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An Inference Hardware Accelerator for EEG-based Emotion Detection

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Motivation

- Alzheimer and Amyotrophic Lateral Sclerosis (ALS) patients lose their language capabilities on a late stage
- The Amygdala is compromised only at the end of Alzheimer [2]
- ALS displays only arousal drop with the disease progress [3]

[1]

State-of-the-Art

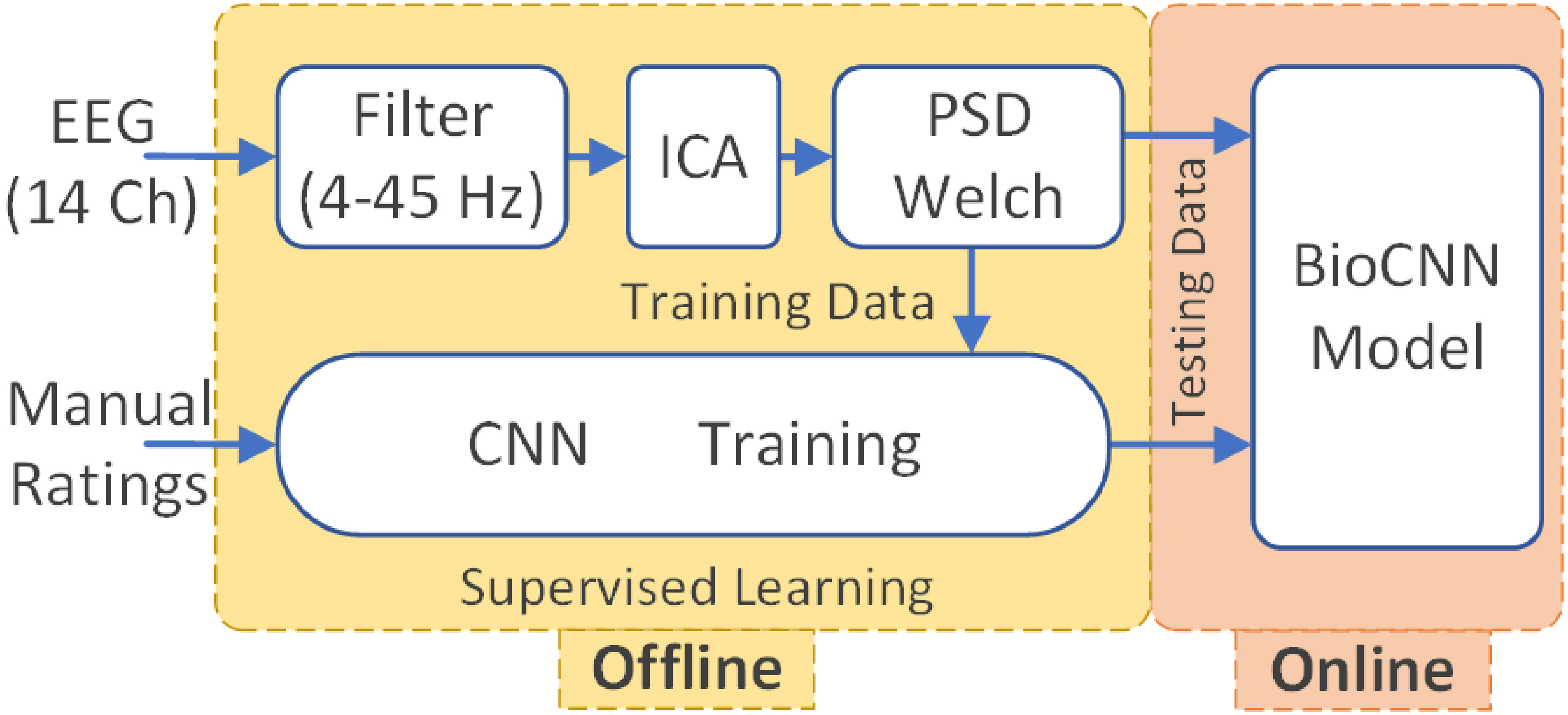
Emotion Detection: Gaining Popularity

- ❖ Shallow Models [4]
- ❖ Deep Models (CNNs+RNNs [5], Ensemble of CNNs [6])
- ❖ Biologically inspired SNNs [7].
- ❖ Diverse Feature extraction methods (Raw [8] [9], DE [10], HOC [11], Asymmetrical indices [10], PSD [4])
- ❖ Training paradigms (Subject dependent [11], Independent [12], and Semi-independent [13])
- ❖ **No HW contribution up to the submission of this paper.**

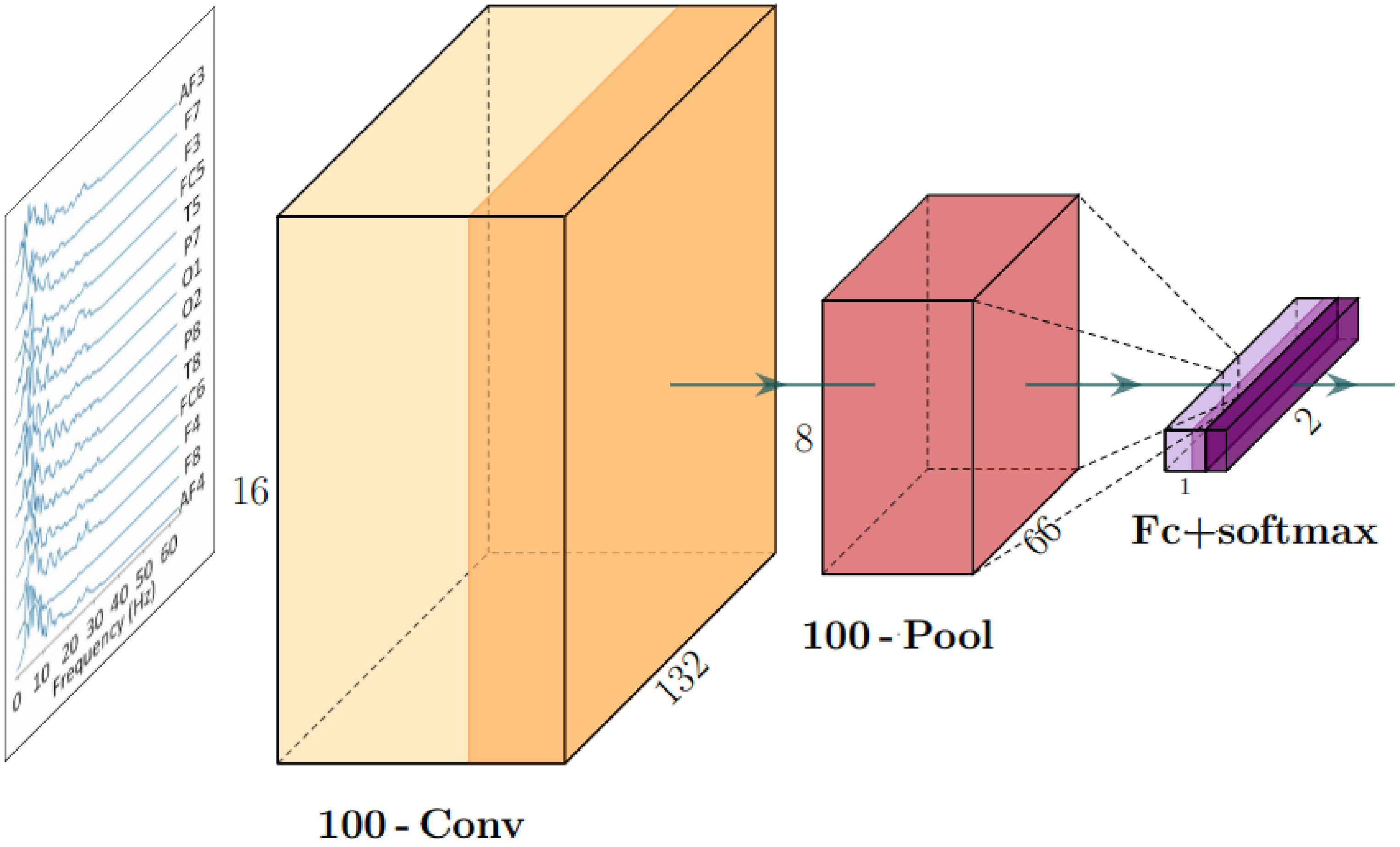
Convolutional Neural Networks in HW: Extremely mature [14] [15] [16] [17] [18] [19] [20] [21] :

- ❖ Sparse exploitation
- ❖ Winograd enhancements
- ❖ Efficient mapping in computing platforms
- ❖ **No contribution aiming to achieve low footprint by trading-off latency**
- ❖ **Biomedical requirements (Robustness, reliability, wearability, area, low-power, and interactivity).**

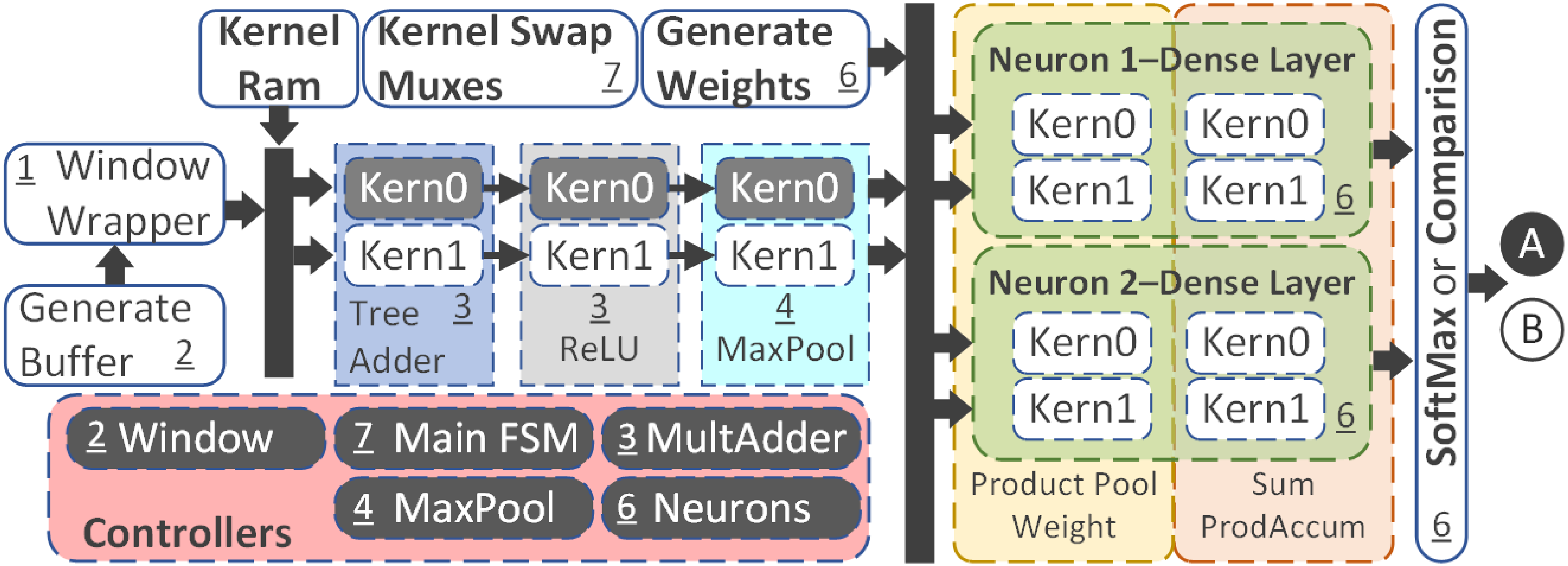
Top Level Diagram of the HW Emotion Classifier



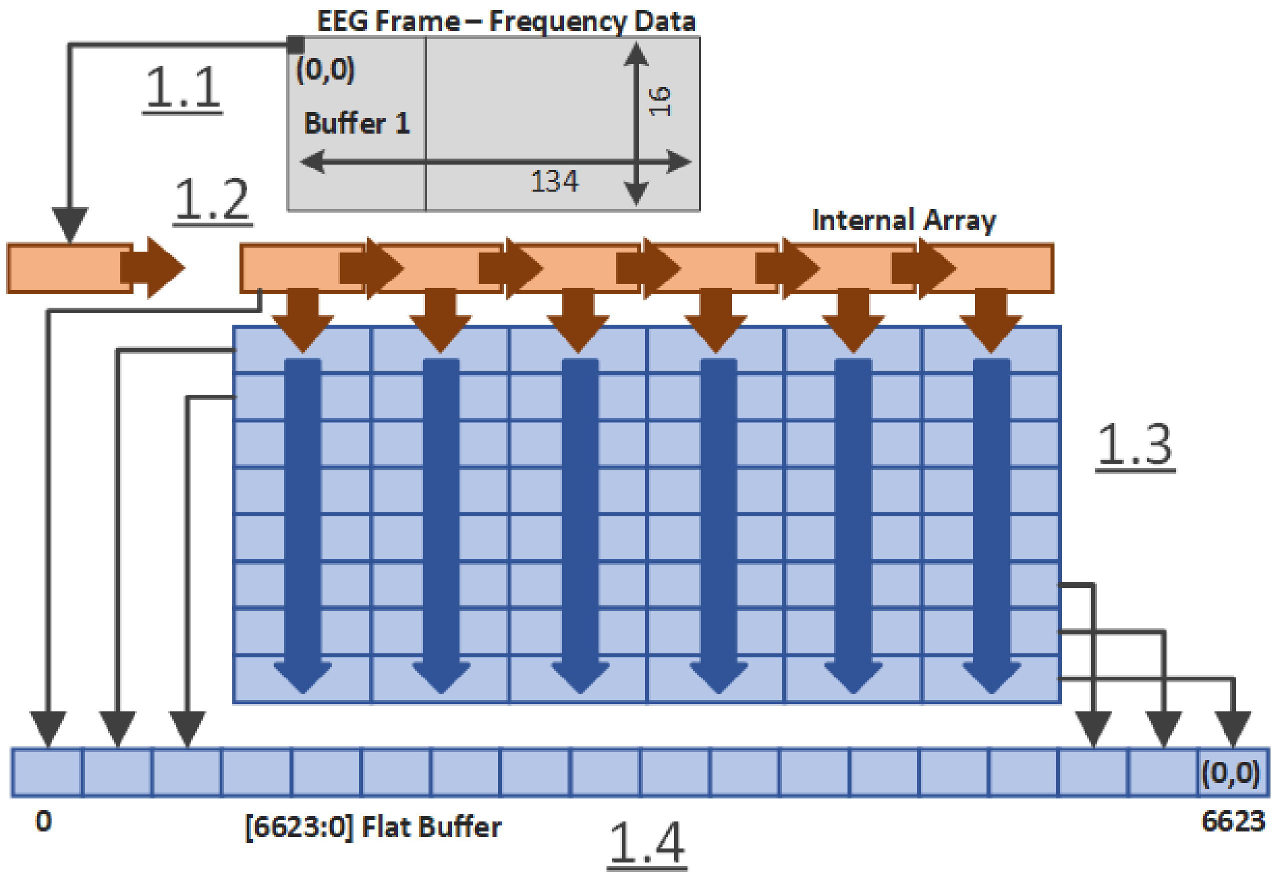
CNN Model – Valence/Arousal

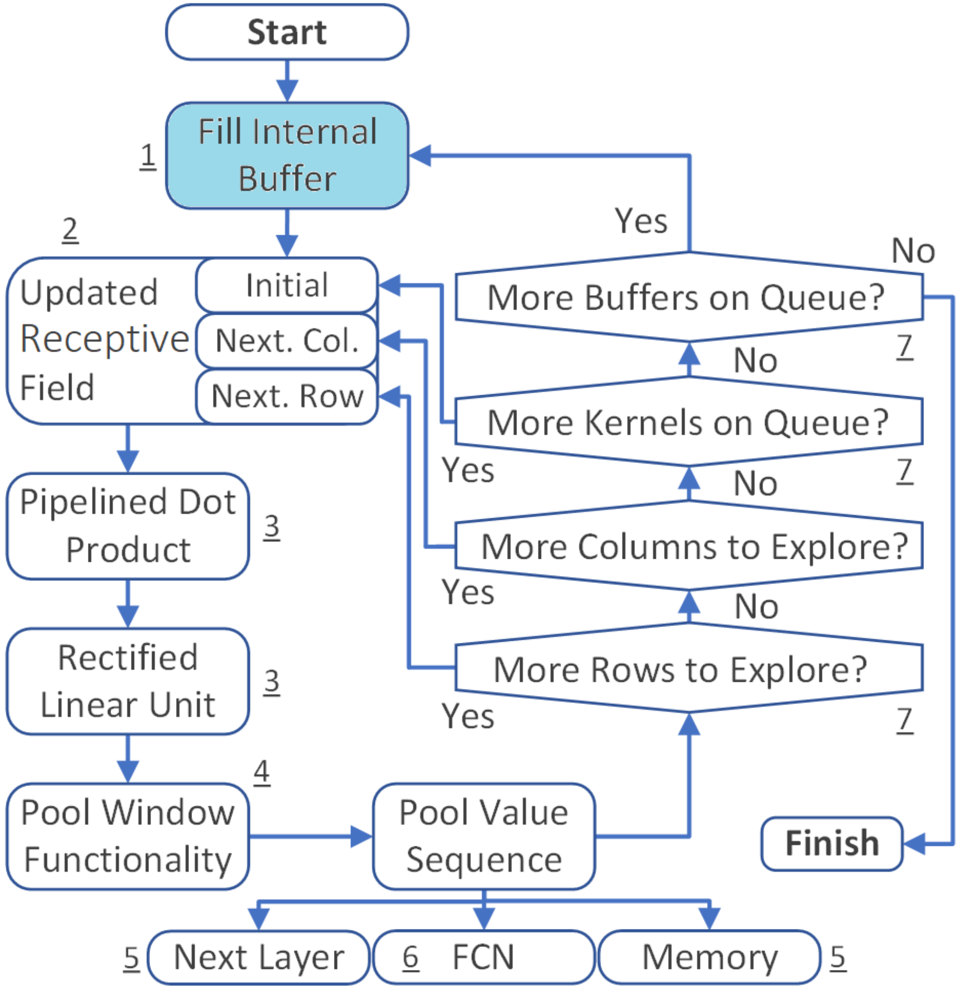


CNN Implementation – Valence/Arousal

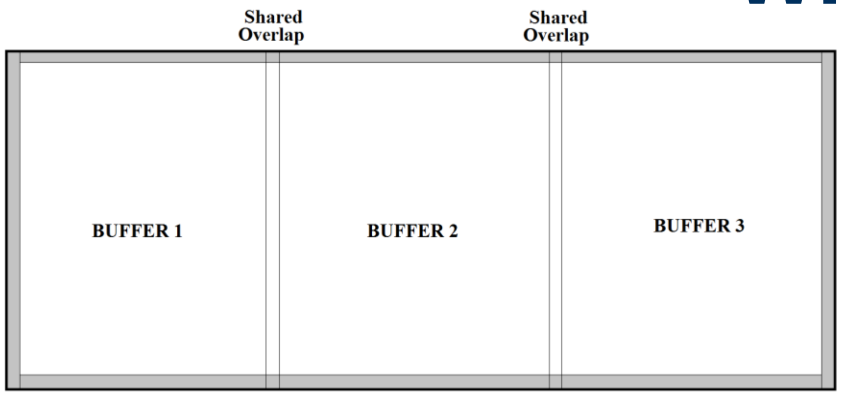


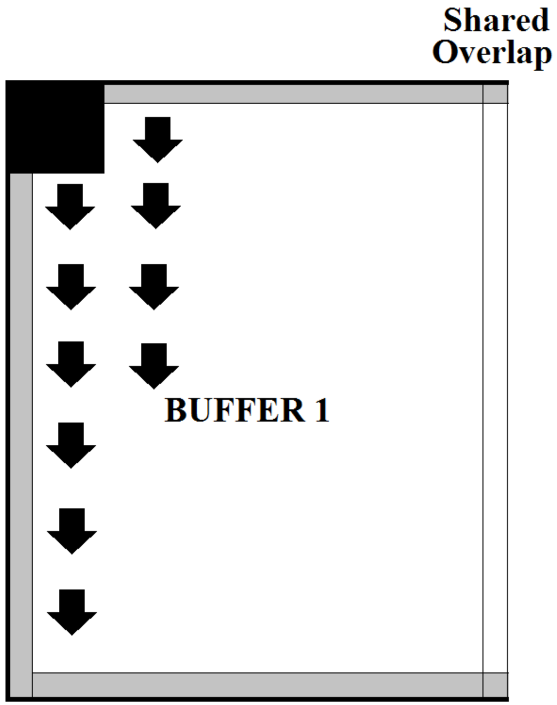
Fill Internal Buffer

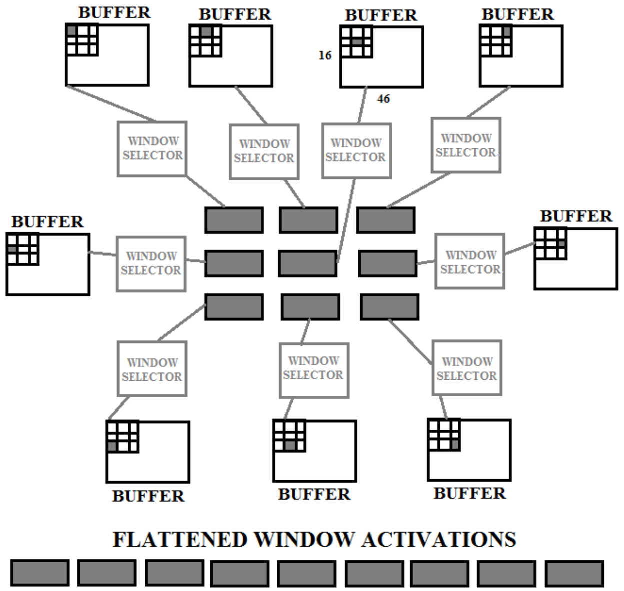


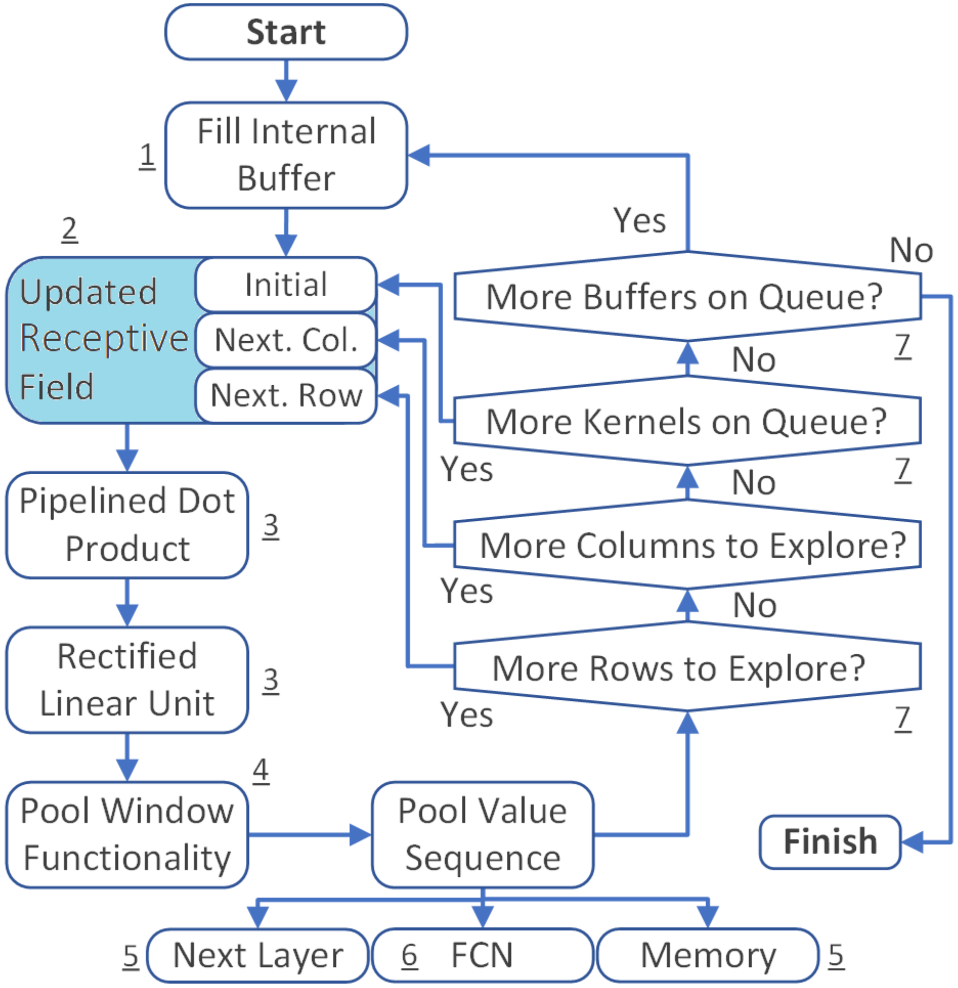


Window Wrapper

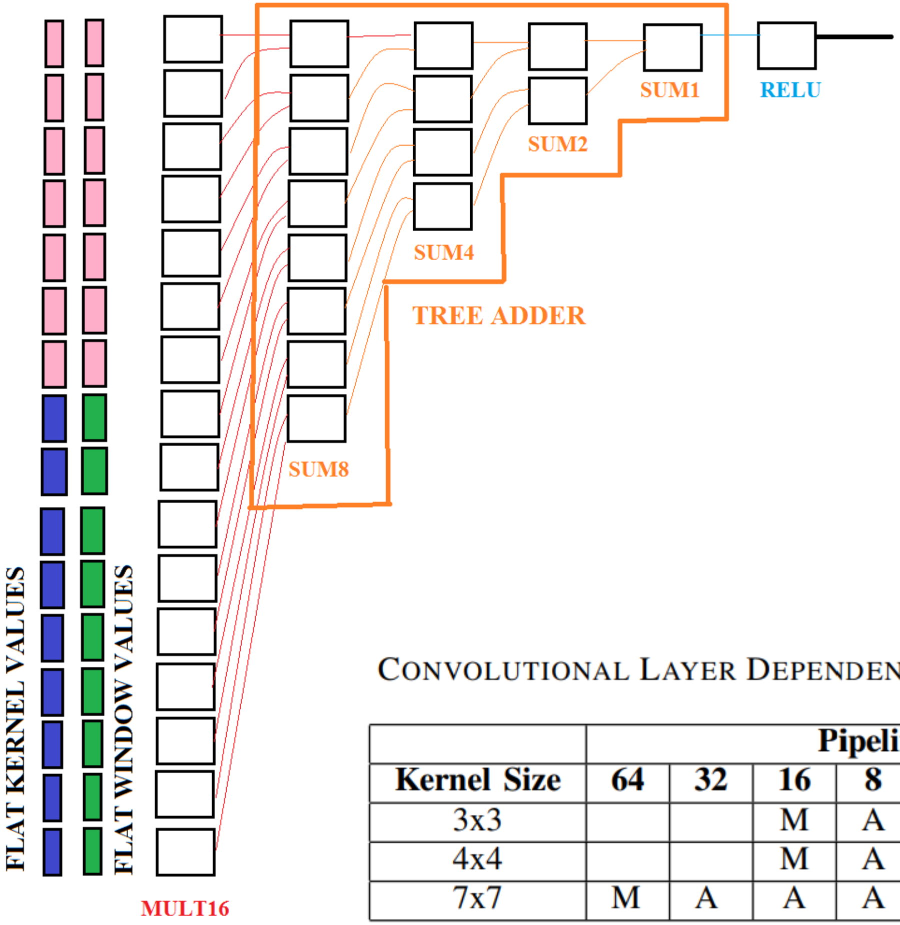






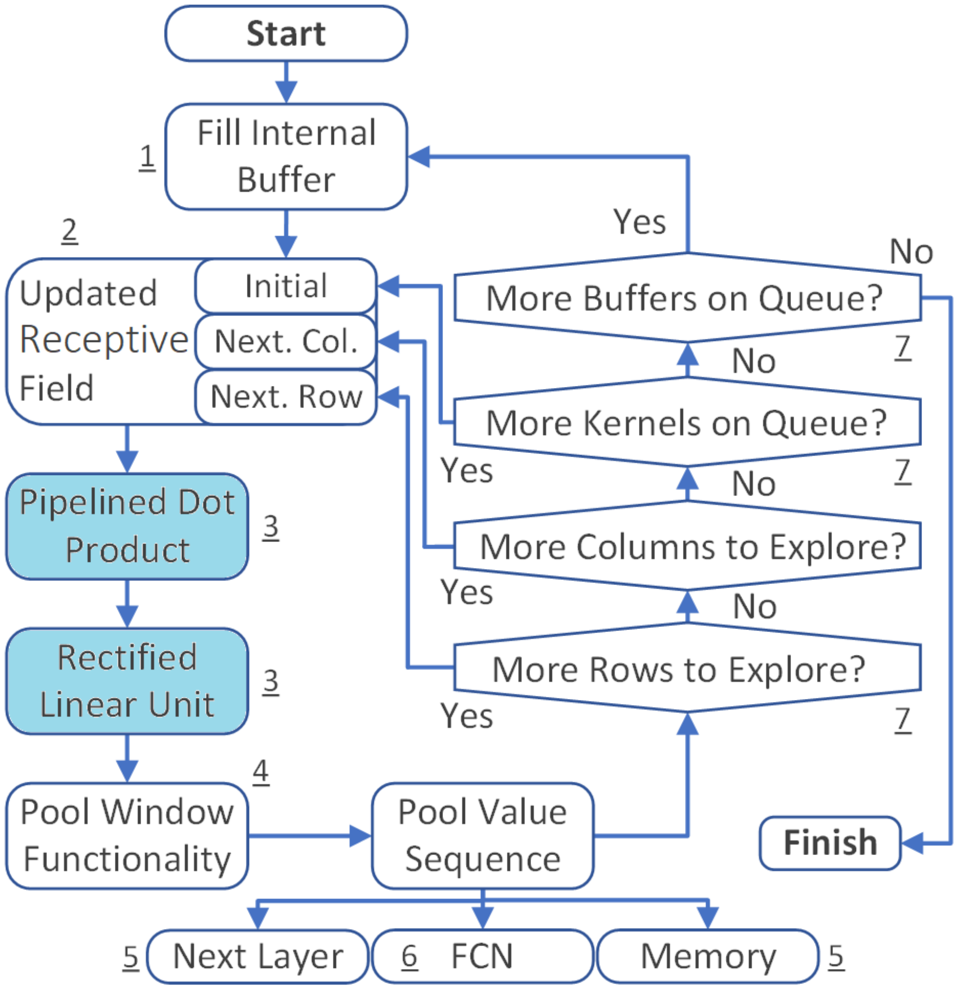


Rectified Convolutional Layer

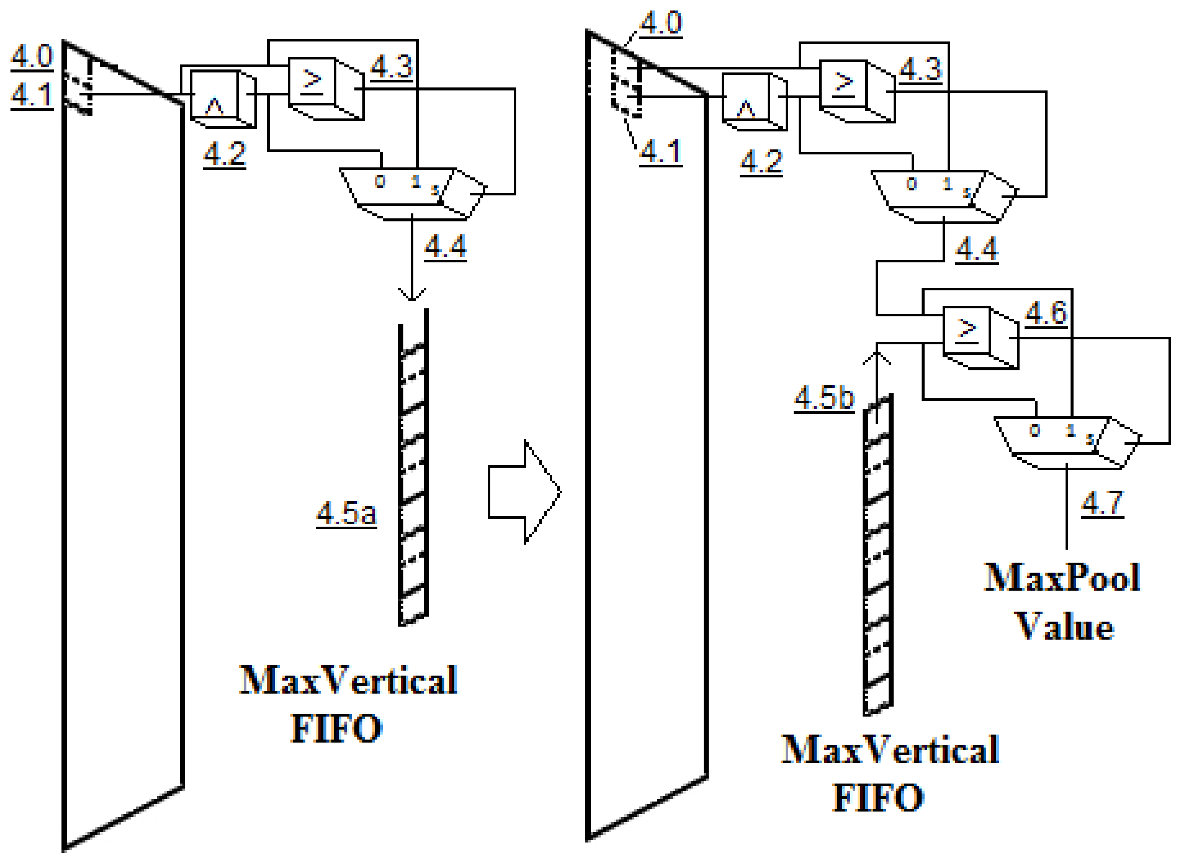


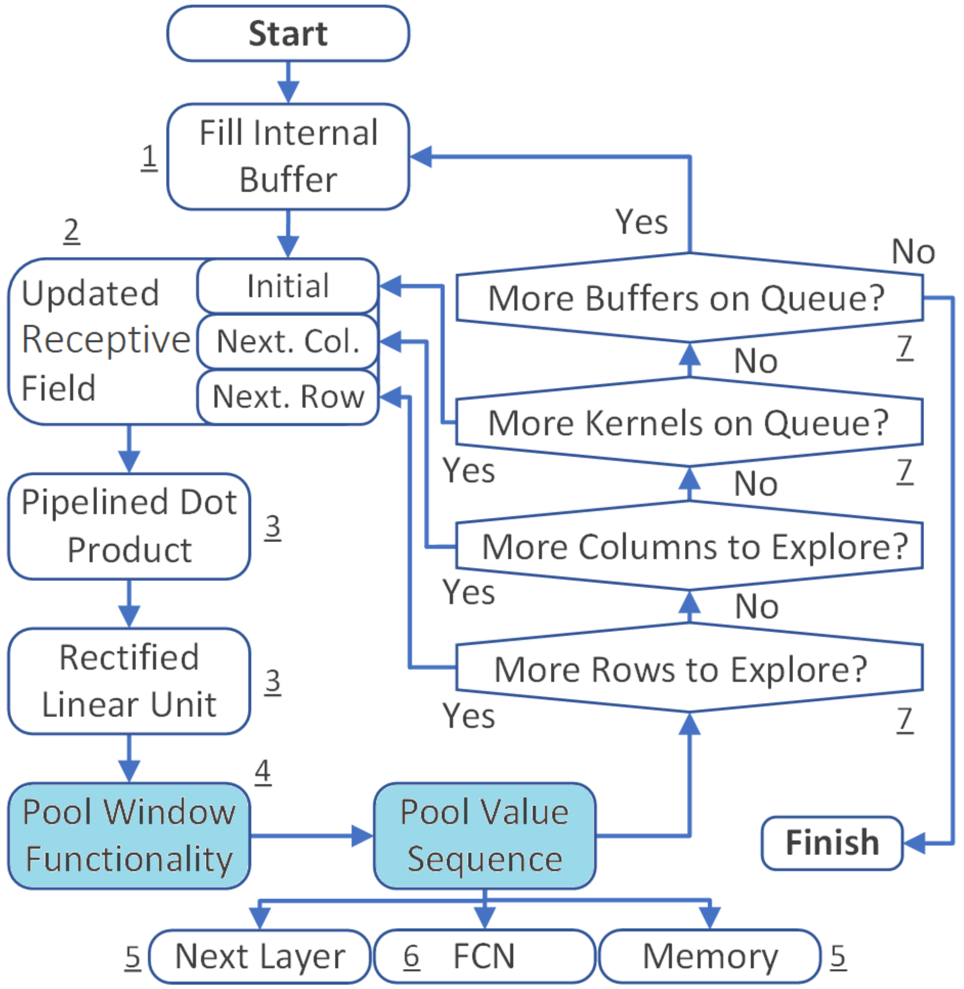
CONVOLUTIONAL LAYER DEPENDENCE ON THE KERNEL SIZE

	Pipeline Stages							
Kernel Size	**64**	**32**	**16**	**8**	**4**	**2**	**1**	**ReLU**
3x3			M	A	A	A	A	R
4x4			M	A	A	A	A	R
7x7	M	A	A	A	A	A	A	R

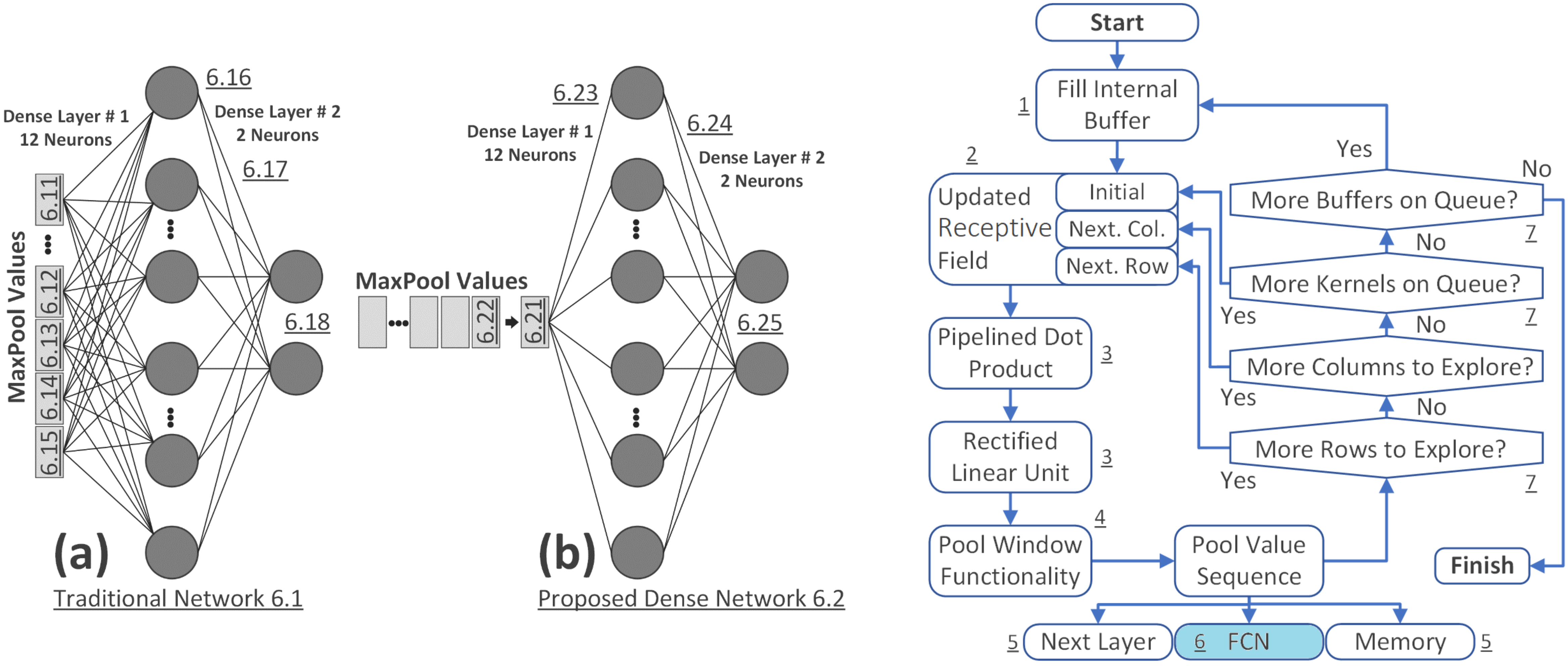


Serialized Max Pooling



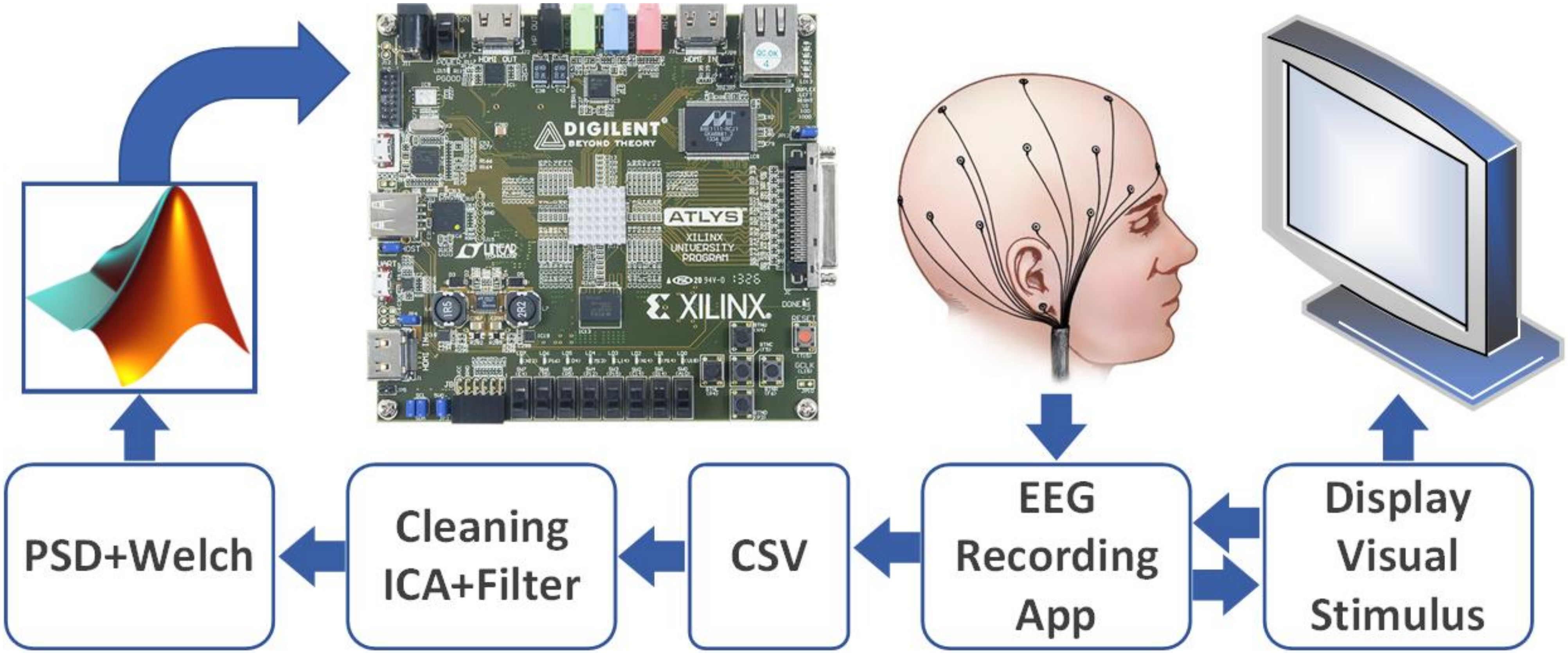


Dense Layer

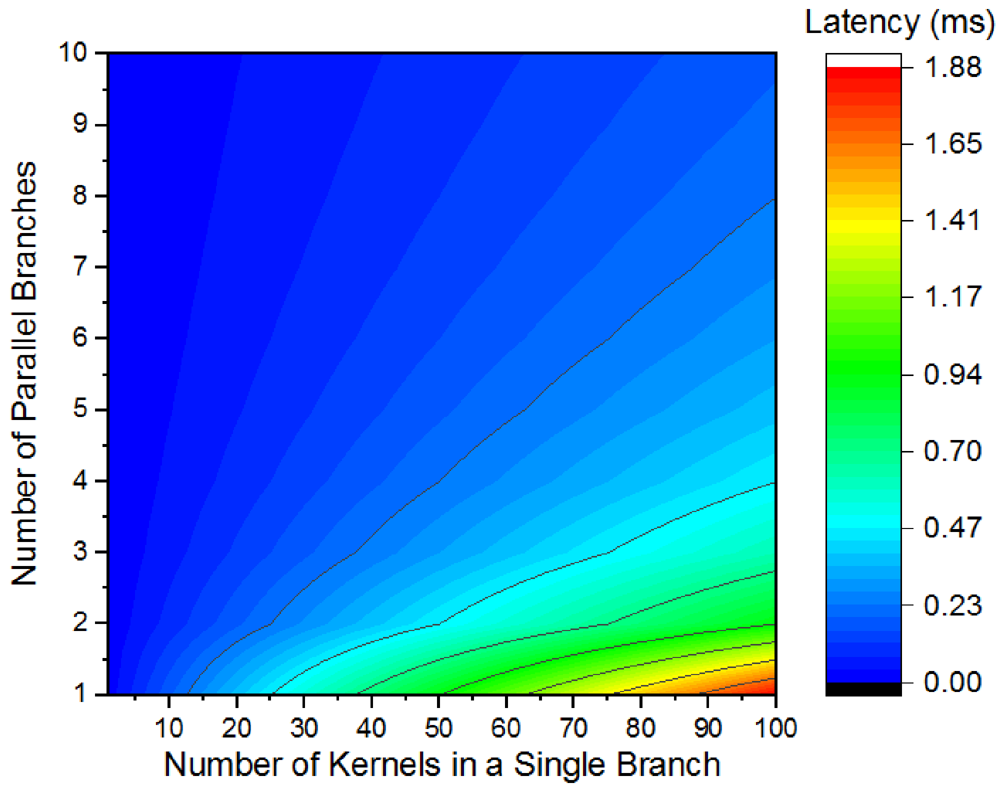


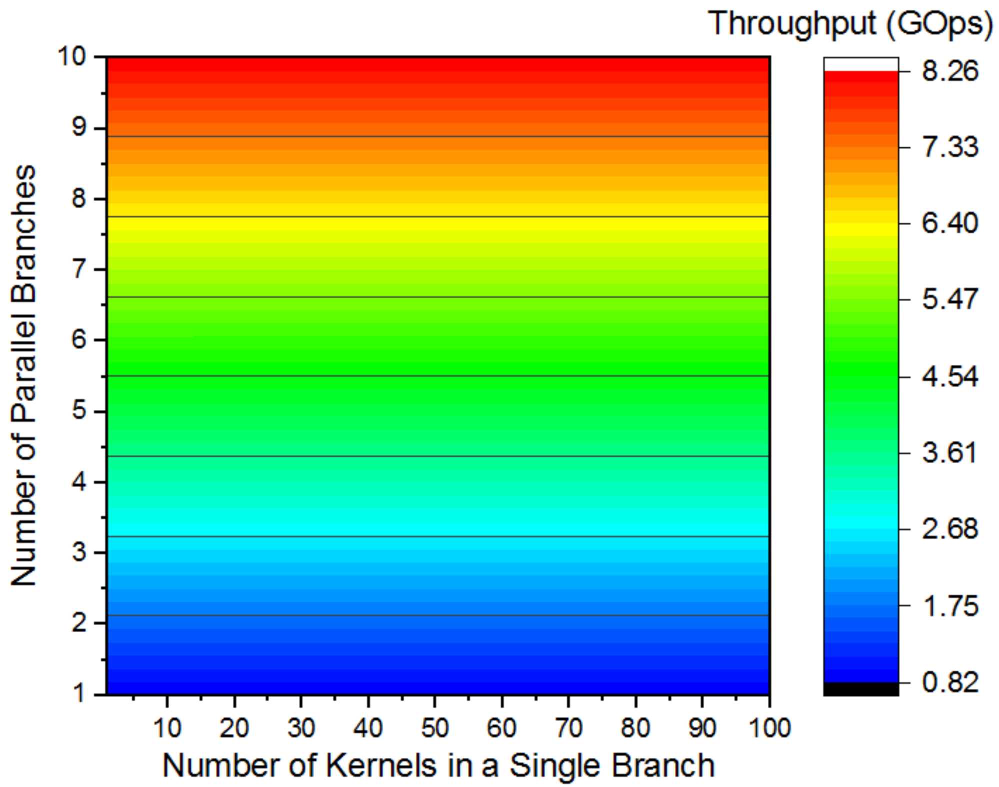
Dense Layer # 1
12 Neurons
Dense Layer # 2
2 Neurons
6.16
6.17
6.18
MaxPool Values
6.11
6.12
6.13
6.14
6.15
(a)
Traditional Network 6.1
6.23
6.24
6.25
Dense Layer # 1
12 Neurons
Dense Layer # 2
2 Neurons
MaxPool Values
6.22
6.21
(b)
Proposed Dense Network 6.2
Start
Fill Internal Buffer
1
2
Updated Receptive Field
Initial
Next. Col.
Next. Row
Pipelined Dot Product
3
Rectified Linear Unit
3
Pool Window Functionality
4
Pool Value Sequence
More Buffers on Queue?
More Kernels on Queue?
More Columns to Explore?
More Rows to Explore?
Yes
No
7
Finish
5
Next Layer
6
FCN
Memory
5

Experimental Framework



Results

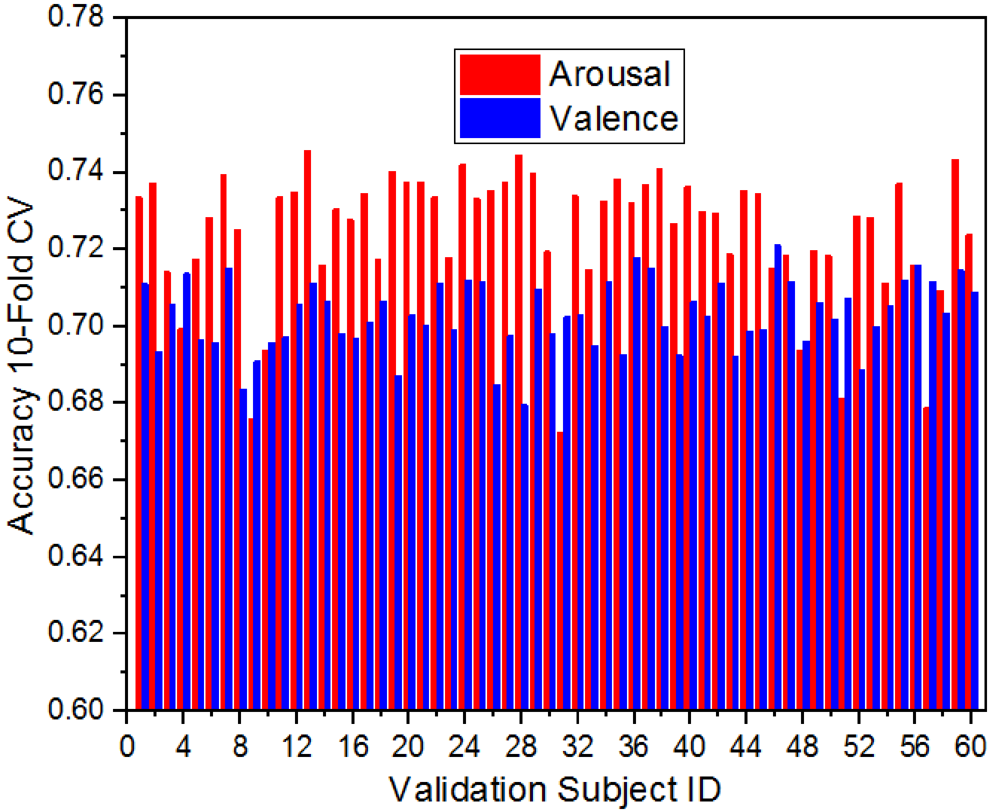




$$L_t = \frac{BK}{N}[14 \times 44 + C + M + S + D + (N-1) + R]$$

$$T_h = N\frac{22 \times 7A_{ccum} + 5A_{ccumPrevK}}{14 \times 44 + C + M + S + D}$$

Results



ACCURACY COMPARISON WITH THE STATE-OF-THE-ART

Model Used	Va[a]	Ar[b]	S[c]	Validation
DEAP EEG[5]	57.6	62	32	L1T.OUT SD
Mahnob-HCI EEG[9]	57.0	52.4	27	20-fold CV SI
DBN DE Features[10]	86.08	N/A	15	CV N/A SD
DBN PSD DEAP F1 score[11]	86.6	86.67	32	5-fold CV SD
DREAMER EEG[12]	62.49	62.17	23	10-fold CV SI
DEAP Hybrid CNN-RNN[6]	72.06	74.12	32	5-fold CV SD
CNN RAW DEAP[13]	81.40	73.36	32	CV N/A SD
Our BioCNN DEAP	**77.57**	**71.25**	**32**	**10-fold CV SD**

[a] Valence [b] Arousal [c] Subject

Results

FIGURES OF MERITS AND BIOCNN COMPARISONS WITH THE STATE-OF-THE-ART

Metrics	[14]	[15]	[16]	[17]	BioCNN
Clock[a]	100	150	150	100	100
Platform	VX485T	VX690T	Z-7045	Z-7020	Atlys
Precision[b]	$32FP$	$16FD$	$16FD$	$16FD$	$16FD$
DSP[c]	2240	2833	780	206	32
BRAM[c]	1024	1248	486	144	10
LUT[c]	186251	350892	182616	38136	26228
FF[c]	205704	311904	127653	42618	15180
Performance[d]	61.62	354	136.97	39.78	1.65
Power[e]	18.61	26	9.63	2.03	0.15
Efficiency[f]	3.31	13.62	14.22	19.6	11

a. MHz b. bits c. Used Resources d. GOps e. W f. GOps/W

Conclusion

- Novel FPGA-based CNN implementation geared to biomedical applications with aggressive pipelining, low footprint, and high resource re-utilization.
- Two algorithms for pipelined max-pooling and serialized processing of max-pooled values in a dense output layer are also proposed.
- The current topology requires no soft core, which reduces further its area and logic requirements.
- Pioneer in Hardware classification of Emotions achieving a classification accuracy (Valence: 77.57%, Arousal: 71.25%)
- The throughput presented of 1.65GOps is in line with the real-time requirement of a wearable device with an energy efficiency of 11 GOps/w and a power consumption of 150mW.
- The achieved latency of 1ms is much smaller than the 150ms required for human-machine interactions.
- Algorithmic potential to be used in other biomedical applications (ECG, blood pressure monitor, hearing aid and EEG-based emotion detection).

Thank you!

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