Segmentation of pathologies in Human Brain MRI's with uncertainty

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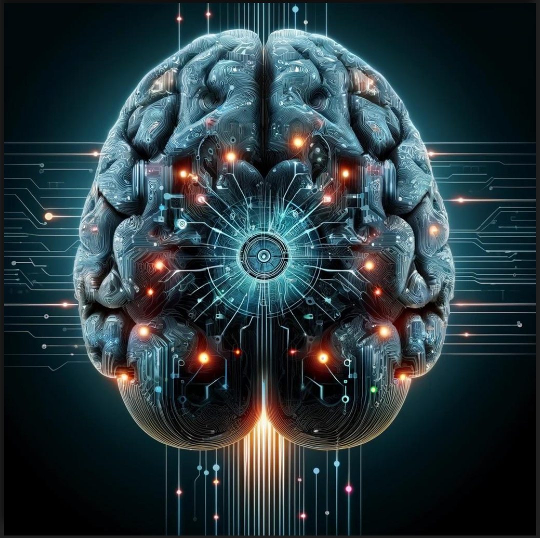
Segmentation In Medical Imaging with Deep Learning (1/2)

- Segmentation of brain MRIs on various datasets using Deep Learning algorithm

- Quantifying the uncertainty of segmentations provided by the neural network leads to a better interpretation by medical teams

- Quantifying uncertainty in deep learning remains a key unresolved issue

- Implementation of several methods including Deep Ensemble and Monte Carlo Dropout



Segmentation In Medical Imaging with Deep Learning (2/2)

- State of the Art and Uncertainty Metrics
- iSeg-2017 : 6-month infant brain MRI Segmentation
- Experimentations
- Achievements This Semester
- Future Work

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Quantifying Prediction Uncertainty (1/2)

Estimating Prediction Uncertainty :

- **Average Probability Image**:
  - Mean probability for each pixel across all model predictions
  - Central estimate of the segmentation
  - Formula : $\overline{X}_i = \frac{1}{N} \sum_{j=1}^{N} X_{ij}$

- **Standard Deviation Map**:
  - Standard deviation for each pixel across all model predictions
  - Highlights variability and uncertainty in predictions
  - Formula:

$$\sigma_i = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (X_{ij} - \overline{X}_i)^2}$$

Steps :

- Mean probability calculation for each pixel from all models
- Standard deviation calculation for each pixel from all models

Provides comprehensive view of prediction reliability.

Formulas:

- **Mean Probability** for each pixel :

$$\overline{X}_i = \frac{1}{N} \sum_{j=1}^{N} X_{ij}$$

- **Standard Deviation**:

$$\sigma_i = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (X_{ij} - \overline{X}_i)^2}$$

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Quantifying Prediction Uncertainty (2/2)

Estimating Prediction Uncertainty with Shannon Entropy

- Entropy calculated for each pixel across all model predictions
- Measures the unpredictability and information content of the segmentation
- Formula : $H(X_i) = -\sum_{c=1}^{C} p_{ic} \log_2(p_{ic})$

Where:

- X_i is the pixel i
- p_{ic} is the predicted probability for class c at pixel i
- C is the total number of classes

Steps :

- Calculate the probability distribution p for each class c at each pixel
- Compute the Shannon entropy for each pixel using the probability distribution

Provides a detailed view of prediction uncertainty based on the distribution of predicted probabilities

State of the Art and Uncertainty Metrics : Monte Carlo Dropout

Monte Carlo Dropout Technique

- **Developed by**: Yarin Gal and Zoubin Ghahramani (2016)

Overview:

- **Dropout Regularization**: Randomly deactivate neurons during each forward pass to prevent overfitting
- **Bayesian Approximation**: Treats each forward pass as a sample from a Bayesian posterior distribution by applying dropout during both training and testing
- **Predictive Distribution**: Perform multiple forward passes (30-100) for each input to generate a distribution of predictions

State of the Art and Uncertainty Metrics : Monte Carlo Dropout

Key Steps:

- **Training**:
  - Train with dropout enabled (e.g., 0.4 dropout rate).
- **Testing/Inference** :
  - Keep dropout enabled and perform multiple forward passes (e.g., 100).
- **Aggregation** :
  - Calculate mean and variance of predictions

State of the Art and Uncertainty Metrics : Deep Ensembles

Deep Ensembles Technique

- **Developed by** : Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell (2017)

Overview:

- **Multiple Models** : Train multiple independent neural networks with different initializations
- **Ensemble Predictions** : Each model makes a separate prediction for the same input
- **Robustness** : Aggregating predictions from different models enhances robustness and captures uncertainty

Key Steps :

- **Training** :
  - Train 5 networks separately with different initializations
- **Prediction** :
  - Each network makes its own prediction
- **Aggregation** :
  - Compute mean and variance of predictions

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Construction of the Final Prediction in Binary Segmentation

Model Output :

- **Probabilities** : Each pixel is assigned a probability $\boldsymbol{p}$ (between 0 and 1) indicating the confidence that the pixel belongs to the target class
- **Shape** : For an input image of dimensions *(H, W)* the model output is also *(H, W)*, with each value representing a probability

Classification Threshold :

- **Threshold** $\boldsymbol{t}$: Probabilities are converted into binary classification using a threshold, typically $\mathbf{t} = 0.5$
- **Decision** :
  - If $\boldsymbol{p} \geq \boldsymbol{t}$: the pixel is classified as the target class
  - If $\boldsymbol{p} < \boldsymbol{t}$: the pixel is classified as the background class

Result Interpretation :

- **Probabilities** : Display the predicted probabilities for each pixel
- **Binary Predictions** : Binary classification of each pixel using the threshold **t**. (1 = target class, 0 = background class)

iSeg-2017 : 6-month infant brain MRI Segmentation

- iSeg-2017 challenge focuses on comparing semi-automatic algorithms for segmenting 6-month infant brain MRIs using T1 and T2 images
- Critical for studying the dynamic first year of postnatal human brain development and associated cognitive and motor functions
- Intense phase at 6 months presents the lowest tissue contrast, posing significant challenges for accurate segmentation
- Engages researchers to develop and test automatic segmentation algorithms for white matter, gray matter, and cerebrospinal fluid

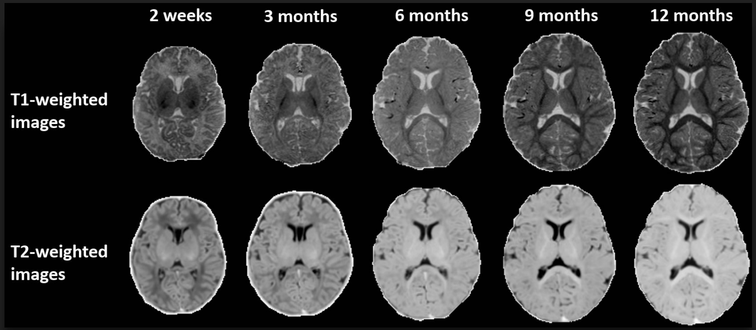

Figure 1 : MIICCAI Grand Challenge on iSeg-2017, 6-Month infant Brain MRI Segmentation, [iSeg-2017]

Experimentations : Segmentation of Brain Area

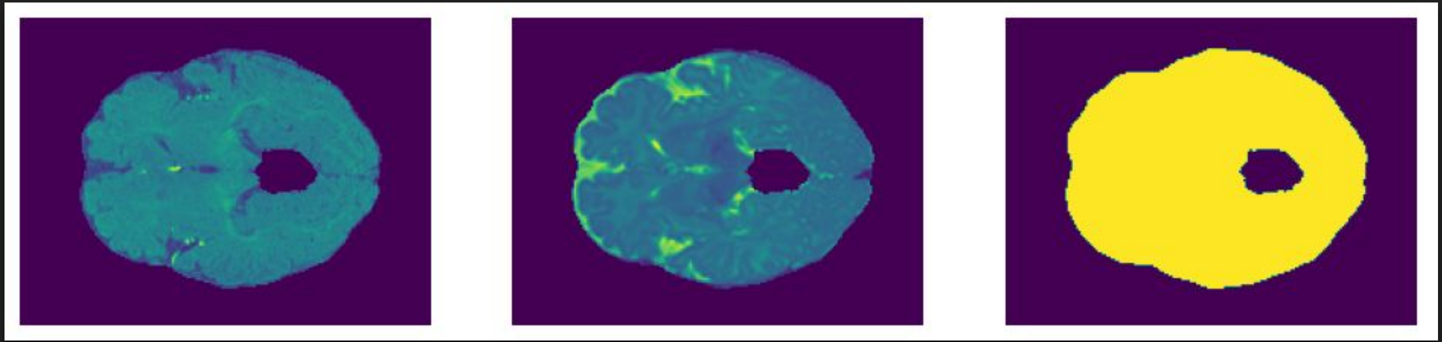

Figure 2 : Input for the segmentation of the brain area

Deep Ensembles for Uncertainty Estimation

- ❖ 5 networks are trained separately
- ❖ Each network is independently initialized

Monte Carlo Dropout for Uncertainty Estimation

- ❖ 100 predictions with Dropout Rate of 0.4

Experimentations : Segmentation of Brain Area

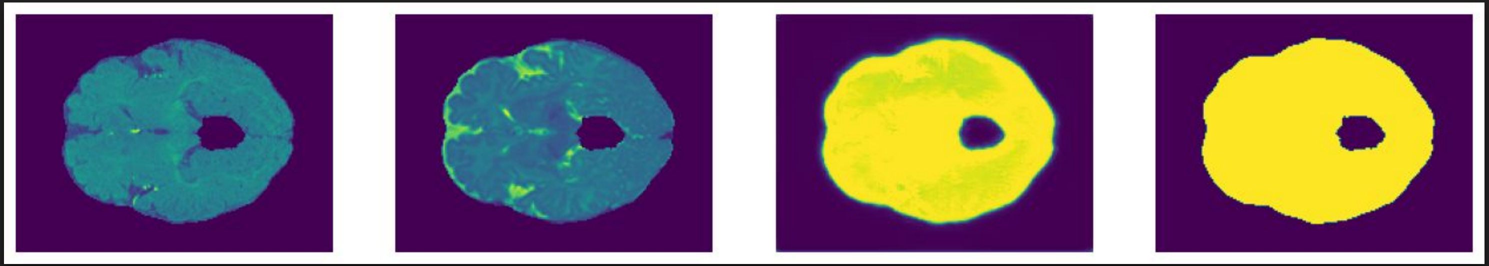

Figure 3 : Mean prediction with Deep Ensembles Method, for Patient 1, slice *sz // 2*

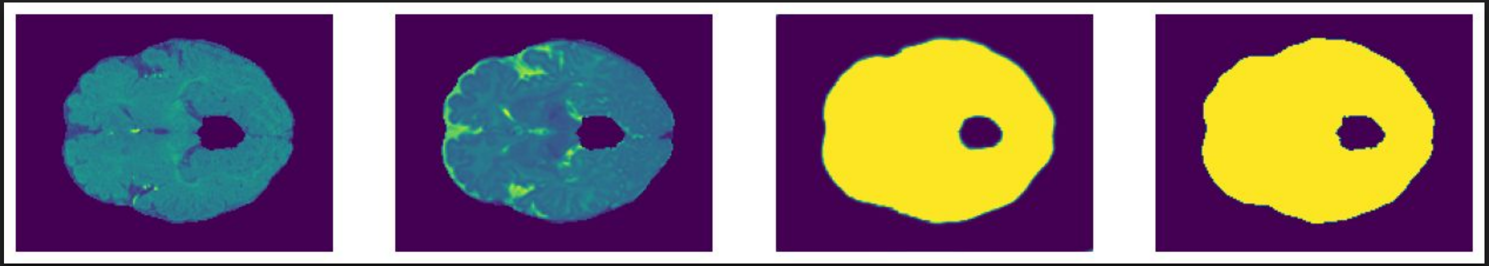

Figure 4 : Mean prediction with Monte Carlo Dropout Method for Patient 1, slice *sz // 2*

Experimentations : Segmentation of Brain Area

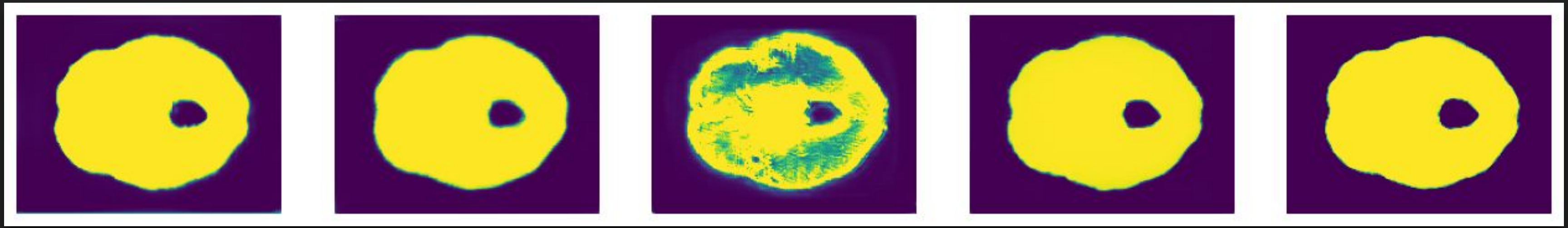

Figure 5 : Predictions from the 5 Networks in the Ensemble

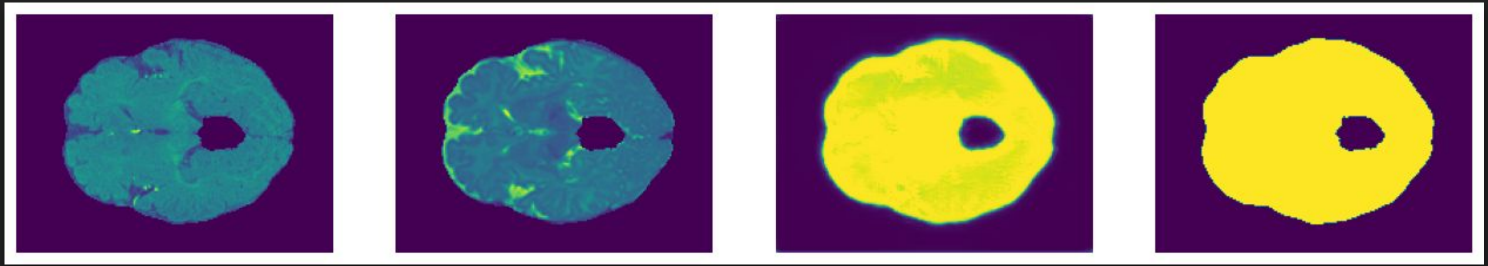

Figure 6 : Mean prediction with Deep Ensembles Method, for Patient 1, slice *sz // 2*

Experimentations : Segmentation of Brain Area with Deep Ensembles

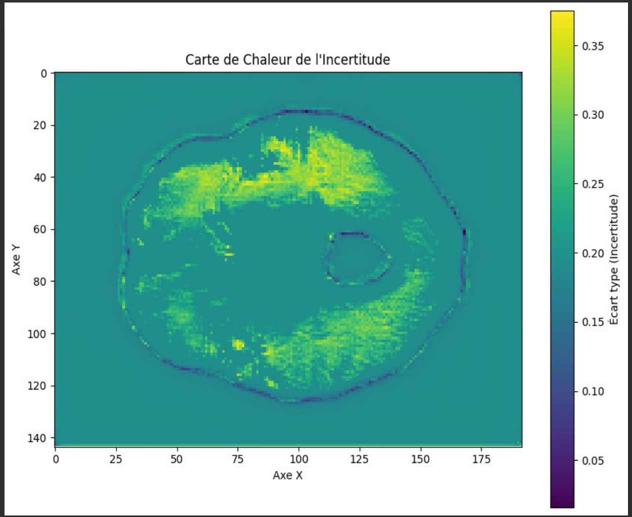

Figure 7 : Standard Deviation Map for Deep Ensembles

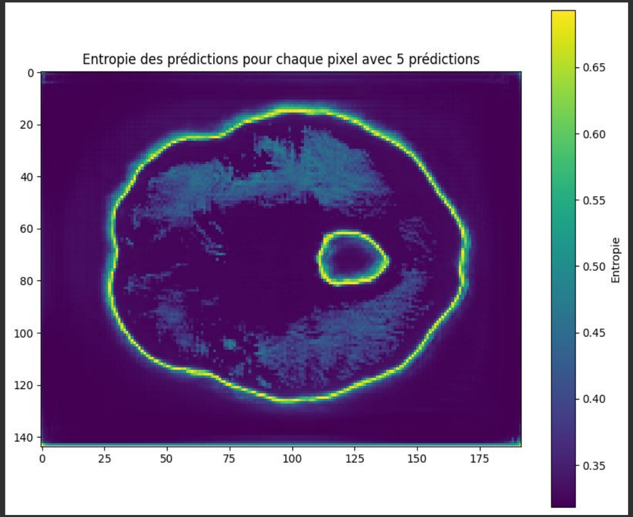

Figure 8 : Shannon Entropy for Deep Ensembles

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Experimentations : Segmentation of Brain Area with Monte Carlo Dropout

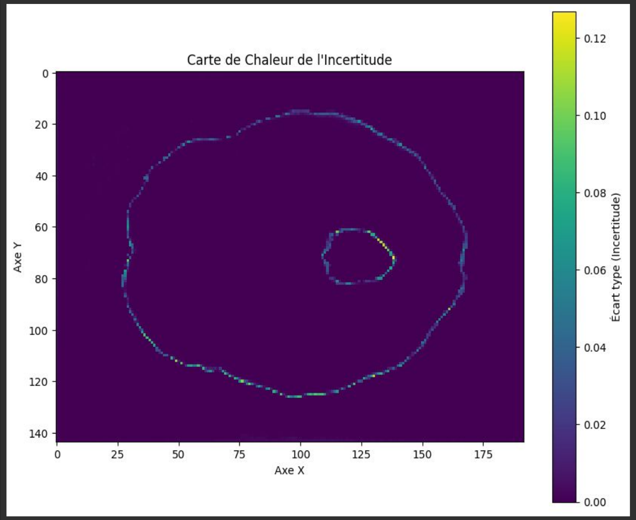

Figure 9 : Standard Deviation Map for Monte Carlo Dropout

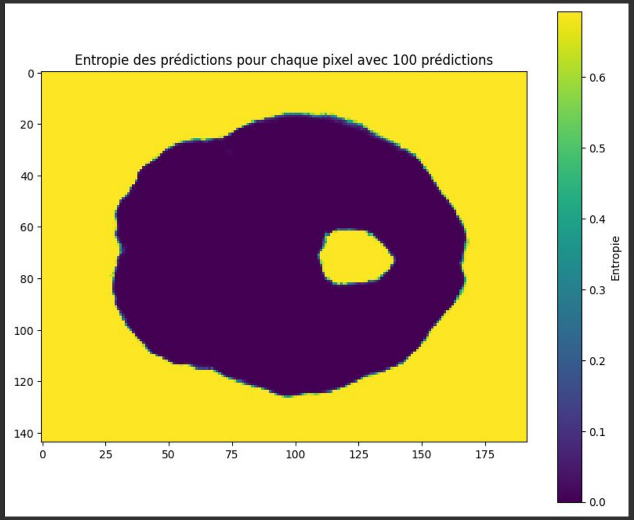

Figure 10 : Shannon Entropy for Monte Carlo Dropout

Experimentations : Segmentation of Brain Area

Dice Formula :

$$D = \frac{2\times|X\cap Y|}{|X|+|Y|}$$

where:

- $|X \cap Y|$ represents the number of elements common to both sets X and Y.
- $|X|$ and $|Y|$ are the respective sizes of sets X and Y.

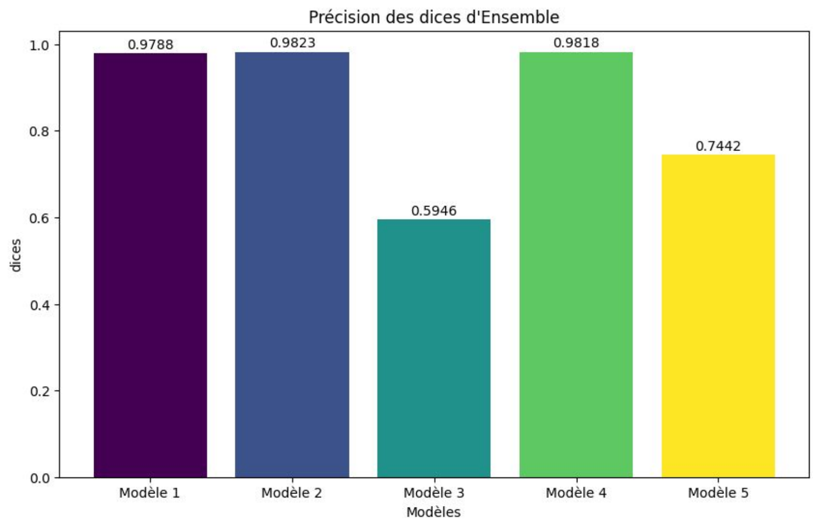

Figure 11 : Dice coefficients of the 5 networks for the same input

Experimentations : Segmentation of White and Gray Matter

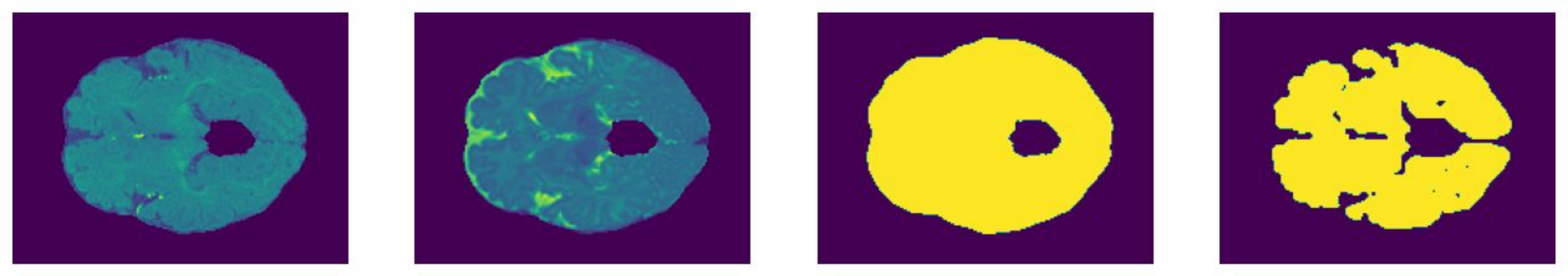

Figure 12 : Input for the segmentation of White and Gray matter

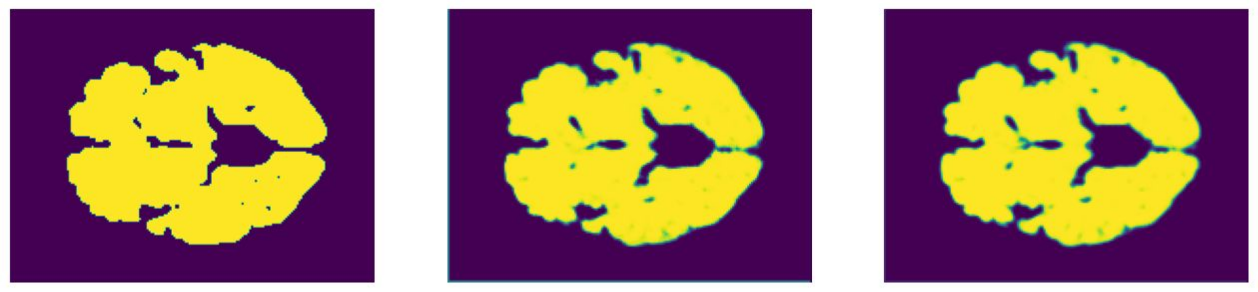

Figure 13 : GroundTruth vs Mean Prediction for Deep Ensembles vs Monte Carlo Dropout

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Experimentations : Segmentation of White and Gray Matter with Monte Carlo Dropout

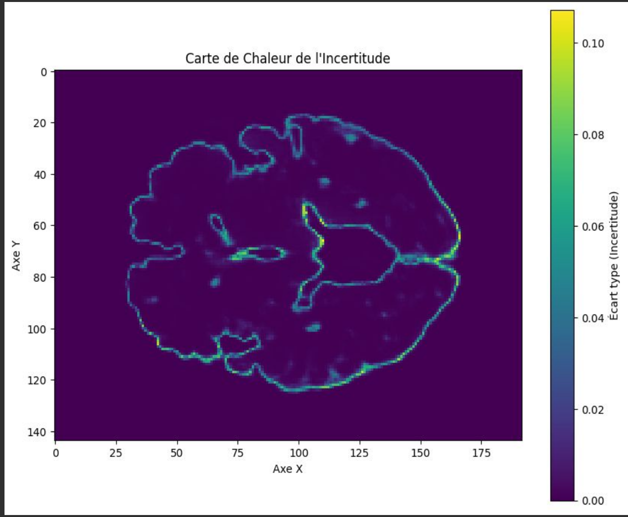

Figure 14 : Standard Deviation Map for Monte Carlo Dropout

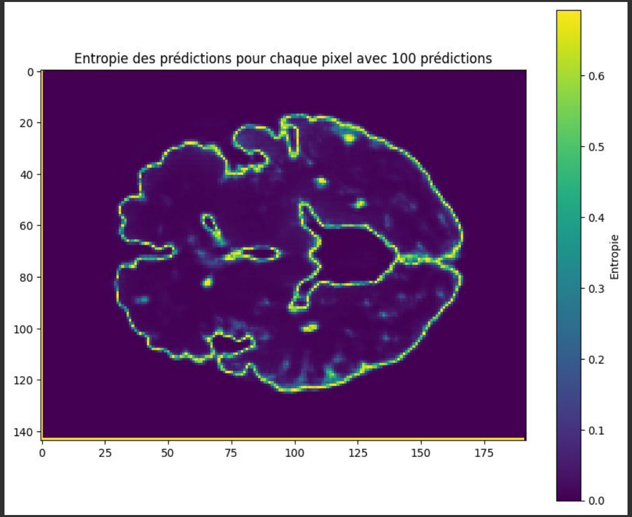

Figure 15 : Shannon Entropy for Monte Carlo Dropout

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Experimentations : Segmentation of White and Gray Matter with Deep Ensembles

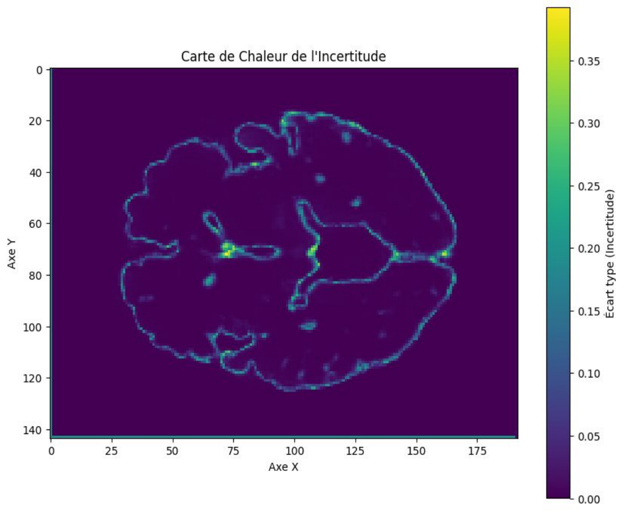

Figure 16 : Standard Deviation Map for Deep Ensembles

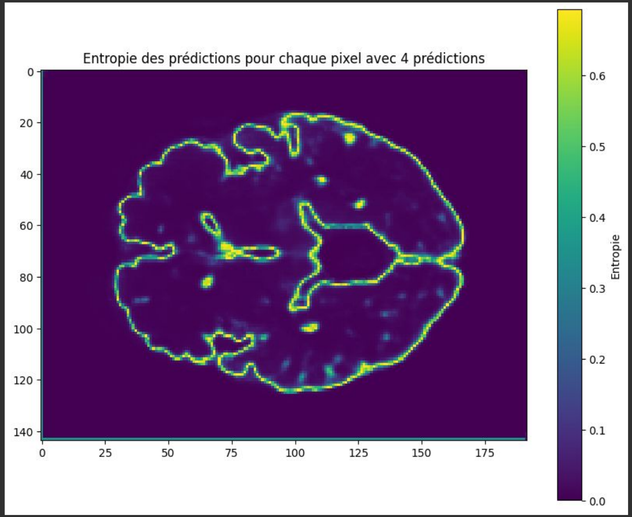

Figure 17 : Shannon Entropy with Deep Ensembles

Experimentations : Segmentation of White Matter with Deep Ensembles

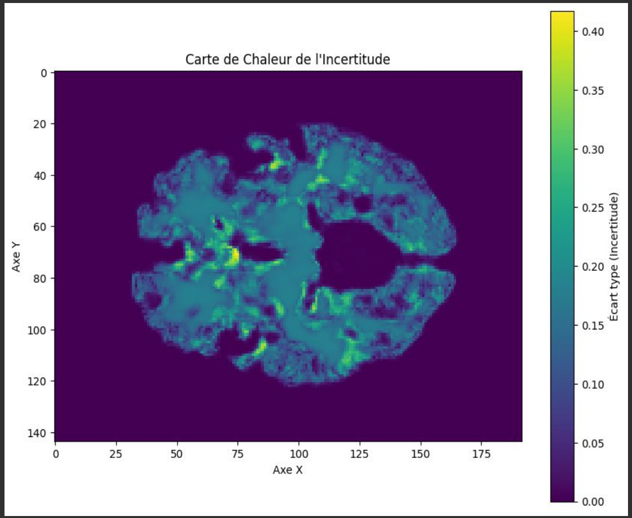

Figure 18 : Standard Deviation Map for Deep Ensembles

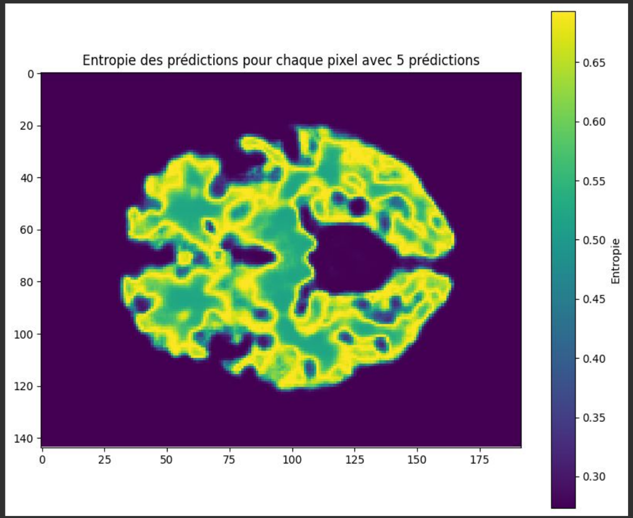

Figure 19 : Shannon Entropy with Deep Ensembles

Experimentations : Segmentation of White Matter with Monte Carlo Dropout

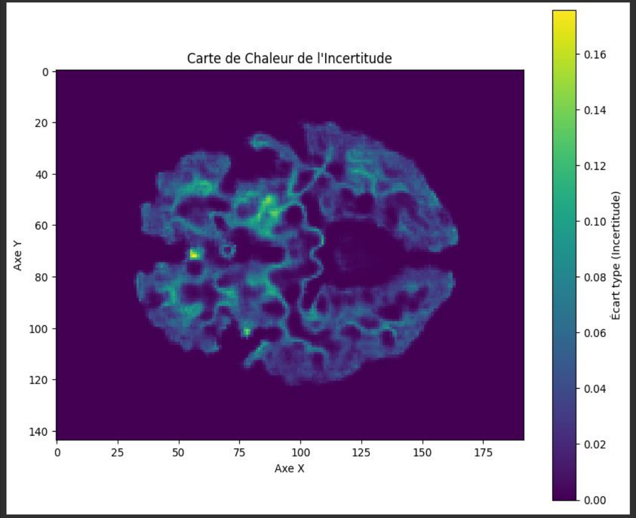

Figure 20 : Standard Deviation Map with Monte Carlo Dropout

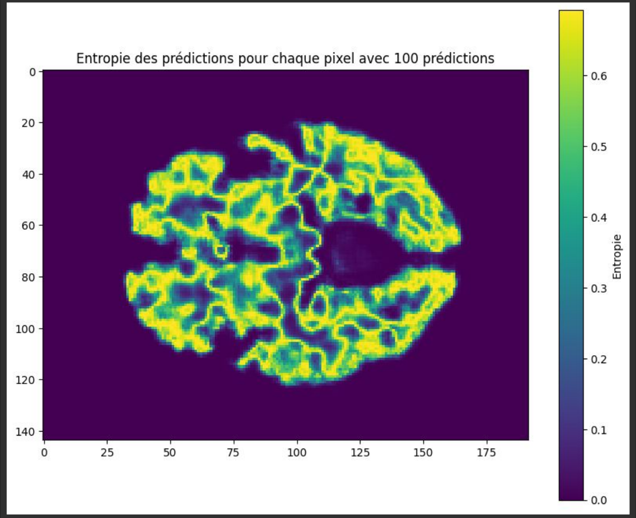

Figure 21 : Shannon Entropy with Monte Carlo Dropout

Related Work : Achievements for this Semester

Experimentation:

❖ Experimented with two methods for uncertainty quantification
❖ Compared the effectiveness of both methods

Segmentation:

❖ Performed basic segmentation tasks using a U-net model

Uncertainty Measures:

❖ Implemented basic uncertainty measures including mean, standard deviation, and Shannon entropy

Future Work : Research Focus for Next Semester

Identifying Sources of Uncertainty:

- ❖ Differentiating between aleatoric uncertainty (data-related) and epistemic uncertainty (model-related)
- ❖ Objective: Determine which type of uncertainty is being measured and identify its source

Dataset:

- ❖ Work with MRBrains dataset

Complex Segmentations:

- ❖ Perform segmentations on even more complex structures

References

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