Developing brain tumor diagnosis applications based on Artificial Neural Networks

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Journée de la SAGIP

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INTRODUCTION

1

INTRODUCTION

1

Cases and Mortality

Increasing amount of cancer cases

25% of glioblastoma patients **survive** more than **one** year

2

The diagnosis task

Rarity can cause **misinterpretation**

3–5% day-to-day radiologist error rate

3

MRI Segmentation

Manual MRI Segmentation is **time consuming** and **expensive**

Increasing amount of data to process

4

Life expectancy

Survival prediction hard to establish

Lack of variables in the common diagnosis system

INTRODUCTION

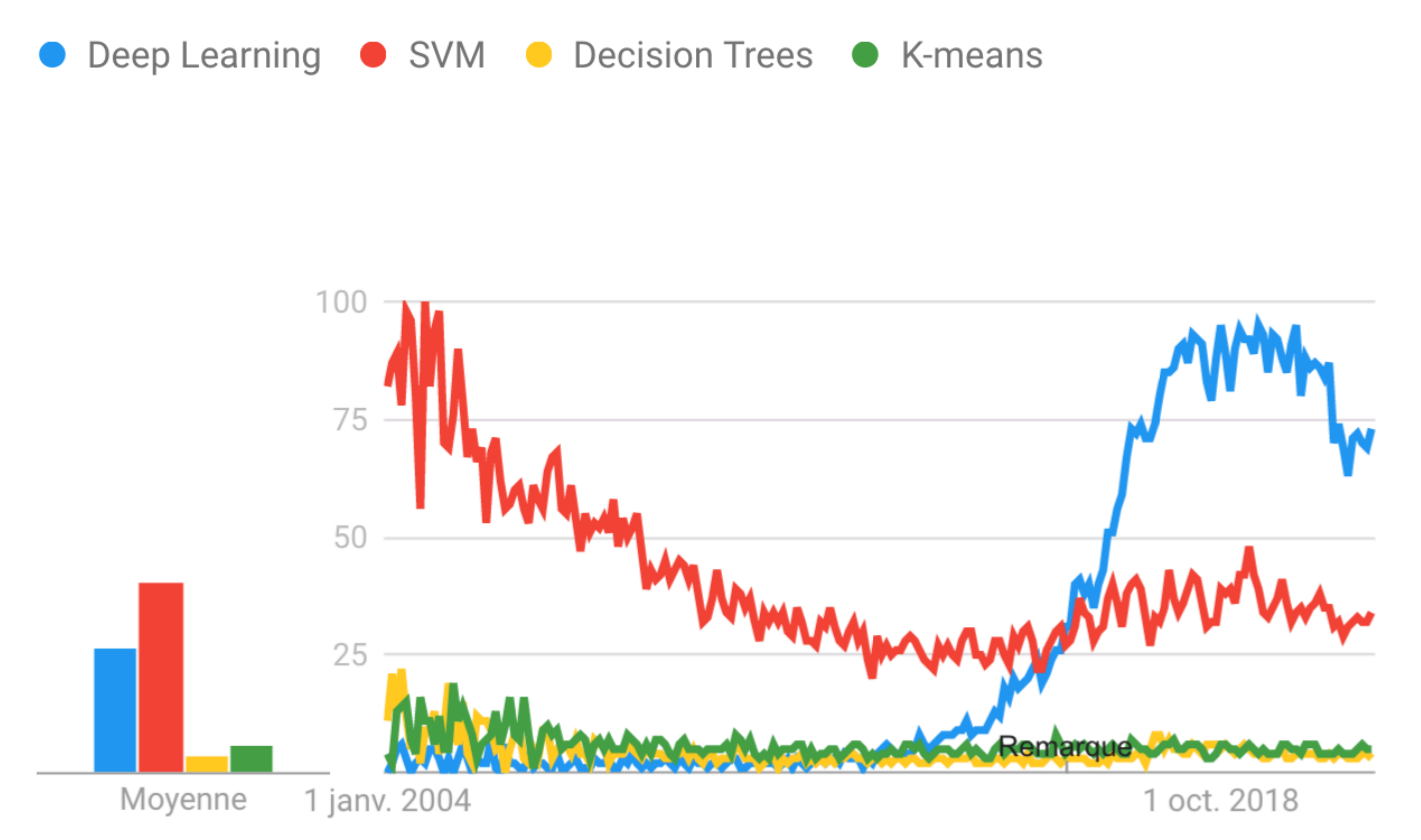

Fig 1. Trends of Deep Learning in recent years. Source : Google Trend

Deep Learning (DL) for MRI Analysis

- Convolutional Neural Nets (CNN) proven efficient in the medical field
- Fully automate the recognition system
- Outperforming human accuracy
- Strong research community

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1 INTRODUCTION

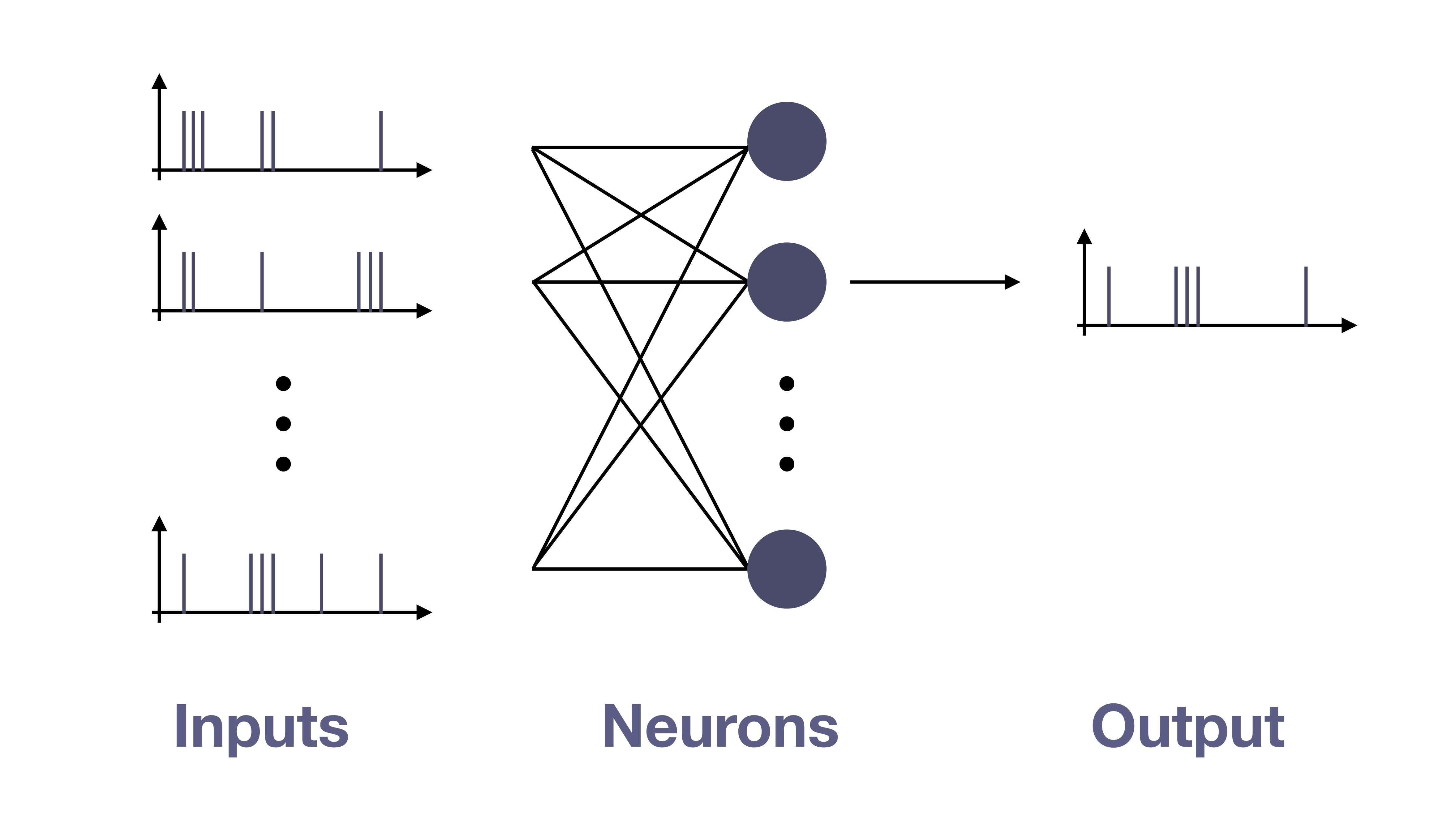


Fig 2. A Spiking Neural Network

- **Spike-based computation**
- Rise of Spiking Neural Nets. (SNN)
- Towards a non-abstract AI
- Cost-efficient models
- Easy large-scale deployment

PROBLEMS AND OBJECTIVES

II

PROBLEMS AND OBJECTIVES

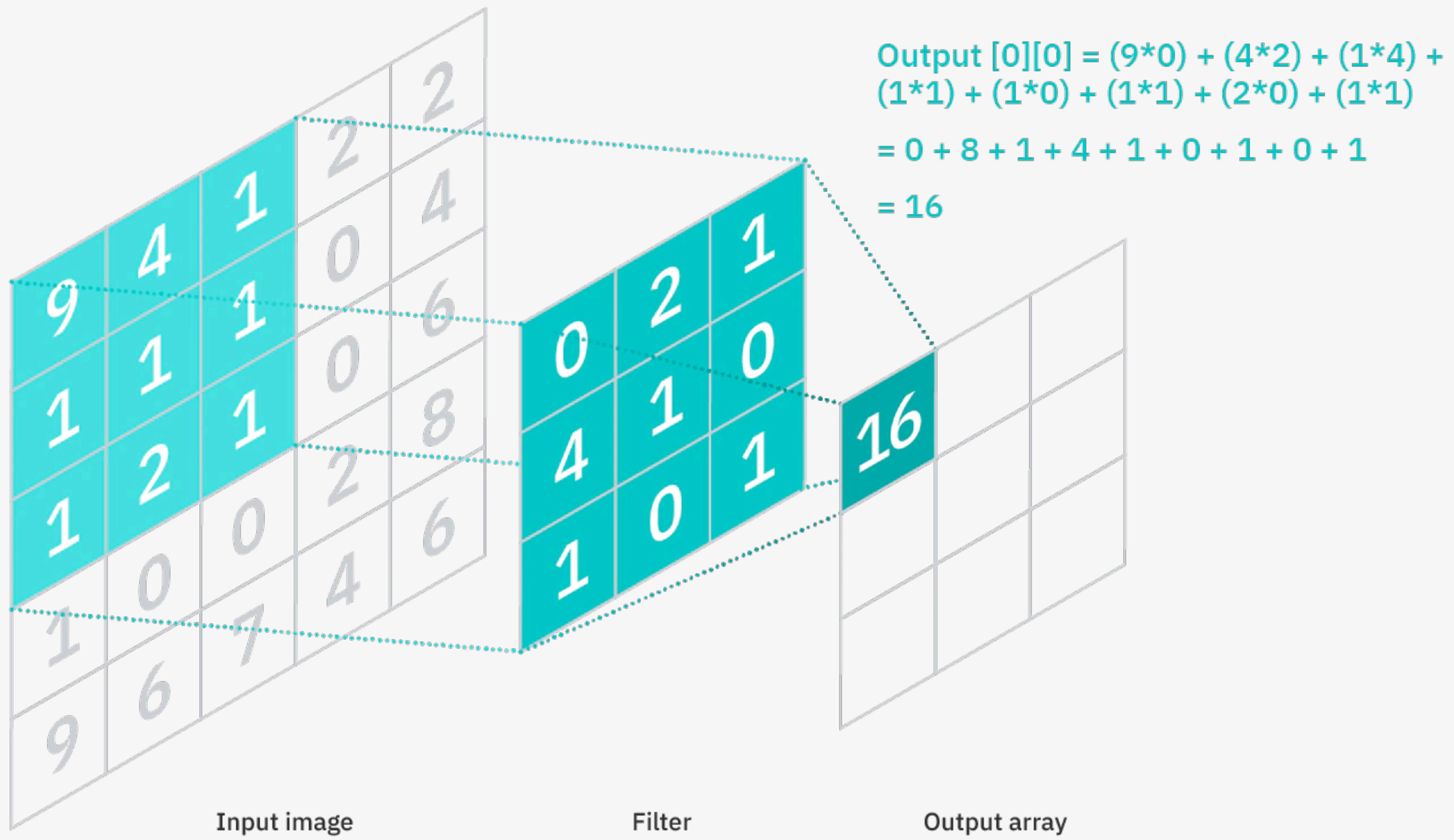


Fig 3. Feature map creation in a convolutional neural network. Source : ibm.com

- CNN
- Long training time
- GPU dependent
- High energy cost
- Blackbox effect
- No architecture rules
- Lesion specific

PROBLEMS AND OBJECTIVES

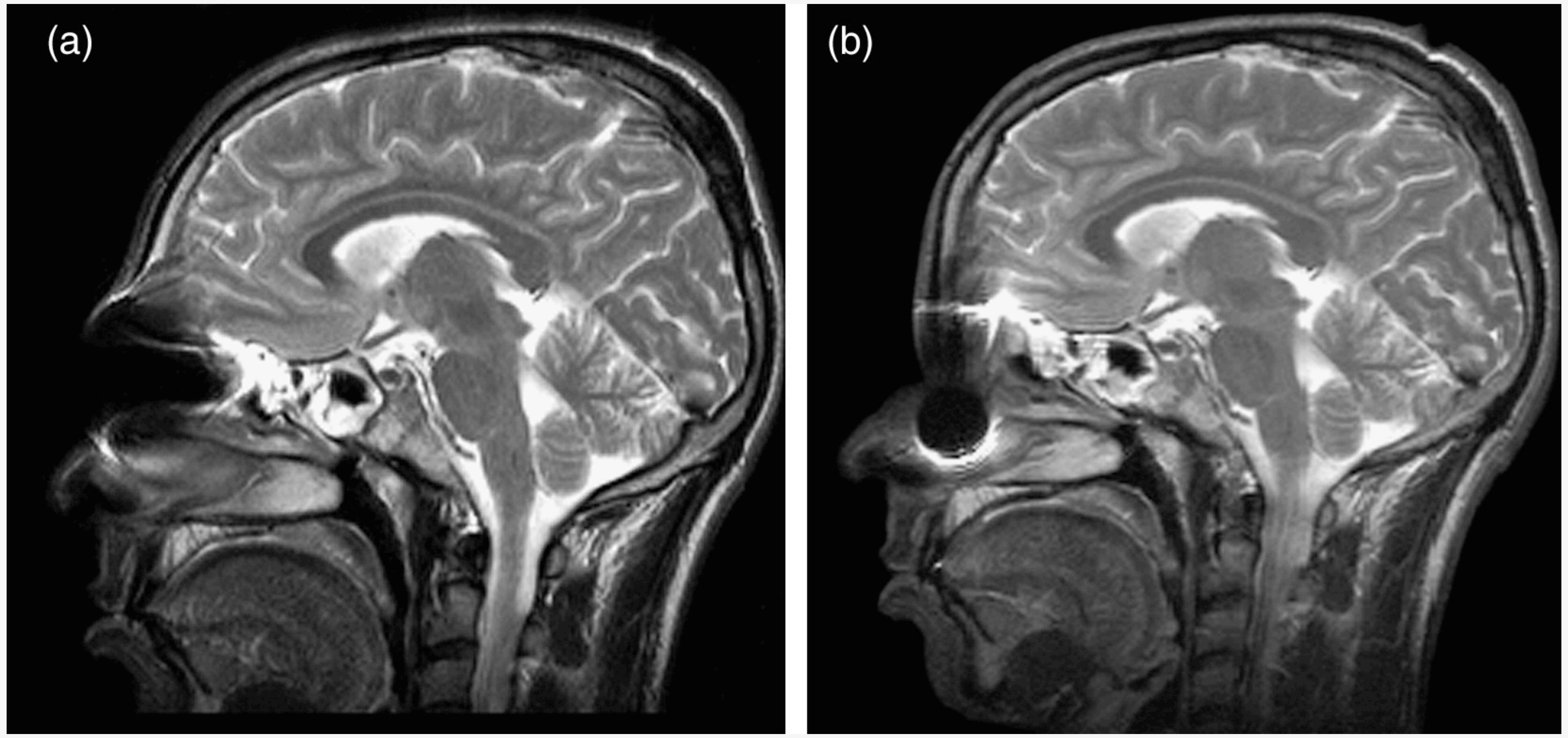


Fig 4. Artifact form a small metal flake in the right frontal sinus. Source : Prabhjot Kaur et al. Protocol error artifacts in MRI: Sources and remedies revisited. 2007.

Brain Imaging

- High dimensionality
- Heavy pre-processing
- Ethics and data unavailability
- High data variation

PROBLEMS AND OBJECTIVES

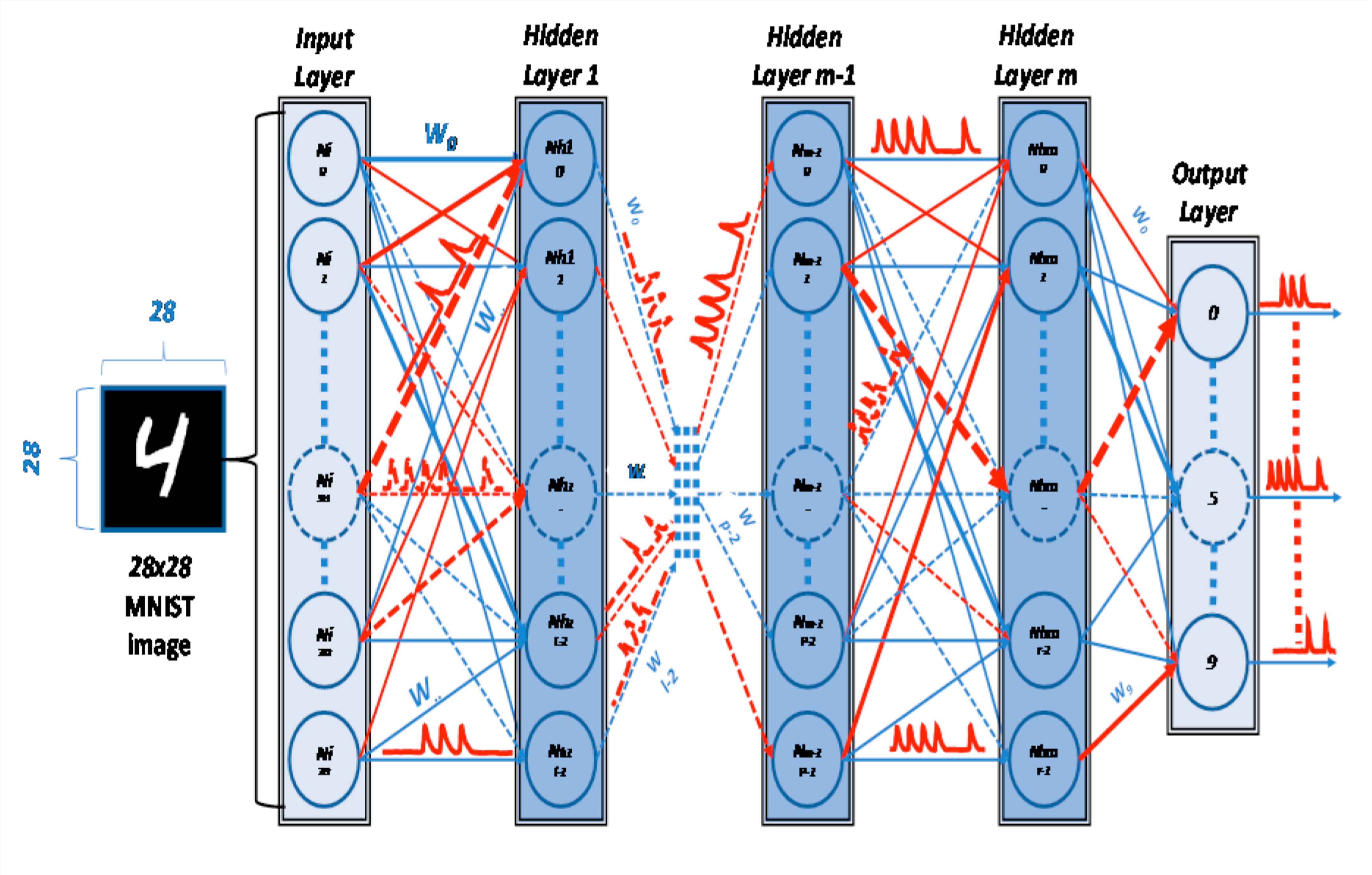


Fig 5. The MNIST task by an SNN. Source : Al-Hamid, Ali A., and HyungWon Kim. Optimization of Spiking Neural Networks Based on Binary Streamed Rate Coding. 2020.

- Spiking Neural Networks
- Hard to apply
- MRI are hard to encode
- Young simulators
- Small amount of ressources

PROBLEMS AND OBJECTIVES

Objective #1

Redefine Deep Learning based methods to fit the power efficiency requirements of healthcare providers.

Objective #2

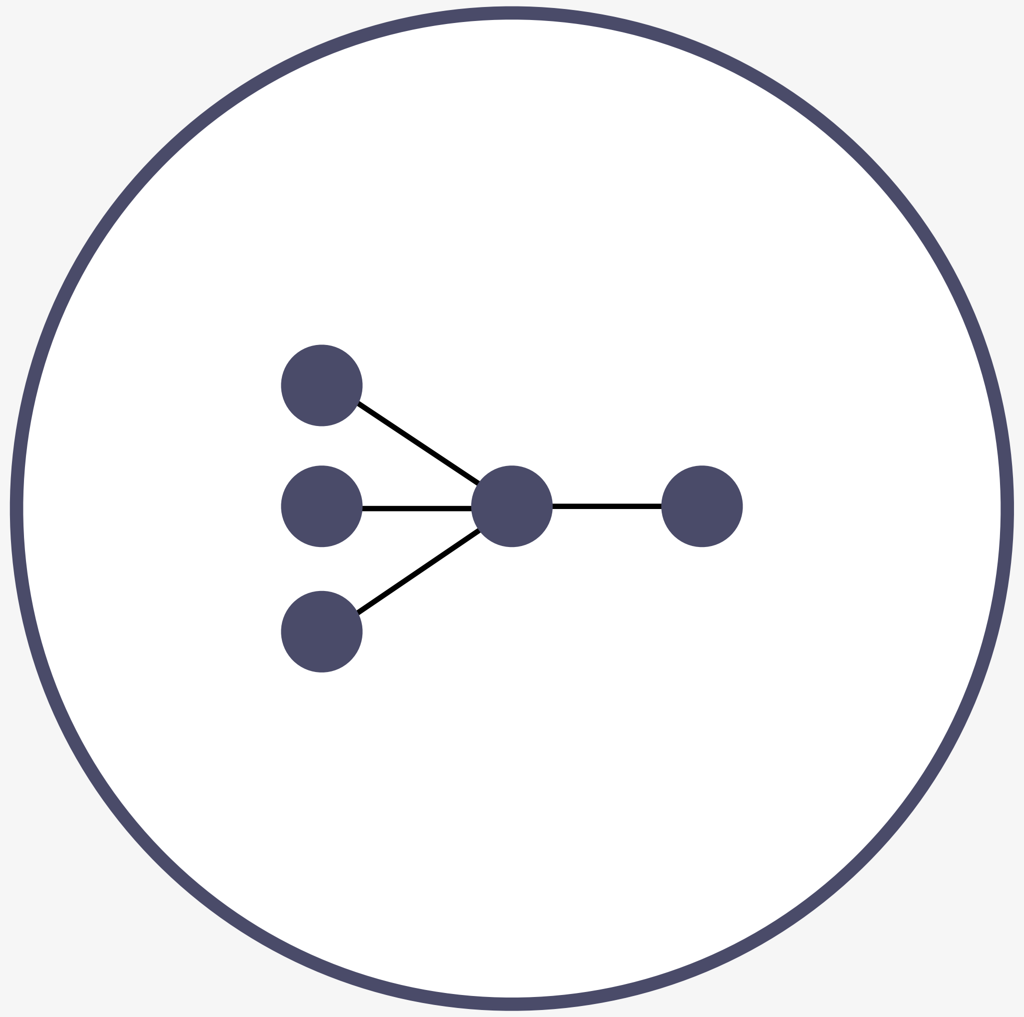
Explore new methods of MRI segmentation aiming for lighter and faster diagnosis systems.

Objective #3

Explore the use of biological neurons to build a biologically plausible tumor recognition system.

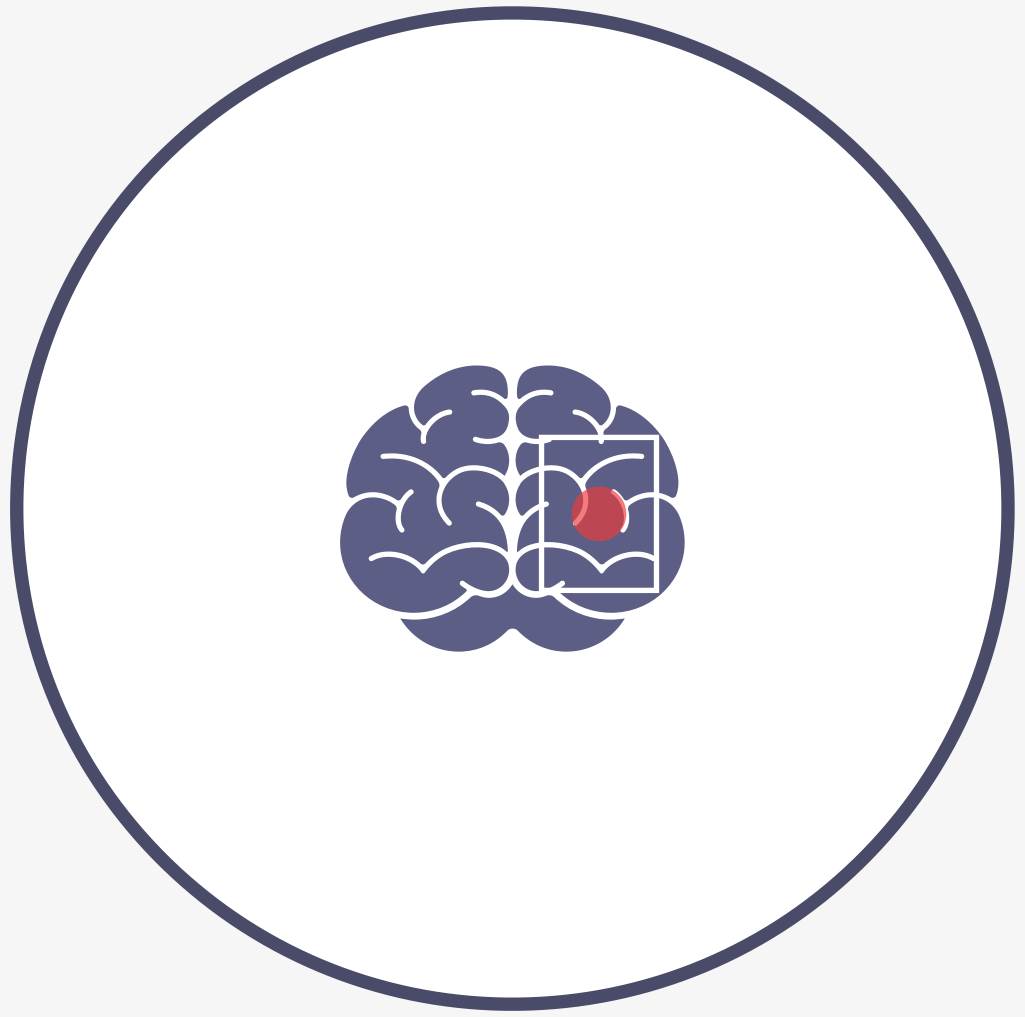
METHODS

2 METHODS



CNN Compression

Use an existing CNN and compress it for deployment on low-power hardware.



Pulse Coupled Neural Nets for tumor recognition

Move MRI segmentation to lighter and faster models.

SNN for tumor patch classification

Explore the efficiency of biological neurons for complex visual tasks.

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METHODS

Dataset

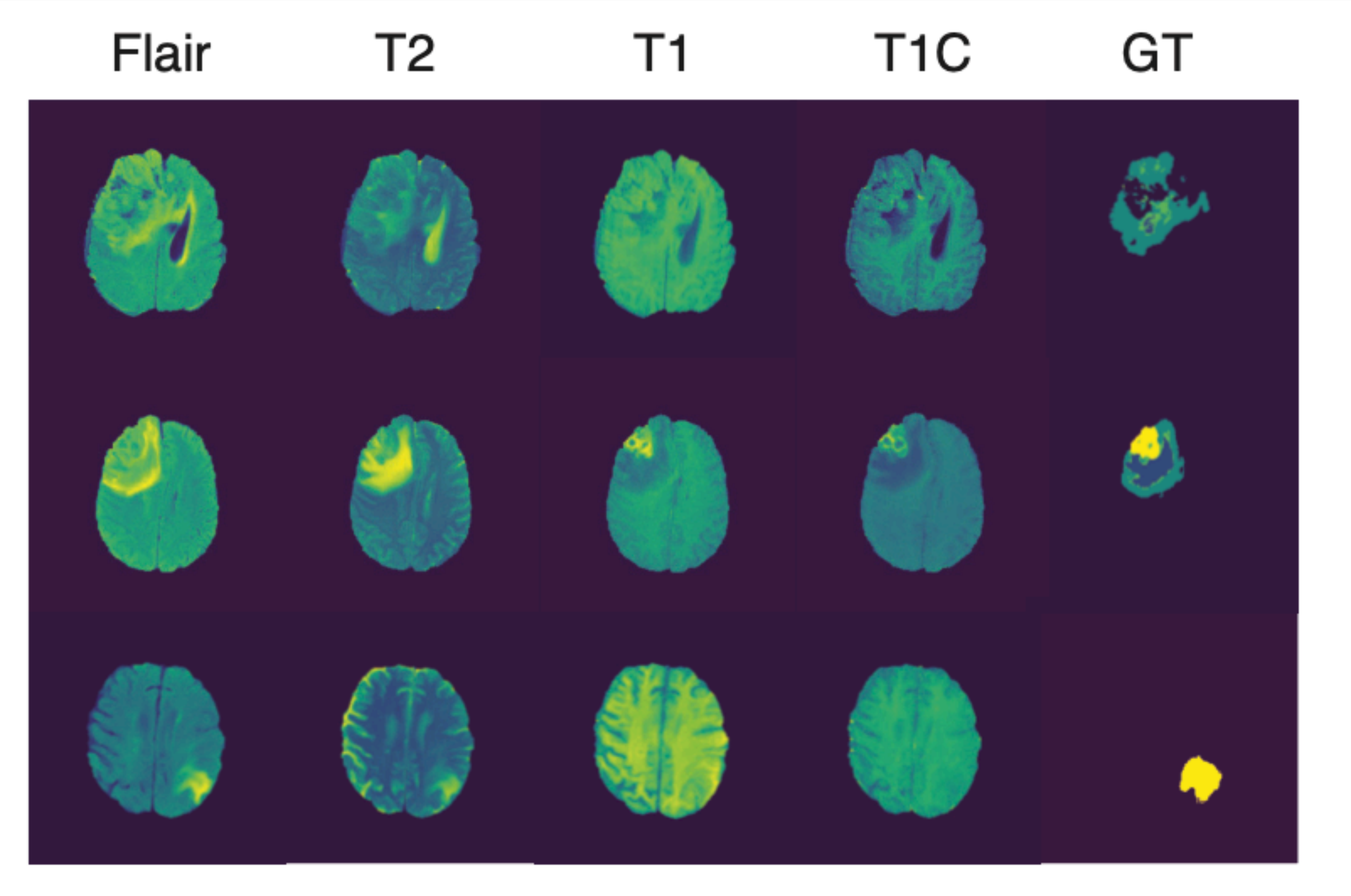
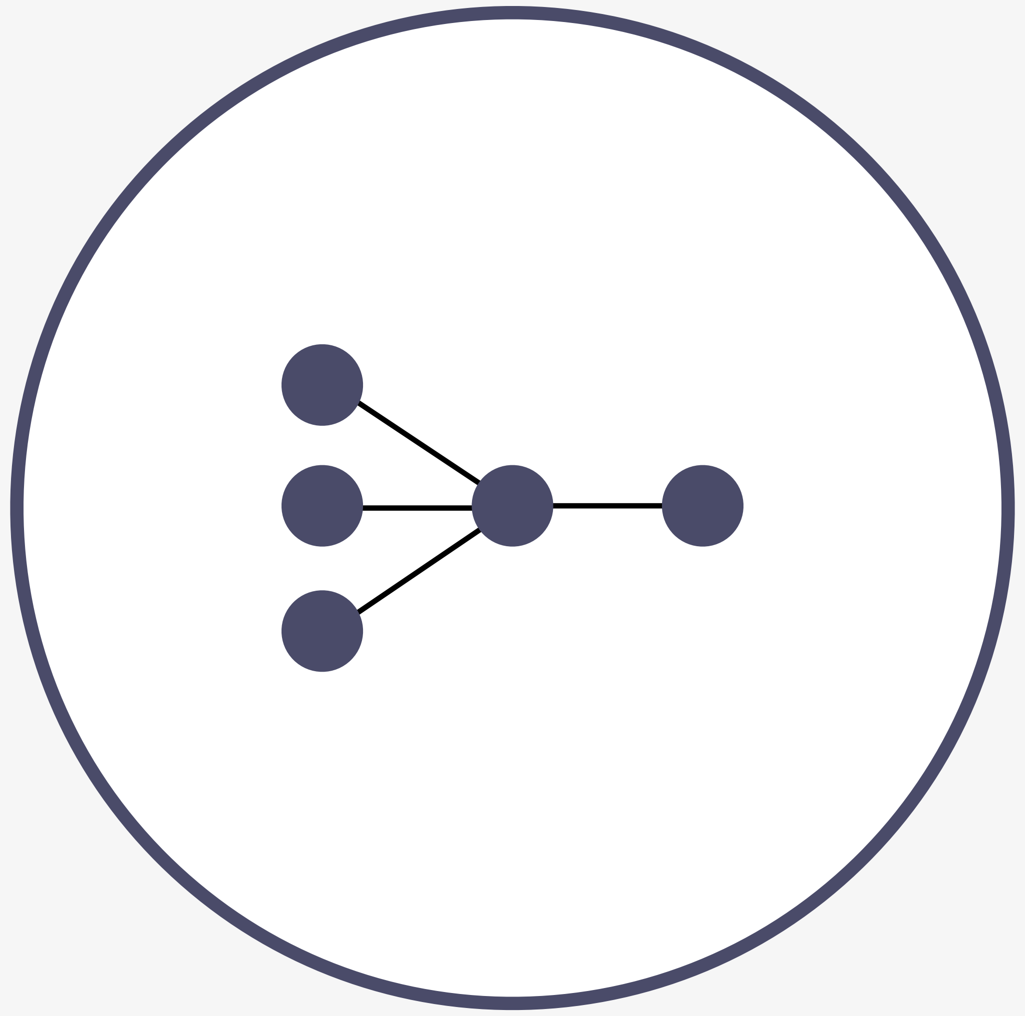


Fig 6. MRI cases taken from the BraTS dataset.

BraTS Dataset :

- Pre-operative MRI scans
- Manually segmented by 1-4 raters
- Four MRI sequences : Flair, T2, T1, T1C
- Contains 4 unhealthy cell labels
- Focused on segmentation and overall survival

METHODS



CNN Compression

3 METHODS

1. CNN Compression

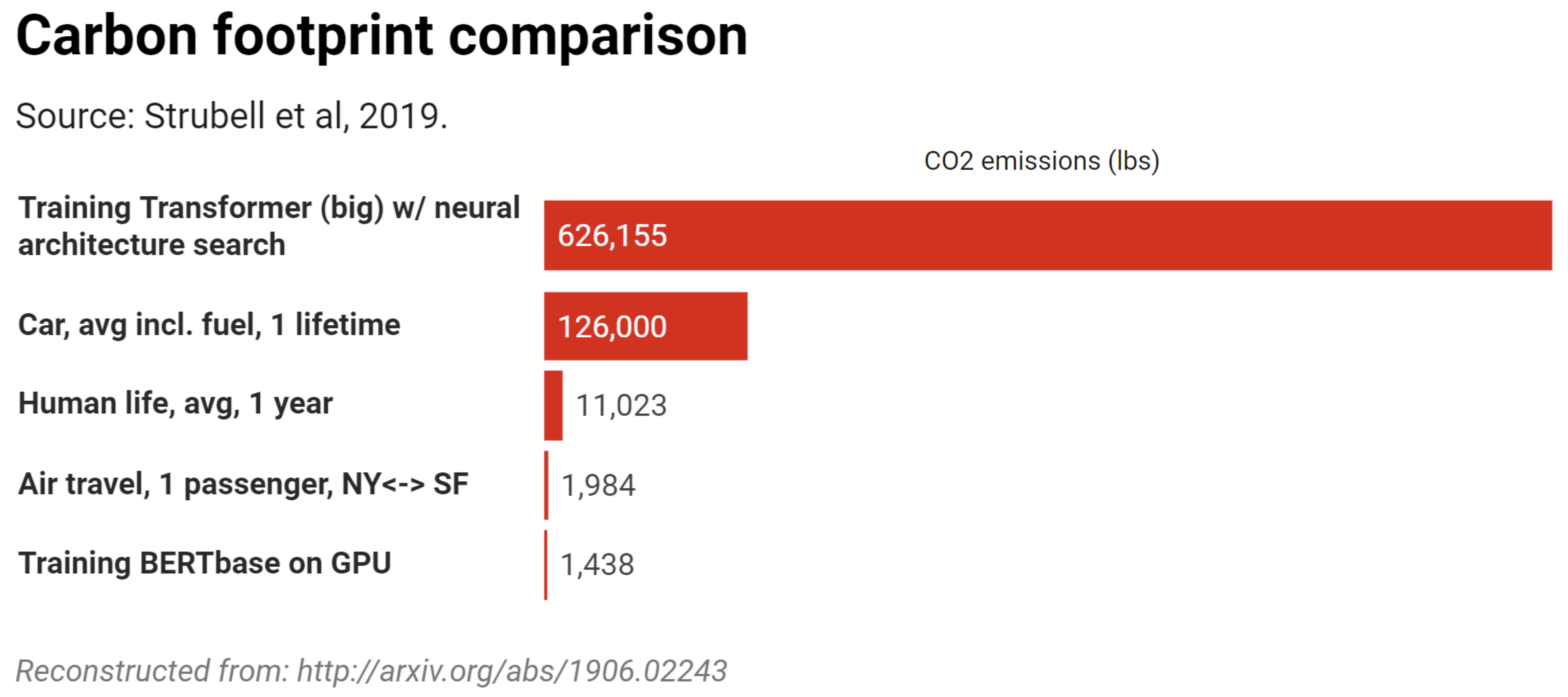


Fig 7. Carbon footprint benchmark including a DL model. Source : Strubell et al. Energy and Policy Considerations for Deep Learning in NLP. 2019.

Motivations :

- Reduce costs
- Limit energy consumption
- Ease training
- Improve inference performances

METHODS

1. CNN Compression

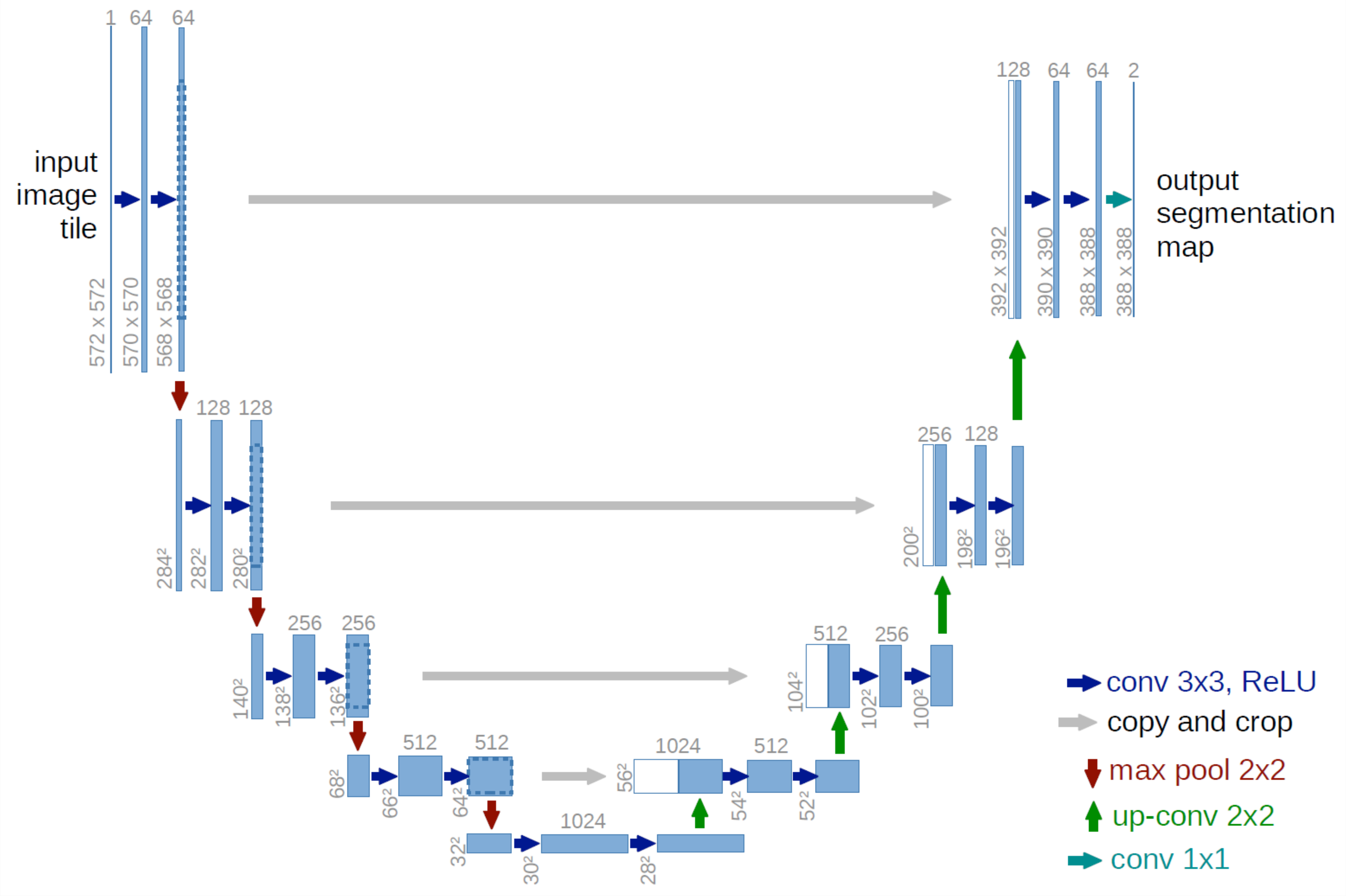


Fig 8. U-Net architecture for medical image segmentation. Source : Olaf Ronneberger et al. U-Net: Convolutional Networks for Biomedical Image Segmentation. 2015.

I NVIDIA Jetson Xavier

	MAXN	10W	15W	30W_ALL
CPU Cores	8	2	4	8
CPU Max Freq. (MHz)	1377	520	6700	900
GPU Max Freq. (MHz)	2265.6	1200	1200	1200
Memory Max Freq. (MHz)	2133.6	1066	1333	1600

Fig 9. NVIDIA Jetson Xavier properties. Source : Niepceron et al. 2020.

- Small weight and size
- Low power consumption
- Deep Learning Accelerator
- JetPack SDK
- Large memory

2 Group Normalization

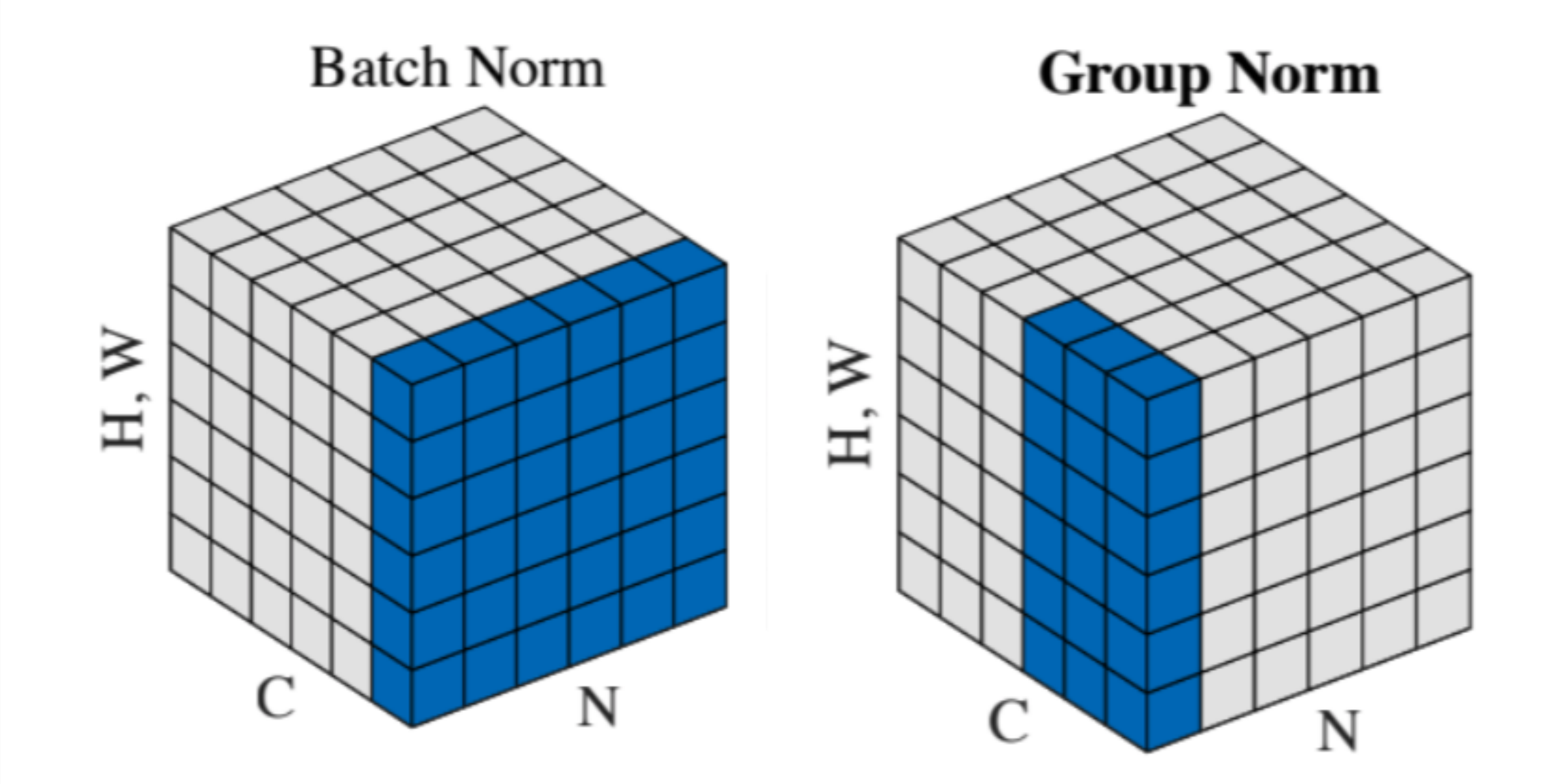


Fig 10. Normalization method comparison. Source : Yuxin Wu, Kaiming He. Group Normalization 2018.

- Deals with batch statistics estimation
- Prevents the use of large batches
- Ideal for resource-constrained systems

3 Depthwise Separable Convolution (DSC)

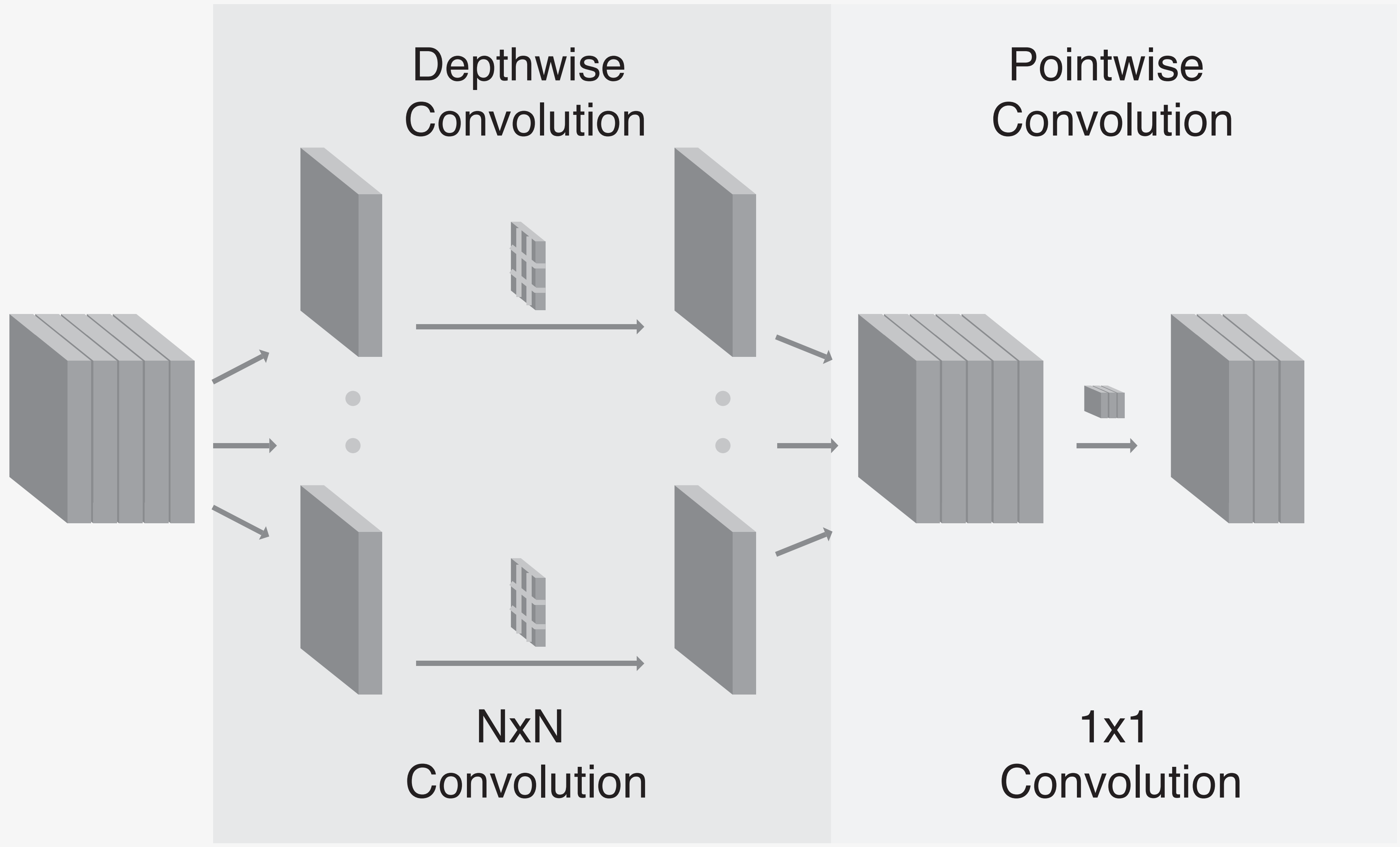


Fig 11. Depthwise Separable Convolution. Source : Niepceron et al. Moving Medical Image Analysis to GPU Embedded Systems: Application to Brain Tumor Segmentation. 2020.

- Factorization of the conv. process
- Conv. performed on individual channels
- Breaks down kernel dimension
- Reduces de number of parameters

4 Cost efficient conv. block.

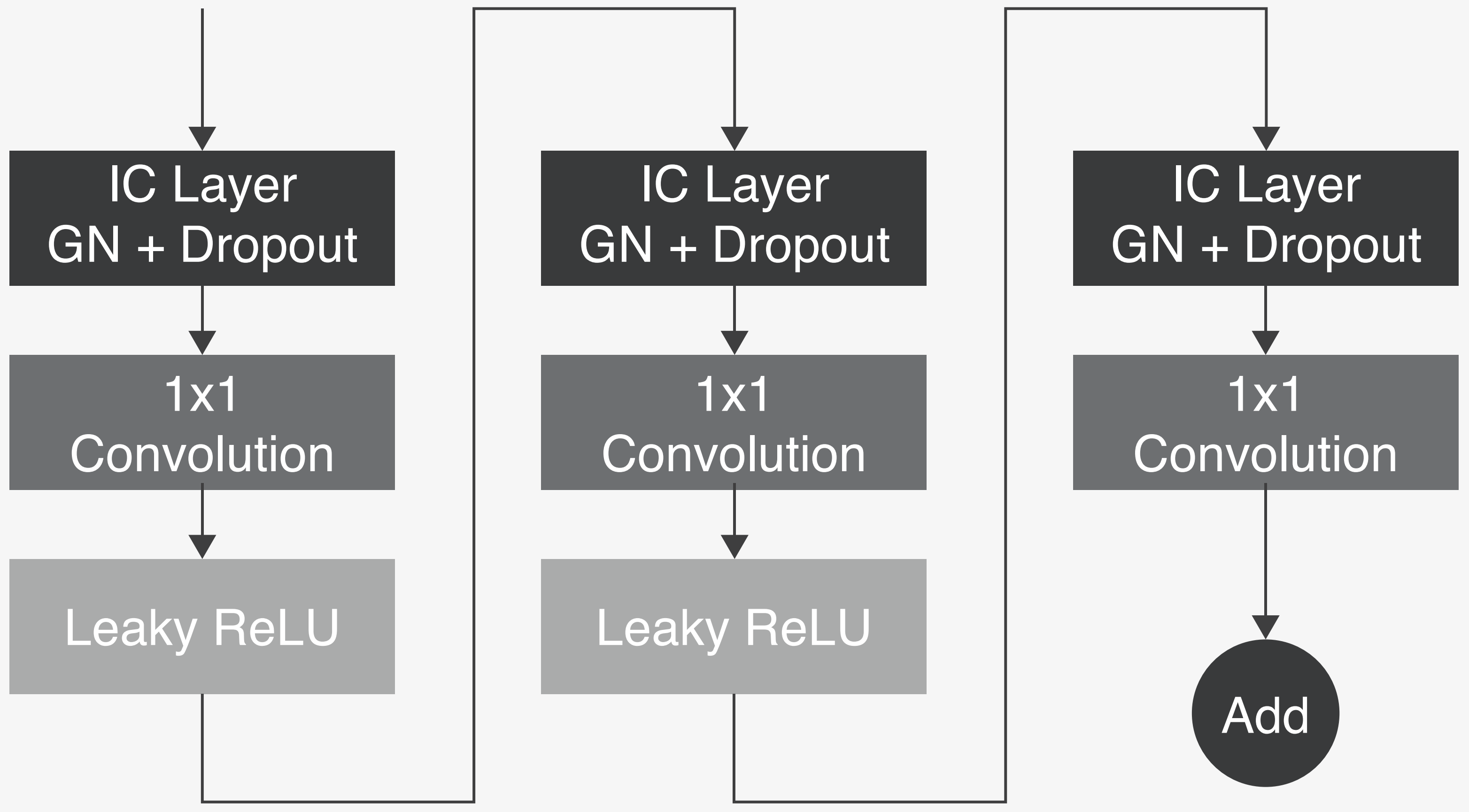


Fig 12. Depthwise Convolutional Block. Source : Niepceron et al. 2020.

- Independent Component Layer
- ResNet-like conv. block.
- Replacing each U-net conv.

METHODS

1. CNN Compression

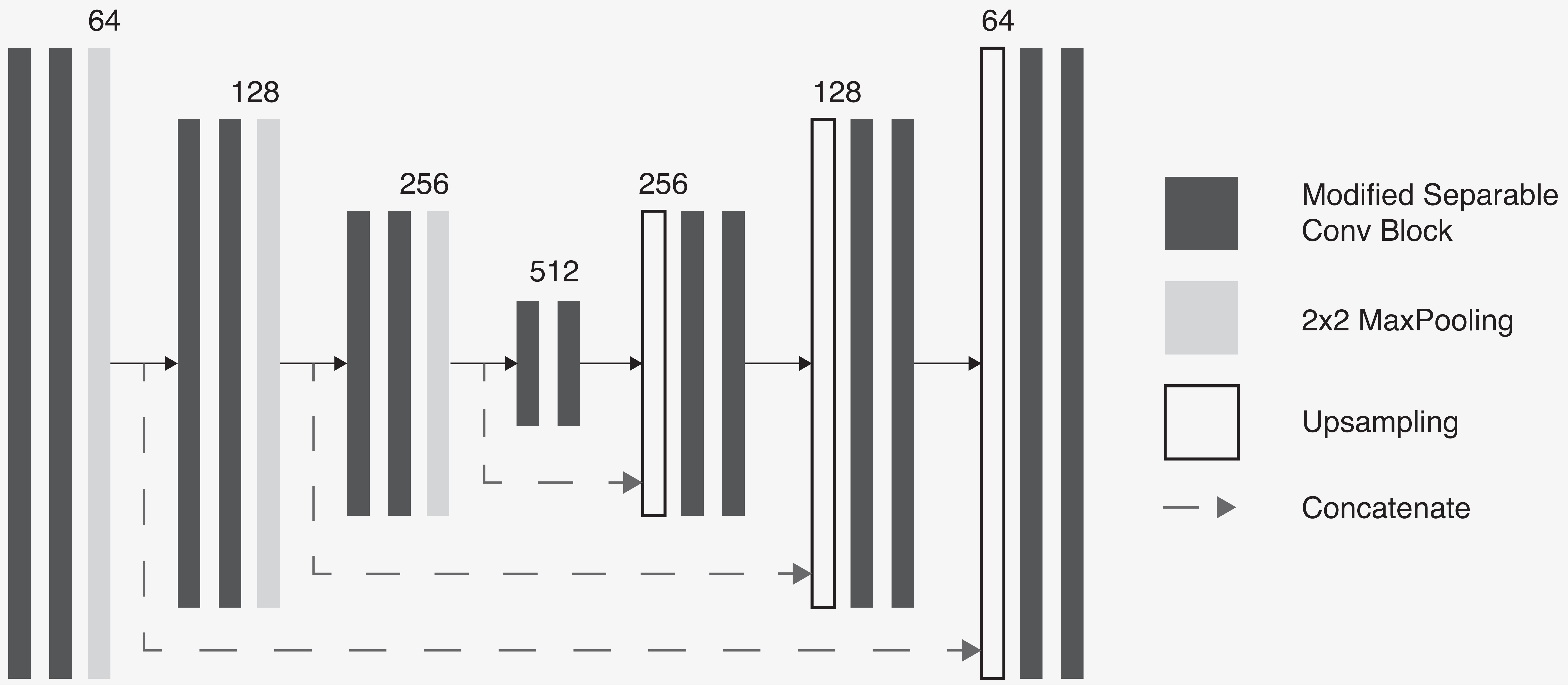


Fig 13. Compressed U-Net architecture. Source : Niepceron et al. 2020.

2 METHODS

**Pulse Coupled Neural Nets
for tumor recognition**

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METHODS

2. PCNN for visual diagnosis

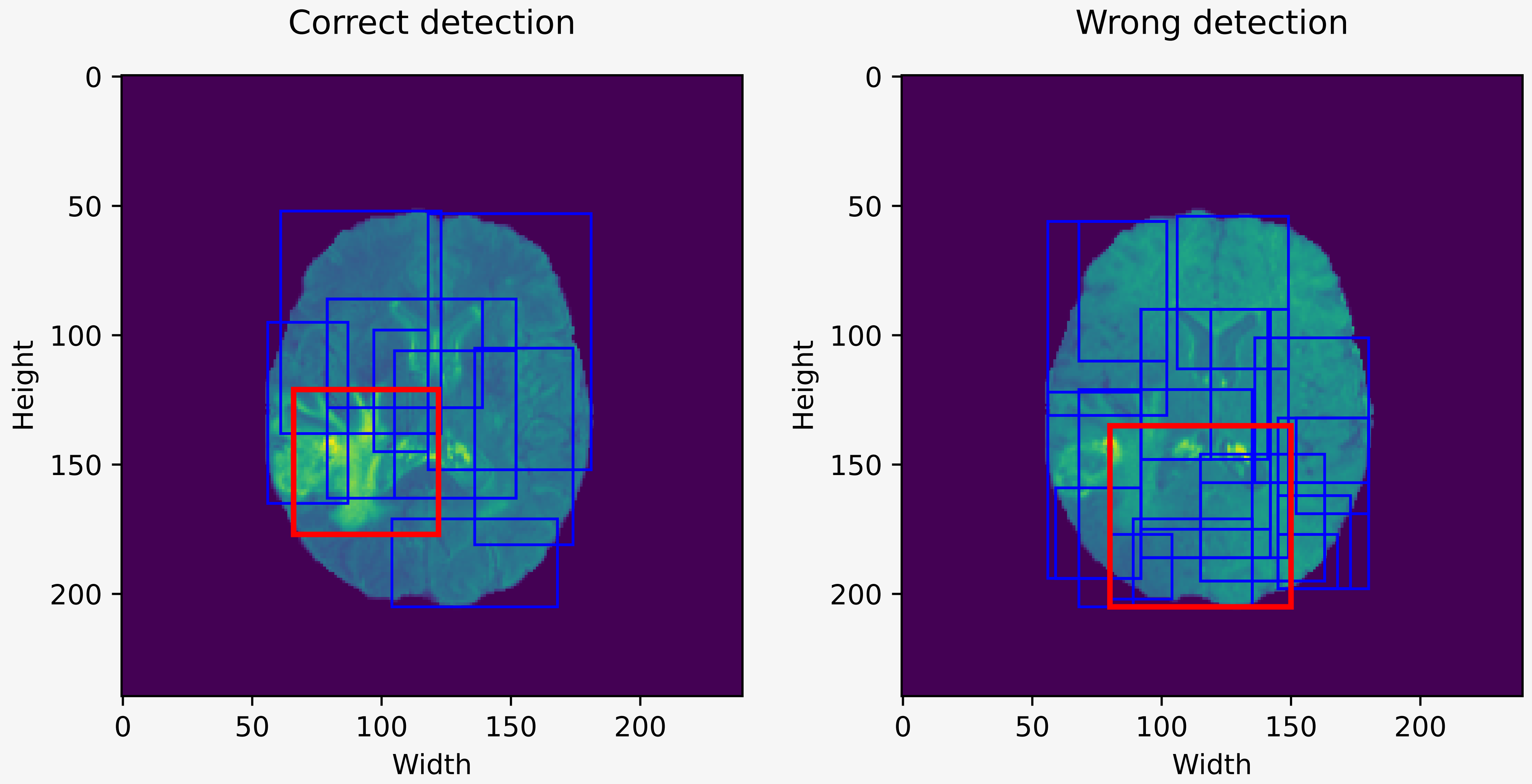

Fig 14. Detection of a brain tumor. Source : Niepceron et al. 2021.

Motivations :

- Detection does not need training
- Need for fast and light detection tool
- PCNN aims for segmentation and is invariant to variations

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METHODS

2. PCNN for visual diagnosis

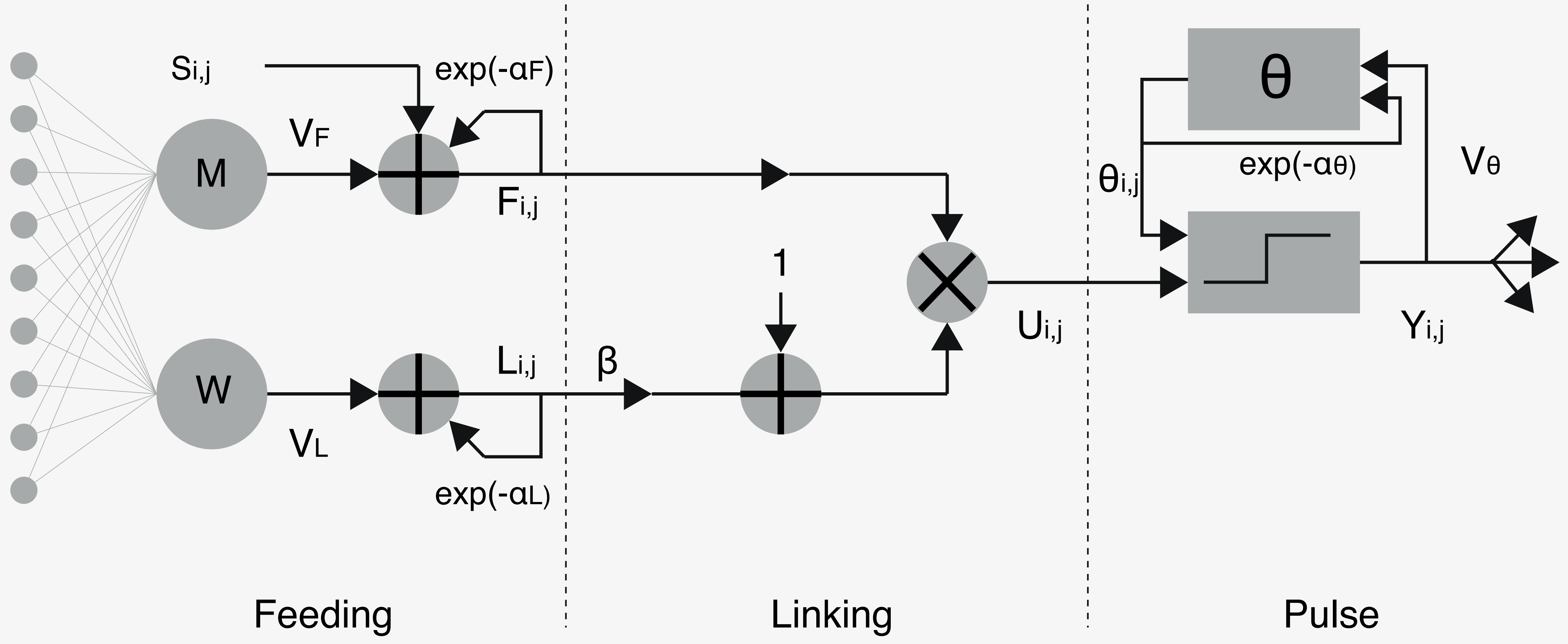

Fig 15. Standard PCNN. Source : Niepceron et al. 2021.

- Laterally-connected neurons
- 2D input image
- **Feeding :** Computes voltage with input stimulus
- **Linking :** Updates neuron's internal activity
- **Pulse :** Fire if membrane potential exceeds threshold

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METHODS

2. PCNN for visual diagnosis

Unit-linking

- Simplified version of PCNN
- Reduced computational cost
- Reduced parameters

Changes

- **Feeding :** Now equal to the intensity of a pixel
- **Linking :** Allows a neuron to fire when one or more neighbors fired

Fast-linking

- Uses Spiking cortical neurons
- Fast linking synapses
- Neurons fire faster

Changes

- **Feeding :** As for Unit-linking
- **Pulse :** Combines stimulus and synaptic modulation to charge the membrane

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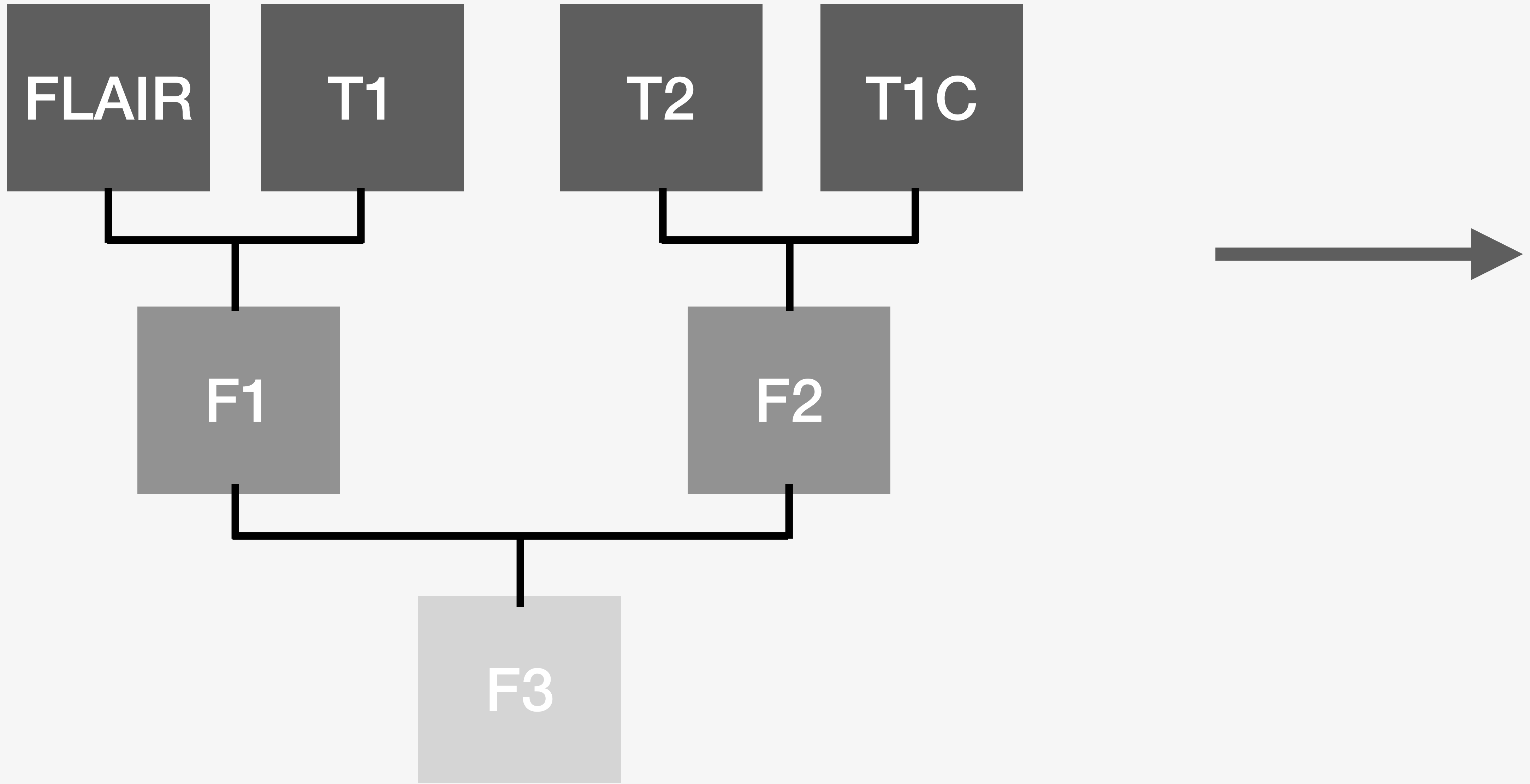
METHODS

2. PCNN for visual diagnosis

- Fusion strategy using Discrete Wavelet Transform
- Histogram matching necessary at each step



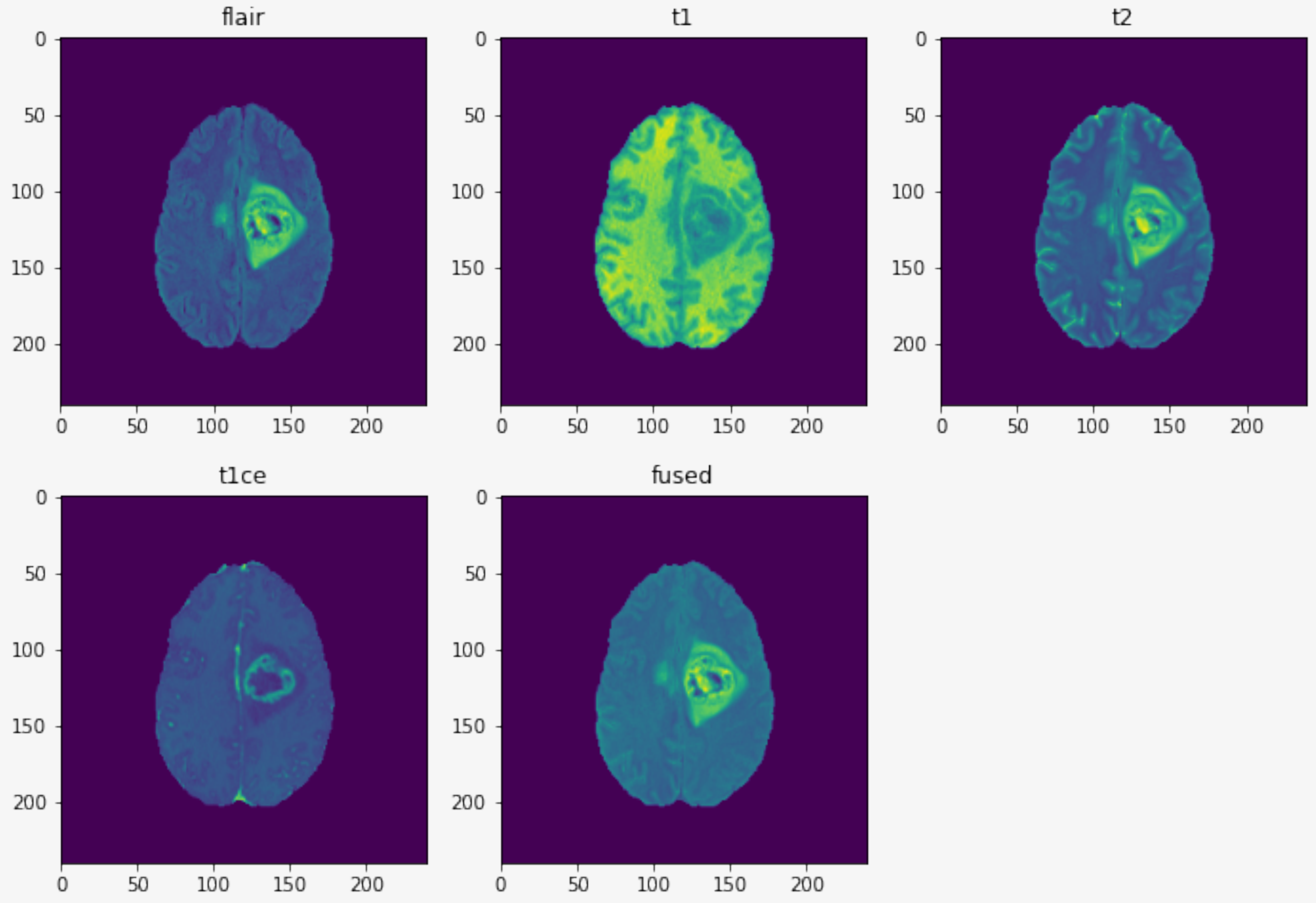
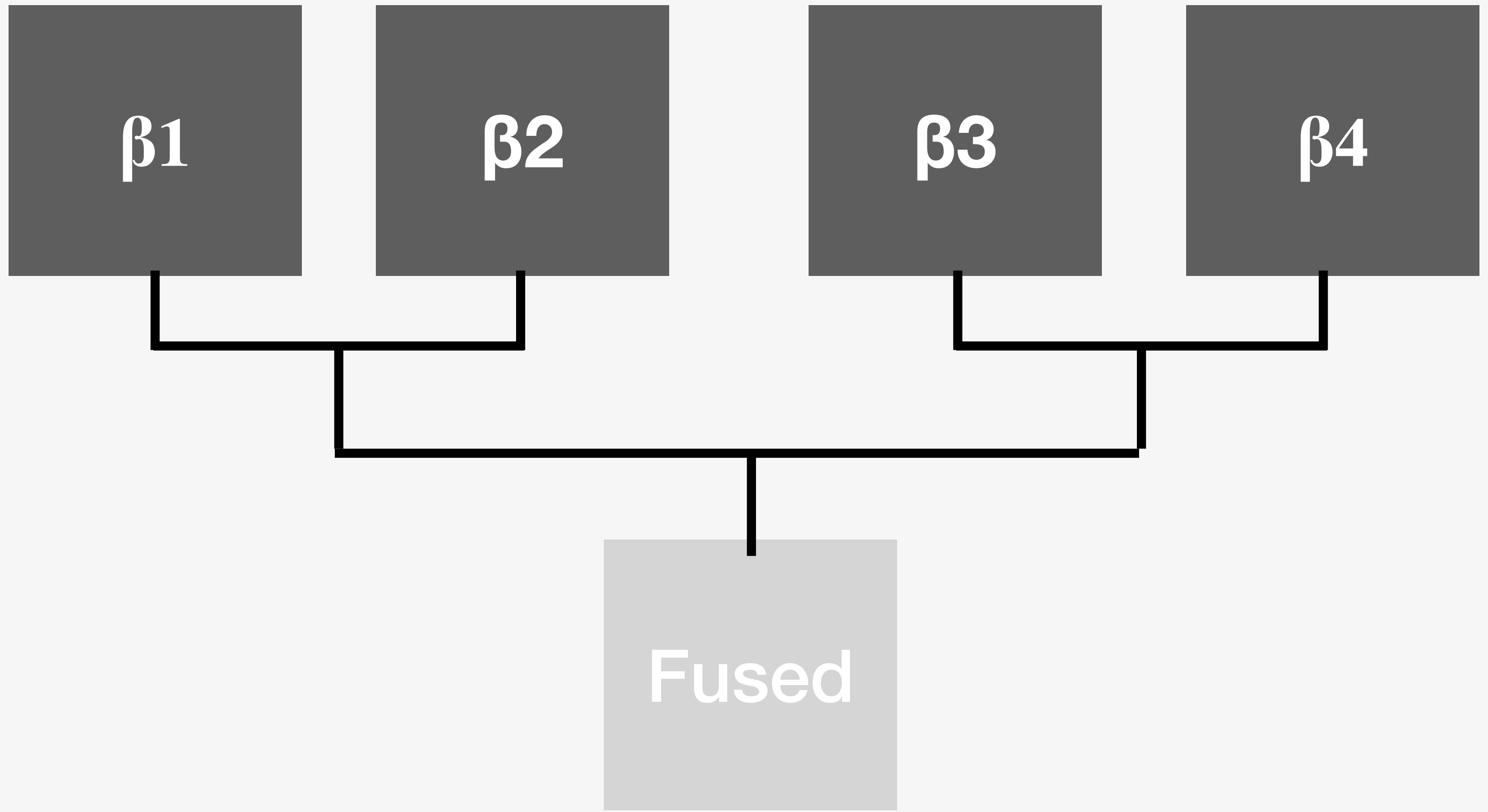


Fig 16. Results of MRI fusion. Source : Niepceron et al. 2021.

3 METHODS

2. PCNN for visual diagnosis

- Fusion strategy using m-PCNN
- No pre-processing required



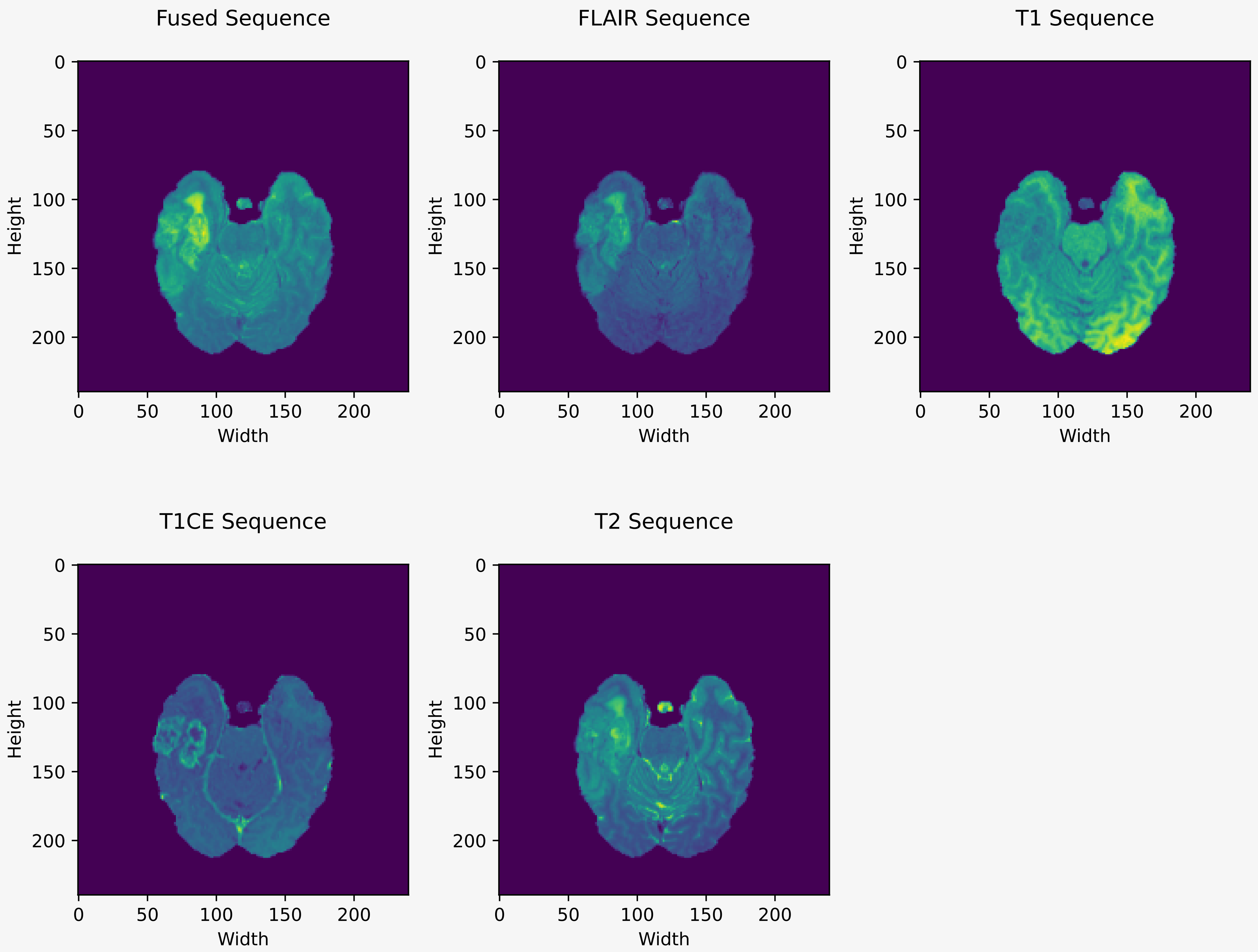


Fig 17. Results of MRI m-PCNN fusion. Source : Niepceron et al. 2021.

METHODS

2. PCNN for visual diagnosis

- Parameters setting
- Differential Evolution for optimization
- Dice Score as loss function $\frac{2|Y \cap \hat{Y}|}{|Y| + |\hat{Y}|}$
- Iteration number constrained to 10

Model	Standard PCNN	ULPCNN	FLSCM
β	0.47	0.47	0.44
α_θ	0.0125	0.015	-
α_F	0.96	-	-
α_L	0.81	-	-
V_θ	20	20	20
V_F	0.21	-	-
V_L	0.36	-	-
W	3x3 gaussian kernel	-	-
M	W	-	-
α_U	-	-	0.49

Fig 18. PCNN Parameters. Source : Niepceron et al. 2021.

METHODS

2. PCNN for visual diagnosis

- Image Signature as feature extraction
- Gets the firing activity as a time-series
- Comparison with regions of interest
- Already used for object detection without region selection methods

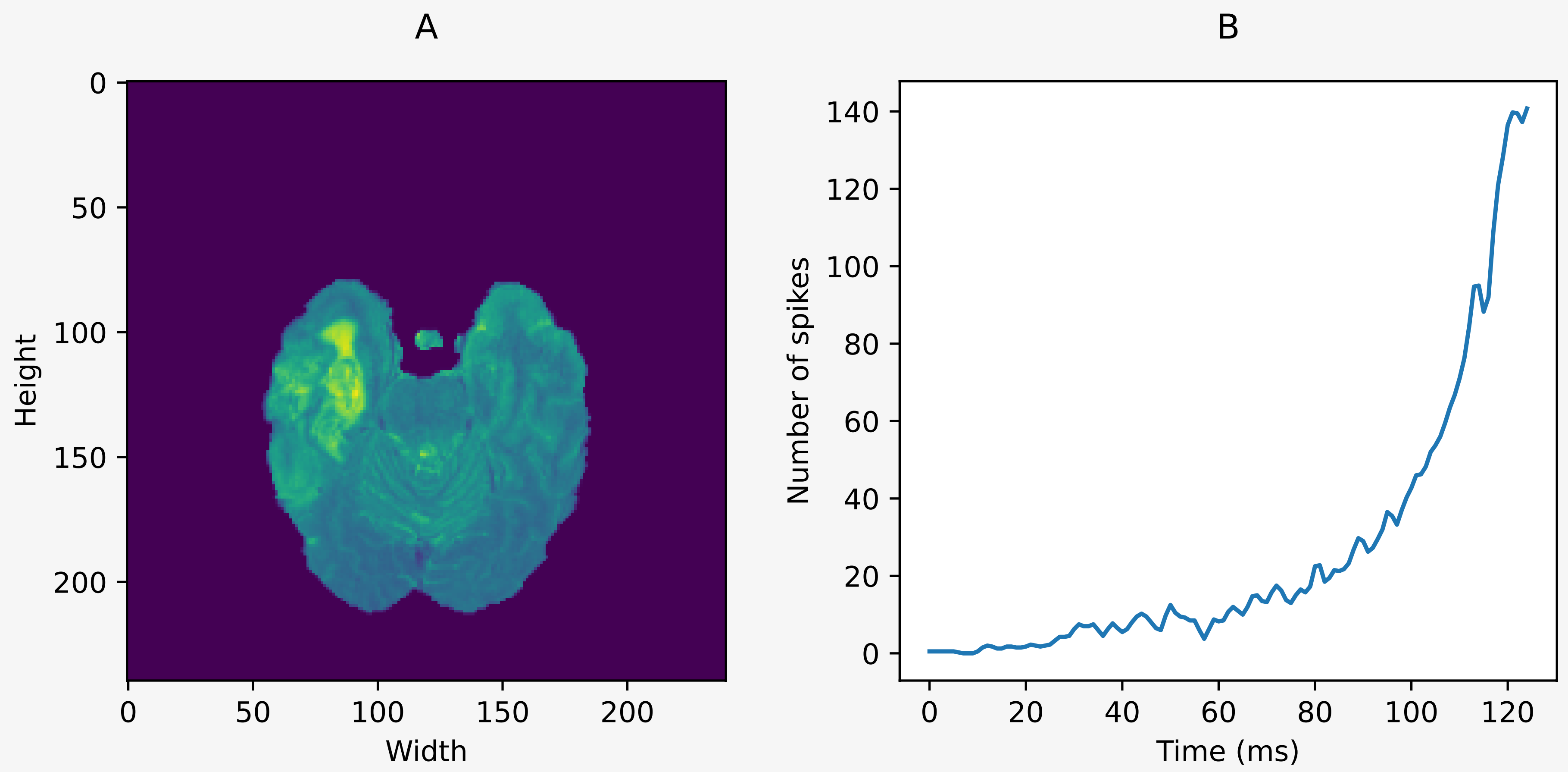


Fig 19. Image Signature (B) of an MRI Slice (A). Source : Niepceron et al. 2021.

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METHODS

2. PCNN for visual diagnosis

Fig 20. The Selective Search algorithm. Source : arthurdouillard.com.

METHODS

2. PCNN for visual diagnosis

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

SNN for tumor patch classification

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METHODS

3. SNN for tumor patch classification

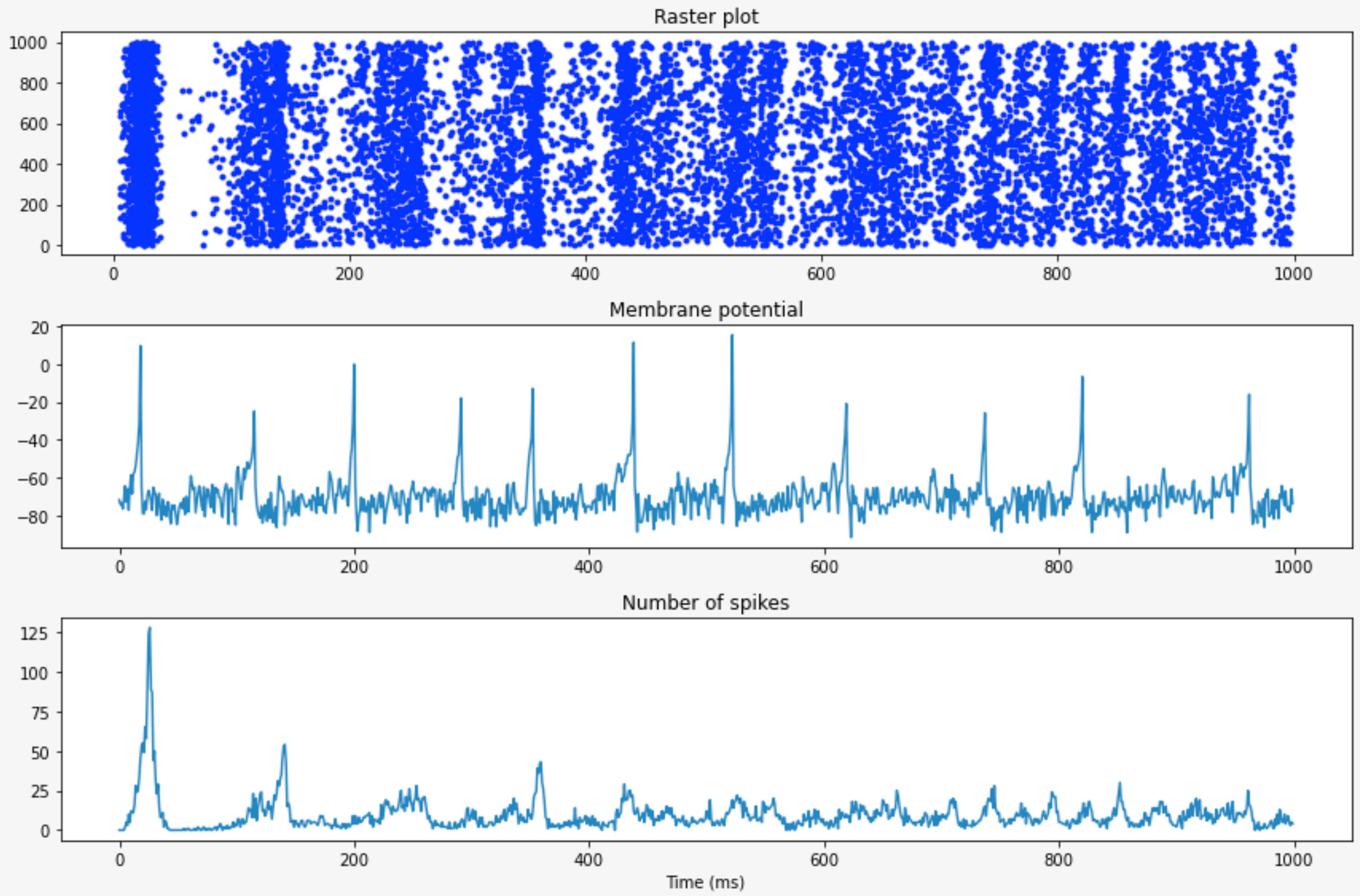

Fig 22. Izhikevich neuron activity. Source : annarchy.readthedocs.io

Motivations :

- Fast computation
- No need for deep models
- Steps towards biologically plausible vision systems

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Hypothesis #1

Biologically plausible feature extraction is enough to discriminate tumor regions.

?

Hypothesis #2

MRI classification can be seen as a spike pattern recognition problem.

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Hypothesis #3

Segmentation can be done by patches classification with STDP learning

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METHODS

3. SNN for tumor patch classification

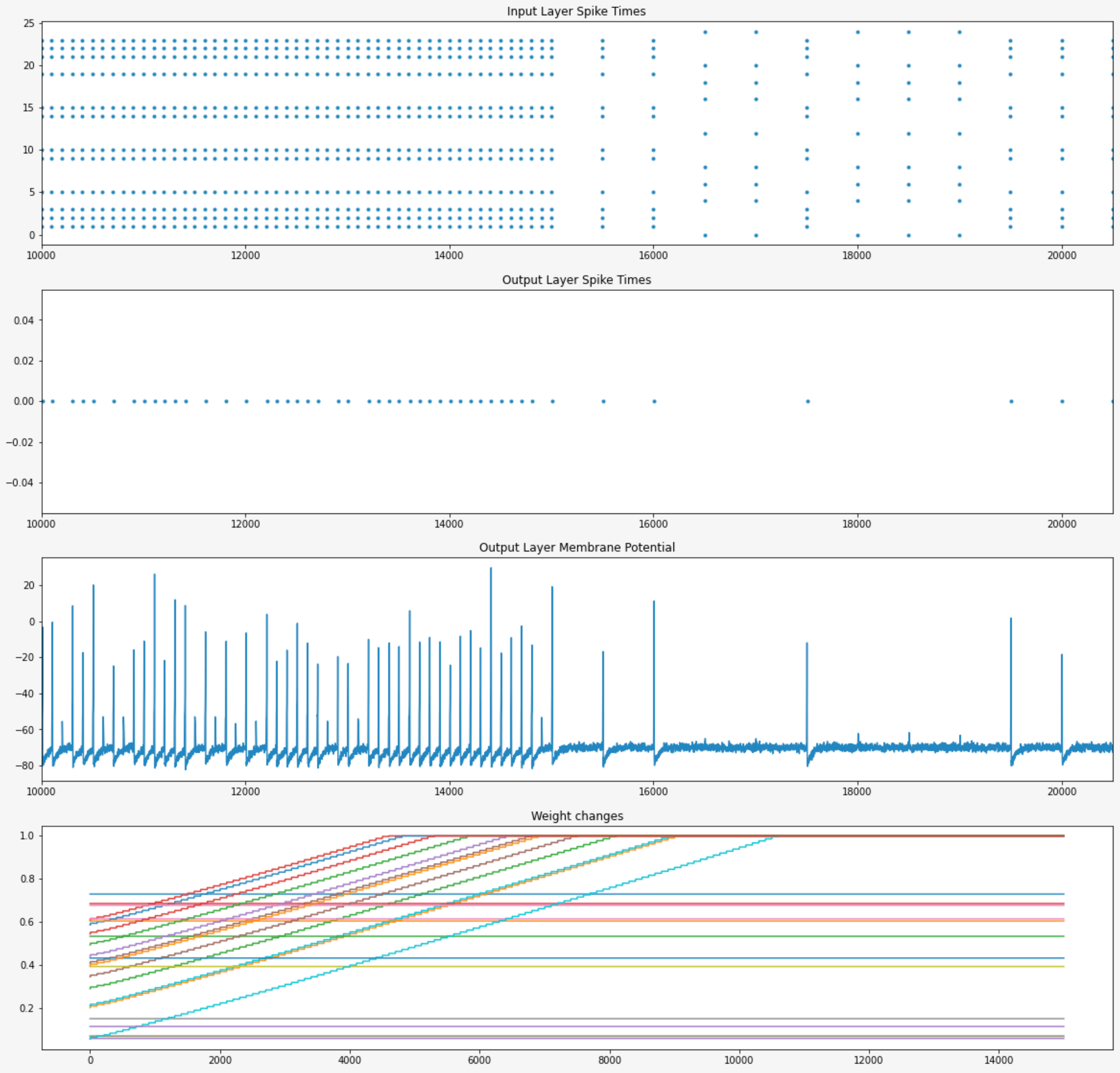

Fig 23. Spike Pattern recognition. Source : Brad Niepceron.

- **Pattern Recognition**
- Simple architecture
- STDP / DA-STDP Learning (Hebbian rule)
- Reward can be induced for supervised learning
- Temporal and rate coding friendly
- Ideal for subregion classification

RESULTS

IV

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RESULTS

1. CNN Compression

DETAILS	Dice Score **72 %** of reduction Decreased training time Lesion independent

LIMITS	Feature Maps DSC not GPU supported

	Dice Score		
Method	Complete	Core	Enhancing
Proposed	**0.81**	**0.77**	**0.53**
Zhao (Zhao et al., 2018)	0.82	0.72	0.62
Pereira (Pereira, Pinto, Alves, & Silva, 2016)	0.84	0.72	0.62
Dong (Dong et al., 2017)	0.86	0.86	0.65

Fig 24. Results of our compressed U-Net. Source : Niepceron et al. 2020.

RESULTS

2. PCNN for tumor detection

DETAILS (SEGMENTATION)

Dice Score
Early stopping
FLSCM time : 17 sec
ULPCNN time : 17 sec
PCNN time : 60 sec

LIMITS

Single class
Morphological processing

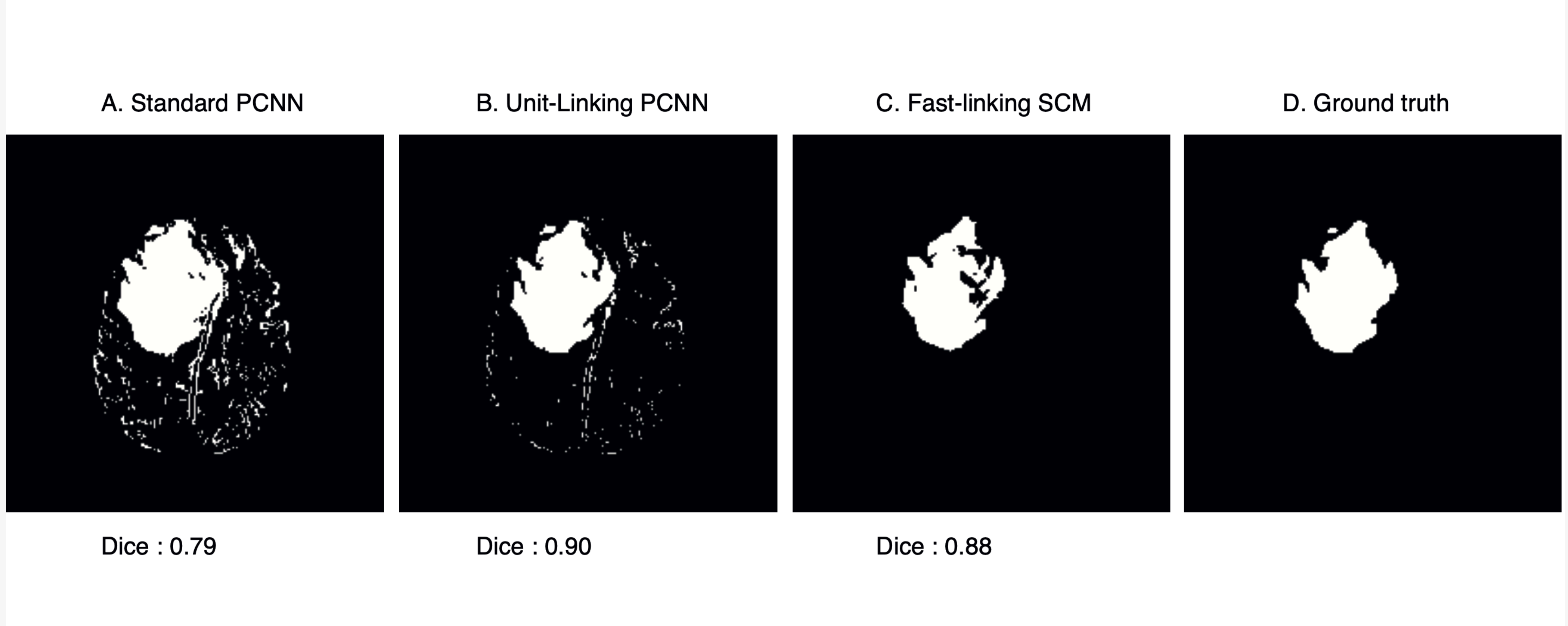

Fig 25. PCNN Segmentation results. Source : Niepceron et al. 2020.

4

RESULTS

2. PCNN for tumor detection

DETAILS (DETECTION)	Intersec. Over Union Accurate bounding boxes Fast computation

LIMITS	Selective Search param. Small tumorous regions Fusion parameters Whole tumor

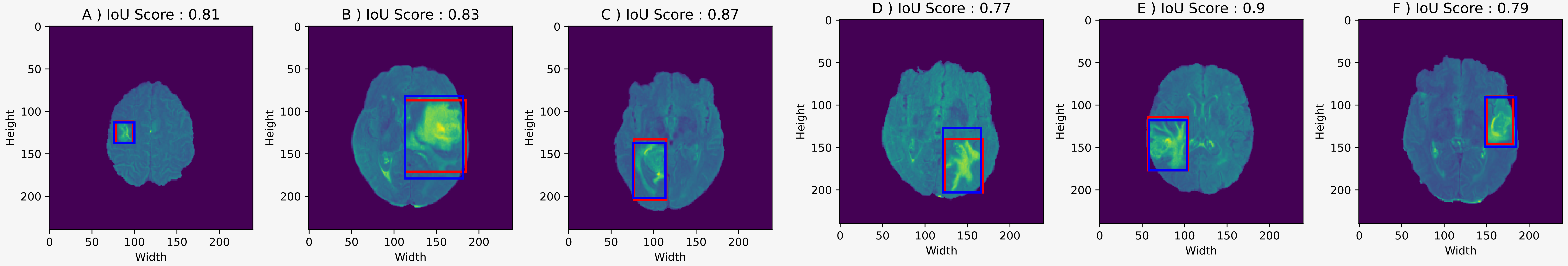

Fig 26. PCNN Detection results. Source : Niepceron et al. 2020.

CONCLUSION

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CONCLUSION

Objective #1

Redefine Deep Learning based methods to fit the power efficiency requirements of healthcare providers.

→ **2 Millions param. U-net**

Objective #2

Explore new methods of MRI segmentation aiming for lighter and faster diagnosis systems.

→ **Tumor extraction with PCNN**

Objective #3

Explore the use of biological neurons to build a biologically plausible tumor recognition system.

→ **Harder than expected**

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QUESTIONS

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