Machine learning and Deep learning in Healthcare context

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Introduction – CEHEADS research group in NMBU

- Centre for Healthcare Data Science - https://ceheads.wordpress.com/
- Data science approaches for medical application.
- Feature engineering, feature selection, multivariate & multi-source analysis, machine learning, deep learning and related software development.

Former members

Current members

Key Collaboration partners

Oslo University Hospital

Maastro

Amsterdam UMC Universitair Medische Centra

CAIR Centre for Artificial Intelligence Research

NTNU

Aarhus University Hospital

Universitätsklinikum Erlangen

Introduction – Institute for Cancer Research in OUS

Introduction – Institute for Cancer Research in OUS

- One of the largest cancer research environment in Norway https://www.ous-research.no/institute/
- Located within the Radium Hospital buildings
- Basic, translation and clinically oriented research
- Close collaboration between researchers and clinicians, diagnosticians including surgeons, oncologists and pathologists.

https://oslo-proton-research.no

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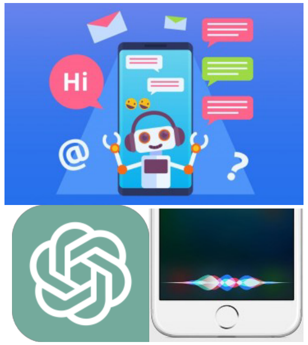
Break

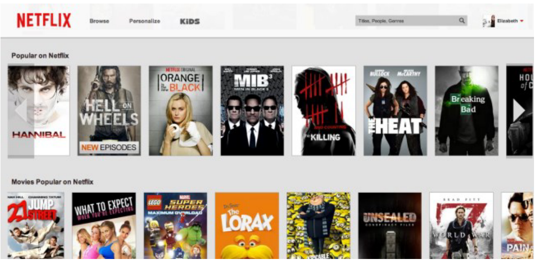
Artificial Intelligence

“AI” is everywhere…

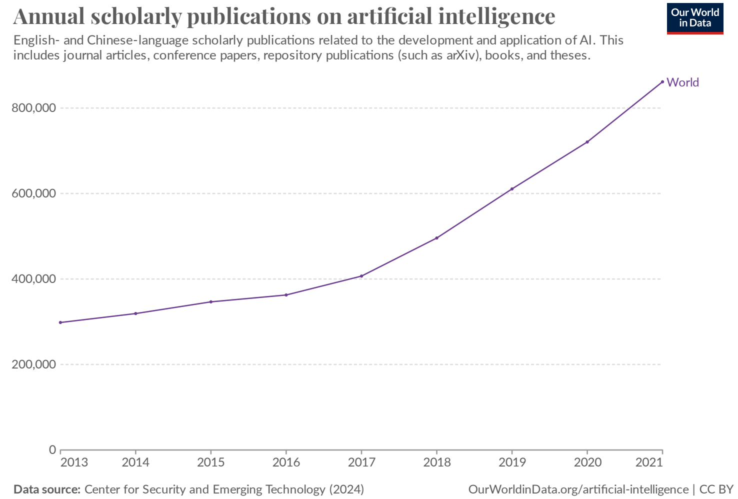


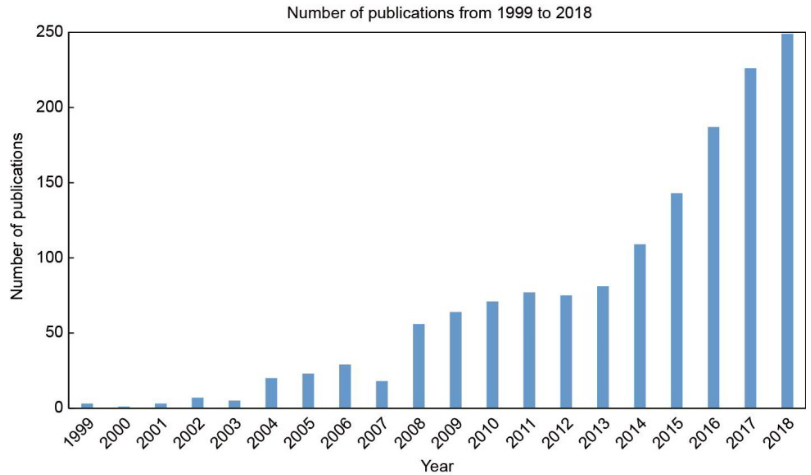
Chatbots

Smart houses



Recommendation systems



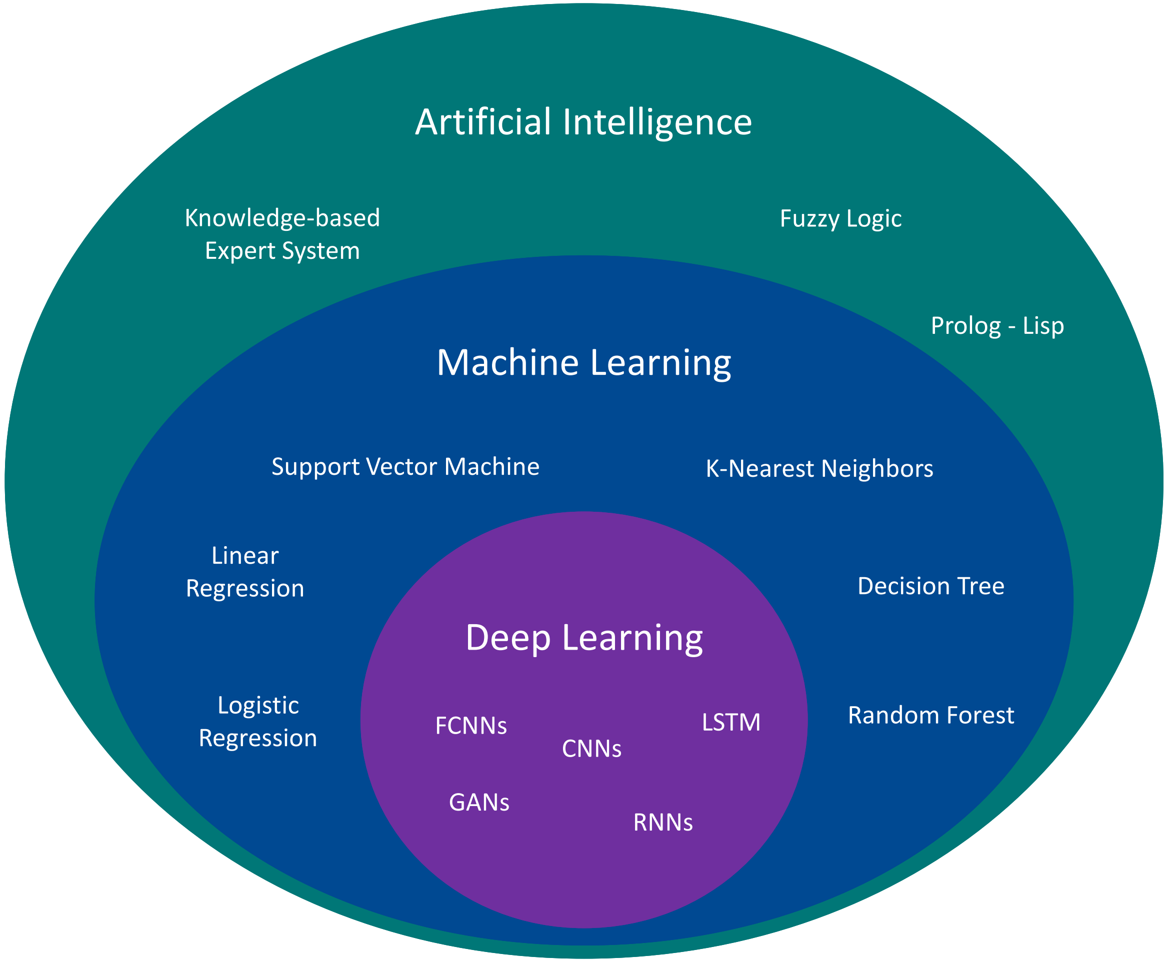


“AI” or “ML” and the topic of “biomedicine” or “biomedical.”

G. Rong, A. Mendez, E. Bou Assi et al., (2020) Artificial Intelligence in Healthcare: Review and Prediction Case Studies, Engineering, https://doi.org/10.1016/j.eng.2019.08.015

Artificial Intelligence

- **Artificial intelligence**
  - Able to conduct tasks that require human intelligence
  - Originally rule-based
- **Machine learning**
  - Learn from data
  - Recognize patterns
- **Deep learning**
  - Neural network



Artificial Intelligence

Descriptive models

Predictive models

Unsupervised Learning

- No labels / outputs for the observations are given to the learning algorithm, leaving it on its own to find structure in its input.
- Example: Clustering, Principal component analysis

Supervised Learning

- Learns a general rule that maps inputs to outputs, by generalizing from the training data to unseen situations.
- Example: Regression, Classification

Semi-supervised Learning

- Some (often most) of the target outputs in the training-set are missing.
- When the cost associated with the labeling process renders a fully labeled training set infeasible.

Reinforcement Learning

- Virtual agents interact with the environment
- Learning from the rewards/punishment received from the environment
- Examples: self-driving car, chatbot

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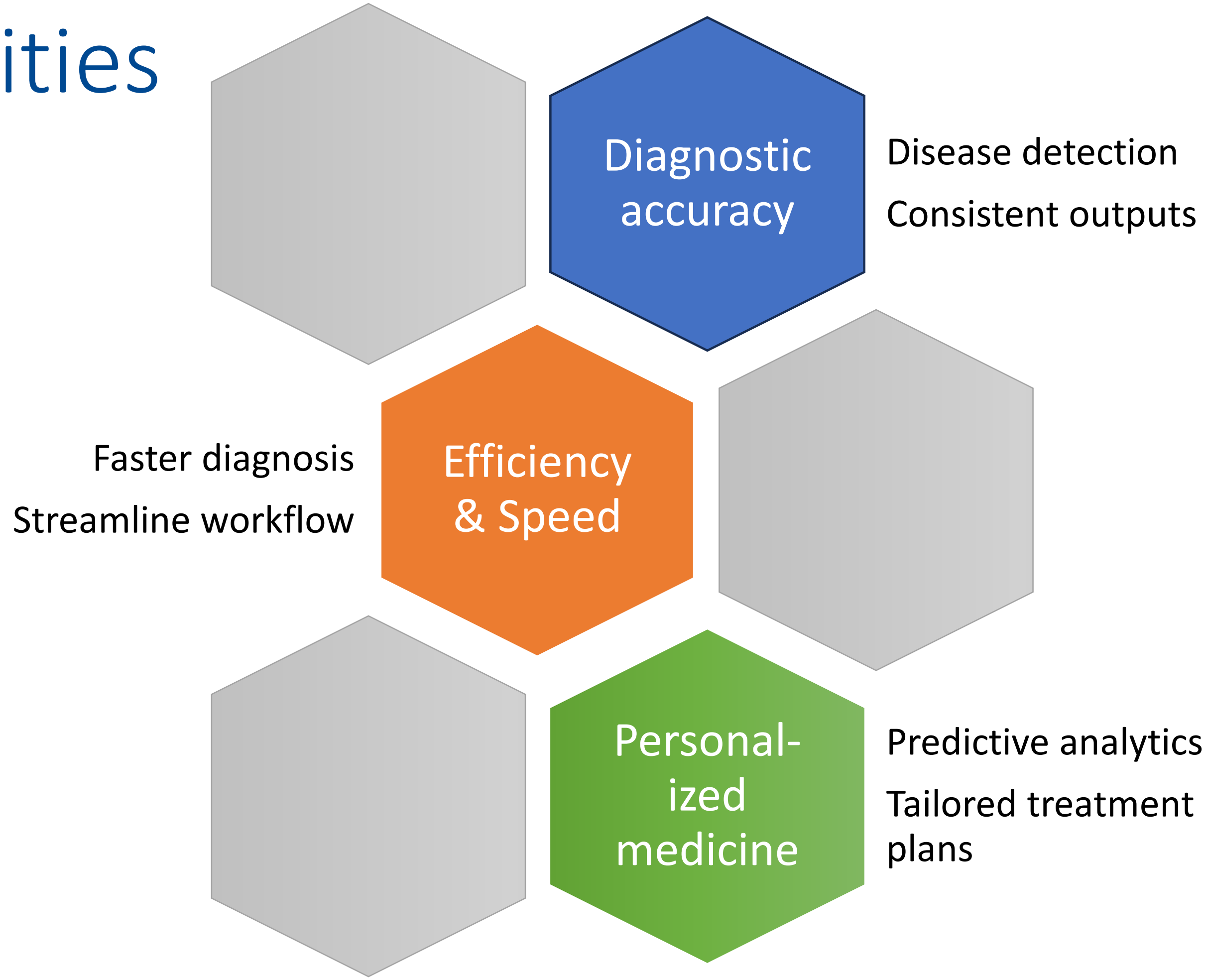
Opportunities



Opportunities – Examples

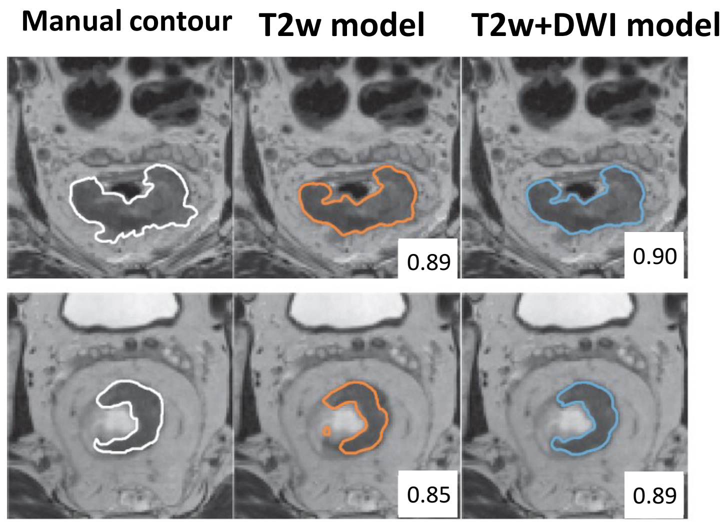
Cancer gross tumour volume automatic segmentation

Radiotherapy requires accurate and precise definition of target volumes and organs at risk, typically contoured manually.

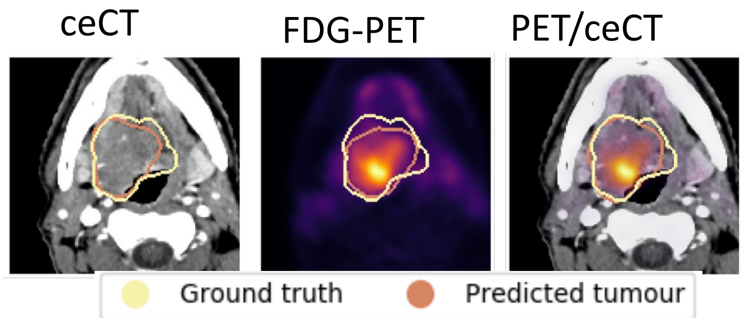
Limitations of manual contouring
Time-consuming and prone to intra- and interobserver variation.

AI for automatic segmentation
Potential to reduce contouring time and variability.

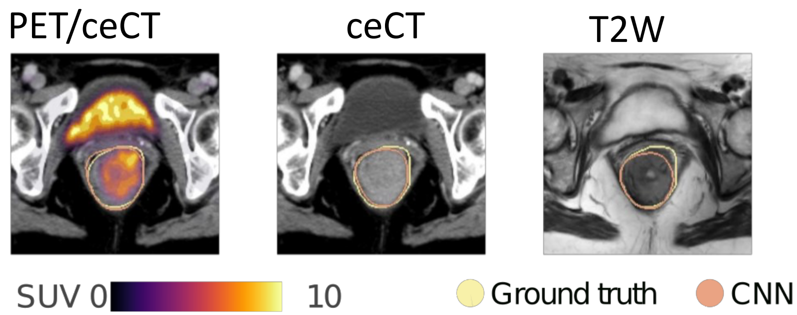
Rectal cancer



Head & neck cancer



Anal cancer



Moe Y et al. 2021. Eur J Nucl Med Mol Imaging 48:2782-2792
Groendahl A et al. 2021. Acta Oncol. 61:89–96.
Knuth F et al. 2021. Acta Oncol 61:255-263

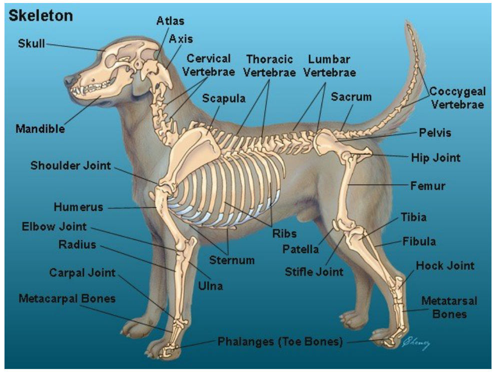
Opportunities – Examples

Automatic screening for joint dysplasia

Screening program in Norway to find joint dysplasia in dogs to prevent them from breeding.

The number of scrutinizers in Norway is limited.

AI for automatic classification
Potential to reduce screening time with high accuracy.



https://healthyhomemadedogtreats.com/20-basic-dog-anatomy-facts-for-beginners/

Normal

Osteo-arthrosis

Ununited anconeal process

Normal

Hip dysplasia
- severely noncongruent hip joints

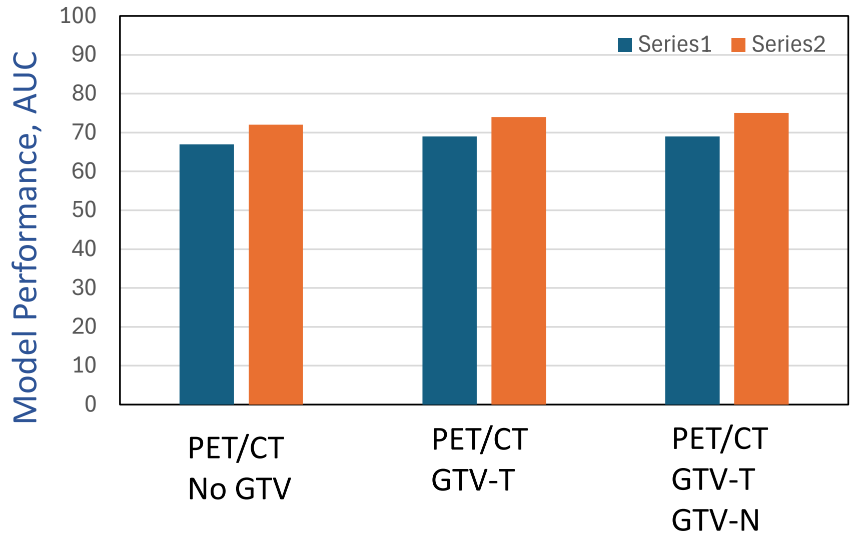
Hauback et al. 2025. Deep learning can detect elbow disease in dogs screened for elbow dysplasia. Veterinary Radiology & Ultrasound 66(1), e13465

Opportunities – Examples

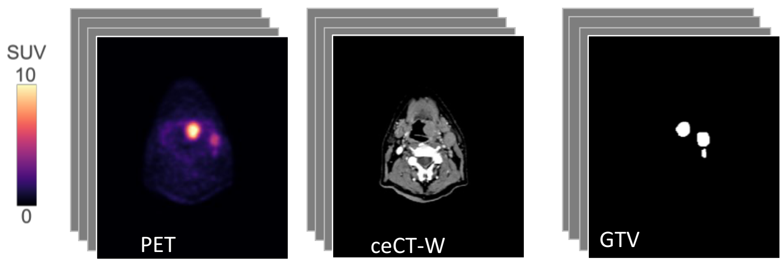
Personalized medicine

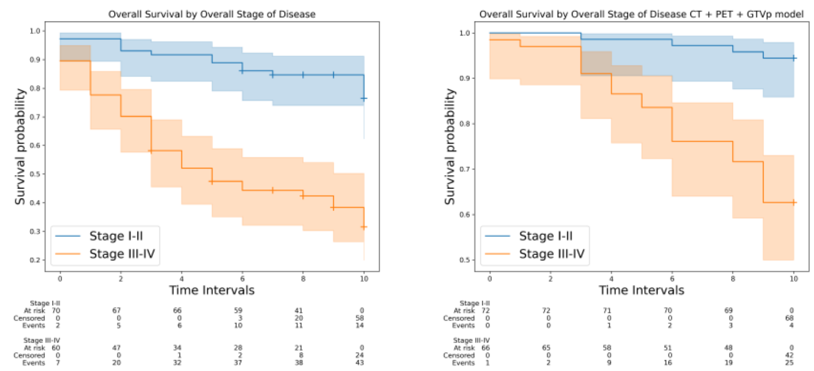
AI predicts disease progression and treatment outcomes based on individual patient data, enhancing personalized care.

AI for treatment outcome prediction
Potential to identify patients in the higher risk group based on medical imaging data



Input data





(a) Observed ground truth for the OUS data.

(b) Model prediction for the OUS data.

Huynh et al. 2023. Head and neck cancer treatment outcome prediction: A comparison between machine learning with conventional radiomics features and deep learning radiomics. Frontiers in Medicine 10:1217037

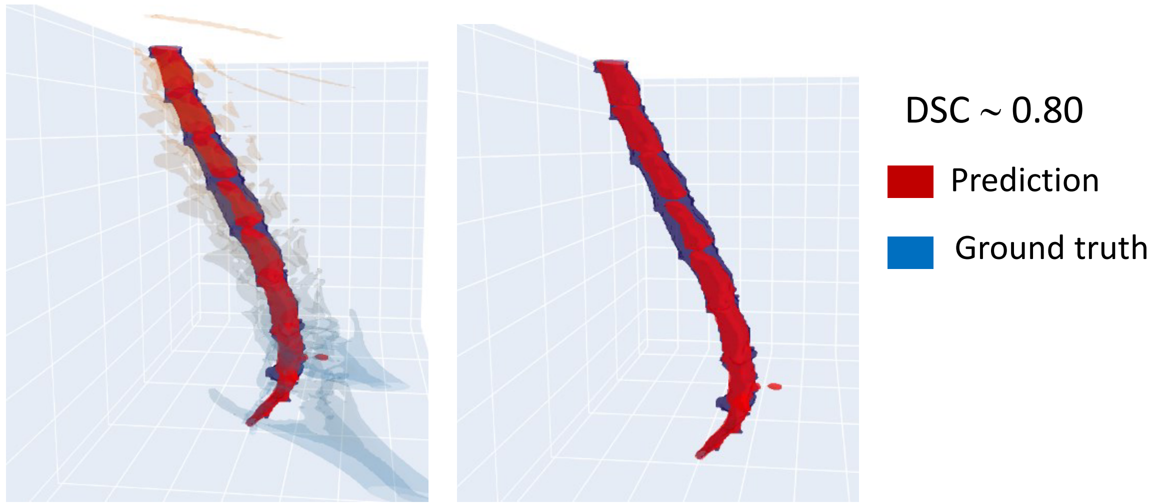
Opportunities – Examples

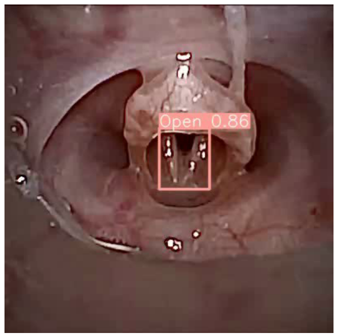
Aiding data analysis

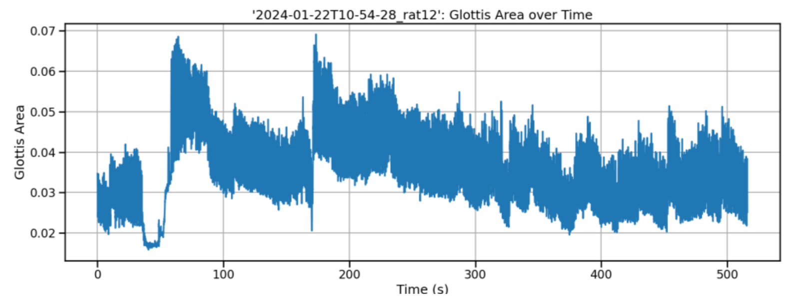
Deep learning can be used for speeding up research and clinical pipeline

AI for extracting respiratory condition from video
Use object detection to find the vocal cord status at different timestamps from a video

AI for estimation of spinal canal volume and subsequent anesthesia dosage
Use auto-segmentation of the spinal canal from CT

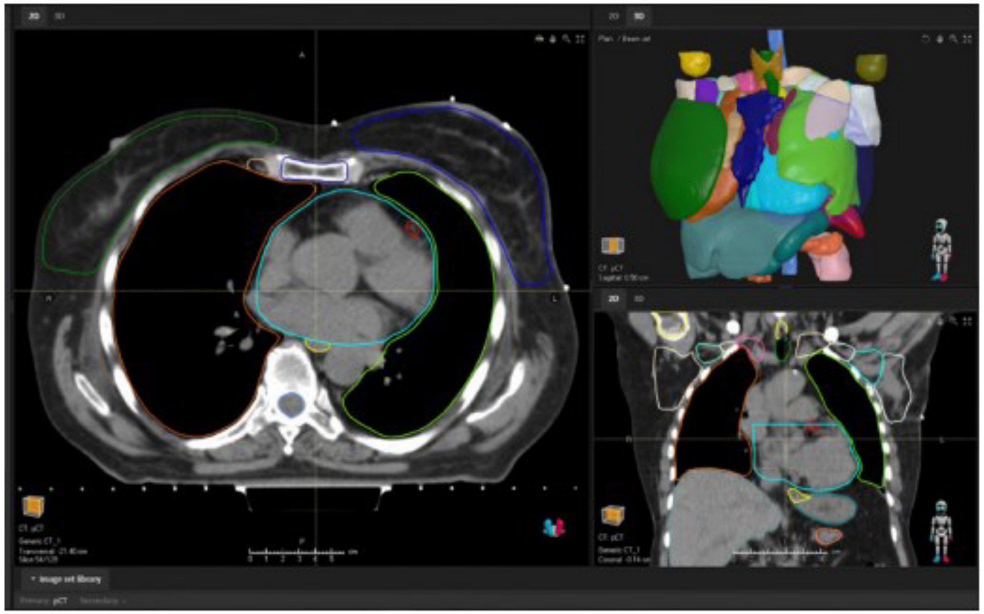






AntiFENT project, headed by Dr. Nora Digranes,
Department of Companion Animal Clinical Sciences,
Faculty of Veterinary Medicine, NMBU

Real world examples



RayStation – Organ at risk auto-segmentation

BoneView – Bone fracture detection

Pauling, Cato, et al. "Commercially available artificial intelligence tools for fracture detection: the evidence." *BJR| Open* 6.1 (2024): tzad005.

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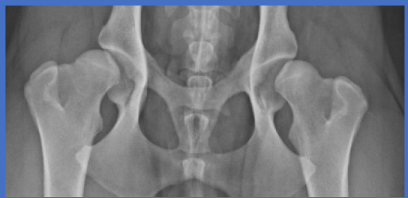
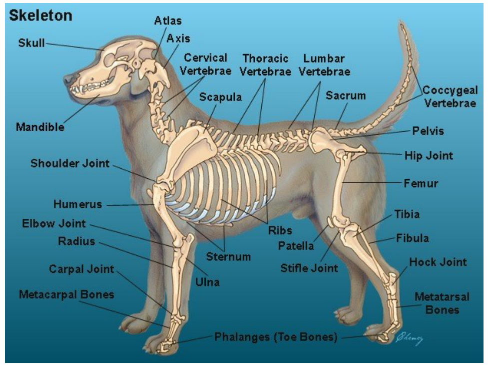
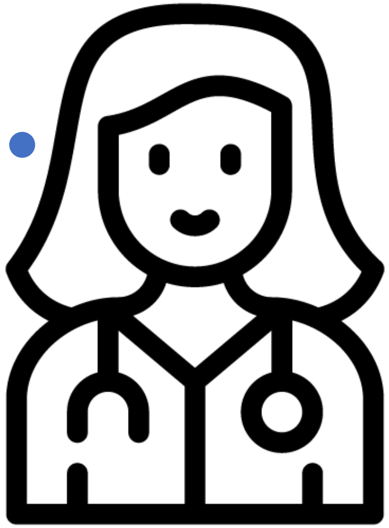
ML/DL pipeline



+ ML = ??

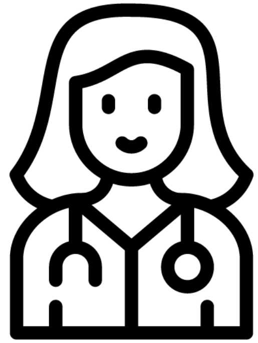




General AI proje

What do you want to achieve/benefit from?
What kind of input data do you have?
How much data do you have?
…

Data availability? Feasibility? HR?
Software + hardware?
Domain knowledge?
…



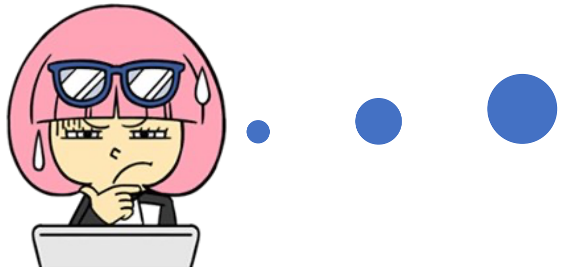
Insufficient data/ more than expected

Define problem, goal, scope → Data collection

Meeting minutes, Project plans, DMP

Raw data

ML/DL pipeline



Number of features (cols)?
Categorical features: category ratios?
Continuous features: statistical info (mean, range, median, skewness)?
Correlation?
…

Insufficient data/ more than expected

Insufficient data (small N)/ Require other info

Define problem, goal, scope → Data collection → Data Summary & preprocessing

Meeting minutes, Project plans, DMP

Raw data

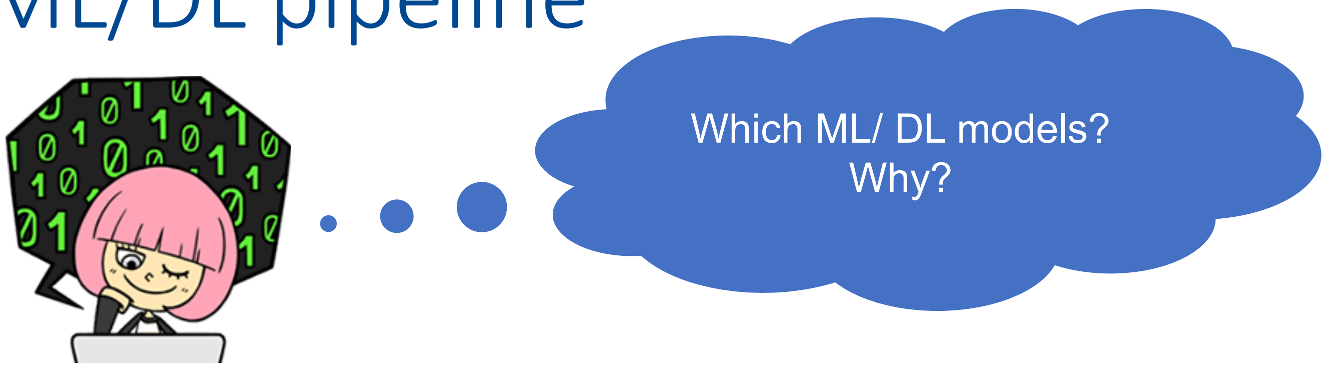
Analysis reports, Preprocessed data

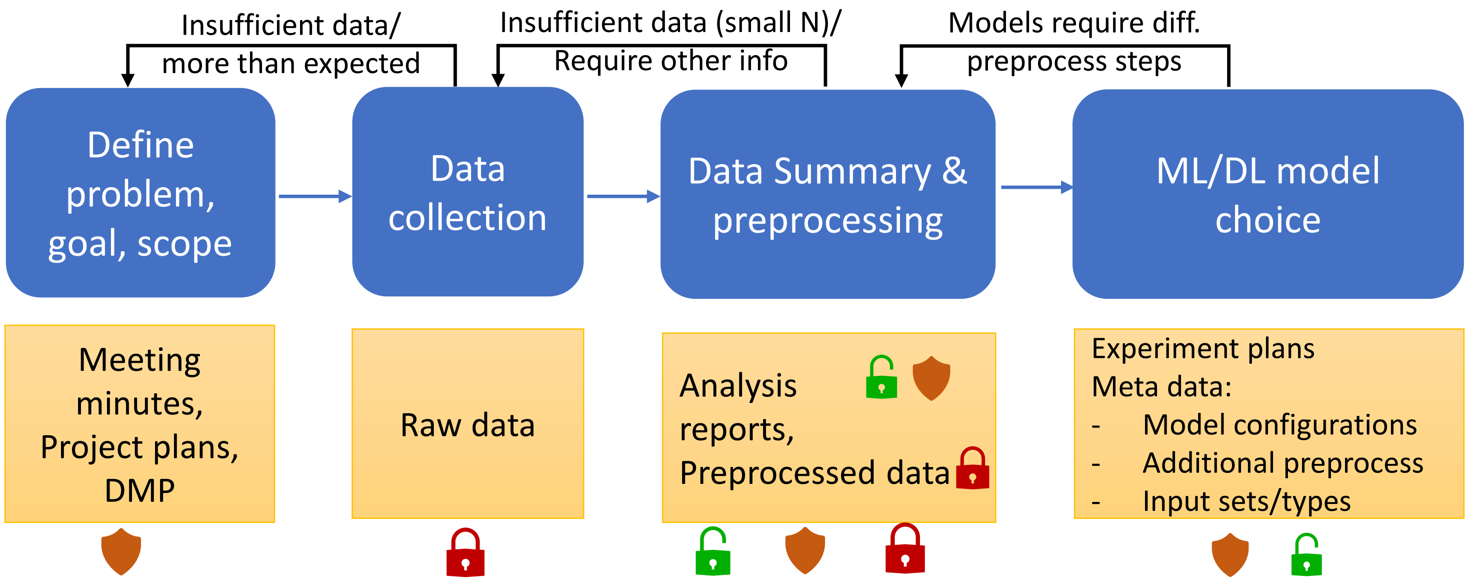
Actions:
Missing data handling (removal/imputation)
Dummy vars.
Normalization
Feature engineer (new cols, latent var.)
…

Most important

Time-consuming

ML/DL pipeline





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ML/DL pipeline

Automated process

Hardware dependence

Insufficient data/ more than expected

Insufficient data (small N)/ Require other info

Models require diff. preprocess steps

Underfit/ overfit res.

Define problem, goal, scope → Data collection → Data Summary & preprocessing → ML/DL model choice → Model tuning / training

Define problem, goal, scope: Meeting minutes, Project plans, DMP

Data collection: Raw data

Data Summary & preprocessing: Analysis reports, Preprocessed data

ML/DL model choice:
Experiment plans
Meta data:
- Model configurations
- Additional preprocess
- Input sets/types

Model tuning / training: Model predictions, Model performance

ML/DL pipeline

Insufficient data/ more than expected

Insufficient data (small N)/ Require other info

Models require diff. preprocess steps

Underfit/ overfit res.

Results not follow literatures

Define problem, goal, scope	Data collection	Data Summary & preprocessing	ML/DL model choice	Model tuning / training	Post-processing & results reports
Meeting minutes, Project plans, DMP	Raw data	Analysis reports, Preprocessed data	Experiment plans Meta data: - Model configurations - Additional preprocess - Input sets/types	Model predictions, Model performance	Perf. Metrics visualization, Use-case visualization

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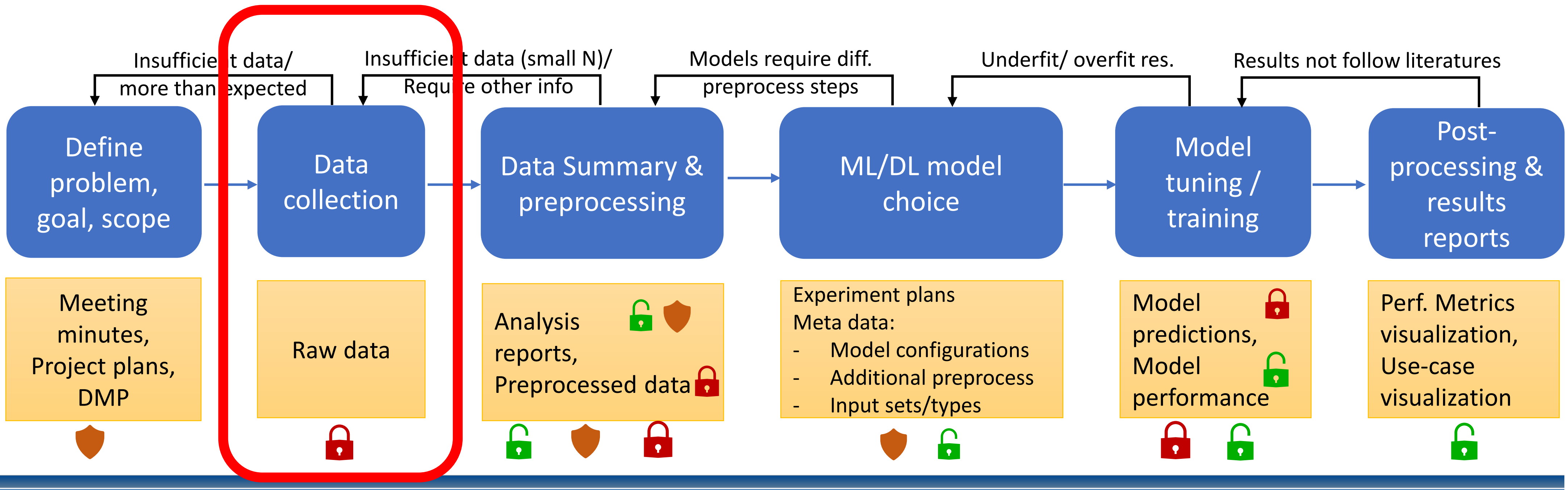
Data collection and storage



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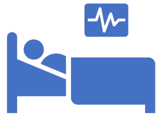
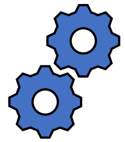
Data collection and storage

- Medical data: data received from hospitals
  - Demographic: age, gender, nationality, race
  - Clinical information: smoke habit…
  - Clinical measured data: blood type, blood sugar, …
  - Image data: CT, PET, MR scans
  - Diagnosis data: HPV, cancer stages, cancer sites,
  - Post diagnosis image data: cancer, affected lymph node segmentation (contour)

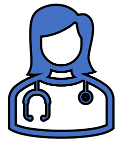
(by patients)



(by machines)



(by doctors)



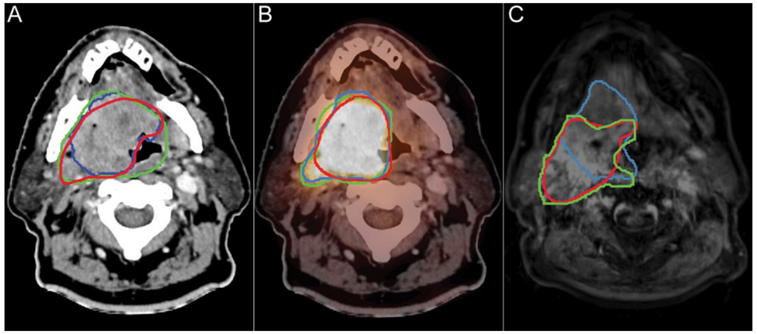
Data collection and storage

- Can be from difference sources and formats
- Can contain personal information
  - → required permission to use, secured storage; (Consent for research, DPO, REC)
  - → you cannot get to their database but have multiple excel reports as raw data
  - → data may be limited
- Can contain missing data, different conventions between centers (sources)
- Image data (raw) can be extremely large & required special program to read
- May contain errors: patients lied, faulty/old machine, doctors (inter-intra observer variation)

DPO: Data Protection Office
REC: Research Ethics Committee

Data collection and storage

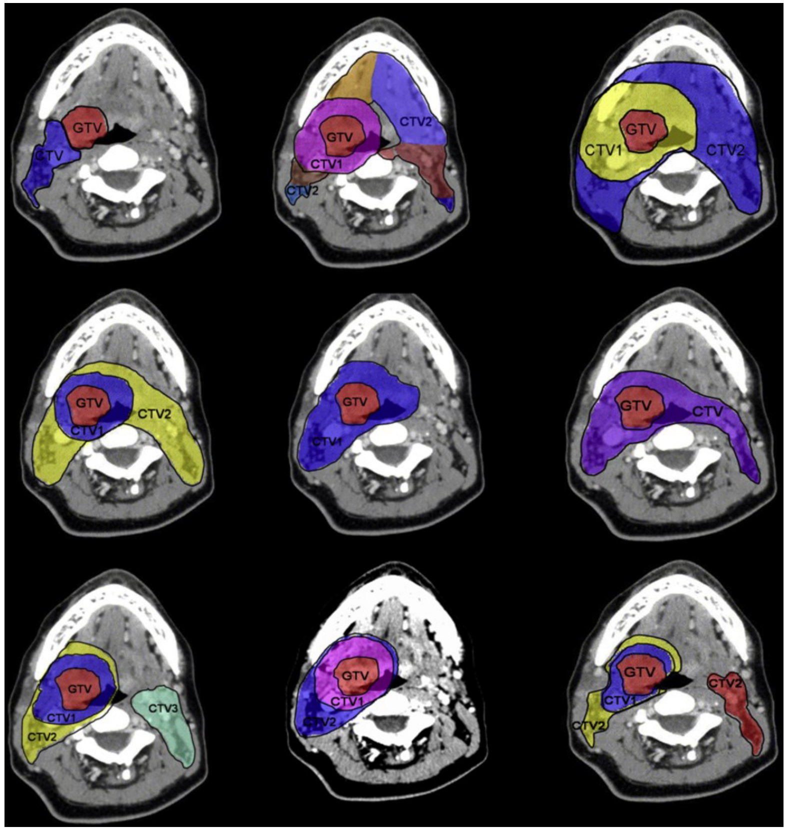
- Inter-observer variation: same image, different observers, different contours
- Intra-observer variation: same image, same observer, different contours



CT PET/CT MRI

(3 observers)

Anderson et al., 2014. Interobserver and intermodality variability in GTV delineation on simulation CT, FDG-PET, and MR Images of Head and Neck Cancer. *Jacobs journal of radiation oncology*, *1*(1), p.006.



(9 observers)

Hong, T.S., Tomé, W.A. and Harari, P.M., 2012. Heterogeneity in head and neck IMRT target design and clinical practice. *Radiotherapy and Oncology*, *103*(1), pp.92-98.

Data collection and storage

- Data generated:
  - Raw data for ML/DL
  - Meta data for tracking and report (sources, patient id, original column names, original images with original voxel sizes)
- Usually large in size
- Require secured storage
- Only store anonymized data (GPDR)

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- Introduction
- AI & Relationship between AI – ML – DL, supervised vs unsupervised ML
- What AI can do in medical context
- The ML and DL pipeline/workflow in healthcare data
- Data collection and storage
- Data summary & preprocessing
- ML/DL model choice
- Model tuning and model training
- Data management challenge and current solutions
- Integration into clinical pipeline
- Conclusion

Break

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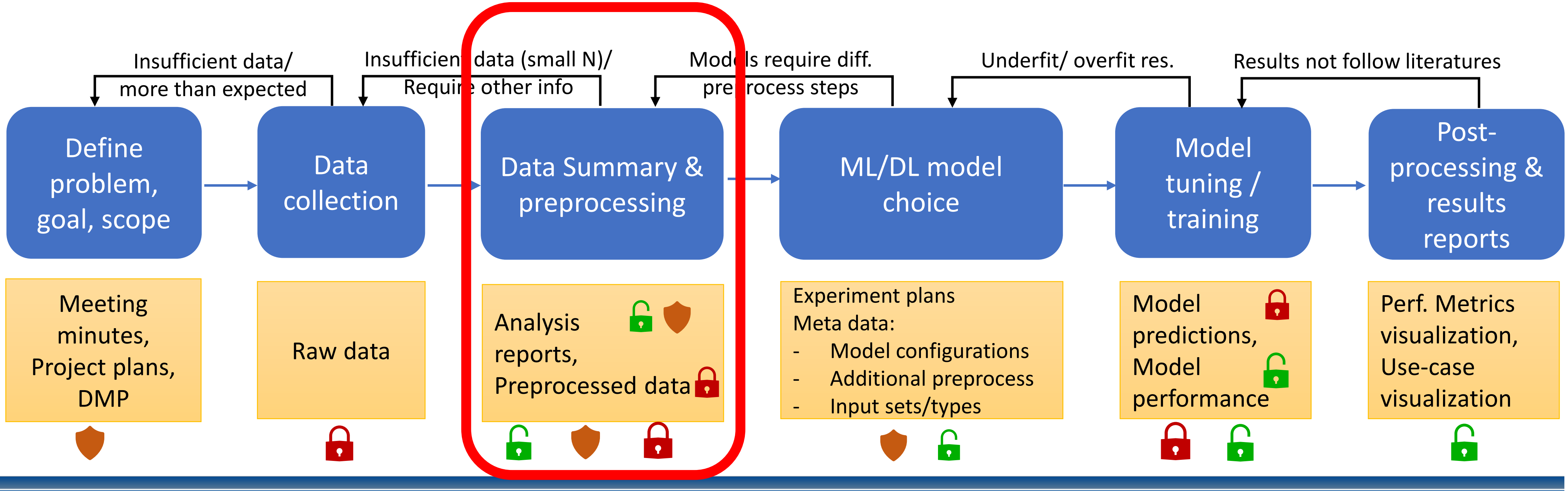
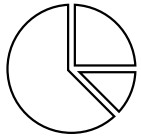
Data summary & preprocessing

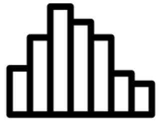


Data summary & preprocessing

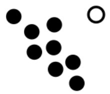
- **Data summary**: overview of the data
  - How many items in total & how many usable samples?



  - % ratio between categories
  - Histogram of continuous features (variables/columns)



  - Data relevance: for ex., data provided by old/deprecated scanners are irrelevant
  - Any missing data?
  - Outliers?



  - Duplicated observation or columns?
  - Weird data (especially image data)

Data summary & preprocessing

- Data summary is important for
  - Determine preprocessing methods
  - Choose suitable models
  - Avoid useless choices/models/experiment/input data
  - Explain the results
- → never go directly into preprocessing & model training without this step

Data summary & preprocessing

- Data preprocessing:
  - Utilize the model
    - ML/DL model only work on numeric data
    - Add useful features
  - Depend on both data and the models being used
    - Solve problems found in data summary
    - Z-score normalization is necessary for linear models, SVM, logistic models

Data summary & preprocessing

- Must-do preprocessing techniques:
  - Remove irrelevant features: unrelated information, outdated/useless samples
  - Handle missing data: row-wised or column-wise, removal or imputation
  - Handle outlier samples: removal or cut-off value or transformation
  - Handle categorical features: dummy columns generation or numeric coding for each levels
  - For images: resample/resize/crop

Data summary & preprocessing

- May-be-useful preprocessing techniques
  - Data standardization: centering and scaling
  - Data transformation: polynomial, …
  - Feature engineering: create new columns, reduce number of columns (PCA/PLS), radiomics features from images…
  - Windowing (different from windowing in datastream) for image data
  - Data augmentation to reduce overfitting

→ Can solve different problems/challenges found during the data summary processes (For example, limited data, data variability, low data quality)

PCA: Principal component analysis
PLS: Partial least square

Data summary & preprocessing

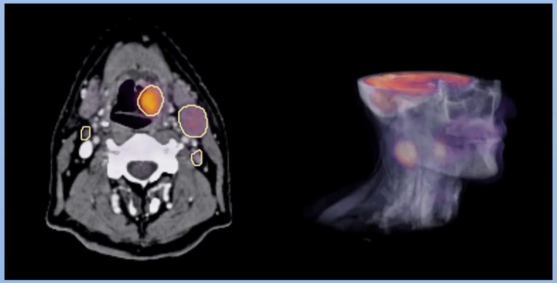
Challenges – Limited data

Problems during data acquisition process:

- Small sample size: <1000
- Research data requires consents from patients
- Missing data (different treatment arms)

Potential solutions:

- Image augmentation
- Data sharing
- Transfer learning



Data summary & preprocessing

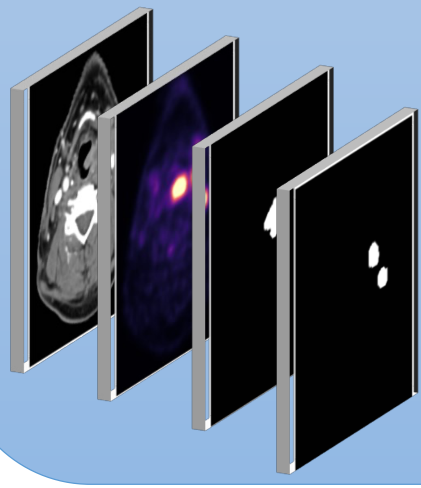
Challenges – Data variability

Data with high variability:

- Data can come from different scanners / different sources (CT, PET, MRI…)
- Different hospitals have different conventions
- Inter- & Intra observer variation

Potential solutions:

- Multi-modality models
- Normalization techniques



Data summary & preprocessing

Challenges – Data quality

Data may have low quality:

- Can be due to old infrastructures, or human errors
- Noise & redundancy within the data

Potential solutions:

- Remove redundant data
- Preprocessing techniques

HU = Hounsfield Units

Data summary & preprocessing

Challenges – Data quality

Data may have low quality:

- Can be due to old infrastructures, or human errors
- Noise & redundancy within the data
- The computational expense of multi-dimensional data

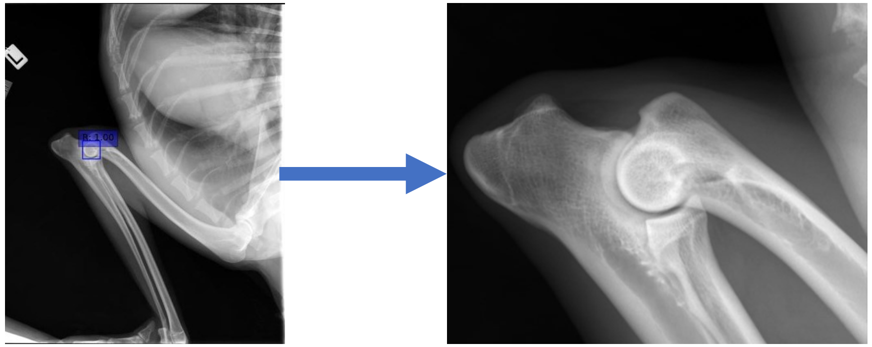
Potential solutions:

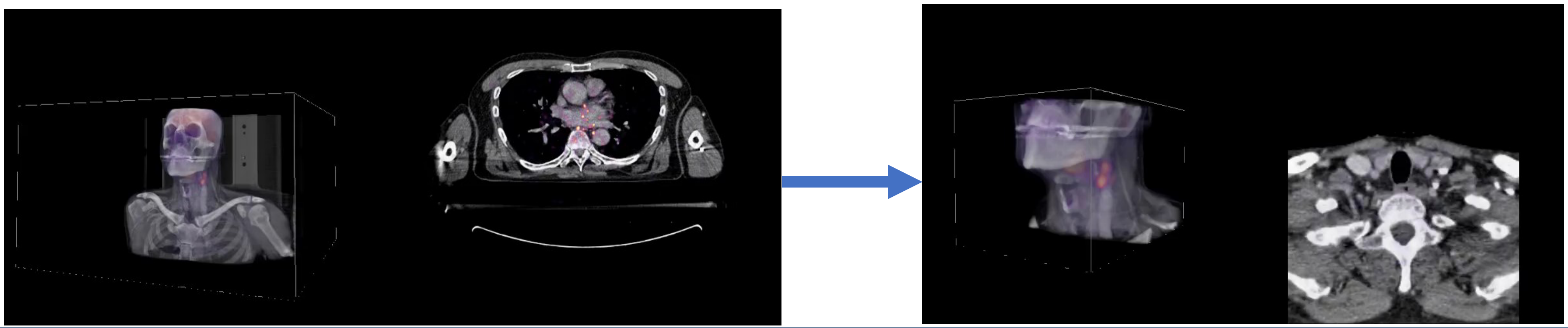
- Remove redundant data
- Preprocessing techniques
- Cropping to Region of interest (ROI) / Volume of interest (VOI) cropping

Data summary & preprocessing

Challenges – Data quality – Examples

- Most of the 3D CT/PET images are just the background
- Other structures inside the images may confuse the AI model
- Region of interest (ROI) / Volume of interest (VOI) cropping





Data summary & preprocessing

- Data generated:
  - Analysis reports
  - cooked/preprocessed data (cleaner copies of raw data, usually larger in size)
- Usually, only the data after the must-do preprocessing are saved to disk
- Saved preprocessed data are the primary input for ML/DL models
- Other preprocessing methods (depending on model types and experiment settings) are combined with the next step (model choices & settings):
  - Windowing: different window center and width
  - Image normalization methods

  →We don’t want to many copies of the large data

  →Trade-off between storage space & training speed

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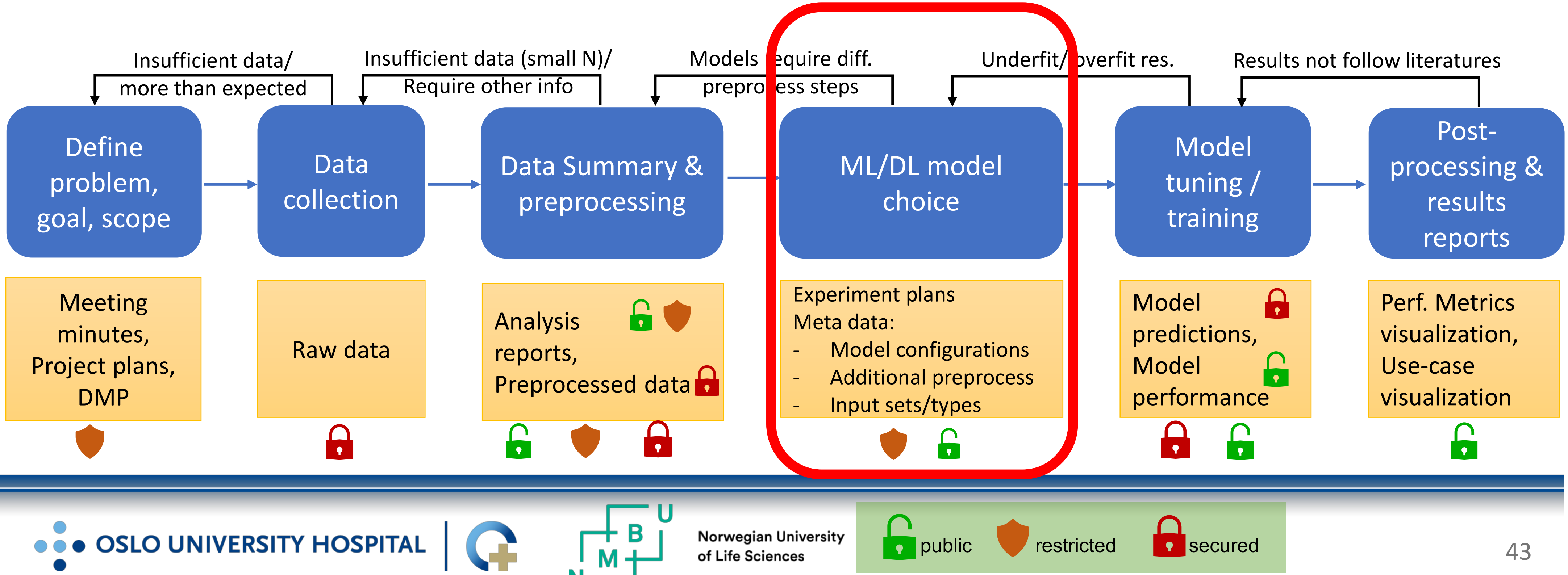
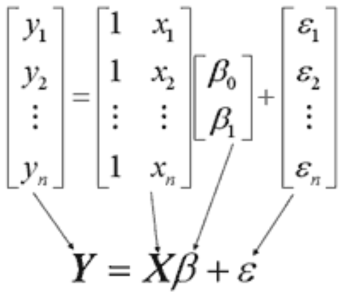
ML/DL model choice

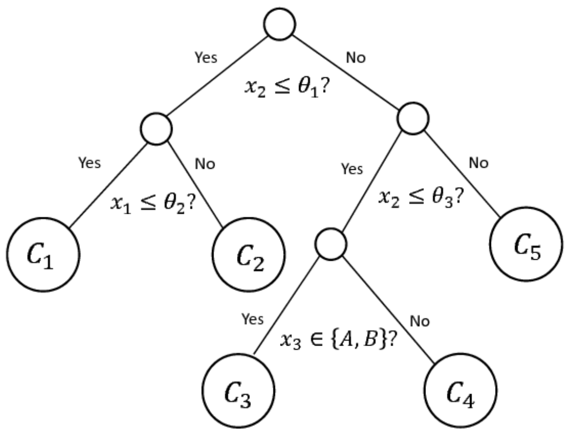


ML/DL model choice

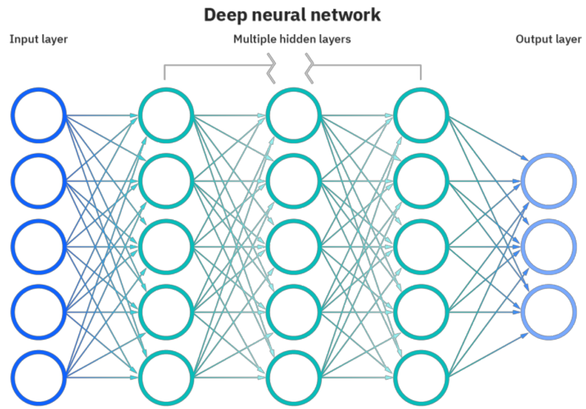
- ML/DL can have different complexity levels (number of trainable parameters / weights)



Linear models



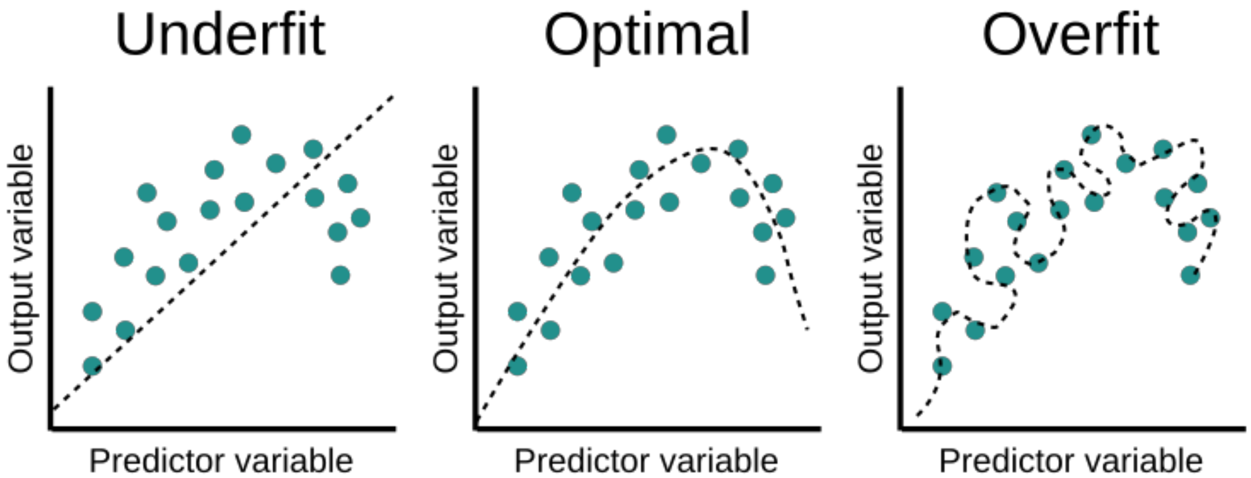
Tree-based models (Decision tree, Random forest (RF), ensembles)



Neural network (NN)
Convolutional neural network (CNN)

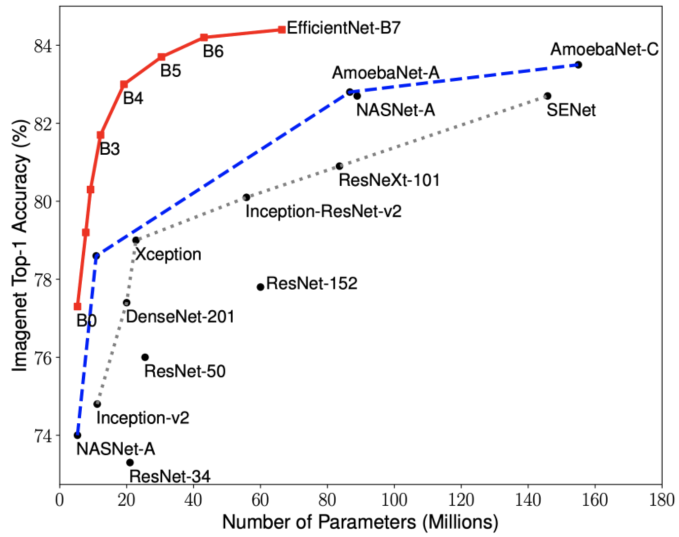
ML/DL model choice

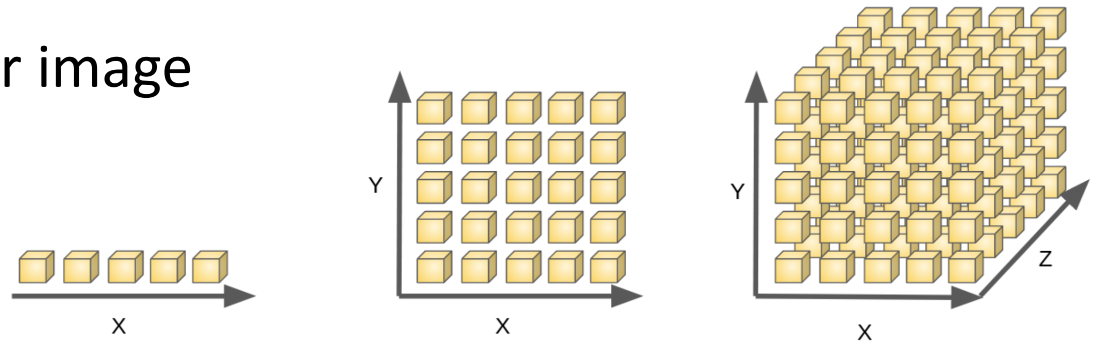
- Model with higher complexity levels (DL models) fits better but are also prone to overfitting



ML/DL model choice

- The curse of multi-dimensionality
- When working with images data, the CNN (DL model) needs millions – hundreds millions parameters
- Model files (containing all parameters/weights) can reach about 1GB
- Requires GPU + software → docker image for training on HPC





CNN: Convolutional neural network

Tan, M., & Le, Q. (2019, May). Efficientnet: Rethinking model scaling for convolutional neural networks. In International conference on machine learning (pp. 6105-6114). PMLR.

ML/DL model choice

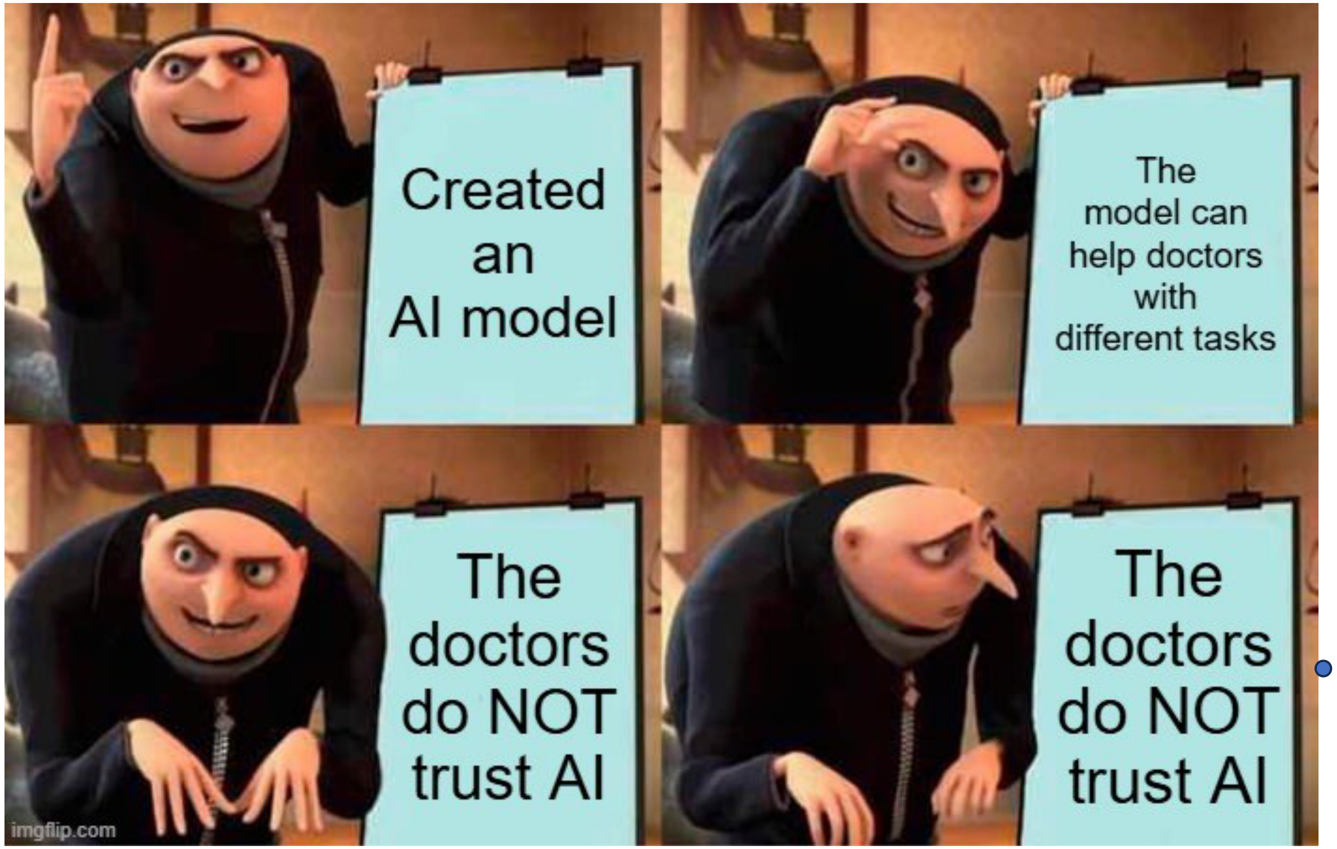
- Choosing the right model is important
- Examples:
  - Wide-short data (too many columns, few samples)
    - most predictive models are unreliable → descriptive model for explainability (biomarker usecase)
    - Complex model (RF, NN) may overfit
  - Long data (large N):
    - Only models support iterative training (train by batches)
    - Most tree-based model are unusable without large RAM
    - The <u>longer</u> and (maybe) wider the data, the better NNs perform
- CNN is currently superior when we have image input and decent data (~100 for 3d, ~5k for 2d)
- Newer & more powerful models (Vision Transformer, Foundation Model) require even more data → not always the best choice in medical context
- Note: when data is of limited number and in low quality, simple methods would outperform NN (DL)

RF: Random forest
NN: Neural network

https://sebastianraschka.com/blog/2022/deep-learning-for-tabular-data.html#why-do-tree-based-models-still-outperform-deep-learning-on-tabular-data-2022-07

ML/DL model choice

Other challenges – Model trustworthiness



What if the model is wrong?

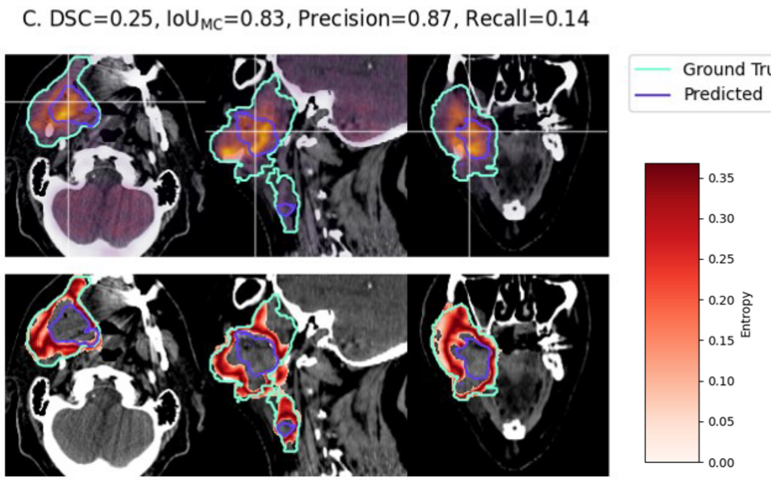
How did the model make the prediction?

ML/DL model choice

Other challenges – Model trustworthiness

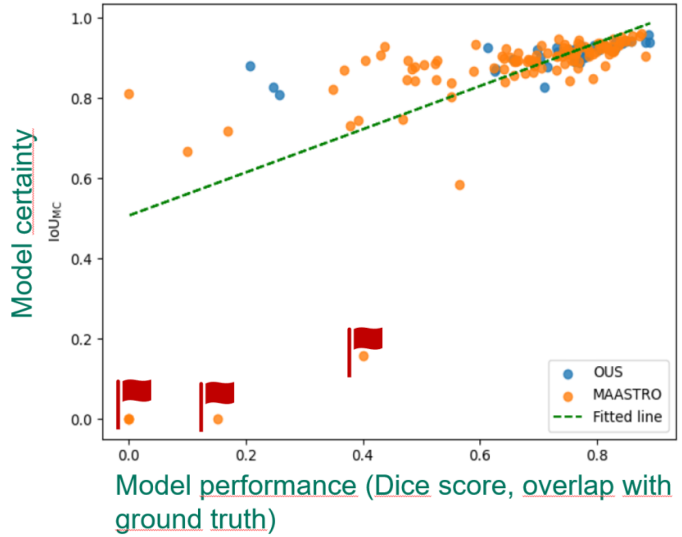
- Low error-tolerance → ensure high precision & possibility to detect potential error

Voxel-wise uncertainty



- Higher entropy voxel values indicate higher uncertainty.

Patient-wise uncertainty



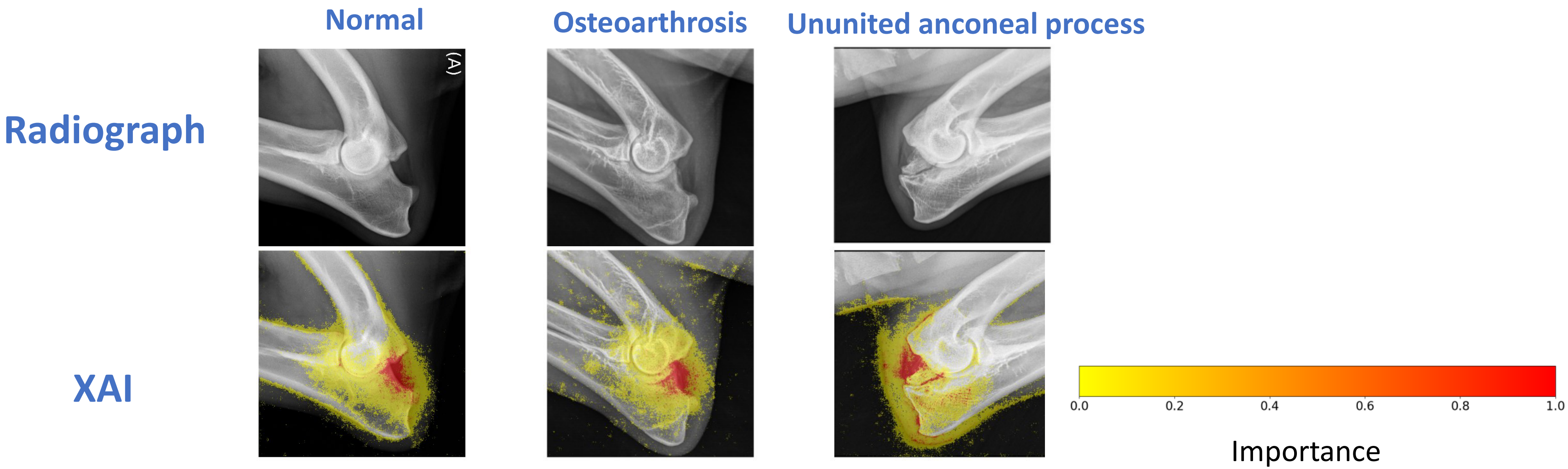
- Low model certainty can flag patients requiring human review

Huynh BN et al. 2024. Deep learning with uncertainty estimation for automatic tumor segmentation in PET/CT of head and neck cancers: Impact of model complexity, image processing and augmentation. *Biomed. Phys. Eng. Express.* doi: 10.1088/2057-1976/ad6dcd

ML/DL model choice

Other challenges – Model trustworthiness

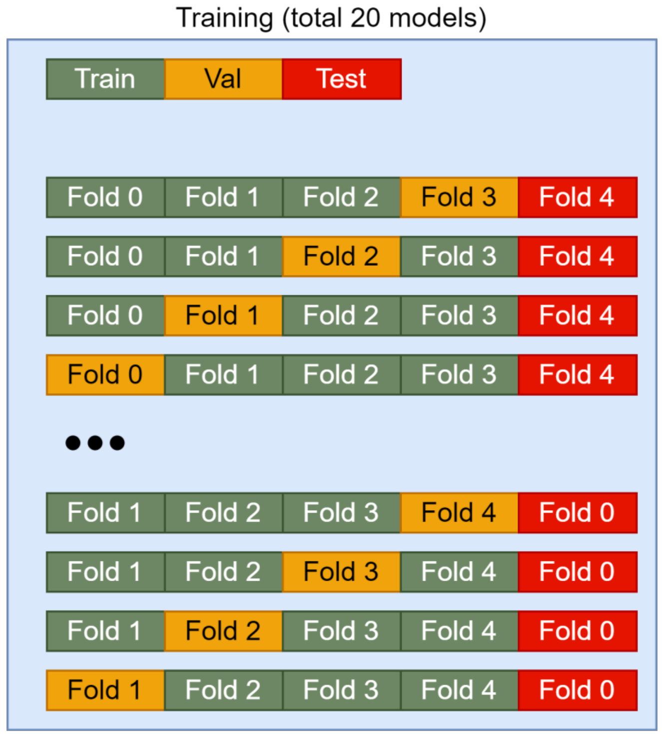
- Low error-tolerance → ensure high precision & possibility to detect potential error
- "Black box" problem → increase model transparency & interpretability



Hauback et al. 2025. Deep learning can detect elbow disease in dogs screened for elbow dysplasia. Veterinary Radiology & Ultrasound 66(1), e13465

ML/DL model choice

- Training strategy:
  - ❑ Train – val – test split
    - ▪ Uniform characteristic data
    - ▪ For NN, only one model can run inference
    - ▪ Cons: may not learn all knowledge from the data
  - ❑ K-fold cross-validation:
    - ▪ Usually when data is limited
    - ▪ Finding best combination of model hyperparameters (config.)
    - ▪ Cons: for NN, requires all [k] models when running inference
- Splitting with stratification (based on the data summary step) vs randomly splitting
- External validation



Huynh BN, Groendahl AR, Tomic O, Liland KH, Knudtsen IS, Hoebers F, van Elmpt W, Malinen E, Dale E and Futsaether CM (2023) Head and neck cancer treatment outcome prediction: a comparison between machine learning with conventional radiomics features and deep learning radiomics. Front. Med. 10:1217037. doi: 10.3389/fmed.2023.1217037

ML/DL model choice

- Data generated: experimental plans with meta data about
  - model type: LM, RF, NN, CNN
  - hyperparameters (configurations): loss function, # trees, regularizer,…
  - preprocessing methods (also configurations): normalizer, transformer,…
  - splitting strategy: # train – val – test, which fold for each experiment (model training)
- Important for tracking experiments and report results from different settings

LM: Linear model
RF: Random forest
NN: Neural network
CNN: Convolutional neural network

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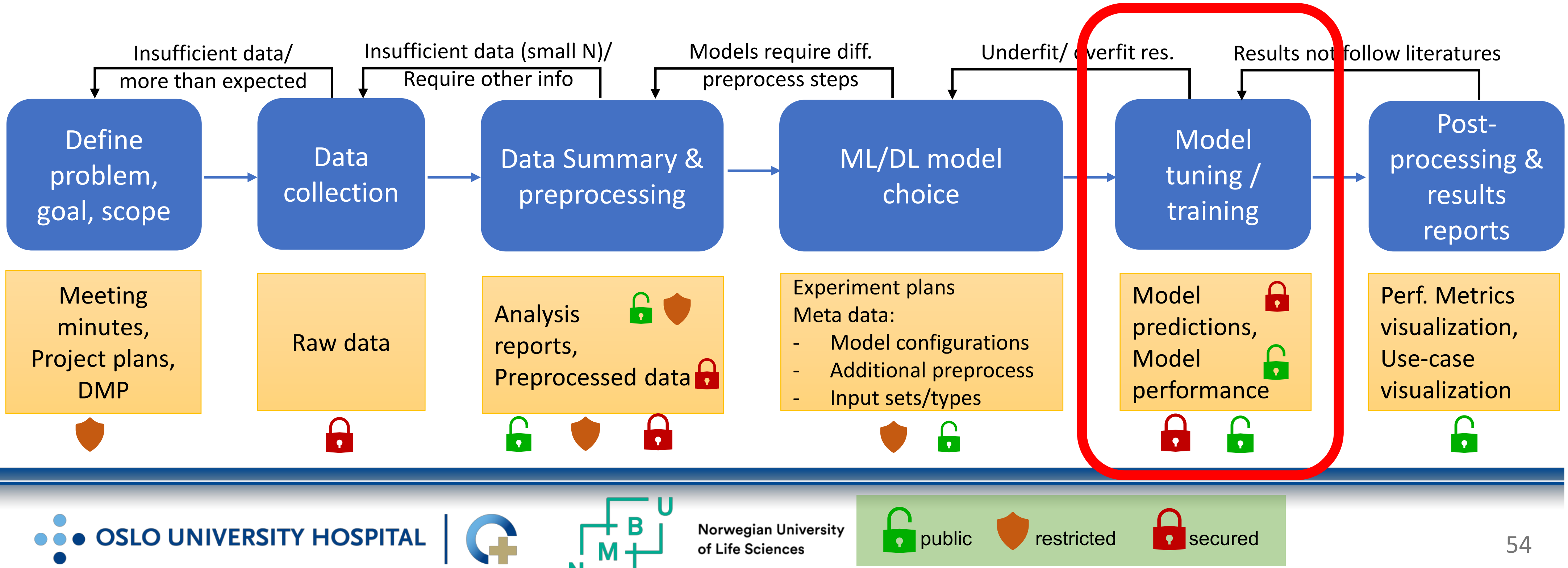
Model tuning and training



Model tuning and training

- From previous steps: experimental plan with meta data
- Models and their validation predictions are saved in every timesteps (model checkpoints & validation-set prediction checkpoints)
- From temporary results (metrics based on prediction checkpoints) → adjustment to experimental plan (addition and modification in model config, preprocessing methods, data splitting strategy)
- Model performance are usually monitored in every timestep (checkpoints)
- → based on the performance log (metric log), the best model is selected → test-set prediction

Model tuning and training

- Data generated:
  - Model checkpoints: trained models of different settings at different timepoints
  - Prediction checkpoints: Temporary validation predictions (at different timesteps)
  - Post-process results/prediction (if any)
  - Metrics logs: Metrics evaluation (per sample & per model) at different timesteps
  - All predictions (val + test) from best models
  - Meta data: which model settings/configurations, at which timestep, which post-process methods

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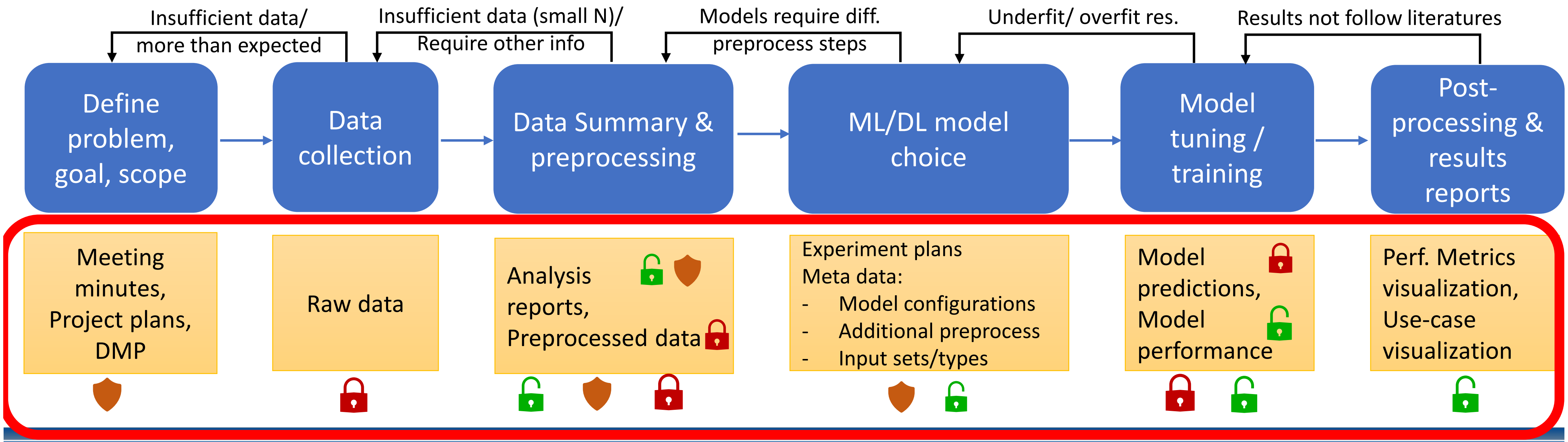
Data management challenges & current solutions

- A lot data and meta data have been generated during the process
- Many problems



public restricted secured

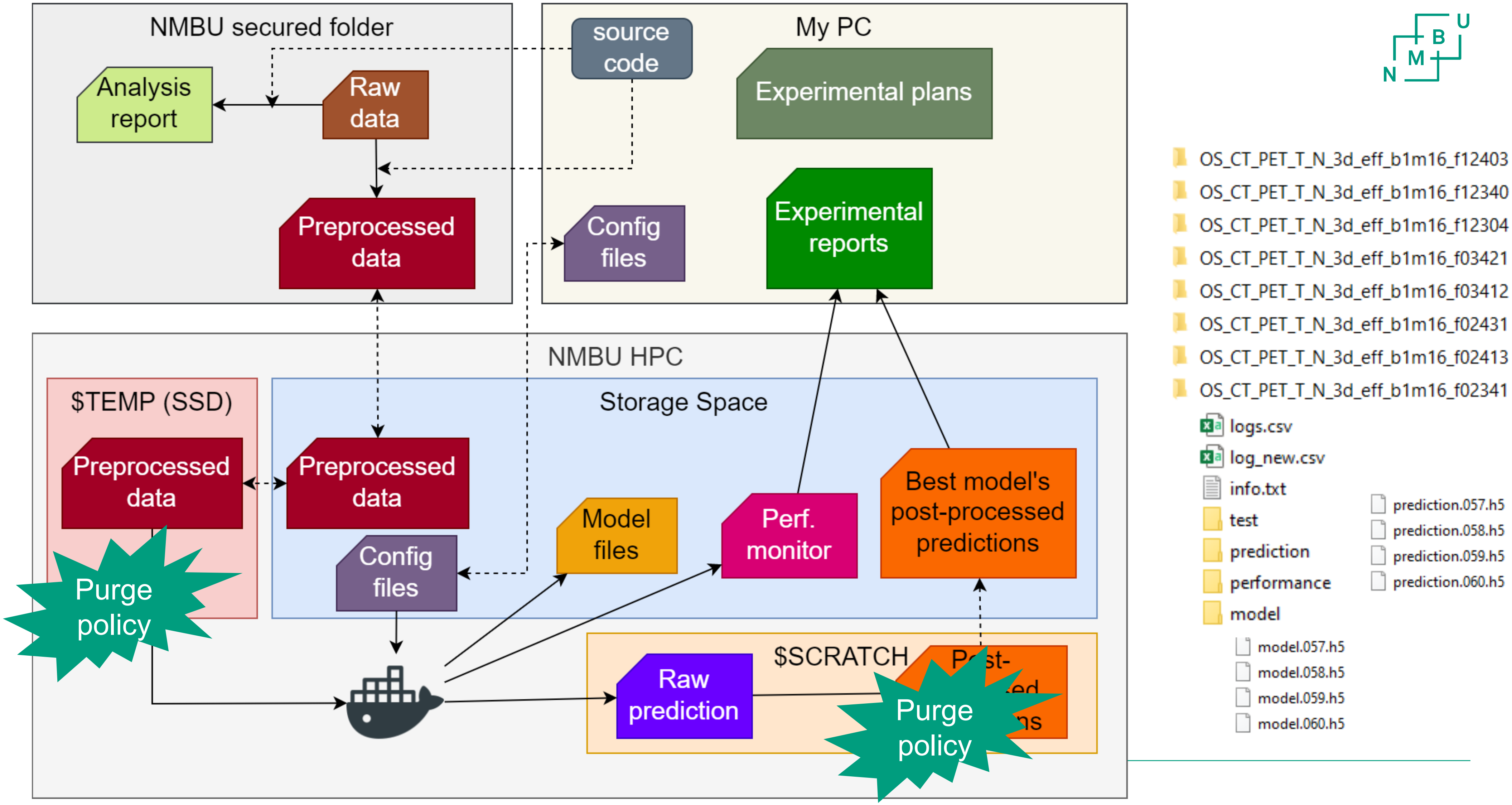
Data management challenges & current solutions

- A lot data and meta data have been generated during the process
- Many problems:
  - Personal data handling
  - Meta data tracking
  - Temporary data generated during training (a lot)
  - Very large files (curse of multidimensionality)
  - Data life cycle: which to save, which to remove after analysis

Data management challenges & current solutions

- Personal data: anonymize based on institute policy
- Meta data of the data (pid mapping to raw data, image info…): documents (xls, csv) in secured folder; should be easy to read for stakeholders
- Meta data of models: models should be duplicable, portable
  - Configuration files (json, xml, yaml) for model generation → duplicability
  - Config (model, preprocess, dataset splits) usually also included into trained model file (model checkpoints) that are saved on disk → portability

- Meta data for results: trackable (mapping back to each experiment & checkpoint)
  - Directory based: names as plan-name, csv files for tracking results, folders containing model predictions, model files, metrics of each models before/after post-processing
  - Documents for experimental plans (xls, csv): contain name, model, config file locations, overall results/perf., (date/time …)



NMBU secured folder
Analysis report
Raw data
Preprocessed data
source code
My PC
Experimental plans
Config files
Experimental reports
NMBU HPC
$TEMP (SSD)
Preprocessed data
Purge policy
Storage Space
Preprocessed data
Config files
Model files
Perf. monitor
Best model's post-processed predictions
$SCRATCH
Raw prediction
Purge policy
OS_CT_PET_T_N_3d_eff_b1m16_f12403
OS_CT_PET_T_N_3d_eff_b1m16_f12340
OS_CT_PET_T_N_3d_eff_b1m16_f12304
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performance
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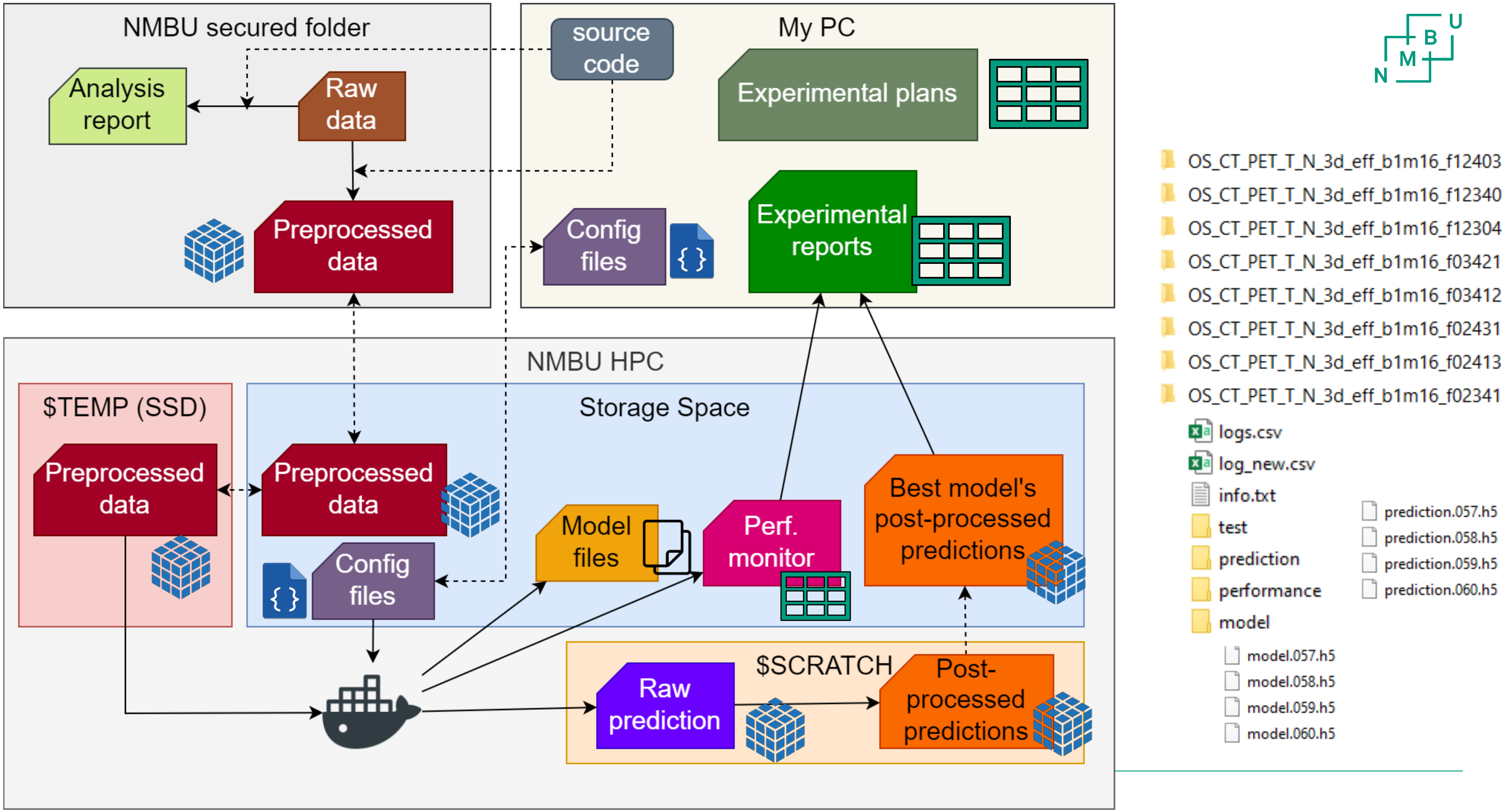
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model.058.h5
model.059.h5
model.060.h5
prediction.057.h5
prediction.058.h5
prediction.059.h5
prediction.060.h5

Data management challenges & current solutions

- Relational database system is not feasible
- MongoDB (NoSQL, object-oriented DB) can handle dynamic data: mix between tabular data and semi-object data (config.) ; and map to the location of model files and multidimensional data files
- Pros:
  - Data management system (all functionality of DB) to handle different data types
  - Possibility for real-time perf monitor (→stop unnecessary experiments early)
  - Ease of report and visualization
- Cons:
  - Difficulty when integrating to the pipeline + deployment
  - Preprocessing data still partially manually

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- What AI can do in medical context
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- Model tuning and model training
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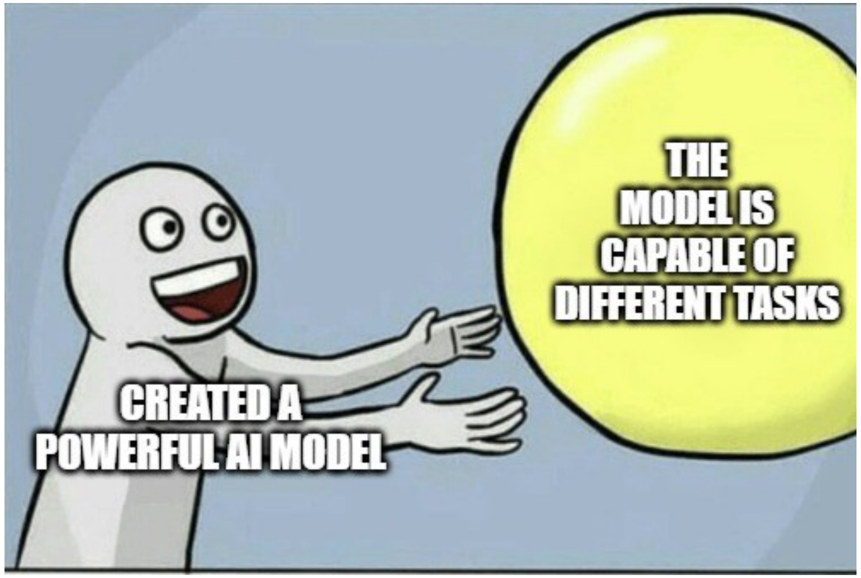
- Conclusion

Break

AI integration into clinical pipeline

- Developing an AI model and deploying it in clinical practice are two different stories



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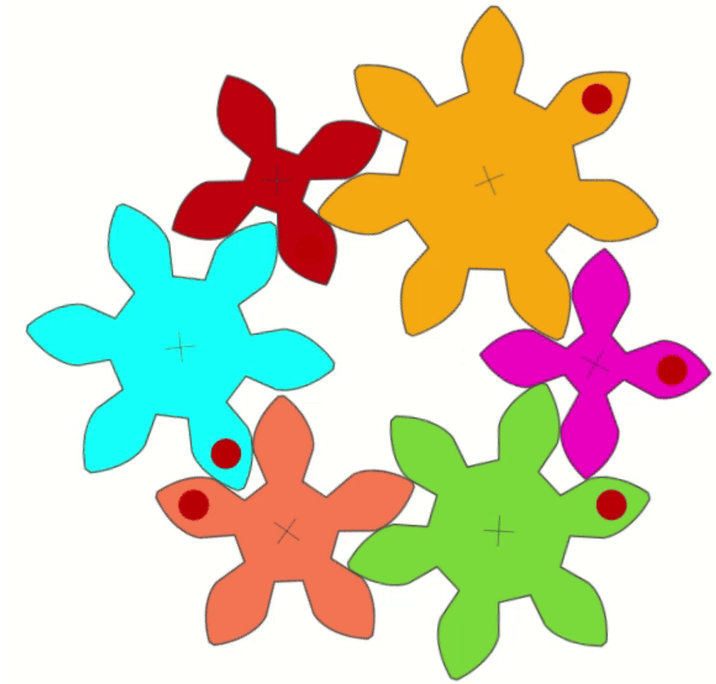
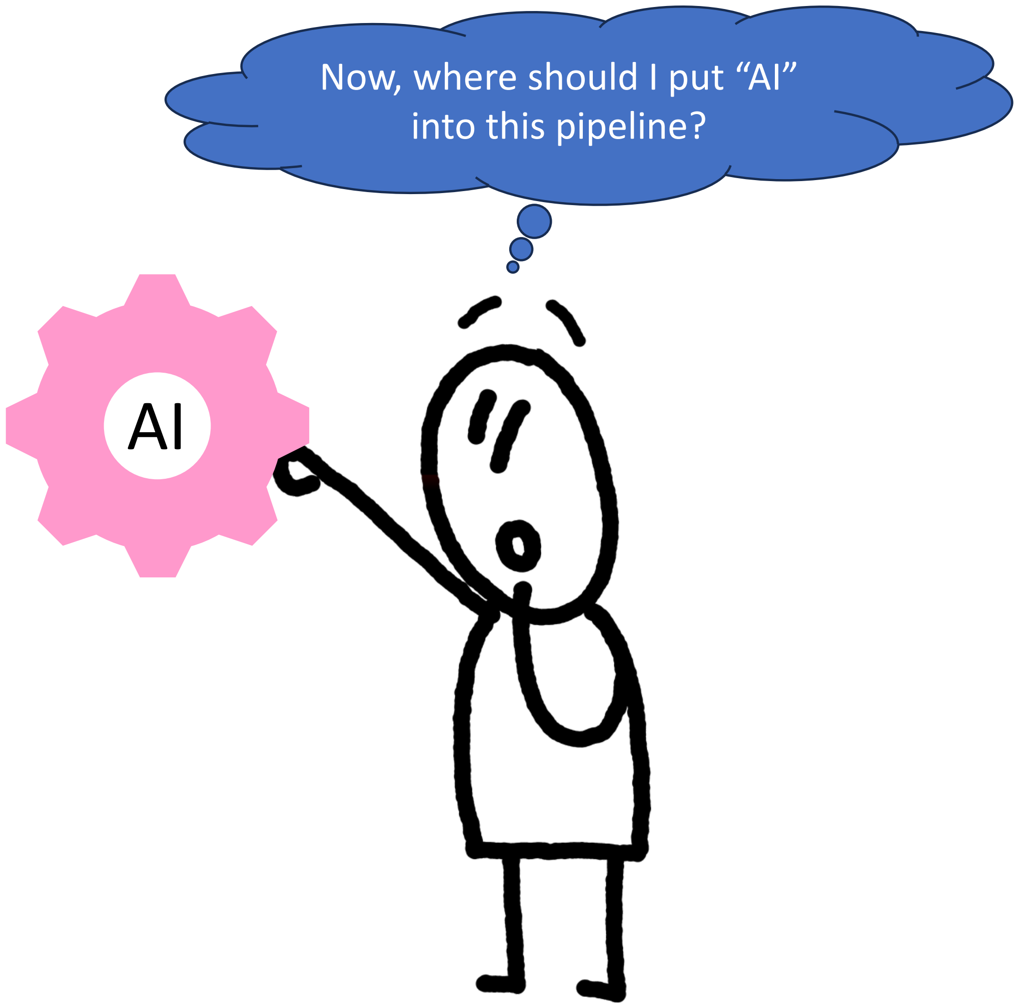
AI integration into clinical pipeline

- Developing an AI model and deploying it in clinical practice are two different stories
  - Hardware and software compatibility
  - Compliance with the hospital IT system



Clinical Pipeline



AI integration into clinical pipeline

- Developing an AI model and deploying it in clinical practice are two different stories
  - Hardware and software compatibility
  - Compliance with the hospital IT system
- Integration of AI models should not complicate existing clinical pipeline

Conclusions

- Healthcare data can be from different sources and can in different format.
- In healthcare use cases, data summary and preprocessing are the most important, intensive and time-consuming part.
- Based on the data, we can choose the right models, pre/post-processing methods.
- DBMS integration can help to ease some steps in the pipeline.
- Many aspects should be considered for streamline integration of AI into clinical practice

Thank you!