

Engineering Goals



Develop Machine Learning Based Navigational System

Develop a novel machine learning algorithm that implements an HDM, RCNN, and SLAM systems.



Implement Computer Vision and Augmented Reality System

Develop a computer vision and augmented reality environment and implement onto an AR headset.



Real World Viability Testing and Data Validation

Test algorithmic accuracy and system viability through observation of spinal reconstruction surgeries.

Development Process

01

Learning

The first step was learning radiology and geometric analysis of the spinal column.

02

Analyze

Analyze the dataset and the underlying mechanisms and suggest ML algorithms.

03

Development

Develop three algorithms that predict and spinal behavior and anatomy.

06

Real-World Testing

Test viability of algorithm in conjunction with the AR Headset.

05

AR Development

Transfer algorithms onto the Microsoft HoloLens and test system stability.

04

Theoretical Testing

Test algorithms in a purely computational environment with emphasis on accuracy.

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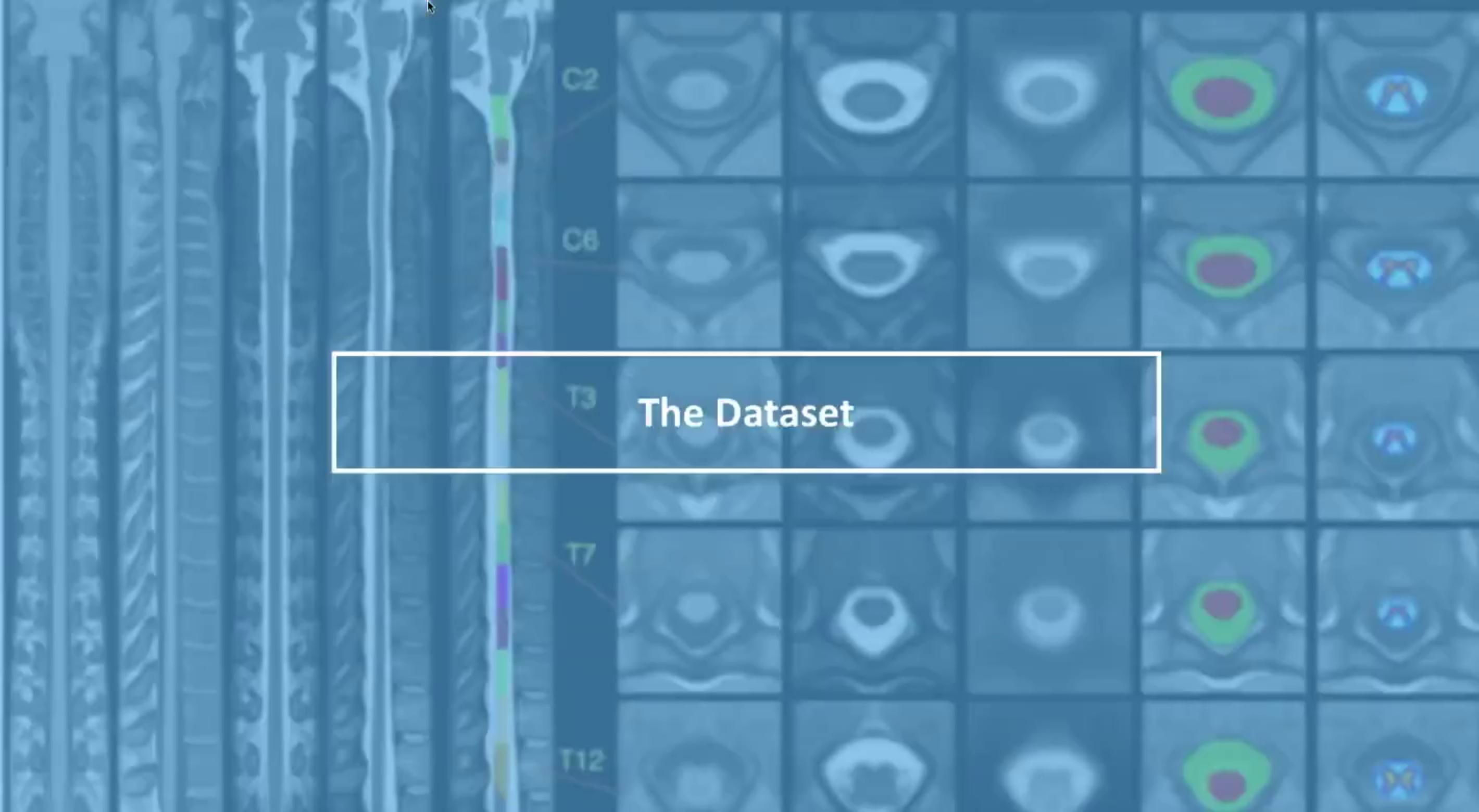
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Test algorithms in a purely computational environment with emphasis on accuracy.



The Dataset

An overview

The Dataset

The data is from three Universities associated with Spine Web. The scans are from Stanford University's Imaging Clinic (Radiology), University of Hawaii at Manoa , and Oxford University.



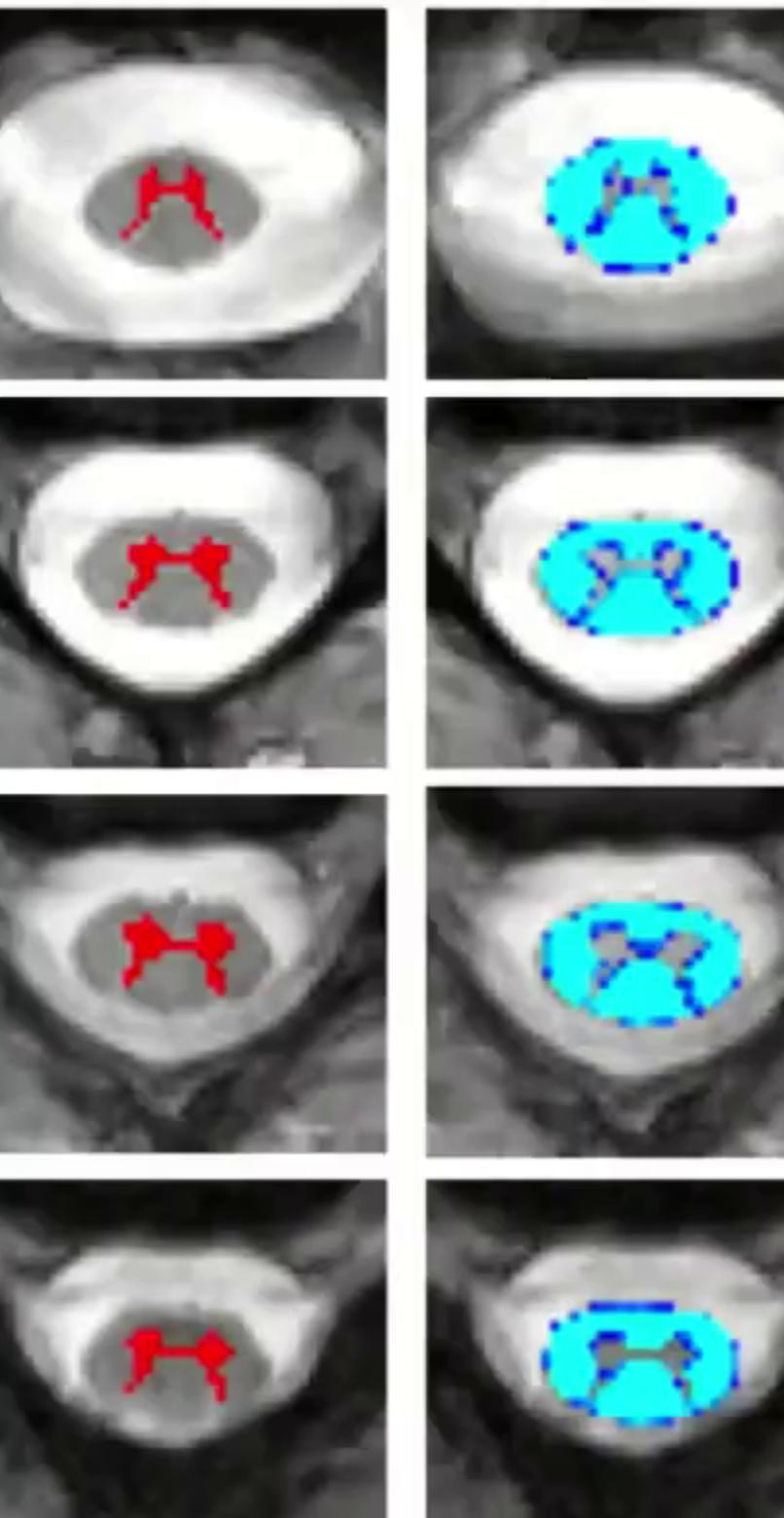
A morphologically comprehensive dataset of 2,000 scans of MRI and CT Scans



Patient characteristics vary from gender, age, medical conditions, height, weight, and spine-specific diseases

Utilization of small data

The data was split 40% training 60% validation as back propagation is far more beneficial to refine nuances in medical imaging.

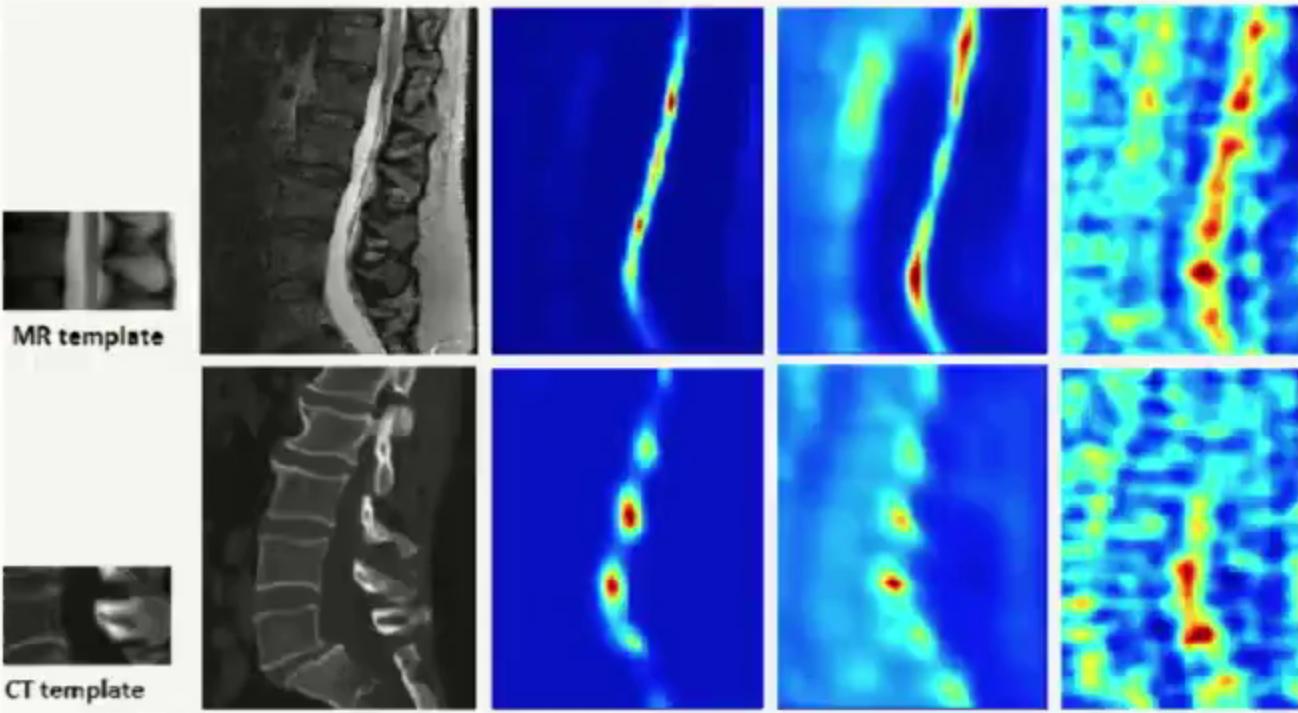


Accounting for Variation in the Data Set

01.

Different Machines

Companies use different hardware in their imaging devices resulting in discrepancies of radiology outputs

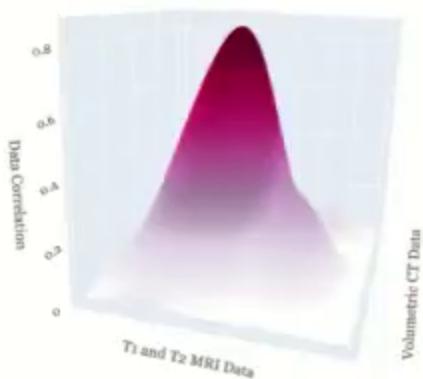


02.

Patient Morphology

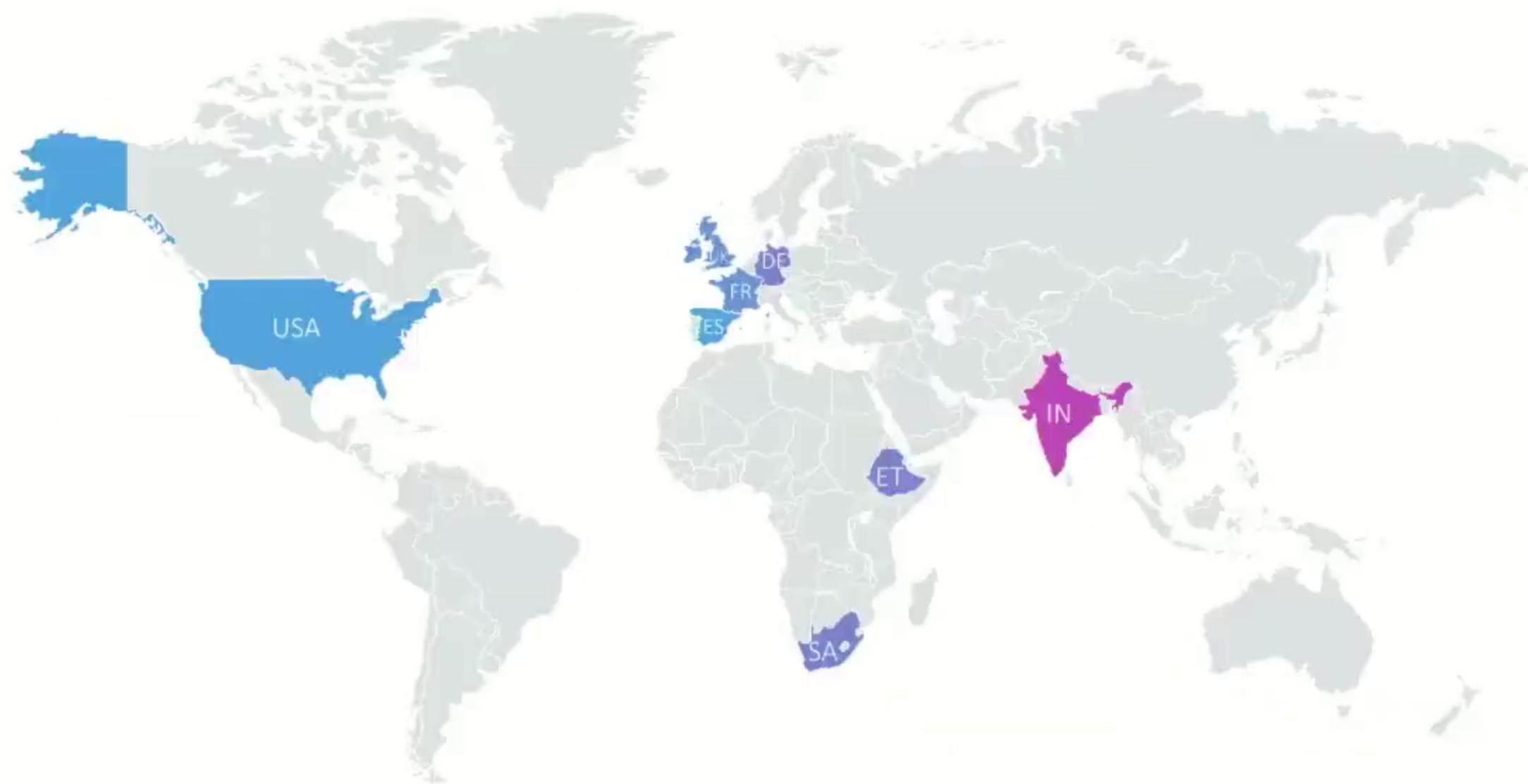
From patient to patient various factors from age to gender affect morphology and thus classification

HDM Gaussian Data Density Distribution of CT and MRI Training Dataset



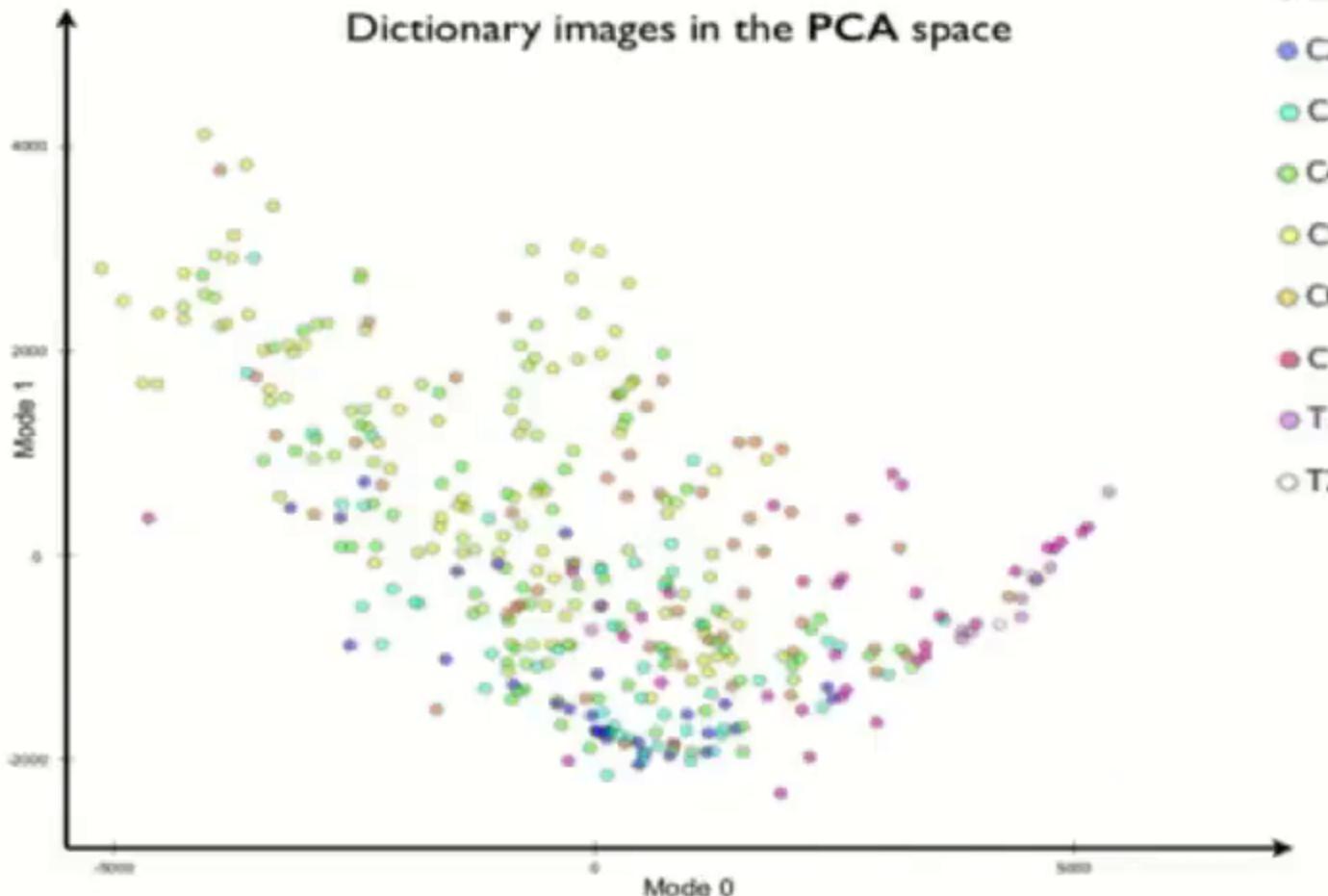
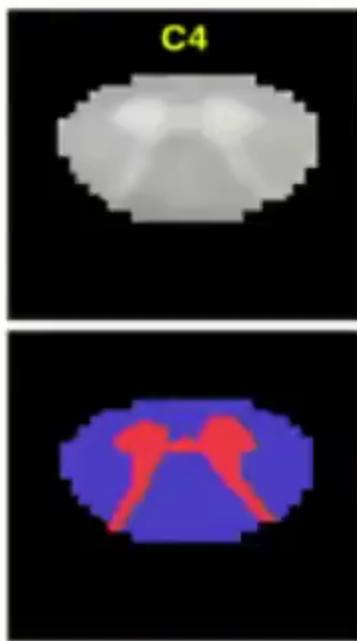
Dataset Geographic Distribution

Where are the medical scans from?



Dataset Optimization: Principal Component Analysis

Dictionary images and
manual WM/GM
segmentations after
pre-processing



01. Data Compression

By finding eigenvalues similar to each other data was compressed by 72%.

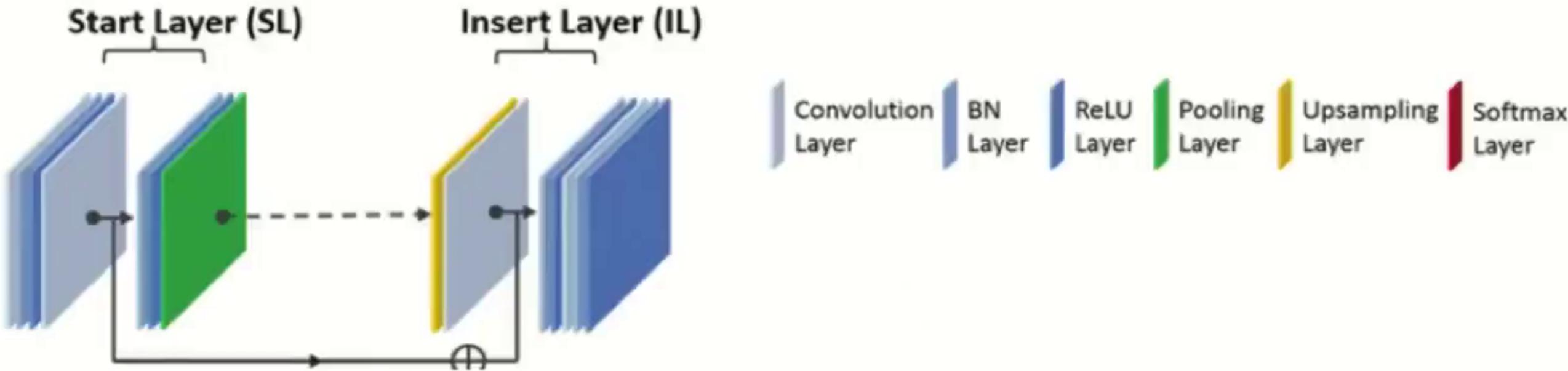
02. Training Time Reduction

By reducing the memory usage on the GPUs they ran more efficiently ultimately reducing training time.

03. Computational Efficiency

By placing vertebral sections in a component space the prediction times were performed in constant or near-linear time.

Shortcut Connection (SC)



Prevention of Data Degradation

By skipping layers of the encoder portion of the network, the resolution of the reconstructed medical scans is higher.

34% Faster |

34% faster between training and prediction time as layers are skipped

27% Better |

Resulted in a 27% increase in reconstructed resolution as a result of shortcut connections

The Algorithms

Input Layer $\in \mathbb{R}^{16}$

Hidden Layer $\in \mathbb{R}^{12}$

Hidden Layer $\in \mathbb{R}^9$

Hidden Layer $\in \mathbb{R}^6$

Hidden Layer $\in \mathbb{R}^6$

Hidden Layer $\in \mathbb{R}^{10}$

Hidden Layer $\in \mathbb{R}^{12}$

Output Layer

Mathematical Modeling

Feature Extraction and Fusion: Where w_k is the feature filer. The first two summations are weights and the the second two are adjustable biases.

$$E(v, h) = - \sum_{K=1}^K h^k \cdot (\varpi^k * v) - \sum_{K=1}^K h^k b_k - \sum_{i,j} h_{i,j}^k - c \sum_{i,j} v_{i,j}$$

The template matching is done through the comparison of L2 distances where f_{dp} is the deep feature descriptor defined by the neural network.

$$r(P, T) = \exp(-\epsilon ||f_{dp}(i_p) - f_{dp}(T)||^2)$$

The coefficient vector a_p is iteratively updated: $a_p + \Delta a_p$, leading to the progressive alignment of the vertebra parts. The updated a_p warps the planar temple and the 3D vertebra.

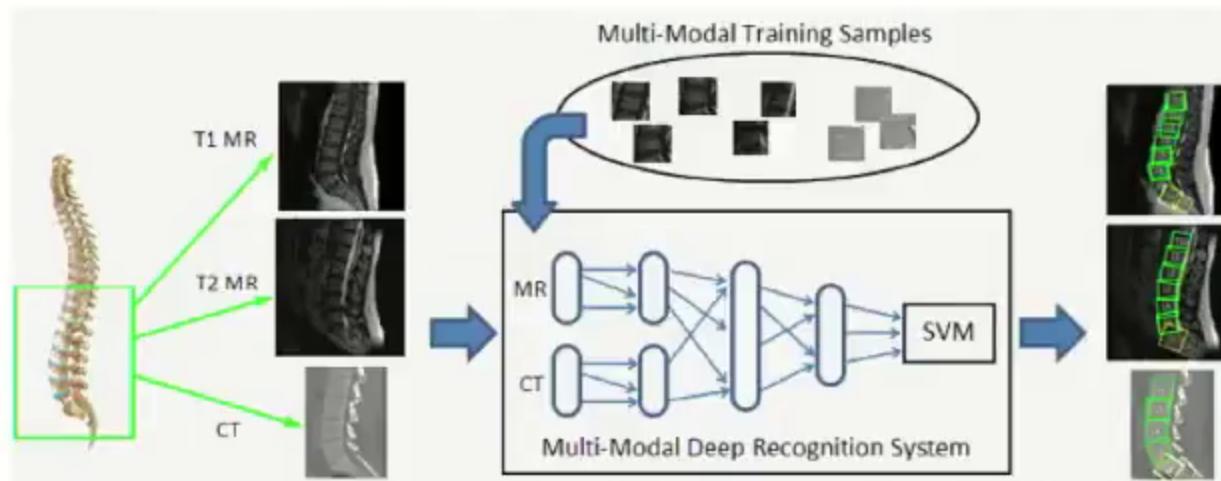
$$J(a_p) = \left(\frac{\partial d(a_p)}{\partial a_p^1}, \dots, \frac{\partial d(a_p)}{\partial a_p^k} \right)^T$$

Utilizing Computer Vision Systems and Machine Learning to Develop a Live Time Navigational and Diagnostic Device for Spinal Reconstructions

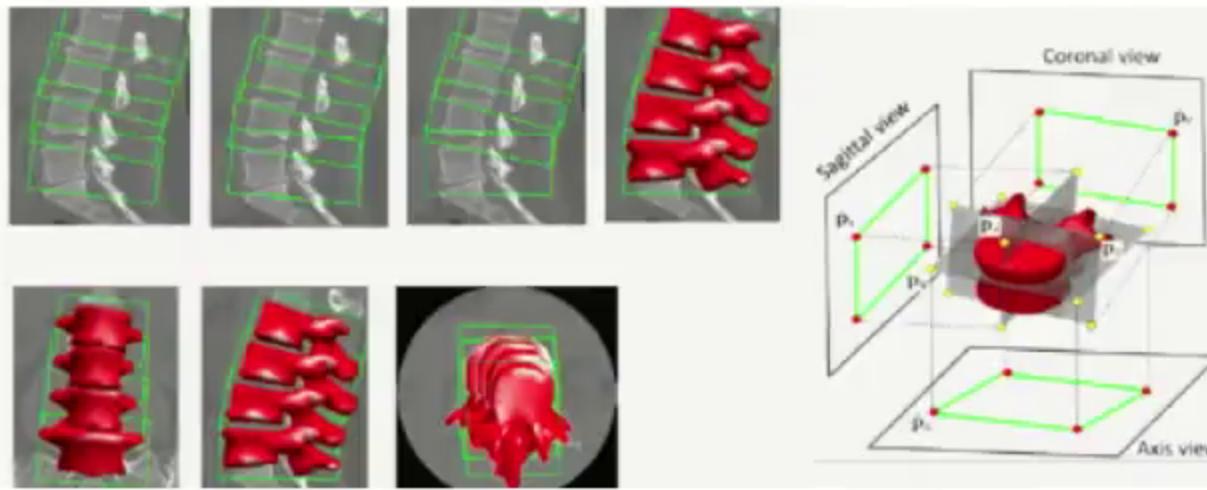
By: Krithik Ramesh

Hierarchical Deformable Model

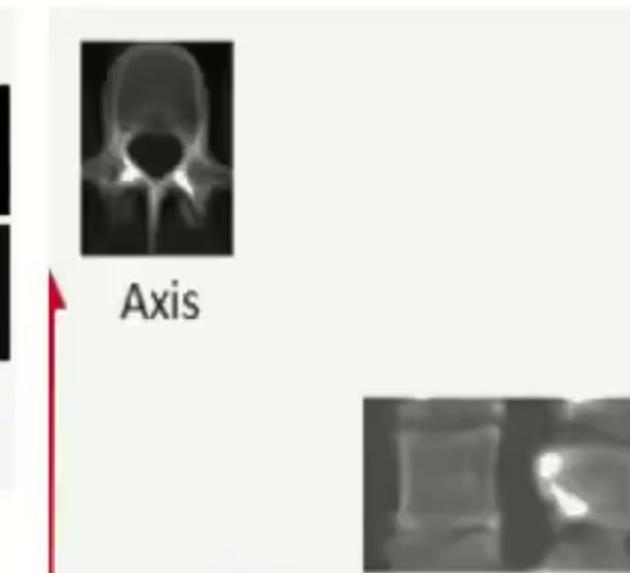
Predicting Spinal Behavior using 3D reconstruction and Feature Fusion



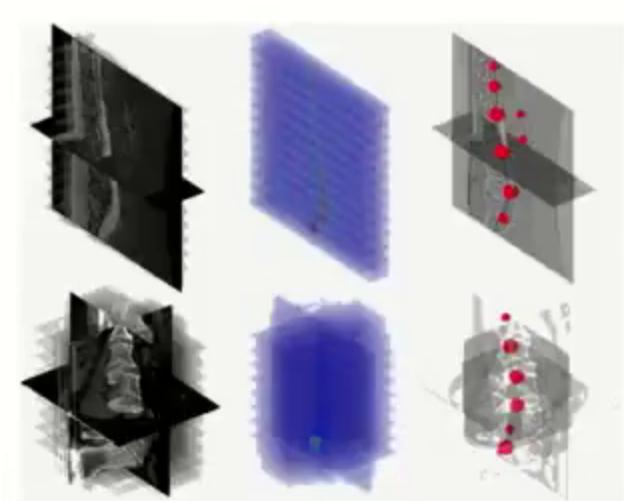
Step 1: Multi-Modal Feature Extraction and Vertebrae Detection



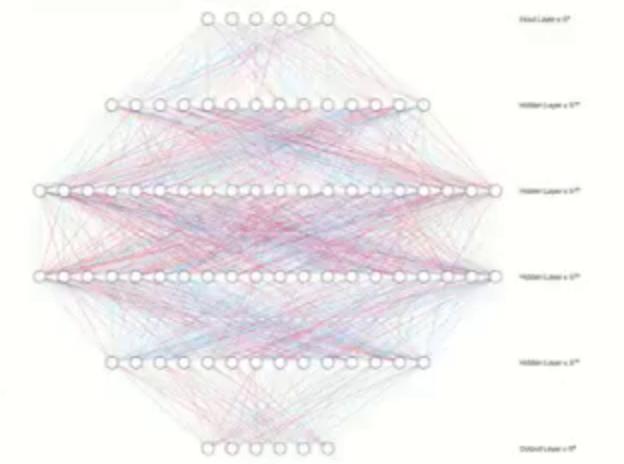
Step 3: Global Shape Registration and Pose Estimation



Planar Reconstruction Orientation



Step 2: Center points for Global Reconstruction



Boltzmann Machine Architecture

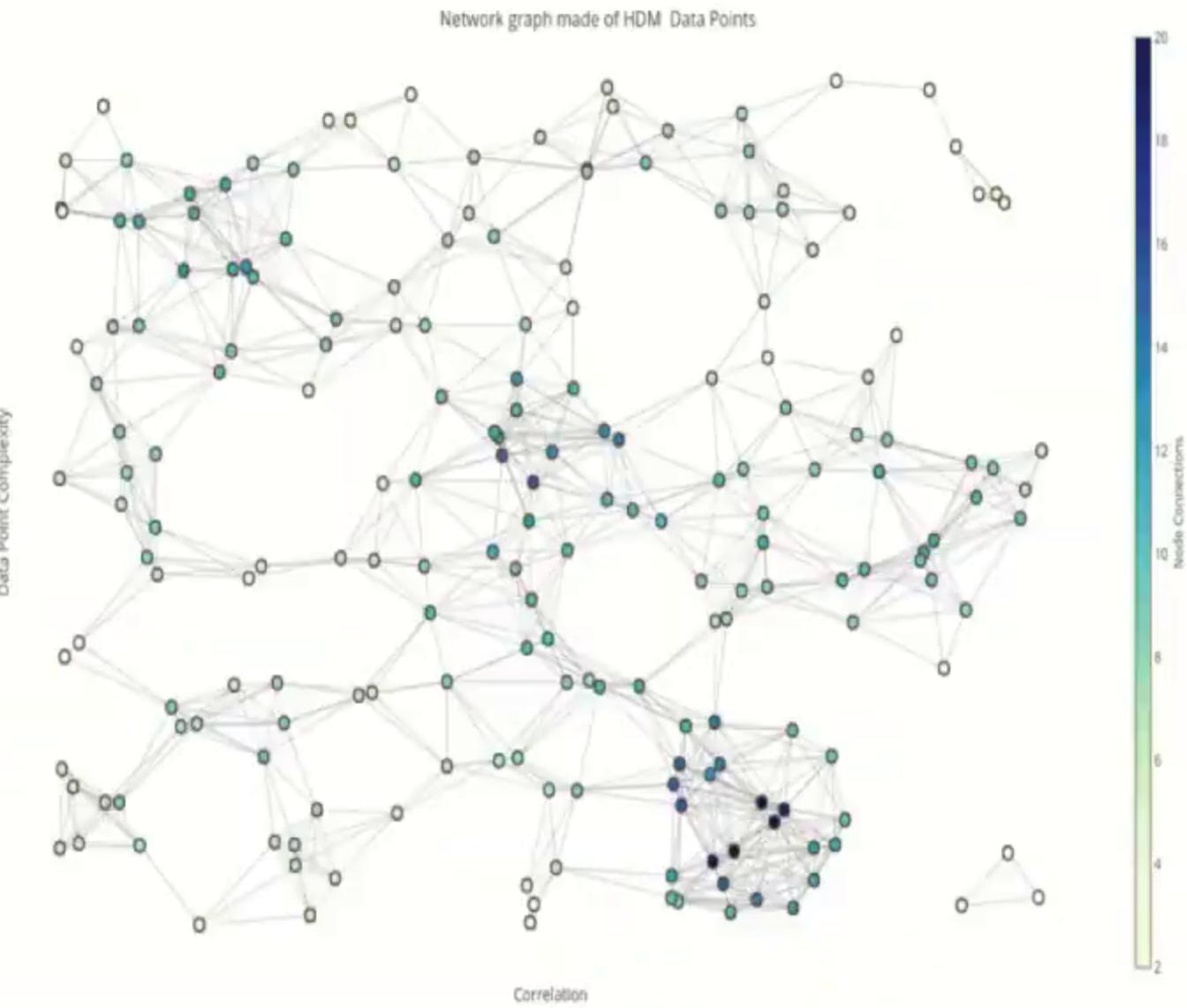
Network Graph of Hierarchical Deformable Model

01. Anatomical Landmarking

Each Node represents a significant anatomical landmark that was categorized. (e.g. c1 vertebrae, radicular – medullary artery sequence)

02. Priority Sequence

Gives the ability to prioritize certain parts of the spine based on biomechanical integrity.



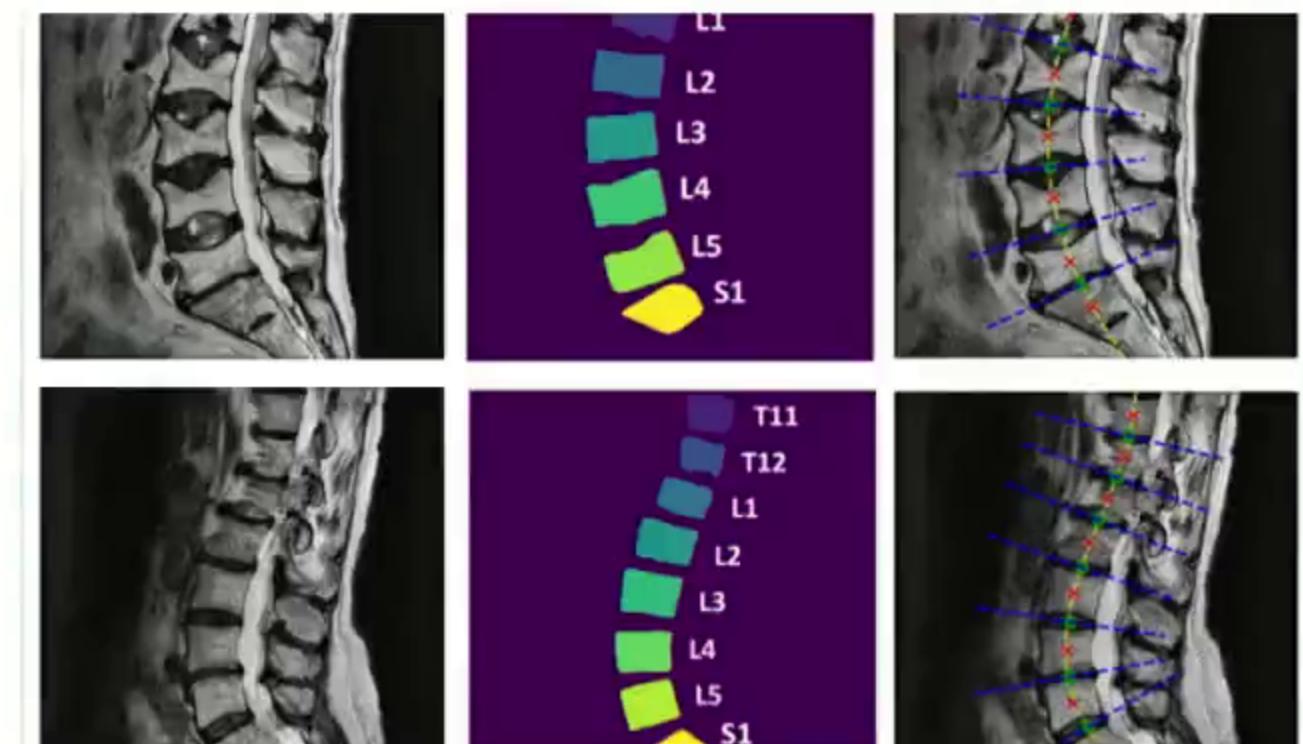
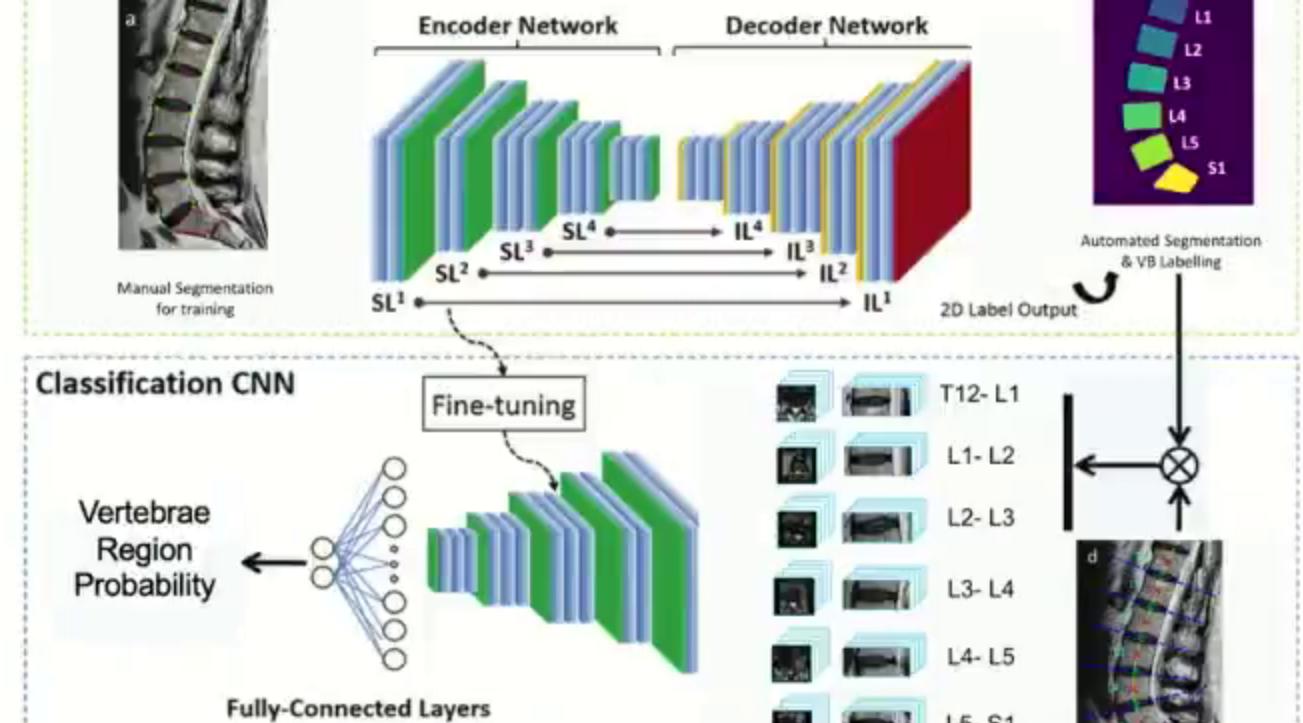
Region-Based Convolution Neural Network

01. Segmentation CNN

Classifies individual vertebra and segments geometry in spinal column.

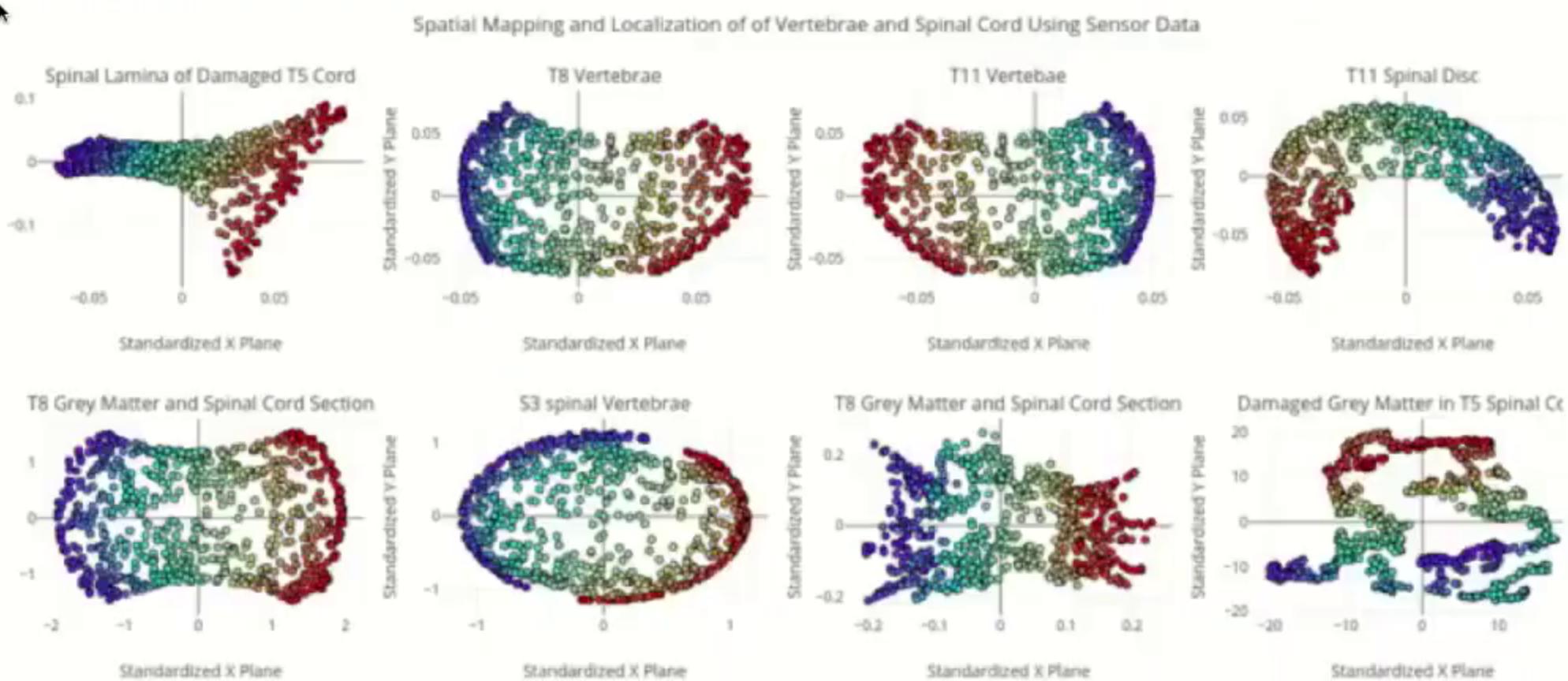
02. Classification CNN

Labels each vertebrae e.x. T10, T11, S1,S2.



Simultaneous Localization and Mapping

3D Spatial Mapping of Environment using sensor array on HoloLens.



01. Reconstruction of Environment

Uses depth perception sensor to reconstruct a 3D environment for analysis.

02. Cross-Validate with HDM

Exports telemetry data of 3D reconstructions with HDM to validate what structure is being seen in person.

$O(n^3)$ | The most computationally expensive algorithm of the three implemented.

SDK | Implementation done using Microsoft HoloLens SDK that better utilizes the sensor array at a low-level.

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Background



Engineering
Goals



Development
and Design



Testing and
Data Analysis



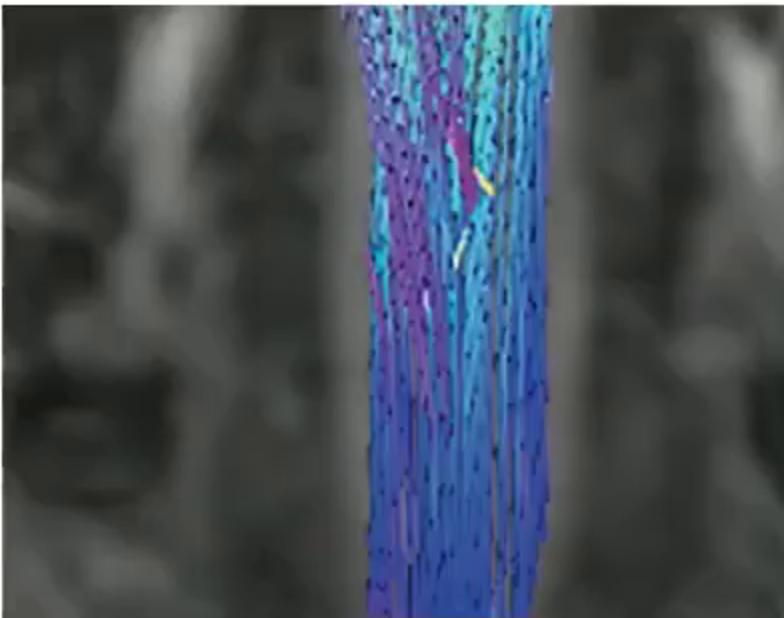
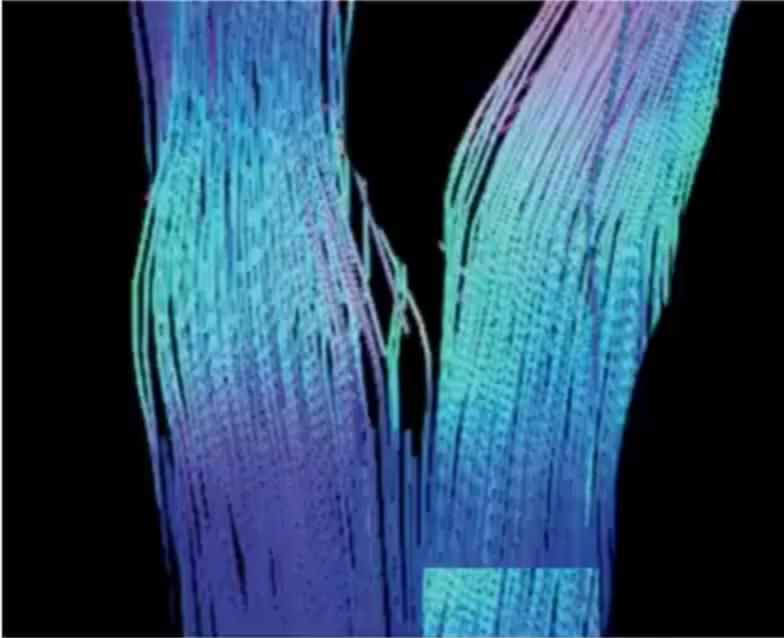
Results and
Future Steps



Diffusion Tensor Imaging

01. Fibrous Tracking

Allows for Tracking of the spinal cord

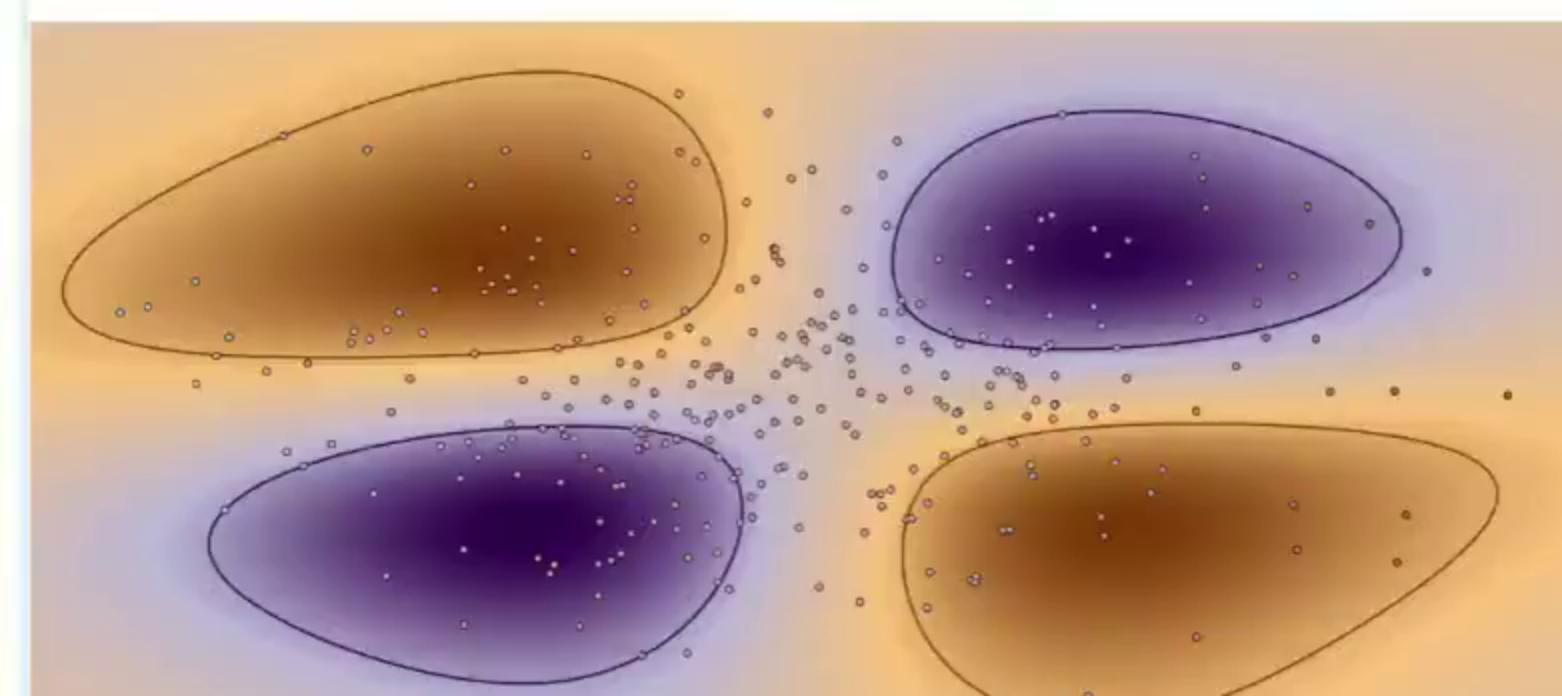
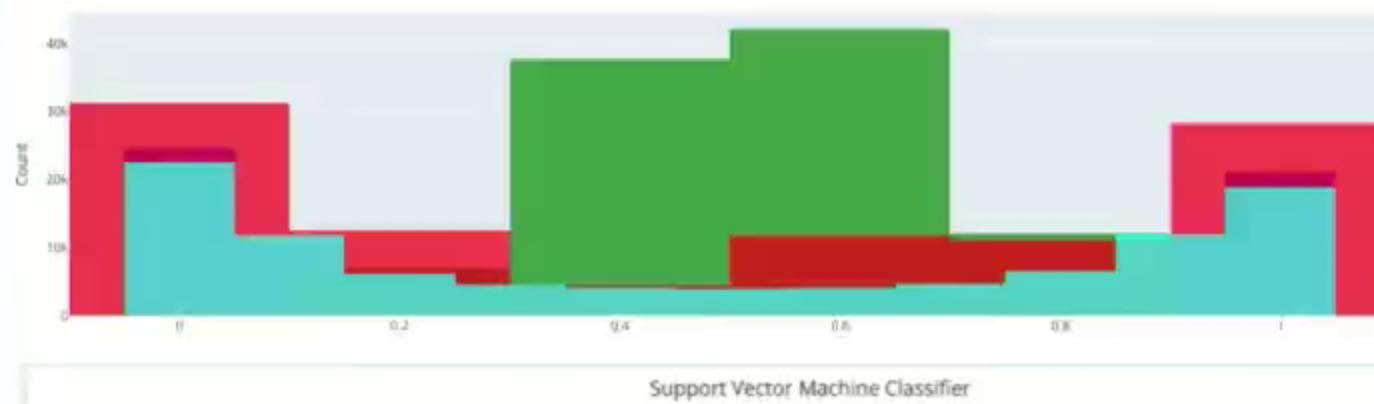
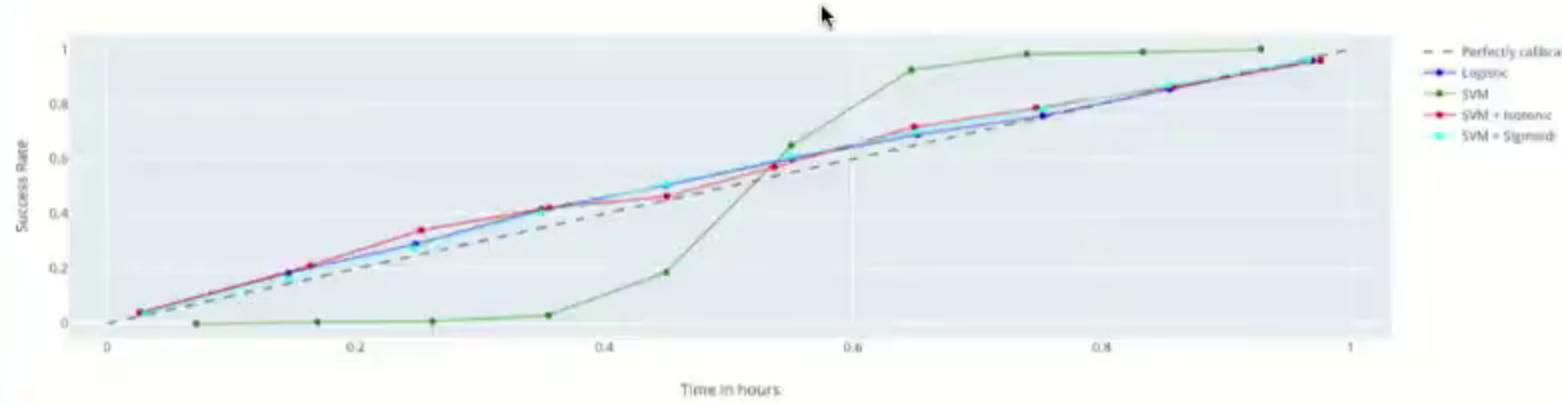


01. Nervous and Blood Vessel Mapping

It's now that much easier and more effective to start your



Support Vector Machine



01. Computationally Inexpensive

Prediction of vertebra can be done in constant time $O(p)$. This drastically reduces latency in the algorithm while the system is running.

02. High Accuracy

The SVM is highly accurate with the final accuracy after training being 99.7%.

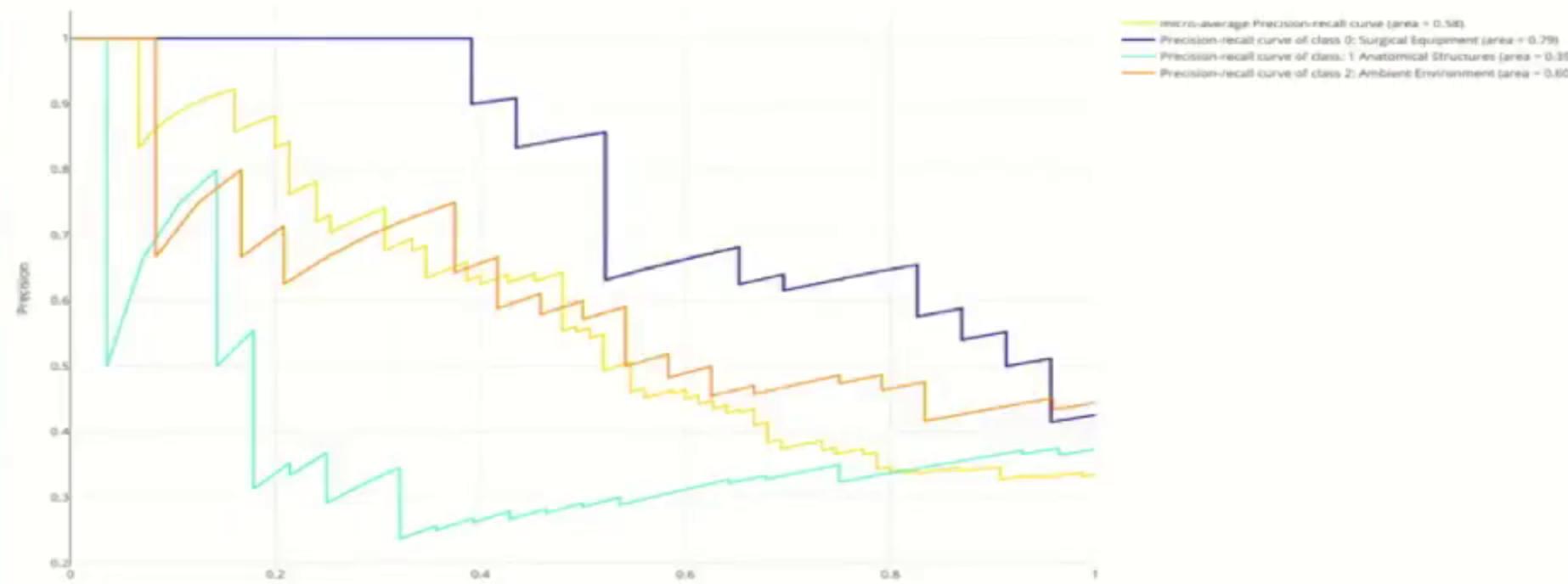
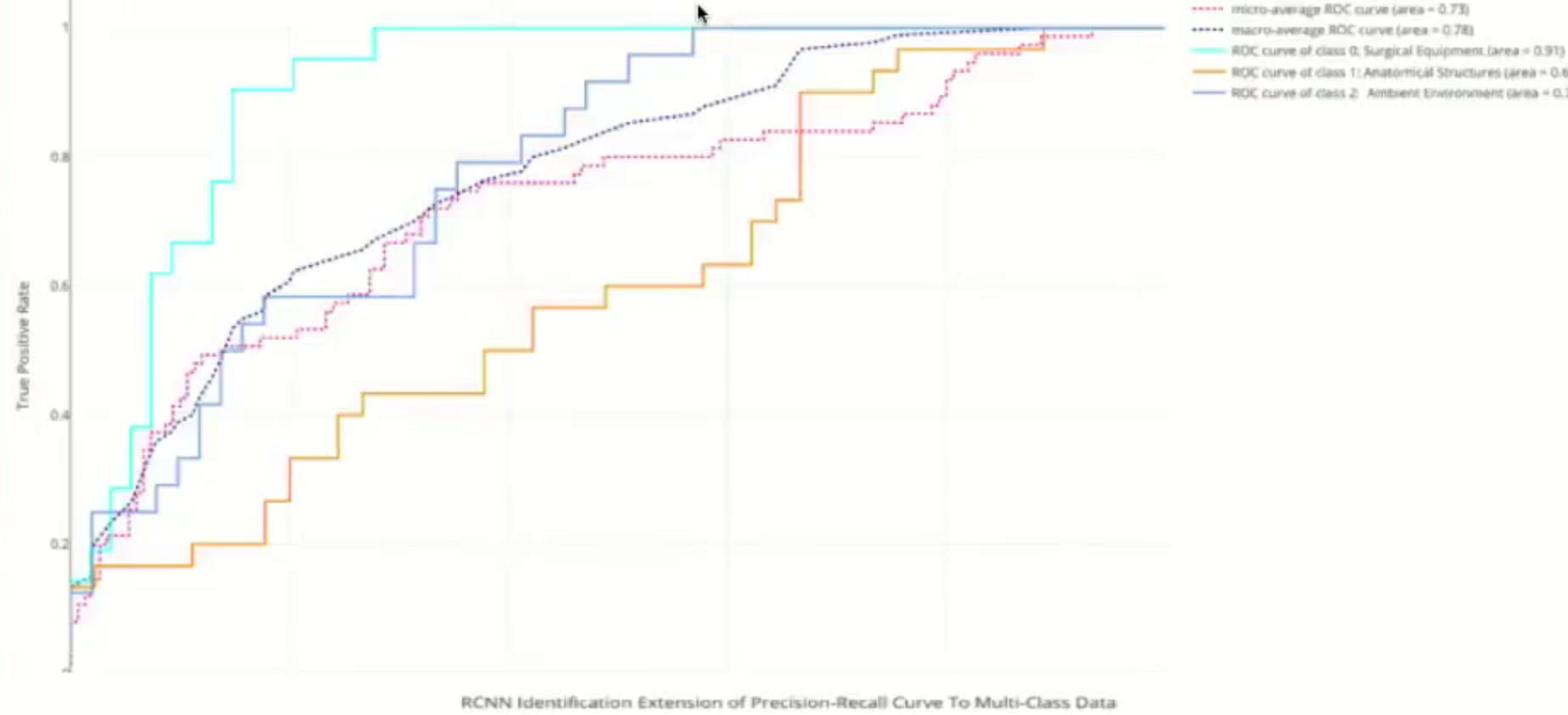
Region-Based Convolution Neural Network

1. Strong Receiver Operating Characteristic

The area under the curve for the three classes: (Surgical Equipment, Anatomical Structures, and Ambient Environment) ranged between 0.73, 0.91

2. Convergence on Recall V.S. Precision

All three classes that were trained converged on on the precision recall spectrum indicating a balanced dataset and well-trained model.

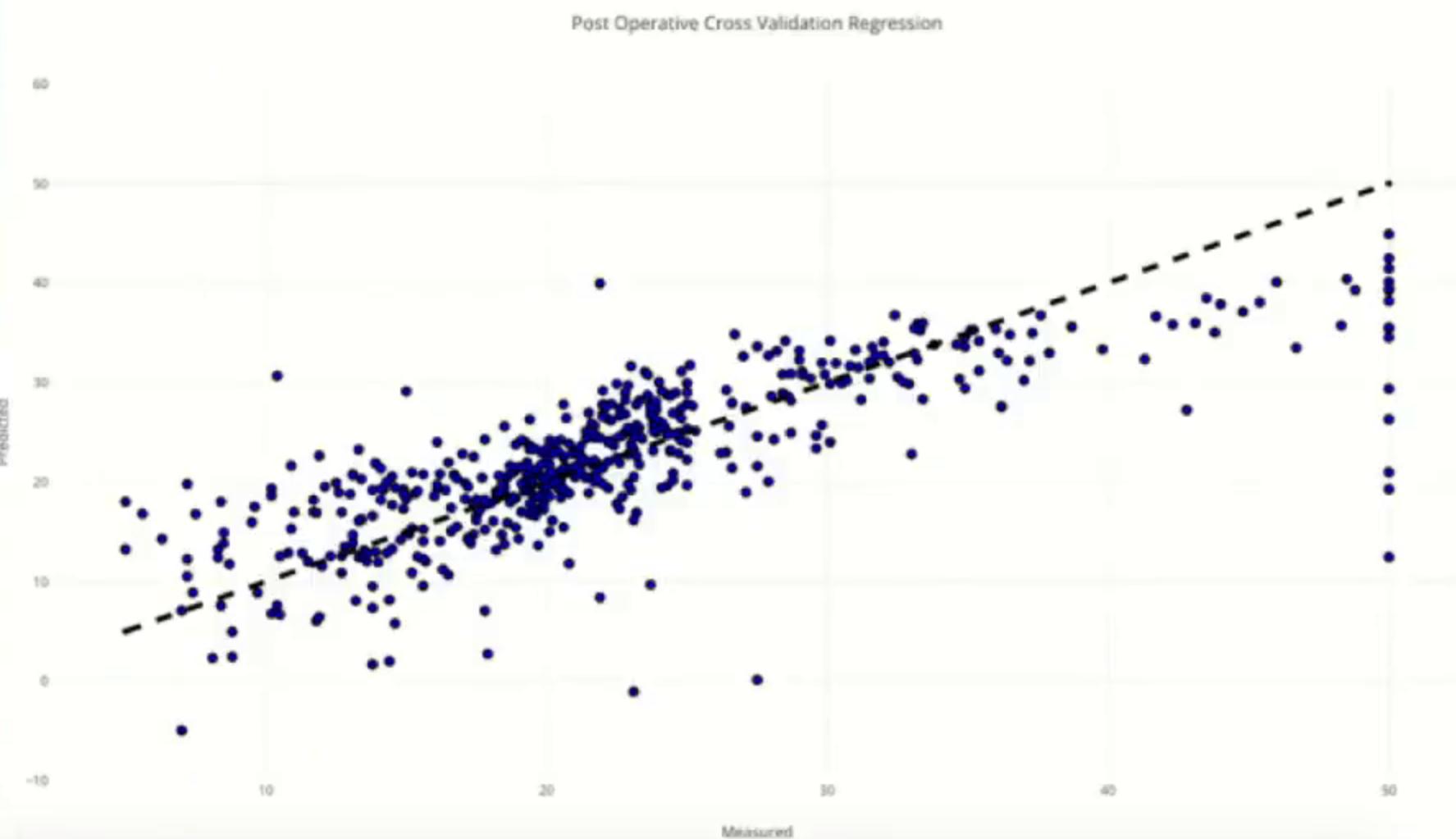


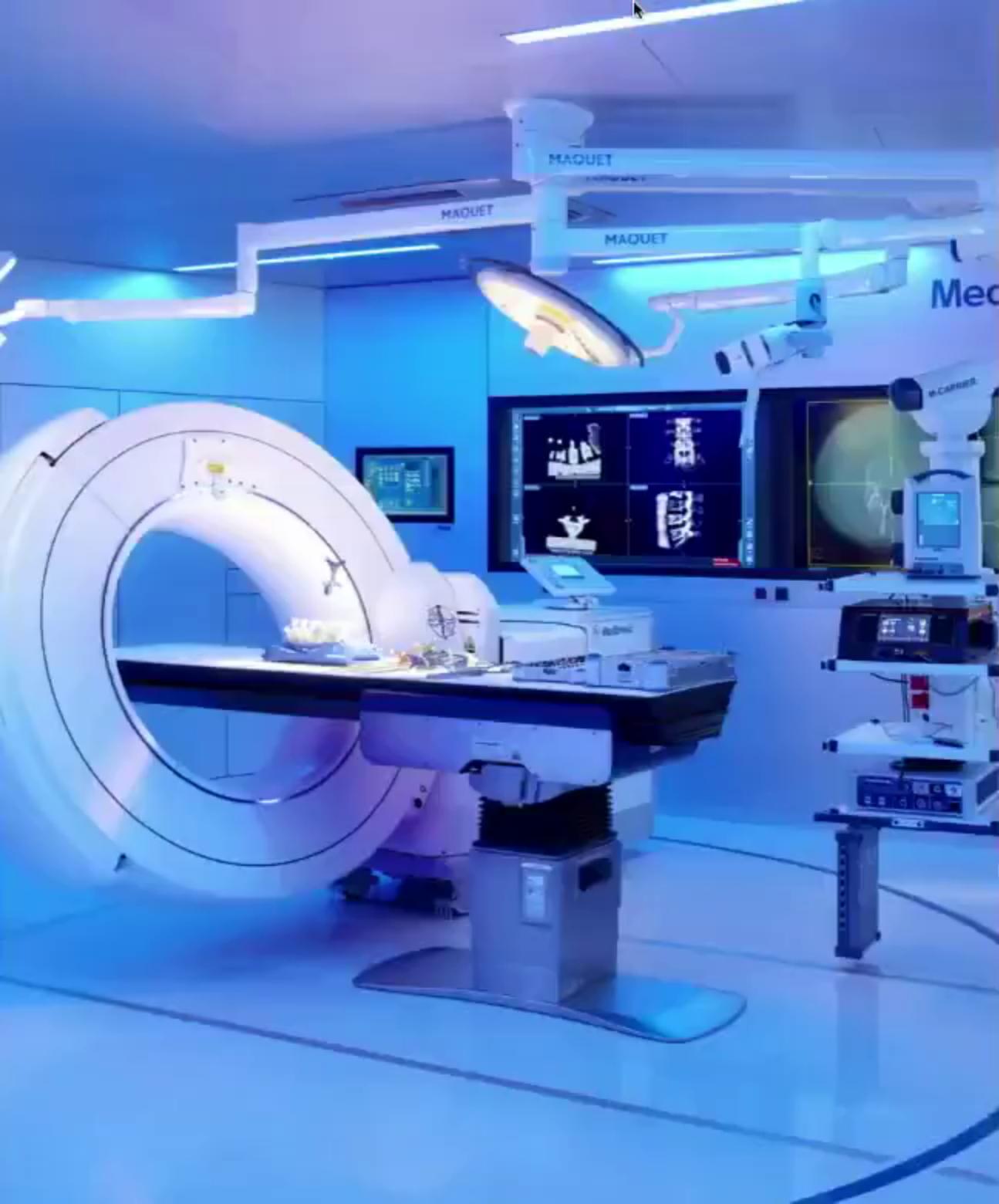
Logistic Regression

01.

High Correlation

The r^2 value for the identification and classification of anatomical features



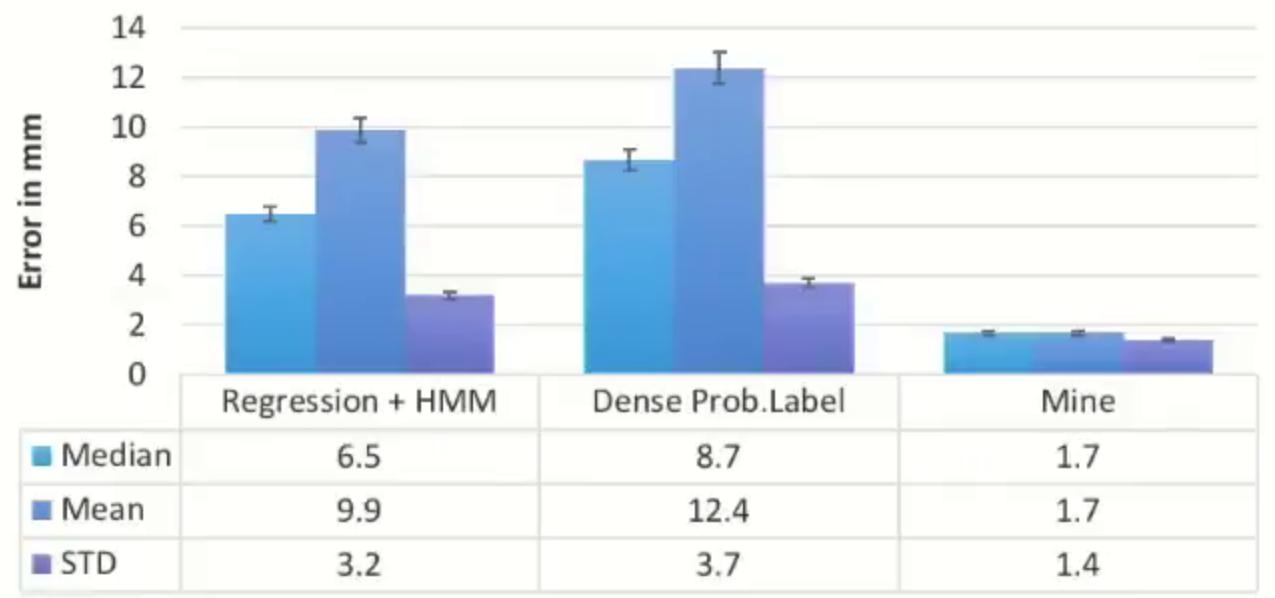


Existing Navigational Systems: Fluoroscopy

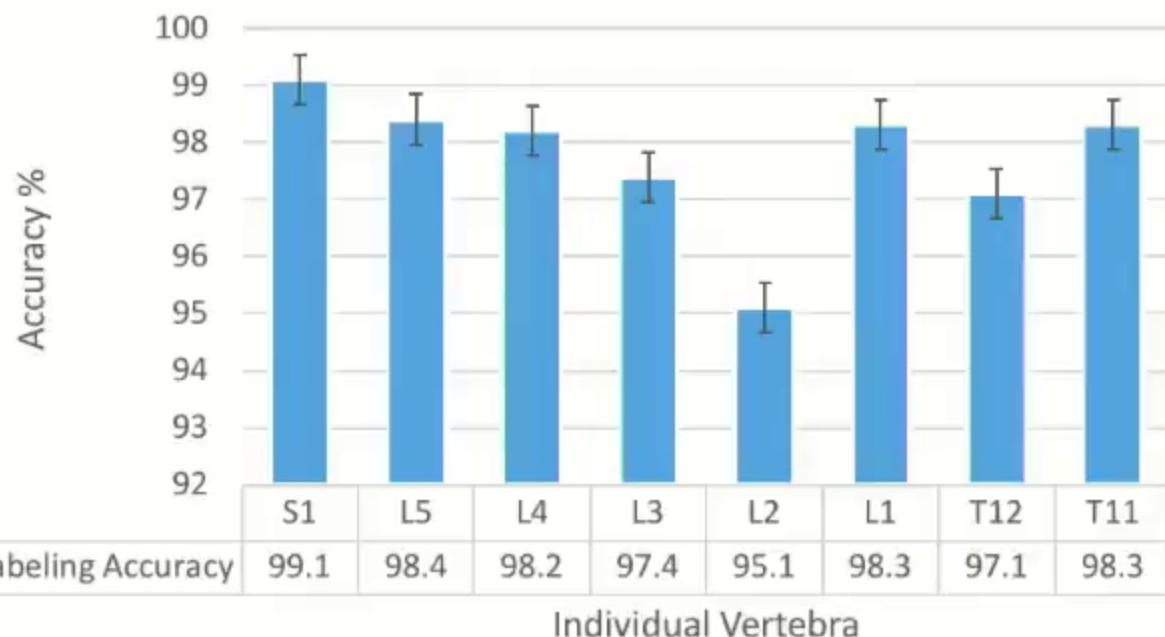
- ✓ Poses significant physiological harm to both the patient and surgical team as a result of X-Ray Radiation
- ✓ Limited visual acuity and anatomical accuracy as a result of 2D views and latency in 3D reconstructions.
- ✓ Expensive system that not many be accessible to developing regions and even rural hospitals.

Results

Comparative Analysis of Vertebra Localization Precision



Labeling Accuracy Of Lower Spine



01

Increased Accuracy

The experimental algorithm has a labeling accuracy of 98.6% while the comparative baseline currently used in research is roughly 86%.

02

Increased Precision

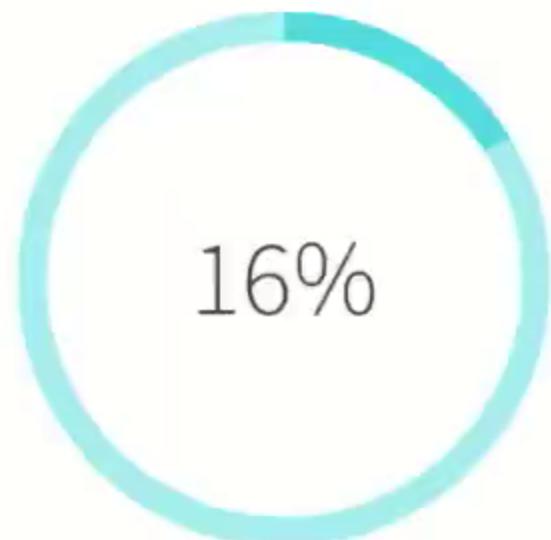
A comparative analysis of 2 different algorithms for anatomical mapping of the spine had mean errors of 9.9mm and 12.4mm compared to the 1.7mm of the experimental system developed.

03

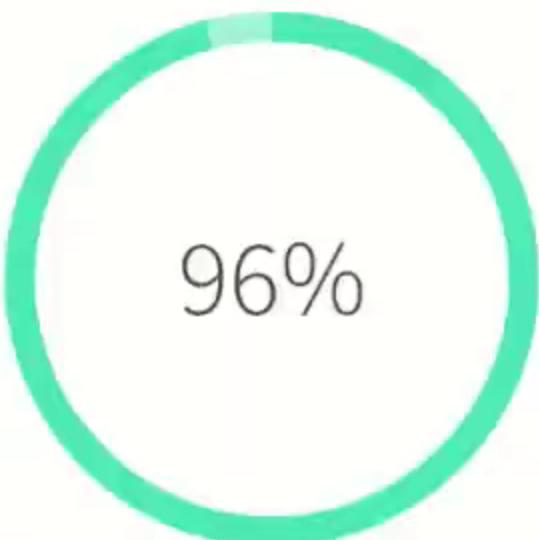
Decreased Detection Time

The average detection time for the control systems was approximately 7.80 seconds for the entire spine region the experimental system took approximately 5.83 seconds after already passing through the HDM

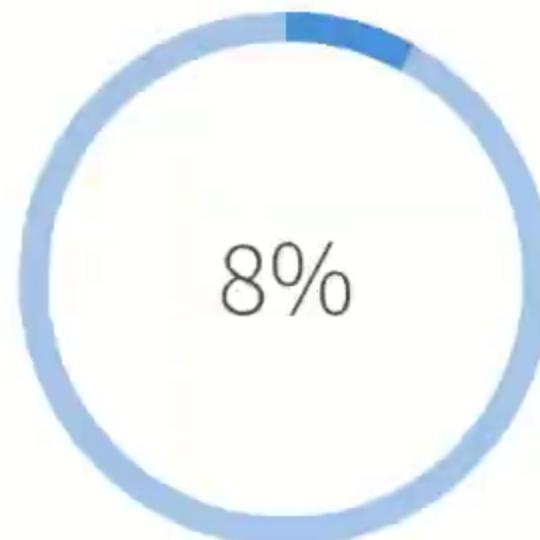
Practical and Economic Viability



Reduction in operating
time



Cheaper than
fluoroscopy



Reduction in recovery
time

Questions!