



The Abdus Salam
**International Centre
for Theoretical Physics**

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

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

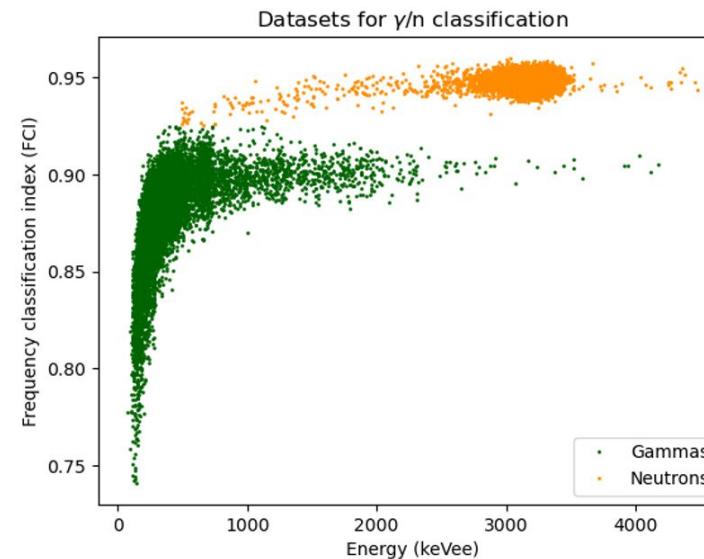
- Tagged dataset of **gamma and neutron events** from **Deuterium-Deuterium (DD)** and **Deuterium-Tritium (DT)** generators.
- The dataset was recorded at the **Neutron Science Facility (NSF)** of the **Nuclear Science and Instrumentation Laboratory (NSIL)**, IAEA.
- The detector is based on a small **CLYC** ($\text{Cs}_2\text{LiYCl}_6:\text{Ce}$) crystal (0.5 in diameter by 30 mm length) coupled to a 4-element SiPM array.
- The data were **sampling 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



IAEA
International Atomic Energy Agency



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



IAEA
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ML and SoC-FPGA for real-case applications

Gamma/neutron
discrimination



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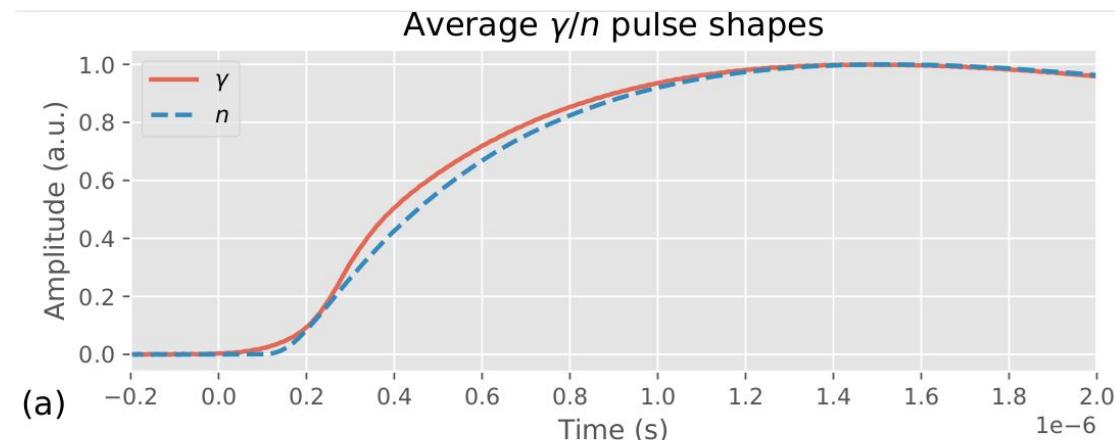
It accommodates various sub-assemblies, including: **(i)** input power monitoring and management sub-system, **(ii)** digital interface controller, **(iii)** digital signal processing block, **(iv)** data storage, and **(v)** analog interface domain.

ML and SoC-FPGA for real-case applications

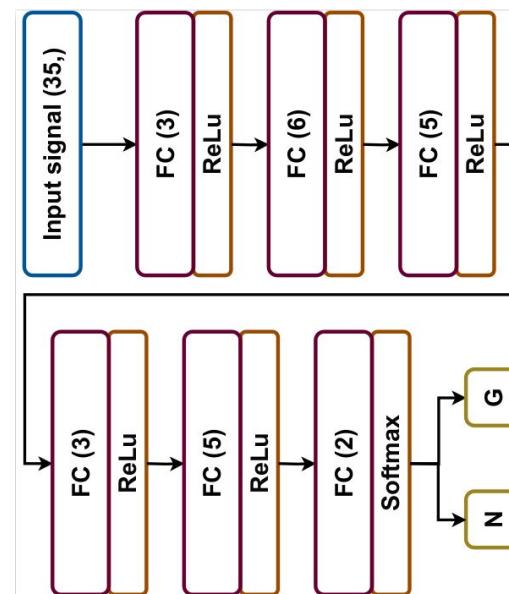
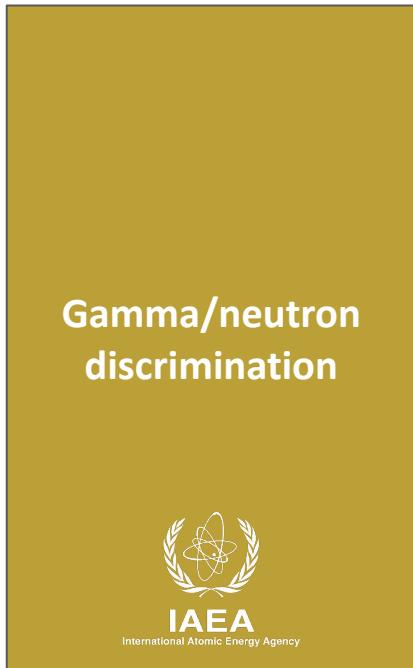
Gamma/neutron
discrimination



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ML and SoC-FPGA for real-case applications

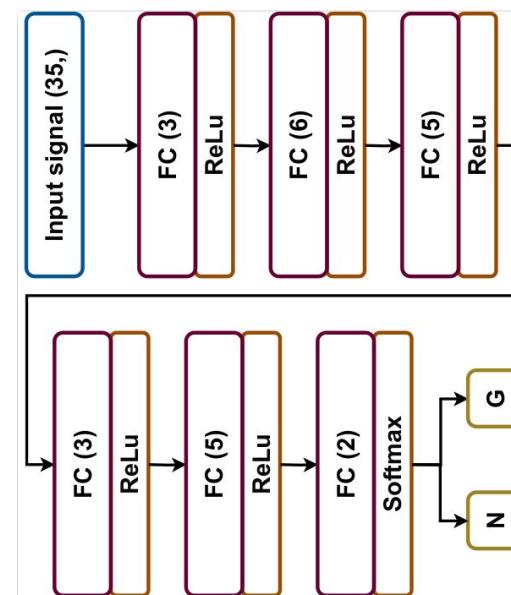


ML and SoC-FPGA for real-case applications

Gamma/neutron
discrimination



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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



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

ML and SoC-FPGA for real-case applications

Gamma/neutron
discrimination



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- Overall accuracy
 - Teacher architecture (original): **99.00%**
 - Student architecture (compressed): **98.20%**
- SoC memory footprint in terms of resource utilization @200MHz
 - Artix-7 platform: **below 35%**

ML and SoC-FPGA for real-case applications

Gamma/neutron
discrimination



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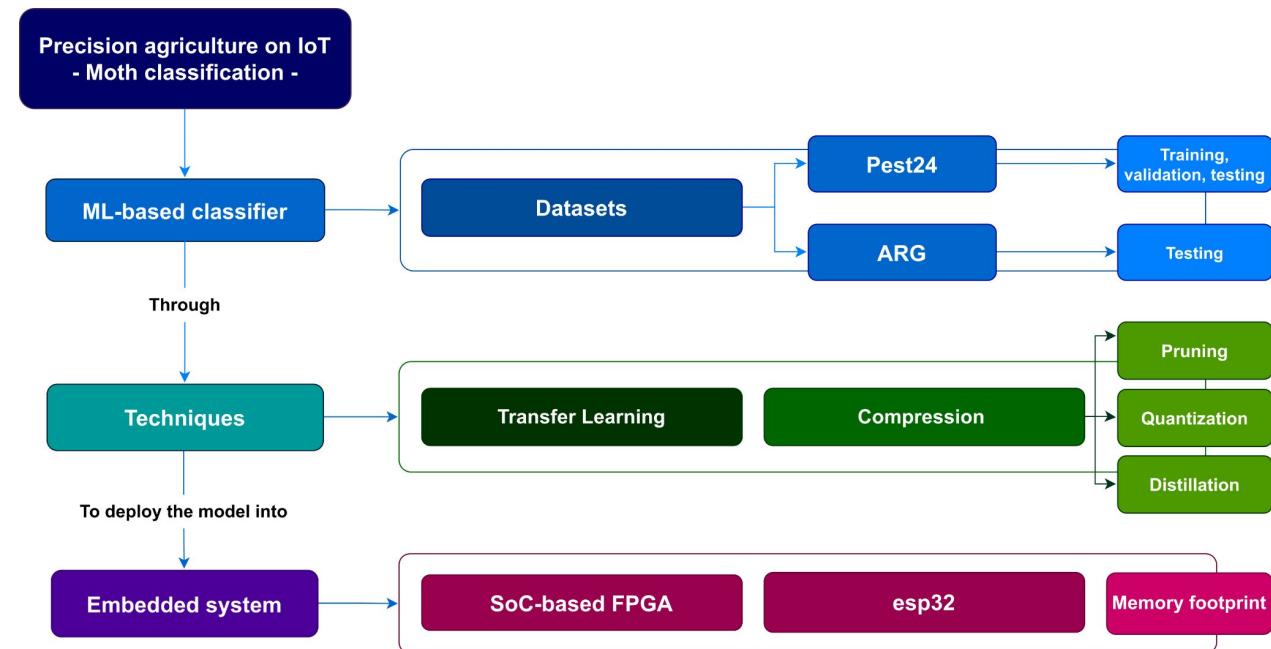
- Overall accuracy
 - Teacher architecture (original): **99.00%**
 - Student architecture (compressed): **98.20%**
- SoC memory footprint in terms of resource utilization @200MHz
 - Artix-7 platform: **below 35%**
- SoC latency
 - Artix-7 platform: **45 clk cycles (@200MHz)**



Image classification based on CNN

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

Precision agriculture on the edge

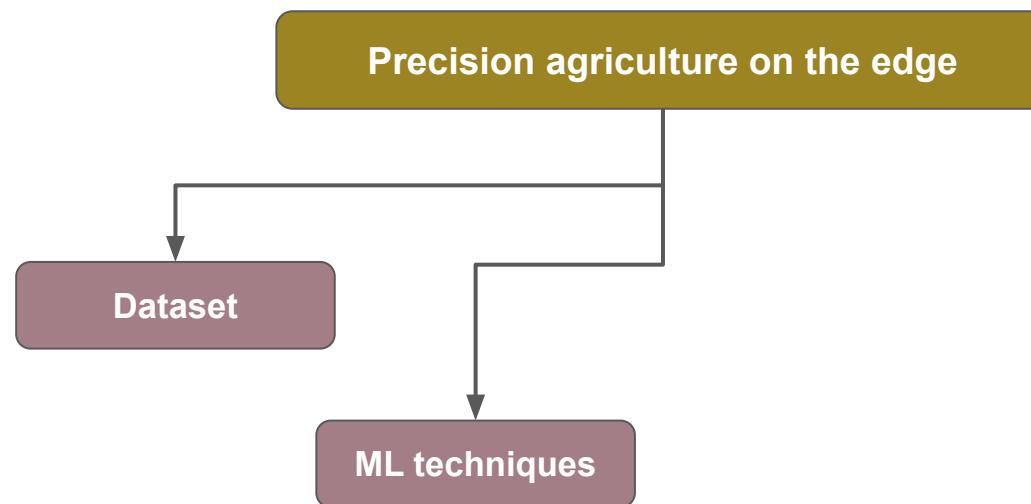
ML and SoC-FPGA for real-case applications



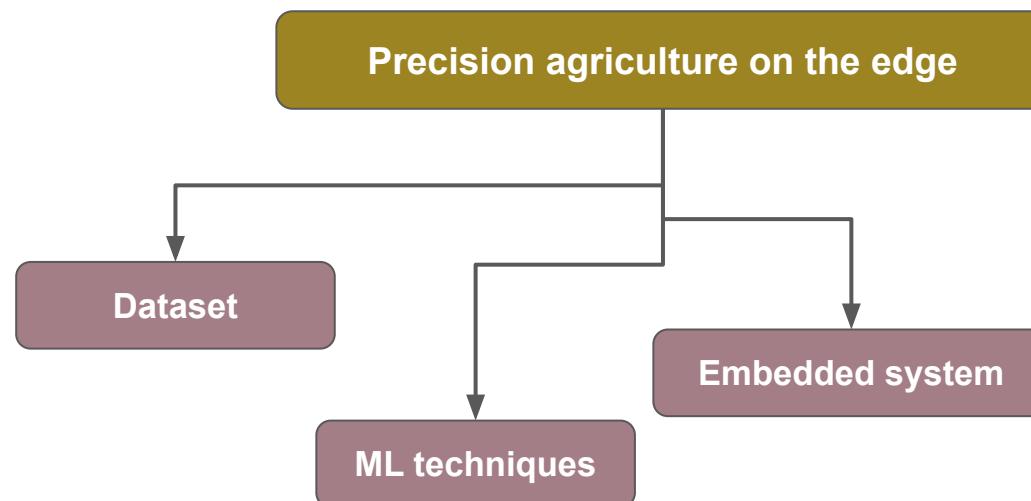
Precision agriculture on the edge

Dataset

ML and SoC-FPGA for real-case applications

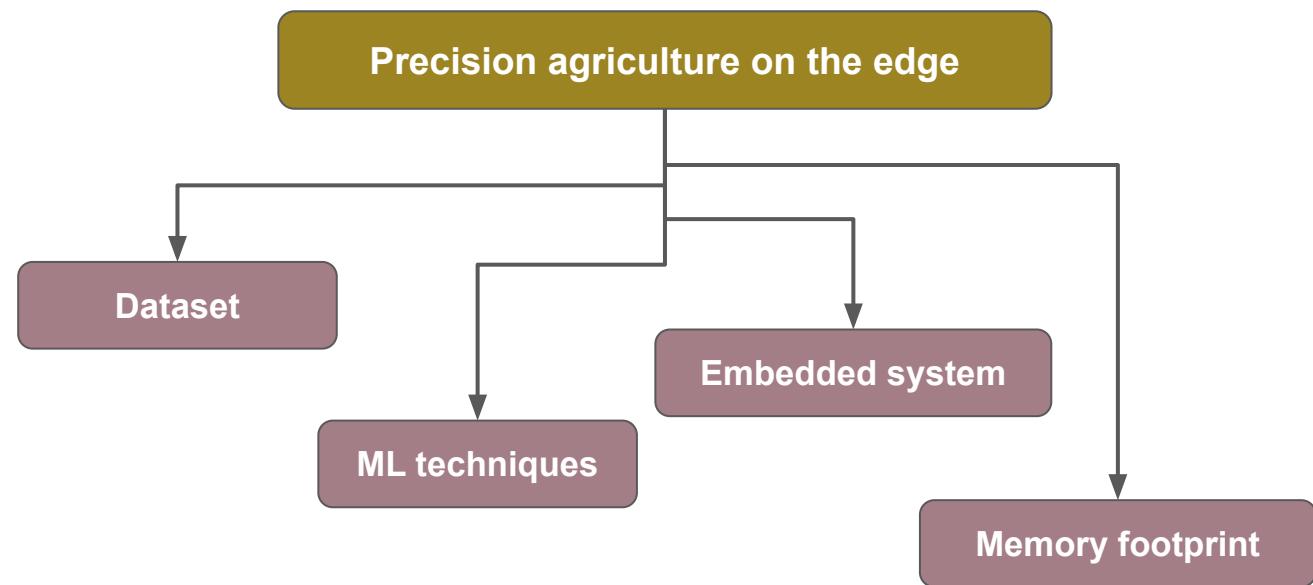


ML and SoC-FPGA for real-case applications



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

Nectras IoT trap

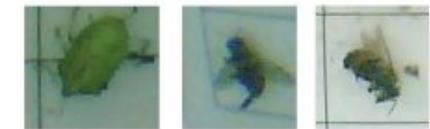


Precision agriculture on the edge

Captured image



Other insects

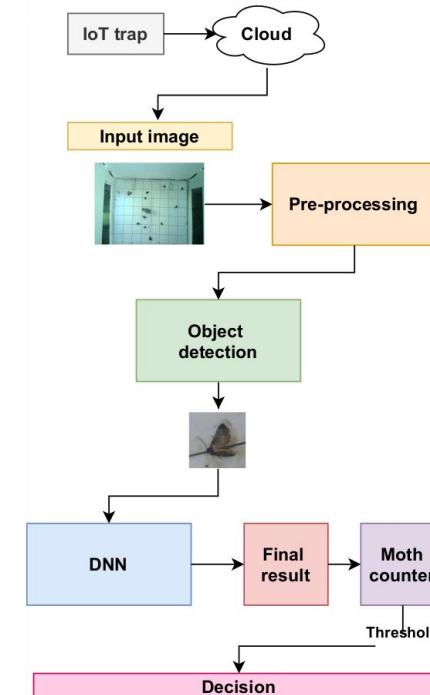


Lobesia botrana



ML and SoC-FPGA for real-case applications

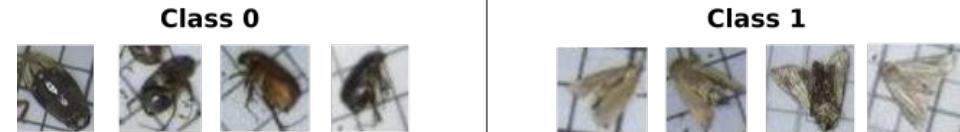
Pest classification
in fruit crops



ML and SoC-FPGA for real-case applications

Pest classification
in fruit crops

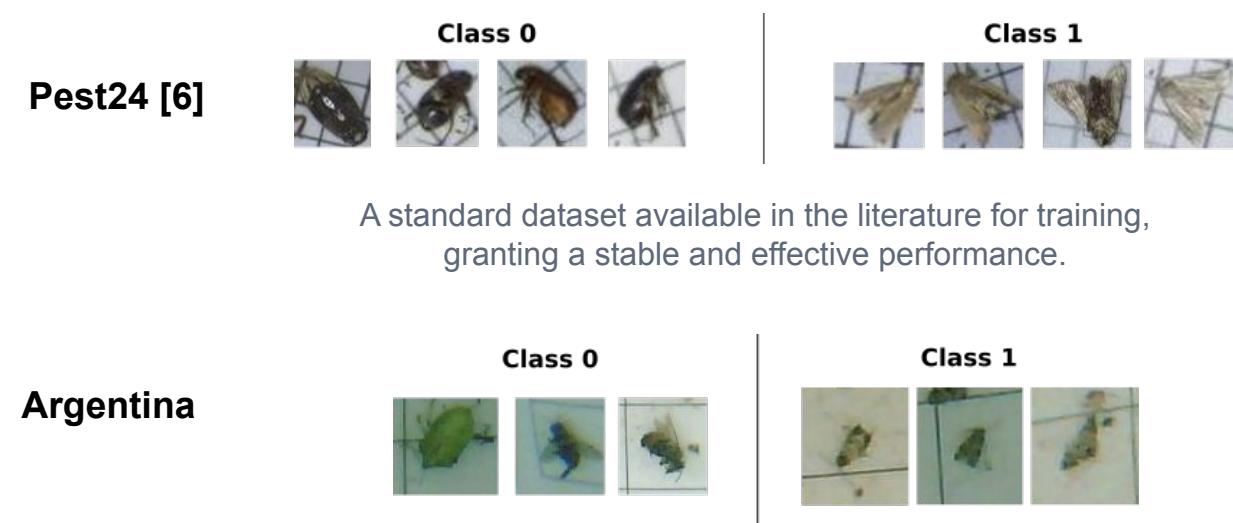
Pest24 [6]



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

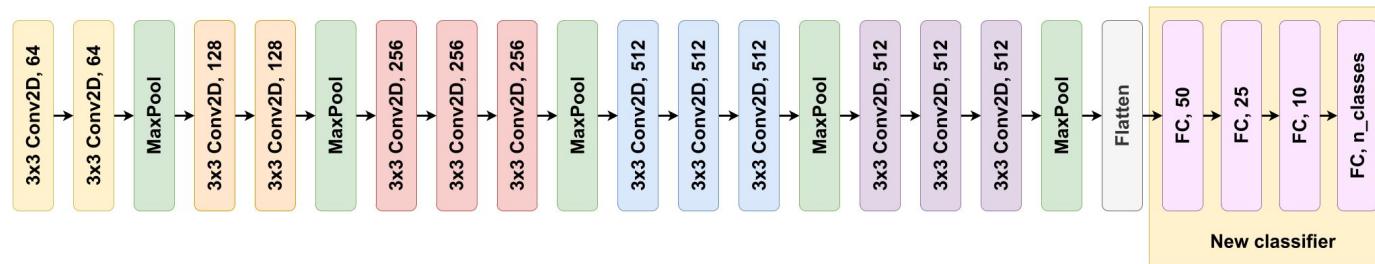


A standard dataset available in the literature for training,
granting a stable and effective performance.

Images provided by the system in Argentina.

ML and SoC-FPGA for real-case applications

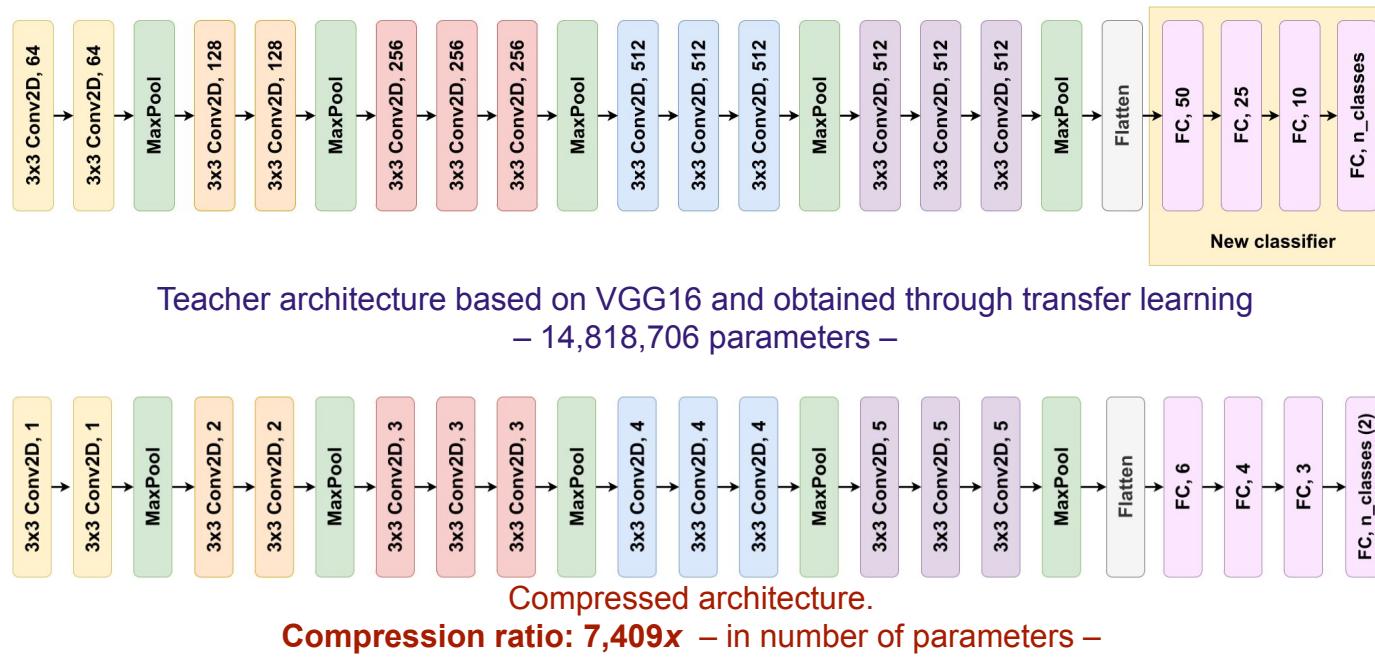
Pest classification
in fruit crops



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

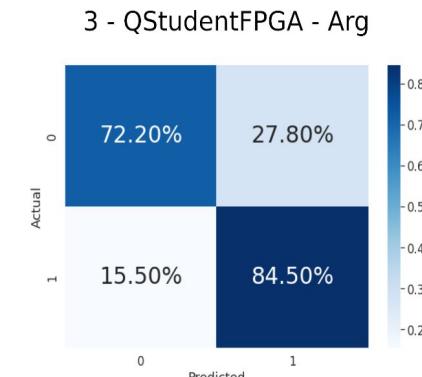
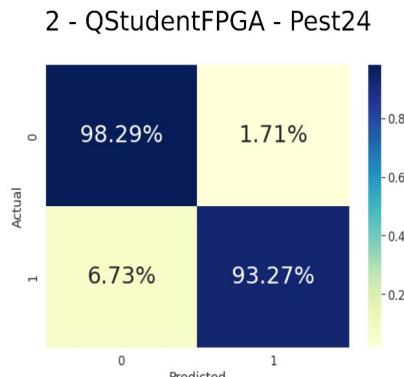
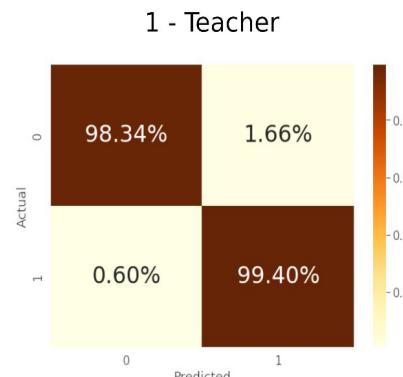
ML and SoC-FPGA for real-case applications

Pest classification
in fruit crops



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

- Overall accuracy
 - Teacher architecture: **98.87%**
 - Student architecture: **95.78%**
-

ML and SoC-FPGA for real-case applications

Pest classification
in fruit crops

- Overall accuracy
 - Teacher architecture: **98.87%**
 - Student architecture: **95.78%**
- SoC memory footprint in terms of resource utilization @200MHz
 - KRIA platform: **below 21%**
 - PYNQ-Z1 platform: **below 63%**



Water Quality Monitoring

ML and SoC-FPGA for real-case applications

Water quality
monitoring

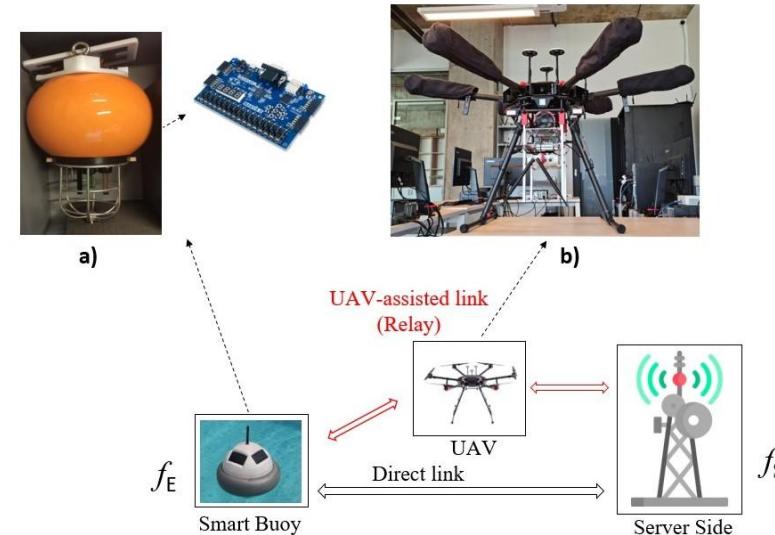


Dunav River,
Novi Sad, Serbia

ML and SoC-FPGA for real-case applications

Water quality
monitoring

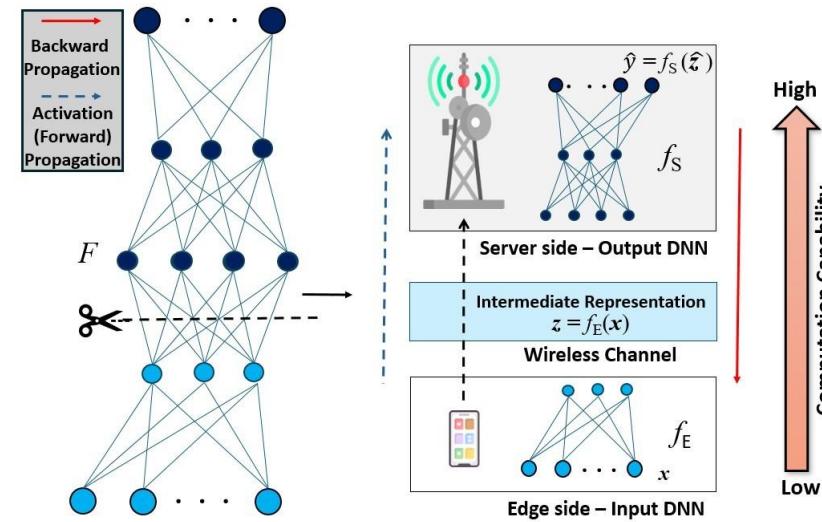
- Hardware setup



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

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.

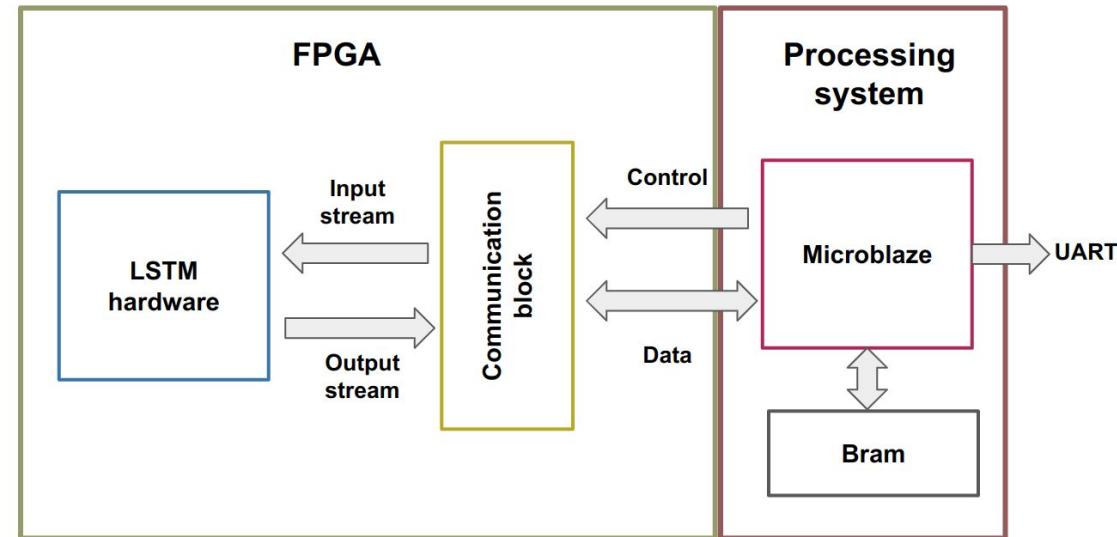
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LSTM-DO-T	39,951	156.06	0.0520	0.0081	0.97
LSTM-DO-S	871	3.40	0.0574	0.0087	0.96

- 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



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 [μs]	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

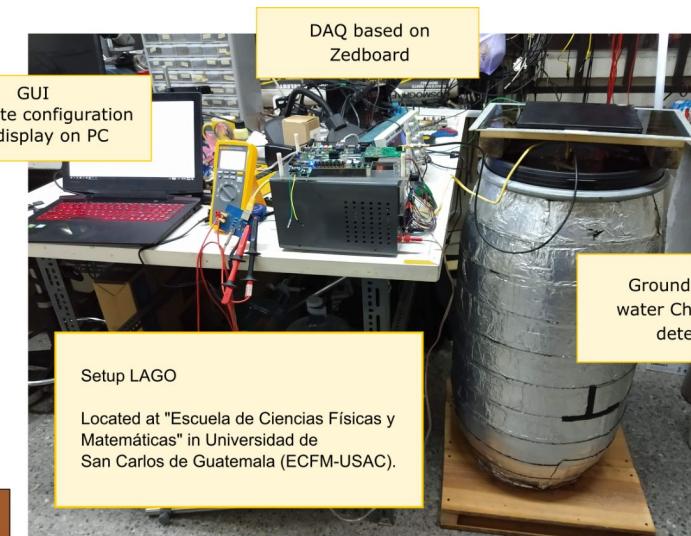
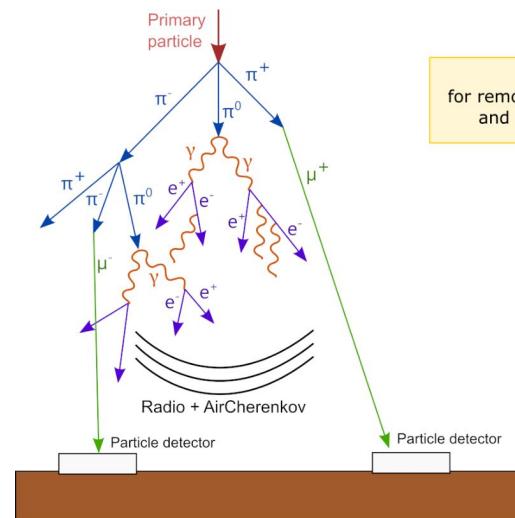
- **Design trade-offs:**
 - high performance that comes with higher resource and power demands,
 - balanced design that attempts to optimize both performance and resource utilization,
 - efficiency-oriented that prioritizes lower resource and power consumption, sometimes at the expense of speed.



Pulse shape discriminator for cosmic rays studies

ML and SoC-FPGA for real-case applications

Pulse shape
discriminator
for cosmic rays
studies

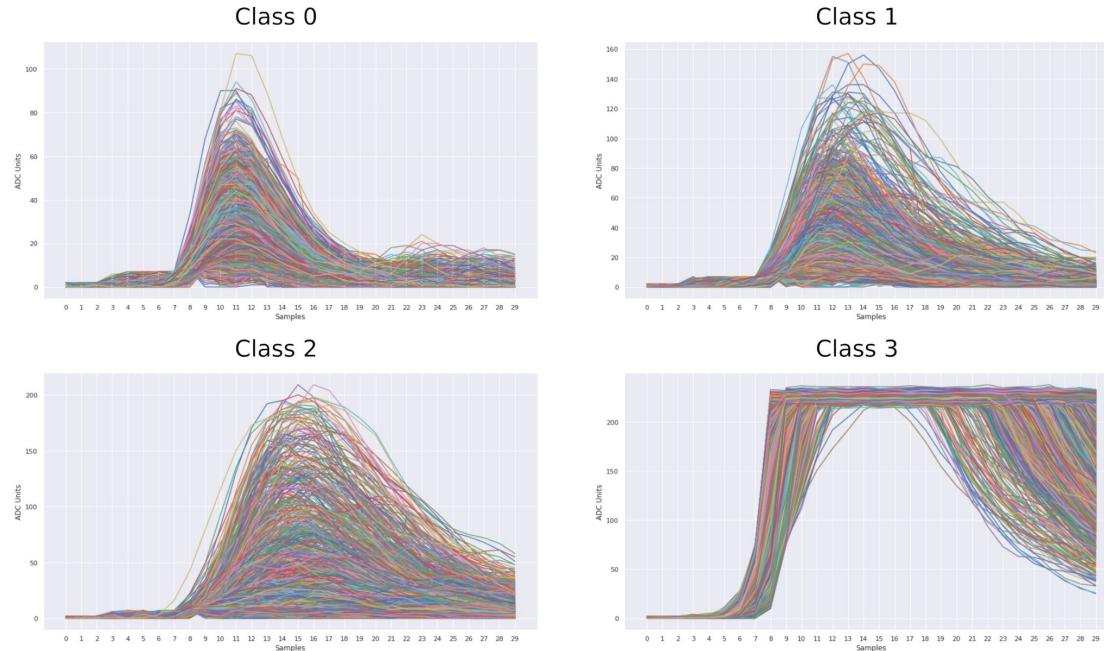


Setup LAGO
Located at "Escuela de Ciencias Físicas y Matemáticas" in Universidad de San Carlos de Guatemala (ECFM-USAC).

Ground-based
water Cherenkov
detector

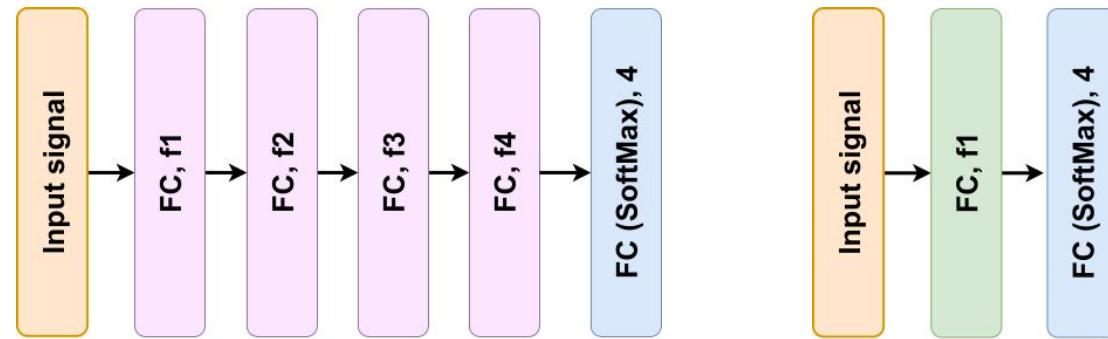
ML and SoC-FPGA for real-case applications

Pulse shape
discriminator
for cosmic rays
studies



ML and SoC-FPGA for real-case applications

Pulse shape
discriminator
for cosmic rays
studies



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

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

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%**

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%**
- SoC memory footprint in terms of resource utilization @200MHz
 - **Below 27%**

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%**
- SoC memory footprint in terms of resource utilization @200MHz
 - Below 27%
- SoC latency @200MHz
 - **10 clock cycles**

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, 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)
```

PYNQ™

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]))
```



Copahue volcano seismic event detection

ML and SoC-FPGA for real-case applications

Copahue volcano
seismic event
detection

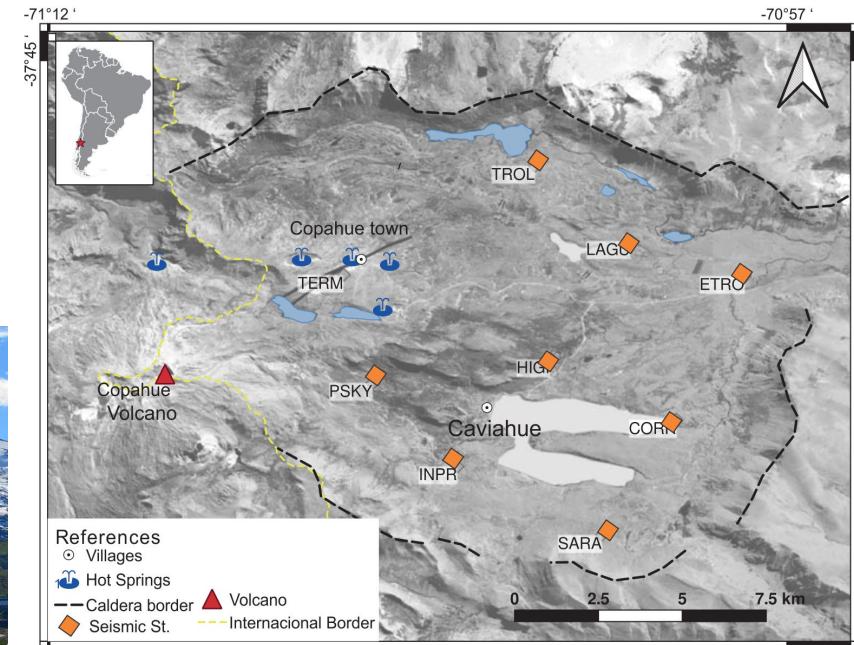
Copahue Volcano



ML and SoC-FPGA for real-case applications

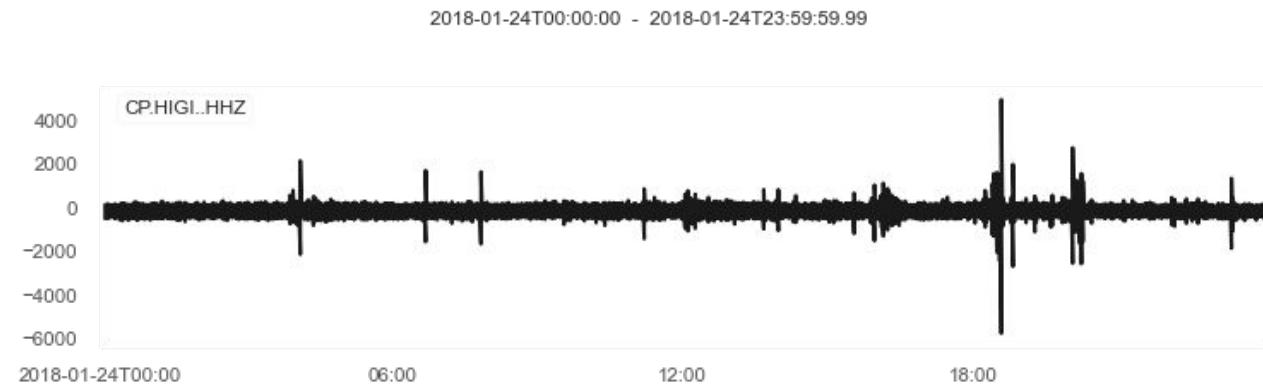
Copahue volcano
seismic event
detection

Copahue Volcano



ML and SoC-FPGA for real-case applications

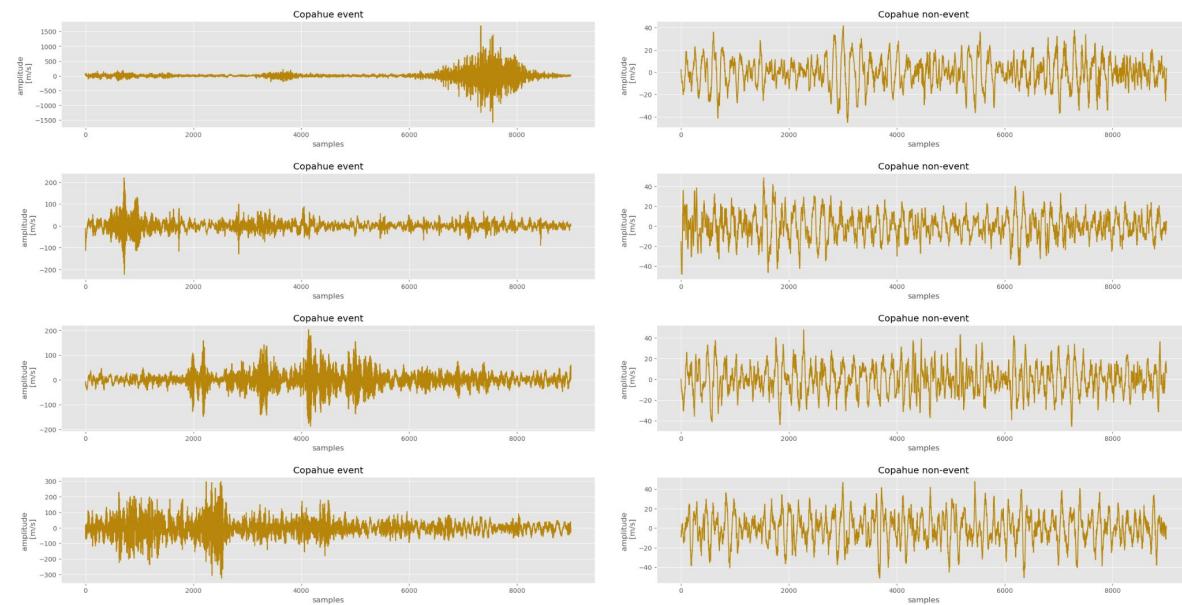
Copahue volcano
seismic event
detection



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 Río Negro.

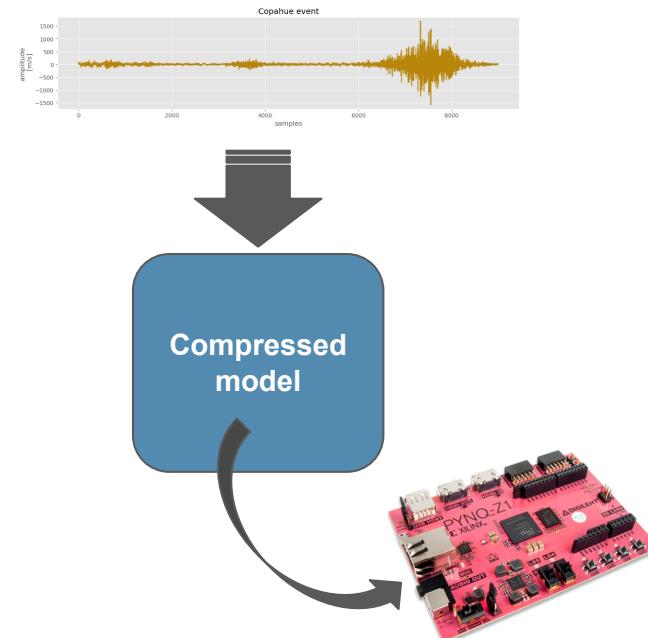
ML and SoC-FPGA for real-case applications

Copahue volcano
seismic event
detection



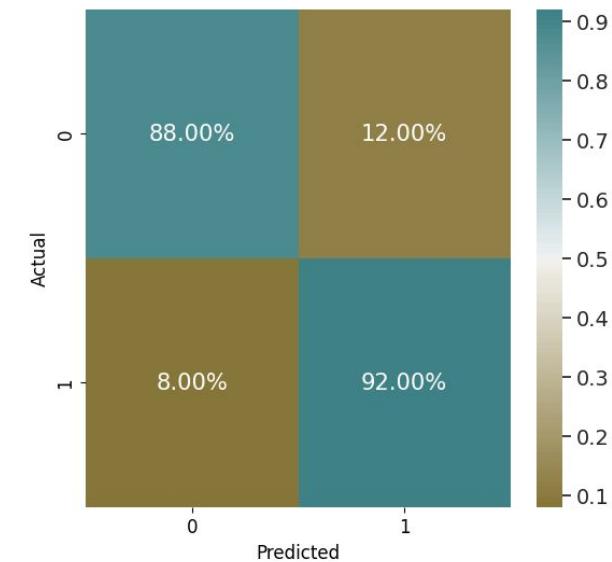
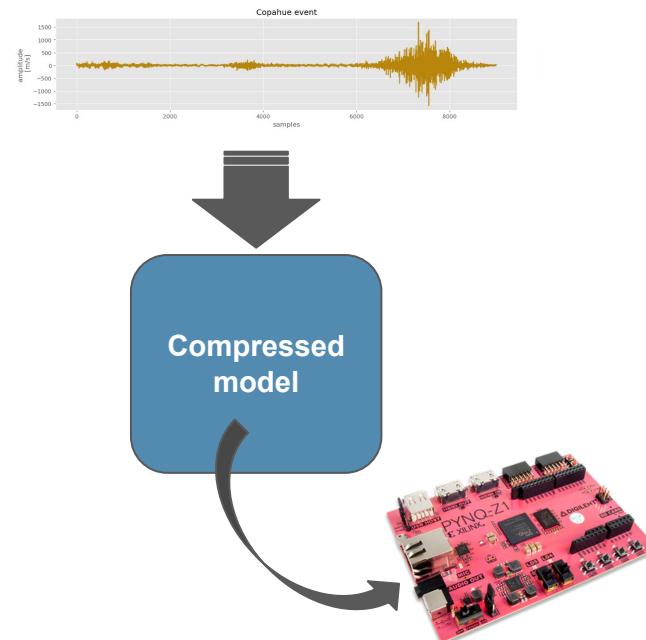
ML and SoC-FPGA for real-case applications

Copahue volcano
seismic event
detection



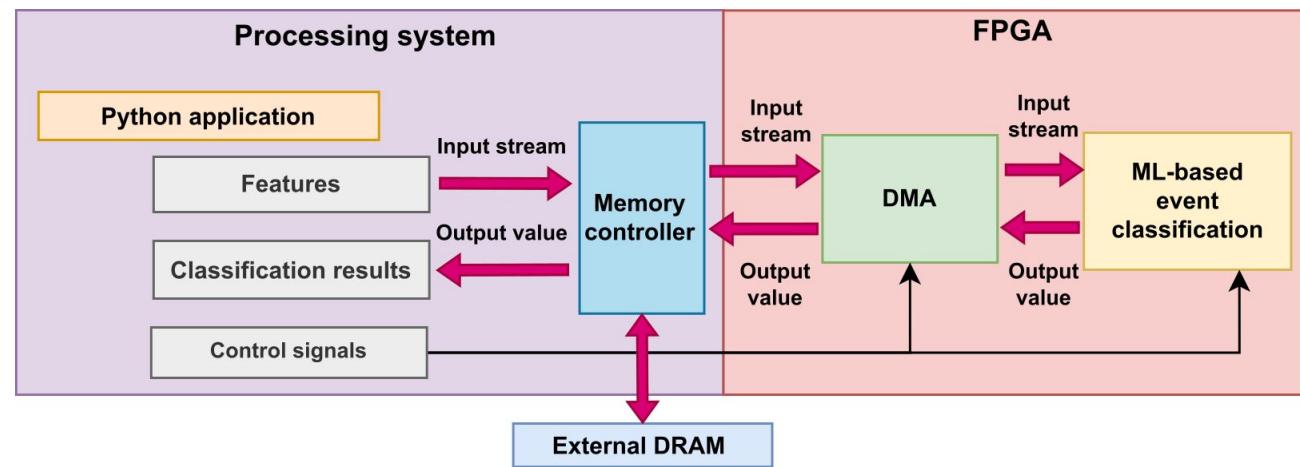
ML and SoC-FPGA for real-case applications

Copahue volcano
seismic event
detection



ML and SoC-FPGA for real-case applications

Copahue volcano
seismic event
detection



PYNQ™



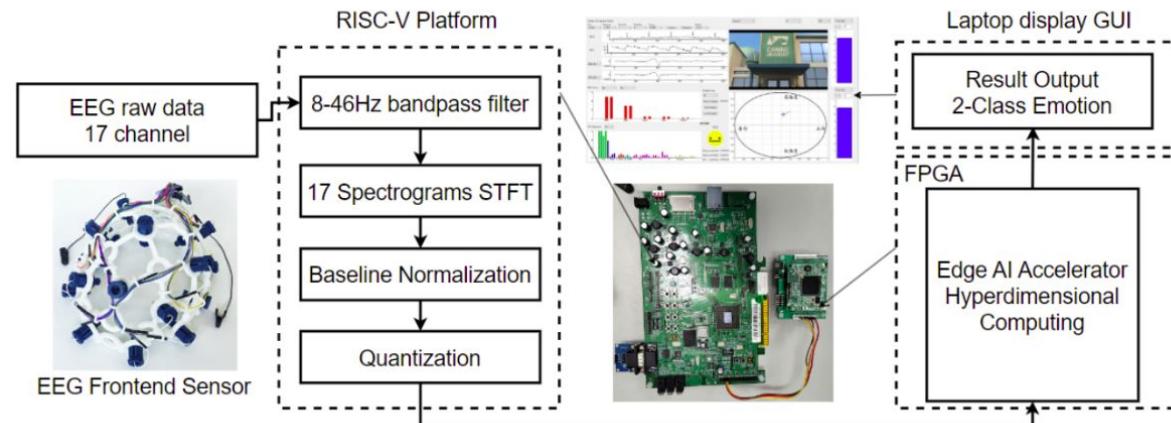


Applications based on the state of the art

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]

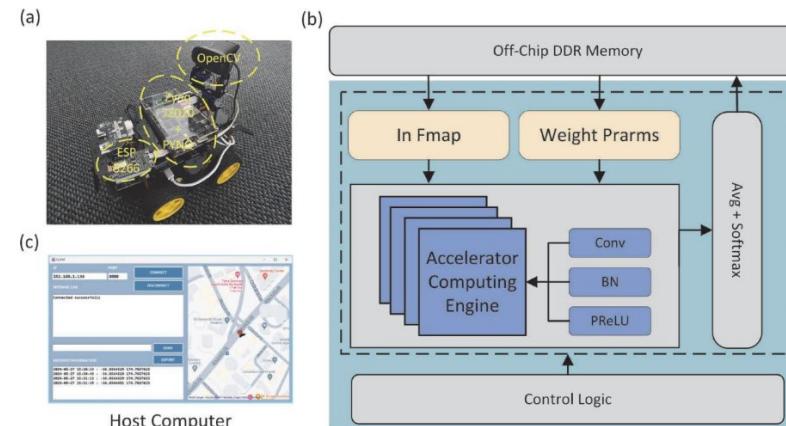


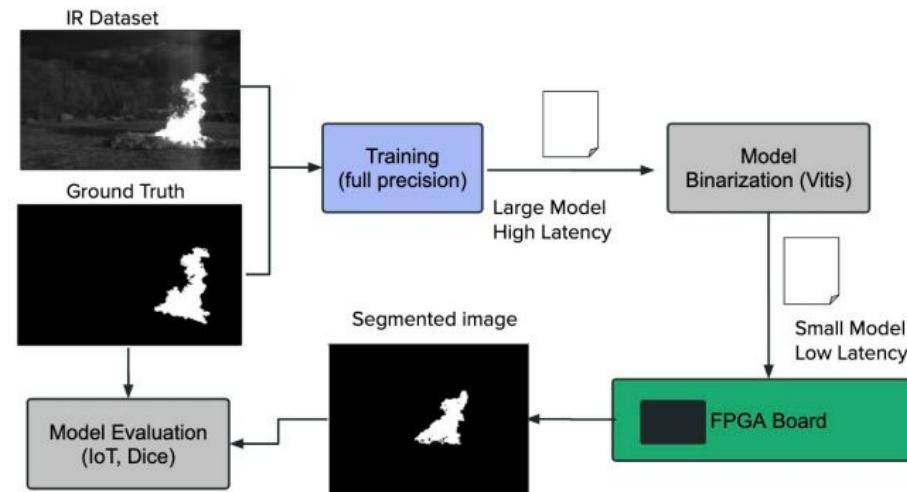
FIGURE 1. Railway faults detection system. (a) System components. (b) Hardware accelerator computation module. (c) Communication module and host computer interface.

[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]

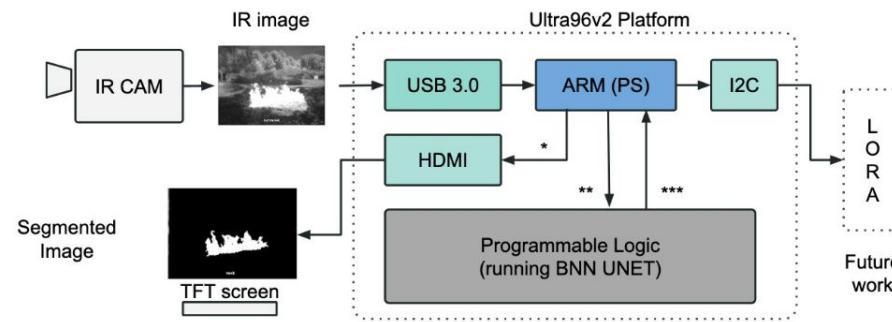


[3] Garduño, E., Ciprian-Sánchez, J., Vazquez-García, V., González-Mendoza, M., Rodríguez-Hernández, G., Palacios-Rosas, A., ... & Ochoa-Ruiz, G. (2023). An FPGA smart camera implementation of segmentation models for drone wildfire imagery. *Computación y Sistemas*, 27(4), 965-977.

ML and embedded systems for real-case applications

Drone wildfire
imagery

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

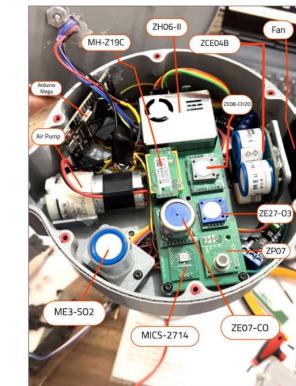
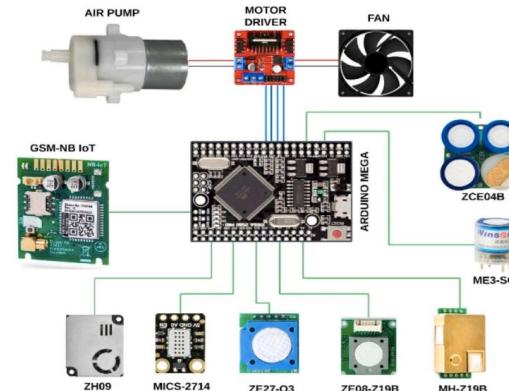


[3] Garduño, E., Ciprian-Sanchez, J., Vazquez-Garcia, V., Gonzalez-Mendoza, M., Rodriguez-Hernandez, G., Palacios-Rosas, A., ... & Ochoa-Ruiz, G. (2023). An FPGA smart camera implementation of segmentation models for drone wildfire imagery. *Computación y Sistemas*, 27(4), 965-977.

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]

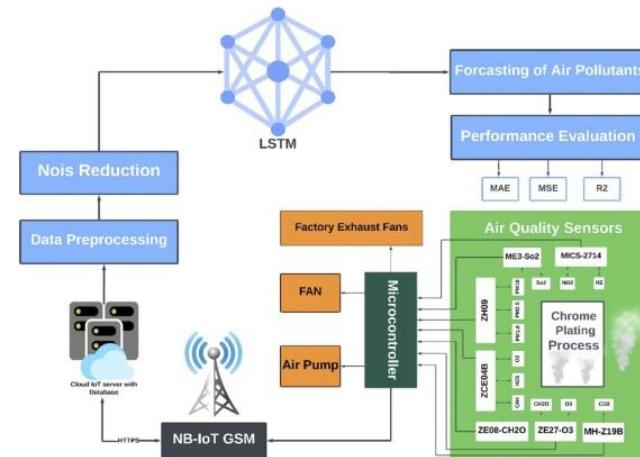


[4] Ramadan, M. N., Ali, M. A., Khoo, S. Y., Alkhedher, M., & Alherbawi, M. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. Ecotoxicology and environmental safety, 283, 116856.

ML and embedded systems for real-case applications

Monitoring and forecasting of air pollution

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

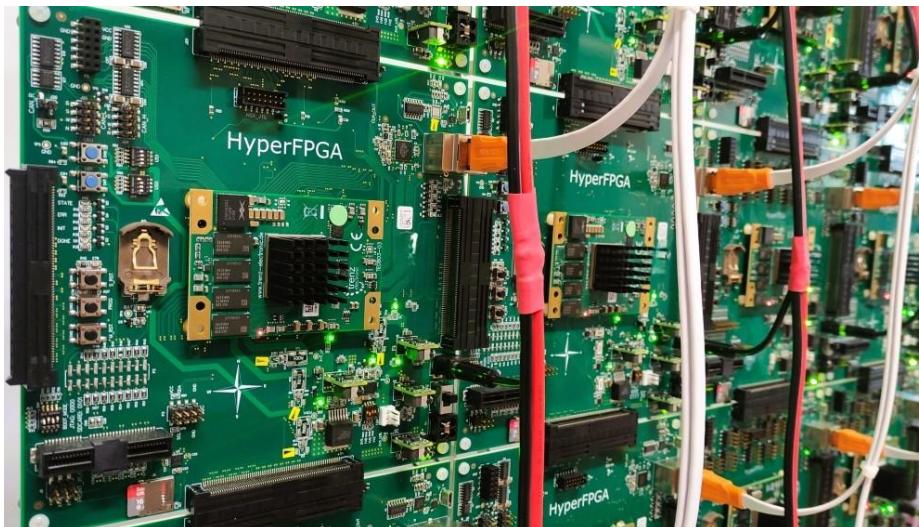


[4] Ramadan, M. N., Ali, M. A., Khoo, S. Y., Alkhedher, M., & Alherbawi, M. (2024). Real-time IoT-powered AI system for monitoring and forecasting of air pollution in industrial environment. Ecotoxicology and environmental safety, 283, 116856.

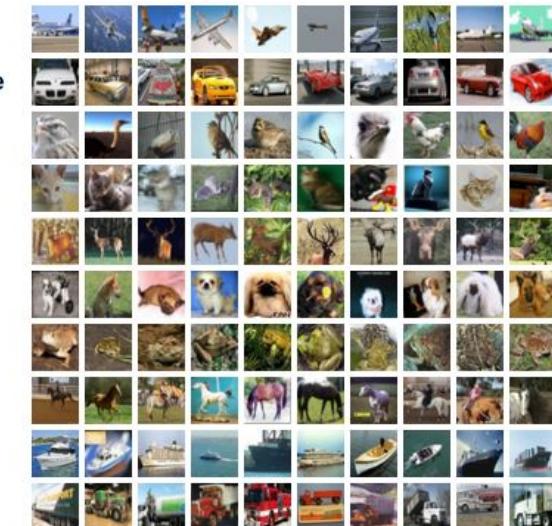


Demo:

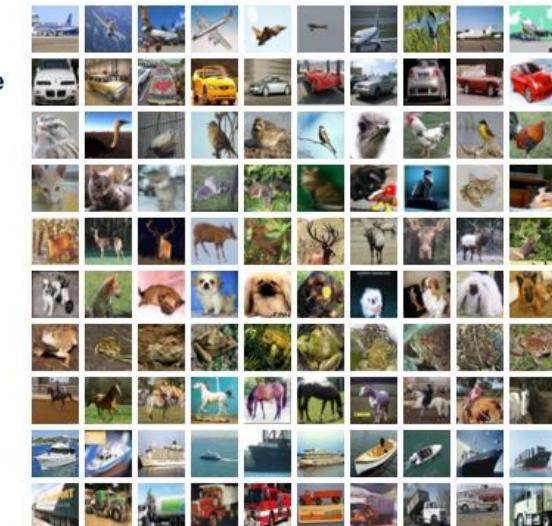
CIFAR-10 classification running on the HyperFPGA



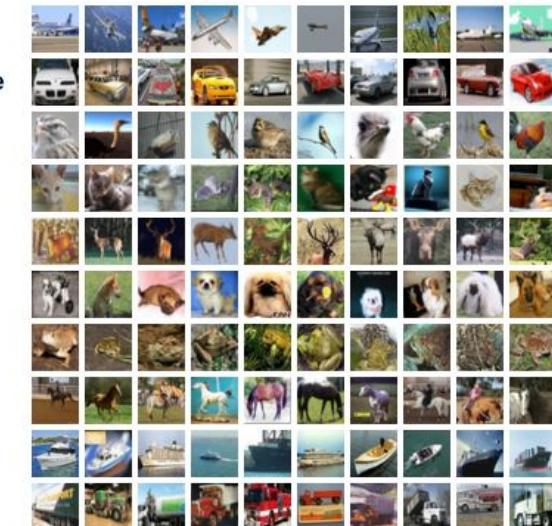
airplane



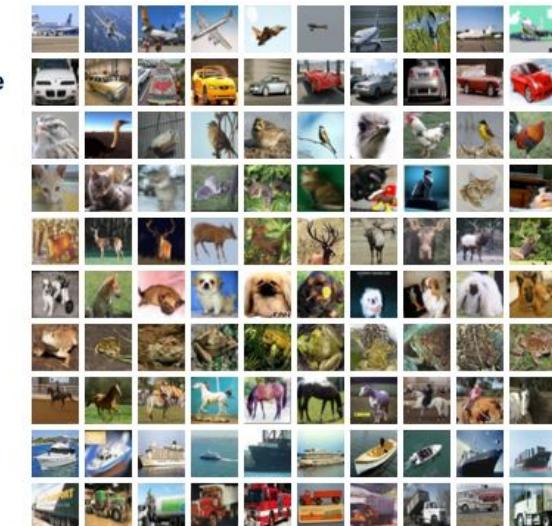
automobile



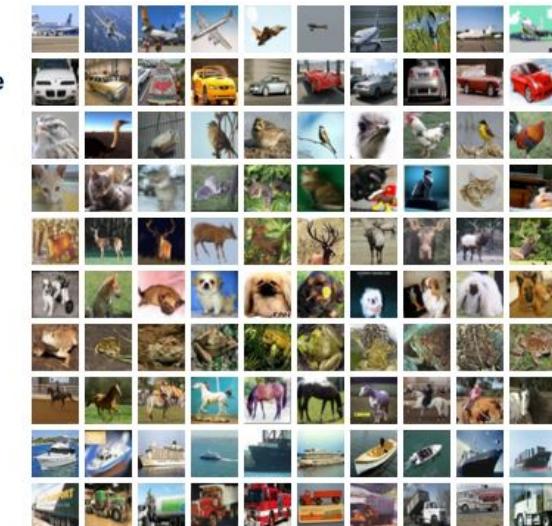
bird



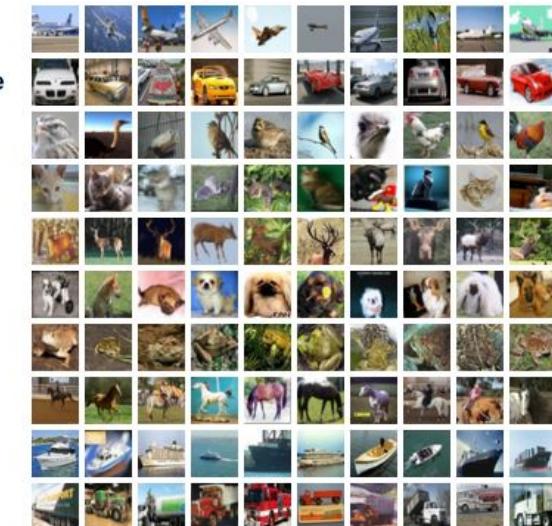
cat



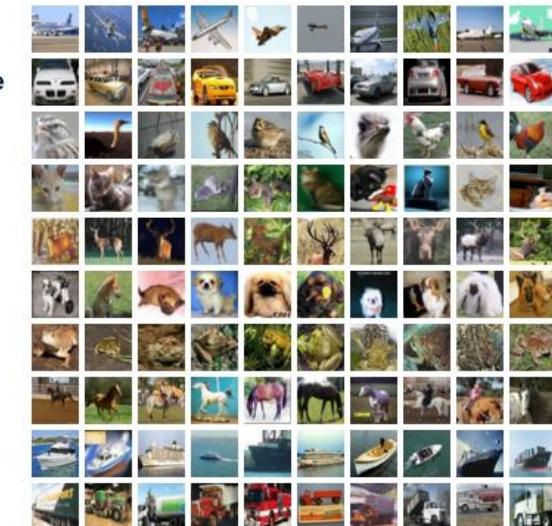
deer



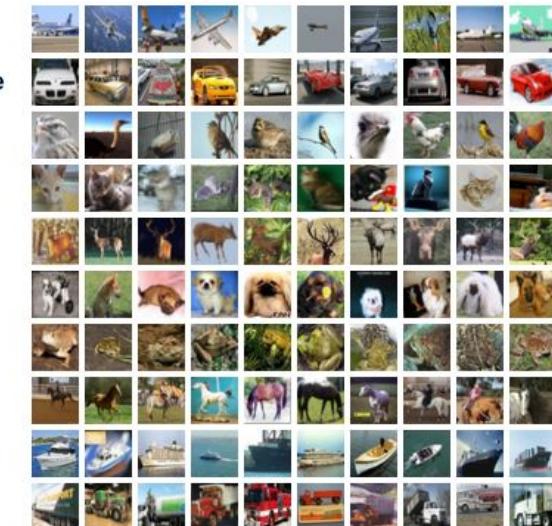
dog



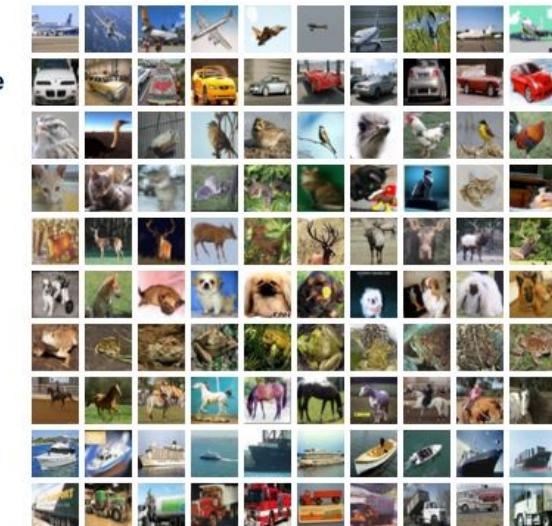
frog



horse



ship



truck



The Abdus Salam
**International Centre
for Theoretical Physics**

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

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

Perú - Online - 2025 -



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