When IoT meets AI: The marvelous world of TinyML

Dr. Marco Zennaro
the Abdus Salam International Centre for Theoretical Physics - Italy

Prof. Marcelo José Rovai
UNIFEI - Universidade Federal de Itajubá, Brazil

UNIFEI

IoT

Internet of Things (IoT)

“The IoT can be viewed as a global **infrastructure** for the information society, enabling advanced services by interconnecting (**physical** and **virtual**) things based on existing and evolving interoperable information and communication technologies (ICT).”— Recommendation ITU-T Y.2060

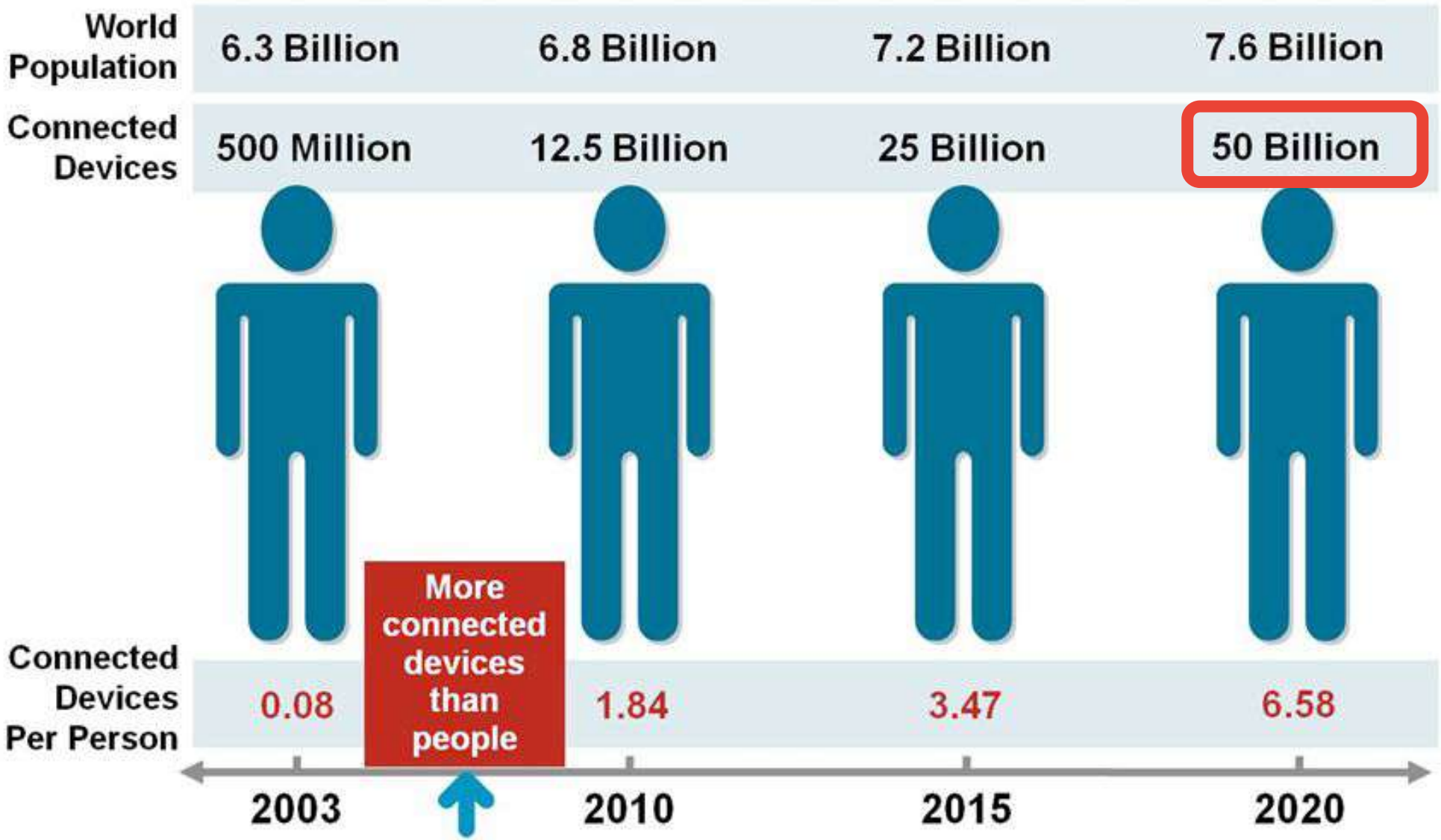
Device — ITU definition

“A device is a piece of equipment with the **mandatory capabilities** of **communication** and optional capabilities of sensing, actuation, data capture, data storage and data processing. Some devices also execute operations based on information received from the information and communication networks.”

— Recommendation ITU-T Y.2060

Fundamental characteristics — ITU

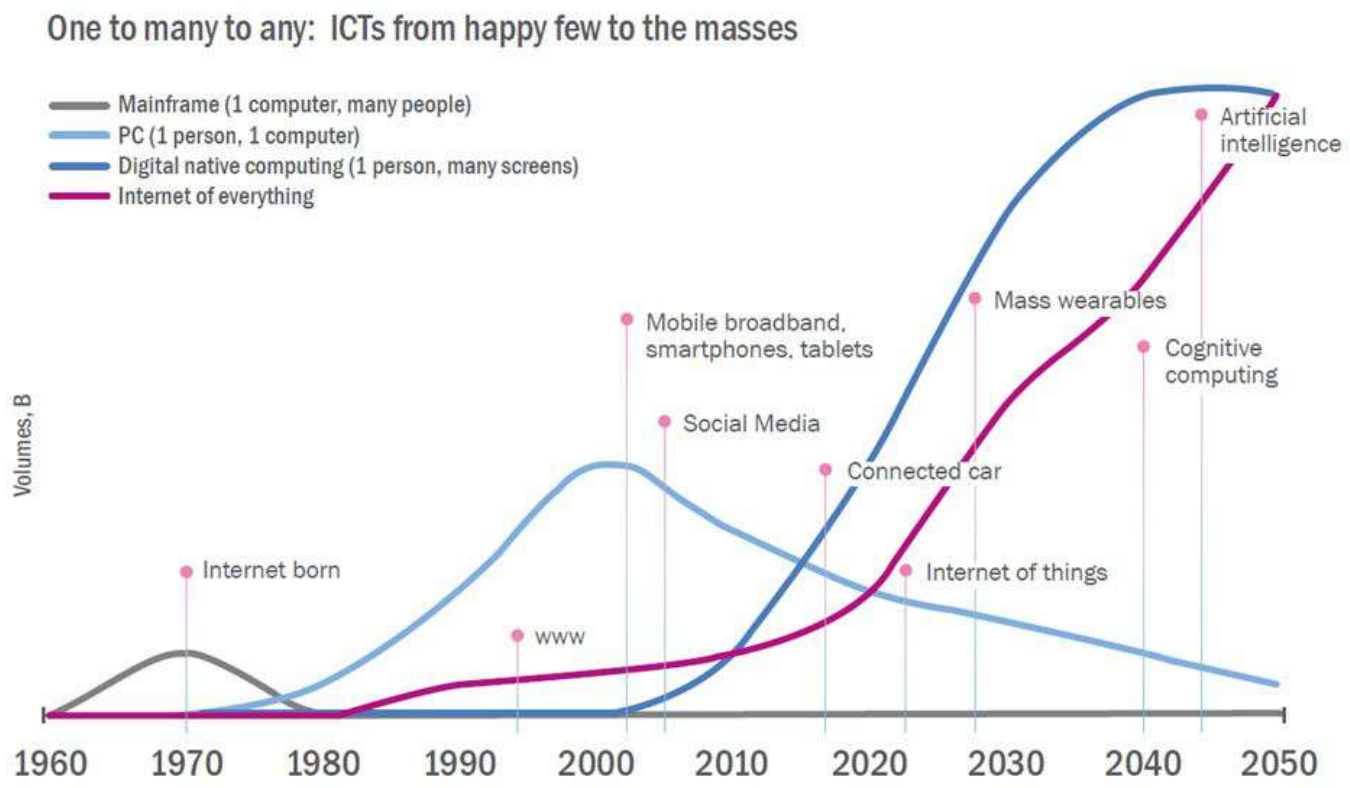
Enormous scale: The number of devices that need to be managed and that communicate with each other will be at least an order of magnitude larger than the devices connected to the current Internet. The ratio of communication triggered by devices as compared to communication triggered by humans will noticeably shift towards device-triggered communication.



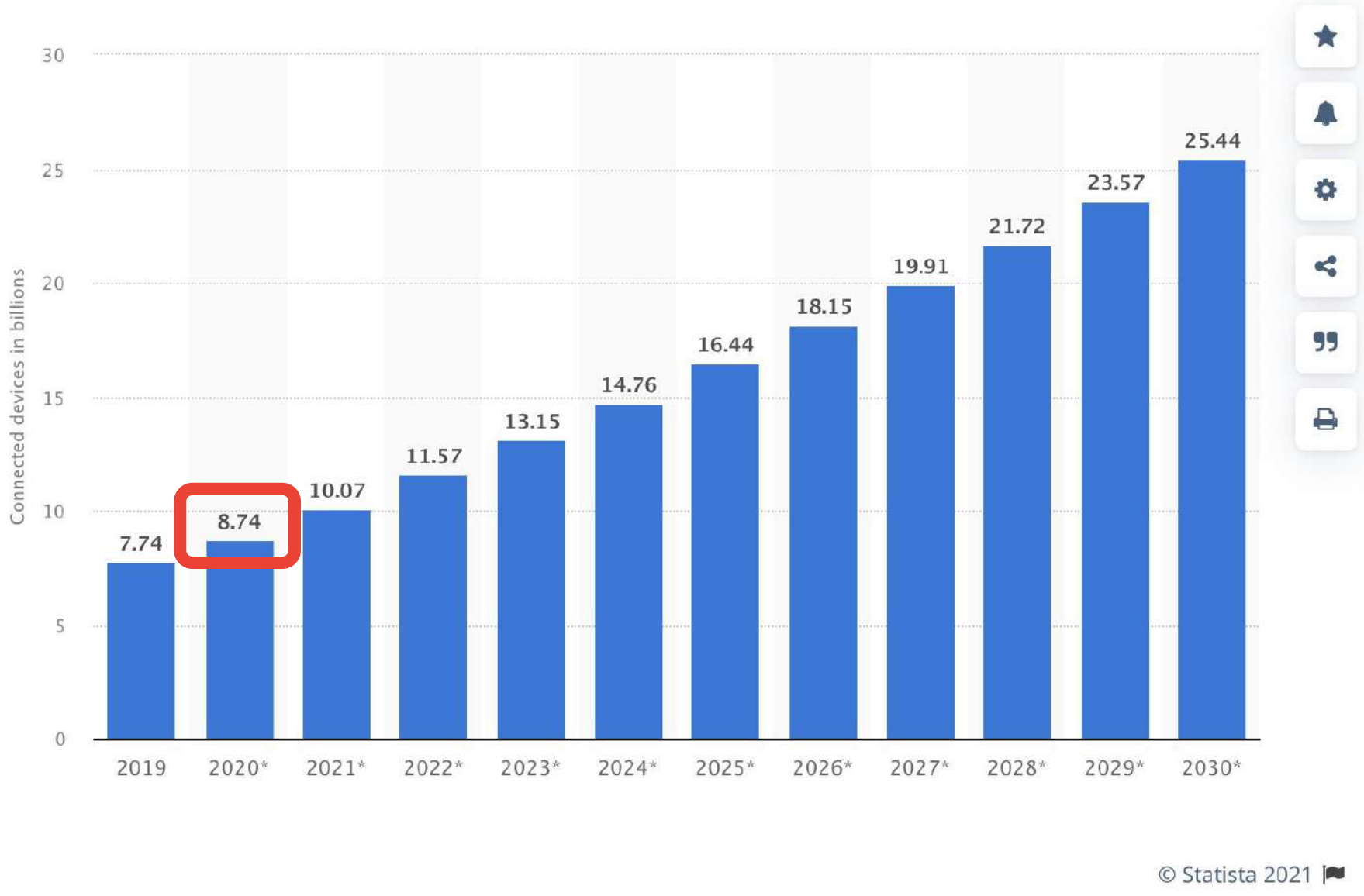
Source: Cisco IBSG, April 2011

One to many to any

History of the future



2020 statistics



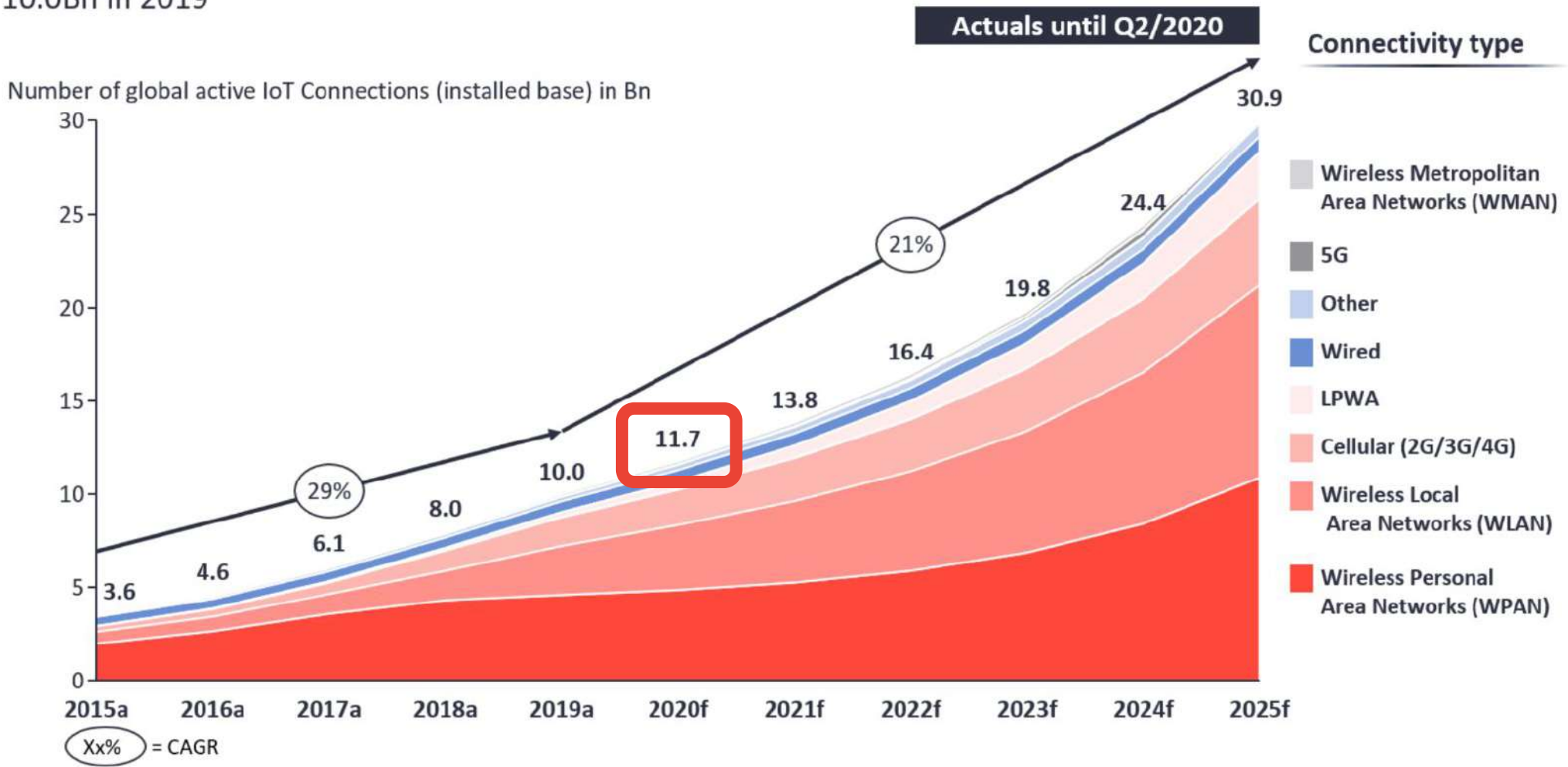
2020 statistics

IOT ANALYTICS

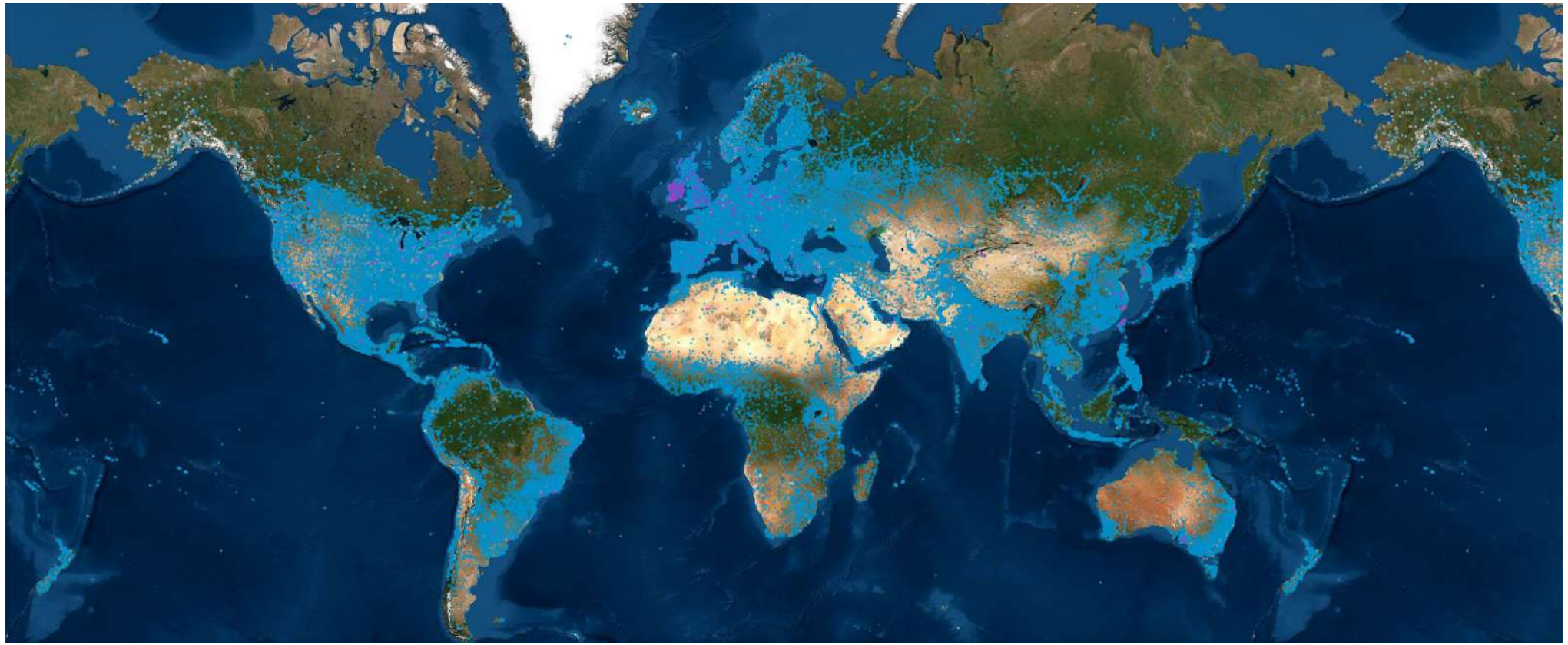
Insights that empower you to understand IoT

Global Number of Connected IoT Devices

10.0Bn in 2019

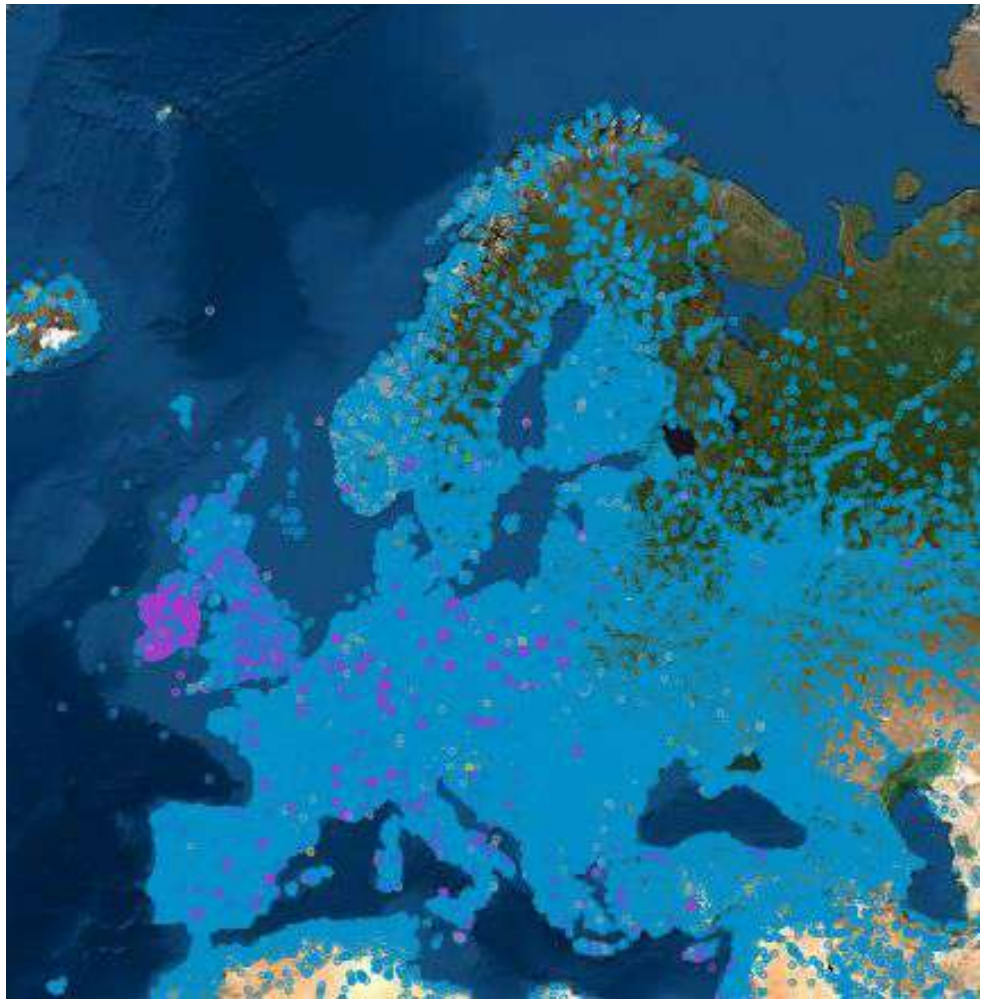


Worldwide distribution



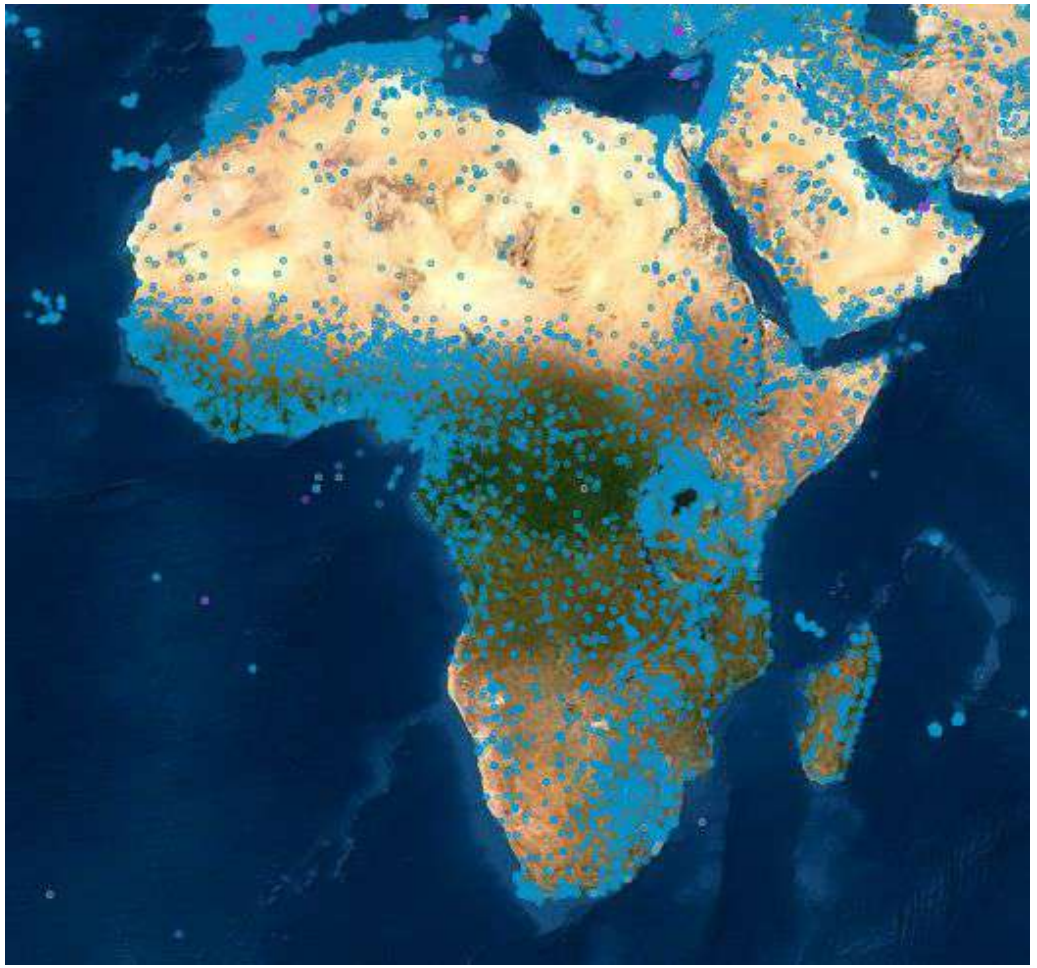
Credit: https://www.thingful.net

Worldwide distribution



Credit: https://www.thingful.net

Worldwide distribution



Credit: https://www.thingful.net

IoT and SDG


SUSTAINABLE DEVELOPMENT GOALS
17 GOALS TO TRANSFORM OUR WORLD
1 NO POVERTY
2 ZERO HUNGER
3 GOOD HEALTH AND WELL-BEING
4 QUALITY EDUCATION
5 GENDER EQUALITY
6 CLEAN WATER AND SANITATION
7 AFFORDABLE AND CLEAN ENERGY
8 DECENT WORK AND ECONOMIC GROWTH
9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION AND PRODUCTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE, JUSTICE AND STRONG INSTITUTIONS
17 PARTNERSHIPS FOR THE GOALS
SUSTAINABLE DEVELOPMENT GOALS

IoT and SDG

➤ SDG 2: ZERO HUNGER:

An estimated 821 million people were undernourished in 2017. Annual cereal production will need to rise to about 3 billion tonnes and annual meat production will need to rise by over 200 million tonnes to reach 470 million tonnes to feed 9.1 billion people by 2050.

➤ SDG 13 & 15: CLIMATE ACTION and LIFE ON LAND:

Given current concentrations and on-going emissions of greenhouse gases, it is likely that by the end of this century, the increase in global temperature will exceed 1.5°C. Global emissions of carbon dioxide (CO2) have increased by almost 50 per cent since 1990

Drivers and obstacles for IoT

↑ Low cost of devices (MCU and sensors)

↑ Wireless standards

↓ Lack of Internet connectivity

↓ Lack of IoT infrastructure

↓ Complex ecosystem

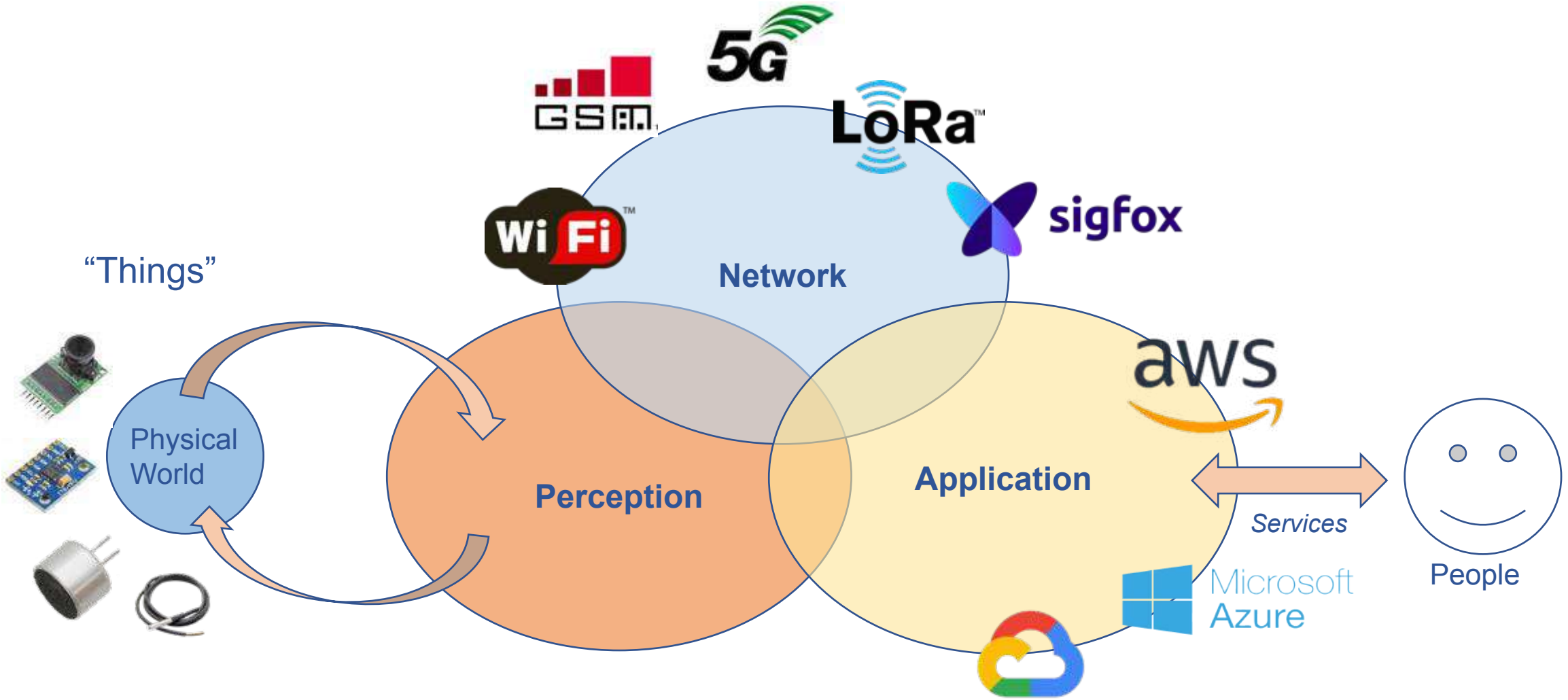
Device — ITU definition

“A device is a piece of equipment with ~~the~~ ~~mandatory capabilities of communication~~ ~~and optional~~ capabilities of sensing, actuation, data capture, data storage and data processing. Some devices also execute operations ~~based on information received from the information and communication networks~~.”

— Recommendation ITU-T Y.2060

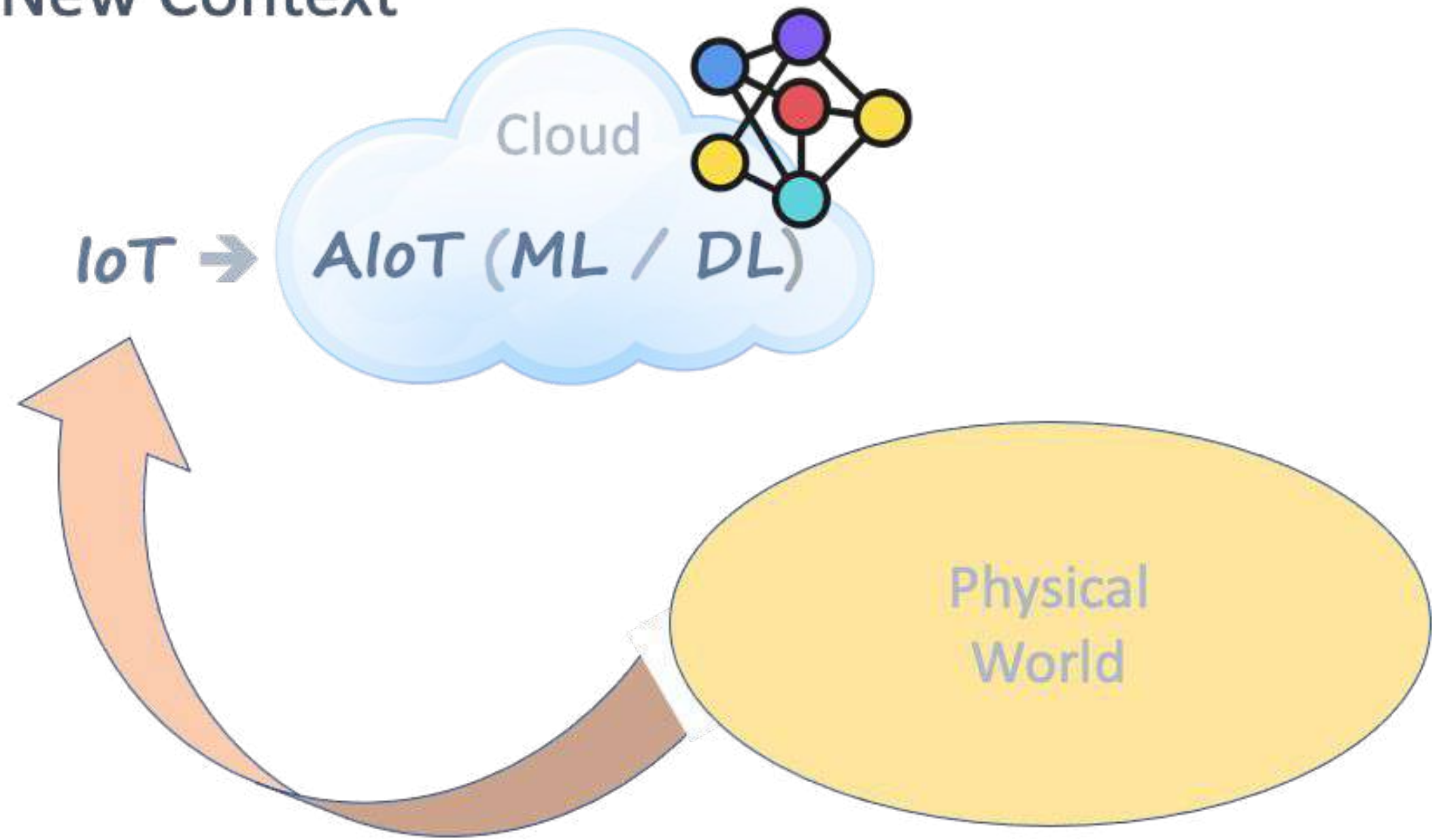
IoT

Classical IoT Architecture

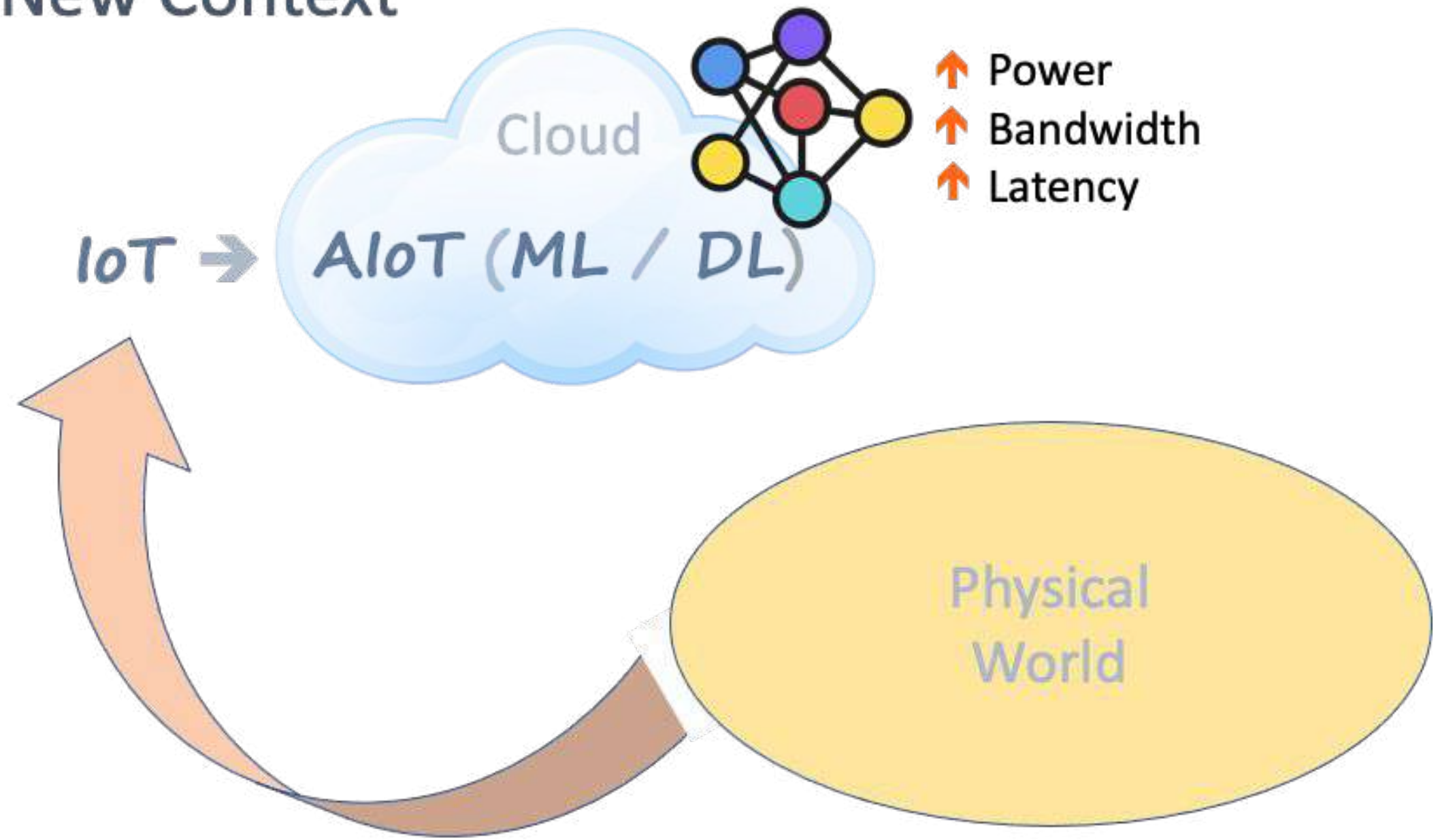


5 Quintillion bytes of data produced every day by IoT, but less than 1% is used. HBR/CISCO

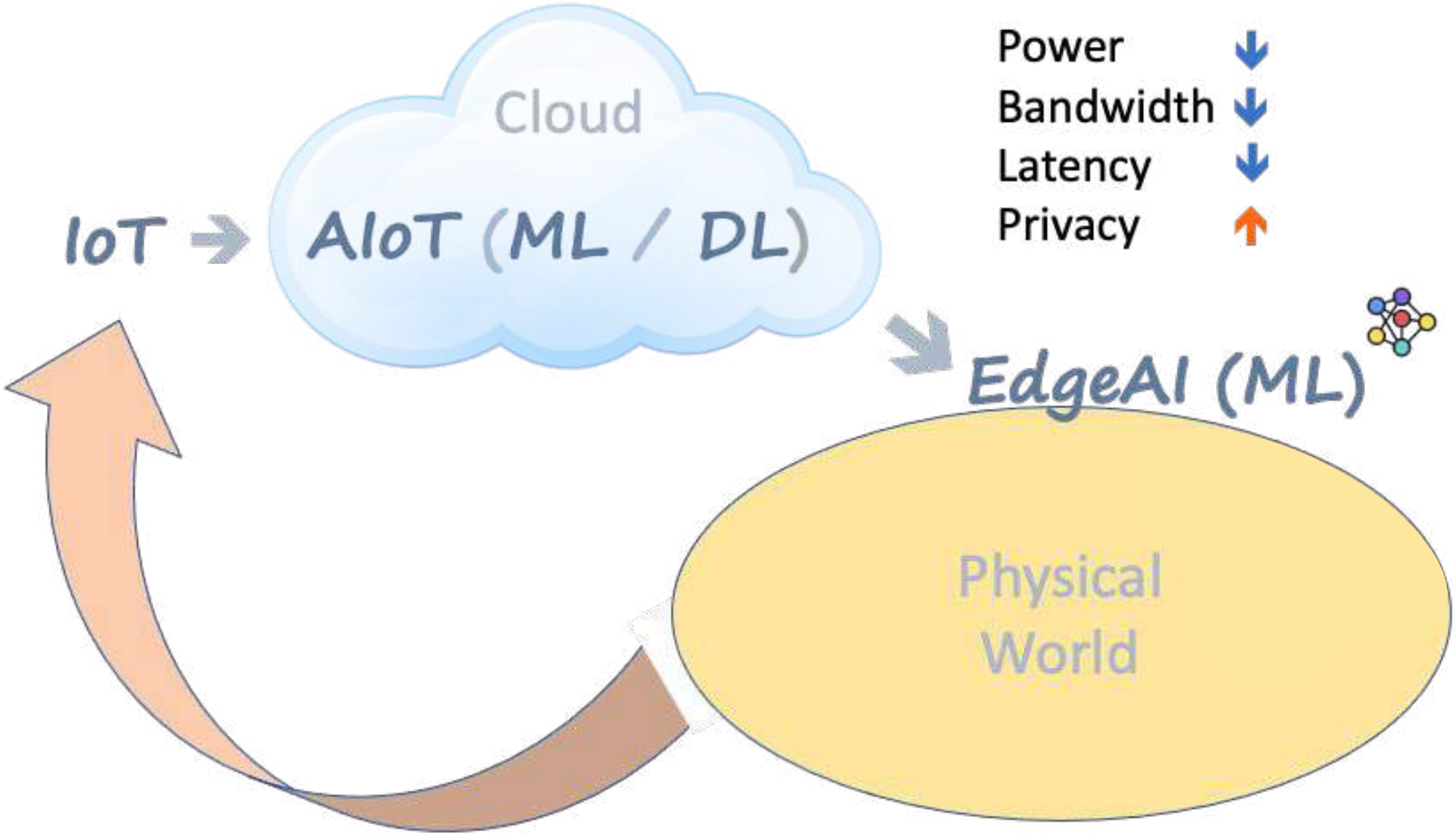
New Context



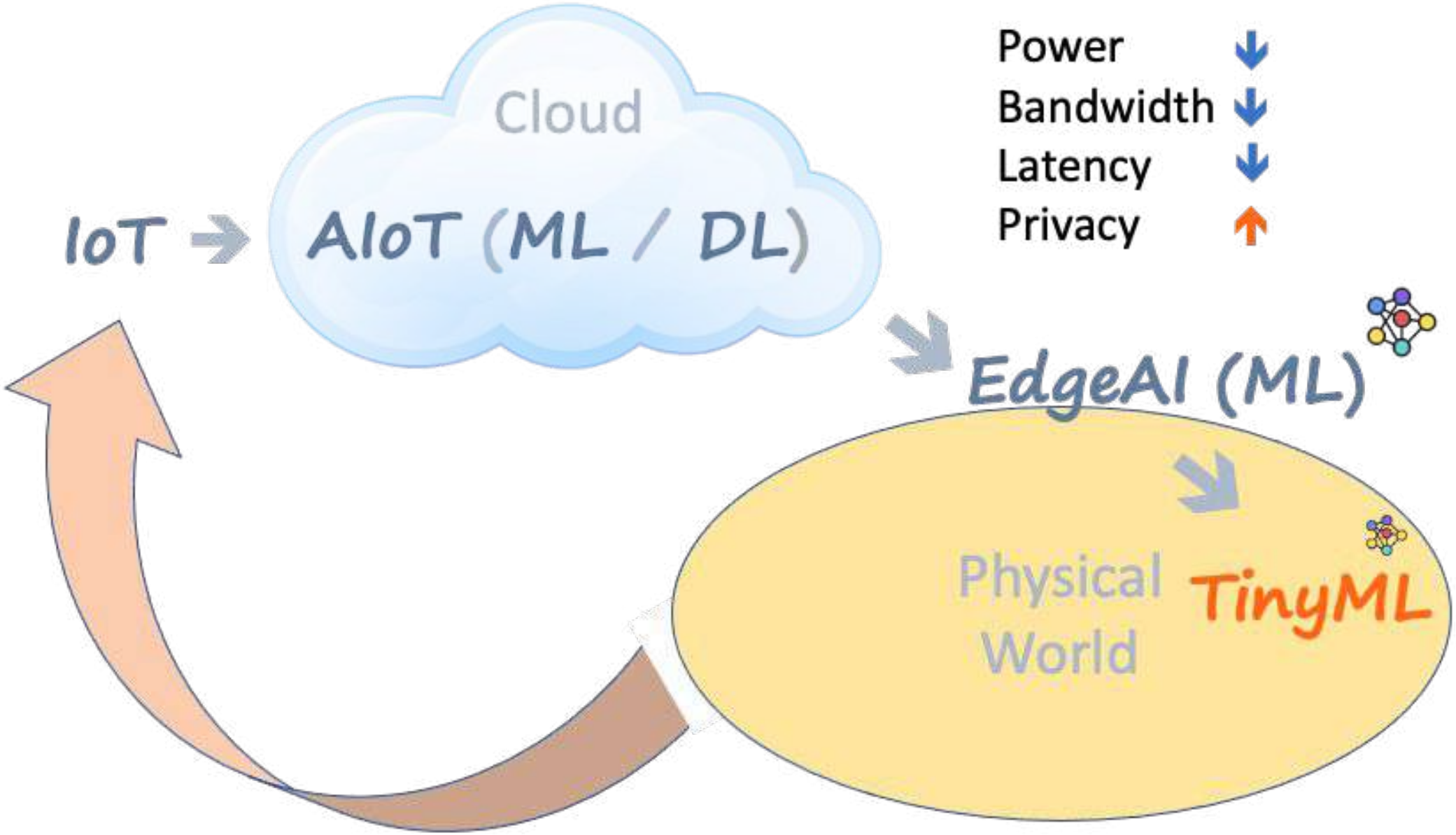
New Context


Cloud
IoT
AIoT (ML / DL)
Power
Bandwidth
Latency
Physical World

New Context


Cloud
IoT
AIoT (ML / DL)
Power
Bandwidth
Latency
Privacy
EdgeAI (ML)
Physical World

New Context


Cloud
IoT
AIoT (ML / DL)
Power
Bandwidth
Latency
Privacy
EdgeAI (ML)
Physical World
TinyML

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

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**)?

TinyML

Fastest-growing field of **ML**

Algorithms, hardware, software

On-device sensor analytics

Low power consumption

Always-on ML

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

TinyML

Fastest-growing field of **ML**

Algorithms, hardware, software

On-device sensor analytics

Low power consumption

Always-on ML

Battery-operated

EdgeML (Pi)

Autonomous Car Control

Image Recognition

EdgeML (P↑)

Autonomous Car Control

Image Recognition

TinyML (P↓)

KeyWord Spotting

Environmental Control

Motion & biometric

Image Spot

TinyML Application Areas

Predictive Maintenance

Motion, current, audio and camera

- ➔ Industrial
- ➔ White goods
- ➔ Infrastructure
- ➔ Automotive

Asset Tracking & Monitoring

Motion, temp, humidity, position, audio and camera

- ➔ Logistics
- ➔ Infrastructure
- ➔ Buildings

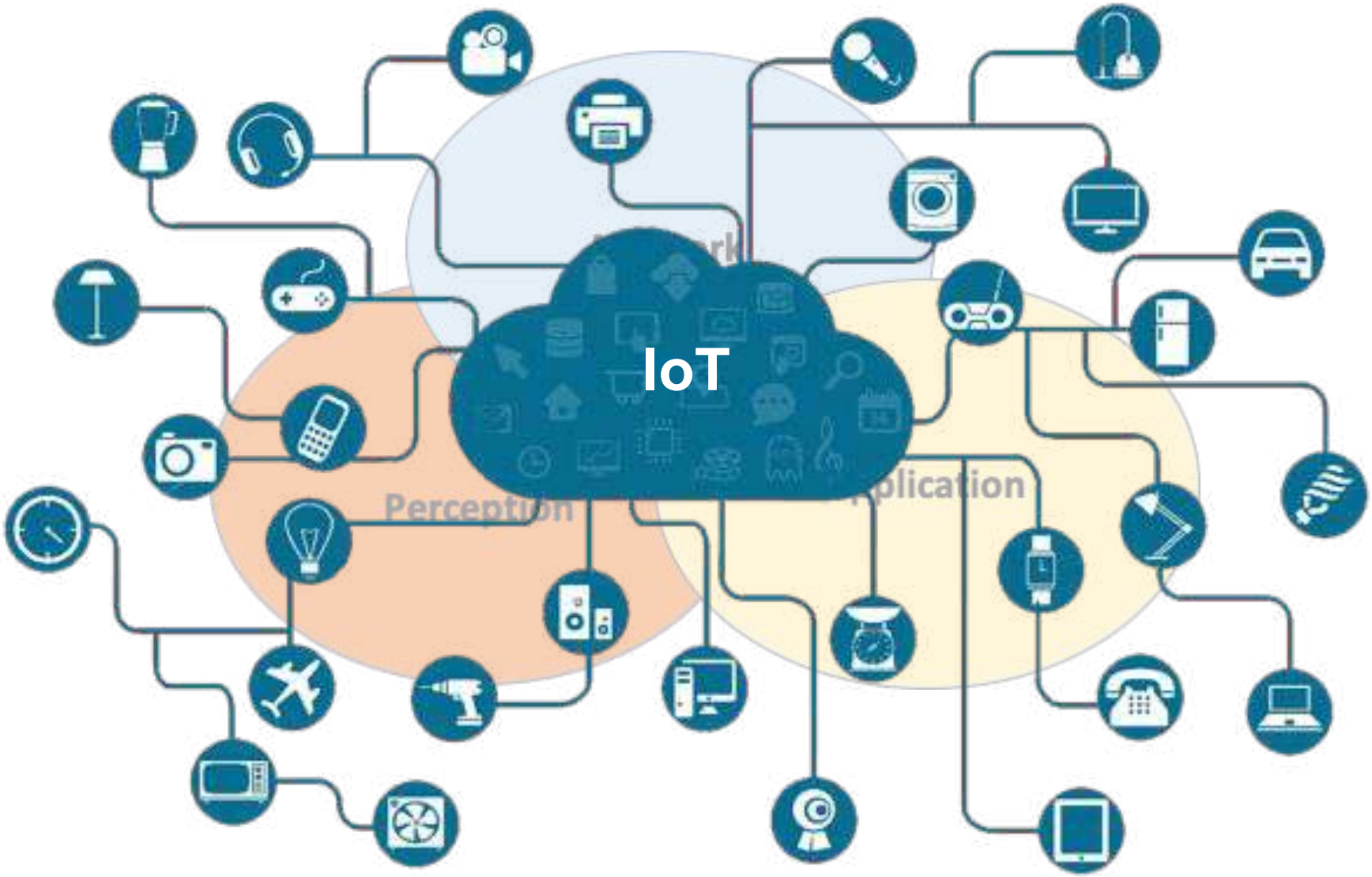
Human & Animal Sensing

Motion, radar, audio, PPG, ECG

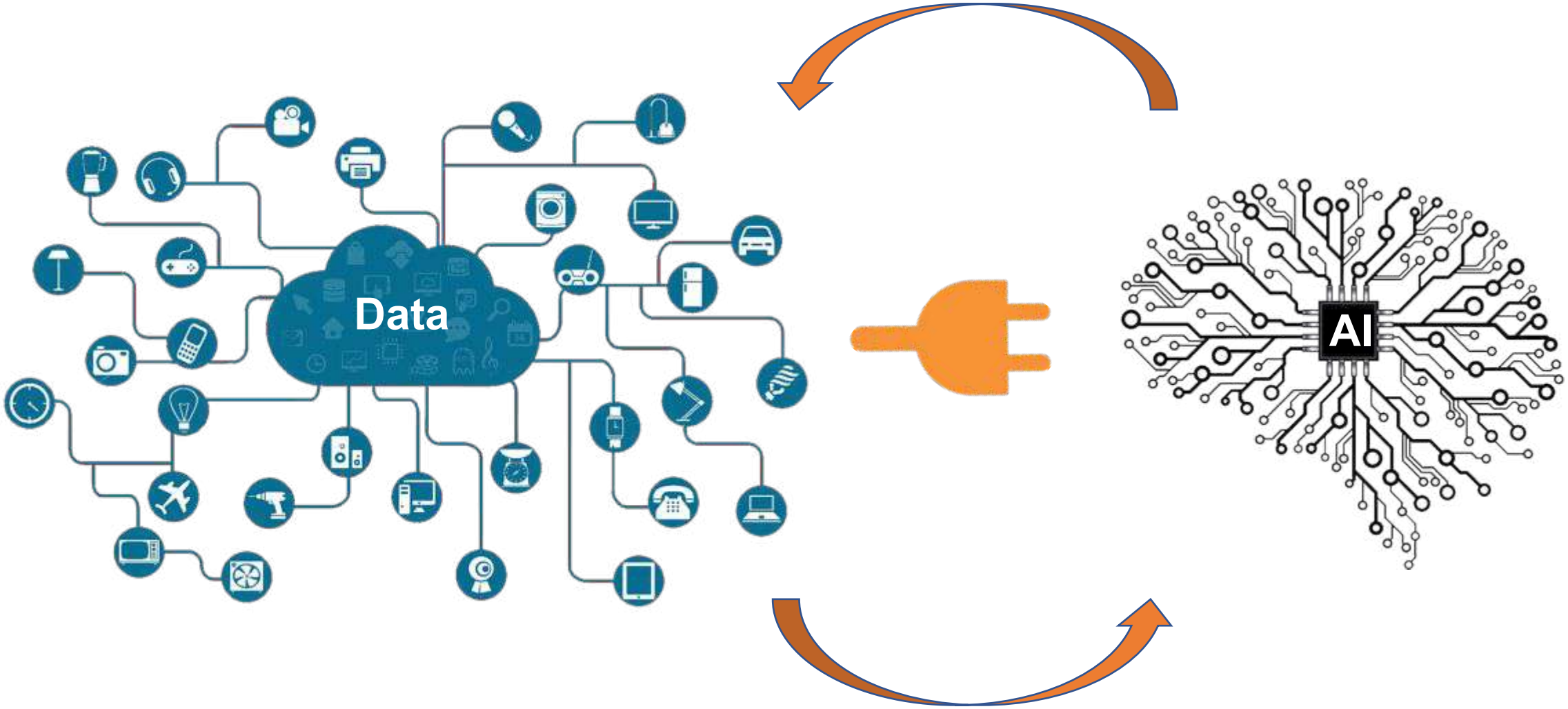
- ➔ Health
- ➔ Consumer
- ➔ Industrial

EDGE IMPULSE

IoT - Architecture



Endpoints devices ⇨ Data + AI ⇨ Value



Endpoints Have **Sensors**, Tons of Sensors

Motion Sensors
Gyroscope, radar, magnetometer, accelerator

Acoustic Sensors
Ultrasonic, Microphones, Geophones, Vibrometers

Environmental Sensors
Temperature, Humidity, Pressure, IR, etc.

Touchscreen Sensors
Capacitive, IR

Image Sensors
Thermal, Image

Biometric Sensors
Fingerprint, Heart rate, etc.

Force Sensors
Pressure, Strain

Rotation Sensors
Encoders

Endpoints Have **Sensors**, Tons of Sensors

Motion Sensors
Gyroscope, radar, magnetometer, accelerator

Acoustic Sensors
Ultrasonic, Microphones, Geophones, Vibrometers

Environmental Sensors
Temperature, Humidity, Pressure, IR, etc.

Touchscreen Sensors
Capacitive, IR

Image Sensors
Thermal, Image

Biometric Sensors
Fingerprint, Heart rate, etc.

Force Sensors
Pressure, Strain

Rotation Sensors
Encoders

Biometric Sensors

Non-invasive Glucose Monitoring

Fingerprint + Photoplethysmography (**PPG**)

ECG Sensor

Source: Jacobs School of Engineering/UC San Diego

[Atrial Fibrilation Detecion with TinyML: https://youtu.be/y5gMA3tBZmY](https://youtu.be/y5gMA3tBZmY)

Endpoints Have **Sensors**, Tons of Sensors

Motion Sensors
Gyroscope, radar, magnetometer, accelerator

Acoustic Sensors
Ultrasonic, Microphones, Geophones, Vibrometers

Environmental Sensors
Temperature, Humidity, Pressure, IR, etc.

Touchscreen Sensors
Capacitive, IR

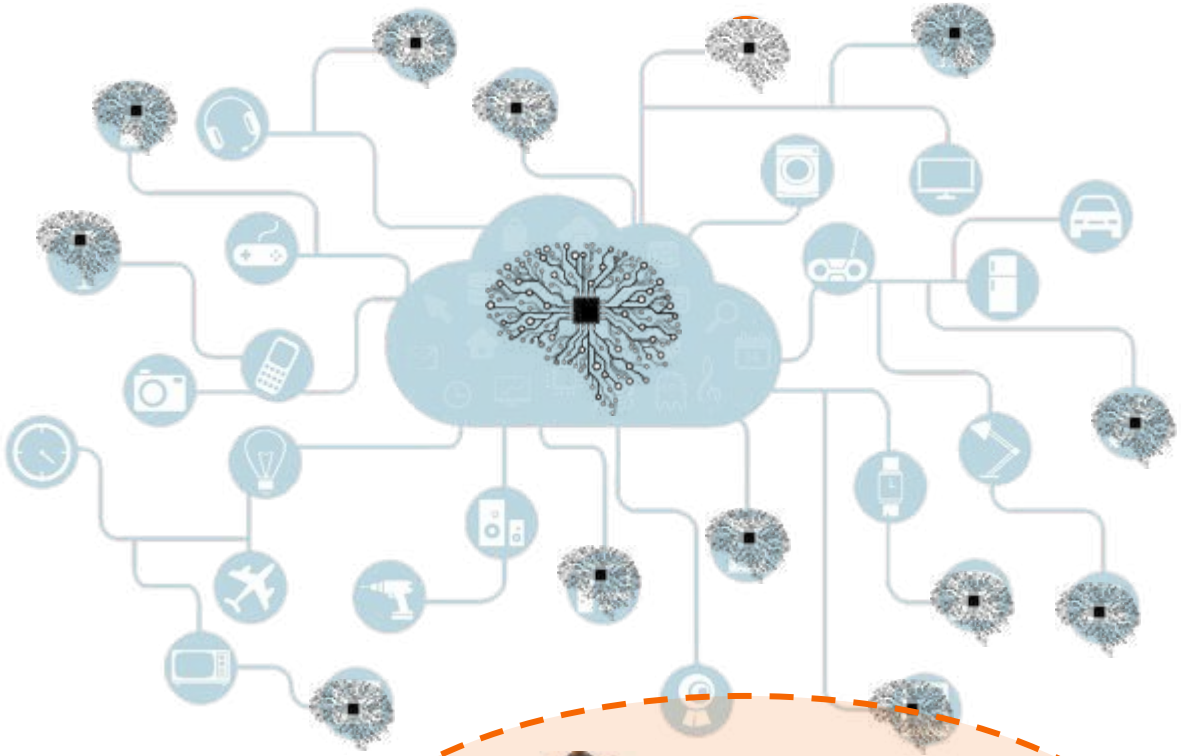
Image Sensors
Thermal, Image

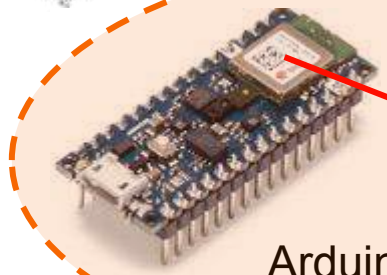
Biometric Sensors
Fingerprint, Heart rate, etc.

Force Sensors
Pressure, Strain

Rotation Sensors
Encoders

ML (AI) at the “edge of the edge”⇨TinyML





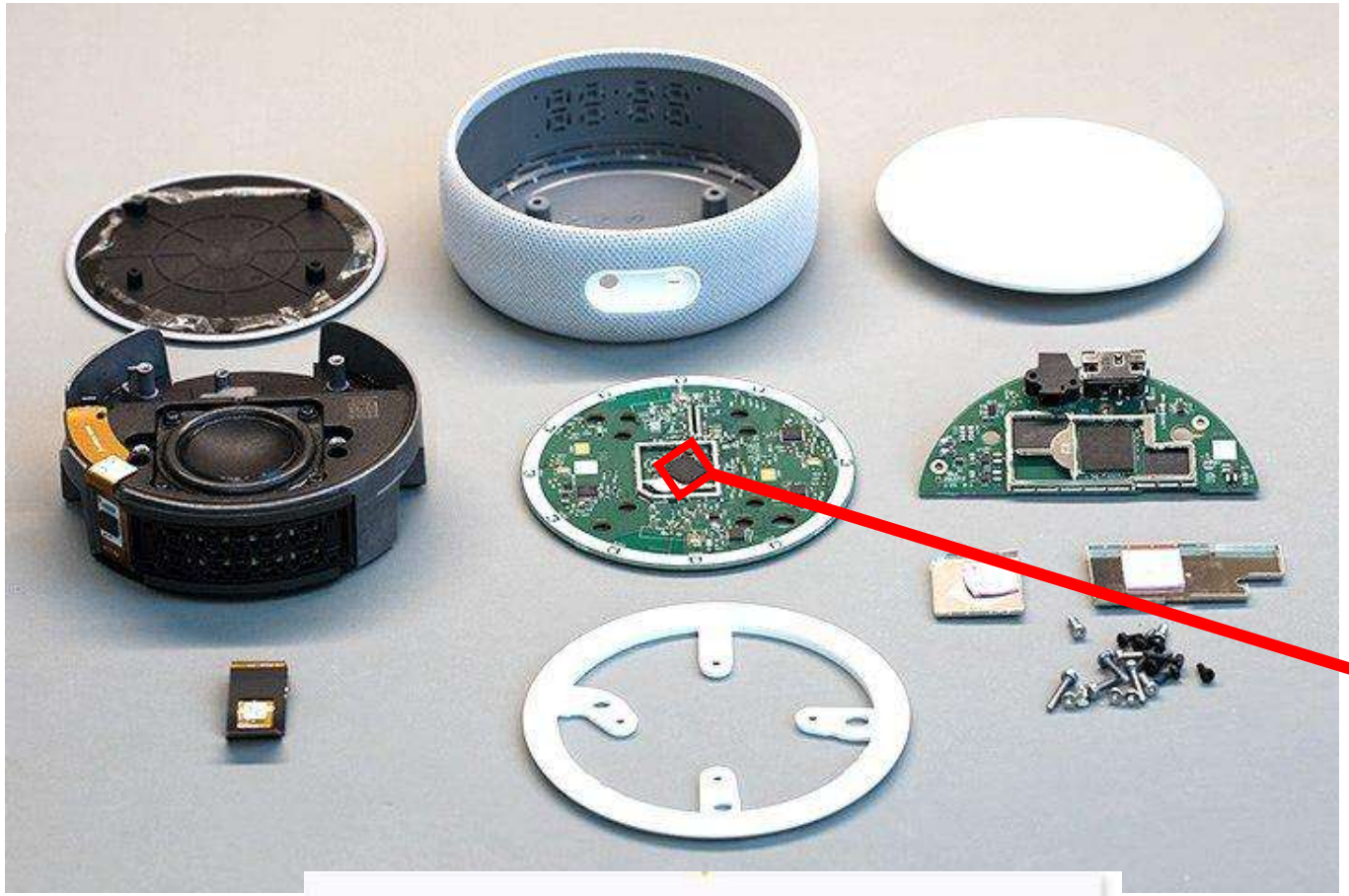
ARM Cortex-M4

Arduino
Nano BLE Sense

TinyML enables machine intelligence right next to the physical world

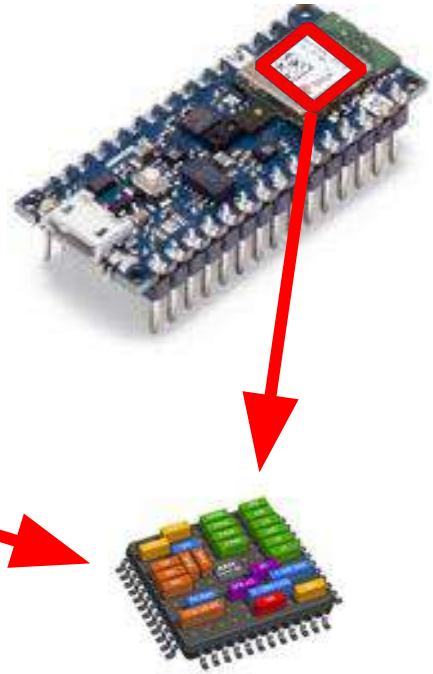
ML at microprocessor level avoid issues as Latency, Power Consuming, and Security

Echo-Dot Teardown vs Arduino Nano BLE Sense



MediaTek 7658CSN: Wi-Fi +ARM® Cortex-R4

Nordic nRF52840-M4



MCUs enable **TinyML**

SIZE

LOW POWER

LOW COST

MCUs enable **TinyML**

SIZE

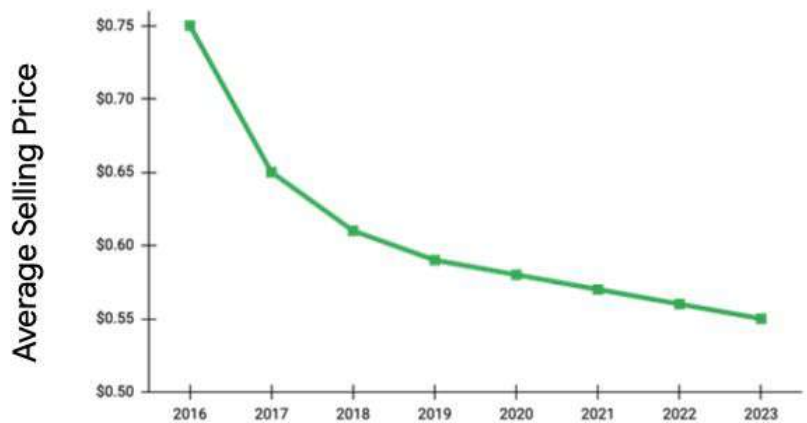
LOW POWER

LOW COST

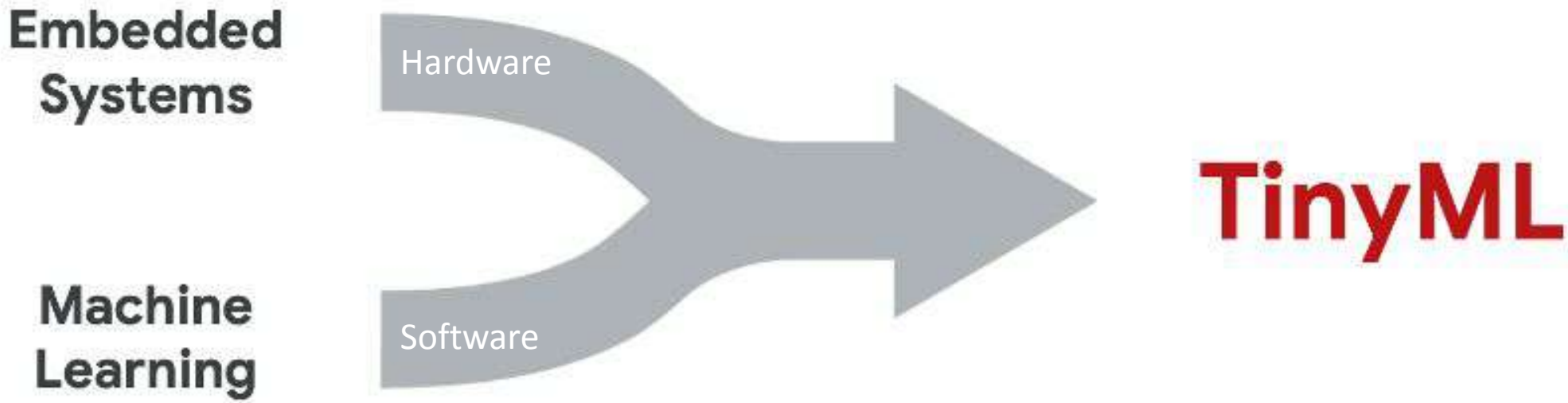
< 140 µW

Syntiant NDP100

MCUs enable **TinyML**



What Makes TinyML?



Hardware

EdgeML

TinyML

Video Classification 2 MB+

Object Detection Complex Voice Processing 1 MB+

Image Classification 250 KB+

KeyWord Spotting Audio Classification 50 KB

Anomaly Detection Sensor Classification 20 KB

Rpi-Pico (Cortex-M0+)

Arduino Nano (Cortex-M4)

Arduino Pro (Cortex-M7)

RaspberryPi SmartPhone (Cortex-A)

Jetson Nano (Cortex-A + GPU)

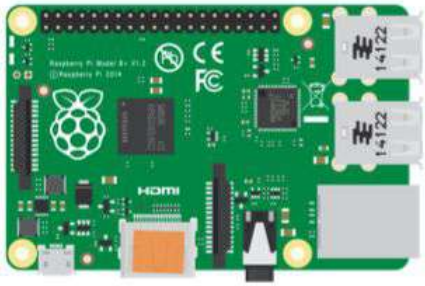
Source: Edge Impulse

Software

TensorFlow

TensorFlow Lite

Train a model → Convert model → Optimize model → Deploy model at Edge → Make inferences at Edge



Raspberry Pi

Linux

iOS

(TFL Micro)

Microcontroller

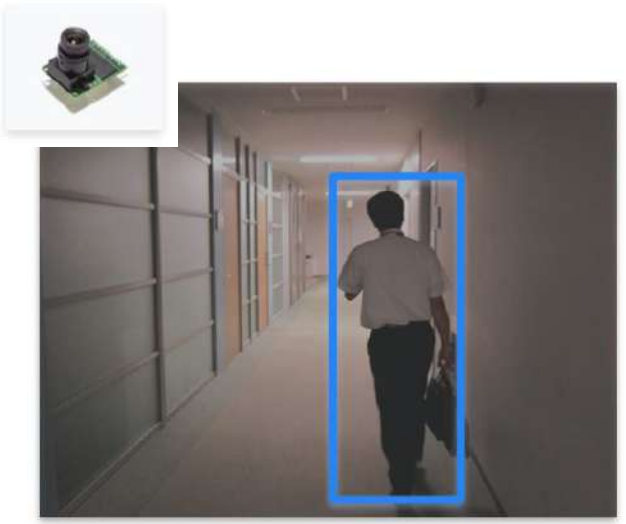
TinyML Application

Examples

Sound

Vibration

Vision



Sound

Vibration

Vision


amazon


amazon

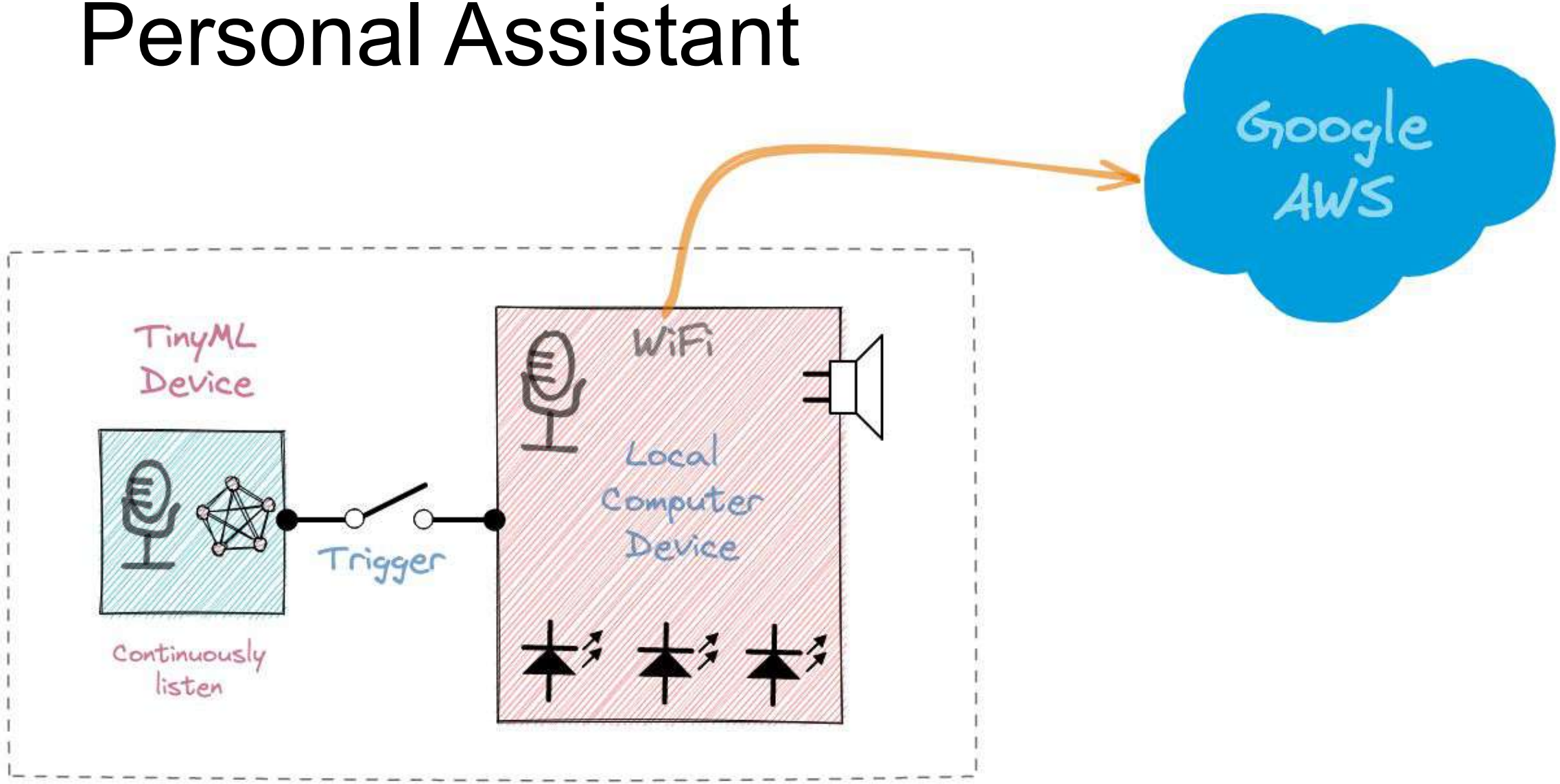

amazon

More than just voice

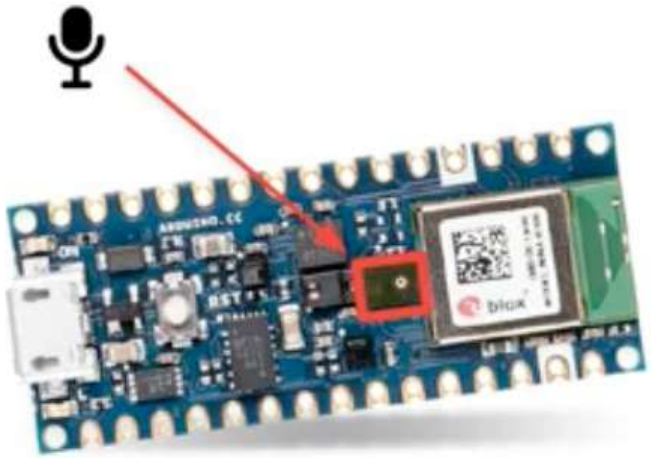
- Security (Broken Glass)
- Industry (Anomaly Detection)
- Medical (Snore, Toss)
- Nature (Bee, Mosquito sound)

Personal Assistant

Personal Assistant



“Cascade” Detection: multi-stage model



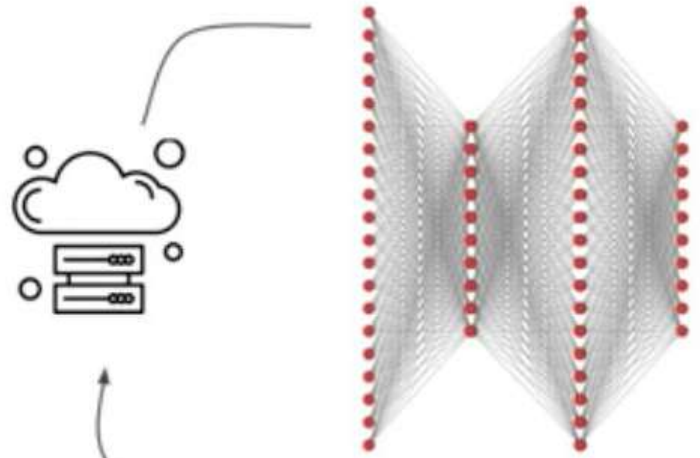
1 Continuously listen on the microcontroller

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

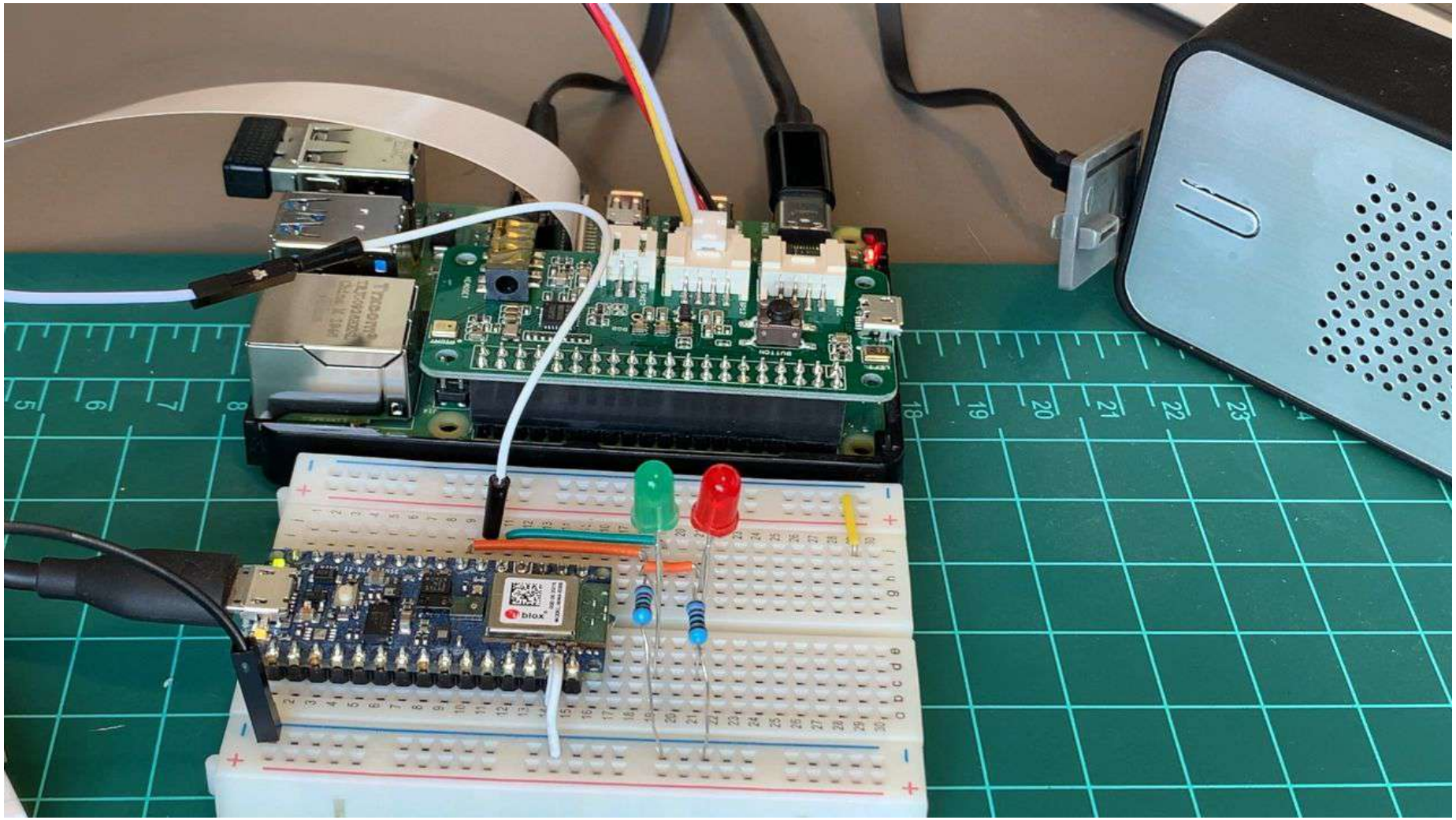
3 Process on a secondary larger model on a larger local device

4 Send the data to the cloud when triggered

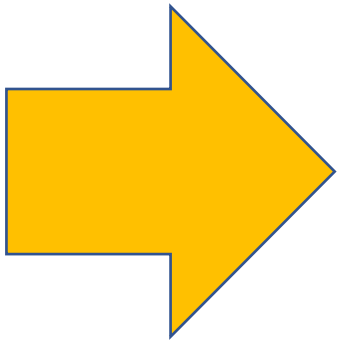
5 Process the full speech data with a large model in the cloud



KeyWord Spotting (KWS)



https://mjrobot.org/2021/01/27/building-an-intelligent-voice-assistant-from-scratch/

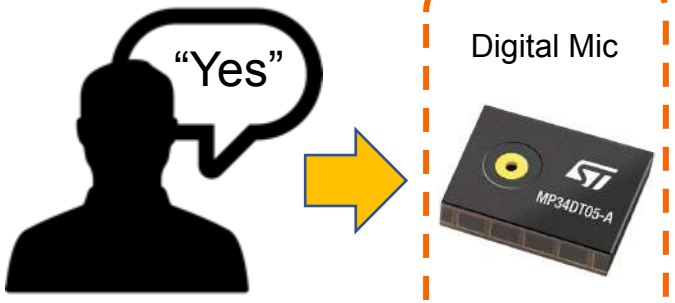


Sound

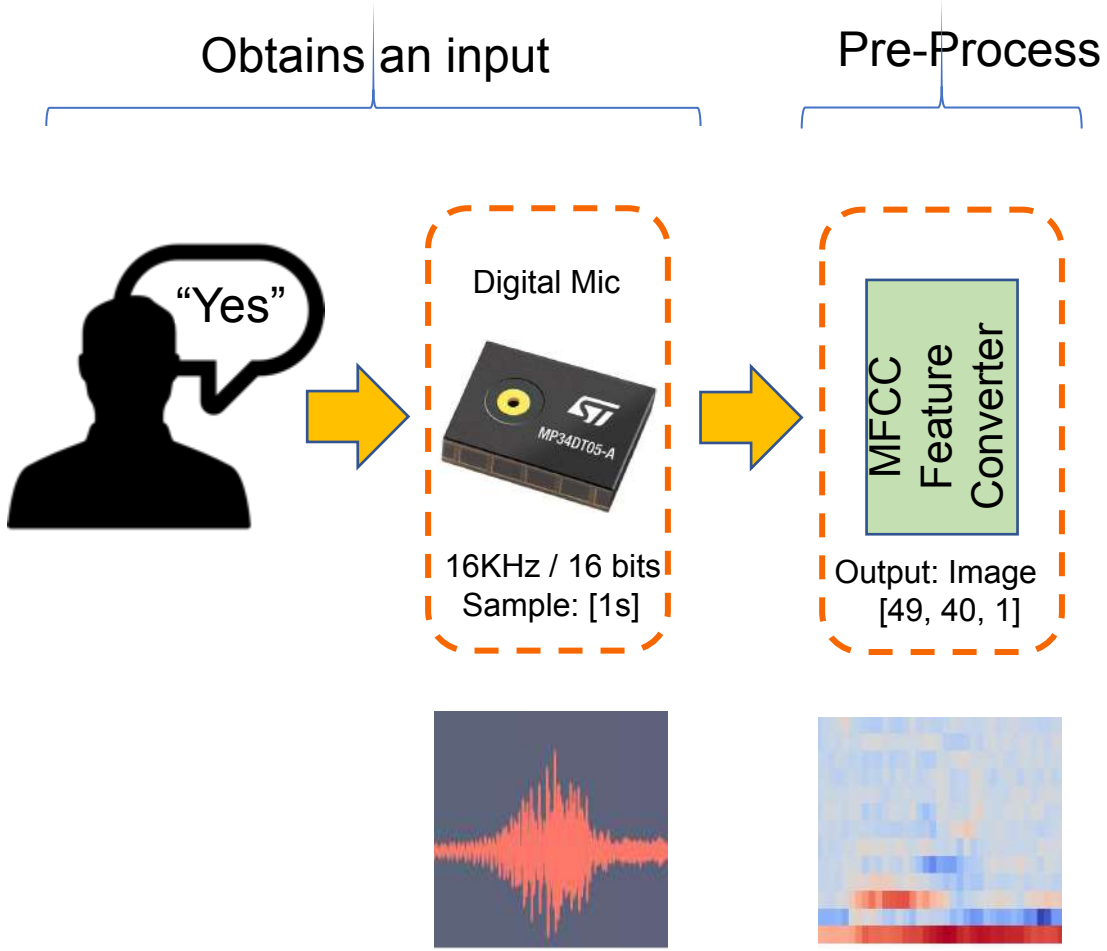
Image

KeyWord Spotting (KWS) - **Inference**

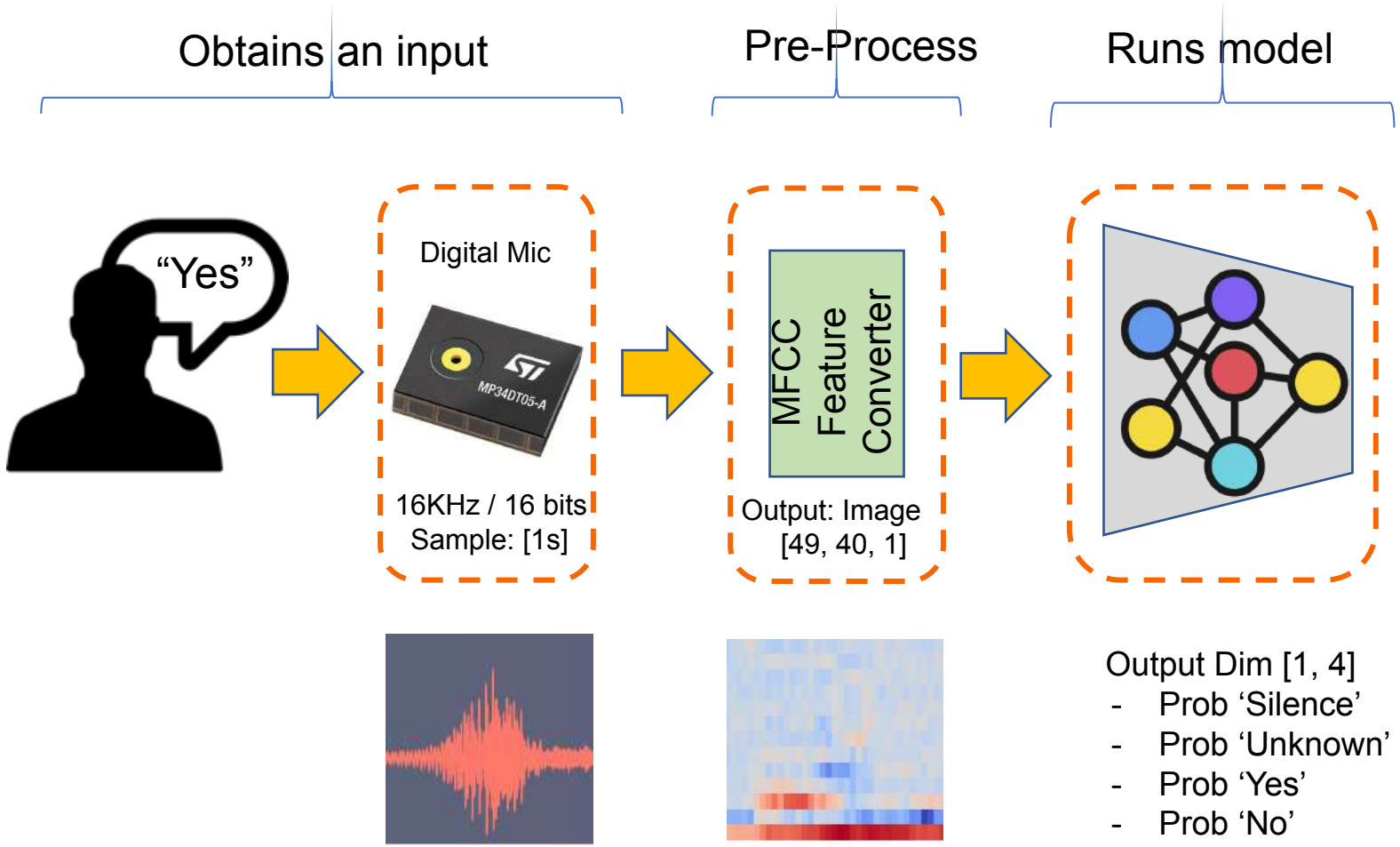
Obtains an input



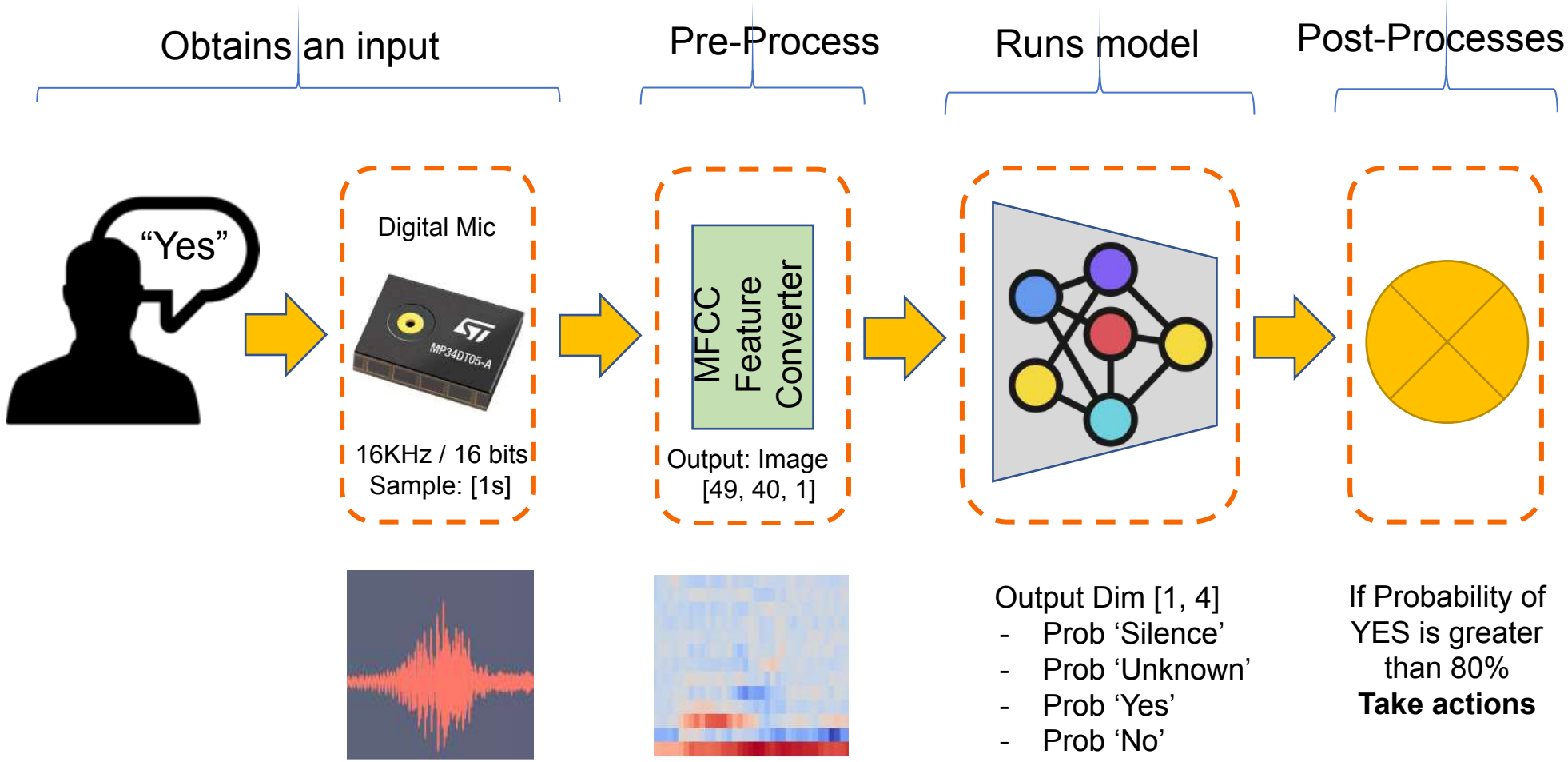
KeyWord Spotting (KWS) - Inference



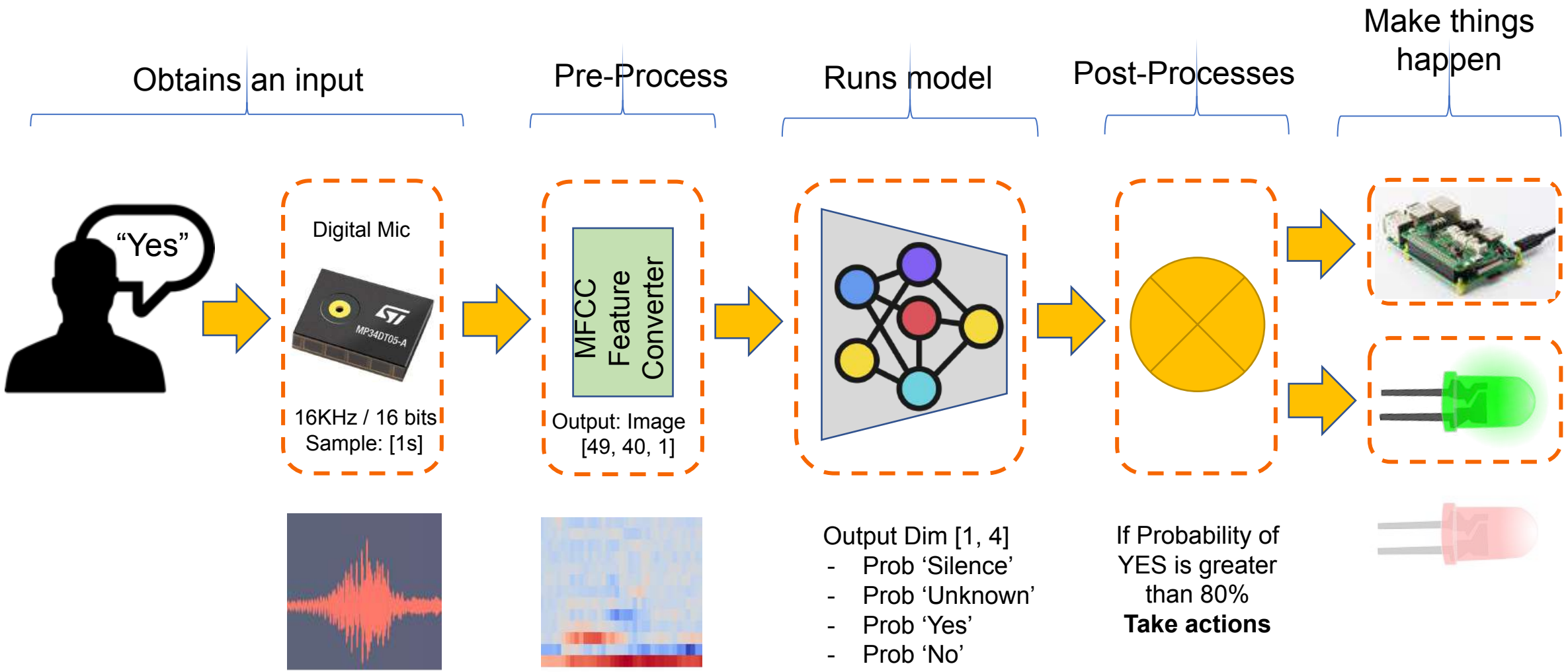
KeyWord Spotting (KWS) - Inference



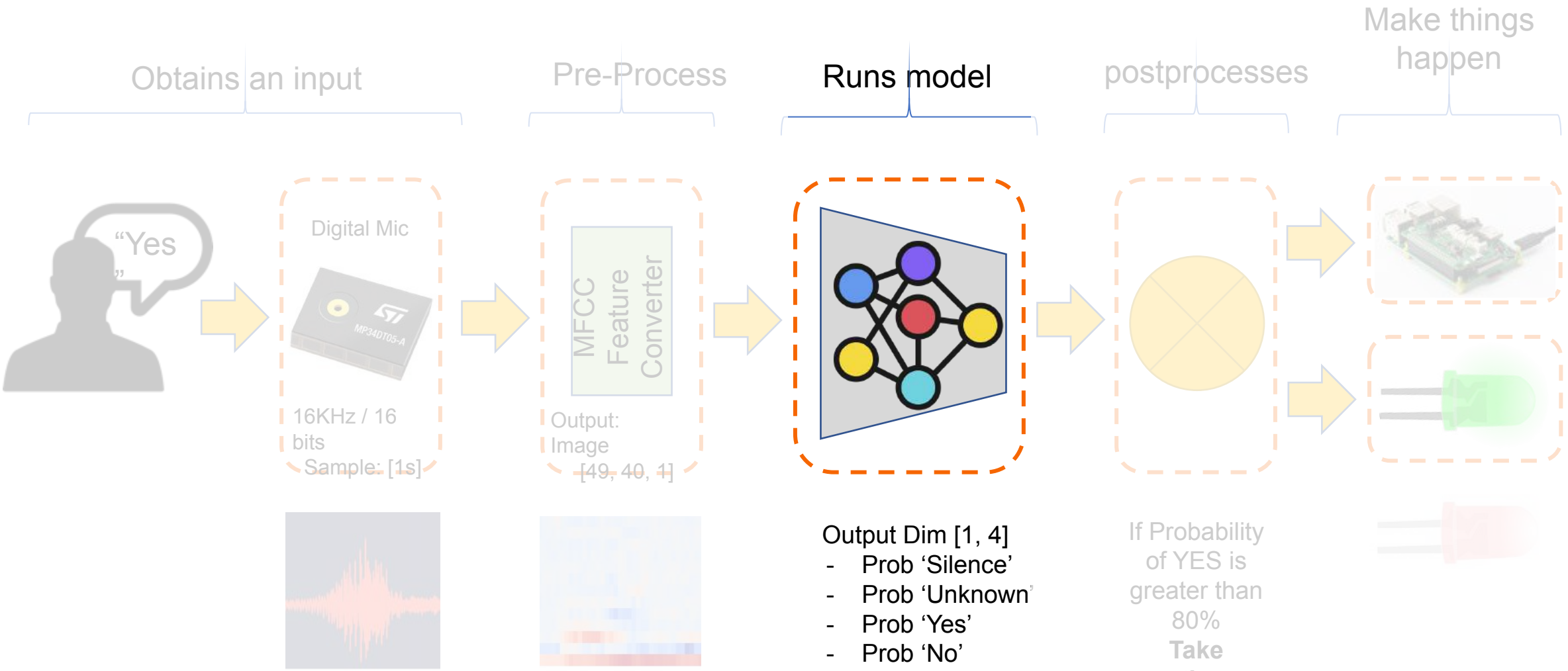
KeyWord Spotting (KWS) - Inference



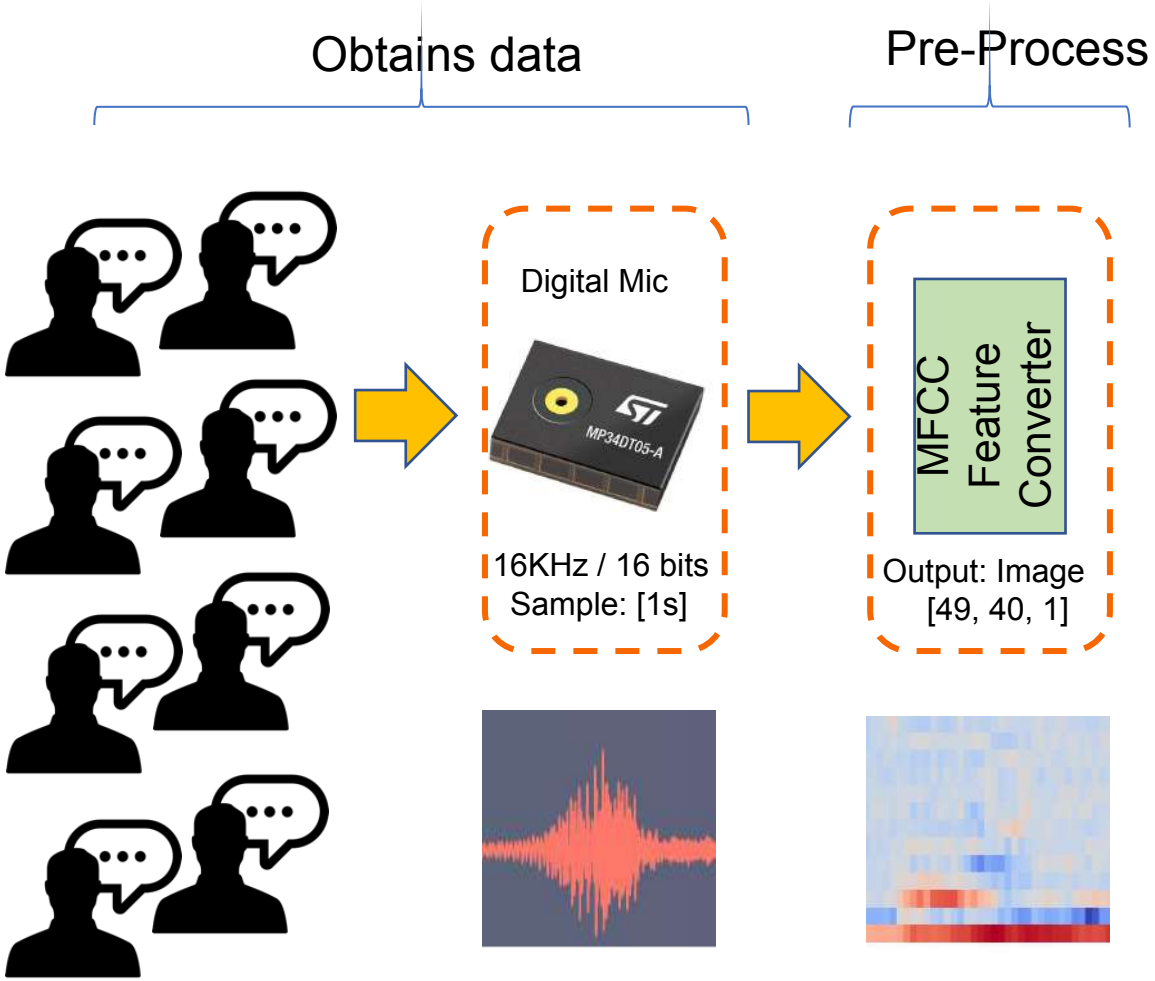
KeyWord Spotting (KWS) - Inference



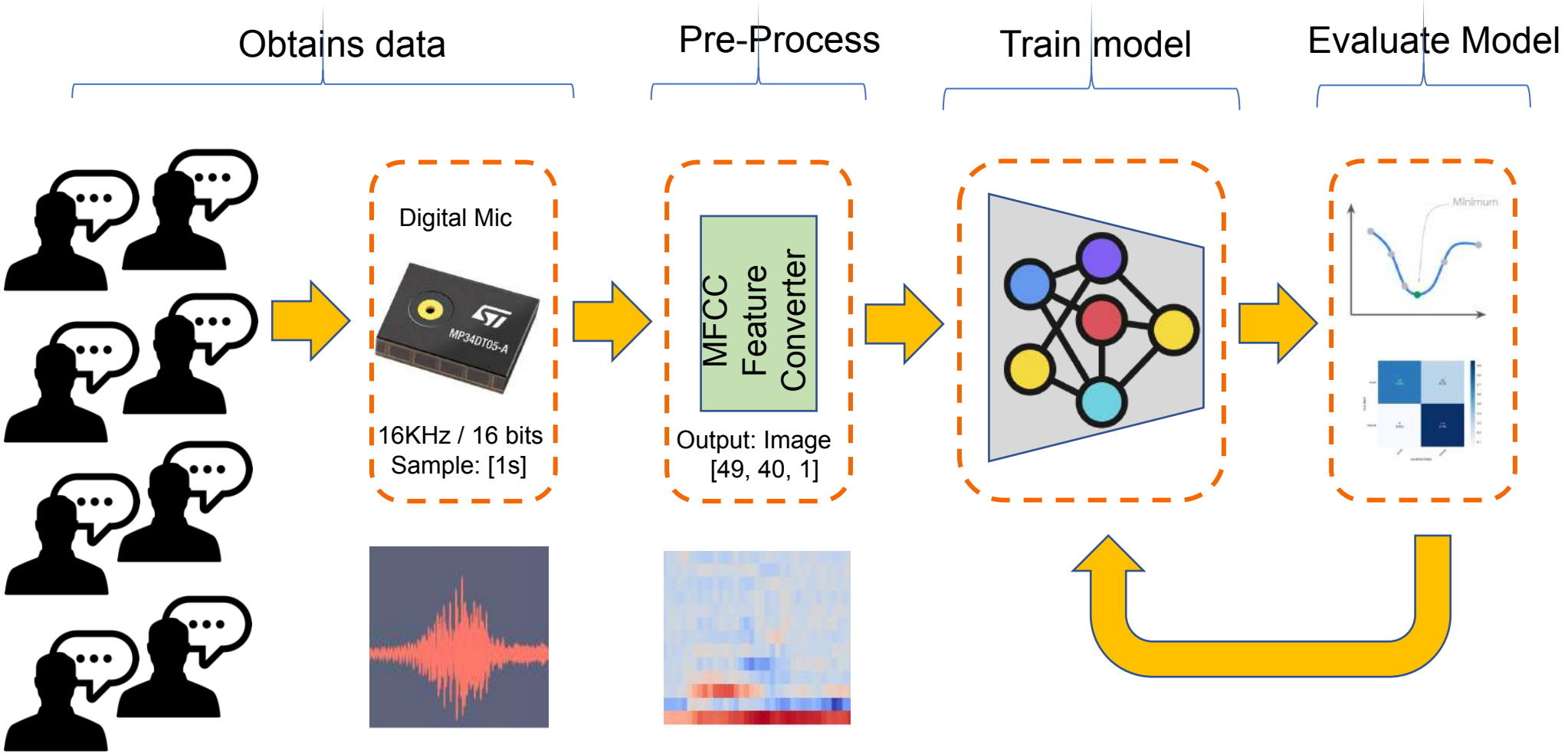
KeyWord Spotting (KWS) - **Model**



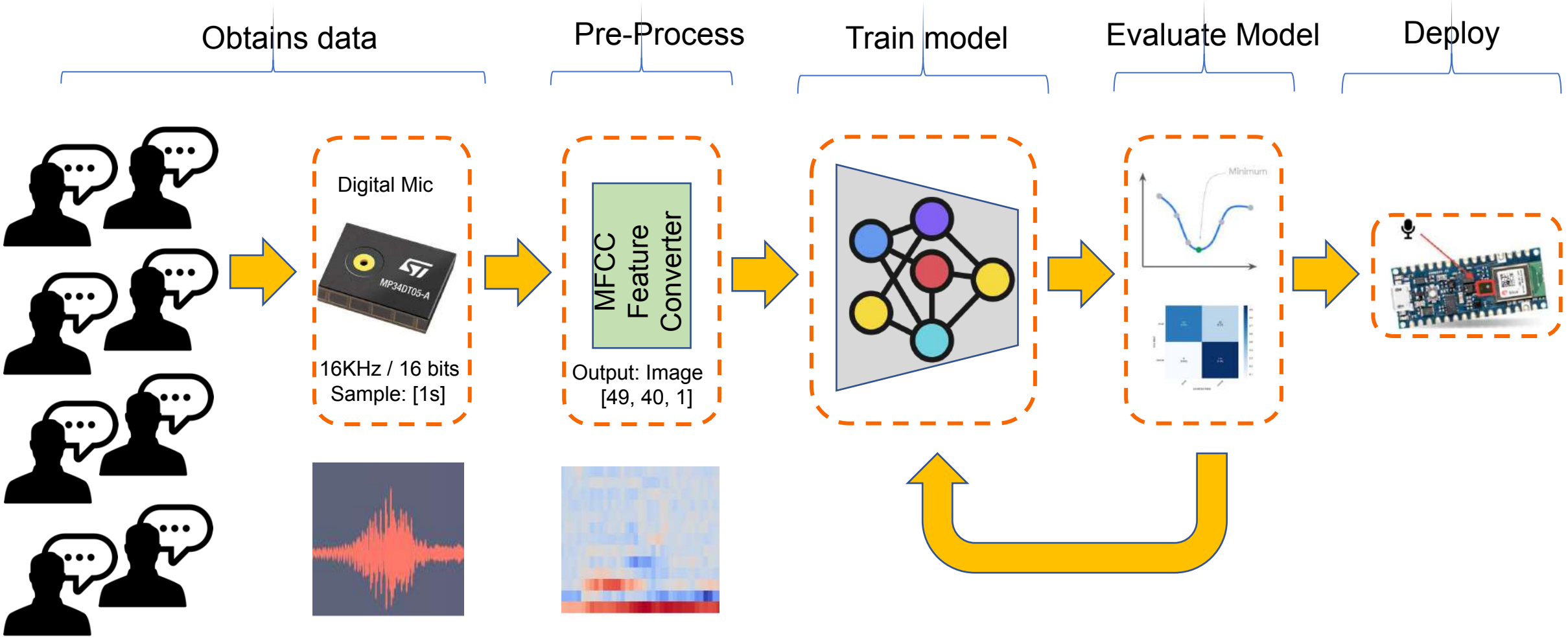
KeyWord Spotting (KWS) – Create Model (Training)



KeyWord Spotting (KWS) – Create Model (Training)



KeyWord Spotting (KWS) – Create Model (Training)



Sound

Vibration

Vision

Cow Monitoring

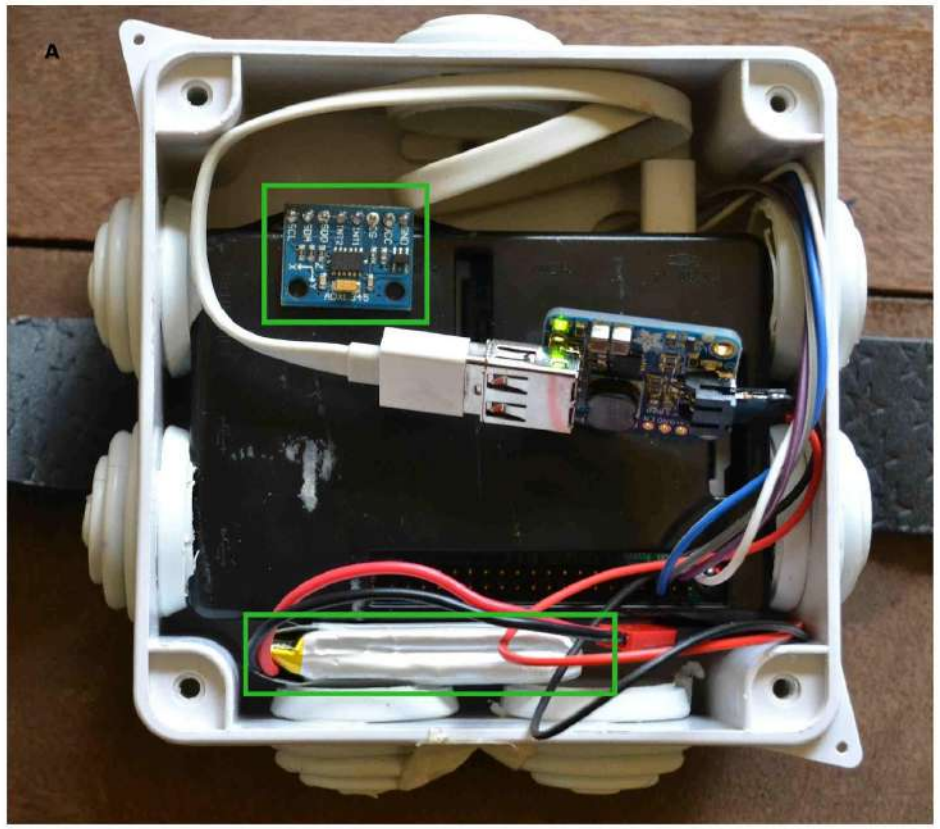
Using the Internet of Things for Agricultural Monitoring

"We aim to deploy a variety of sensors for agricultural monitoring. One of the projects involves using accelerometer sensors to monitor activity levels in dairy cows with a view to determining when the cows are on heat or when they are sick."

Ciira wa Maina, Ph.D.

Senior Lecturer
Department of Electrical and Electronic Engineering
Dedan Kimathi University of Technology
Nyeri Kenya
Email: ciira.maina@dkut.ac.ke

Kenia



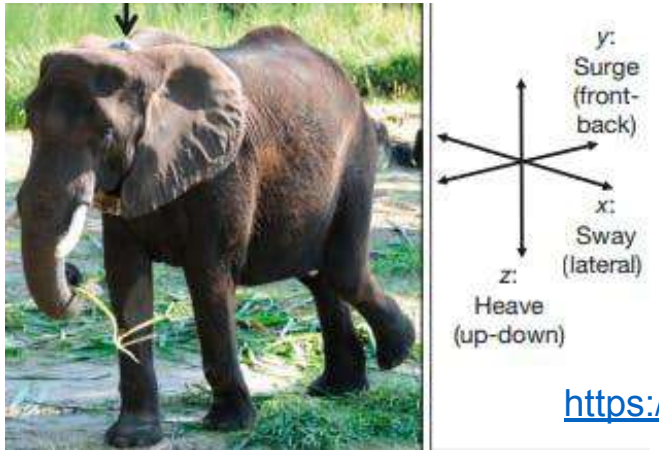
https://sites.google.com/site/cwamainadekut/research

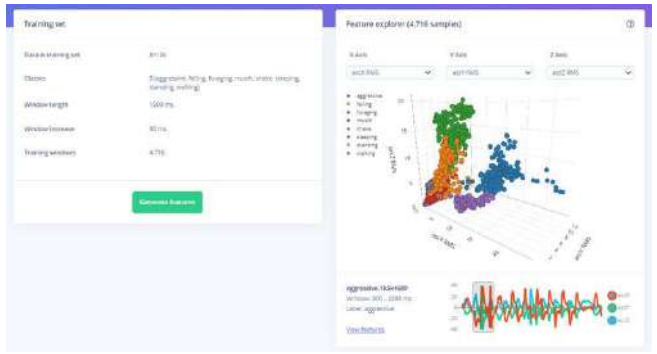
Predict and classify common Elephant behavior

Aggressive

Standing

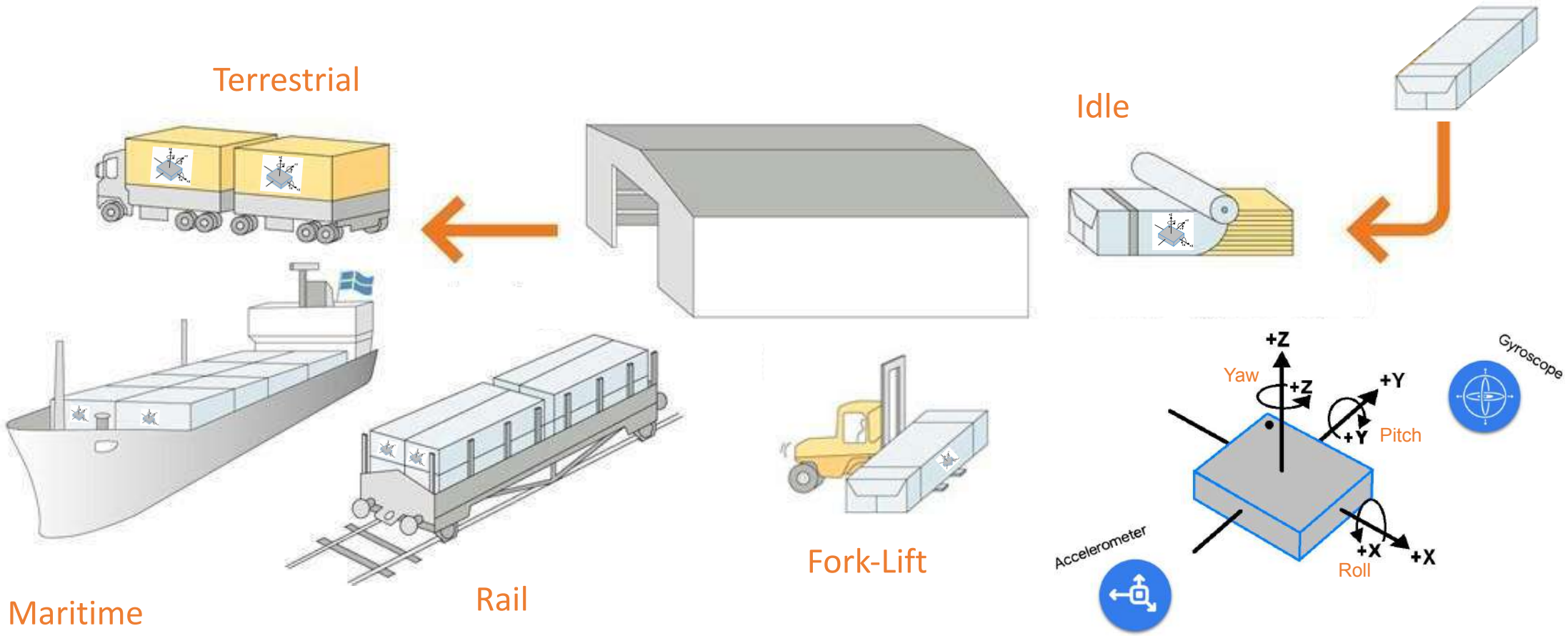
Sleeping

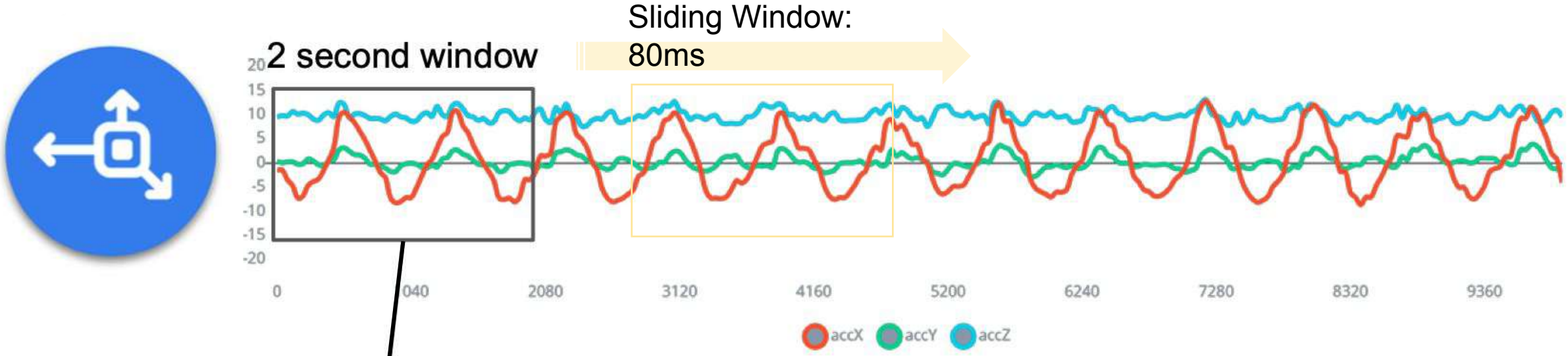




https://www.hackster.io/dhruvsheth_/eletect-tinyml-and-iot-based-smart-wildlife-tracker-c03e5a

Mechanical Stresses in Transport





375 Raw Features

- Raw Data from sensor

Manual Feature Extraction

Spectral Analysis

33 Features

- RMS
- PSD

NN Classifier

Classes

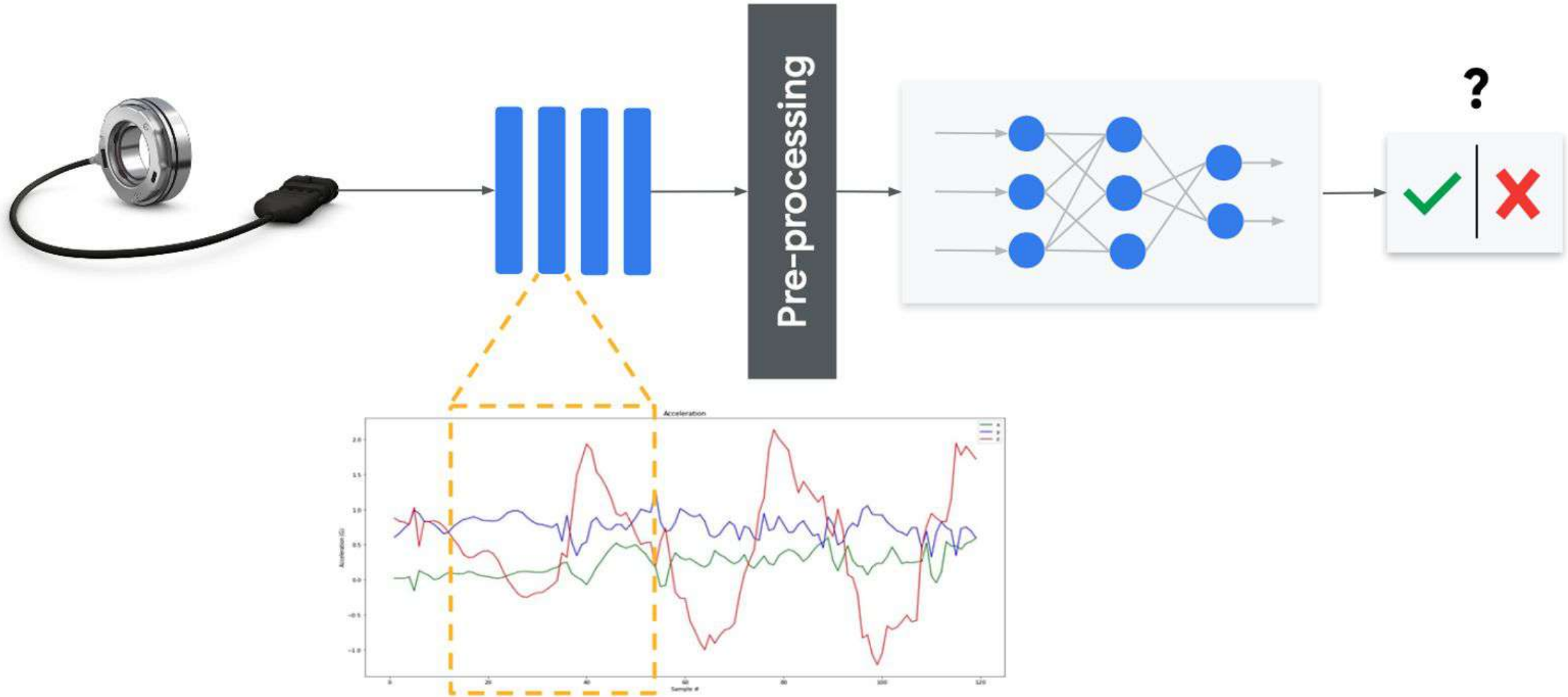
- Terrestrial
- Maritime
- Fork-Lift
- Rail
- Idle

Application: Factory machinery

Ball Bearings

Accelerometer

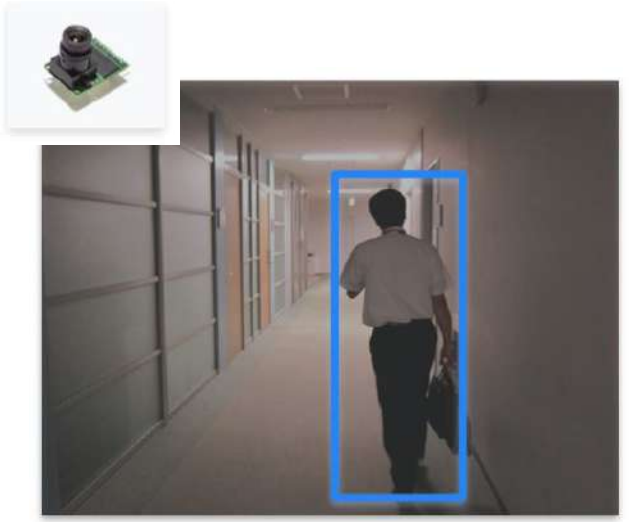
Anomaly Detection



Sound

Vibration

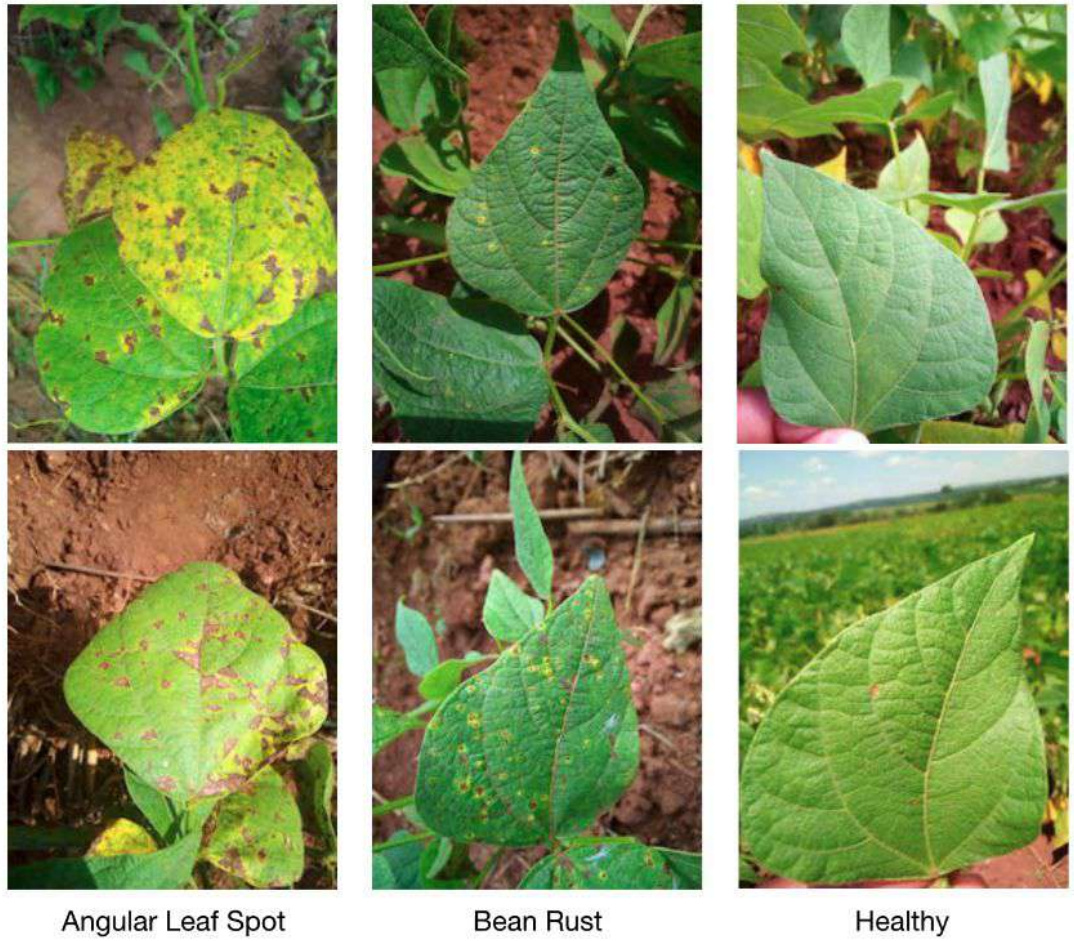
Vision



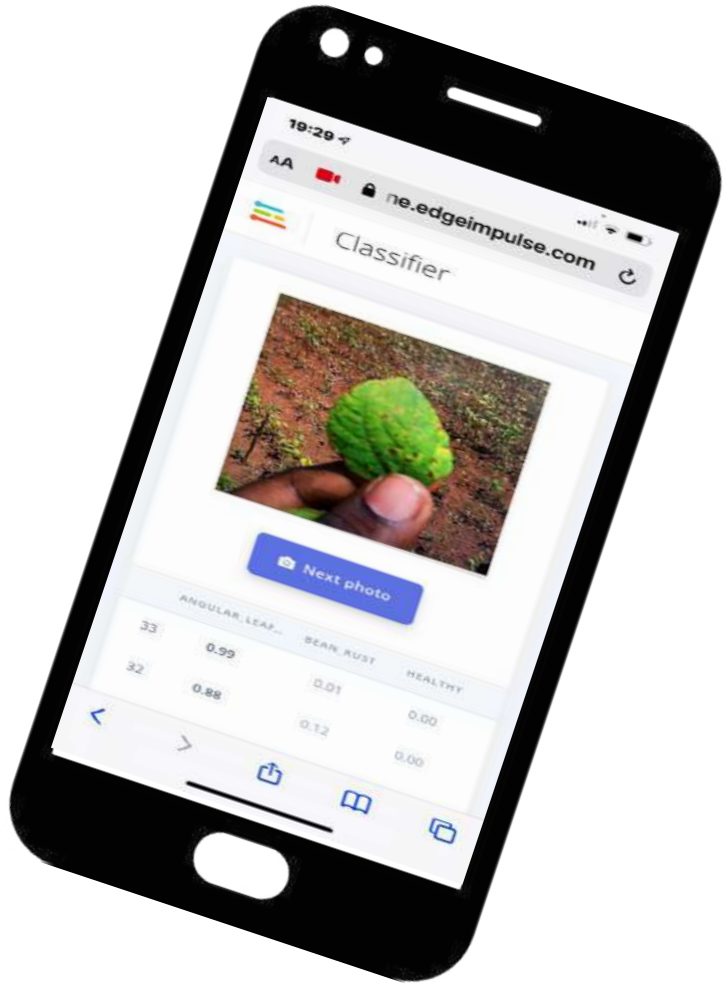
Detecting Diseases in the Bean plants

AIR Lab Makerere University

UGANDA

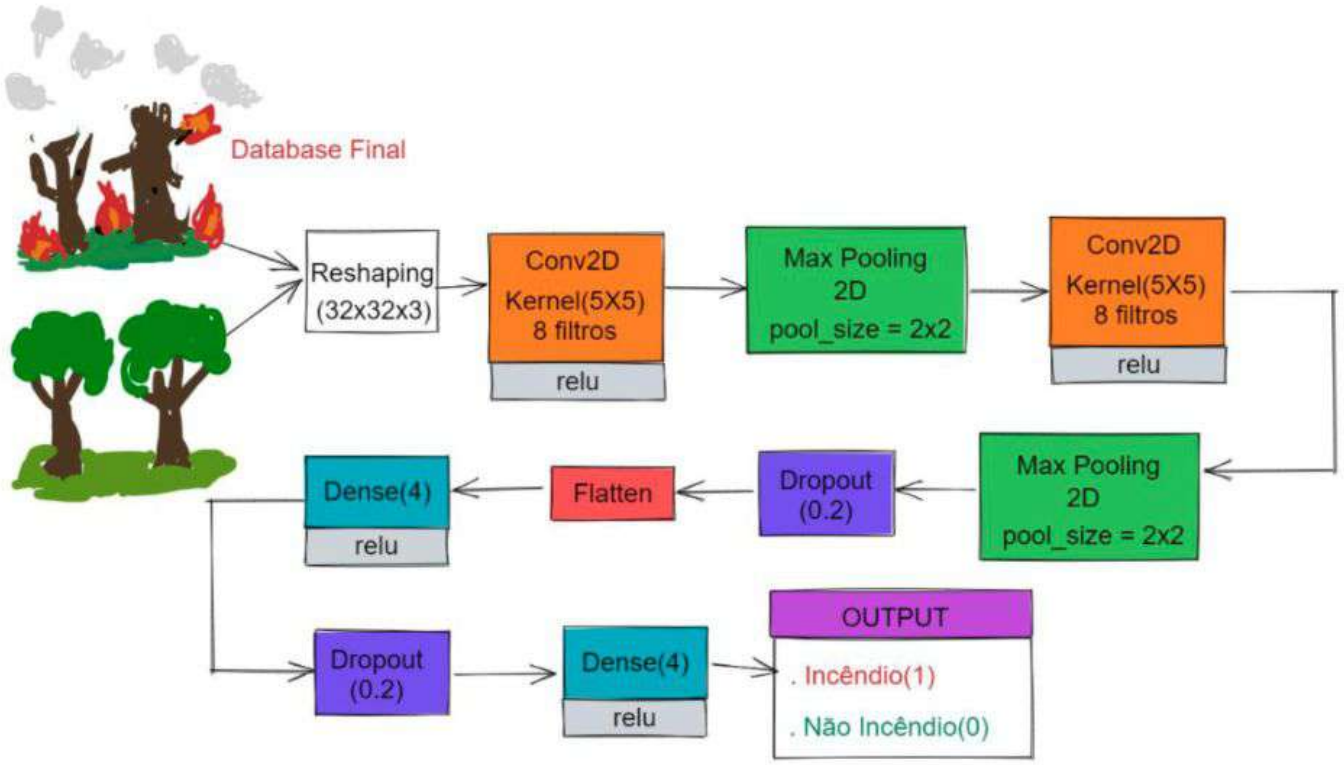


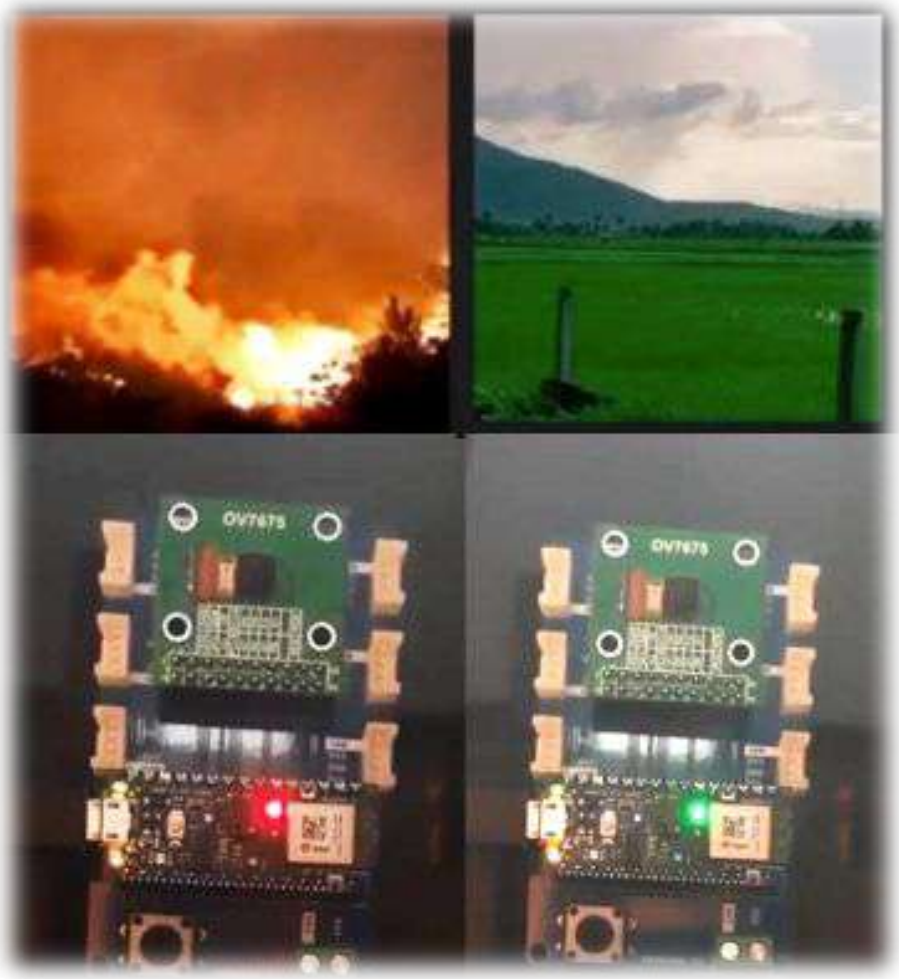
Angular Leaf Spot | Bean Rust | Healthy



Dataset: https://github.com/AI-Lab-Makerere/ibean/

Forest Fire Detection





https://github.com/Mjrovai/UNIFEI-IESTI01-T01-2021.1/blob/main/00_Curso_Folder/2_Applications/Group_Projects-Final%20Reports/Projeto_final_Fire_detection/trabalho_final_Fire_Detection.pdf

Person Detection

Person Detection

✔

X

Mask Detection

✔

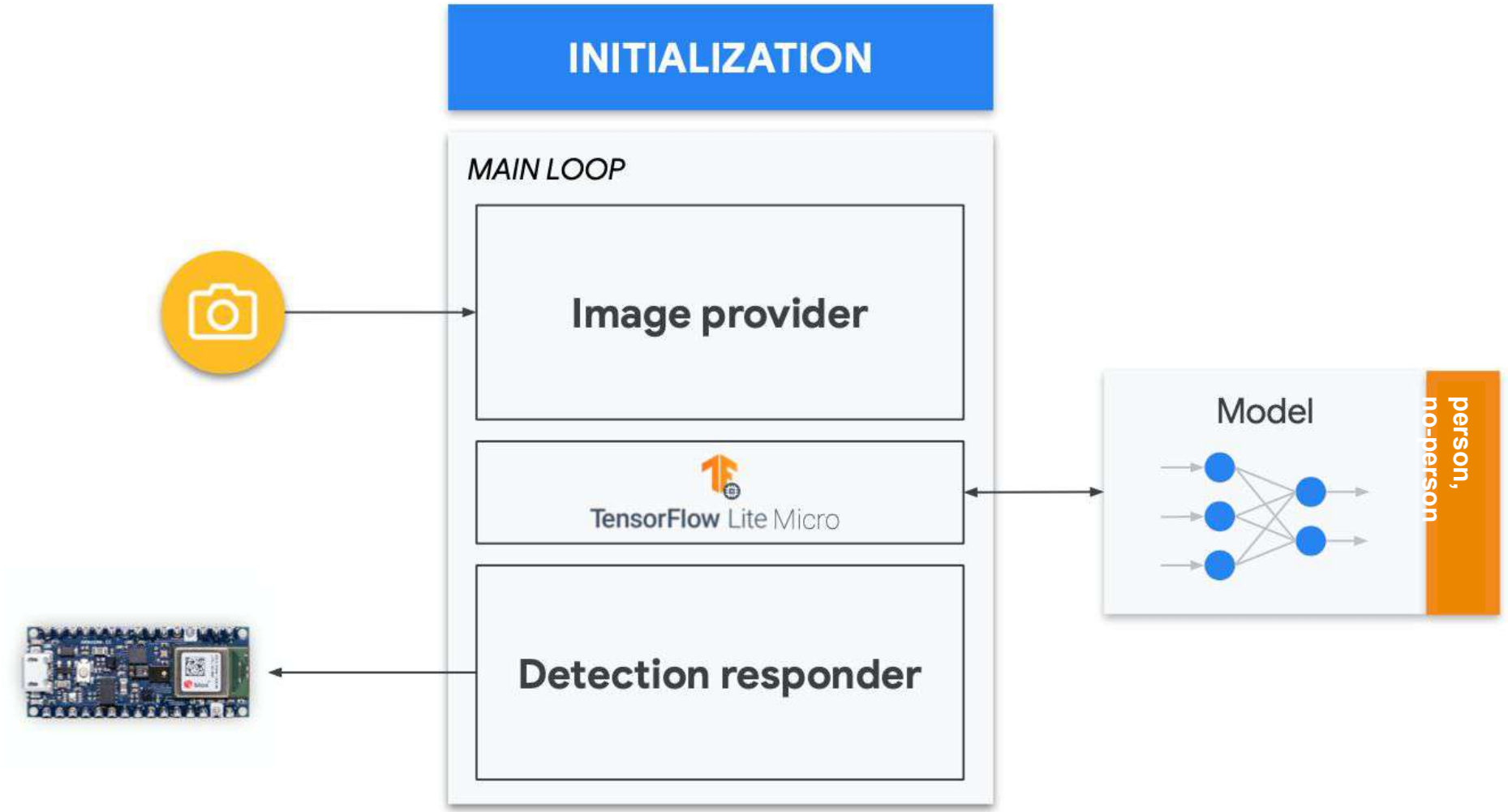
X

Person Detection

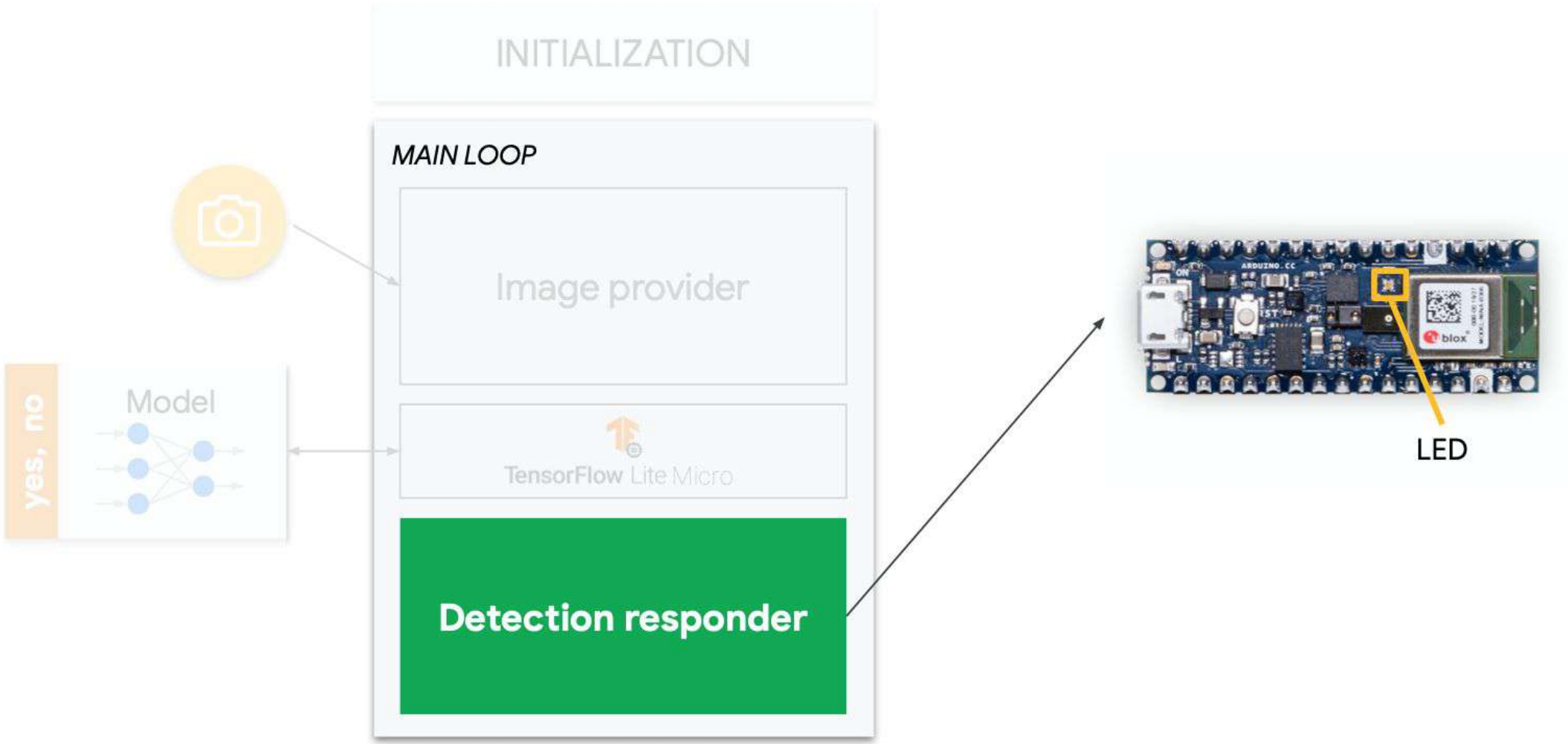
✔

X

Person Detection **Components**



Post-processing



TinyML Projects – UNIFEI / IESTI01

- Mask Detection [Docs] [Video]
- Forest Fire Detection [Docs] [Video]

- Covid Detection (cough) [Docs] [Video]
- Seismic Detection [Docs] [Video]

- Personal Trainer [Docs] [Video]

TinyML Projects – Select HW examples

- Coffee Disease w/ Seeed Maix Bit [Video] [Docs]

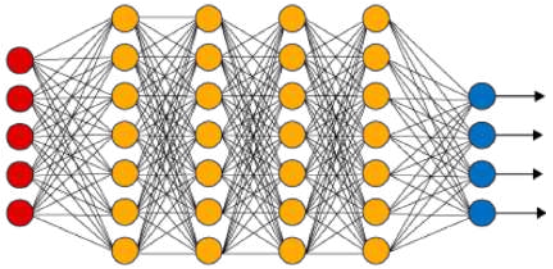
- Listening Temperature w/ Nano 33 [Docs]

- Motion Recognition w/ RPi Pico [Docs]
- Gesture Recognition w/ Wio Terminal [Docs]

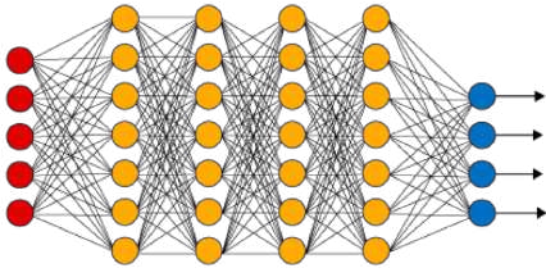
How to Train a ML Model?

Machine Learning Workflow

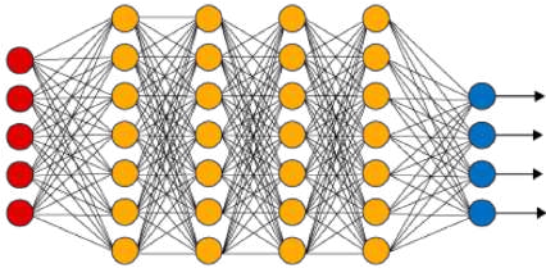
Machine Learning Workflow

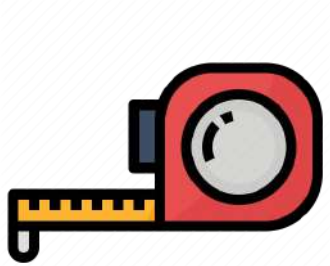


Machine Learning Workflow



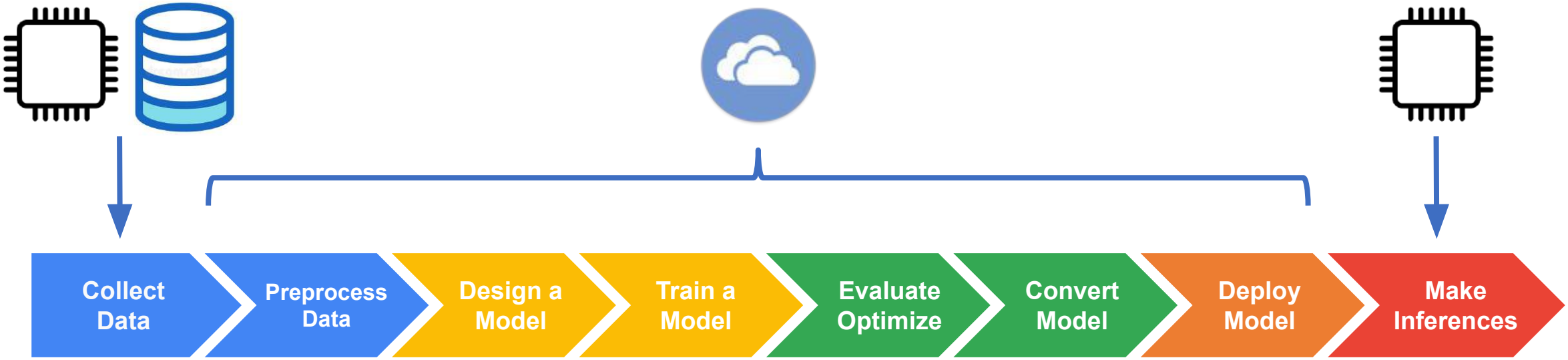
Machine Learning Workflow ("What")



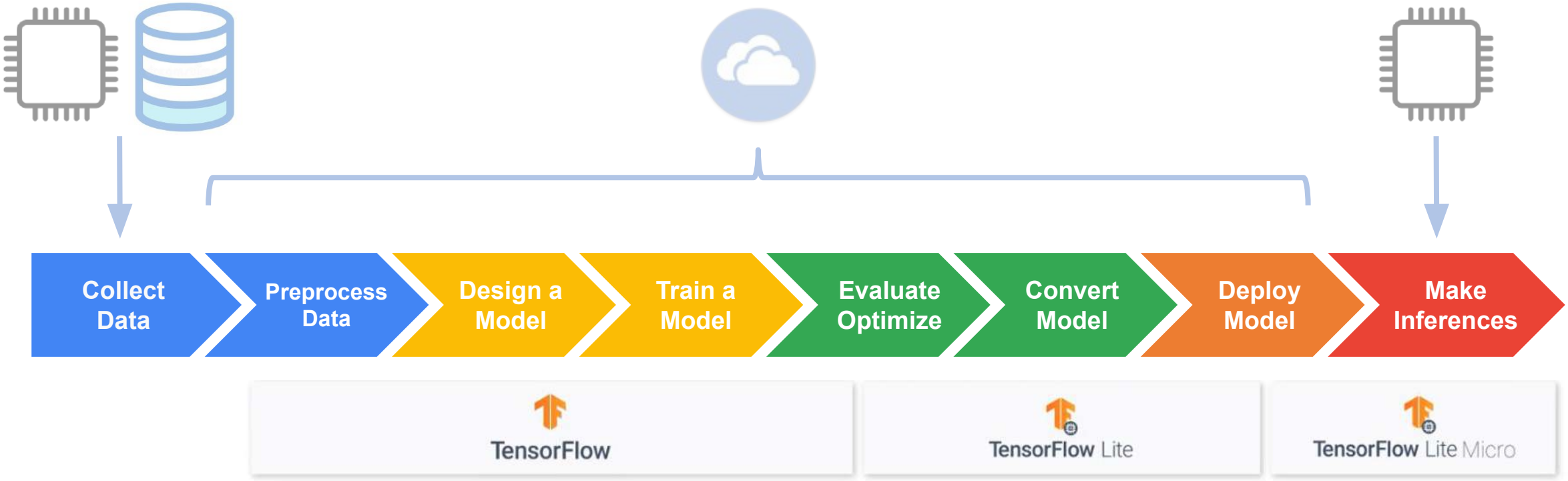


Collect Data → Preprocess Data → Design a Model → Train a Model → Evaluate Optimize → Convert Model → Deploy Model → Make Inferences

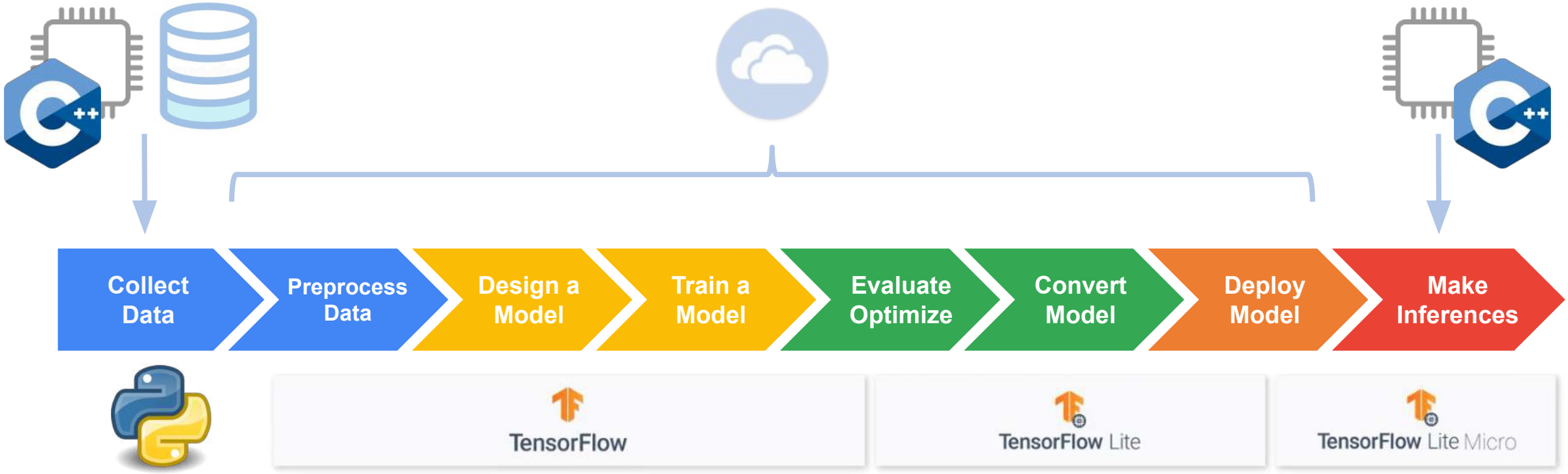
Machine Learning Workflow ("Where")



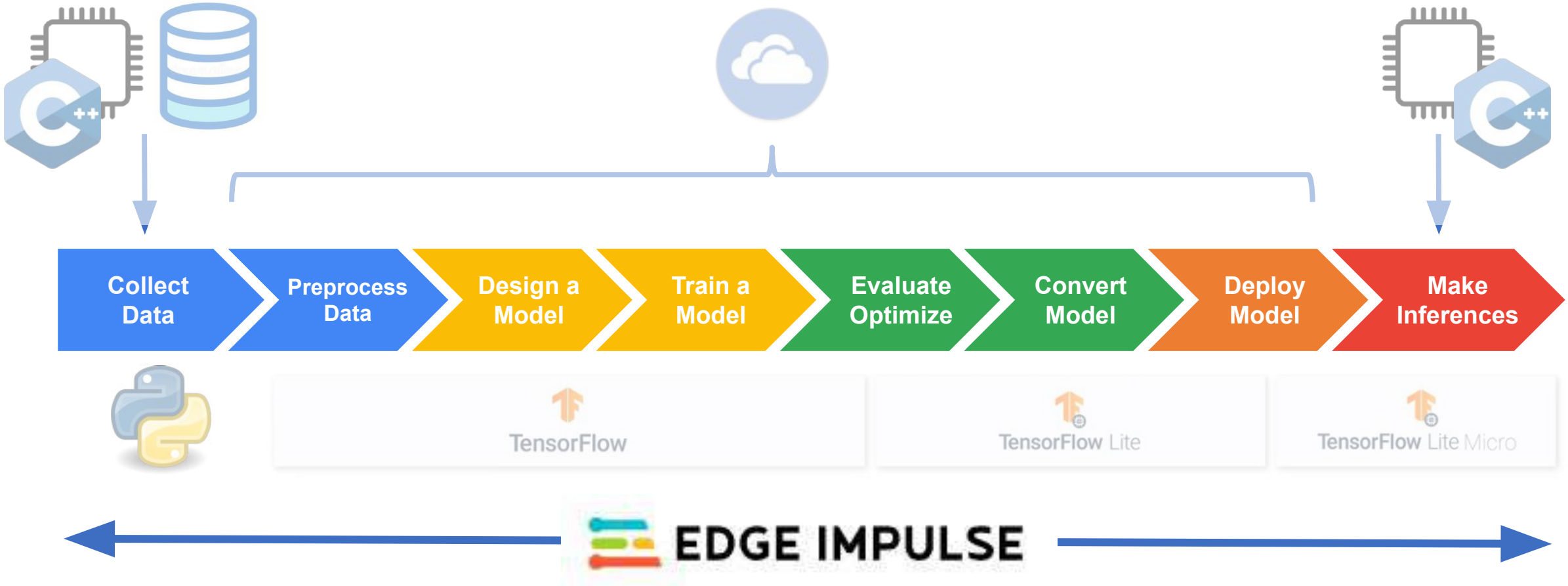
Machine Learning Workflow ("How")



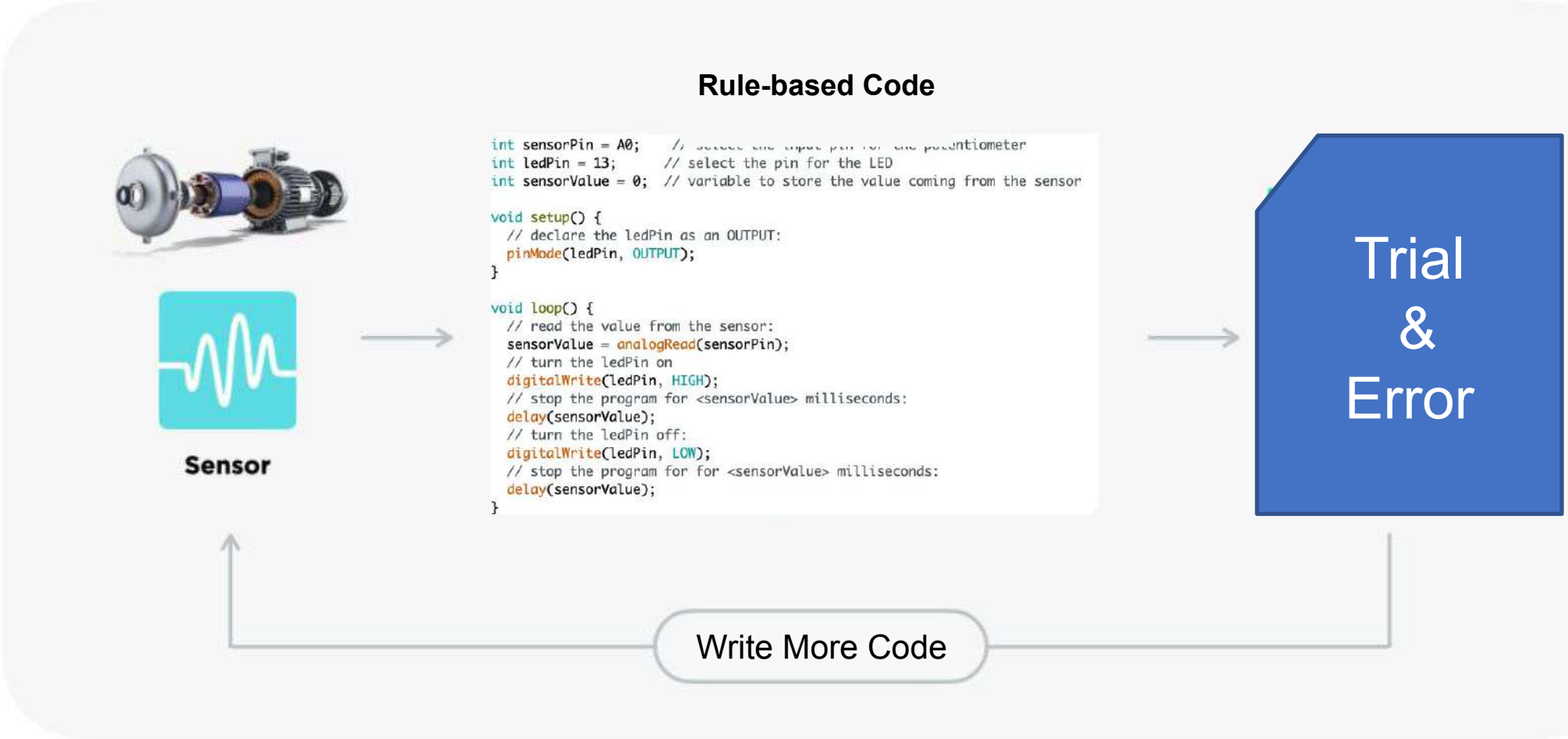
Machine Learning Workflow ("How")



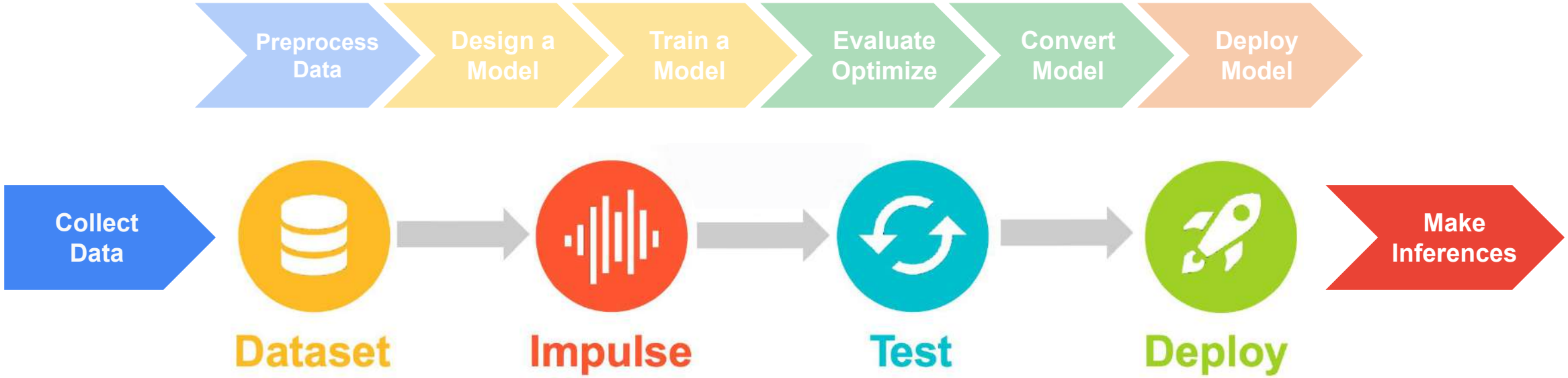
Machine Learning Workflow ("How")



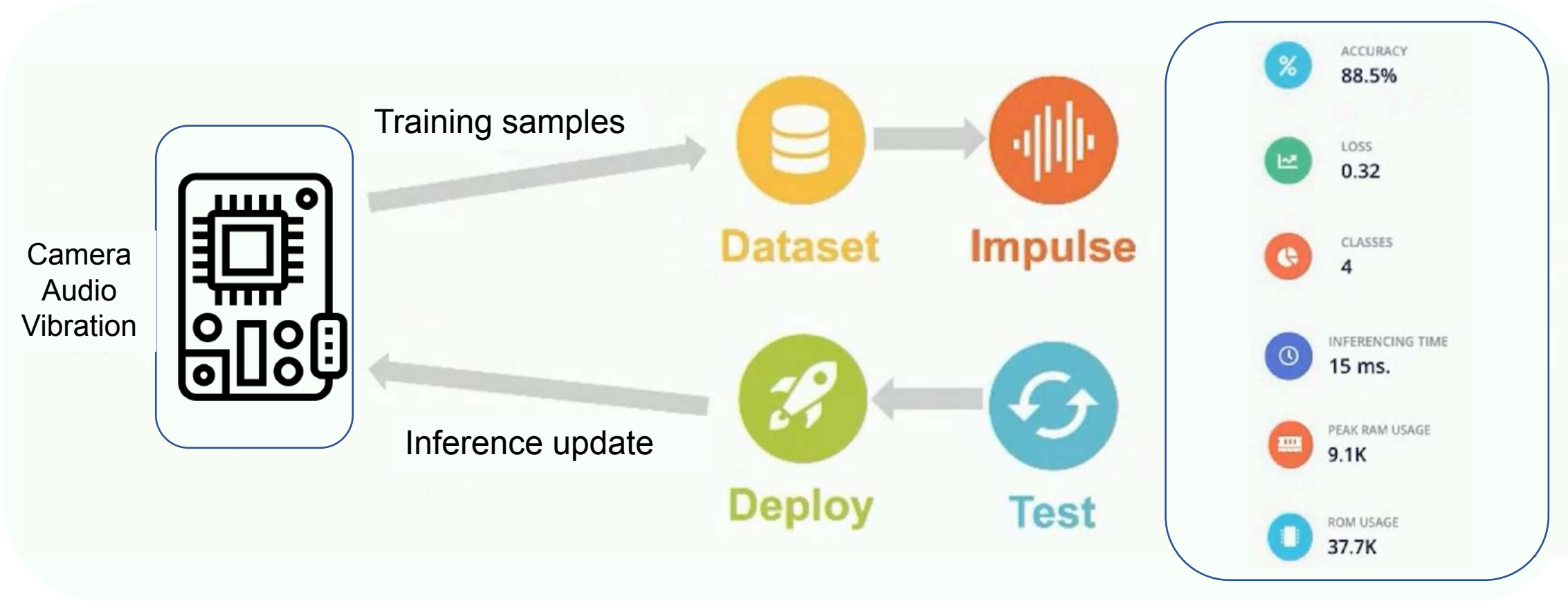
From rule-based engineering to…



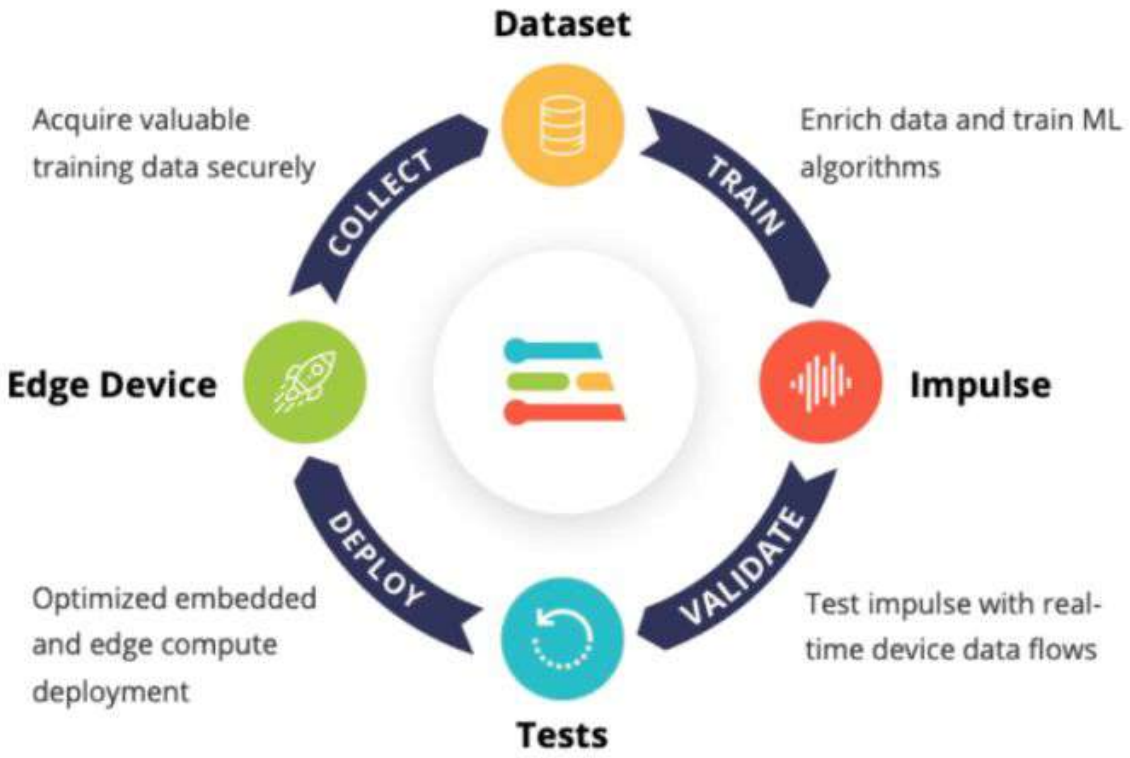
Data-driven engineering

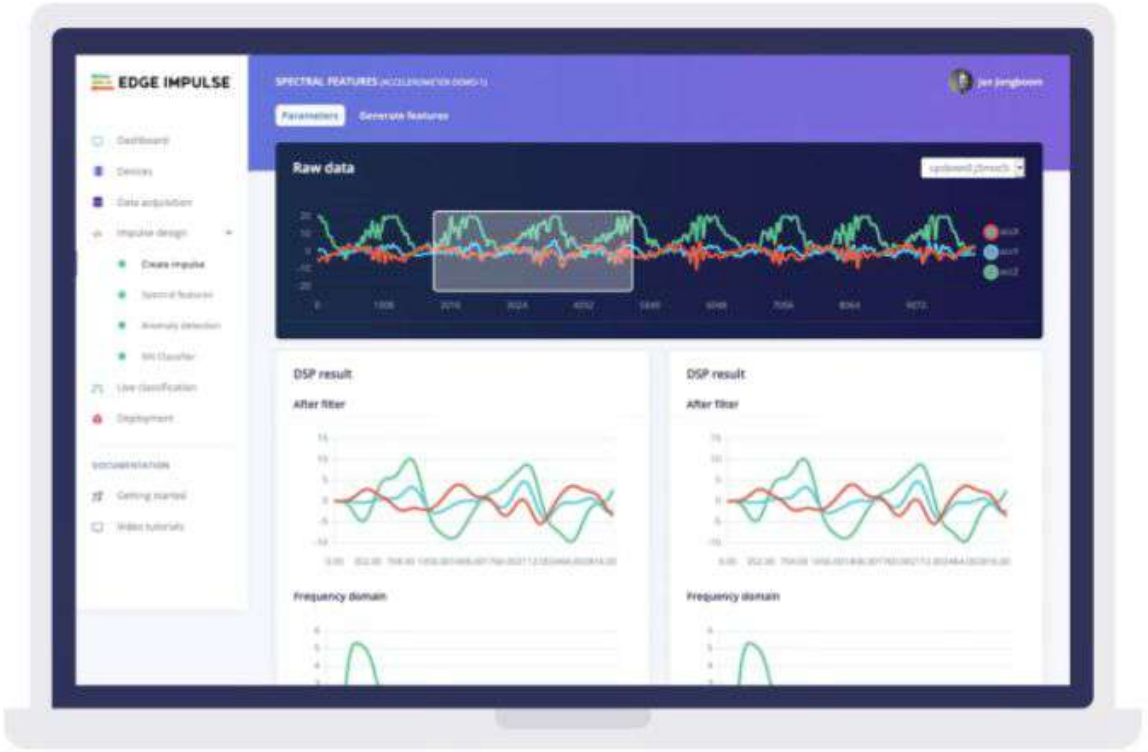

Preprocess Data
Design a Model
Train a Model
Evaluate Optimize
Convert Model
Deploy Model
Collect Data
Dataset
Impulse
Test
Deploy
Make Inferences

Data-driven engineering



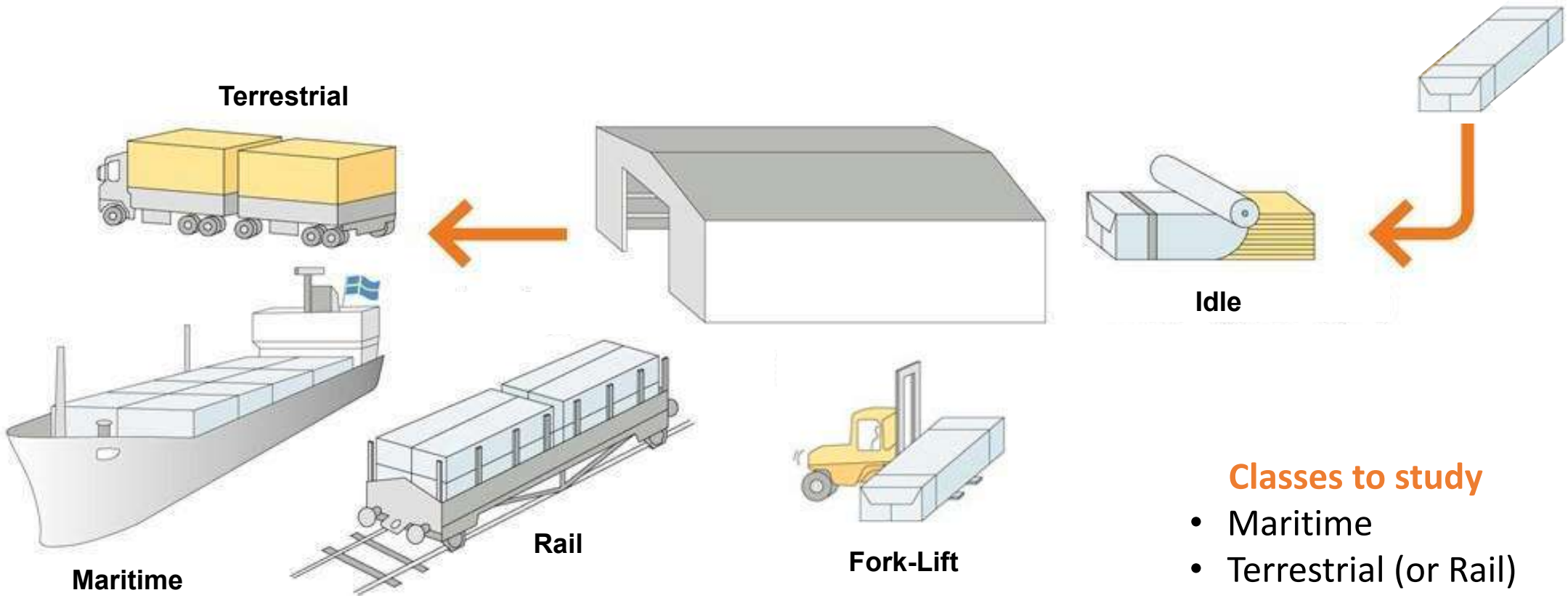
EI Studio - Embedded ML platform ("AutoML")





Learn more at http://edgeimpulse.com

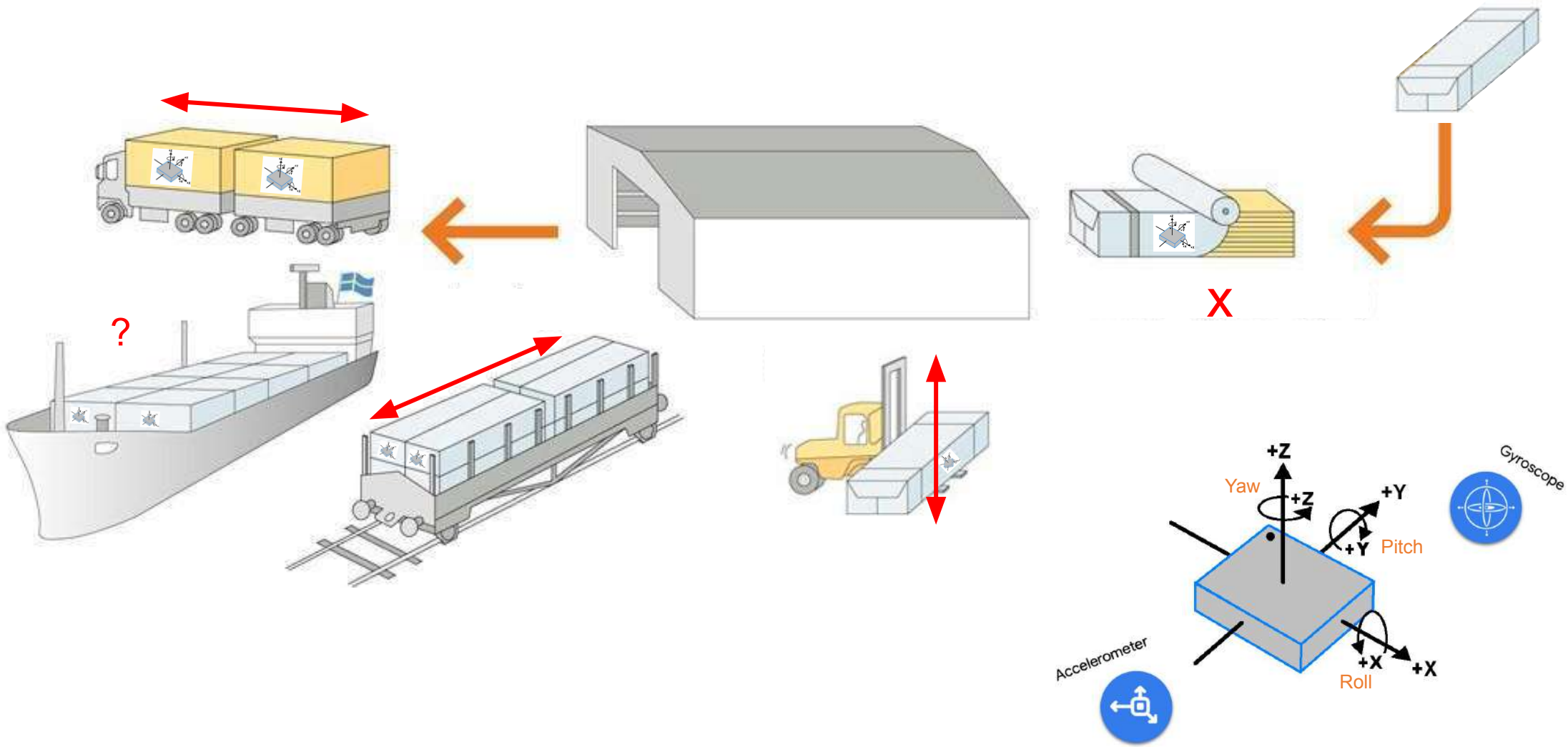
Case Study: Mechanical Stresses in Transport



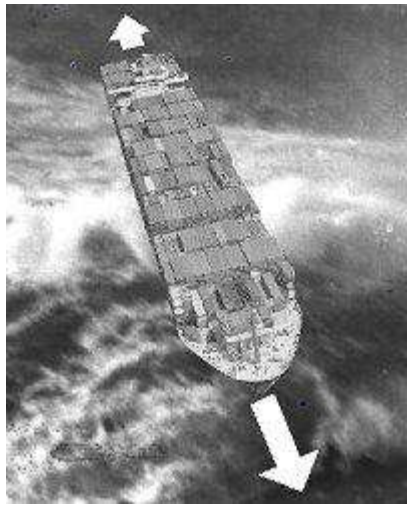
Classes to study

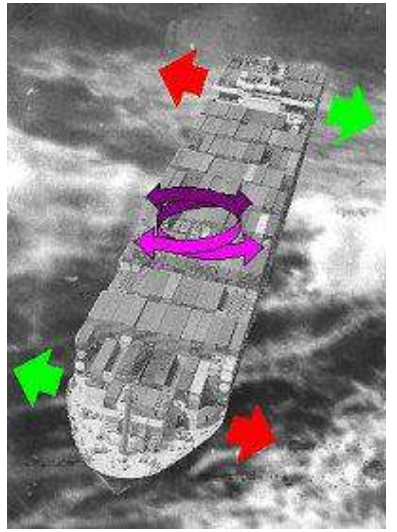
- Maritime
- Terrestrial (or Rail)
- Lift
- Idle

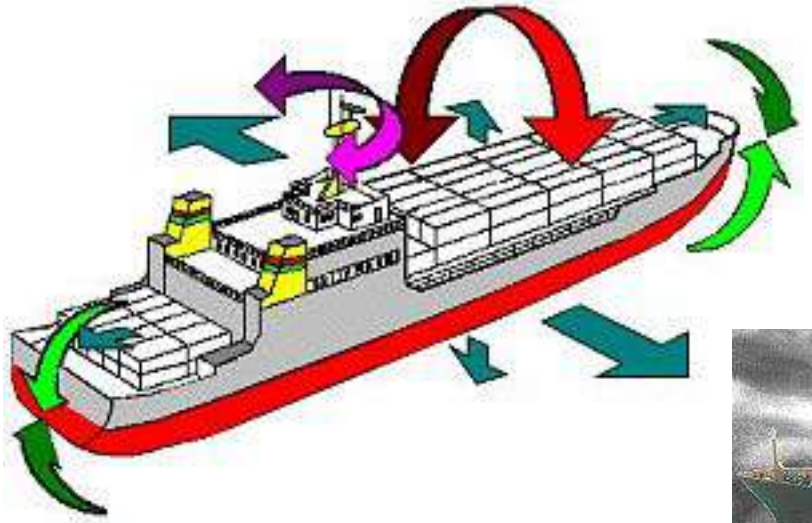
Machine Learning Workflow

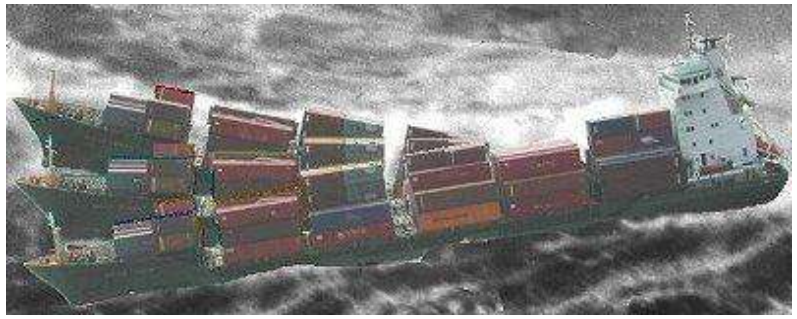

?
X
+Z
Yaw
+Z
+Y
+Y
Pitch
Gyroscope
Accelerometer
+X
+X
Roll

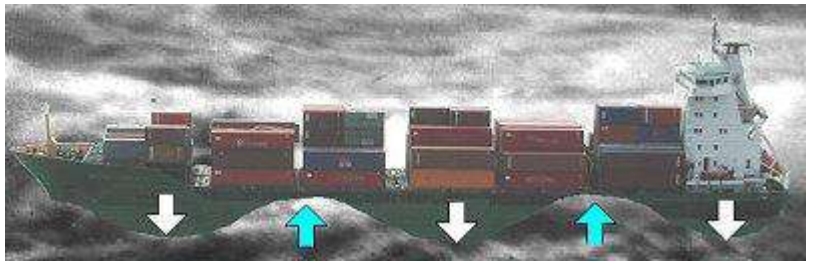
Mechanical Stresses in Maritime Transport





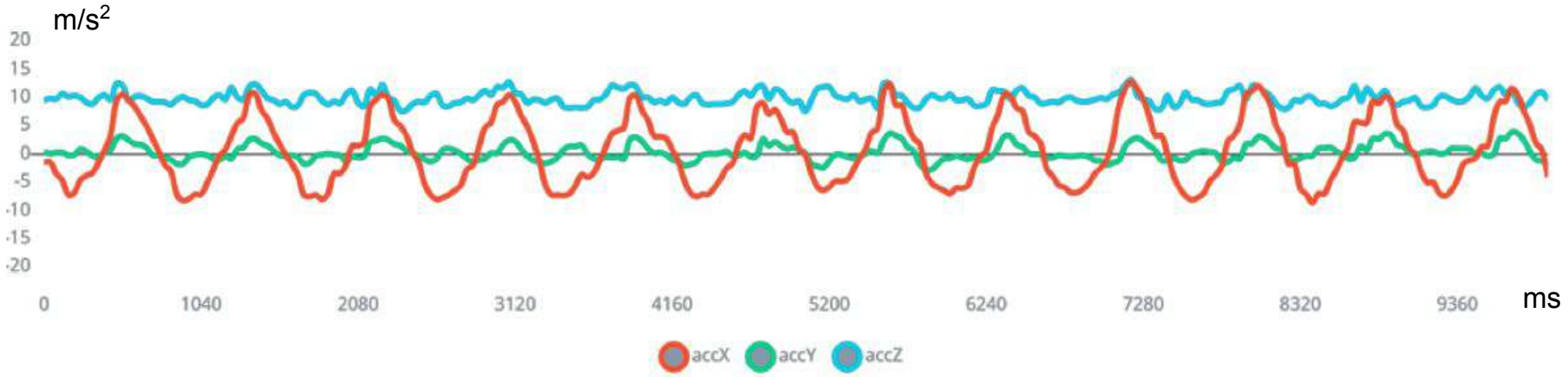


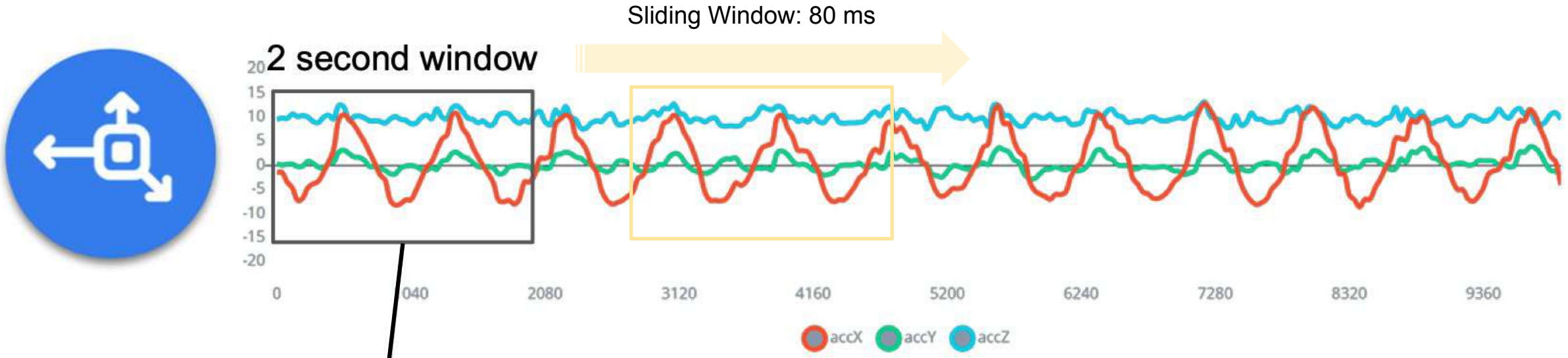




https://www.containerhandbuch.de/chb_e/stra/index.html?/chb_e/stra/stra_02_03_03.html

Example: 10 seconds of accelerometer data, captured with a sample rate: 62.5 Hz





375 Raw Features

- Raw Data from sensor

Manual Feature Extraction

Spectral Analysis

33 Features

- RMS
- FFT
- PSD

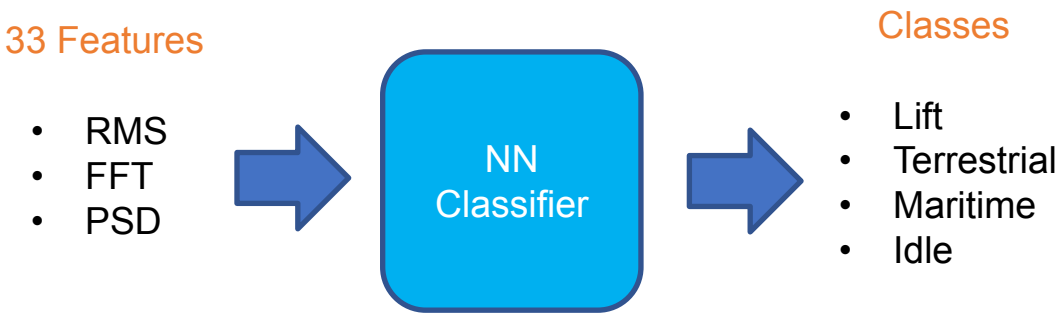
NN Classifier

Classes

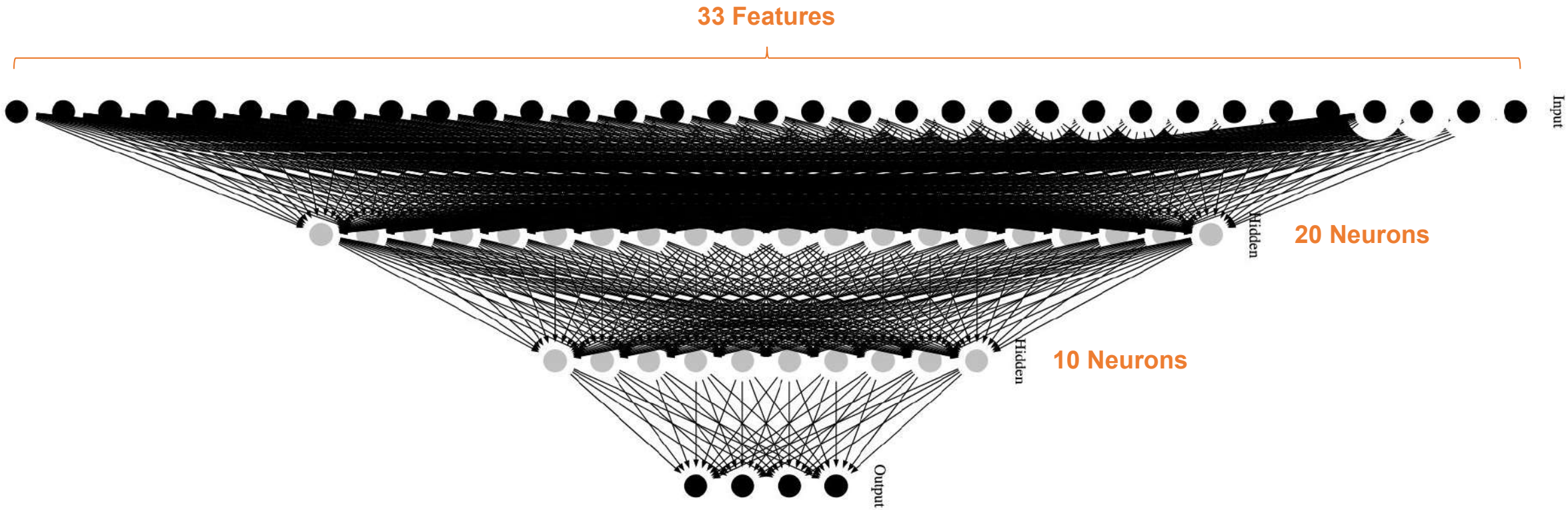
- Lift
- Terrestrial
- Maritime
- Idle

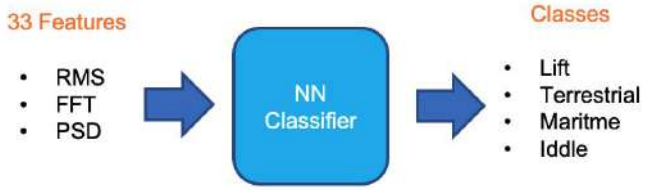
Model Design (NN Classifier)

Model Design (NN Classifier)

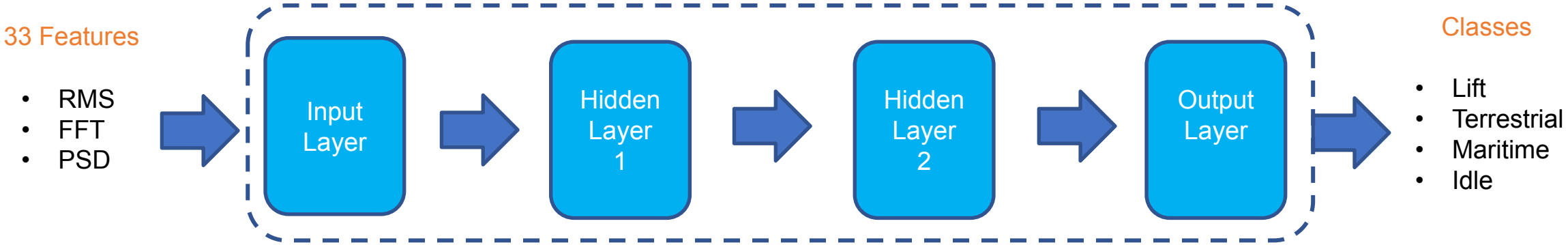


Model Design (DNN Classifier)

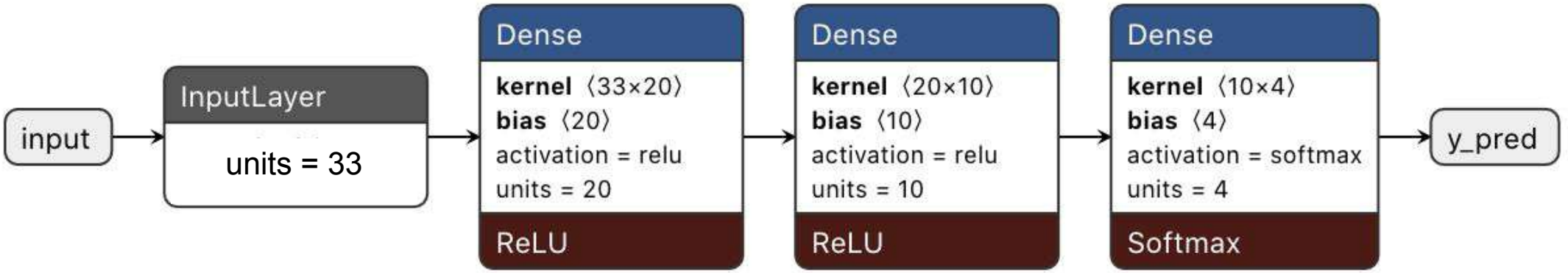




Model Design (DNN Classifier)

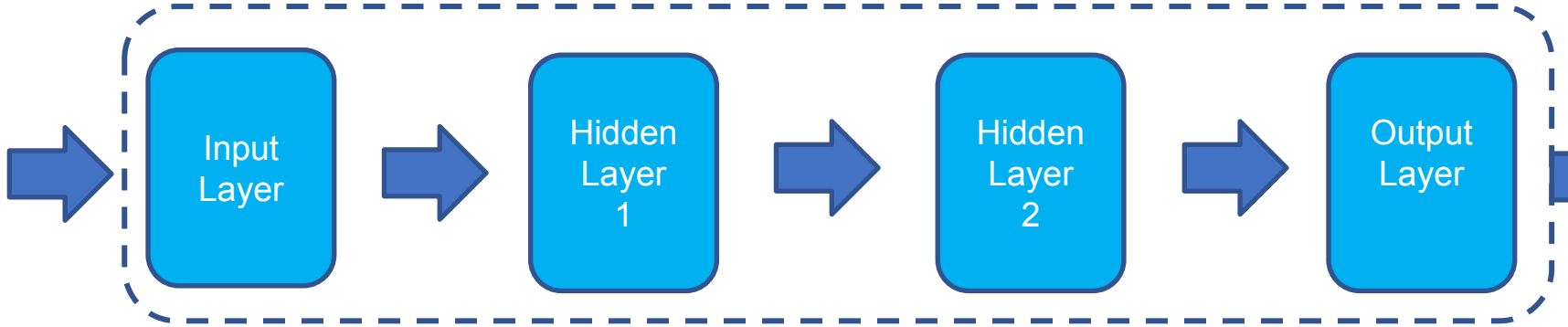


Model Design (DNN Classifier)



33 Features

- RMS
- FFT
- PSD

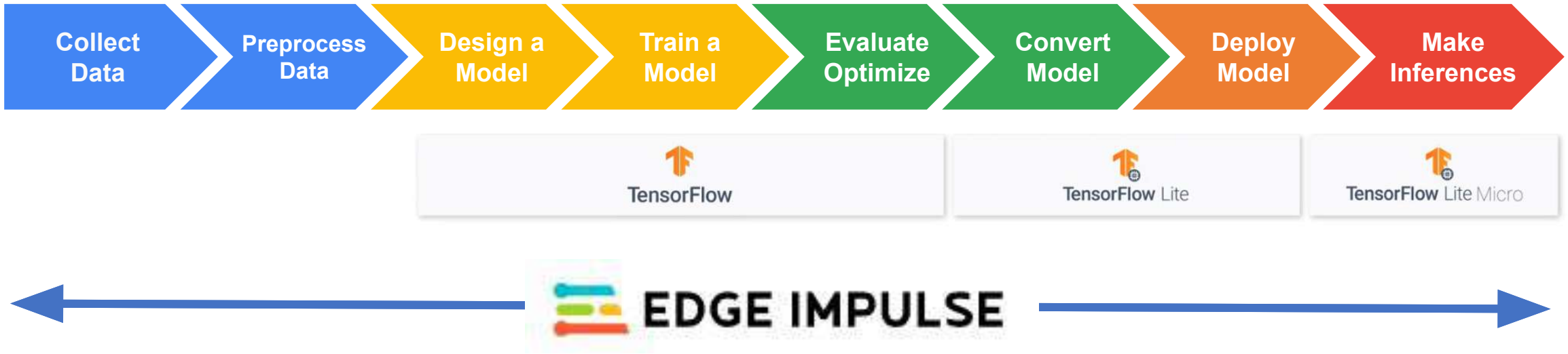


Classes

- Lift
- Terrestrial
- Maritime
- Idle

Train, Evaluate, Convert, Deploy the Model

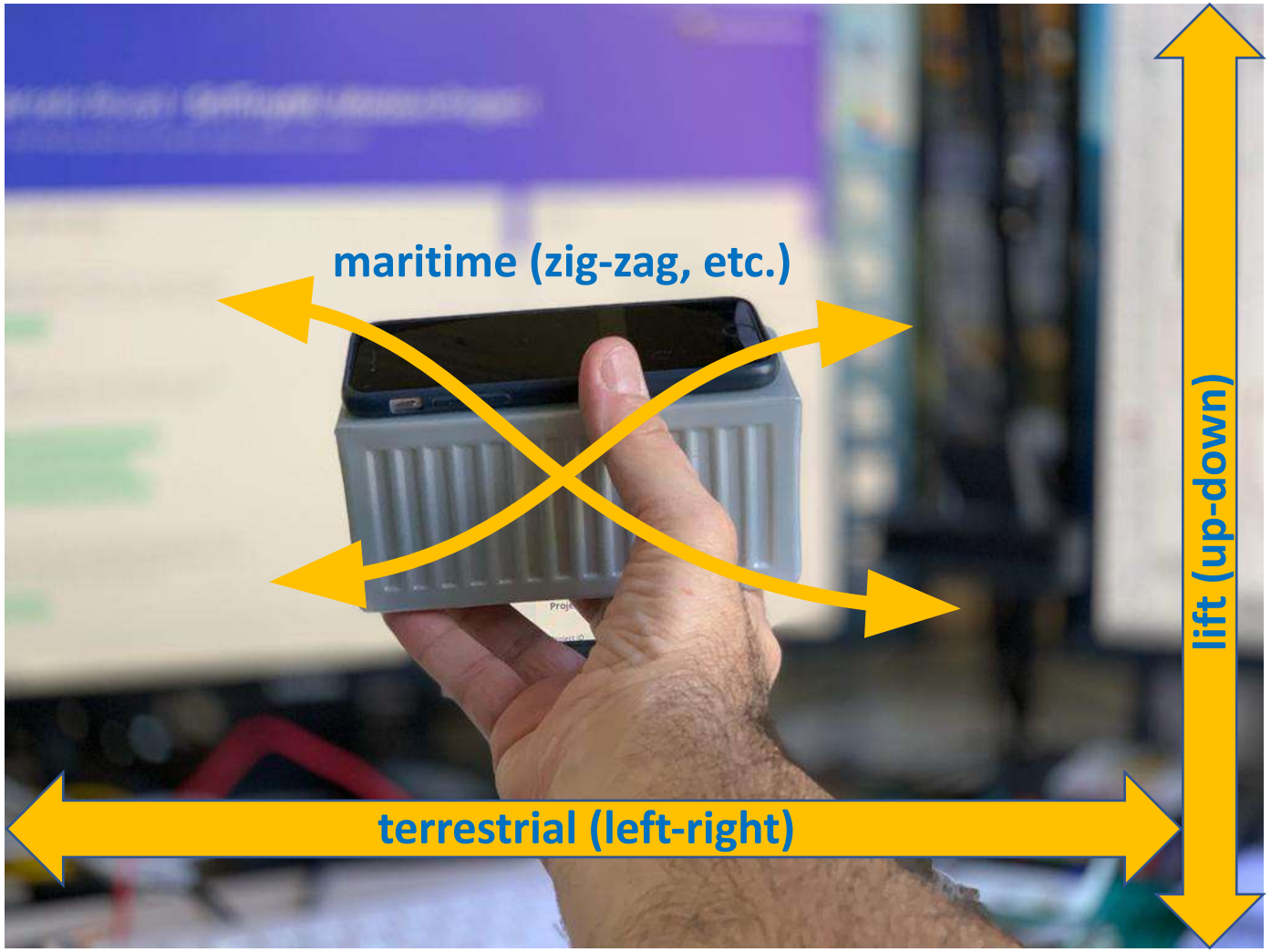
Train, Evaluate, Convert, Deploy the Model



Motion Classification

Transportation Classes:

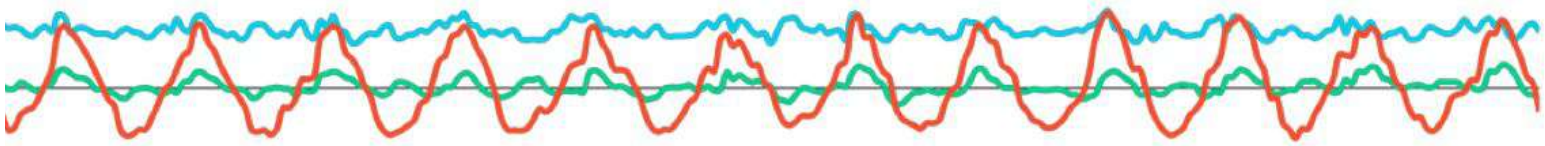
- **lift** (up-down)
- **terrestrial** (left-right)
- **maritime** (zig-zag, etc.)
- **idle**

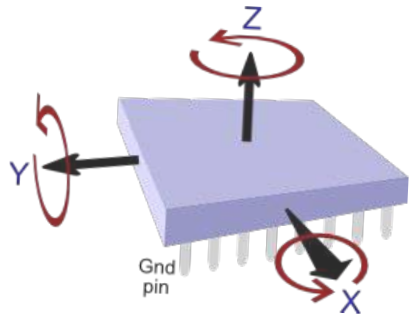


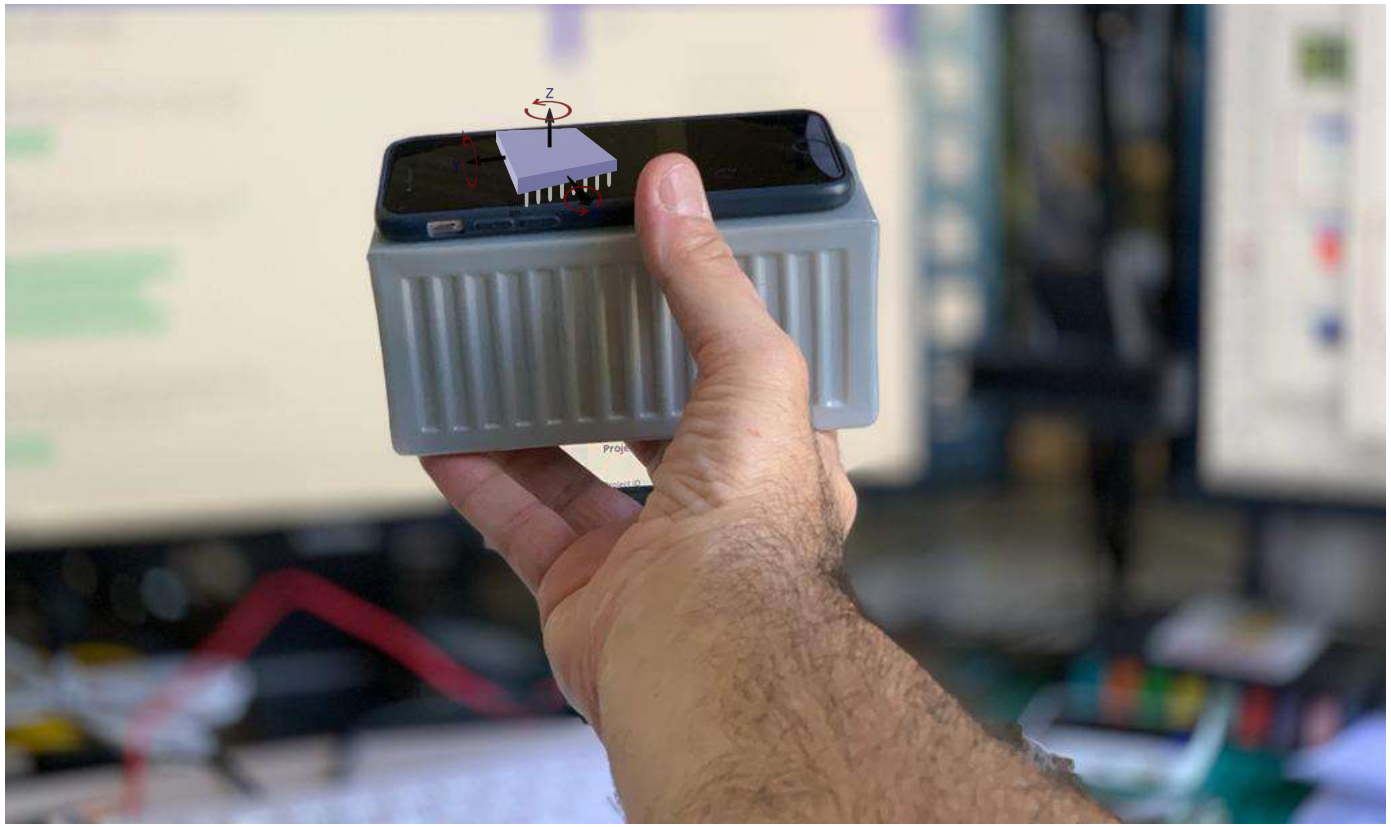
Motion Classification

Transportation Classes

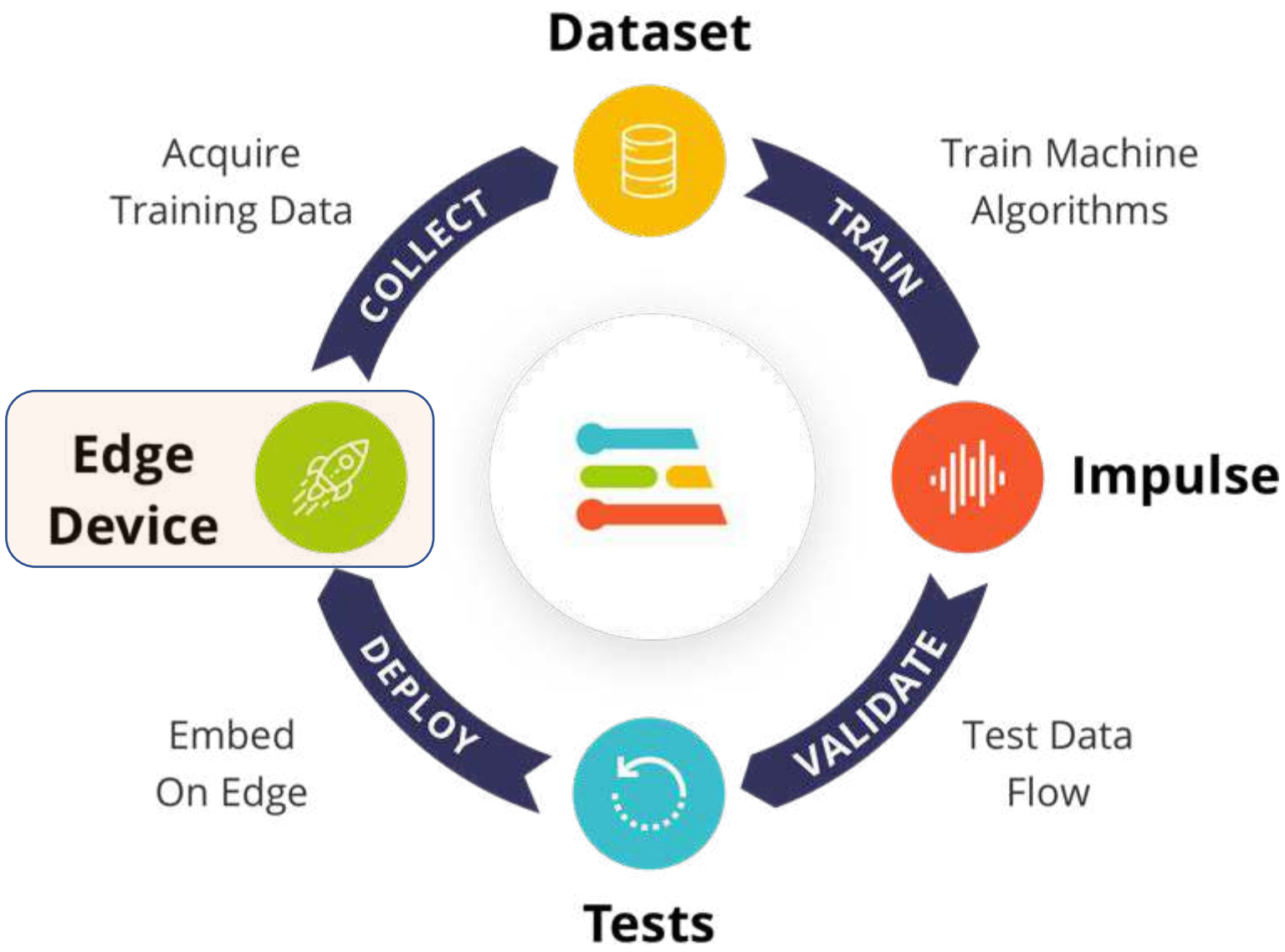
- **lift** (up-down)
- **terrestrial** (left-right)
- **maritime** (zig-zag, etc.)
- **idle**





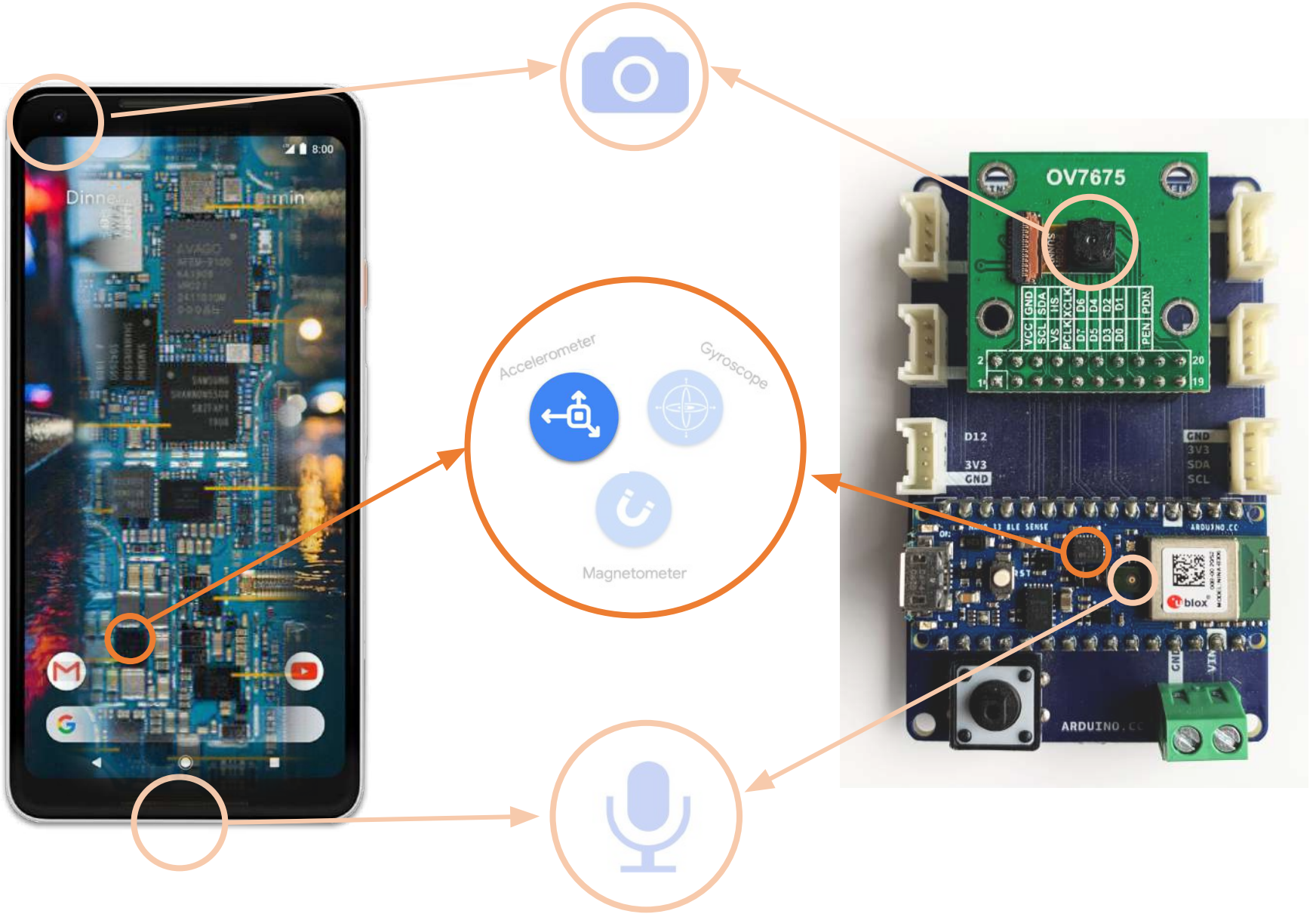


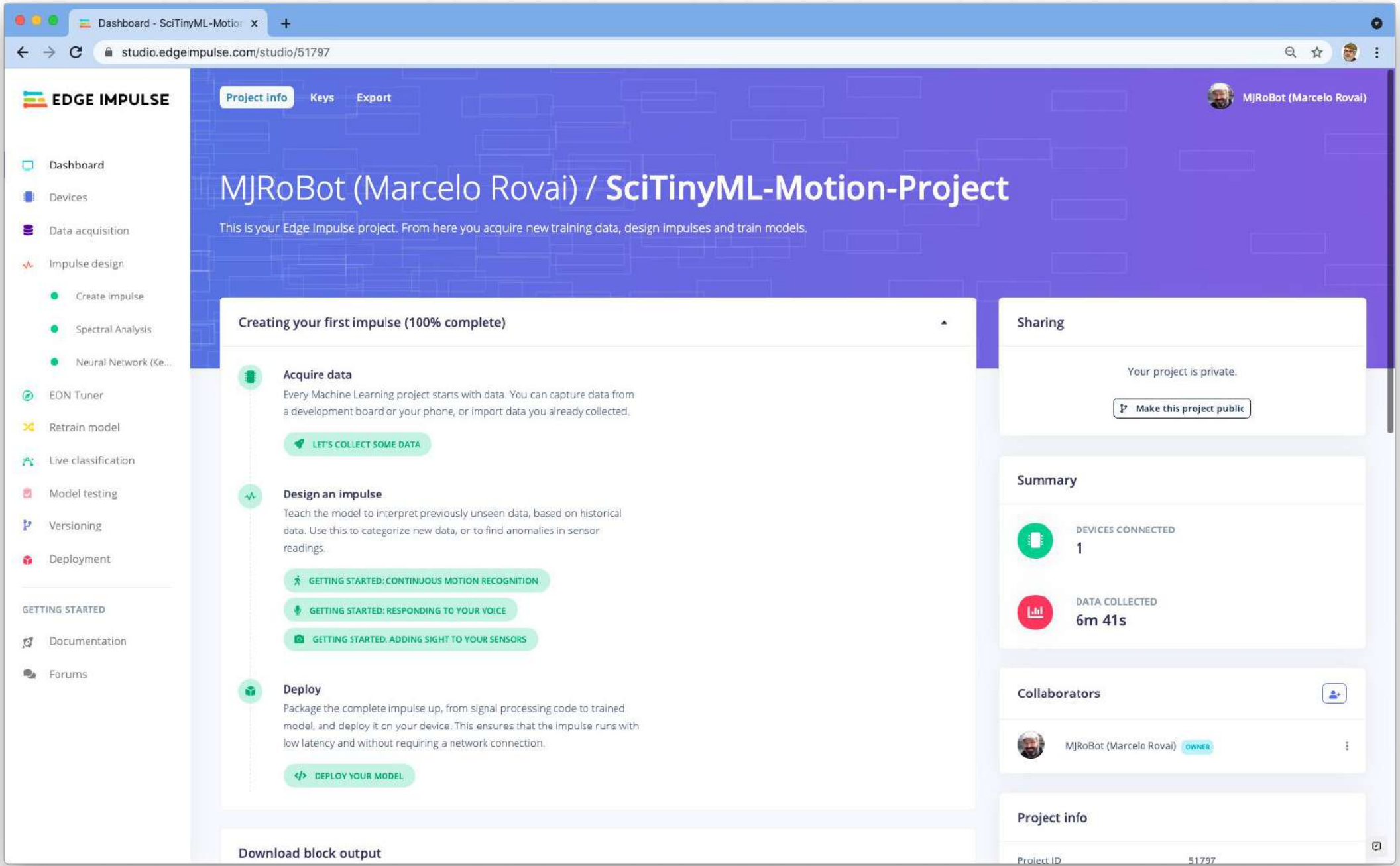
Data: collect & test using accelerometer as sensor

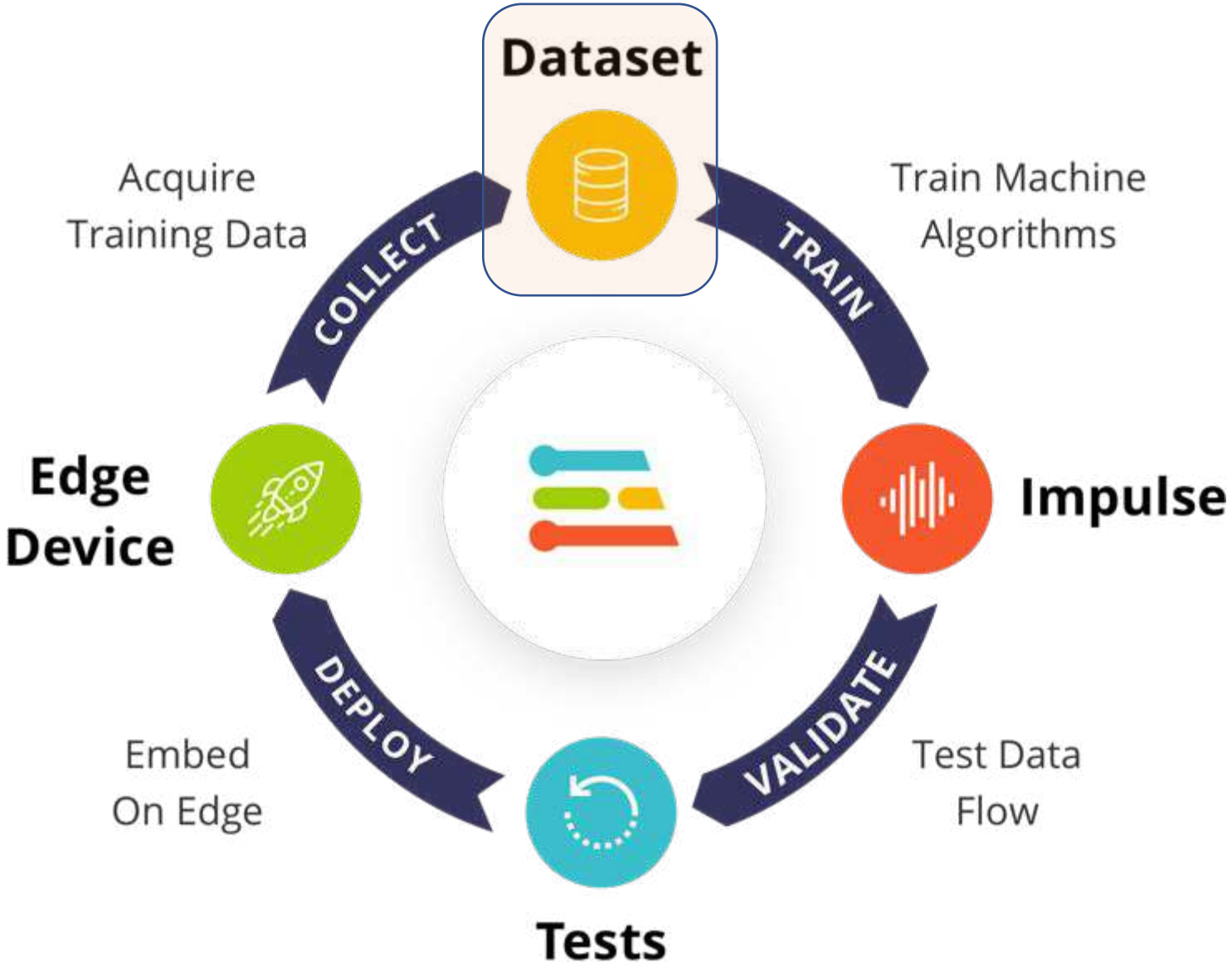


- Pre-Processing Data
- Design a Model
- Train a Model

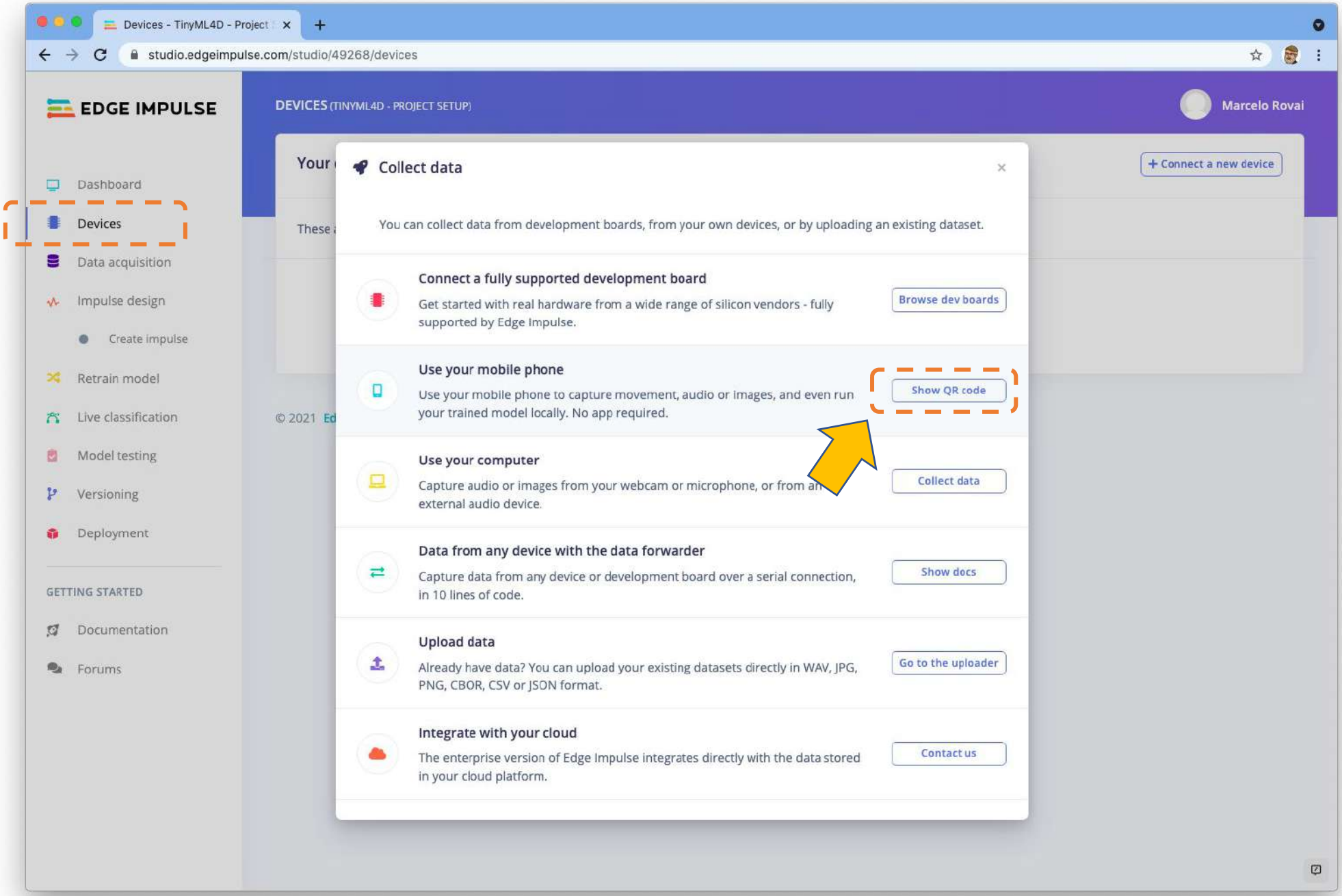
Sensor - IMU (Inertial Measurement Unit)

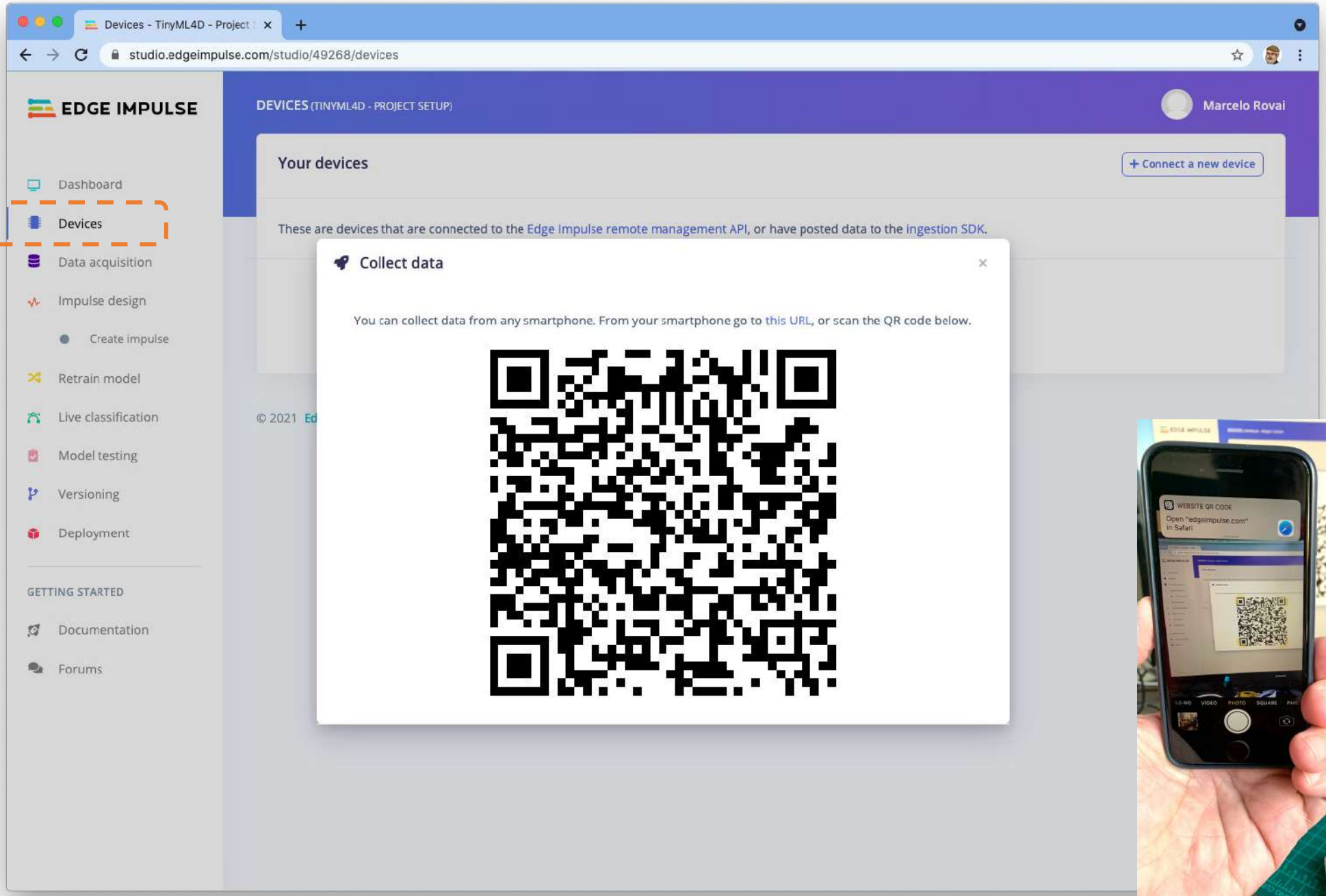



Dashboard - SciTinyML-Motion
studio.edgeimpulse.com/studio/51797
EDGE IMPULSE
Project info
Keys
Export
MJRoBot (Marcelo Rovai)
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Spectral Analysis
Neural Network (Ke...
EON Tuner
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
MJRoBot (Marcelo Rovai) / SciTinyML-Motion-Project
This is your Edge Impulse project. From here you acquire new training data, design impulses and train models.
Creating your first impulse (100% complete)
Acquire data
Every Machine Learning project starts with data. You can capture data from a development board or your phone, or import data you already collected.
LET'S COLLECT SOME DATA
Design an impulse
Teach the model to interpret previously unseen data, based on historical data. Use this to categorize new data, or to find anomalies in sensor readings.
GETTING STARTED: CONTINUOUS MOTION RECOGNITION
GETTING STARTED: RESPONDING TO YOUR VOICE
GETTING STARTED: ADDING SIGHT TO YOUR SENSORS
Deploy
Package the complete impulse up, from signal processing code to trained model, and deploy it on your device. This ensures that the impulse runs with low latency and without requiring a network connection.
DEPLOY YOUR MODEL
Download block output
Sharing
Your project is private.
Make this project public
Summary
DEVICES CONNECTED
1
DATA COLLECTED
6m 41s
Collaborators
MJRoBot (Marcelo Rovai) OWNER
Project info
Project ID
51797

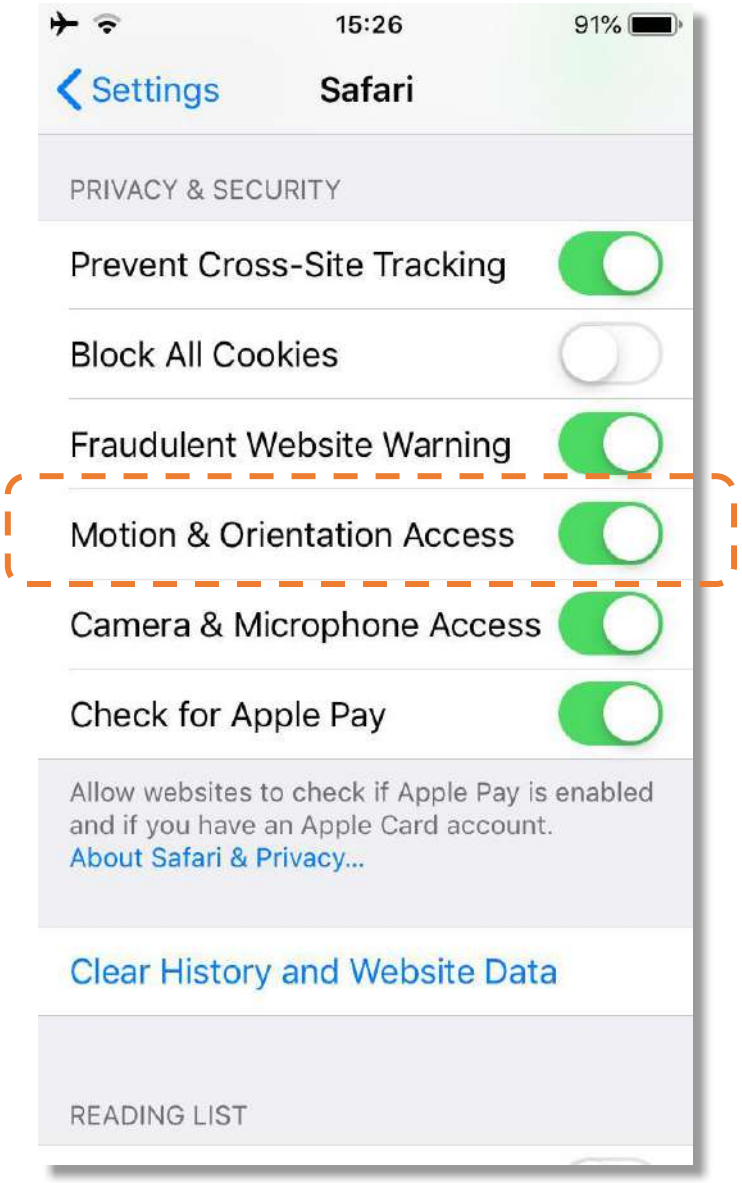


- Pre-Processing Data
- Design a Model
- Train a Model

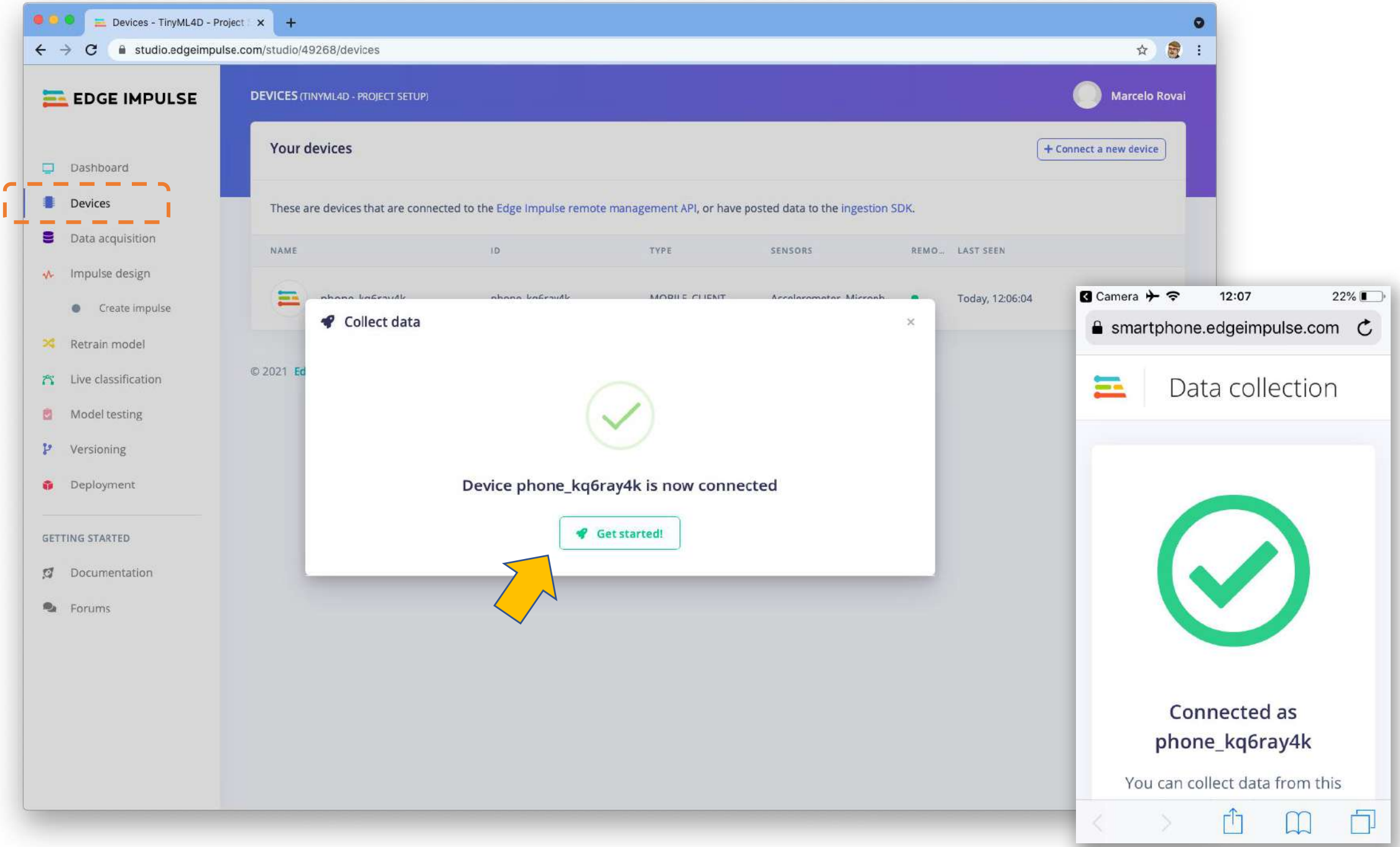

Devices - TinyML4D - Project
studio.edgeimpulse.com/studio/49268/devices
EDGE IMPULSE
DEVICES (TINYML4D - PROJECT SETUP)
Marcelo Rovai
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
+ Connect a new device
Collect data
You can collect data from development boards, from your own devices, or by uploading an existing dataset.
Connect a fully supported development board
Get started with real hardware from a wide range of silicon vendors - fully supported by Edge Impulse.
Browse dev boards
Use your mobile phone
Use your mobile phone to capture movement, audio or images, and even run your trained model locally. No app required.
Show QR code
Use your computer
Capture audio or images from your webcam or microphone, or from an external audio device.
Collect data
Data from any device with the data forwarder
Capture data from any device or development board over a serial connection, in 10 lines of code.
Show docs
Upload data
Already have data? You can upload your existing datasets directly in WAV, JPG, PNG, CBOR, CSV or JSON format.
Go to the uploader
Integrate with your cloud
The enterprise version of Edge Impulse integrates directly with the data stored in your cloud platform.
Contact us

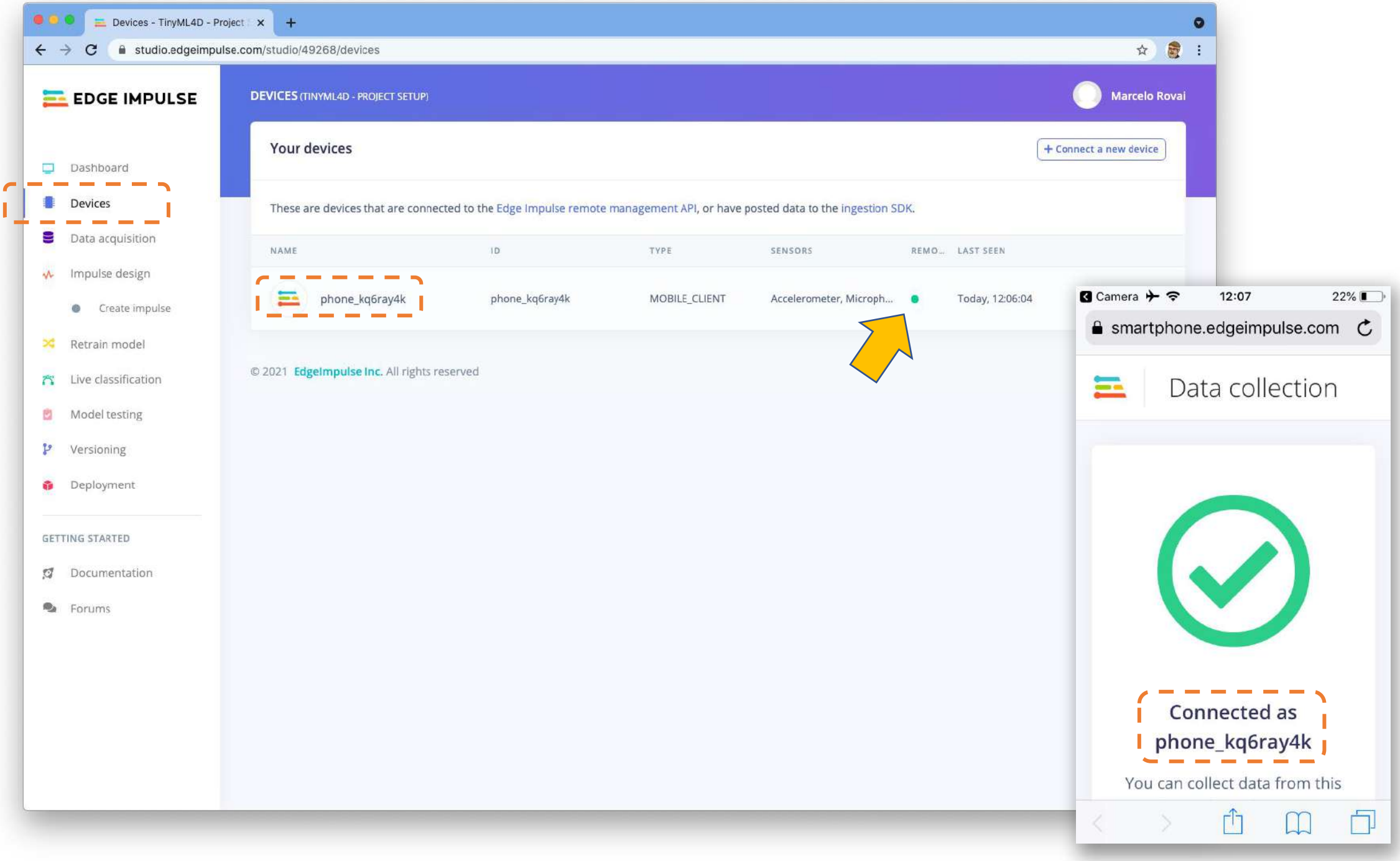

Devices - TinyML4D - Project
studio.edgeimpulse.com/studio/49268/devices
EDGE IMPULSE
DEVICES (TINYML4D - PROJECT SETUP)
Marcelo Rovai
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
Your devices
+ Connect a new device
These are devices that are connected to the Edge Impulse remote management API, or have posted data to the ingestion SDK.
Collect data
You can collect data from any smartphone. From your smartphone go to this URL, or scan the QR code below.

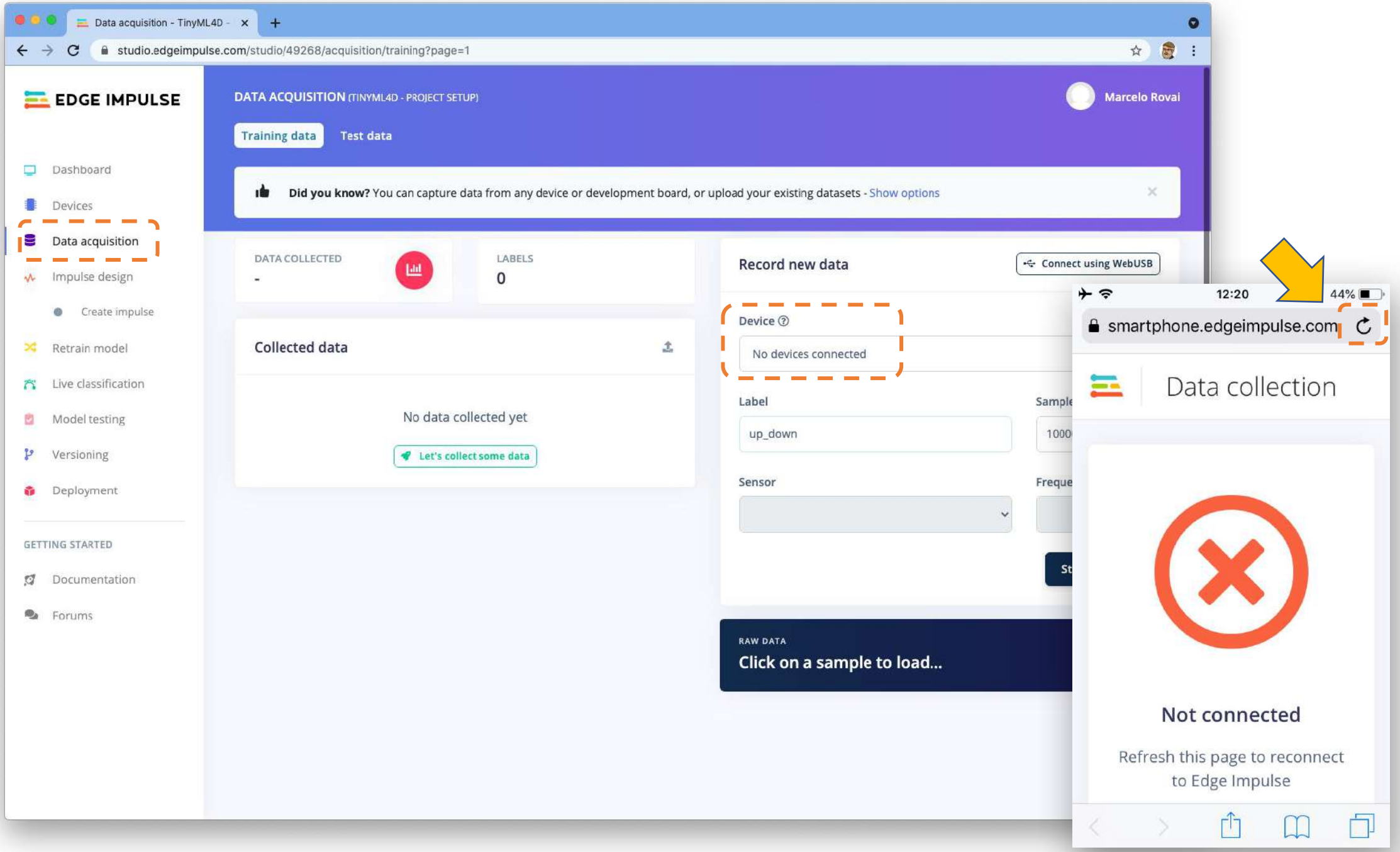

WEBSITE QR CODE
Open "edgeimpulse.com" in Safari



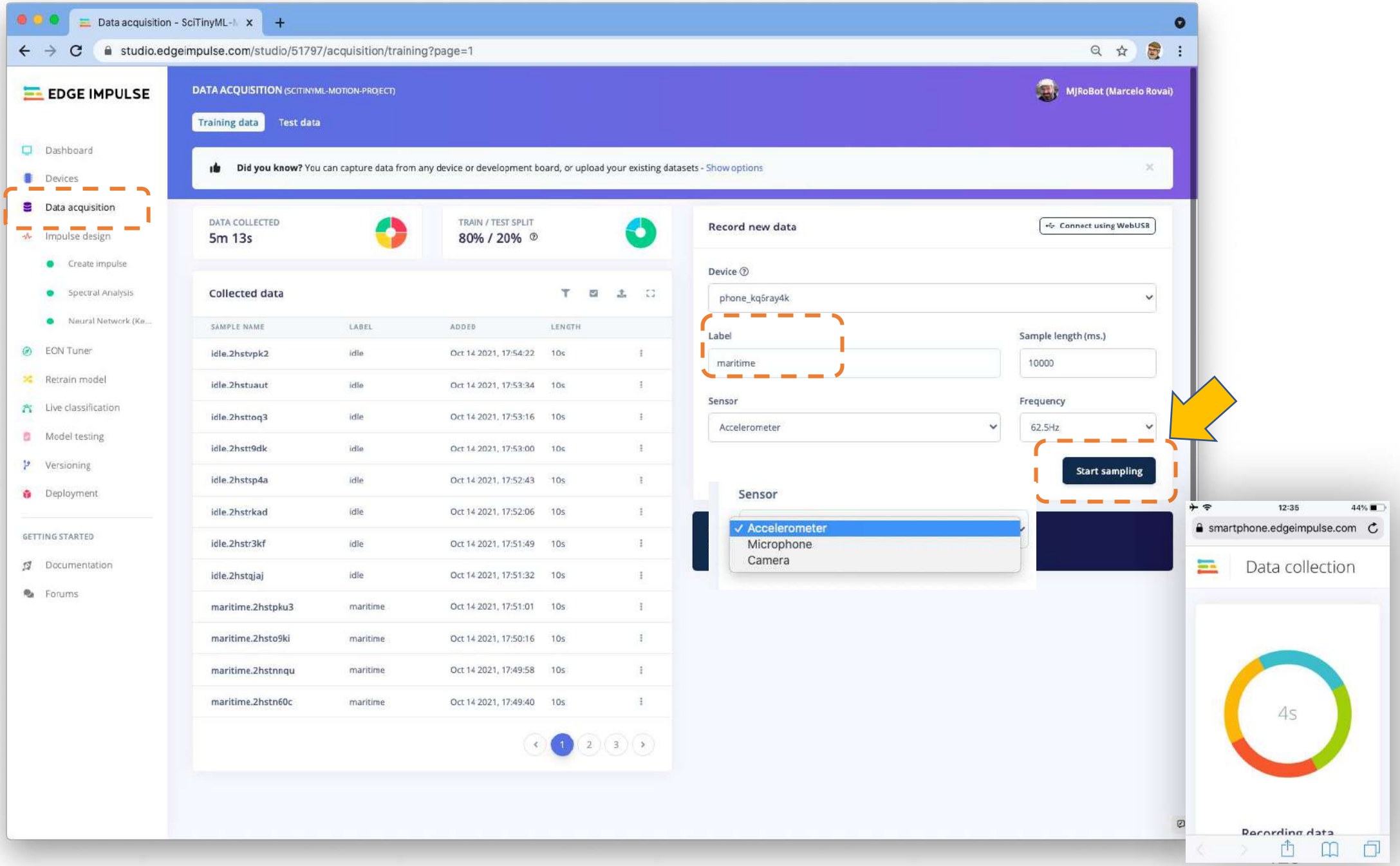
Depending on your mobile OS version and/or your Browser, could be necessary to give access to device IMU sensor


Devices - TinyML4D - Project
studio.edgeimpulse.com/studio/49268/devices
EDGE IMPULSE
DEVICES (TINYML4D - PROJECT SETUP)
Marcelo Rovai
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
Your devices
+ Connect a new device
These are devices that are connected to the Edge Impulse remote management API, or have posted data to the ingestion SDK.
NAME
ID
TYPE
SENSORS
REMO...
LAST SEEN
Today, 12:06:04
© 2021
Collect data
Device phone_kq6ray4k is now connected
Get started!
Camera
12:07
22%
smartphone.edgeimpulse.com
Data collection
Connected as
phone_kq6ray4k
You can collect data from this

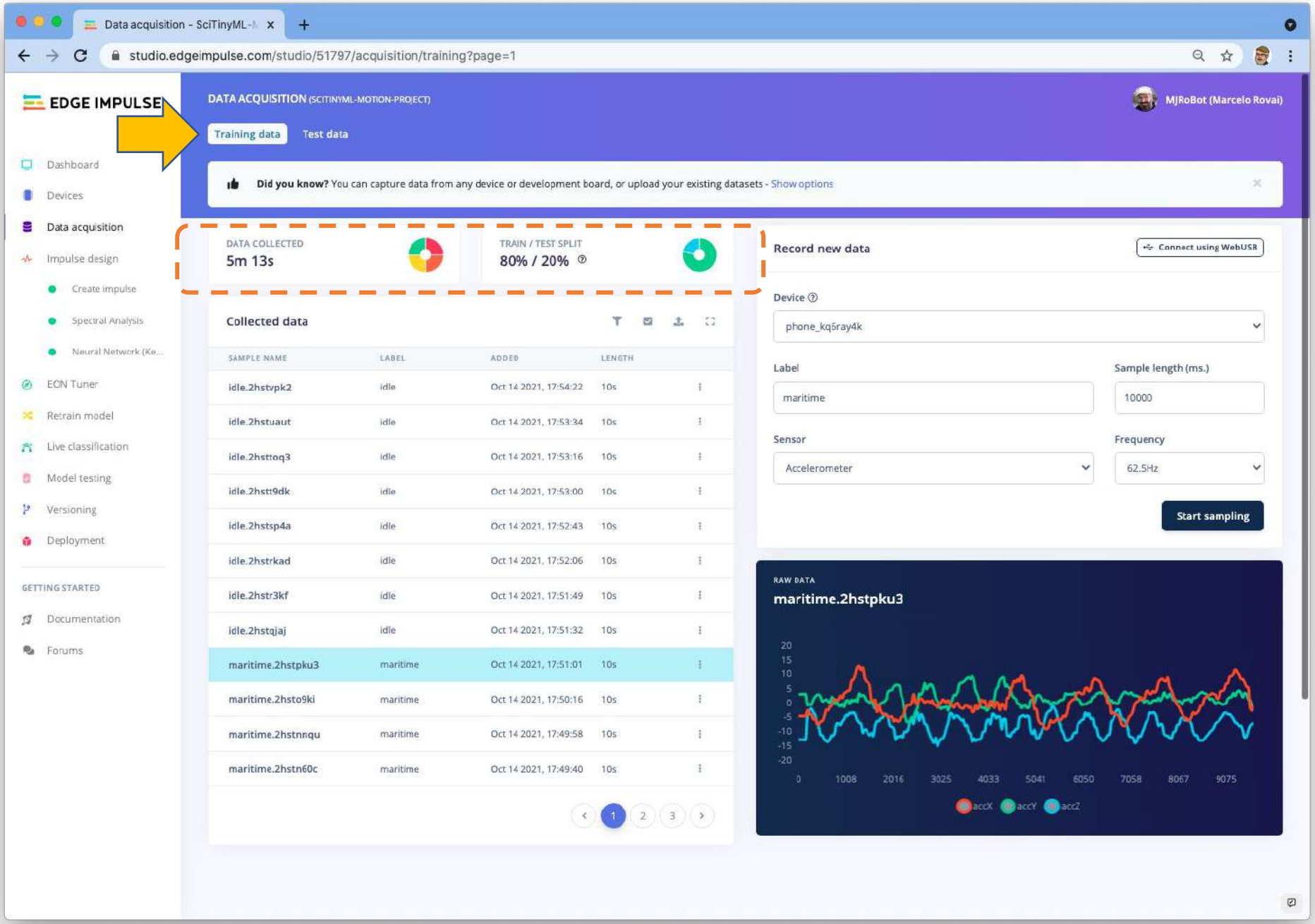

Devices - TinyML4D - Project
studio.edgeimpulse.com/studio/49268/devices
EDGE IMPULSE
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
DEVICES (TINYML4D - PROJECT SETUP)
Marcelo Rovai
Your devices
+ Connect a new device
These are devices that are connected to the Edge Impulse remote management API, or have posted data to the ingestion SDK.
NAME
ID
TYPE
SENSORS
REMO..
LAST SEEN
phone_kq6ray4k
phone_kq6ray4k
MOBILE_CLIENT
Accelerometer, Microph...
Today, 12:06:04
© 2021 EdgeImpulse Inc. All rights reserved
Camera
12:07
22%
smartphone.edgeimpulse.com
Data collection
Connected as
phone_kq6ray4k
You can collect data from this


Data acquisition - TinyML4D -
studio.edgeimpulse.com/studio/49268/acquisition/training?page=1
EDGE IMPULSE
DATA ACQUISITION (TINYML4D - PROJECT SETUP)
Marcelo Rovai
Training data
Test data
Did you know? You can capture data from any device or development board, or upload your existing datasets - Show options
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
DATA COLLECTED
-
LABELS
0
Collected data
No data collected yet
Let's collect some data
Record new data
Connect using WebUSB
Device
No devices connected
Label
up_down
Sensor
RAW DATA
Click on a sample to load...
12:20
44%
smartphone.edgeimpulse.com
Data collection
Not connected
Refresh this page to reconnect to Edge Impulse

Collect Data



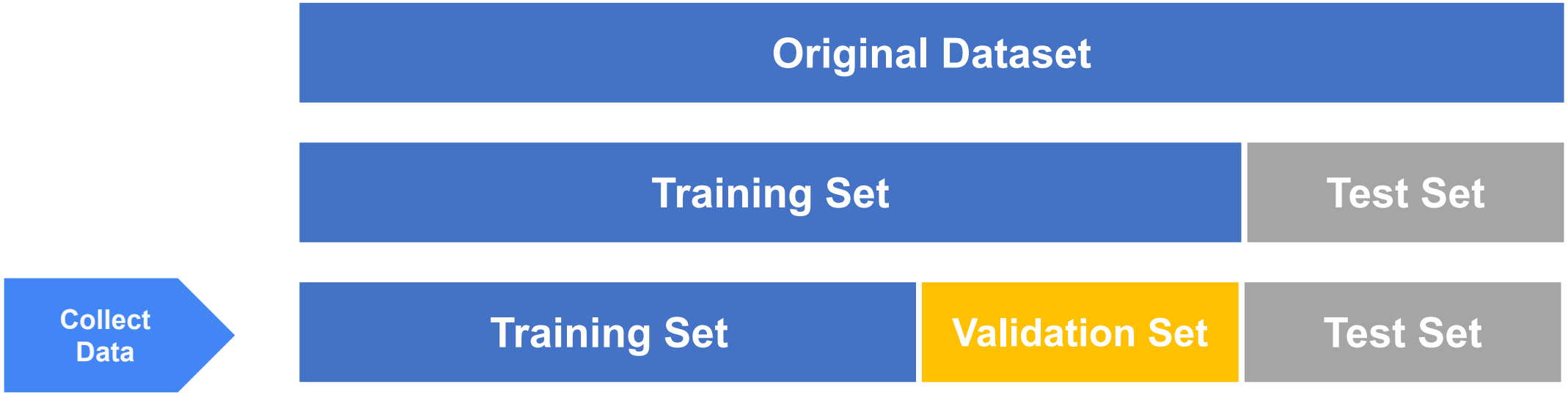
Collect Data

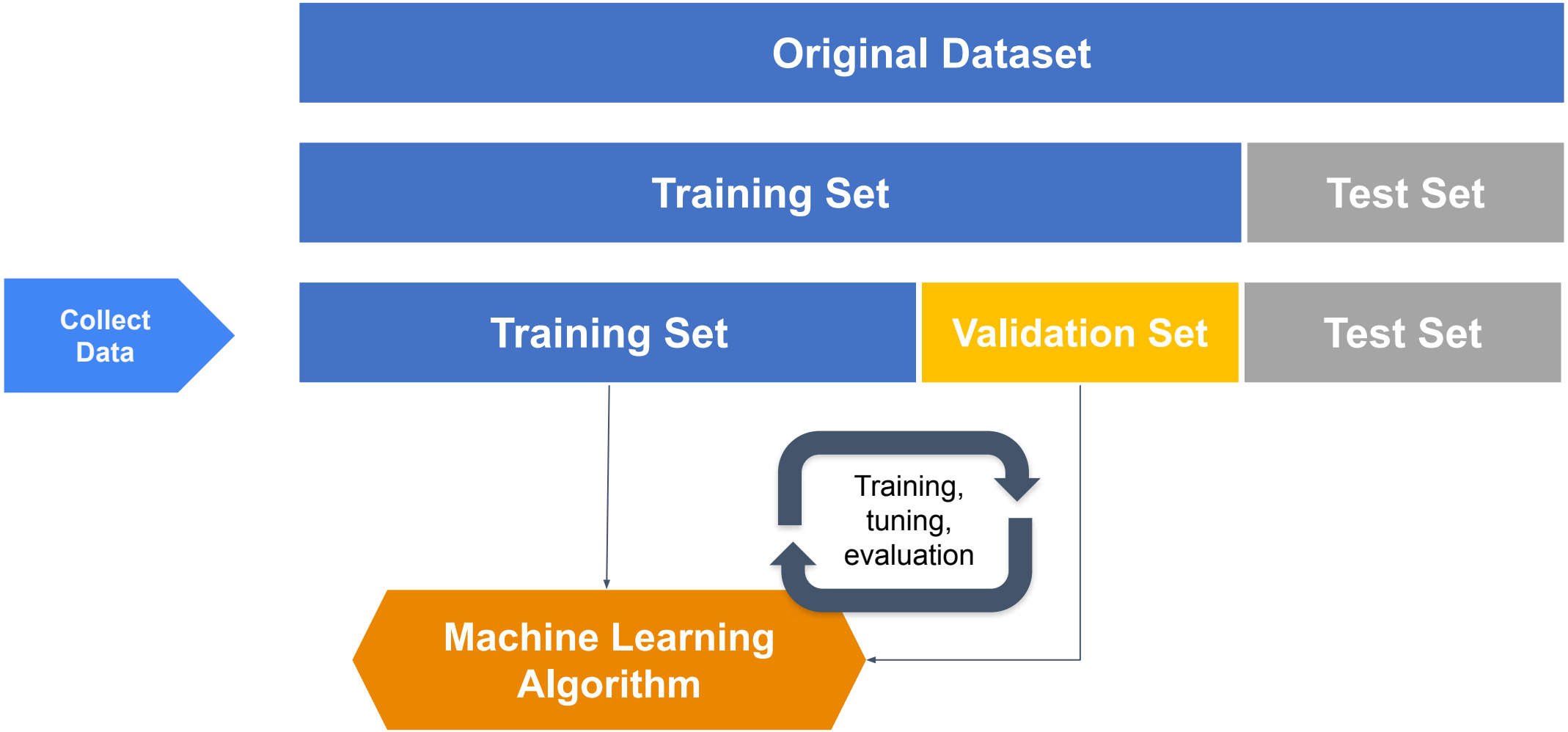


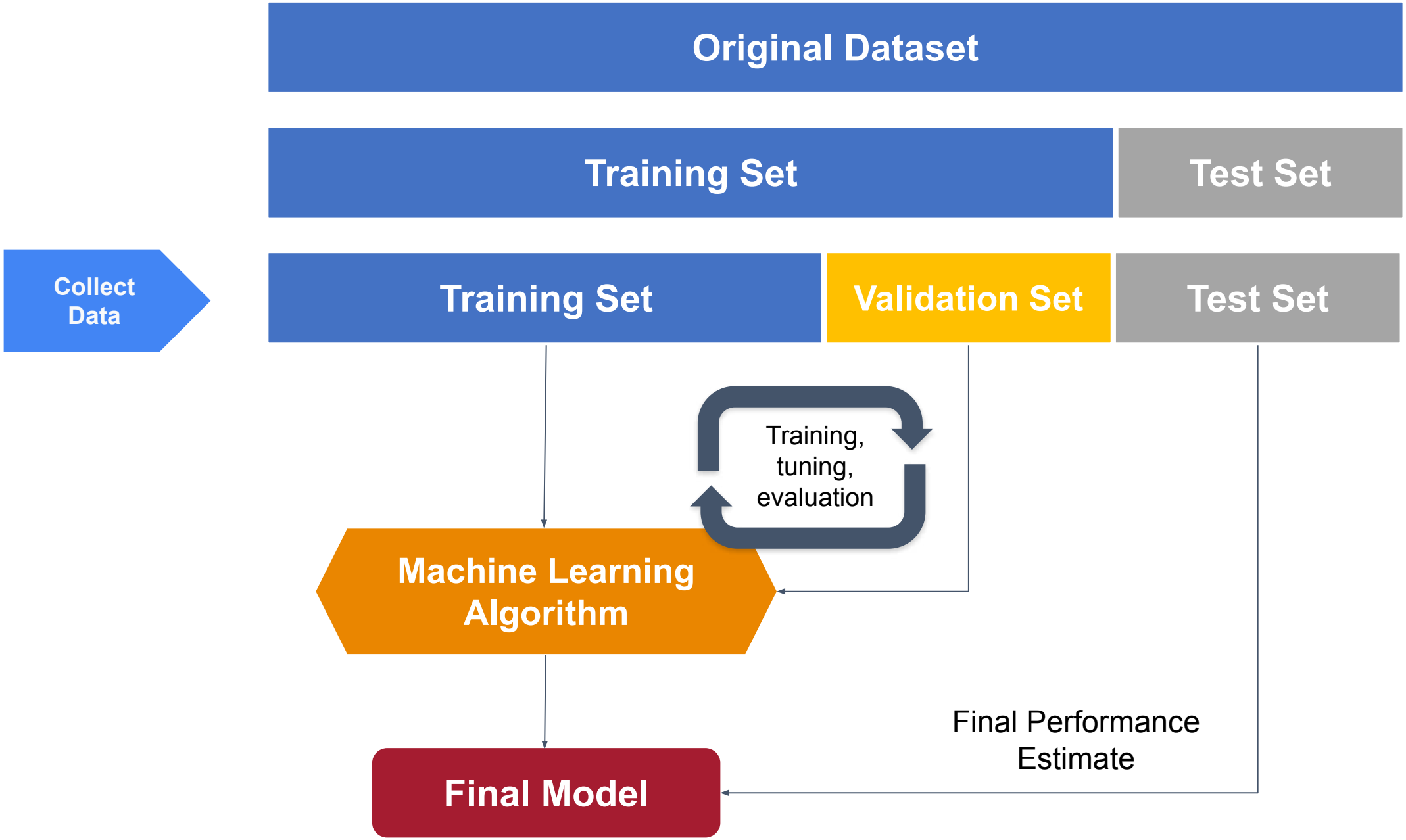
Collect Data

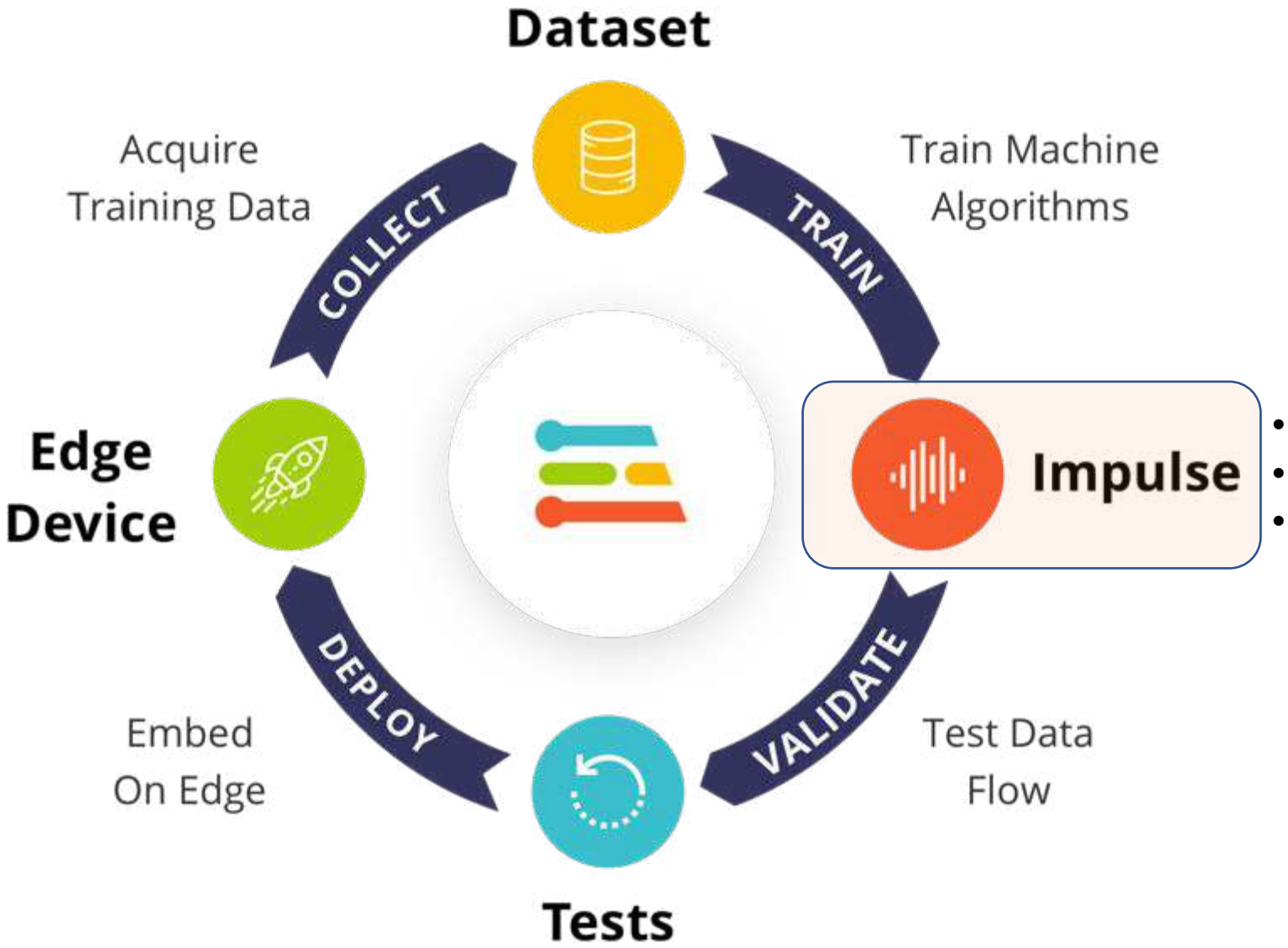
Original Dataset


Original Dataset
Collect Data
Training Set
Test Set

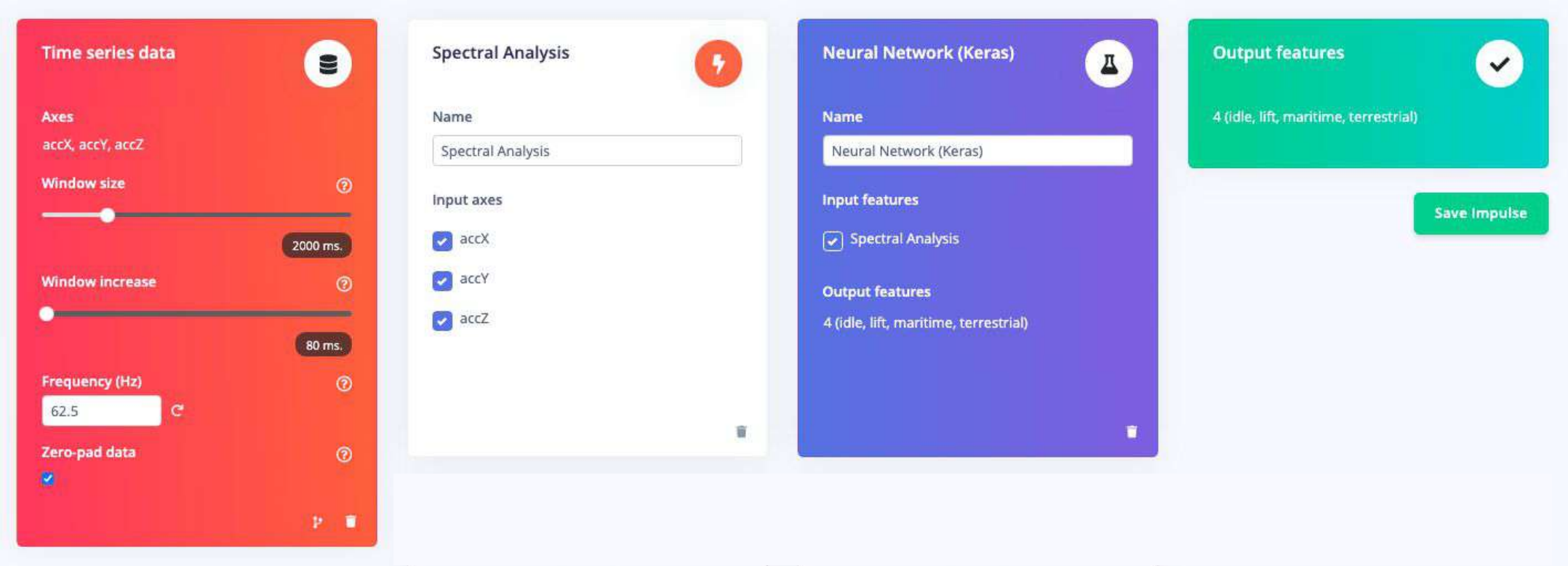

Original Dataset
Training Set
Test Set
Collect Data
Training Set
Validation Set
Test Set

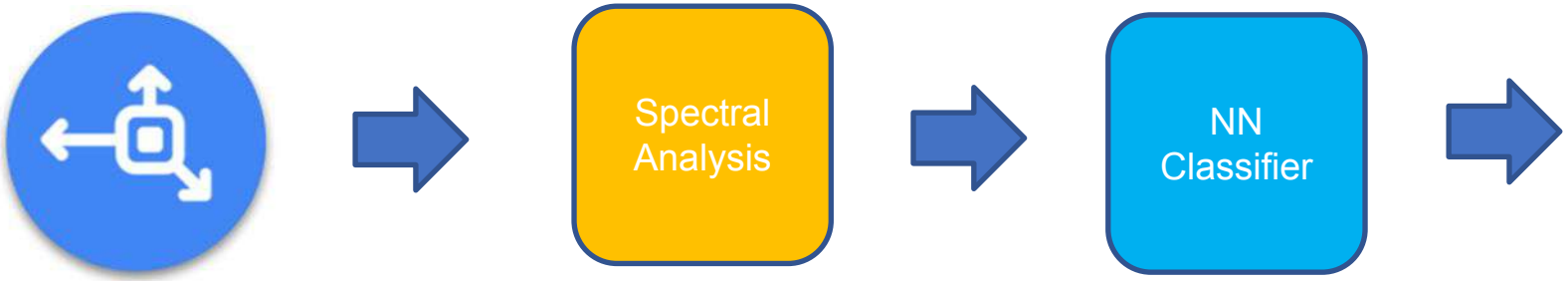

Original Dataset
Training Set
Test Set
Collect Data
Training Set
Validation Set
Test Set
Training, tuning, evaluation
Machine Learning Algorithm


Original Dataset
Training Set
Test Set
Collect Data
Training Set
Validation Set
Test Set
Training, tuning, evaluation
Machine Learning Algorithm
Final Performance Estimate
Final Model



- Pre-Processing Data
- Design a Model
- Train a Model

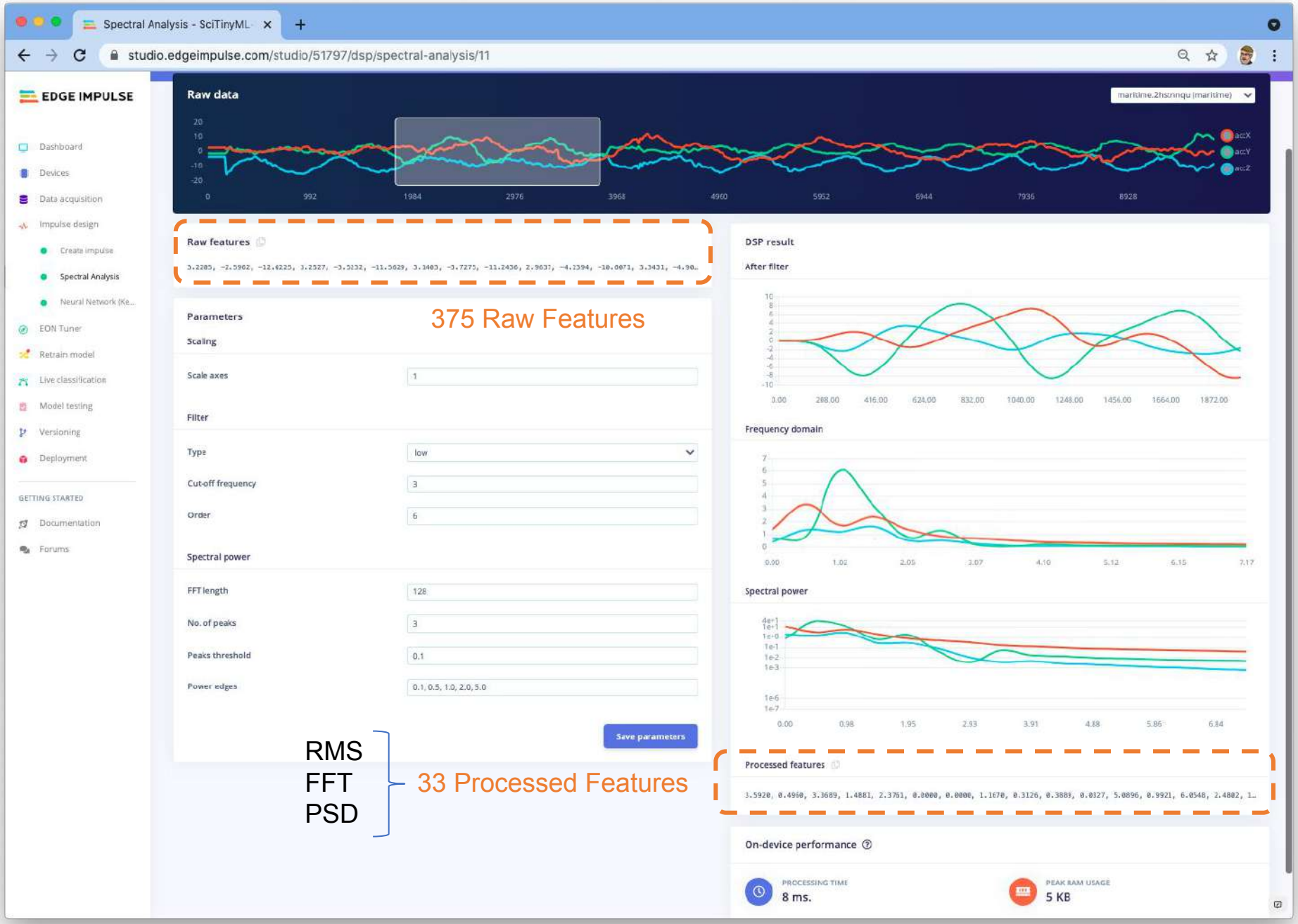




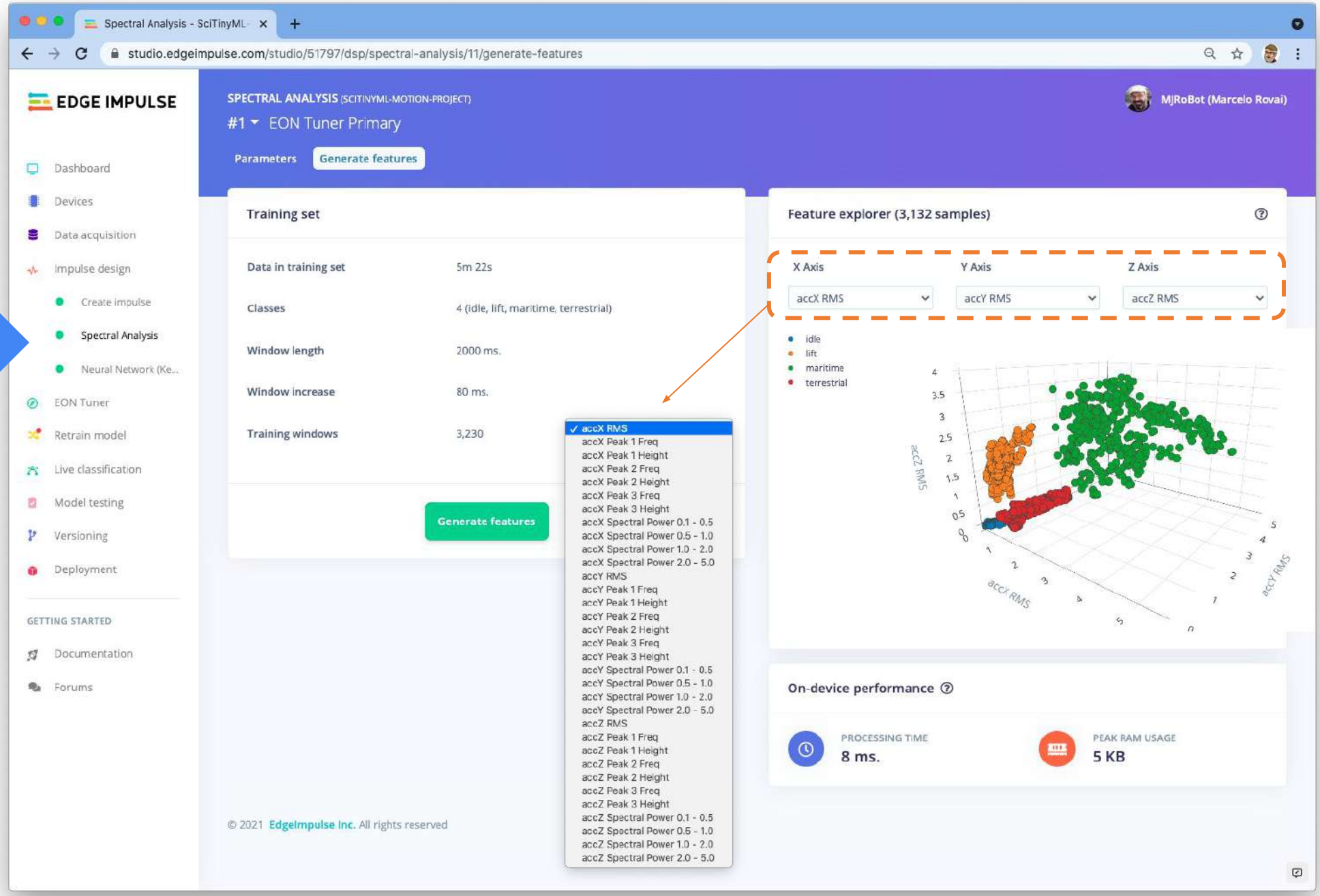
Classes

- Lift
- Terrestrial
- Maritime
- Idle

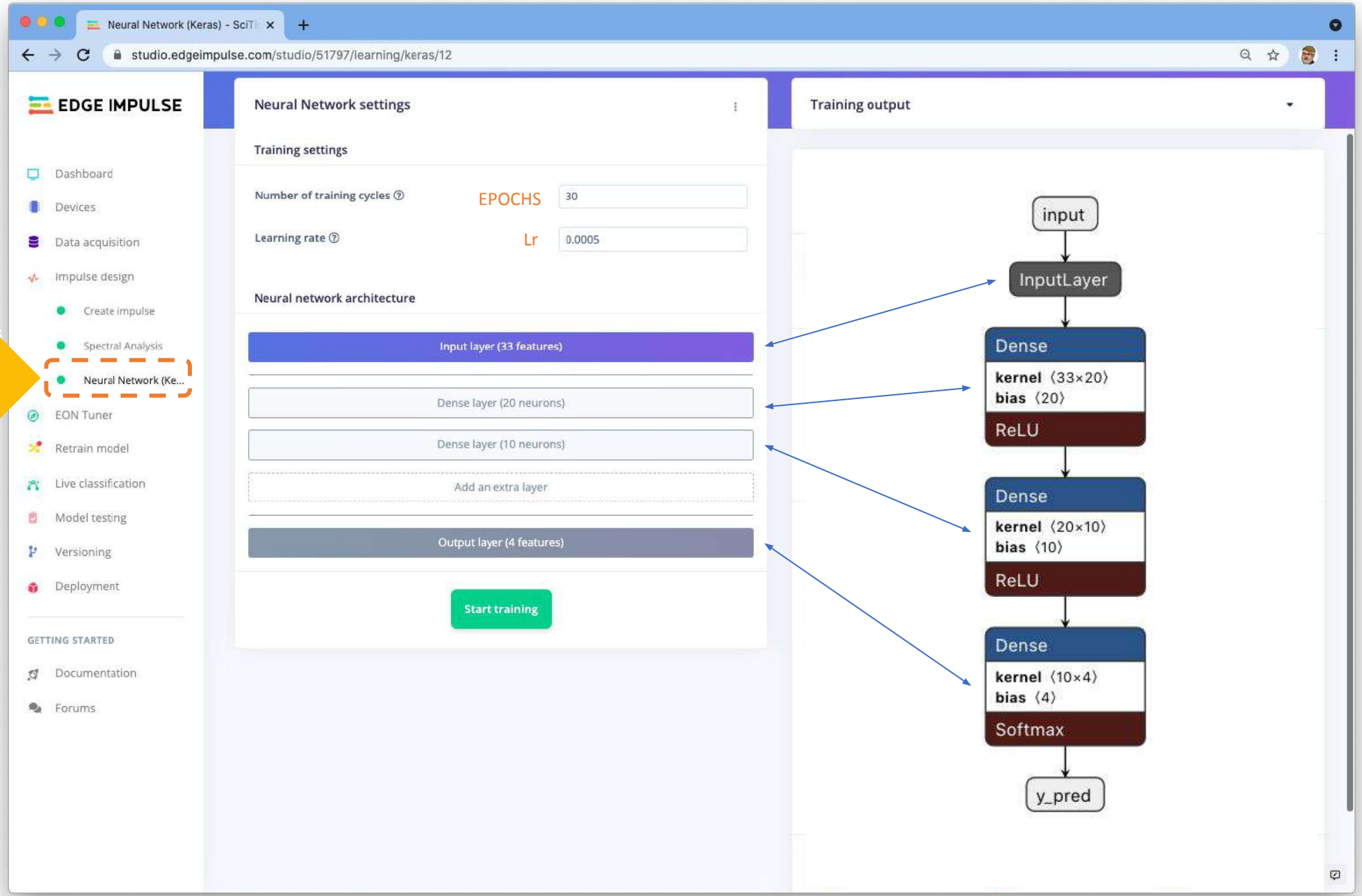
Preprocess Data



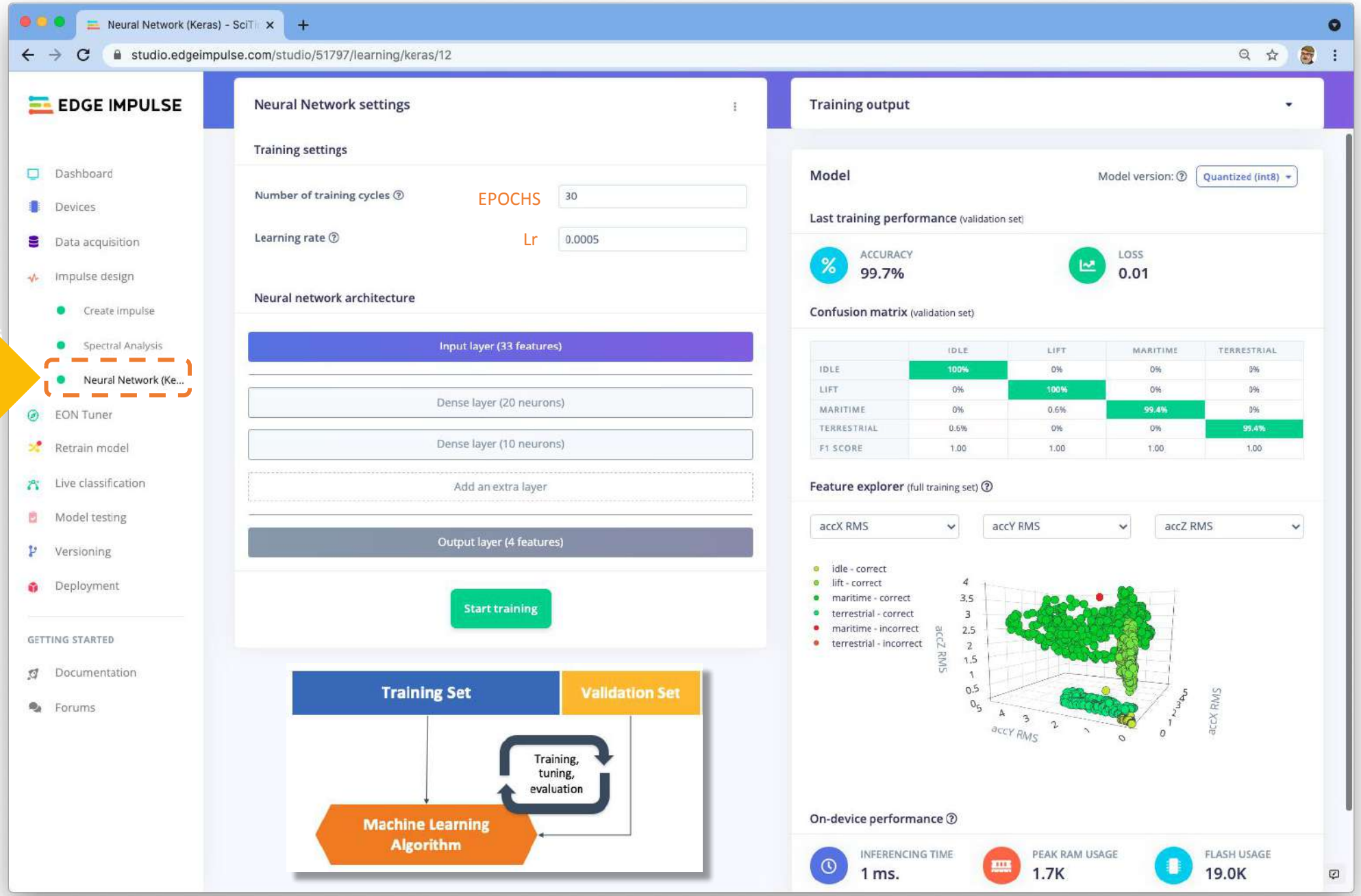
Preprocess Data



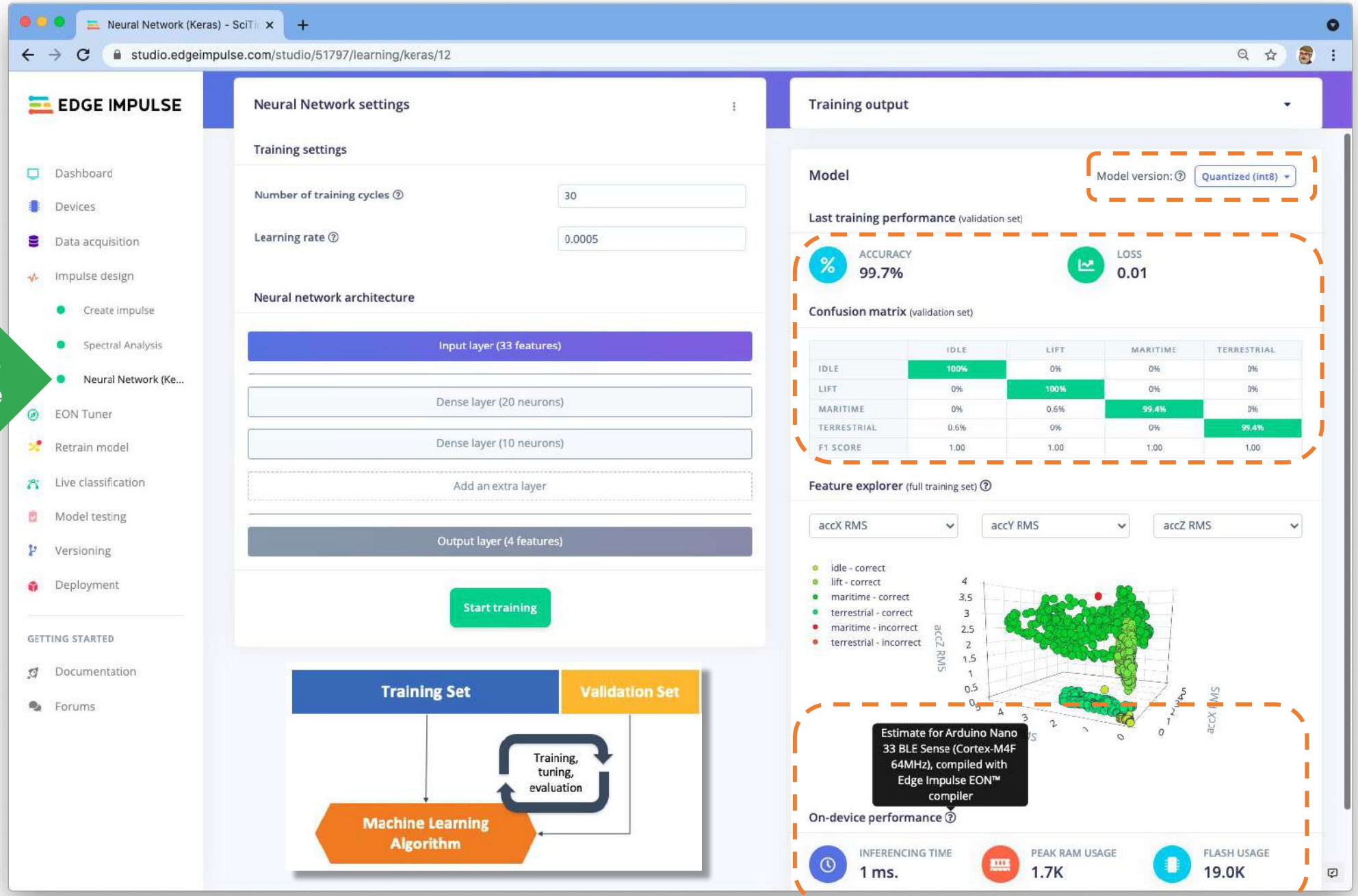
Design a Model

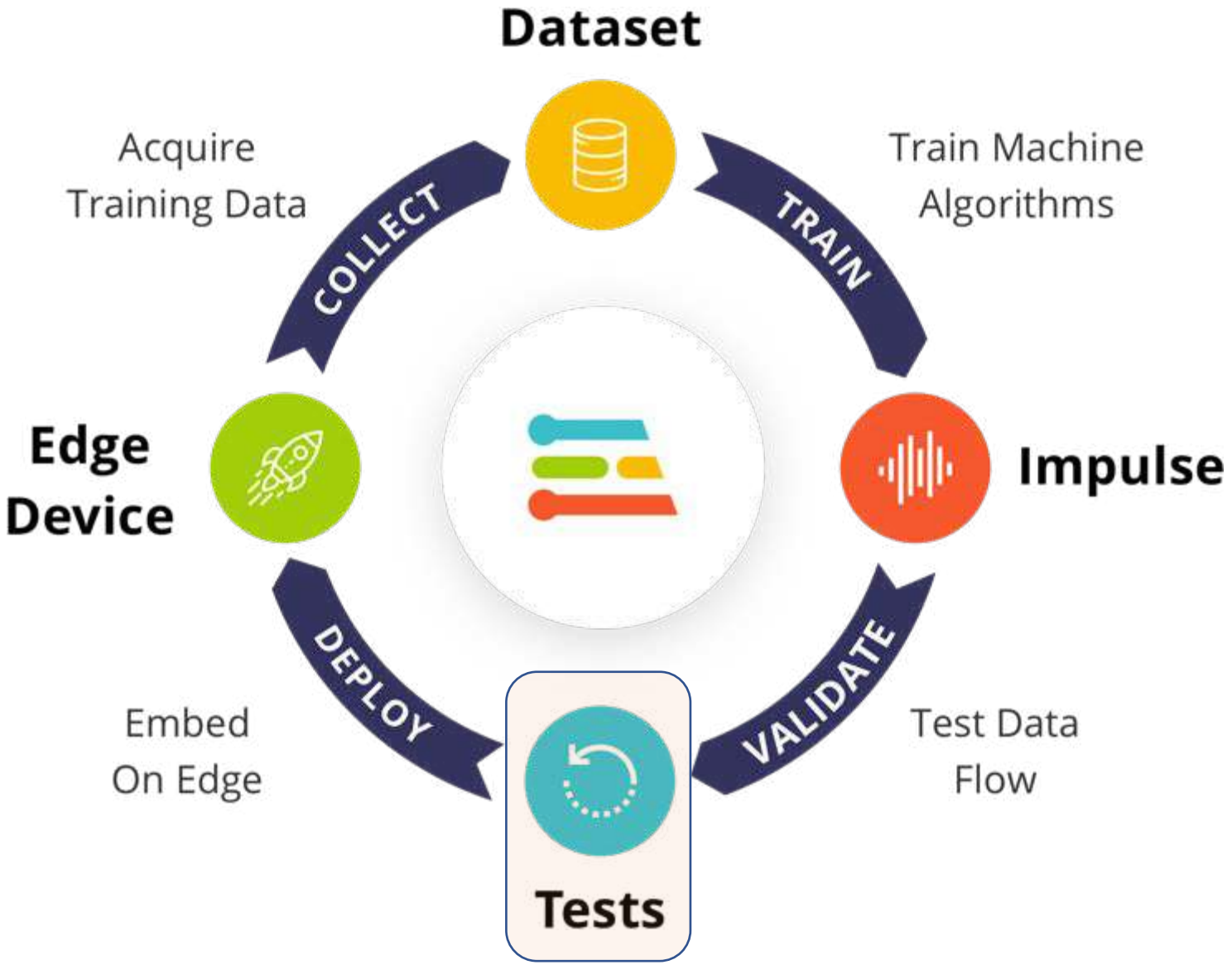


Train a Model



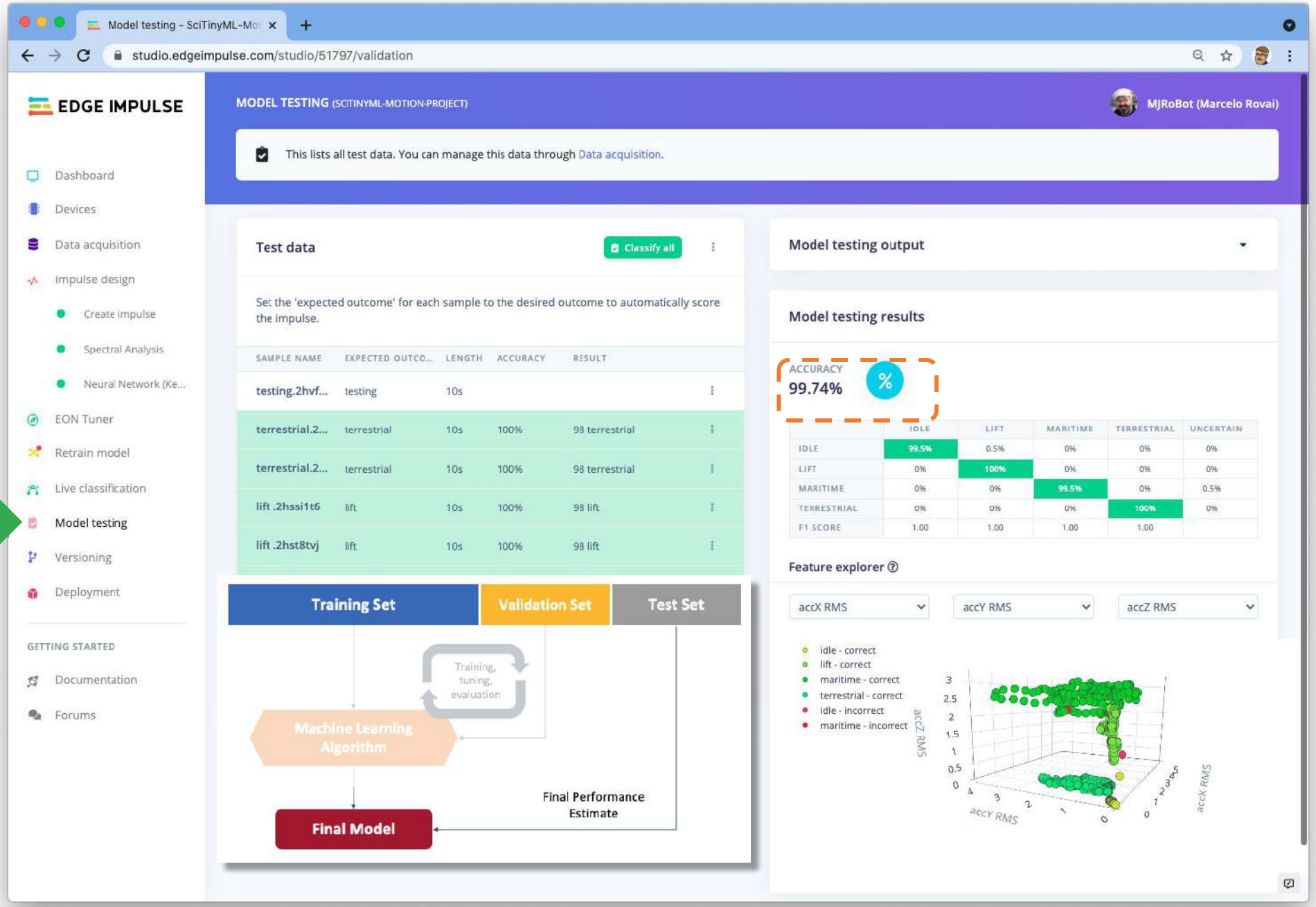
Evaluate
Optimize

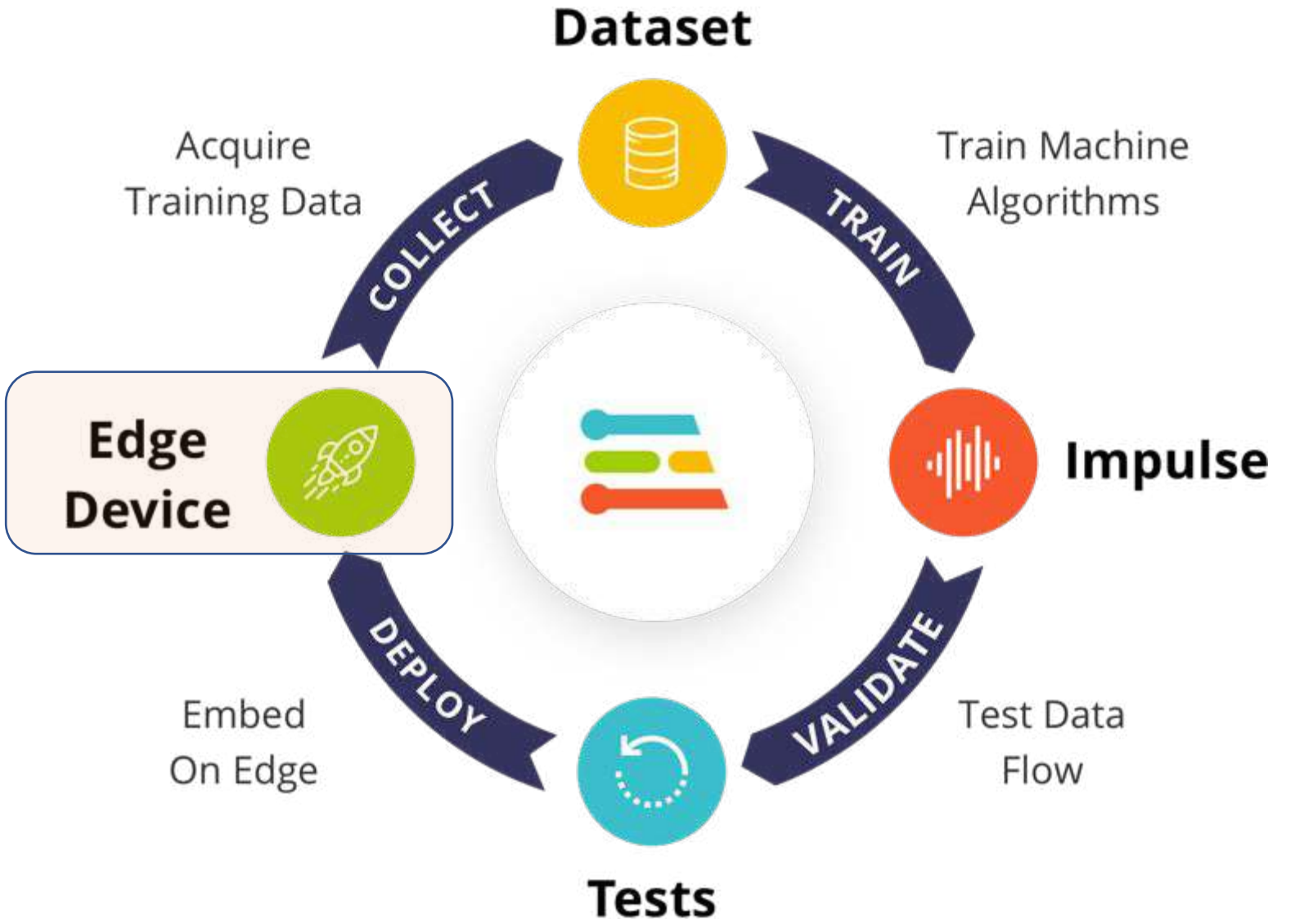




- Pre-Processing Data
- Design a Model
- Train a Model

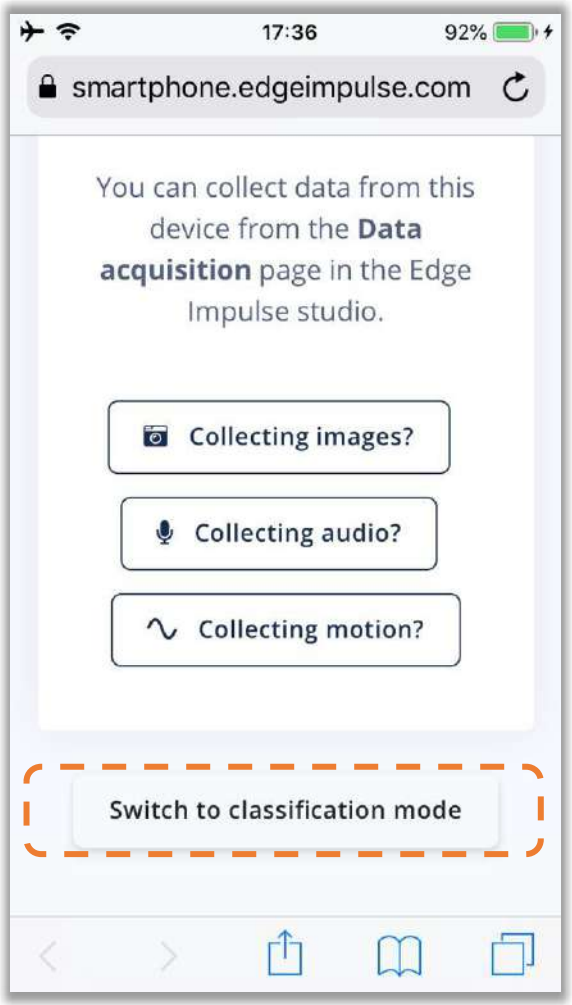
Evaluate
Optimize

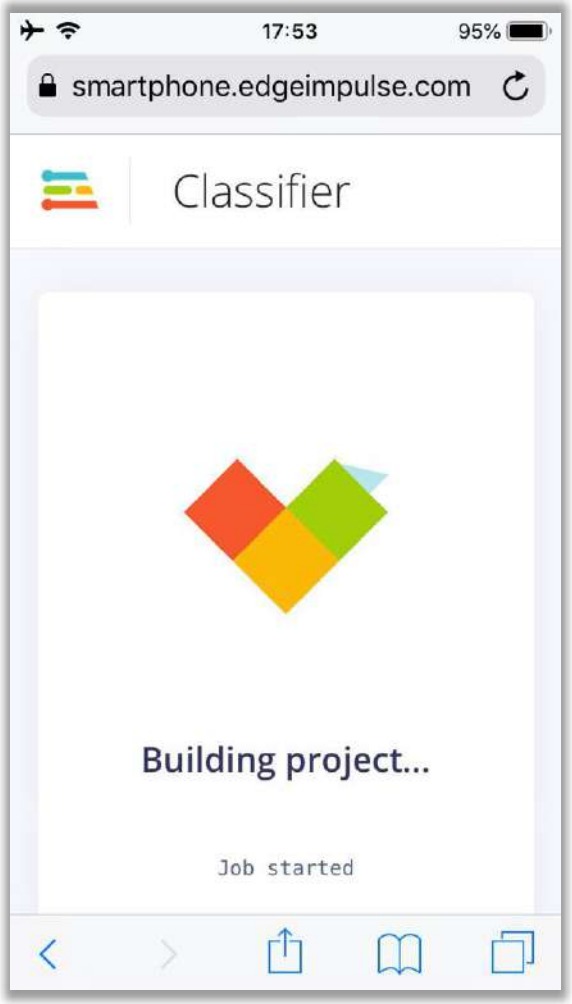




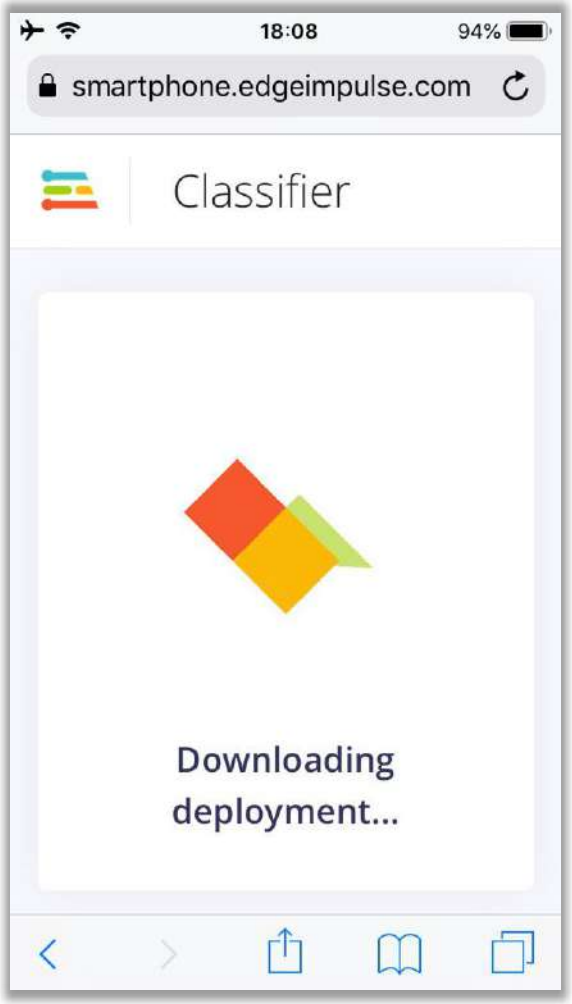
- Pre-Processing Data
- Design a Model
- Train a Model

Convert Model

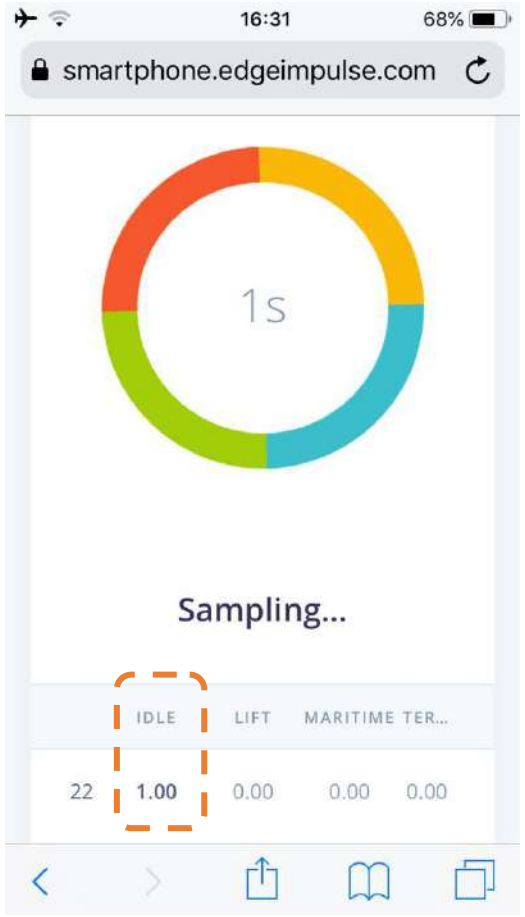


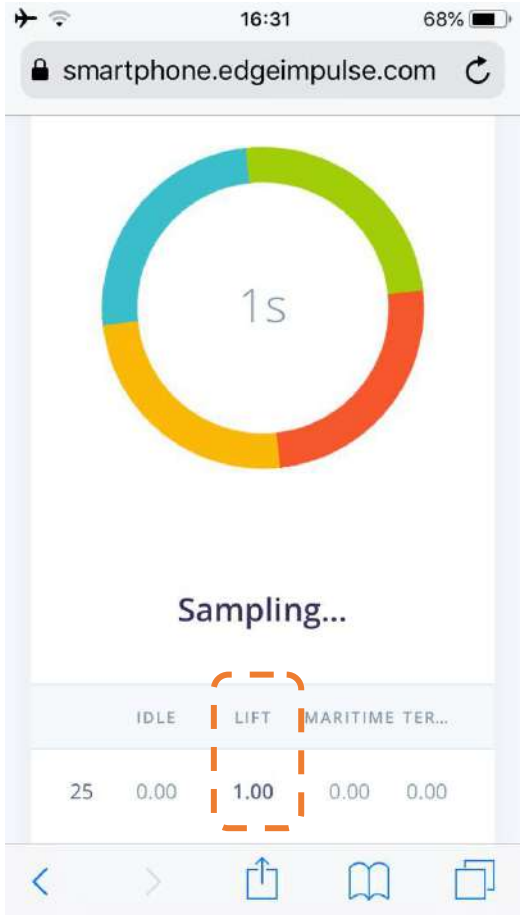


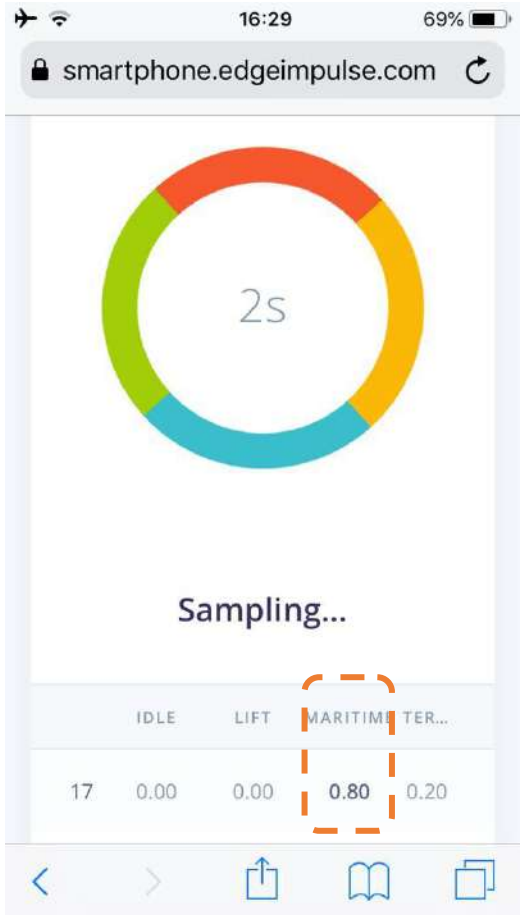
Deploy Model

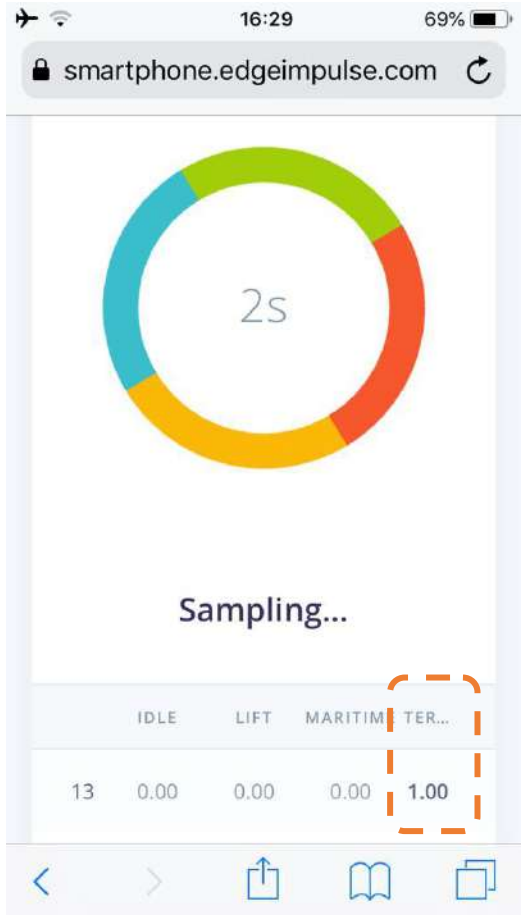


Make Inferences



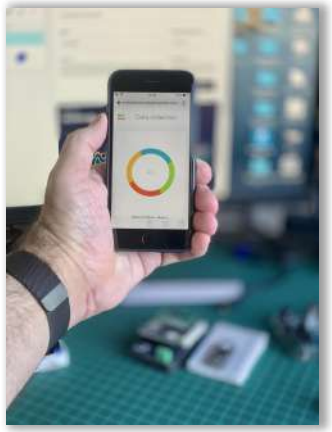


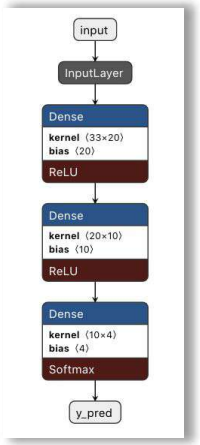


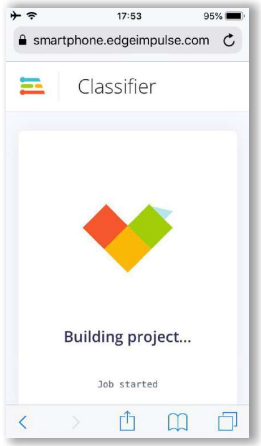


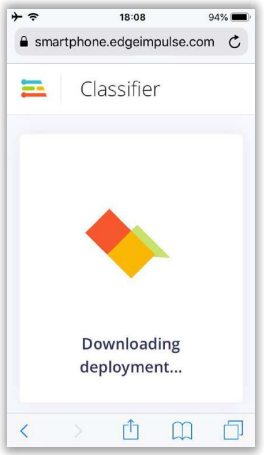
Motion Classification - Summary

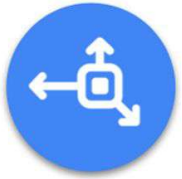
Collect Data → Preprocess Data → Design a Model → Train a Model → Evaluate Optimize → Convert Model → Deploy Model → Make Inferences





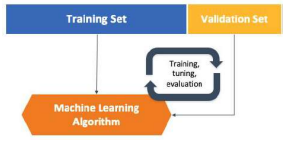


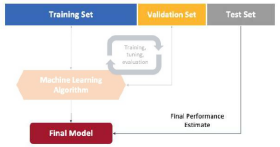




Spectral Analysis

NN Classifier

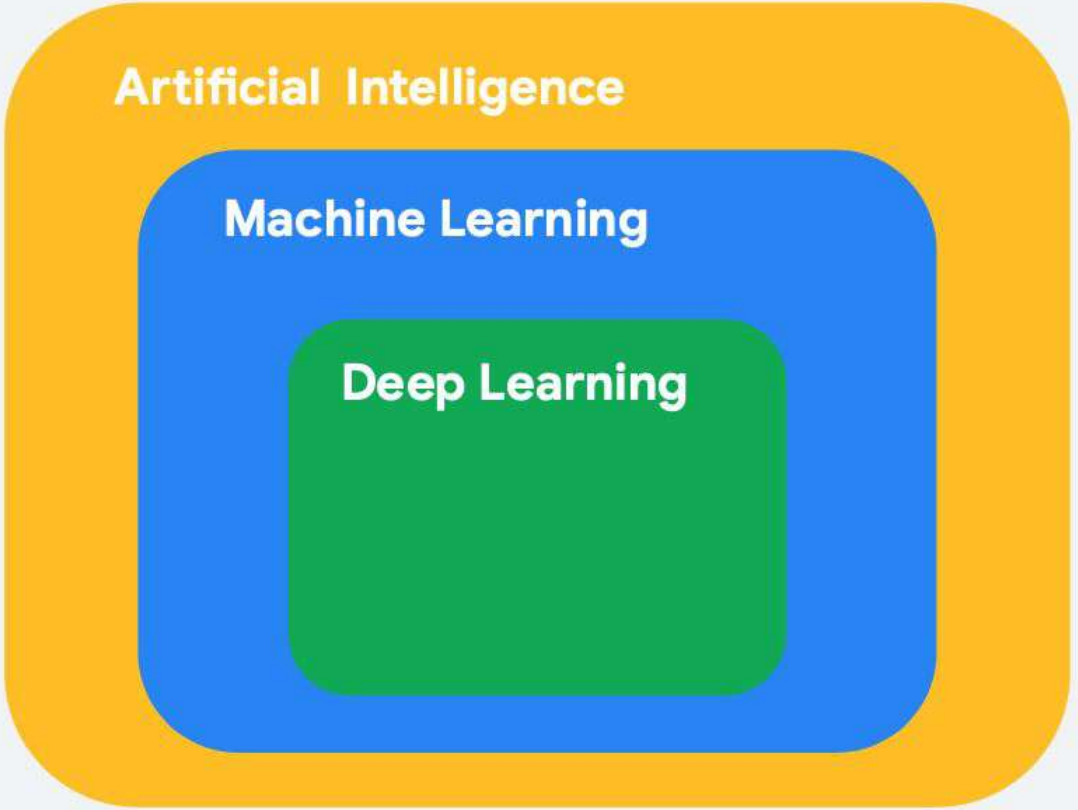




What AI really is?

What is (Deep) Machine Learning?

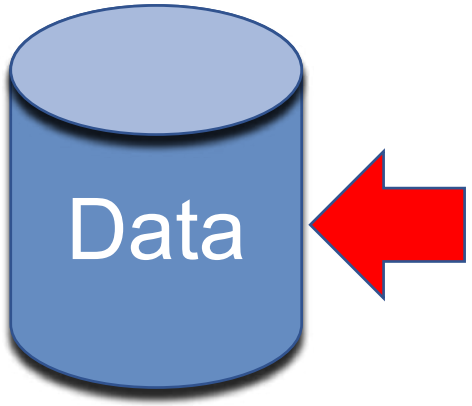
1. Machine Learning is a subfield of Artificial Intelligence focused on developing algorithms that learn to solve problems by analyzing data for patterns
2. **Deep Learning** is a type of Machine Learning that leverages **Neural Networks** and **Big Data**

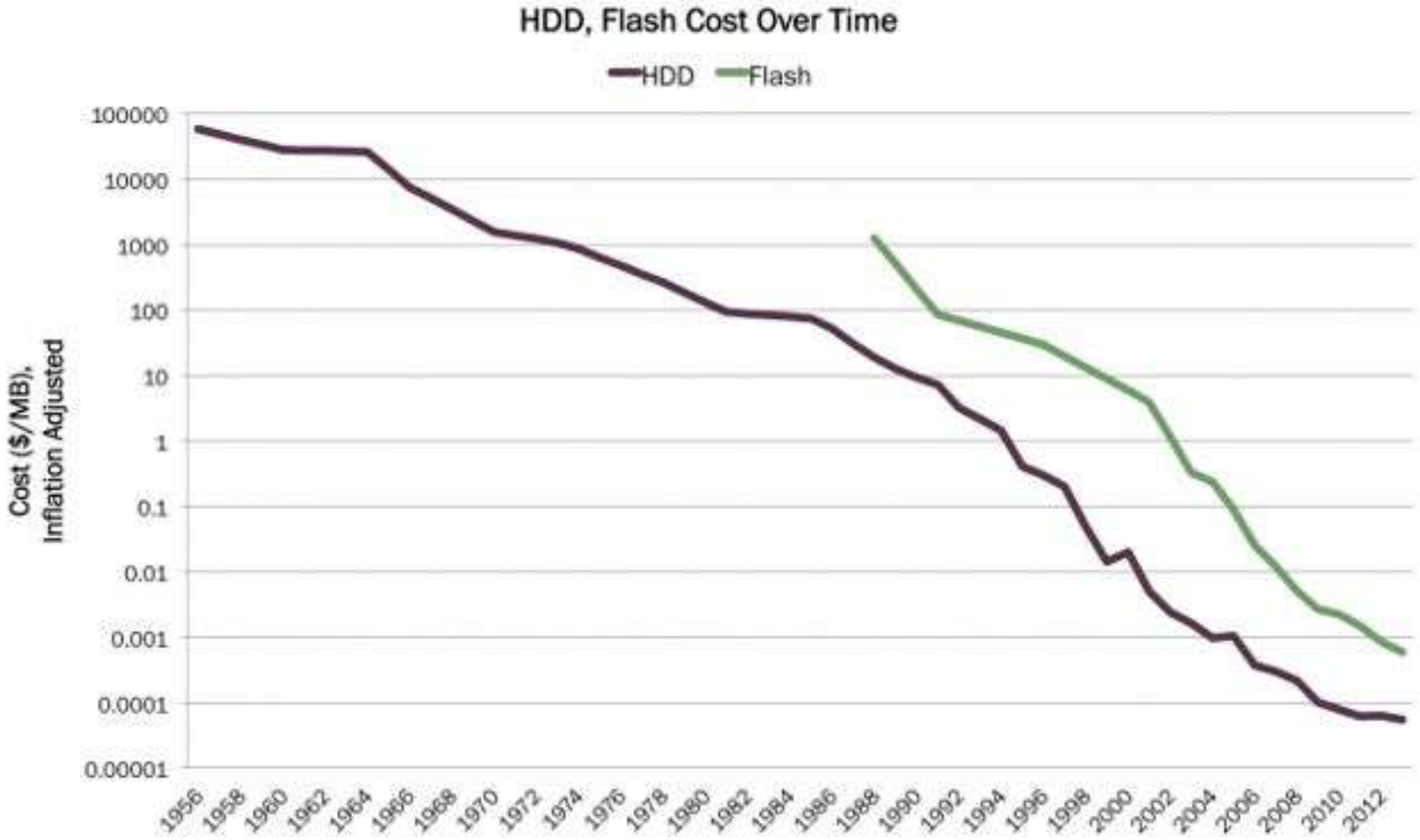


AI starts with … Data, lot of data (Big Data)

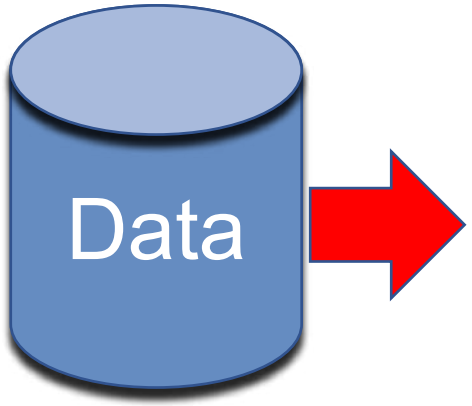
- ✔ Low storage cost & capacity
- ✔ High Performance & Low cost

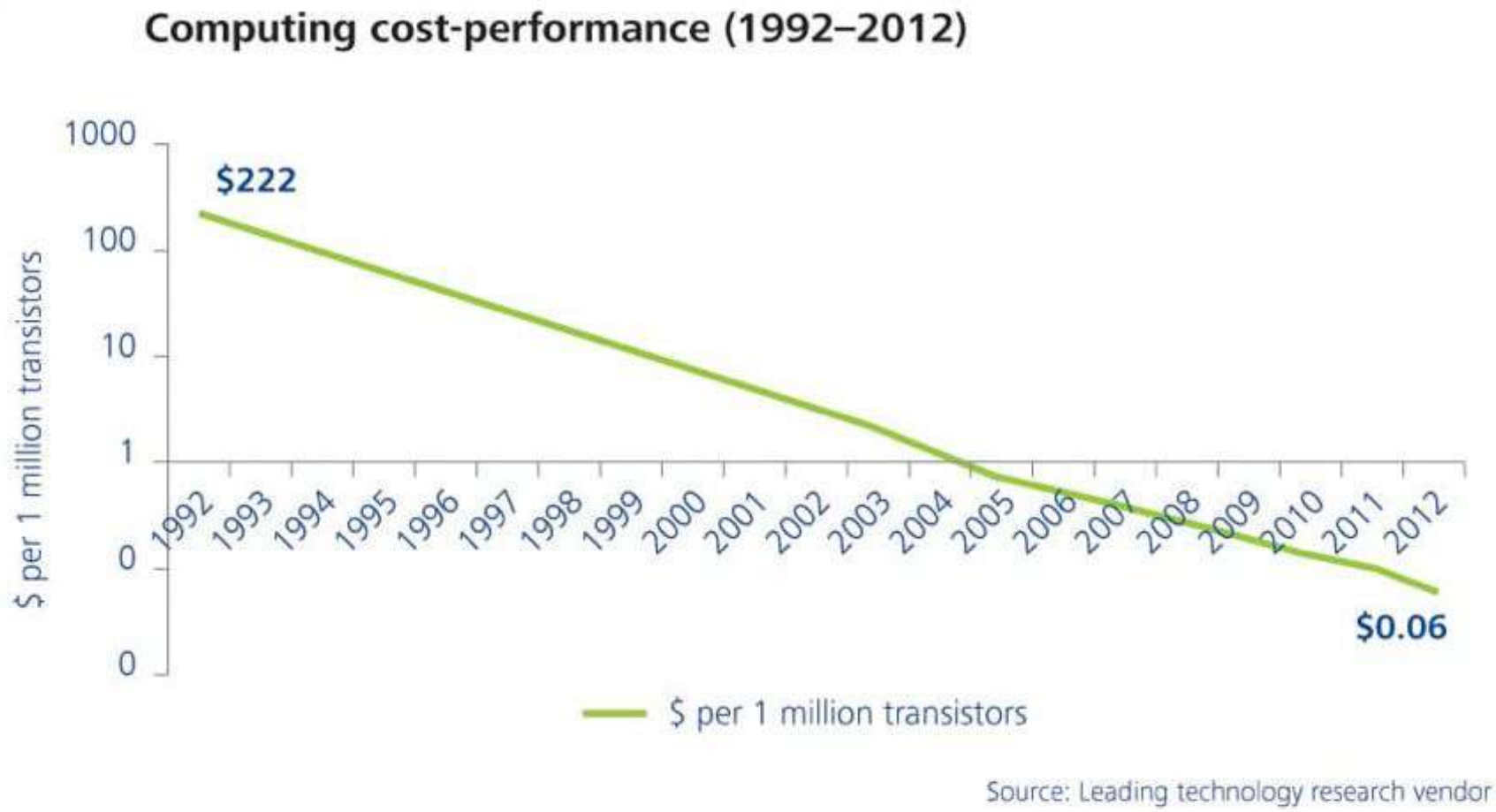
Data ⇨ Storage



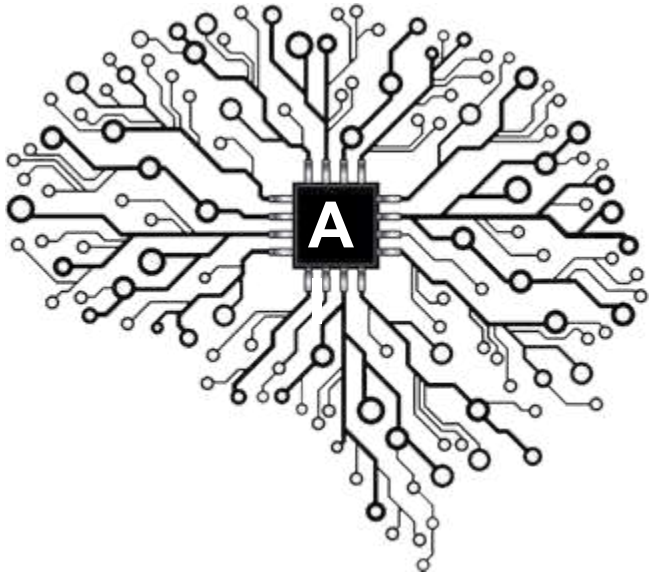


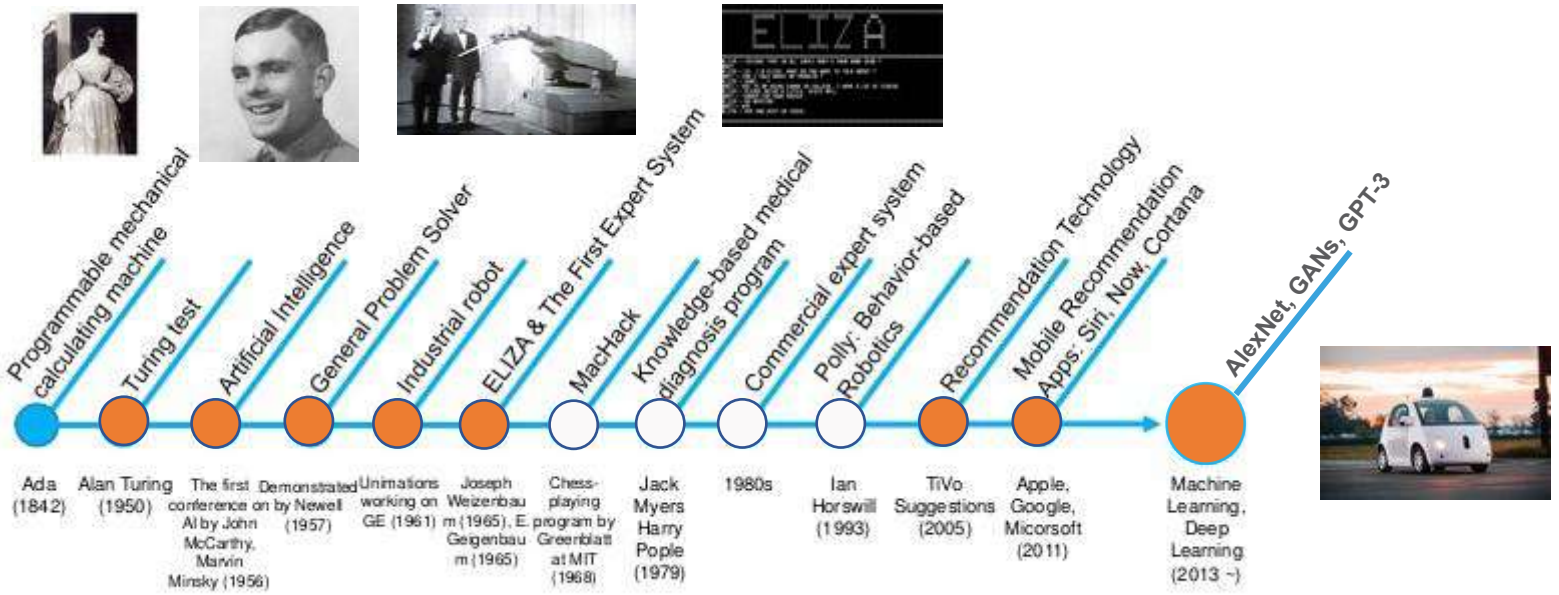
Data ⇨Processing





Artificial Intelligence – AI Timeline





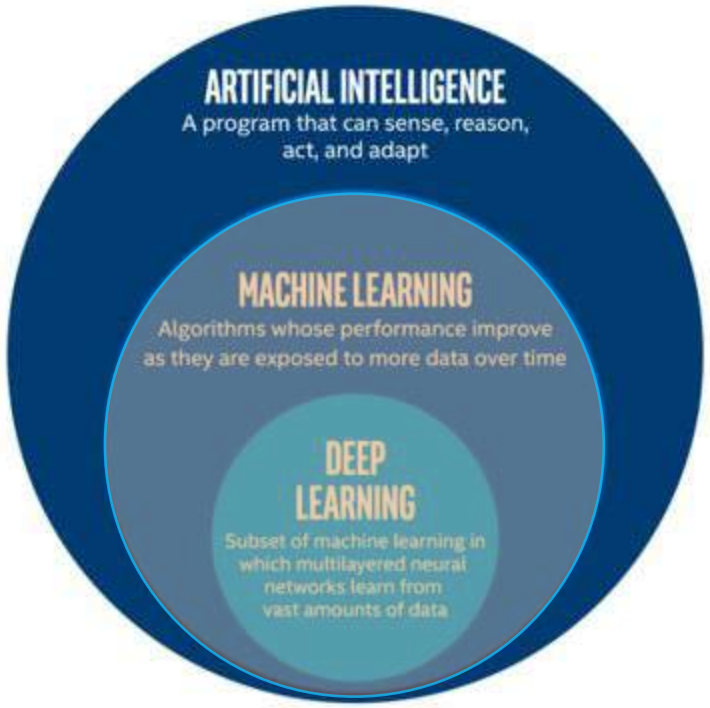
1951: Claude Shannon's maze-solving robots

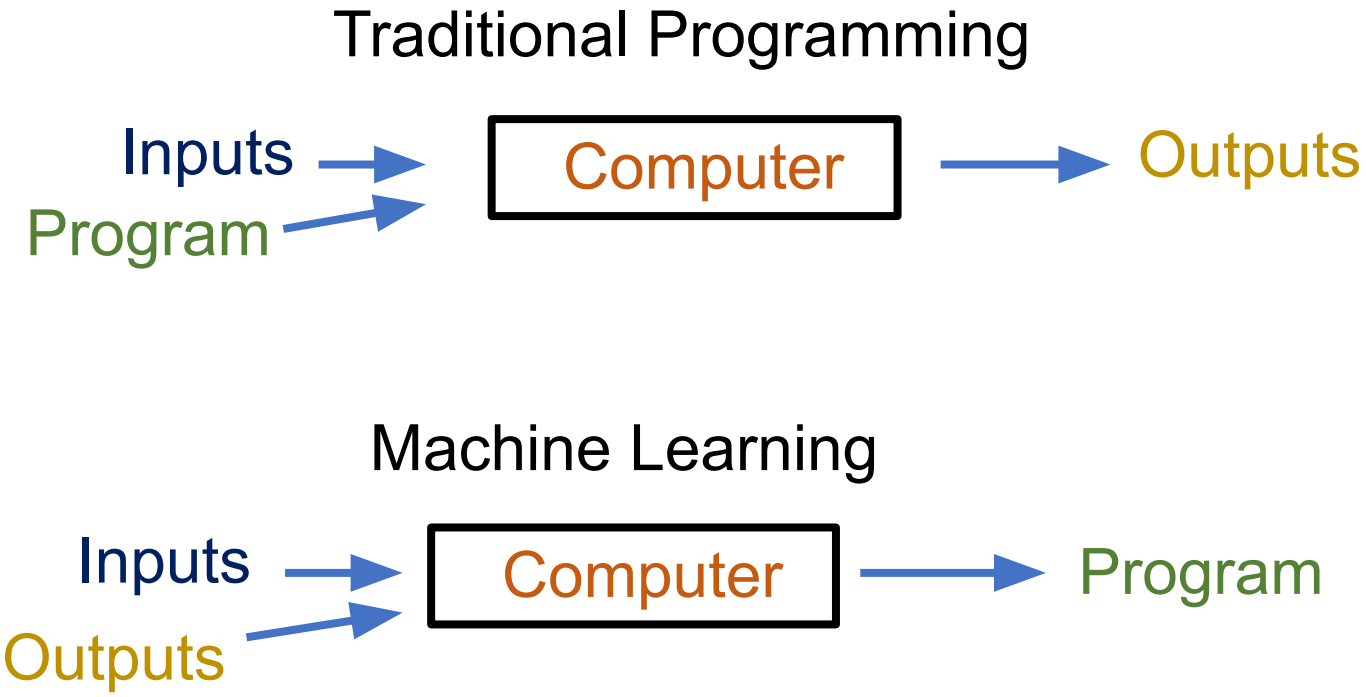
1955: Arthur Samuel's Checkers, the world's first self-learning program

AI Winter
Many false starts and dead-ends leave AI out in the cold

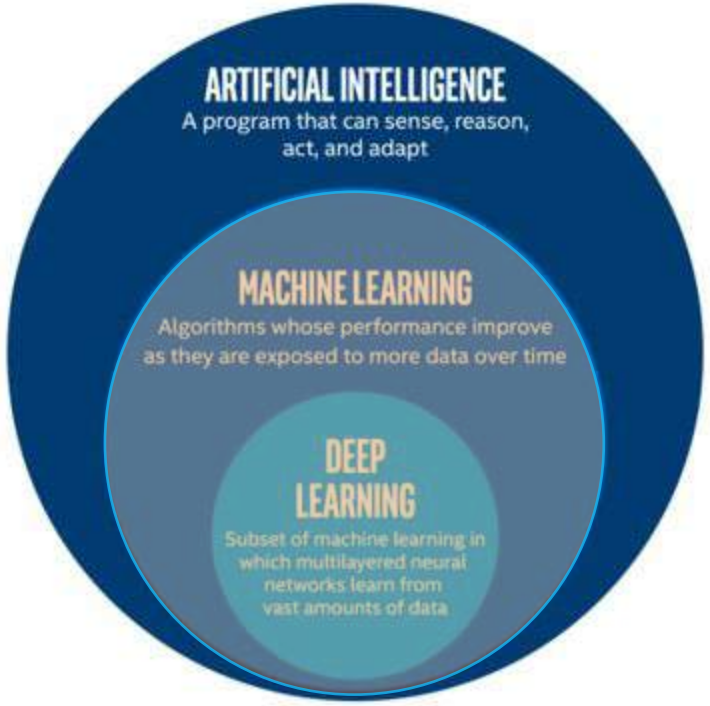
https://en.wikipedia.org/wiki/Timeline_of_artificial_intelligence

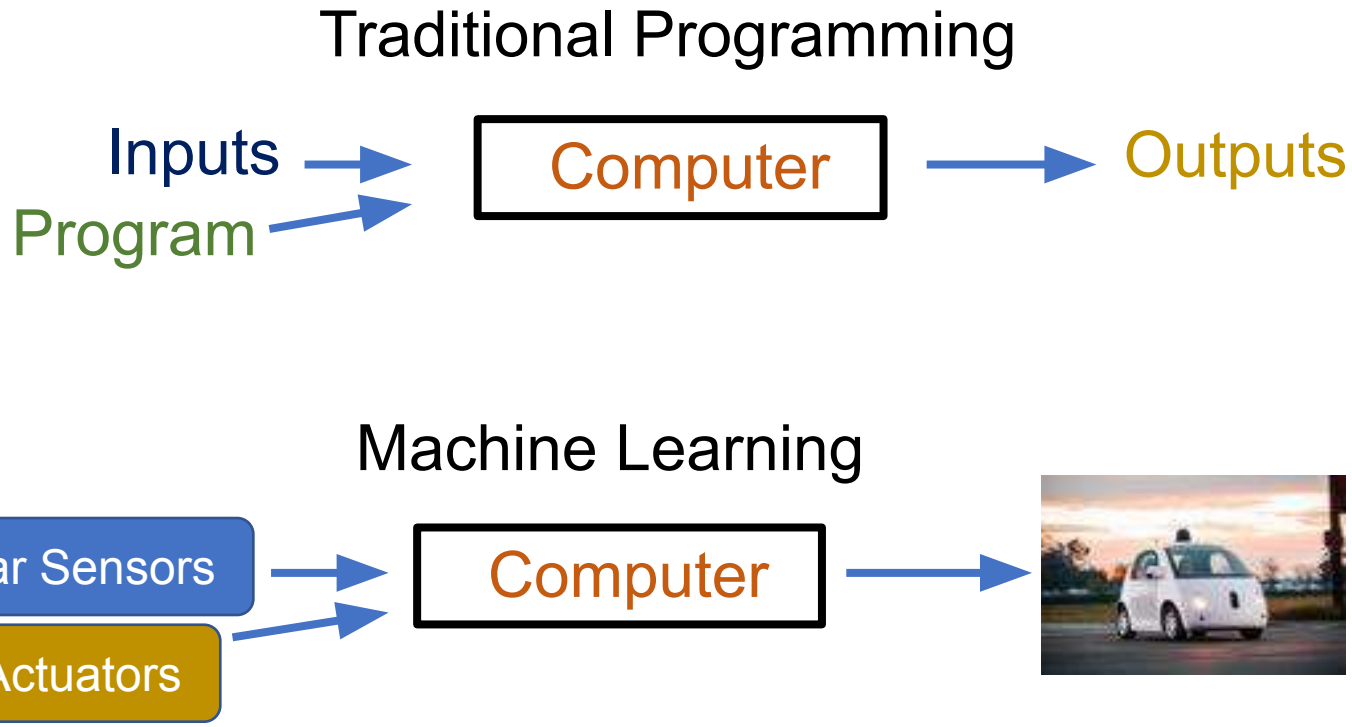
AI ⇨ Machine Learning (ML)



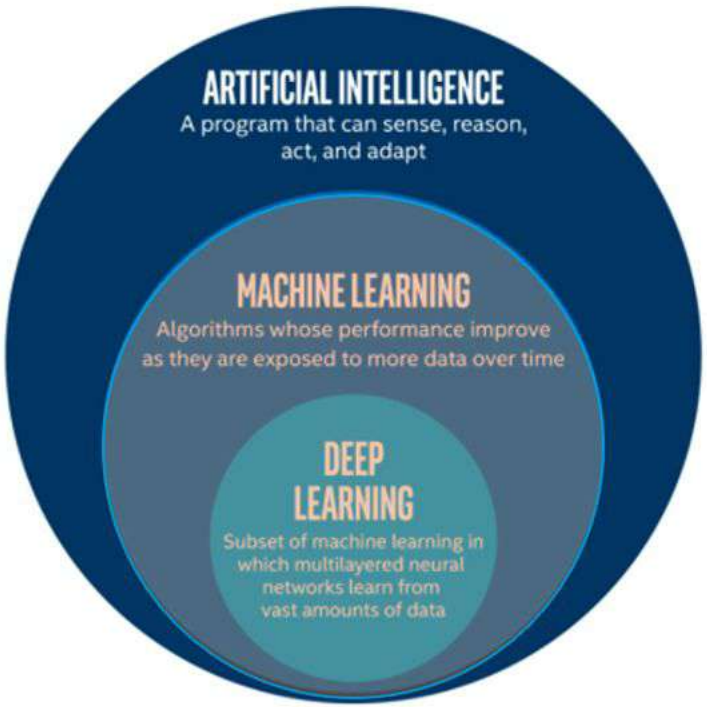


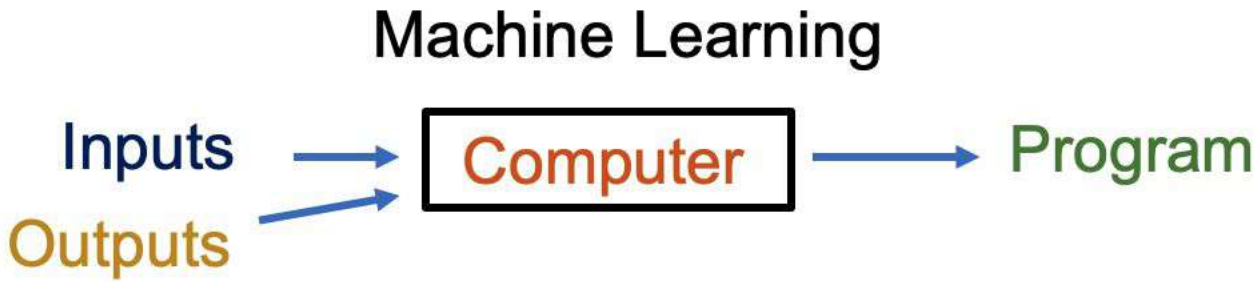
AI ⇨ Machine Learning (ML)

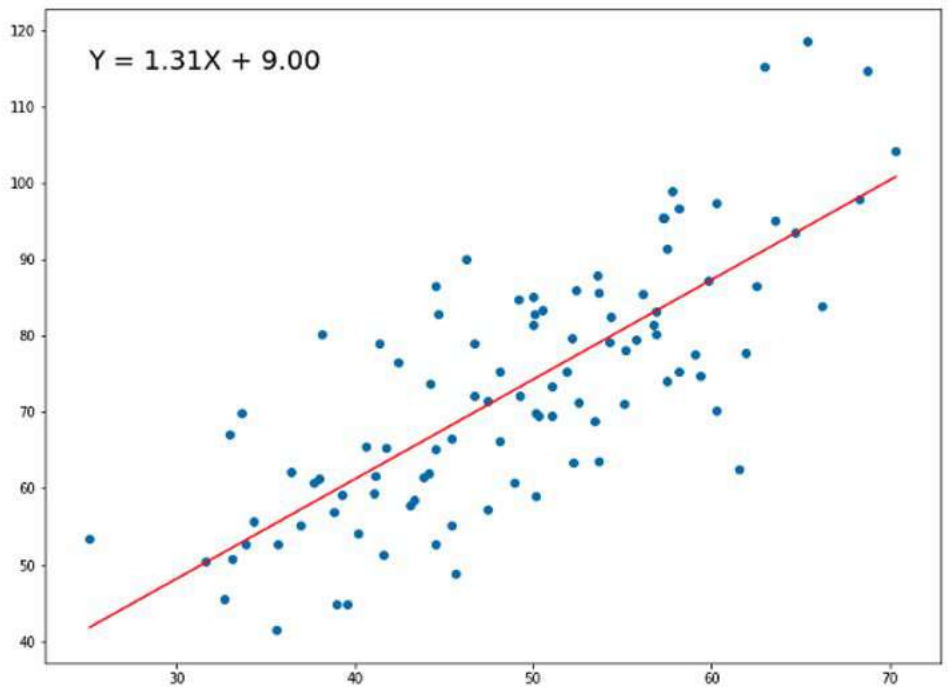




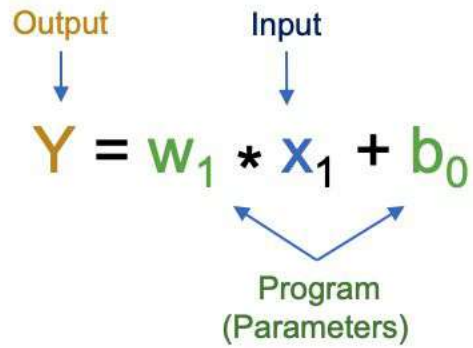
AI ⇨ Machine Learning (ML)





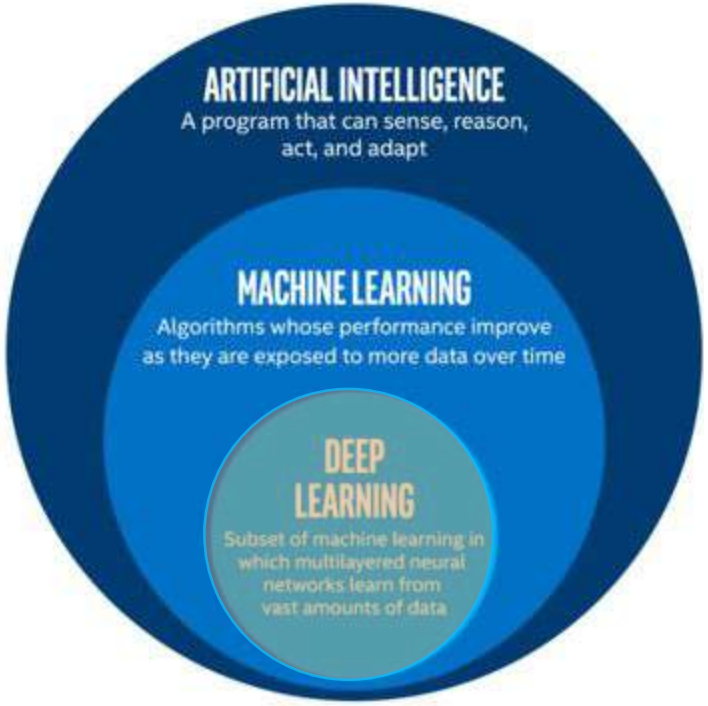


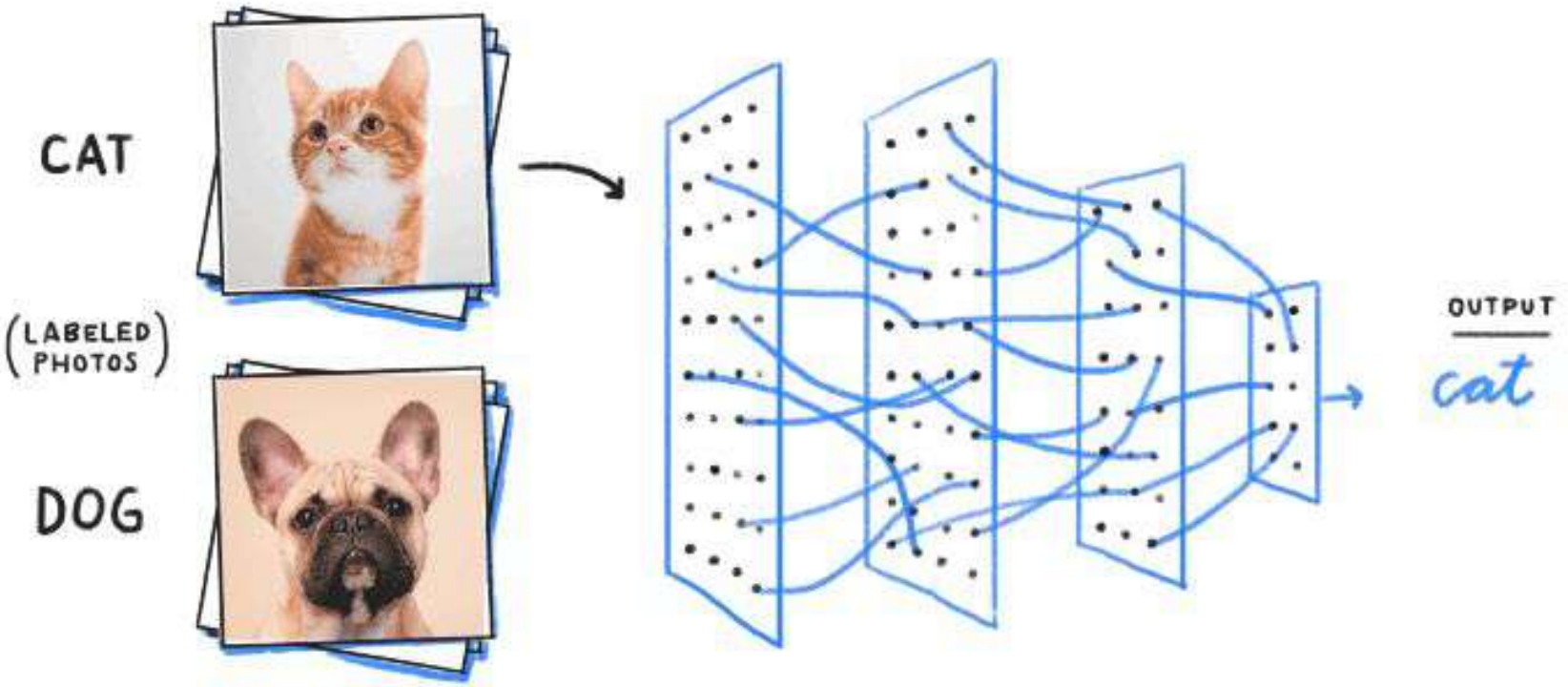
https://towardsdatascience.com/linear-regression-using-least-squares-a4c3456e8570



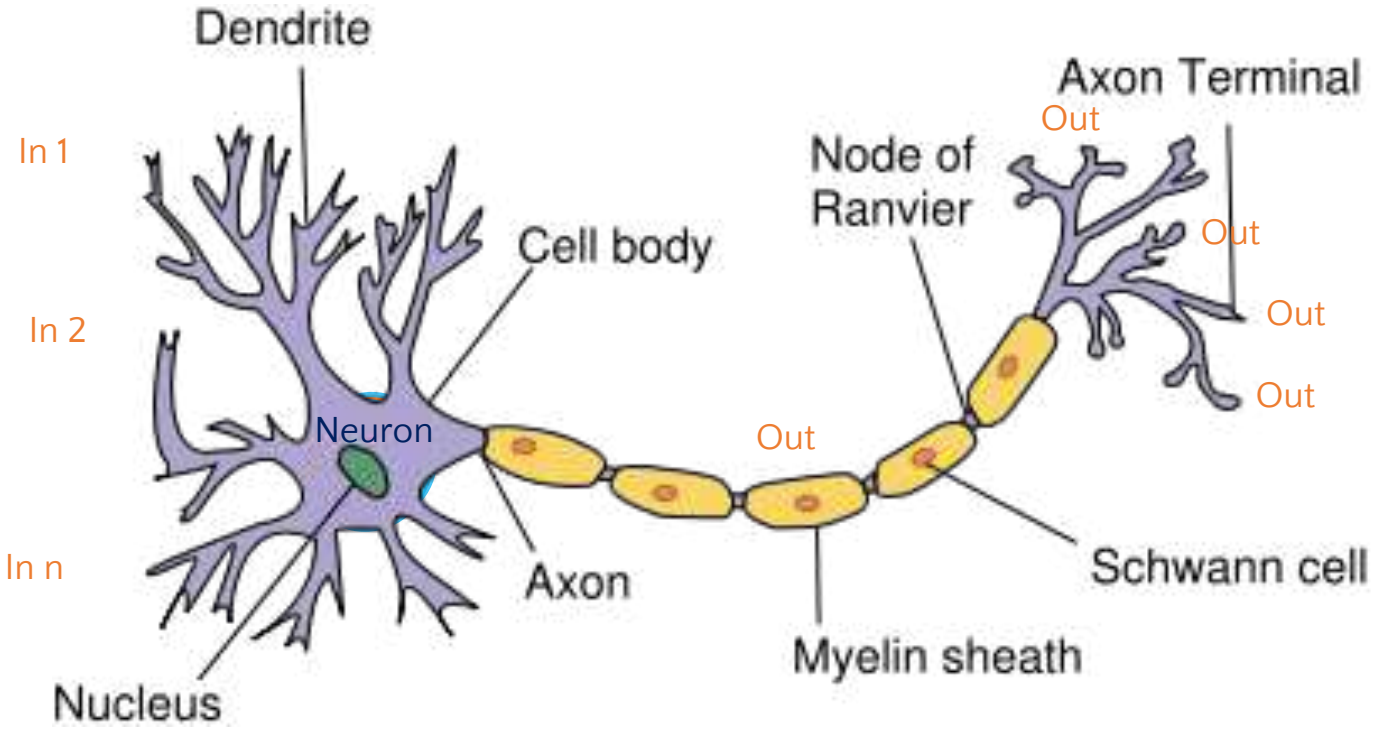
AI ⇨ Deep Learning (DL)

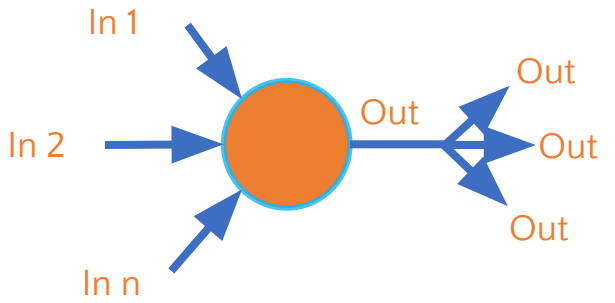
Deep Learning: Subset of Machine Learning in which multilayered neural networks learn from vast amounts of data

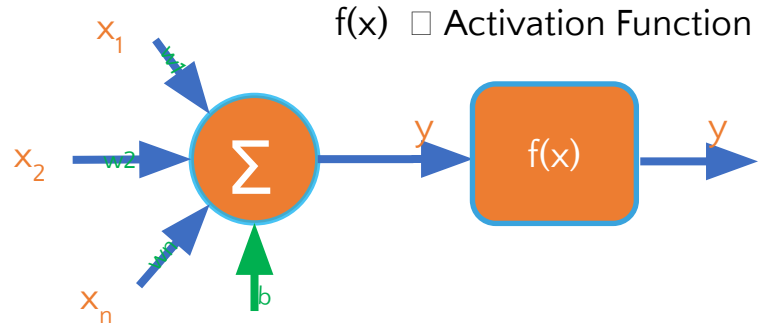




Neuron (Perceptron)



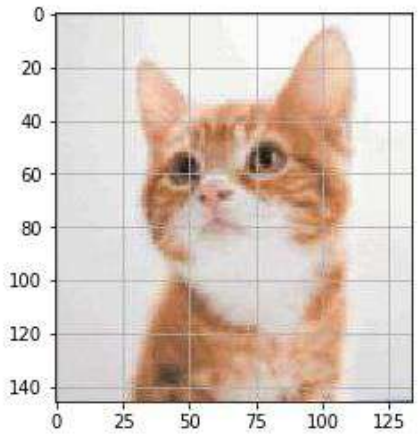




Parameters

$$y = f(\sum_{i=1}^{n} x_i w_i + b)$$

Artificial Neural Network



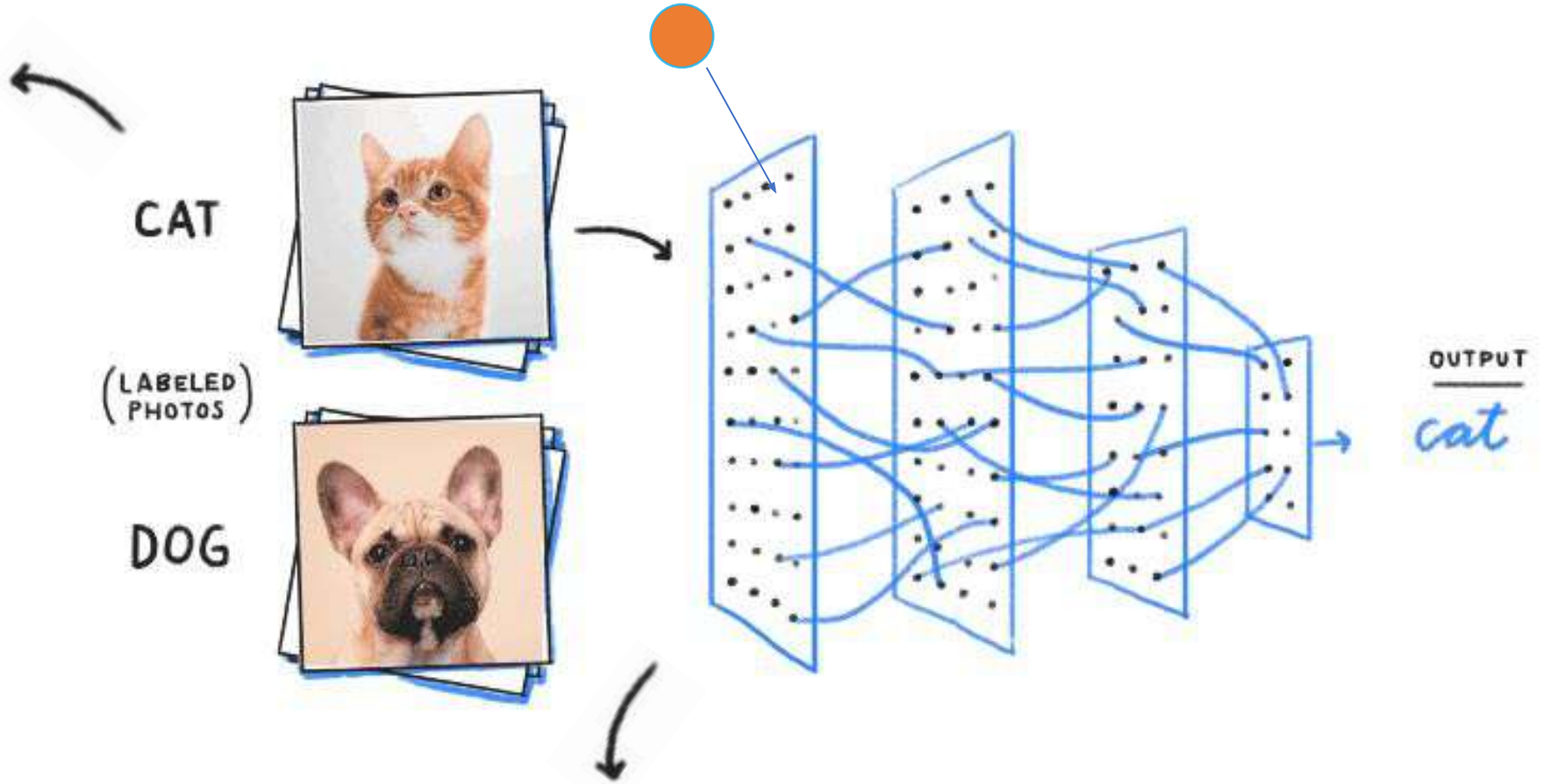
(146, 134, 3)

RGB

```
[[227, 228, 227, ..., 249, 249, 249],
 [219, 219, 219, ..., 249, 249, 249],
 [221, 221, 221, ..., 249, 249, 249],
 ...,
 [209, 209, 209, ..., 220, 220, 218],
 [209, 209, 209, ..., 205, 205, 204],
 [208, 209, 209, ..., 124, 119, 121]]
```

146 * 134 * 3 = 57,486 pixels

[227, 228, 227… 124, 119, 121]



CNN (Layer 1)

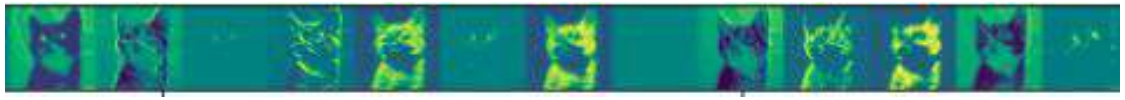
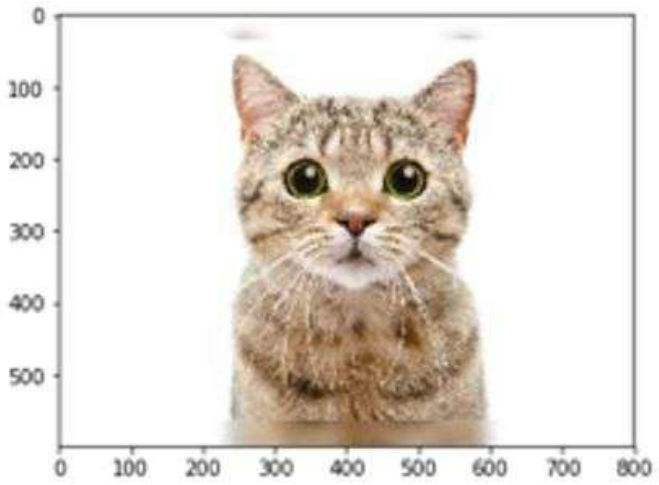


Image Classification

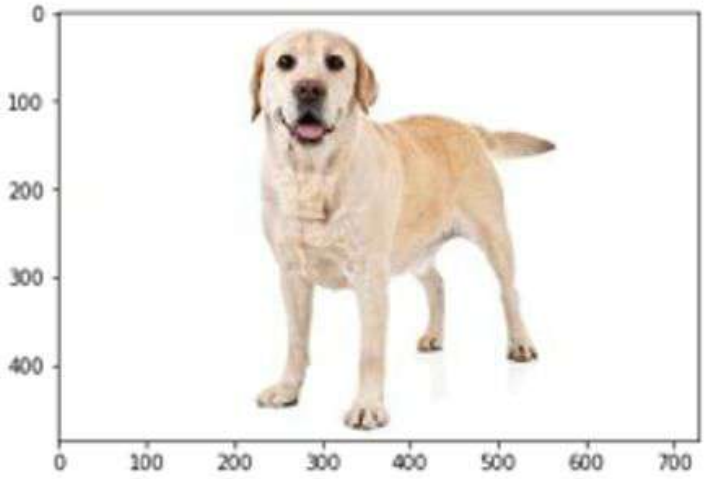
```
[PREDICTION]        [Prob]

Egyptian cat        : 64%
tabby               : 14%
bucket              : 3%
```



```
[PREDICTION]        [Prob]

Labrador retriever  : 83%
golden retriever    : 13%
bloodhound          : 0%
```



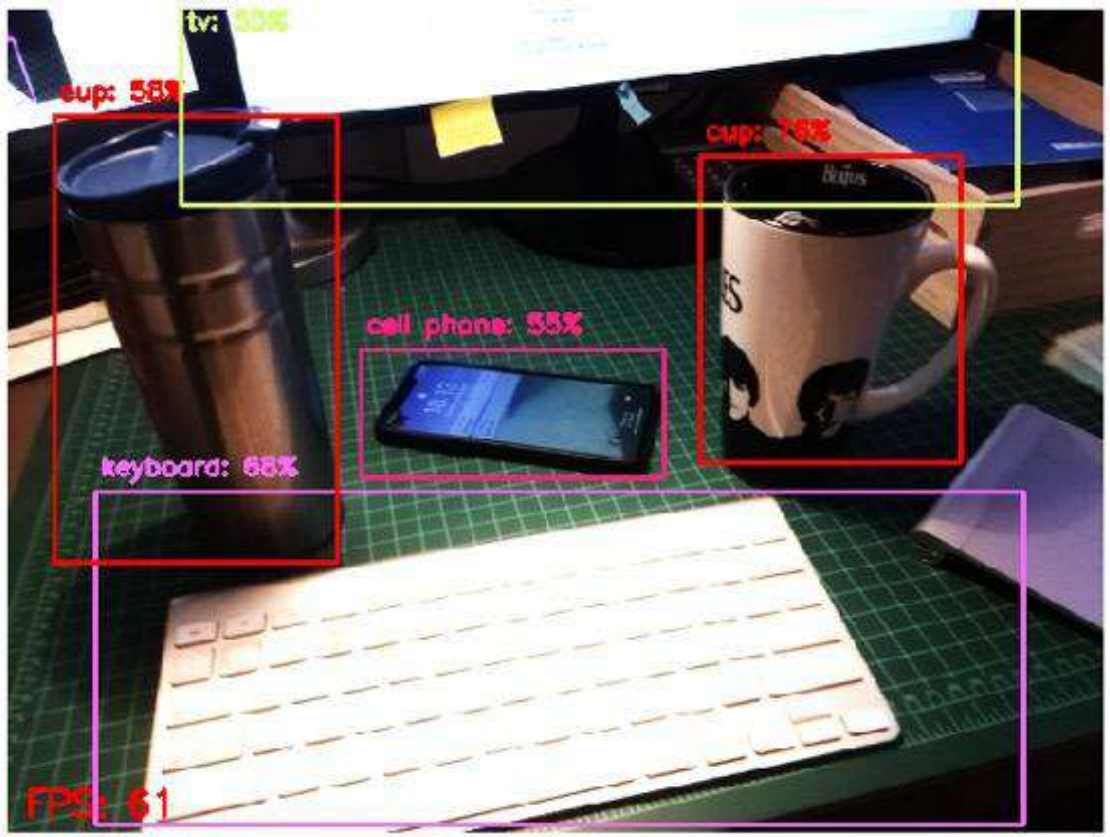
```
[PREDICTION]        [Prob]

German shepherd     : 60%
dhole               : 16%
malinois            : 7%
```

https://www.hackster.io/mjrobot/exploring-ia-at-the-edge-97588d

Object Detection

Photos

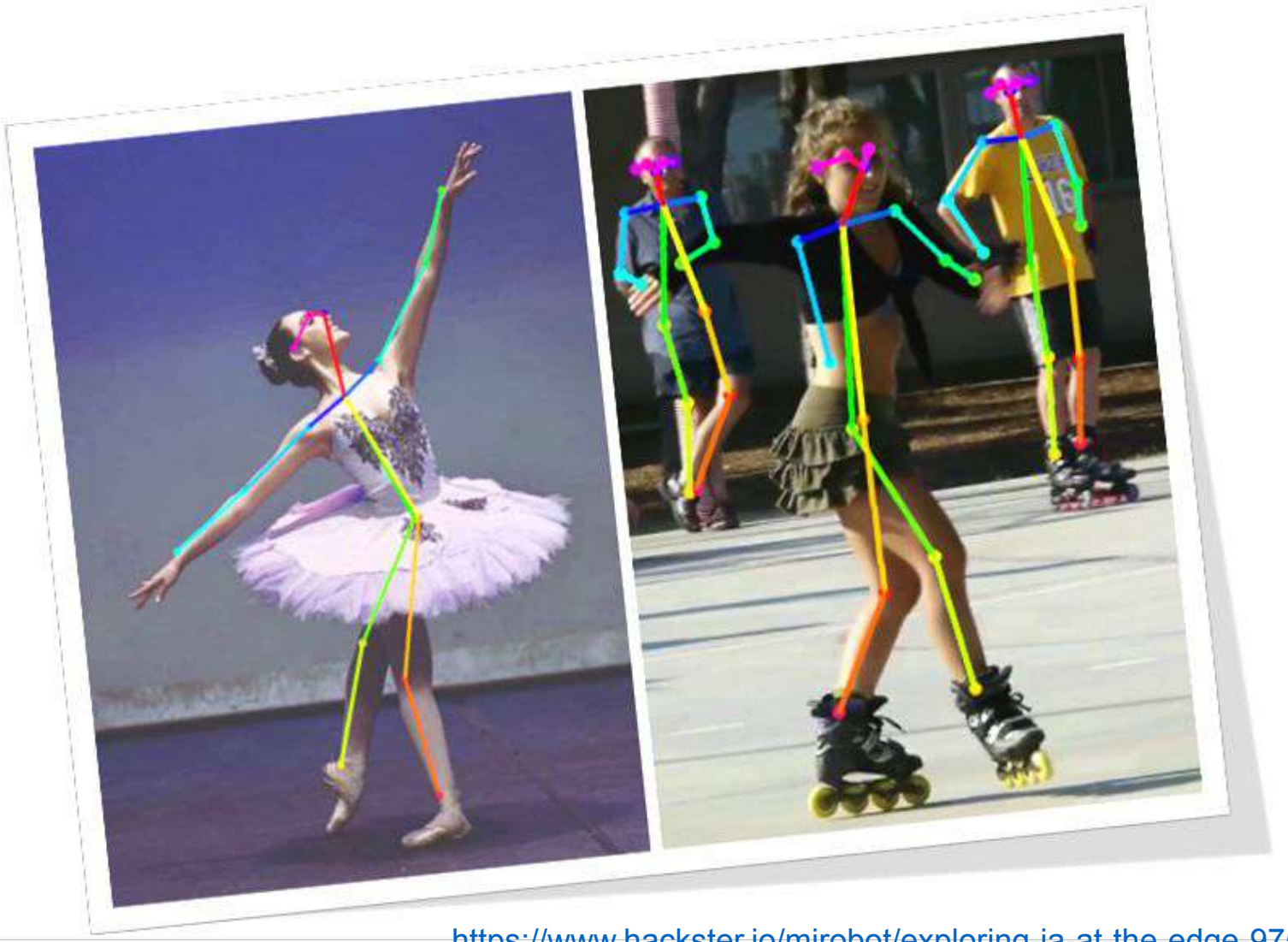


Live Video

https://www.hackster.io/mjrobot/exploring-ia-at-the-edge-97588d

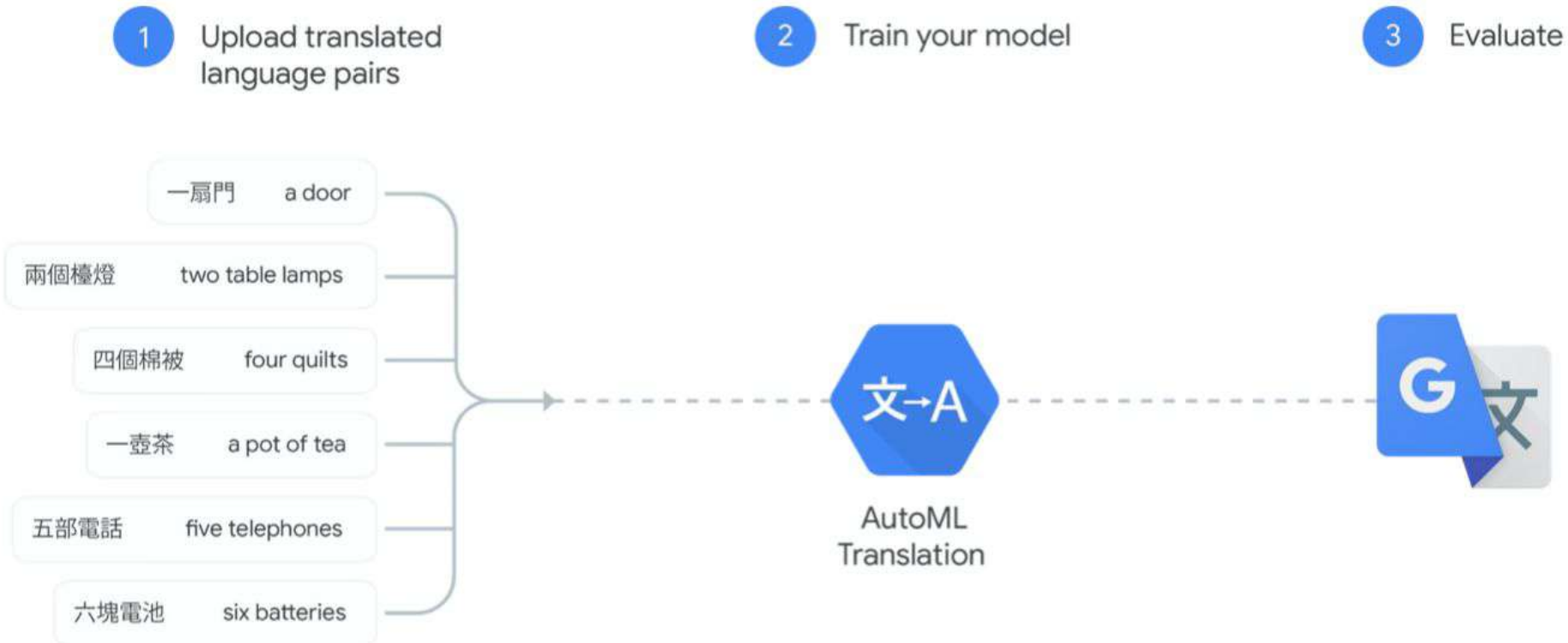
Segmentation

Pose Estimation

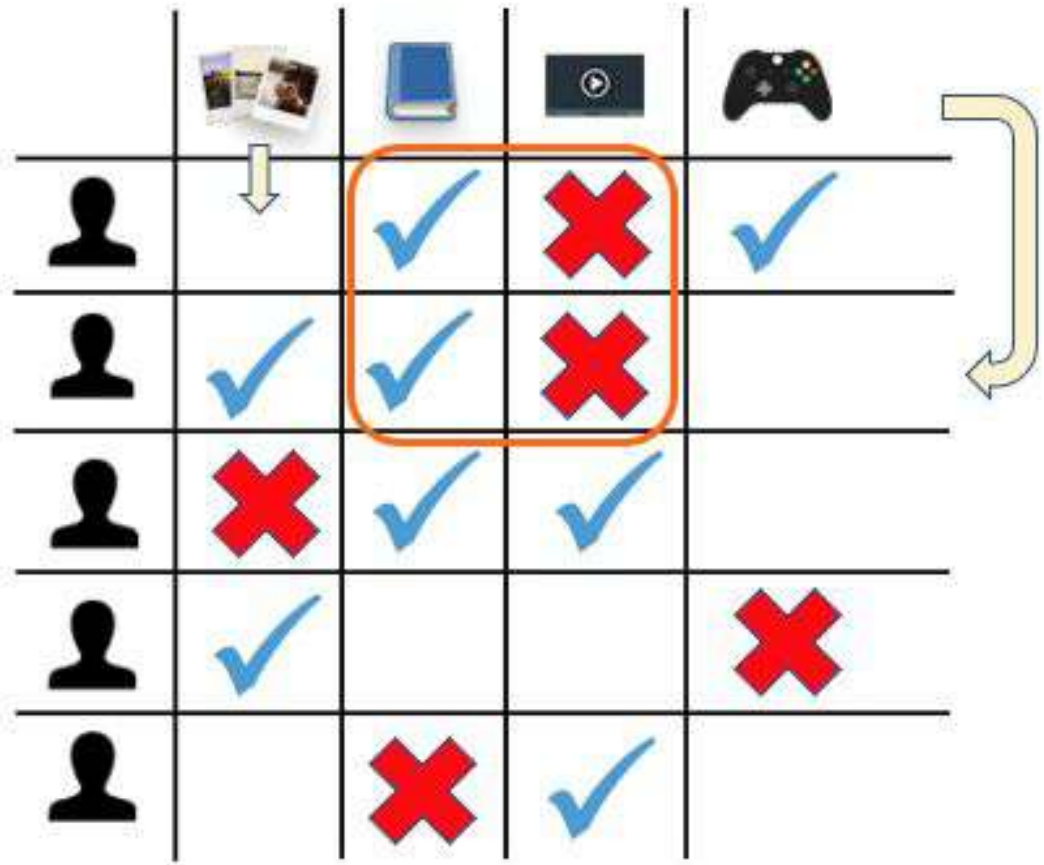


https://www.hackster.io/mjrobot/exploring-ia-at-the-edge-97588d

Machine Translation



Recommendations

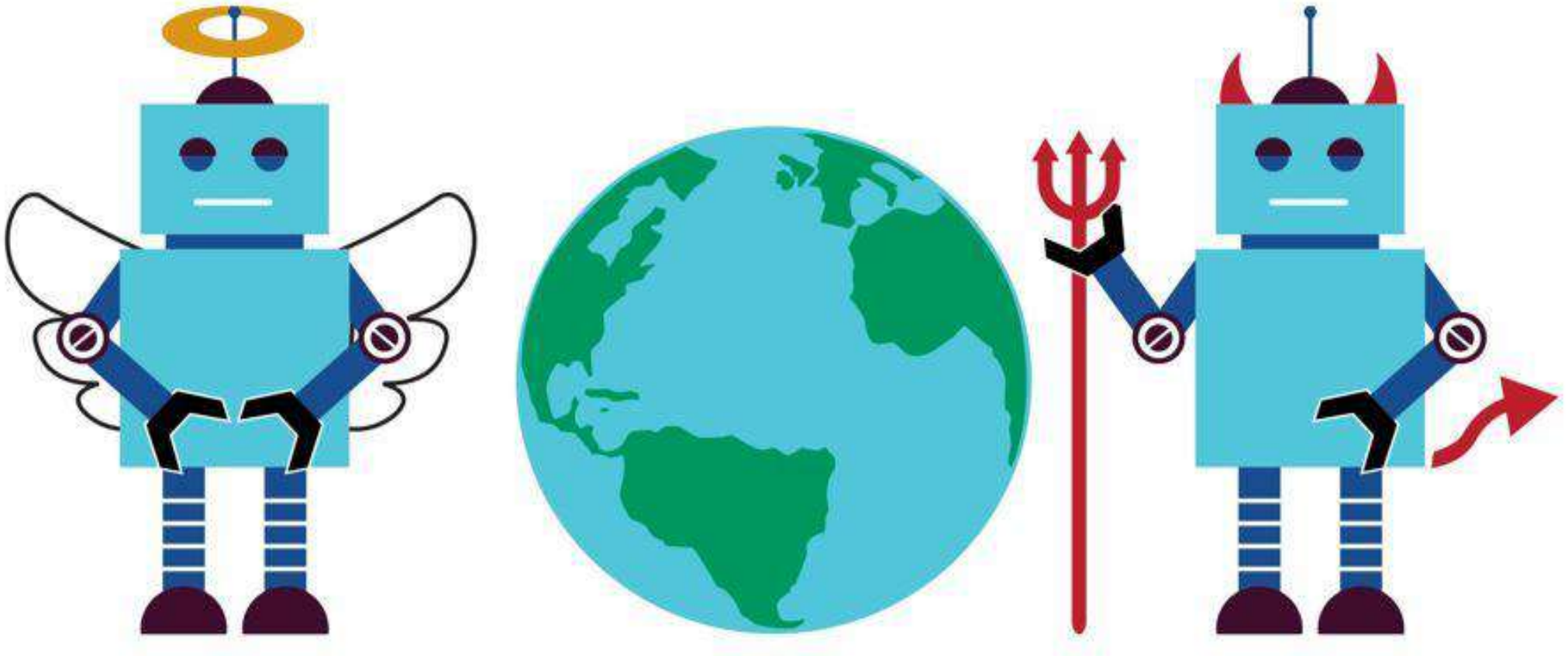


General AI does not exist (yet)

Dedicated ML Applications

- Image Classification
- Object Detection
- Pose Estimation
- Voice Recognition
- Gesture Recognition
- Anomaly Detection
- Natural Language Processing (NLP)

Responsible AI



Learning more about Embedded ML

Twitter: @mjrovai

instructables.com/member/mjrovai

github.com/Mjrovai

hackster.io/mjrobot

medium.com/@rovai

MJRoBot.org

- **Deploy machine learning models on mobile and IoT devices:**
  - https://www.tensorflow.org/lite
- **The Embedded Machine Learning Revolution:**
  - https://www.wevolver.com/article/the-embedded-machine-learning-revolution-the-basics-you-need-to-know
- **"Listening Temperature" with TinyML**
  - https://www.hackster.io/mjrobot/listening-temperature-with-tinyml-7e1325
- **Introduction to Embedded Machine Learning (Coursera Course)**
  - https://www.coursera.org/learn/introduction-to-embedded-machine-learning
- **Exploring AI at the Edge!**
  - https://towardsdatascience.com/exploring-ia-at-the-edge-b30a550456db
- **TinyML - Motion Recognition Using Raspberry Pi Pico**
  - https://www.hackster.io/mjrobot/tinyml-motion-recognition-using-raspberry-pi-pico-6b6071

Thanks

And stay safe!

UNIFEI