Representation of human brain MRI images through generative models

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Content

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Introduction

“Medical imaging is arousing growing interest in fundamental computer vision models, accelerating deep learning in this field.”
B.Azad et al. (2023)

Challenge: **Criticality of massive data management in hospitals**

STATE-OF-THE ART

State of the Art : Compression

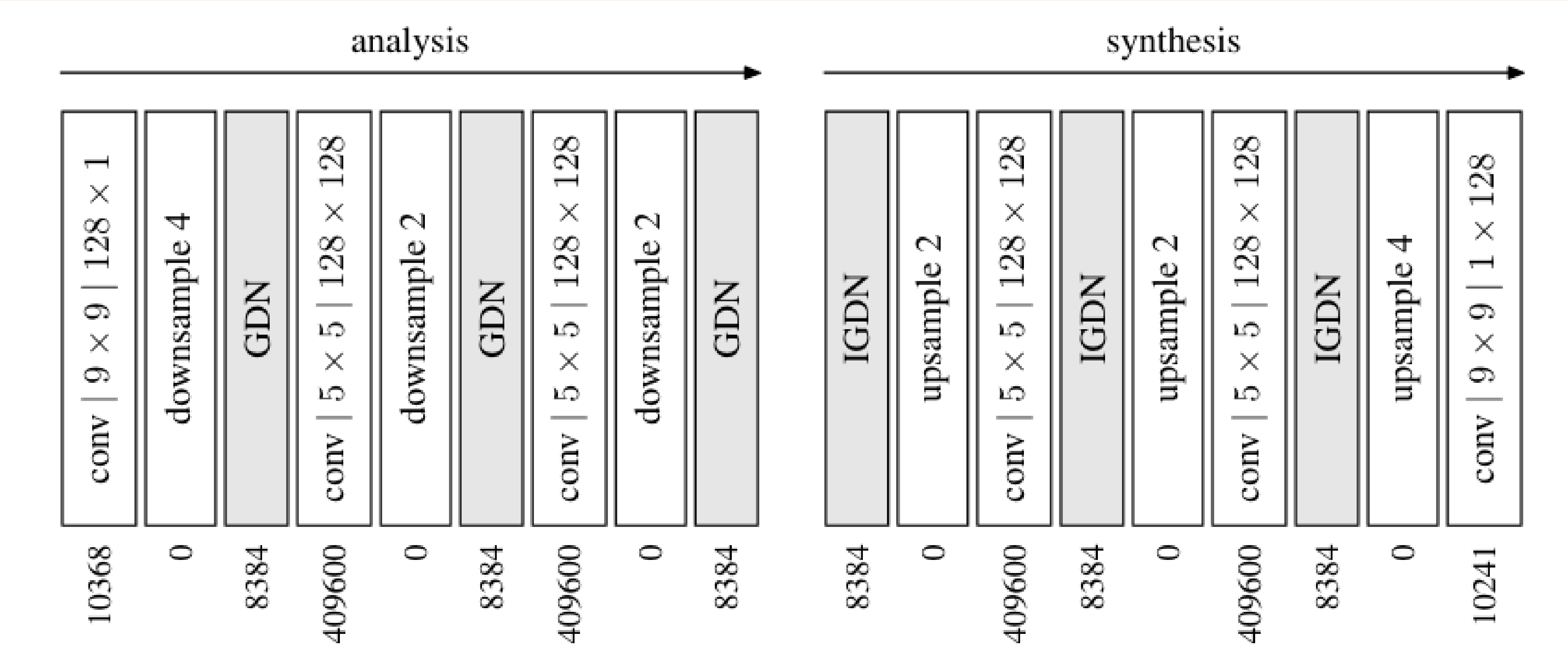

Figure 1: Ballé et al. (2016) Schematic representation of a neural network-based image compression architecture [1]

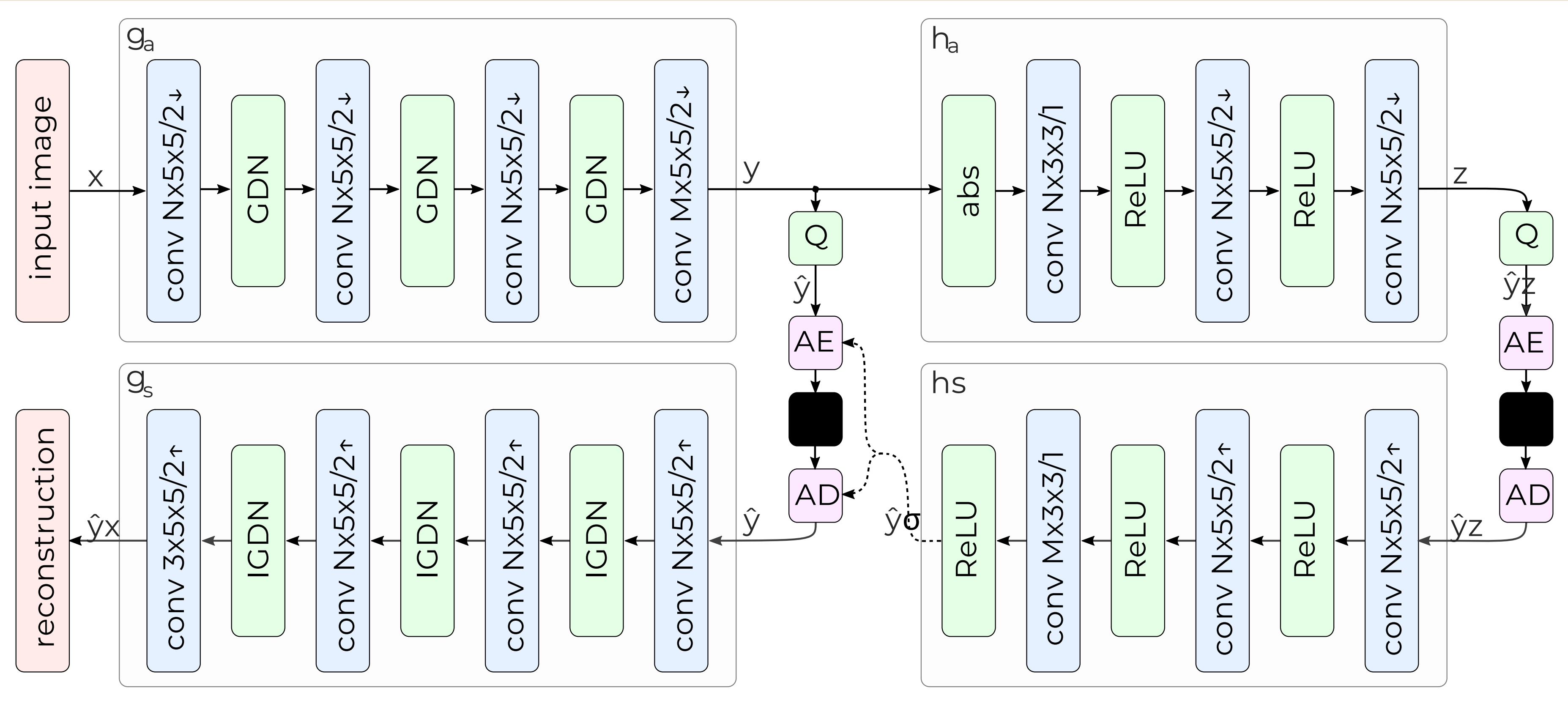

Figure 2: Ballé et al. (2018) Enhanced image compression model featuring a hierarchical structure with a hyperprior [2]

State of the Art : Data Augmentation

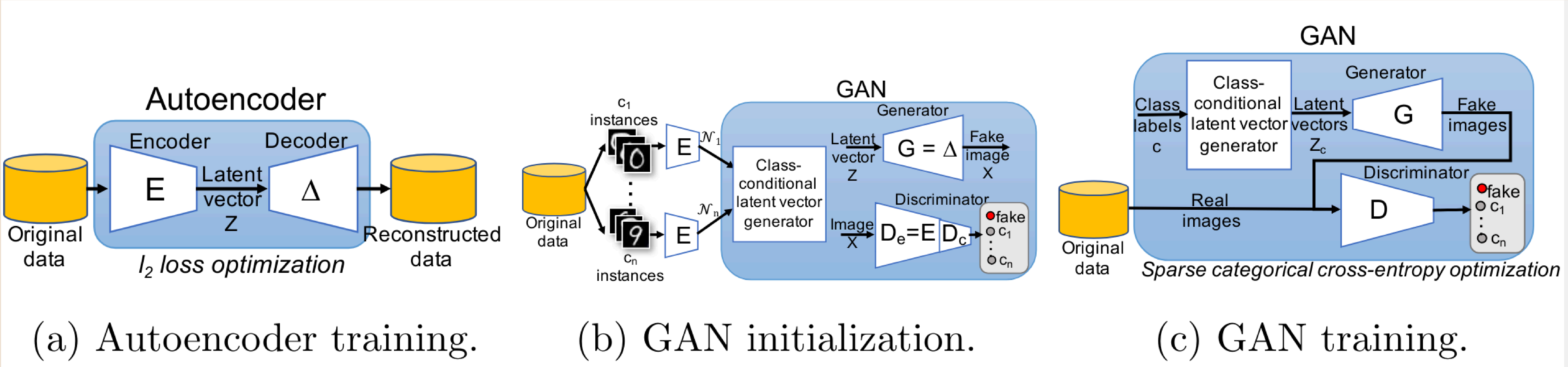

Figure 3: Mariani et al. (2018) BAGAN (Balancing Generative Adversarial Network) methodology for addressing class imbalance in image datasets [3]

State of the Art : Interpolation

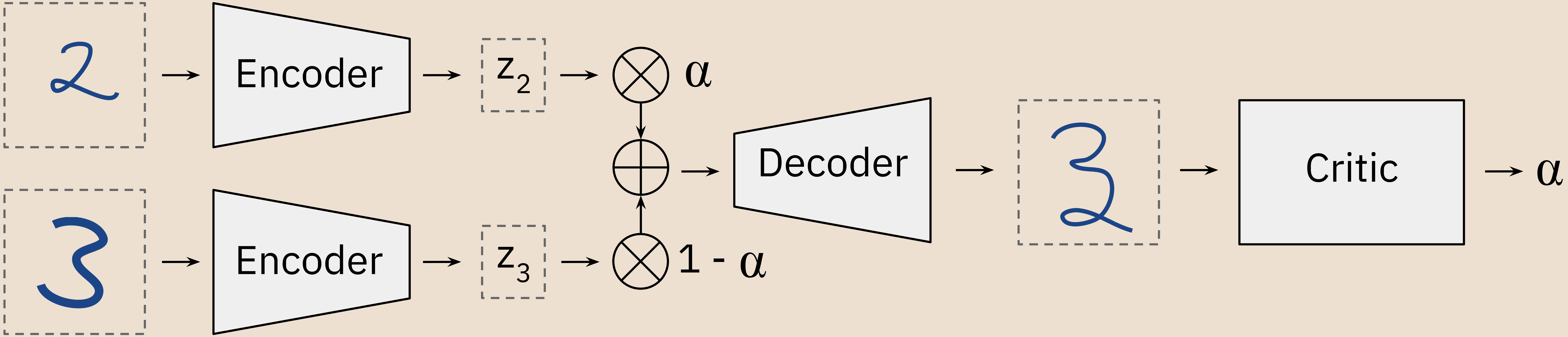

Figure 4: Goodfellow et al. (2018) Adversarially Constrained Autoencoder Interpolation (ACAI) [4]

DATASET

CONTRIBUTIONS

Contributions : CNN

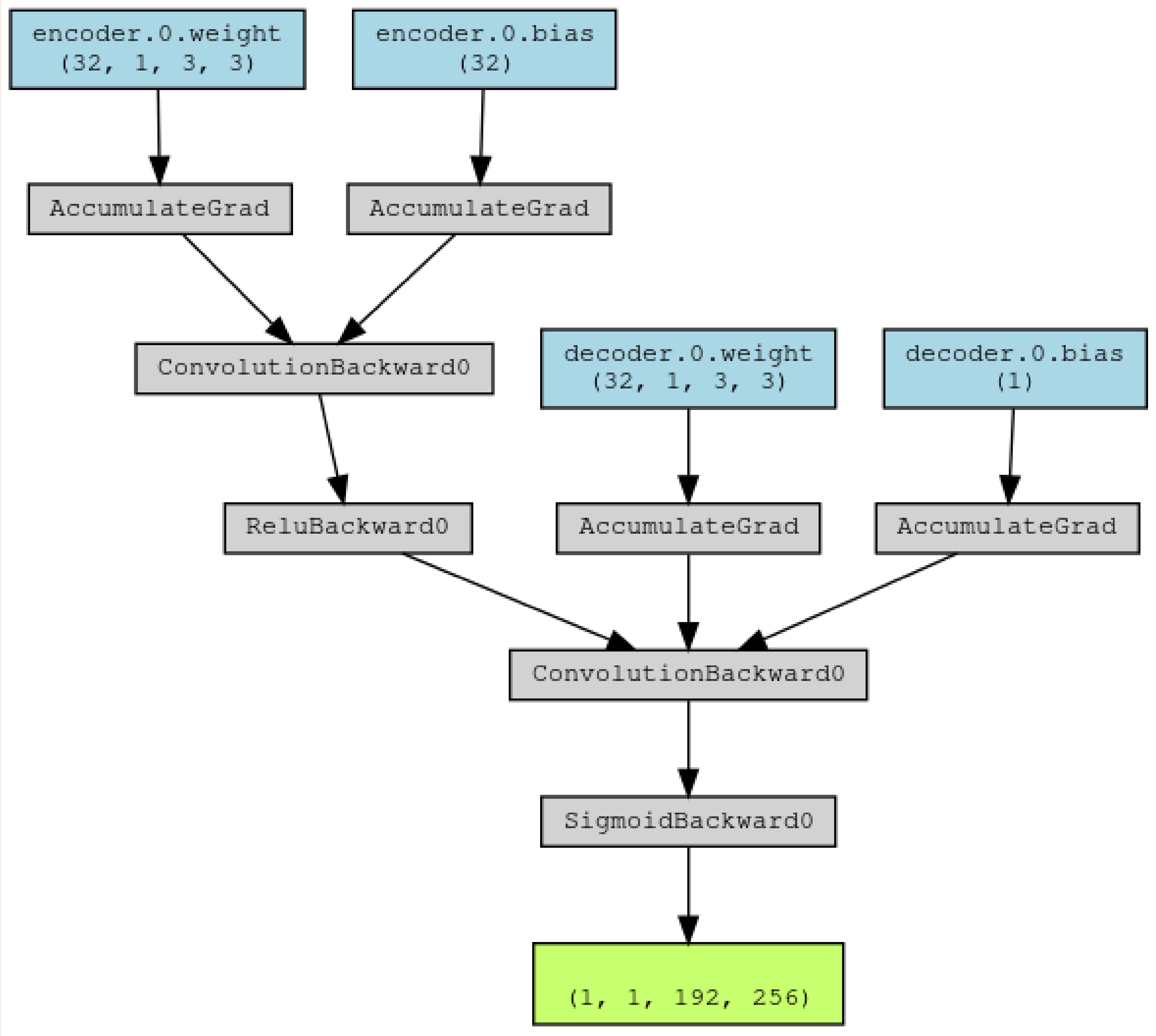

Figure 5: Schematic representation of the minimal autoencoder architecture employed in our study

Contributions : Generative U-Net

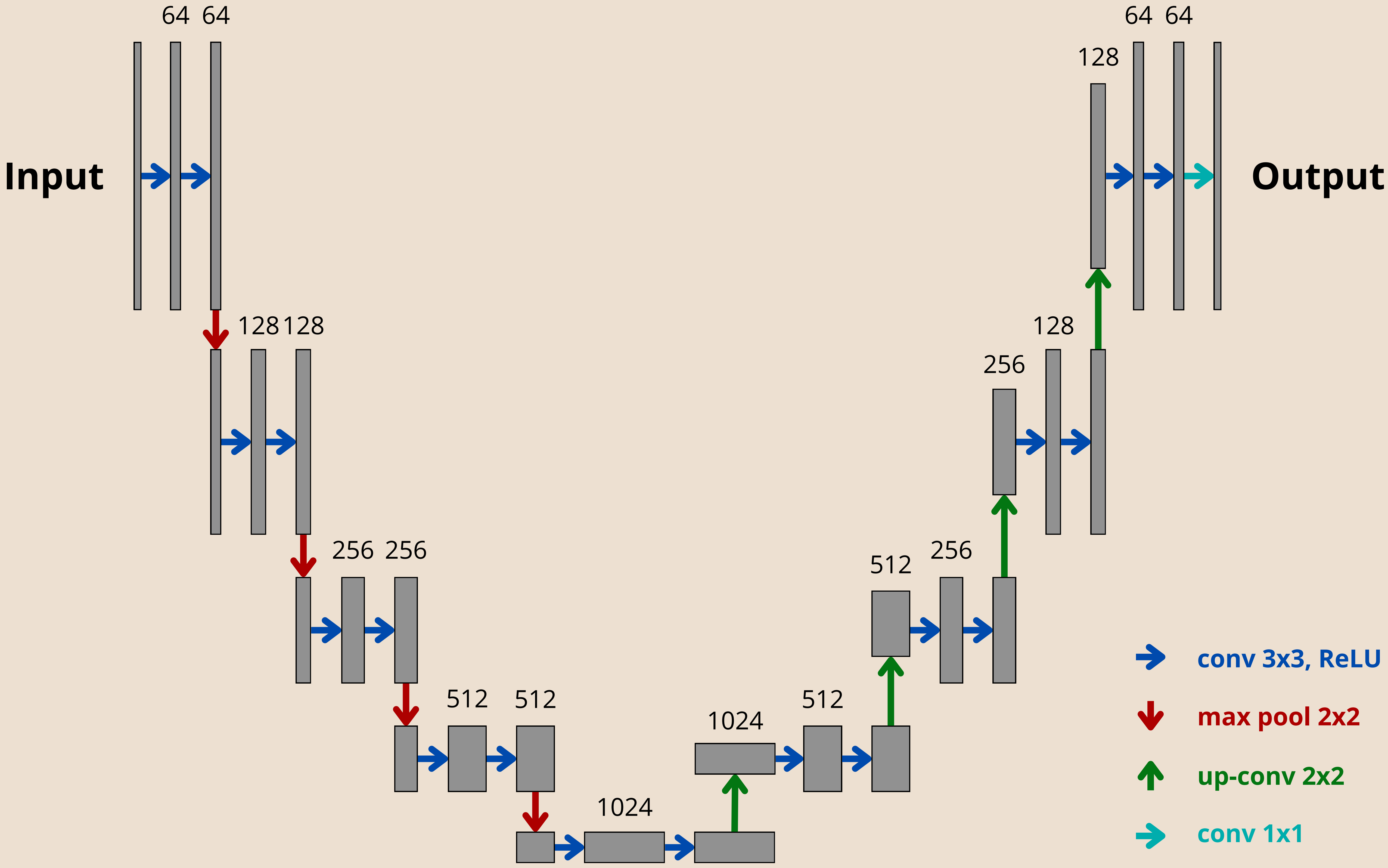

Figure 6: U-Net representation without skip connections

Contributions : Generative U-Net Variation

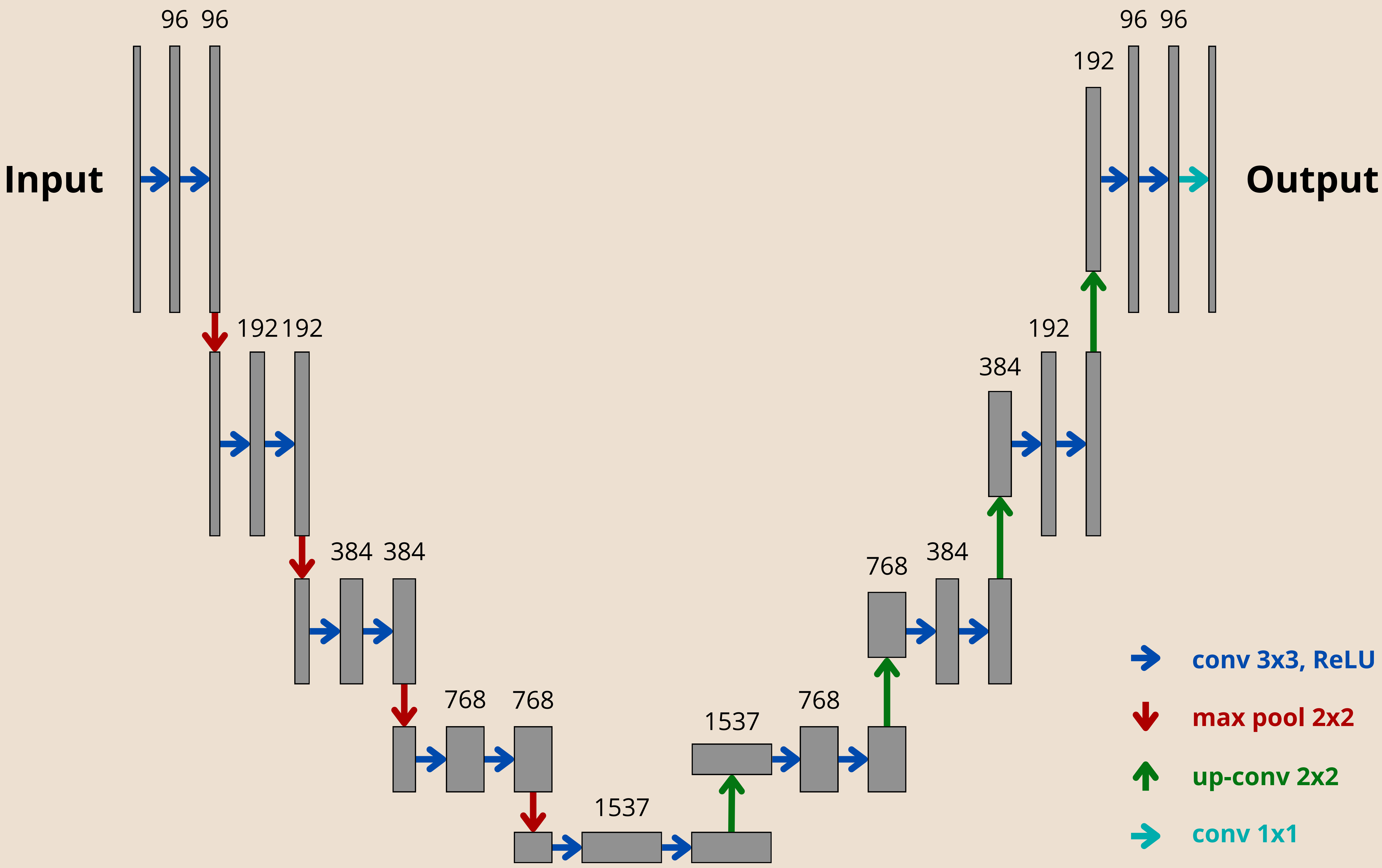

Figure 7: U-Net representation without skip connections with channels multiplied by 1.5

Contributions : Generative U-Net Variation

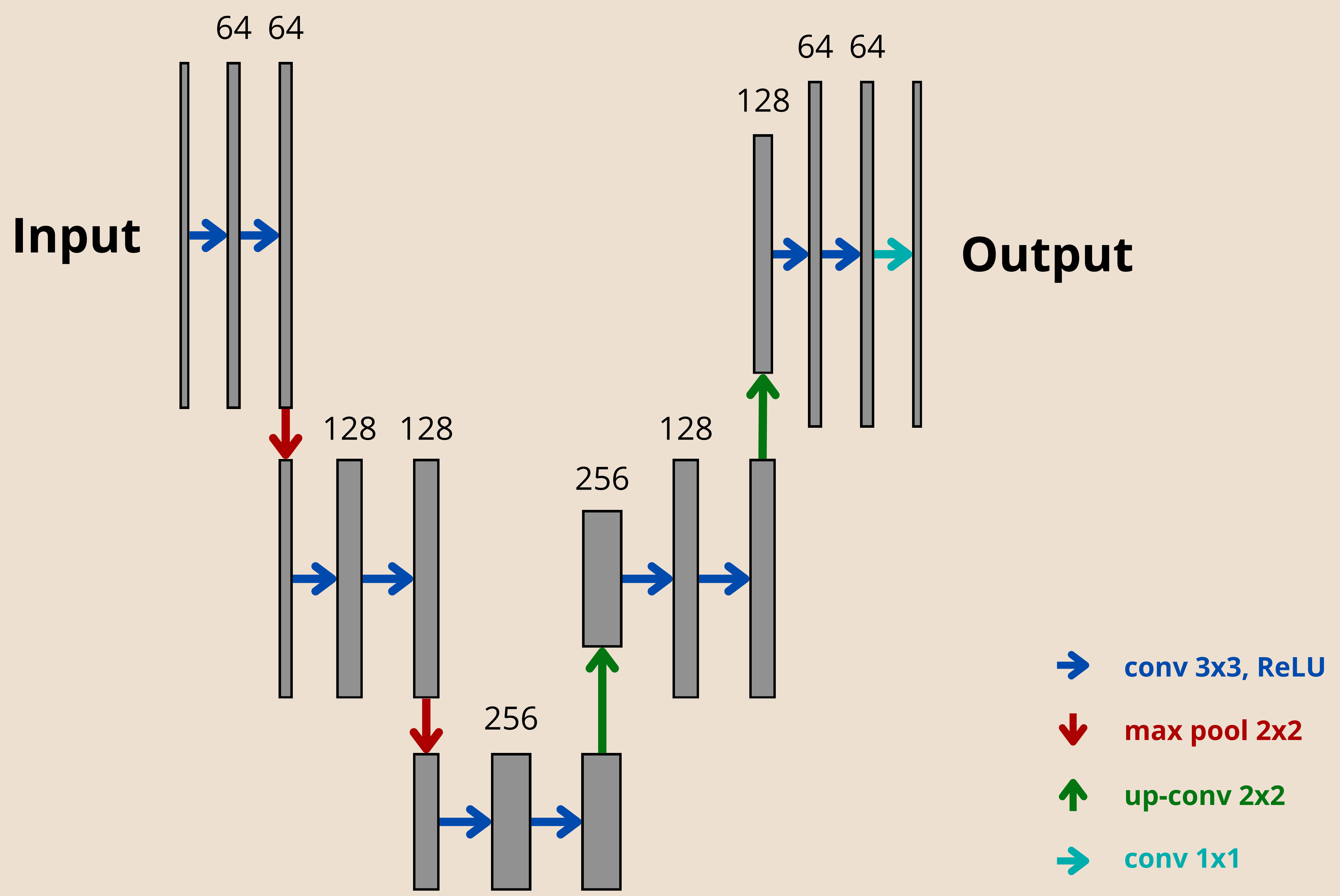

Figure 8: U-Net representation without skip connections with only 2 layers

Contributions : Data Augmentation

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

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

4. Decoding
5. Output

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Contributions : Data Augmentation

Interpolation Between n Images

$$z_{interpolated} = \sum_{i=1}^{n} \alpha_i z_i$$

Constraints

$$\forall \alpha \in [0;1], \forall n \in \mathbb{N},$$

$$\sum_{i=1}^{n} \alpha_i = 1$$

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BENCHMARK

Benchmark : Qualitative Results

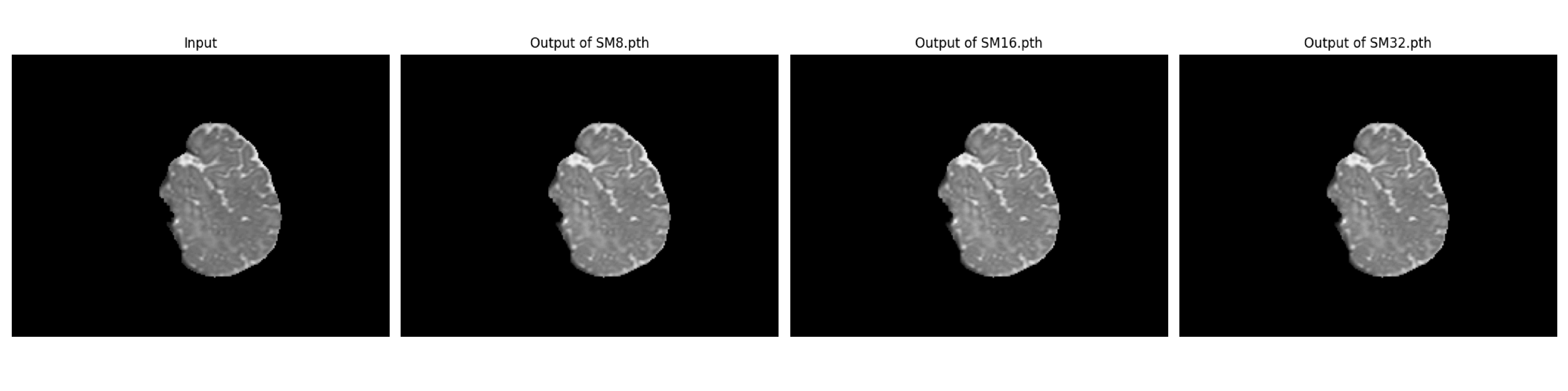

Figure 9: Visual comparison of reconstruction quality for three CNN configurations (8, 16, and 32 channels)

Benchmark : Qualitative Results

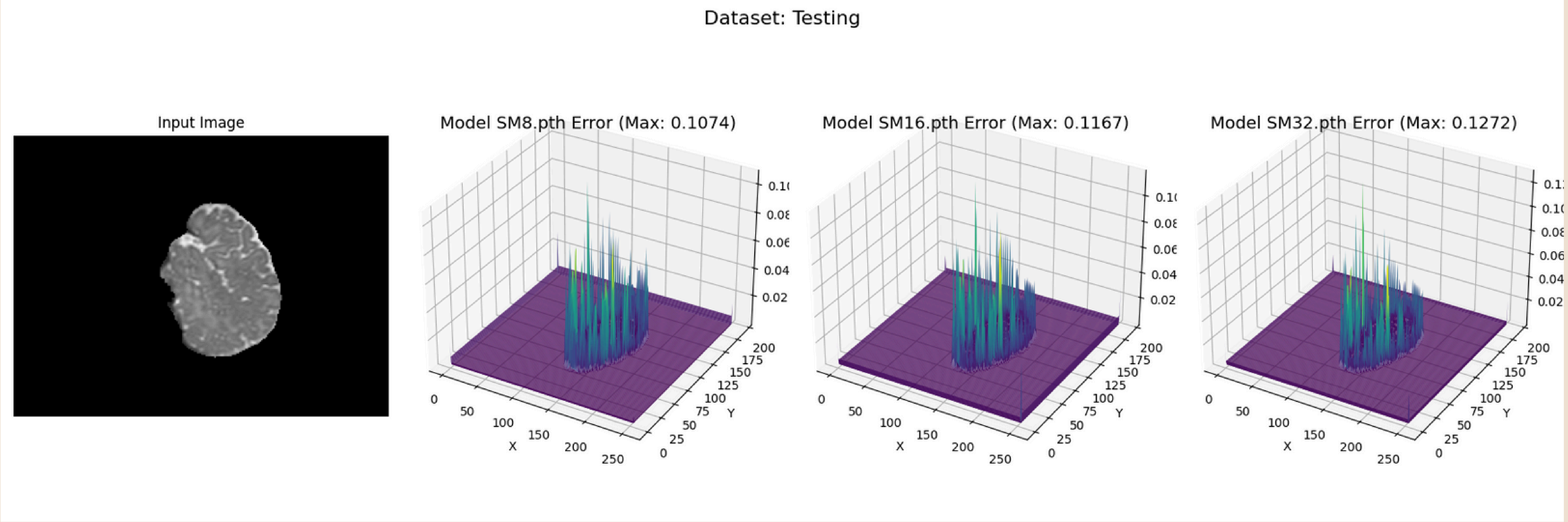

Figure 10: Topographic error visualization for CNN reconstructions with 8, 16, and 32 channel

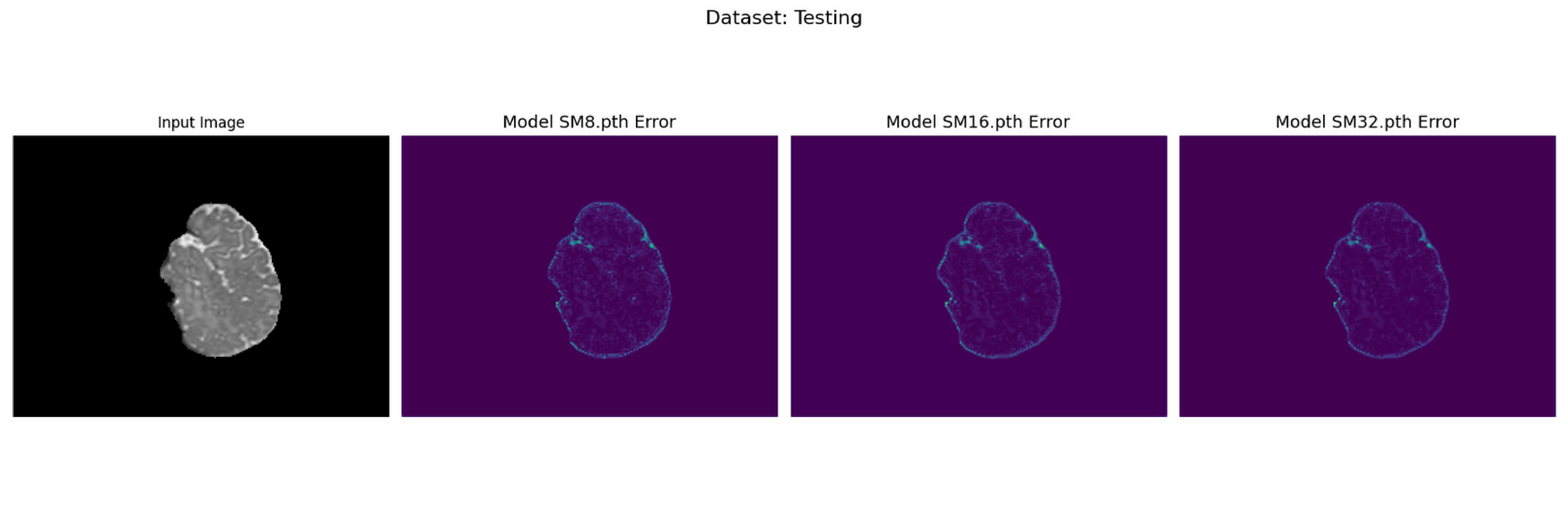

Figure 11: 2D error visualization for CNN reconstructions with 8, 16, and 32 channel

Benchmark : Qualitative Results

Figure 12: Comparison of U-Net, V1 [64, 128, 256, 512] and V2 [96, 192, 384, 768], reconstructions with input image

Benchmark : Qualitative Results

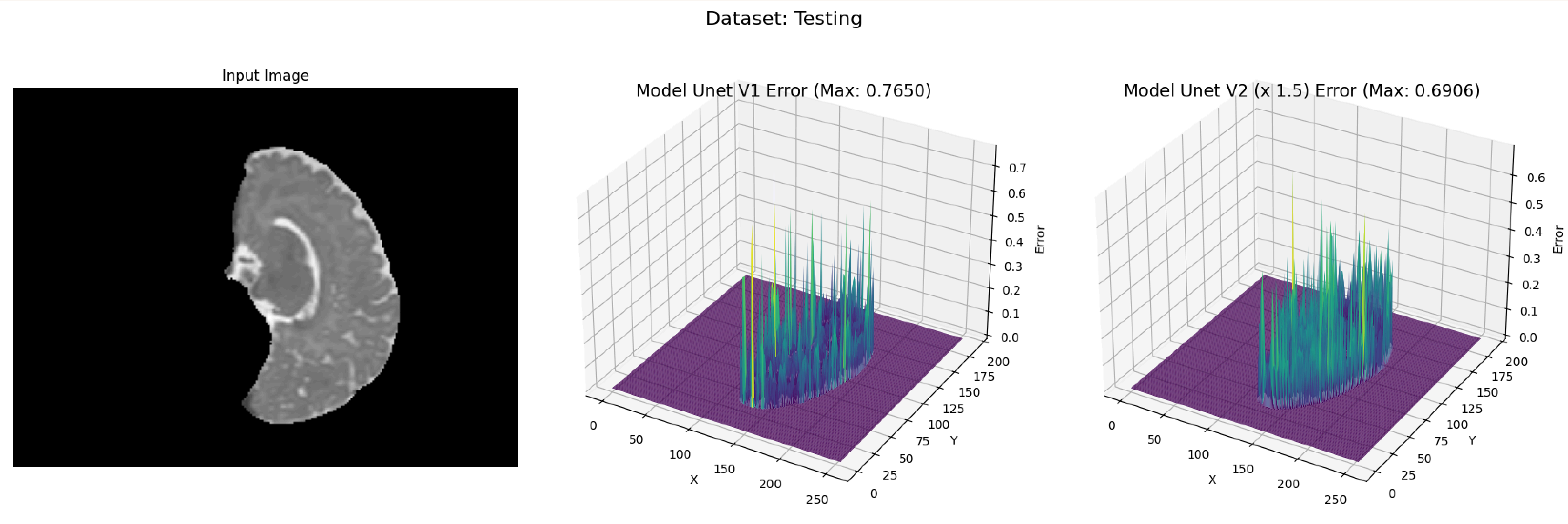

Figure 13: Topographic error visualization of U-Net, V1 and V2, reconstructions with input image

Benchmark : Qualitative Results

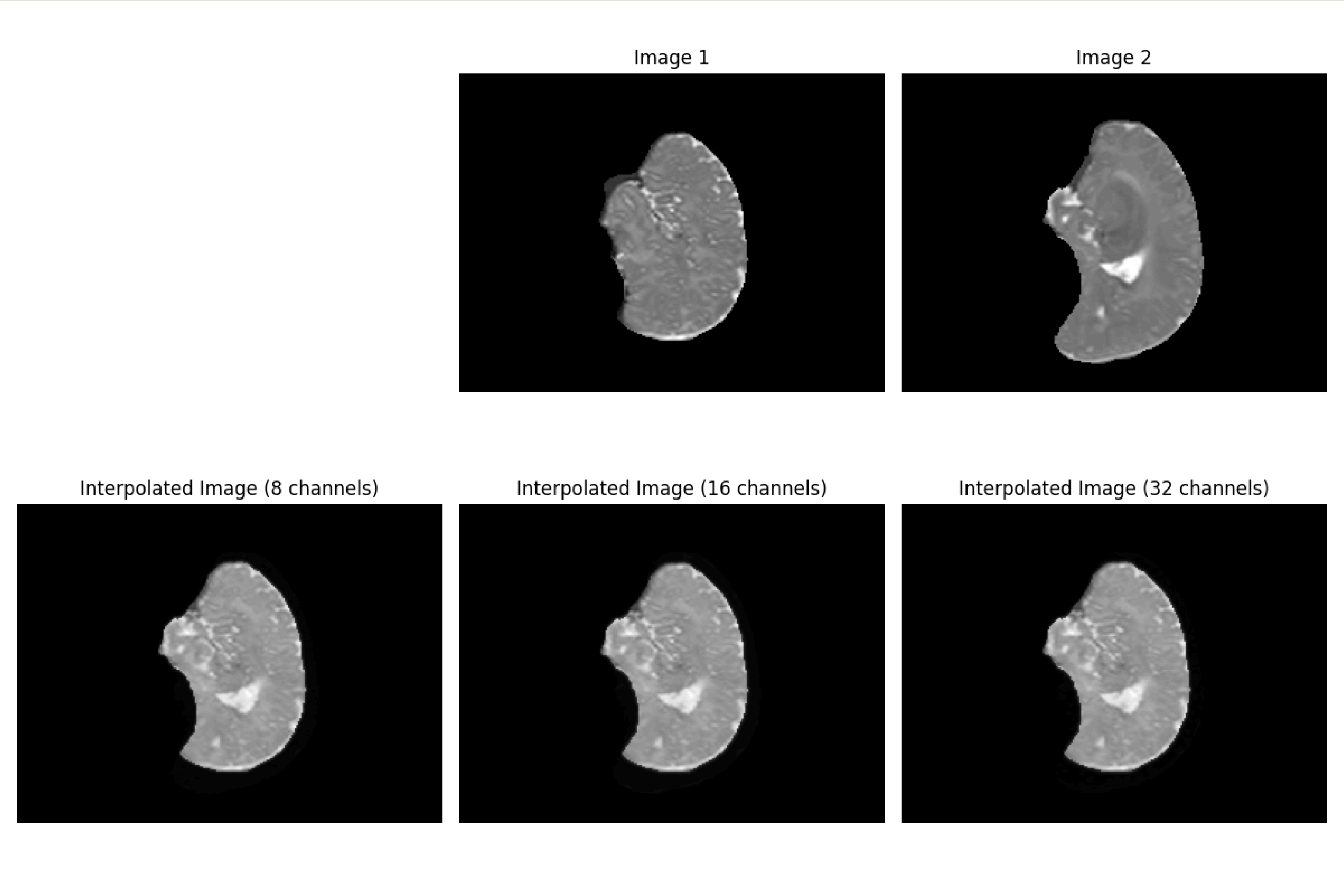

Figure 13: Comparative analysis of brain MRI interpolation results

Benchmark : Quantitative Results

	CNN 8 channels	CNN 16 channels	CNN 32 channels
PSNR	9.180-48.161	8.556-47.426	8.516-48.570

Table 1: Reconstruction performance comparison for various CNN configurations

Table 2: Reconstruction performance comparison for various generative UNet configurations without skip connections

	Unet V1	Unet V2 (x1.5)
PSNR	0.572–25.668	6.863–27.583
MSE	0.047	0.027
SSIM	0.038	0.044

Benchmark : Quantitative Results

	Best CNN	Best Unet
SSIM	0.03	0.04
LPIPS	0.16–0.47	0.21–0.47
Novelty Score	4.46–11.0	4.17–11.72

Table 3: Performance results for interpolation using the best CNN and best UNet

CONCLUSION

Conclusion : Future directions

Architecture	Data Augmentation	Dataset
1	2	3
Hybrid model Improve existing ones	Investigate impact of data augmentation	Expanding dataset

Bibliography

[1] Ballé, Johannes, Valero Laparra, and Eero P. Simoncelli.
”End-to-end optimized image compression.” arXiv preprint arXiv:1611.01704 (2016).

[2] Ballé, Johannes, et al.
”Variational image compression with a scale hyperprior.” arXiv preprint arXiv:1802.01436 (2018).

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

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

[5] O.Ronneberger et al.
”U-net : Convolutional Networks for Biomedical Image Segmentation.” arXiv preprint arXiv:1505.04597 (2015).

[6] Liu, Xuan, Zhang, Lu, Guo, Zihao, Han, Tailin, Ju, Mingchi, Xu, Bo, Liu, Hong
Medical Image Compression Based on Variational Autoencoder, Mathematical Problems in Engineering, 2022, 7088137, 12 pages, 2022. https://doi.org/10.1155/2022/70821