

Hands-on Introduction to Deep Learning

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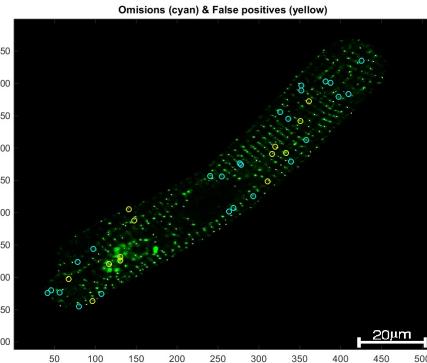
Centre de Recerca en Enginyeria Biomèdica



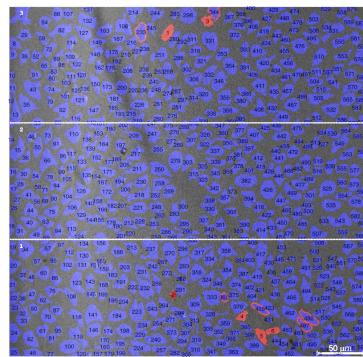
16th International Work-Conference on Artificial Neural Networks IWANN 2021
(June, 16th-18th, 2021, virtual conference)

ANALYSIS OF MEDICAL & BIOLOGICAL IMAGES

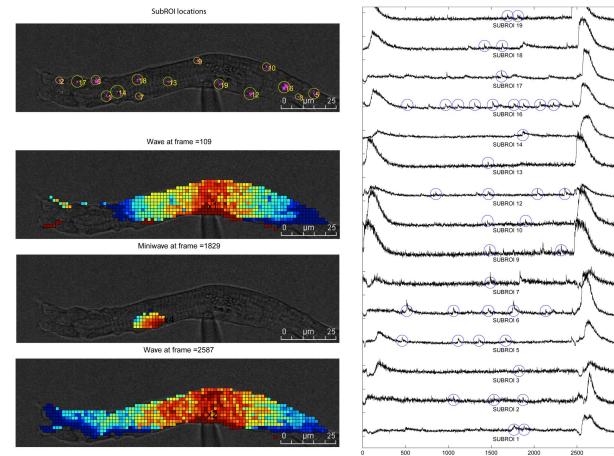
Molecular receptors



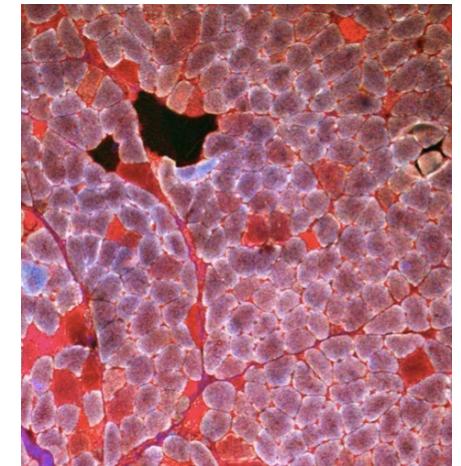
Cell cultures



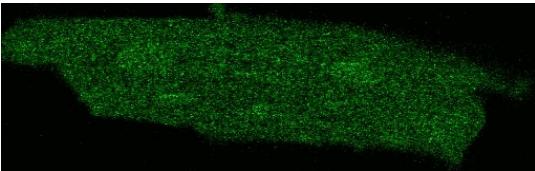
Calcium dynamics



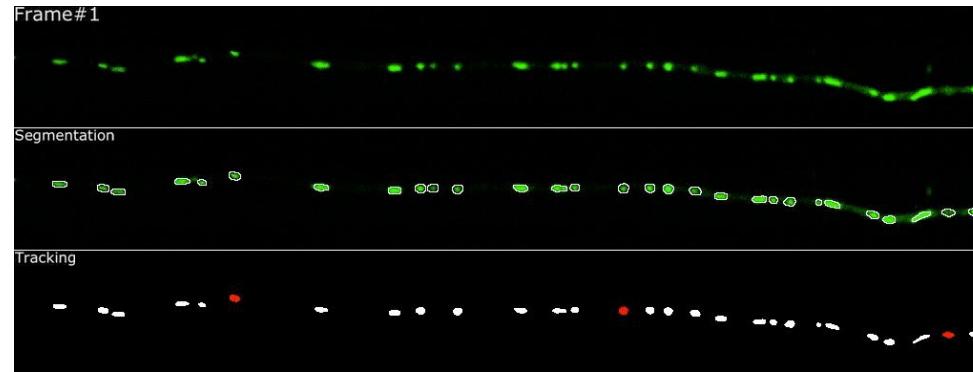
Digital Pathology



Single-cell experiments

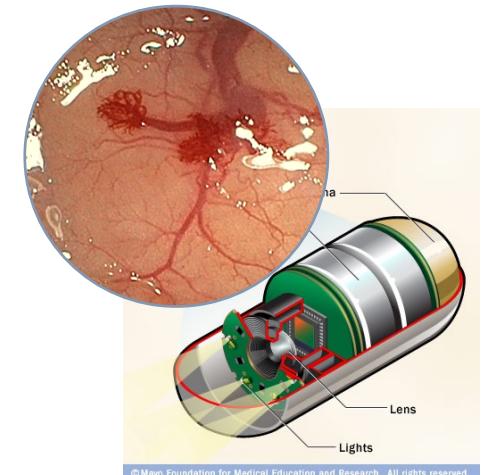


Mitochondrial transport



Extraction & analysis of multiscale biomarkers

Wireless endoscopy



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SCOPE

YES

DL Image Analysis – Computer Vision
Convolutional Neural Networks
Basic interpretability methods
Basic ideas + Implementation
Exploratory methods

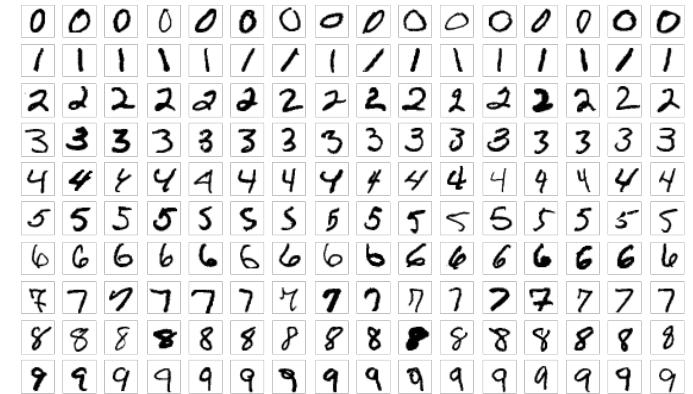
NO

Recurrent networks – LSTM –Time signals
Generative Adversarial Networks (GAN)
No deep Reinforcement Learning
In-depth description of the methods

Overview and methodology

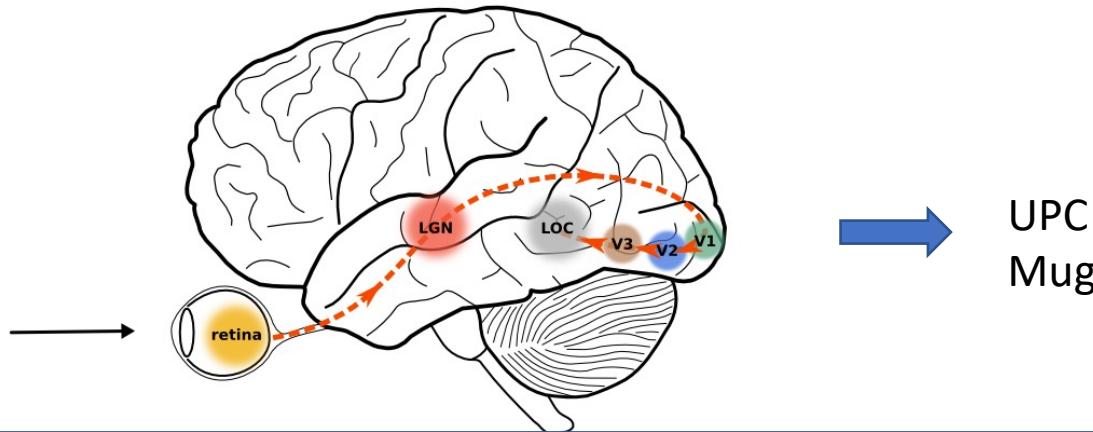
- General introduction
- MNIST data exploration
- The Traditional ML approach
- The DL approach: Transfer learning vs. Trained features
- DL interpretability

MNIST dataset – Handwritten digits



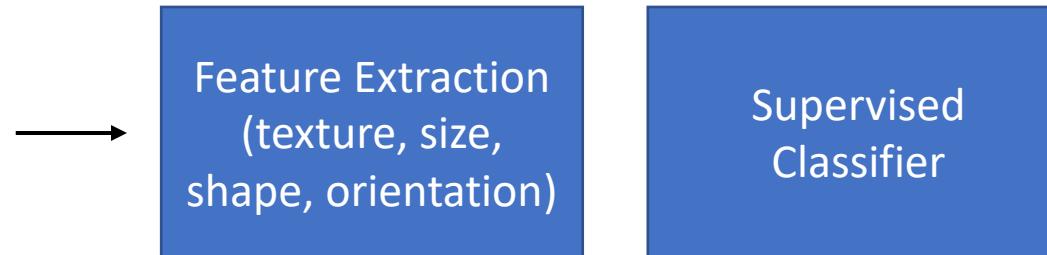
CHANGE IN PARADIGM

Human pattern
recognition



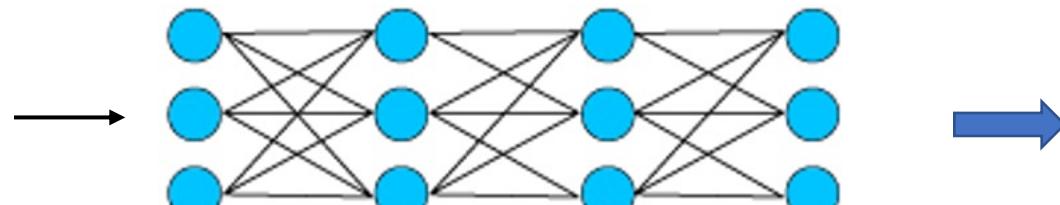
UPC
Mug

Traditional
Machine Learning



UPC
Mug

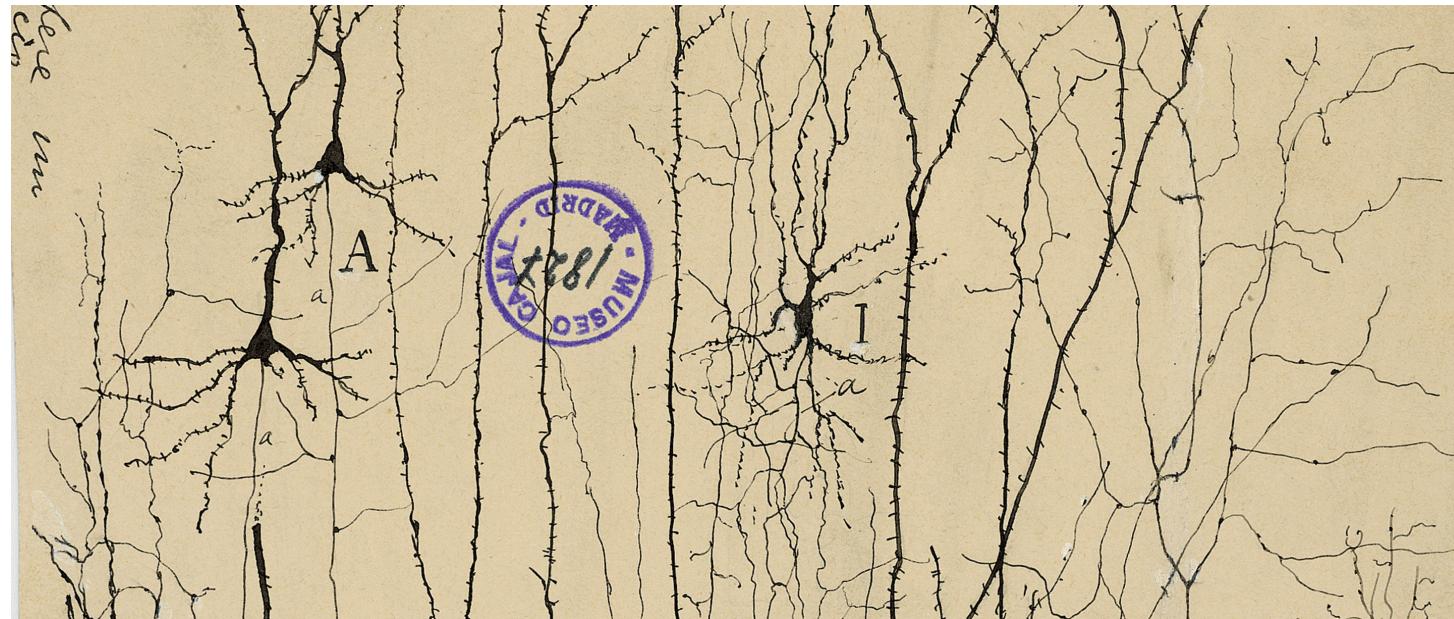
Deep Learning



Feature extraction + Classification

UPC
Mug

Emulating human mind



Cajal & Golgi **Nobel 1906**

Hebbian learning 1949

Hodkin & Huxley 1952 **Nobel 1963**

Hubel & Wiesel 1959 Visual Cortex **Nobel 1981**

Back-propagation Applied to Handwritten Zip Code Recognition (1989)

Convolutional Networks For Images, Speech, And Time Series (1995)

Gradient-based Learning Applied To Document Recognition (1998)

<http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf>

<http://yann.lecun.com/exdb/publis/pdf/lecun-bengio-95a.pdf>

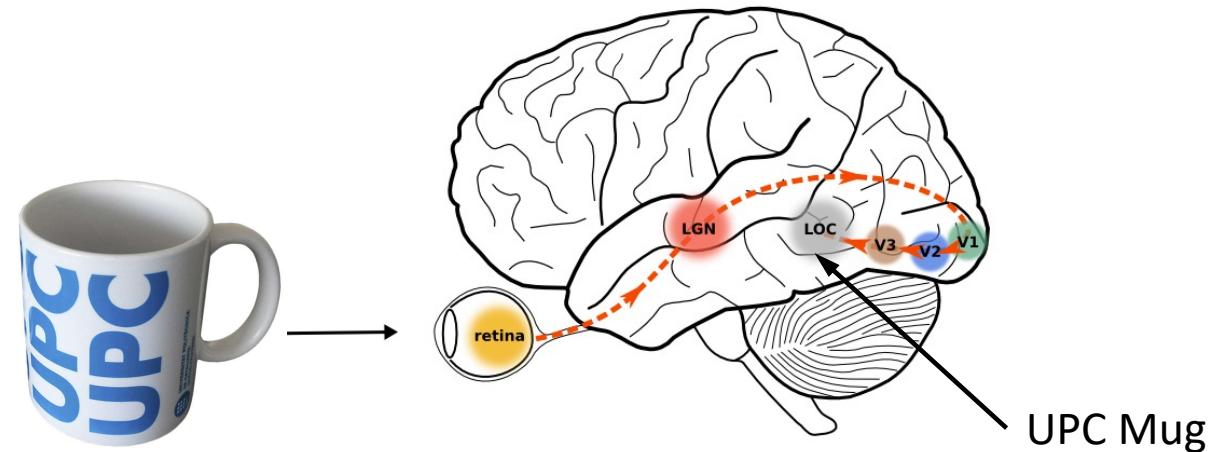
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Deep Learning – Convolutional Neural Networks

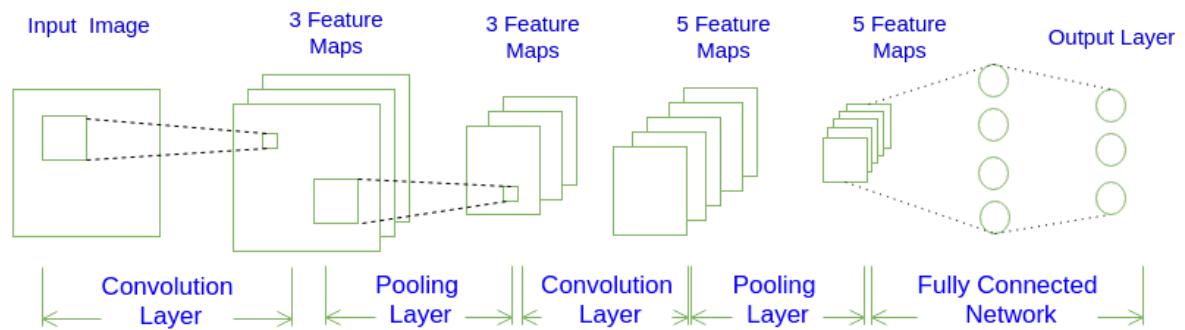
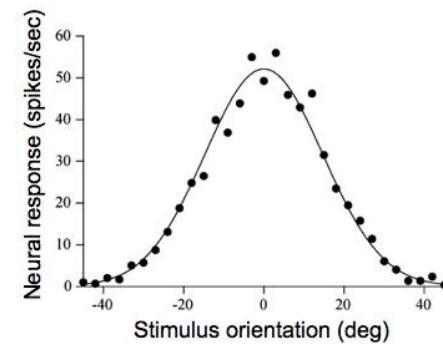
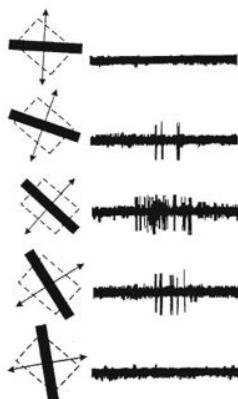
Hubel & Wiesel: Neural basis of visual perception

LGN: Lateral Geniculate Nucleus

V1: Primary Visual cortex

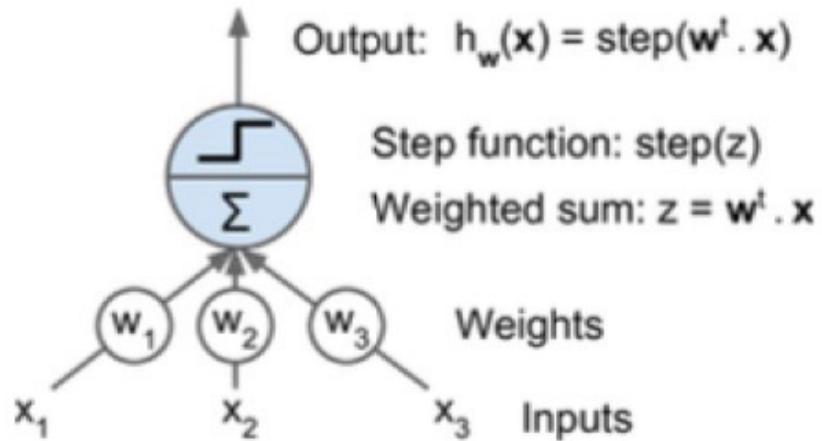


V1 physiology: orientation selectivity

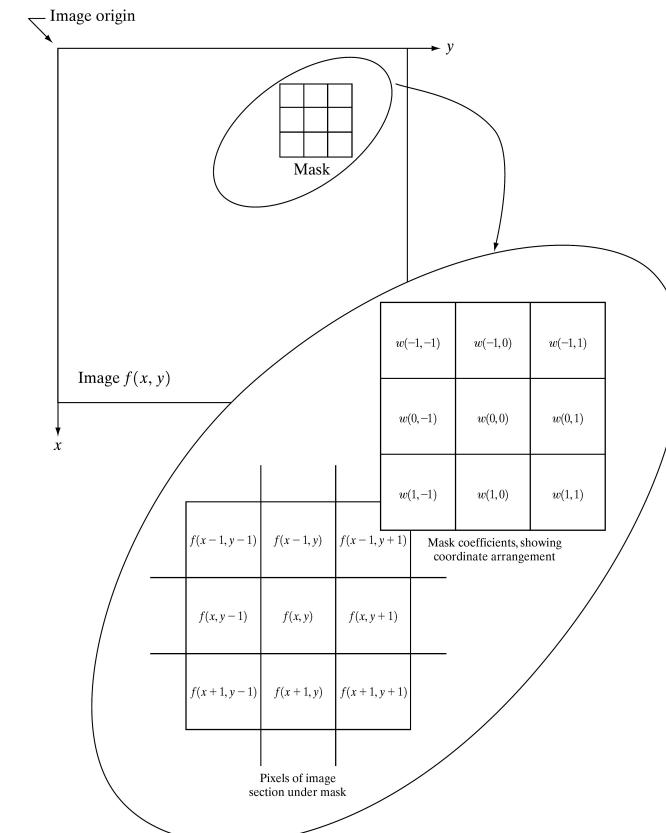


Convolutional filters

Neural Network



Training / learning weights:
Hebbian rule “wiring by firing”

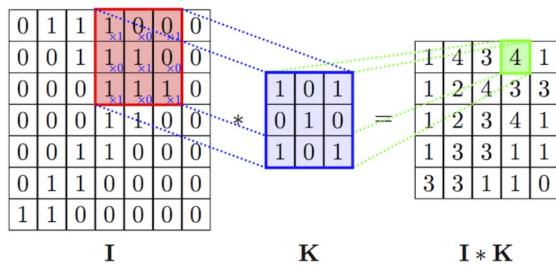


$$g(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) \cdot f(x + s, y + t)$$

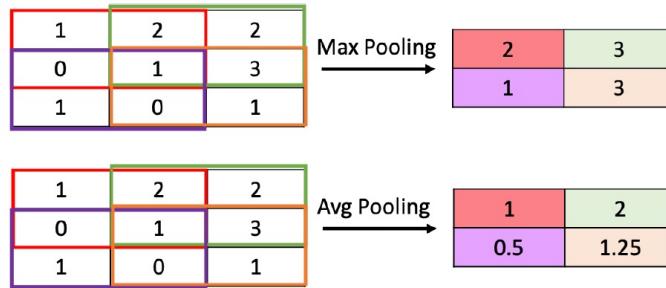


Basic elements of a CNN arquitecture

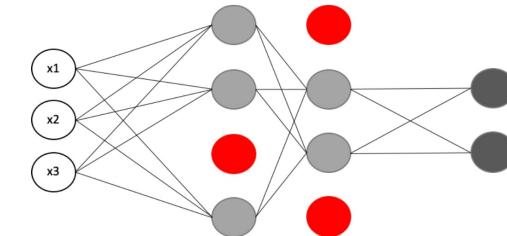
Convolutional layers



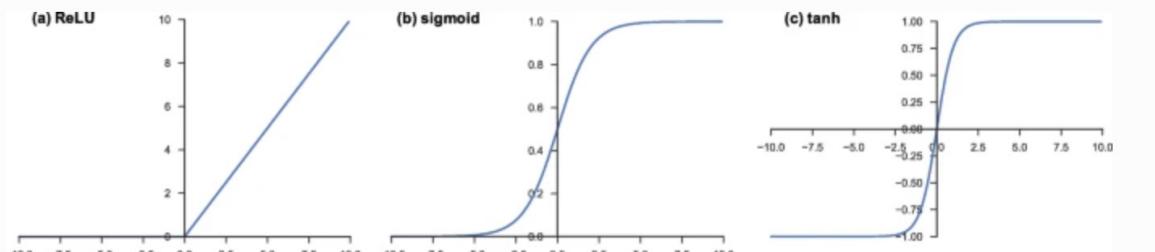
Pooling layers



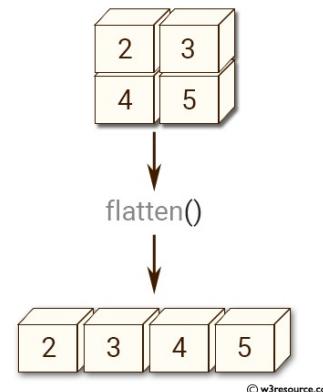
Dropout layers



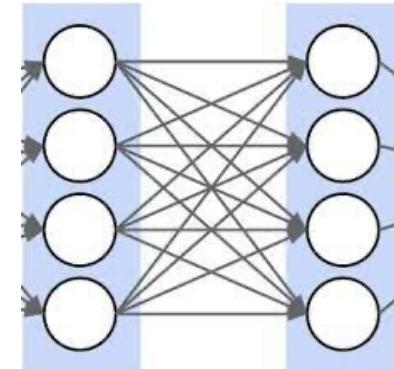
Activation layers



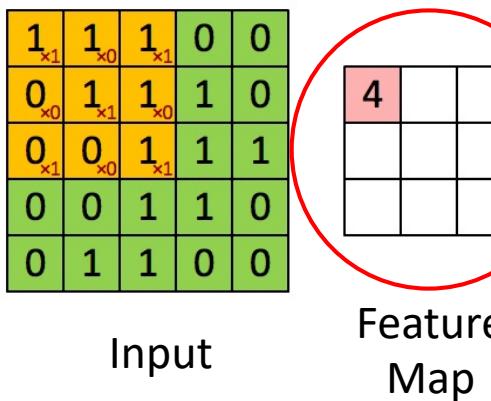
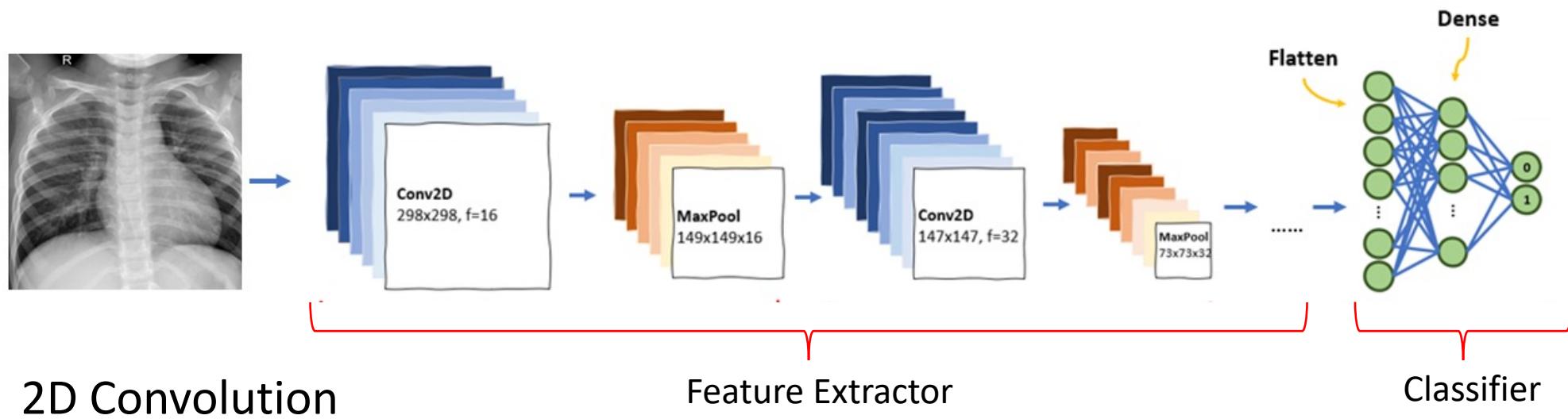
Flatten layers



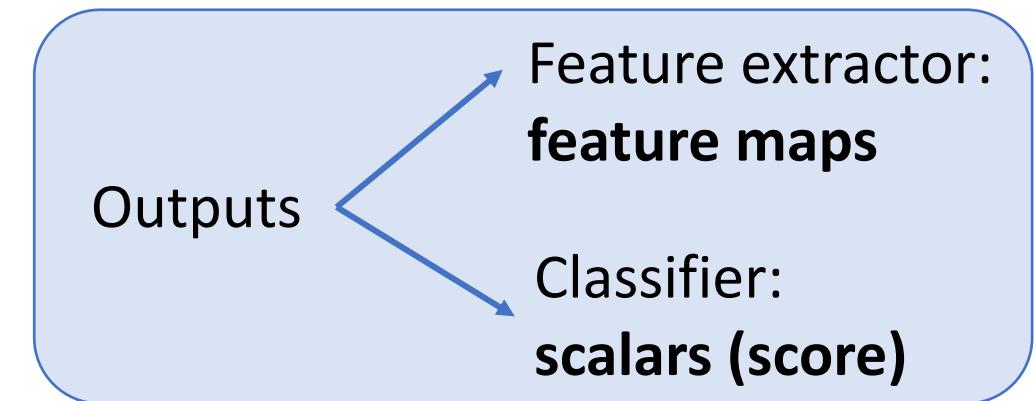
Fully connected layers
(Classification)



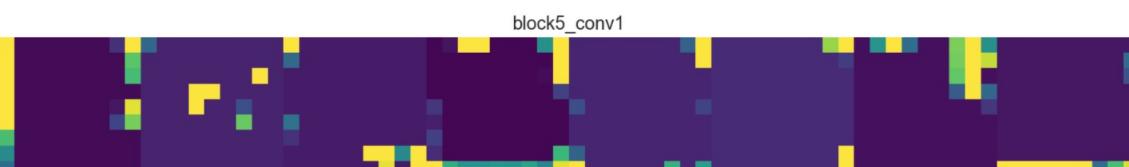
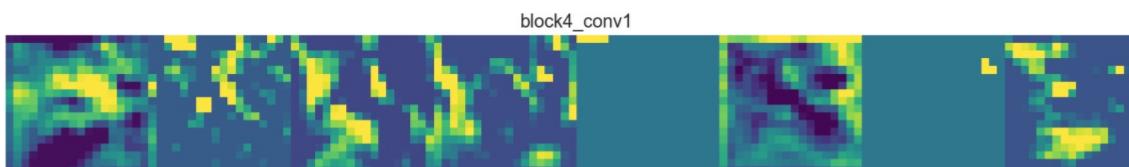
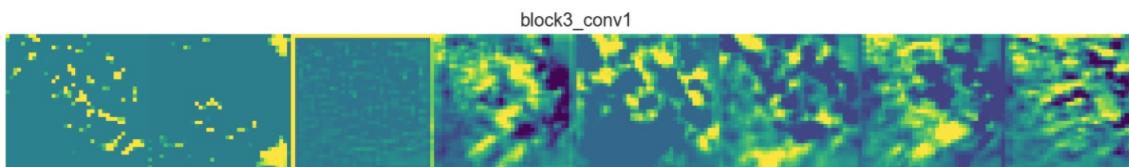
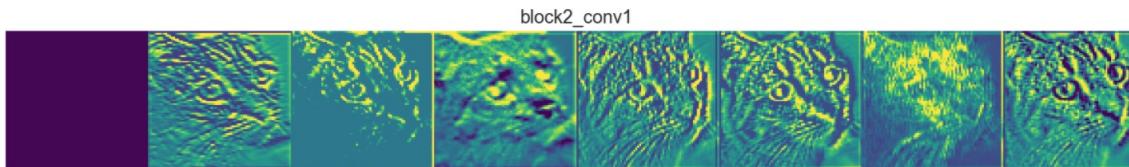
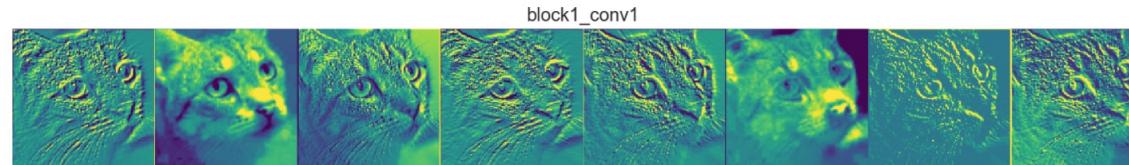
CONVOLUTIONAL NEURAL NETWORKS



retain spatial
information of
the input

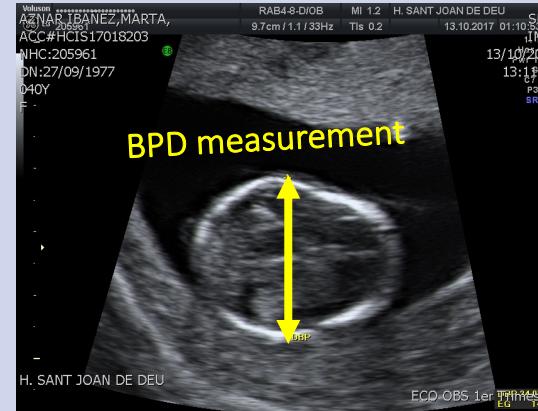
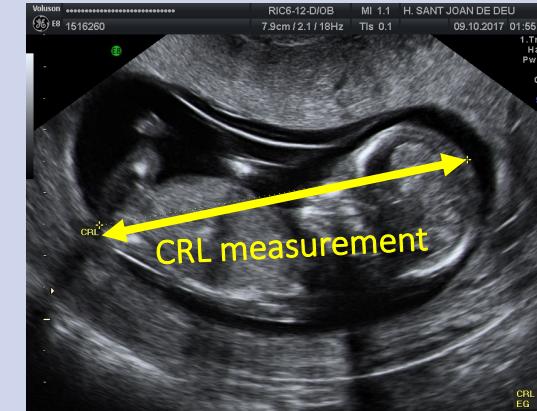
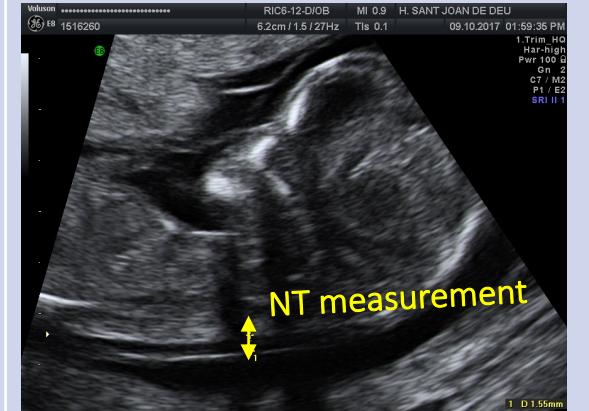


CNN: FEATURE MAPS



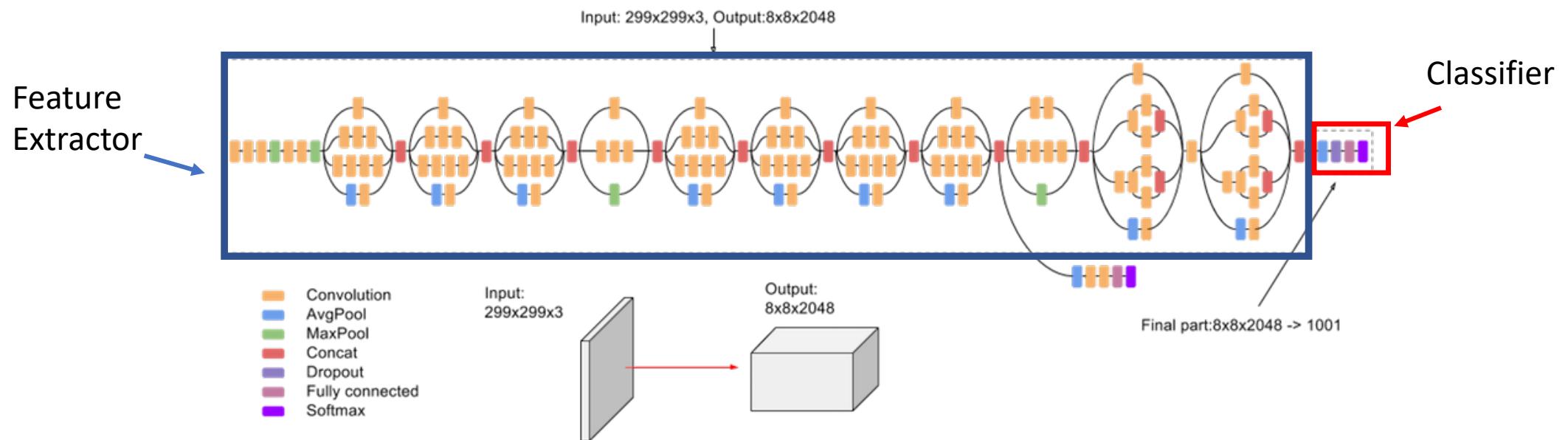
abstraction

EXAMPLE: FETAL BIOMETRIC PLANES

PLANE	BPD	CRL	NT
MEASUREMENT	Biparietal Diameter (BPD)	Crown-Rump length (CRL)	Nuchal Translucency (NT)
MAIN UTILITY	Check fetal development and establish gestational age	Establishes gestational age	Detect chromosomal anomalies
EXAMPLE	 <p>BPD measurement</p>	 <p>CRL measurement</p>	 <p>NT measurement</p>

TRANSFER LEARNING WITH INCEPTION V3

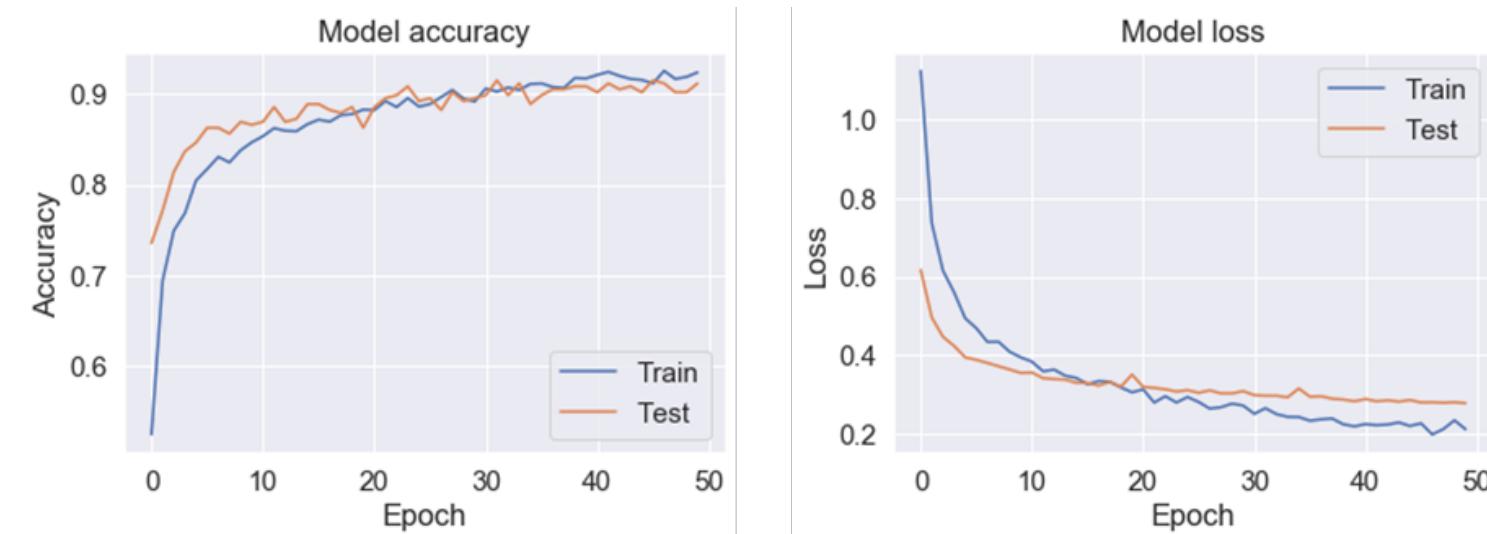
- Inception V3 was trained with ImageNet dataset (1.2M images of 1000 different classes)



- Trainable Parameters: 24M → 6127

4. EXPERIMENTAL RESULTS AND ANALYSIS

MODEL PERFORMANCE



Predicted class

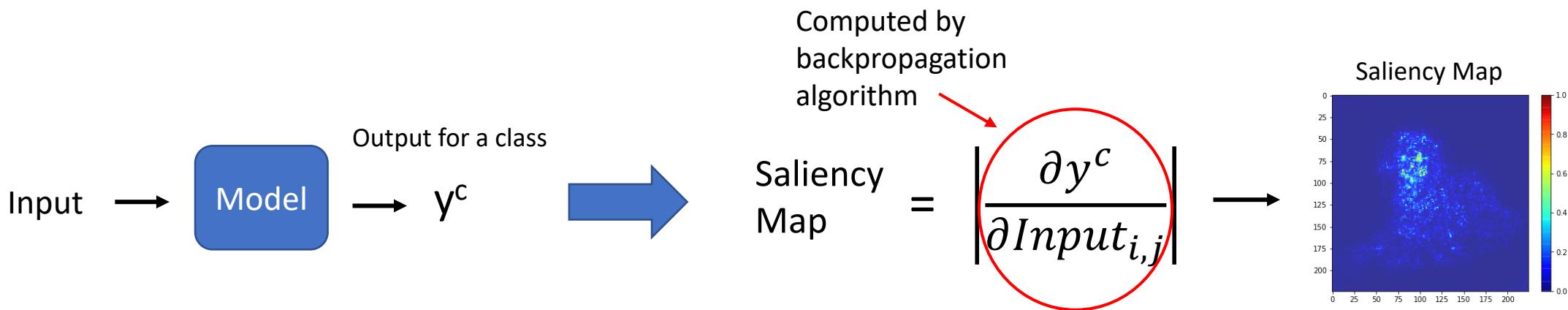
True class			
	BPD	CRL	NT
BPD	0.90	0.05	0.05
CRL	0.03	0.93	0.04
NT	0.02	0.06	0.92

INTERPRETABILITY METHODS

FINAL MASTER THESIS: VISUAL INTERPRETABILITY
OF DEEP LEARNING ALGORITHMS IN MEDICAL
APPLICATIONS, Christian Jorba, MASTER IN ENGINEERING
PHYSICS - UPC

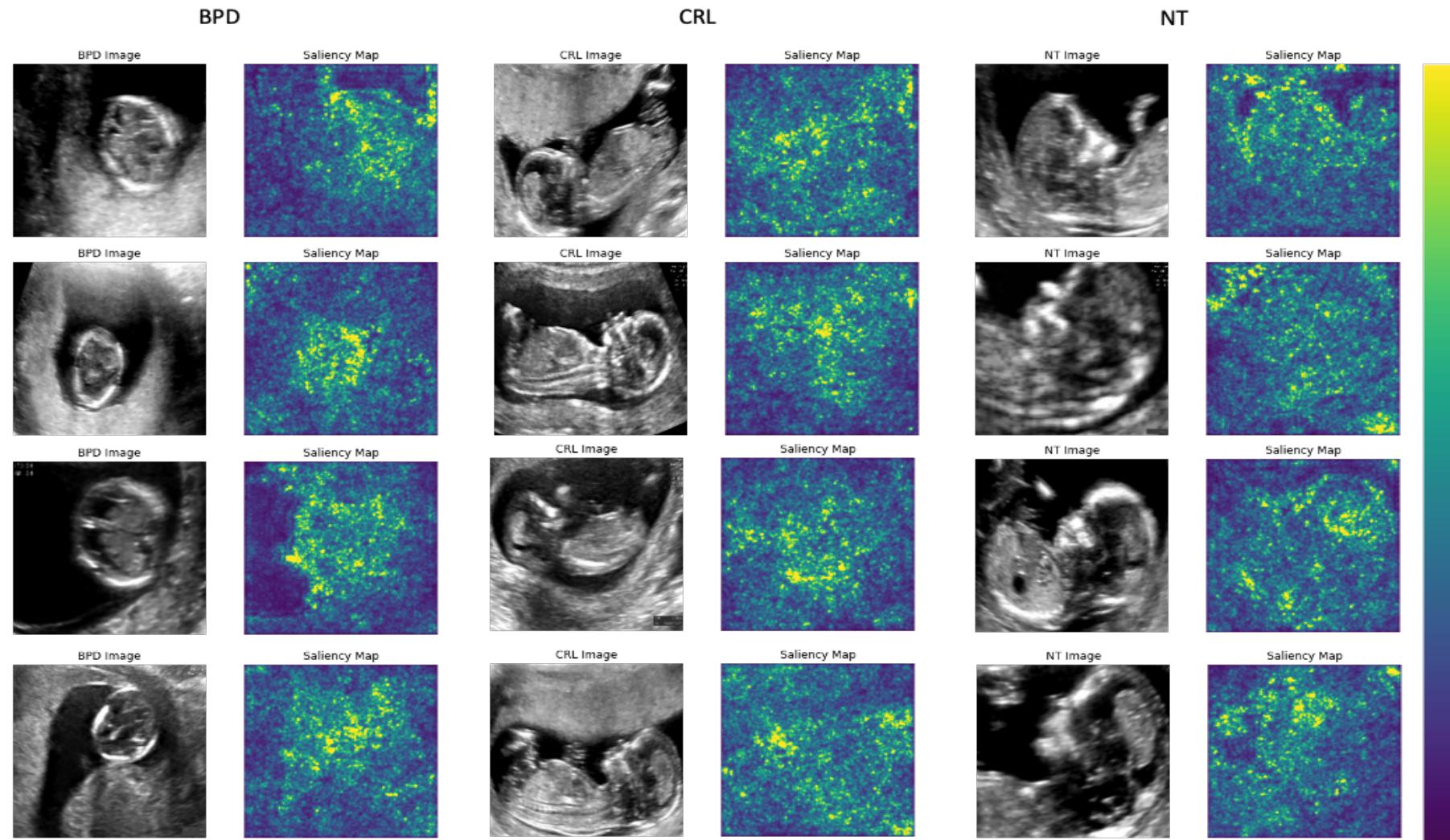
SALIENCY MAPS

- This method shows the most sensible parts of the input image for the model



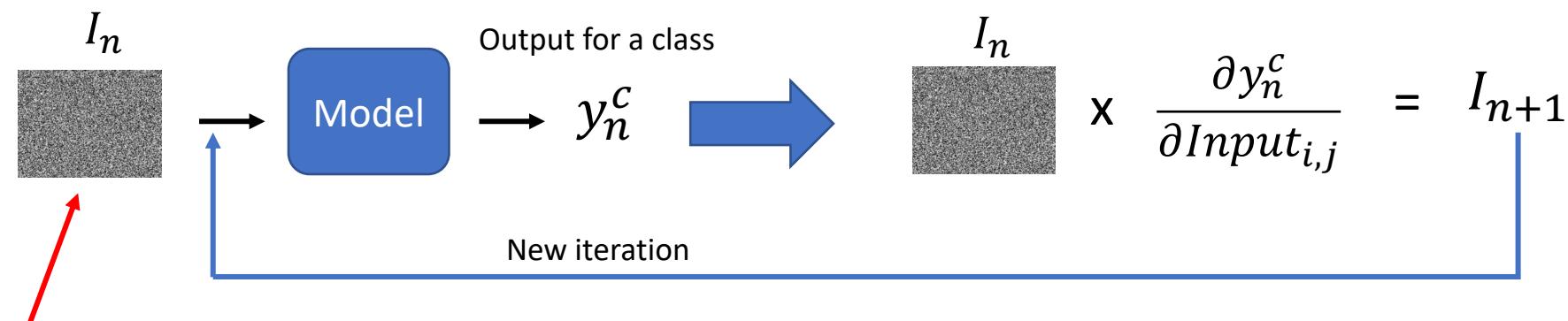
- High values represent the most important features or regions of the input to be classified in a specific class
- Fast to compute

SALIENCY MAPS



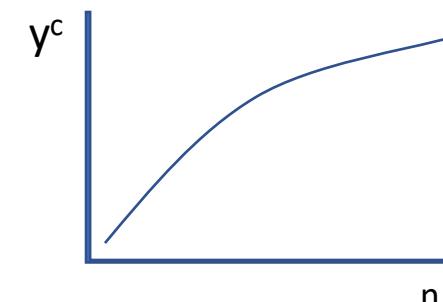
ACTIVATION MAXIMIZATION

- Method that allows to obtain an input that maximizes the score of a certain class
- Useful to see what patterns of the input are characteristics of each class



Starts with a neutral
image (noise)

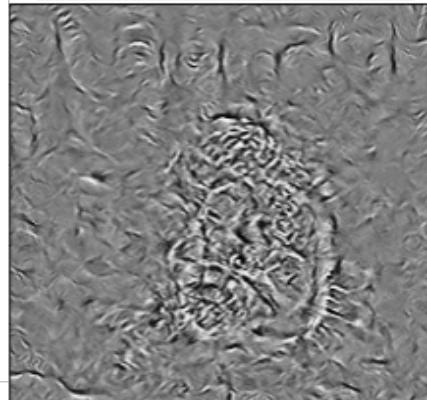
- Slow performance



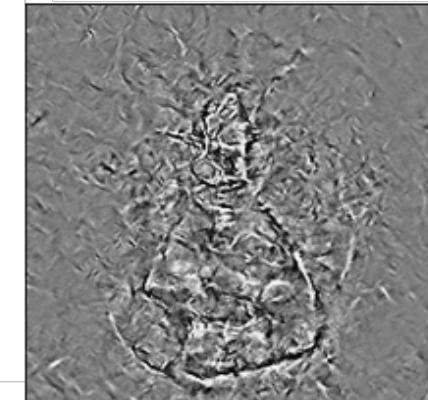
We are getting the image
that best represents a class

ACTIVATION MAXIMIZATION

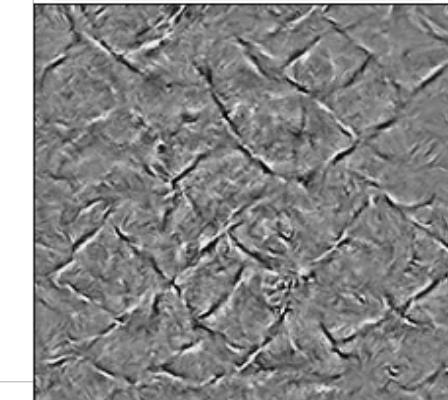
BPD class Maximization



CRL class Maximization



NT class Maximization



BPD image example



CRL image example

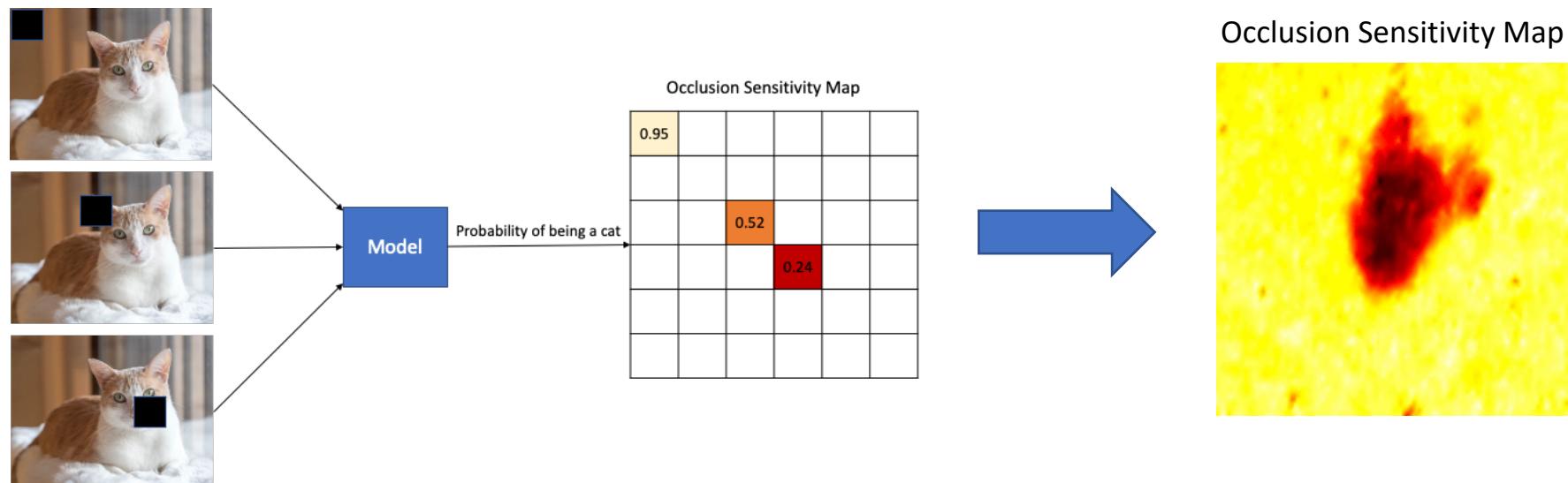


NT image example



OCCLUSION SENSITIVITY MAPS

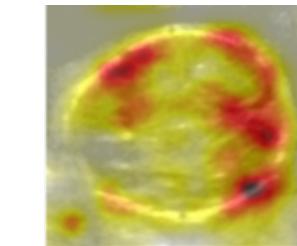
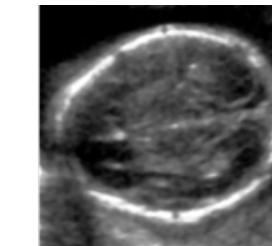
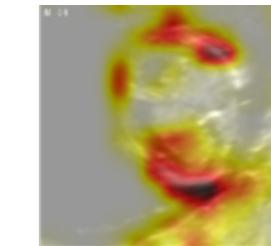
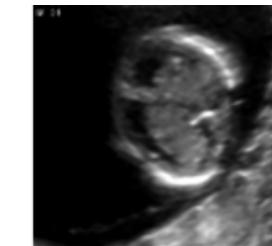
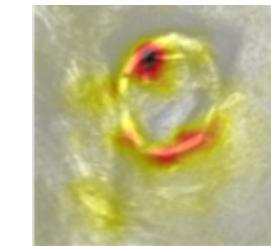
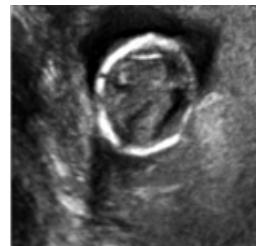
- Technique based on dividing the input image into a grid, and hiding each cell to make a prediction with the model
- High score → unimportant feature | Low score → important feature



- Slow process

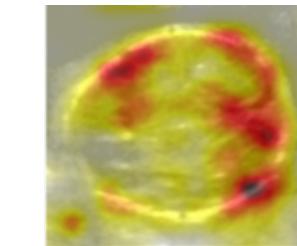
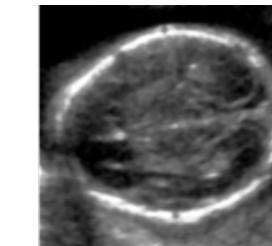
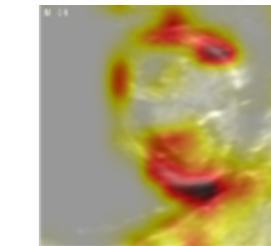
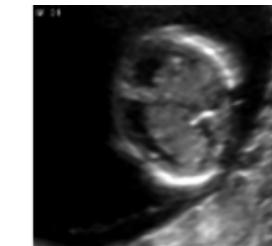
OCCLUSION SENSITIVITY

Example 1



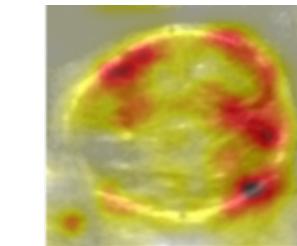
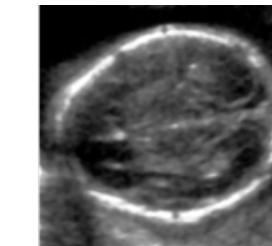
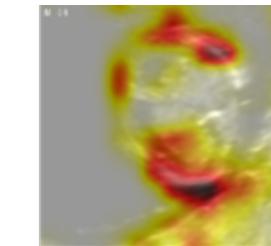
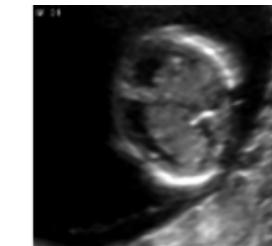
Example 2

BPD

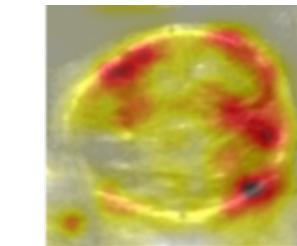
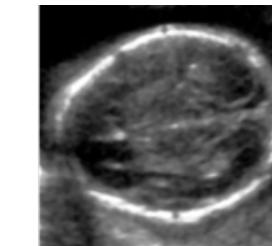
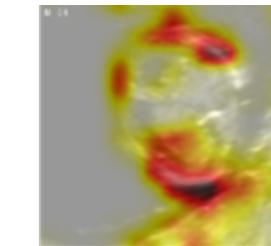
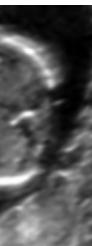
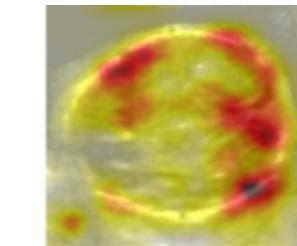
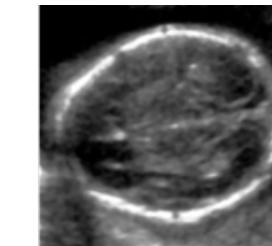
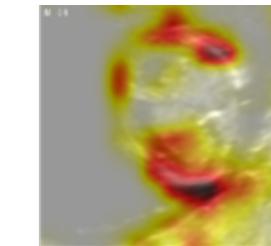
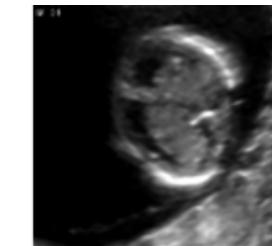


Example 3

CRL



NT

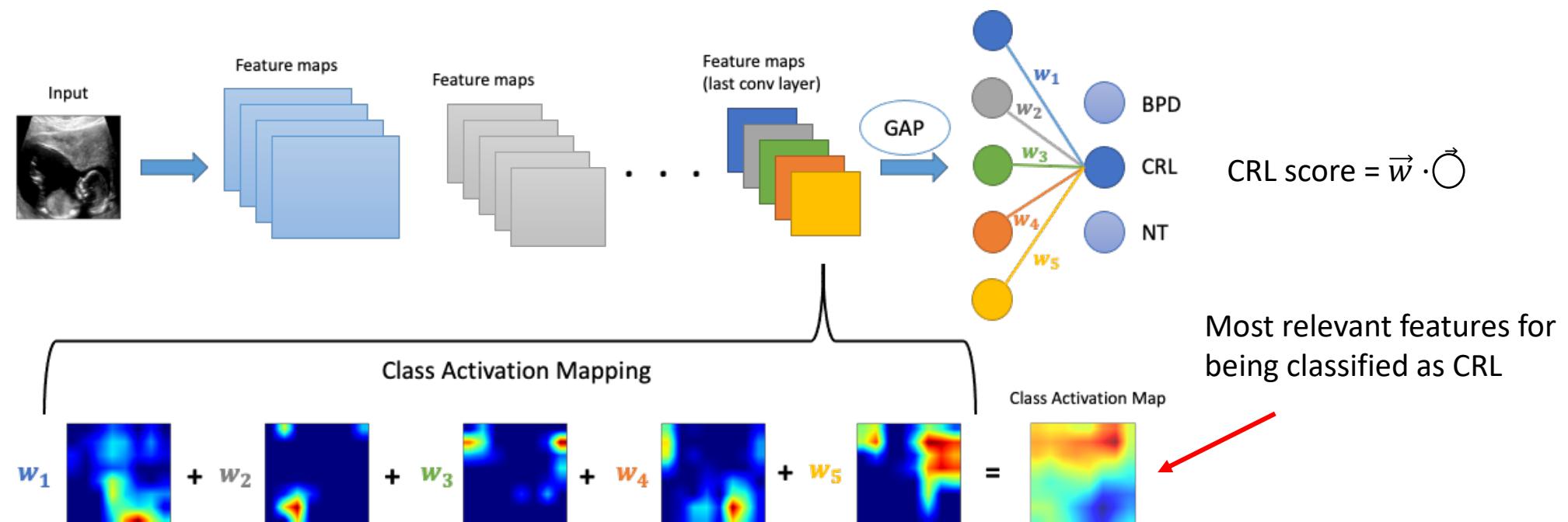


CLASS ACTIVATION MAPPING

Locate in which parts the classifier is focusing to decide that a sample belongs to one class or another

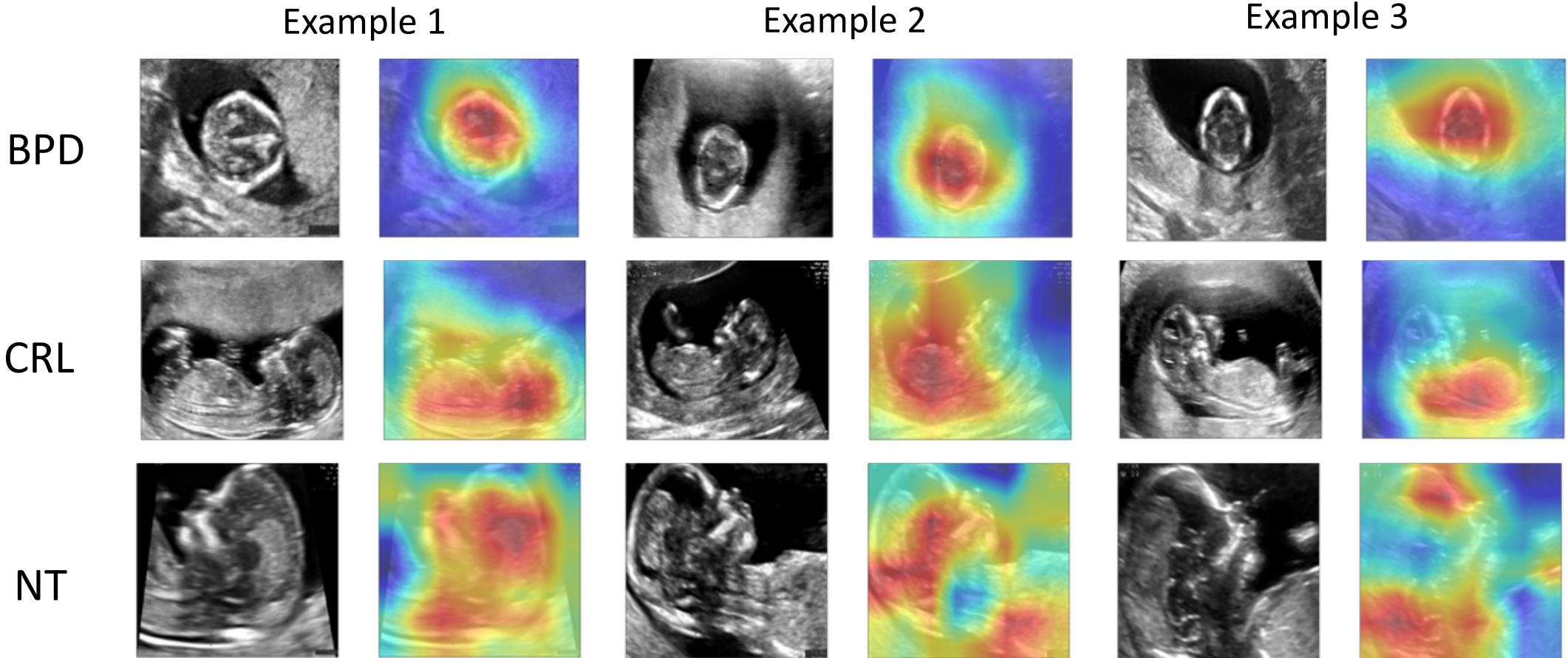
- CAM takes advantage of

- An specific CNN architecture (GradCAM generalizes it)
- Feature maps retain spatial information



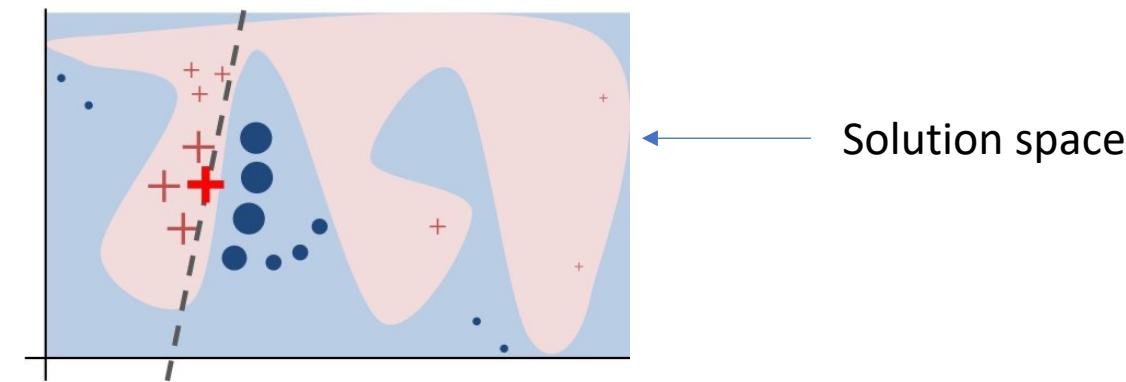
- Very fast to compute

CLASS ACTIVATION MAPPING



Local interpretable model-agnostic explanations (LIME)

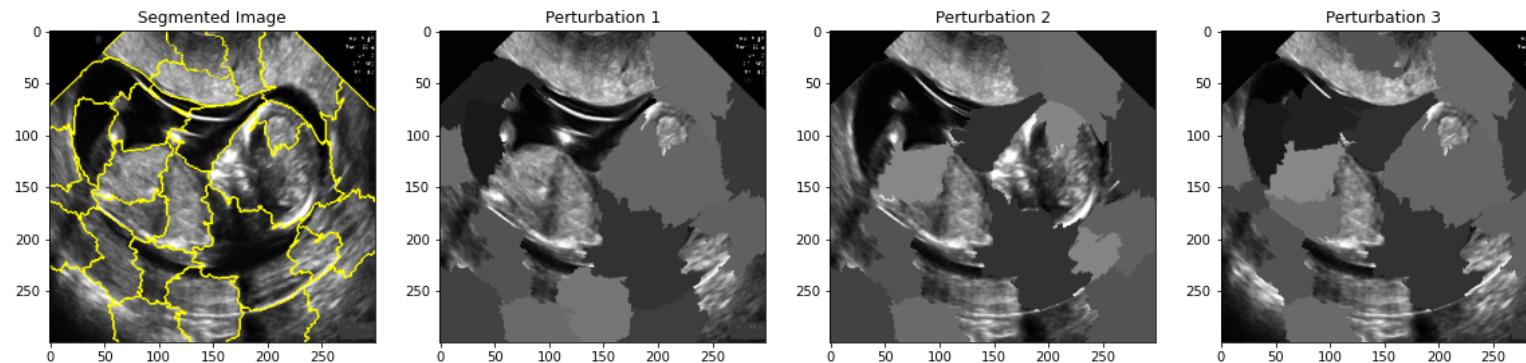
- This method consists of building a simpler model, normally a linear model, on top of the CNN
- By doing that, we can interpret the complex model using the simple one



- How can we obtain the points near the prediction of the simple that we want to interpret? → **Superpixels**

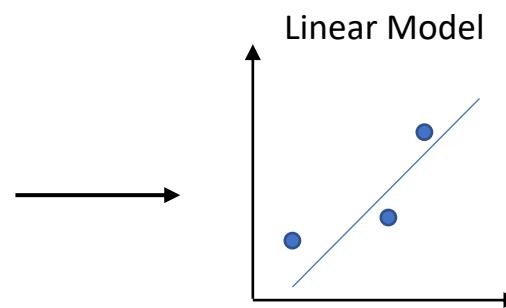
LIME

- Superpixels are obtained by segmentation and they are randomly perturbed



- Disturbed superpixels are encoded with a 0 in the feature vector, while the active pixels with a 1

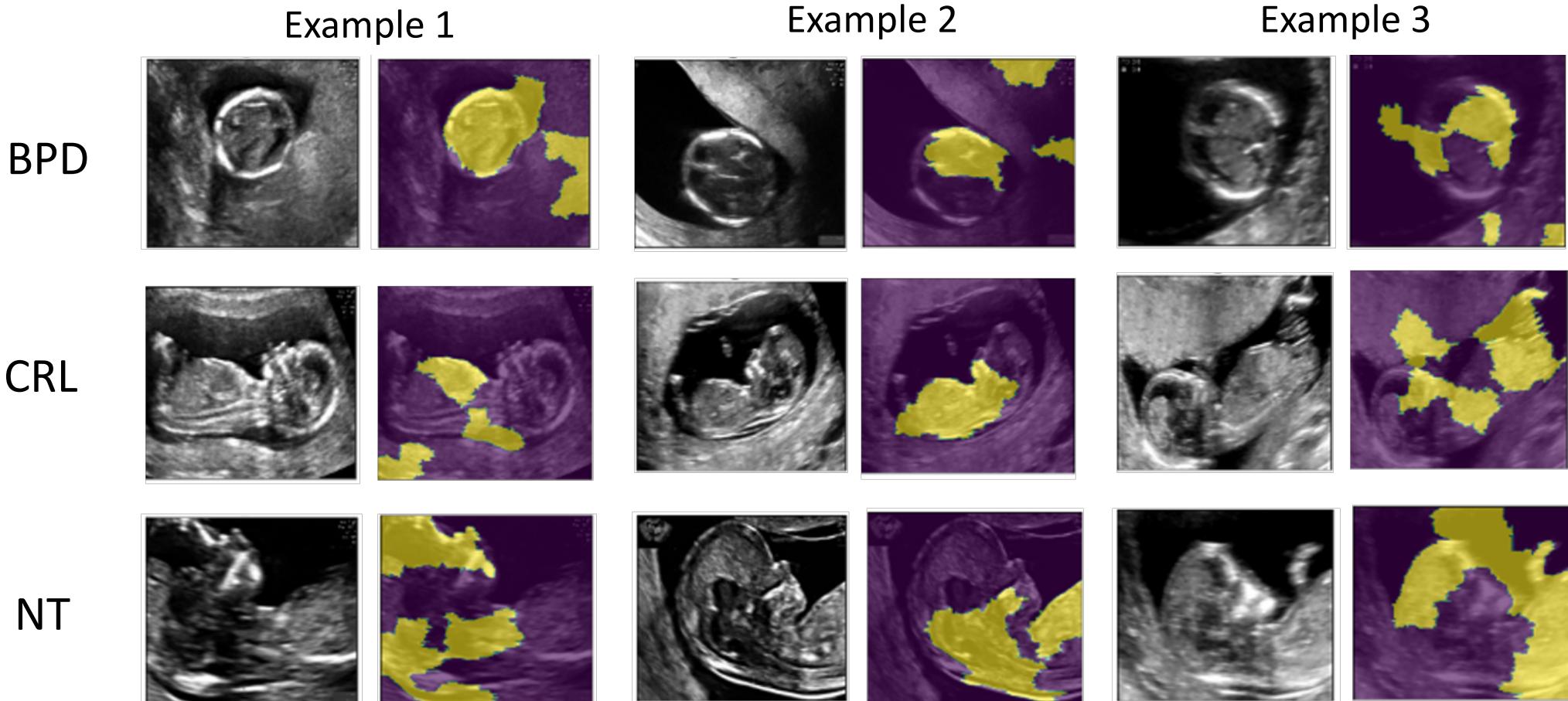
Feature Vectors	Score
(0, 1, 1, 0,)	→ 0.91
(1, 1, 1, 0,)	→ 0.74
(0, 0, 1, 1,)	→ 0.55



Weights are the
importance of each
superpixel or feature

- Very slow

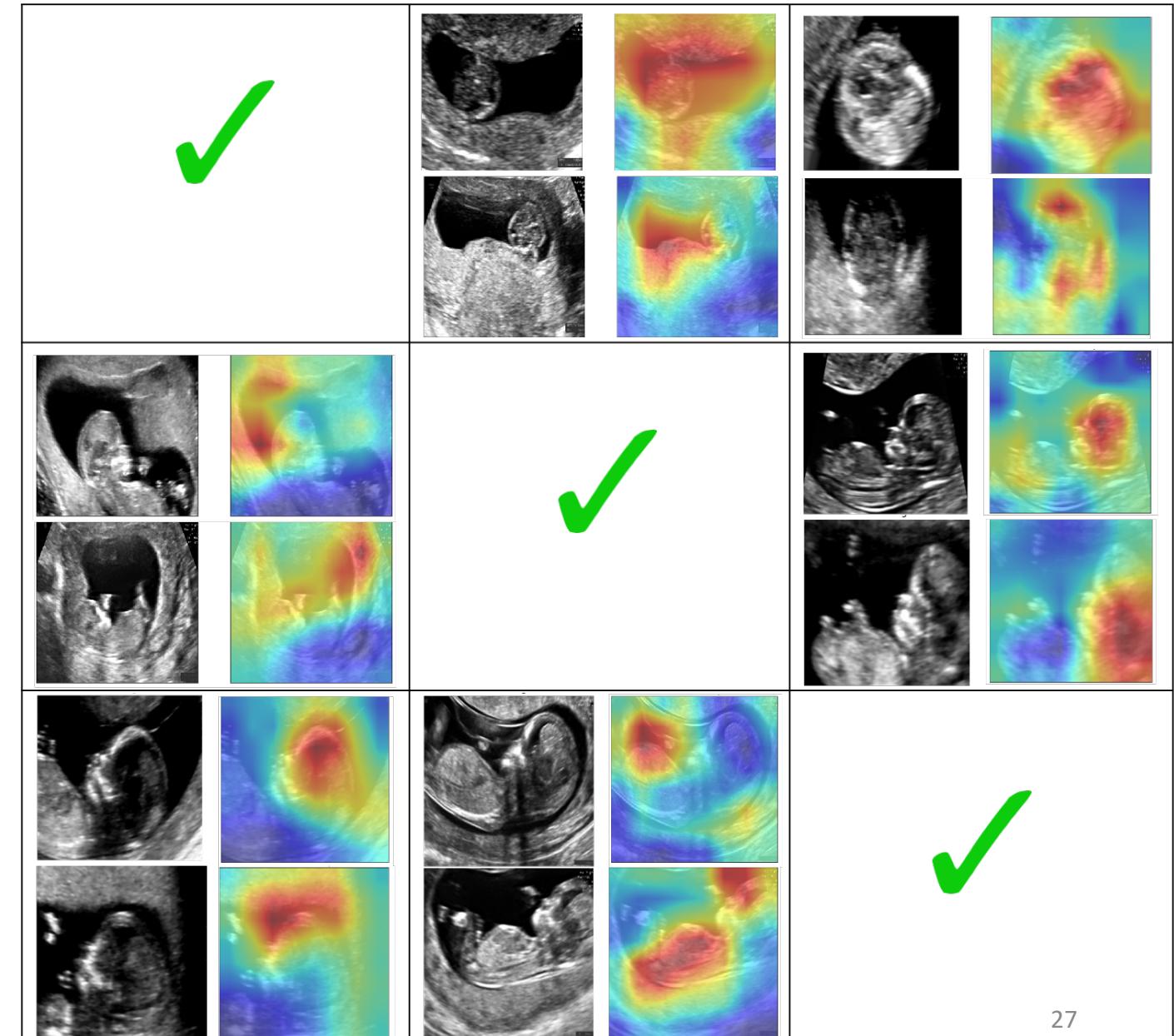
LIME



MISCLASSIFICATIONS

Predicted class

	BPD	CRL	NT
BPD	✓	✗	✗
CRL	✗	✓	✗
NT	✗	✗	✓



CONCLUSIONS

- Transfer Learning works very well with ultrasound images
- All interpretation techniques gives you valid information
- Our results are extrapolable to other problems
- Occlusion method gives us the best results for well classified samples
- CAM works well to explain misclassified samples