Magnetogram-to-Magnetogram (M2M): Generative Forecasting of Solar Evolution

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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.

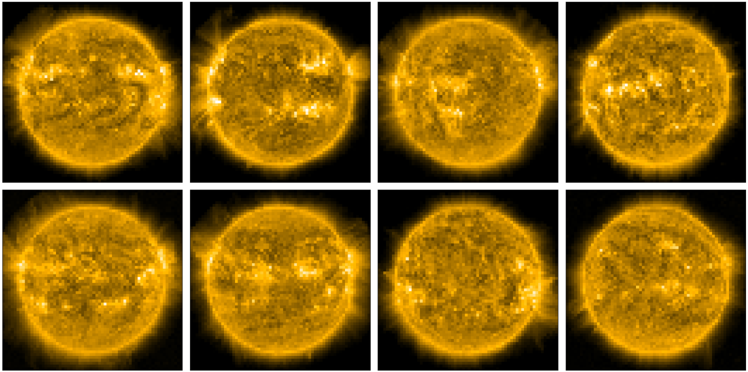
Data sources

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,
  3. 94 Å 24h before flaring time,
  4. 131 Å 24h before flaring time,
  5. 193 Å 24h before flaring time.
- The total number of paired images is 43912.

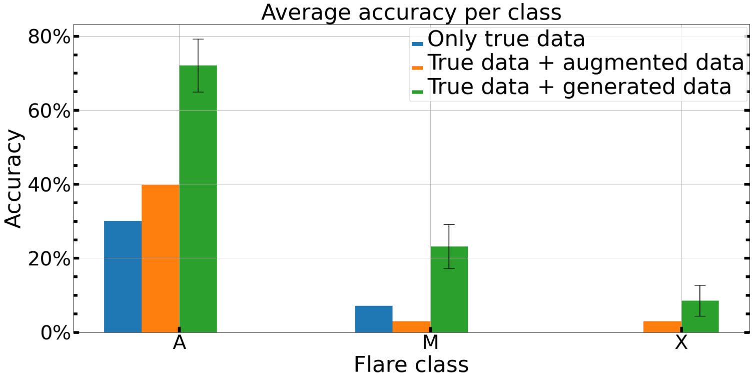
1. Introduction
2. The dataset
3. Experiments and Discussion
4. Results
5. Conclusion

Previous work of Diffusion Model in Solar Physics



F. P. Ramunno et al 2023 (under review)

Previous work of Diffusion Model in Solar Physics



Generated augmentations are better than classical augmentations (F. P. Ramunno et al 2023 (under review)).

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,

  we noise the target image with a certain number of timesteps t and then we concatenate them channel-wise and pass through the model.

Experiments setup and labelling systems

We use the following setup:

- Image resolution: [128x128, 256x256],

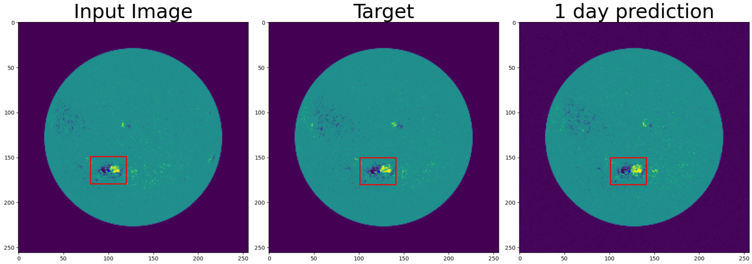
We perform the following distinct experiments:

- Magnetograms 24h to Magnetograms at flaring time,
- Magnetograms + 94 Å 24h to Magnetograms at flaring time,
- Magnetograms + 131 Å 24h to Magnetograms at flaring time,
- Magnetograms + 193 Å 24h to Magnetograms at flaring time

Metric Results

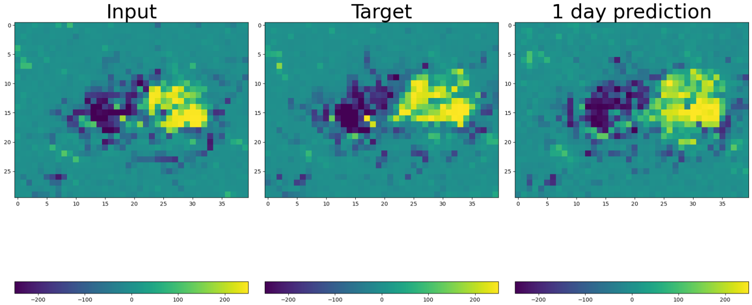
Metric	Mag	Mag + 94 Å	Mag + 131 Å	Mag + 193 Å
FID ↓	**0.009**	0.262	0.226	0.259
LPIPS ↓	**0.026 ± 0.014**	0.032 ± 0.016	0.032 ± 0.017	0.032 ± 0.019
PSNR ↑	**21.1 ± 1.92**	20.1 ± 1.99	20.0 ± 1.98	20.0 ± 2.03
SSIM ↑	**0.691 ± 0.047**	0.667 ± 0.051	0.650 ± 0.064	0.660 ± 0.054

Visual inspection



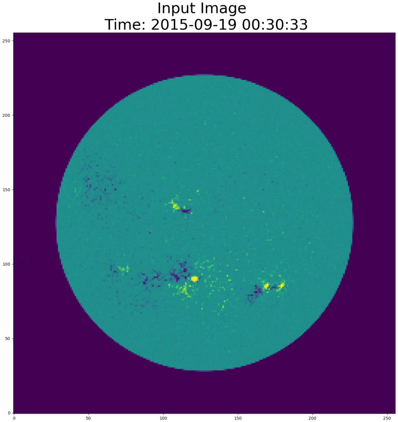
2015-08-23 15:06:37

Visual inspection

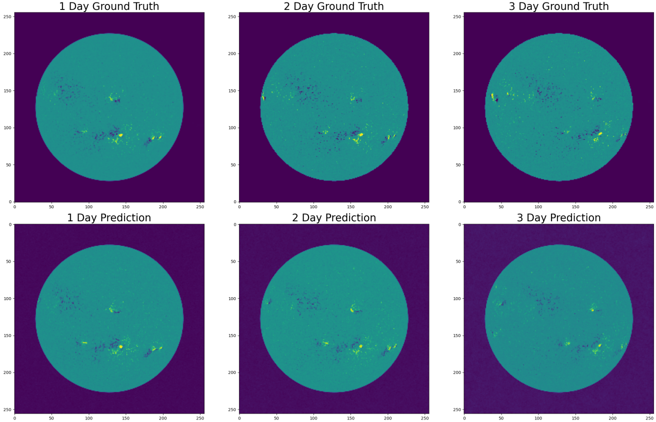


2015-08-23 15:06:37 AR=12403

Zero shot prediction



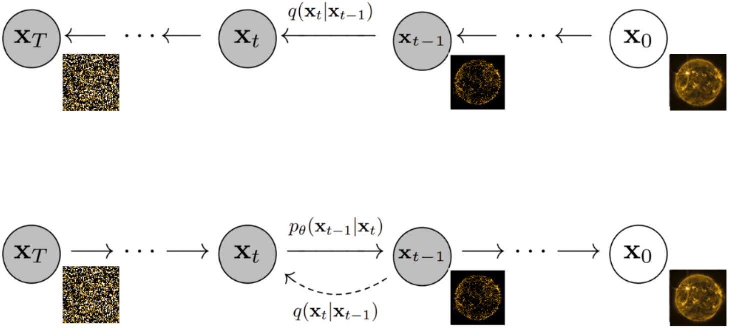
Zero shot prediction



Conclusion

- The usage of more wavelengths is not enhancing the model results, thus it is better to use magnetogram only as input data,
- The average percentage variation in terms of the total unsigned magnetic flux is around 6%, but more analysis are needed,
- The model is able to do "zero-shot" prediction more than one day in advance,
- We want to determine:
  1. The total unsigned magnetic flux,
  2. The net magnetic flux,
  3. The area of the active region,
  4. The orientation of the polarity inversion line,

What are the DDPMs?



Adapted from Ho et al. 2020

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):

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

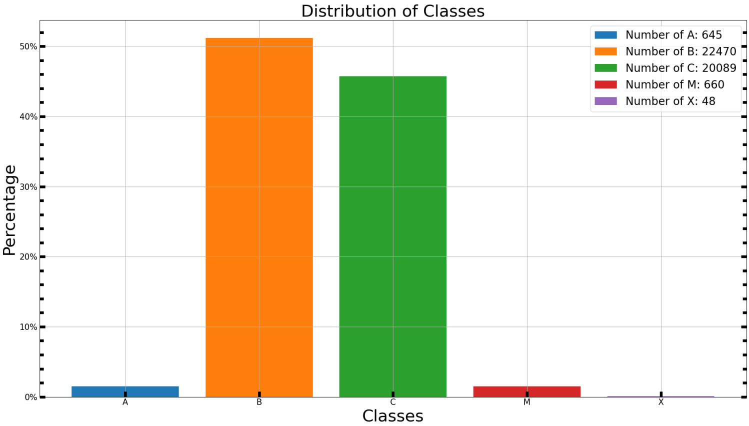
- Reverse process or denoising (Ho et al., 2020):

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

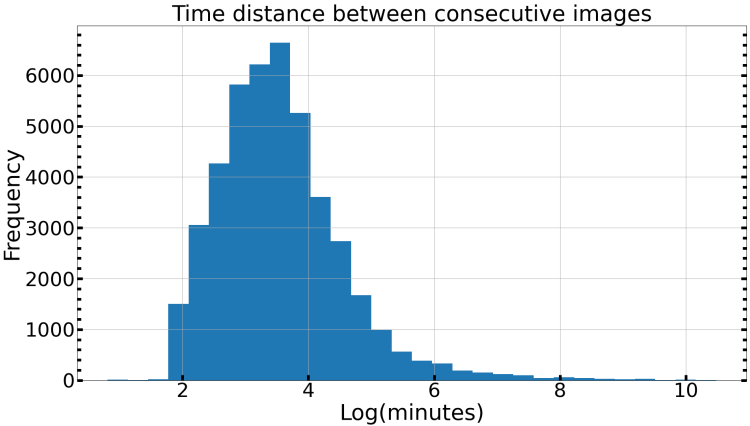
- Classifier Free Guidance (Ho Salimans, 2022)

$$\tilde{\epsilon_\theta}(z, c) = \epsilon_\theta(z, c) + w \cdot (\epsilon_\theta(z, c) - \epsilon_\theta(z)) \tag{3}$$

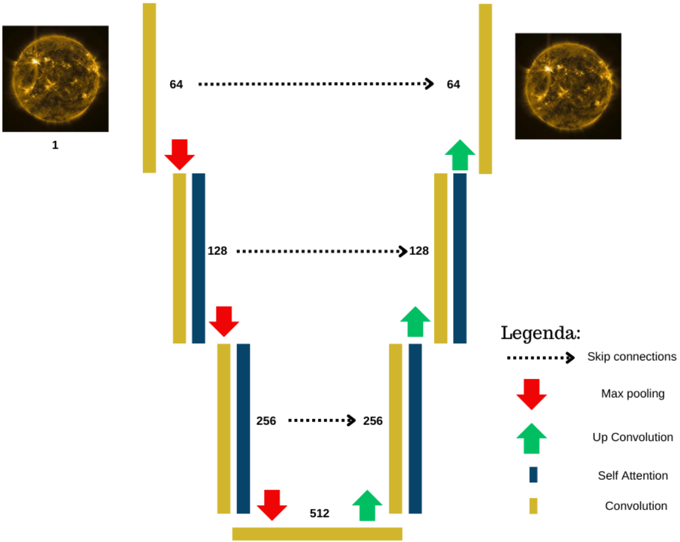
Distribution of the images per GOES class



Time distribution



Unet



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. $\mathsf{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathsf{MAX}^2}{\mathsf{MSE}}\right)$
- SSIM:
  1. $\mathsf{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$
- LPIPS: L2 Norm in a VGG latent space.