Using Deep Learning in flare forecasting

Paloma Jol, D. S. Bloomfield, S. Régnier

Dept. of Mathematics, Physics and Electrical Engineering, Northumbria University, Newcastle Upon Tyne, UK

E-mail: paloma.jol@northumbria.ac.uk

Abstract

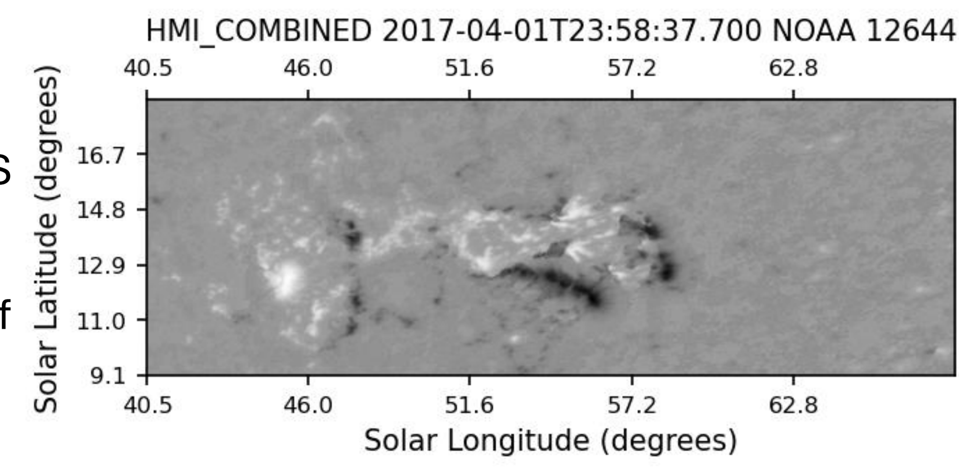
This work aims to predict solar flares within a forecasting window by training a Deep Learning model. We use images obtained from the Solar Dynamics Observatory (SDO) Space weather HMI Active Region Patch (SHARPs) specifically the radial component of the magnetic field. By using the whole active region image observations as input, we want to improve our understanding of the physics leading up to flares and thus also improve our ability to forecast them. We looked at magnetogram images between 2013-2023 with cadence of 24 hours and the corresponding GOES X-ray flux in the next 24 hours to create the image and flare-outcome label pairs. Filtering was performed to limit our set to single NOAA number HARP regions within ±75° longitude. With HARP separated data sets for training and testing our model we implemented a Convolutional Neural Network and a Fully Convolutional Network for the binary classification of flare events with GOES X-ray flare class above C1. Our best models show a TSS of 0.53 and 0.56 on the testing data.

1 – Introduction

- Solar flares are large eruptions of electromagnetic radiation from the Sun which can affect the Earth's atmosphere and the radio communications.
- Since the delay between the flare event and their near-Earth effects is only 8 minutes, it is essential we can forecast these events in advance.
- Current flare forecasting uses a feature extraction on input + machine learning (e.g. FLARECAST; Georgoulis et al. 2021)
- More recently Deep learning model are being applied directly on image/video with learned feature extraction within the model (Berger et al. 2022, Guastavino et al. 2023, Pandey et al. 2023)

2 – Data

- We use B_R - component magnetogram images taken by the Helioseismic and Magnetic Imager (HMI) instrument on the Solar Dynamics Observatory (SDO) (Bobra et al. 2011)
- Only single NOAA number HARPs within ±75° longitude, at 24h cadence
- Flare activity taken from GOES X-ray flux, where flare **≥C1-class**
- Flare: No Flare **class imbalance** of approximately 1:6



3 – Methods

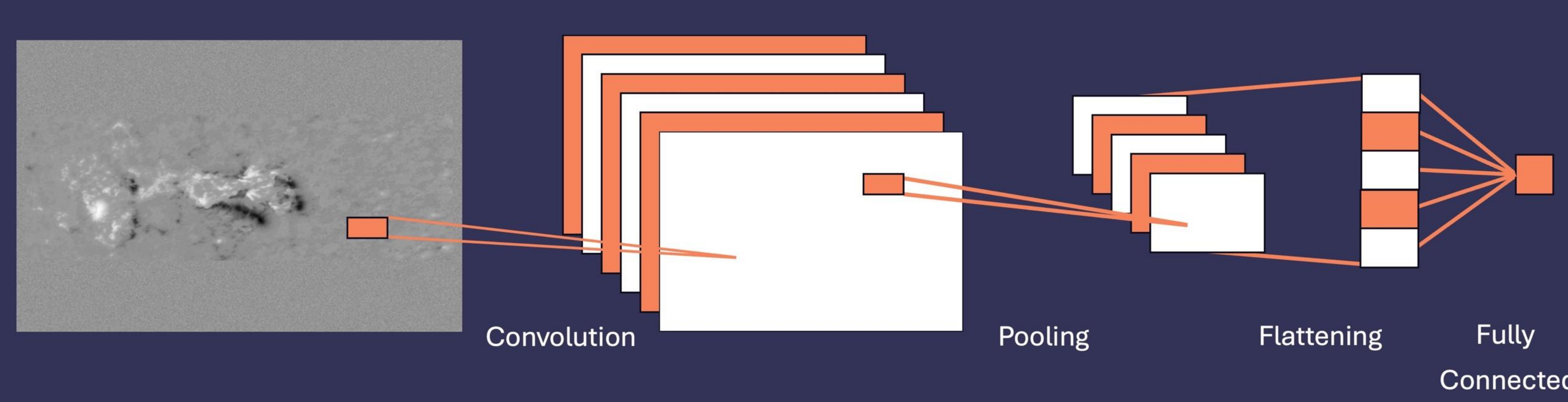
- Deep Learning is a form of machine learning that combines the feature extraction and the classifier into one trainable model.
- Use *BCEWithLogitsLoss* function with penalty value to correct more for getting the 'yes' flare wrong
- Use a **Convolutional Neural Network (CNN)** with filled images of fixed size (408,1080) with Fully Connected layers

  OR

  Use a **Fully Convolutional Network (FCN)** with variable image size by replacing Fully Connected by Adaptive Pooling layer
- Use **True Skill Statistic (TSS)** as it is insensitive to the class imbalance

$$TSS = \frac{TP}{TP + FN} - \frac{FP}{FP + TN}$$

CNN architecture



Filled Input image
Original image is padded with Gaussian noise to (408,1080)

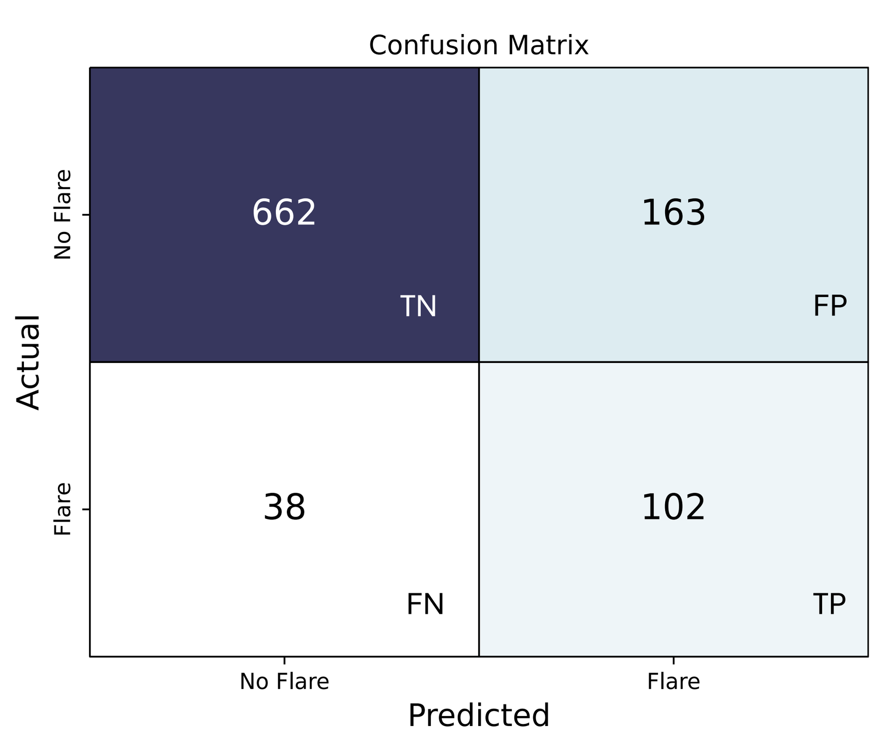
Feature Extraction

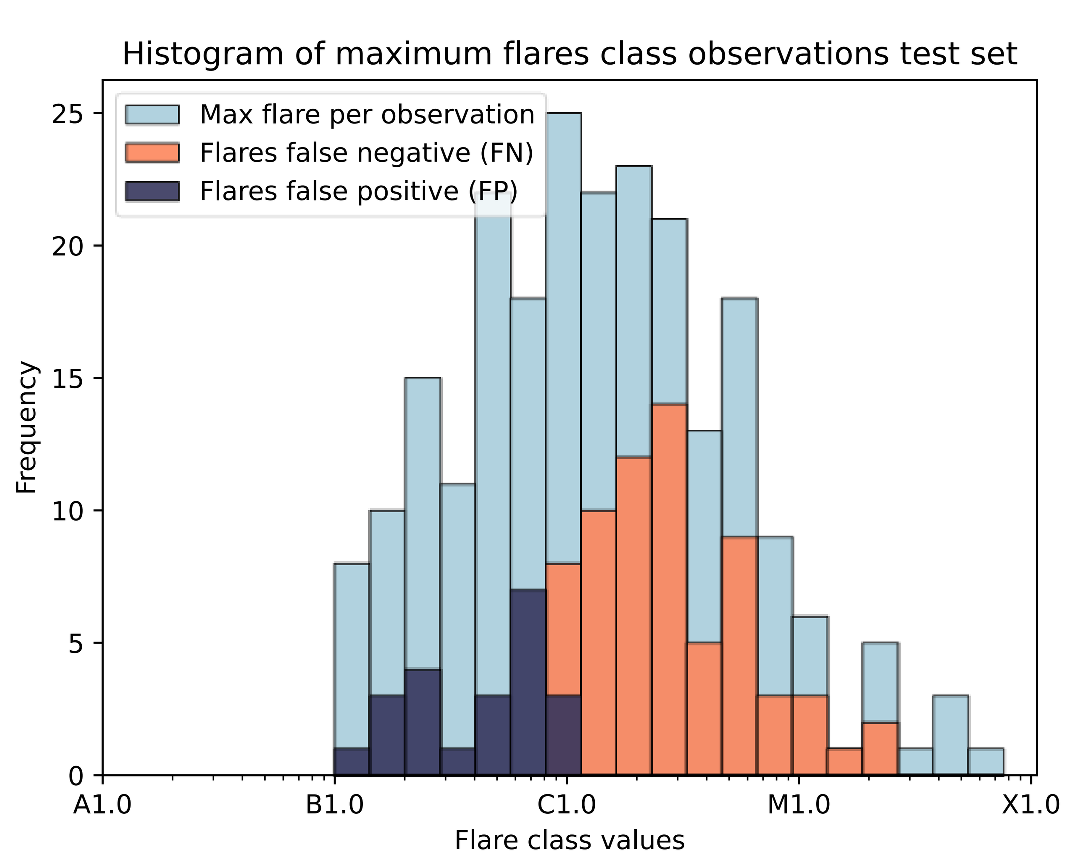
Classification

4 – Results

CNN

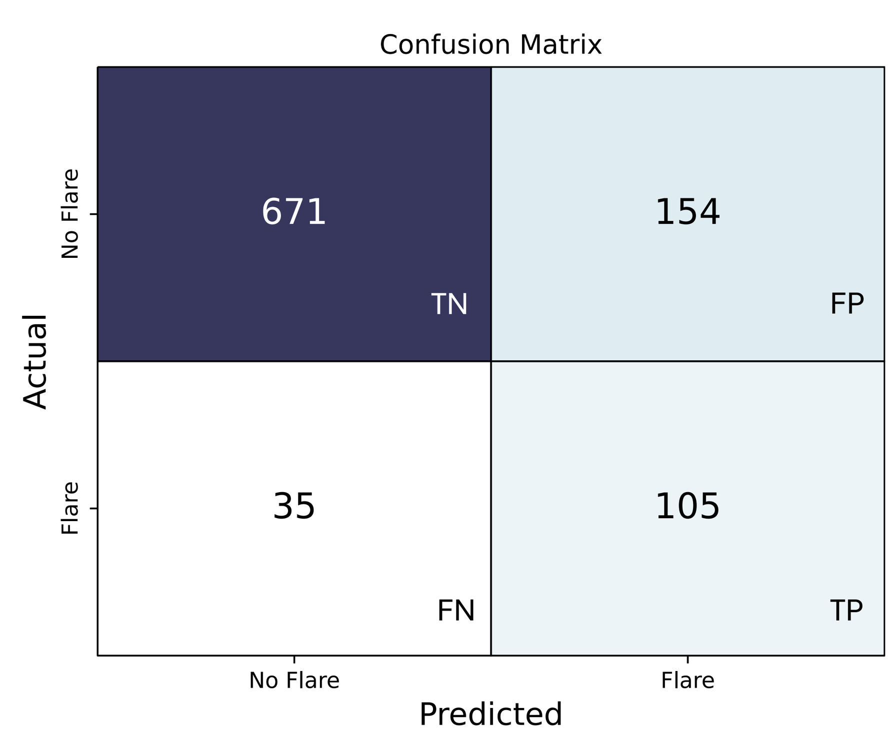
- Trained an CNN for 20 epochs, high levels of overfitting in training
- Some False Positives do have some B-class flaring activity
- Correctly predict about 75% of ≥C1-class, but high false detection of 20%
- Achieves a TSS of 0.53

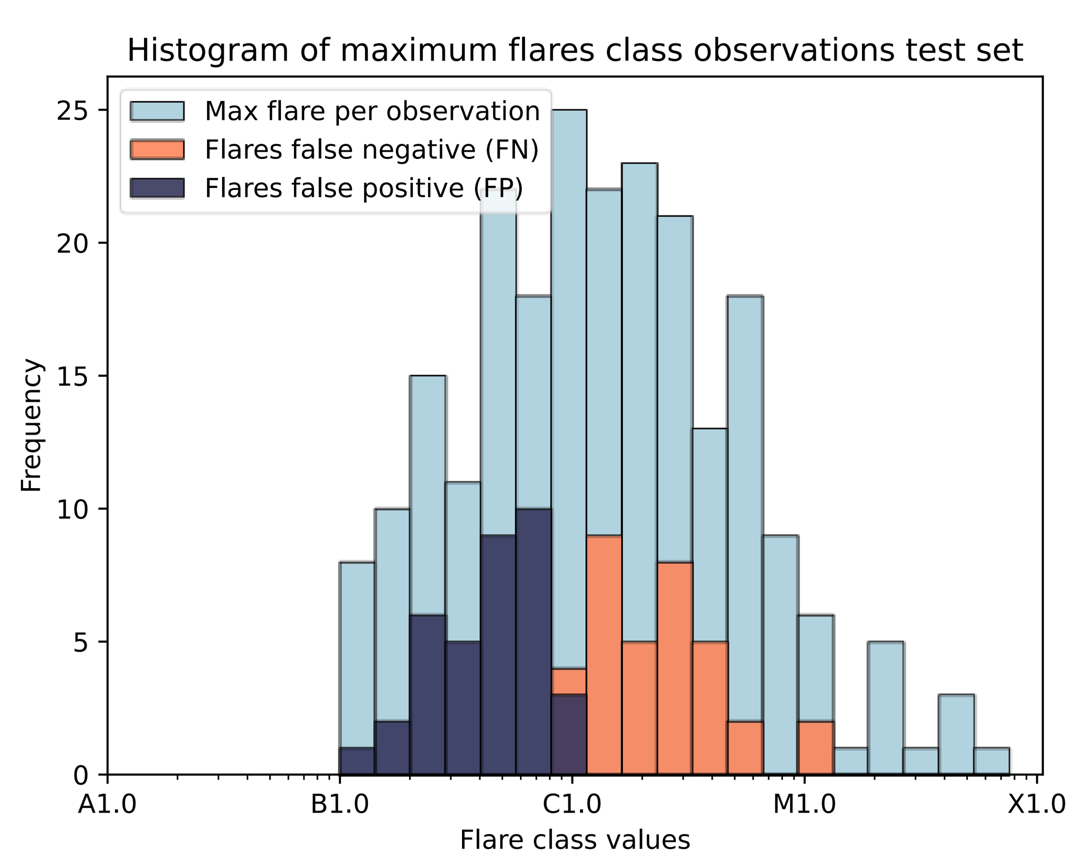




FCN

- Trained an FCN with Data Augmentation injection at epoch 20
- Still high rates of false detection, but higher portion show B-class activity
- Most False Negatives in range C1-C6, with most M-class flares correct
- Achieves a TSS of 0.56



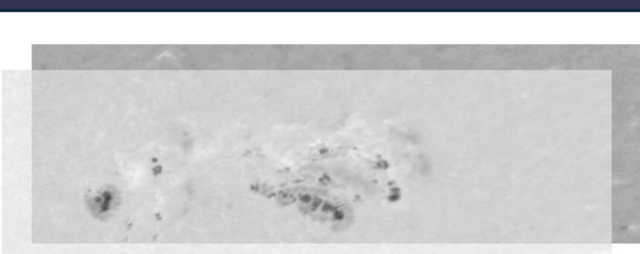


5 – Summary

- Predicting solar flares of ≥C1-class in next 24 hour using magnetogram data from 2013-2023
- Dataset of 9000 images of magnetic field and flare history
  - Includes various image sizes
  - Strong class imbalance
- Trained an CNN using fixed-size filled images and an FCN using variable-size images
- Models correctly predict about 75% ≥C1 flares but 20% false detection
- The FCN does well in predicting M-class flares but small sample size
- TSS of 0.53 and 0.56 achieved on the testing set
- Questions remain on whether the SHARP image size is leading to a bias. And which areas of the image are important for the classification
- Work to interpret the model's decisions is still pending, which could provide insights into the achieved metrics

6 – Future Work

- Single line-of-sight magnetogram alone might not be sufficient to get a reliable forecast.



- We have collected **magnetogram and continuum** images to use as input
- The 2D input shows promising results with first metrics showing lower loss and similar TSS as their tuned 1D equivalent

References

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