A Convolutional Neural Network (CNN) for handwritten digit recognition on FPGA using HLS

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Project repository here
[1]

Goals & Outline

Goals

- Creation of a NN for handwritten digit classification.
- Implementation of the NN on FPGA using HLS/Vivado.
- Prove that HW solutions is faster than SW (C) solutions.

Outline:

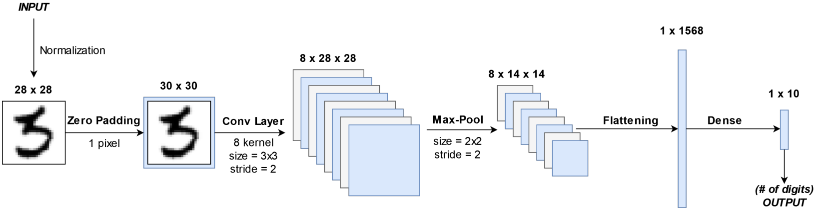
The (C)NN model

CNN architecture choosed:

- image-processing task;
- no need of manual feature extraction: done automatically;
- less number of parameters than other NNs.

API: Python Keras/Tensorflow [2].

Model as simple as possible:



Other model configurations

Same model but different number of filters:

(epochs = 50, validation split = 0.2)

filter number	# param	last val. acc.	test acc.	pred. time (ms)
8	**15k**	**97.78**	**98.07**	**36∼38**
16	31.5k	98.14	98.27	38
32	63k	98.17	98.37	38∼40
64	126k	98.32	98.38	38∼40

Same model but different number of filters + 1 dense layer:

(epochs = 50, validation split = 0.2)

filter number	# param	last val. acc.	test acc.	pred. time (ms)
8	158k	92.67	93.18	38
16	315k	93.80	93.42	50
32	630k	94.98	95.05	50
64	1256k	94.73	94.23	52

Training

TrainX shape = (60000, 28, 28)
Training epochs = 10 (empiric)

Layers' trainable parameters:

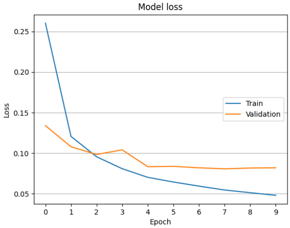
Layer (type)	Output Shape	Param #
ZeroPadding2D	(30, 30, 1)	0
Conv2D	(28, 28, 8)	80
MaxPooling2D	(14, 14, 8)	0
Flatten	(1568)	0
Dense	(10)	15690
TOT		**15770**

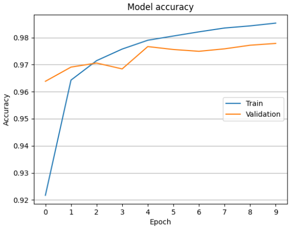
Accuracy:

- validation set (20% of test set): 97.78%
- test set (#10000 samples): **98.070%**

Mean time for a prediction: ~**35 ms**

Training history:

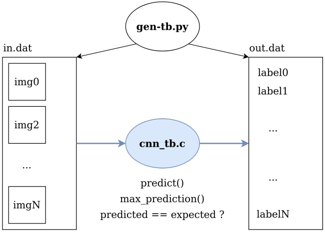




C cnn() function

```
void cnn(float img_in [IMG_ROWS][IMG_COLS], float prediction[DIGITS])
{
  // Normalization and padding.
  float pad_img [PAD_IMG_ROWS][PAD_IMG_COLS] = { 0 };
  normalization_and_padding(img_in, pad_img);
  // Convolution.
  float features [FILTERS][IMG_ROWS][IMG_COLS] = { 0 };
  convolutional_layer(pad_img, features);
  // Pooling.
  float pool_features [FILTERS][POOL_IMG_ROWS][POOL_IMG_COLS] = { 0 };
  max_pooling_layer(features, pool_features);
  // Flattening.
  float flat_array [FLAT_SIZE] = { 0 };
  flattening_layer(pool_features, flat_array);
  // Dense.
  dense_layer(flat_array, prediction);
}
```

C `main()` / testbench



- MNIST TestX samples: 10000 N: 100 $\sim$ 250
- Accuracy: $\frac{\text{correct predictions}}{\text{total predictions}}$ Test successfull $\Leftrightarrow$ Accuracy $\geq$ 95%

Mean time for a prediction:

- **0.82 ms** - O0 ($\sim$40x faster than Python)
- **0.17 ms** - O3 ($\sim$200x faster than Python)

Code optimizations for FPGA

CNN do not need all the data from the previous layer to start computing the output response for the current layer [3].

C implementation not optimized for FPGA deployment:

- data input/output with std array;
- does not create/support parallelism (dataflow).

Optimize code:

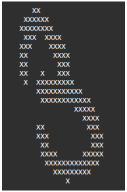
1. `hls::stream` [4] between functions:
   FIFO with blocking API `read()` and `write()`.
2. New function `dataflow_section(img1,img2,...,img8)`:
   Clone input image `FILTER_NUMBER` times.

C simulation

Total predictions: 500.
Correct predictions: 98.20 % → **OK**.
Average latency: 2.33 ms → a little bit more than C.

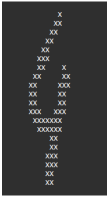
Some bad classifications:

(images normalized and rounded)



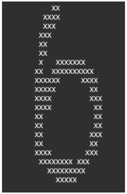
Expected: **3**

Got:
0: 0.000002
1: 0.000000
2: 0.001373
3: 0.213332
4: 0.000003
5: 0.000935
6: 0.000000
7: 0.000000
8: 0.783027
9: 0.001329



Expected: **4**

Got:
0: 0.000000
1: 0.000045
2: 0.000020
3: 0.000661
4: 0.253086
5: 0.000059
6: 0.000414
7: 0.000036
8: 0.000321
9: 0.745357



Expected: **6**

Got:
0: 0.735325
1: 0.000000
2: 0.000000
3: 0.000000
4: 0.000000
5: 0.000019
6: 0.264633
7: 0.000000
8: 0.000004
9: 0.000020

C synthesis I

Common parameters:

- Target device: **xc7a200tfbg484-1**
- Target clock period: **10ns** (clock freq.: 100 *MHz*)

Different *"levels of optimization"* (directives):

1. No directives

Target	Estimated	Uncertainty
10.00 ns	7.300 ns	2.70 ns

Modules & Loops	Issue Type	Violation Type	Distance	Slack	Latency(cycles)	Latency(ns)	Iteration Latency	Interval	Trip Count	Pipelined	BRAM	DSP	FF	LUT	URAM
cnn				-	361721	3,617E6	-	361722	-	no	231	69	16679	18273	0
dataflow_section				-	342698	3,427E6	-	342698	-	no	215	69	16409	17588	0
pad_for_rows				-	17160	1,720E5	572	-	30	no	-	-	-	-	-
VITIS_LOOP_102_1				-	1860	1,860E4	62	-	30	no	-	-	-	-	-

C synthesis II

❷ Default directives

Target	Estimated	Uncertainty
10.00 ns	7.300 ns	2.70 ns

Modules & Loops	Issue Type	Violation Type	Distance	Slack	Latency(cycles)	Latency(ns)	Iteration Latency	Interval	Trip Count	Pipelined	BRAM	DSP	FF	LUT	URAM
cnn				-	19523	1,950E5	-	19524	-	no	264	104	40089	30930	0
cnn_Pipeline_pad_for_rows_pad_for_cols				-	920	9,200E3	-	920	-	no	0	0	1018	419	0
cnn_Pipeline_VITIS_LOOP_102_1_VITIS_LOOP_103_2				-	903	9,030E3	-	903	-	no	0	0	45	167	0
dataflow_section	II Violation			-	17695	1,770E5	-	17695	-	no	248	104	39017	29916	0

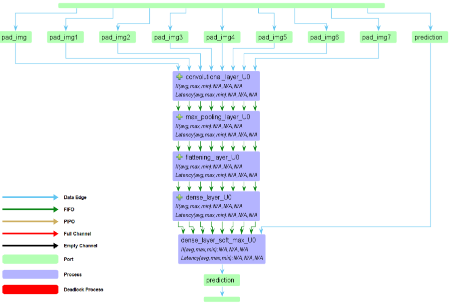
❸ Dataflow directive

Target	Estimated	Uncertainty
10.00 ns	7.241 ns	2.70 ns

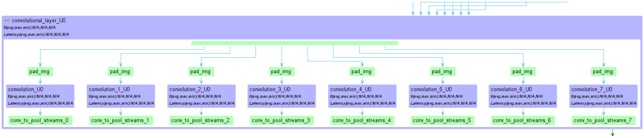
Modules & Loops	Issue Type	Violation Type	Distance	Slack	Latency(cycles)	Latency(ns)	Iteration Latency	Interval	Trip Count	Pipelined	BRAM	DSP	FF	LUT	URAM
cnn				-	5825	5,825E4	-	5826	-	no	384	129	46902	38213	0
cnn_Pipeline_pad_for_rows_pad_for_cols				-	920	9,200E3	-	920	-	no	0	0	1018	419	0
cnn_Pipeline_VITIS_LOOP_102_1_VITIS_LOOP_103_2				-	903	9,030E3	-	903	-	no	0	0	45	167	0
dataflow_section				-	3997	3,997E4	-	3998	-	dataflow	368	129	45828	37234	0
convolutional_layer				-	3997	3,997E4	-	3998	-	dataflow	0	80	20585	18273	0
max_pooling_layer				-	792	7,920E3	-	793	-	dataflow	0	0	3513	4049	0
flattening_layer				-	198	1,980E3	-	199	-	dataflow	0	0	353	825	0
dense_layer				-	2013	2,013E4	-	2014	-	dataflow	320	40	15584	9632	0
dense_layer_soft_max				-	871	8,710E3	-	871	-	no	0	9	1071	1689	0

C synthesis III

Dataflow view:



(zoom on convolutional_layer)



Validation and implementation

C/RTL Cosimulation → **OK**

Modules & Loops	Avg II	Max II	Min II	Avg Latency	Max Latency	Min Latency
cnn	6747	6747	6747	6746	6746	6746
cnn_Pipeline_pad_for_rows_pad_for_cols	6747	6747	6747	918	918	918
cnn_Pipeline_clone_for_rows_clone_for_cols	6747	6747	6747	901	901	901
dataflow_section	6747	6747	6747	4922	4922	4922

```
Total predictions:  100
Correct predictions:  99.00 %
Average latency:  0.290000 (ms)
*** C/RTL co-simulation finished:  PASS ***
```

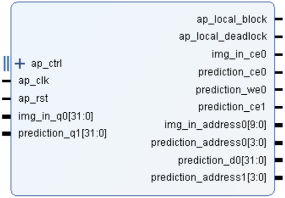
→ prediction time: **0.067** ms

Implementation (Vivado)

	Verilog
SLICE	12940
LUT	26381
FF	38178
DSP	129
BRAM	224
URAM	0
LATCH	0
SRL	1007
CLB	0

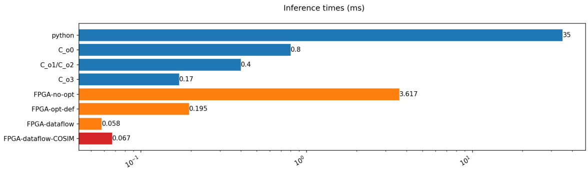
	Verilog
CP required	10.000
CP achieved post-synthesis	8.123
CP achieved post-implementation	9.449

Timing met



Conclusions

Main goal reached: **HW faster than SW**.



But, as future works:

- `grid-search` on NN architecture could increase accuracy ($>$ performance) and reduce FPGA area ($<$ price);
- using *fixed-point* arithmetic could reduce area;
- small SW changes could improve parallelism.

References

[1] *Github: HLS-CNN*. [Project repository]. URL: https://github.com/FedericoSerafini/HLS-CNN.

[2] Francois Chollet et al. *Keras*. 2015. URL: https://github.com/fchollet/keras.

[3] Duda S. *How to Implement a Convolutional Neural Network Using High Level Synthesis*. Ed. by amiq.com. [Online; posted 14-December-2018]. 2018. URL: https://www.amiq.com/consulting/2018/12/14/how-to-implement-a-convolutional-neural-network-using-high-level-synthesis/.

[4] *Vitis High-Level Synthesis User Guide: HLS Stream Library*. [Online; visited june-2022]. URL: https://docs.xilinx.com/r/en-US/ug1399-vitis-hls/HLS-Stream-Library.

Thank you for your attention.