

Intelligence artificielle pour la segmentation automatique du Pelvis et Thorax et pour la génération de plans de traitements de cancers pelviens en radiothérapie externe

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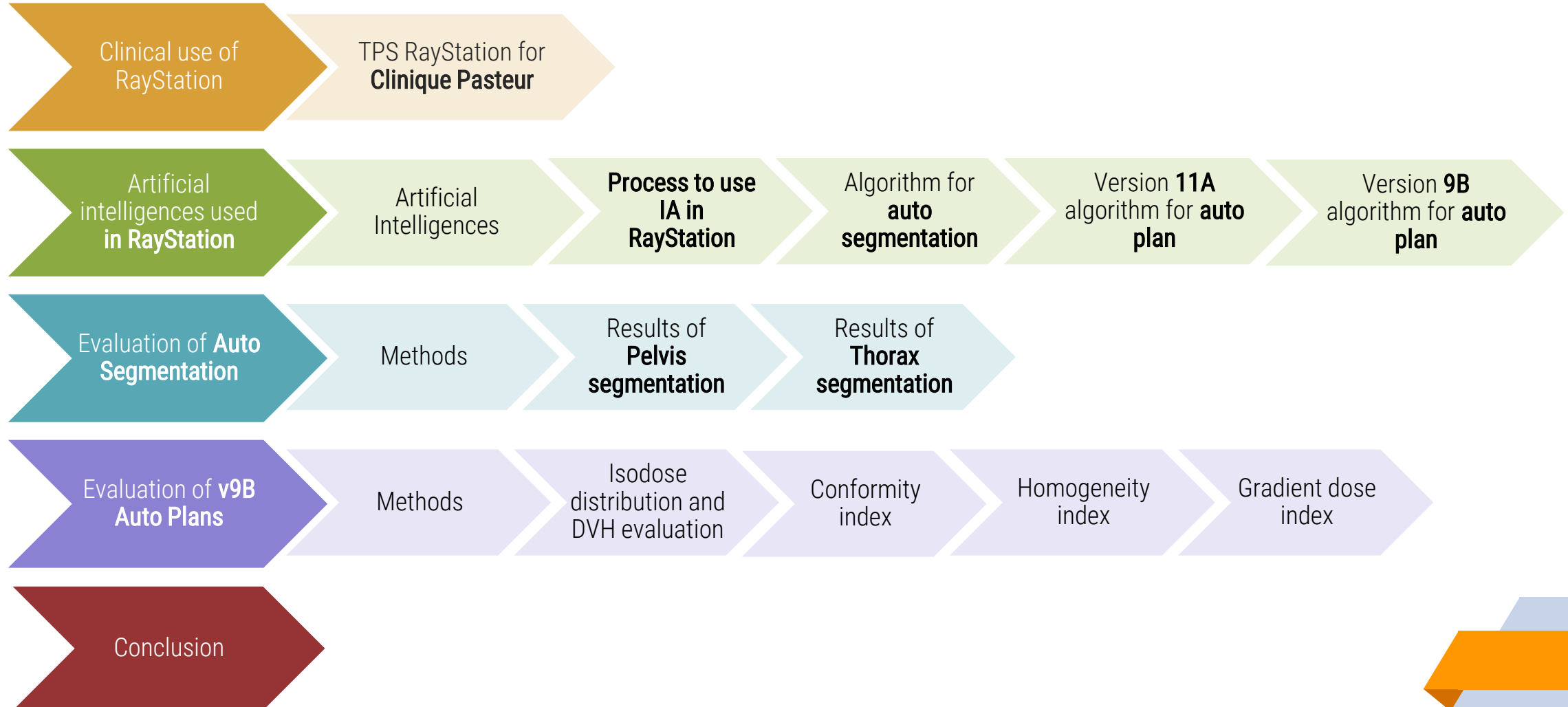
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⁴ LAAS CNRS, Université de Toulouse, CNRS, INSA, UPS, Inserm ToNIC, UMR 1214 Toulouse NeuroImaging Center, Toulouse, France



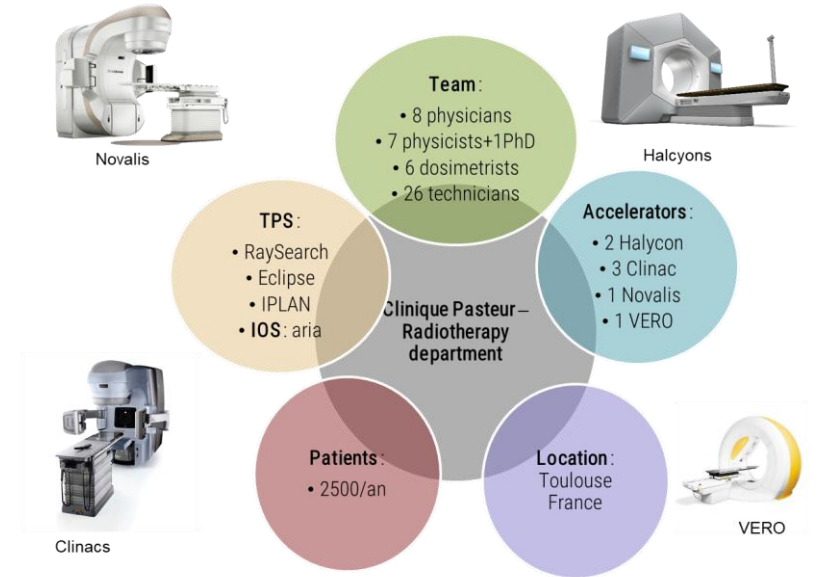
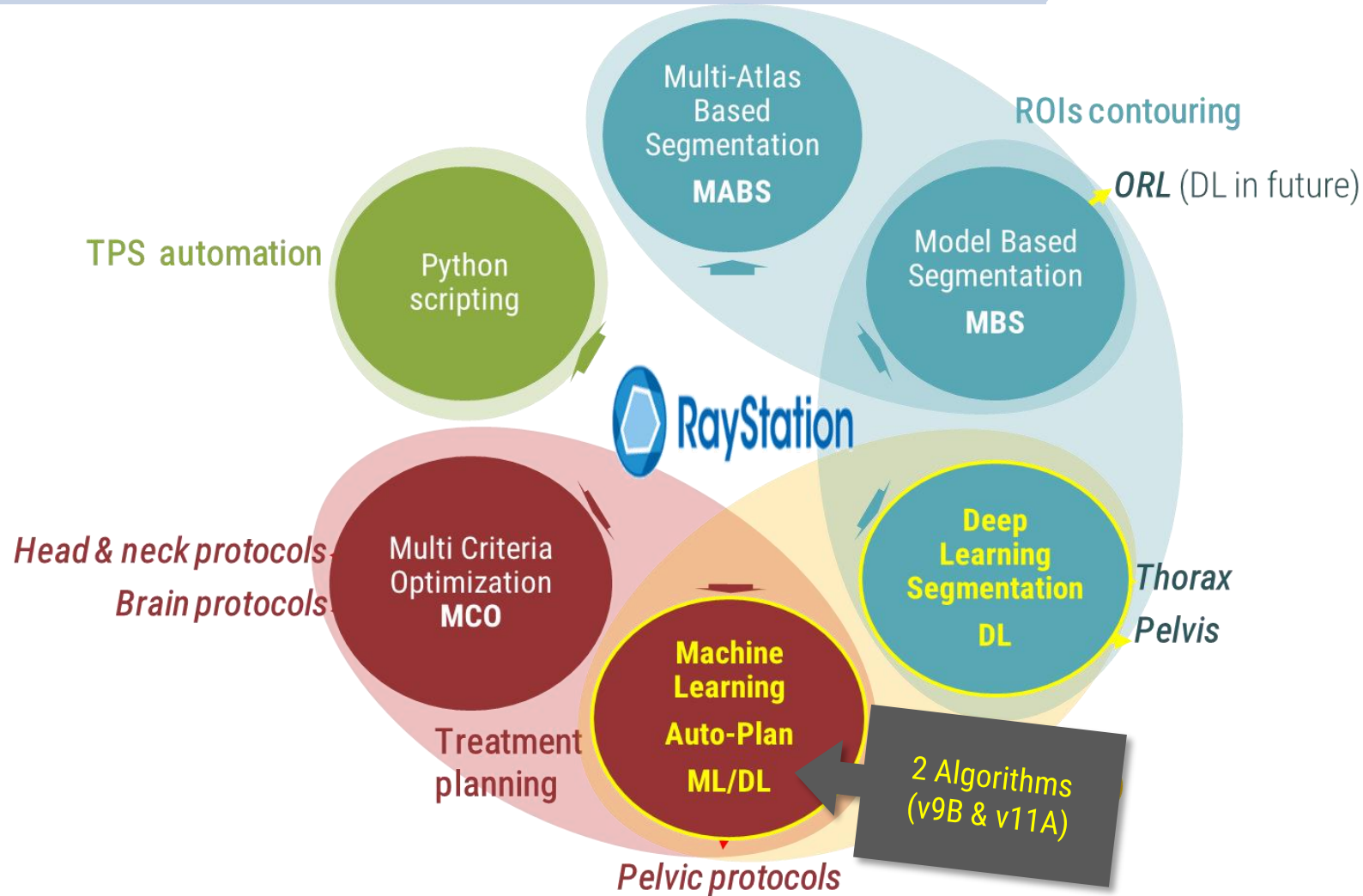
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Raystation

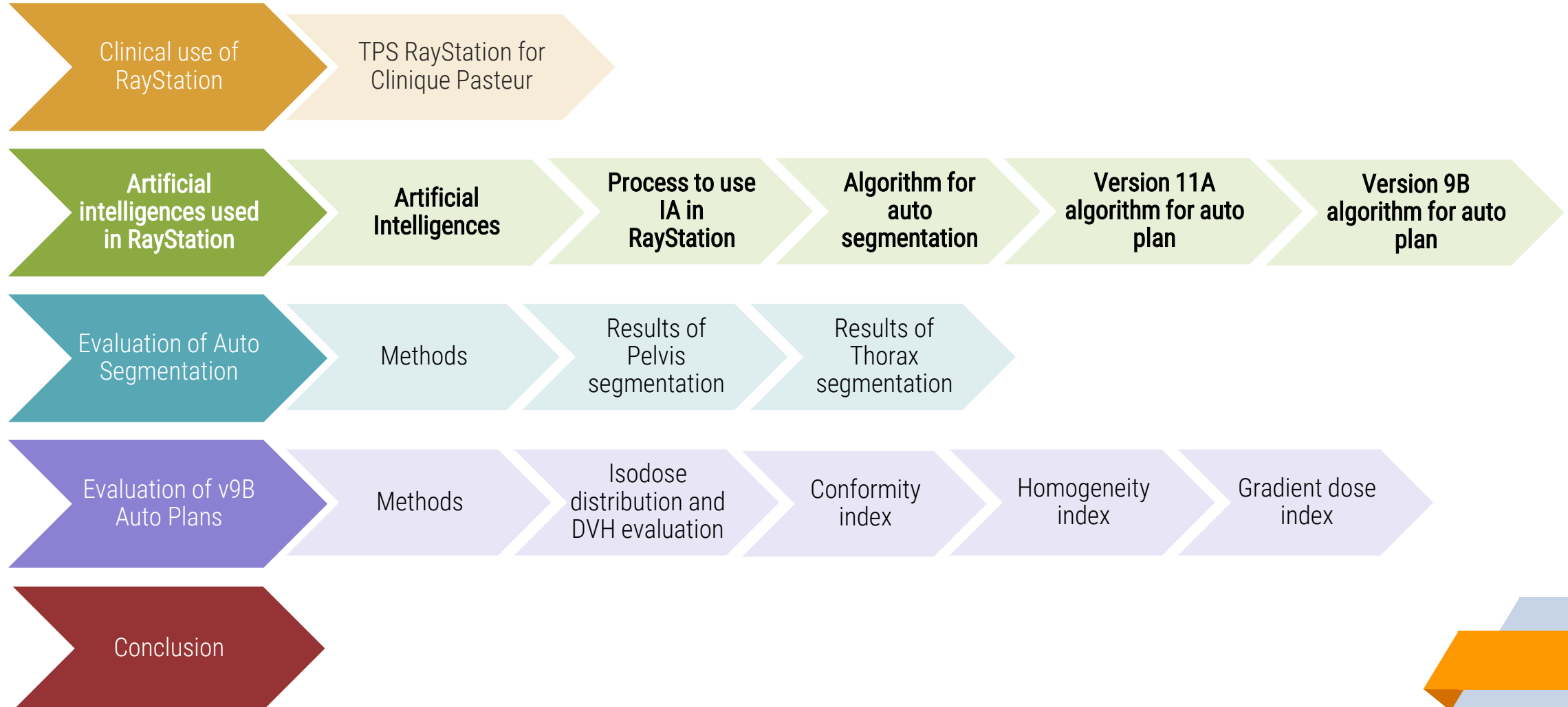
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- Choice of Raystation :**
- Unifying TPS
 - Automatic organ contouring
 - Automatic treatment planning
 - Automate TPS with Python script

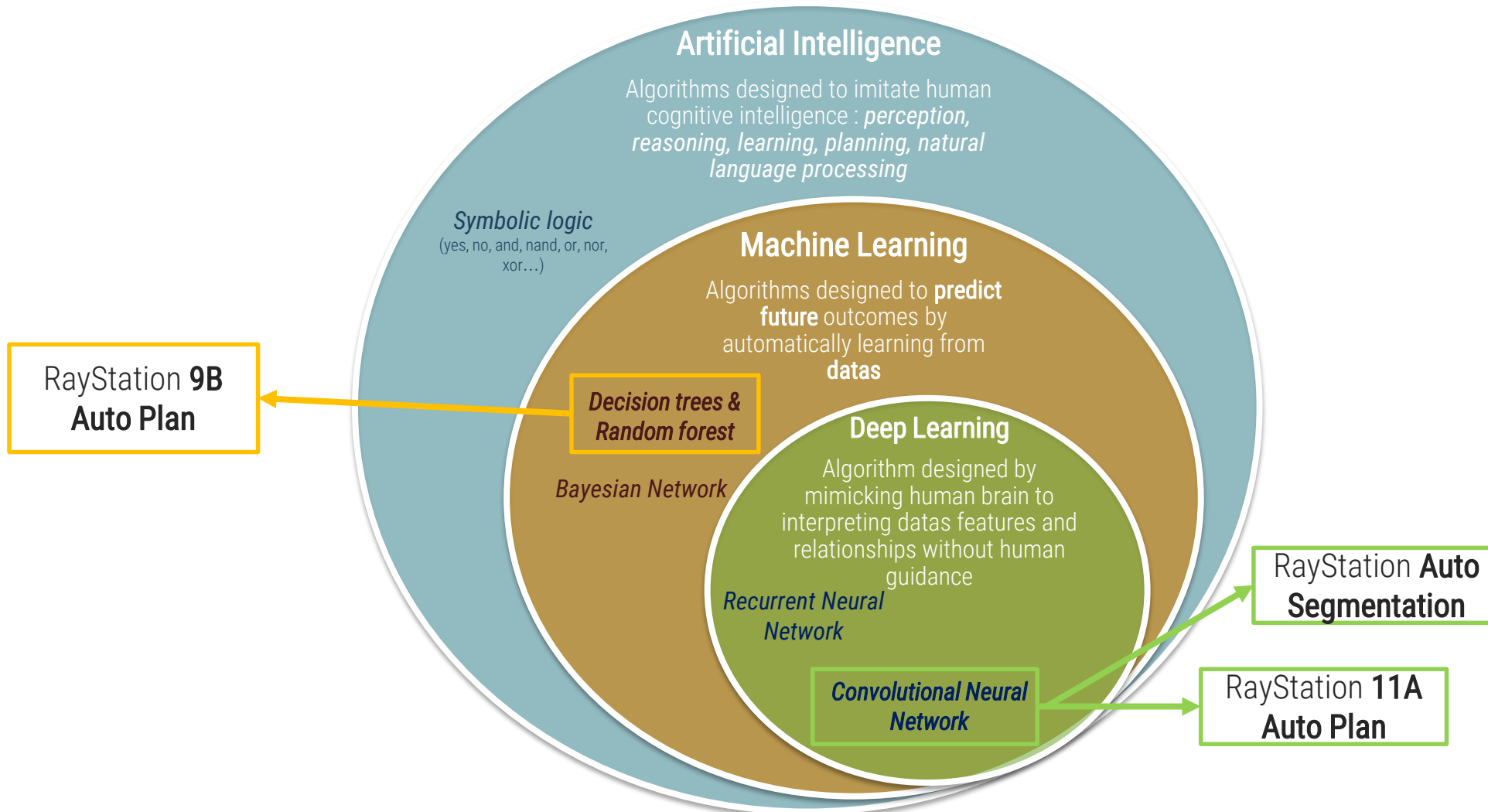
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IA to generate treatment plans in RayStation

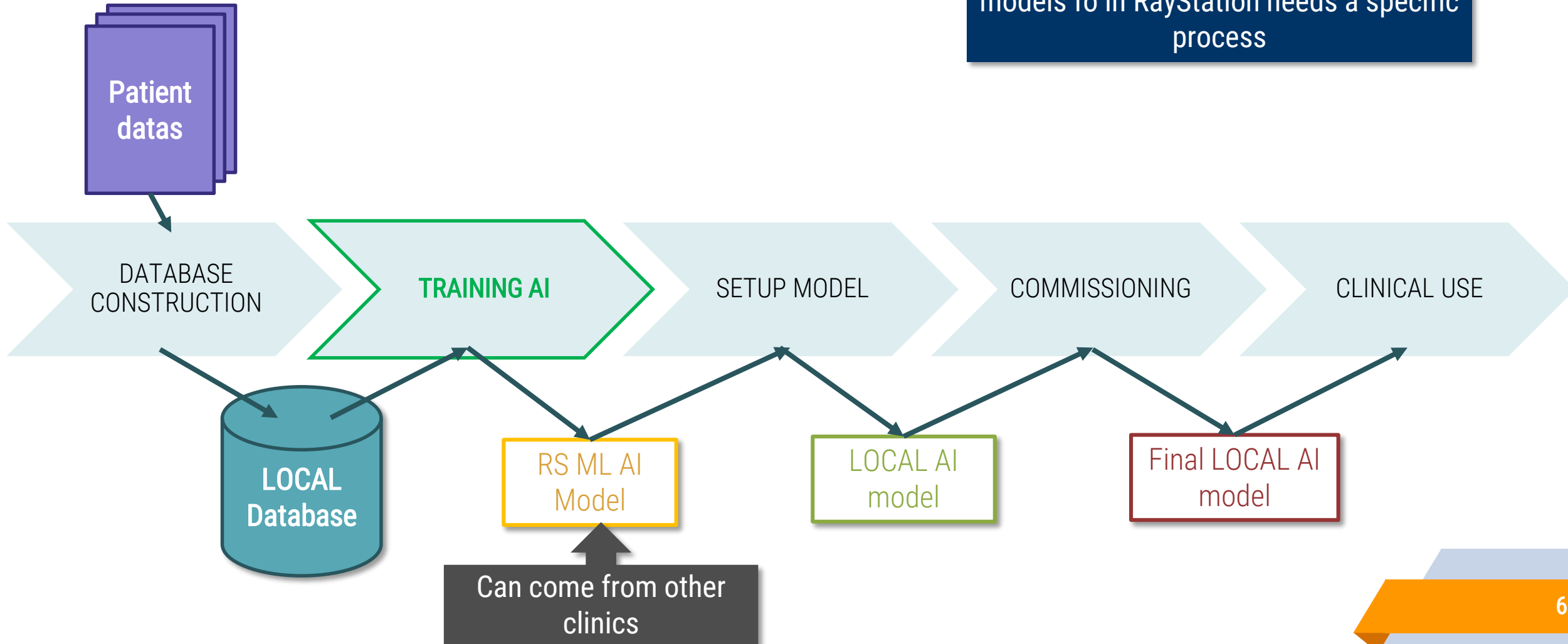
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Process to use Artificial Intelligences in RayStation

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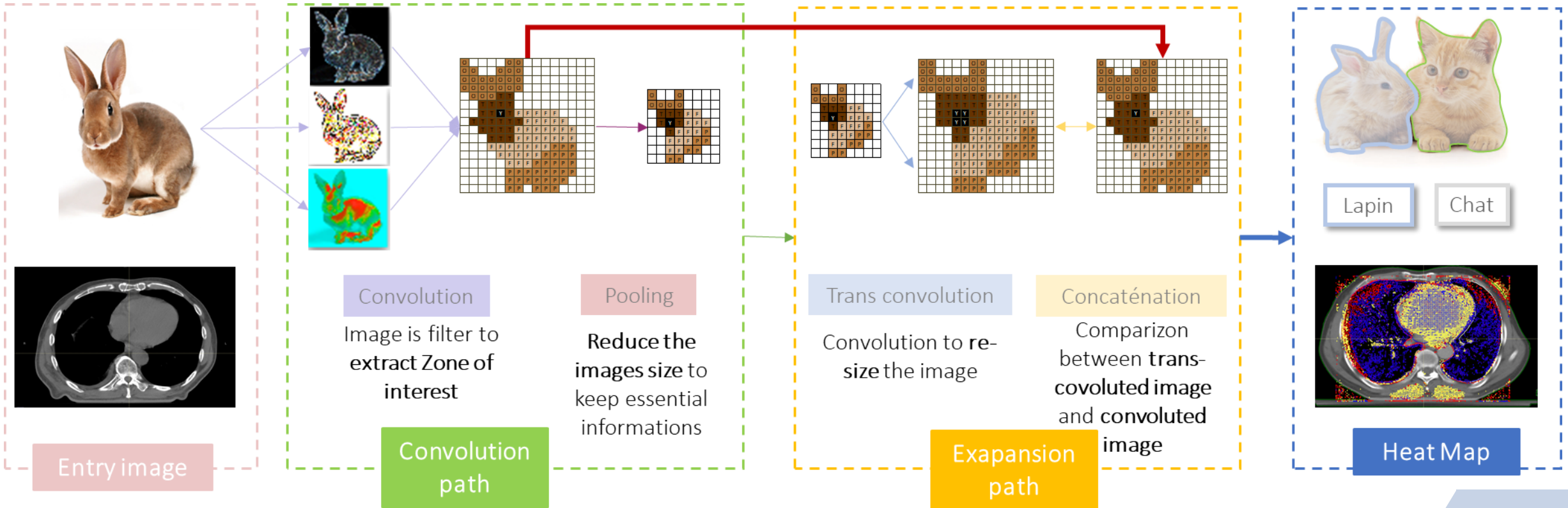
Clinical use of Artificial Intelligences models fo in RayStation needs a specific process



Algorithm for automatic segmentation

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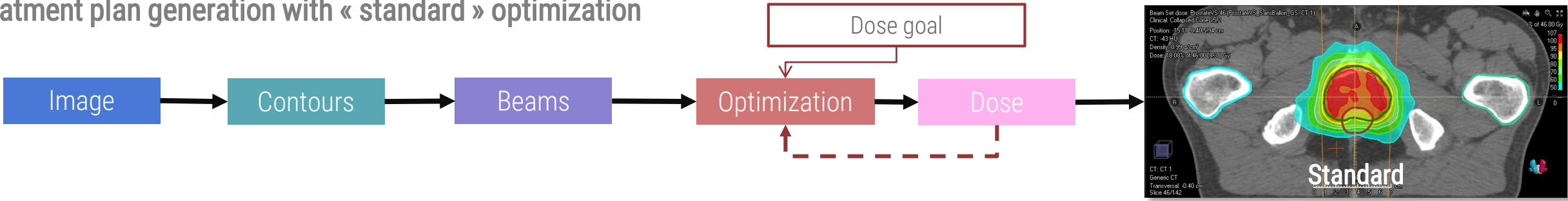
FCNN gives a category (ROI) to every voxel of the image



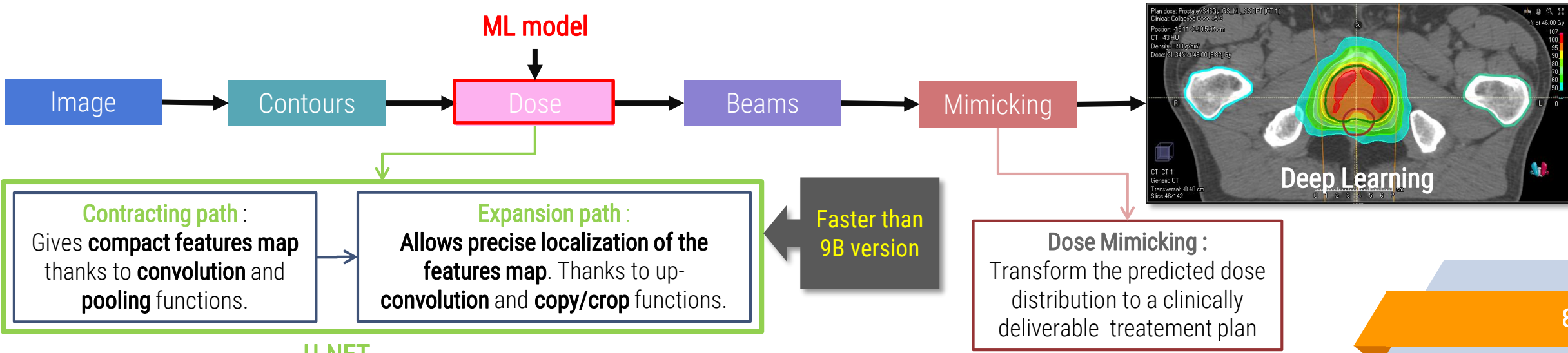
11A algorithm for automatic treatment plan generation

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Treatment plan generation with « standard » optimization



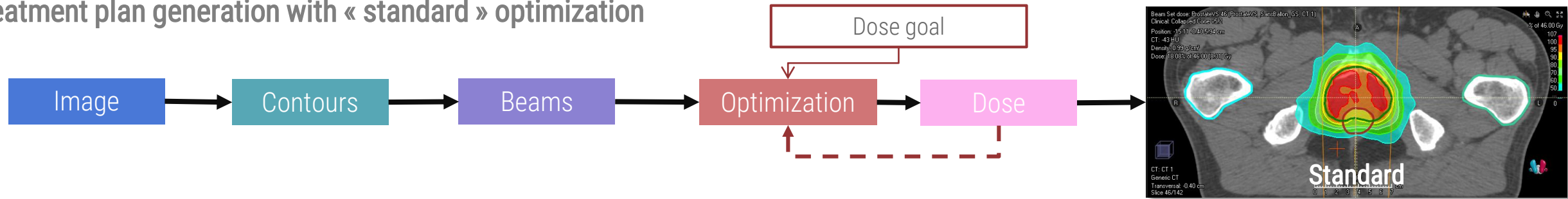
Treatment plan generation with a model of Machine Learning



9B algorithm for automatic treatment plan generation

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Treatment plan generation with « standard » optimization



Treatment plan generation with a model of Machine Learning

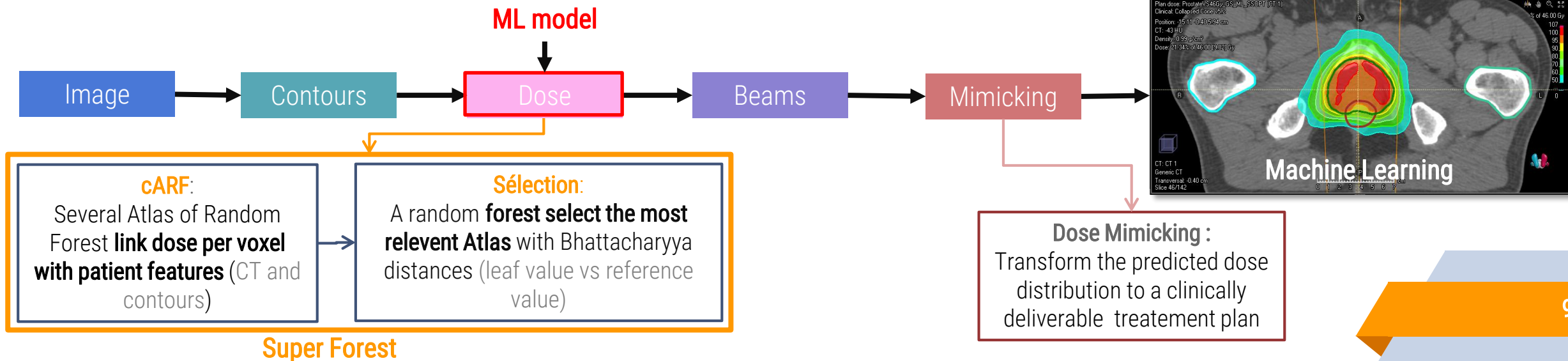
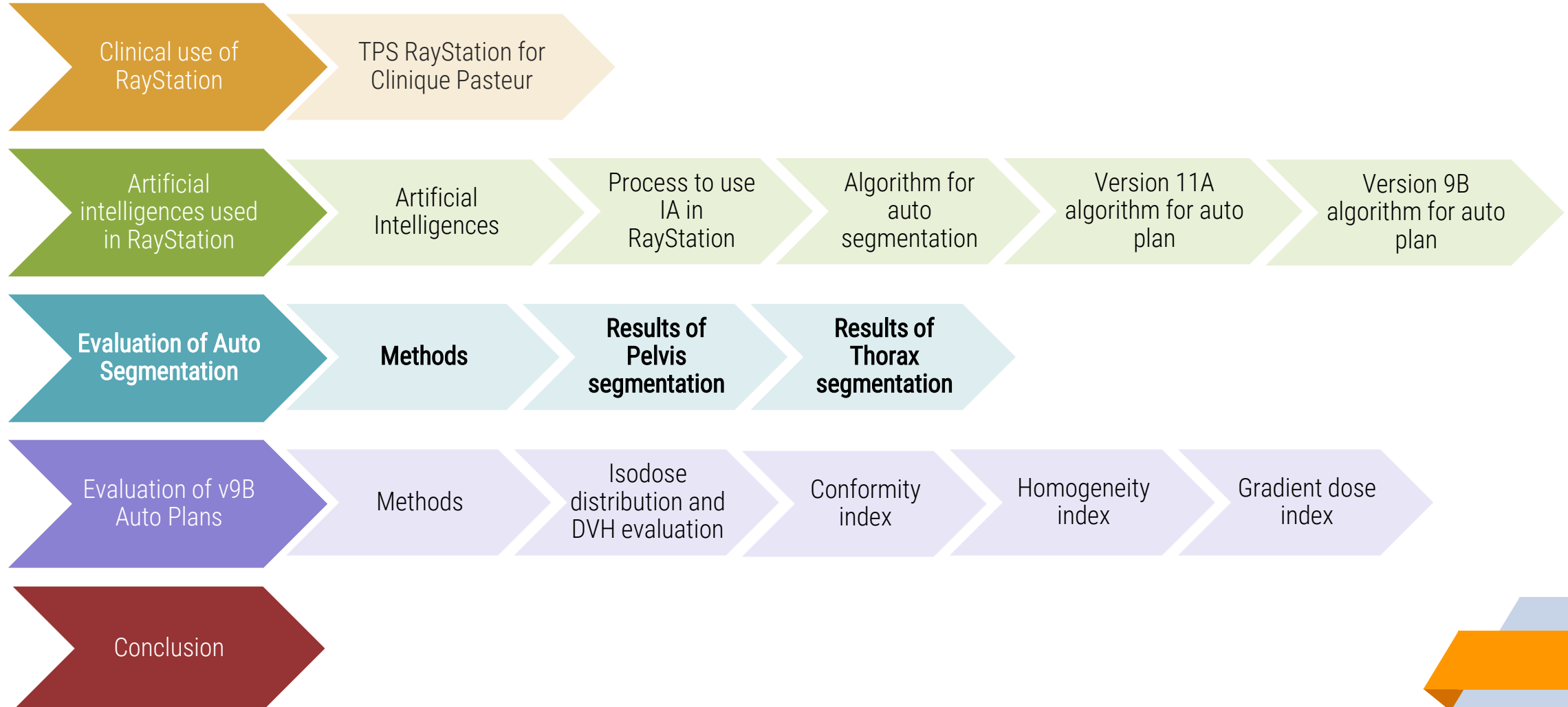


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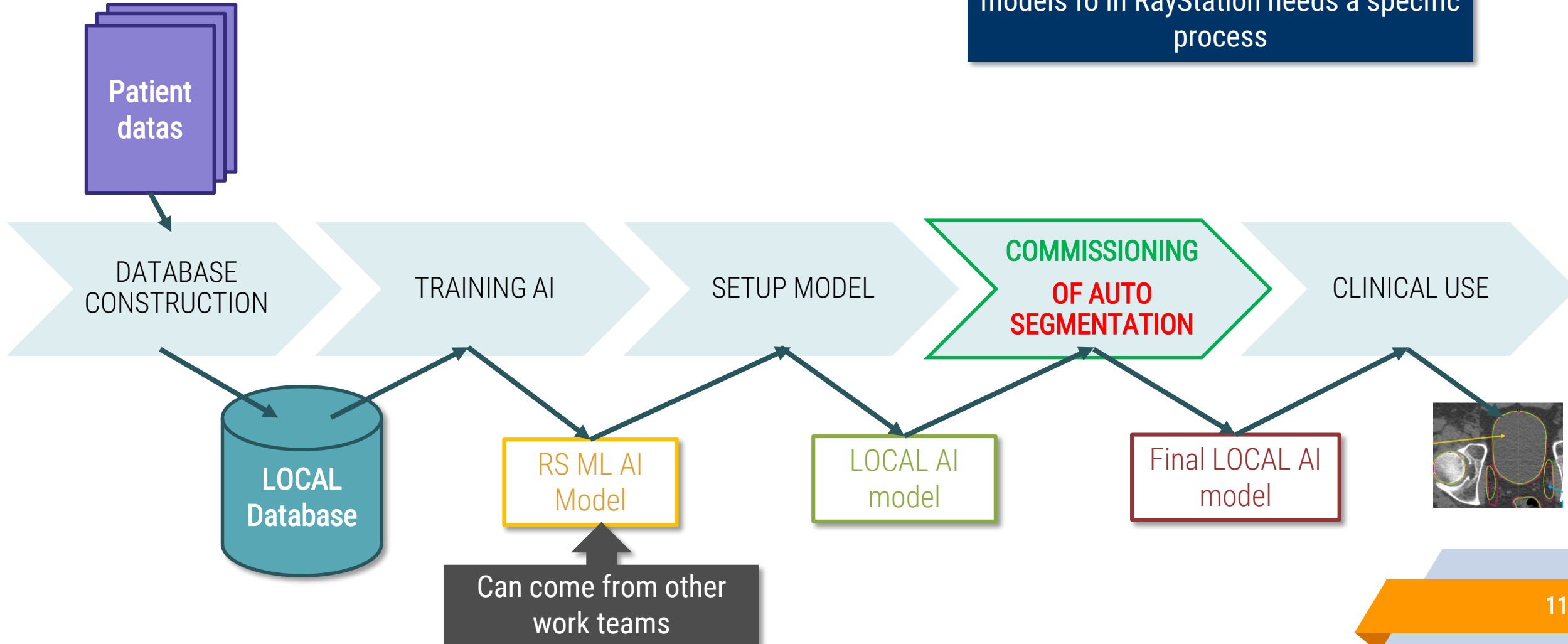
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Process to use artificial intelligences

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Clinical use of Artificial Intelligences models fo in RayStation needs a specific process



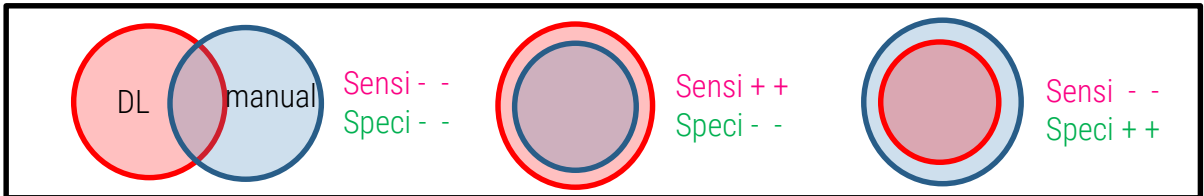
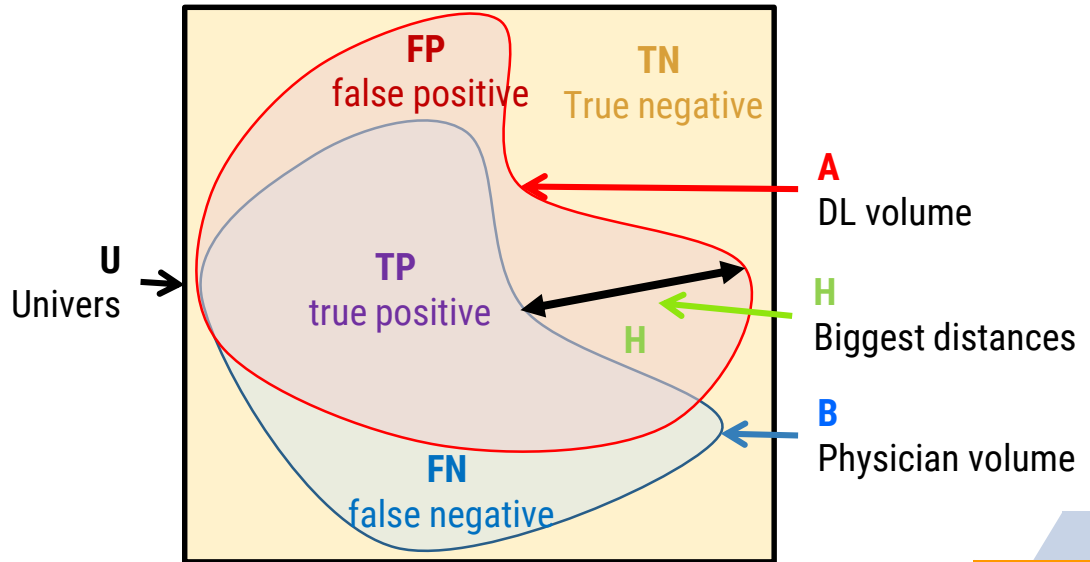
Method to evaluate of Auto segmentation

Introduction - Clinical Use of RS | IA Theory | **Auto Segmentation** | Auto Plan | Conclusion

- ❖ **Compare timing** of manual contours VS segmentation
- ❖ **Calculation** similarity **index** : Dice, Jaccard, **Sensibility** et **Specificity** and Mean and Hausdorff **distances (H)**
- ❖ **If bad results** (all index < 0,8) : **Qualitative review of physician** to decided to accept or not the auto segmentation model

$$Dice = \frac{2TP}{A + B} \quad Jaccard = \frac{TP}{TP + FP + FN}$$

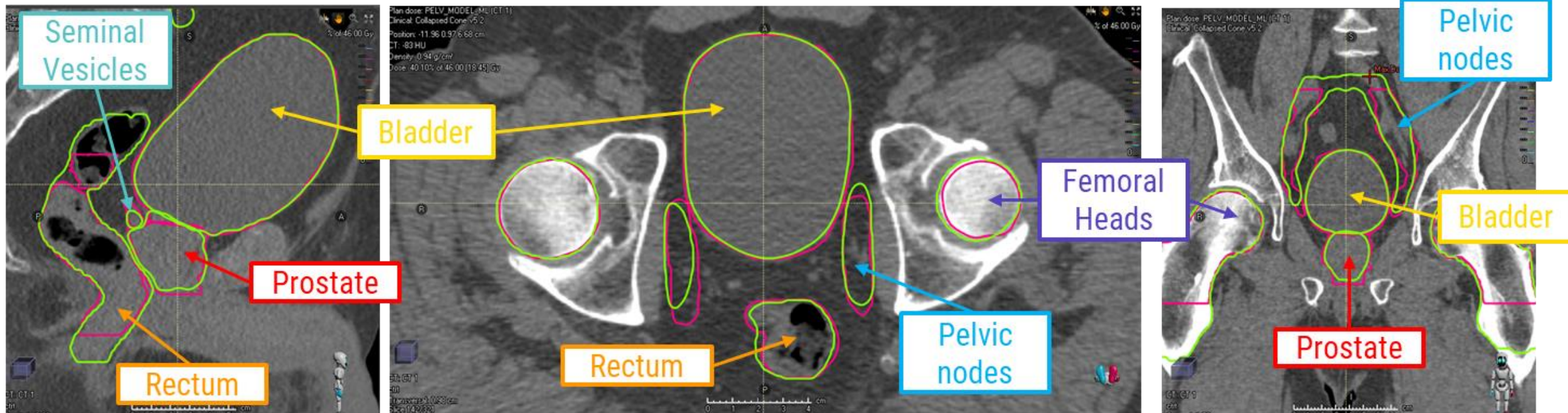
$$Sensibility = \frac{TP}{B} \quad Specificity = \frac{TN}{U - B}$$



Automatic segmentation of Pelvis

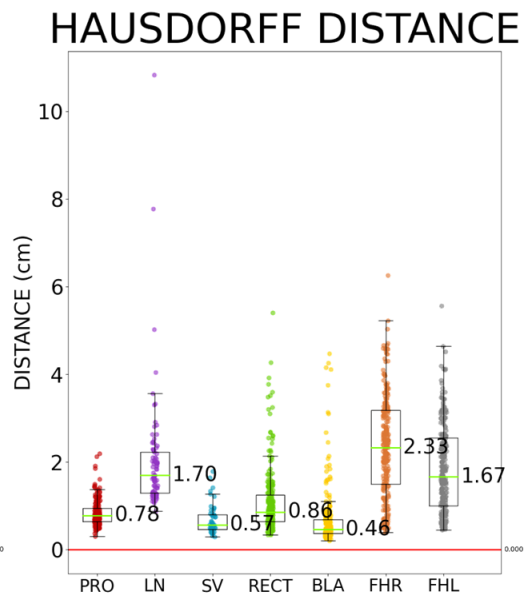
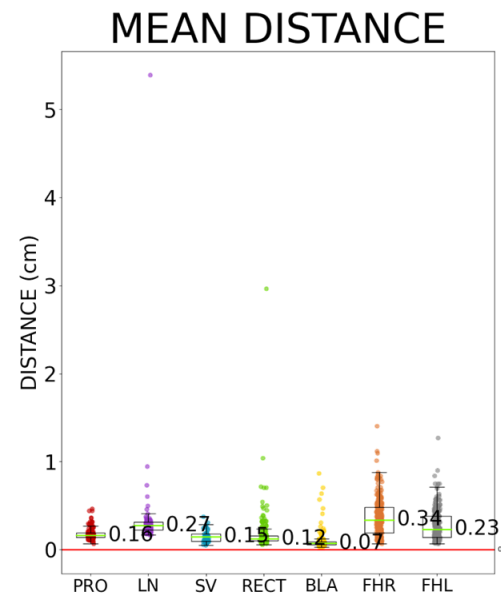
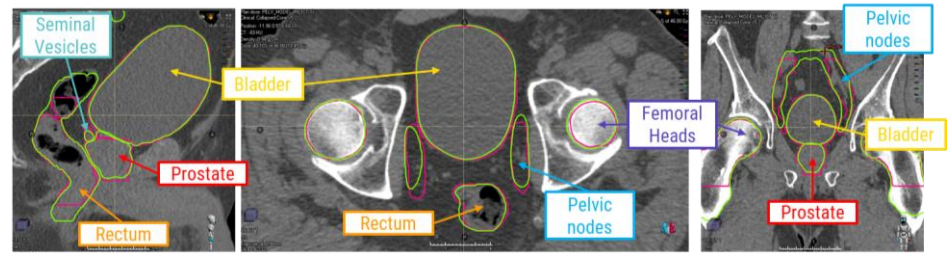
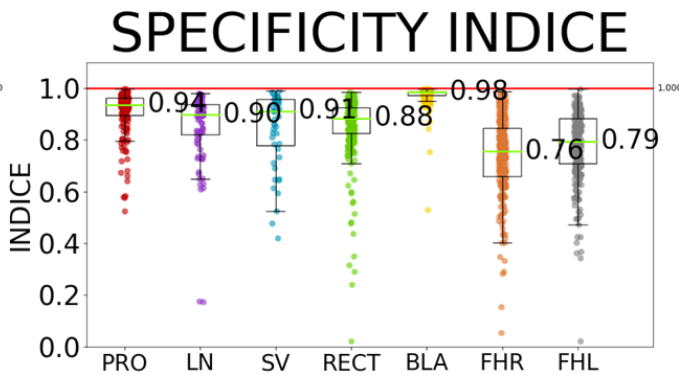
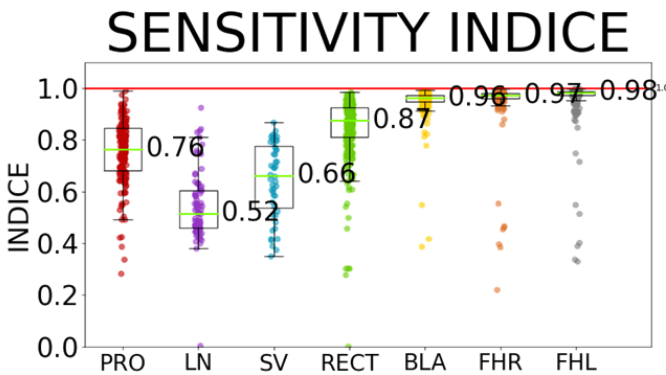
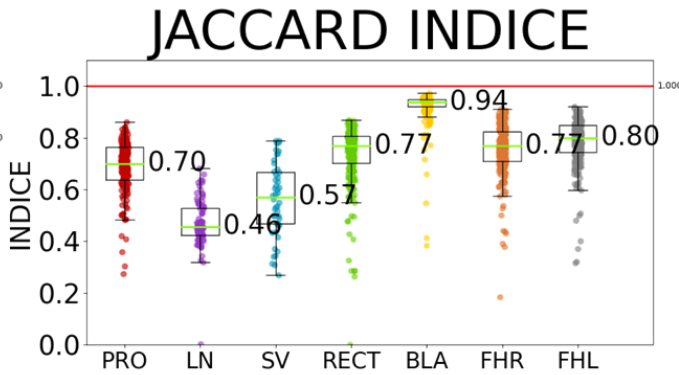
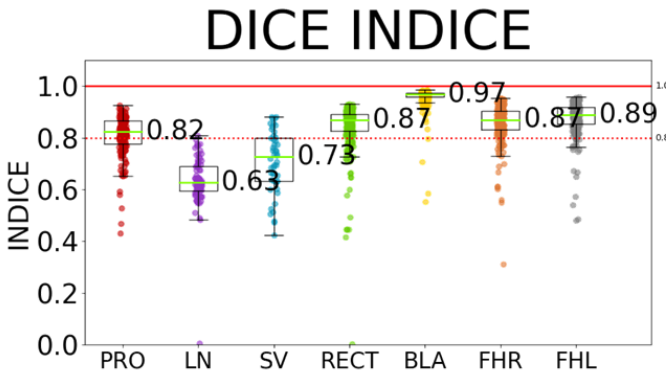
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Physician contours : minimum 10 minutes
Deep Learning contours : 30 secondes



Method to evaluate of Auto segmentation

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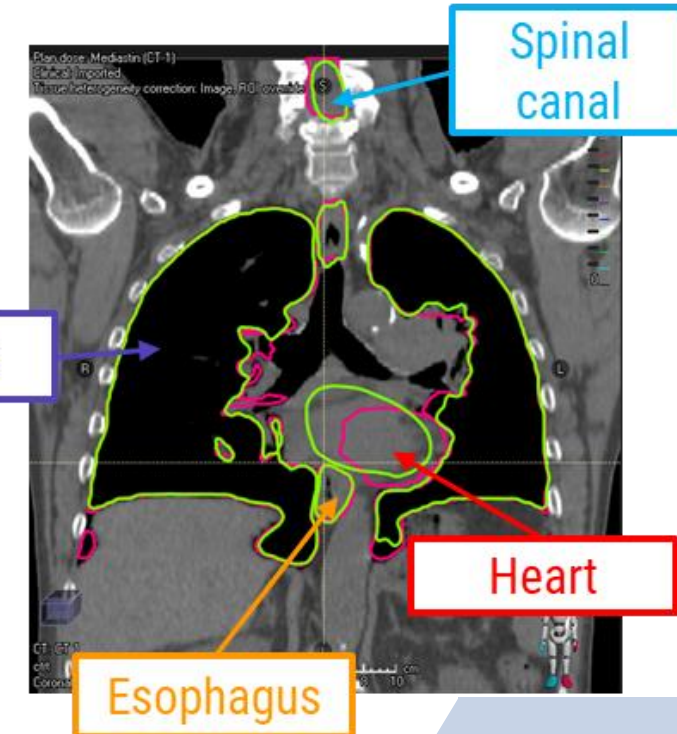
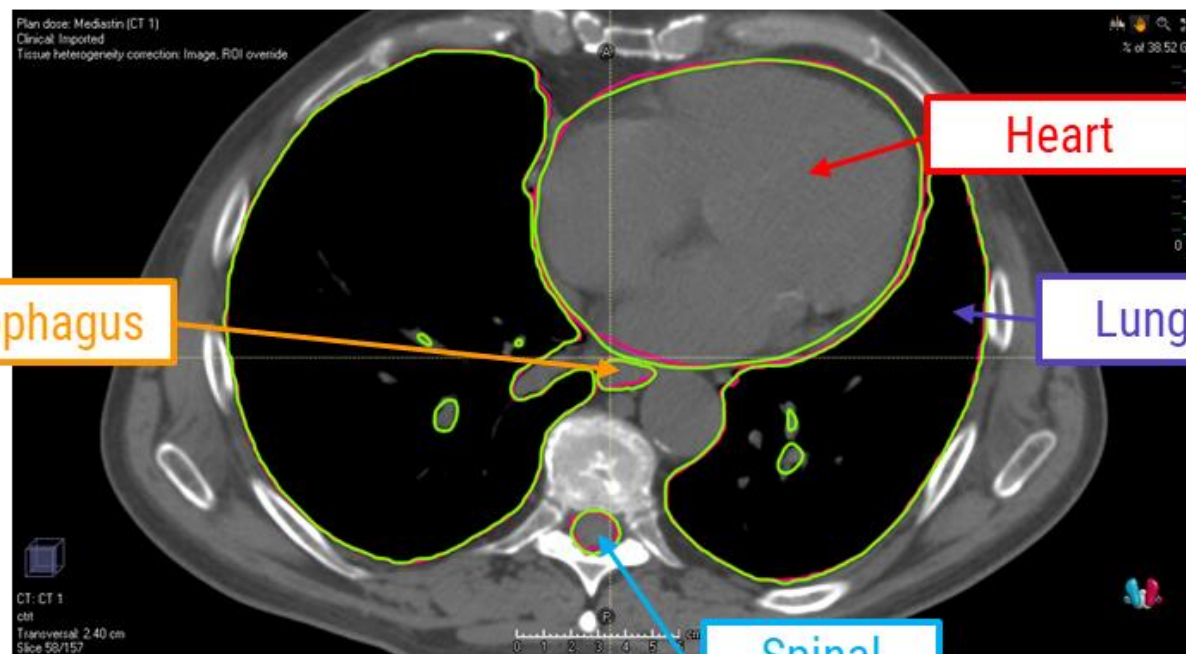
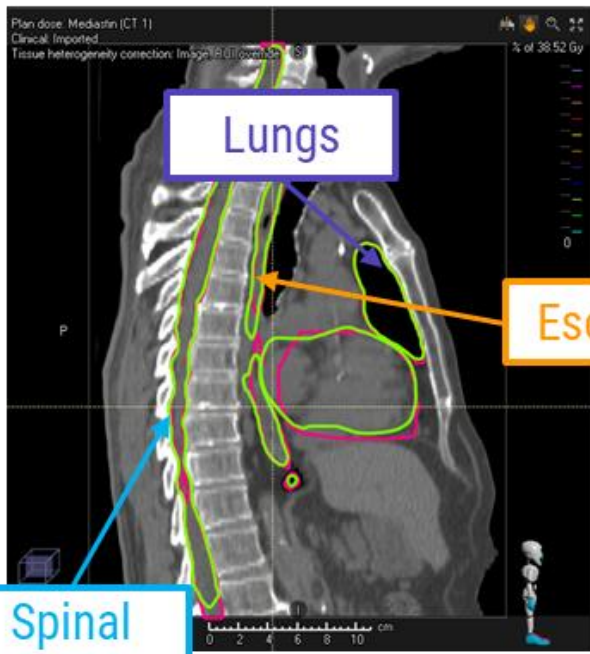
Dice < 0,8 for Seminal vesicles and Lymphatic nodes, but high specificity (accepted with manual corrections)
 Dice > 0,8 for Prostate, Bladder, Rectum, Femoral Heads (accepted with manual corrections)

Model accepted clinically

Automatic segmentation for Thorax

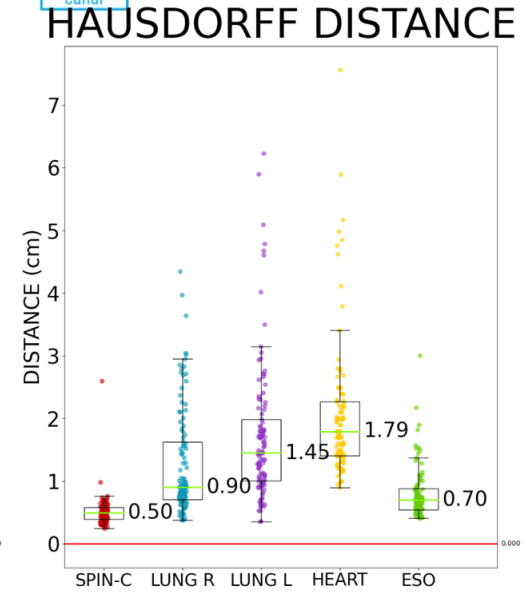
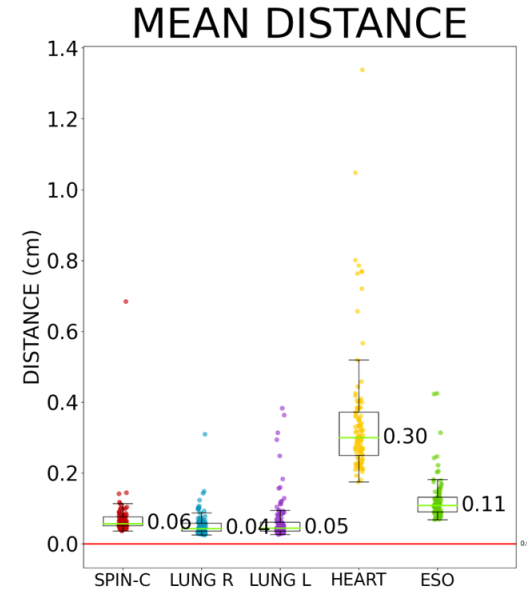
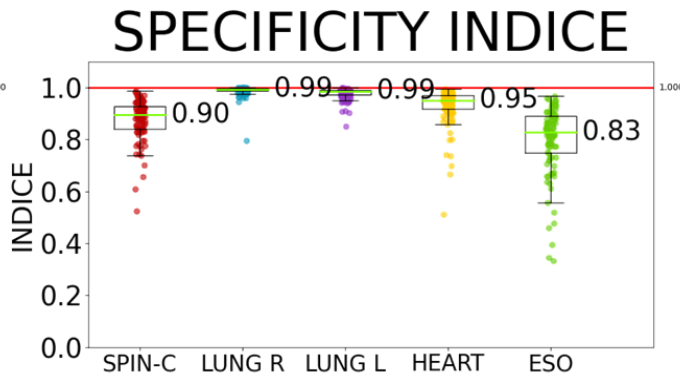
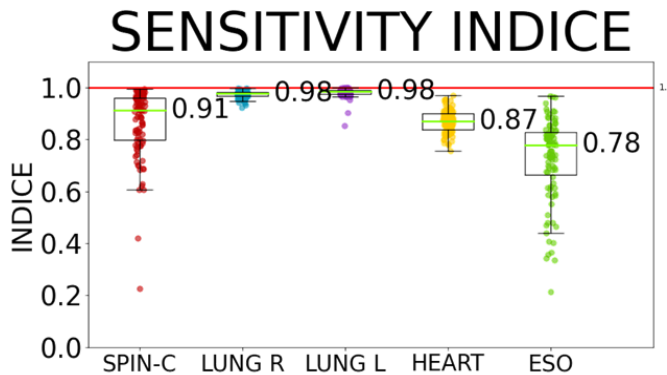
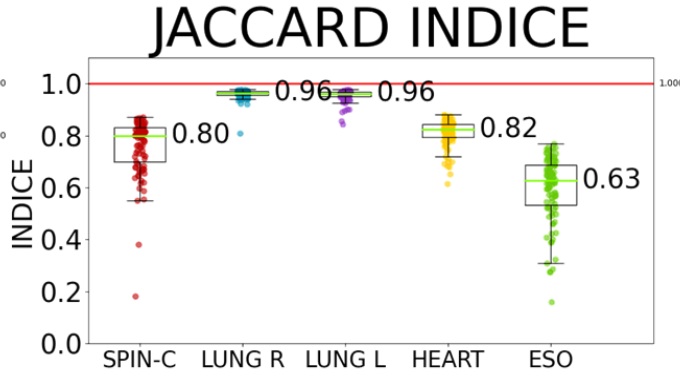
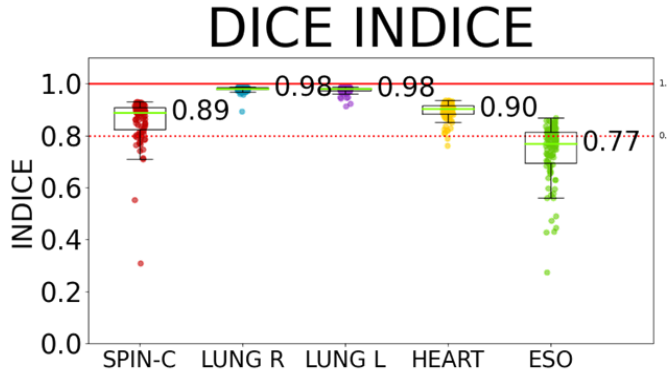
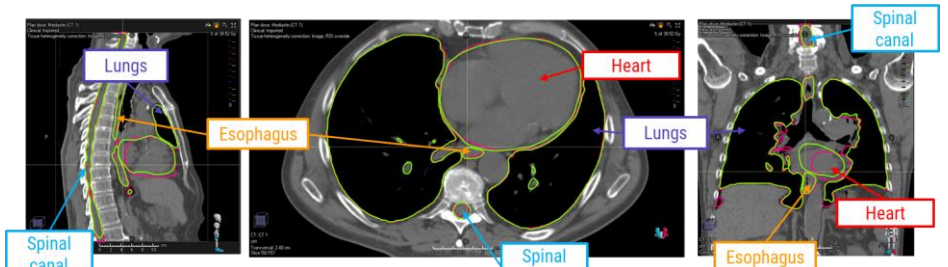
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Physician contours : minimum 10 minutes
Deep Learning contours : 30 secondes



Method to evaluate of Auto segmentation

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Dice > 0,8 for Spinal canal, lungs and heart (accepted with manual corrections)
 Dice < 0,8 esophagus (accepted **but new model for esophagus considered**)
Model accepted clinically

Process to use artificial intelligences

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Clinical use of Artificial Intelligences models fo in RayStation needs a specific process

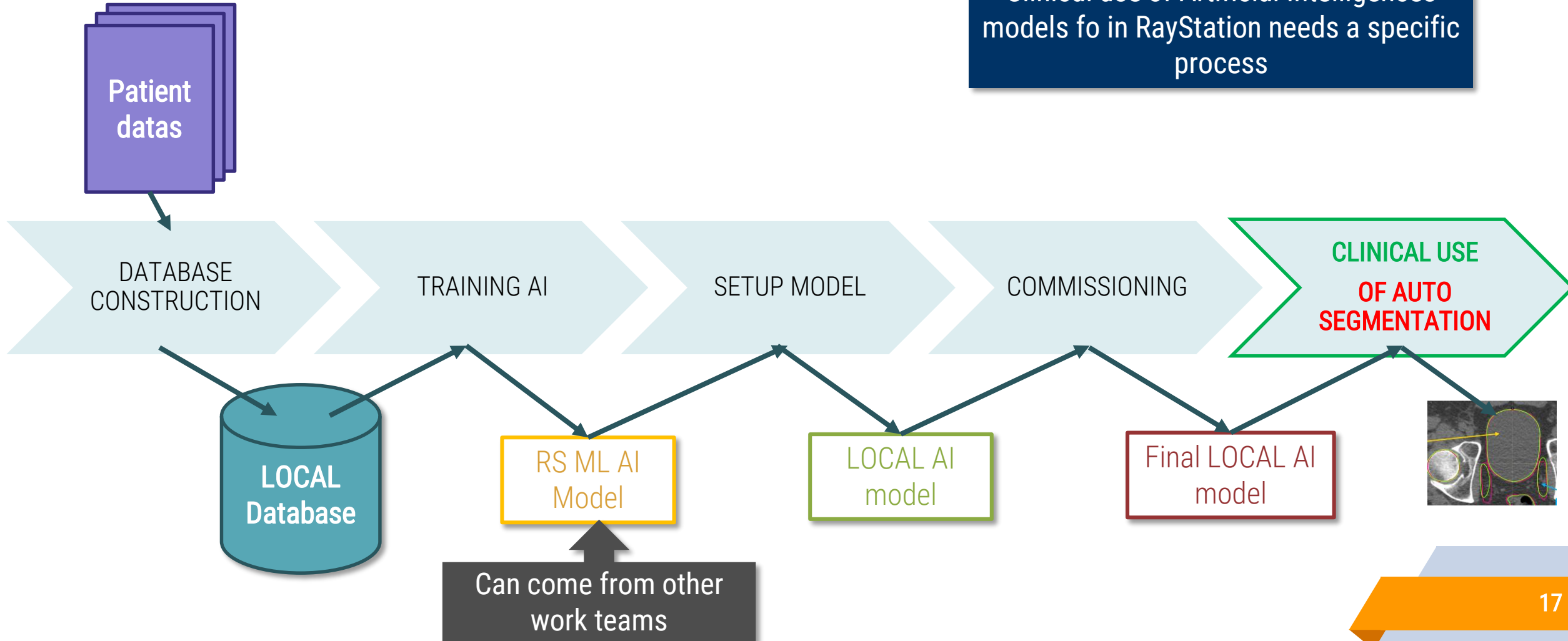
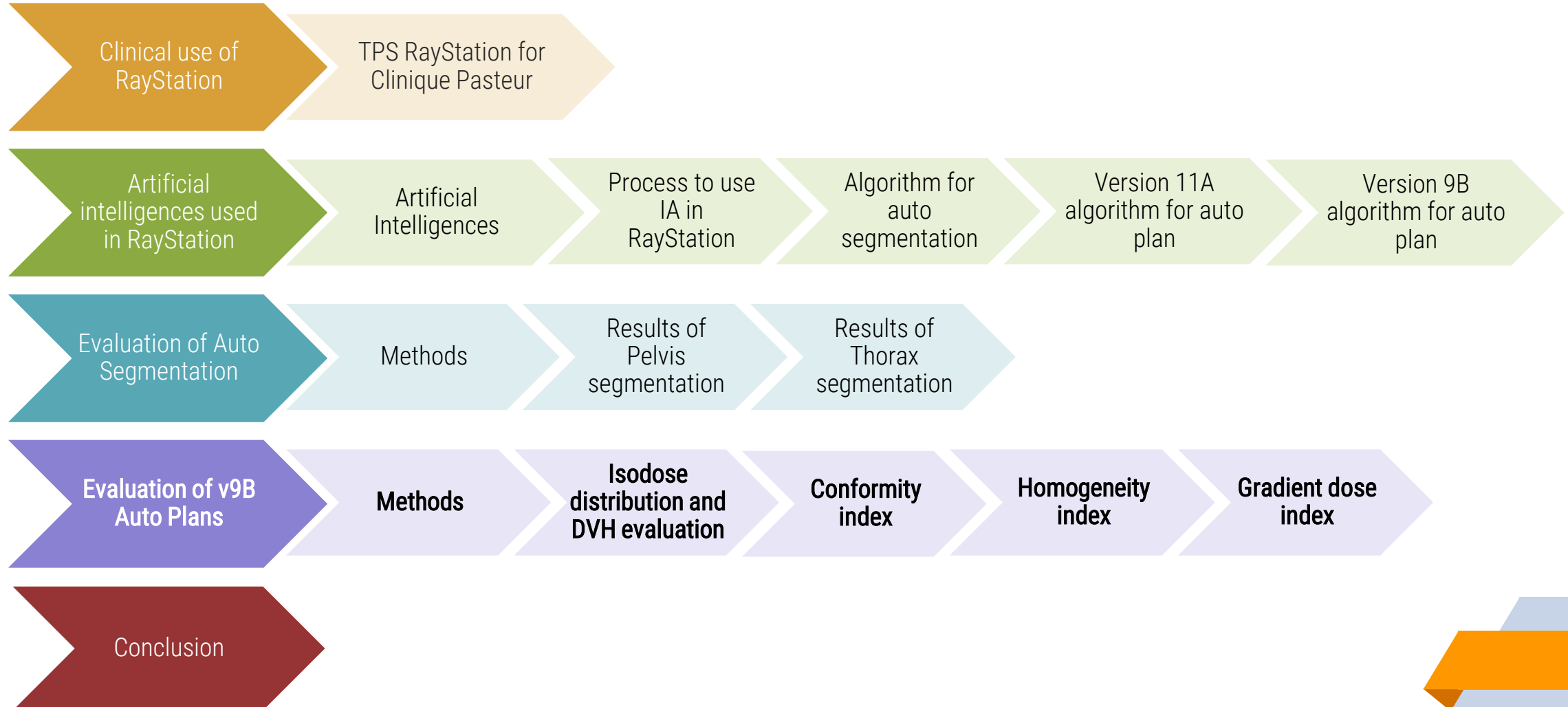


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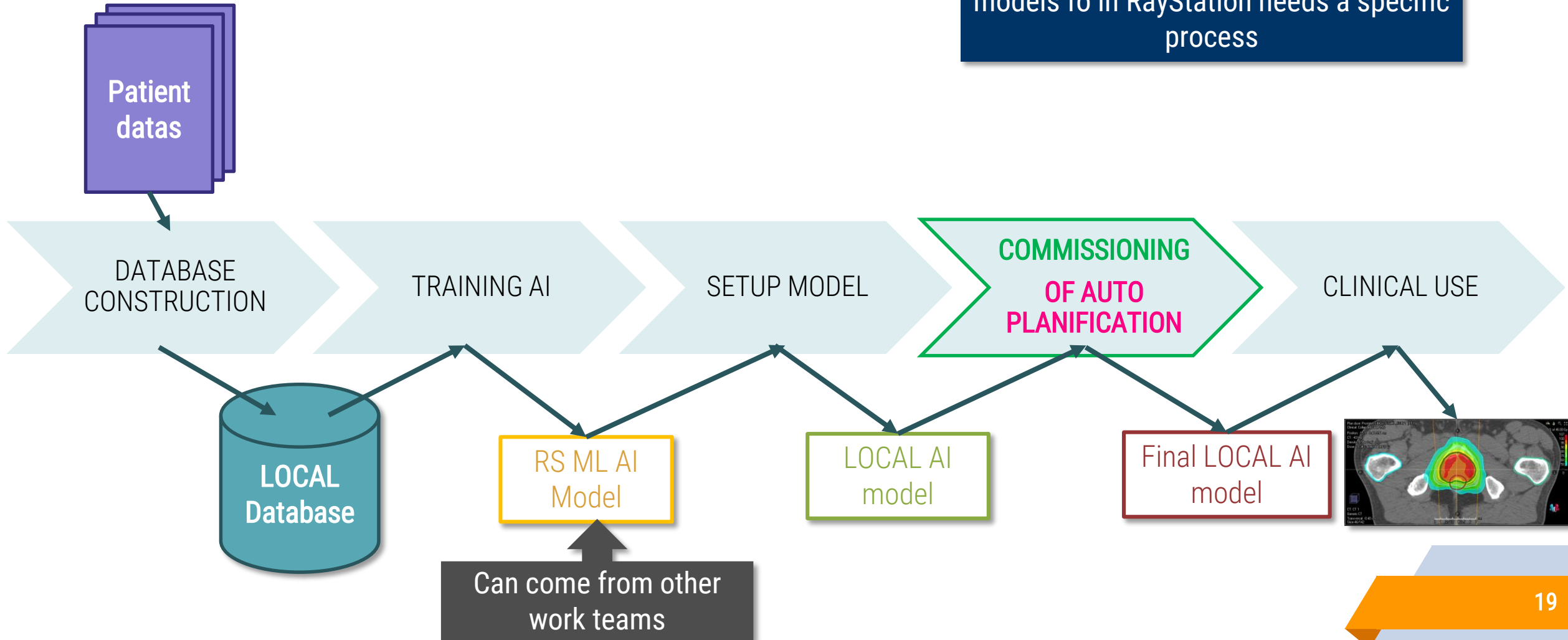
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Process to use Artificial Intelligences in RayStation

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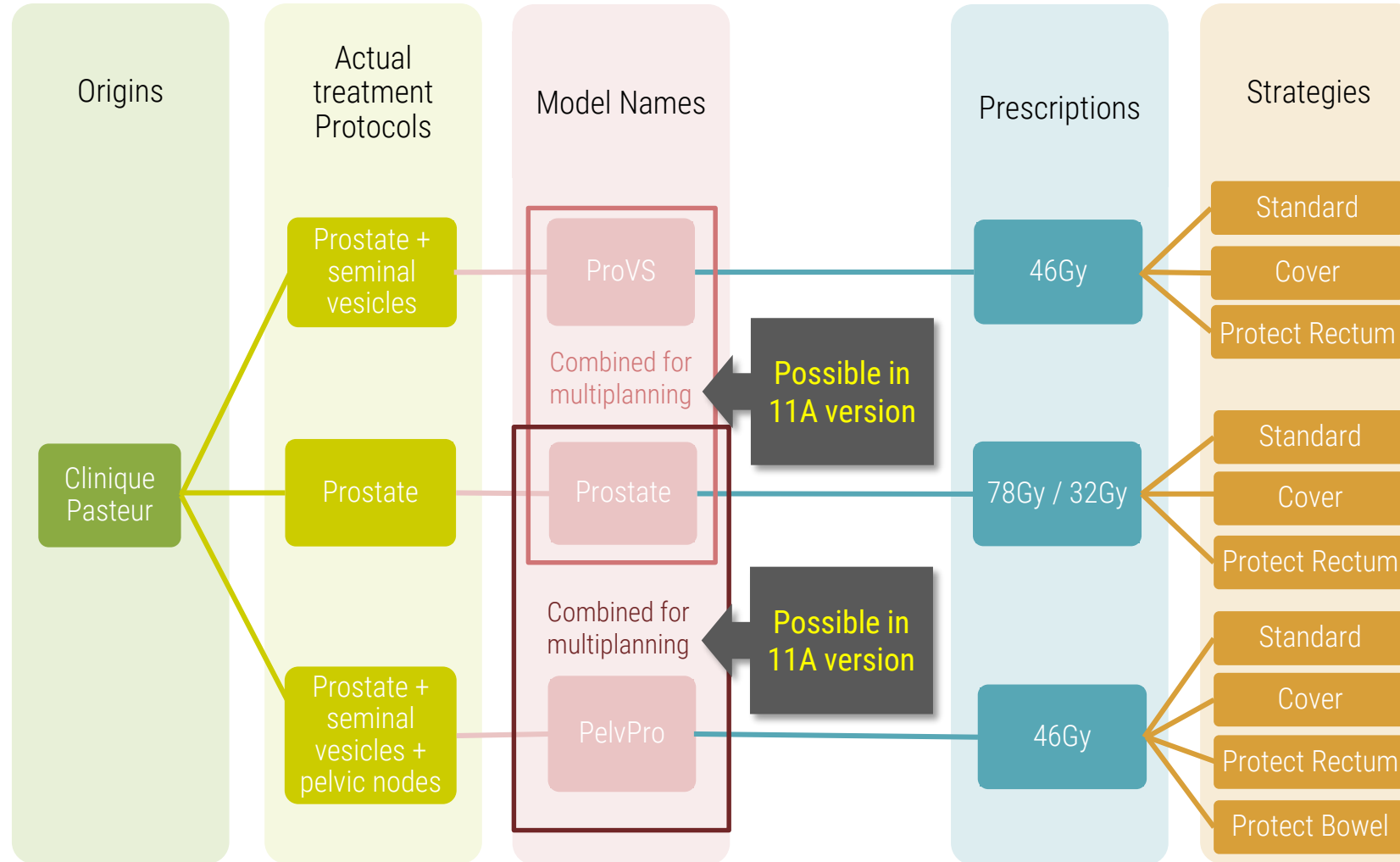
Clinical use of Artificial Intelligences models fo in RayStation needs a specific process



LOCAL Pelvic models for auto planning

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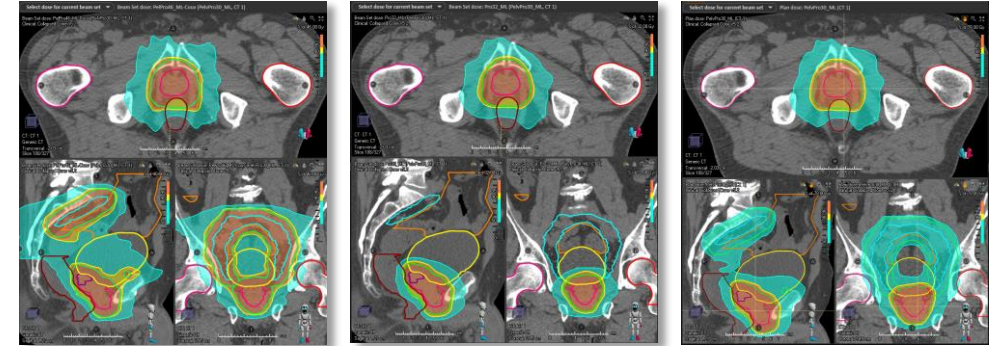
3 LOCAL ML models in 9B and 5 LOCAL ML models in 11A and their strategies from the 2 LOCAL databases



Method to evaluate of Auto Plans Commissioning of ML model

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- ❖ **Qualitative review** of the **dose distributions** and **DVH** curves :
- ❖ **Quantitative evaluation** of the protocol specific **clinical goals**
- ❖ **Comparison** between the **automated plans with ML** and the **standard optimized plans** with **index** :



Conformity index

$$Conformity = \frac{Volume_{target}}{Volume_{isodose_ref}}$$

Homogeneity index

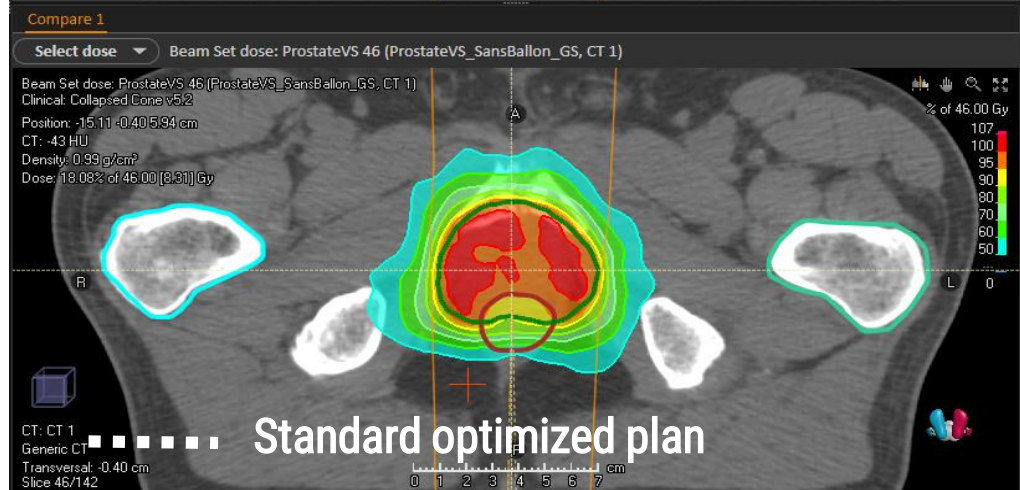
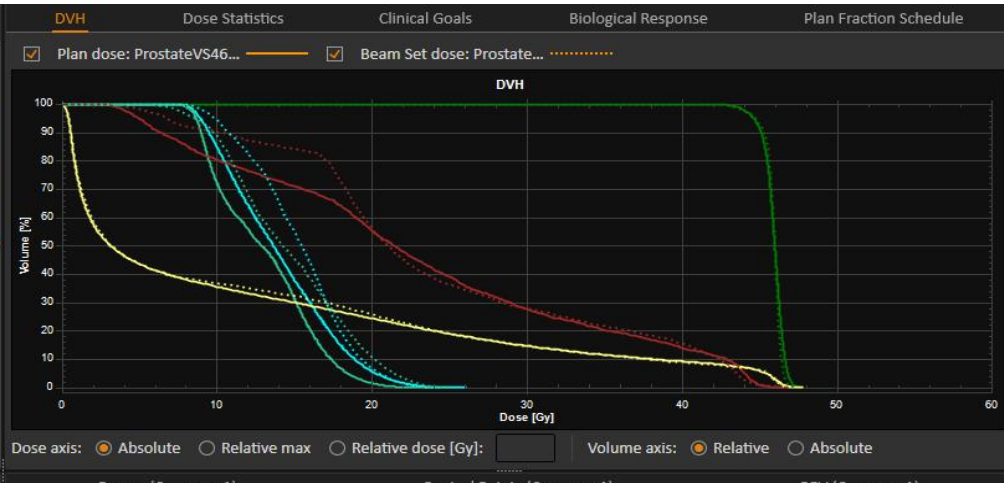
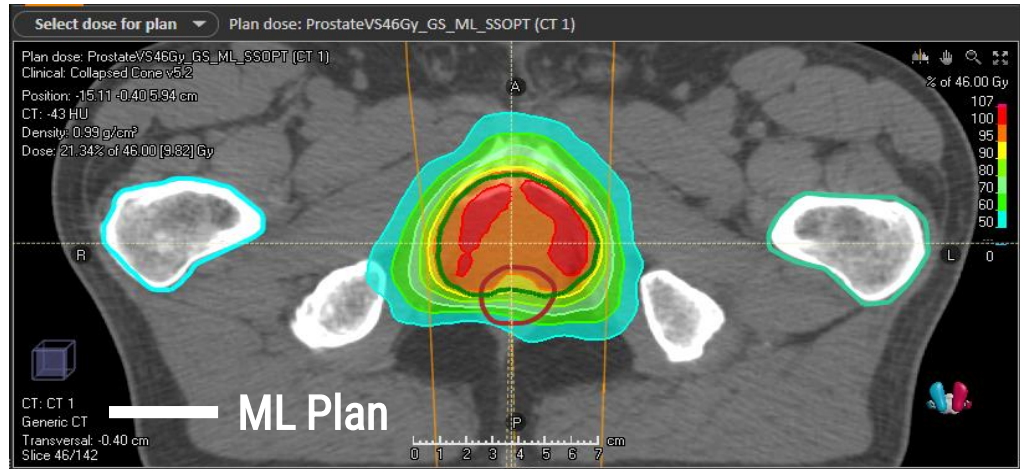
$$Homogeneity = \frac{D_2 - D_{98}}{D_{50}}$$

Dose Gradient index

$$Gradient = \frac{Volume_{isodose\ 50\%}}{Volume_{isodose_ref}}$$

Standard vs ML : review of the dose distributions and DVH curves

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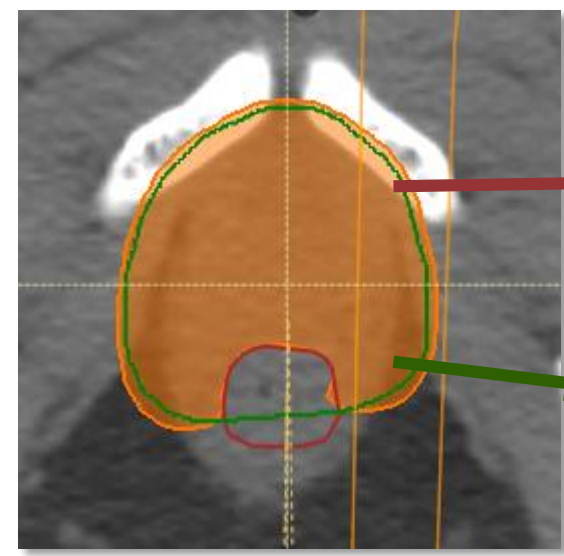
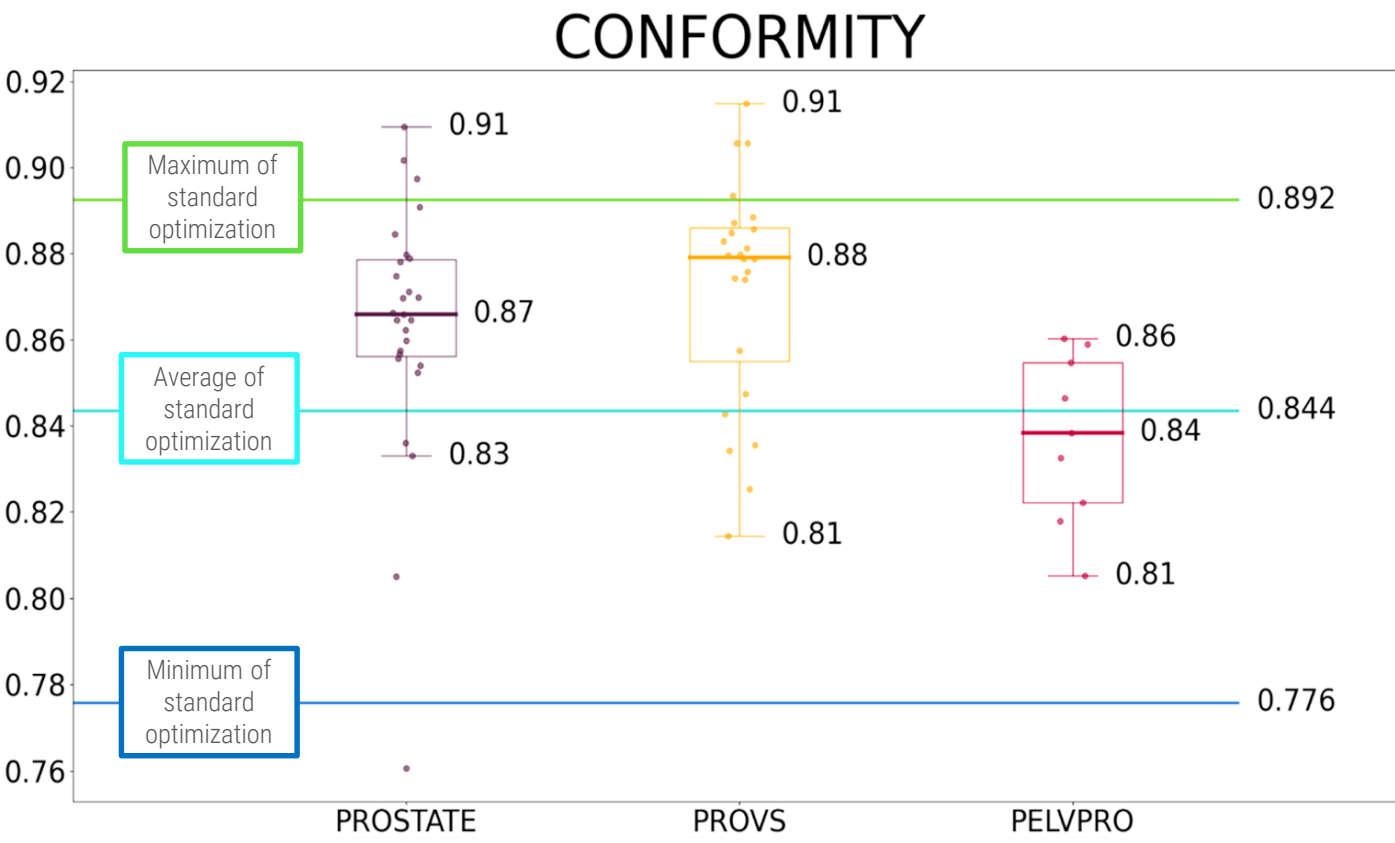
- ✓ 85% of 50 evaluated plans are clinically acceptable without additional optimization
- ✓ ML algorithm generate plan in **16 minutes** = twice faster than standard optimization

Standard vs ML : Conformity index

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$$Conformity = \frac{Volume_{target}}{Volume_{isodose_ref}}$$

Goal = 1



Isodose Volume of 95% of dose prescription (reference)

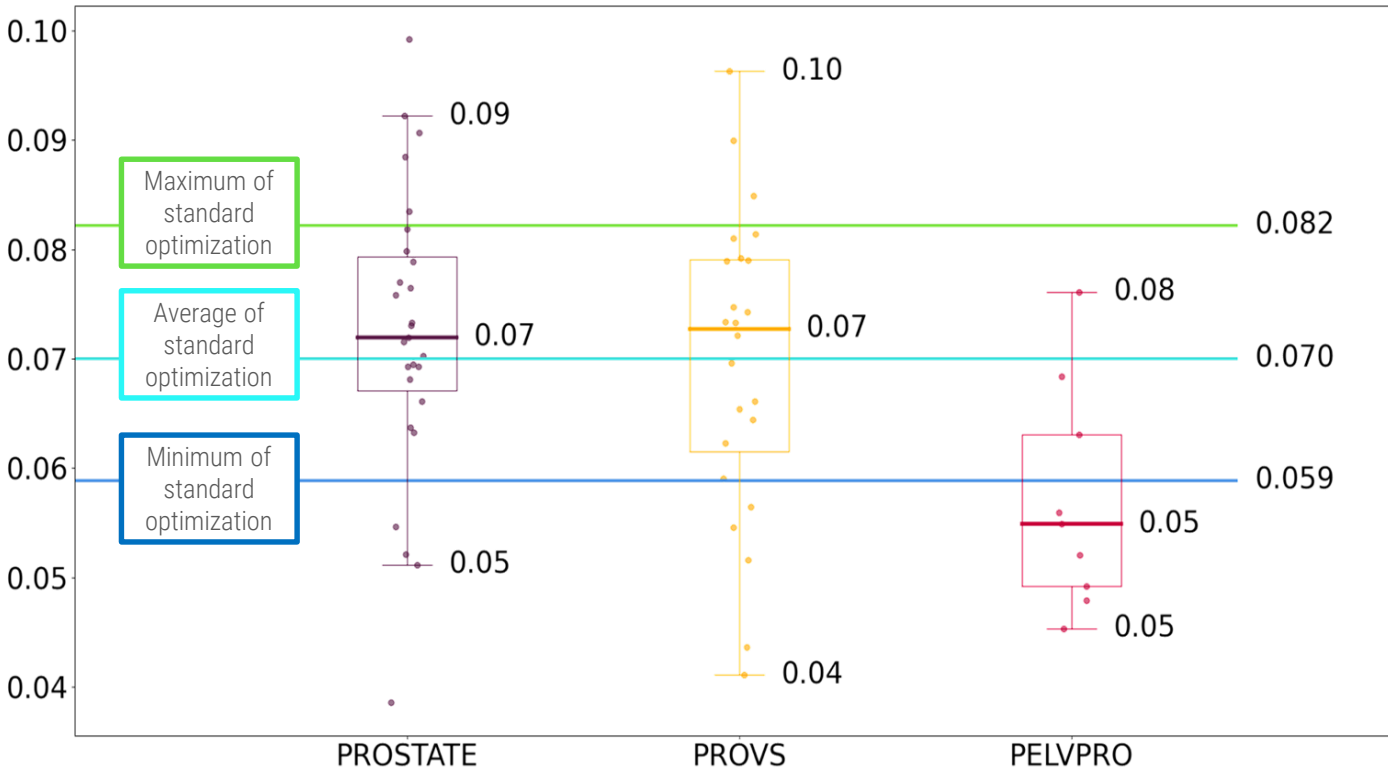
Planning Target Volume (PTV)

Results of ML between 0,91 and 0,76 : LOCAL ML models have **equivalent or best conformity** than standard optimized plans

Standard vs ML : Homogeneity index

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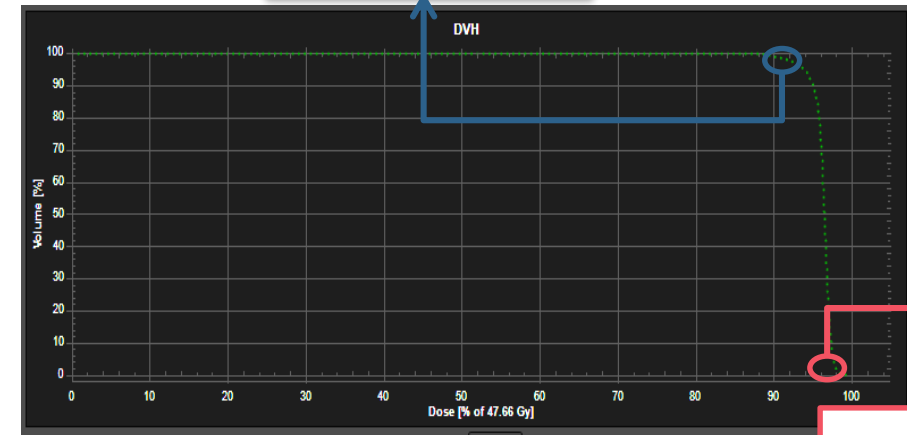
HOMOGENEITY



$$Homogeneity = \frac{D_2 - D_{98}}{D_{50}}$$

Dose at 98% of PTV

Goal = 0



Dose at 2% of PTV

Results of ML between 0,04 and 0,1 : LOCAL ML models have **equivalent homogeneity** indices than standard optimized plan.

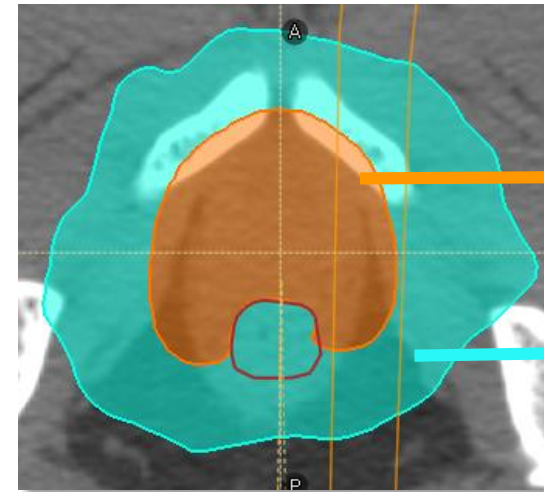
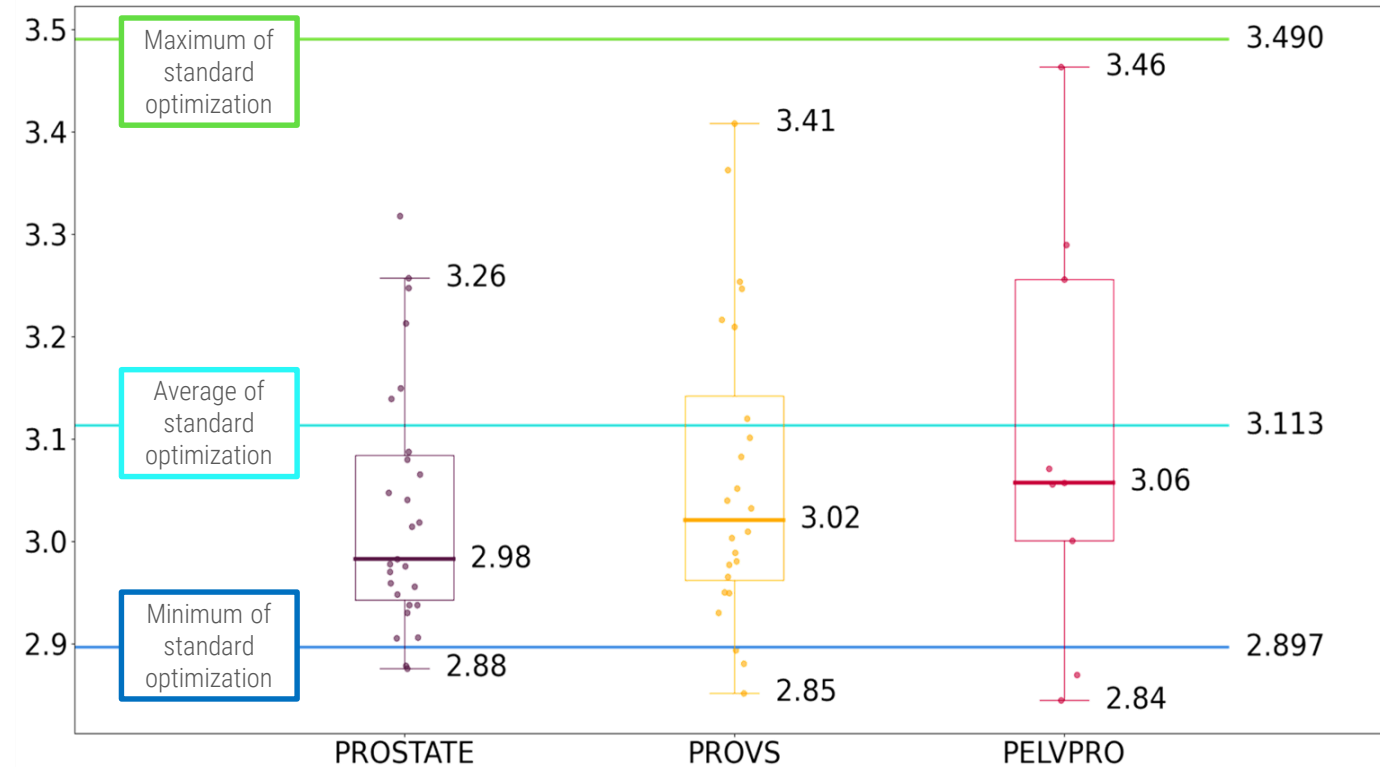
Standard vs ML : Dose gradient index

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$$Gradient = \frac{Volume_{isodose\ 50\%}}{Volume_{isodose_ref}}$$

Goal = 1

GRADIENT DOSE



Isodose volume of D95% (reference)

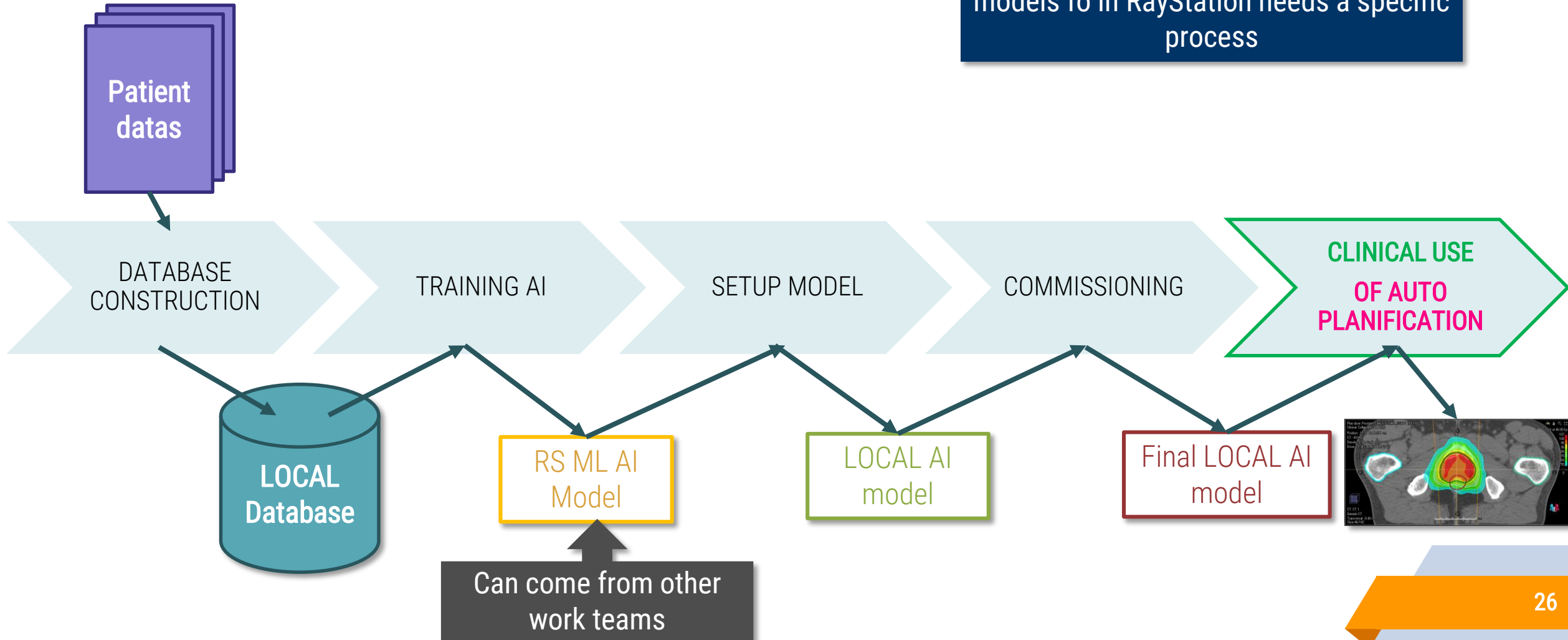
Isodose volume of D50%

Results of ML between 3,46 and 2,84 : LOCAL ML models **equivalent or best dose gradient** than standard optimized plans

Process to use Artificial Intelligences in RayStation

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Clinical use of Artificial Intelligences models fo in RayStation needs a specific process



Conclusion and future work

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Automatic segmentation

- ✓ **Fast calculation** (30 seconds)
- ✓ **Method reliable** (good results)
- ✓ RaySearch **provide commissioned model**
- ✗ **Limited evaluation** (needs qualitative review : time consuming)
- ✗ **Construction of database is time consuming**

- 🔄 **Evaluation of ORL model** on going (verry promising)
- 🔄 **New databases** to create **new models**
- 🔄 Creation of **user friendly algorithm for database construction**

Automatic planification

- ✓ **Fast calculation** (16 minutes / BeamSet)
- ✓ **ML plans are equivalent** to standard optimized plans
- ✓ **Adjustement of model very usefull**
 - 1 model = **several** close **treatment protocols** and **strategies**
- ✓ RaySearch **provide commissioned ML models** and systematically **help for adjustments**
- ✗ **Construction of database** and **adjustement of ML on-site are time consuming** and need a **dedicated person**
- 🔄 **Evaluation of the new algorithm** (9B VS 11A)
- 🔄 Evaluation with **Complexity index**

IA method allows homogenization of clinical practices and saves a considerable amount of time at least 2 times faster