

IEEE Custom Integrated Circuits Conference

An In-Memory-Computing Charge-Domain Ternary CNN Classifier (Best Student Paper Candidate)

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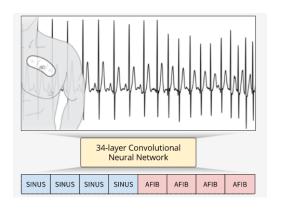
Outline

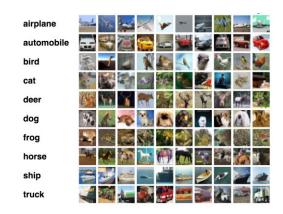
- Motivations
- Existing Works
- Theoretical Concept of the Proposed Work
- Circuit Implementation
- Measurement results
- Summary



Quest for Energy Efficient Edge Computing System

Increasing need from various applications:







Pattern Recognition

Image Classification

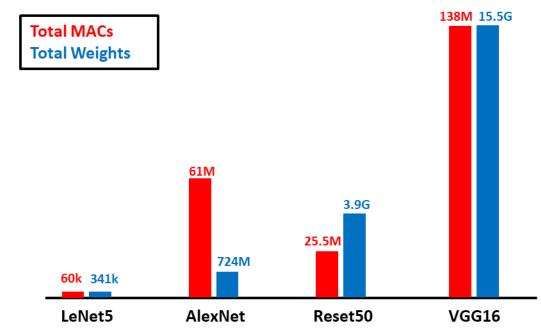
Object recognition



Challenges on Energy Efficient NN Inference

High computation energy

High memory access energy



[V. Sze, Proceedings of the IEEE 105.12 2017]

Challenges on Energy Efficient NN Inference

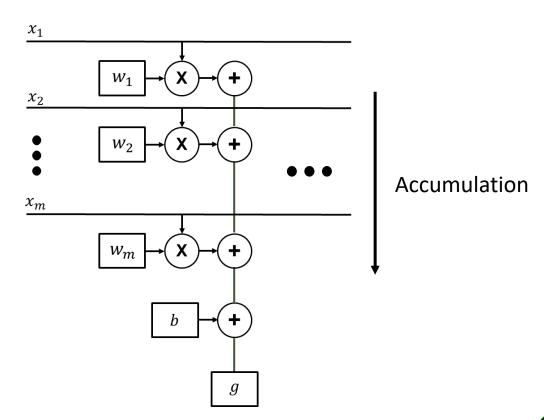
$$h = g \left[\left(\sum_{i=1}^{m} w_i * x_i + b \right) \right]$$

 x_i : Input activation

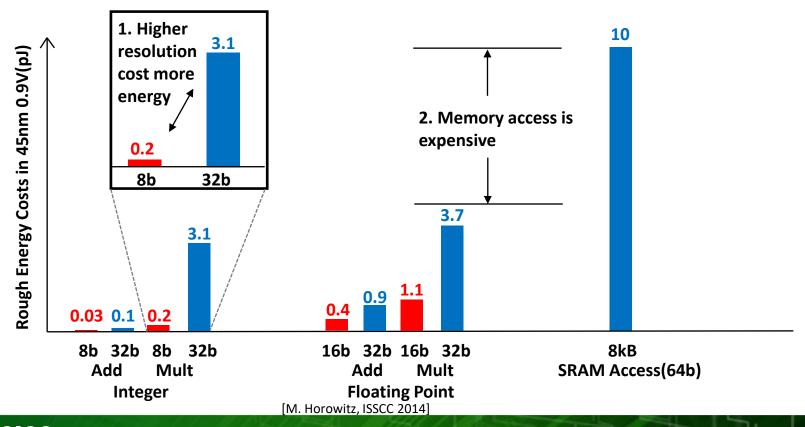
 w_i : Weight b: Bias

h: Output to next layer

g: Activation function



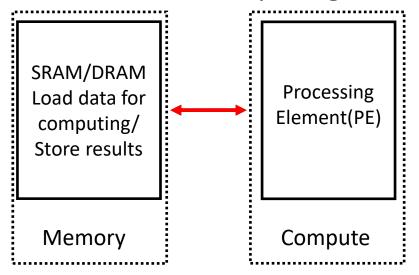
Challenges on Energy Efficient NN Inference





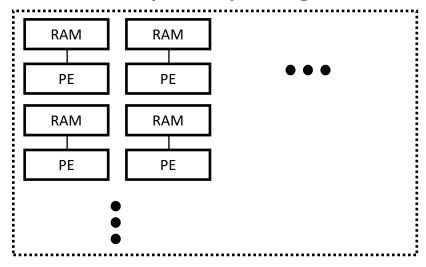
Solutions to Energy Efficient NN Inference

Conventional computing:



Memory access can easily dominate energy/throughput

• In-memory-computing:

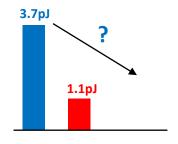


Minimized data movement from distributed memory

Solutions to Energy Efficient NN Inference

Reduced Resolution Network:

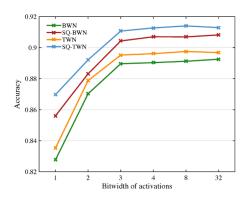
32b Floating point \rightarrow ?



Multiplying energy cost

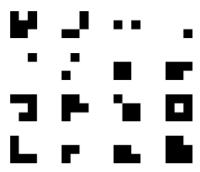
Solutions to Energy Efficient NN Inference

Reduced Resolution Network:



CIFAR-10, ResNet-56
Activations are quantized to 1/2/3/4/8/32b

[Y. Dong, IJCV 2019]



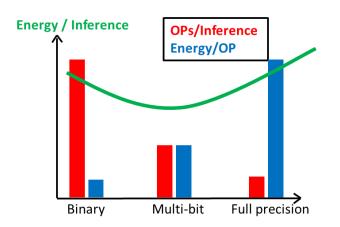
Visualization of filters from binary neural network

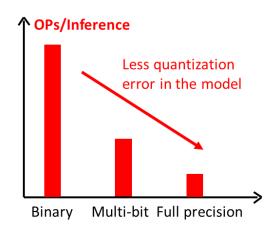
[M. Courbariaux, arXiv 2016]

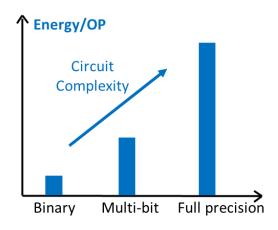
Energy Cost of NN Inference

$$Power = Rate \times \frac{Energy}{Inference} = Rate \times \frac{Operations}{Inference} \times \frac{Energy}{Operation}$$

[B. Murmann, ISSCC 19 Tutorial]







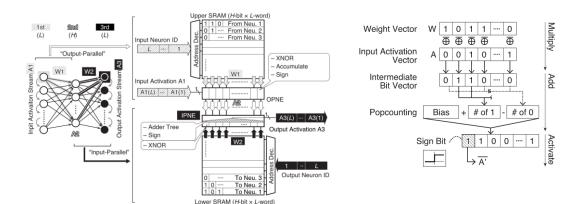
Outline

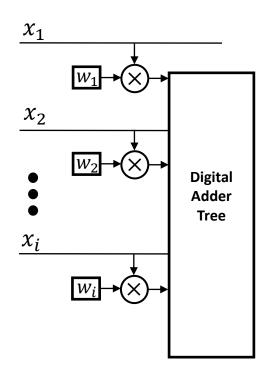
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Existing works

• Digital Domain:

- Bit error free ©
- High power from digital adder tree 🖰
- Low throughput 🕾



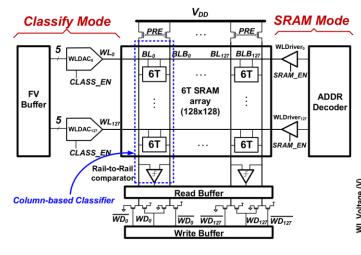


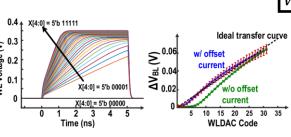
[K. Ando, JSSC 18]



Existing works

- Current Domain:
 - High throughput ©
 - PVT-robustness 🙈
 - Consumes static current 🕾





 x_1

 x_2

 x_i

[J. Zhang, JSSC 17]

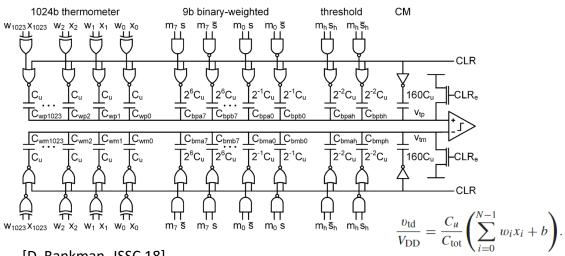


ADC

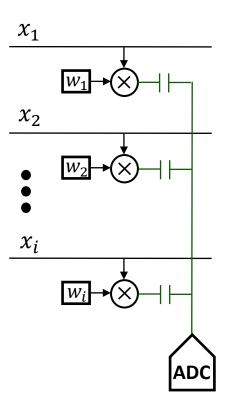
Existing works

Charge Domain:

- High throughput [©]
- No static current ©
- Large operations/inference 😕



[D. Bankman, JSSC 18]

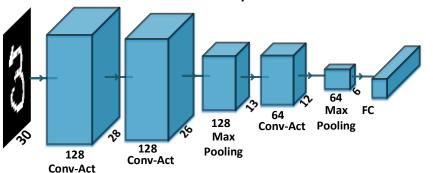


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Comparison of Model Size

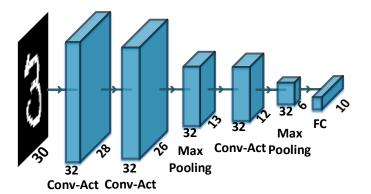
Baseline test: 98% Accuracy on MNIST



Layer	Туре	Size Channel		Filter Size	
1	CONV-TN	30x30	1(input)		
2	CONV-TN	28x28	128		
2p	MAX POOL	26x26	128	2x2	
3	CONV-TN	13x13	64		
3р	MAX POOL	12x12	04		
4	FC	(Flatten 6x6x64) 2304 - 10			

1b Resolution 1.38x10⁸ OPs

~4x Bigger model size

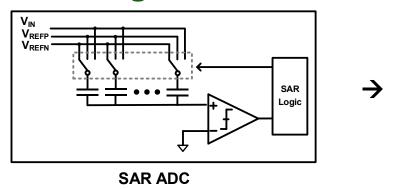


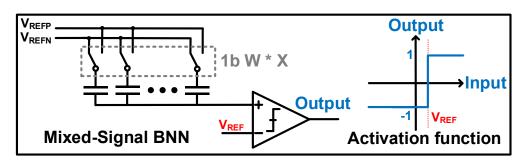
Layer	Туре	Size	Channel	Filter Size	
1	CONV-TN	30x30	1(input)		
2	CONV-TN	28x28			
2p	MAX POOL	26x26	32	2x2	
3	CONV-TN	13x13			
3р	MAX POOL	12x12			
4	FC	(Flatten 6x6x32) 1152 - 10			

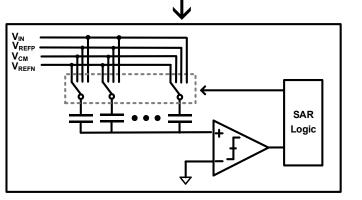
1.5b Resolution 3.57x10⁷ OPs {w,x from -1,0,1}

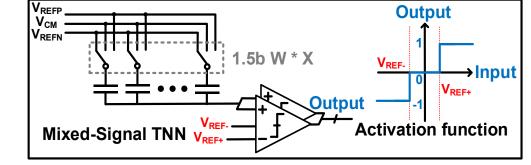


Mixed Signal BNN vs TNN



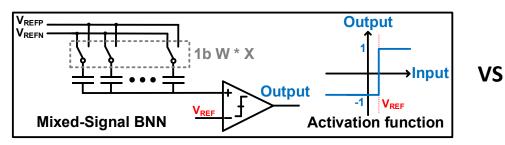


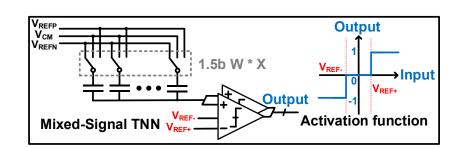




SAR ADC with V_{CM} based switching

Mixed Signal BNN vs TNN





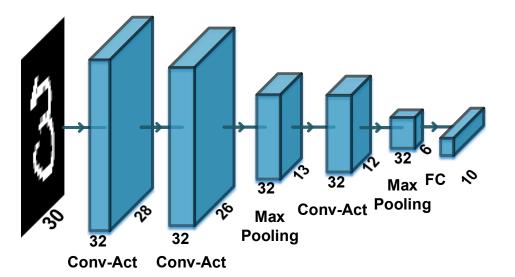
	Hardware Complexity	Operations Inference (@same accuracy)	Energy χ Operation = (CDAC signal swing)	Energy Inference
BNN			<u> </u>	<u> </u>
TNN		©		©

OPs/Inference ↓ 75% Energy/Operation ↓ 31% Energy/Inference ↓ 82%

Outline

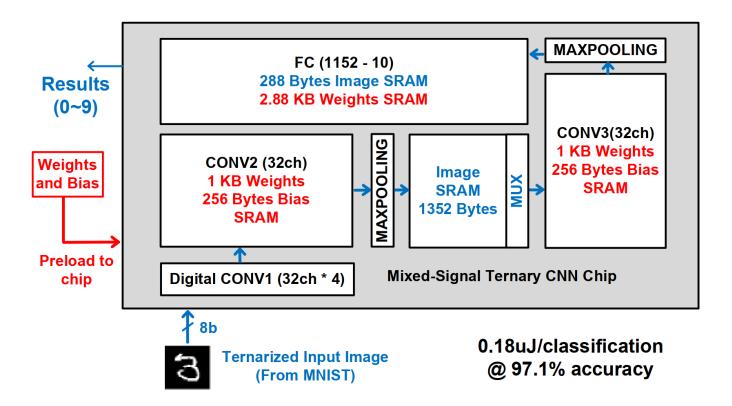
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On-chip Neural Network Model



Layer	Type	Size	Channel	Filter Size	Dilated
1	CONV-TN	30x30	1(input)		2
2	CONV-TN	28x28		2x2	2
2p	MAX POOL	26x26	32		1
3	CONV-TN	13x13	32		1
3р	MAX POOL	12x12			1
4	FC	(Flatte			

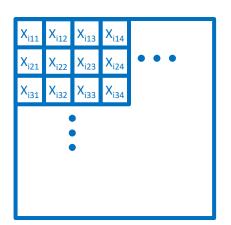
Chip Architecture



CONV1 – Example of One-Channel Convolution



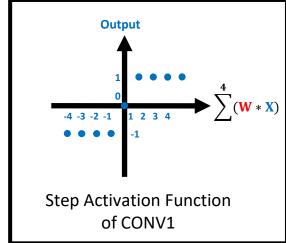
Filter0 2x2 Dilated L = 2

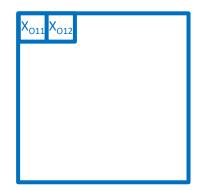


Ternarized Input Image 1ch

$$X_{011} = STEP(W_{11} * X_{i11} + W_{12} * X_{i13} + W_{21} * X_{i31} + W_{22} * X_{i33})$$

$$X_{012} = STEP(W_{11} * X_{i12} + W_{12} * X_{i14} + W_{21} * X_{i32} + W_{22} * X_{i34})$$

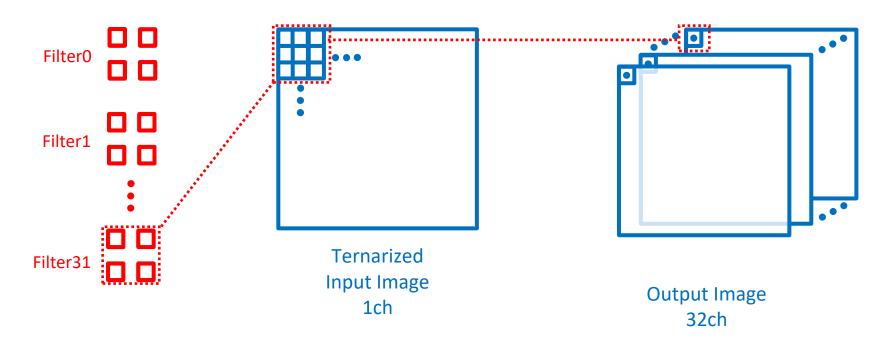




Output Image 1ch

 $W,X \in \{-1,0,1\}$

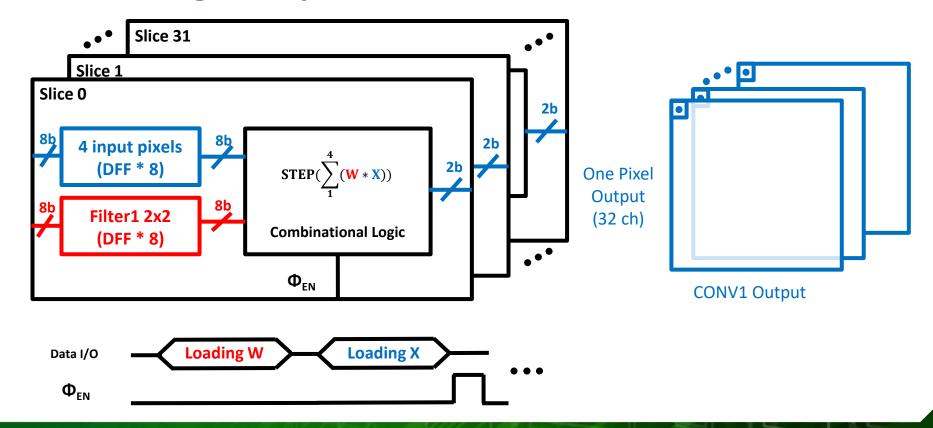
CONV1 – Example of 32-Channel Convolution



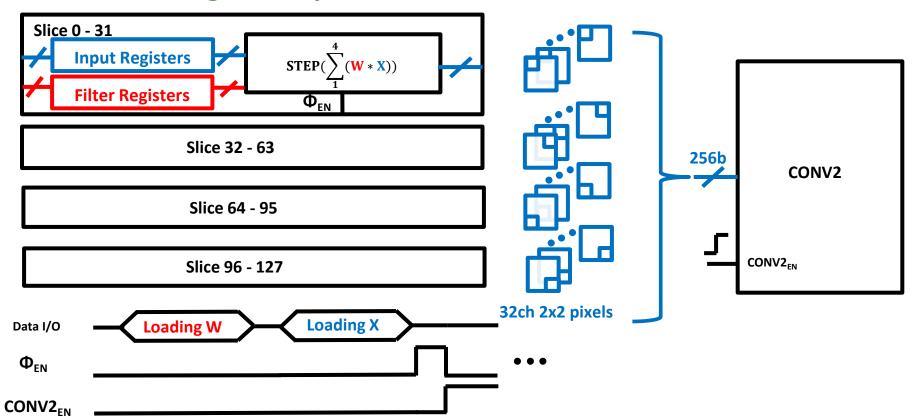
W,X ∈ {-1,0,1}



CONV1 – Digital Implementation

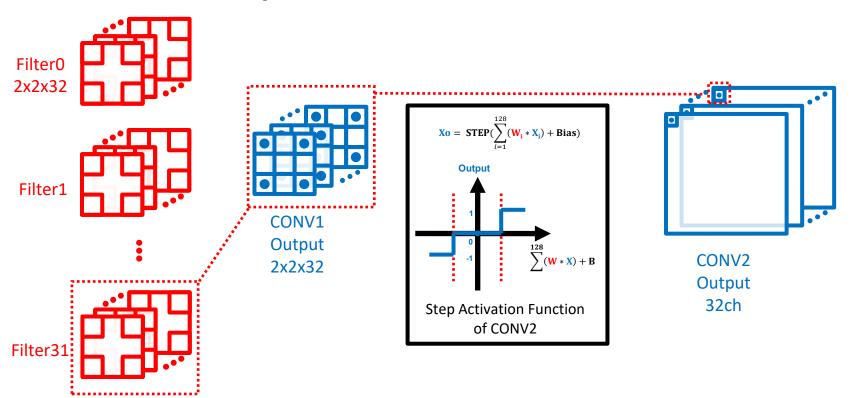


CONV1 – Digital Implementation



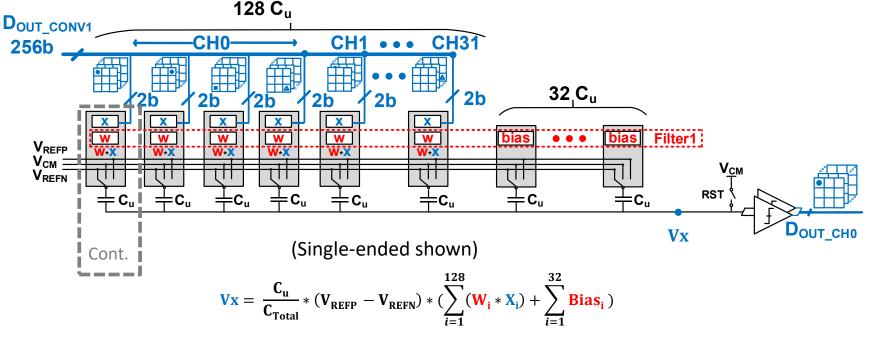


CONV2 – Example of 32-Channel Convolution





CONV2 – Implementation of One-Channel SC Neuron

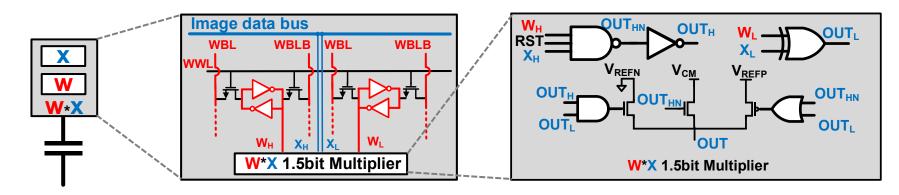


$$C_{Total} \approx 160 C_u$$

$$(\mathbf{W_i} * \mathbf{X_i})$$
, Bias $\in \{ \mathbf{V_{REFP}}, \mathbf{V_{CM}}, \mathbf{V_{REFN}} \}$



CONV2 – Synapse Design



DEC	BIN	Voltage
1	10	V_{REFP}
-1	11	V _{REFN}
0	ОХ	V _{CM}

Encoding for simplicity:

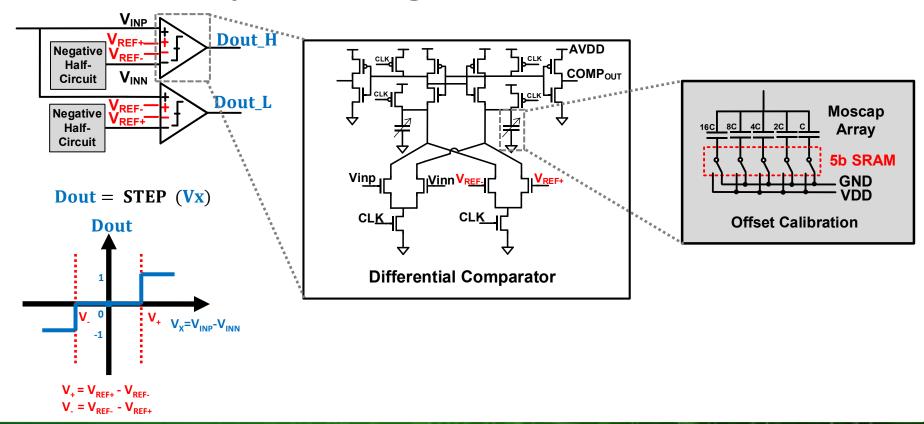
1.5b Multiplier
$$\rightarrow$$

$$|N1_{H} \longrightarrow OUT_{H}$$

$$|N1_{L} \longrightarrow OUT_{L}$$

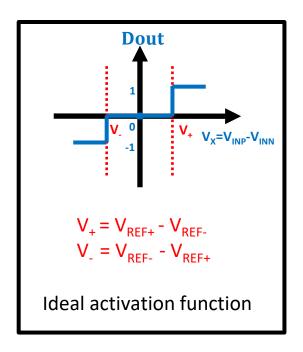
$$|N2_{L} \longrightarrow OUT_{L}$$

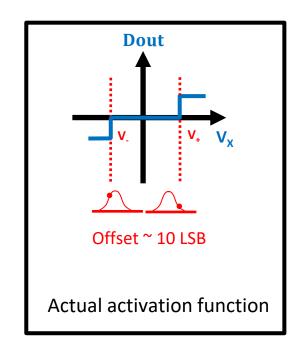
CONV2 – Comparator Design



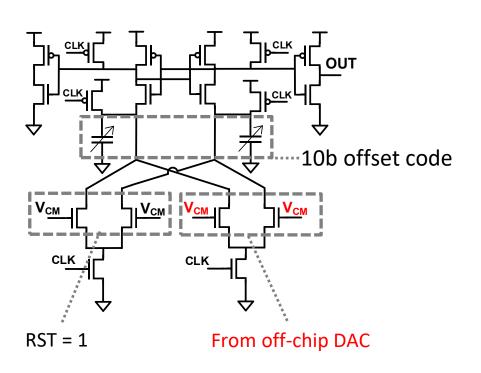
CONV2 – Effect of Comparator Offset

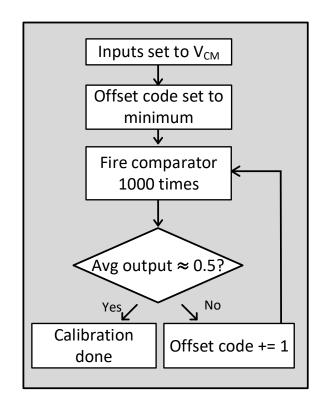
$$Dout = STEP(Vx)$$



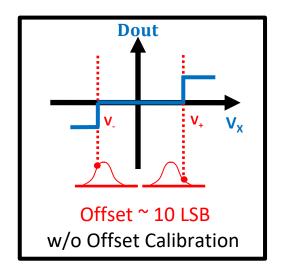


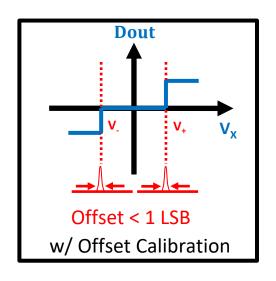
CONV2 – Foreground Comparator Offset Calibration



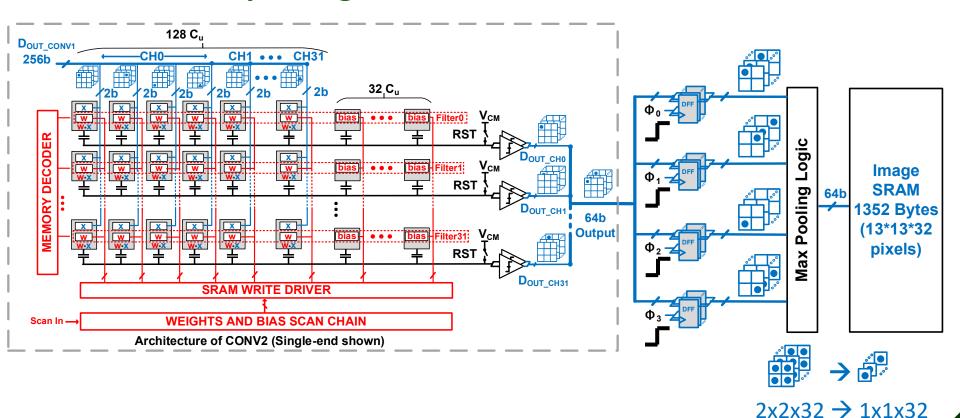


CONV2 – Foreground Comparator Offset Calibration

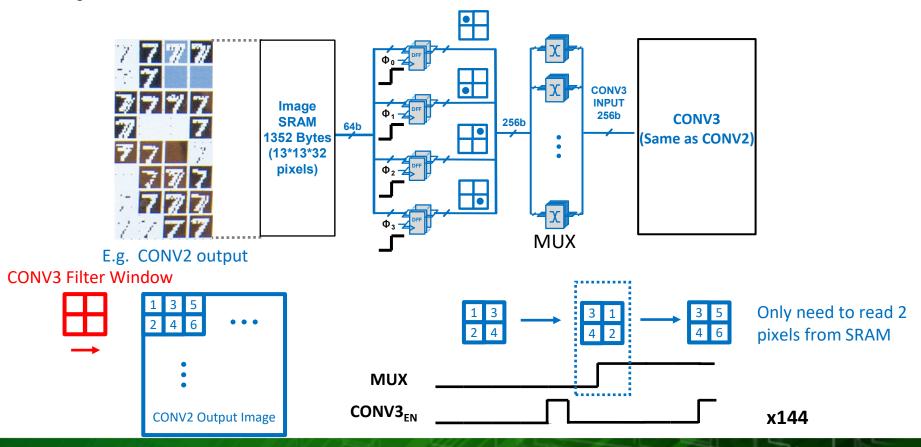




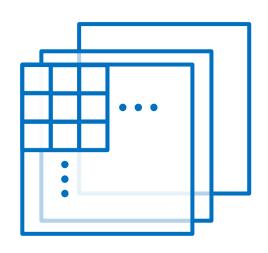
CONV2 – Maxpooling



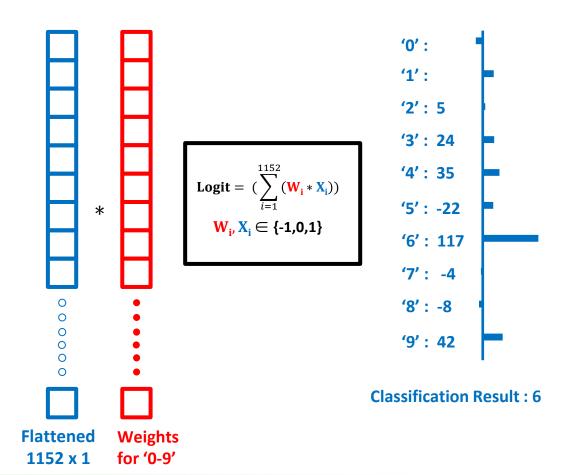
Datapath from CONV2 to CONV3



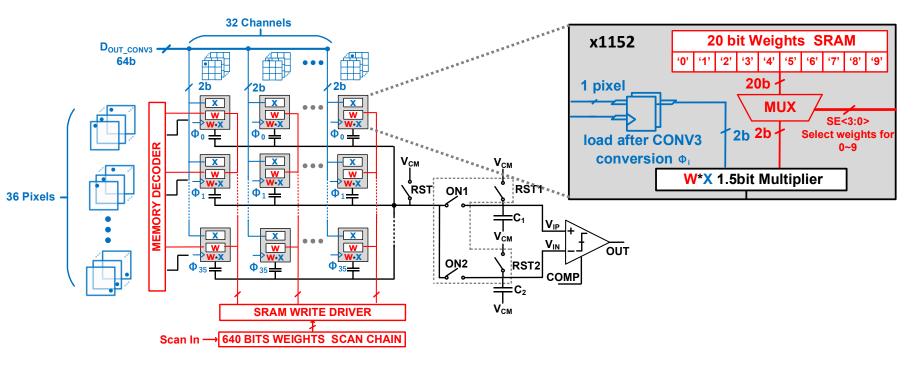
FC Layer Operation



CONV3 Output Image 6x6x32



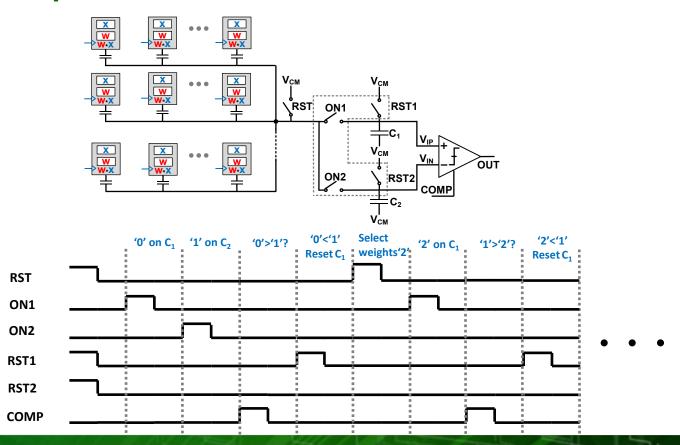
FC Layer Implementation



(Single-ended shown)



FC Layer Implementation





Outline

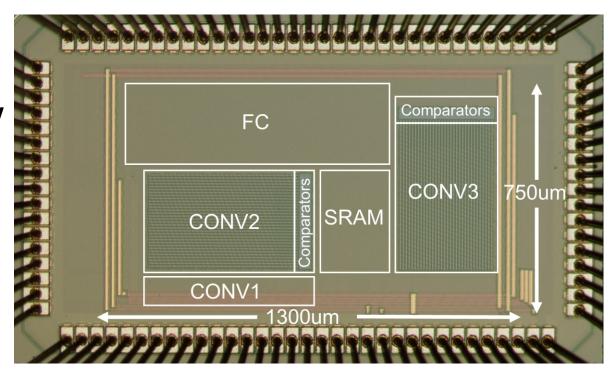
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Die Photo

40nm LP CMOS

Active Area: 0.98mm²

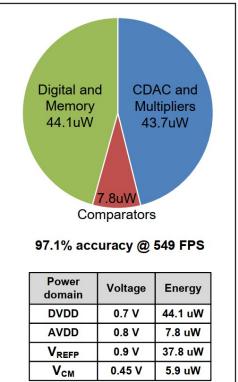
• Supply: 0.8V/0.7V/0.9V





Measurement Results





Comparison table

	This	s work	JSSC'18 K. Ando [1]	ISSCC'18 D. Bankman [2]	JSSC'20 Y. Cheng [3]	CICC'20 C. Yu [4]	JSSC'19 H. Valavi [5]
Technology	4	0nm	65nm	28nm	55nm	65nm	65nm
Circuit Type	1	d-Signal e-domain	Digital	Mixed-Signal Charge-domain	Mixed-Signal Current-domain	Mixed-Signal Current-domain	Mixed-Signal Charge-domain
Bit Precision	1	1.5b	1/1.5b	1b	1-8b	1-5b	1b
Area(mm2)	().98	3.9	4.6	5.85	0.055	12.6
Area Eff.(GOPS/mm2)	4	169 ¹	105	67	N/A	N/A	1498
Operating VDD(V)	0.8/	0.7/0.9	0.55-1.0	0.8/0.8	0.9	0.8/0.45	0.94/0.68/1.2
Energy Eff.(TOPS/W)	5	556 ²	2.3-6.0	532	40.2	490-15.8	866
Dataset	М	NIST	MNIST	CIFAR-10	MNIST	MNIST	MNIST
Accuracy	97	7.1%³	90.1%	86.05%	98.56%	96.2%	98.6%
FPS	,	549	N/A	237	N/A	N/A	651
Power(mW)	0	.096	N/A	0.899	N/A	N/A	N/A
Operations / Inference	TNN	BNN (simu)	N/A	N/A	N/A	N/A	5.3x10 ⁸
	3.57x10 ⁷	1.38x10 ⁸					
MACs Energy / Inference	0.09uJ	0.52uJ	N/A	N/A	N/A	N/A	0.8uJ
Total Energy / Inference	0.18uJ	0.7uJ	N/A	3.8uJ	N/A	N/A	N/A
All operations on chip	,	Yes	No	Yes	No	No	No

¹Based on SC neuron

³10 runs average on 10,000 test set images.



²Based on MACs energy efficiency

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Summary

- A 1.5b charge domain ternary CNN classifier is proposed:
 - Fully on-chip NN with lowest energy/inference reported for >97% MNIST accuracy
 - Compared to BNN with same accuracy:

82%
$$\downarrow \frac{Energy}{Inference}$$

Energy / Inference

