Class-N-Diff: Classification-Induced Diffusion Model Can Make Fair Skin Cancer Diagnosis

COPENHAGEN 47TH ANNUAL International Conference of the IEEE Engineering in Medicine and Biology Society
IEEE EMBS

Nusrat Munia, Abdullah Imran

Department of Computer Science
University of Kentucky, Lexington, KY, USA

Significance

- Skin cancer diagnosis models often fail to generalize across skin tones due to **imbalanced** datasets
- **Class-conditioned generative models** can help to generate class-faithful, diverse dermoscopic images

Contributions

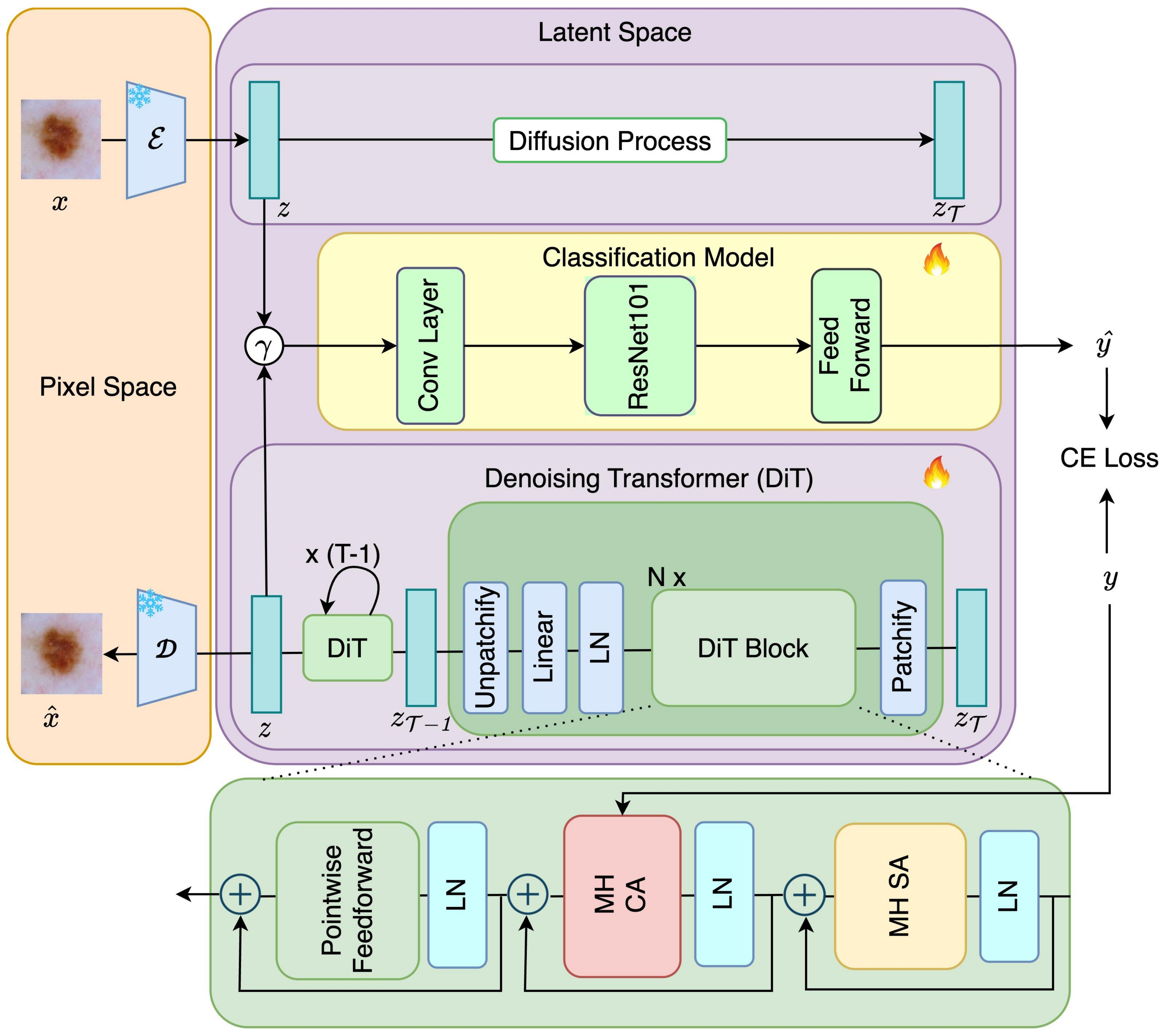
- **Class-N-Diff:** A novel diffusion-based model that jointly trains a classifier for conditional image generation
- The classifier acts as a training guide, improving the fidelity and class alignment of generated samples

Methods

Our proposed **Class-N-Diff** model consists of:

- A Diffusion Transformer (DiT) and a ResNet101-based classifier
- A shared training loop based on the value of γ, where classification loss improves generation quality
- Combined Loss Function:

$$L = Diffusion\ Loss + \lambda * Classification\ Loss$$



Proposed Class-N-Diff framework

Dataset and Experiment

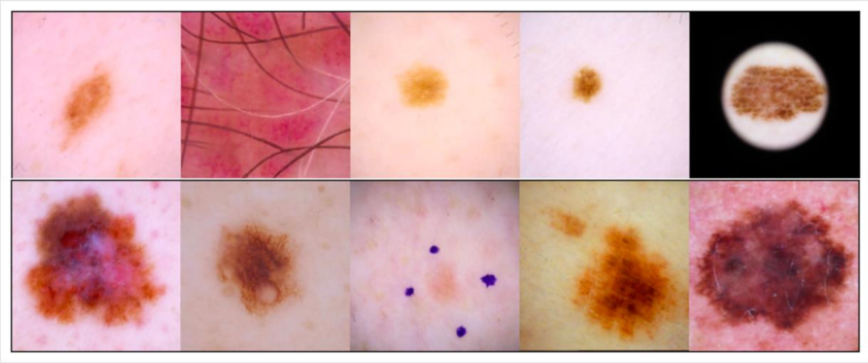
- Class-N-Diff Training: ISIC 2016-20 (Benign: 52874, Malignant: 5090)
- Classification model evaluation datasets:

Dataset	Benign	Malignant	Dataset	Benign	Malignant
DDI	485	171	ISIC-2018	420	443
Fitzpatrick17k	759	252	Atlas	1,518	504
ASAN	793	59	MClass	160	40

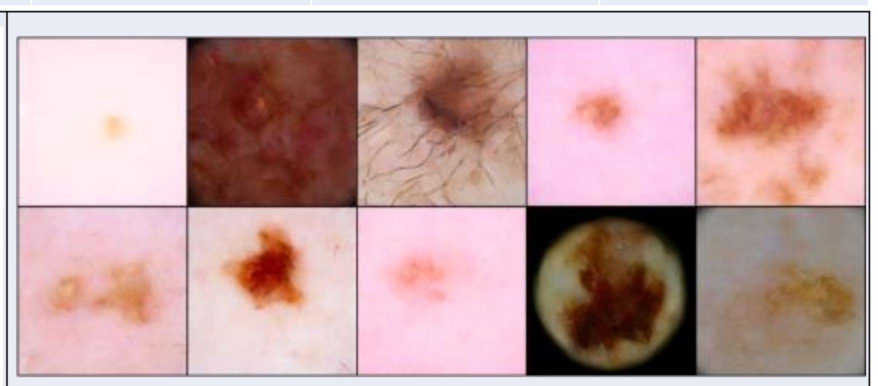
Model	Setting	Description
Conditional DiT	1	DiT without the classification model
Class-N-Diff	2	γ = 0.25, and λ = 0.2
	3	Periodically increase γ from 0 to 1, and λ = 0.2, Optimizer step: once in three steps
	4	Periodically increase γ from 0 to 1, and λ = 0.2, Optimizer step: every step
	5	Periodically increase γ from 0 to 1, and λ = 0.3, Optimizer step: once in three steps

Results

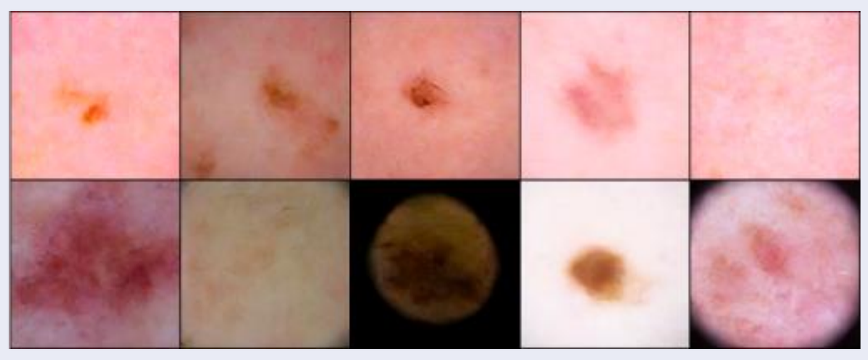
Model	Setting	FID (5k)	FID (10k)	FID (20k)	MS-SSIM
Conditional DiT	1	69.100	48.750	45.770	0.583
Class-N-Diff	2	27.210	15.940	18.270	0.372
	3	3.930	2.710	**2.420**	0.316
	4	**2.690**	**2.640**	2.750	0.462
	5	4.290	3.900	2.430	**0.285**



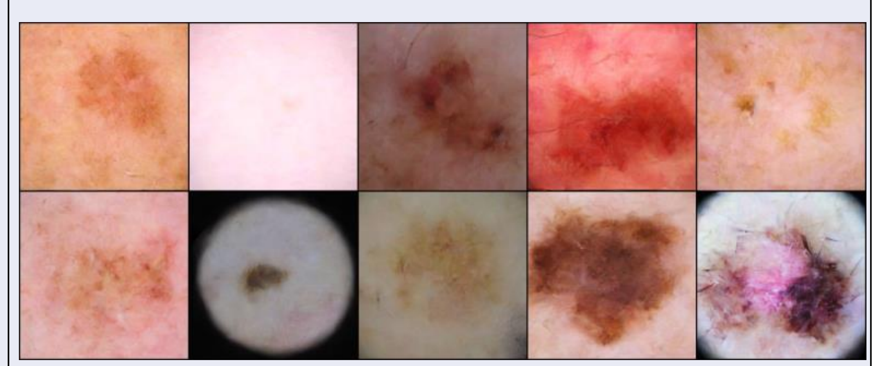
ISIC real data samples



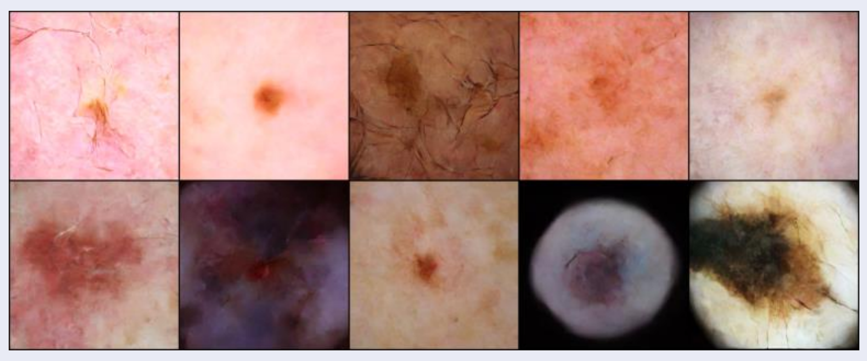
Class Conditional DiT (1)



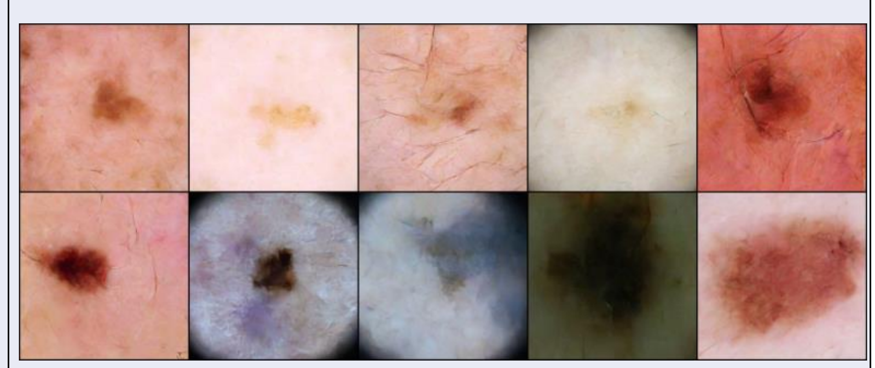
Class-N-Diff (2)



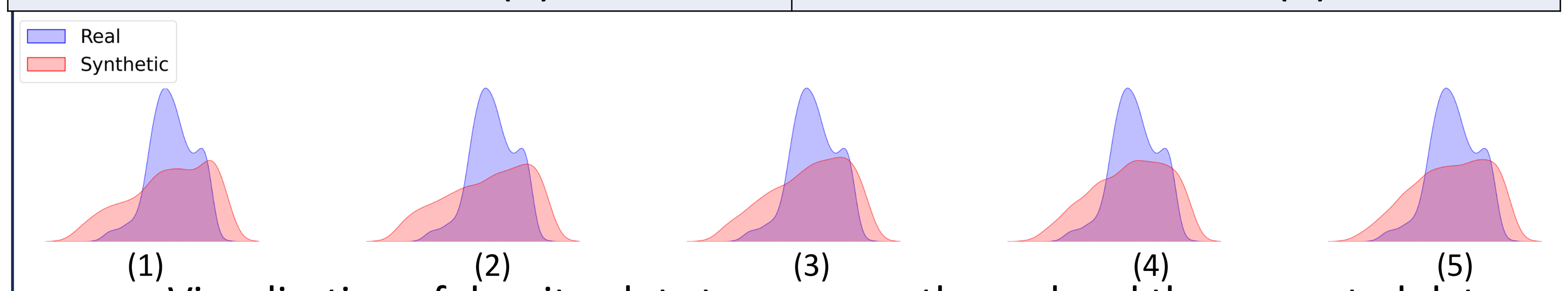
Class-N-Diff (3)



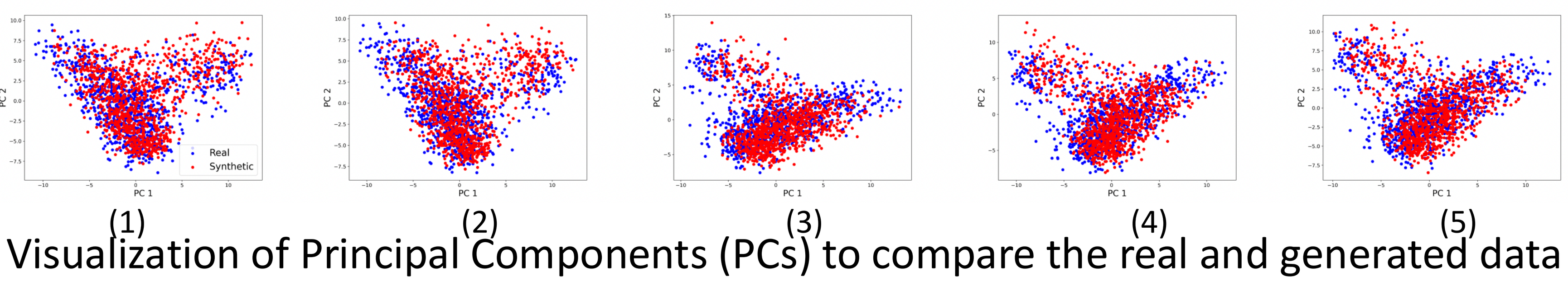
Class-N-Diff (4)



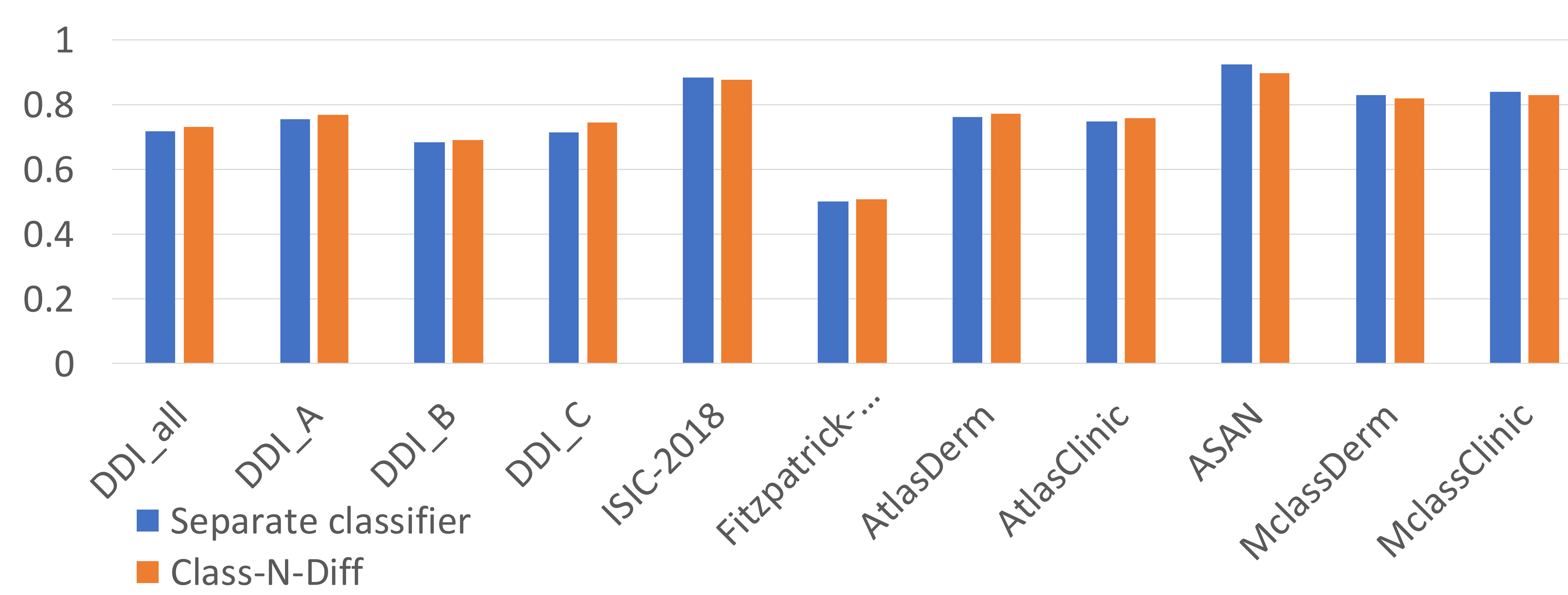
Class-N-Diff (5)



Visualization of density plots to compare the real and the generated data



Visualization of Principal Components (PCs) to compare the real and generated data



Class-N-Diff Classification Accuracy Performance Comparison

Conclusion

- Class-N-Diff can generate realistic and diverse dermoscopic images leading to fairer diagnostic classification
- Shows promise for building equitable diagnostic systems through classification-guided generation

References

1. W. Peebles et al., “Scalable Diffusion Models with Transformers,” CVPR, 2023
2. K. He et al., “Deep Residual Learning for Image Recognition,” CVPR, 2016
3. ISIC Archive 2016–2020: International Skin Imaging Collaboration Dataset.
4. R. Daneshjou et al., “Disparities in dermatology AI performance on a diverse, curated clinical image set,” Science Advances

Contact: nusrat.munia@uky.edu

Code: https://github.com/Munia03/Class-N-Diff