MODERN RADIOLOGY
eBook

AI in Radiology

ESR EUROPEAN SOCIETY OF RADIOLOGY

Preface

Modern Radiology is a free educational resource for radiology published online by the European Society of Radiology (ESR). The title of this second, rebranded version reflects the novel didactic concept of the ***ESR eBook*** with its unique blend of text, images, and schematics in the form of succinct pages, supplemented by clinical imaging cases, Q&A sections and hyperlinks allowing to switch quickly between the different sections of organ-based and more technical chapters, summaries and references.

Its chapters are based on the contributions of over 100 recognised European experts, referring to both general technical and organ-based clinical imaging topics. The new graphical look showing Asklepios with fashionable glasses, symbolises the combination of classical medical teaching with contemporary style education.

Although the initial version of the ***ESR eBook*** was created to provide basic knowledge for medical students and teachers of undergraduate courses, it has gradually expanded its scope to include more advanced knowledge for readers who wish to 'dig deeper'. As a result, ***Modern Radiology*** covers also topics of the postgraduate levels of the ***European Training Curriculum for Radiology***, thus addressing postgraduate educational needs of residents. In addition, it reflects feedback from medical professionals worldwide who wish to update their knowledge in specific areas of medical imaging and who have already appreciated the depth and clarity of the ***ESR eBook*** across the basic and more advanced educational levels.

I would like to express my heartfelt thanks to all authors who contributed their time and expertise to this voluntary, non-profit endeavour as well as Carlo Catalano, Andrea Laghi and András Palkó, who had the initial idea to create an ***ESR eBook***, and - finally - to the ESR Office for their technical and administrative support.

Modern Radiology embodies a collaborative spirit and unwavering commitment to this fascinating medical discipline which is indispensable for modern patient care. I hope that this ***educational*** tool may encourage curiosity and critical thinking, contributing to the appreciation of the art and science of radiology across Europe and beyond.

Minerva Becker, Editor
Professor of Radiology, University of Geneva, Switzerland

/ Copyright and Terms of Use

How to cite this work:

European Society of Radiology,
Tugba Akinci D'Antonoli, Marcio A. B. C. Rockenbach, Vera Cruz e Silva,
Merel Huisman, Elmar Kotter, Emmanouil Koltsakis, Peter M. A. van Ooijen, Erik R. Ranschaert, Pinar Yilmaz
(2024) ESR Modern Radiology eBook:

- **Artificial Intelligence in Radiology. DOI 10.26044/esr-modern-radiology-08**

CHAPTER OUTLINE:

/ Signage

CORE KNOWLEDGE

FURTHER KNOWLEDGE

ATTENTION

COMPARE

QUESTIONS

HYPERLINKS

REFERENCES

CHAPTER OUTLINE:

MODERN RADIOLOGY eBook

Based on the ESR Curriculum for Radiological Education

AI in Radiology

CHAPTER OUTLINE:

AUTHORS

Editors: Merel Huisman | Elmar Kotter | Peter M. A. van Ooijen | Erik R. Ranschaert

Members: Tugba Akinci D' Antonoli | Marcio Aloisio Bezerra Cavalcanti Rockenbach Vera Cruz e Silva | Emmanouil Koltsakis | Pinar Yilmaz

AFFILIATION

European Society of Medical Imaging Informatics (EuSoMII) Education Committee

<↑> HYPERLINK

info@eusomii.org

Chapter Outline

CHAPTER OUTLINE:

/ Introduction

/ Why Should We Learn About AI?

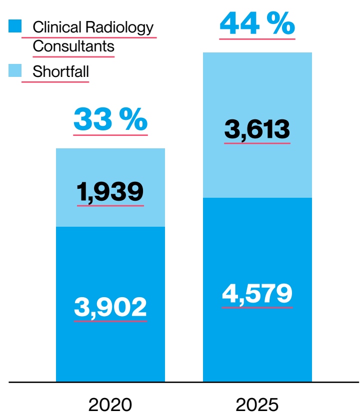
/ Artificial intelligence (AI) is a rapidly growing field, influencing every aspect of our lives, including the way we practice medicine. Healthcare workers should **keep up with the pace of digital development** to advance the field.

/ While the volume and complexity of imaging is skyrocketing, there is a rise in workforce shortages and strain on radiologists. As a result, quality decreases and reporting backlogs are growing. **AI may increase both the speed and quality** of reporting, while boosting physicians job satisfaction.

/ The use of AI in healthcare poses **potential risks**, such as large number of errors or additional unnecessary costs. Therefore, we should learn more about AI in order to deploy AI tools safely and effectively in medicine.

/ In the following section we will learn more about the applications of AI in radiology, **but first let's look at the brief history of and fundamental information about AI.**

Forecast Shortfall of Clinlcial Radiolgy Consultants in UK 2020-2025



<∞> REFERENCE

Adapted from Clinical radiology UK workforce census 2020 report

https://www.rcr.ac.uk/publication/clinical-radiology-uk-workforce-census-2020-report

/ AI in Radiology

CHAPTER OUTLINE:

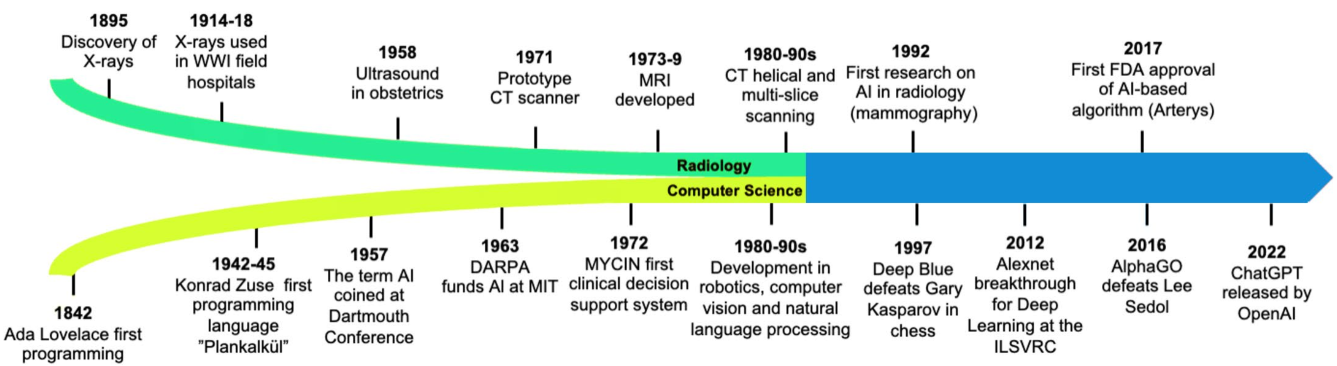
/ Brief History of AI in Radiology

/ Ada Lovelace conceptualised the first programming in 1842, marking the birth of computer science.

/ In 1895, William Conrad Roentgen discovered the first X-ray, leading to the emergence of radiology as a specialty.

/ Krizhevsky et al., won the ImageNet challenge in 2012 with AlexNet, a convolutional neural network, and the field of Deep Learning has skyrocketed.

/ First AI-based algorithm is cleared by FDA in 2017 and officially entered to clinical setting.



<∞> REFERENCE

Adapted from Clin Transl Sci (2020) 13, 216–218; doi:10.1111/cts.12704

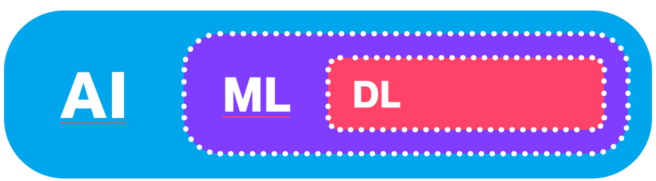
/ **AI** in Radiology

Definitions

>|< COMPARE

- **Artificial Intelligence (AI):** a field within computer science focused on creating solutions capable of **performing tasks that are typically associated with human intelligence**. It is a broad term that encompasses a wide range of technologies, and even a basic rule-based model can be considered a form of AI.

- **Machine Learning (ML):** a subset of AI that revolves around the creation of algorithms capable of learning from data and making predictions. However, these algorithms still rely on **human supervision**. ML is not a new concept within the AI field. In computer vision, traditional ML algorithms often entail image processing and explicit feature extraction.



- **Deep Learning (DL):** a subset of ML that utilises **neural networks** to learn patterns in data. It is considered a relatively new field within AI and has experienced a surge in popularity in recent years. Training a DL model usually requires large amounts of data and computational resources due to the complexity of neural network architectures. Nowadays, that's feasible thanks to graphic cards specialised in matrix operations.

<!> ATTENTION

AI is an umbrella term and can be applied to many domains in many forms.

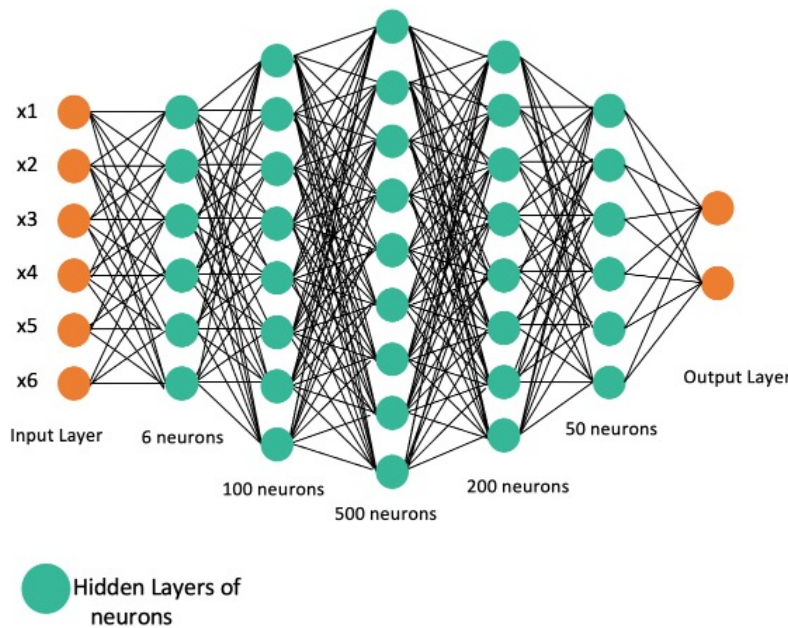
In this chapter we focus mainly on **deep learning in image recognition**.

CHAPTER OUTLINE:

>|< COMPARE

/ **Artificial Neural Network (ANN):** a type of machine learning algorithm that mimics the structure and function of the human brain. They contain multiple neurons organised in hierarchical layers. The layers closest to the input layer are responsible for processing and transforming the input data to extract relevant features, whereas the output layer is responsible for the final output.

/ **Deep neural network (DNN):** a specific type of neural network composed of multiple intermediate layers (i.e., hidden layers). They can be used to train powerful models based on large amounts of data.



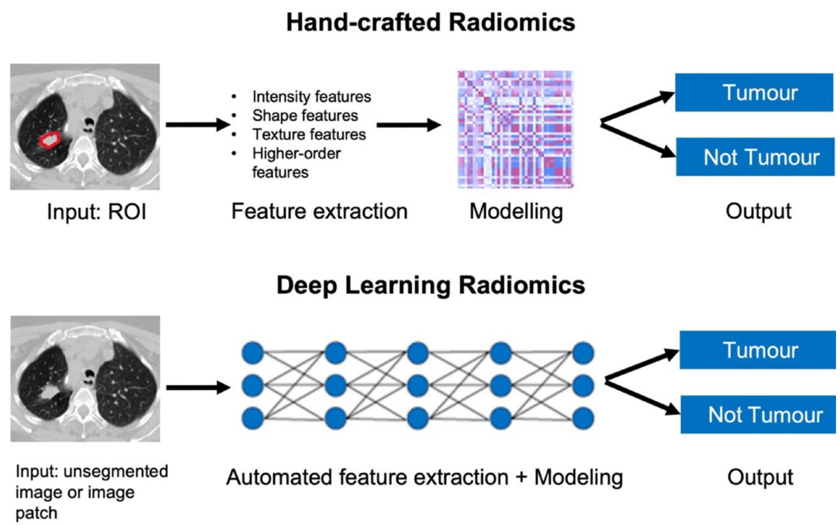
<∞> REFERENCE

Adapted from M. Bahi and M. Batouche, "Deep Learning for Ligand-Based Virtual Screening in Drug Discovery," doi: 10.1109/PAIS.2018.8598488

Radiomics: refers to **extracting quantifiable and minable features** from medical images. It is a rapidly growing research field and mostly applied in the field of oncological imaging.

Currently, radiomics is still **largely a research area**, but efforts are being made to translate these research findings into the clinic.

Depending on whether one uses **hand-crafted or deep learning approaches**, the radiomics workflow may include clinical and imaging data curation, image pre-processing, image segmentation, feature extraction, model development, and model validation.



Courtesy of Tugba Akinci D'Antonoli

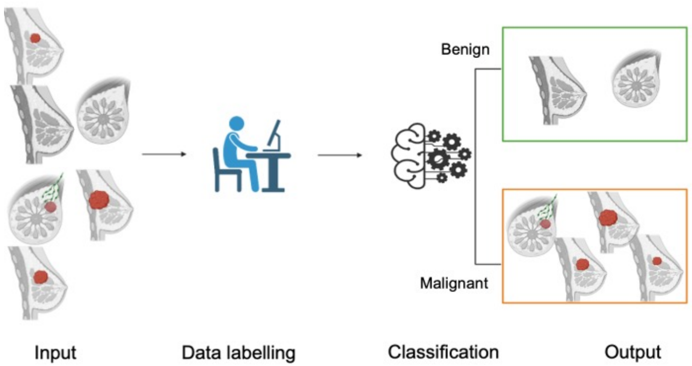
Fundamentals of AI

CHAPTER OUTLINE:

Supervised Learning

Supervised learning is a ML paradigm that uses **human-labelled** training data. Then, the model predicts (this is called 'classification') outcomes on a new, unlabelled data set. It is the most **commonly used technique**.

Labels can be for example a **region of interest (ROI)** that points to a malignant breast tumour (see image below), a **bounding box** that indicates a focal lesion, or **text-based label** such as "fracture".



Created with BioRender.com

FURTHER KNOWLEDGE

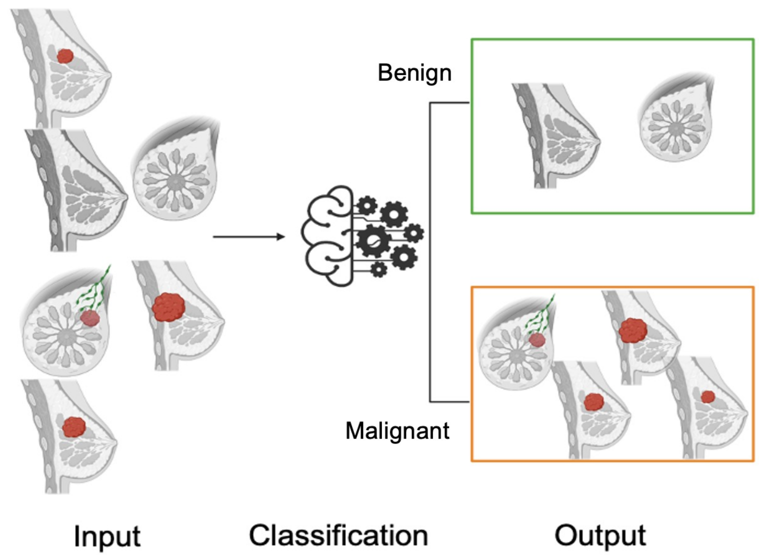
Common supervised methods:

- **Regression** → estimates relationships between variables.
- **Decision tree algorithms, DTA** (e.g., random forest) → DTA are used for classification & regression tasks; they have a hierarchical tree structure with a root node, branches, internal nodes and leaf nodes.
- **Support Vector Machine (SVM)** → are used for classification & regression tasks; they are especially useful to classify data into 2 groups.

CHAPTER OUTLINE:

/ Unsupervised Learning

- / **Unsupervised Learning** bypasses manual data label-ling through clustering tech-niques such as k-means.
- / The model is fed with typically a large amount of **unlabelled data**, and then finds patterns based on the data structure.
- / Unsupervised learning is typically used for **large sets of unstructured data**, e.g., in discovering new biomarkers.
- / In medical imaging, a common example is Generative Adver-sarial Network (GAN), used to make synthetic (=fake) images.

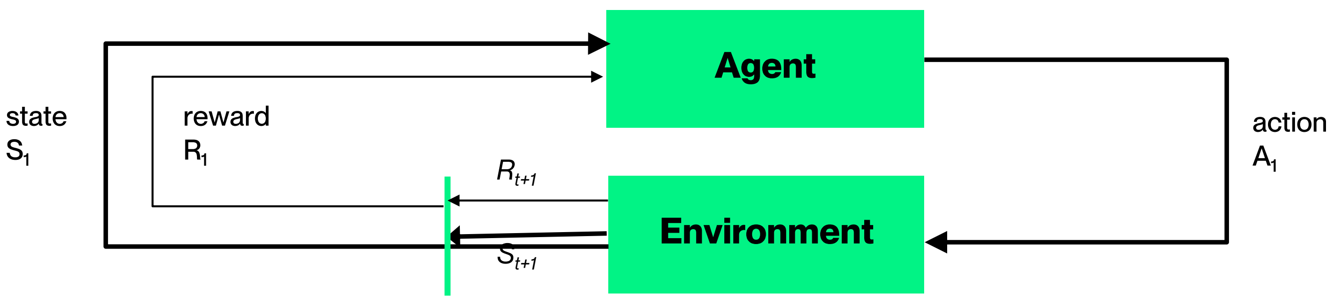


Created with BioRender.com

/ Reinforcement Learning

Reinforcement learning is a learning approach based on **rewards and punishments**. An agent interacts with the environment by sensing its state and learning to perform actions to maximise long-term rewards.

By this approach, the agent must maintain a balance between reward and punishment with trial and errors to favour the actions that will yield the greatest benefit.



<∞> REFERENCE

Adapted from the image by Shweta Bhatt.

https://towardsdatascience.com/reinforcement-learning-101-e24b50e1d292

Advanced Topics about AI

CHAPTER OUTLINE:

/ Deep Learning Applications in Medical Imaging

Medical imaging has been one of the main areas of interest when it comes to developing deep learning models for medical applications. Many examples can be found on algorithms developed for different imaging modalities (MR, CT, X-ray, ultrasound). On the next few pages, you will find the types of tasks where deep learning has been used, along with some examples of models:

Classification: train a model that is able to categorise images.

Examples:

- Binary classification: Normal vs abnormal chest X-ray without specification of a pathology.
- Positive for a specific disease vs negative (e.g., classification of brain MRs in positive or negative for Alzheimer's Disease).
- Anatomical planes (multi-class) classification: axial vs coronal vs sagittal.

Detection: the goal of these algorithms is to identify anatomical or pathological 'objects' within an image.

Often the detected object can be highlighted with the use of **bounding boxes (see image).**

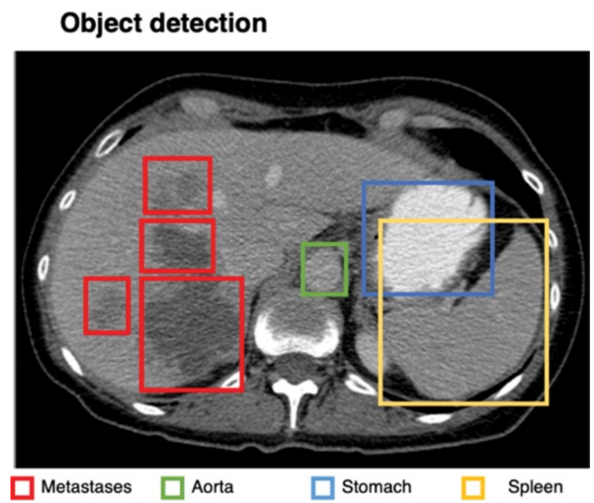
Examples include:

/ Landmark detection for spinal surgery planning on X-rays

/ Lung nodule detection on CT scans

/ Kidney stone detection on CT scans

/ Liver lesion detection on CT scans



<·> REFERENCE

Cheng PM. Published Online: September 01, 2021

https://doi.org/10.1148/rg.2021200210

Segmentation: task of dividing the pixels of an image into multiple regions or segments, where each segment corresponds to a particular object or class (e.g., an organ or pathology).

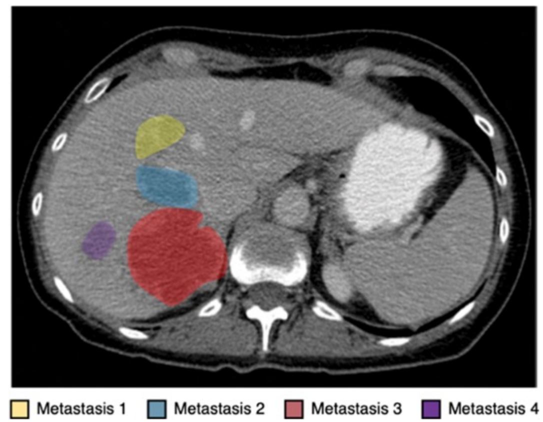
In general, this is the first step facilitating classification or quantification (e.g., measurement) as a next step.

This type of application is one of the popular uses of DL in medical imaging.

Examples:

- Prostate segmentation on MR
- Liver segmentation on CT
- Brain tumour segmentation on MR
- Cardiac segmentation on CTA
- Pulmonary tumour segmentation on CT
- Stroke segmentation on CT/MR

Segmentation of liver metastases on a CT scan.



<∞> REFERENCE

Cheng PM. Published Online: September 01, 2021

https://doi.org/10.1148/rg.2021200210

Image enhancement: deep learning models can be trained to perform tasks that improve image quality (or maintain image quality with lower dose) on medical images.

Applications include

- **Denoising:** DL algorithms can learn to distinguish noise from the underlying signal. Noise can then be removed, while preserving the most important imaging features.
- **Super-resolution:** DL models can learn to increase the spatial resolution (i.e., create high-resolution images from low-resolution images).
- **Artifact removal:** removal of artifacts that impact image quality (such as motion artifacts, beam hardening).
- **Virtual contrast enhanced scans:** DL models can be trained to simulate contrast-enhanced images based on a non-contrast study.

Non-interpretive use cases

Use cases or applications that do not have diagnostic or prognostic primary outcomes, but facilitate the digital radiological workflow, from patient scheduling to communication of results (see next page for examples). These applications are relatively novel and mostly still **under development**, but they hold great potential.

Some common examples:

- **Scheduling support:** can help with workflow optimisation, by automating the process of scheduling studies and making sure that the workload is adequate for the department.
- **Automation of radiology protocols:** based upon the available clinical information, AI can help identify the optimal image acquisition protocol, e.g., if an abdominal CT should be acquired with or without IV contrast.
- **Worklist prioritisation:** some machine learning models are built to identify urgent studies that require prompt interpretation by a radiologist. This way, we can ensure that high priority studies are reviewed first.
- **Hanging protocols:** some AI tools can help determining the layout by which radiology images are displayed according to the specific clinical scenario / study protocol.

Vendors and clinicians have had a “tunnel vision” towards inter-pretive use cases, while there is an array of use cases beyond decision-making support (i.e., beyond making the diagnosis).

Imaging value chain | Non-interpretive use cases

Merel Huisman ESSR 2023

Upstream Workflow

- Demand forecasting vs. staffing
- Scheduling optimisation
- Patient preparation (chatbot / GenAI)
- Modality selection
- Protocol selection
- Contrast agent & dose reduction
- Automatic quality control and rescan
- Post-processing
- Triaging (worklist)
- Clinical information (LLM's)
- Hands-free personalised navigation
- Automated personalised hanging protocols

Decision-making

Downstream Reporting | Communication

- Automatic guideline recommendations
- Prepopulating reports
- Auto-structuring
- Automated impression
- Laterality/age/ gender correction
- Multi-media enhanced reports
- Patient friendly reports & translation
- Critical findings & follow-up
- Management
- Billing
- Resident Education
- Business Intelligence (Dashboards)

CHAPTER OUTLINE:

/ Algorithm Development, Deployment, and Evaluation

>|< COMPARE

Use Case Definition

/ Define the goal of the algorithm (i.e., the clinical **condition to be targeted** by the application)

/ Define the inclusion and exclusion criteria associated with the clinical condition

/ Identify the **data elements** required for model development

Dataset Preparation

/ Collect **data** that is **representative** of the clinical condition

/ Label / annotate the collected data (this is the **ground truth** that will be used to train and test the model)

/ **Split** the dataset into training, validation and testing sets

Model Training

/ Evaluate what type of data **preprocessing** will be required

/ Choose the right model architecture approach for the task defined in the previous steps

/ Use the **training and validation** sets to evaluate performance of models trained with different approaches

Internal Validation

/ **Select** the model with the best performance on the validation set

/ Evaluate the **model performance** on the independent (i.e., holdout) **test set**

/ This performance will be an **approximation of the generalisability** of the model (i.e., how well the model would perform in another dataset)

External Validation

/ Evaluate **model performance** on external data - (e.g., data from other healthcare institutions)

/ Evaluates **model generalisability and reproducibility** (i.e., usefulness in varying settings / populations)

/ Helps to identify model **bias** (e.g., poor subgroup performance)

Clinical Deployment

/ Models are implemented in the **clinical workflow**, usually after a **pilot**

/ **Seamless integration** is not trivial but critical

/ Regulatory clearance is required (e.g., **CE-mark**)

/ **Usability factors** beyond model performance should be considered (e.g., how and when, speed, human-machine interaction)

Post-market Surveillance

/ Model output should be **continuously monitored** to detect performance drops in case of changing clinical parameters (called **data set shift**)

/ **Adverse events** related to model use should be reported

/ **User feedback** should be collected

/ **Model updates** can be implemented to address any issues that may be identified

Algorithmic performance is constantly evaluated throughout model training, and then final performance is assessed on the test set, and later on external data during external validation.

Performance should always be evaluated **using multiple performance metrics** to get a comprehensive understanding of its strengths and weaknesses. The choice depends on the type of problem, disease prevalence and clinical context.

Common performance metrics in ML:

- **Dice similarity coefficient:** a pixel-based overlap measure between predicted and true areas in segmentation tasks, ranging from 0 (no overlap) to 1 (perfect overlap)
- **Mean squared error (MSE) / Mean absolute error (MAE):** assesses the quality of a regression model
- **Precision (=positive predictive value)*:** proportion of true positives out of all positive predictions, depends on prevalence
- **Recall (=sensitivity)*:** proportion of true positives out of all actual positive samples, independent on prevalence
- **Accuracy*:** proportion of correct predictions out of all predictions (%correct), intuitive but can overestimate performance
- **F1-score*:** metric for confidently predicting and not missing disease in a low prevalence setting, preferred over accuracy in rare diseases
- **Area under the ROC curve (AUC-ROC):** a graphical summary statistic for model discrimination plotted as the true positive rate against the false positive rate at multiple classification thresholds

*Derived from confusion matrix (see next page)

The **confusion matrix** is critical to the model performance evaluation in classification tasks (e.g., benign vs. malignant lesion). It provides a comprehensive summary of the model's predictions compared to the ground truth labels (actual class).

		Prediction: POSITIVE	Prediction: NEGATIVE
Actual (Ground truth)	POSITIVE	TRUE POSITIVE (TP) Hit	FALSE NEGATIVE (FN) Type II error (miss)
	NEGATIVE	FALSE POSITIVE (FP) Type I error (false alarm)	TRUE NEGATIVE (TN) **Correct rejection**

Based on the confusion matrix, multiple performance metrics can be derived, including:

- **Sensitivity:** TP / (TP + FN). Measures the model's ability to correctly identify positive cases (abnormalities) from all the actual positive cases
- **Specificity:** TN / (TN + FP). Measures the model's ability to correctly identify negative cases (normal cases) from all the actual negative cases

AI in clinical trials:

- AI tools that are used in the setting of centralised image reading for clinical trials also require proper technical and clinical validation. Ground truth consistency and adequate population representation (including disease phenotypes, scanners and acquisition protocols variability) are equally essential in this scenario for training and testing of the algorithms.
- AI can support/facilitate some trial-related tasks and/or image analysis, such as: patient selection according to inclusion criteria, image quality assessment from uploaded scans and evaluation of quantitative imaging biomarkers, bringing also notorious decrease of image annotation/reading time and reduction of inter-reader variability.

<∞> REFERENCE

Check out for more information:

https://www.eusomii.org/w60-validation-of-automated-image-analysis-tools-in-the-absence-of-a-ground-truth-by-marco-during/

/ Data Sharing

Development and improvement of AI is largely based on the algorithm's learning experience. As algorithms learn from data, a more comprehensive data access is crucial for improved accuracy and implementation and, ultimately, for a better service provided to healthcare.

GDPR - General Data Protection Regulation

In May 25th 2018 GDPR came into effect. It applies to all EU member states and concerns processing of **personal data**, including (although not specifically designed for) data concerning health.

GDPR is a **binding law** and supersedes pre-existing laws.

PERSONAL DATA:

any information relating to an identified or identifiable natural person

PROCESSING:

any operation or set of operations which is performed on personal data

DATA CONCERNING HEALTH:

any information relating to an identified or identifiable natural person

<!> ATTENTION

Identified or identifiable natural person is a key concept in the matter of data protection.

<∞> REFERENCE

Take a look:

https://gdpr-info.eu/

A particular setting where GDPR is of utmost importance is in Medical Devices (MD) development and commercialisation, specifically those implementing AI software, where access to appropriate datasets determines its performance and conformance to the **intended use**.

The EU Medical Device Regulation (MDR) replaced the EU Medical Device Directive (MDD) as of May 26, 2021. It imposes stringent regulatory requirements that need to be met before medical devices can be used in clinical practice. **The EU Medical Device Regulations (MDR) requires compliance with the GDPR.**

<!> ATTENTION

AI-based software tools are seen as a medical device and are regulated as such.

MDR applies to instrument, apparatus, appliance, software, implant, reagent, material, or other article for any of the following:

- diagnosis, prevention, monitoring, treatment, or alleviation of a disease
- investigation, replacement, or modification of an anatomical, physiological, or pathological process
- providing data via in-vitro examination of samples derived from a human body

The **intended use** comprises:

(1) the actual medical purpose

(2) the authorised use, understood as defining the intended users and use environment, target patient population, or body parts

Techniques to mitigate data protection risks according to GDPR

- **Pseudonymisation** - means the processing of personal data in such a manner that the personal data can no longer be attributed to a specific data subject without the use of additional information, provided that such additional information is kept separately. Pseudonymised data qualifies as personal data under GDPR.
- **Anonymisation** - anonymous data is data from which no connection to a specific identifiable person can be drawn and falls outside applicability of the GDPR.

In the specific case of the health sector, where it is crucial to keep traceability, pseudonymisation is an example of an appropriate data protection safeguard.

REFERENCES

Check out for more information::

https://www.eusomii.org/protection-of-patient-data-in-eu-vs-us-by-erik-ranschaert-md-phd-2/
https://www.linkedin.com/pulse/anonymisation-now-house-cards-magali-feys

Health data may be processed:

- When the patient gives **explicit and unambiguous consent** to the use of their data
- When it is in the patient's **vital interest**
- For **healthcare purposes**
- For **public interest** in the area of public health
- For **archiving purposes** in the public interest, **scientific or historical research purposes or statistical purposes**
- In the field of **employment, social security and social protection law**

<∞> REFERENCE

European Society of Radiology (ESR). The new EU General Data Protection Regulation: what the radiologist should know. Insights Imaging. 2017 Jun;8(3):295-299. doi: 10.1007/s13244-017-0552-7. Epub 2017 Apr 24. PMID: 28439718; PMCID: PMC5438318.

/ Possible Benefits, Risks, Available Evidence

AI applications in the clinical setting, specifically in the radiology workflow, comprise not only image recognition and support on decision-making (radiologist-centered) but also upstream and downstream procedures. For a smooth workflow, AI algorithms should be fully integrated in the PACS workstations.

Some possible **benefits** include automation of time-consuming tasks, namely in:

- Optimisation of worklist (e.g., facilitating the analysis of emergency examinations) and scheduling
- Modality and protocol selection
- Image acquisition time and radiation dose reduction
- Image processing
- Lesion detection, measurement and grading
- Reporting and communication to clinicians and patients
- Billing

<∞> REFERENCE

Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks | SpringerLink

Other available current applications include scan-related automated processes such as:

- Patient positioning at the isocenter (CT and MRI)
- Identification of the region of interest (MRI)
- Equipment maintenance (CT)

To be highlighted is that simultaneous time and costs saving, paired with reduced radiological workload and increased productivity and efficiency will primarily benefit the patient, but also the radiologist, referral physicians and the healthcare system in general.

Ultimately, AI solutions might also support an extension of healthcare services coverage where there is a shortage of practitioners.

<∞> REFERENCE

European Society of Radiology (ESR). The new EU General Data Protection Regulation: what the radiologist should know. Insights Imaging. 2017 Jun;8(3):295-299. doi: 10.1007/s13244-017-0552-7. Epub 2017 Apr 24. PMID: 28439718; PMCID: PMC5438318.

Some inherent risks need to be accounted for in AI applications, such as:

- **Unintended bias** potentially causing health disparities (e.g., gender, race, socioeconomic status)
- **Performance drop** in the clinical setting, or in certain subgroups
- **Inconsistent performance** of the algorithm over time
- **Overcomplicating** healthcare and **adding costs** without efficiency nor quality gains
- Lack of reimbursement (country-specific).
- **Post-market surveillance failure** (mandatory according to MDR)
- **Liability issues** (a malpractice aspect in the United States) on the final patient outcome - who is liable? the AI developer? The company which commercialises the algorithm? Or the radiologist?
- **Cyberattacks and data leakage.**
- **Automation bias** (i.e., humans following the AI blindly even if it is giving wrong advice)
- **Technical push > clinical pull** (i.e., developing tools because it is possible, not because it is needed)

It is essential to be aware of the **actual clinical problems** and the **appropriateness** of the AI-based solutions in a particular clinical setting; see AI as a means not as an end goal.

REFERENCE

Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks | SpringerLink

Future Aspects

/ Future Aspects

- Currently AI algorithms in radiology are narrowly focused, targeting a specific imaging feature or task (called a **point solution**).
- In future, this might change with artificial general intelligence (AGI) and eventually AI could execute many tasks at a human level capability with limited human supervision.
- In that case the day-to-day tasks of a radiologist might change drastically; we would have more time for patient contact, complex cases, and multi-disciplinary team meetings.

>|< COMPARE

NARROW AI (POINT SOLUTION)	GENERAL AI
Application specific/task limited	Perform general (human) intelligence tasks
Fixed domain models provided by programmers	Self-learns and reasons with its operating environment
Learns from thousands of labelled examples	Learns from few examples and/or from unstructured data
Reflective tasks with no understanding	Full range of human cognitive abilities
Knowledge does not transfer to other domain tasks	Leverages knowledge transfer to new domains and tasks
Today's AI in radiology	Future's AI in radiology?

CHAPTER OUTLINE:

Large Language Models (LLM)

- LLMs are deep neural networks trained to generate human-level text.
- The GPT (generative pretrained transformer) family of LLMs are currently on the rise and are already being used in many areas of medicine and radiology.
- To date, several articles have been published using GPT-3.5 and GPT-4 showing that LLMs can support decision-making in mammography, write medical articles, or pass radiology board exams.
- There may be more to come in the near future, and LLMs may facilitate our path to AGI.

User prompt (text) 〉 **LLM (e.g., GPT-4)** 〉 **Generated text**

CHAPTER OUTLINE:

/ Take-Home Messages

- AI is a multidisciplinary effort where computer scientists, medical physicists, and clinical experts collaborate in all steps of the process to achieve clinically applicable solutions.
- Machine Learning uses algorithms capable of learning from data and making predictions, whereas Deep Learning is a subset of ML and utilises Deep Neural Networks to learn patterns in data.
- There is a wide range of areas where Deep Learning can be applied in radiology, including imaging and non-imaging use cases.
- Compliance with GDPR is fundamental: Data collection should be minimised and used fairly, with clear and legitimate purpose. Data should not be stored longer than necessary and must be protected with appropriate cybersecurity measures.
- Benefits of AI implementation include reduction of image interpretation and processing time, optimisation of worklists and reduction of radiation dose.
- Risks and limitations of AI include performance drop, liability issues, cyberattacks and data leakage.
- Radiologists should become familiar with these and take advantage of this enormous potential for better patient care.

CHAPTER OUTLINE:

References

- Hosny, A., Parmar, C., Quackenbush, J. et al. Artificial intelligence in radiology. Nat Rev Cancer 18, 500–510 (2018). https://doi.org/10.1038/s41568-018-0016-5
- Gabriel Chartrand, Phillip M. Cheng, Eugene Vorontsov, Michal Drozdzal, Simon Turcotte, Christopher J. Pal, Samuel Kadoury, and An Tang. Deep Learning: A Primer for Radiologists. RadioGraphics 2017 37:7, 2113-2131. https://doi.org/10.1148/rg.2017170077
- Phillip M. Cheng, Emmanuel Montagnon, Rikiya Yamashita, Ian Pan, Alexandre Cadrin-Chênevert, Francisco PerdigónRomero, Gabriel Chartrand, Samuel Kadoury, and An Tang. Deep Learning: An Update for Radiologists. RadioGraphics 2021 41:5, 1427-1445. https://doi.org/10.1148/rg.2021200210
- Bradley J. Erickson, Panagiotis Korfiatis, Zeynettin Akkus, and Timothy L. Kline. Machine Learning for Medical Imaging.RadioGraphics 2017 37:2, 505-515. https://doi.org/10.1148/rg.2017160130
- https://gdpr-info.eu/
- European Society of Radiology (ESR). The new EU General Data Protection Regulation: what the radiologist should know. Insights Imaging. 2017 Jun;8(3):295-299. doi: 10.1007/s13244-017-0552-7. Epub 2017 Apr 24. PMID: 28439718; PMCID: PMC5438318
- Regulation 2017/745 Recital 47, arts. 62(4)(h), 72(3), 92(4), 110(1)–(2) (EU).
- The Future of Medical Device Regulation: Innovation and Protection (pp. 77-90). Cambridge: Cambridge University Press. doi:10.1017/9781108975452.007
- Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks | SpringerLink.
- https://www.linkedin.com/pulse/anonymisation-now-house-cards-magali-feys
- https://www.monash.edu/researchinfrastructure/mbi/research/imaging-analysis/motion-artefact-removal-in-mri
- https://discourse.slicer.org/t/new-extension-fully-automatic-whole-body-ct-segmentation-in-2-minutes-using-totalsegmentator/26710
- A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems 25, 2012.

/ Further Reading

- Artificial Intelligence in Medical Imaging: Opportunities, Applications and Risks 1st ed. 2019 Edition by Erik R. Ranschaert (Editor), Sergey Morozov (Editor), Paul R. Algra (Editor), Springer.
- Pesapane, F., Codari, M. & Sardanelli, F. Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. Eur Radiol Exp 2, 35 (2018). https://doi.org/10.1186/s41747-018-0061-6
- Mazurowski MA, Buda M, Saha A, Bashir MR. Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI. J Magn Reson Imaging. 2019 Apr;49(4):939-954. doi: 10.1002/jmri.26534. Epub 2018 Dec 21. PMID: 30575178; PMCID: PMC6483404.
- Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer. 2018 Aug;18(8):500-510. doi: 10.1038/s41568-018-0016-5. PMID: 29777175; PMCID: PMC6268174.
- Kelly BS, Judge C, Bollard SM, Clifford SM, Healy GM, Aziz A, Mathur P, Islam S, Yeom KW, Lawlor A, Killeen RP. Radiology artificial intelligence: a systematic review and evaluation of methods (RAISE). Eur Radiol. 2022 Nov;32(11):7998-8007. doi: 10.1007/s00330-022-08784-6. Epub 2022 Apr 14. Erratum in: Eur Radiol. 2022 May 20;: PMID: 35420305; PMCID: PMC9668941.
- Kulkarni S, Seneviratne N, Baig MS, Khan AHA. Artificial Intelligence in Medicine: Where Are We Now? Acad Radiol. 2020 Jan;27(1):62-70. doi: 10.1016/j.acra.2019.10.001. Epub 2019 Oct 19. PMID: 31636002.

Test Your Knowledge

/ Test Your Knowledge

<?> QUESTION

1

What is TRUE about Deep Neural Networks?

- ☐ Their success is due to better hardware (graphic cards) specialised in matrix operations
- ☐ Need artificial biological, highly interconnected neurons to operate
- ☐ Are the only form of machine learning
- ☐ Need the manual extraction and coding of knowledge

/ Test Your Knowledge

<?> ANSWER

1 What is TRUE about Deep Neural Networks?

- ■ Their success is due to better hardware (graphic cards) specialised in matrix operations
- ☐ Need artificial biological, highly interconnected neurons to operate
- ☐ Are the only form of machine learning
- ☐ Need the manual extraction and coding of knowledge

/ Test Your Knowledge

<?> QUESTION

2 The different Machine Learning methods are:

- ☐ Pre-coded and post-coded learning
- ☐ Bottom-up and top-down learning
- ☐ Supervised learning, unsupervised learning and reinforcement learning
- ☐ Single-shot learning and multi-shot learning

/ Test Your Knowledge

<?> ANSWER

2 The different Machine Learning methods are:

- ☐ Pre-coded and post-coded learning
- ☐ Bottom-up and top-down learning
- ■ Supervised learning, unsupervised learning and reinforcement learning
- ☐ Single-shot learning and multi-shot learning

/ Test Your Knowledge

<?> QUESTION

3 What is TRUE about Data Sharing?

- ☐ Anonymisation allows safe data sharing and backtracking to the patient's original data
- ☐ Pseudonymous data is considered personal data under the GDPR
- ☐ For healthcare purposes patient data can be processed without consent
- ☐ Software does not always fall under the MDR

/ Test Your Knowledge

<?> QUESTION

3 What is TRUE about Data Sharing?

- [ ] Anonymisation allows safe data sharing and backtracking to the patient's original data
- [x] Pseudonymous data is considered personal data under the GDPR
- [ ] For healthcare purposes patient data can be processed without consent
- [ ] Software does not always fall under the MDR

/ Test Your Knowledge

<?> QUESTION

4 Regarding Algorithm Evaluation, which of followings is a suitable metric to evaluate a segmentation task?

- ☐ Mean squared error
- ☐ Precision
- ☐ F1-score
- ☐ Dice similarity coefficient

CHAPTER OUTLINE:

/ Test Your Knowledge

<?> ANSWER

4 Regarding Algorithm Evaluation, which of followings is a suitable metric to evaluate a segmentation task?

- ☐ Mean squared error
- ☐ Precision
- ☐ F1-score
- ■ Dice similarity coefficient

/ Test Your Knowledge

<?> QUESTION

5

Regarding Deep Learning Applications in Medical Imaging, splitting an image into multiple regions, where each region corresponds to a particular object or class, is an example of:

- ☐ Classification
- ☐ Image Enhancement
- ☐ Detection
- ☐ Segmentation

/ Test Your Knowledge

<?> ANSWER

5 Regarding Deep Learning Applications in Medical Imaging, splitting an image into multiple regions, where each region corresponds to a particular object or class, is an example of:

- ☐ Classification
- ☐ Image Enhancement
- ☐ Detection
- ■ Segmentation

EUROPEAN SOCIETY OF RADIOLOGY