Determining the Parameter for the Linear Force-Free Magnetic Field Model with Multi-Dipolar Configurations Using Deep Neural Networks

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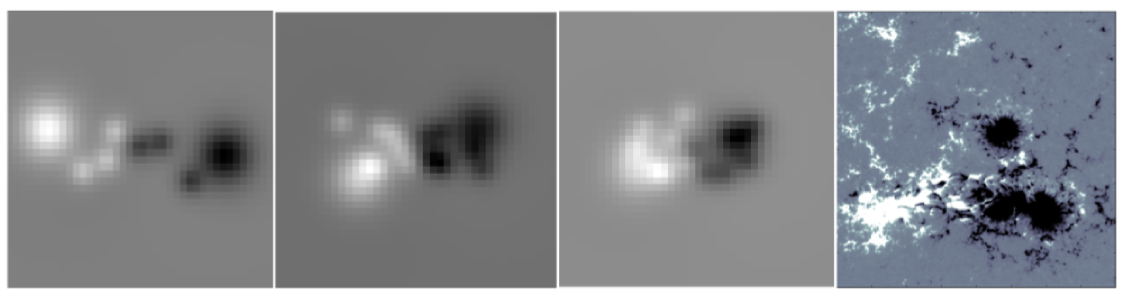
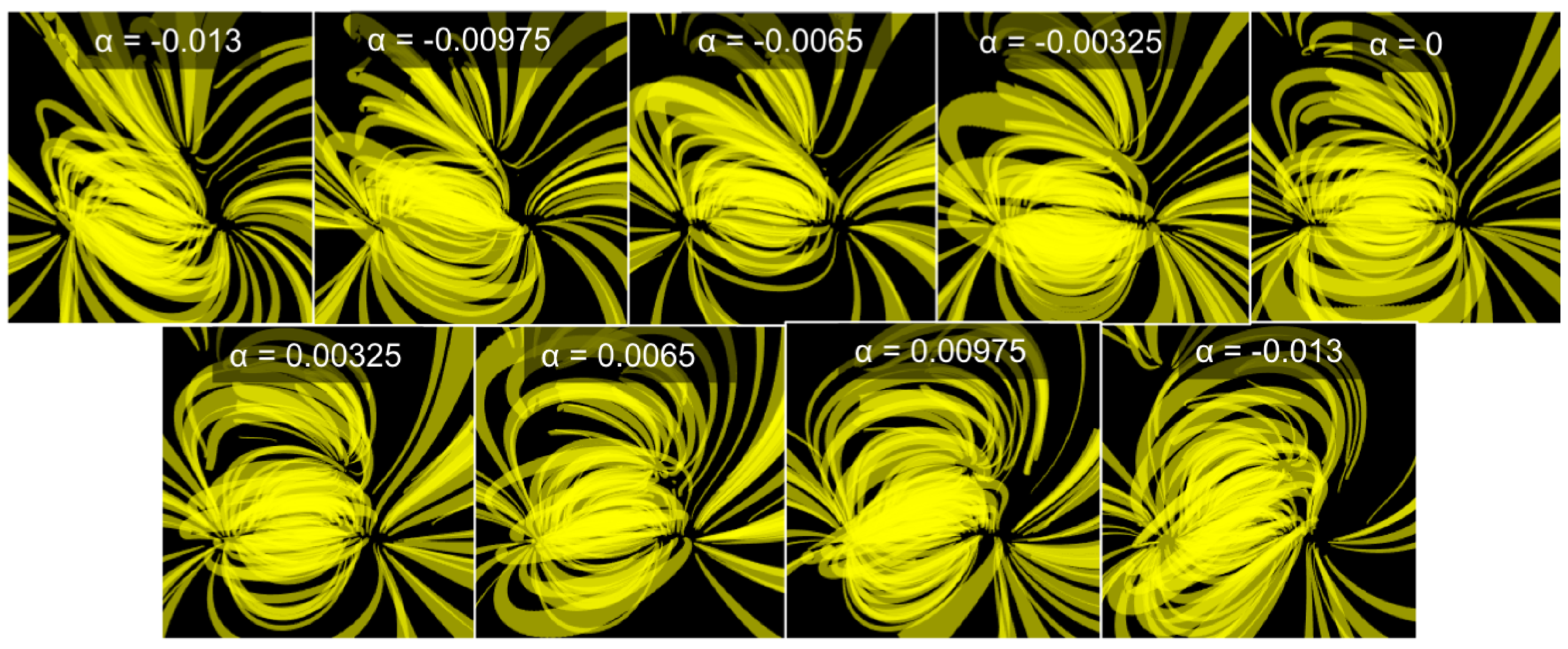
Introduction

- We employed a simple one-parameter model to model active regions with multi-polar configurations.
- LFFF model is assumed as it provides the single parameter alpha.
- Pseudo-coronal loop images are formed from the multi-polar configurations.
- Alpha value determined by CNN classification and regression.
- Method extended to include active region AR11117.
- Response of pseudo-coronal loop images to that of real coronal loop images observed.



a. Multi-polar configurations and vector magnetogram of AR11117



b. Pseudo-coronal loops for AR11117

Linear Force-Free Field

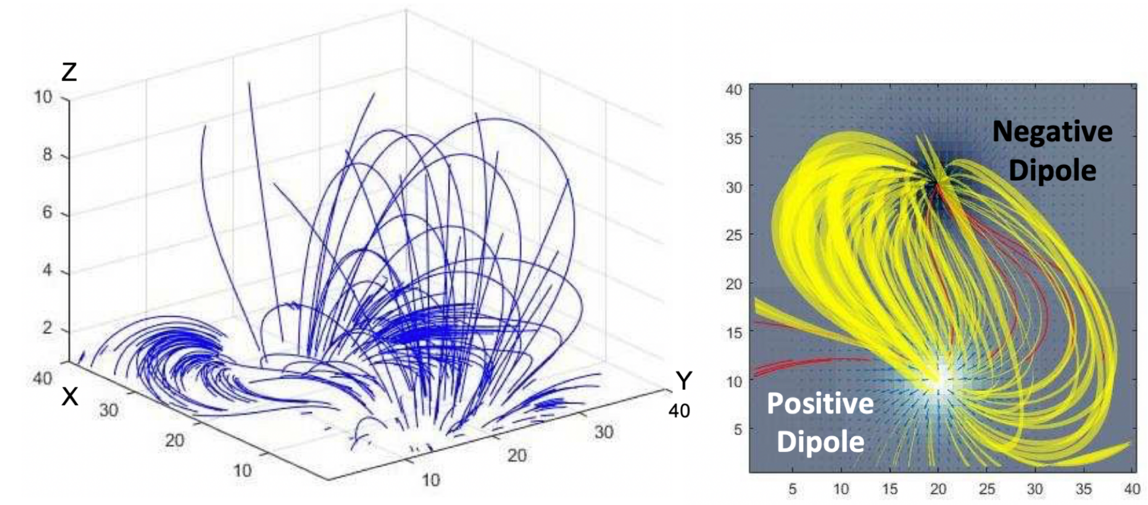
- Certain assumptions need to be made about the nature of the magnetic field in order to model a solar coronal magnetic field, **B**.
- In the region between the photosphere and the upper corona, the plasma forces are dominated by the magnetic field.
- Based on this observation, all lower order non-magnetic forces can be neglected to the first order. This model leads to the force-free approximation.
- A force-free magnetic field gives the simplest model for the corona, which is non-potential. It occurs when the electric current density vector is parallel to the magnetic field which causes the Lorentz forces to disappear. The linear force free fields are characterized by

$$\nabla \cdot \mathbf{B} = \mathbf{0}, \tag{1}$$

and

$$(\nabla \times \mathbf{B}) = \alpha \mathbf{B}. \tag{2}$$

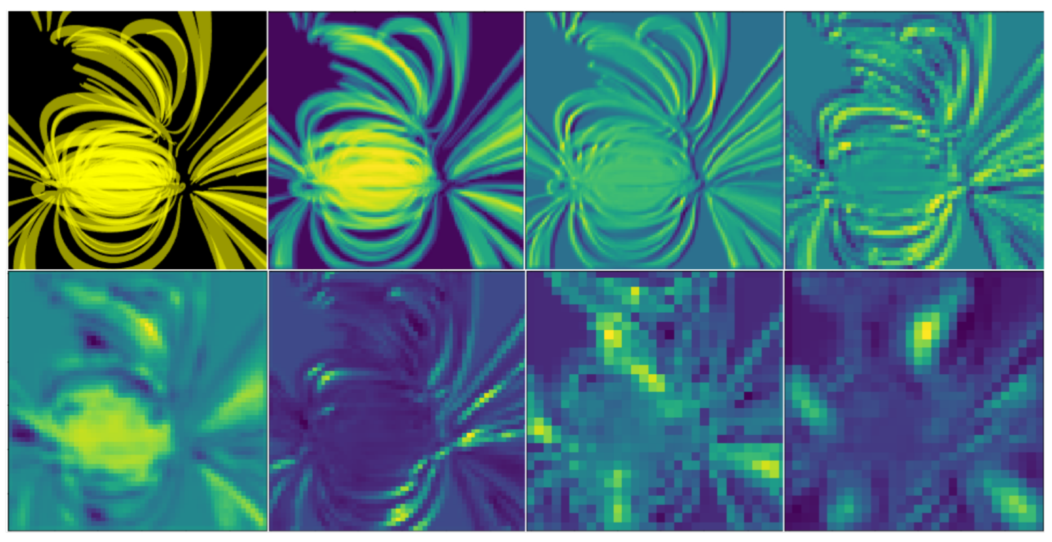
- The case where α = constant is called a linear force-free field (LFFF).



a. Extrapolated field lines from the multi-dipolar configurations used to form pseudo coronal loops

b. Corresponding pseudo-coronal loops

CNN Results



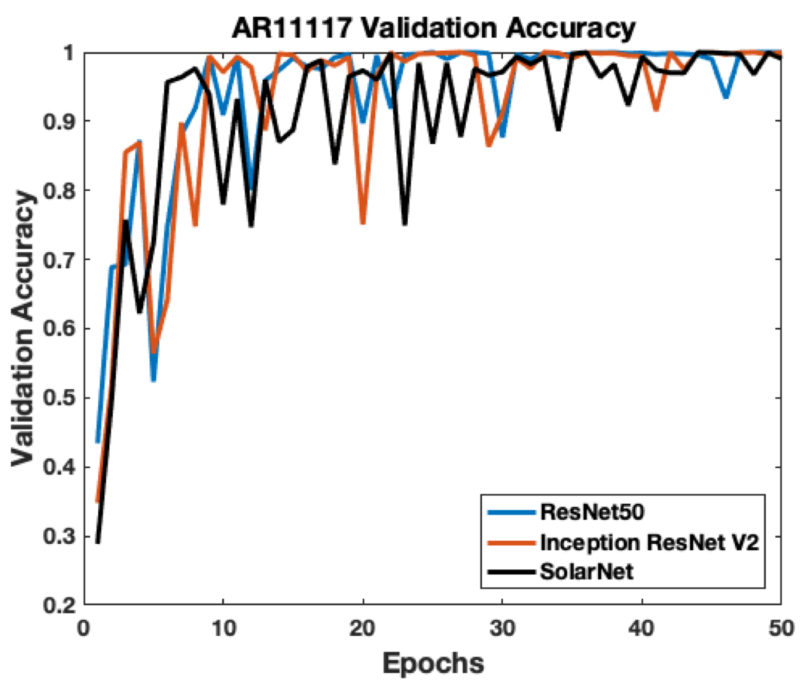
Visualizing the CNN layers showing the various features learned in convolutional filters

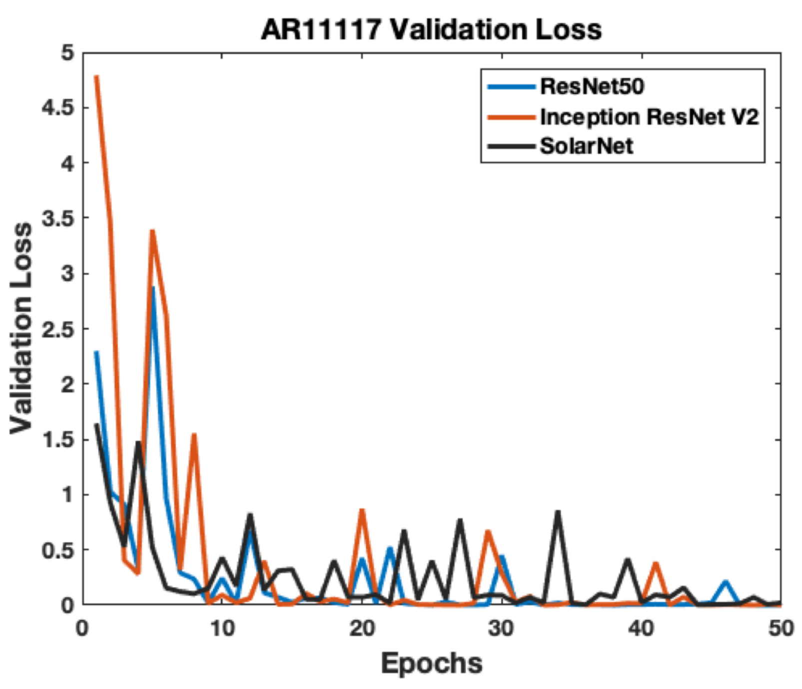
- The tables below show the classification accuracy for the CNN models used along with the results from transfer learning applied.

Model	Metric	Dataset			
		Four Dipoles	Eight Dipoles	Sixteen Dipoles	AR 11117
ResNet_50	Training Accuracy	99.92%	99.63%	99.89%	99.77%
	Validation Accuracy	99.47%	96.20%	96.66%	99.98%
	Test Accuracy	99.64%	95.93%	96.31%	99.98%
	Training Time/epoch	~185 sec	~185 sec	~185 sec	~300 sec
Inception Resnet V2	Training Accuracy	99.69%	99.68%	99.80%	99.90%
	Validation Accuracy	98.52%	97.05%	97.64%	100%
	Test Accuracy	98.98%	97.11%	97.61%	100%
	Training Time/epoch	~300 sec	~300 sec	~300 sec	~420 sec
SolarNet	Training Accuracy	98.11%	94.77%	95.77%	98.41%
	Validation Accuracy	97.84%	92.84%	94.53%	99.04%
	Test Accuracy	97.69%	92.28%	94.49%	98.92%
	Training Time/epoch	~91 sec	~89 sec	~94 sec	~275sec

Model	Base Dataset	Target Dataset	Metric	Accuracy %
ResNet50	Sixteen Dipoles	Four Dipoles	Training	97.02%
			Validation	94.48%
			Time/epoch	88 sec
		Eight Dipoles	Training	95.92%
			Validation	93.76%
			Time/epoch	88 sec
SolarNet	Sixteen Dipoles	Four Dipoles	Training	98.60%
			Validation	98.25%
			Time/epoch	72 sec
		Eight Dipoles	Training	95.41%
			Validation	91.95%
			Time/epoch	72 sec

	Predicted Class											Per Class %
Actual Class	0	1	2	3	4	5	6	7	8	9	10	
0	726	24	0	0	0	0	0	0	0	0	0	96.80%
1	8	734	0	8	0	0	0	0	0	0	0	97.87%
2	0	5	729	15	0	0	0	1	0	0	0	97.20%
3	0	0	3	726	21	0	0	0	0	0	0	96.80%
4	0	0	0	8	730	12	0	0	0	0	0	97.33%
5	0	0	0	0	9	733	8	0	0	0	0	97.73%
6	0	0	0	0	0	7	737	5	1	0	0	98.27%
7	0	0	0	0	0	0	11	732	7	1	0	97.60%
8	0	0	0	0	0	0	0	8	722	20	0	96.27%
9	0	0	0	0	0	0	0	0	12	728	10	97.07%
10	0	0	0	0	0	0	0	0	0	35	715	95.33%

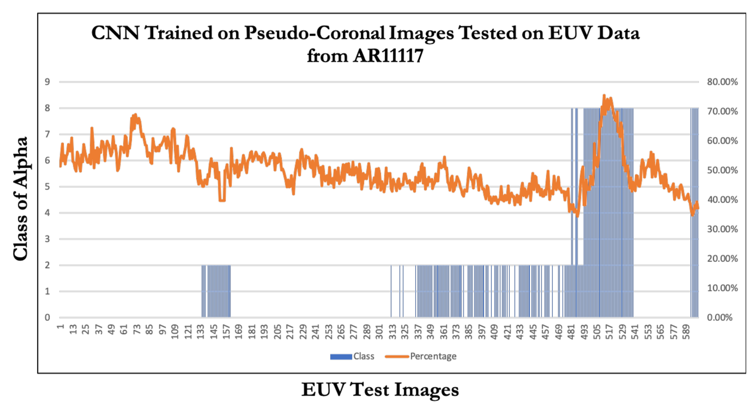


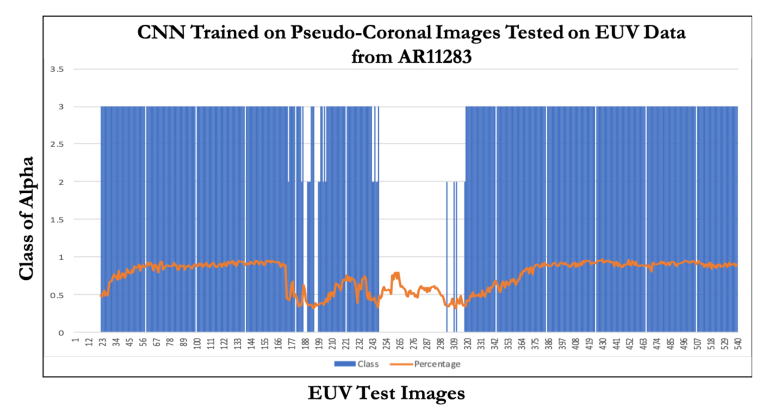


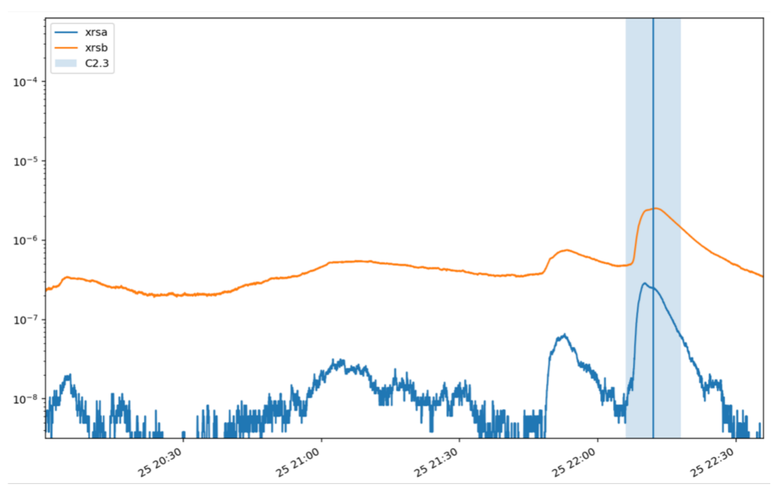
- When used with regression to predict the Alpha values we obtained an MAPE of 4% - 9%.

CNN - Alpha Response on EUV Data

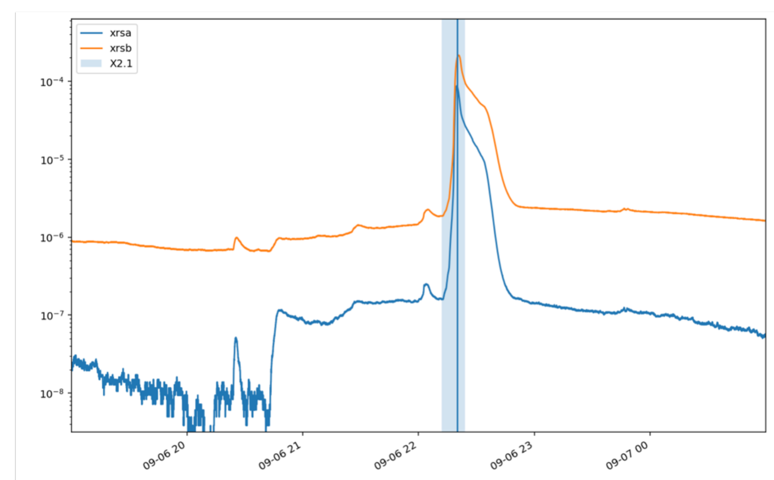
- In the process of validating our pseudo-coronal loop renderings we observed a change in the class of alpha when tested against EUV images of the same active region.
- This alpha change corresponds with flare events and provides a global nonpotential value using EUV data.
- We observed this on two active regions, AR11117 and AR11283.







a. GOES X-Ray Flux for AR11117 on October 25, 2010



b. GOES X-Ray Flux for AR12283 on September 6, 2011

- Based on these results we are looking at SHARP parameters and their response during flaring events.
- We are also looking at predicting these parameters from AIA EUV data.

Conclusion

We demonstrated the effectiveness of determining the alpha parameter from the CNN training of pseudo-coronal loops. The method also indicates a correlation between change in alpha value and EUV data during flare events. We are further exploring this correlation and its effect on space weather.

Major References

[1] B. Benson, W. David Pan, G. A. Gary, Q. Hu, and T. Staudinger, "Determining the parameter for the linear force-free magnetic field model with multi-dipolar configurations using deep neural networks," *Astronomy and Computing*, vol. 26, pp. 50 – 60, 2019.

[2] G. A. Gary, "Linear force-free magnetic fields for solar extrapolation and interpretation," *The Astrophysical Journal Supplement*, vol. 69, pp. 323–348, Feb 1989.