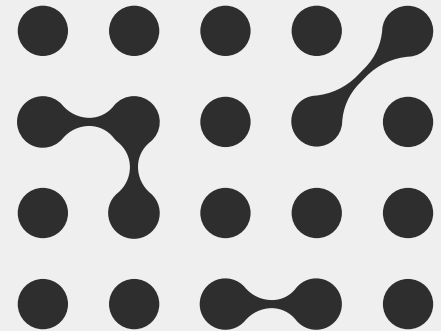


SMAI Project Final-Eval

Gradient-Based learning applied to document recognition

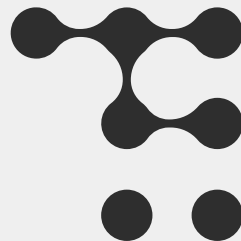
Team 54

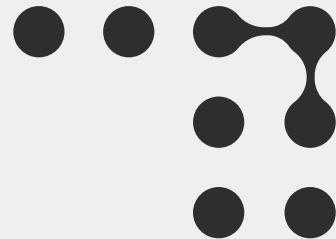
- | | |
|-------------|------------|
| - Kshitijaa | 2019115005 |
| - Ihita | 2021701007 |
| - Ashuthosh | 2019112003 |



Contents

- Gradient-Based learning applied to document recognition:
Summary
- What is LeNet and its use cases?
- Architecture and working
 - A note on sparse connectivity
- Implementation
 - Framework
 - Training on MNIST
 - Comparison with other classifiers
 - Idea of an alternative approach





LeNet ?

What is LeNet?

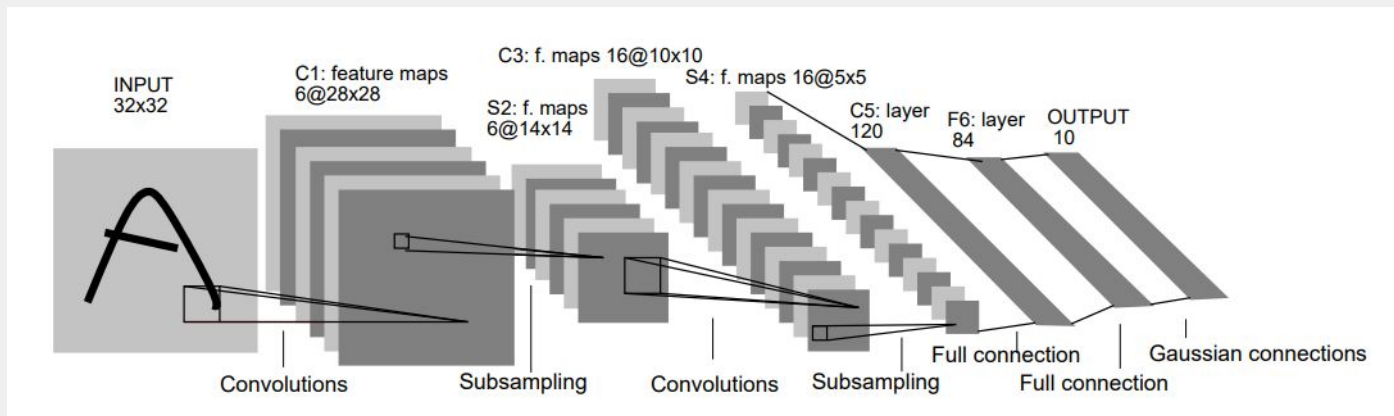
Applications



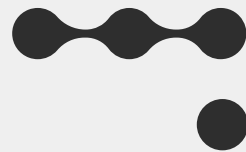
What is LeNet?



- LeNet-5, 1996
- First generation CNN
- Preceded by 4 other architectures



Applications

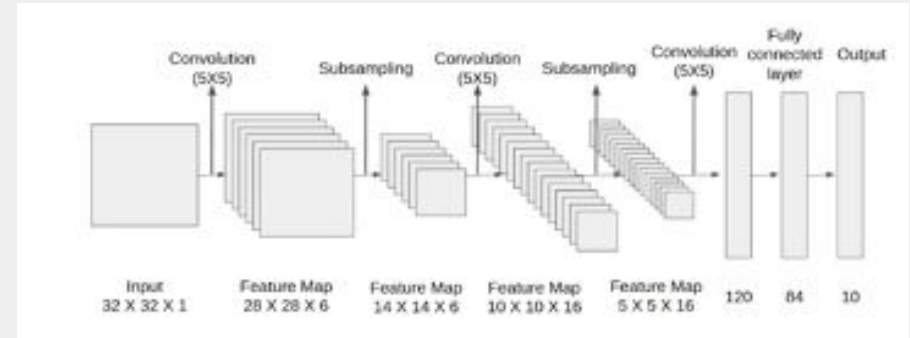


- Document recognition:
 - Many handwritten documents require digitization;
 - A well-trained LeNet can be used to digitize using maximal probable estimate
 - Main use-case:
 - Post office automatic pincode classifier
 - Good accuracy, matches or exceeds human throughput
-

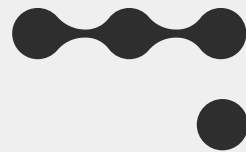
Architecture



Layer	# filters / neurons	Filter size	Stride	Size of feature map	Activation function
Input	-	-	-	32 X 32 X 1	
Conv 1	6	5 * 5	1	28 X 28 X 6	tanh
Avg. pooling 1		2 * 2	2	14 X 14 X 6	
Conv 2	16	5 * 5	1	10 X 10 X 16	tanh
Avg. pooling 2		2 * 2	2	5 X 5 X 16	
Conv 3	120	5 * 5	1	120	tanh
Fully Connected 1	-	-	-	84	tanh
Fully Connected 2	-	-	-	10	Softmax



Working



- The layers are a combination of Convolutional and average pooling ones, eventually leading to dense layers that do the classification from the extracted features.
- The kernels for convolution are learned using backpropagation;

- Non-linearities used:

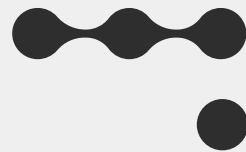
- Tanh

$$A \tanh(s \cdot x) = A \frac{e^{sx} - e^{-sx}}{e^{sx} + e^{-sx}}, \quad A = 1.7159, s = 2/3$$

- Softmax

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^N e^{x_j}}$$

A note on Sparse connectivity



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	X				X	X	X			X	X	X	X		X	X
1	X	X				X	X	X			X	X	X	X		X
2	X	X	X				X	X	X			X		X	X	X
3		X	X	X			X	X	X	X			X		X	X
4			X	X	X			X	X	X	X		X	X		X
5				X	X	X			X	X	X	X		X	X	X

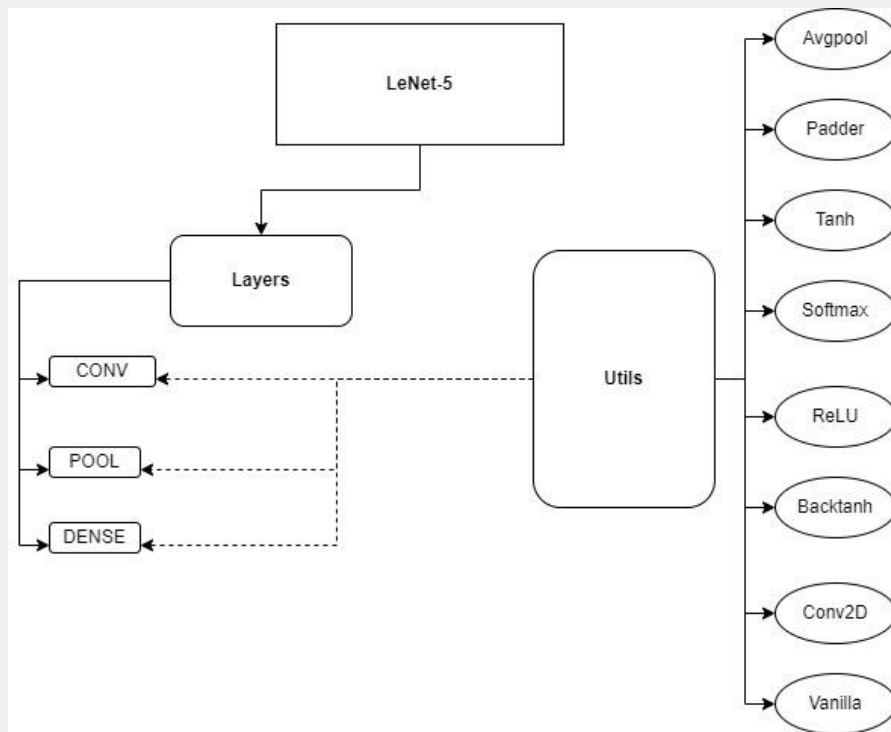
TABLE I

EACH COLUMN INDICATES WHICH FEATURE MAP IN S2 ARE COMBINED
BY THE UNITS IN A PARTICULAR FEATURE MAP OF C3.

- In the network, between S2 and C3 the authors use a constructed map to take the 6 different channels of the output to 16 channels using 2D Convolution.
- Why we use Sparse connectivity:

Implementation

Framework



Training on MNIST



- *Modified National Institute of Standards and Technology*
- -70000 images of handwritten digits, original paper uses SVM to classify



Lenet using inbuilt (keras)



- We also made a model of LeNet on Keras using the inbuilt sequential model to compare with our implementation
- Benchmark

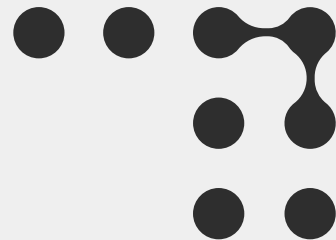


Idea of an alternative approach



- A CNN uses shared weights to identify image based features using the convolution operation.
- We can reshape the input image to a normal column vector and interpret it as the input layer to an MLP.
- Every conv layer \rightarrow a normal weight, bias MLP layer
But the weight matrix will be sparse circulant.
Thus, backprop becomes very intuitive because we can implement a normal MLP and only change the values of the weights and not the positions.

$$\begin{pmatrix} k1 & k2 & 0 & k3 & k4 & 0 & 0 & 0 & 0 \\ 0 & k1 & k2 & 0 & k3 & k4 & 0 & 0 & 0 \\ 0 & 0 & 0 & k1 & k2 & 0 & k3 & k4 & 0 \\ 0 & 0 & 0 & 0 & k1 & k2 & 0 & k3 & k4 \end{pmatrix} \cdot \begin{pmatrix} x1 \\ x2 \\ x3 \\ x4 \\ x5 \\ x6 \\ x7 \\ x8 \\ x9 \end{pmatrix}$$



THANK YOU!

