Brain tumor detection using Selective Search and Pulse-Coupled Neural Network feature extraction

Brad Niepceron, Ahmed Nait-Sidi-Moh and Filippo Grassia. University of Picardie Jules Vernes

Speaker : *Brad Niepceron. brad.niepceron@etud.u-picardie.fr . bniepce.github.io/resume/*

IRSH 2021

UNIVERSITÉ de Picardie Jules Verne

Laboratoire des Technologies Innovantes

INTRODUCTION

1

Why are computer-aided tumor diagnosis systems needed ?

Increasing amount of worldwide cases, high mortality caused by brain tumors [1]

3-5 % day-by-day radiologist error rate [2][3]

Time consumption and cancer care cost [4]

Improving early detection to anticipate therapy and reduce costs

Which methods are considered ?

Local and global feature extractions

All sorts of neural networks [5]

Machine learning algorithms and radiomic features extraction [6]

The state-of-the-art clearly tends towards deep learning models

What are the limits of state-of-the-art methods ?

Heavy computational and energy costs [7]

Dependency to GPU hardware [8]

Require a large amount of labeled data [9]

Lack of explainability [10]

Do not fit health-care providers requirements

State-of-the-art propositions to tackle the aforementioned issues

Cost / Hardware

Compress deep neural networks

Use neural computation

Data ethics and privacy

Rely on unsupervised / non-trainable methods and benchmark datasets

Use generative models

Explainability

Open up the blackbox nature of neural networks (layerwise relevance propagation)

Rely on bio-plausible models

Neural Computation + non-trainable method + bio-plausible model

↓

Pulse-Coupled Neural Network (PCNN)

METHODS

Dataset | Model | Application to tumor detection

II

02

METHODS

2.1 Dataset

- BraTS Dataset
- Pre-operative MRI scans
- **Manually** segmented by 1-4 raters
- Four MRI sequences : **Flair, T2, T1, T1C**
- Automatically extended with bounding boxes
- No pre-processing -> low computational workload

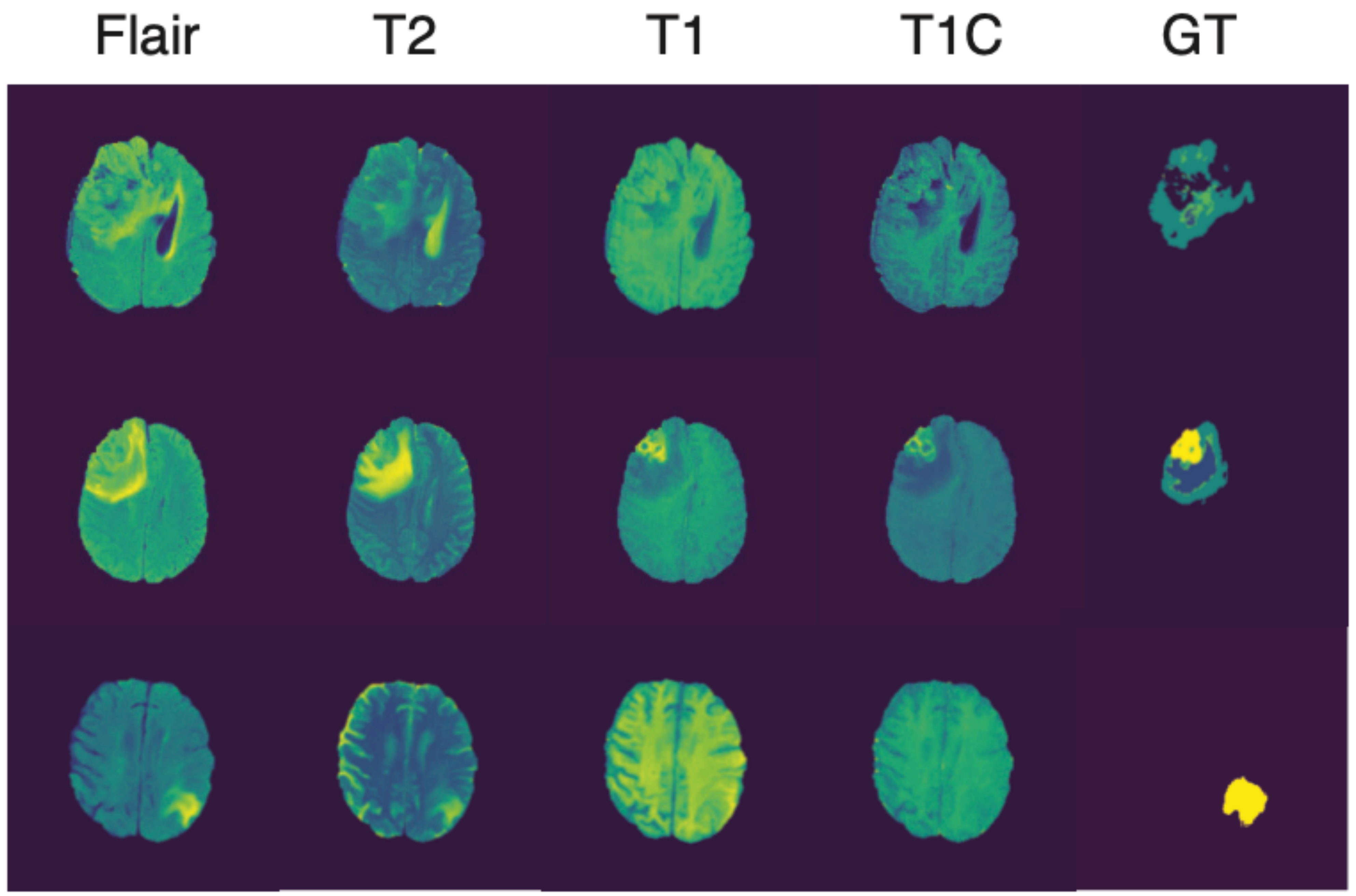


Fig 1. Cases from the BraTS dataset. Source : Niepceron et al. 2020.

02

METHODS

2.2 Model

- Pulse-Coupled Neural Network (PCNN)
- Laterally-connected neurons
- 2D input image
- Fixed synaptic weights
- Iterative, outputs a map of neuronal activity
- **Feeding :** Computes voltage with input stimulus
- **Linking :** Updates neuron's internal activity
- **Pulse :** Fire if membrane potential exceeds threshold

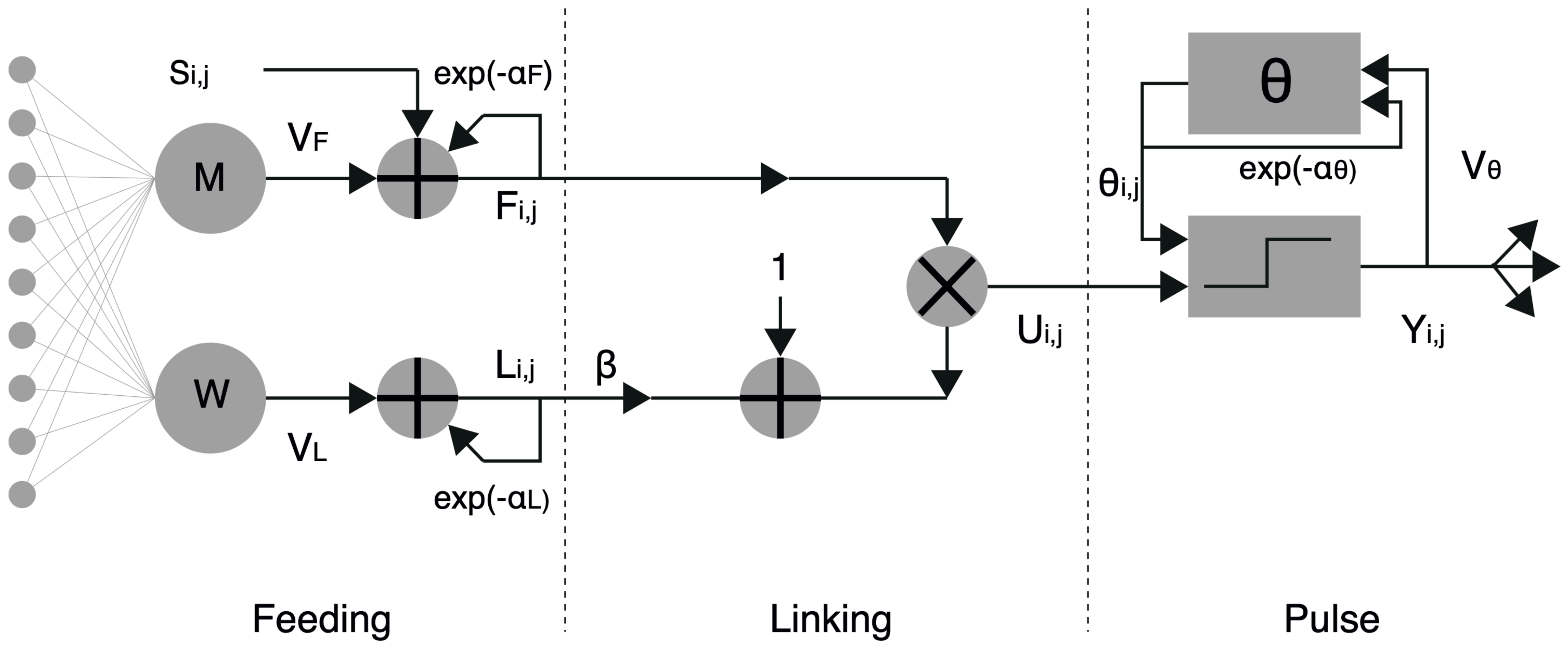


Fig 2. Standard PCNN Model. Source : Niepceron et al. 2021.

UNIVERSITÉ de Picardie Jules Verne
Laboratoire des Technologies Innovantes

Considerations using PCNN

Tedious to tune

Scans are not 2-dimensional

Not originally made for detection purposes

2.3 Application to tumor detection

- Fast Linking Spiking Cortical Model (FLSCM)
- Uses Spiking cortical neurons
- Fast linking synapses
- **Pulse :** Combines stimulus and synaptic modulation to charge the membrane
- Neurons fire faster

02 METHODS

2.3 Application to tumor detection

- Medical image fusion with m-PCNN
- Inputs are merged in the internal state
- Parameter **beta** to control each sequence importance

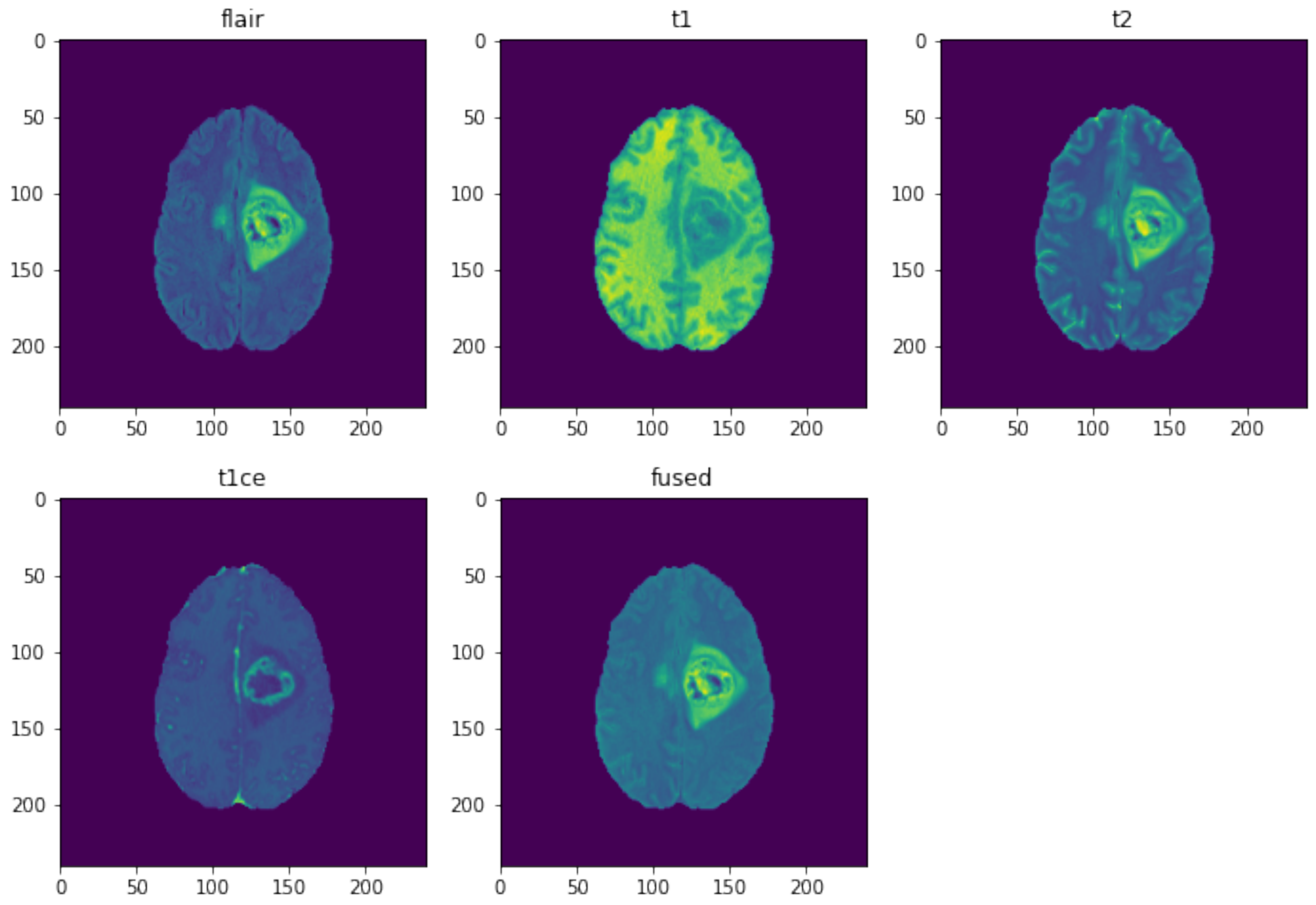


Fig 3. Example of fusion on one MRI slice. Source : Niepceron et al. 2021.

02

METHODS

2.3 Application to tumor detection

- Feature extraction with FLSCM
- PCNN image signature theory
- Gets the firing activity as a time-series
- Any sub-structure signature is contained in the original image signature

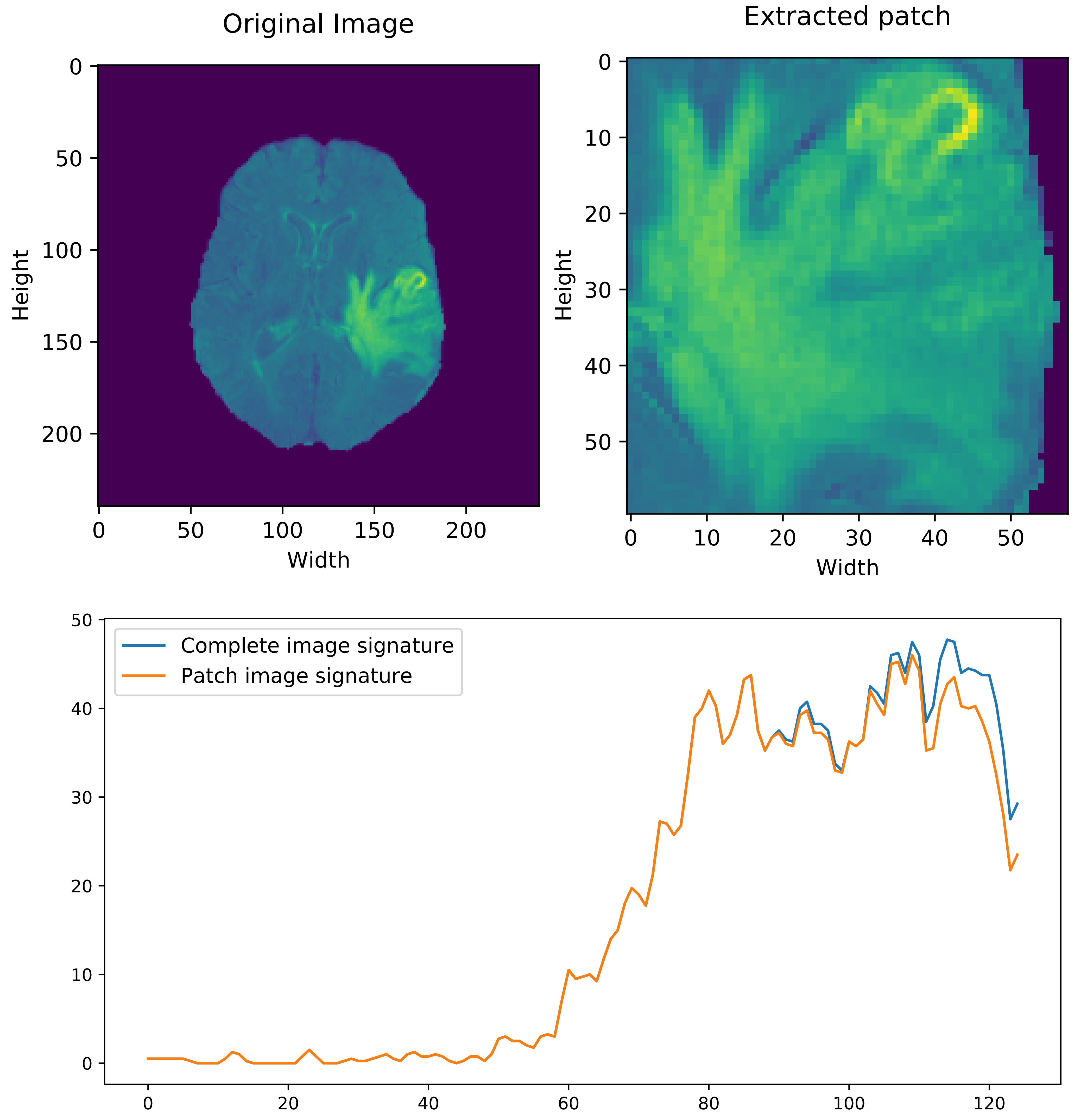


Fig 4. Comparison of the local and global PCNN signatures. Source : Niepceron et al. 2021.

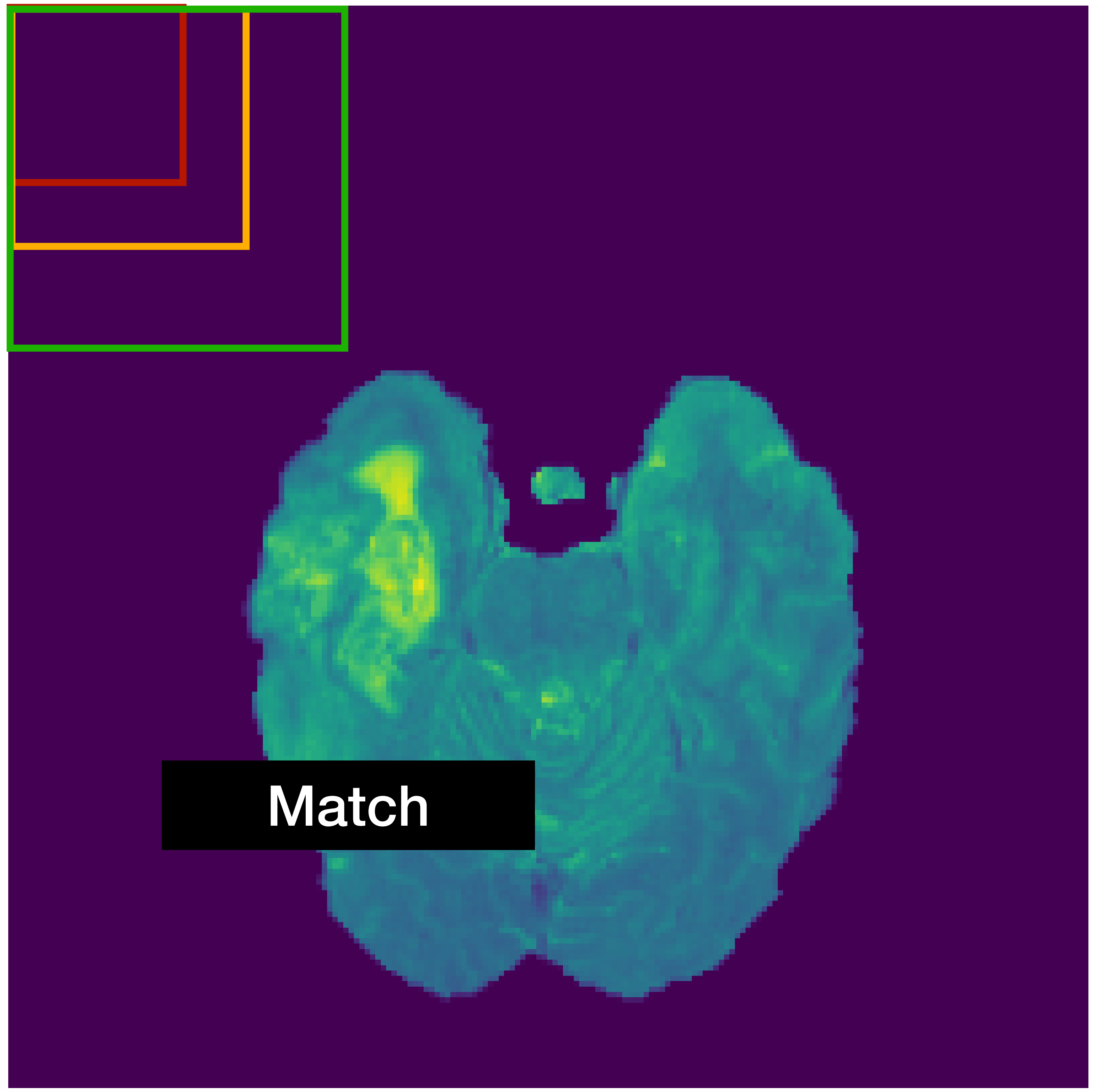
UNIVERSITÉ de Picardie Jules Verne

Laboratoire des Technologies Innovantes

METHODS

2.3 Application to tumor detection

- Simple object detection [11]
- Sliding window
- Comparing local signature to global signature
- Proven to work with clear background
- Computationally expensive
- Do not fit tumor shapes



METHODS

2.3 Application to tumor detection

Fig 5. The Selective Search algorithm. Source : arthurdouillard.com.

METHODS

2.3 Application to tumor detection

Step 1 : Compute Selective Search on M to create B_{ij} bounding boxes
Step 2 : Remove boxes with area greater than threshold θ
Step 3 : Extract image patches P_{ij} from the boxes
Step 4 : Convert each P_{ij} to signature S_{ij}
Step 5 : Compute the Euclidean distance between each S_{ij} and the signature M_{sign} obtained from M
Step 6 : Retain B_{min} the box that gives the smallest distance D_{min} as the complete tumor detection box

Fig 6. Tumor detection algorithm based on PCNN feature extraction. Source : Niepceron et al. 2021.

EXPERIMENTS AND RESULTS

EXPERIMENTS AND RESULTS

3.1. Experiments

- Experiment details
- Ran on CPU
- Model evaluated by Intersection over Union (IoU)

$$IoU = \frac{B \cap G}{B \cup G}$$

- Optimized fusion parameter tuning with differential evolution

- Entropy / Standard Deviation

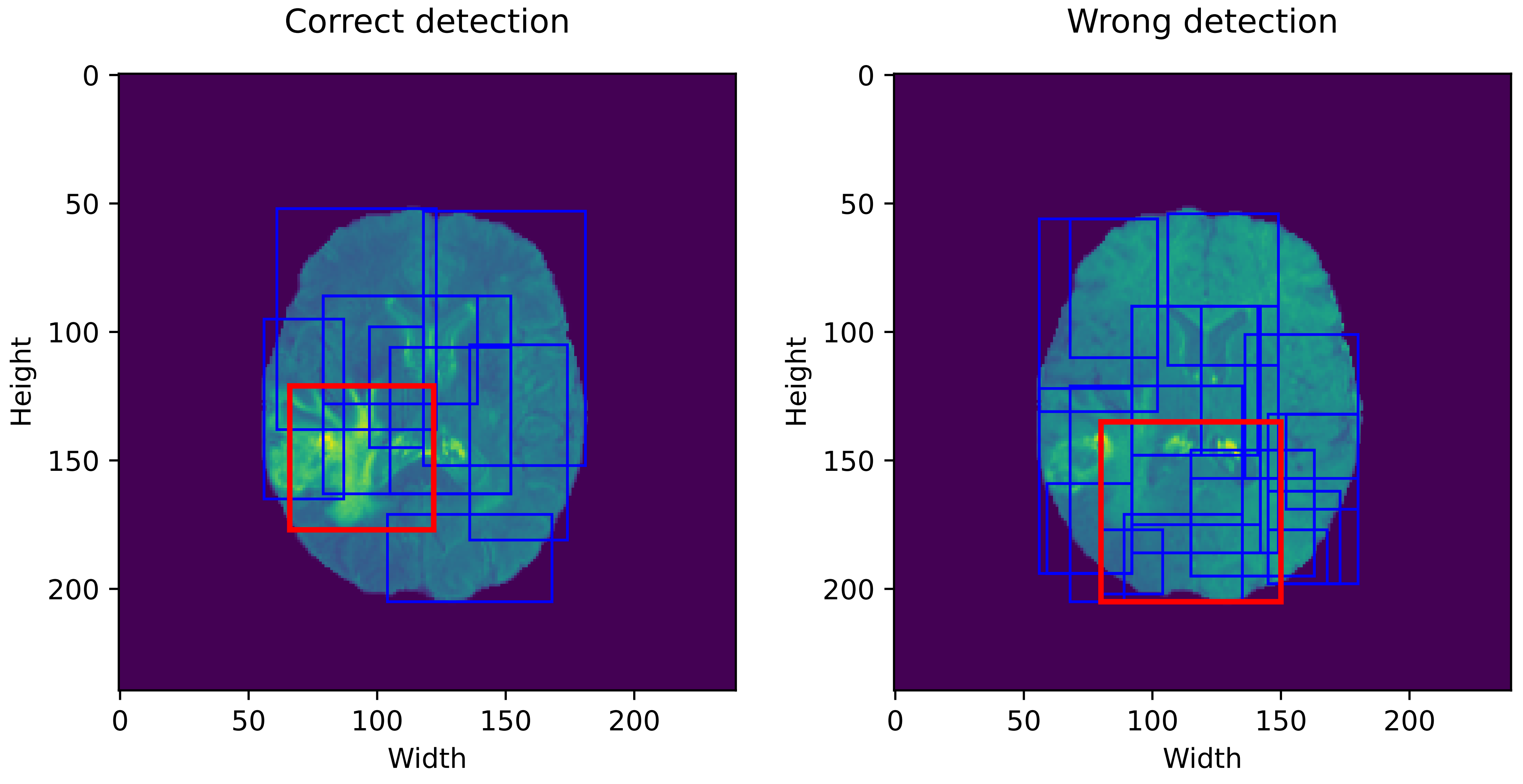


Fig 7. Comparing detection accuracy with different fuse parameters. Source : Niepceron et al. 2021.

UNIVERSITÉ de Picardie Jules Verne

Laboratoire des Technologies Innovantes

03

EXPERIMENTS AND RESULTS

3.2. Results

RESULTS	Average 0.78 IoU score 3 to 8 seconds per slice

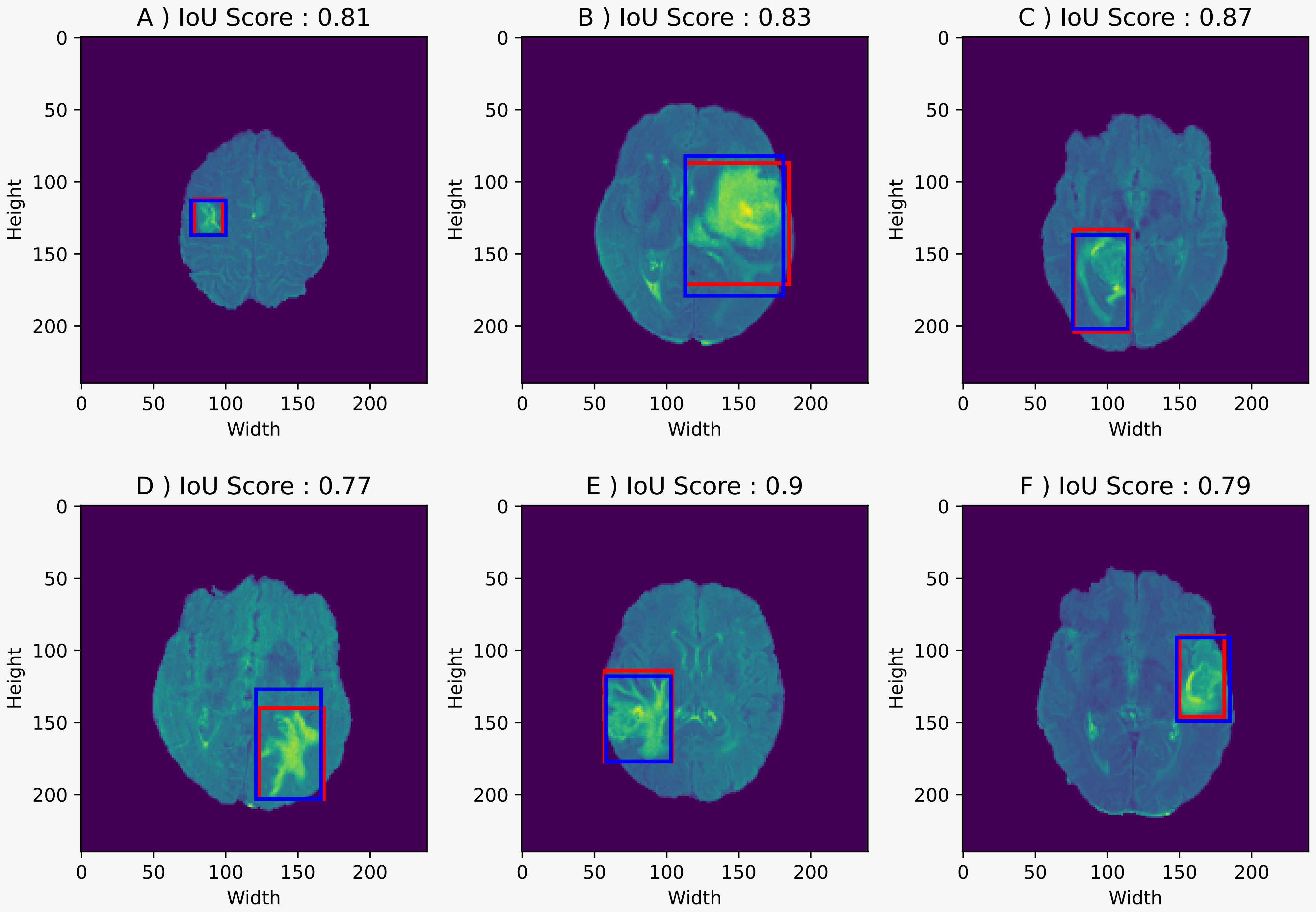


Fig 8. Results of PCNN tumor detection. Source : Niepceron et al. 2021.

UNIVERSITÉ de Picardie Jules Verne

Laboratoire des Technologies Innovantes

EXPERIMENTS AND RESULTS

3.2. Results

LIMITS	Selective Search param. Small tumorous regions Whole tumor

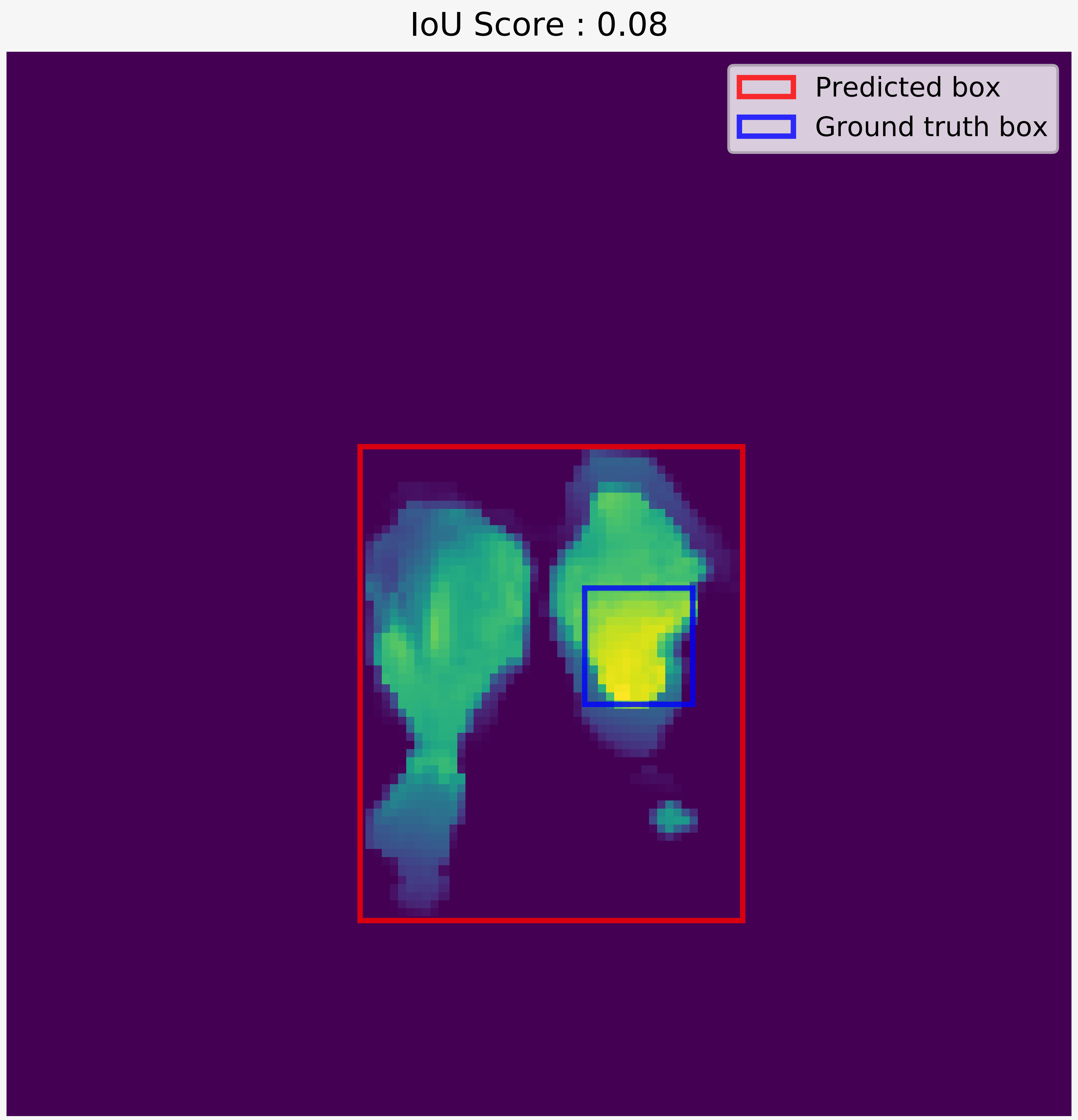


Fig 9. Example of poor early detection. Source : Niepceron et al. 2021.

DISCUSSION AND CONCLUSION

IV

Extension to multi-label detection

Tuning the fusion for one particular label detection

Run the algorithm on the detected patch

Use image pre-processing to ease the region proposal

Add a classifier (SVM) for full recognition

Highlights

Promising results using neural computation

Proof of PCNN efficiency in medical image analysis

Not relying on trainable synapses

Fast and efficient alternative to deep learning methods

Thank you.

Brad Niepceron, Ahmed Nait-Sidi-Moh and Filippo Grassia. University of Picardie Jules Vernes

Speaker : *Brad Niepceron. brad.niepceron@etud.u-picardie.fr*

UNIVERSITÉ de Picardie Jules Verne

Laboratoire des Technologies Innovantes

A

REFERENCES

[1] Sung, Hyuna et al. "Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries." CA: A Cancer Journal for Clinicians 71 (2021): 209 - 249.

[2] Bruno, Michael A. et al. "Understanding and Confronting Our Mistakes: The Epidemiology of Error in Radiology and Strategies for Error Reduction." Radiographics : a review publication of the Radiological Society of North America, Inc 35 6 (2015): 1668-76.

[3] Berlin, Leonard. "Radiologic errors and malpractice: a blurry distinction." AJR. American journal of roentgenology 189 3 (2007): 517-22

[4] Mariotto, Angela B et al. "Projections of the cost of cancer care in the United States: 2010-2020." Journal of the National Cancer Institute 103 2 (2011): 117-28

A

REFERENCES

[5] Suganyadevi, S. et al. “A review on deep learning in medical image analysis.” International Journal of Multimedia Information Retrieval (2021): 1 - 20.

[6] Vial, Alanna et al. “The role of deep learning and radiomic feature extraction in cancer-specific predictive modelling: a review.” Translational cancer research 7 (2018): 803-816.

[7] Strubell, Emma et al. “Energy and Policy Considerations for Deep Learning in NLP.” ACL (2019).

[8] Goel, Abhinav et al. “A Survey of Methods for Low-Power Deep Learning and Computer Vision.” 2020 IEEE 6th World Forum on Internet of Things (WF-IoT) (2020): 1-6.

[9] Najafabadi, Maryam Mousaarab et al. “Deep learning applications and challenges in big data analytics.” Journal of Big Data 2 (2014): 1-21.

[10] Bibal, Adrien et al. “Legal requirements on explainability in machine learning.” Artificial Intelligence and Law (2020): 1 - 21.

[11] Gu, X.: Feature extraction using unit-linking pulse coupled neural network and itsapplications. Neural Processing Letters27, 25–41 (2007)

[12] Zhan, K., Shi, J., Li, Q., Teng, J., Wang, M.: Image segmentation using fast linkingscm. In: International Joint Conference on Neural Networks (IJCNN). pp. 1–8.IEEE (2015)