



WALC 2023

Applied AI

Embedded ML (TinyML) Intro & Applications

Prof. Marcelo J. Rovai

rovai@unifei.edu.br

UNIFEI - Federal University of Itajuba, Brazil
TinyML4D Academic Network Co-Chair

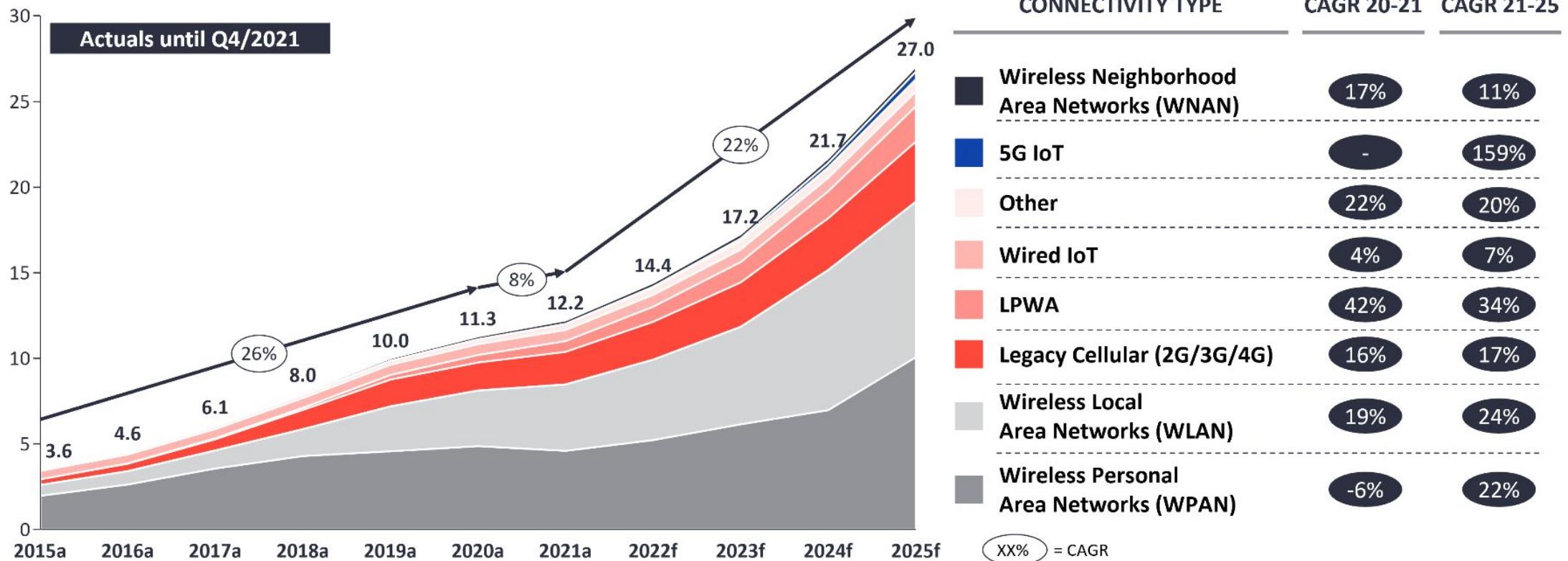


TINYML4D

Internet of Things (IoT)

Global IoT Market Forecast [in billion connected IoT devices]

Number of global active IoT Connections (installed base) in Bn

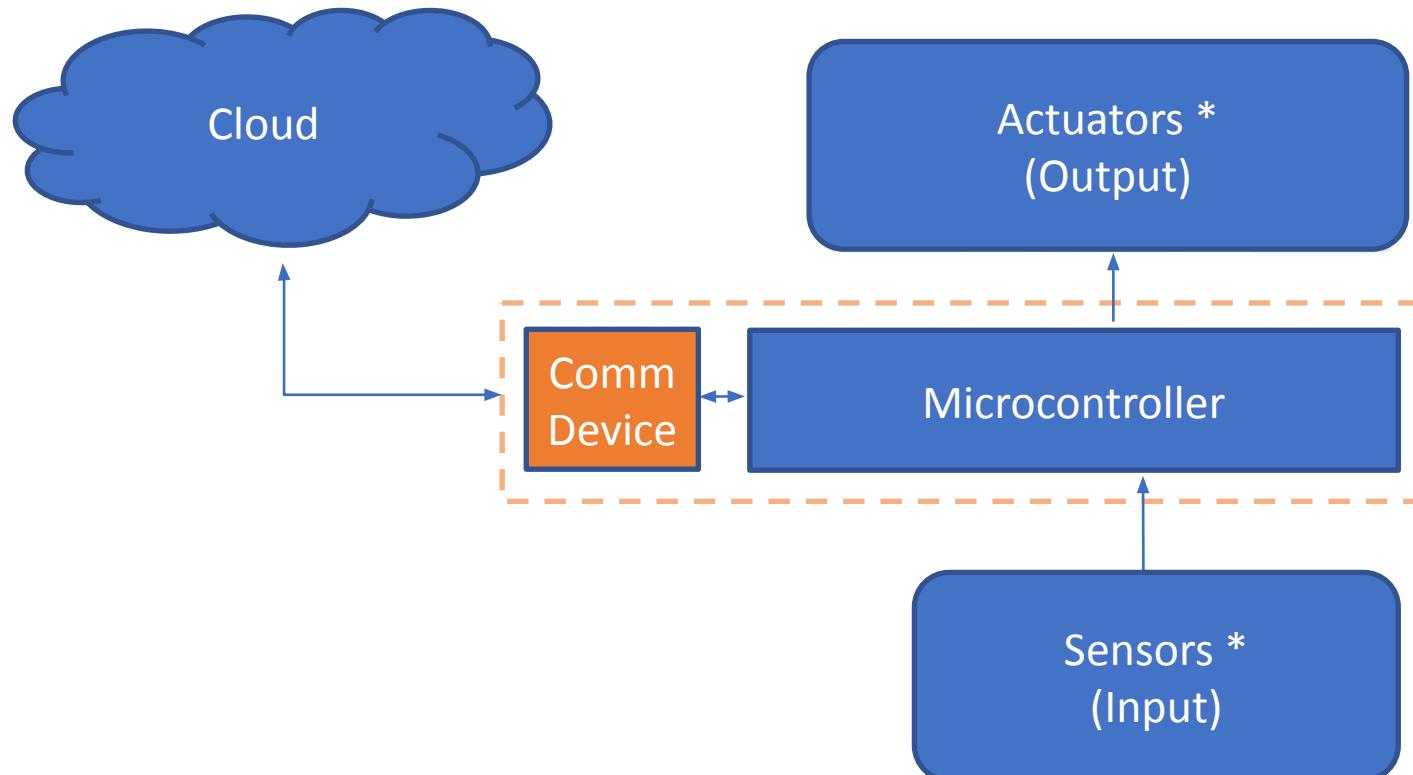


Note: IoT Connections do not include any computers, laptops, fixed phones, cellphones or tablets. Counted are active nodes/devices or gateways that concentrate the end-sensors, not every sensor/actuator. Simple one-directional communications technology not considered (e.g., RFID, NFC). Wired includes Ethernet and Fieldbuses (e.g., connected industrial PLCs or I/O modules); Cellular includes 2G, 3G, 4G; LPWAN includes unlicensed and licensed low-power networks; WPAN includes Bluetooth, Zigbee, Z-Wave or similar; WLAN includes Wi-fi and related protocols; WMAN includes non-short range mesh, such as Wi-SUN; Other includes satellite and unclassified proprietary networks with any range.

Source: IoT Analytics Research 2022. We welcome republishing of images but ask for source citation with a link to the original post and company website.

<https://iot-analytics.com/number-connected-iot-devices>

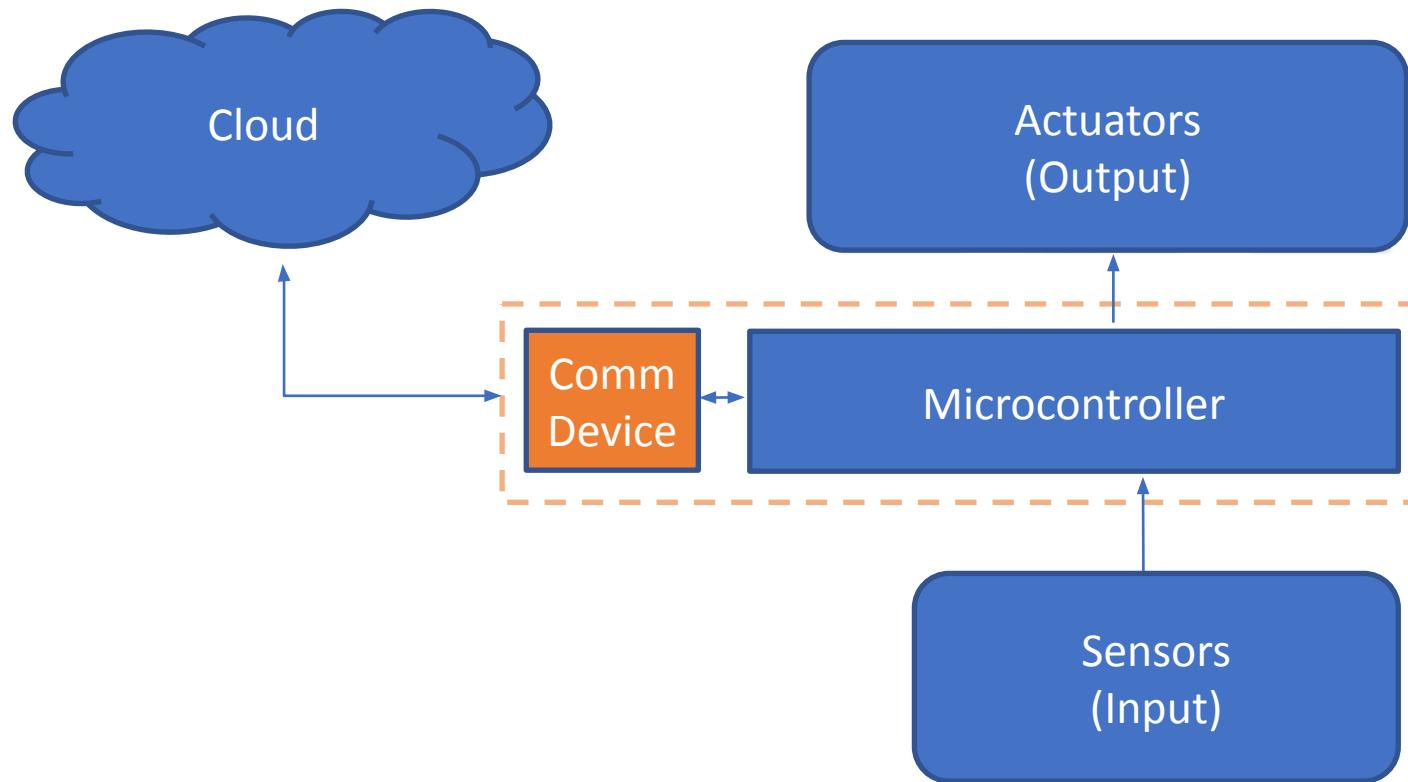
Typical IoT Project



* “Things”



Typical IoT Project



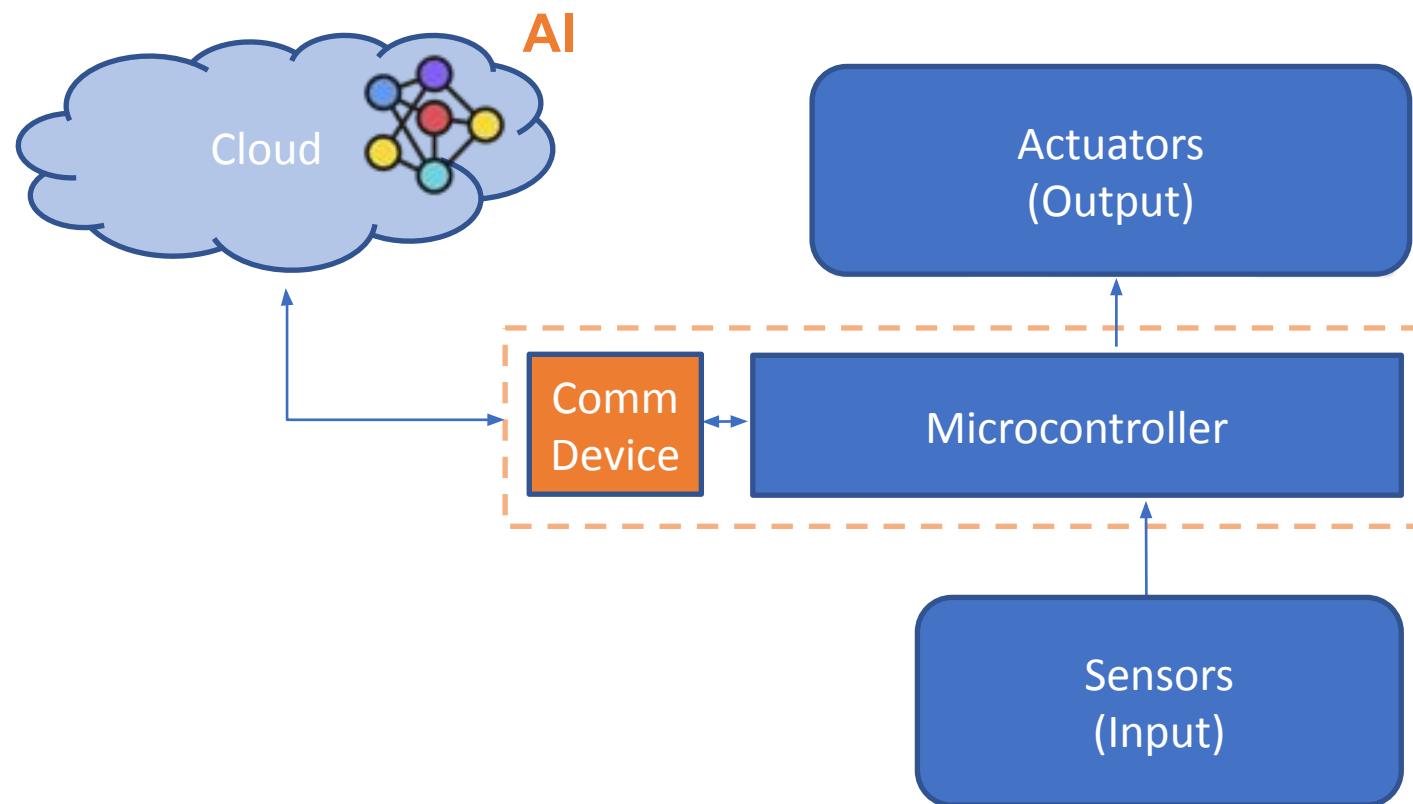
5 Quintillion
bytes of data produced
every day by IoT

<1%
of unstructured data is
analyzed or used at all

Source: Harvard Business Review, [What's Your Data Strategy?](#), April 18, 2017

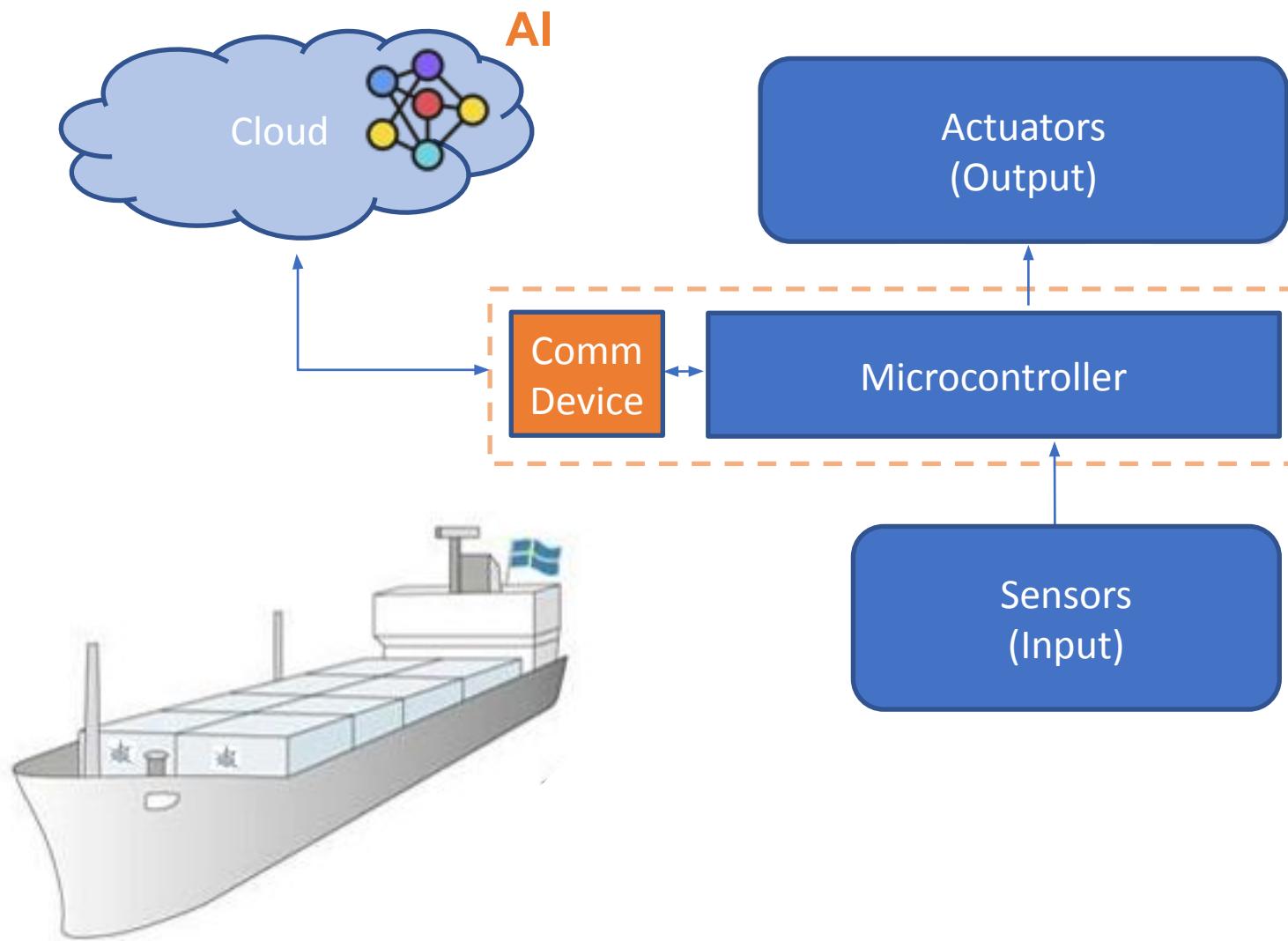
Cisco, [Internet of Things \(IoT\) Data Continues to Explode Exponentially. Who Is Using That Data and How?](#), Feb 5, 2018

Typical AIoT Project



Typical AIoT Project ...

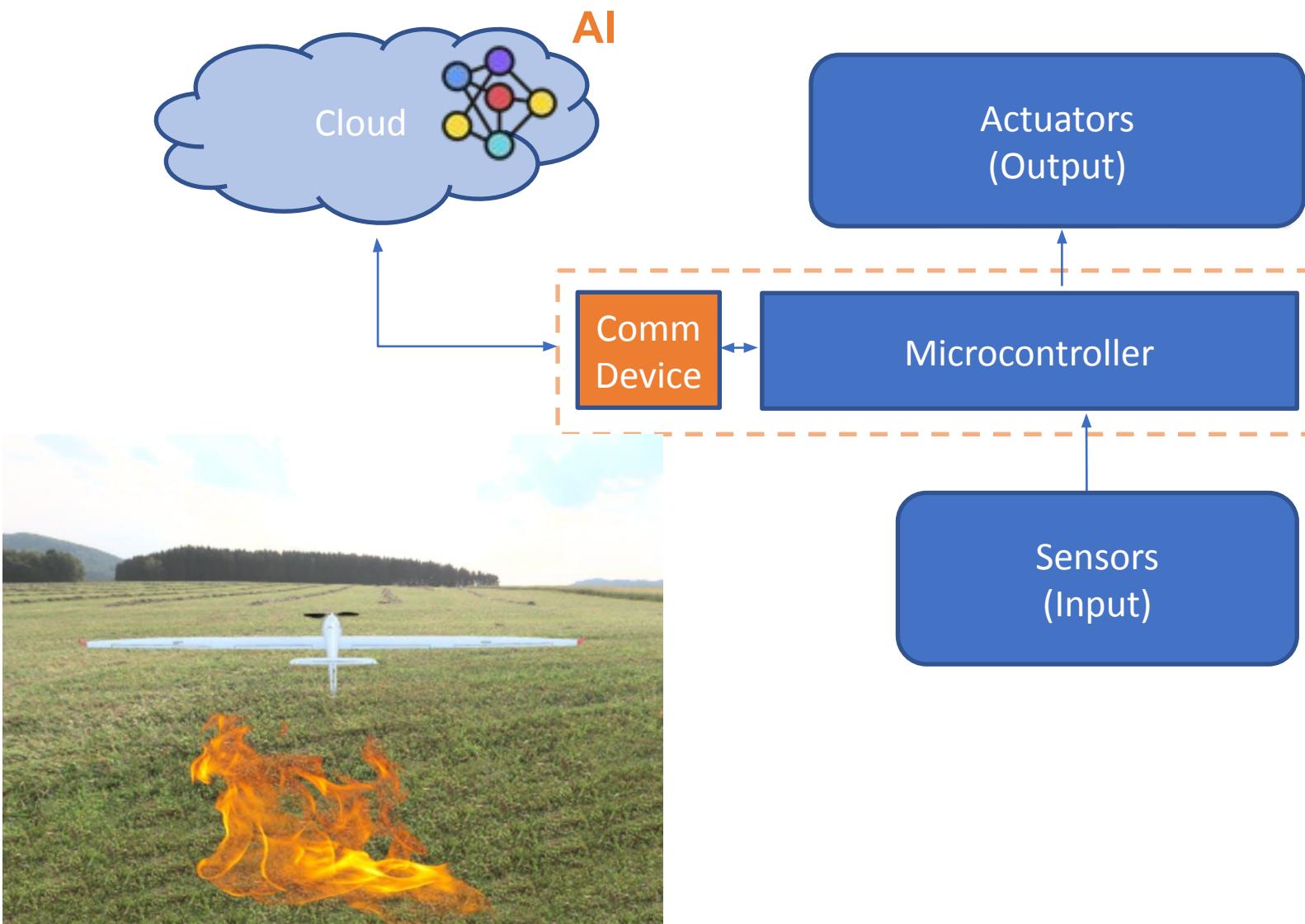
... Issues



Bandwidth

Typical AIoT Project ...

... Issues



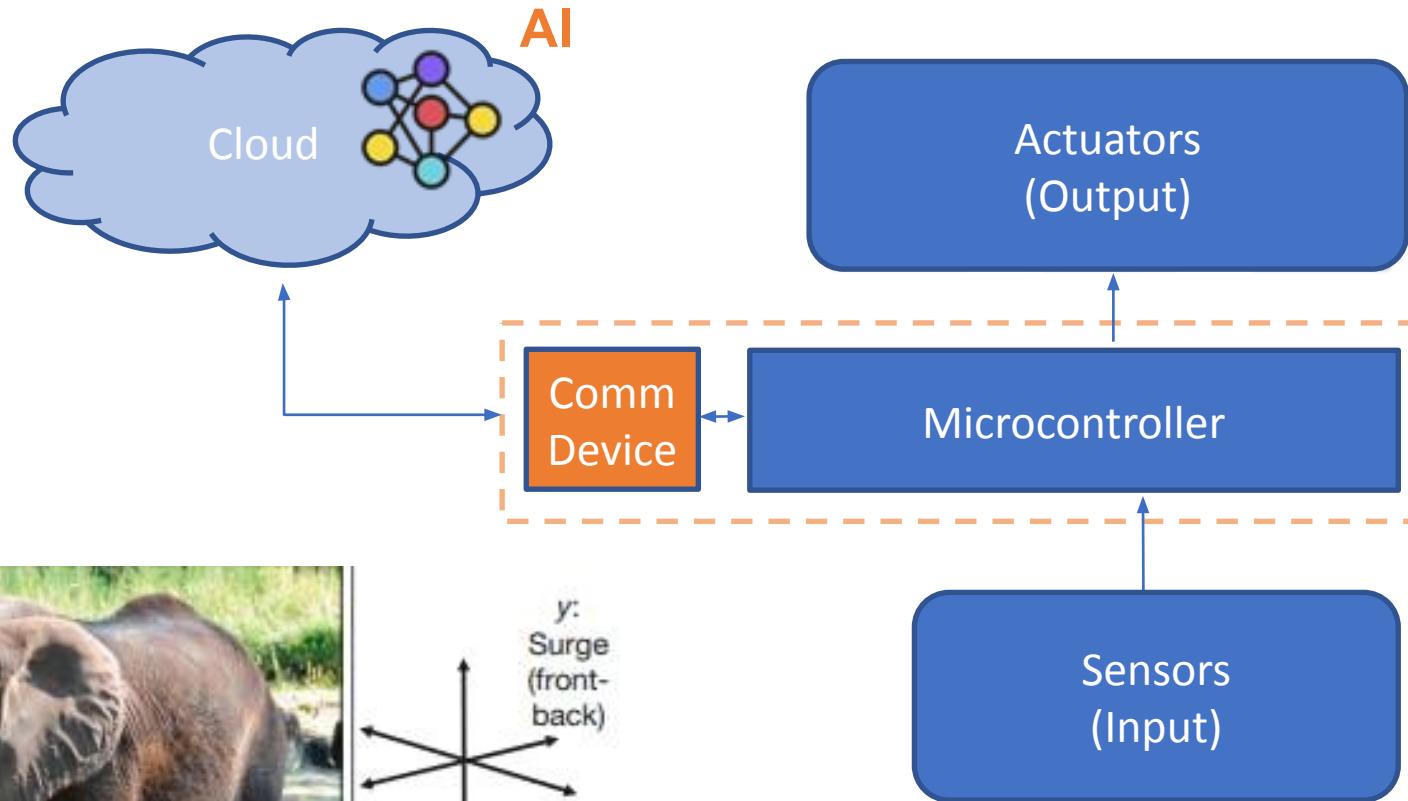
Bandwidth
Latency

Typical AIoT Project ...

... Issues



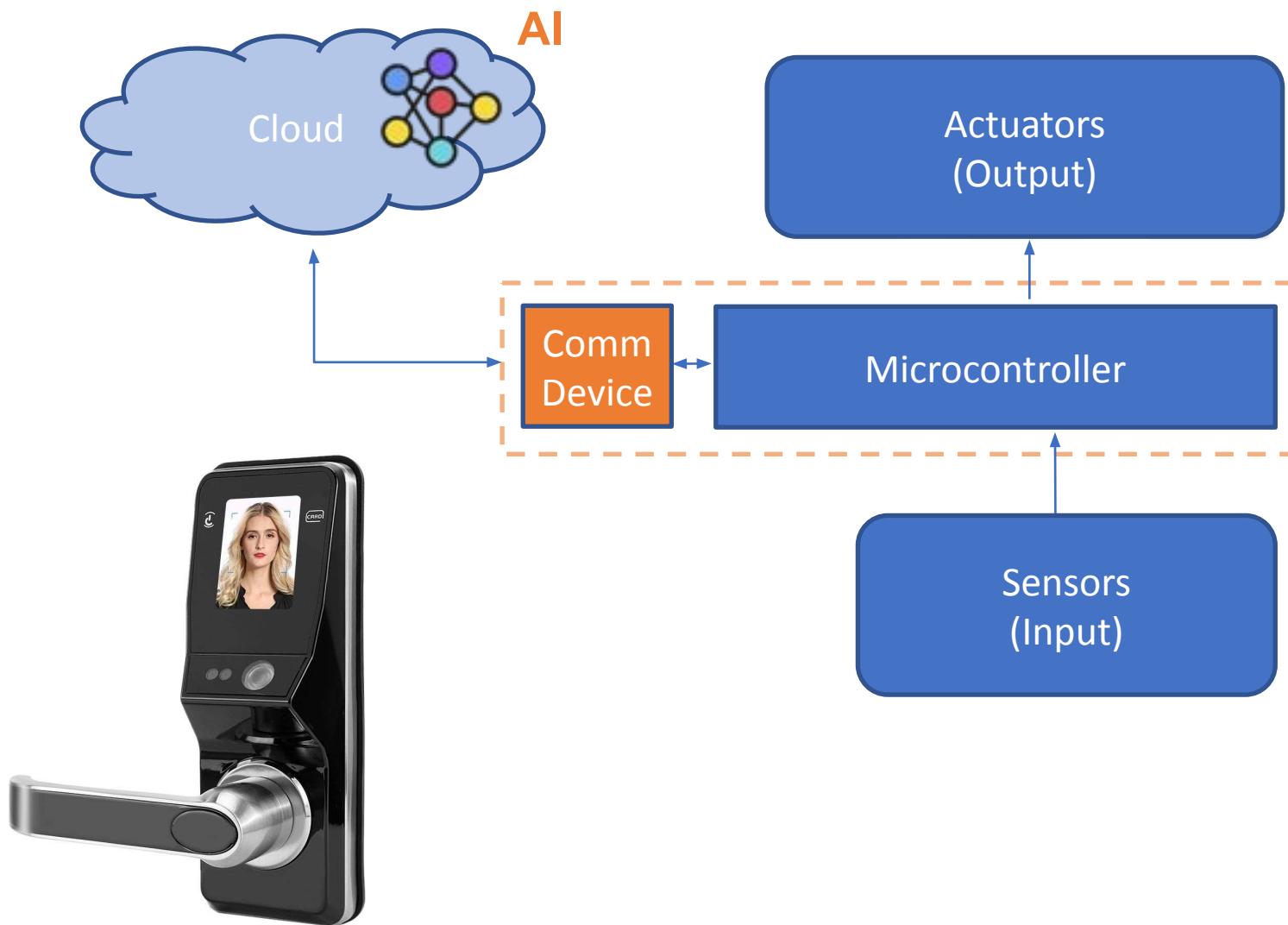
y : Surge (front-back)
 x : Sway (lateral)
 z : Heave (up-down)



Bandwidth
Latency
Energy

Typical AIoT Project ...

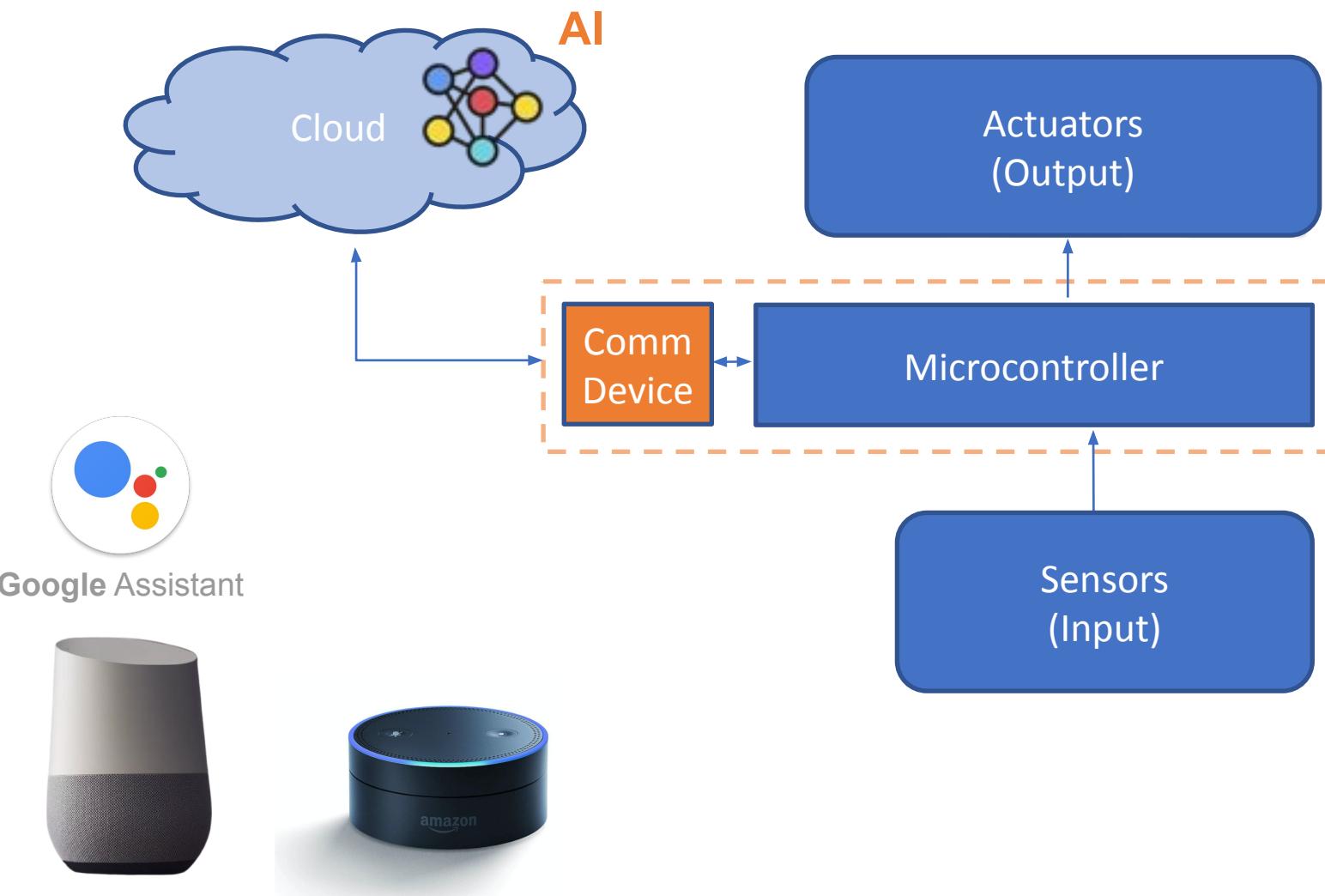
... Issues



Bandwidth
Latency
Energy
Reliability

Typical AIoT Project ...

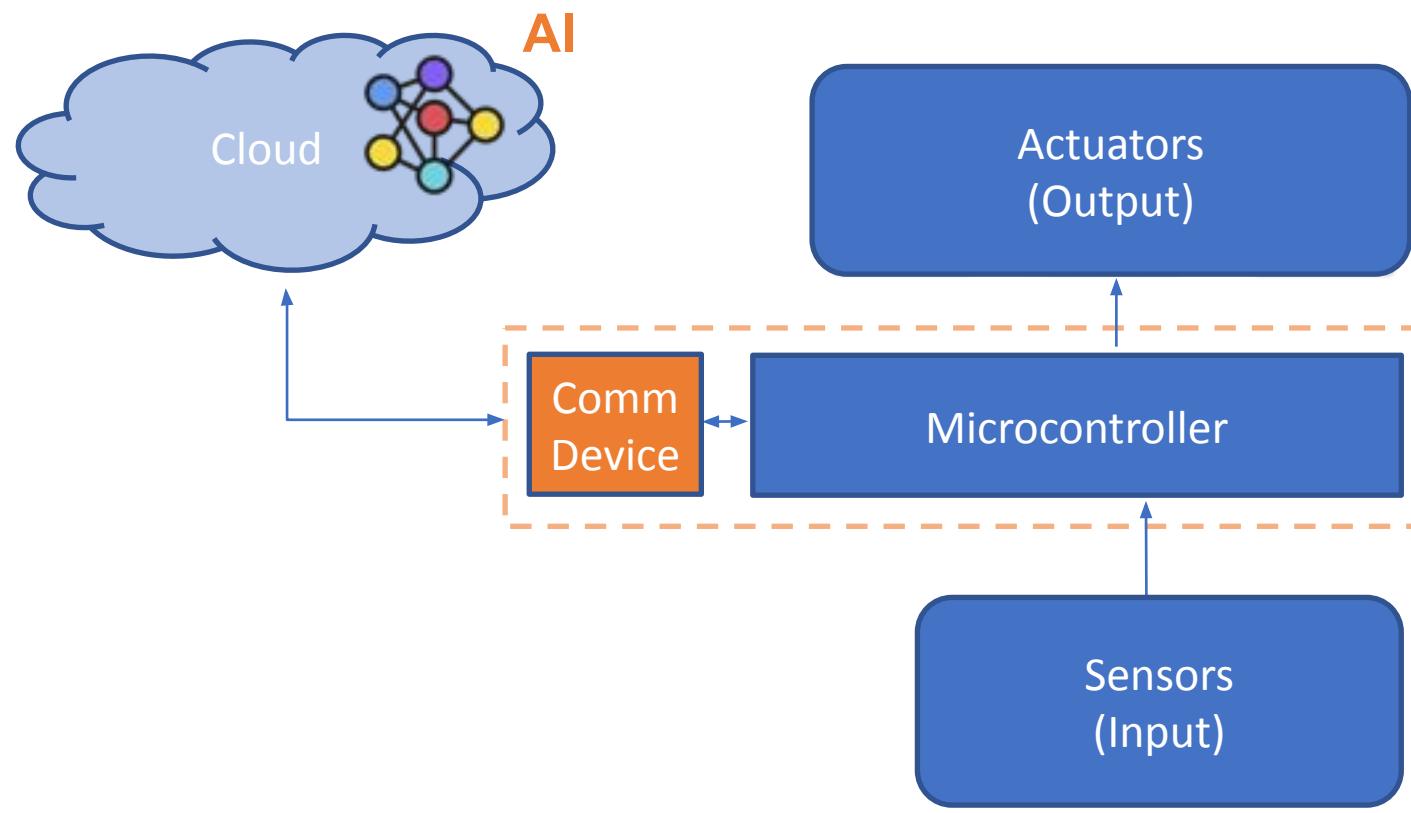
... Issues



Bandwidth
Latency
Energy
Reliability
Privacy

Typical AIoT Project ...

... Issues

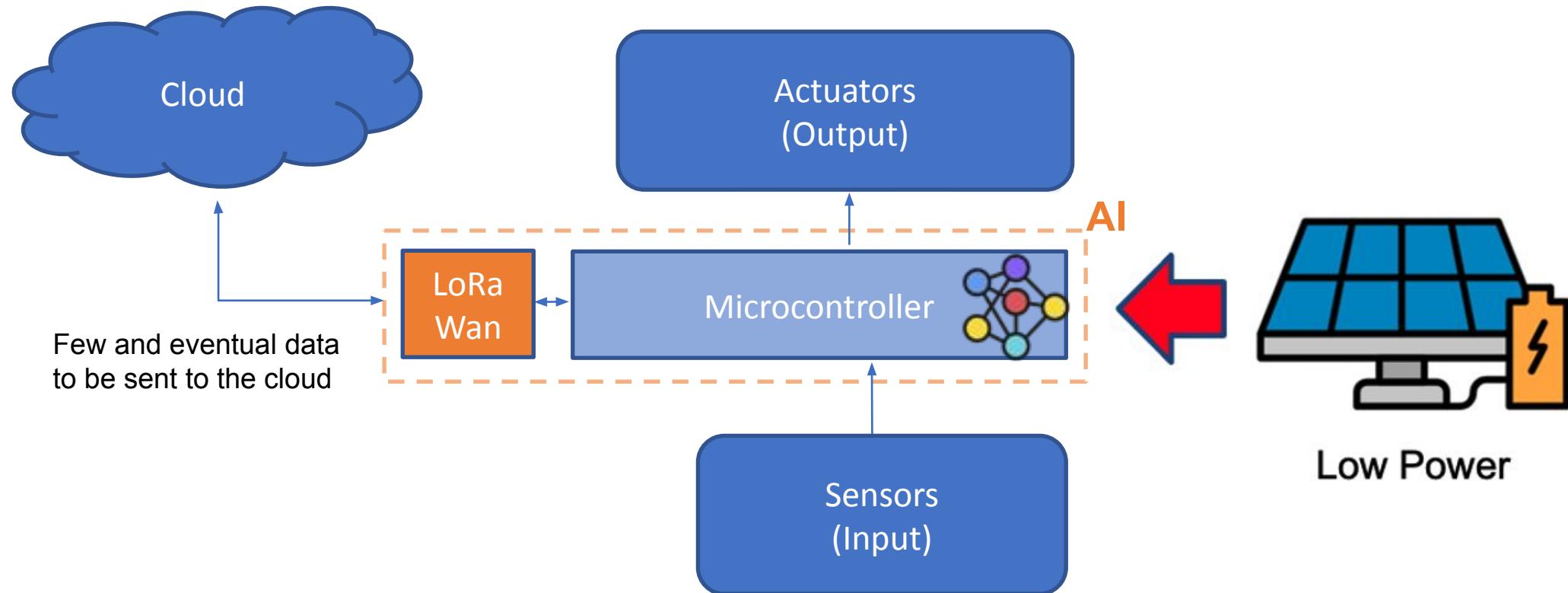


Bandwidth
Latency
Energy
Reliability
Privacy

... Solution ?

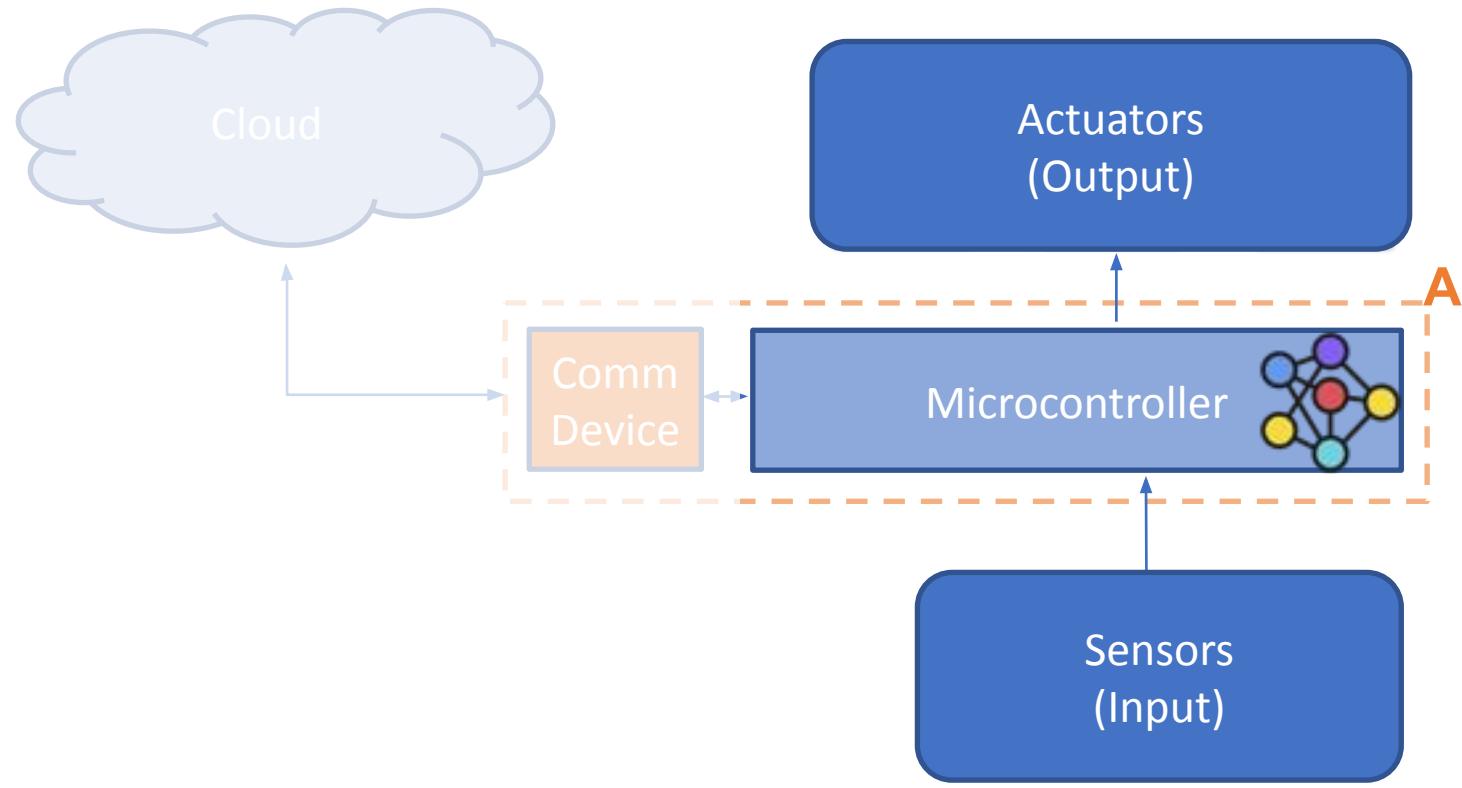
IoT 2.0 * – Edge AI/ML

* Intelligence of Things

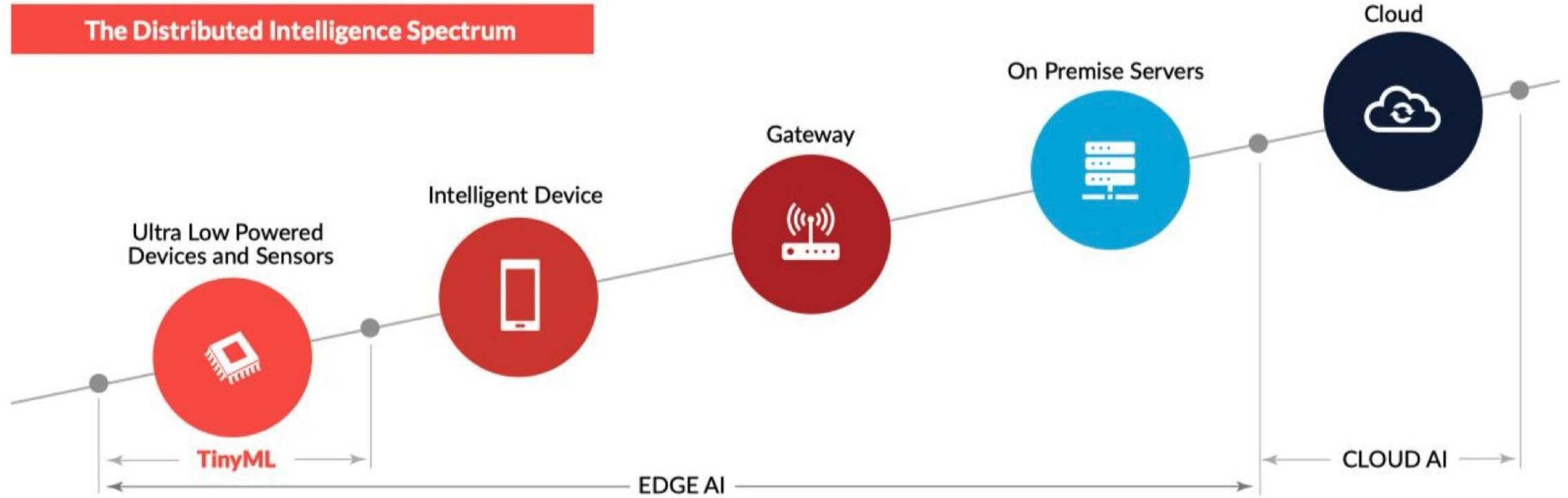


... Solution -> ML goes close to data

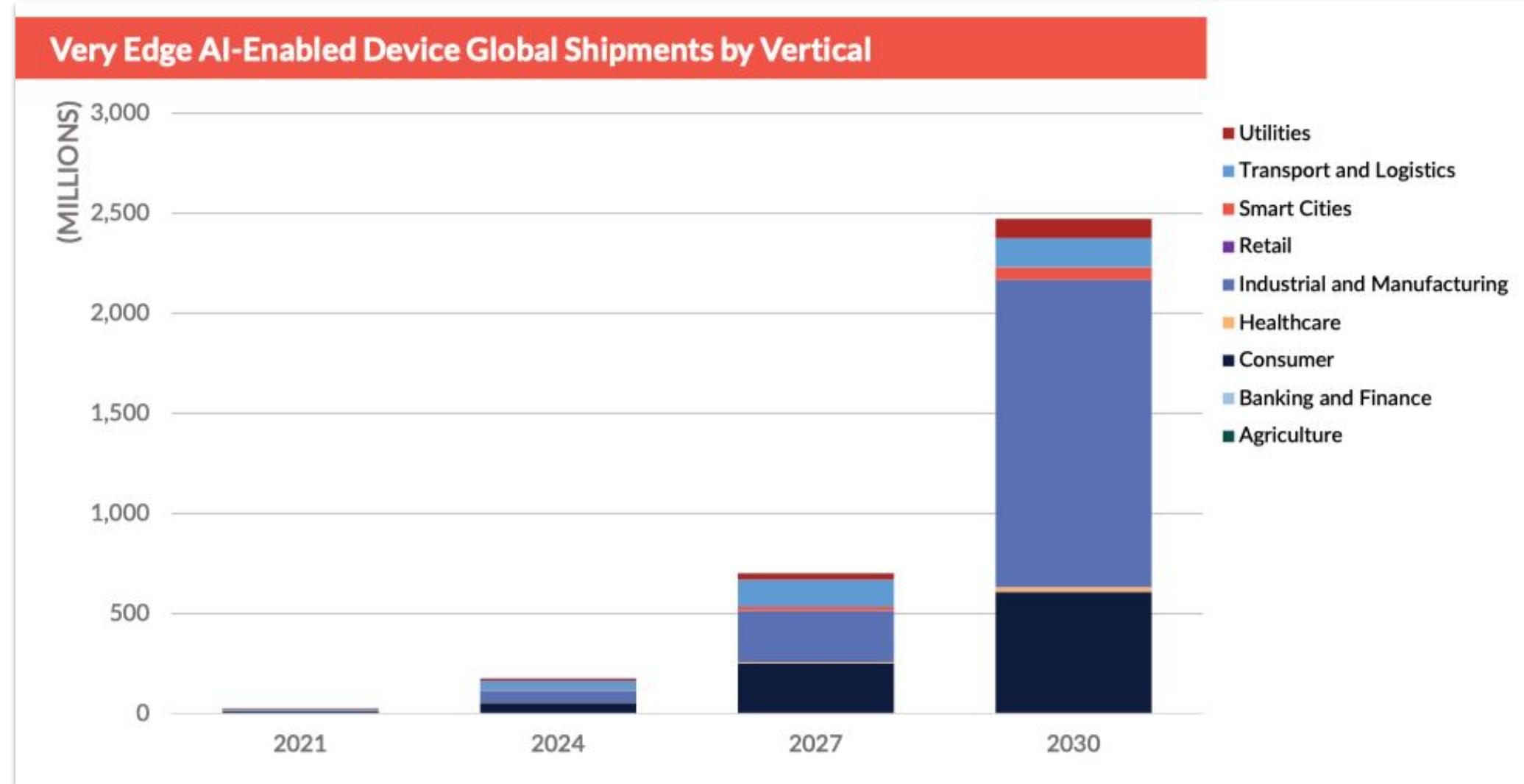
When to use an Edge AI/ML approach:



Bandwidth
Latency
Energy
Reliability
Privacy

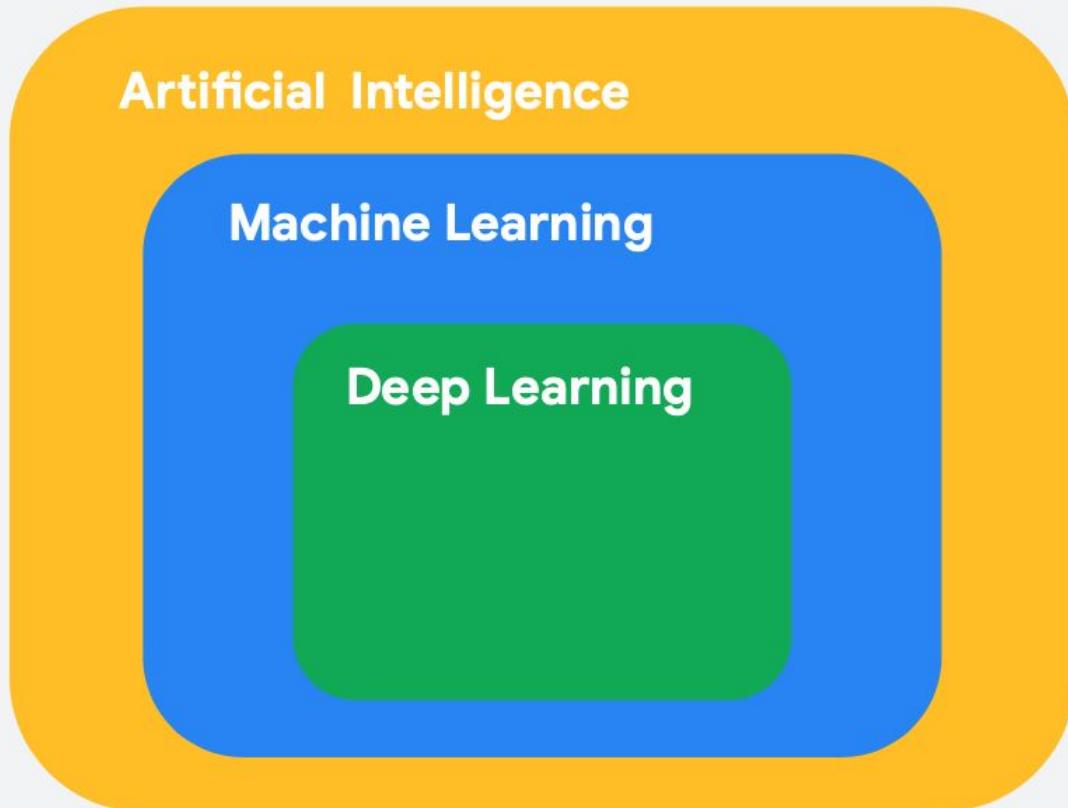


Market Forecast



Embedded ML (TinyML)

Introduction



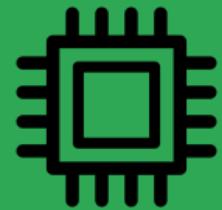
AI: Any technique that enables computers to mimic human behavior

ML: Ability to learn without explicitly being programmed

DL: Extract patterns from data using neural networks

EdgeAI/ML

TinyML



Edge AI (or Edge ML) is the processing of Artificial Intelligence algorithms on edge, that is, on users' devices. The concept derives from **Edge Computing**, which starts from the same premise: data is stored, processed, and managed directly at the Internet of Things (IoT) endpoints.

TinyML is a subset of **EdgeML**, where sensors are generating data with ultra-low power consumption (batteries), so that we can ultimately deploy machine learning continuously ("always on devices")

What is Tiny Machine Learning (**TinyML**)?

TinyML



Fastest-growing field of **ML**



What is Tiny Machine Learning (**TinyML**)?

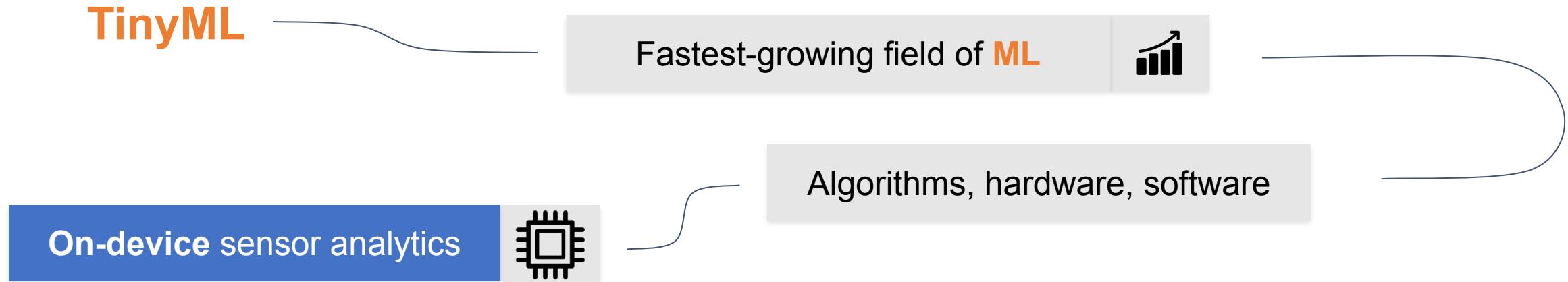
TinyML

Fastest-growing field of **ML**

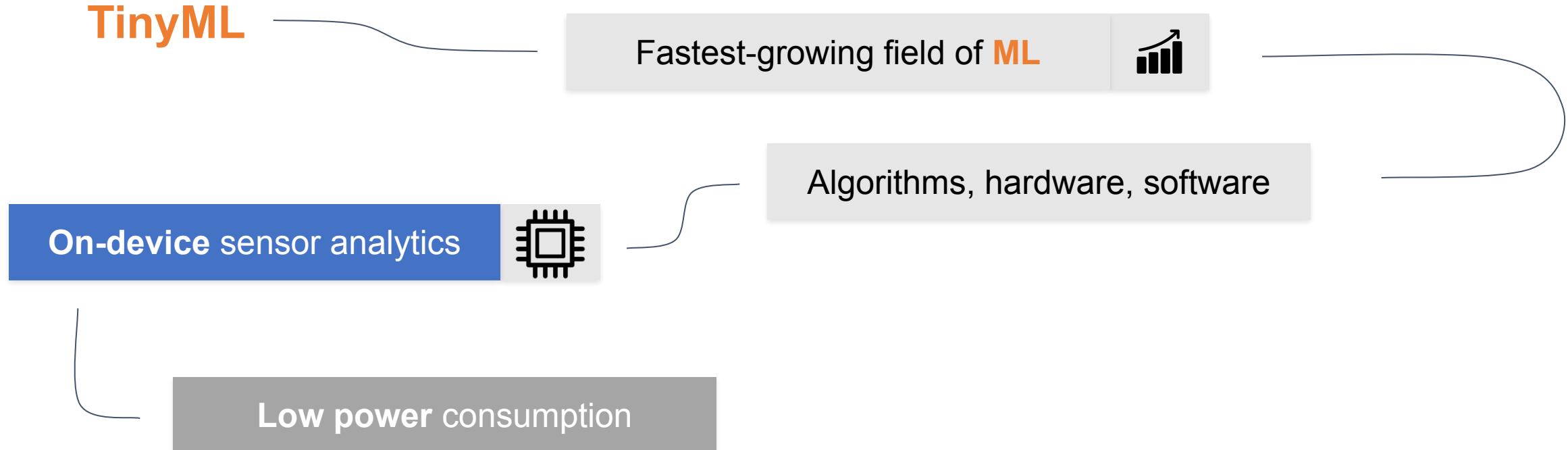


Algorithms, hardware, software

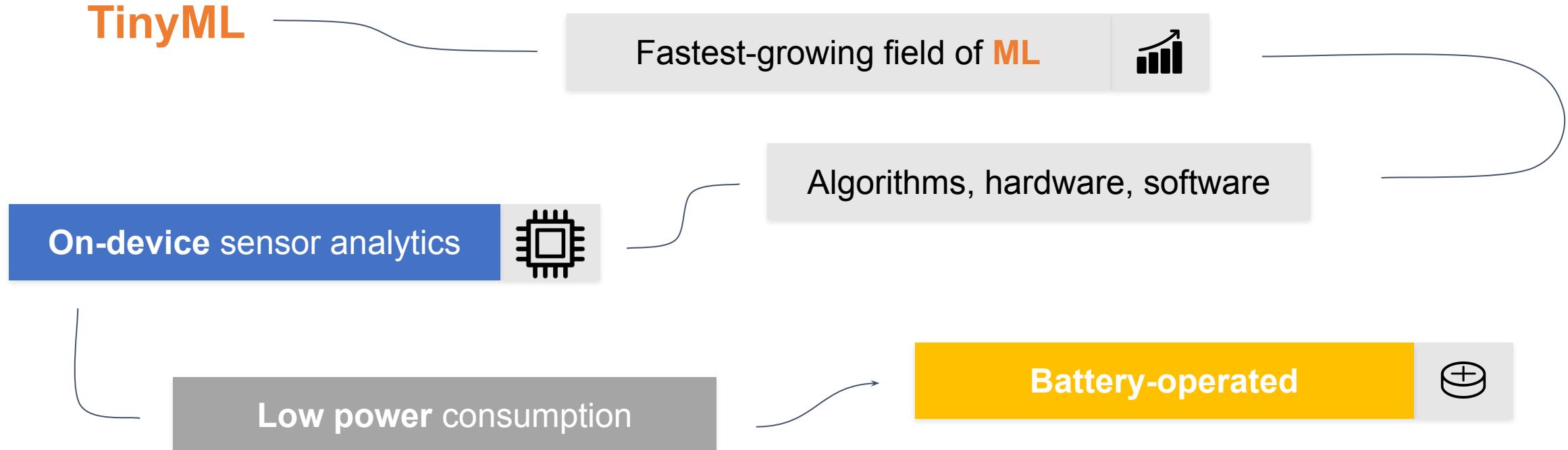
What is Tiny Machine Learning (**TinyML**)?



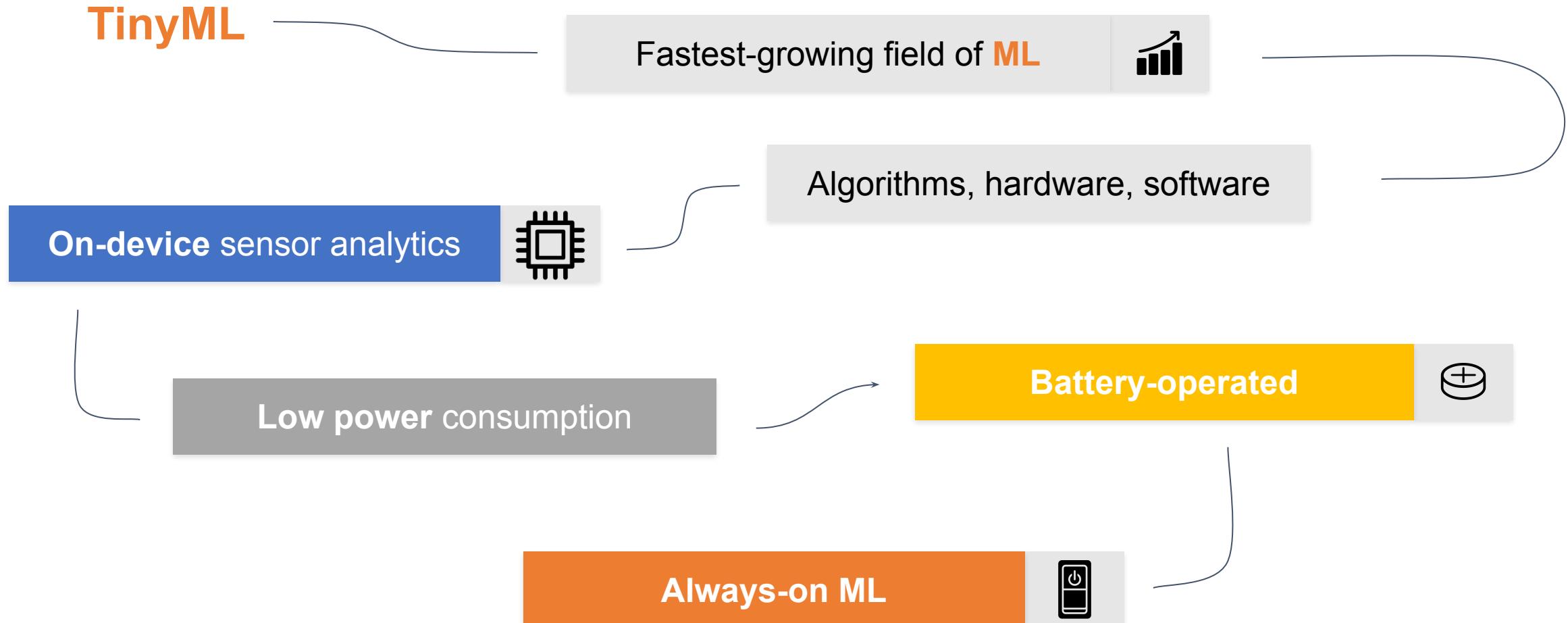
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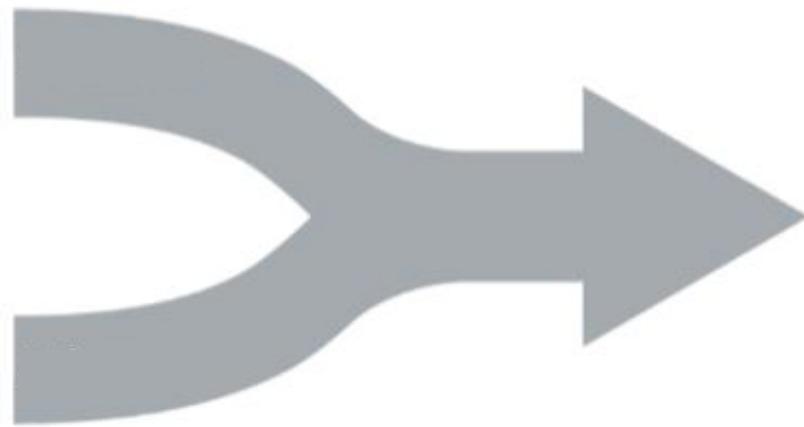
What is Tiny Machine Learning (**TinyML**)?



What Makes **TinyML** ?

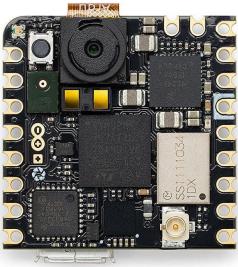
Embedded
Systems

Machine
Learning

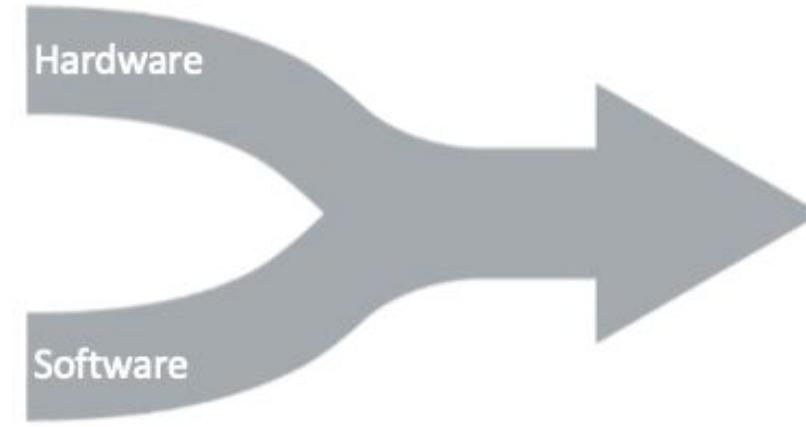


TinyML

What Makes **TinyML** ?

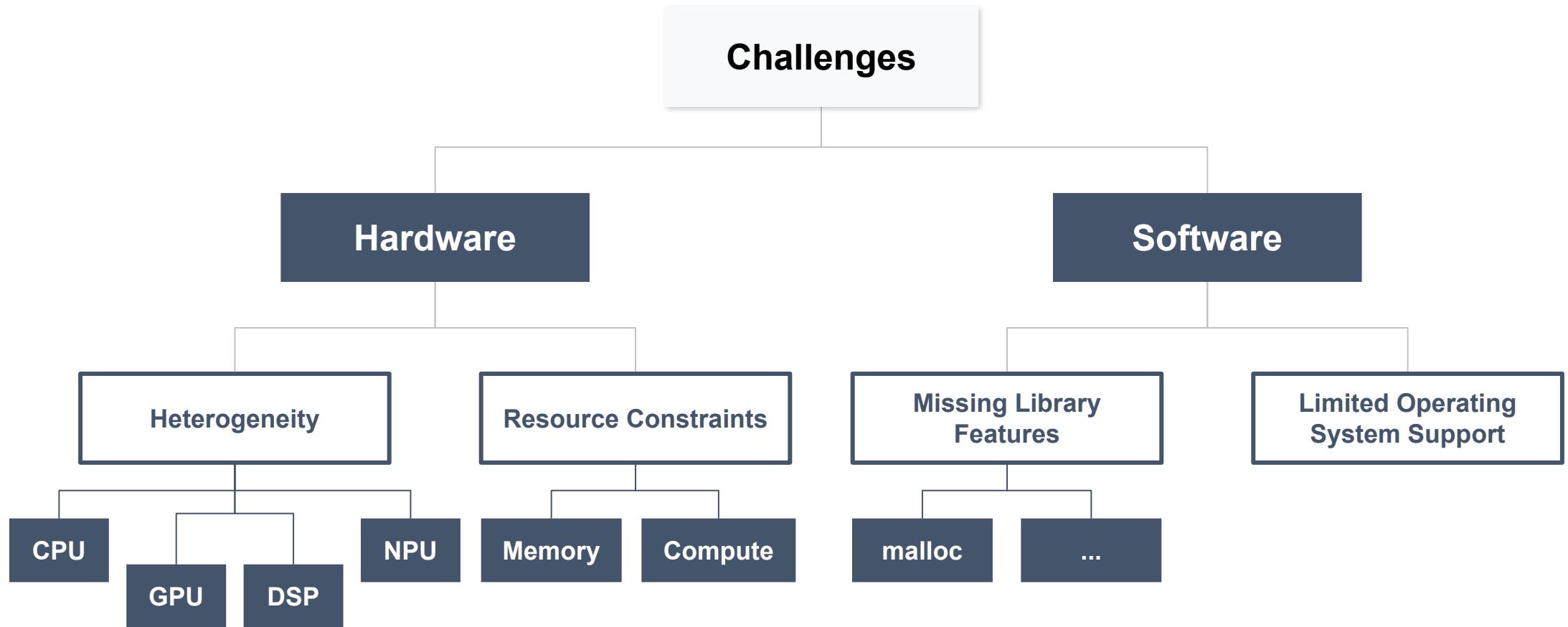


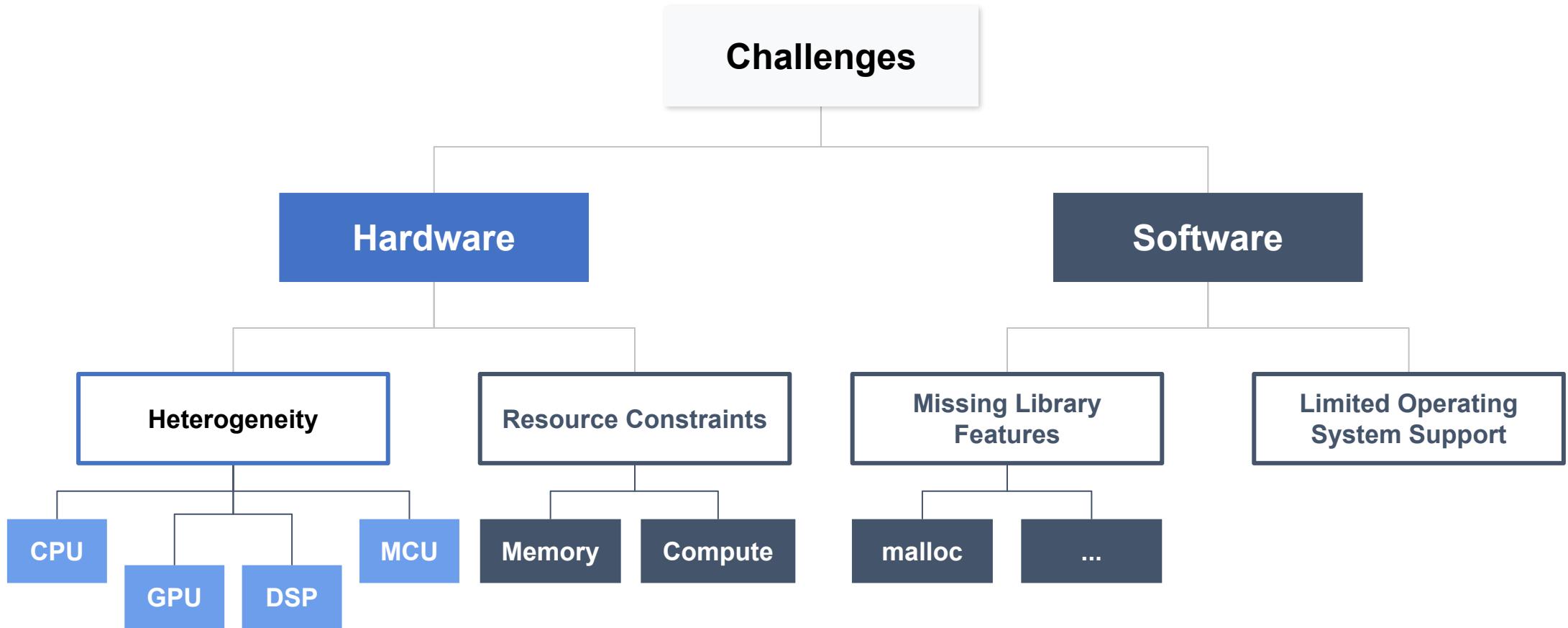
TensorFlow Lite



TinyML

TinyML Challenges



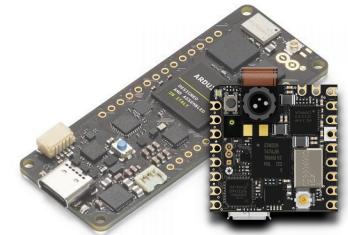


250 Billion
MCUs today

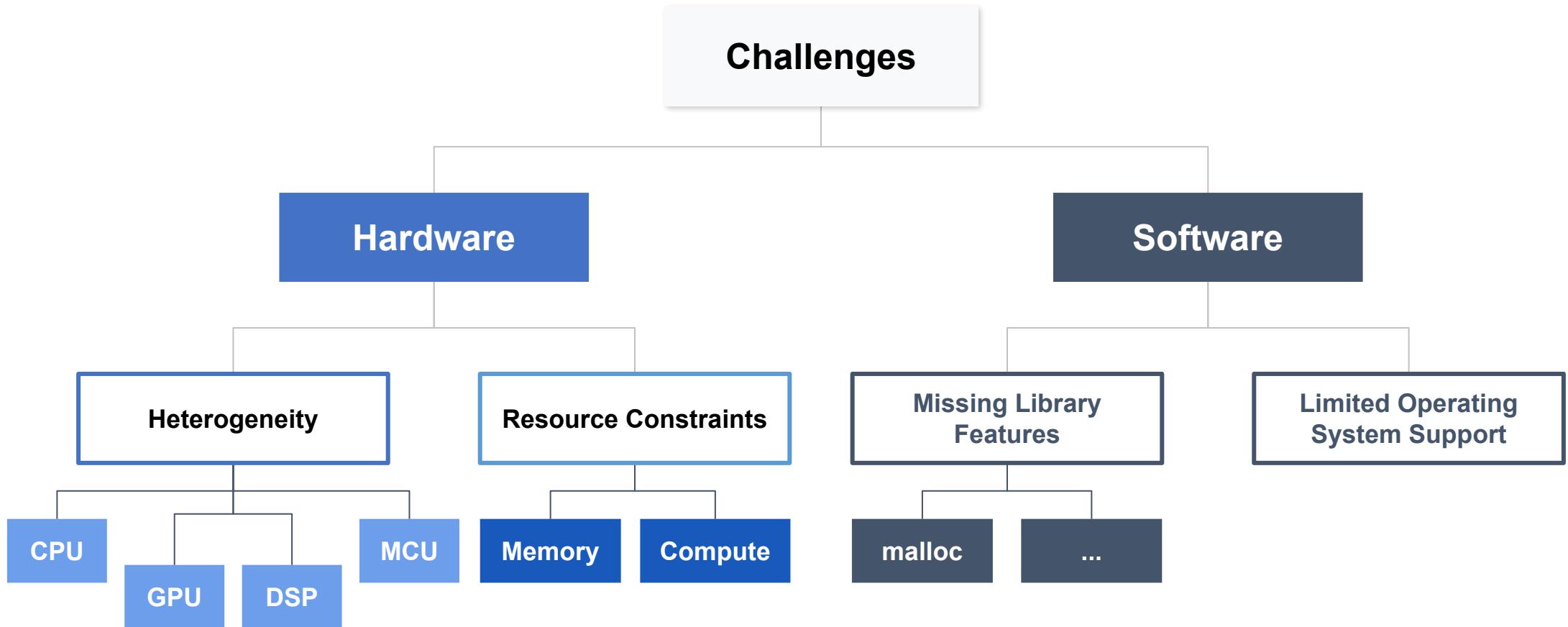
Hardware



Hardware



	Raspberry Pico (W)	Arduino Nano Sense	ESP 32	Seeed XIAO Sense / ESP32S3	Arduino Pro
32Bits CPU	Dual-core Arm Cortex-M0+	Arm Cortex-M4F	Xtensa LX6 Dual Core	Arm Cortex-M4F (BLE) Xtensa LX7 Dual Core	Dual Core Arm Cortex M7/M4
CLOCK	133MHz	64MHz	240MHz	64 / 240MHz	480/240MHz
RAM	264KB	256KB	520KB (part available)	256KB / 8MB	1MB
ROM	2MB	1MB	2MB	2MB / 8MB	2MB
Radio	(Yes for W)	BLE	BLE/WiFi	BLE / WiFi (ESP32S3)	BLE/WiFi
Sensors	No	Yes	No	Yes (Sense)	Yes (Nicla)
Bat. Power Manag.	No	No	No	Yes	Yes
Price	\$	\$\$\$	\$	\$\$	\$\$\$\$\$



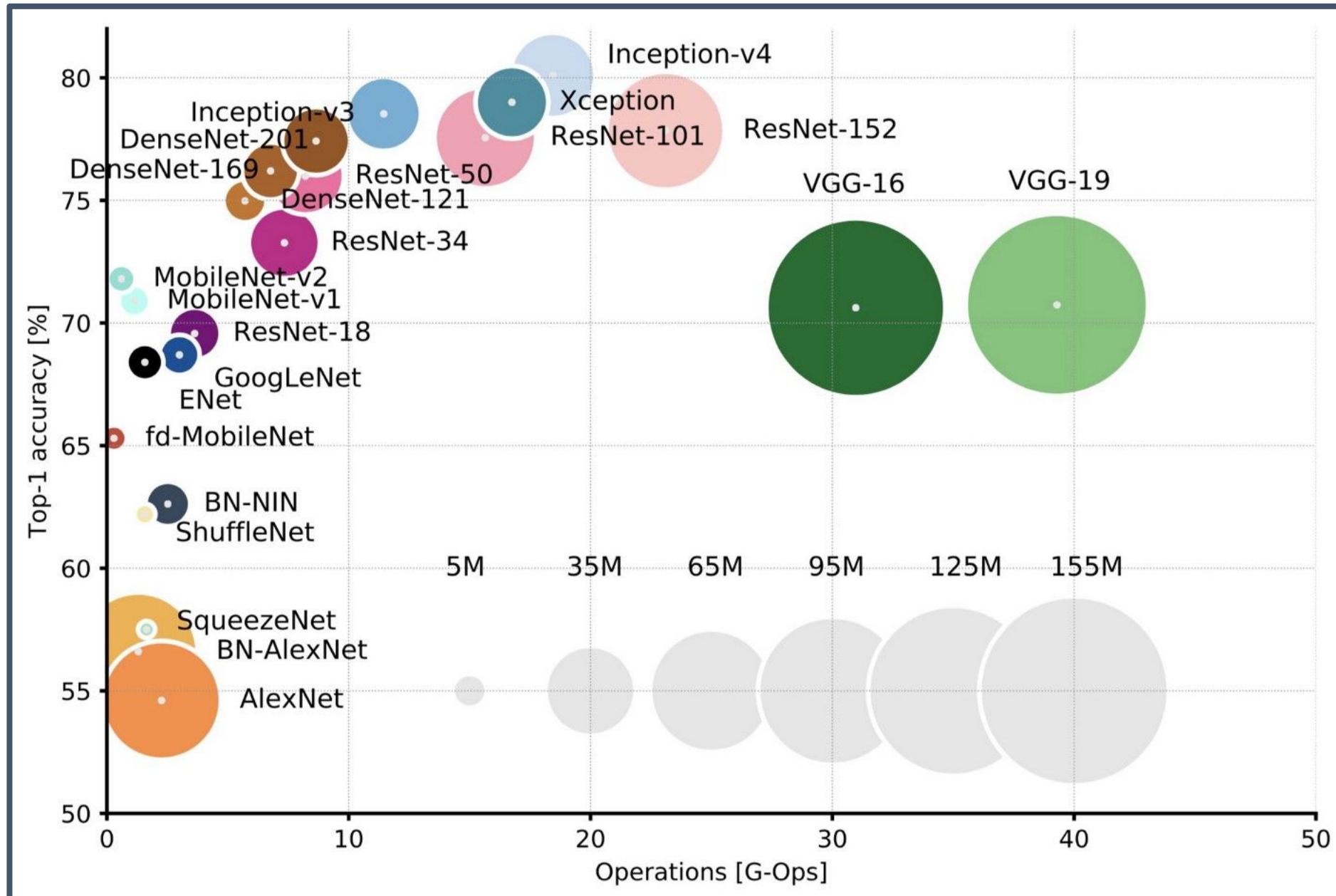
Hardware

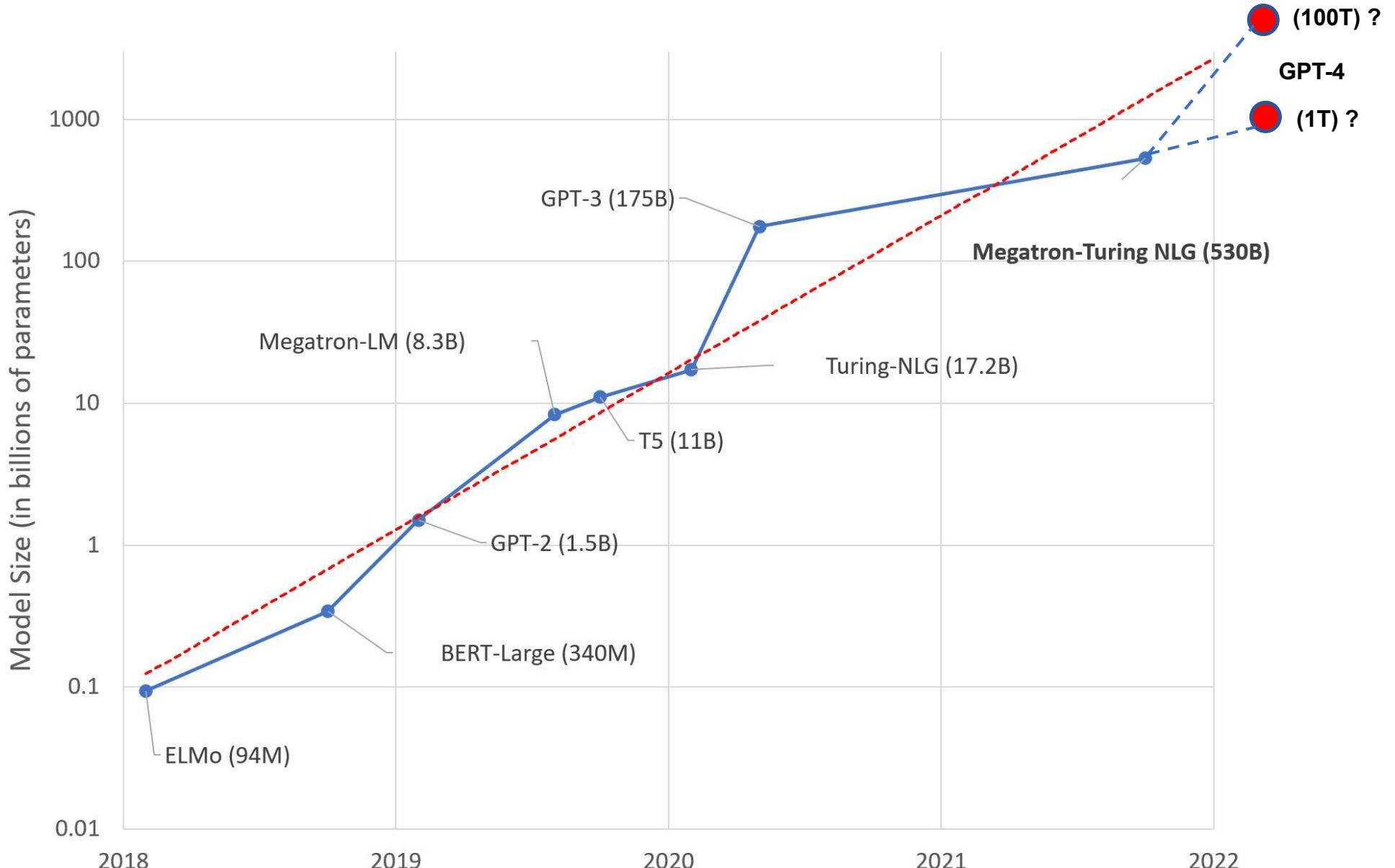


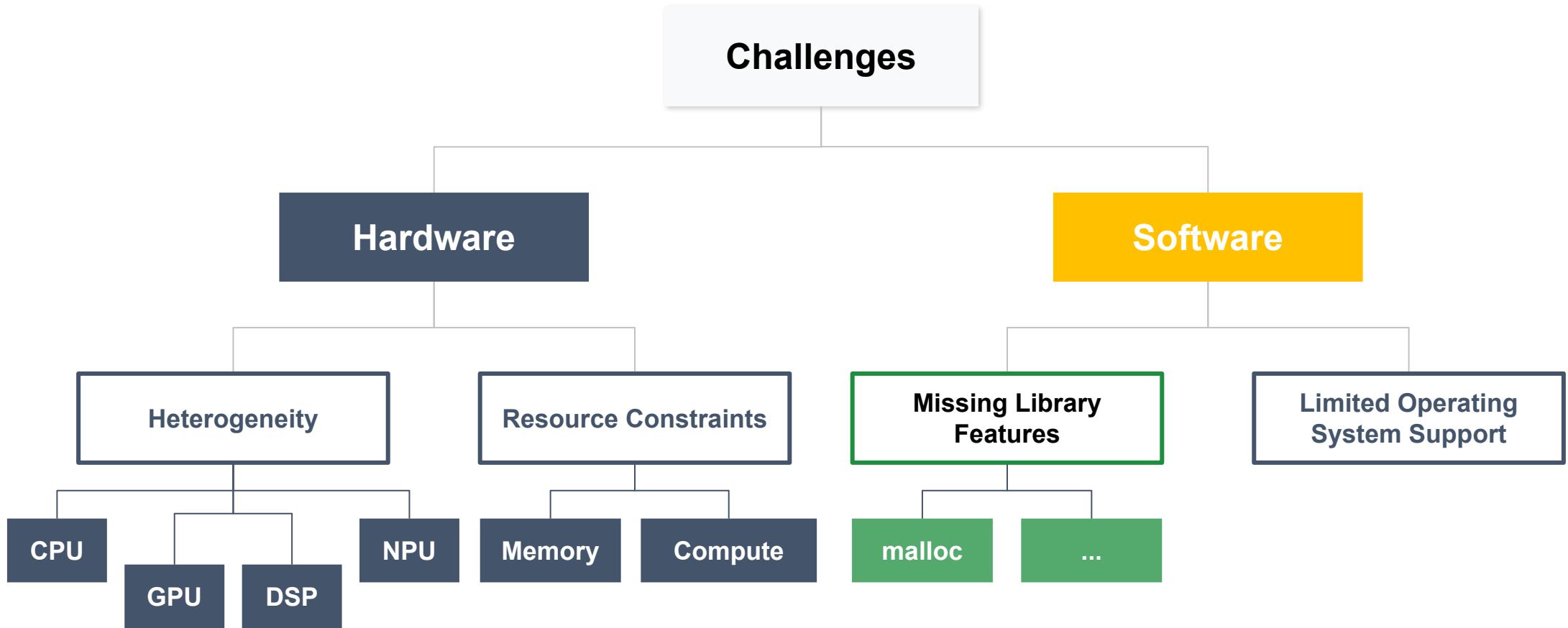
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Bat. Power Manag.	No	No	No	Yes	Yes
Price	\$	\$\$\$	\$	\$\$	\$\$\$\$\$

<https://arxiv.org/pdf/1910.01108.pdf>

<https://towardsdatascience.com/neural-network-architectures-156e5bad51ba>







Datasets Preprocessing

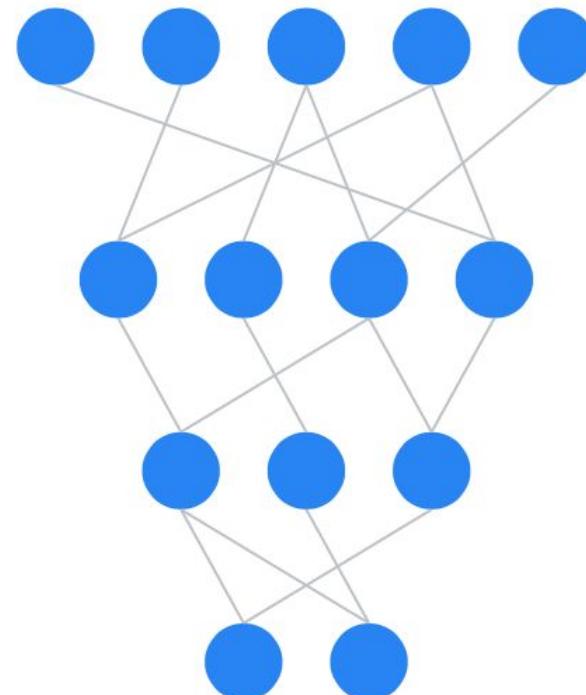
Quantization Pruning

Resource constraints

Sound

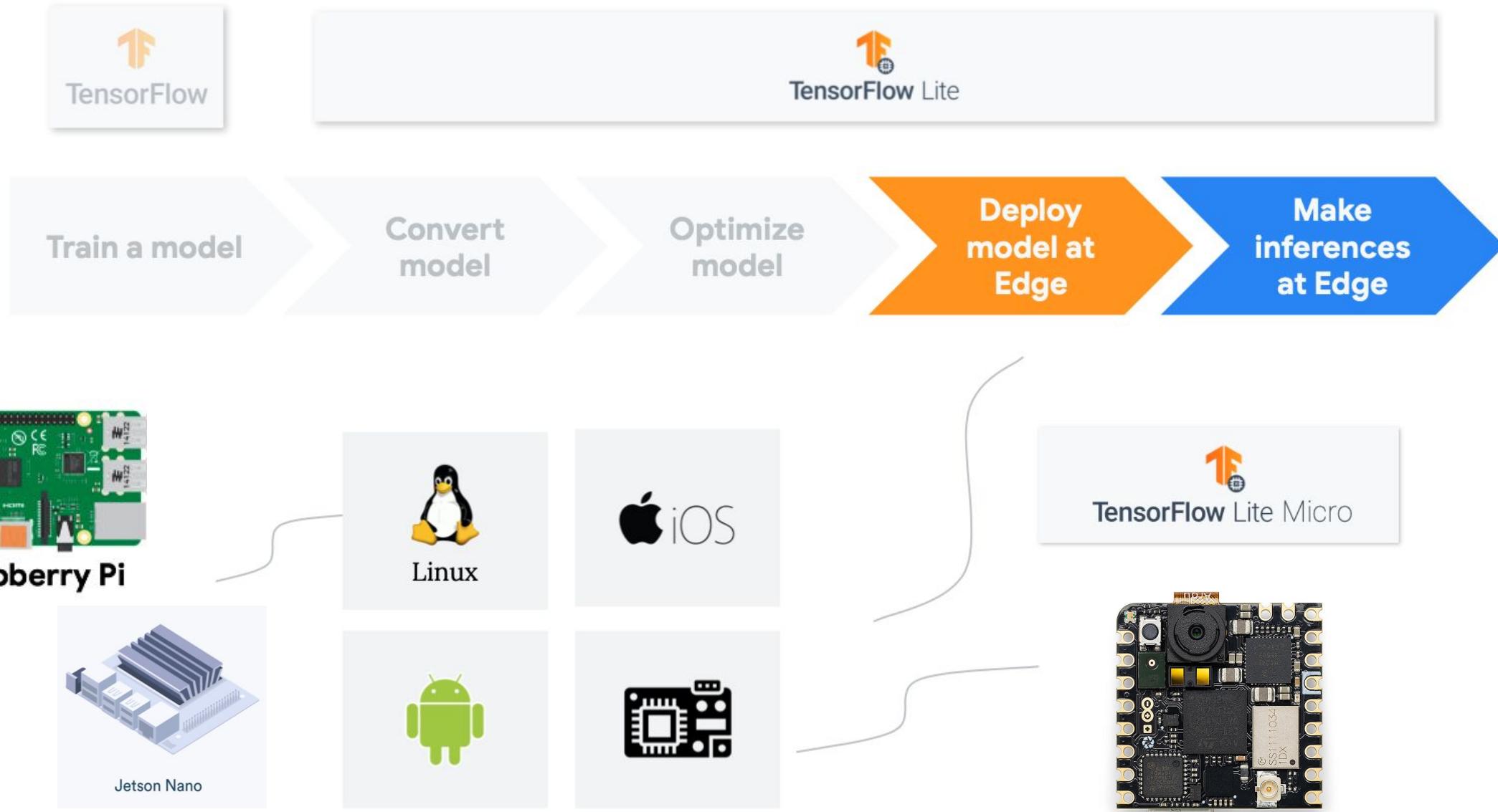
Vision

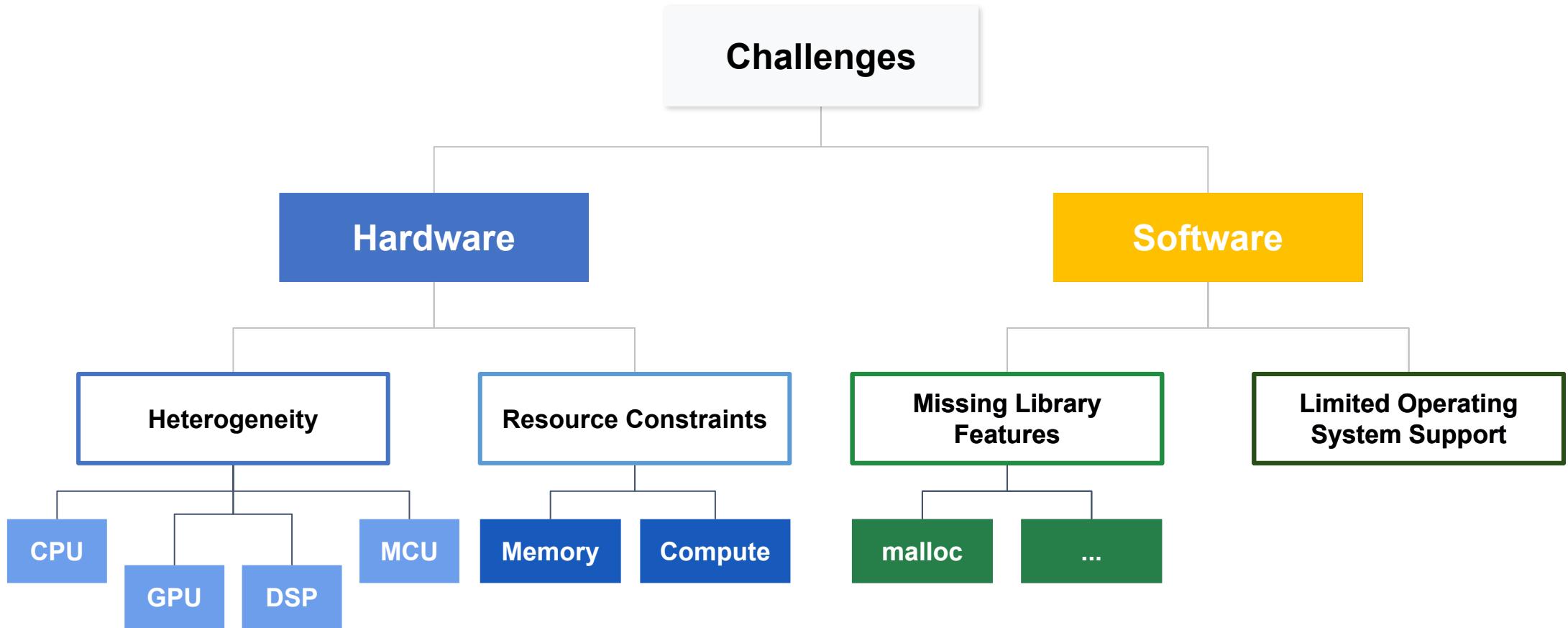
Vibration



End-to-end **TinyML** application design

Software





Application Complexity vs. HW

Power



EdgeML

TinyML

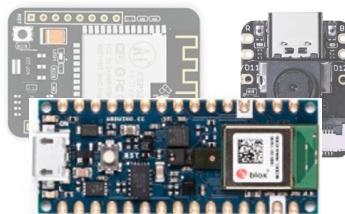


Anomaly Detection
Sensor Classification
20 KB



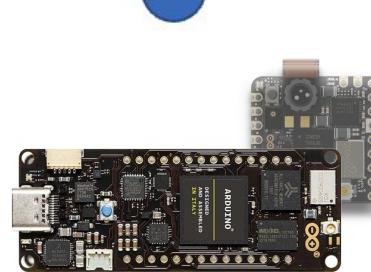
Rpi-Pico
(Cortex-M0+)

KeyWord Spotting
Audio Classification
50 KB



Arduino Nano
(Cortex-M4)

ESP32



Arduino Pro
(Cortex-M7)

Image
Classification
250 KB+



Object Detection
Complex Voice
Processing
1 MB+



RaspberryPi
(Cortex-A)

Video
Classification
2 MB+

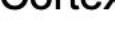


SmartPhone
(Cortex-A)

Jetson Nano
(Cortex-A + GPU)

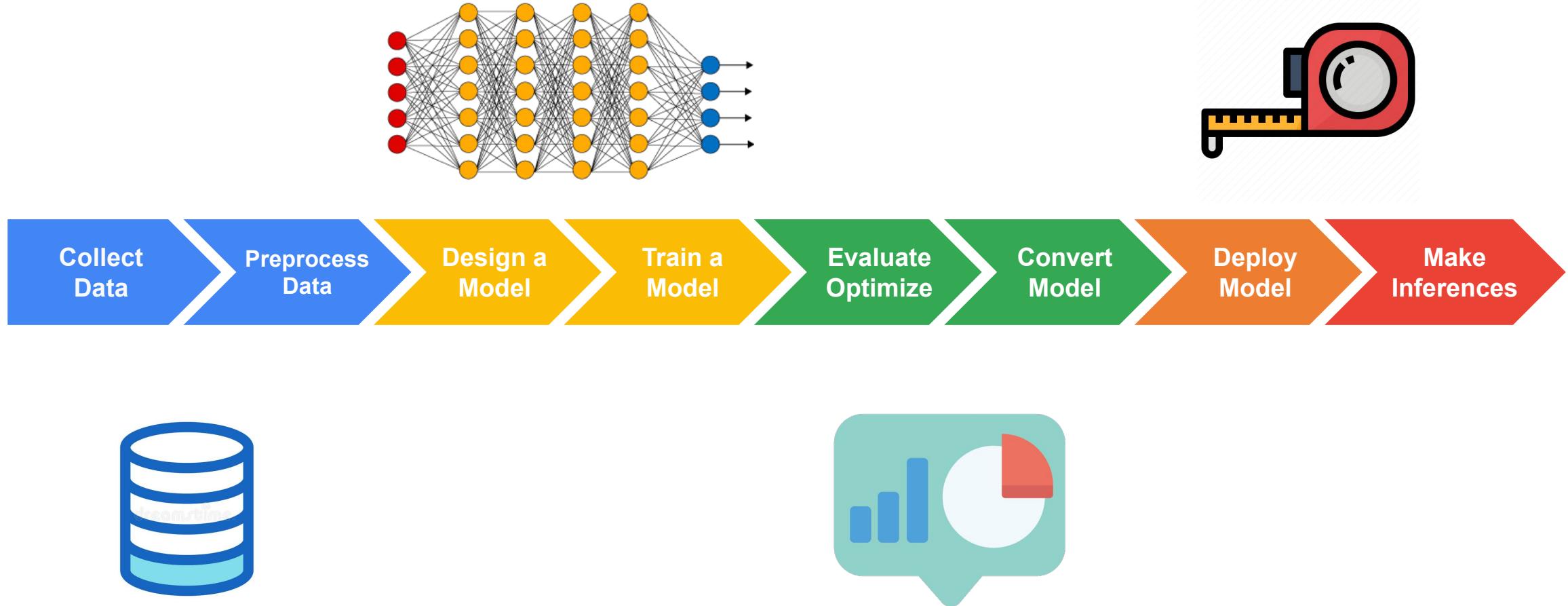
Application Complexity ↑

CPU Power / Memory →

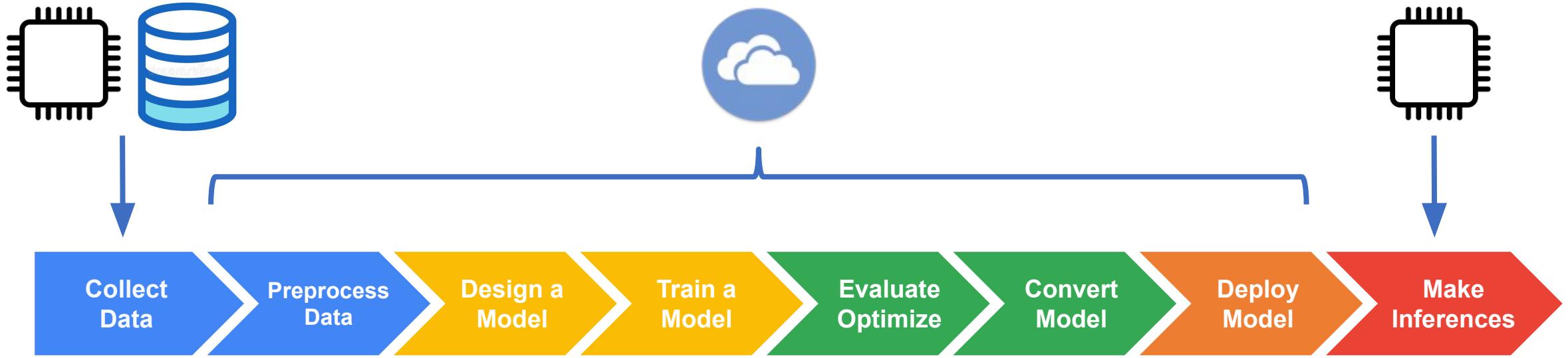


How to Train a ML Model?

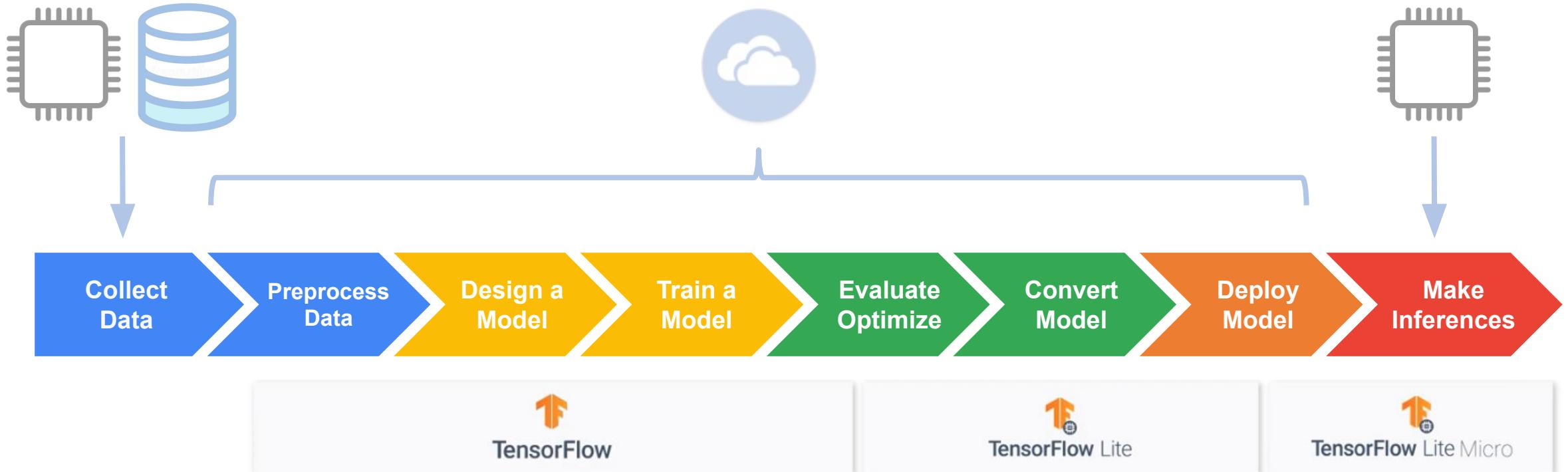
Machine Learning Workflow (“What”)



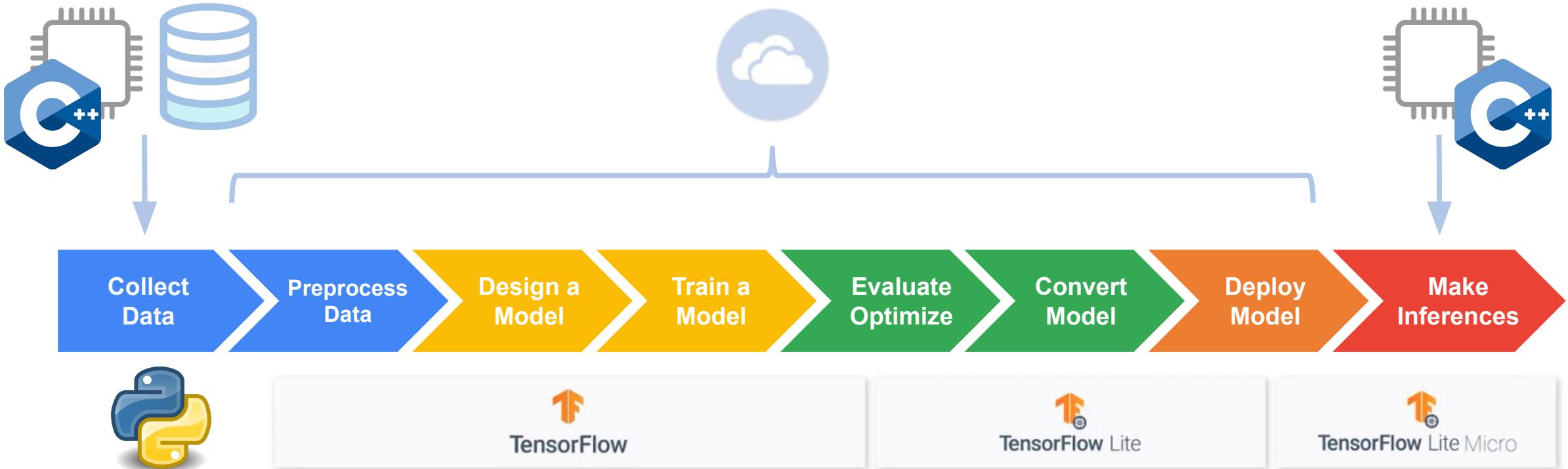
Machine Learning Workflow (“Where”)



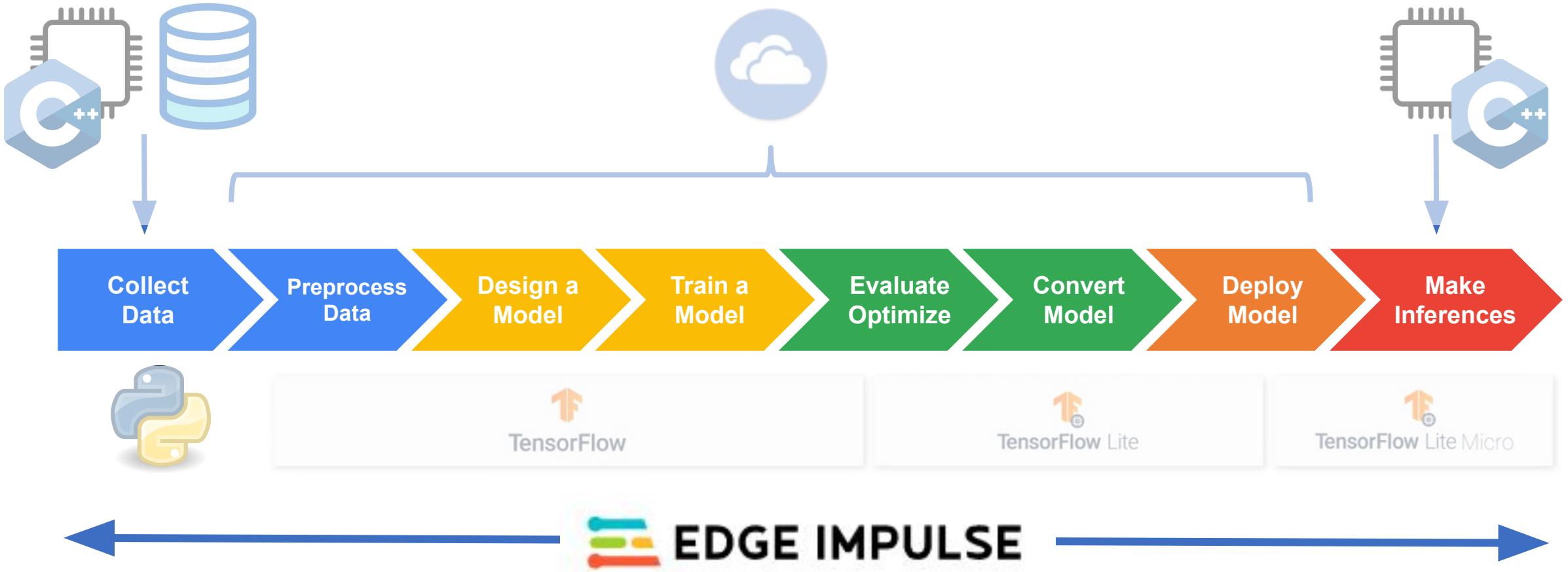
Machine Learning Workflow (“How”)

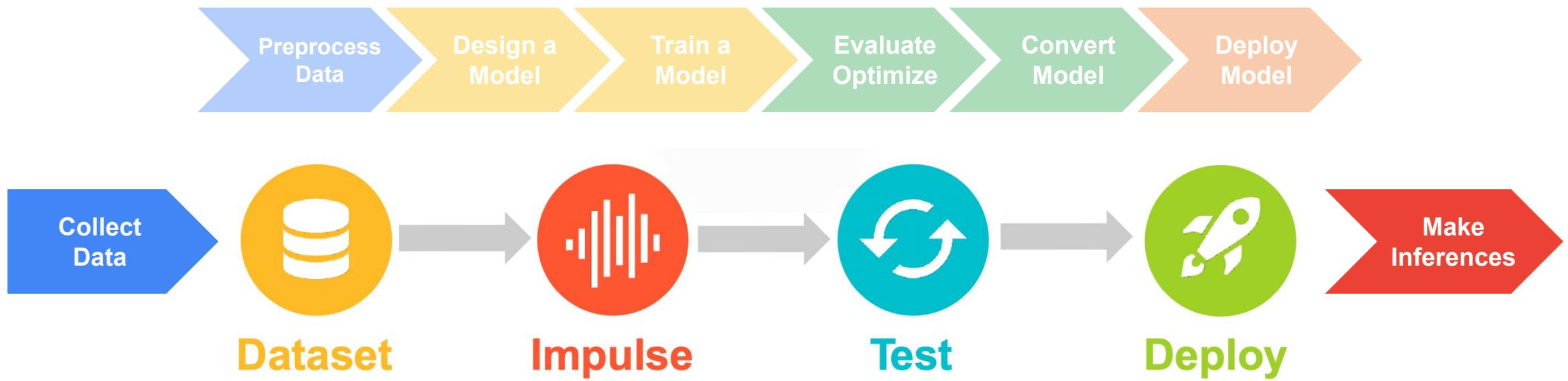


Machine Learning Workflow (“How”)

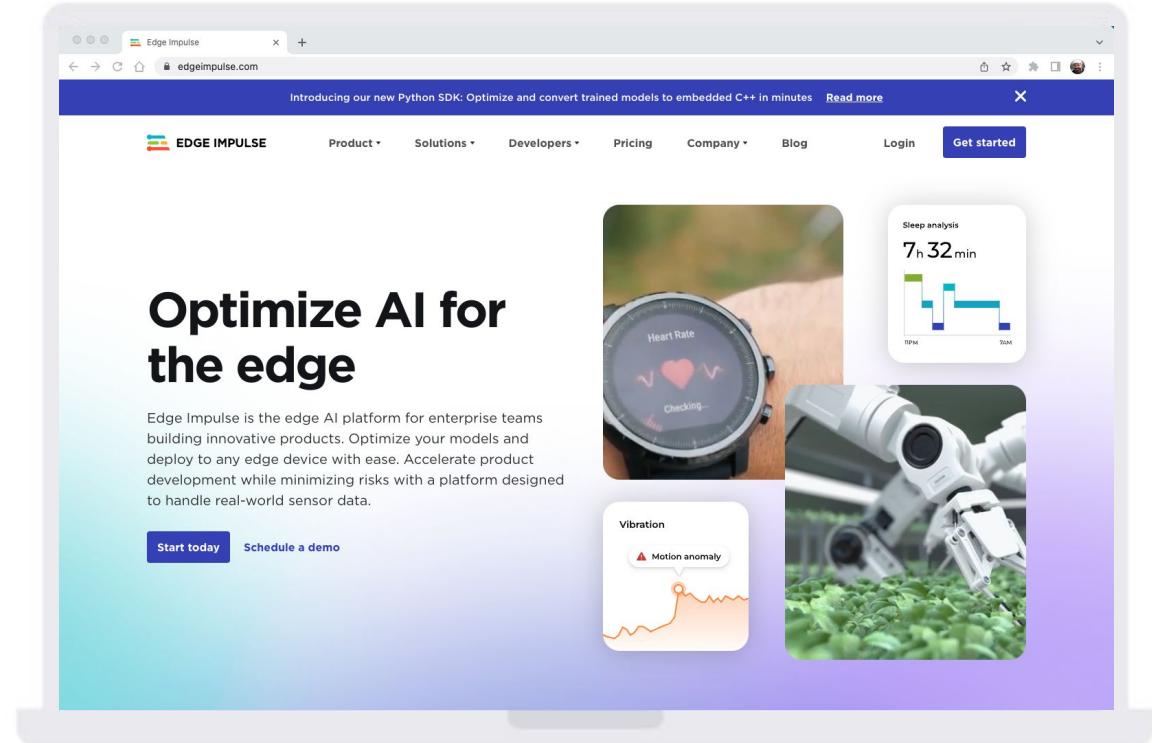
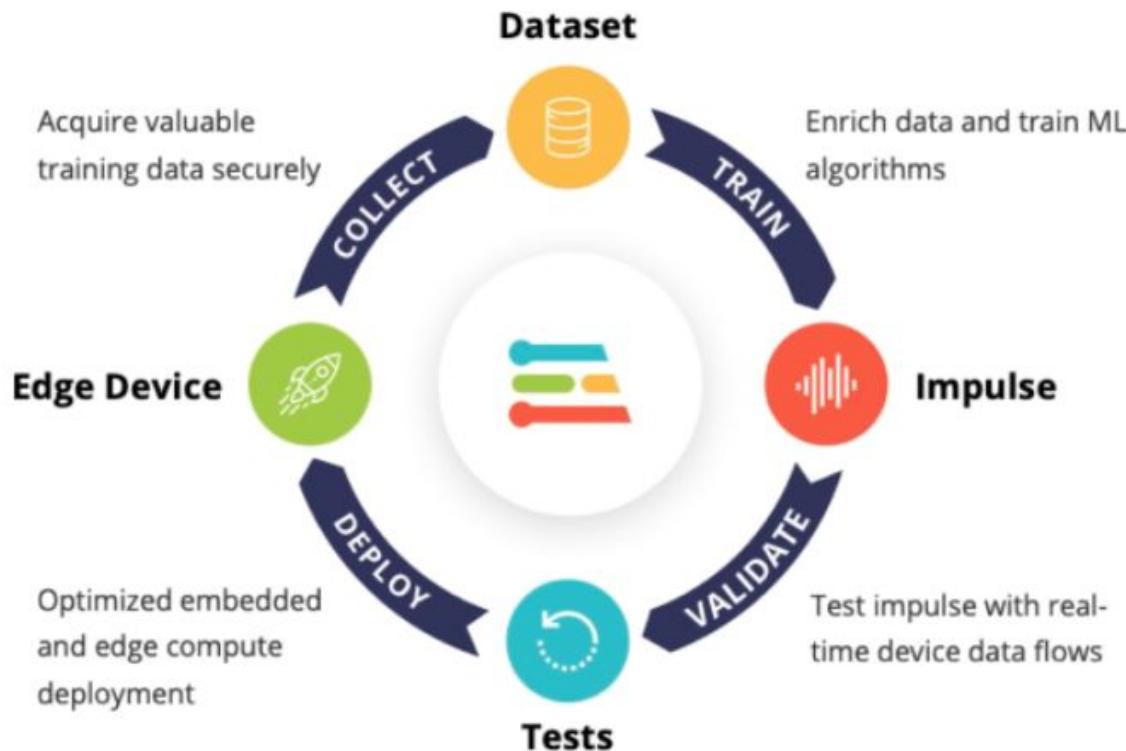


Machine Learning Workflow (“How”)





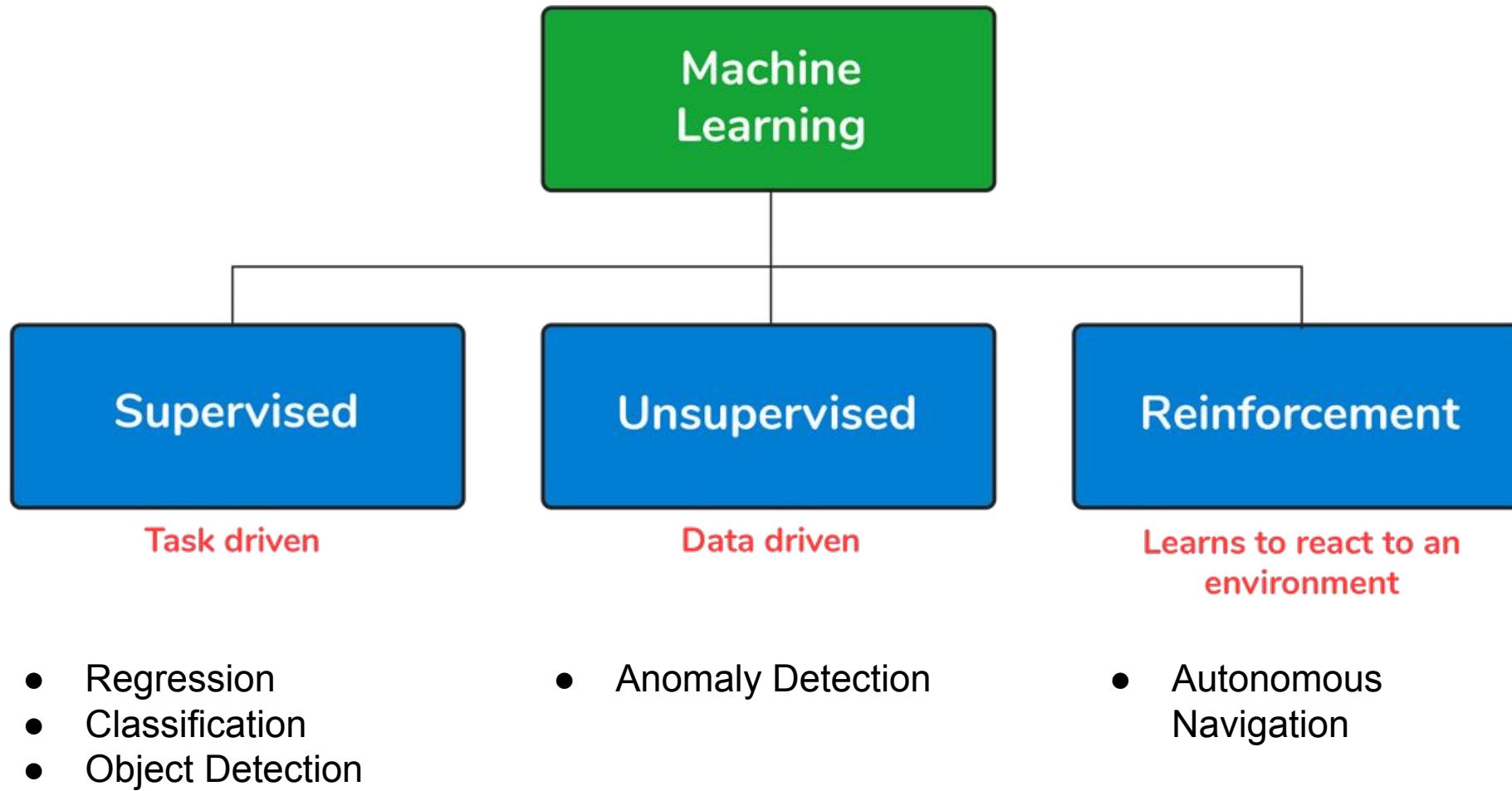
EI Studio - Embedded ML platform (“AutoML”)



Learn more at <http://edgeimpulse.com>



TinyML Application Examples



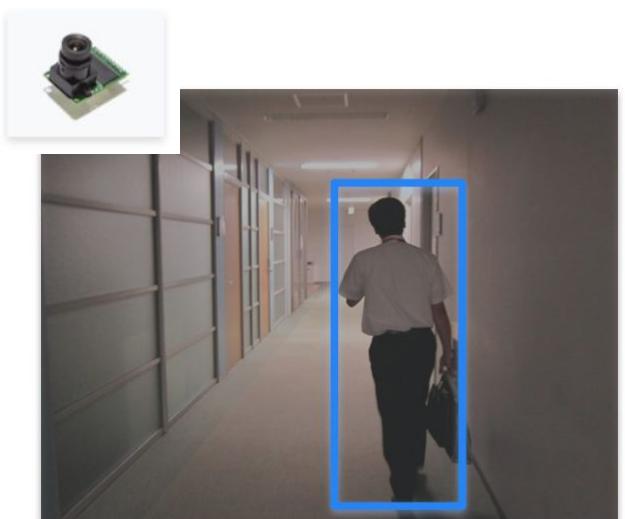
Sound



Vibration



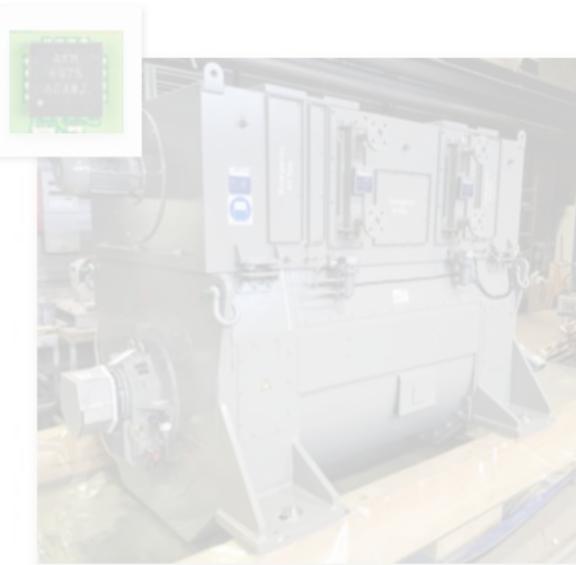
Vision



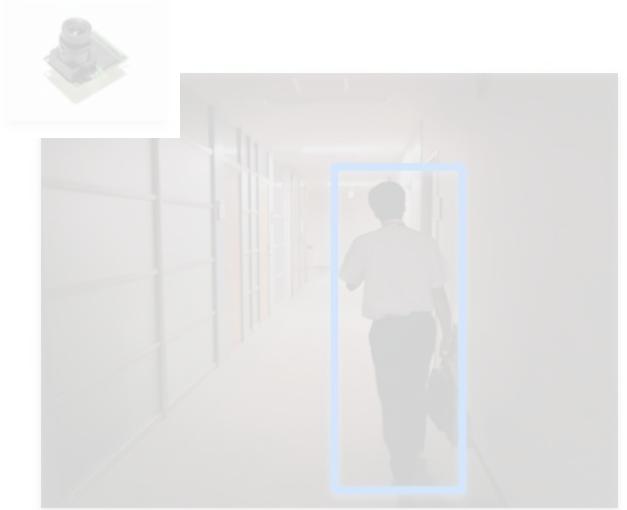
Sound



Vibration



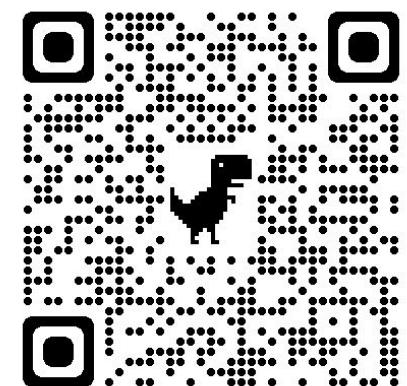
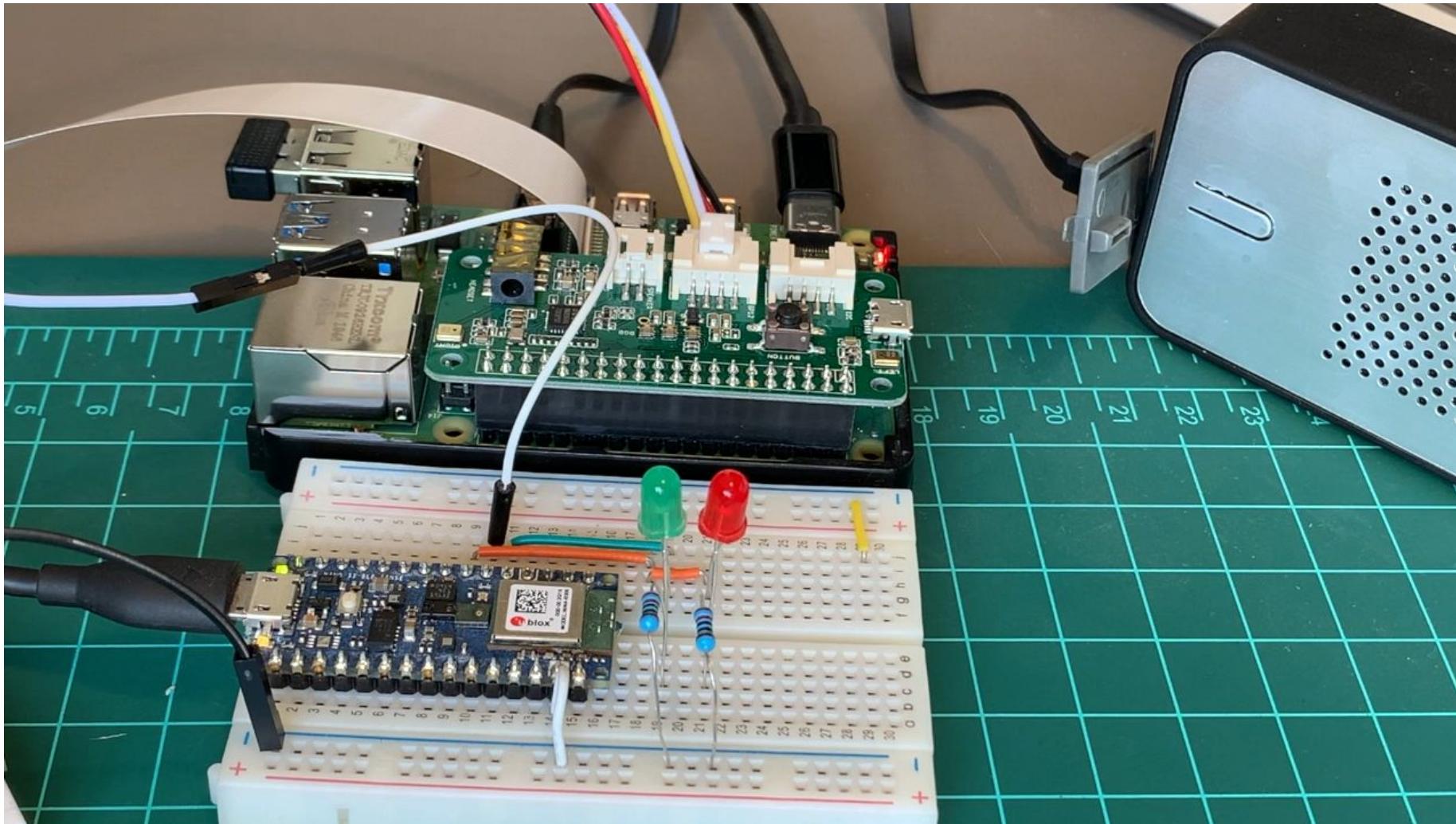
Vision



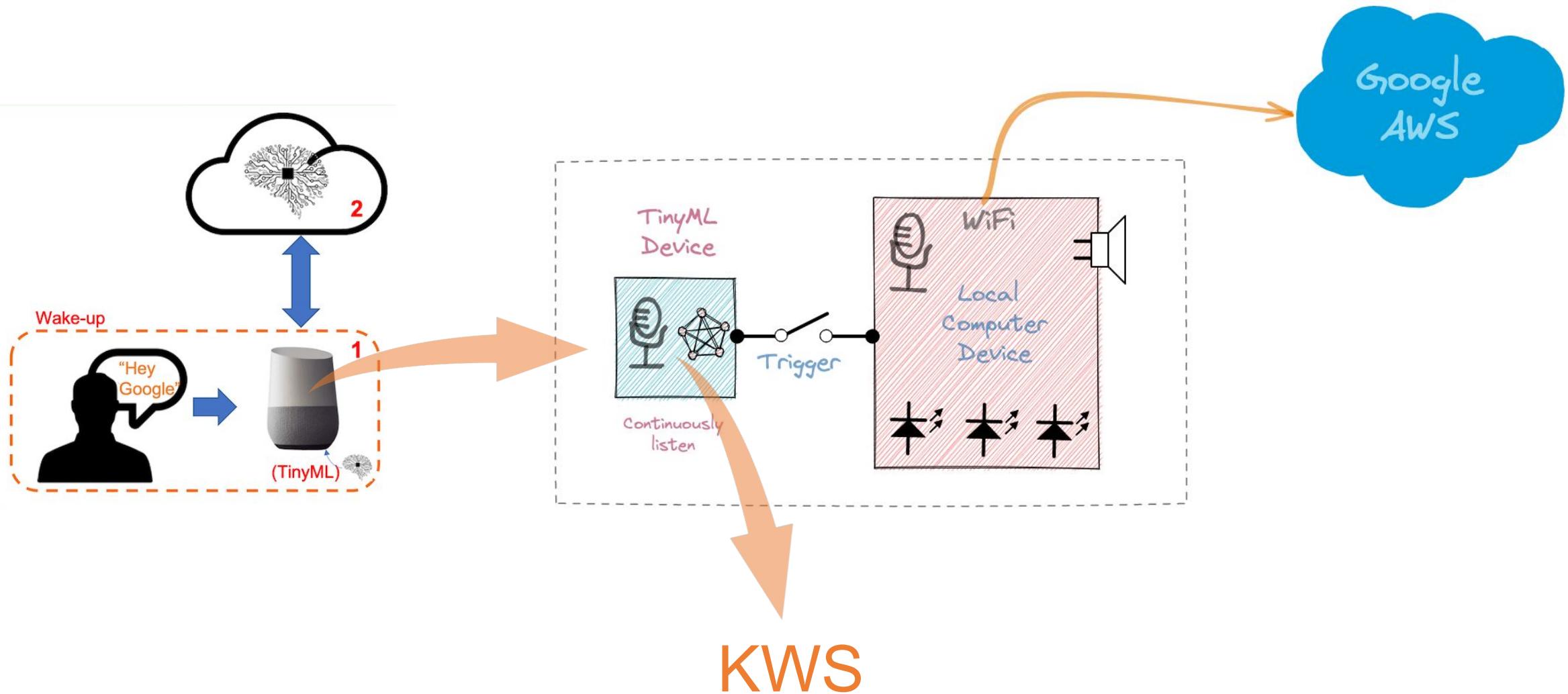
Personal Assistant



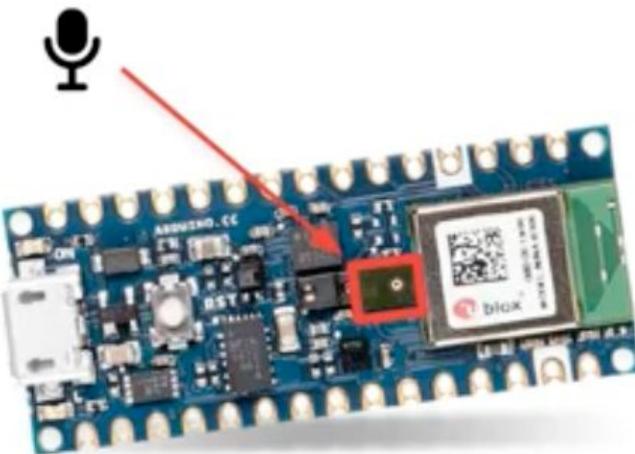
Personal Assistant



Personal Assistant



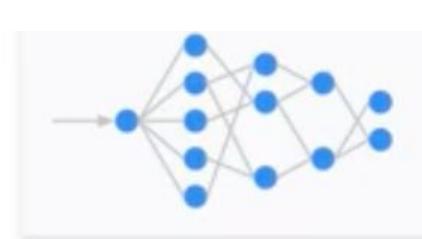
“Cascade” Detection: multi-stage model



1 Continuously listen on the microcontroller

2

Process the data with **TinyML** at the edge



3

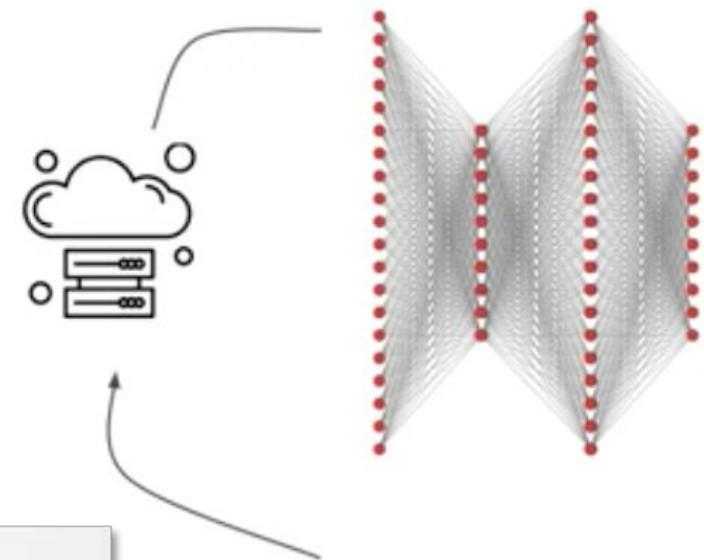
Process on a secondary larger model on a larger local device



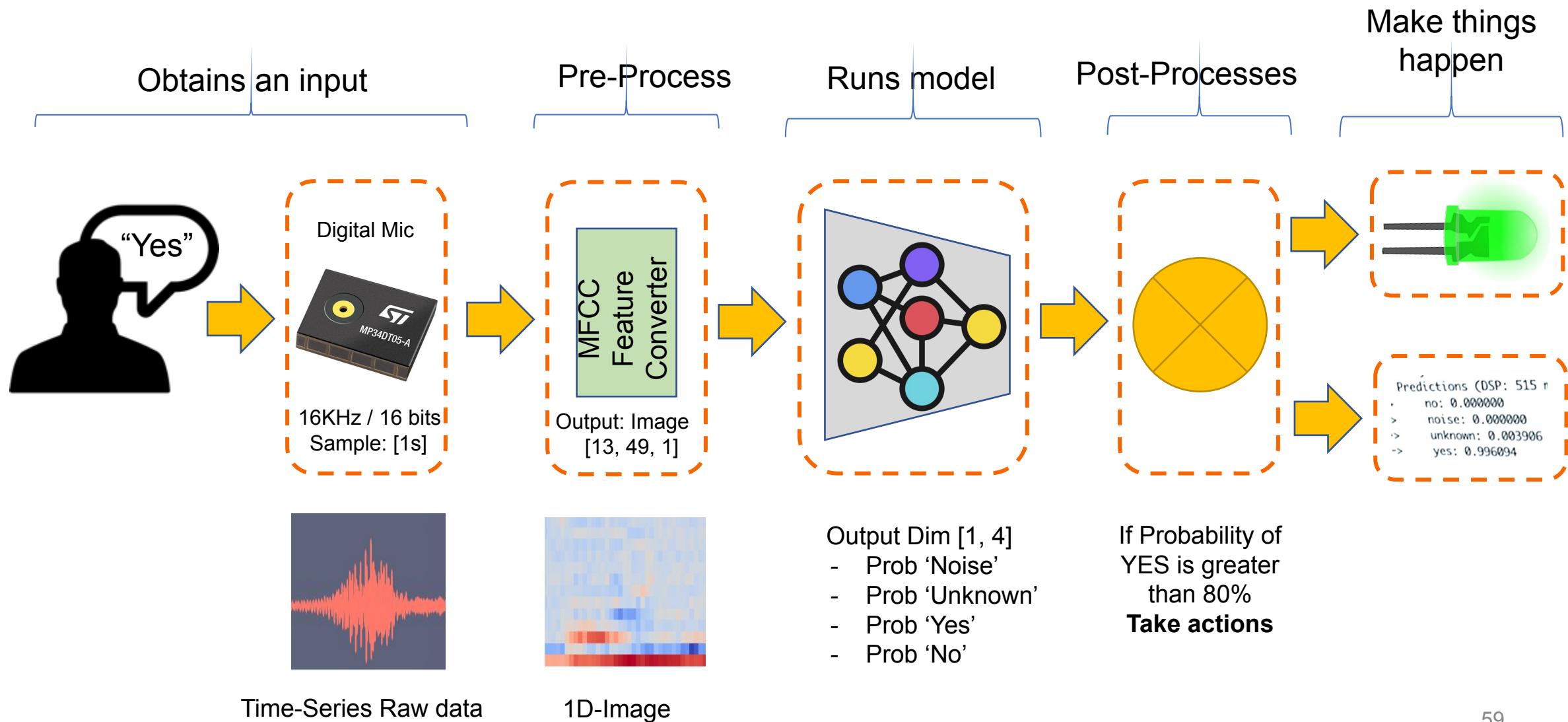
4

Send the data to the cloud when triggered

5 Process the full speech data with a large model in the cloud



KeyWord Spotting (KWS) - Inference





Moez Altayeb
University of Khartoum, Sudan
ICTP, Trieste, Italy
mohedahmed@hotmail.com

ABSTRACT

Every year more than one billion people are infected and more than one million people die from vector-borne diseases including malaria, dengue, zika and chikungunya. Mosquitoes are the best known disease vector and are geographically spread worldwide. It is important to raise awareness of mosquito proliferation by monitoring their incidence, especially in poor regions. Acoustic detection of mosquitoes has been studied for long and ML can be used to automatically identify mosquito species by their wingbeat. We present a prototype solution based on an openly available dataset on the Edge Impulse platform and on three commercially-available TinyML devices. The proposed solution is low-power, low-cost and can run without human intervention in resource-constrained areas. This insect monitoring system can reach a global scale.

Classifying mosquito wingbeat sound using TinyML

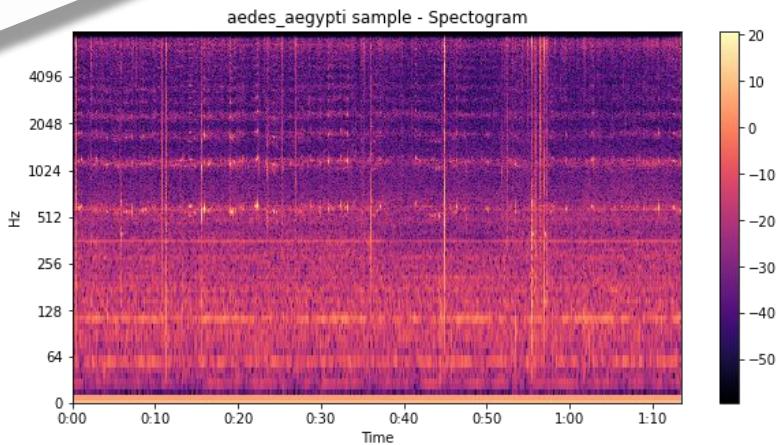
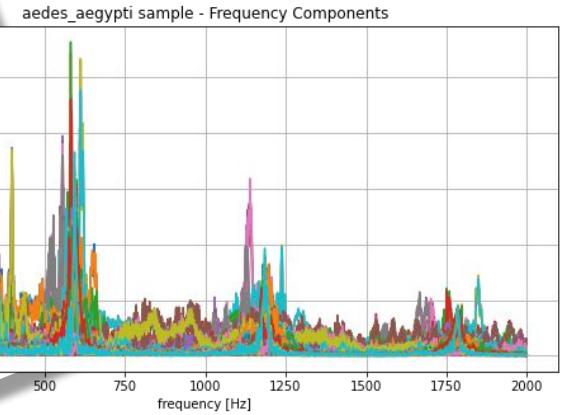
Marcelo Rovai
Universidade Federal de Itajubá
Itajubá, Brazil
rovai@unifei.edu.br

Marco Zennaro
ICTP
Trieste, Italy
mzennaro@ictp.it

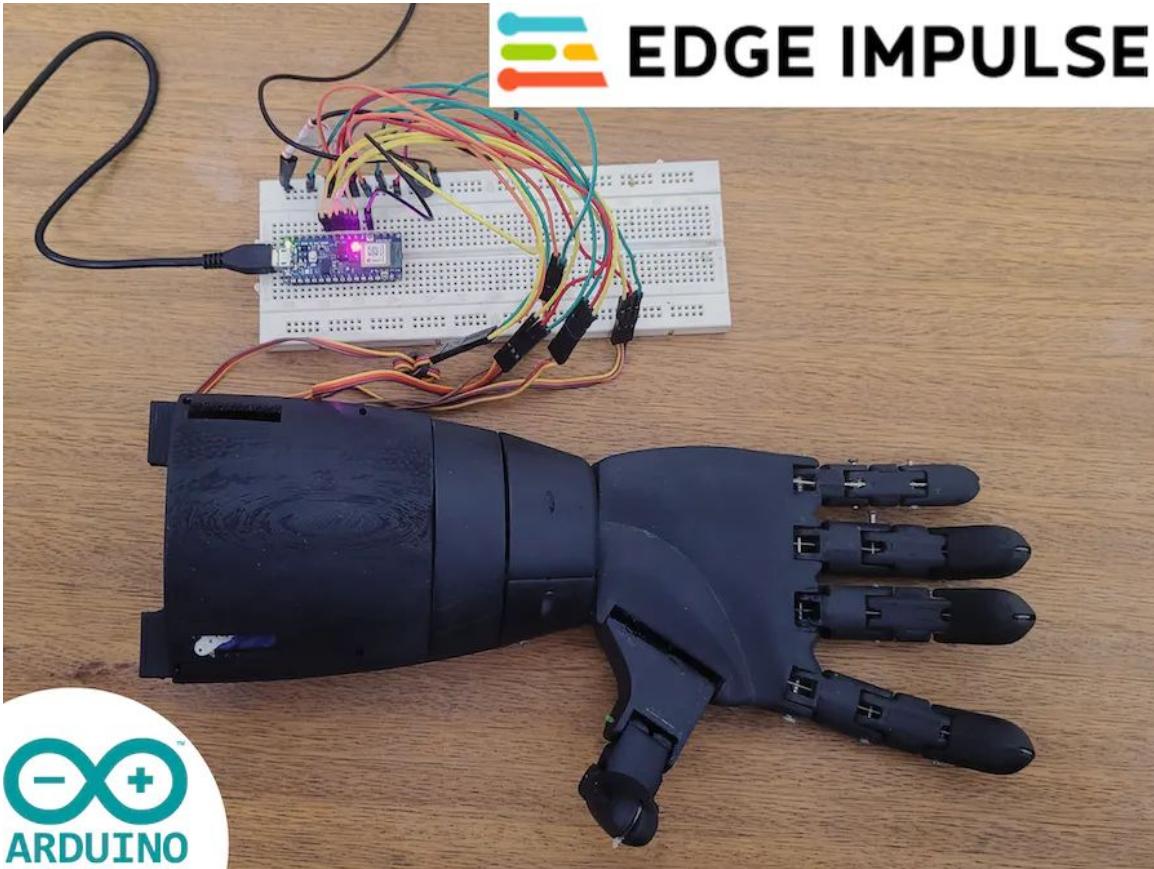
affected. People from poor communities with little access to health care and clean water sources are also at risk. Although anti-malarial drugs exist, there's currently no malaria vaccine.

Vector-borne diseases also exacerbate poverty. Illness prevent people from working and supporting themselves and their families, impeding economic development. Countries with intensive malaria have much lower income levels than those that don't have malaria.

Countries affected by malaria turn to control rather than elimination. Vector control means decreasing contact between humans and disease carriers on an area-by-area basis. It is therefore of great interest to be able to detect the presence of mosquitoes in a specific area. This paper presents an approach based on TinyML and on embedded devices.

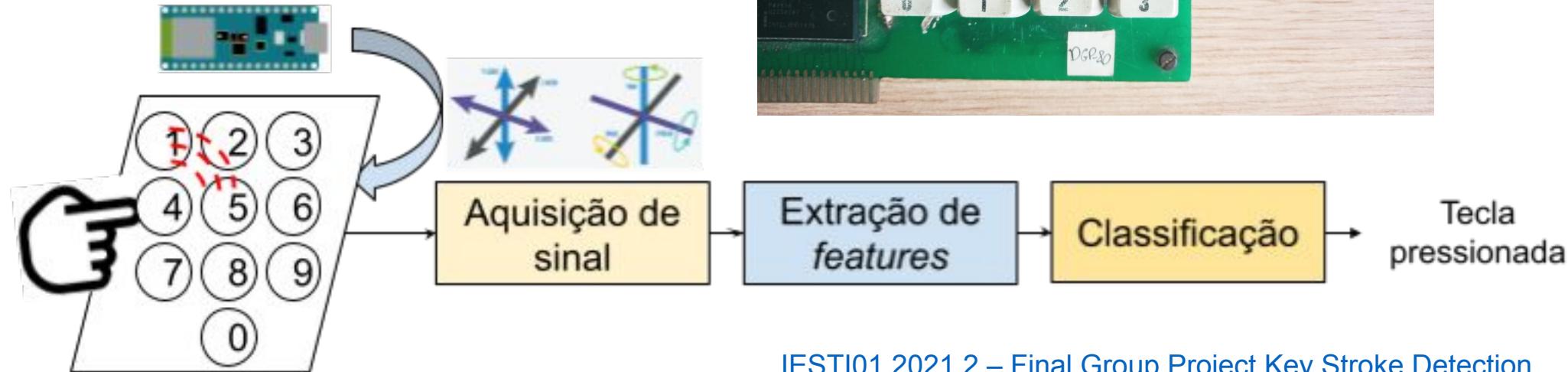


Bionic Hand Voice Commands Module



<https://www.hackster.io/ex-machina/bionic-hand-voice-commands-module-w-edge-impulse-arduino-aa97e3>

Keystroke **Sound** Detection



[IESTI01 2021.2 – Final Group Project Key Stroke Detection](#)



Renam Castro
Professor IFESP

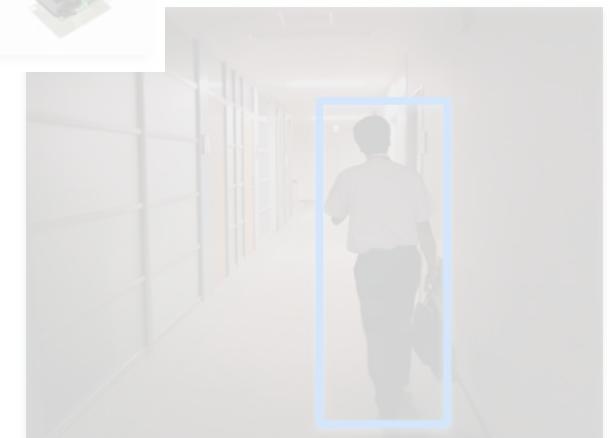
Sound



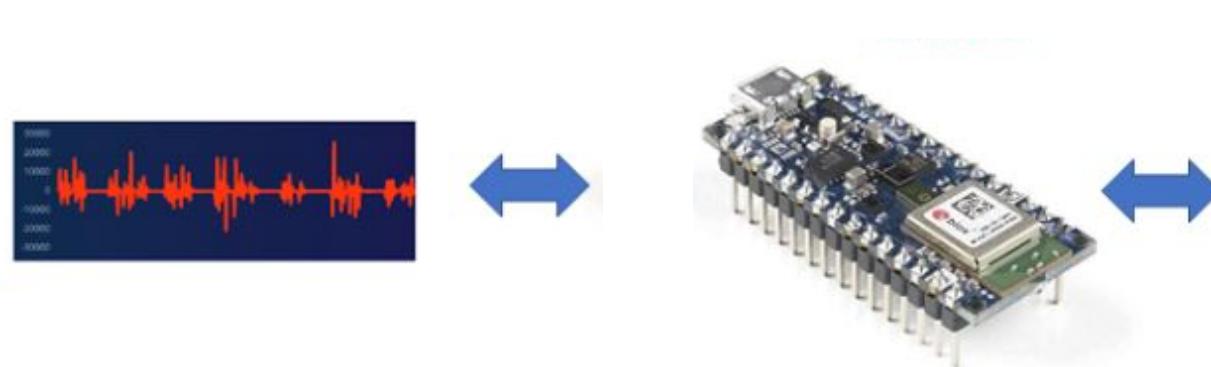
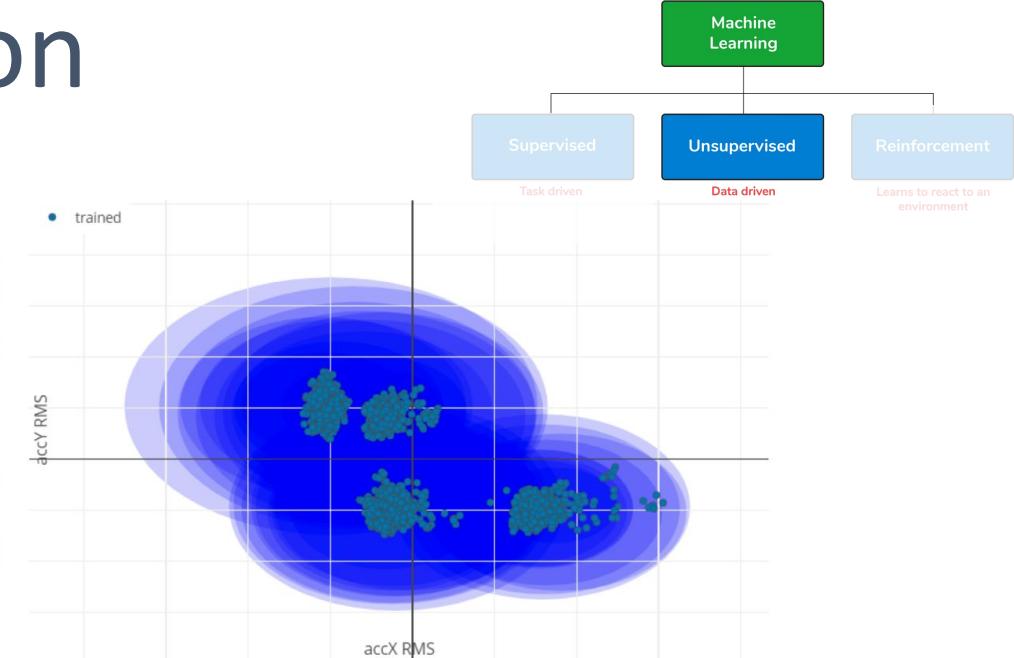
Vibration



Vision

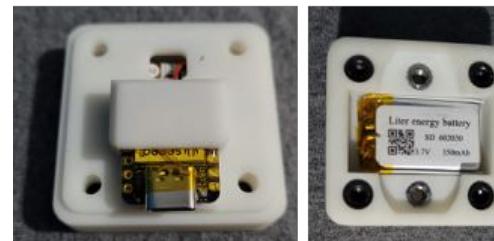
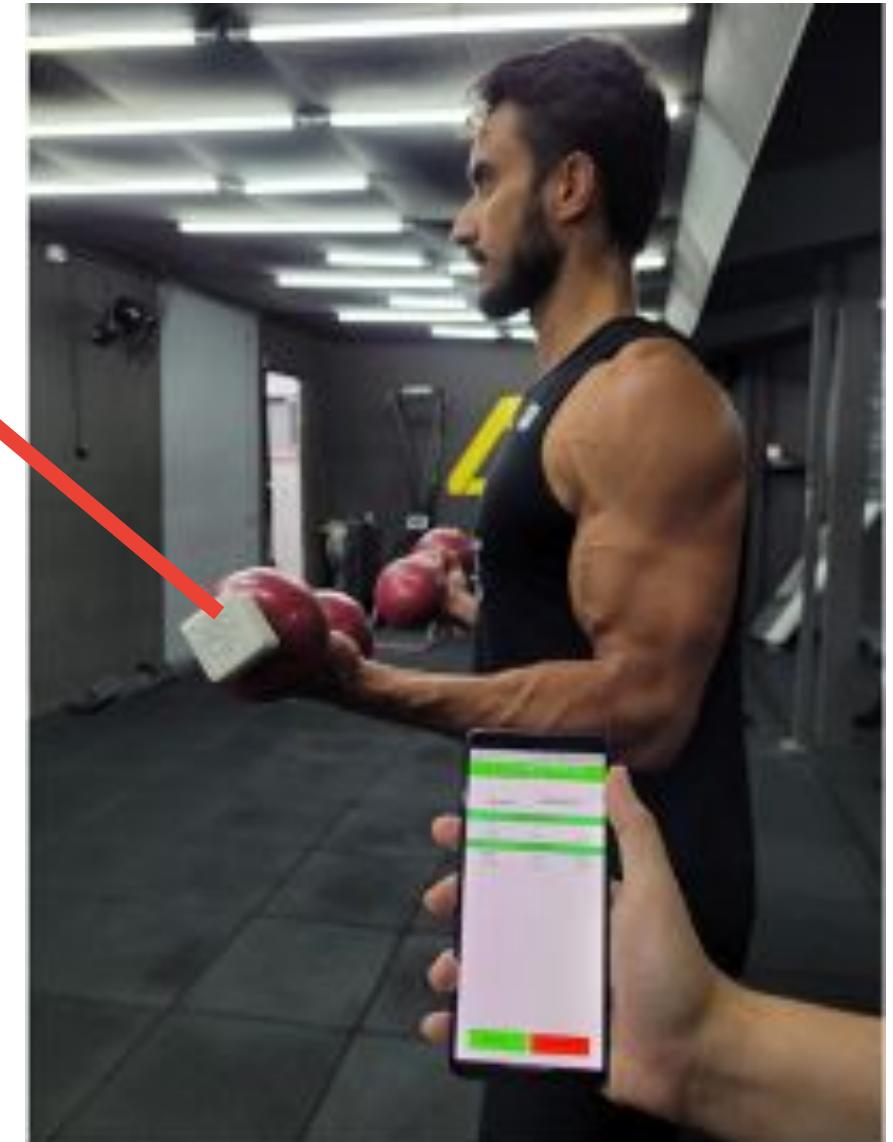
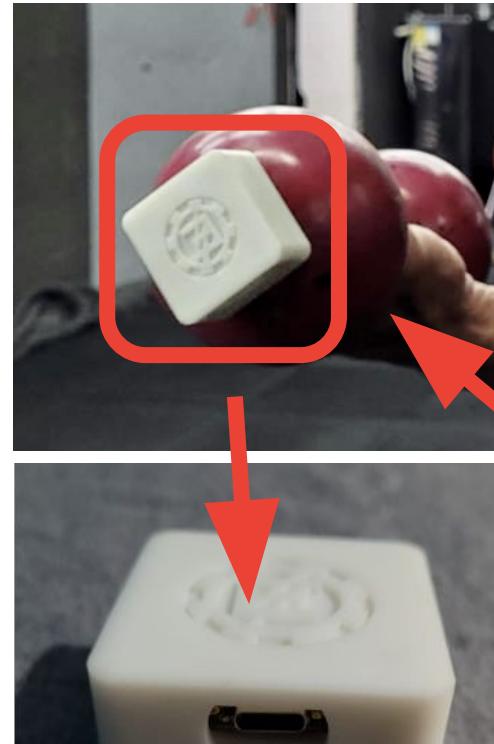


Industrial – Anomaly Detection



IESTI01 2021.2 - Final Group Project: Bearing Failure Detection

Movement Classification



Movement Classification



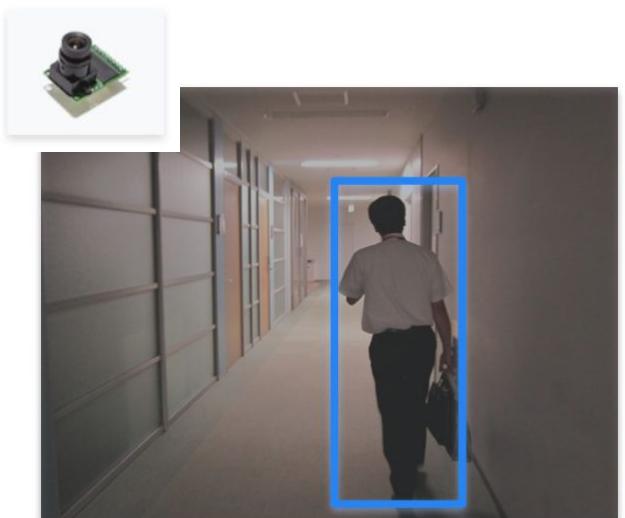
Sound



Vibration



Vision



Computer Vision Main Types

Image Classification (Multi-Class Classification)

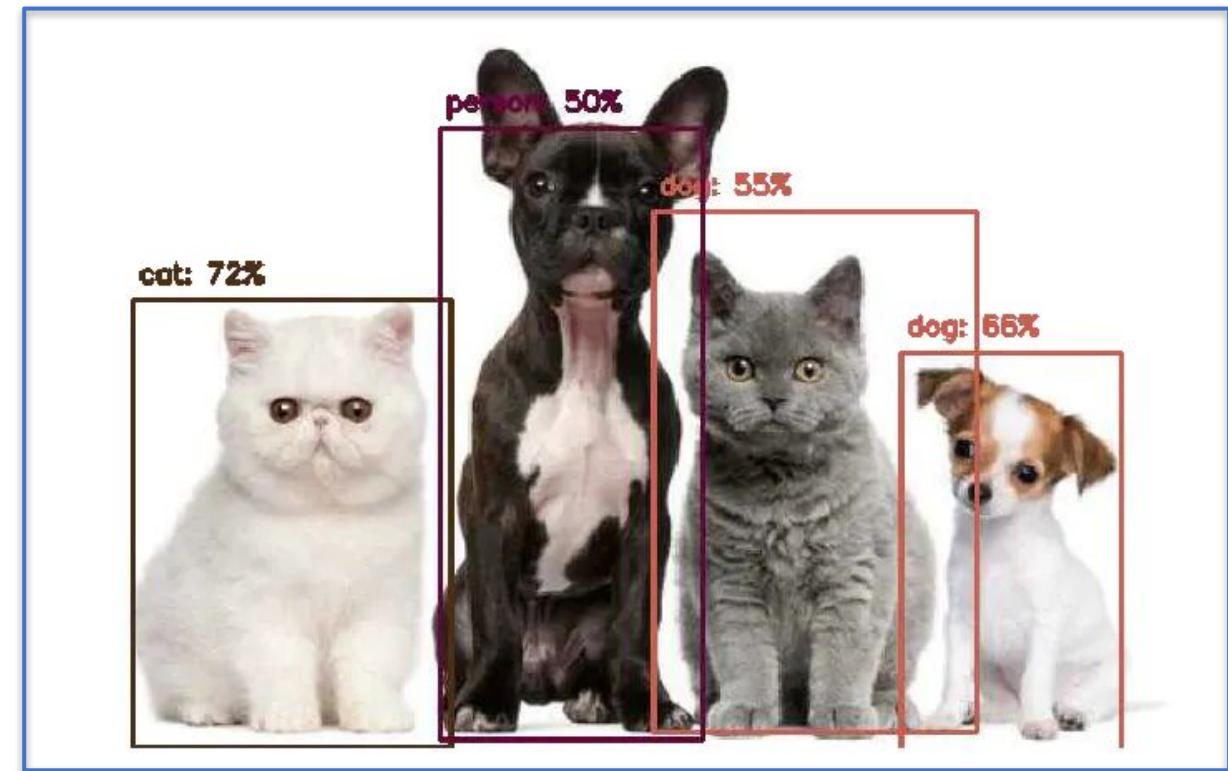


Cat: 70%



Dog: 80%

Object Detection Multi-Label Classification + Object Localization



Computer Vision Main Types

Image Classification (Multi-Class Classification)

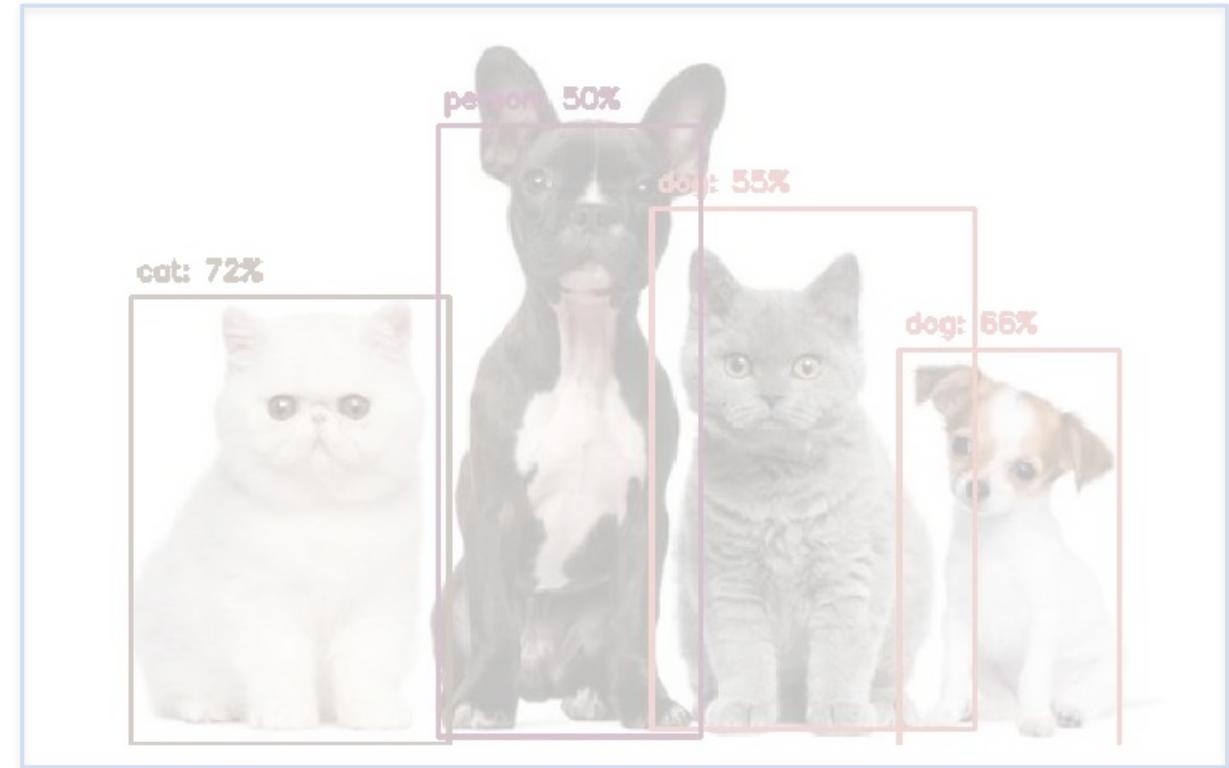


Cat: 70%



Dog: 80%

Object Detection Multi-Label Classification + Object Localization



Forest Fire Detection



[TinyML Aerial Forest Fire Detection](#)



[IESTI01 - Forest Fire Detection – Proof of Concept](#)

Coffee Disease Classification



<https://www.hackster.io/Yukio/coffee-disease-classification-with-ml-b0a3fc>

Introdução

O Brasil é responsável por 50% do café exportado globalmente, o que é uma atividade importante para o país; geralmente a análise e classificação de doenças em plantas é feita manualmente, que não são acessíveis para pequenos produtores.

Com o aumento do poder de processamento das placas-mãe microcontroladas e processadores dedicados ao machine learning, a tarefa de embarcar todos meios tem-se tornado possível em diversas áreas.



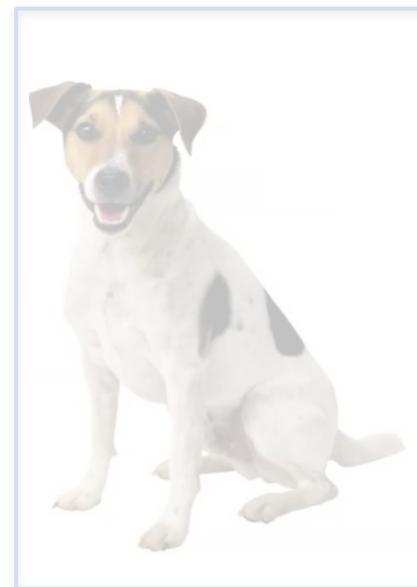
João Vitor Yukio Bordin Yamashita
Graduando em Engenharia Eletrônica pela UNIFEI

Computer Vision Main Types

Image Classification
(Multi-Class Classification)

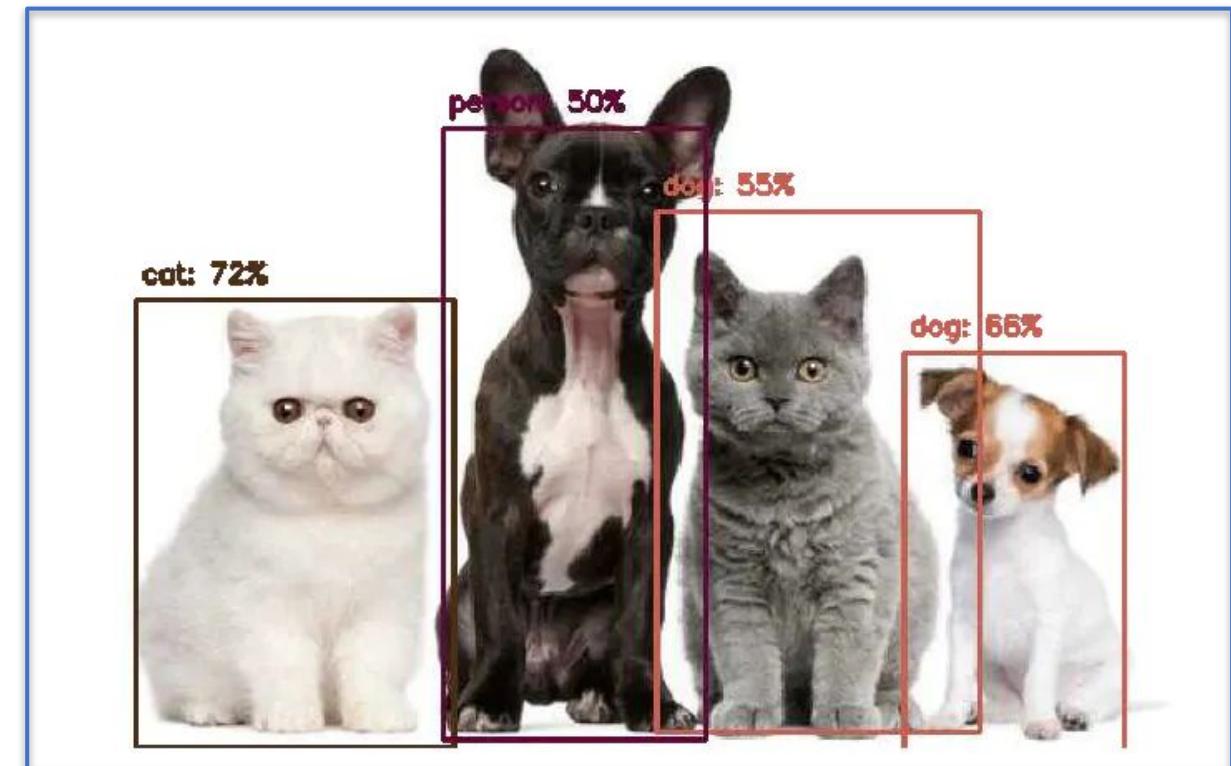


Cat: 70%

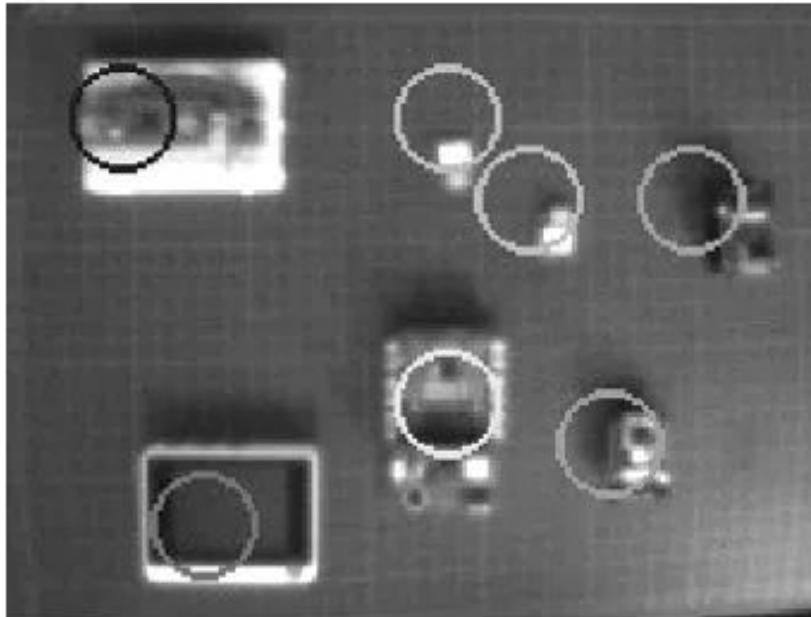


Dog: 80%

Object Detection
Multi-Label Classification + Object Localization



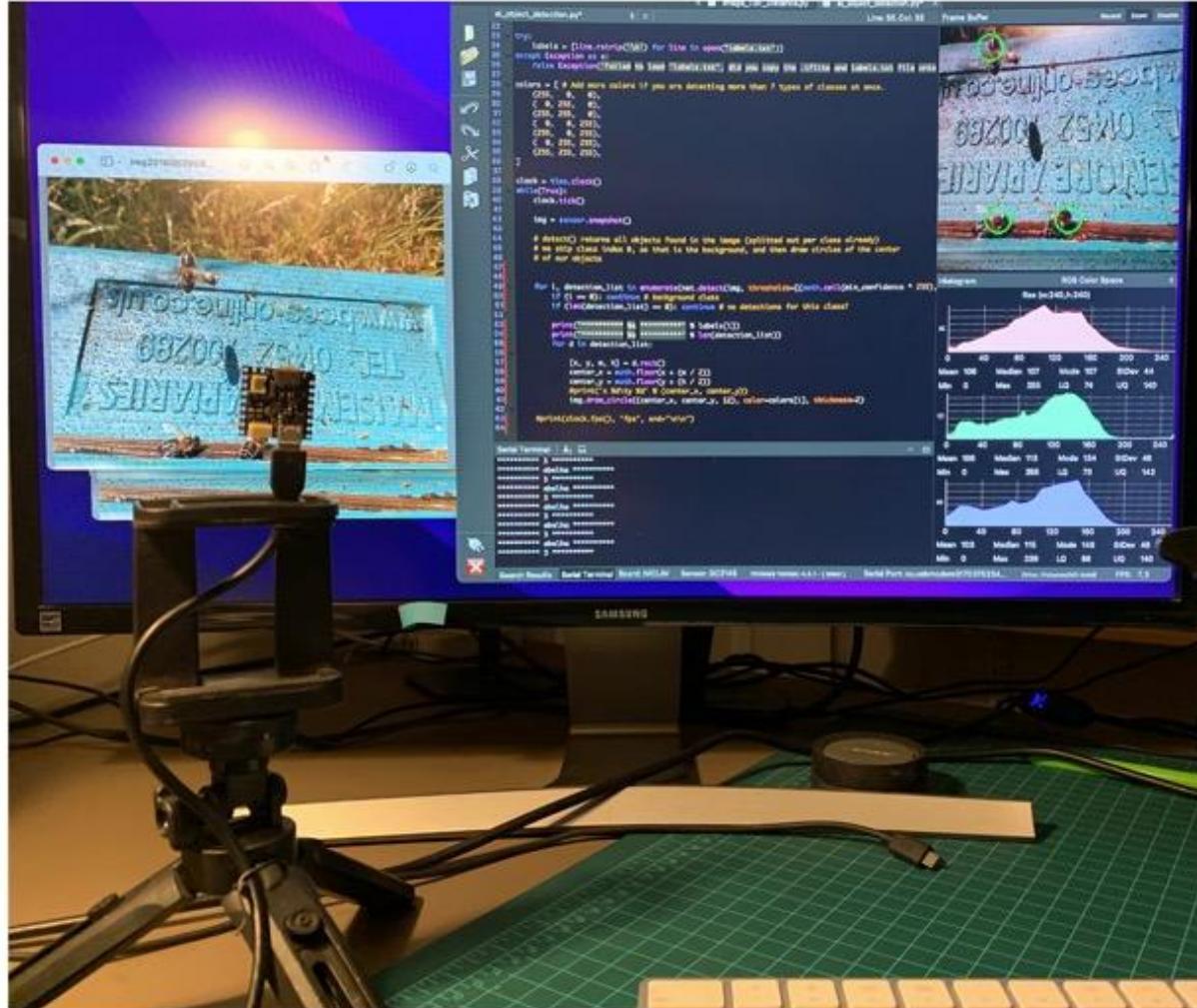
Detecting Objects using TinyML (FOMO)



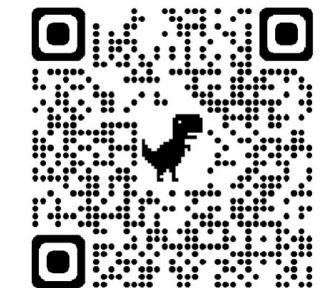
```
***** espcam *****
x 70  y 150
x 130  y 170
*****
***** nano *****
x 70  y 110
*****
***** pico *****
x 150  y 30
*****
***** wio *****
x 50  y 50
*****
***** xiao *****
x 150  y 110
x 130  y 130
6.97512 fps
```

[EdgeAI made simple - Exploring Image Processing \(Object Detection\) on microcontrollers with Arduino Portenta, Edge Impulse FOMO, and OpenMV](#)

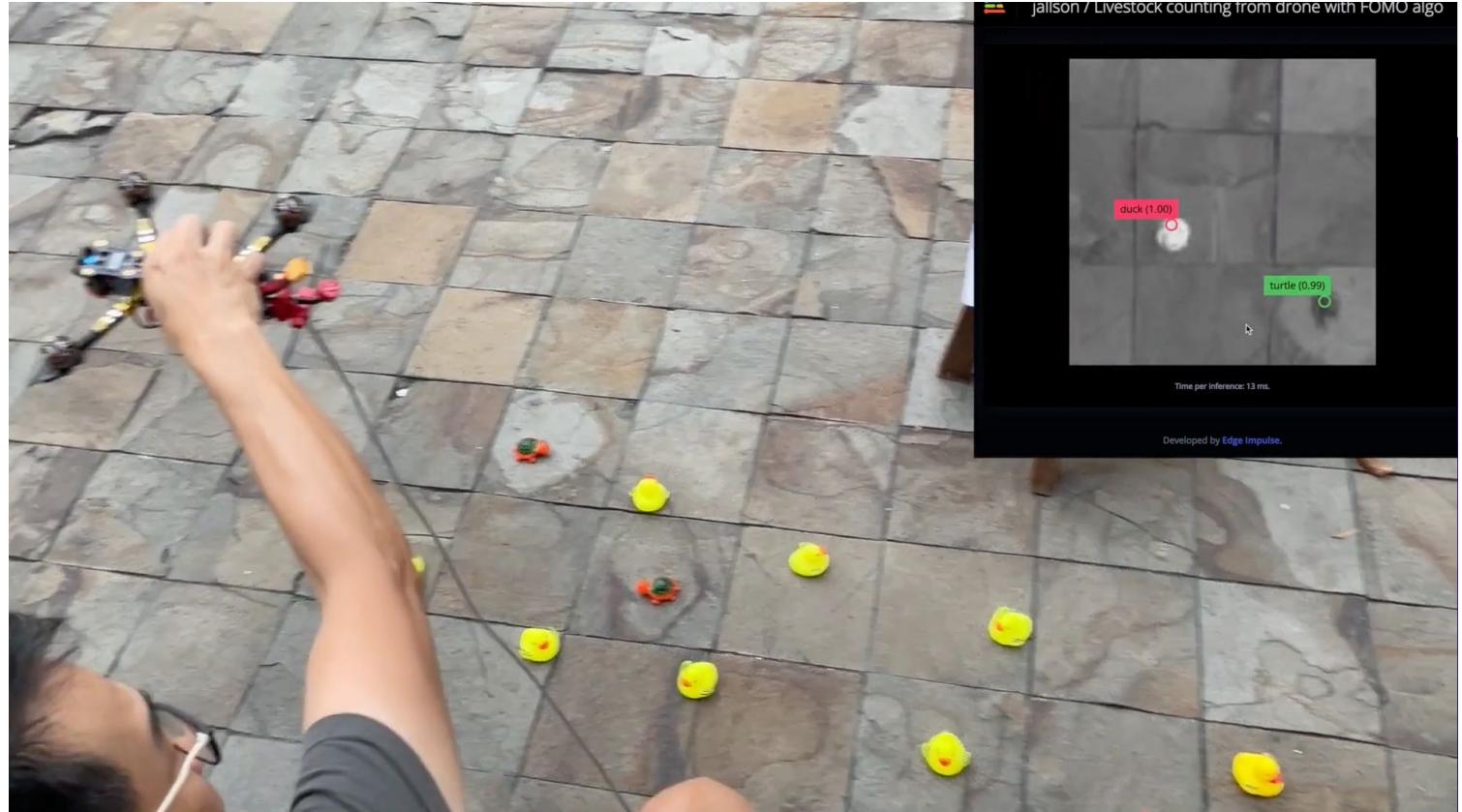
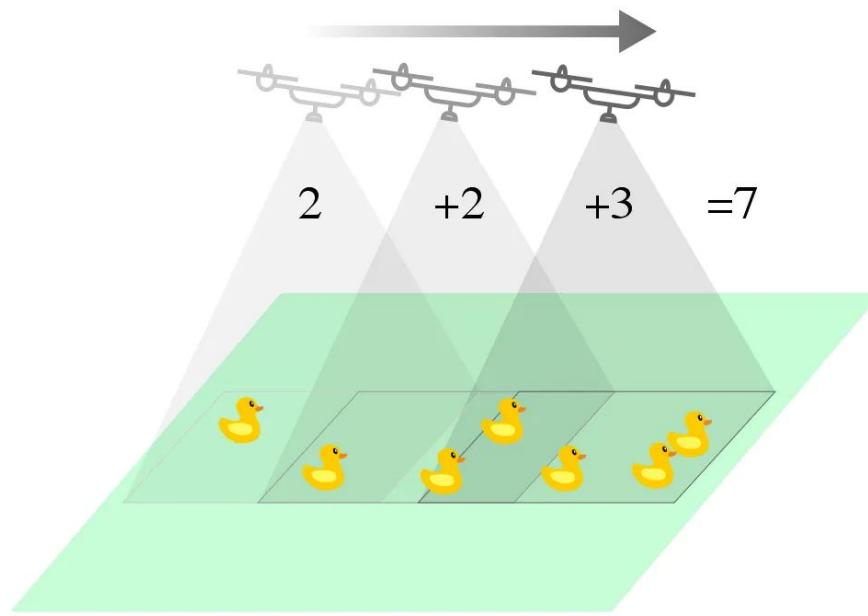
Detecting Objects using TinyML (FOMO)



MicroPython



Livestock / Wildlife Counting from Drone with FOMO

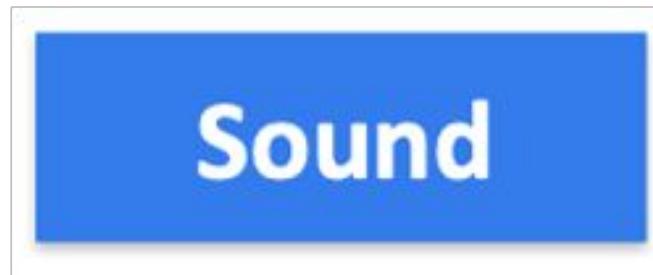


<https://www.hackster.io/jallsonsuryo/livestock-wildlife-counting-from-drone-with-fomo-algorithm-a2f734>

Other TinyML / MCUs Project Examples



- Image Classification with [ESP32-CAM](#) [\[Doc\]](#)
- Image Classification with [Portenta H7](#) [\[Doc\]](#)
- Object Detection with [Portenta H7](#) [\[Doc\]](#)



- Listening Temperature with [Nano 33](#) [\[Doc\]](#)
- COPD Detection with [Nano 33](#) [\[Doc\]](#)
- Sound Classification with [XIAO BLE Sense](#) [\[Doc\]](#)

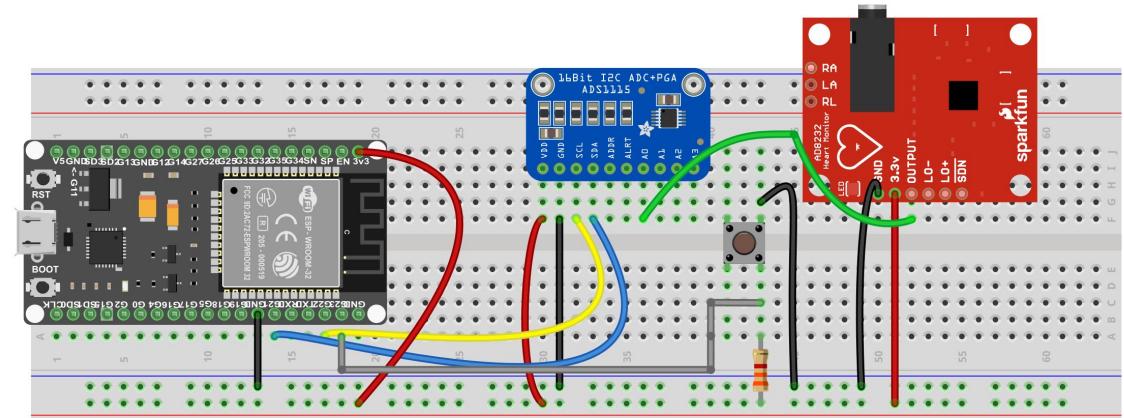


- Motion Recognition with [RPi Pico](#) [\[Doc\]](#)
- Gesture Recognition with [Wio Terminal](#) [\[Doc\]](#)
- Anomaly Detection with [XIAO BLE Sense](#) [\[Doc\]](#)

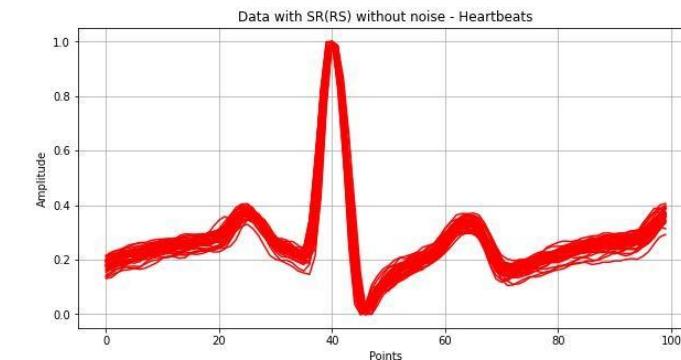
Other Sensors / MCUs / Models

Examples

AD8232 - Single Lead Heart Rate Monitor



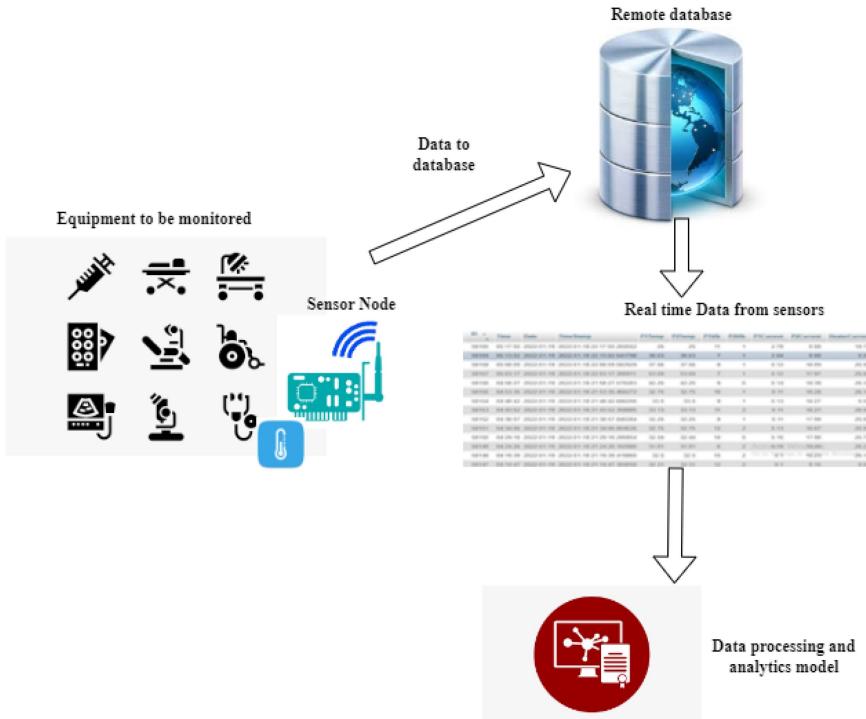
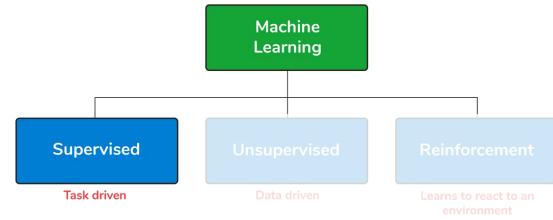
fritzing



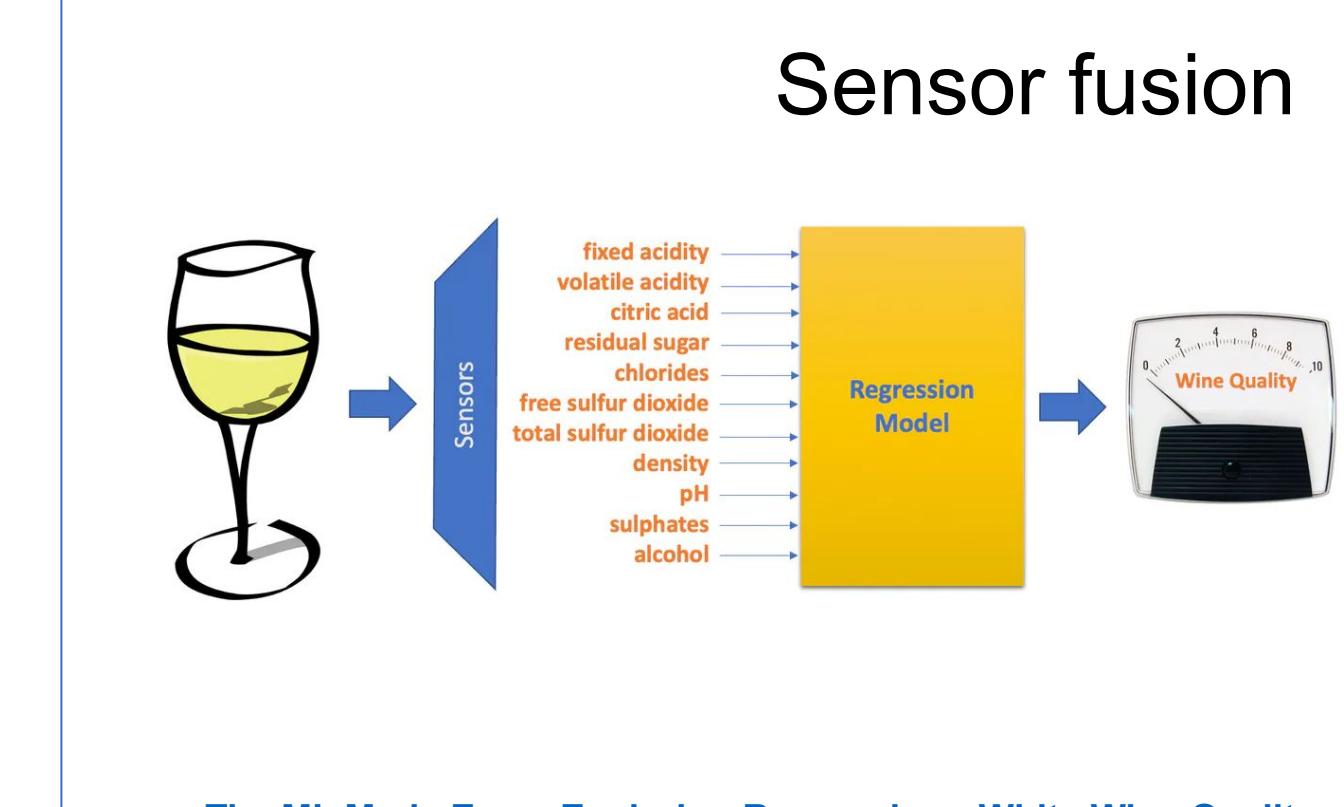
Guilherme Silva
Engenheiro - UNIFEI

[Atrial Fibrillation Detection on ECG using TinyML](#)
Silva et al. UNIFEI 2021

Regression on TinyML

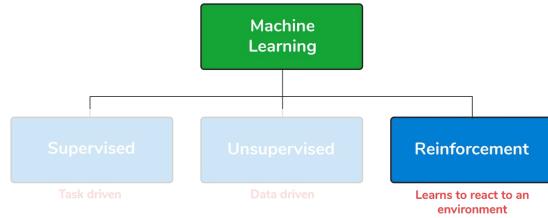


[On-Device IoT-Based Predictive Maintenance Analytics Model: Comparing TinyLSTM and TinyModel from Edge Impulse](#)



[TinyML Made Easy: Exploring Regression - White Wine Quality](#)

Reinforcement on TinyML



Deep Reinforcement Learning for Autonomous Source Seeking on a Nano Drone

Bardienus P. Duisterhof^{1,3} Srivatsan Krishnan¹ Jonathan J. Cruz¹ Colby R. Banbury¹ William Fu¹
Aleksandra Faust² Guido C. H. E. de Croon³ Vijay Janapa Reddi^{1,4}

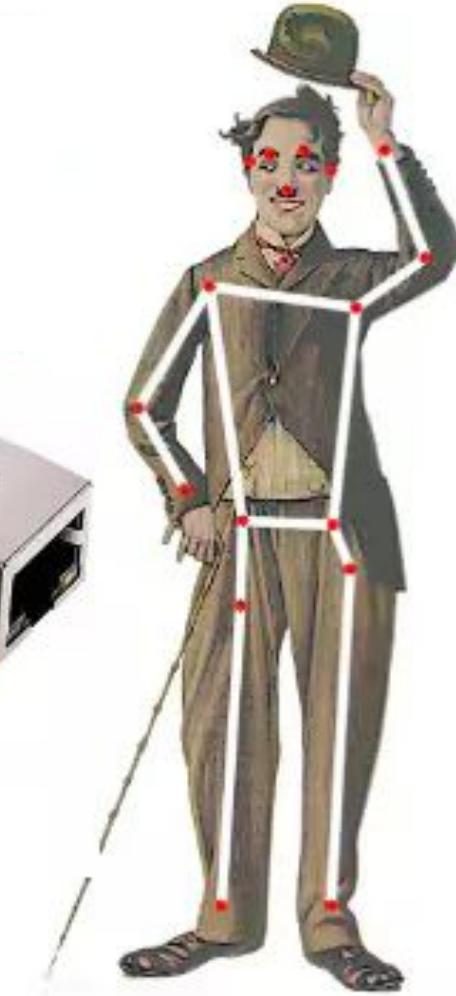
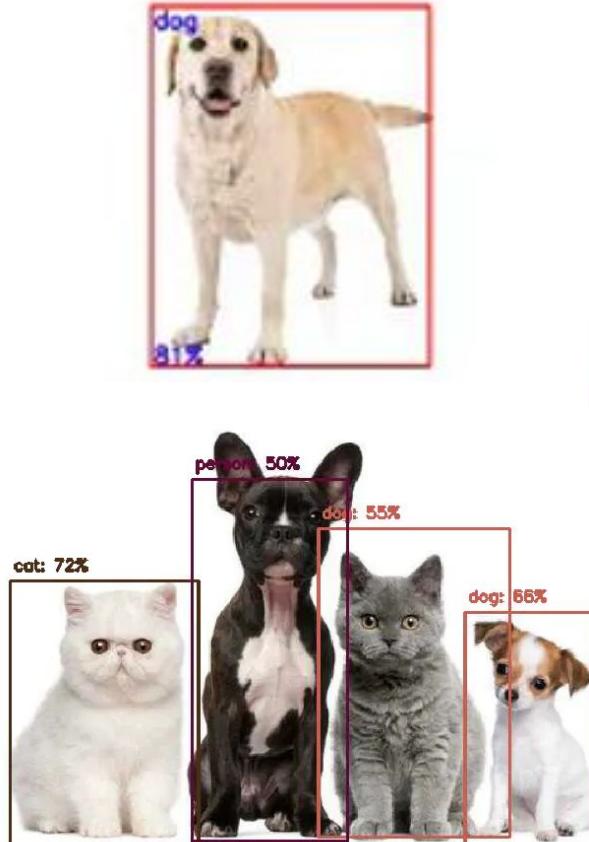
¹Harvard University, ²Robotics at Google, ³Delft University of Technology, ⁴The University of Texas at Austin



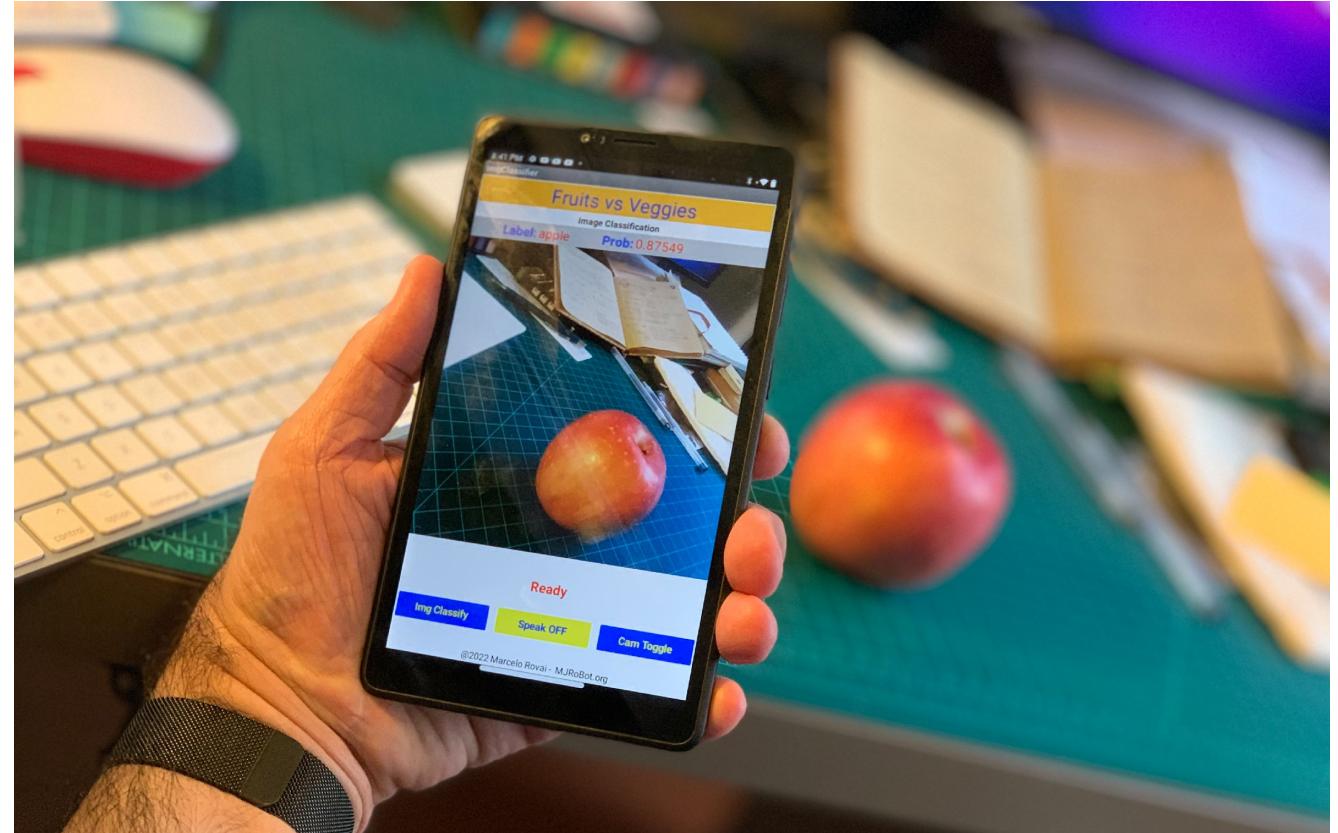
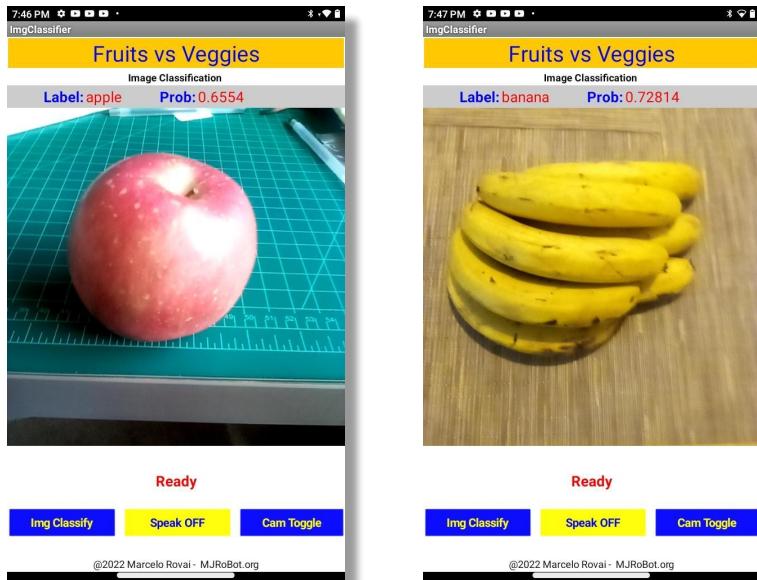
<https://arxiv.org/abs/1909.11236>

<https://youtu.be/wmVKbX7MOnU>

Exploring AI at the edge (Computer Vision)



Classifying Images using Smartphones



<https://www.hackster.io/mjrobot/app-inventor-edgeml-image-classification-fruit-vs-veggies-b671da>

Thanks

