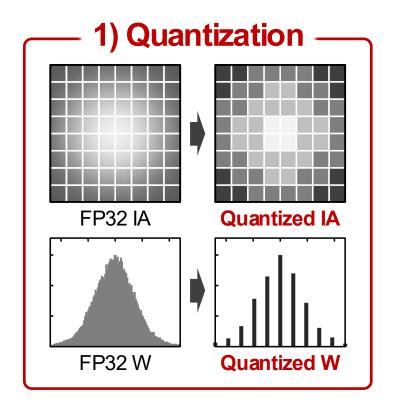
HNPU-V2: A 46.6 FPS DNN Training Processor for Real-World Environmental Adaptation based Robust Object Detection on Mobile Devices

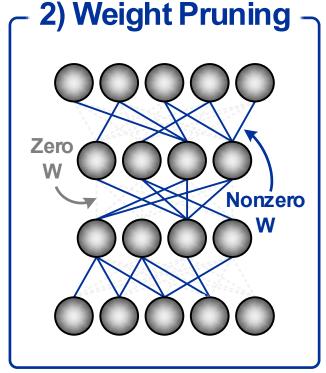
Donghyeon Han, Dongseok Im, Gwangtae Park, Youngwoo Kim, Seokchan Song, Juhyoung Lee, and Hoi-Jun Yoo

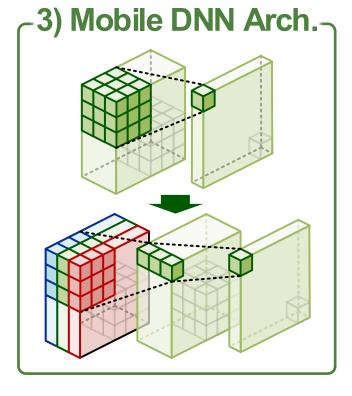
Semiconductor System Lab. School of EE, KAIST

Development of DNN for Mobile Platforms

- Smarter DNNs: # of Parameter ▲
- Lightweight DNNs for Mobile Devices
 - Quantization, weight pruning, pointwise or depthwise CONV ...

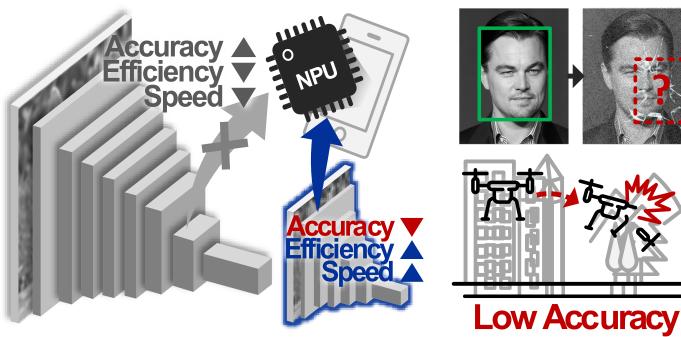


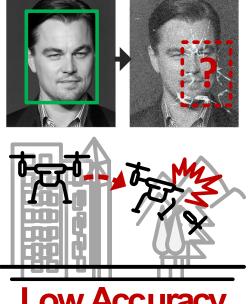


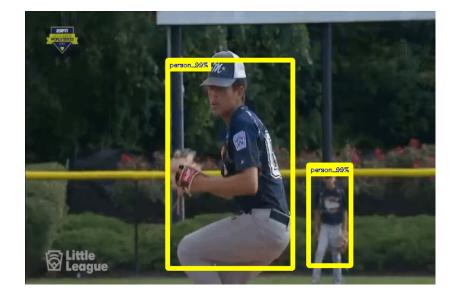


Disadvantages of Mobile-oriented DNNs

- Low Detection Accuracy in Practice
- Performance Degradation After Unexpected Situations
 - Low network capacity → Loosing generality → Sensitive to accident

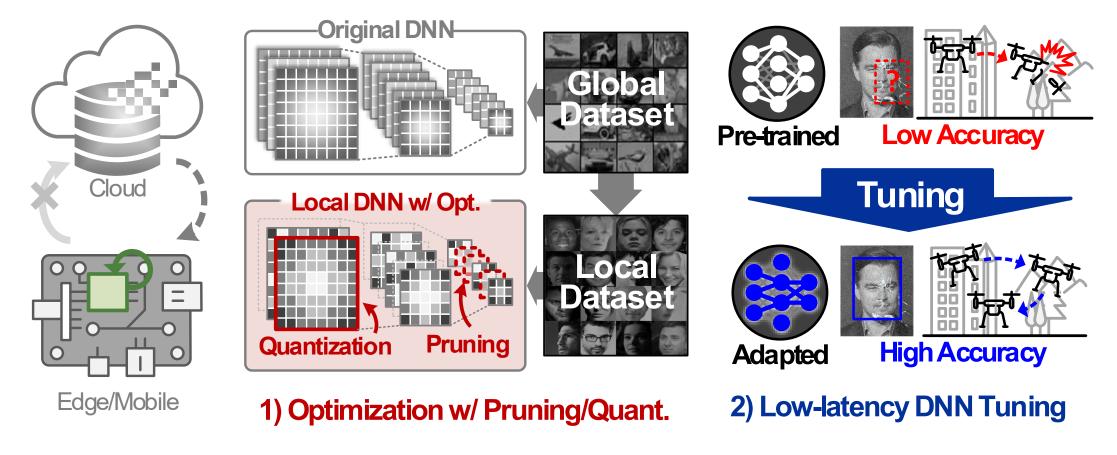






Promising Solution: On-device DNN Training

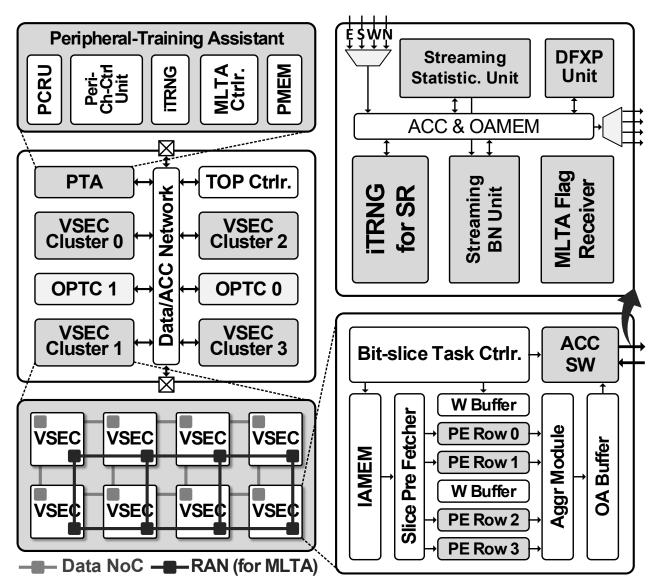
- Personalization: High Accuracy only for User-specific Task
- Adaptation: Performance Recovery using Online Tuning



Overall Architecture of HNPU-V2

32 Versatile Sparsity Expl oitation Cores (VSEC)

- Bit-slice = 4b
- Computing unit: 4b×4b
- Support (4,8,12,16)-bit
- DFXP* + Stochastic rounding
- Input slice skip
- Weight skip
- 2 OPTC**s & 1 PTA***
- 2-D Mesh NoC



Overall Architecture of HNPU-V2

*True-Random Number Generator

** Pruning-aware Channel Reordering Unit

***Reconfigurable Accumulation Network

1. intrinsic-TRNG*

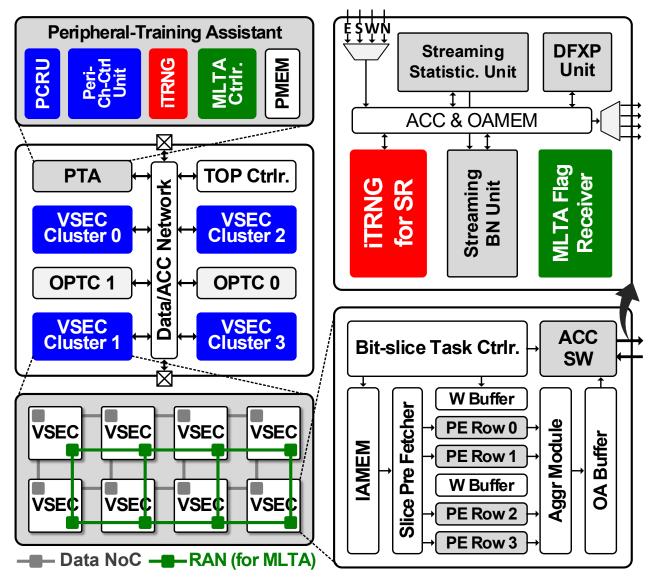
- Truly random bit-streams
- Stochastic rounding for lowprecision training

2. VSEC w/ PCRU**

- Input zero-slice skipping
- Pruned Ch skip

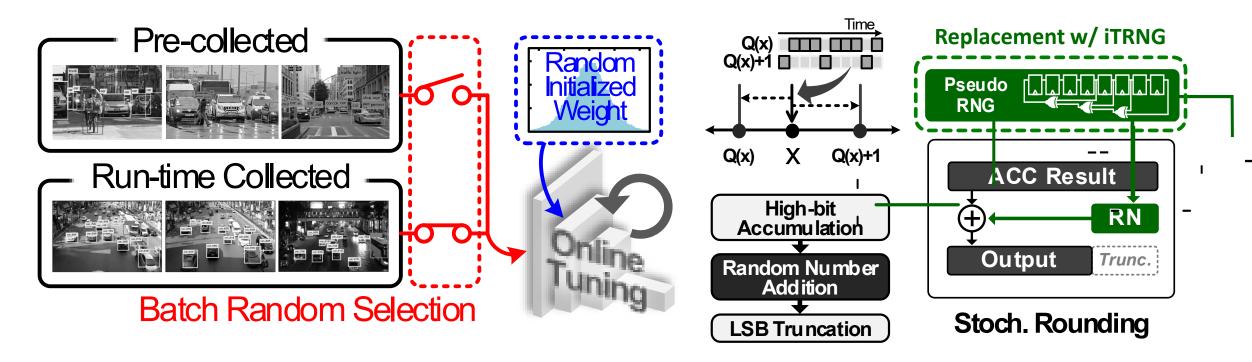
3. Multi-Learning Task Aalloc.

- Flag based RAN*** control
- To support backward unlocking



Various Usages of RNG

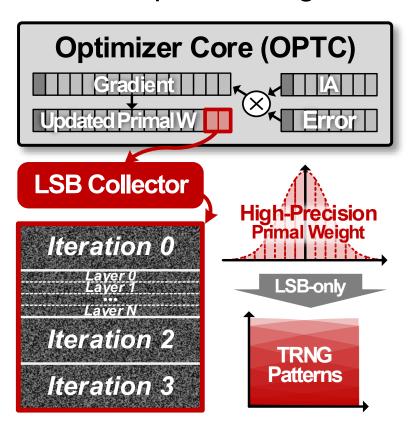
- Example 1: Basic Training Functionality
 - Ex) Weight initialization, batch selection,
- Example 2: Stochastic Rounding*
 - For Low-precision computing during the FXP based DNN training



Two Different Types of iTRNGs in HNPU-V2

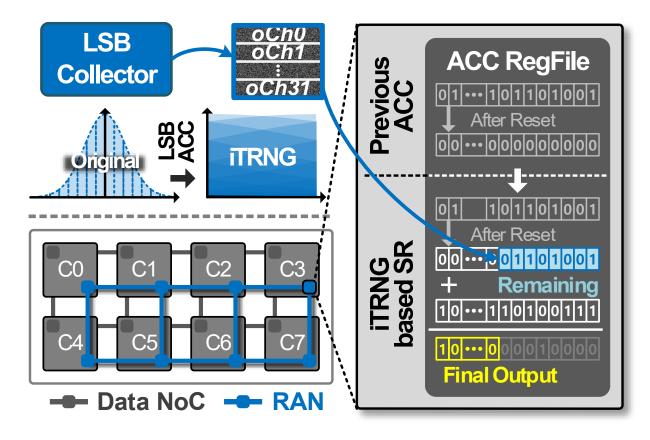
1st iTRNG: Placed in PTA

 Extracting & cumulating LSB bitstream of primal weight



2nd iTRNG: Placed in ACC SW

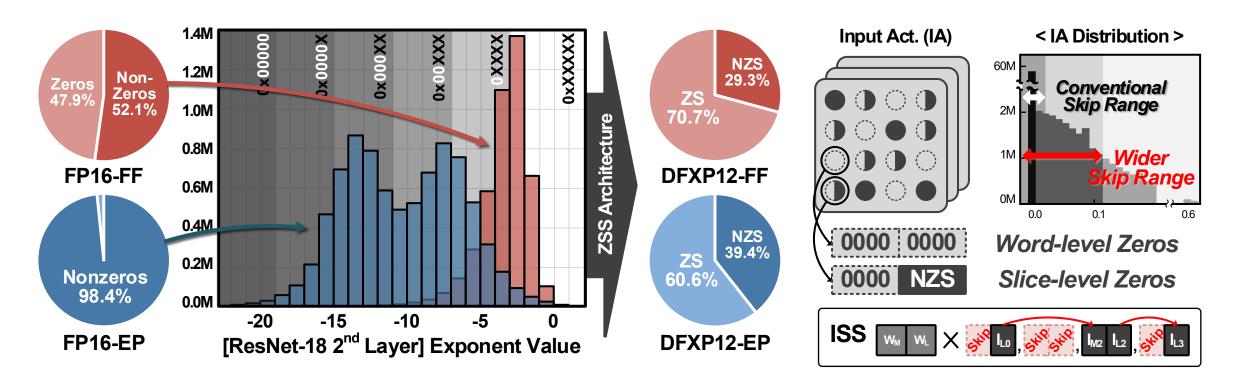
Adding random noise → Remaining
 LSB bit-stream of accum results



Input-slice Skipping* (ISS)

Bit-slice-level Sparsity Exploitation

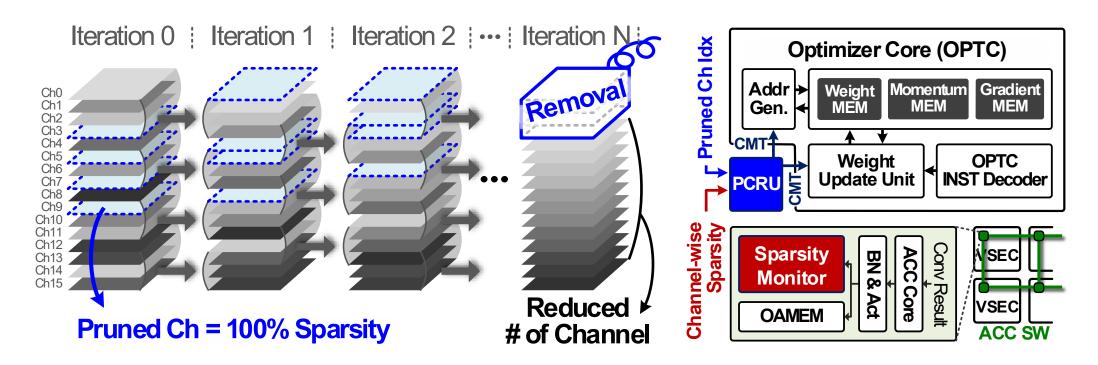
- Most of data: placed near zero (Gaussian-like distribution)
- Giving possibility of skipping MSB zeros even with non-ReLU / EP Stage



Pruning-aware Ch Reordering Unit (PCRU)

Supporting Weight Pruning w/ Channel Removal

- Receiving pruned channel index → Considering Ch as 100% sparsity
- OPTC: updating weights by referring the pruning-aware Ch mapping table
 - → New weight: changed order & excluded Ch



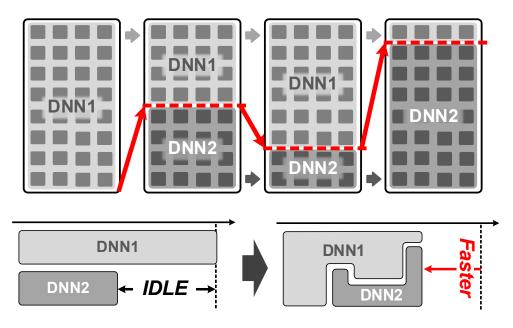
Opposite Properties of Two Processors

Problems of GANPU*

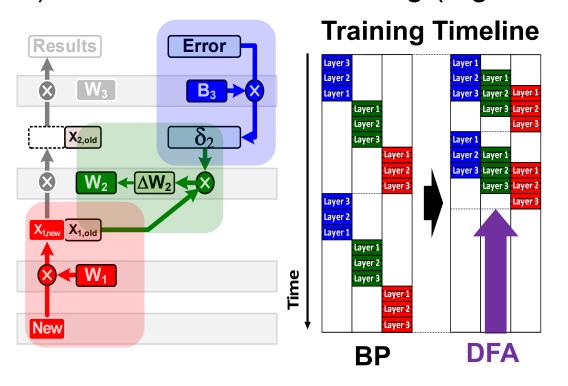
- High Reconfigurability
- Single-LT Supporting
 - Back-propagation (FF → EP → WG)

Problems of DF-LNPU**

- Low Reconfigurability
- Multi-LT Allocation
 - Backward unlocking (e.g. DFA)

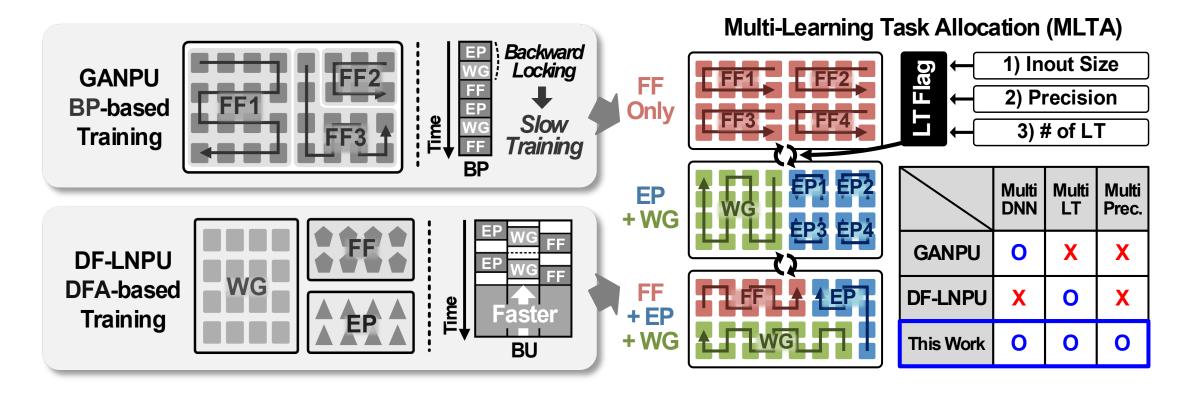


Workload Opt. w/ Dynamic Core Alloc.



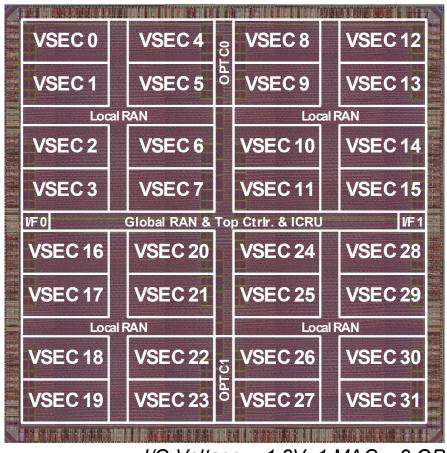
Multi-Learning Task Allocation in HNPU-V2

- RAN w/ Learning-Task-flag → Indicating Training Stages
- Dynamic Core Allocation according to Three Parameters
 - 1) Inout Size, 2) Bit-precision, 3) Learning tasks (Training stages)



Chip Summary

Chip Photograph & Performance Summary



I/O Voltage = 1.8V, 1 MAC = 2 OP

	Specifications				
Technology	Samsung 28nm 1P8M CMOS				
Die Area	3.6mm × 3.6mm (12.96mm ²)				
Supporting BU	BP, DFA [6], (Programmable)				
Op. Condition	0.63V (@ 10MHz) ~ 1.0V (@ 250MHz)				
Data Type	DFXP + SR (4/8/12/16)-bit × (4/8/12/16)-bit				
Area Efficiency	59-to-9334 GOPS/mm ²				
	Sparsity (IS, W) [%]	(0,0)	(50,50)	(90,90)	
Power [mW]	250MHz, 1.0V	1032	850	616	
	10MHz, 0.63V	24.1	19.8	14.6	
Energy Efficiency @ 10MHz [TOPS/W]	16b×16b	2.04	6.01	98.1	
	8b×8b	6.81	19.9	220	
	4b×4b	20.4	49.8	332	

Chip Performance Comparison

	JSSC'20	ISSCC'20	S.VLSI'20	HNPU-V1	HNPU-V2
Backward Unlocking	0	X	Χ	X	0
Low-precision Training	DFXP	Χ	X	SDFXP	DFXP+SR
Robustness for Non-ReLU	X	X	X	Zero-s i ce Skip	Zero-slice Skip
Technology	65nm	65nm	65nm	28nm	28nm
MAX Core Frequency	200MHz	200MHz	200MHz	250MHz	250MHz
Supporting Precision	FXP13/16	FP 8/16	FP 8/16	FXP 4/8/12/16	FXP 4/8/12/16
Throughput [GOPS]	155	1080	763	4526	7072
Area Efficiency* [(GOPS or GFLOPS)/mm ²]	26.9	33.3	47.7	349	545
Energy Efficiency* [(TOPS or TFLOPS)/W]	0.62	1.67	1.79	4.74	7.89

^{56%}

67% 🔺

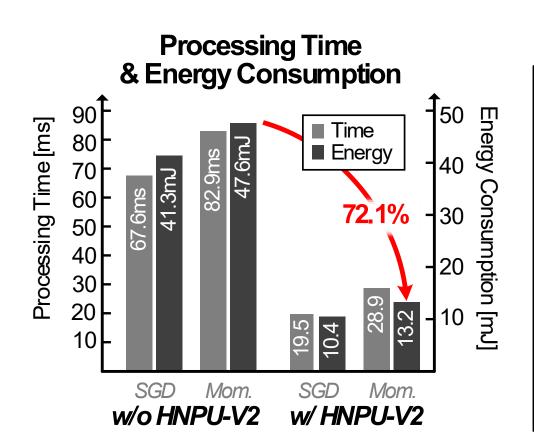
^{*}Measured @ Object Detection Scenario (Tiny-yolo-v3 w/ 20% Pruning)

Object Detection Performance Comparison

Highest Framerate: 46.6 FPS

*Total number of detections in a single image

Lowest Energy Consumption: 0.95 mJ/frame



< Object Detection Comparison Table >

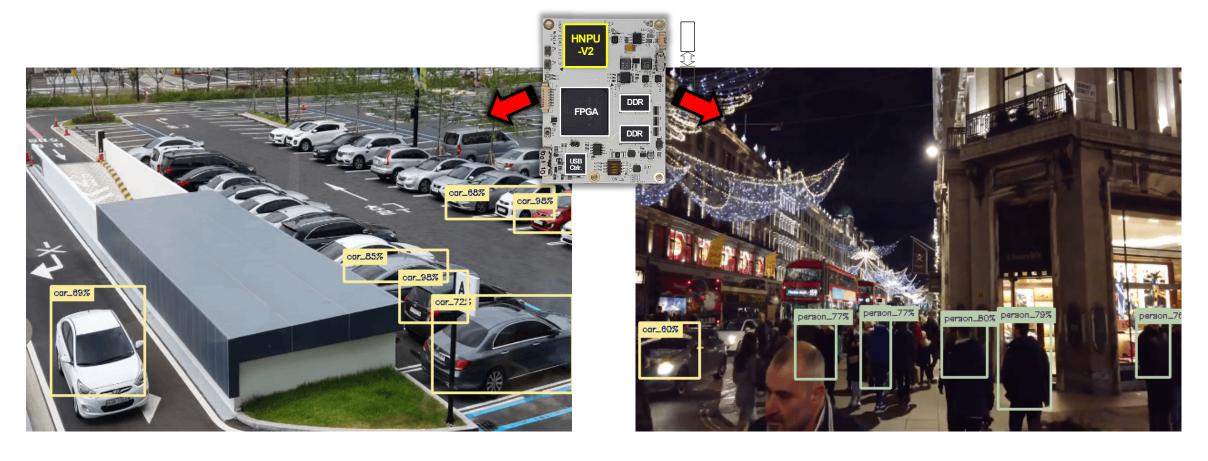
	TCAS-I '18	JSSC '20	A-SSCC 21	HNPU V1	HNPU V2
# of Detection*	1	1	>1	>1	>1
Backward Unlocking	X	0	X	X	0
Operating Frequency	200 MHz	200 MHz	200 MHz	200 MHz	100 MHz
Framerate (FPS)	30.4	34.4	25.2	26.7	46.6
Energy per Frame [mJ/frame]	4.14	4.88	2.13	1.68	0.95

75% 🔺

44% **T**

Robust Object Detection w/ DNN Training

- HNPU-V2: Online DNN Tuning for Accuracy Compensation
- Automatic Accuracy Recovery from Unexpected Situations



Conclusion

intrinsic-TRNG

- On-chip random number generation for DNN training functionality
- Stochastic rounding → Low-precision DNN training
- Versatile Sparsity Exploitation Core with PCRU
 - Input-slice skipping w/ workload balancing
 - Pruning-aware online DNN tuning by supporting channel removal
- Multi-Learning-Task-Allocation w/ LT-flag based RAN Control
 - Enable BU for low-latency online DNN tuning

HNPU-V2: A 0.95 mJ/frame DNN Training Processor for 46.6 FPS Real-time Environmental Adaptation

Thank You!

• Questions? Feel Free to Contact Me!

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- Personal Web-site:
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 - https://www.youtube.com/channel/UC1JOzBOZtHnWPEgP2QVdRQQ/
- Zoom Meeting:

https://zoom.us/j/6238458176?pwd=QldmbnhDOWNFdU9wcDhIKzdDN2ZiZz09 (Password: Donghyeon)