A Computer Vision Approach for Real-time Solar Event Detection

Y. Aytac[a], H. R. Marlowe[a], and J. Kozyra[b]
[a]Amazon Web Services, [b]NASA

1. Introduction

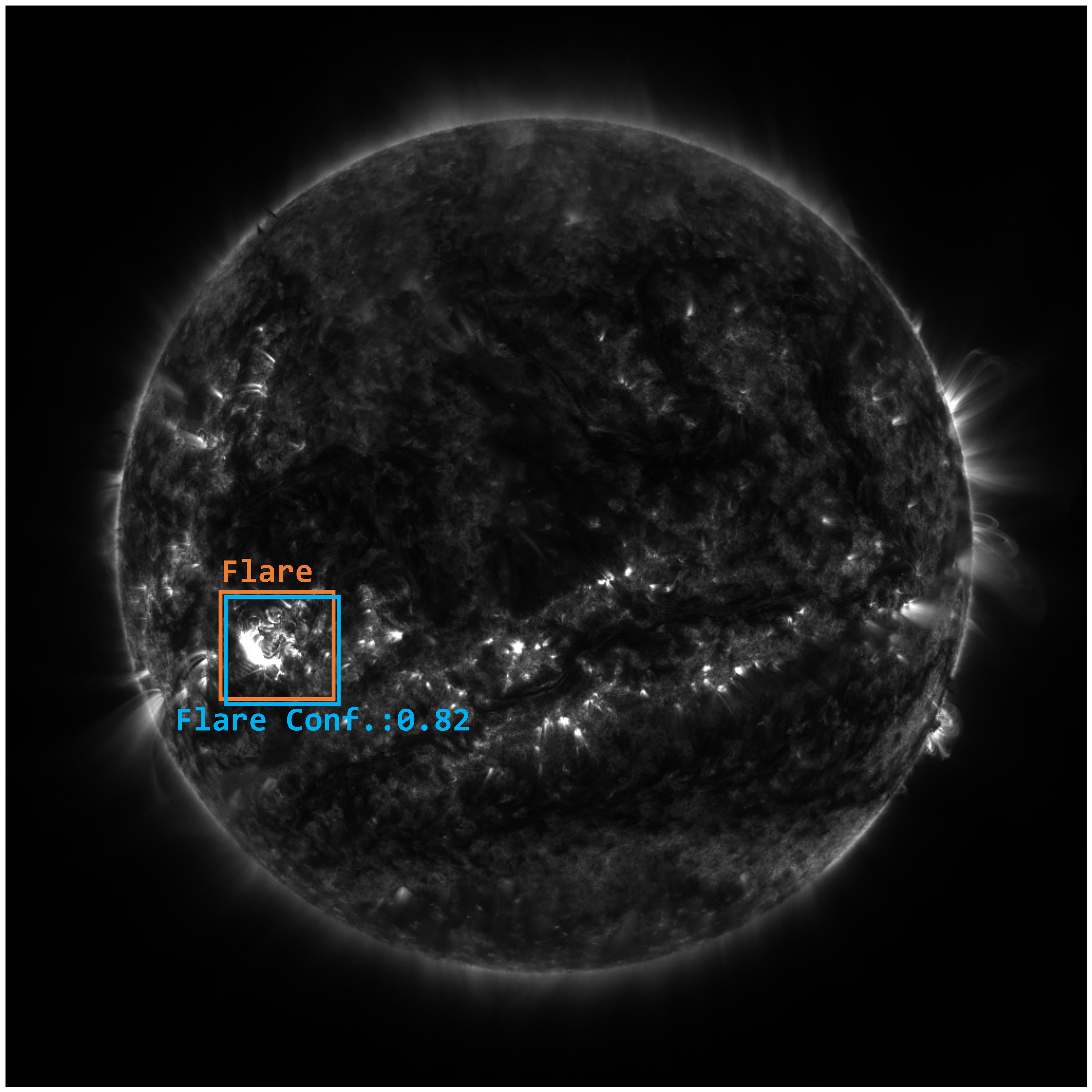
We present a solar event object detector for automated detection and alerting in real time, and automated event labeling for historic solar flare observations.
The open-source python library SunPy interfaces for the Heliophysics Event Knowledgebase (HEK) and the Federated Interned Data Obtainer (FIDO) are used to obtain, and prepare the data including reported Solar Event and solar imagery acquired data from the Solar Dynamics Observatory's Atmospheric Imaging Assembly (AIA).

2. Data

To process the 171.0 Angstrom AIA level1 data, we queried the Joint Science Operations Center (JSOC) for the most recent pointing information and updated the image metadata. We then scaled the images to 0.6″ per pixel and derotated each to align the y-axis with solar North.

Finally, we normalized each image to the exposure time resulting images with units of DN/pixel/s.
The original dimensions of the SDO AIA imagery is 4096x4096 pixel^2. To optimize speed/performance in our training module, we have resized these images to 1024x1024 pixel^2 using the bicubic interpolation method.

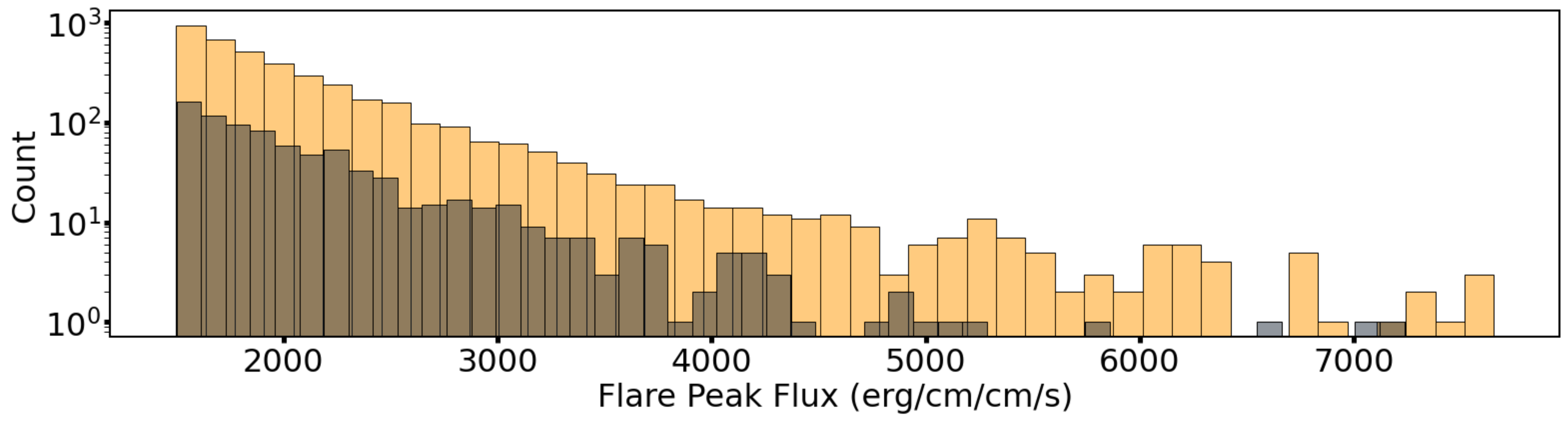
For model training, the the Monochromatic single channel images are saved in .png format. The flare peak flux distribution for the train and test sets are plotted in the top right figure.



3. Modelling

A CenterNet (v.2) model is trained using full-disk solar images with train and validation sets split by event date such that 80% of data is included in training and 20% in validation. We have used data from 2010 - 2015 for training, and 2015 - 2018 for validating the model.

Solar flare events with flux rates above 1500 erg/cm^{2}s are used to train the models which includes the C, M and X solar flare flux categories. As an input to the training algorithm, the normalized images are used at the Level 1.5 stage of the dataset. Further data augmentation are applied during training to optimize model performance.



For each Solar Flare event exceeding our flux rate threshold, only one image at the peak intensity is captured. The flux rate distribution for the train and validation sets are shown in the figure above.

4. Results

We used the F-1 Score at 0.25% IOU threshold as the main evaluation metric. The baseline model performance is achieved 0.44 F-1 Score.

$$F_\beta = (1+\beta^2)\,\frac{\text{precision} \times \text{recall}}{\beta^2 \times \text{precision}+\text{recall}}$$

We noticed that the model was repeatedly making false predictions near the bright spots on the Solar surface. Augmentation with 0.5-1 random brightness is used mainly to address this issue. The remaining augmentation methods are introduced to the training loop for the model generalization.
Included augmentations are *random-flip*, *contrast*, *rotation*, *saturation*, and *brightness* that resulted an 8% point improvement in F1-Score.

Overall the best F-1 Score of 0.82 is achieved with the flares of interest. The model can run in real-time at a 90 FPS inference rate for 1024X1024 pixel full disk images when tested on a single NVIDIA Tesla V100 GPU.

5. Conclusion

The results demonstrate the potential of computer vision object detection and classification methods for solar event detection to be used independently or in conjunction with more traditional approaches.
The same method can easily be extend in other types of Solar events for which archival data is available.

6. References

https://sunpy.org/ ||. https://aia.lmsal.com/
https://github.com/xingyizhou/CenterNet2 || Probabilistic two-stage detection, Zhou et. al.