

**Department of Mathematics and Computer Science**  
**Specialization : Machine learning for data science**

**Supervised research project presentation**  
**Title**

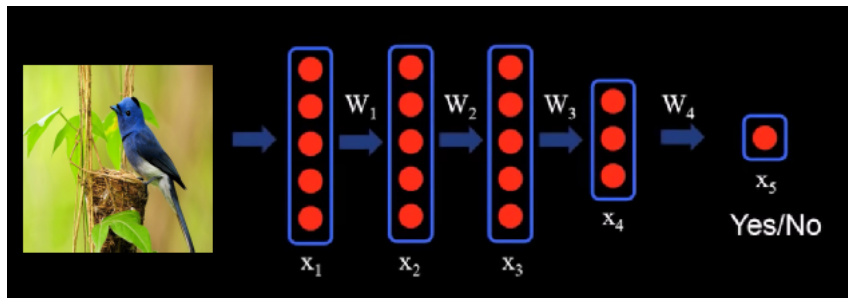
# Deep learning and machine learning methods for image classification

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24 May 2016

- 1 Problem description and goal
- 2 Scope of deep learning
- 3 Example of application
- 4 Structure of deep neural networks
- 5 Mimicking the human brain
- 6 Experimental results
- 7 Theoretical foundation of Deep neural networks
- 8 Conclusion
- 9 References

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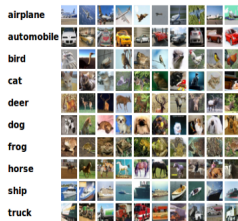
- 1-How to classify images ?
- 2-What are the criteria of decision making ?
- 3-What's the appropriate learning algorithm for computer vision ?
- 4-Is deep learning making machine learning obsolete ?

## Our approach :

1-Choose two different datasets.



MNIST dataset



CIFAR-10 dataset

2-Select four different learning algorithms and implement them.

*Logistic Regression, Multi Layer Perceptron, Support Vector Machine and Convolution Neural Networks*

3-Evaluate the performance of each algorithm with the accuracy criterion.

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- 1-High energy physics : higgs boson discovery.
- 2-Cancer detection : breast cancer .
- 3-Medical diagnosis and decision support.
- 4-The inner structure of DNA and the the close relationship between chromosomes.
- 5-Predict earthquakes and climate change.

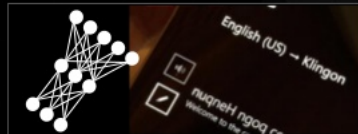


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## PRACTICAL DEEP LEARNING EXAMPLES



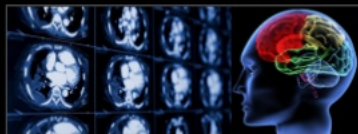
Image Classification, Object Detection, Localization,  
Action Recognition, Scene Understanding



Speech Recognition, Speech Translation,  
Natural Language Processing



Pedestrian Detection, Traffic Sign Recognition



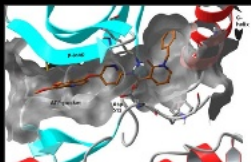
Breast Cancer Cell Mitosis Detection,  
Volumetric Brain Image Segmentation

# DEEP LEARNING REVOLUTIONIZING MEDICAL RESEARCH



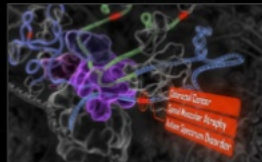
Detecting Mitosis in Breast Cancer Cells

— IOSIA



Predicting the Toxicity of New Drugs

— Johannes Kepler University

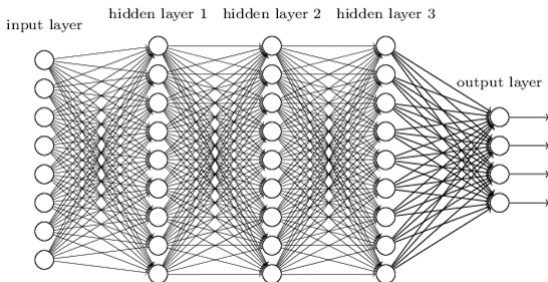


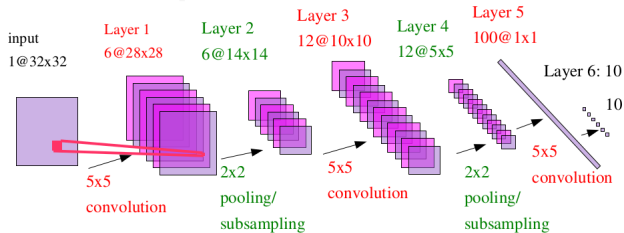
Understanding Gene Mutation to Prevent Disease

— University of Toronto

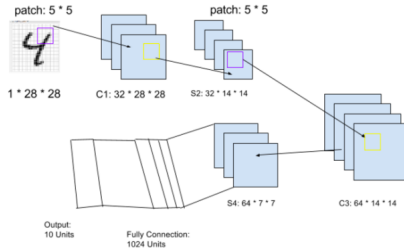
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## Deep neural network





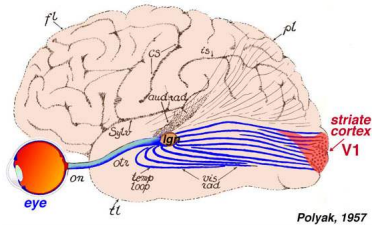
Yann Lecun, Convolutional Neural Networks, University of New York



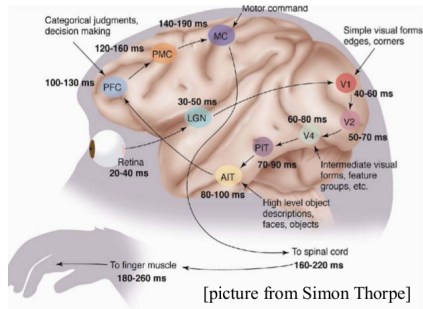
## Convolutional Neural Network for MNIST handwritten digit recognition

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Visual input to the brain goes from eye to LGN and then to primary visual cortex, or area V1, which is located in the posterior of the occipital lobe.  
Adapted from Polyak (1957).



[Gallant &amp; Van Essen]

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Gradient iterations Learning algorithms	Accuracy with different number of gradient iterations					
	20	25	100	200	500	1000
Logistic Regression			95.9%	96.32%	<b>96.46 %</b>	96.46%
Multi layer perceptron with 25 hidden neurons	89.14%	90.14%	91.05%	92.02%	92.74%	<b>92.85 %</b>
Multi layer perceptron 300 hidden neurons	96.28%	96.62%	98%	98.12%	98.21%	<b>98.22 %</b>
Multi layer perceptron 300-150 hidden neurons			<b>10.05 %</b>			
Multi layer perceptron 300-150-75 hidden neurons			<b>11.35 %</b>			

Accuracy Learning algorithms		Accuracy
Support Vector Machine (SVM)	Linear Kernel	93.98%
	Polynomial Kernel	<b>98.08 %</b>
	Gaussian Radial Kernel	94.46
Convolutional neural network (CNN)	5 epochs with two hidden layers	95.11%
	10 epochs with two hidden layers	<b>95.66 %</b>

## Our results on MNIST dataset

Accuracy Learning algorithms		Accuracy
Multi Layer Perceptron (MLP) [13]	4 hidden layers (2000-1500-1000-500) with <b>5 % translation</b>	99.06%
	5 hidden layers (2500-2000-1500-1000-500)	98.53% after 14 epochs
Multi-Column Deep Neural Network (MCDNN) [14]		99.77%
Neural network with DropConnected [15]		<b>99.79 %</b>

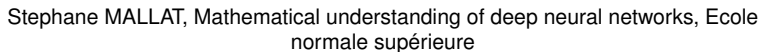
## Benchmark results on MNIST dataset

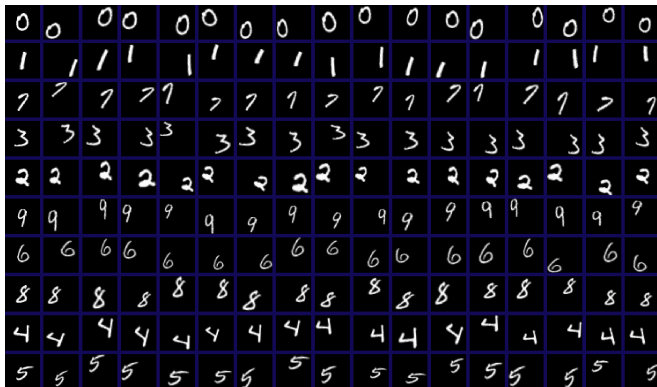
Learning algorithms \ Accuracy	Accuracy on CIFAR-10
Fractional max-pooling [18]	96.53 %
Simple CNN [19]	95.59 %
Init CNN [20]	94.16%
MCDNN [14]	88.79%

Benchmark results on CIFAR-10

- 1- Fractional max pooling [18] :  $\alpha \times \alpha$  is non integer  $\Rightarrow$  reduces overfitting.
  - 2- Striding : the convolutional layer uses a filter of  $2 \times 2$  and slides it over the entire image.
  - 3- Good initialization [20] : pre-initialize weights of each convolutional layer then normalize the variance of the output of each layer to be equal one. Layer sequential unit variance (LSUV).
  - 4- MCDNN [14] : different way of training for each column (deep). The final prediction is the average of individual prediction of each DNN.
  - 5- DropConnect [15] : improvement of Dropout  $\Rightarrow$  DropConnect sets a randomly selected subset of weights within the network.
- Dropout, randomly select subset of activations and set them to zero within each layer.

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Translation phenomenon in MNIST dataset



Elastic deformation and rotation in MNIST dataset

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- 1-There is no learning algorithm better than the other regardless context and type of data.
- 2-Deep learning methods are not always required to do classification.
- 3-Deep convolutional neural networks are able to reduce dimension.
- 4- Deep Convolution neural networks are able to compute hierarchical invariants of complex symmetries.
- 5-Deep neural networks are biologically inspired of human cortical cortex.
- 6- What do next ? strong mathematical and theoretical foundation, convergence guarantee, notion of complexity and approximation  
brain neuro-plasticity understanding, close relationship with particle and statistical physics.

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