From Image Guidance to Image Analytics for Precision Spine Surgery

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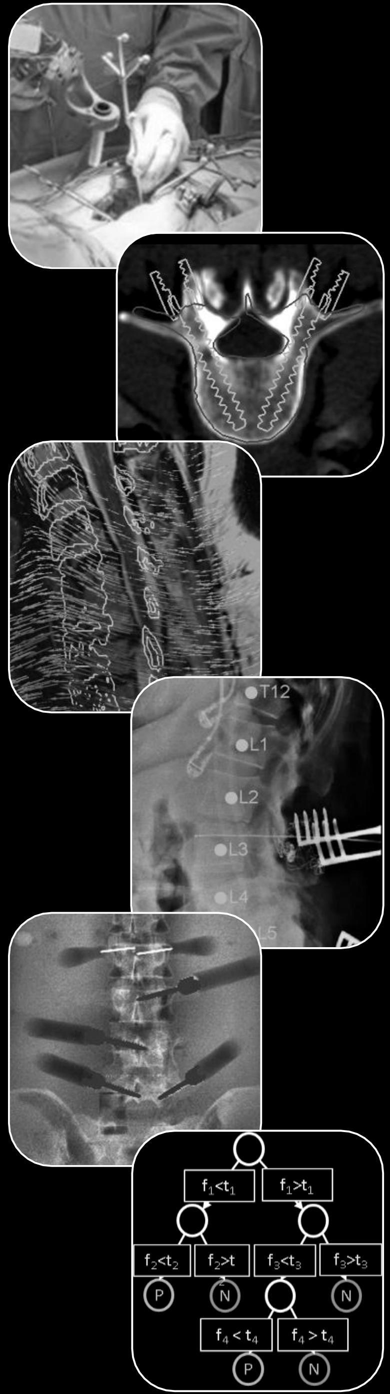
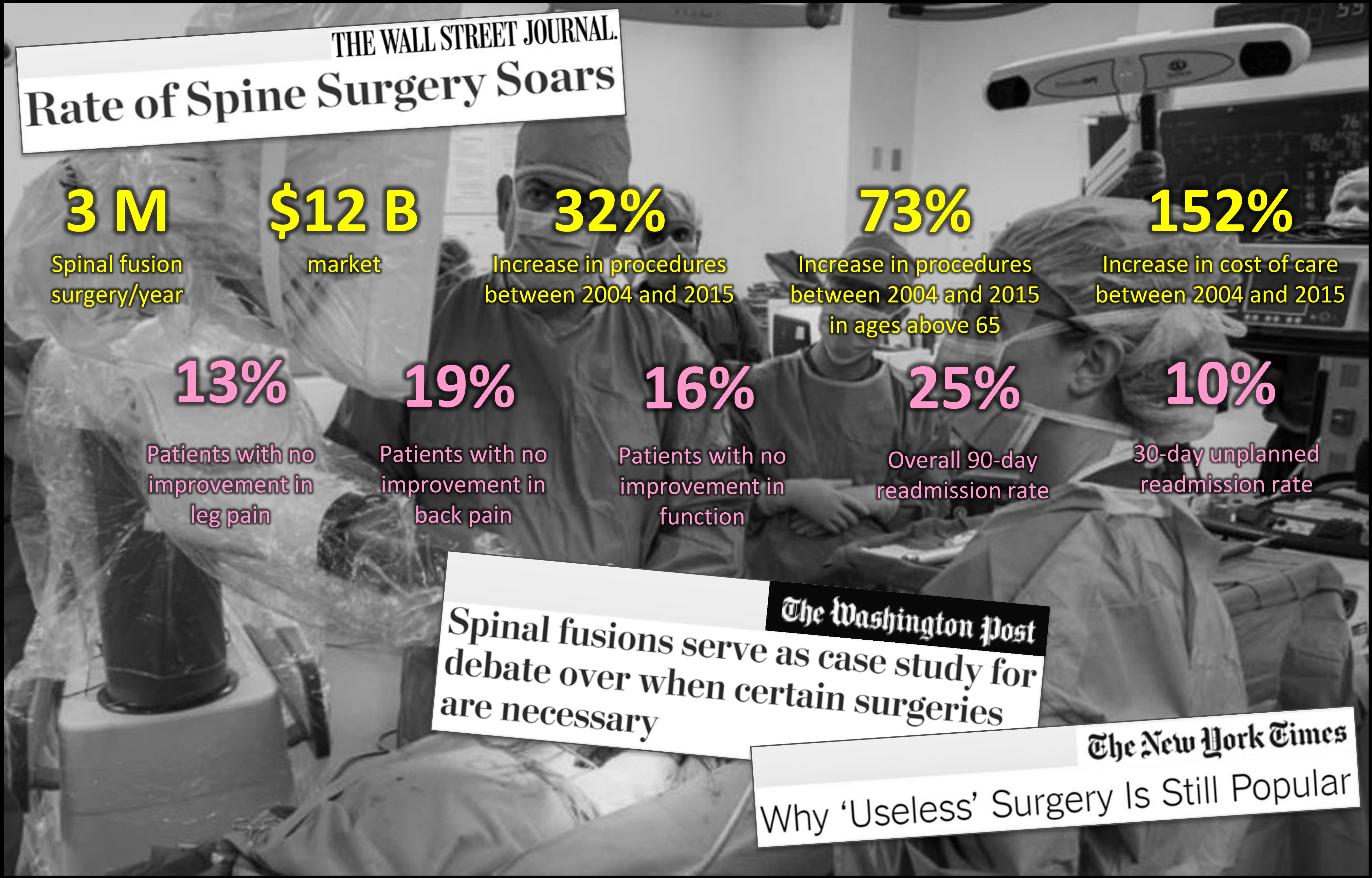
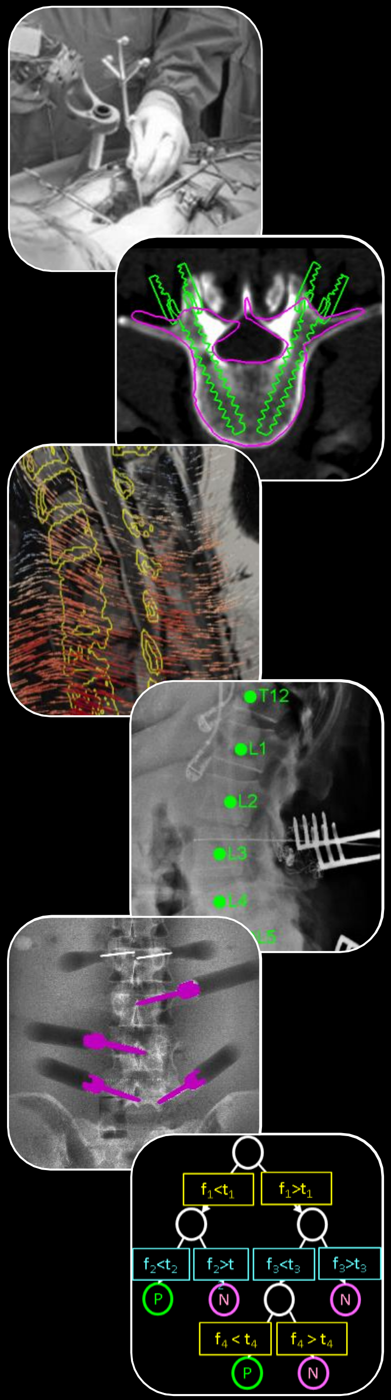




1. Martin 2019; 2. Khor 2018; 3. Baaj 2017; 4. Adogwa 2017



Tools for Image-Guided Surgery

Automatic Planning

Statistical atlas / Active shape model (ASM) registration

Deformable Image Registration

Multi-modality (CT and MRI)

Target Localization

Vertebrae labeling

Surgical Device Localization

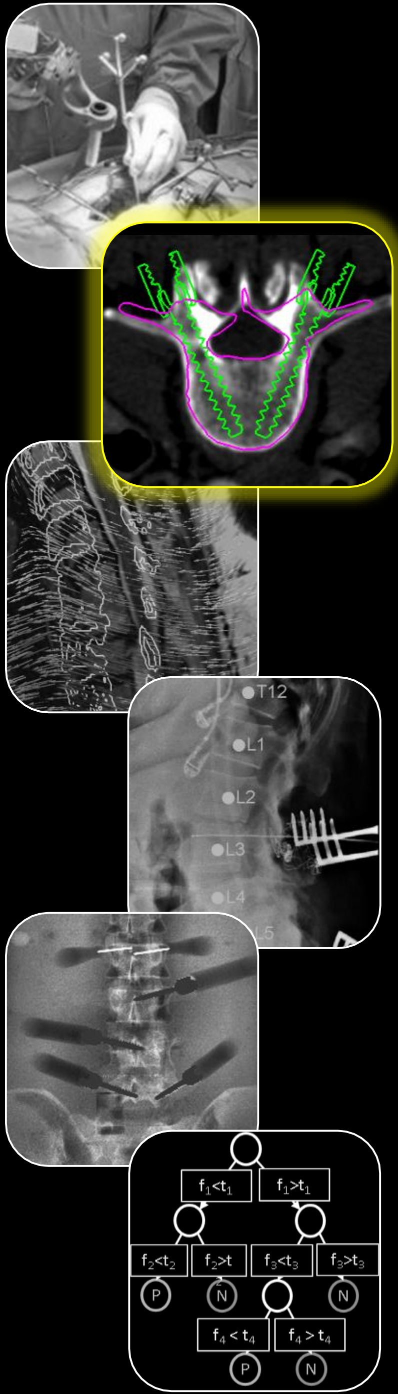
Implants (rigid and deformable) and robotics

→ Re-Purposed to Image Analytics at Scale

High-level feature extraction

Input to predictive models, clinical decision support (CDS)

Automatic Surgical Planning



Surgical Navigation

Mainstay for spinal MIS

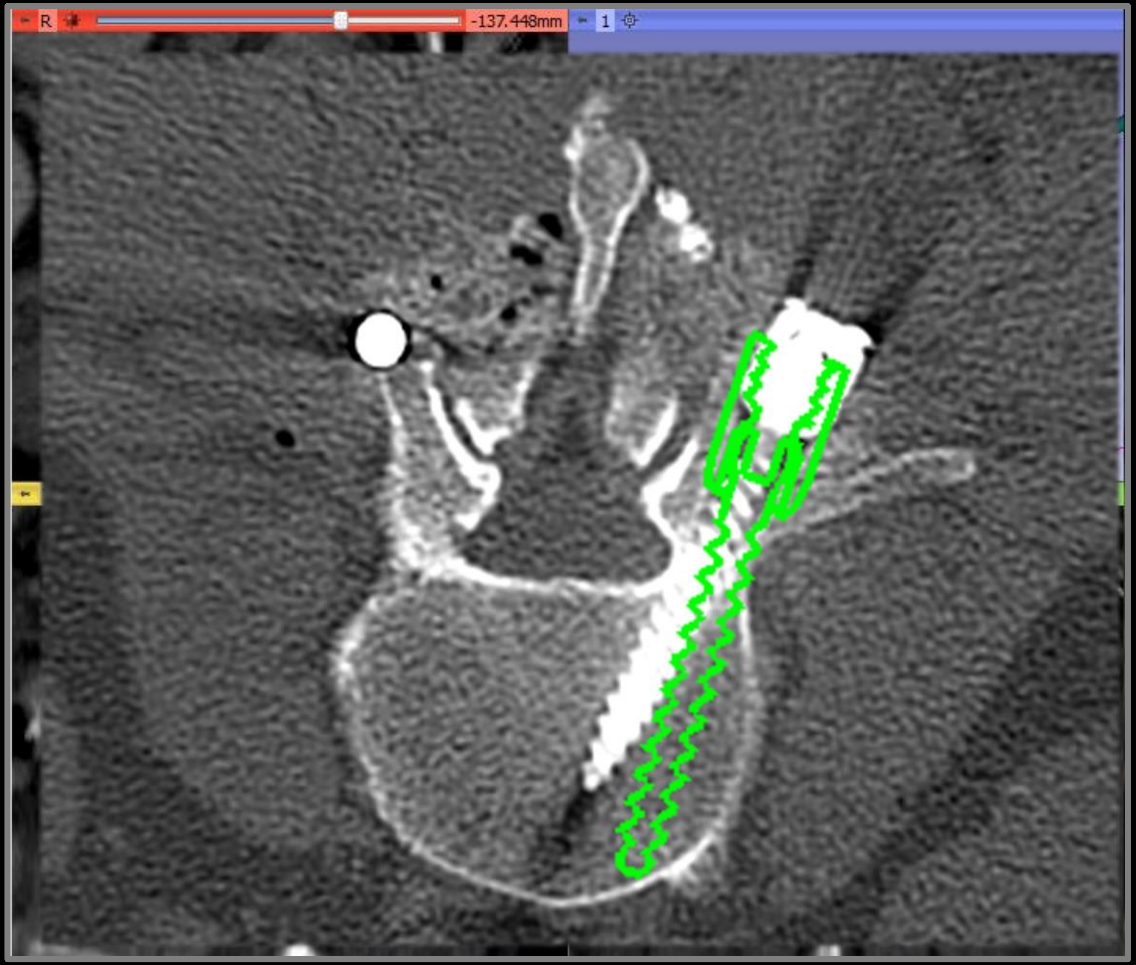
Free-hand screw placement

Robotic Assistance

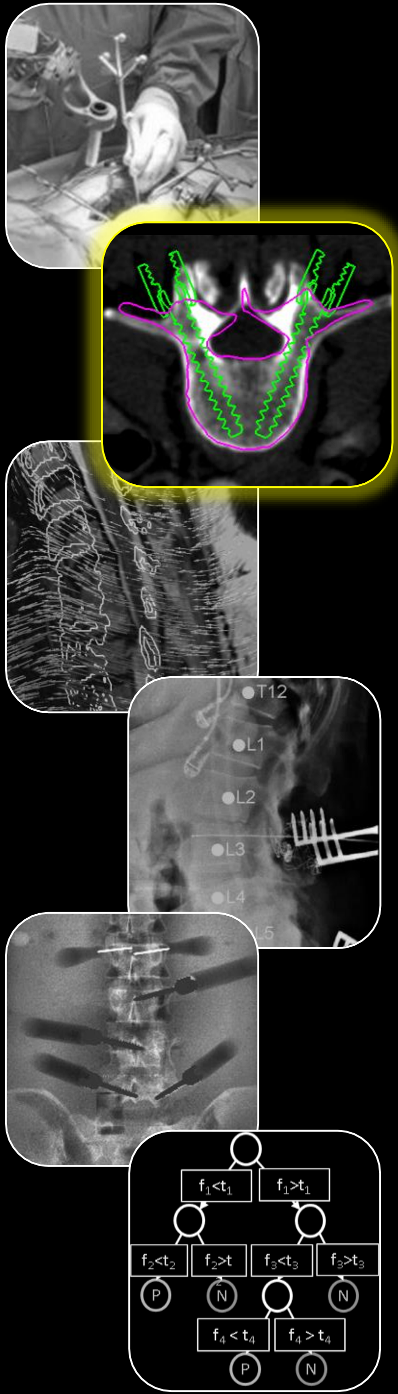
Planning is *required* for robot positioning

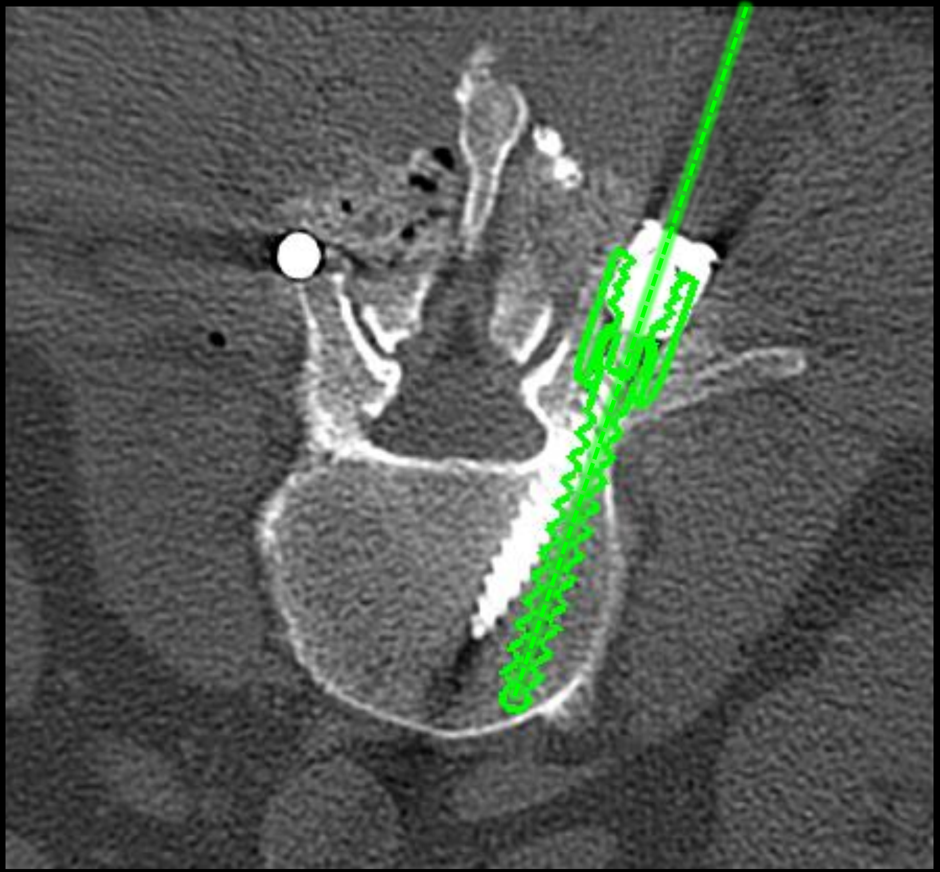
Quality Assurance

Analyze deviations between planned and delivered



Automatic Surgical Planning





→ **Automatic, High-Level Image Feature Extraction**

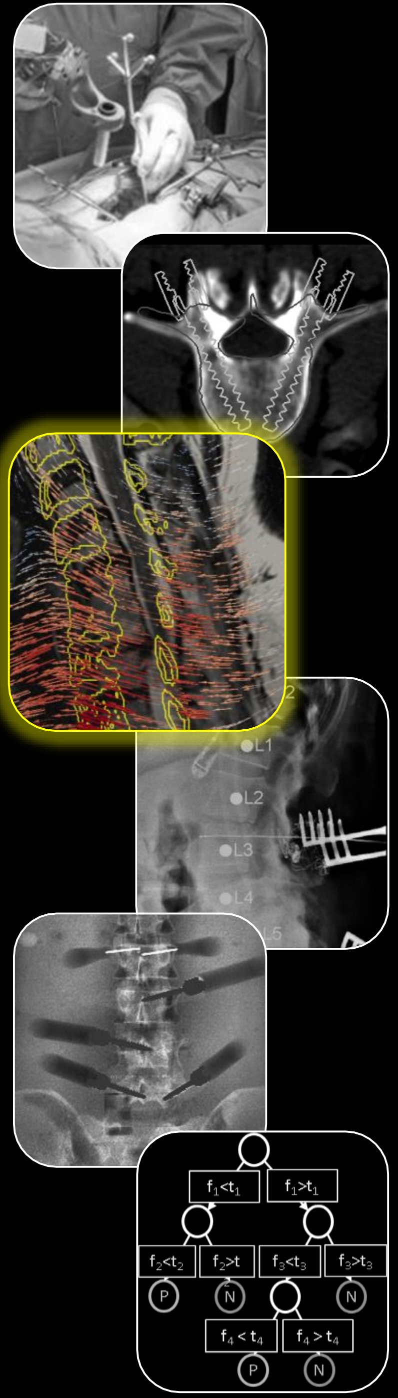
Definition of a "reference plan"

Patient-specific planning

Surgeon-specific prefs via atlas

Post-operative QA

Retrospective analysis, correlation with outcomes

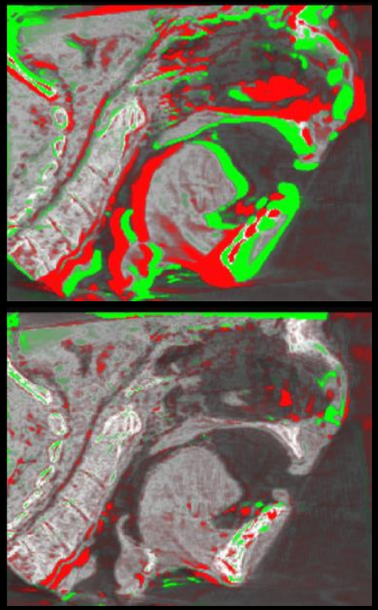


Deformable Image Registration

CT-CBCT

Demons

$$\vec{d} = \frac{2(m-f)(\vec{\nabla} f + \vec{\nabla} m)}{k(m-f)^2 + \left|\vec{\nabla} f + \vec{\nabla} m\right|^2}$$



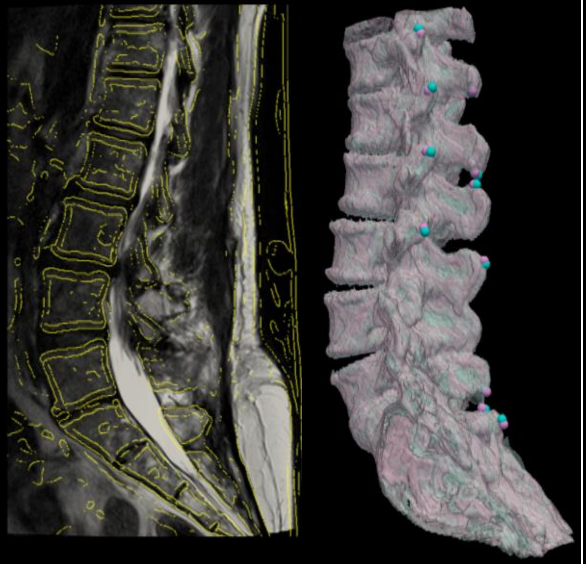
Nithiananthan et al., Med Phys (2011) (2012)

• • •

MRI-CT

MIND Demons

$$m_{I,i}(\boldsymbol{x}) = c \exp\left(-\frac{d(I,\boldsymbol{x},\boldsymbol{r}_i)}{V(I,\boldsymbol{x})}\right)$$

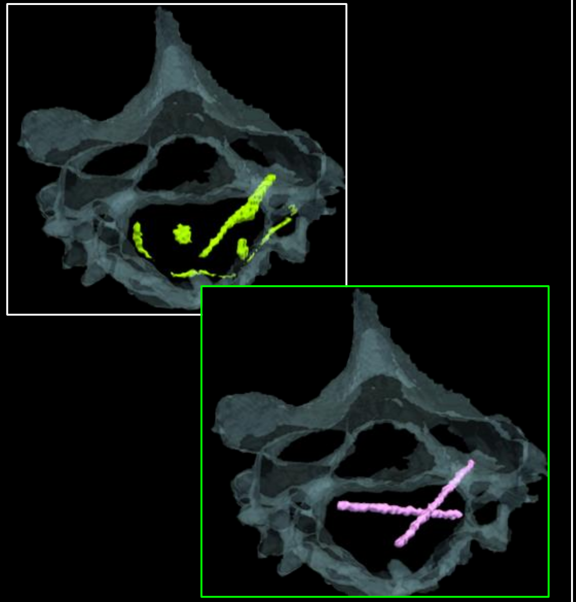


Reaungamornrat et al.
IEEE-TMI (2016) and Med Phys (2017)

Free-Form Deformation

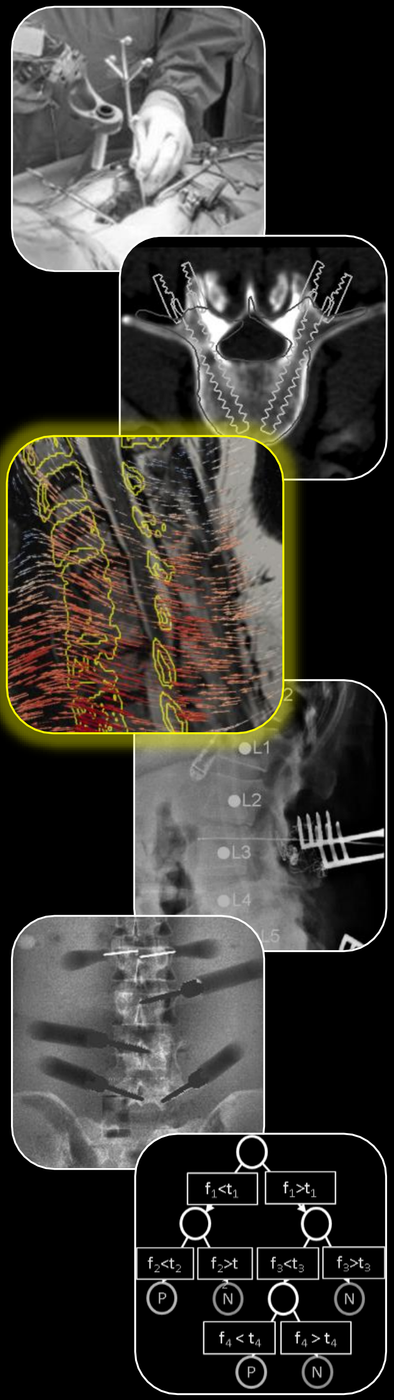
MI B-Spline + Rigid Constraint

$$MI - \sum_{\boldsymbol{x}} c_x \{\lambda_A A + \lambda_P P + \lambda_O O\}_I$$



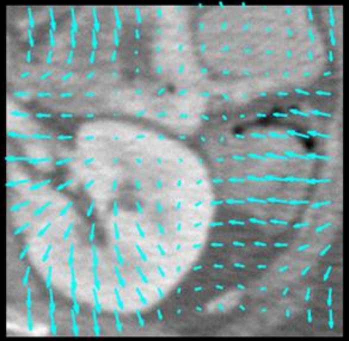
Reaungamornrat et al.,
Phys Med Biol 59(14) (2014)

Deformable Image Registration

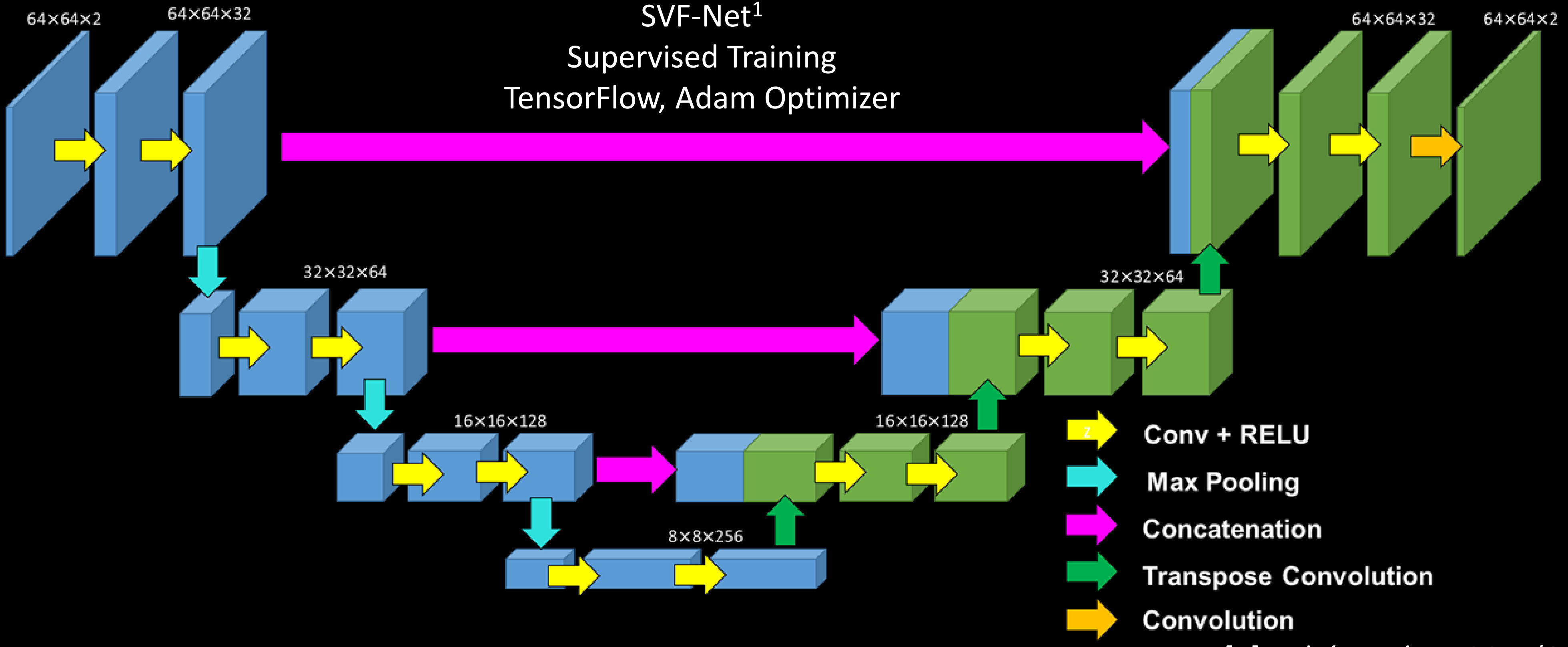


Input
Images to Register

Output
Displacement
Vector Field

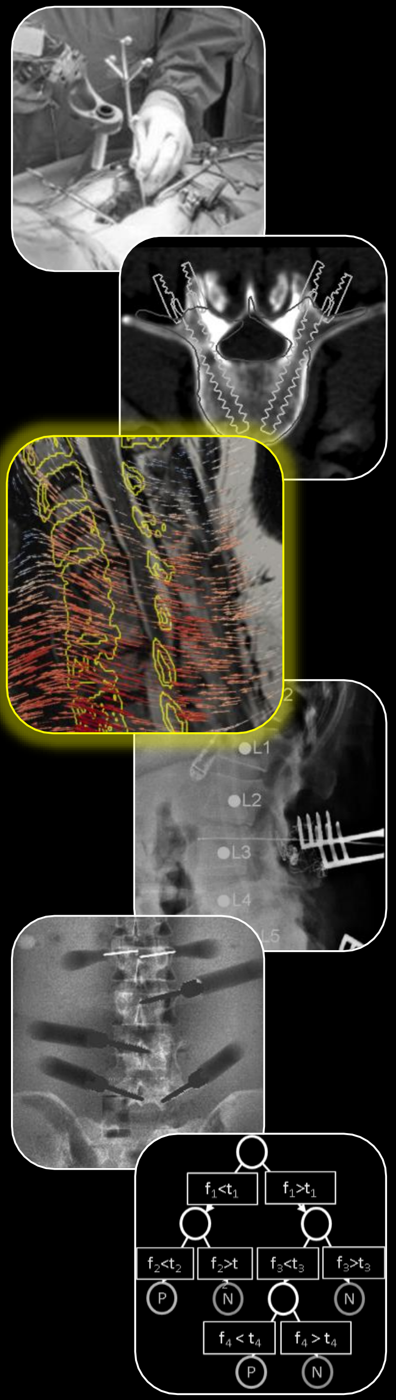


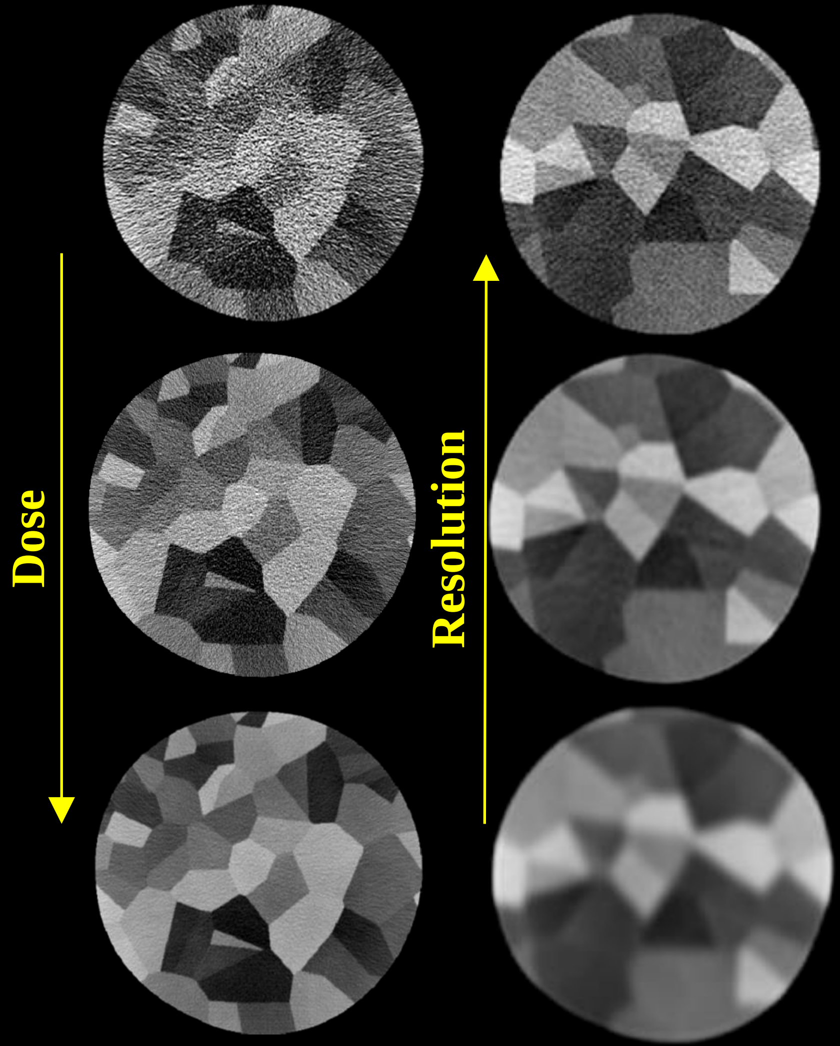
U-Net Architecture
SVF-Net[1]
Supervised Training
TensorFlow, Adam Optimizer



[1] Rohé *et al.* MICCAI (2017)

Deformable Image Registration

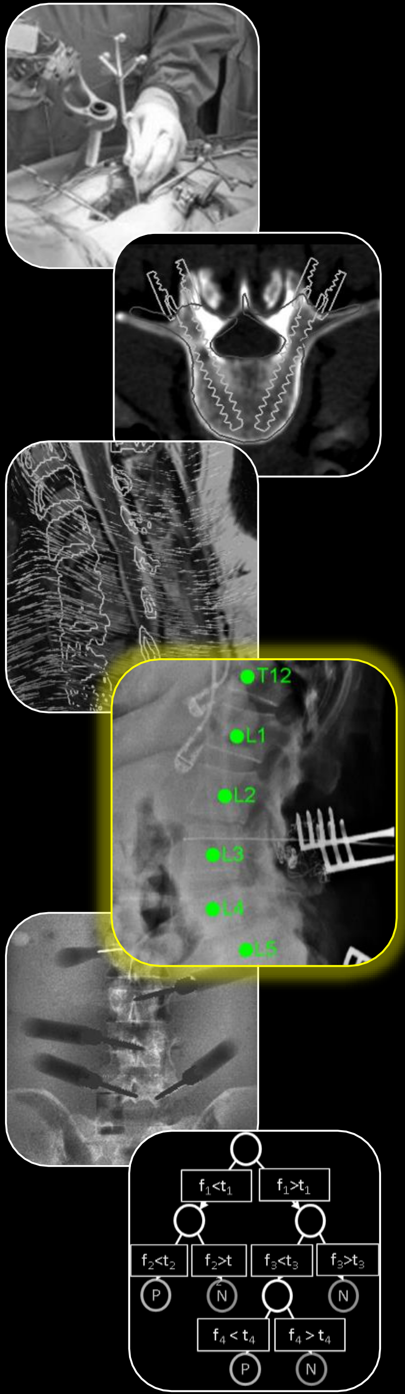




→ Suitability to Deformable Registration in Large Datasets

Widely varying imaging protocols (dose, noise, resolution)

Matching statistics is optimal…
but a *diverse* training set
yields a robust single network.



Target Localization

Automatic Vertebral Labeling in CT

Relatively simple networks for object detection in 2D – YOLO[1]

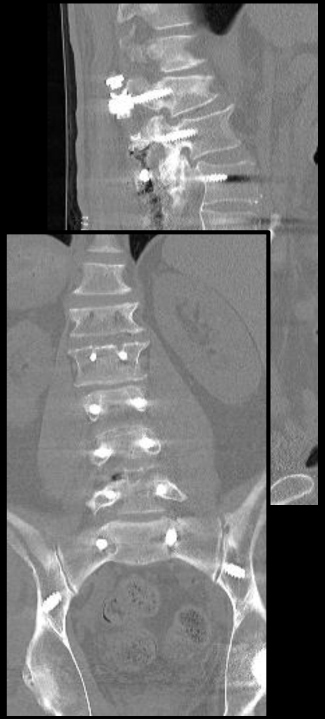
Combine slice-by-slice detections

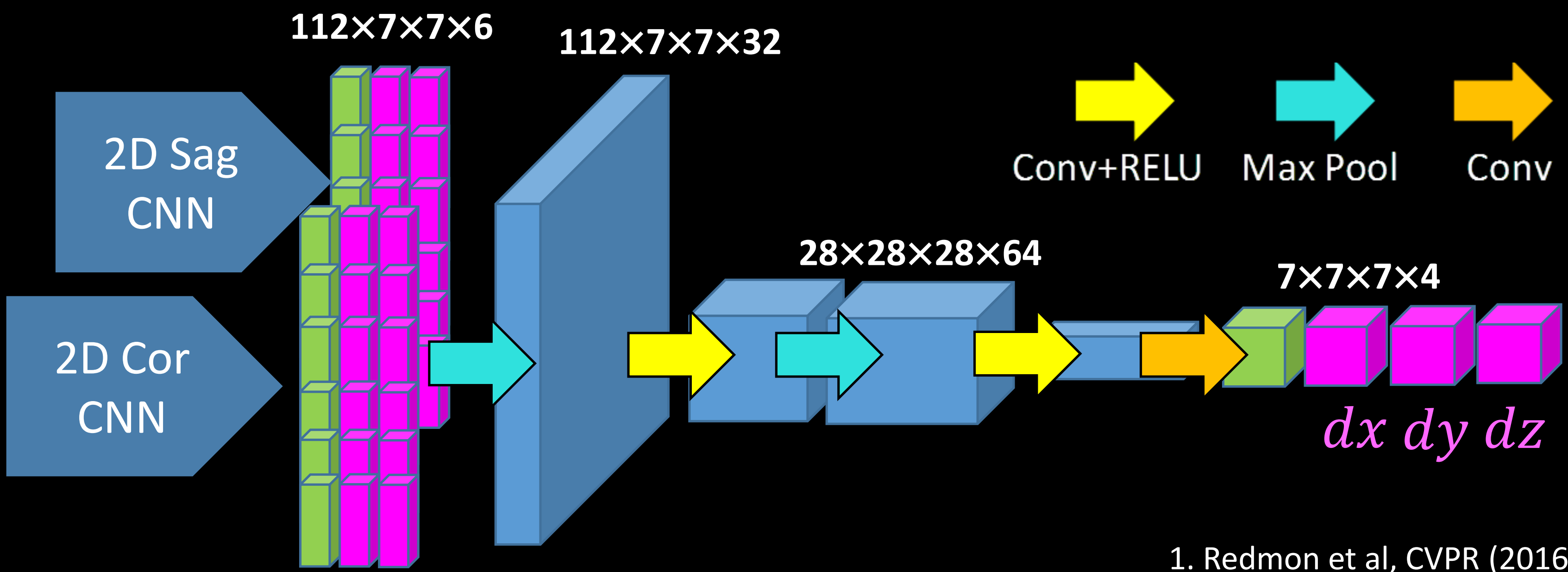
Alternatively, 3D CNN – requires ~100x more memory

Deeper network to improve accuracy – Inception V2 Network

42 layers deep (combines 7x7, 5x5, and 3x3 convolutions) F-RCNN

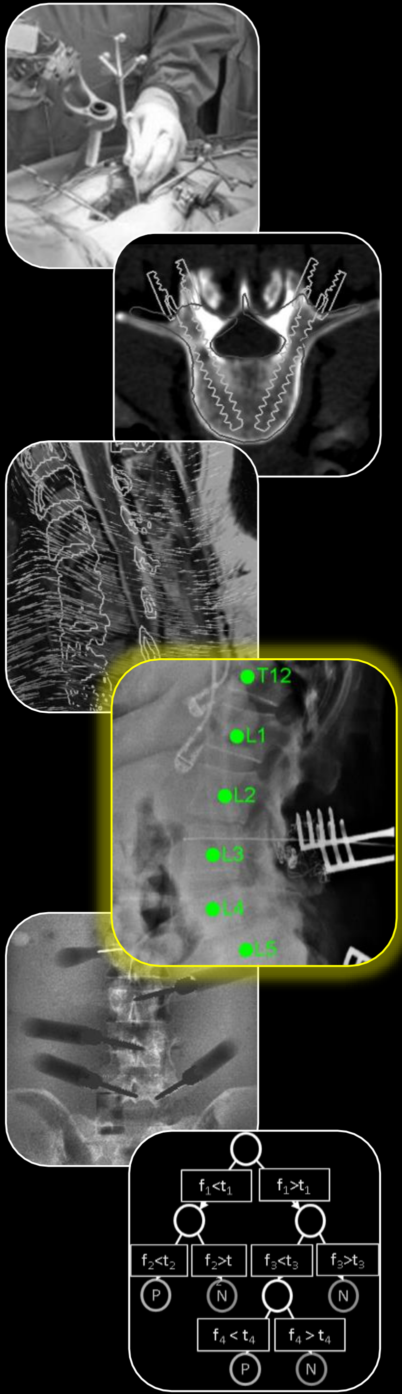
→ **Ortho-2D** (parallel orthogonal slice detections)

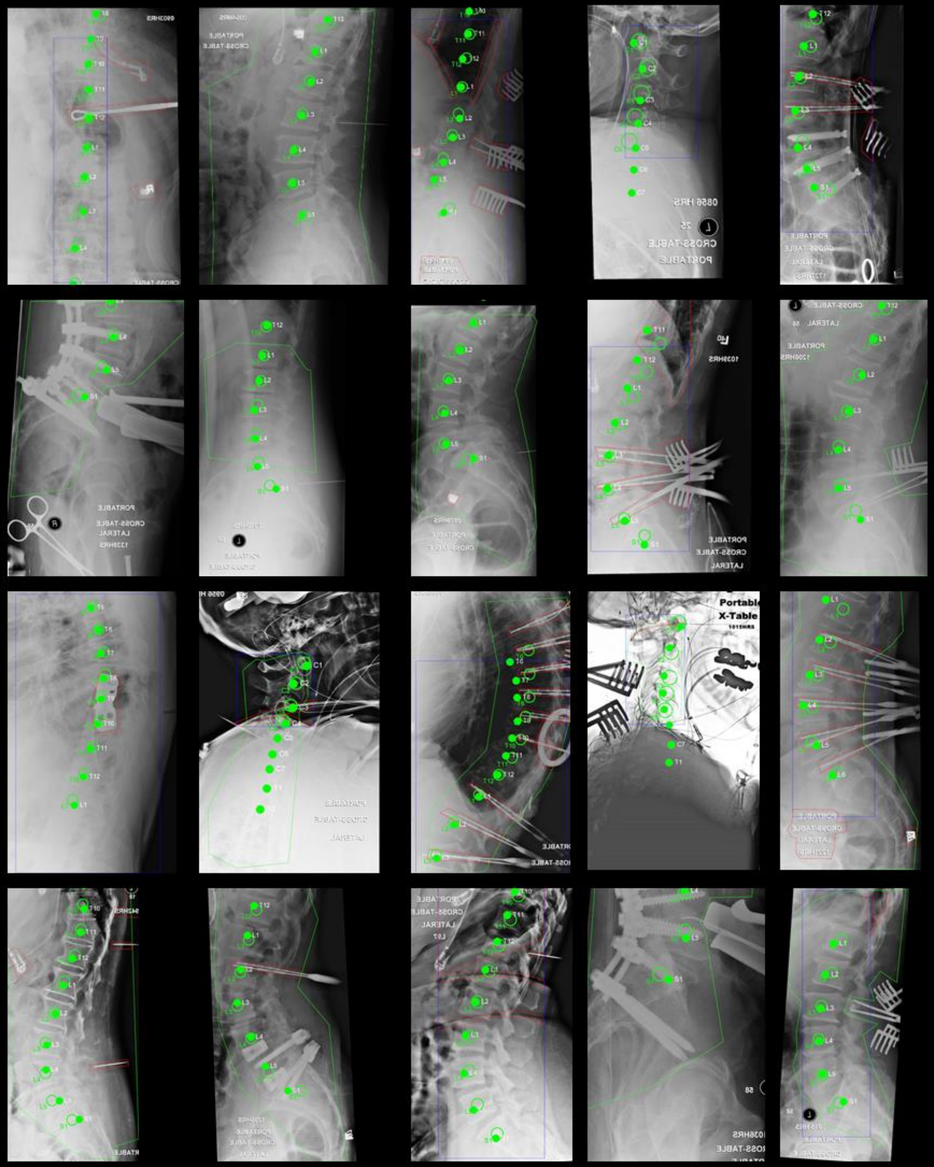


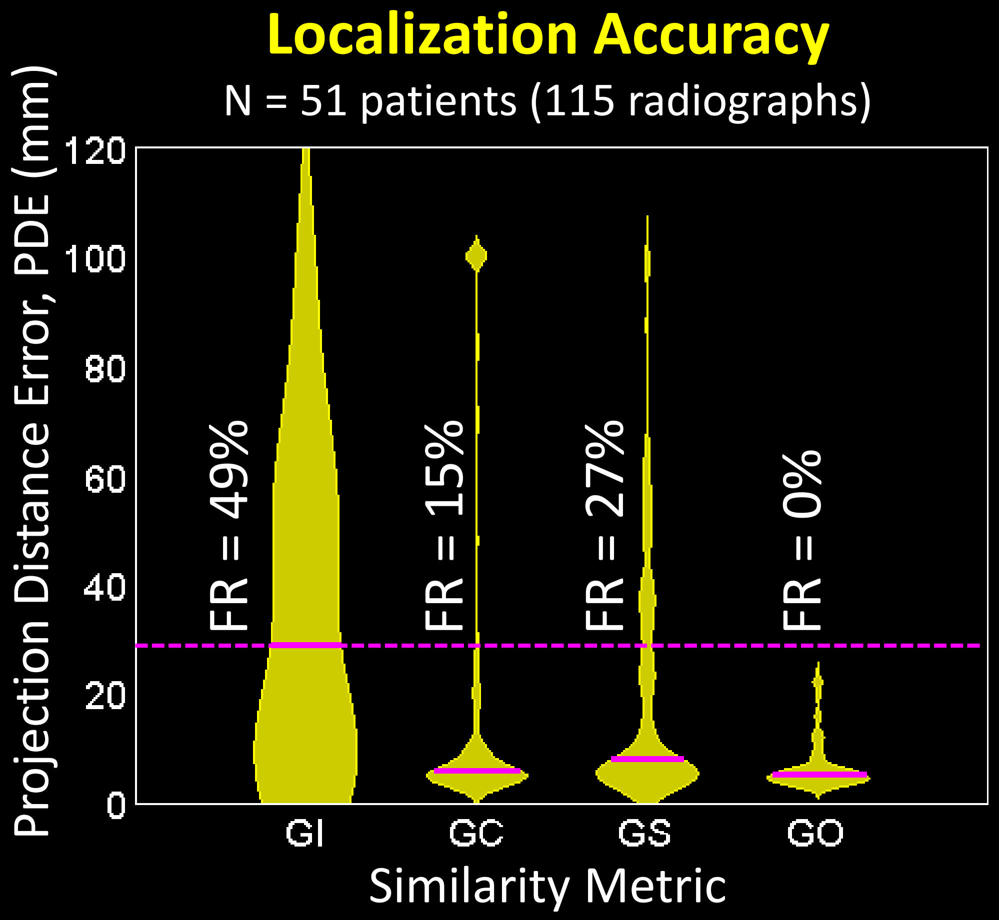


1. Redmon et al, CVPR (2016)
Levine et al., SPIE Medical Imaging (2019)

Target Localization

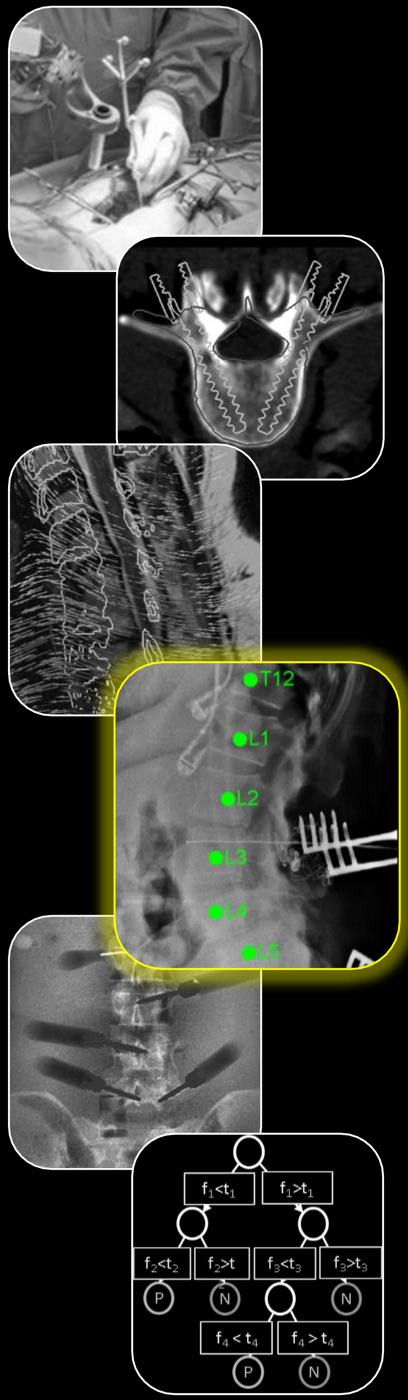


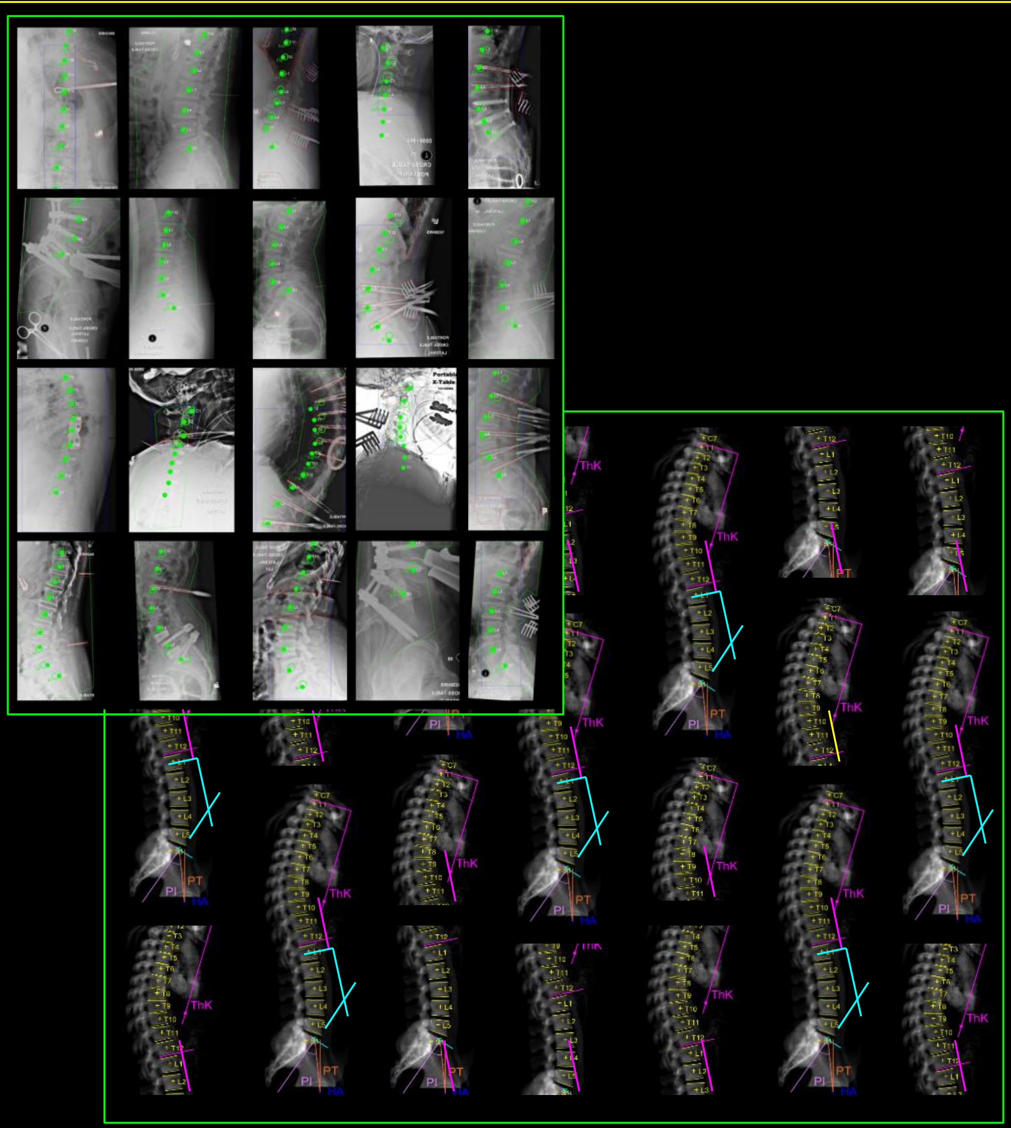




De Silva et al., Phys Med Biol 61(8) (2016)

Target Localization



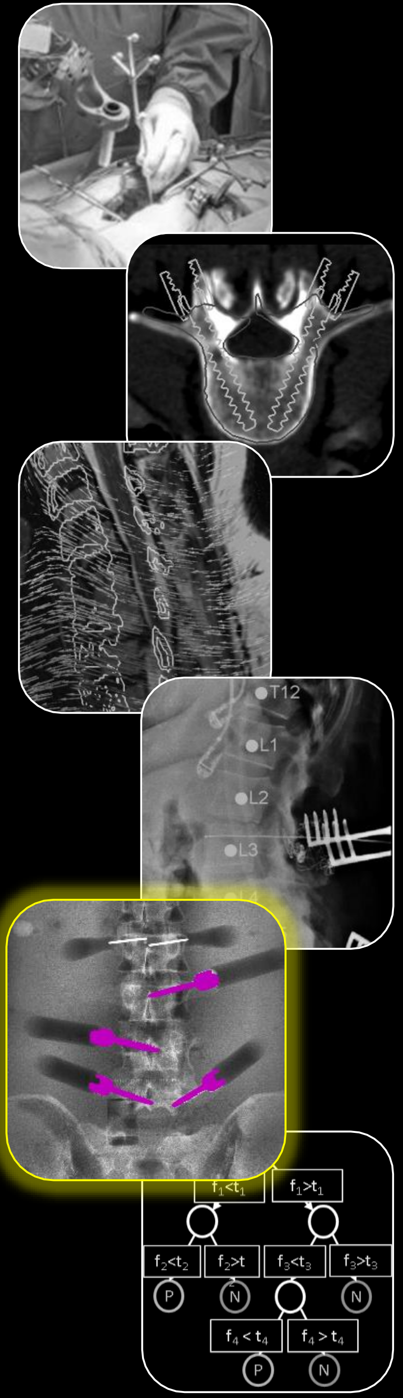


→ Automatic Spine Labeling

Suitability to large datasets
Determination of levels treated
Initialization of planning / registration

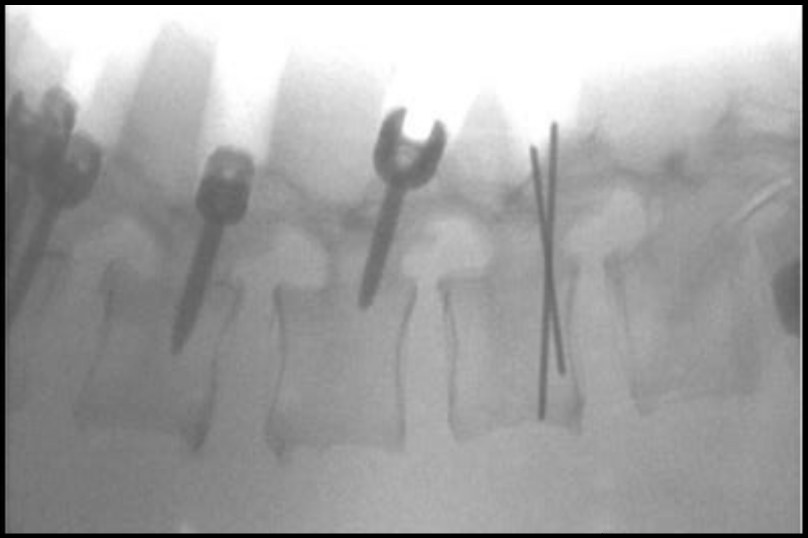
→ Automatic GSA

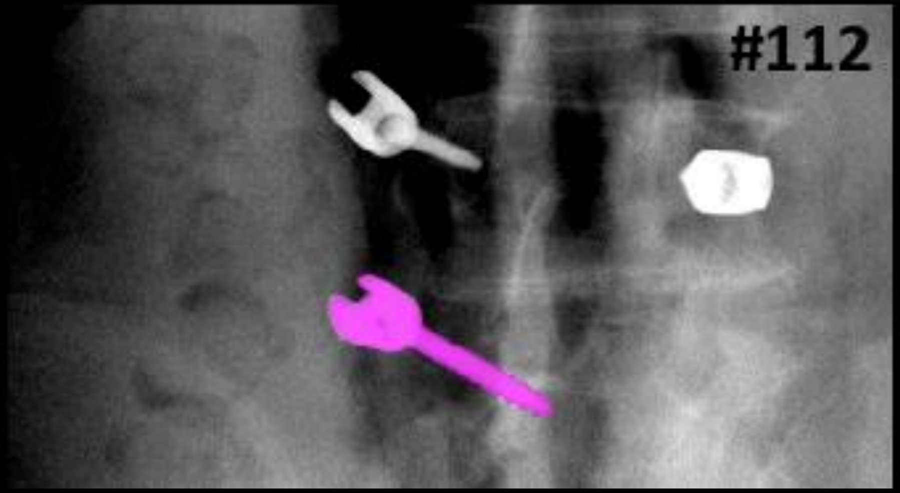
A strong determinant of clinical outcome
High-level feature extraction:
- Preoperative GSA
- Change (preop-to-postop) GSA



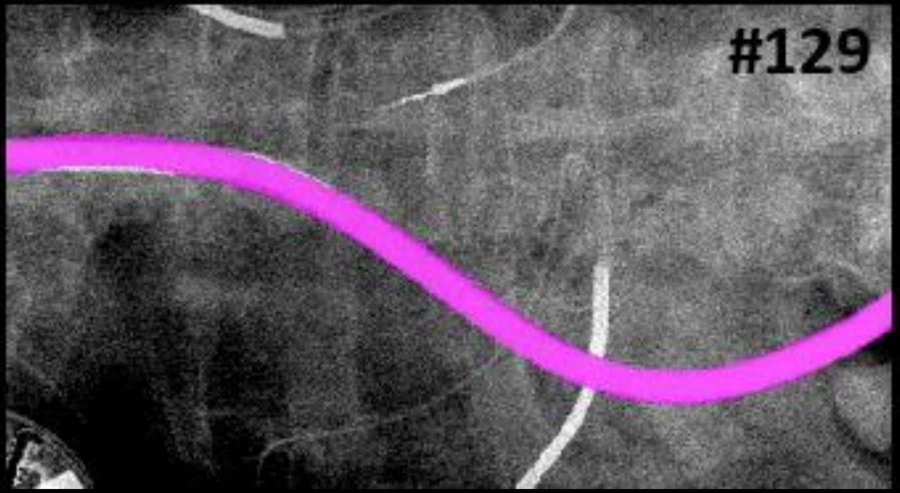
Device Localization

$$\hat{u} = \arg_{u} \max \sum_{\theta} GC\left(P_{\theta}, \int_{\vec{r}} C(u)\, d\vec{r}\right)$$



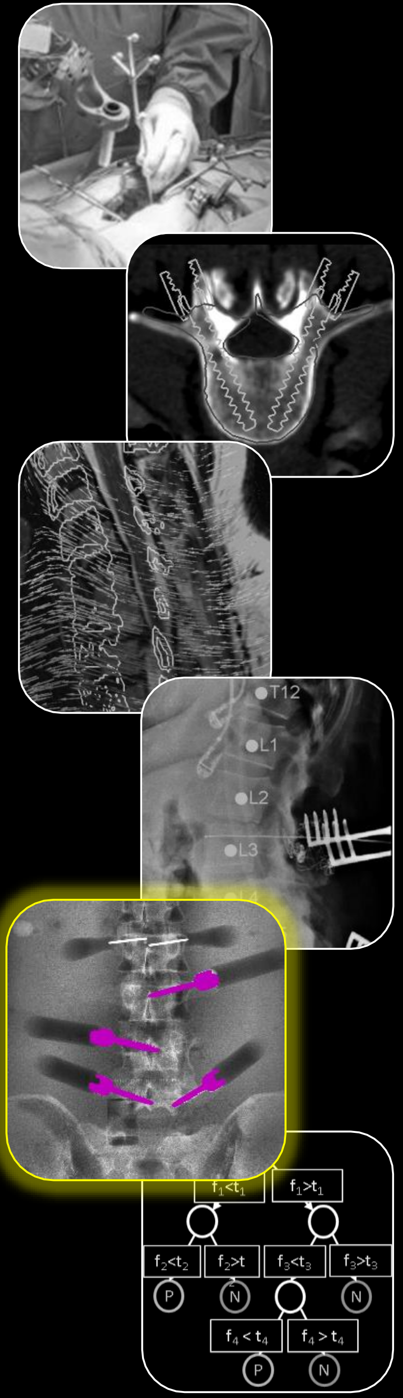


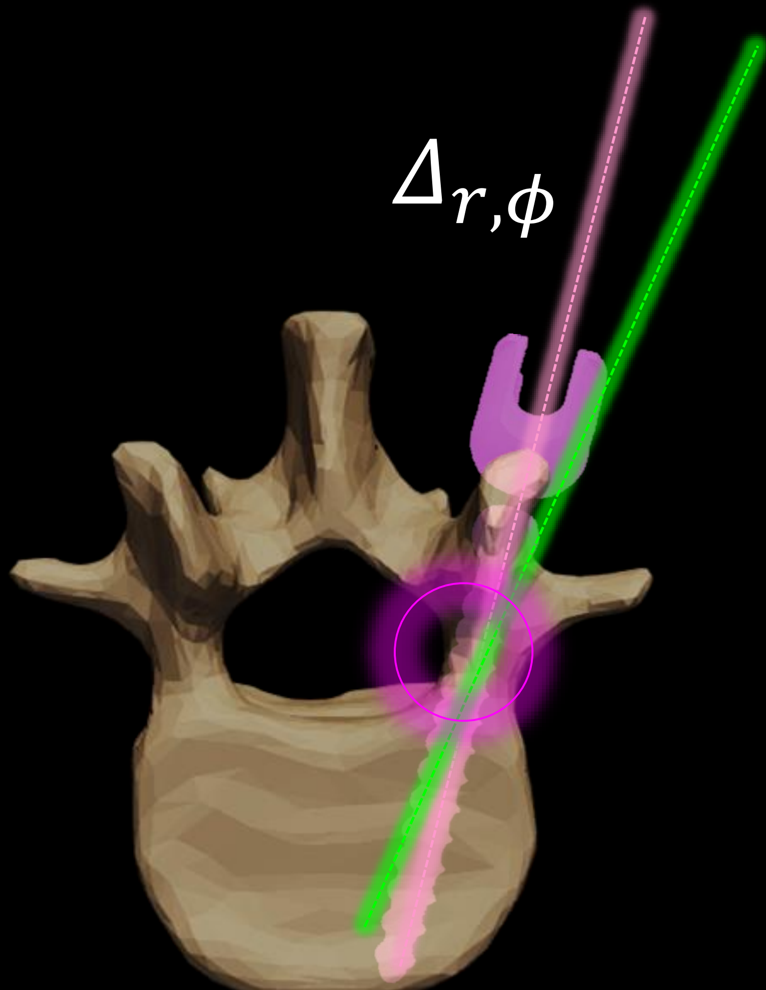
$C(u)$ $\int_{\vec{r}} C(u)\, d\vec{r}$



Uneri et al. Phys Med Biol (2015)

Device Localization





→ High-Level Feature Extraction

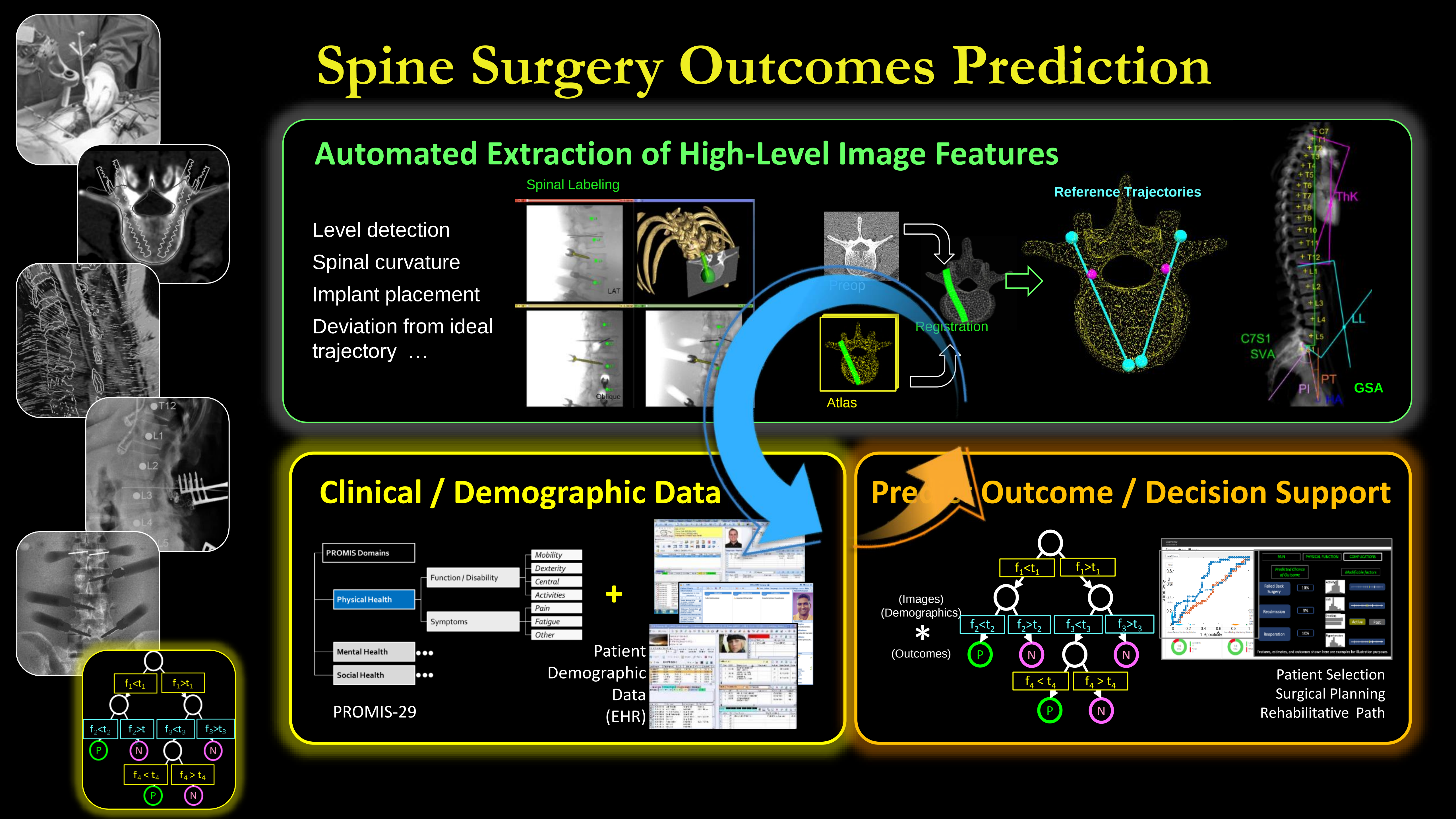
Automatic determination of breach

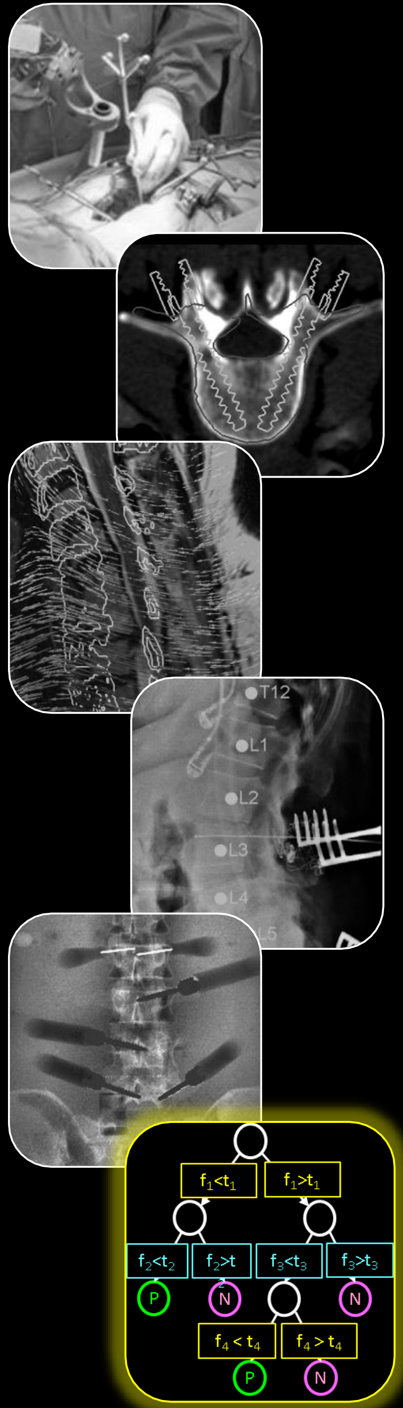
$$\Lambda_{screw} \cap \Lambda_{vertebrae}$$

Number and type of screws

Planned vs delivered position

$$\Delta_{r,\phi} = \vec{d}_{screw} - \vec{d}_{plan}$$


Spine Surgery Outcomes Prediction
Automated Extraction of High-Level Image Features
Level detection
Spinal curvature
Implant placement
Deviation from ideal trajectory …
Spinal Labeling
LAT
Oblique
Preop
Registration
Atlas
Reference Trajectories
C7
ThK
LL
C7S1 SVA
PT
PI
GSA
T12
L1
L2
L3
L4
Clinical / Demographic Data
PROMIS Domains
Physical Health
Function / Disability
Symptoms
Mental Health
Social Health
Mobility
Dexterity
Central
Activities
Pain
Fatigue
Other
PROMIS-29
+
Patient Demographic Data (EHR)
Predict Outcome / Decision Support
(Images)
(Demographics)
*
(Outcomes)
f1<t1
f1>t1
f2<t2
f2>t2
f3<t3
f3>t3
f4 < t4
f4 > t4
P
N
Patient Selection
Surgical Planning
Rehabilitative Path



Spine Surgery Outcomes Prediction

Classifier: $f(x) = \sum_{t=1}^{T} \alpha_t h_t(x)$

h_t : decision tree with index t
x_n : input for n^{th} observation

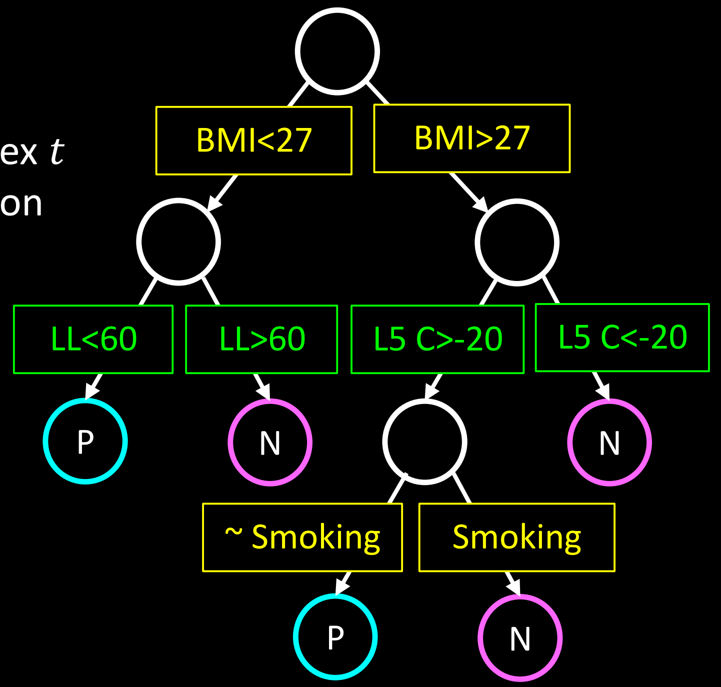
Weights: $\alpha_t = \frac{1}{2} \log \frac{1-\epsilon_t}{\epsilon_t}$

Classification Error:

$$\epsilon_t = \sum_{n=1}^{N} d_n^{(t)} I(y_n \neq h_t(x_n))$$

y_n : true outcome variable
I : indicator function
$d_n^{(t)}$: weight of the observation n in t

Boosted Decision Tree

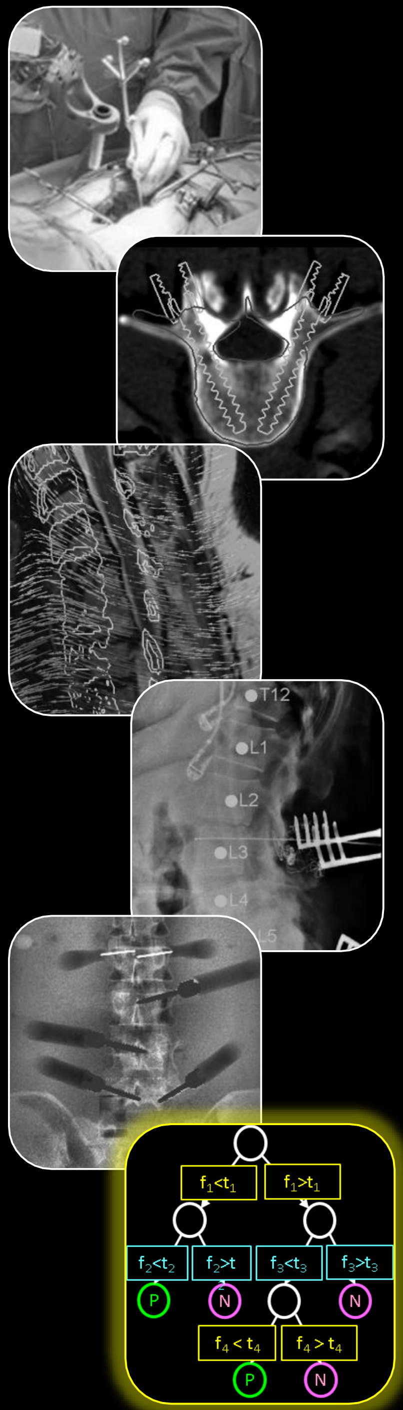


Ada-Boost classifier
N classes = 2
N samples = 84

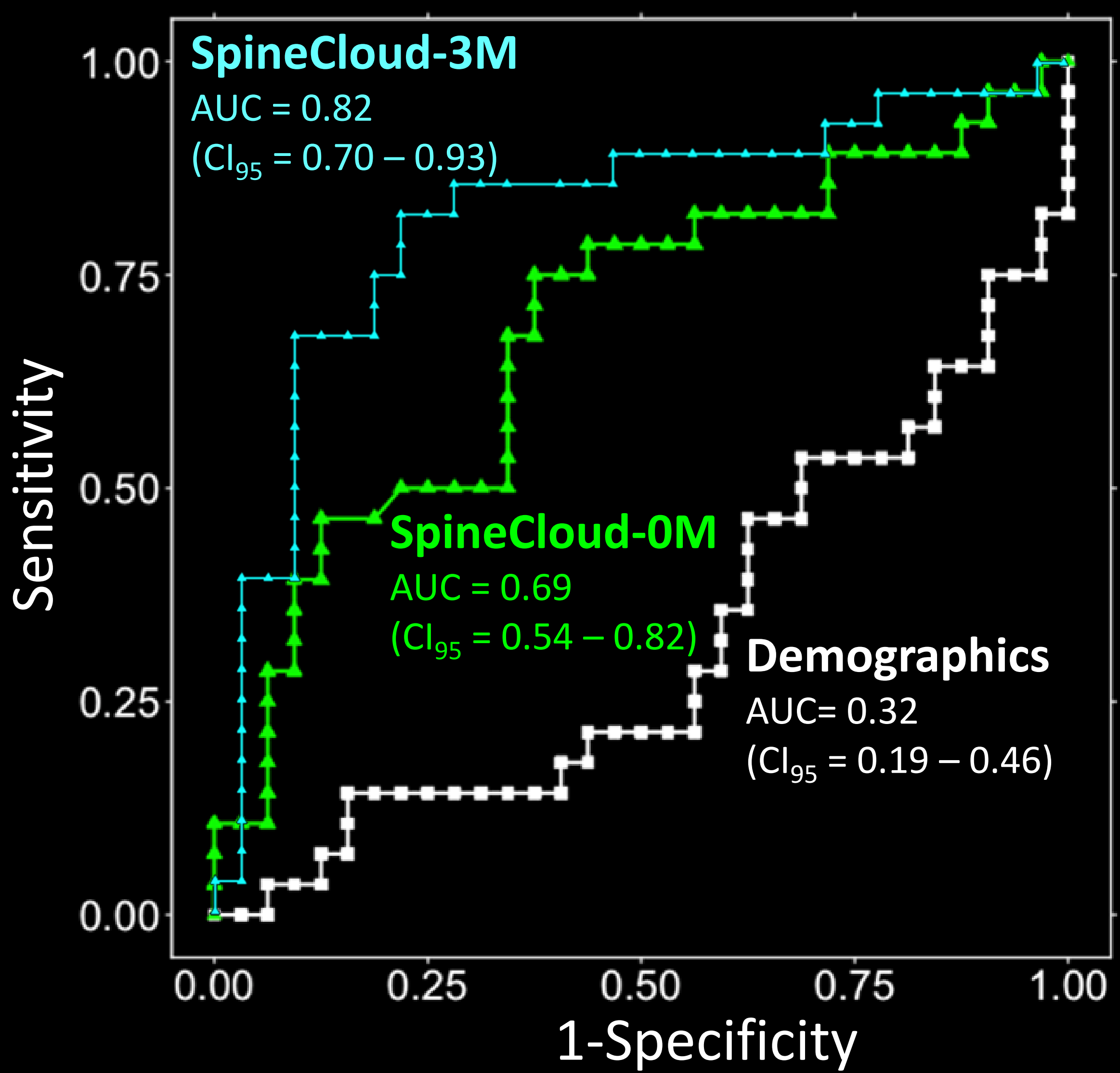
Learning cycles = 30
Learning rate = 0.1
K-fold cross validation

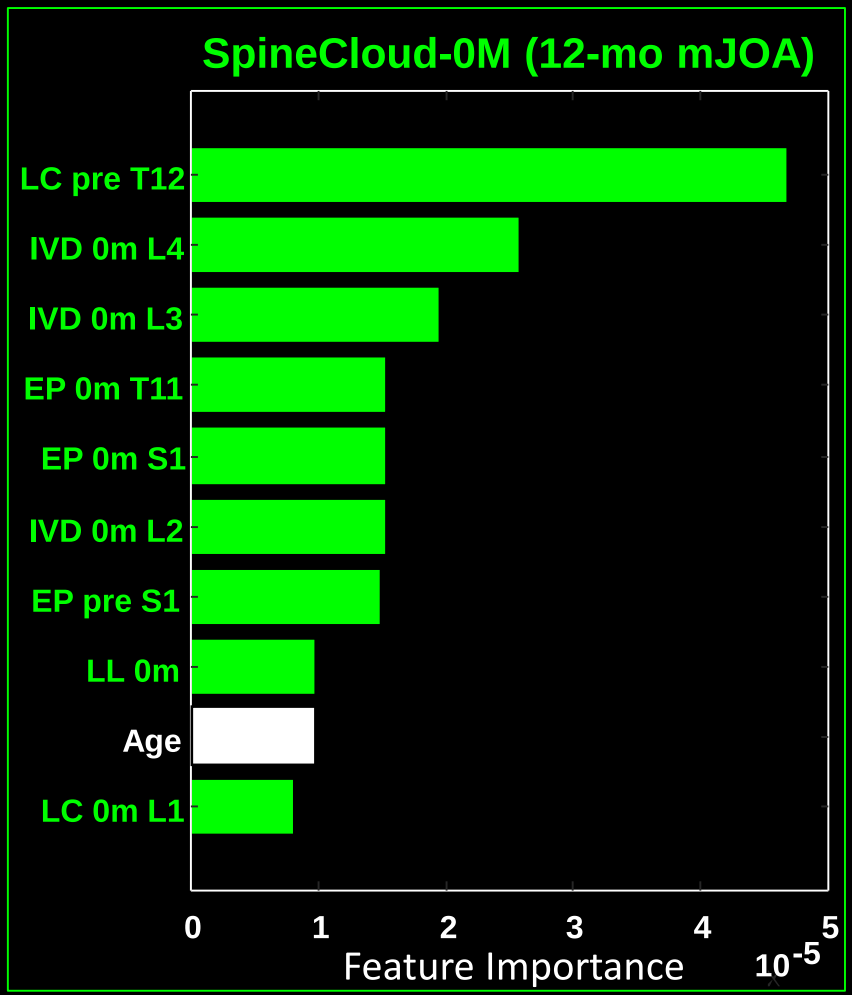
Friedman et al.. Ann. Stat. (2000)
H. Ishwaran, Electr. J. Stat. (2007)

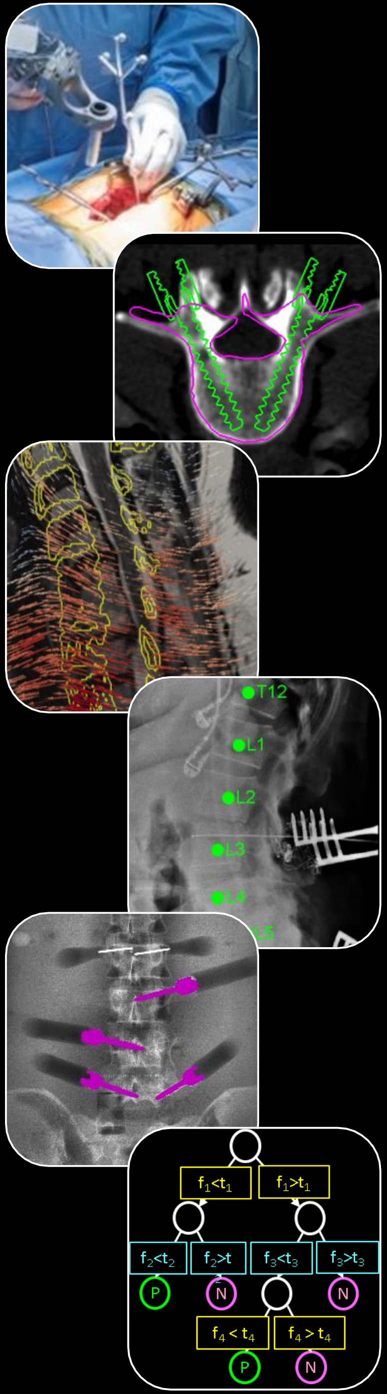
Spine Surgery Outcomes Prediction



12 Months (mJOA Function)







New role for image registration / analysis methods developed for high-precision IGS

High-level feature extraction → Input to predictive models

A New "Precision" Paradigm for Surgery

Geometric precision

- Millimeter targeting via navigation, robotics, etc.

Precision medicine

- Patient-specific feature guide optimal treatment pathway

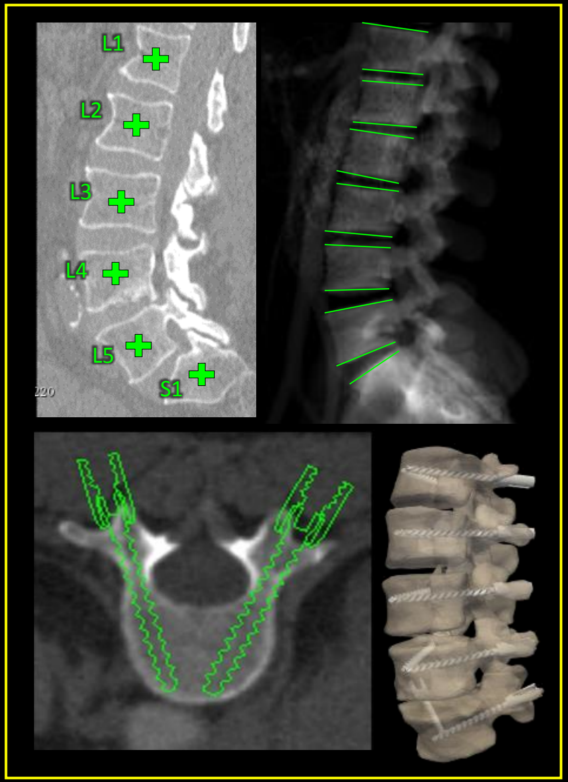
Explainable model → Actionable CDS

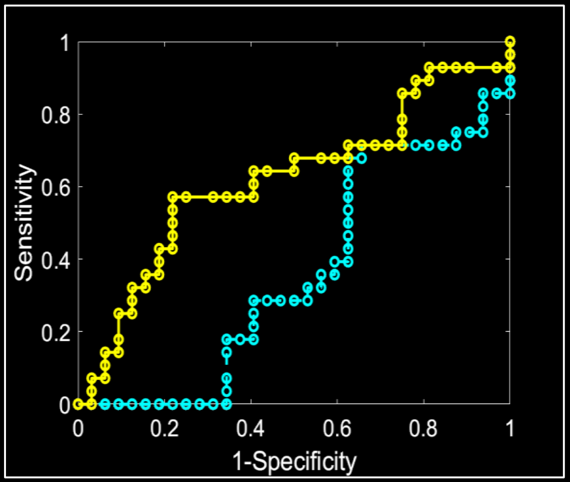
Features that cannot be derived from demographics alone

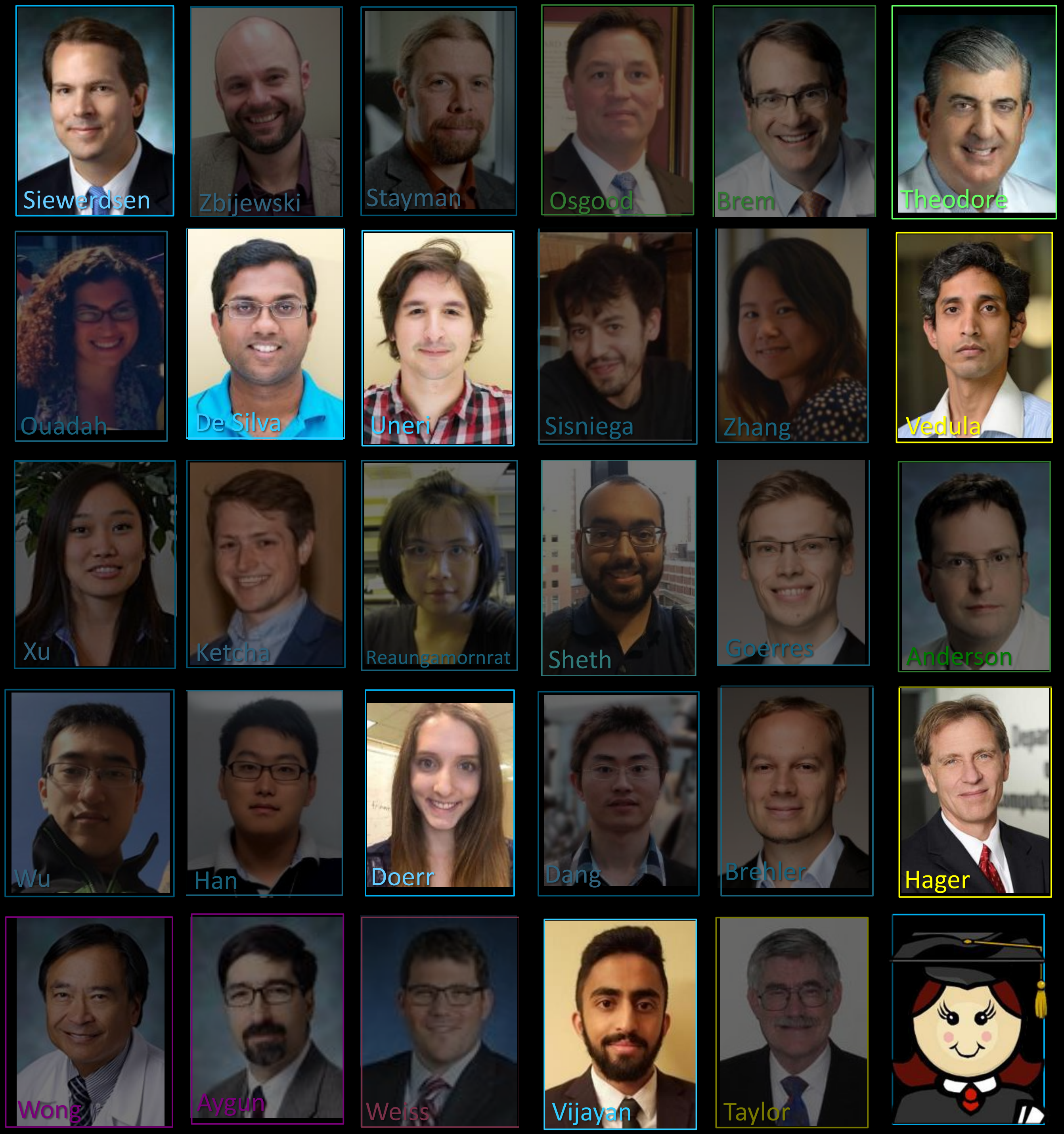
- E.g., N levels to treat, targeted degree of curvature

Identify features that could improve trajectory, outcomes

Guide patient selection, planning, and rehabilitative pathway







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