Hands-on Introduction to Deep Learning

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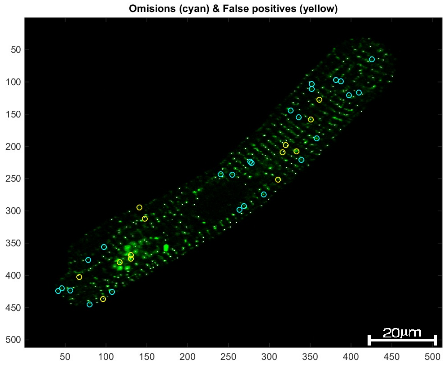
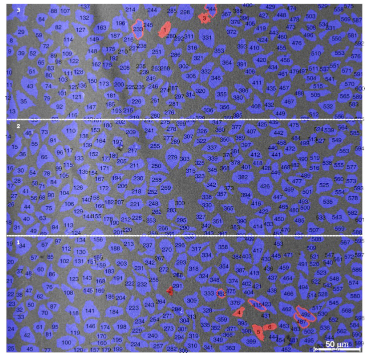
(June, 16th-18th, 2021, virtual conference)

ANALYSIS OF MEDICAL & BIOLOGICAL IMAGES

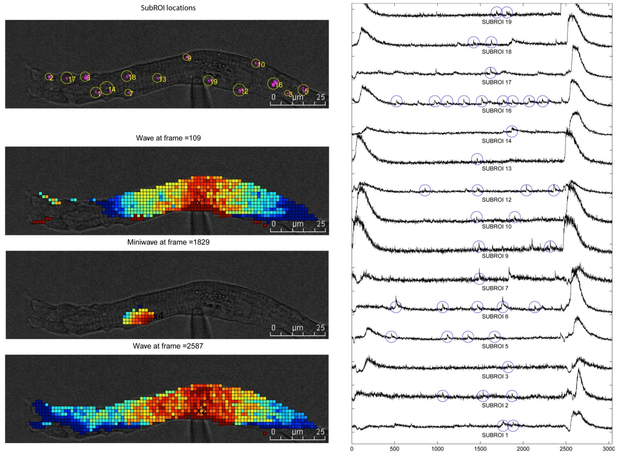
Molecular receptors



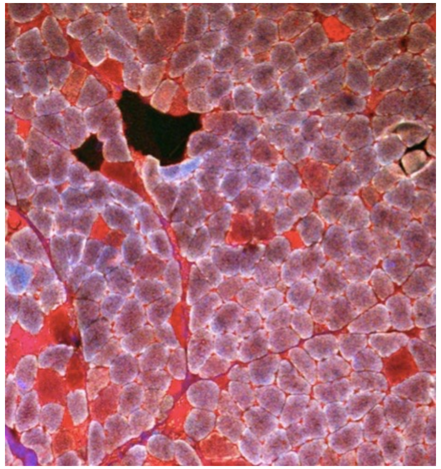
Cell cultures



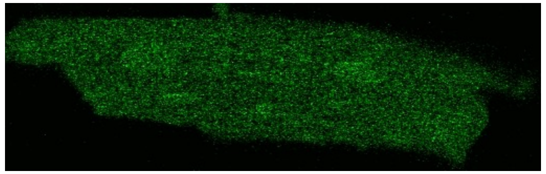
Calcium dynamics



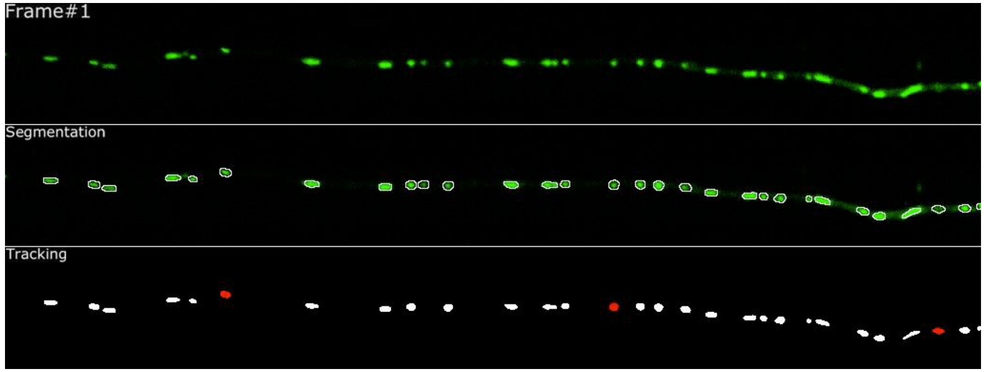
Digital Pathology



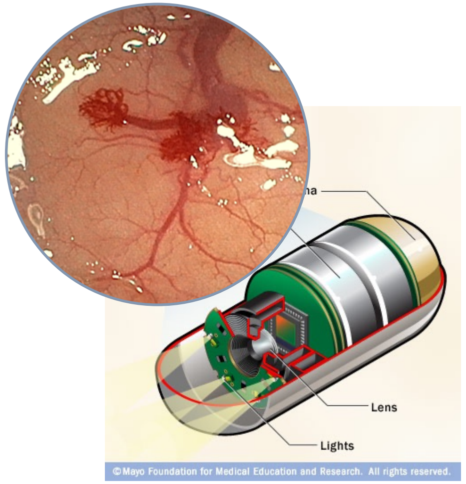
Single-cell experiments



Mitochondrial transport



Wireless endoscopy



Extraction & analysis of multiscale biomarkers

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

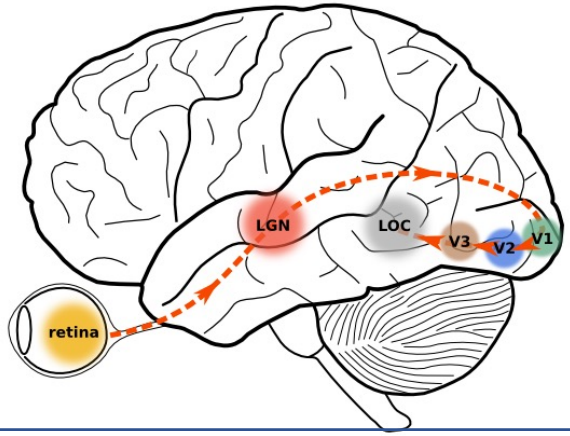
- General introduction
- MNIST data exploration
- The Traditional ML approach
- The DL approach: Transfer learning vs. Trained features
- DL interpretability

Google Colaboratory GitHub TensorFlow + Keras python™

https://github.com/raulbenitez/IWANN2021_DL_tutorial

CHANGE IN PARADIGM

Human pattern recognition



UPC Mug

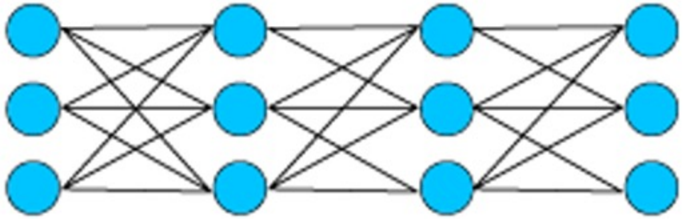
Traditional Machine Learning

Feature Extraction (texture, size, shape, orientation)

Supervised Classifier

UPC Mug

Deep Learning



Feature extraction + Classification

UPC Mug

Emulating human mind

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)

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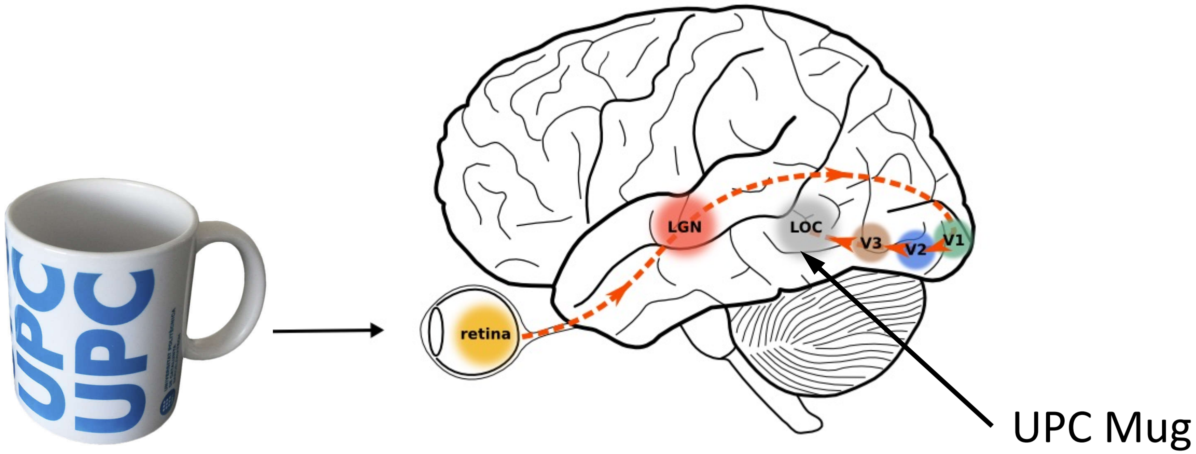
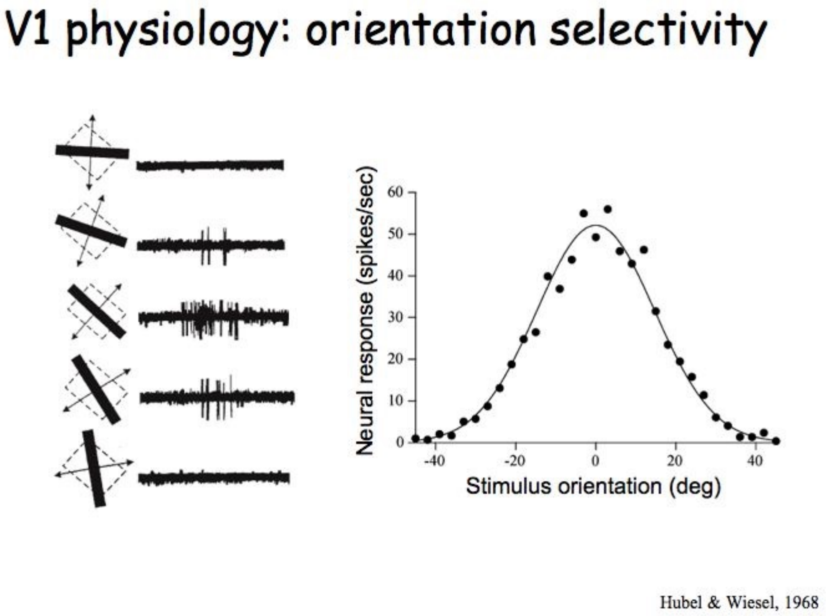
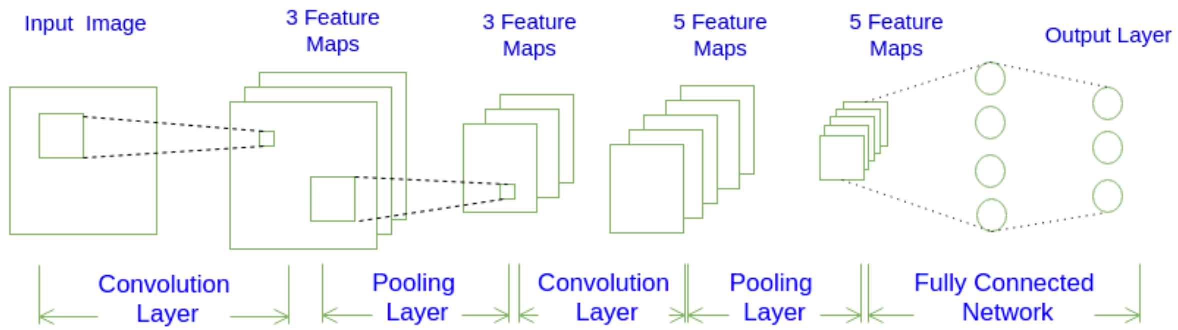
Cajal & Golgi Nobel 1906
Hebbian learning 1949
Hodkin & Huxley 1952 Nobel 1963
Hubel & Wiesel 1959 Visual Cortex Nobel 1981

Deep Learning – Convolutional Neural Networks

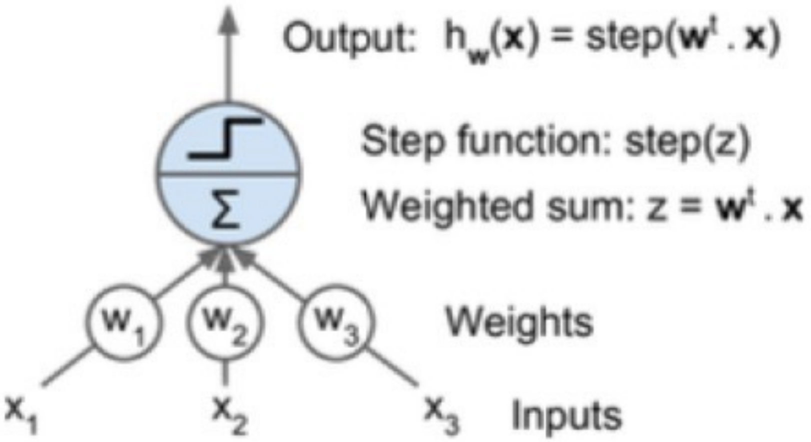
Hubel & Wiesel: Neural basis of visual perception
LGN: Lateral Geniculate Nucleus
V1: Primary Visual cortex





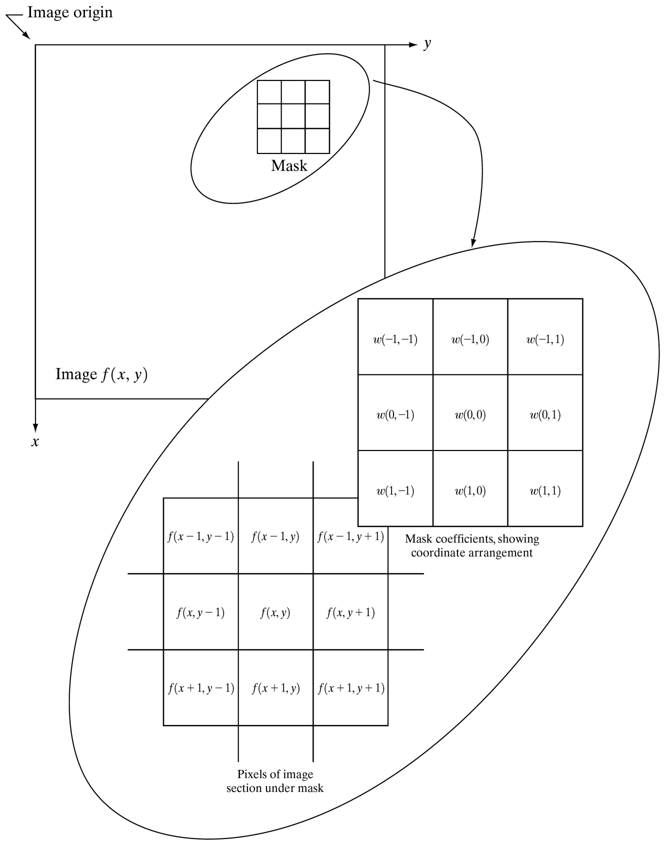


Neural Network



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

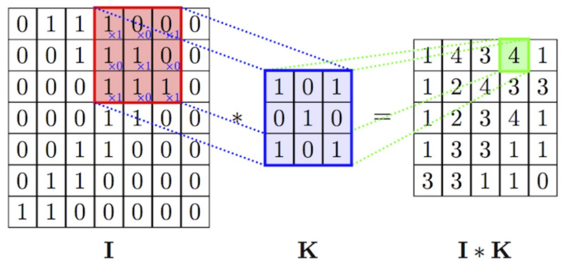
Convolutional filters



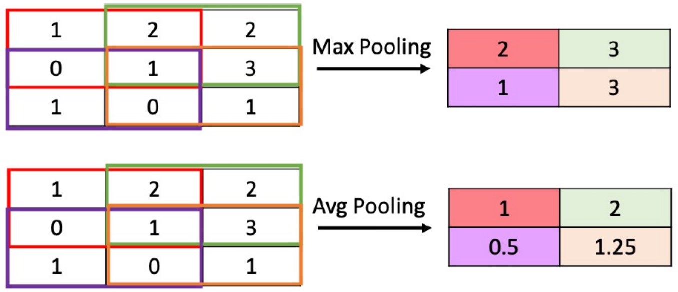
$$g(x,y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) \cdot f(x+s, y+t)$$

Basic elements of a CNN arquitecture

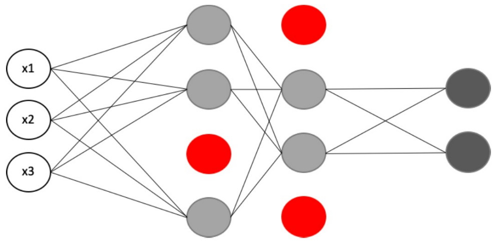
Convolutional layers



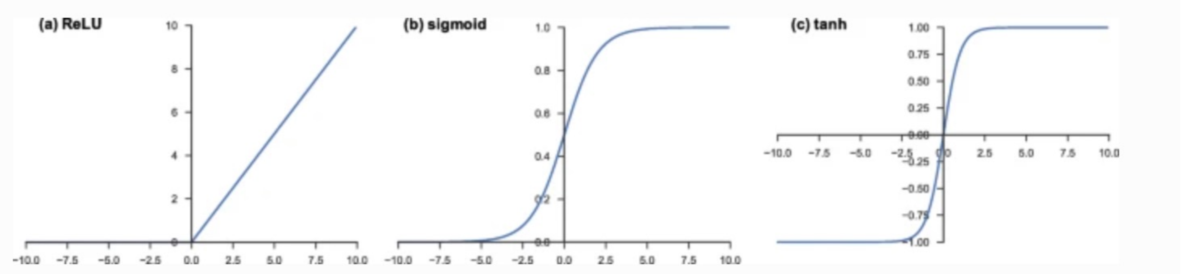
Pooling layers



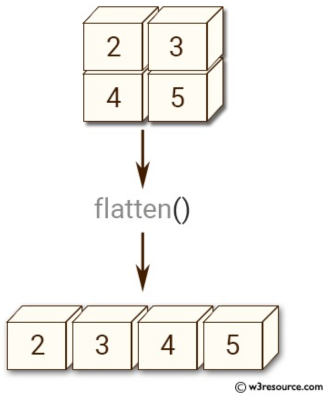
Dropout layers



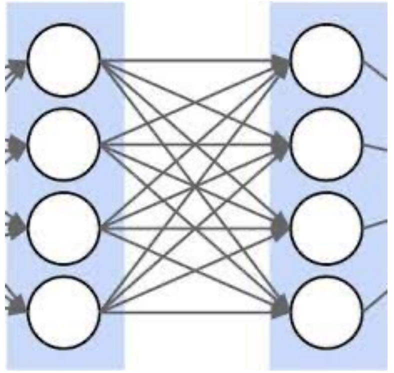
Activation layers



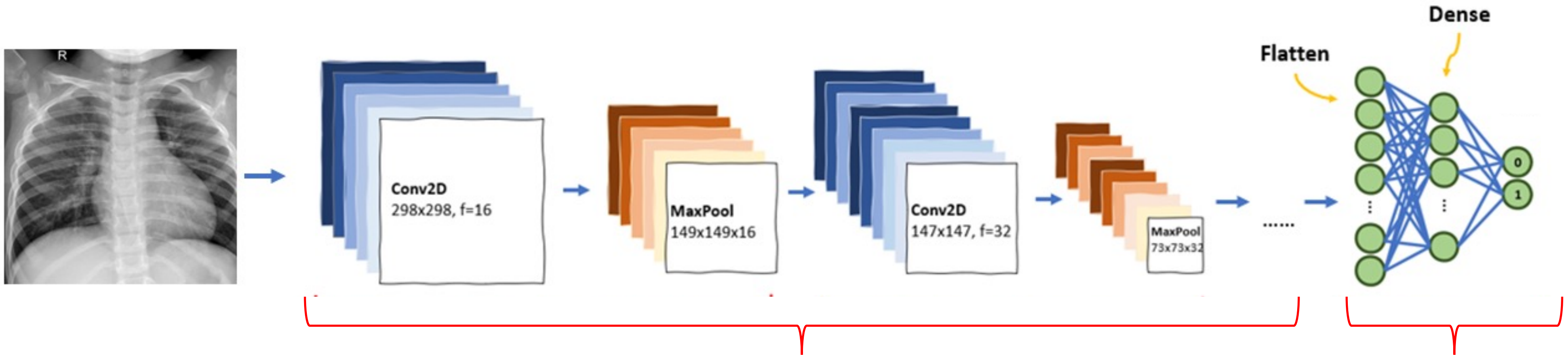
Flatten layers



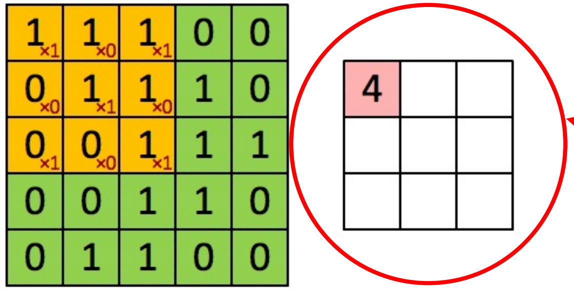
Fully connected layers (Classification)



CONVOLUTIONAL NEURAL NETWORKS



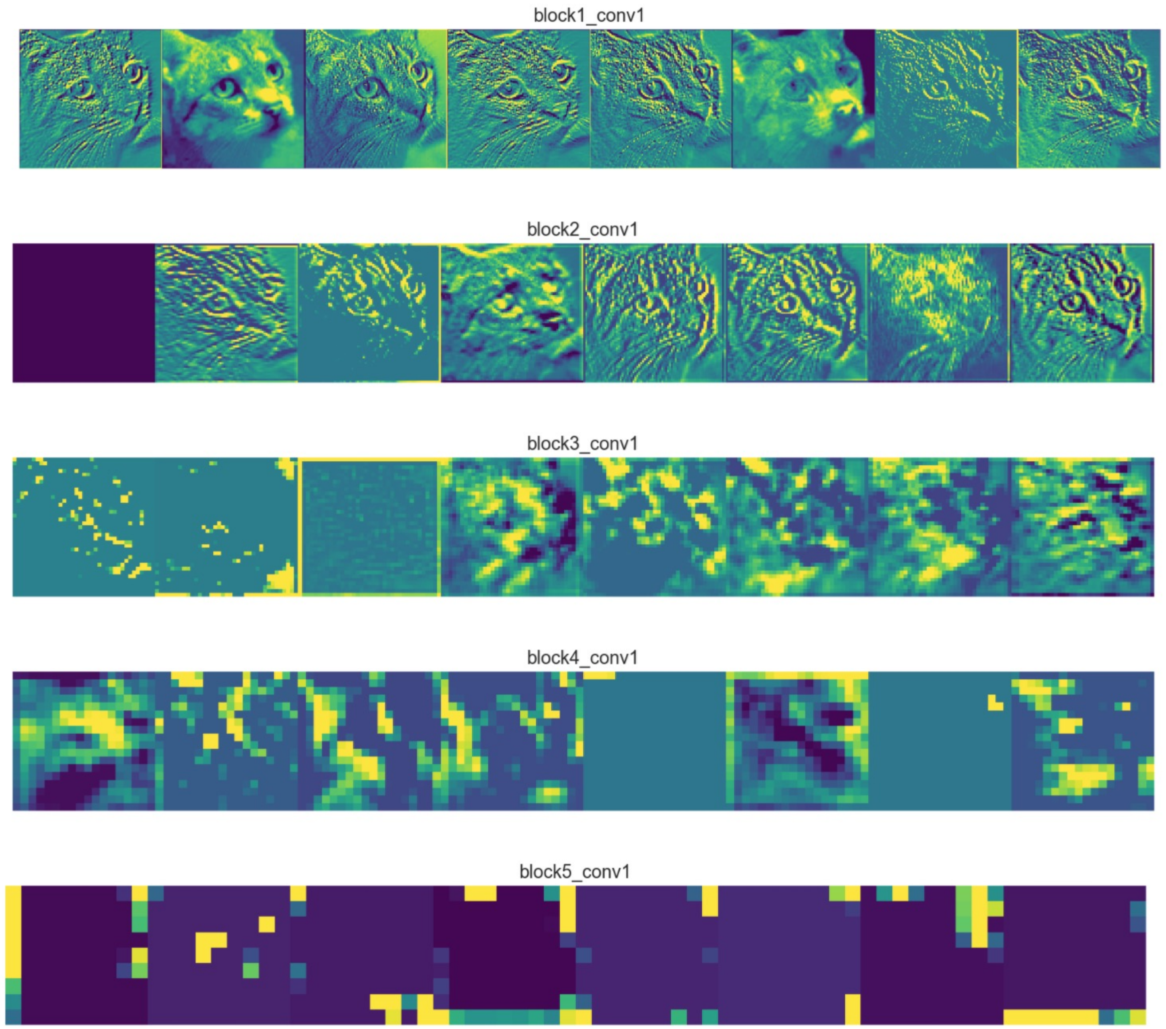
2D Convolution

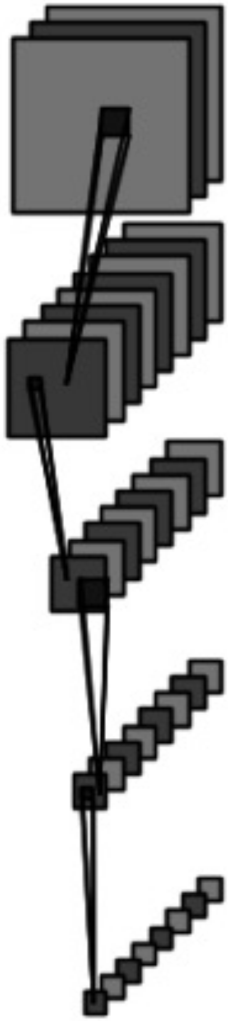


retain spatial information of the input

Outputs
- Feature extractor: **feature maps**
- Classifier: **scalars (score)**

CNN: FEATURE MAPS





abstraction

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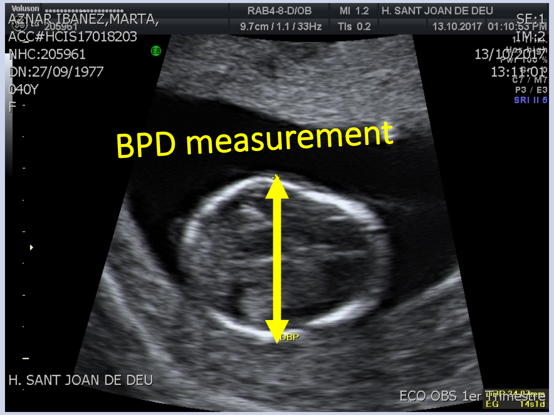
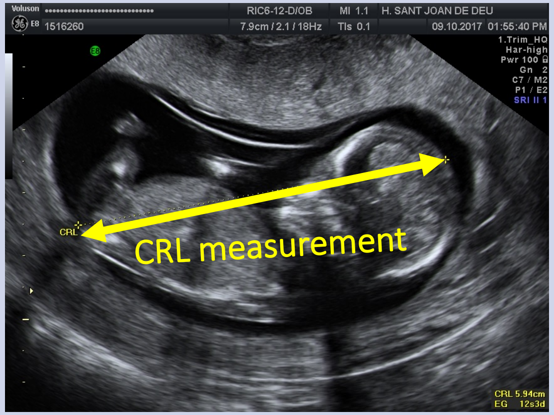
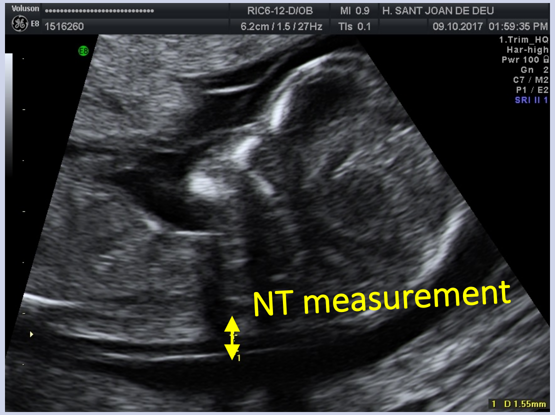
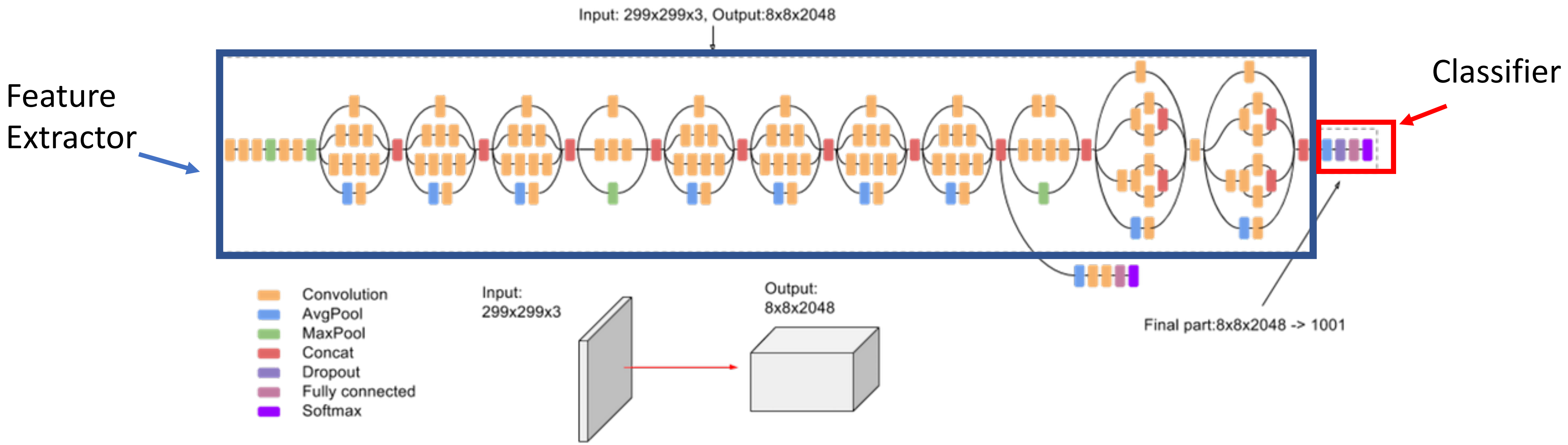
EXAMPLE: FETAL BIOMETRIC PLANES

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

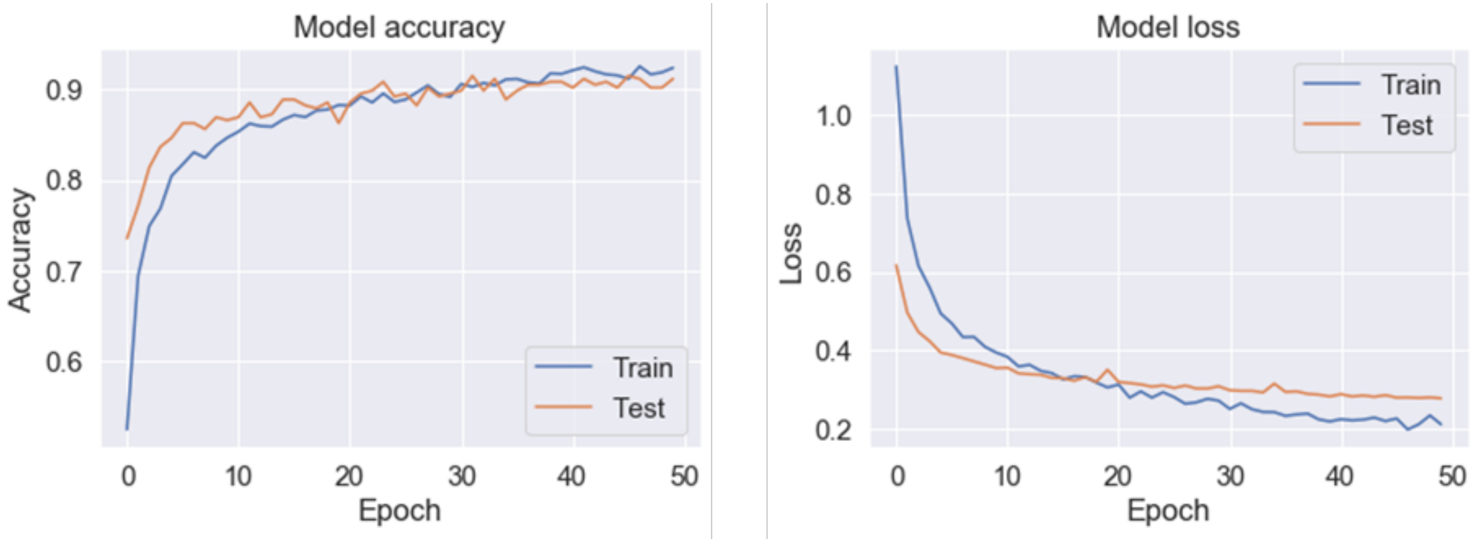
- Inception V3 was trained with ImageNet dataset (1.2M images of 1000 different clases)



- Trainable Parameters: 24M → 6127

4. EXPERIMENTAL RESULTS AND ANALYSIS

MODEL PERFORMANCE



Predicted class

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

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INTERPRETABILITY METHODS

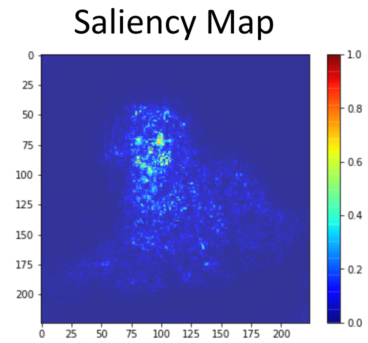
SALIENCY MAPS

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

Input → Model → y^c (Output for a class)

Computed by backpropagation algorithm

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



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

- Fast to compute

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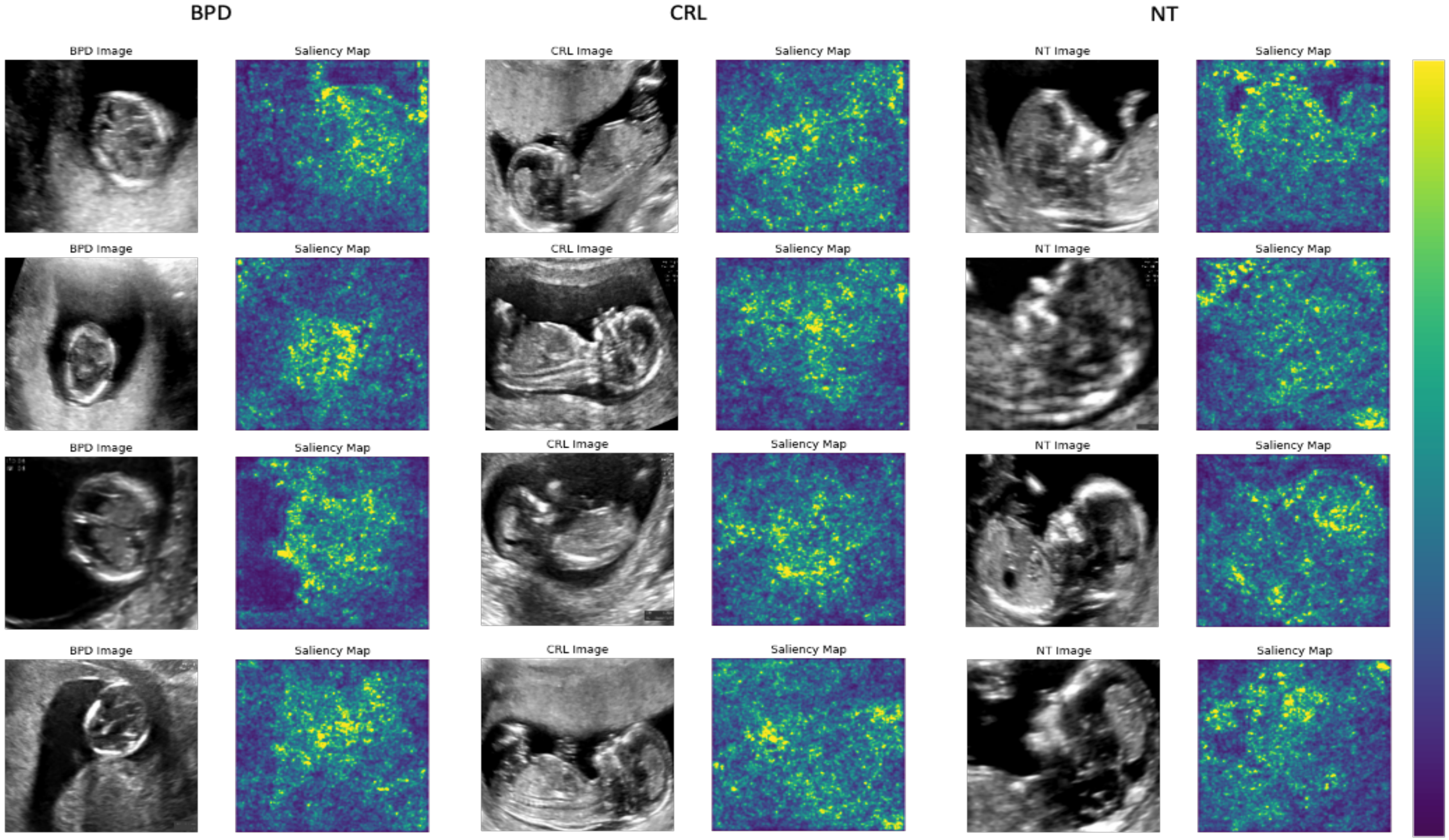
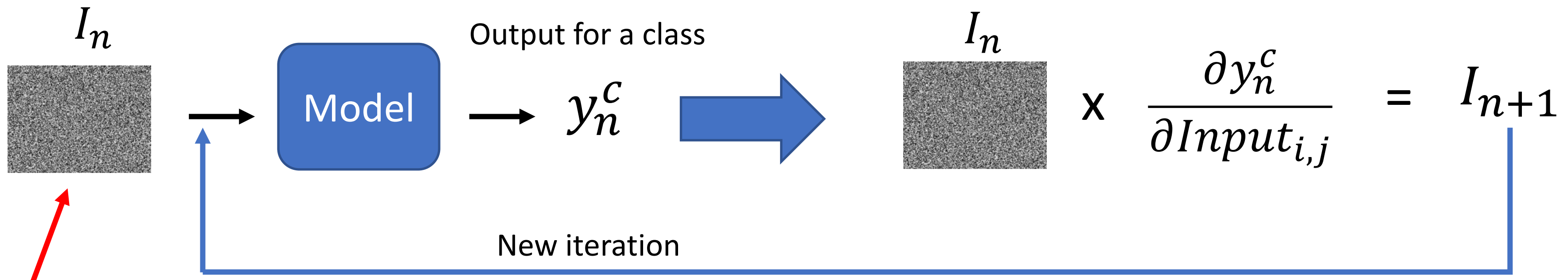
SALIENCY MAPS



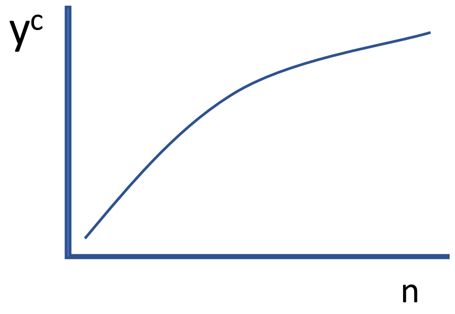
ACTIVATION MAXIMIZATION

- 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)

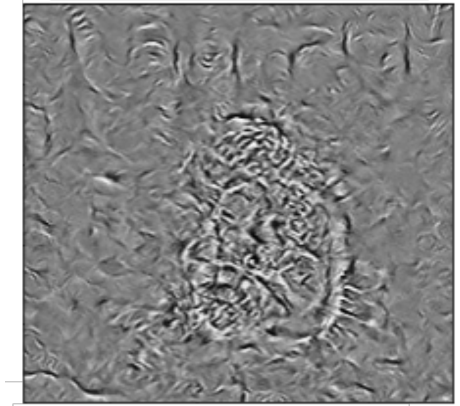


We are getting the image that best represents a class

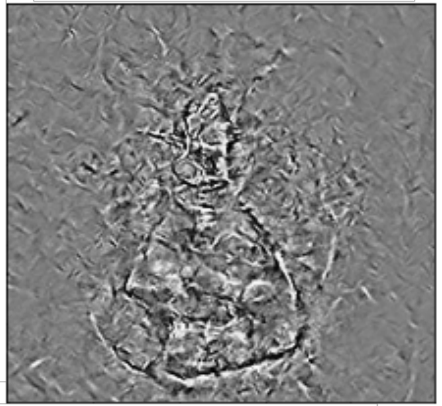
- Slow performance

ACTIVATION MAXIMIZATION

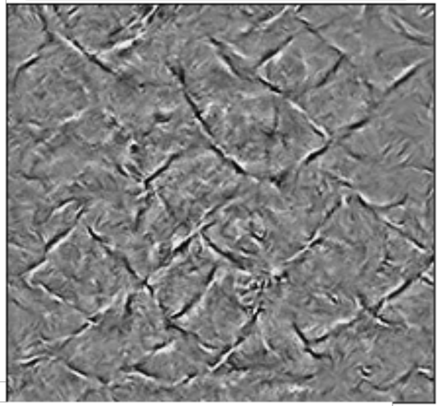
BPD class Maximization



CRL class Maximization



NT class Maximization



BPD image example

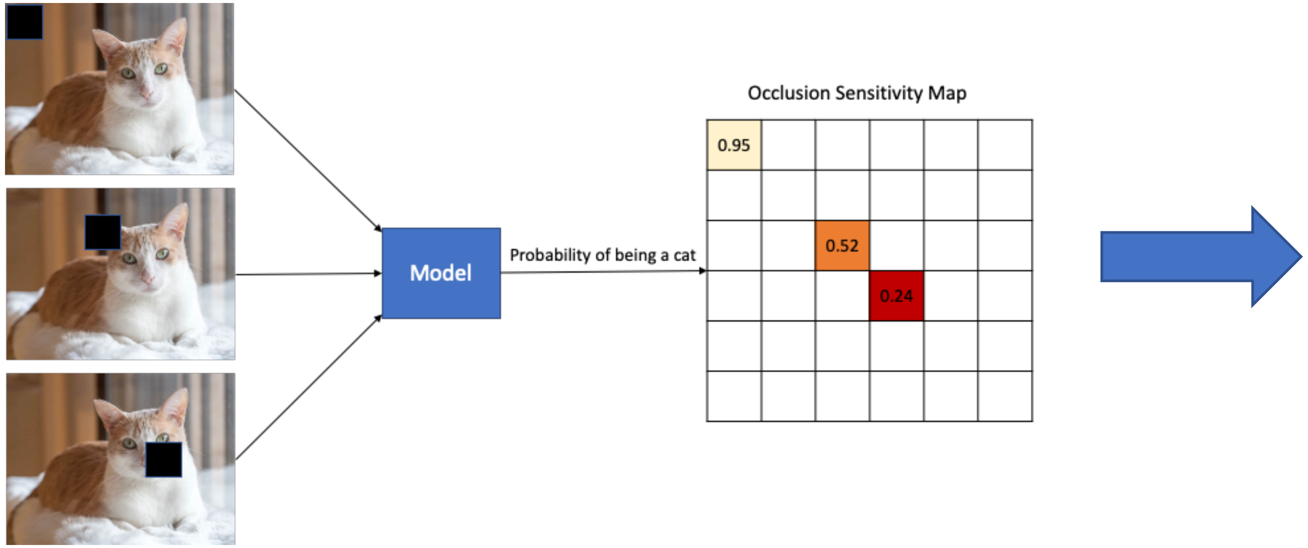
CRL image example

NT image example

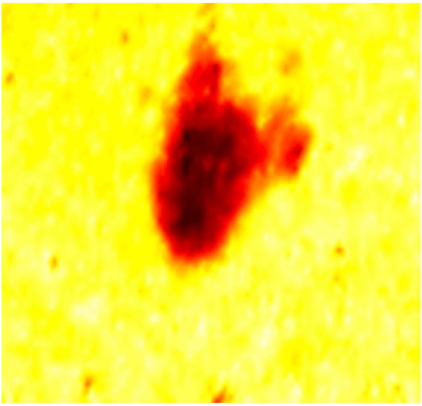
OCCLUSION SENSITIVITY MAPS

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

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



Occlusion Sensitivity Map



- Slow process

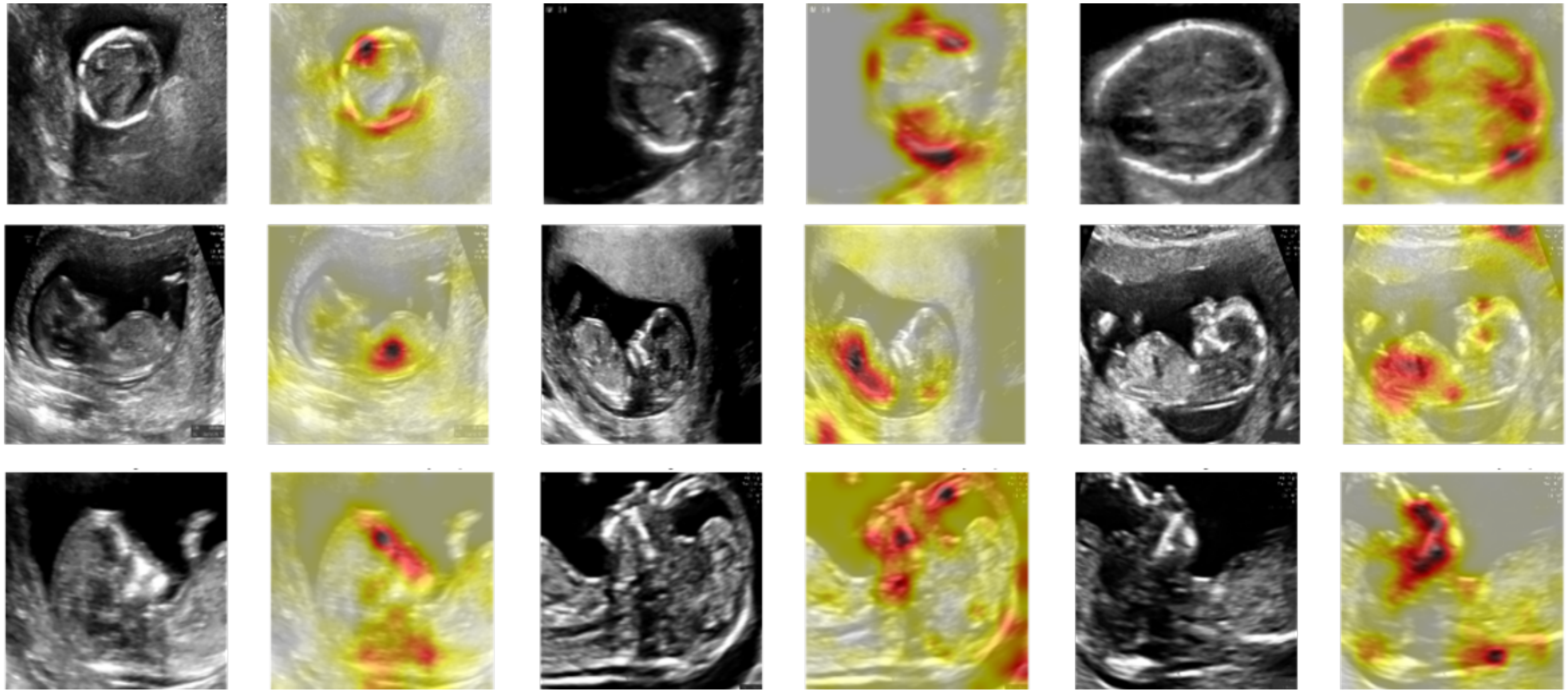
OCCLUSION SENSITIVITY

Example 1 Example 2 Example 3

BPD

CRL

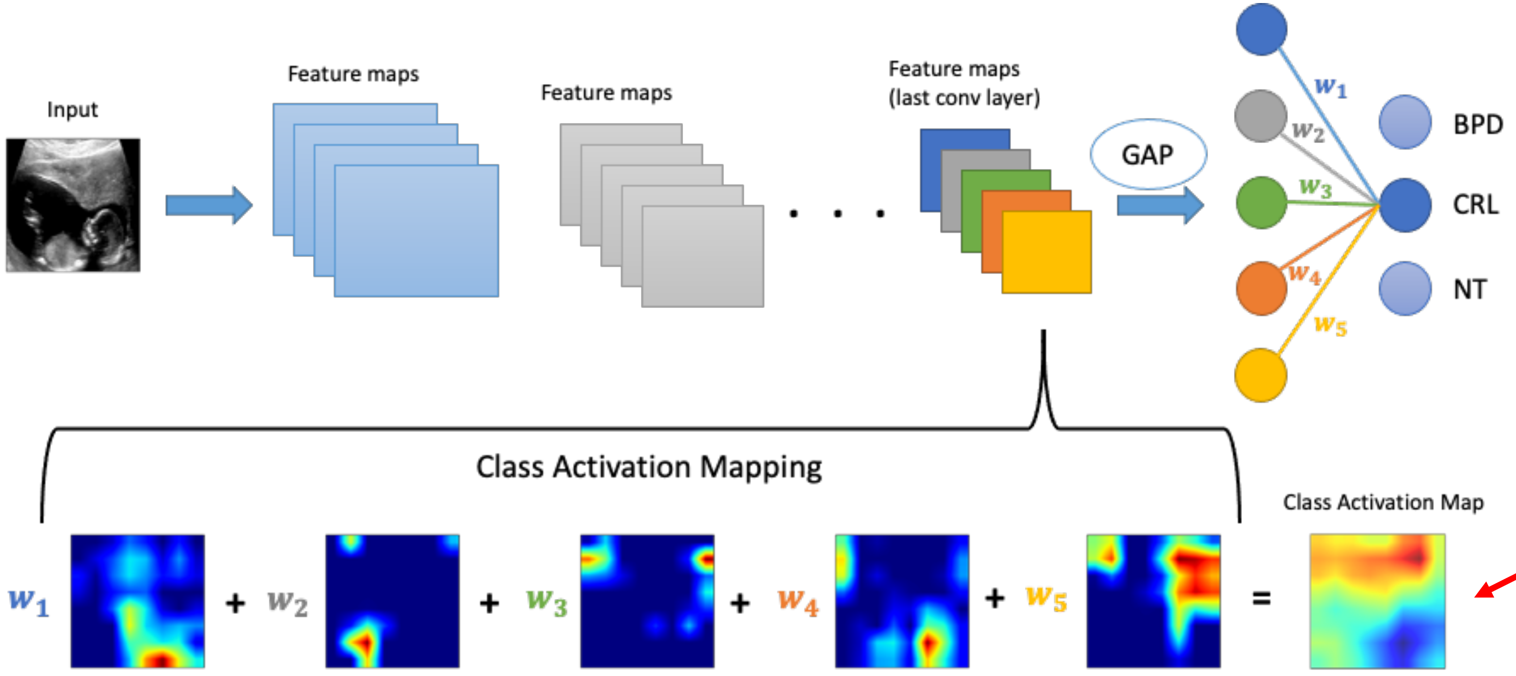
NT



CLASS ACTIVATION MAPPING

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

- CAM takes 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

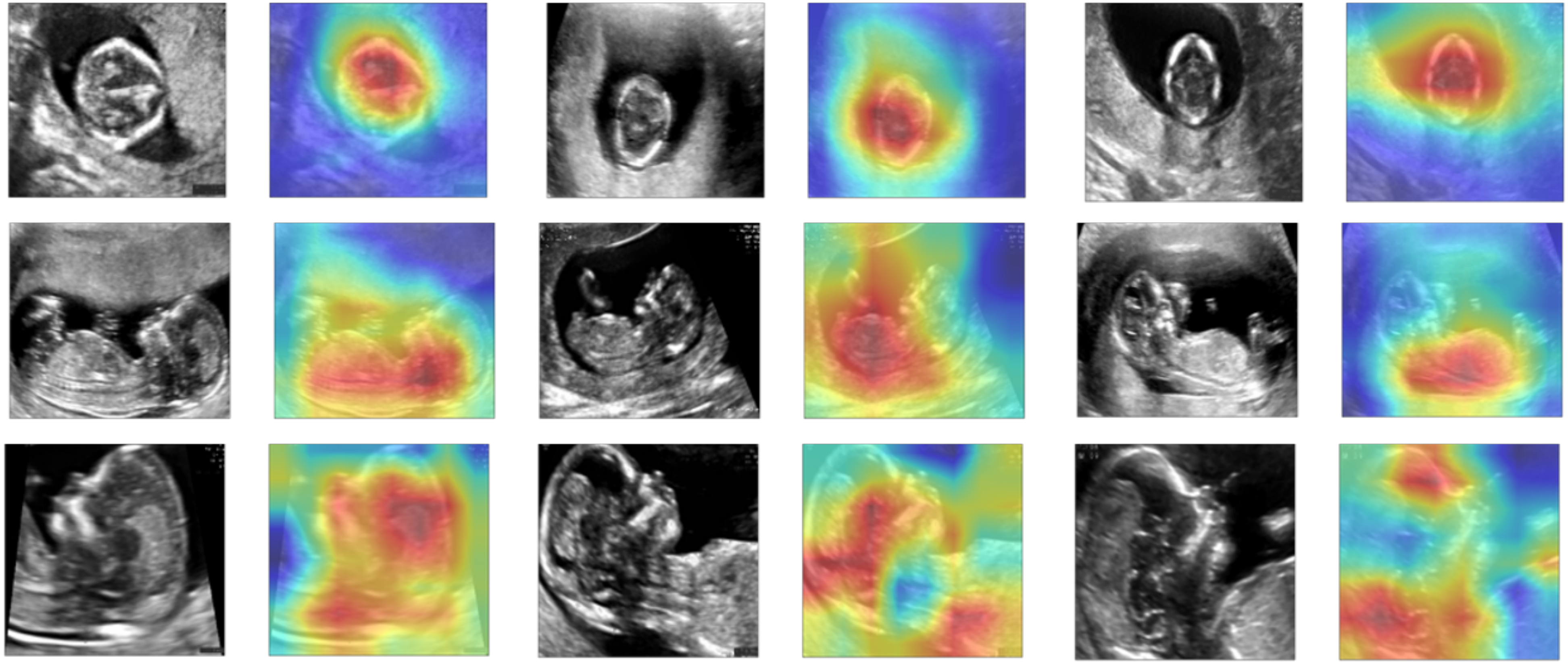
CLASS ACTIVATION MAPPING

Example 1 | Example 2 | Example 3

BPD

CRL

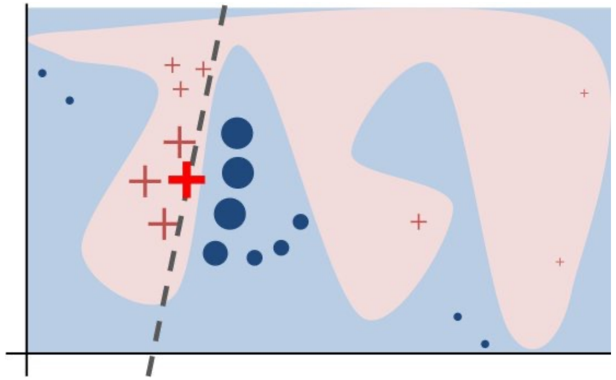
NT



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

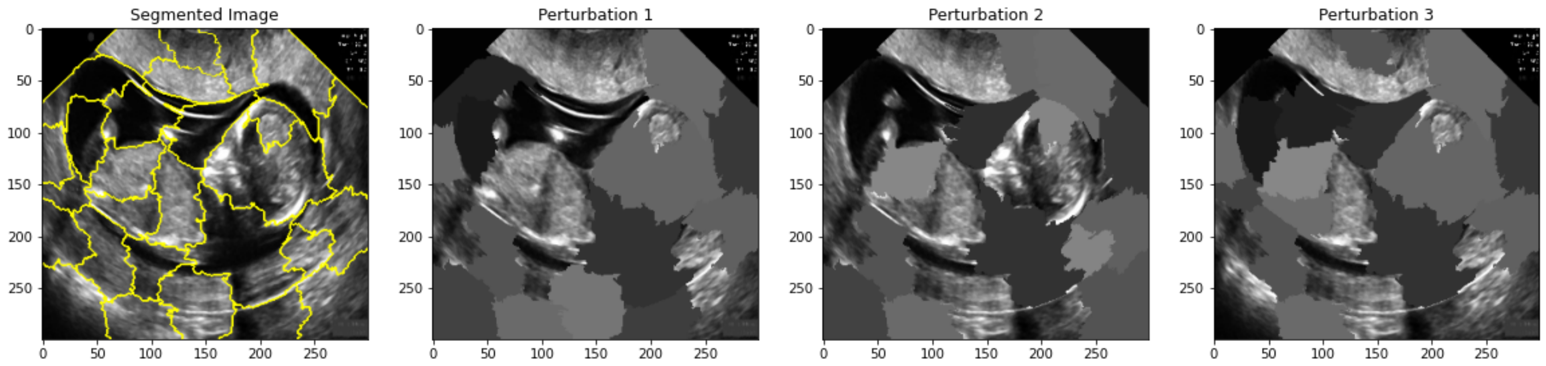


Solution space

- 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 randomly perturbed

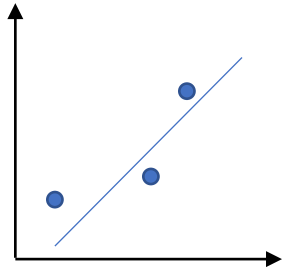


- Disturbed superpixels are encoded with a 0 in the feature vector, while the active pixels with a 1

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

→

Linear Model



Weights are the importance of each superpixel or feature

- Very slow

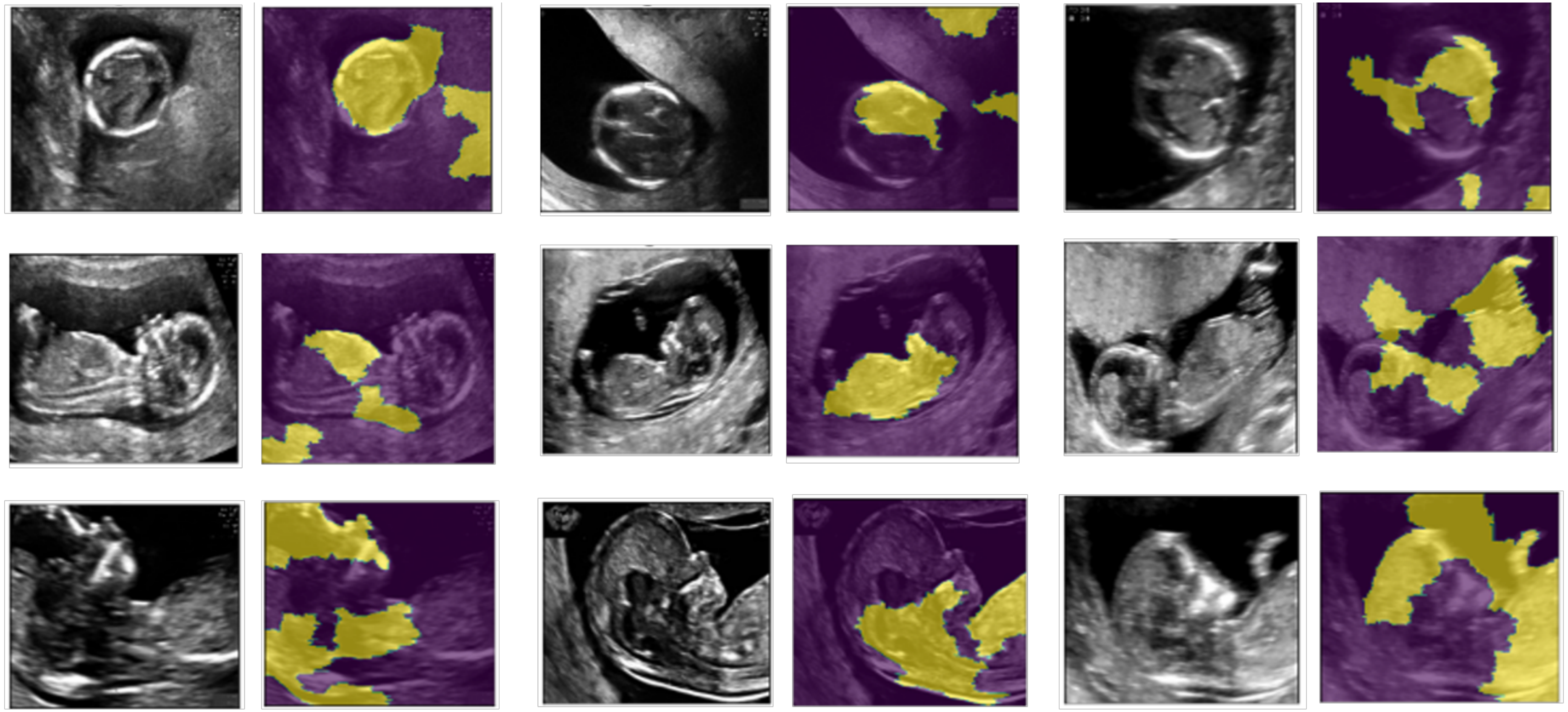
LIME

Example 1 Example 2 Example 3

BPD

CRL

NT

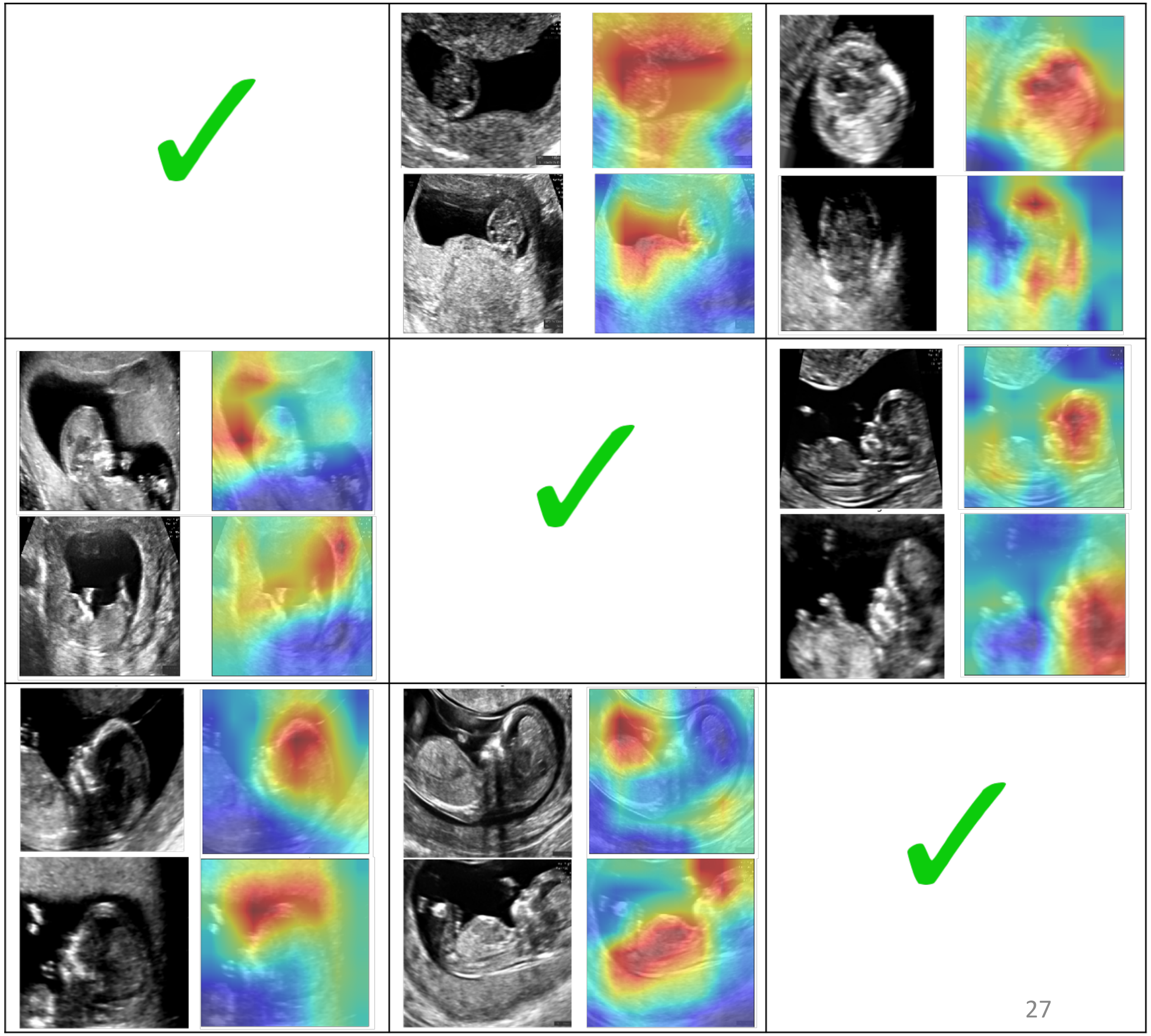


MISCLASIFICATIONS

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