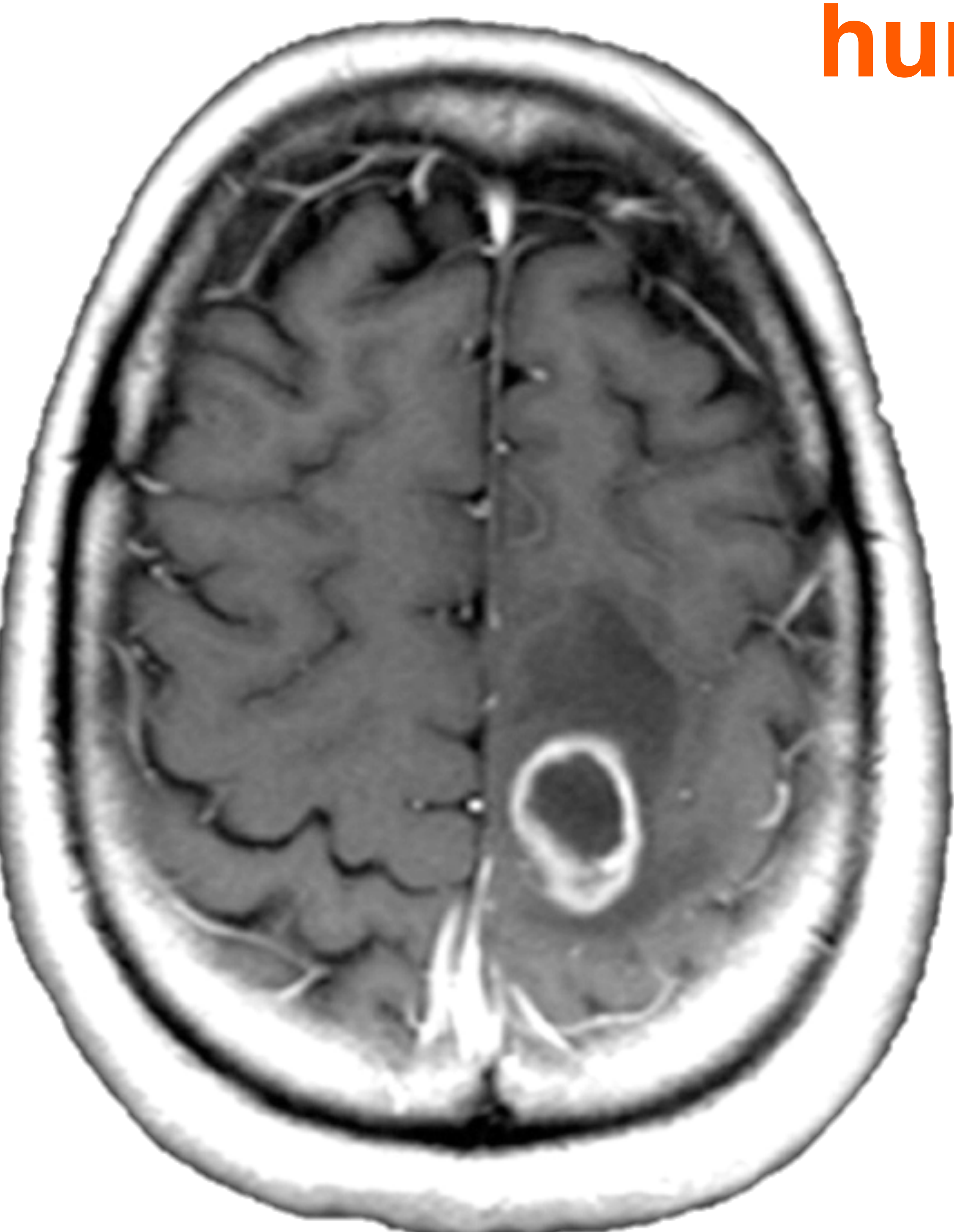
Predicción de supervivencia en glioblastoma: humano contra máquina



David Molina-García
Mathematical Oncology Laboratory
Ciudad Real (Spain)

Imaging biomarker

In medicine, an imaging biomarker is a feature of an image relevant to a patient's diagnosis. For example, a lesion in the lung detected by imaging can lead to the suspicion of a neoplasm. The lesion itself serves as a biomarker, but the minute details of the lesion serve as biomarkers as well. Some of the imaging biomarkers used in lung nodule assessment include size, spiculation, calcification, cavitation, location within the lung, rate of growth, and rate of metabolism. Spiculation increases the probability of the lesion being cancer. A slow rate of growth indicates benignity. These variables can be added to the patient's history, physical exam, laboratory tests, and pathology to reach a proposed diagnosis.

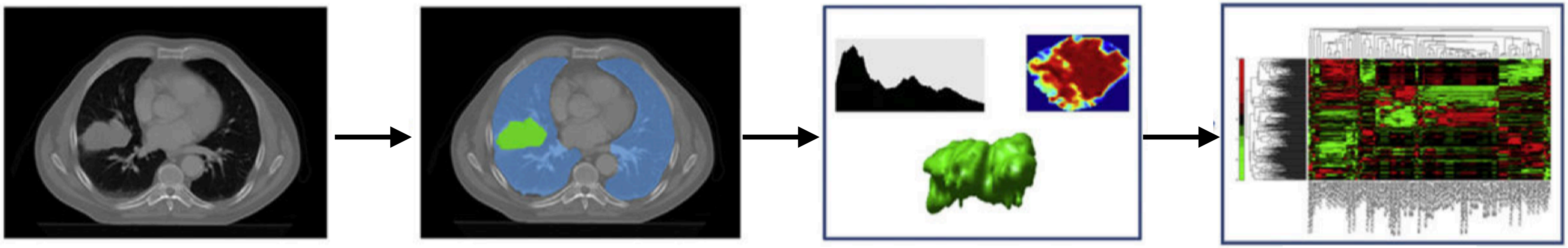
Radiology

ORIGINAL RESEARCH ■ SPECIAL REPORT

Radiomics: Images Are More than Pictures, They Are Data[1]

Robert J. Gillies, PhD
Paul E. Kinahan, PhD
Hedvig Hricak, MD, PhD, Dr(hc)

In the past decade, the field of medical image analysis has grown exponentially, with an increased number of pattern recognition tools and an increase in data set sizes. These advances have facilitated the development of processes for high-throughput extraction of quantitative features that result in the conversion of images into mineable data and the subsequent analysis of these data for decision support; this practice is termed *radiomics*. This is in contrast to the traditional practice of treating medical images as pictures intended solely for visual interpretation. Radiomic data contain first-, second-, and higher-order statistics. These data are combined with other patient data and are mined with sophisticated bioinformatics tools to develop models that may potentially improve diagnostic, prognostic, and predictive accuracy. Because radiomics analyses are intended to be conducted with standard of care images, it is conceivable that conversion of digital images to mineable data will eventually become routine practice. This report describes the process of radiomics, its challenges, and its potential power to facilitate better clinical decision making, particularly in the care of patients with cancer.



Imaging **Segmentation** **Feature extraction** **Analysis**

Different protocols, machines, etc.

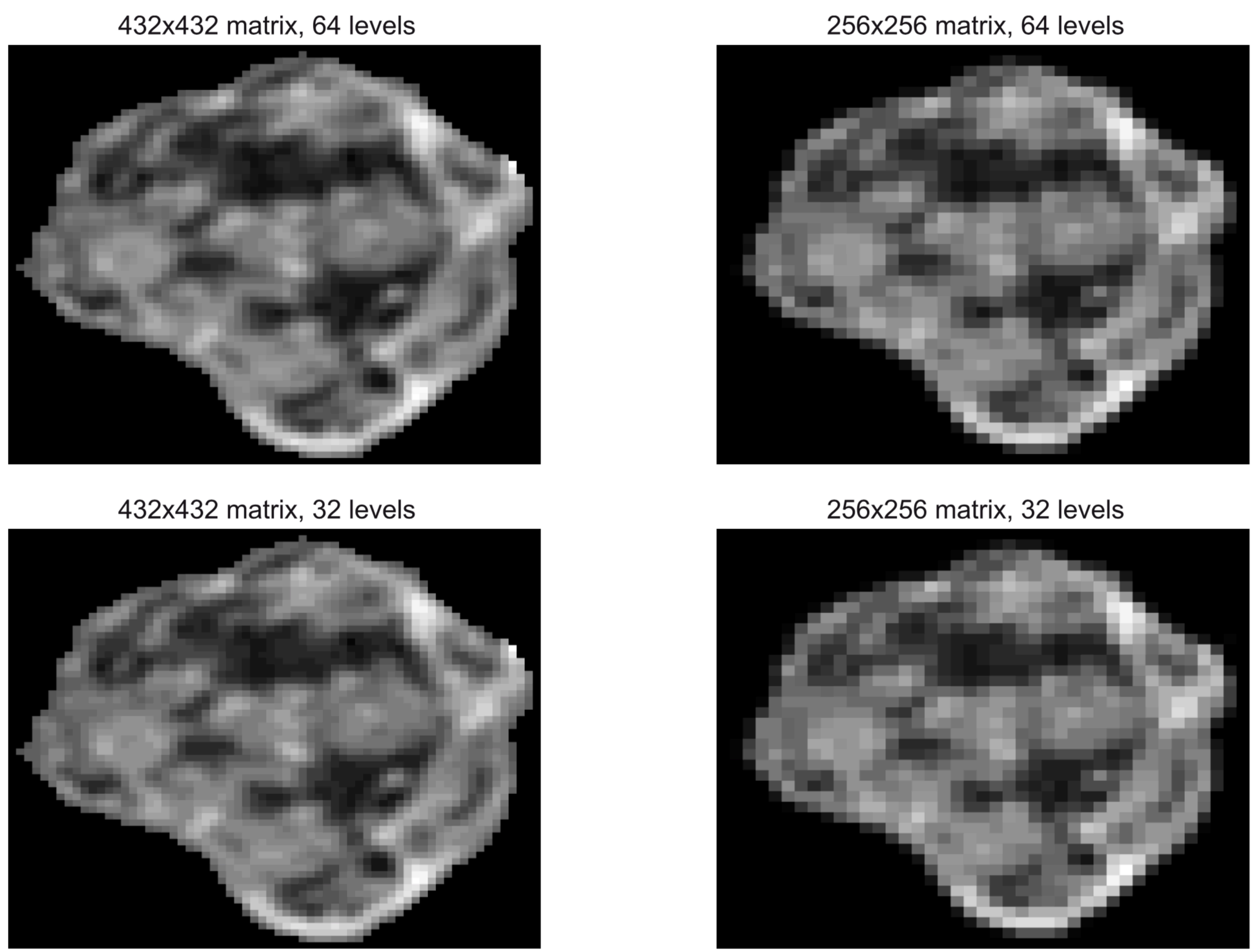
Bad (rough), vs automatic vs good

Which ones? Robustness

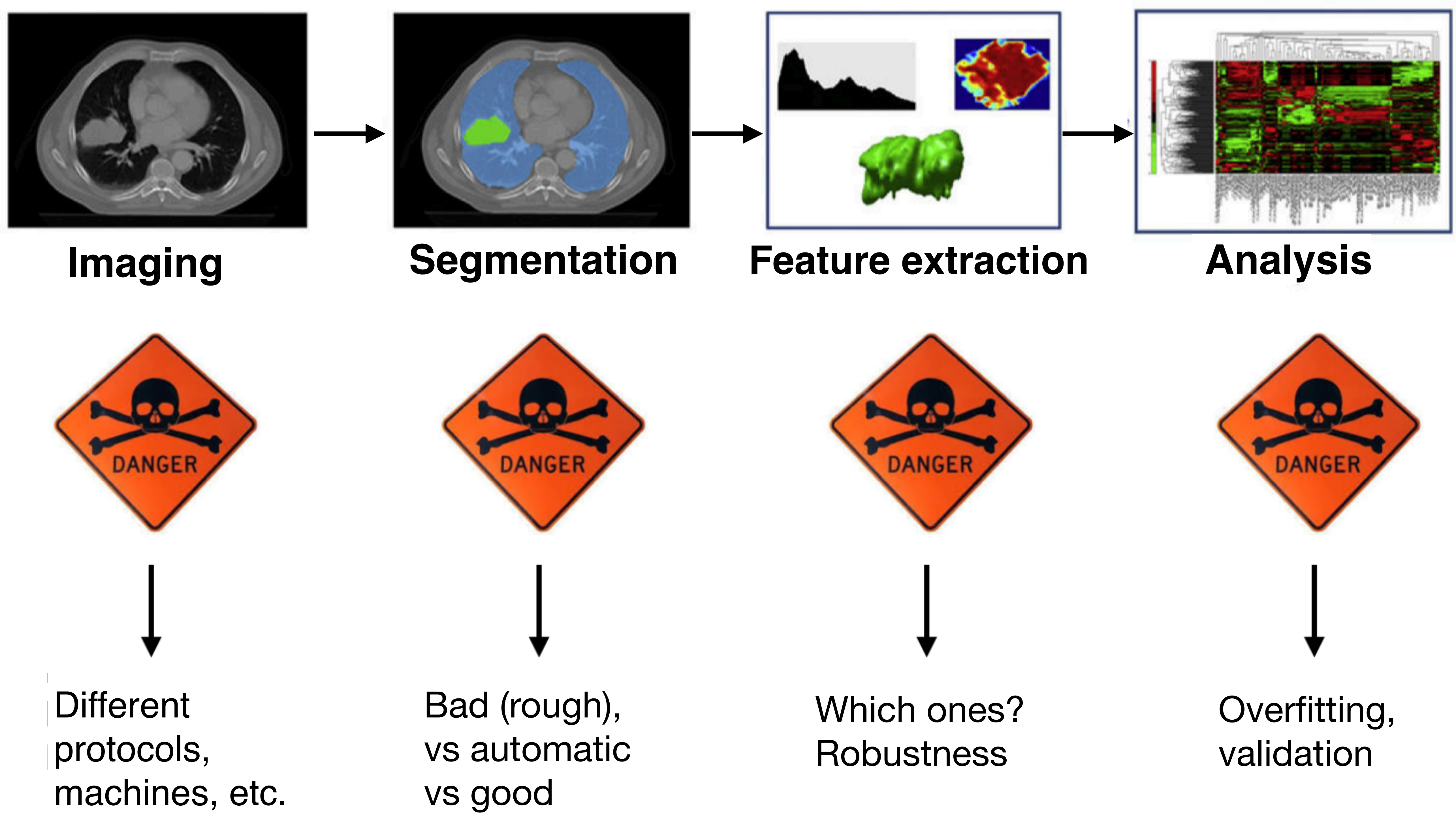
PLOS ONE

RESEARCH ARTICLE

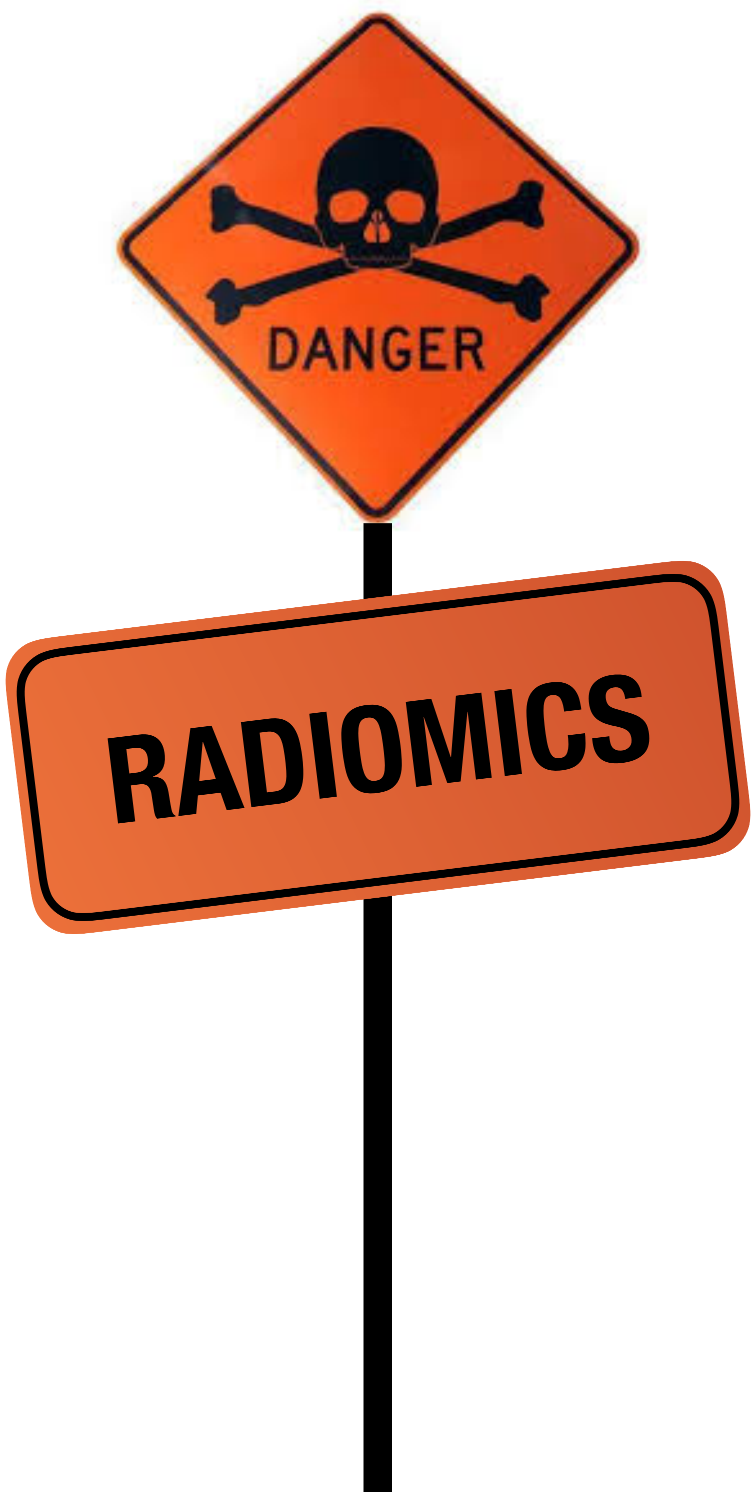
Lack of robustness of textural measures obtained from 3D brain tumor MRIs impose a need for standardization

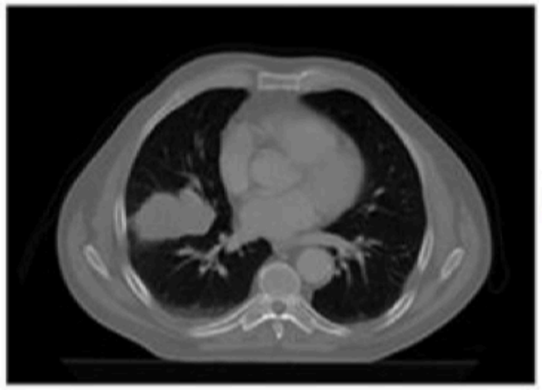


Citation: Molina D, Pérez-Beteta J, Martínez-González A, Martino J, Velasquez C, Arana E, et al. (2017) Lack of robustness of textural measures obtained from 3D brain tumor MRIs impose a need for standardization. PLoS ONE 12(6): e0178843. https://doi.org/10.1371/journal.pone.0178843

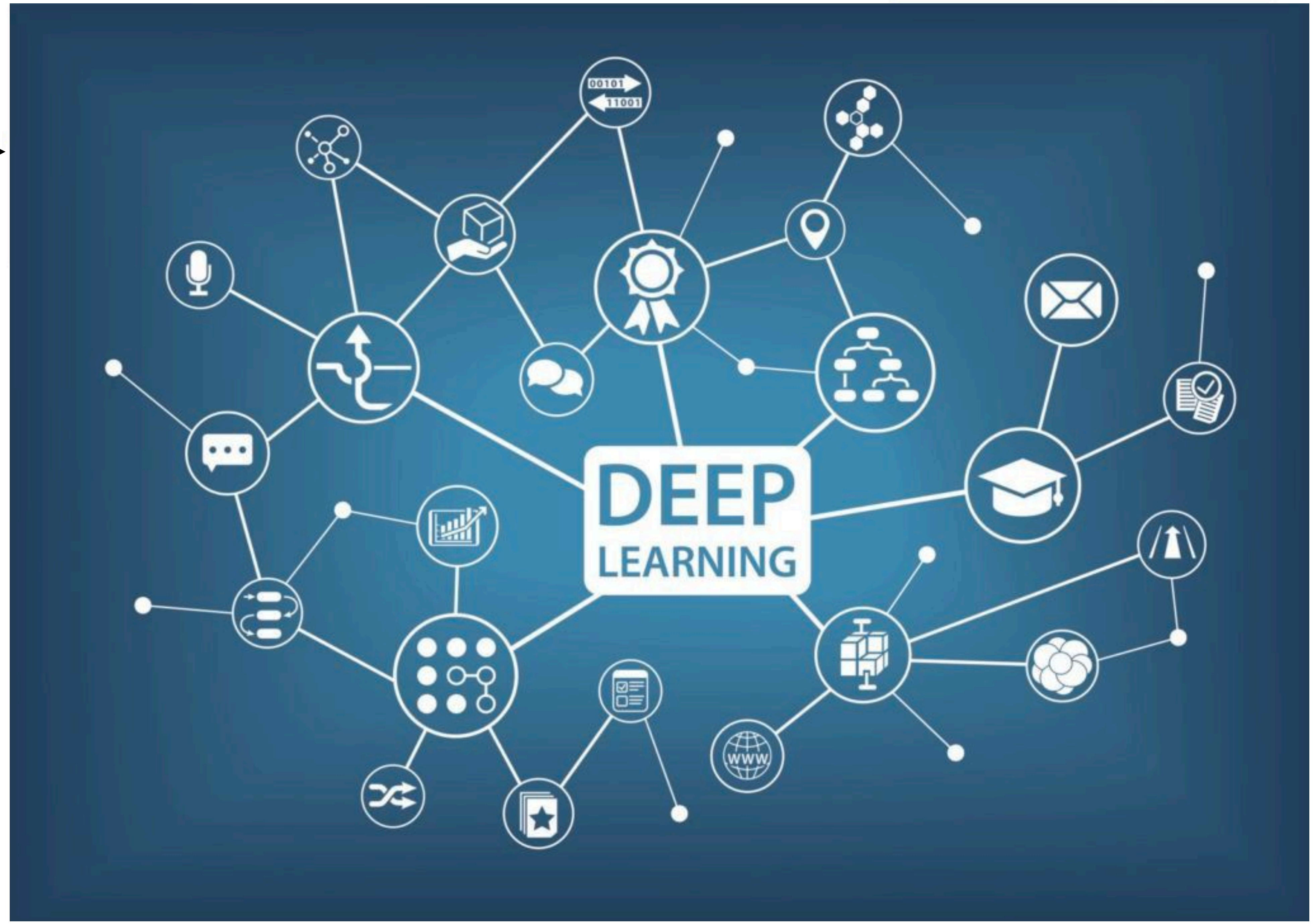

Imaging
Segmentation
Feature extraction
Analysis
DANGER
DANGER
DANGER
DANGER
Different protocols, machines, etc.
Bad (rough), vs automatic vs good
Which ones? Robustness
Overfitting, validation

Many (most?) wrong results





Imaging



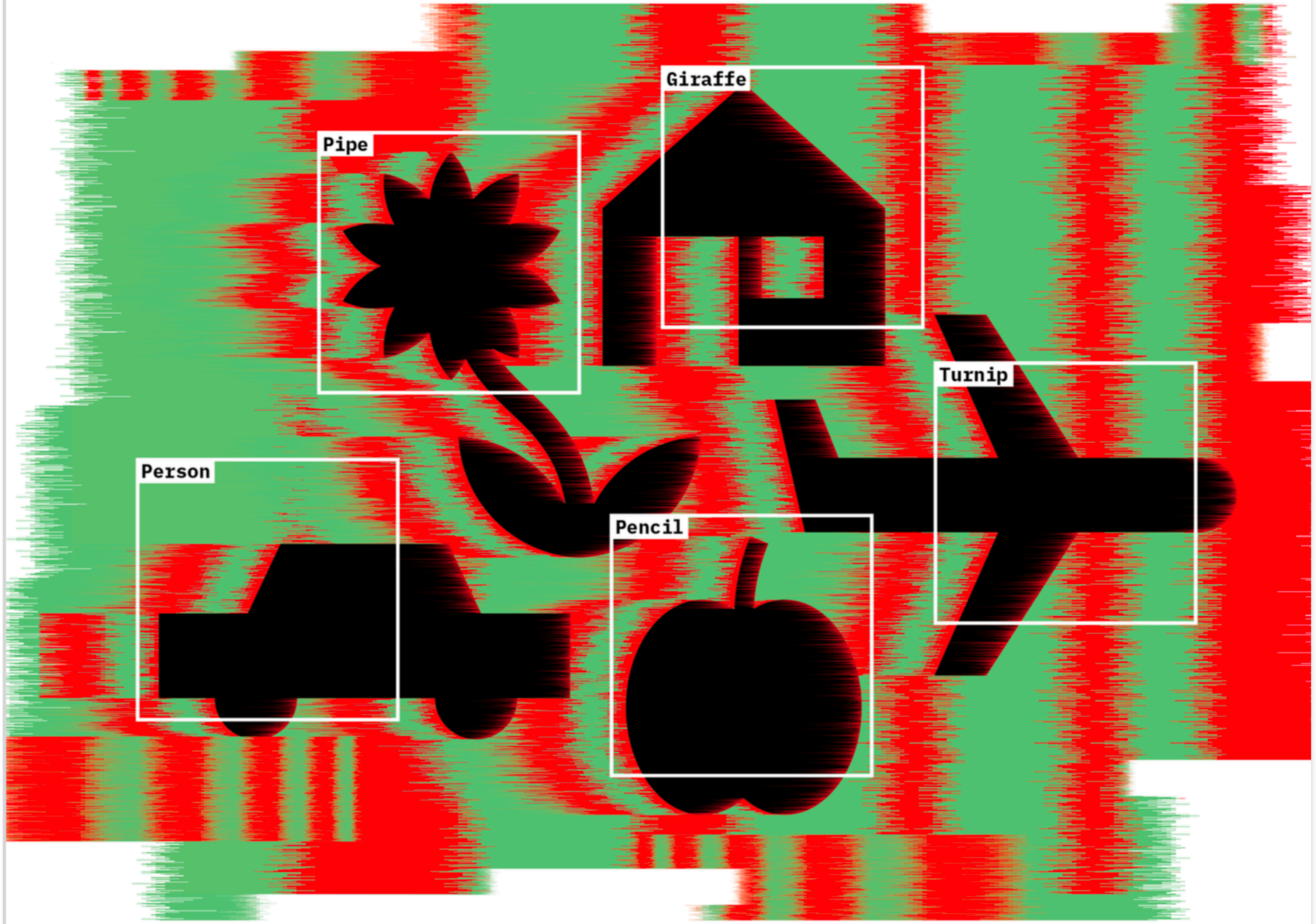


ILLUSTRATION BY EDGAR BĄK

DEEP TROUBLE FOR DEEP LEARNING

BY DOUGLAS HEAVEN

ARTIFICIAL-INTELLIGENCE RESEARCHERS ARE TRYING TO FIX THE FLAWS OF NEURAL NETWORKS.

A self-driving car approaches a stop sign, but instead of slowing down, it accelerates into the busy intersection. An accident report later reveals that four small rectangles had been stuck to the face of the sign. These fooled the car's onboard artificial intelligence (AI) into misreading the word 'stop' as 'speed limit 45'.

Such an event hasn't actually happened, but the potential for sabotaging AI is very real. Researchers have already demonstrated how to fool an AI system into misreading a stop sign, by carefully positioning stickers on it[1]. They have deceived facial-recognition systems by sticking a printed pattern on glasses or hats. And they have tricked speech-recognition systems into hearing phantom phrases by inserting patterns of white noise in the audio.

These are just some examples of how easy it is to break the leading pattern-recognition technology in AI, known as deep neural networks (DNNs). These have proved incredibly successful at correctly classifying all kinds of input, including images, speech and data on consumer preferences. They are part of daily life, running

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Review

Machine learning applications in cancer prognosis and prediction

Konstantina Kourou [a], Themis P. Exarchos [a,b], Konstantinos P. Exarchos [a], Michalis V. Karamouzis [c], Dimitrios I. Fotiadis [a,b,*]

[a] *Unit of Medical Technology and Intelligent Information Systems, Dept. of Materials Science and Engineering, University of Ioannina, Ioannina, Greece*
[b] *IMBB — FORTH, Dept. of Biomedical Research, Ioannina, Greece*
[c] *Molecular Oncology Unit, Department of Biological Chemistry, Medical School, University of Athens, Athens, Greece*

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Review

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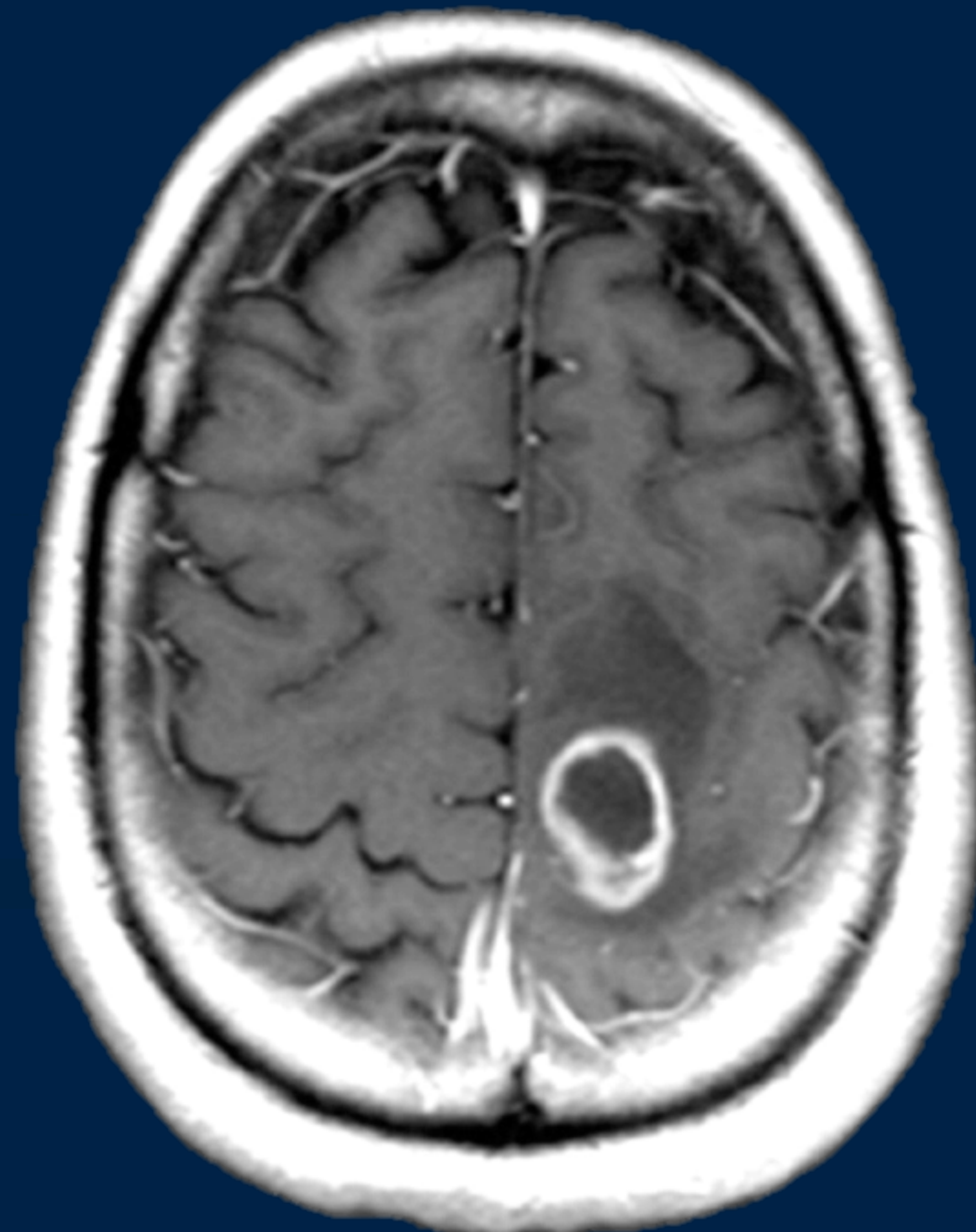
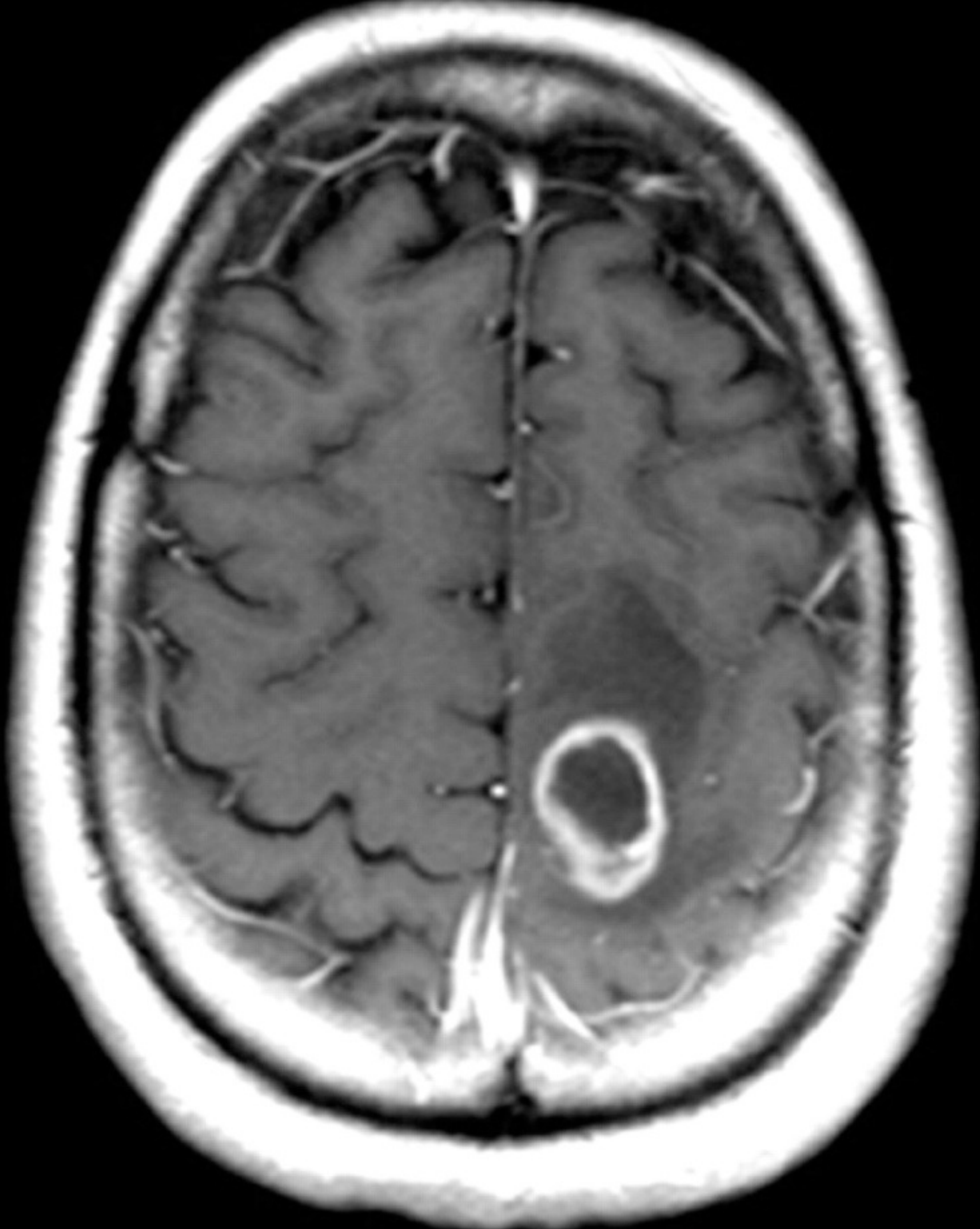
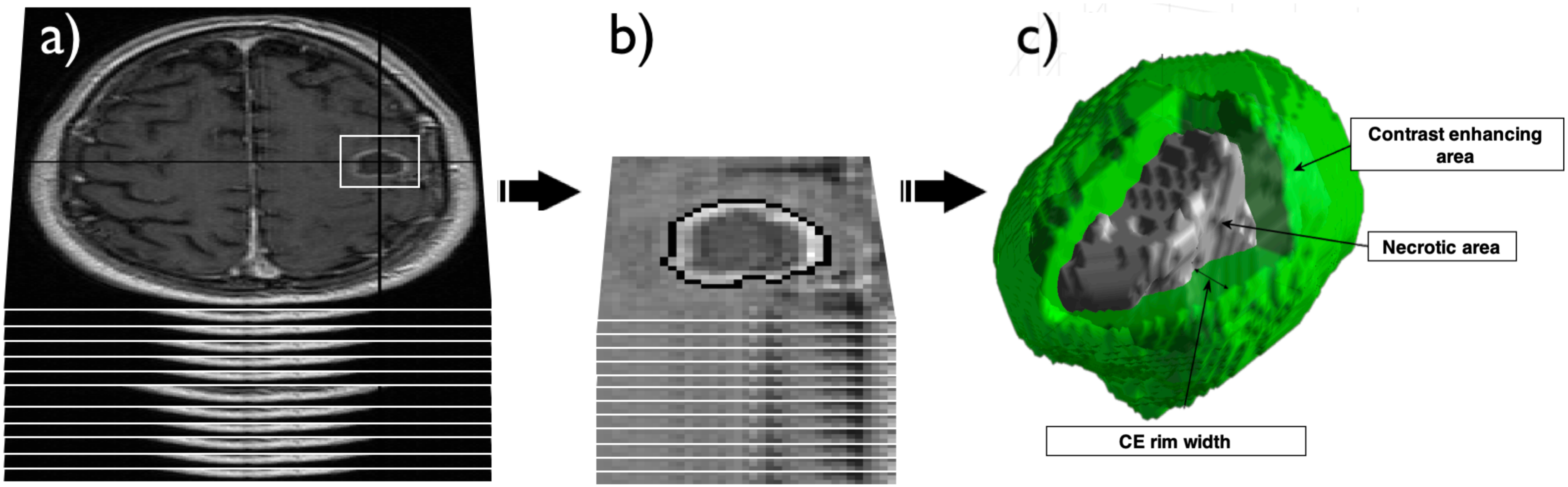
+250 articles/year

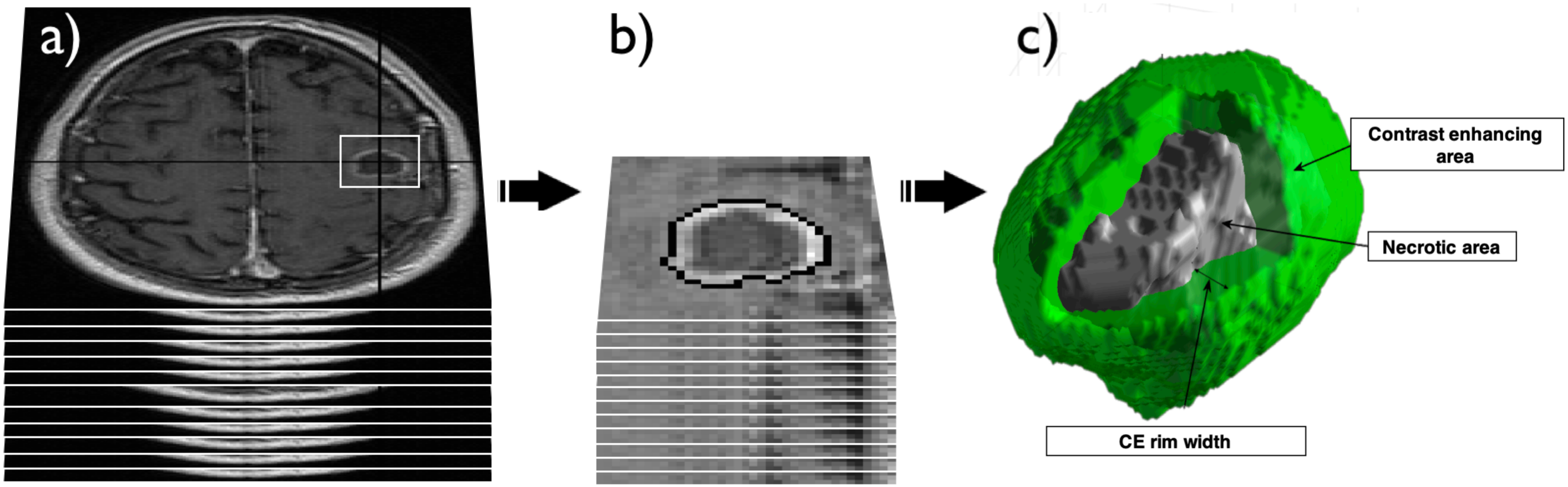


MATHEMATICAL
ONCOLOGY
LABORATORY

3D pretreatment postcontrast T1-MRI




a)
b)
c)
Contrast enhancing area
Necrotic area
CE rim width



We obtained 43 imaging measures:

Morphological parameters

- Total tumor volume
- CE volume
- Necrotic volume
- 3D tumor diameter
- CE rim width
- Surface regularity

Textural parameters

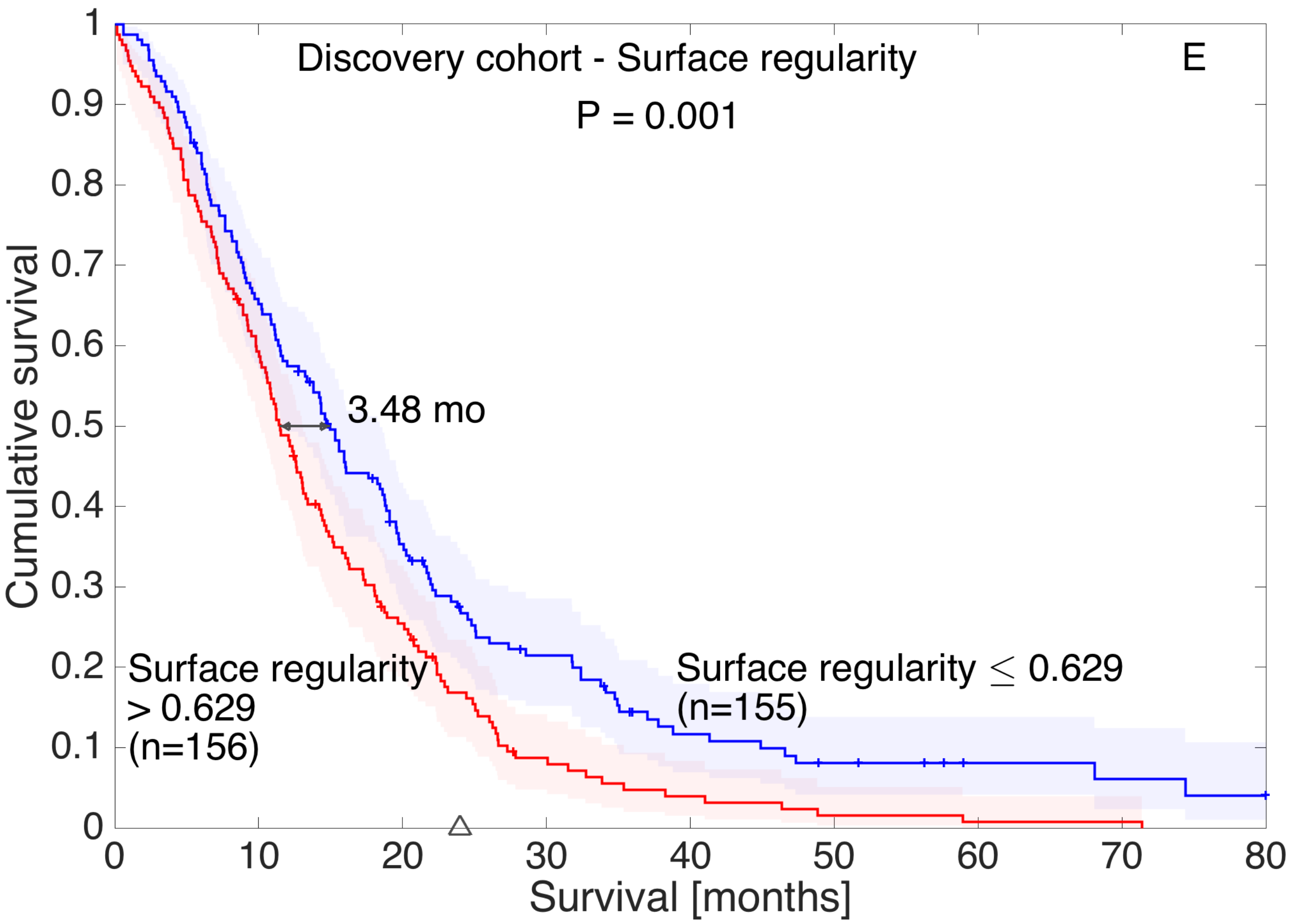
- Co-occurence matrices
- Run-length matrices
- Spatial p-energies

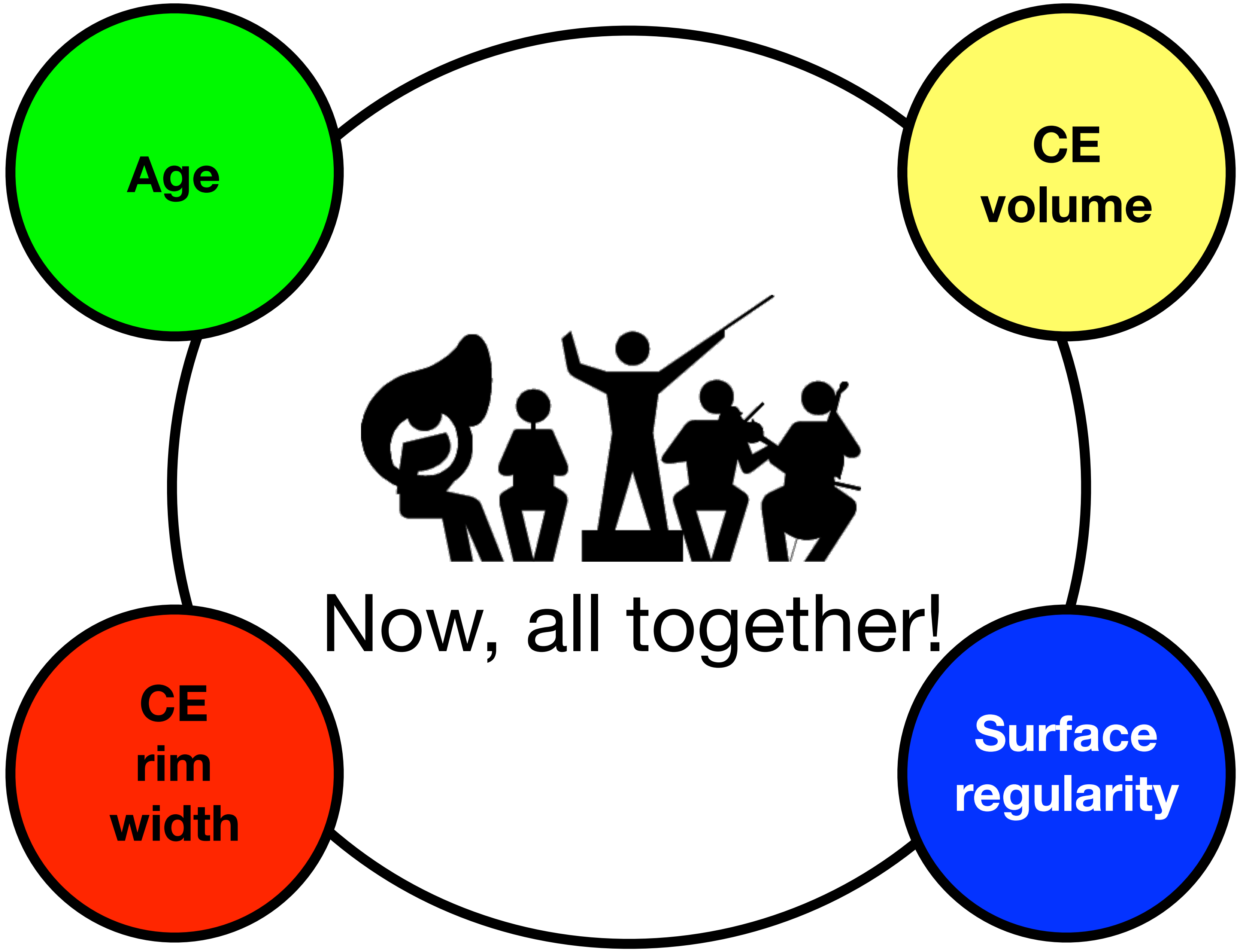
4 outstanding parameters

1. Age
2. CE volume
3. CE rim width
4. Surface regularity

4 outstanding parameters

1. Age
2. CE volume
3. CE rim width
4. Surface regularity





Linear human knowledge-based methods

Optimized Linear Predictive Model (OLPM)

$$OLPM = 0.030 \cdot age - 0.340 \cdot CE\ rim\ width - 1.100 \cdot Surface\ regularity + 0.012 \cdot CE\ volume$$

5 different approaches

Machine learning-based methods

1. Neural networks (NN)

2. Original Support vector machines (RFF_SVM)

3. SVM with Gaussian Kernel (libSVM)

4. Decision trees (DT)

Linear human knowledge-based methods

5. Optimized Linear Predictive Model (OLPM)

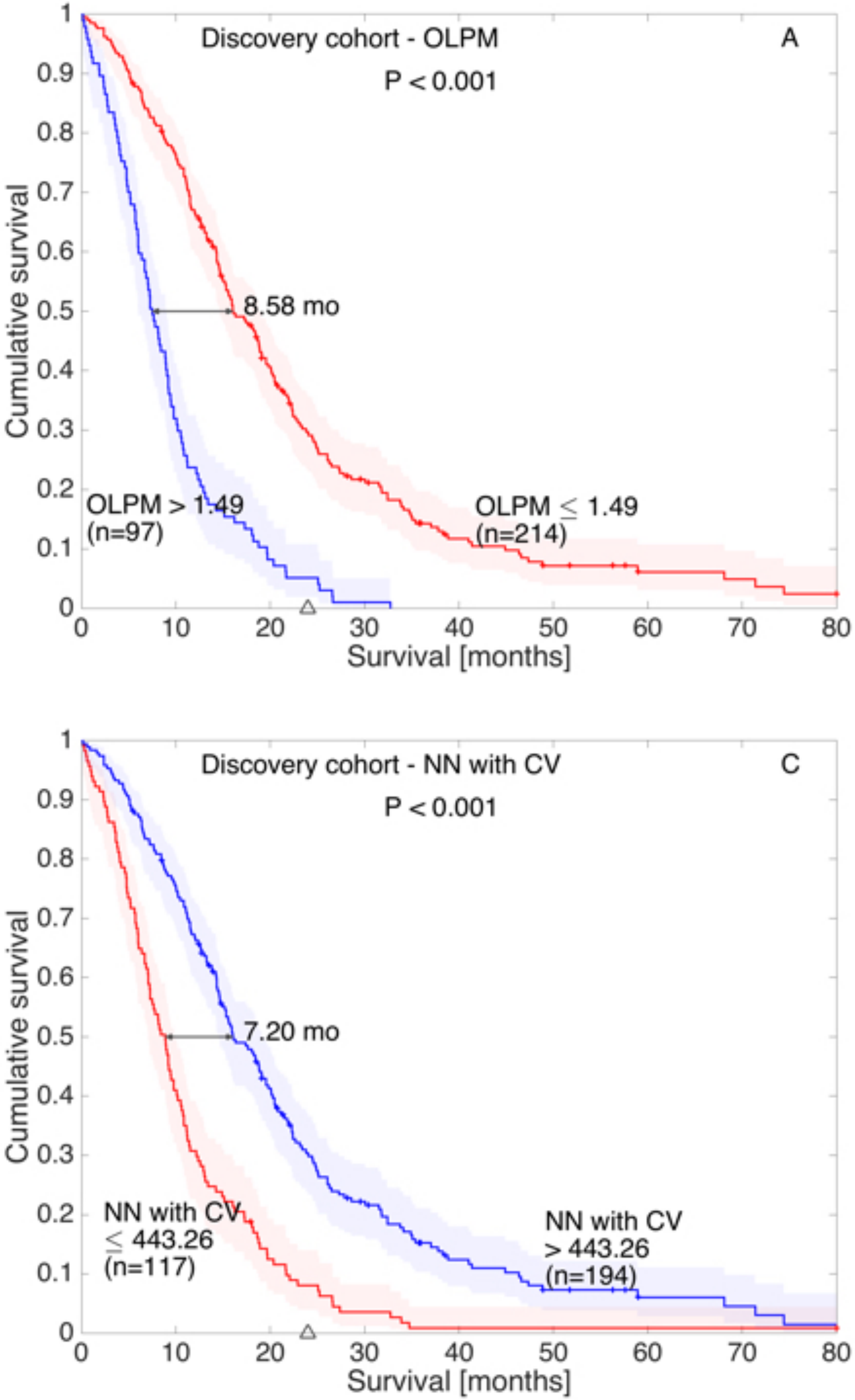
$$OLPM = 0.030 \cdot age - 0.340 \cdot CE\ rim\ width - 1.100 \cdot Surface\ regularity + 0.012 \cdot CE\ volume$$

	Our approaches		
	# Parameters	c-index training	c-index validation
OLPM	4	0,771	**0,817**

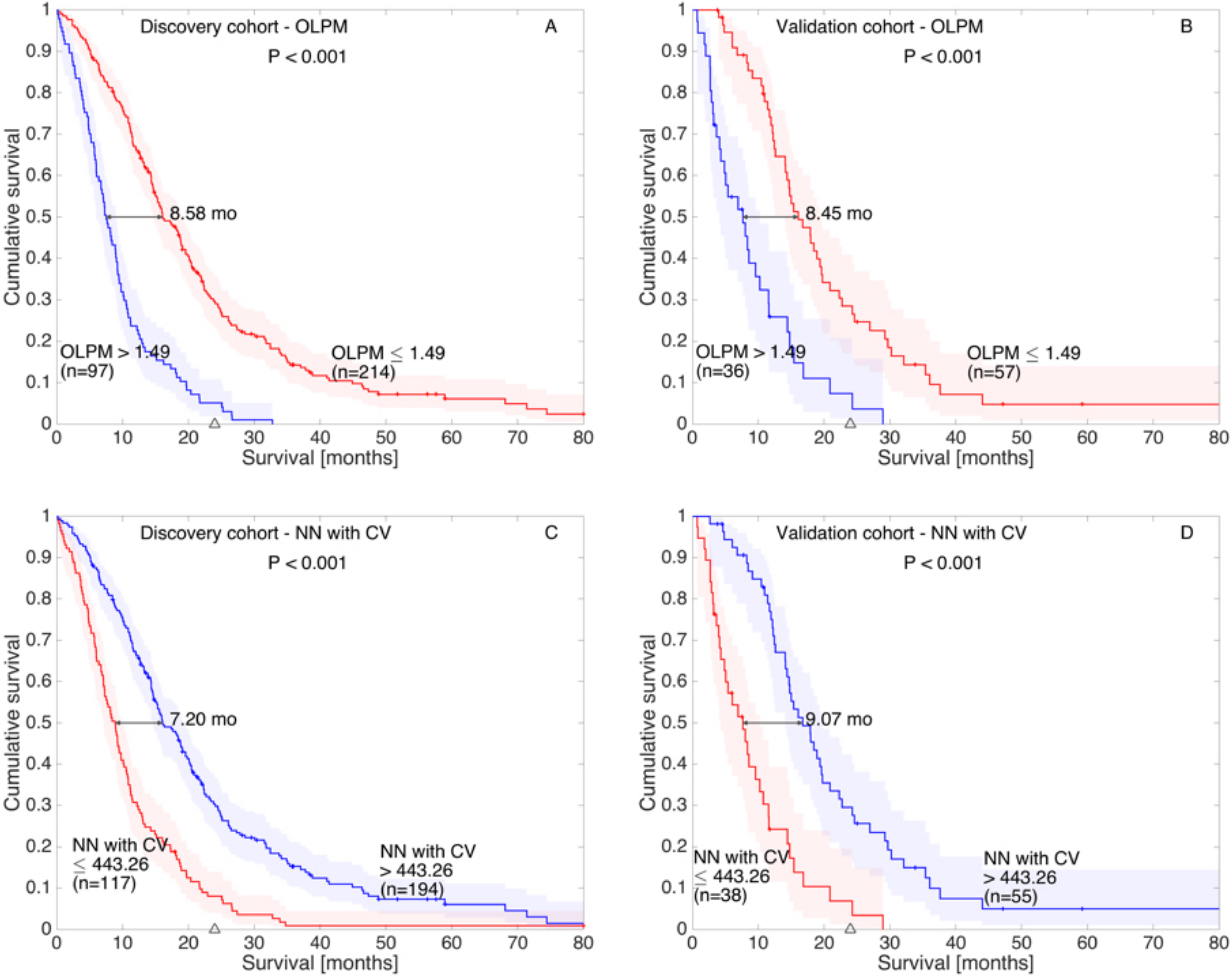
	Our approaches		
	# Parameters	c-index training	c-index validation
OLPM	4	0,771	**0,817**
NN	44	0,794	0,746
RFF_SVM	44	0,801	0,766
libSVM	44	0,751	0,700
RT	44	0,741	0,630

	Our approaches		
	# Parameters	c-index training	c-index validation
OLPM	4	0,771	**0,817**
NN	44	0,794	0,746
RFF_SVM	44	0,801	0,766
libSVM	44	0,751	0,700
RT	44	0,741	0,630
NN	4	0,740	0,751
RFF_SVM	4	0,747	0,783
libSVM	4	0,739	0,756
RT	4	0,696	0,681

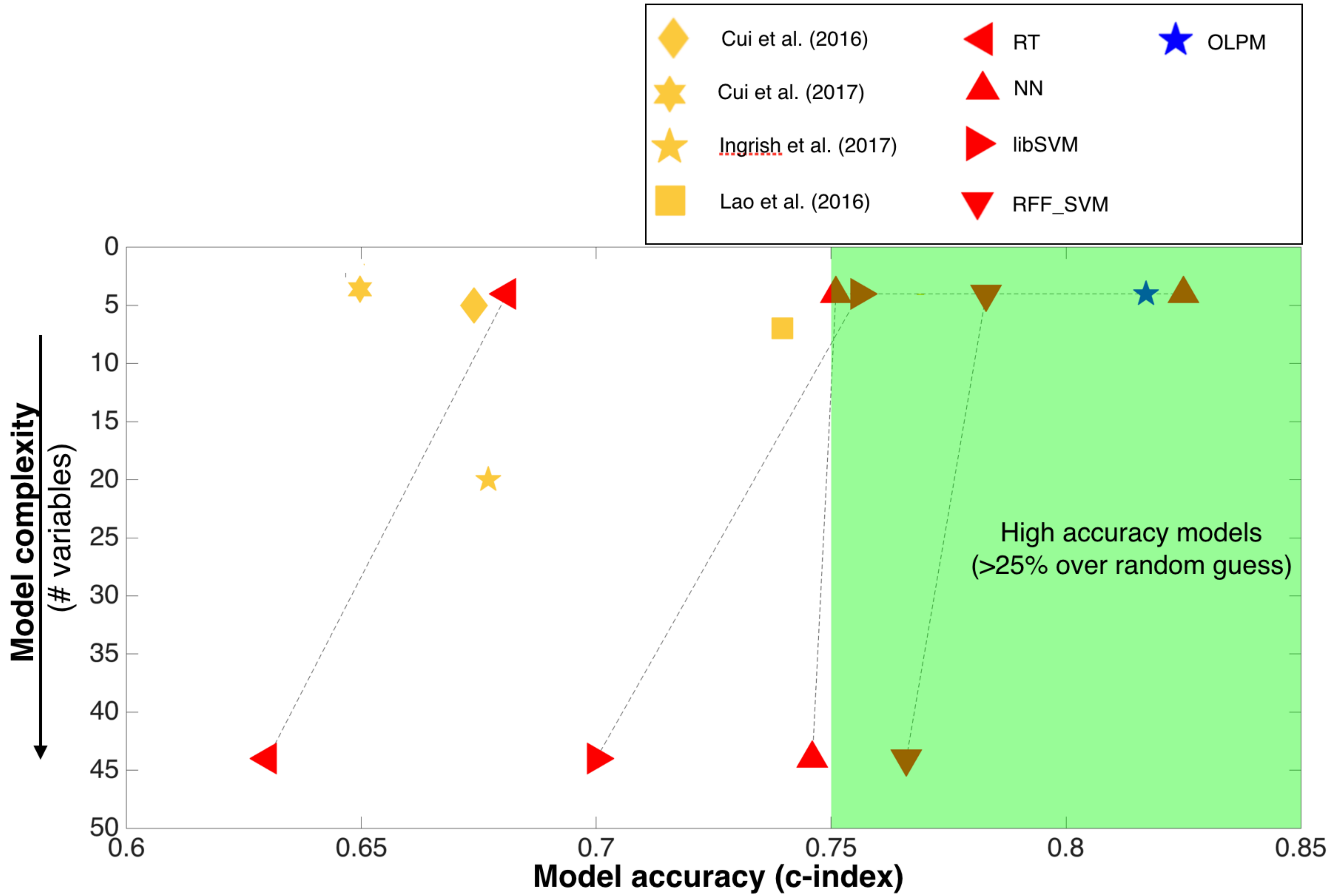
	Our approaches		
	# Parameters	c-index training	c-index validation
OLPM	4	0,771	**0,817**
NN	44	0,794	0,746
RFF_SVM	44	0,801	0,766
libSVM	44	0,751	0,700
RT	44	0,741	0,630
NN	4	0,740	0,751
RFF_SVM	4	0,747	0,783
libSVM	4	0,739	0,756
RT	4	0,696	0,681
NN with CV	4	0,791	**0,825**



Discovery cohort - OLPM
A
P < 0.001
8.58 mo
OLPM > 1.49
(n=97)
OLPM ≤ 1.49
(n=214)
Cumulative survival
Survival [months]
Discovery cohort - NN with CV
C
P < 0.001
7.20 mo
NN with CV
≤ 443.26
(n=117)
NN with CV
> 443.26
(n=194)
Cumulative survival
Survival [months]



Discovery cohort - OLPM
A
P < 0.001
8.58 mo
OLPM > 1.49
(n=97)
OLPM ≤ 1.49
(n=214)
Validation cohort - OLPM
B
P < 0.001
8.45 mo
OLPM > 1.49
(n=36)
OLPM ≤ 1.49
(n=57)
Discovery cohort - NN with CV
C
P < 0.001
7.20 mo
NN with CV
≤ 443.26
(n=117)
NN with CV
> 443.26
(n=194)
Validation cohort - NN with CV
D
P < 0.001
9.07 mo
NN with CV
≤ 443.26
(n=38)
NN with CV
> 443.26
(n=55)
Cumulative survival
Survival [months]



Cui et al. (2016)
Cui et al. (2017)
Ingrish et al. (2017)
Lao et al. (2016)
RT
NN
libSVM
RFF_SVM
OLPM
High accuracy models
(>25% over random guess)
Model complexity
(# variables)
0
5
10
15
20
25
30
35
40
45
50
0.6
0.65
0.7
0.75
0.8
0.85
Model accuracy (c-index)

Conclusions

1. Real machine learning
2. Use of only significant parameters
3. Take into account human ideas


the rematch
1:57
1:58

Perez García, Víctor M

Pérez Beteta, Julián

Arana, Estanislao

MATHEMATICAL
ONCOLOGY
LABORATORY

MATHEMATICAL
ONCOLOGY
LABORATORY

http://matematicas.uclm.es/molab