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Methods for large-scale image classification and application to biomedical data

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Master Thesis - MLG Presentation

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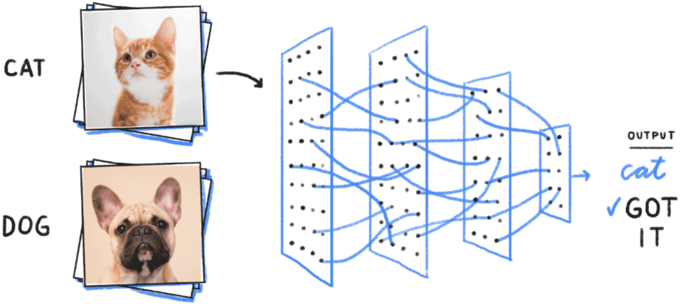
Faculté des Sciences ULB

Problem definition

Image classification problem

- Classify images into classes
- Image recognition
- Detecting specific features and recurrent patterns
- Using AI methods

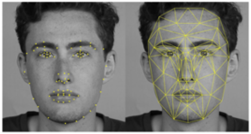


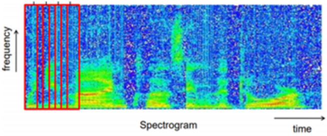
Dog/Cat image recognition. Figure from [1]

Life applications

Some examples of application that are tackled in the thesis:

- Google Images
- Face recognition
- Musical images analysis (notes, spectrogram, ...)
- **Medical images analysis**





From left to right: Image labeling from Google, face recognition, music spectrogram. Figure from [2]

Medical field

- Radiography, magnetic resonance imaging, histological images, ...
- Question: Is the patient reached by a disease ?
  $\rightarrow$ detect **tumors** such as mammographic mass or brain lesions
- State-of-the-art on breast cancer detection

Breast cancer detection: benign vs malignant tumor. Figure from [3]

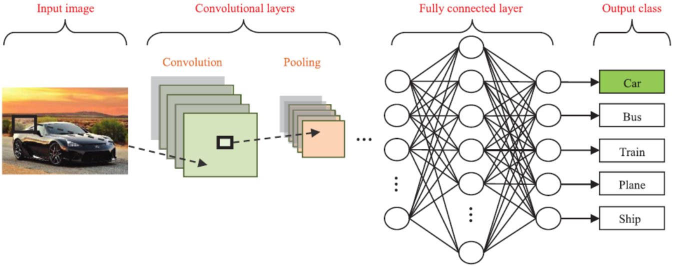
Materials & Methods

Overview of classification methods

- Supervised and Unsupervised learning
- Multiple classification models: Decision trees, random forests, K-means, SVM, ...
- What is the best model for images ?
  $\rightarrow$ **Convolutional Neural Networks** (CNN), why ?

Focus on CNN

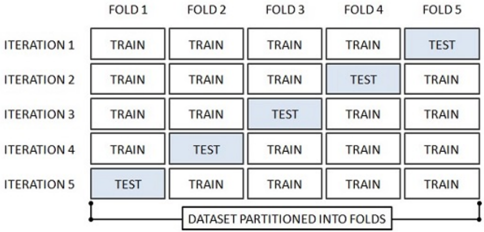
- Convolutional layers: extract the high-level features
- Pooling layers: dimensionality reduction
- Fully-connected layer: looks at the output of the previous layer and determines which features most correlates with a class
  $\rightarrow$ **Transfer learning**: knowledge about the data are stored and used for the future



Classic CNN architecture. Figure from [4]

Evaluation methods

- Compute prediction accuracy and precision
- Represented on ROC curves $= \frac{\text{True Positive Rate}}{\text{False Positive Rate}}$
- Overfit? Underfit?
- Cross-validation



5-fold CV. Figure from [5]

Breast cancer detection

State-of-the-art: Breast cancer detection

Methodology used by Ragab et al. [6]:

- Image preprocessing: enhancement and segmentation
- Feature extraction: CNN → ROI labelled benign or malignant
- Classification: SVM classifies benign / malignant and find the best hyperplane

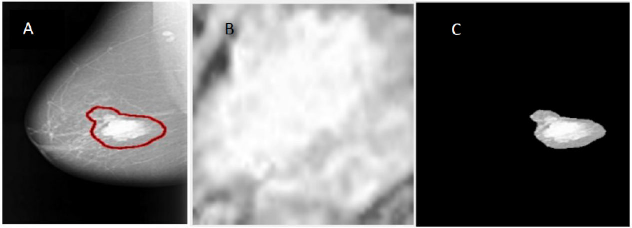
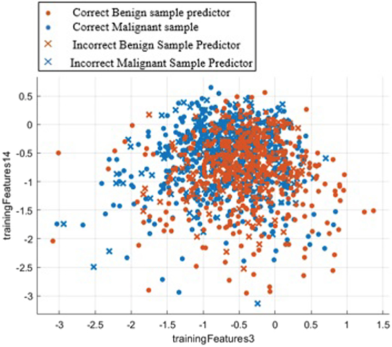


Image segmentation. Figure from [6]

State-of-the-art: Breast cancer detection

Results obtained :

- Accuracy : 80.5%
- Precision : 86%



SVM classification result from [6]

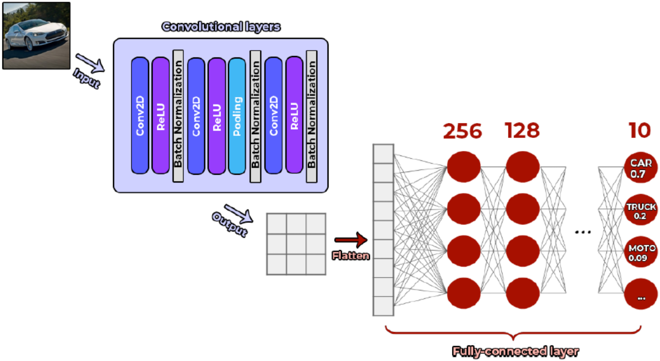
State-of-the-art: Breast cancer detection

- Are these results optimized ?
- How to correctly preprocess images ? Is it the same for non-medical and medical images ?
- How to enhance the good prediction rate of a CNN ?

CNN implementation

Implementation of a CNN

- Practice and create my own model to experiment parameters
- On the CIFAR-10 dataset (airplane, auto, bird, cat, ...)
- Implemented with keras library from Python

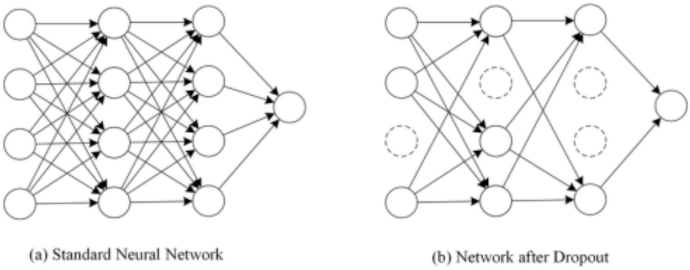


Baseline of my CNN implemented

Implementation of a CNN I

How to improve accuracy ? $\rightarrow$ **regularization !**

- Dropout

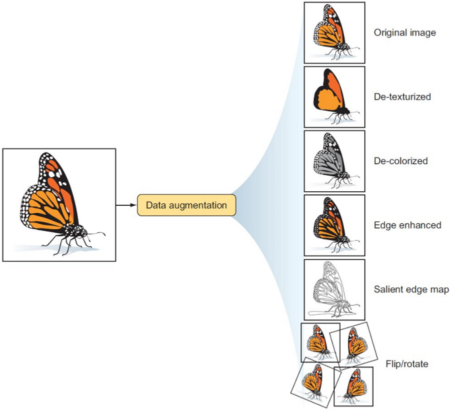


Dropout neural network model. Figure from [7]

- Weight decay

Implementation of a CNN II

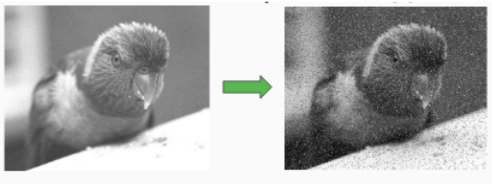
- Data augmentation



Data augmentation examples. Figure from [8]

Implementation of a CNN III

- Noise as regularizer ? How the model react to noise ?



Gaussian noise.

Also take a look of the training parameters:

- Epochs number
- Optimizer: SGD, RMSProp, AdaDelta, ...

$\Rightarrow$ Which regularizer to use ? How to chose the right value ?

On a medical case...

Leukemia subtypes detection

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Leukemia subtypes detection I

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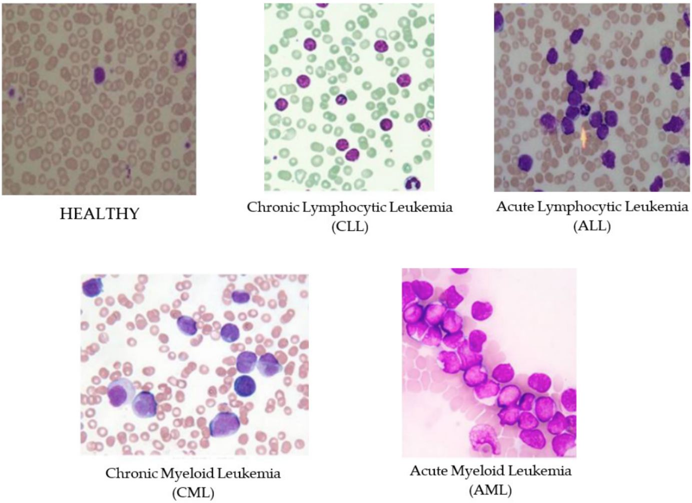
Let's now apply what we have learned from the experiments on CIFAR-10 on medical images.

- 4 subtypes of leukemia detection = 4 target classes

Cell type	Acute	Chronic
Lymphocitic	Acute Lymphocitic Leukemia (ALL)	Chronic Lymphocitic Leukemia (CLL)
Myelogenous	Acute Myelogenous Leukemia (AML)	Chronic Myelogenous Leukemia (CML)

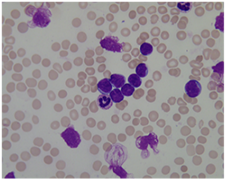
Leukemia subtypes detection II



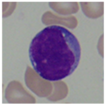
Leukemia subtypes illustration. Figure from [9]

Leukemia subtypes detection: datasets I

- ALL-IDB dataset
  - ALL-IDB separated in 2 sets: ALL-IDB1, ALL-IDB2
  - ALL-IDB1: 108 images of average size 2592 x 1944 → huge! need preprocessing → **downsample**, still working?
  - ALL-IDB2: 260 images of the ROI (blast cell) of ALL-IDB1, size 250 x 250
  - including 180 ALL and 188 healthy patients



ALL-IDB1



ALL-IDB2

Leukemia subtypes detection: datasets II

$\Rightarrow$ Is the computational time for preprocessing on ALL-IDB1 worth or is it preferable to directly use ALL-IDB2? But do ALL-IDB2 give enough information?

- DEMIR-LEUKEMIA dataset
  - Complementary to ALL-IDB $\rightarrow$ add CLL, AML and CML cases
  - 177 AML images, 185 CLL images, 185 CML images
  - Variable sizes
- Based on the work "Identification of Leukemia Subtypes from microscopic images" from Ahmed et al. [9]

Leukemia subtypes detection: experiments

- Experiment first only on HEALTHY/ILL case (binary classification) using ALL-IDB dataset
- Next experiment on 4 subtypes + healthy detection (5 classes) using ALL-IDB and DEMIR-LEUKEMIA datasets
- Comparison of my results with those presented in the article. How does it differ? Why?
- Are the efficient regularizers for CIFAR-10 also efficient in this case?

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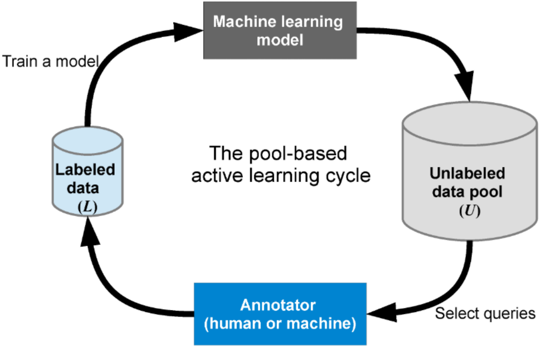
Interactive image annotation & active learning

Automated labelling: active learning

Actually in the medical field, image recognition is mostly used as **computer-aided** detection in addition to an expert point-of-view. Nevertheless, the final goal is that the computer detection can be used independently. $\rightarrow$ **Active learning**



Active learning cycle. Figure from [10]

Automated labelling: active learning

- What does active learning bring more than classic learning?
- What are the best methods and models?
- How strong do we have to consider the oracle (annotator)?
- ...

$\Rightarrow$ We need to progress on interactive image annotation !

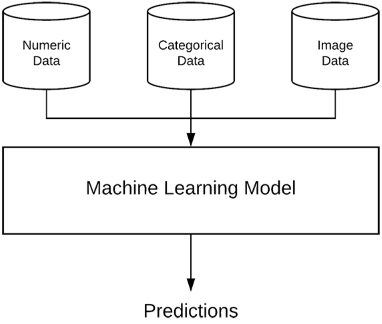
CNN extension

What about extending a neural network?

Extending the neural network

In medical image analysis, the image is just one variable among others → combine with other variables (age, healthy condition, ...) → extend the NN

- Multiple inputs data (ex: numerical + images)
- Multiple models (ex: MLP + CNN)



Still very fuzzy topic, may be tackled for further work.

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[9] Nizar Ahmed et al. "Identification of Leukemia Subtypes from Microscopic Images Using Convolutional Neural Network". In: *MDPI* (2019).

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The End

Thank you for your attention