Metabolic Intelligence

SOCIETÀ ITALIANA DI FISICA

MODEL-FREE SEMANTIC SEGMENTATION FOR THE EARLY DETECTION OF METABOLIC ABNORMALITIES THROUGH MACHINE-LEARNING ALGORITHMS

Giada Bianchetti[1,2], Marco De Spirito[1,2], Giuseppe Maulucci[1,2]

[1] Neuroscience Department – Biophysics Section - Università Cattolica del Sacro Cuore, Rome
[2] Fondazione Policlinico Universitario «A. Gemelli» IRCSS, Rome

Tuesday, September 14, 2021

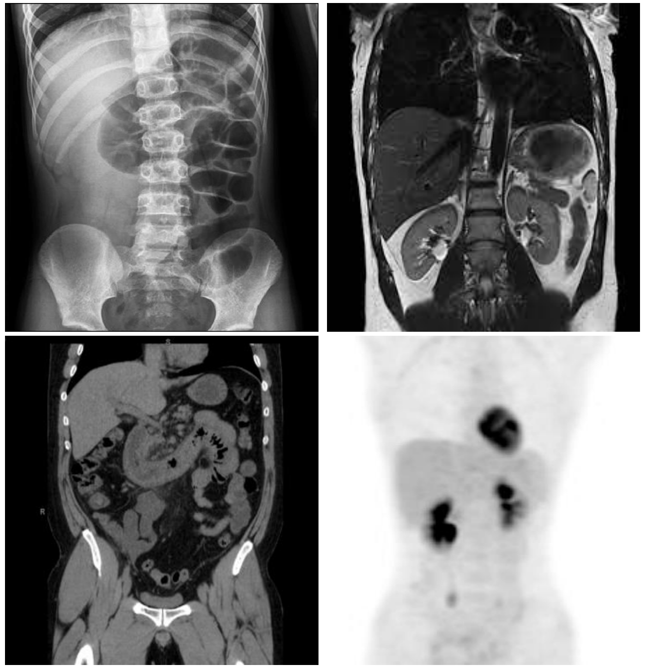
107° Congresso Nazionale – Società Italiana di Fisica

Introduction

Medical Imaging

MEDICAL IMAGING

Technique and process of imaging
the interior of a body



Introduction

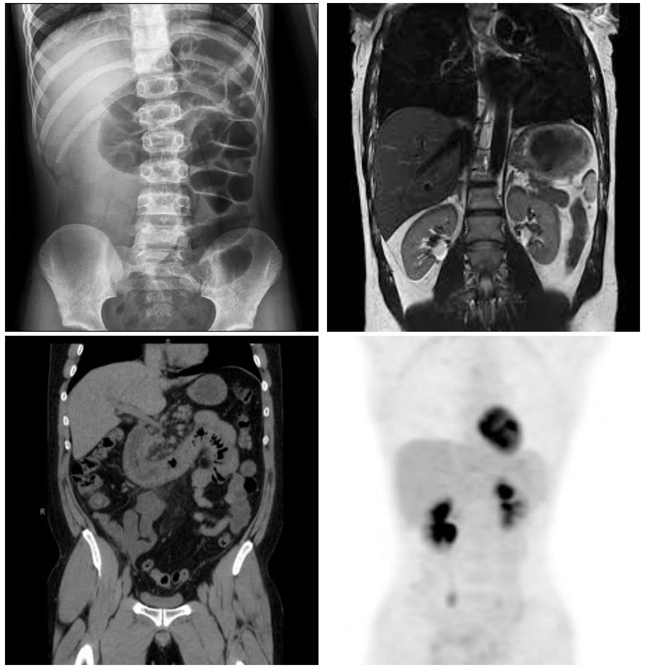
Medical Imaging

MEDICAL IMAGING

Technique and process of imaging
the interior of a body

clinical analysis

medical intervention



Introduction

Medical Imaging

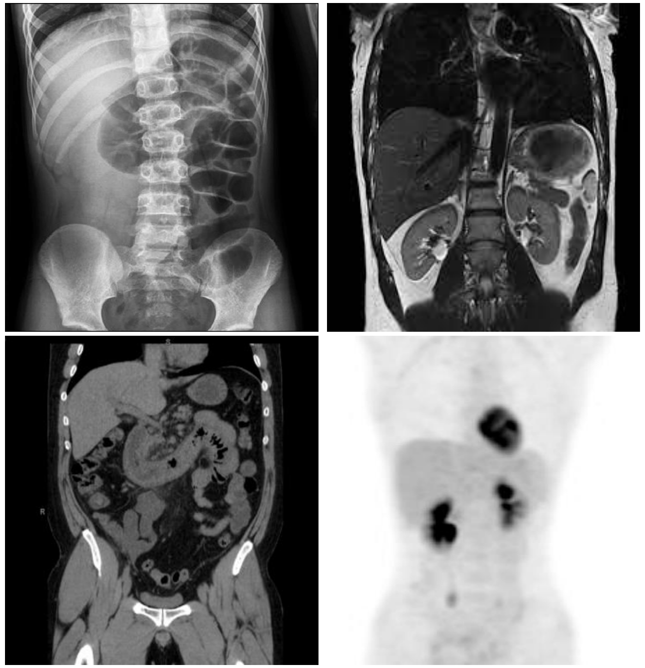
MEDICAL IMAGING

Technique and process of imaging
the interior of a body

clinical analysis

medical intervention

CANCER DIAGNOSIS



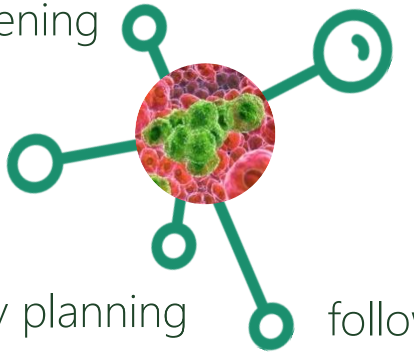
Introduction

Cancer diagnosis

MEDICAL IMAGING

↓

CANCER DIAGNOSIS



Introduction

Cancer diagnosis

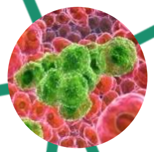
MEDICAL IMAGING

↓

CANCER DIAGNOSIS →

- ❖ Localization
- ❖ Identification
- ❖ Spreading

⇒ prognosis



screening

staging

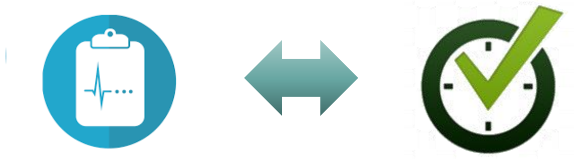
long-term monitoring

therapy planning

follow-up

Introduction

The importance of early detection



Good prognosis

Early detection

SCREENING

DIAGNOSTIC METHODS

- ✓ to differentiate between cancer and other processes
- ✓ to precisely determine the location and the extension of the tumor

Introduction

Diagnostic imaging

DIAGNOSTIC IMAGING

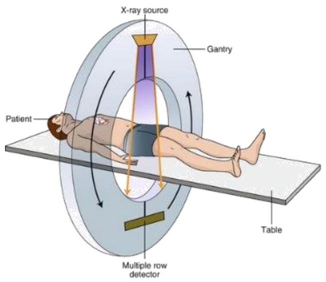
- STRUCTURAL
- FUNCTIONAL

Introduction
Diagnostic imaging

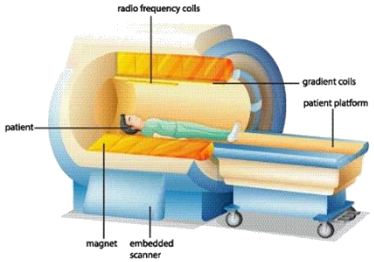
DIAGNOSTIC IMAGING

- ❖ STRUCTURAL
- ❖ FUNCTIONAL

Computed Tomography (CT)



Magnetic Resonance (MRI)



Introduction

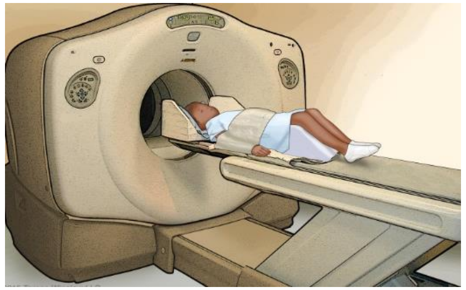
Diagnostic imaging

DIAGNOSTIC IMAGING

- STRUCTURAL
- FUNCTIONAL

Positron Emission Tomography (PET)

Single-Photon Emission Computed Tomography (SPECT)



Introduction

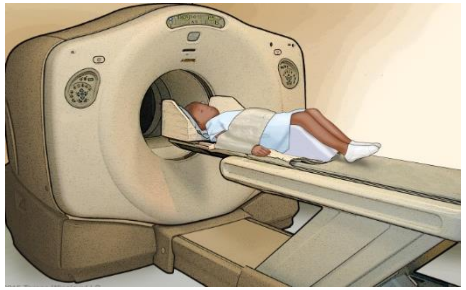
Diagnostic imaging

DIAGNOSTIC IMAGING

- STRUCTURAL
- FUNCTIONAL

POSITRON EMISSION TOMOGRAPHY (PET)

Single-Photon Emission Computed Tomography (SPECT)



Introduction

Diagnostic imaging

DIAGNOSTIC IMAGING

- STRUCTURAL
- FUNCTIONAL

POSITRON EMISSION TOMOGRAPHY (PET)

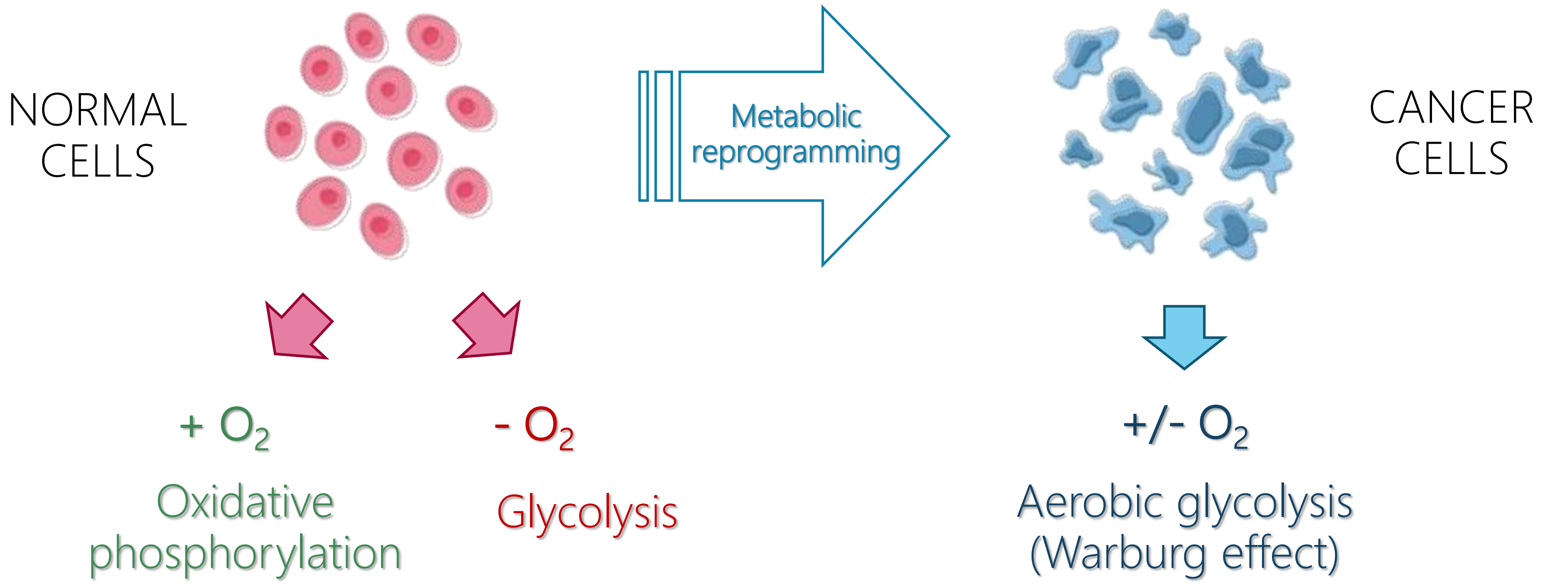
non-destructive

non-invasive

tissue metabolism

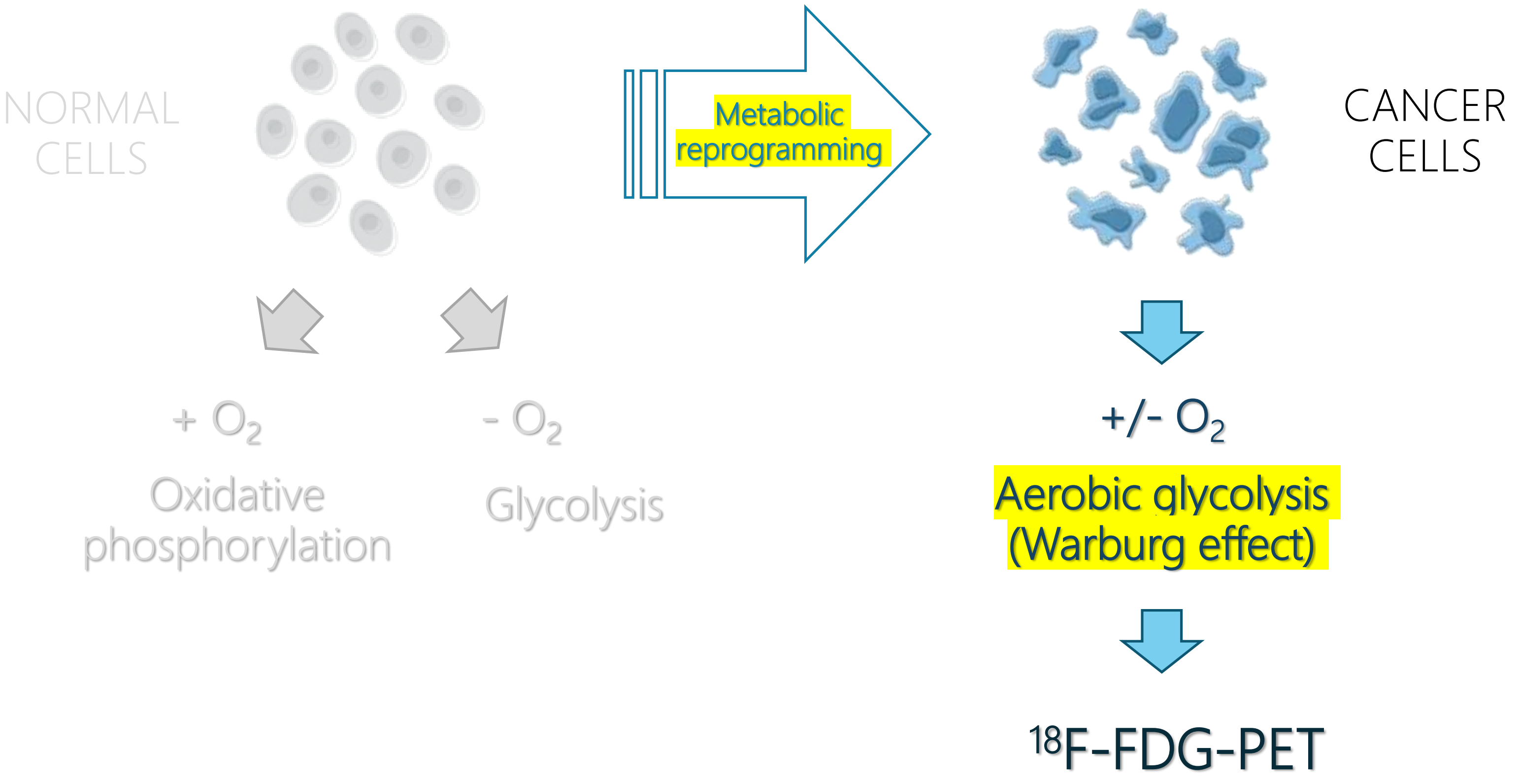
Introduction

Warburg Effect



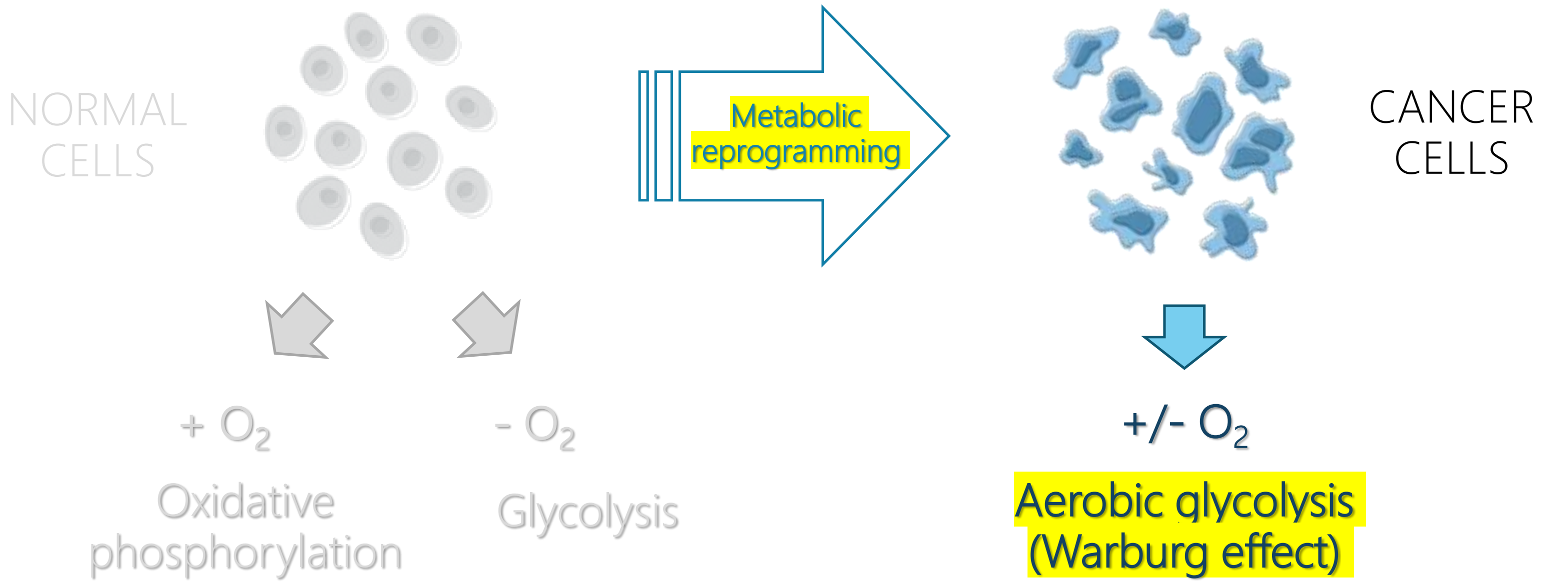
Introduction

Warburg Effect

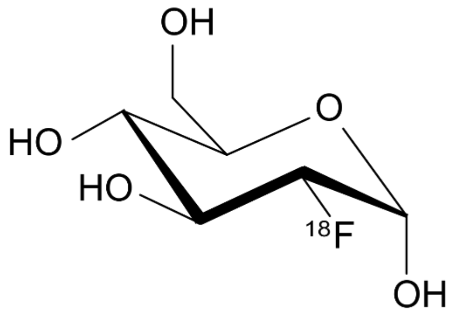


Introduction

Warburg Effect



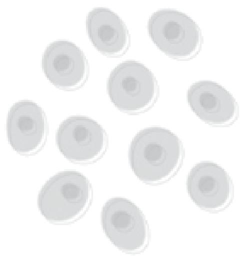
^{18}F-FDG-PET



Introduction

Warburg Effect

NORMAL CELLS



Metabolic reprogramming

CANCER CELLS

+ O_2

Oxidative phosphorylation

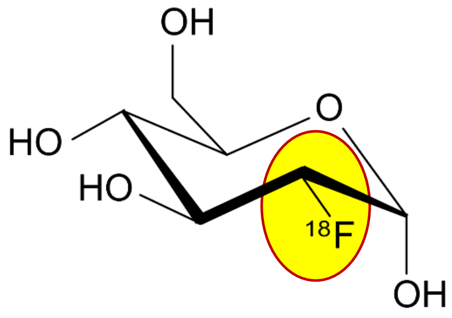
- O_2

Glycolysis

+/- O_2

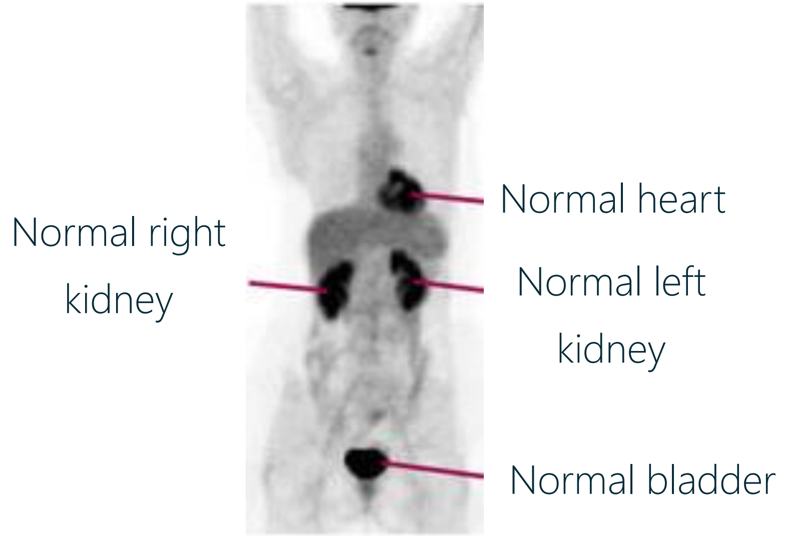
Aerobic glycolysis (Warburg effect)

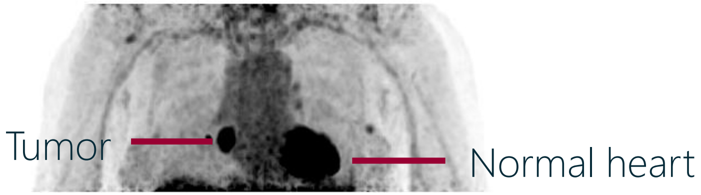
^{18}F-FDG-PET



Introduction

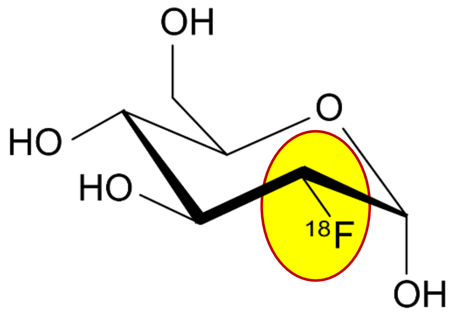
Warburg Effect





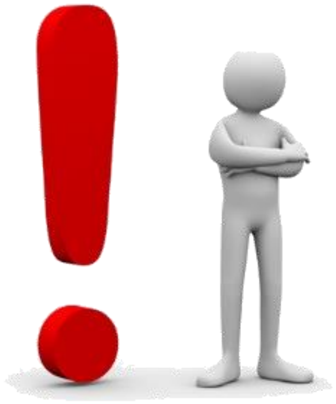
Aerobic glycolysis (Warburg effect)

^{18}F-FDG-PET



Introduction

FDG-PET: limits



- High physiological activity in organs (liver, brain)
- Suboptimal preparation of diabetic patients
- Infectious and/or inflammatory processes

Signal to noise ratio

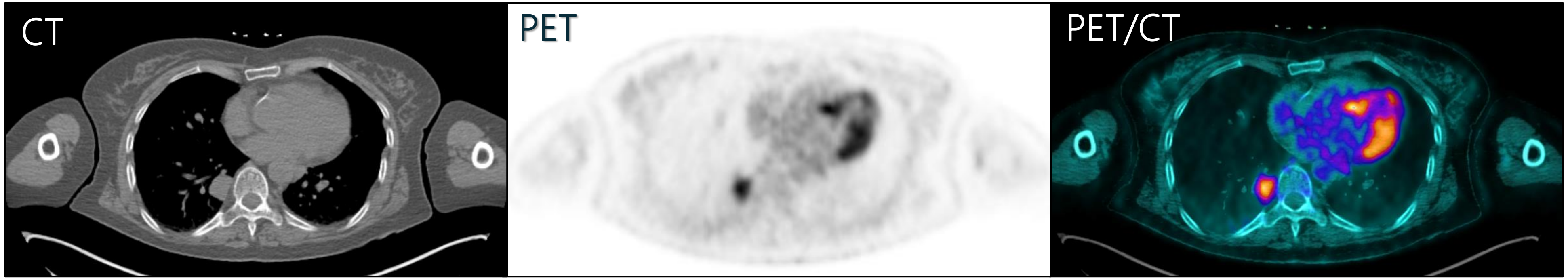
False-positive results

Multi-modal approaches

PET/CT fusion imaging

MULTI-MODAL IMAGING APPROACHES → PET/CT fusion

- × Artifacts due to physiologic motions
- × Spatial misregistration

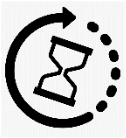


Dynamic PET imaging

A deeper metabolic characterization

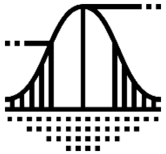
Registration of the tracer kinetics over time → pharmacokinetic

i. temporally resolved
ii. pixel resolution



Time consuming

Instrumental and analysis factors



Mathematical models for data analysis

Invasive continuous monitoring

Dynamic PET imaging

A deeper metabolic characterization

Time consuming

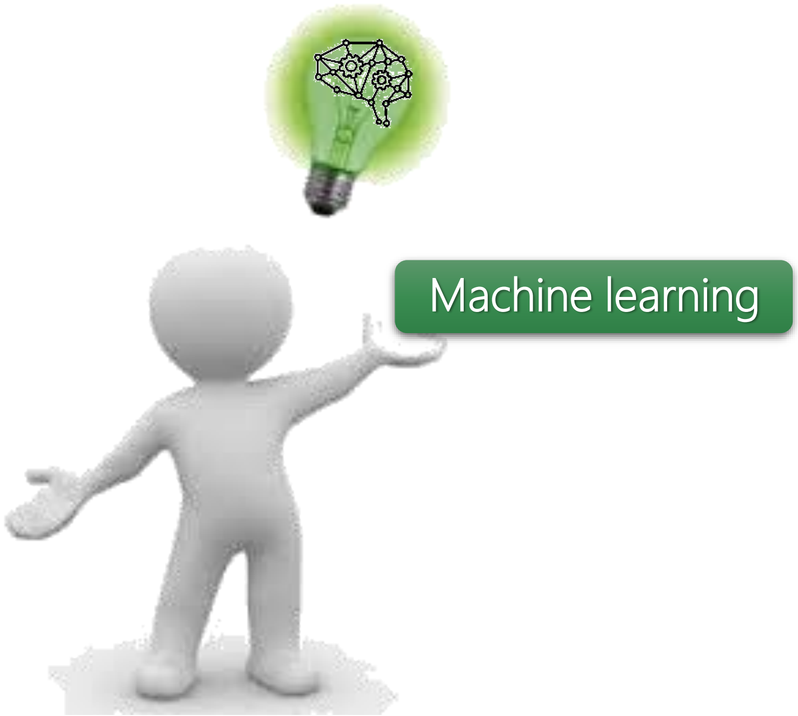
Instrumental and analysis factors

Mathematical models for data analysis

Invasive continuous monitoring

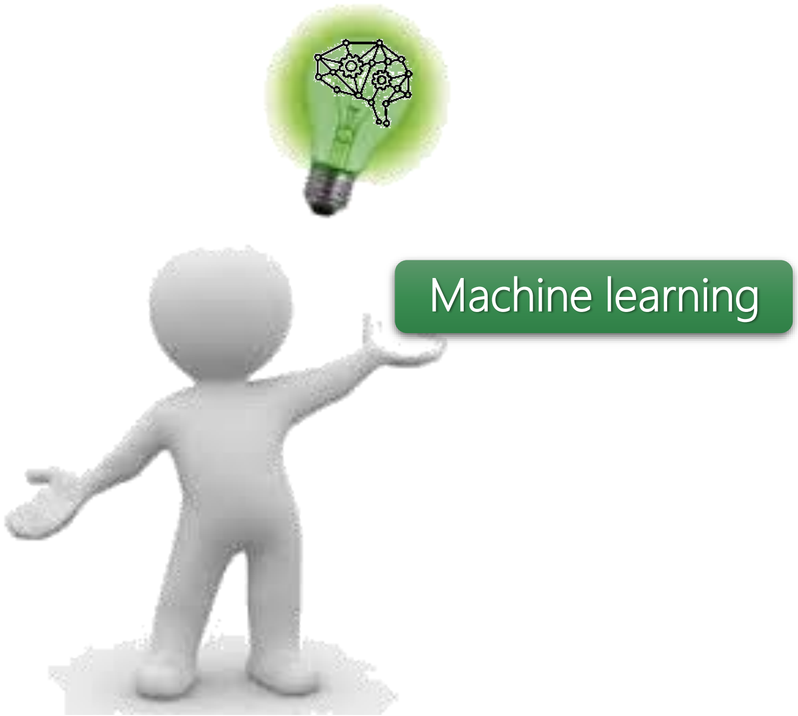
Dynamic PET imaging

A deeper metabolic characterization



Bio-image analysis

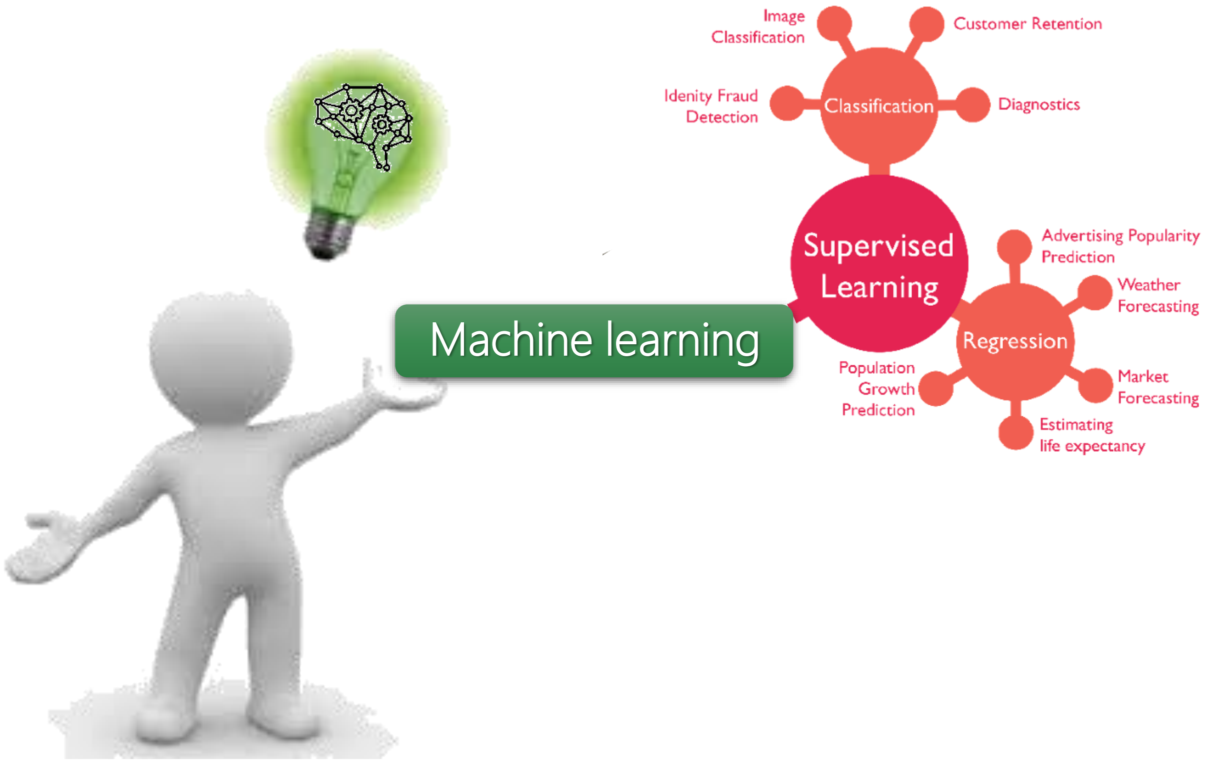
Introduction of Machine-Learning



- Provide a way for analysis automation
- Avoid manual adjustments of pipeline
- More flexible for multidimensional data analysis tasks
- Provide new insights in metabolic features

Machine Learning

Introduction



Example **inputs** and **desired outputs** (given by a "teacher")

to learn a <u>general rule</u> that <u>maps inputs to outputs</u>.

Pixel-classification

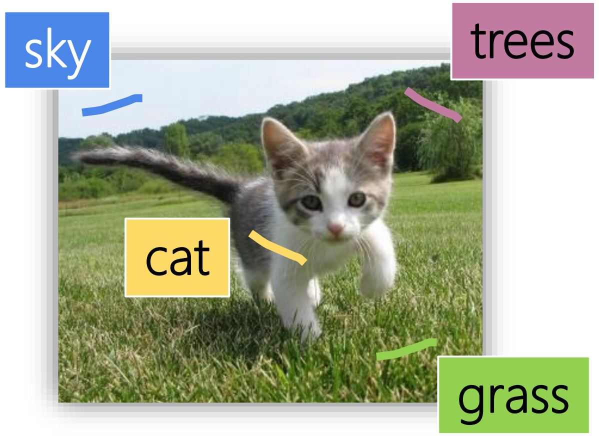
Pixel-classification

How it works

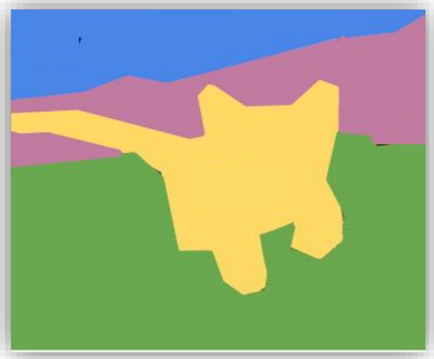
Pixel-classification

- Relies on examples provided by the user => *training set*
- The algorithm bases its decisions on criteria called *features*
- Generalize as well as possible on unseen data => *test set*

Input image



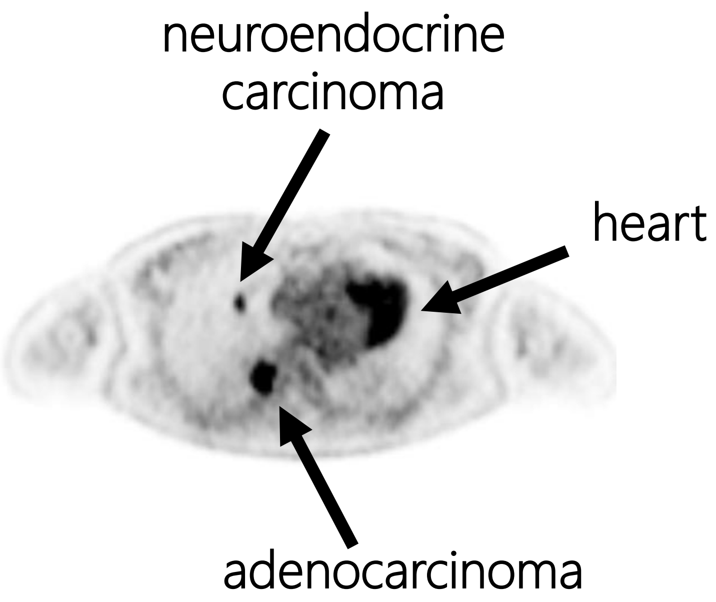
User annotations



Semantic segmentation

Pixel-classification

What it can do



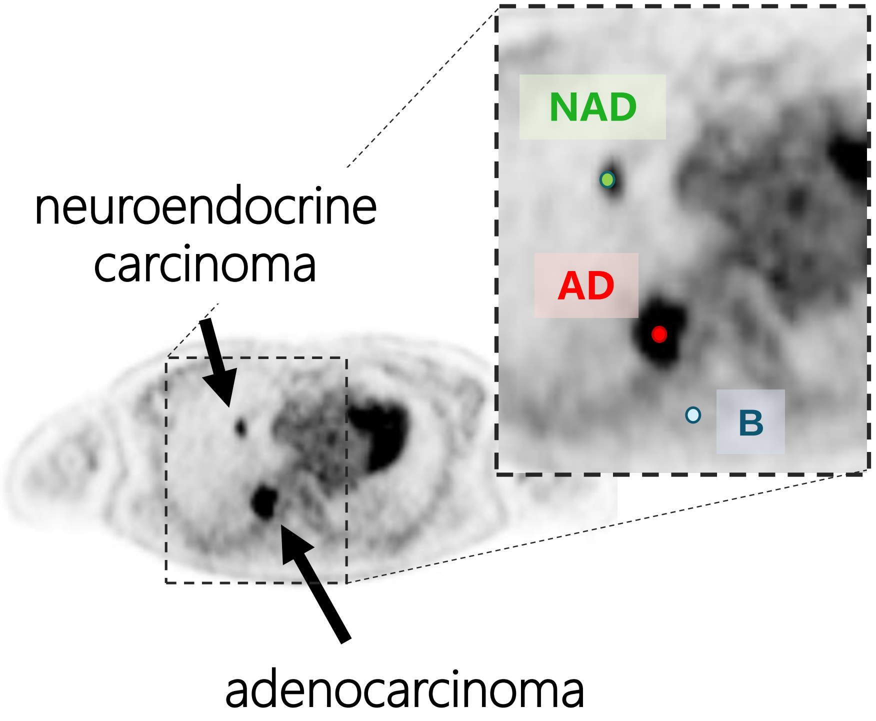
No differences in intensity

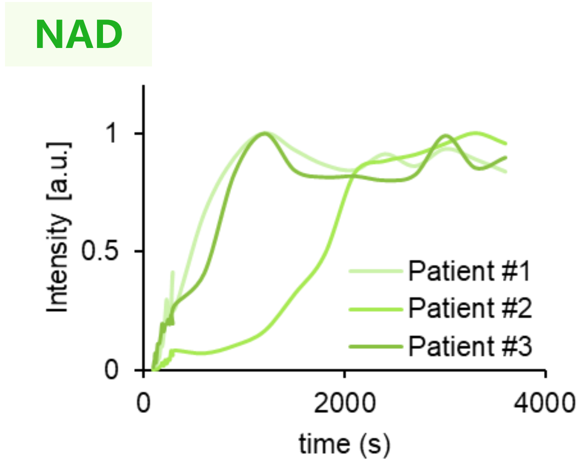
Pixel-classification

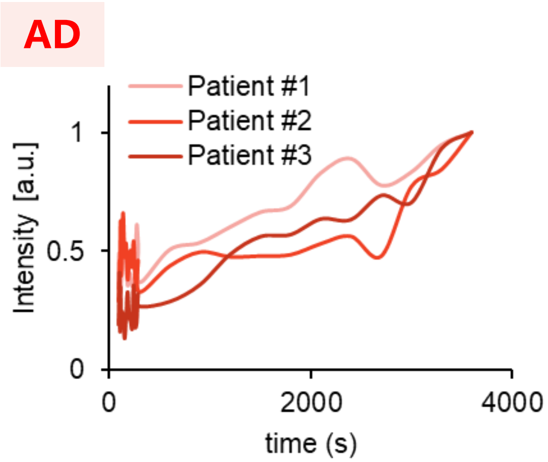
What it can do

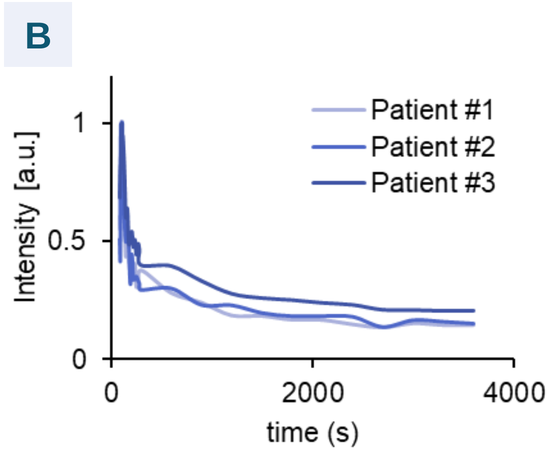
What about the kinetic of FDG uptake?

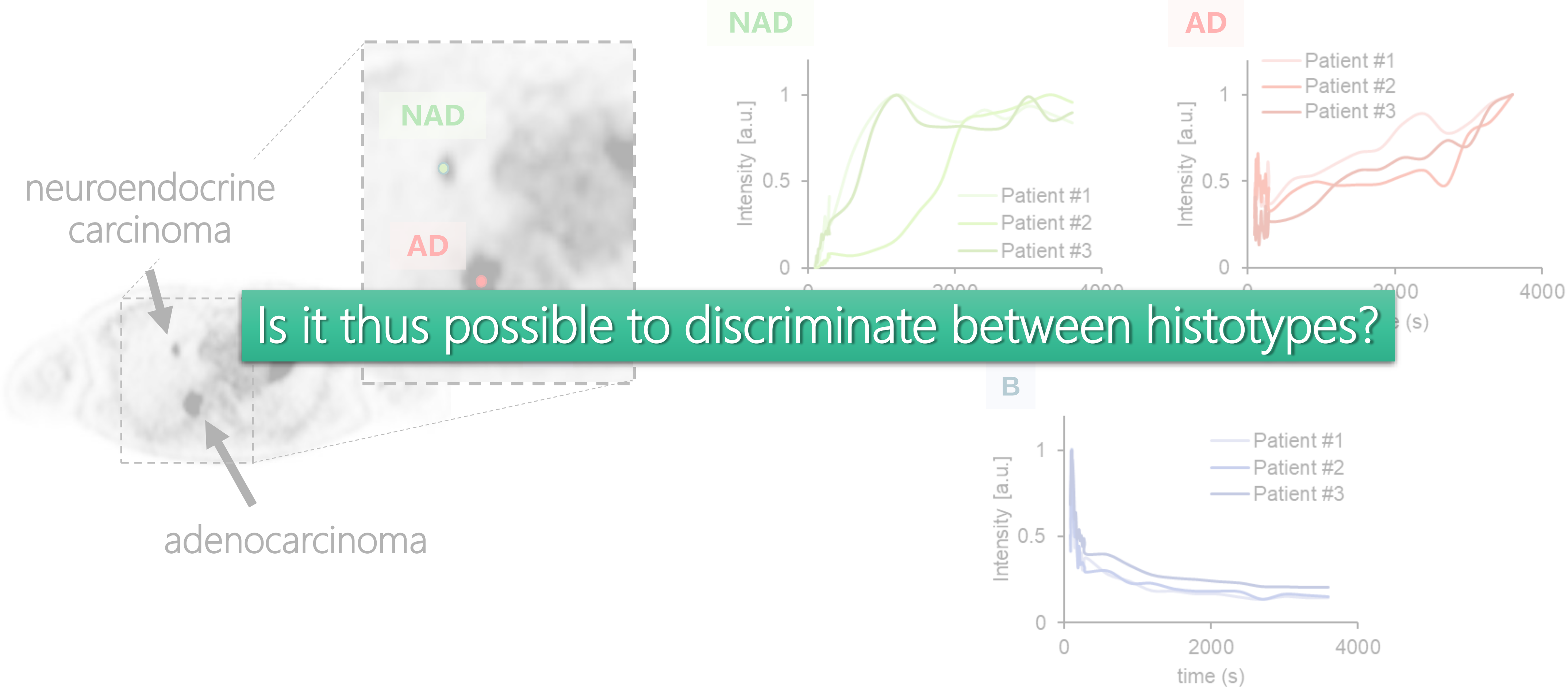
What about the kinetic of FDG uptake?











Is it thus possible to discriminate between histotypes?

Is it thus possible to discriminate between histotypes?

- Model-free
- Machine-learning based

METHOD

Identification of different histotypes

Probability of tumor's spreading

Is it thus possible to discriminate between histotypes?

dPET stack

Detection of AD

Detection of NAD

Localization

Probability

dPET stack

Detection of AD

Detection of NAD

Localization

Probability

47 time-channels

512x512 pixel resolution

Ilastik

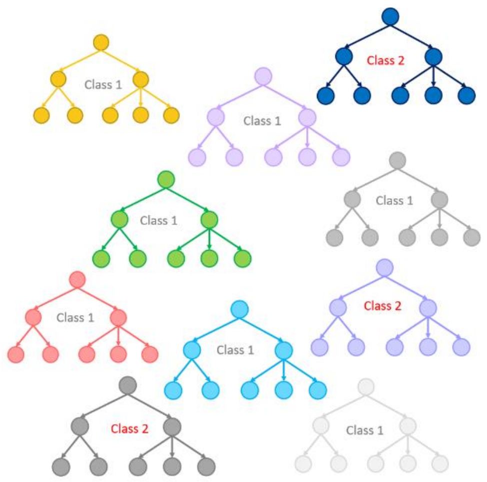
dPET stack

Detection of AD

Detection of NAD

Localization

Probability



Adenocarcinoma (AD)

Non-Adenocarcinoma (NAD)

Background

multiple decision trees taken into
consideration for the final classification

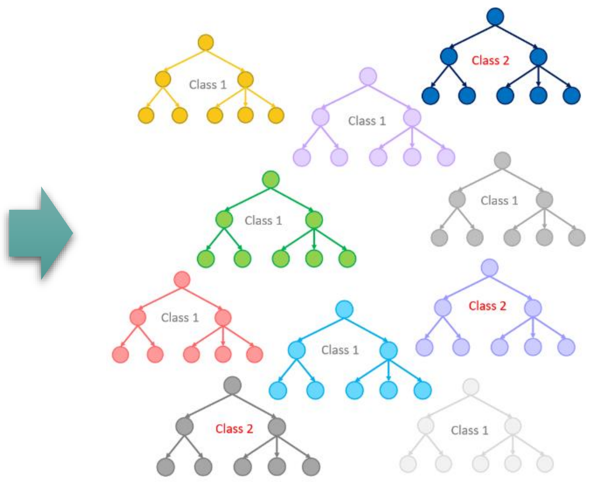
dPET stack

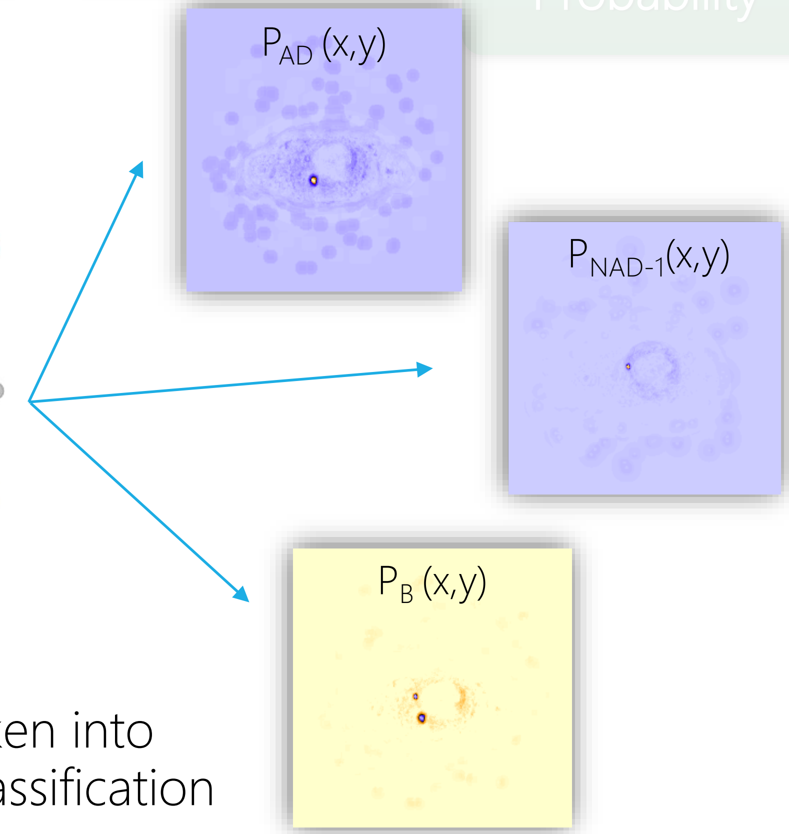
Detection of AD

Detection of NAD

Localization

Probability





multiple decision trees taken into consideration for the final classification

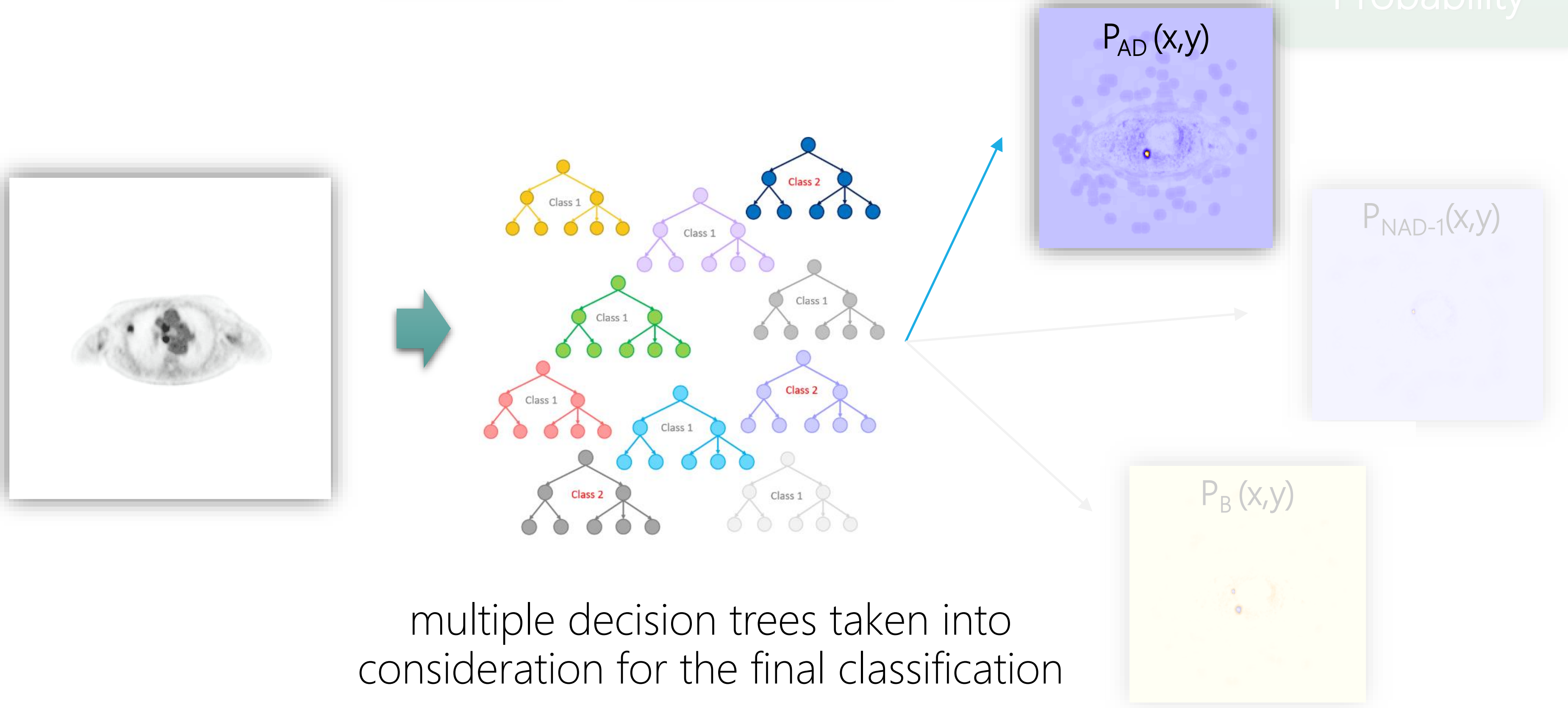
dPET stack

Detection of AD

Detection of NAD

Localization

Probability



multiple decision trees taken into consideration for the final classification

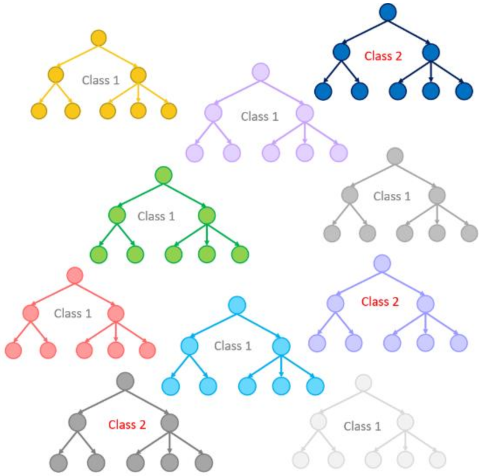
dPET stack

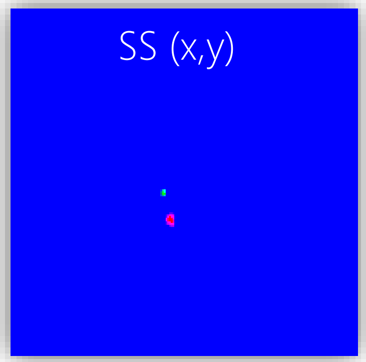
Detection of AD

Detection of NAD

Localization

Probability





multiple decision trees taken into consideration for the final classification

dPET stack

Detection of AD

Detection of NAD

Localization

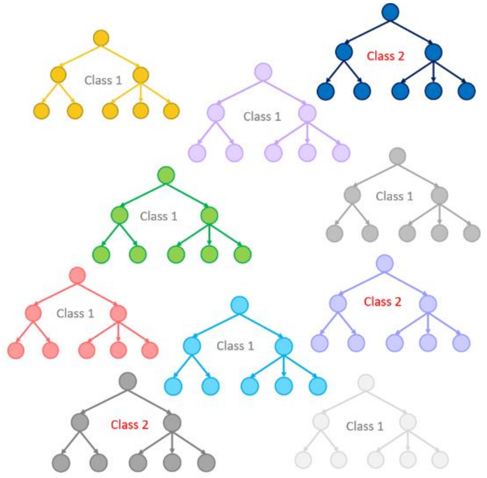
Probability

47 time-channels + 1 (semantic segmentation)

512x512 pixel resolution

Metabolic Intelligence

dPET stack | Detection of AD | **Detection of NAD** | Localization | Probability



Non-Adenocarcinoma (NAD)

Background

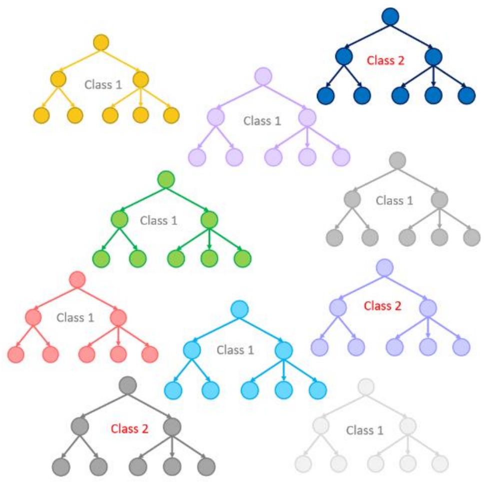
dPET stack

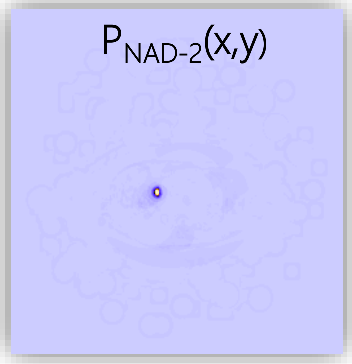
Detection of AD

Detection of NAD

Localization

Probability





Background

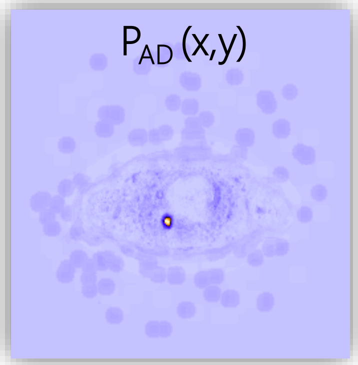
Localization

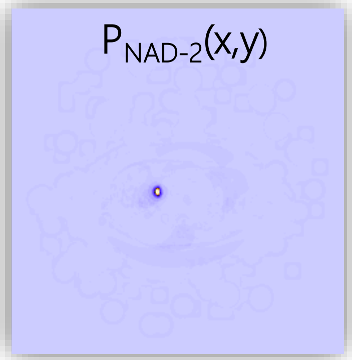
Probability

dPET stack

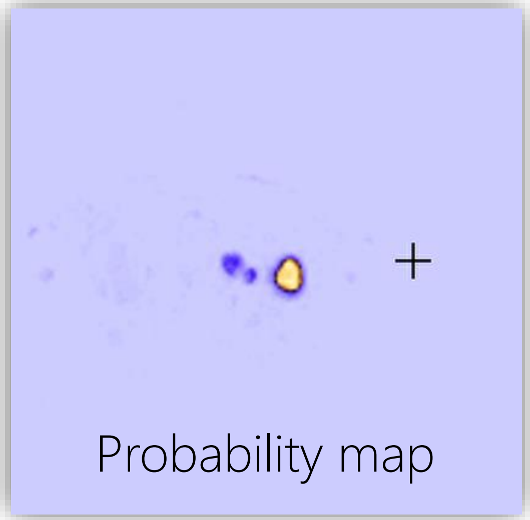
Detection of AD

Detection of NAD



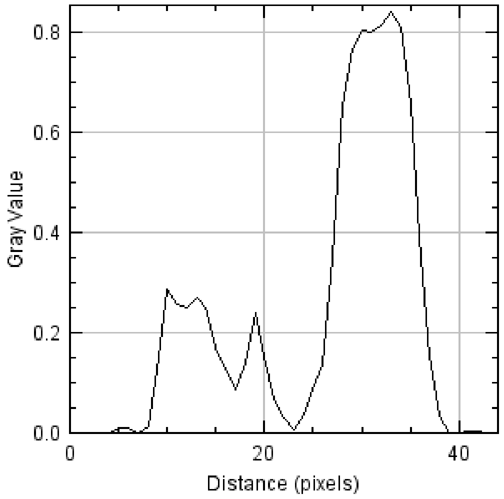


Analysis of maxima of probability



Probability map

Probability profile



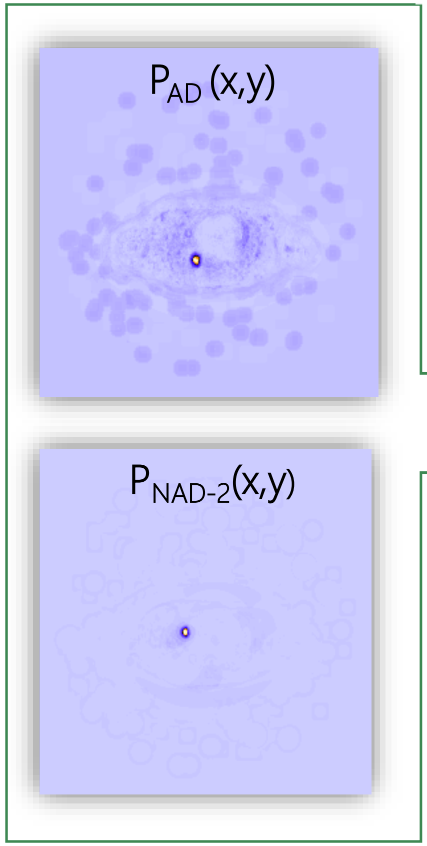
dPET stack

Detection of AD

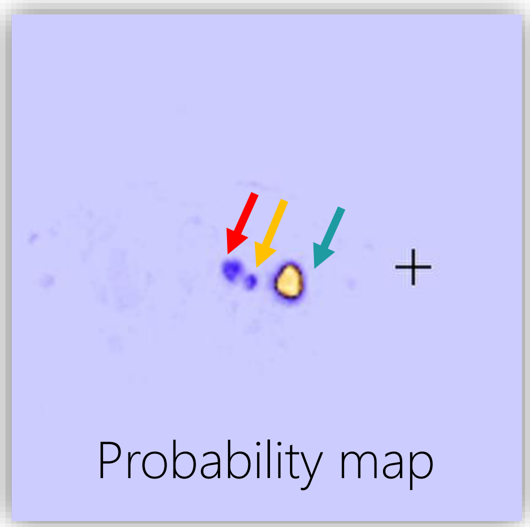
Detection of NAD

Localization

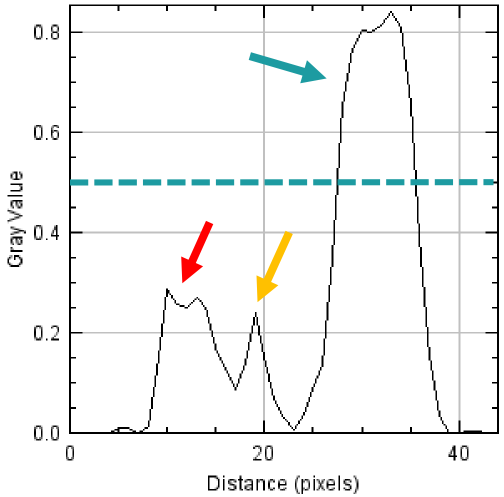
Probability



Analysis of maxima of probability



Probability profile



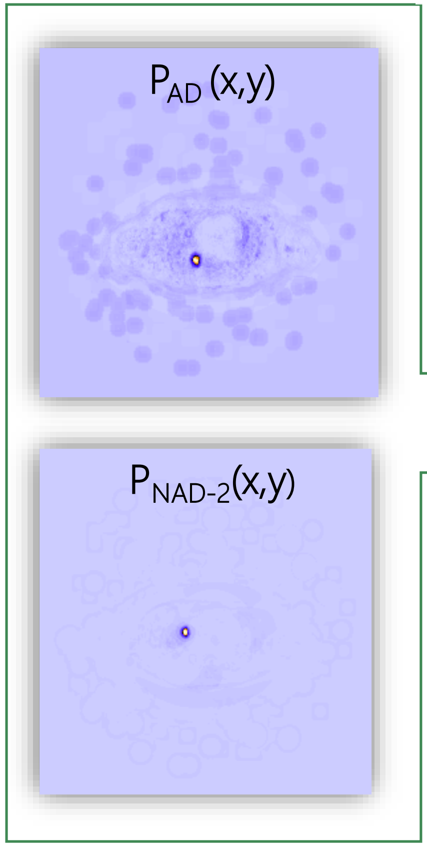
Localization

dPET stack

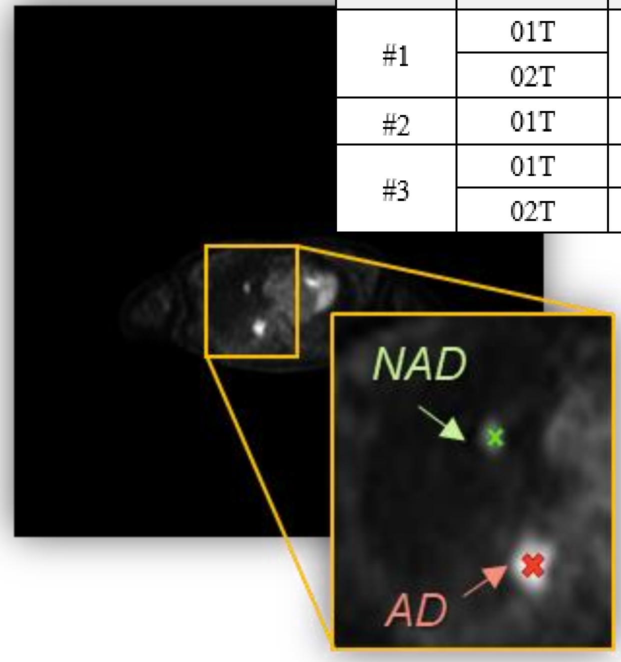
Detection of AD

Detection of NAD

Probability



Analysis of maxima of probability



Patient	# Tumors	Histotype	Classification Output	X (pixel)	Y (pixel)
#1	01T	NSCLC	AD	97	120
	02T			109	141
#2	01T	NSCLC	AD	104	152
#3	01T	AD	AD	117	155
	02T	LCNEC	NAD	112	135

Metabolic Intelligence

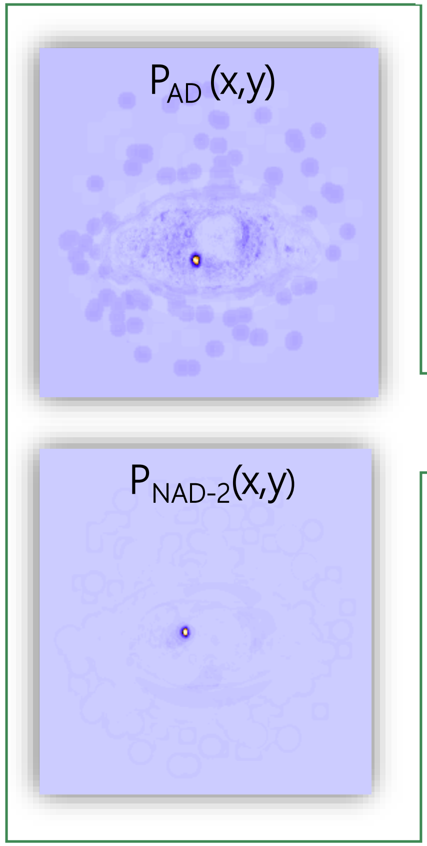
Localization

dPET stack

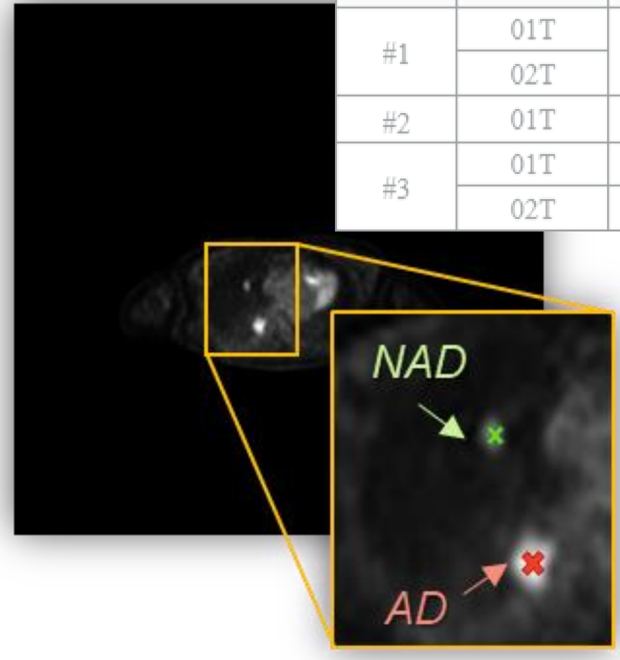
Detection of AD

Detection of NAD

Probability



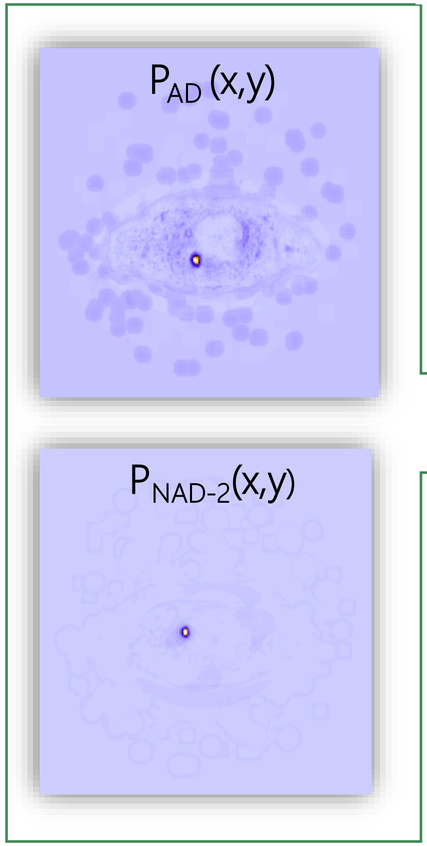
Analysis of maxima of probability



Patient	# Tumors	Histotype	Classification Output	X (pixel)	Y (pixel)
#1	01T	NSCLC	AD	97	120
	02T			109	141
#2	01T	NSCLC	AD	104	152
#3	01T	AD	AD	117	155
	02T	LCNEC	NAD	112	135

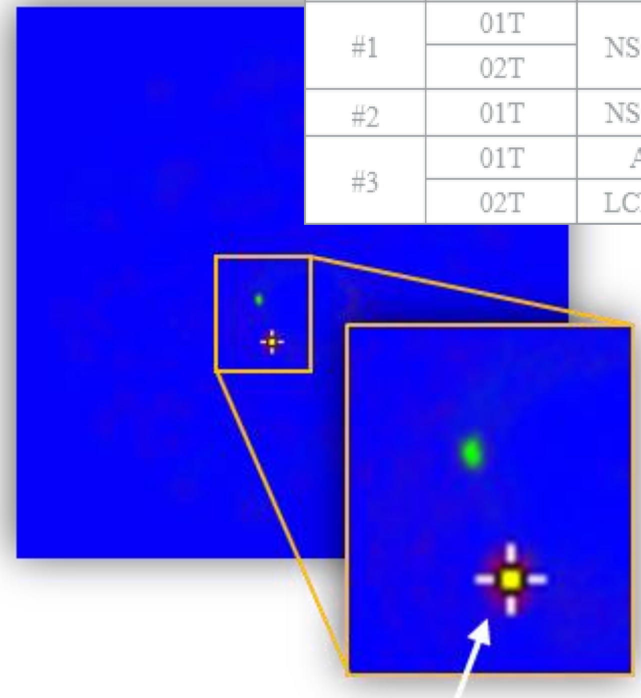
dPET stack | Detection of AD | Detection of NAD | Localization | **Probability**

Probability



Analysis of maxima of probability

Patient	# Tumors	Histotype	Classification Output	Probability	Uncertainty
#1	01T	NSCLC	AD	1	0
	02T			0.64	0
#2	01T	NSCLC	AD	0.93	0.13
#3	01T	AD	AD	0.94	0.12
	02T	LCNEC	NAD	1	0



$P_{AD} = 0.94$

Tumor's spreading

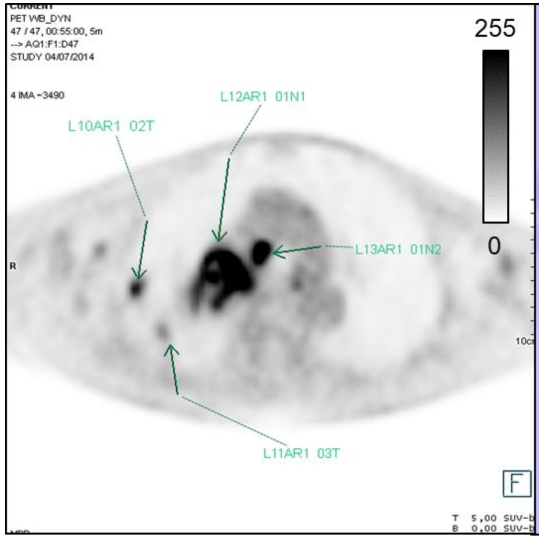
Evaluation of the lymph-node metastatic risk

Analysis of maxima of probability

Presence of local maxima associated to lymph-nodes

Tumor's spreading

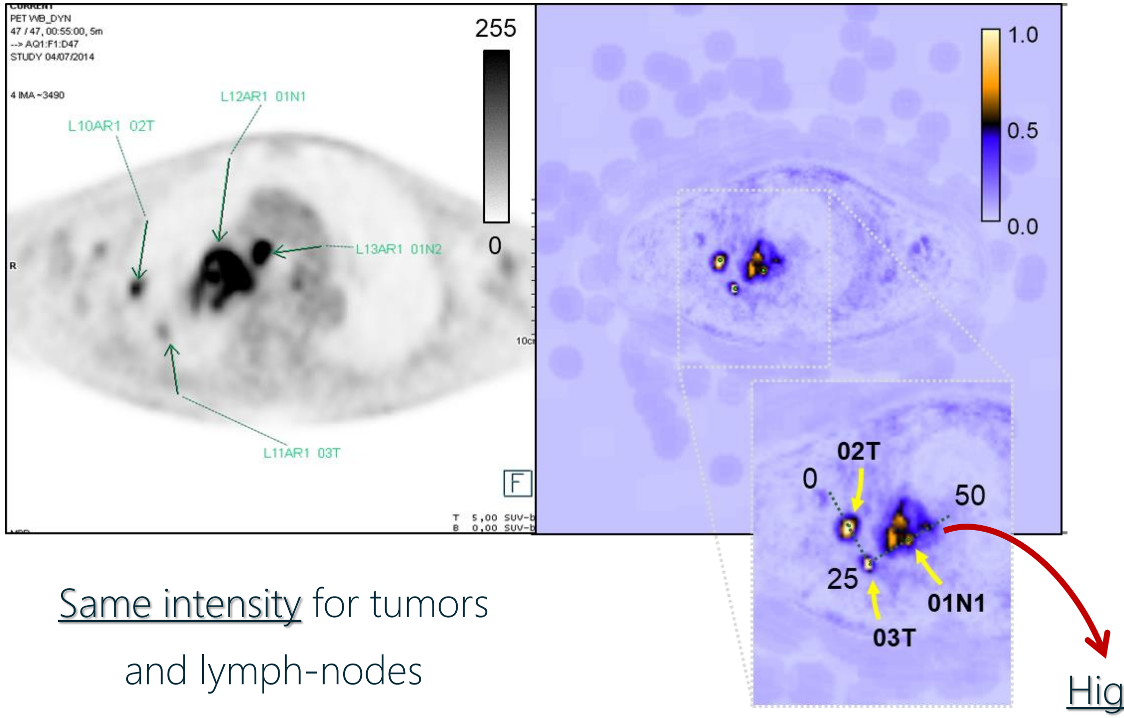
Evaluation of the lymph-node metastatic risk



Same intensity for tumors
and lymph-nodes

Tumor's spreading

Evaluation of the lymph-node metastatic risk

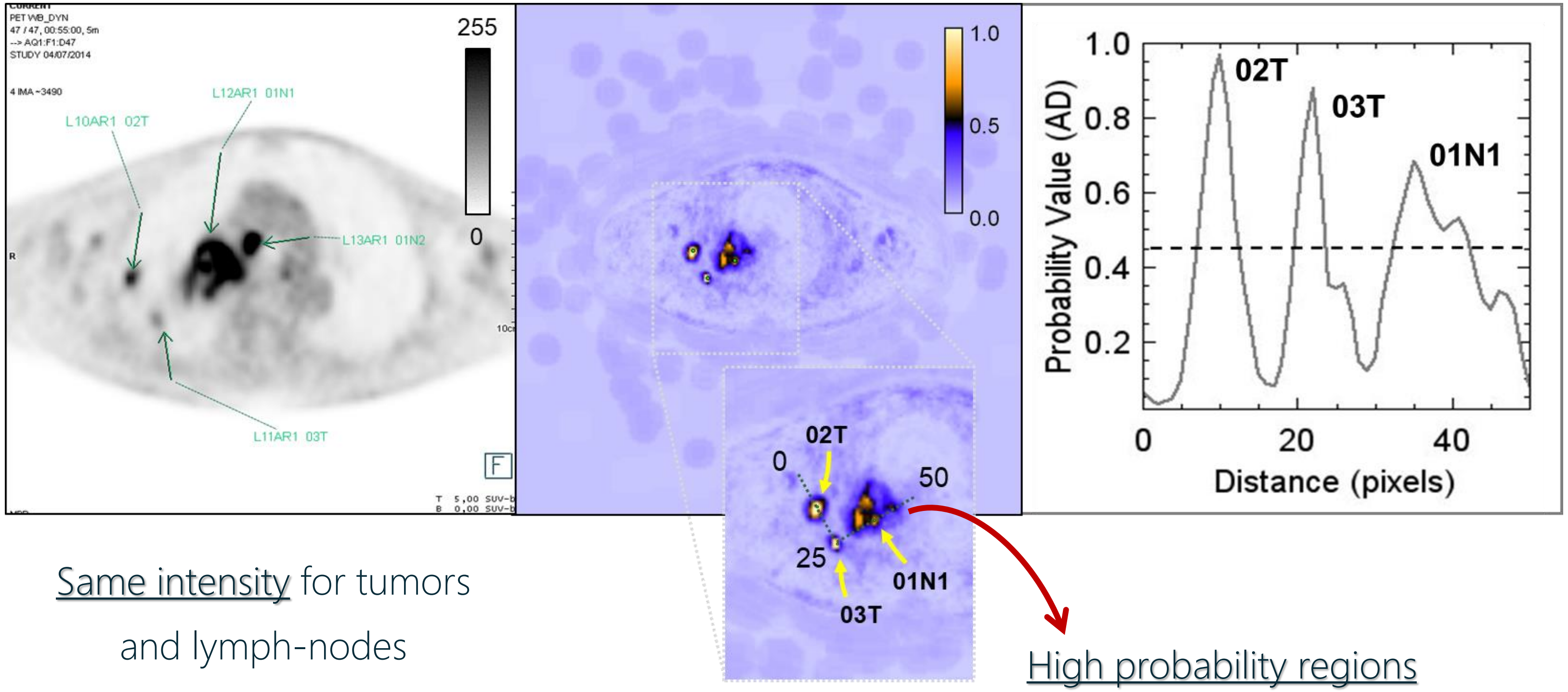


Same intensity for tumors and lymph-nodes

High probability regions revealed by the classifier

Tumor’s spreading

Evaluation of the lymph-node metastatic risk



Same intensity for tumors and lymph-nodes

High probability regions revealed by the classifier

Early detection of impaired metabolism regions

Metabolic Intelligence

Conclusions, limits and future perspectives

- ❖ Model-free
- ❖ Multi-stage pixel classification
- ❖ Combining spatial features and uptake kinetic

Automated detection and classification of AD and NAD on dPET imaging data

Optimal performances

Increased specificity

- × Limited number of analyzed patients → to be increased for workflow optimization
- × Still requires the temporal information → time consuming

- ✓ Automatic and accurate localization and discrimination of tumors
- ✓ Detection of tumor's spreading beyond the primary lesion into lymphatic system
- ✓ Speed-up and furnish further evidence in diagnosis and staging of lung cancer

→ early and accurate classification of tumors and metastatic lymph-nodes

1921 UN SECOLO DI STORIA DAVANTI A NOI 2021

UNIVERSITÀ CATTOLICA del Sacro Cuore

SOCIETÀ ITALIANA DI FISICA

MI Metabolic Intelligence

Department of Neuroscience - Section of Biophysics
Università Cattolica del Sacro Cuore

Fondazione Policlinico Universitario "A. Gemelli" IRCSS

Università Cattolica del Sacro Cuore

Thanks!

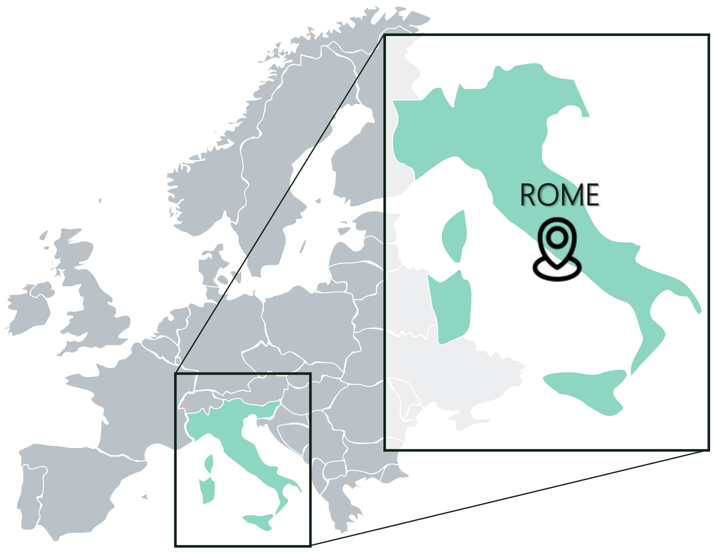

Prof. Giuseppe Maulucci


Prof. Marco De Spirito


Giada Bianchetti


Alessio Abeltino


Cassandra Serantoni



Questions?

giada.bianchetti@unicatt.it

Metabolic Intelligence Website
www.metabolicintelligence.org