Radiomics in medical imaging: an overview

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Outline

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Definitions, objectives and applications

What is radiomics? (1/2)

A closer look at the word:

- ▷ **Radio**: related to Radiology
- ▷ **–omics**: indicating something big, numerous; i.e., large-scale datasets and/or large amounts of features.

What is radiomics? (2/2)

Some definitions:

- ‘**High-throughput** extraction of **large amounts of features** from radiographics images’ (Lambin et al., 2012)
- ‘Conversion of images into **mineable data** and subsequent analysis of these data for **decision support**’ (Gillies, Kinahan, and Hricak, 2016)
- ‘Extraction of **sub-visual**, yet **quantitative** image features [...] from radiological images’ (Thawani et al., 2018)
- ‘Detecting **clinically-relevant** features from radiological imaging that are **difficult for the human eye to perceive**’ (Vial et al., 2018)

Objectives and areas of potential application

Objectives: to support clinical decision-making by establishing quantitative links between radiological images and clinical endpoints.

Areas of potential applications:

- **Oncological disorders**
  - Solid tumours
- Neurodegenerative diseases
  - Alzheimer's, Parkinson's, etc.
- Cardiovascular conditions
  - Atherosclerosis, cardiac anomalies, etc.

Applications (oncology)

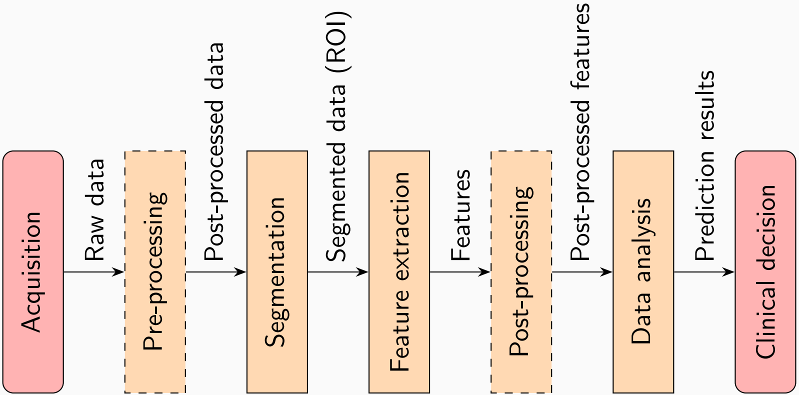
- **Computer-assisted Diagnosis**
    - Benign vs. malignant
    - Primary vs. metastatic
    - Prediction of histological subtype
- **Patient stratification and therapy planning**
    - Prediction of overall and disease-free survival
    - Prediction of response to therapy
- **Clinical follow-up**
    - Tracking the disease evolution over time

Rationale

- Tumour **heterogeneity** (*texture*) is considered a strong indicator of disease aggressiveness and a predictor of survival (Bashir et al., 2016; O'Connor et al., 2015; Mayerhoefer et al., 2020)
- Tumour **morphology** (contour smoothness, roundness, elongation; presence of spiculation, lobulation and other signs) is a strong predictor of benignity/malignancy (Truong et al., 2014; MacMahon et al., 2017)

The radiomics process

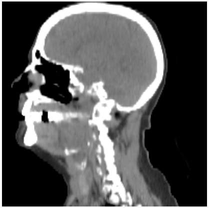
Overall pipeline



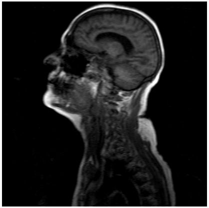
Acquisition

- **Computed Tomography** (CT)
  - Tissue density
- **Magnetic Resonance Imaging** (MRI)
  - Tissues relaxation properties (to an RF excitation)
- **Positron Emission Tomography** (PET)
  - Metabolic activity (glucose consumption)

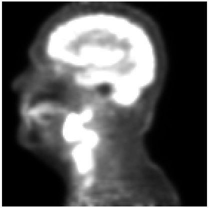
CT



MRI



PET



Pre-processing

A fundamental step in the pipeline with significant effects on the overall results; sometimes overlooked.

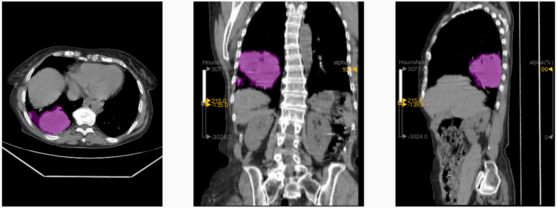
Can involve one or more of the following operations:

- **Windowing** (clipping)
- **Intensity quantisation**
- **Filtering**
  - To reduce noise
  - To highlight features at different spatial scales

Segmentation

Consists of two steps:

- ▷ Identification of the *region of interest* (ROI)
- ▷ Separation of the ROI from the background (*delineation*)



Feature extraction

Calculation of quantitative parameters (*features*) from the ROI. Ideally the features should be:

- **Discriminative** – i.e., they should correlate strongly with the clinical endpoint investigated
- **Reproducible** and re-usable across different centres
- **Stable** to variations in the acquisition and pre-processing settings
- Physically/clinically **interpretable**
- As **few** as possible

Feature extraction: possible approaches

Hand-designed

- Mostly defined **a priori** (little or no training needed)
- Relatively **intuitive** / **interpretable** features
- Low computational demand
- Need to **find the right method** for any specific task

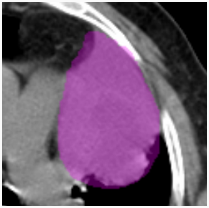
Deep learning

- Based on **modules** and sets of **free parameters** (to be determined by training)
- Features **difficult to interpret**
- Require **large datasets** for training and dedicated hardware
- **Generalizable** results

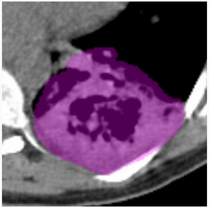
Texture features

Aim at quantifying the spatial variation of the signal in the region of interest. Some intuitive concepts related to texture:

- Contrast
- Granularity (fine/coarse)
- Stationariness
- Uniformity



Contrast (-)
Stationariness (+)
Uniformity (+)

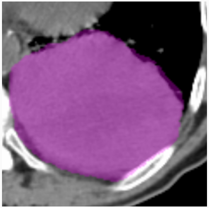


Contrast (+)
Stationariness (-)
Uniformity (-)

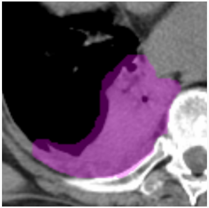
Shape features

Aim at quantifying the human perception of some intuitive concepts – e.g.:

- Compactness
- Elongatendess
- Eccentricity
- Roundess
- Spiculatedness
- Symmetry



Compactness (+)
Roundness (+)
Symmetry (+)



Compactness (-)
Elongatedness (+)
Symmetry (-)

Post-processing

The features can be further processed in order to:

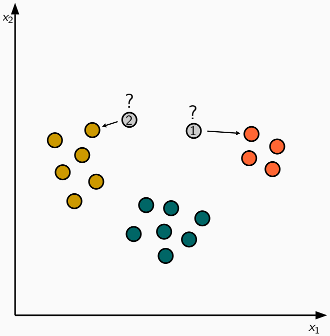
- Reduce their number (*curse of dimensionality*)
- Increase their discrimination capability

Common approaches:

- **Feature selection**
- **Feature generation** (Principal Components Analysis, Linear Discriminant Analysis, etc.)

Data analysis

- **Classification**
  - Usually cross-sectional
    - Prediction of phenotype (benign vs. malignant, primary vs. metastatic, etc.)
- **Regression**
  - Usually longitudinal
    - Prediction of outcome over time (survival analysis)



Tools

Software tools for radiomics

- **Freeware**
  - LIFEx: stand-alone application with GUI
  - PyRadiomics: open-source python package; a GUI is also available through 3D Slicer extension
- **Commercial**
  - TexRAD: stand-alone application with GUI

Issues and challenges

Methodological issues

- **Standardisation**
  - Need for standardised procedures and settings in all the steps of the radiomics process[1]
- **Data availability**
  - Demand for large, open-access datasets of pre-classified cases[2]

[1] The Image Biomarker Standardization Initiative – IBSI (Hatt et al., 2018)
[2] The Cancer Imaging Archive (Clark et al., 2013)

User experience challenges

- **Accountability**
  - Need to be in control of each step of clinical decision-making; reluctance to give that control to a machine (Shaikh et al., 2017)
- **Perception**
  - Ability of the user to interpret and understand the data
- **Provenance**
  - Willingness to accept the results of an algorithm

Conclusions

Conclusions

- Radiomics is a rapidly evolving discipline with potential applications in clinical decision making
- It is a strongly inter-disciplinary topic which requires collaboration and skills from different areas (Medicine, Engineering, Statistics, Mathematics and Computer Science)
- Further effort is needed (particularly towards standardisation) for translation into clinical practice

Thank you for your attention

Any questions?

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