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Medical Imaging Databank of the Valencia Region

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Automatic Semantic Segmentation of Structural Elements related to the Spinal Cord in the Lumbar Region by using Convolutional Neural Networks

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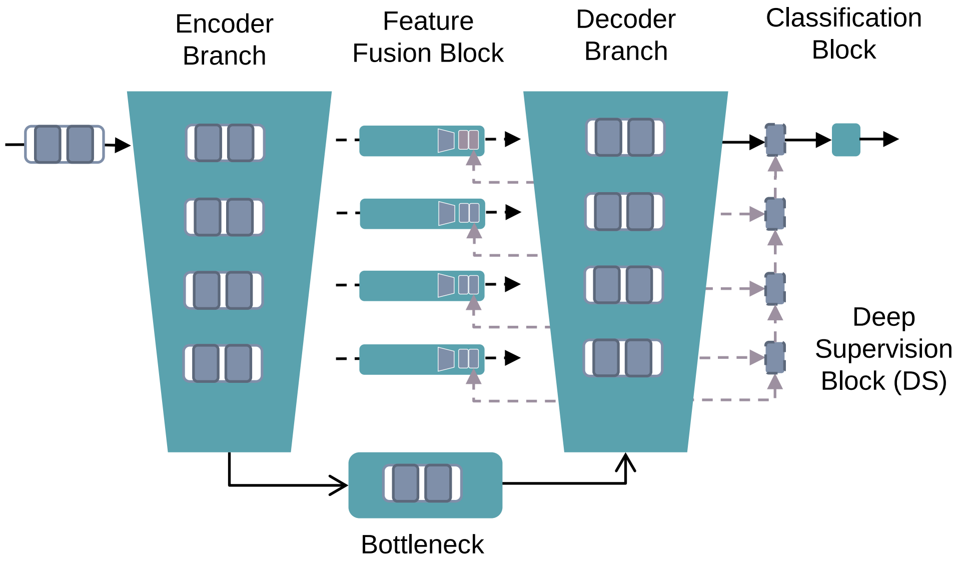
Introduction

Automated semantic segmentation of multiple structural elements in spinal cord can bring many benefits, such as:

- Optimization the process of the diagnosis for helping doctors.
- It facilitates the assessment of structural changes over time.
- Perform forecasts of future pathologies.

Proposed Approach

Design variations from existing convolutional neural networks (CNN) architectures » Improve performance



Modular Architecture

Base Line	Convolutional Block	Feature Fusion Block
- UNET - FCNs	- UNET - VGG16 - Inception	- Skip Connections - Attention Gate

[1] J. Long et al., *IEEE CVPR* 2015; [2]O. Ronneberger et al., *Springer 2015*; [3]K. Simonyan et al., *arXiv:1409.1556, 2014*;

Used Resources: Lumbar Spine MRI Dataset

MR images of lumbar scans extracted from the Medical Imaging Databank of the Valencian Region (BIMCV) database

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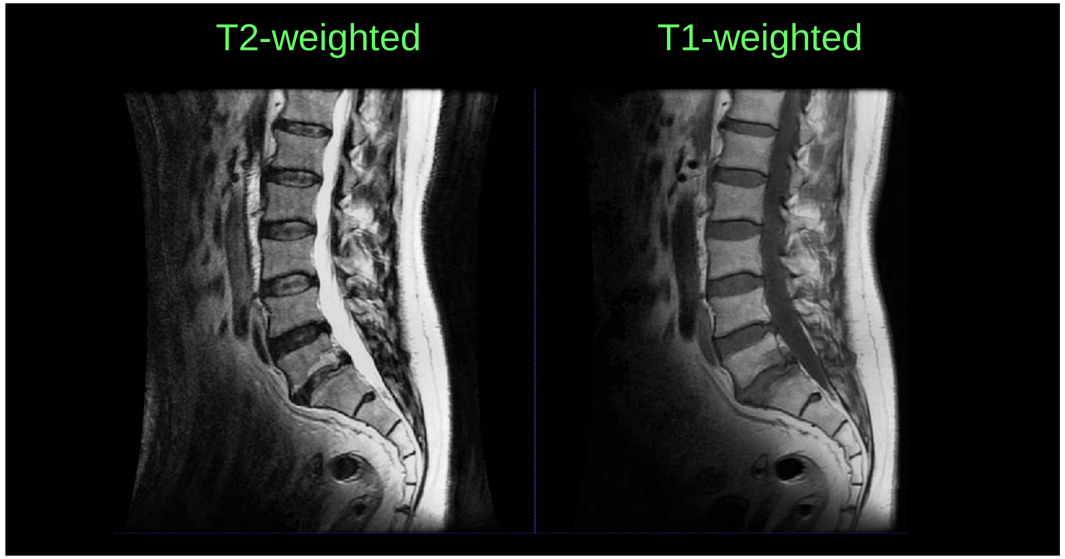


	Train	Test	Total
MRI T2w and T1w	60	15	75
Images 2D	716	179	895
Patches 256×256	6,069	1,551	7,620

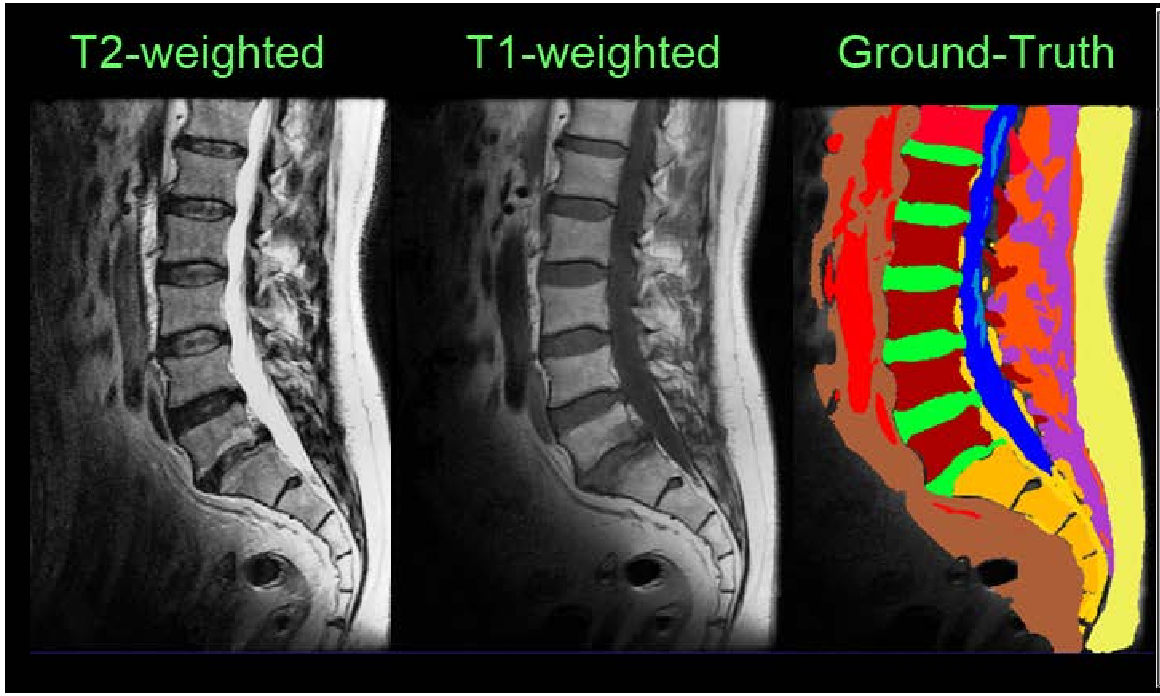
Dataset summary, 75 study cases (patients) used for training and testing

Parameter	Range of values	Average
Repetition time	5.6 ms to 6940 ms	2596 ms
Echo time	1.76 ms to 137 ms	65.66 ms
Cutting thickness	3.5 mm to 6.0 mm	4.78 mm
Pixel area in the sagittal plane	0.31×0.31 to 1.25×1.25 in mm	0.586×0.586 in mm

Range of values for different configuration parameters from the scan devices

https://bimcv.cipf.es/bimcv-projects/project-midas/

Used Resources: Image Labels and Ground-Truth Data

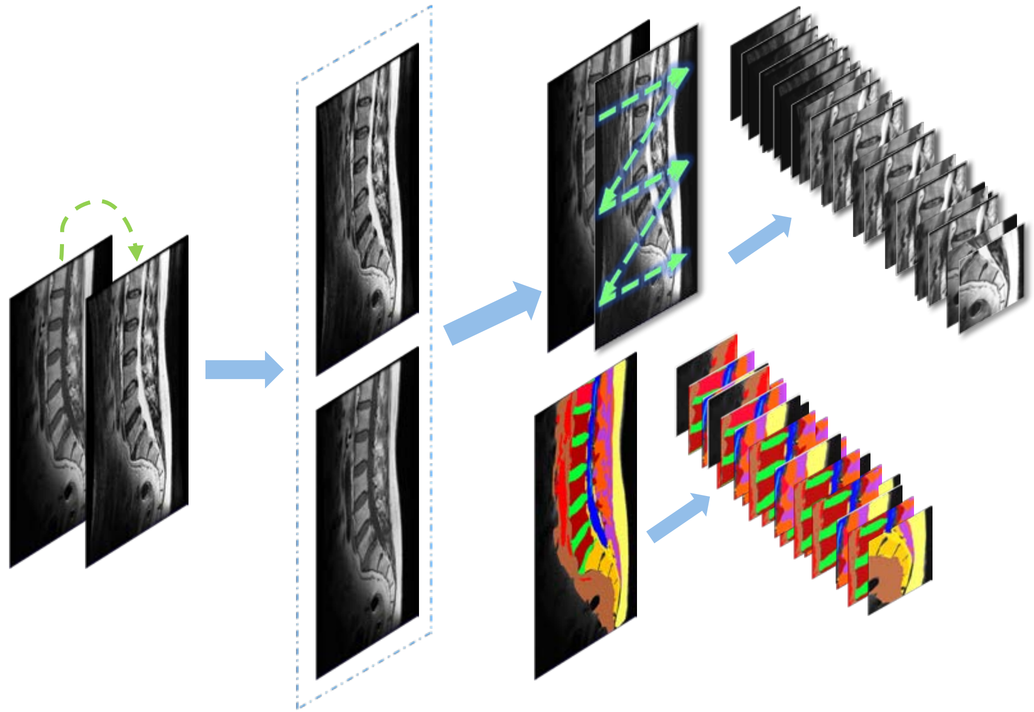


Class #	Class Id
0	Background
1	Vertebrae
2	Sacrum
3	Intervertebral Discs
4	Spinal Cavity
5	Subcutaneous Fat
6	Epidural Fat
7	Intramuscular Fat
8	Retroperitoneal Fat
9	Nerve Root
10	Blood Vessels
11	Muscle

Example of MR image and mask, on the left the T2-weighted and T1-weighted MR image, in the middle the corresponding ground-truth semantic segmentation, on the right the label summary

Used Resources: MR pre-processing and Data Augmentation

Pre-processing Steps



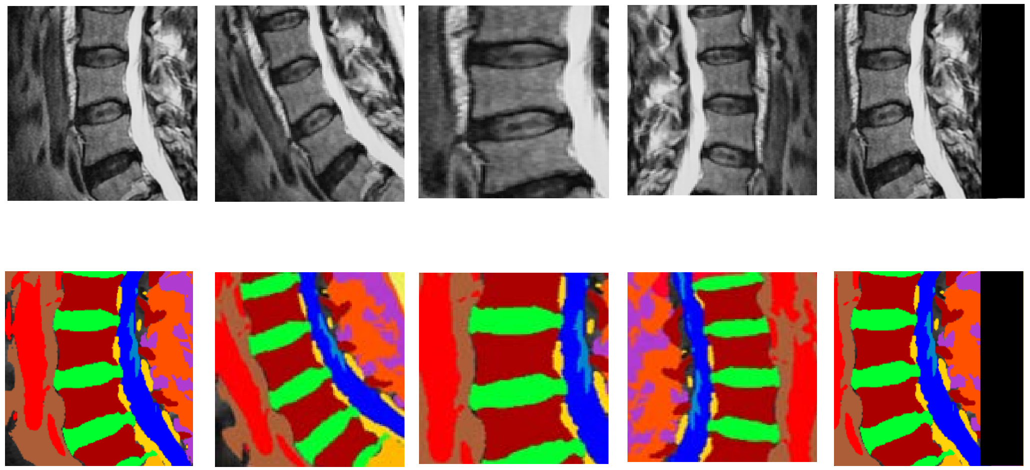
Linear Image Registration (T1w to T2w)

Z-score Normalization

$$x' = \frac{x - \mu}{\sigma}$$

Patch Extraction 256×256; Step 192×192 pixels

Data Augmentation



(a) (b) (c) (d)

(a) Random rotation (±20 degrees)

(b) Zoom (0.5-1.5)

(c) Horizontal flip (Bernoulli p = 1/2)

(d) Random shift (up to 10%).

Designed and implement topologies: CNN Arquitecture

Variations designed from the U-Net architecture. Mainly, the variations consist in adding one or several modules:

(A) Attention Gates (AGs) for replacing the skip connections

(D) Deep supervision blocks between convolutional blocks of the decoder branch

(M) Multikernels - Inception Block

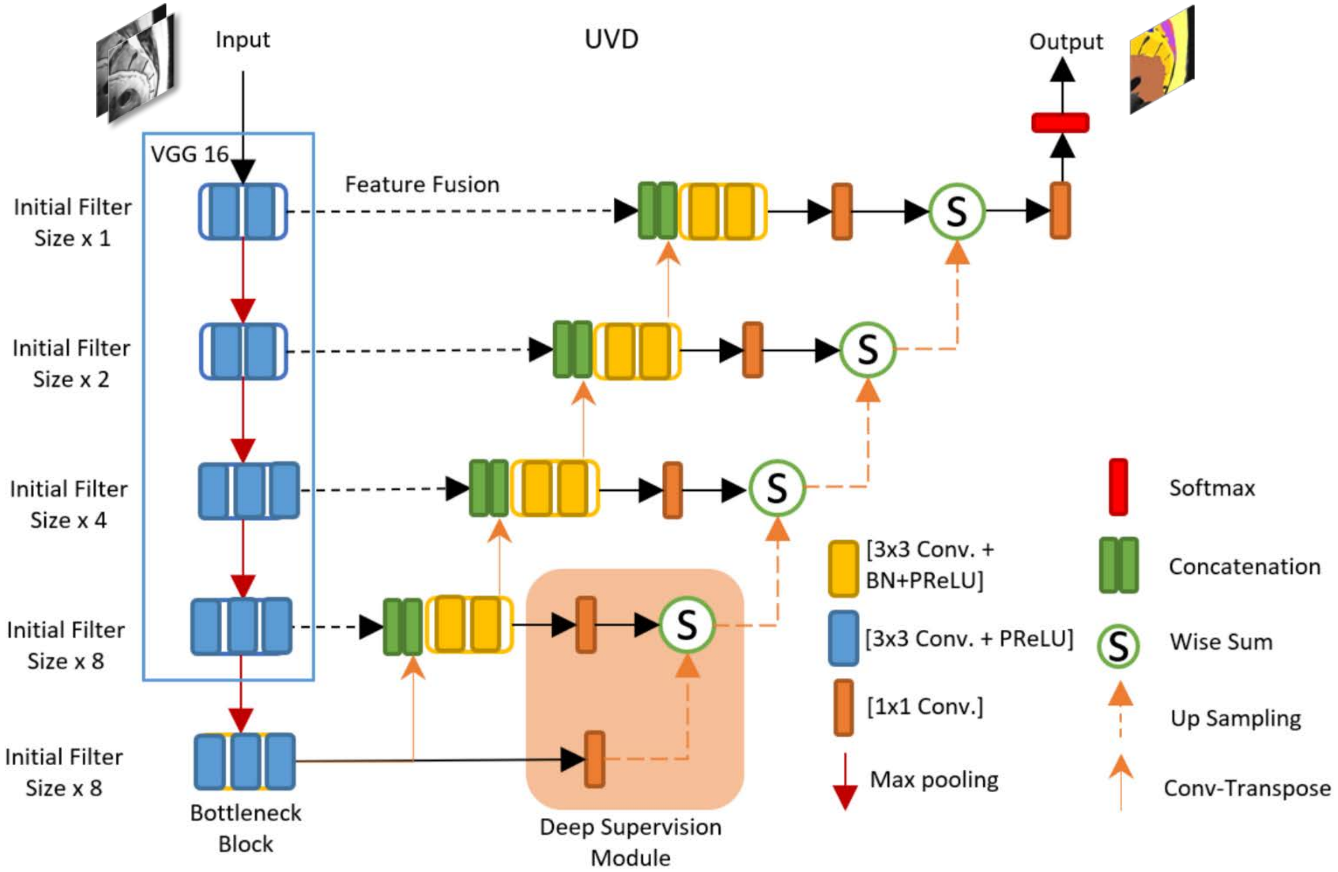
(V) VGG16 used as the encoder branch (descending path). The two variants that include VGG16 do not use transfer learning.

ID	Configuration	Optimiser	Lr	Act-Conv	Initial Filter Size
UAD	U-Net + attGate + DS	RMSprop	0.001	ReLU	16
UVAD	U-Net + VGG16 + attGate + DS	Adam	0.00033	PReLU	32
UAMD	U-Net + attGate + multKernel + DS	Adam	0.00033	ReLU	16
UVD	U-Net + VGG16 + DS	Adam	0.00033	PReLU	32
UMD	U-Net + multKernel + DS	Adam	0.00033	ReLU	32
UD	U-Net + DS	Adam	0.00033	ReLU	64
U1	U-Net	Adadelta	1.0	ReLU	64
FCN	FCN8	Adam	0.00033	ReLU	32

Parameter settings of the CNN Architectures with the best results

[1] J. Long et al., *IEEE CVPR* 2015; [2]O. Ronneberger et al., *Springer 2015*; [3]K. Simonyan et al., *arXiv:1409.1556, 2014*; [4]*G. Zeng* et al., *Springer, 2017*

Used Resources: CNN Arquitecture



Design of the proposed architecture which obtained the best results.

Train 5 Iterations (K-Fold cross Validation)

Evaluation Metrics:

Intersection over Union (IoU), for each individual class *c*

$$IoU_c = \frac{m_{cc}}{t_c + m_c - m_{cc}}$$

The global metric reported:

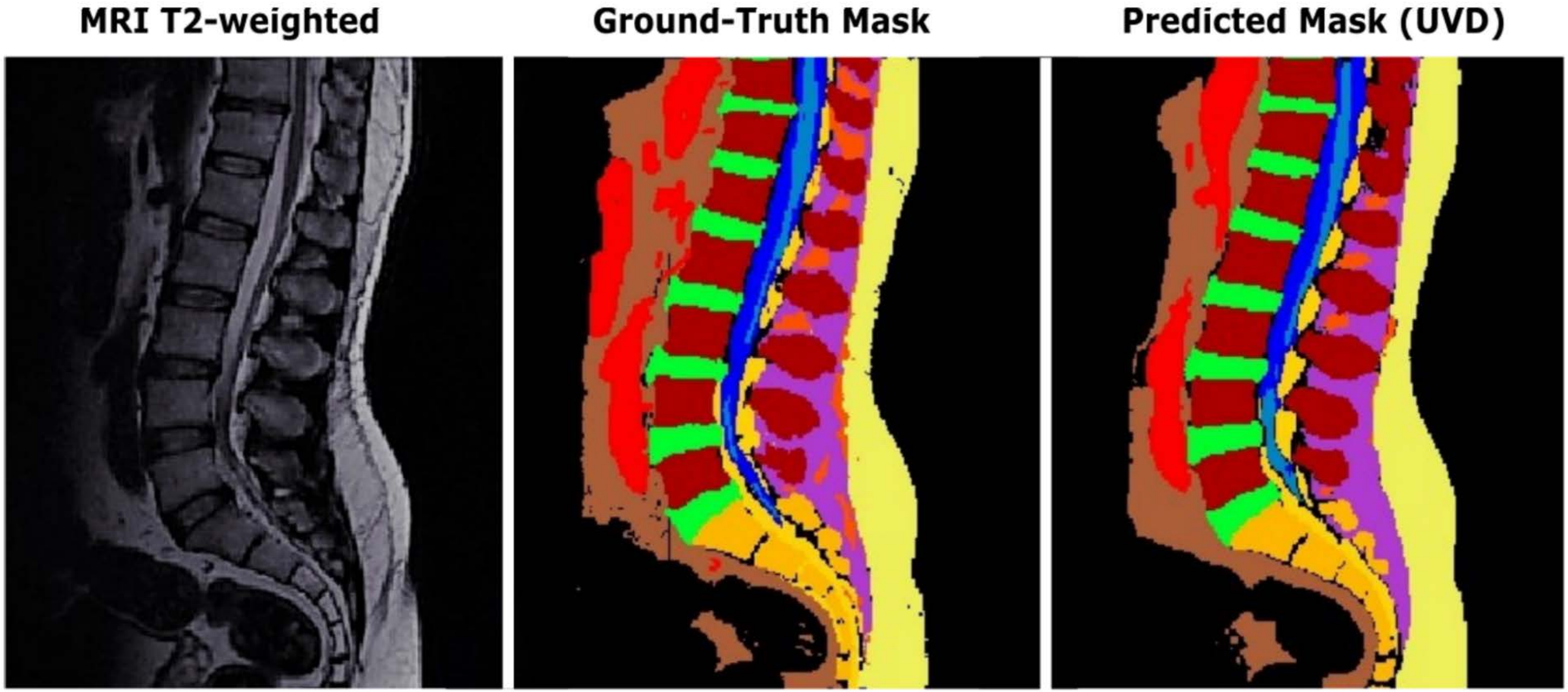
$$IoU = \frac{1}{|C^*|} \sum_{c \in C^*} IoU_c$$

- m_{cc}, count of pixels of class *c* correctly predicted
- t_c, total amount of pixels of the class *c* according to the ground-truth
- m_c, amount of pixels of the class *c* by the model

Results: Numeric Evaluation

Class #	Class Id	UAD	UVAD	UAMD	UVD	UMD	UD	U1	FCN
		Networks – IDs							
0	**Background**	84.1%	84.4%	83.4%	**87.4%**	86.2%	83.2%	86.2%	87.1%
1	**Vertebrae**	80.5%	81.1%	80.8%	**84.5%**	83.6%	80.7%	82.4%	80.6%
2	**Sacrum**	76.3%	77.7%	76.0%	**81.1%**	79.7%	77.2%	80.5%	76.6%
3	**Intervertebral Discs**	83.9%	84.2%	84.0%	**85.4%**	84.3%	83.7%	83.8%	82.5%
4	**Spinal Cavity**	66.3%	65.8%	65.1%	**67.3%**	67.0%	65.4%	66.7%	62.9%
5	**Subcutaneous Fat**	91.0%	90.6%	90.6%	**92.5%**	91.9%	90.4%	91.9%	91.8%
6	**Epidural Fat**	43.7%	44.1%	43.2%	**54.5%**	52.4%	44.1%	51.3%	49.0%
7	**Intramuscular Fat**	50.1%	48.8%	48.5%	**58.5%**	56.6%	48.2%	55.8%	55.0%
8	**Retroperitoneal Fat**	64.7%	64.4%	62.2%	**71.2%**	69.1%	62.3%	69.3%	70.5%
9	**Nerve Root**	15.1%	32.1%	16.3%	35.2%	**36.1%**	22.4%	34.3%	20.5%
10	**Blood Vessels**	54.8%	55.7%	53.5%	**63.0%**	59.8%	52.1%	59.2%	60.6%
11	**Muscle**	73.2%	73.1%	72.8%	**77.8%**	76.7%	72.3%	76.1%	75.9%
	IoU without Background	63.6%	65.2%	63.0%	**70.1%**	68.8%	63.5%	68.3%	66.0%
	IoU with Background	65.3%	66.8%	64.7%	**71.5%**	70.3%	65.2%	69.8%	67.8%

Results: Visual Evaluation



Conclusions

- UVD architecture outperforms the two baseline architectures: the standard U-Net and the FCN. Architecture UMD slightly improves the baseline; the remaining proposed architectures do not improve the baseline.

- The obtained results make it possible to use the output of architectures UVD or UMD to generate non-perfect but high-quality semantic segmentations which can be used as a starting point to manually segment more MR images.

- The integration of modules like deep supervision, spatial attention (attention gates), multi-kernels or the VGG16 topology for the encoder branch improved the performance of the original U-Net architecture, but when combined do not get the best results.

- The current results are not yet useful to support radiology tasks, but further analyses are being carried out

Future lines

- The segmentation of soft tissues and the detection of nerves still need to be significantly improved.

- The use of multiple kernels at input improved the accuracy for detecting nerves, but it is still not enough when the goal is to detect the compression of nerve roots due to a pathology.

Involved Institutions

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Anatomy of the Spine

http://bimcv.cipf.es/proyectos/midas-2/

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Automatic Semantic Segmentation of Structural Elements related to the Spinal Cord in the Lumbar Region by using Convolutional Neural Networks

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References

[1] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in The *IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* June 2015.

[2] O. Ronneberger, P. Fischer, and T. Brox, “U-net: Convolutional networks for biomedical image segmentation,” in *International Conference on Medical image computing and computer-assisted intervention. Springer*, 2015, pp. 234–241.

[3] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,”*arXiv preprint arXiv:1409.1556*, 2014.

[4] G. Zeng, X. Yang, J. Li, L. Yu, P.-A. Heng, and G. Zheng, “3d u-net with multi-level deep supervision: fully automatic segmentation of proximal femur in 3d mr images,”in *International workshop on machine learning in medical imaging*. Springer, 2017, pp. 274–282.

[5] C.-Y. Lee, S. Xie, P. Gallagher, Z. Zhang, and Z. Tu, “Deeply-supervised nets,” in *Artificial intelligence and statistics*, 2015, pp. 562–570.

[6] O. Oktay, J. Schlemper, L. L. Folgoc, M. Lee, M. Heinrich, K. Misawa,K. Mori, S. McDonagh, N. Y. Hammerla, B. Kainzet al., “Atten-tion u-net: Learning where to look for the pancreas,”*arXiv preprint arXiv:1804.03999*, 2018.

[7] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich,“Going deeper with convolutions,”in *Proceedings of the IEEE conference on computer vision and pattern recognition*,2015,pp.1–9.

Thank you!

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MIDAS Massive Image Data Anatomy of the Spine