

Liberté Égalité Fraternité





### AdaptING :

Adaptive architectures for embedded artificial INtelliGence

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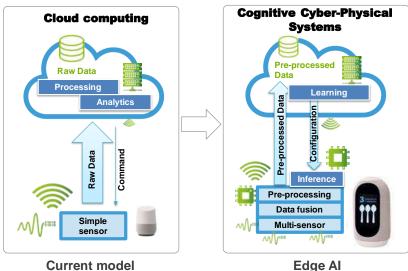




## **Motivation**

Current AI applications are based on cloud servers.

- Data privacy issues
- Bandwidth limitations
- Excessive power consumption
- High latency response



Source: Denis Dutoit (CEA)

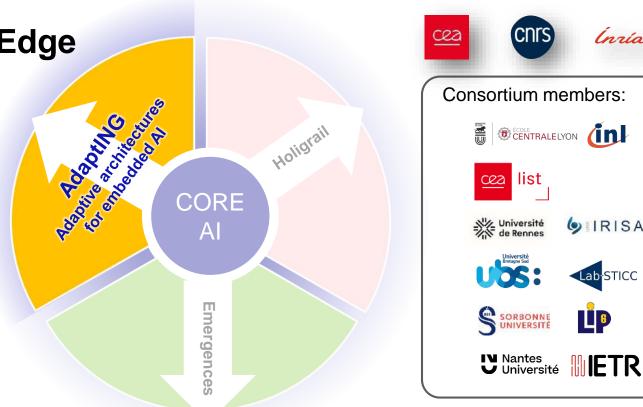
Versatile and intelligent edge devices will address the *new era* Frugal embedded AI architectures with local learning are key to overcome current limitations AI reliability (i.e., capability to provide correct results) is a must have AdaptING targets on developing these new architectures



### From Cloud to Edge

Challenges:

- 1. Flexibility
- 2. Learning-on-Chip
- 3. Energy efficiency
- 4. Reliability



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# Challenges: Flexibility

A flexible architecture able to run different AI algorithms

Taking into account the application constraints in terms of accuracy, energy, latency and reliability

- For the same result, the architecture can be:
  - Executed faster with high power consumption and low latency
  - Executes slowly with lower power consumption but higher latency









## **Challenges: Learning-on-Chip**



Evolves the AI model retrain paradigm from server to edge device Learning-on-chip:

- Guarantee privacy
- Energy reduction since no data has to be systematically transferred to and from the cloud

Training at device level is not trivial



- Not possible to embed huge databases in the device
- Catastrophic forgetting issues when retraining an AI model
- Energy budged is reduced



## Challenges: Energy efficiency

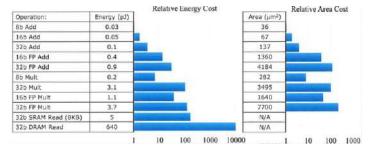
High-throughput architectures (GPU, TPU)

- Good efficiency but high power consumption ⇒ Not for embedded solutions
  Specialized AI architectures
- High energy efficiency but reduced flexibility

Achieving at the same time flexibility and energy efficiency is a major challenge !

The main energy efficient killer is the data movement between device memory and processing elements.

 $\Rightarrow$ Reducing the data movement is key to minimize the power consumption



Source: Mark Horowitz, "Computing's energy problem (and what we can do about it)", ISSCC 2019



## **Challenges: Reliability**



Similar to traditional computing hardware, is subject to errors that can have several sources: variability in fabrication process parameters, latent defects or even environmental stress

One of the overlooked aspects is the role that hardware errors can have in AI decision

There is a common belief that AI applications have an intrinsic high-level or resilience w.r.t. errors and noise

However, Hardware for AI is not always immune to HW errors



Traditional online fault-testing is not straightforward on AI-HW Safety techniques like Dual-Core Lock Step (DCLS), doubles the area and the power consumption



### **Consortium members**

École Centrale de Lyon, Institut des Nanotechnologies de Lyon (ECL-INL)



#### Project coordinator

Previous works in the field

- Hardware accelerators in deep-learning applications
  through Approximate Computing
- Design and implement a precision re-configurable systolic array-based hardware accelerator for DNNs
- Analyze the impact of hardware faults on the reliability, safety, trust, and explainability of AI decisions



		Al-c	hip	
Al-accelerator			Microprocessor	
Computation core PE arrays and engines		Interconnect (ROCC)	Host processor (RISC-V)	(AXI)
Reg File		troller	L1-cache I+D	Inte
DMA		acc. C-V)	L2-cache (SRAM)	
	Off-	chip mem (DRAM)	ory	Sensor (image)

Commissariat à l'énergie atomique et

aux énergies alternatives (CEA)

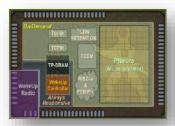
#### Project coordinator

Previous works in the field

- Open-source AI training tool (N2D2)
- ASIC design with low power techniques for High Performance Computing
- Design of AI architectures optimized for embedded platforms



Ivan MIRO PANADES



SamurAI: Edge AI architecture





### **Consortium members**

Université Rennes, IRISA /INRIA

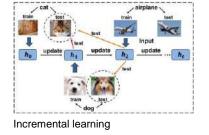
Université de Rennes

Previous works in the field

- Algorithms related to federated, incremental and few shot learning
- Algorithms related to "explainable AI" in a adapting system ⇒ learning shift monitoring
- Strong expertise in fault-tolerant architectures and fault mitigation in existing architectures



Elisa Fromont



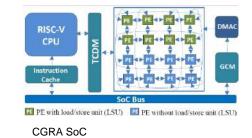
Université Bretagne Sud / Lab-STICC



Previous works in the field

- Al accelerators targeting Content Addressable Memories (CAM) and prototyped on FPGA
- Coarse-grained reconfigurable architecture and associated compilation tool have been proposed for low power design
- Dataflow and near-memory computing







### **Consortium members**

Sorbonne Université LIP6 (SU-Lip6)



Previous works in the field

- Embedded smart system design for medical device and diagnosis support
- Frugal AI and incremental learning as well as lightweight deep network design
- Precision Tuning Using Stochastic Arithmetic
- High-coverage compact functional test set for neuromorphic processors



PINNA



Cyclope: polyps detect capsule

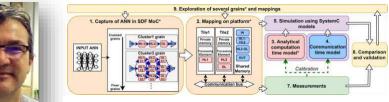
Nantes Université - IETR

Previous works in the field

Sebastien

PILLEMENT

- High Level models for performance evaluation of embedding AI and related design space exploration methodology
- Design of reliable architecture using reconfiguration integrating fault-tolerant mechanisms
- Specific methodology to evaluate different fault-tolerant strategies in the early-stage of the design process for critical applications



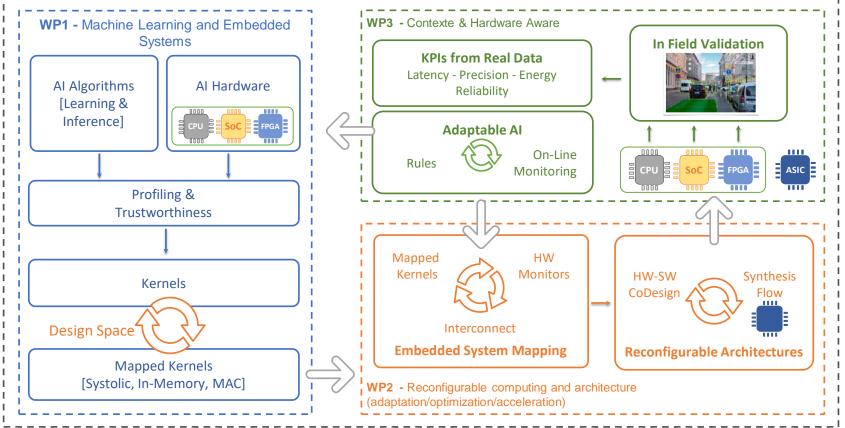
**IN** Nantes

Université

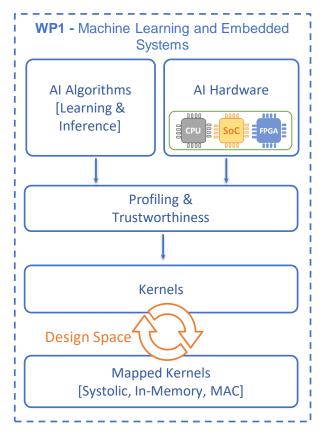
AI performance estimation



WP0 - Project management







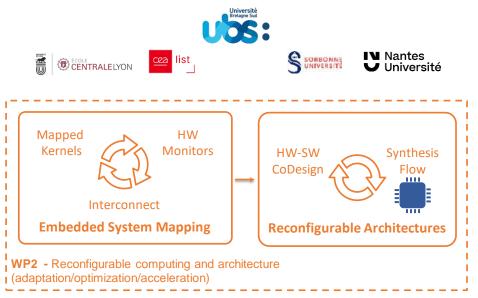
- WP1 explore AI (learning and inference models) at the algorithmic level
- **Identify AI algorithms** and use cases that will be used during the project.
- **Profiled AI models** on HW architectures (bottleneck, memory requirements and energy consumption)
- Emergences and HOLIGRAIL computing kernels are also explored
- Outcomes: mapped kernels used by WP2 and the use case definition that will be used in WP3.
- 9 Ph.D. thesis (6 of them will be co-supervised by two partners)
- 1 Post-Doc





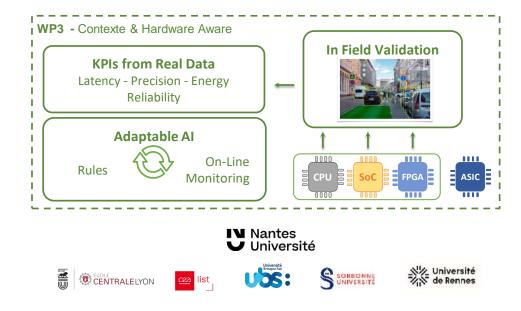
- Research of **methodologies and tools** for designing AI reconfigurable architectures.
- Explored mapped kernels from WP1: inference, training and monitoring kernels.
- Different HW/SW implementations are considered, varying in energy efficiency, latency, precision, and trustworthiness..
- The goal is to **select the kernel to be used and how they have to be interconnected** in terms of technology and topology to generate the AI reconfigurable architectures for a given use case.
- The resulting architectures will be heterogeneous, including components like CPUs, SoCs, FPGAs, and ASICs.
- HW/SW co-design and synthesis flow to estimate the energy efficiency and the latency of the reconfigurable architecture

- Synthetized reconfigurable architectures will be used in WP3 for the context aware monitoring and in-field validation
- 9 Ph.D. thesis (8 co-supervised by two partners)
- 2 Post-Docs





- WP3 focuses on **online monitoring** and validation of AI architectures.
- It builds upon the AI architectures provided by WP2, incorporating reconfigurability mechanisms and hardware (HW) monitors
- WP3 designs and implements online monitoring solutions for these architectures.
- · Using AI architectures in the field with real data
- Online monitoring determines the status of running AI algorithms using information from embedded HW monitors
- **Status is evaluated** in terms of Latency, Accuracy, Energy, and Trustworthiness (KPIs).
- In mission mode, external context and data can change, triggering reconfiguration based on status
- Reconfiguration can involve training Al with new data, modifying Al structure to adapt to new data or adjust KPIs, or signaling inadequate reconfiguration mechanisms.



- Solutions for inadequate mechanisms include modifying Al architecture or identifying new Al algorithms
- 7 Ph.D. theses (2 co-supervised by two partners)



## AdaptING community

- 27 permanent researchers
- 3 research engineers
- 25 PhD students
- 2 PostDoc students
- 10 internships students



### CORE 201 Torrange

### **KPI evaluation**

Al, especially deep neural networks, presents challenges for hardware due to its complexity, including energy consumption, memory requirements, computation speed, and scalability.

There is a need for AI hardware accelerators capable of handling high-dimensional and computationallyintensive workloads.

AdaptING aims to design adaptable AI-HW architectures that are flexible like general-purpose processors and more efficient than current AI accelerators.

KPI	Examples		
Accuracy	Number of correct inferences/total inferences		
Energy	Joule/Inference; Joule/training		
Latency	Second/inference; second/training		
Adaptability	Highest variation of conditions (internal/external) that can be tolerate thanks to the reconfigurability of the architecture		
Trustworthiness	Inference/training confidence level		





## **Project outcomes**

Algorithmic

• Identification and characterization of applications and AI models (including real-time, mission- and safetycritical applications)

Architecture

• Development of flexible architectures

System

- Virtual prototype of the AI-HW architectures as an open-hardware platform for validation through simulation/emulation.
- Deployment of different AI models

Comparison of the real prototype (physical implementation) with state-of-the-art open AI-HW architectures such as the Pulp platform, Gemini, and Eyeriss, based on Key Performance Indicators.

Federation of French Hardware AI community

 $\Rightarrow$  GDR SoC2, GDR IASIS, GDR BioComp, GDR RADIA, Summer School



## **Exploitation**



The results of AdaptING can be further exploited through **technology transfers** with the objective to be integrated in **industrial products** and **open-source platforms** for embedded AI.

Examples are the N2D2 platform, PNeuro and NeuroCorgi platforms from CEA, PULP ecosystem from ETHZ and industrial solutions provided by companies (i.e. Greenwaves and Asygn).

Maturation of architectures: from low TRL (4/5) on AdaptING to high TRL (6/7) on DeepGreen







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