Is synthetic data from generative models ready for image recognition?

GISLab Short-Term Course 2025 Summer

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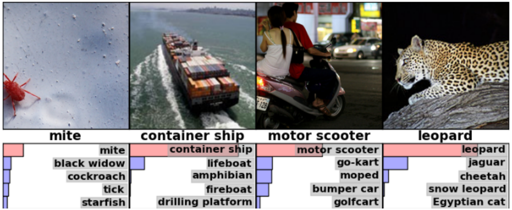
Outline

- 1. Introduction to Image Classification using Deep Learning
- 2. Traditional Data Augmentation Methods
- 3. Generative Models for Data Augmentation
- 4. Remote Sensing Dataset for Diaster Events: xBD
- Project - **Explore whether generated images can benefit image classification**

Image Classification: Overview

Figure: Overview of image classification.

Background: Image Classification with Deep Learning



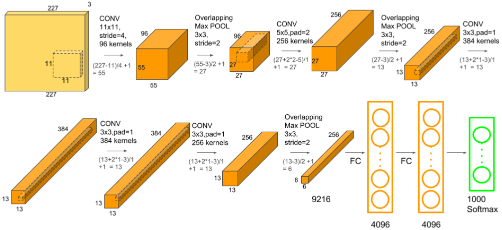
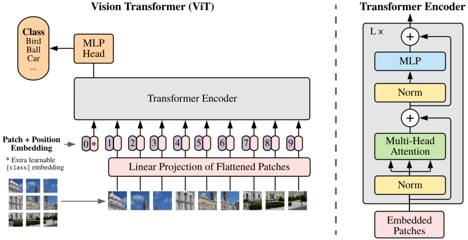


Figure: Left: AlexNet on ILSVRC-2010 (Berg, Deng, and Fei-Fei, 2010) Right: Architecture of AlexNet (Krizhevsky, Sutskever, and Hinton, 2012).

Berg, et al. Large Scale Visual Recognition Challenge 2010, 2010.
Krizhevsky, et al. ImageNet Classification with Deep Convolutional Neural Networks, NeurIPS, 2012.

Architecture Evolution of Image Classification

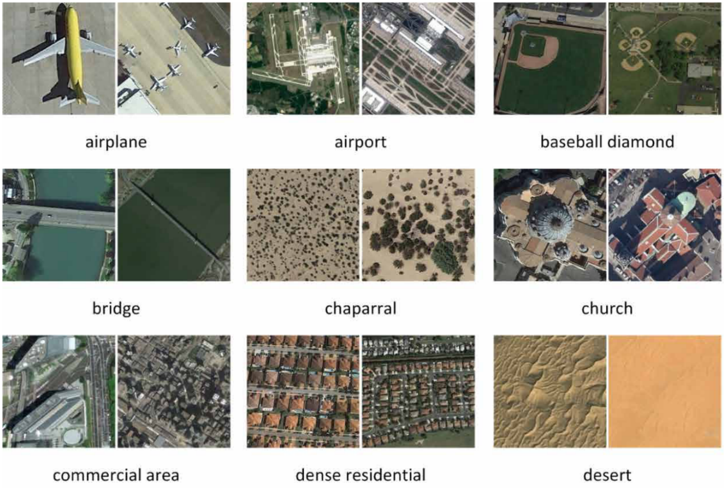
- **NeurIPS 2012: AlexNet (CNN)**
  (Krizhevsky, Sutskever, and Hinton, 2012)
- **CVPR 2016: ResNet (CNN)**
  (He, Zhang, et al., 2016)
- **ICLR 2021: Vision Transformers (ViT)**
  (Dosovitskiy et al., 2021)
- **ICCV 2021: Swin Transformer (ViT)**
  (Liu et al., 2021)
- **ICML 2021: CLIP (ViT)**
  (Radford et al., 2021)
- **CVPR 2022: MAE (ViT)**
  (He, Chen, et al., 2022)
- **TMLR 2022: CoCa (ViT)**
  (Yu et al., 2022)



Overview of Vision Transformer (Dosovitskiy et al., 2021).

Krizhevsky, et al. ImageNet Classification with Deep Convolutional Neural Networks, NeurIPS, 2012.
He, Zhang, et al. Deep Residual Learning for Image Recognition, CVPR, 2016.
Dosovitskiy, et al. An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale, ICLR, 2021.
Liu, et al. Swin Transformer: Hierarchical Vision Transformer Using Shifted Windows, ICCV, 2021.
Radford, et al. Learning Transferable Visual Models From Natural Language Supervision, ICML, 2021.
He, Chen, et al. Masked Autoencoders Are Scalable Vision Learners, CVPR, 2022.
Yu, et al. CoCa: Contrastive Captioners Are Image-Text Foundation Models. TMLR. 2022.

Image Classification Dataset: RESISC45



Example images from the RESISC45 remote sensing scene classification dataset (Cheng, Han, and Lu, 2017).

Cheng, et al. Remote Sensing Image Scene Classification: Benchmark and State of the Art. Proceedings of the IEEE. 2017.

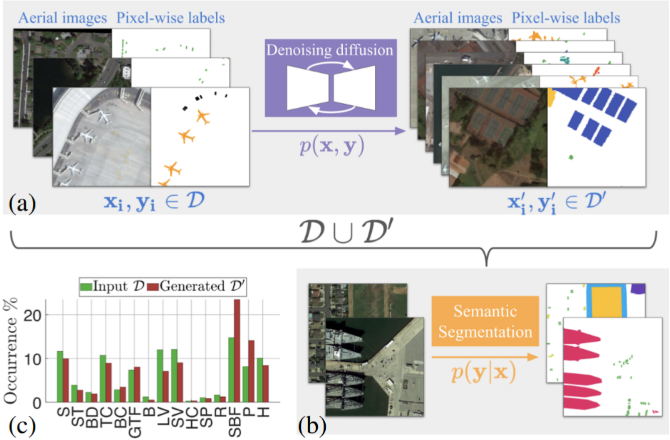
Traditional Data Augmentation Methods

- **Geometric Transformations: Rotation**, **Flipping** (horizontal/vertical), **Scaling**, **Translation**, **Cropping**
- **Color Jittering:** Adjusting brightness, contrast, saturation, and hue
- **Noise Injection:** Adding random noise to images
- **Cutout** (DeVries and Taylor, 2017)
- **CutMix** (Yun et al., 2019)
- **Copy-Paste** (Ghiasi et al., 2021)

There is also a comprehensive study entitled 'How to train your ViT? Data, Augmentation, and Regularization in Vision Transformers' (Steiner et al., 2022).

DeVries, et al. Improved Regularization of Convolutional Neural Networks with Cutout, arXiv, 2017.
Yun, et al. CutMix: Regularization Strategy to Train Strong Classifiers With Localizable Features, ICCV, 2019.
Ghiasi, et al. Simple copy-paste is a strong data augmentation method for instance segmentation, CVPR, 2021.
Steiner, et al. How to Train Your ViT? Data, Augmentation, and Regularization in Vision Transformers. TMLR. 2022.

Generative Models for Data Augmentation



SatSyn (Toker et al., 2024) proposes a generative model (diffusion model) to generate both images and corresponding masks for satellite segmentation. The synthetic dataset is used for data augmentation, yielding significant quantitative improvements in satellite semantic segmentation compared to other data augmentation methods.

Toker, et al. SatSynth: Augmenting Image-Mask Pairs through Diffusion Models for Aerial Semantic Segmentation, CVPR, 2024.

Generated Text-Image Dataset Improving Image Classification

Dataset	Task	CLIP-RN50	CLIP-RN50+SYN	CLIP-ViT-B/16	CLIP-ViT-B/16+SYN
CIFAR-10	o	70.31	80.06 (+9.75)	90.80	92.37 (+1.57)
CIFAR-100	o	35.35	45.69 (+10.34)	68.22	70.71 (+2.49)
Caltech101	o	86.09	87.74 (+1.65)	92.98	94.16 (+1.18)
Caltech256	o	73.36	75.74 (+2.38)	80.14	81.43 (+1.29)
ImageNet	o	60.33	60.78 (+0.45)	68.75	69.16 (+0.41)
SUN397	s	58.51	60.07 (+1.56)	62.51	63.79 (+1.28)
Aircraft	f	17.34	21.94 (+4.60)	24.81	30.78 (+5.97)
Birdsnap	f	34.33	38.05 (+3.72)	41.90	46.84 (+4.94)
Cars	f	55.63	56.93 (+1.30)	65.23	66.86 (+1.63)
CUB	f	46.69	56.94 (+10.25)	55.23	63.79 (+8.56)
Flower	f	66.08	67.05 (+0.97)	71.30	72.60 (+1.30)
Food	f	80.34	80.35 (+0.01)	88.75	88.83 (+0.08)
Pets	f	85.80	86.81 (+1.01)	89.10	90.41 (+1.31)
DTD	t	42.23	43.19 (+0.96)	44.39	44.92 (+0.53)
EuroSAT	si	37.51	55.37 (+17.86)	47.77	59.86 (+12.09)
ImageNet-Sketch	r	33.29	36.55 (+3.26)	46.20	48.47 (+2.27)
ImageNet-R	r	56.16	59.37 (+3.21)	74.01	76.41 (+2.40)
Average	/	55.13	59.47 (+4.31)	65.42	68.32 (+2.90)

Table 1: **Main Results on Zero-shot Image Recognition.** All results are top-1 accuracy on test set. o: object-level. s: scene-level. f: fine-grained. t: textures. si: satellite images. r: robustness.

Synthetic text-image datasets generated by generative models can significantly improve image classification performance, as demonstrated in (He et al., 2023).

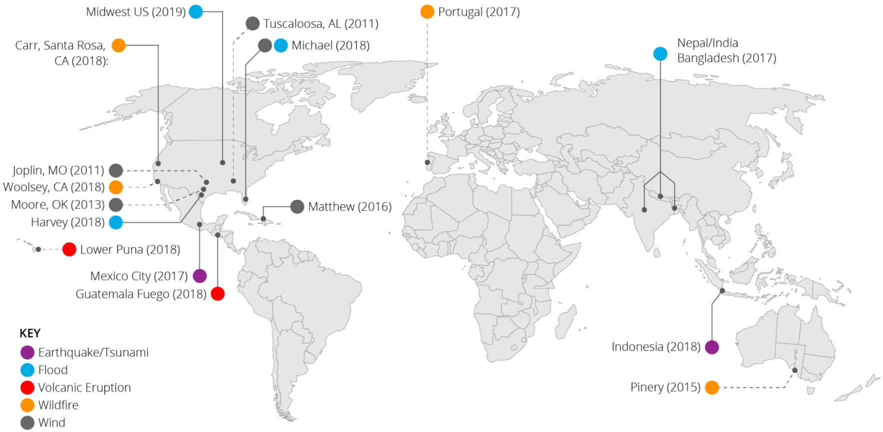
He, et al. Is synthetic data from generative models ready for image recognition?, ICLR, 2023.

xBD: A Large-Scale Disaster Damage Dataset

Pre-disaster imagery (top) and post-disaster imagery (bottom). From left to right: Hurricane Harvey; Joplin tornado; Lower Puna volcanic eruption; Sunda Strait tsunami. Imagery from DigitalGlobe.
xBD (Gupta et al., 2019)

Gupta, et al. xBD: A Dataset for Assessing Building Damage from Satellite Imagery, arXiv, CVPRW, 2019.

xBD: Global Coverage of Disaster Types



Disaster types and disasters represented in xBD around the world.
xBD (Gupta et al., 2019)

Gupta, et al. xBD: A Dataset for Assessing Building Damage from Satellite Imagery, arXiv, CVPRW, 2019.

Project Assignment: Overview

Project: Can Generated Images Improve Remote Sensing Image Classification?

Objective:
Investigate whether combining real images and generated images can improve remote sensing image classification.

Pipeline:
In this project, you will experiment with three different training settings to evaluate the impact of generated data:

1. **Real Dataset Only:** Train the classification model using only real images from the xBD dataset.
2. **Generated Dataset Only:** Train the model using only synthetic images generated by commercial generative models.
3. **Combined Dataset:** Train the model using both real and generated images together.

Compare the classification performance across these three settings to analyze the effect of synthetic data.

Project Assignment: Dataset

Dataset: xBD Disaster Damage Dataset

- Use the **xBD** remote sensing disaster dataset.
- The dataset includes **6 disaster classes**.
- For each class, use **100 real images** (total: 600 real images).

Project Assignment: Generative Models

Image Generation:

- We consider generated images as the result of **text-guided image editing**: for each case, you input a **pre-event image** and a **text description** (e.g., "flooded", "collapsed building"), and the model yields a generated (post-event) image.
- Use commercial generative models such as **GPT-4o Image Generation(GPT-Image-1)** (OpenAI, 2025), **Gemini-2** (Google, 2024), or **SeedEdit 3.0** (Wang et al., 2025) to create synthetic images for each disaster class.

OpenAI. GPT-Image-1, 2025.
Google. Experiment with gemini 2.0 flash native image generation, 2024.
Wang, et al. SeedEdit 3.0: Fast and High-Quality Generative Image Editing. arXiv. 2025.

Project Assignment: Classification Models

Recommended Baseline Models:

- **OpenAI CLIP** (Radford et al., 2021) - models
- **RemoteCLIP** (Liu, Chen, Guan, et al., 2024) - models
- **Git-RSCLIP** (Liu, Chen, Zhao, et al., 2025) - models

All of the above follow ViT configurations. For code and tutorials:

- CLIP training example
- ViT tutorials
- For more Remote Sensing Foundation Models, ref to huggingface collection.
- The latest strong baseline RSFM 'SkySense-O' (Zhu et al., 2025). GitHub

Radford, et al. Learning Transferable Visual Models From Natural Language Supervision, ICML, 2021.
Liu, Chen, Guan, et al. RemoteCLIP: A Vision Language Foundation Model for Remote Sensing. TGRS. 2024.
Liu, Chen, Zhao, et al. Text2Earth: Unlocking text-driven remote sensing image generation with a global-scale dataset and a foundation model. GRSM. 2025.
Zhu, et al. SkySense-O: Towards Open-World Remote Sensing Interpretation with Vision-Centric Visual-Language Modeling, CVPR, 2025.

Project Assignment: Data Augmentation Protocol

- For each disaster class, generate **1**$\times$**–4**$\times$ synthetic images (i.e., 100, 200, 300, or 400 synthetic images per class).
- Explore and compare different ratios of real to synthetic images (e.g., 1:1, 1:2, 1:3, 1:4).
- The augmented dataset for each class will range from **200 to 500 images**.

Project Assignment: Evaluation

Evaluation:

- Use **standard accuracy**, **F1 score**, and **confusion matrix** to measure performance.
- Always evaluate on a **held-out real (unseen) test set**.
- Include **curve or bar plots** comparing classification performance across different real:synthetic ratios.

Appendix

Additonal Text-Image Remote Sensing Datasets

Text-to-Image Generation:

- **RSICD** (Lu et al., 2018): Remote Sensing Image Captioning Dataset with 10,921 images and five captions per image.
- **RSICap** (Hu et al., 2025): High-quality dataset with 2,585 human-annotated image-caption pairs.
- **UCM-Captions** (Qu et al., 2016): Derived from the UC Merced Land Use Dataset, containing 2,100 images with five captions each.
- **RESISC45** (Cheng, Han, and Lu, 2017): It is a publicly available benchmark for REmote Sensing Image Scene Classification (RESISC), created by Northwestern Polytechnical University (NWPU). This data set contains 31 500 images, covering 45 scene classes with 700 images in each class.

Lu, et al. Exploring Models and Data for Remote Sensing Image Caption Generation. TGRS. 2018.
Hu, et al. RSGPT: A remote sensing vision language model and benchmark. ISPRS. 2025.
Qu, et al. Deep semantic understanding of high resolution remote sensing image, CITS, 2016.
Cheng, et al. Remote Sensing Image Scene Classification: Benchmark and State of the Art. Proceedings of the IEEE. 2017.

Generative Modeling

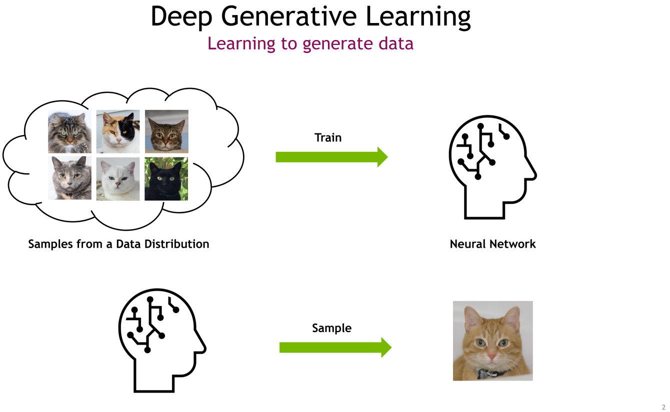


Figure: Illustration of generative modeling (Vahdat Arash, Song, and Meng, 2023).

Vahdat Arash et al. CVPR 2023 Tutorial Denoising Diffusion-based Generative Modeling: Foundations and Applications, 2023.

Timeline of Generative Models

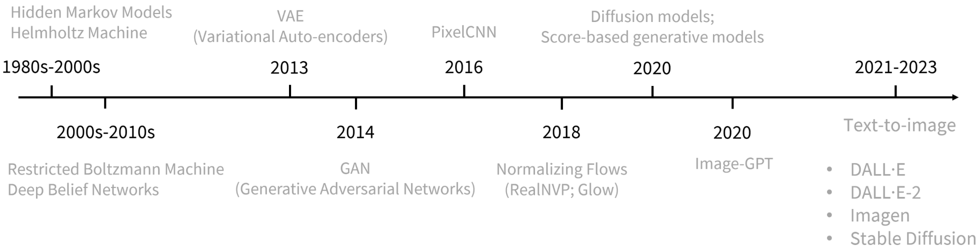


Figure: Timeline of key developments in generative models (Deng, 2024).

Deng, [CS7352] Advanced Neural Network Theory and Application, SJTU Spring, 2024.

Background: Diffusion Models

Denoising diffusion models consist of two processes:

- A forward diffusion process that gradually adds noise to the input.
- A reverse denoising process that learns to generate data by denoising.

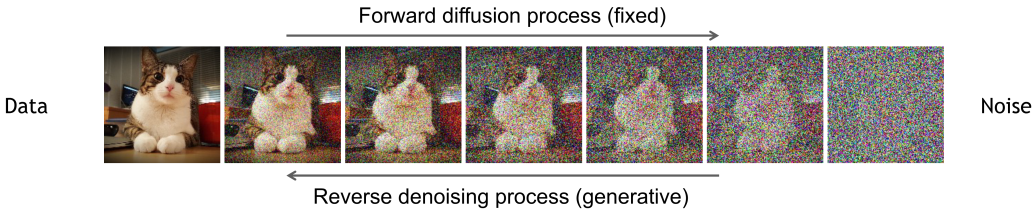


Figure: Diffusion models generate data through iterative denoising (Sohl-Dickstein et al., 2015; Ho, Jain, and Abbeel, 2020).

Sohl-Dickstein, et al. Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML, 2015.
Ho, et al. Denoising Diffusion Probabilistic Models, NeurIPS, 2020.

Diffusion Models: Forward and Reverse Processes

Forward (Diffusion) Process:

$$q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\,\mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

$$q(\mathbf{x}_{1:T} \mid \mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t \mid \mathbf{x}_{t-1})$$

$$\text{Equivalently, } \mathbf{x}_t = \sqrt{\bar{\alpha}_t}\,\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\,\boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

Reverse (Denoising) Process:

$$p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t))$$

$$p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T) \prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t)$$

where $\mathbf{x}_0$ is the data, β_t is the noise schedule, and $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$. $p(\mathbf{x}_T) = \mathcal{N}(\mathbf{0}, \mathbf{I})$.
Diffusion models generate data by learning to reverse a gradual noising process. (Sohl-Dickstein et al., 2015; Ho, Jain, and Abbeel, 2020)

Sohl-Dickstein, et al. Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML, 2015.
Ho, et al. Denoising Diffusion Probabilistic Models, NeurIPS, 2020.

Diffusion Models: Training and Inference

Training Objective:

$$\mathcal{L}_{\text{simple}} = \mathbb{E}_{\mathbf{x}_0,\boldsymbol{\epsilon},t}\left[\left\|\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t)\right\|^2\right]$$

where $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$.

Inference (Sampling):

- Start from pure noise: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- For $t = T, \ldots, 1$:
  - Predict noise: $\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)$
  - Compute mean: $\boldsymbol{\mu}_\theta(\mathbf{x}_t, t)$
  - Sample: $\mathbf{x}_{t-1} \sim \mathcal{N}(\boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t))$
- Repeat until $\mathbf{x}_0$ (generated sample)

Training: Minimize the simplified objective (Ho, Jain, and Abbeel, 2020).
Inference: Iteratively denoise from random noise to generate data.

Ho, et al. Denoising Diffusion Probabilistic Models, NeurIPS, 2020.

Application in Remote Sensing Image Generation: Text2Earth

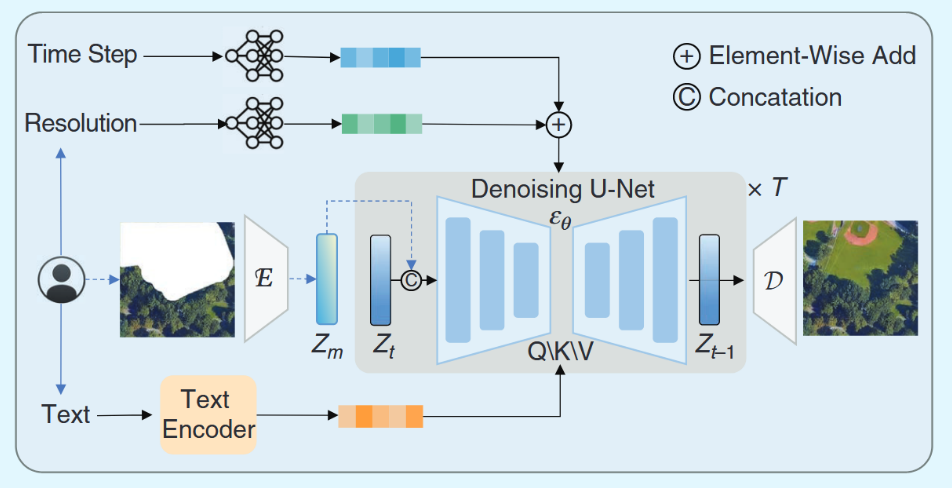


Figure: Text2Earth: Foundation model for text-driven Earth observation (Liu et al., 2025).

Liu, et al. Text2Earth: Unlocking text-driven remote sensing image generation with a global-scale dataset and a foundation model. GRSM. 2025.

Text2Earth: Example Results

Figure: Example results generated by Text2Earth (Liu et al., 2025).

Liu, et al. Text2Earth: Unlocking text-driven remote sensing image generation with a global-scale dataset and a foundation model. GRSM. 2025.

Application in Remote Sensing Image Generation: CRS-Diff

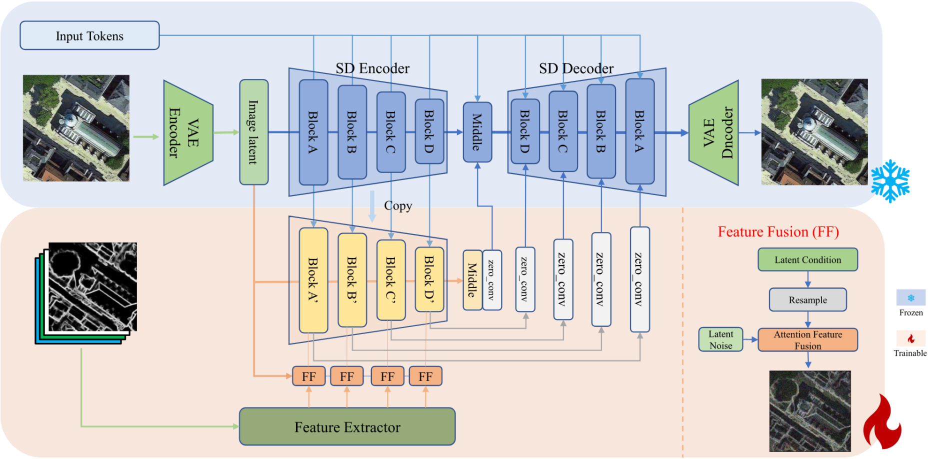


Figure: CRS-Diff: Controllable remote sensing image generation framework (Tang, Li, et al., 2024).

Tang, et al. CRS-Diff: Controllable Remote Sensing Image Generation with Diffusion Model. TGRS. 2024.

CRS-Diff: Example Results

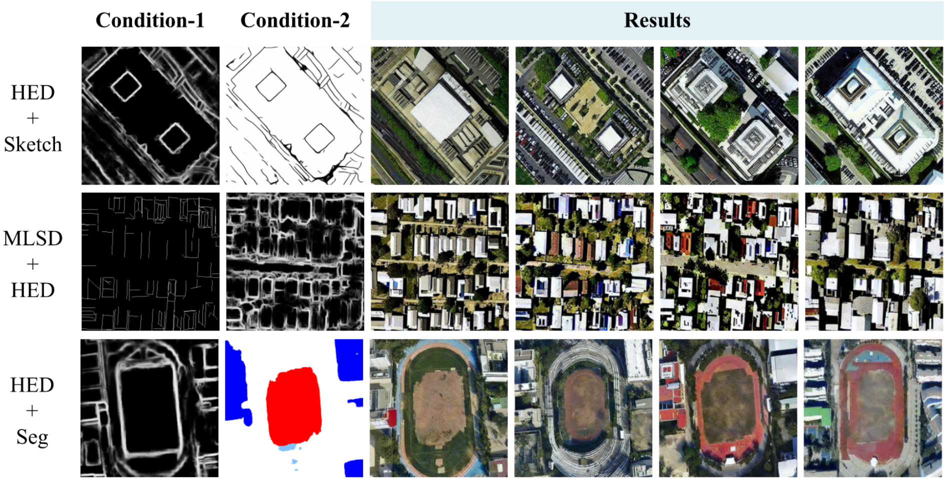


Figure: Example results generated by CRS-Diff (Tang, Li, et al., 2024).

Tang, et al. CRS-Diff: Controllable Remote Sensing Image Generation with Diffusion Model. TGRS. 2024.

DiffusionSat: Framework Overview

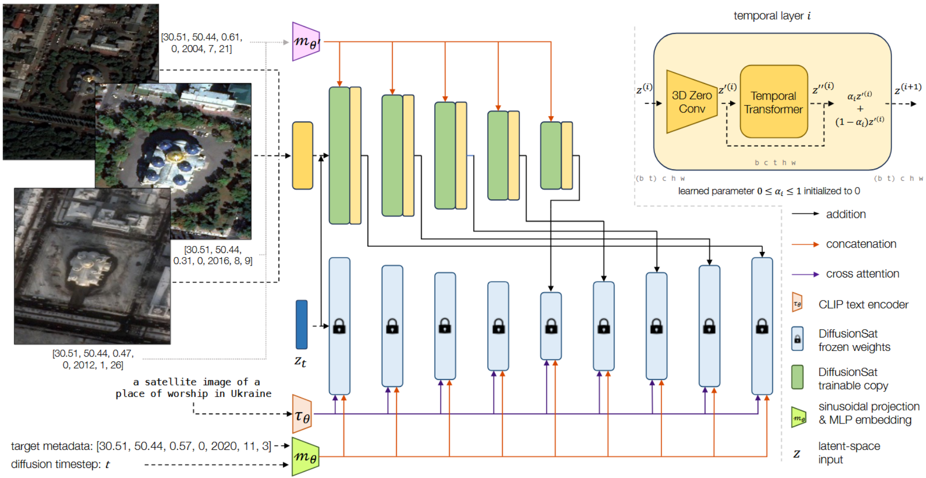


Figure: DiffusionSat: A generative foundation model for satellite imagery (Khanna et al., 2024).

Khanna, et al. DiffusionSat: A Generative Foundation Model for Satellite Imagery, ICLR, 2024.

DiffusionSat: Super-Resolution Results

Figure: Example results: DiffusionSat for multi-spectral super-resolution (Khanna et al., 2024).

Khanna, et al. DiffusionSat: A Generative Foundation Model for Satellite Imagery, ICLR, 2024.

DiffusionSat: Inpainting Results

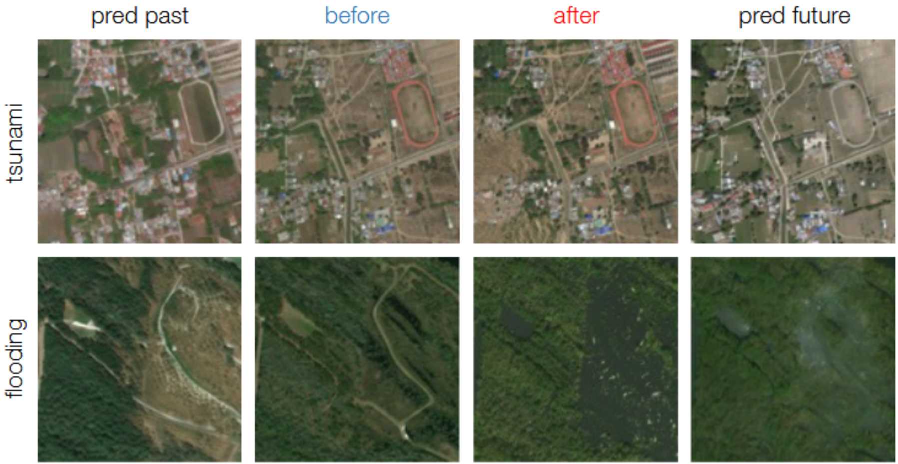


Figure: Example results: DiffusionSat for remote sensing image inpainting (Khanna et al., 2024).

Khanna, et al. DiffusionSat: A Generative Foundation Model for Satellite Imagery, ICLR, 2024.