Unit-5

AI for Image Processing

The role of medical image computing and ML in health care, Deep Learning and ML in imaging: Basic principles, how to develop AI Applications, A standard Approach for preparing Imaging data for ML tasks in Radiology, AI in Medicine: Validation and Study Design, Enterprise Imaging.

The Role of Medical Image Computing and ML in Healthcare :-

Due to continuing technological advances in medical image acquisition, novel imaging modalities are being introduced in medical practices, such as multi-slice (volumetric) and multi-energy CT, multi-parametric and multi-frame (dynamic) MRI, multi-dimensional (3D+time) US, multi-planar interventional imaging in multi-modal (hybrid) PET/CT and PET/MRI imaging technologies.

The analysis of the large amounts of imaging data created by these modalities has become a tremendous challenge and a real bottleneck for diagnosis, therapy planning and follow-up, and biomedical research.

PACS - Picture Archiving and Communication systems.

In order to optimally exploit all available imaging data and to support the effective use of "Big Data" involving medical images in the context of personalized medicine, reliable computer-aided image analysis becomes indispensable to extract and quantify the relevant information from the imaging data, to fuse complementary information and to support the interpretation thereof.

Medical Image Analysis:

Medical image analysis involves measurements in medical images.
i.e, the extraction of relevant quantitative information from the images.
Many applications in computer vision involve the detection (or) recognition of an object in an image.
Medical image analysis often concerns the quantification of specific geometric features of the objects of interest the assessment of anatomical changes over time & the detection and characterization of morphological variation b/w subjects.
The analysis of 3D shap and shape variability of anatomical objects in images is thus a fundamental problem in medical image analysis.

Image Segmentation:

Image segmentation involves the detections of the objects of interest in the image and defining their boundaries,
i.e, discriminating b/w the image voxels that belong to a particular object and those that do not belong to the object.

Image segmentation is a prerequisite for quantification of the geometric properties of the obj, in parcular its volume or shape.
Image segmentation can be performed in different ways:

- Boundary wise by delineating the contour in surface of the obj in one (2D) or multiple (3D) image slices
- Region-wise by grouping voxels that are likely to belong to the same obj into one or multiple regions or voxel-wise by assigning each voxel in the image as belonging to a particular object, tissue class or background.

Class labels assigned to a voxel can be probabilistic, resulting in a soft or fuzzy segmentation of the image.
Accurate 3D segmentation of complex shaped objects in medical images is usually complicated by the limited resolution of the images and by the fact that the resolution is often not isotropic.

Image Registration:

Image registration involves determining the spatial relationship b/w different images. i.e, establishing spatial correspondences b/w images or image matching, in particular based on the image content itself.
After proper registration, the images can be resampled onto a common geometric space and fused.

Image Visualization:

The information that is extracted from the images ideally needs to be presented in the most optimal way to support diagnosis and therapy planning.

For 3D medical images, 2D-multi-planner visualization is not well suited to assess structural relationships within and b/w objects in 3D, for which true 3D visualization approaches are to be preferred.

In clinical applications such as image-based surgery planning or image guided intra-operative navigation, additional tools need to be provided to manipulate the objects in the 3D scene, to add virtual objects to the scene or to fuse the virtual reality scene with real-world images.

Image segmentation, registration and visualization should not be seen as separate subproblems in medical image analysis that can be addressed independently, each using a specific set of strategies.

For instance, image registration can be used as a computational strategy for image segmentation by matching the image to be segmented to a similar image that has been previously segmented.

Challenges:

Medical image analysis is complicated by different factors, in particular the complexity of the data, the complexity of the objects of interest, and the complex validation.

Complexity of the Data:

Medical images are typically 3D tomographic images.

Instead of processing the data in 2D slice by slice, 3D processing is usually more effective as it allows to take spatial relationships in all three dimensions into account, provided that the resolution of the data in-plane and out-plane is comparable.

Medical images are based on different physical principles, and the quantification of the images is complicated by the ambiguity that is induced by the intrinsic limitations of the image acquisition process, in particular limited resolution.

Complexity of the Objects of Interest:

The objects of interest in medical images are typically anatomical structures, either normal or pathological, that can be rigid or flexible to some extent.

Anatomical structures may exhibit complex shape, such as the cortical surface of the brain, the cerebral and coronary vessels, or the bronchial tree in the lung.

Such complex shapes can not easily be described by a mathematical model.

Complexity of the Validation:

Medical image analysis involves the quantification of internal structures of interest in real-world clinical images that are not readily accessible from the outside.

Apart from accuracy, precision, consistency, and robustness of the method are to be considered as well when evaluating its clinical usability.

Medical Image Computing :-

Medical image computing, which is a branch of scientific computing at the intersection of medical imaging, computer vision and ML, aims of developing computational strategies for medical image analysis that can cope with the complexity of medical imaging data to enable automated analysis with sufficient accuracy and robustness.

Such strategies rely on mathematical models that incorporate prior knowledge about the typical appearance of the objects of interest in the images, including photometric properties, geometric properties, and context.

Model-based image analysis involves the construction of an appropriate parameterized representation for the model, the derivation of fit of the model to the data, and the selection of a suitable optimization strategy for finding the optimal parameters of the model instance the best fits the image data.

The models need to be sufficiently flexible to account for image appearance variations, due to eg. variability in the image aquisition itself, normal biological shape variability, motion and deformation, and pathology.

The flexibility of the model is determined by the specific representation that is chosen for the model, its parameterization and number of degrees of freedom, and by the constraints imposed on its parameters.
More sophisticated approaches are needed that incorporate appn. specific information about the images to be analyzed.
By adapting a multi-variate Gaussian model for the underlying distribution of the data or by using dimensionality reduction techniques such as PCA.
Recent advances in SL of models from training data, especially DL based on CNN, have shown great promise for many problems in computer vision, including image classification, object recognition, and segmentation.
Neural networks define highly complex function classes and large amounts of data are typically necessary for them to converge to a stable solution with good generalization ability.
The analysis of shape and shape-variability which is a fundamental problem in medical image analysis, typically includes dispersed non-local patterns derived from dense spatial correspondences b/w heterogeneous images analyzed jointly, for which it is not evident how this problem could be formulated as a classification problem using current NN architecture.

Model Based Image Analysis:

Model-based image analysis makes use of a model

of the image appearance of the objects of interest in the images.
The model represents prior knowledge about the geometric, photometric, and contextual properties of the objects of interest in the images.
The model is fitted to the image data using a suitable measure for the goodness of fit.

Using Bayes rule the a posteriori probability can be written as

$$prob(M(\theta) \mid I) = \frac{prob(I \mid M(\theta)) \cdot prob(M(\theta))}{prob(I)}$$

Energy Minimization:

By adopting a Gibbs distribution for both the prior and the data likelihood, this optimization problem can be formulated as energy minimization:

$$prob(M(\theta)) = \frac{\exp(-E_{int}(\theta))}{Z_{int}}$$

Classification / Regression:

Feature vector-based classification / regression is a very flexible approach for image analysis, in the sense that multiple, separately computed sets of features, related to different object properties. (or computed from different subparts of the data.

Due to the large number of parameters in such n/ws, different aspects related to n/w architecture, optimization, regulations, data sampling, and augmentation have to be carefully considered.

Computational Strategies:

Model-based computational strategies for medical image computing can be broadly classified as either flexible shape fitting or pixel classification.

Flexible Shape Fitting:

Flexible shape fitting makes use of a more (or) less global parametric model of the image appearance of the object, including photometric, geometric, and contextual properties that is fitted to the actual image data by optimization of an objective function that evaluates the goodness of fit ~~of~~ the model instance.

When deterministic constraints imposed on the flexibility of the model are a necessarily largely heuristic in nature, statistical models aim at avoiding heuristics by learning suitable model constraints from the data itself, based on a representative training set of examples, typically derived from a DB of similar images acquired from different subjects.

A popular strategy for landmark-based statistical shape modeling are point Distribution Model (PDM).

A PDM is constructed by statistical analysis of the observed variations in the locations of corresponding landmark points defined on all object shapes in a representative training set of shape instances, after appropriate spatial normalization of all shapes ~~of~~ to a common coordinate space to eliminate irrelevant, pose related variability.

Image registration establishes dense spatial correspondence b/w two images based on a suitable local or global similarity measure.

Image ~~segmen~~ registration is ~~fr~~ frequently used in medical image analysis for inter-subject spatial normalization, for the construction of mean shape templates, for atlas based segmentation, for quantification of local shape differences and characterization of shape variability b/w groups, and for spatio-temporal analysis of motion or disease evolution.

Pixel Classification:

Pixel classification aims at assigning an object label or its probability to each voxel in the image individually, mainly based on local intensity information alone.

Model-based VS classification adopts a parametric model for the expected intensities of the objects of interest, typically a Gaussian mixture model, and estimates the optimal parameters of the model and the classification simultaneously by maximizing the posterior probability of the labels given the data and the model, for instance using the EM- expectation-maximization algm.

Intensity-based classification of pixels can be extended to more general feature-based classification of individual pixels or entire images. DL deals with the issue of optimal feature selection by using a NN with multiple hidden layers to learn the optimal features simultaneously while training the classifier such that overall classification performance is optimized.

DL and ML in Imaging : Basic Principles :-

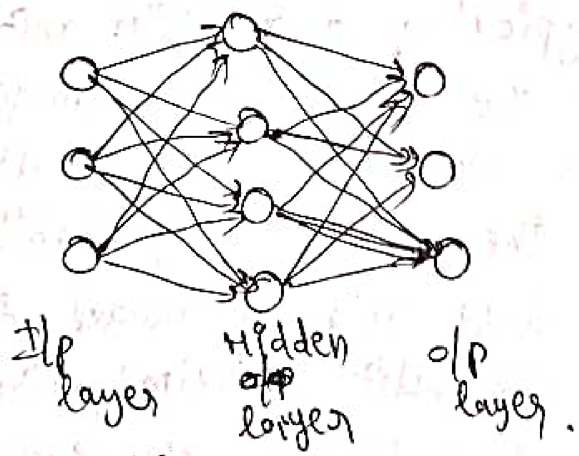
ML is a component of A.I that primarily focuses on finding patterns.

Features and Classes :

SML, which is the type of ML in which known examples are used to train an algm to properly classify future | unseen examples into the correct classes.

Given a collection of labeled images, a first task is to compute "features" that are strong indicators.

Often many features are calculated, then a "feature reduction", or "feature selection" step is performed in which duplicative or non-informative features are removed from the feature vectors.



Architecture of NN

Neural Networks :

NN were the earliest form of ML and were based on our understanding of how the brain and its neurons work.

A critical element of the NN was to "learn", and that was accomplished by adjusting the weights and connected the nodes.
Backpropagation is the general term used for taking the error observed at the o/p and adjusting the weights to reduce the error for the next set of examples provided to the n/w.

SVM:

The SVM alg^m was invented by Vladimir Vapnik and Alexey Chervonenkis in 1963.
Two key concepts of the SVM are the plane that separates two classes and the challenge of mapping points from their original space to a space that allows them to be separated by a plane.
The name SVM indicates that the concept of the separating plane is central to the SVM method.
The SVM alg^m constructs a hyperplane or set of hyperplanes in a high-dimensional space.
Selecting and adjusting hyperparameters are still very much an art that requires experience with both ML alg^ms and images.
SVM can also be used for regression and outlier ~~detection~~. identification.

Decision Trees:

A decision consists of a series of decisions.

A decision tree typically is constructed to make the most "important" decisions first, and that should result in the fewest decisions having to be made.

Calculate the entropy of each feature across the samples, allowing us to calculate each feature information gain.

Information gain calculates the expected reduction in entropy due to sorting on the attribute.

Gini Index is another option for selecting features: An attribute with lower Gini would be the one selected.

Bayes Networks:

Bayesian n/ws arguably are not really ML but rather focus on using probabilities learned from the training data to predict the classes / outcome.

"Bayes law" states that the probability of A given B is equal to the probability of B given A, times the probability of A, divided by the probability of B.

$$P(B|A) = \frac{P(A|B)\,P(B)}{P(A)}$$

A Bayesian n/w represents a set of variables and their conditional dependencies as a directed acyclic graph. ~~which as a step~~

In theory, the features (probabilities) should be independent, but often they are not.

DL:

A popular contest for measuring ML performance is the ImageNet challenge, in which ML algms are given a large collection of images and labels indicating what is present in the image.

Fully Connected Layers:

DL gets its name because it uses NN with many layers.

The traditional NN consists of nodes and connectors that simply multiply and apply an activation function.

These layers are usually referred to as "fully connected" layers.

Convolutional Layers:

For image-based tasks, it is quite common to use several layers of convolutions at the i/p.

Pooling Layers:

Pooling layers, in which the outputs of adjacent convolutions are combined into a single o/p.

The most common pool function is "max pool".

Activation Layers:

A key component of learning is to have non-linearity in the system, and what is the primary function of activation layers.

eg: sigmoid, hyperbolic tangent, ReLU

Output Layer:

The final o/p layer is a special case of an activation function, and for that, more sophisticated layer types are often used.

If the task is regression, a linear o/p is appropriate.
If the task is classification, the softmax function often performs well.
The softmax function will take a vector of values and convert them to an arbitrary sized o/p vector, and the sum of all the o/p values is one.

Residual Layer:

Residual layer, in which gets its name because it uses a "bypass" layer that is essentially the identity function, and then the o/p of a layer (or group of layers) is compared with the identity function.
This is important because the reduction in layers both reduces the number of potential parameters to adjust when learning and also reduces the chance of overfitting to the training data.

Deep Learning Architectures:

DL systems can include many different types of layers, in various sequences, each layer has a number of parameters, such as how many nodes or other layer-specific configurations such as size of a convolution kernel or size of the pooling window.

CNN are a common DL architecture for images, particularly for image classification tasks.
eg: AlexNet, VGGNet, GoogLeNet, ResNet, U-nets, SegNet

FCN – Fully Connected Networks.

GAN - Generalized Adversarial Networks are a very different type of network that are designed to create images rather than classify ~~or~~ segment them.

How to Develop AI Applications :-

The data science and AI have introduced in daily-life applications, speech and face recognition, self-driving cars and NLP must be highlighted.

The increased computational capabilities, thanks to the progressive growth in the performance of GPU, combined with the potential for pattern recognition of deep ANN, have allowed for the management of huge amounts of data with an efficiency that was not possible a decade ago.

The advantage over using traditional n/w architectures is that the convolution allows for a significant reduction of the number of free parameters of the n/w and does not require for the previous extraction of hand-crafted features.

RSNA - Radiological Society of North America

ESR - European Society of Radiology.

Applications of AI in Radiology :-

Image acquisition:

Creation of study protocols: The creation of some patient-specific acquisition protocols largely depends on the clinical indications for the imaging procedure.

A significant amount of data from the patient is taken into consideration at the same time including results of other diagnostics, such as blood tests and previous examinations perform

Optimized MR and CT image quality:

MR machines include methods to shorten times and improve signal homogeneity, like CT machines include image filters and radiation dose reduction functionalities like dose modulation

SNR - Signal to Noise Ratio

AI will help to automatically extract image quality indicators as they are generated and store relationships b/w protocol parameters and quality to train new algms of optimization

Assessment of Image Quality:

AI will help both in the automated quality assurance tests performed phantom-less using patients data and in the appn of algms for the detection of 'abnormal behaviours' of image quality in a specific ~~image~~ machine using methods similar to those being used in the banking sector to detect suspicious (or) fraudulent operations.

Image Interpretation:

Automated hanging protocols:

AI will help to not only load the most relevant series but also going to the slices in the specific organ (or) region anatomy relevant from the clinical data.

PACS - Picture Archiving and Communication System.

Radiomics and Imaging biomarkers analysis:

AI will significantly help the field of imaging biomarkers in two different steps:

→ segmentation

→ Data mining.

COPD – Chronic Obstructive Pulmonary Disease

ROI – Region of Interest

AIF – Arterial Input Function

In the field of radiomics, there is a need to introduce ML techniques to process all the quantitative information generated beyond basic descriptive statistics and to extract the relationship of biomarkers with clinical endpoints.

Automated Image interpretation:

The excellent performance of CNN allows for training new algorithms able to classify studies according to a huge amount of image features that the n/w is able to extract.

Images interpretation is more than reading images but putting together all the information of the patient to achieve a proper diagnosis ~~of the patient to achieve a~~ for clinical decision.

Reporting:

Speech Recognition:

AI will help to minimize the error rate in transcription of radiology reports assisted by speech recognition.

DTW – Dynamic Time Warping

Text Translation: AI will allow to have an ontology-based electronic health record (EHR).

with the items translated to several languages.

Automated annotation through keywords:

The automated conversion of clinical data and radiology reports into keywords from MeSH (Medical Subject Headings) to RadLex (Radiology Lexicon) dictionaries will allow to seamlessly label the examinations and make them useful for training new AI algms for image interpretation.

Knowledge extraction through data exploitation:

Processing radiology reports:

Techniques like NLP can be applied for the automated extraction of semantic information from free-text radiology reports already stored in radiology information systems (RIS), PACS and EHR.

Image Based search engines:

eg: Google

Population health:

the biorepositories will allow for the app^n of AI algms in order to extract information about the relationship b/w image features and clinical endpoints.

Management:

In the field of management in radiology, AI will allow for the optimization of imaging equipment utilization and appropriate scheduling of staff and examinations.

Development of AI app^ns in Radiology:

→ Clinical problem definition

→ Engineering the AI technology.

→ Dataset collection
→ Data Annotation.
→ Training
→ Testing

Training ⇒ labels i/p training data → CNN → o/p labels.

Testing ⇒ I/p testing data previously unseen → Tuned CNN → o/p labeled data.

Resources Framework:

For the development of AI appl^ns within radiology departments (or medical imaging research groups, there is a need for a paradigm shift in the processes and in the profession also involved in the data workflows.

Expertise Dealing with AI computing infrastructure and processing algm's is a challenges task that requires very specific profiles with knowledge in fields such as computer science, statistics, mathematics, image processing, ML, etc.

Computing Resources, medical images are large files processing these images is a challenging task which requires powerful hardware.

Software Resources many advances in DL libraries have been accomplished.

Data Scientists	
H/w	S/w
Labeled Data.	

Data sources: To develop AI $alg^{m}s$ annotated datasets are required. The quality of the datasets has a great impact in the performance of the AI models.

A Standard Approach for Preparing Imaging Data for ML tasks in Radiology:-

Data:

The traditional paradigm of hypothesis-driven medical research largely rests on clinical studies involving cohorts of a few hundred (or) thousand patients.

Modern ML techniques benefit from exponentially larger volumes of data.

- The term "big data" has been used since the 1990s to describe volumes of digital data in excess of those required for traditional scientific research.

It is estimated that 2.5 quintilion bytes of digital data is produced every day, 90% of which are unstructured.

It has been shown that algorithmic performance on computer vision tasks increases longarithmically based on volume of training data size.

Not All Data is Created Equal:

Good quality data management should enable both human and machine interrogators to establish data's identity, usefulness and accessibility quickly and easily.

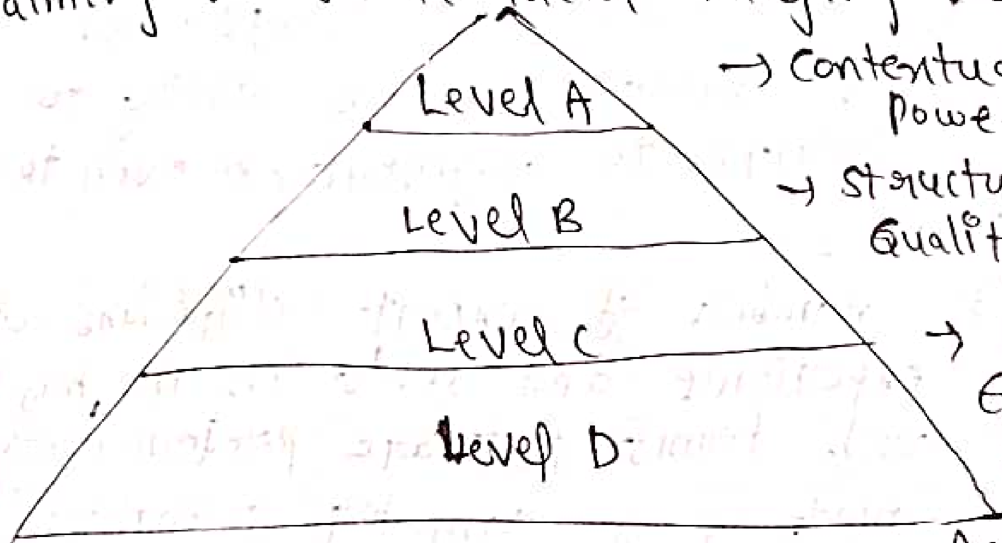
The MIDaR Scale:

There is no standard definition of what

encompasses a baseline medical imaging dataset for ML.

The ideal medical image dataset for an ML application has adequate data volume, annotation, truth, and reusability.

The MIDaR scale is designed to objectively clarify "data readiness" for all interested parties, including researchers seeking imaging data and clinical providers and patients aiming to share their imaging data.



→ Contextual, Annotated, Powered

→ Structured, Visualisable, Quality Controlled

→ Anonymised, Ethical clearance, Extracted, Access Controlled

→ Inaccessible, unknown quality, unknown quantity, Un-anonymised.

MIDaR Level D:

→ Contains Patient Identifiable Information.
PII - Personally Identifying Information.

→ Unverified in Quantity.

→ Inaccessible to Researchers

MIDaR Level C:

→ Ethical Approval

→ Data Extraction.

→ Access Control

MIDaR Level B:

→ Data selection.

→ Quality control

→ Data visualization.

MDDaR Level A:

→ Data Labelling

→ Powering.

AI in Medicine: Validation and Study Design:

AI applied to medicine is expected to have a significant impact on clinical practice. Companies and academic groups world wide have recognised the potential of technologies such as DL to enhance healthcare, and many research teams are now racing to produce AI systems to augment (or even to replace) doctors.

The limited number of expert clinicians with meaningful experience and skills in AI has led to research teams that are predominantly or entirely made up of computer scientists, engineers and developers.

The Validation of AI Technologies in Medicine:

Two fundamental questions regarding the validity of the change:

→ It is safe?

→ It is effective?

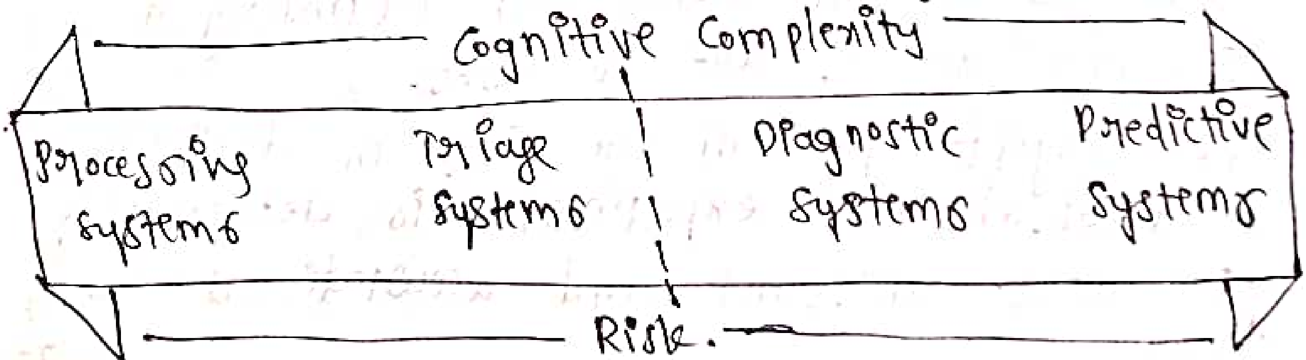
Safety is almost never absolute; few aspects of clinical medicine are completely free from risk of harm.

Determination of acceptable risk is complex, generally involving government regulatory bodies and a range of experts, including clinicians, statisticians, health economists and possibly others.

efficiency and performance depend upon the purpose of the AI system.
When considering safety and efficiency, we need to recognise that AI applied to human medicine is different from most other forms of technology.
The risk to life and health in medical research requires us to put safety first.

<u>Safety in Medical AI:</u>

A key issue related to the question of medical AI safety is the notion of autonomy.
AI systems can perform a range of tasks in medical imaging. These can be simple, such as image processing tasks that humans find tedious and mechanical or complex and cognitive, such as diagnosing a disease or even predicting that will happen to a patient in the future.
"risk increases with increasing complexity".



Diagnostic and predictive systems that can perform at or above the level of a human expert offer the possibility of removing humans from the loop.

<u>Accessing Model Efficacy using clinical studies:</u>
Epidemiological studies of people in a clinical

setting are associated with a well-understand and accepted set of methods for performing experiments that allow us to answer key questions to some degree of certainty while avoiding undue risk of harm to patients.
Clinical studies come in many shapes and sizes for answering different questions, including observational studies such as surveys, case control studies, cohort studies and experimental designs such as randomised controlled trials.

The clinical Question:

The most important element of study design is your clinical question.
The question has two key elements : the task and the comparison.
The task is the question at hand. Measuring the size of an anatomical structure, triaging urgent cases and diagnosing a specific disease are all tasks.
The largest problem we face in designing a medical AI experiment is determining the most relevant and accurate ground truth.

The Ground Truth:

Most diseases, pathologies and outcomes have subjective definitions.
Missing data is fairly common in medical research, where patients or observations which are intended to be included in the study are not available for some reason.

Bias can occur due to medical management heterogeneity. Errors also commonly impact on the quality of the ground truth.
eg: transcription errors in radiology reports can result in mislabelling of cases.
An inaccurate ground truth can lead to both -ve and +ve bias in the results of medical AI experiments.

The Target Population:

The target population is the group of patients upon whom your system is designed to work.

Target Population
→ Training set
→ Test set / cohort

As a general rule of Thumb, you should always consider the big three demographic factors : Race / ancestry
Age, sex.

The Cohort:

It is the set of people the system is tested on, often called the test set in the machine learning literature.
Many teams building medical AI appear to favour the former, selecting cohort / test sets of the bare minimum size that they have estimated able to prove their system is safe and effective.
The factors that determine how reliable your results will be are the effect size and the sample size.

Stratification means that there are subgroups in your cohort, in which your model performance may be systematically different.

Metrics:

There are many possible ways to present results for a medical AI study and many ways to measure performance.

These performance measures are called metrics.

	Case +ve	Case -ve
Predicted +ve	True +ve	False +ve
Predicted -ve	False -ve	True -ve

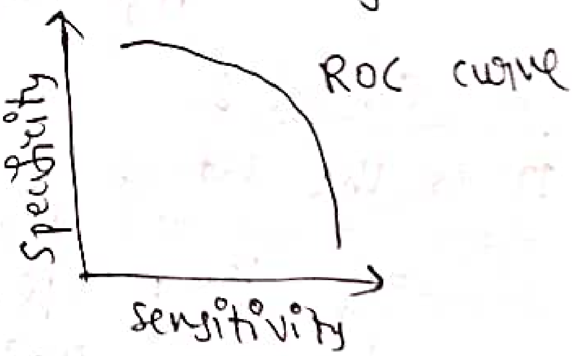
Confusion matrix

$$\text{sensitivity} = \frac{\text{True +ve's}}{\text{Case +ve's}}$$

$$\text{Specificity} = \frac{\text{True -ve's}}{\text{Case -ve's}}$$

Sensitivity and specificity are prevelence-invariant metrics, maning that they will remain same.

$$\text{PPV} = \frac{\text{True +ve's}}{\text{Predicted +ves}}$$



The Analysis:

There are really two approaches for statistical analysis in medical research, both of which are useful. There are:

→ Estimating metric uncertainty using confidence intervals

→ NH significance testing using P-values.

There are three other ways that multiple hypotheses testing commonly affects medical AI studies: the use of ~~commonly~~ public data sets, the use of hand-crafted features and data dredging.

Enterprise Imaging:

The first PACS - Picture Archiving and Communication Systems have been implemented in radiology. ~~More than~~ This has been supported by introducing the DICOM standard in 1993.

Cardiology has been one of the first departments outside radiology using the similar DICOM image objects as radiology for angiography. It has been usual to have separate solutions for different clinical applications based on departmental image acquisition and storage eg. for ultrasound studies, cardiological imaging, ophthalmology etc.

VNA - Vendor Neutral Archive.

Basic Principles of Enterprise Imaging (EI):

In healthcare provider institutions, it is expected to have access to almost all clinical information as part of an EHR - Electronic Health Record.

The HIMSS-SIIM collaborative work group has identified several key elements for a successful enterprise imaging program.

→ Governance
→ Enterprise imaging strategy
→ Enterprise imaging platform (infrastructure)
→ Clinical images and multimedia content

→ EHR enterprise viewer
→ Image exchange services
→ Image analytics
The implementation of enterprise imaging should be based on an IT strategy, which is accepted by the leadership and in line with the governance.

Enterprise Imaging Platform:

An enterprise imaging platform should provide different functionalities. There is the central core with storage, interfacing imaging devices and providing worklist services.

On the other side, the enterprise imaging platform has to serve all different image ~~re~~sources, which could be DICOM-based or non-DICOM based, which is relevant e.g. for mobile applications or video data.

Compared with the traditional PACS work flow, there are new and different requirements in an enterprise imaging environment.

The procedural imaging is relevant for documentation of therapeutic procedures, which might be percutaneous or surgical processes.

Evidence imaging is dedicated to the documentation of clinical findings.

The development of an EI platform in a hospital will impact several workflows in many departments.

Enterprise Imaging should provide a standardized access to all imaging studies integrated in the EHR.

Technical considerations for the deployment of enterprise viewers include optimized installation and support resources.

Health information exchange is getting more and more relevant in modern healthcare systems. EI platforms will provide large data collections.

An enterprise imaging platform should be able to support improved collaboration and patient care with external physicians and patients themselves.