

# Fully automated longitudinal segmentation of new or enlarging Multiple Sclerosis (MS) lesions using 3D convolution neural networks

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## Introduction and Purpose

- Quantification of new and enlarging Multiple Sclerosis (MS) lesions (lesion activity) from follow-up MRI scans is an important surrogate of clinical disease activity
- Manual assessment is time consuming, **inter-rater variability is high** (Egger et al., 2017), and only few fully automated methods are available so far
- **Deep-learning** methods like convolutional neural networks (CNN) **show promising results** for lesion segmentation (Danelakis et al., 2018)

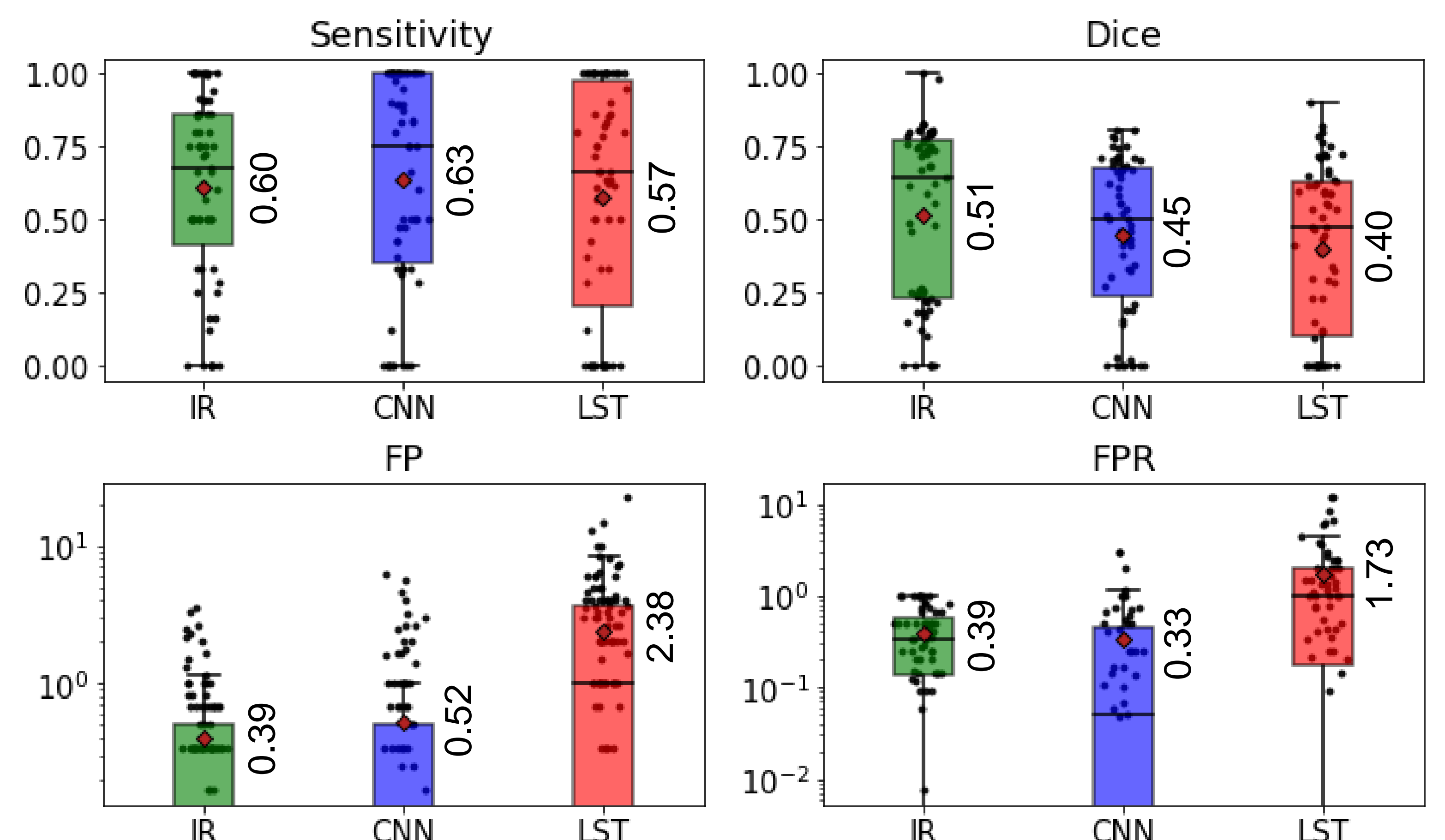
## Methods

- 3D-CNN with an encoder-decoder (**U-Net-like**) architecture
- **Input: 2 FLAIR images** – baseline (BL) and follow-up (FU)
- **Output: 3D mask indicating new or enlarged lesions**
- **Pretrained on 1809 single time point** routine data
- **Trained on 587 BL-FU pairs** from clinical routine

### Evaluation data:

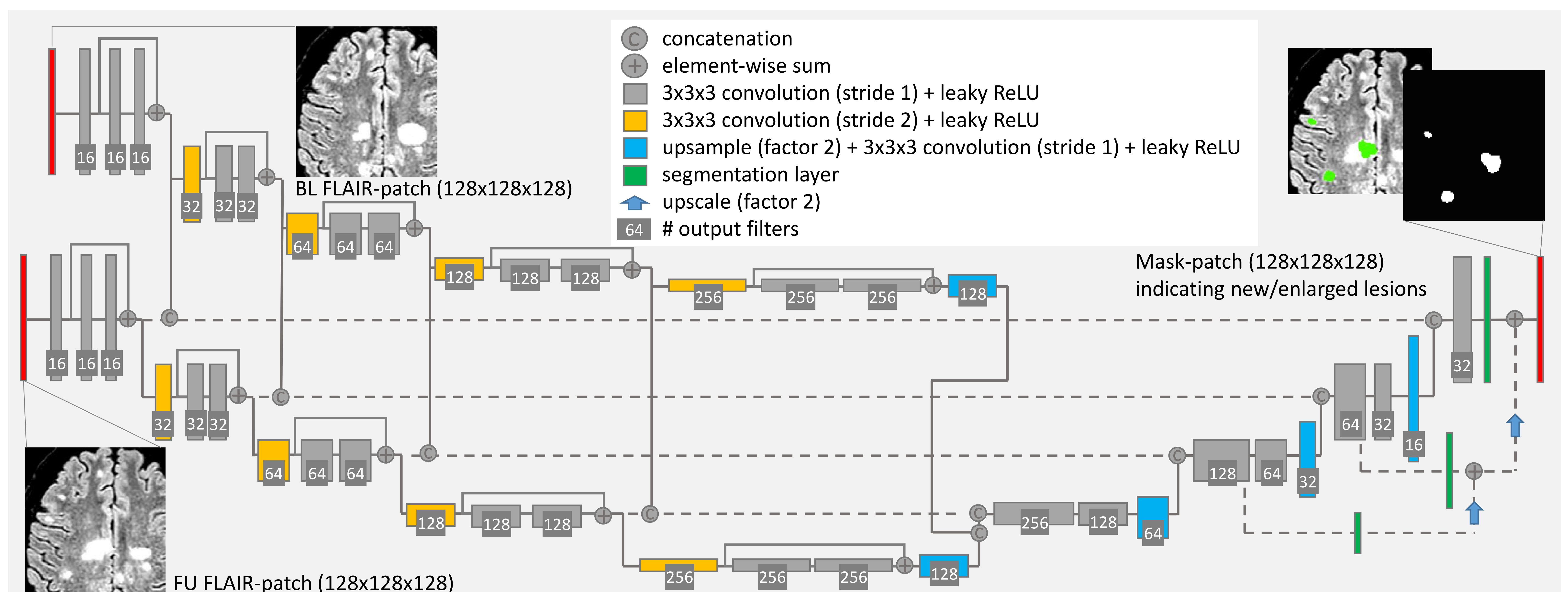
- 89 data (BL,FU), 3T Philips Ingenia, University Hospital of Zurich, Switzerland; age: 36.76 ( $\pm$  8.67); follow-up time: 2.21 ( $\pm$  1.09) years
- 27 data (BL,FU), 1.5T Siemens Avanto; Multiple Sclerosis Centre of the University Hospital Zurich, Switzerland; age: 38.92 ( $\pm$  10.49); follow-up time: 5.93 ( $\pm$  0.56) years

- **Performance measures:** mean lesion-wise sensitivity, dice coefficients, lesion-wise number of false positives (FP) and false positive rate (FPR)



## Conclusion

- **Low inter-rater performance** signifies the **complexity and uncertainty of identifying new and enlarging lesions**
- Automated CNN-based approach can **quickly (<1 min)** provide an **independent and deterministic assessment** of lesions from BL and FU scans to support diagnosis and **potentially mitigate inter-rater variability**
- **Outperforms non-deep learning method (LST)**



- **2-3 independent ground-truth** segmentations available
- Compared to lesion segmentation toolbox (LST) (Schmidt et al., 2019, <http://www.applied-statistics.de/lst.htm>)

## Results

- Lesion masks were compared **between raters (inter-rater, IR)** as well as to the **results provided by the CNN** and the **compared LST method**

### Disclosures

CWE has received travel grants from Merck Sereno and Sanofi Genzyme. PM has received travel grants from Merck Sereno. SS reports compensation for consulting, serving on scientific advisory boards, speaking, or other activities from Biogen, Celgene, Merck, Sanofi and TEVA.

### References

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