DIFF-LUNG: DIFFUSION-BASED TEXTURE SYNTHESIS FOR ENHANCED PATHOLOGICAL TISSUE SEGMENTATION IN LUNG CT SCANS

R.N Khiati[1,4], PY Brillet[2], Aurélien Justet[3], Radu Ispas[4] and Catalin Fetita[1]

[1]SAMOVAR, Telecom SudParis, IP Paris, Evry, France ; [2]Avicenne Hospital, AP-HP, Bobigny, France ; [3]Pneumologie et Médecine Nucléaire CHU Caen, France ; [4]Keyrus France, Levallois-Perret, France

INTRODUCTION

- **Problem:** Accurate segmentation of lung pathologies (fibrosis, GGO, emphysema) is hindered by class imbalance in datasets
- **Proposed Solution**
  - Use DiffLung, a mask-guided diffusion model to generate synthetic lung textures for underrepresented classes
  - Augment data during segmentation model training to improve accuracy
- **Contribution:** Introduce Class-Balanced Mask Ablated Training (CBMAT) to prioritize rare classes during generation

METHODS

Mask-Guided Conditional Generation

Loss controlling texture generation based on lung pathology labels

$$L_m = E[||\varepsilon - \varepsilon_t(x_t, t \mid m)||^2]$$

Class-Balanced Mask Ablated Training (CBMAT)

The ablation probability is inversely proportional to class frequency

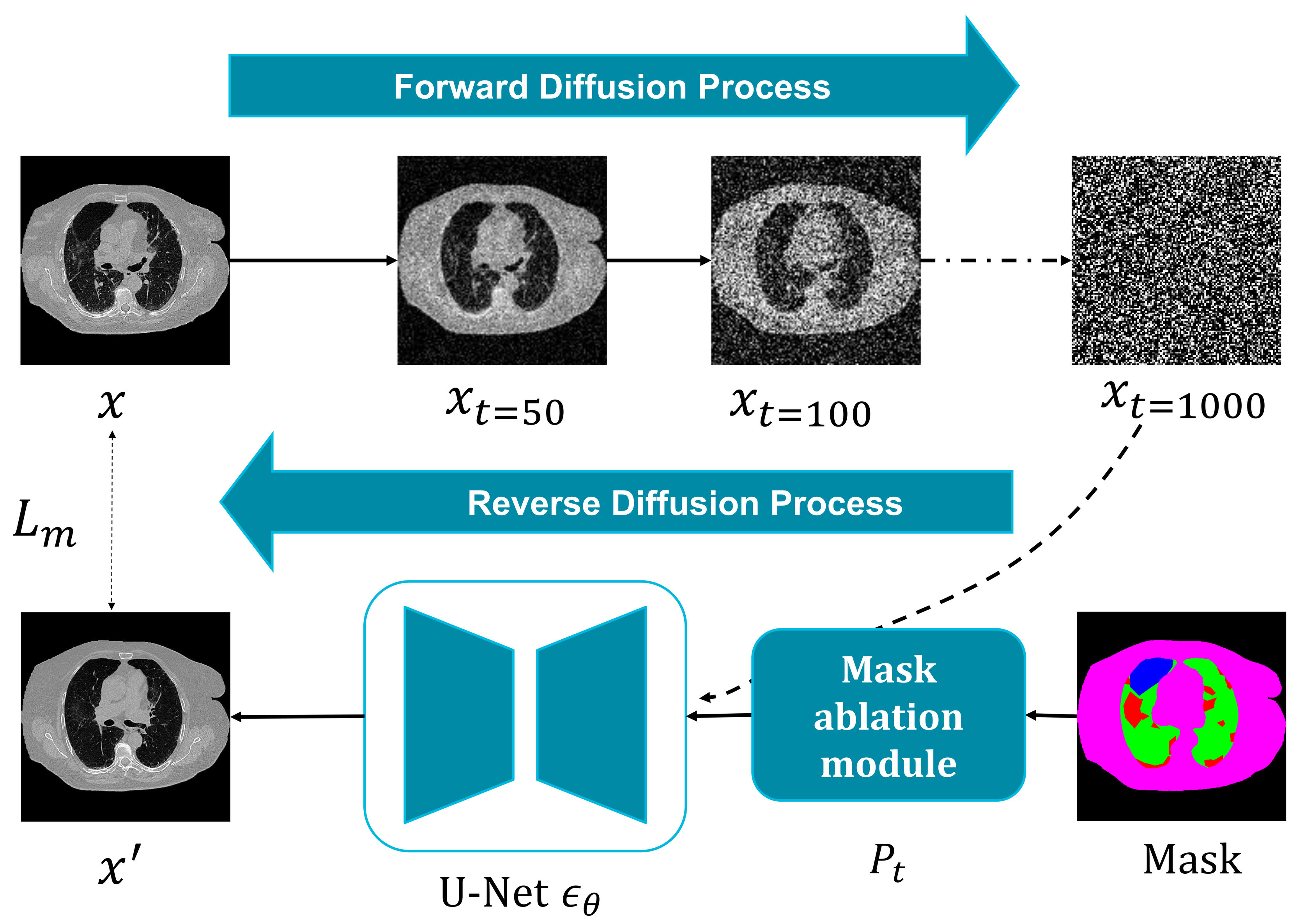
$$P_{initial}(class_i) = 1 - f_i$$

To stabilize training, we apply cosine annealing to reduce ablation over time:

$$P_t = P_{initial} \cdot (1 + \cos(\pi t / T)) / 2$$

Mask Generation Process

Spatial augmentations (rotation, copy-paste, dilation) only within healthy lung areas



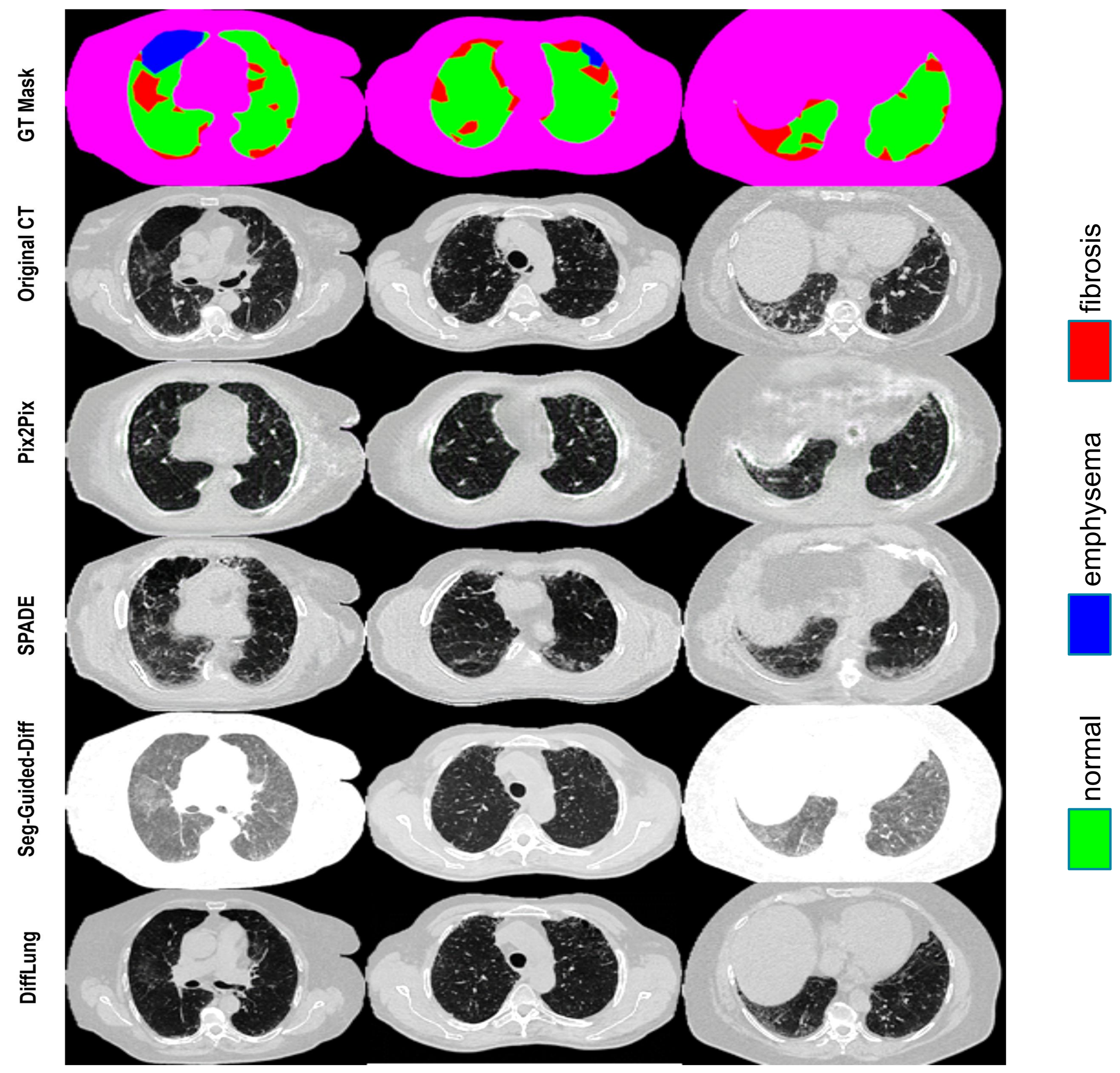
REFERENCES

1. Jonathan Ho et al, DDPM, Neural Information Processing Systems, 2020
2. Nicholas Konz et al, Anatomically-Controllable DM, Medical Image Computing, 2024
3. Taesung Park et al, SPADE GAN, Computer Vision and Pattern Recognition, 2019
4. Phillip Isola et al, Pix2Pix, Computer Vision and Pattern Recognition, 2018

RESULTS

Enhanced generation of pathological CT slices using DiffLung (CBMAT)

- **Qualitative evaluation**



- **Quantitative evaluation**

Model	PSNR ↑	SSIM ↑	FLOPS ↓ (GFLOPS)	Time ↓ (s/image)
Pix2Pix	17.56	0.61	15	0.18
SPADE	19.20	0.66	25	0.37
Seg-Guided-Diffusion	19.64	0.68	4000	21
DiffLung (CBMAT)	20.70	0.71	4000	21

- Comparison of models in terms of PSNR, SSIM,FLOPS, and Inference time per image

Comparison of data augmentation strategies for a baseline UNet model training:

- *standard augmentation, seg-guided diffusion, DiffLung*

Model	Dice - Healthy ↑	Dice - Emphysema ↑	Dice - Fibrosis ↑
ref-UNet	0.91	0.60	0.72
Seg-Guided-UNet	0.90	0.73	0.76
DiffLung-UNet	0.92	0.80	0.81

- Dice scores per class for different augmented models

CONCLUSION

- DiffLung uses a diffusion model guided by anatomical masks to generate realistic pathological CT textures
- The CBMAT strategy ensures underrepresented classes are emphasized during generation
- Demonstrated significant segmentation improvement, especially for rare pathologies