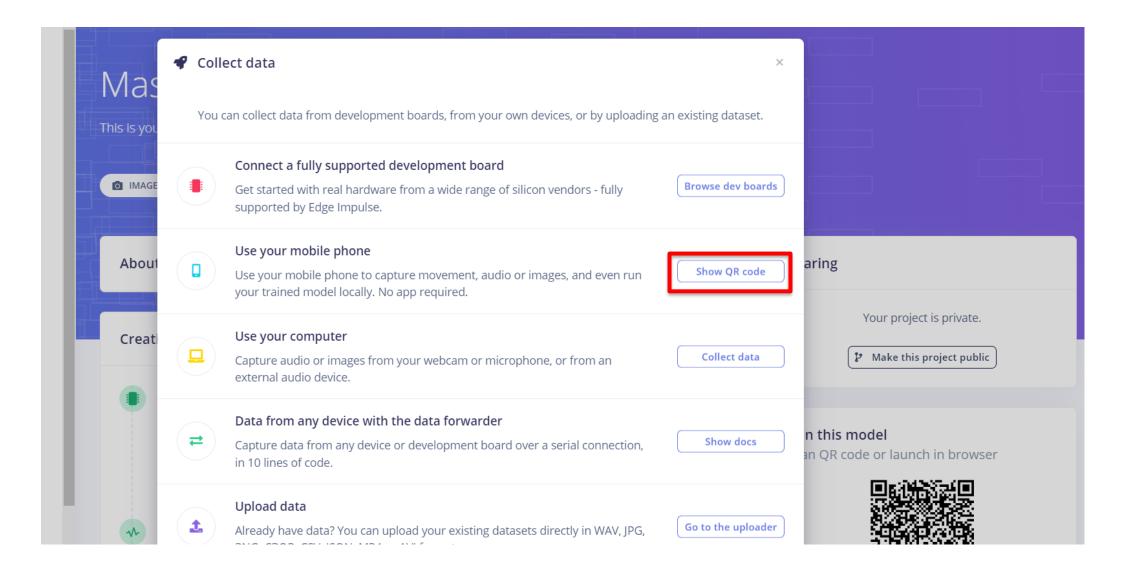


The picture you'll take



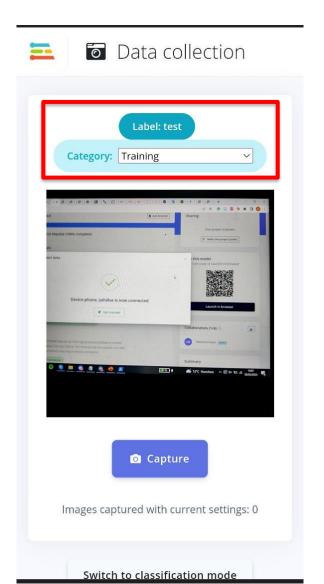
The label to assign to the picture

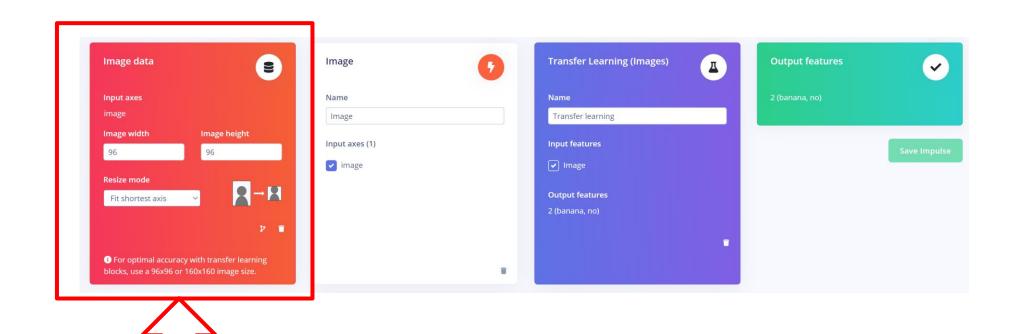
Use mobile phone to faster collect the data (but they'll be different!)



Data collection



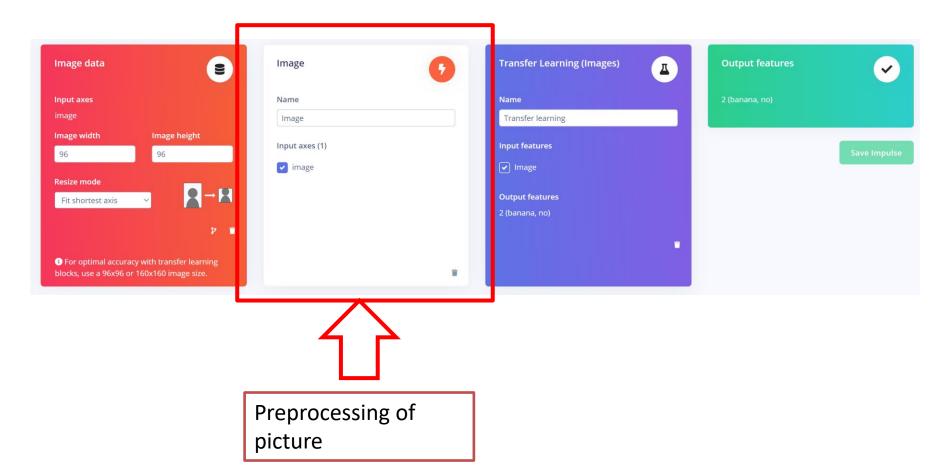


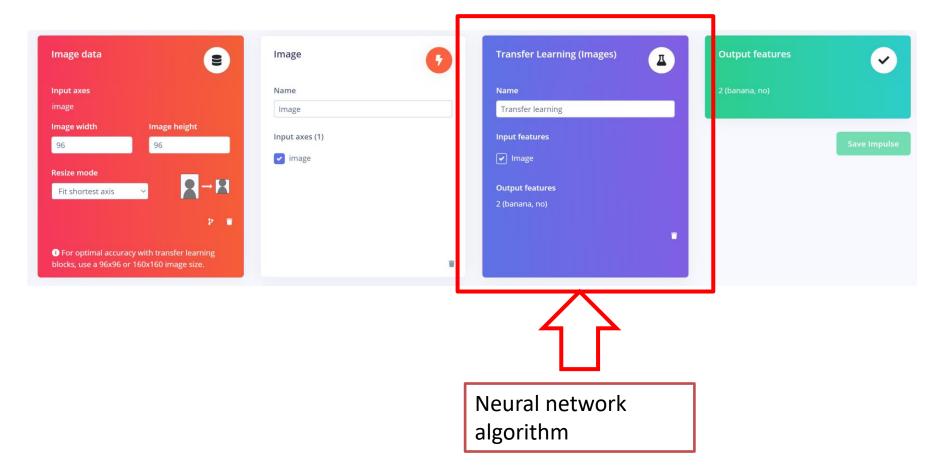


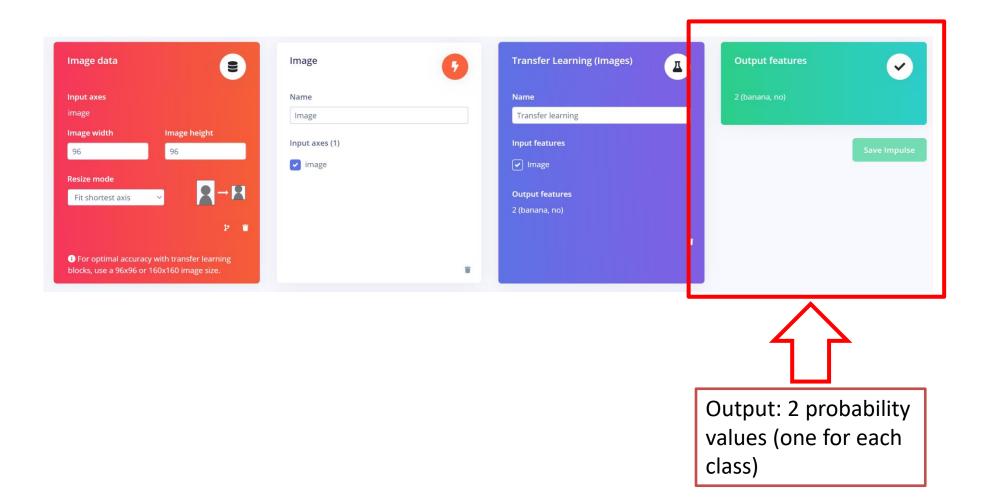


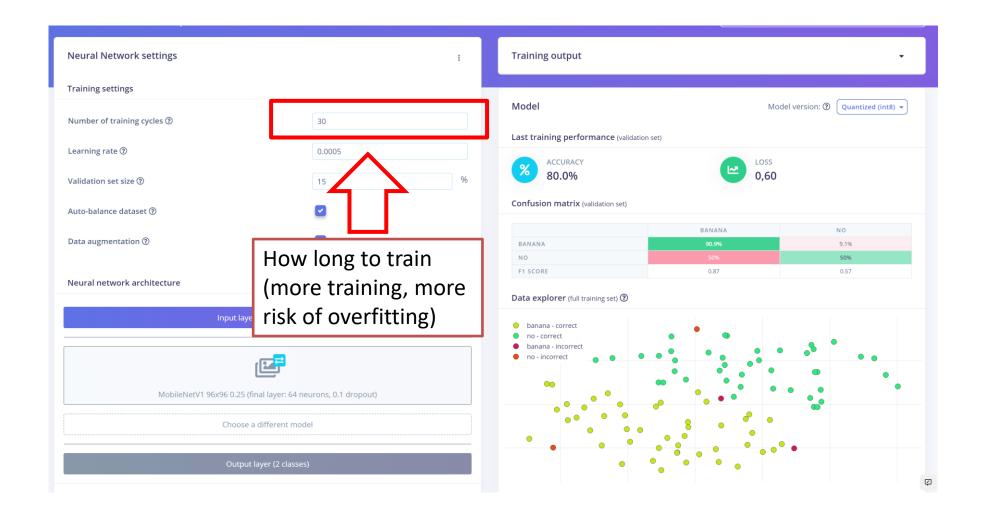
taken

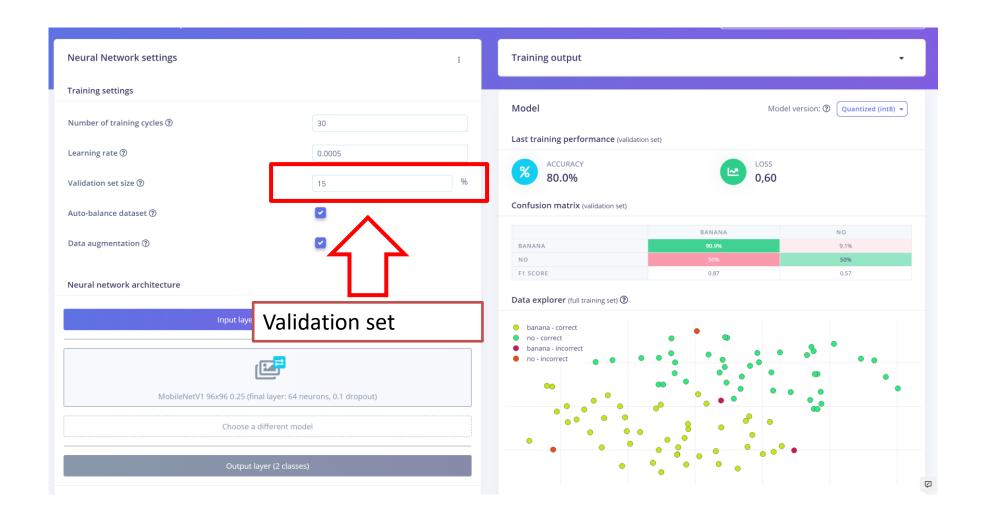
Resize of the picture

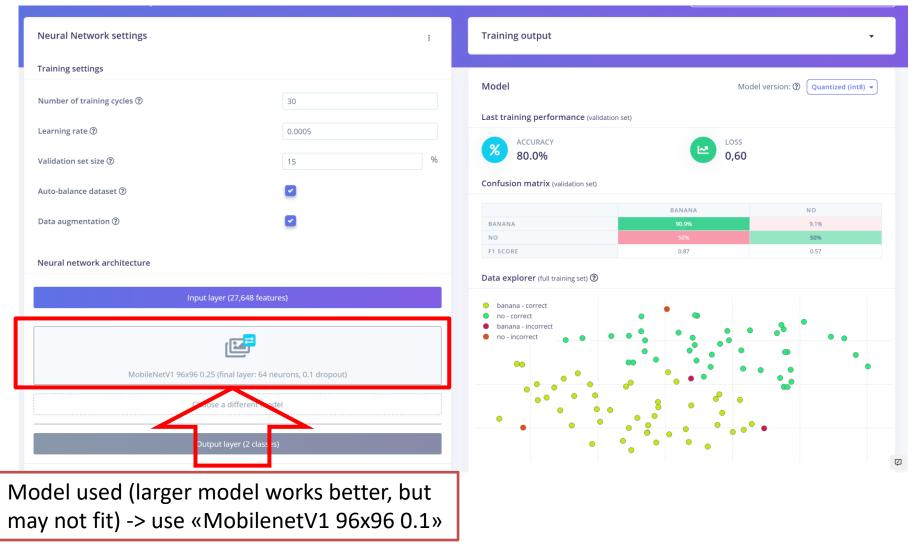


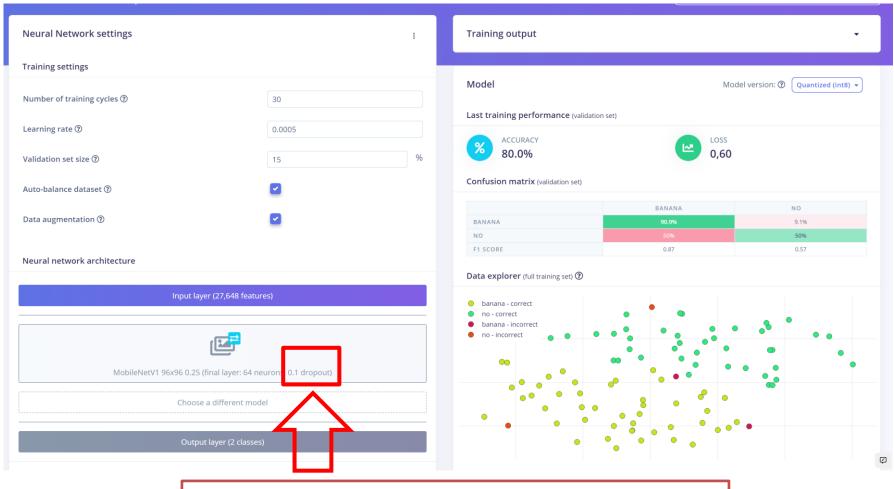




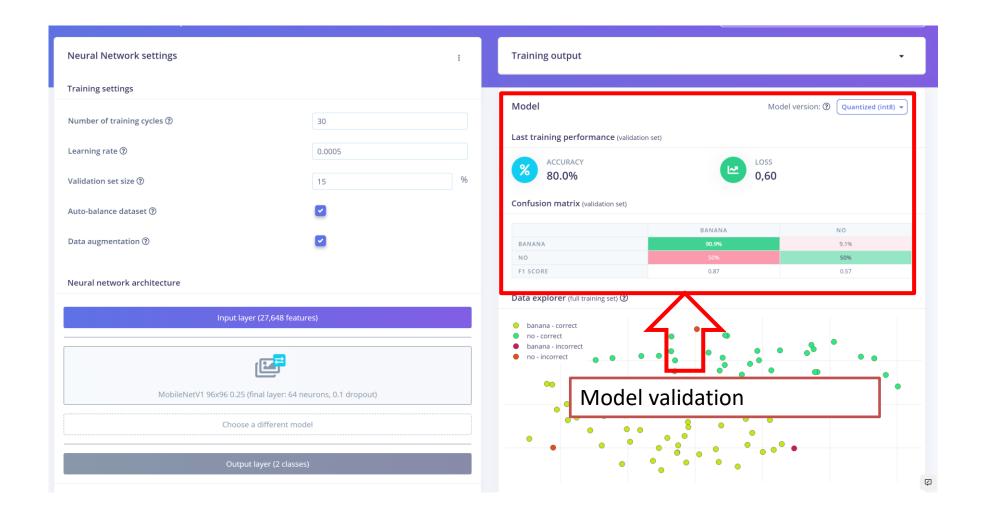




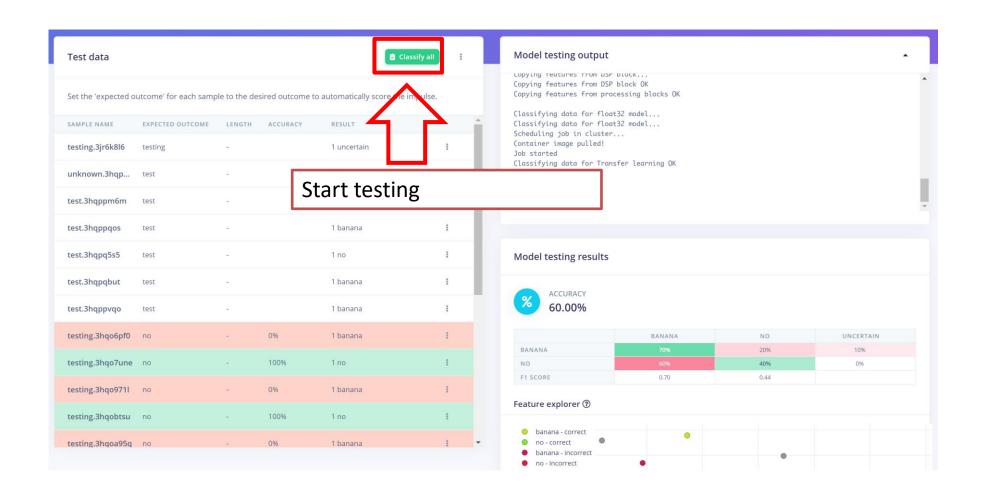


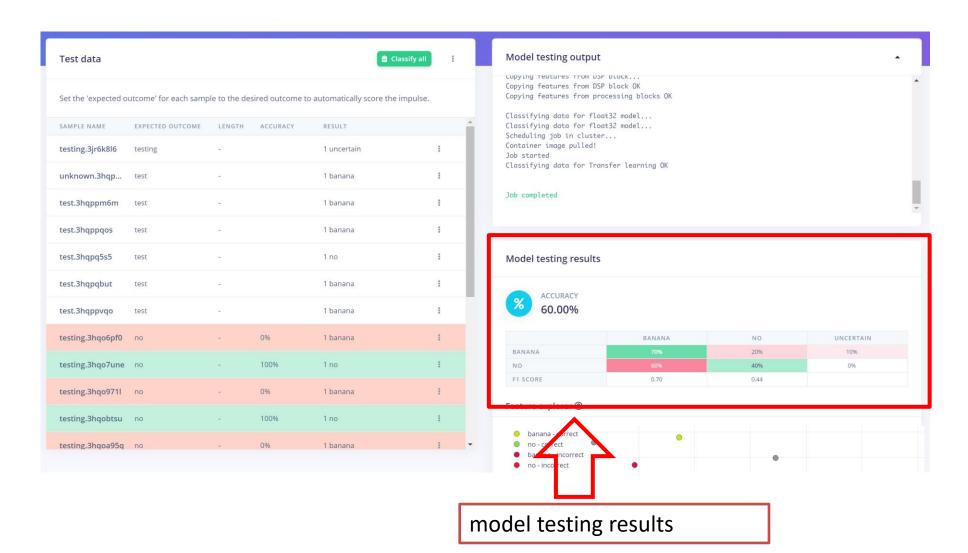


Dropout may help avoid overfitting

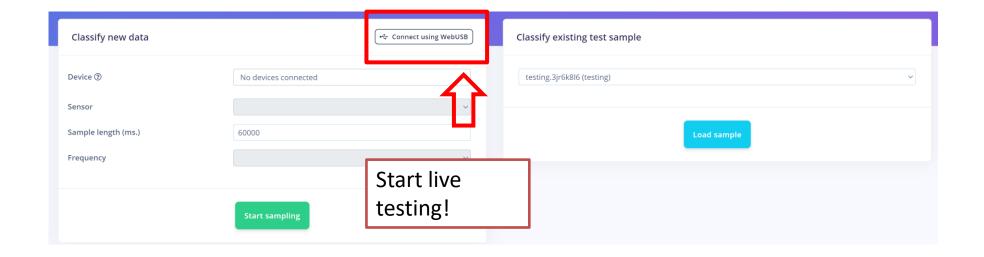


Testing the algorithm





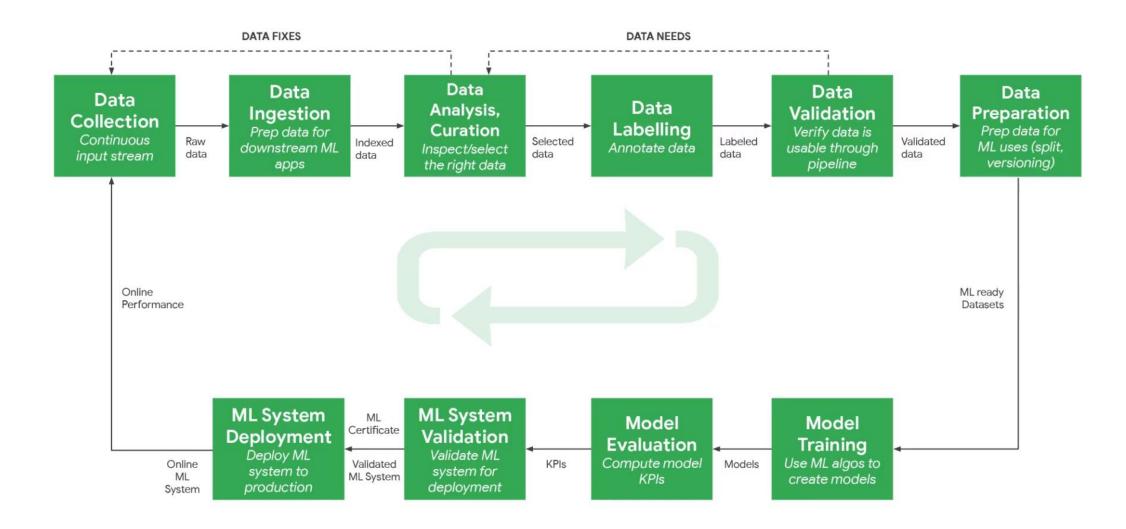
Live testing



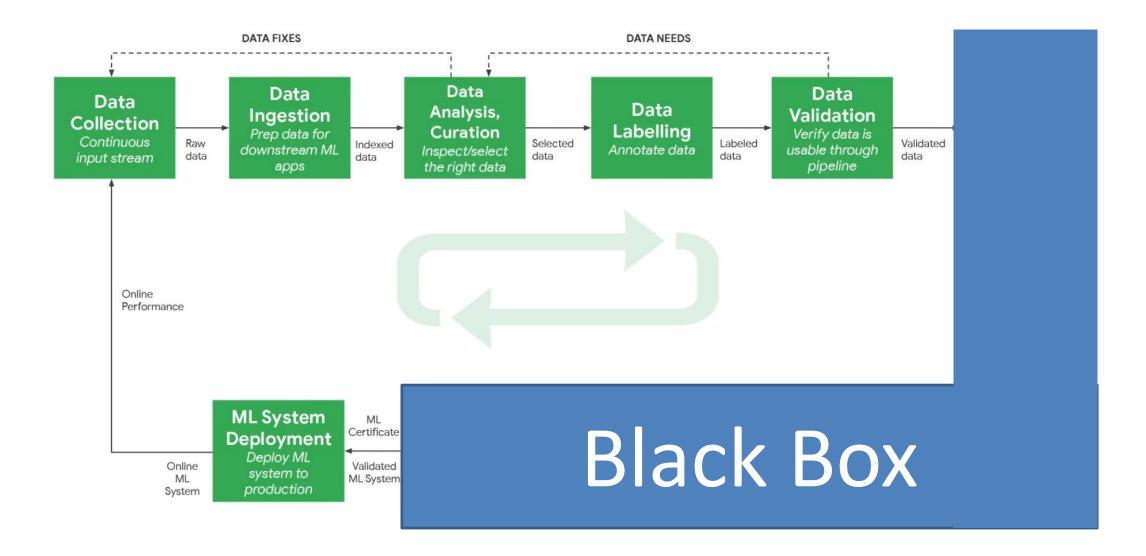


Hands on session

ML real life cycle



What we'll do today



Hands on session

- Collect the data for an object dectection algorithm:
 - Start from data of a single point of view, with the object fixed in one position
- Use the algorithm itself as a black box
 - Use standard configurations as seen in the slide
- Complicate the problem
 - Change the point of view, change the position of the object
 - Try occluding the object (do not capture it entirely, put a notebook covering half of it)
 - Deformate it!
 - Remember to give the algorithm an equal number of object and other!
- Start again from the beginning



Appendix

Credits and reference

- "TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers", Daniel Situnayake, Pete Warden, O'Reilly Media, Inc.
- Online course:
 - https://www.edx.org/professional-certificate/harvardx-tiny-machine-learning
- A lot more material on TinyML:
 - http://tinyml.seas.harvard.edu/
- https://petewarden.com/2018/05/28/why-you-need-to-improve-your-training-data-and-how-to-do-it/
- Cats pictures and challenges in OD/C: https://github.com/maxis42/Convolutional-Neural-Neural-Networks-Stanford-CS231n/blob/master/Lectures/lecture2.pdf and lectures of the Artificial Neural Network and Deep Learning course by prof. Boracchi
- Special thanks to M. Azzolini, M. Aldrighetti, E. Martello, and F. Zanotelli, who let me use the pictures that they collected for their project at CFP G. Veronesi at Rovereto

https://docs.edgeimpulse.com/docs/development-platforms/officially-supported-mcu-targets/arduino-nano-33-ble-sense

https://cdn.edgeimpulse.com/firmware/arduino-nano-33-ble-sense.zip