# Machine Learning and SoC-based FPGA for real-case applications

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MLab-STI, ICTP

Perú - Online - 2025 -

# ML and SoC/FPGA
## Applications

- Gamma/Neutron discrimination.
- Pest classification in fruit crops.
- Pulse shape discriminator for cosmic rays studies.
- Volcanic seismic event detection.
- Object detection for adverse weather conditions, particularly haze and fog.
- Water quality monitoring.

# Gamma/Neutron discrimination

# ML and SoC-FPGA for real-case applications

**Gamma/neutron discrimination**

IAEA
International Atomic Energy Agency

- Tagged dataset of **gamma and neutron events** from Deuterium-Deuterium (DD) and Deuterium-Tritium (DT) generators.
- The dataset was recorded at the **Neutron Science Facility (NSF) of the Nuclear Science and Instrumentation Laboratory (NSIL), IAEA.**
- The detector is based on a small **CLYC** (Cs2LiYCl6:Ce) crystal (0.5 in diameter by 30 mm length) coupled to a 4-element SiPM array.
- The data were **sampled at 4 GSPS with 10-bits resolution** using a CAEN DT5761 digitizer.
- **The total gamma and neutron events in this dataset are 10,913 and 27,696, respectively.**

# ML and SoC-FPGA for real-case applications

**Gamma/neutron discrimination**

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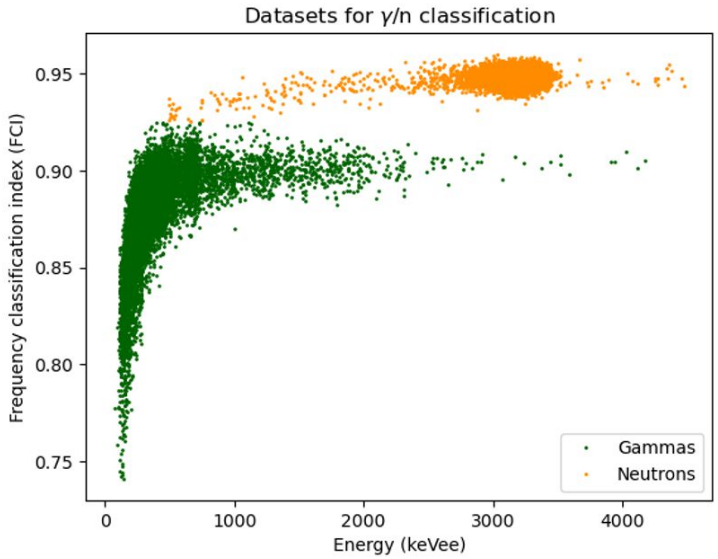


*Morales, I. R., Crespo, M. L., Bogovac, M., Cicuttin, A., Kanaki, K., & Carrato, S. (2023). Gamma/neutron classification with SiPM CLYC detectors using frequency-domain analysis for embedded real-time applications. Nuclear Engineering and Technology.*

Dataset from https://doi.org/10.5281/zenodo.8037059

# ML and SoC-FPGA for real-case applications

Gamma/neutron discrimination

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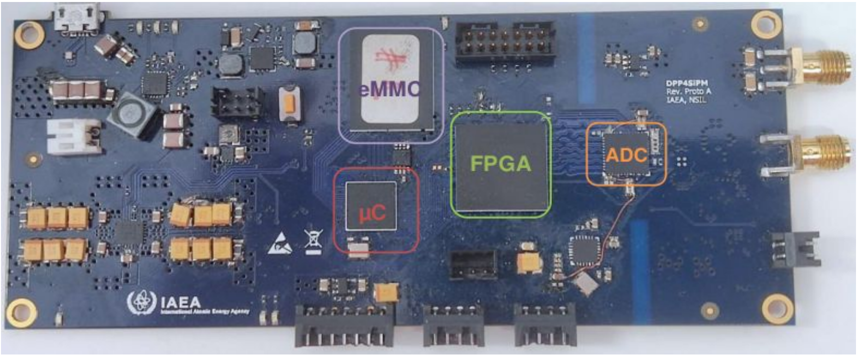


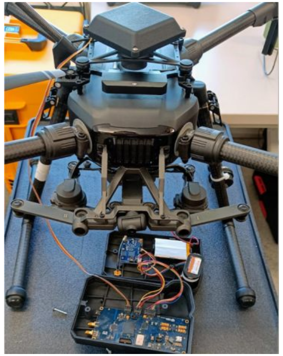

# ML and SoC-FPGA for real-case applications

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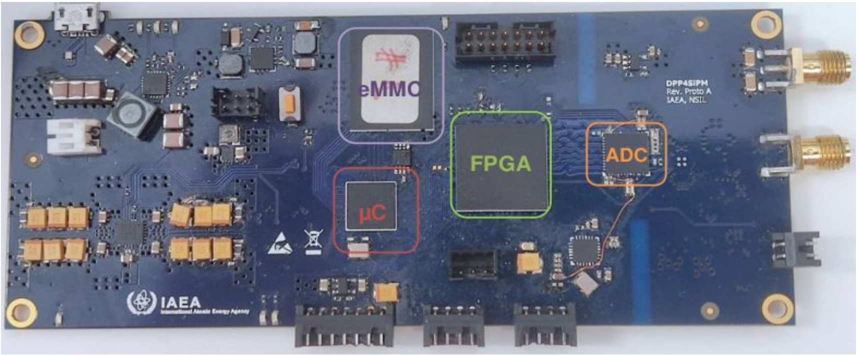


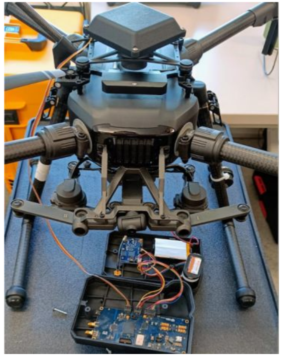

It accommodates various sub-assemblies, including: **(i)** input power monitoring and management sub-system, **(ii)** digital interface controller, **(iii)** digital signal processing block, **(iv)** data storage, and **(v)** analog interface domain.

# ML and SoC-FPGA for real-case applications

Gamma/neutron discrimination

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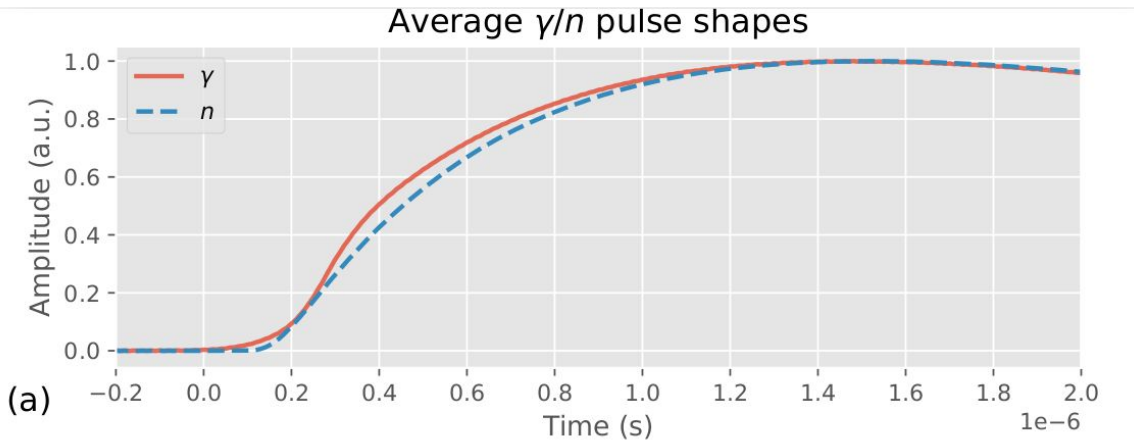

# ML and SoC-FPGA for real-case applications

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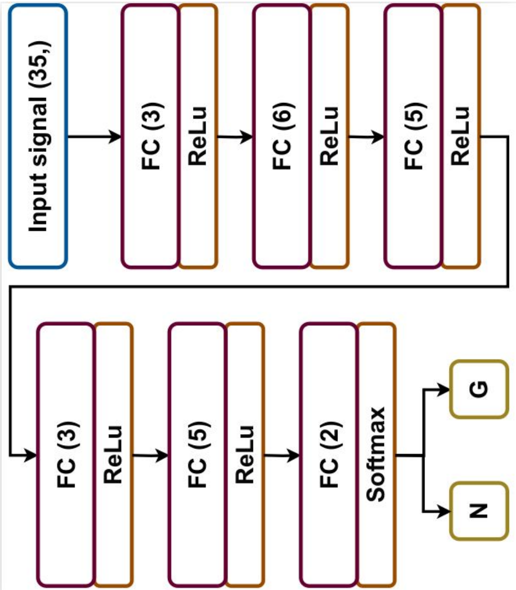

# ML and SoC-FPGA for real-case applications

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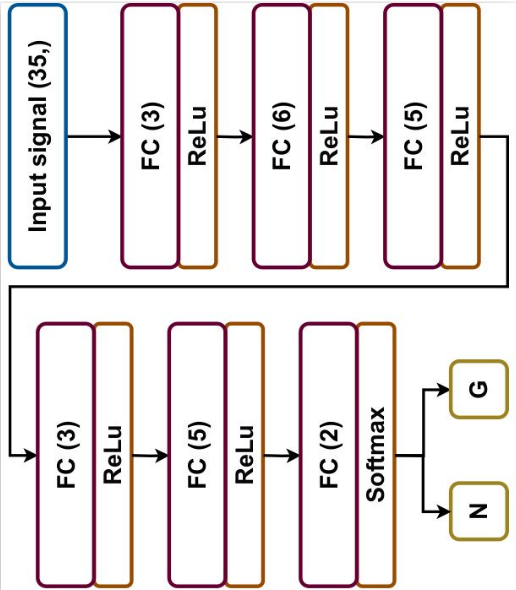


Teacher architecture with **2,623 parameters** distributed in 6 hidden layers (MLP).

Compressed architecture with **217 parameters**, distributed in 6 hidden layers (MLP).

**Input size reduction**:
35 samples of the leading edge of the pulse.

# ML and SoC-FPGA for real-case applications

**Gamma/neutron discrimination**

IAEA
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- **Overall accuracy**
  - Teacher architecture (original): **99.00%**
  - Student architecture (compressed): **98.20%**

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  - Artix-7 platform: **below 35%**

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---

- **SoC latency**
  - Zedboard platform: **45 clk cycles (@200MHz)**

# Image classification based on CNN

# ML and SoC-FPGA for real-case applications

Pest classification in fruit crops

Precision agriculture on the edge

# ML and SoC-FPGA for real-case applications

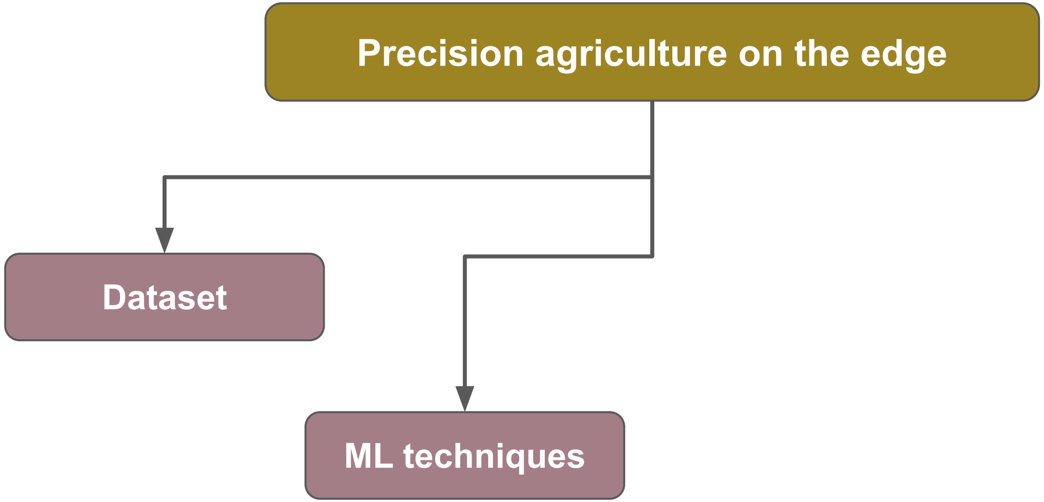
Pest classification in fruit crops

Precision agriculture on the edge

Dataset

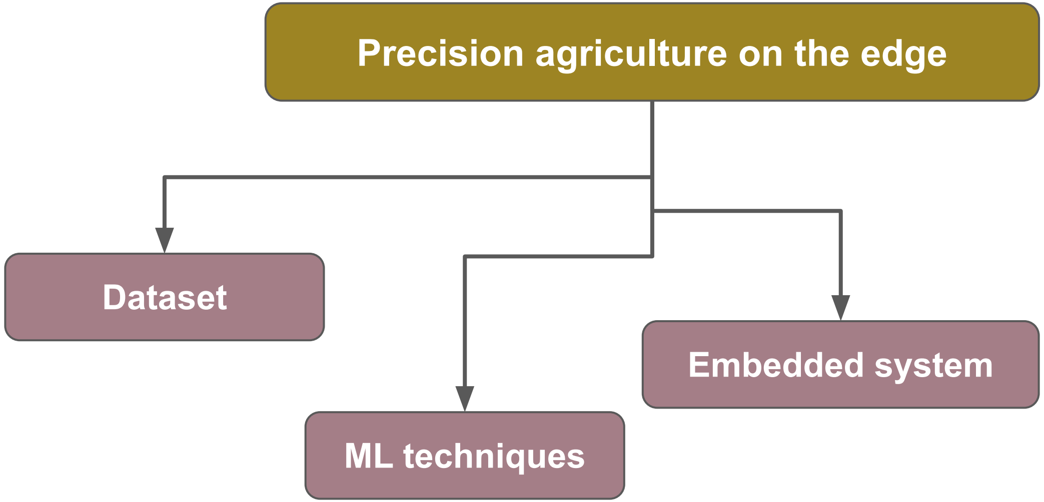
# ML and SoC-FPGA for real-case applications

Pest classification in fruit crops



# ML and SoC-FPGA for real-case applications

**Pest classification in fruit crops**



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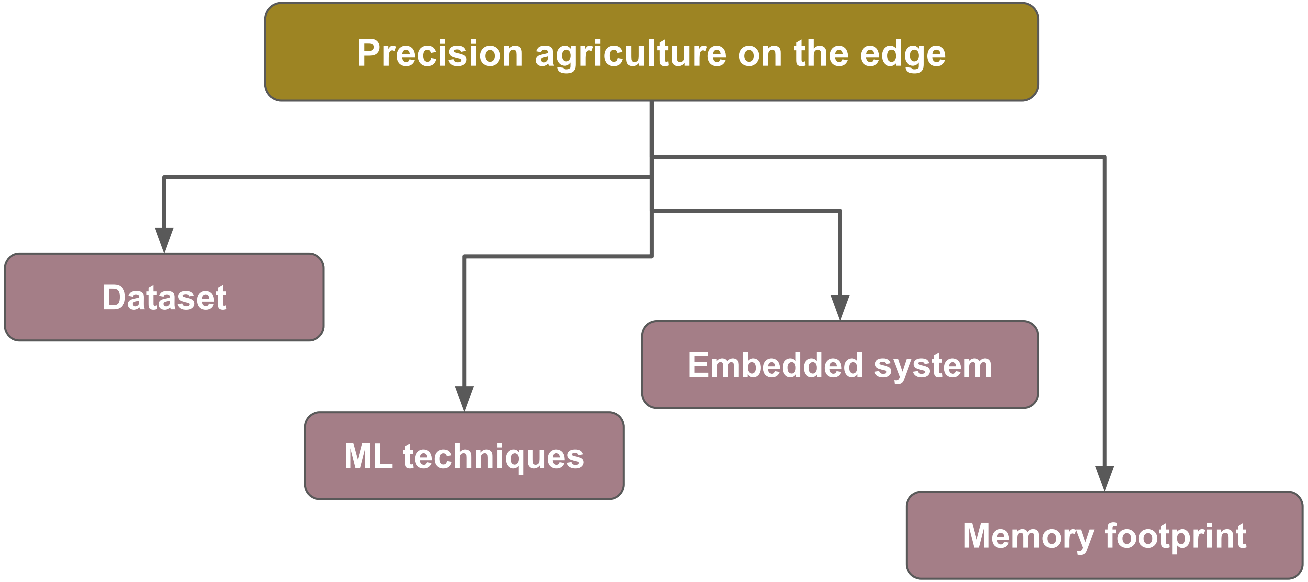


# ML and SoC-FPGA for real-case applications

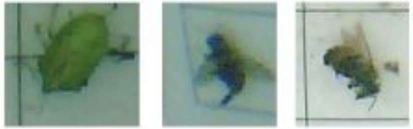
**Pest classification in fruit crops**

**Precision agriculture on the edge**

Nectras IoT trap

Captured image

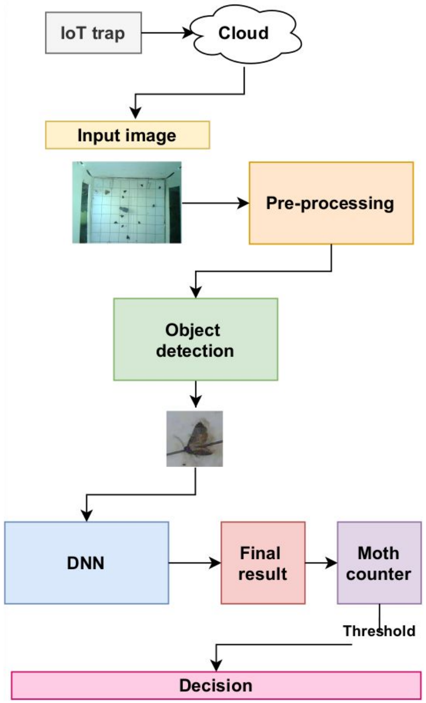
Other insects



Lobesia botrana

# ML and SoC-FPGA for real-case applications

Pest classification in fruit crops



# ML and SoC-FPGA for real-case applications

**Pest classification in fruit crops**

**Pest24 [6]**


A standard dataset available in the literature for training, granting a stable and effective performance.

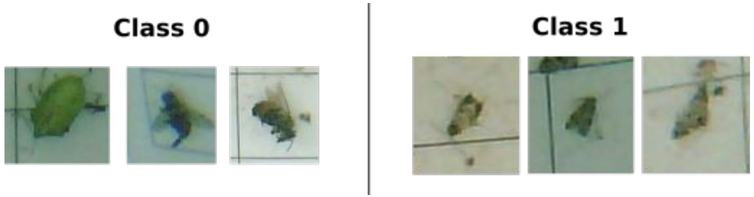
# ML and SoC-FPGA for real-case applications

**Pest classification in fruit crops**

**Pest24 [6]**


A standard dataset available in the literature for training, granting a stable and effective performance.

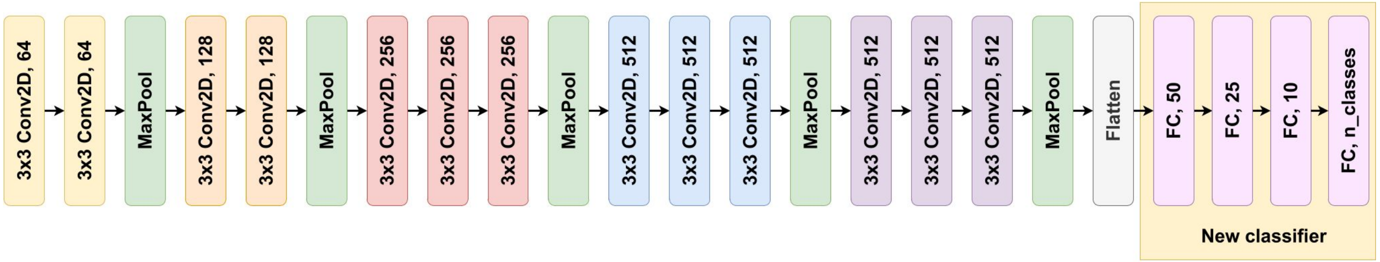
**Argentina**




Images provided by the system in Argentina.

# ML and SoC-FPGA for real-case applications

**Pest classification in fruit crops**




Teacher architecture based on VGG16 and obtained through transfer learning
– 14,818,706 parameters –

# ML and SoC-FPGA for real-case applications

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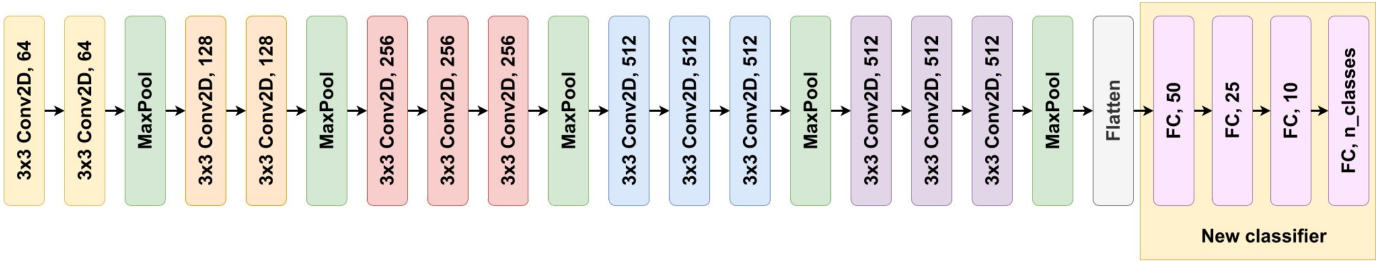


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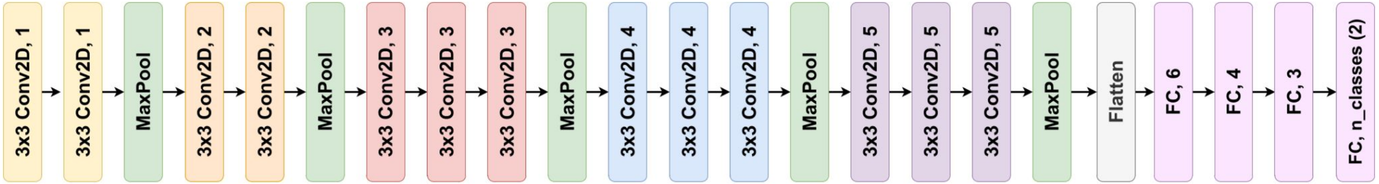
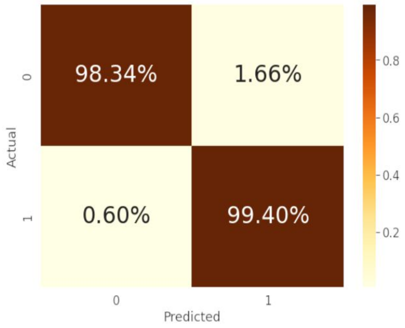



Compressed architecture.
**Compression ratio: 7,409*x*** – in number of parameters –

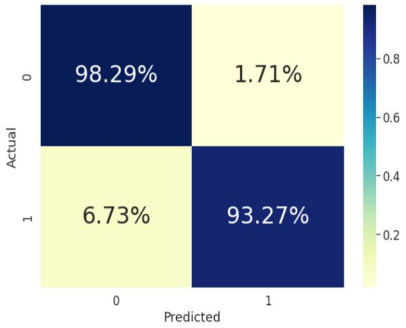
# ML and SoC-FPGA for real-case applications

**Pest classification in fruit crops**

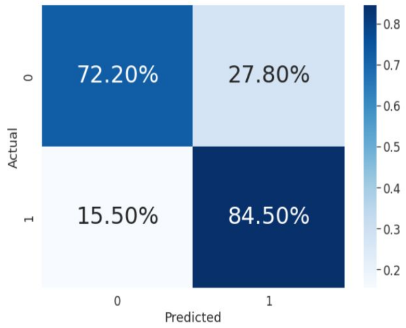
1 - Teacher




2 - QStudentFPGA - Pest24




3 - QStudentFPGA - Arg



# ML and SoC-FPGA for real-case applications

Pest classification in fruit crops

- **Overall accuracy**
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  - Student architecture: **95.78%**

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---

- **SoC memory footprint in terms of resource utilization @200MHz**
  - KRIA platform: **below 21%**
  - PYNQ-Z1 platform: **below 63%**

# ML and SoC-FPGA for real-case applications

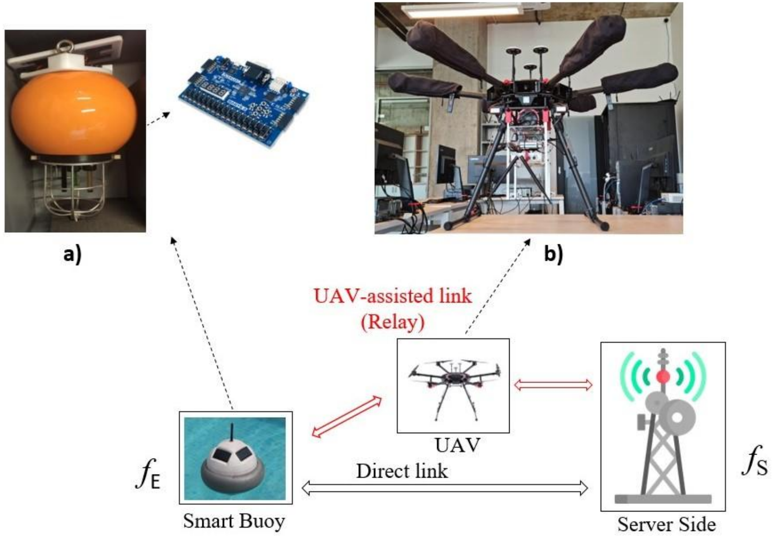
**Water quality monitoring**

**Dunav River,
Novi Sad, Serbia**

# ML and SoC-FPGA for real-case applications

Water quality monitoring

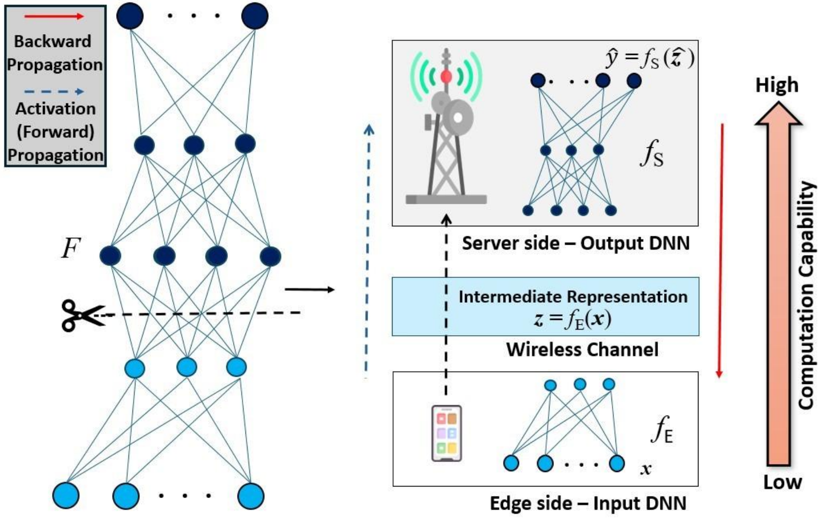
- **Hardware setup**



# ML and SoC-FPGA for real-case applications

Water quality monitoring

- **Split-inference stage**



# ML and SoC-FPGA for real-case applications

Water quality monitoring

PERFORMANCE EVALUATION OF THE TEACHER (LSTM-DO-T) AND STUDENT (LSTM-DO-S) MODELS.

| **Model** | **Parameters** | **Size [KB]** | **MAE** | **MSE** | $R^2$ |
|---|---|---|---|---|---|
| LSTM-DO-T | 39,951 | 156.06 | 0.0520 | 0.0081 | 0.97 |
| LSTM-DO-S | 871 | 3.40 | 0.0574 | 0.0087 | 0.96 |

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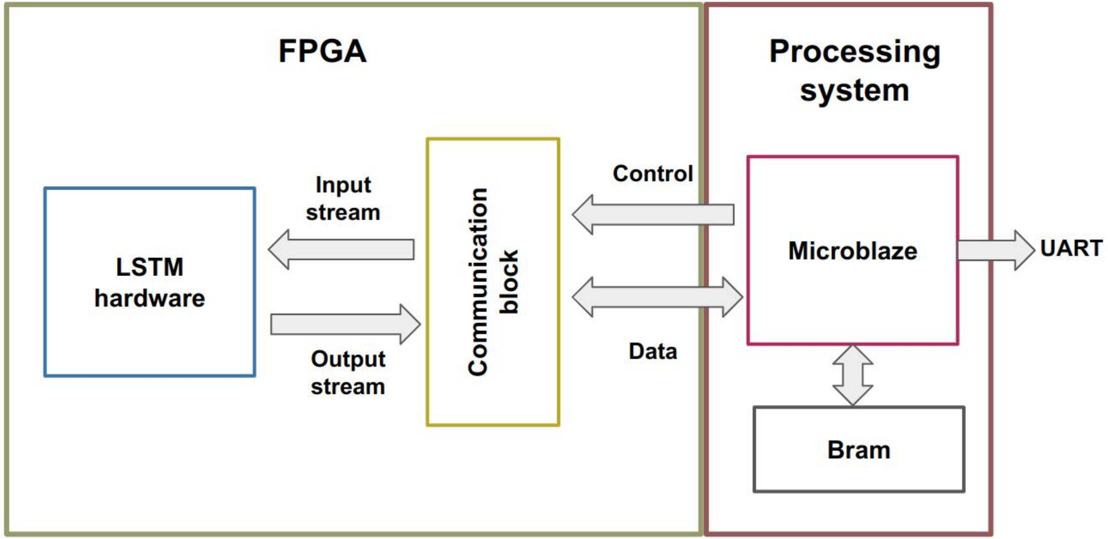
- **Three LSTM inference variations**
  - LSTM-DO-S: the complete student network,
  - Split-A: a configuration with two stacked LSTM layers,
  - Split-B: a configuration containing a single LSTM layer.

# ML and SoC-FPGA for real-case applications

Water quality monitoring

- **Block design**



ICTP The Abdus Salam International Centre for Theoretical Physics

# ML and SoC-FPGA for real-case applications

Water quality monitoring

- **Results - LSTM Inference stage**

IMPLEMENTATION RESULTS FOR LSTM-BASED ACCELERATORS. FPGA PART: XC7A35TCSG325-1.

| Metrics | LSTM-DO-S | Split-A | Split-B |
|---|---|---|---|
| **BRAM** | 31% | 16% | 20% |
| **DSP** | 55% | 33% | 17.7% |
| **LUT** | 50% | 40% | 28% |
| **FF** | 17% | 16% | 13% |
| **Overall max utilization** | 61% | 60% | 48% |
| **Latency** [$\mu s$] | 2.82 | 2.85 | 3.54 |
| **Frequency [MHz]** | 80 | 80 | 80 |
| **Scalability** | 1 | 1 | 2 |
| **Power consumption [W]** | 0.887 | 0.862 | 0.829 |

# ML and SoC-FPGA for real-case applications

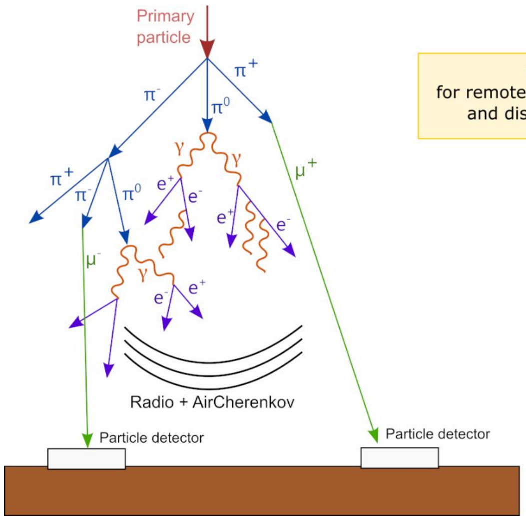
**Water quality monitoring**

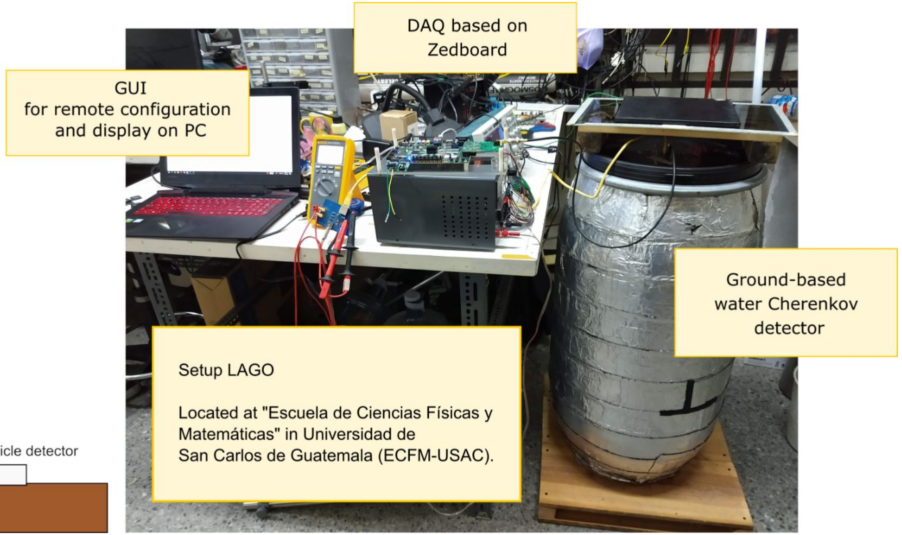
- **Design trade-offs:**
  - high performance that comes with higher resource and power demands,
  - balanced design that attempts to optimize both performance and resource utilization,
  - efficiency-oriented that prioritizes lower resource and power consumption, sometimes at the expense of speed.

# Pulse shape discriminator
# for cosmic rays studies

# ML and SoC-FPGA for real-case applications

**Pulse shape discriminator for cosmic rays studies**



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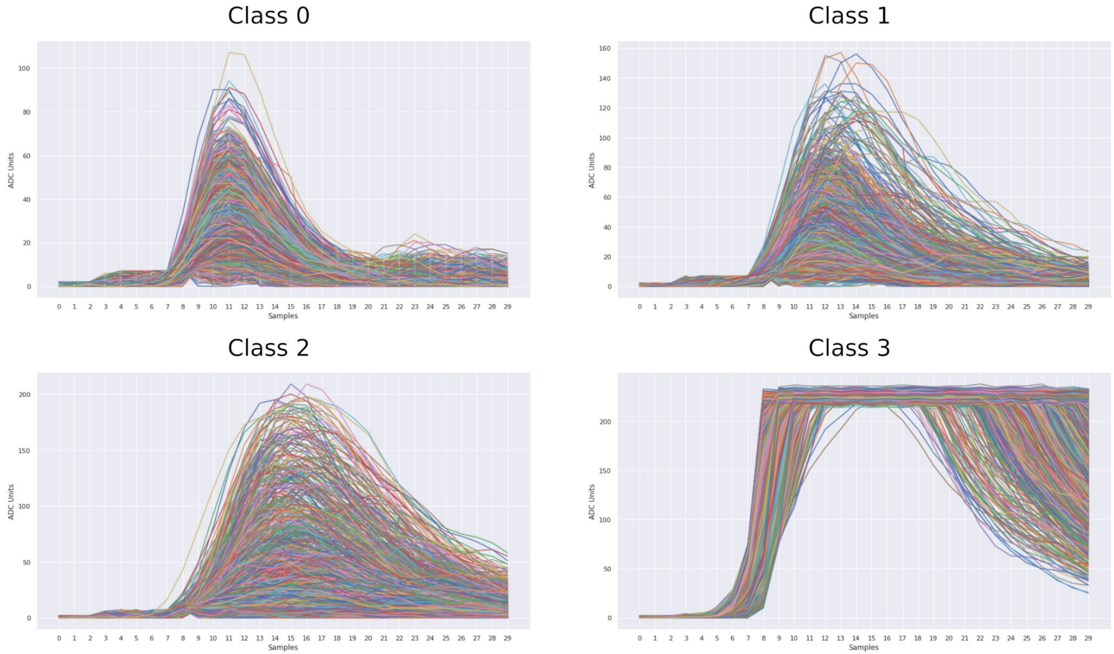
Pulse shape discriminator for cosmic rays studies



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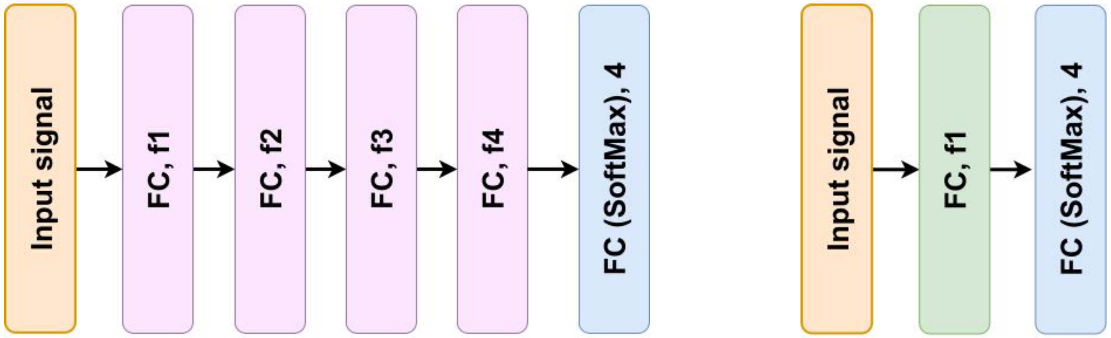


**Left.** Teacher architecture based on MLP - **16,352** parameters.

**Right:** Distilled architecture - **529** parameters
Compression ratio: 30.91*x.*

# ML and SoC-FPGA for real-case applications

**Pulse shape discriminator for cosmic rays studies**

- **Overall accuracy**
    - Teacher architecture: **99.70%**
    - Student architecture: **98.96%**
        - **8-bit fixed point**
        - **Target sparsity: 20%**

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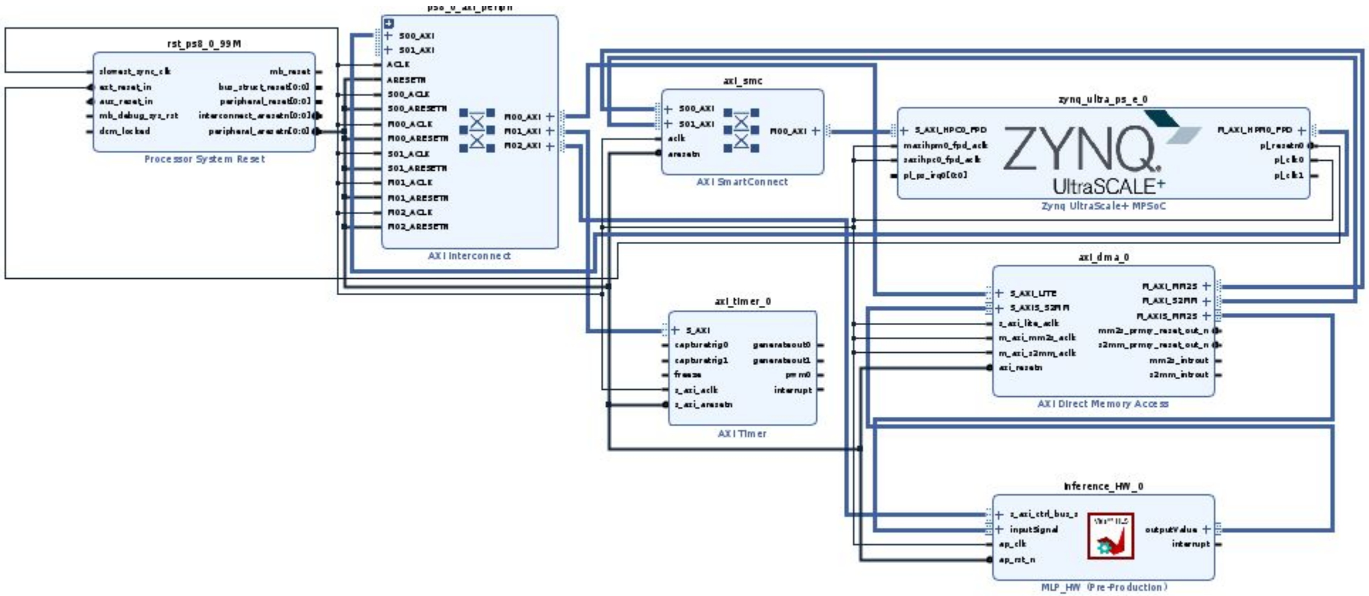
- **SoC latency @200MHz**
  - Artix-7: **10 clock cycles**

# ML and SoC-FPGA for real-case applications

Pulse shape discriminator for cosmic rays studies



# ML and SoC-FPGA for real-case applications

Pulse shape discriminator for cosmic rays studies

## Pulse shape discriminator for cosmic rays

In [ ]:
```
from pynq import Overlay
```

In [ ]:
```
ol = Overlay("hw/inference_PYNQ.bit")
```

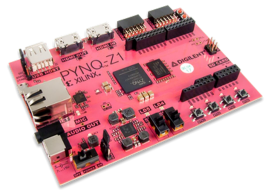
In [ ]:
```
ol.ip_dict
```

In [ ]:
```
dma = ol.axi_dma_0
dma_send = ol.axi_dma_0.sendchannel
dma_recv = ol.axi_dma_0.recvchannel
```

In [ ]:
```
from pynq import allocate
import numpy as np

data_size = 30
input_buffer = allocate(shape=(data_size,), dtype=np.uint32)
```

In [ ]:
```
x3 = [0, 2, 0, 0, 0, 0, 2, 14, 68, 231, 232, 232, 232, 230, 232,
      231, 233, 232, 231, 231, 232, 232, 231, 230, 232, 231, 232, 231, 231, 230]
for i in range(0, data_size):
    input_buffer[i] = x3[i]
```

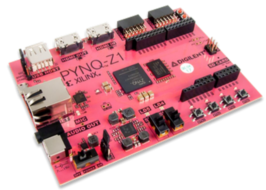
In [ ]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(15,7))
plt.xlabel('Samples', fontsize=11)
plt.ylabel('Amplitude', fontsize=11)
plt.grid(True, alpha=1.0)
plt.plot(x3, 'o', label="Signal 1", color='navy', markersize=7, lw=1)
```



# ML and SoC-FPGA for real-case applications

**Pulse shape discriminator for cosmic rays studies**

```
In [ ]: hls_ip = ol.inference_HW_0

In [ ]: hls_ip.register_map

In [ ]: # Initialize HLS IP core

        CONTROL_REGISTER = 0x0
        hls_ip.write(CONTROL_REGISTER, 0x81) # 0x81 will set bit 0

In [ ]: hls_ip.register_map

In [ ]: # Start the DMA transfer
        dma_send.transfer(input_buffer)

In [ ]: output_buffer = allocate(shape=(4,), dtype=np.uint32)

In [ ]: dma_recv.transfer(output_buffer)

In [ ]: for i in range(4):
            print((output_buffer[i]))
```




PYNQ™

# Copahue volcano seismic event detection

# ML and SoC-FPGA for real-case applications

**Copahue volcano seismic event detection**

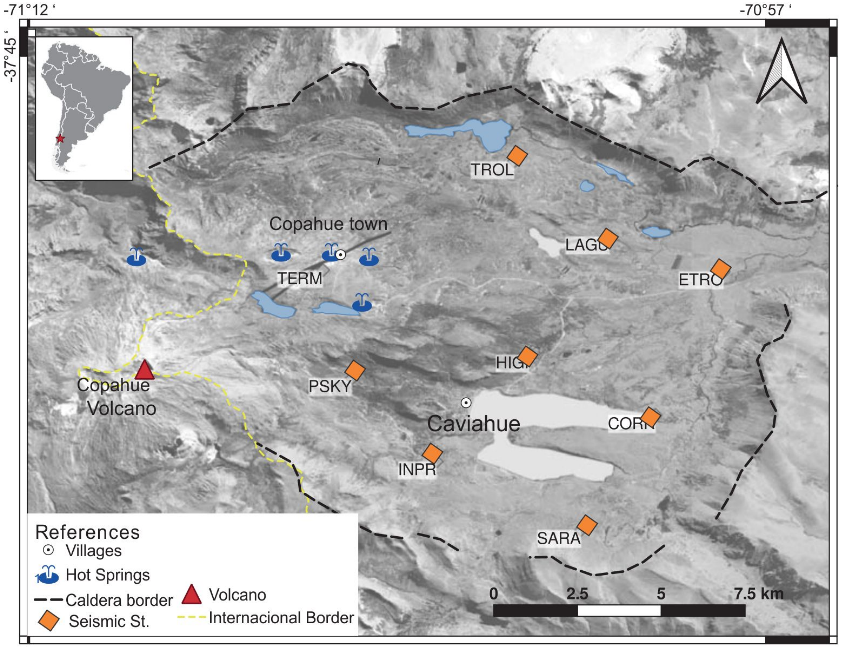
## Copahue Volcano


- Active stratovolcano located on the border between Argentina and Chile.
- Its summit is at an altitude of 2,997 m.

# ML and SoC-FPGA for real-case applications

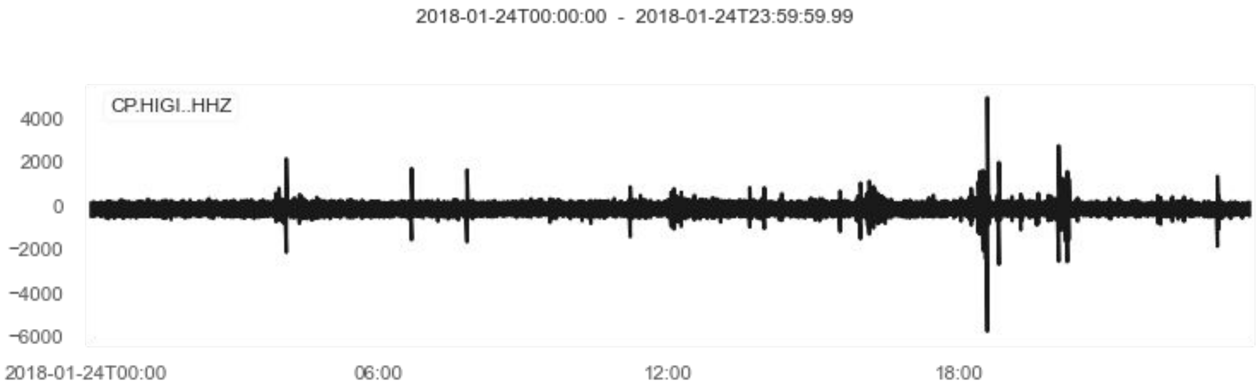
Copahue volcano seismic event detection

**Copahue Volcano**



# ML and SoC-FPGA for real-case applications

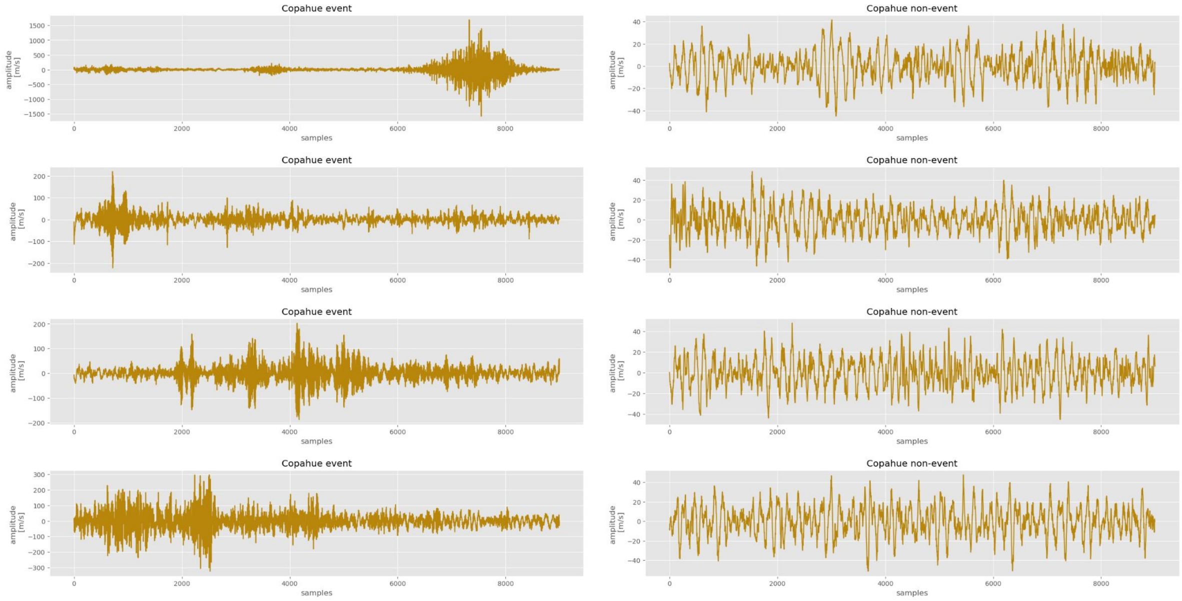
**Copahue volcano seismic event detection**




The signals used in this research were obtained from Montenegro's Ph.D. thesis [1], and were provided by "Laboratorio de Estudios y Seguimientos de Volcanes Activos’ (LESVA), Universidad Nacional de Rio Negro.

# ML and SoC-FPGA for real-case applications

Copahue volcano seismic event detection



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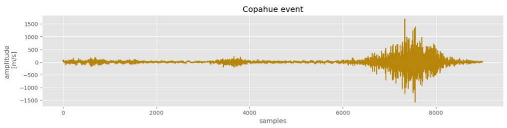
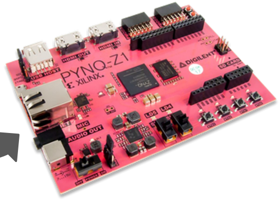
**Copahue volcano seismic event detection**




**Compressed model**



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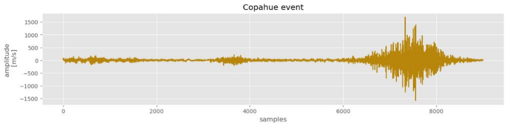
Copahue volcano seismic event detection

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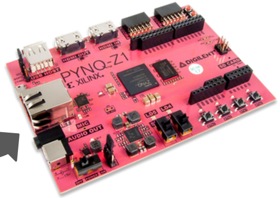

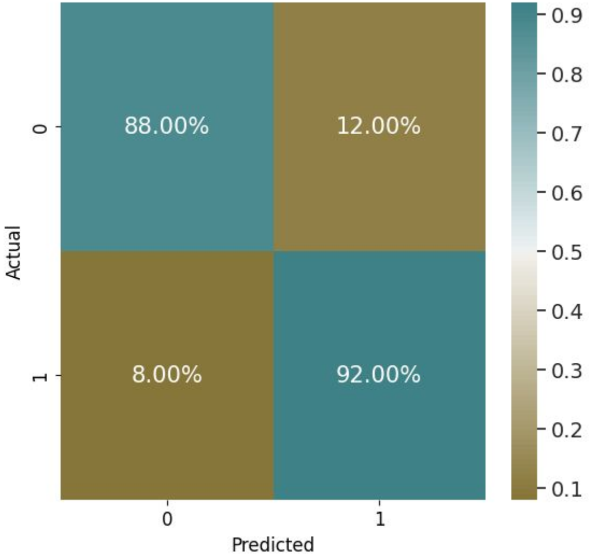

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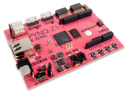
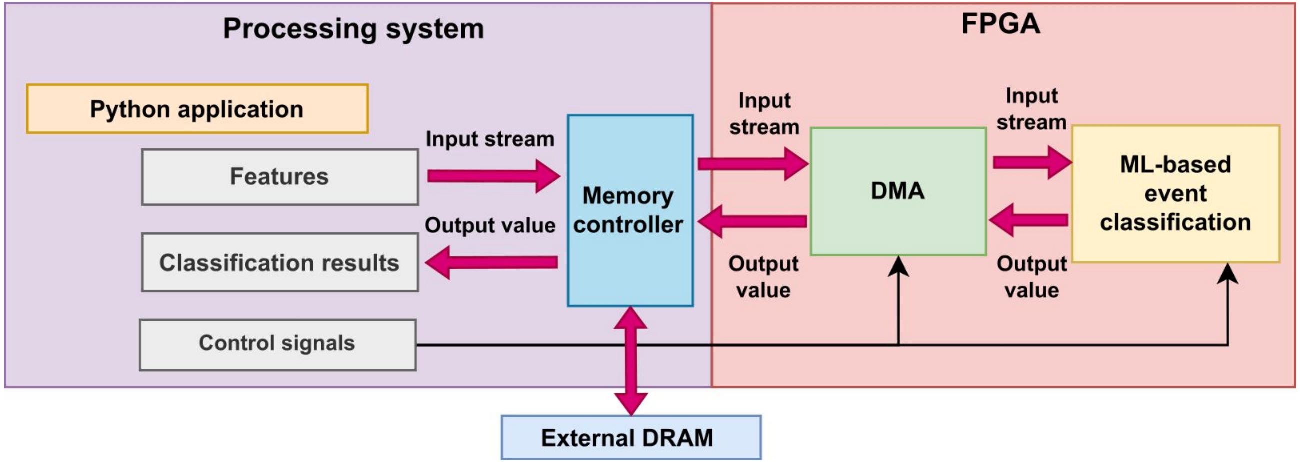
PYNQ



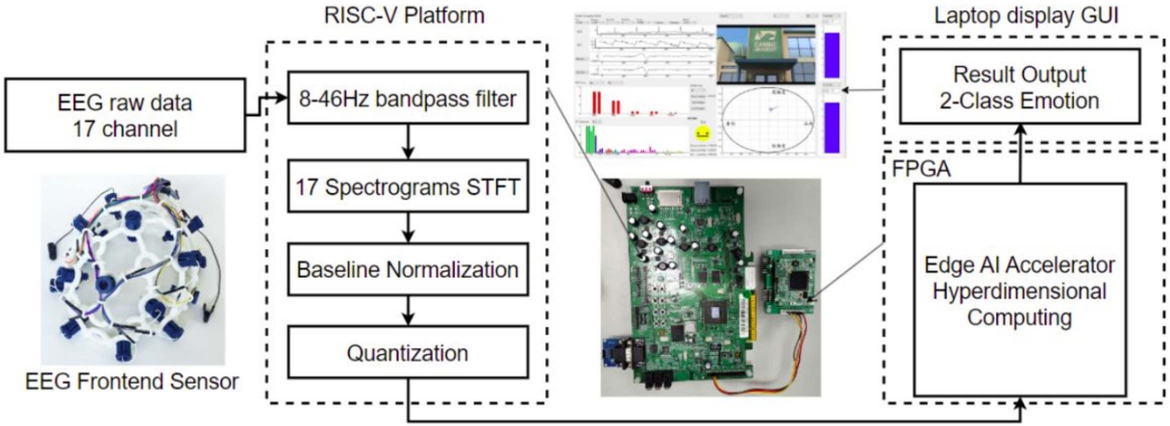


# Applications based on the state of the art

# ML and embedded systems for real-case applications

**Emotion recognition**

An Edge AI Accelerator Design Based on HDC Model for Real-time EEG-based Emotion Recognition System with RISC-V FPGA Platform [1]




[1] Li, J. Y., & Fang, W. C. (2024, May). An edge ai accelerator design based on hdc model for real-time eeg-based emotion recognition system with risc-v fpga platform. In *2024 IEEE International Symposium on Circuits and Systems (ISCAS)* (pp. 1-5). IEEE.

# ML and embedded systems for real-case applications

**Railway Fault Detection**

An Efficient FPGA-Based Edge AI System for Railway Fault Detection [2]

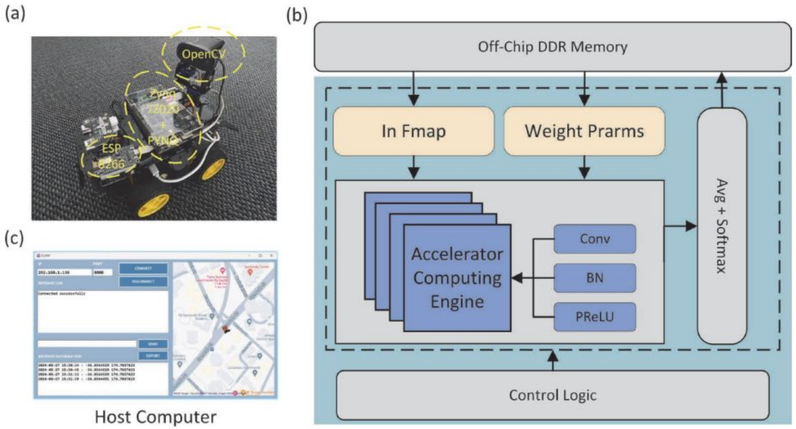


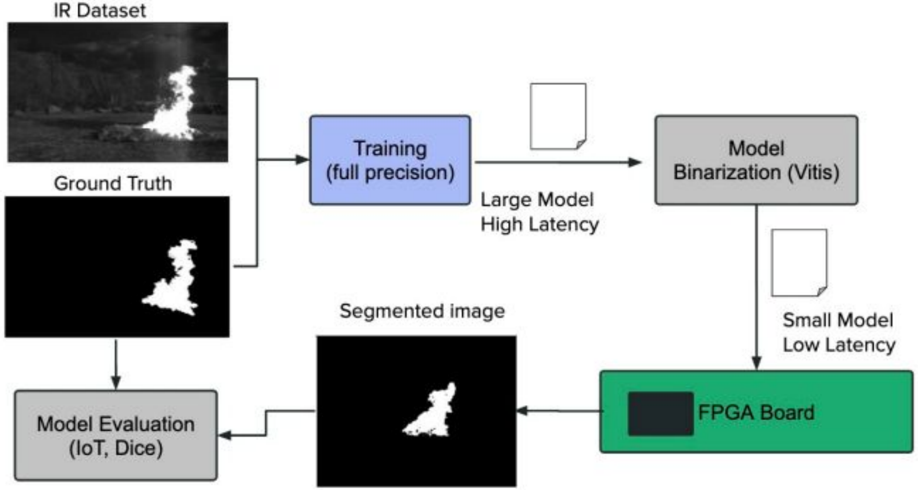

**FIGURE 1.** Railway faults detection system. (a) System components. (b) Hardware accelerator computation module. (c) Communication module and host computer interface.

[2] Fu, Y., Yan, D., Li, J., Ma, S. L., Sham, C. W., & Chou, H. F. (2025). An Efficient FPGA-Based Edge AI System for Railway Fault Detection. IEEE Consumer Electronics Magazine.

# ML and embedded systems for real-case applications

**Drone wildfire imagery**

An FPGA smart camera implementation of segmentation models for drone wildfire imagery [3]





[3] Garduño, E., Ciprian-Sanchez, J., Vazquez-Garcia, V., Gonzalez-Mendoza, M., Rodriguez-Hernandez, G., Palacios-Rosas, A., ... & Ochoa-Ruiz, G. (2023). An FPGA smart camera implementation of segmentation models for drone wildfire imagery. Computación y Sistemas, 27(4), 965-977.

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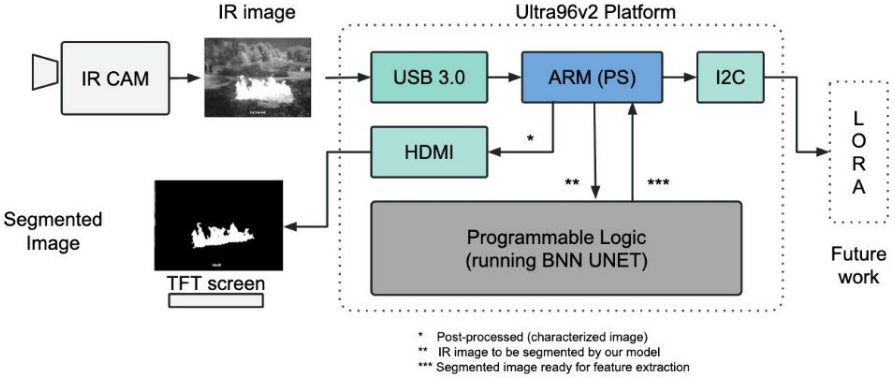


[3] Garduño, E., Ciprian-Sanchez, J., Vazquez-Garcia, V., Gonzalez-Mendoza, M., Rodriguez-Hernandez, G., Palacios-Rosas, A., ... & Ochoa-Ruiz, G. (2023). An FPGA smart camera implementation of segmentation models for drone wildfire imagery. Computación y Sistemas, 27(4), 965-977.

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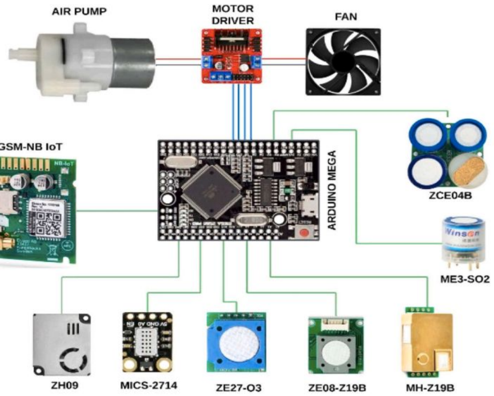
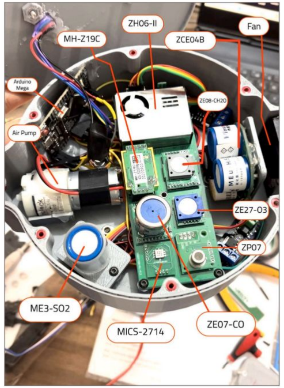
# ML and embedded systems for real-case applications

**Monitoring and forecasting of air pollution**

Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment [4]




[4] Ramadan, M. N., Ali, M. A., Khoo, S. Y., Alkhedher, M., & Alherbawi, M. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. Ecotoxicology and environmental safety, 283, 116856.

# ML and embedded systems for real-case applications

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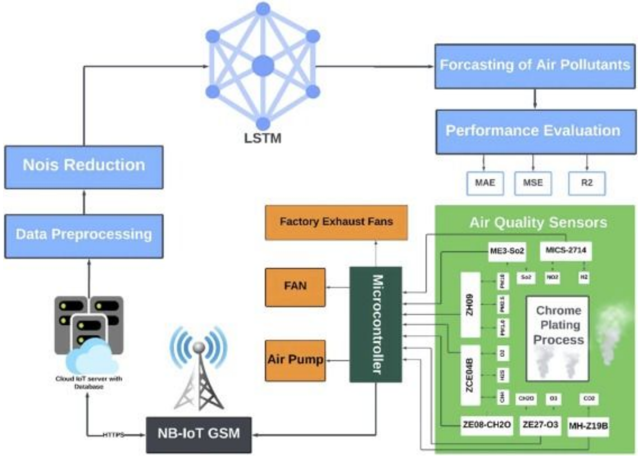
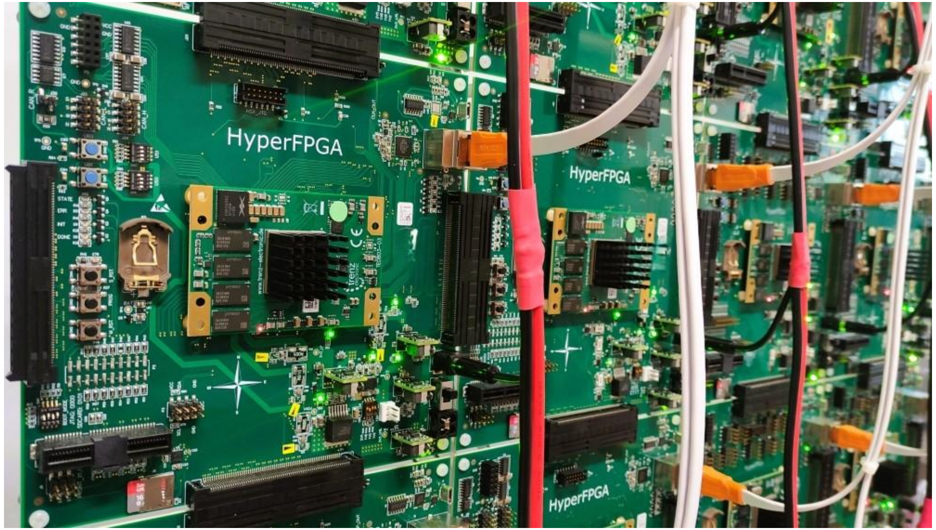
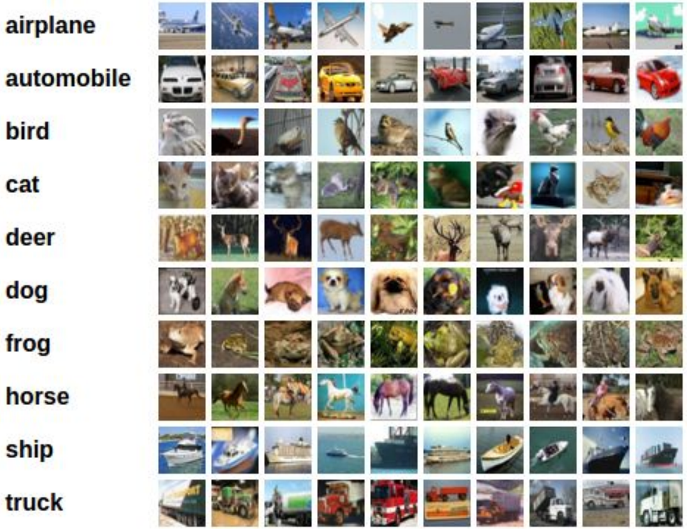



[4] Ramadan, M. N., Ali, M. A., Khoo, S. Y., Alkhedher, M., & Alherbawi, M. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. Ecotoxicology and environmental safety, 283, 116856.

# Demo:

## CIFAR-10 classification running on the HyperFPGA


HyperFPGA
HyperFPGA
HyperFPGA


airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck

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# Machine Learning and SoC-based FPGA for real-case applications

**Romina Soledad Molina, Ph.D.**
MLab-STI, ICTP

Perú - Online - 2025 -

Universidad Tecnológica del Perú