

FPG-AI: a Technology Independent Framework for Edge AI Deployment Onboard Satellite, and its Characterisation on NanoXplore FPGAs

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Outline

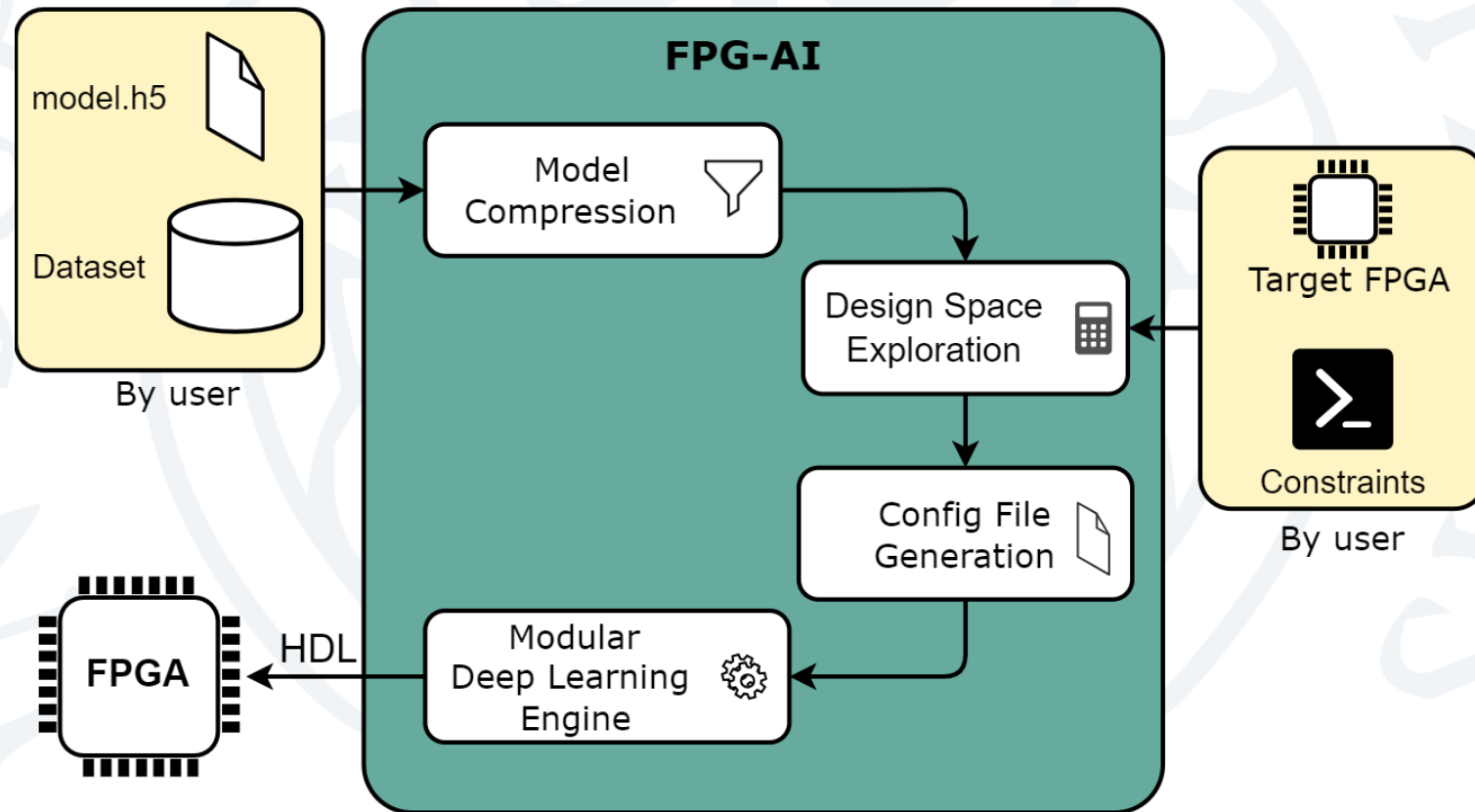
1. Background: FPG-AI Toolflow for CNNs
2. On-going Design Activities
3. CNN Implementation Flow for NX
4. Benchmarking
5. Next Steps – Hardware Prototyping

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Background: FPG-AI Toolflow for CNNs

- Automation toolflow for efficient deployment of pre-trained CNN models on FPGA technology [\[1\]](#), [\[2\]](#)



Model Compression

- **Post-training** quantization:
 - **Layer-wise** quantization applied on layers' inputs and weights
 - **Truncation** at layers' output for further memory footprint reduction
 - From **floating-point** to **fixed-point** arithmetic for boosting hardware efficiency:
 - Timing performance
 - Area consumption
 - Power consumption
- **Layer folding**: Batch Normalization, Average Pooling

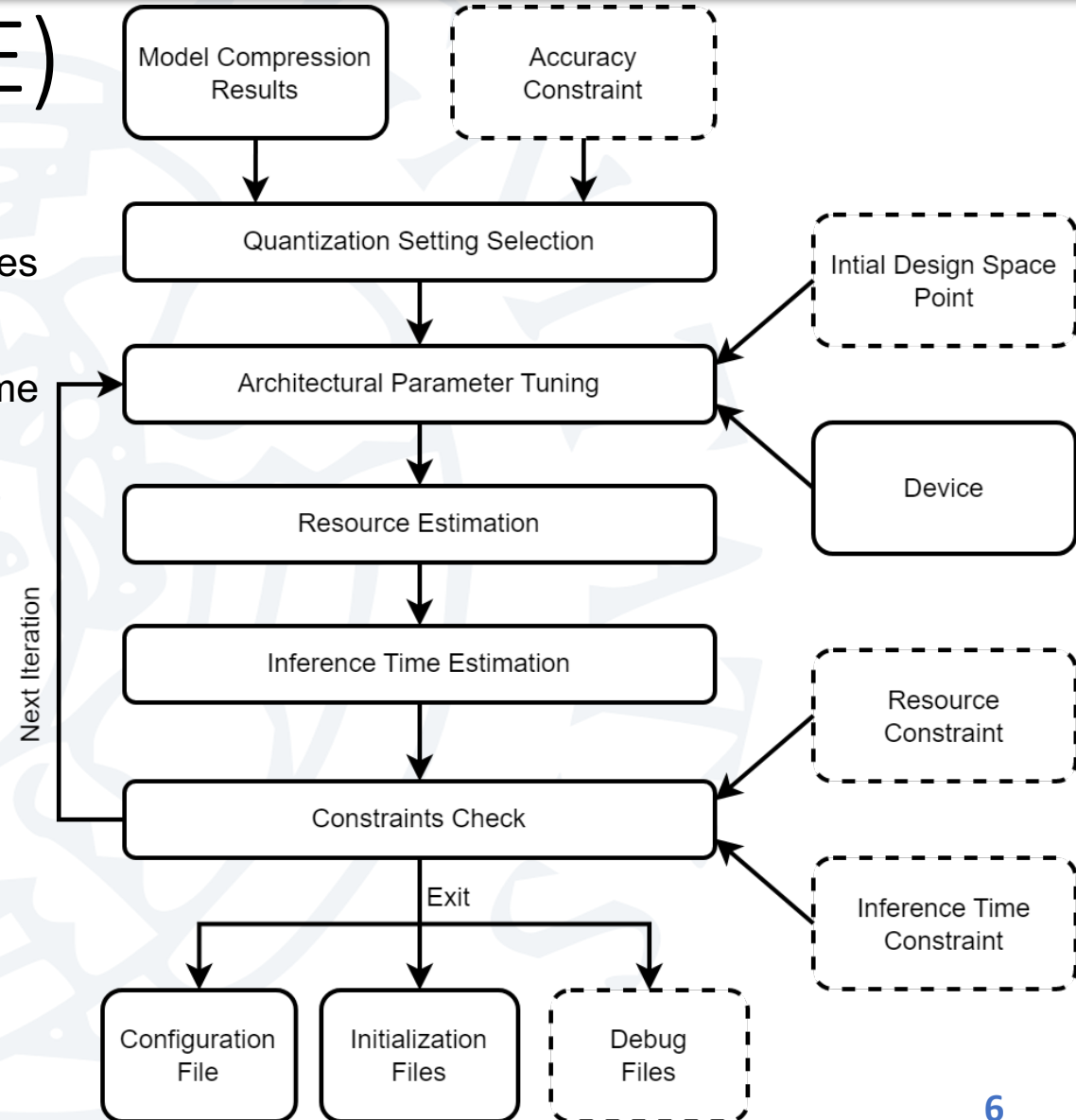


Design Space Exploration (DSE)

- DSE inputs:
 - CNN model
 - Target FPGA
 - User's constraints (optional)
 - Parameters initial values
 - Minimum accuracy
 - Maximum inference time
 - Resources limitation

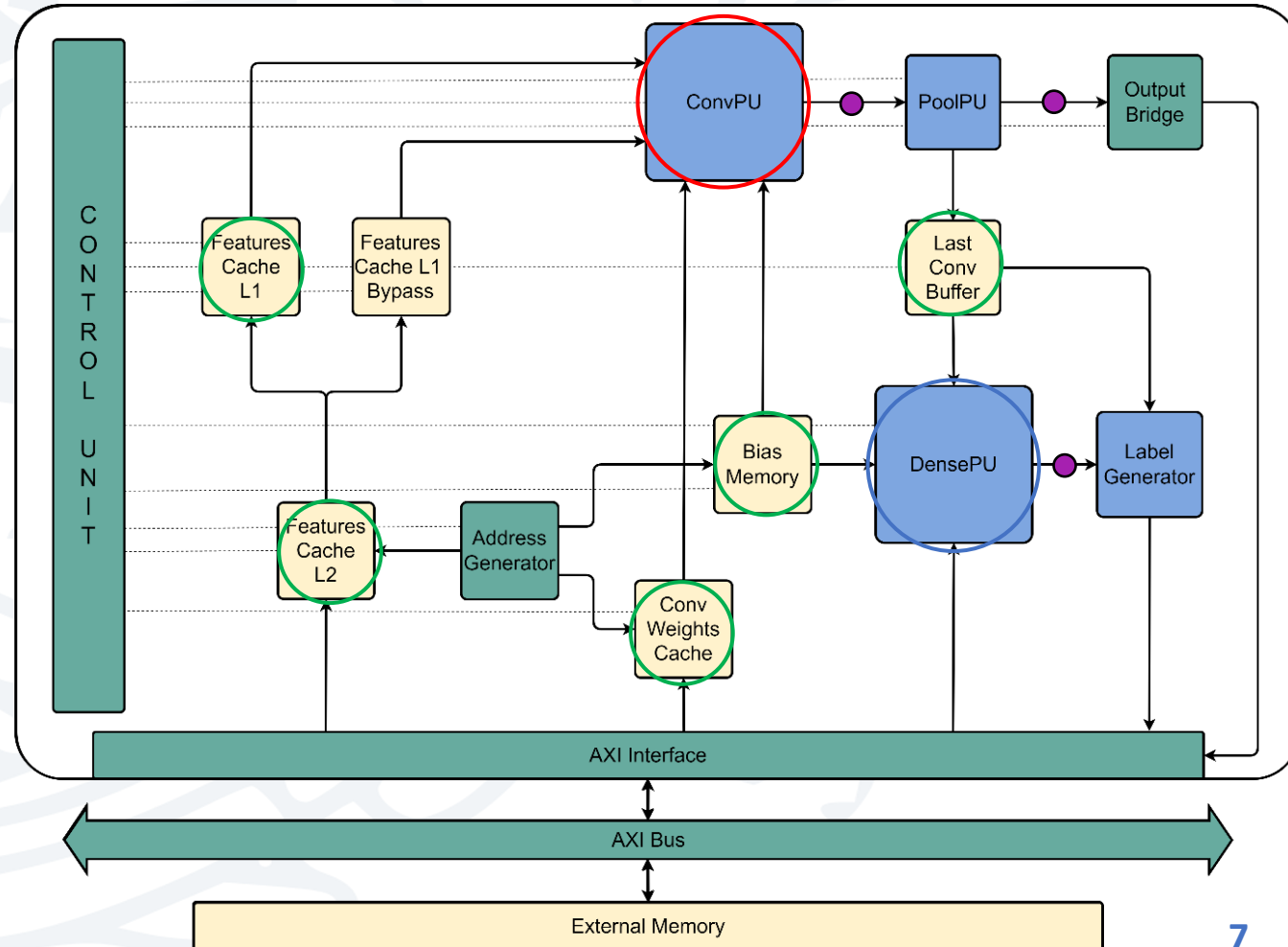
- Exploration of the architectural parameters space through an iterative algorithm
 - Detailed analytical Modular Deep-learning Engine (MDE) model for performance and resource estimation

- DSE outputs:
 - MDE configuration file
 - Initialization files for memories (Weights, Images for TBs, ..)
 - Textual debug files (optional Test Vectors for verification)



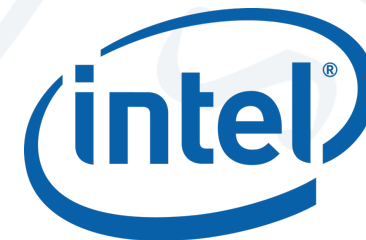
Modular Deep Learning Engine (MDE)

- **High portability:** no third-party IPs used
- **High scalability** in terms of DSP/On-chip Memory utilization
- **Easily configurable** through a file (.vhd)
 - **Model parameters:**
 - Input shape, # Layers, Layers type, # Classes, etc.
 - **Quantization parameters:**
 - Inputs/weights bitwidths, **Truncation** and **Saturation** bits
 - **Architectural parameters:**
 - **# MAC units (N_{PE}), # Neurons, Memory primitives for each IP, etc.**



FPG-AI Key Features

- High degree of customization with respects to user's constraints on:
 - Resource consumption (DSP/On-chip memories)
 - Post-quantization application metric deviations
 - Inference time
 - Competitive device portability of the Modular Deep Learning Engine (MDE) thanks to:
 - Absence of third-party IPs
 - High scalability in terms of DSP/On-chip memory usage
 - Fine-grain configurable through a .vhd file
- ➔ Enabling the implementation on FPGAs from different vendors and heterogeneous resource budgets!

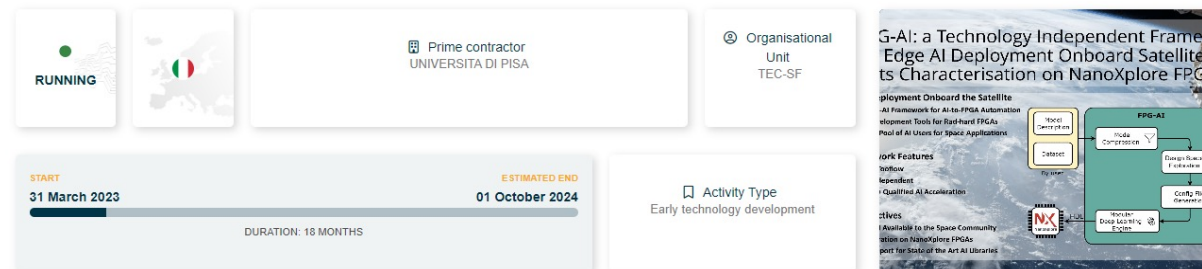
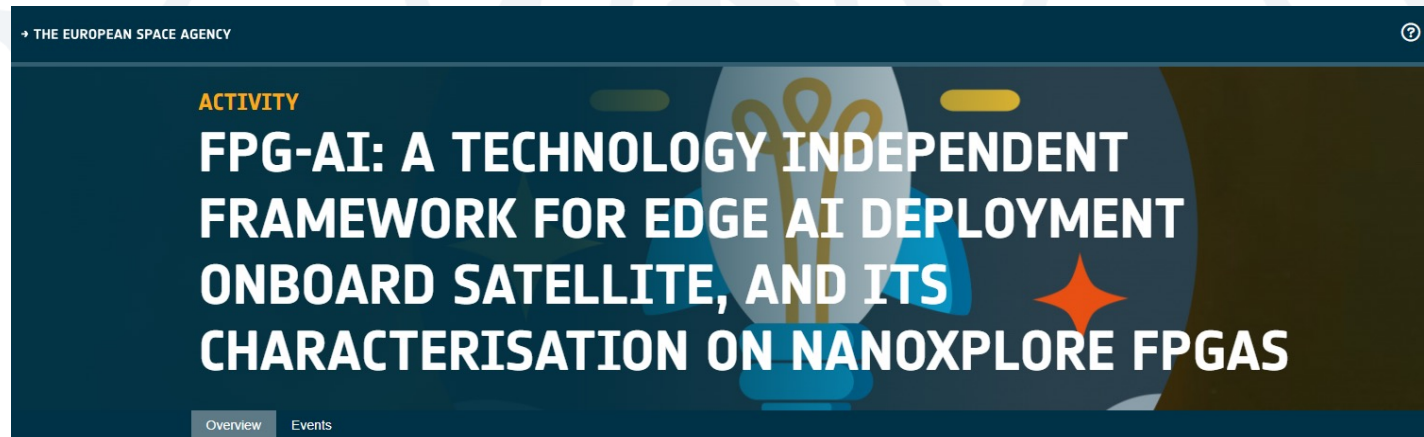


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FPG-AI: Current Objectives

- Enabling the support for NanoXplore FPGA devices
- Extension of FPG-AI to Recurrent Neural Networks (RNNs)



RUNNING

Prime contractor
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Organisational Unit
TEC-SF

START: 31 March 2023 | ESTIMATED END: 01 October 2024 | DURATION: 18 MONTHS

Activity Type
Early technology development

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Deployment Onboard the Satellite

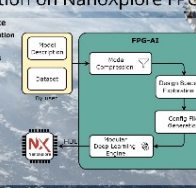
- AI Framework for AI-to-FPGA Automation
- Deployment Tools for High-End FPGAs
- Pool of AI Users for Space Applications

Work Features

- Software Independent
- Qualified AI Acceleration

Deliverables

- Available to the Space Community
- Deployable on NanoXplore FPGAs
- Open Source of the Art AI Libraries



Team Composition



- Full Prof. Luca Fanucci
- Responsible for Management tasks



- ESA Staff Silvia Moranti
- **Technical Officer**
- ESA/ESTEC Microelectronics Section



- Assistant Prof. Pietro Nannipieri
- Responsible for Hardware Prototyping and Dissemination Activity



- M. Sc Tommaso Pacini
- PhD Candidate
- Responsible for Extension to RNNs, Extension to NX FPGAs, Benchmark Activity



- M. Sc Matteo Dada
- Scholarship holder
- Working on Extension to RNNs



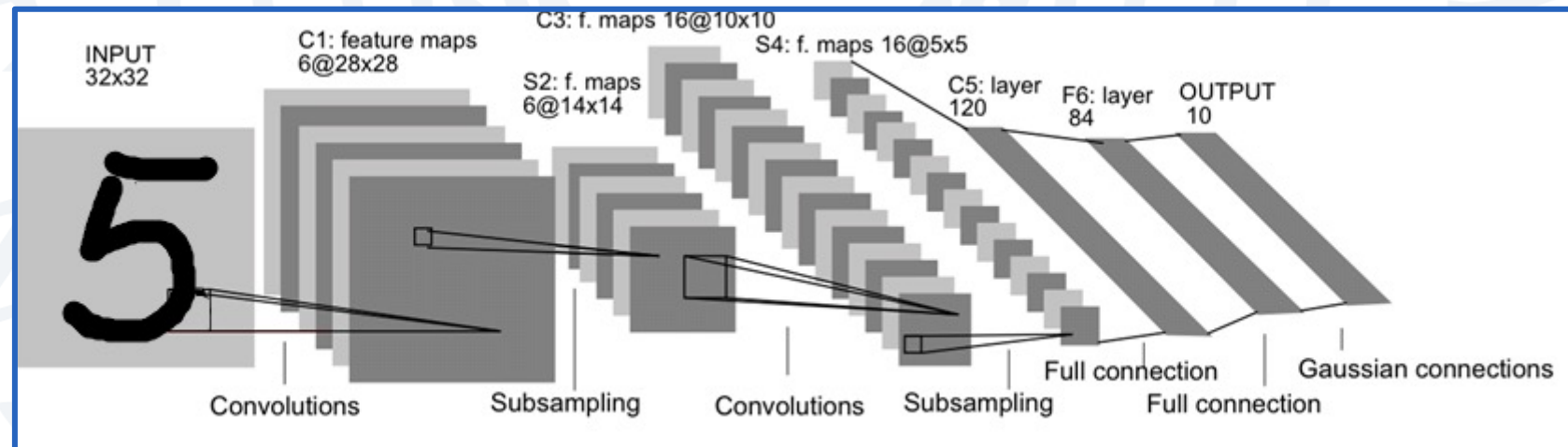
- M. Sc Student Tommaso Bocchi
- Working on Extension to NX FPGAs, Hardware Prototyping, Benchmark Activity

Outline

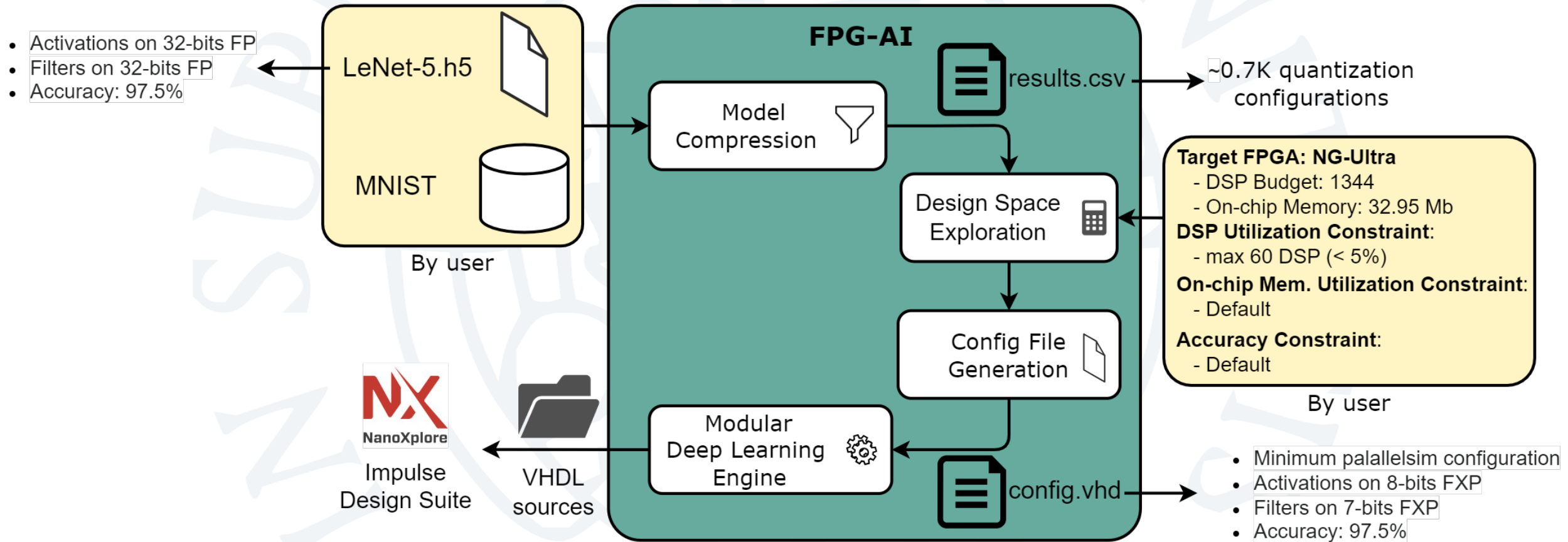
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Case Study

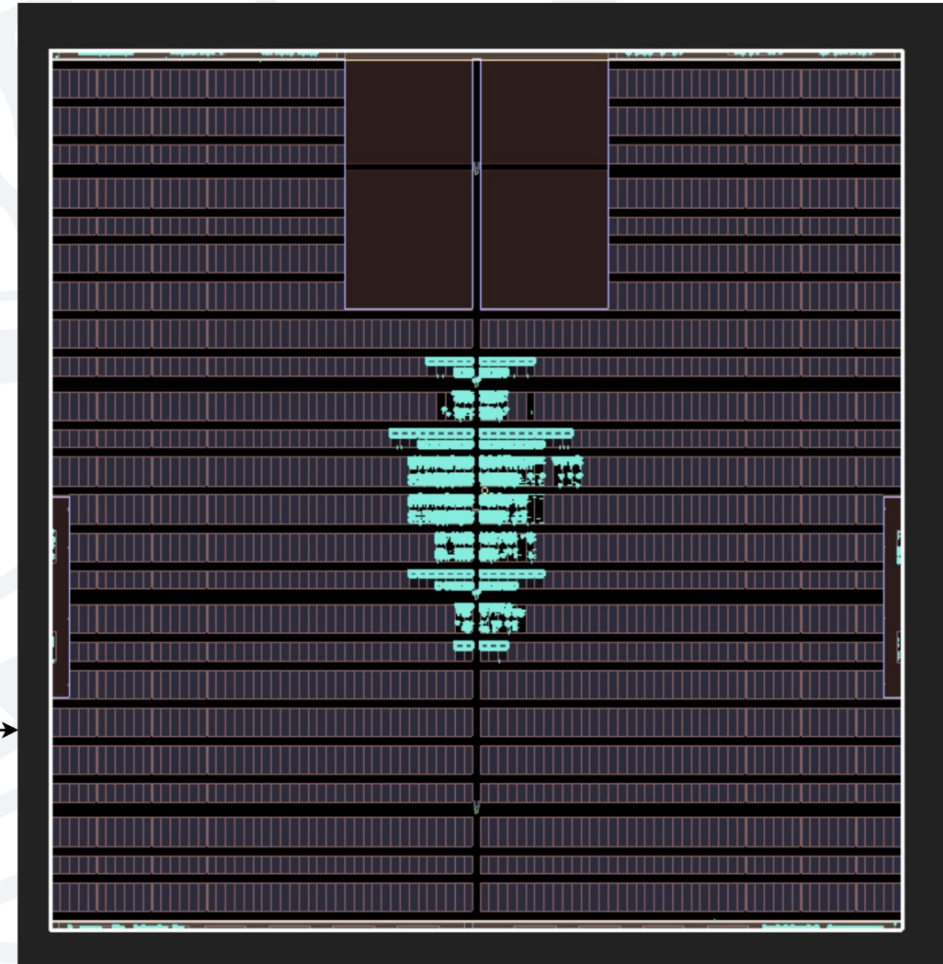
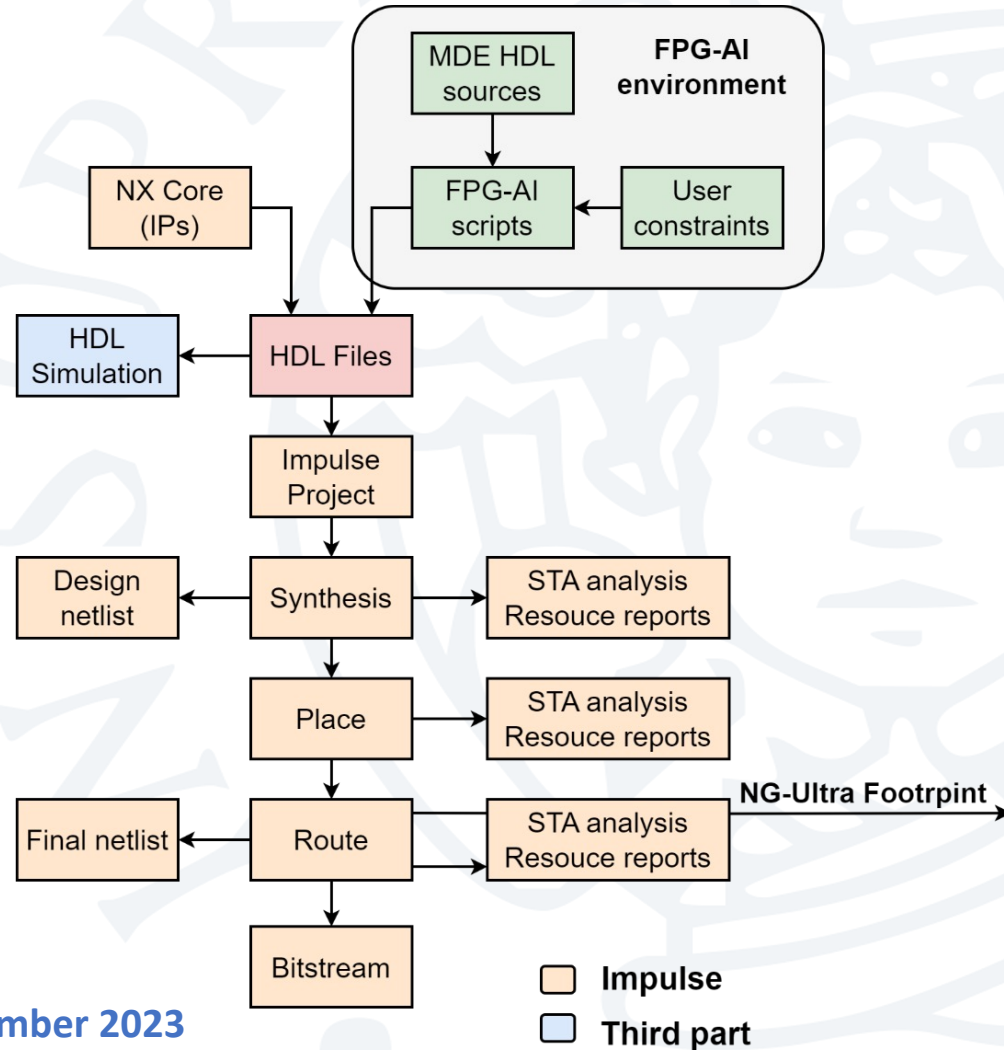
- Selected Convolutional Neural Network: **LeNet-5**
- Classification class: digits recognition
- Model topology: 2 Convolutional layers + 3 Fully Connected layers
- Total parameters: **44426 (~1.36 Mb)**



Design Flow – FPG-AI



Design Flow – NX Impulse



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Comparison – Selected Devices

The logo for Xilinx ZYNQ, featuring the word "ZYNQ" in a bold, sans-serif font with a registered trademark symbol. To the right of the text is a stylized graphic consisting of two overlapping trapezoidal shapes, one in a dark blue color and one in a light grey color.The logo for NanoXplore NG-Ultra, featuring the letters "NG" in white inside a red arrow-shaped box pointing to the right. To the right of this box is the word "ultra" in a bold, black, sans-serif font.

- Xilinx: **Z-7045**
- Technology: 28 nm
- Resources:
 - DSPs: 900 (DSP48E1)
 - On-chip memory: ~19.16 Mb
- Synthesis/Implementation strategy:
 - Default
- Timing corner analyzed:
 - Worst (0.922V, 100°C)
- NanoXplore: **NG-Ultra FF-1760**
- Technology: 28 nm
- Resources:
 - DSPs: 1344
 - On-chip memory: ~32.95 Mb
- Synthesis/Implementation strategy:
 - Default
- Timing corner analyzed:
 - Worst (0.95V, 125°C)

Comparison – Resources

Xilinx Z-7045	Design Step	Slice LUTs	Slice Registers	LUT as Memory	Block RAM	DSPs
	Synthesis	7471 (3.42%)	3015 (0.69%)	0 (0%)	5 (0.92%)	59 (6.56%)
	Implementation	7083 (3.24%)	3015 (0.69%)	1496 (2.13%)	5 (0.92%)	59 (6.56%)

64.25 Kb

0.18 Mb

NanoXplore NG-ULTRA	Design Step	4-LUT	DFF	Register file block	DSP	Memory block
	Synthesis	6194 (2%)	3540 (1%)	129 (5%)	51 (4%)	15 (3%)
	Place	6106 (2%)	3554 (1%)	129 (5%)	51 (4%)	15 (3%)
	Route	6106 (2%)	3578 (1%)	129 (5%)	51 (4%)	15 (3%)

72.56 Kb

0.703 Mb

Comparison – Timing

Xilinx Z-7045	Design Step	Required [MHz]	Actual [MHz]	Critical Path	
				Routing delay [ns]	Data delay [ns]
	Synthesis	113.64	114.44	3.242	5.017
Implementation	113.70		2.933	5.003	

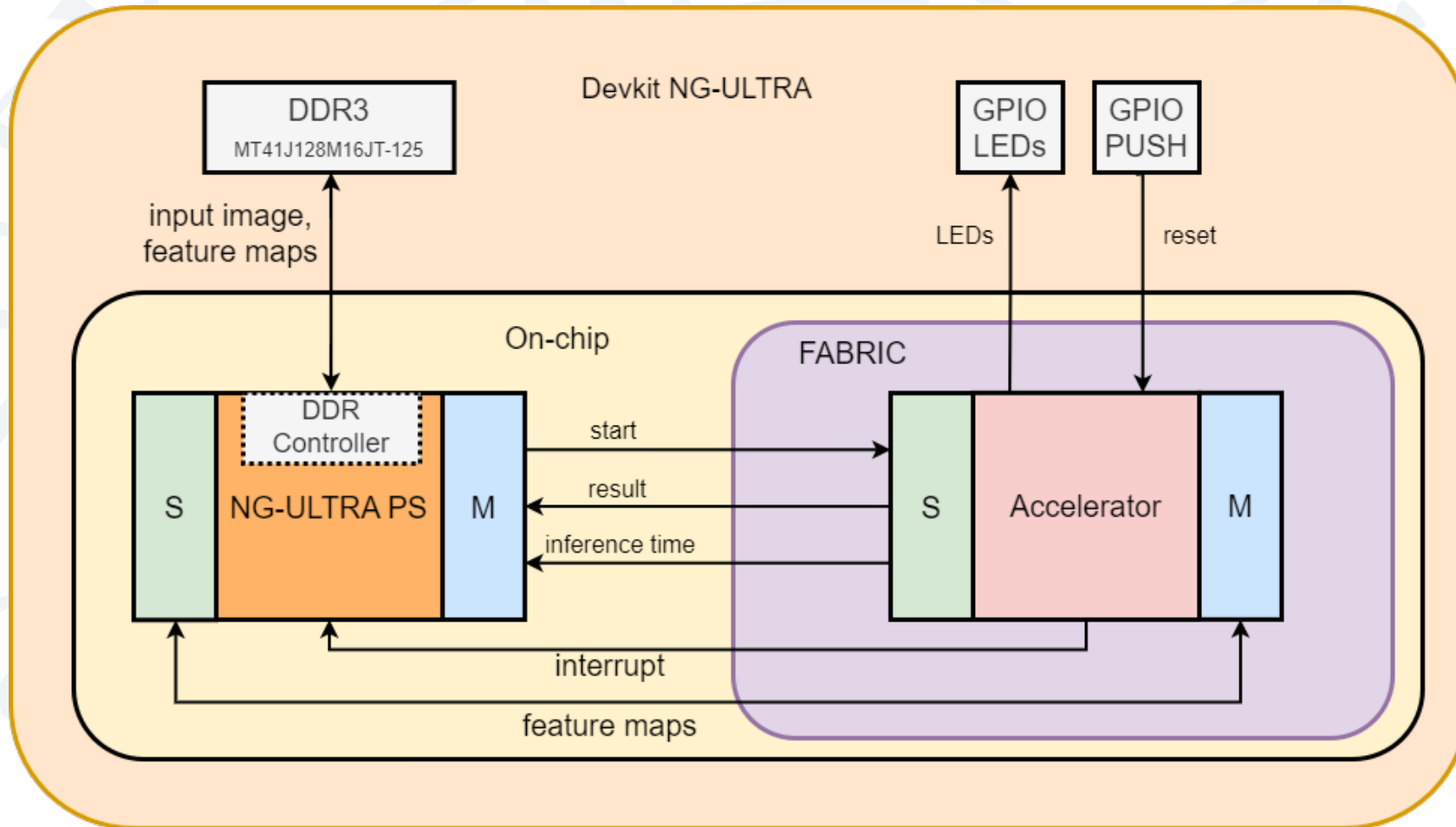
NanoXplore NG-ULTRA	Design Step	Required [MHz]	Actual [MHz]	Critical Path	
				Routing delay [ns]	Data delay [ns]
	Synthesis	40.000	81.726	7.329	4.194
Place	47.239*		15.899	4.319	
Route	40.393*		19.988	3.833	

*default seed option

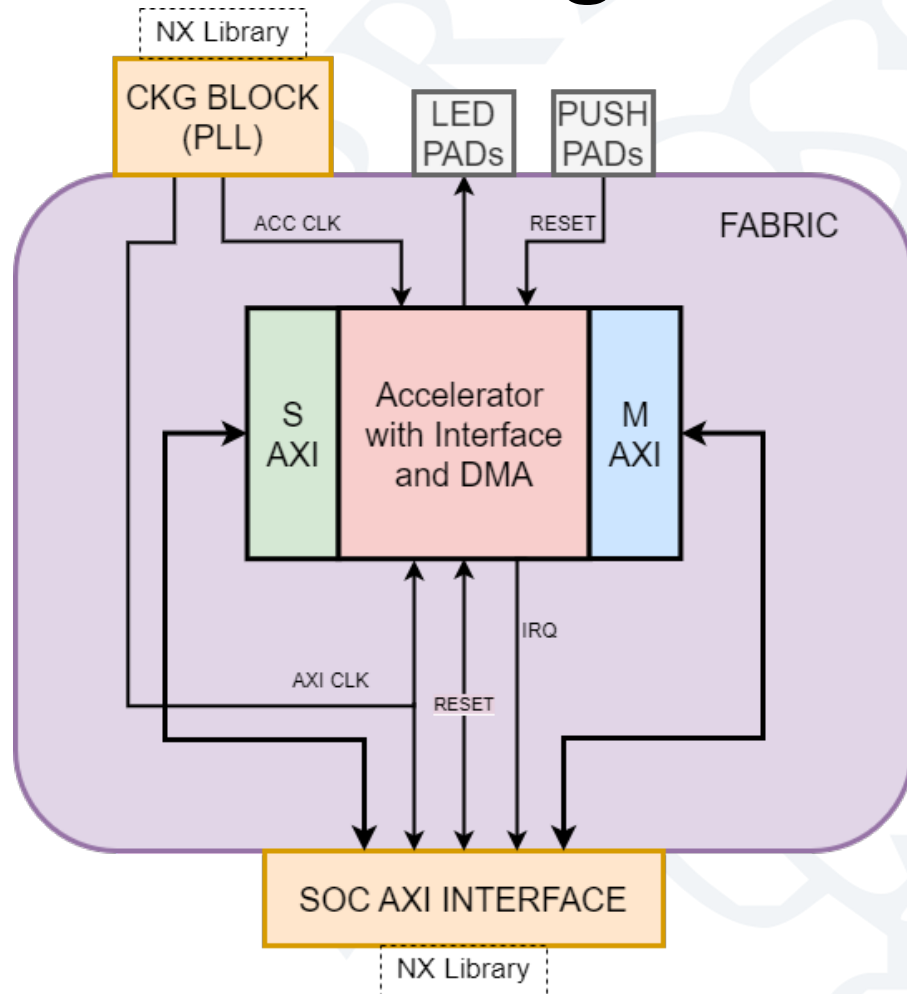
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Hardware Prototype Concept



FPG-AI Integration within NX System



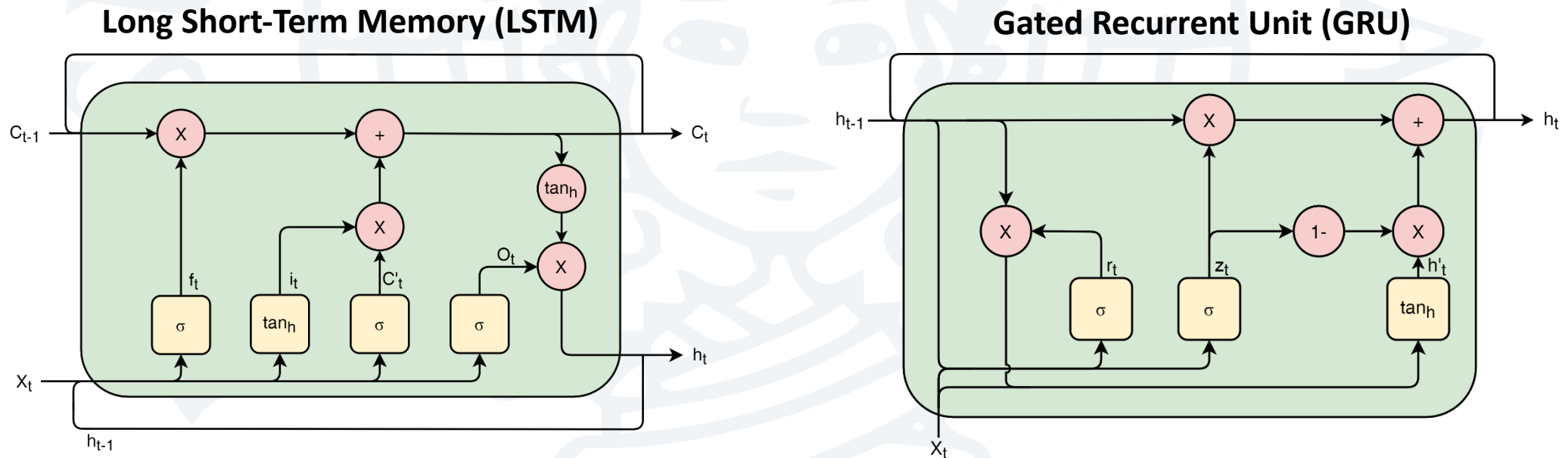
- Accelerator with both master and slave AXI interfaces
- Direct communication with DDR through Handmade DMA
- AXI SOC interface (NX Library) between PS and PL
- Clocks provided by PLL inside CKG blocks

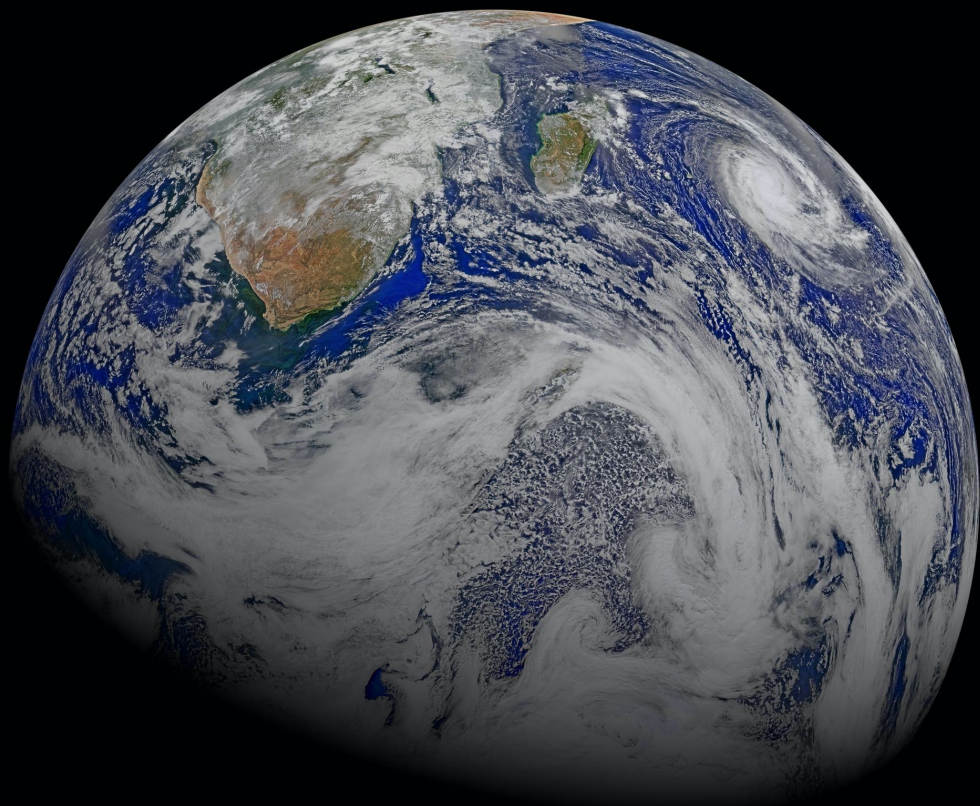
Conclusions

- **End-to-end Flow:** we identified a ready-to-use toolflow (FPG-AI + Impulse) to map CNN-based algorithms on NX FPGAs
- **Efficient System Integration:** the user can easily integrate the AXI memory-mapped accelerator provided by FPG-AI into a multi-peripheral system
- **Fine-grain Control:** the user can drive the DSE process to meet different application constraints (throughput, accuracy) or to tune resource utilization for further facilitating system integration
- **Comparison Results:** resource consumption aligned to Xilinx devices but with lower implementation frequencies

Parallel Activity – Extension to RNNs

- Enabling FPG-AI support for Recurrent Neural Networks (RNNs)
- Few tool flows in the literature supporting this model topology
- Results collected for an FDIR application onboard the satellite [3]





THANKS!

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References

- [1] T. Pacini, E. Rapuano, L. Fanucci: “FPG-AI: A Technology-Independent Framework for the Automation of CNN Deployment on FPGAs”, IEEE ACCESS Journal, March 2023
- [2] T. Pacini, E. Rapuano, P. Nannipieri, L. Fanucci: “A Technology-Independent Toolflow for Automating AI Deployment on FPGAs for On-board Satellite Applications”, 5th Space FPGA Users Workshop, March 2023
- [3] T. Pacini, E. Rapuano, L. Tuttobene, P. Nannipieri, L. Fanucci, S. Moranti, “Towards the Extension of FPG AI Toolflow to RNN Deployment on FPGAs for On board Satellite Applications”, European Data Handling & Data Processing (EDHPC) for Space Conference, October 2023