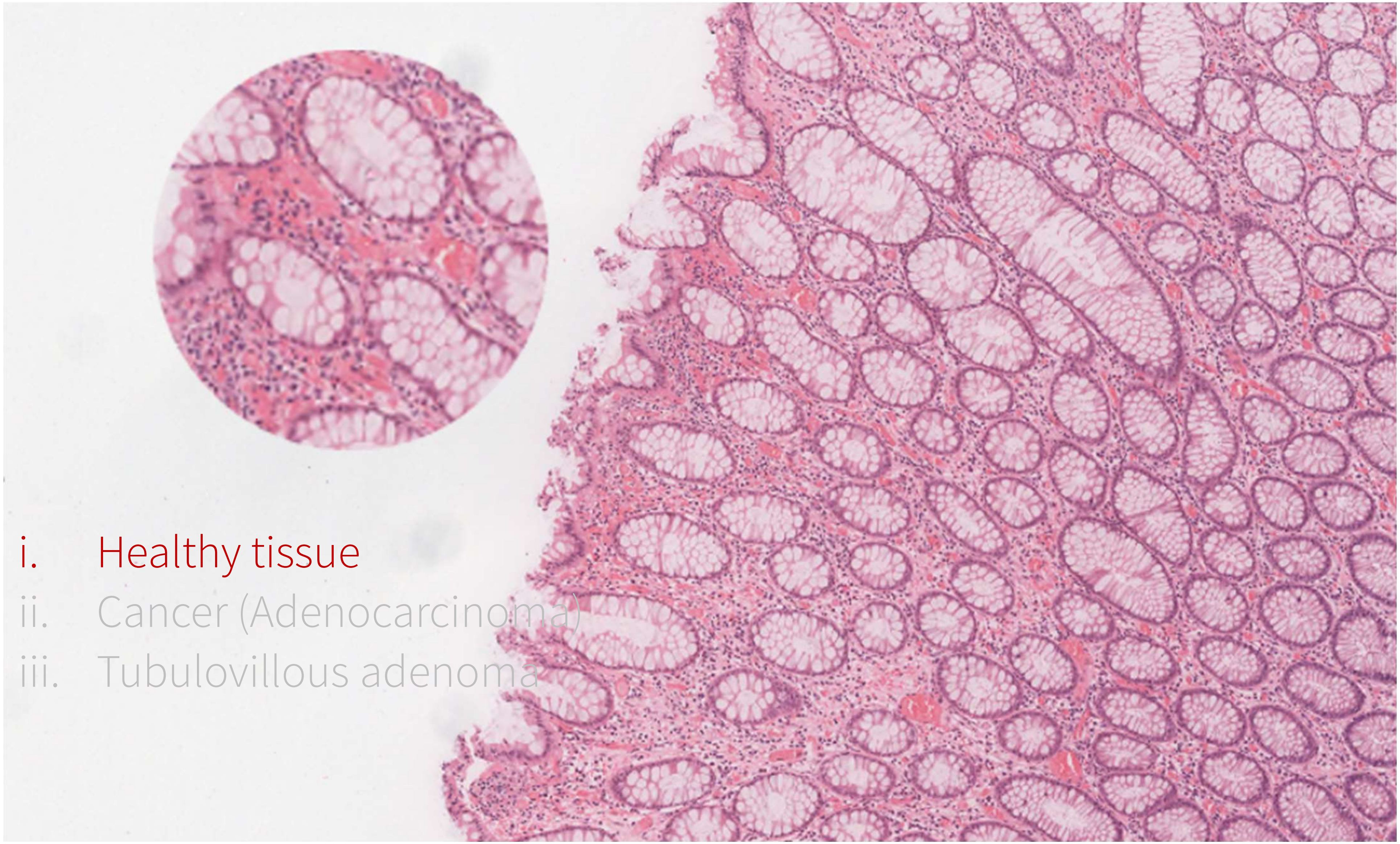
Introduction

CRC histological analysis



i. Healthy tissue

ii. Cancer (Adenocarcinoma)

iii. Tubulovillous adenoma

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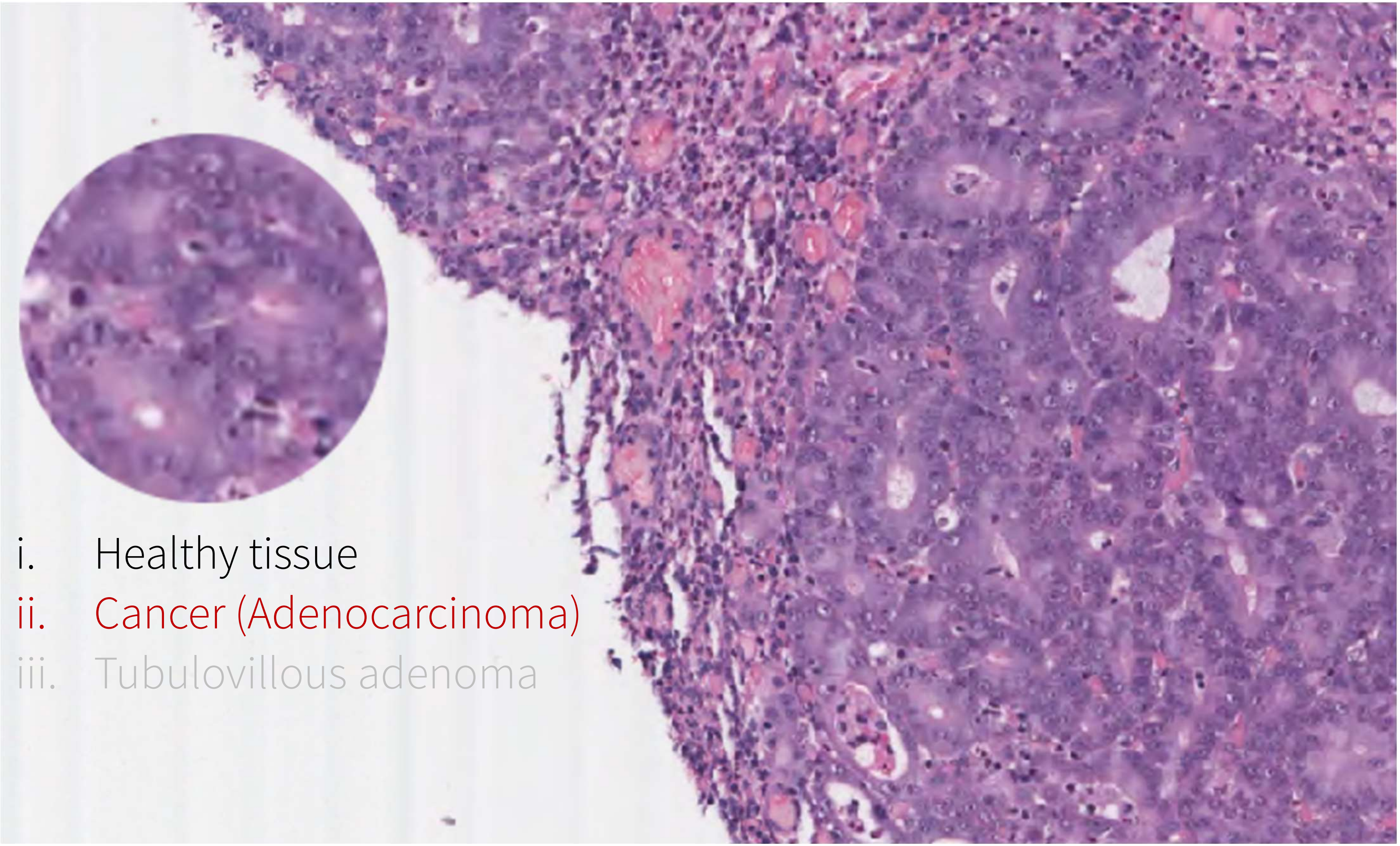

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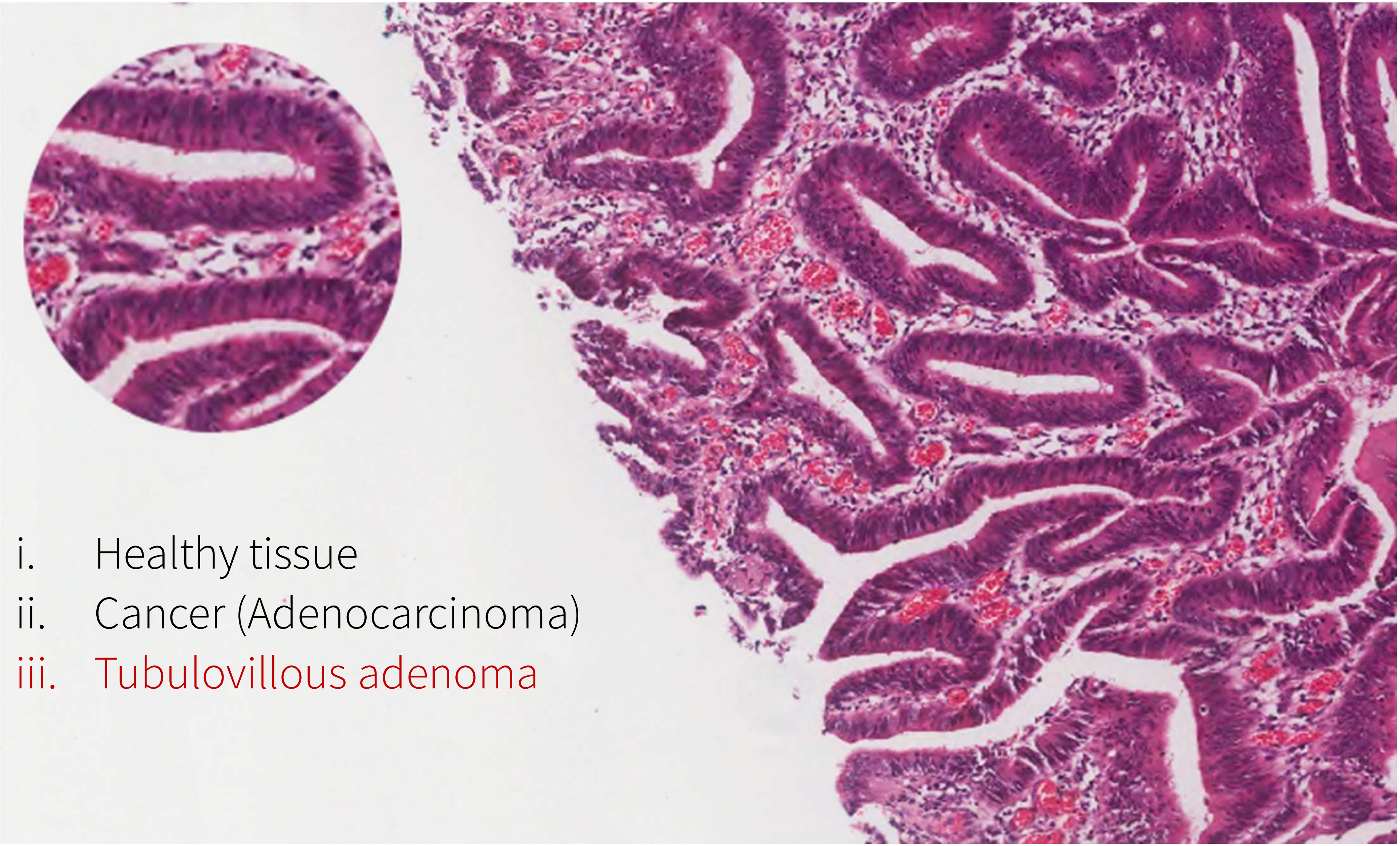

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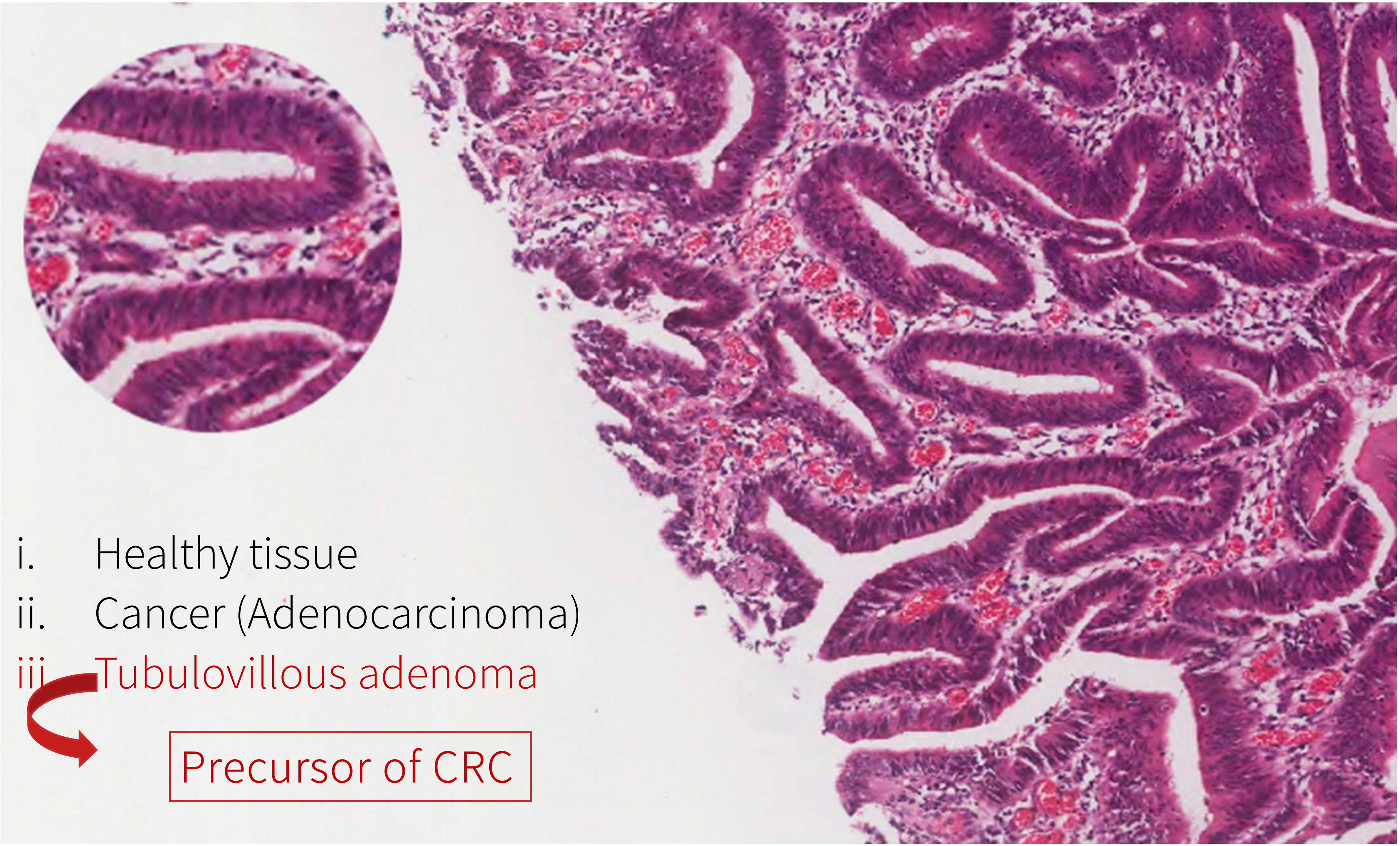

i. Healthy tissue
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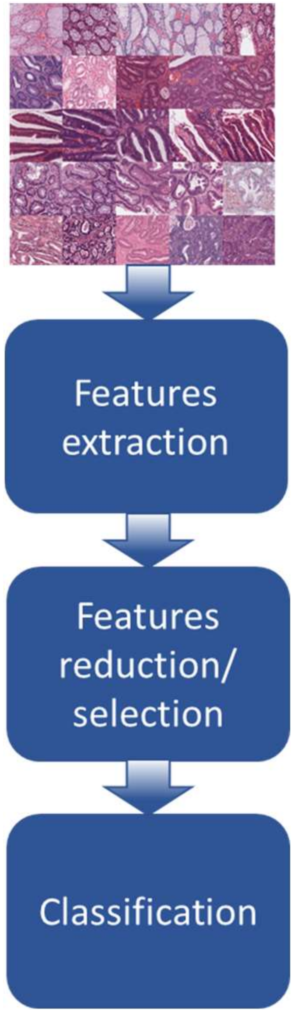
Precursor of CRC

Introduction

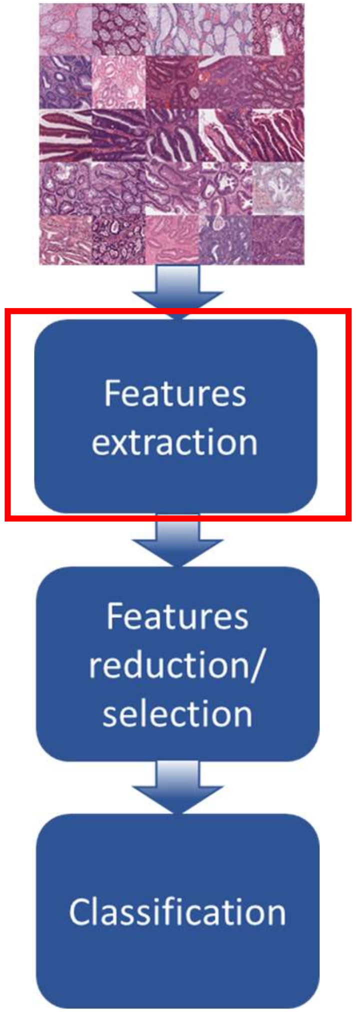
Why CNNs ?



- Typical approach for histological images analysis:
    i. Features extraction
    ii. Features reduction/selection
    iii. Classification

- The dependence on a fixed set of handcrafted features is a major limitation to the robustness

Why CNNs ?



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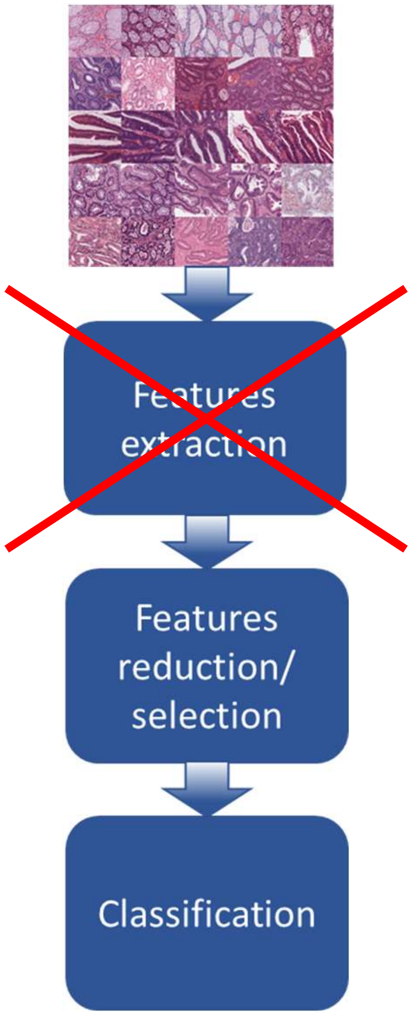


- An answer to such limitation is deep learning (DL) and in particular CNNs.

Pros:

✓ DL extract hierarchical knowledge from the data itself.

✓ No needs for handcrafted features

Cons:

x Huge dataset (10^6 images)

x High computational power

x Both difficult to find in everyday clinic.

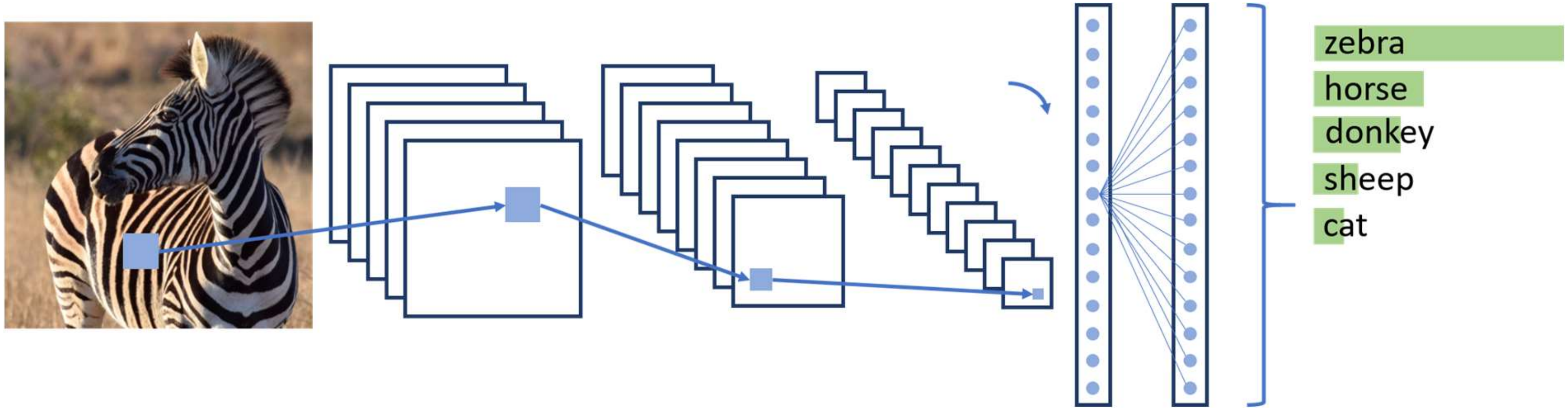
Why CNNs ?

- We evaluate a CNN-based approach to automatically differentiate
  i. healthy tissues
  ii. tubulovillous adenomas
  iii. cancerous samples

- We investigate both full training and transfer learning from different domains to overcome issues related training (dataset dimension, computational resources and time).

Convolutional Neural Networks (CNNs)

- Deep, feed-forward artificial neural networks, successfully applied to computer vision.
- Basically a CNN transforms the original image layer by layer from the original pixel values to the final class scores.



- It is made up of multiple locally connected trainable stages, piled one after the other, with two or more fully-connected layers as the last step

Convolutional Neural Networks (CNNs)

- The **first part** of the network is devoted to **learning image representation**. Successive layers learn features at an increasing level of abstraction.

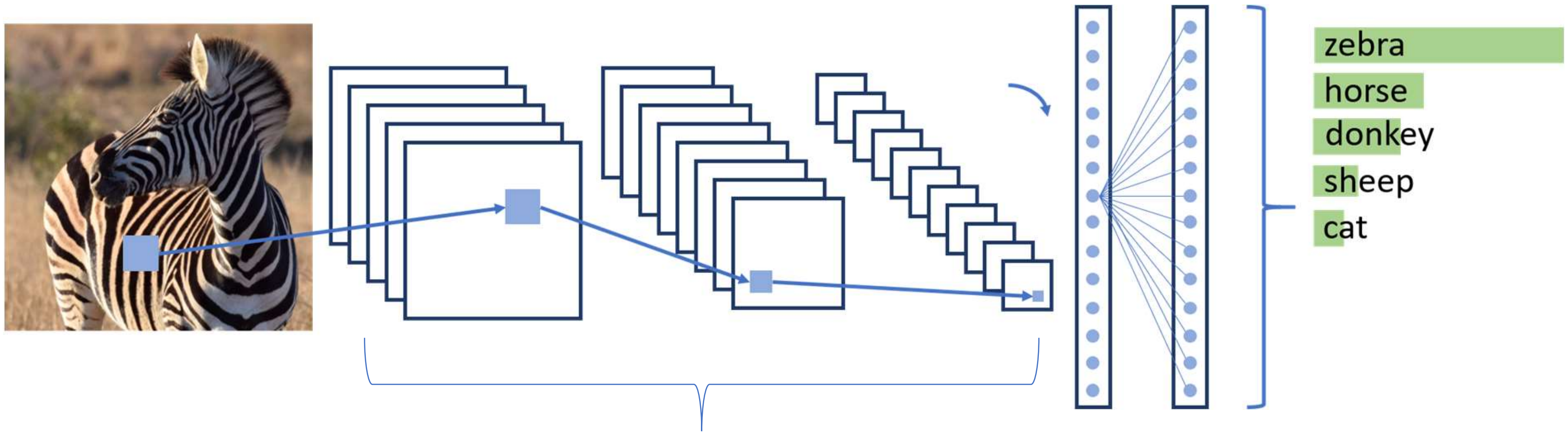
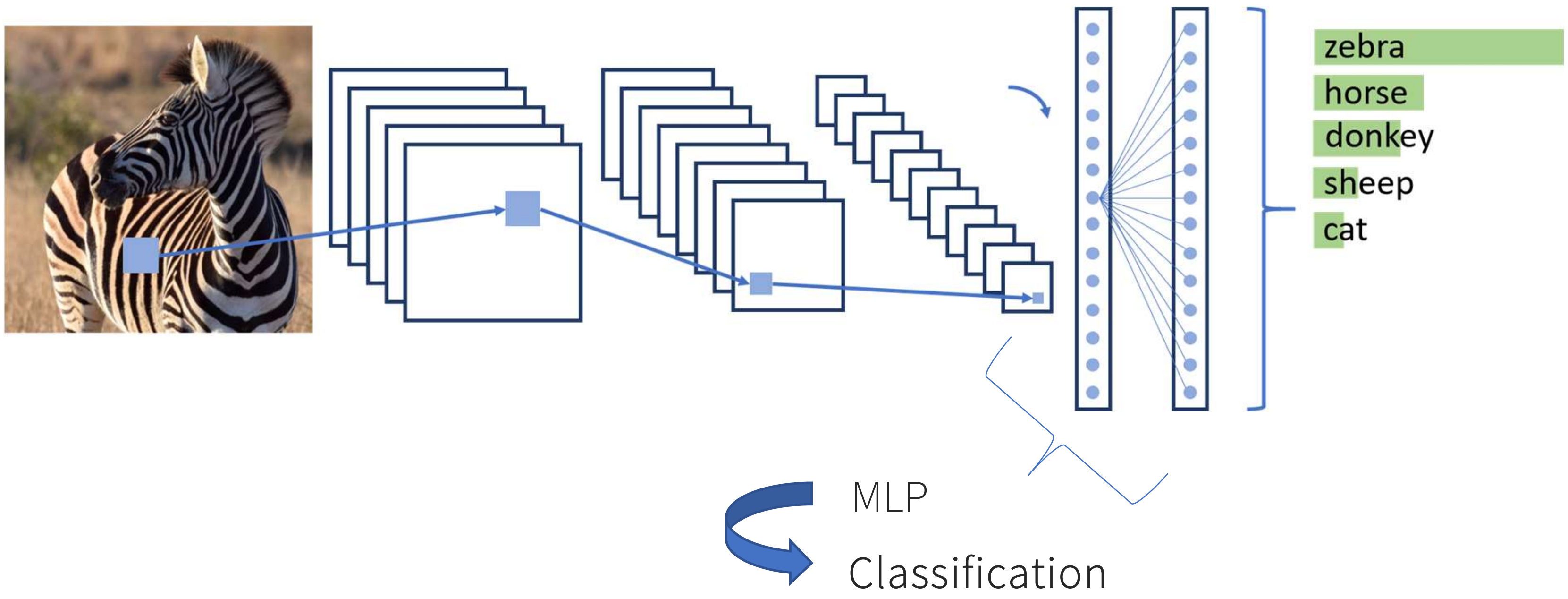


Image representation at increasing level of abstraction

Features learning

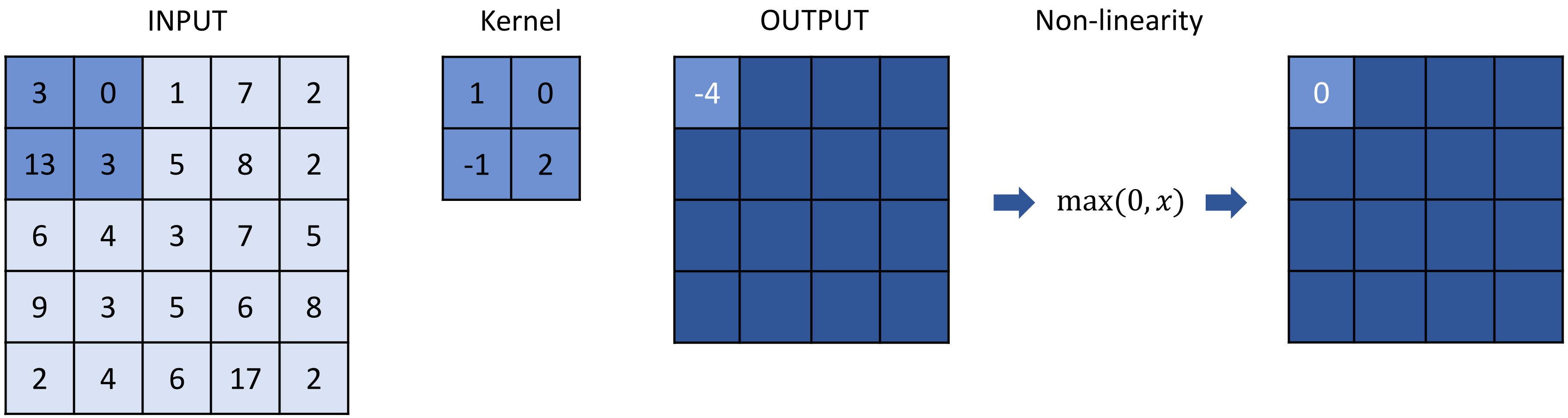
Convolutional Neural Networks (CNNs)

- The last fully connected part is devoted to classification and acts like a traditional multilayer perceptron (MLP).



Convolutional Neural Networks (CNNs)

- CNNs are characterized by two main types of building blocks
  i. Convolutional blocks (CONV): perform a 2D convolution operation on the input image and apply a non-linear transfer function.



$$3 * 1 + 0 * 0 + 13 * (-1) + 3 * 2 = -4$$

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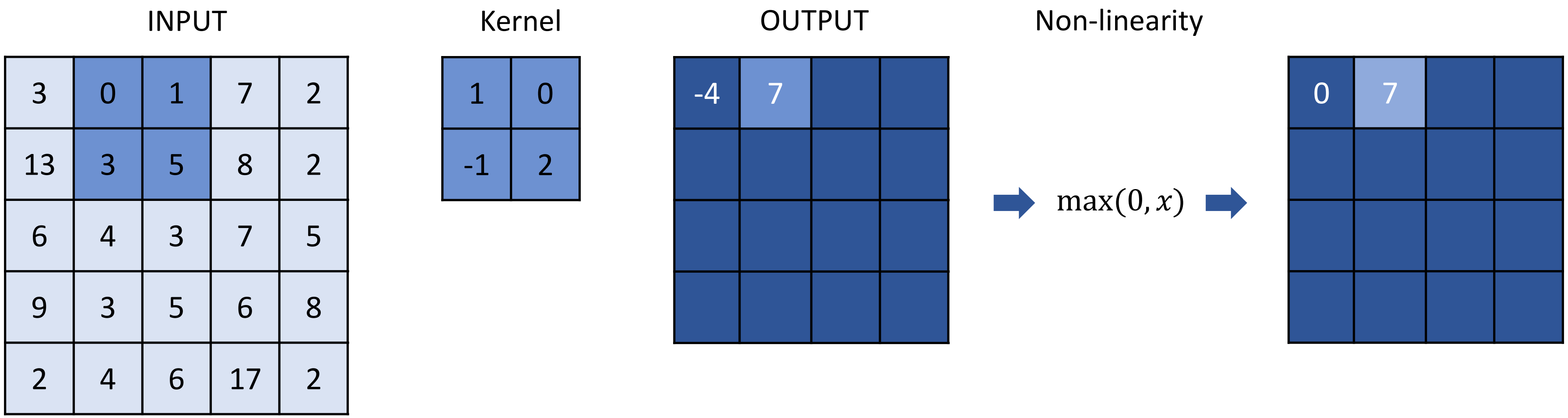

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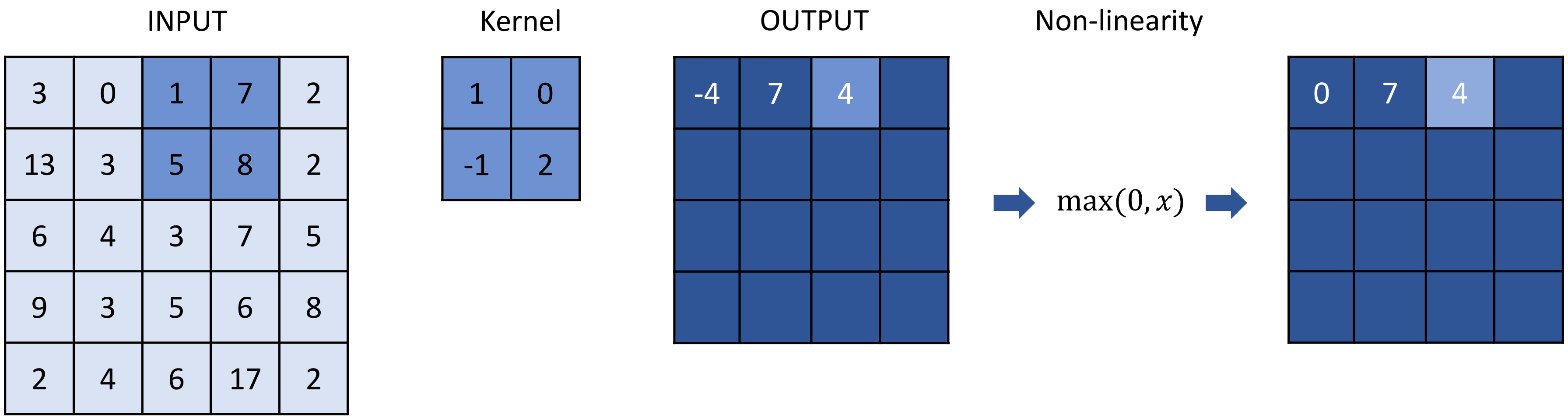

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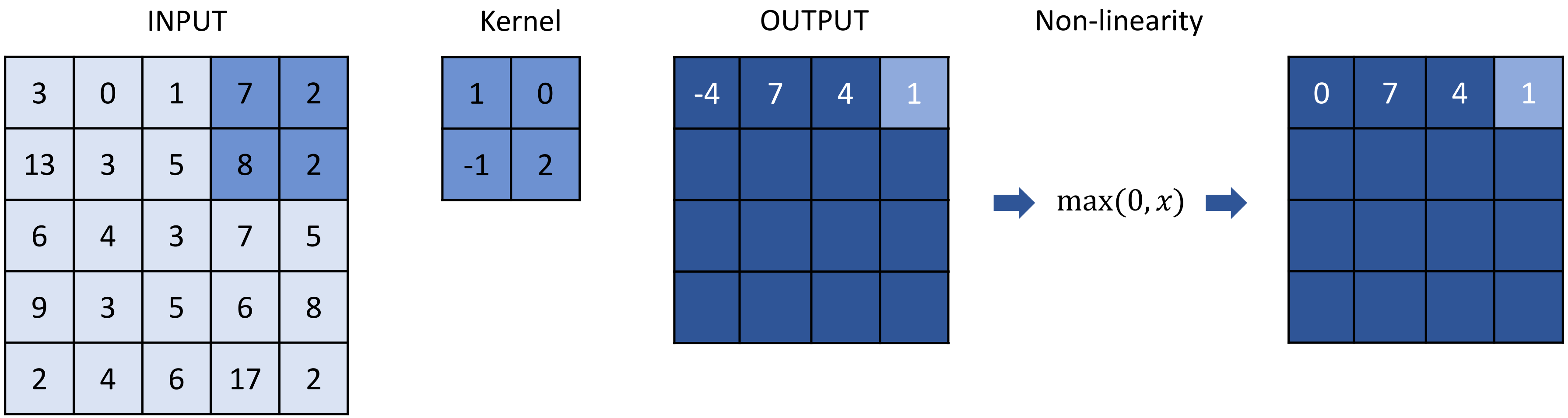

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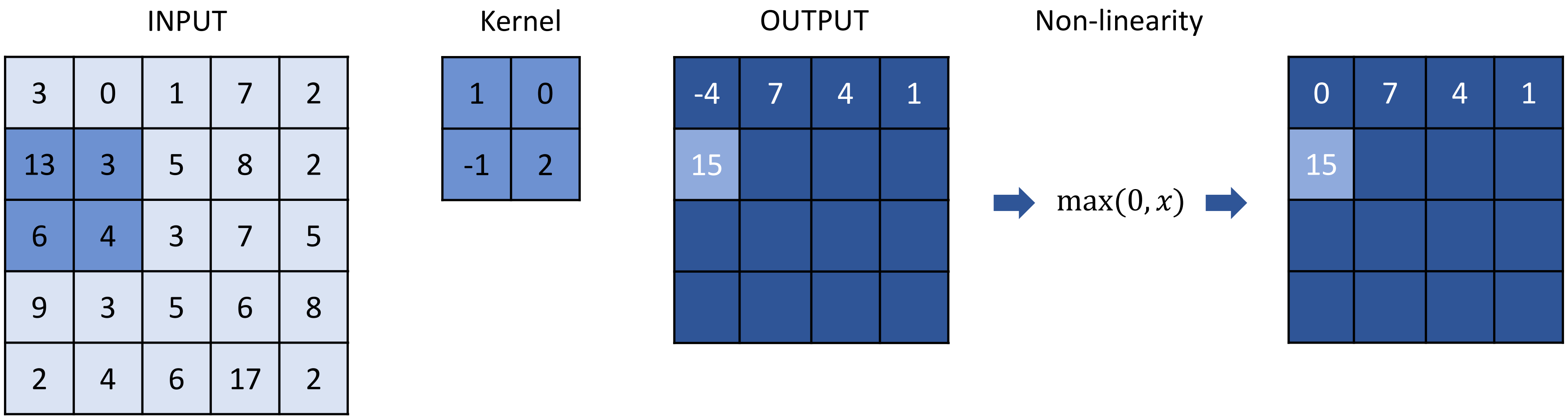

Convolutional Neural Networks (CNNs)

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INPUT

3	0	1	7	2
13	3	5	8	2
6	4	3	7	5
9	3	5	6	8
2	4	6	17	2

Kernel

1	0
-1	2

OUTPUT

-4	7	4	1
15	5	16	9
3	11	10	17
15	11	13	-7

Non-linearity

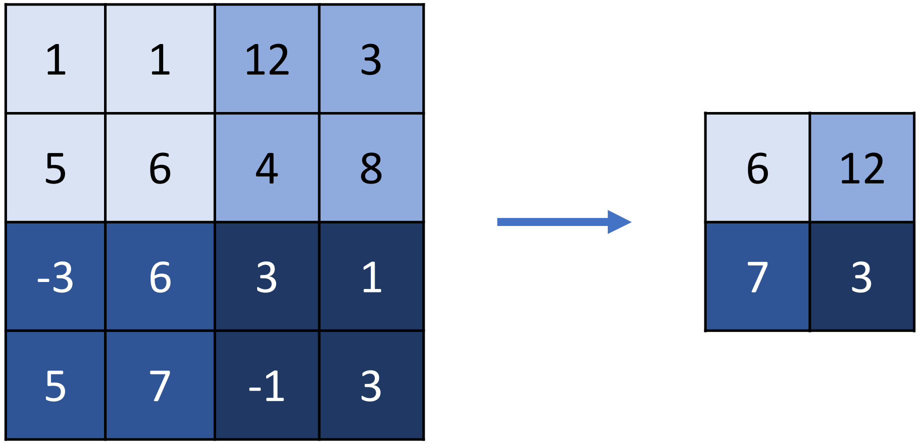
$$\rightarrow \max(0, x) \rightarrow$$

0	7	4	1
15	5	16	9
3	11	10	17
15	11	13	0

Introduction

Convolutional Neural Networks (CNNs)

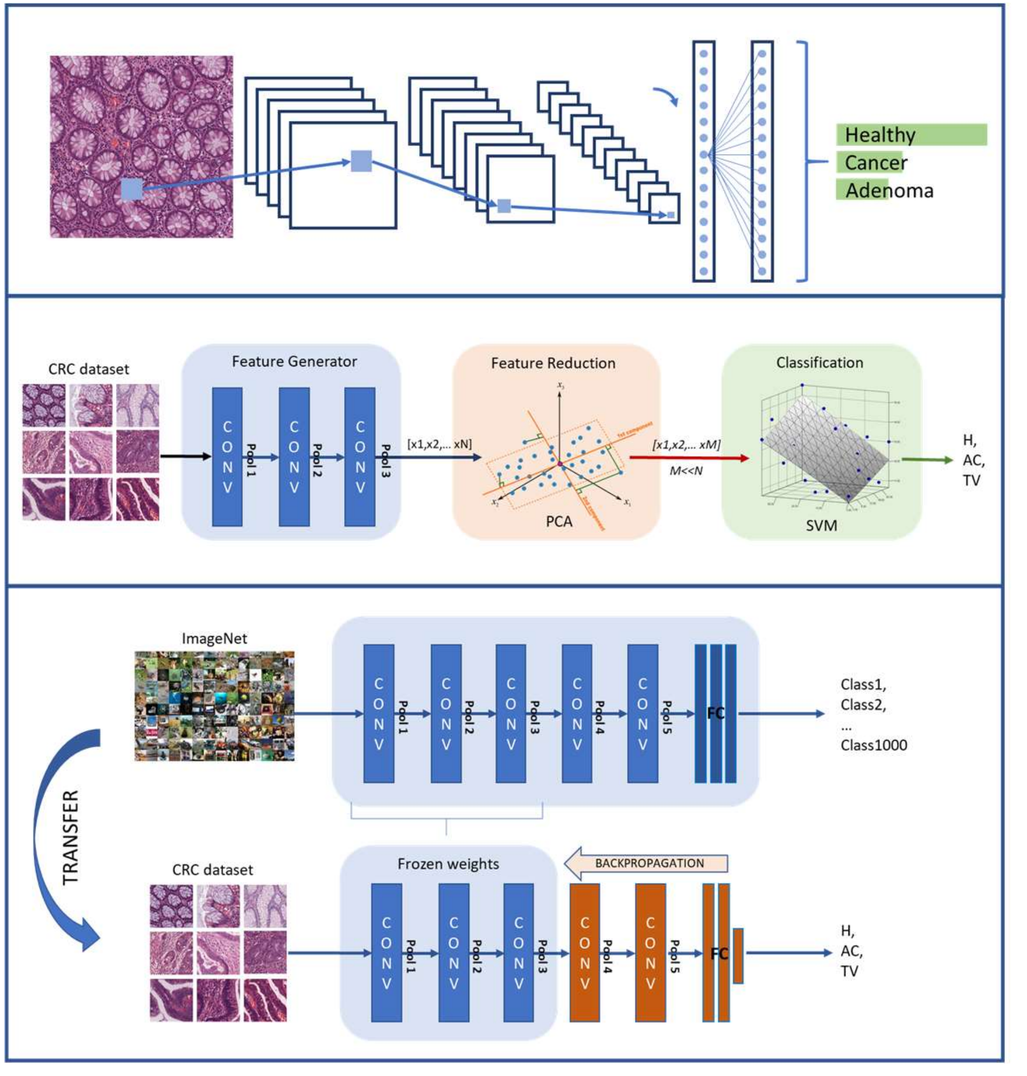
- CNNs are characterized by two main types of building blocks
  - ii. Pooling blocks (POOL): perform a nonlinear down-sampling of the input (e.g. by applying a max function).



Materials and methods

Overview

- CNN full training (random weights).
- CNN as features generator
- CNN fine tuning



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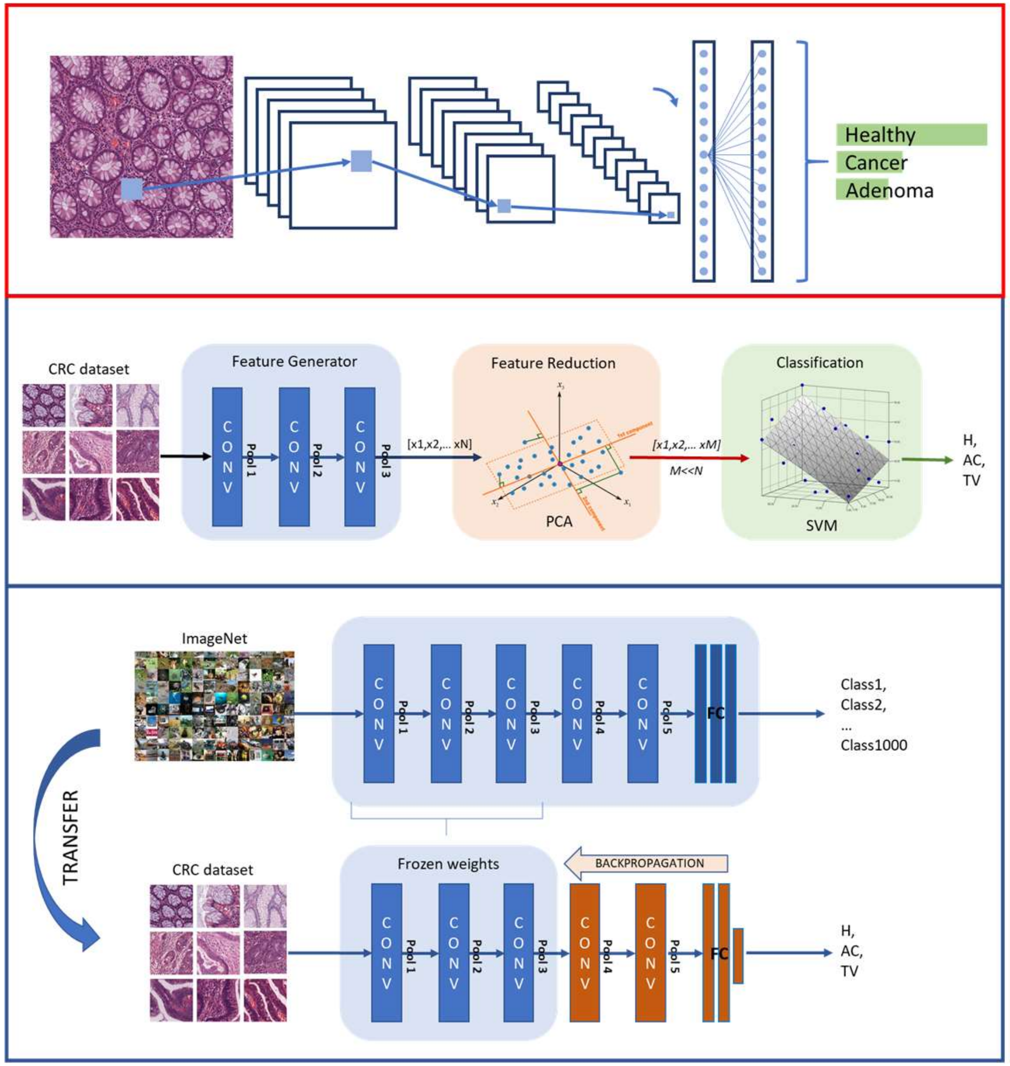
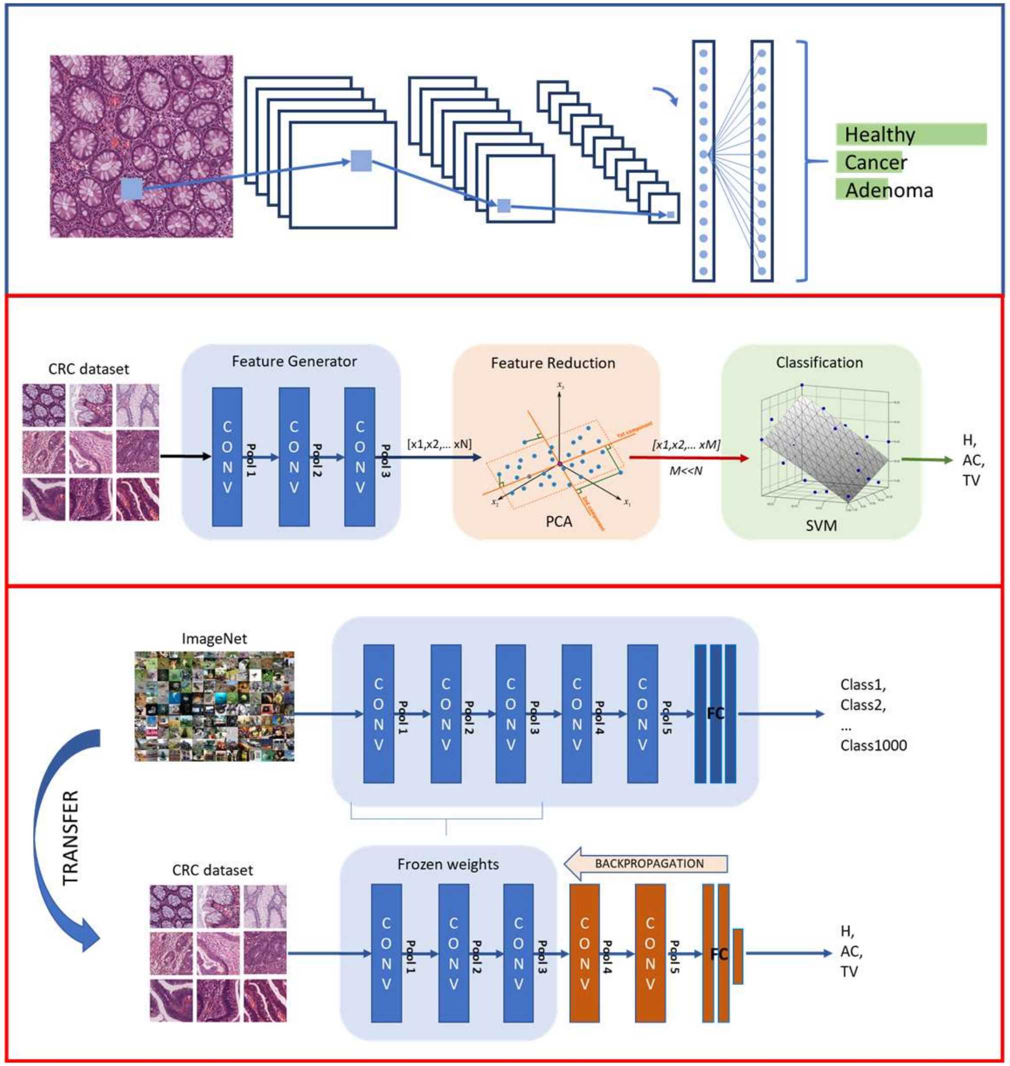


Materials and methods

Overview

- CNN full training (random weights).
- Transfer learning
    i. CNN as features generator
- Transfer learning
    i. CNN fine tuning



Transfer learning from pretrained CNN

- The basis of transfer learning are:
  i. Top-most blocks are tailored to a specific classification task.
  ii. Lower-level features are ideally generalizable.

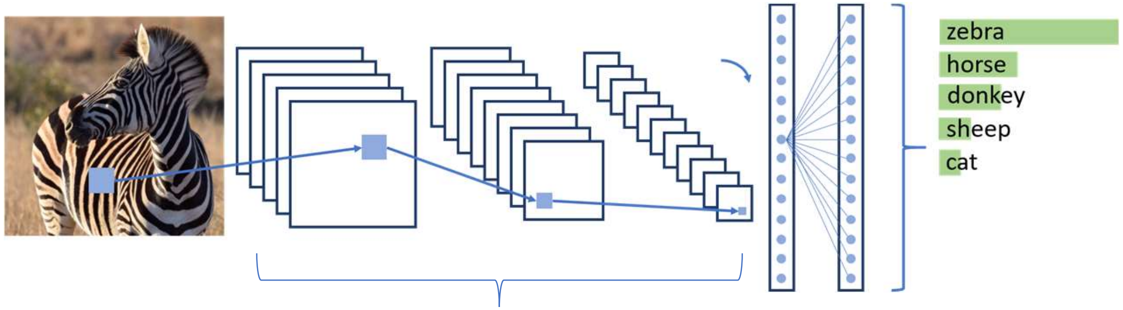


Image representation at increasing level of abstraction

Features learning

- Actual opinion is that transfer learning had to happen between two similar imaging domains.

Transfer learning from pretrained CNN

- Our pretrained model:
  i. VGG16 trained on the ImageNet 2012 dataset (1.2 million photographs from1000 different categories of natural objects).

- Content and characteristics are completely different from our target.

Materials and methods

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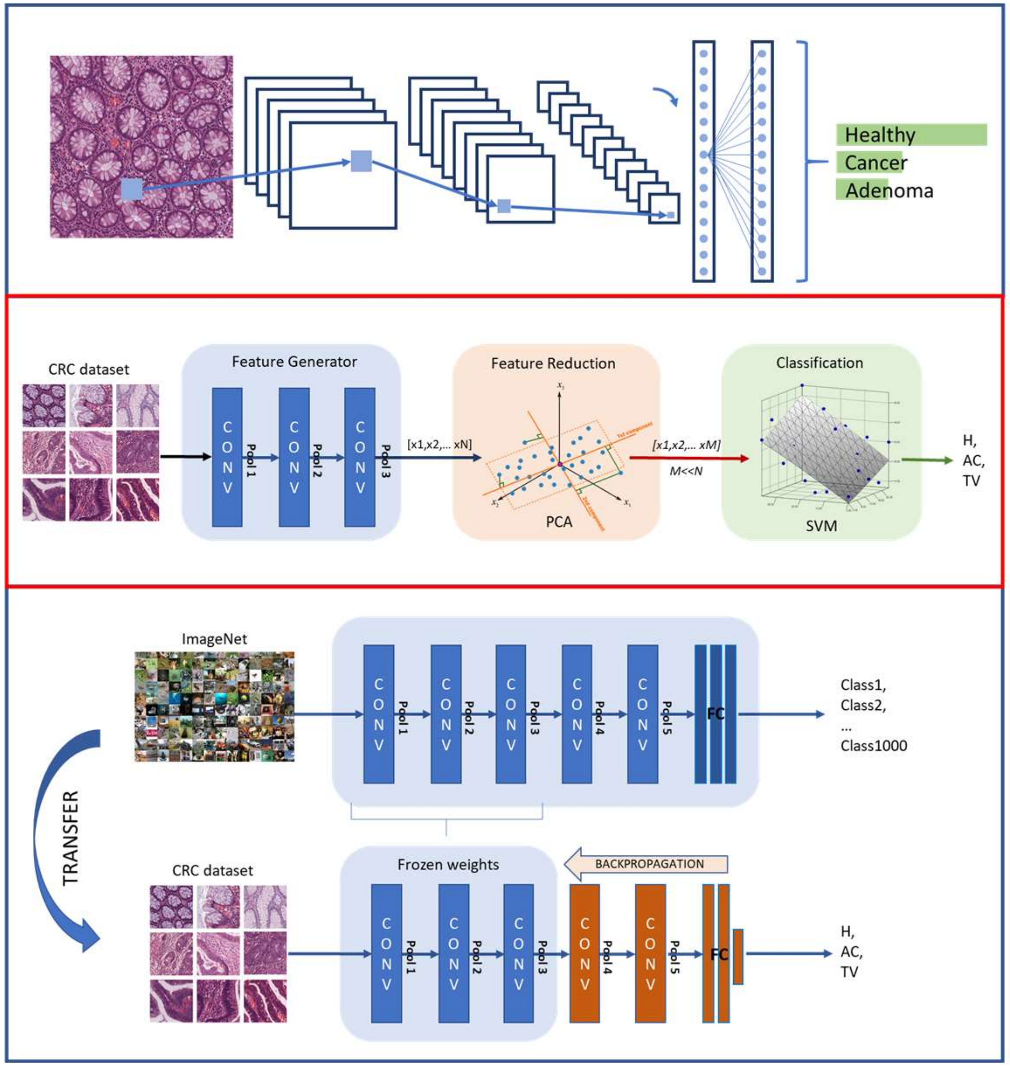
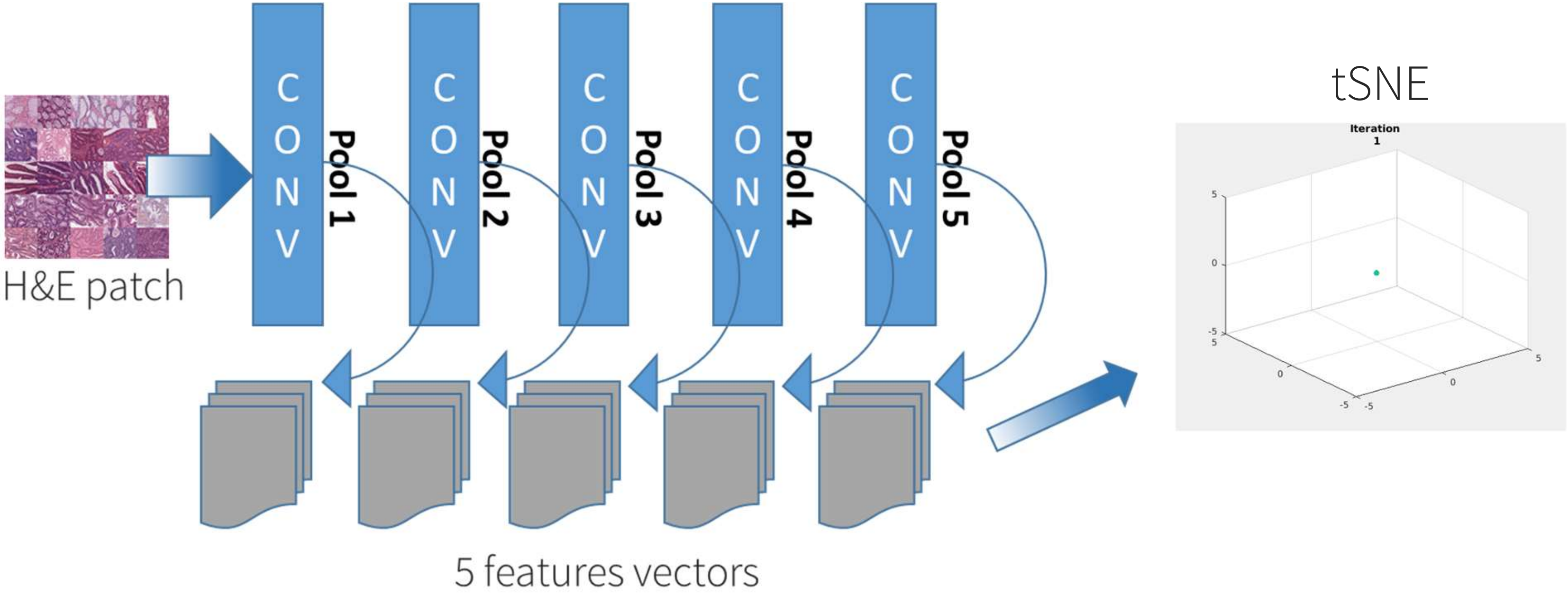
- Transfer learning
  i. CNN fine tuning



CNN as features generator

- Preliminary step to analyse discriminative capabilities of CNN major block:
  i. 1500 random patches from training set fed into the net.
  ii. Features extraction from pool layers.
  iii. tSNE algorithm.

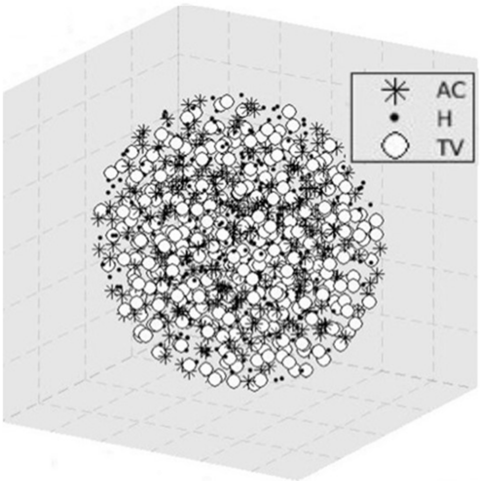


Materials and methods

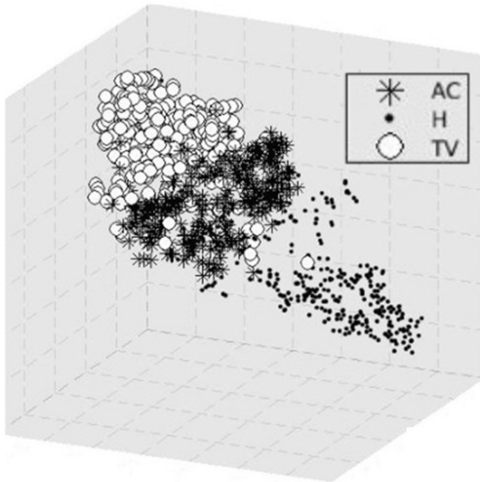
CNN as features generator

- Stochastic Neighbour Embedding (t-SNE) method is a qualitative non-linear dimensionality reduction technique

POOL 1



POOL 3

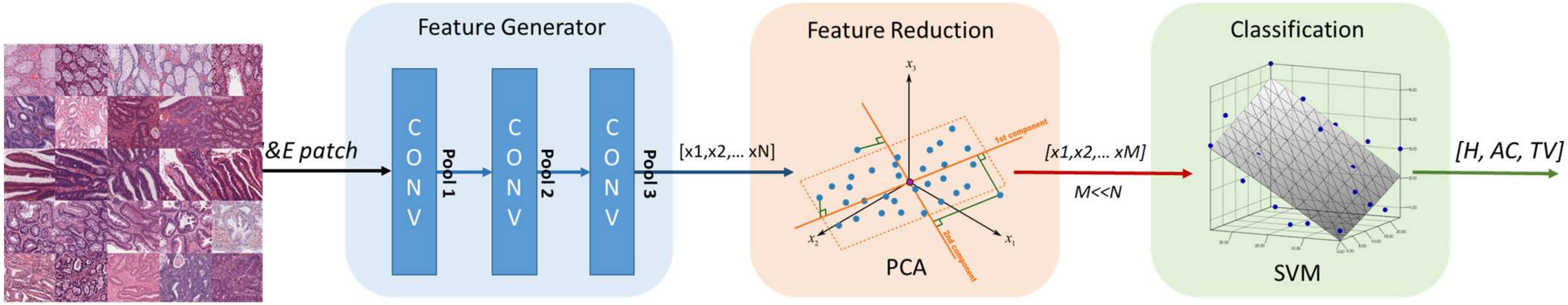


- POOL3 layer was qualitative identified as most performing.

Materials and methods

CNN as features generator

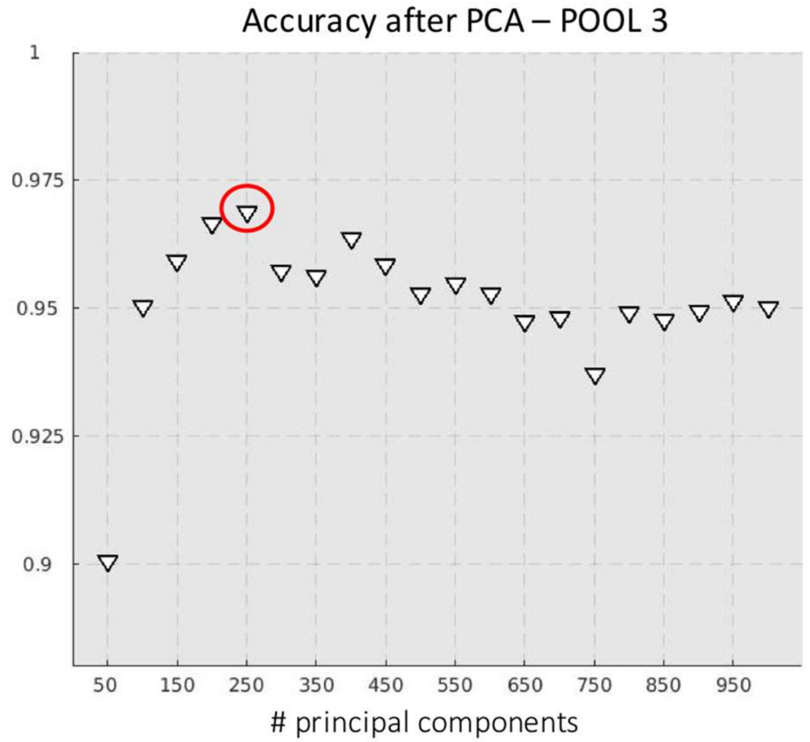
- On POOL3 features vector:
  i. Features reduction (Principal Component Analysis).
  ii. Classification with Support Vector Machine (Gaussian radial basis function).



CNN as features generator

- PCA features reduction:
  i. The optimal # of principal components found by means of a sequential procedure.

- SVM classification:
  i. Bayesian Optimization for SVM hyperparameters.



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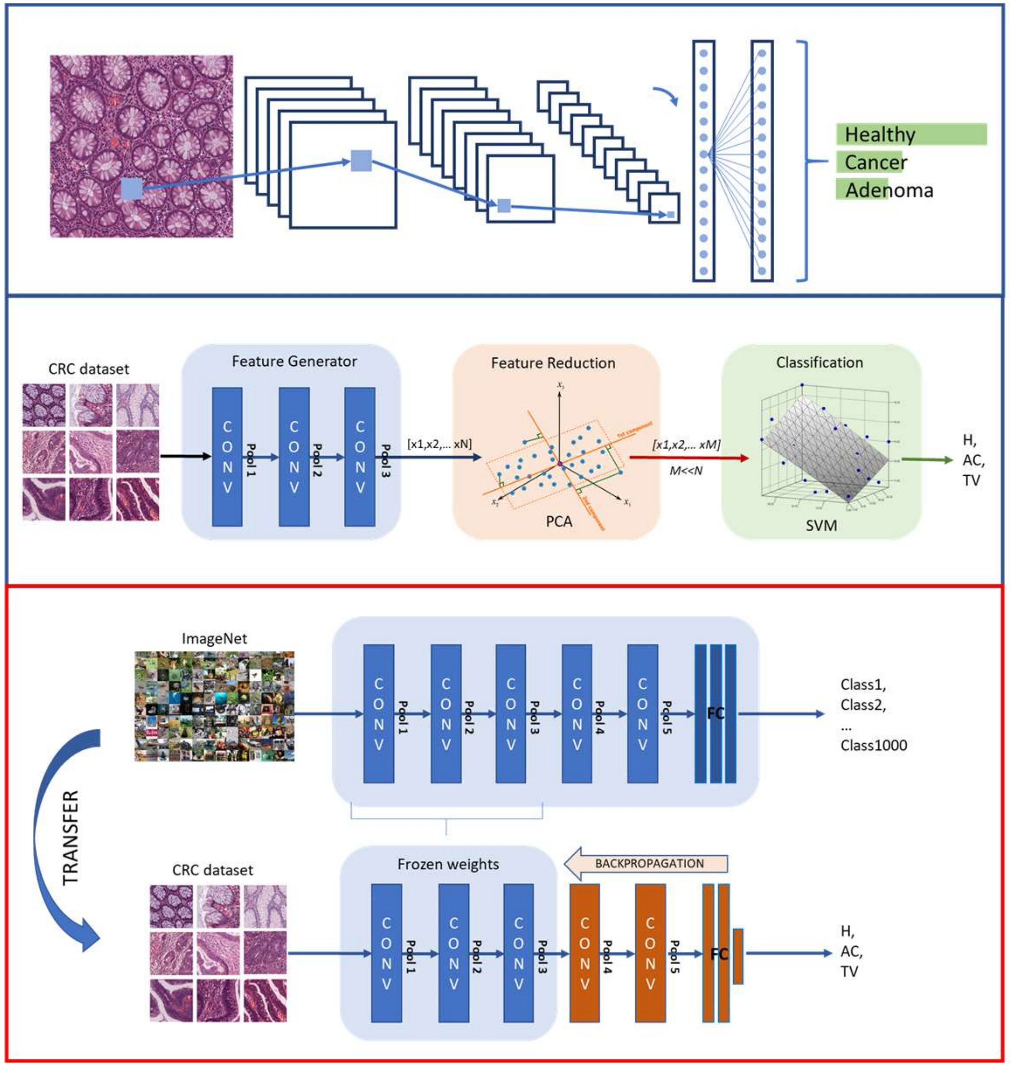
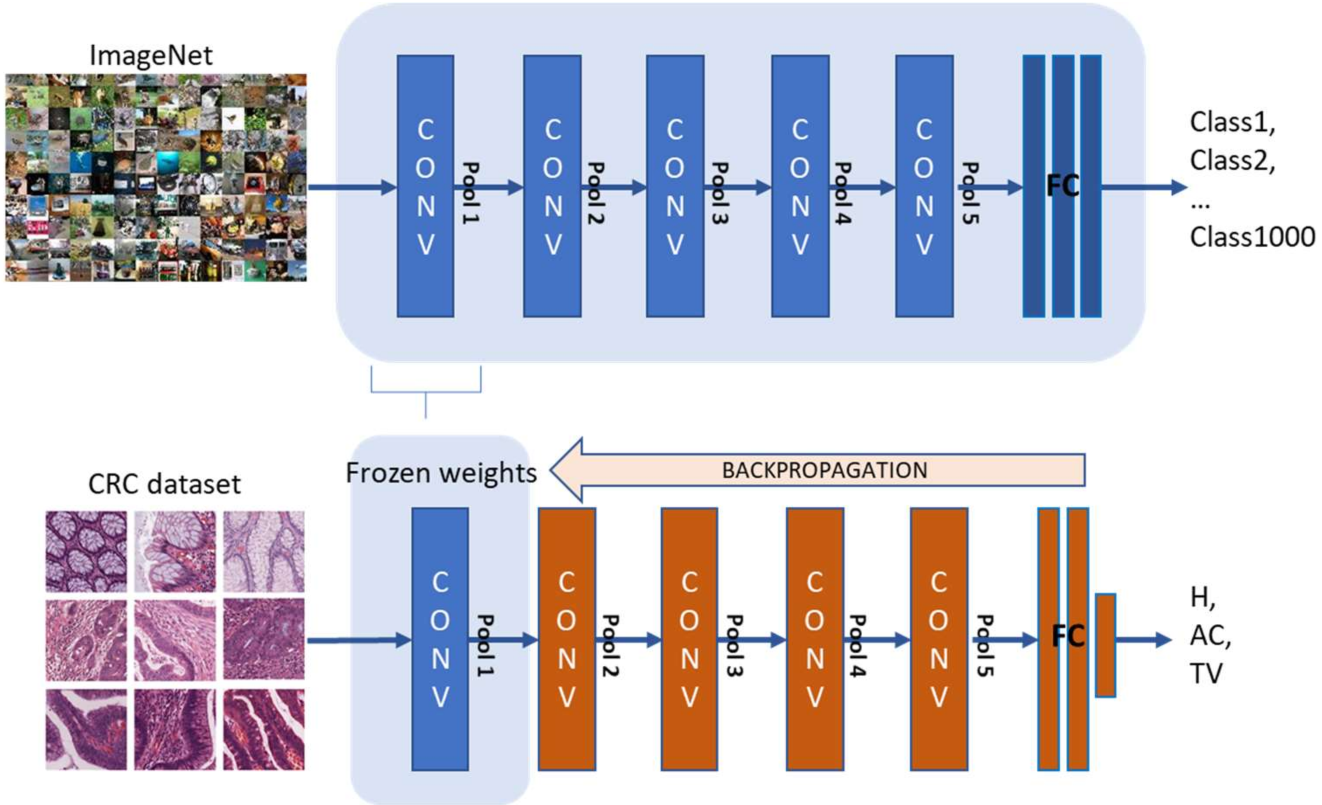


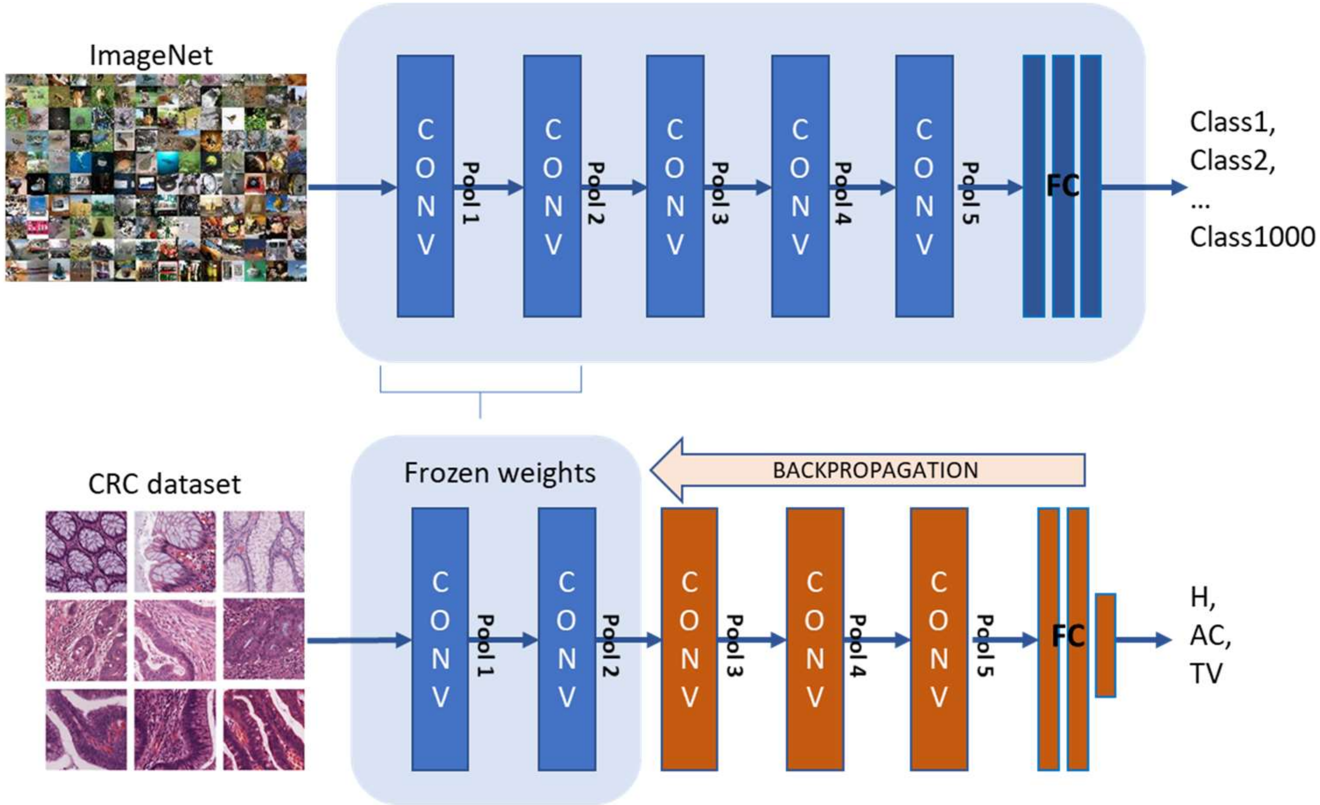
Materials and methods

CNN fine tuning



- Different configuration for the fine tuning by changing the starting block for the backpropagation algorithm

CNN fine tuning



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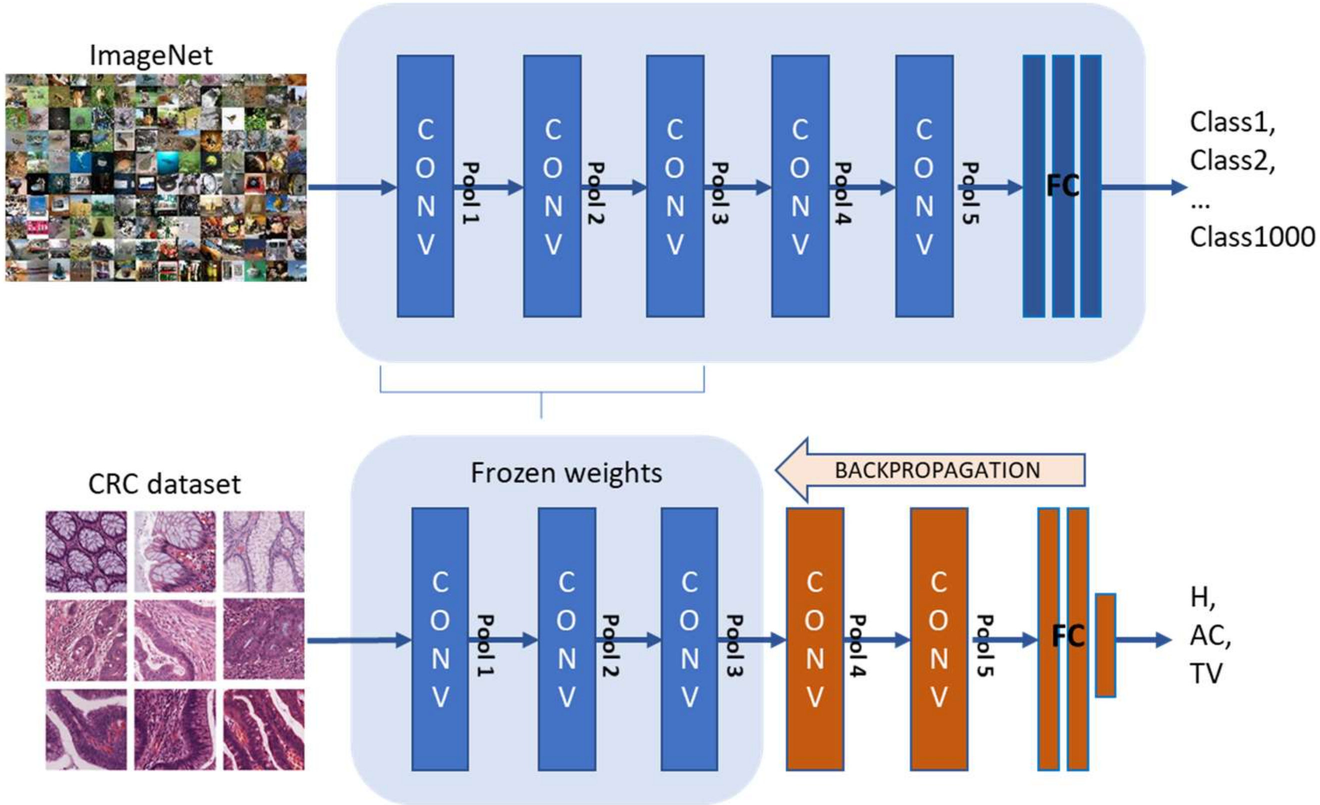

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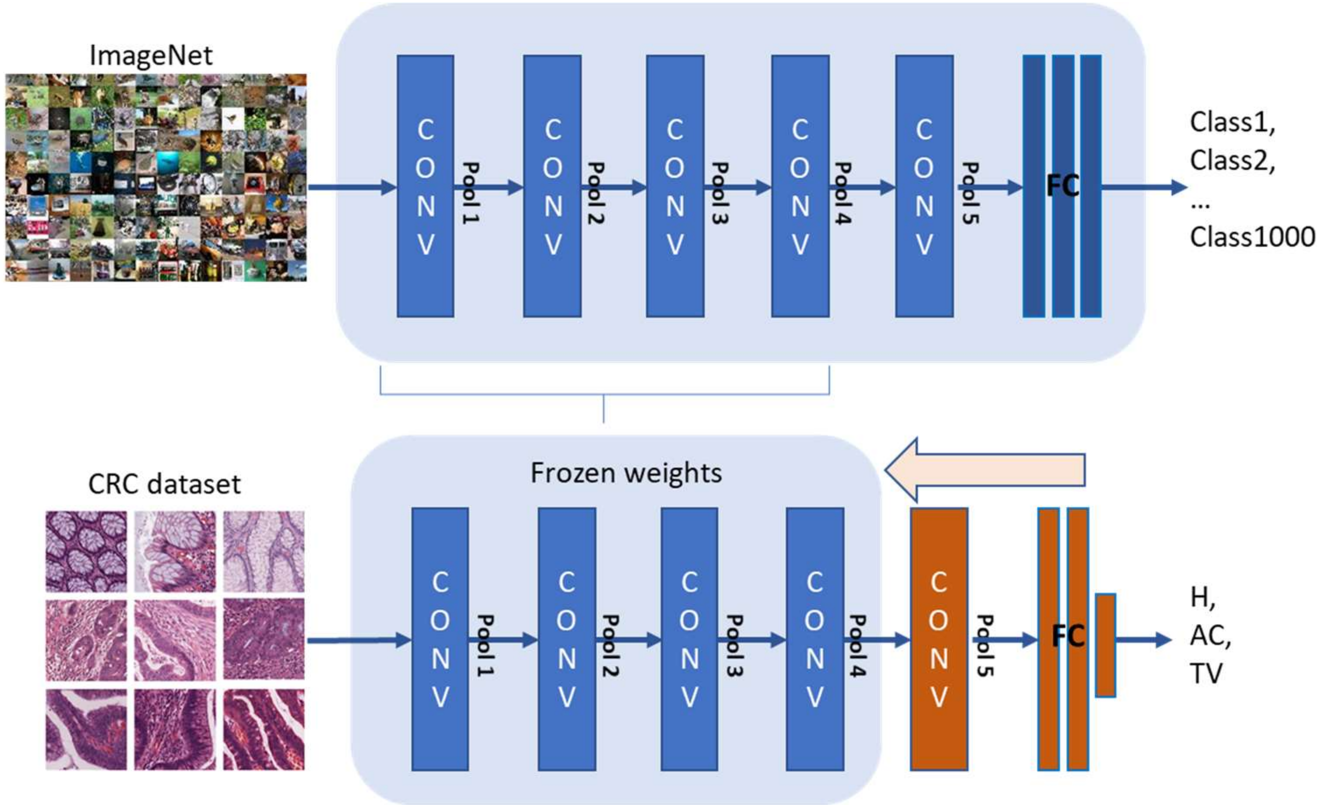

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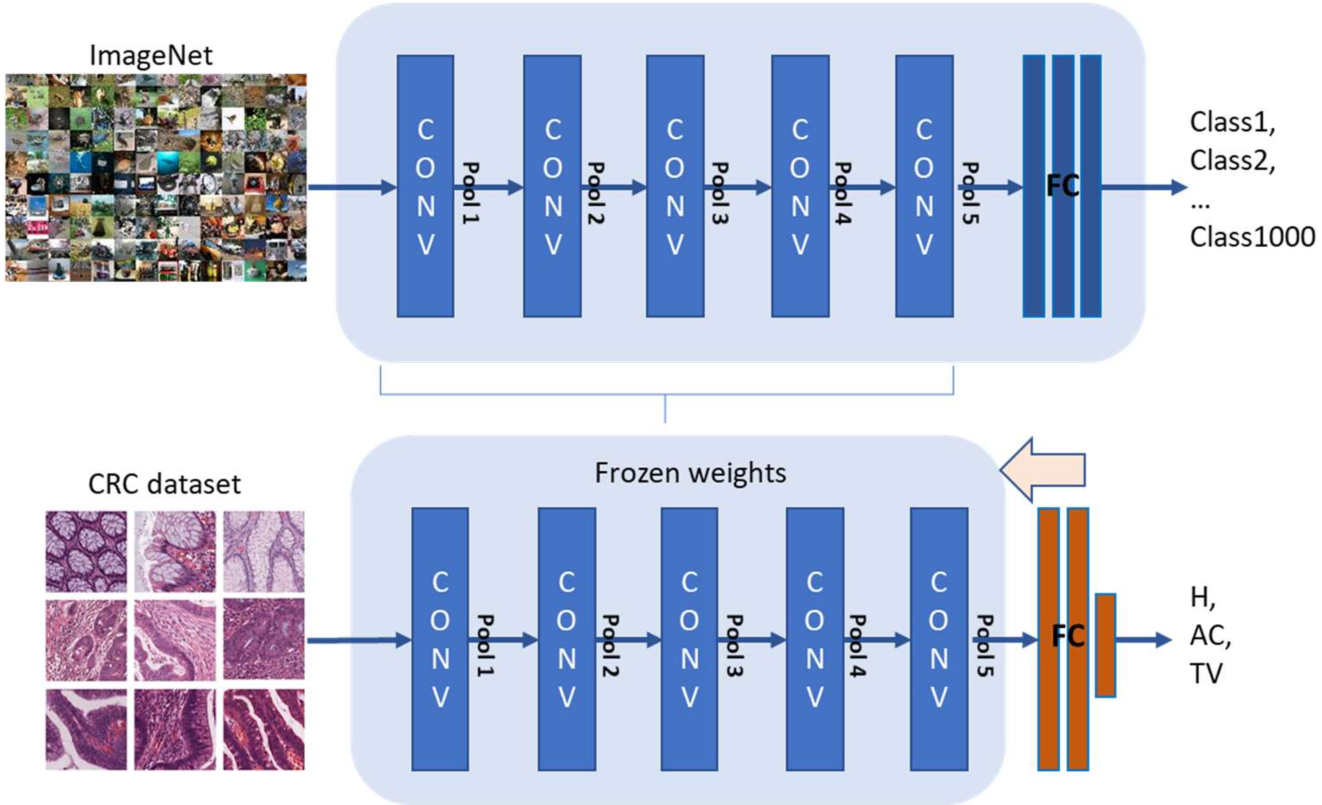

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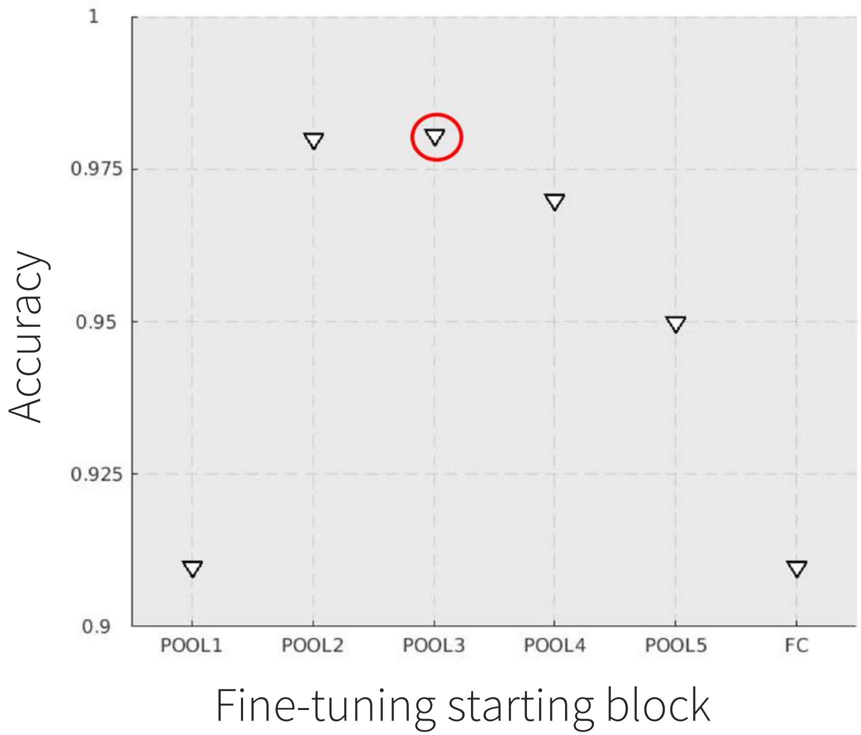

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