Hands-on Introduction to Deep Learning

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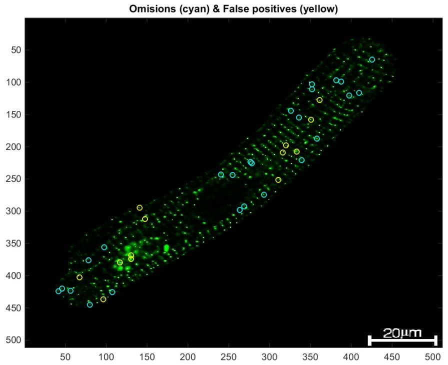
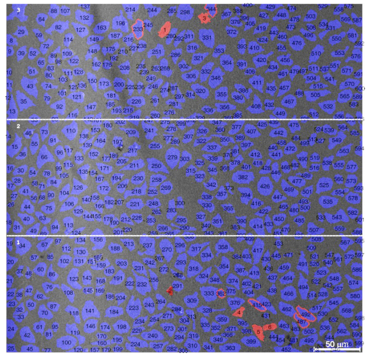
ANALYSIS OF MEDICAL & BIOLOGICAL IMAGES

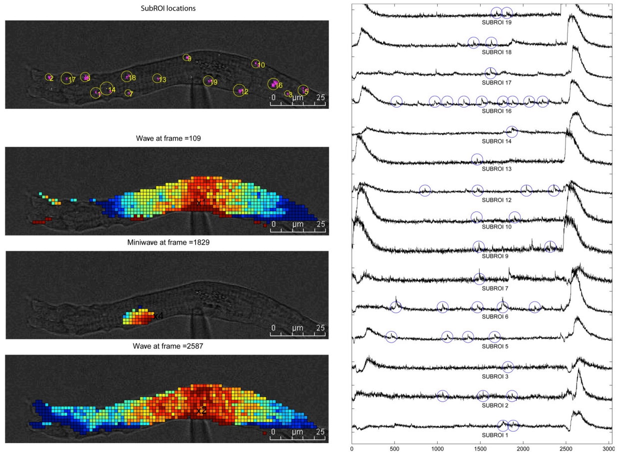
Molecular receptors



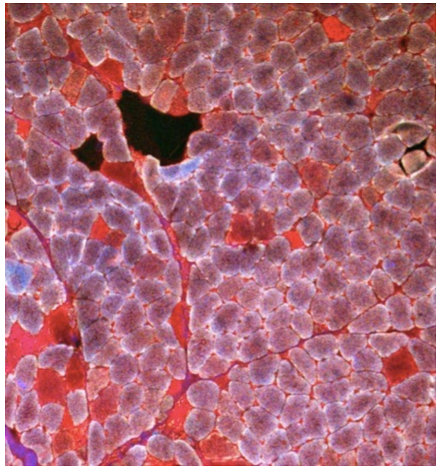
Cell cultures



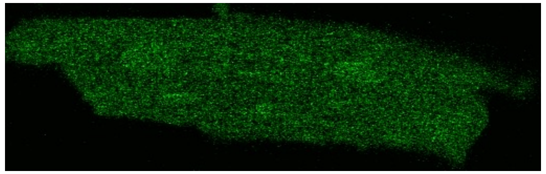
Calcium dynamics



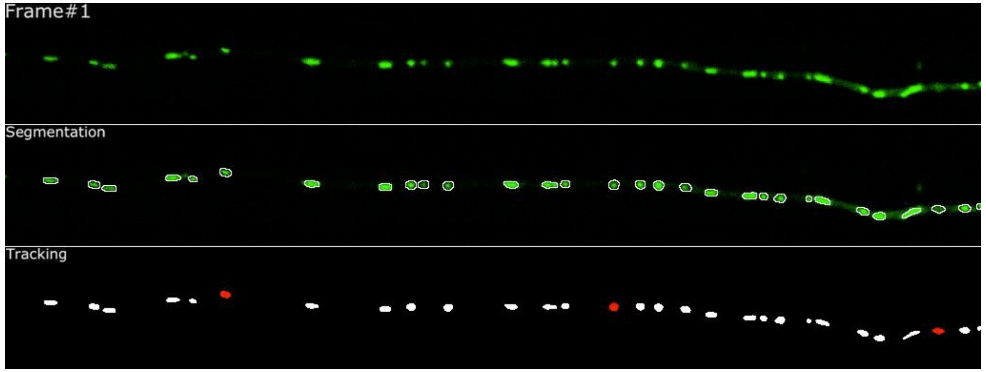
Digital Pathology



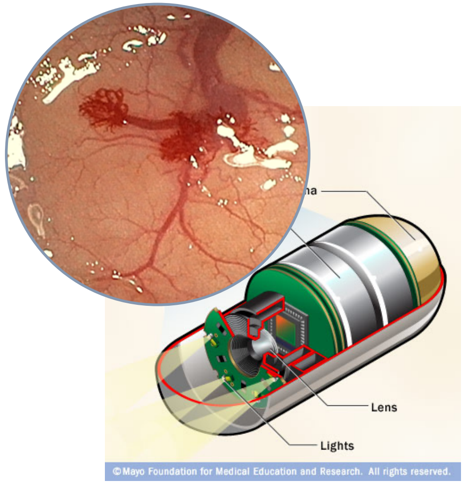
Single-cell experiments



Mitochondrial transport



Wireless endoscopy



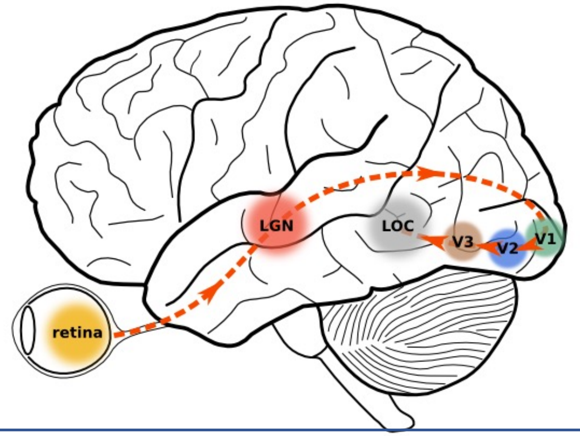
Extraction & analysis of multiscale biomarkers

Overview

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

CHANGE IN PARADIGM

Human pattern recognition



→ UPC Mug

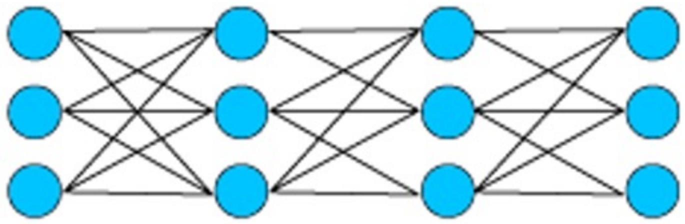
Traditional Machine Learning

Feature Extraction (texture, size, shape, orientation)

Supervised Classifier

→ UPC Mug

Deep Learning

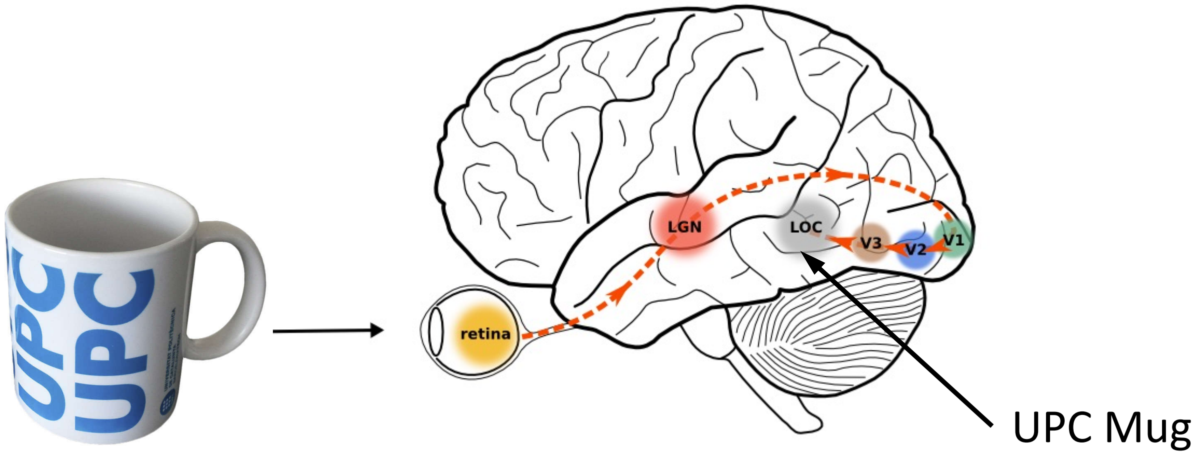


Feature extraction + Classification

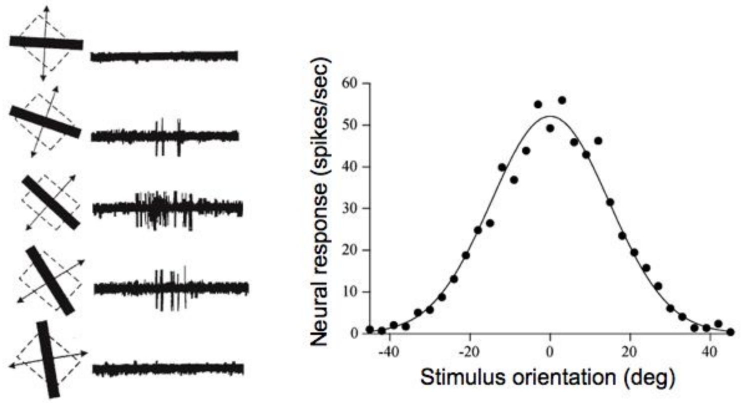
→ UPC Mug

Deep Learning – Convolutional Neural Networks

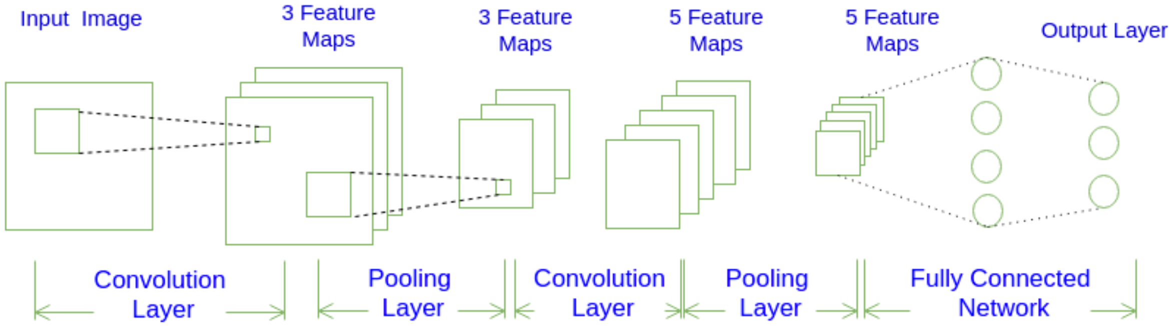
Hubel & Wiesel: Neural basis of visual perception
LGN: Lateral Geniculate Nucleus
V1: Primary Visual cortex



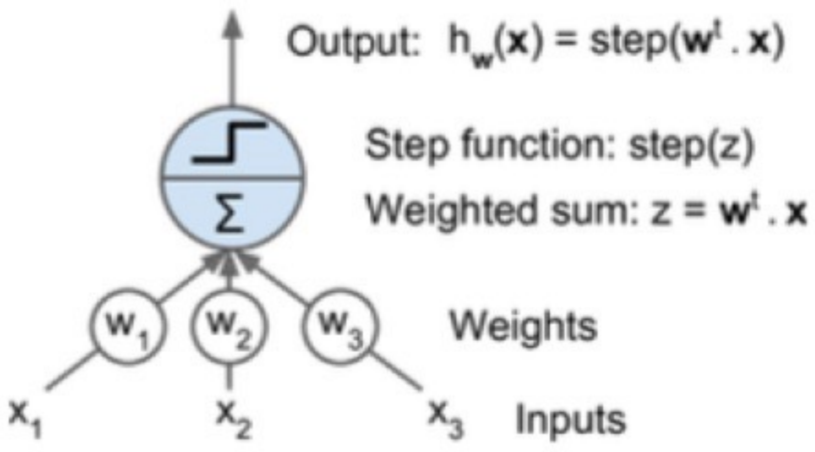
V1 physiology: orientation selectivity



Hubel & Wiesel, 1968

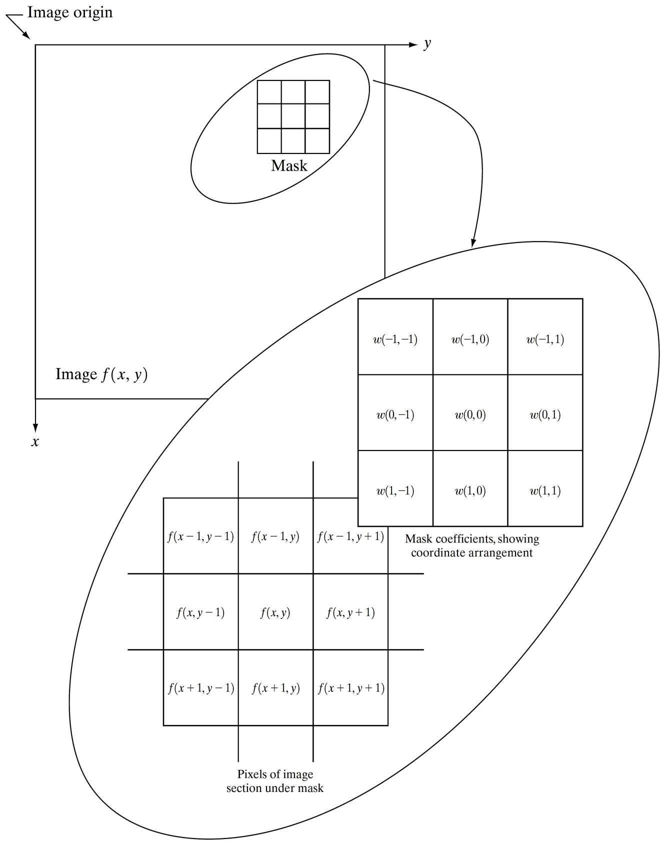


Neural Network



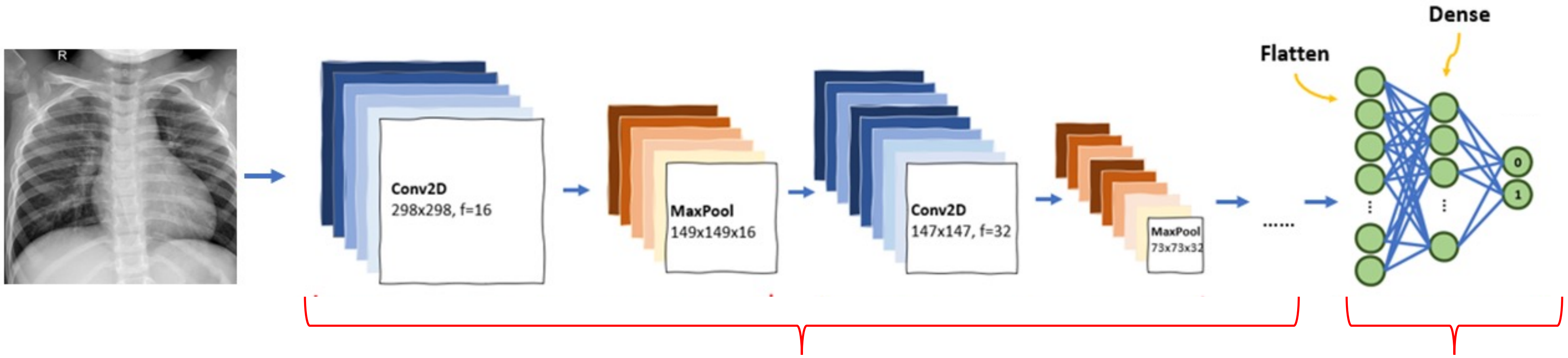
Training / learning weights:
Hebbian rule “wiring by firing”

Convolutional filters



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

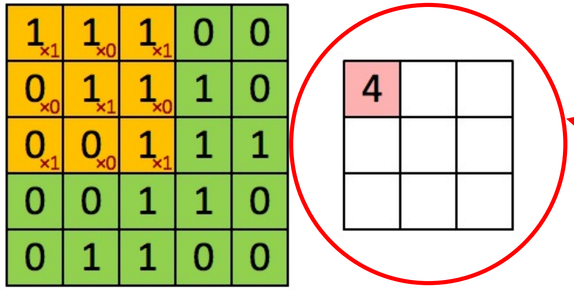
CONVOLUTIONAL NEURAL NETWORKS



Feature Extractor

Classifier

2D Convolution



Input

Feature Map

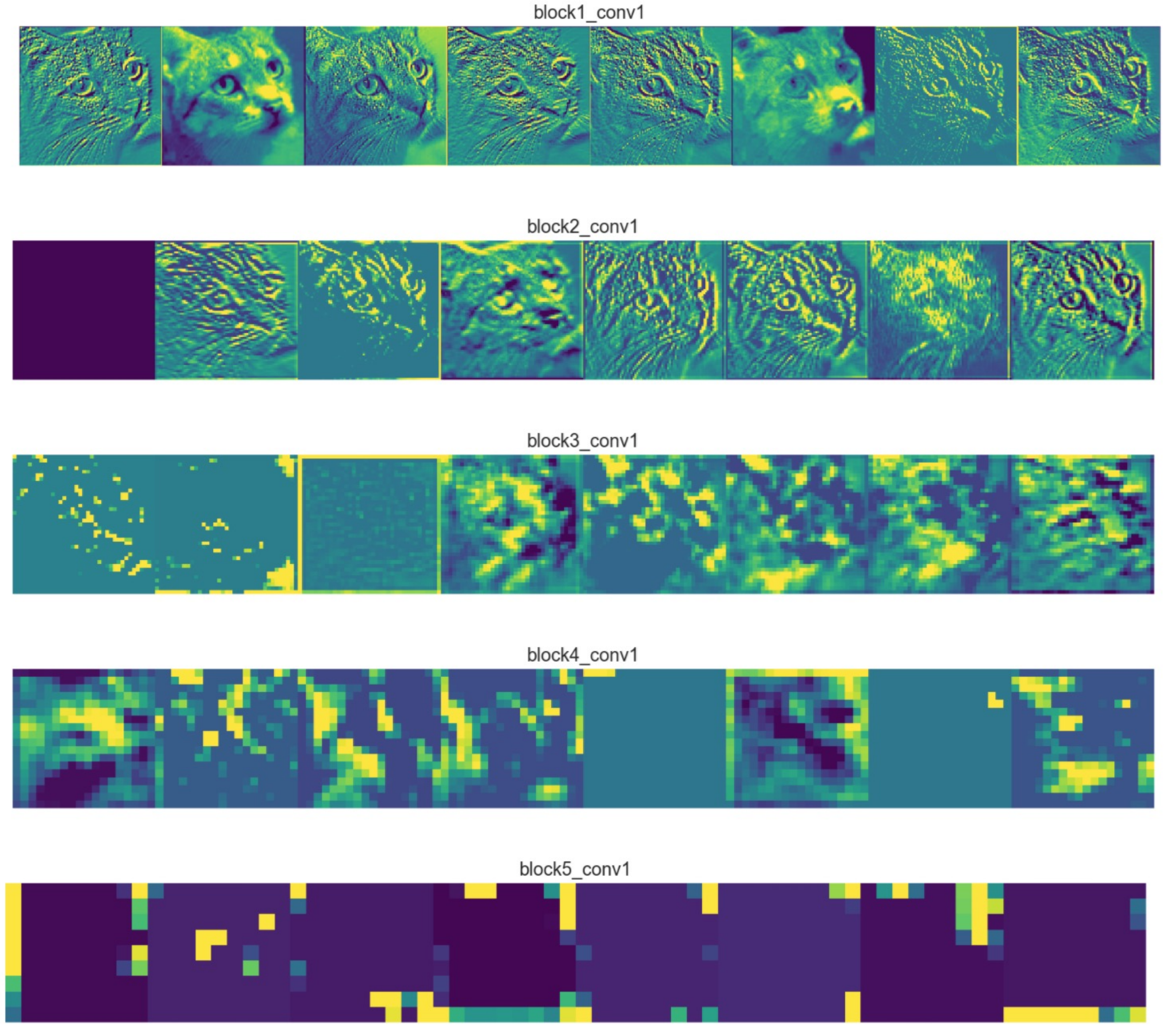
retain spatial information of the input

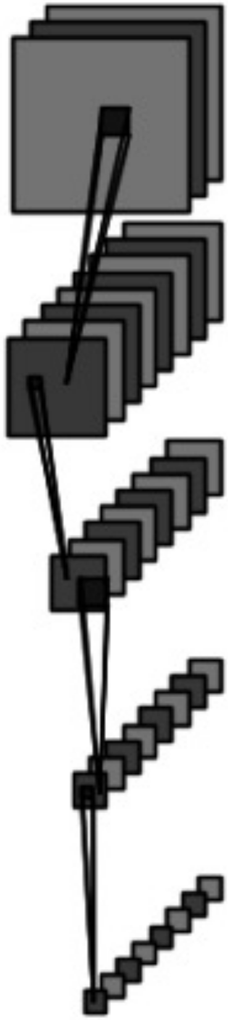
Outputs

Feature extractor: **feature maps**

Classifier: **scalars (score)**

CNN: FEATURE MAPS





abstraction

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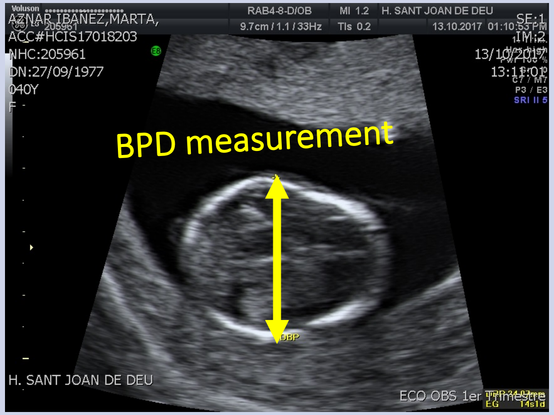
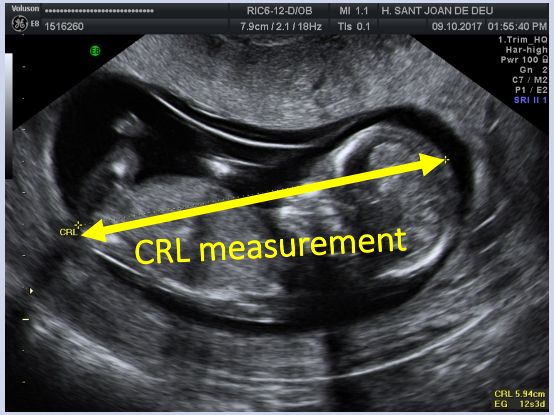
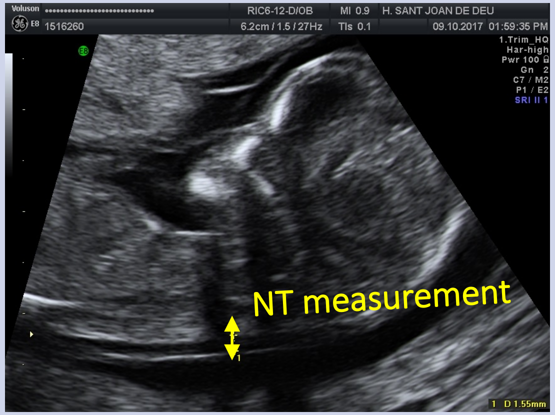
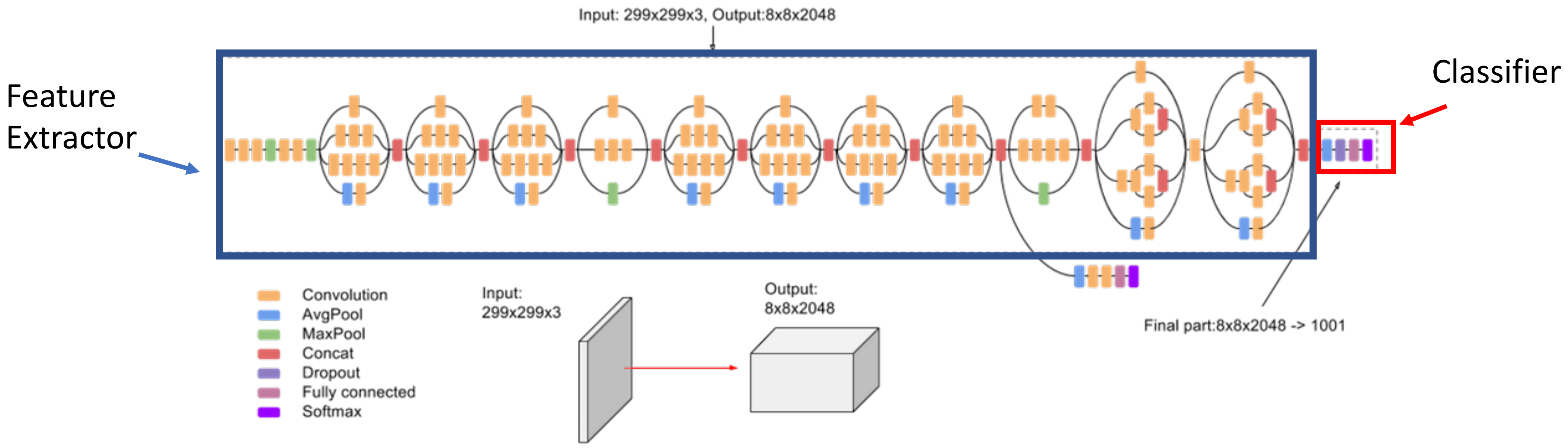
EXAMPLE: FETAL BIOMETRIC PLANES

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			

TRANSFER LEARNING WITH INCEPTION V3

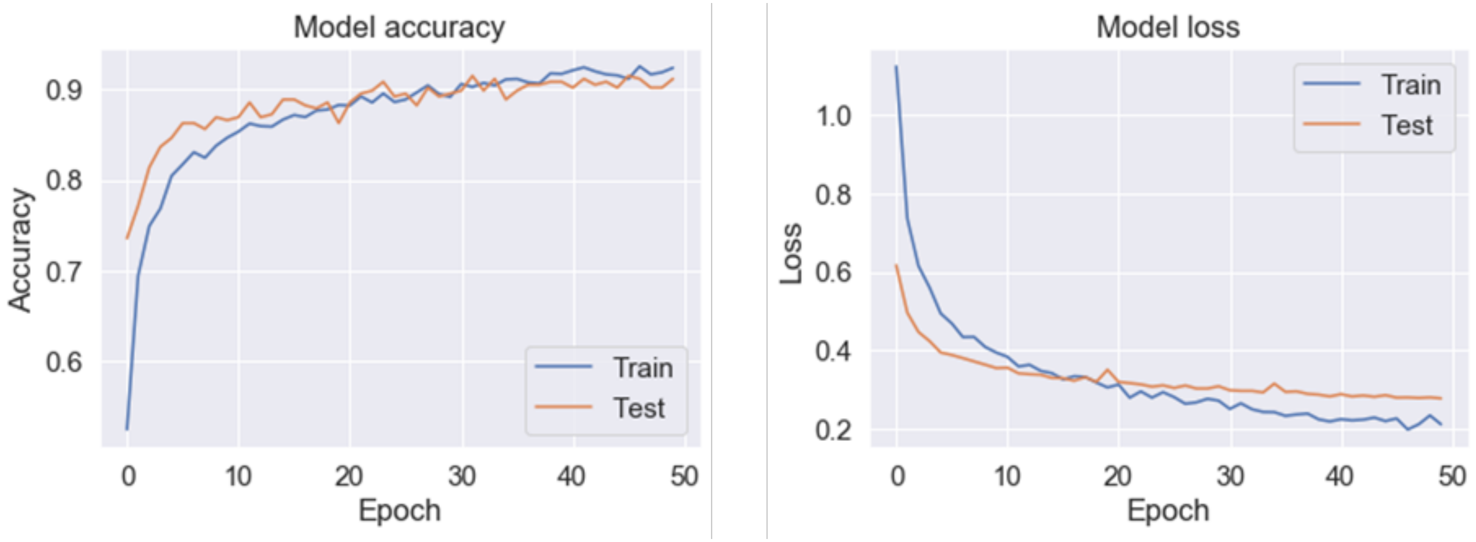
- Inception V3 was trained with ImageNet dataset (1.2M images of 1000 different clases)



- Trainable Parameters: 24M → 6127

4. EXPERIMENTAL RESULTS AND ANALYSIS

MODEL PERFORMANCE



Predicted class

Correct 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

SALIENCY MAPS

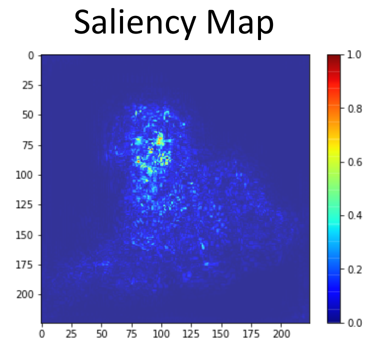
- This method shows the most sensible parts of the input image for the model

Computed by backpropagation algorithm

Output for a class

Input → Model → y^c ⇒

$$\text{Saliency Map} = \left|\frac{\partial y^c}{\partial Input_{i,j}}\right| \longrightarrow$$

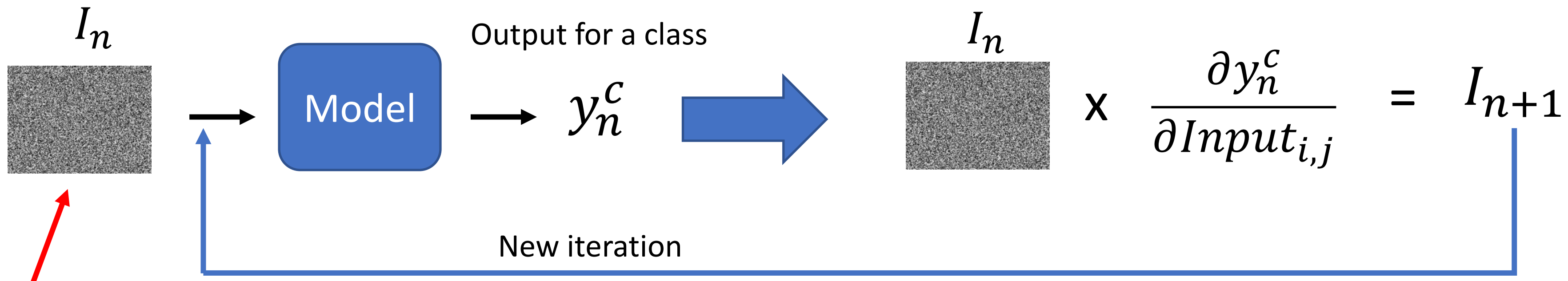


- High values represent the most important features or regions of the input to be classified in an specific class

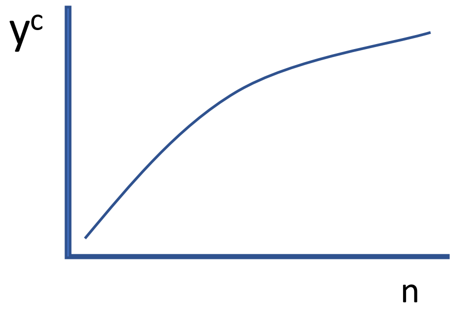
- Fast to compute

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)



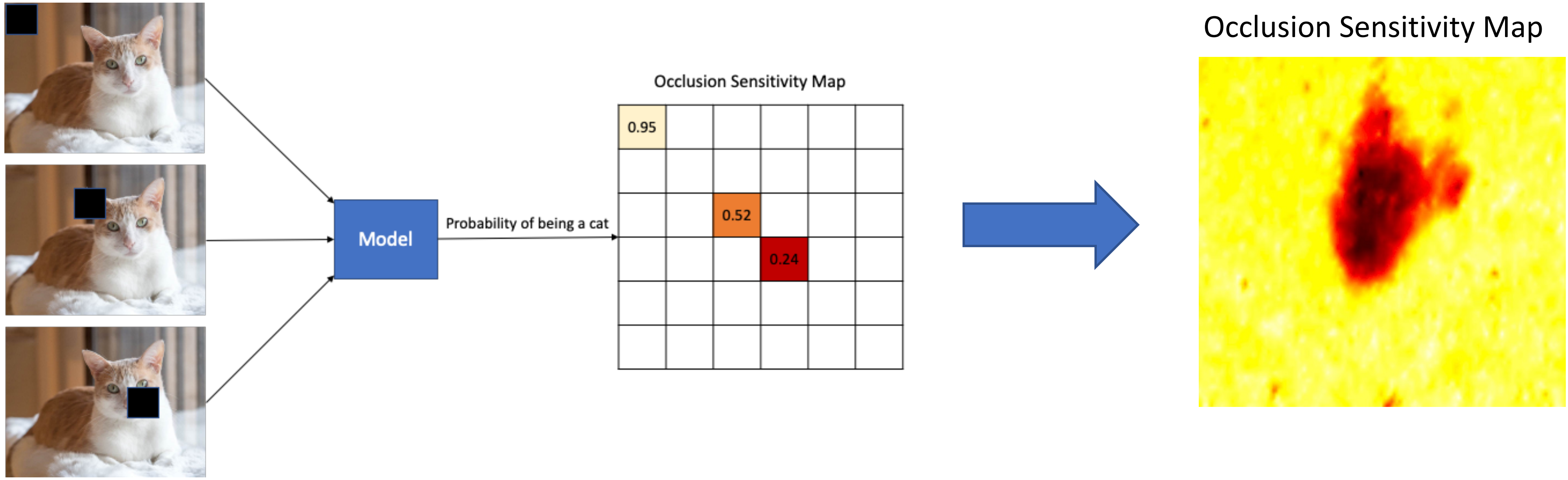
We are getting the image that best represents a class

- Slow performance

OCCLUSION SENSITIVITY

- Technique based on dividing the input image into a grid, and hidding each cell to make a prediction with the model

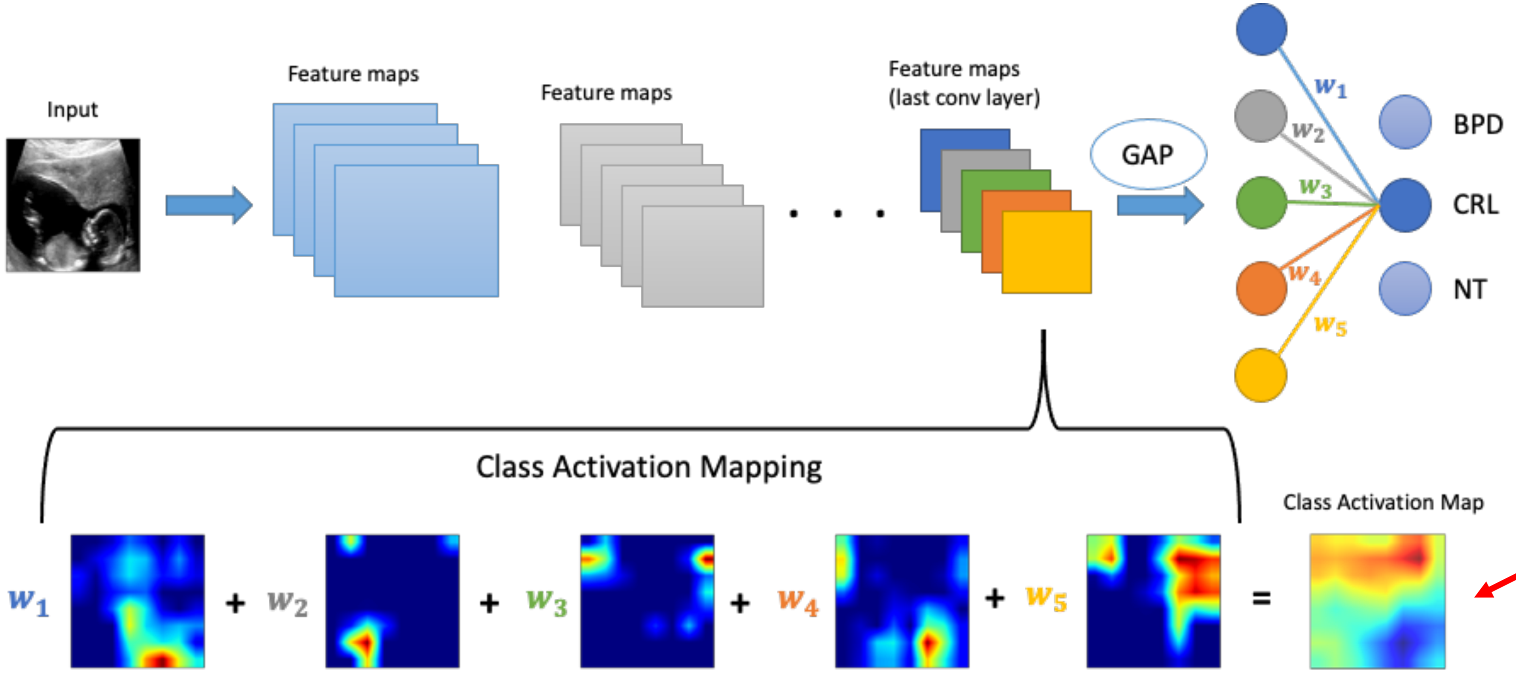
- High score → unimportant feature | Low score → important feature



- Slow process

CLASS ACTIVATION MAPPING

- CAM takes adventage of
  - An specific CNN architecture (GradCAM generalizes it)
  - Feature maps retain spatial information



CRL score = $\vec{w} \cdot \vec{\bigcirc}$

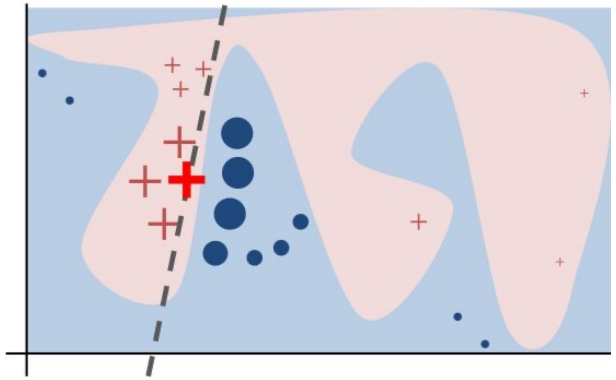
Most relevant features for being classified as CRL

- Very fast to compute

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

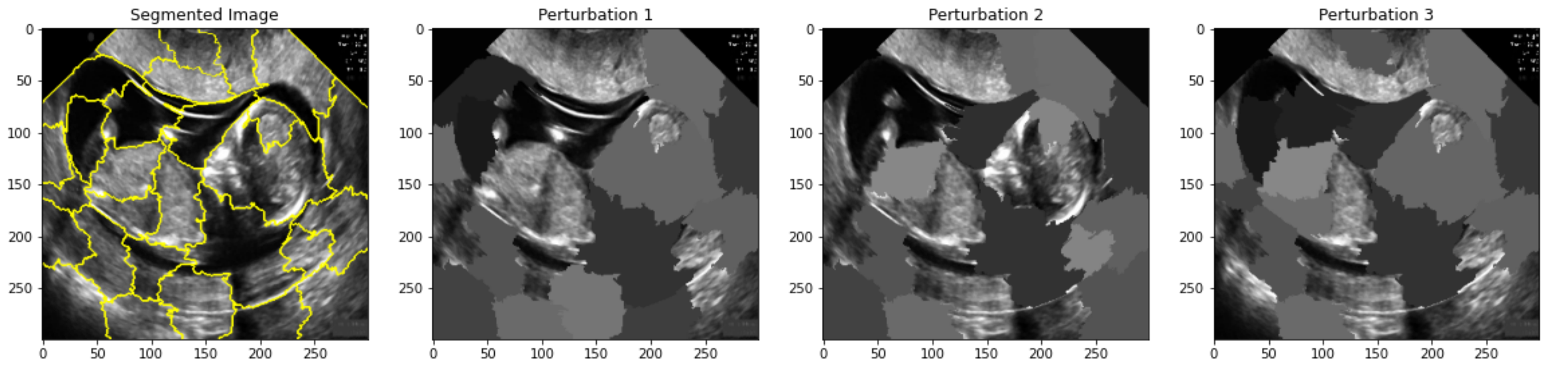


Solution space

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

LIME

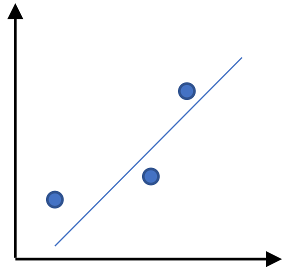
- Superpixels are obtained by segmentation and they are disturbed randomly



- 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

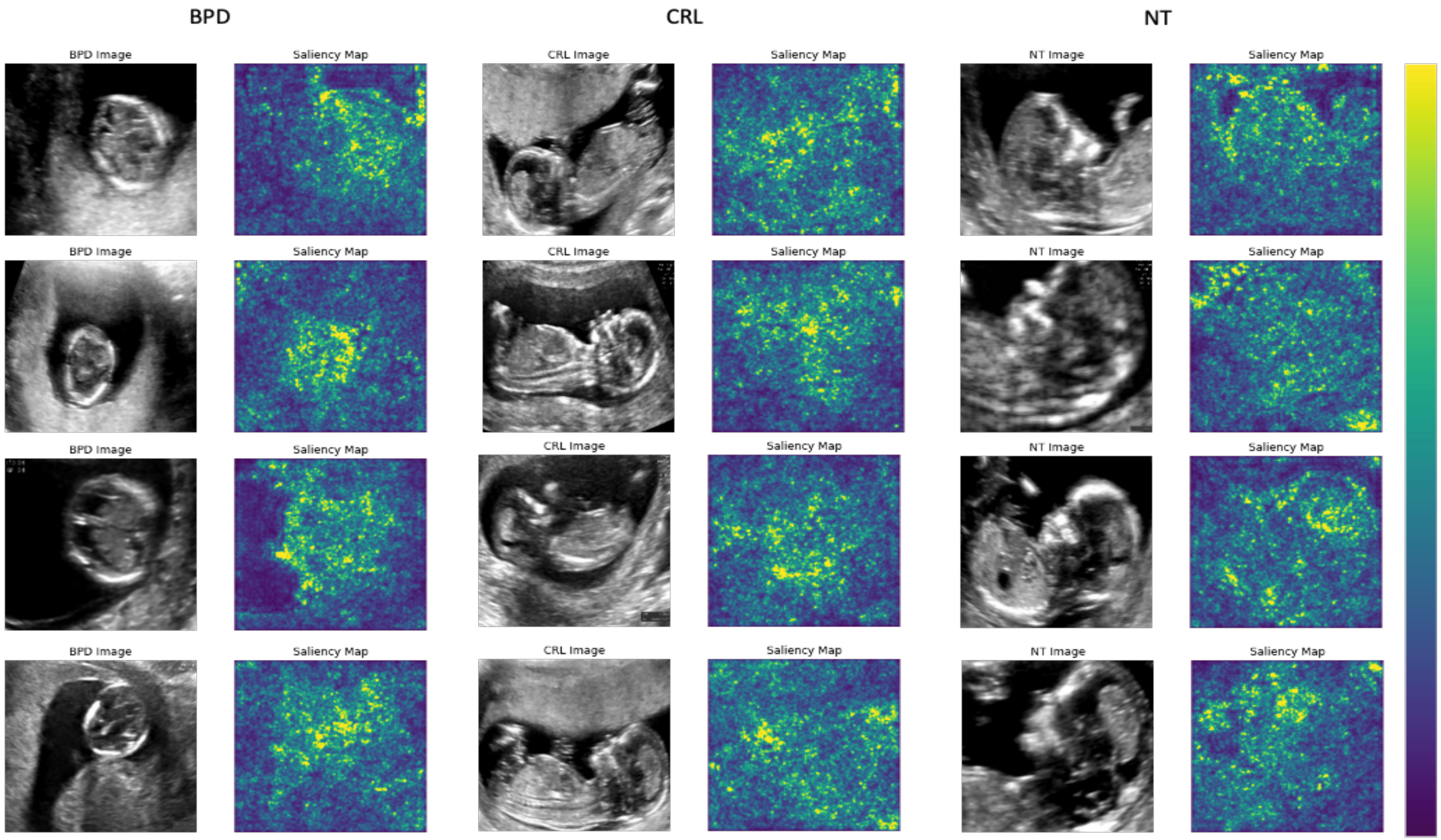
→



Weights are the importance of each superpixel or feature

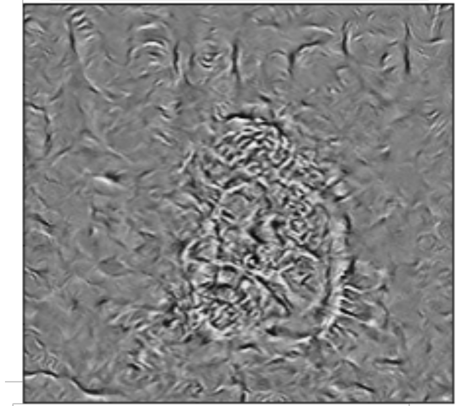
- Very slow

SALIENCY MAPS

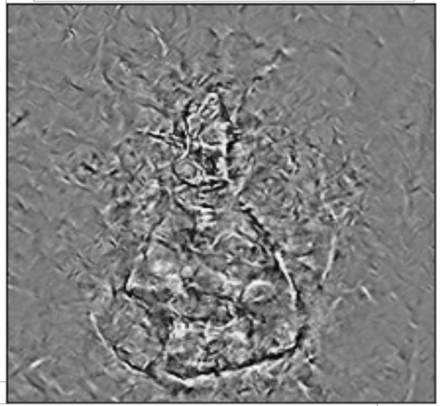


ACTIVATION MAXIMIZATION

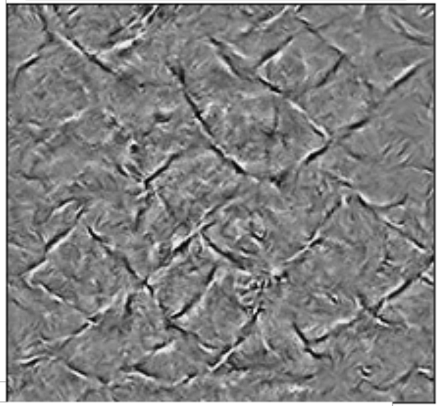
BPD class Maximization



CRL class Maximization



NT class Maximization

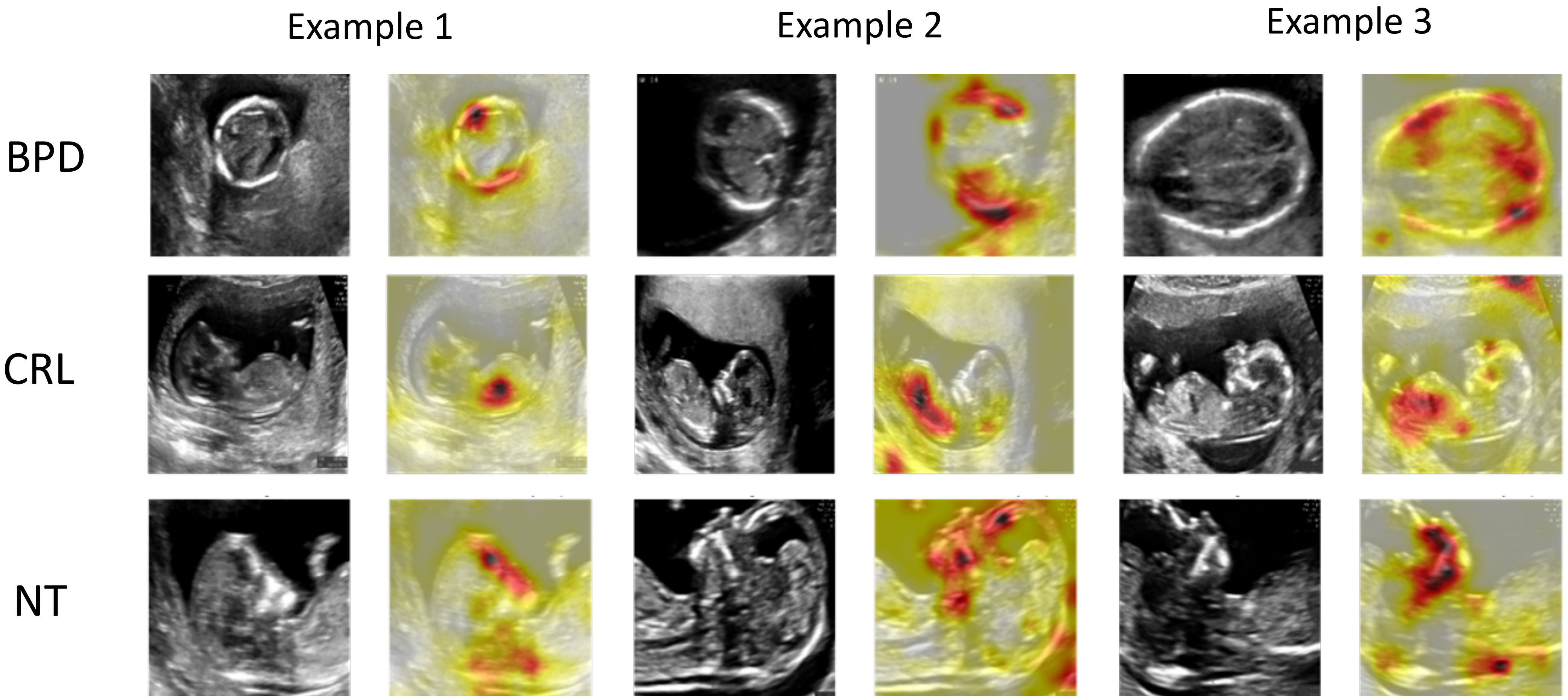


BPD image example

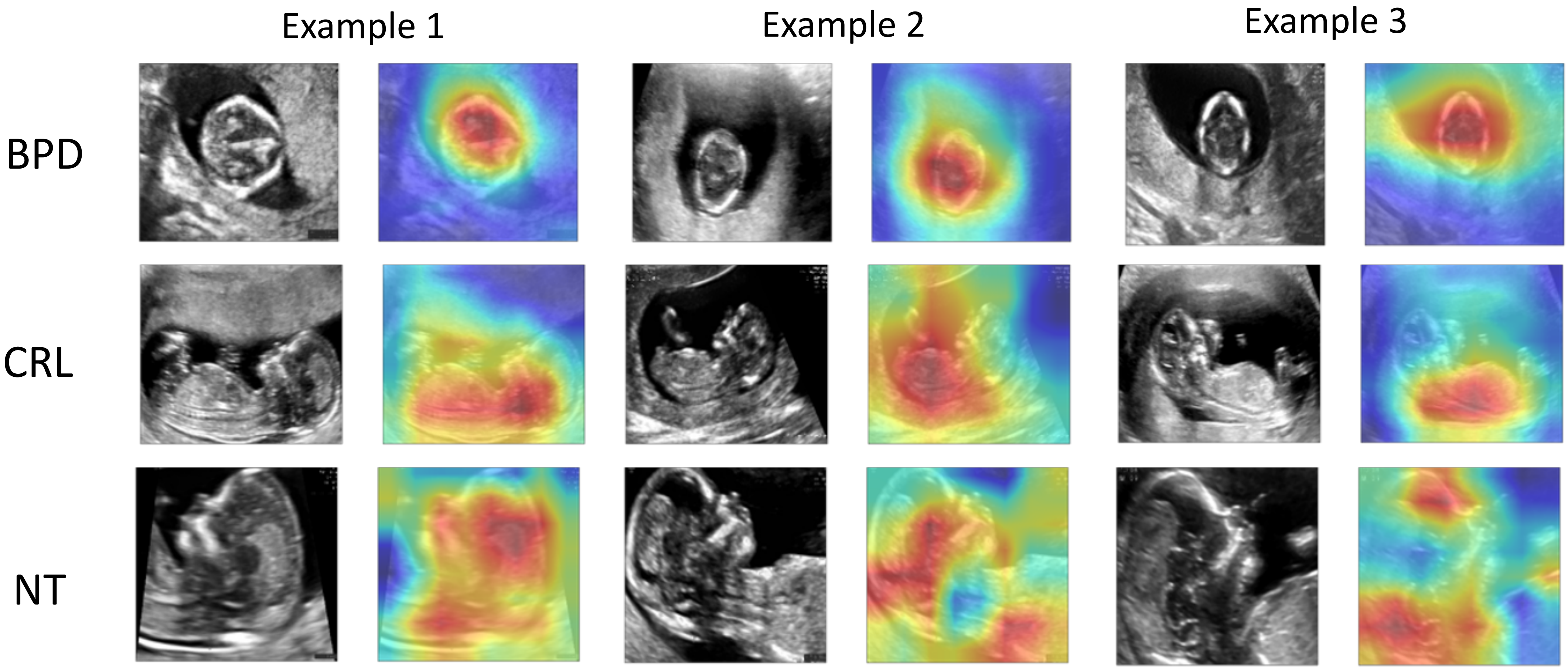
CRL image example

NT image example

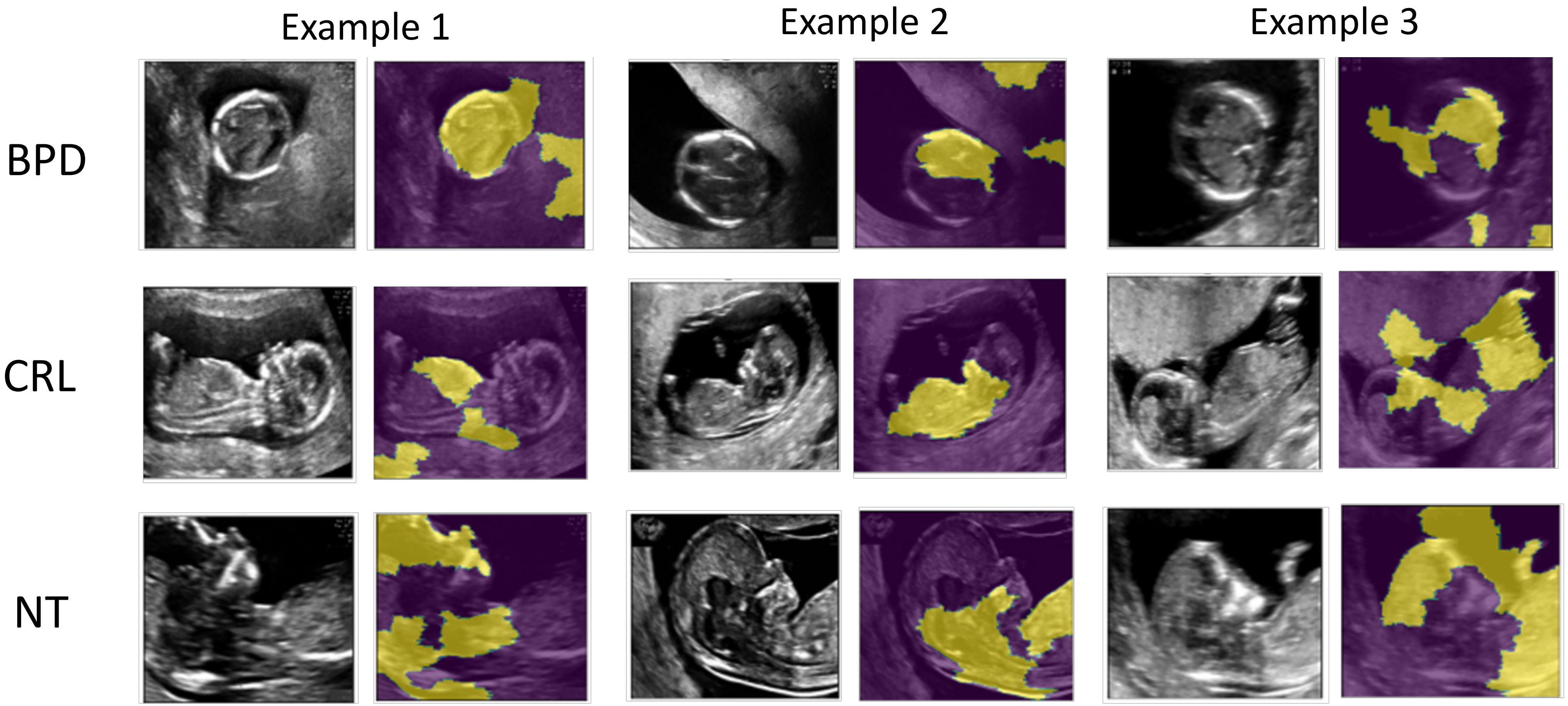
OCCLUSION SENSITIVITY



CLASS ACTIVATION MAPPING



LIME

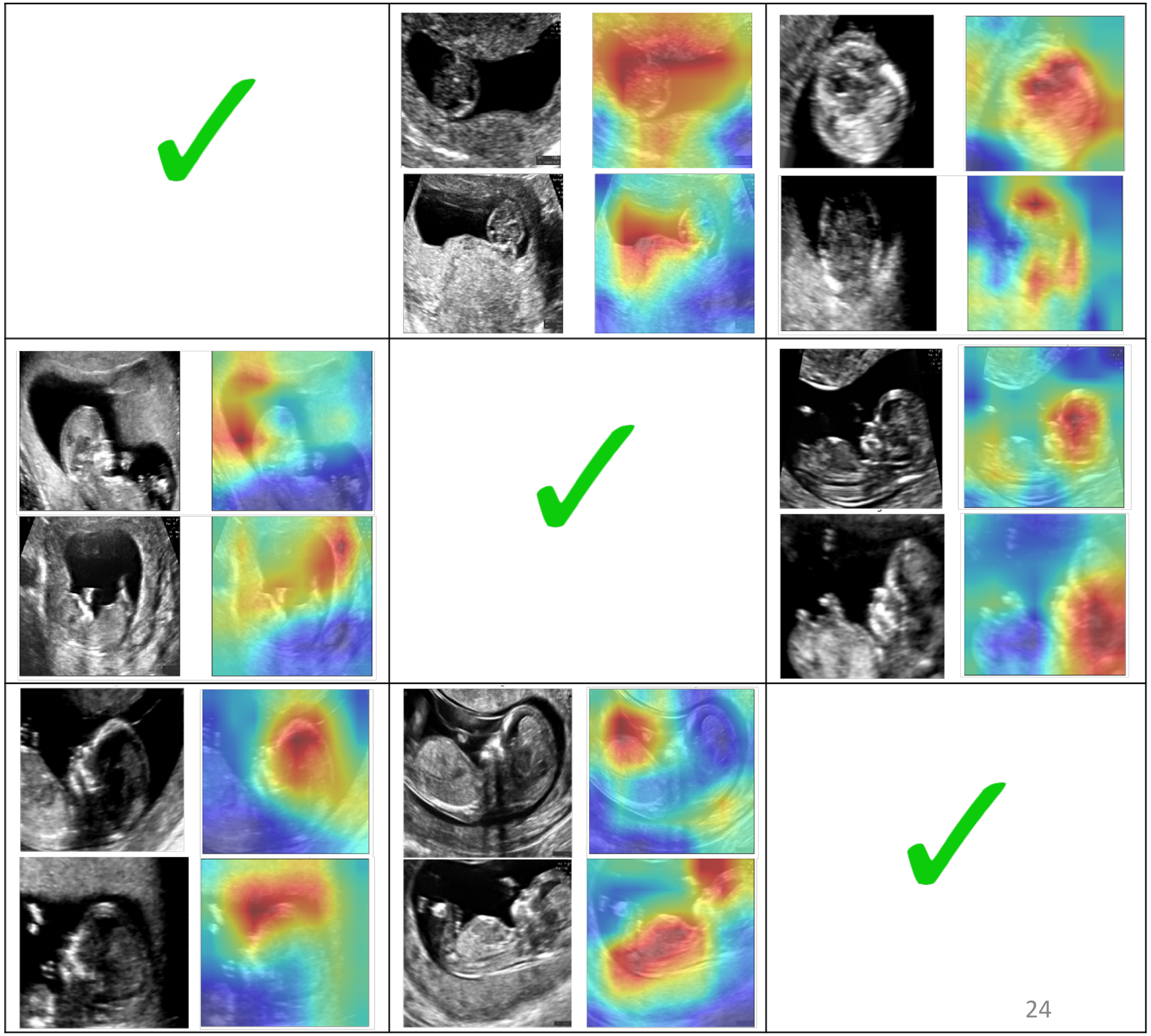


MISCLASIFICATIONS

Predicted class

Correct class

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



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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