Advancing Solar Flare Forecasting: Predicting Solar Flares via a Deep Learning Approach Using Time Series of SDO/HMI Line-of-Sight Magnetograms

Elizabeth Doria Rosales[1, 2] Vincenzo Carbone[2] Mariarosaria Falanga[3] Angelo Ciaramella[4] Emanuel Di Nardo[4] Antonio Ielo[2]

1. University of Trento 2. University of Calabria 3. University of Salerno 4. University Parthenope of Naples

Abstract ID: #253

Abstract: Solar flares, sudden bursts of electromagnetic energy originating from magnetically active regions on the solar surface, pose significant risks to satellite infrastructure, communication systems, and power grids. Predicting these events is crucial for both physicists and governmental agencies. Recent observations and research have revealed that solar flares are more complex phenomena than previously thought, as they extend from the corona to the lower photosphere, underlining the interconnected nature of the Sun's atmospheric layers and emphasizing the need for a comprehensive understanding of solar flare dynamics to improve space weather forecasting and our ability to protect space-based technology and infrastructure. Conventional approaches to this problem rely on features extracted from line-of-sight (LoS) magnetograms of solar active regions, which have traditionally been linked to increased flare activity. More recent methodologies leverage temporal series of LoS magnetograms to extract as much information as possible from available data, progressing towards a fully automated flare forecasting system. Despite these advancements, recent studies with LoS magnetograms haven't shown significant improvements over previous methods, raising doubts about their effectiveness. We propose a deep learning-based approach to address this challenge. We model the solar flare forecasting problem as a binary time series classification task using line-of-sight (LoS) magnetograms obtained from the Solar Dynamics Observatory's Helioseismic and Magnetic Imager (SDO/HMI). These magnetograms provide crucial data capturing magnetic field variations on the solar surface, which are essential for predicting solar activity. Our primary objective is to distinguish between active regions likely to produce M- or X-class flares within a 24-hour window and those remaining inactive. Such a classifier could be instrumental in the development of an early warning system for solar flares. Our proposed approach consists of two phases: firstly, a Convolutional Neural Network (CNN) autoencoder performs feature extraction from the magnetograms. Secondly, a Long Short-Term Memory (LSTM) binary classifier processes the extracted features to predict flare activity. Our proposed methodology achieves a remarkable 90% test accuracy. It is validated against test case AR HARP 377, demonstrating its efficacy in solar flare prediction.

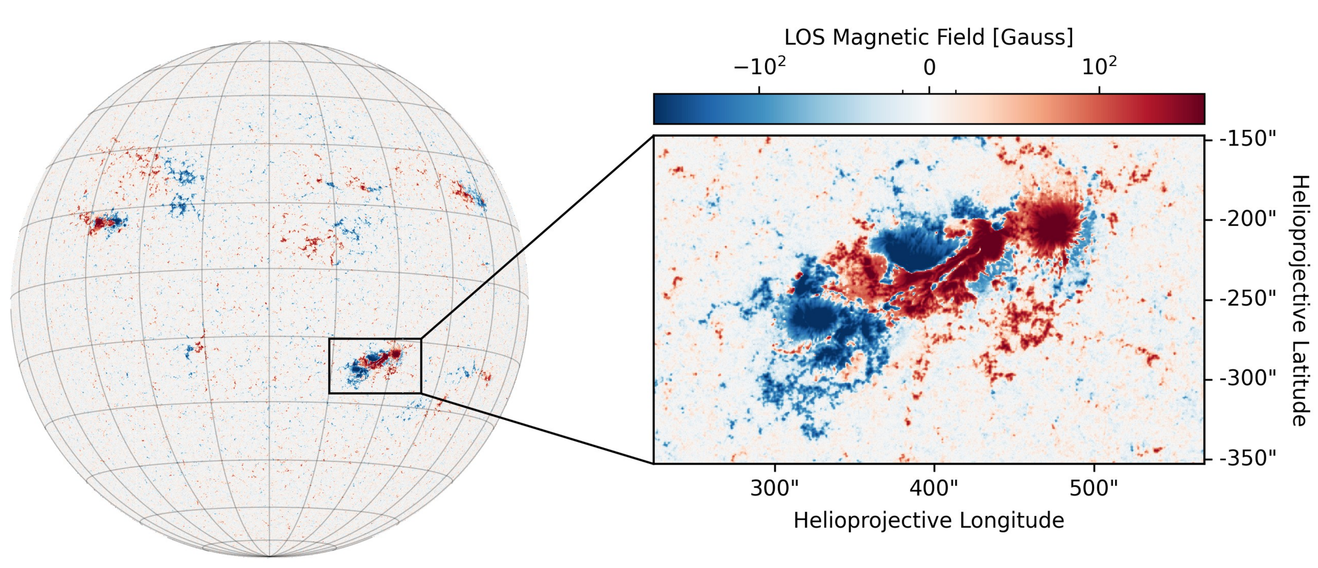
SDO/HMI and GOES/XRS Data

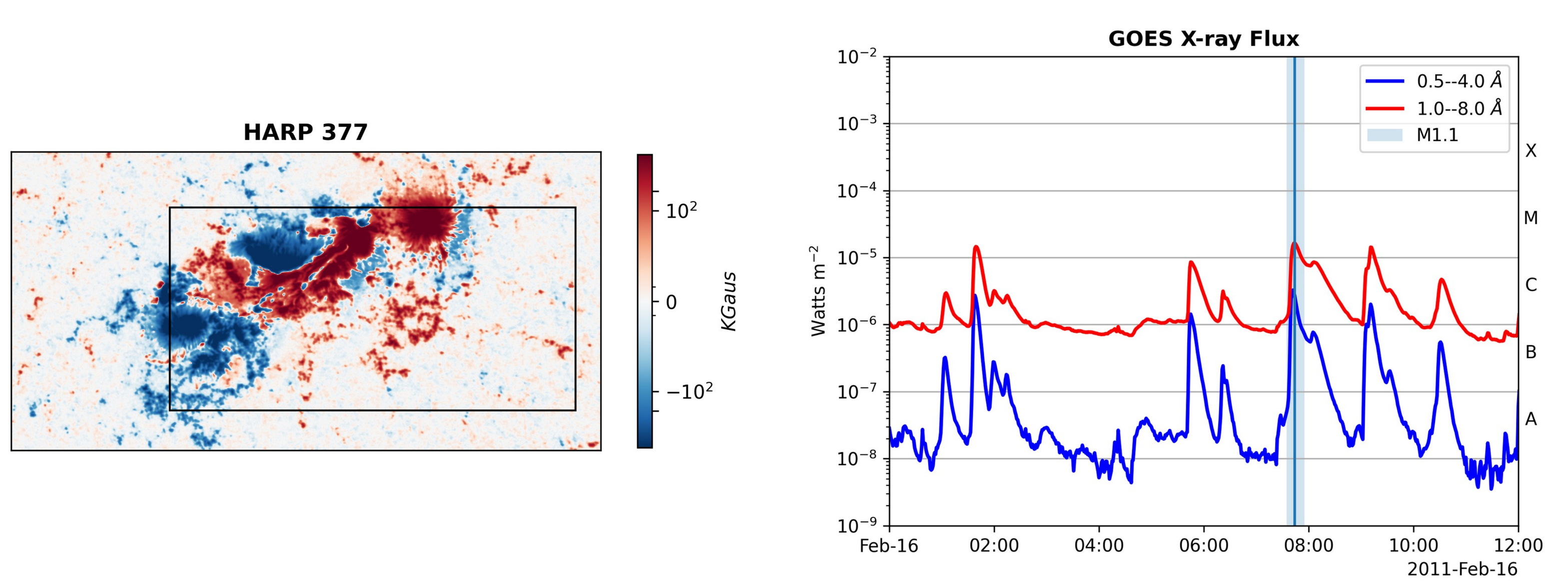
Data Description

Solar Dynamics Observatory (SDO)/Helioseismic and Magnetic Imager (HMI)

Geostationary Operational Environmental Satellites (GOES)

Full Disk Line-of-Sight Magnetograms 2011.02.16 01:12:00 TAI (HARP 377)

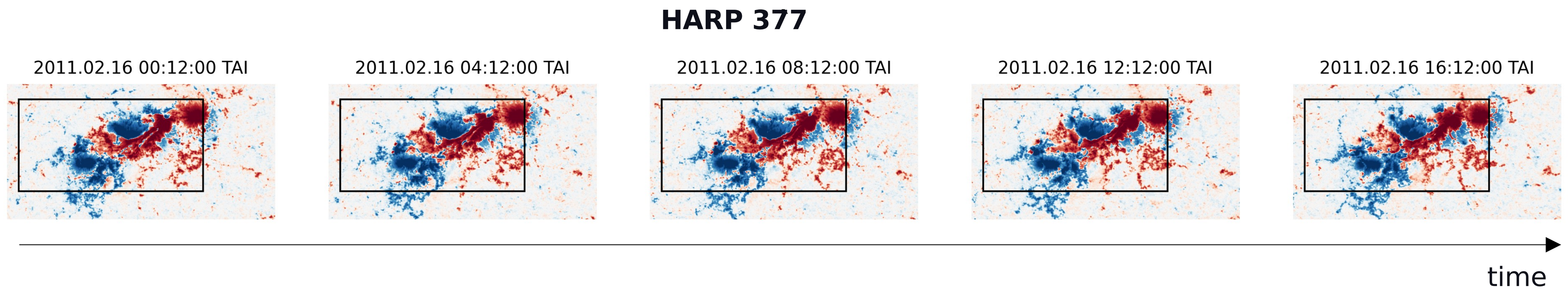


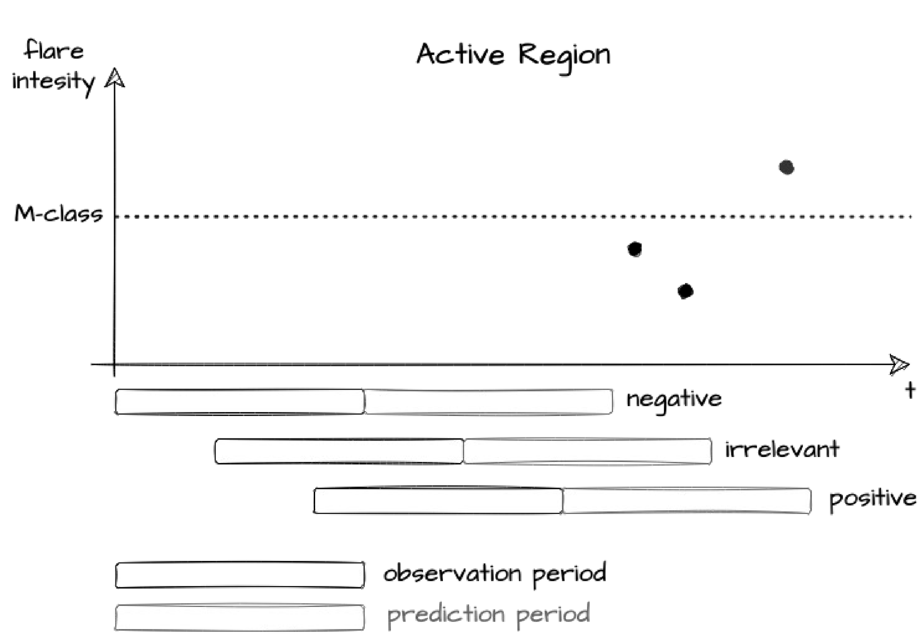


Data from May 2010 to December 2022
809 Flaring Active Regions

Video Sample Extraction and Labeling

HARP 377





Weak flares: A-/B-/C-class
Strong flare: M-/X- class

	Prediction period		
Observation period	Quiet	Weak	Strong
Quiet	(-)	(?)	(+)
Weak		(?)	(+)
Strong			(+)

Observation and prediction period of 24 hr with a 12 minute step.

Train/Validation/Test Sets

Due to the temporal coherence of an active region in its lifetime, a random split of data samples will have samples coming from the same active region categorized into different splits. Such correlation constitutes an undesirable information leakage among splits. To avoid this we adopt an active-region-based split, where data samples from the same active region must belong to the same split.

Solar flare data exhibit prominent class imbalance, with positive (minority class) samples significantly outnumbered by negative (majority class) samples. We handle the class imbalance problem using random undersampling: we randomly remove samples from the majority class until the numbers of positive and negative samples are equalized.

Training:
negative: 4754 [50.00%]
positive: 4754 [50.00%]

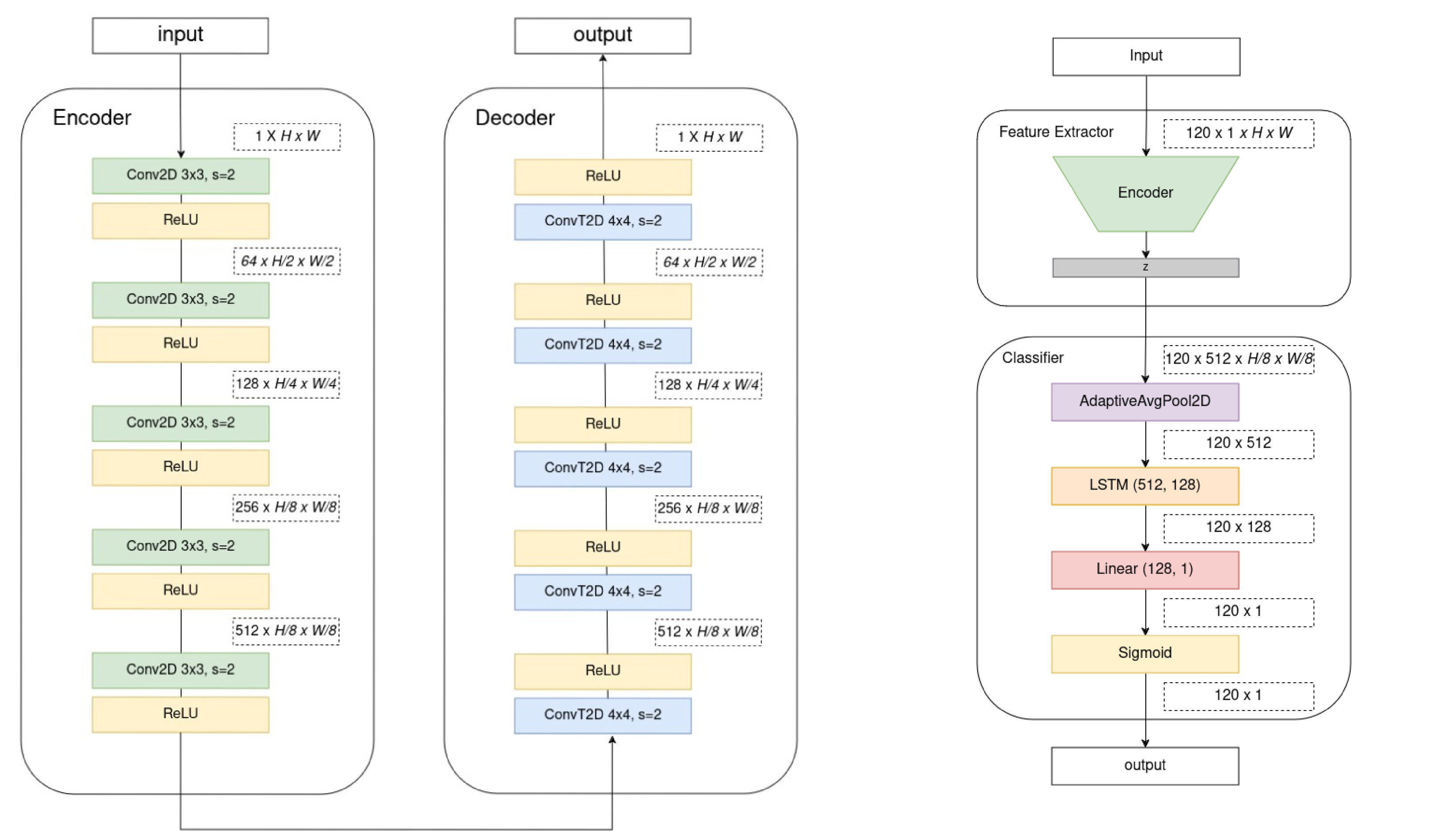
Validation:
negative: 1063 [50.00%]
positive: 1063 [50.00%]

Test:
negative: 501 [50.00%]
positive: 501 [50.00%]

Percentage Dataset Splitting:
Training: 75.25%
Validation: 16.82%
Test: 7.93%

Model and results

Models



$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

$$\mathrm{BCE}(y,\hat{y}) = -\left[y\cdot\log(\hat{y}) + (1-y)\cdot\log(1-\hat{y})\right]$$

Results