Human brains MRI Images representation through generative models

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Objectives

Compression

Data Augmentation

State of the art

Data augmentation

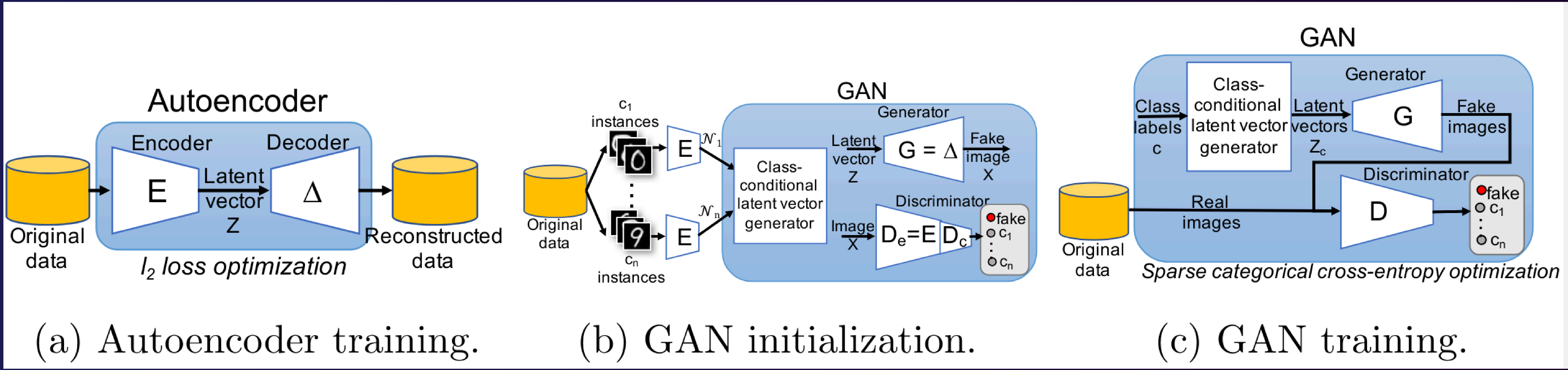


Figure 1: Mariani et al. (2018) BAGAN (Balancing Generative Adversarial Network) methodology for addressing class imbalance in image datasets [1]

Interpolation

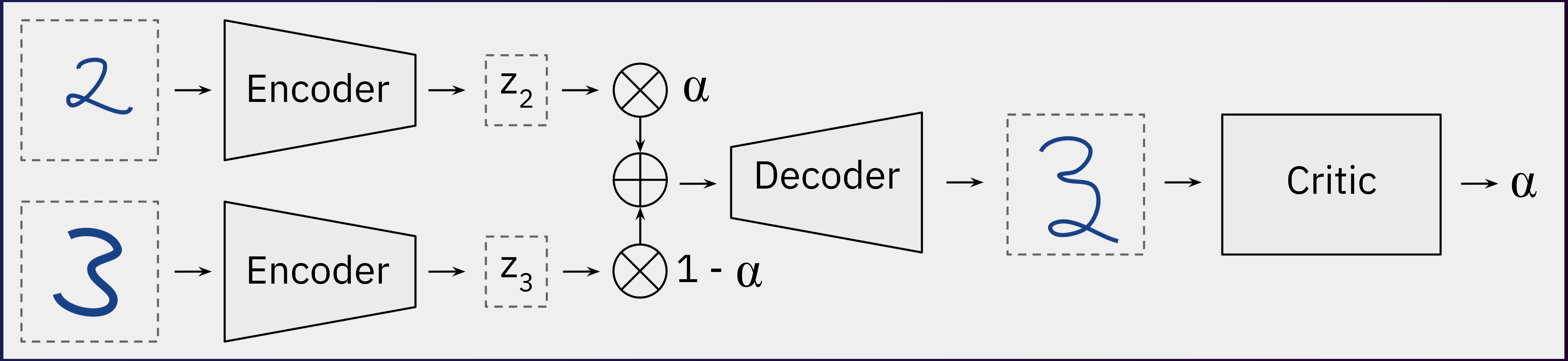


Figure 2: Goodfellow et al. (2018) Adversarially Constrained Autoencoder Interpolation (ACAI) [2]

Data Augmentation

Interpolation Method

1. Input: $x_1 \quad x_2$
2. Encoding: $z_1 \quad z_2$
3. Interpolation Method

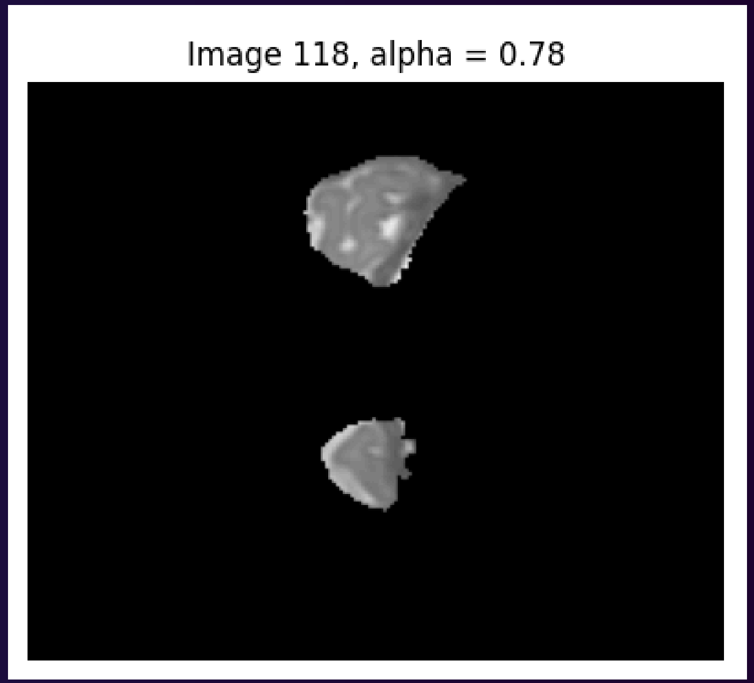
$$z_{interpolated} = \alpha z_1 + (1 - \alpha) z_2$$

$$\alpha \in [0, 1]$$

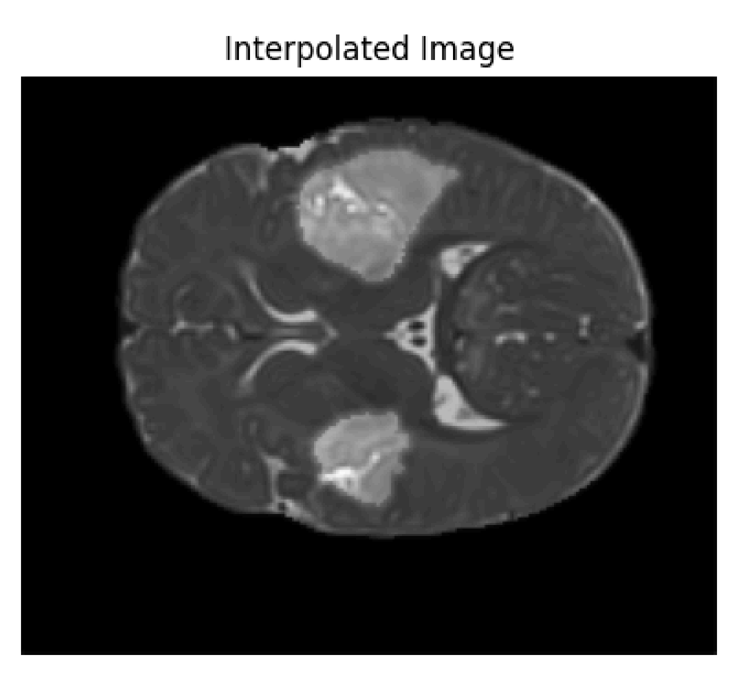
4. Decoding
5. Output

Interpolation

Figure 3: Random images from dataset

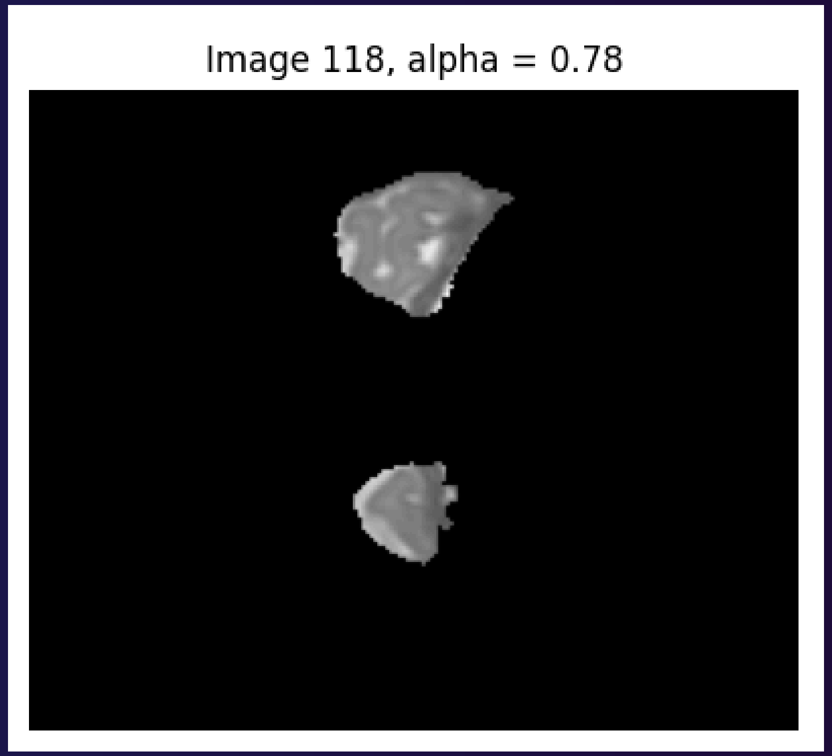


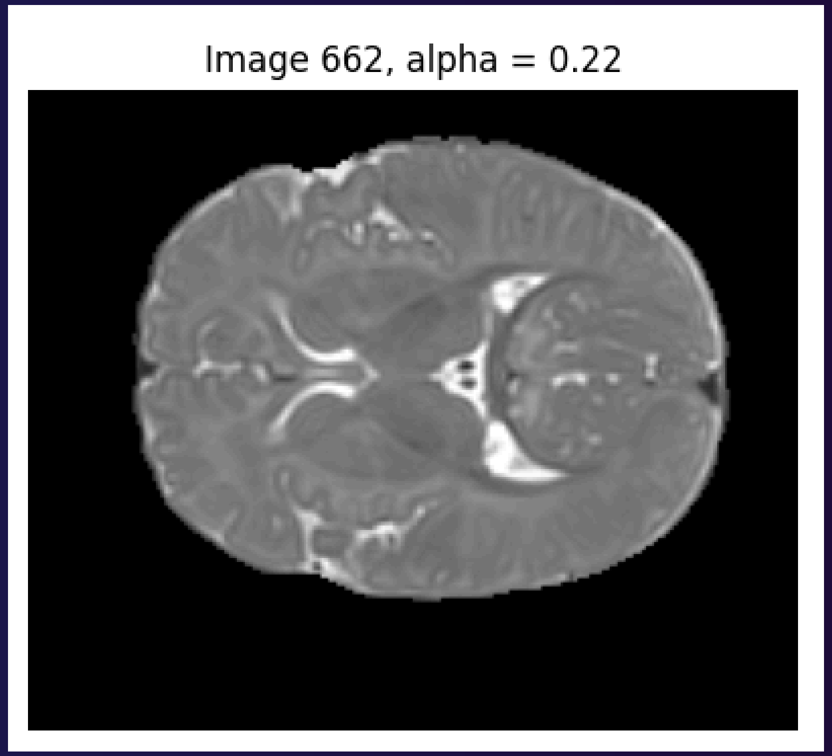
Problem



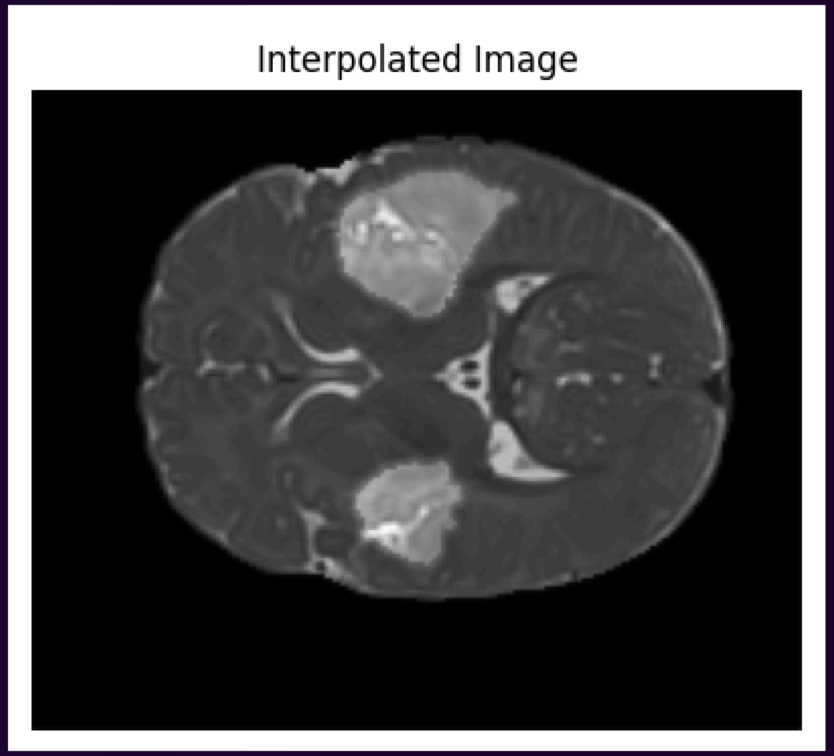
Interpolation

Figure 3: Random images from dataset





Problem



Solution

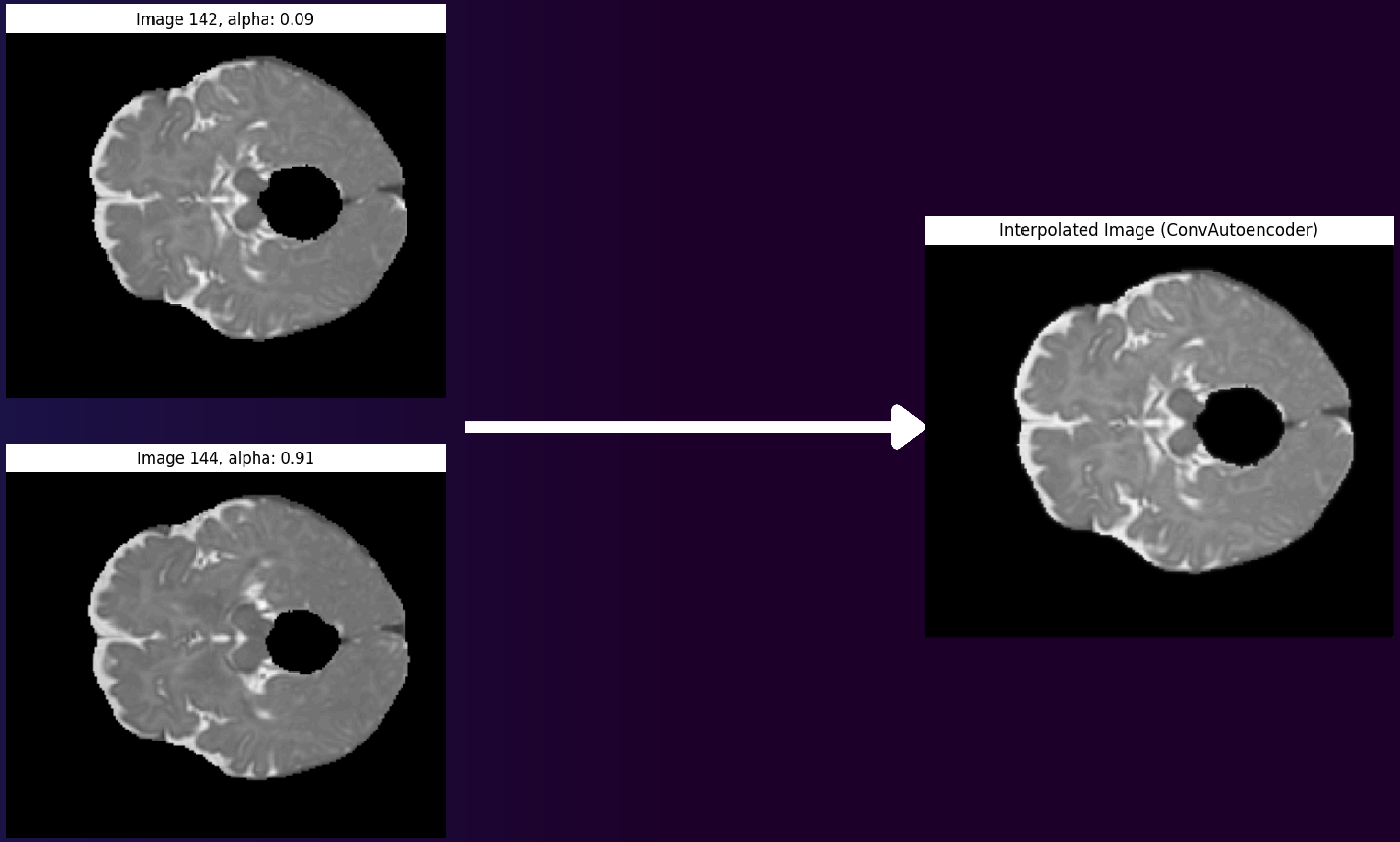
same patient

spacial closeness

Configurations

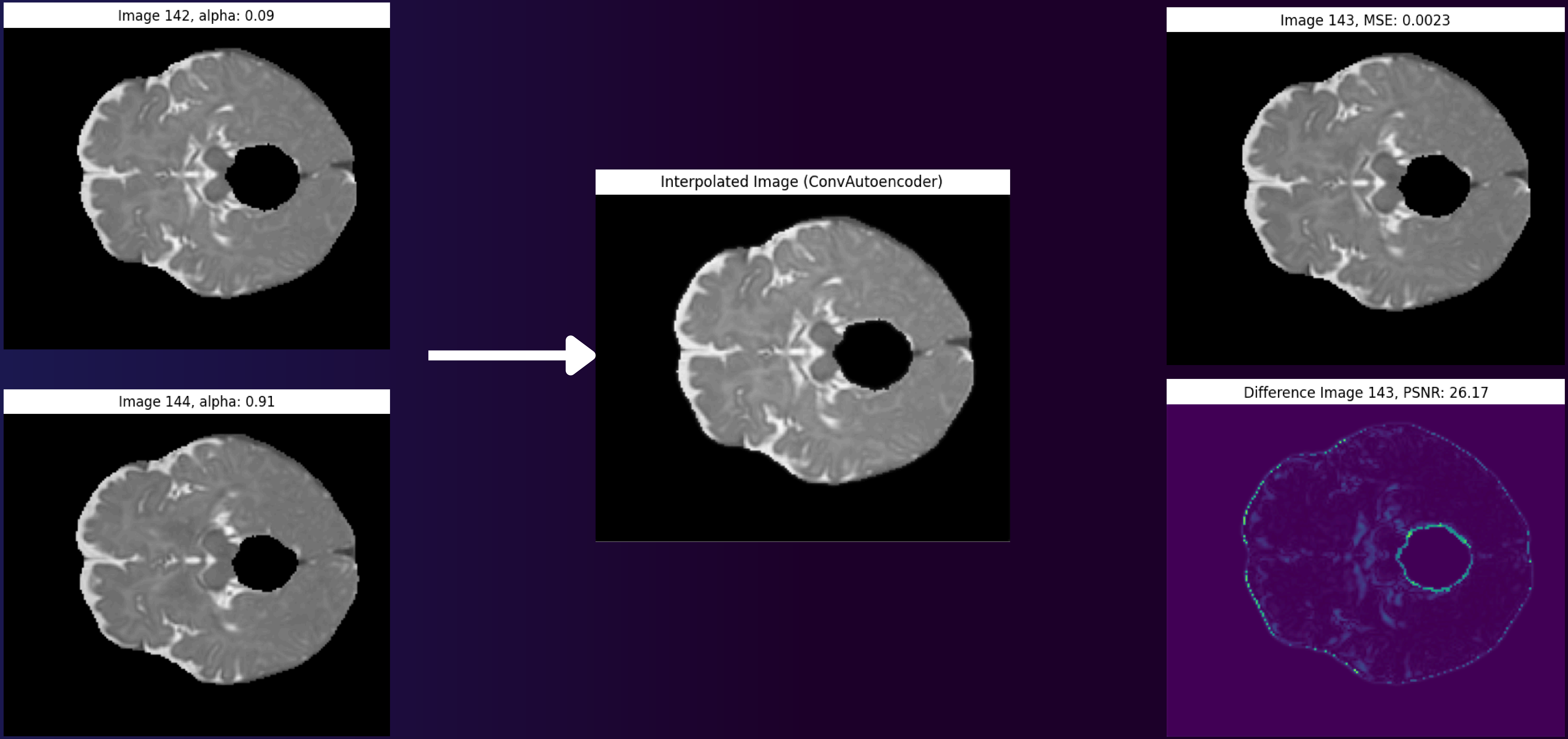
Config 1: interpolate even/odd images

Figure 4: Images from dataset with an even index



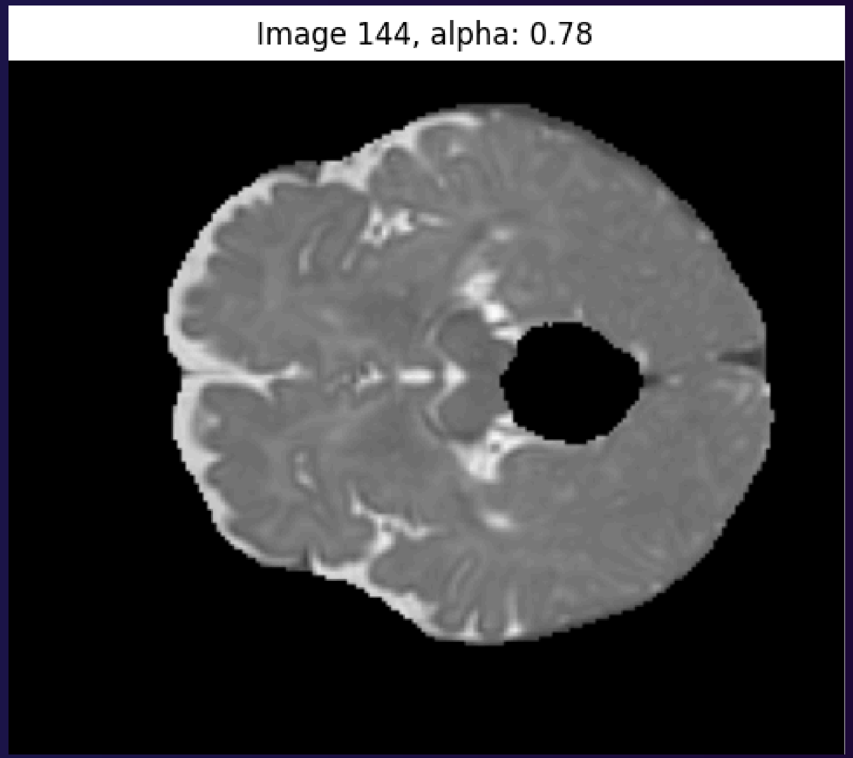
Config 1: interpolate even/odd images

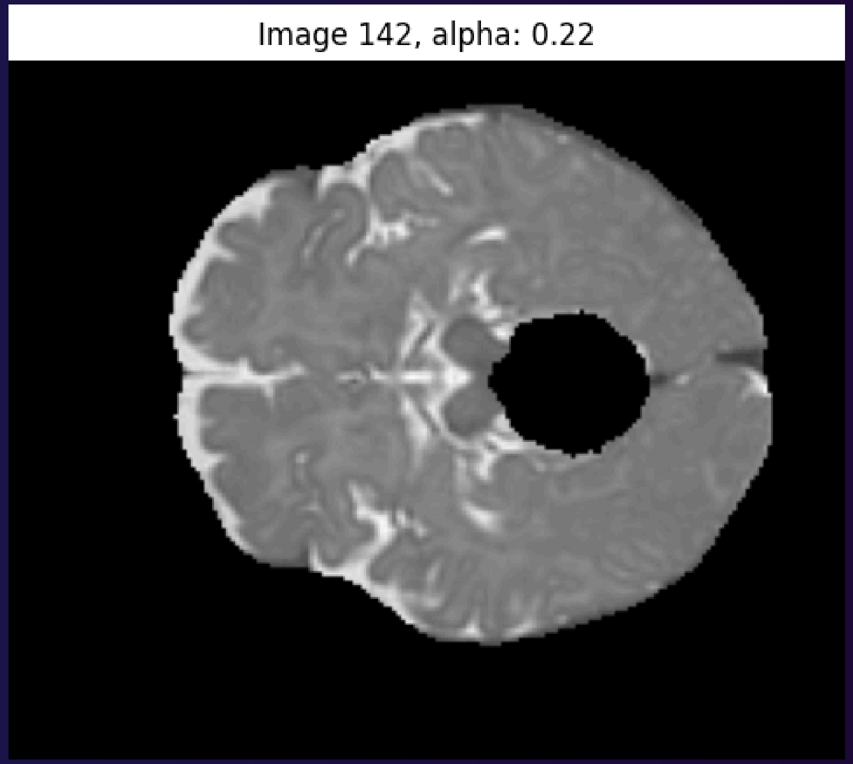
Figure 4: Images from dataset with an even index



Config 2: interpolate 2 images with noise injection

Figure 5: Added noise to latent representation





noise range (-0.01, 0.01)

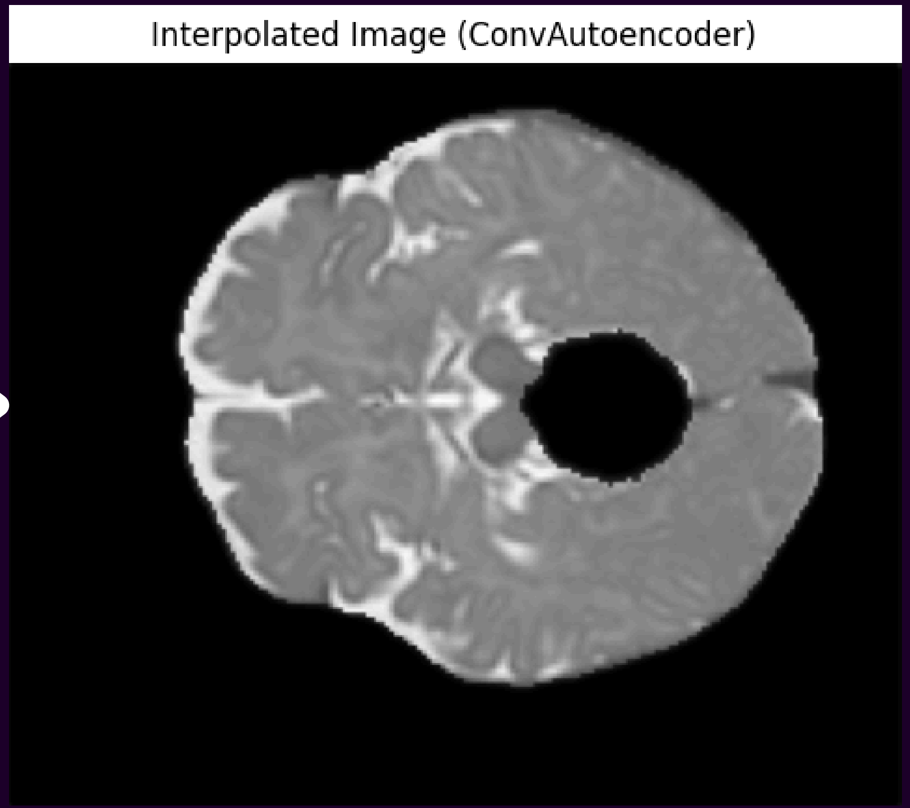


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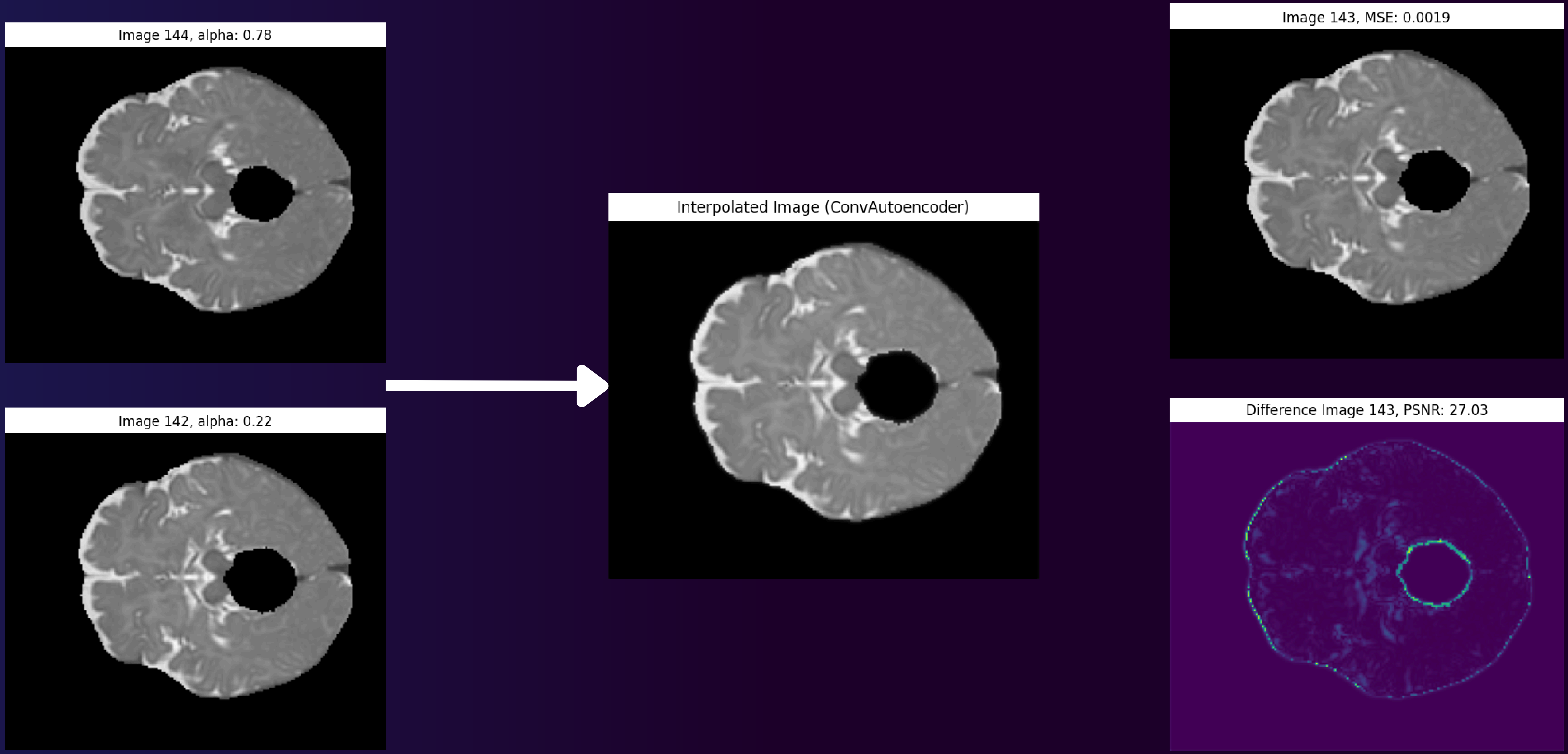
Figure 5: Added noise to latent representation



Config 3: interpolate multiple images

$$\forall \alpha \in [0;1], \forall n \in \mathbb{N}, z_{interpolated} = \sum_{i=1}^{n} \alpha_i z_i, \sum_{i=1}^{n} \alpha_i = 1$$

Config 3: interpolate multiple images

$$\forall \alpha \in [0;1], \forall n \in \mathbb{N}, z_{interpolated} = \sum_{i=1}^{n} \alpha_i z_i, \sum_{i=1}^{n} \alpha_i = 1$$

$$W_i = 1 - \frac{|i - \lfloor n/2 \rfloor|}{n+1}$$

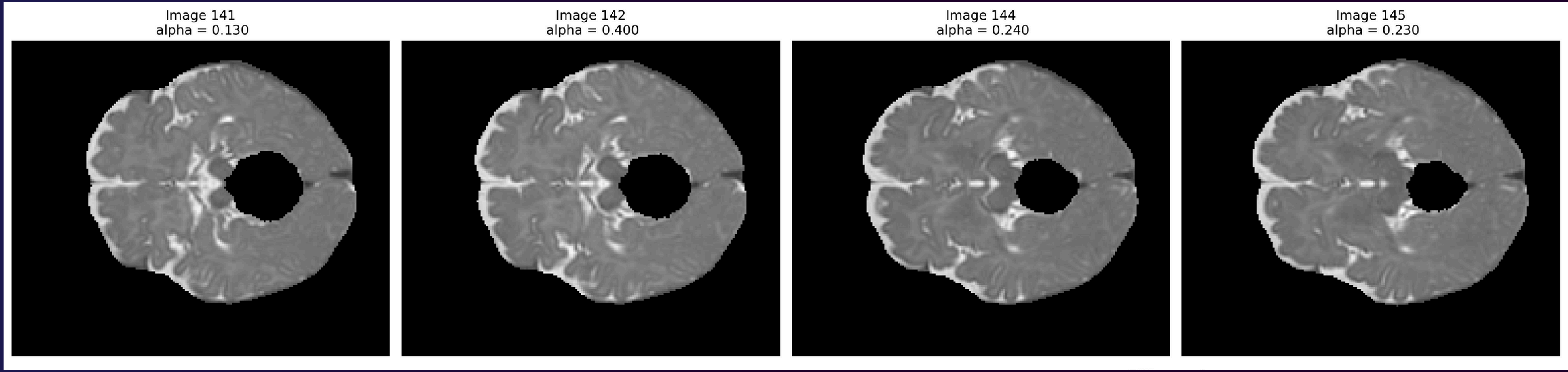
$$R_i = W_i * rand(0,1)$$

$$\alpha_i = \frac{R_i}{\sum_{i=0}^{n-1} R_i}$$

- n: number of images to interpolate
- $i \in [0, n-1]$: the index of the image
- $\lfloor n/2 \rfloor$: the index of the central point

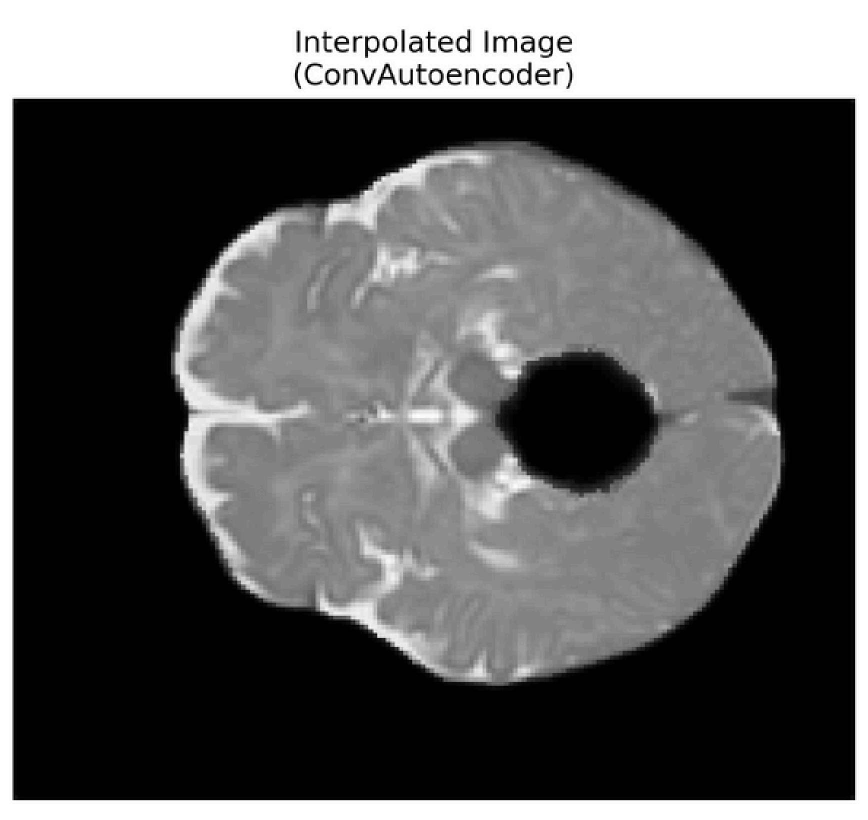
Config 3: interpolate multiple images

Figure 6: 4 Images from dataset



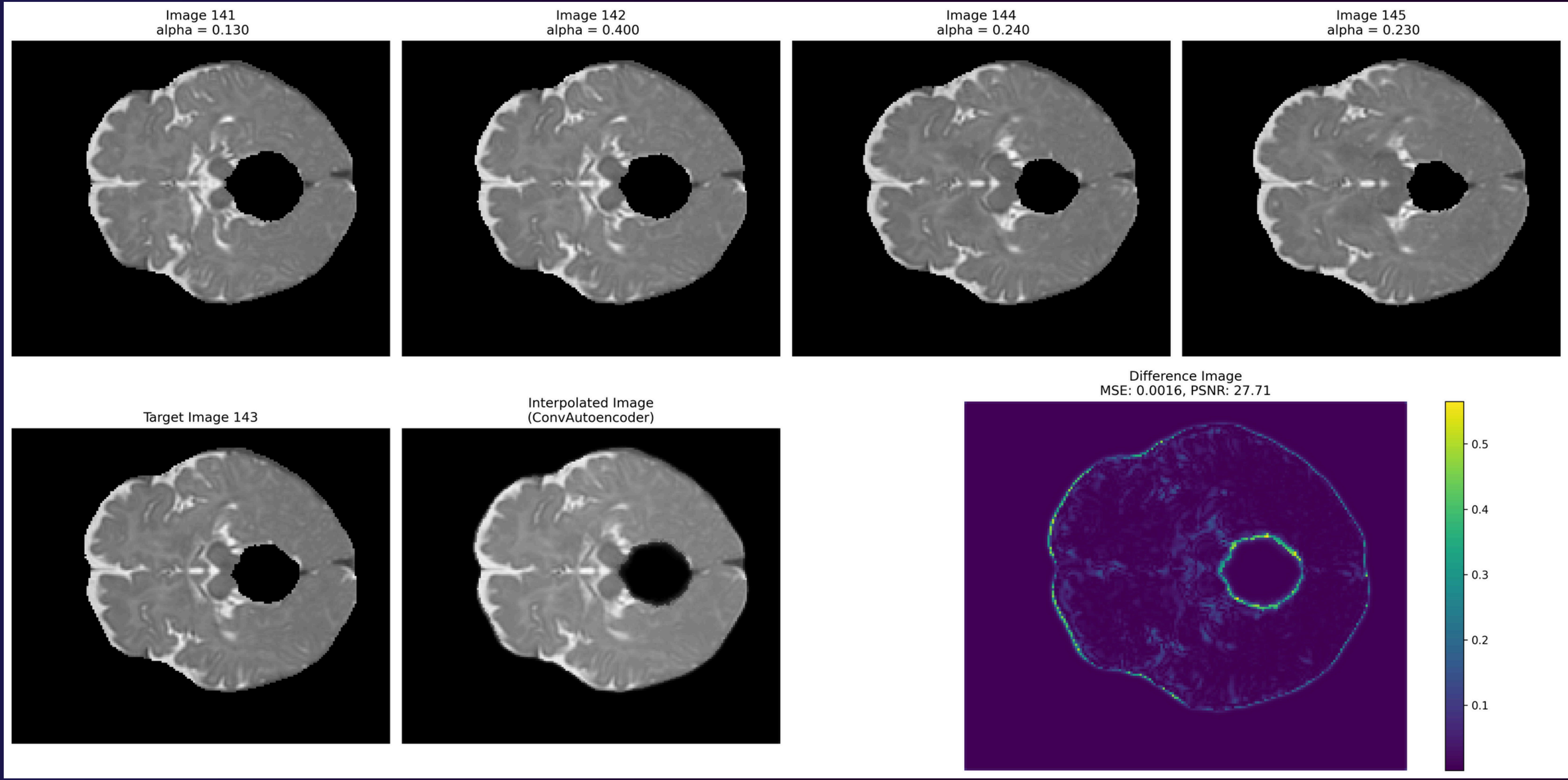
$$\forall \alpha \in [0;1], \sum_{i=1}^{4} \alpha_i = 1$$

$$z_{interpolated} = \alpha_1 z_1 + \alpha_2 z_2 + \alpha_3 z_3 + \alpha_4 z_4$$



Config 3: interpolate multiple images

Figure 6: 4 Images from dataset



Metric comparison

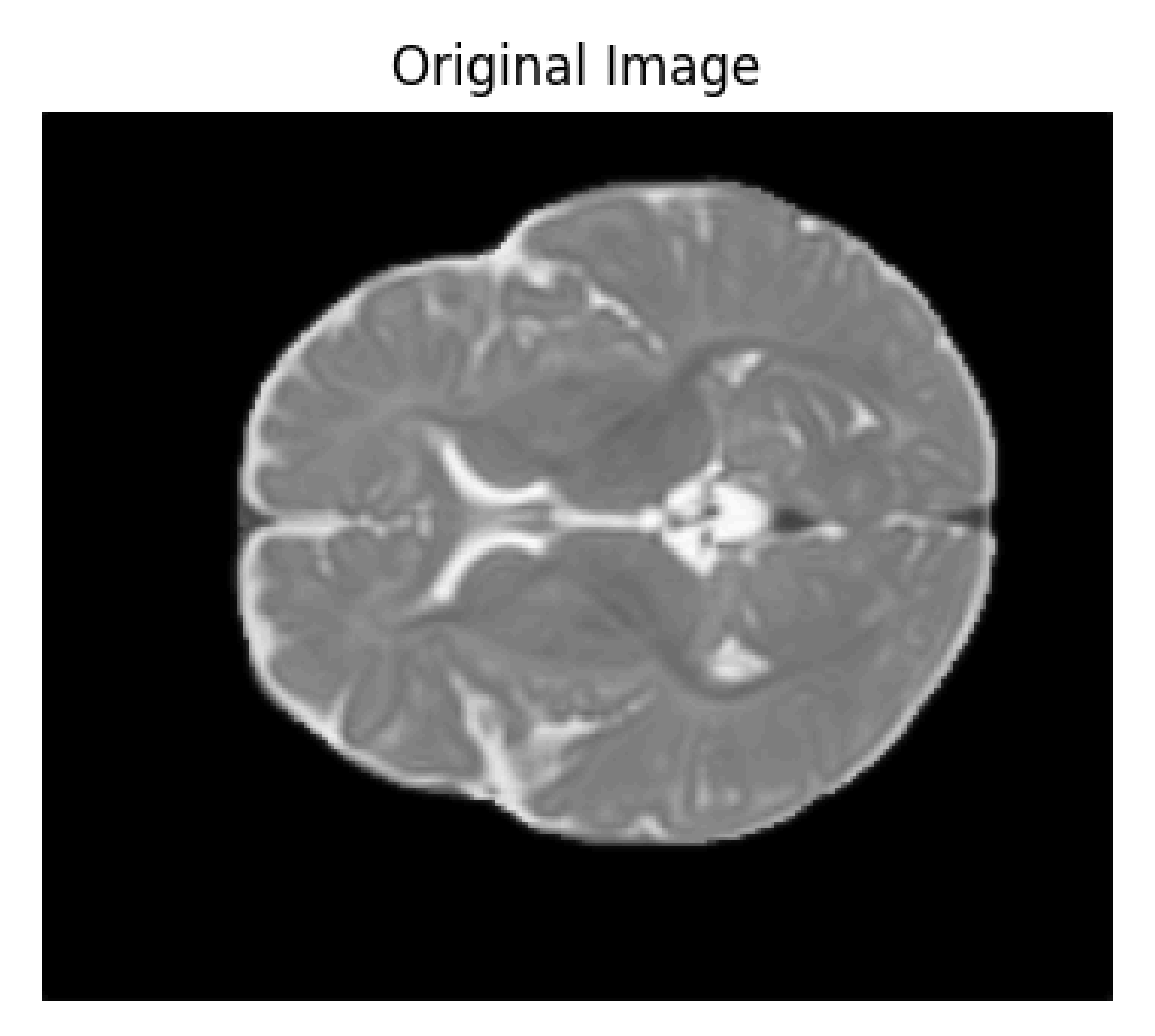
Table 1: MSE scores achieved by different interpolations

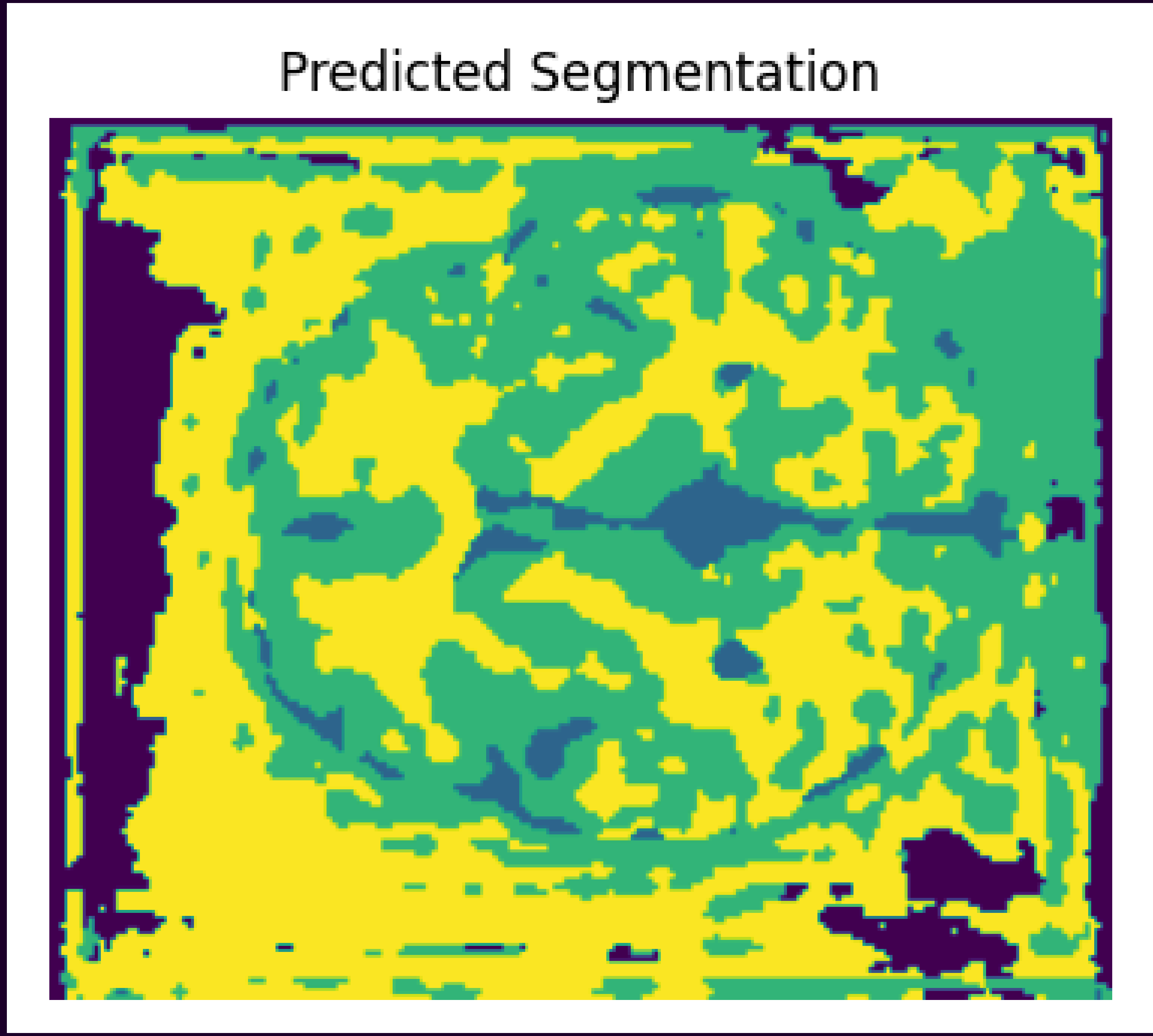
Metric	Even/Odd index	Latent space noise	Multi-image
Mean Squared Error	0.0002 ± 0.0043	0.0002 ± 0.0045	0.0005 ± 0.0055

Segmentation Experiments

Segmentation

Figure 7: Segmentation of interpolated images





Augmented dataset

Table 2: Dataset sizes for different interpolation configurations

Configuration	Generated dataset size	Augmented dataset size
Even/Odd index interpolation	360	784
Even + Odd augmented dataset	720	1144
Latent space noise injection	360	784
Multi-image interpolation	695	1119

Segmentation

- Integration of **weighted augmented data** in the training process
- Systematic **weight analysis** ranging from **0.05 to 0.95** (step size: 0.05)
- Comprehensive assessment of **weight coefficients' impact** on model performance
- Selection and analysis of representative weighting scenarios

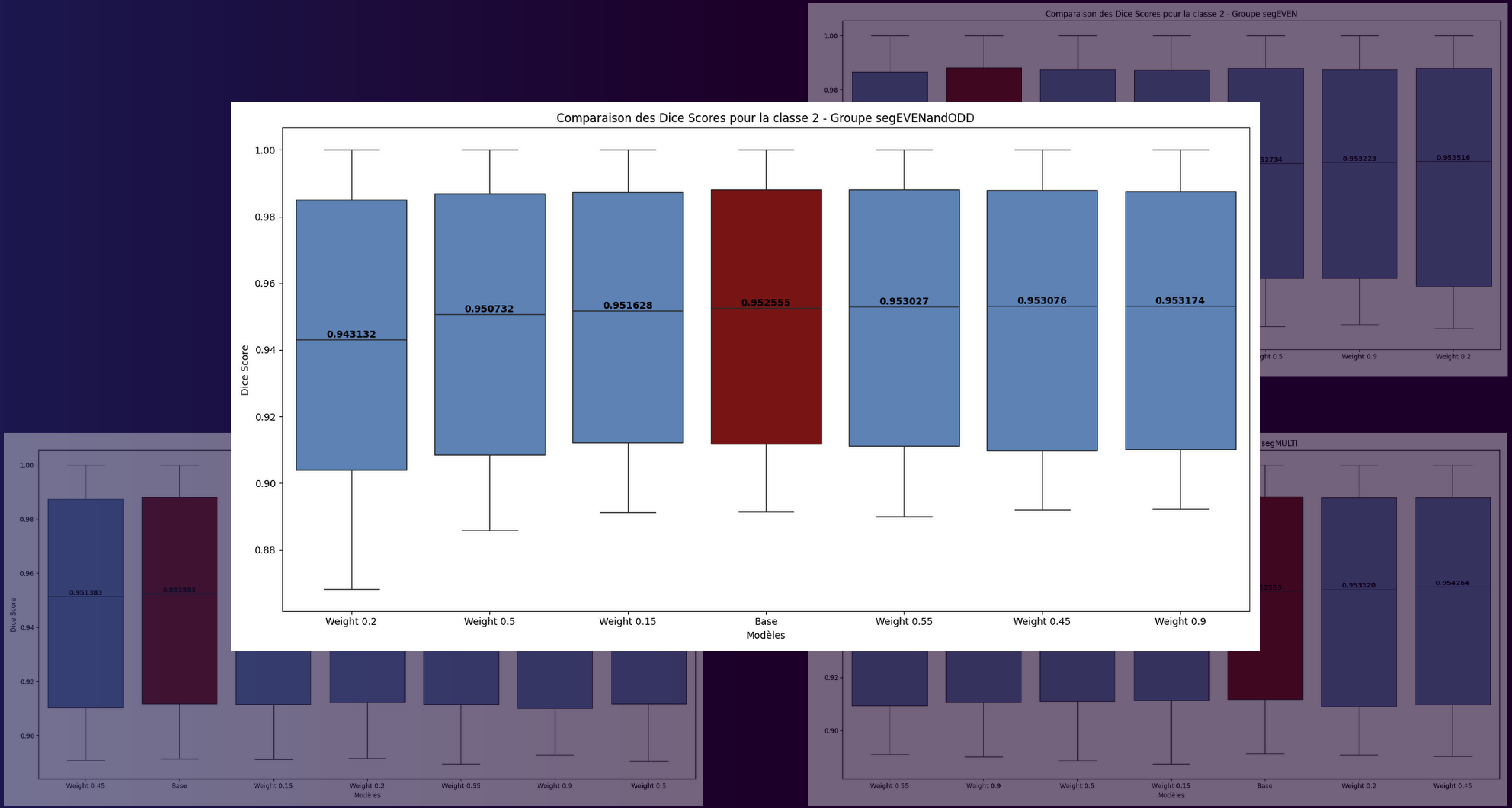
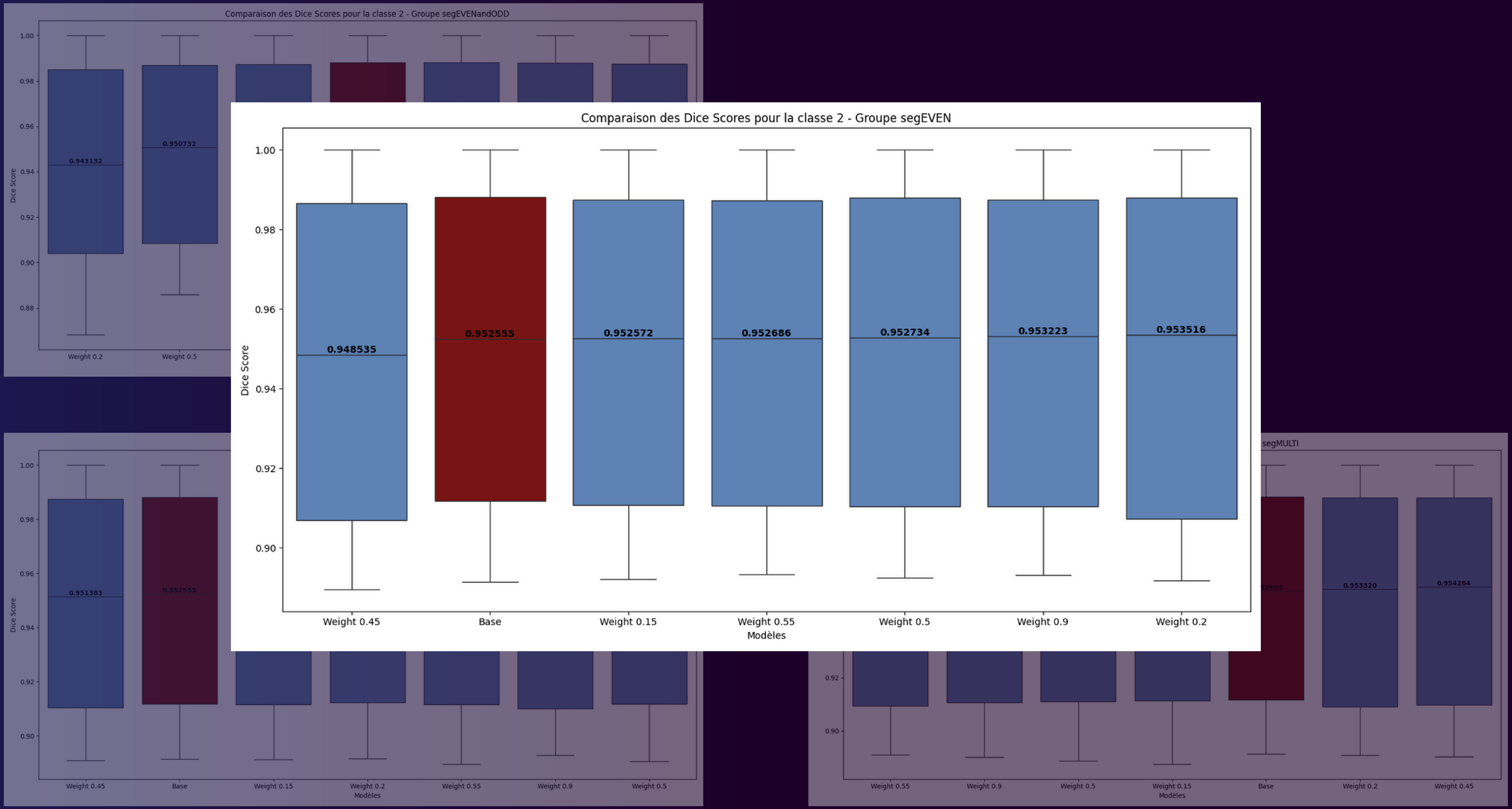


Figure 8: Comparative results of the Dice scores for classe 2 across selected models with different weights, compared to the baseline segmentation model.



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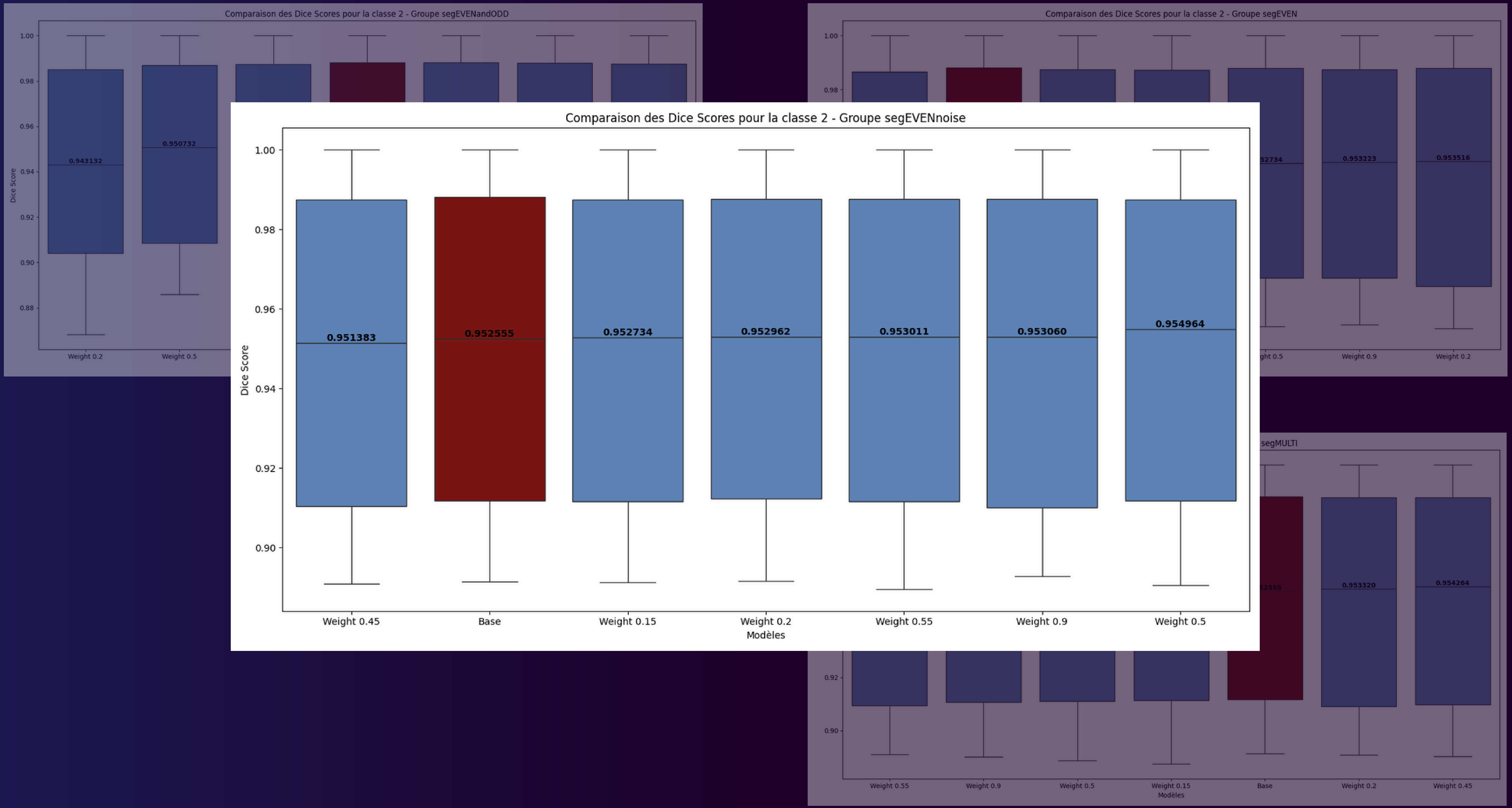

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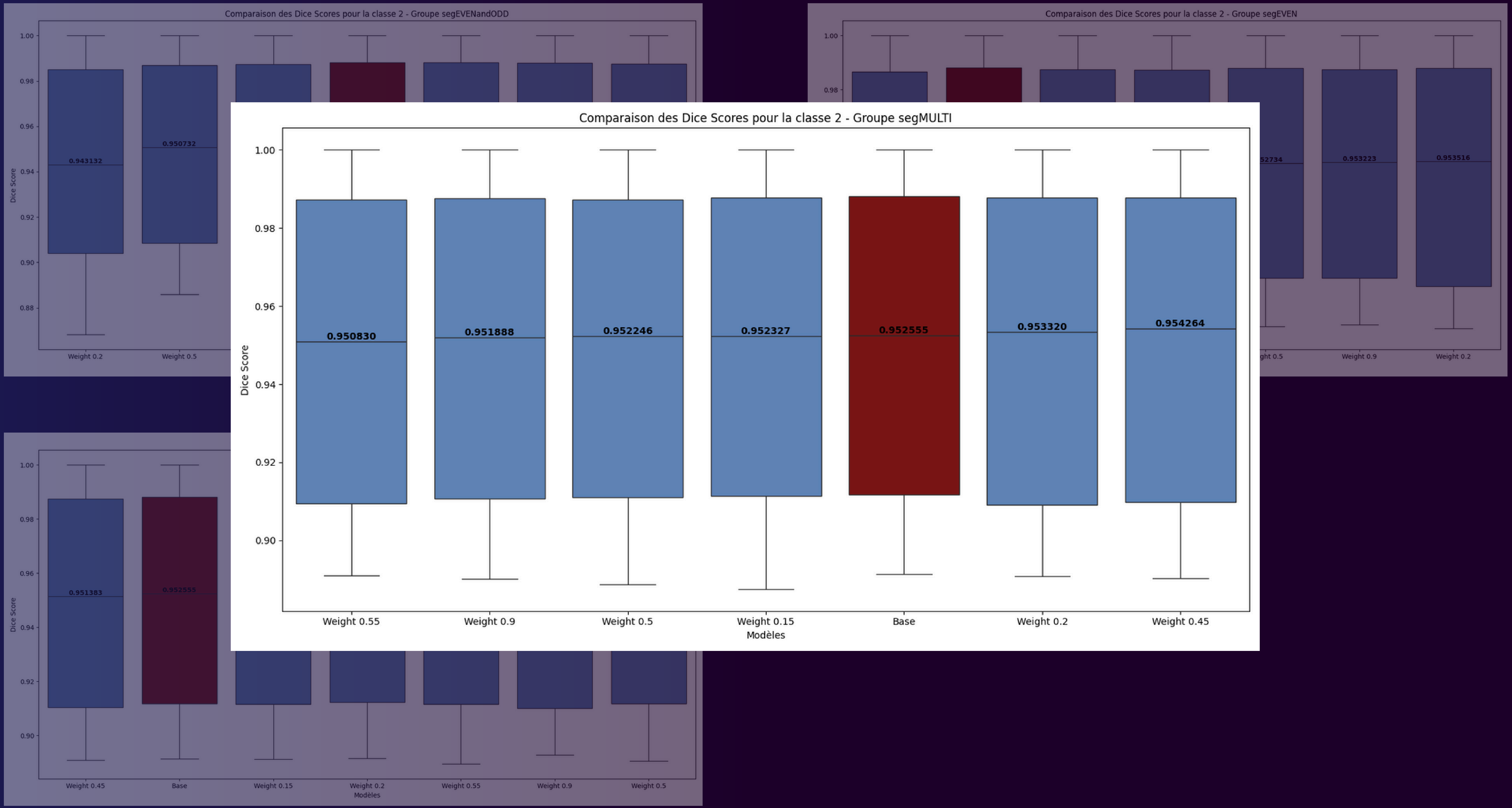

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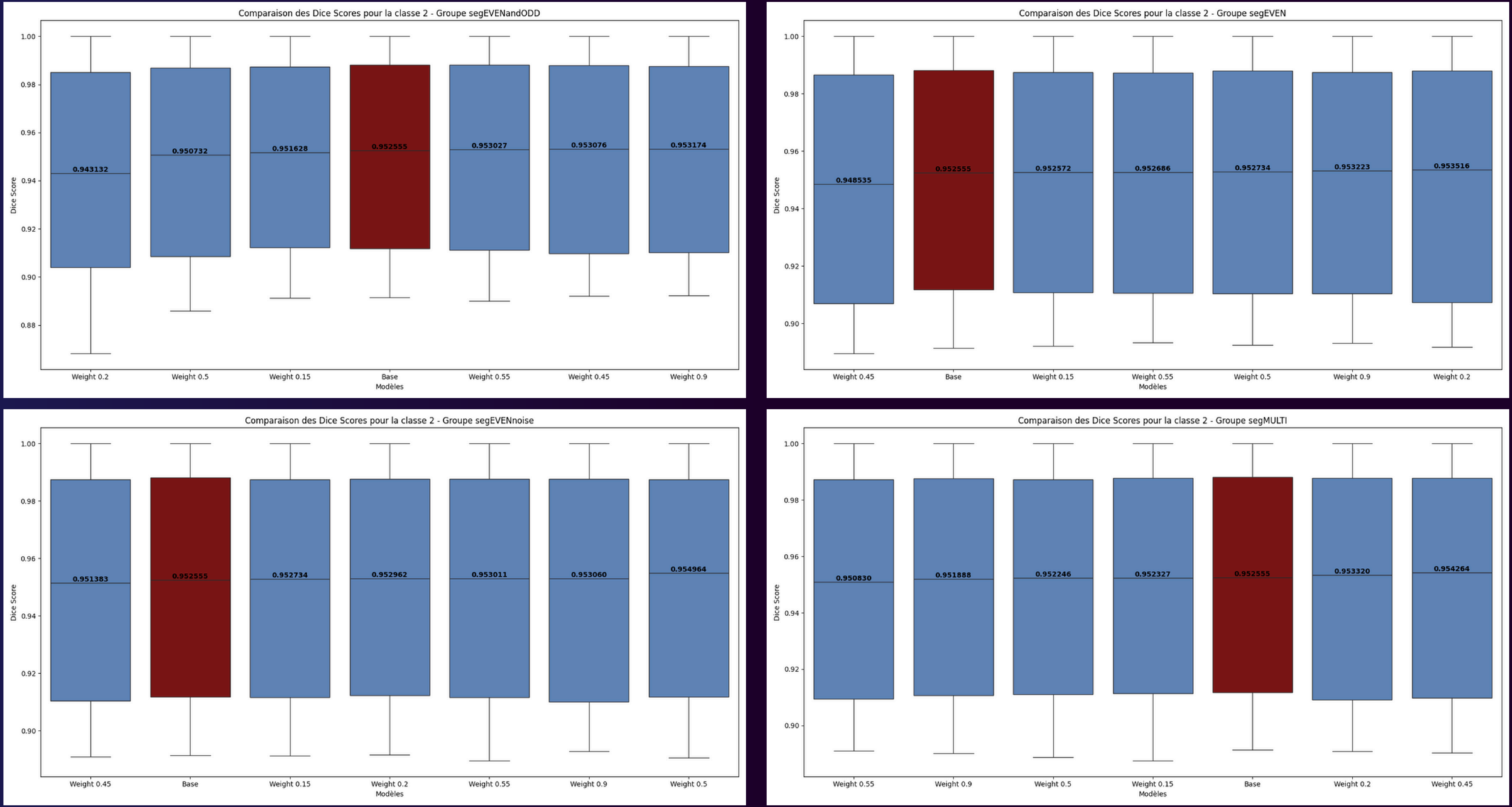

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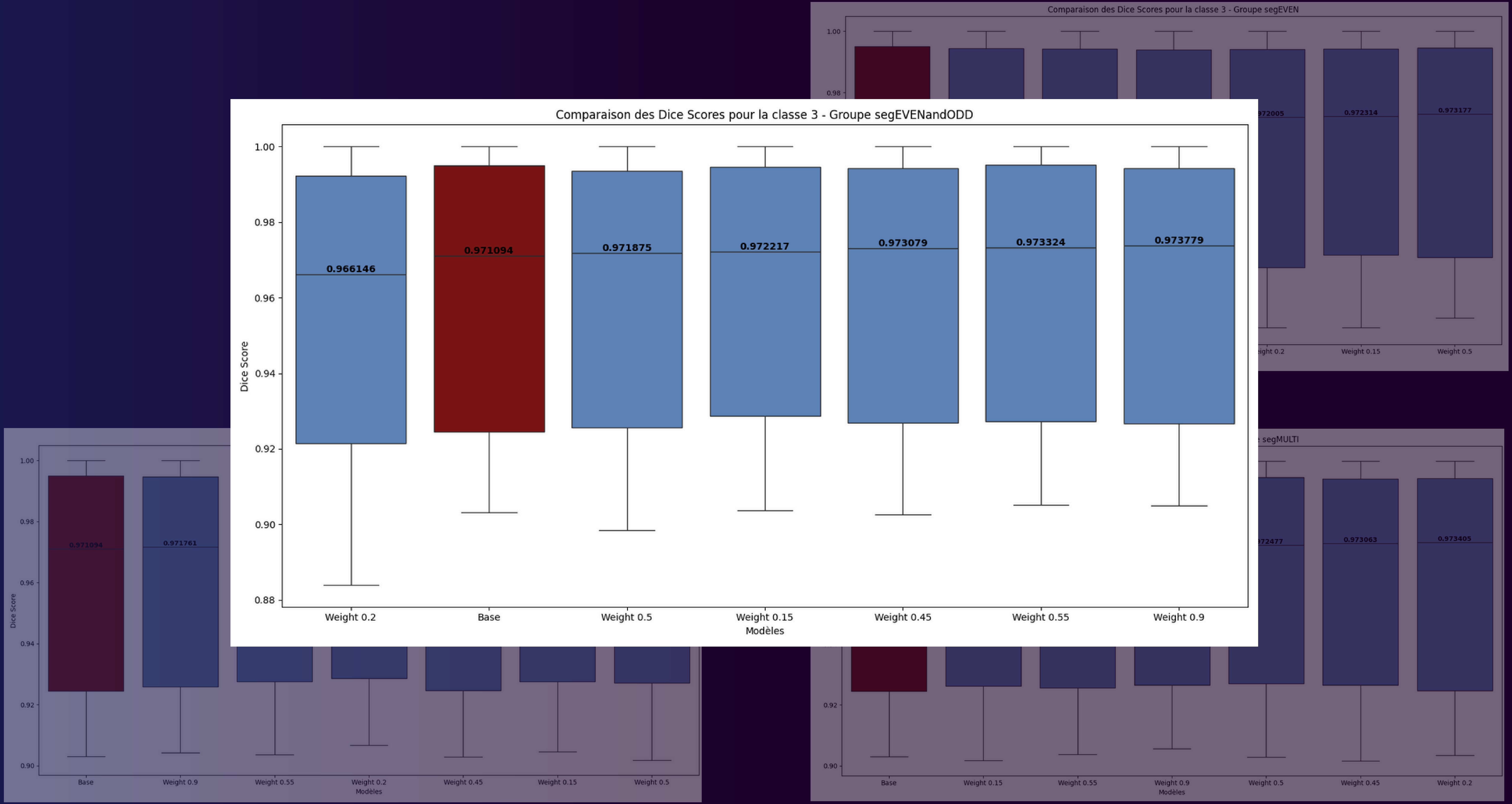


Figure 9 : Comparative results of the Dice scores for classe 3 across selected models with different weights, compared to the baseline segmentation model.

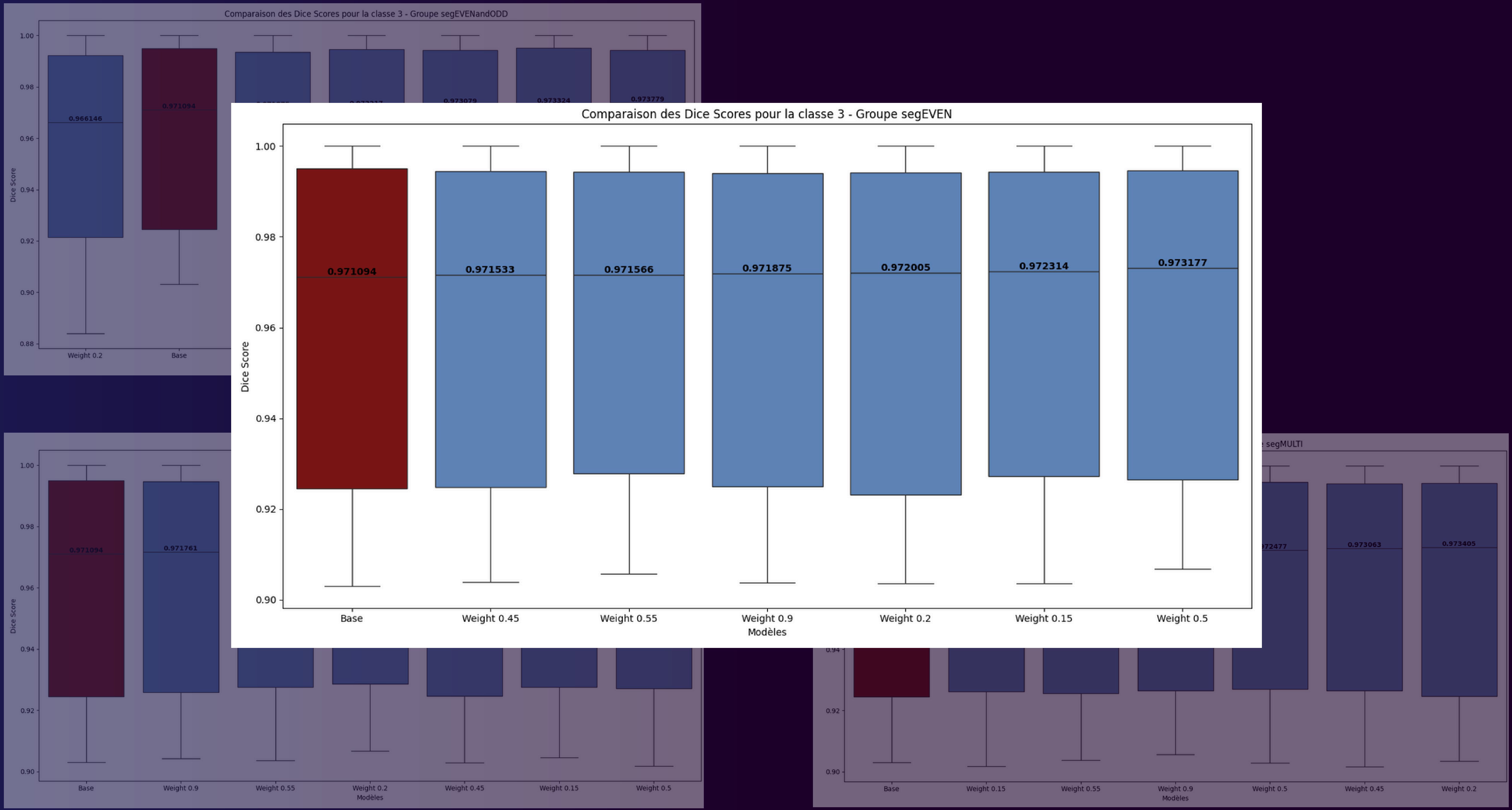
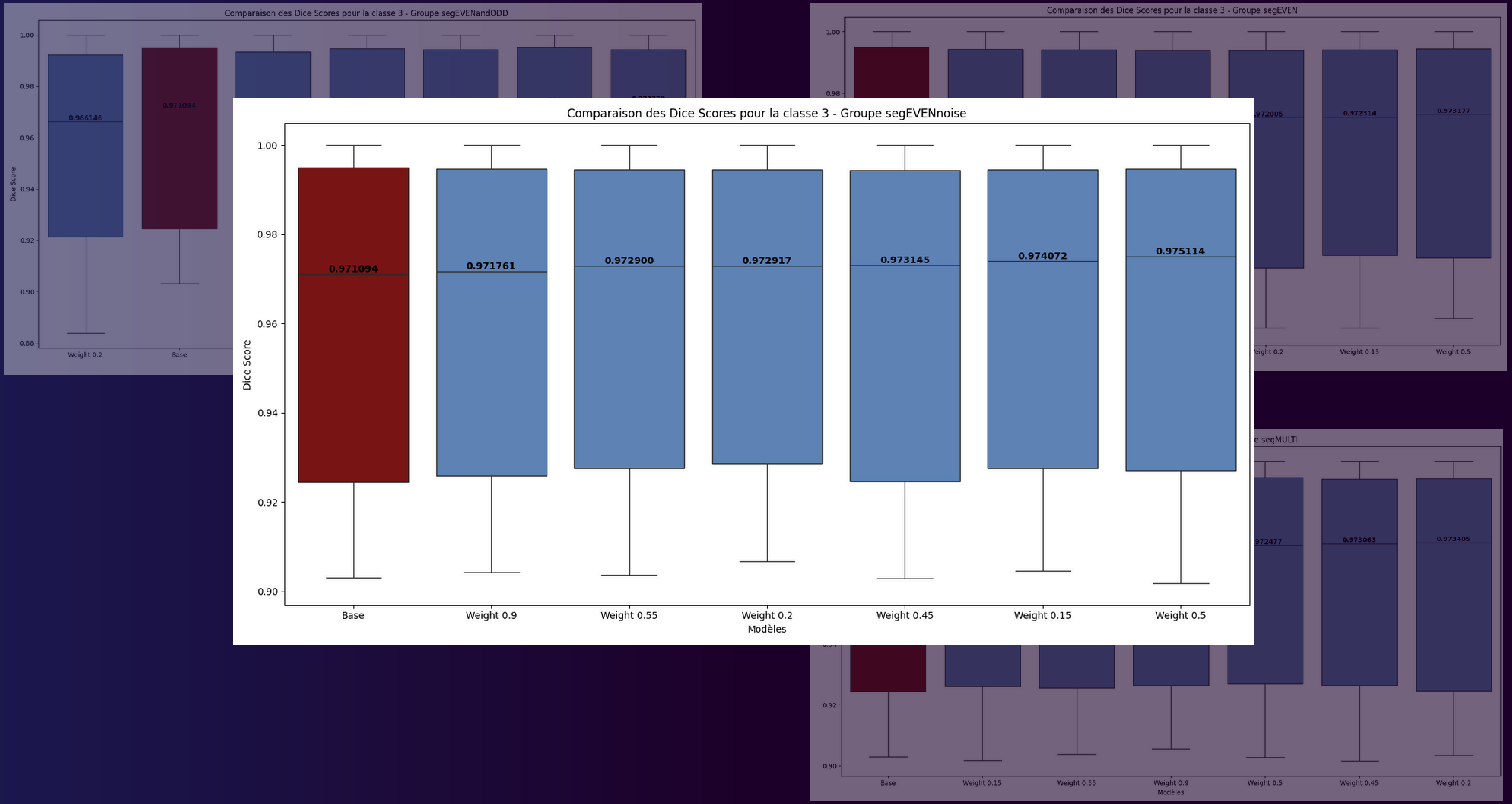


Figure 9 : Comparative results of the Dice scores for classe 3 across selected models with different weights, compared to the baseline segmentation model.



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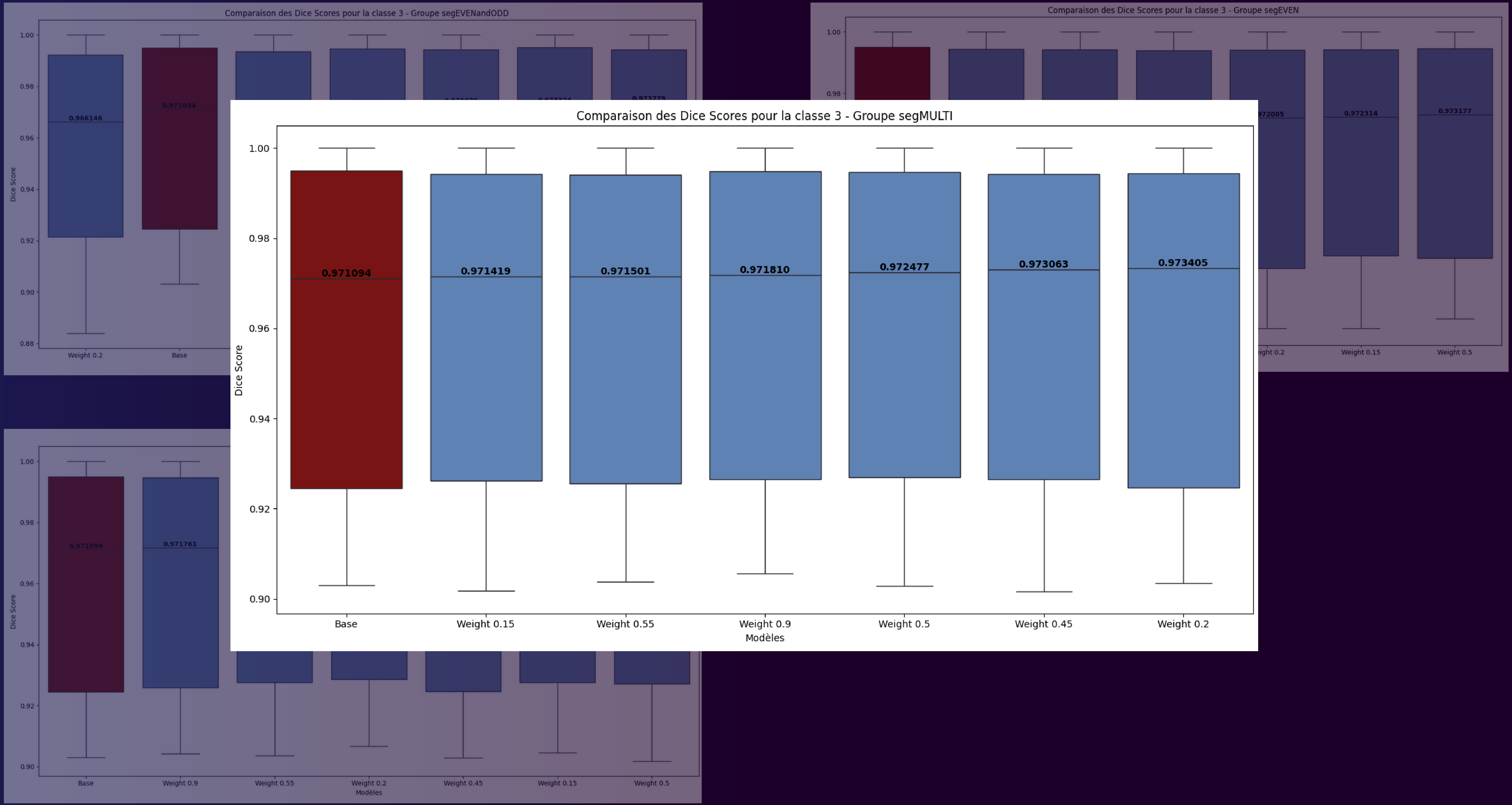

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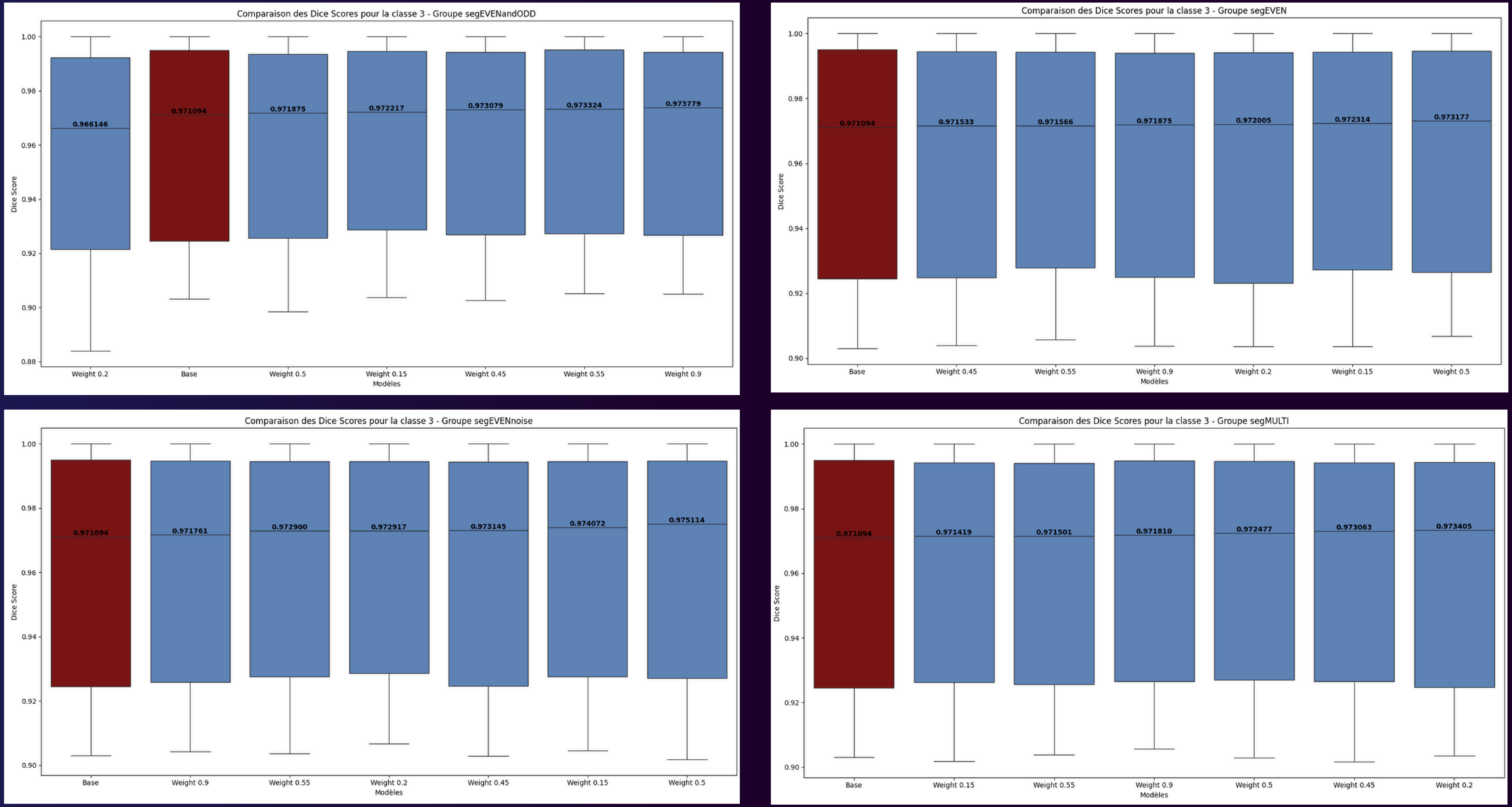


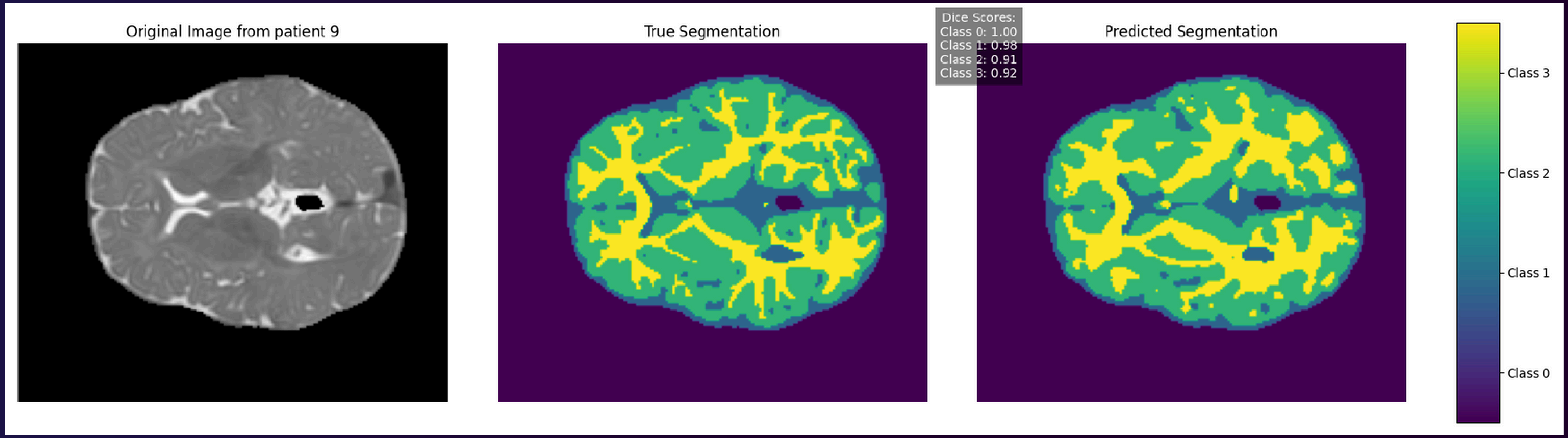
Figure 9 : Comparative results of the Dice scores for classe 3 across selected models with different weights, compared to the baseline segmentation model.

Segmentation Improvements

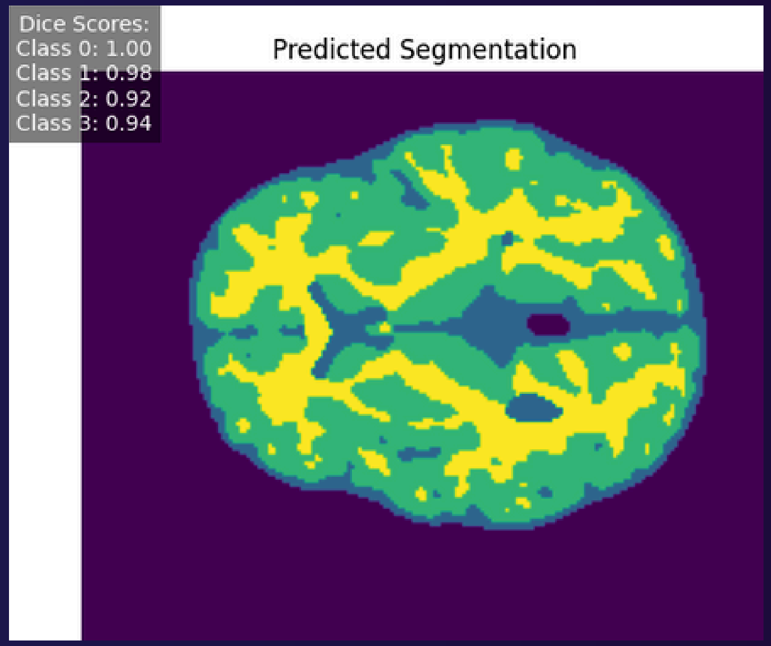
Method	Class			
	0: Background	1: Cerebrospinal Fluid	2: Gray Matter	3: White Matter
segEVEN	$-0.03 \pm 0.09\%$	$-0.03 \pm 0.25\%$	$0.10 \pm 0.52\%$	$0.24 \pm 0.22\%$
segEVENandODD	$-0.04 \pm 0.10\%$	$-0.06 \pm 0.16\%$	$0.07 \pm 1.05\%$	$0.28 \pm 0.79\%$
segEVENnoise	$-0.03 \pm 0.07\%$	$-0.02 \pm 0.26\%$	$0.25 \pm 0.61\%$	$0.41 \pm 0.71\%$
segMULTI	$-0.03 \pm 0.03\%$	$-0.04 \pm 0.15\%$	$0.18 \pm 0.36\%$	$0.24 \pm 0.28\%$

Table 3: Segmentation performance improvements (%) over baseline model (trained without data augmentation) across different data augmentation configurations

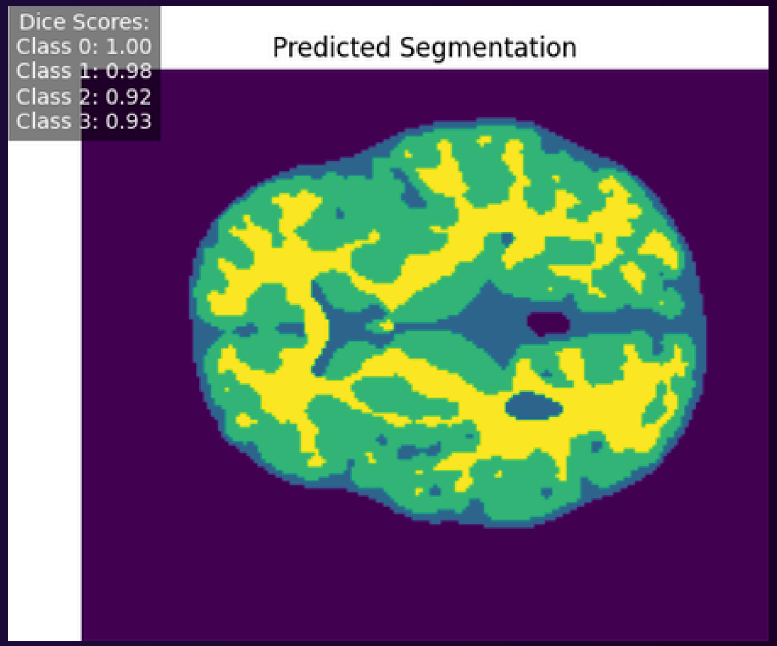
Figure 10: Comparative analysis of segmentation performance across configurations VS baseline model



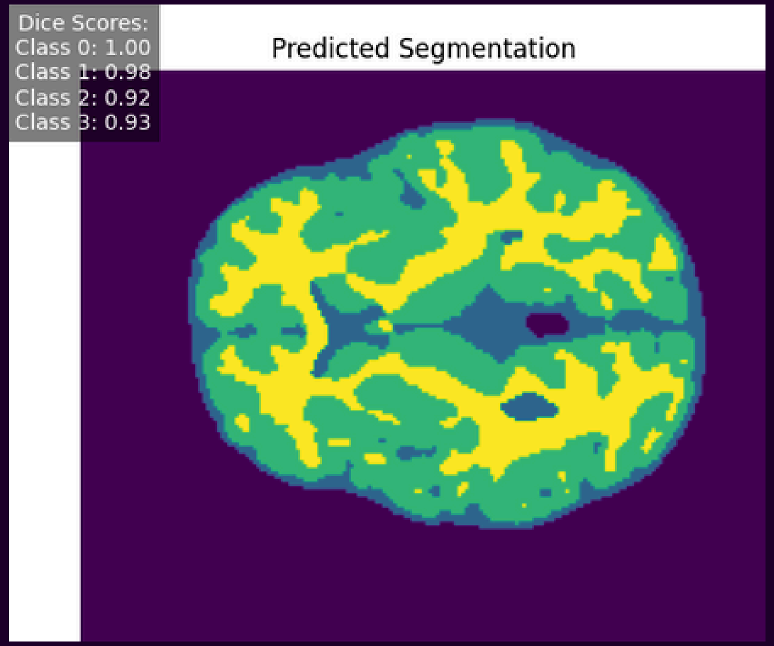
Even



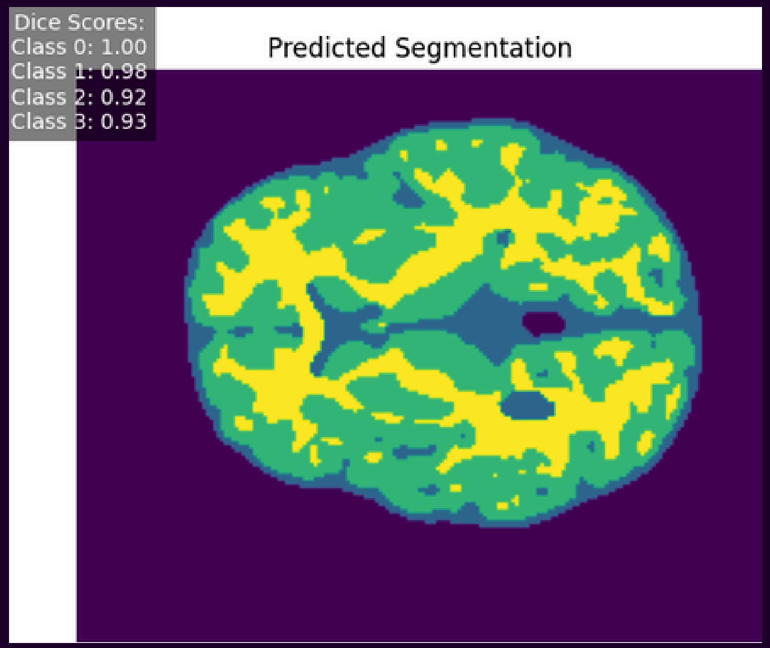
Even & Odd



Noise



Multi



Conclusion: Future directions

1

Investigate pixel intensity distributions

2

Expanding dataset

Bibliography

[1] MARIANI, Giovanni, SCHEIDEGGER, Florian, ISTRATE, Roxana, et al.
”Bagan:Data augmentation with balancing gan”. arXiv preprint arXiv:1803.09655, (2018).

[2] Berthelot, David, et al.
”Understanding and improving interpolation in autoencoders via an adversarial regularizer.” arXiv preprint arXiv:1807.07543 (2018).