Segmentation Algorithms for Diagnosis and Classification of Lumbar Spinal Stenosis

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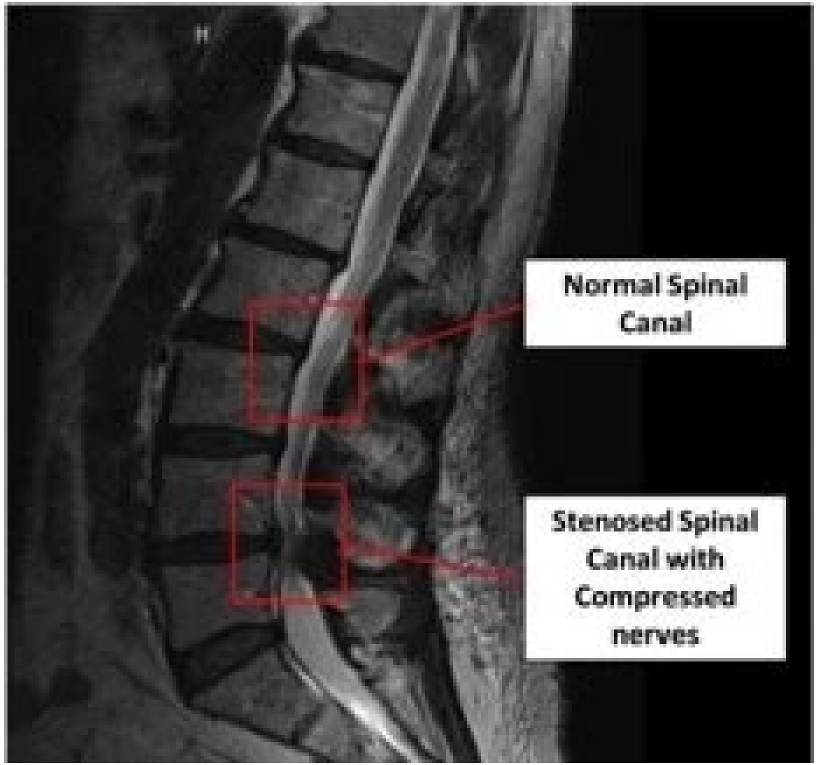
Introduction to lumbar spinal stenosis

- Lumbar spinal stenosis (LSS) is the most common degenerative spinal disease in elderly patients.[1]
- Central LSS is as narrowing of the central spinal canal and/or lateral recesses in the lower back with consequent compression of nerves and spinal cord.[2]
- Caused by congenital stenosis and/or degenerative changes involving a combination of the intervertebral disc, facet joints, and ligamentum flavum.[3]



Lumbar Stenosis Treatment - New Jersey - Centers for Neurosurgery, Spine & Orthopedics. (2022, May 24). Centers for Neurosurgery Spine & Orthopedics. https://www.cnsomd.com/surgery-conditions/degenerative-spine-conditions/lumbar-stenosis/

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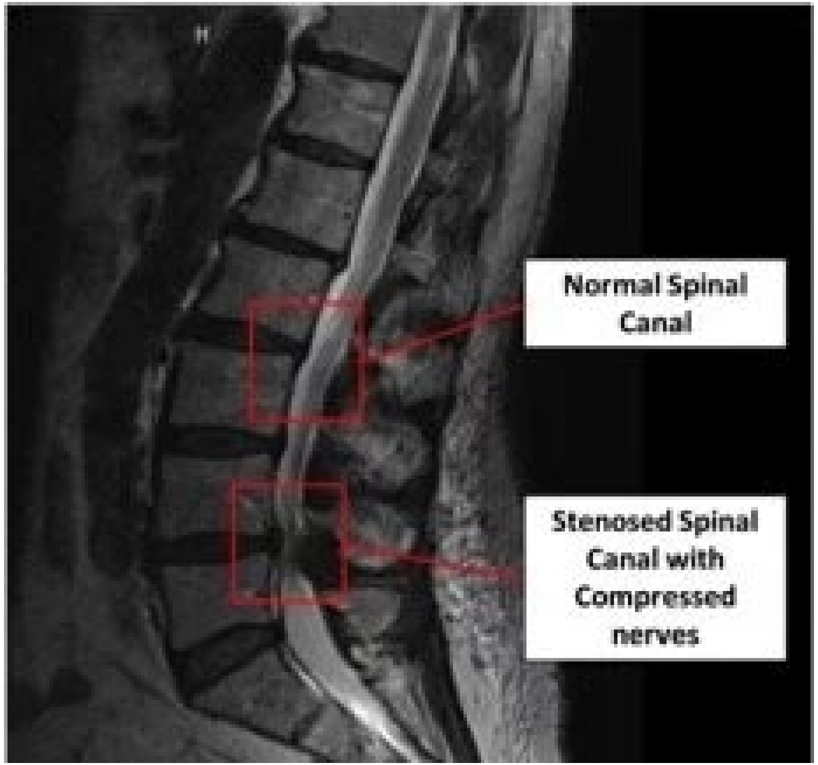
<u>Importance of early diagnosis:</u> can help prevent progression of symptoms and improve outcomes.



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Why is LSS important to study?

Prevalence

- Common condition, especially in older adults. As population ages, prevalence of LSS is expected to increase, making it an important public health concern.[4]
- Back pain is one of the most important causes of lifelong disability worldwide.[5]
- Affects an estimated 103 million people worldwide.[6]
- Most frequent indication for spinal surgery in patients over 65 years.[7]

Quality of life

- Common cause of chronic low back and leg pain.
- Symptoms like numbness, weakness in the legs affect a patient's ability to perform daily activities.
- Anxiety, depression, and social isolation due to symptoms.

Financial, economic, and societal burden

- Significant healthcare costs for both patient and healthcare system.[9]
- Common cause of disability.
- Effects on private and professional lives with decreased functional capacity.[10]
- Societal burden (missed work, ongoing use of medical services, and narcotic dependence).[11]
- Out-of-control costs will likely prompt more rationing of medical services in general and spine care in particular [12] unless clinical evidence is presented on how to realize cost savings with technology advancements.[13, 14]

Emerging treatments:

- Minimally invasive surgical techniques, regenerative medicine approaches, etc.

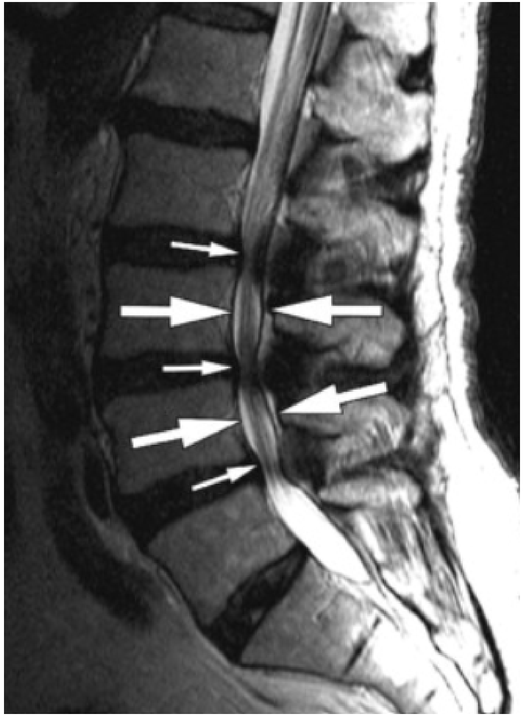
- A large percentage of LSS patients who eventually undergo surgical treatment report significant pain relief post-op, but there is no guarantee these invasive techniques will help everyone.[15]

- Continued research needed to determine safety and efficacy of these treatments and to improve outcomes for patients.

Lumbar spinal stenosis diagnosis:

Typically diagnosed through a combination of methods:

- **Medical history**
- **Physical examination**
  - Range of motion, strength, reflexes, arterial palpation, specific maneuvers.
- **Imaging studies**
  - X-rays, MRI, and CT.
- **Other tests**
  - Nerve conduction studies (measure the electrical activity in the nerves)
  - Electromyography EMG (measures muscle activity)



Themes, U. (2019, August 25). *Spinal Stenosis: Lumbar*. Radiology Key. https://radiologykey.com/spinal-stenosis-lumbar/

Katz, J. N., Zimmerman, Z. E., Mass, H., & Makhni, M. C. (2022). Diagnosis and Management of Lumbar Spinal Stenosis. *JAMA*, *327*(17), 1688. https://doi.org/10.1001/jama.2022.5921

Lumbar spinal stenosis diagnosis - challenges:

- Variability in symptoms.
- Difficulty distinguishing from other spinal conditions.
- Subjective interpretation of imaging results.
- Symptoms may overlap with other spinal conditions.[8]
- Accurate diagnosis is critical for developing appropriate treatment plans.

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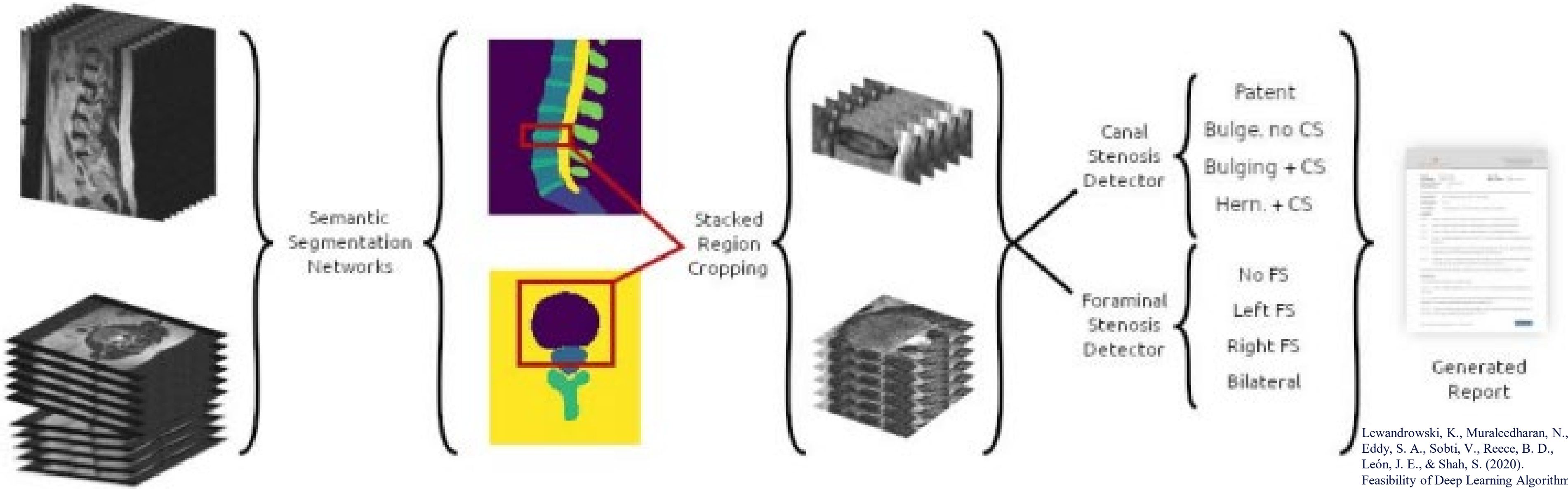
How segmentation algorithms can aid in diagnosis:

- Identify specific features of spinal stenosis.
- Quantify degree of narrowing.
- Assist in differential diagnosis.

Katz, J. N., Zimmerman, Z. E., Mass, H., & Makhni, M. C. (2022). Diagnosis and Management of Lumbar Spinal Stenosis. *JAMA*, *327*(17), 1688. https://doi.org/10.1001/jama.2022.5921

What are segmentation algorithms?

Automated techniques for separating an image into its component parts and identifying regions of the image (which in our case correspond to different anatomical structures or pathologies).



High-level architectural diagram of the implemented deep learning algorithm used to generate automated MRI reports.

Lewandrowski, K., Muraleedharan, N., Eddy, S. A., Sobti, V., Reece, B. D., León, J. E., & Shah, S. (2020). Feasibility of Deep Learning Algorithms for Reporting in Routine Spine Magnetic Resonance Imaging. *The International Journal of Spine Surgery*, *14*(s3), S86–S97. https://doi.org/10.14444/7131

Why are we using segmentation algorithms?

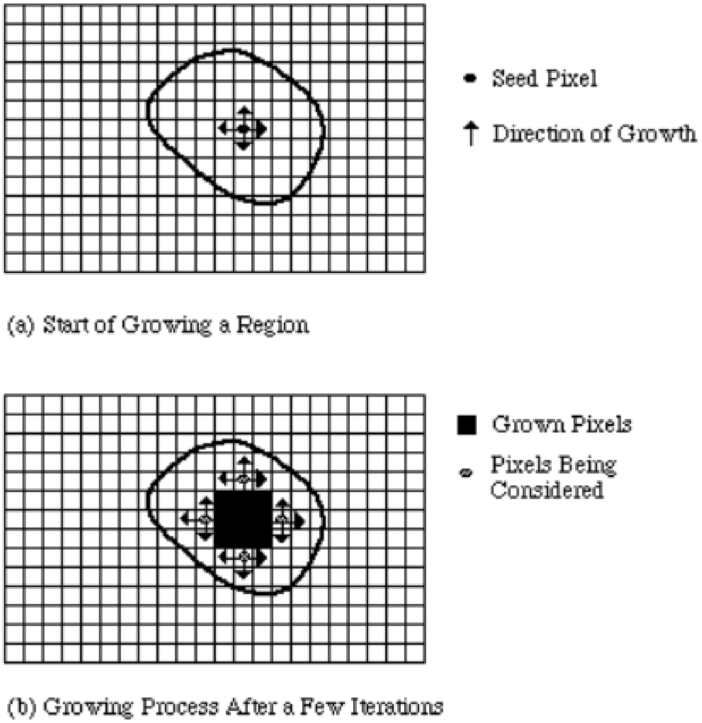
- Allow for **accurate and precise identification** and delineation of structures, in LSS specifically, of the dimensions of the spinal canal and spinal nerve roots and degree of stenosis.
- **Automate the segmentation process.**
- **Save time** and **increase consistency.**
- **Identify subtle changes** in the spinal structures that may not be apparent to the human eye.
  - Due to low contrast of MRI images, boundary between spine and surrounding structures is often unclear, especially the boundary of the dural sac, which coincides with adjacent background.
- Provide **reproducible results**.
- Allow for **earlier detection** and intervention of lumbar spinal stenosis.

Sharma, N., Ray, A., Shukla, K. K., Sharma, S., Pradhan, S., Srivastva, A., & Aggarwal, L. (2010). Automated medical image segmentation techniques. *Journal of Medical Physics*, *35*(1), 3. https://doi.org/10.4103/0971-6203.58777 ;
Li, H., Luo, H., Huan, W., Shi, Z., Yan, C., Wang, L., Mu, Y., & Liu, Y. (2021b). Automatic lumbar spinal MRI image segmentation with a multi-scale attention network. Neural Computing and Applications, 33(18), 11589–11602. https://doi.org/10.1007/s00521-021-05856-4

Segmentation techniques used for MRI of lumbar spine

Region-growing [16]

- Identifies pixels or voxels with similar characteristics (e.g., intensity, texture, etc.) and groups them together into regions.
- Starts with a seed point or region and then adds neighboring pixels or voxels that meet certain criteria until the entire object of interest has been segmented.

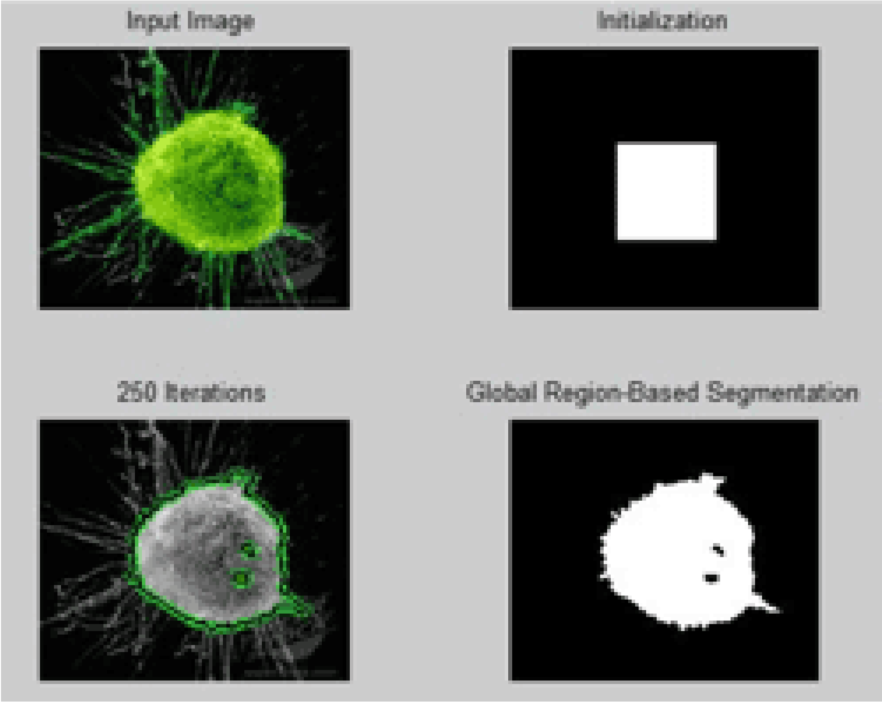


Region Growing. (n.d.). https://users.cs.cf.ac.uk/dave/Vision_lecture/node35.html

Segmentation techniques used for MRI of lumbar spine

Active contour models (aka snakes): [17]

- Uses an energy minimization approach to find the best possible contour/boundary that fits object of interest.
- Similar to a rubber band stretching and contracting to conform to the shape of an object, with the energy of the system being the tension of the rubber band.
- By iteratively minimizing the energy of the system, the algorithm can accurately locate the object's boundary.

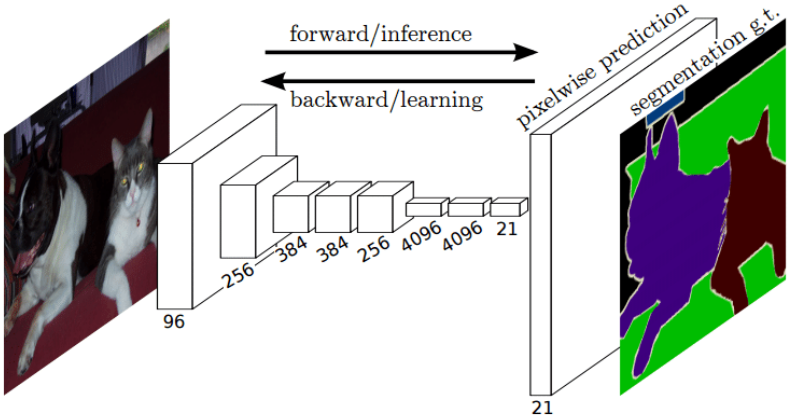


Chopra, A.R., & Dandu, B. (2012). Image Segmentation Using Active Contour Model.

Segmentation techniques used for MRI of lumbar spine

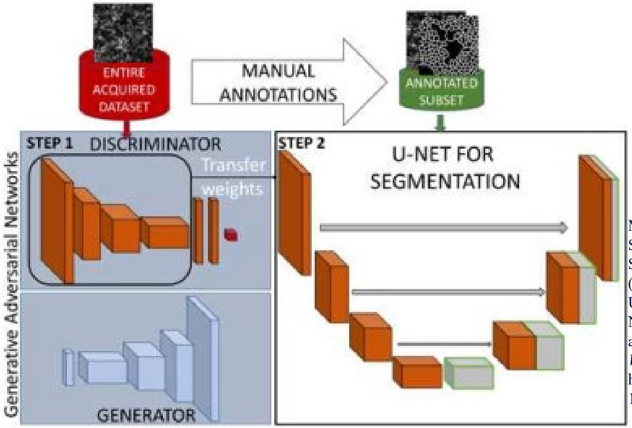
Machine learning-based algorithms: [18, 19]

- Learn from data and make predictions or decisions without being explicitly programmed.
- Analyze large amounts of data and identifies patterns and relationships within that data then uses this information to create a model that can predict outcomes or make decisions based on new data.
- The more data the algorithm is trained on, the more accurate its predictions or decisions can become.
- Including deep learning techniques such as convolutional neural networks (CNNs) and generative adversarial networks (GANs).



Sharma, V., Bishnu, A., & Patel, L. (2017). Segmentation Guided Attention Networks for Visual Question Answering. *Meeting of the Association for Computational Linguistics*. https://doi.org/10.18653/v1/p17-3008

CNN for image segmentation.



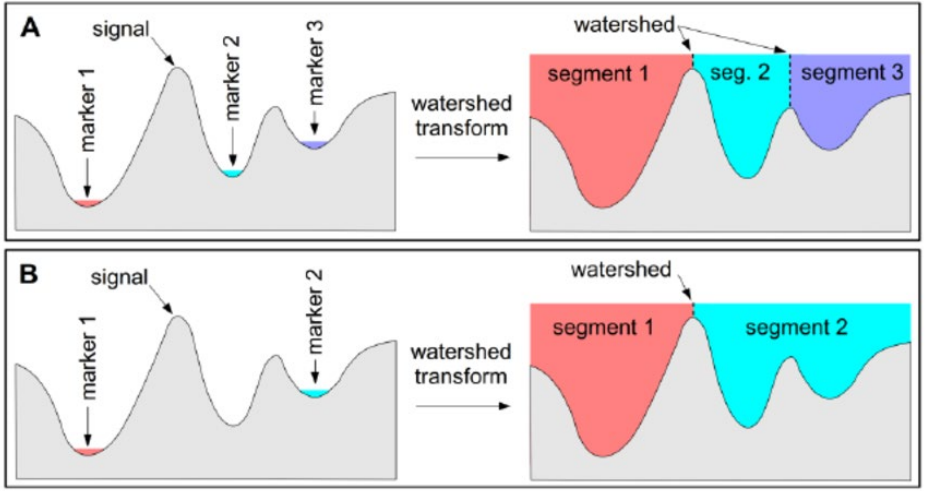
Majurski, M., Manescu, P., Padi, S., Schaub, N. J., Hotaling, N., Simon, C. G., & Bajcsy, P. (2019). Cell Image Segmentation Using Generative Adversarial Networks, Transfer Learning, and Augmentations. *Computer Vision and Pattern Recognition*. https://doi.org/10.1109/cvprw.2019.00145

GAN-based transfer learning for a U-Net segmentation

Segmentation techniques used for MRI of lumbar spine

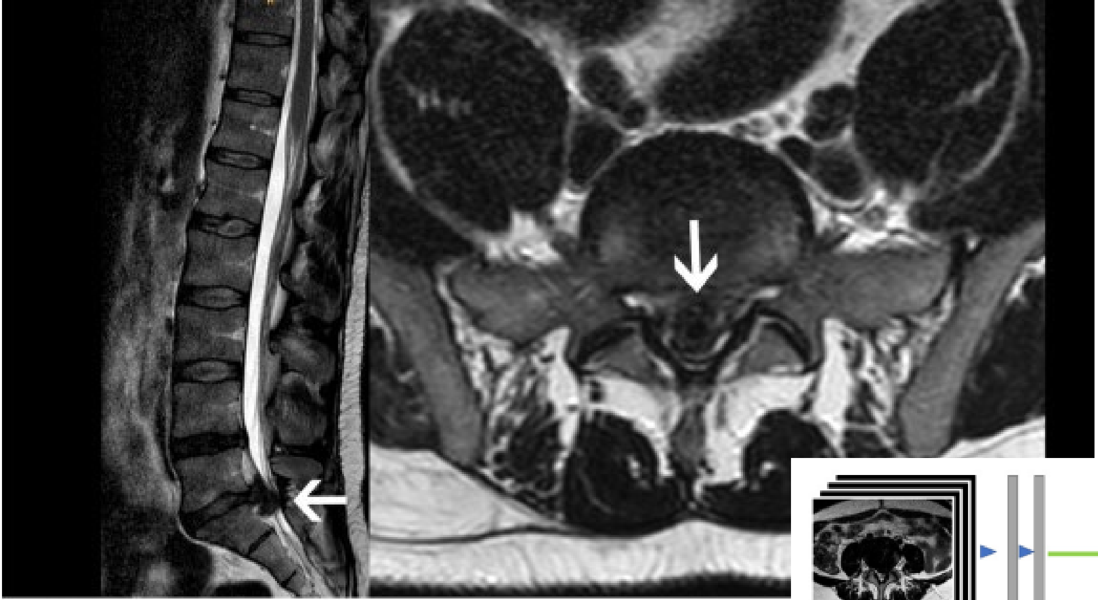
Watershed transform: [20]

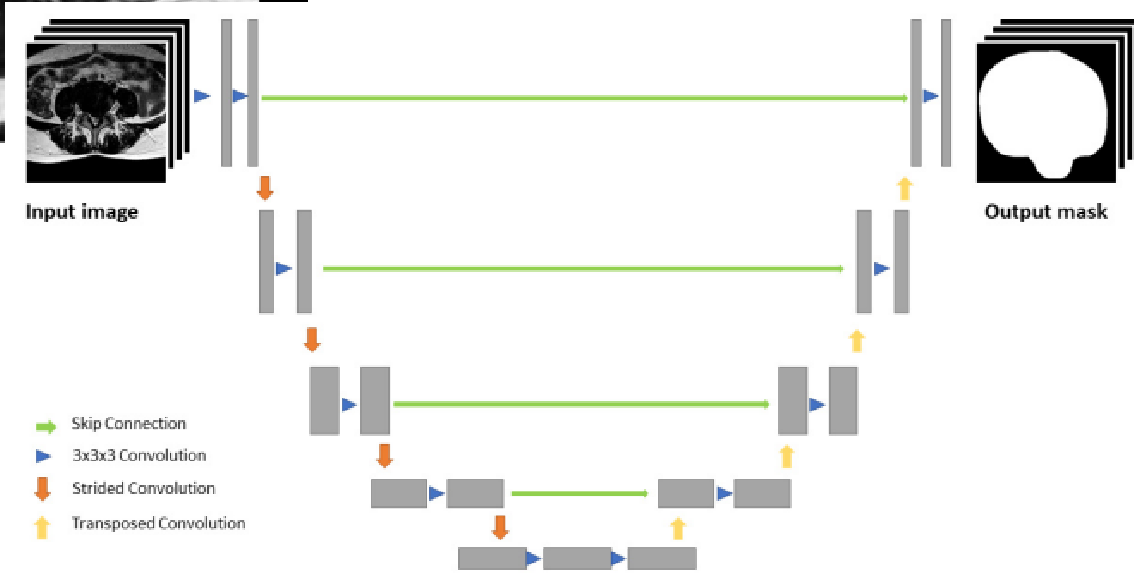
- Identifies object boundaries by simulating a flooding process.
- Treats the image as a topographical map (valleys and ridges represent object boundaries), then simulates a rainfall, with each pixel or voxel representing a water droplet.
- Droplets merge and flow into the valleys until they reach a boundary ridge, which separates the different objects.



Fisher, A. C. (2014). Cloud and Cloud-Shadow Detection in SPOT5 HRG Imagery with Automated Morphological Feature Extraction. *Remote Sensing*, *6*(1), 776–800. https://doi.org/10.3390/rs6010776

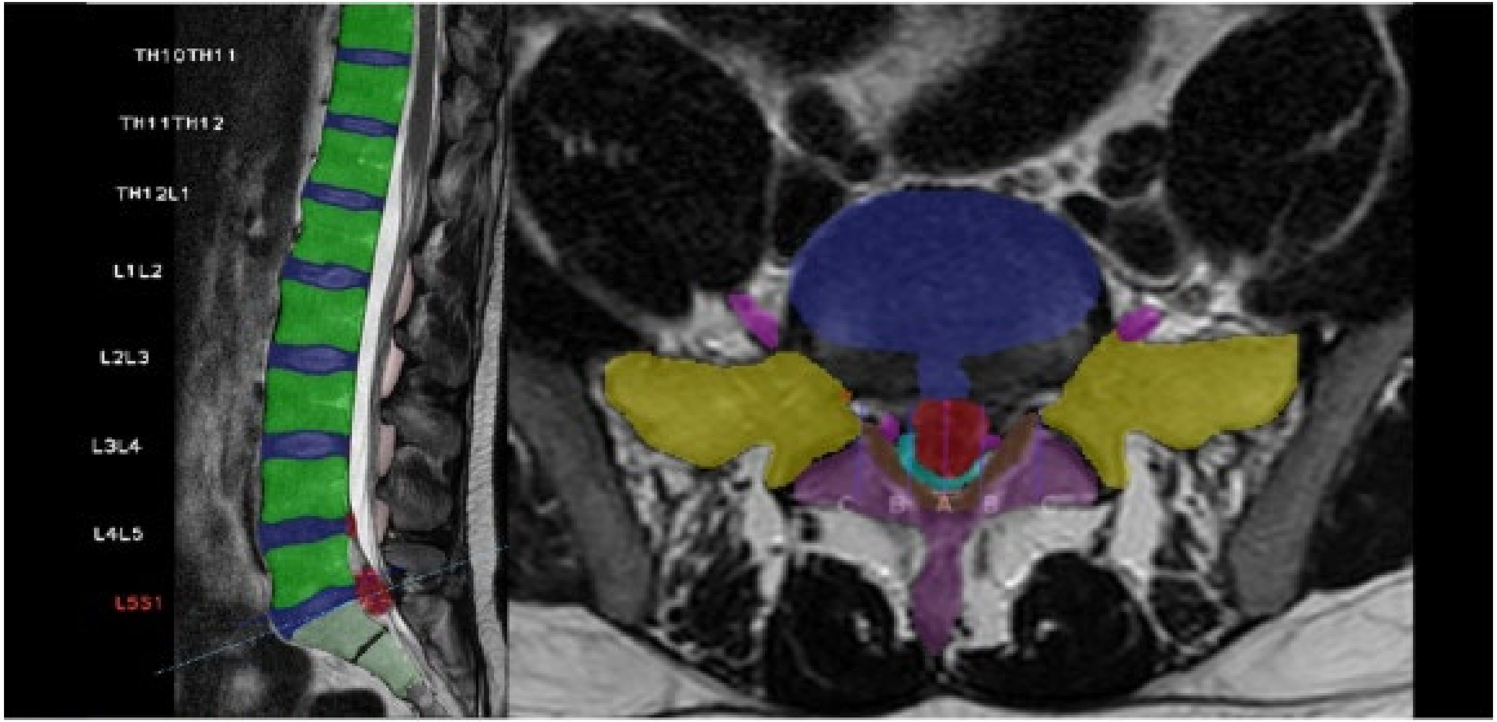
Example of U - Net - like segmentation architecture





Lehnen, N. C., Haase, R., Faber, J., Rüber, T., Vatter, H., Radbruch, A., & Schmeel, F. C. (2021). Detection of Degenerative Changes on MR Images of the Lumbar Spine with a Convolutional Neural Network: A Feasibility Study. *Diagnostics*, *11*(5), 902. https://doi.org/10.3390/diagnostics11050902

U-Net-like segmentation architecture output masks and excerpt of written report generated by software



Hernia : L5S1 disc is herniated.
Hernia size on this slice: 13.0 mm.
median.

There is absolute. stenosis

NerveRootCompression : There is nerve root compression.Roots: [S1S2_Left] are compressed.Roots: [S1S2_Left] are deviated.Roots: [L5S1_Left ,L5S1_Right ,S1S2_Right] are normal.

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Why is MRI considered the golden -standard* tool to evaluate LSS?

Soft tissue visualization:

- Excellent soft tissue contrast allows for visualization of spinal cord, nerve roots, and ligaments.
- Easier to identify areas of stenosis and nerve root compression.

Multiplanar imaging:

- Axial, sagittal, and coronal.
- More comprehensive assessment of the lumbar spine.

Non-invasive:

- No radiation exposure, unlike CT.
- Safer for patients.

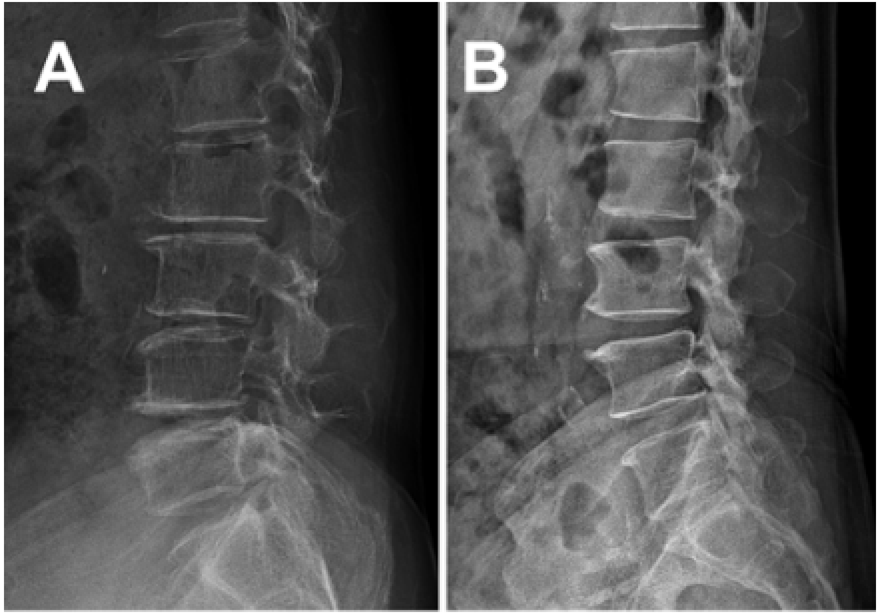
High diagnostic accuracy:

- For LSS, sensitivity and specificity values reported to be as high as 90-95%.

* Difficult to promptly examine all suspected cases with MRI considering the modality's high cost and limited accessibility. Radiography is efficient for screening due to low cost, rapid operability, and wide availability, but diagnostic accuracy is relatively poor.

Kim, T., Kim, Y., Park, S., Lee, J. S., Lee, C., Kang, H., Kim, C. H., Kim, K., & Chung, C. K. (2022). Diagnostic triage in patients with central lumbar spinal stenosis using a deep learning system of radiographs. *Journal of Neurosurgery*, *37*(1), 104–111. https://doi.org/10.3171/2021.11.spine211136

Case example



Two middle-aged women present to clinic with low-back pain and radiating leg pain.

Their spinal radiographs are shown in Fig. A and B.

A spine doctor may suspect that the patient in Fig. A has substantial LSS based on reduced disc height and multilevel spondylosis and would then recommend further imaging i.e. MRI.

The other patient, in Fig B, has a radiograph that reveals less spondylosis and normal disc height and further imaging may not be determined to be warranted.

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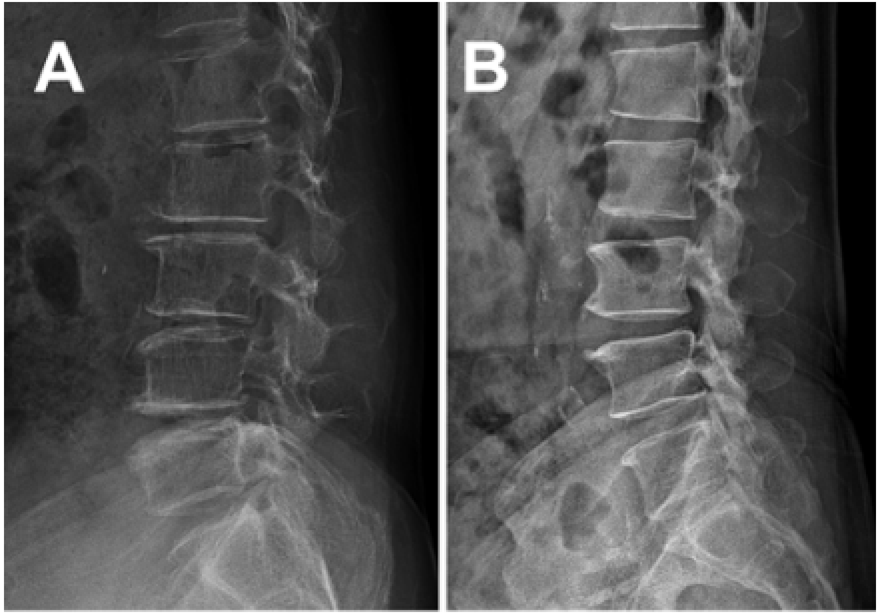

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Unfortunately, the physician would be **incorrect.**

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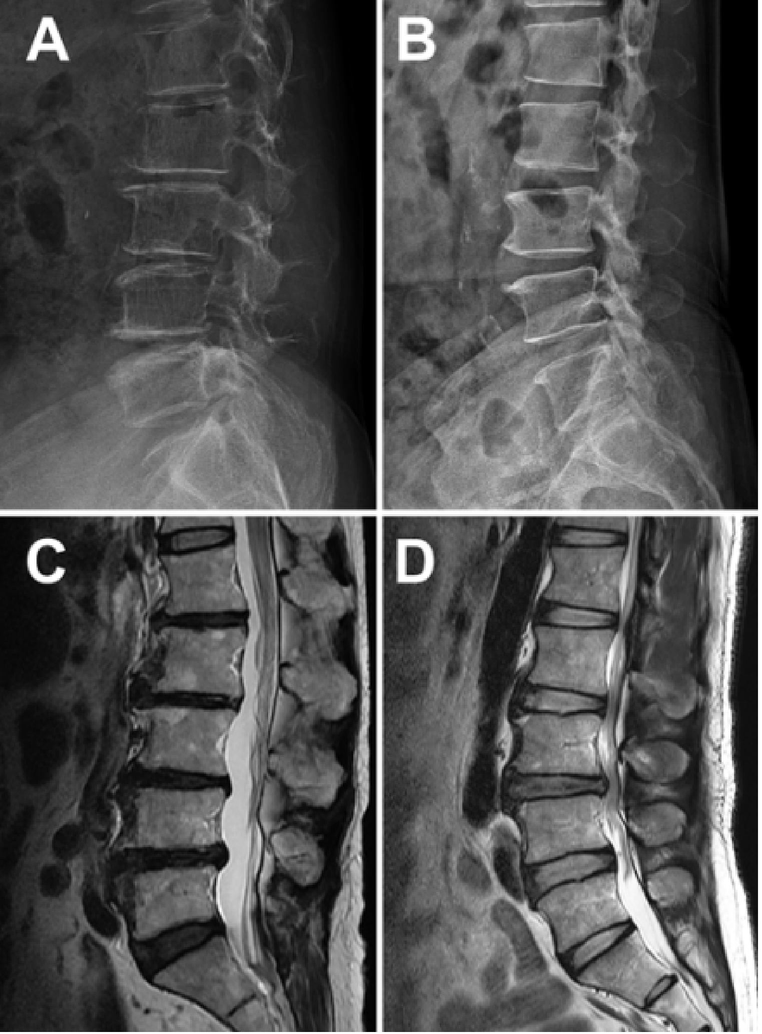


MRI of the patient shown in Fig. A (Fig. C) shows a wide spinal canal and absence of central stenosis despite radiography showing reduced disc space and multilevel spondylosis.

MRI of the patient shown in Fig. B (Fig. D) reveals severe central stenosis despite initial radiography showing normal disc height and minimal spondylosis.

Kim, T., Kim, Y., Park, S., Lee, J. S., Lee, C., Kang, H., Kim, C. H., Kim, K., & Chung, C. K. (2022). Diagnostic triage in patients with central lumbar spinal stenosis using a deep learning system of radiographs. *Journal of Neurosurgery*, *37*(1), 104–111. https://doi.org/10.3171/2021.11.spine211136

How are we grading the MRIs to train the algorithm?

<u>Five domains:</u>

1. Central spinal stenosis (axial)
2. Foraminal stenosis (sagittal)
3. Laterale recessus stenosis (axial)
4. Facet arthrosis (axial)
5. Modic changes (sagittal)

Internal grading form excerpt

7. Chirurgische relevantie afwijkingen (alleen scoren indien het niveau op de transversale coupes is afgebeeld)	Niveau L1-L2: ☐ Afwijking(en) indicatie voor operatie ☐ Geen afwijking/afwijking(en) geen indicatie voor operatie Niveau L2-L3: ☐ Afwijking(en) indicatie voor operatie ☐ Geen afwijking/afwijking(en) geen indicatie voor operatie Niveau L3-L4: ☐ Afwijking(en) indicatie voor operatie ☐ Geen afwijking/afwijking(en) geen indicatie voor operatie Niveau L4-L5: ☐ Afwijking(en) indicatie voor operatie ☐ Geen afwijking/afwijking(en) geen indicatie voor operatie Niveau L5-S1: ☐ Afwijking(en) indicatie voor operatie ☐ Geen afwijking/afwijking(en) geen indicatie voor operatie

CRF - Baseline MRI

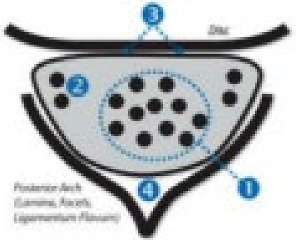
Naam beoordelaar	
UIC	
Datum MRI	
De MRI is:	☐ 1. goed te beoordelen ☐ 2. matig te beoordelen ☐ 3. slecht te beoordelen
Indien matig of slecht, toelichting:	

***Opmerking:** niveau's waarvoor geen score gegeven kan worden omdat deze niet op de transversale scans staan mogen open gelaten worden*

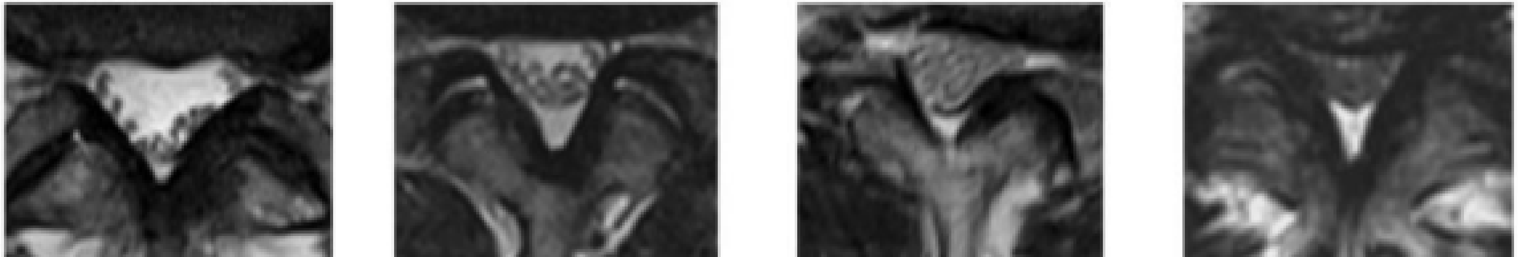
1. Niveau van afwijking die klachten veroorzaakt (combinatie mogelijk)	☐ L1-L2 ☐ L2-L3 ☐ L3-L4 ☐ L4-L5 ☐ L5-S1 ☐ Geen zichtbare afwijking als verklaring voor de klachten
2. Mate van centrale stenose	Niveau L1-L2: ☐ Normal ☐ Mild spinal stenosis ☐ Mild-moderate spinal stenosis ☐ Moderate spinal stenosis ☐ Moderate-severe spinal stenosis ☐ Severe spinal stenosis Niveau L2-L3: ☐ Normal ☐ Mild spinal stenosis ☐ Mild-moderate spinal stenosis ☐ Moderate spinal stenosis ☐ Moderate-severe spinal stenosis ☐ Severe spinal stenosis Niveau L3-L4: ☐ Normal ☐ Mild spinal stenosis ☐ Mild-moderate spinal stenosis ☐ Moderate spinal stenosis

Internal LUMC grading form

Domain 1: Central spinal stenosis

	Normal	Mild Spinal Stenosis	Moderate Spinal Stenosis	Severe Spinal Stenosis
				
1	• Free distribution of nerve roots, without crowding	• Slight crowding of nerve roots	• Crowding of nerve roots, resulting in a "speckled" appearance of CSF interspersed with nerve roots	• Complete effacement of CSF, resulting in nerve roots not being individually distinguishable
2	• Traversing dorsal and ventral nerve roots in the lateral recesses are distinct	• Traversing dorsal and ventral nerve roots in the lateral recesses remain distinct, but there may be abutment of the nerve roots in the lateral recesses	• Difficult to differentiate the traversing nerve roots in the lateral recesses	• Cannot discretely identify nerve roots in the lateral recesses
3	• Anterior margin of the thecal sac is flat or convex	• Anterior margin of the thecal sac is flat or concave	• Anterior margin of the thecal sac is concave	• Anterior margin of the thecal sac is concave
4	• Posterior epidural fat is preserved (dependent on level)	• Posterior epidural fat is preserved (dependent on level)	• Posterior epidural fat is preserved (dependent on level)	• ***Posterior epidural fat may be partially or completely effaced***

Axial T2-weighted image examples



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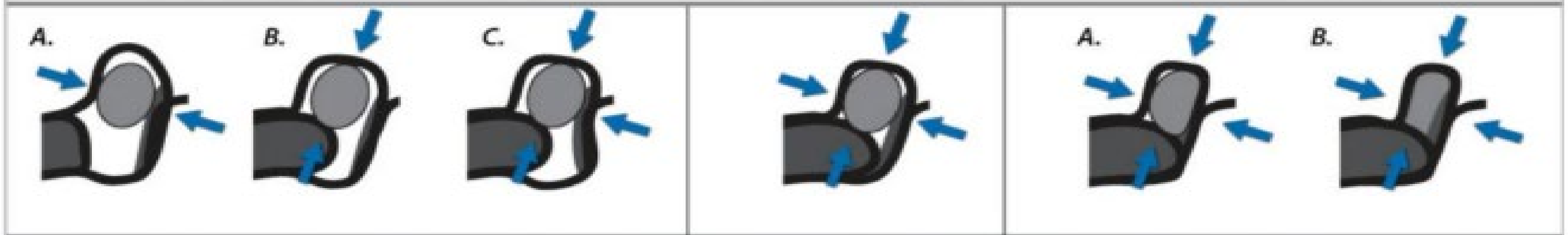
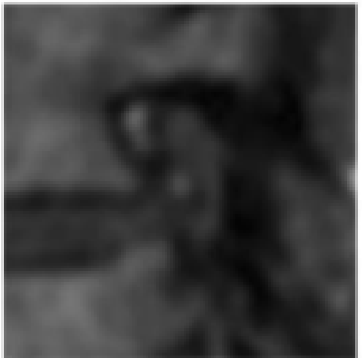
Domain 2: Foraminal stenosis

Mild neuroforaminal stenosis	Moderate stenosis	Severe stenosis



Mild neuroforaminal stenosis	Moderate stenosis	Severe stenosis
• Nerve root is in contact the walls of the neural foramen in two planes (either in anterior-posterior dimension; A or cranial-caudel dimension; B), or in 3 planes; C. • Aside from mild narrowing of the foramen and contact with the exiting nerve root, the epidural fat is otherwise maintained.	• Effacement of epidural fat in four planes with contact of the nerve root.	• Compression of the exiting nerve root; A or complete effacement of epidural fat; B.

Sagittal T1-weighted image examples



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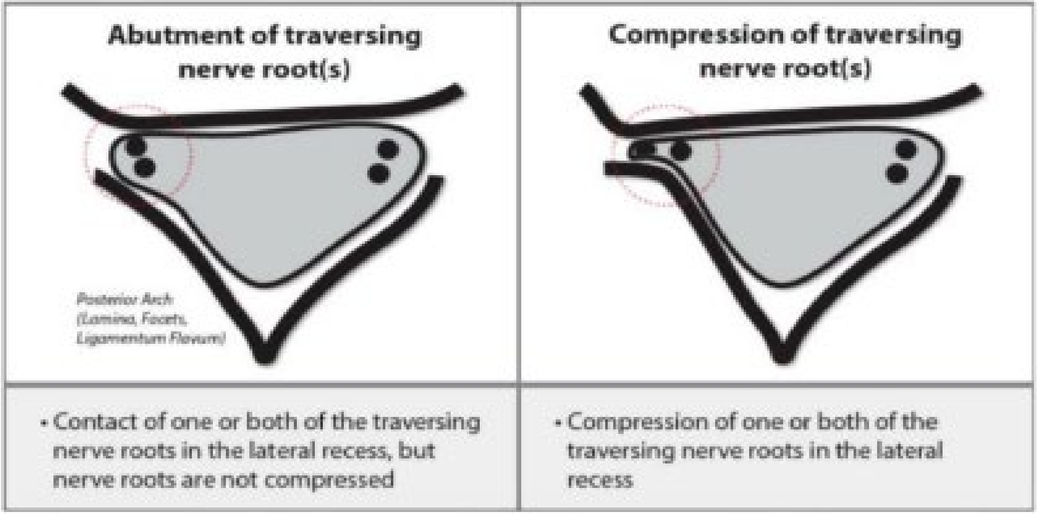
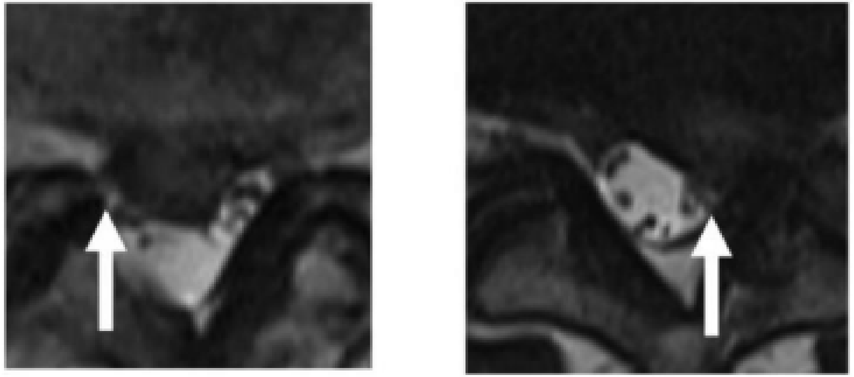
Domain 3: Lateral recess stenosis



Axial T2-weighted image examples



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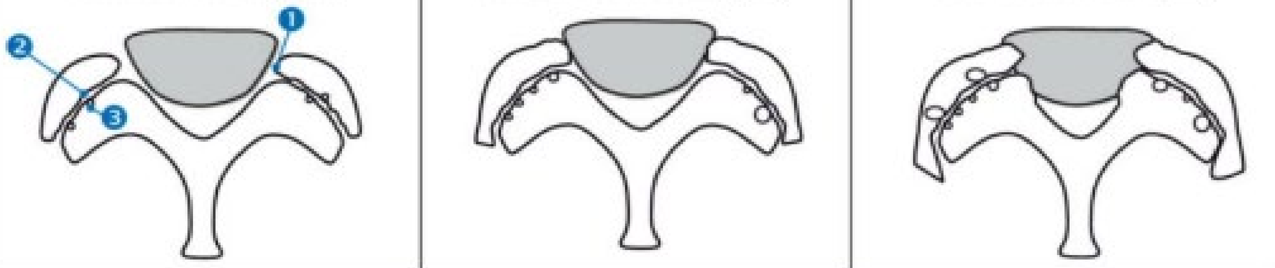
Domain 4: Facet arthrosis

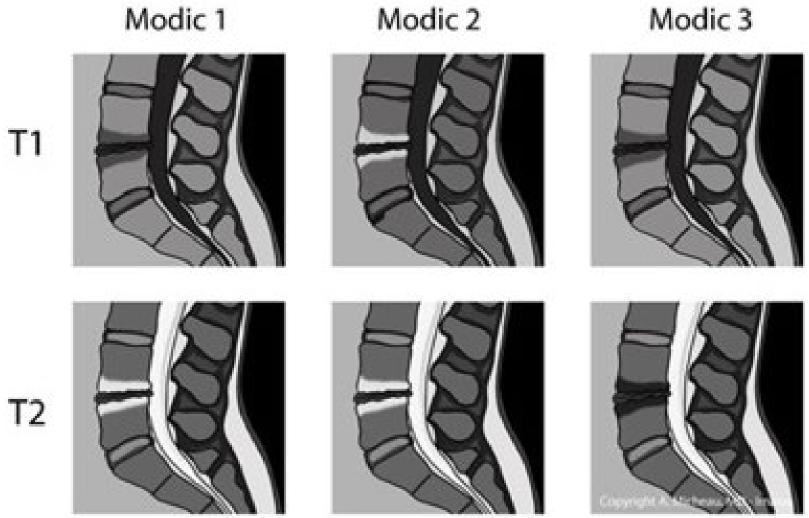


Mild Facet Arthropathy	Moderate Facet Arthropathy	Severe Facet Arthropathy
1 • Minimal to small osteophytes	• Moderate-size osteophytes	• Bulky osteophytes with dorsal mass effect on the thecal sac
2 • Mild subchondral irregularity	• Moderate subchondral irregularity	• Marked subchondral irregularity
3 • Tiny to small subchondral cysts	• Moderate-size subchondral cysts or synovial cysts	• Large subchondral cysts or synovial cysts
	• *Effusion, periarticular edema or osseous edema*	• *Effusion, periarticular edema or osseous edema*

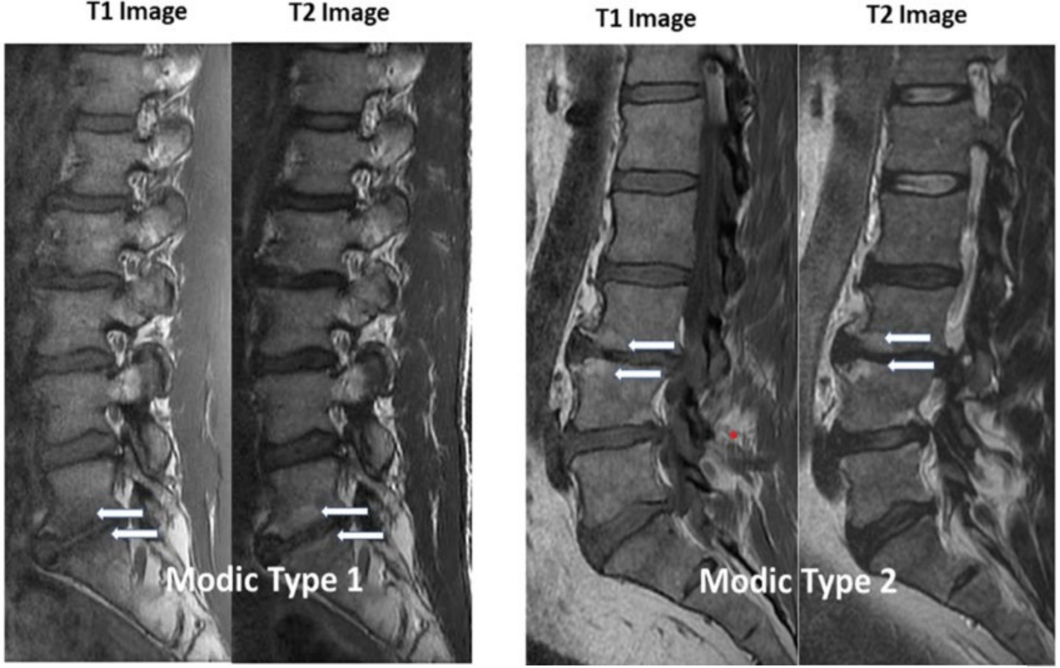
Axial T2-weighted image examples

Miskin, N., Isaac, Z., Lu, Y., Makhni, M. C., Sarno, D. L., Smith, T. W., Zampini, J. M., & Mandell, J. C. (2021). Simplified Universal Grading of Lumbar Spine MRI Degenerative Findings: Inter-Reader Agreement of Non-Radiologist Spine Experts. *Pain Medicine*, *22*(7), 1485–1495. https://doi.org/10.1093/pm/pnab098

Domain 5: Modic changes



Smale, S. (2017, September 27). *Modic changes & Spinal degeneration — Rayner & Smale*. Rayner & Smale. https://www.raynersmale.com/blog/2015/8/21/modic-changes



Francio, V. T., Sherwood, D. R., Twohey, E., Barndt, B., Pagan-Rosado, R., Eubanks, J. H., & Sayed, D. (2021). Developments in Minimally Invasive Surgical Options for Vertebral Pain: Basivertebral Nerve Ablation – A Narrative Review. *Journal of Pain Research*, *Volume 14*, 1887–1907. https://doi.org/10.2147/jpr.s287275

Type 1: Fibrovascular changes in subchondral bone marrow such as edema and inflammation.

- Acute degenerative changes often associated with pain.
- High signal intensity on T2 low signal intensity on T1 images.

Type 2: Replacement of bone with fatty yellow marrow.

- Increased signal intensity in both T1 and T2 images.

Type 3: Replacement of bone with bony sclerosis where there is little residual marrow.

- Low signal intensity on both T1 and T2 images.

Järvinen, J., Karppinen, J., Niinimäki, J., Haapea, M., Grönblad, M., Luoma, K., & Rinne, E. (2015). Association between changes in lumbar Modic changes and low back symptoms over a two-year period. *BMC Musculoskeletal Disorders*, *16*(1). https://doi.org/10.1186/s12891-015-0540-3 ;

Next steps:

1. Finish manually grading MRs and compare inter-reader variability.

1. Finish building segmentation algorithm for grading spinal stenosis severity.

1. Build training set:
    - Train model with large portion of the available data.
    - Adjust weights and biases of model through backpropagation.
    - Minimize the loss function and optimize the model's performance.

1. Evaluate performance of model during training with validation set:
    - Helps to prevent overfitting, which occurs when the model memorizes the training set rather than learning to generalize to new data.
    - Adjust hyperparameters of the model, such as the learning rate or number of layers.

1. Evaluate final performance of model after training is complete via test set:
    - Represents new, unseen data that the model has not been exposed to during training or validation.
    - Provides unbiased estimate of the model's performance on new data.
    - Must be large enough to provide statistically significant evaluation of the model's performance.

1. Publish model.

Acknowledgements

Carmen Vleggeert-Lankamp, MD, MSc, PhD.

Eduard Verheijen, MD/PhD candidate.

Usha Mohunlol, European Coordinator Euroscholars Program.

Footnotes

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Footnotes continued

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