Dense convolutional neural network in embedded systems

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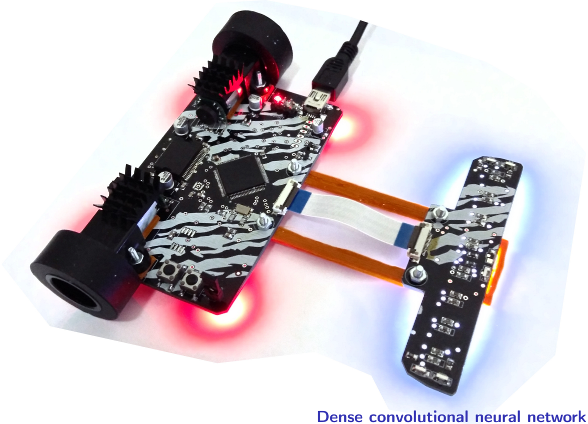
Motivation

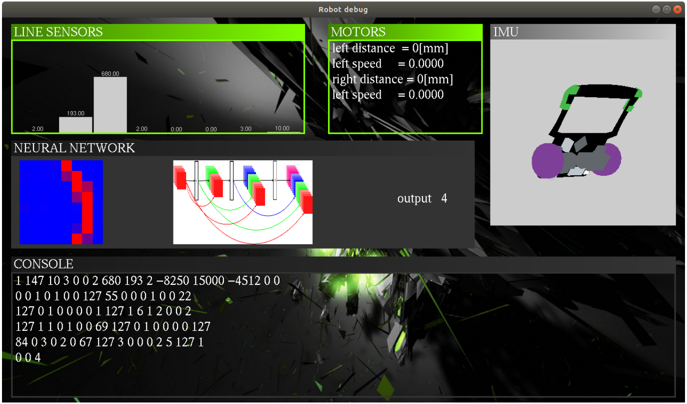
- build smarter robots
- embedded particle filtering
- embedded localization
- embedded decision making

- only one MCU
- no C++ libs
- obsolete architectures
- float instead of int



Motivation

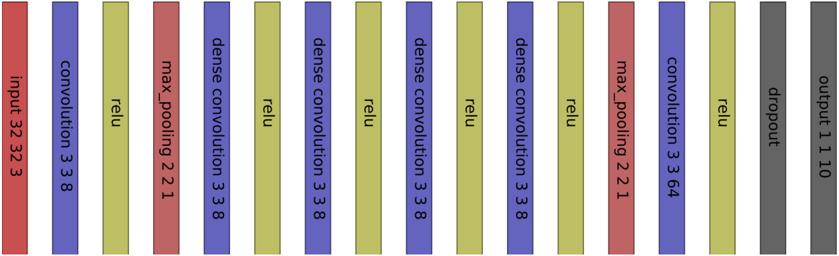
- line type classification
- prediction curve type
- predictive braking
- map creating



Target hardware

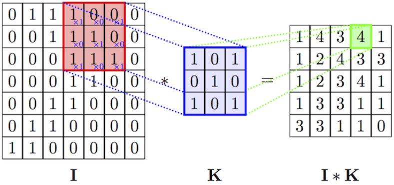
target	bits	features	frequency
AVR Atmega 328	8	single cycle ADD, MUL	20MHz
ARM Cortex M0	32	single cycle ADD, MUL	48MHz
ARM Cortex M4, M7	32	SIMD DUAL 16bit MAC , FPU ...	72MHz 216MHz

Convolutional neural network



- input tensor (image)
- convolutional layer
- dense convolutional layer
- relu layer (nonlinearity)
- pooling layer
- full connected layer

Discrete convolution



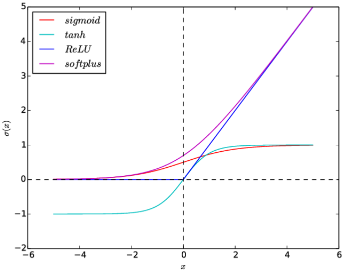

```
for (unsigned y = 0; y < input_height; y++)
for (unsigned x = 0; x < input_width; x++)
{
    float sum = 0.0;

    for (unsigned ky = 0; ky < kernel_height; ky++)
    for (unsigned kx = 0; kx < kernel_width; kx++)
    {
      sum+= kernel[ky][kx]*input[y + ky][x + kx];
    }

    output[y + kernel_height/2][x + kernel_width/2] = sum;
  }
}
```

Activation function

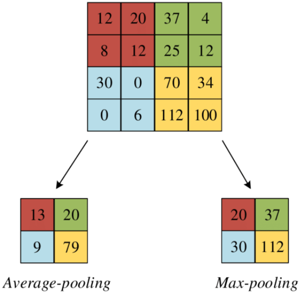
tanh, sigmoid, gaussian, **RELU**, leaky RELU ...



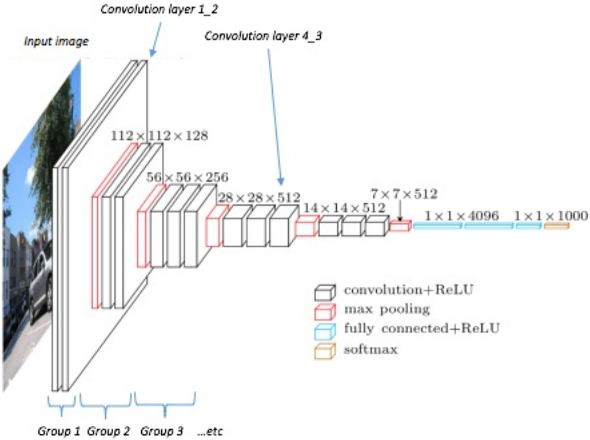
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{df(x)}{dx} = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

Pooling


12 20 37 4
8 12 25 12
30 0 70 34
0 6 112 100
13 20
9 79
Average-pooling
20 37
30 112
Max-pooling

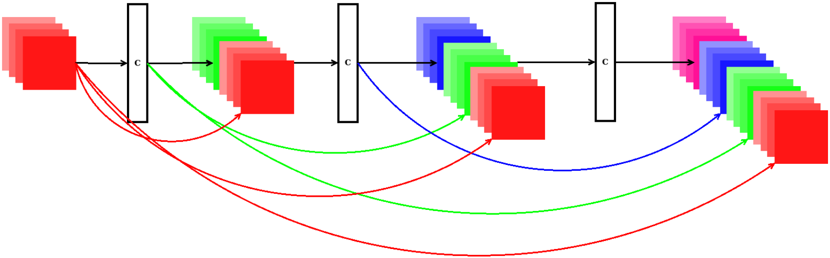
Convolutional neural network - CNN



Dense CNN

State of the art in image recognition.

architecture	depth	params	CIFAR 10	CIFAR 100
ResNet	110	1.7M	13.63%	44.74%
ResNet Stochastic Depth	110	1.7M	11.66%	37.8%
DenseNet k = 12	40	1.0M	**7.0%**	**27.55%**
DenseNet k = 24	100	27.2M	**5.83%**	**23.42%**

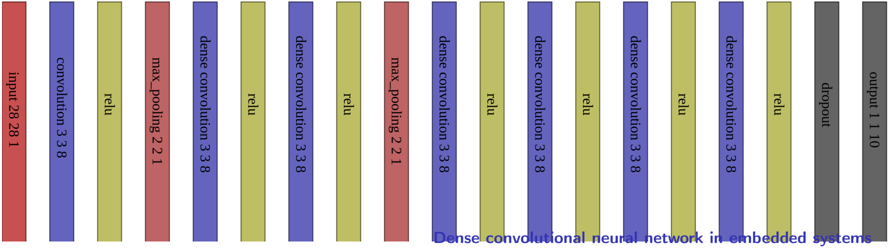


Network example - MNIST handwritten digits recognition

- training count 50000
- testing count 10000
- input size 28x28x1 pixels

Tested architecture

C8 - P2 - D8 - D8 - P2 - D8 - D8 - D8 - D8 - FC



Training result

Network success rate - confusion matrix

976	0	1	0	1	1	6	0	1	1
1	1129	0	0	0	0	3	3	0	0
1	3	1028	1	0	0	0	6	1	1
0	0	0	995	0	4	0	0	0	1
0	0	0	0	973	0	1	0	2	7
0	1	0	4	0	885	2	0	1	5
0	0	1	0	1	1	942	0	0	0
1	1	1	6	1	1	0	1018	0	6
1	1	1	3	0	0	4	1	967	1
0	0	0	1	6	0	0	0	2	987
99.592	99.471	99.612	98.515	99.084	99.215	98.33	99.027	99.281	97.82

9900	100	99%

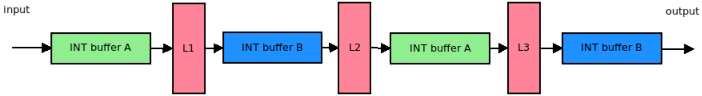
Embedded network implementation

convert float weights to int8_t

$$scale = max(|\vec{w}|_1)$$
$$\vec{w}' = \vec{w}\frac{127}{scale}$$

use double buffer memory trick

- unsigned buffer_size = $\max_i$(layers[i].input_size());
- buffer_a = new int8_t(buffer_size);
- buffer_b = new int8_t(buffer_size);



Optimize kernel - templates

```
templete<unsigned int kernel_size>
void convolution()
{
  for (unsigned y = 0; y < input_height; y++)
  for (unsigned x = 0; x < input_width; x++)
  {
      int sum = 0;

      for (unsigned ky = 0; ky < kernel_size; ky++)
      for (unsigned kx = 0; kx < kernel_size; kx++)
      {
        sum+= kernel[ky][kx]*input[y + ky][x + kx];
      }

      output[y + kernel_size/2][x + kernel_size/2] = (sum*scale)/127;
    }
  }
}
```

Optimize kernel - unrolling

```
templete<unsigned int kernel_size>
void convolution()
{
  for (unsigned y = 0; y < input_height; y++)
  for (unsigned x = 0; x < input_width; x++)
  {
      int sum = 0;

      if (kernel_size == 3)
      {
        sum+= kernel[0][0]*input[y + 0][x + 0];
        sum+= kernel[0][1]*input[y + 0][x + 1];
        sum+= kernel[0][2]*input[y + 0][x + 2];

        sum+= kernel[1][0]*input[y + 1][x + 0];
        sum+= kernel[1][1]*input[y + 1][x + 1];
        sum+= kernel[1][2]*input[y + 1][x + 2];

        sum+= kernel[2][0]*input[y + 2][x + 0];
        sum+= kernel[2][1]*input[y + 2][x + 1];
        sum+= kernel[2][2]*input[y + 2][x + 2];
      }

      output[y + kernel_size/2][x + kernel_size/2] = (sum*scale)/127;
    }
  }
}
```

3.6x speed up

Optimize kernel - SIMD

```
sum+= kernel[0][0]*input[y + 0][x + 0];
sum+= kernel[0][1]*input[y + 0][x + 1];
sum+= kernel[0][2]*input[y + 0][x + 2];
```

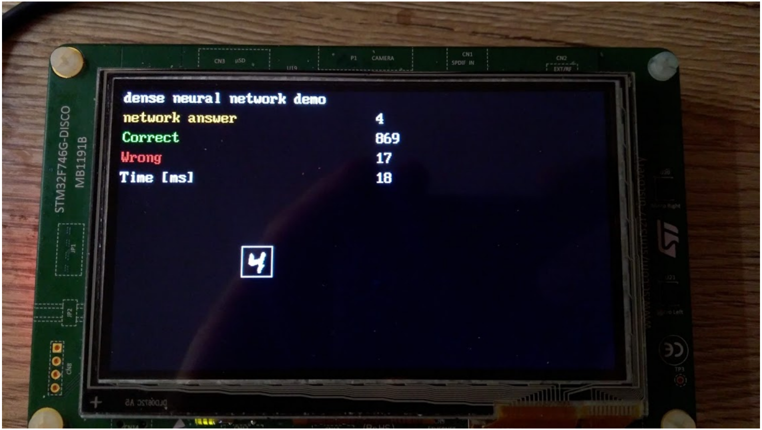
```
smlabb  r2, fp, sl, r2
ldrsb.w sl, [r8, #1]
ldrsb.w fp, [r0, #-24]

smlabb  r2, fp, sl, r2
ldrsb.w sl, [r8, #2]
ldrsb.w fp, [r0, #-23]

smlabb  r2, fp, sl, r2
ldrsb.w sl, [r8, #3]
ldrsb.w fp, [r0, #-22]
```

Results

- float network accuracy 99%
- int8 network accuracy 98.97%
- runtime on 216MHz Cortex M7 18ms (72Mop/s)



Usefull links

- ImageNet Classification with Deep Convolutional Neural Networks https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf
- Alex Krizhevsky web, https://www.cs.toronto.edu/~kriz/
- Deep Belief Nets in C++ and CUDA C: Volume III https://www.amazon.com/Deep-Belief-Nets-CUDA-Convolutional/dp/1530895189
- Deep Learning (Adaptive Computation and Machine Learning https://www.amazon.com/Deep-Learning-Adaptive-Computation-Machine/dp/0262035618
- Densely Connected Convolutional Networks https://arxiv.org/pdf/1608.06993.pdf
- MNIST dataset http://yann.lecun.com/exdb/mnist/
- Digital signal processing for STM32 microcontrollers using CMSIS https://www.st.com/resource/en/application_note/dm00273990.pdf
- CMSIS-NN: Efficient Neural Network Kernels for Arm Cortex-M CPUs https://arxiv.org/pdf/1801.06601.pdf

Q&A

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www.youtube.com/channel/UCzVvP2ou8v3afNiVrPAHQGg