STIX solar flare image classification and reconstruction with machine learning

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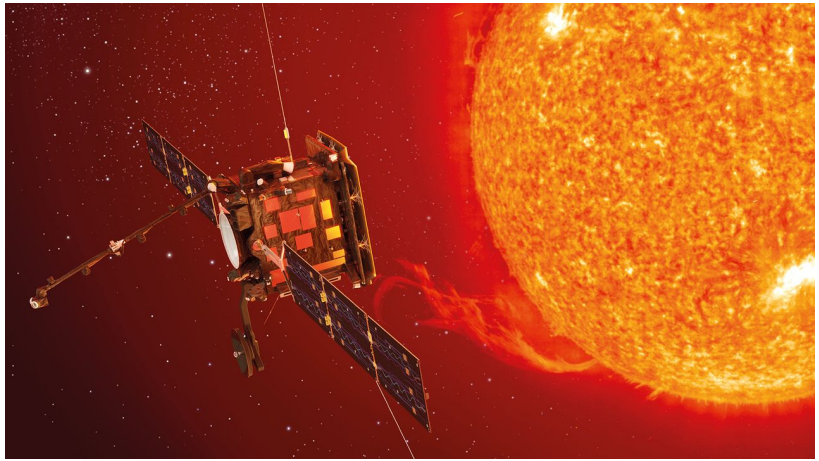
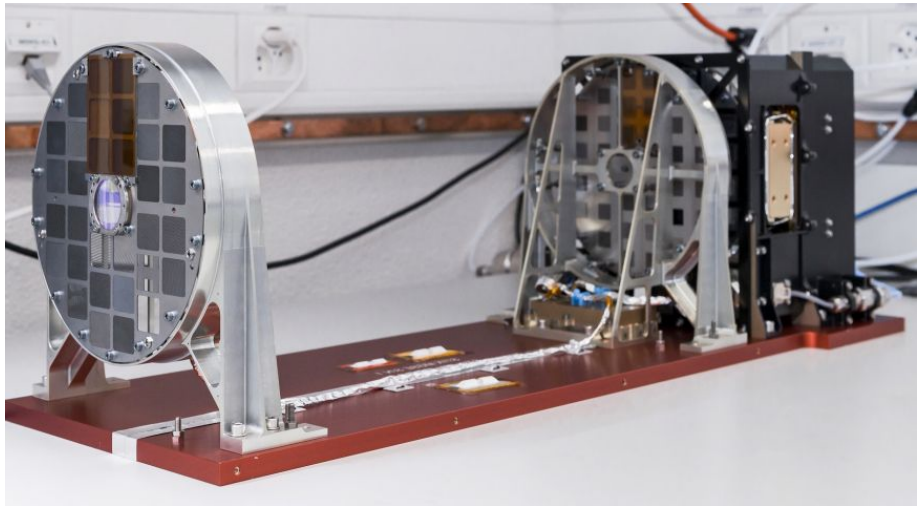
The Spectrometer/Telescope for Imaging X-rays (STIX) onboard Solar Orbiter

- STIX is an X-ray imager on-board Solar Orbiter
- STIX measures spectra & timing and takes images of solar flare hard X-rays

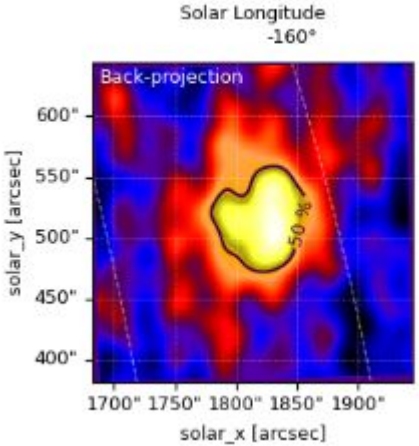


Solar Orbiter, Launched on Feb 10, 2020

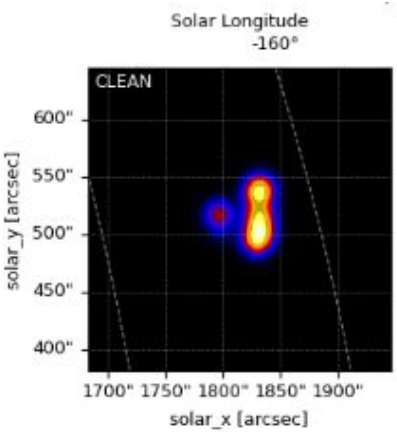
- X-ray detector energy range: 4 - 150 keV
- Each of 32 collimators measures a Spatial Fourier component
- Image reconstruction based on the Fourier-transform



Why we are using machine learning



CLEAN



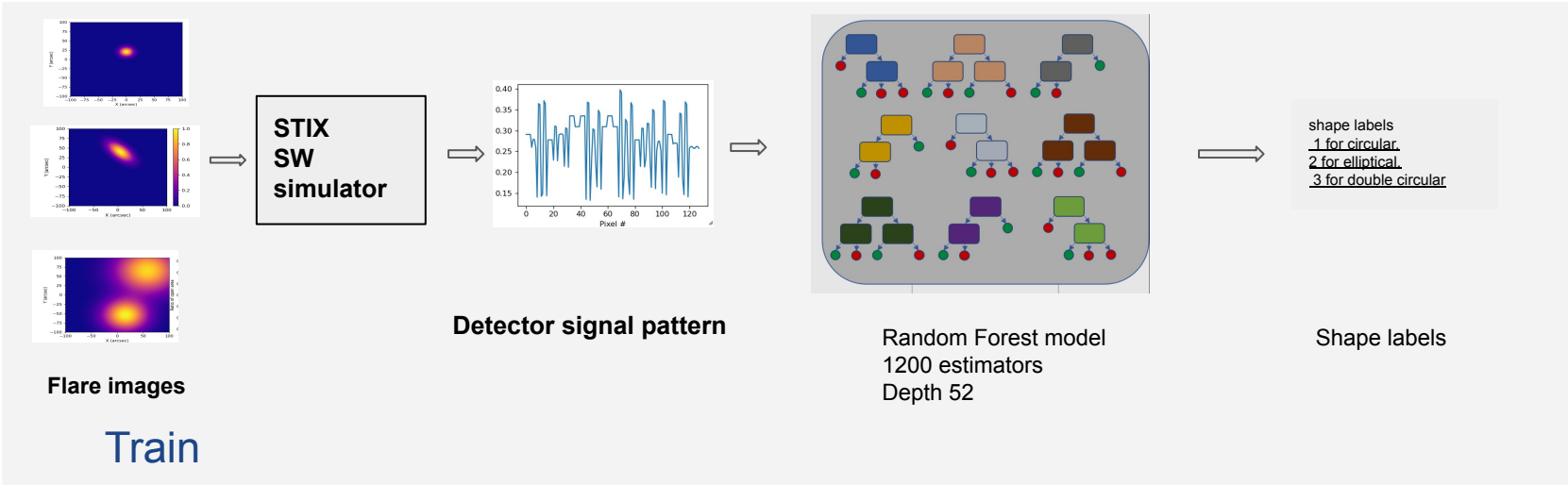
Dirty image from inverse Fourier transform

One source, multiple sources, any artifacts?

Motivations to use machine learning techniques

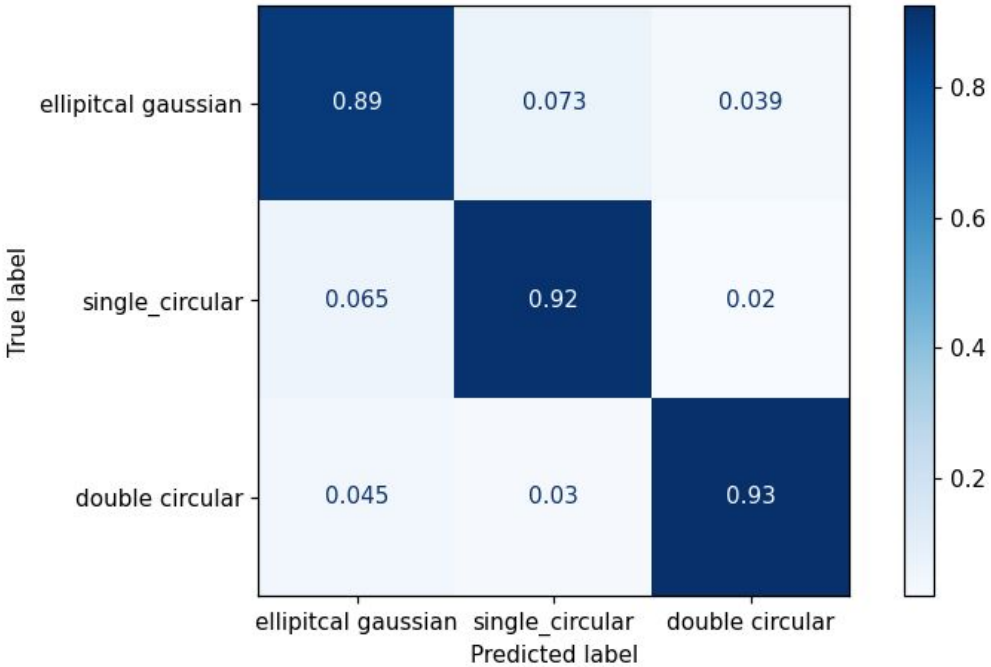
- Identify source shapes (one source, multiple sources, etc.)
- Image reconstruction

X-ray image classification with random forest



- 30,000 simulated images of different shapes used for training
- Other machine learning algorithms tried, but best results obtained with random forest

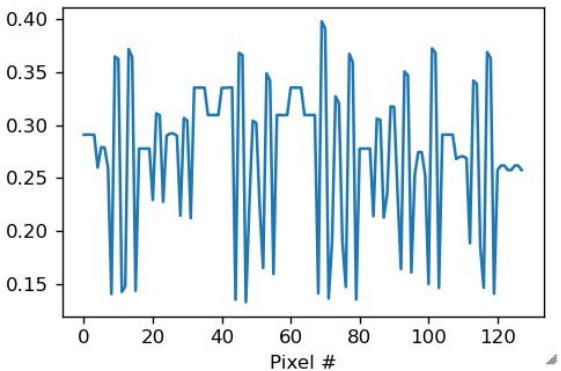
Performance of the RF image classification model



Simulated images used for validation
Accuracy ~ 90%

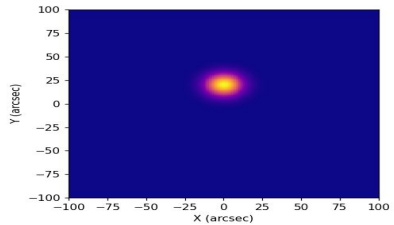
Parameterized image reconstruction using neural networks

- Most solar flare X-ray images have one of the three shapes
  - Circular Gaussian
  - Elliptical Gaussian
  - Double-circular Gaussian



Nb. of photons recorded by pixels (signal pattern)

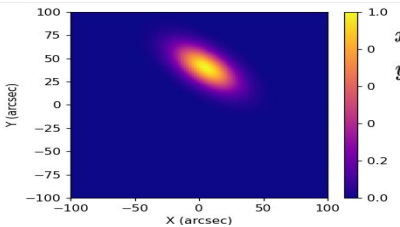
Machine learning?



$$f(x,y) = \exp\left[-\left(\left(\frac{x-x_0}{2\sigma}\right)^2 + \left(\frac{y-y_0}{2\sigma}\right)^2\right)\right]$$

Circular Gaussian:

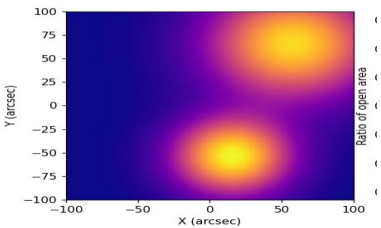
3 free parameters



$$x_p = (x-h)\cos(\theta) - (y-k)\sin(\theta);$$
$$y_p = (x-h)\sin(\theta) + (y-k)\cos(\theta);$$
$$u = (x_p/a)^2 + (y_p/b)^2;$$
$$f(x,y) = \exp(-u/2)$$

Elliptical Gaussian:

5 free parameters

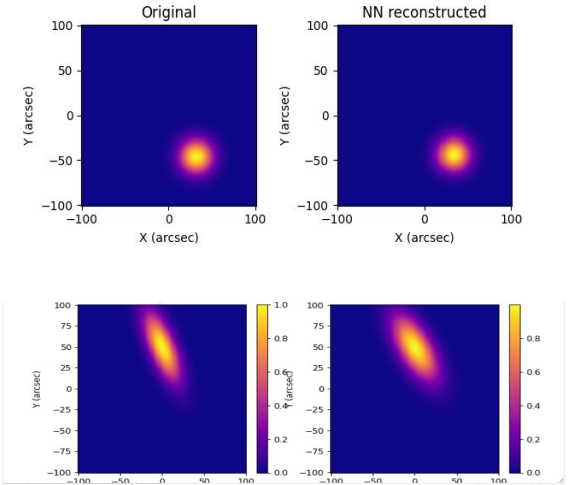


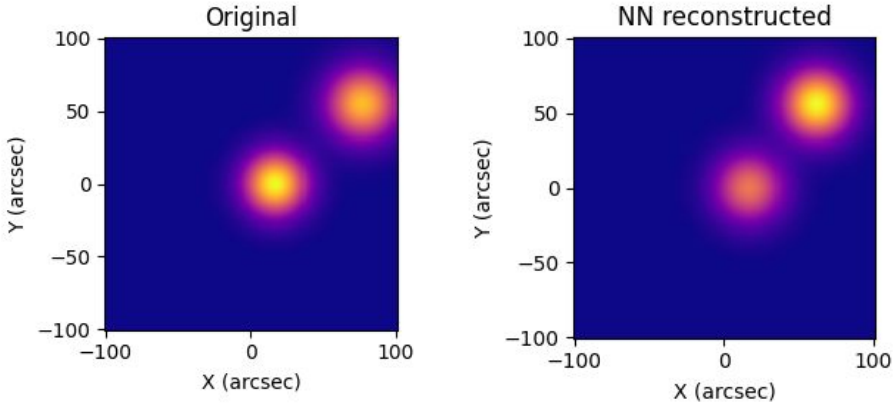
Elliptical Gaussian: 7 free parameters

Parameterized flare image reconstruction with neural network

- Neural network architecture
  - two hidden layers
  - Activation function ReLU
- Detector readouts as inputs (124 channels)
- Shape parameters as outputs
  - Seven parameters for double-circular
  - Four of seven set to zeros for circular Gaussian shapes
  - Two of seven set to zeros for elliptical Gaussian
- 300,000 simulated samples used for training

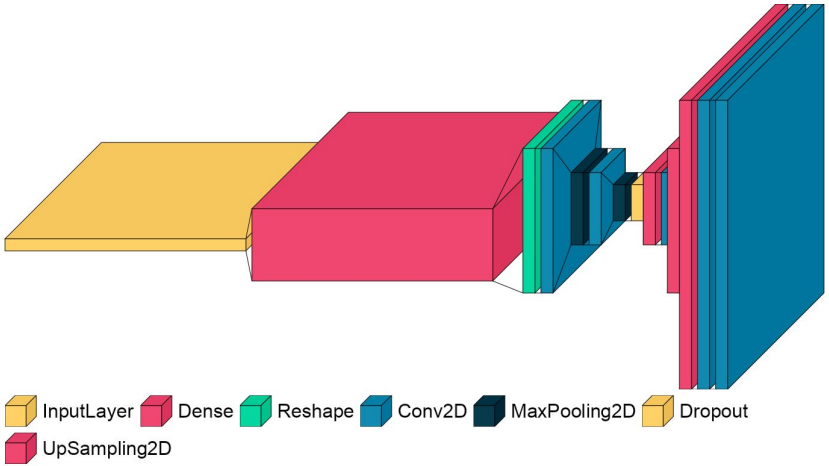
Performance of the neural network image reconstruction model

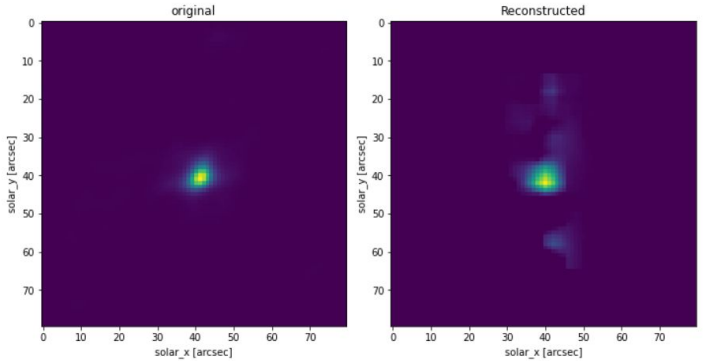




- Difference between original source centers and reconstructed centers < 5 arcsec
- Diff. between original radius (or width/height) vs reconstructed < 2 arcsec

Direct image reconstruction with deep learning





- Detector signal pattern as input and images as outputs
- ~ 3000 flare images observed in 2021 and 2022 used for training
- Promising results obtained from preliminary tests
- Further optimization ongoing

Conclusion

- Random Forest model achieved 90% accuracy for flare image classification
- Image reconstruction results with neural networks are comparable to those with the traditional algorithms.