

Embedded ML (TinyML) Intro & Applications

Marco Zennaro, PhD

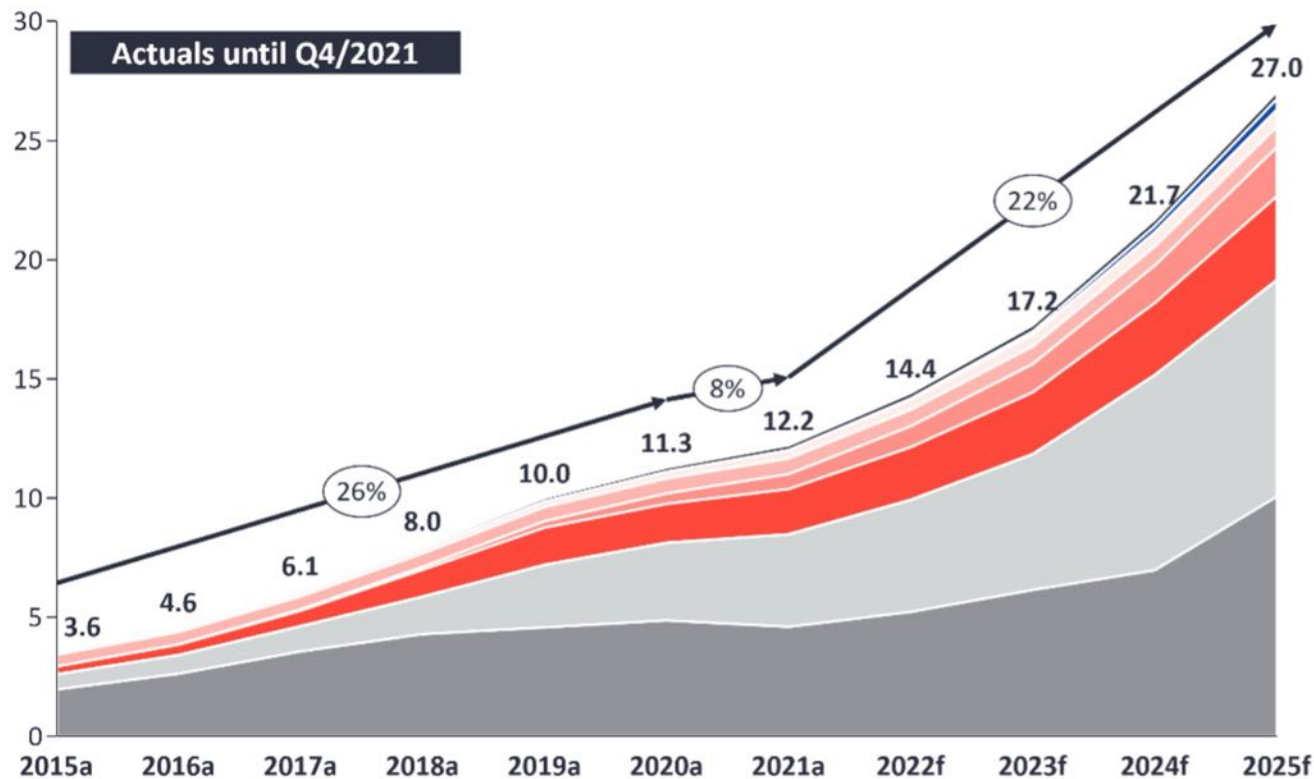
TinyML4D Academic Network Co-Chair



Internet of Things (IoT)

Global IoT Market Forecast [in billion connected IoT devices]

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



| CONNECTIVITY TYPE | CAGR 20-21 | CAGR 21-25 |
|--|------------|------------|
| Wireless Neighborhood Area Networks (WNAN) | 17% | 11% |
| 5G IoT | - | 159% |
| Other | 22% | 20% |
| Wired IoT | 4% | 7% |
| LPWA | 42% | 34% |
| Legacy Cellular (2G/3G/4G) | 16% | 17% |
| Wireless Local Area Networks (WLAN) | 19% | 24% |
| Wireless Personal Area Networks (WPAN) | -6% | 22% |

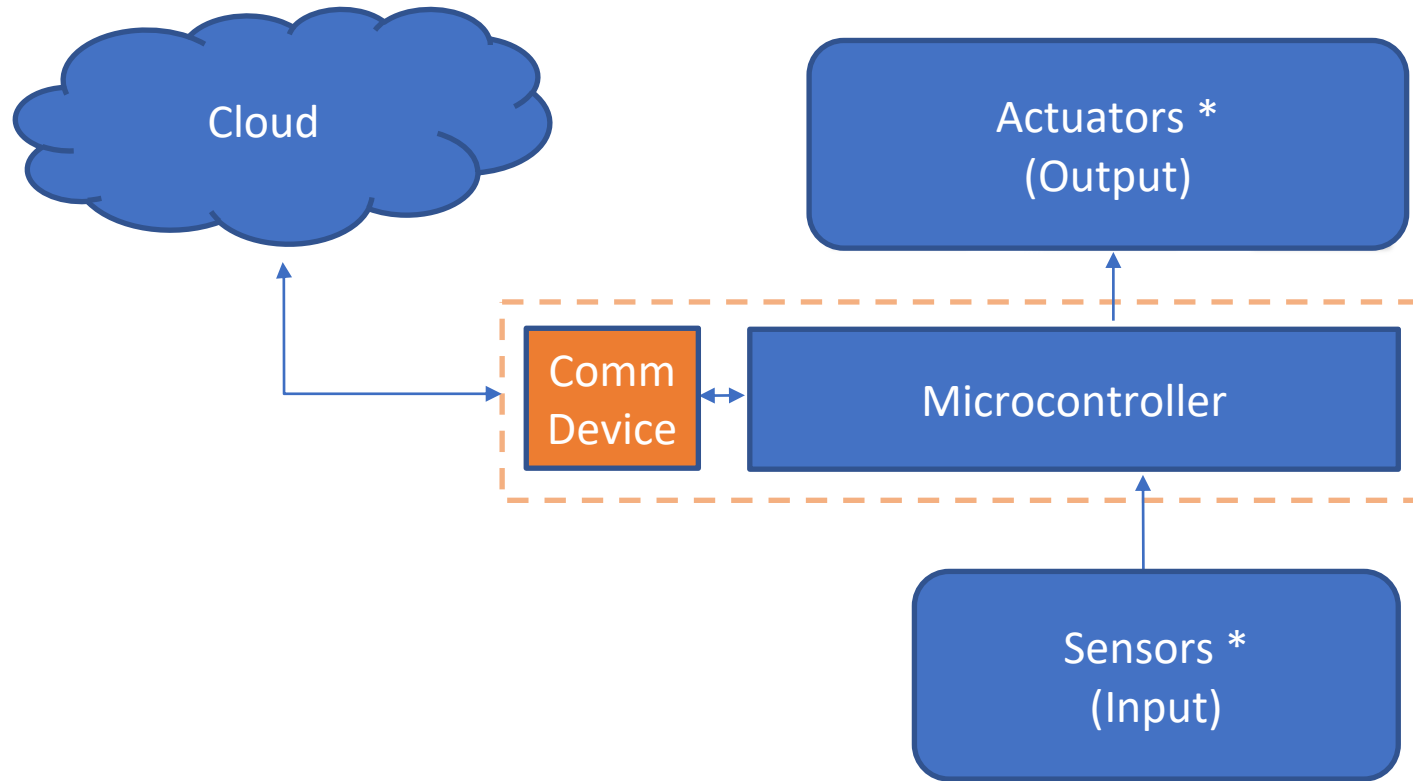
XX% = CAGR

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; WNAN 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>

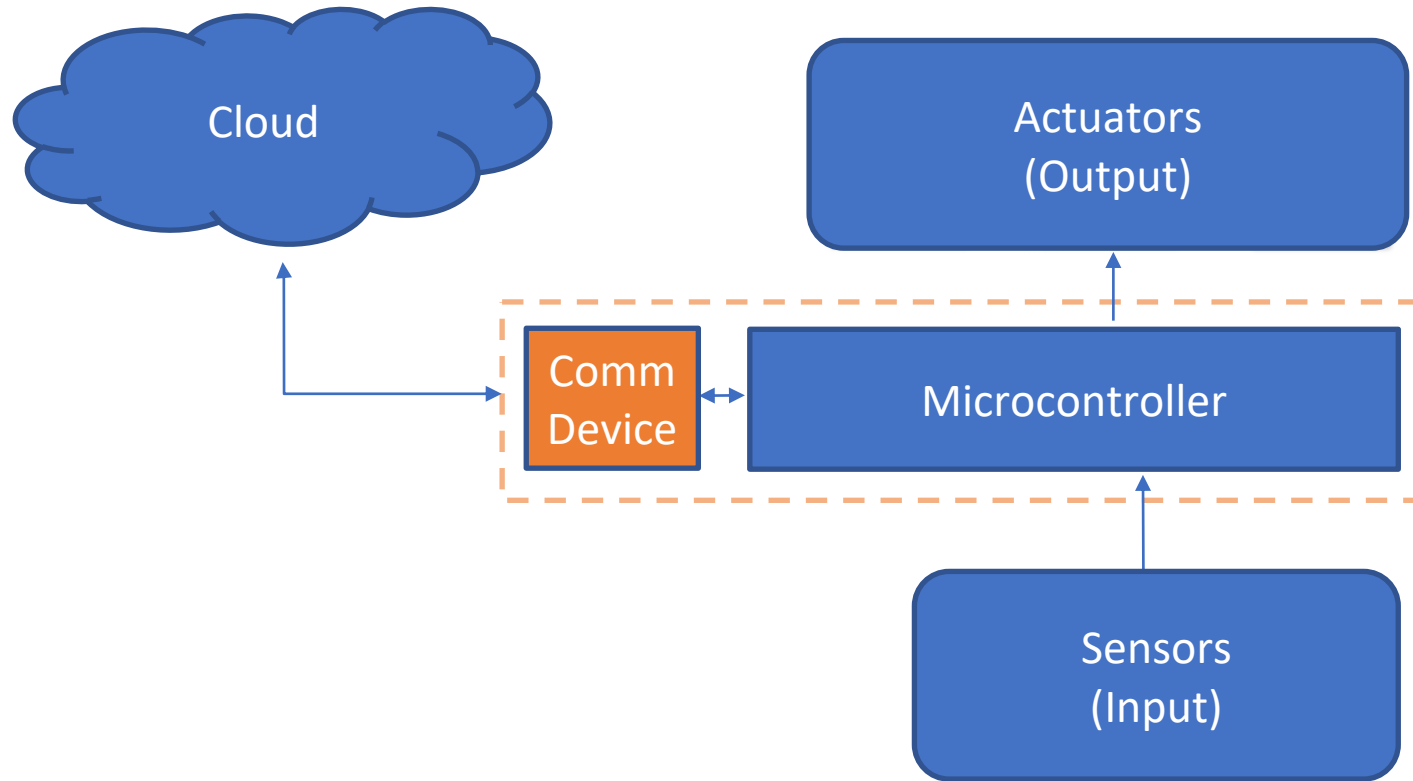
Typical IoT Project



* “Things”



Typical IoT Project



5 Quintillion

bytes of data produced every day by IoT

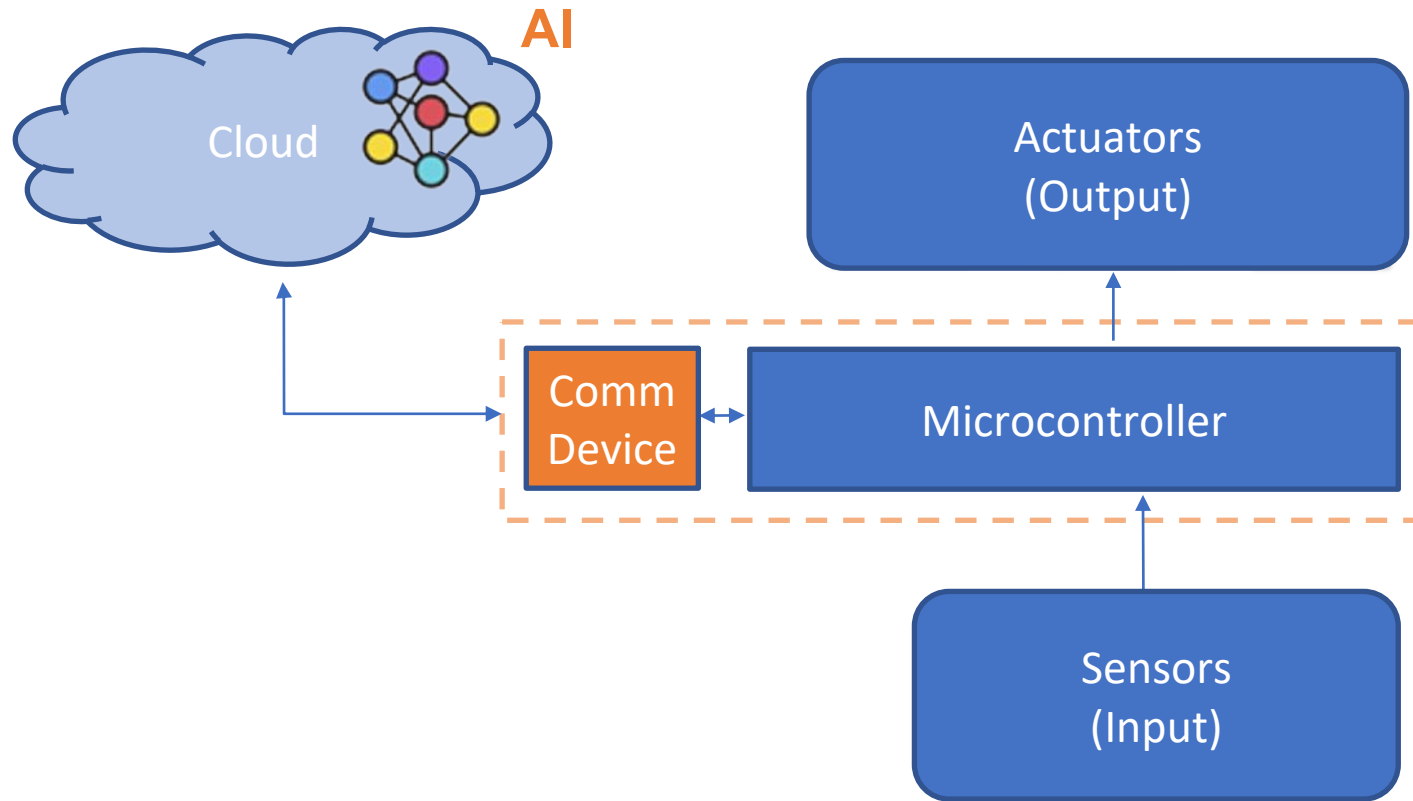
<1%

of unstructured data is analyzed or used at all

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

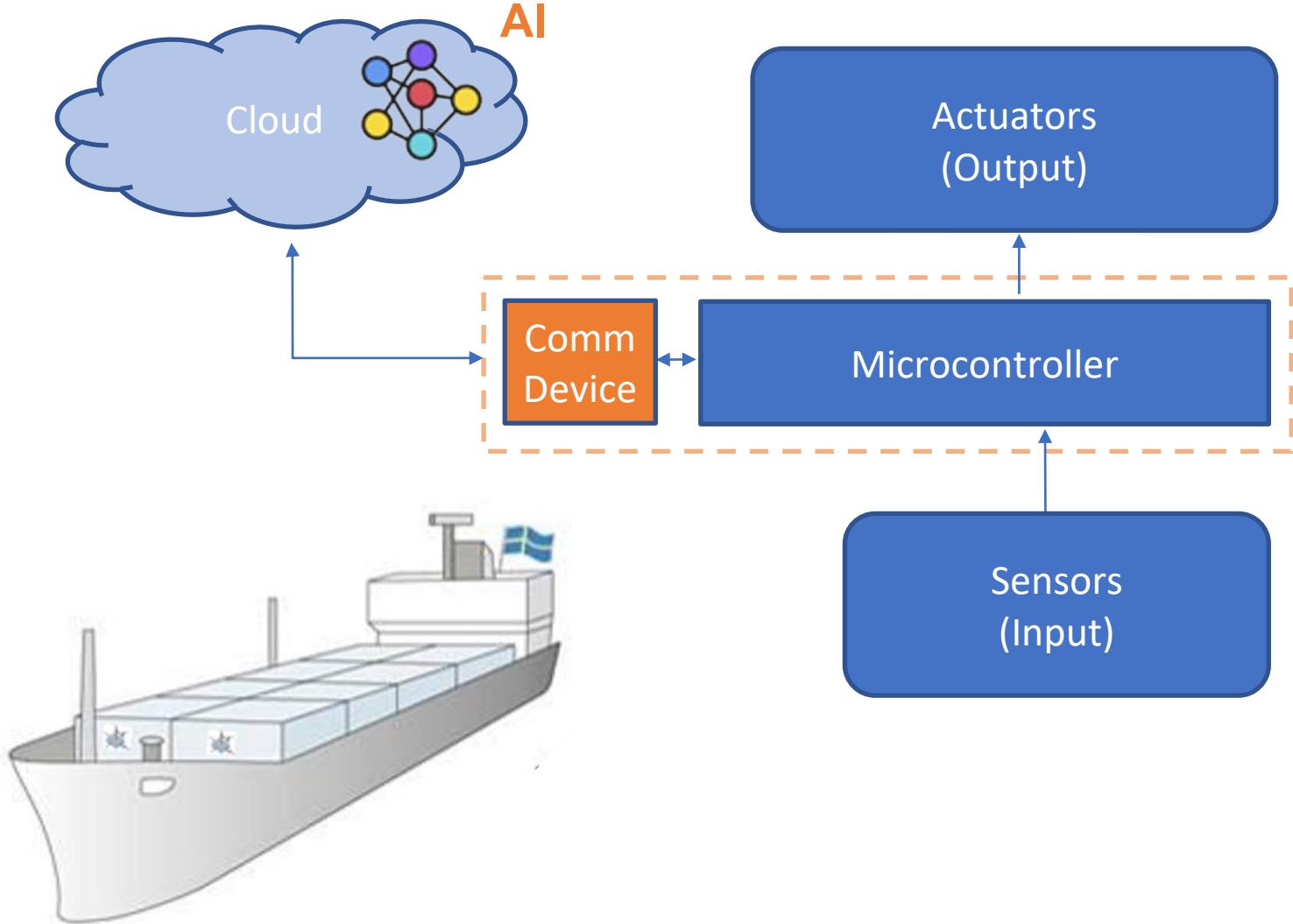
Cisco, [Internet of Things \(IoT\) Data Continues to Explode Exponentially. Who Is Using That Data and How?](#), Feb 5, 2018

Typical AIoT Project



Typical AIoT Project ...

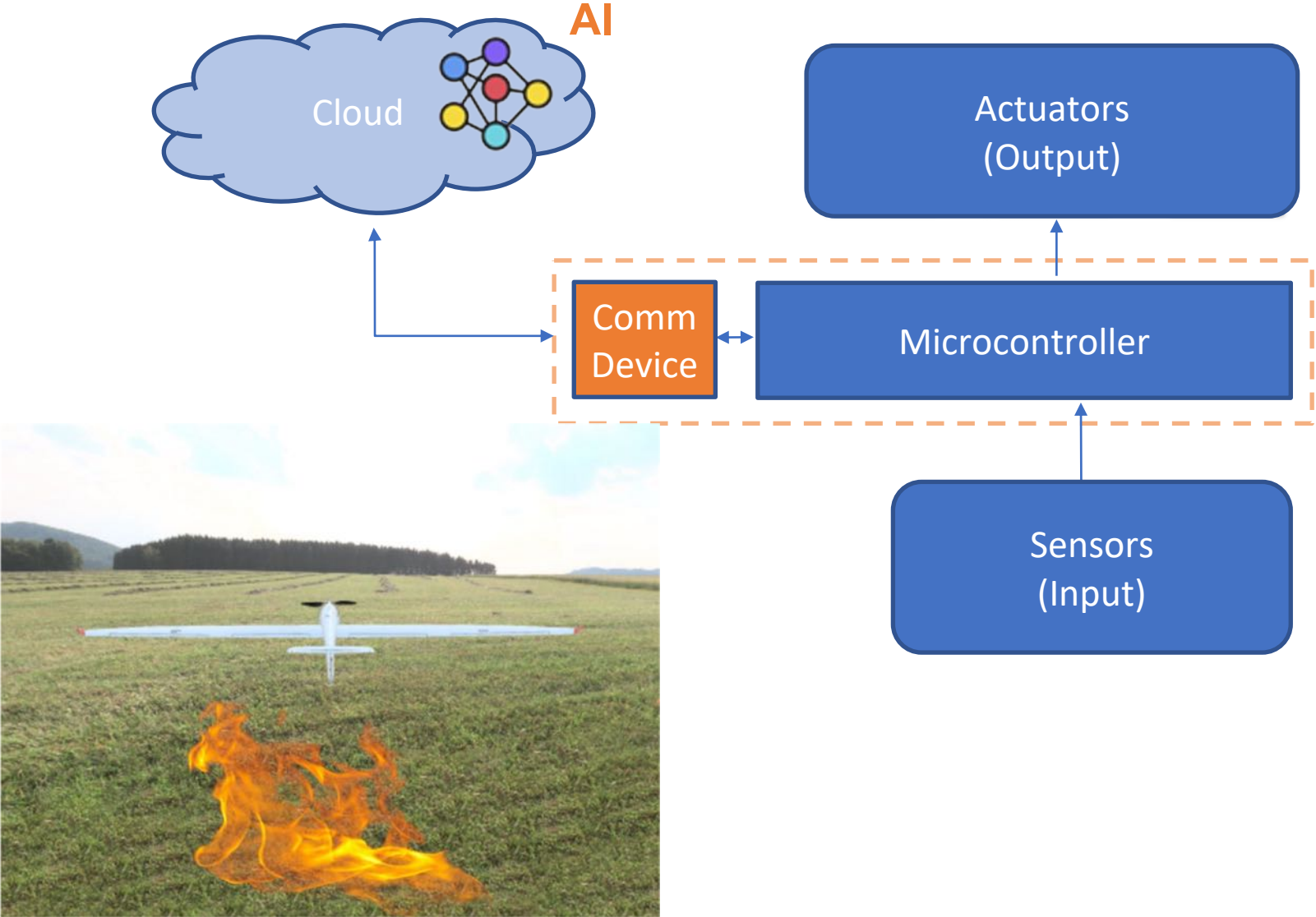
... Issues



Bandwidth

Typical AIoT Project ...

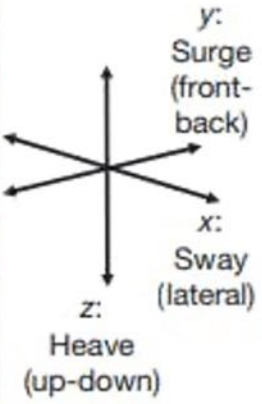
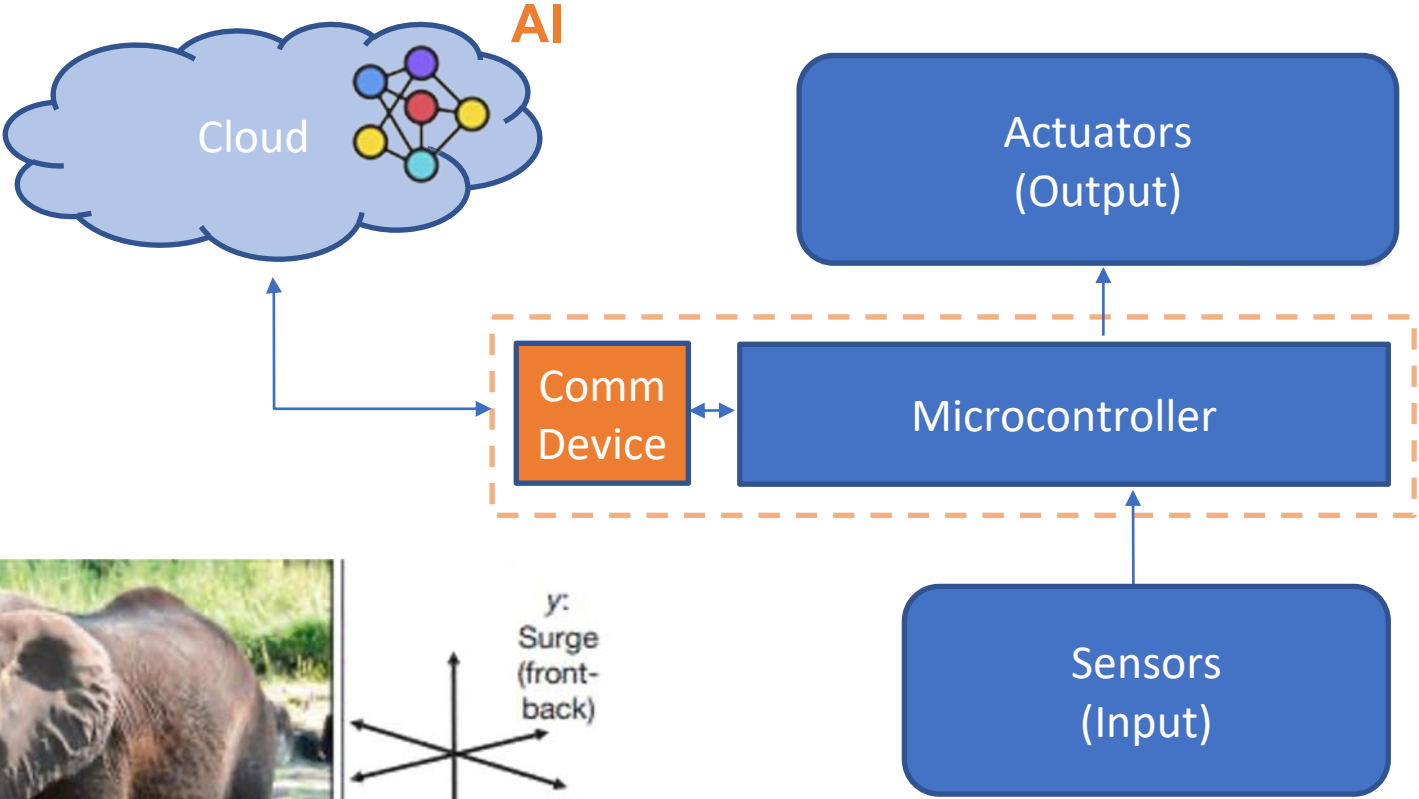
... Issues



Bandwidth
Latency

Typical AIoT Project ...

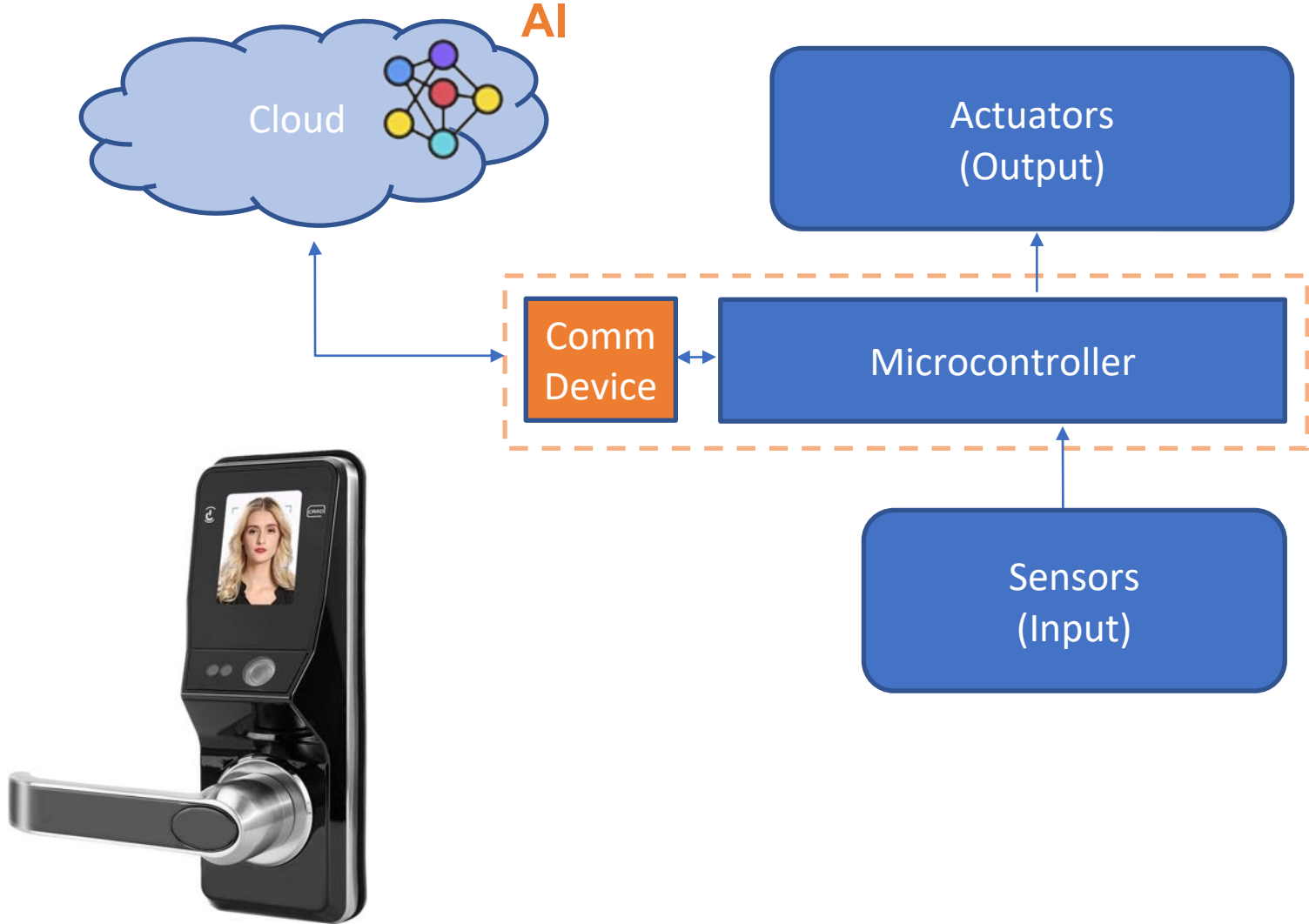
... Issues



Bandwidth
Latency
Energy

Typical AIoT Project ...

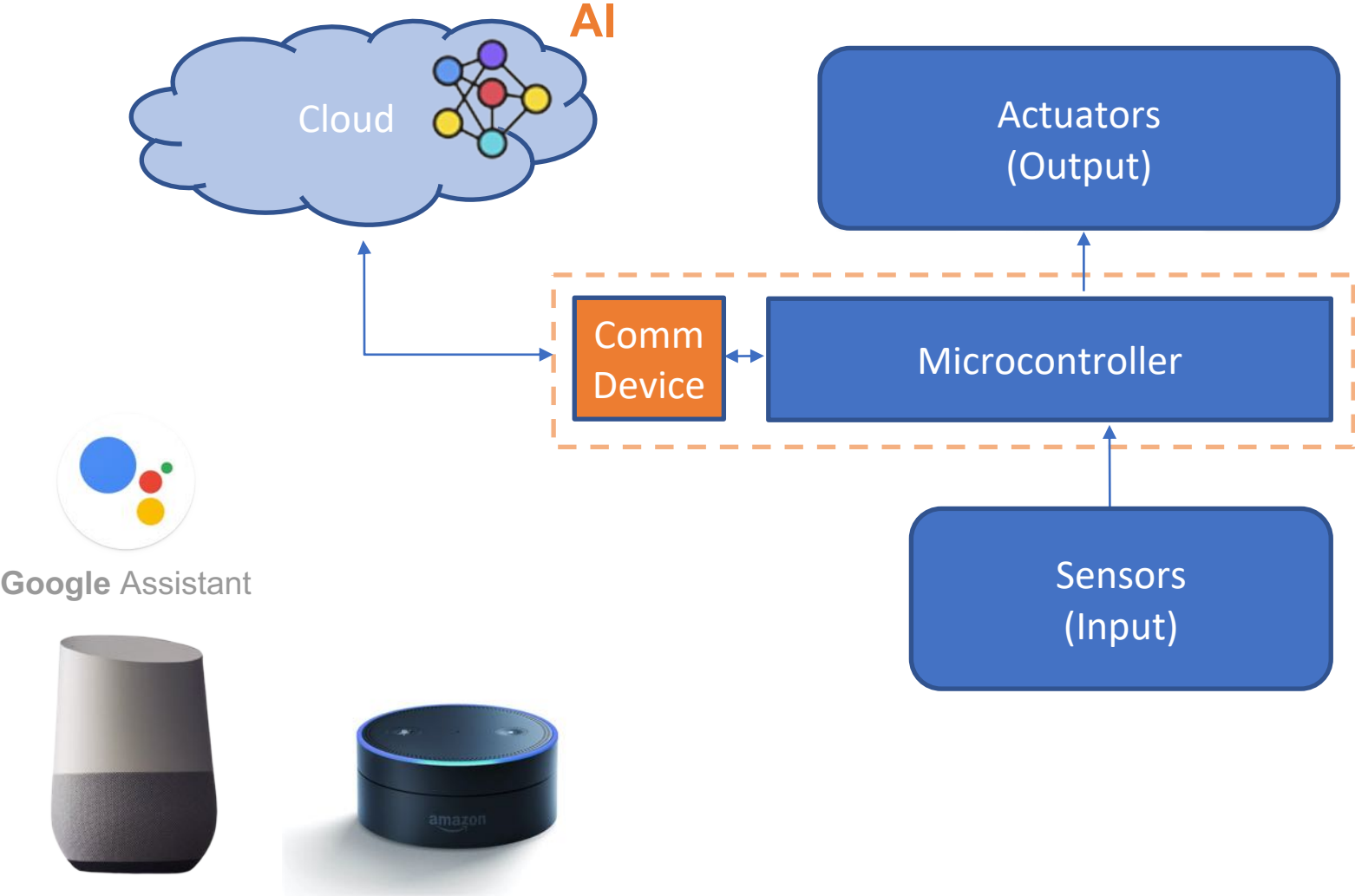
... Issues



- Bandwidth
- Latency
- Energy
- Reliability

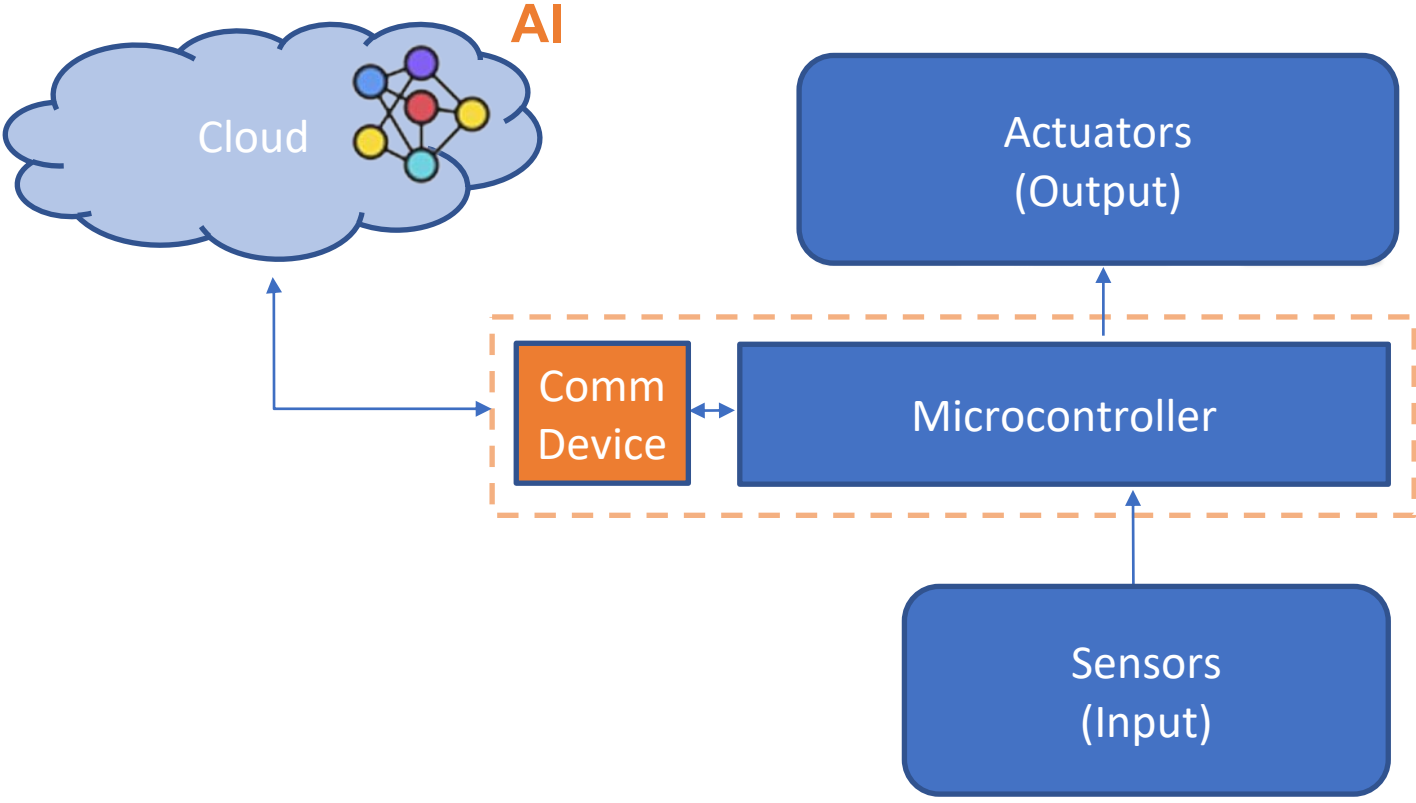
Typical AIoT Project ...

... Issues



- Bandwidth
- Latency
- Energy
- Reliability
- Privacy

Typical AIoT Project ...

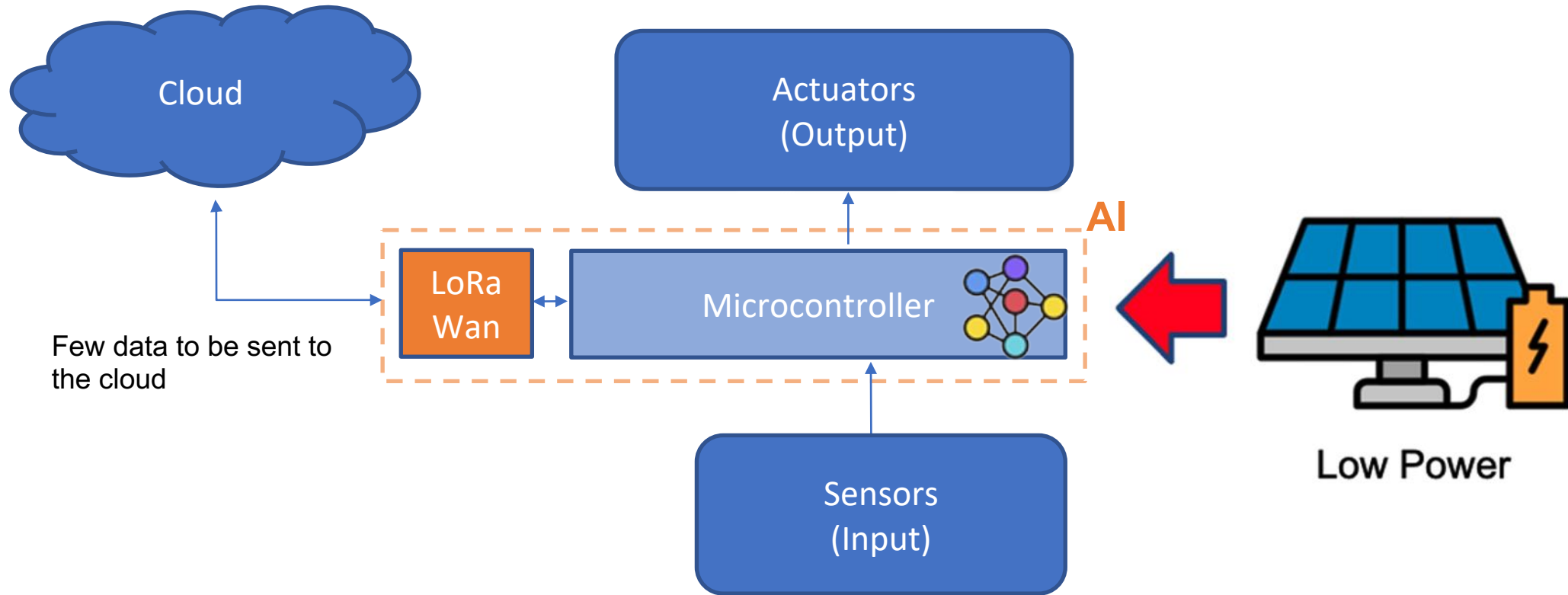


... Issues

- Bandwidth
- Latency
- Energy
- Reliability
- Privacy

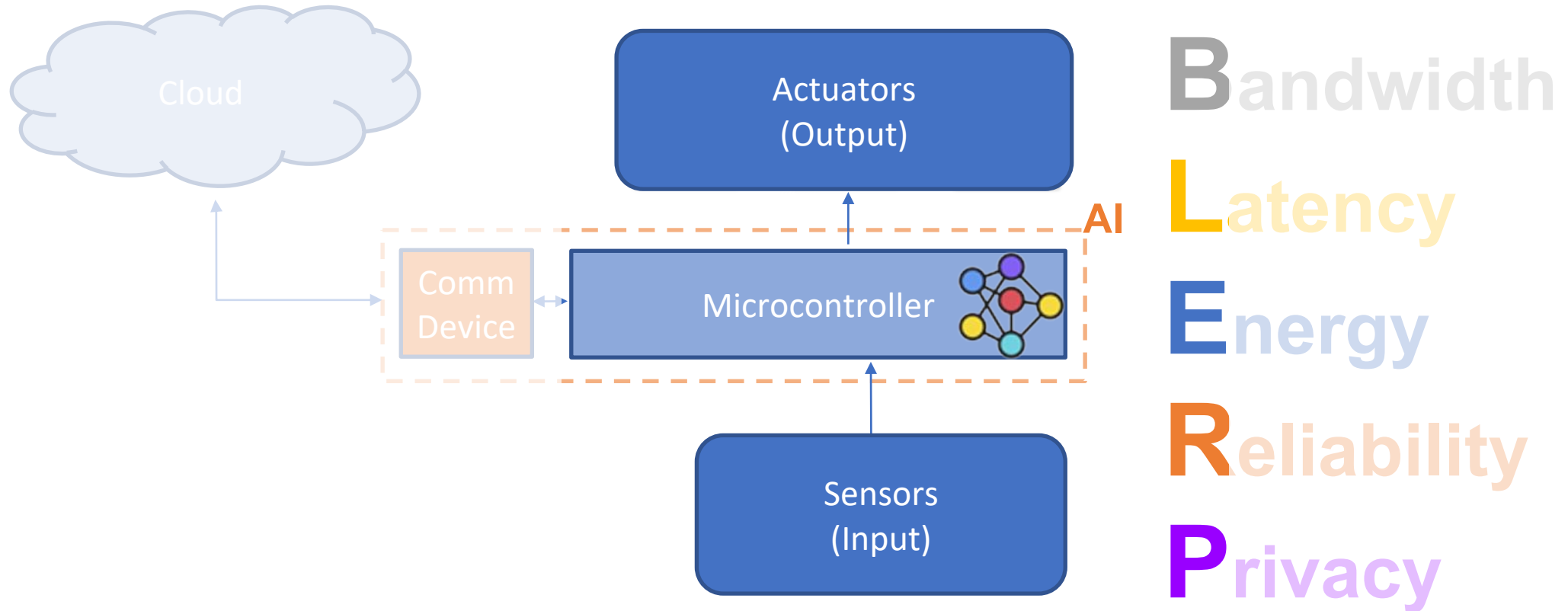
... Solution ?

IoT 2.0 * – Edge AI/ML * Intelligence of Things

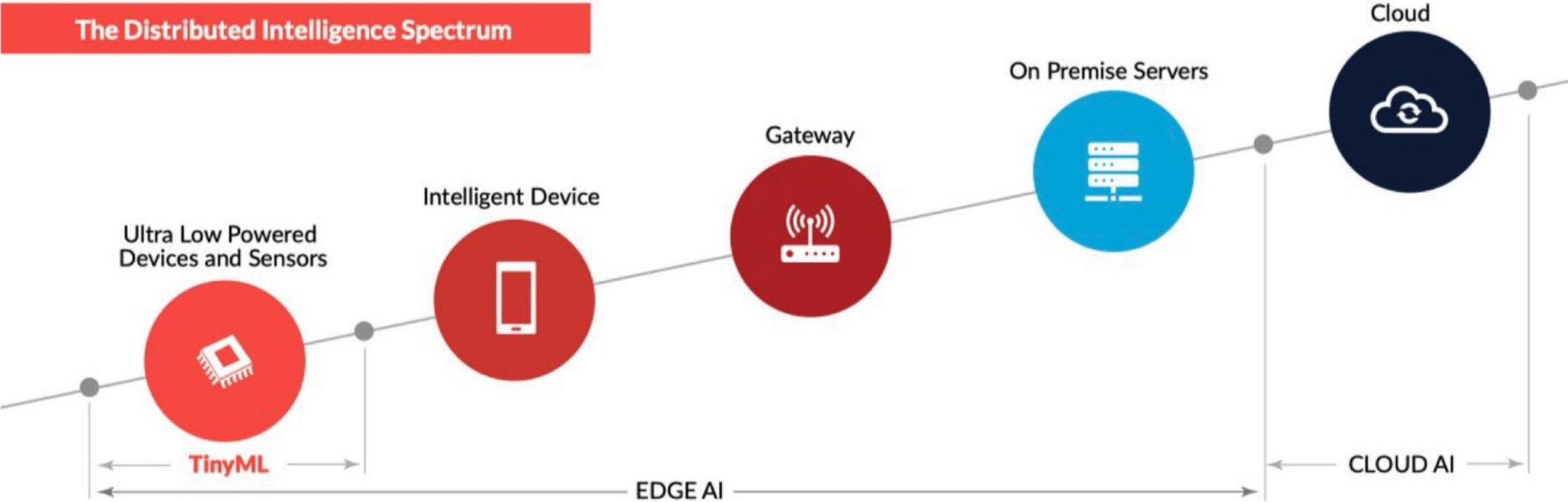


... **Solution** -> ML goes close to data

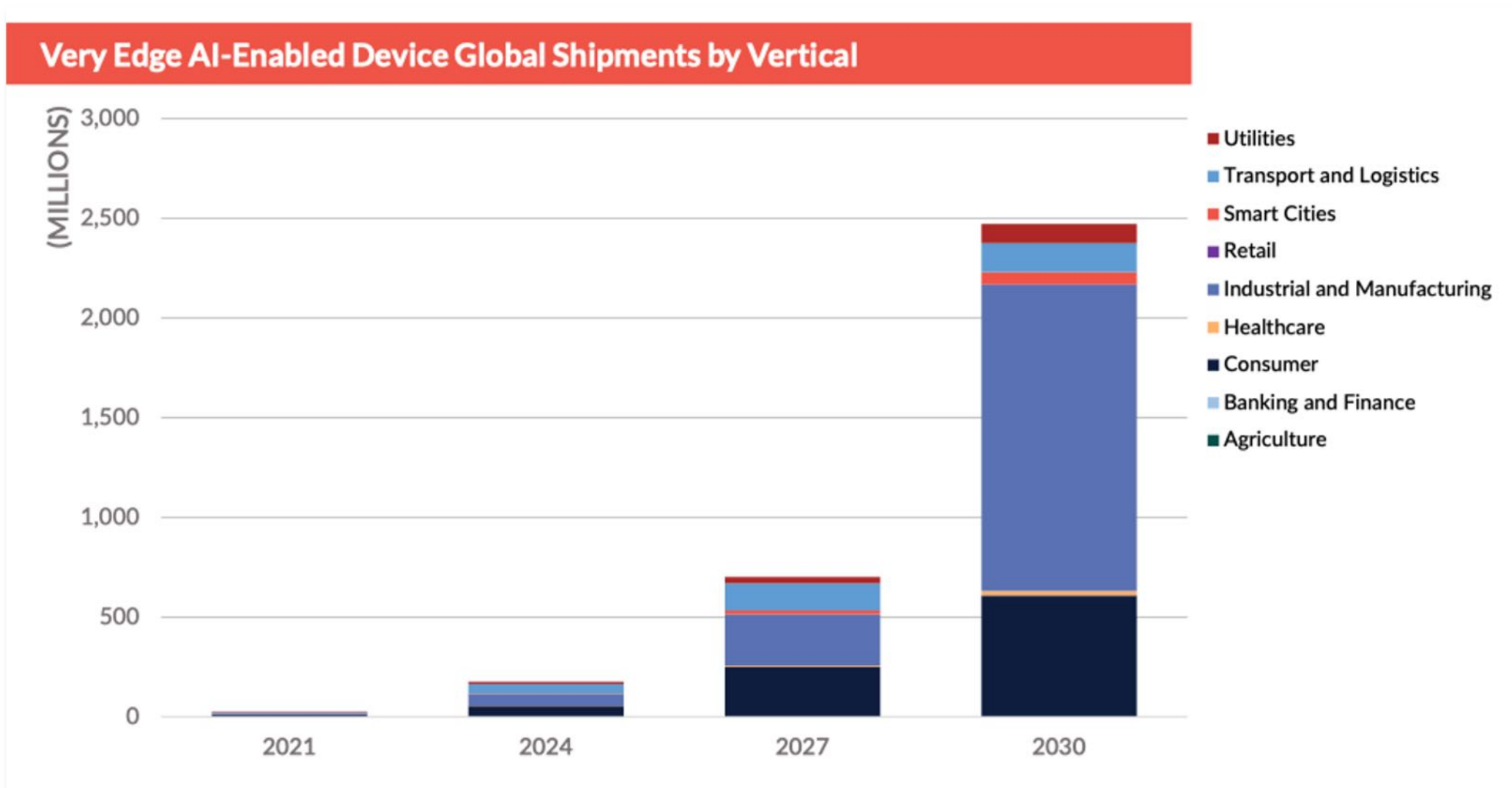
When to use an Edge AI/ML approach:



The Distributed Intelligence Spectrum

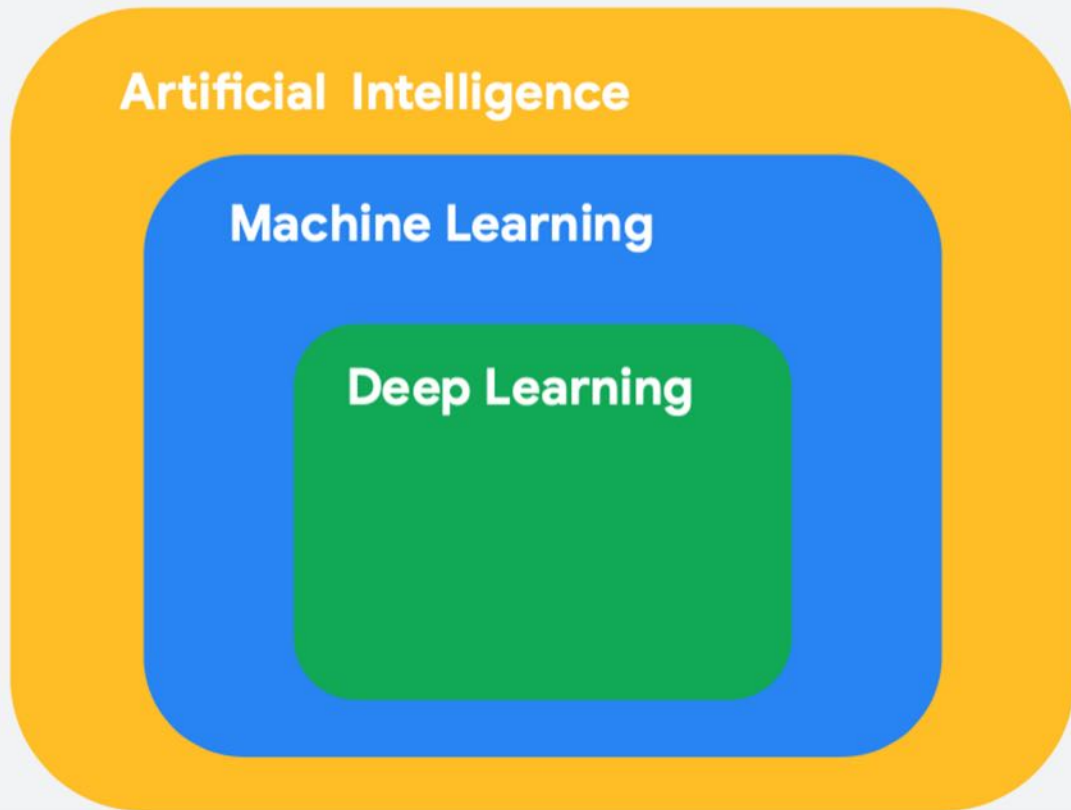


Market Forecast



Embedded ML (TinyML)

Introduction



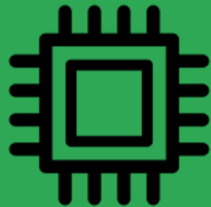
AI: Any technique that enables computers to mimic human behavior

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**)?

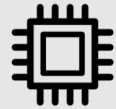
TinyML

Fastest-growing field of **ML**



Algorithms, hardware, software

On-device sensor analytics



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

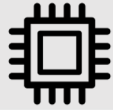
TinyML

Fastest-growing field of **ML**



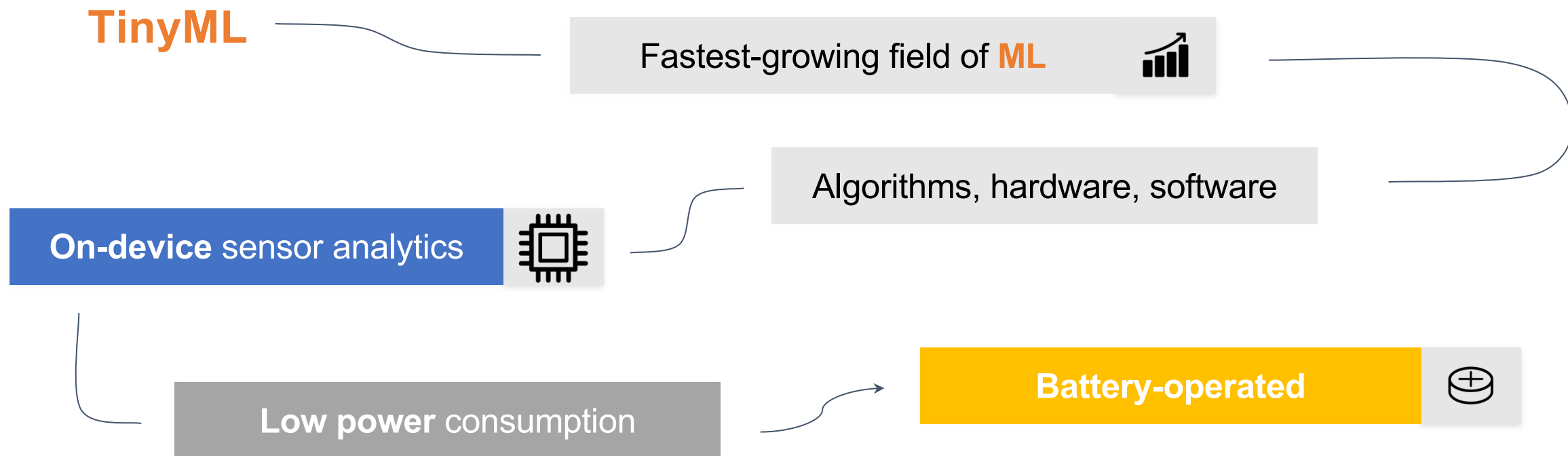
Algorithms, hardware, software

On-device sensor analytics

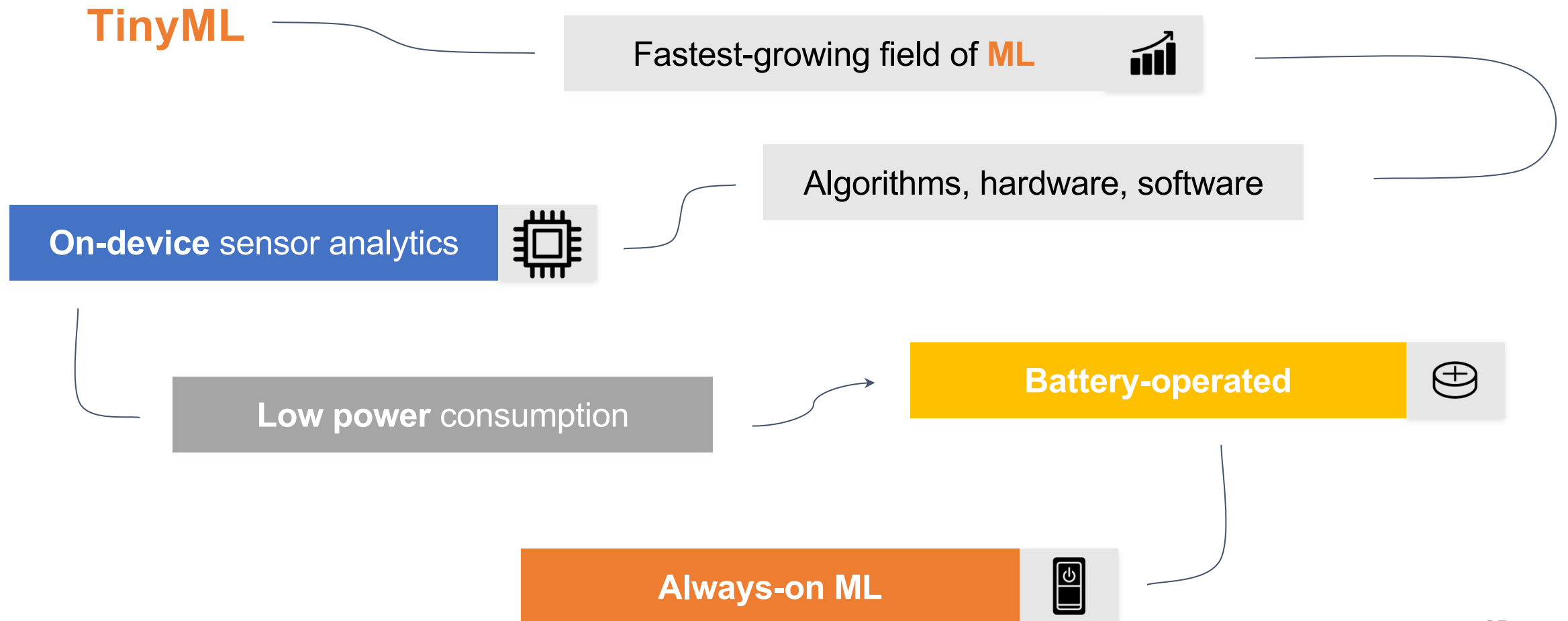


Low power consumption

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



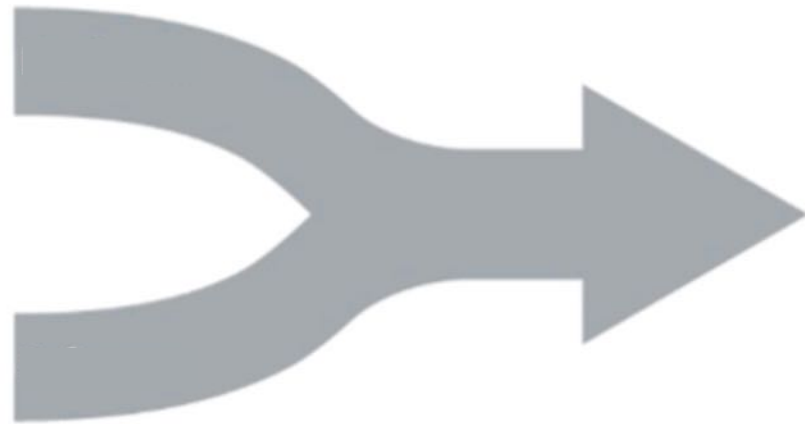
What is Tiny Machine Learning (**TinyML**)?



What Makes **TinyML** ?

**Embedded
Systems**

**Machine
Learning**



TinyML

What Makes **TinyML** ?



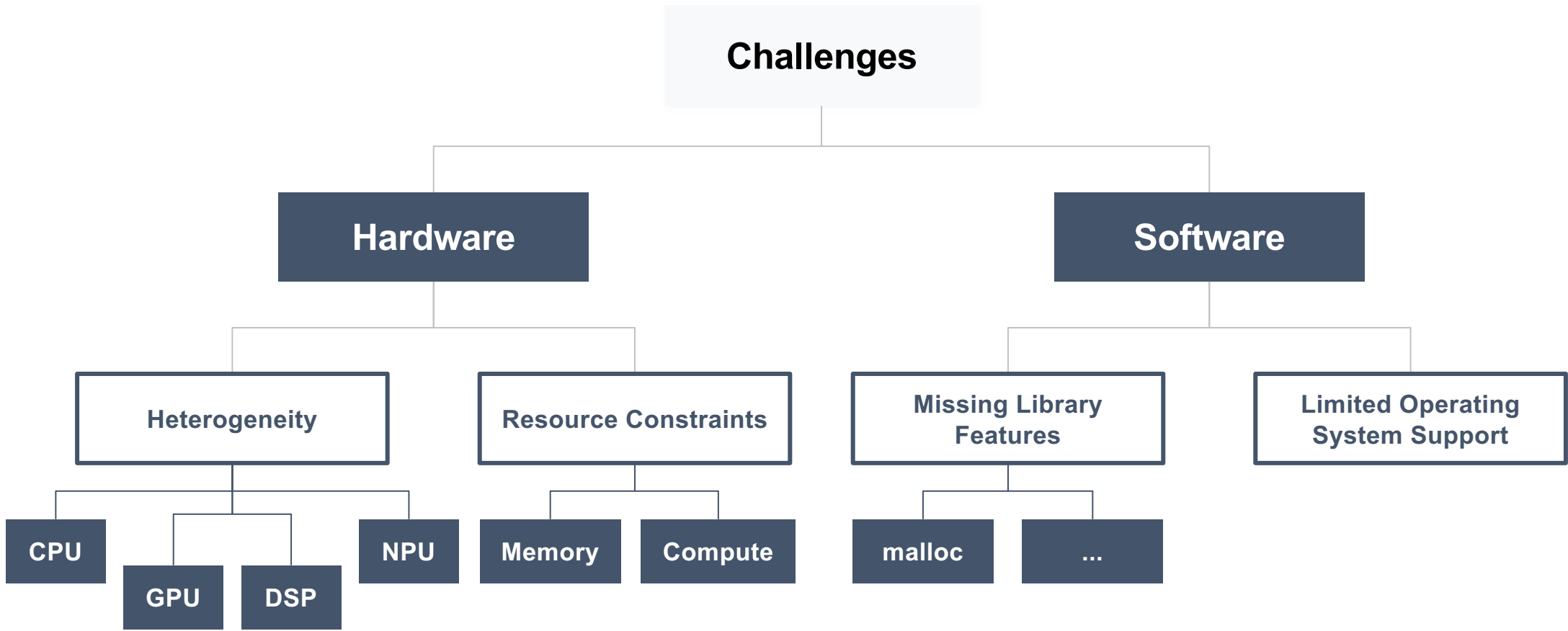
TensorFlow Lite

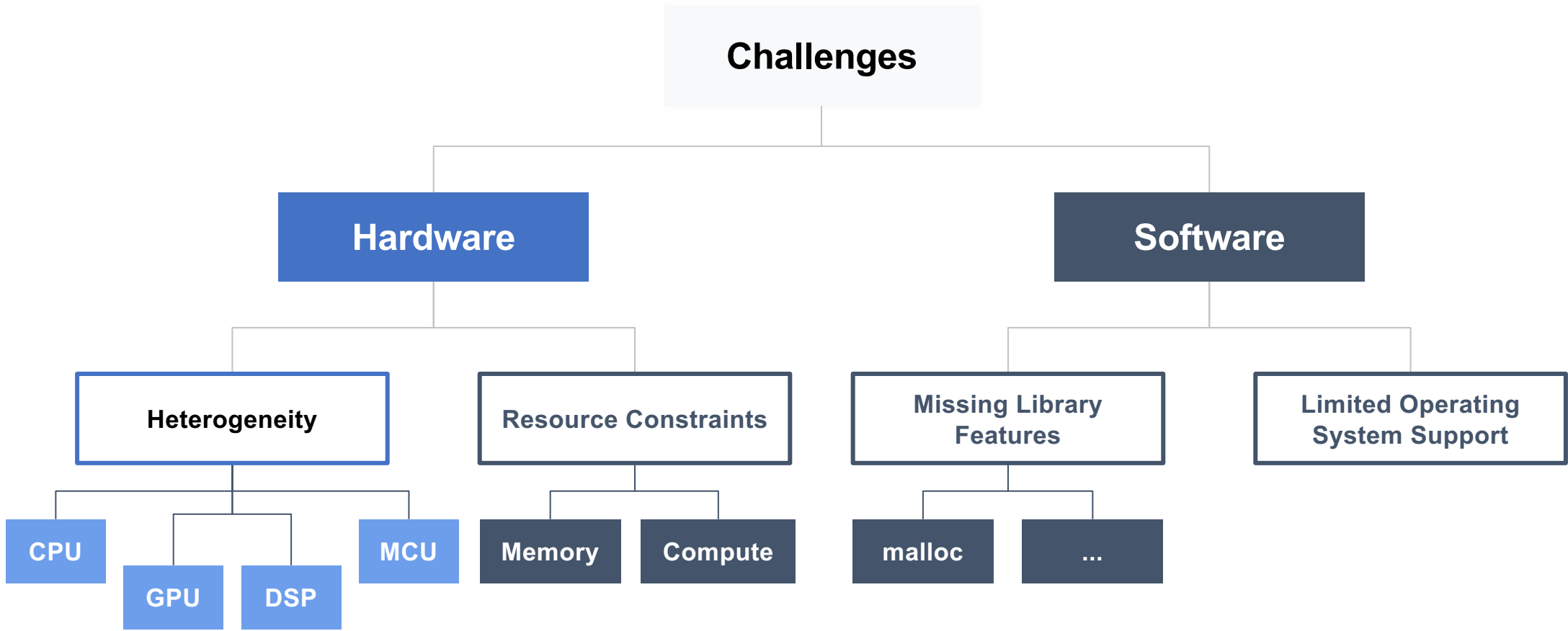
Hardware

Software

TinyML

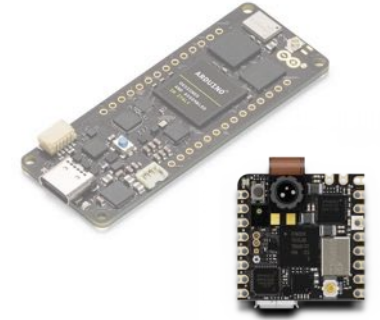
TinyML Challenges





250 Billion
MCUs today

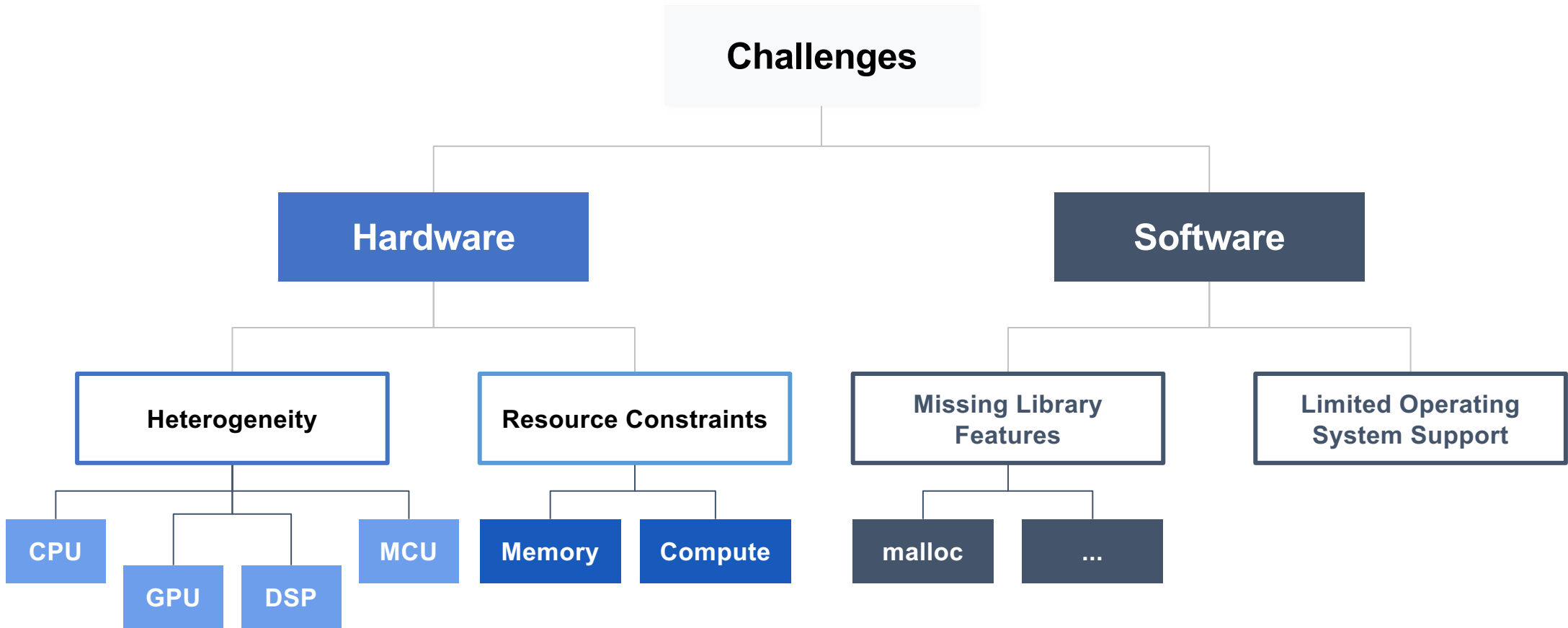
Hardware



Hardware



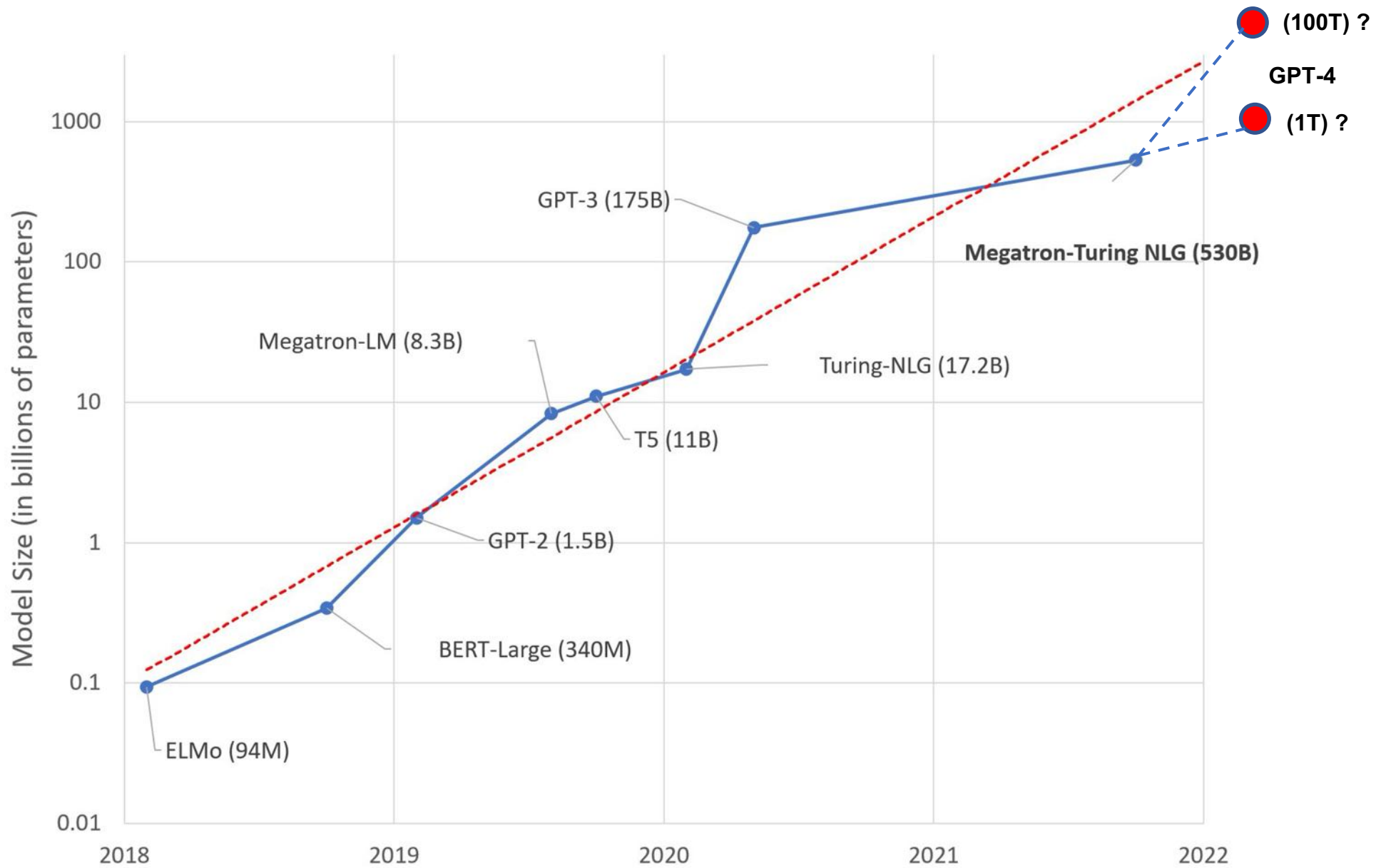
| | Raspberry Pico (W) | Arduino Nano Sense | ESP 32 | Seeed XIAO Sense / ESP32S3 | Arduino Pro |
|--------------------------|--------------------------|--------------------|------------------------|--|----------------------------|
| 32Bits CPU | Dual-core Arm Cortex-M0+ | Arm Cortex-M4F | Xtensa LX6 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 | \$ | \$\$\$ | \$ | \$\$ | \$\$\$\$\$ |

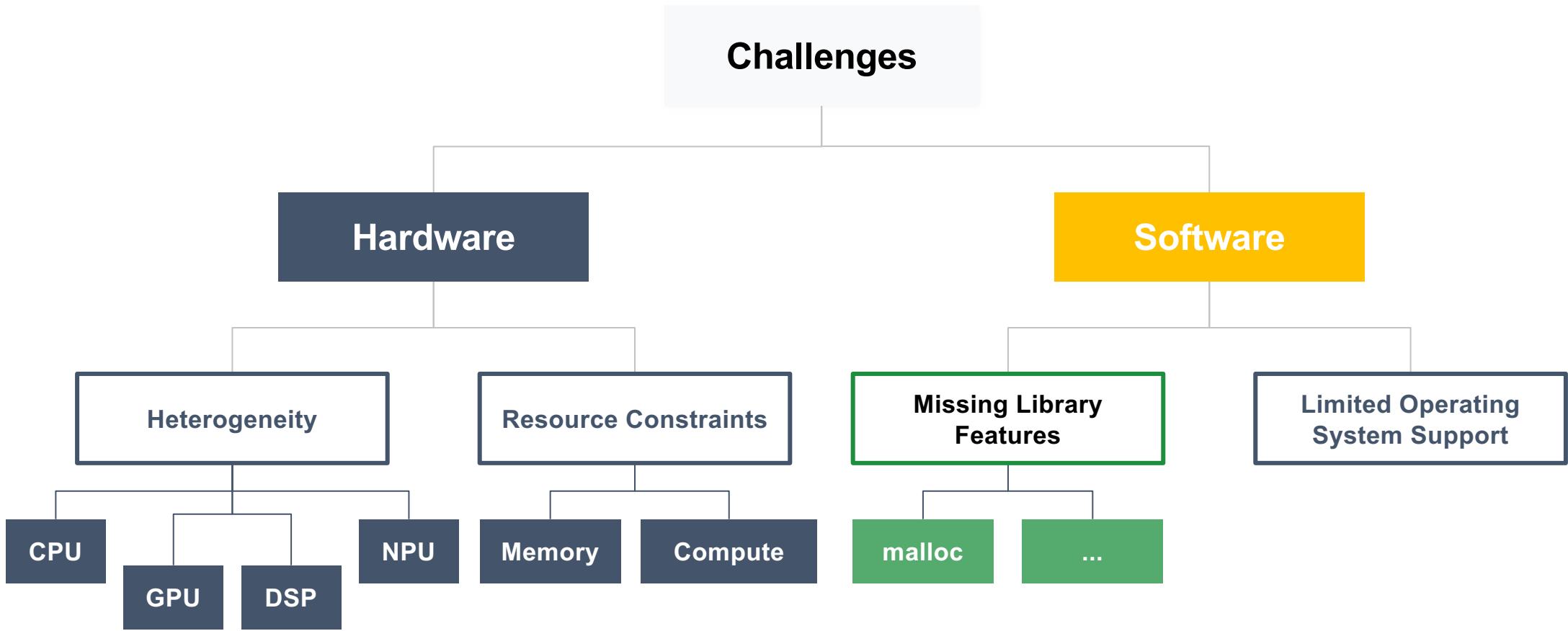


Hardware



| | 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 | \$ | \$\$\$ | \$ | \$\$ | \$\$\$\$\$ |





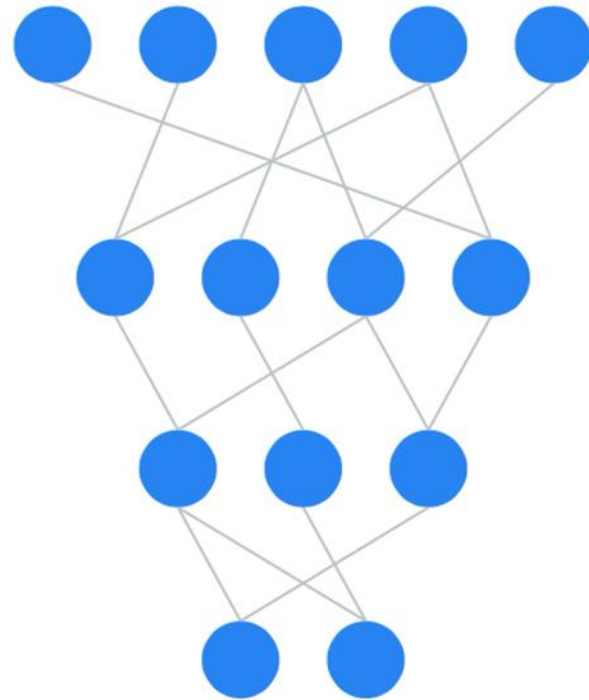
Datasets Preprocessing

Sound

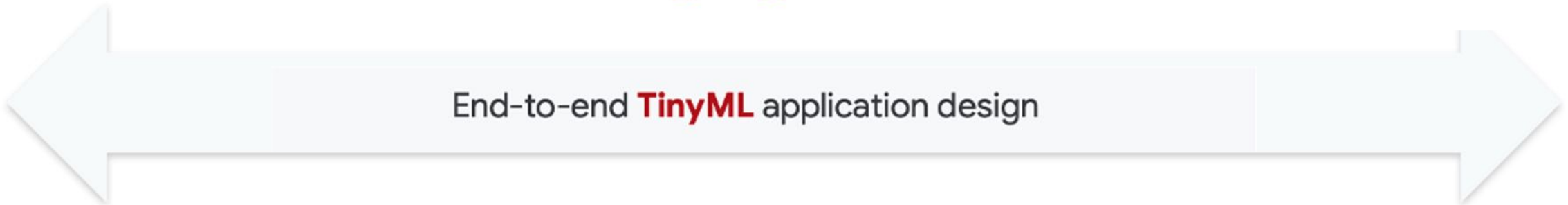
Vision

Vibration

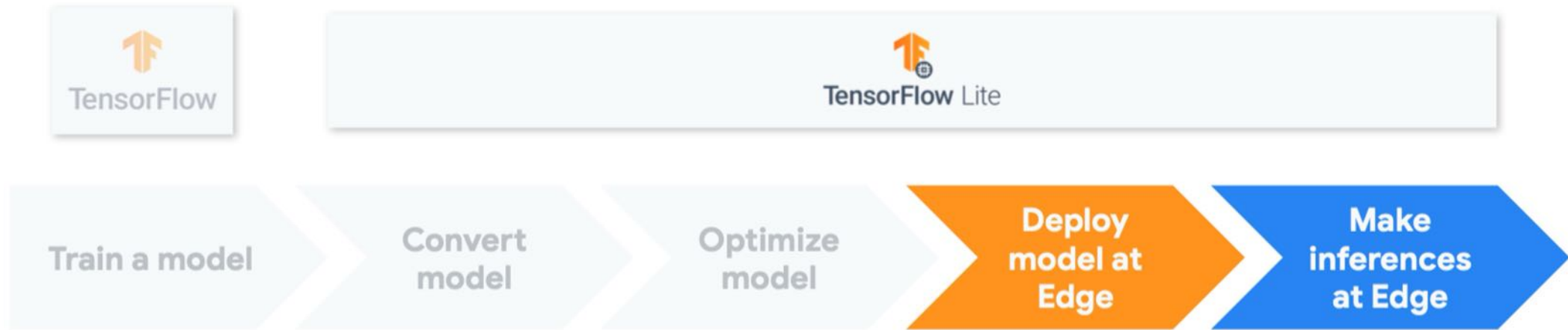
Quantization Pruning



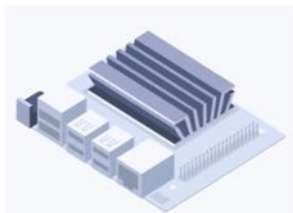
Resource constraints



Software



Raspberry Pi



Jetson Nano



Linux



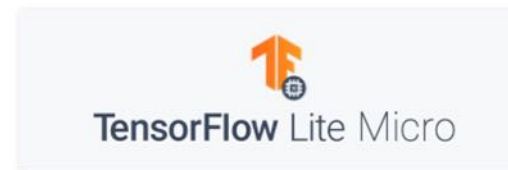
iOS



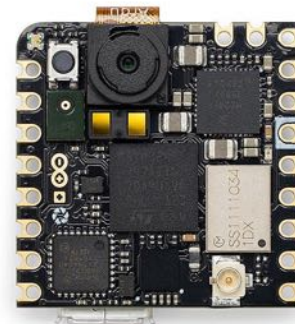
Android

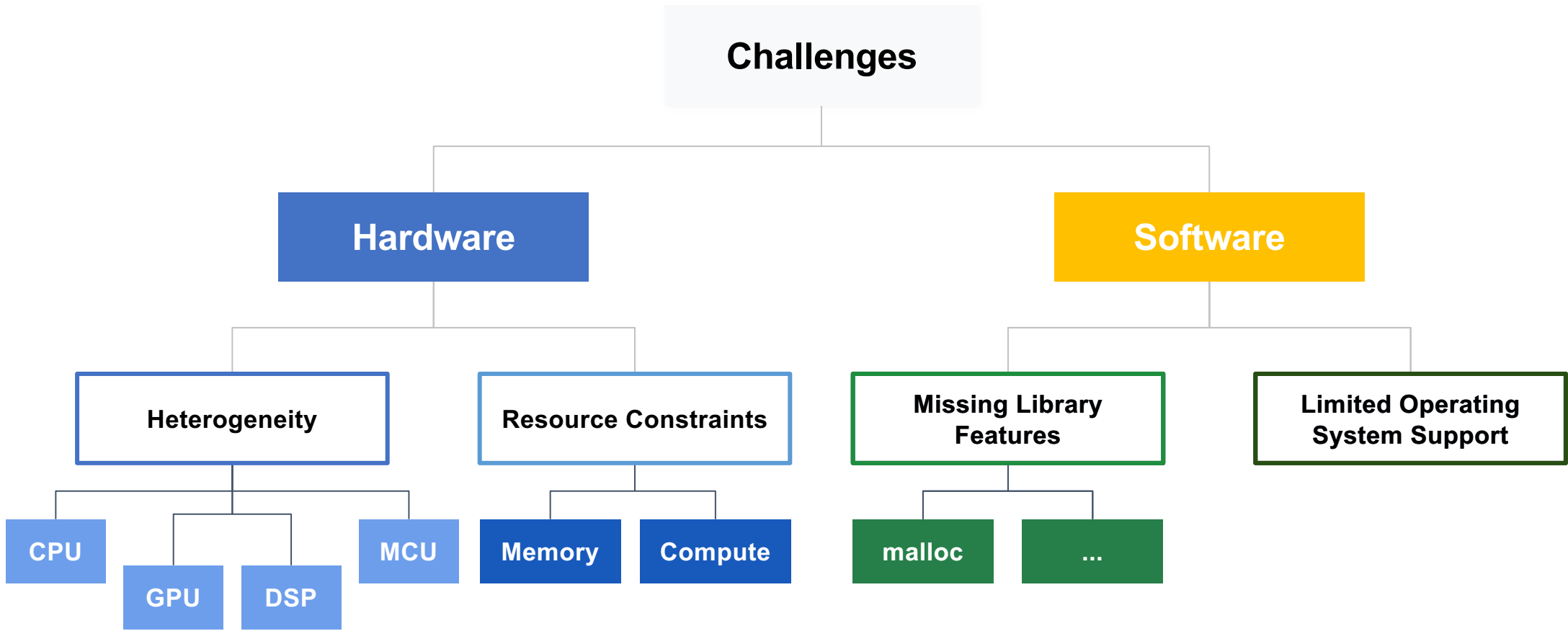


Microcontroller

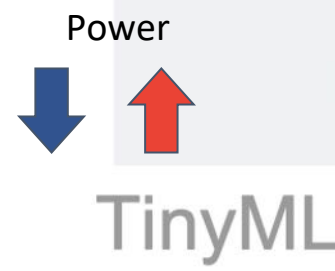


TensorFlow Lite Micro





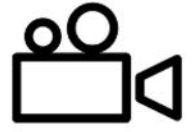
Application Complexity vs. HW



EdgeML

Application Complexity ↑

CPU Power / Memory →



Anomaly Detection
 Sensor Classification
 20 KB



Rpi-Pico
 (Cortex-M0+)

KeyWord Spotting
 Audio Classification
 50 KB



Arduino Nano
 (Cortex-M4)



Arduino Pro
 (Cortex-M7)

Image
 Classification
 250 KB+



Object Detection
 Complex Voice
 Processing
 1 MB+



Video
 Classification
 2 MB+



RaspberryPi
 (Cortex-A)



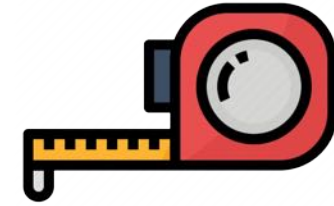
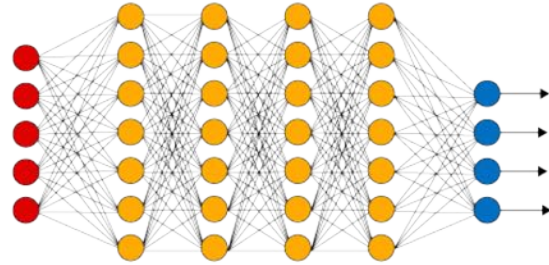
SmartPhone
 (Cortex-A)



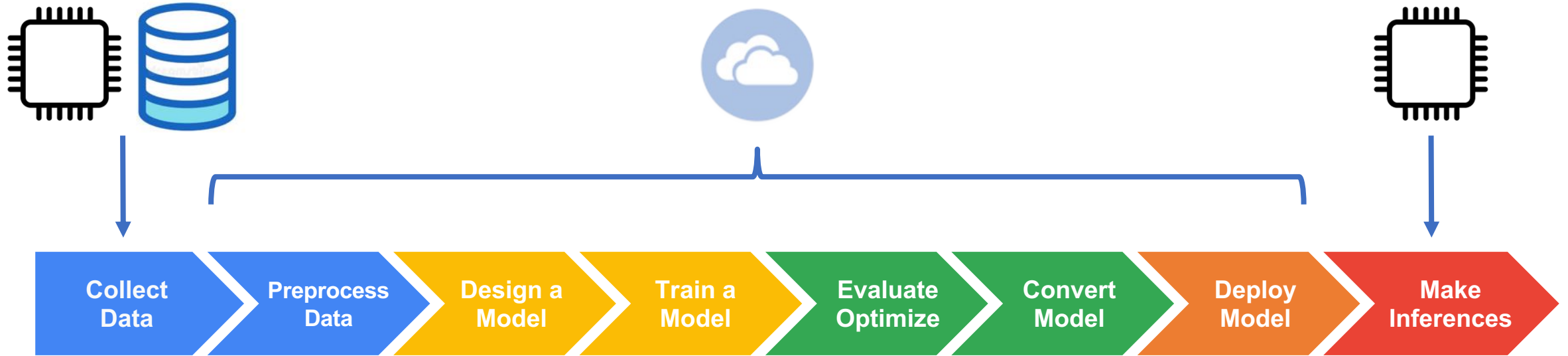
Jetson Nano
 (Cortex-A + GPU)

How to Train a ML Model?

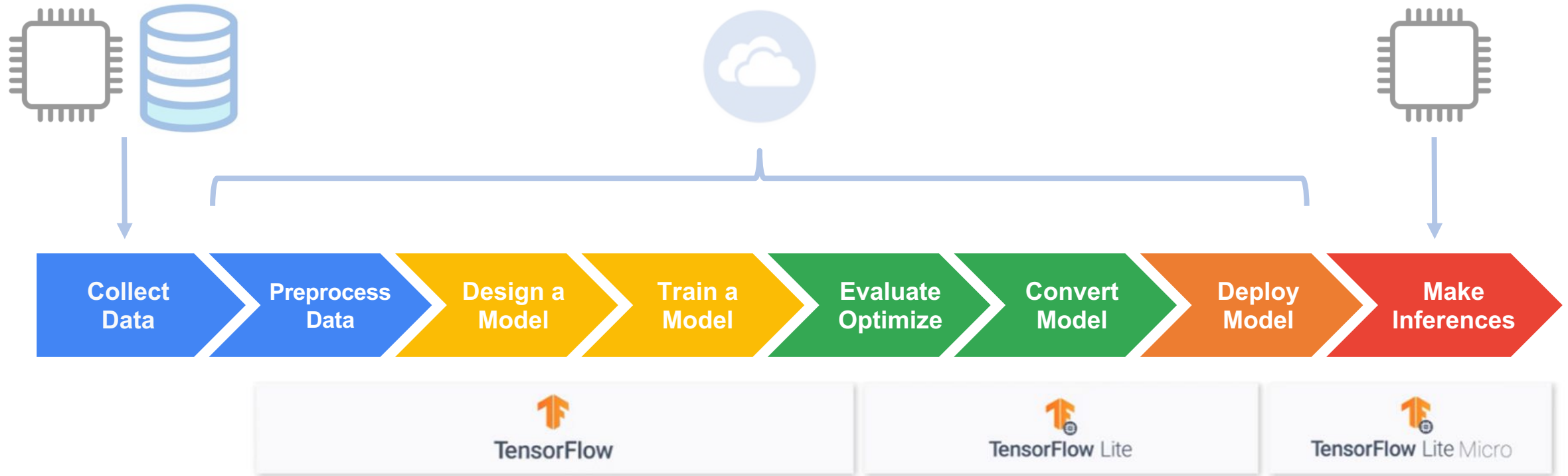
Machine Learning Workflow (“What”)



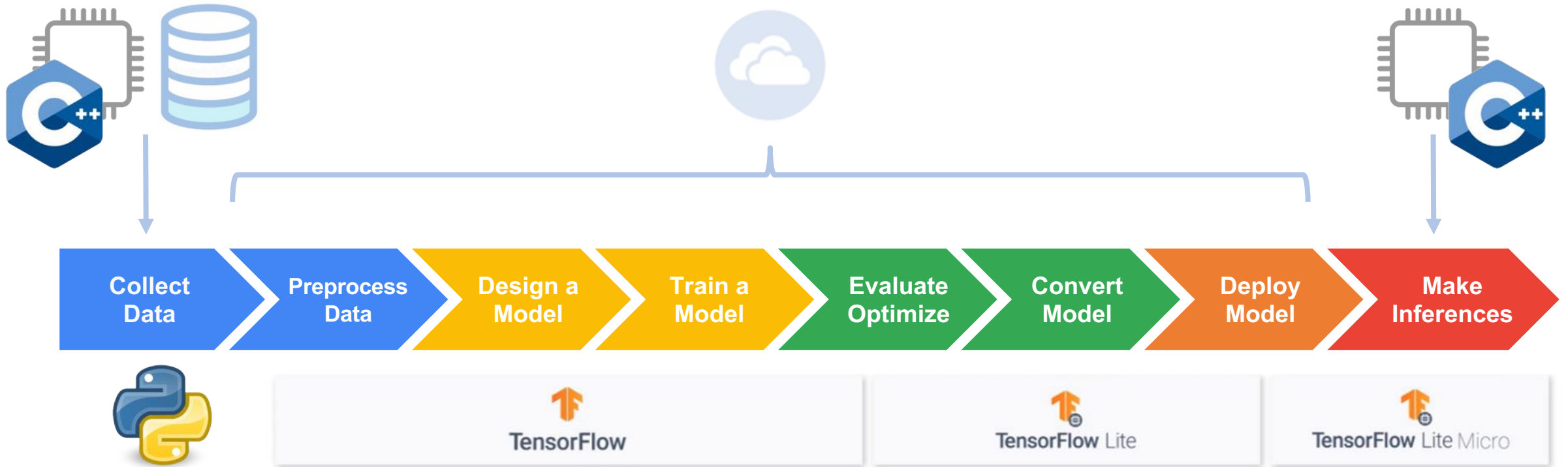
Machine Learning Workflow (“Where”)



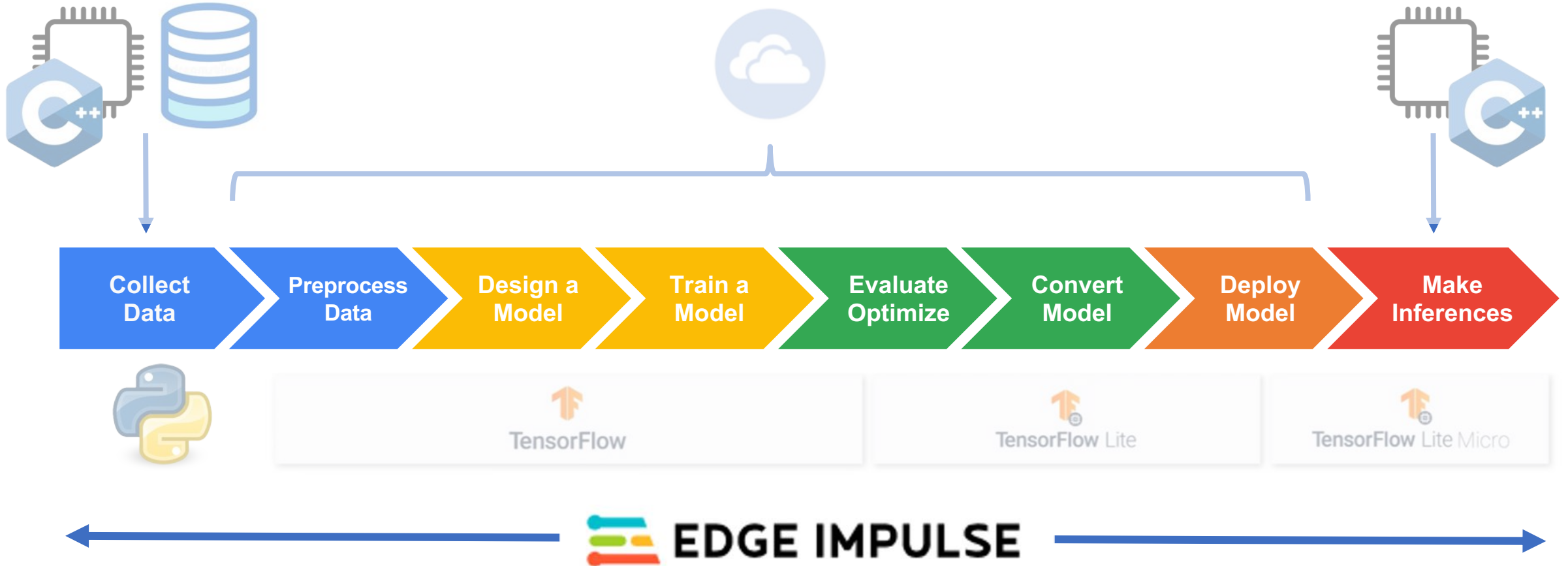
Machine Learning Workflow (“How”)



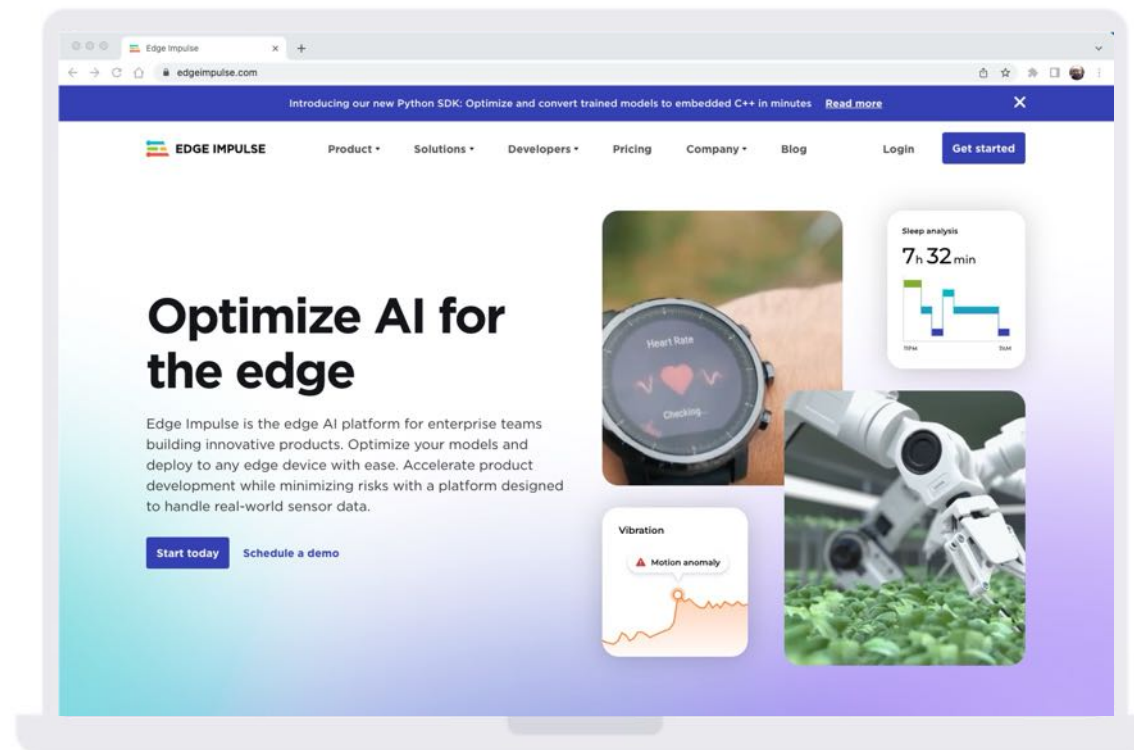
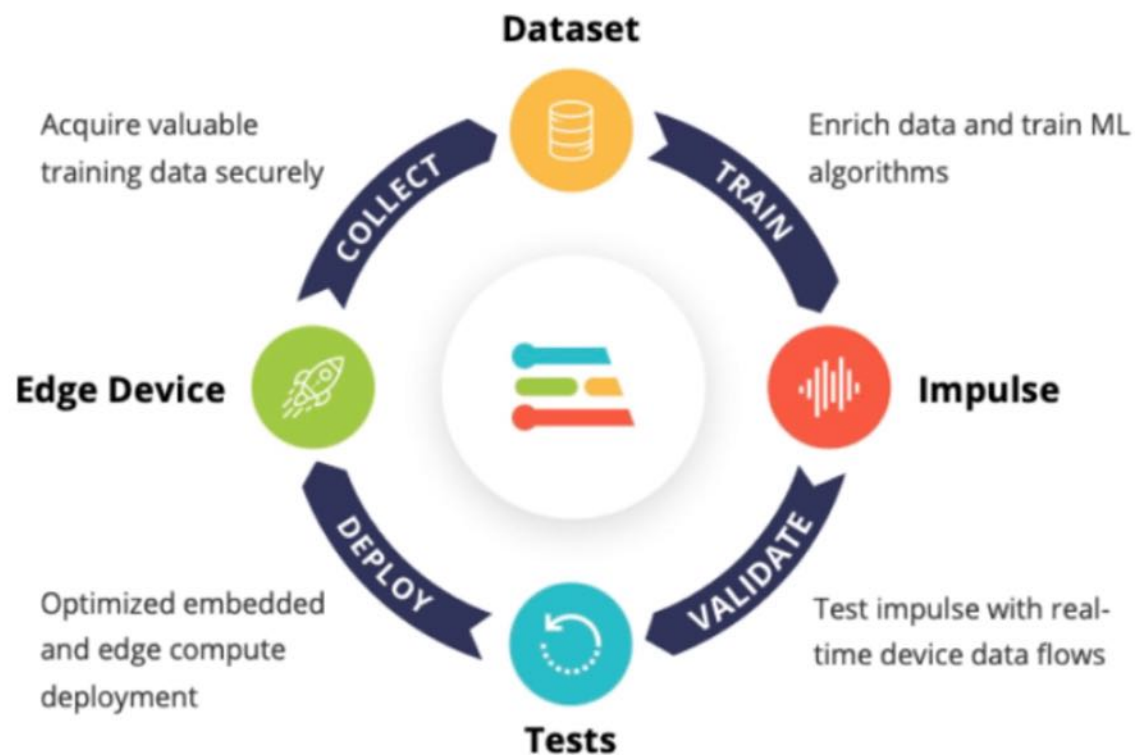
Machine Learning Workflow (“How”)



Machine Learning Workflow (“How”)



EI Studio - Embedded ML platform (“AutoML”)

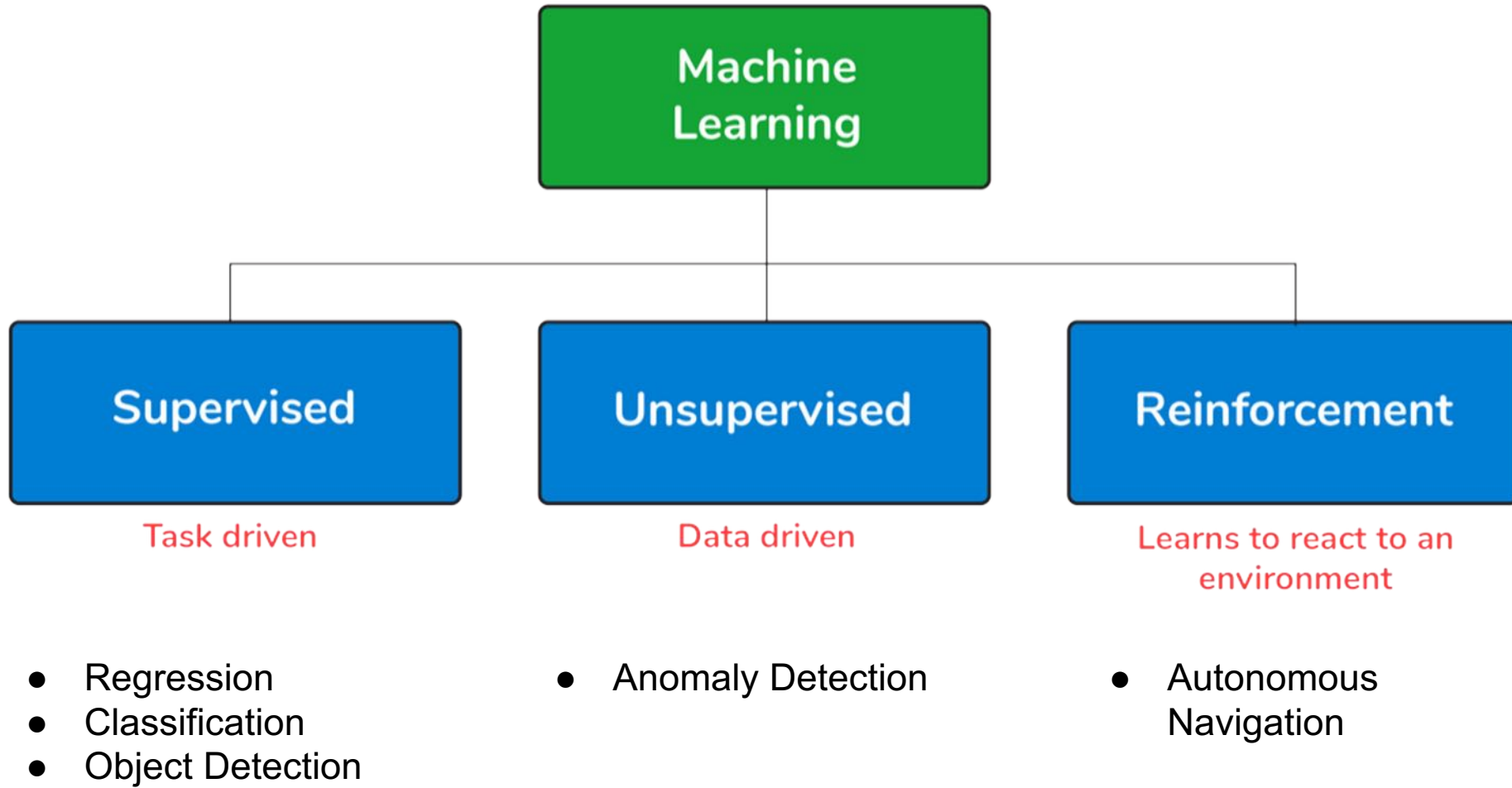


Learn more at <http://edgeimpulse.com>



TinyML Applications

Examples



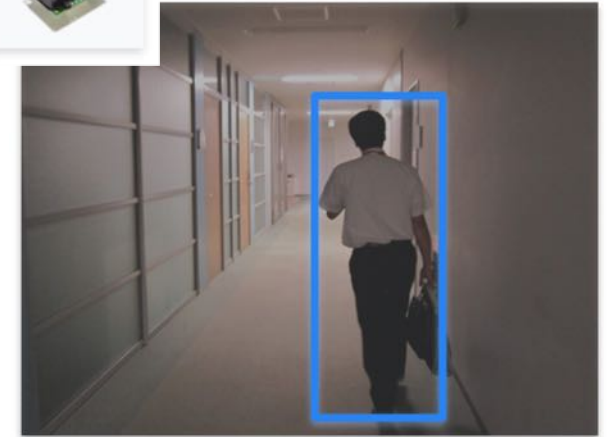
Sound



Vibration



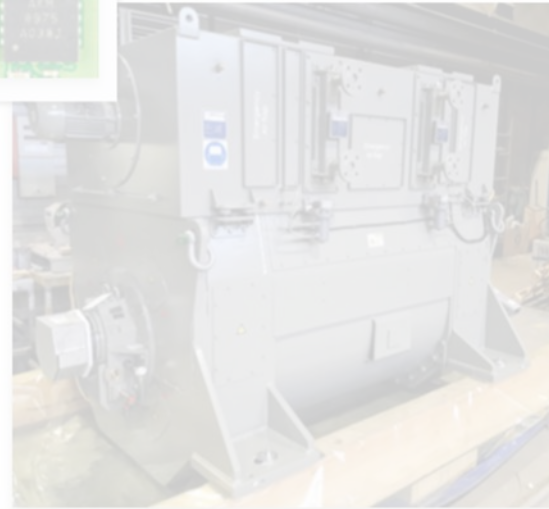
Vision



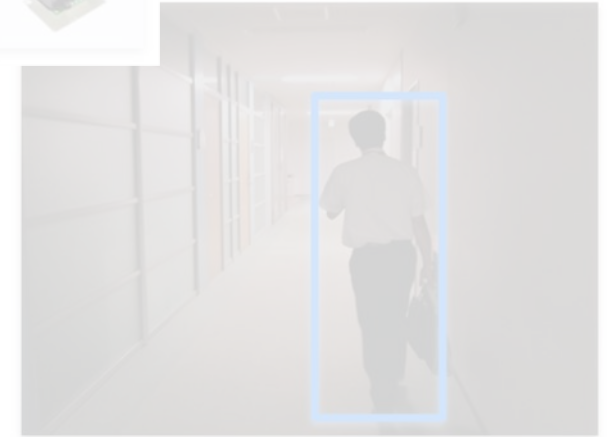
Sound



Vibration



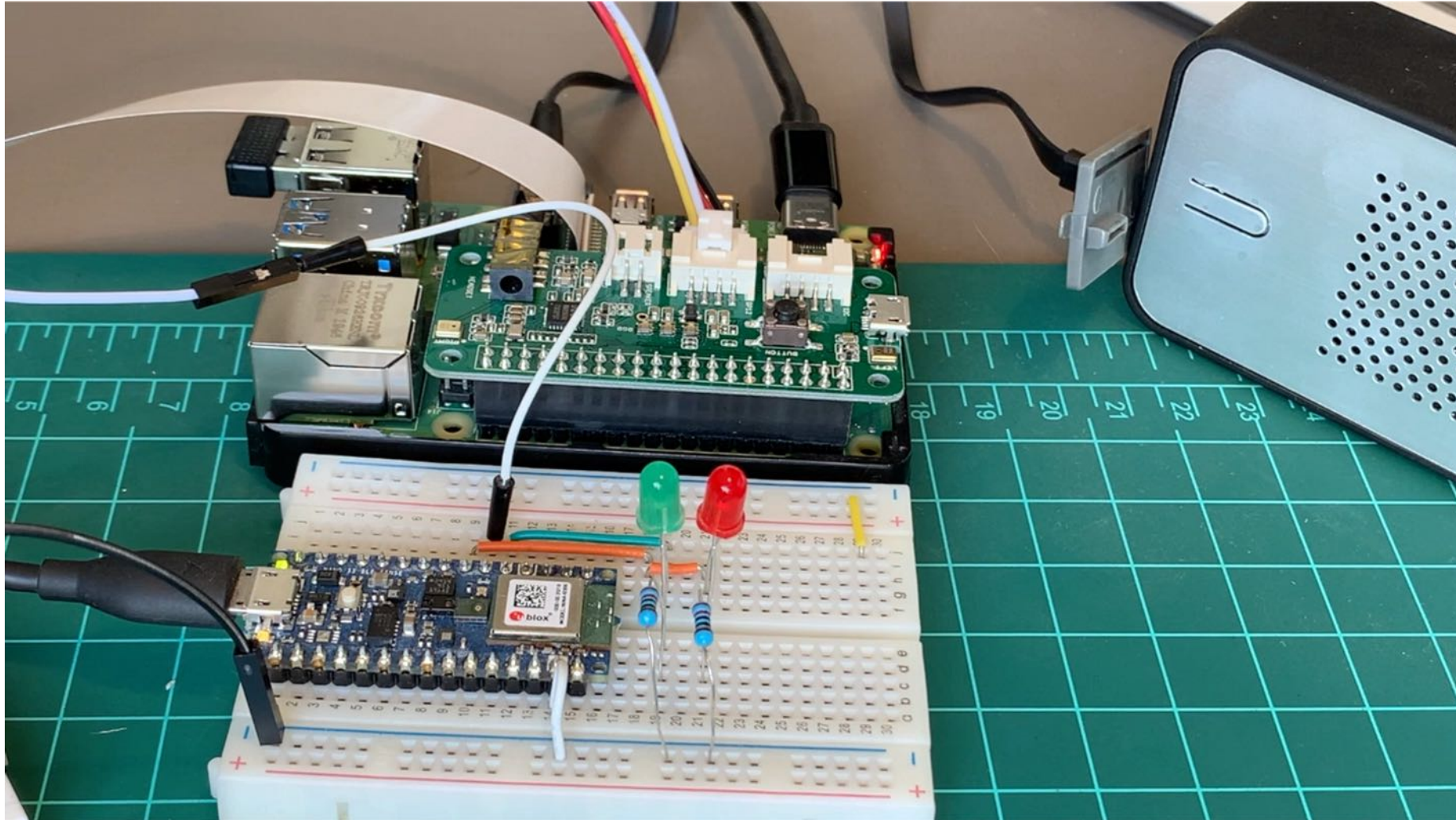
Vision



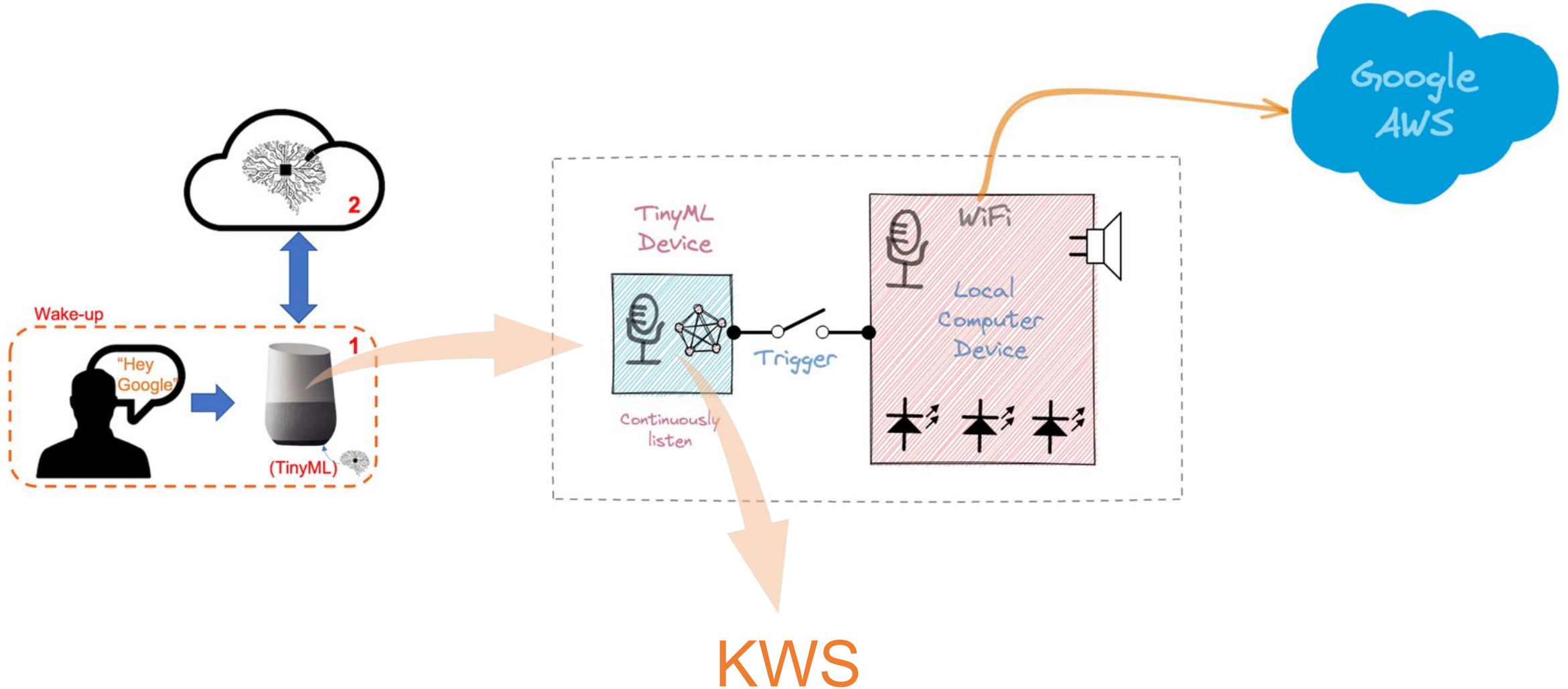
Personal Assistant



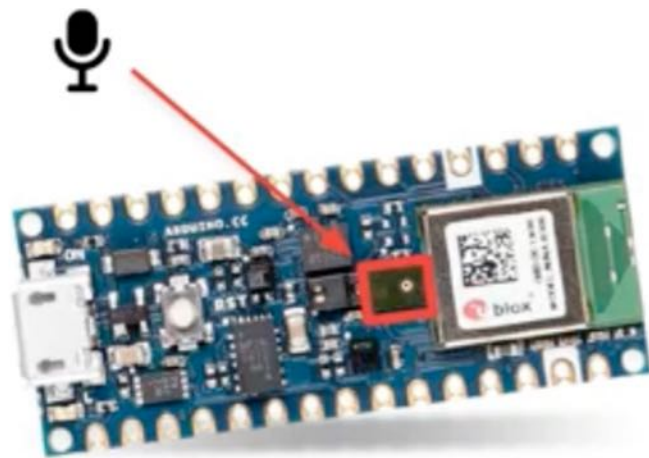
Personal Assistant



Personal Assistant

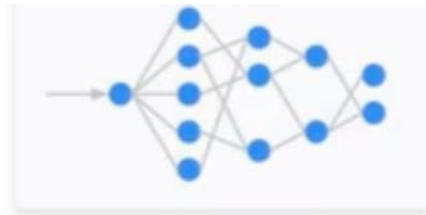


“Cascade” Detection: multi-stage model



1 Continuously listen on the microcontroller

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

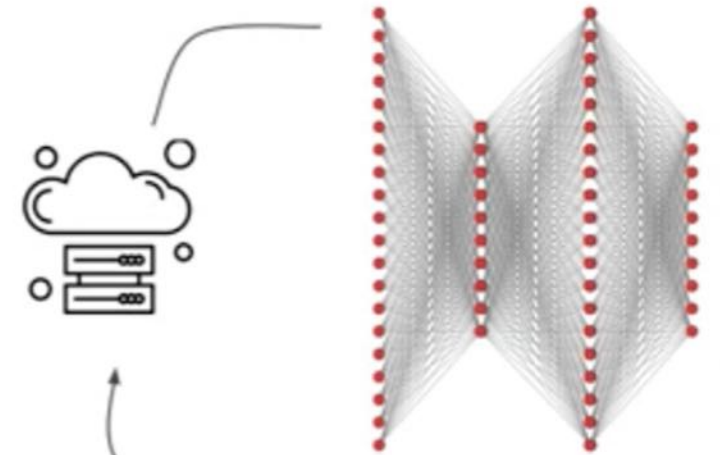


3 Process on a secondary larger model on a larger local device

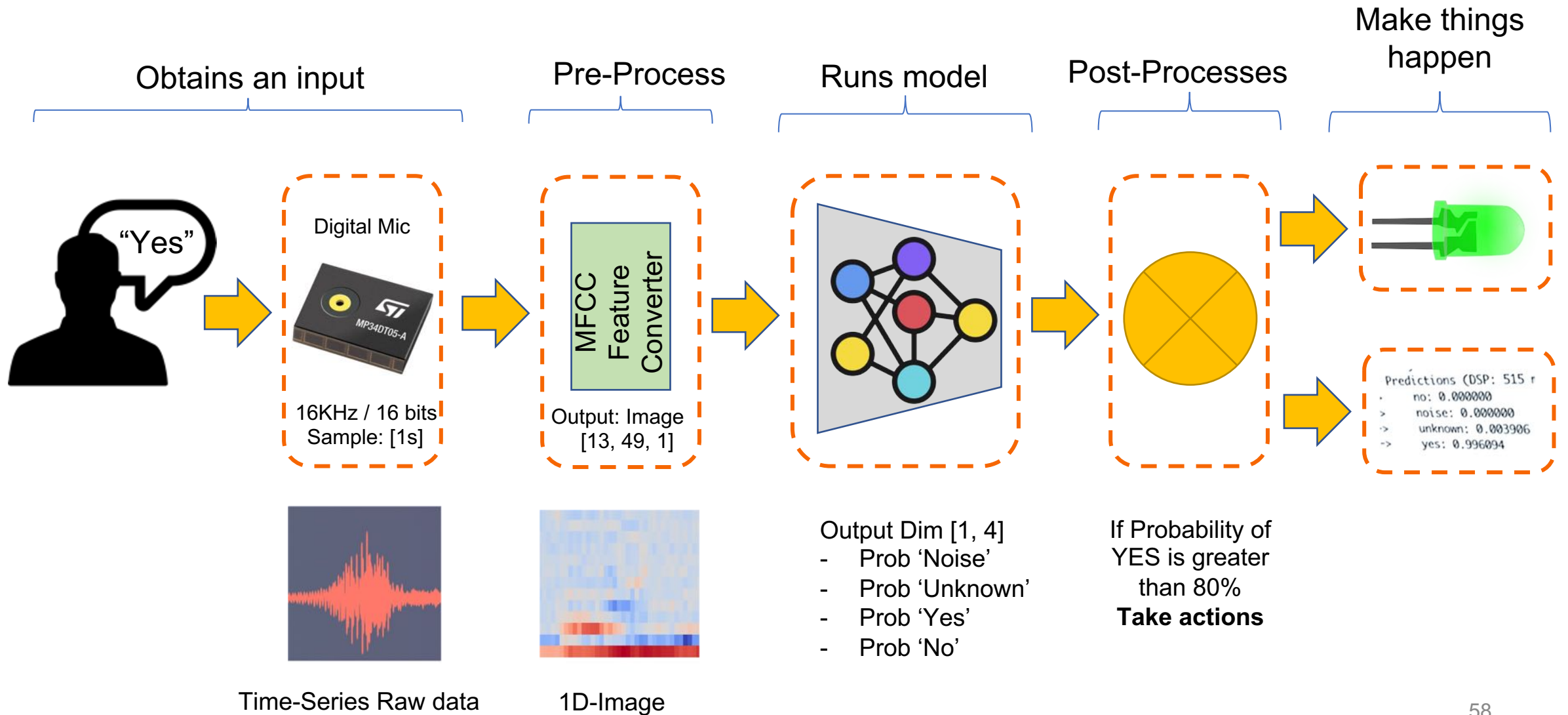


4 Send the data to the cloud when triggered

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



KeyWord Spotting (KWS) - Inference





Classifying mosquito wingbeat sound using TinyML

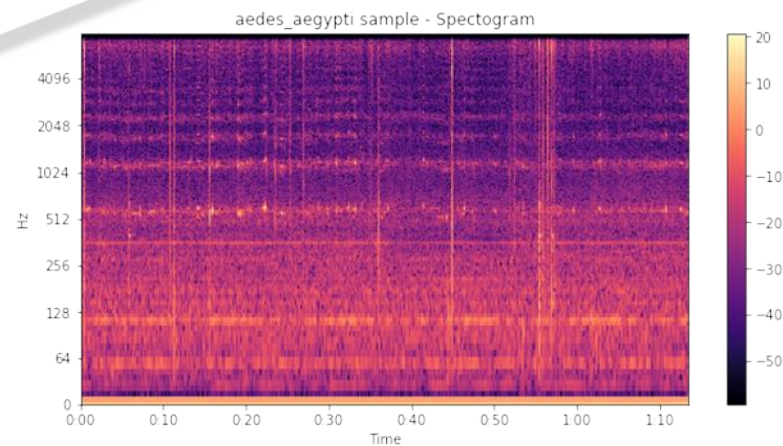
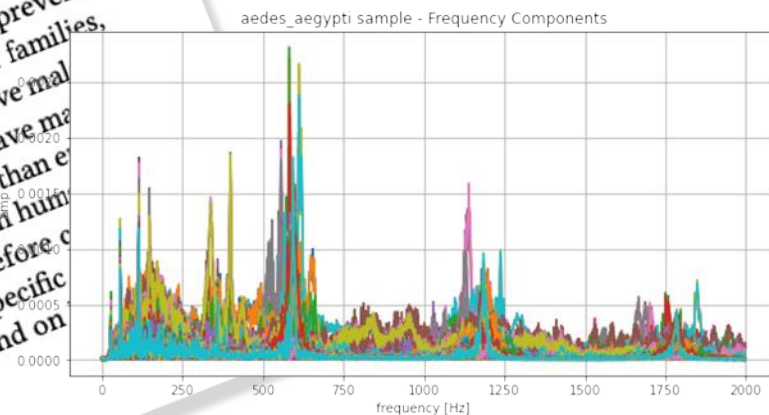
Moez Altayeb
University of Khartoum, Sudan
ICTP, Trieste, Italy
mohedahmed@hotmail.com

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

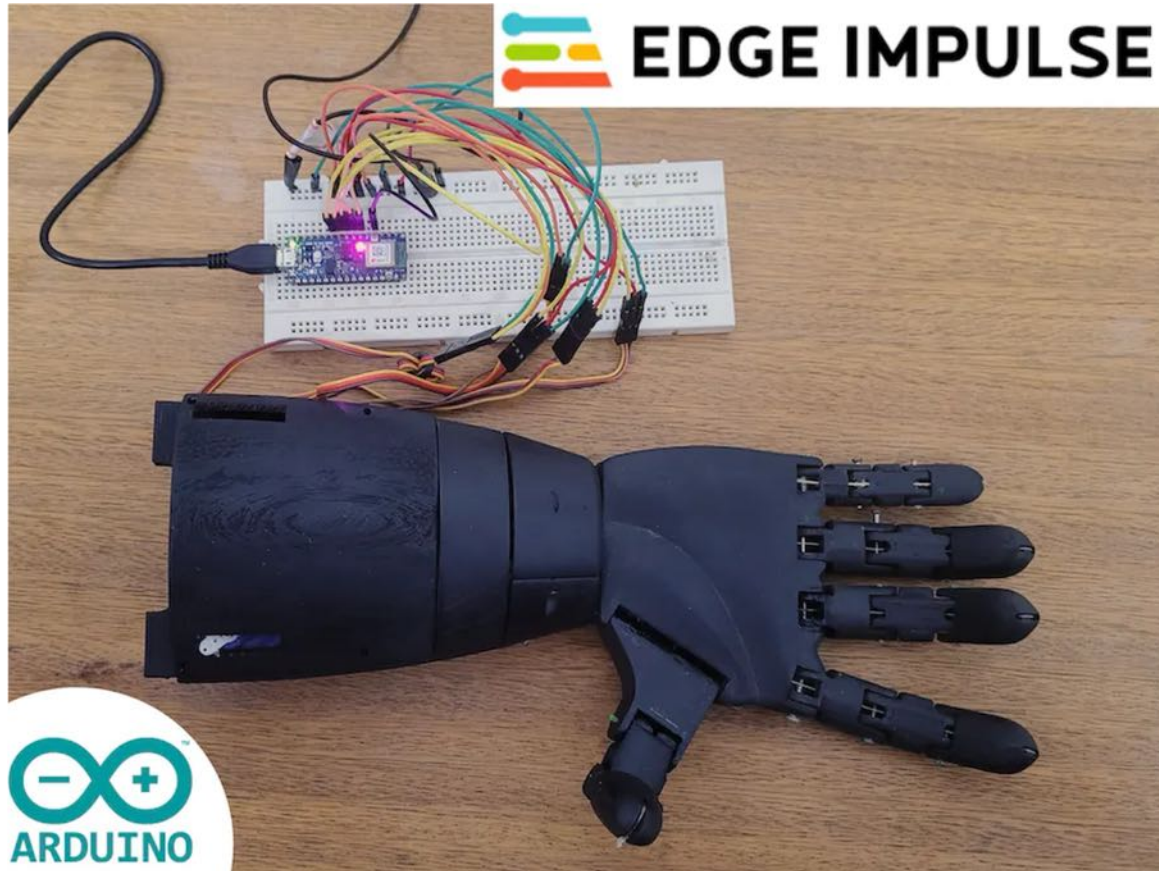
Marco Zennaro
ICTP
Trieste, Italy
mzennaro@ictp.it

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.

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 eradicating disease carriers on an area-by-area basis. It is therefore possible 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.

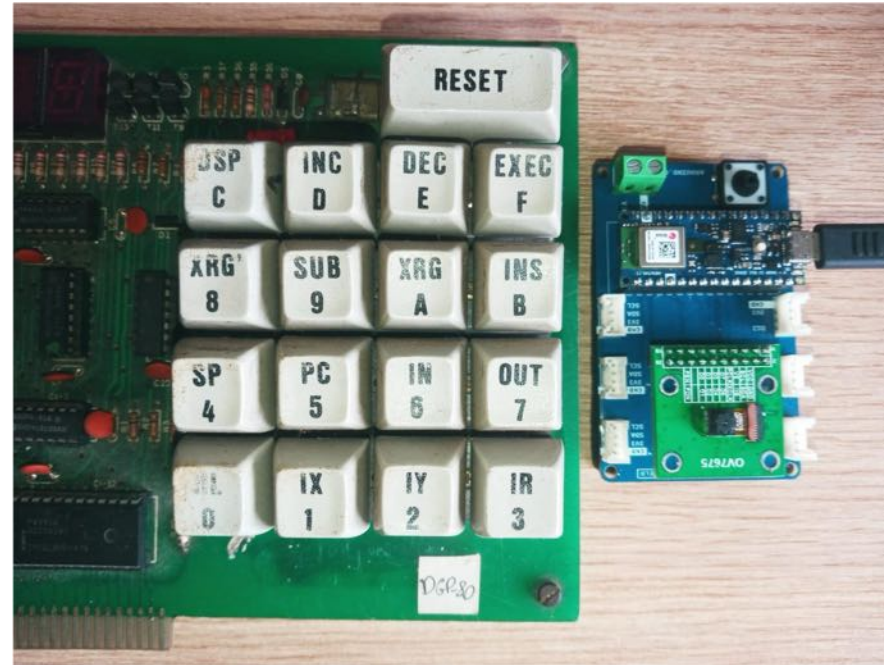


Bionic Hand Voice Commands Module

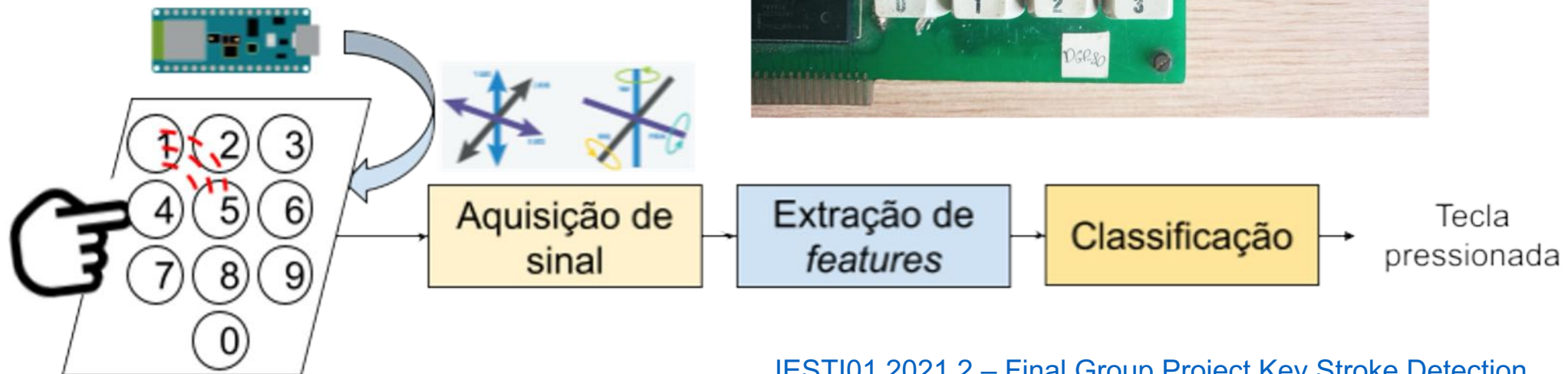


<https://www.hackster.io/ex-machina/bionic-hand-voice-commands-module-w-edge-impulse-arduino-aa97e3>

Keystroke **Sound** Detection



Renam Castro
Professor IFESP



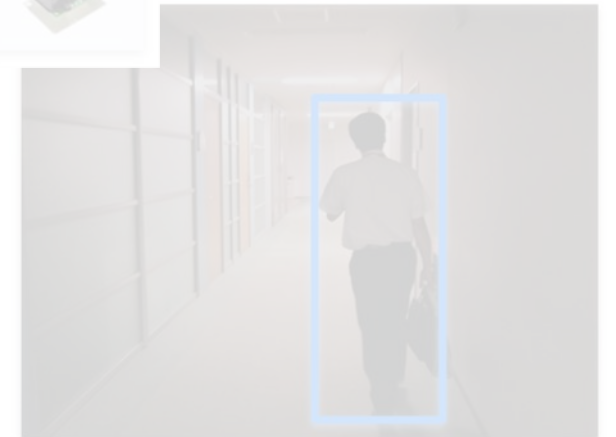
Sound



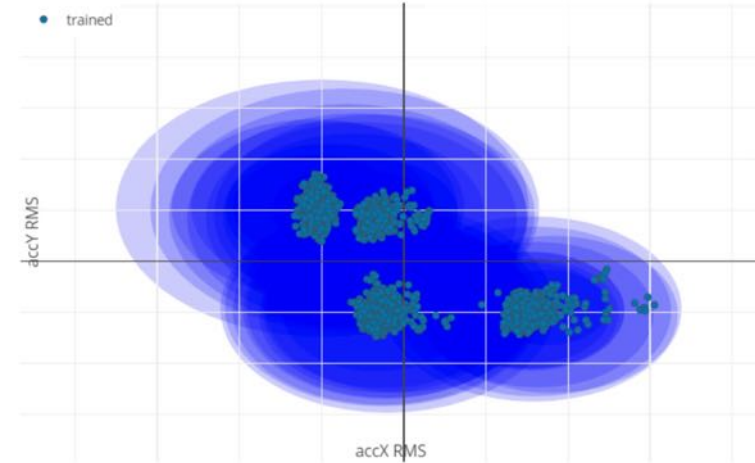
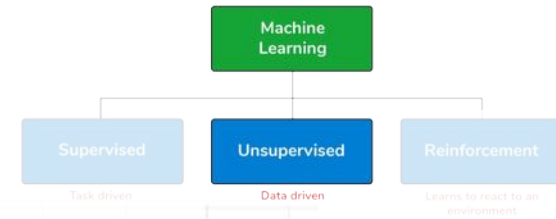
Vibration



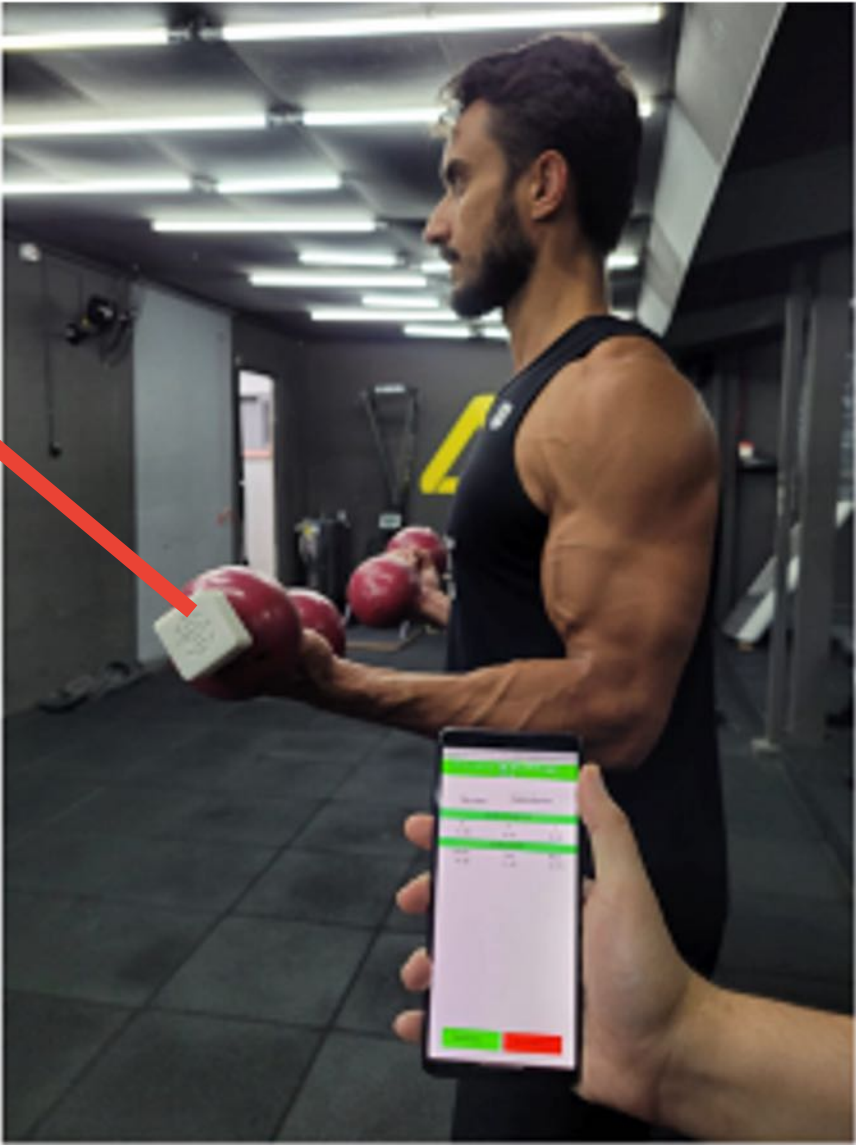
Vision



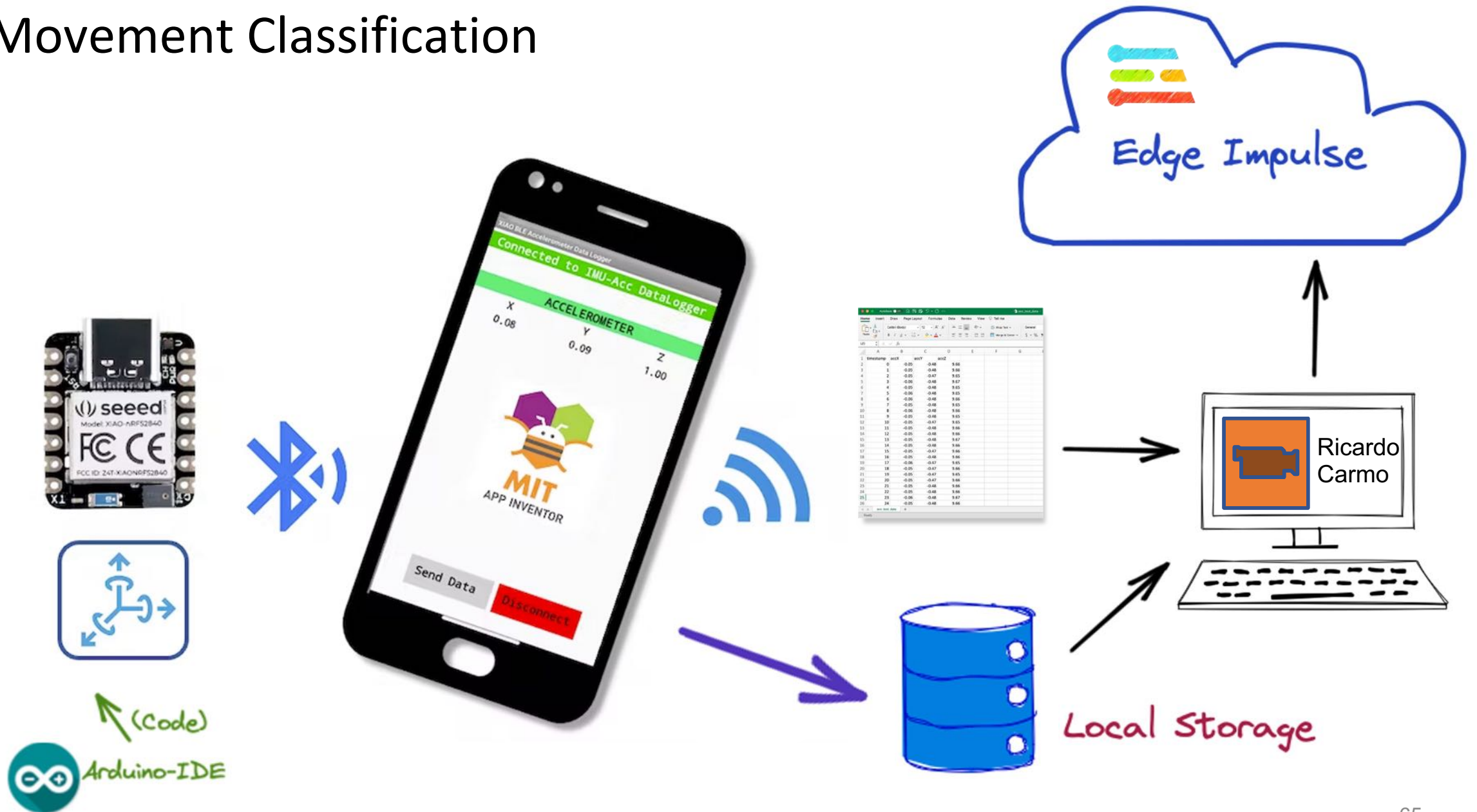
Industrial – Anomaly Detection



Movement Classification



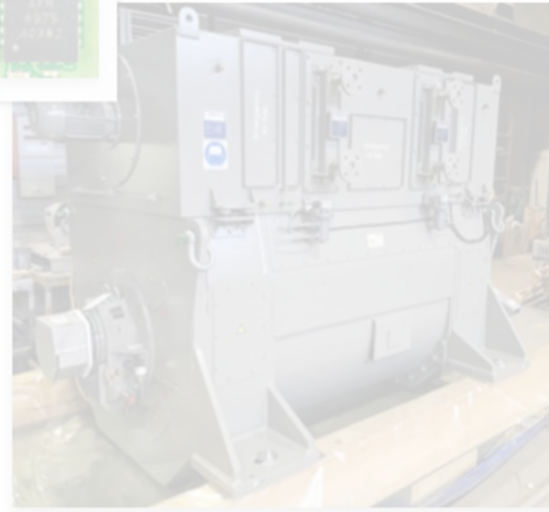
Movement Classification



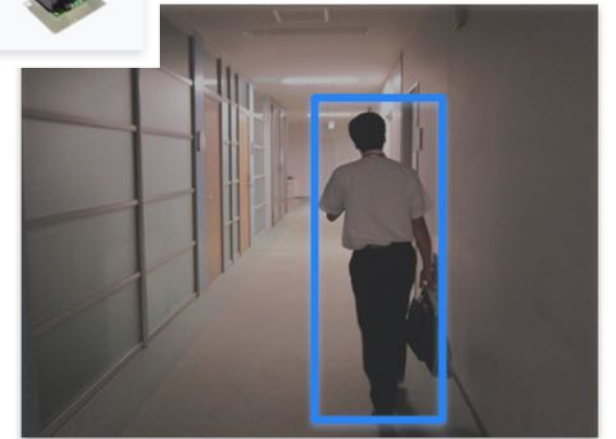
Sound



Vibration



Vision



Computer Vision Main Types

Image Classification (Multi-Class Classification)

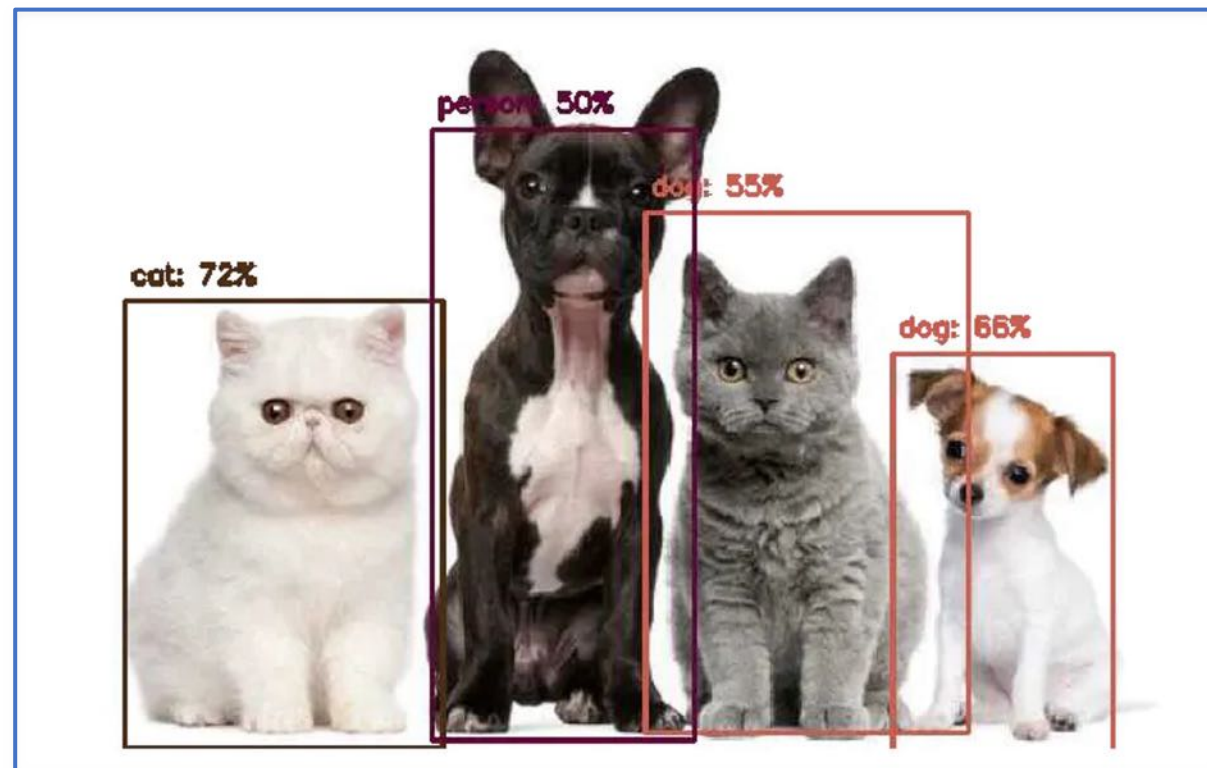


Cat: 70%



Dog: 80%

Object Detection Multi-Label Classification + Object Localization

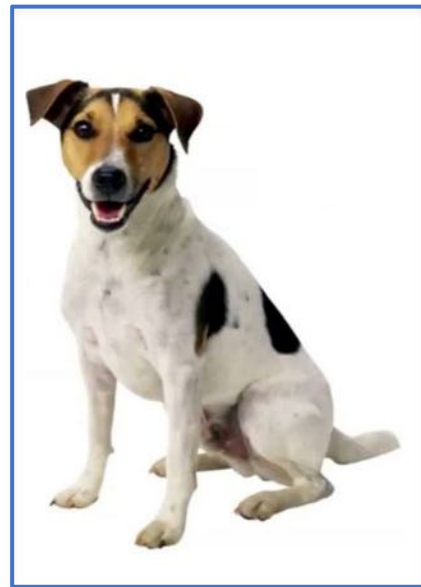


Computer Vision Main Types

Image Classification (Multi-Class Classification)

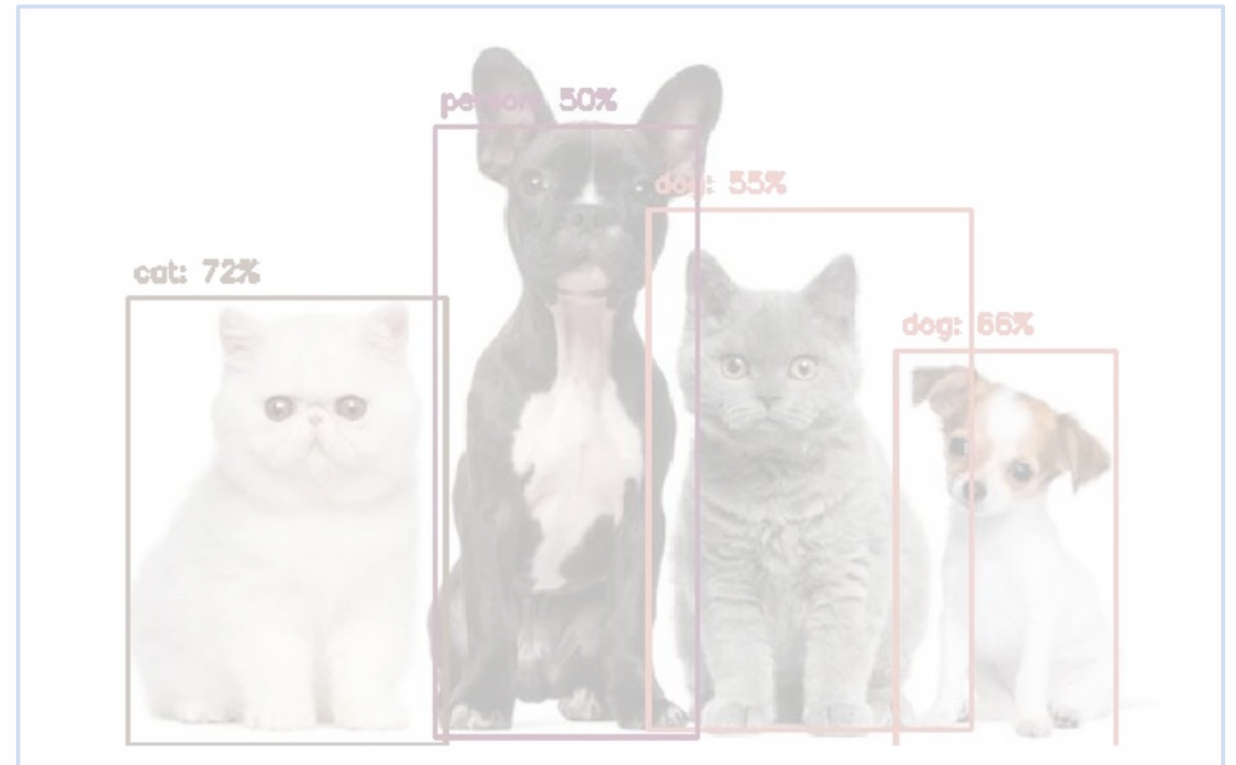


Cat: 70%



Dog: 80%

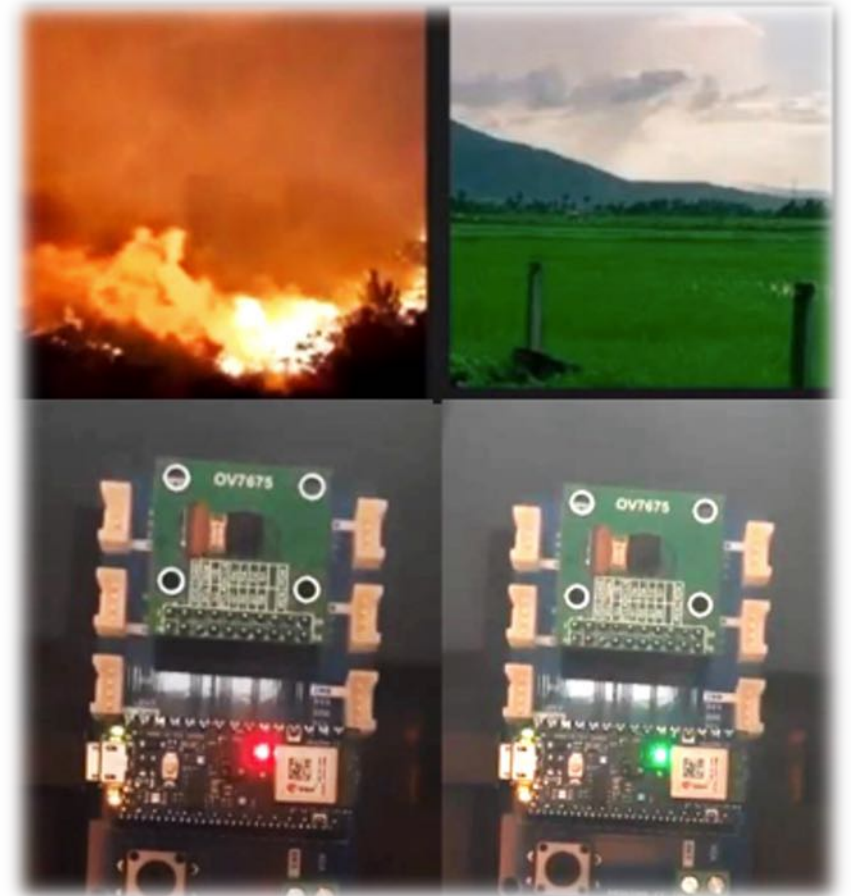
Object Detection Multi-Label Classification + Object Localization



Forest Fire Detection



[TinyML Aerial Forest Fire Detection](#)



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

Coffee Disease Classification



João Vitor Yukio Bordin Yamashita
Graduando em Engenharia Eletrônica pela UNIFEI

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

Computer Vision Main Types

Image Classification (Multi-Class Classification)

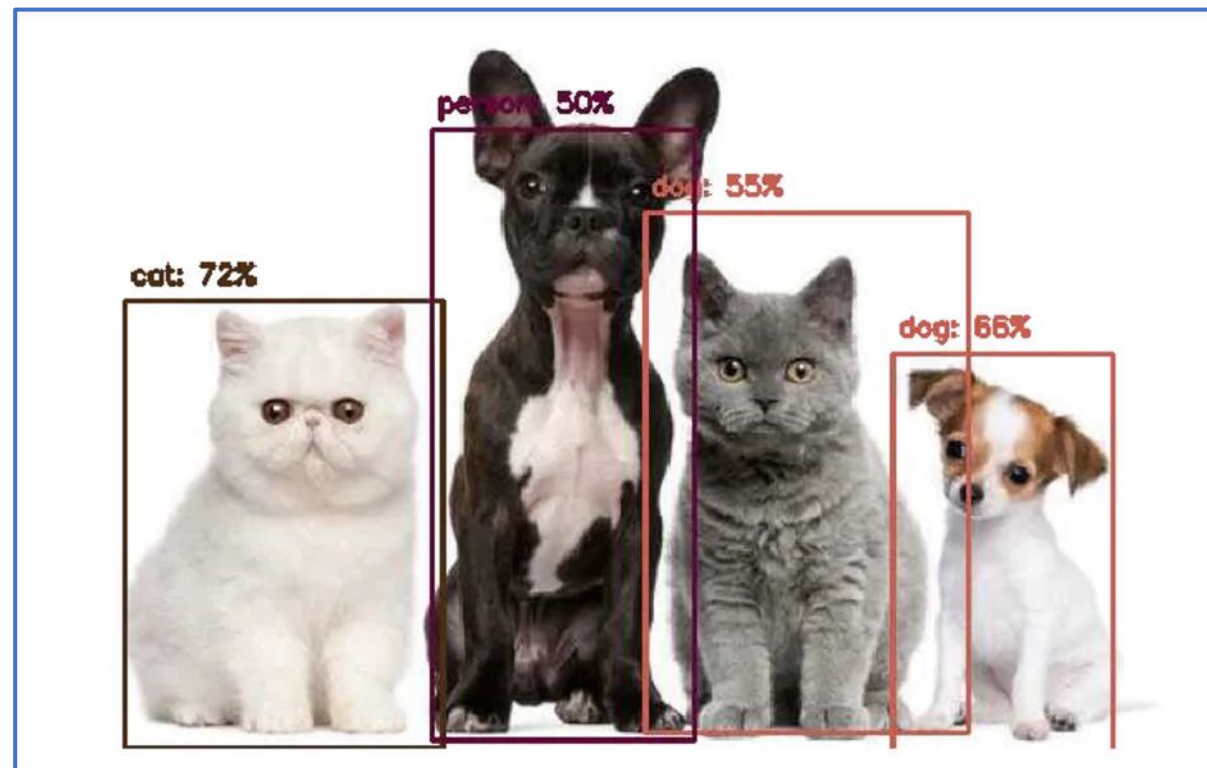


Cat: 70%

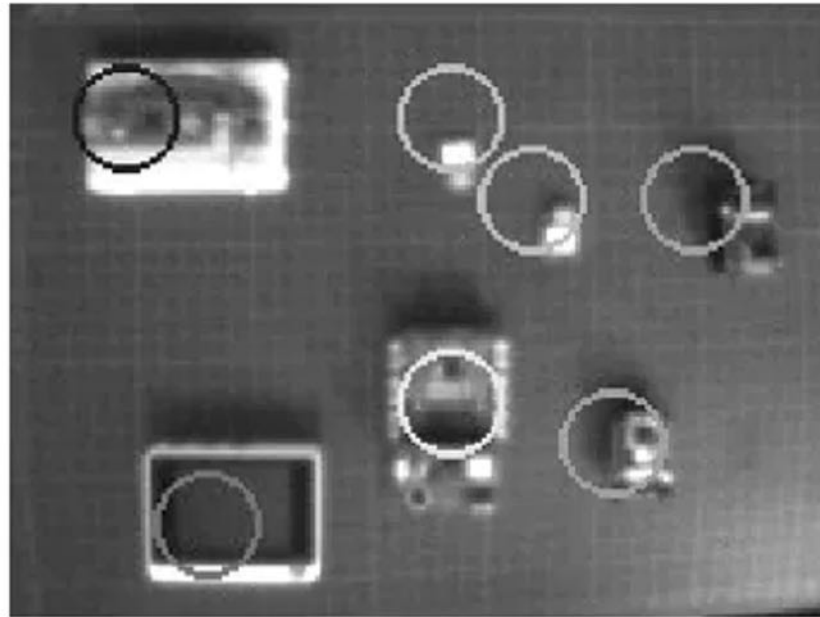


Dog: 80%

Object Detection Multi-Label Classification + Object Localization



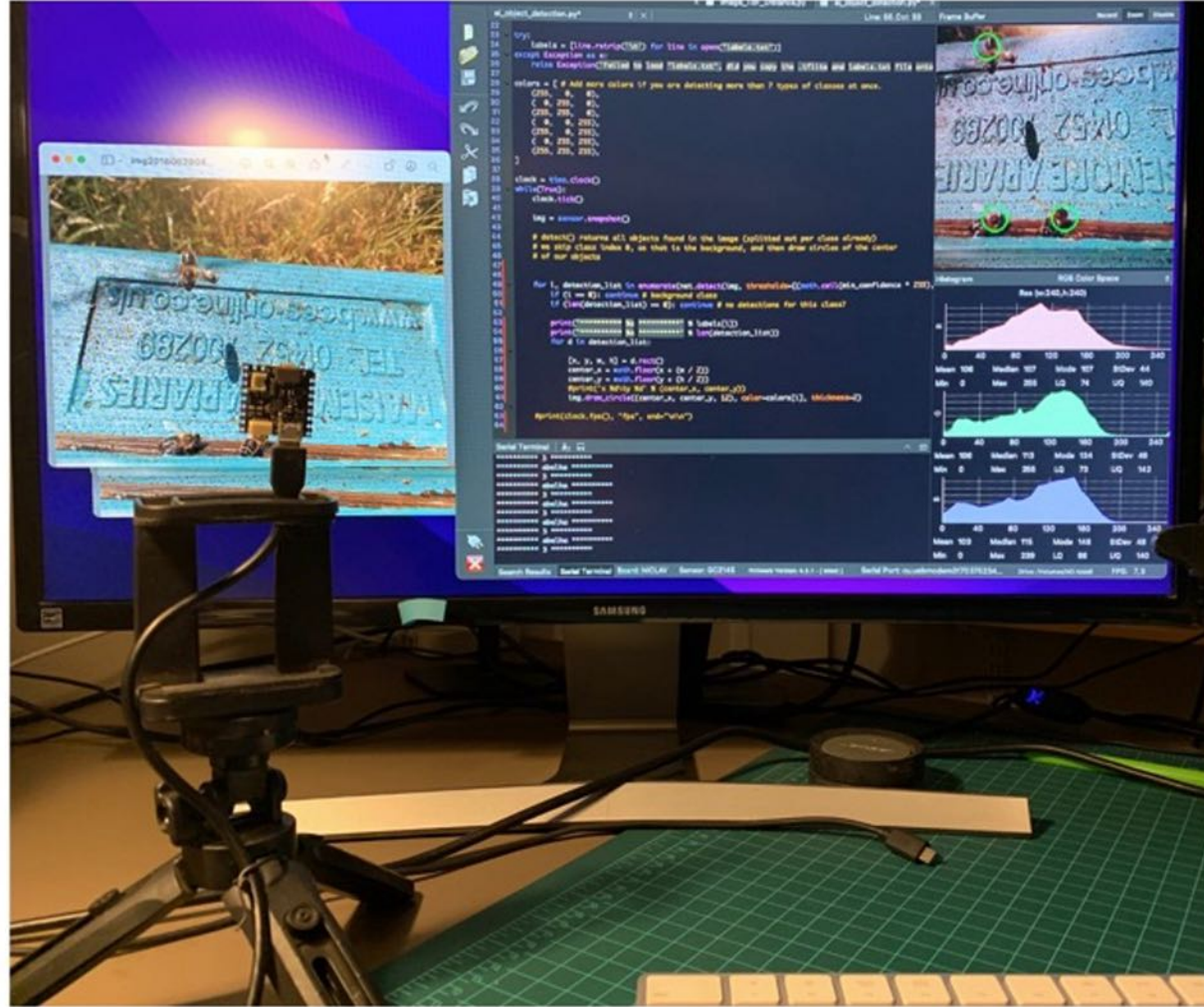
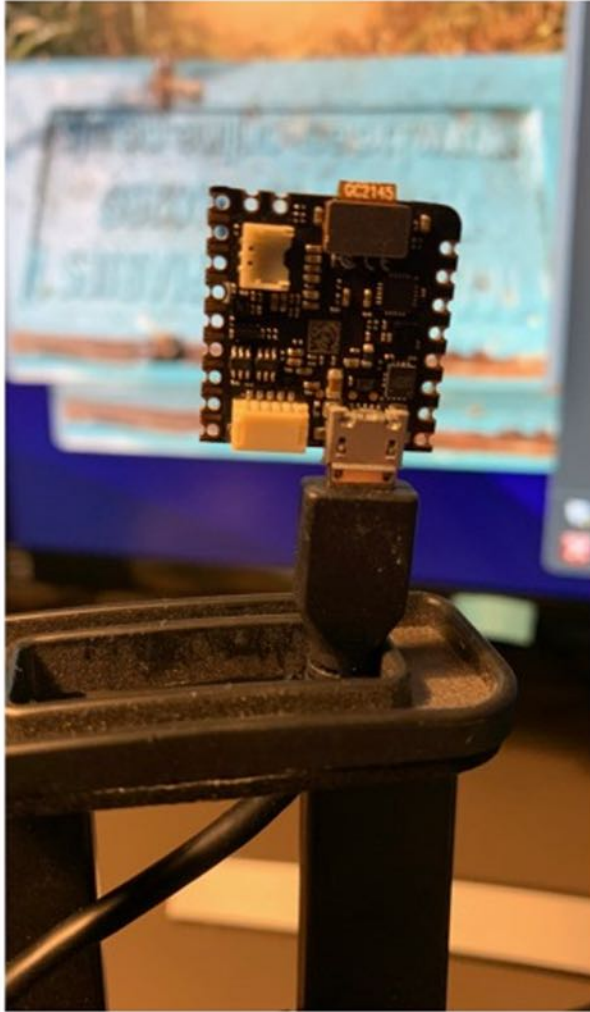
Detecting Objects using TinyML (FOMO)



```
***** 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](#)

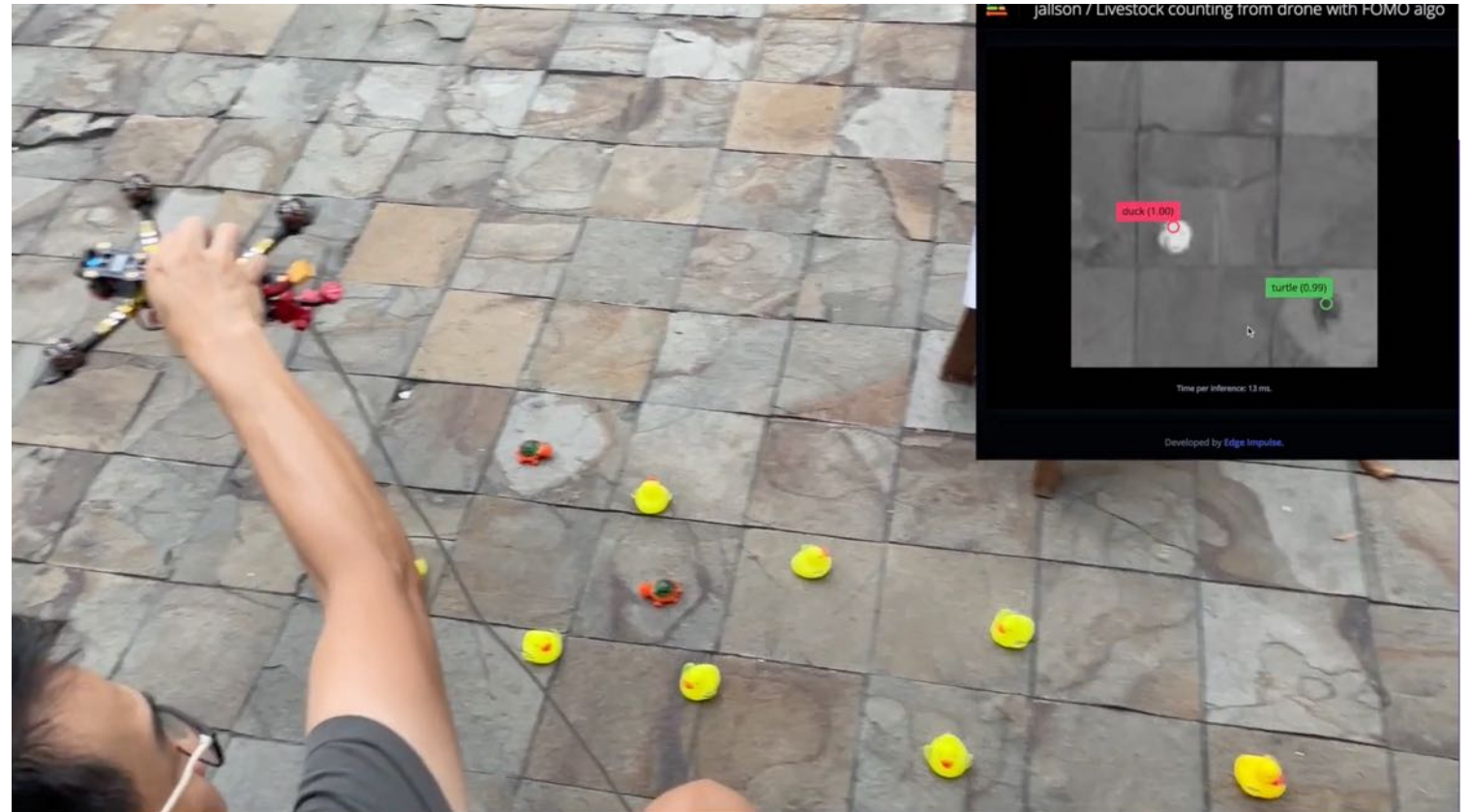
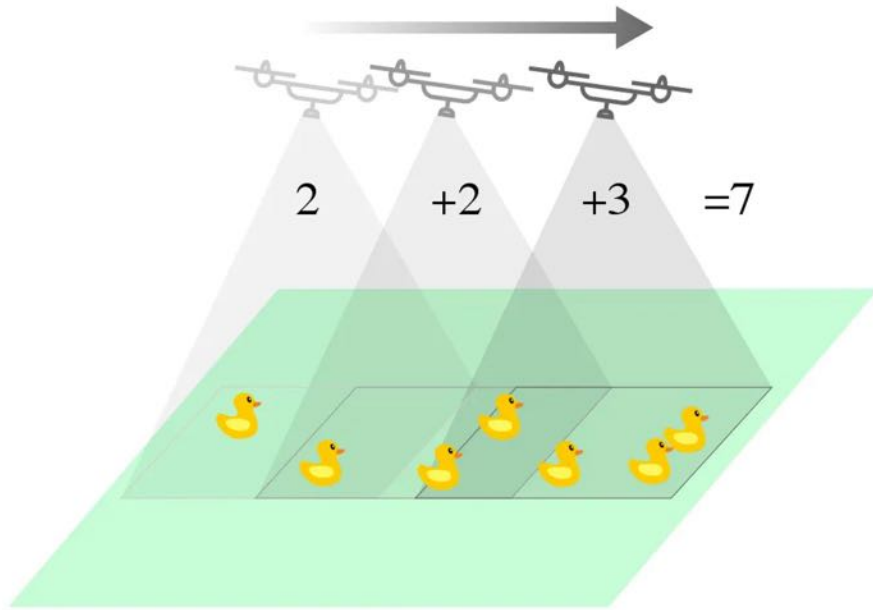
Detecting Objects using TinyML (FOMO)



MicroPython



Livestock / Wildlife Counting from Drone with FOMO



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

Other TinyML / MCUs Project Examples

Vision

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

Sound

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

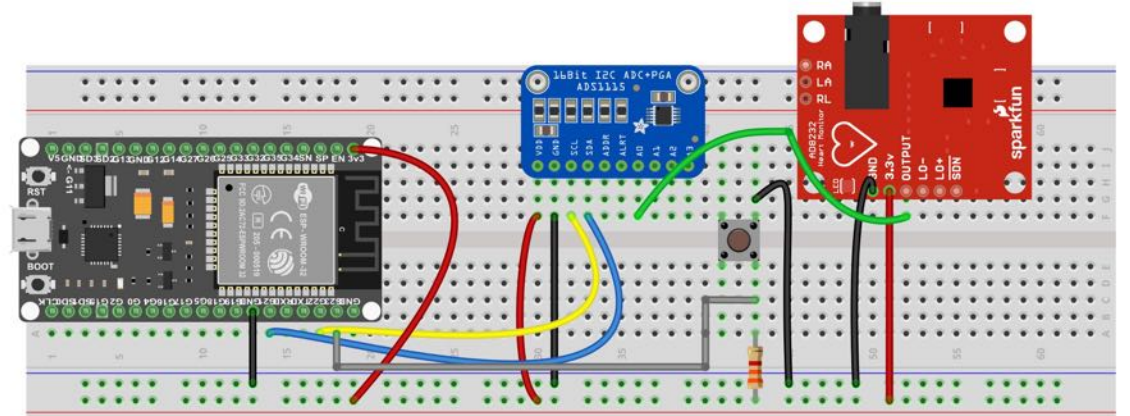
Vibration

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

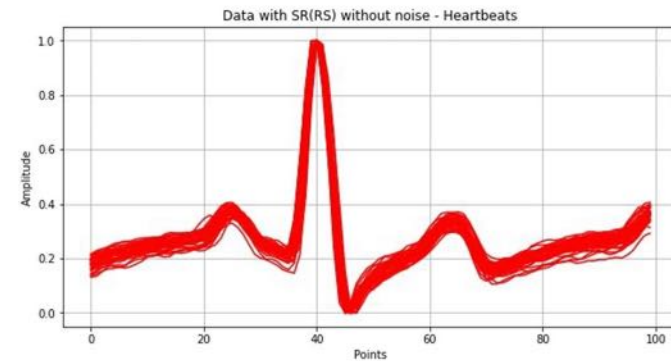
Other Sensors / MCUs / Models

Examples

AD8232 - Single Lead Heart Rate Monitor



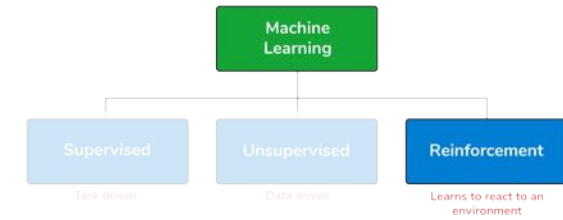
fritzing



Guilherme Silva
Engenheiro - UNIFEI

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

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>

TinyML Academic Network

Widening access to applied machine learning by establishing best practices in education.

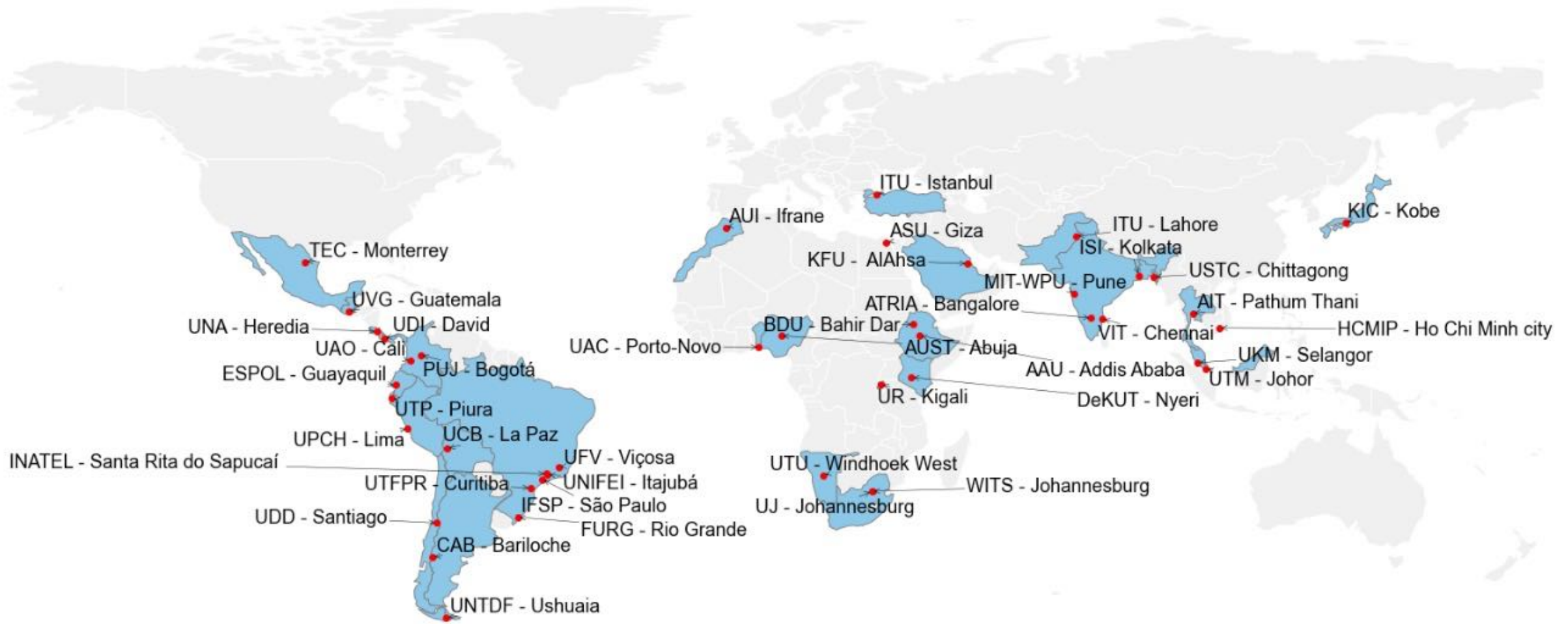


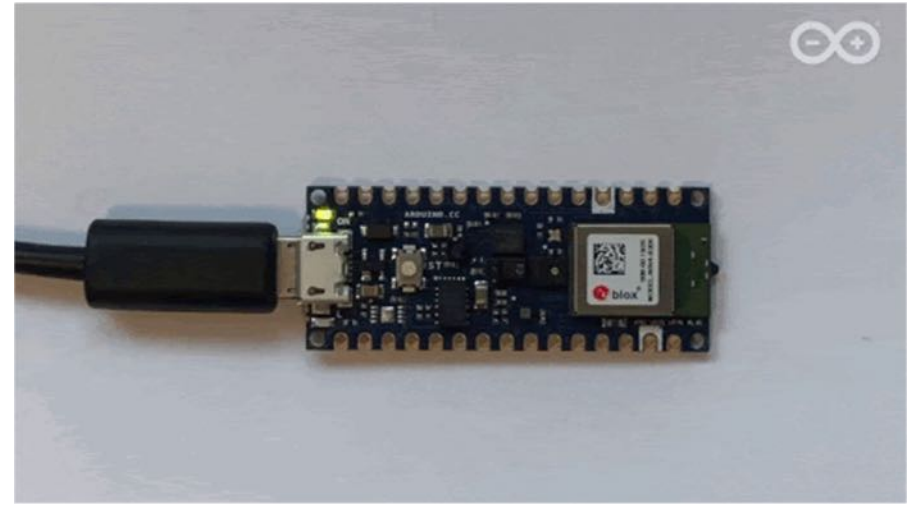
Harvard John A. Paulson
School of Engineering
and Applied Sciences



EDGE
IMPULSE

TinyML4D Academic Network - March 2023





tinymledu.org

The screenshot shows a web browser window with the URL `tinymledu.org`. The page features a dark blue header with navigation links: `TinyMLedu`, `Home`, `Courses & Materials`, `4D Network`, `Show & Tell`, `SciTinyML`, and `Research`. Below the header is a large dark blue banner with the text **Welcome to the Tiny Machine Learning Open Education Initiative (TinyMLedu)**. Underneath the banner are four white buttons with dark blue text: `Take a Free Course or Teach Your Own`, `Explore our 4D Academic Network`, `Attend our SciTinyML Workshop`, and `View our Research Projects` (with `Learn More About Us` below it). Below the banner, a white section contains the text: **If you want to be more involved with our effort to help improve access to TinyML educational materials and hardware resources worldwide reach out to us at edu@tinymledu.org!**. This is followed by a horizontal line and the text **Thanks to all of our sponsors!**, another horizontal line, and a row of logos including the Harvard logo, `Harvard John A. Paulson School of Engineering and Applied Sciences`, the `TINY ML` logo, and the `Google` logo. At the bottom, the top of logos for `EDGE`, `OTR`, and `MIT` are visible.

2021 activities

**SciTinyML:
Scientific Use of
Machine Learning on
Low-Power Devices**

18 - 22 October 2021
An ICTP Virtual Meeting
Trieste, Italy

ICTP

Further information:
<http://www.ictp.it/SciTinyML>

Topics:

- ML general concepts
- Scientific Applications of ML
- Introduction to TinyML
- Examples of TinyML applications

How to apply:
Online application:
<http://www.ictp.it/SciTinyML>
Forms available and encouraged to apply

Registration:
Free of charge

Deadline:
8 October 2021

Directors:

- J. J. Gray, ICTP, Italy
- M. J. Heule, University of Illinois, USA
- M. J. Heule, ICTP, Italy

Organiser:

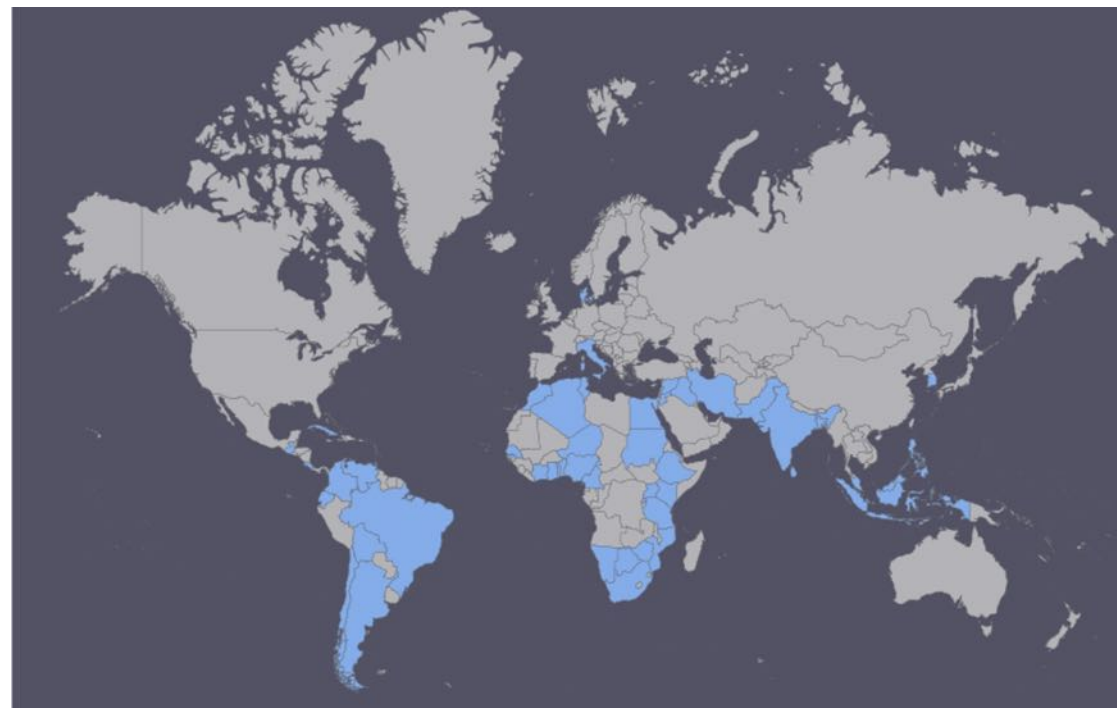
- J. J. Gray, ICTP, Italy

Speakers:

- G. B. Smith, National University, USA
- S. J. Kim, National University, USA
- M. J. Heule, University of Illinois, USA
- M. J. Heule, ICTP, Italy
- M. J. Heule, ICTP, Italy

Organizing Institutions:

- National University of Science and Technology, Pakistan
- ICTP, Italy



210 participants from 48 countries

2022 activities



TinyML is a subset of Machine Learning focused on developing models that can be executed on small, real-time, low-power, and low-cost embedded devices. This allows for new scientific applications to be developed of an extremely low cost and of large scale.

Directors:
 Prof. Alessandro Di Lorenzo, School of Engineering and Applied Sciences, Harvard University, USA
 Dr. Giovanni Borelli, ANSYS Corporation, USA

Description:
 The TinyML process starts with collecting data from an IoT device, then training the collected dataset to extract knowledge patterns from patterns and their associated labels. This model is then deployed on a low-power embedded device. The resulting model is then deployed on an embedded device where it is used to extract new sensor data. In summary, TinyML is a process that involves data collection, model training, and deployment on a low-power embedded device. The resulting model is then deployed on an embedded device where it is used to extract new sensor data. In summary, TinyML is a process that involves data collection, model training, and deployment on a low-power embedded device.

Topics:

- Introduction to TinyML
- Training models on the TinyML hardware
- Deployment of TinyML applications
- Scientific Applications of TinyML

Local Organizer:
 Maria D'Amico, ICTP

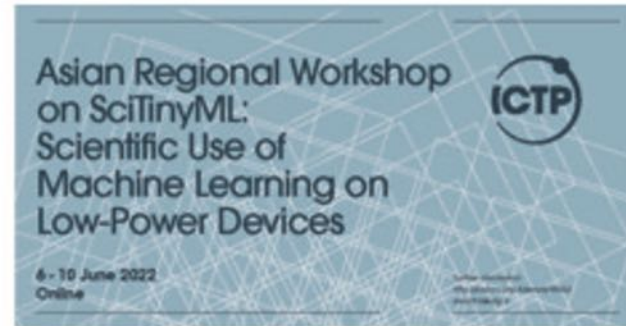
How to apply:
 Online application: <http://tinyml.aas.harvard.edu/2022>
 Forms available upon request to apply

Grants:
 Funding will be given to African participants that are part of the ICTP TinyML Academic Network

Deadline:
 15 April 2022



187 participants
 29 African countries



TinyML is a subset of Machine Learning focused on developing models that can be executed on small, real-time, low-power, and low-cost embedded devices. This allows for new scientific applications to be developed of an extremely low cost and of large scale.

Directors:
 Prof. Alessandro Di Lorenzo, School of Engineering and Applied Sciences, Harvard University, USA
 Dr. Giovanni Borelli, ANSYS Corporation, USA

Description:
 The TinyML process starts with collecting data from an IoT device, then training the collected dataset to extract knowledge patterns from patterns and their associated labels. This model is then deployed on a low-power embedded device. The resulting model is then deployed on an embedded device where it is used to extract new sensor data. In summary, TinyML is a process that involves data collection, model training, and deployment on a low-power embedded device.

Topics:

- Introduction to TinyML
- Training models on the TinyML hardware
- Deployment of TinyML applications
- Scientific Applications of TinyML

ICTP Scientific Contact:
 Maria D'Amico, ICTP

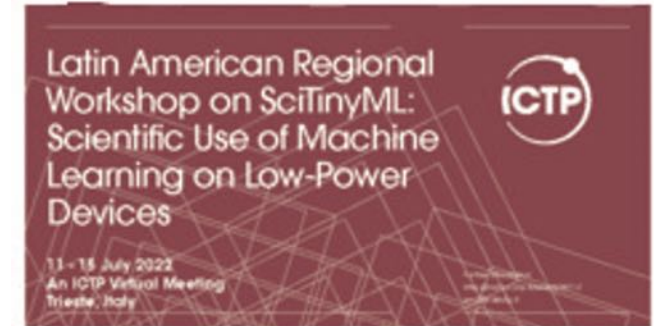
How to apply:
 Online application: <http://tinyml.aas.harvard.edu/2022>
 Forms available upon request to apply

Registration:
 Funding will be given to Asian participants that are part of the ICTP TinyML Academic Network

Deadline:
 22 May 2022



100 participants
 8 Asian countries



The workshop will be bilingual (English and Spanish).
 TinyML is a subset of Machine Learning focused on developing models that can be executed on small, real-time, low-power, and low-cost embedded devices. This allows for new scientific applications to be developed of an extremely low cost and of large scale.

Directors:
 Prof. Alessandro Di Lorenzo, School of Engineering and Applied Sciences, Harvard University, USA
 Dr. Giovanni Borelli, ANSYS Corporation, USA

Description:
 The TinyML process starts with collecting data from an IoT device, then training the collected dataset to extract knowledge patterns from patterns and their associated labels. This model is then deployed on a low-power embedded device. The resulting model is then deployed on an embedded device where it is used to extract new sensor data. In summary, TinyML is a process that involves data collection, model training, and deployment on a low-power embedded device.

Topics:

- Introduction to TinyML
- Training models on the TinyML hardware
- Deployment of TinyML applications
- Scientific Applications of TinyML

Local Organizer:
 Maria D'Amico, ICTP

How to apply:
 Online application: <http://tinyml.aas.harvard.edu/2022>
 Forms available upon request to apply

Registration:
 Funding will be given to the participants that are part of the ICTP TinyML Academic Network

Deadline:
 29 June 2022



183 participants
 17 LatAm countries

April 2023 ICTP virtual workshop



TinyML is a subfield of Machine Learning focused on developing models that can be executed on small, real-time, low-power, and low-cost embedded devices. This allows for new scientific applications to be developed at an extremely low cost and at large scale.

Directors:

B. PLANCHER, Barnard College, USA
V. J. REDD, Harvard University, USA
M. BONAI, Federal University of Itajuba, Brazil

Description:

TinyML represents a collaborative effort between the embedded power systems and Machine Learning communities, which traditionally have operated independently.

TinyML has a significant role to play in achieving the SDGs and facilitating scientific research in areas such as environmental monitoring, physics of complex systems and energy management.

The TinyML process starts with collecting data from IoT devices, then training the collected dataset to extract knowledge patterns, these patterns are then packaged into a TinyML model that considers the target microprocessor's limited resources such as memory, processing power, and energy.

Through hands-on examples, this workshop will focus on both introductory and advanced topics in TinyML to pave the way to the development of real-world applications.

Topics:

- Introduction to TinyML
- Getting Started with the TinyML Kit
- Examples of TinyML Applications
- The TinyML Development Workflow
- Scientific Applications of ML
- Recent Research and Advanced Topics in TinyML

Local Organiser:

M. ZENNARO, ICTP, Italy

How to apply:

Online application:
<http://indico.ictp.it/event/10144/>

Female scientists are encouraged to apply.

Registration:

There is no registration fee.

Deadline:

7 April 2023



SciTinyML

Scientific Use of Machine Learning on Low-Power Devices



TinyMLedu [↗](#)

Home

Schedule April 17-21

Call for Show and Tell Talks

Team

Updated: 2/23

by @plancherb1

| Day | Date | Topics | Speakers and Materials |
|-------|-----------|--|---|
| Day 1 | Monday | Introduction to (tiny)ML 10:00 AM Workshop Opening and Schedule 10:30 AM Keynote 11:15 AM Introduction to Machine Learning 12:15 PM Introduction to Embedded ML 12:55 PM Day Closing | Marco Zennaro of ICTP Diego Mendez Chaves of Pontificia Universidad Javeriana Robert Thas John of Versus |
| Day 2 | Tuesday | Hands-on Introduction to TinyML 10:00 AM Day Opening 10:05 AM Edge Impulse Overview and New Features 10:40 AM Hands-on Motion Classification and Anomaly Detection 12:10 PM AI Ethics: Avoiding Bias 12:55 PM Day Closing | Marco Zennaro of ICTP Shawn Hymel of Edge Impulse José Antonio Bagur Nájera of Universidad del Valle de Guatemala Viola Schiaffonati and Manuel Roveri of Politecnico di Milano |
| Day 3 | Wednesday | Expanding Your Options and Devices 10:00 AM Day Opening 10:05 AM Leveraging Other Microcontrollers and Sensors 11:00 AM WebUSB and FOMO 11:30 AM Adding IoT to a Project with Blues Wireless 11:55 AM Industry 5.0 with Jetson Nano 12:25 PM MLOps: Scaling Deployments 12:55 PM Day Closing | Marco Zennaro of ICTP Marcelo Rovai of Federal University of Itajuba - UNIFEI Jeremy Ellis of School District 75 Mission Peter Ing of TFG (The Foschini Group) Marcelo Pias of Federal University of Rio Grande - FURG Colby Banbury of Harvard University |
| Day 4 | Thursday | TinyML Show and Tell 10:00 AM Day Opening 10:05 AM Selected Show and Tell Talks 12:55 PM Day Closing | Brian Plancher of Barnard College, Columbia University |
| Day 5 | Friday | Advanced Scientific TinyML 10:00 AM Day Opening 10:05 AM Scientific Applications of TinyML 1 10:50 AM TinyML and Sustainability 11:20 AM TinyML and Robotics 11:50 AM Scientific Applications of TinyML 2 12:55 PM Workshop Closing and Future Events | Marco Zennaro of ICTP Matthew Stewart of Harvard University Bardienus Duisterhof of Carnegie Mellon University - CMU |

Local/Relevant Applications

Timothy Kudzanayi Kuhamba

Thanx Marisa^{a*}, Munyaradzi Munochiveyi^{a*}, Wadzanai Julius Zondai^{a*}, Ramson Munyaradzi Nyamukondiwa^a, Isheanesu Newengo^b

Case Study Zimbabwe

A DEEP LEARNING BASED APPROACH FOR
FOOT AND MOUTH DISEASE DETECTION



Local/Relevant Applications

VEGETABLE DISEASE AND INSECT PEST RECOGNITION BASED ON TINYML: Cotton Case in Benin

James O. ADEOLA
IMSP - UAC

Dr Marco
Zenaro
ICTP Italy

Dr Jules
DEGILA
IMSP Benin



Local/Relevant Applications

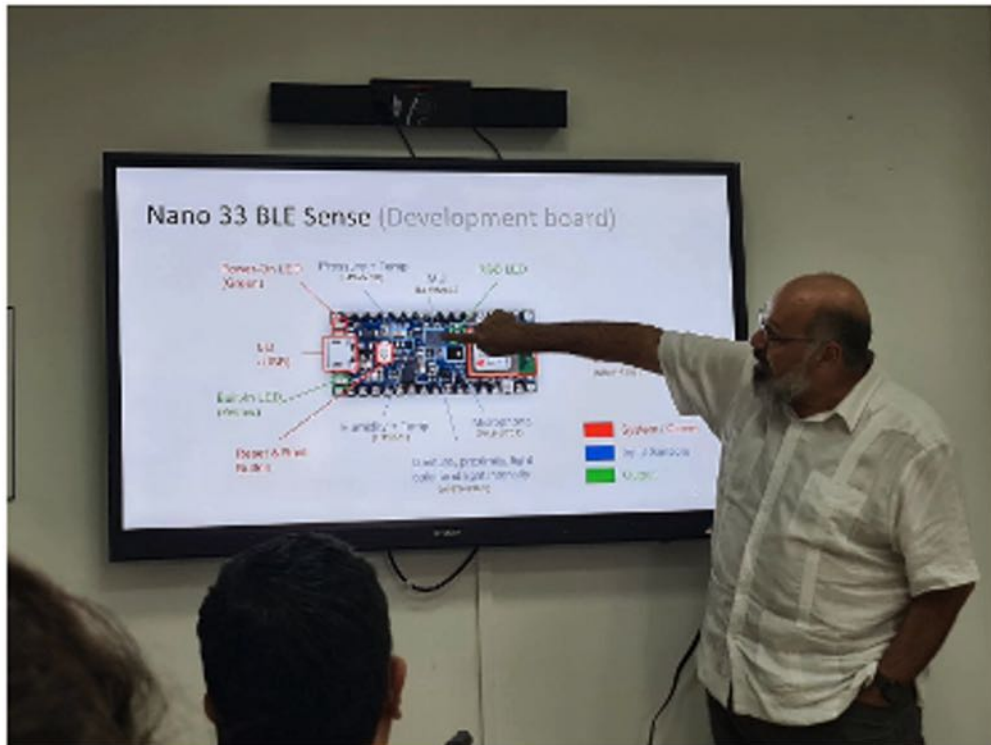


Outreach activities



Solomon from Ethiopia

Marcelo Rovai at WALC 22 - Udl, Panama



- 5 days Workshop
- 46 remote and 16 in site participants from Latin America

TinyML Academic Network @ UN 2022

Science-Policy Brief for the Multistakeholder Forum on Science, Technology and Innovation for the SDGs, May 2022

TinyML: Applied AI for Development

Marco Zennaro (ICTP/UNESCO), Brian Plancher (Harvard University), Vijay Janapa Reddi (Harvard University)

Abstract

Artificial intelligence (AI) will likely be an instrumental part of progress towards the United Nations' Sustainable Development Goals (SDGs). However, its adoption and impact are limited by the immense power consumption, strong connectivity requirements and high costs of cloud-based deployments. TinyML is a new technology that allows machine learning (ML) models to run on low-cost, low-power microcontrollers, circumventing many of these issues. We believe that TinyML has a significant role to play in achieving the SDGs and facilitating scientific research in areas such as environmental monitoring, physics of complex systems and energy management. To broaden access and participation and increase the impact of this new technology, we present an initiative that is creating and supporting a global network of academic institutions working on TinyML in developing countries. We suggest the development of additional open educational resources, South-South academic collaboration and pilot projects of at-scale TinyML solutions aimed at addressing the SDGs.

Challenges with Machine Learning in Developing Countries

Machine learning has a huge potential to tackle societal issues in diverse fields that include agriculture, conservation and healthcare. A recent study [1] highlights the influence of AI on all aspects of

main energy consumer component of an embedded system.

3. **Privacy:** Applications that send data from the point of collection to the cloud may leak private information as data must be transmitted over the internet.

TinyML Academic Network @ UN 2023

Bridging the Digital Divide: the Promising Impact of TinyML for Developing Countries

Marco Zennaro (ICTP/UNESCO), Brian Plancher (Barnard College, Columbia University), Vijay Janapa Reddi (Harvard University)

Abstract

The rise of TinyML has opened up new opportunities for the development of smart, low-power devices in resource-constrained environments. This technology has particular relevance for developing countries, where access to energy and computing resources is often limited. In light of this, a network of 40 universities has been established over the past two years with the goal of promoting the use of TinyML in developing regions. The members of this network have taught courses at their home institutions and have completed their first research projects covering topics ranging from the diagnosis of respiratory diseases in Rwanda to assistive technology development in Brazil, bee population monitoring in Kenya and estimating the lifespan of the date palm fruit in Saudi Arabia. These initial projects demonstrate the potential

Papers published

Mihigo, **Irene Niyonambaza**, et al. "On-Device IoT-Based Predictive Maintenance Analytics Model: Comparing TinyLSTM and TinyModel from Edge Impulse." *Sensors* 22.14 (2022): 5174.

Altayeb, Moez, Marco Zennaro, and **Marcelo Rovai**. "Classifying mosquito wingbeat sound using TinyML." *Proceedings of the 2022 ACM Conference on Information Technology for Social Good*. 2022.

Bamoumen, Hatim, et al. "How TinyML Can be Leveraged to Solve Environmental Problems: A Survey." *2022 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*. IEEE, 2022.

Avellaneda, Diego, **Diego Mendez**, and Giancarlo Fortino. "A TinyML Deep Learning Approach for Indoor Tracking of Assets." *Sensors* 23.3 (2023): 1542.

Papers published

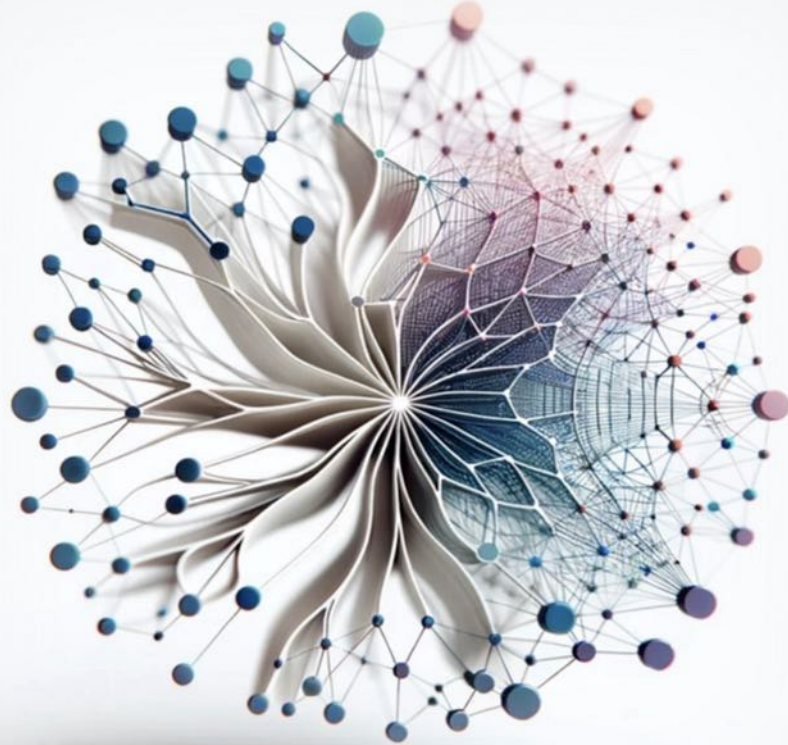
Avellenada, Diego, **Diego Mendez**, and Giancarlo Fortino. "BLE-based Indoor Positioning Platform Utilizing Edge Tiny Machine Learning." 2022 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCoM/CyberSciTech). IEEE, 2022.

Plancher, Brian, and Vijay Janapa Reddi. "TinyMLedu: The tiny machine learning open education initiative." Proceedings of the 53rd ACM Technical Symposium on Computer Science Education V. 2. 2022.

G. Silva, M.D. Lima, **J.A.F. Filho** and **M.J. Rovai** " "Atrial Fibrillation and Sinus Rhythm detection using TinyML (Embedded Machine Learning). "IX Latin American Congress on Biomedical Engineering" and "XXVIII Brazilian Congress on Biomedical Engineering"

João Vitor Yamashita et al.. "Coffee disease classification at the edge using deep learning". [Smart Agricultural Technology Volume 4](#), August 2023, 100183

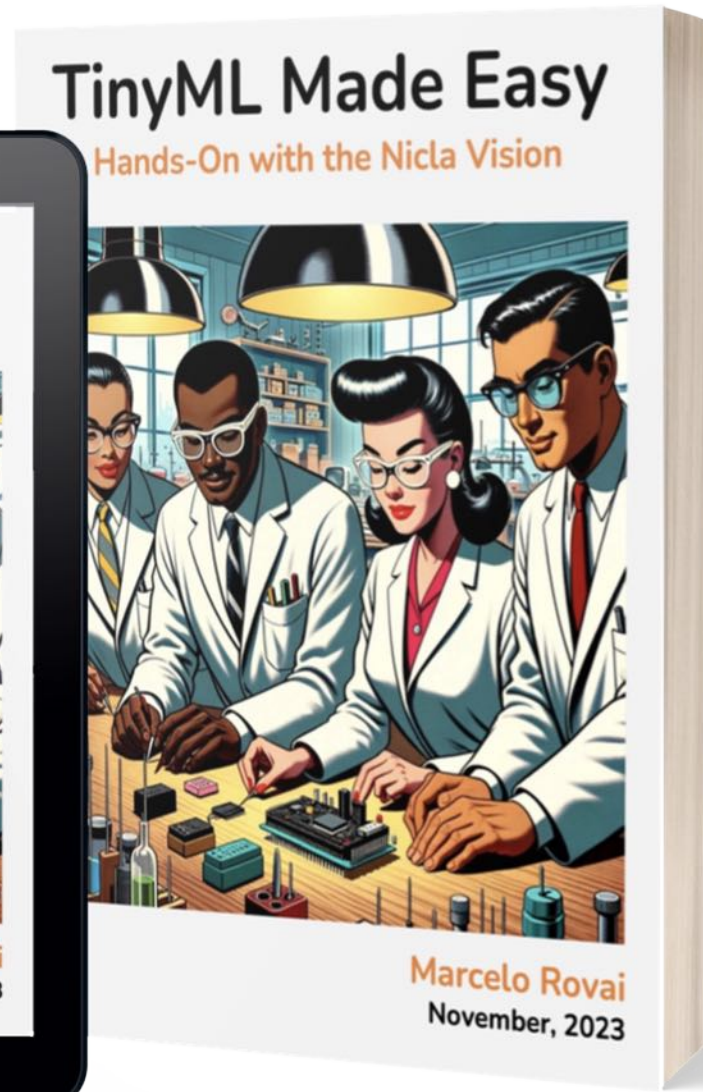
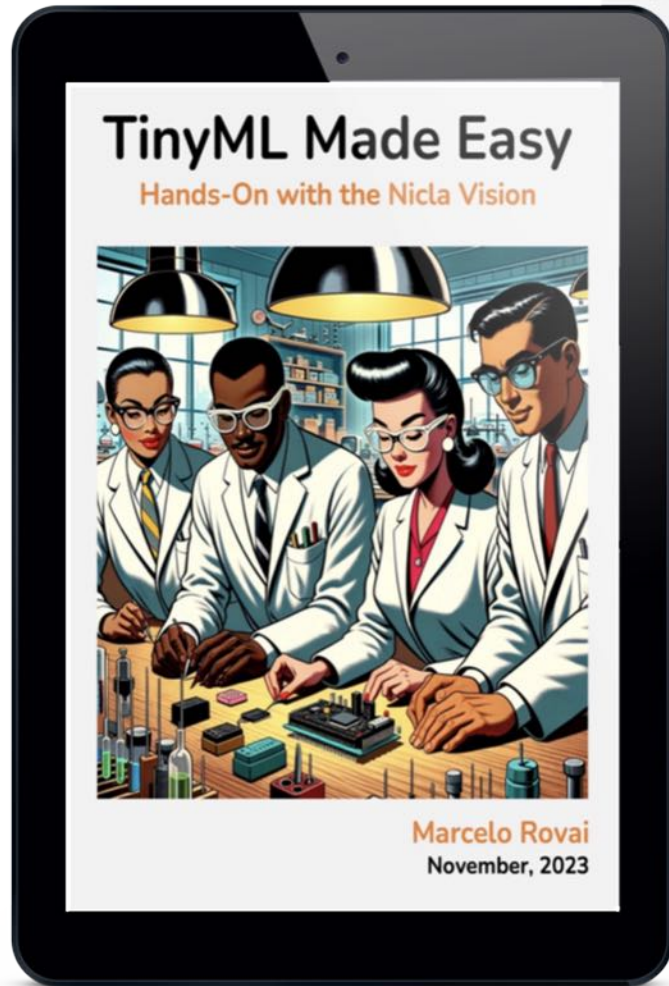
Machine Learning Systems with TinyML



Edited by Prof. Vijay Janapa Reddi
Harvard University



https://github.com/harvard-edge/cs249r_book



Thanks

