



# Artificial Intelligence in Agriculture

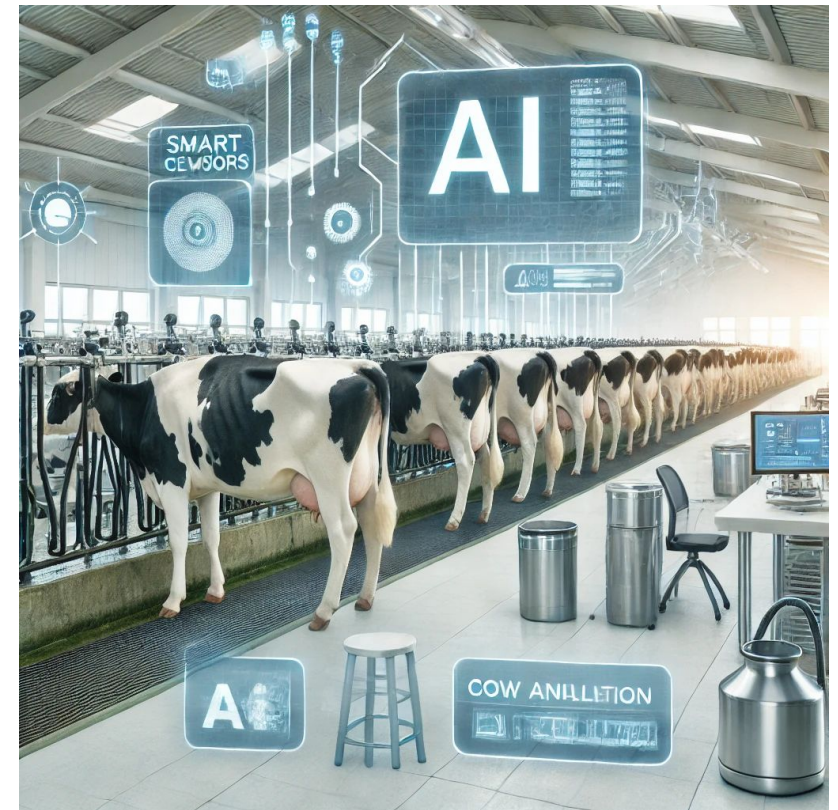
## AI Insights for Dairy Cows

DS 413/513 & DS 413/513L

Maristela Rovai, DVM, Ph.D.



Prof. Marcelo J. Rovai  
Federal University of Itajuba, Brazil



**Marcelo Rovai** is an educator and professional in the field of engineering and technology, holding the title of Professor Honoris Causa from the Federal University of Itajubá, Brazil. His educational background includes an Engineering degree from UNIFEI and an advanced specialization from the Polytechnic School of São Paulo University. Further enhancing his expertise, he earned an MBA from IBMEC (INSPER) and a Master's in Data Science from the Universidad del Desarrollo (UDD) in Chile.

With a career spanning several high-profile technology companies such as AVIBRAS Airspace, ATT, NCR, and IGT, where he served as Vice President for Latin America, he brings a wealth of industry experience to his academic endeavors. He is a prolific writer on electronics-related topics and shares his knowledge through open platforms like Hackster.io. In addition to his professional pursuits, he is dedicated to educational outreach, serving as a volunteer professor at UNIFEI and engaging with the TinyML4D group as a Co-Chair, promoting TinyML education in developing countries. His work underscores a commitment to leveraging technology for societal advancement.



# Content

- **AI** Introduction and Applications
- **Lab** – Image Classification

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- **Lab** – Image Classification

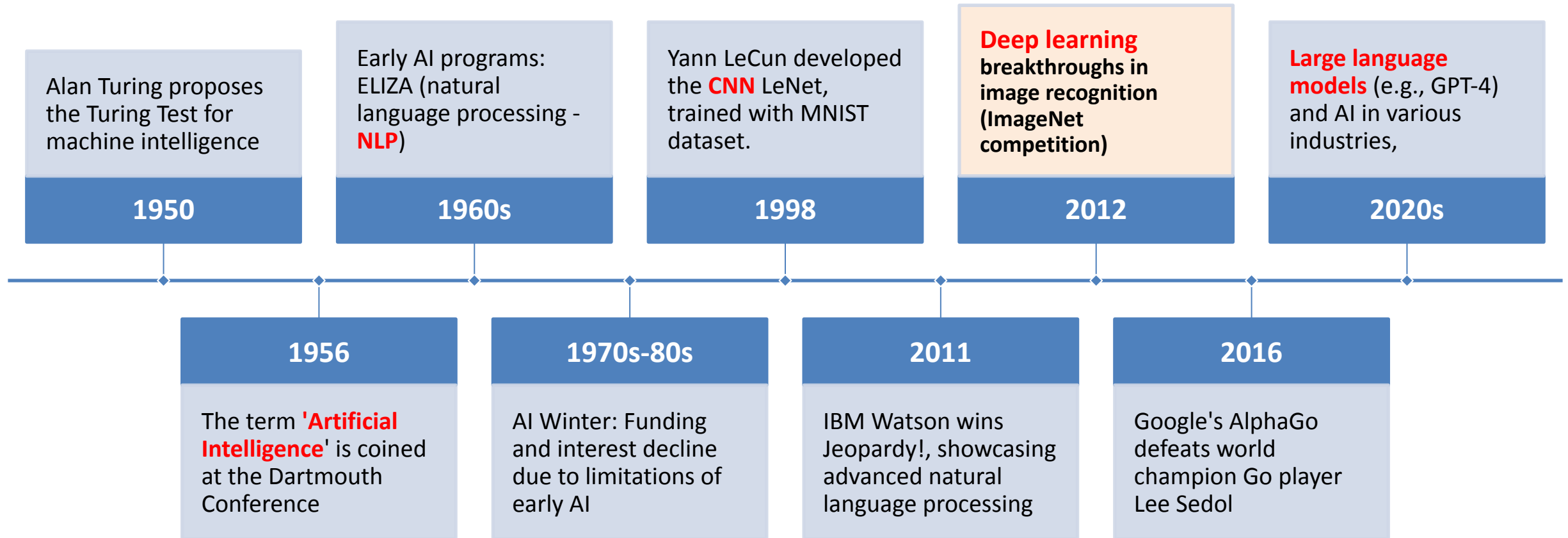


# What is AI?

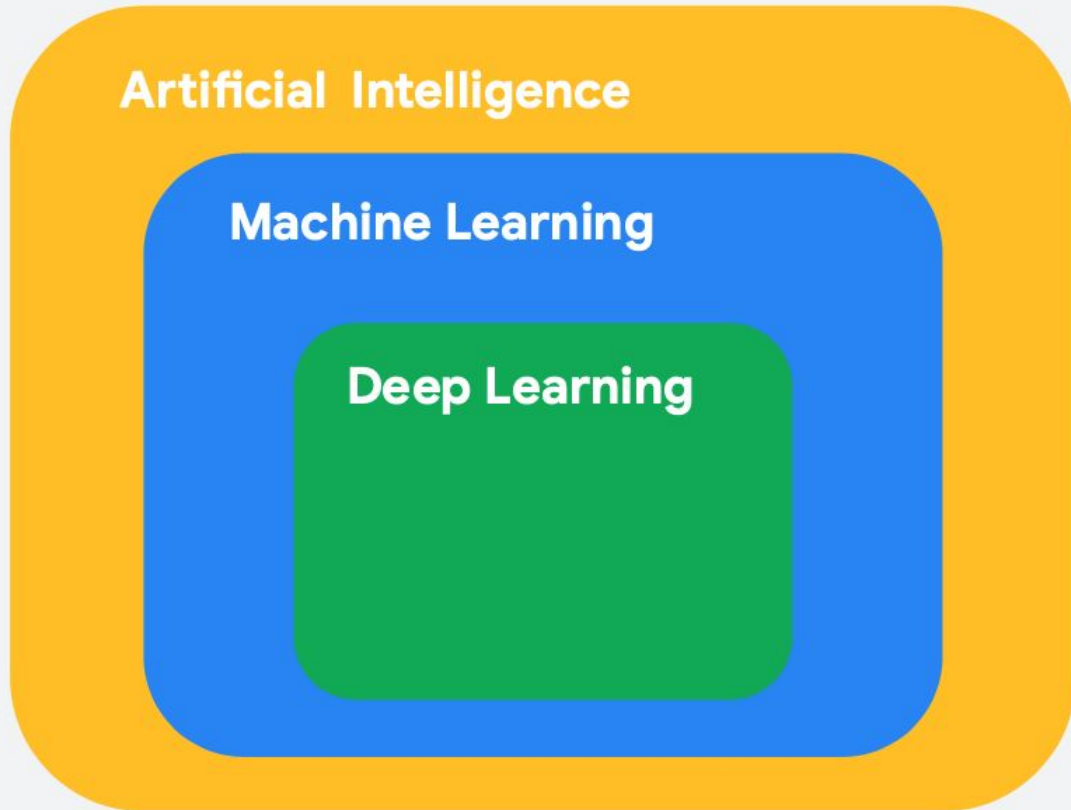
Artificial Intelligence (AI) is the simulation of human intelligence in machines that can perform tasks like learning, reasoning, and problem-solving.



# A Brief History of Artificial Intelligence



# Teaching computers how to learn a task directly from raw data



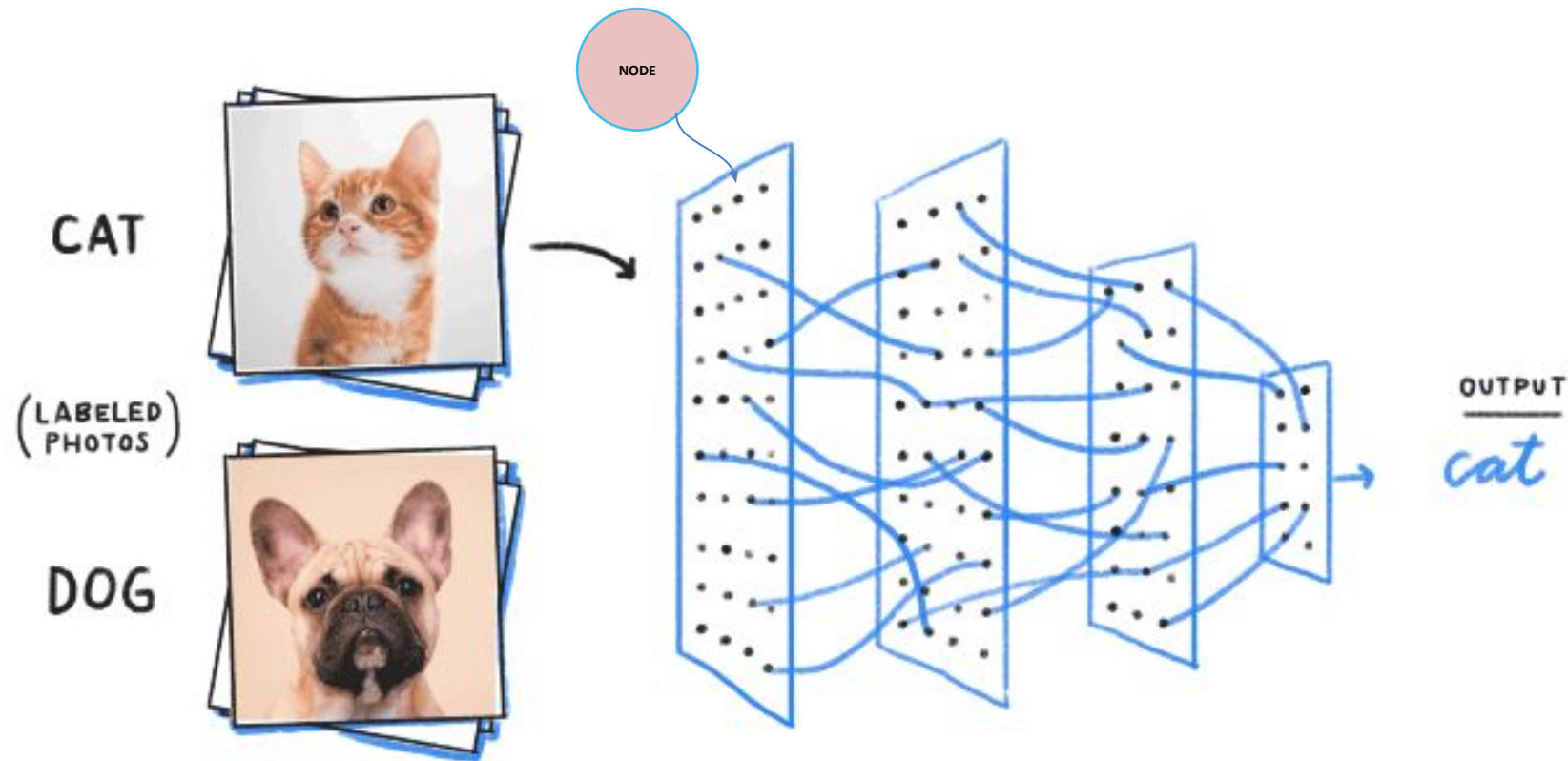
**AI: Any technique that enables computers to mimic human behavior**

**ML: Ability to learn without explicitly being programmed**

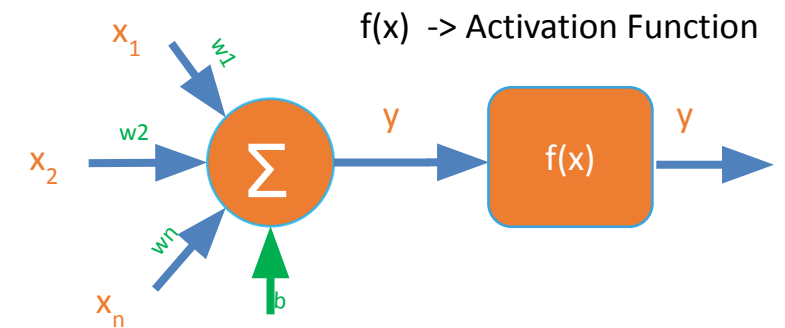
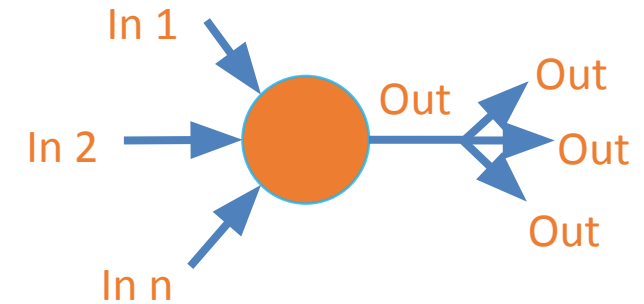
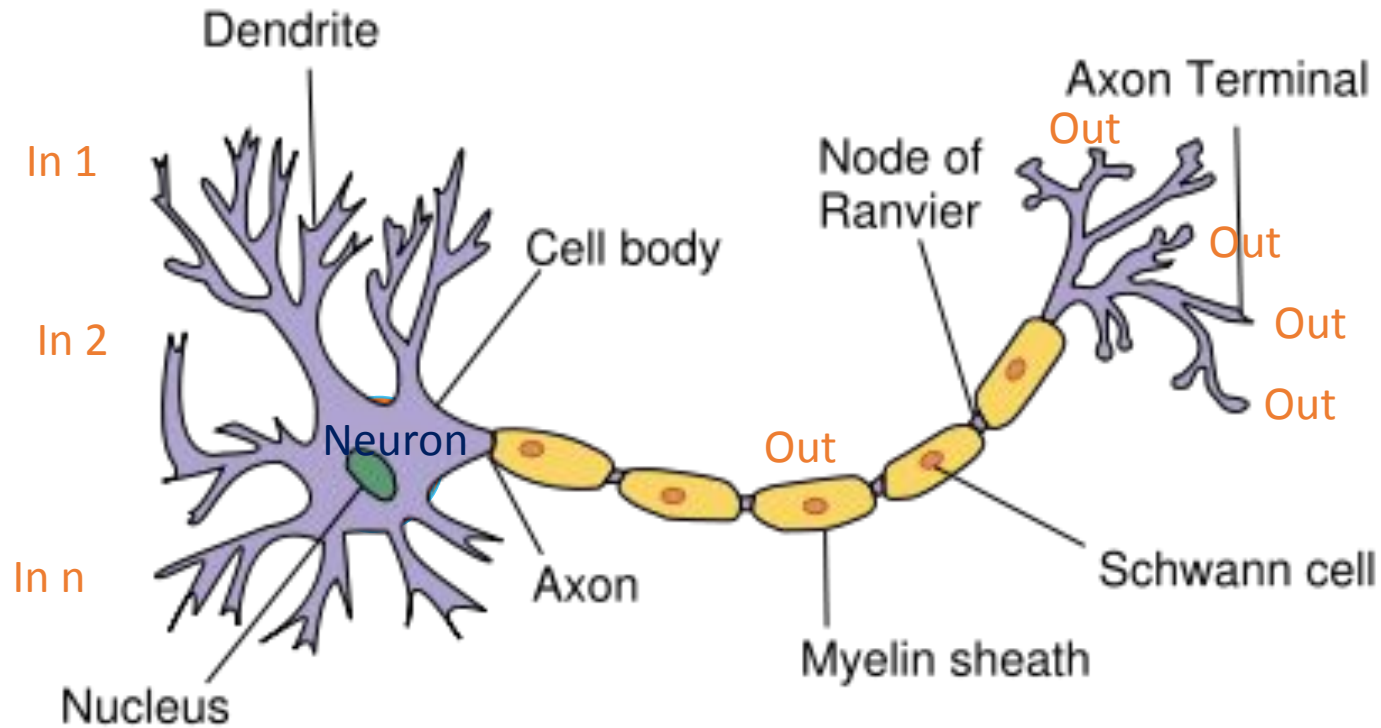
**DL: Extract patterns from data using neural networks**

# (Deep) Machine Learning

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



# Neuron (Perceptron)



Parameters

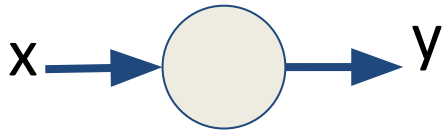
$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$

$$y = a x + b$$

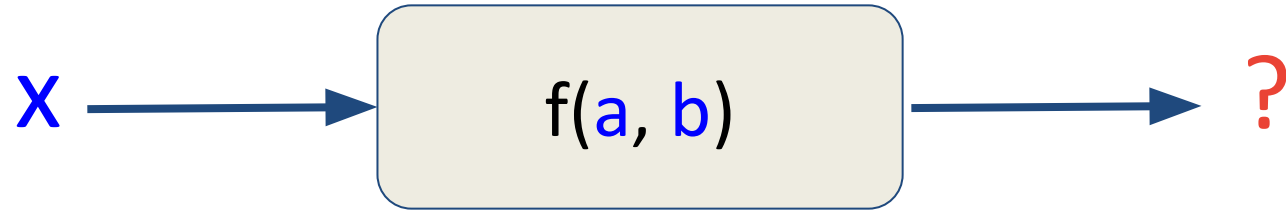
Perceptron (P)



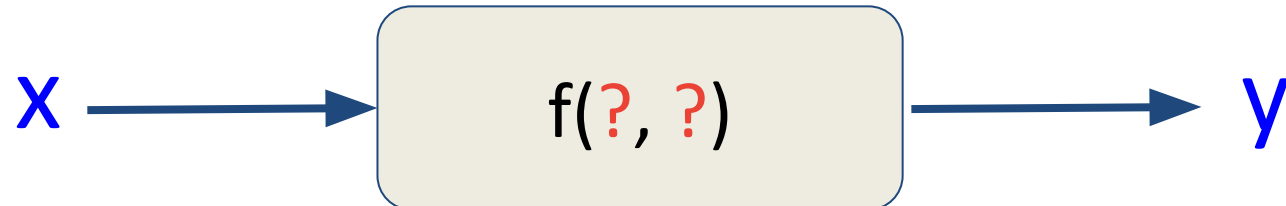
$$y = \textcircled{a}x + \textcircled{b}$$



## Traditional Computation



## Machine Learning



# Neural Network Architectures

Vibration  
Analysis

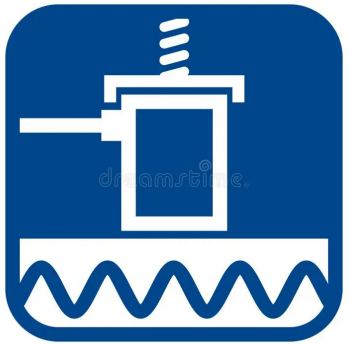


Image  
Classification



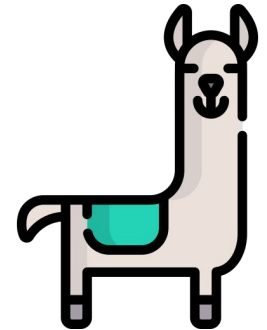
Text  
Generation



Image  
Generation



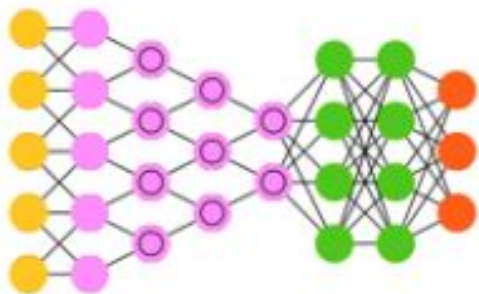
Large Language  
Models- LLMs



Deep Feed Forward (DFF)



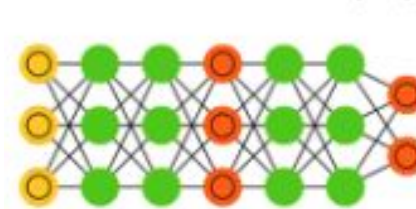
Deep Convolutional Network (DCN)



Gated Recurrent Unit (GRU)



Generative Adversarial Network (GAN)

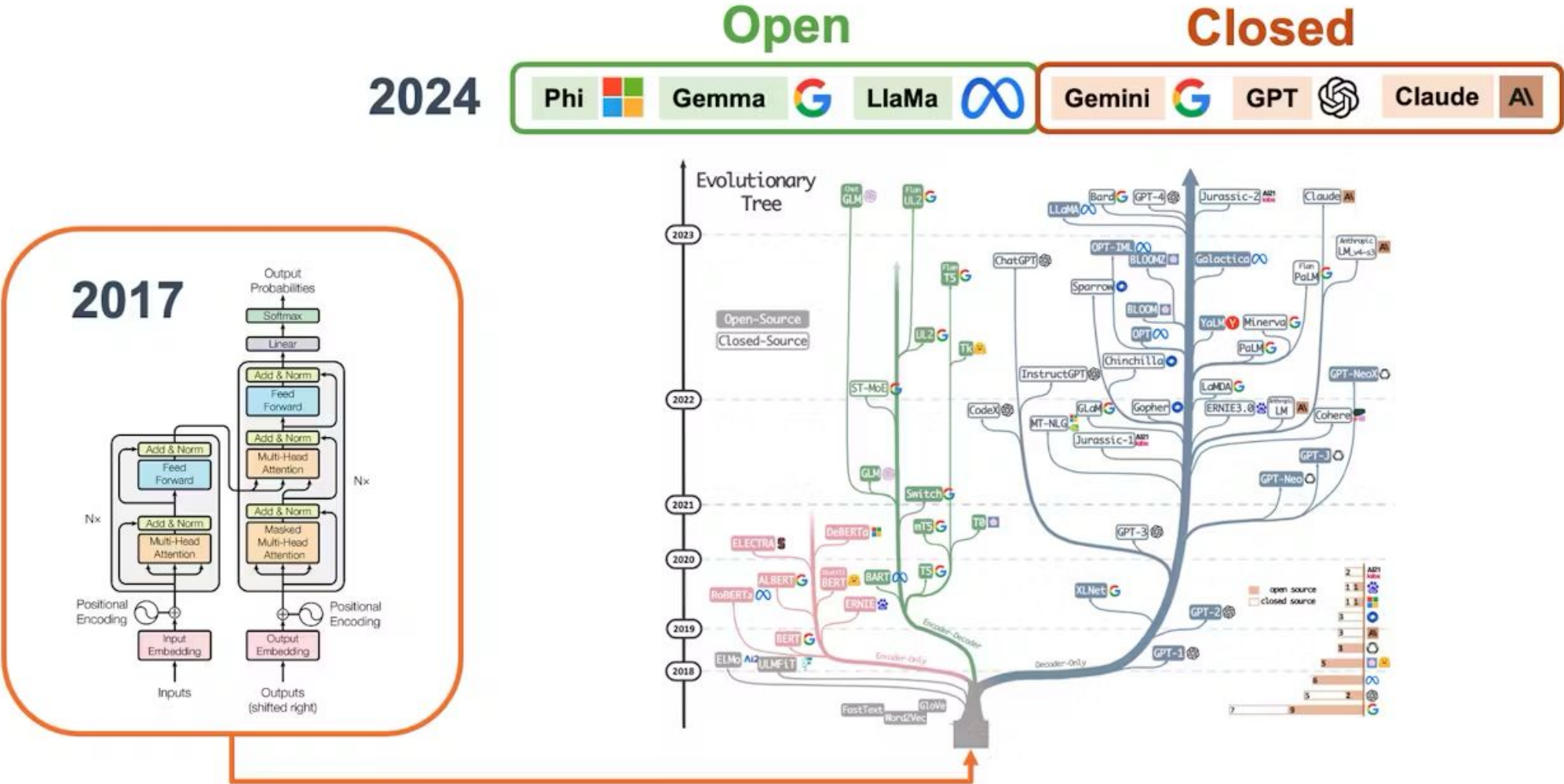
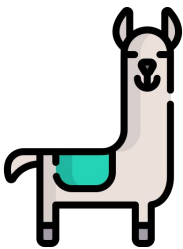


Attention Network (AN)





# LLMs (Large Language Models)



# Deep Learning and AI: Why now?

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Neural networks date back decades, so why do they dominate?



BIG  
DATA



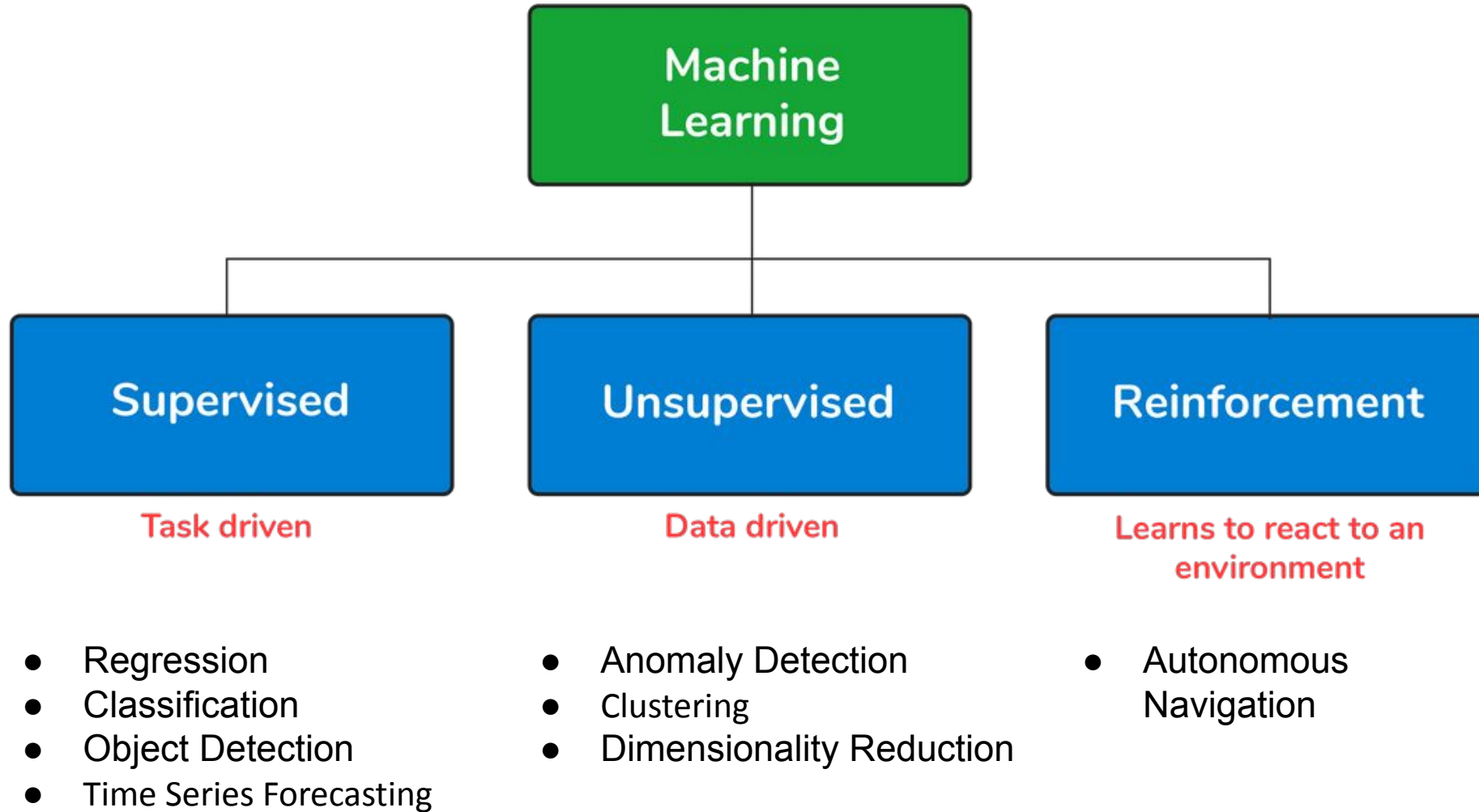
HARDWARE  
(GPUs)



SOFTWARE  
(NN Models)

# AI (ML/DL) Applications

Examples



Models

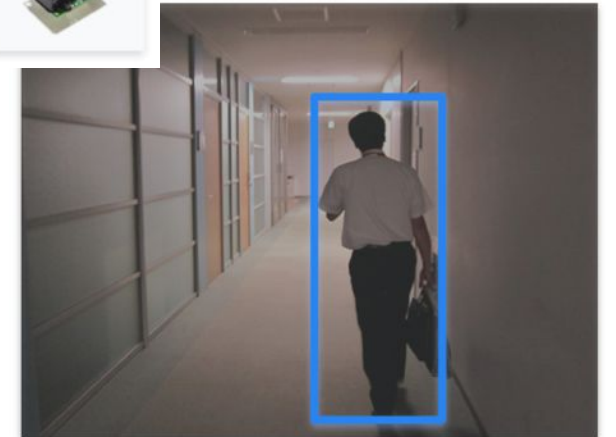
# Sound



# Vibration



# Vision

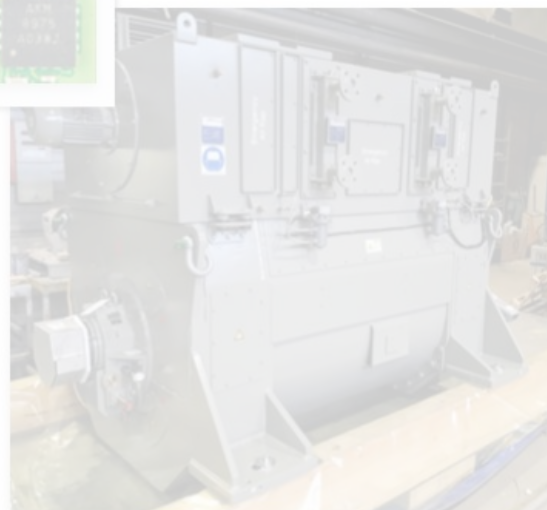


## Sensors

# Sound



# Vibration



# Vision





# Personal Assistant







# Classifying mosquito wingbeat sound using TinyML

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

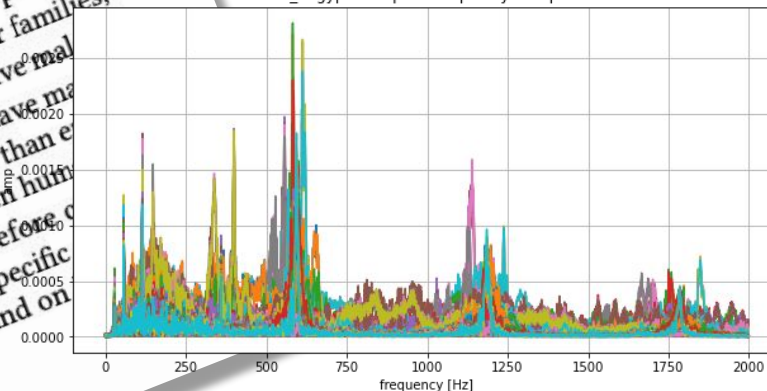
Marco Zennaro  
ICTP  
Trieste, Italy  
mzennaro@ictp.it

## ABSTRACT

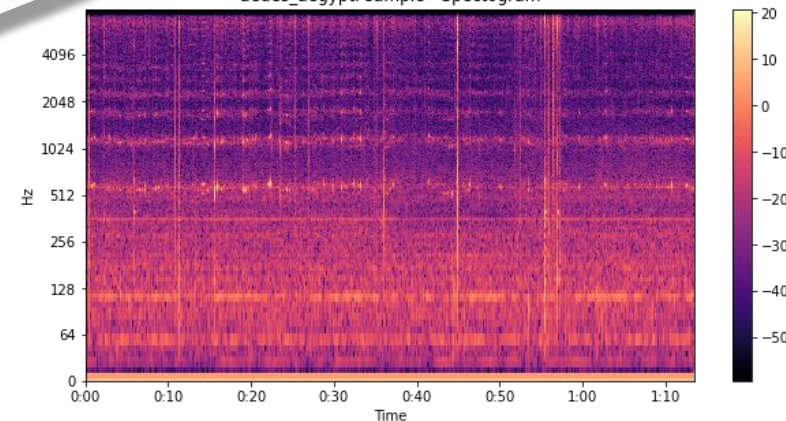
Every year more than one billion people are infected and more than one million people die from vector-borne diseases including malaria, dengue, zika and chikungunya. Mosquitoes are the best known disease vector and are geographically spread worldwide. It is important to raise awareness of mosquito proliferation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

affected. People from poor communities with little access to health care and clean water sources are also at risk. Although anti-malarial drugs exist, there's currently no malaria vaccine. Vector-borne diseases also exacerbate poverty. Illness prevents people from working and supporting themselves and their families, impeding economic development. Countries with intensive malaria have much lower income levels than those that don't have malaria. Countries affected by malaria turn to control rather than eradication. Vector control means decreasing contact between human disease carriers on an area-by-area basis. It is therefore possible to be able to detect the presence of mosquitoes in a specific paper presents an approach based on TinyML and on embedded devices.

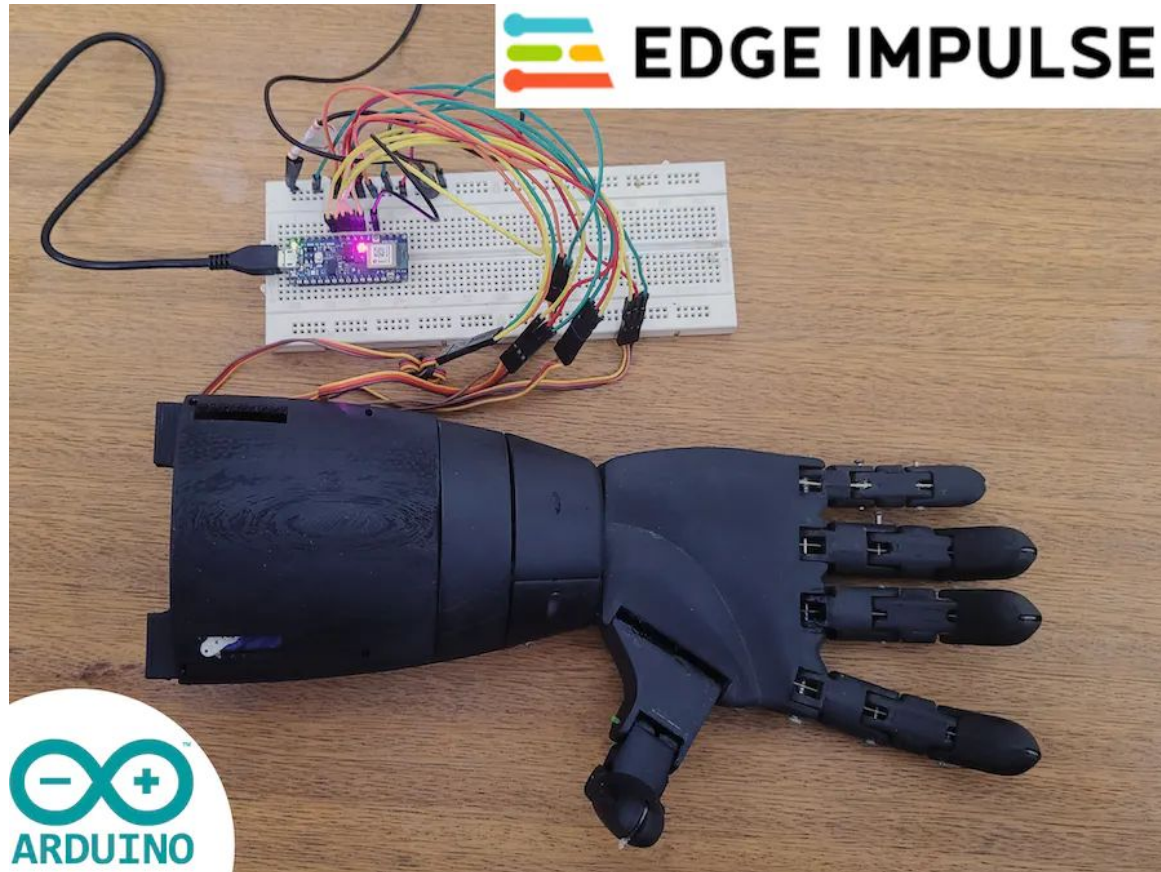
aedes\_aegypti sample - Frequency Components



aedes\_aegypti sample - Spectrogram



# Bionic Hand Voice Commands Module

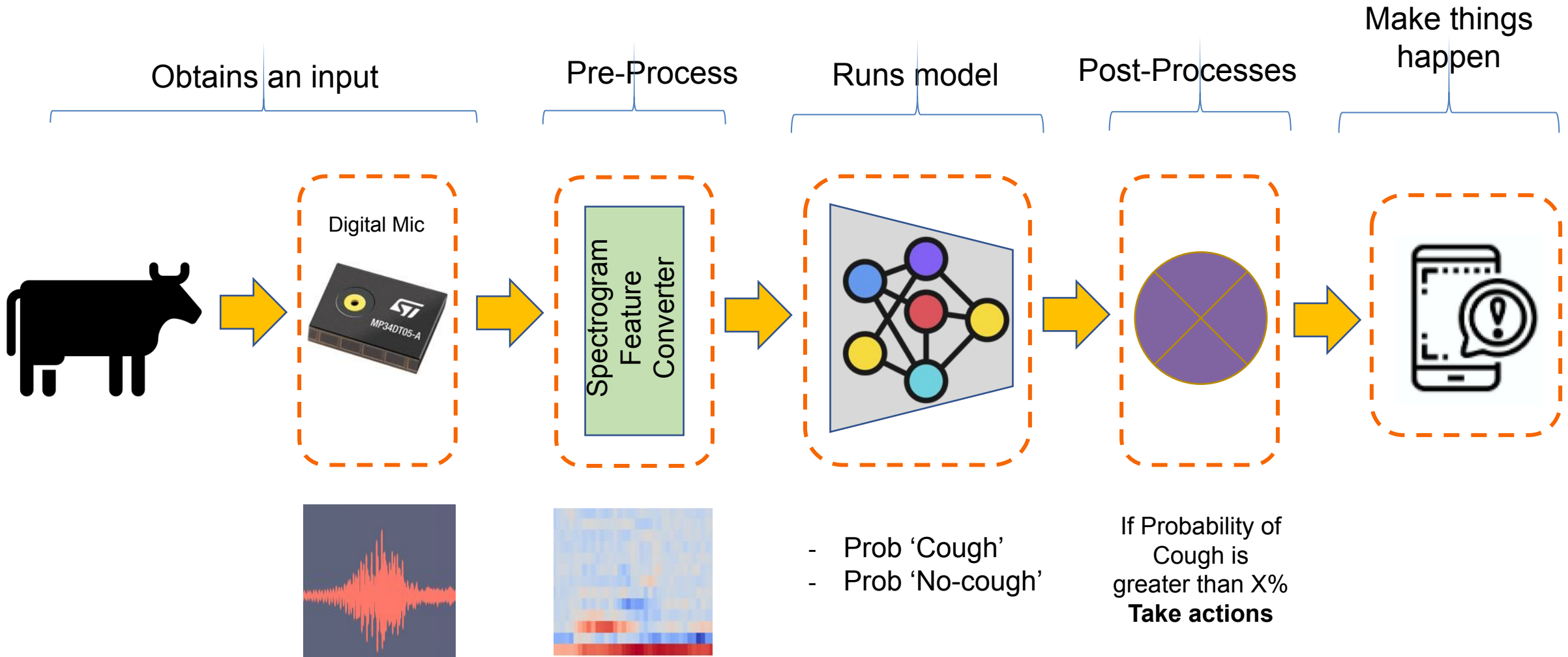


<https://www.hackster.io/ex-machina/bionic-hand-voice-commands-module-w-edge-impulse-arduino-aa97e3>



# Automatic cough detection for BRD

(Bovine Respiratory Disease)



# Sound



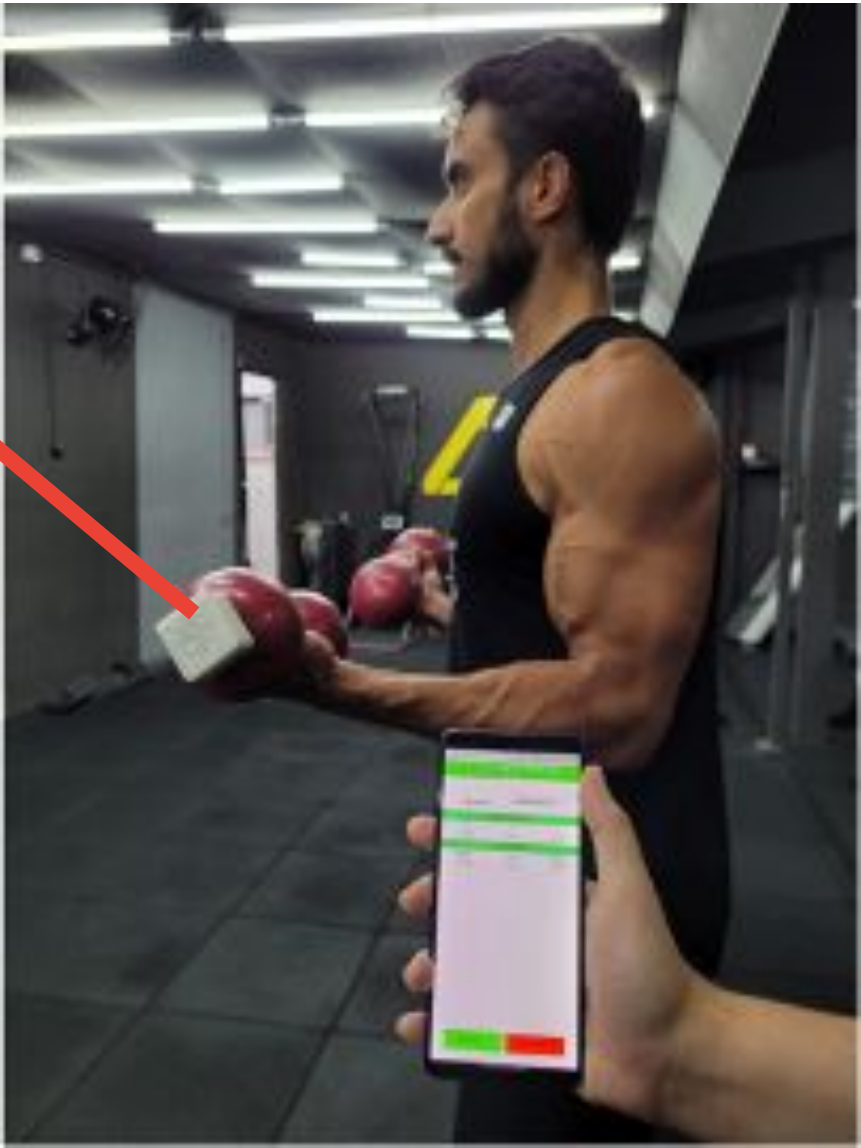
# Vibration



# Vision



# Movement Classification





# Predict and classify common Elephant behavior



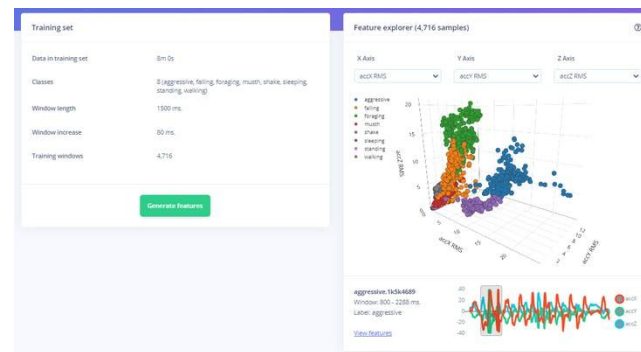
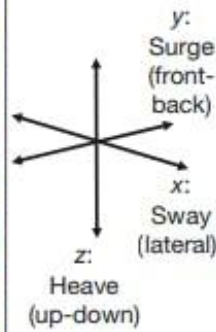
Aggressive



Standing

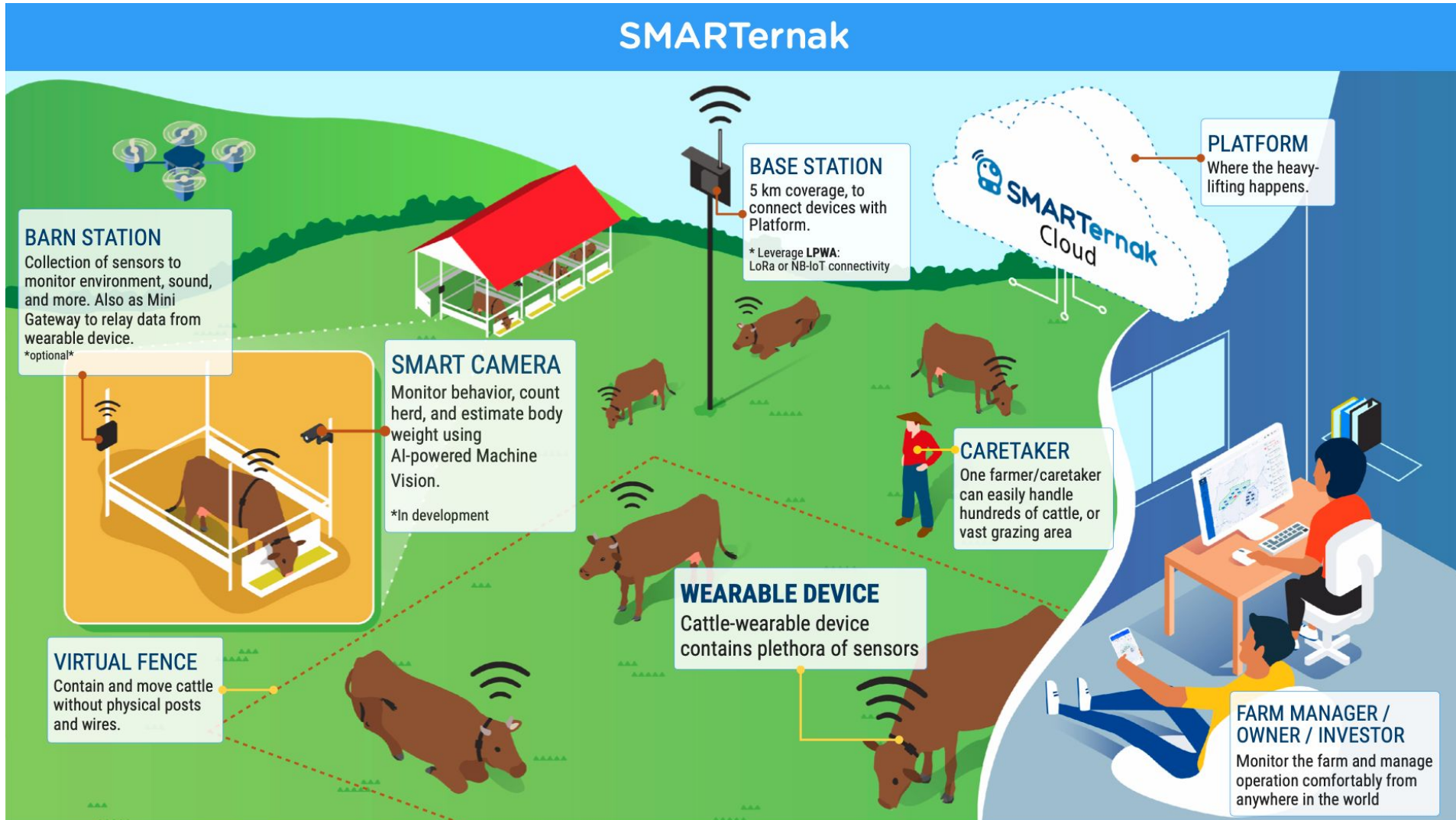


Sleeping



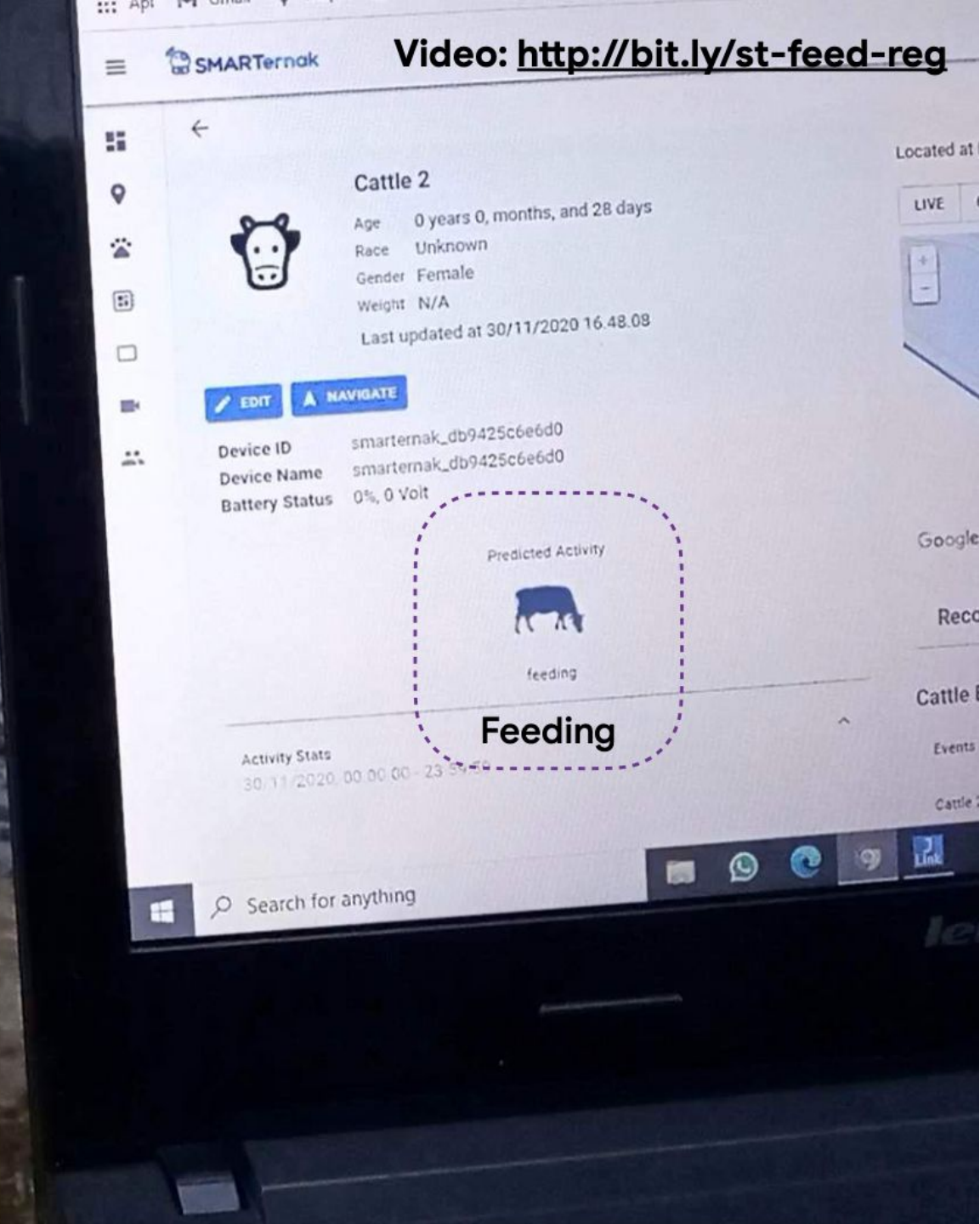
[https://www.hackster.io/dhruvsheth\\_/eletect-tinyml-and-iot-based-smart-wildlife-tracker-c03e5a](https://www.hackster.io/dhruvsheth_/eletect-tinyml-and-iot-based-smart-wildlife-tracker-c03e5a)

# Smart Cattle-Farm - Animal Behavior





# On-device Activity Prediction



Video: <http://bit.ly/st-feed-reg>

## Cattle 2

Age 0 years 0, months, and 28 days  
Race Unknown  
Gender Female  
Weight N/A  
Last updated at 30/11/2020 16:48:08

EDIT

NAVIGATE

Device ID smarternak\_db9425c6e6d0  
Device Name smarternak\_db9425c6e6d0  
Battery Status 0%, 0 Volt

Predicted Activity



feeding

Feeding

Activity Stats

30/11/2020, 00:00:00 - 23:59:59



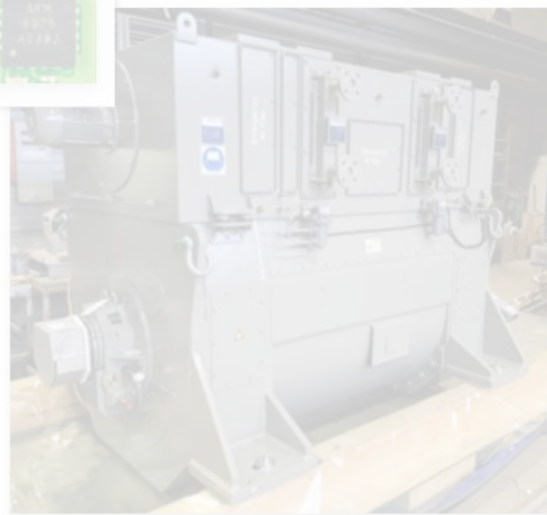
Search for anything



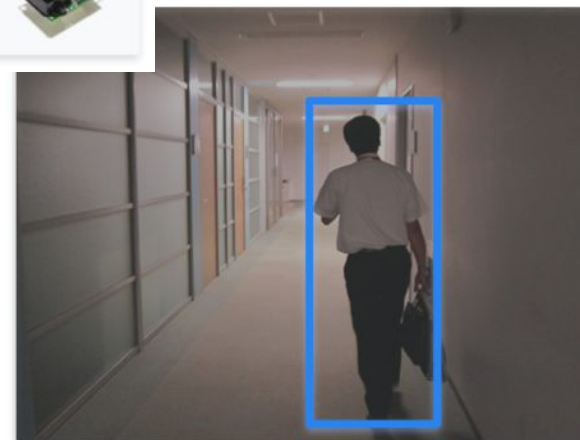
# Sound



# Vibration



# Vision



# Computer Vision Recognition Tasks

## Image Classification (Multi-Class Classification)

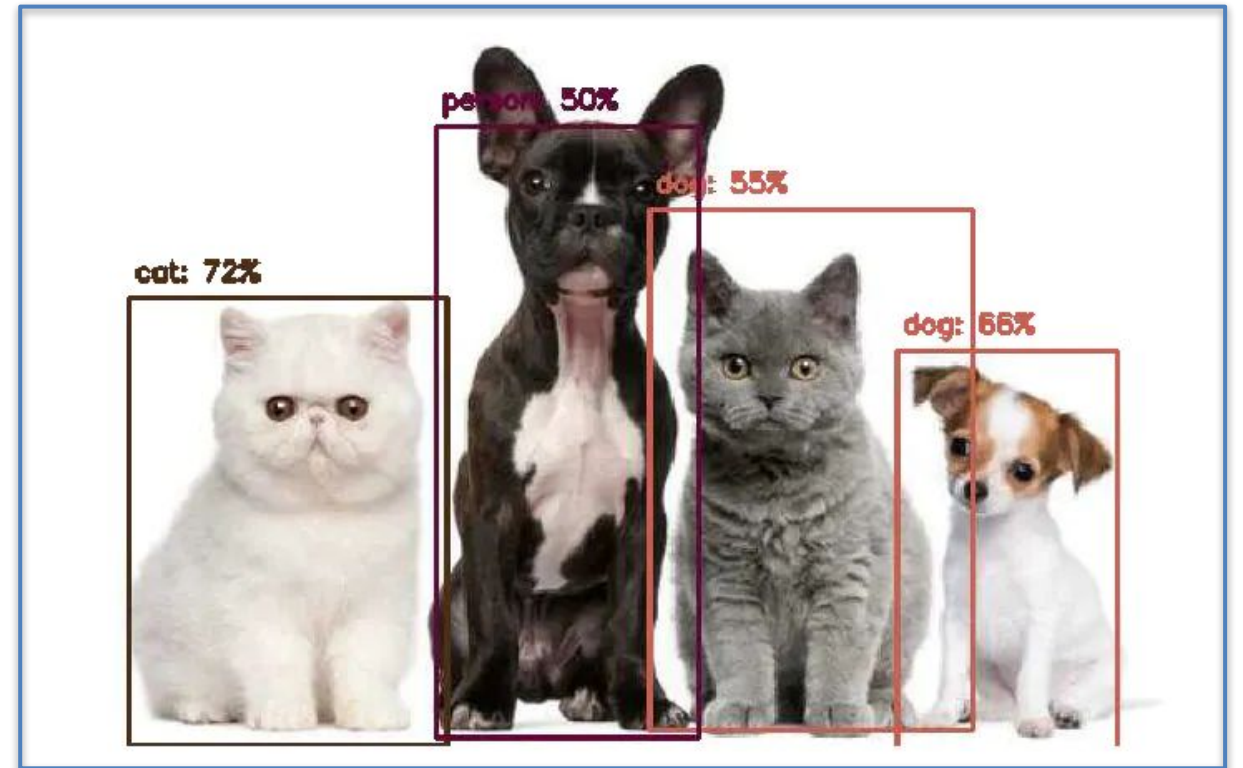


Cat: 70%



Dog: 80%

## Object Detection Multi-Label Classification + Object Localization





# Computer Vision Recognition Tasks

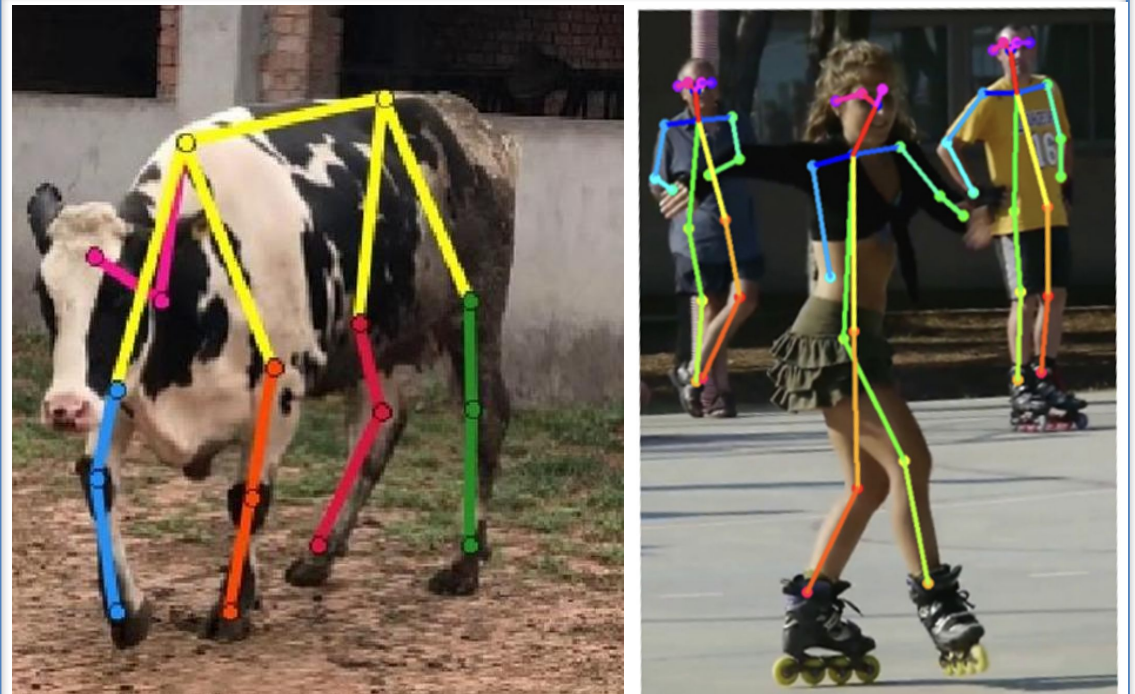
## Instance Segmentation

Each **pixel** in an image IS CLASSIFIED into a predefined category.



## Pose Estimation

**Key points (or landmarks)** on the object, such as joints on a human or animal body are detected



# Computer Vision Recognition Tasks

## Image Classification (Multi-Class Classification)

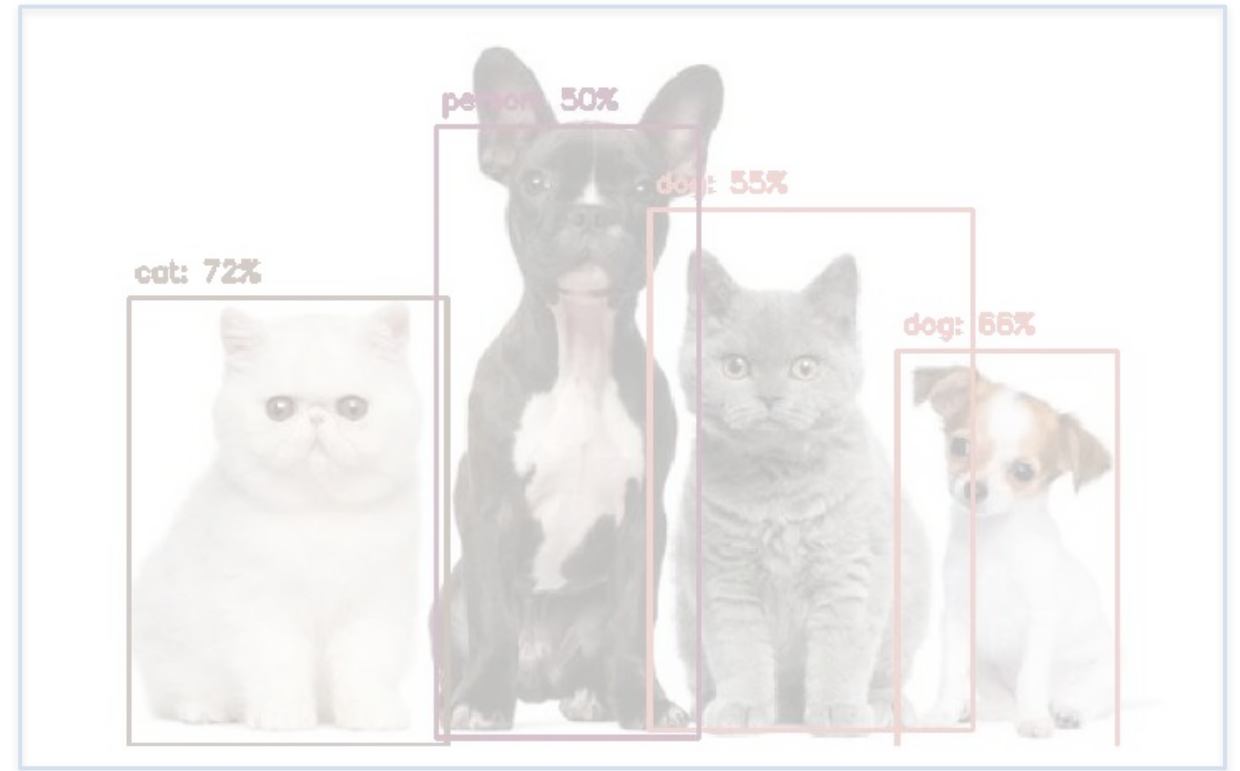


Cat: 70%



Dog: 80%

## Object Detection Multi-Label Classification + Object Localization





# Detecting Diseases in the Bean plants



AIR Lab Makerere University  
UGANDA



Angular Leaf Spot



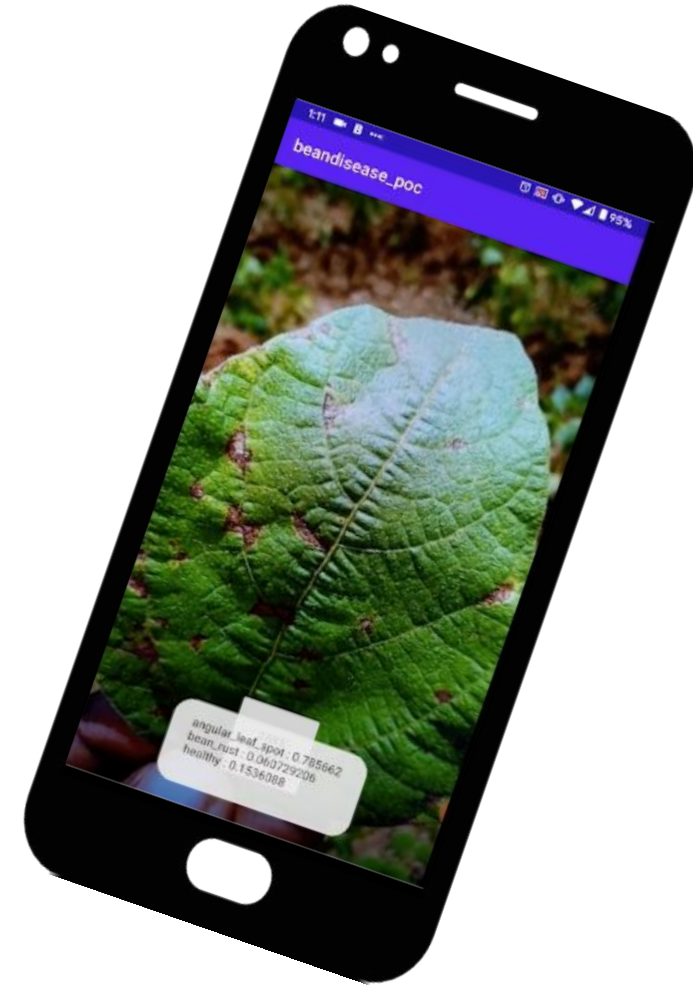
Bean Rust



Healthy



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



[Learn the steps to build an app that detects crop diseases](#)  
(Android Studio)

# Forest Fire Detection



[TinyML Aerial Forest Fire Detection](#)



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



# Coffee Disease Classification

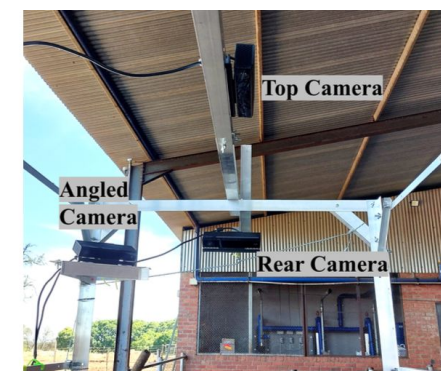
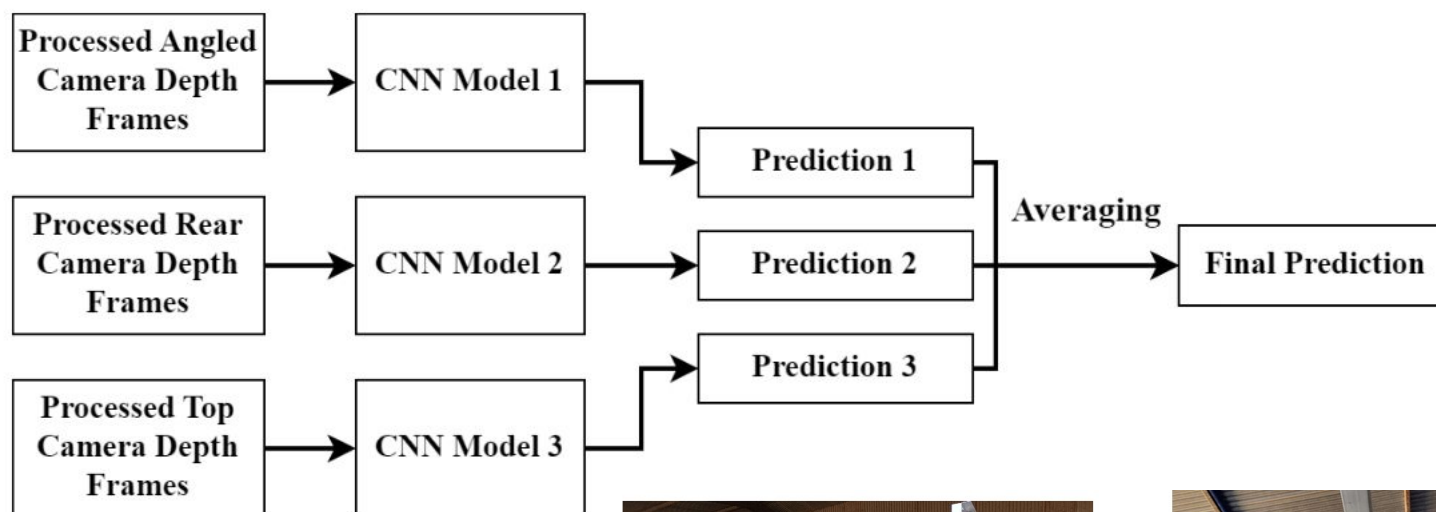
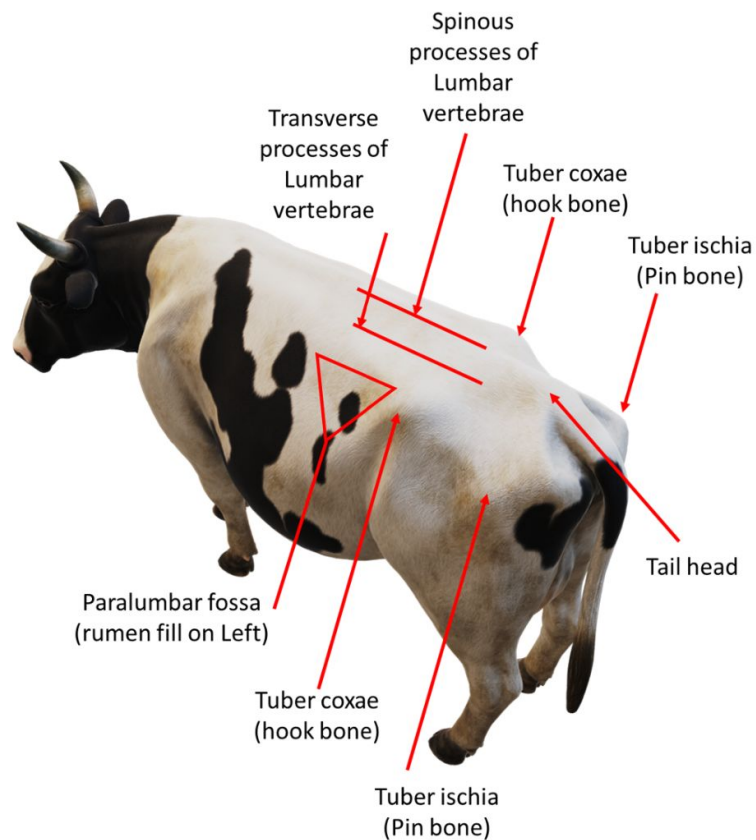


**João Vitor Yukio Bordin Yamashita**

Graduando em Engenharia Eletrônica pela UNIFEI

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

# Automated Cow Body Condition Scoring (BCS)



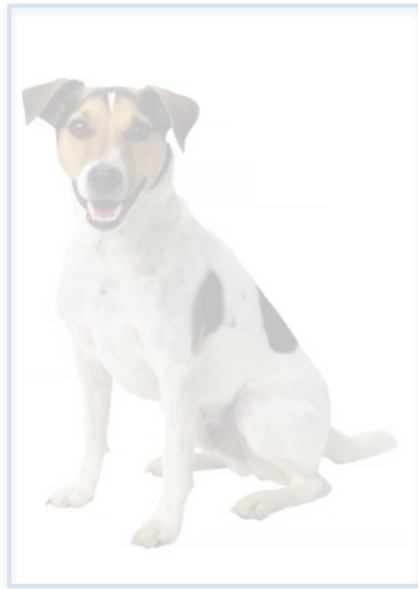


# Computer Vision Recognition Tasks

## Image Classification (Multi-Class Classification)

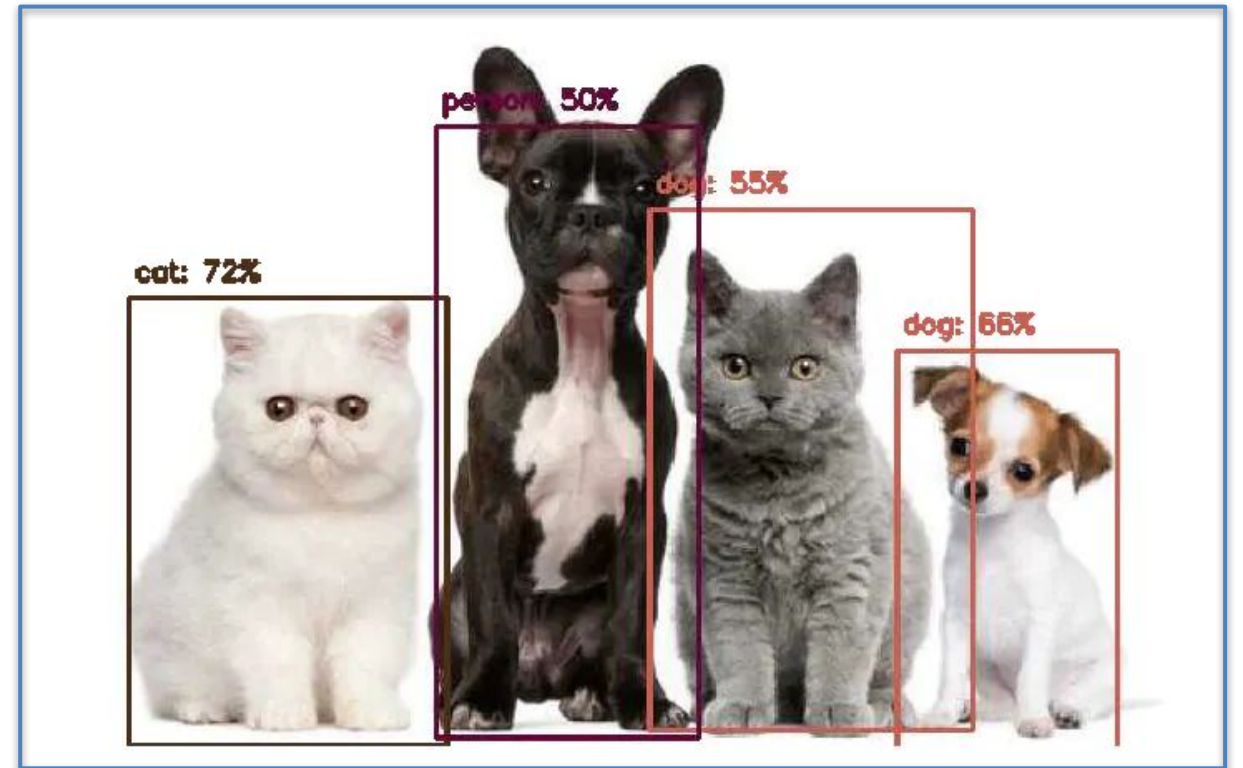


Cat: 70%

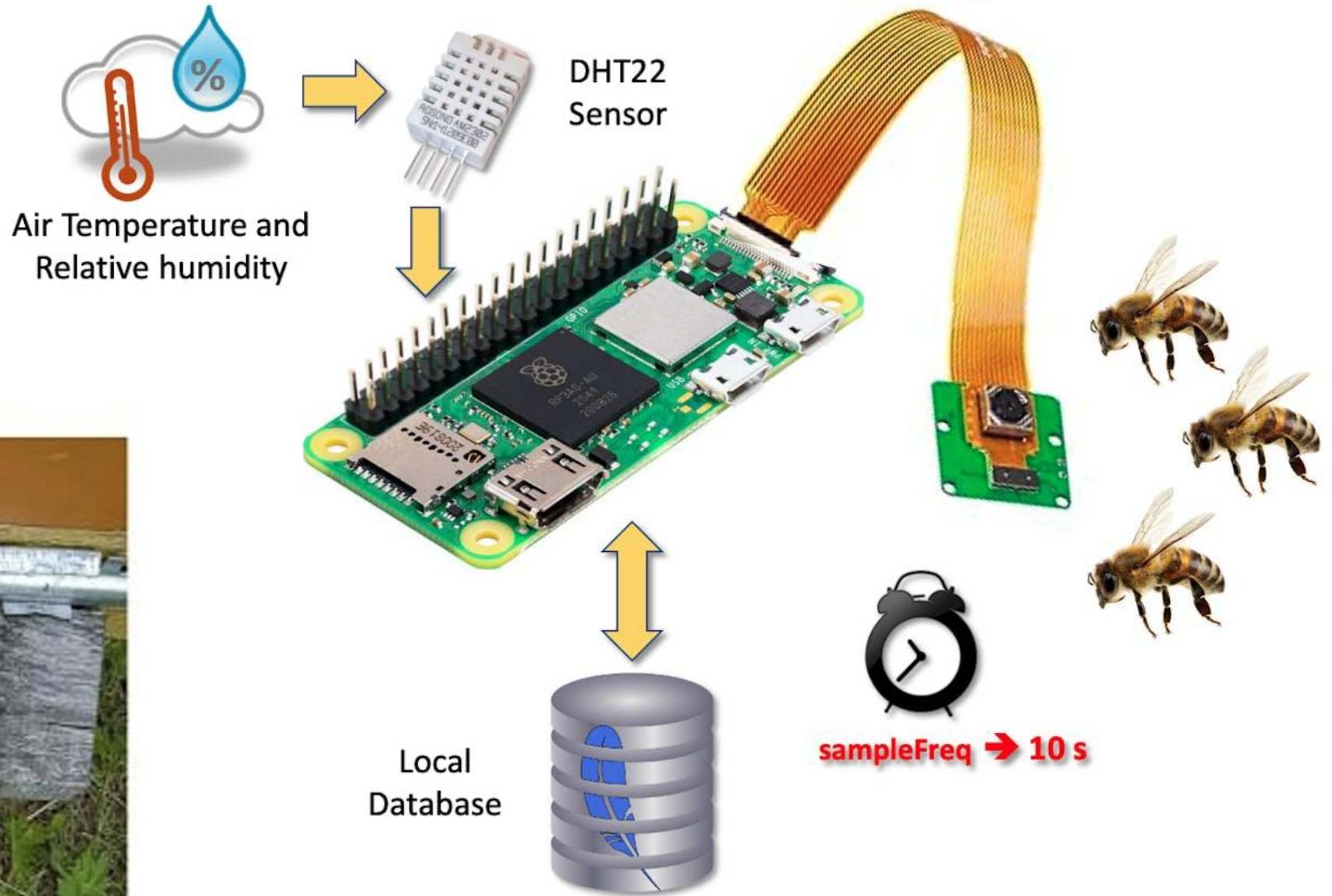


Dog: 80%

## Object Detection Multi-Label Classification + Object Localization



# Bee Counting



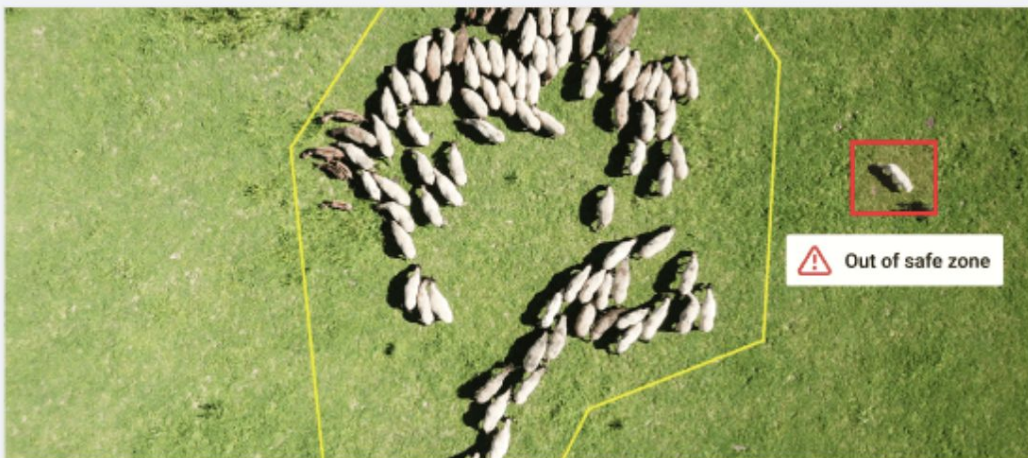


# Ant Detection



Ant Detection



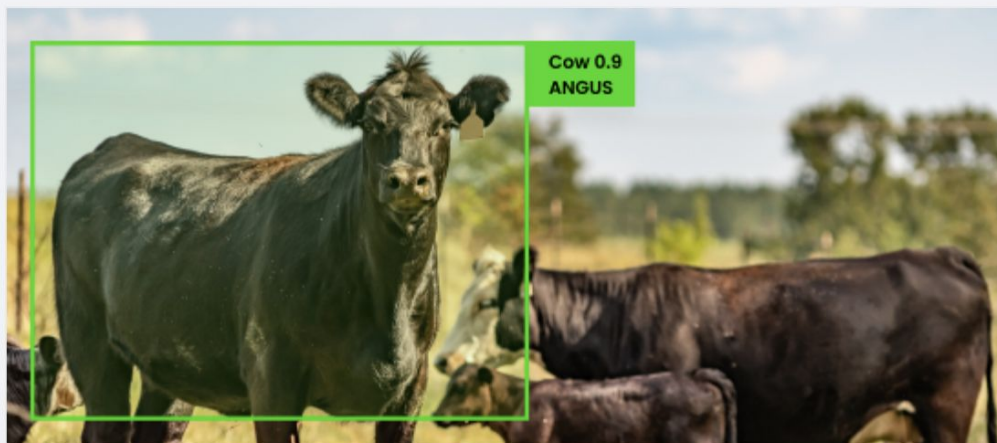


**Perimeter Fence Detection**



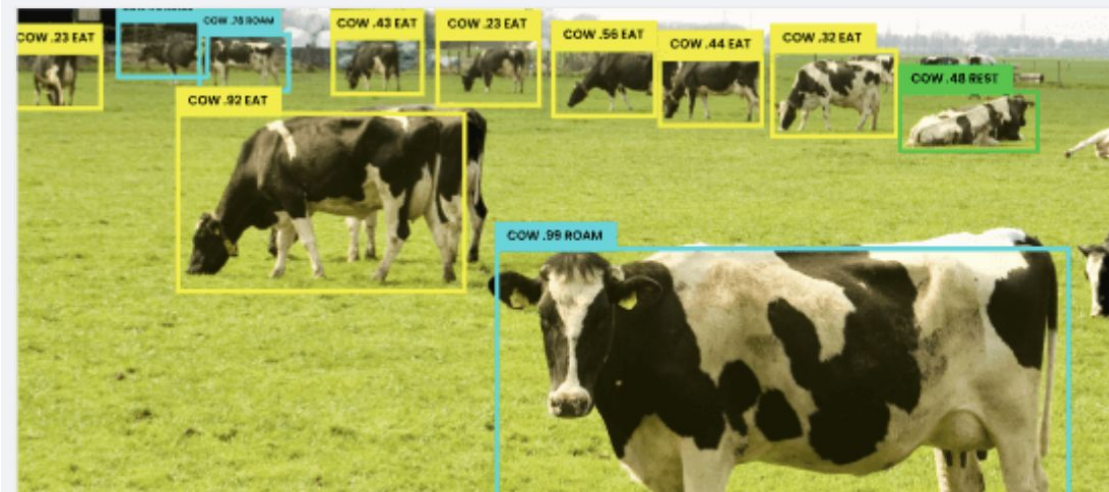
**Improper wiping**

<https://www.cattle-care.com/individual>



**Breed Identification**

<https://www.folio3.ai/animal-detection/>



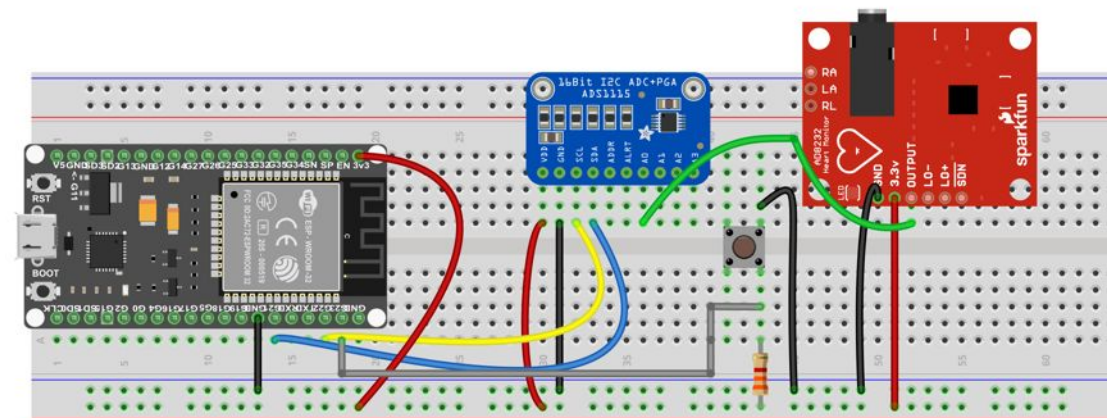
**Cattle Gender/Pose Detection**



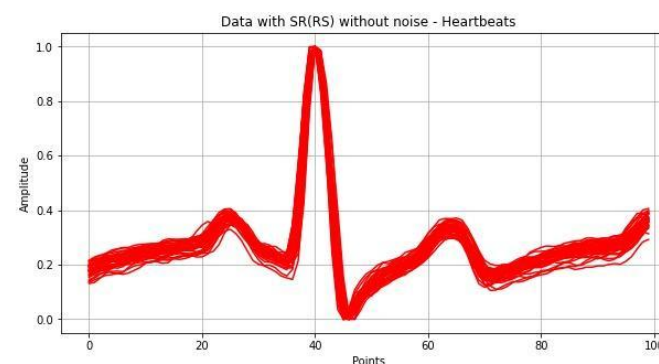
# Other Sensors / Models

Examples

# Atrial Fibrillation Detection on ECG



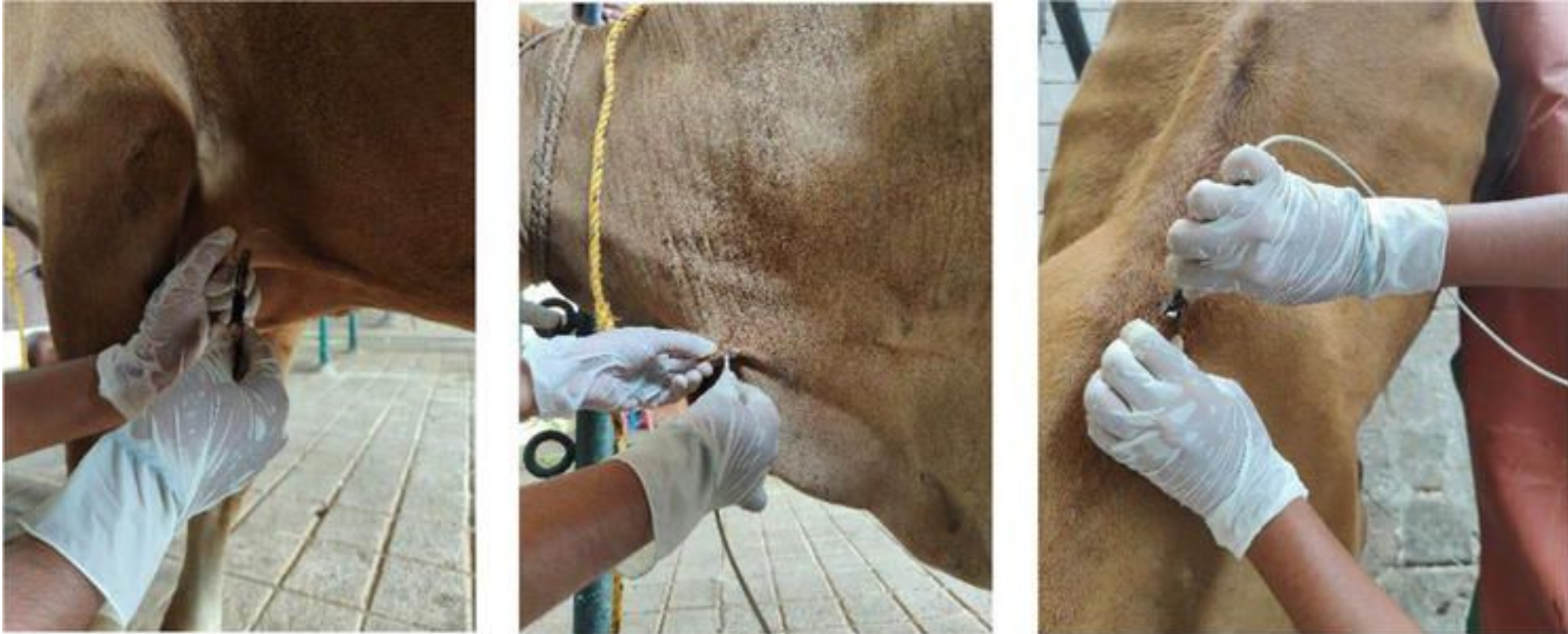
fritzing



**Guilherme Silva**  
Engenheiro - UNIFEI

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

# ECG: Detecting Cardiac Diseases in Cattle

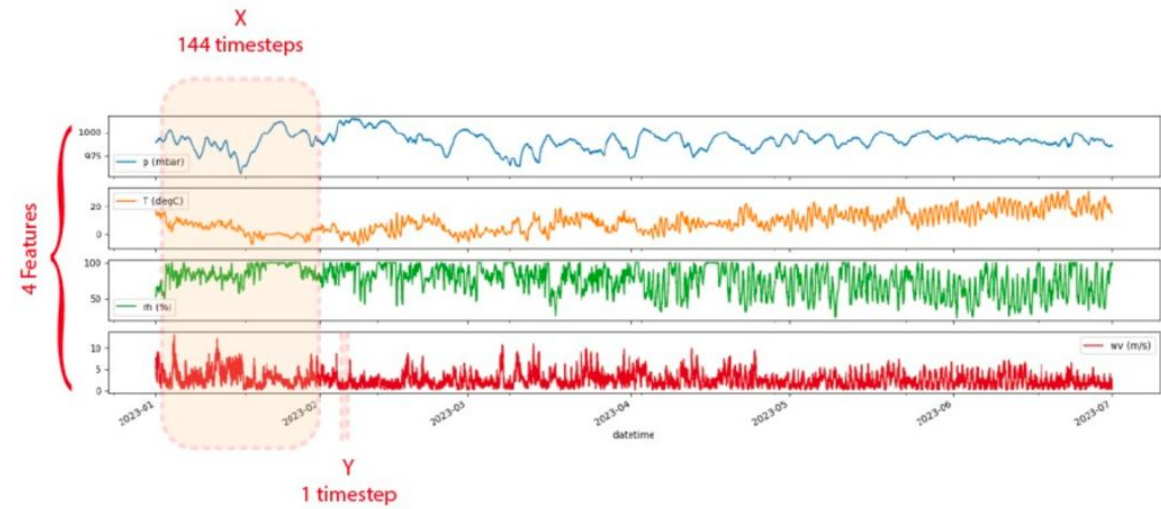


Interpretation of ECG in cattle is useful in many medical-veterinarian decisions because it permits the observation of many heart diseases in cattle (myocardial dystrophy, atrial and ventricular enlargements, pericardium effusion, etc.).

<https://www.intechopen.com/chapters/82061>



# Humidity Forecasting (RNN-LSTM)



ESP32 LSTM Phenolic Sponge Moisture

# Content

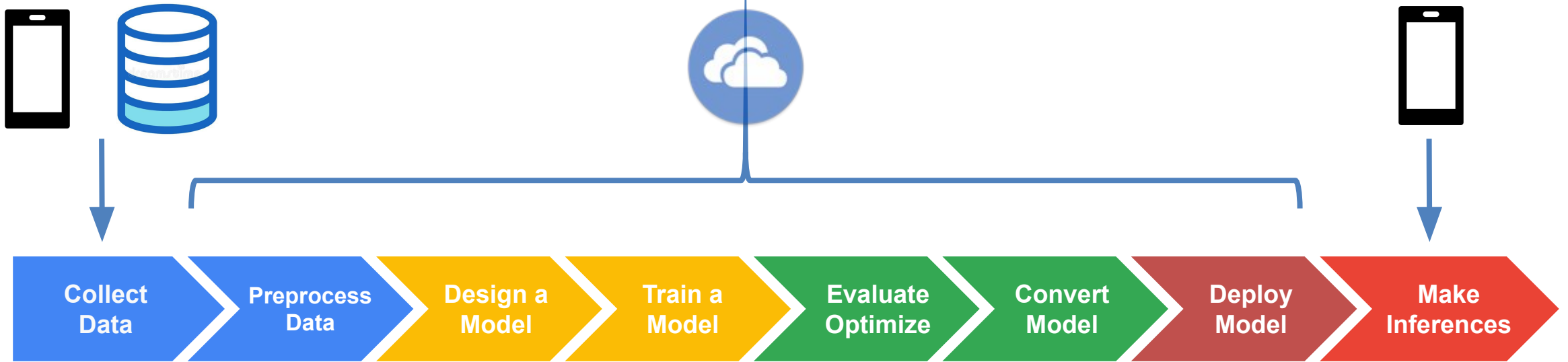
- AI Introduction and Applications
- **Lab** – Image Classification

# Machine Learning Workflow

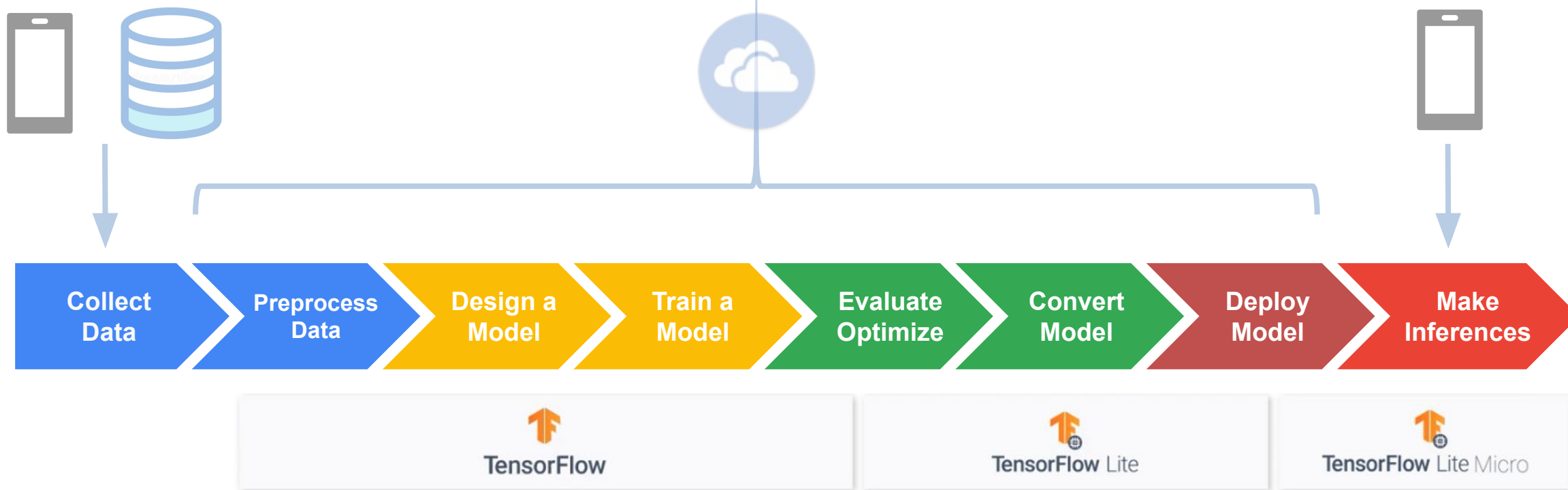




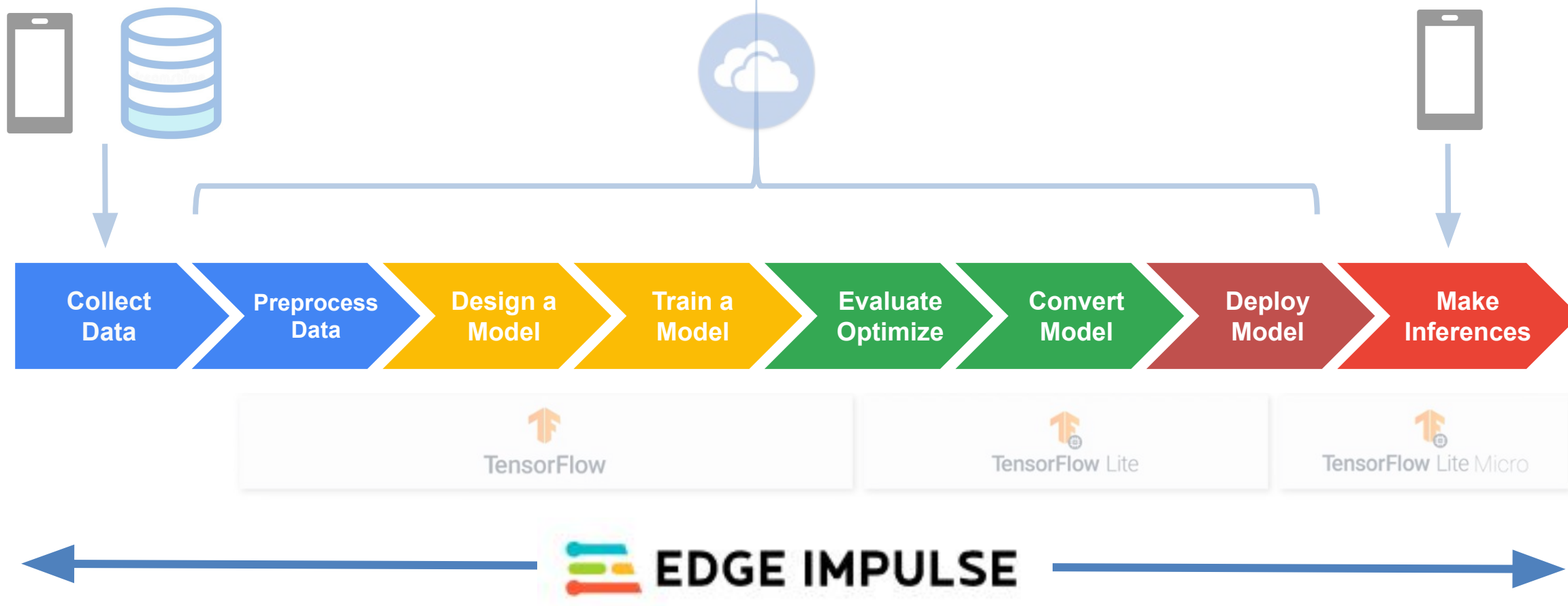
# Machine Learning Workflow (“Where”)



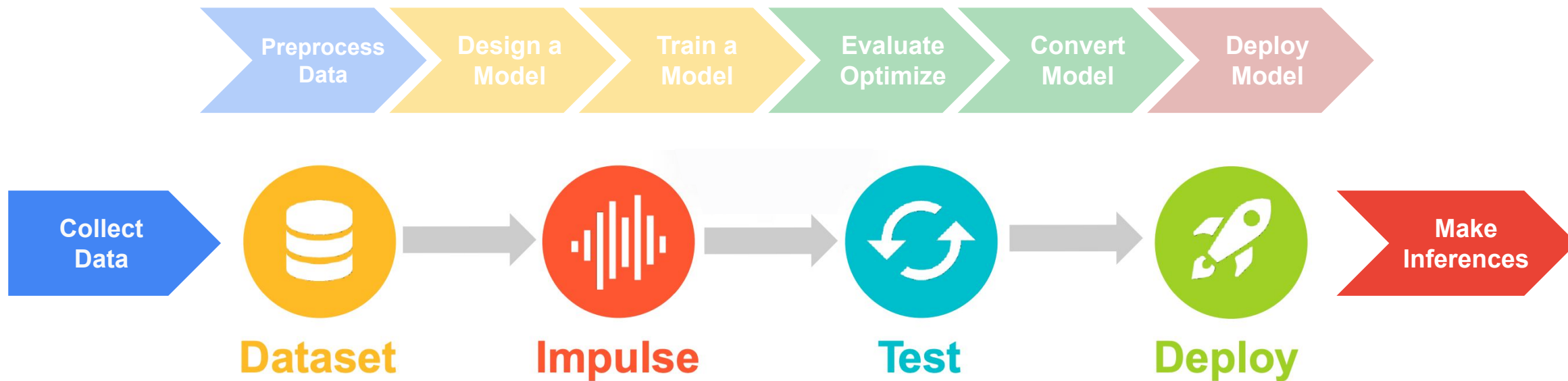
# Machine Learning Workflow (“How”)



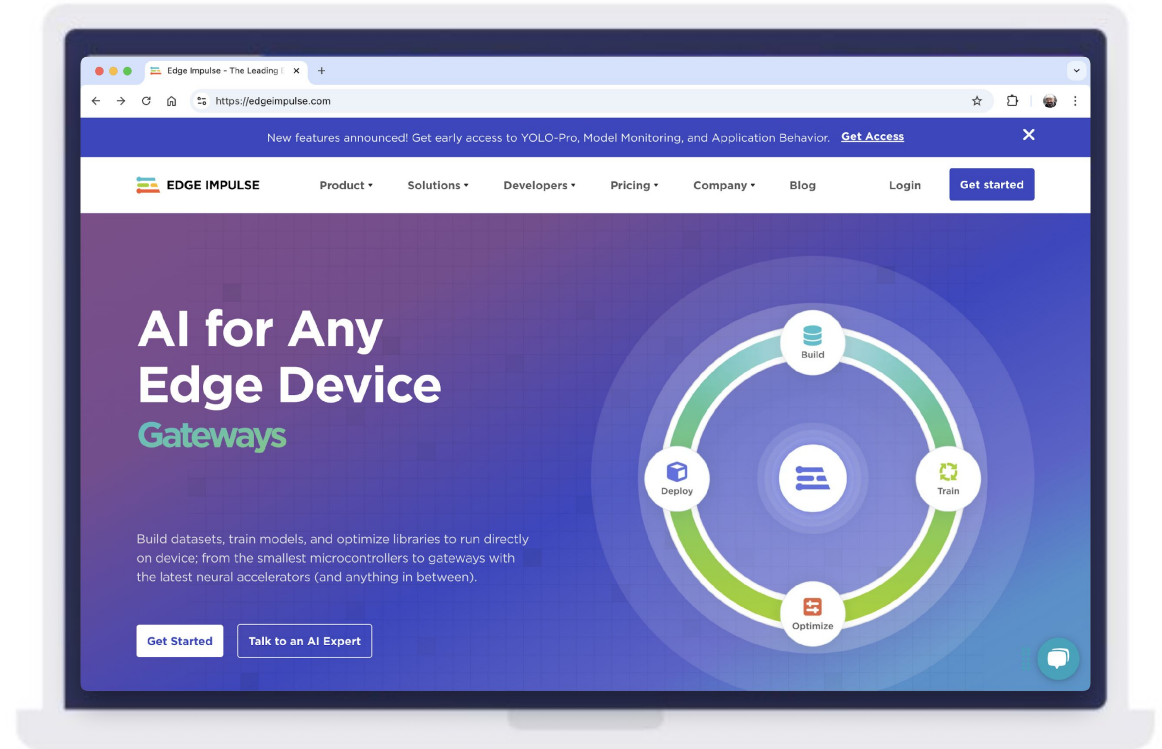
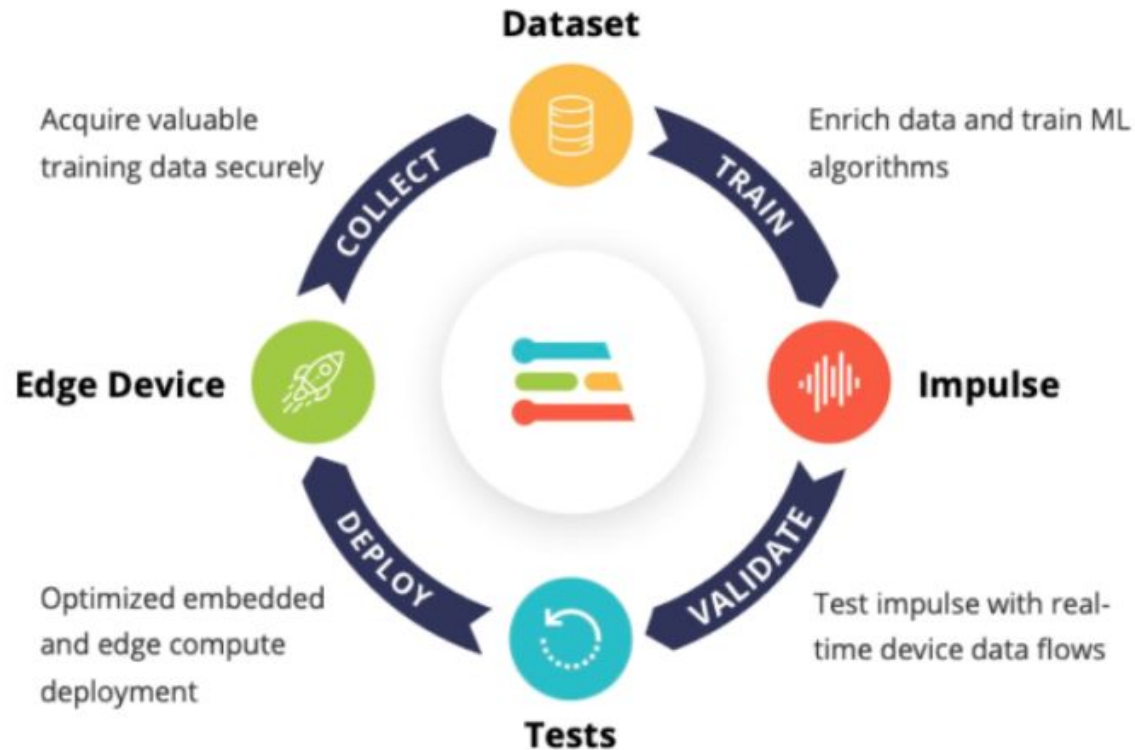
# Machine Learning Workflow (“How”)



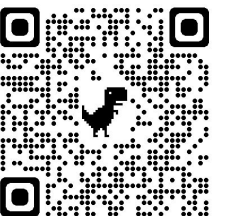




# EI Studio - Embedded ML platform (“AutoML”)



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

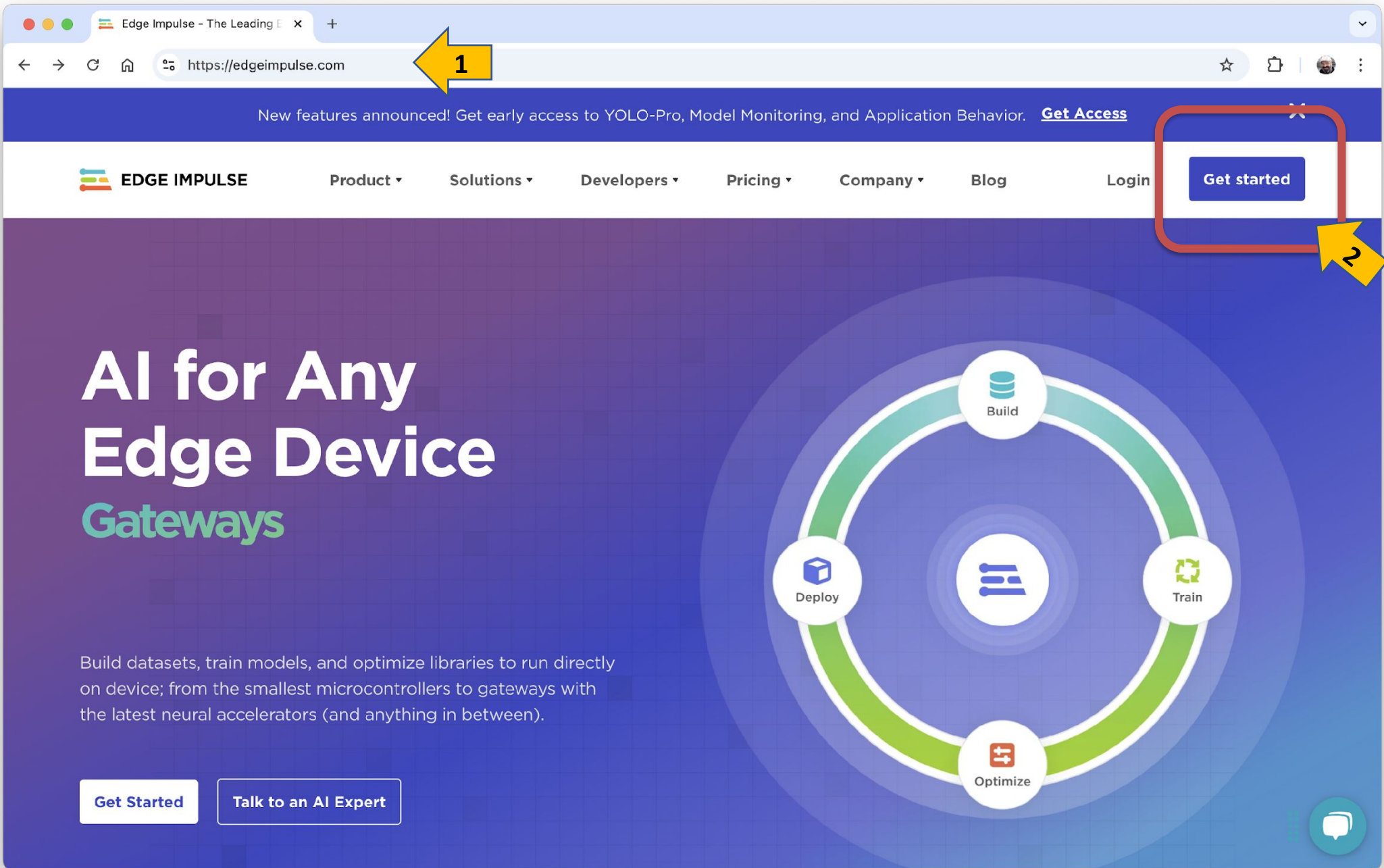


# Image Classification Project

## Edge Impulse Studio

<https://studio.edgeimpulse.com/public/540912/live>







Sign up - Edge Impulse x +

https://studio.edgeimpulse.com/get-started

 **EDGE IMPULSE**

### Sign up

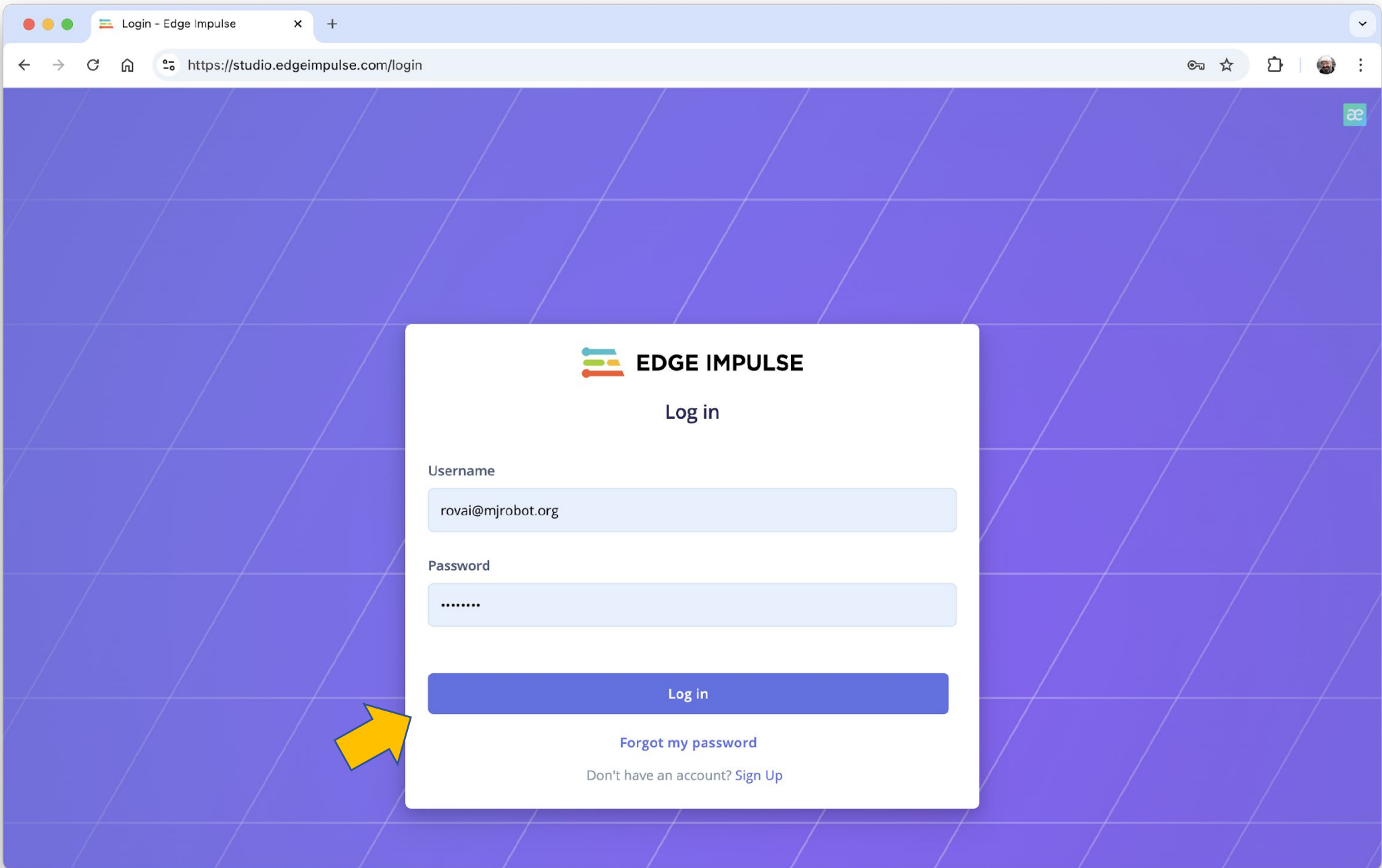
First name Last name

What describes your role?

Already have an account? [Log in](#)

[Continue](#)





Profile - Projects - Edge Impulse

https://studio.edgeimpulse.com/studio/profile/projects?autoredirect=1&createNewProject=1

EDGE IMPULSE



MJRoBot

(Marcelo Rovai)

ENTERPRISE

Enable MFA

Multi-factor authentication is now available for all users. [Set up now.](#)

Organizations

EIE

Create a new project

Enter the name for your new project:

SDSU - Image Classification

Choose your project type:

☒ Personal

20 min job limit, 4GB or 4 hours of data, limited collaboration.

☐ Enterprise

No job or data size limits, higher performance, custom blocks.

Create under organization: Edge Impulse Experts

Choose your project setting:

☒ Public

Anyone on the internet can view and clone this project under the licence: [Apache 2.0](#). Only invited users will be able to edit.

☐ Private (0 of 2 remaining)

Only invited users can edit and view your project.

Create new project

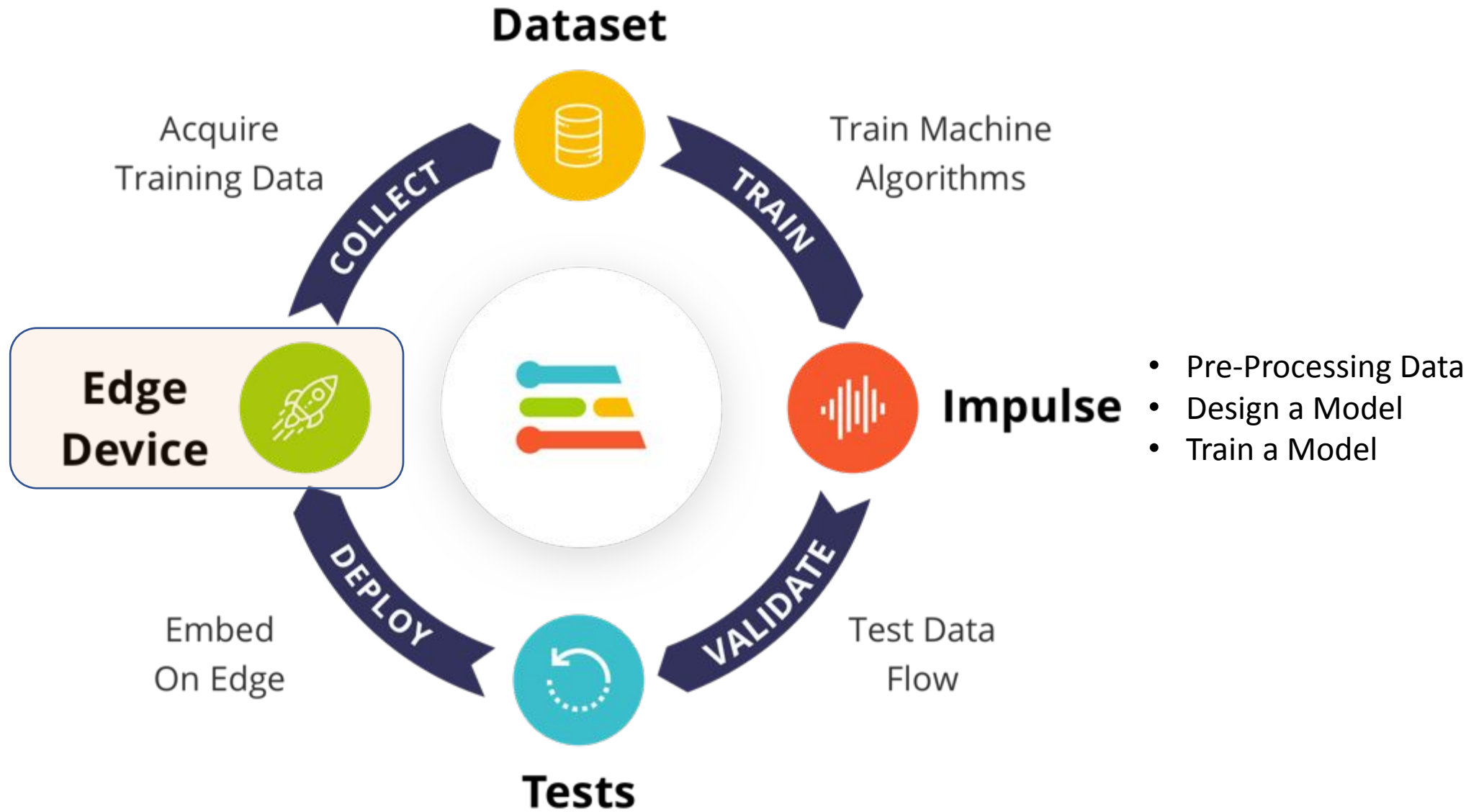
MJRoBot (Marcelo Rovai) / video\_tinyml\_raw

# Medicine Classifier

- Classes:
  - prodR
  - prodD
  - prodT
  - backG



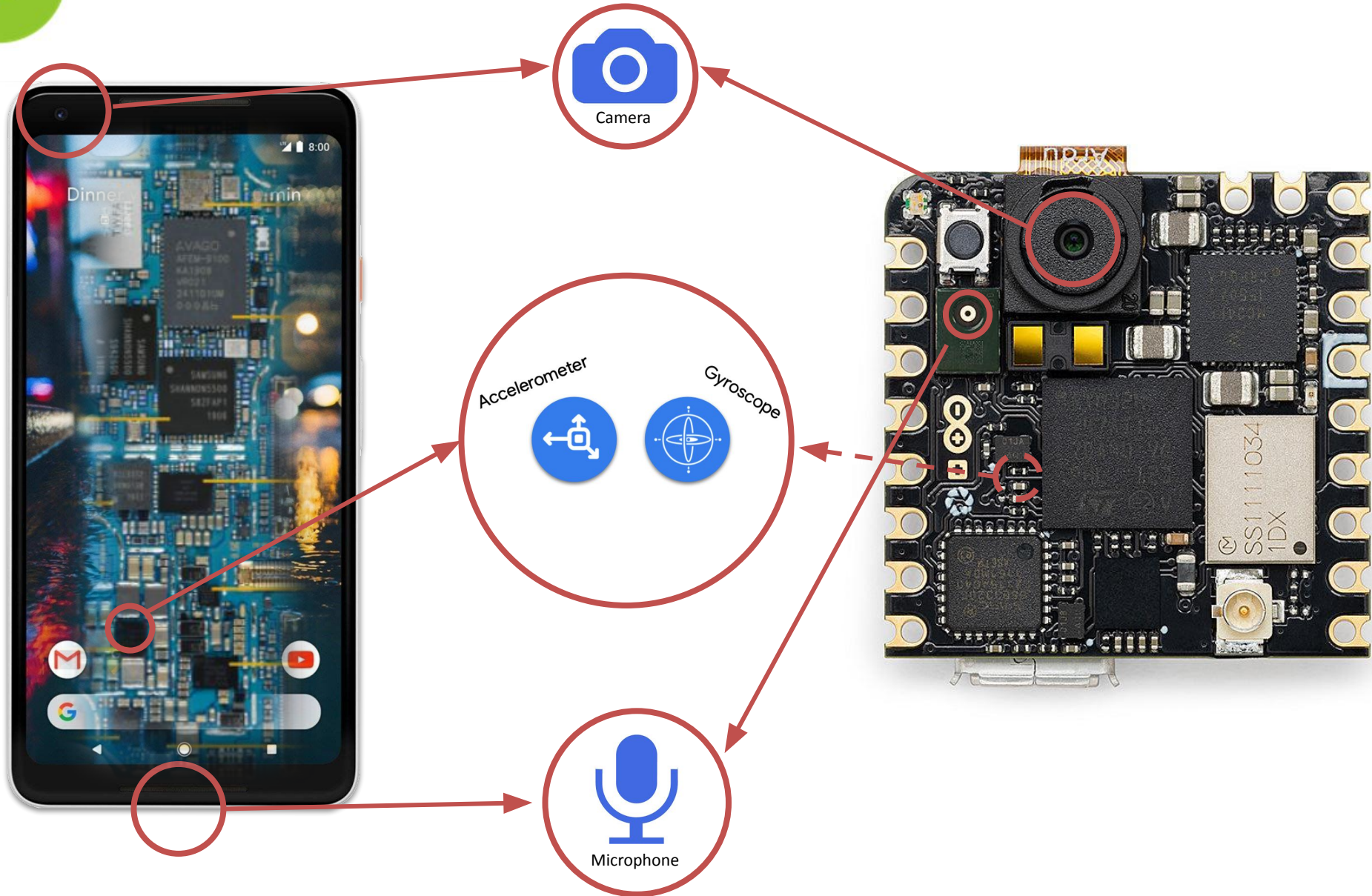




Edge  
Device



& Sensors



SDSU - Image Classification

https://studio.edgeimpulse.com/studio/540912/acquisition/training?page=1

☆

EDGE IMPULSE

Dashboard

Devices

Data acquisition

Experiments

Impulse design

Create impulse

Retrain model

Live classification

Model testing

Deployment

Versioning

GETTING STARTED

Documentation

Forums

MJRoBot (Marcelo Rovai) / SDSU - Image Classification PERSONAL

Target: Raspberry Pi 5

Dataset

Data explorer

Data sources

CSV Wizard

Dataset

Add data

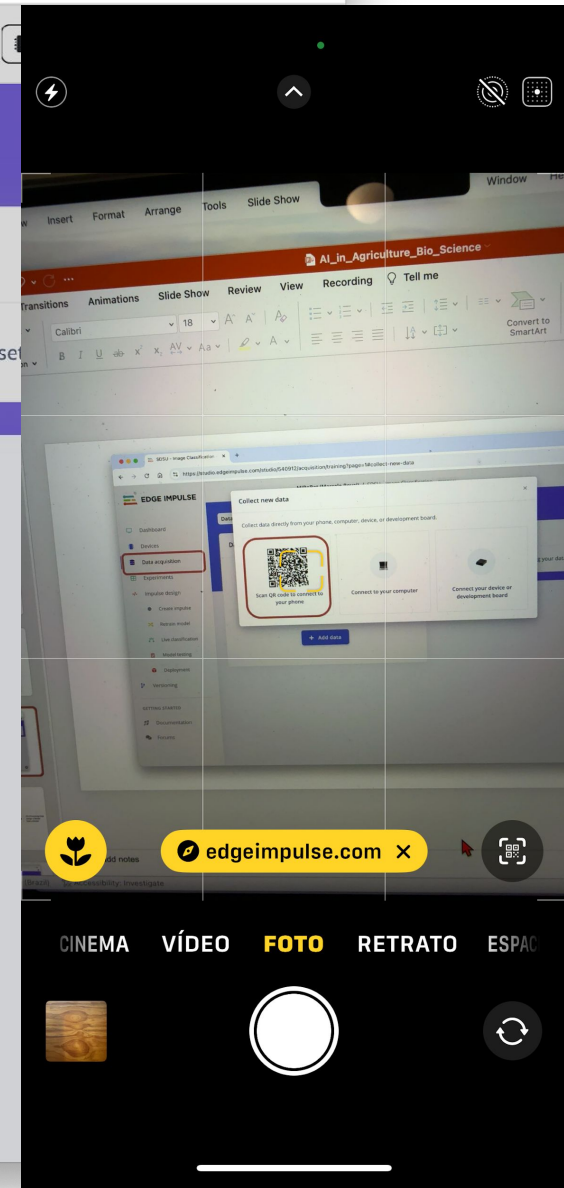
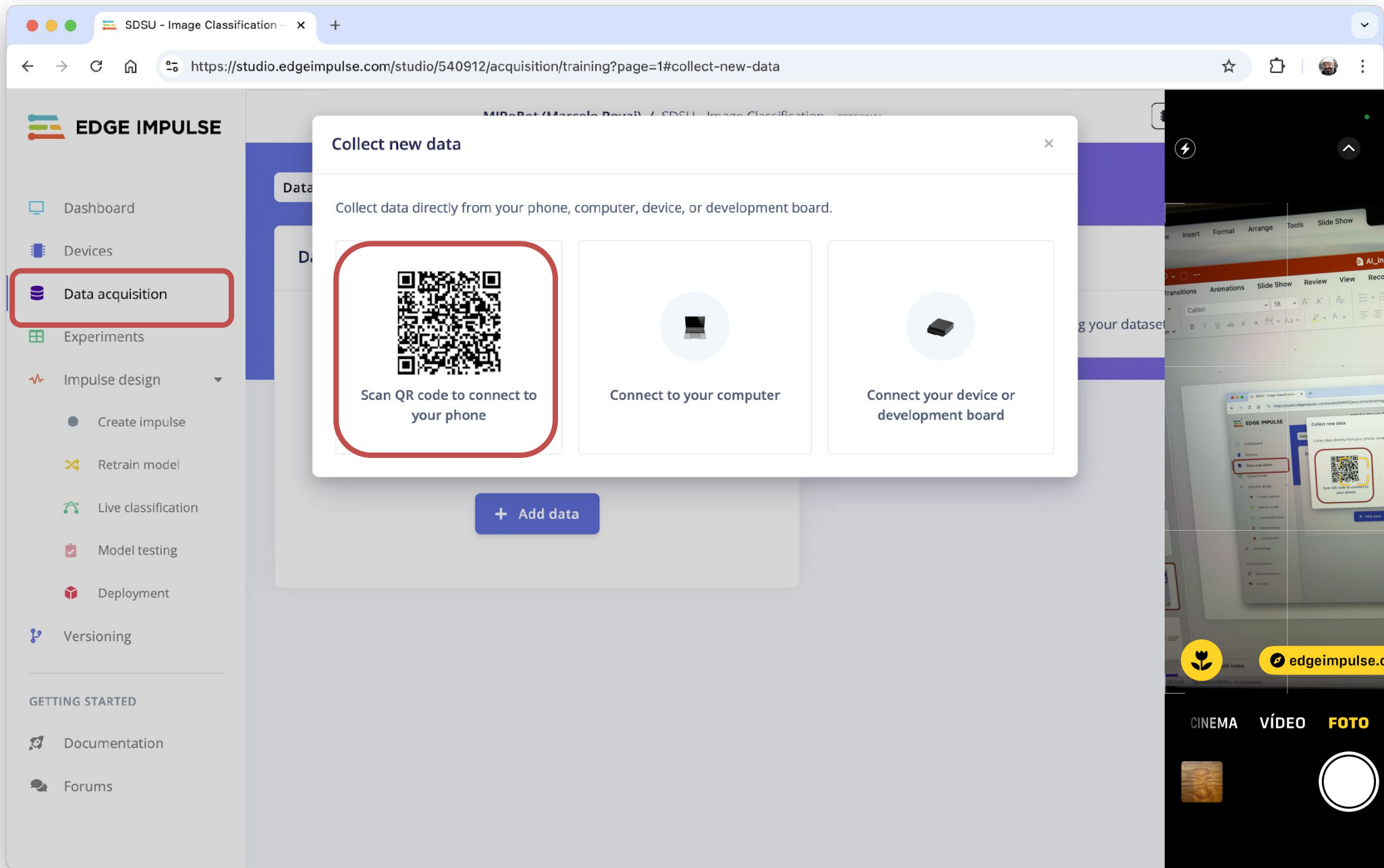
Start building your dataset by adding some data.

+ Add data

Collect data

Connect a device

to start building your dataset.





SDSU - Image Classification - x +

https://studio.edgeimpulse.com/studio/540912/acquisition/training?page=1

**EDGE IMPULSE**

- Dashboard
- Devices
- Data acquisition**
- Experiments
- Impulse design
  - Create impulse
  - Retrain model
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**Collect new data**

✓

**Device "phone\_m23dz5xi" is now connected**

Use the 'Record new data' section to collect data from this device.

[Get started!](#)

[< Back](#)

16:48

Camera

smartphone.edgeimpulse.com

**Data collection**

✓

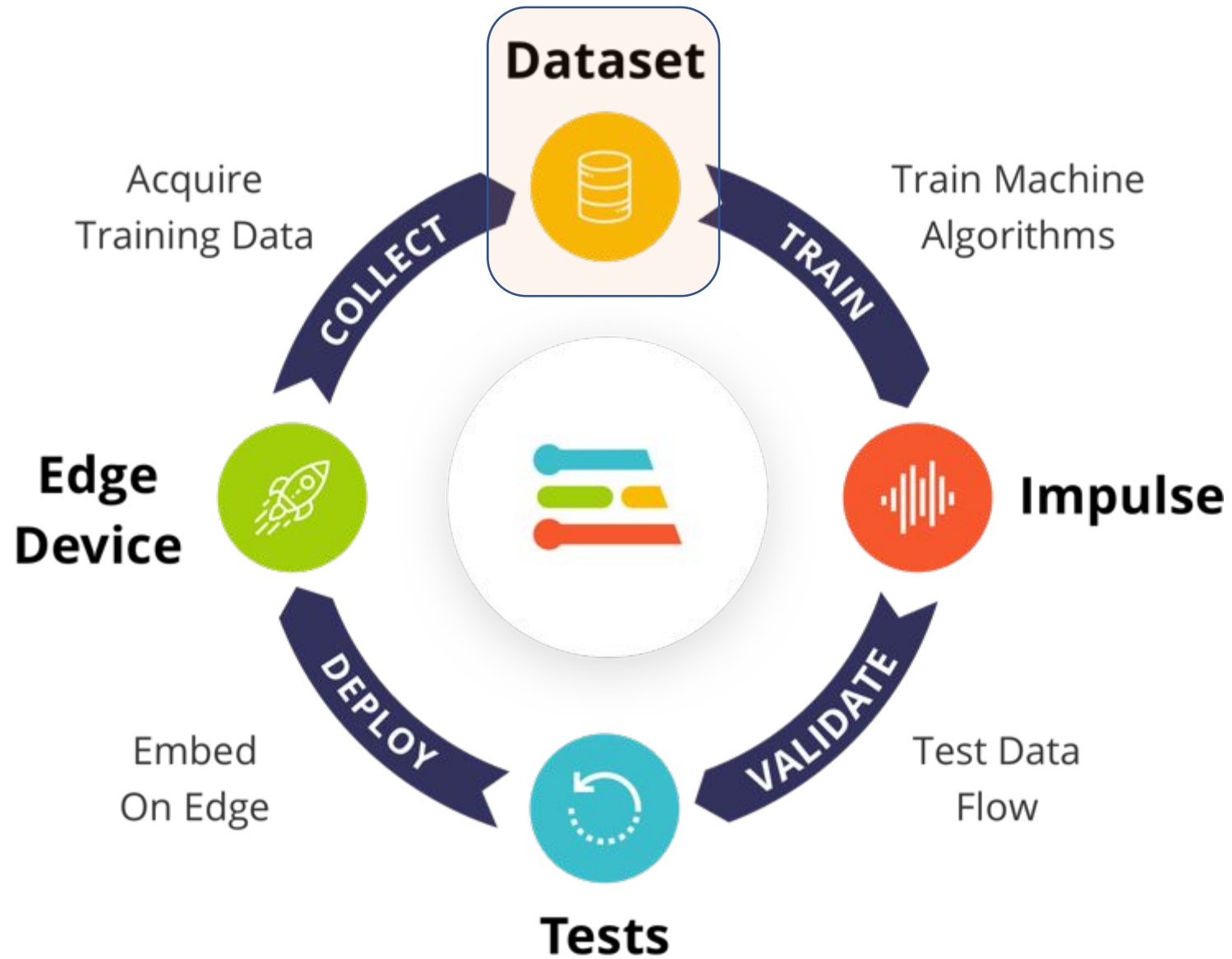
**Connected as phone\_m23dz5xi**

You can collect data from this device from the **Data acquisition** page in the Edge Impulse studio.

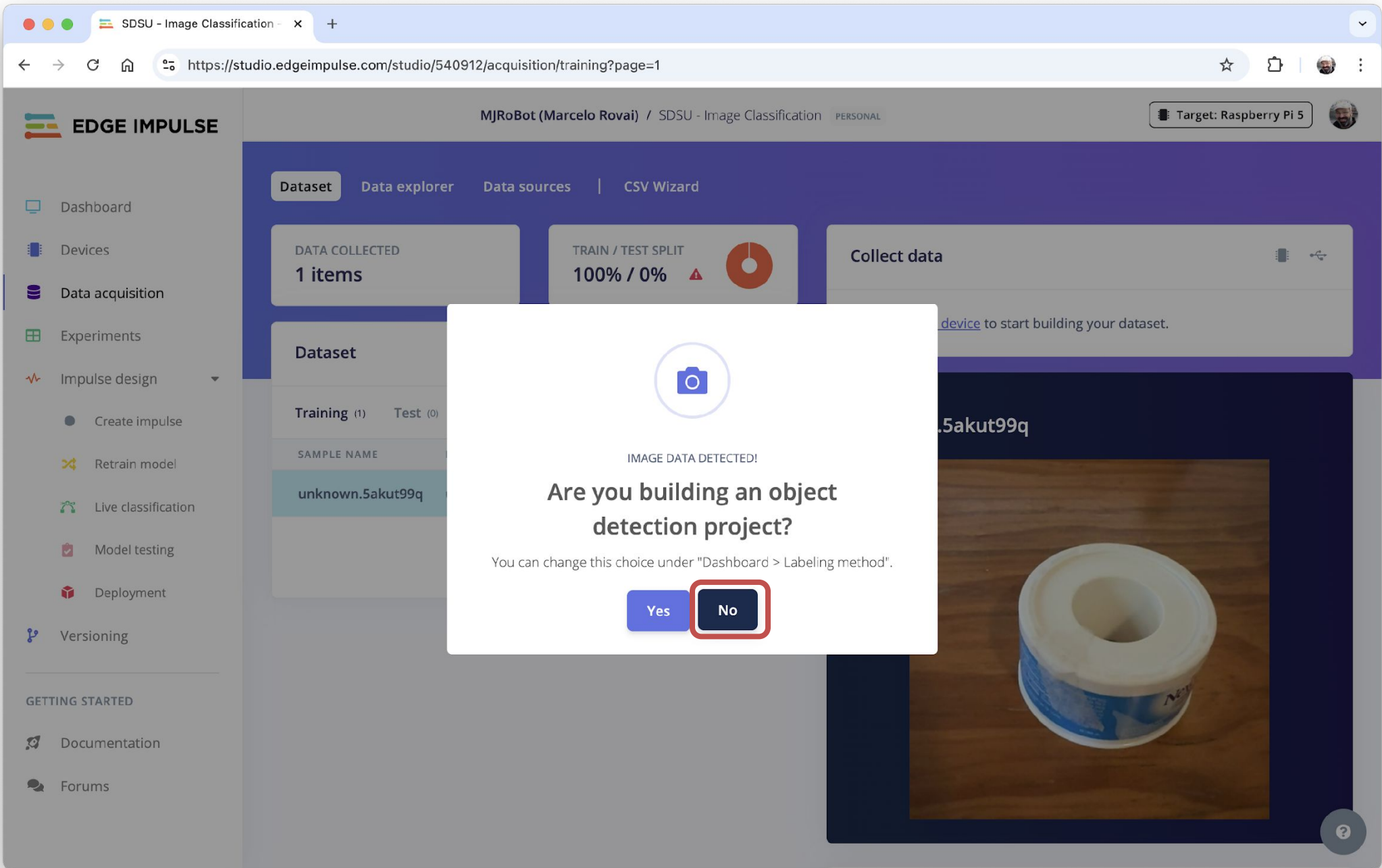
[Collecting images?](#)

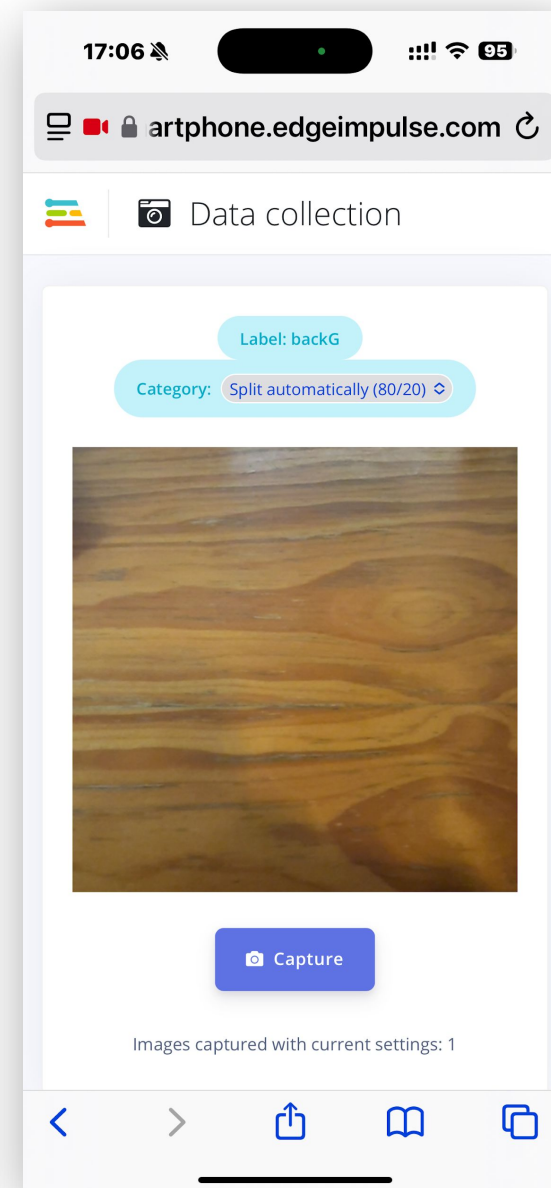
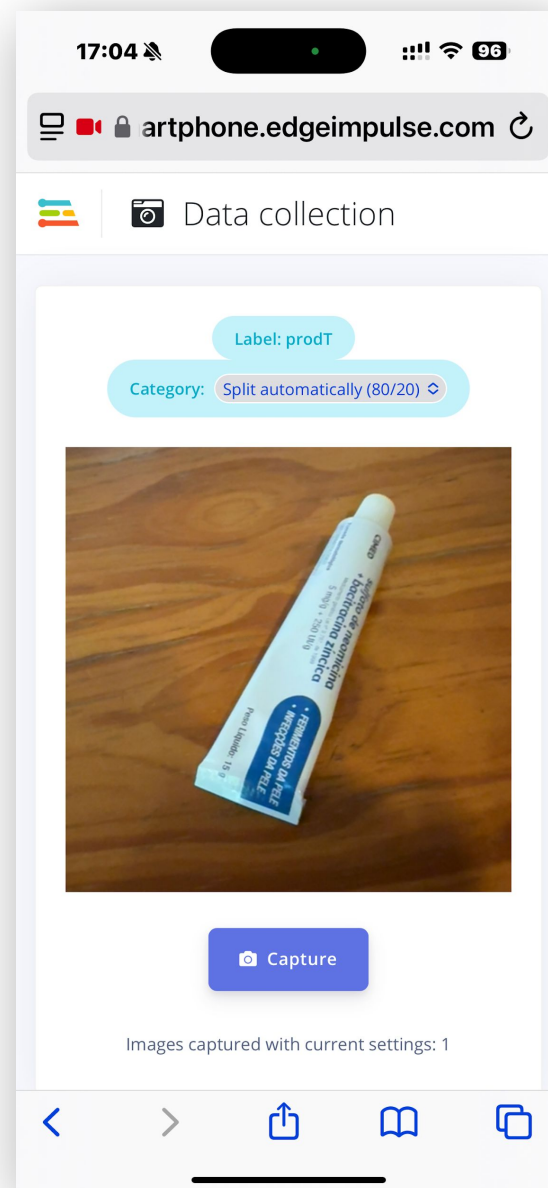
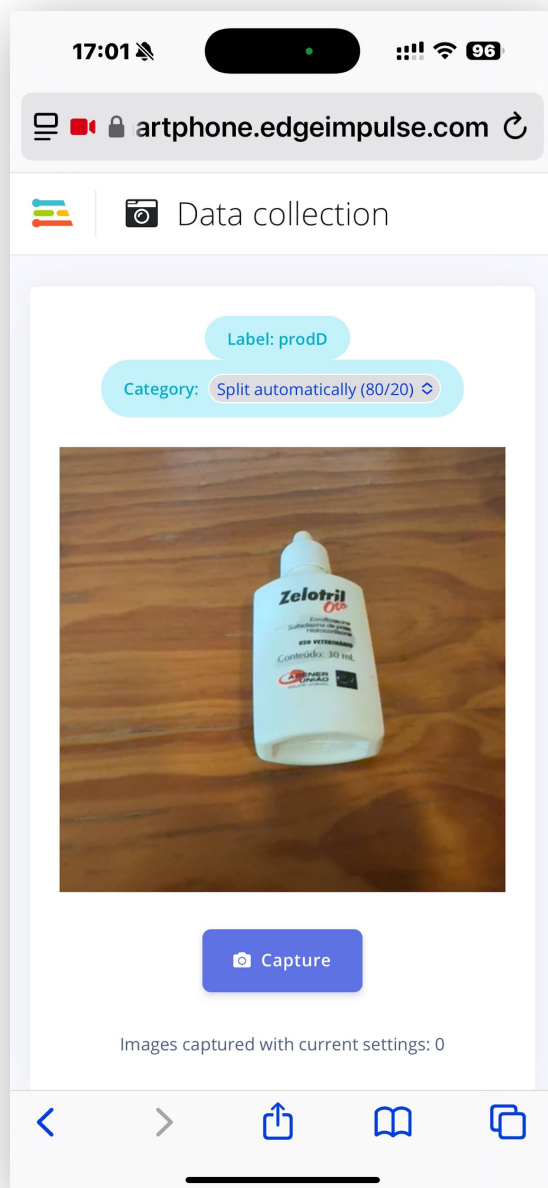
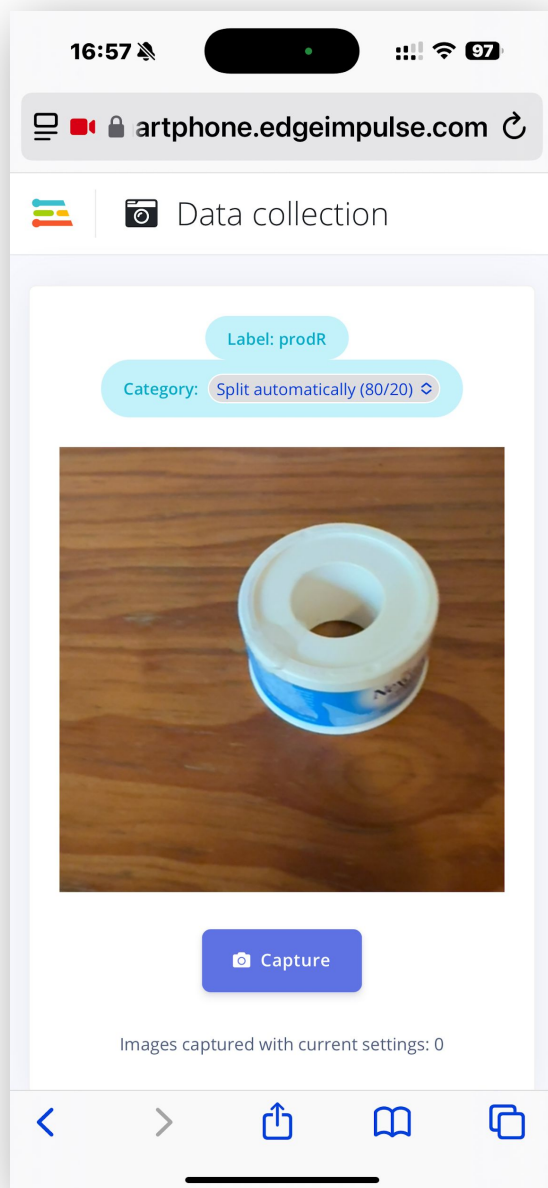
[Collecting audio?](#)

[Collecting motion?](#)



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







Collect Data

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MJRoBot (Marcelo Rovai) / SDSU - Image Classification PERSONAL

Target: Raspberry Pi 5

Dataset

Data explorer

Data sources

CSV Wizard

DATA COLLECTED

200 items

TRAIN / TEST SPLIT

83% / 17%

Collect data

[Connect a device](#) to start building your dataset.

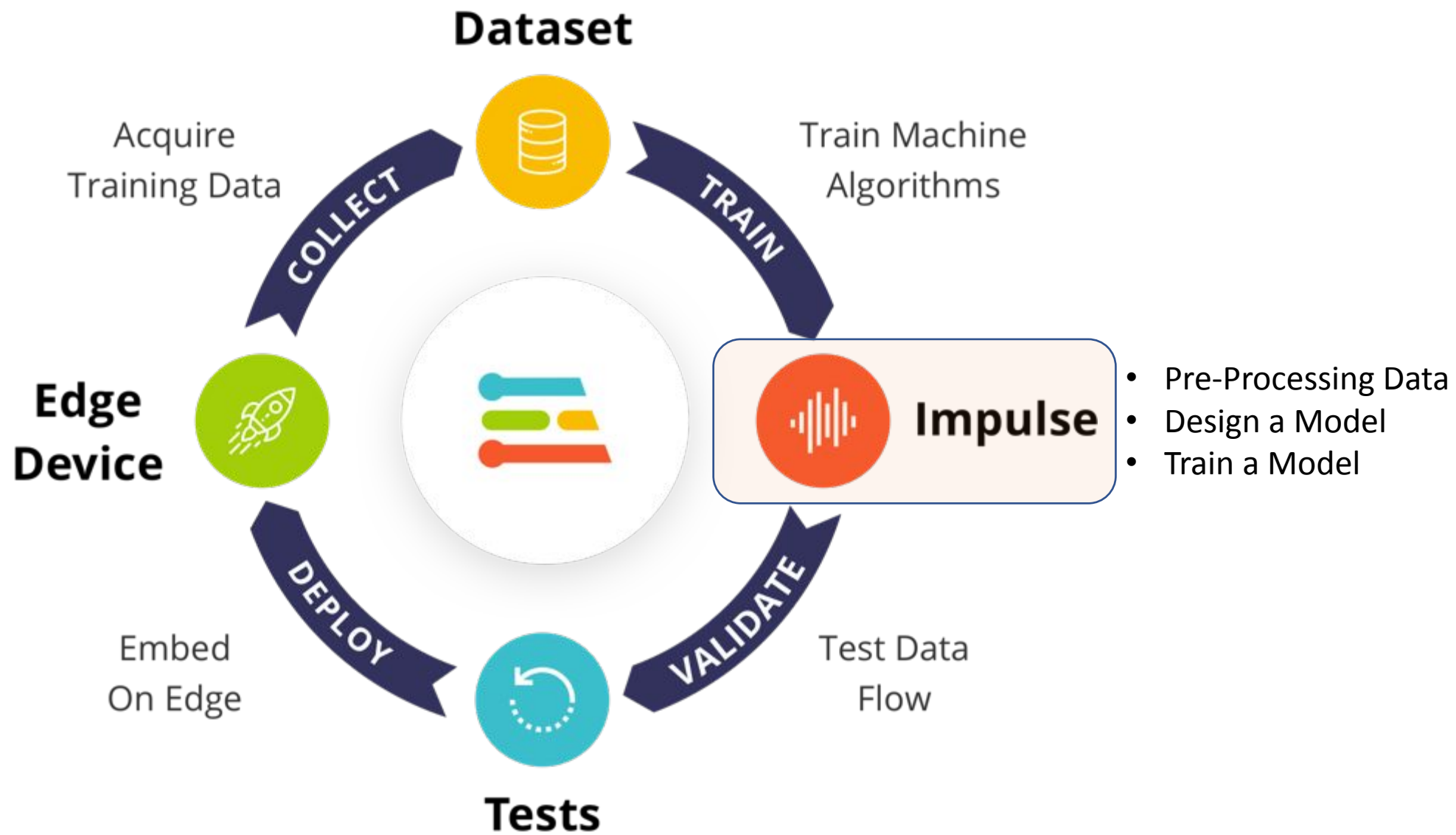
Dataset

Training (166)

Test (34)

RAW DATA

prodT.5akvinki



SDSU - Image Classification

https://studio.edgeimpulse.com/studio/540912/impulse/1/create-impulse

MJRoBot (Marcelo Rovai) / SDSU - Image Classification PERSONAL Target: Raspberry Pi 5

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Impulse #1

An impulse takes raw data, uses signal processing to extract features, and then uses a learning block to classify new data.

Image data

Input axes  
image

Image ...

Image h...

96

96

Resize mode  
S 

Image

Name  
Image

Input axes (1)  
Image  
image

Transfer Learning (Images)

Name  
Transfer learning

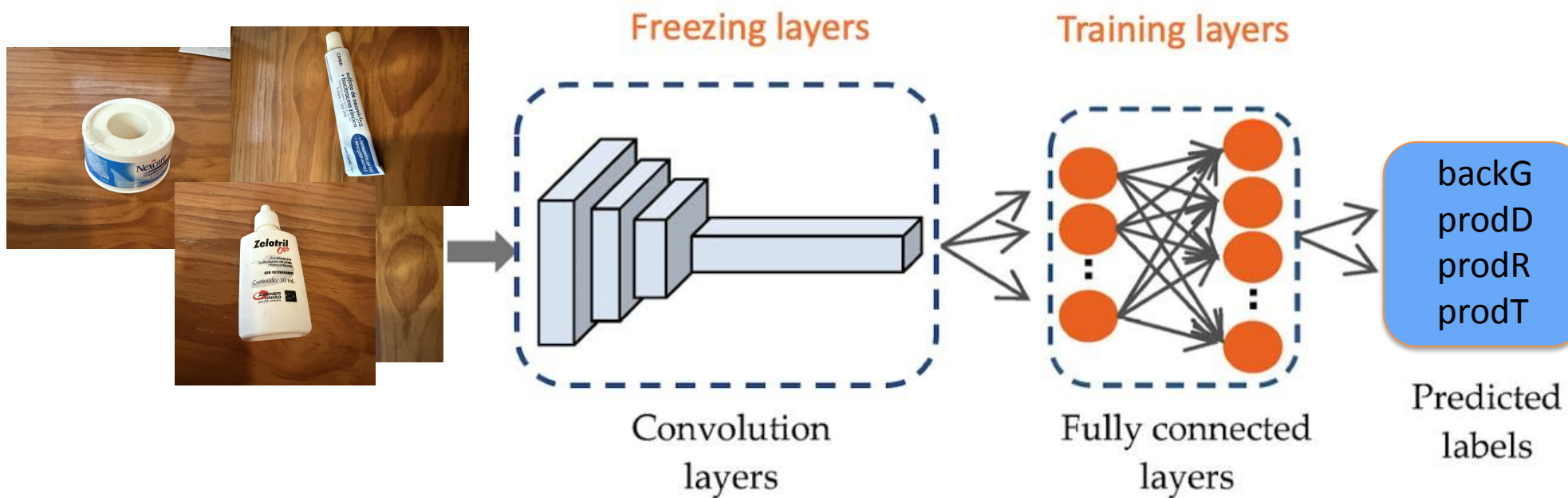
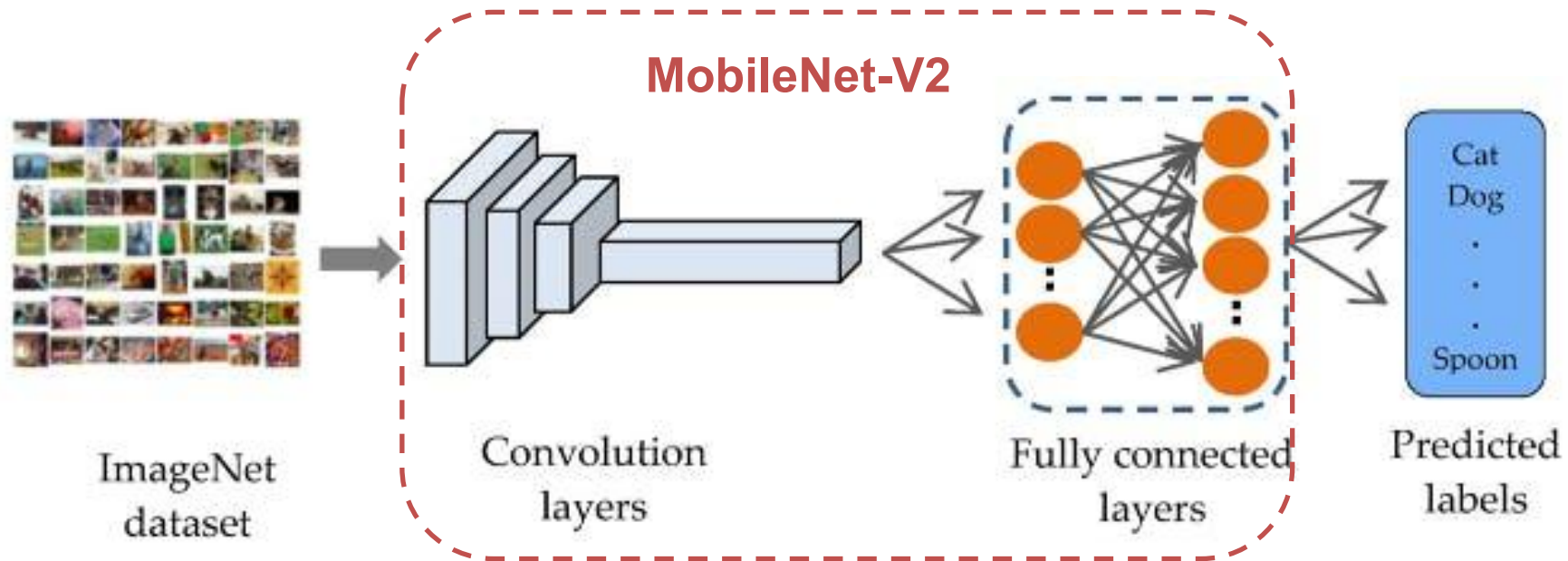
Input features  
☒ Image

Output features  
5 (backG, prodD, prodR, prodT, unknown)

Output features

5 (backG, prodD, prodR, prodT, unknown)

Save Impulse





SDSU - Image Classification

https://studio.edgeimpulse.com/studio/540912/impulse/1/dsp/image/2

MJRoBot (Marcelo Rovai) / SDSU - Image Classification PERSONAL Target: Raspberry Pi 5

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**Parameters** Generate features

**Raw data** Show: prodD prodD.5akvf5fd (pre)



**Raw features**

0x697994, 0x6c7e9d, 0x7183a3, 0x7285a4, 0x7484a5, 0x7684a8...

**Parameters**

**Image**

Color depth ③ RGB

Save parameters

**DSP result**

**Image** 96x96x3 = 27,648



**Processed features**

0.4118, 0.4745, 0.5804, 0.4235, 0.4941, 0.6157, 0.4431, 0...

Preprocess  
Data



SDSU - Image Classification

https://studio.edgeimpulse.com/studio/540912/impulse/1/dsp/image/2/generate-features

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ParametersGenerate features

Training set

Data in training set166 items

Classes4 (backG, prodD, prodR, prodT)

Generate features

Feature generation output (0)

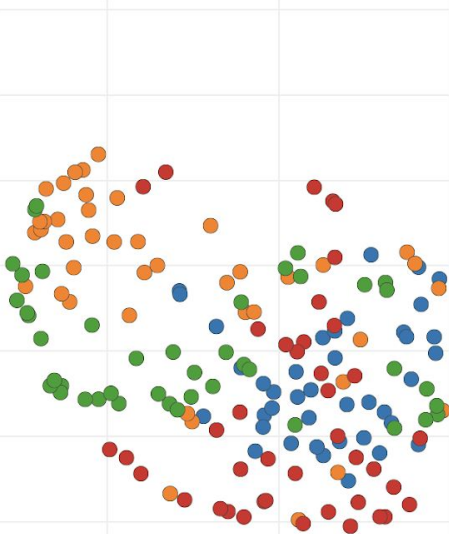
Creating job... OK (ID: 25038003)

Scheduling job in cluster...  
Container image pulled!  
Job started  
Fetching info for data items...  
Fetching info for data items OK

Scheduling job in cluster...  
Container image pulled!  
Job started  
Creating windows from files...  
[1/1] Creating windows from files...  
[1/1] Creating windows from files...

Feature explorer

backG  
prodD  
prodR  
prodT



On-device performance ?

PROCESSING TIME  
1 ms.

PEAK RAM USAGE  
4 KB

Preprocess  
Data

## Neural Network settings



# Hyperparameters

### Training settings

Number of training cycles ?

Use learned optimizer ?



Learning rate ?

Training processor ?



Data augmentation ?



### Advanced training settings



Validation set size ?

%

Split train/validation set on metadata key ?

Batch size ?

Auto-weight classes ?



Profile int8 model ?



## Neural network architecture

# Model Design

Input layer (27,648 features)



MobileNetV2 96x96 0.35 (final layer: 16 neurons, 0.1 dropout)

Choose a different model

Output layer (4 classes)

Save & train



Last training performance (validation set)

%

ACCURACY  
85.3%

📈

LOSS  
0.43

Confusion matrix (validation set)

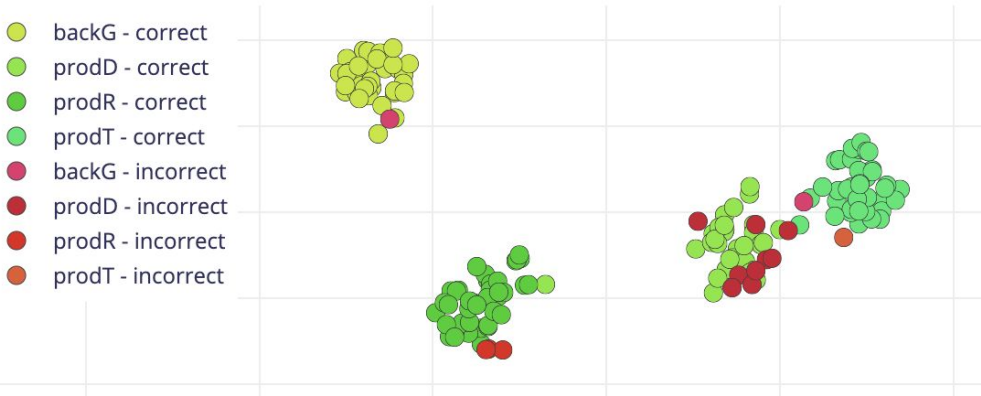
|          | BACKG | PRODD | PRODR | PRODT |
|----------|-------|-------|-------|-------|
| BACKG    | 77.8% | 11.1% | 11.1% | 0%    |
| PRODD    | 0%    | 71.4% | 0%    | 28.6% |
| PRODR    | 0%    | 0%    | 85.7% | 14.3% |
| PRODT    | 0%    | 0%    | 0%    | 100%  |
| F1 SCORE | 0.88  | 0.77  | 0.86  | 0.88  |

Metrics (validation set)



| METRIC                       | VALUE |
|------------------------------|-------|
| Area under ROC Curve ?       | 0.98  |
| Weighted average Precision ? | 0.87  |
| Weighted average Recall ?    | 0.85  |
| Weighted average F1 score ?  | 0.85  |

Data explorer (full training set) ?





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Design a Model

Train a Model

### Neural Network settings

#### Training settings

Number of training cycles ②

Use learned optimizer ② ☐

Learning rate ②

Training processor ②

Data augmentation ② ☒

#### Advanced training settings

#### Neural network architecture

Input layer (27,648 features)

MobileNetV2 96x96 0.35 (final layer: 16 neurons, 0.1 dropout)

Choose a different model

Output layer (4 classes)

Save & train

### Training output

Converting TensorFlow Lite int8 quantized model...  
Attached to job 25038061...  
Loading data for profiling...  
Loading data for profiling OK

Creating embeddings...  
[ 0/166] Creating embeddings...  
[166/166] Creating embeddings...  
Creating embeddings OK (took 5 seconds)

Calculating performance metrics...  
Calculating inferencing time...  
INFO: Created TensorFlow Lite XNNPACK delegate for CPU.  
Calculating inferencing time OK  
Calculating float32 accuracy...

### Model

Model version: ②

#### Last training performance (validation set)

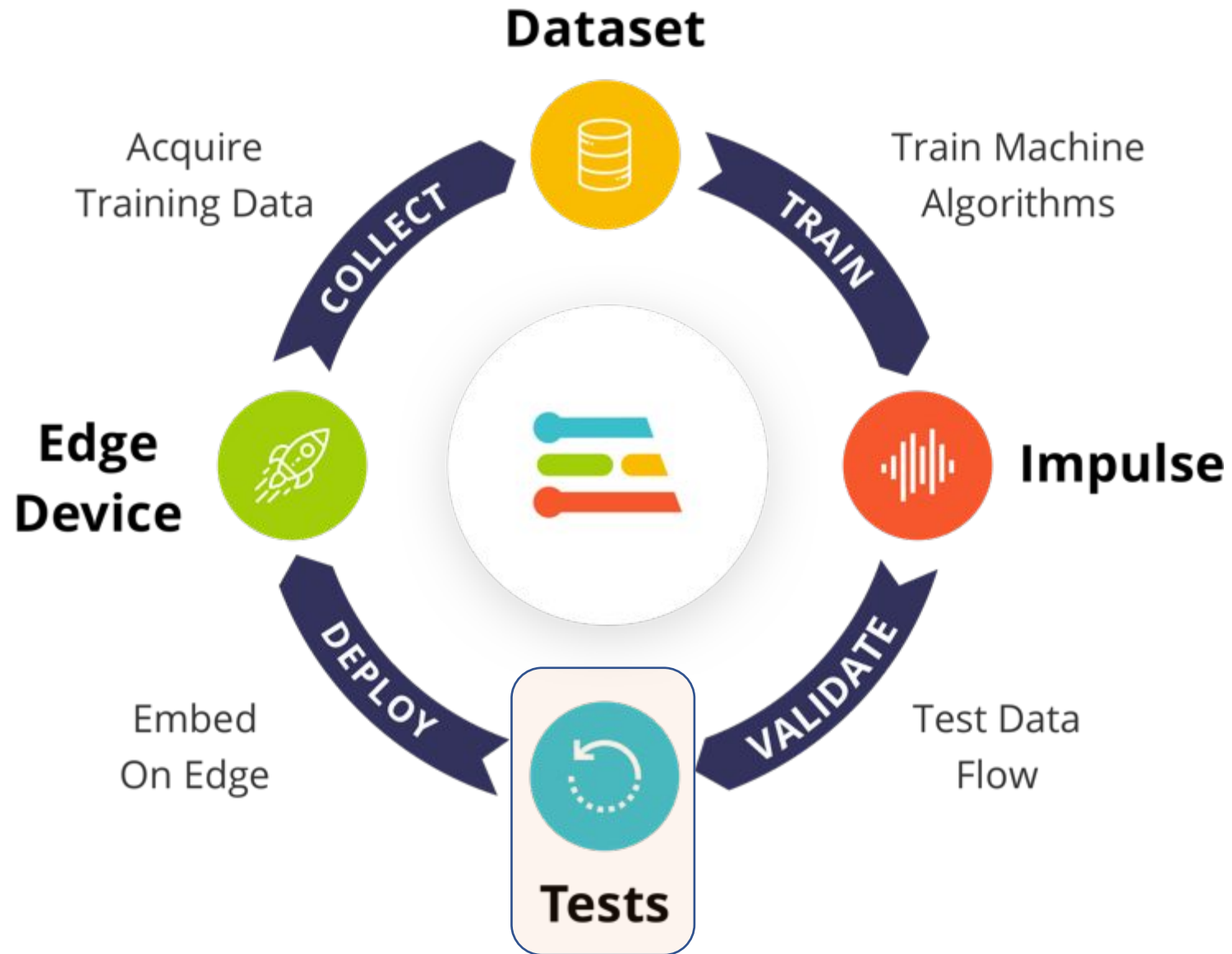
**ACCURACY** 85.3% **LOSS** 0.43

#### Confusion matrix (validation set)

|          | BACKG | PRODD | PRODR | PRODT |
|----------|-------|-------|-------|-------|
| BACKG    | 77.8% | 11.1% | 11.1% | 0%    |
| PRODD    | 0%    | 71.4% | 0%    | 28.6% |
| PRODR    | 0%    | 0%    | 85.7% | 14.3% |
| PRODT    | 0%    | 0%    | 0%    | 100%  |
| F1 SCORE | 0.88  | 0.77  | 0.86  | 0.88  |

#### Metrics (validation set)

| METRIC                 | VALUE |
|------------------------|-------|
| Area under ROC Curve ② | 0.98  |



- Pre-Processing Data
- Design a Model
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Evaluate  
Optimize

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Test data

Classify all

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

| SAMPLE NAME    | EXPECTED OUTCOME | ACCURACY | RESULT      |
|----------------|------------------|----------|-------------|
| backG.5akvm3dv | backG            | 100%     | 1 backG     |
| backG.5akvm0es | backG            | 100%     | 1 backG     |
| backG.5akvlvkq | backG            | 100%     | 1 backG     |
| backG.5akvlsrf | backG            | 100%     | 1 backG     |
| backG.5akvlpnm | backG            | 100%     | 1 backG     |
| backG.5akvlfes | backG            | 100%     | 1 backG     |
| backG.5akvlb4n | backG            | 100%     | 1 backG     |
| backG.5akvrrc  | backG            | 0%       | 1 uncertain |
| backG.5akvkmq6 | backG            | 100%     | 1 backG     |
| backG.5akvkktr | backG            | 100%     | 1 backG     |
| prodT.5akvimph | prodT            | 0%       | 1 prodD     |

Model testing output

Classifying data for float32 model...  
Scheduling job in cluster...  
Container image pulled!  
Job started  
INFO: Created TensorFlow Lite XNNPACK delegate for CPU.  
  
Classifying data for Transfer learning OK  
  
Generating model testing summary...  
Finished generating model testing summary  
  
Job completed (success)

Results

Model version: Unoptimized (float32)

ACCURACY

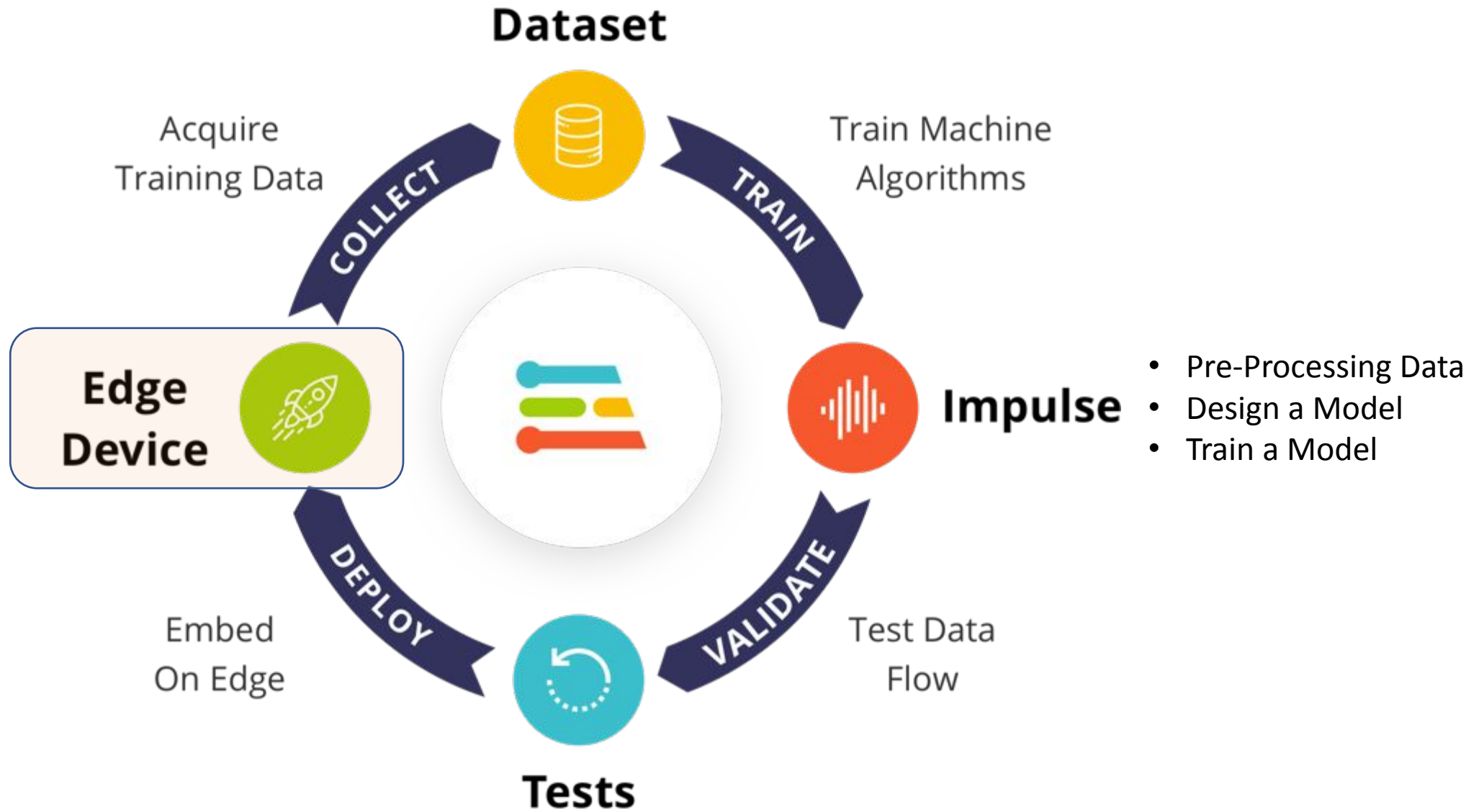
88.24%

Metrics for Transfer learning

| METRIC                     | VALUE |
|----------------------------|-------|
| Area under ROC Curve       | 1.00  |
| Weighted average Precision | 0.95  |
| Weighted average Recall    | 0.94  |
| Weighted average F1 score  | 0.94  |

Confusion matrix

|          | BACKG | PRODD | PRODR | PRODT | UNCERTAIN |
|----------|-------|-------|-------|-------|-----------|
| BACKG    | 90%   | 0%    | 0%    | 0%    | 10%       |
| PRODD    | 0%    | 87.5% | 0%    | 0%    | 12.5%     |
| PRODR    | 0%    | 0%    | 85.7% | 0%    | 14.3%     |
| PRODT    | 0%    | 11.1% | 0%    | 88.9% | 0%        |
| F1 SCORE | 0.95  | 0.88  | 0.92  | 0.94  |           |





Deploy Model

SDSU - Image Classification

← → ↺ 🏠 🔍 ☆ 📄 👤 ⋮

https://studio.edgeimpulse.com/studio/540912/impulse/1/deployment

EDGE IMPULSE

MJRoBot (Marcelo Rovai) / SDSU - Image Classification PERSONAL

Target: Raspberry Pi 5

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Configure your deployment

You can deploy your impulse to any device. This makes the model run without an internet connection, minimizes latency, and runs with minimal power consumption. [Read more.](#)

🔍

Search deployment options

DEFAULT DEPLOYMENT

C++ library

A portable C++ library with no external dependencies, which can be compiled with any modern C++ compiler.

MODEL OPTIMIZATIONS

Model optimizations can increase on-device performance but may reduce accuracy.

Quantized (int8)

Selected ✓

|          | IMAGE | TRANSFER LEARNING | TOTAL  |
|----------|-------|-------------------|--------|
| LATENCY  | 1 ms. | 4 ms.             | 5 ms.  |
| RAM      | 4.0K  | 334.7K            | 334.7K |
| FLASH    | -     | 585.8K            | -      |
| ACCURACY |       |                   | -      |

Unoptimized (float32)

Select

|          | IMAGE | TRANSFER LEARNING | TOTAL  |
|----------|-------|-------------------|--------|
| LATENCY  | 1 ms. | 2 ms.             | 3 ms.  |
| RAM      | 4.0K  | 893.7K            | 893.7K |
| FLASH    | -     | 1.6M              | -      |
| ACCURACY |       |                   | 88.24% |

To compare model accuracy, run model testing for all available optimizations.

Run model testing

Run this model

Scan QR code or launch in browser to test your prototype

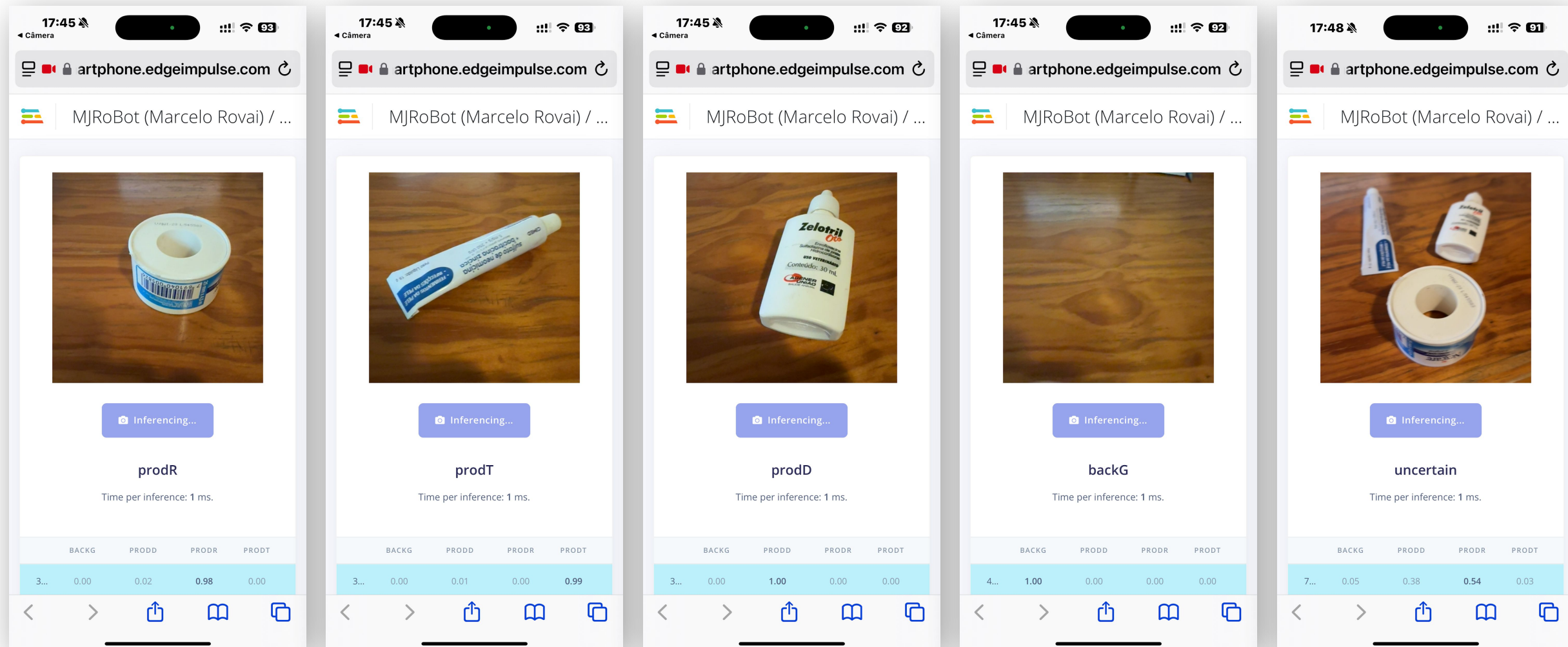


Launch in browser

?

Make  
Inferences

# Inference – Real World



# Conclusion

# How AI is Shaping Agriculture (Animal Farms)

- AI applications in diagnostics, treatment, surgery assistance, behavior analysis, and livestock management are transforming veterinary care.
- AI tools in radiography, ultrasound, and MRI help detect animal diseases early. AI-based image recognition improves diagnostic accuracy.
- AI analyzes cow behavior and physiological data to detect early signs of disease like mastitis or lameness, allowing for timely intervention.
- Wearable devices with AI monitor animal health in real-time, tracking heart rate, activity, and vital signs, providing insights for early interventions.
- Machine learning models track and analyze animal behavior, identifying patterns in stress, anxiety, or abnormal behavior.
- In livestock farming, AI helps manage herd health, improve nutrition, and enhance overall productivity by monitoring animals' welfare in real-time.



# Ethical Considerations and future of AI

- Ethical concerns in AI use for dairy farming include data privacy, algorithm biases, and ensuring that AI tools are used for the welfare of the animals.
- The future holds advanced AI tools like 3D-printed prosthetics, AI-enhanced diagnostics, and collaborations between AI researchers and veterinarians.
- AI advancements will lead to further integration of predictive analytics, automated health monitoring, and new tools for precision dairy farming.

# To learn more ...

## Online Courses

[Harvard School of Engineering and Applied Sciences - CS249r: Tiny Machine Learning Professional Certificate in Tiny Machine Learning \(TinyML\) – edX/Harvard](#)  
[Introduction to Embedded Machine Learning - Coursera/Edge Impulse](#)  
[Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse](#)  
[UNIFEI-IESTIO1 TinyML: “Machine Learning for Embedding Devices”](#)

## Books

[“Python for Data Analysis” by Wes McKinney](#)  
[“Deep Learning with Python” by François Chollet - GitHub Notebooks](#)  
[“TinyML” by Pete Warden and Daniel Situnayake](#)  
[“TinyML Cookbook 2nd Edition” by Gian Marco Iodice](#)  
[“Technical Strategy for AI Engineers, In the Era of Deep Learning” by Andrew Ng](#)  
[“AI at the Edge” book by Daniel Situnayake and Jenny Plunkett](#)  
[“XIAO: Big Power, Small Board” by Lei Feng and Marcelo Rovai](#)  
[“MACHINE LEARNING SYSTEMS for TinyML” by a collaborative effort](#)

## Projects Repository

[Edge Impulse Expert Network](#)

On the [\*\*TinyML4D website\*\*](#), You can find lots of educational materials on TinyML. They are all free and open-source for educational uses – we ask that if you use the material, please cite them! TinyML4D is an initiative to make TinyML education available to everyone globally.

# Questions?

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