The International Workshop on Edge Artificial Intelligence for Industrial Applications (EAI4IA)

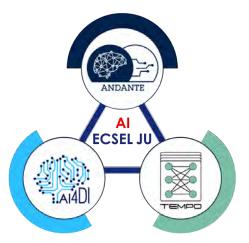
ANDANT

ECSEL JU

TEMPO

Vienna, Austria 25-26 July 2022

The International Workshop on Edge Artificial Intelligence for Industrial Applications (EAI4IA)



Benchmarking Neuromorphic Computing for Inference

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Presentation Outline



- Challenges of IoT/ Edge Computing
- Benchmarking: State-of-the-Art
- Unfair / Fair Benchmarking
- Use-Case dependent Benchmarking
- Conclusions and Outlook

Challenges of IoT / Edge Computing

- What is the best solution for my application?
 - Objective is Hardware comparison and KPIs estimation
- Applications for neuromorphic computing
 - Industrial plant \rightarrow Condition Monitoring

 - Automotive \rightarrow Autonomous Driving

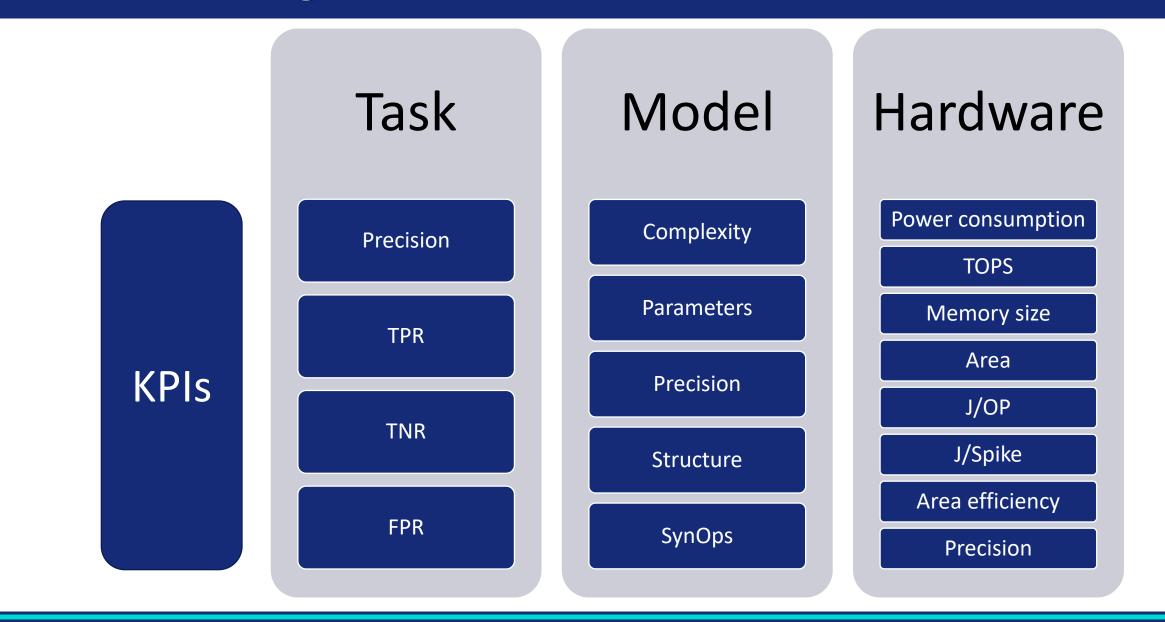
 \rightarrow Ambient Assisted Living

- People
- Ecosystems \rightarrow Animals monitoring
- Conditions
 - Distributed deployment
 - Continuous Monitoring (low-latency)
 - Battery powered operation (low-power)
 - Wireless communication (without cloud connection)





Benchmarking: State-of-the-Art



Benchmarking: State-of-the-Art

Table 1.4 Typical display of performance comparison of neuromorphic hardware platforms,adapted from [34].

adapted from [5+].						
DLI Accelerator	Туре	Target application	Performance			
NVIDIA Jetson Nano	GPU	Embedded	472 GOPS @ 5 – 10 W			
Nvidia Jetson TX2	GPU	Edge	1,3 TOPS @ 7,5 W			
NVIDIA Jetson AGX Xavier	GPU	Edge	30 TOPS @ 30 W			
NVIDIA Drive AGX Pegasus	GPU	Automotive	320 TOPS			
Intel Movidius Myriad 2 bzw. Myriad X	Chip	Embedded/Edge DL/Vision	4 TOPS @ 1 W (Myriad X)			
MobilEye EyeQ4	Chip	Automotive	2.5 TOPS @ 3 W			
GreenWaves GAP8	Chip	Battery powered AI	200 MOPS bis 8 GOPS @ <100mW			
Canaan Kendryte K210	Chip	Embedded Vision & Audio	250 GOPS @ 300mW			
Google Coral Edge TPU	Chip	Edge	4 TOPS @ <2,5W			
Lattice sensAI Stack	Soft IP-Core	Embedded	<1 mW – 1 W			
Videantis v-MP6000UDXM	Soft IP-Core	Embedded DL/Vision	<6,6 TOPS @ 400 MHz			

Table 1.5 Recent display of performance comparison of neuromorphic hardware platforms,adapted from [35].

Eyeriss		Eyeriss	ENVISION	Thinker	UNPU	Thi	s work
Technology		65nm	28nm	65nm	65nm	6	5nm
Area		1176k gates	1950k gates	2950k gates	4.0mm×4.0mm	2695k gates	
		(NAND-2)	(NAND-2)	(NAND-2)	(Die Area)	(NAND-2)	
On-chip SRAM (kB)		181.5	144	348	256	246	
Max Core Frequency (MHz)		200	200	200	200	200	
Bit Precision		16b	4b/8b/16b	8b/16b	1b-16b	8b	
Num. of MACs		168 (16b)	512 (8b)	1024 (8b)	13824 (bit-serial)	384 (8b)	
DNN Model		AlexNet	AlexNet	AlexNet	AlexNet	sparse AlexNet	sparse MobileNet
Batch Size		4	N/A	15	N/A	1	1
Core Frequency (MHz)		200	200	200	200	200	200
Bit Precision		16b	N/A	adaptive	8b	8b	8b
Inference/sec	(CONV only)	34.7	47	-	346	342.4	-
	(Overall)	-	-	254.3	-	278.7	1470.6
Inference/J	(CONV only)	124.8	1068.2	-	1097.5	743.4	-
	(Overall)	-	-	876.6	-	664.6	2560.3

Benchmarking: Combined KPIs

	Task	Model	Hardware	Combined
	Precision	Complexity	Power consumption TOPS	Configuration time
KPIs	TPR	Parameters	Memory size Area	
	TNR	Precision of parameters	J/OP	Latency
	FPR	Structure	J/Spike Area efficiency Precision	Energy/Inference

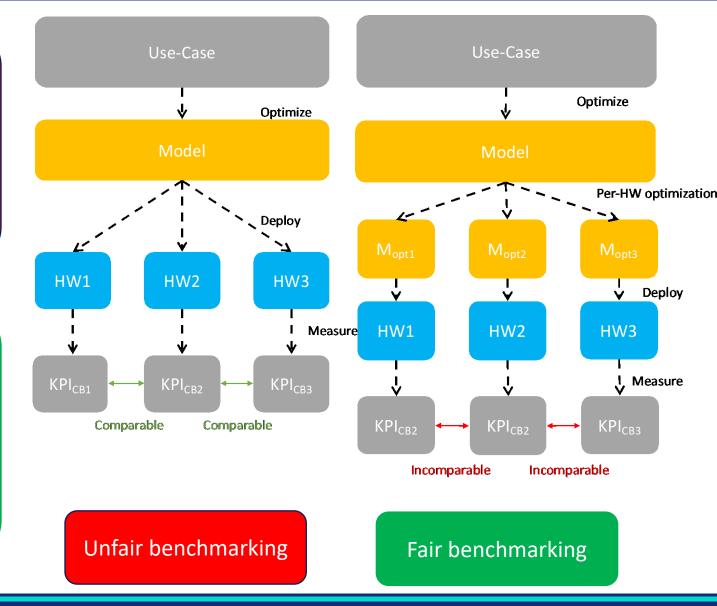
Unfair / Fair Benchmarking

Unfair Benchmarking

- Same NN is deployed in each hardware platform
- Hardware KPIs can be compared since Task and Model KPIs are same
- However, all capabilities of the hardware are not exploited and the models are not optimized and the comparison is misleading

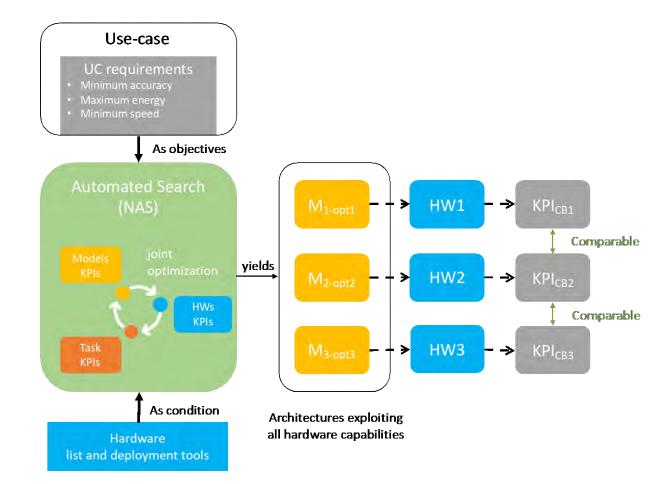
Fair benchmarking

- Exploits all capabilities of the hardware
- Different NN models are deployed on the hardware
- Thus Model and Hardware KPIs cannot be compared
- Over-optimization makes the comparison impossible.



Use-Case dependent Benchmarking

- A benchmarking framework is necessary
- Automated Search is necessary to optmize KPIs
- Each hardware suports different network sizes and layer types
- Benchmarking should compare only architectures exploring all hardware capabilities for the requirements of a certain use case
 - Accuracy, latency, energy per inference
- Hardware device can be selected based on the resulting KPIs



Use-Case dependent Benchmarking

NN	Value									
Quantization	8, 4, 2 bits		Conv2D Input: 64X13X1	13X1 Input: 31X5X32 ix4 Kernel: 3x3 2 → ReLU activation:ReLU	Conv2D Input: 29X3X32 Kernel: 3X3 stride:1 activation:ReLU outputs: 27X1X32	Conv2D Input: 27X1X32 Kernel:12x1 stride:1 activation:ReLU outputs:16X1X16	Conv2D Input: 16X1X16 Kernel:1x1 stride:1 activation:ReLU outputs:16X1X1	FC	FC Input: 32 Kernel:32X1 activation:Sigmoid outputs:1	
SRAM	200 kBytes		Kernel: 4x4 stride:2 - activation:ReLU					Input: 16 Kernel:16X32 activation:ReLU		
Num. Layers	≤ 10		outputs: 31X5X32					outputs:32		
Layer types	Conv1D, Conv2D, Flatten (1x1 Conv), FC, BN	MACs	79360	801792	248832	98304	256	512	32	Total 1.238M
Activation types	ReLU, Sigmoid	Params	512	9216	9216	6144	16	512	32	25801
Max. input size FC layer	1152		Conv2D	Conv2D	Conv2D	Conv2D	Conv2D			
Accuracy	≥92%		Input: 64X13X1 Kernel: 4x8 stride:2 activation:ReLU outputs: 31X3X32	Input: 31X3X32 Kernel: 4x2 stride:1 activation:ReLU	Input: 28X2X32 Kernel: 4X2	Input: 25X1X32 Kernel:10x1 stride:1 activation:ReLU outputs:16X1X16	Input: 16X1X16 Kernel:1x1 stride:1 activation:ReLU outputs:16X1X1	FC Input: 16 Kernel:16X32	FC Input: 32 Kernel:32X1 activation:Sigmoid outputs:1	
Mean Power consumption	< 1 mW				activation:ReLU outputs: 25X1X32			activation:ReLU outputs:32		
Latency	< 5 ms									Total
		MACs	98208	460544	154200	61696	256	544	33	0.776M
		Params	1024	8192	6144	3840	16	512	32	19898

Conclusion and Outlook

- Benchmarking neuromorphic hardware is a hard task
 - Variety of devices
 - Variety of software tools
 - (Un)comparable KPIs
- Not all KPIs are relevant, combined KPIs are more informative
- Use-case based benchmarking should be used
- Benchmarking framework and complete software tool chain are necessary
 - Hardware-aware training
 - Automated search
 - Mapper and compiler

Event Organisers









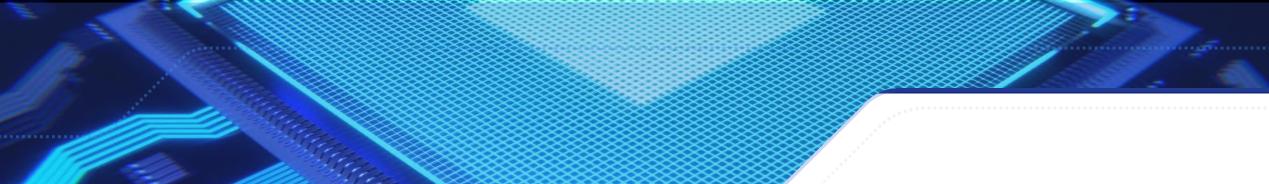


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Thank You For your attention



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