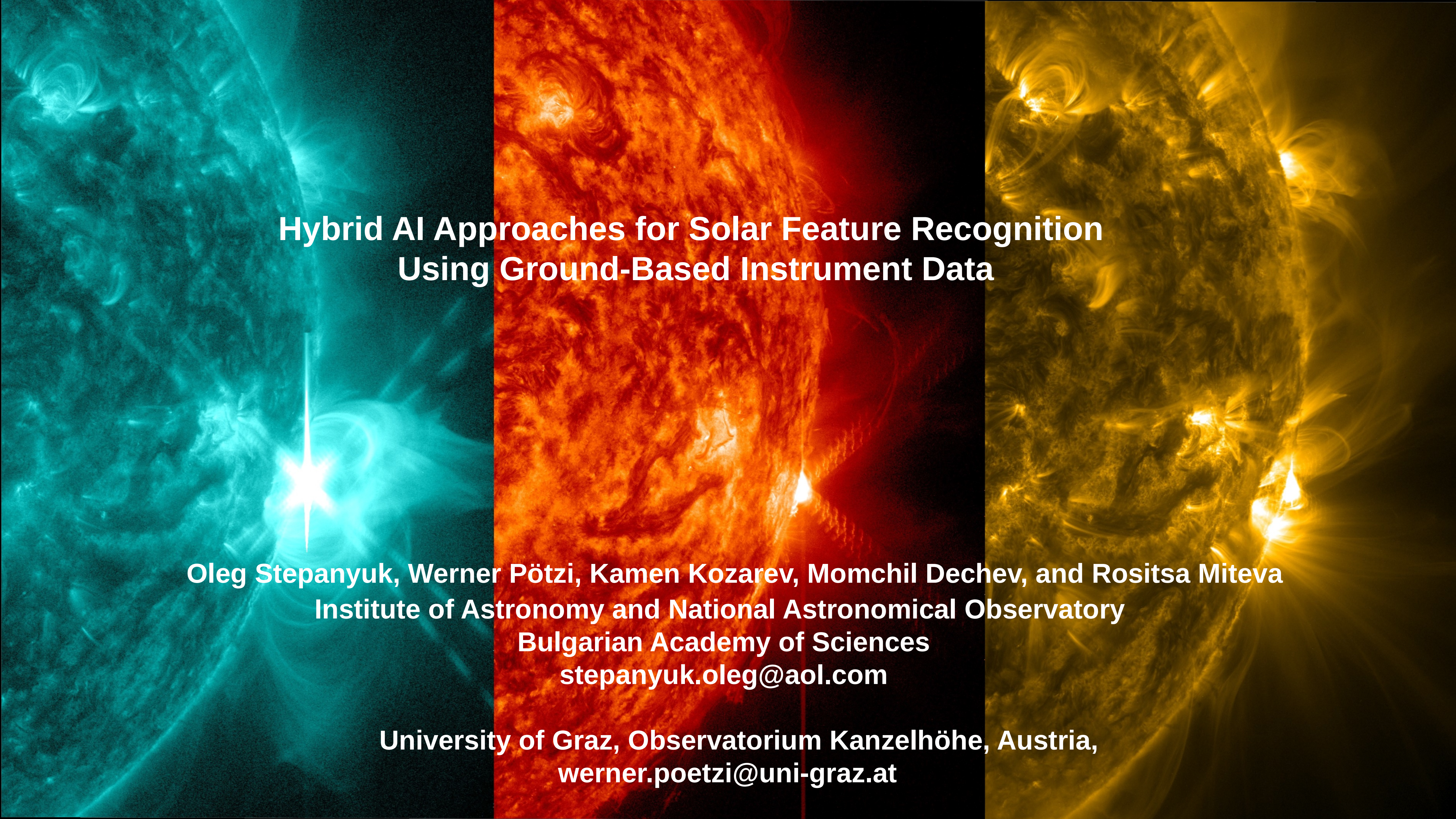

Hybrid AI Approaches for Solar Feature Recognition Using Ground-Based Instrument Data

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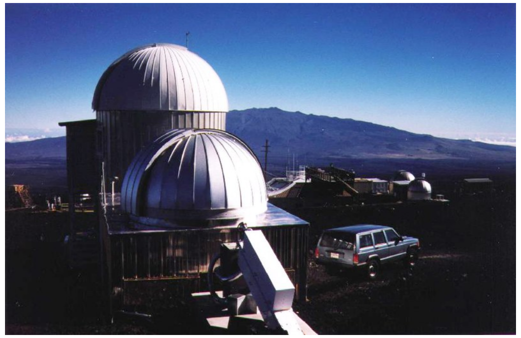
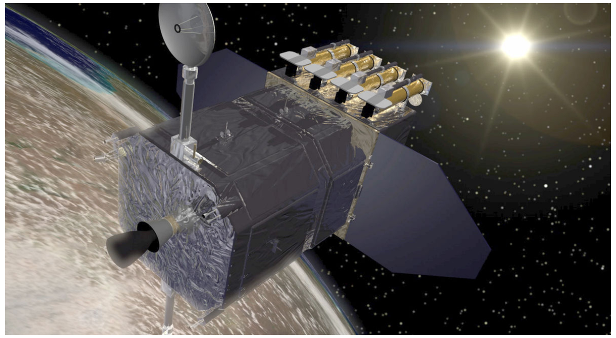
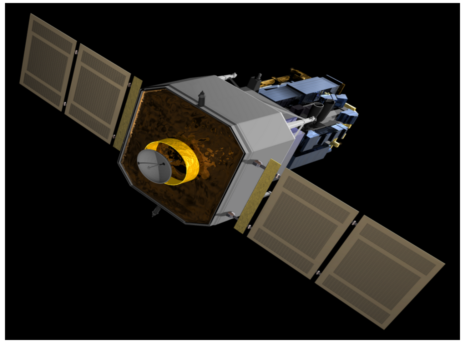
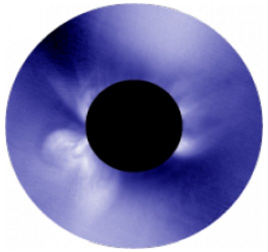
What do we do

Previously we demonstrated a wavelet-based approach for automated solar feature recognition. We have since developed a set of (CNN) models which uses Wavetrack outputs as ground truth. Our initial model performance was shown on a set of SDO AIA instrument data performing segmentation of EUV and shock waves. In this work, we extend our approach for algorithmic and data-driven segmentation of on-disk solar features (prominences and filaments) using data from ground based-instruments.

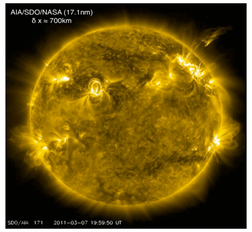




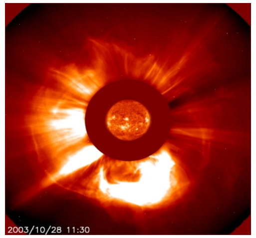




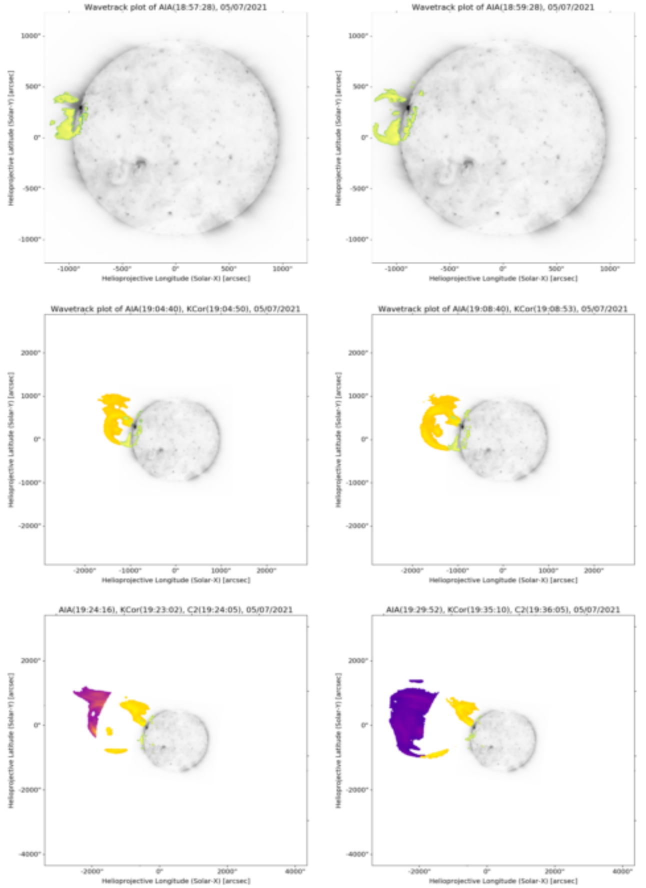
Mauna-Loa K-COR Coronograph



AIA Instrument Onboard SDO Observatory



LASCO Onboard NASA/ESA Soho



Stepanyuk O., Kozarev K "Multi-Instrument Tracking and Observations of a Coronal Mass Ejection Front From Low to Middle Corona". JSWC (2024)

Global Objective:

Develop methodologies and design robust software for multi-instrument solar eruptive feature recognition and tracking for remote and in-situ instruments data.

Current Research :

Adopt our wavelet and data-driven image segmentation techniques for ground-based optical instrument data (K-Cor, Kanzelhöhe, Belogradchik, and Rozhen Observatory data)

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Research Article Open Access

Multi-scale image preprocessing and feature tracking for remote CME characterization

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Topical Issue - CMEs, ICMEs, SEPs: Observational, Modelling, and Forecasting Advance

Research Article Open Access

Multi-instrument observations and tracking of a coronal mass ejection front from low to middle corona

Oleg Stepanyuk* and Kamen Kozarev

Institute of Astronomy and National Astronomical Observatory, Bulgarian Academy of Sciences, Sofia, Bulgaria

A&A, 684, L7 (2024)

Letter to the Editor

Tracking the motion of a shock along a channel in the low solar corona

J. Rigney[1,2,3], P. T. Gallagher[1], G. Ramsay[2], J. G. Doyle[2], D. M. Long[4,3], O. Stepanyuk[5] and K. Kozarev[5]
+

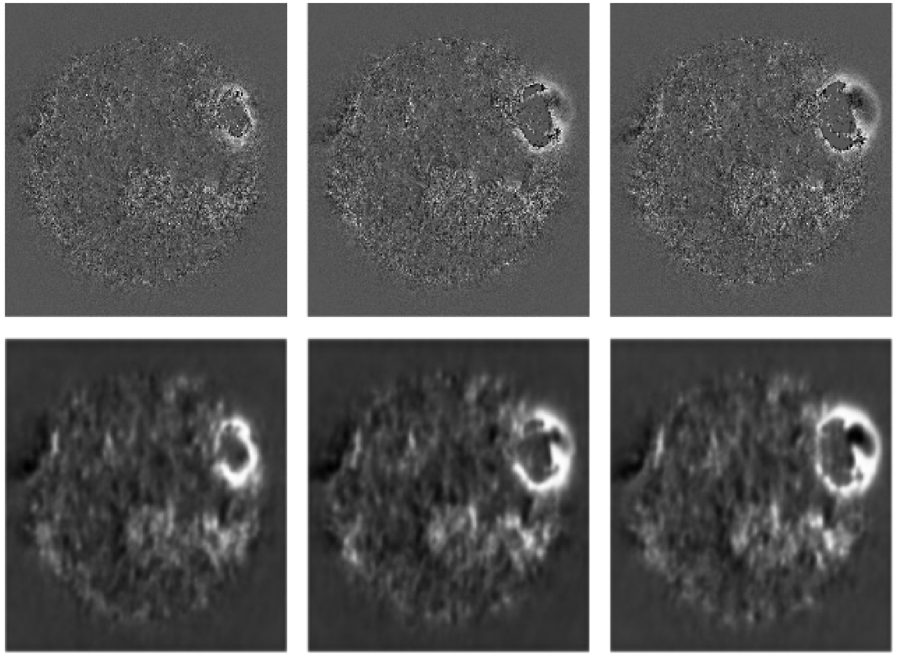
Received: 31 October 2023
Accepted: 21 March 2024

Abstract

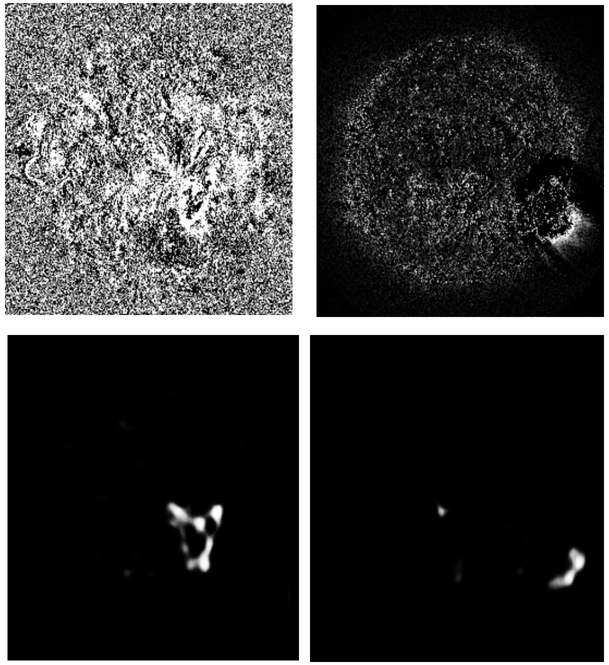
Context. Shock waves are excited by coronal mass ejections (CMEs) and large-scale extreme-ultraviolet (EUV) wave fronts and can result in low-frequency

Segmentation and Tracking, previous results. SDO AIA segmentation performance

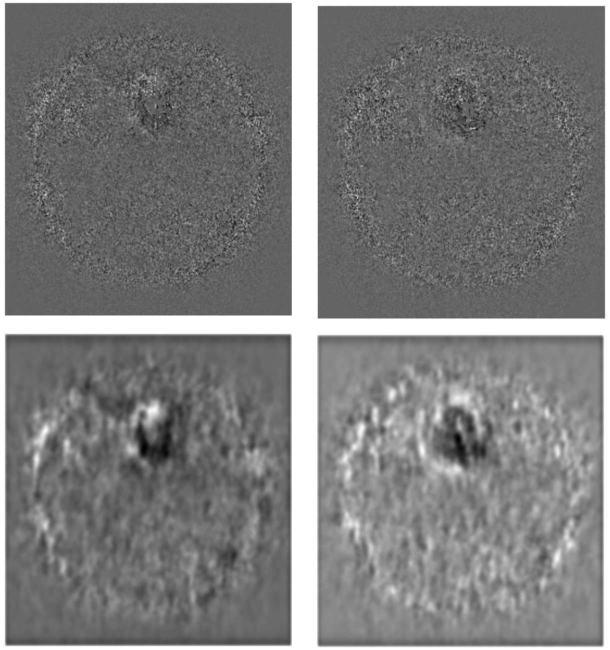
Under Review



2011-06-07. AIA 193 A. CBF evolution. Probabilistic masks (softmax)



29-09-2013/11-05-2011
Filament on disk / on limb recognition

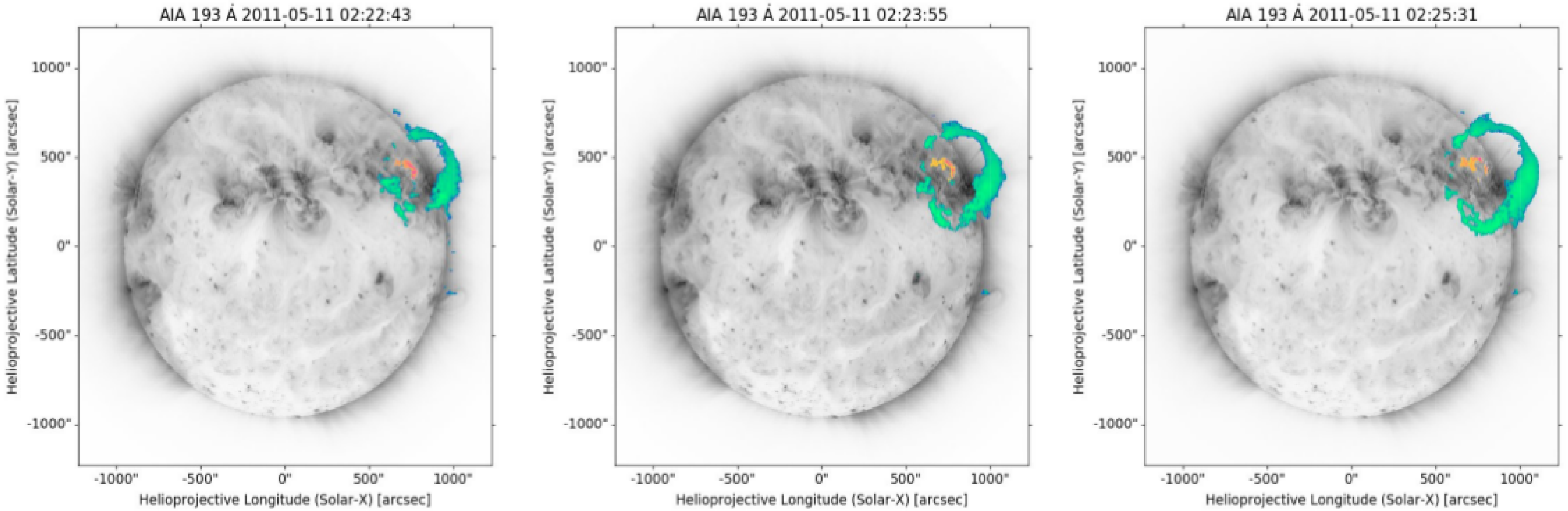


10-05-2022 Shock in the Low Corona
(we previously studied in Rigney at al, A&A L7 (2024))

Models testing by comaring with validation sets according to IoU and Dice metrics: $\mathrm{IoU} = \frac{|A \cap B|}{|A \cup B|}$ $\mathrm{Dice} = \frac{2|A \cap B|}{|A| + |B|}$

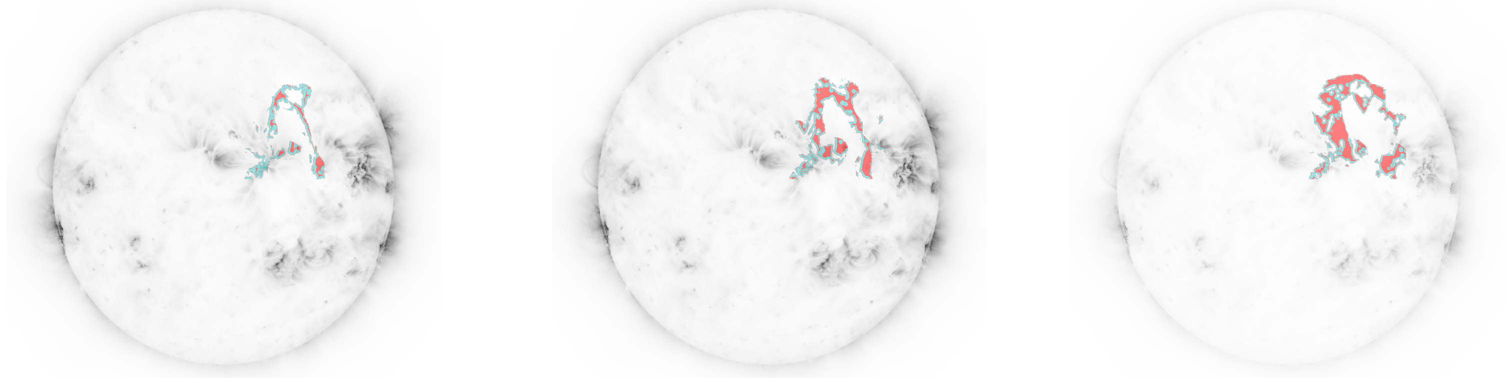
https://gitlab.com/iahelio/helios_cnn/
https://zenodo.org/record/13147358
Pre-trained models for segmentation and tracking of Coronal Bright Fronts from SDO AIA Base Difference images

Filament tracking



CBF and the filament: Combined tracking of the May 11, 2011 event

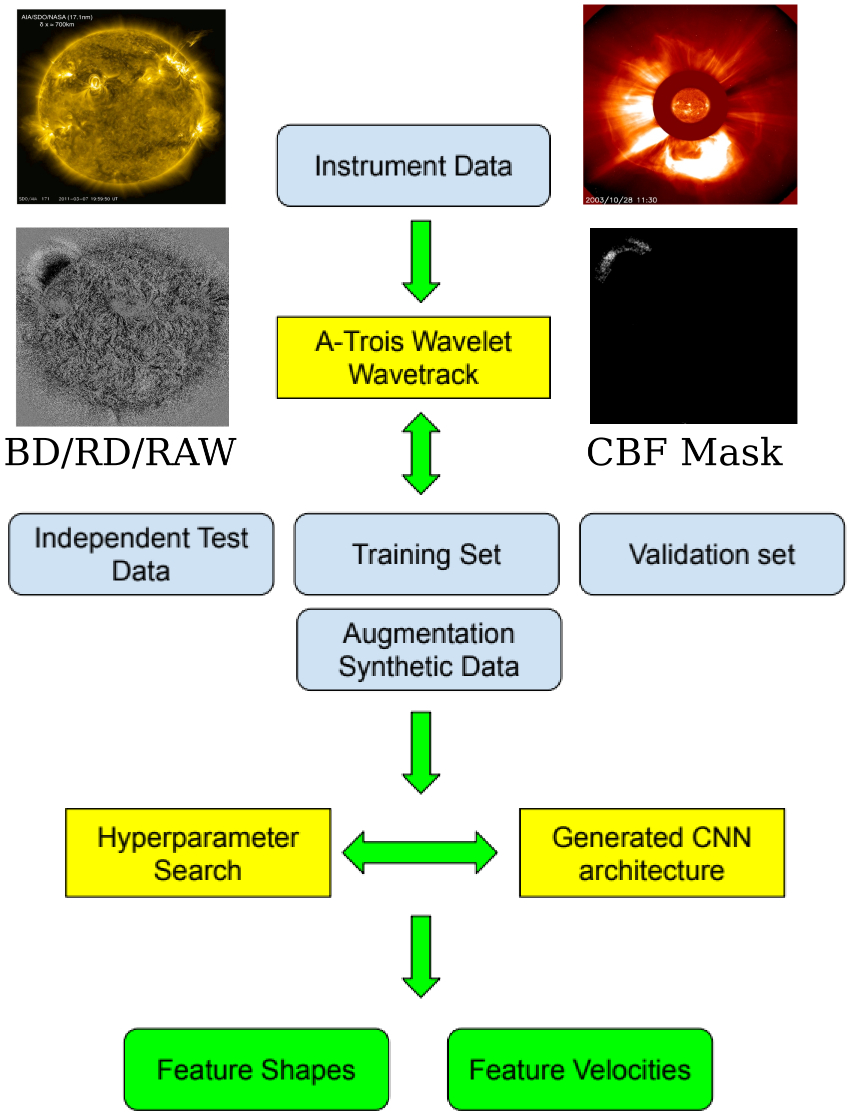
AIA193: 21:31:06 AIA193: 21:39:54 AIA193: 21:49:06



Gigantic filament: Tracking of the September 29, 2013 event

Stepanyuk et. al. J. Space Weather and Space Climate, 2022

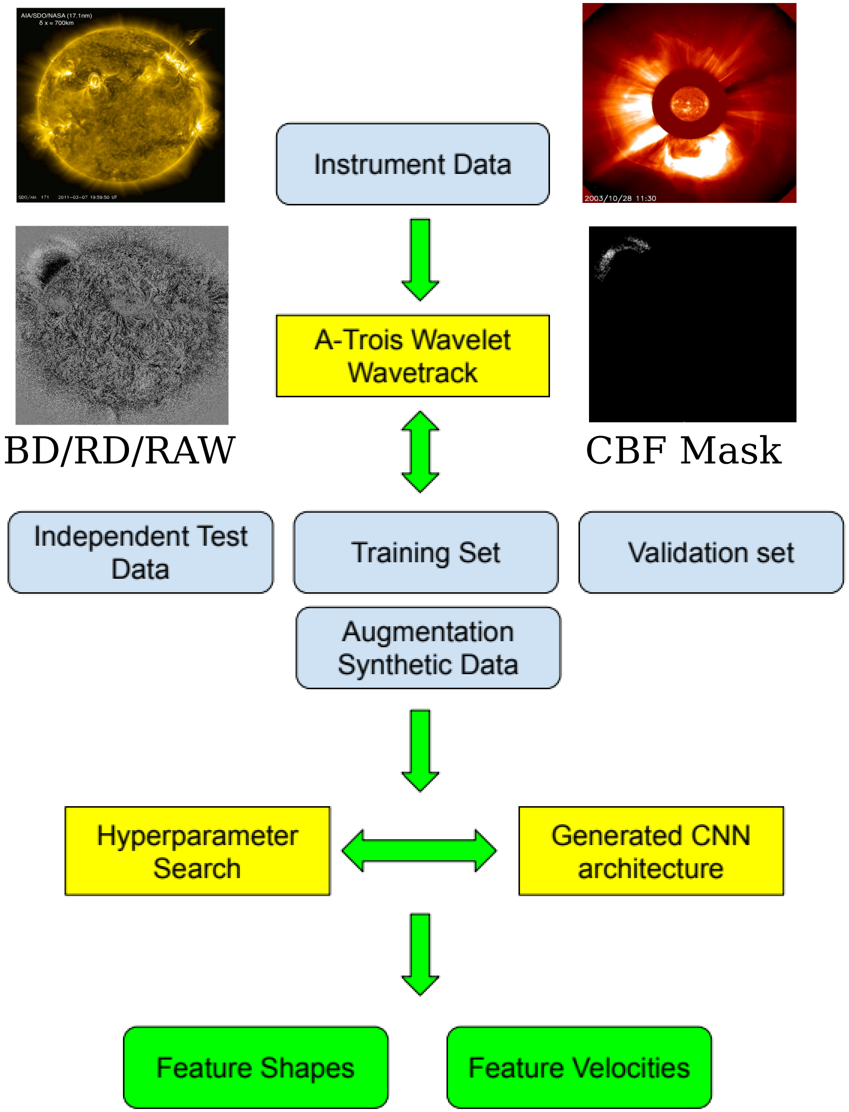
The Method: Hybrid algorithmic / data driven approach. Emphasis on the training data quality



Our approach to the solution:

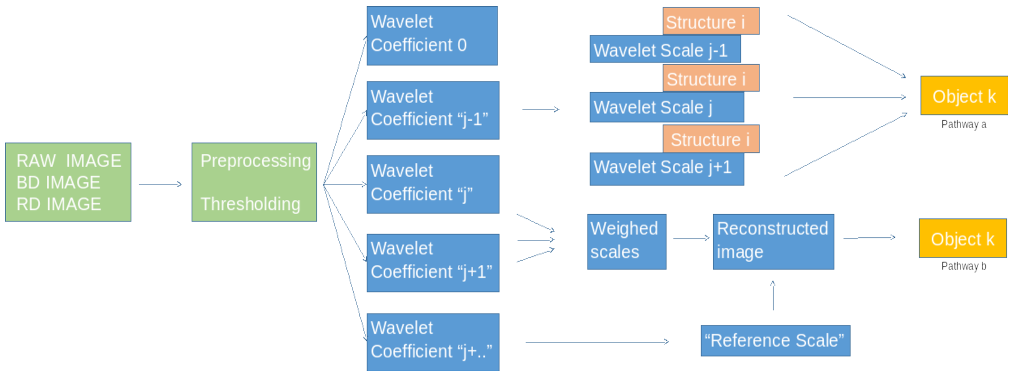
- Hybrid algorithmic → data driven approach. Focus on the training data quality
- Wavetrack - a generalized wavelet based object-oriented framework for solar eruptive feature detection and feature velocity field estimation. About to release version 2.
- We apply Wavetrack to sets of events to generate training sets when ground truth data/masks do not present (K-Cor)
- We perform data augmentation and use extended datasets as training sets
- We explore velocity estimation approaches alternative to FLCT

The Method: Hybrid algorithmic / data driven approach. Emphasis on the training data quality

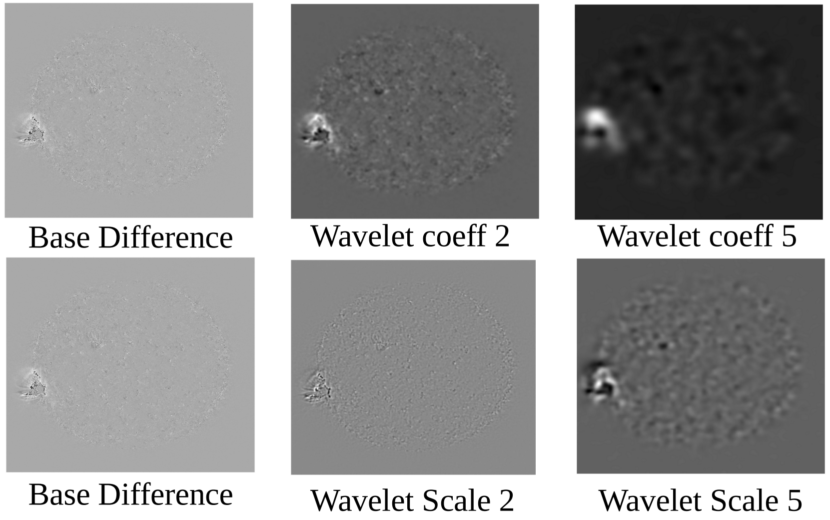


Stepanyuk et. al. J. Space Weather and Space Climate, 2022

Image Processing stages with Wavetrack software



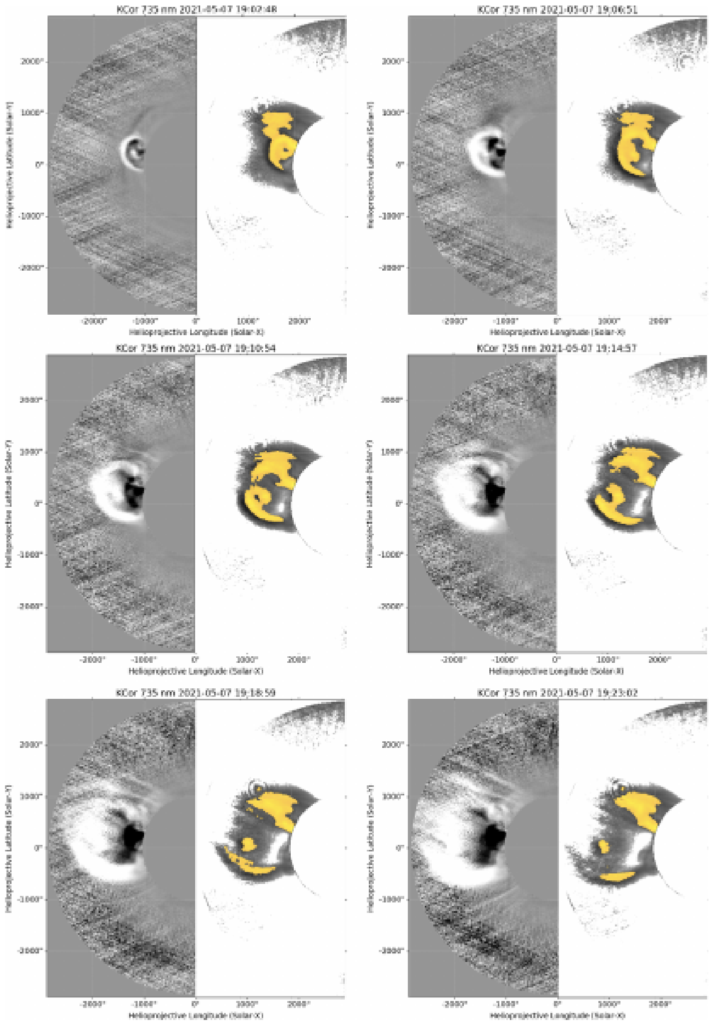
à trous wavelet decomposition

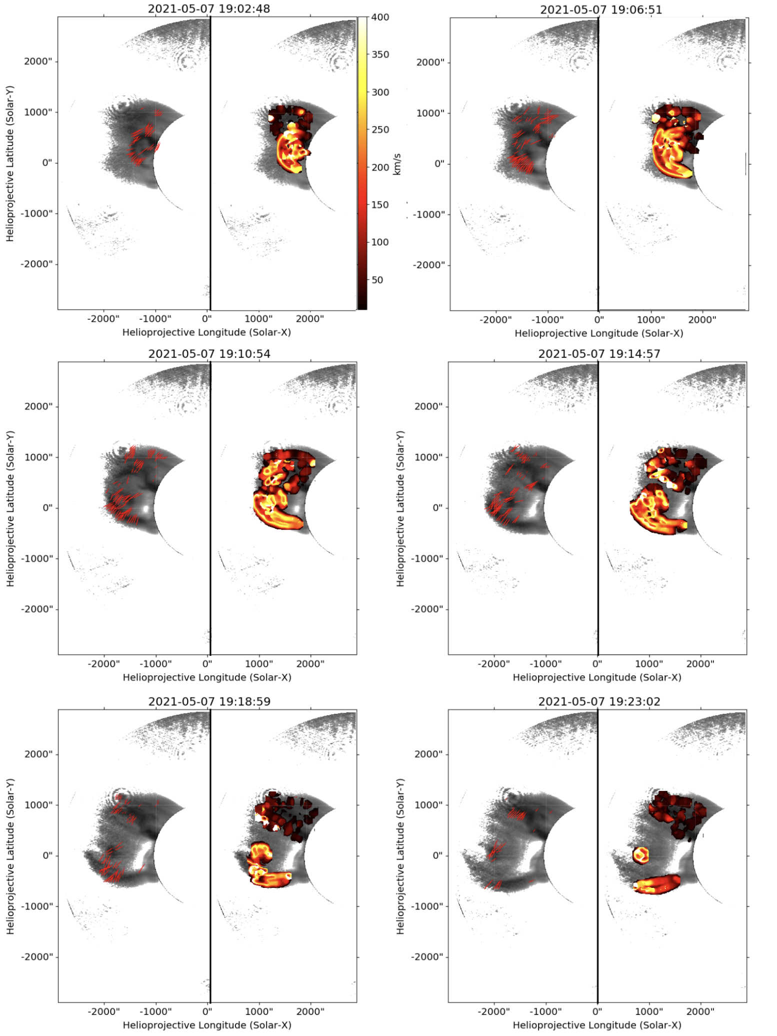


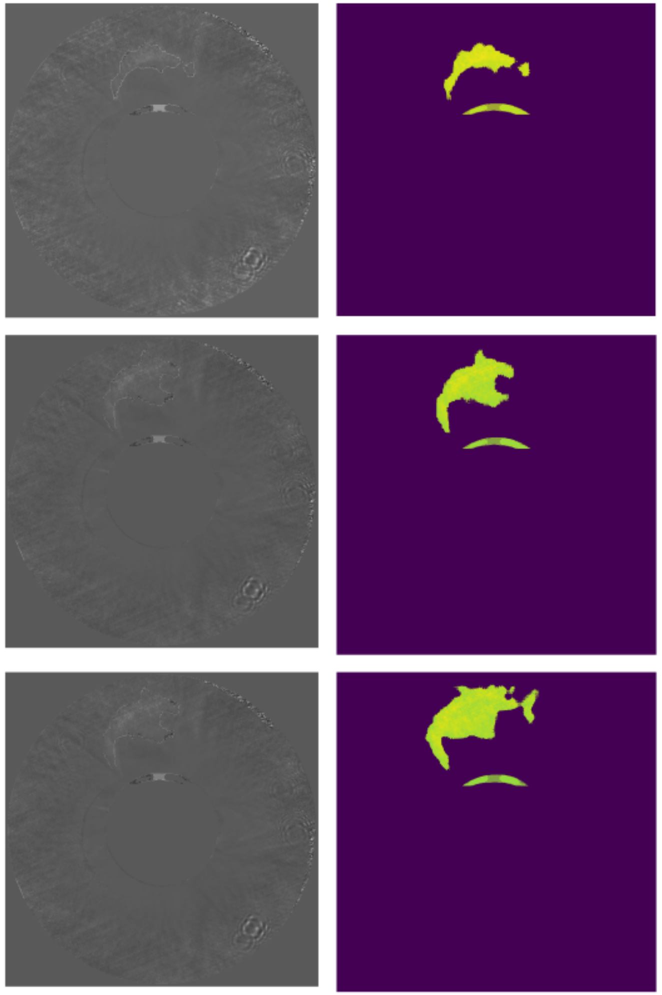
Object condition for a structure:

$$w_j^m > w_{j-1}^m \quad w_j^m > w_{j+1}^m$$

Training data (limb) : Wavetrack feature masks (K-Cor),







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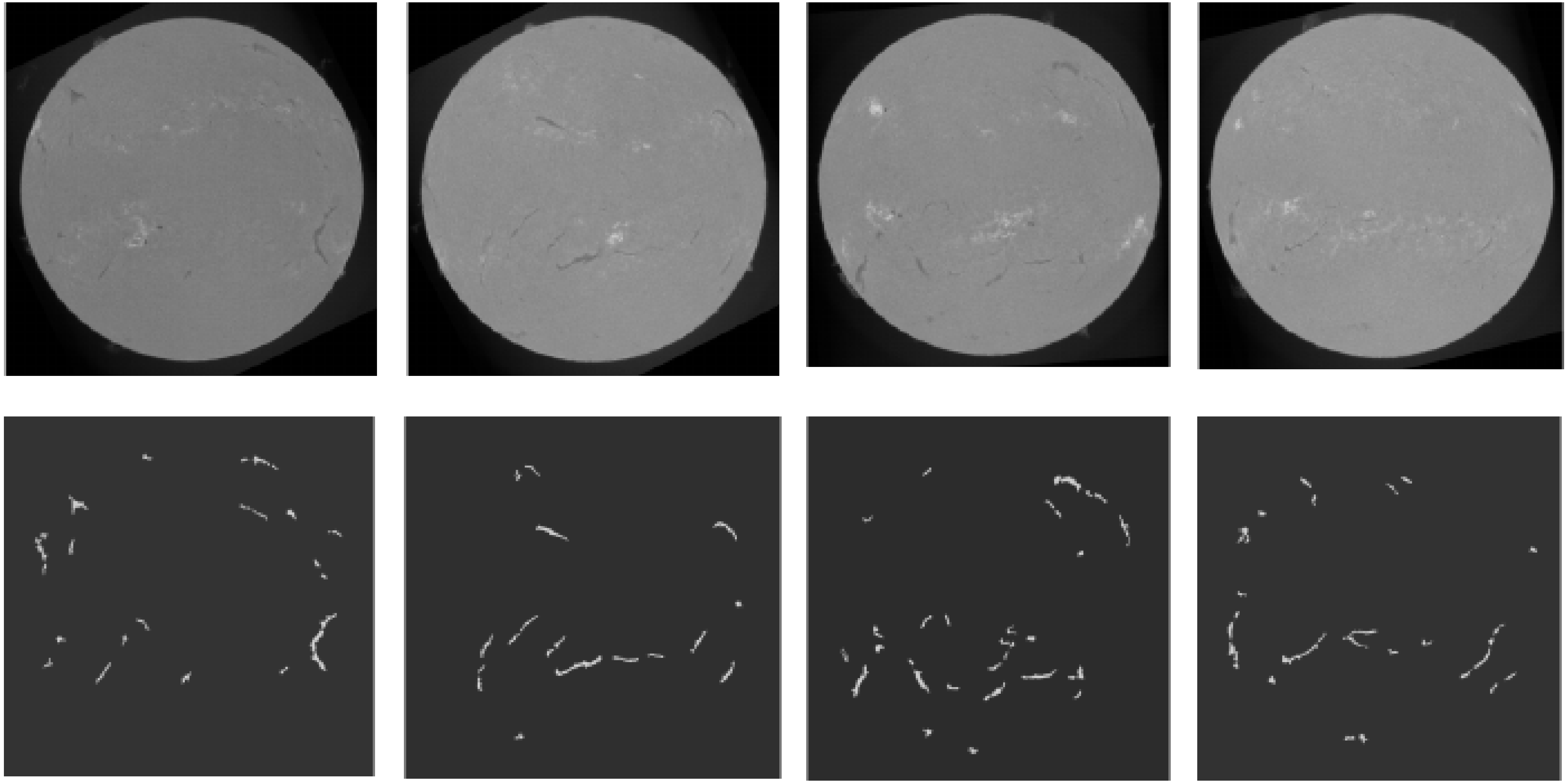
Stepanyuk O., Kozarev K "Multi-Instrument Tracking and Observations of a Coronal Mass Ejection Front From Low to Middle Corona". J. SWSC (2024)

Training data (disk) Kanzelhohe H-alpha (normalized)



Data Driven Image Segmentation: our approach

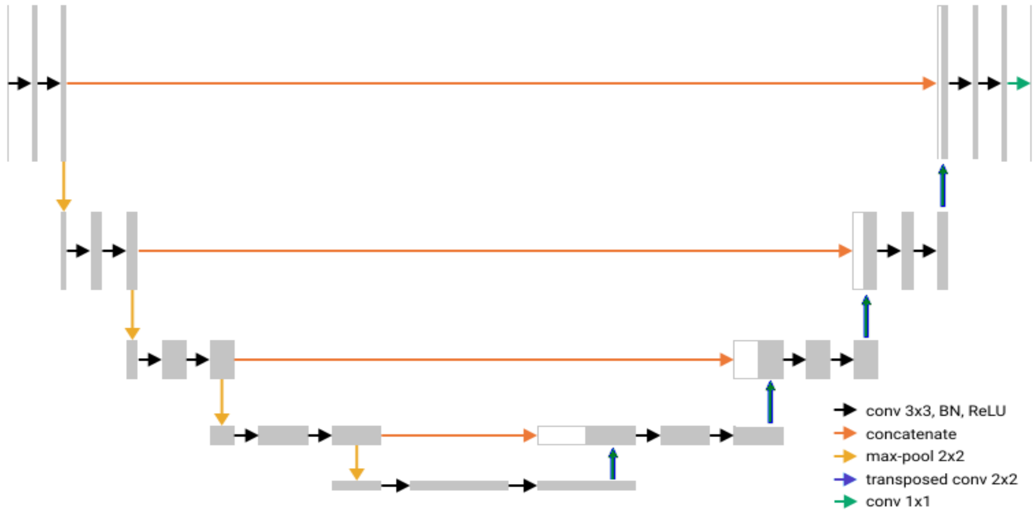
Evolution of image segmentation approaches

LeNet, AlexNet, VGG
GoogLeNet, Inception V3, Inception V5

Hyperparameter search Network architecture

- Instrument specific networks (U-NET Based CNNs)
- Network ensembles
- Each model with it’s own parameters (filters, depth, layers, pooling(reducing/keeping spacial resoliton) at the bottleneck, etc),
- Depending depending on the type of data and studied phenomena (filaments, CBF’s, etc)

  +
- Engineering diverse training sets
- Geometrical and DR/Intensity data augmentation
- Iterative learning of the (non-linear) mapping between BD/RAW images and Wavetrack-obtained masks. Training till “target” performance



U-net architecture. Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. Ronneberger O, et. al (2015). Image Segmentation". ArXiv:1505.0459

U-NET as an image-to-image transformation architecture. It conveys information from early, high-resolution levels to later levels. The ’shortcut’ allows the network to utilize detailed features of the original image, as well as capture higher-level semantics from the deep layers

Advantages:
Connections that bridge the encoder and decoder paths. (preserving the finer details)
Relatively fewer parameters compared to other similar architectures.

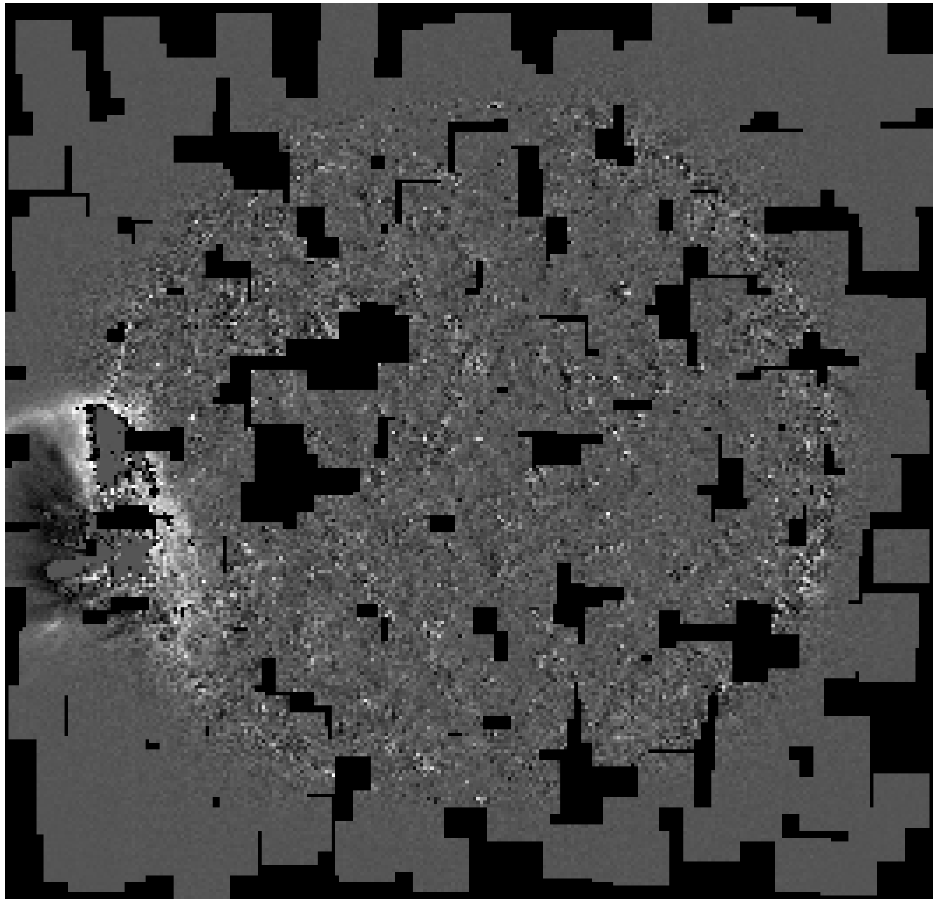
Data Driven Image Segmentation: our approach (automation, object-oriented)

```python
def get_unet_generalized_np(self, n_ch, patch_height, patch_width, depth, start_filters,
    filter_size, use_batch_norm, use_dropout, dropout_rate=0.2):
    inputs = Input(shape=(n_ch, patch_height, patch_width))

    # Downsampling path
    conv_blocks = []
    current_layer = inputs
    for i in range(depth):
        filters = start_filters * (2 ** i)
        conv = Conv2D(filters, (filter_size, filter_size), activation='relu', padding='same', data_
        if use_batch_norm:
            conv = BatchNormalization(axis=1)(conv)  # Note axis=1 for channels_first
        conv = Conv2D(filters, (filter_size, filter_size), activation='relu', padding='same', data_
        if use_batch_norm:
            conv = BatchNormalization(axis=1)(conv)  # Note axis=1 for channels_first
        conv_blocks.append(conv)

        if i < depth - 1:  # No pooling at the bottleneck
            current_layer = MaxPooling2D(pool_size=(2, 2), data_format='channels_first')(conv)
            if use_dropout:
                current_layer = Dropout(dropout_rate)(current_layer)
        else:
            current_layer = conv  # At the bottleneck

    # Upsampling path
    for i in reversed(range(depth - 1)):
        filters = start_filters * (2 ** i)
        up = UpSampling2D(size=(2, 2), data_format='channels_first')(current_layer)
        up = concatenate([conv_blocks[i], up], axis=1)  # Ensure the channel axis is correct for ch

        if use_dropout:
            up = Dropout(dropout_rate)(up)

        conv = Conv2D(filters, (filter_size, filter_size), activation='relu', padding='same', data_
        if use_batch_norm:
            conv = BatchNormalization(axis=1)(conv)  # Note axis=1 for channels_first
        conv = Conv2D(filters, (filter_size, filter_size), activation='relu', padding='same', data_
        if use_batch_norm:
```

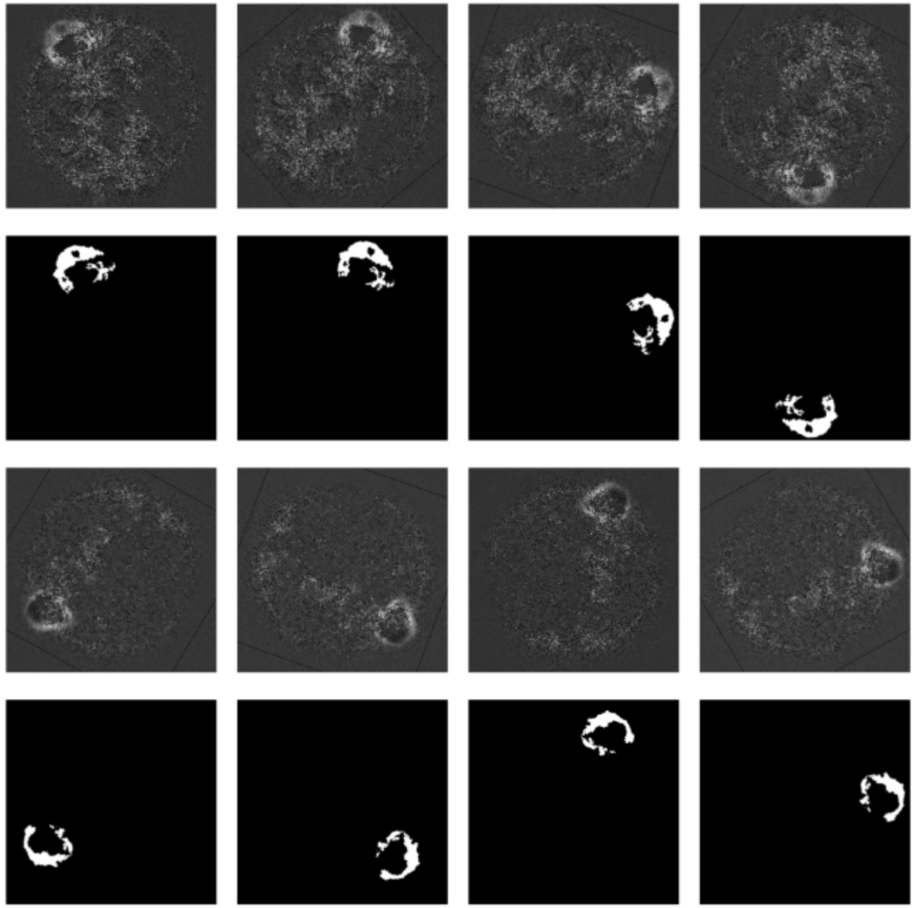
```python
Models for 128 and 256 sized images

model_128 = get_unet_generalized(

    n_ch=3,  # or 1 for grayscale
    patch_height=128,
    patch_width=128,
    depth=3,
    start_filters=64,
    filter_size=(5, 5),
    use_batch_norm=True,
    use_dropout=True,
    dropout_rate=0.2
)


model_256 = get_unet_generalized(

    n_ch=3,  # or 1 for grayscale
    patch_height=256,
    patch_width=256,
    depth=4,
    start_filters=128,
    filter_size=(7, 7),
    use_batch_norm=True,
    use_dropout=True,
    dropout_rate=0.2
)
```

Trainset Engineering. Synthetic data (Concept)

Data Augmentation

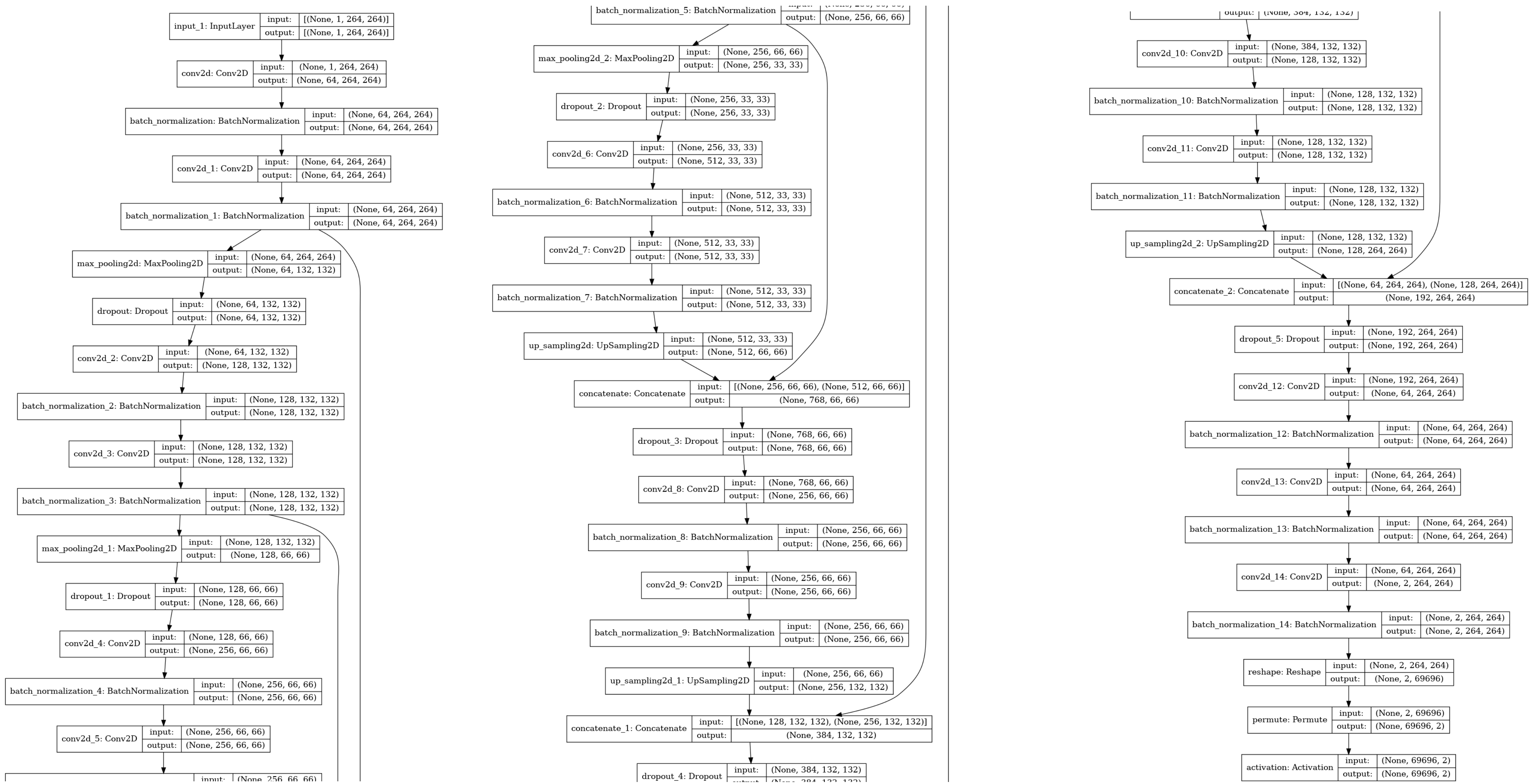


Patches

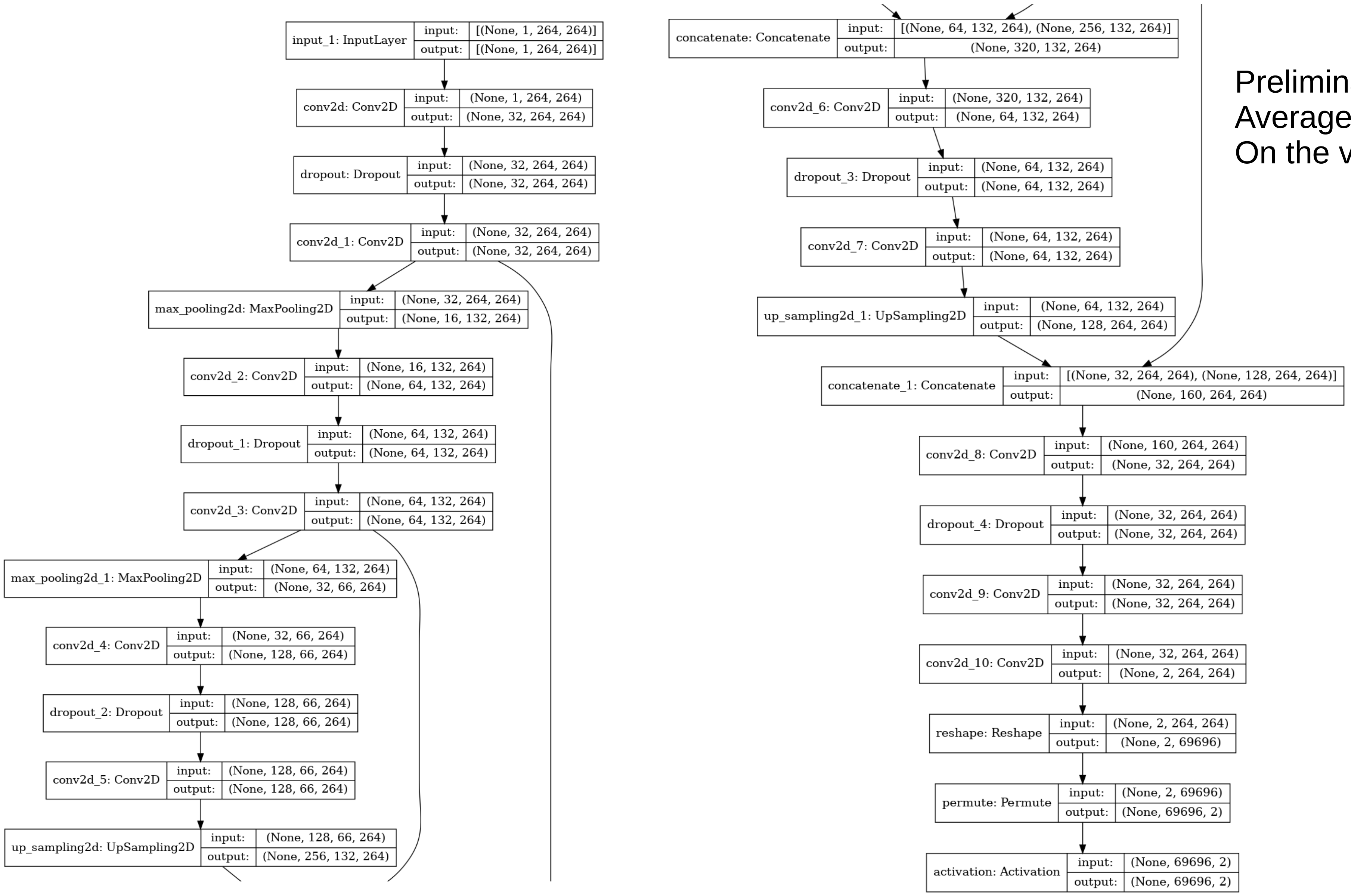


Geometrical / intensity

Hyperparameter search, SDO AIA + synthetic data (larger model)

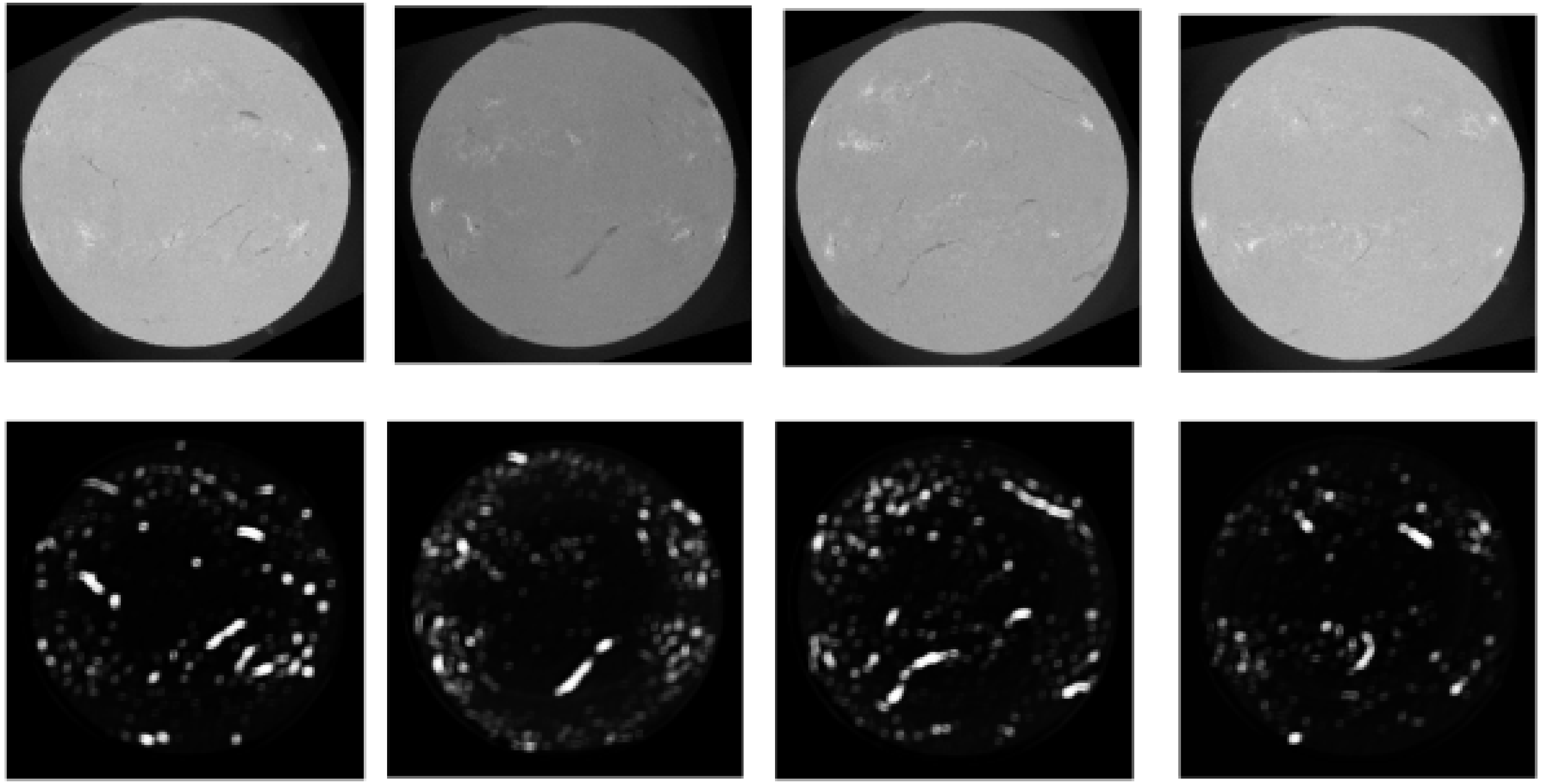


Hyperparameter search, Kanzelhohe observatory data (smaller model)



Preliminary models show
Average IOU 0.76
On the validation set

Hyperparameter search, Kanzelhohe observatory data (smaller model)



Preliminary models show
Average IOU 0.76
On the validation set

Ongoing work

- More precise hyperparameter fine-tuning for each type of the instrument / feature

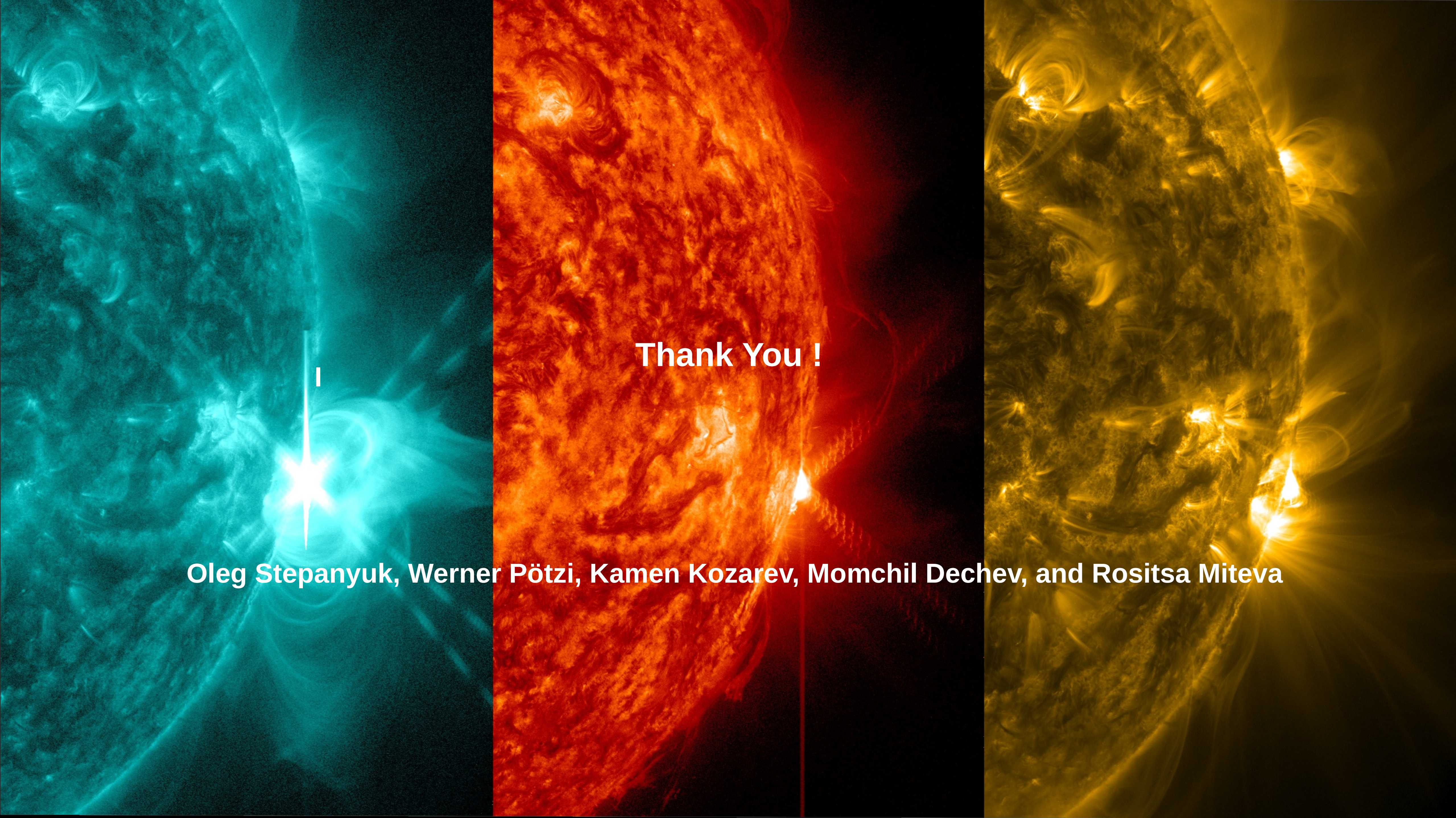
- Improving each model performance by training on larger sets, with strong emphasis on the training data quality

- Validation on independent event data (...as previously done with SDO AIA data)

- Case studies (prominences, filament eruptions)

Acknowledgments

Bilateral project:
Bulgaria-Austria https://astro.bas.bg/project-sun/
Joint observations and investigations of solar chromospheric and coronal activity
(2023-2025) Bulgarian National Science Foundation project No. KP-06-Austria/5 (14-08-2023) and Austria’s Agency for Education and Internationalisation (OeAD) project No. BG 04/2023


Thank You !
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