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

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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.

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Engineering Goals

1. **Develop Machine Learning Based Navigational System**

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

2. **Implement Computer Vision and Augmented Reality System**

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

3. **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.

04

Theoretical Testing

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

05

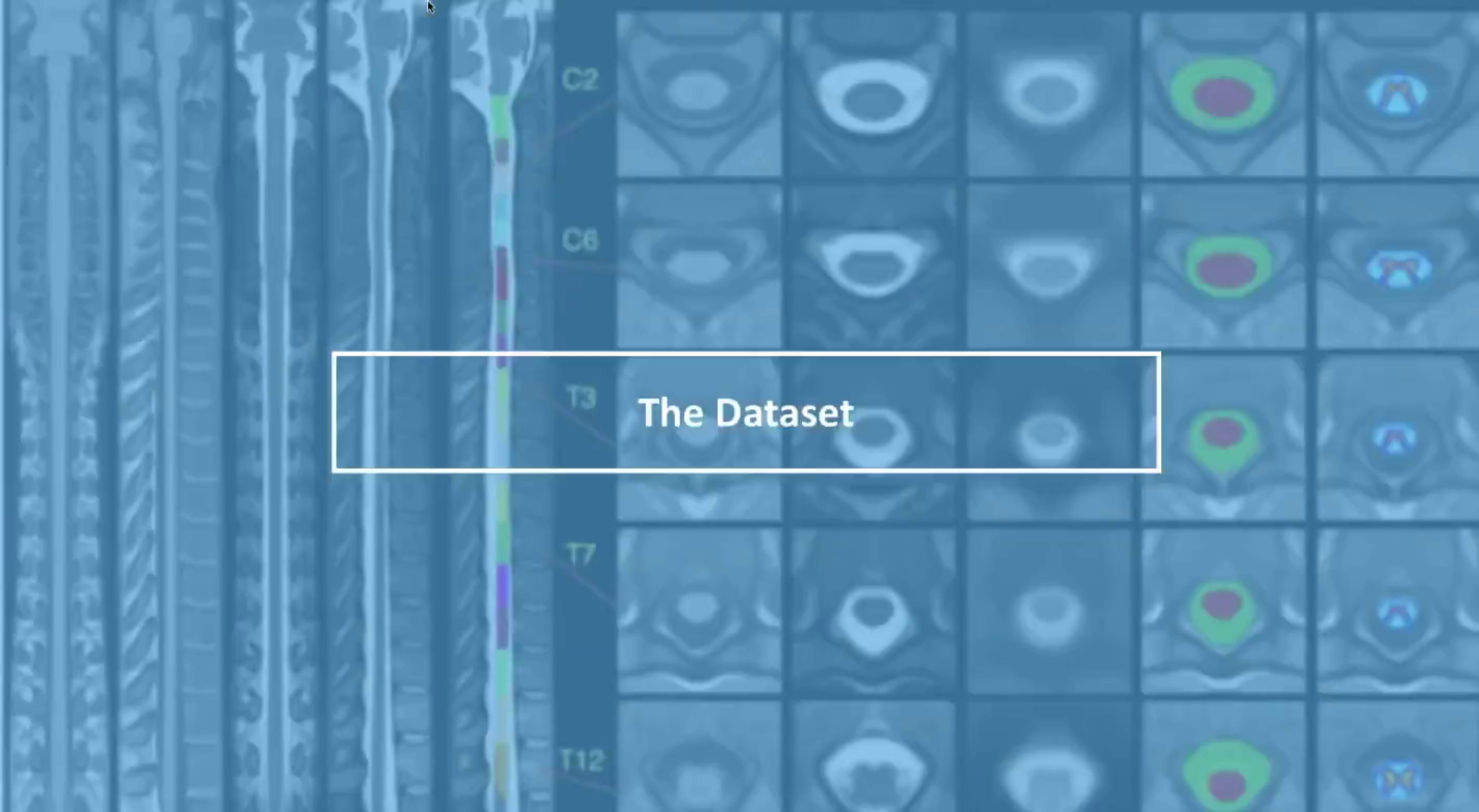
AR Development

Transfer algorithms onto the Microsoft HoloLens and test system stability.

06

Real-World Testing

Test viability of algorithm in conjunction with the AR Headset.


C2
C6
T3
The Dataset
T7
T12

An overview

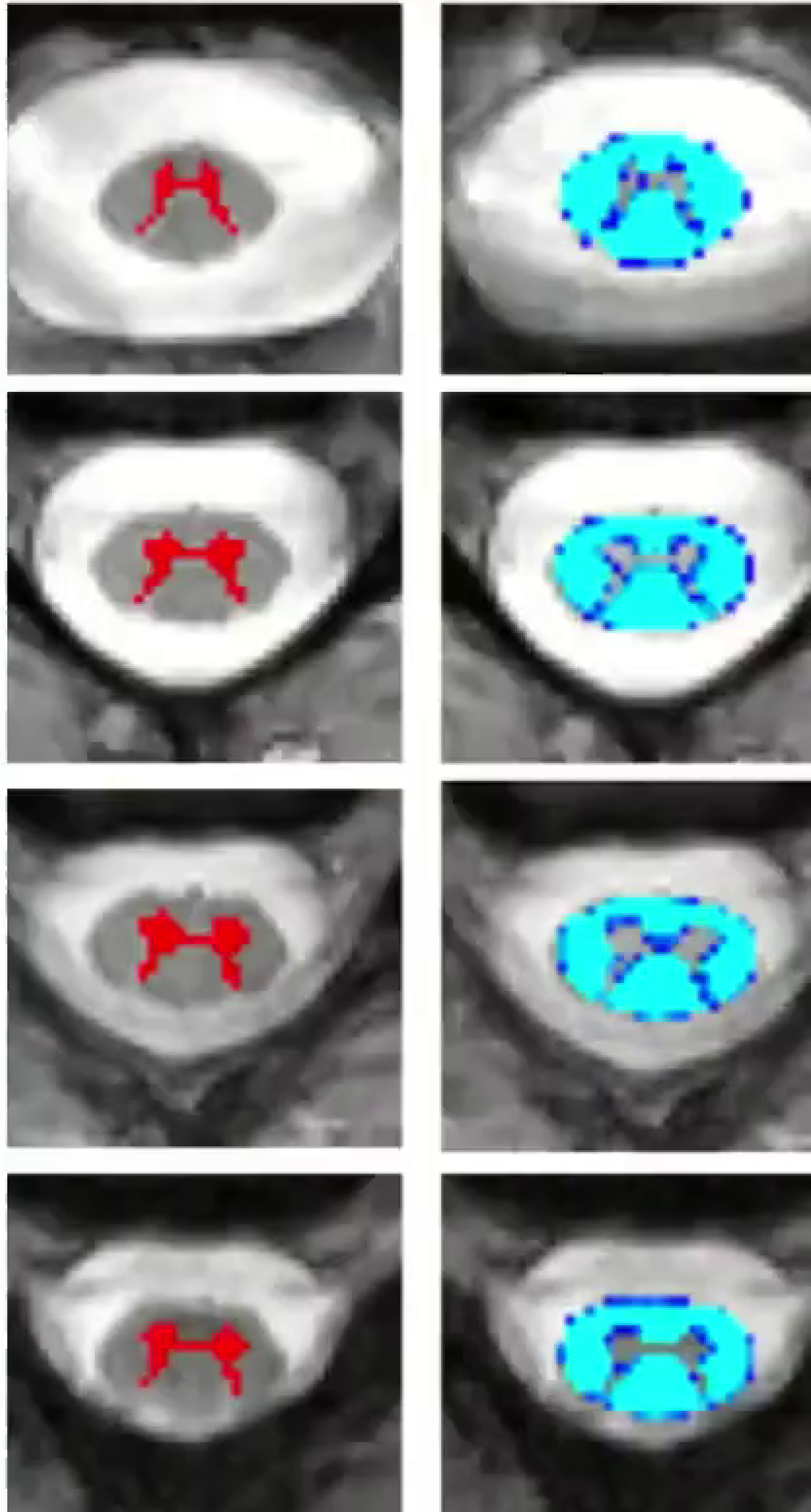
The Dataset

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.

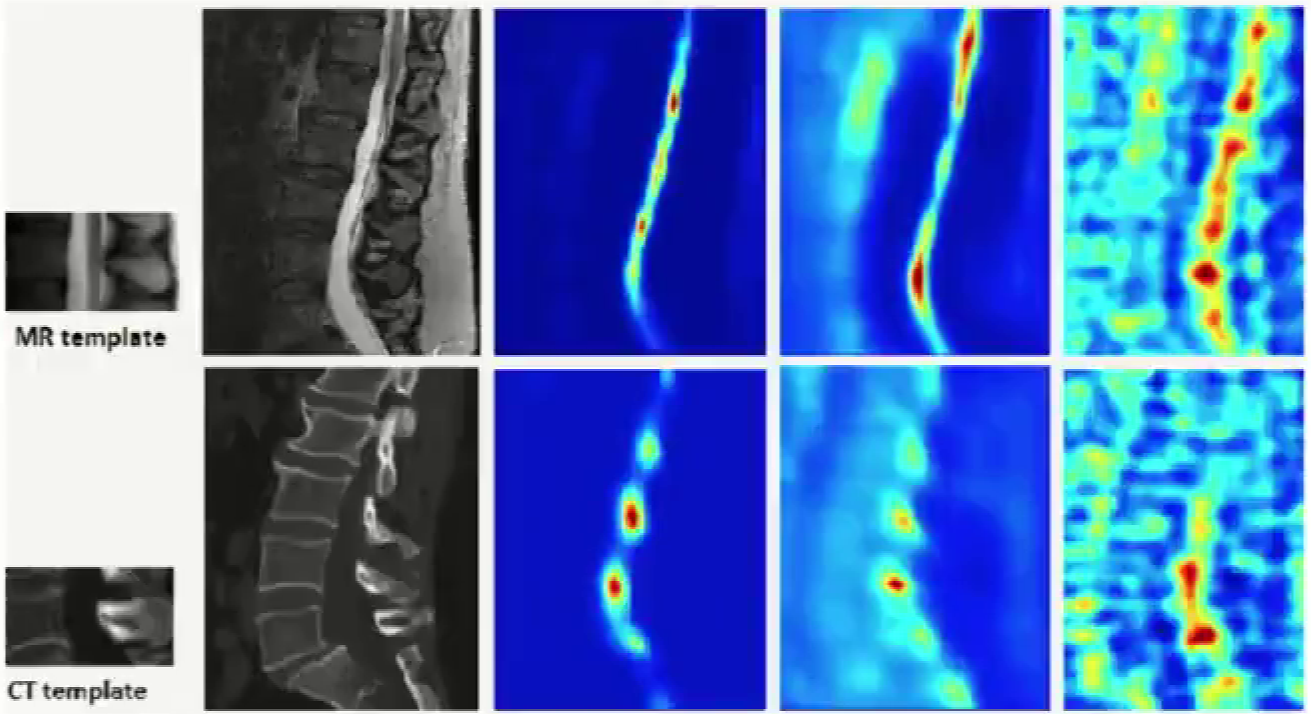
- A morphologically comprehensive dataset of 2,000 scans of MRI and CT Scans
- Patient characteristics vary from gender, age, medical conditions, height, weight, and spine-specific diseases

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

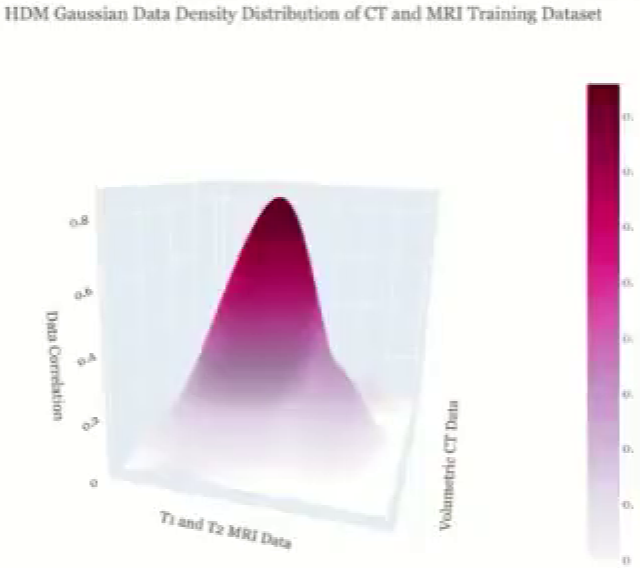


01. **Different Machines**

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

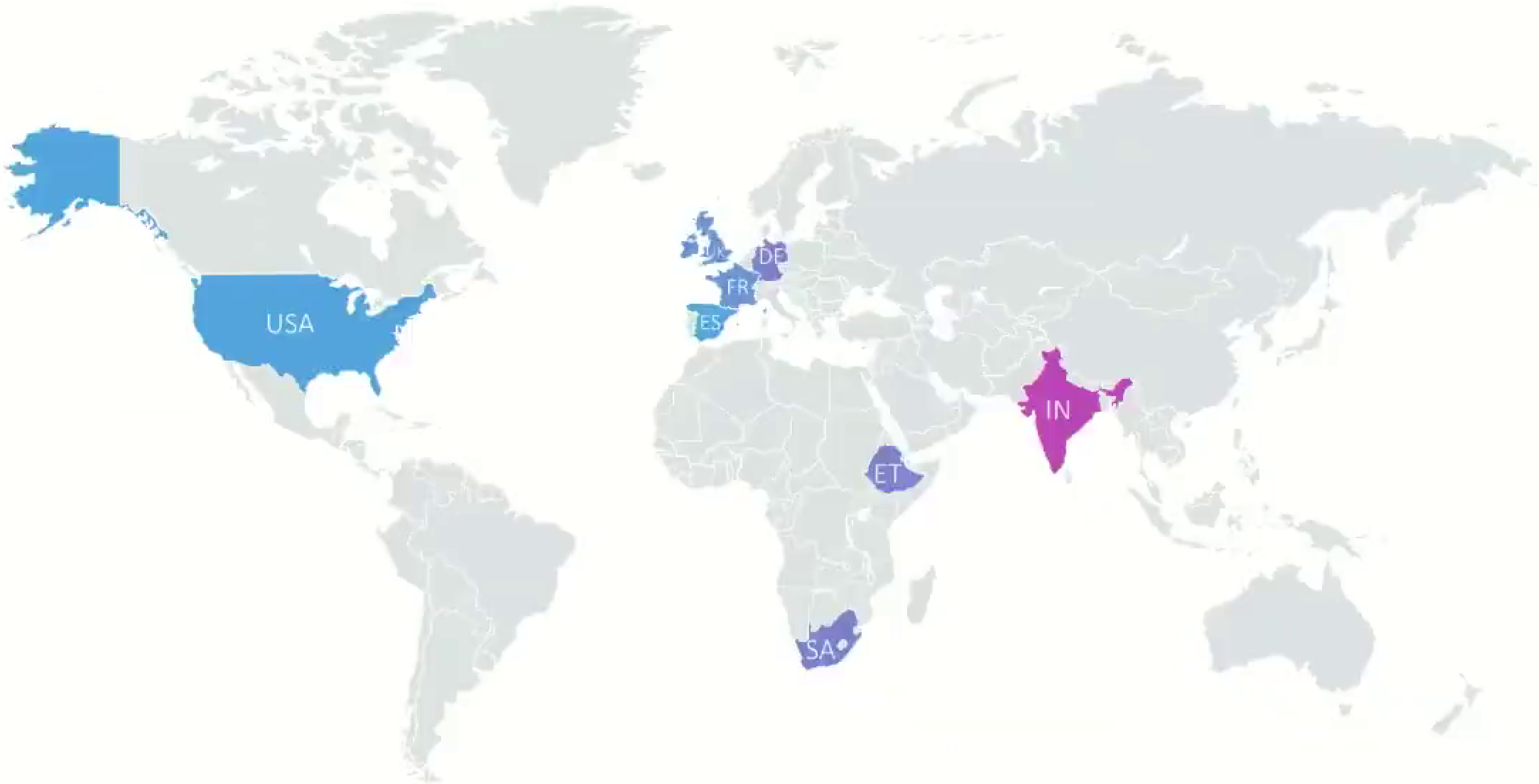
02. **Patient Morphology**

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

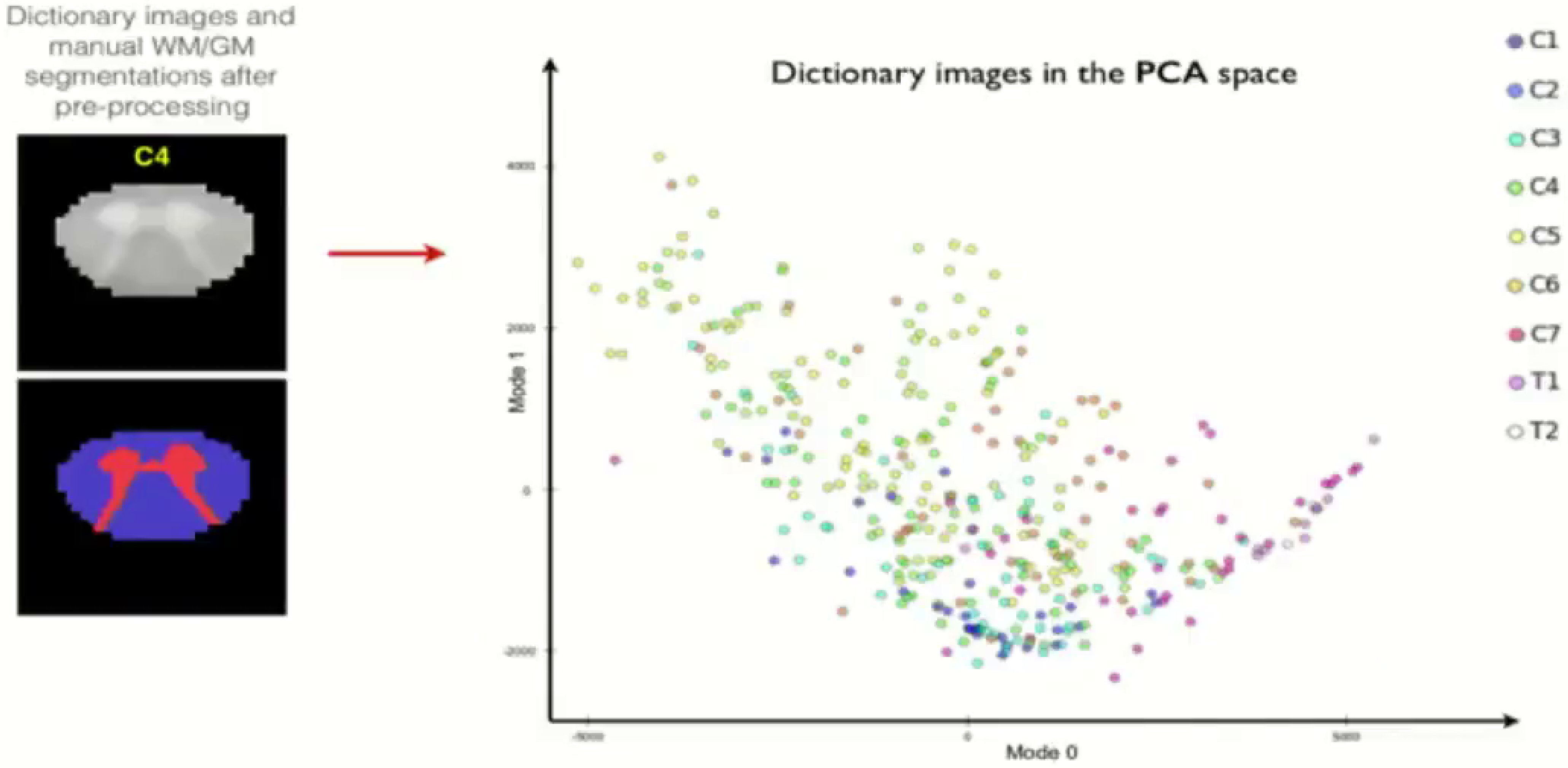


Dataset Geographic Distribution

Where are the medical scans from?



Dataset Optimization: Principal Component Analysis



01. **Data Compression**

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

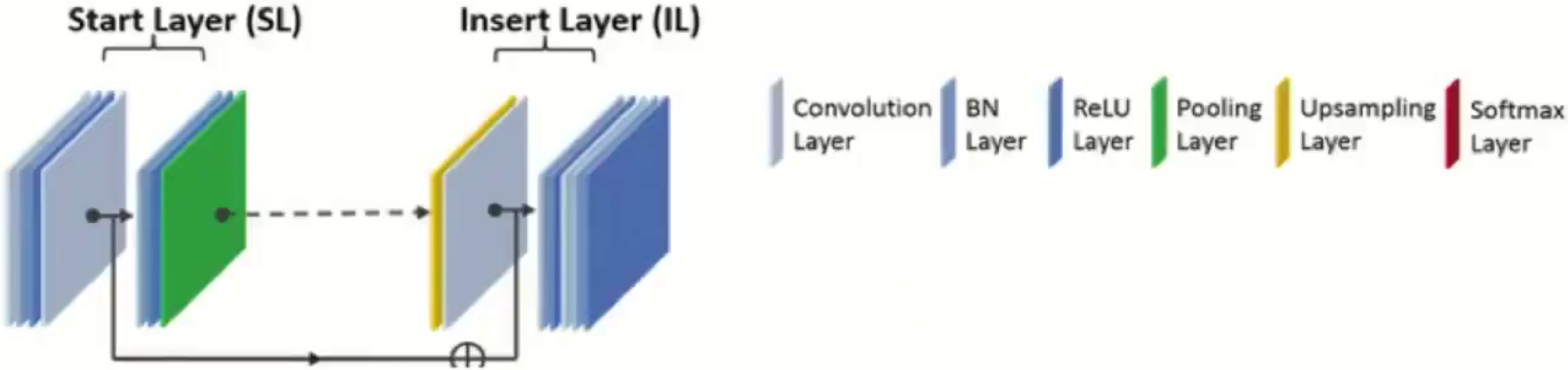
02. **Training Time Reduction**

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)

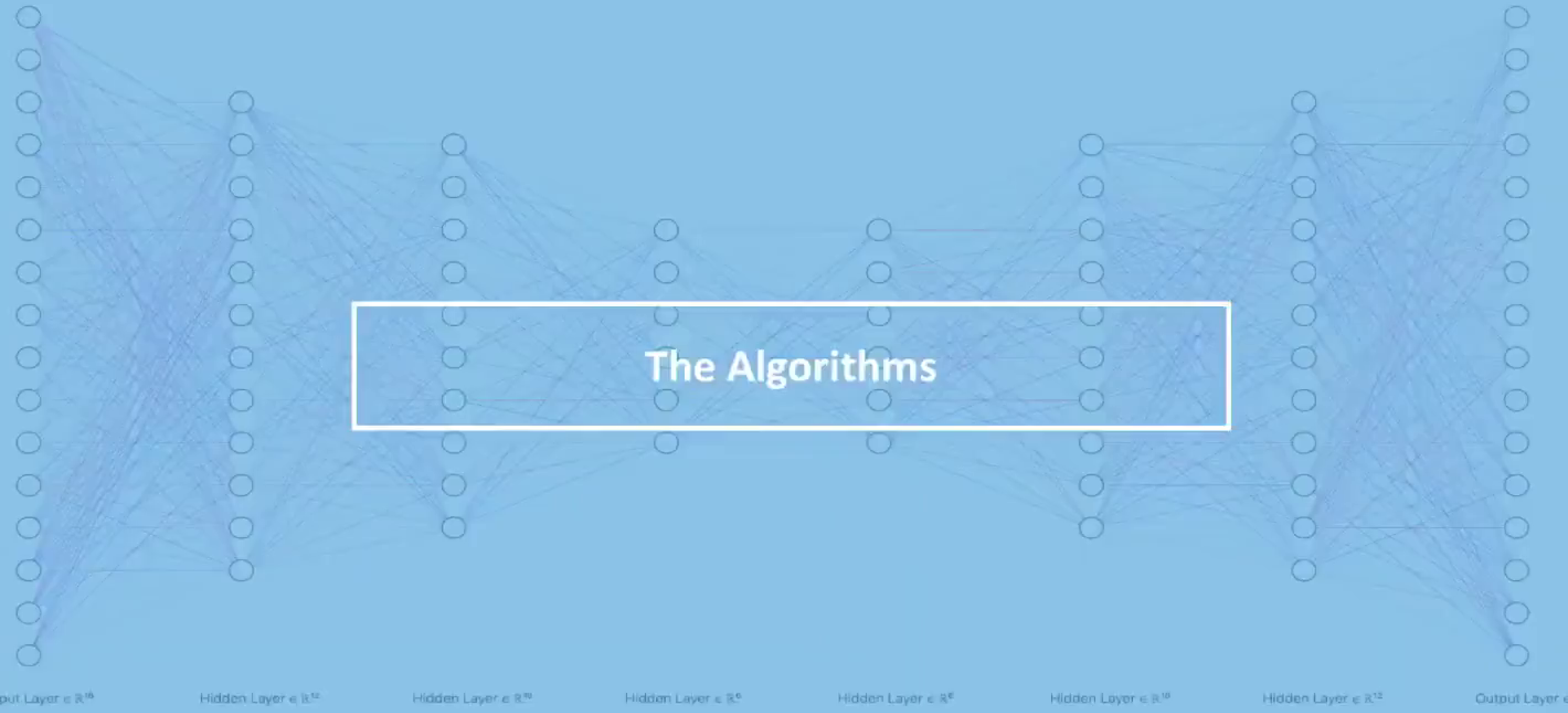


Prevention of Data Degradation

By skipping layers of the encoder portion of the network, the resolution of the reconstructed of 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

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.

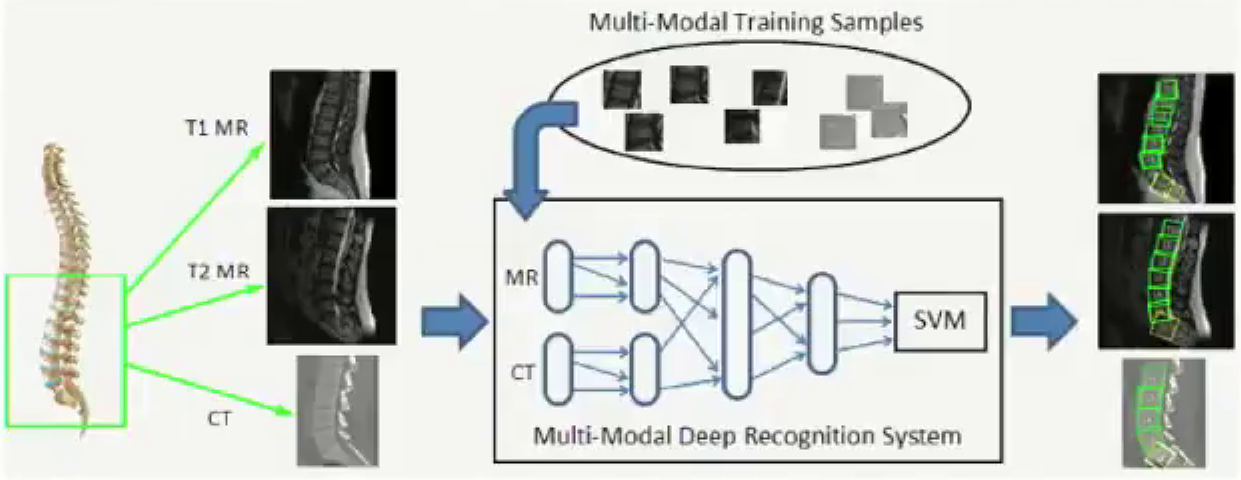
$$r(P,T) = exp(-\epsilon||f_{dp}(i_p) - f_{dp}(T)||^2)$$

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.

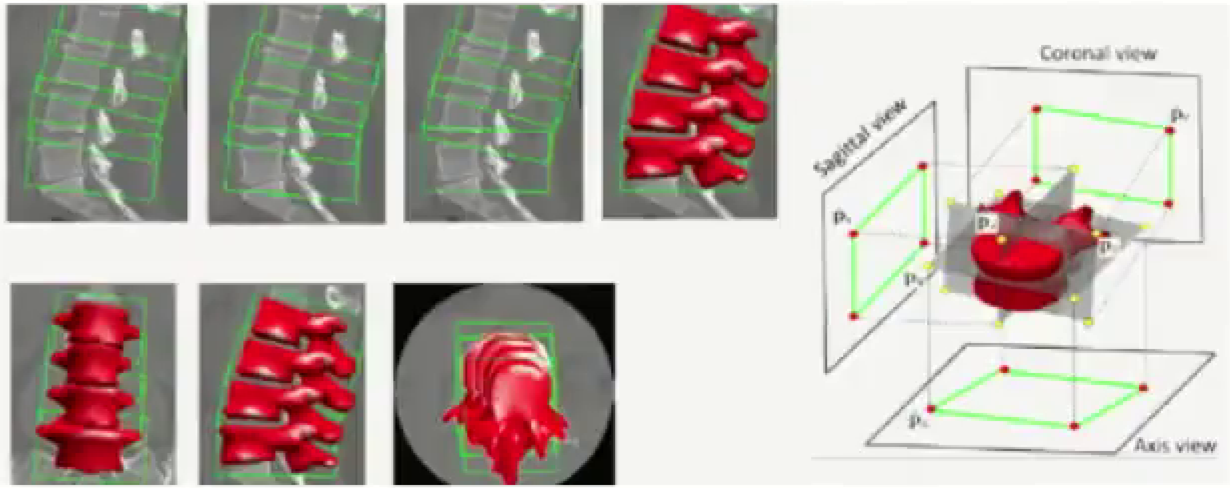
$$J(a_p) = (\frac{\partial d(a_p)}{\partial a_p^1}, \cdots, \frac{\partial d(a_p)}{\partial a_p^k})^T$$

Hierarchical Deformable Model

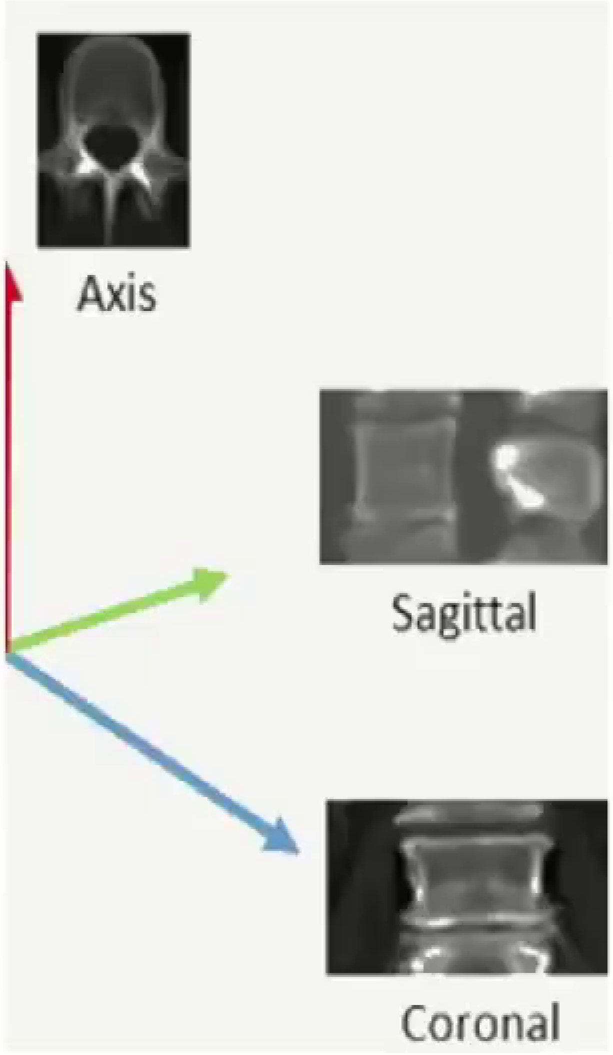
Predicting Spinal Behavior using 3D reconstruction and Feature Fusion



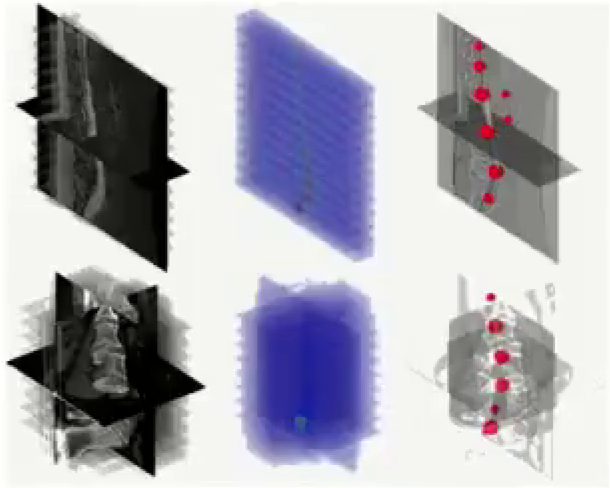
Step 1: Multi-Modal Feature Extraction and Vertebrae Detection



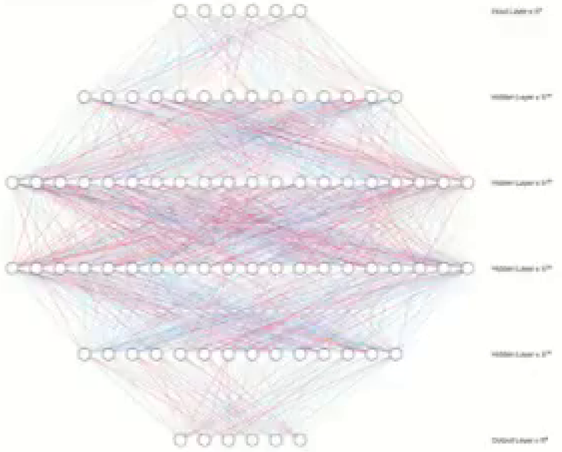
Step 3: Global Shape Registration and Pose Estimation



Planar Reconstruction Orientation



Step 2: Center points for Global Reconstruction



Boltzmann Machine Architecture

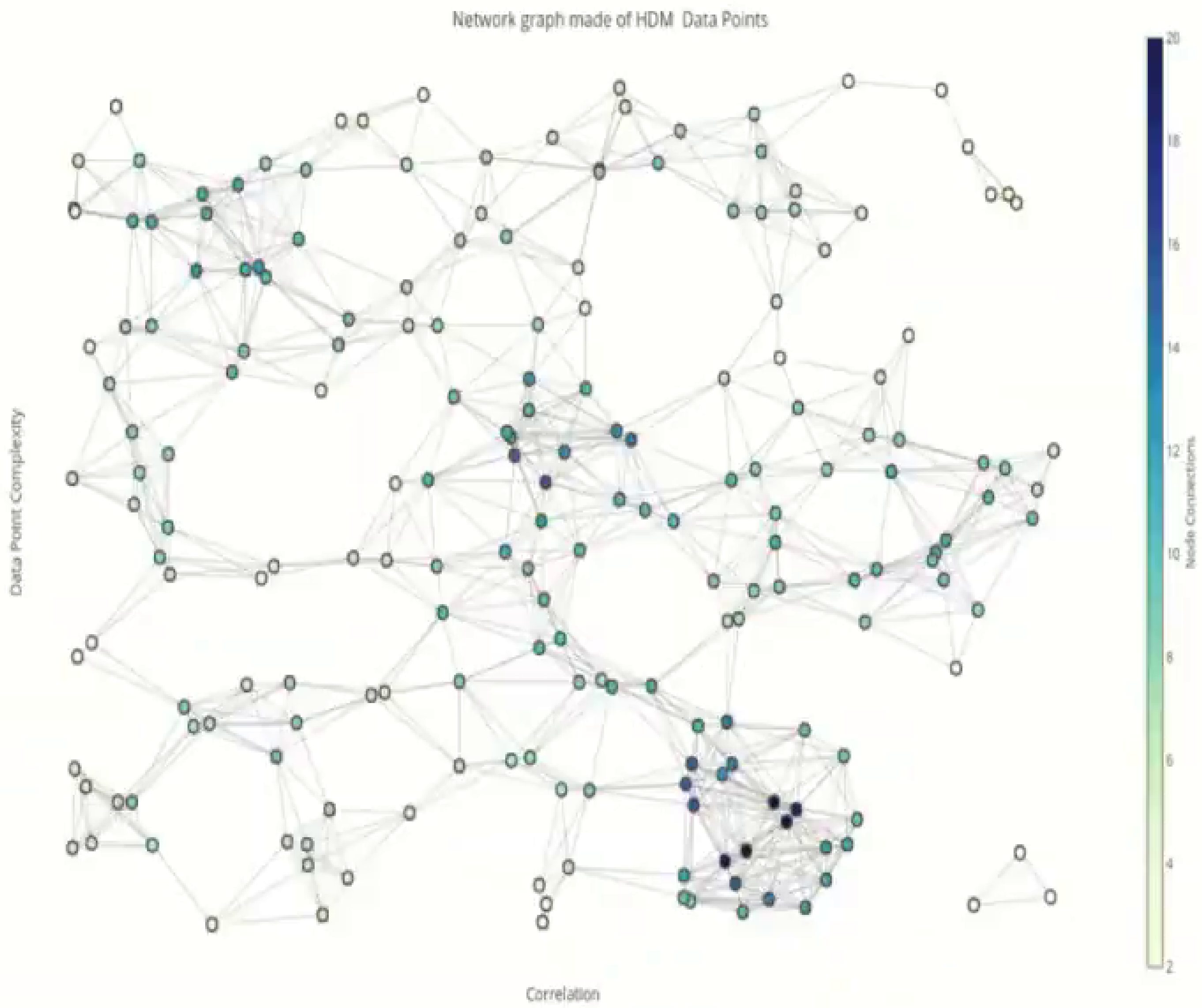
Network Graph of Hierarchical Deformable Model

01. **Anatomical Landmarking**

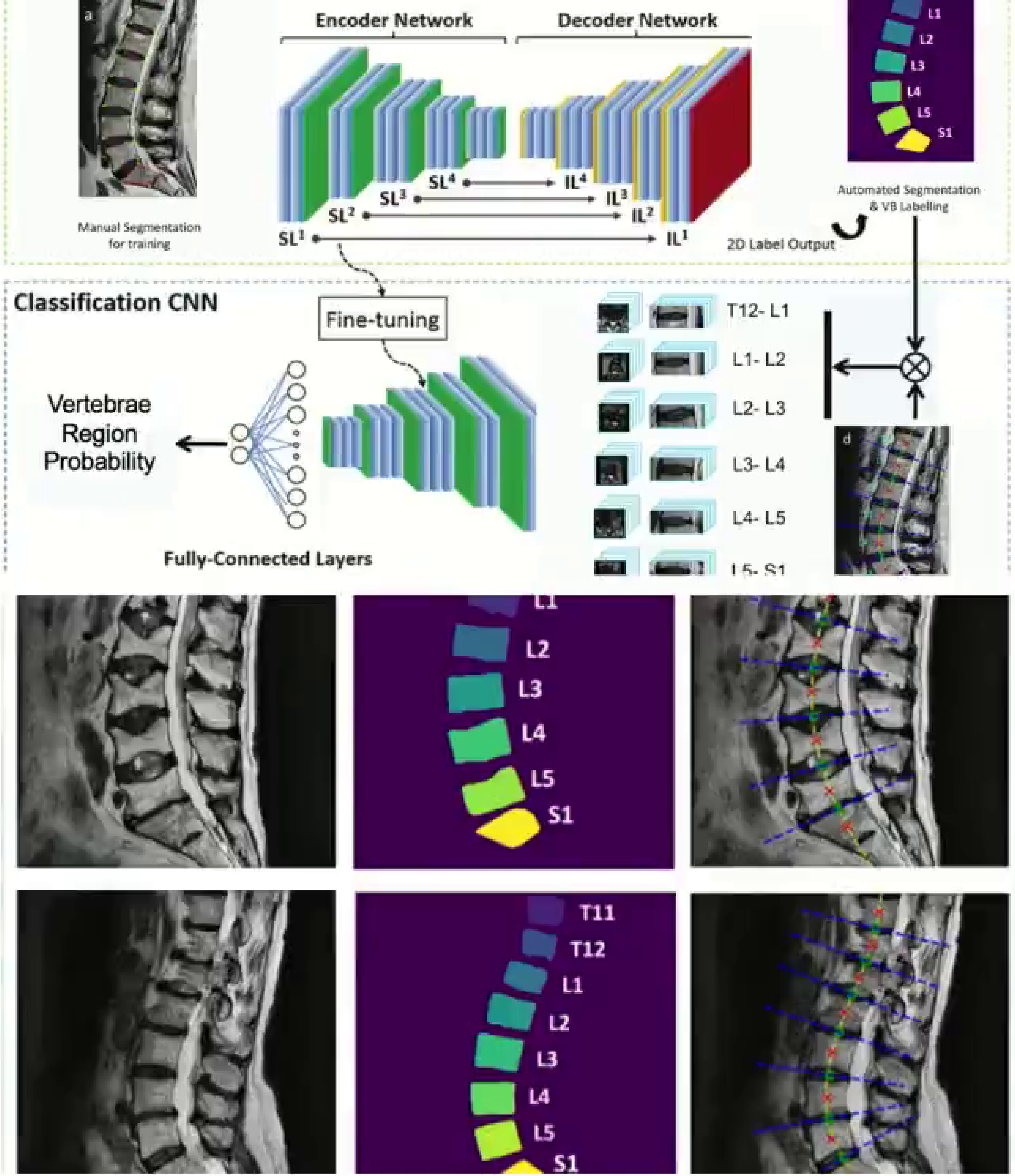
Each Node represents a significant anatomical landmark that was categorized. (e.g. c1 vertebrae, radicular – medullary artery sequence)

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**

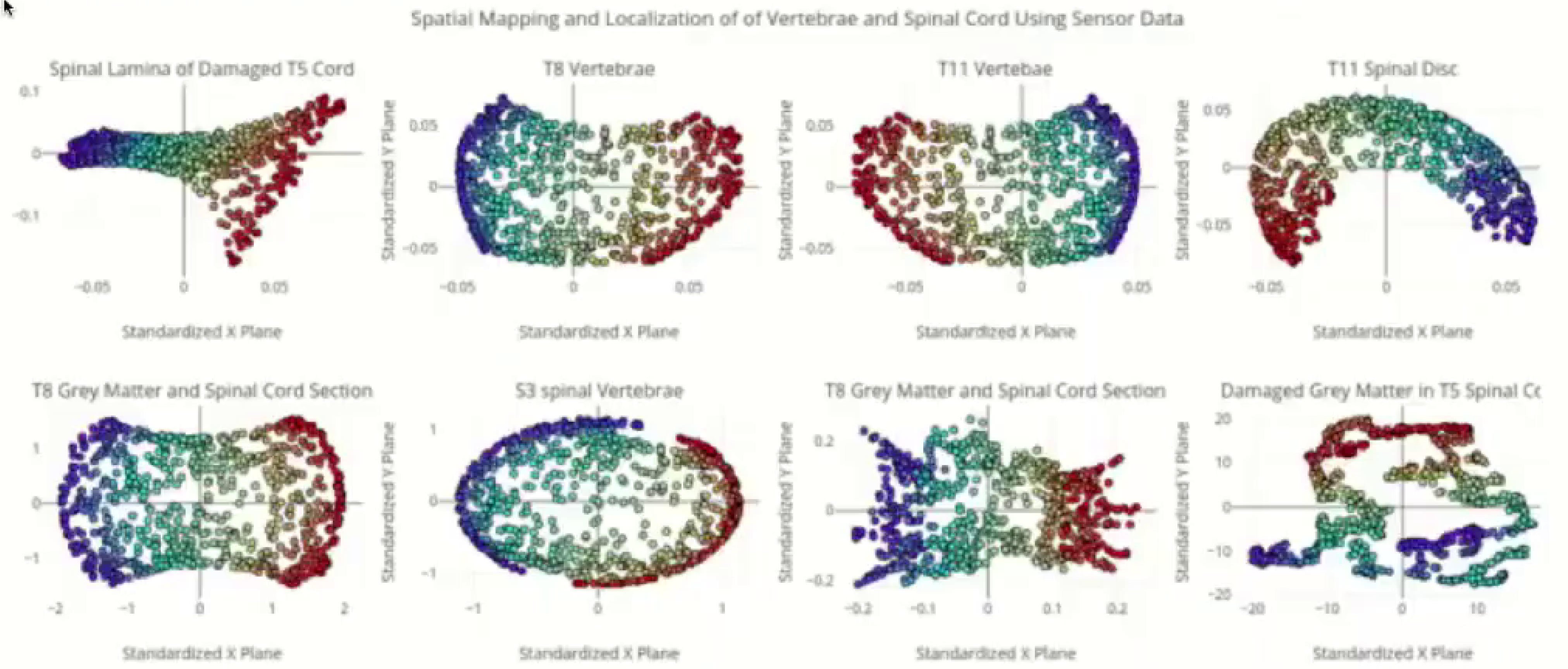
Classifies individual vertebra and segments geometry in spinal column.

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.

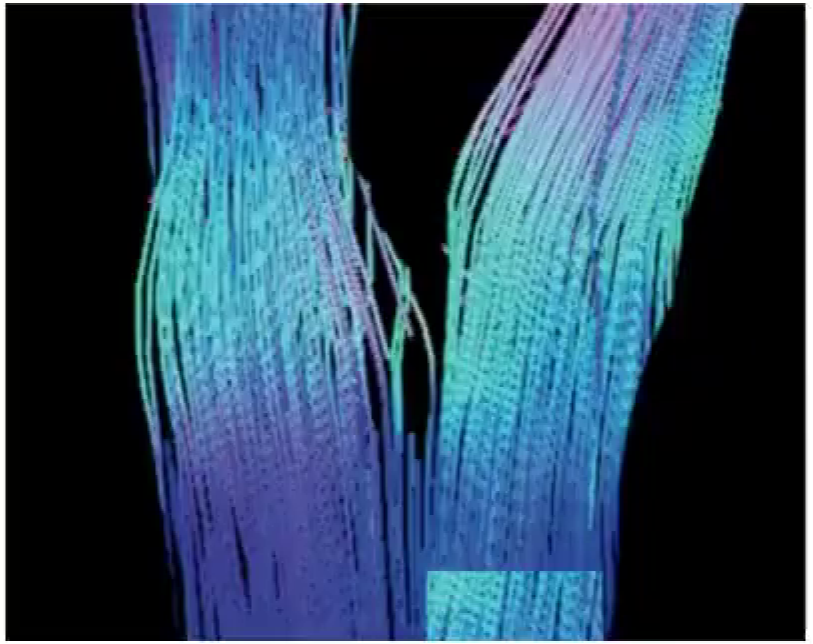
Diffusion Tensor Imaging

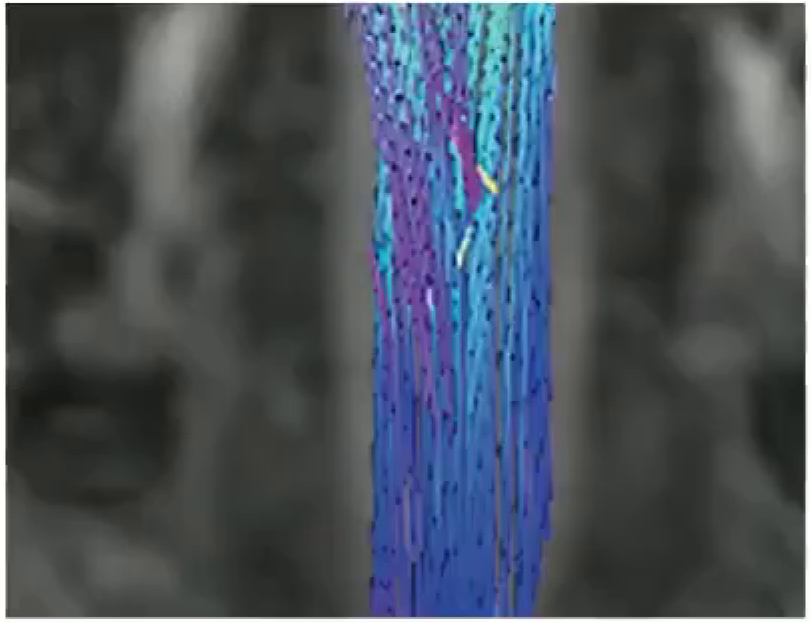
01. **Fibrous Tracking**

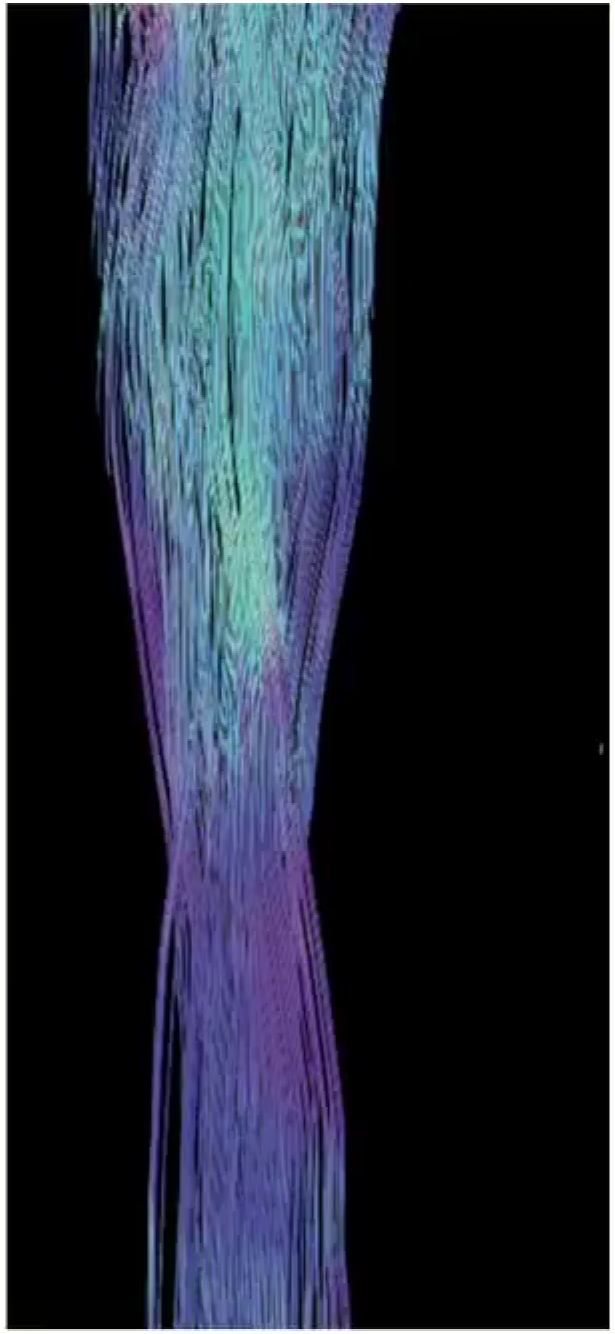
Allows for Tracking of the spinal cord

01. **Nervous and Blood Vessel Mapping**

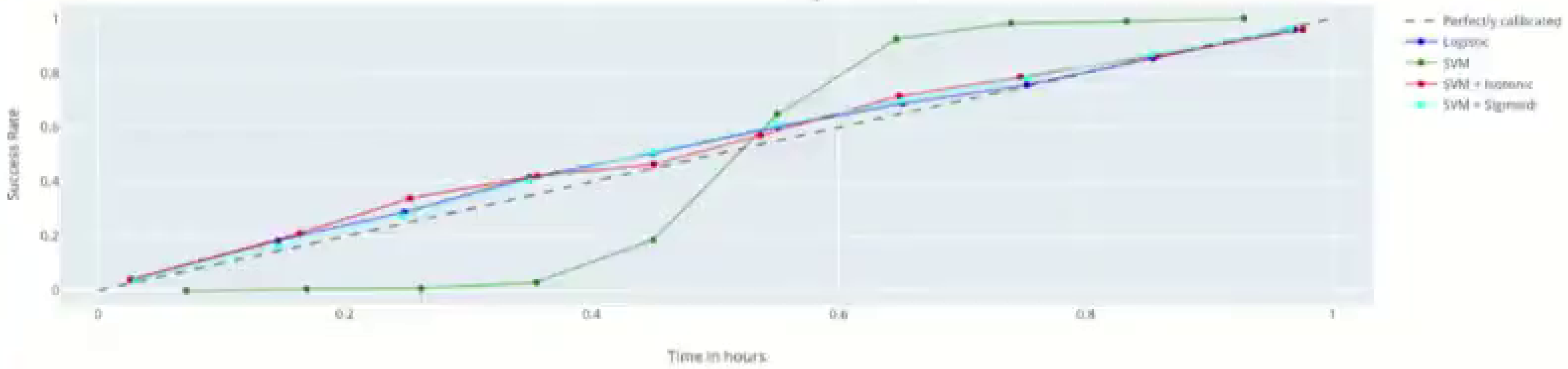
It’s now that much easier and more effective to start your

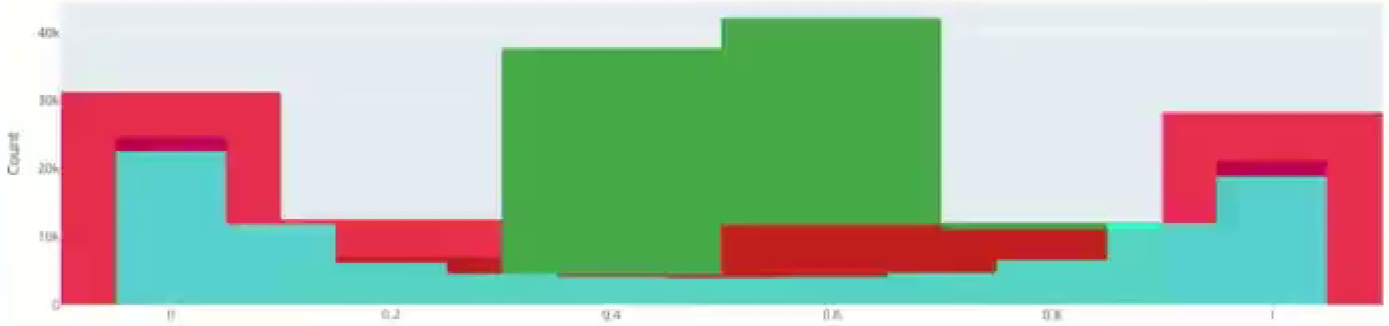


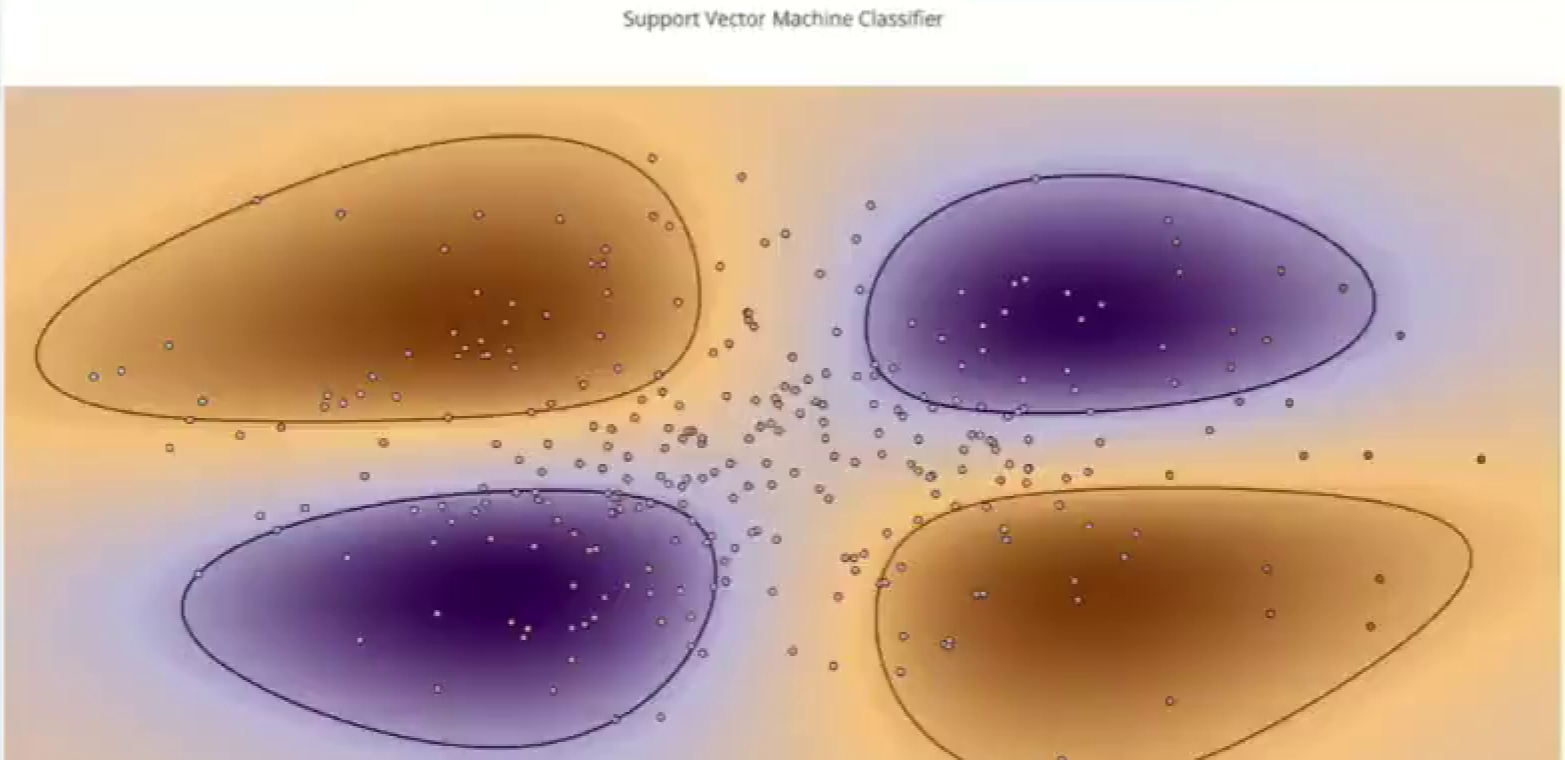





Post Operative Cross Validation Regression
The Results
Measured







Support Vector Machine

01.

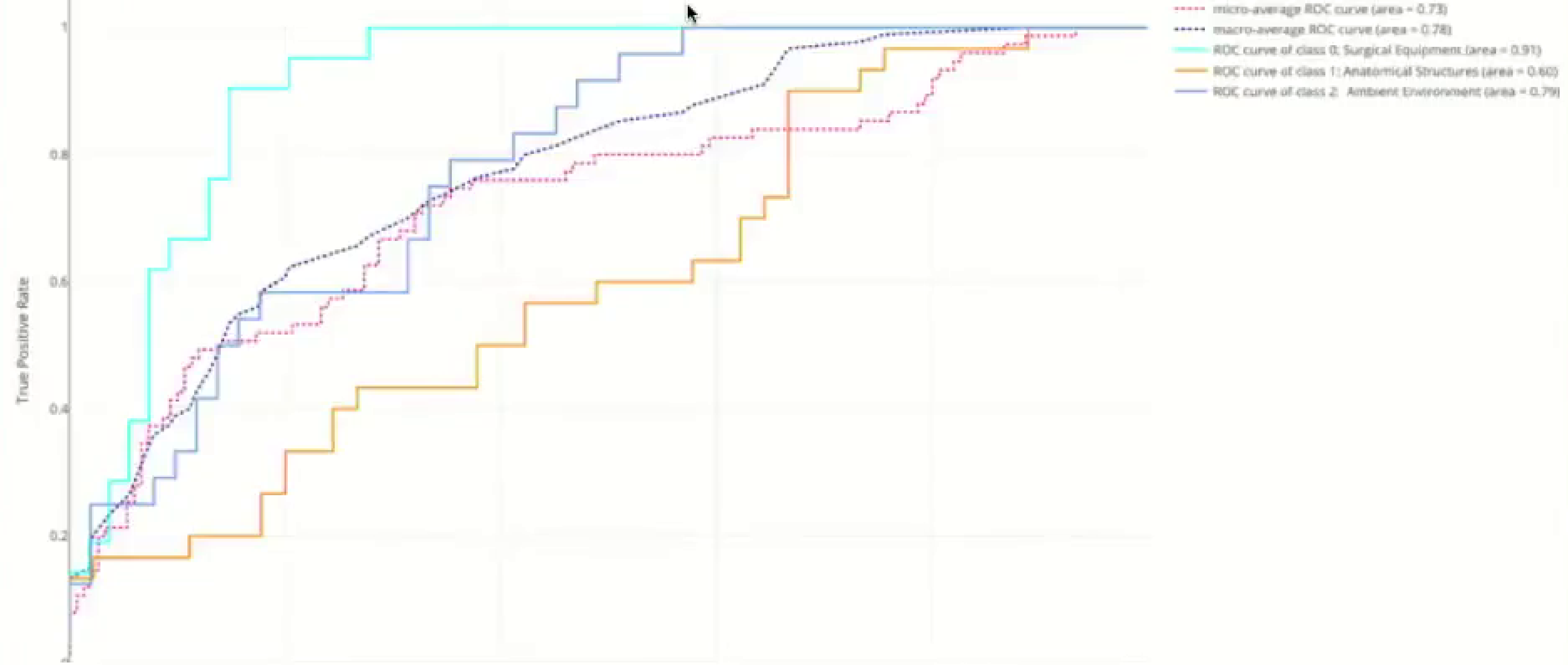
Computationally Inexpensive

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

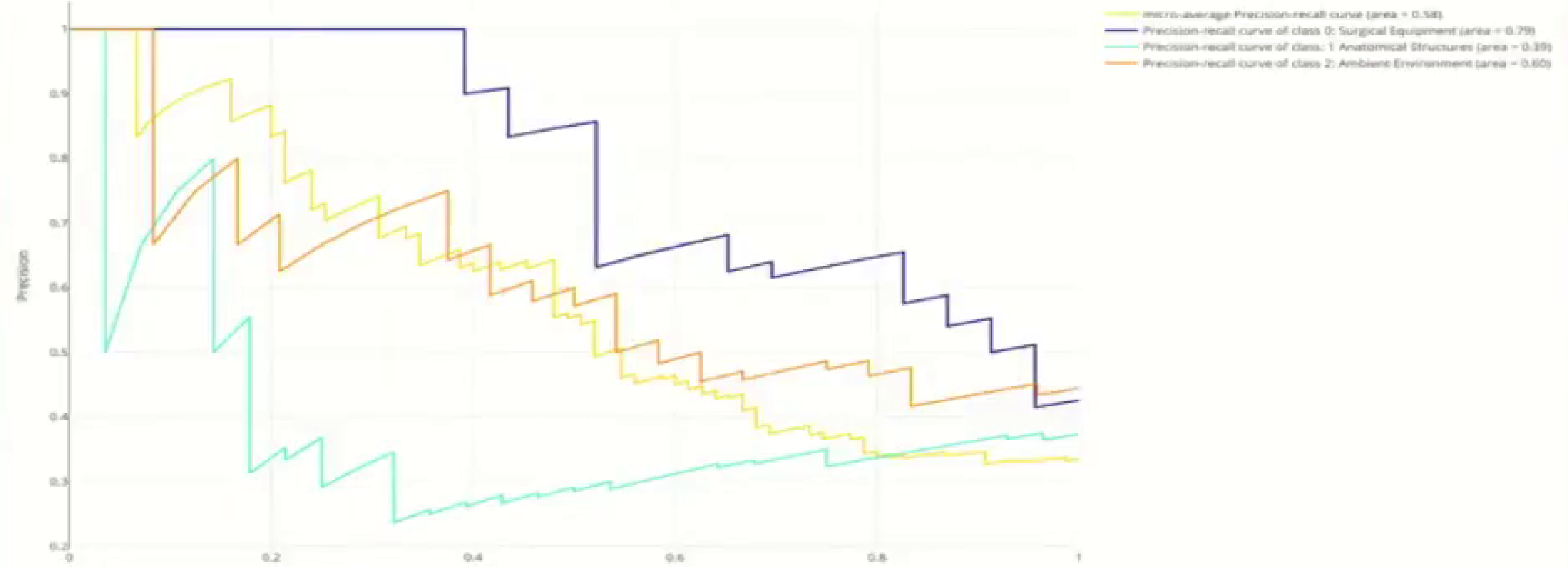
02.

High Accuracy

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



RCNN Identification Extension of Precision-Recall Curve To Multi-Class Data



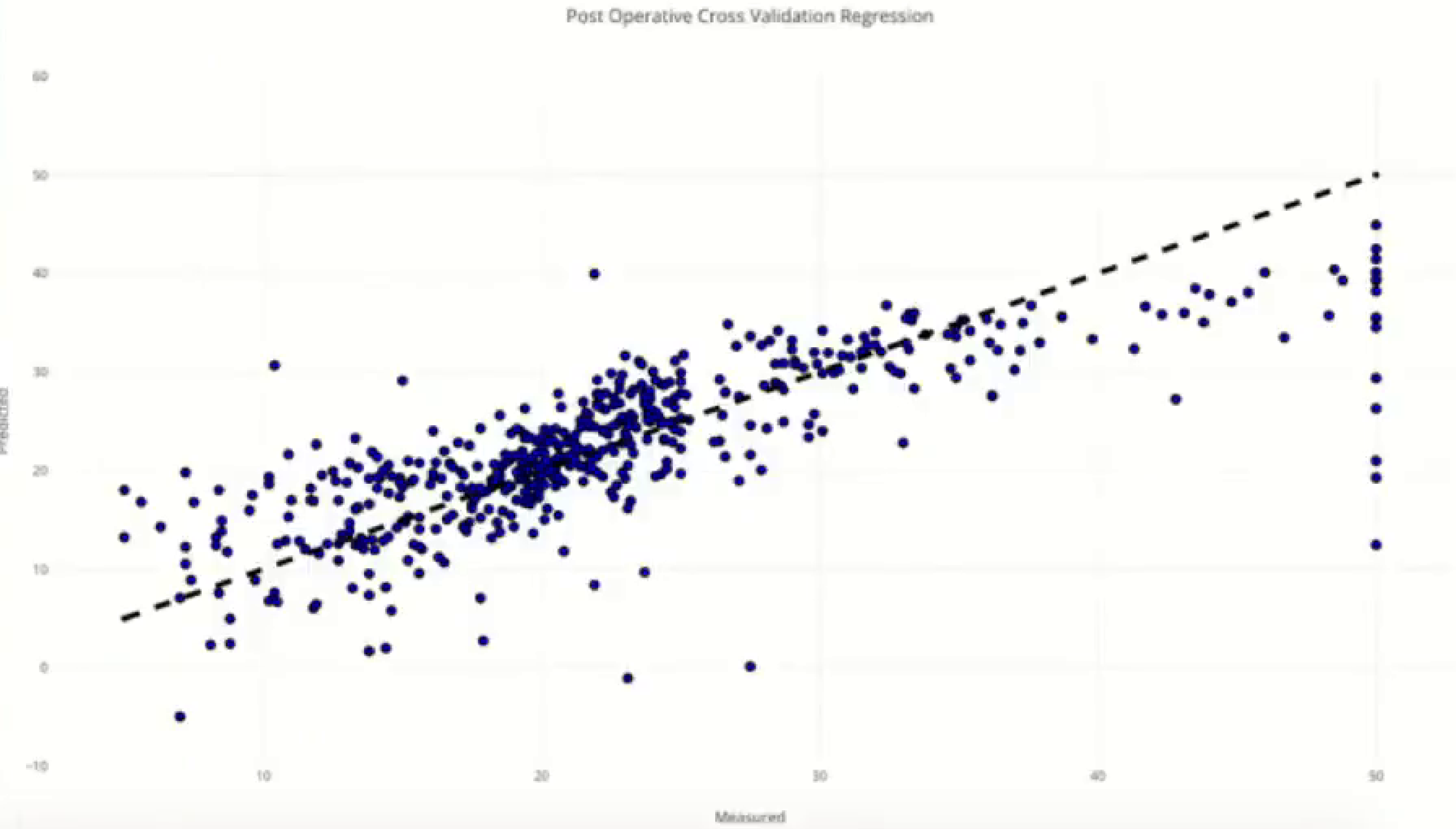
Region-Based Convolution Neural Network

1. Strong Receiver Operating Characteristic

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

2. Convergence on Recall V.S. Precision

All three classes that were trainec converged on on the precision recal spectrum indicating a balanced datase and well-trained model.

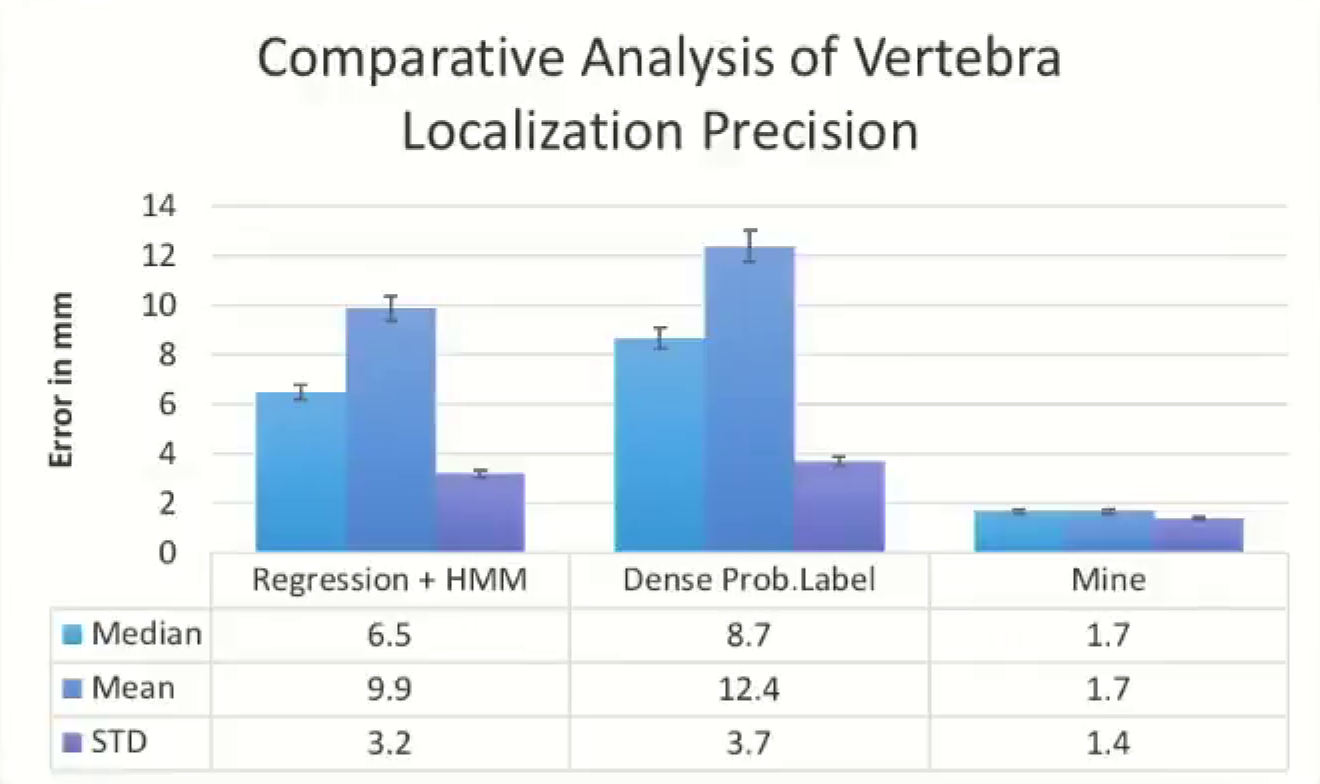


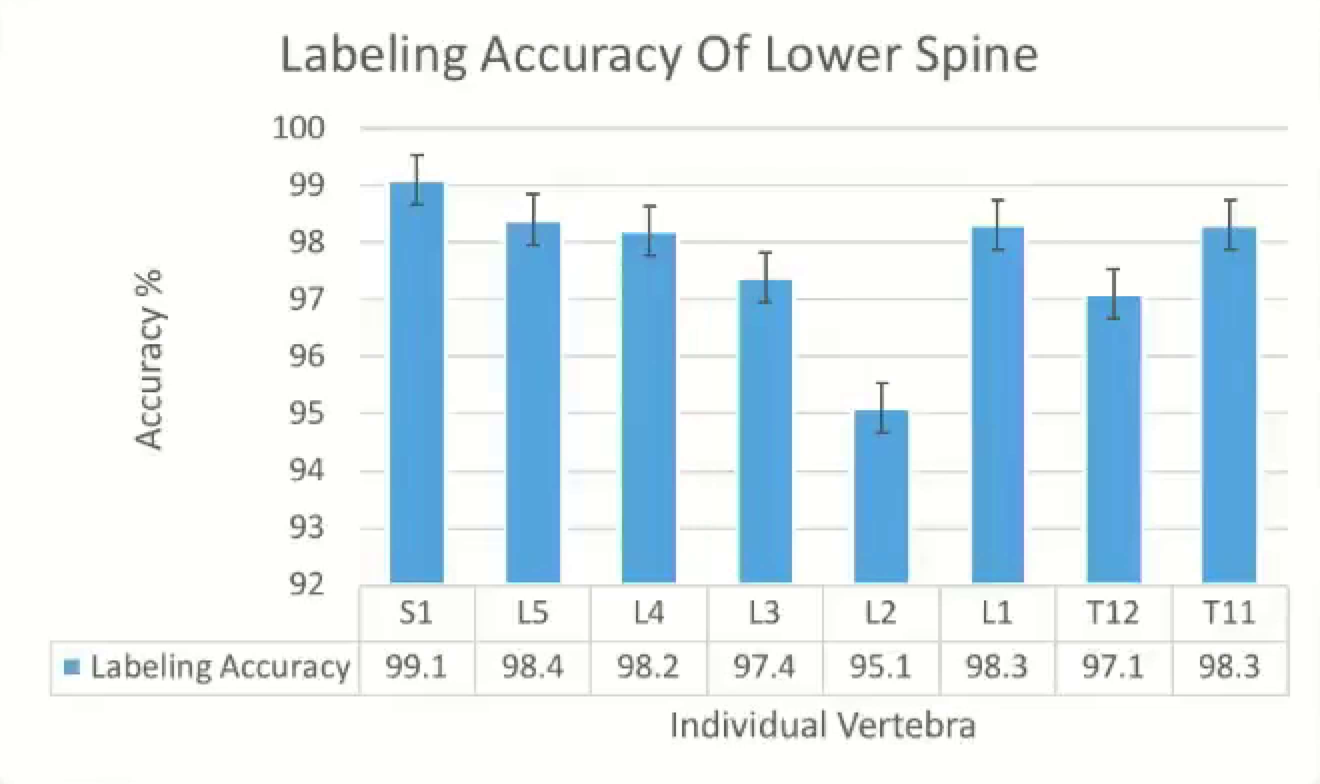
Logistic Regression

01. **High Correlation**

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

Results





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

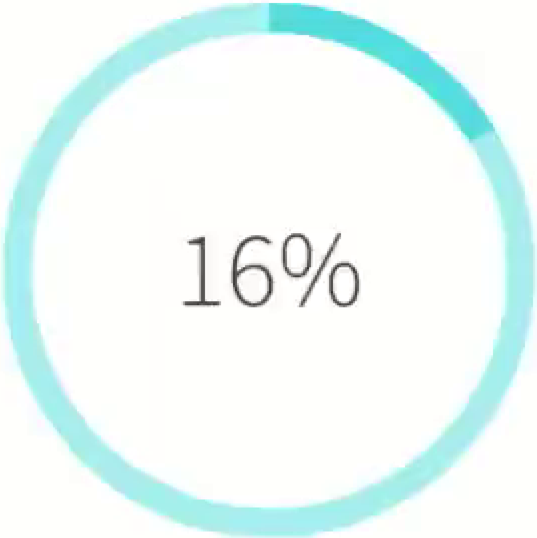
A comparative analysis of 2 different algorithms for anatomical mapping of the spine had mean errors of 9.9mm and 12.4mm compared to the 1.7mm of the experimental system developed.

03

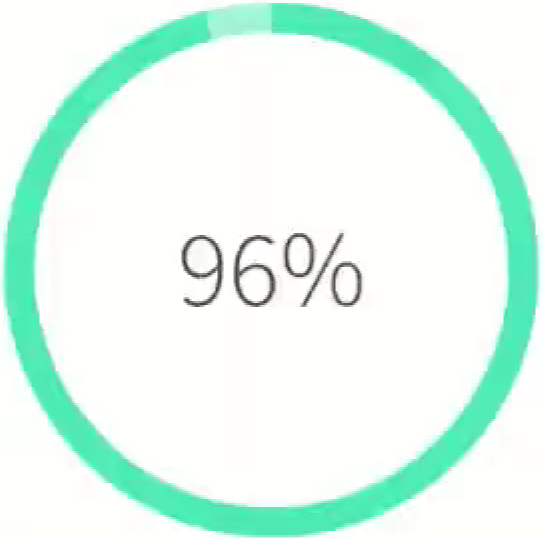
Decreased Detection Time

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

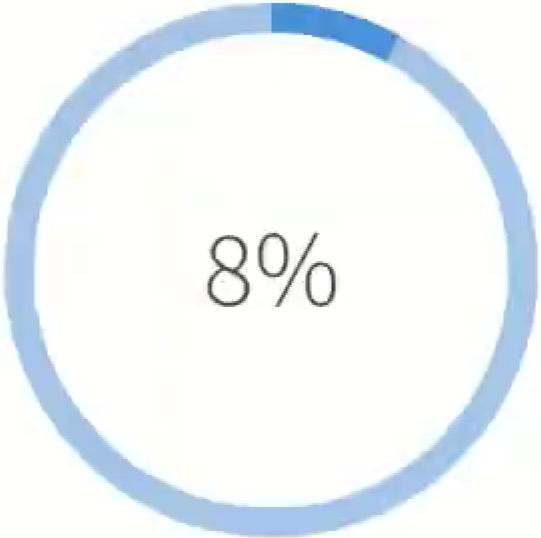
Practical and Economic Viability



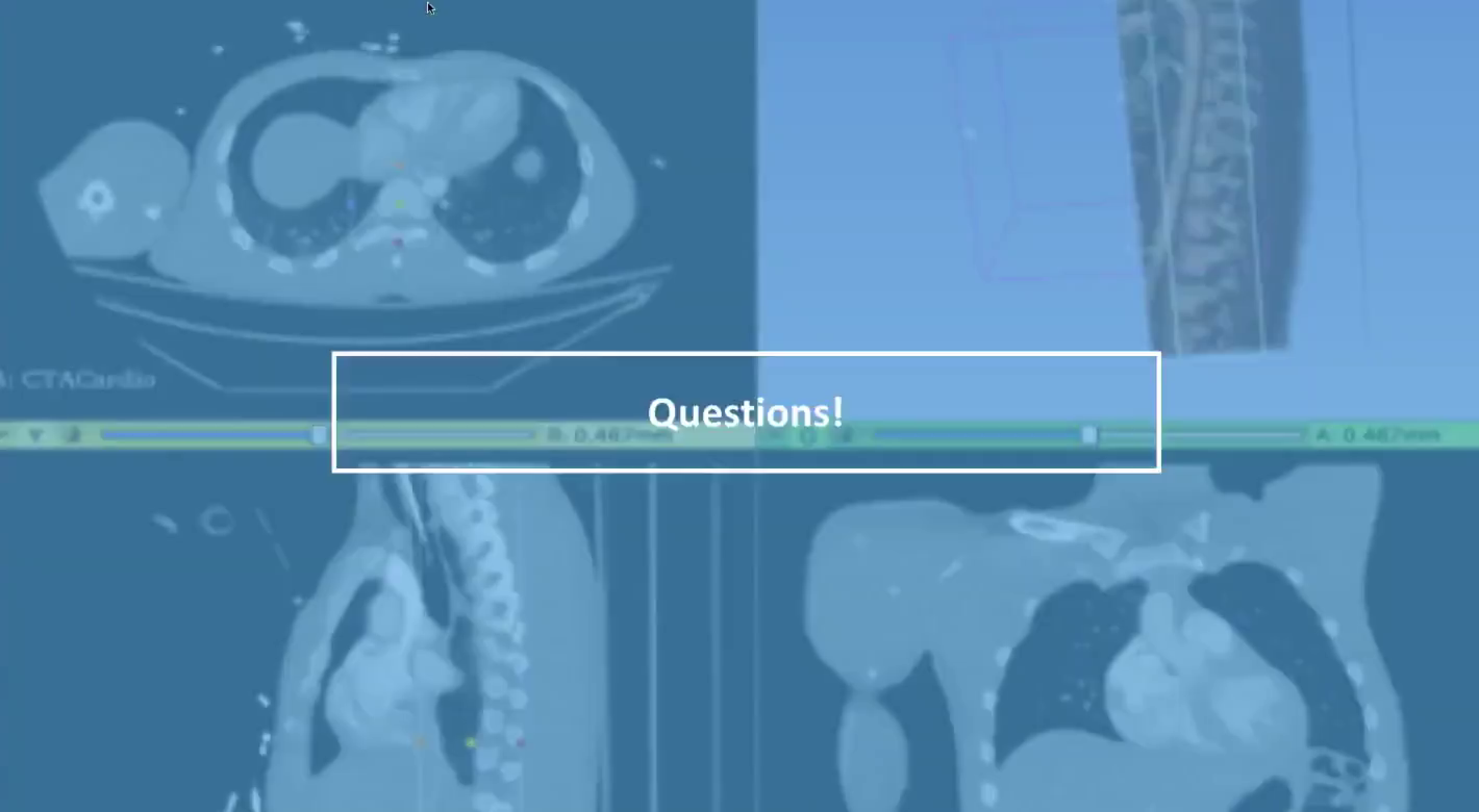
Reduction in operating time



Cheaper than fluoroscopy



Reduction in recovery time



Questions!