Magnetogram-to-Magnetogram: Generative Forecasting of Solar Evolution

European Space Weather Week

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Goal of the project

Machine Learning Goal

Be able to predict the magnetogram 1 day before.

Why do we want to do this analysis?

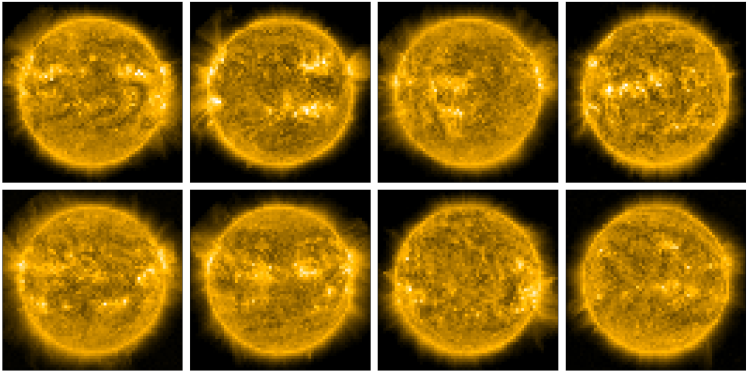
Make more powerful solar flare predictions and better understand the evolution of the active regions.

Data sources

We used the following data sources:

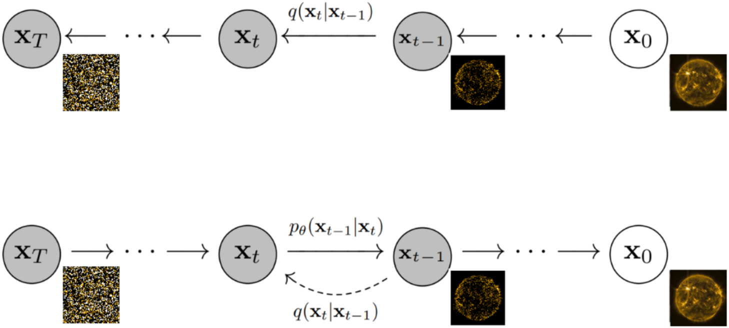
- **Solar Flare events catalogue**: A new catalogue of solar flare events from soft X-ray GOES signal in the period 2013–2020 (Nicola Plutino et al 2023),
- **SDO/HMI**:
  1. Magnetogram 24h before flaring time,
  2. Magnetogram at flaring time,
- The total number of paired images is 43912.

Previous work of Diffusion Model in Solar Physics



Francesco Pio Ramunno et al 2024 "Solar synthetic imaging: Introducing denoising diffusion probabilistic models on SDO/AIA data." Astronomy & Astrophysics. 686(A285)

What are the DDPMs?



Adapted from Ho et al. 2020

Experiments setup and evaluation metrics

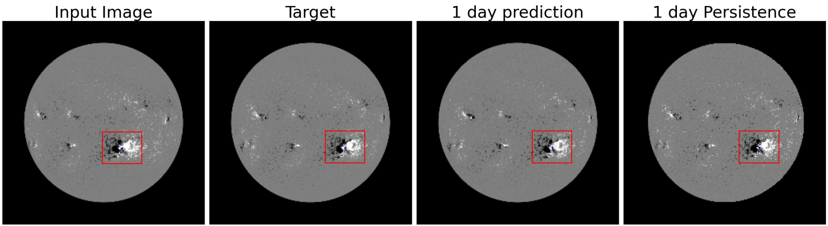
We use the following setup:

- Image resolution: 256x256 pixel,

We evaluate with the following metrics

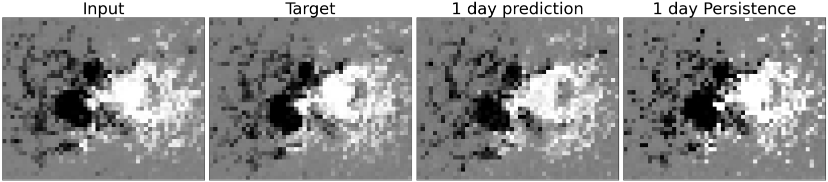
- Computer Science metrics:
  1. PSNR,
  2. SSIM,
  3. LPIPS,
- Physics metrics:
  1. Full disk unsigned magnetic flux,
  2. Full disk net magnetic flux,
  3. Active region unsigned magnetic flux,
  4. Active region net magnetic flux,
  5. Active region size,
  6. Polarity Inversion Line length,
  7. Jaccard Index.

Visual inspection



25 October 2014 - 17:08 UTC

Visual inspection



25 October 2014 - 17:08 UTC

Computer Science Metric Results

Model	PSNR ↑	SSIM ↑	LPIPS ↓
DDPM	$\mathbf{31.2 \pm 0.03}$	0.7 ± 0.0004	$\mathbf{0.03 \pm 0.0002}$
Persistence	15	$\mathbf{0.78}$	0.10

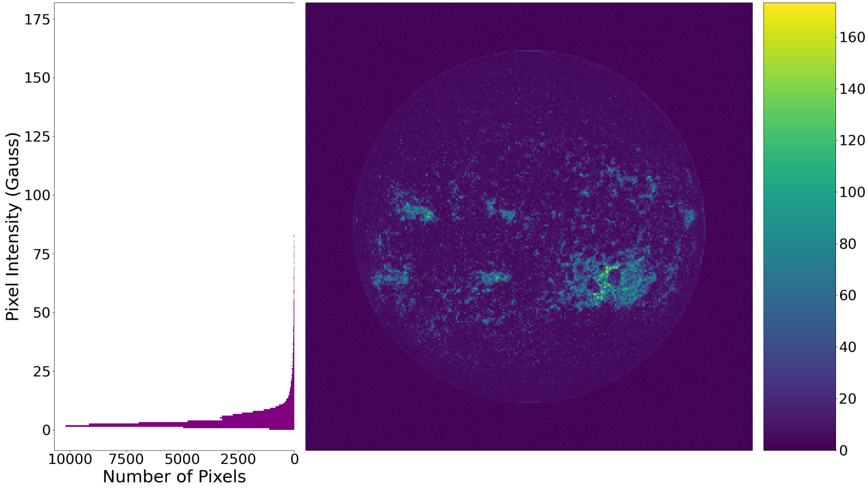
Physics Metric Results

Model	FD TOT Flux	FD NET Flux	AR TOT Flux	AR NET Flux
DDPM	$\mathbf{0.37 \pm 0.004}$	$\mathbf{1.25 \pm 0.0}$	$\mathbf{5.76 \pm 0.14}$	$\mathbf{13.96 \pm 11.15}$
Persistence	2.01	1.25	14.44	42.37

Physics Metric Results

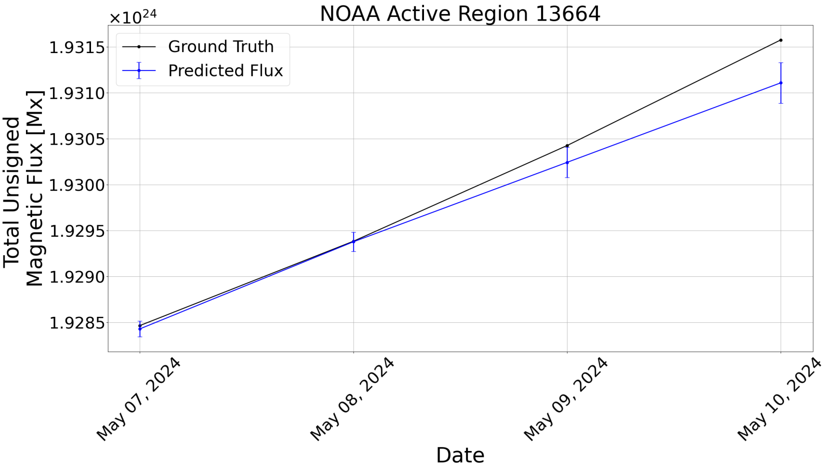
Model	Size AR	PIL length	Jacc Idx ↑
DDPM	$\mathbf{2.9 \pm 0.51}$	$\mathbf{3.34 \pm 1.37}$	$\mathbf{0.65 \pm 0.002}$
Persistence	8.09	5.65	0.55

Where is our prediction less reliable?

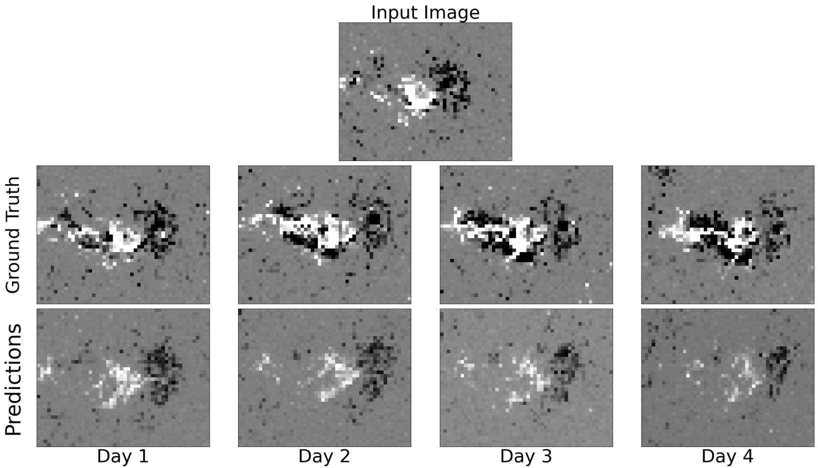


1. Introduction
2. The dataset
3. Model choice and setup
4. Results
5. Additional tests
6. Conclusion

Can we predict the Unsigned Magnetic Flux of unstable AR?



Can we predict the Unsigned Magnetic Flux of unstable AR?



Conclusion

- **Diffusion Model's Performance:**
  - The diffusion model is able to predict the magnetogram 24 h in advance and it beats the persistence model,
  - The model has more difficulties to predict the most unstable region, such as the region around the Polarity Inversion Line, in accordance with our physics knowledge (Kleint, L. 2017, "First Detection of Chromospheric Magnetic Field Changes during an X1-Flare"),
- **Future works:**
  - Inject different types of information (e.g. velocity fields, AIA channels, LoS magnetograms of multiple days) in the model to understand the evolution of these dynamic processes better,
  - Use super resolution to be able to generate images in the full HMI resolution 4kx4k with 0.5" per pixel.

What are the DDPMs?

Diffusion Probabilistic models are very popular nowadays and we can summarize their usage into the following bullet points:

- Forward process or noising process (Ho et al., 2020):

$$q(x_{1:T}|x_0) = \prod_{t=1}^{T} q(x_t|x_{t-1}),\ q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t\mathcal{I}) \tag{1}$$

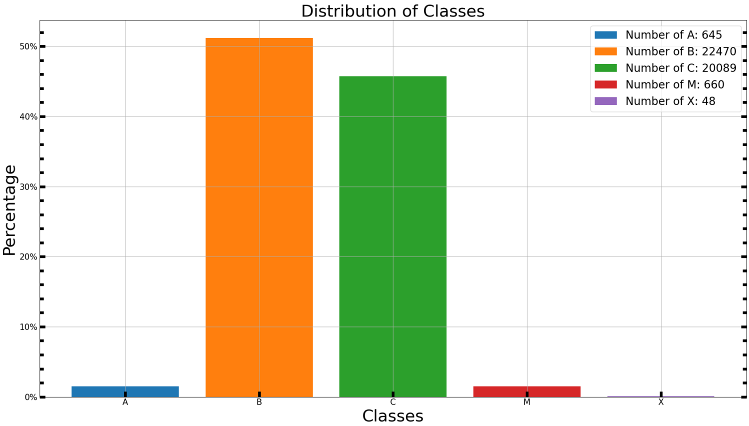
- Reverse process or denoising (Ho et al., 2020):

$$p_\theta(x_{t-1}|x_t) := \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \tag{2}$$

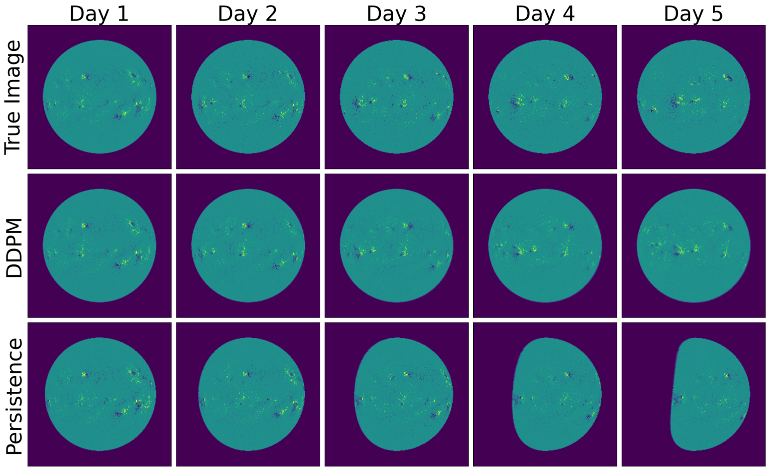
Palette-like approach

- To apply the Denoising Diffusion Probabilistic Models for Image-to-Image translation we applied the Palette approach (Chitwan Saharia et al 2021),
- Given a set of paired data (x_i, y_i), where:
  1. x_i: input image,
  2. y_i: target image,
- Training step: we noise the target image with a random number of timesteps t, we concatenate the target image and the input image channel-wise, pass through the model and we predict the noise that we added on the target image.

Distribution of the images per GOES class



5 days prediction test



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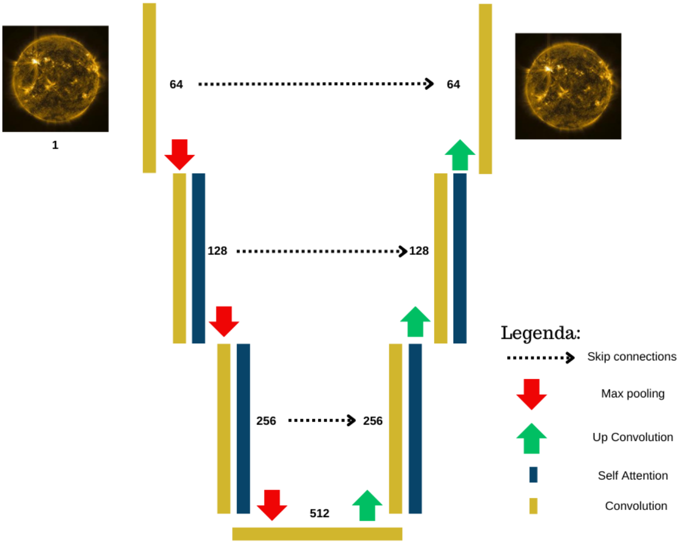

1
64
64
128
128
256
256
512
Legenda:
Skip connections
Max pooling
Up Convolution
Self Attention
Convolution

Metrics

- FID:
  1. $FID(x, g) = ||\mu_x - \mu_g||^2 + \mathrm{Tr}(\Sigma_x + \Sigma_g - 2(\Sigma_x \Sigma_g)^{(1/2)})$,
- PSNR:
  1. $\text{PSNR} = 10 \cdot \log_{10}\left(\frac{\text{MAX}^2}{\text{MSE}}\right)$
- SSIM:
  1. $\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$
- LPIPS: L2 Norm in a VGG latent space.