

When IoT meets AI: The marvelous world of TinyML

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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**

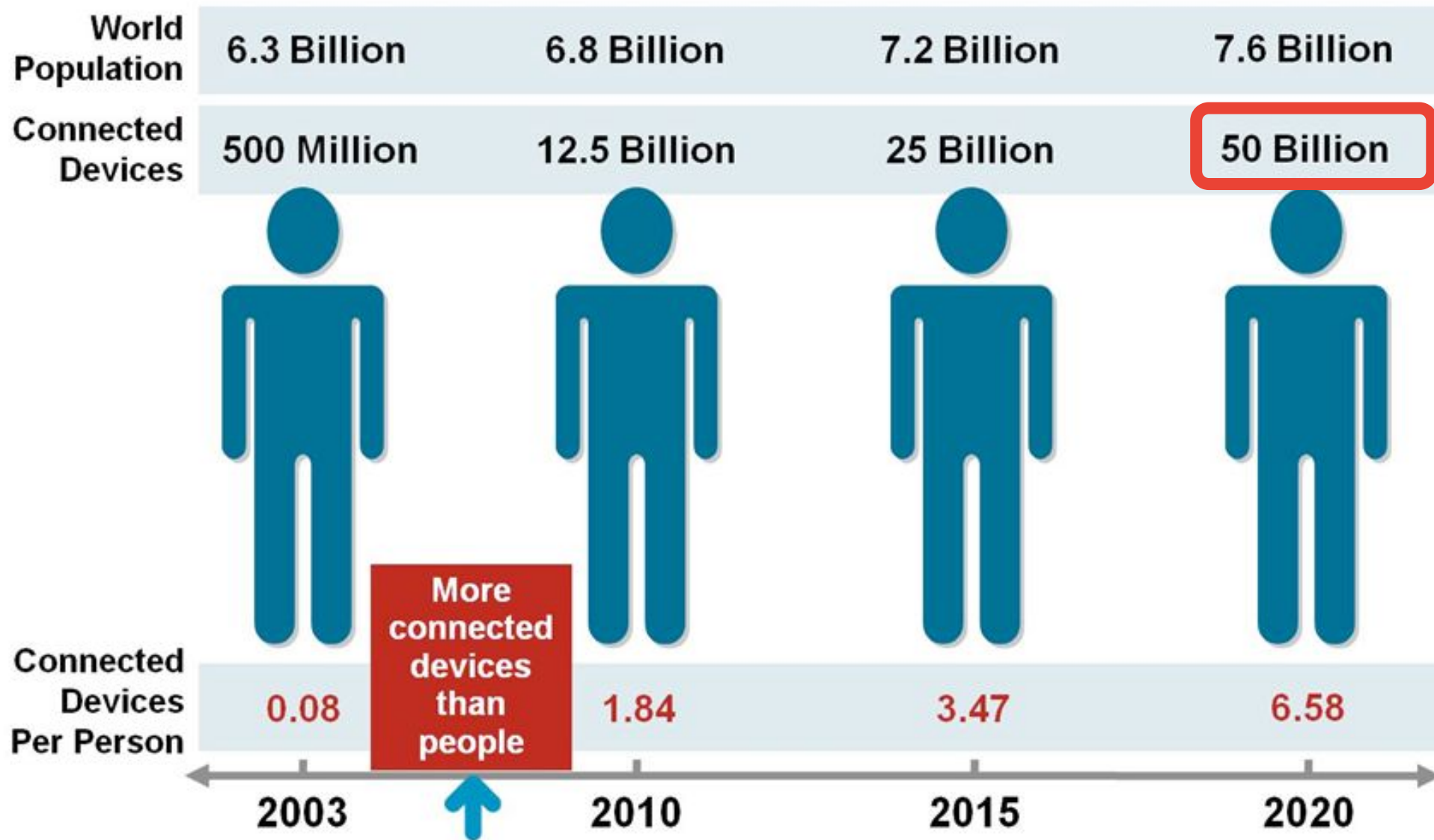
Device — ITU definition

“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.

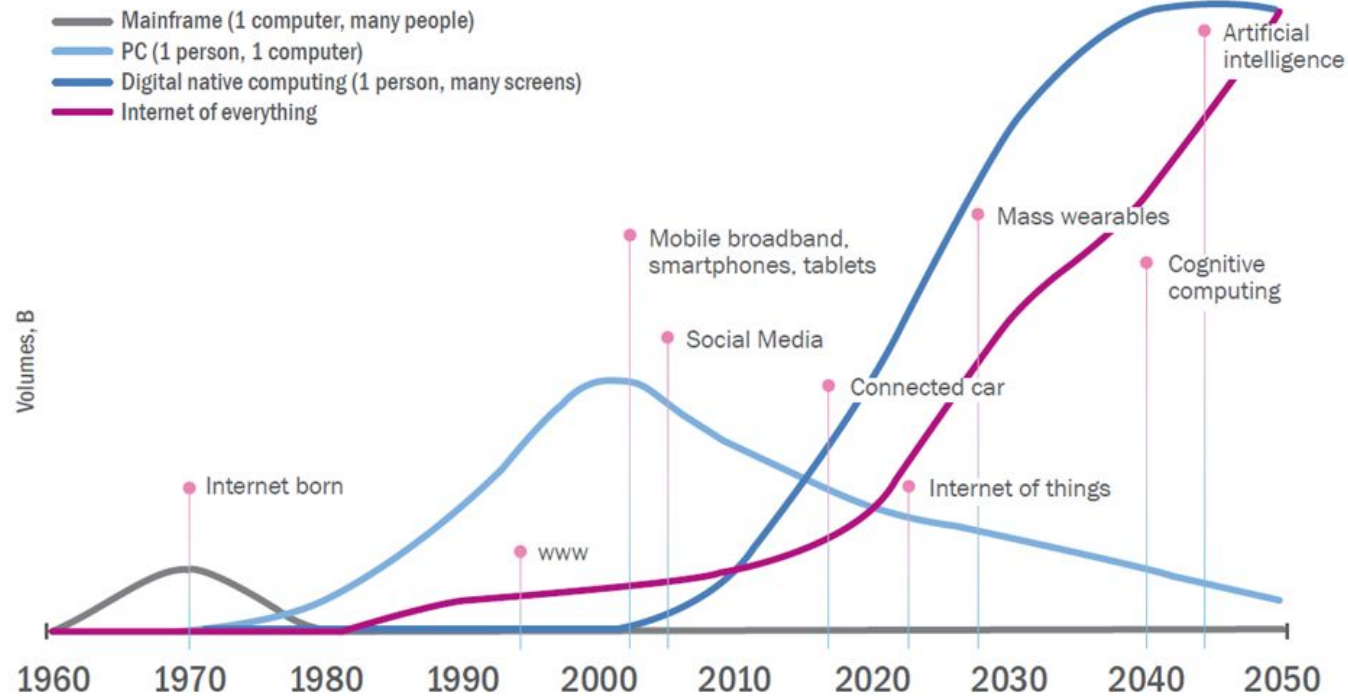


Source: Cisco IBSG, April 2011

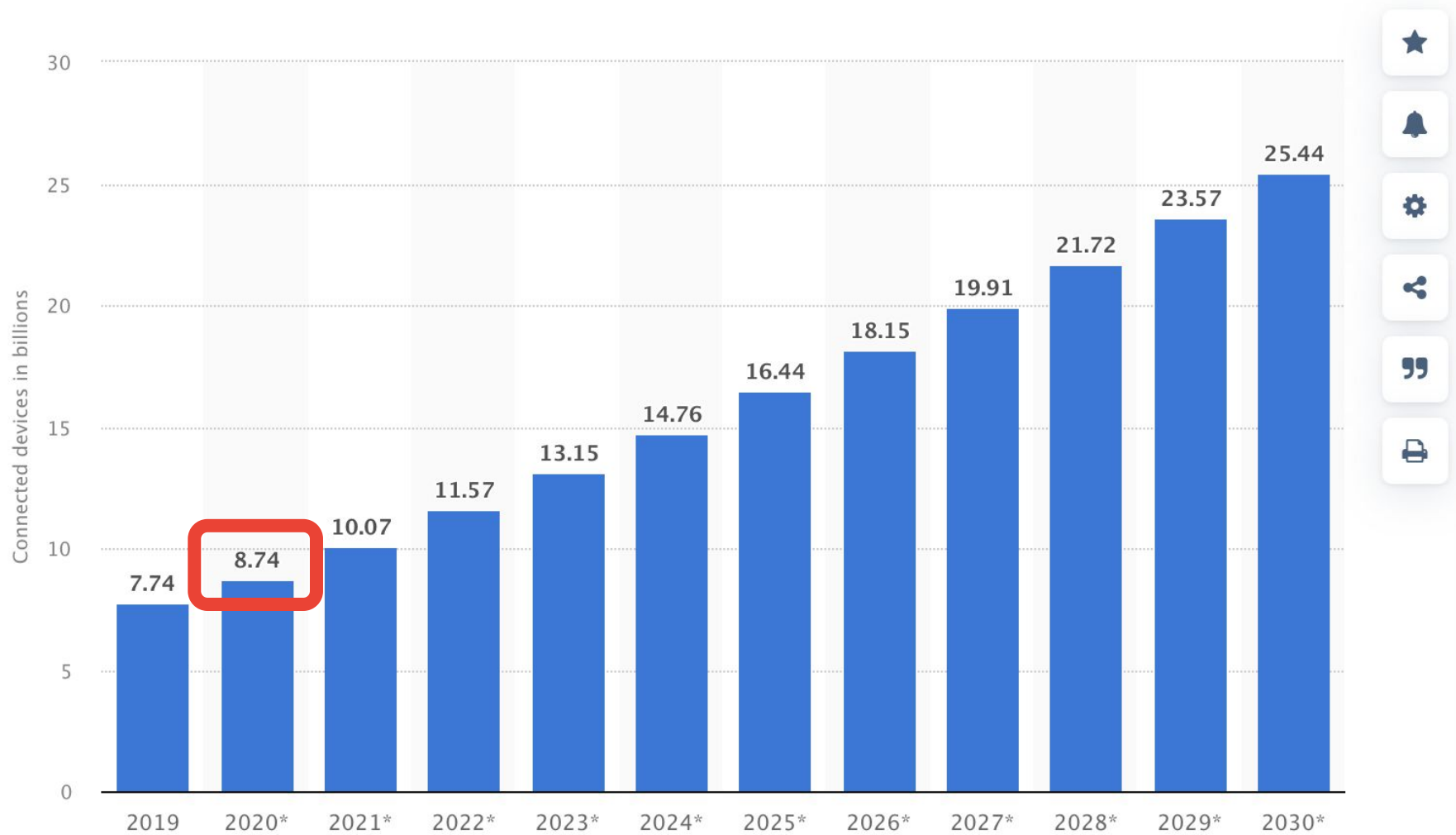
One to many to any

History of the future

One to many to any: ICTs from happy few to the masses



2020 statistics



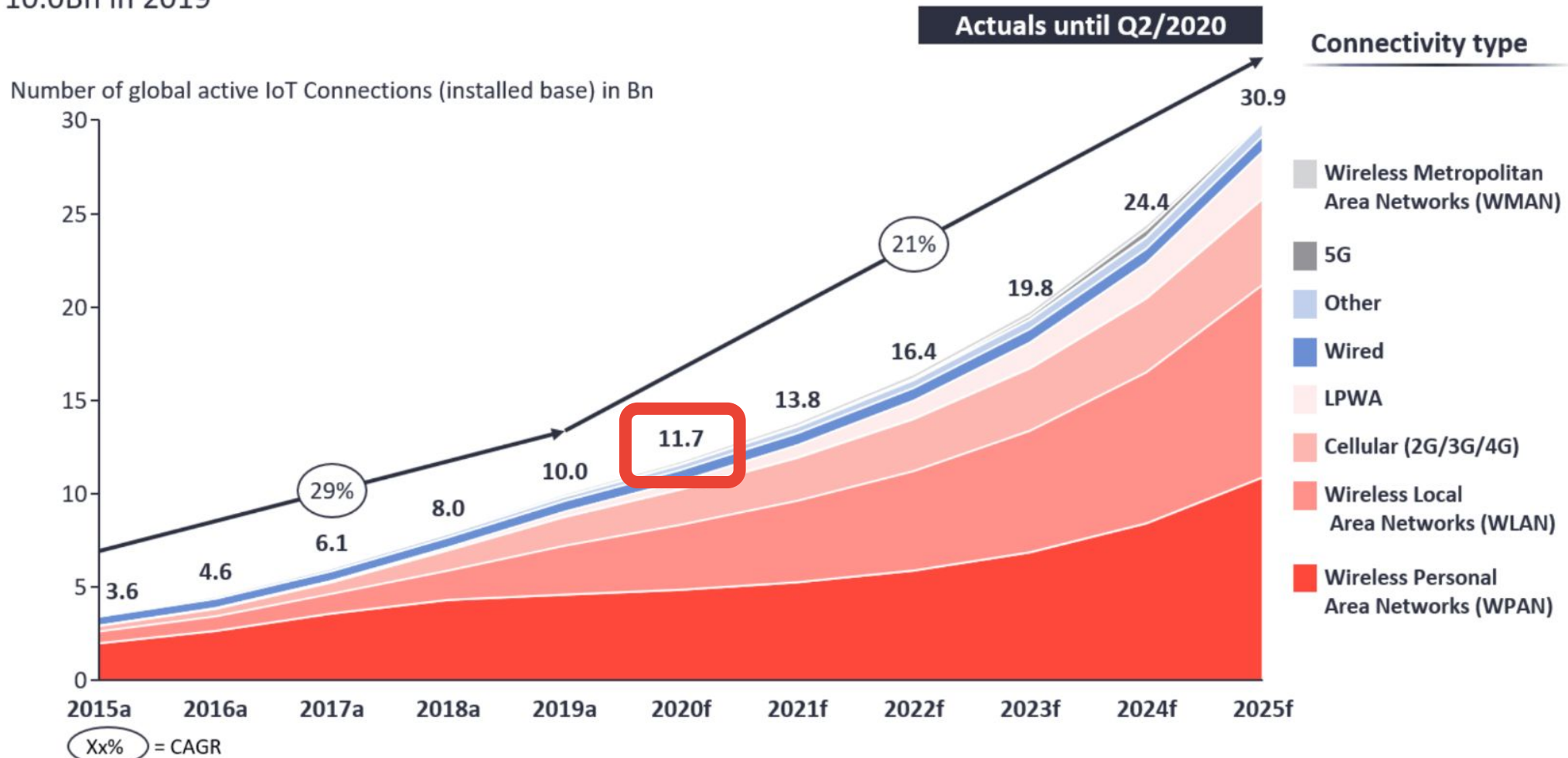
2020 statistics



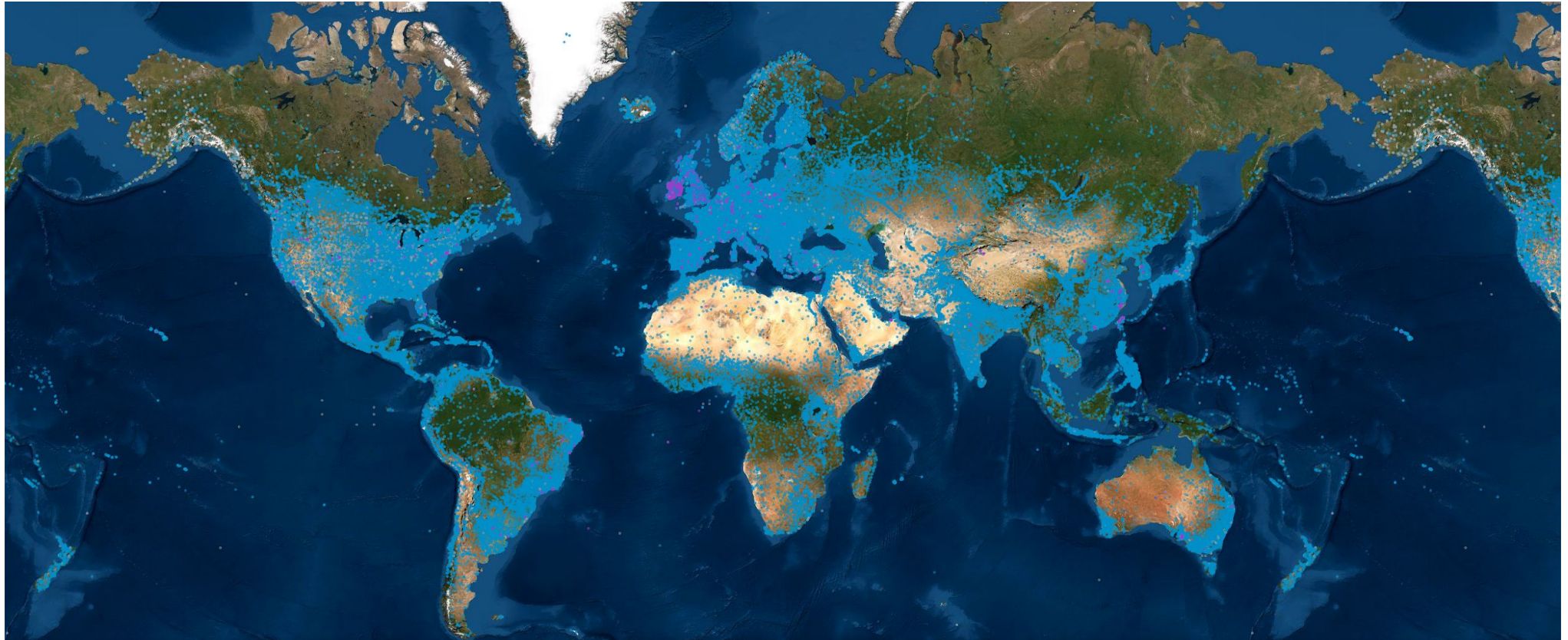
Insights that empower you to understand IoT

Global Number of Connected IoT Devices

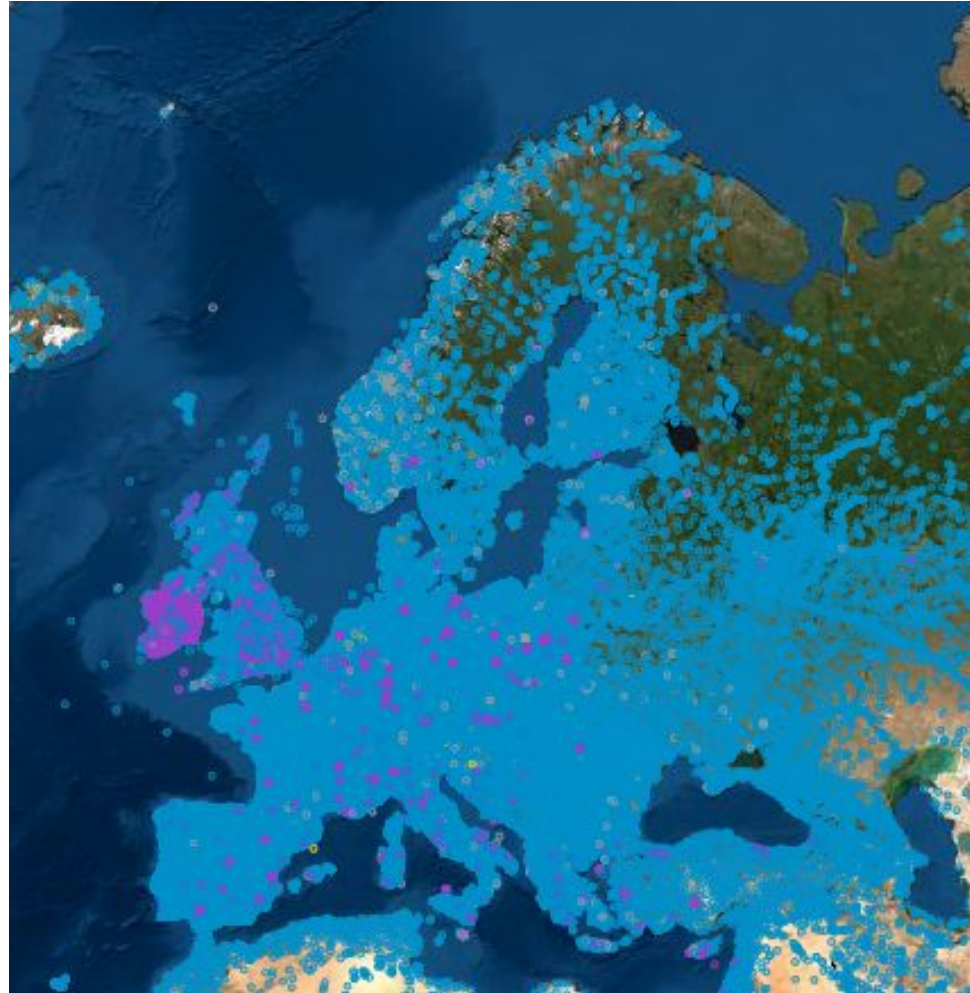
10.0Bn in 2019



Worldwide distribution



Worldwide distribution



Worldwide distribution



IoT and SDG



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

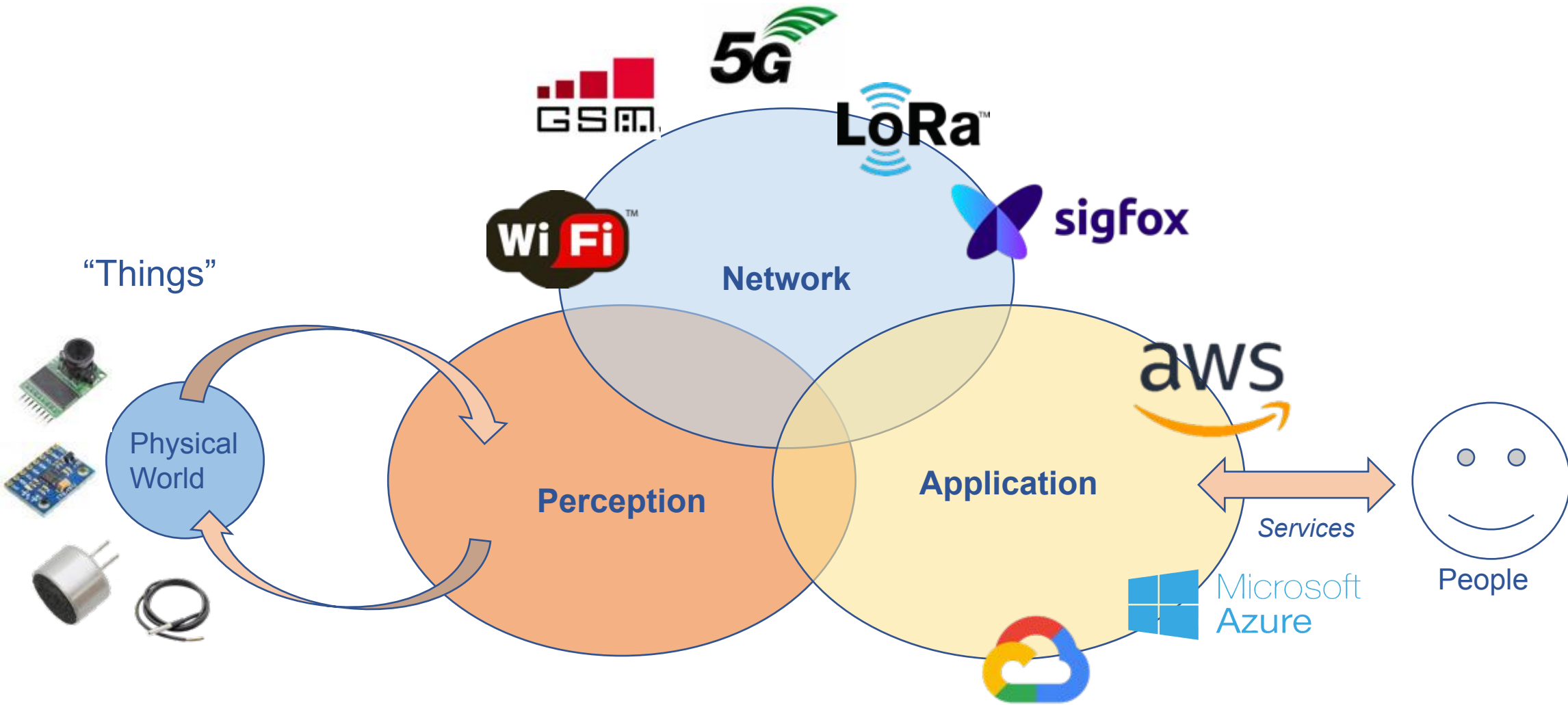
“A device is a piece of equipment with ~~the~~ **mandatory capabilities of communication** and optional capabilities of sensing, actuation, data capture, data storage and data processing. Some devices also execute operations ~~based on information received from the information and communication networks.~~”

— **Recommendation ITU-T Y.2060**

IoT

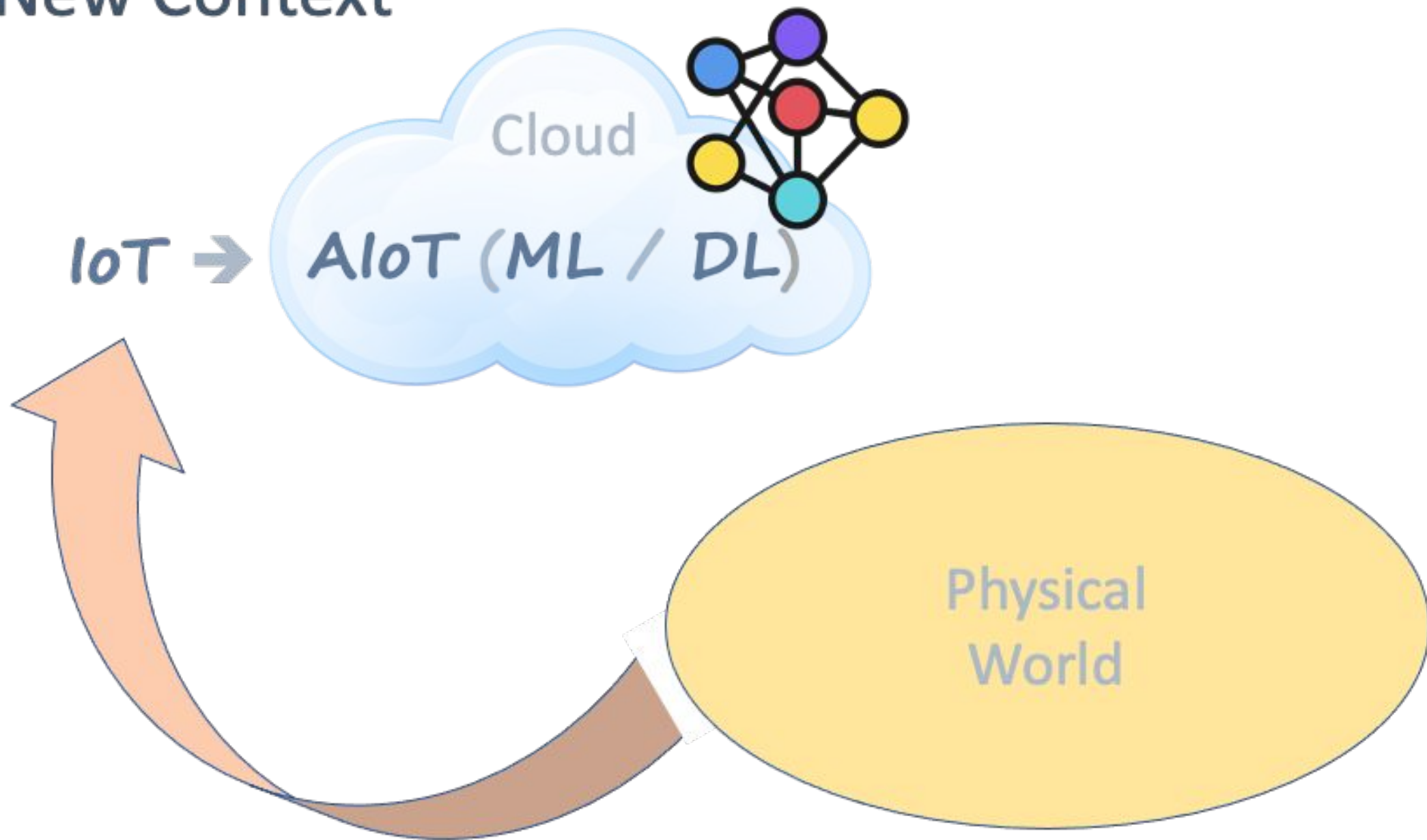


Classical IoT Architecture

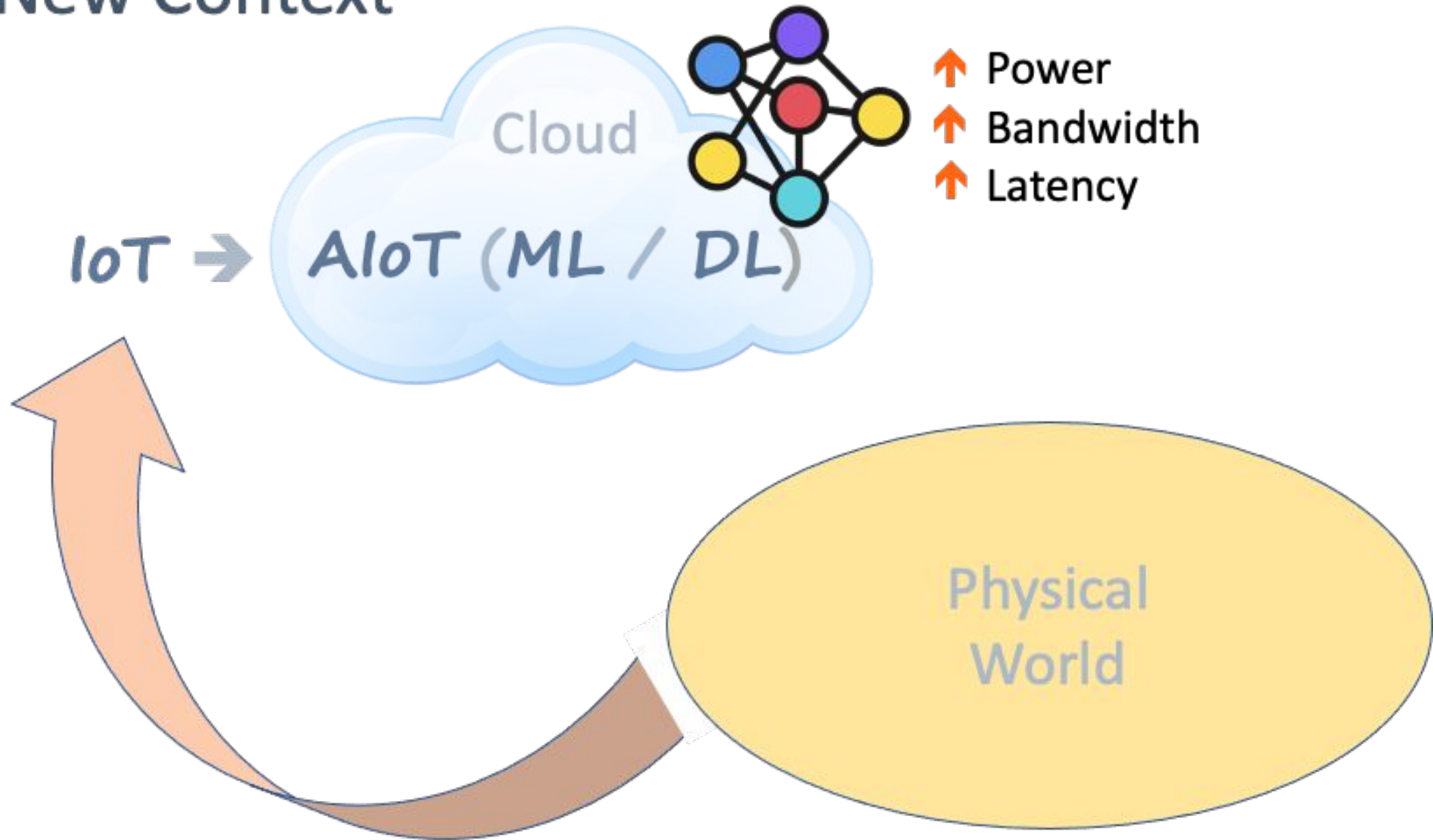


5 Quintillion bytes of data produced every day by IoT, but less than 1% is used. HBR/CISCO

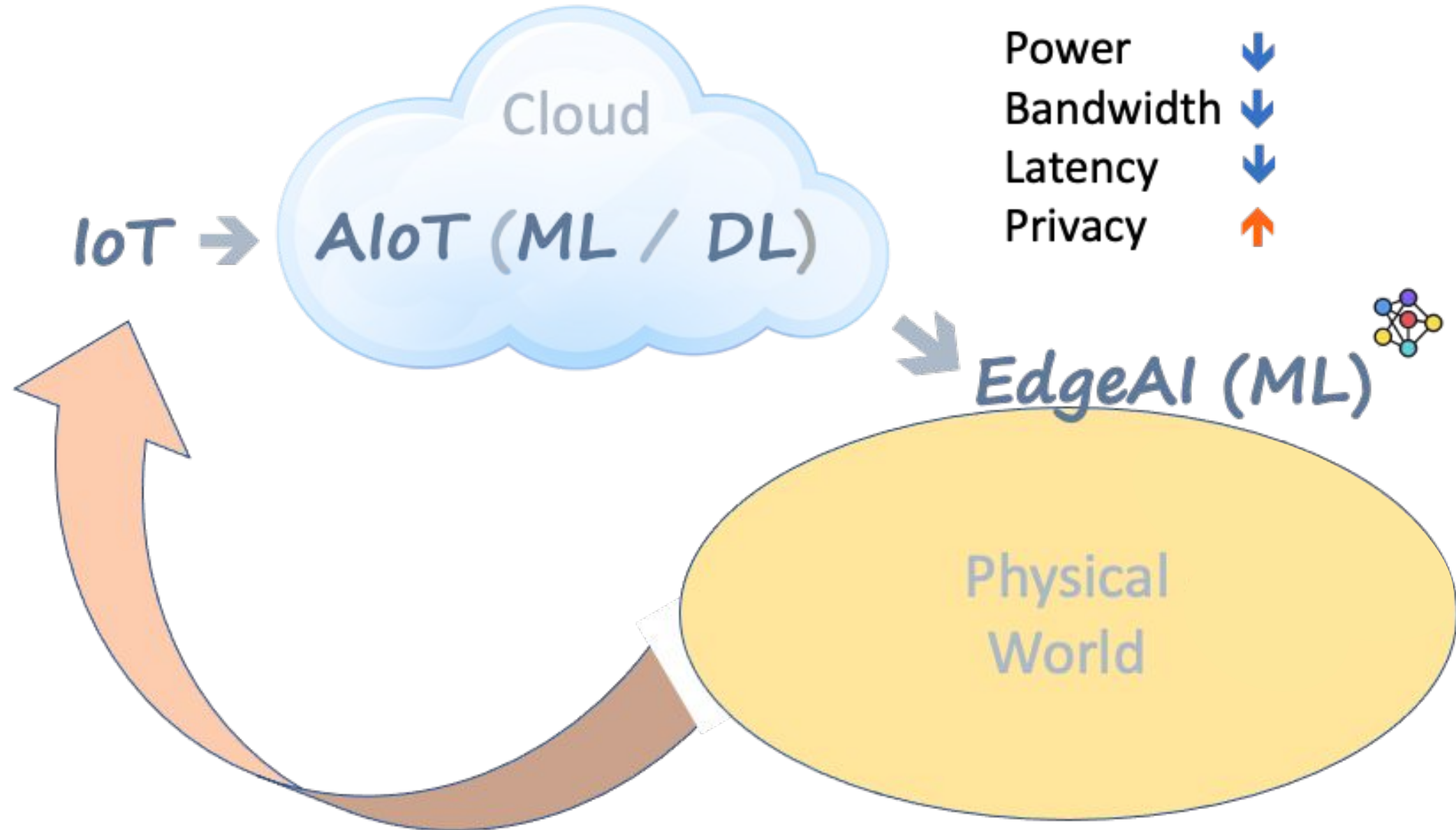
New Context



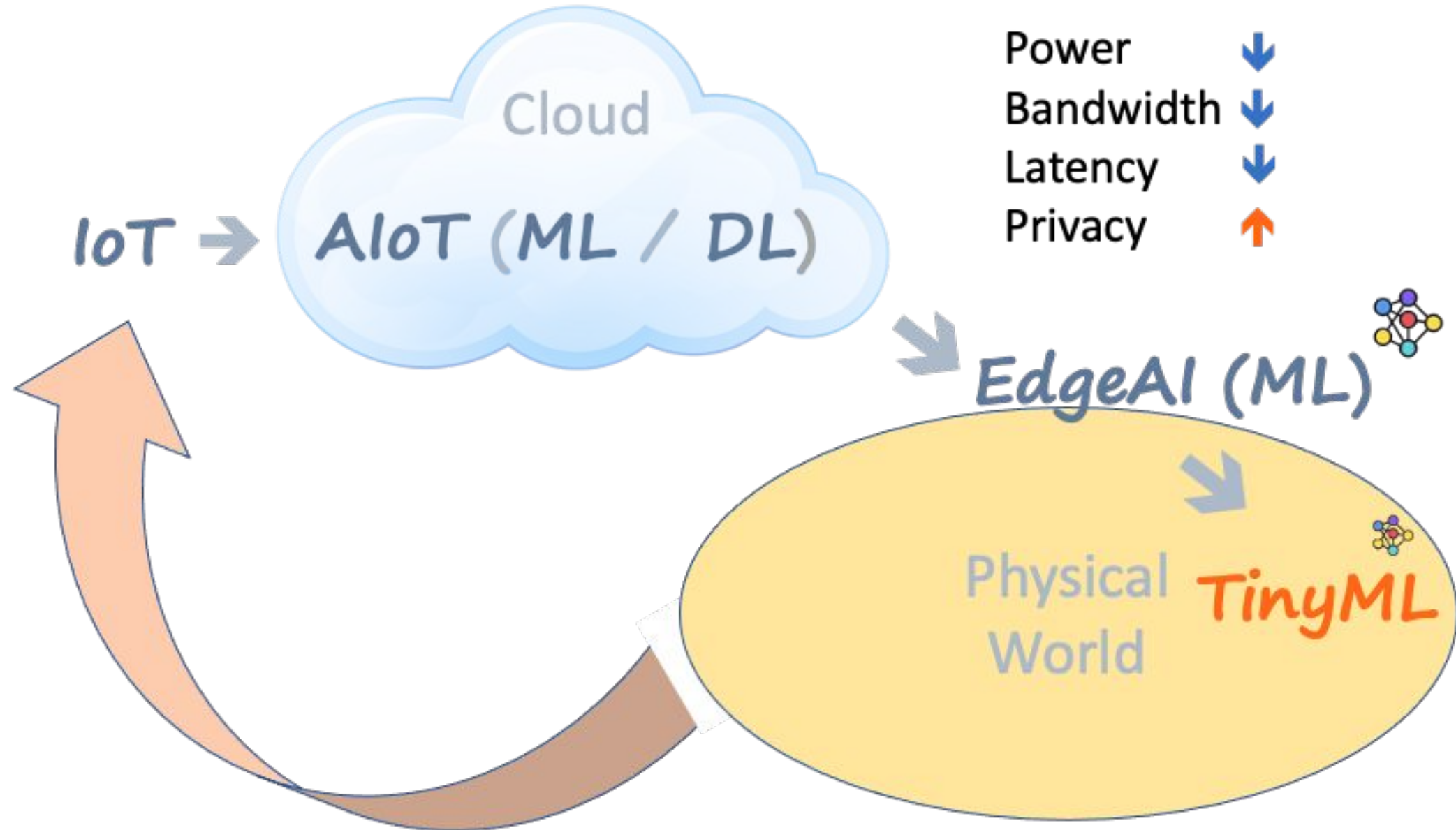
New Context



New Context



New Context



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

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TinyML

Fastest-growing field of **ML**



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Fastest-growing field of **ML**



Algorithms, hardware, software

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

TinyML

Fastest-growing field of **ML**

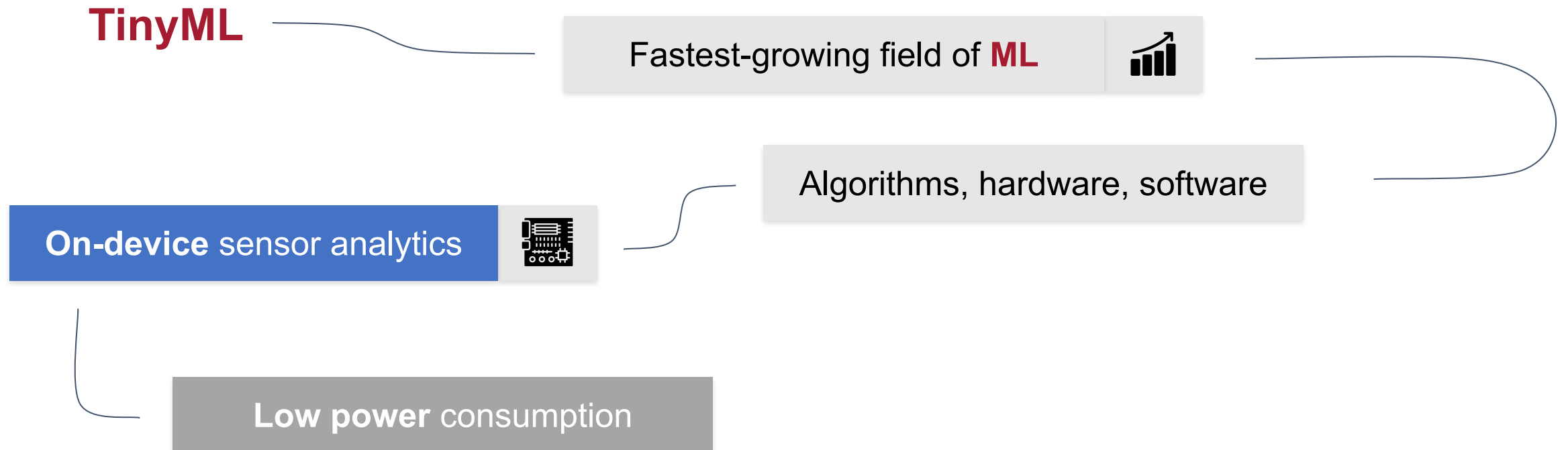


Algorithms, hardware, software

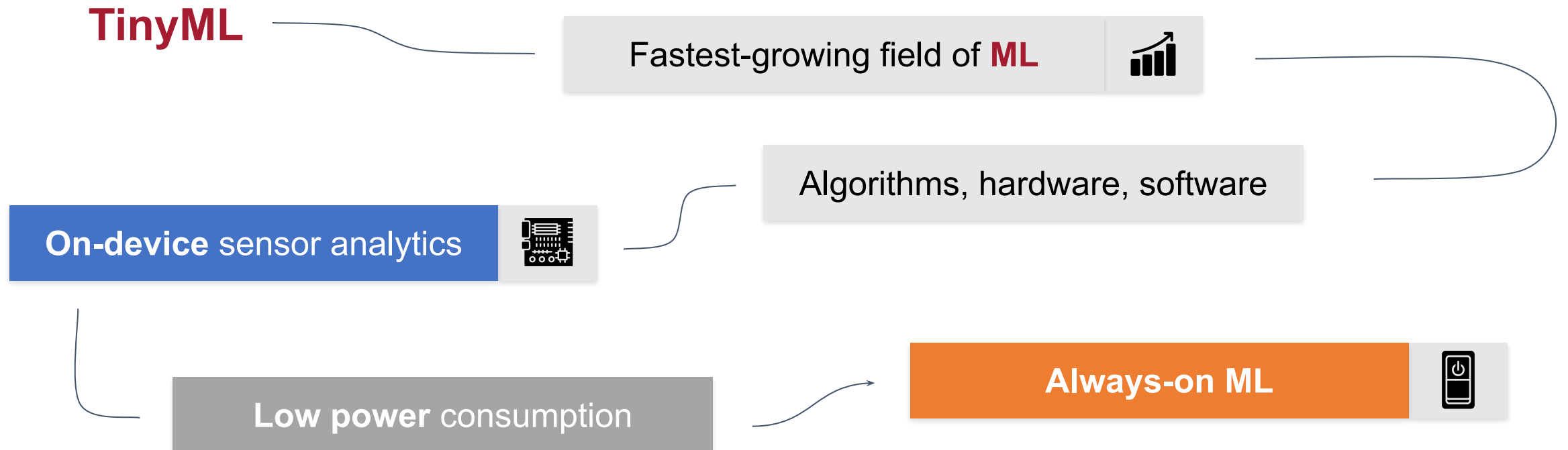
On-device sensor analytics



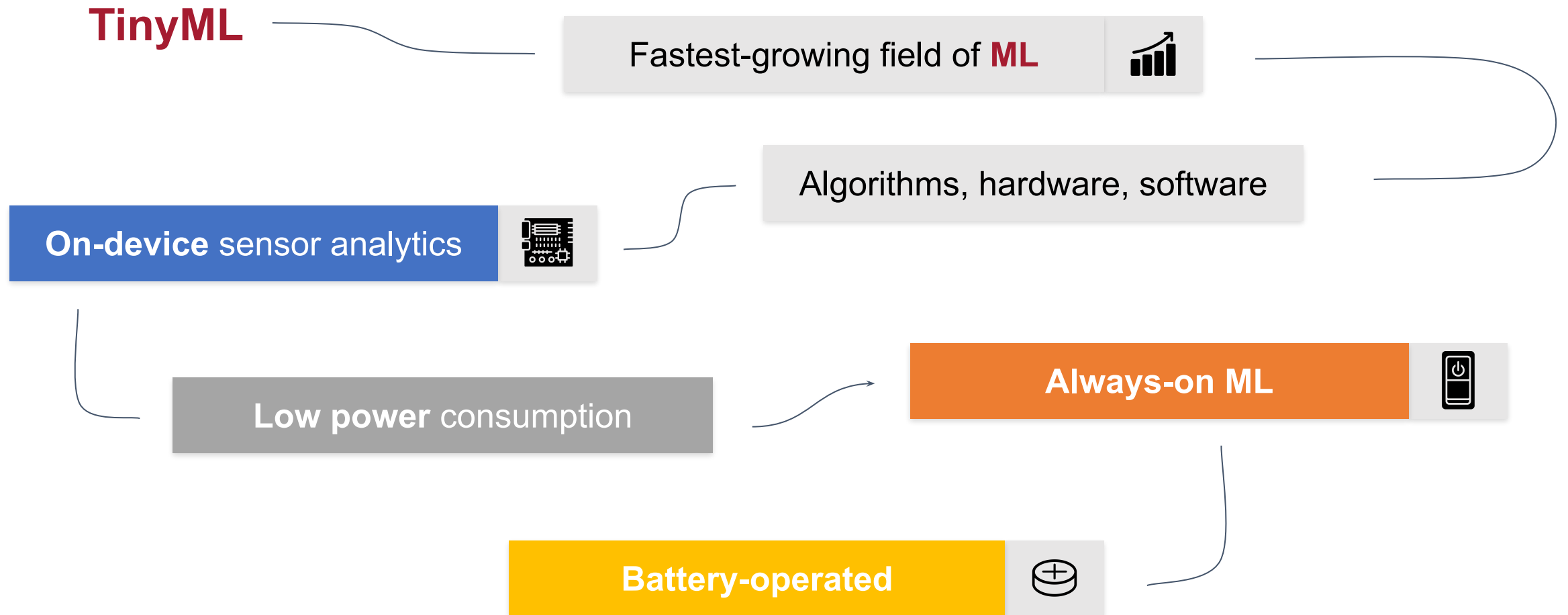
What is Tiny Machine Learning (**TinyML**)?



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



EdgeML (P↑)

Autonomous Car Control



Image Recognition



EdgeML (P↑)

Autonomous Car Control



Image Recognition



TinyML (P↓)

KeyWord Spotting



Environmental Control



Image Spot



Motion & biometric



TinyML Application Areas



Home



Office



Industry



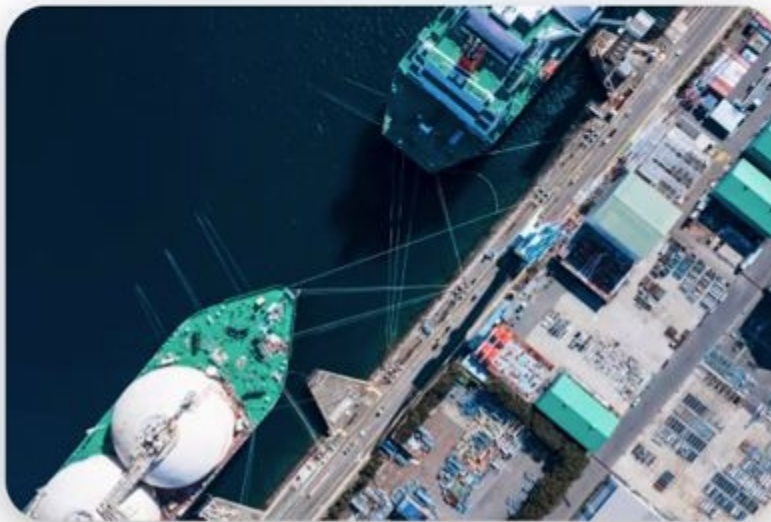
Predictive Maintenance



Motion, current, audio and camera

- Industrial
- White goods
- Infrastructure
- Automotive

Asset Tracking & Monitoring



Motion, temp, humidity, position, audio and camera

- Logistics
- Infrastructure
- Buildings

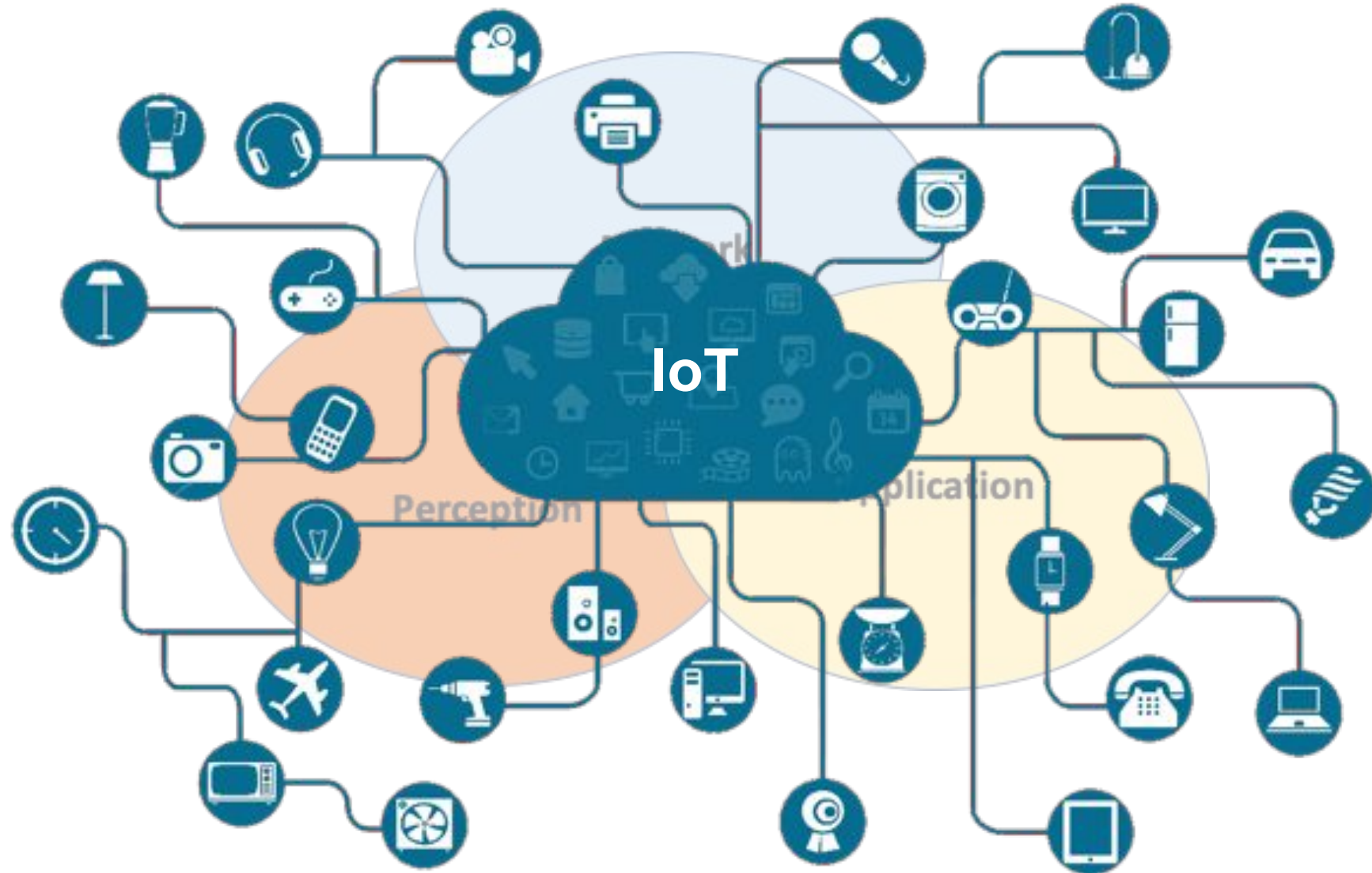
Human & Animal Sensing



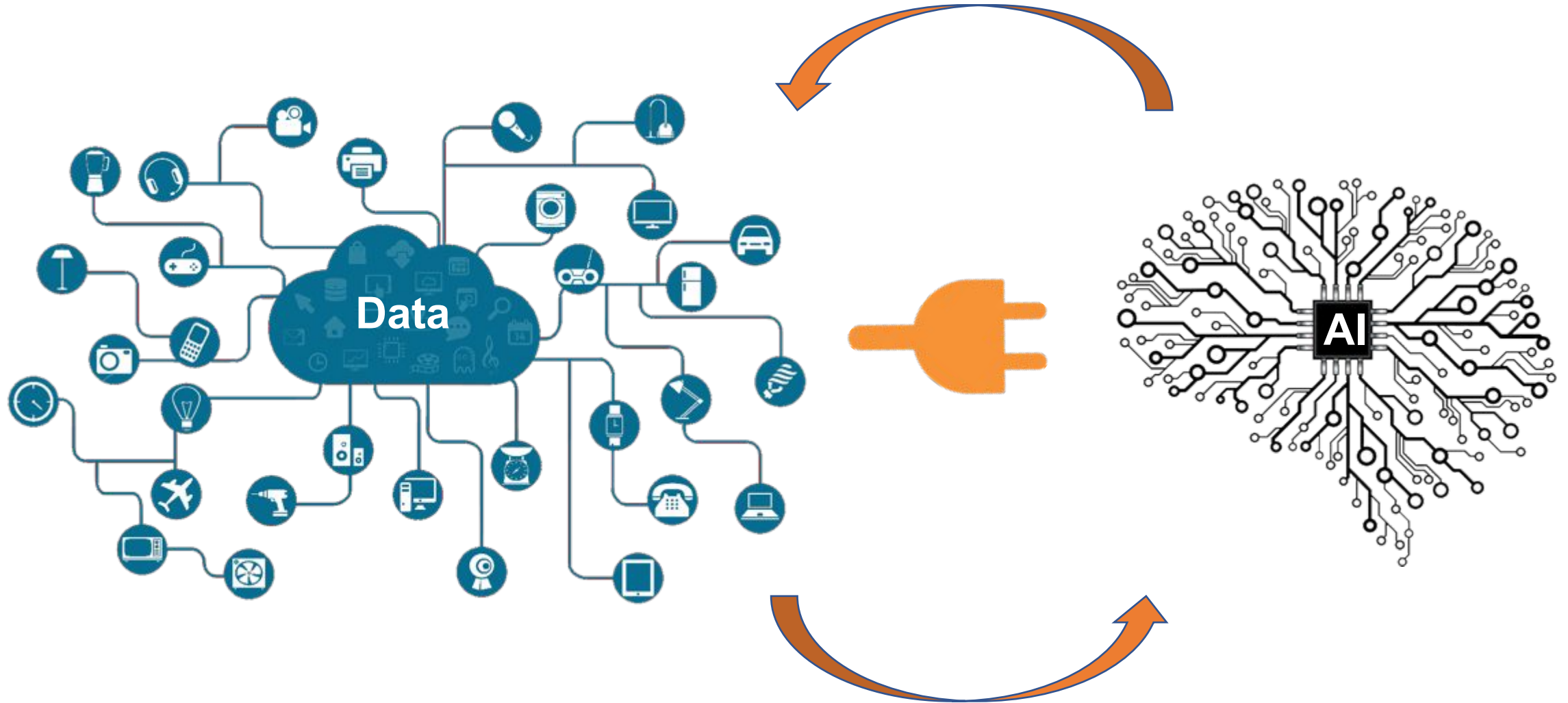
Motion, radar, audio, PPG, ECG

- Health
- Consumer
- Industrial

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

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Thermal, Image

Biometric Sensors

Fingerprint, Heart rate, etc.

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Pressure, Strain

Rotation Sensors

Encoders

Biometric Sensors



Non-invasive Glucose Monitoring



Fingerprint + Photoplethysmography (PPG)



ECG Sensor

Endpoints Have **Sensors**, Tons of Sensors

Motion Sensors

Gyroscope, radar,
magnetometer, accelerator

Acoustic Sensors

Ultrasonic, Microphones,
Geophones, Vibrometers

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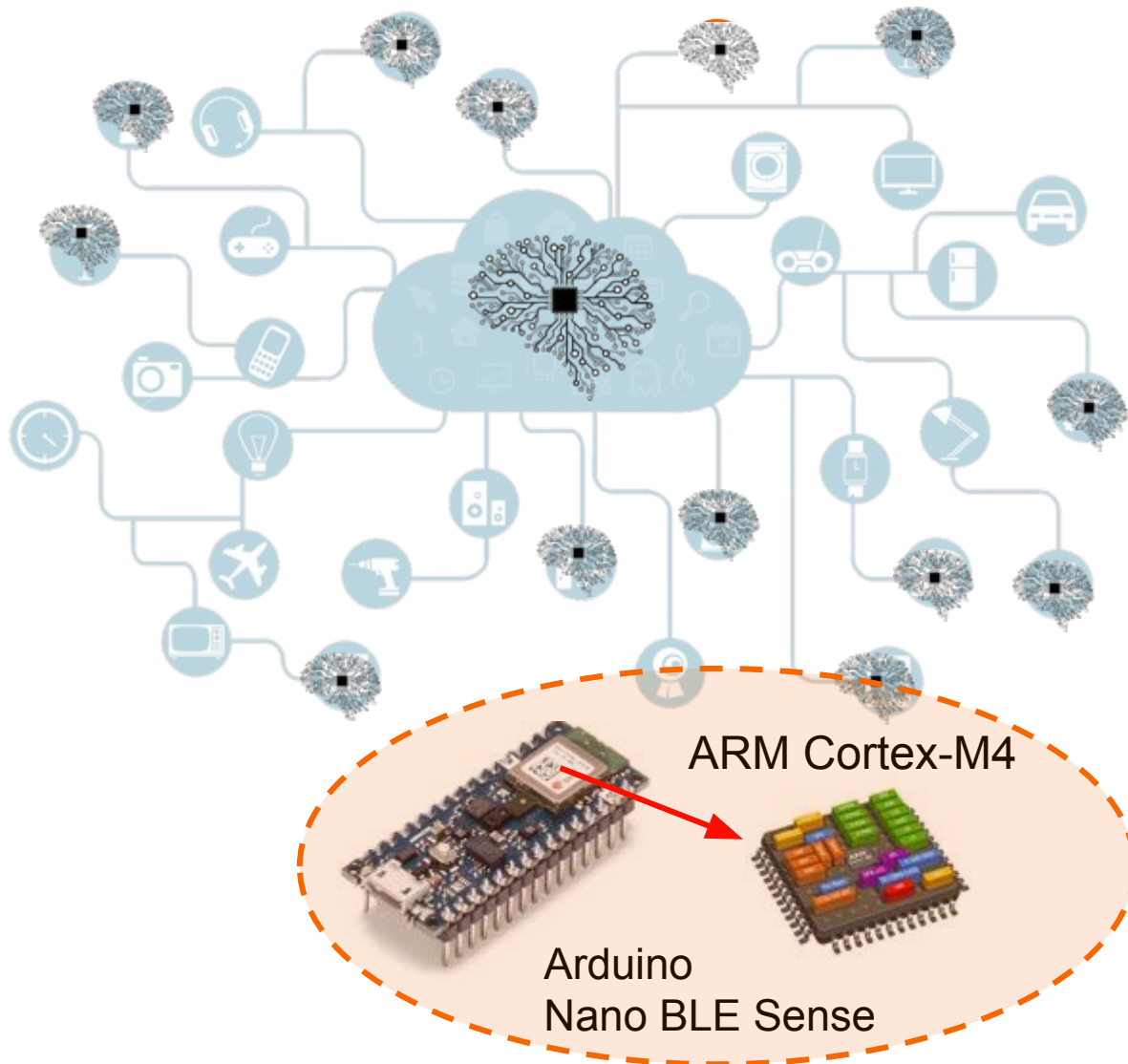
Force Sensors

Pressure, Strain

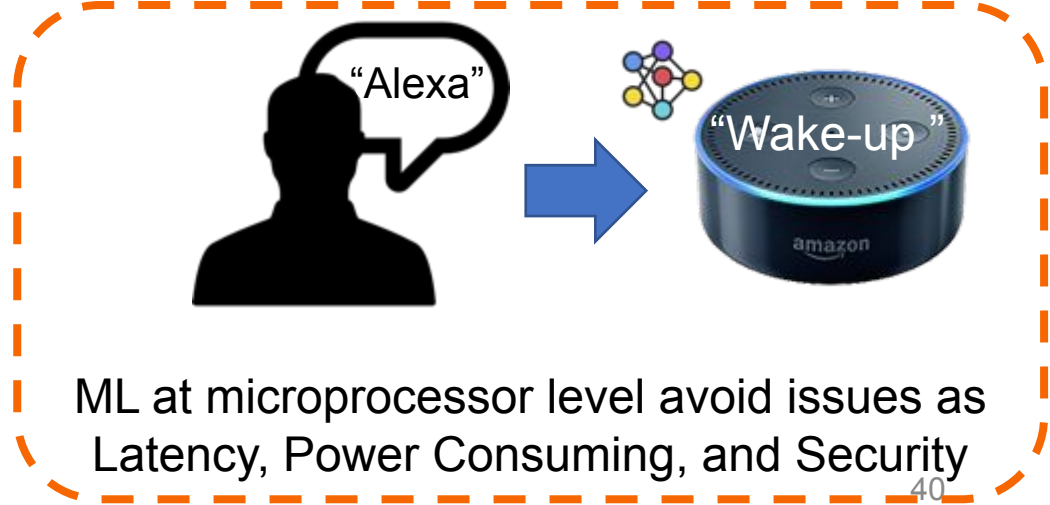
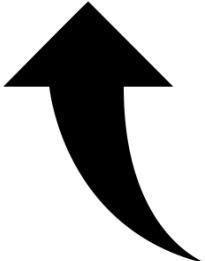
Rotation Sensors

Encoders

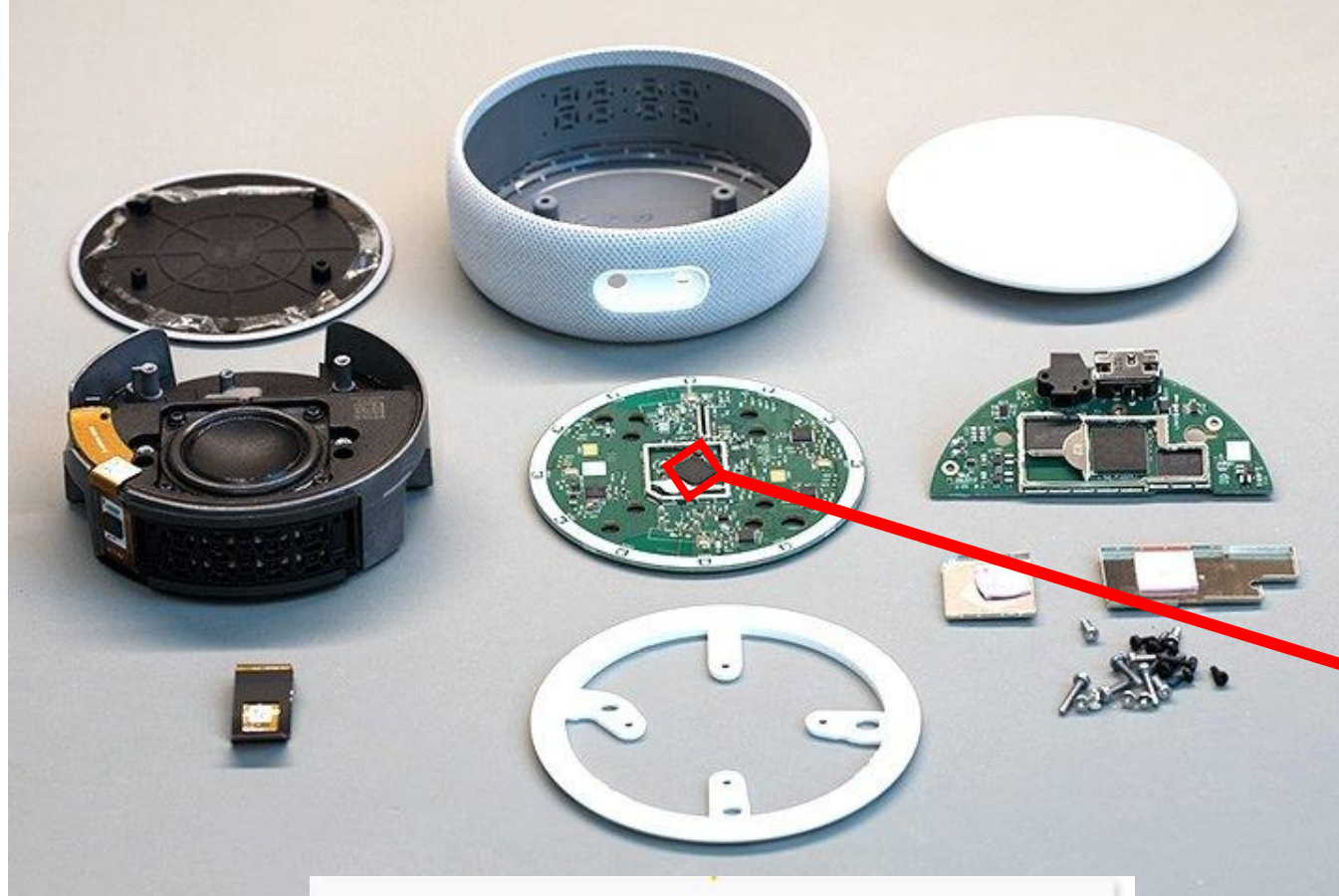
ML (AI) at the “edge of the edge” → TinyML



TinyML enables machine intelligence right next to the physical world

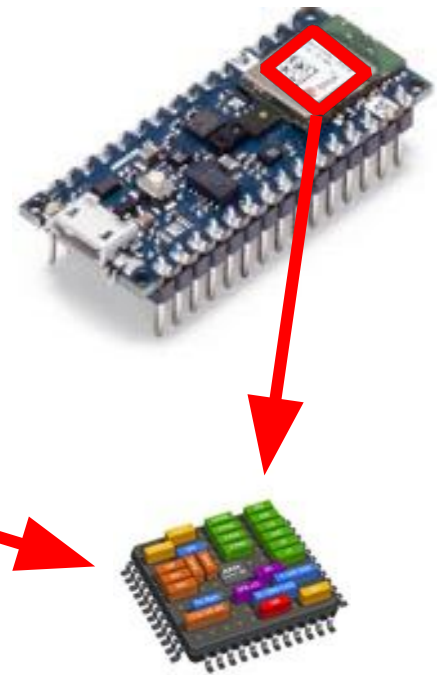


Echo-Dot Teardown vs Arduino Nano BLE Sense



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

Nordic nRF52840-M4

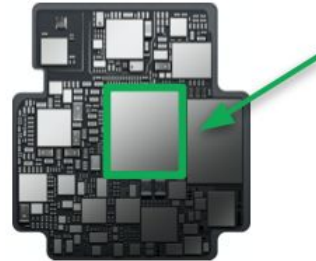


MCUs enable **TinyML**

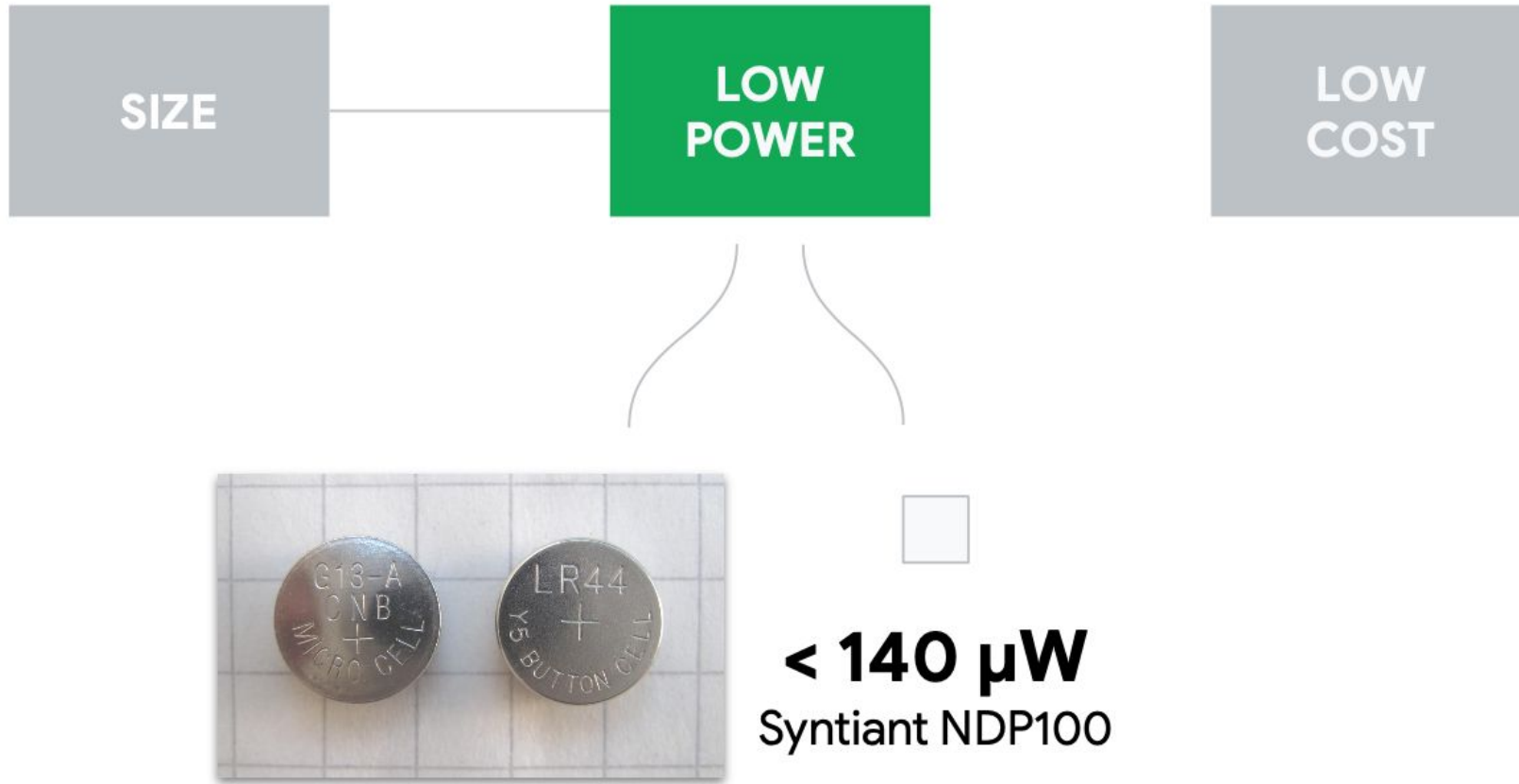
SIZE

LOW
POWER

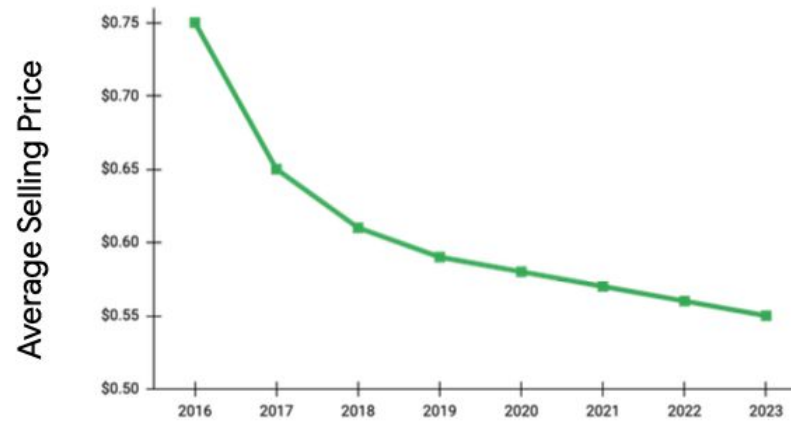
LOW
COST



MCUs enable **TinyML**



MCUs enable **TinyML**



What Makes **TinyML**?

**Embedded
Systems**

Hardware

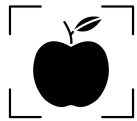
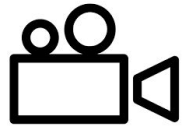
**Machine
Learning**

Software

TinyML



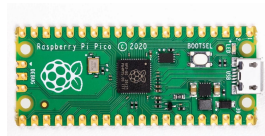
Hardware



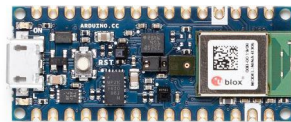
Anomaly Detection
Sensor Classification
20 KB

KeyWord Spotting
Audio Classification
50 KB

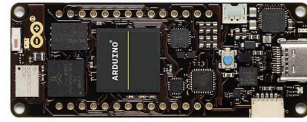
Image
Classification
250 KB+



Rpi-Pico
(Cortex-M0+)



Arduino Nano
(Cortex-M4)



Arduino Pro
(Cortex-M7)

EdgeML

TinyML

Object Detection
Complex Voice
Processing
1 MB+

Video
Classification
2 MB+



RaspberryPi
(Cortex-A)

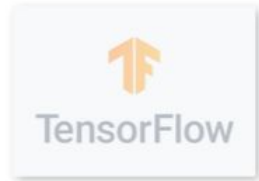


SmartPhone
(Cortex-A)



Jetson Nano
(Cortex-A + GPU)

Software



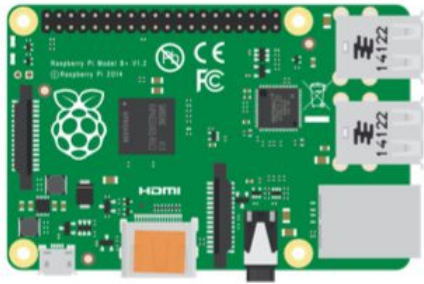
Train a model

Convert
model

Optimize
model

Deploy
model at
Edge

Make
inferences
at Edge



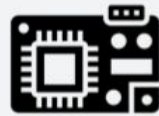
Raspberry Pi



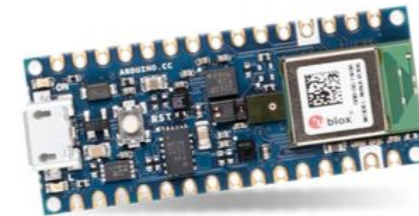
Linux



iOS



(TFL Micro)



Microcontroller

TinyML Application

Examples

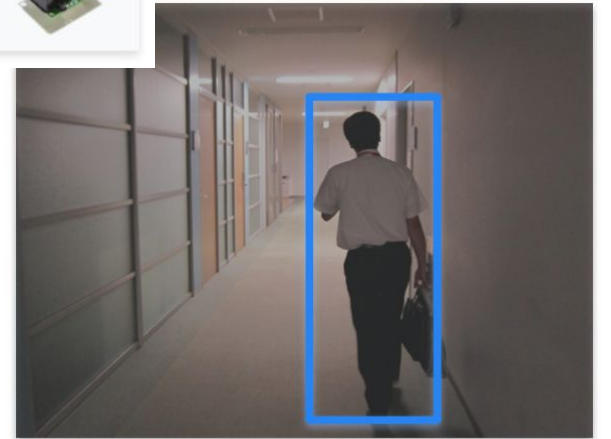
Sound



Vibration



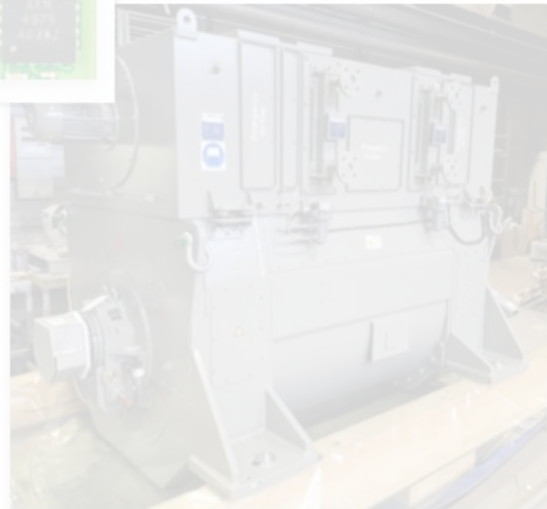
Vision



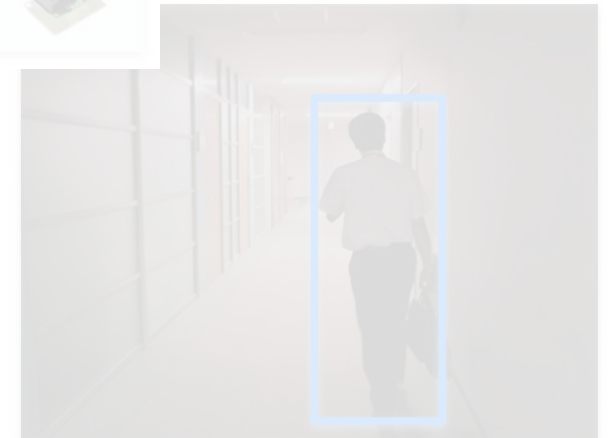
Sound



Vibration



Vision









More than just voice

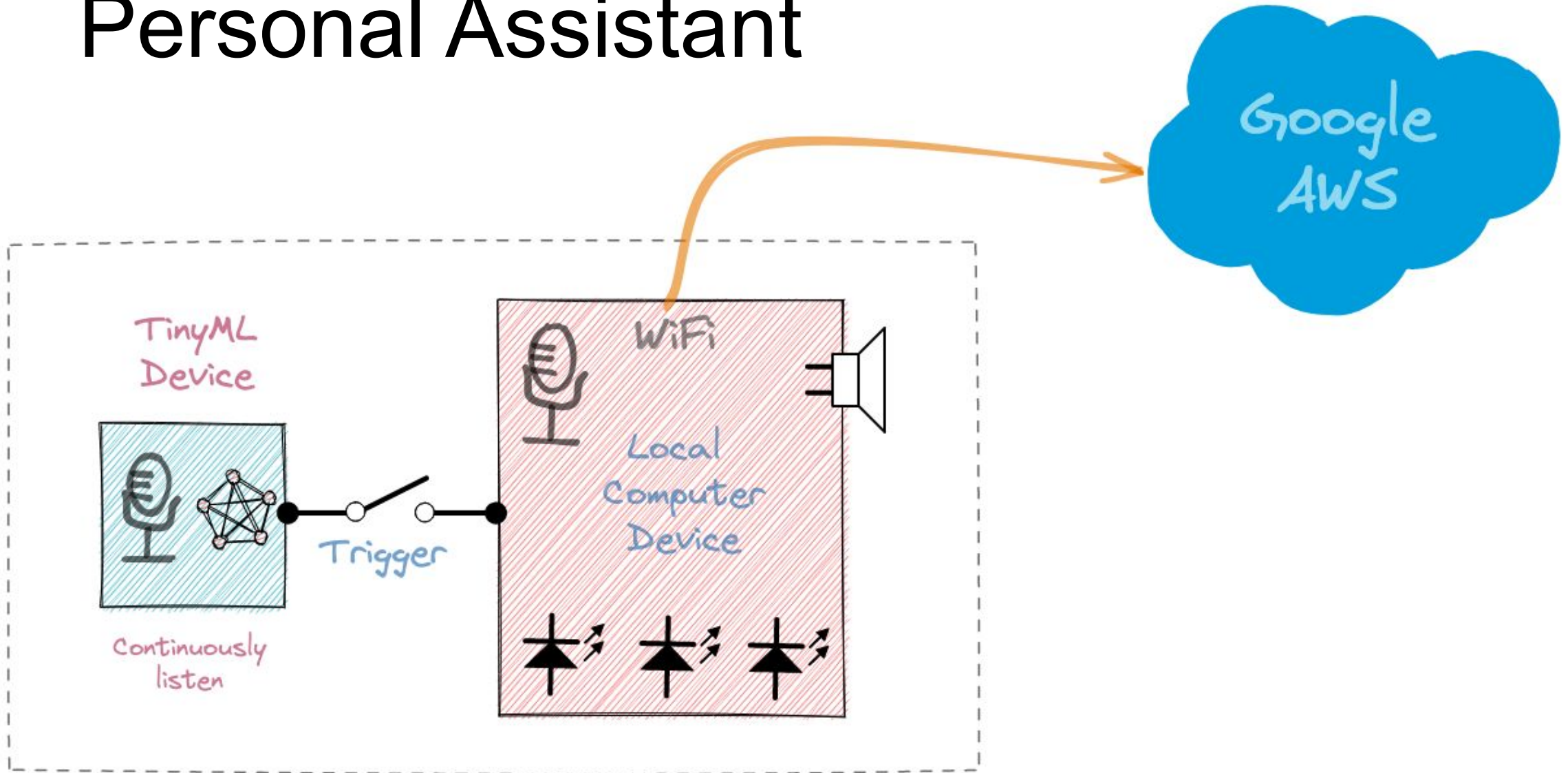
- **Security** (Broken Glass)
- **Industry** (Anomaly Detection)
- **Medical** (Snore, Toss)
- **Nature** (Bee, Mosquito sound)



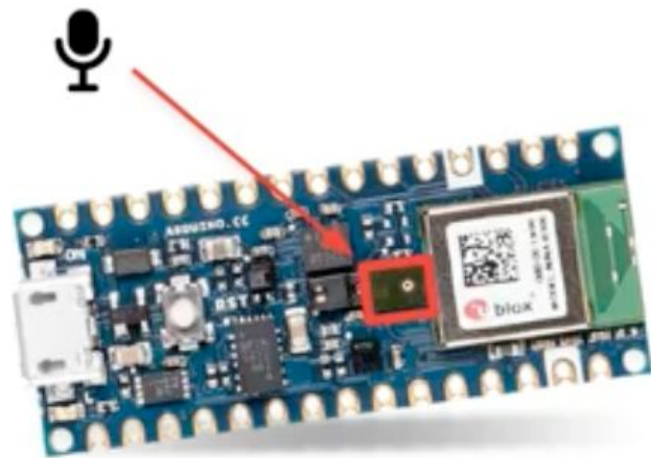
Personal Assistant



Personal Assistant



“Cascade” Detection: multi-stage model



1 Continuously listen on the microcontroller

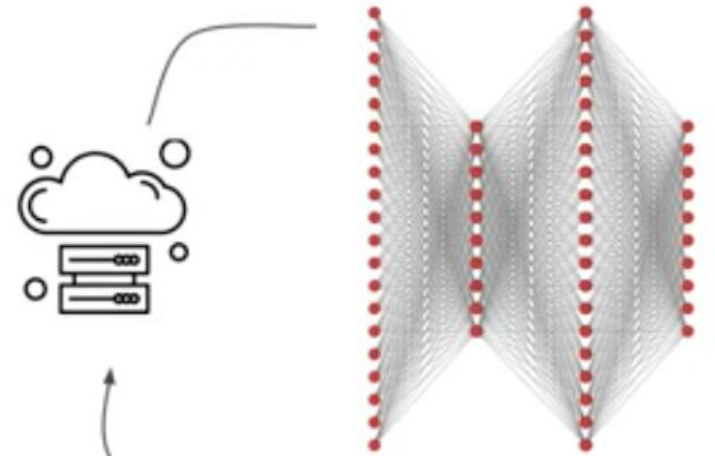
2 Process the data with **TinyML** at the edge



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

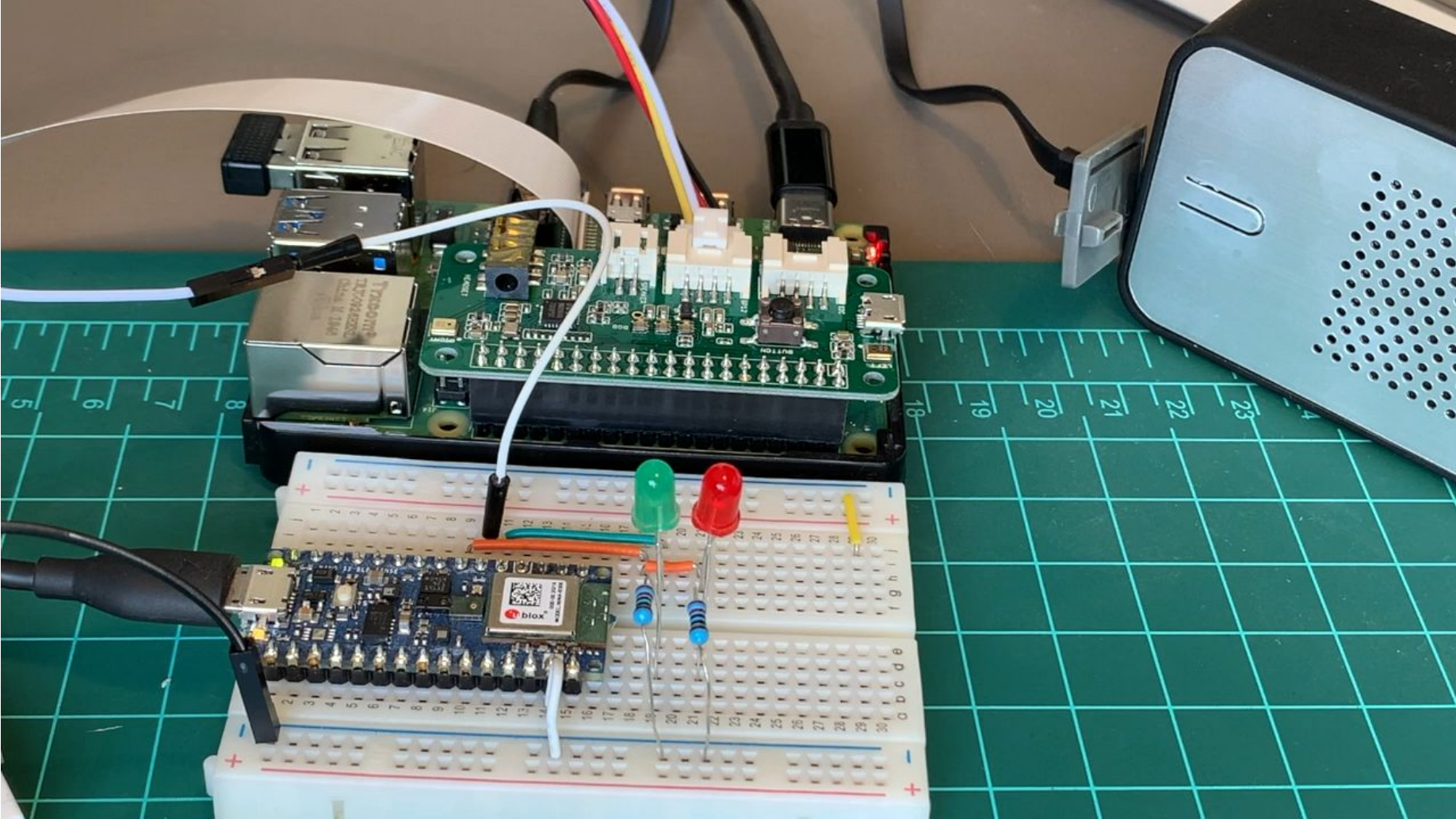


4 Send the data to the cloud when triggered



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

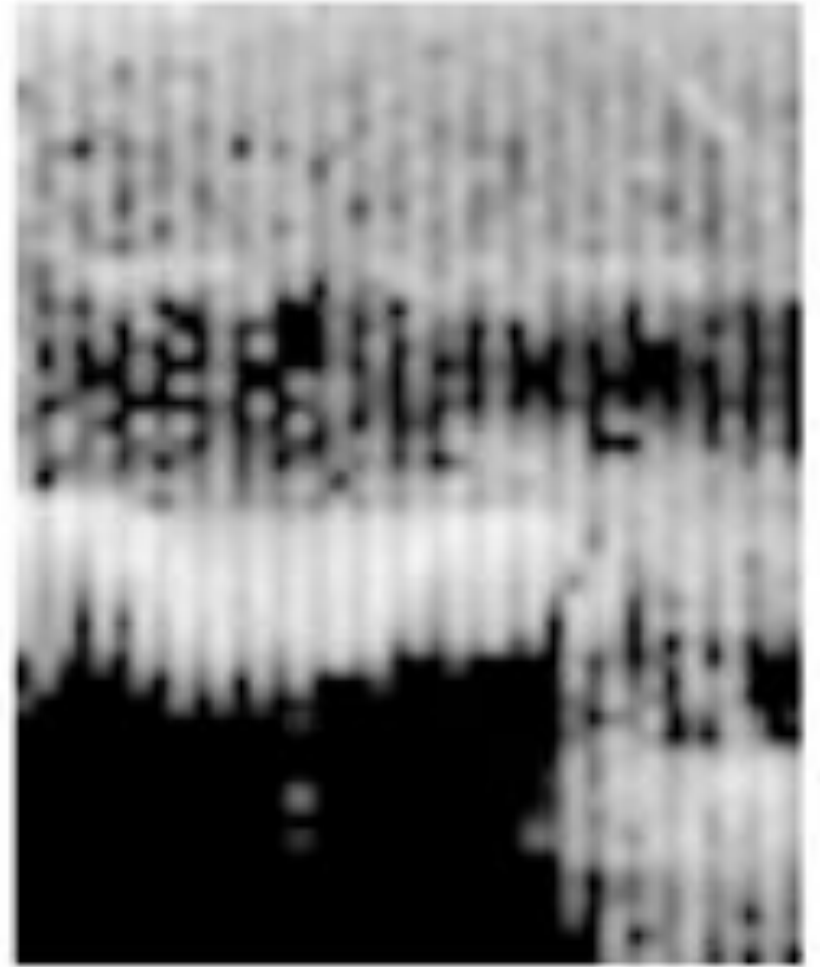
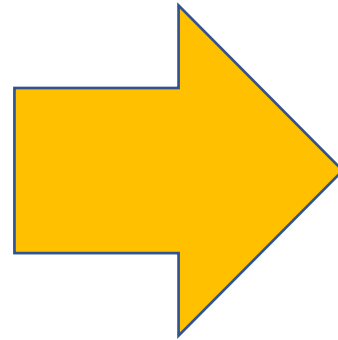
KeyWord Spotting (KWS)



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



Sound



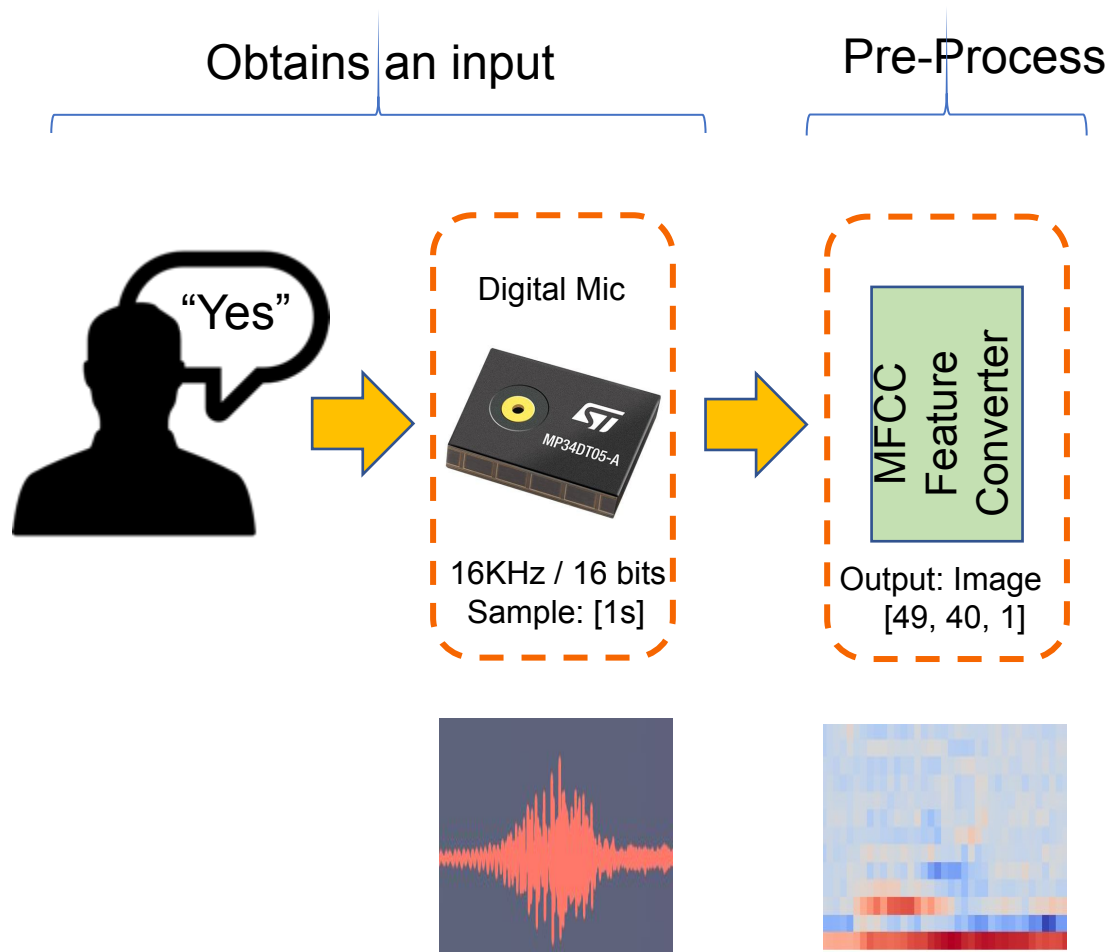
Image

KeyWord Spotting (KWS) - Inference

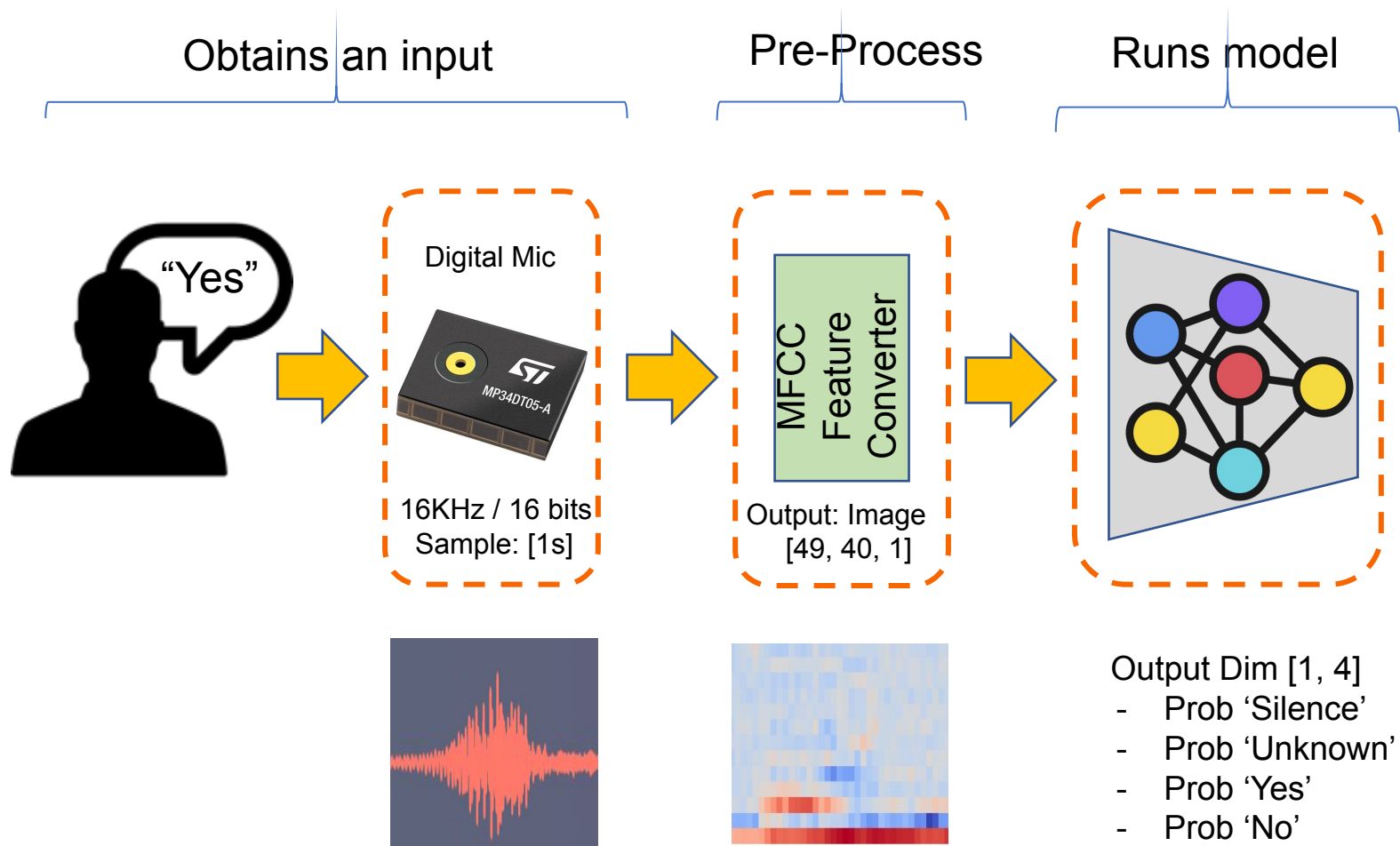
Obtains an input



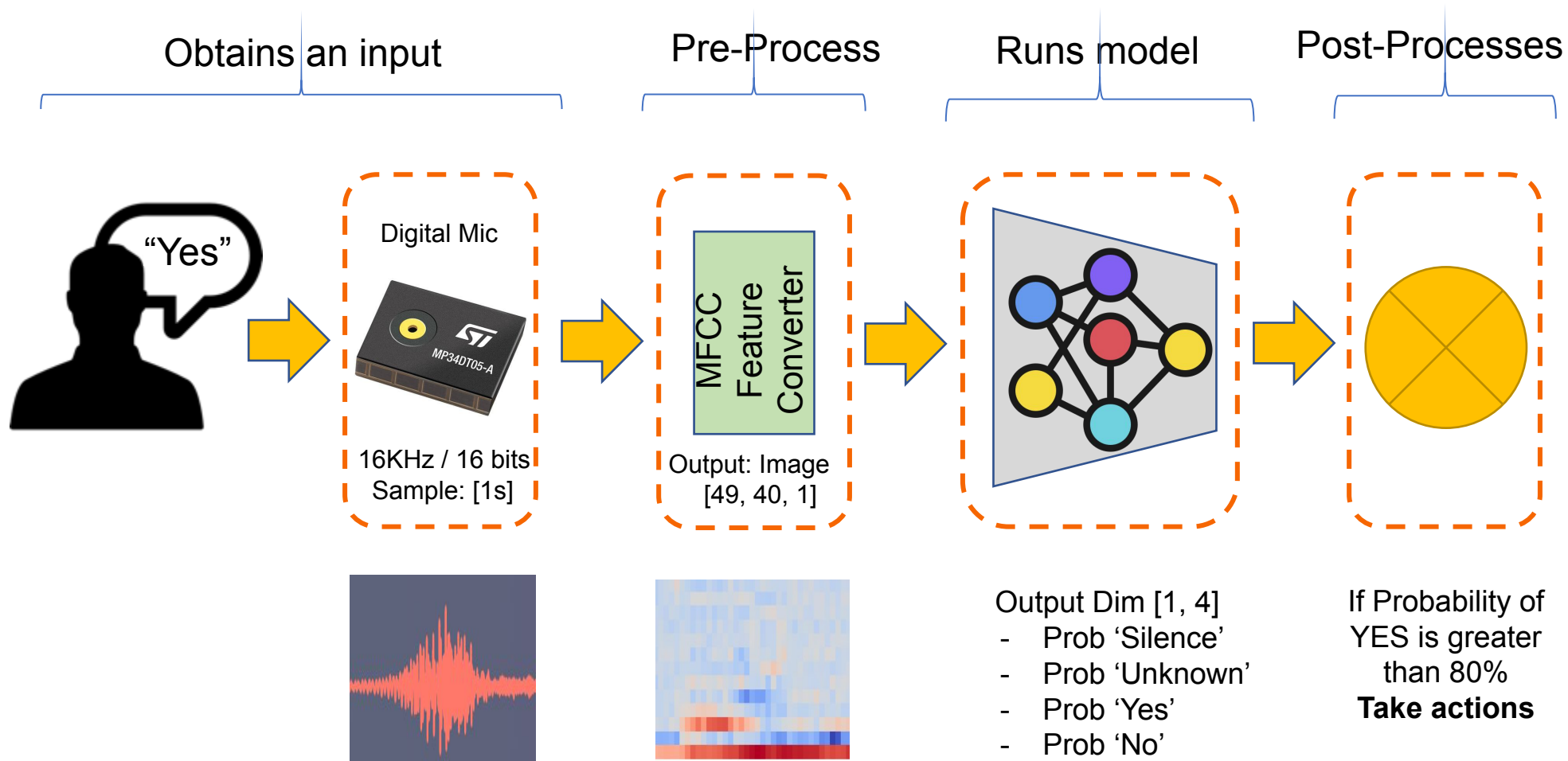
KeyWord Spotting (KWS) - Inference



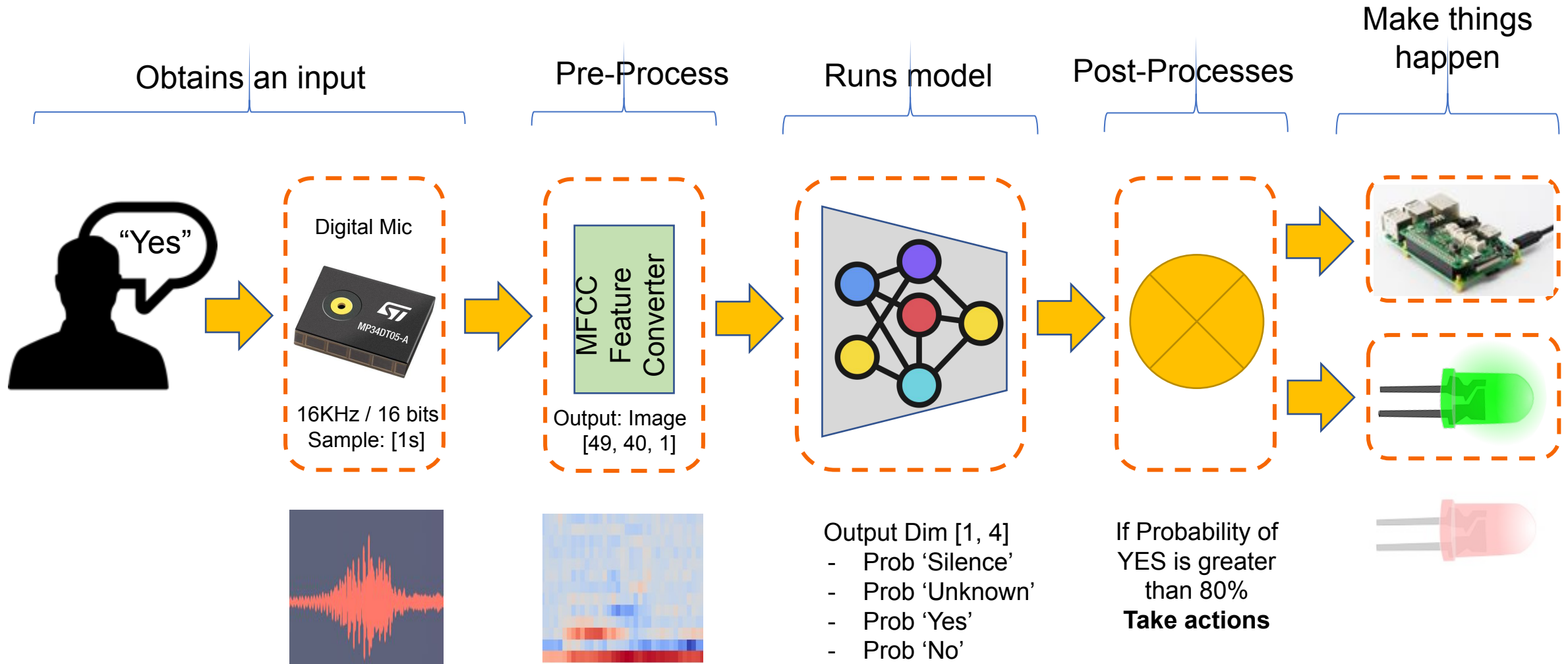
KeyWord Spotting (KWS) - Inference



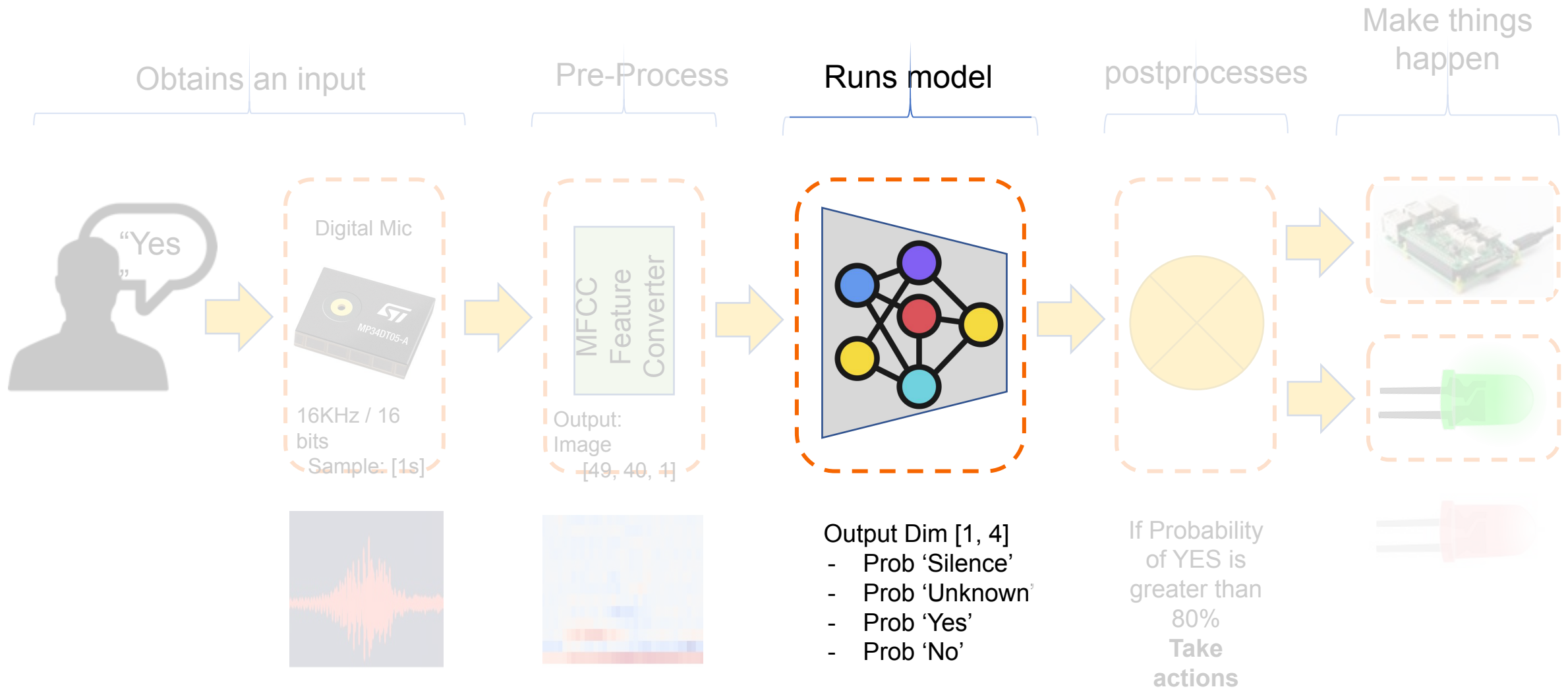
KeyWord Spotting (KWS) - Inference



KeyWord Spotting (KWS) - Inference



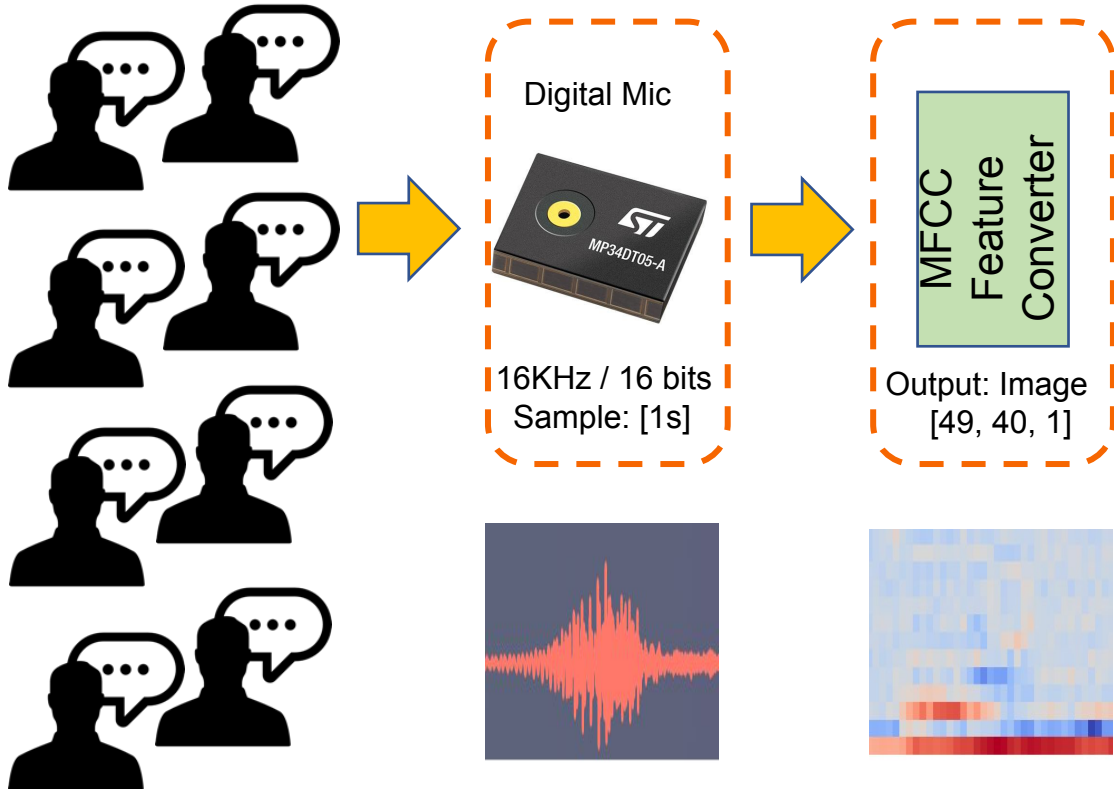
KeyWord Spotting (KWS) - Model



KeyWord Spotting (KWS) – Create Model (Training)

Obtains data

Pre-Process



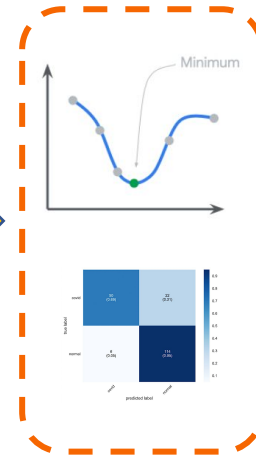
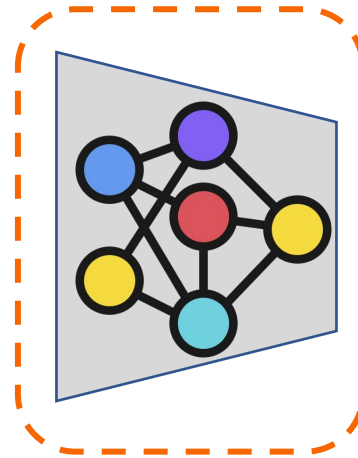
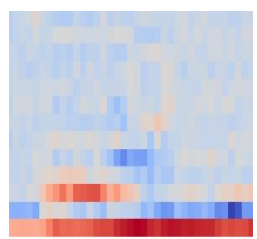
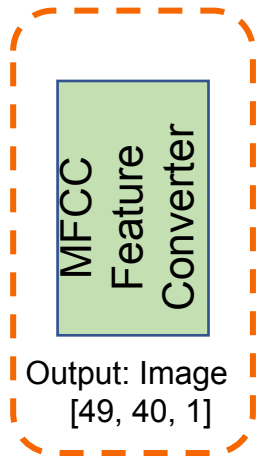
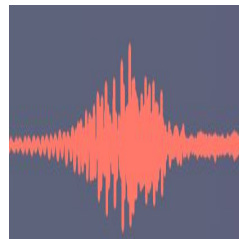
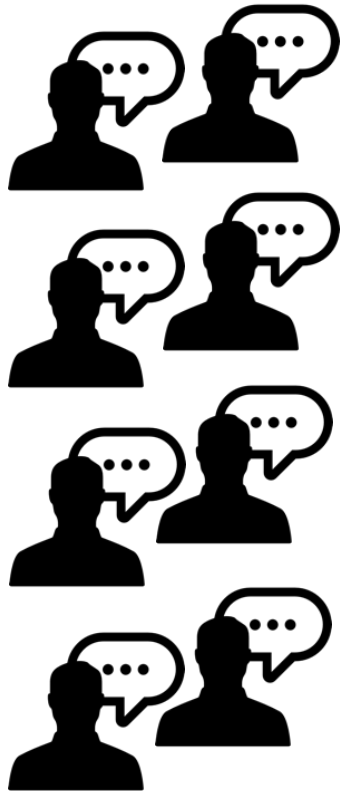
KeyWord Spotting (KWS) – Create Model (Training)

Obtains data

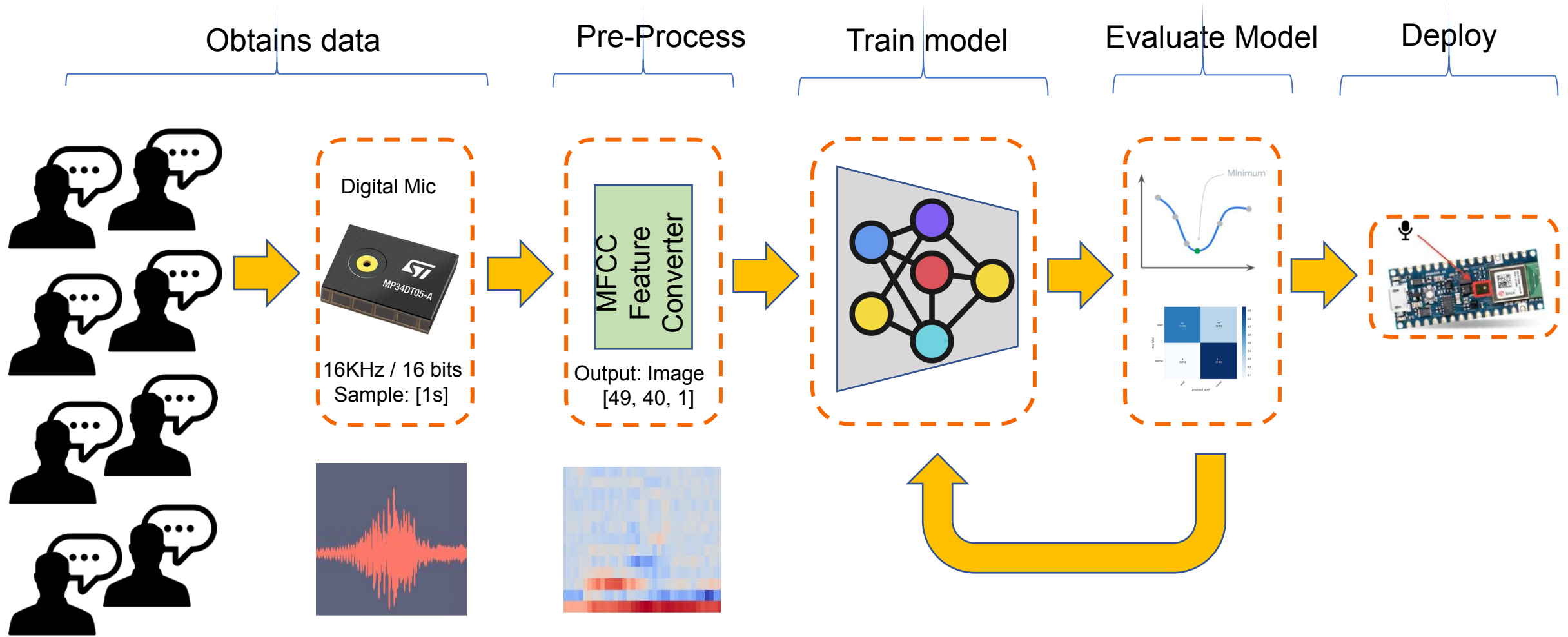
Pre-Process

Train model

Evaluate Model



KeyWord Spotting (KWS) – Create Model (Training)



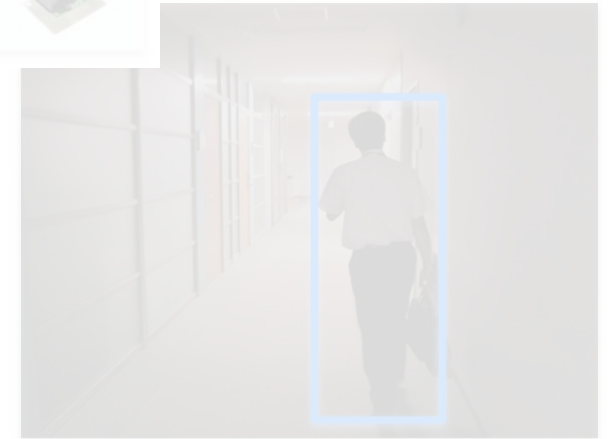
Sound



Vibration



Vision



Cow Monitoring

Using the Internet of Things for Agricultural Monitoring

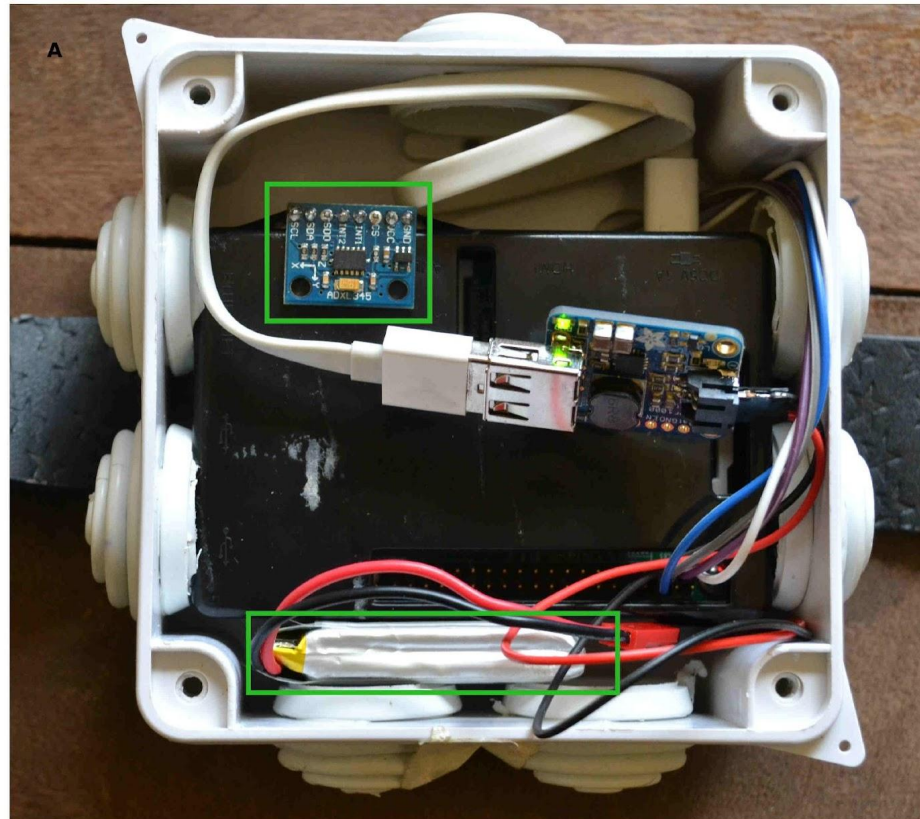
“We aim to deploy a variety of sensors for agricultural monitoring. One of the projects involves using **accelerometer sensors** to monitor activity levels in dairy cows with a view to determining when the cows are on heat or when they are sick.”



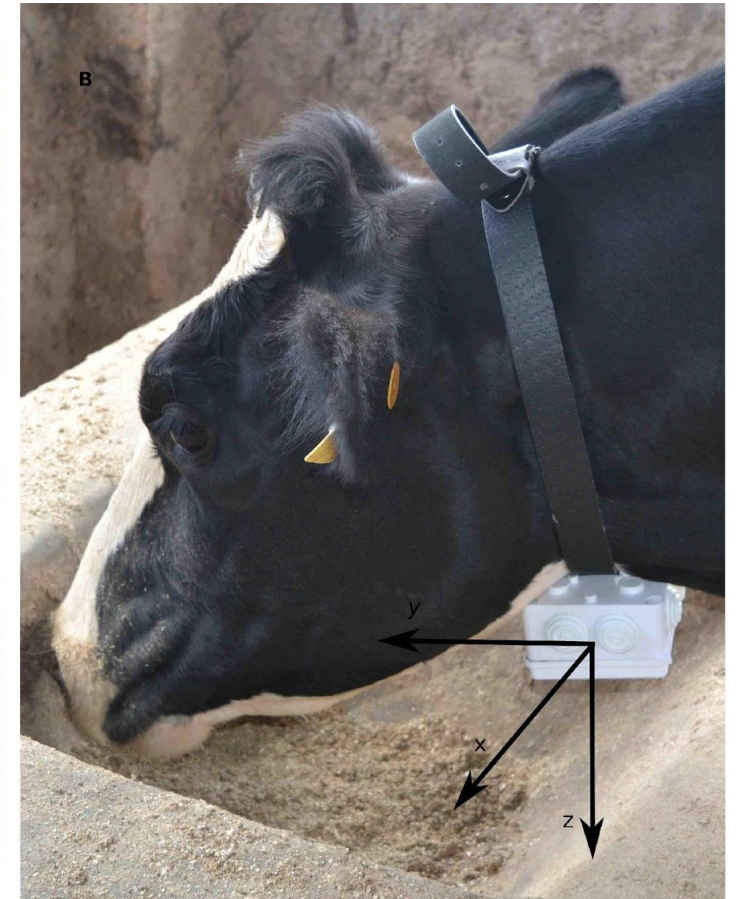
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Senior Lecturer
Department of Electrical and Electronic Engineering
Dedan Kimathi University of Technology
Nyeri Kenya
Email: ciira.maina@dkut.ac.ke

Kenia



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



Predict and classify common Elephant behavior



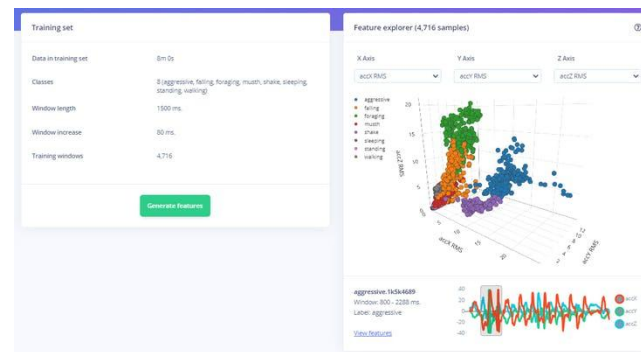
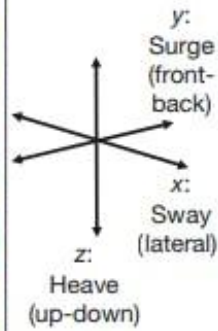
Aggressive



Standing

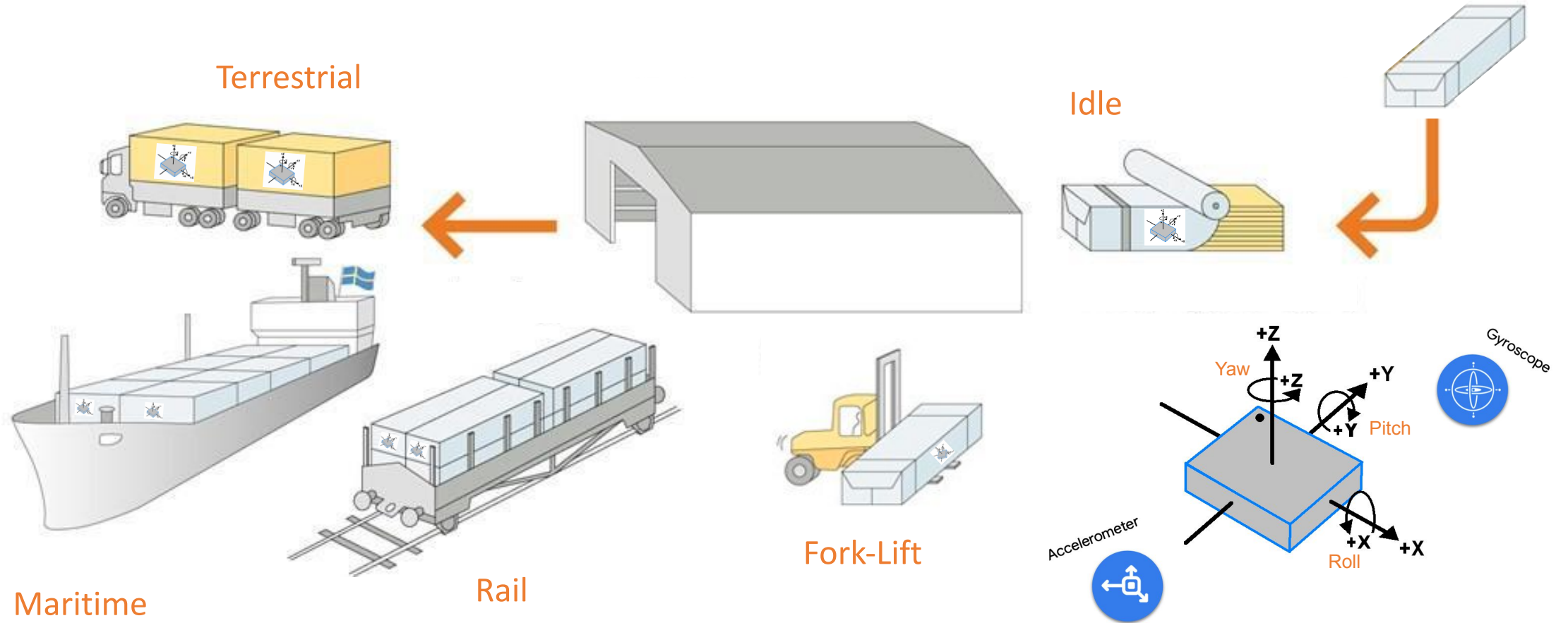


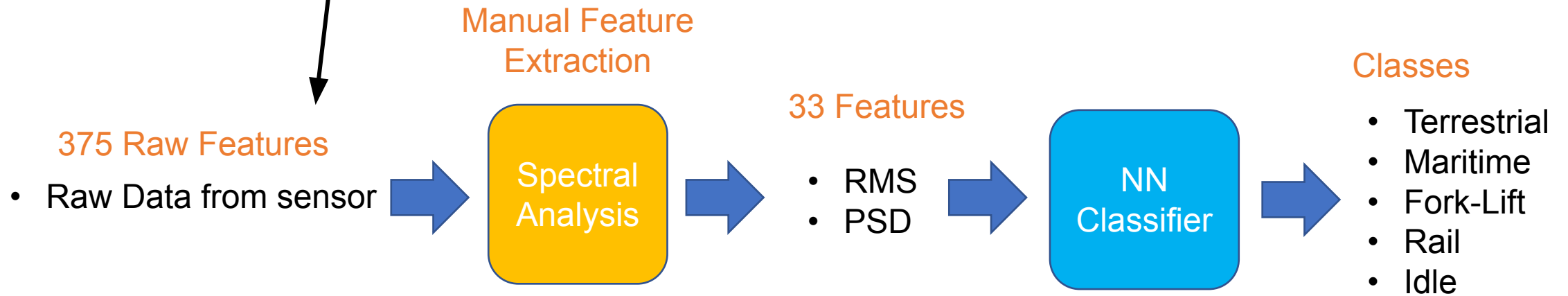
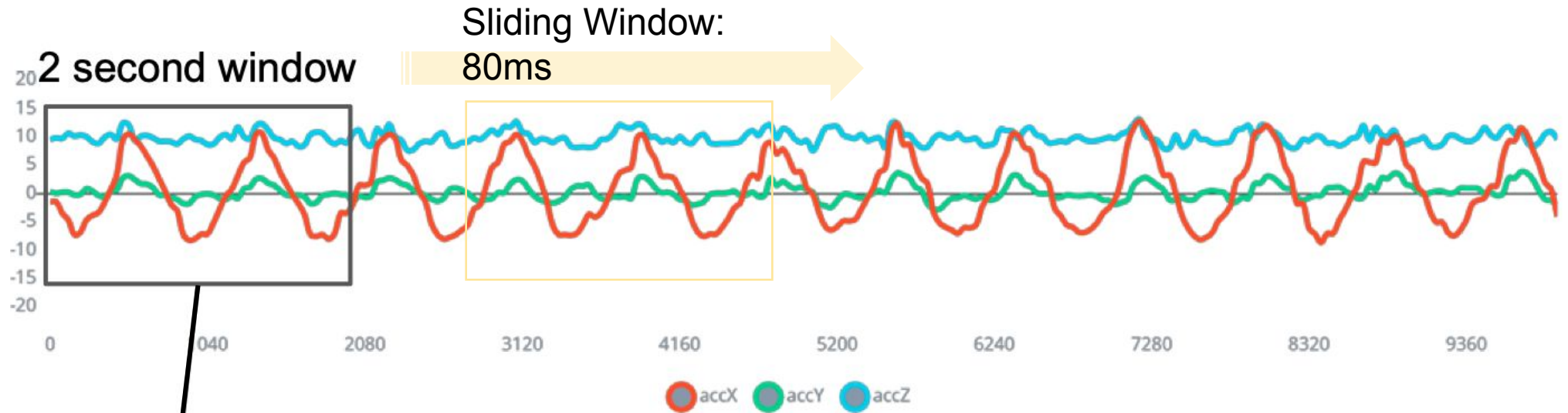
Sleeping



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

Mechanical Stresses in Transport





Application: Factory machinery

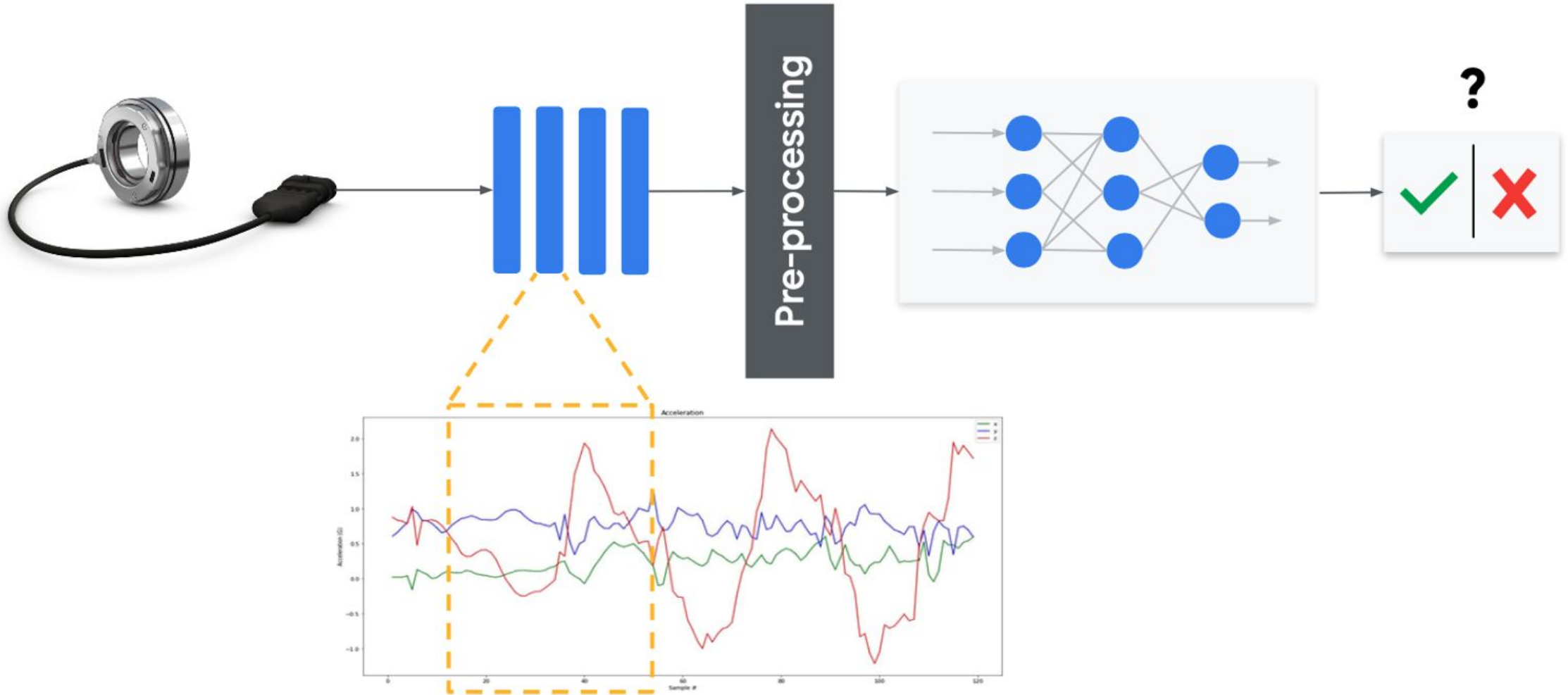


Ball Bearings



Accelerometer

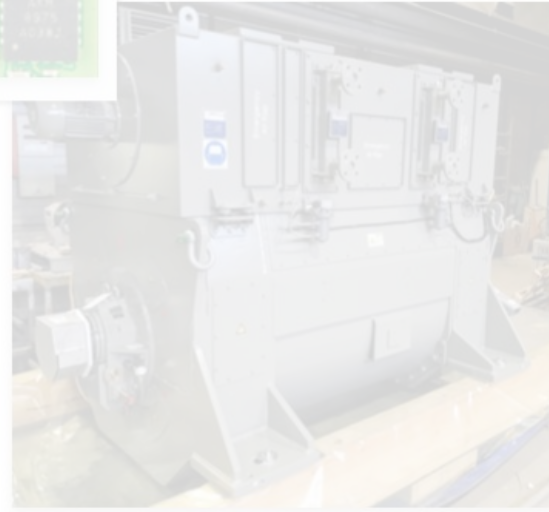
Anomaly Detection



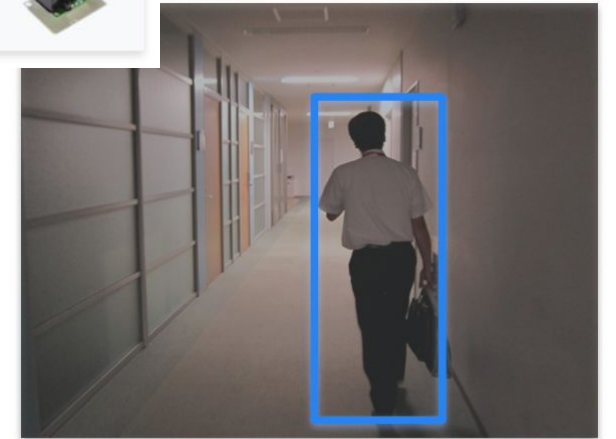
Sound



Vibration



Vision



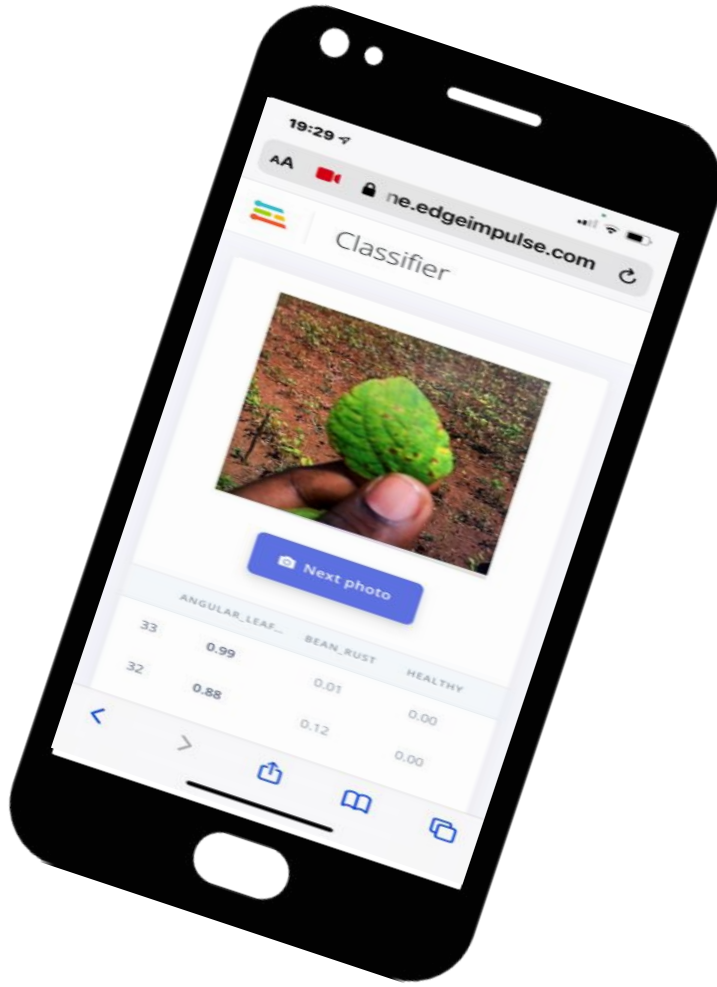
Detecting Diseases in the Bean plants



Angular Leaf Spot

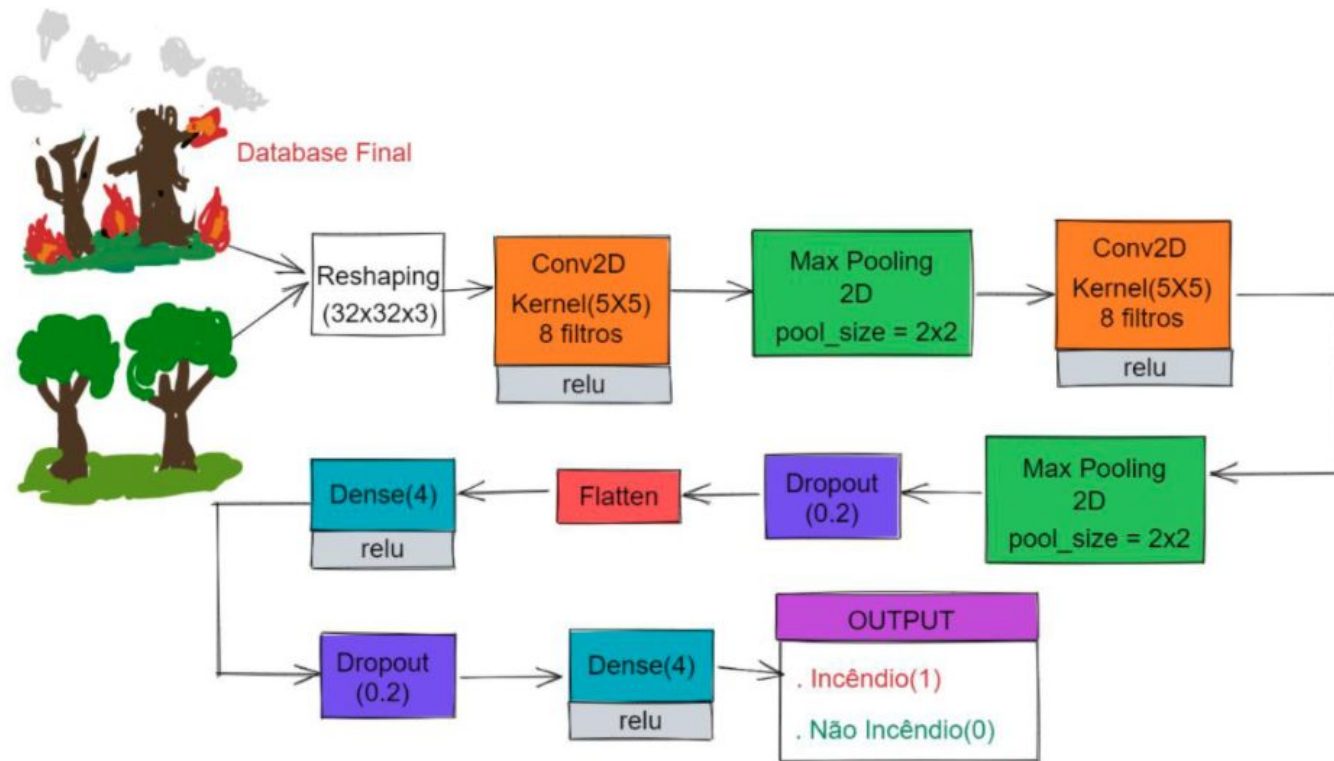
Bean Rust

Healthy



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

Forest Fire Detection



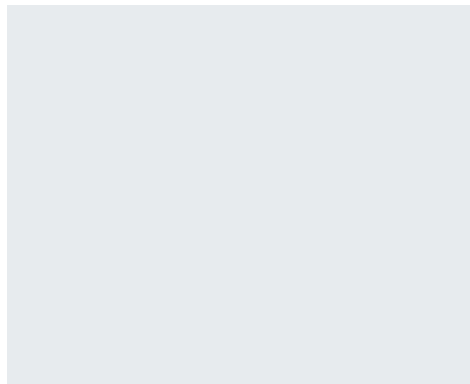
https://github.com/Mjrovai/UNIFEI-IESTI01-T01-2021.1/blob/main/00_Curso_Folder/2_Applications/Group_Projects-Final%20Reports/Projeto_final_Fire_detection/trabalho_final_Fire_Detection.pdf



Person Detection



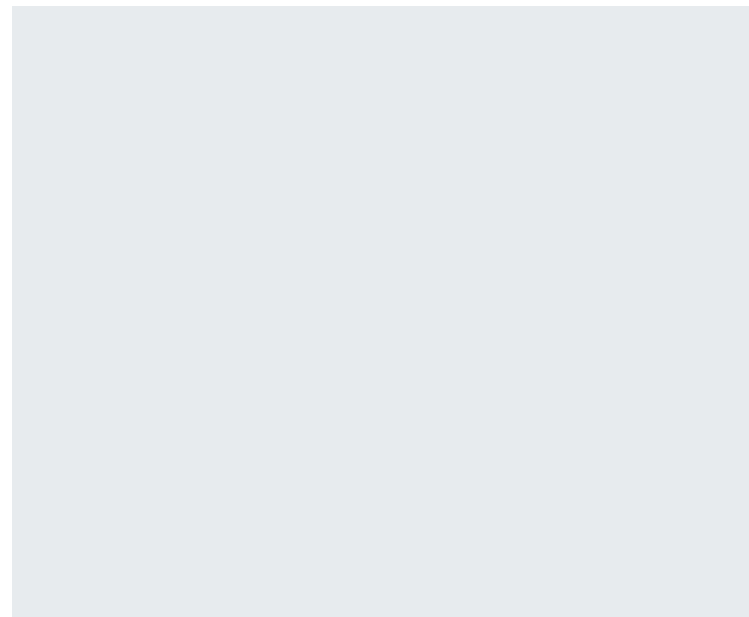
Person Detection



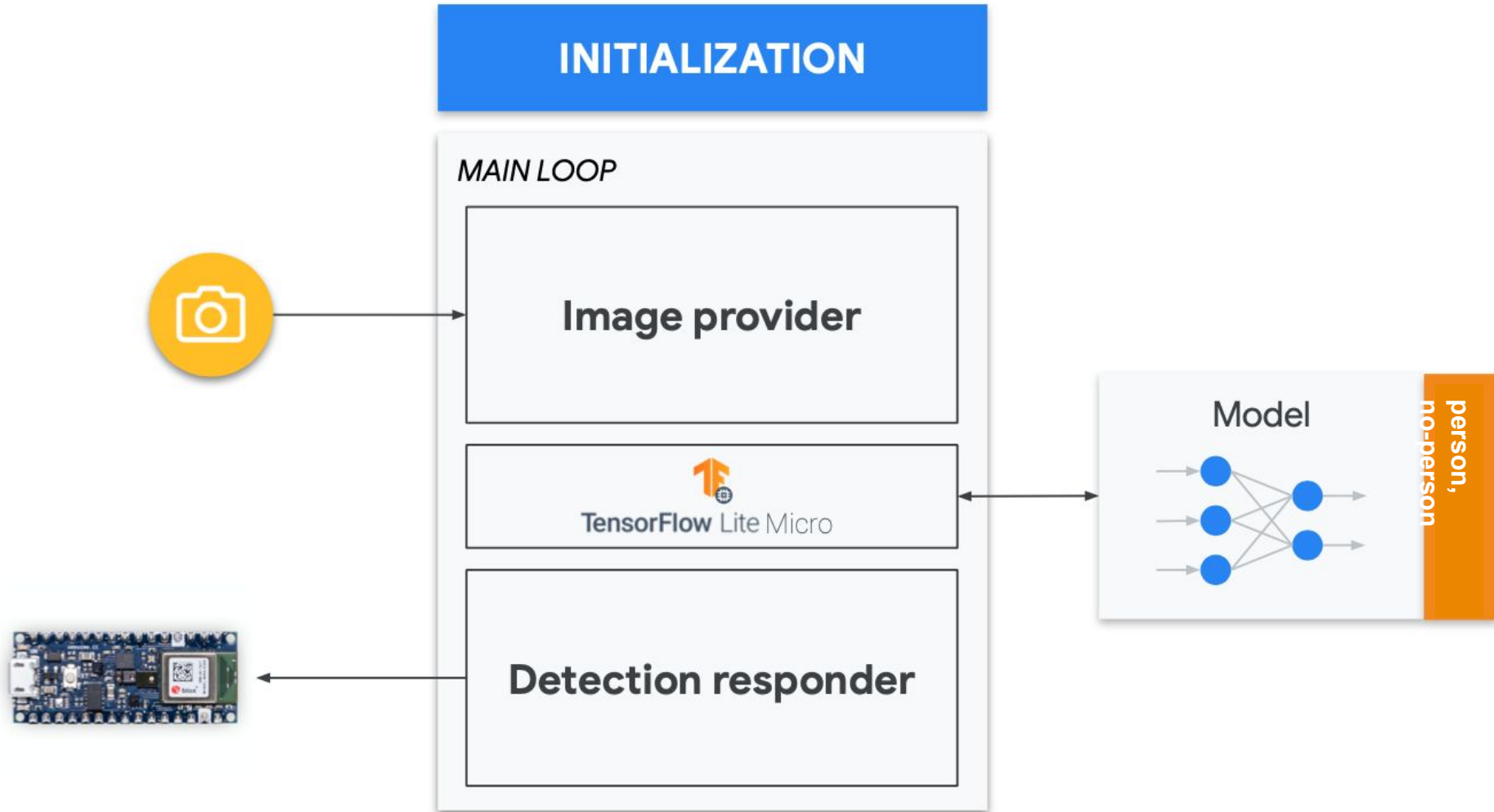
Mask Detection



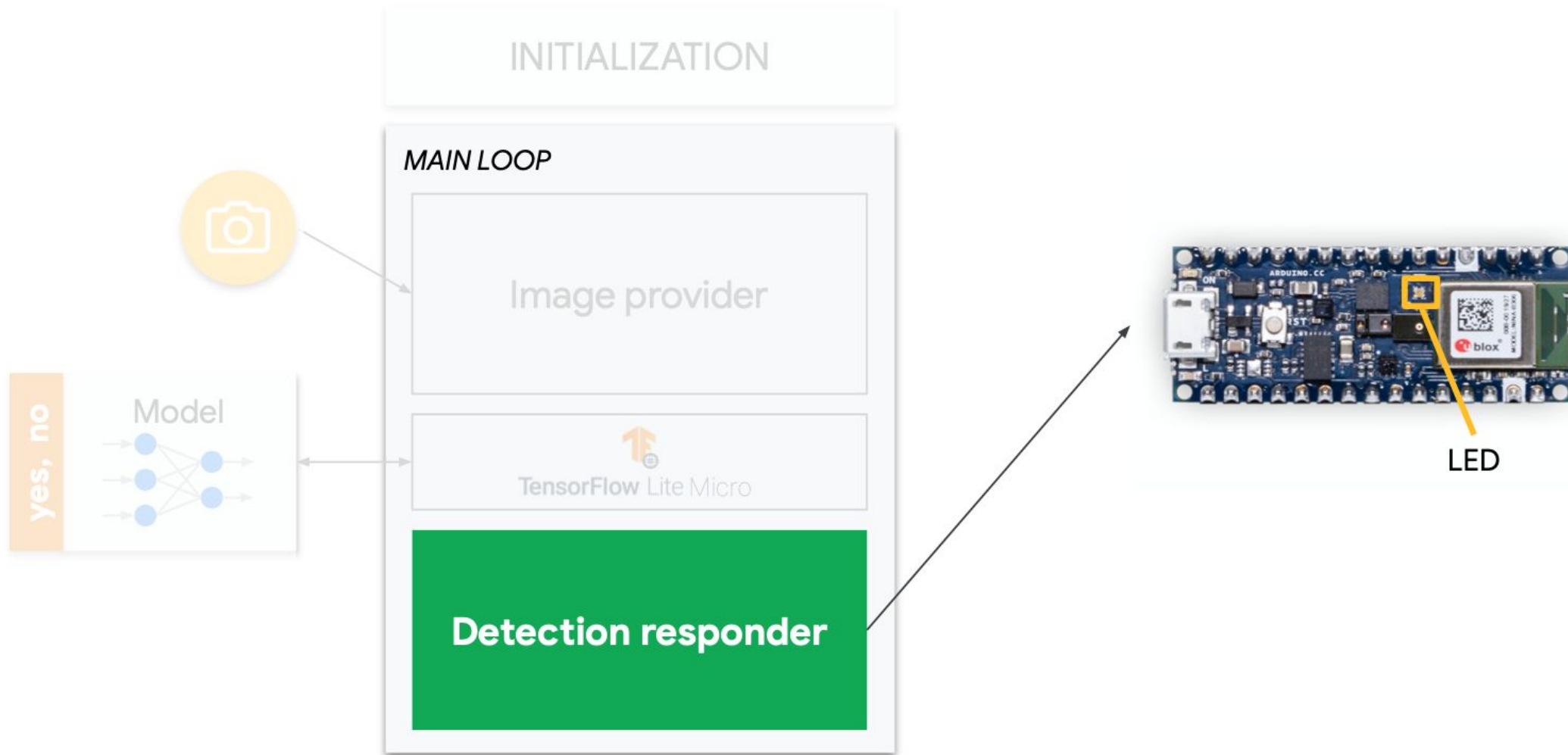
Person Detection



Person Detection Components



Post-processing



TinyML Projects – UNIFEI / IESTI01

Vision

- Mask Detection [\[Docs\]](#) [\[Video\]](#)
- Forest Fire Detection [\[Docs\]](#) [\[Video\]](#)

Sound

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

Vibration

- Personal Trainer [\[Docs\]](#) [\[Video\]](#)

TinyML Projects – Select HW examples

Vision

- Coffee Disease w/ **Seed Maix Bit** [\[Video\]](#) [\[Docs\]](#)

Sound

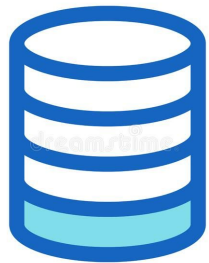
- Listening Temperature w/ **Nano 33** [\[Docs\]](#)

Vibration

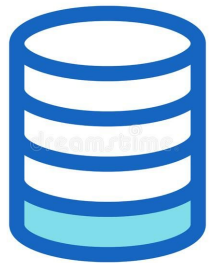
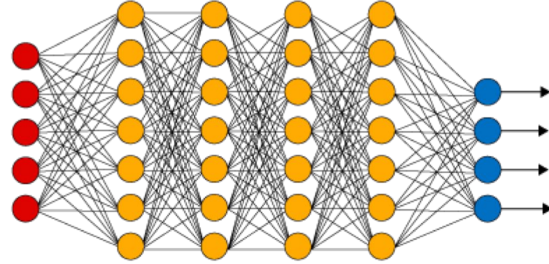
- Motion Recognition w/ **RPI Pico** [\[Docs\]](#)
- Gesture Recognition w/ **Wio Terminal** [\[Docs\]](#)

How to Train a ML Model?

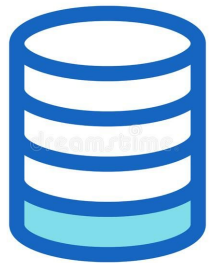
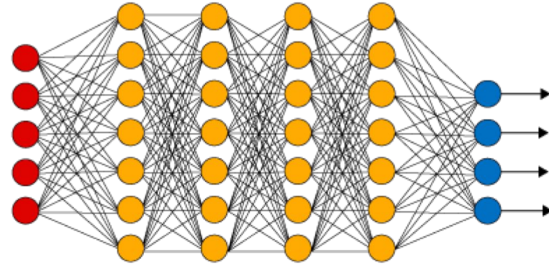
Machine Learning Workflow



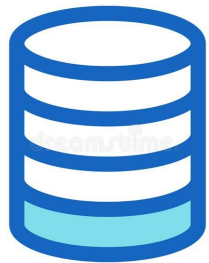
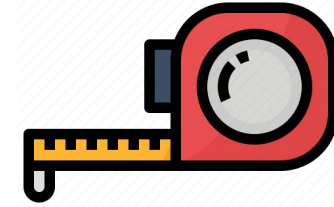
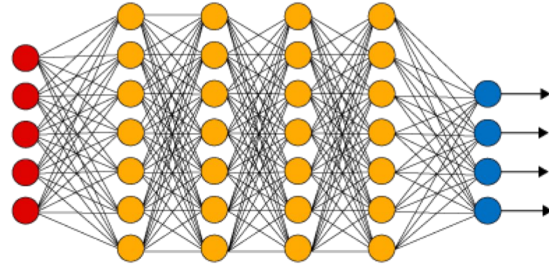
Machine Learning Workflow



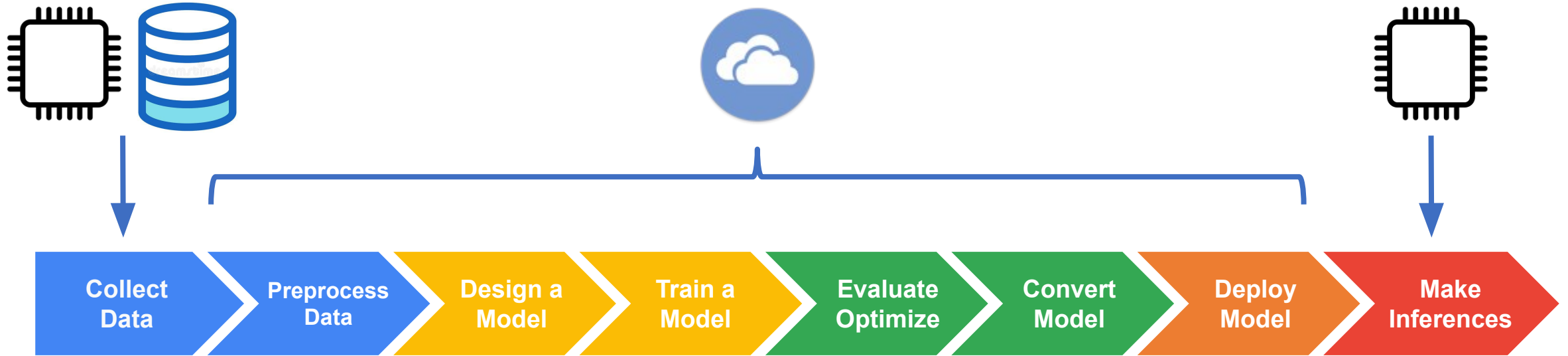
Machine Learning Workflow



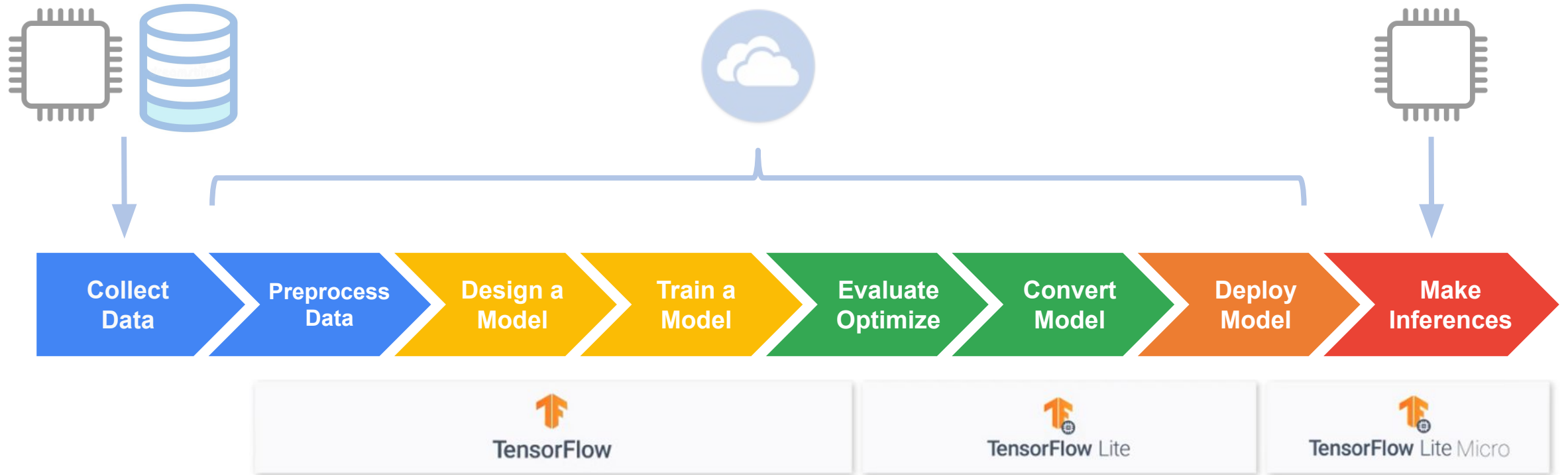
Machine Learning Workflow (“What”)



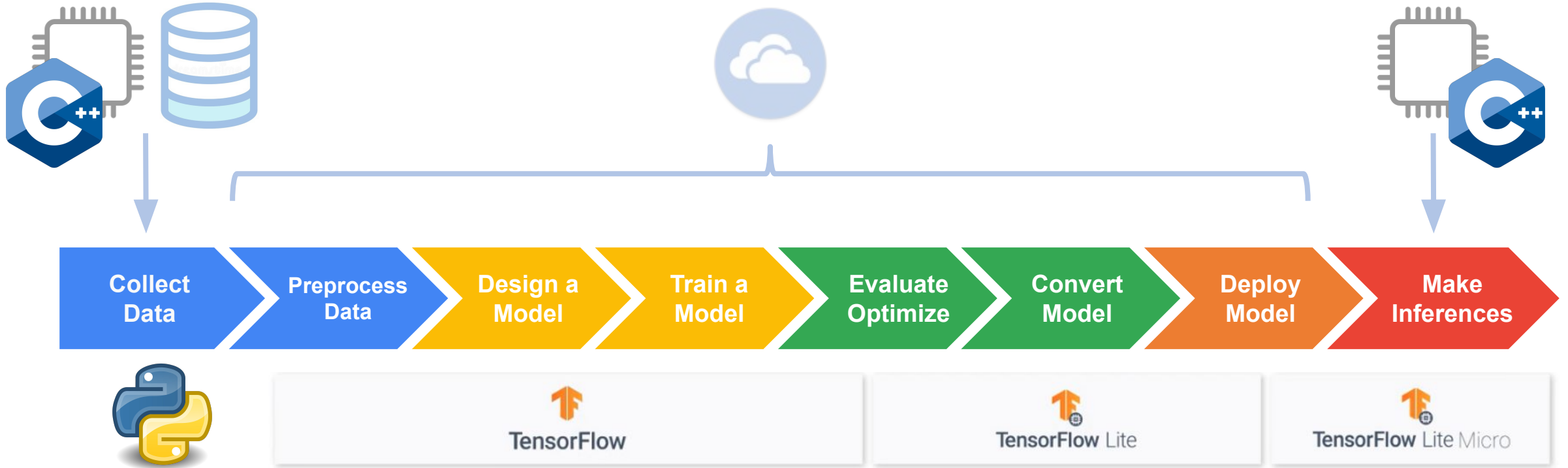
Machine Learning Workflow (“Where”)



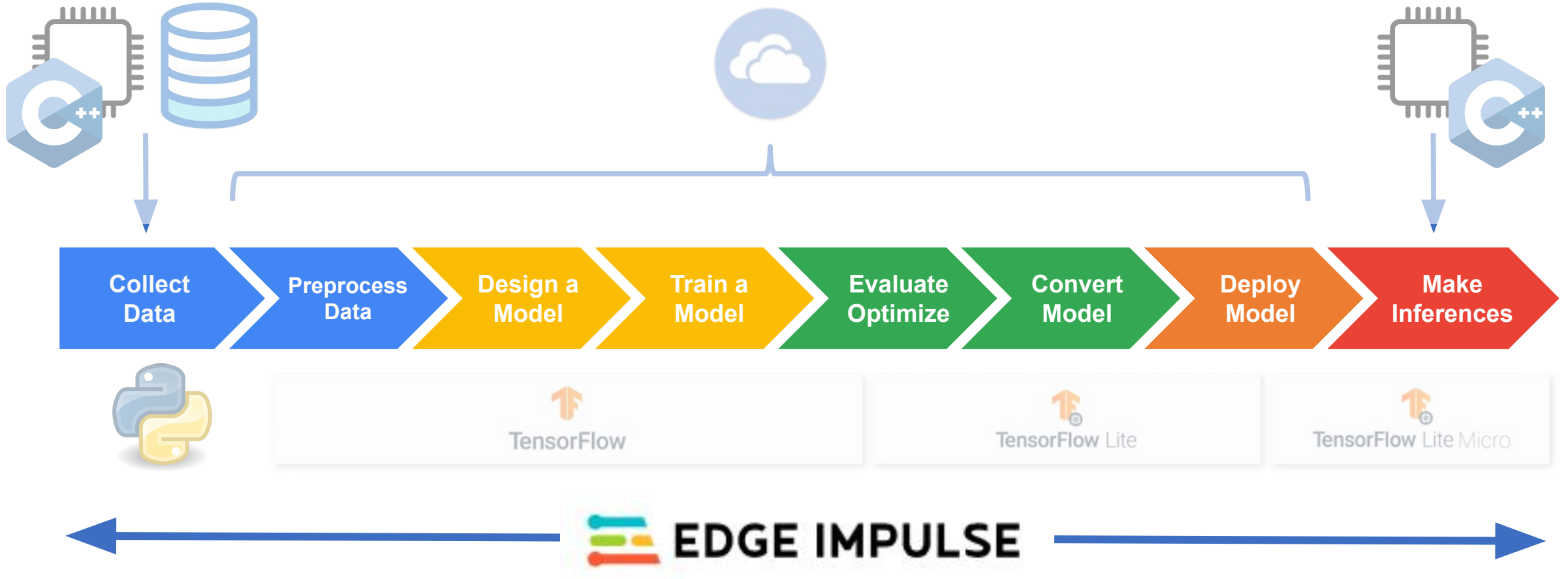
Machine Learning Workflow (“How”)



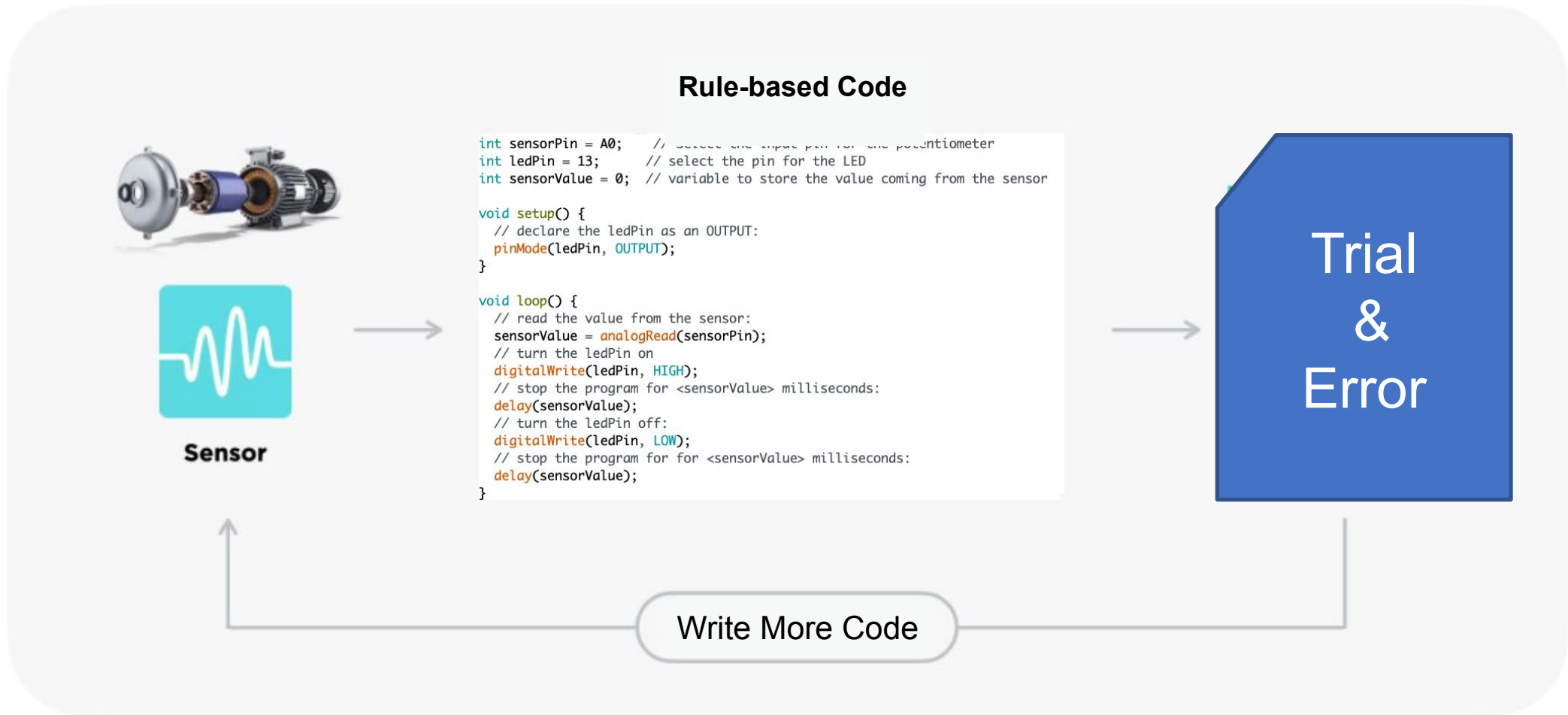
Machine Learning Workflow (“How”)



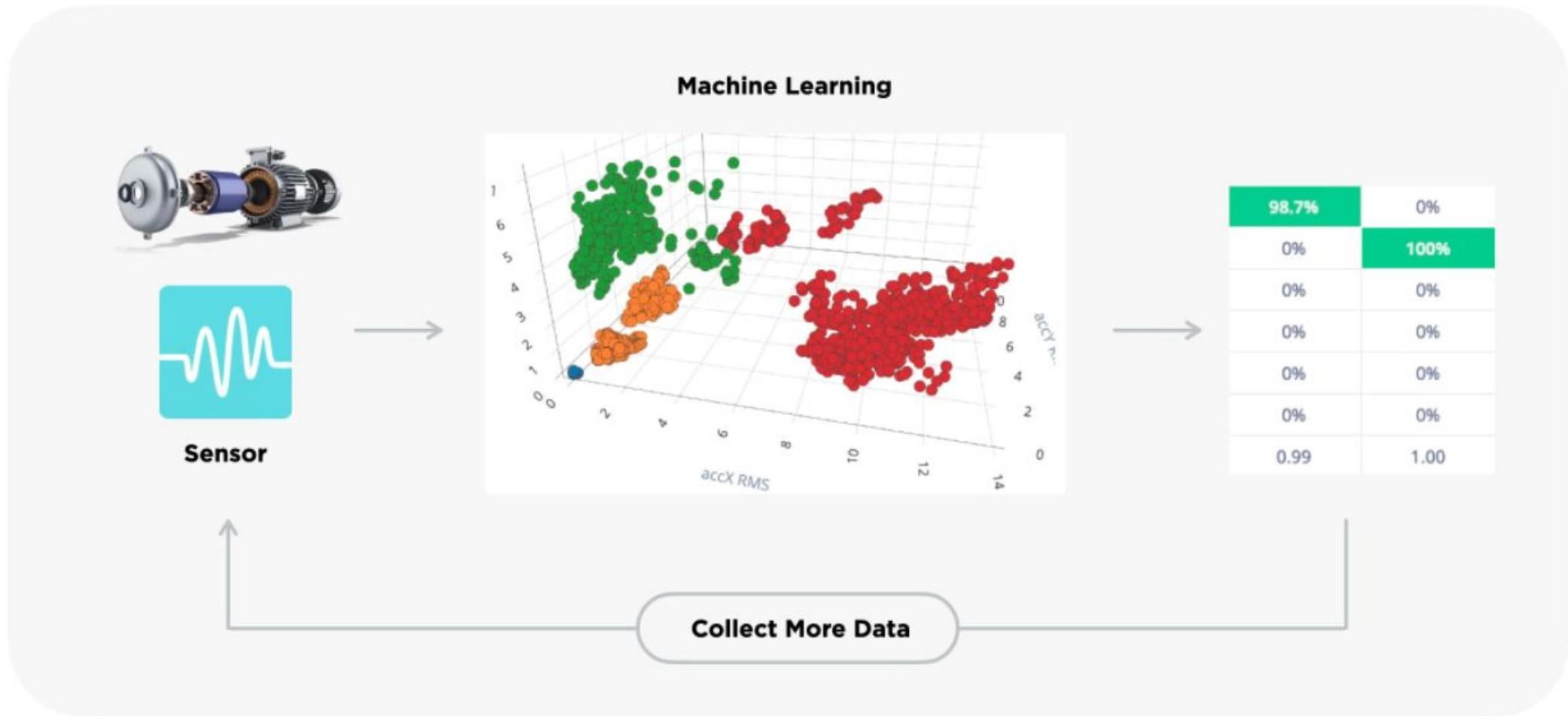
Machine Learning Workflow (“How”)

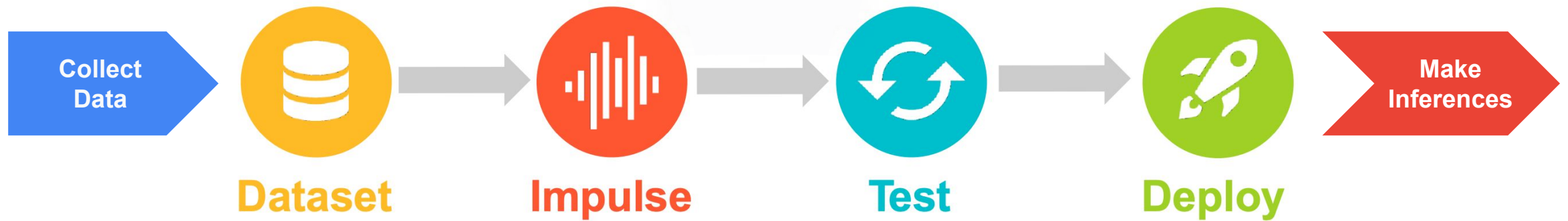


From rule-based engineering to...

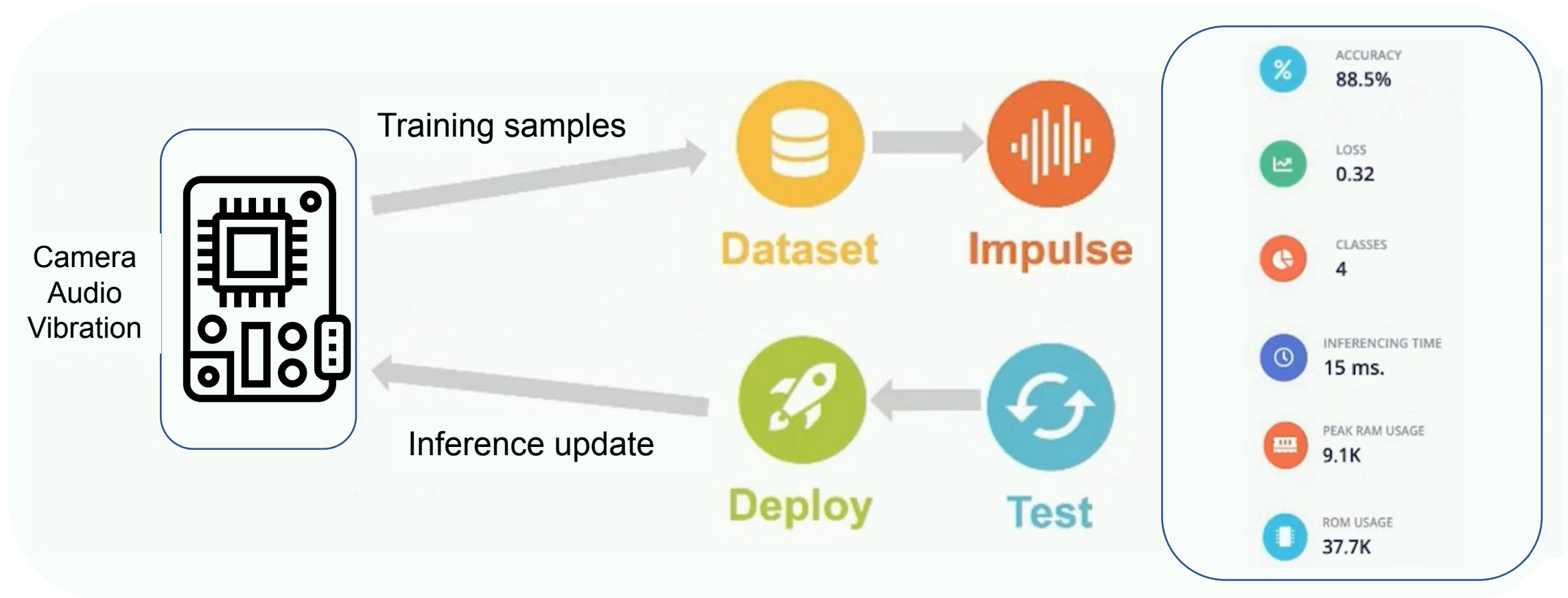


Data-driven engineering

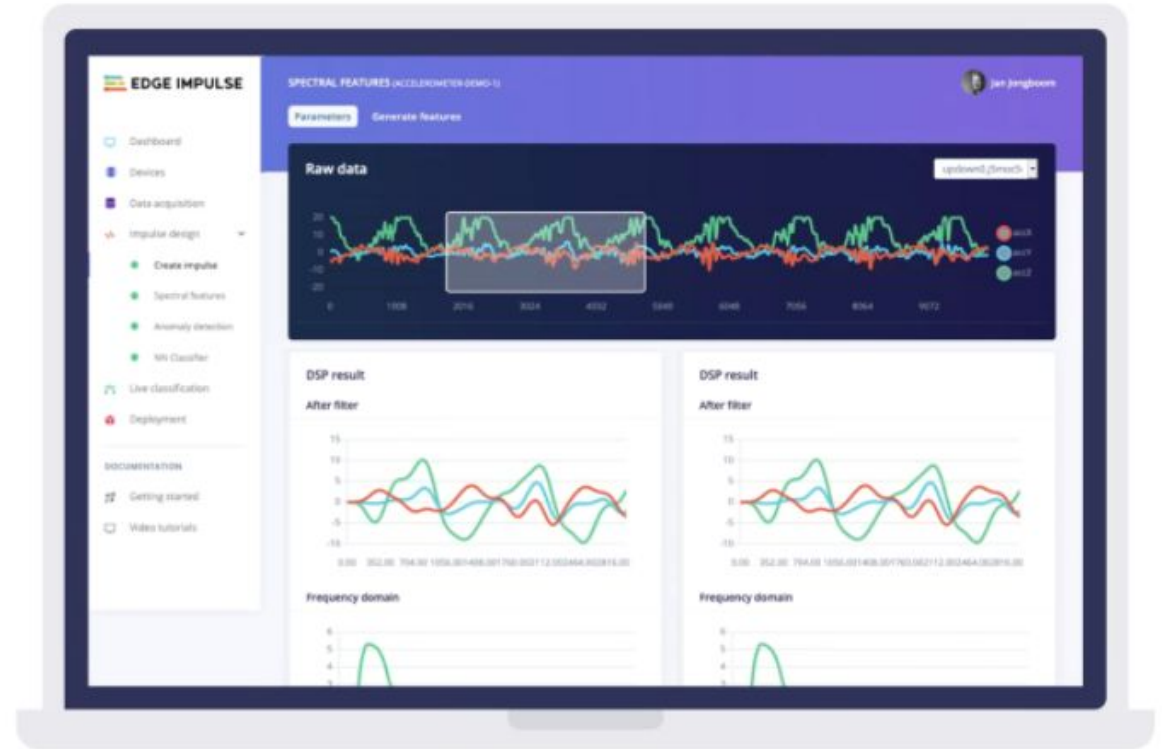
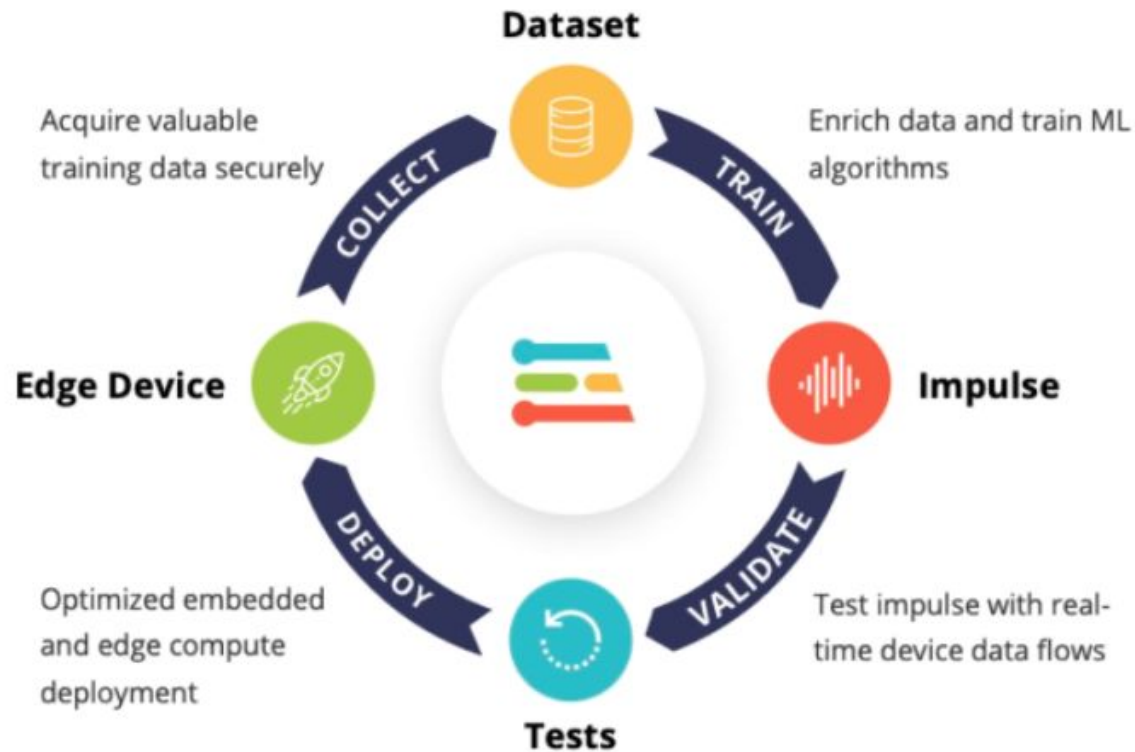




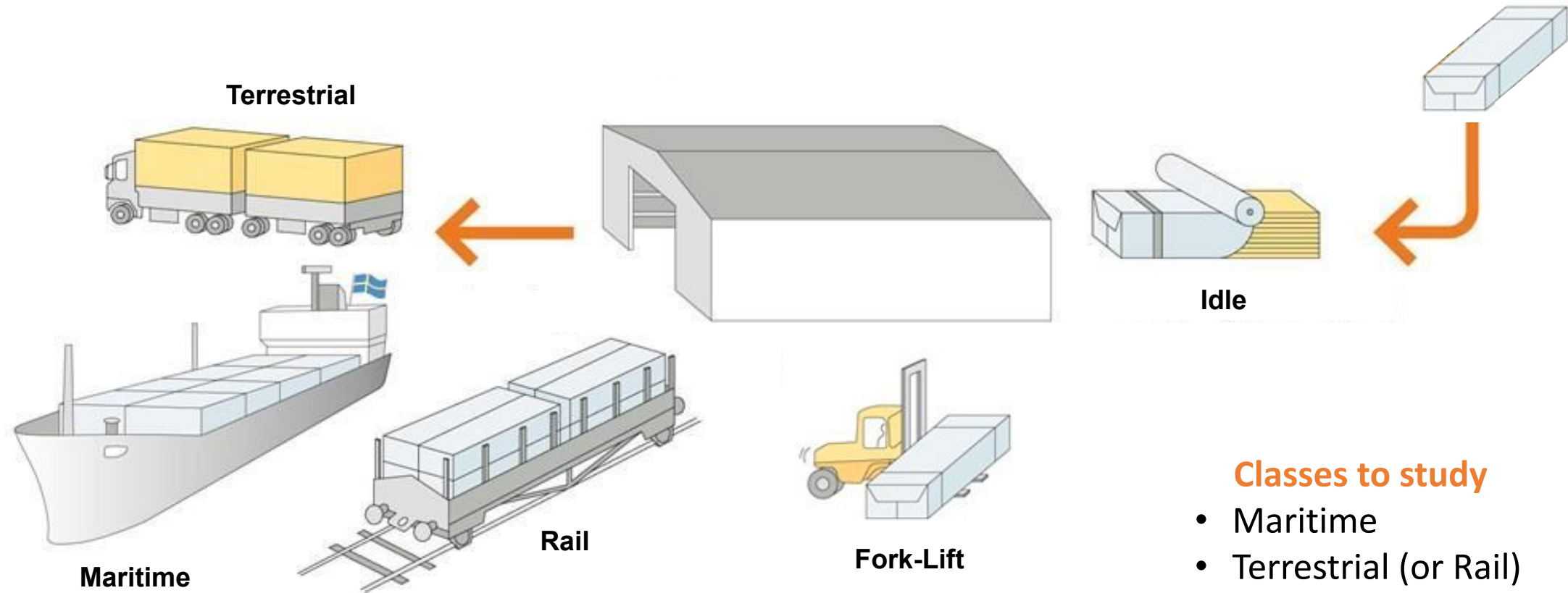
Data-driven engineering



EI Studio - Embedded ML platform (“AutoML”)



Case Study: Mechanical Stresses in Transport

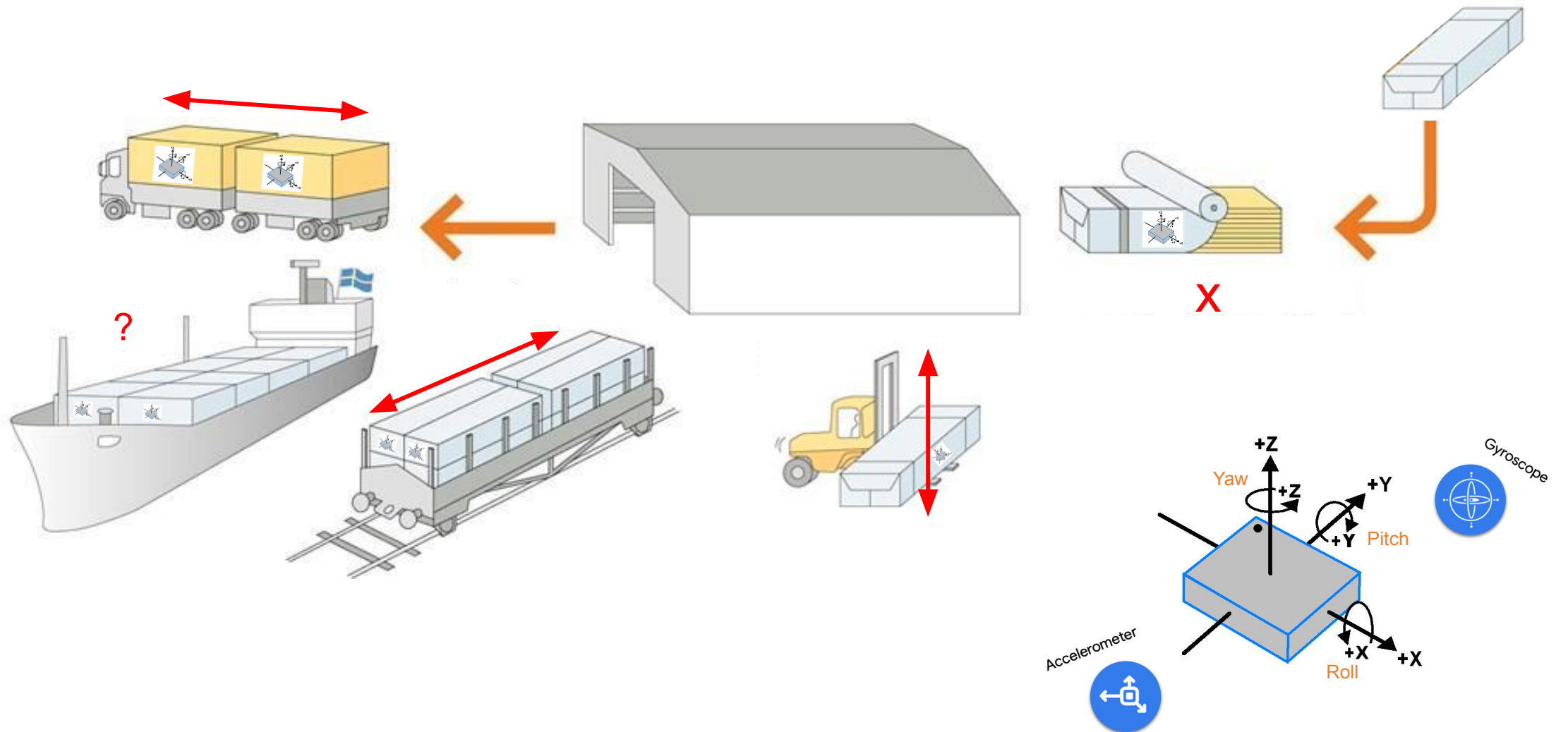


Classes to study

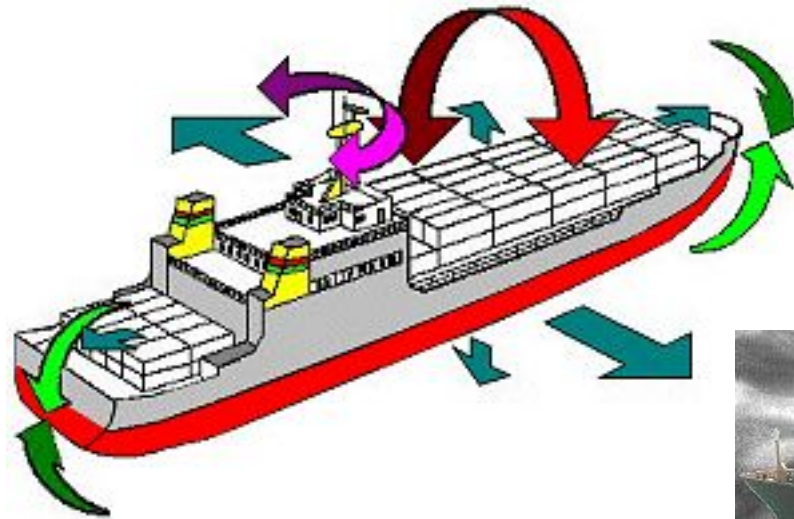
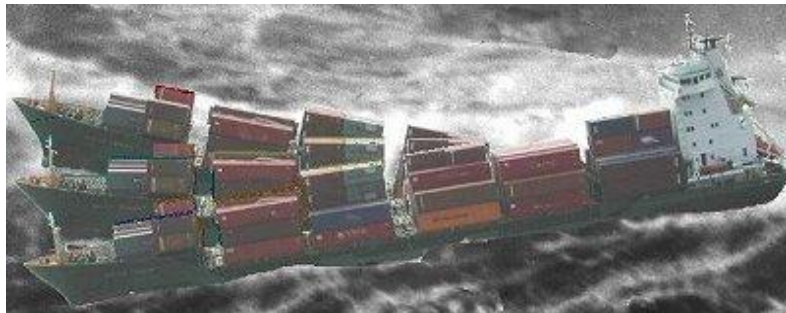
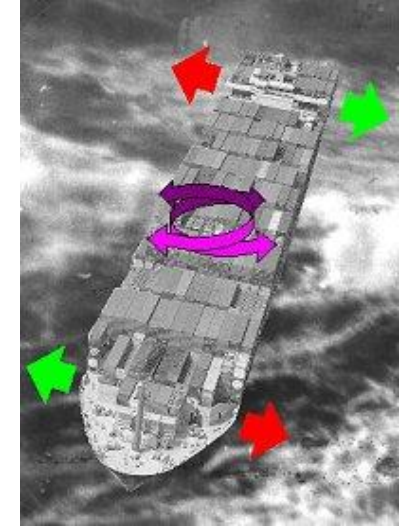
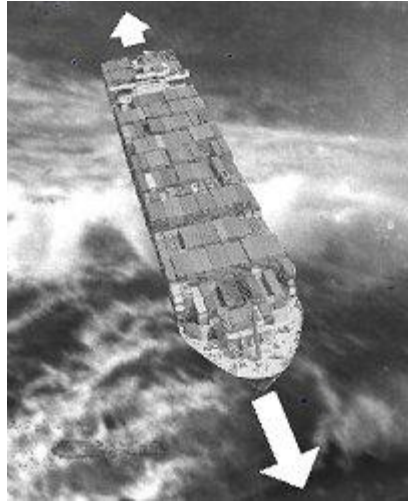
- Maritime
- Terrestrial (or Rail)
- Lift
- Idle

Machine Learning Workflow



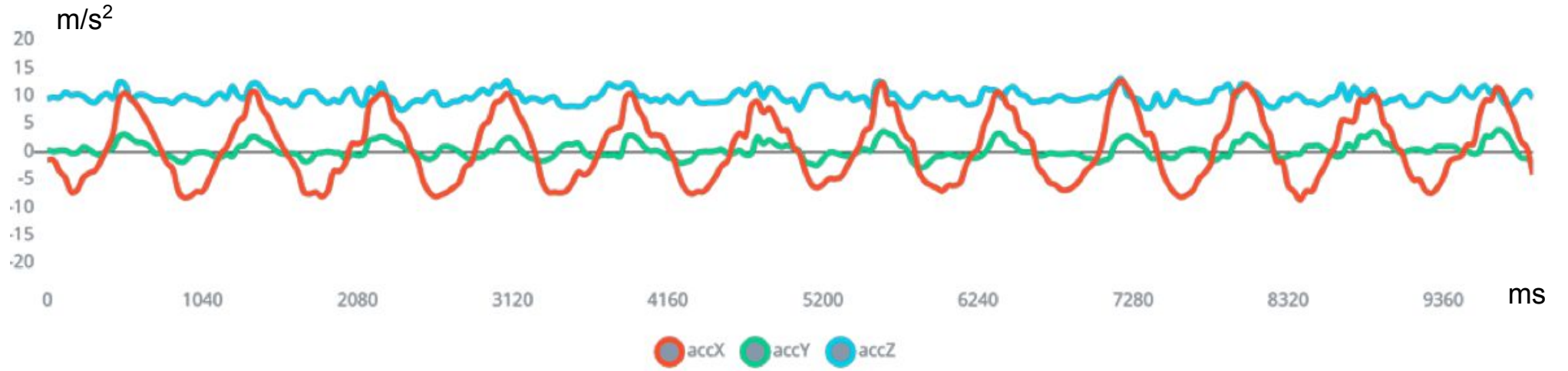


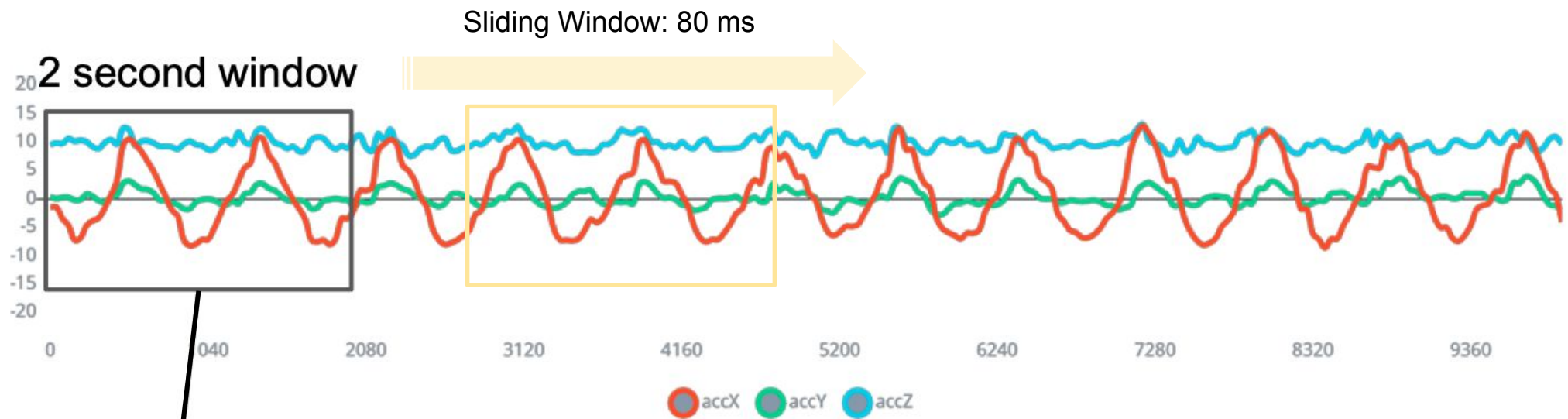
Mechanical Stresses in Maritime Transport



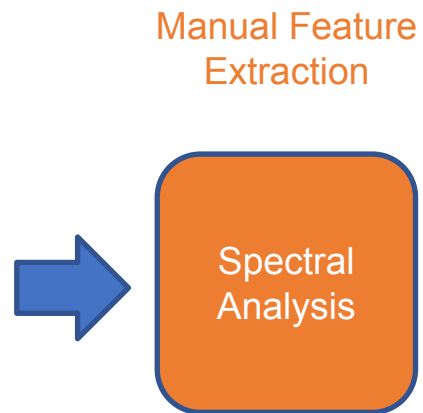


Example: 10 seconds of accelerometer data, captured with a sample rate: 62.5 Hz





- 375 Raw Features
- Raw Data from sensor



- 33 Features
- RMS
 - FFT
 - PSD



Classes

- Lift
- Terrestrial
- Maritime
- Idle

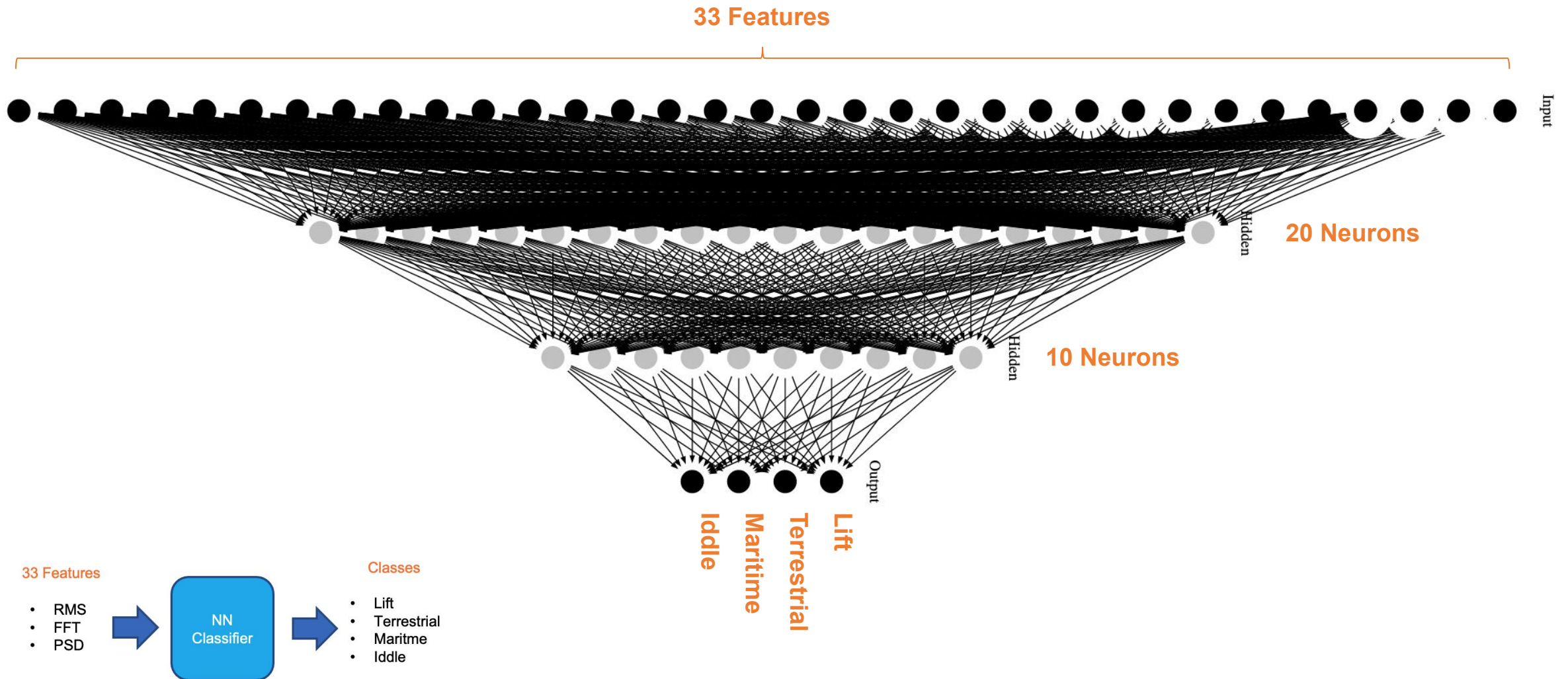
Model Design (NN Classifier)



Model Design (NN Classifier)



Model Design (DNN Classifier)



Model Design (DNN Classifier)

33 Features

- RMS
- FFT
- PSD

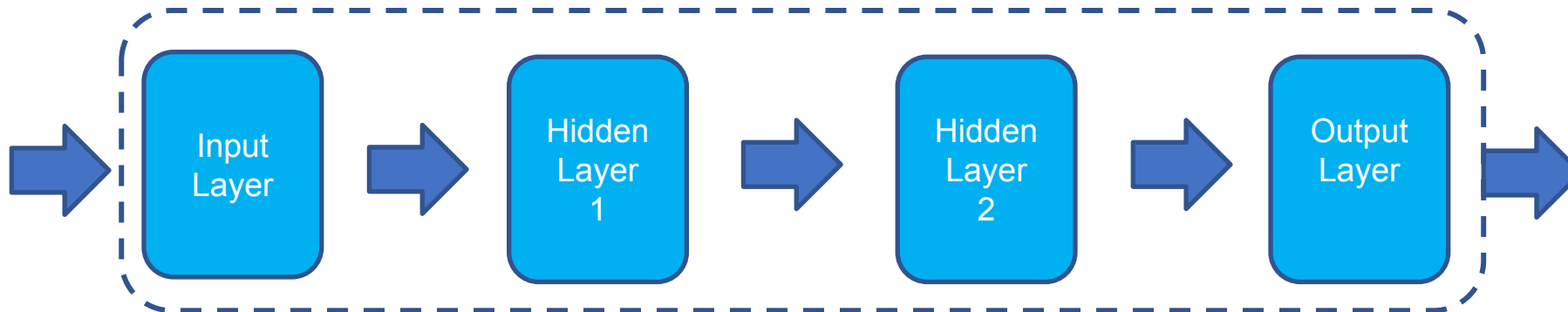


Classes

- Lift
- Terrestrial
- Maritime
- Idle

33 Features

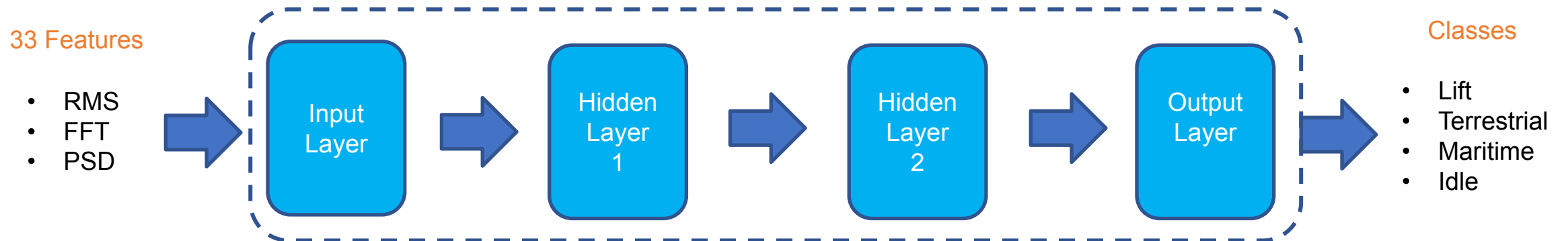
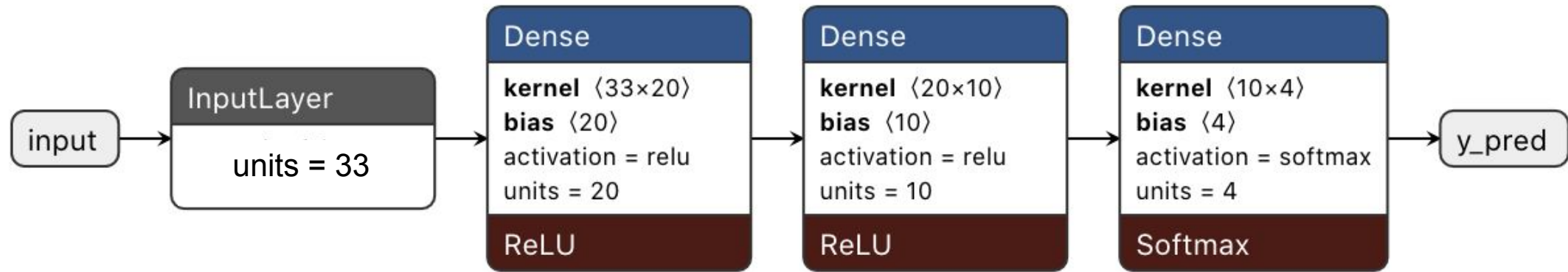
- RMS
- FFT
- PSD



Classes

- Lift
- Terrestrial
- Maritime
- Idle

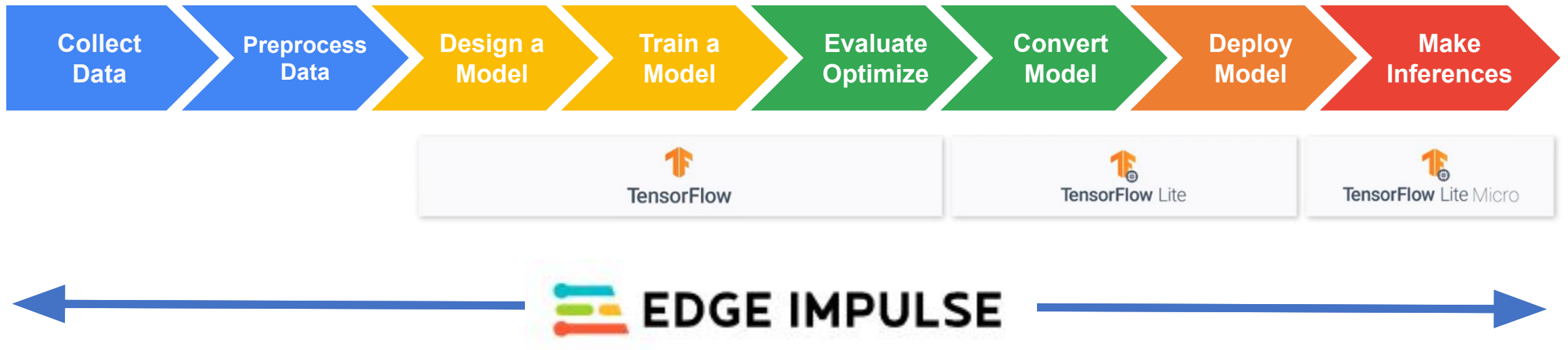
Model Design (DNN Classifier)



Train, Evaluate, Convert, Deploy the Model



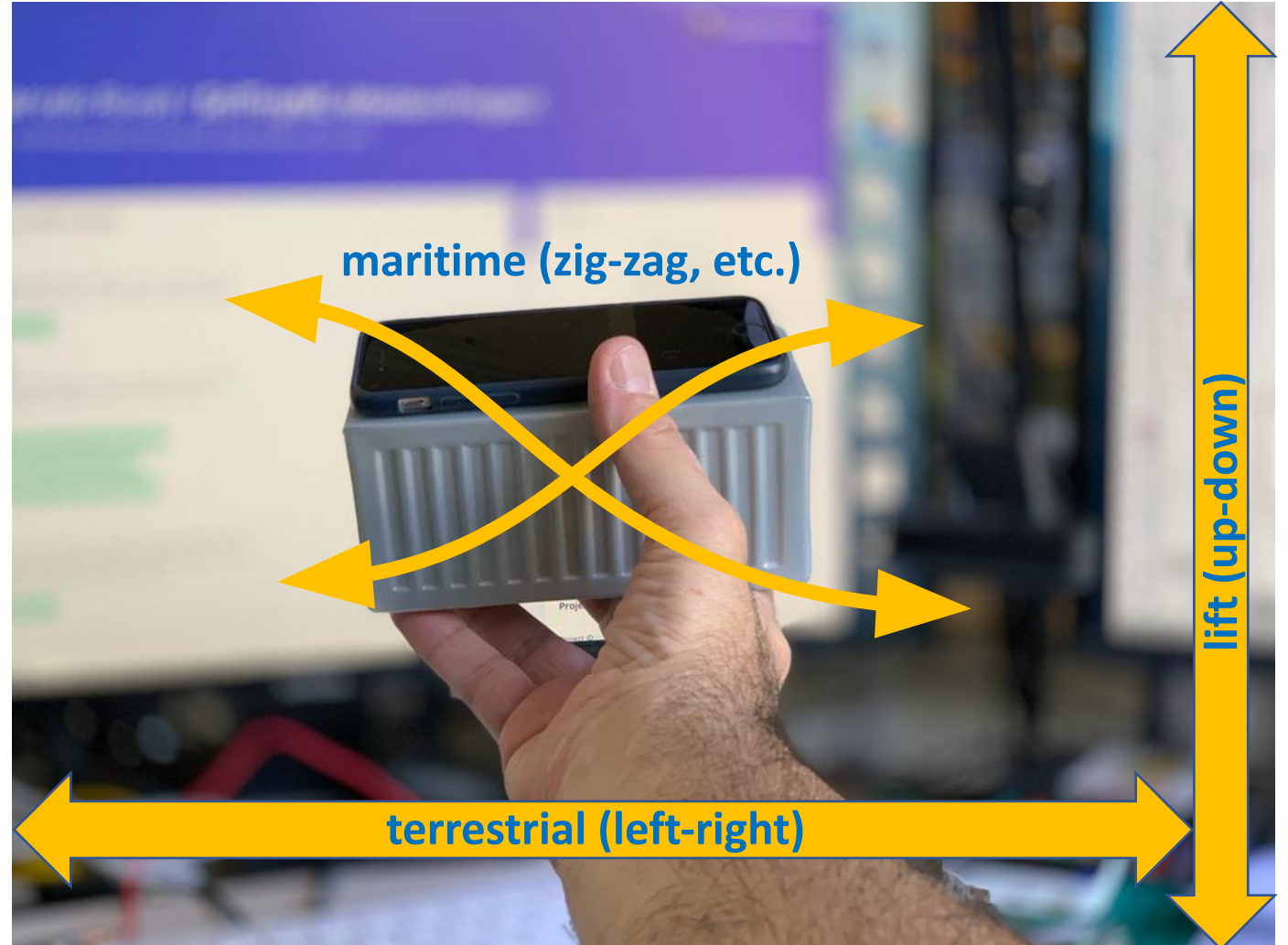
Train, Evaluate, Convert, Deploy the Model



Motion Classification

Transportation Classes:

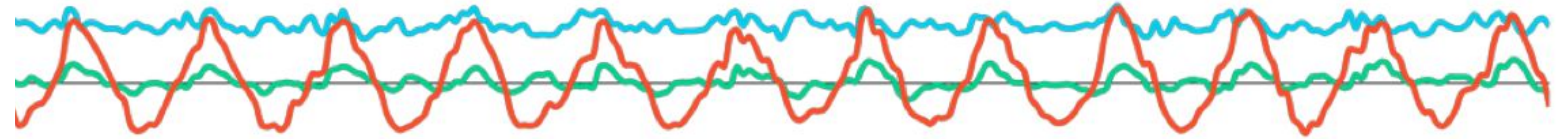
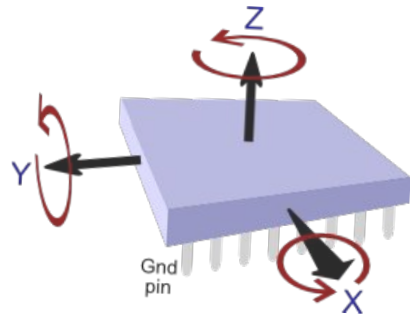
- **lift** (up-down)
- **terrestrial** (left-right)
- **maritime** (zig-zag, etc.)
- **idle**



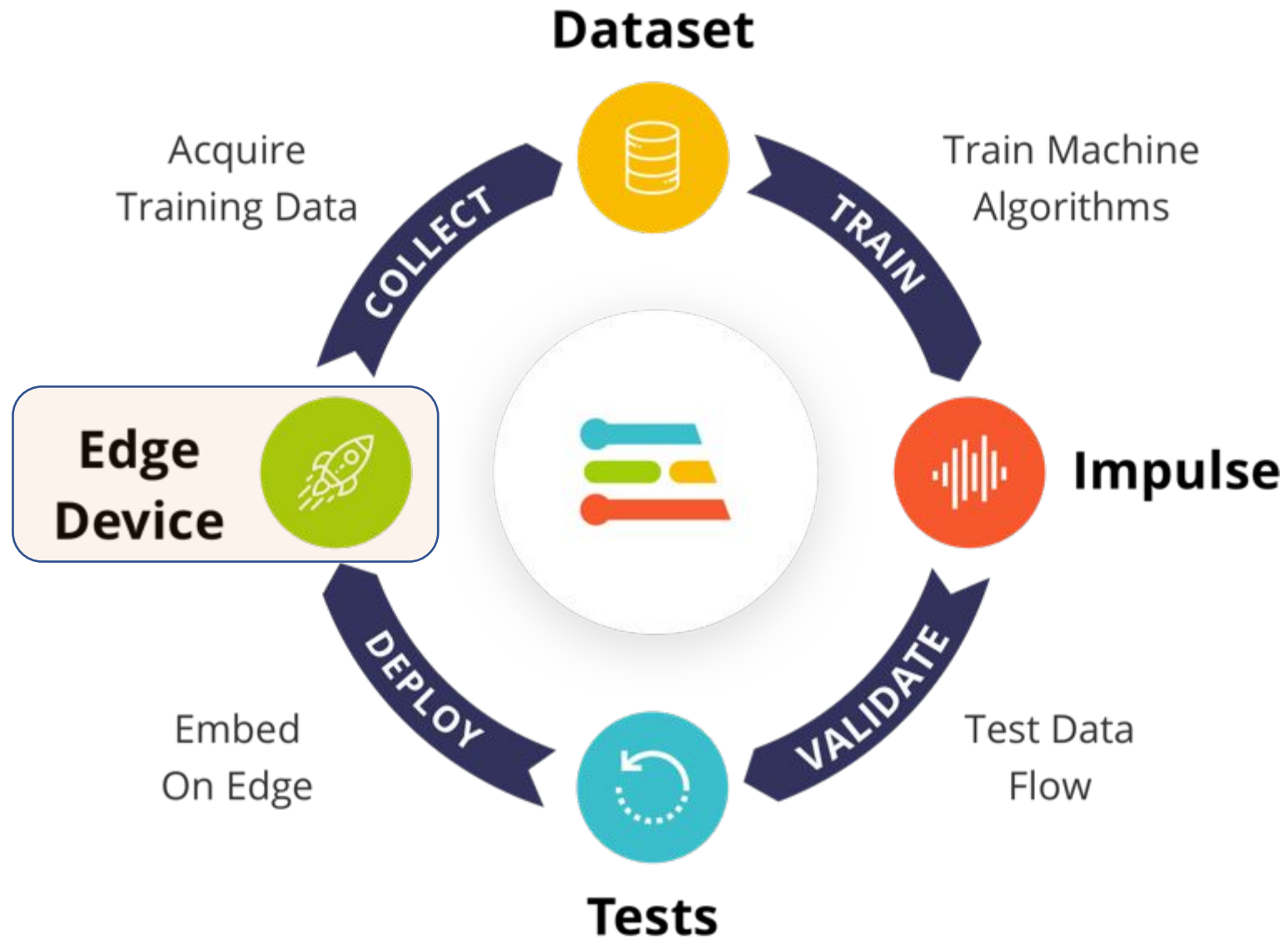
Motion Classification

Transportation Classes

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

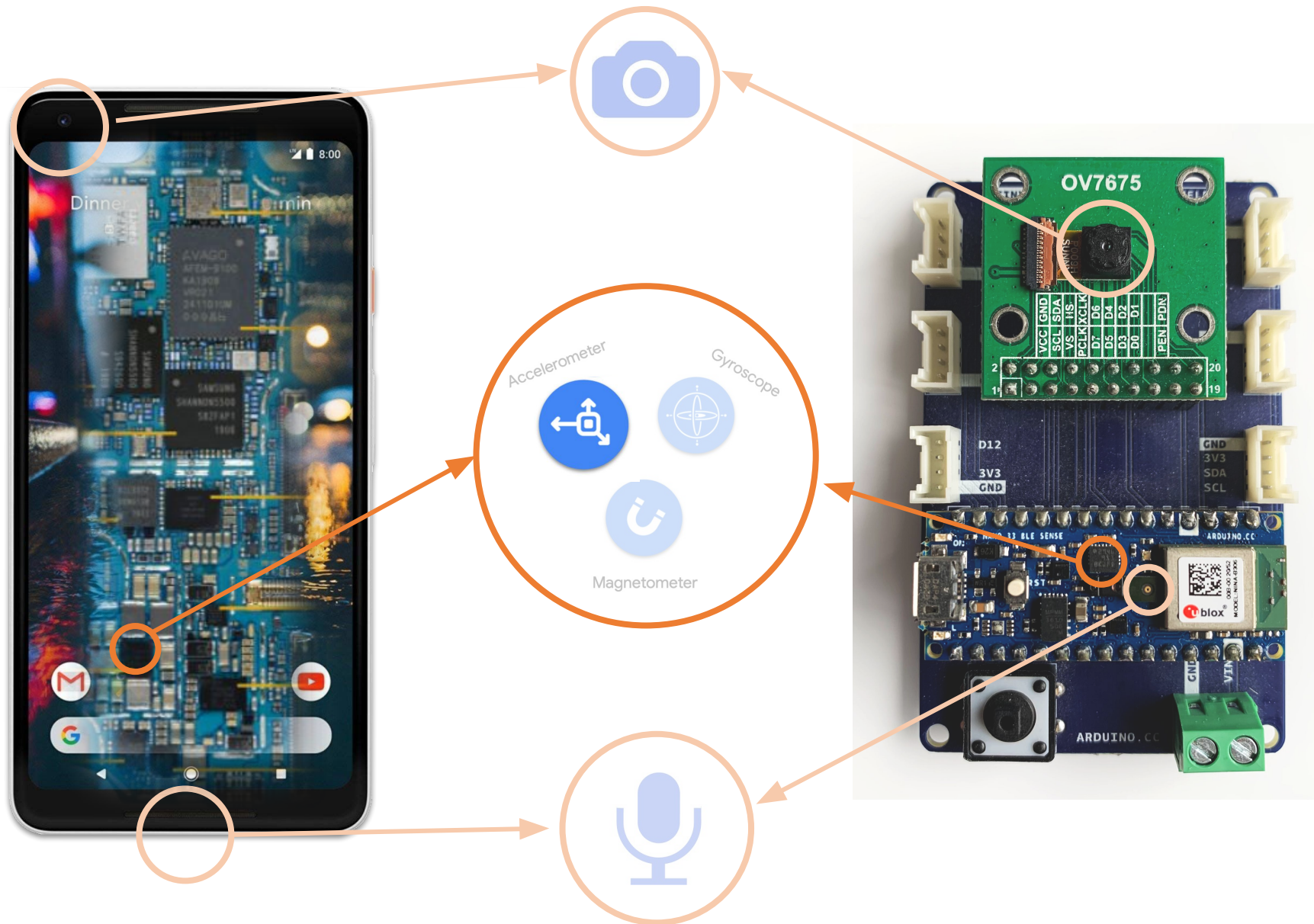


Data: collect & test using **accelerometer** as sensor



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

Sensor - IMU (Inertial Measurement Unit)



Dashboard - SciTinyML-Motion x +

studio.edgeimpulse.com/studio/51797

EDGE IMPULSE

Project info Keys Export

MJRoBot (Marcelo Rovai) / SciTinyML-Motion-Project

This is your Edge Impulse project. From here you acquire new training data, design impulses and train models.

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

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

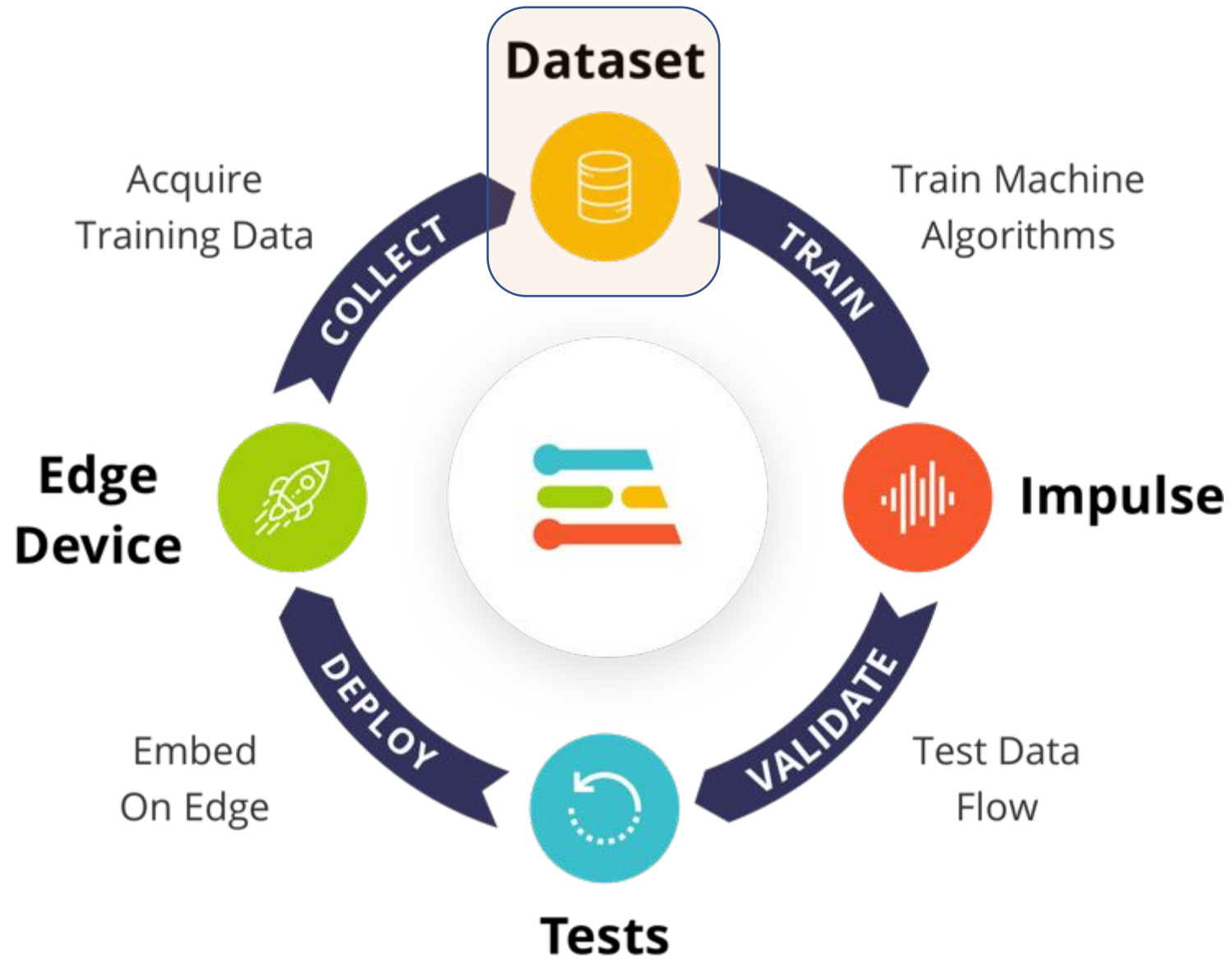
DATA COLLECTED
6m 41s

Collaborators

MJRoBot (Marcelo Rovai) OWNER

Project info

Project ID 51797



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

Devices - TinyML4D - Project x

studio.edgeimpulse.com/studio/49268/devices

EDGE IMPULSE

DEVICES (TINYML4D - PROJECT SETUP)

Marcelo Rovai

+ Connect a new device

Dashboard

Devices

Data acquisition

Impulse design

Create impulse

Retrain model

Live classification

Model testing

Versioning

Deployment

GETTING STARTED

Documentation

Forums

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 x +

studio.edgeimpulse.com/studio/49268/devices

EDGE IMPULSE

DEVICES (TINYML4D - PROJECT SETUP)


Marcelo Roval

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 [X]

You can collect data from any smartphone. From your smartphone go to [this URL](#), or scan the QR code below.



© 2021 Ed

Dashboard

Devices

Data acquisition

Impulse design

Create impulse

Retrain model

Live classification

Model testing

Versioning

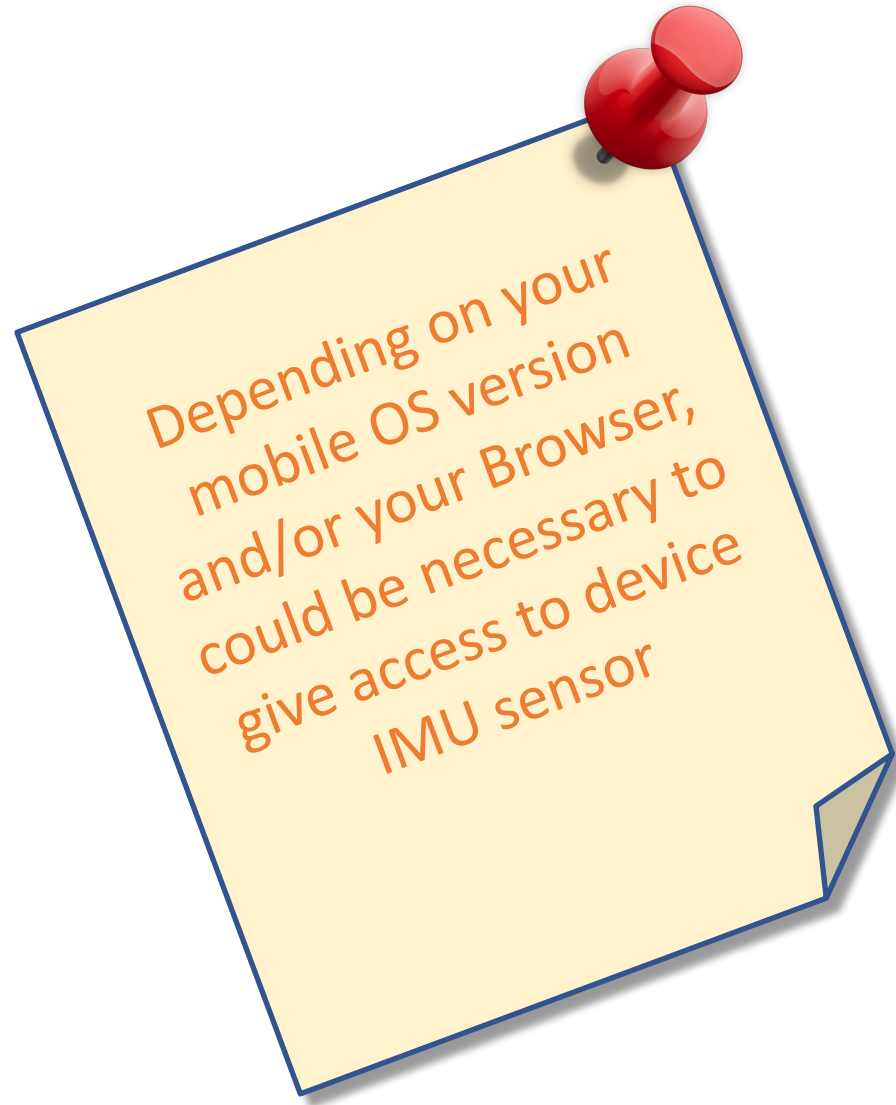
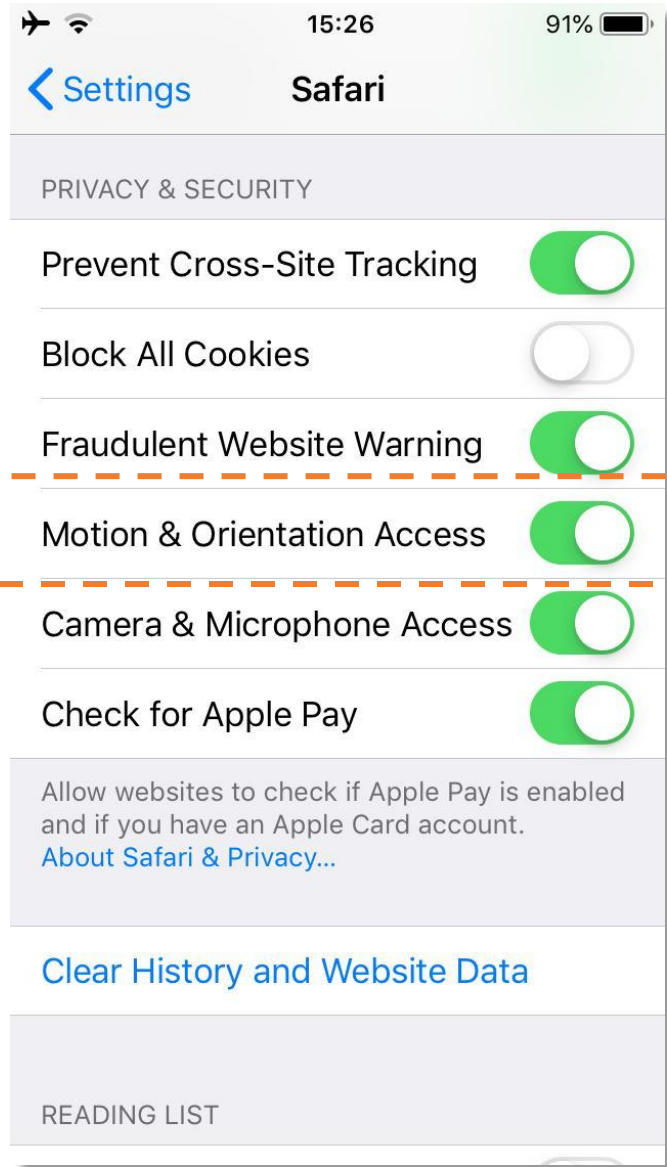
Deployment

GETTING STARTED

Documentation

Forums





Devices - TinyML4D - Project x +

studio.edgeimpulse.com/studio/49268/devices

EDGE IMPULSE

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

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 x +



studio.edgeimpulse.com/studio/49268/devices

EDGE IMPULSE

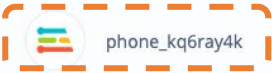
DEVICES (TINYML4D - PROJECT SETUP) Marcelo Roval

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


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Camera 12:07 22%

smartphone.edgeimpulse.com

 Data collection



**Connected as
phone_kq6ray4k**

You can collect data from this

EDGE IMPULSE

DATA ACQUISITION (TINYML4D - PROJECT SETUP)

Training data Test data

Did you know? You can capture data from any device or development board, or upload your existing datasets - [Show options](#)

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...

Marcelo Roval

- Dashboard
- Devices
- Data acquisition
- Impulse design
 - Create impulse
- Retrain model
- Live classification
- Model testing
- Versioning
- Deployment


GETTING STARTED

- Documentation
- Forums

12:20 44%

smartphone.edgeimpulse.com

Data collection



Not connected

Refresh this page to reconnect to Edge Impulse

Navigation icons: back, forward, share, book, tabs



Collect Data

EDGE IMPULSE

DATA ACQUISITION (SCITINYML-MOTION-PROJECT)

MJRoBot (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

DATA COLLECTED 5m 13s

TRAIN / TEST SPLIT 80% / 20%

Record new data Connect using WebUSB

Device phone_kq6ray4k

Label maritime

Sample length (ms.) 10000

Sensor Accelerometer

Frequency 62.5Hz

Start sampling

Sensor

- Accelerometer
- Microphone
- Camera

SAMPLE NAME	LABEL	ADDED	LENGTH
idle.2hstvpk2	idle	Oct 14 2021, 17:54:22	10s
idle.2hstuat	idle	Oct 14 2021, 17:53:34	10s
idle.2hsttoq3	idle	Oct 14 2021, 17:53:16	10s
idle.2hstt9dk	idle	Oct 14 2021, 17:53:00	10s
idle.2hstsp4a	idle	Oct 14 2021, 17:52:43	10s
idle.2hstrkad	idle	Oct 14 2021, 17:52:06	10s
idle.2hstr3kf	idle	Oct 14 2021, 17:51:49	10s
idle.2hstajaj	idle	Oct 14 2021, 17:51:32	10s
maritime.2hstpku3	maritime	Oct 14 2021, 17:51:01	10s
maritime.2hsto9ki	maritime	Oct 14 2021, 17:50:16	10s
maritime.2hstnnqu	maritime	Oct 14 2021, 17:49:58	10s
maritime.2hstn60c	maritime	Oct 14 2021, 17:49:40	10s

12:35 44%

smartphone.edgeimpulse.com

Data collection

4s

Recording data

Collect Data

EDGE IMPULSE

DATA ACQUISITION (SCITINYML-MOTION-PROJECT)

Training data Test data

Did you know? You can capture data from any device or development board, or upload your existing datasets - [Show options](#)

DATA COLLECTED
5m 13s

TRAIN / TEST SPLIT
80% / 20%

Record new data [Connect using WebUSB](#)

Device
phone_kq6ray4k

Label
maritime

Sample length (ms.)
10000

Sensor
Accelerometer

Frequency
62.5Hz

Start sampling

RAW DATA
maritime.2hstpk3

SAMPLE NAME	LABEL	ADDED	LENGTH
idle.2hstvpk2	idle	Oct 14 2021, 17:54:22	10s
idle.2hstuat	idle	Oct 14 2021, 17:53:34	10s
idle.2hsttoq3	idle	Oct 14 2021, 17:53:16	10s
idle.2hstt9dk	idle	Oct 14 2021, 17:53:00	10s
idle.2hstsp4a	idle	Oct 14 2021, 17:52:43	10s
idle.2hstrkad	idle	Oct 14 2021, 17:52:06	10s
idle.2hstr3kf	idle	Oct 14 2021, 17:51:49	10s
idle.2hstajaj	idle	Oct 14 2021, 17:51:32	10s
maritime.2hstpk3	maritime	Oct 14 2021, 17:51:01	10s
maritime.2hsto9ki	maritime	Oct 14 2021, 17:50:16	10s
maritime.2hstnnqu	maritime	Oct 14 2021, 17:49:58	10s
maritime.2hstn60c	maritime	Oct 14 2021, 17:49:40	10s

accX accY accZ

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



Machine Learning
Algorithm

Original Dataset

Training Set

Test Set

Collect Data

Training Set

Validation Set

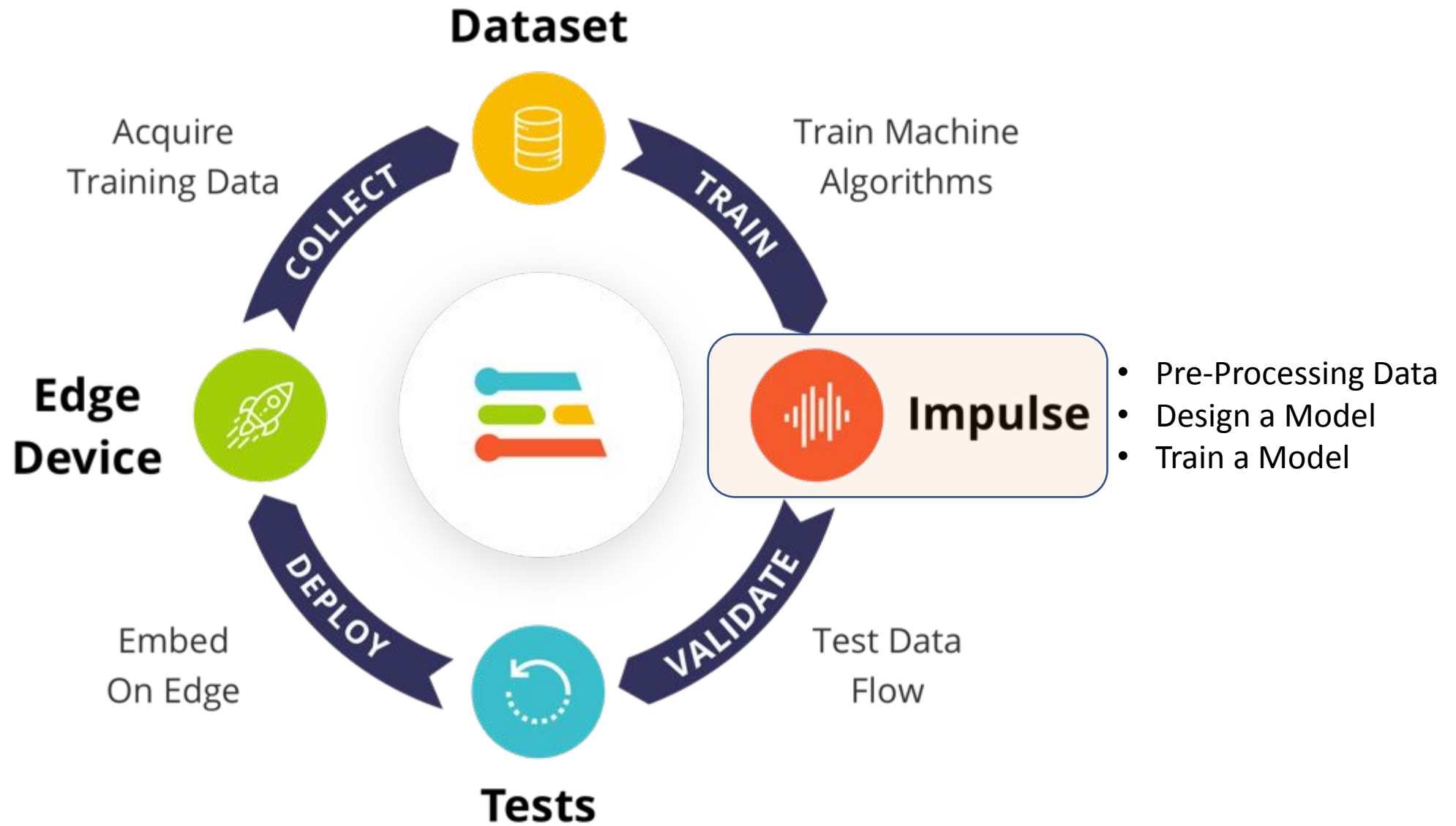
Test Set



**Machine Learning
Algorithm**

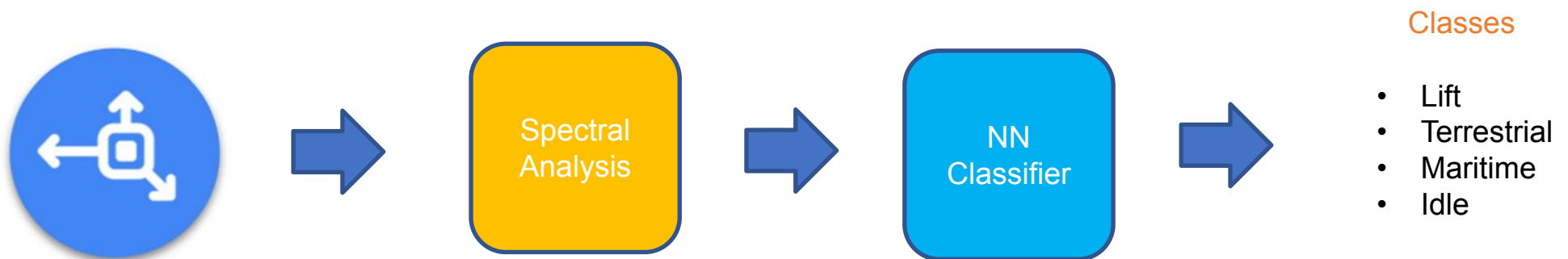
Final Model

Final Performance
Estimate



The screenshot displays a machine learning workflow interface with four main panels:

- Time series data (Red panel):** Shows axes (accX, accY, accZ), window size (2000 ms), window increase (80 ms), frequency (62.5 Hz), and zero-pad data (checked).
- Spectral Analysis (White panel):** Name: Spectral Analysis; Input axes: accX, accY, accZ (all checked).
- Neural Network (Keras) (Purple panel):** Name: Neural Network (Keras); Input features: Spectral Analysis (checked); Output features: 4 (idle, lift, maritime, terrestrial).
- Output features (Green panel):** 4 (idle, lift, maritime, terrestrial); Save Impulse button.



Preprocess Data

The screenshot displays the Edge Impulse Studio interface for spectral analysis. The browser address bar shows the URL: `studio.edgeimpulse.com/studio/51797/dsp/spectral-analysis/11`. The interface is divided into several sections:

- Raw data:** A time-domain plot showing three acceleration channels (accX, accY, accZ) over time. A dashed orange box highlights a segment of the data.
- Raw features:** A list of 375 raw features extracted from the highlighted segment, including values like 3.2285, -2.5962, -12.8225, etc.
- Parameters:** A configuration panel for feature extraction with the following settings:
 - Scaling: 1
 - Filter Type: low
 - Cut-off frequency: 3
 - Order: 6
 - Spectral power: FFT length (128), No. of peaks (3), Peaks threshold (0.1), Power edges (0.1, 0.5, 1.0, 2.0, 5.0)A "Save parameters" button is located at the bottom right of this section.
- DSP result:** A plot showing the signal after filtering, with a dashed orange box around it.
- Frequency domain:** A plot showing the spectral power of the filtered signal.
- Spectral power:** A plot showing the power spectrum of the filtered signal.
- Processed features:** A list of 33 processed features extracted from the DSP result, including values like 3.5928, 0.4968, 3.3689, etc.
- On-device performance:** A section showing performance metrics:
 - Processing Time: 8 ms.
 - Peak RAM Usage: 5 KB.

RMS
FFT
PSD } 33 Processed Features

Spectral Analysis - SciTinyML - x +

studio.edgeimpulse.com/studio/51797/dsp/spectral-analysis/11/generate-features

EDGE IMPULSE

SPECTRAL ANALYSIS (SCITINYML-MOTION-PROJECT)

#1 ▾ EON Tuner Primary

Parameters **Generate features**

Training set

Data in training set	5m 22s
Classes	4 (idle, lift, maritime, terrestrial)
Window length	2000 ms.
Window increase	80 ms.
Training windows	3,230

Generate features

Feature explorer (3,132 samples)

X Axis: accX RMS | Y Axis: accY RMS | Z Axis: accZ RMS

- idle
- lift
- maritime
- terrestrial

On-device performance

PROCESSING TIME: 8 ms.

PEAK RAM USAGE: 5 KB

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Preprocess Data

- ✓ accX RMS
- accX Peak 1 Freq
- accX Peak 1 Height
- accX Peak 2 Freq
- accX Peak 2 Height
- accX Peak 3 Freq
- accX Peak 3 Height
- accX Spectral Power 0.1 - 0.5
- accX Spectral Power 0.5 - 1.0
- accX Spectral Power 1.0 - 2.0
- accX Spectral Power 2.0 - 5.0
- accY RMS
- accY Peak 1 Freq
- accY Peak 1 Height
- accY Peak 2 Freq
- accY Peak 2 Height
- accY Peak 3 Freq
- accY Peak 3 Height
- accY Spectral Power 0.1 - 0.5
- accY Spectral Power 0.5 - 1.0
- accY Spectral Power 1.0 - 2.0
- accY Spectral Power 2.0 - 5.0
- accZ RMS
- accZ Peak 1 Freq
- accZ Peak 1 Height
- accZ Peak 2 Freq
- accZ Peak 2 Height
- accZ Peak 3 Freq
- accZ Peak 3 Height
- accZ Spectral Power 0.1 - 0.5
- accZ Spectral Power 0.5 - 1.0
- accZ Spectral Power 1.0 - 2.0
- accZ Spectral Power 2.0 - 5.0

Neural Network (Keras) - SciTi x +

studio.edgeimpulse.com/studio/51797/learning/keras/12

EDGE IMPULSE

- 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

Neural Network settings

Training settings

Number of training cycles $\textcircled{?}$ **EPOCHS**

Learning rate $\textcircled{?}$ **Lr**

Neural network architecture

- Input layer (33 features)
- Dense layer (20 neurons)
- Dense layer (10 neurons)
- Add an extra layer
- Output layer (4 features)

Start training

Training output

```
graph TD; input([input]) --> InputLayer[InputLayer]; InputLayer --> Dense1[Dense  
kernel (33x20)  
bias (20)  
ReLU]; Dense1 --> Dense2[Dense  
kernel (20x10)  
bias (10)  
ReLU]; Dense2 --> Dense3[Dense  
kernel (10x4)  
bias (4)  
Softmax]; Dense3 --> y_pred([y_pred]);
```

The diagram illustrates the neural network architecture. It starts with an 'input' box leading to an 'InputLayer'. This is followed by three 'Dense' layers: the first has a kernel of 33×20 and bias of 20 with a ReLU activation; the second has a kernel of 20×10 and bias of 10 with a ReLU activation; the third has a kernel of 10×4 and bias of 4 with a Softmax activation. The final output is 'y_pred'. Blue arrows connect the layers in the 'Neural network architecture' section to their corresponding blocks in the 'Training output' diagram.

Design a Model

Train a Model

The screenshot displays the Edge Impulse studio interface for training a neural network. The left sidebar contains navigation options: Dashboard, Devices, Data acquisition, Impulse design (with sub-options: Create impulse, Spectral Analysis, and Neural Network (Ke...)), EON Tuner, Retrain model, Live classification, Model testing, Versioning, and Deployment. Below this is the 'GETTING STARTED' section with Documentation and Forums.

The main area is divided into two panels:

- Neural Network settings:**
 - Training settings:** Number of training cycles (EPOCHS) is 30; Learning rate (Lr) is 0.0005.
 - Neural network architecture:** Input layer (33 features), Dense layer (20 neurons), Dense layer (10 neurons), Add an extra layer, and Output layer (4 features). A 'Start training' button is at the bottom.
- Training output:**
 - Model:** Model version: Quantized (int8).
 - Last training performance (validation set):** ACCURACY 99.7%, LOSS 0.01.
 - Confusion matrix (validation set):**

	IDLE	LIFT	MARITIME	TERRESTRIAL
IDLE	100%	0%	0%	0%
LIFT	0%	100%	0%	0%
MARITIME	0%	0.6%	99.4%	0%
TERRESTRIAL	0.6%	0%	0%	99.4%
F1 SCORE	1.00	1.00	1.00	1.00
 - Feature explorer (full training set):** Includes dropdowns for accX RMS, accY RMS, and accZ RMS. A 3D scatter plot shows data points for 'idle - correct', 'lift - correct', 'maritime - correct', 'terrestrial - correct', 'maritime - incorrect', and 'terrestrial - incorrect'.
 - On-device performance:** INFERRING TIME 1 ms., PEAK RAM USAGE 1.7K, FLASH USAGE 19.0K.

At the bottom, a diagram illustrates the workflow: 'Training Set' and 'Validation Set' feed into a 'Machine Learning Algorithm'. A feedback loop labeled 'Training, tuning, evaluation' connects the algorithm back to the training and validation sets.

Neural Network (Keras) - SciTi x +

studio.edgeimpulse.com/studio/51797/learning/keras/12

EDGE IMPULSE

- 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

Neural Network settings

Training settings

Number of training cycles

Learning rate

Neural network architecture

Input layer (33 features)

Dense layer (20 neurons)

Dense layer (10 neurons)

Add an extra layer

Output layer (4 features)

Start training

Training output

Model Model version:

Last training performance (validation set)

ACCURACY 99.7% **LOSS 0.01**

Confusion matrix (validation set)

	IDLE	LIFT	MARITIME	TERRESTRIAL
IDLE	100%	0%	0%	0%
LIFT	0%	100%	0%	0%
MARITIME	0%	0.6%	99.4%	0%
TERRESTRIAL	0.6%	0%	0%	99.4%
F1 SCORE	1.00	1.00	1.00	1.00

Feature explorer (full training set)

accX RMS accY RMS accZ RMS

- idle - correct
- lift - correct
- maritime - correct
- terrestrial - correct
- maritime - incorrect
- terrestrial - incorrect

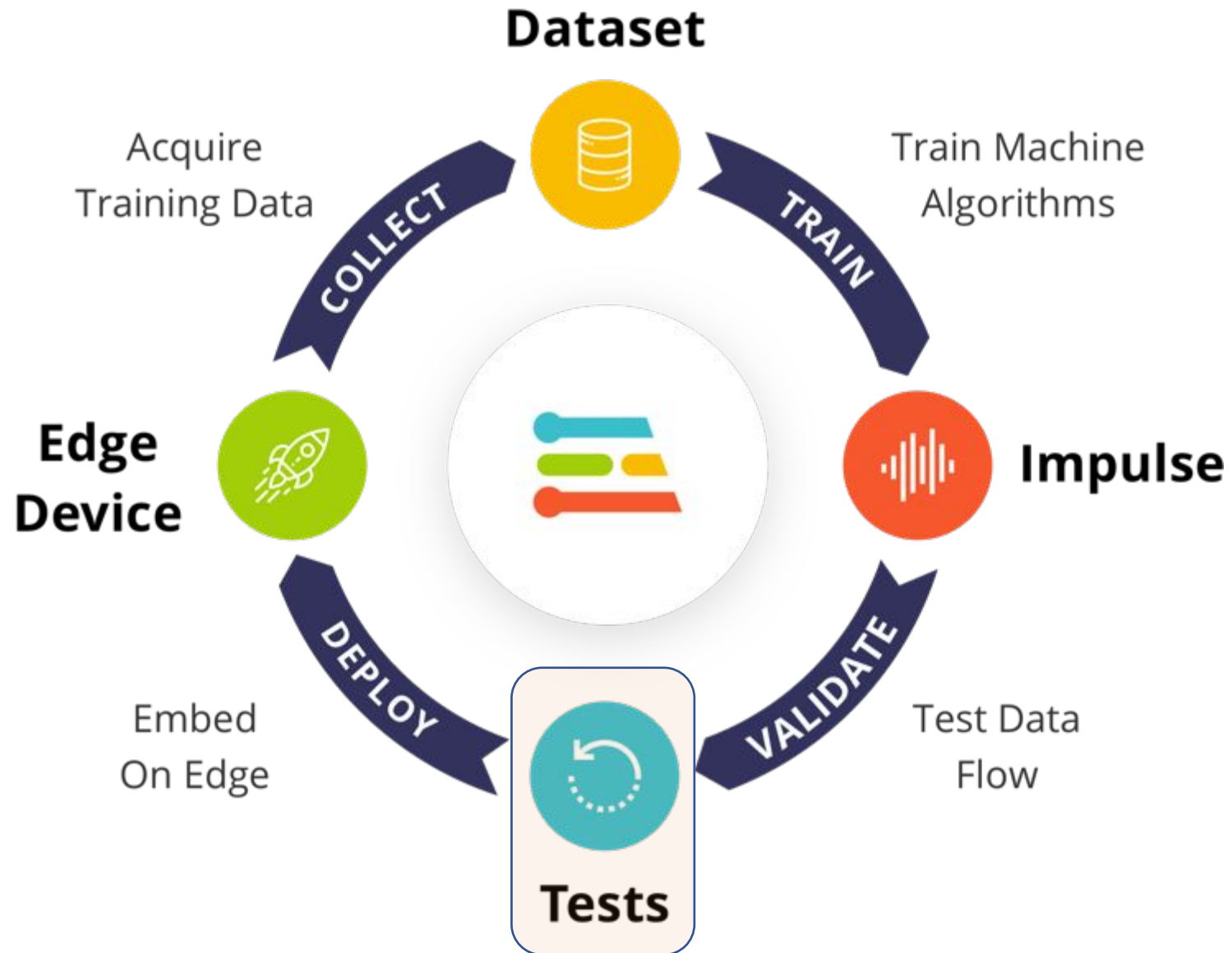
On-device performance

INFERRING TIME 1 ms. **PEAK RAM USAGE 1.7K** **FLASH USAGE 19.0K**

```

graph TD
    TS[Training Set] --> ML[Machine Learning Algorithm]
    VS[Validation Set] --> ML
    ML --> TTE[Training, tuning, evaluation]
    TTE --> ML
  
```

Evaluate Optimize



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

Model testing - SciTinyML-MoI x +

studio.edgeimpulse.com/studio/51797/validation

EDGE IMPULSE

MODEL TESTING (SCITINYML-MOTION-PROJECT) MJRoBot (Marcelo Rovai)

This lists all test data. You can manage this data through Data acquisition.

Test data

[Classify all](#)

Set the 'expected outcome' for each sample to the desired outcome to automatically score the impulse.

SAMPLE NAME	EXPECTED OUTCO...	LENGTH	ACCURACY	RESULT
testing.2hvf...	testing	10s		
terrestrial.2...	terrestrial	10s	100%	98 terrestrial
terrestrial.2...	terrestrial	10s	100%	98 terrestrial
lift .2hssi1t6	lift	10s	100%	98 lift
lift .2hst8tvj	lift	10s	100%	98 lift

Model testing output

Model testing results

ACCURACY 99.74%

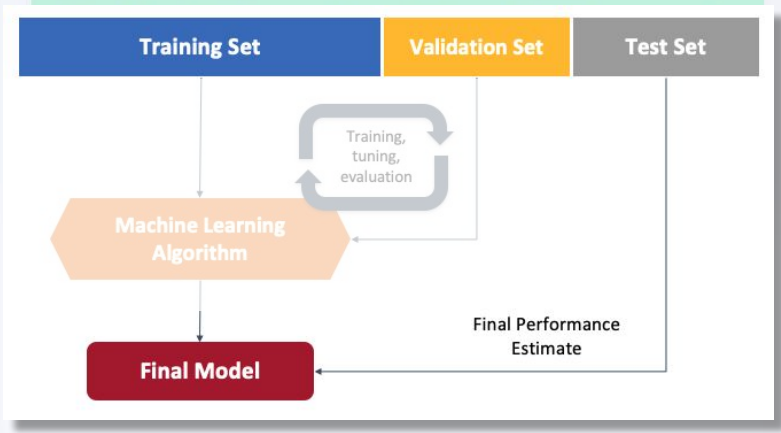
	IDLE	LIFT	MARITIME	TERRESTRIAL	UNCERTAIN
IDLE	99.5%	0.5%	0%	0%	0%
LIFT	0%	100%	0%	0%	0%
MARITIME	0%	0%	99.5%	0%	0.5%
TERRESTRIAL	0%	0%	0%	100%	0%
F1 SCORE	1.00	1.00	1.00	1.00	

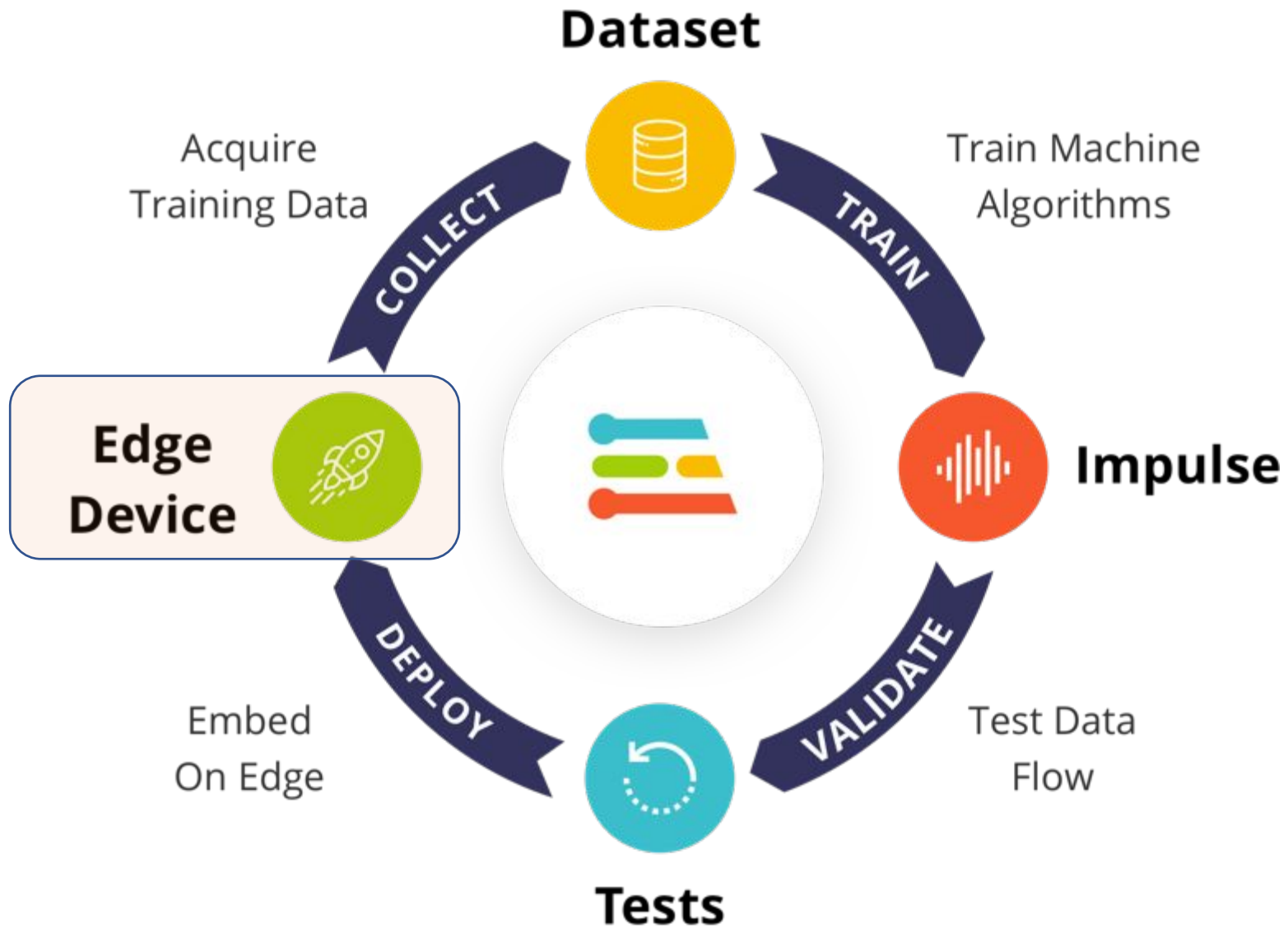
Feature explorer

accX RMS | accY RMS | accZ RMS

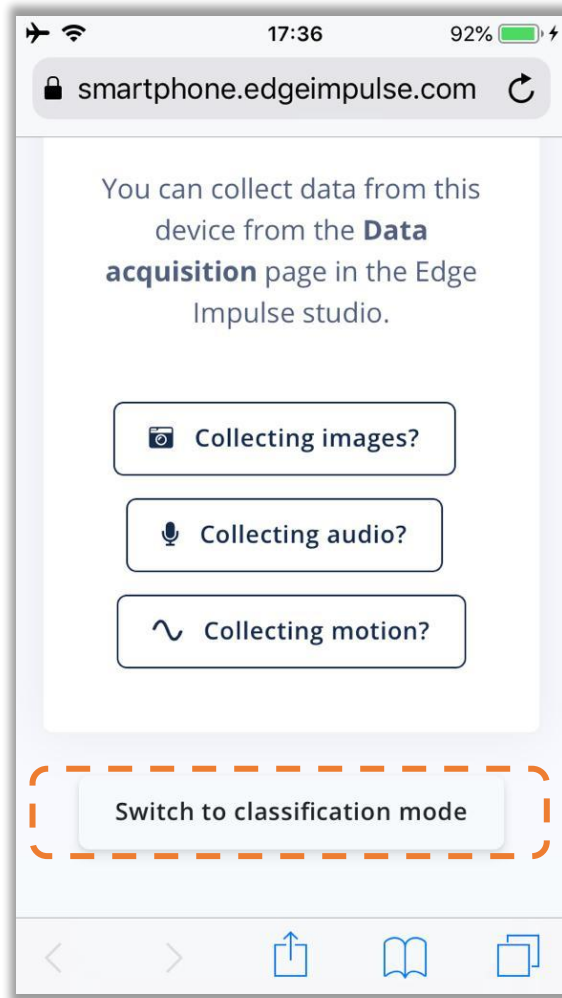
- idle - correct
- lift - correct
- maritime - correct
- terrestrial - correct
- idle - incorrect
- maritime - incorrect

Evaluate
Optimize

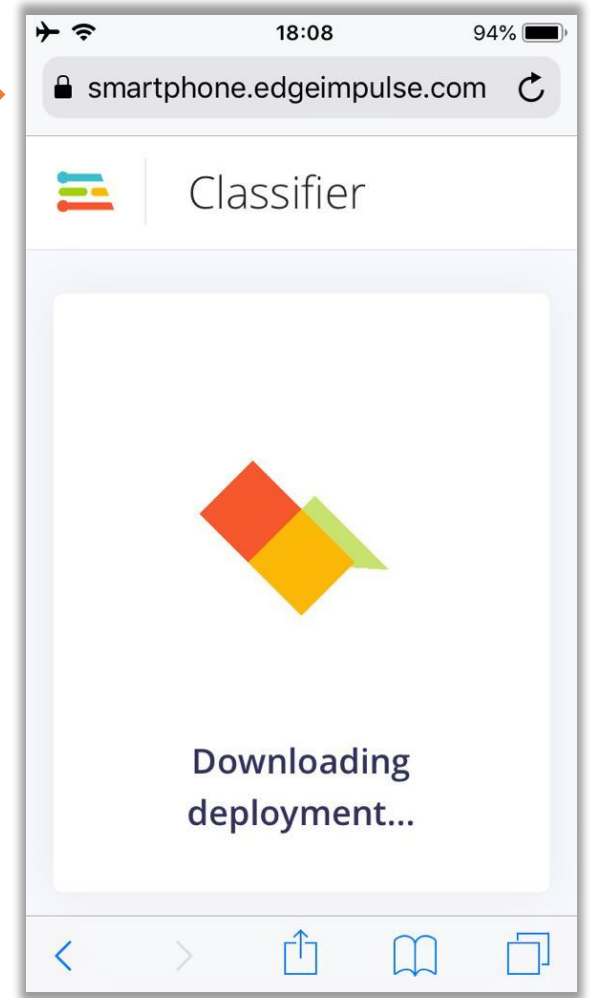
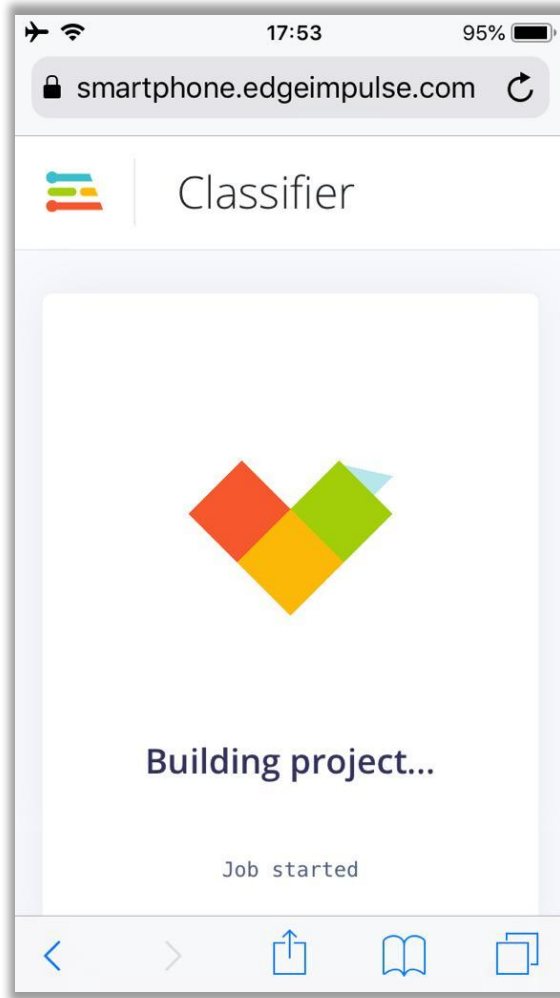




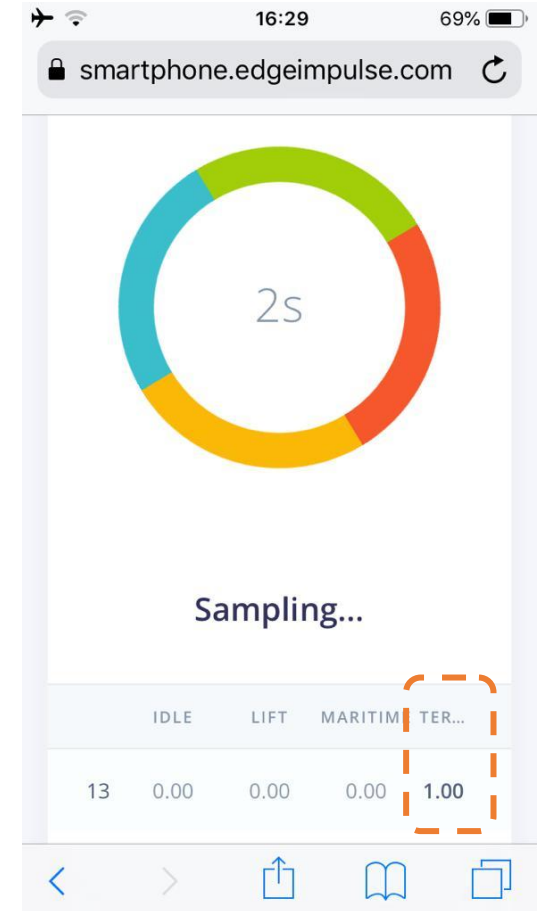
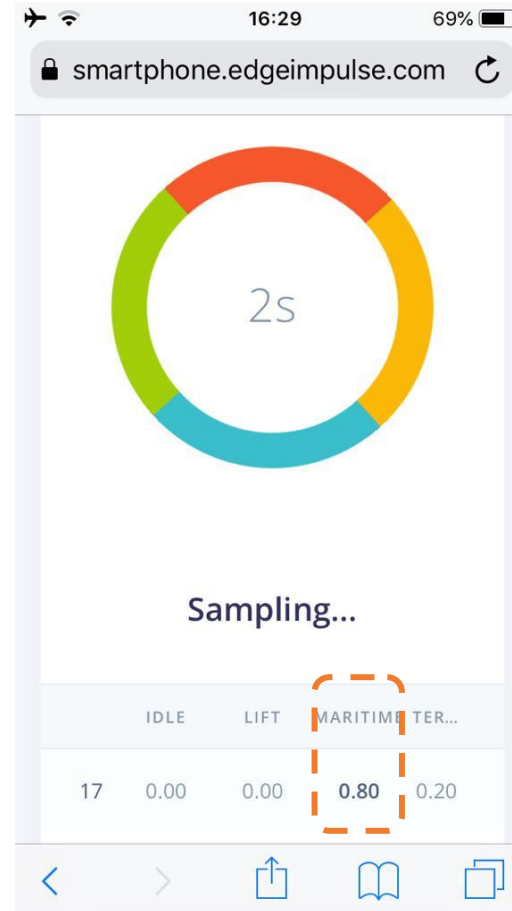
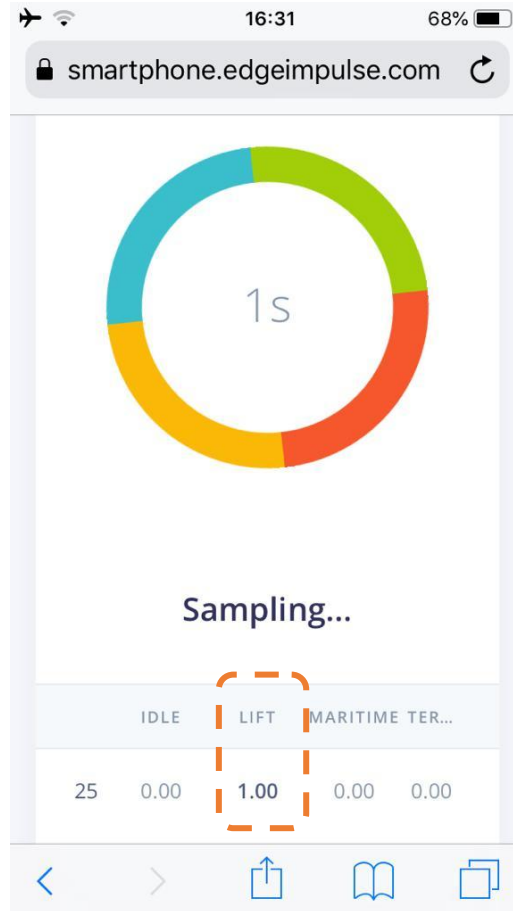
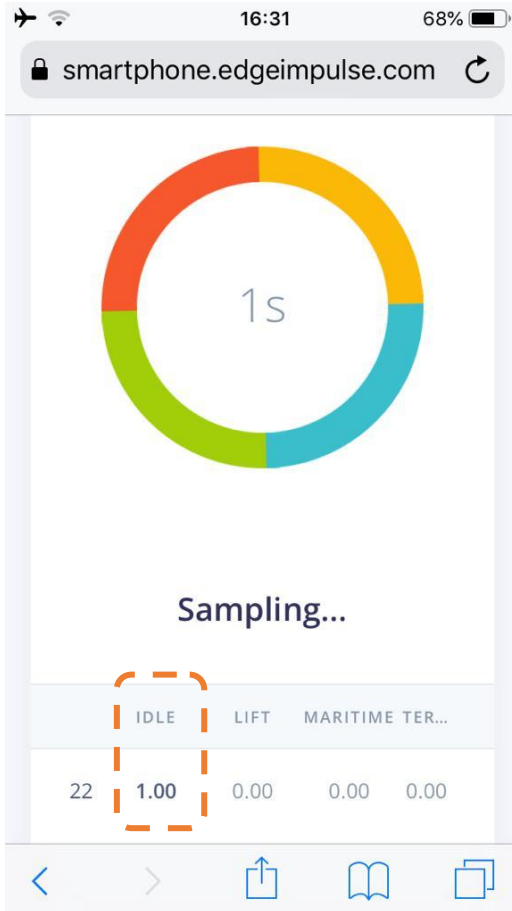
Convert Model



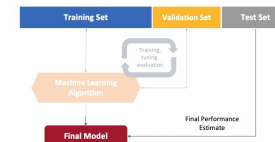
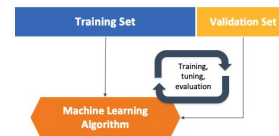
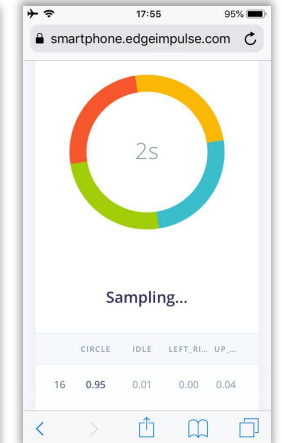
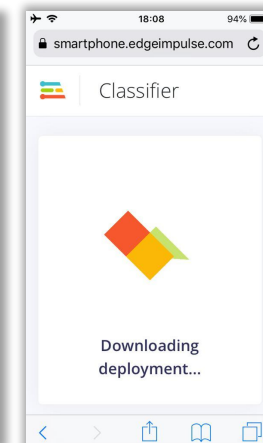
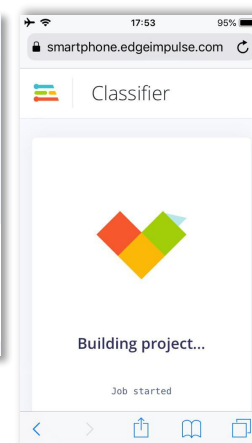
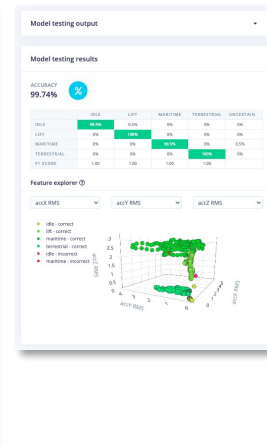
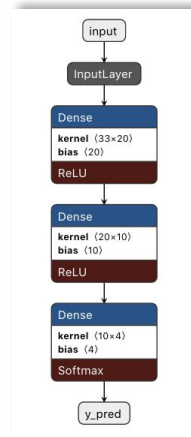
Deploy Model



Make Inferences



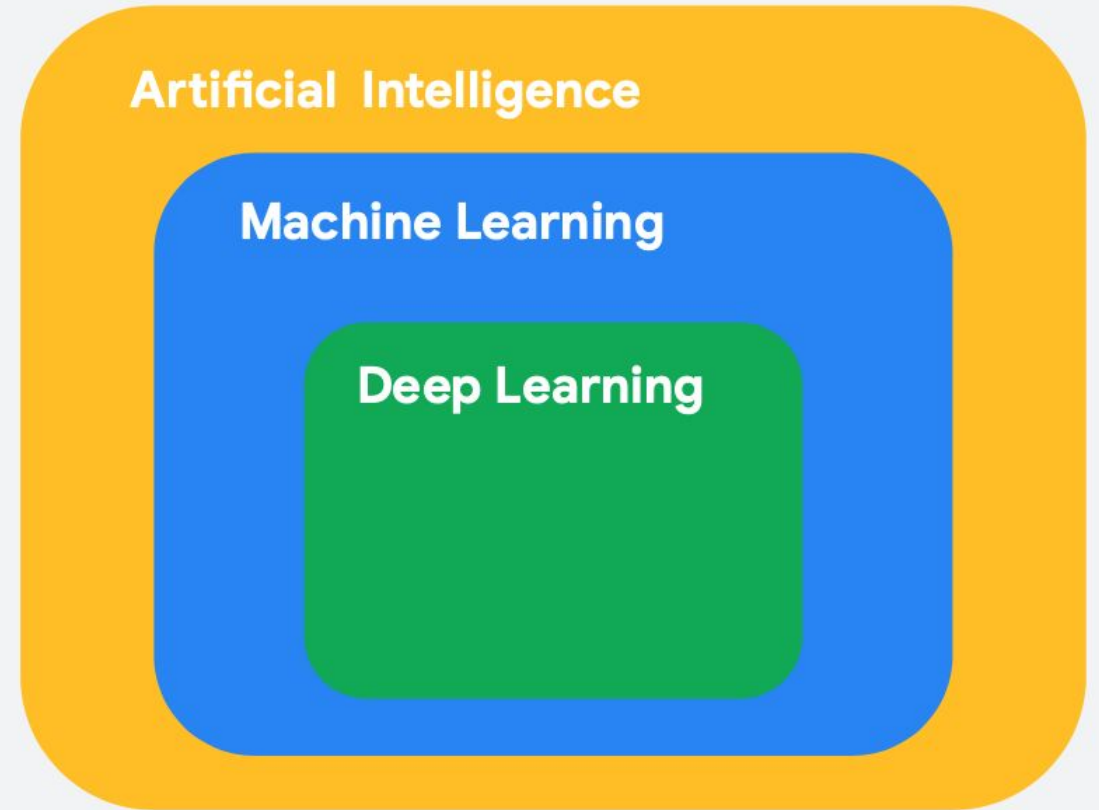
Motion Classification - Summary



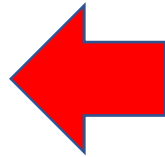
What **AI** really is?

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**

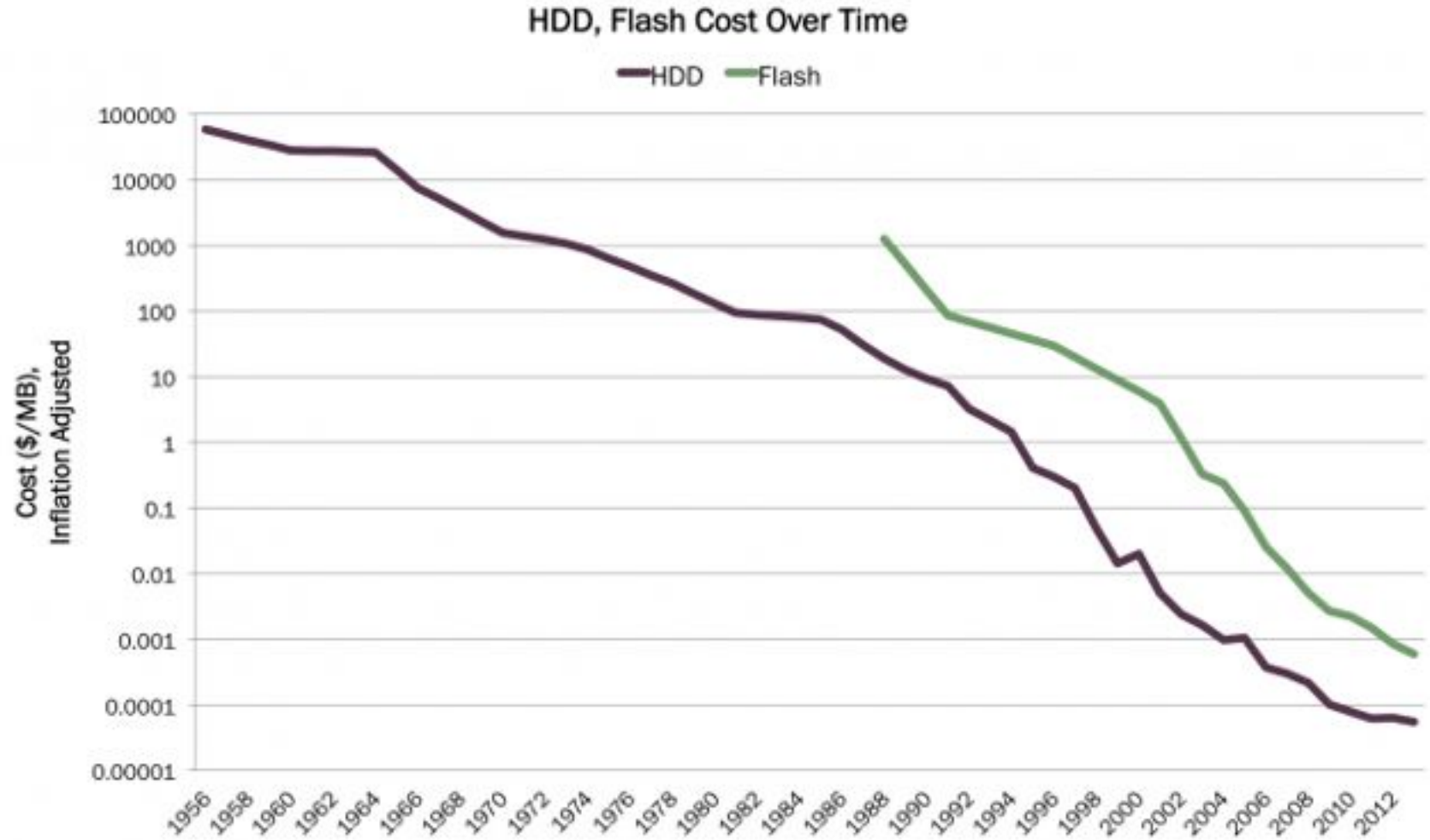
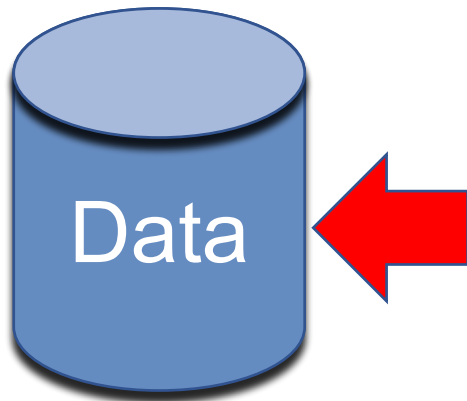


AI starts with ... Data, lot of data (Big Data)

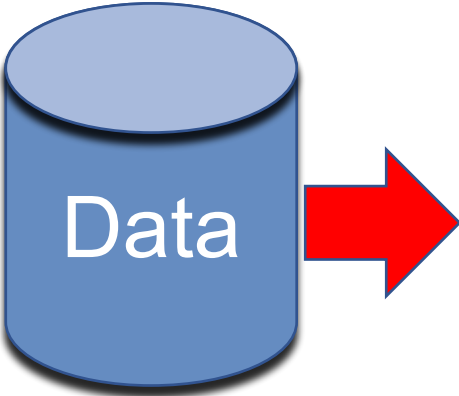


- ✓ Low storage cost & capacity
- ✓ High Performance & Low cost

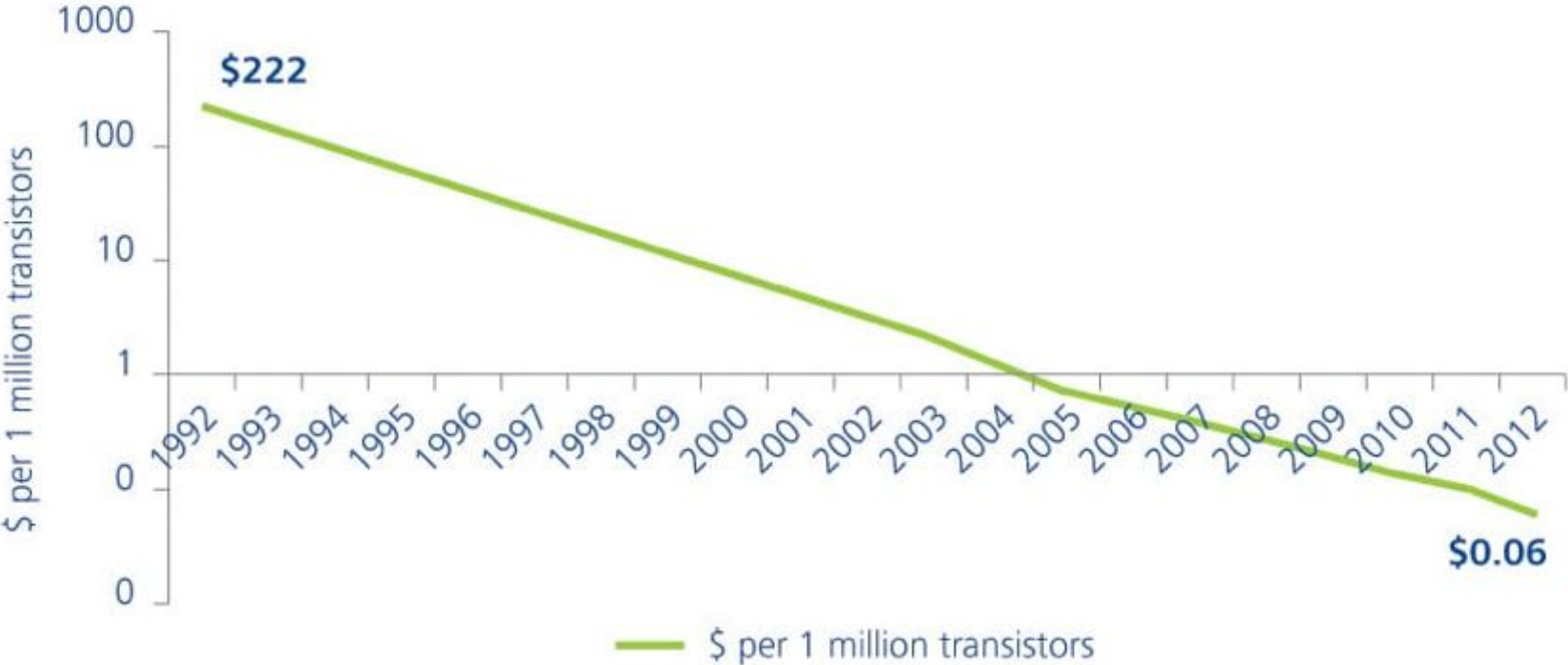
Data → Storage



Data → Processing

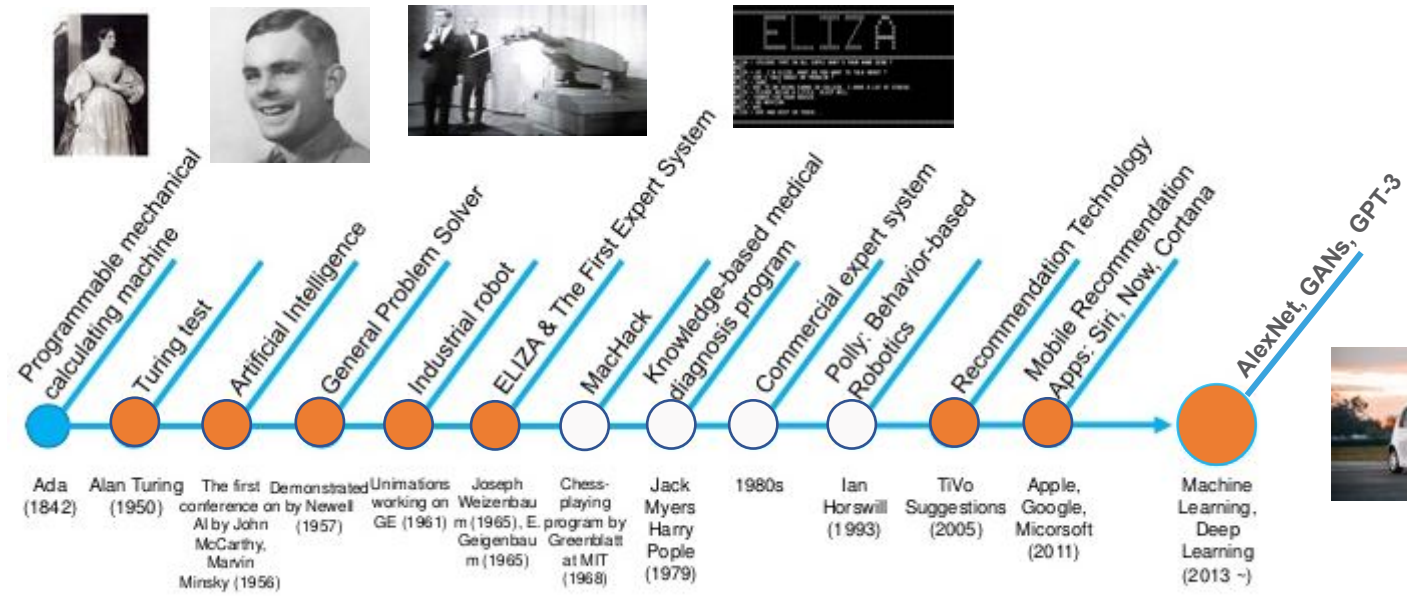
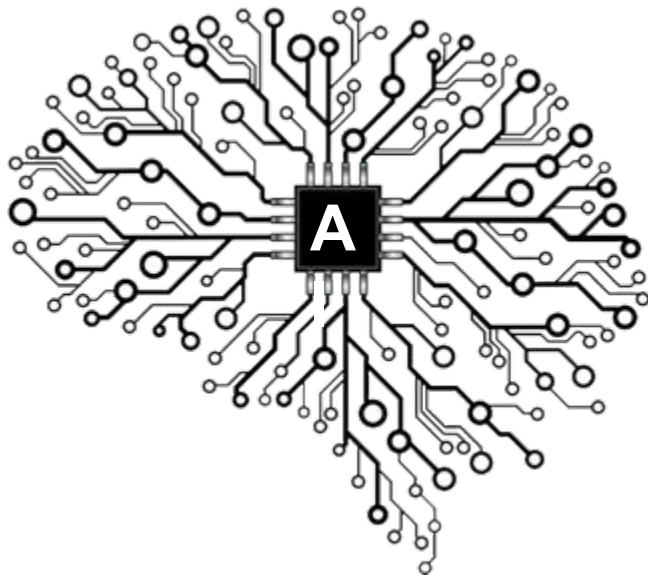


Computing cost-performance (1992–2012)



Source: Leading technology research vendor

Artificial Intelligence – AI Timeline



1951: Claude Shannon's maze-solving robots



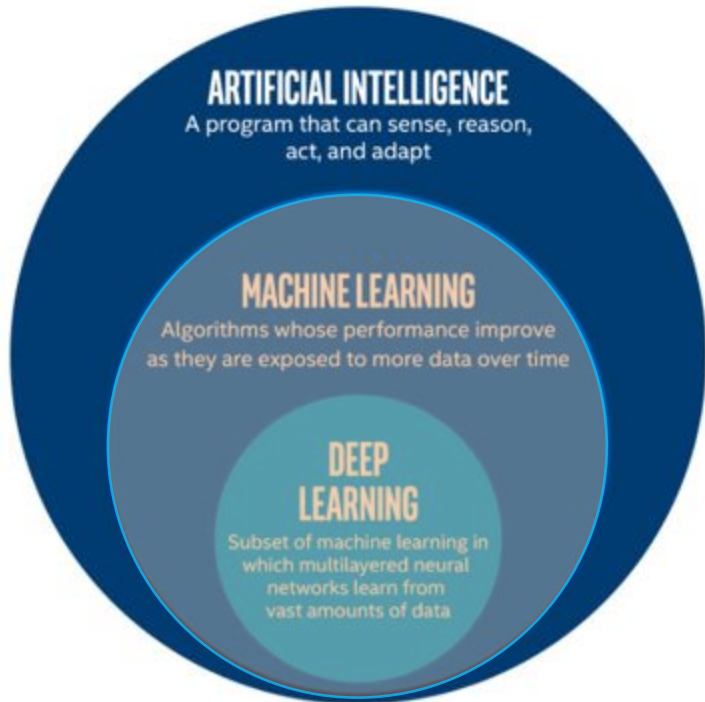
1955: Arthur Samuel's Checkers, the world's first self-learning program



○ 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)



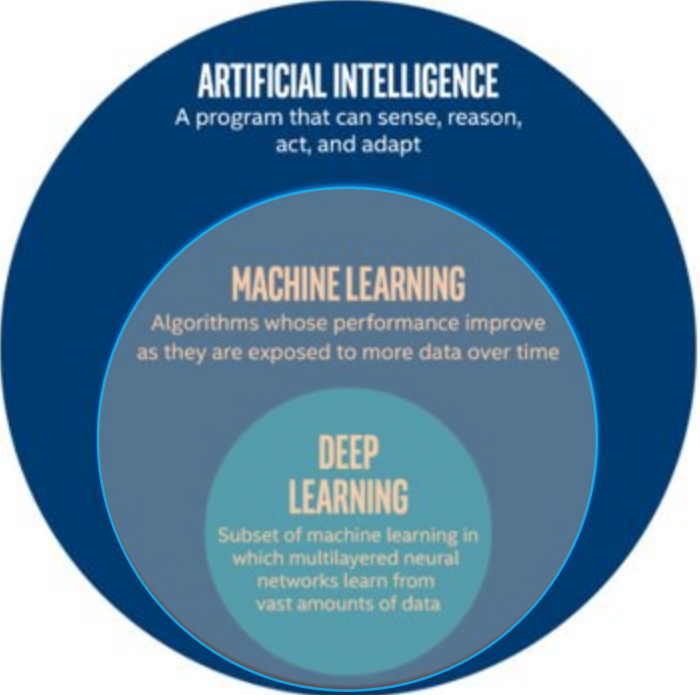
Traditional Programming



Machine Learning



AI → Machine Learning (ML)



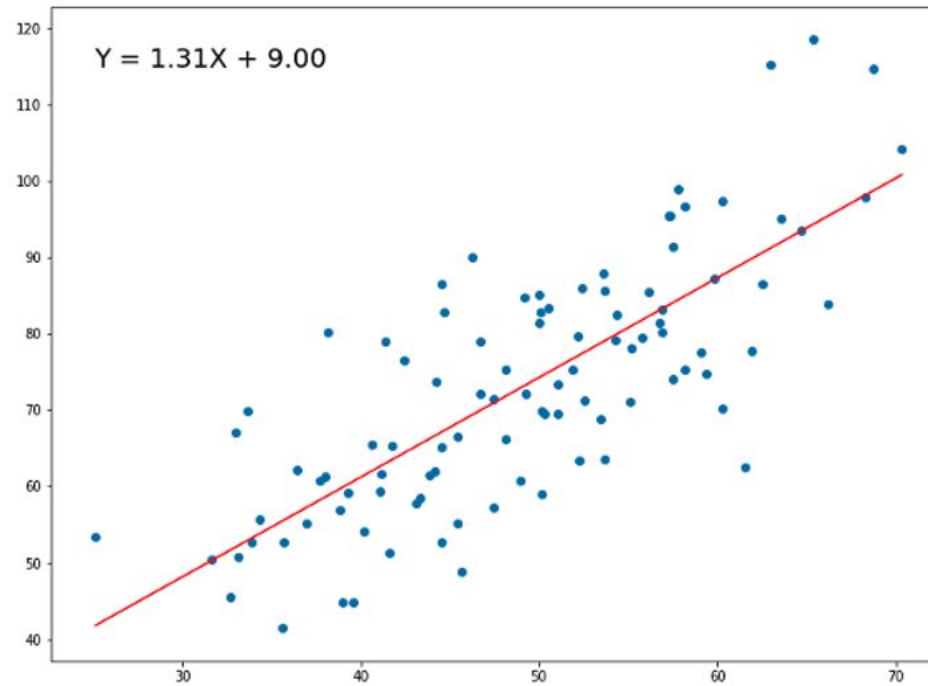
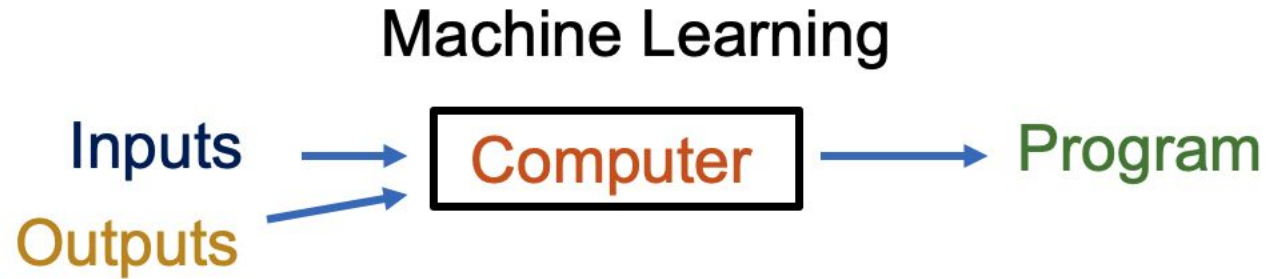
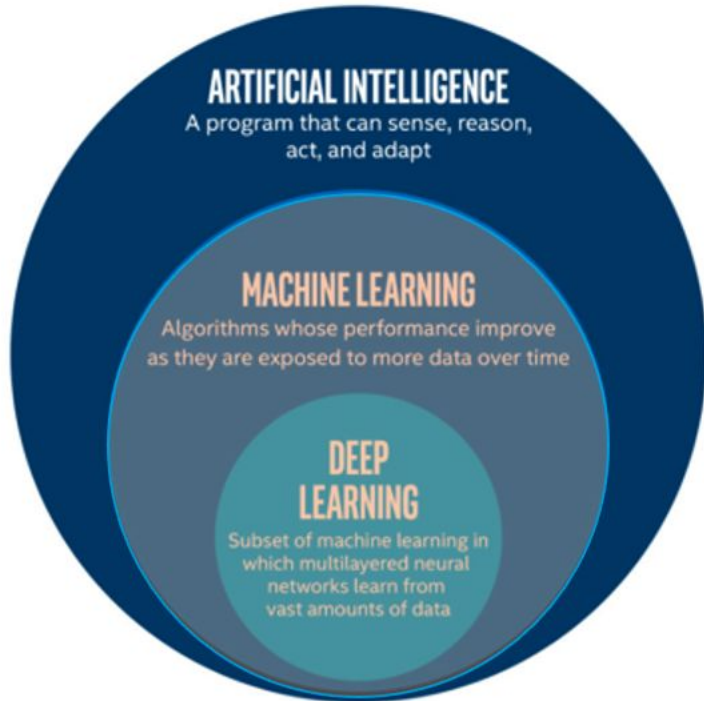
Traditional Programming



Machine Learning



AI → Machine Learning (ML)



Output ↓

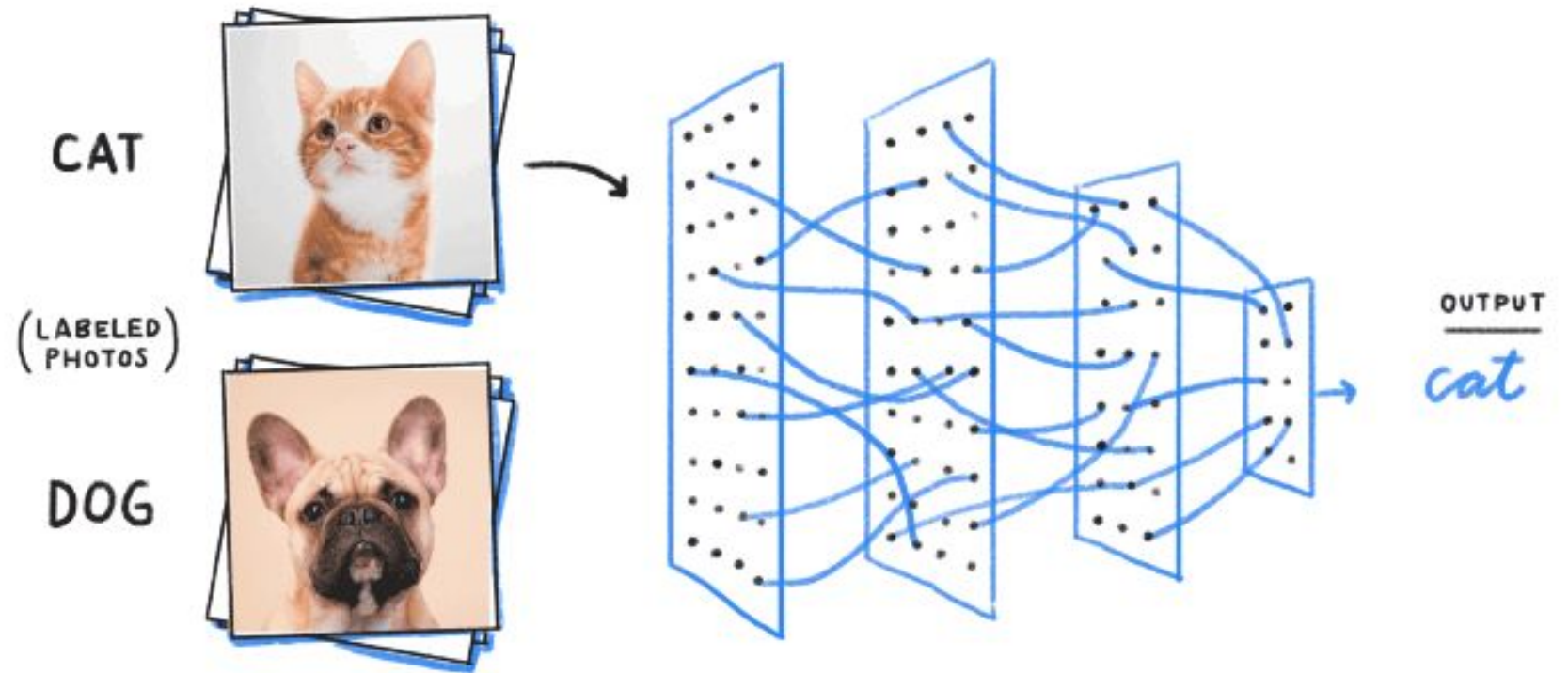
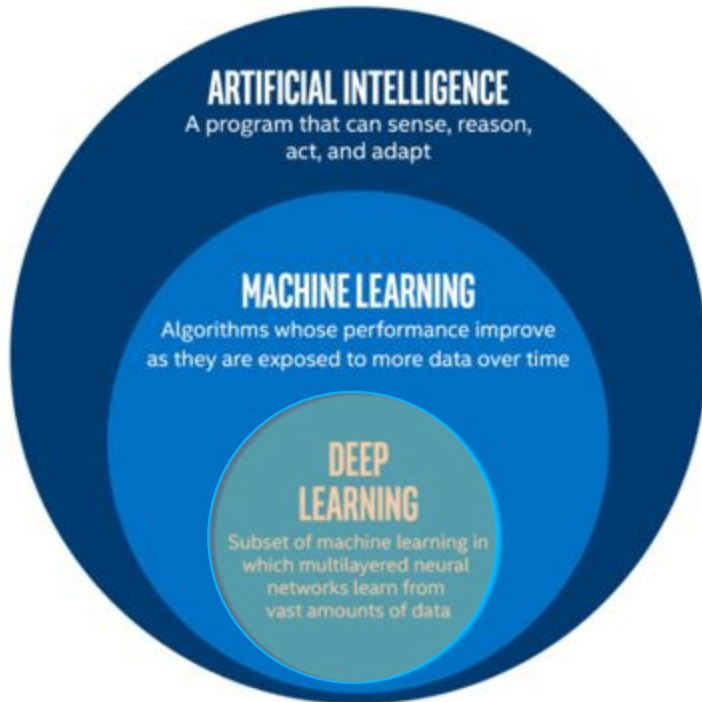
Input ↓

$$Y = w_1 * X_1 + b_0$$

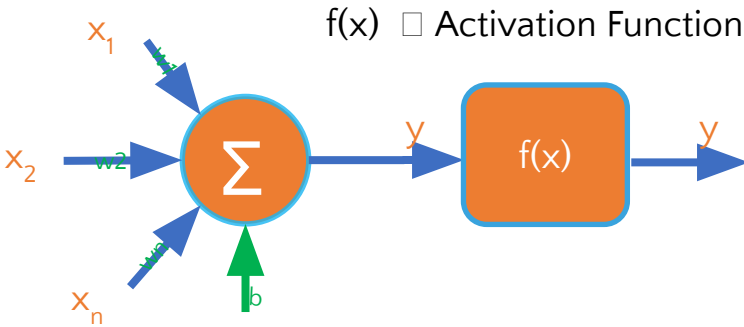
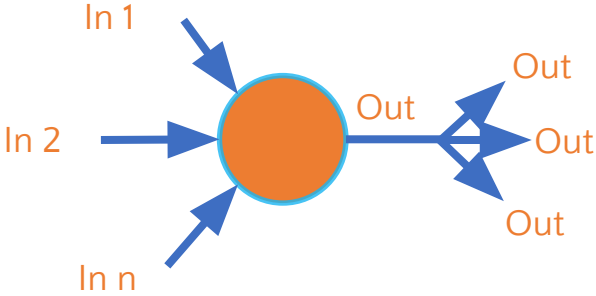
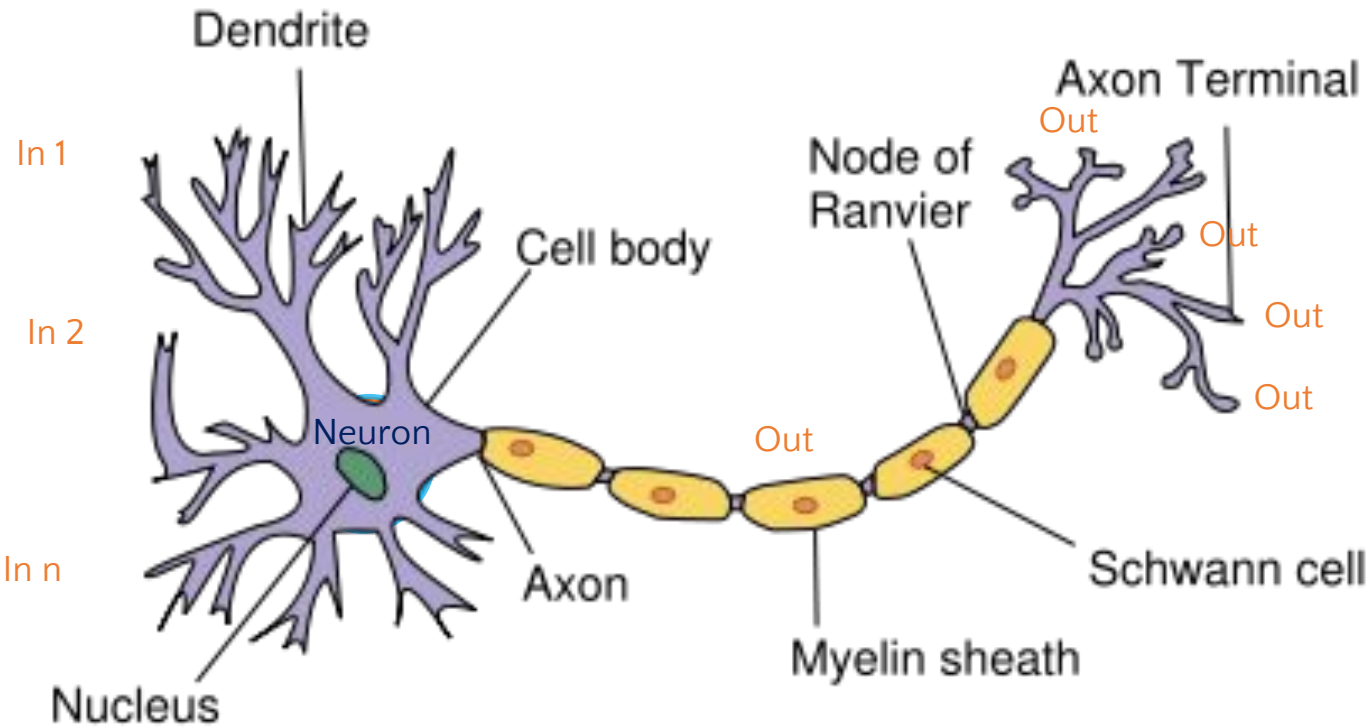
Program (Parameters)

AI → Deep Learning (DL)

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



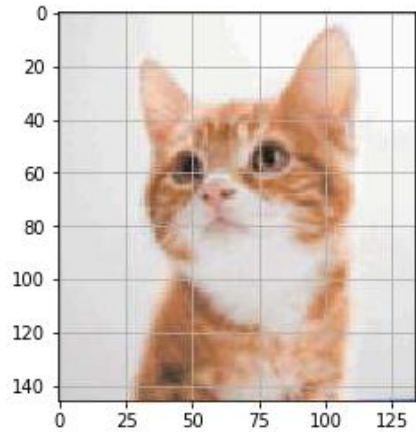
Neuron (Perceptron)



Parameters

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

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]]
```

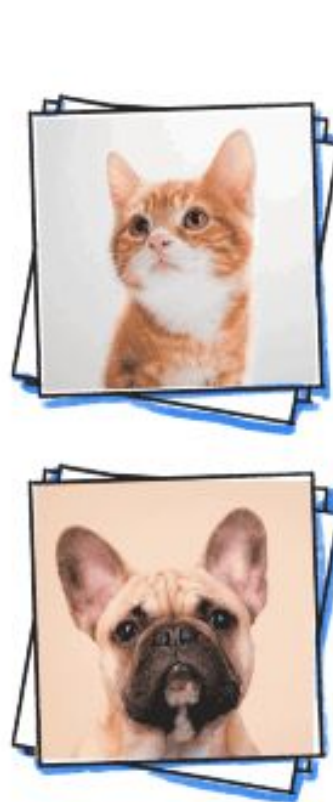
$146 * 134 * 3 = 57,486$ pixels

[227, 228, 227... 124, 119, 121]

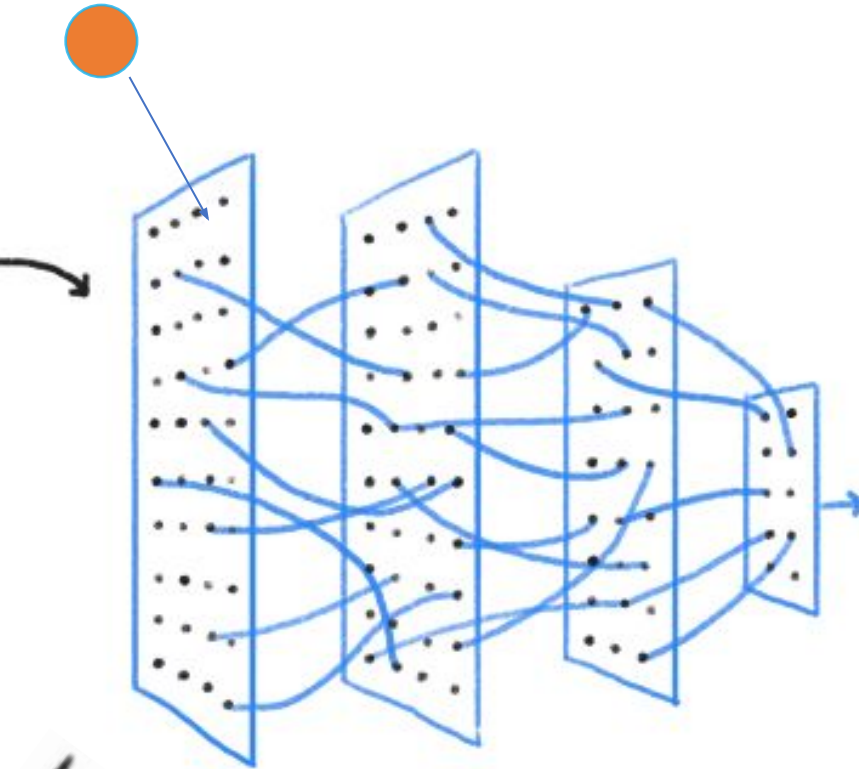
CAT

(LABELED
PHOTOS)

DOG



CNN (Layer 1)

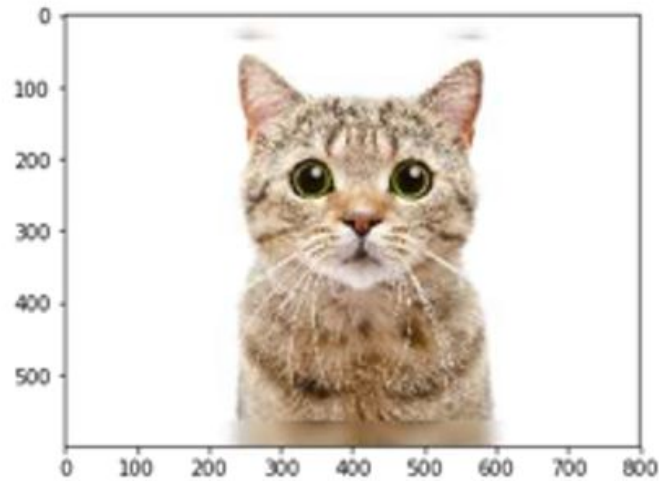


OUTPUT
cat

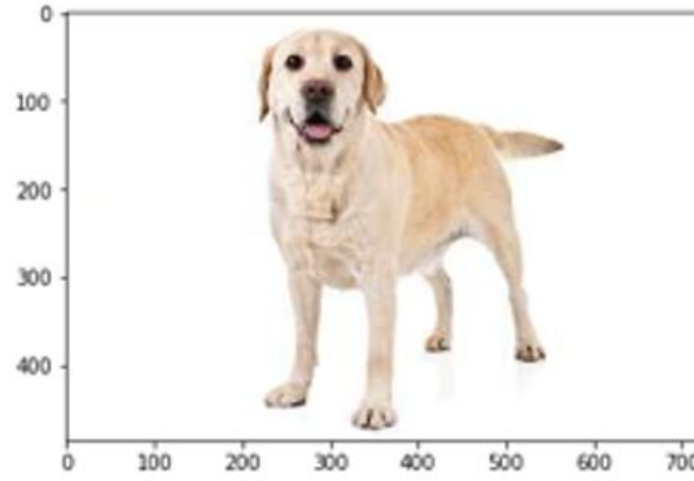


Image Classification

[PREDICTION]	[Prob]
Egyptian cat	: 64%
tabby	: 14%
bucket	: 3%



[PREDICTION]	[Prob]
Labrador retriever	: 83%
golden retriever	: 13%
bloodhound	: 0%

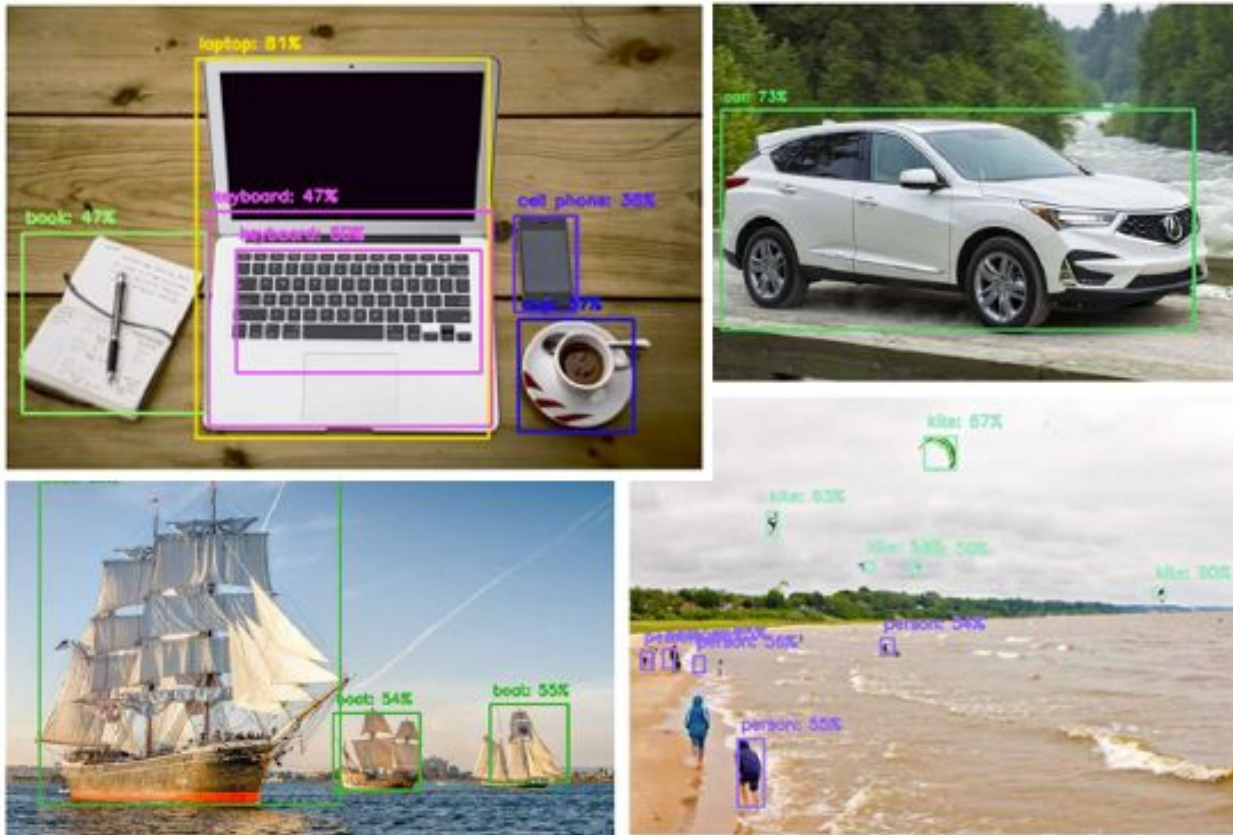


[PREDICTION]	[Prob]
German shepherd	: 60%
dhole	: 16%
malinois	: 7%

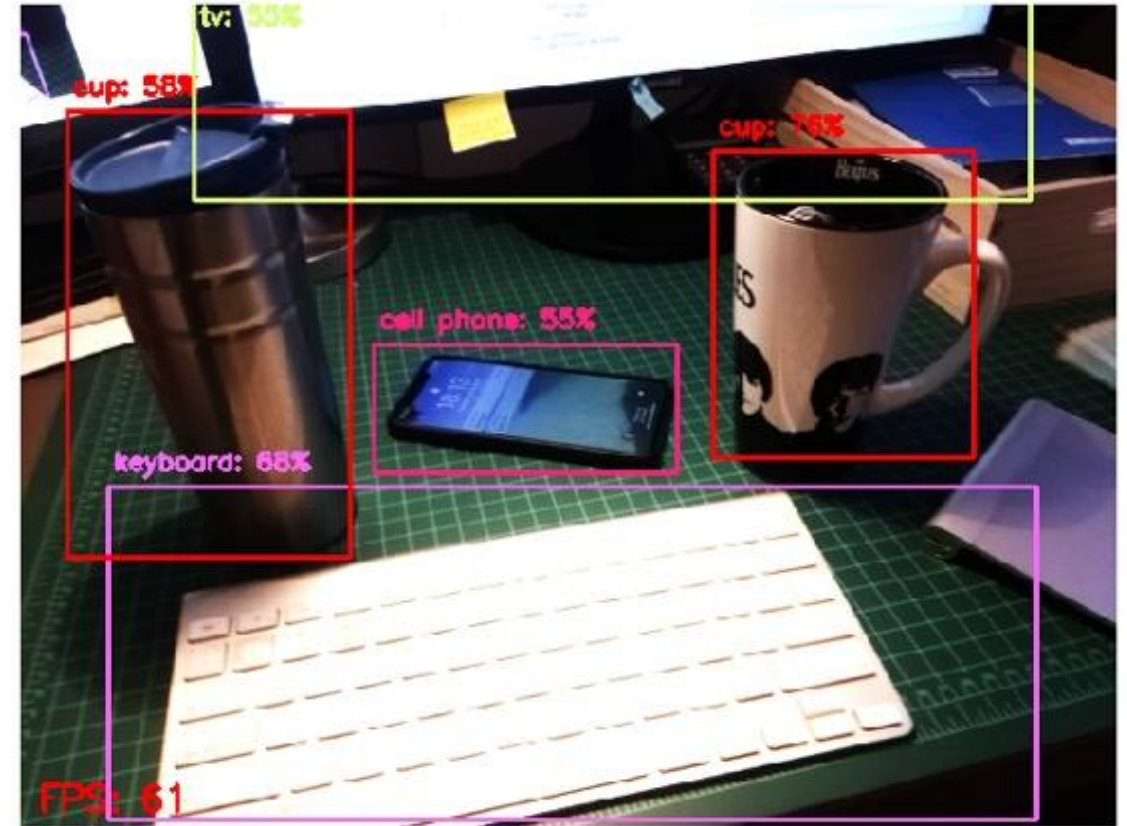


<https://www.hackster.io/mjrobot/exploring-ia-at-the-edge-97588d>

Object Detection



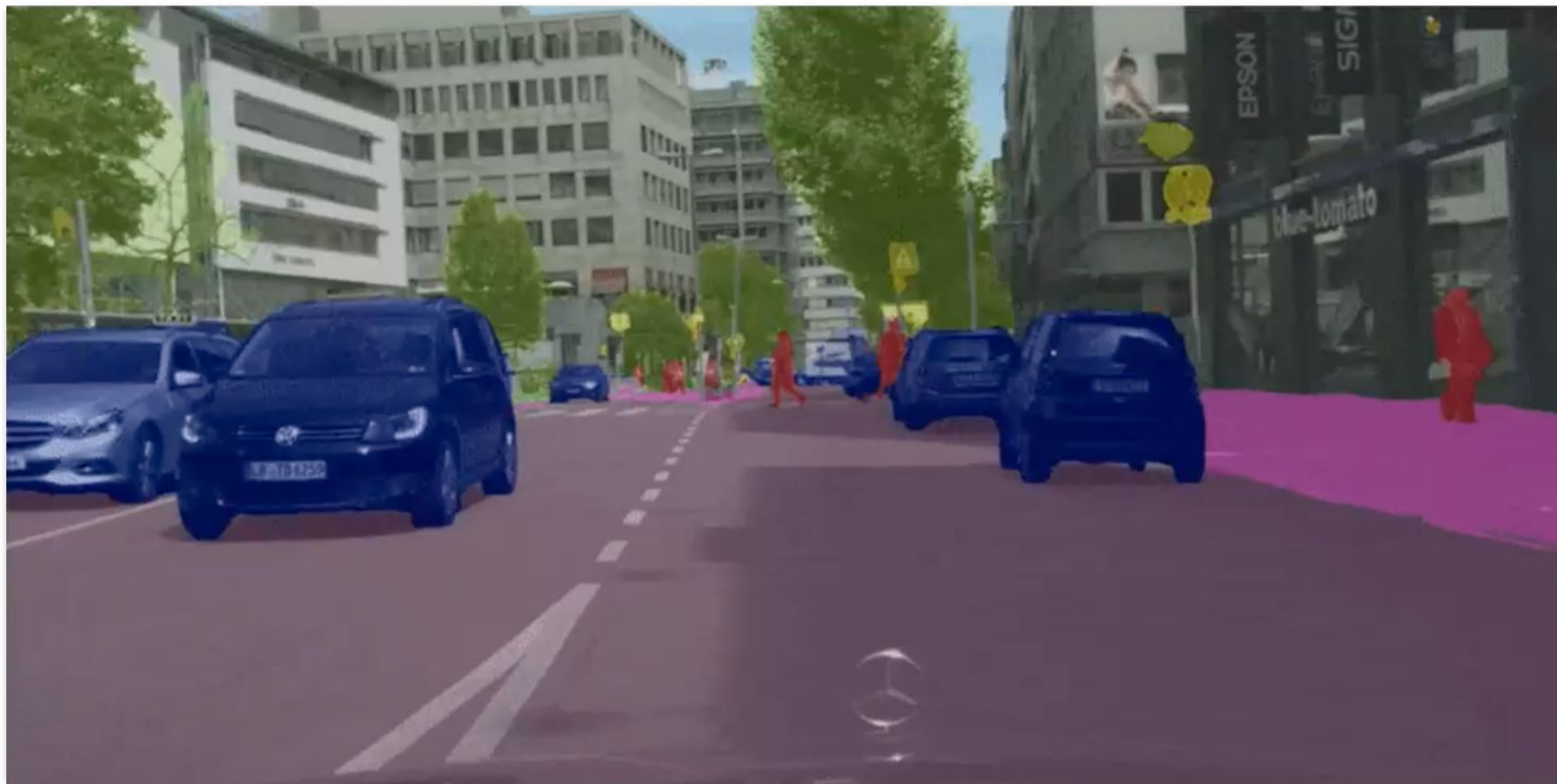
Photos



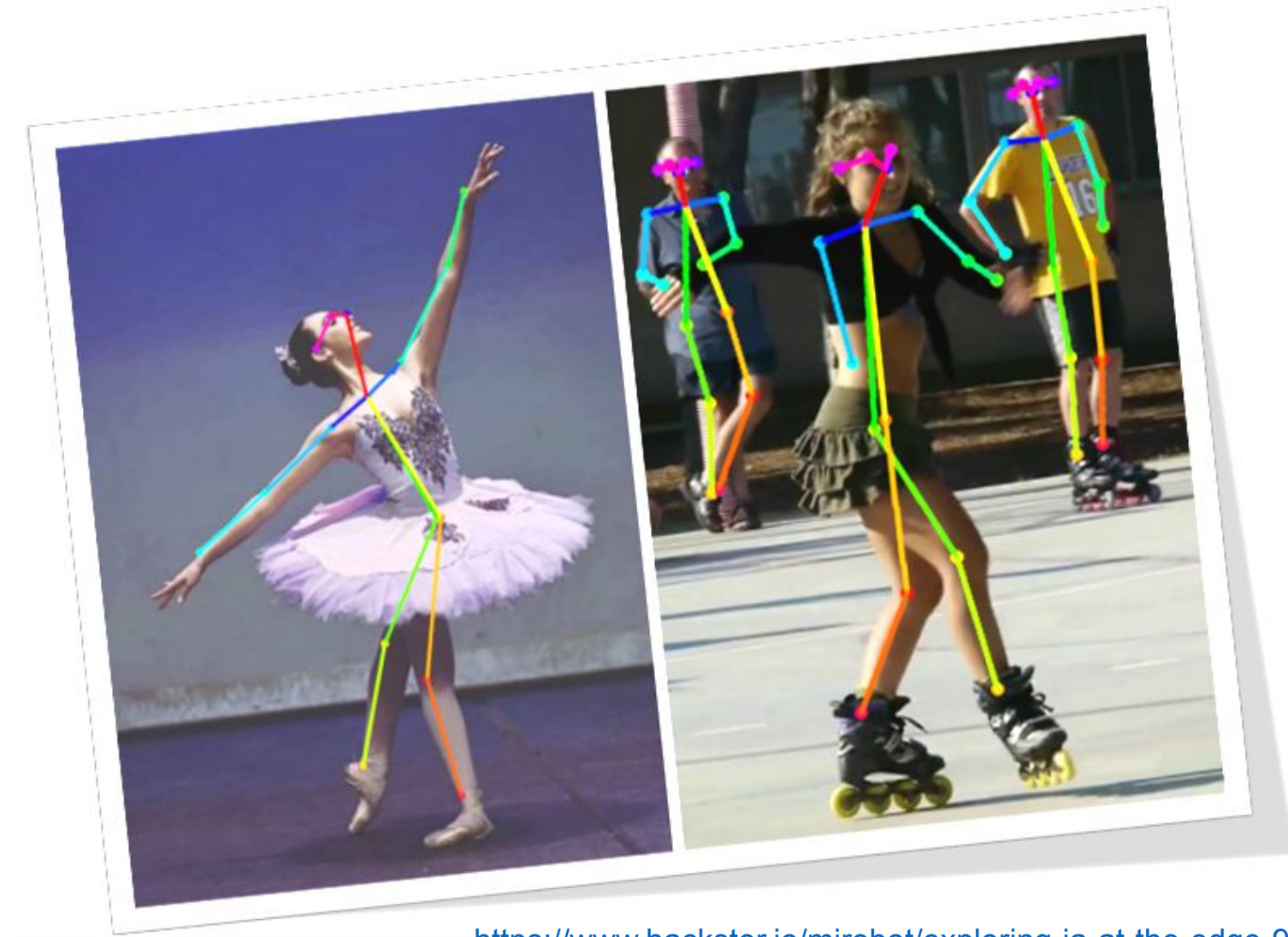
Live Video

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

Segmentation



Pose Estimation



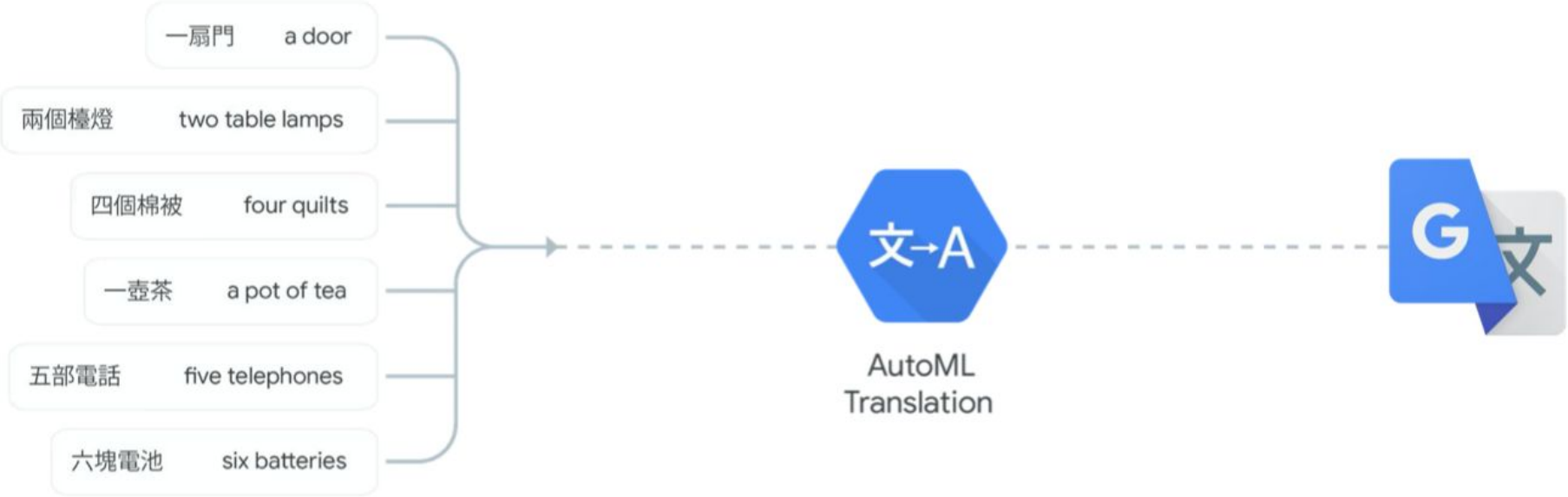
<https://www.hackster.io/mjrobot/exploring-ia-at-the-edge-97588d>

Machine Translation
























1 Upload translated language pairs


2 Train your model

3 Evaluate



Recommendations

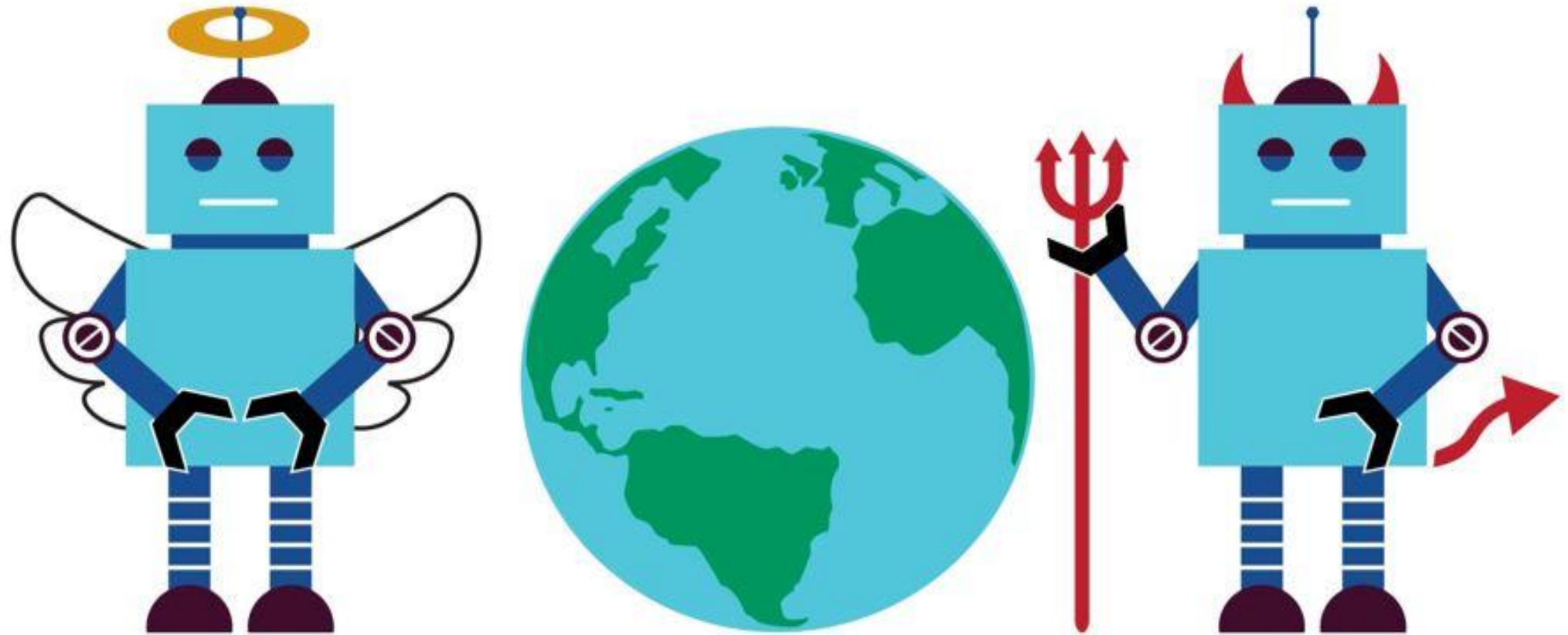


General AI does not exist (yet)

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](https://www.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!



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