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

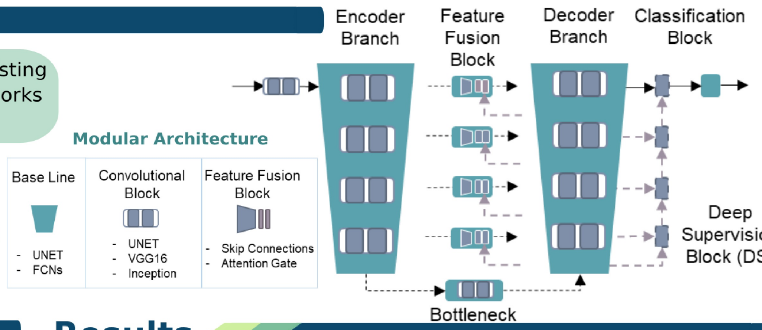
Automated semantic segmentation of multiple structural elements in spinal cord can bring many benefits, such as:

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

Aim

Desing variations from existing convolutional neural networks (CNN) architectures

Improve Performance



Methods

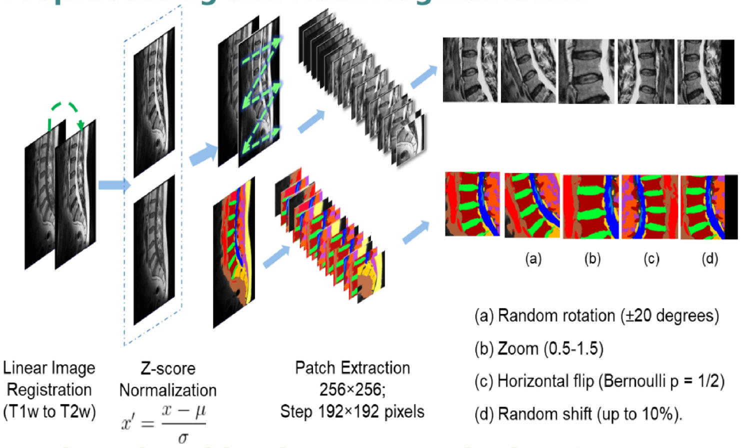
Lumbar Spine Dataset

Magnetic Resonance (MR) images scans extracted from the Medical Imaging Databank of the Valencian Region (BIMCV) database, Spain.

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

* 5-Fold Cross Validation.

Preprocessing and Data Augmentation



Designed and implement topologies CNN

Variations designed from the U-Net architecture [1]. Mainly, the variations consist in adding one or several modules:

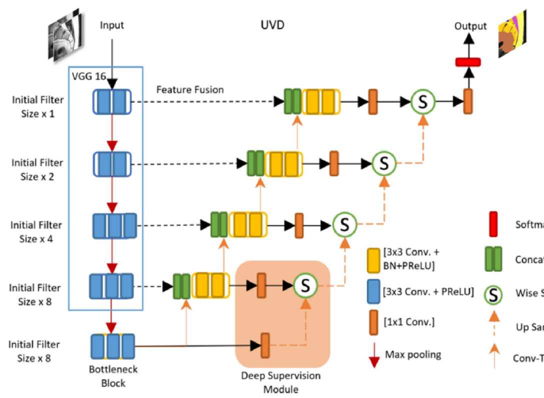
- (A) Attention Gates (AGs) for replacing the skip connections [2].
- (D) Deep supervision blocks between convolutional blocks of the decoder branch [3].
- (M) Multikernels - Inception Block [4]
- (V) VGG16 [5] used as the encoder branch (descending path). The two variants that include VGG16 do not use transfer learning.

ID	Configuration	Optimiser	Lr	Act-Conv	Initial Filter Size
UVD	U-Net + VGG16 + DS	Adam	0.00033	PReLU	32
UMD	U-Net + multKernel + DS	Adam	0.00033	ReLU	32
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

Results

Design of the proposed architecture which obtained the best results.



Evaluation Metrics

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

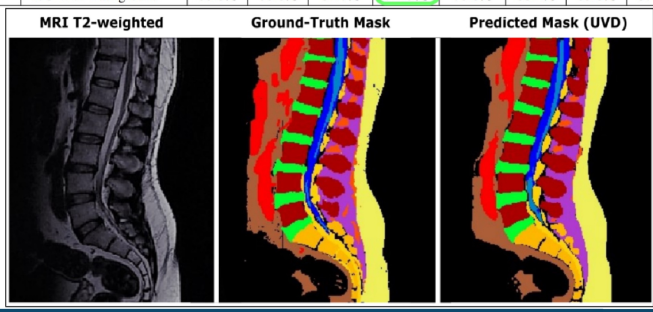
$$IoU_c = \frac{m_{cc}}{t_c + m_c - m_{cc}}$$

The global metric reported:

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

Performance of the automatic semantic segmentation generated by several network architectures measured in terms of the intersection over union (IoU) metric on 12 classes

Class #	Class Id	Networks – IDs							
		UAD	UVAD	UAMD	UVD	UMD	UD	U1	FCN
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%



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.
- As future perspectives, the segmentation of soft tissues and nerves still needs to be improved, specially when the goal is to detect the compression of nerve roots due to a pathology. The current results are not yet useful to support radiology tasks, but further analyses are being carried out.

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ICPR 2020 25th International Conference on Pattern Recognition, Milan, Italy 10 | 15 January 2021
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MIDA
hospital Arnau de Vilanova valencia
Universitat Politècnica de València
Príncipe Felipe Centro de Investigación
Generalitat Valenciana Conselleria d'Educació, Investigació, Cultura i Esport
Fundación para el Fomento de la Investigación Sanitaria y Biomédica de la Comunitat Valenciana
Supported by a grant from Generalitat Valenciana; ACIF/2018/285
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