



**Excellence
Through AI.**

WhiteBox

AI driven back pain assessment

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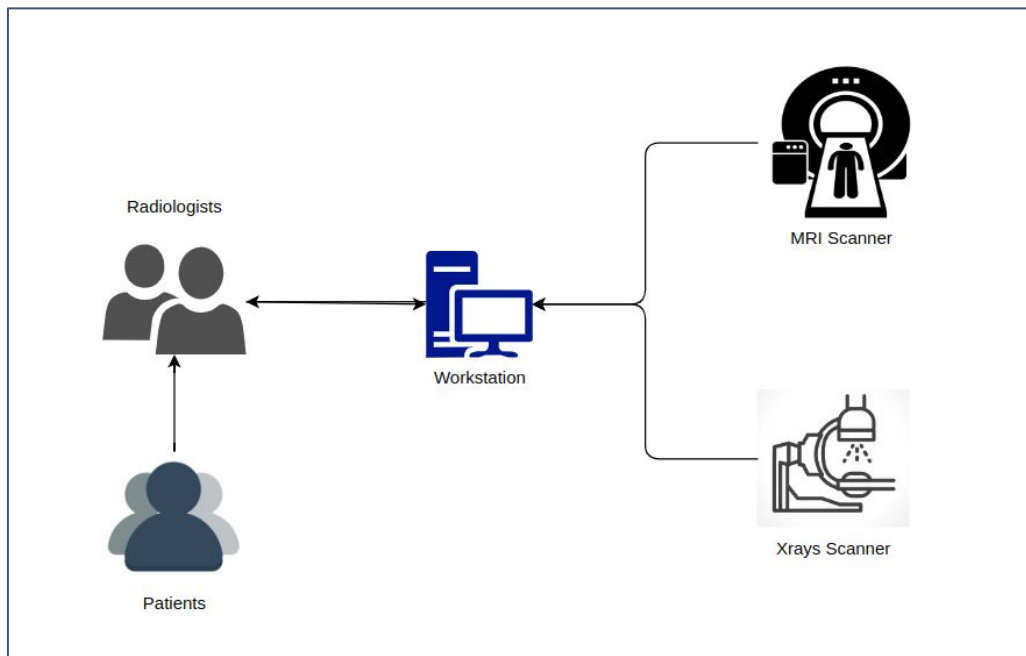
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Lifecycle of a Medical Scan

At the workstation, the data from either the MRI or X-ray scanner is **analyzed**, and interpreted **by radiologists**.



Utilizing time of medical images

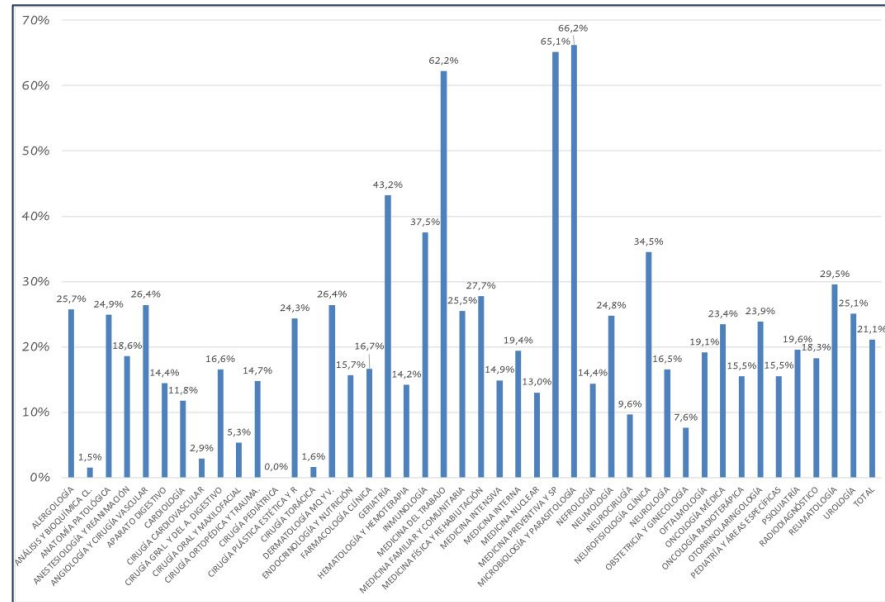
Automating diagnostics can significantly improve the efficiency of medical imaging time.

	X-ray	Ultra-sound	CT Scans	MRI	Fluoro-scopy	Nuclear Medicine	PET-CT Scans	SPECT Scans	Medical Photography
Mar	1	0	0	2	0	1	1	1	0
Apr	1	0	0	3	0	1	2	2	0
May	1	0	0	3	0	1	1	1	0
Jun	1	0	0	3	0	1	1	1	0
Jul	1	0	0	3	0	1	2	2	0
Aug	1	0	0	3	0	1	2	2	0
Sep	1	0	0	3	0	1	1	1	0
Oct	1	0	0	3	0	1	2	1	0
Nov	1	0	0	2	0	1	1	1	0
Dec	1	0	0	2	0	1	1	1	0
Jan	1	0	0	2	0	1	2	1	0
Feb	1	0	0	2	0	1	2	1	0
Mar	1	0	0	2	0	1	2	1	0

Median number of days between 'date of test' and 'date of test report issued' for imaging activity, by modality, March 2021 to March 2022 [2]

Healthcare Workforce Gap

The current **shortage** in health personnel requires innovative approaches.



Number of health personnel demand increase in percentage between 2019-2021 with respect to 2016-2018 [1].

AI-driven solutions:

Enhanced Diagnostics and Predictive Analytics

AI has shown efficacy in early detection of diseases, risk prediction, and personalized treatment plans, ultimately improving patient outcomes.

Workflow Optimization and Efficiency

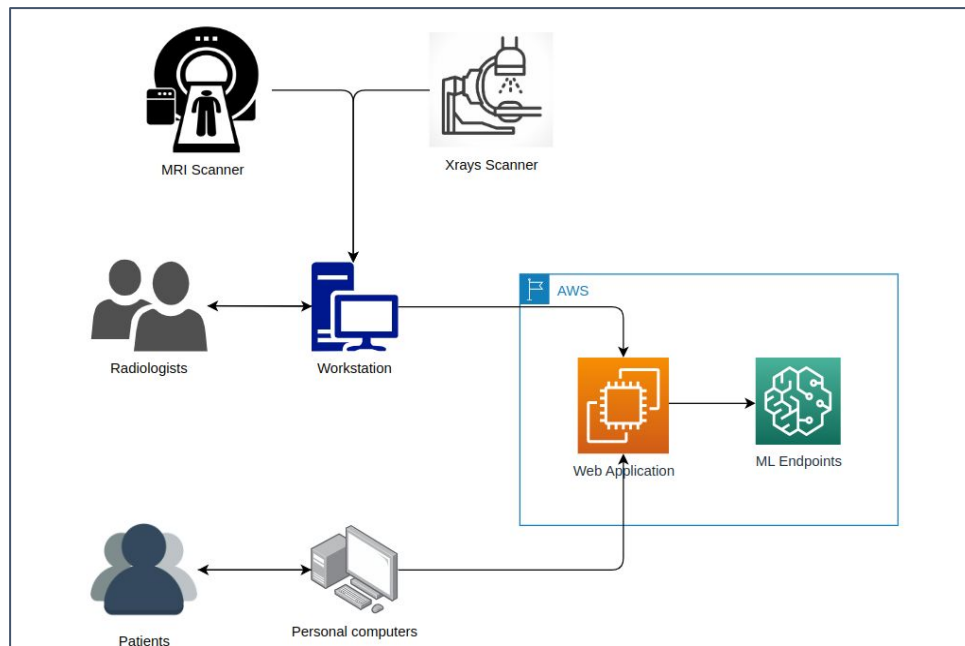
AI-driven decision support allows healthcare professionals to focus more on patient care and complex medical decision-making

Remote Patient Monitoring

To address shortages in certain geographical areas or during public health crises

AI-Boosted Lifecycle of a Medical Scan

The medical data is analyzed by AI and interpreted by radiologists.



Dataset: X-Ray Scans

609 X-Ray scans anterior-posterior x-ray images



Dataset: MRI Scans

515 MRI sequences from the lower back T1 and T2 weighted.



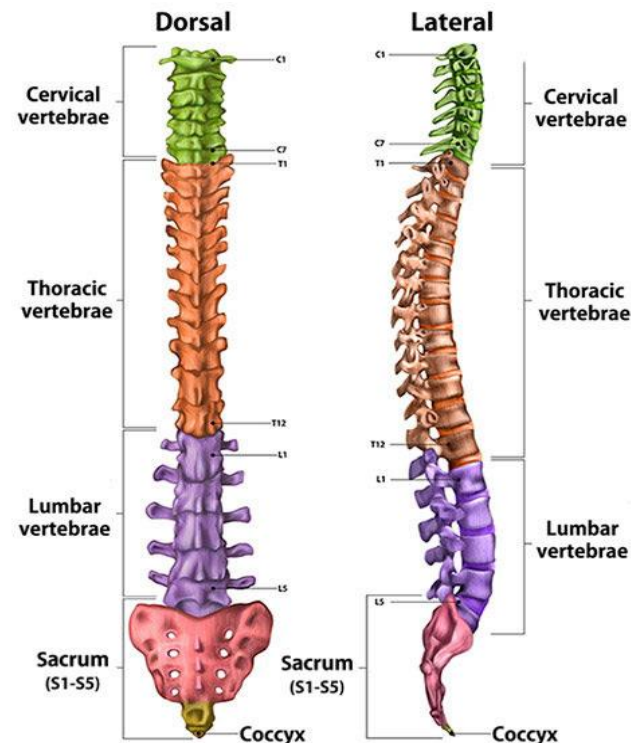
Back pain related measurements

X-Ray:

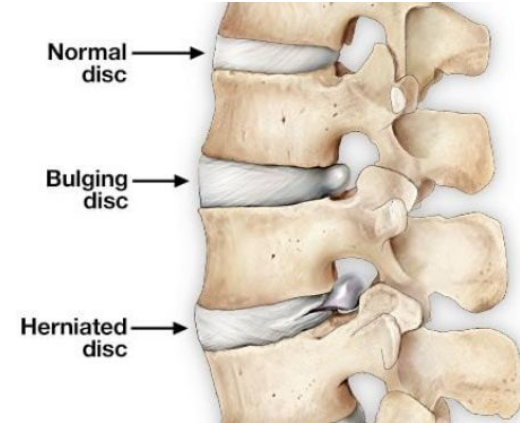
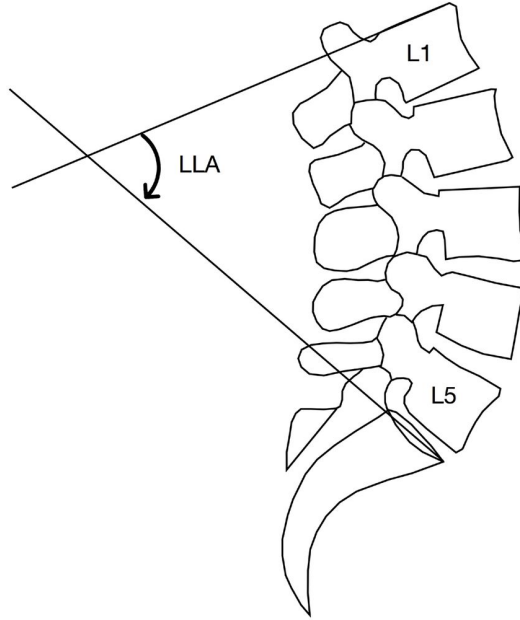
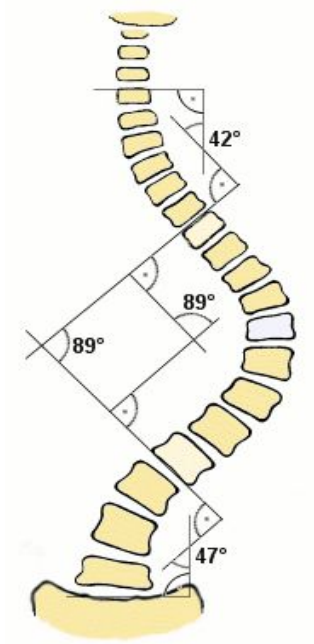
- Cobb Angles
- Spinal Height
- Thoracic Height
- Vertebral Body Height
- Intervertebral disc height

MRI:

- Lumbar Distance
- Lordotic Angle
- Lumbar Curve Area
- Vertebral Body Height
- Intervertebral disc height
- Listhesis Score
- Herniation assessment



Back pain related measurements



Models' Overview




X-Rays Landmark Detection	MRI Landmark Detection	MRI Herniation Detection
 <p>Landmark Detection Model</p> <ul style="list-style-type: none">• Cobb Angles• Spinal Height• Thoracic Height• Vertebral Body Height• Intervertebral Disc height	 <p>Segmentation Model</p> <ul style="list-style-type: none">• Lumbar Distance• Lordotic Angle• Lumbar Curve Area• Vertebral Body Height• Intervertebral Disc Height• Alignment Score• Listhesis Score	 <p>Object Detection Model</p> <ul style="list-style-type: none">• Herniation Detection

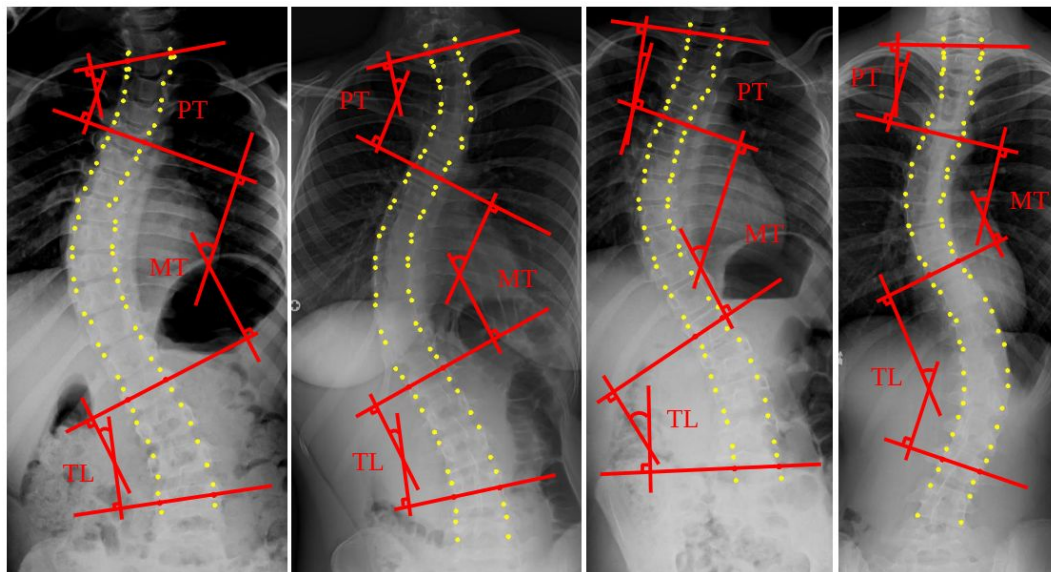
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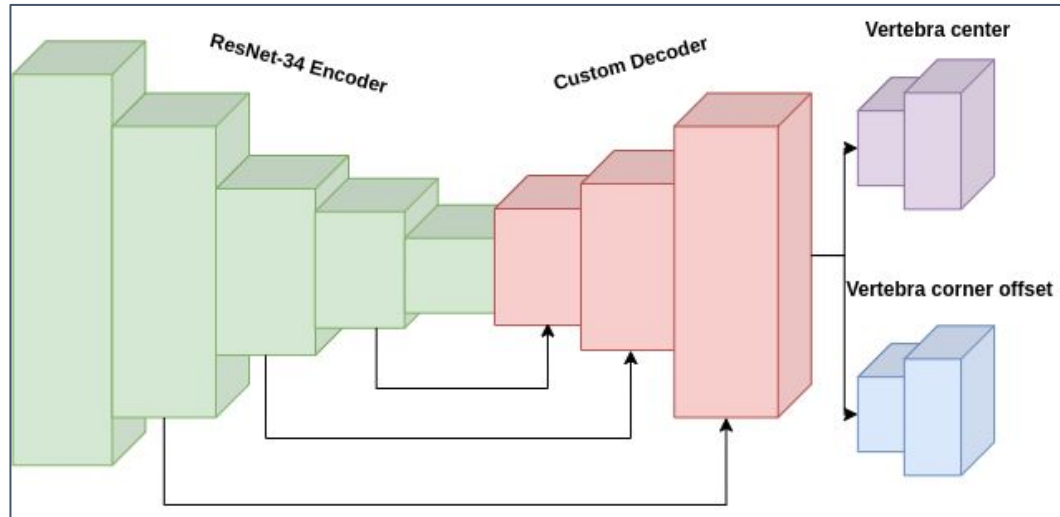
Dataset and Labels

- Dataset obtained from [spineweb](https://spineweb.org/).
- Spinal anterior-posterior x-ray images.
- Landmarks indicating each of the corners of the vertebrae.
- Cobbs' Angles Measurements.



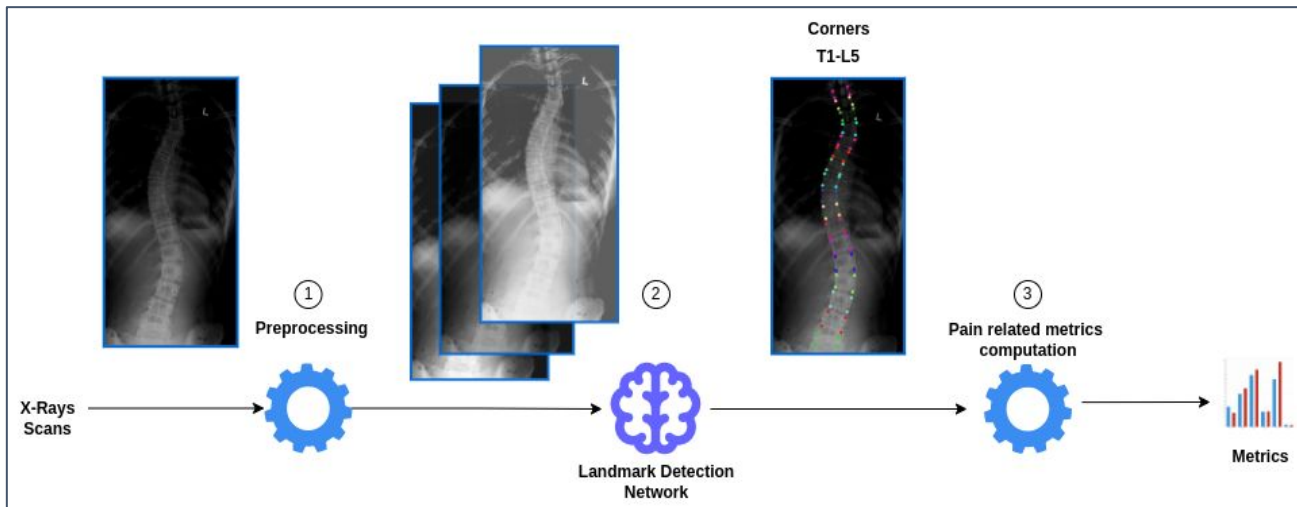
Architecture

- Resnet 34 Backbone pretrained with ImageNet.
- Bilinear pooling decoder.
- 2 Specialized heads.



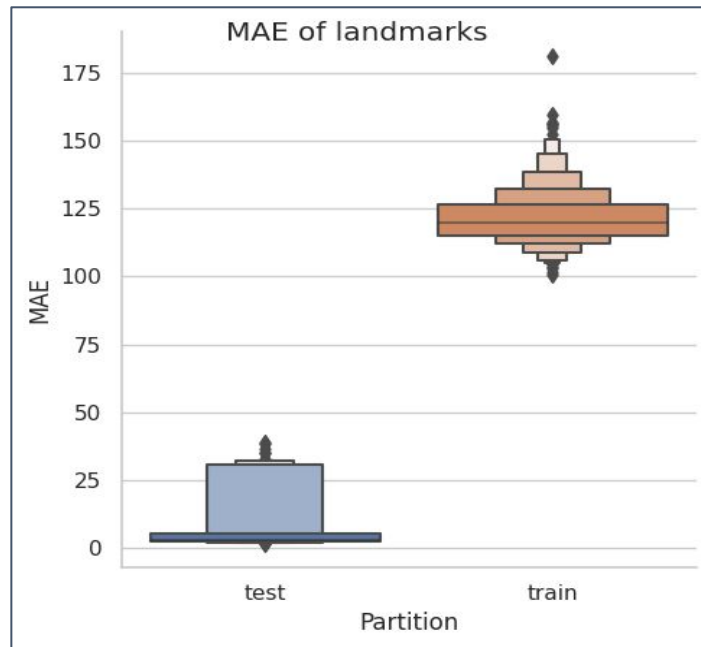
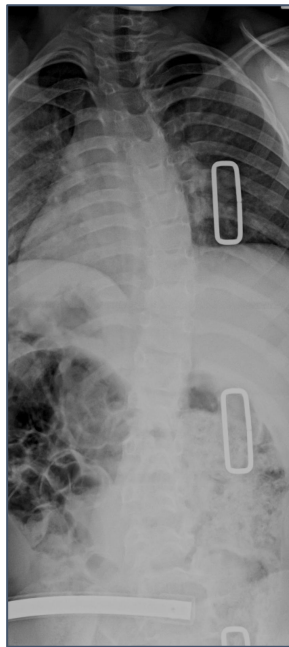
Pipeline

- X-Rays are passed as png files to the pipeline.
- A preprocessing task applies **image enhancement** through **compression** and **equalization**, creating a 3 channels image compatible with the Resnet Backbone.
- The model is applied to detect the corners of the vertebrae from **T1 to L5**.
- **Metrics are computed** using classical algorithms.



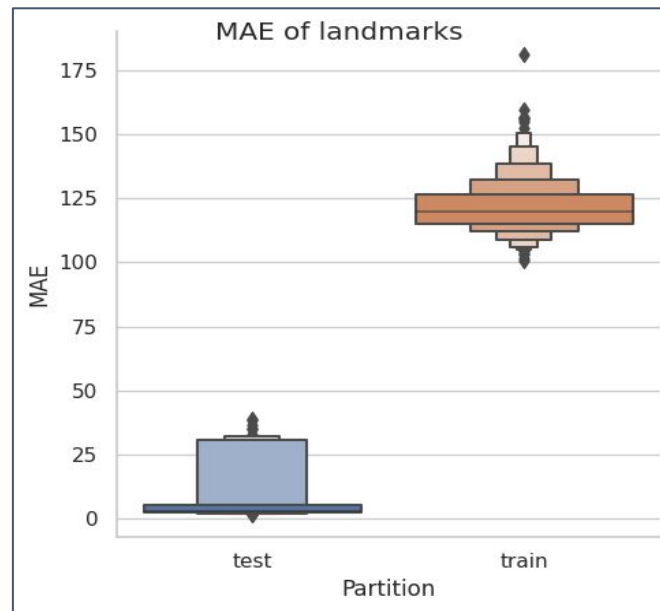
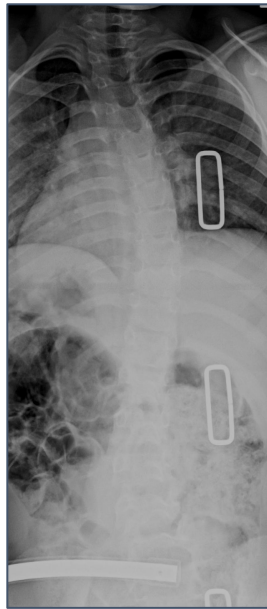
Performance

- The model is **more accurate in the test** set than in the train set.
- The number of **samples** used to compute these metrics is **not representative** enough.



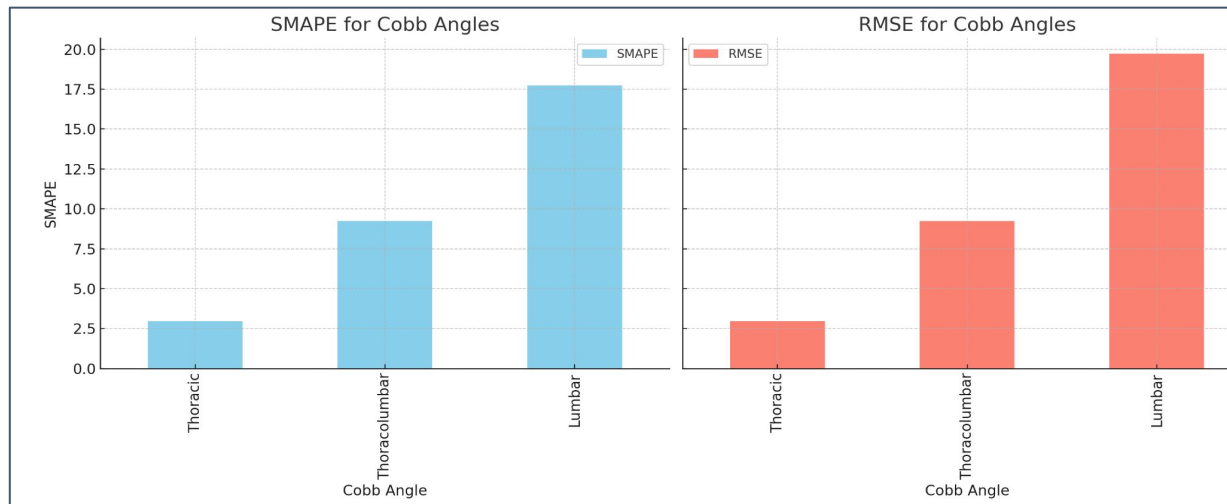
Performance

- The model is **more accurate in the test** set than in the train set.
- The number of **samples** used to compute these metrics is **not representative** enough.
- The **test set** contains more recent X-Rays, therefore they have **higher quality**.



Results: Cobbs' Angles

The lumbar area exhibits a significant increase in error.



- *SMAPE (Symmetric Mean Average Percentage Error) penalizes equally underestimations and overestimations.*
- *RMSE (Root Mean Squared Error) penalizes more the outliers.*



Results: Visualization

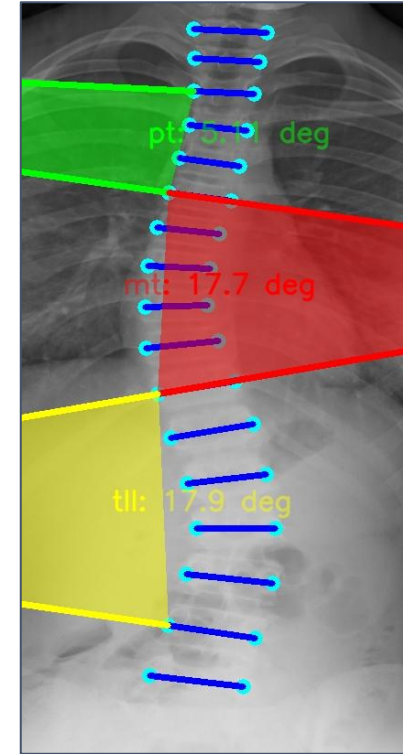
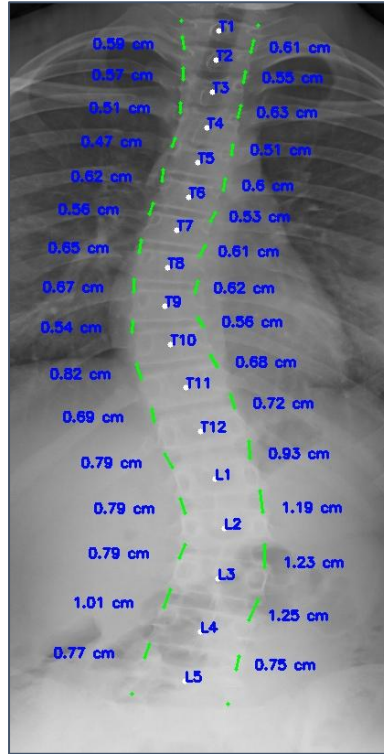
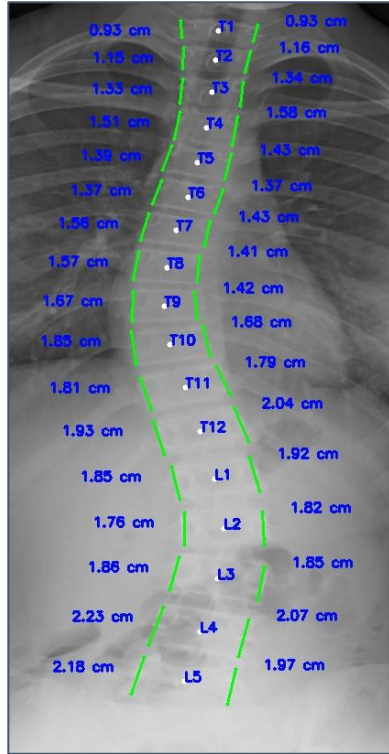


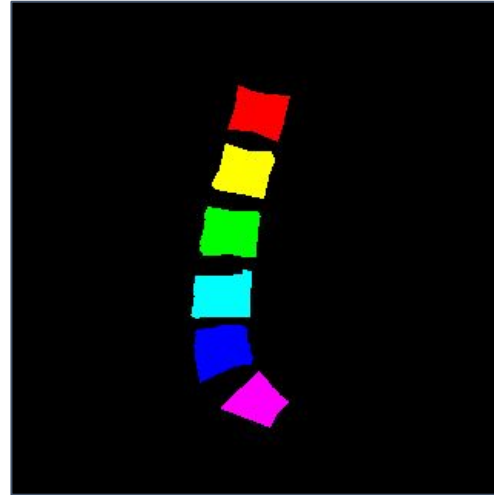
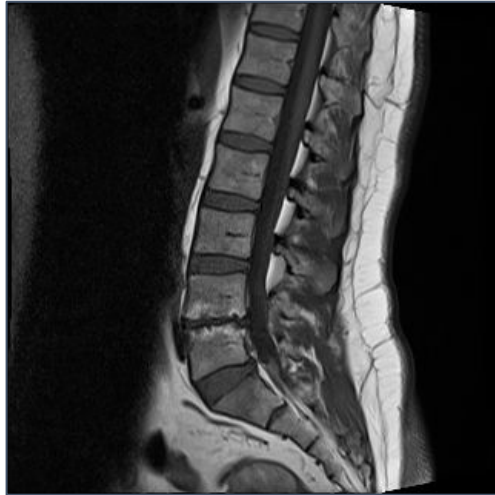
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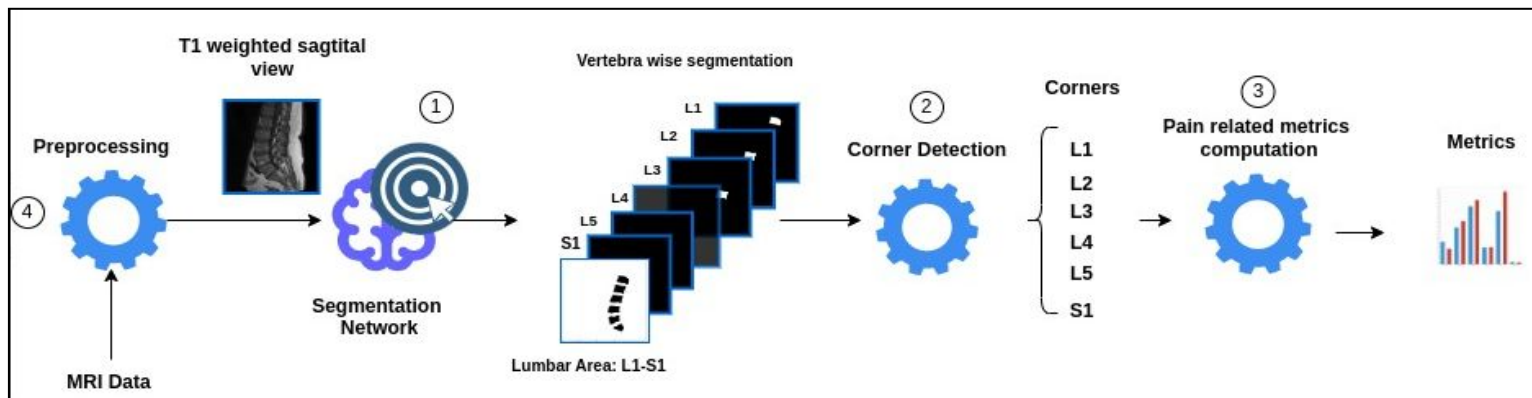
Dataset and Labels

- Dataset obtained from [Mendeley Data](#).
- 515 patients.
- Low Spine Mid-Sagittal Images.
- The lumbar spine vertebrae annotations.



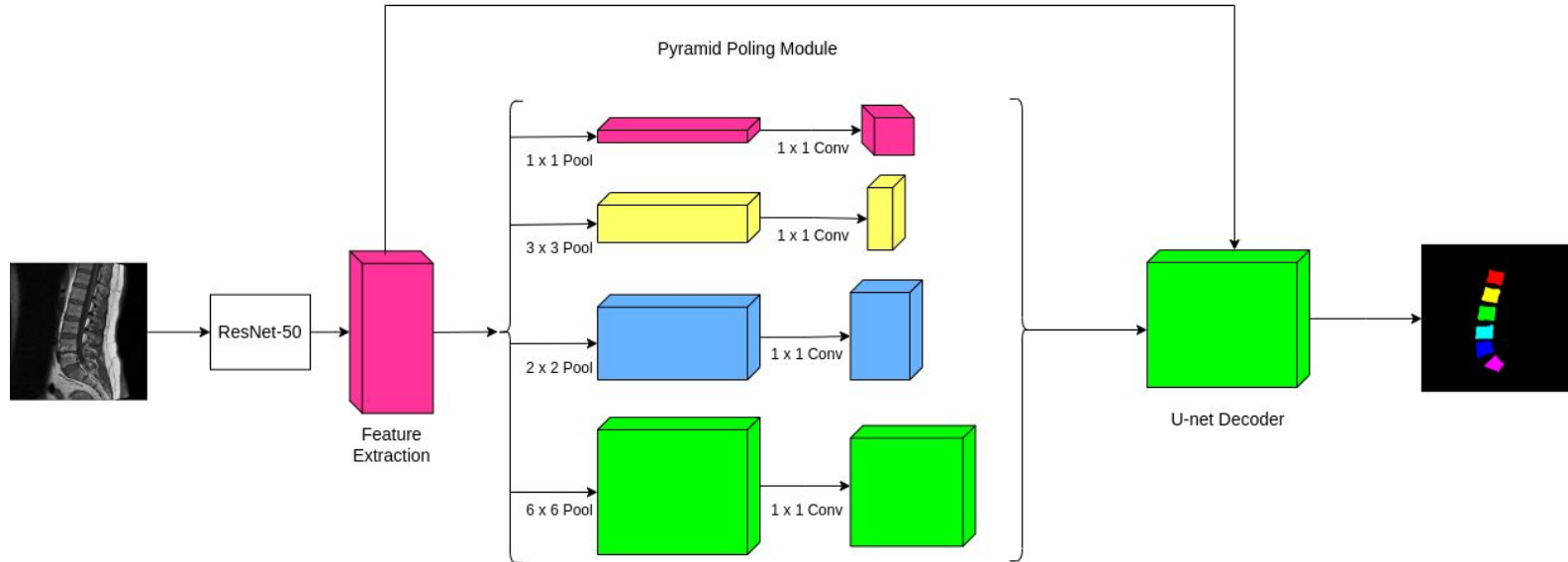
Pipeline

- The **central slice** from the T1 sagittal sequence is extracted.
- The segmentation algorithm isolates each of the vertebrae.
- The **Harris corner detector** detects the corners of the vertebrae from **L1 to S1**.
- Metrics are computed using classical algorithms.

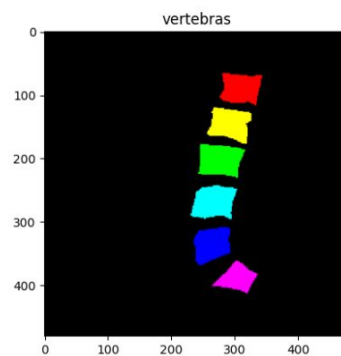
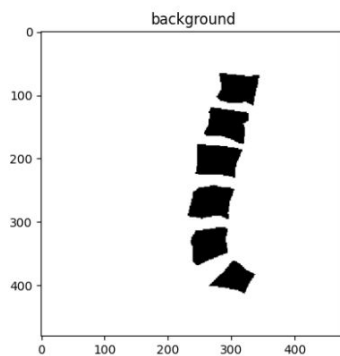
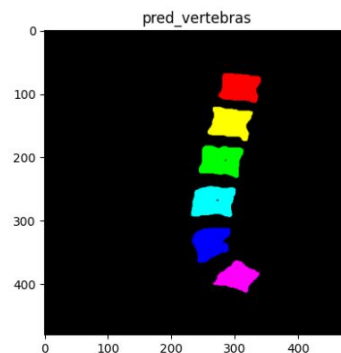
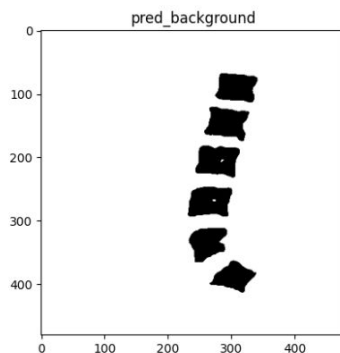
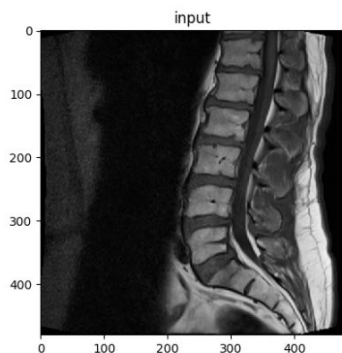


Architecture

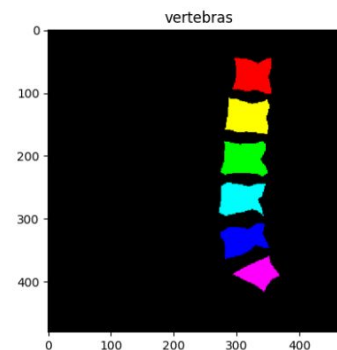
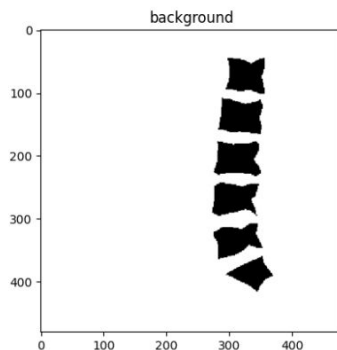
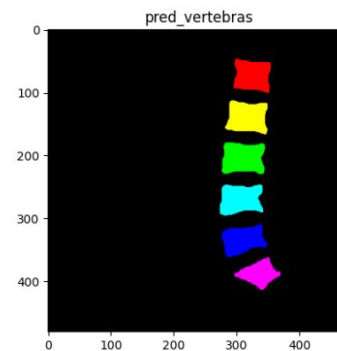
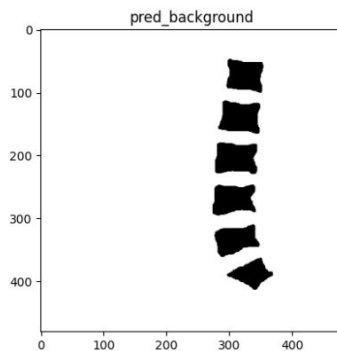
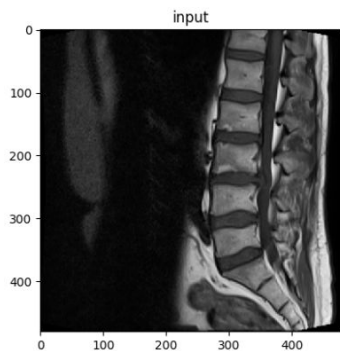
- Resnet 50 Backbone pretrained with ImageNet combined with PSPNet encoder.
- U-Net Decoder.



Segmentation Output

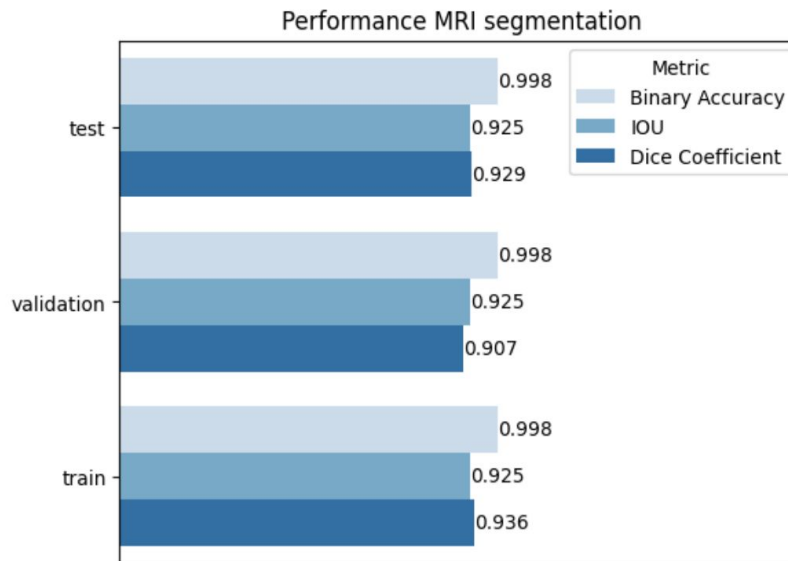


Segmentation Output

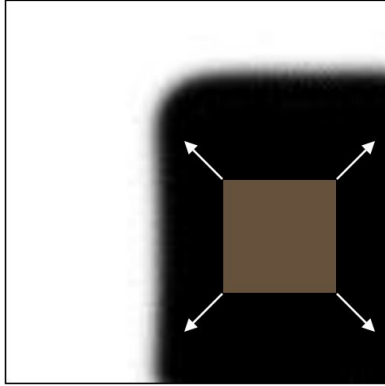


Model Performance

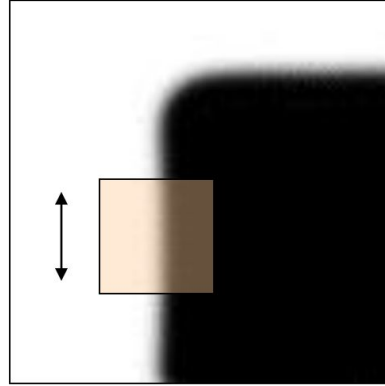
- **DICE** measures the similarity between two sets by considering the intersection and union of their elements.
- **IOU** is another metric that evaluates the overlap between predicted and ground truth regions.
- Dice Coefficient and IOU Metrics: **93% overlap**.



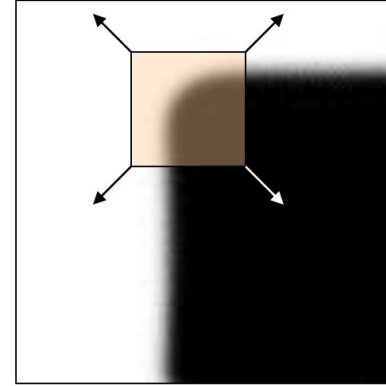
Corner Detection



“flat” region:
no change in
all directions



“edge”:
no change
along the edge
direction



“corner”:
significant
change in all
directions

Harris Corner Detection

Corner Detection: Mathematics

Change in appearance for the shift $[u, v]$:

$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2$$

Diagram illustrating the components of the equation:

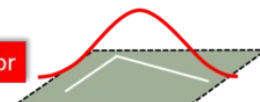
- $w(x, y)$: Window function
- $I(x + u, y + v)$: Shifted intensity
- $I(x, y)$: Intensity

Window function $w(x, y) =$



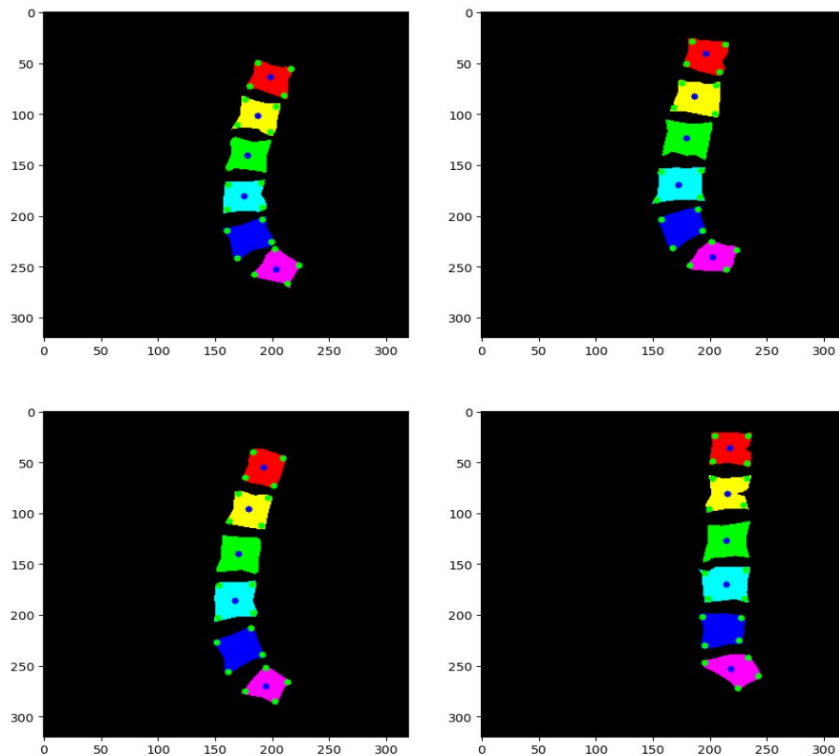
1 in window,
0 outside

or



Gaussian

Corner Detection Output



Results

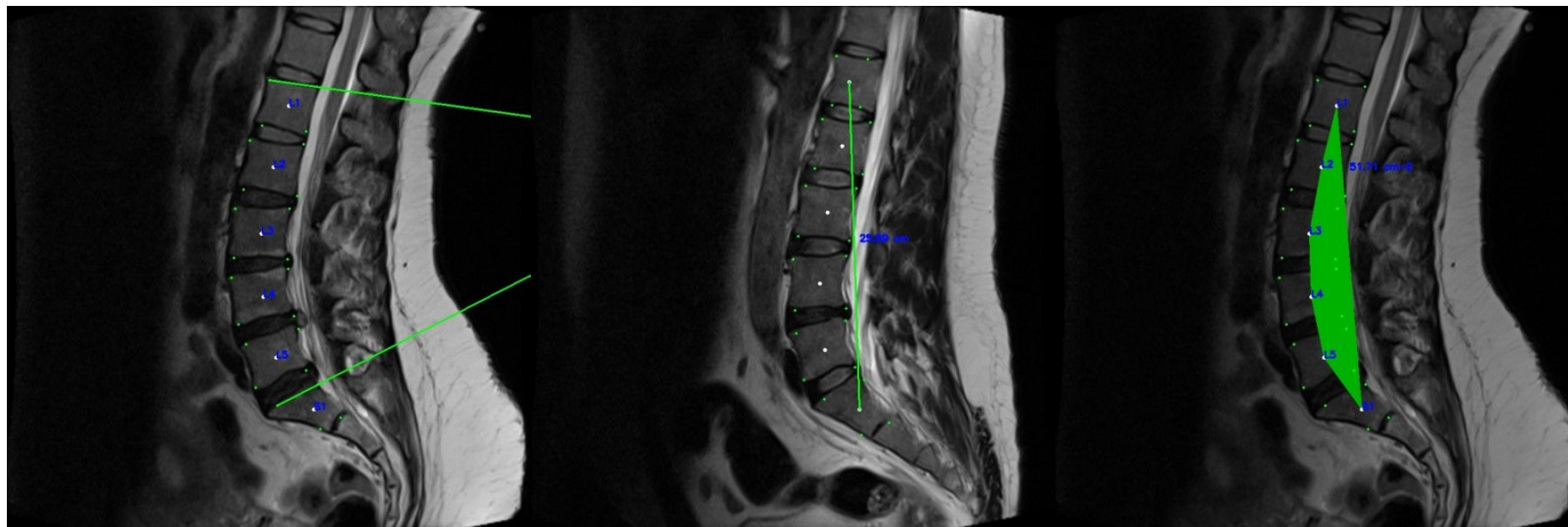


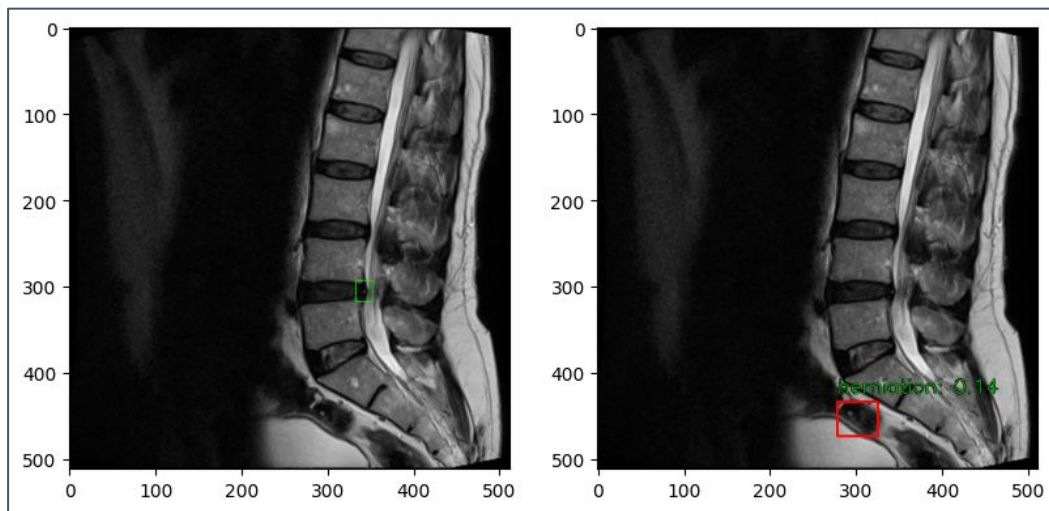
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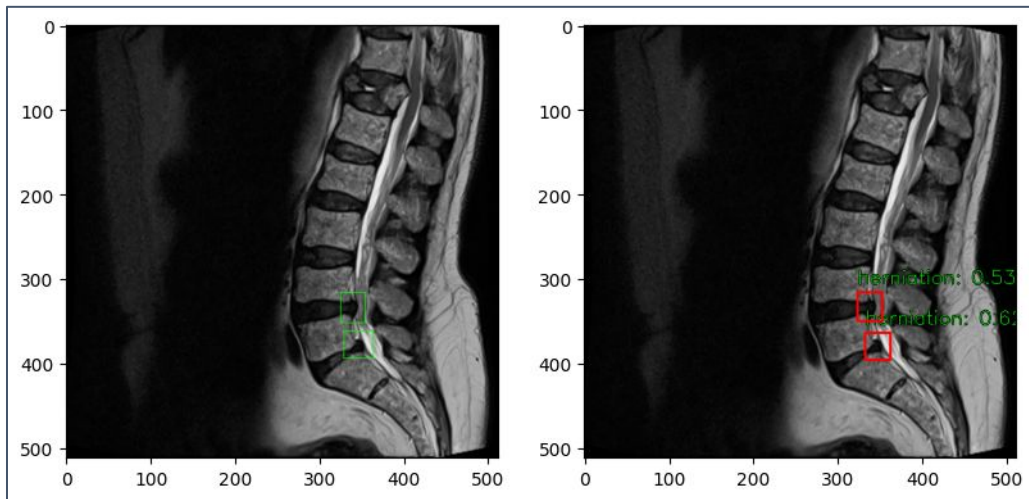
Dataset

- Obtained originally from [Mendeley Data](#).
- This dataset contains **MRI Studies** over the lumbar spine with **T1 and T2** weighted sequences and **radiologists notes** in a table.
- A **radiologist labeled herniations** by looking each of the sequences and the diagnosis annotated.



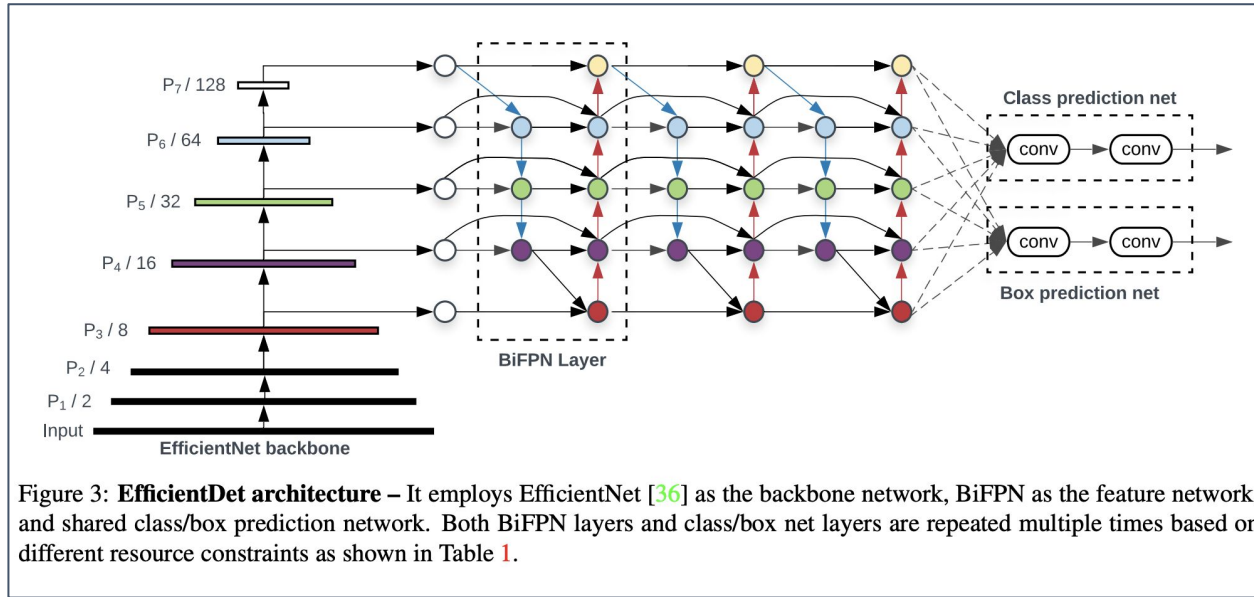
Dataset

- Obtained originally from [Mendeley Data](#).
- This dataset contains **MRI Studies** over the lumbar spine with **T1 and T2** weighted sequences and **radiologists notes** in a table.
- A **radiologist labeled herniations** by looking each of the sequences and the diagnosis annotated.
- **We modified the annotations** in order to give more context to the model.



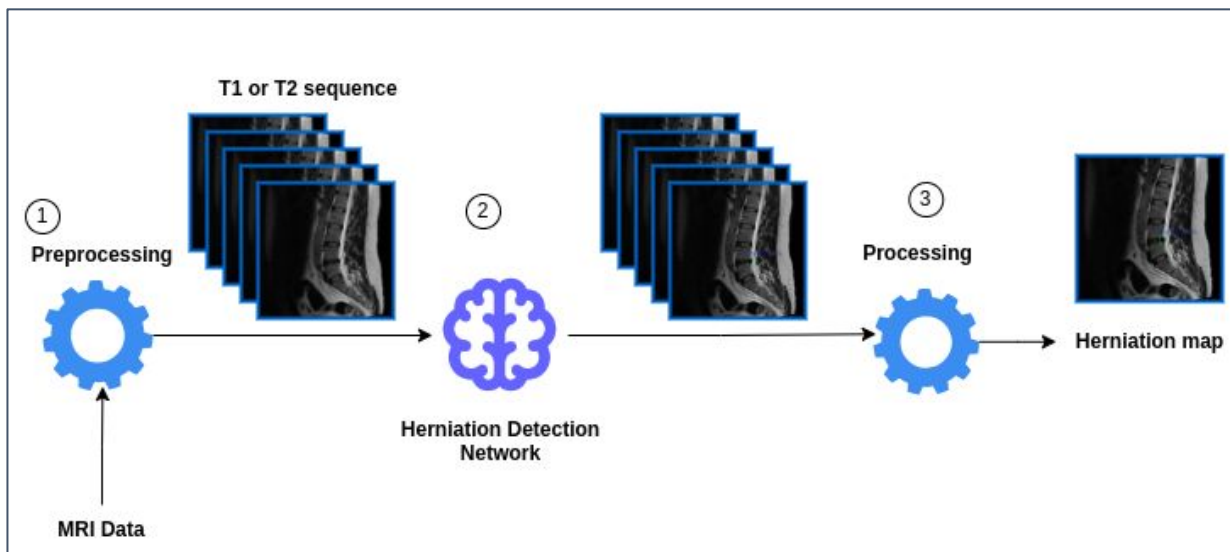
Architecture

- Well suited for **small object detection**.
- As fast as **YOLO**.
- **Pretrained** over the **Coco Dataset**.



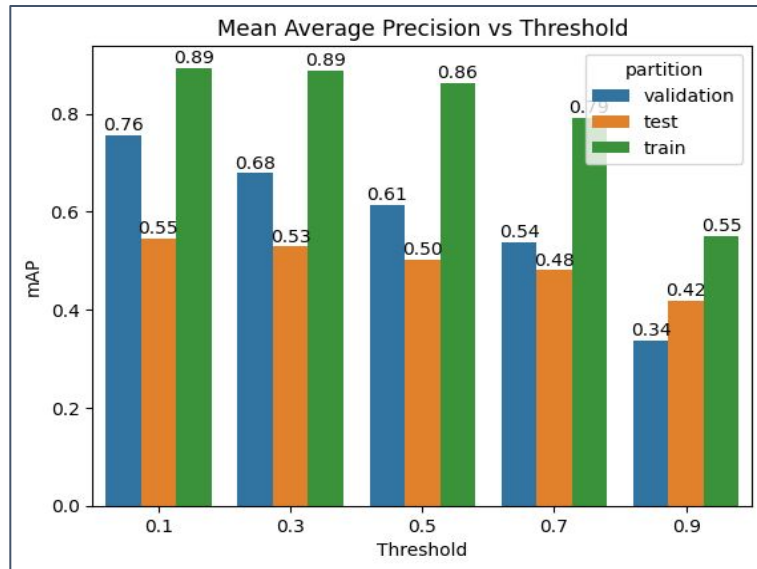
Pipeline

- Given an MRI Scan, 5 slices are extracted from the center of the sequence.
- Each of the slices is passed through the neural network independently.
- A post-processing step verifies consistency among at least three sequences.

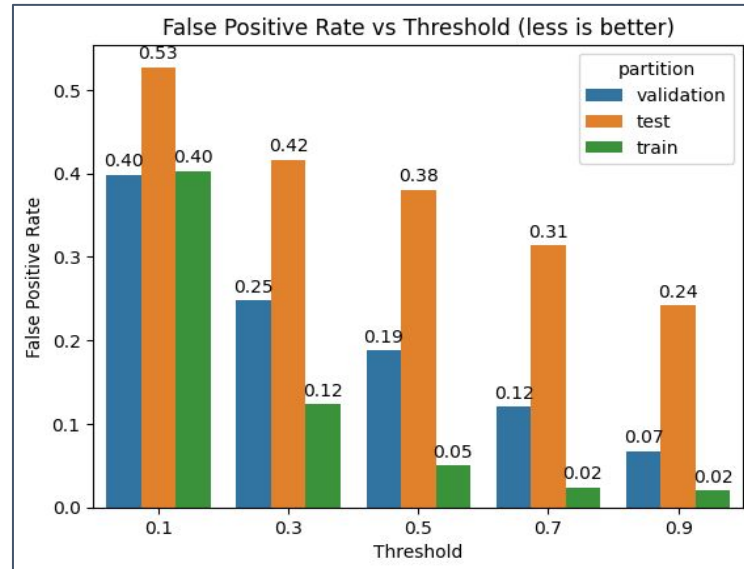


Performance

The model depends heavily on the threshold chosen.



MAP (mean average precision) is an object detection specific metric which quantifies how good a model is detecting objects.



We use the false positive rate to evaluate how prone the model is to identify not existent hernias.

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Conclusion and Future Steps



- Three models have been proposed to **automatize** the **computation and analysis** of **pain related** quantitative metrics.
- Developing each of the models presented its own set of challenges.
- The proposed models **meet** the required expectations for this PoC.



- More data will be utilized to improve model's performance.
- Acquiring **real metrics** value for the MRI lumbar images.
- Validating corner detection performance by comparing predictions to **ground truth**.
- Add in the web application a **tool for correcting wrongly detected images**.

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References

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