

TITAN-ARGOS-TOSCA meeting - 7/6/2024

📍 FORTH, Crete

# Hallucinations & Sparsity in Image Inpainting

Greg Tsagkatakis

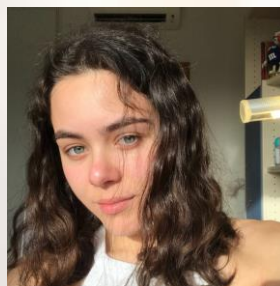
Institute of Computer Science, FORTH  
Computer Science Department, University of Crete



Konstantinos  
Zafeirakis



Manolis  
Kariotakis

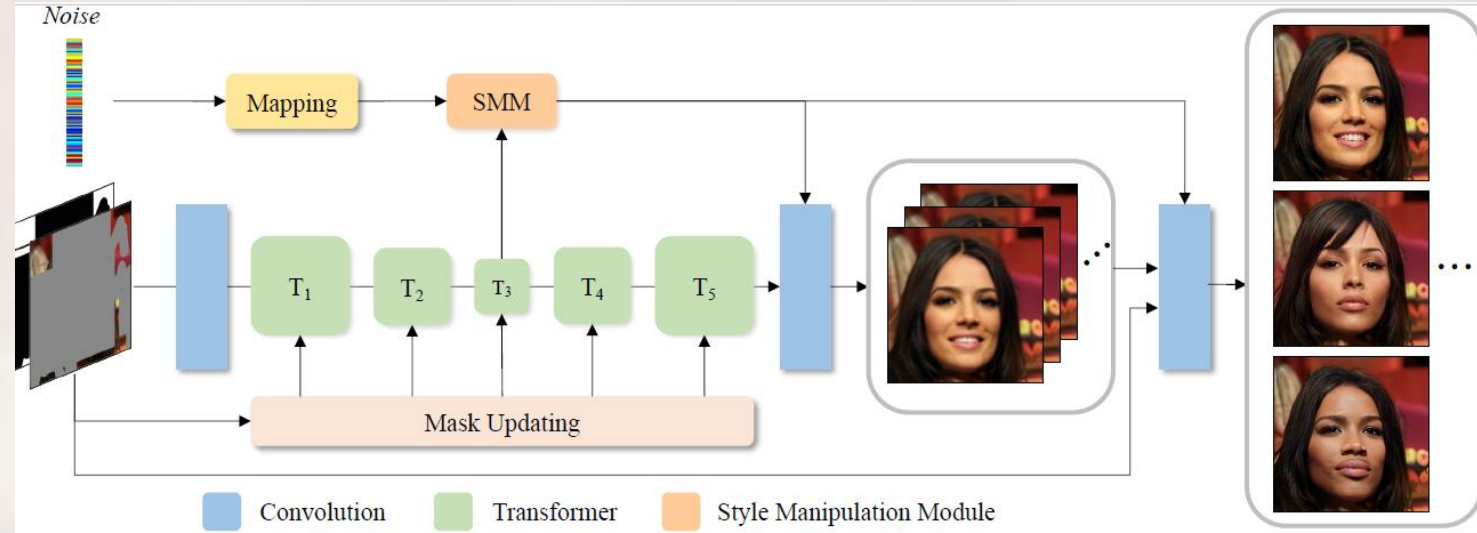


Xristina  
Kopidaki



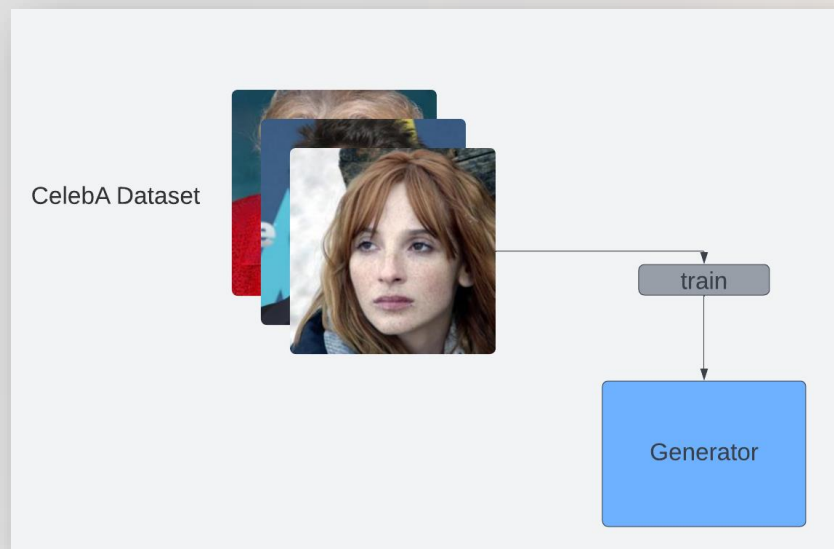
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the European Union

# Image Inpainting

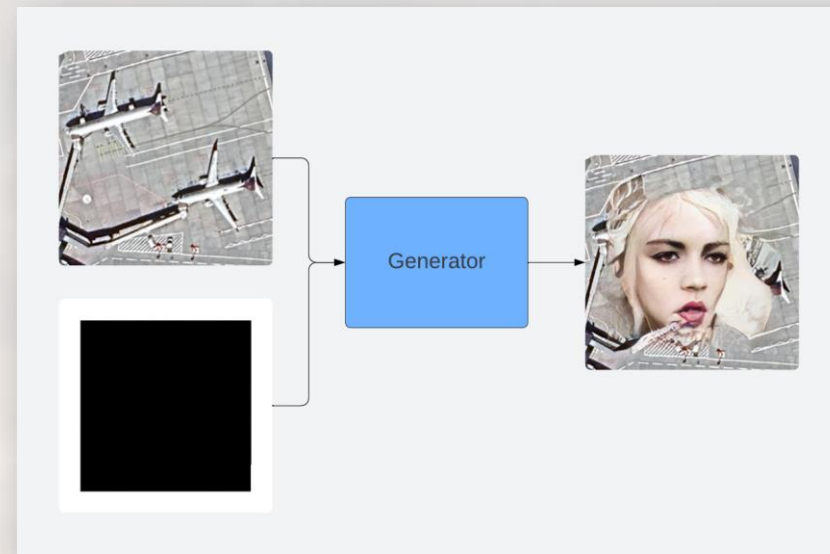


Li, Wenbo, Zhe Lin, Kun Zhou, Lu Qi, Yi Wang, and Jiaya Jia. "Mat: Mask-aware transformer for large hole image inpainting." In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10758-10768. 2022.

# Hallucinations



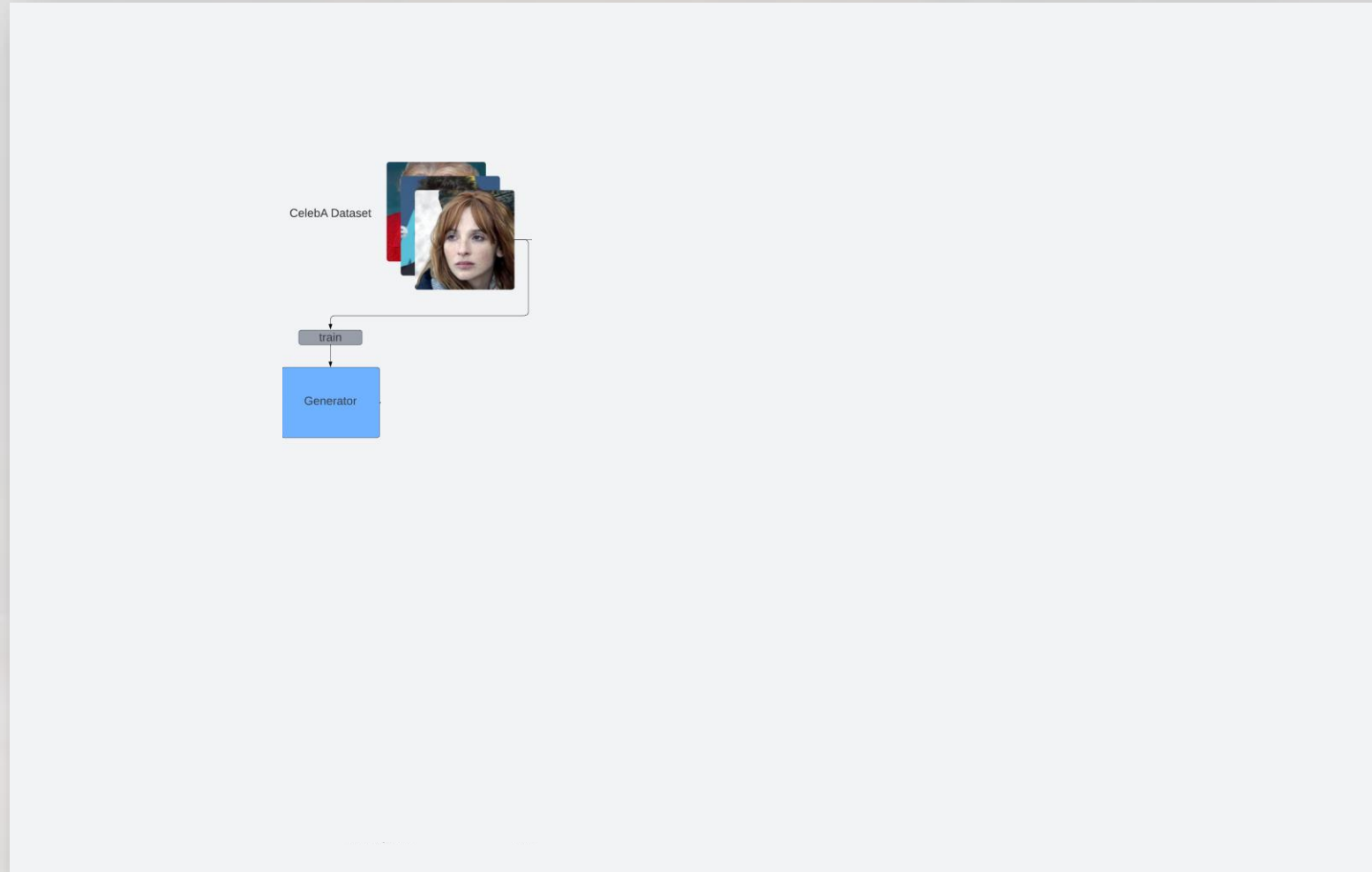
Training w/ CelebA



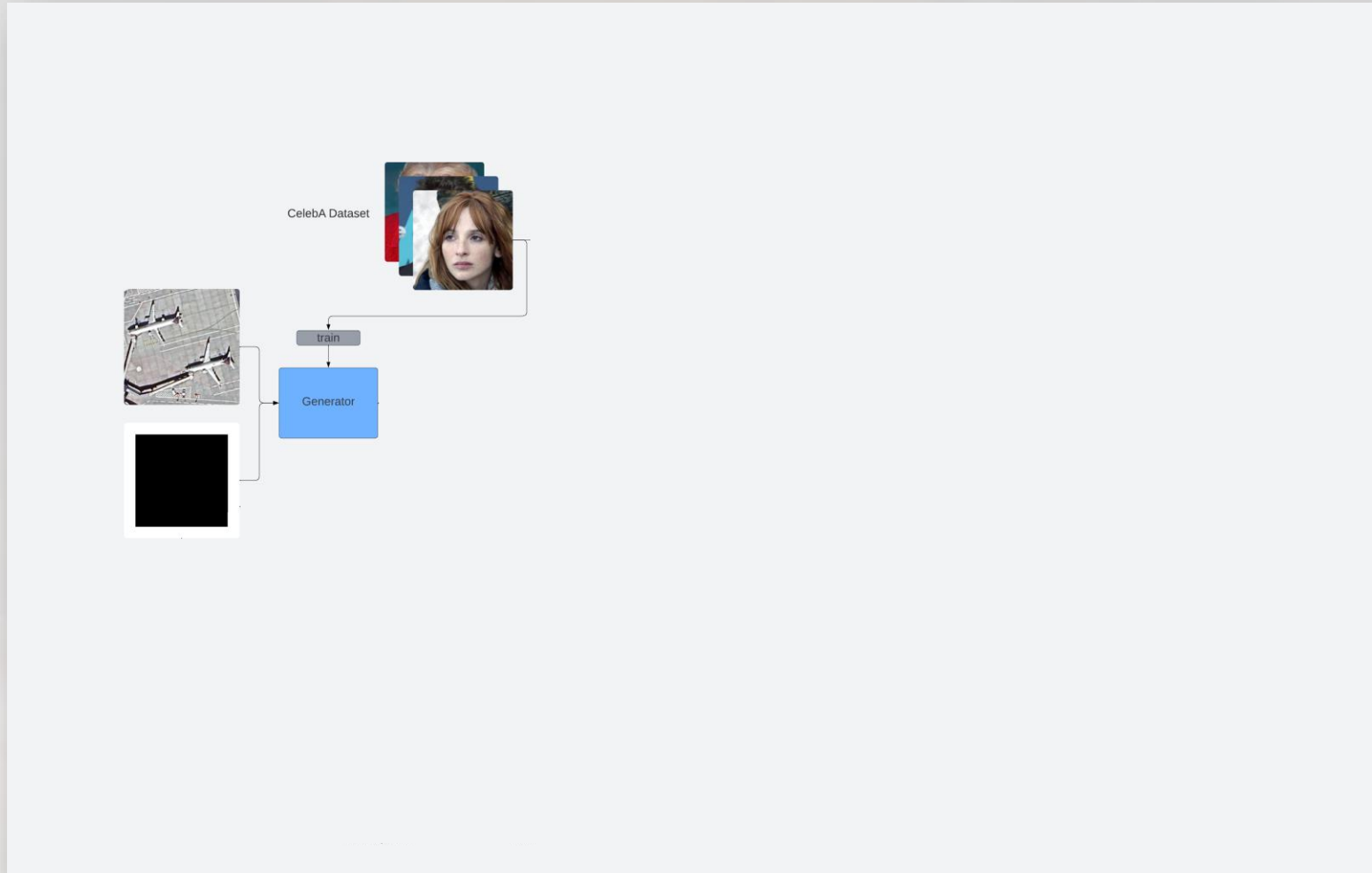
Inference w/ UCMerced



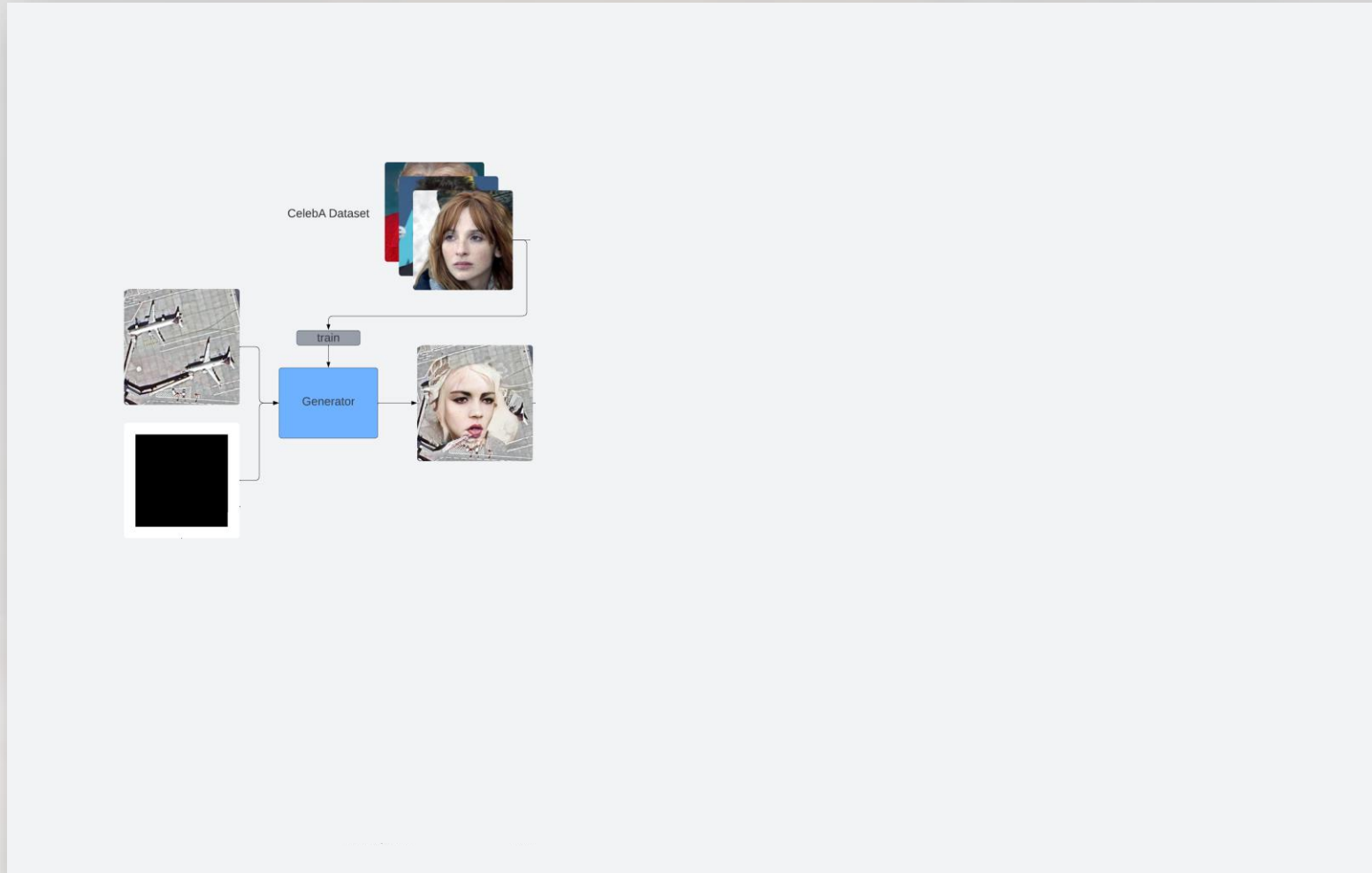
# Proposed Scheme



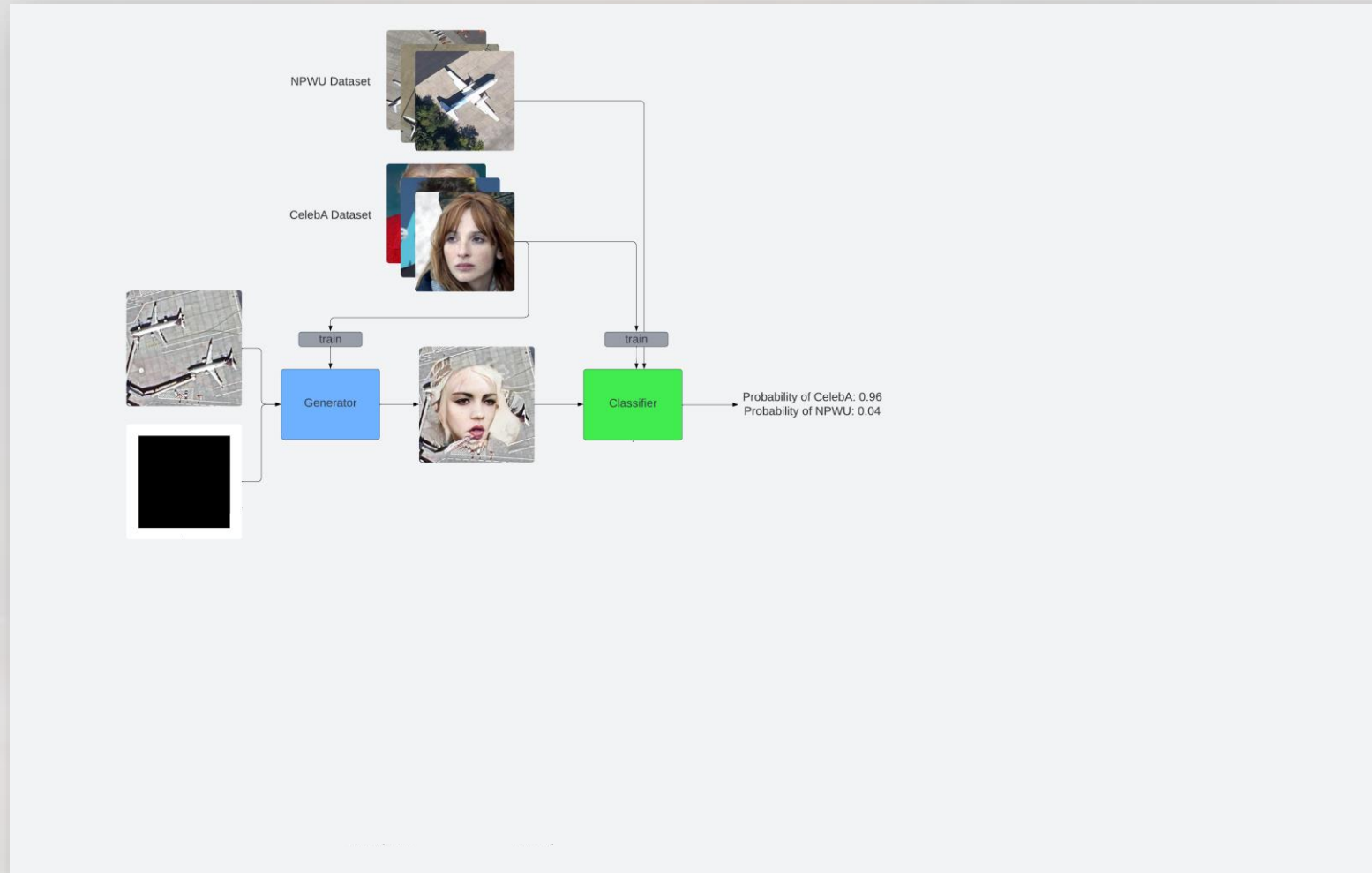
# Proposed Scheme



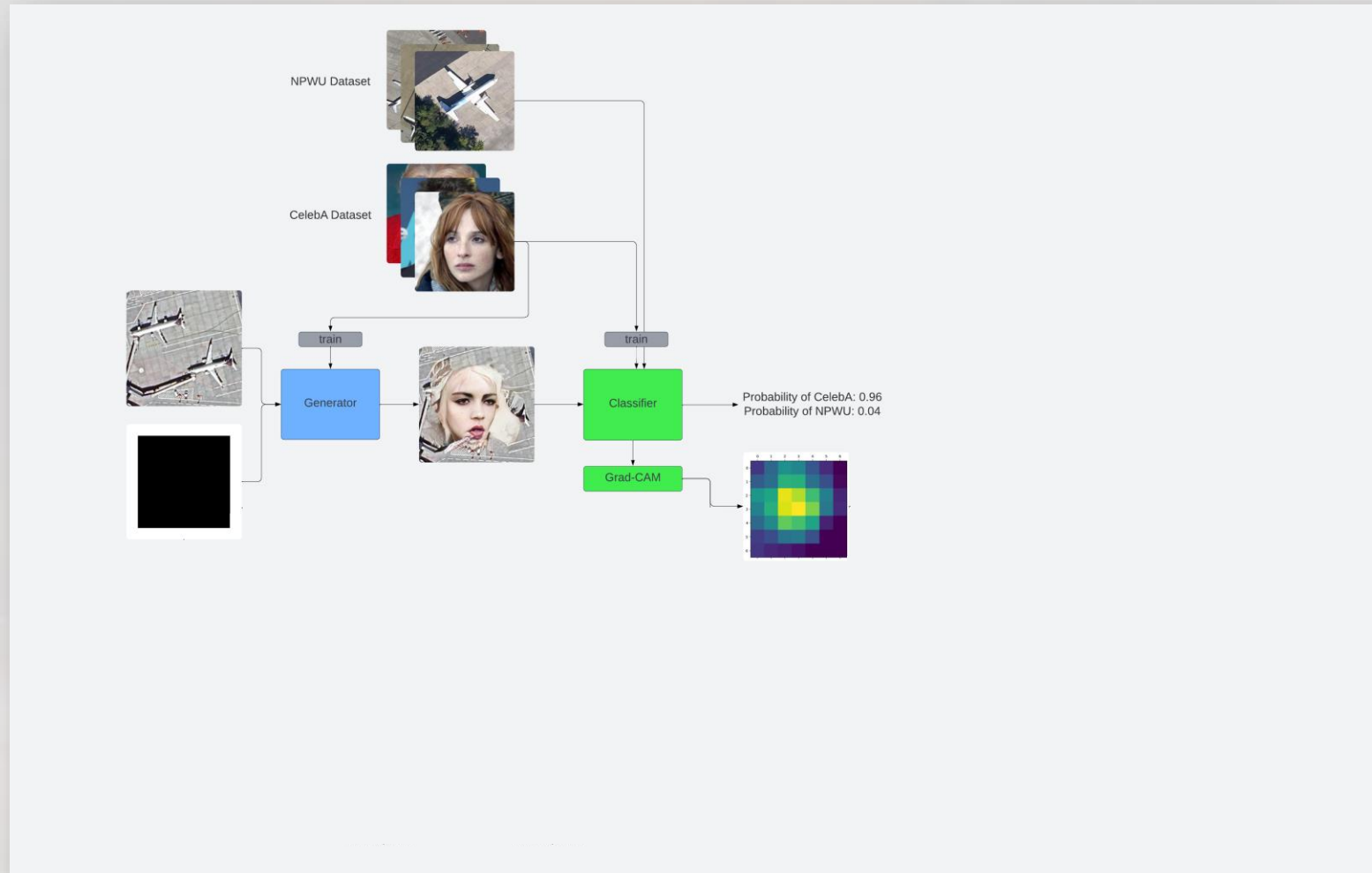
# Proposed Scheme



# Proposed Scheme

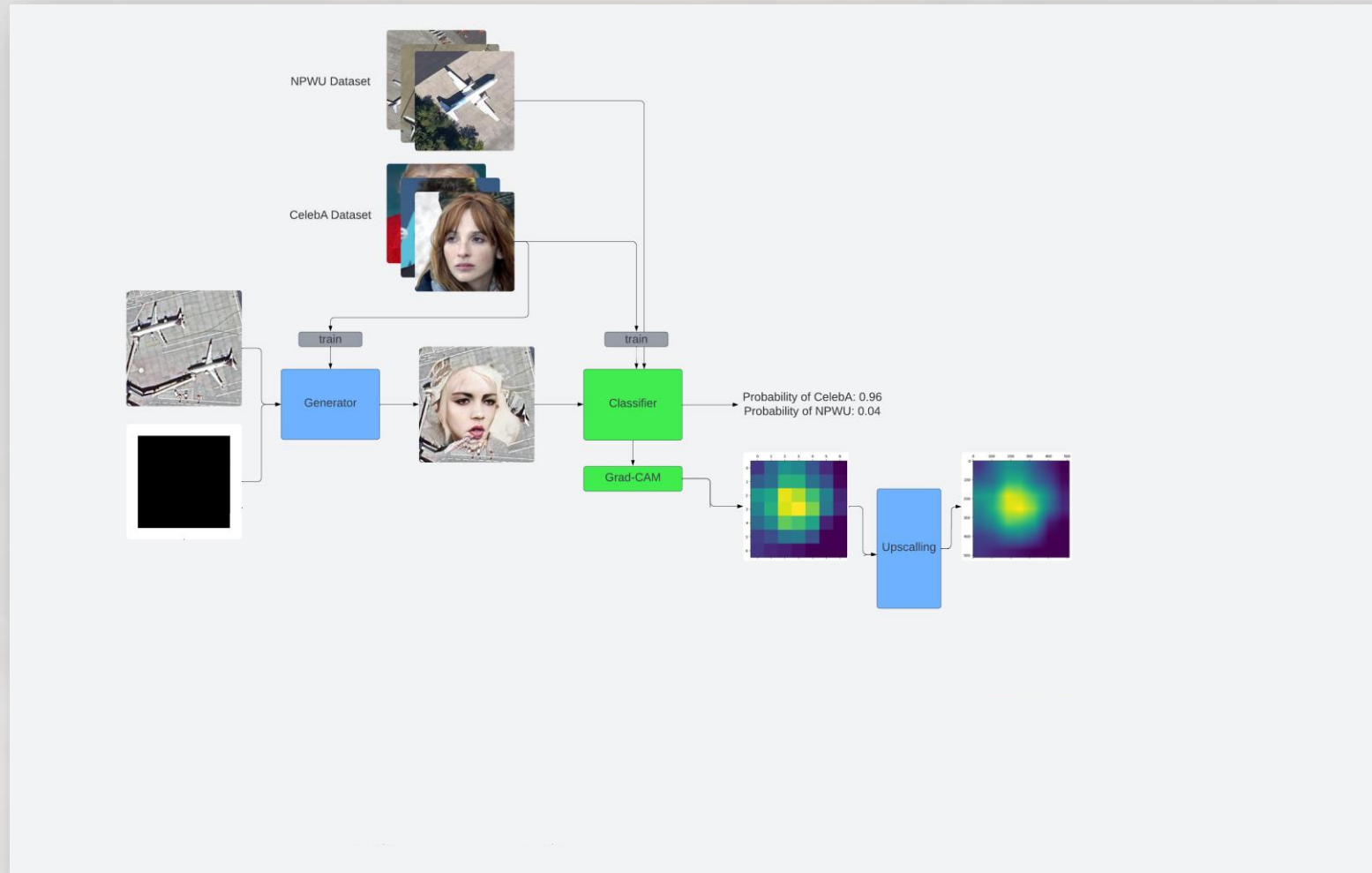


# Proposed Scheme

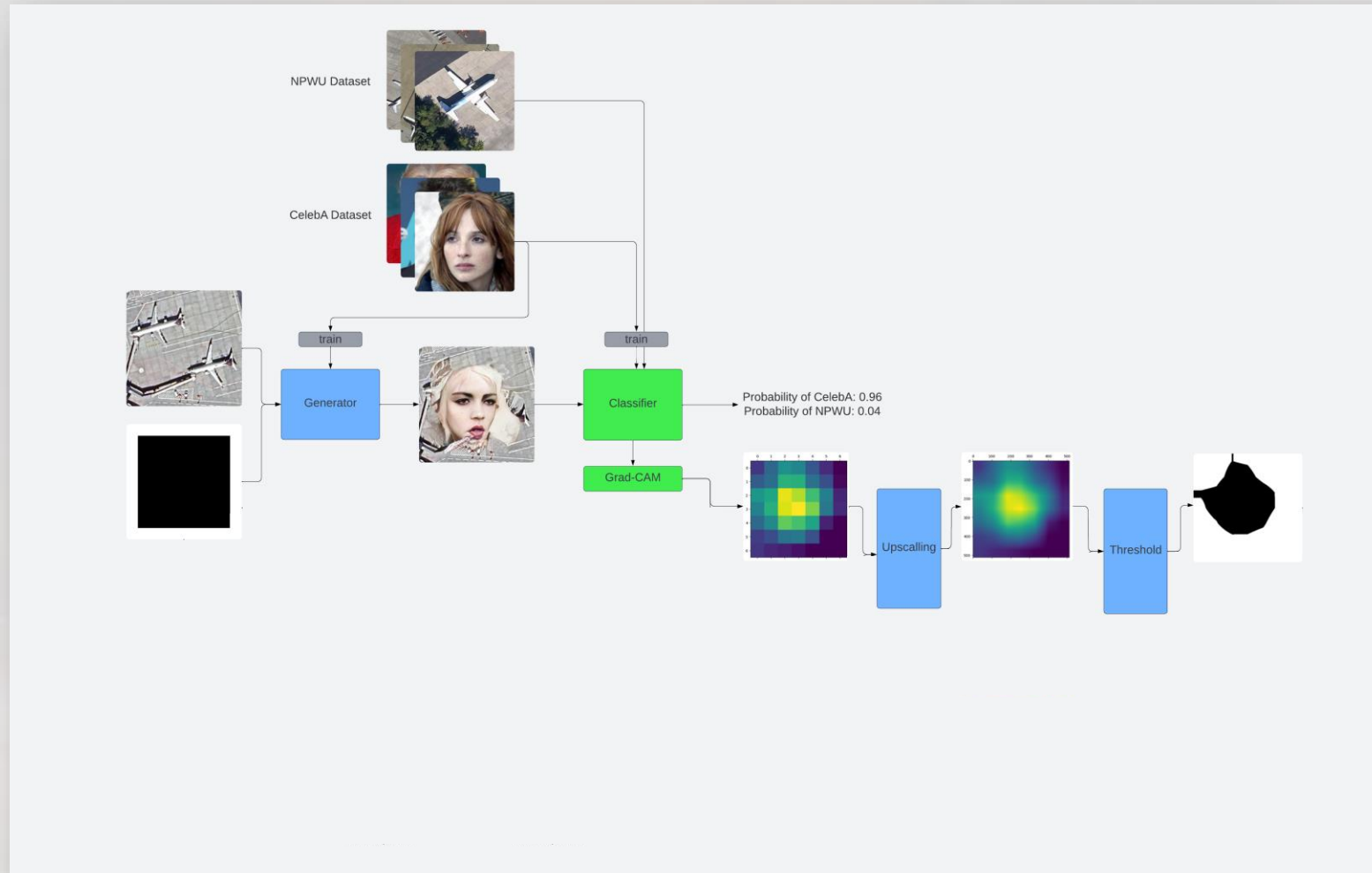




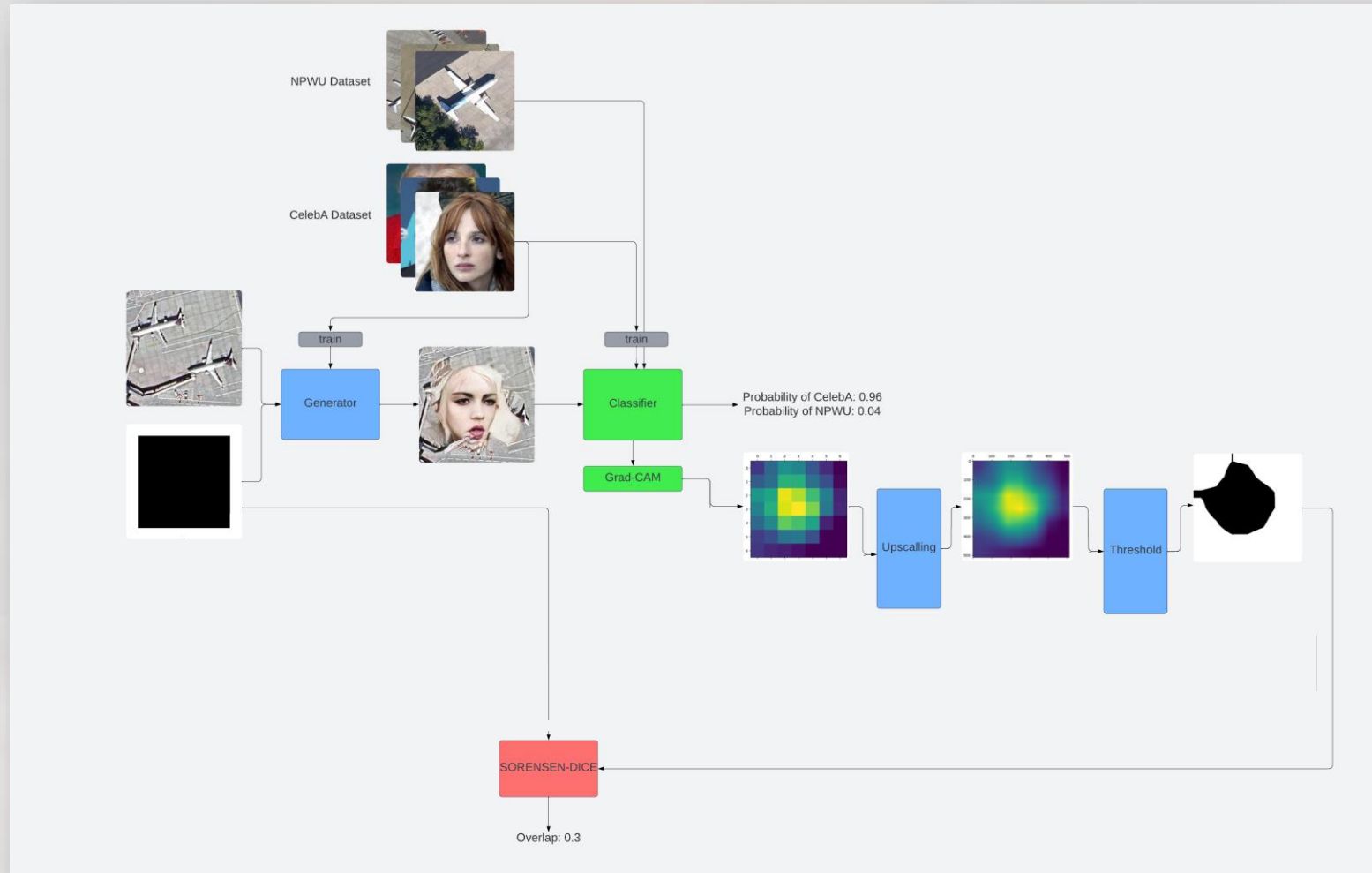
# Proposed Scheme



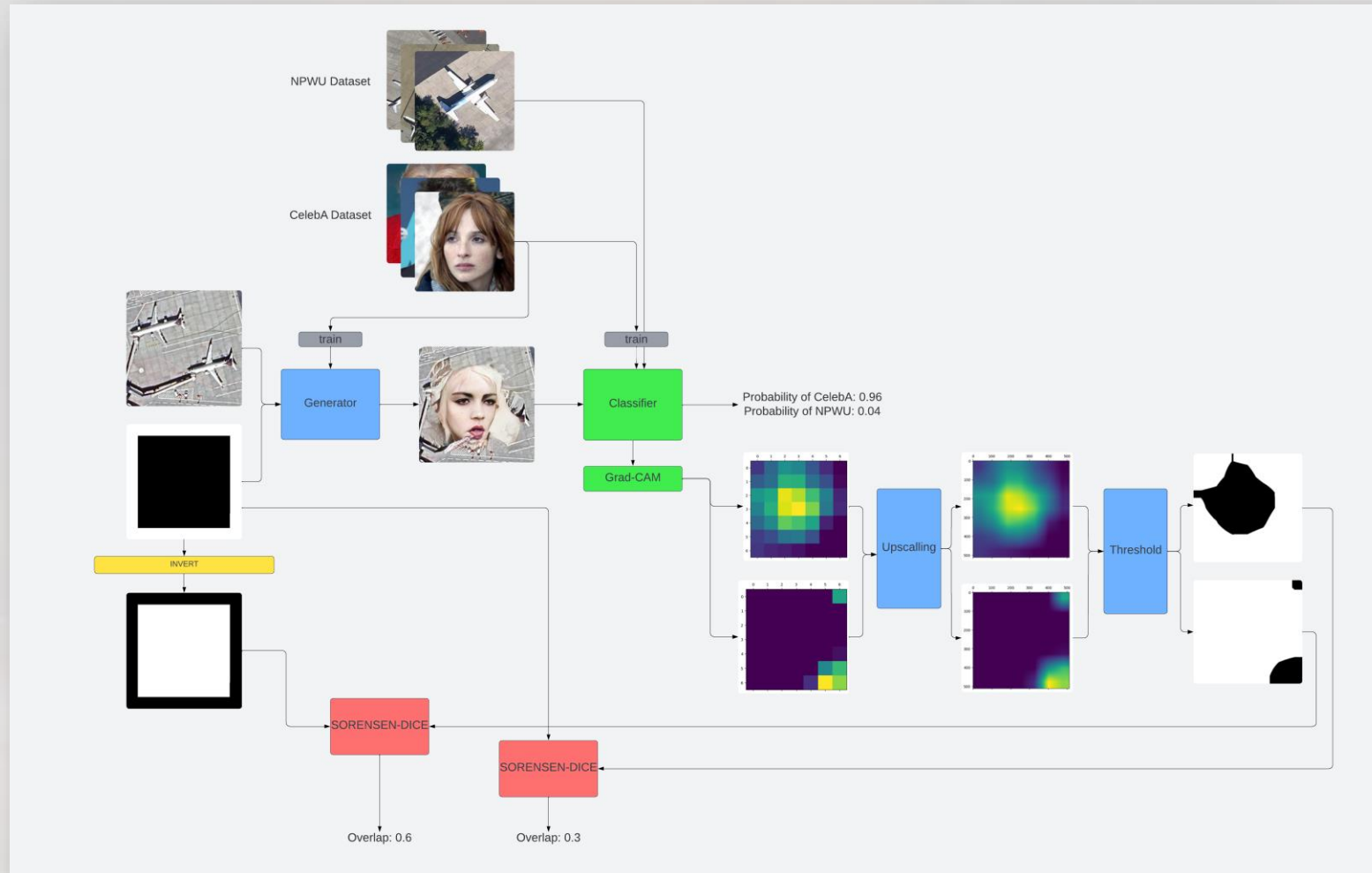
# Proposed Scheme



# Proposed Scheme

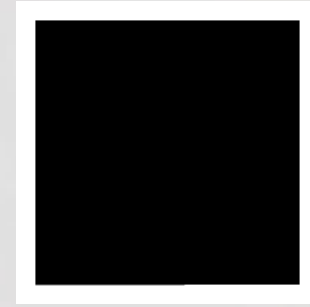
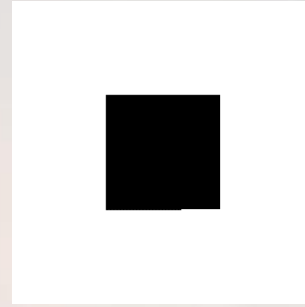
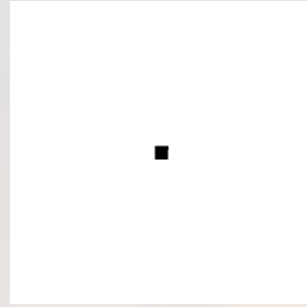


# Proposed Scheme

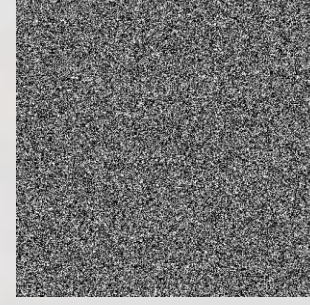
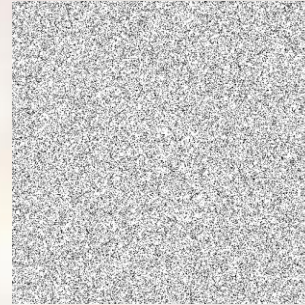
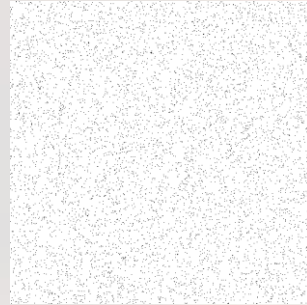


# Masks

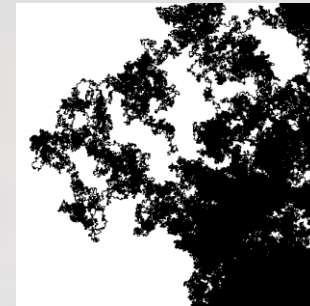
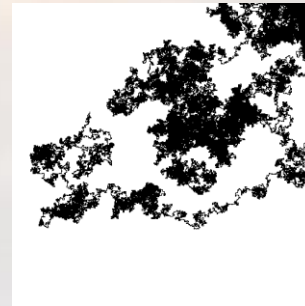
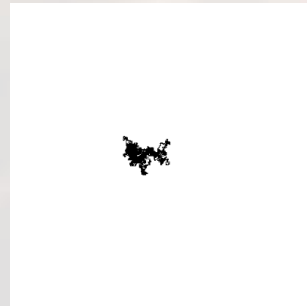
- Rectangular



- Random



- Irregular



# Inpainting with Masks

- Rectangular



- Random



- Irregular



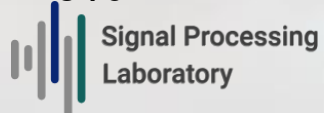
Masking



10%



20%



30%



40%



50%



60%

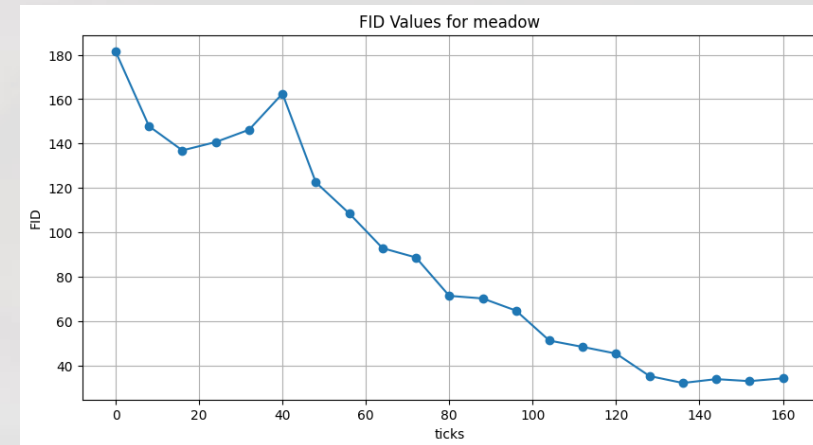


70%

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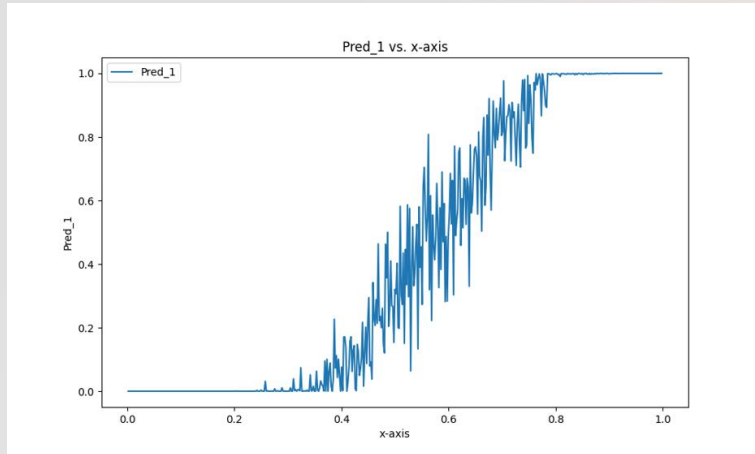
# Training & Evaluation scenarios

- Modules
  - Generator – Inpainter: Mask-Aware Transformer for Large Hole Image Inpainting, CVPR 2022
  - Classifier – Detector: MobileNetV2 (ResNet)
- Scenario #1
  - Generator w/ CelebA
  - Classifier /w CelebA and NPWU (dense residential)
  - Input: NPWU (medium residential)
- Scenario #2
  - Generator w/ CelebA
  - Classifier /w CelebA and NPWU (dense residential)
  - Input: UCMerced (airport)

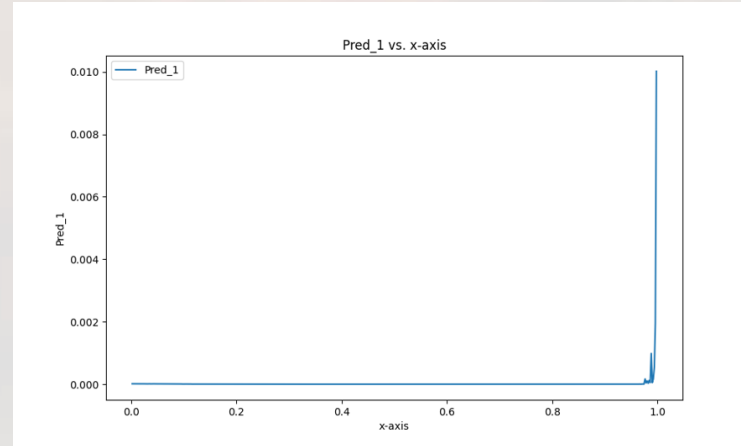


# Initial Results

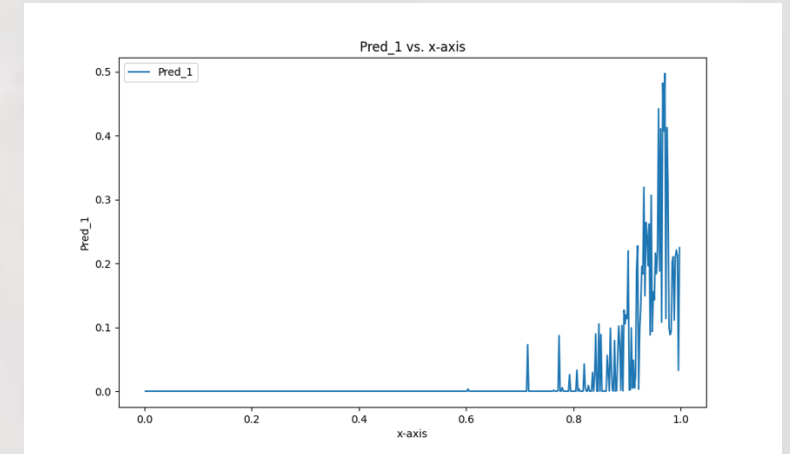
Rectangular



Random



Irregular



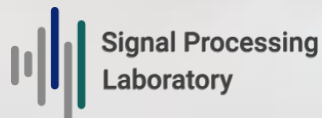




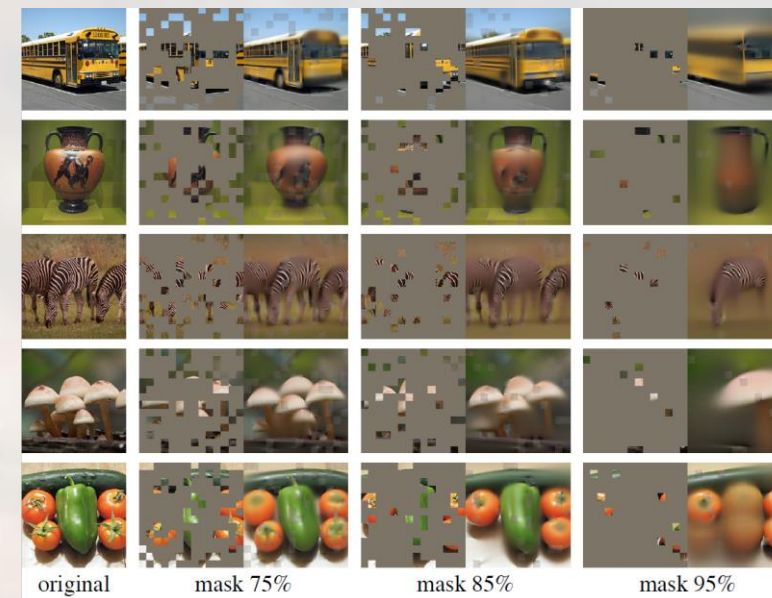
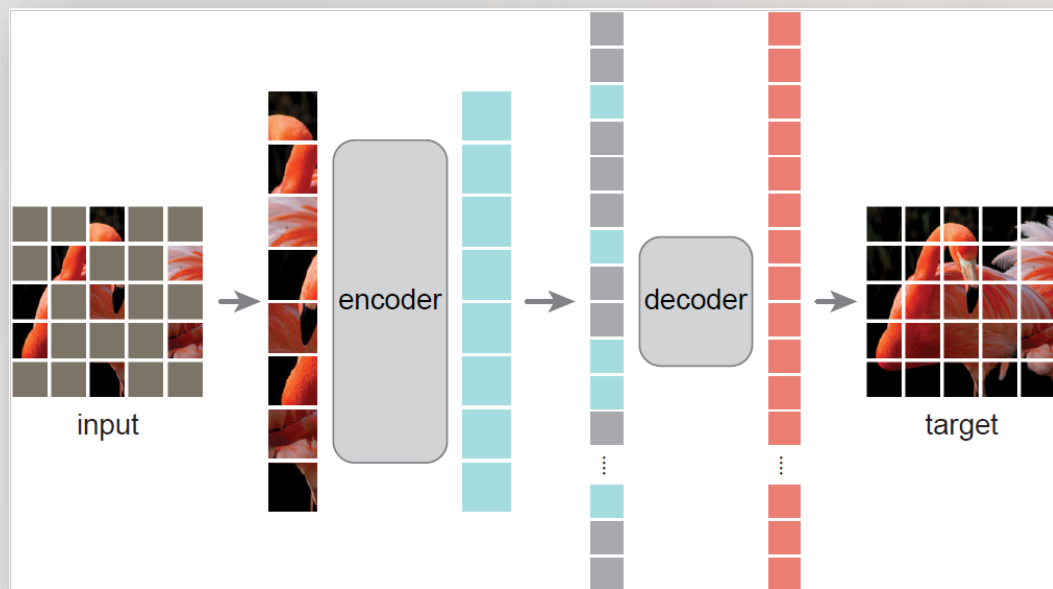
# Leveraging Sparse Input and Sparse Models: Efficient Distributed Learning in Resource-Constrained Environments

Emmanouil Kariotakis<sup>1,2</sup>, Grigorios Tsagkatakis<sup>2,3</sup>, Panagiotis Tsakalides<sup>2,3</sup>, Anastasios Kyrillidis<sup>4</sup>  
<sup>1</sup>ESAT-STADIUS, KU Leuven, <sup>2</sup>Institute of Computer Science - FORTH, <sup>3</sup>Department of Computer Science, University of Crete, <sup>4</sup>Department of Computer Science, Rice University  
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CPAL 2024  
January 03-06

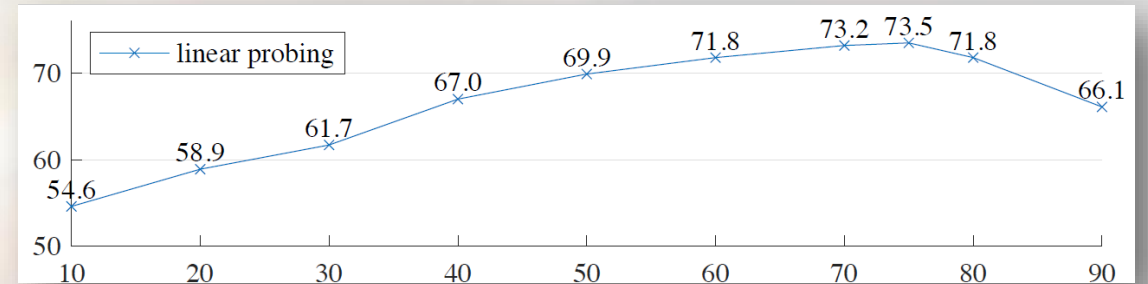
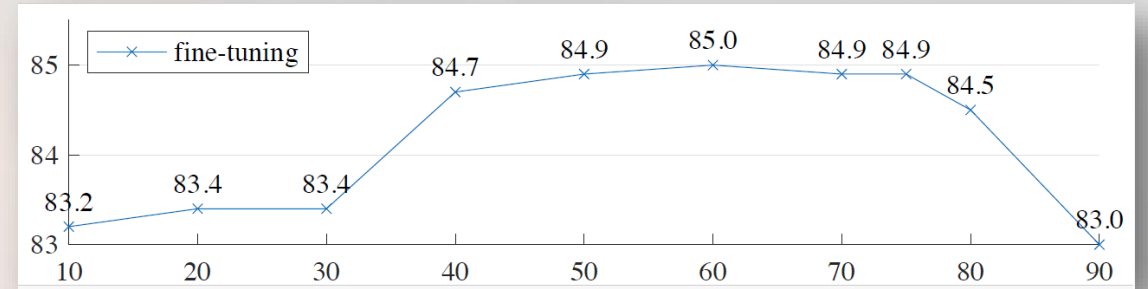
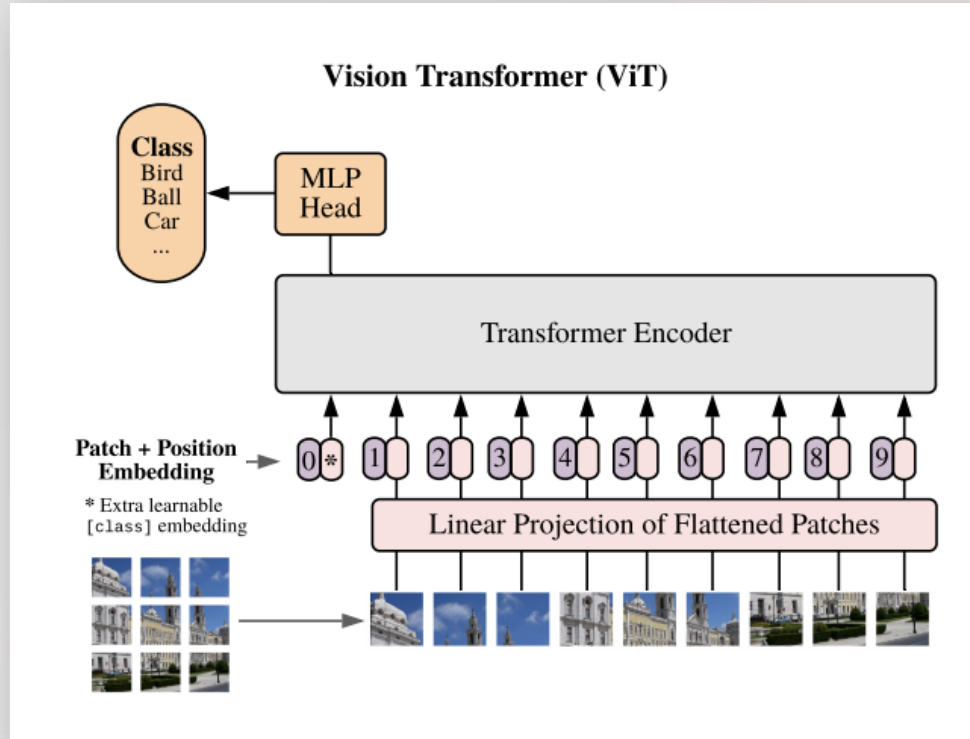


# Masked Autoencoders (MAE)

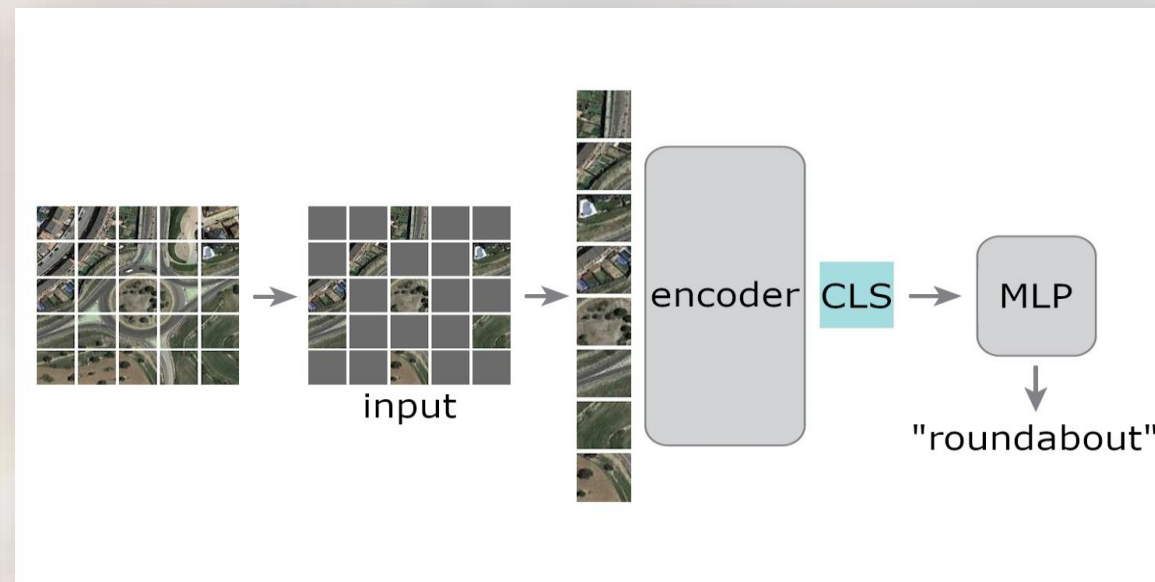
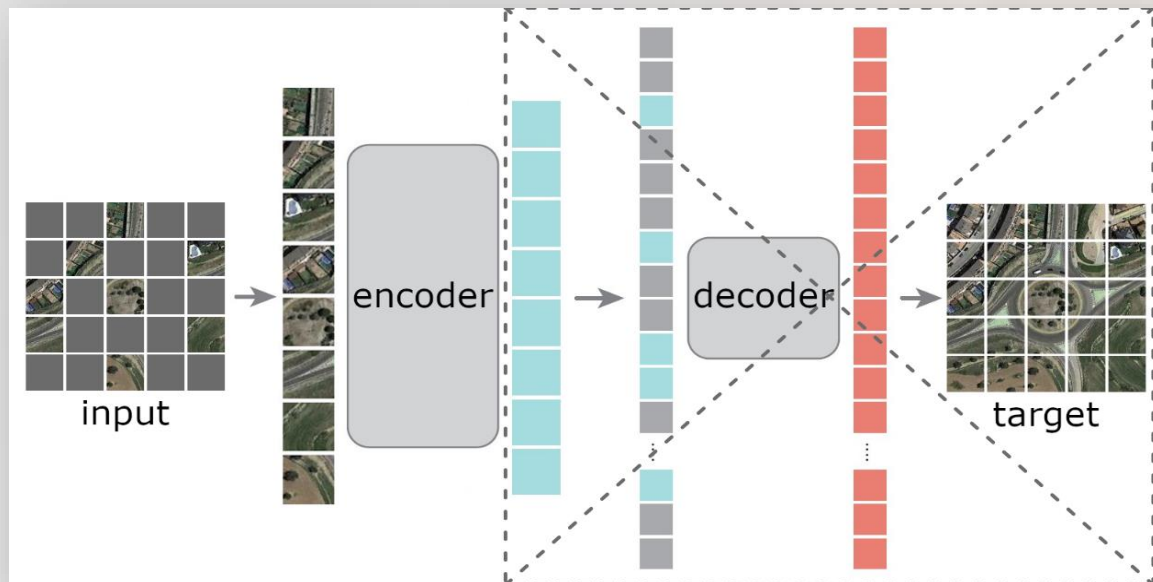


Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 16000–16009, 2022.

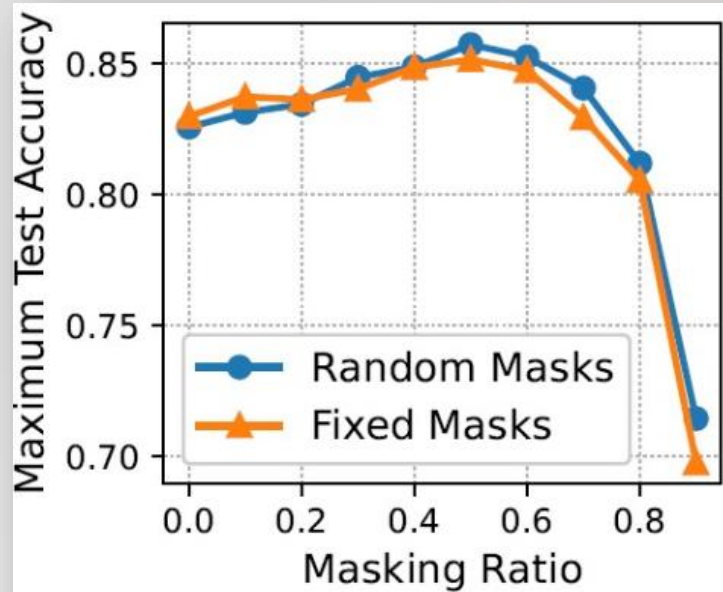
# MAE for Self-supervised Learning



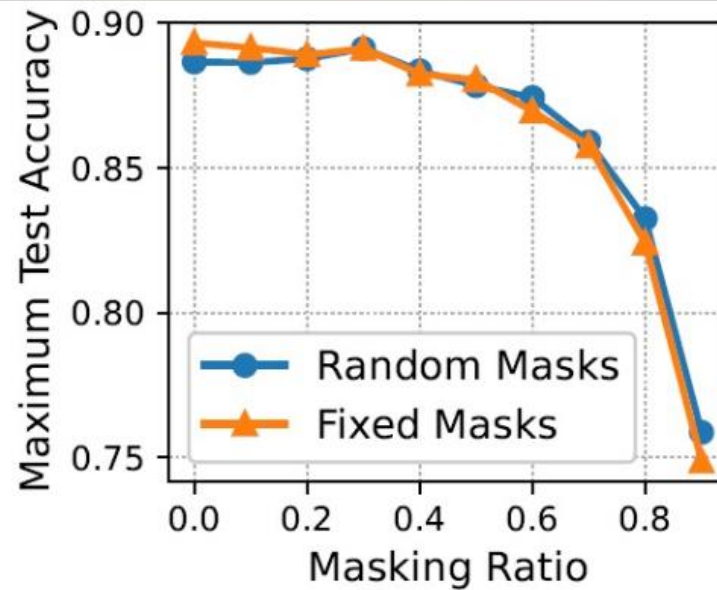
# Sparsified Encoders



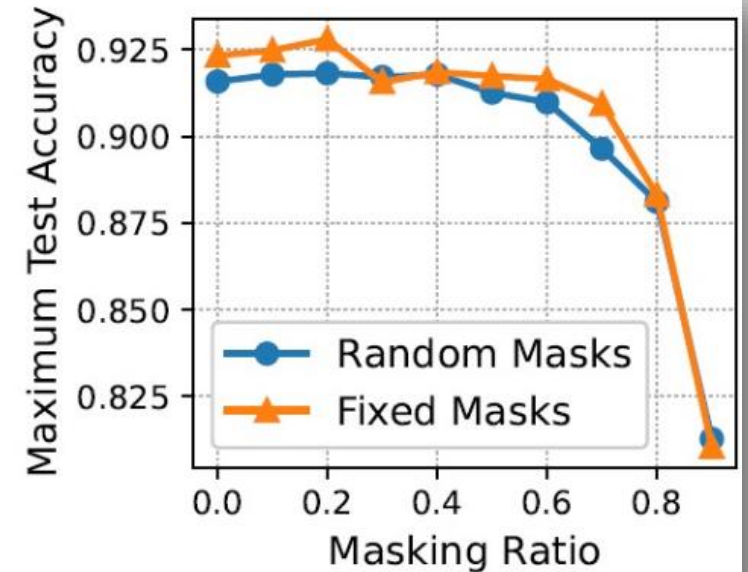
# System Study - Random vs Fixed Masks



(a) CIFAR10



(b) RESISC45



(c) AID

# System Study - Datasets Size

	Masking Ratio	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
CIFAR10	Masked Images Size (in GB)	0.205	0.184	0.164	0.143	0.123	0.102	0.082	0.061	0.041	0.020
	CLS Tokens Size (in GB)	0.1536									
	Max Accuracy	0.823	0.837	0.836	0.840	<b>0.848</b>	<b>0.851</b>	0.847	0.829	0.805	0.697
RESISC45	Masked Images Size (in GB)	7.078	6.370	5.662	4.954	4.247	3.539	2.831	2.123	1.416	0.708
	CLS Tokens Size (in GB)	0.083									
	Max Accuracy	<b>0.893</b>	<b>0.891</b>	0.889	<b>0.891</b>	0.882	0.880	0.869	0.857	0.824	0.749
AID	Masked Images Size (in GB)	12.240	11.016	9.792	8.568	7.344	6.120	4.896	3.672	2.448	1.224
	CLS Tokens Size (in GB)	0.026									
	Max Accuracy	0.923	<b>0.925</b>	<b>0.928</b>	0.916	0.918	0.917	0.916	0.909	0.883	0.810

# Federated Learning & Class Imbalance

