

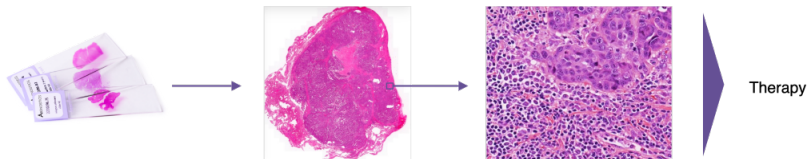
DiffInfinite: Large Mask-Image Synthesis via Parallel Random Patch Diffusion in Histopathology [1]

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Talk by Gabriel Nobis

Challenges in AI for Histopathology



(C1) Whole slide image of size $\sim 100k \times 100k$

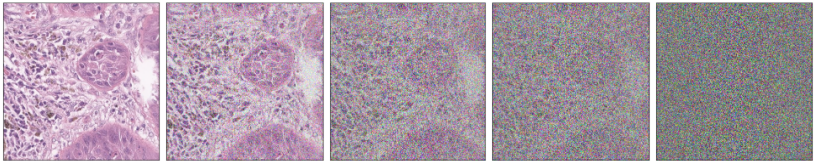
(C2) Sparsely annotated and small datasets [2]

↪ Use generative AI for data augmentation

↪ Generate large images to capture long range correlation

DiffInfinite: A Diffusion Model for Histopathology

Data ——— Destructing data by adding noise ———> Noise



Data ←—— Generating samples by denoising ——— Noise

Diffusion Models are:

- ✓ capable of generating high quality diverse data [3], [4]
- ✓ theoretical well defined [5]
- ✗ slow at sampling time [6]

DiffInfinite Training

Semi-supervised training on tiles:

Use a mixture of 5k labelled tiles of 4 classes and 250k unlabeled tiles leveraging classifier-free guidance [7]

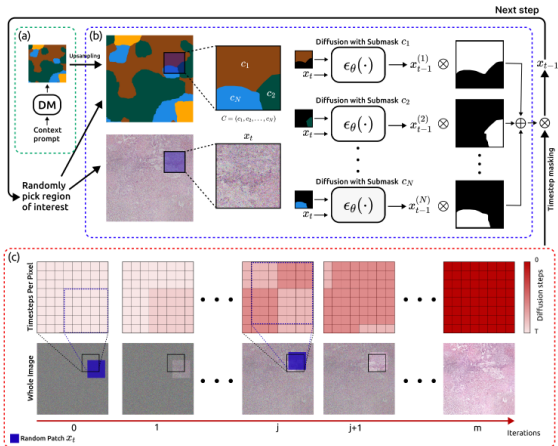
Supervised training on masks:

Train a second diffusion model on segmentation masks

Generate image with mask guidance:

Use the synthetic mask to guide the image generation

DiffInfinite Sampling

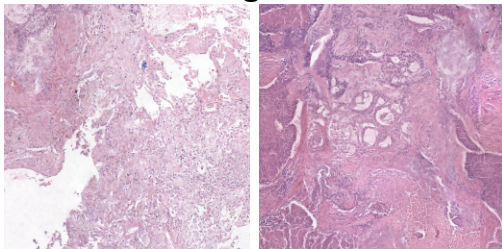


Comparison to DiffCollage [8]

Quantitative evaluation:

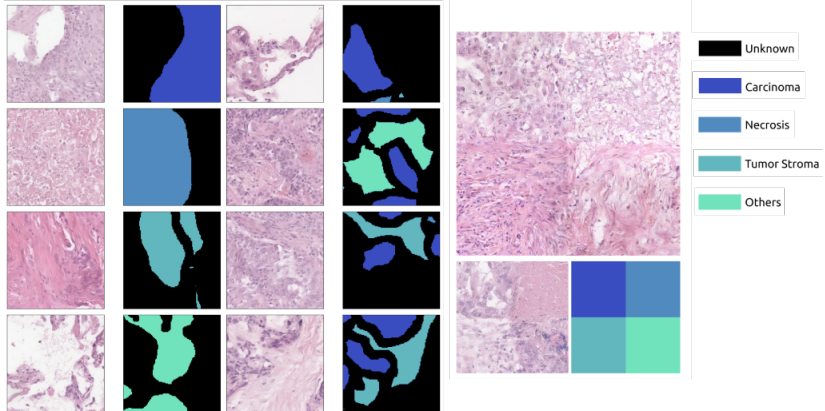
	Improved Precision ↑	Improved Recall ↑
DiffCollage	0.94	0.22
DiffInfinite	0.98	0.44

No tiling effects:



DiffInfinite ↔ DiffCollage

DiffInfinite Samples



DiffInfinite for Data Augmentation

Classification:

	IH1	IH2	IH3	PCam-327K
Drift components	-	Patient change Different center	Patient change Different center	Patient change Different center Indication change Lower resolution
Trained Real	0.846 ± 0.005	0.733 ± 0.021	0.598 ± 0.049	0.60
Trained Synthetic	0.747 ± 0.025	0.753 ± 0.005	0.699 ± 0.002	0.68
Trained Augmented	0.852 ± 0.007	0.732 ± 0.027	0.637 ± 0.025	0.63

Segmentation:

	IH2
Trained Real	0.614 ± 0.009
Trained Synthetic	0.471 ± 0.039
Trained Augmented	0.710 ± 0.021

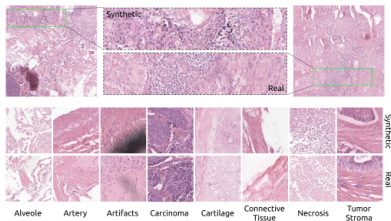
Challenges in AI for Histopathology

(C1) Whole slide image of size $\sim 100k \times 100k$...

(C2) Sparsely annotated small datasets ✓

What about privacy?

Visual evaluation



Quantitative evaluation [9],[10]

	$A \uparrow$		$C_T \rightarrow$	
	<i>tiled</i>	<i>resized</i>	<i>tiled</i>	<i>resized</i>
DiffCollage	0.89	0.97	11.02	7.00
DiffInfinite	0.86	0.98	9.61	11.56

Good enough [11]?

Acknowledgements

We would like to acknowledge our team of pathologists who provided valuable feedback in and outside of the conducted survey - special thank you to Frank Dubois, Niklas Prenissl, Cleopatra Schreiber, Vitaly Garg, Alexander Arnold, Sonia Villegas, Rosemarie Krupar and Simon Schallenberg. Furthermore, we would like to thank Marvin Sextro for his support in the analyses. This work was supported by the Federal Ministry of Education and Research (BMBF) as grants [SyReal (01IS21069B)]. RM-S is grateful for EPSRC support through grants EP/T00097X/1 and EP/R018634/1 and DI for EP/R513222/1. MA is funded by dotPhoton and a UofG Ph.D. scholarship.

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Thank you!