Exploring the ability of Convolutional Neural Networks to predict Solar wind quantities at 1 AU

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Introduction

The solar wind is a continuous stream of charged particles that pervades everything in the solar system, including Earth and other planets. It is made up of two types of the solar wind: fast and slow, with the primary differences being their velocity and origin. When it reaches the Earth, each form of the solar wind has a different effect. The solar magnetic field is included in the solar wind since it is a charged flow. As a result, solar wind has a significant impact on Earth's space weather forecasting and prediction. One of today's issues in space weather forecasting is understanding solar wind dynamics and estimating its velocity hours and days in advance.

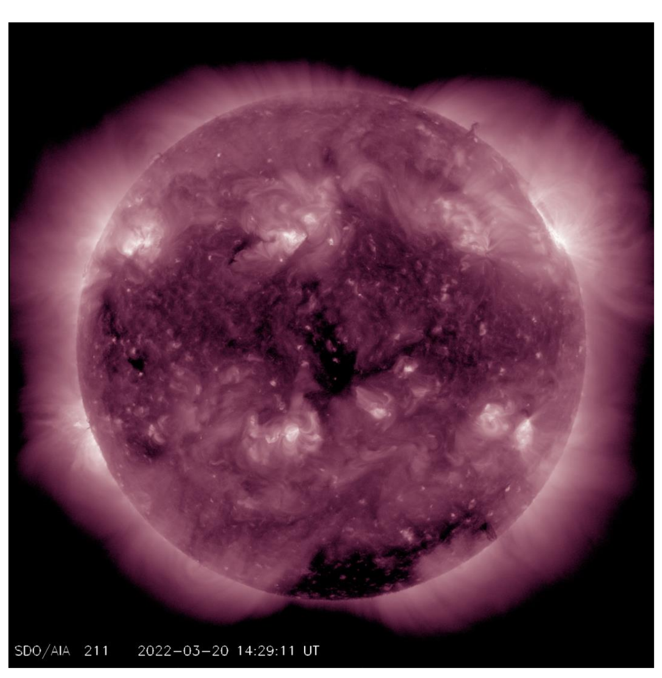
To comprehend and forecast the solar wind speed in a defined interval, this research integrates solar pictures from the Solar Dynamics Observatory's Atmospheric Imagery Assembly and solar wind time-series measurements from the OMNI dataset. We use AIA photos to match solar wind speed data at 1AU with potential solar wind sources using powerful machine learning algorithms. Deep learning is used to discover and classify the characteristics of solar features that cause a shift in solar wind speed, as well as to generate an accurate prediction of its speed at 1AU.

Solar Images

The work presented in this project is based on data from SDO's AIA. The AIA instrument takes full-disk, 4096 X 4096 pixels, imaging observations of the solar photosphere, chromosphere, and corona in two UV channels and seven extreme UV (EUV) channels. The original SDO dataset was processed into a machine-learning-ready dataset (SDOML, Galvez et. al 2019) of ~6.6 that we leveraged for the current work.

The SDOML dataset is a subset of the original SDO data ranging from 2010 to 2018. Images are spatially co-registered, have identical angular resolutions, are corrected for instrumental degradation over time, and have exposure corrections applied. All the instruments are temporally aligned. AIA images in the SDOML dataset are available at a sampling rate of 6 min. The 512 X 512 pixel full-disk images have a pixel size of ~4"8'.

The project uses 7 EUV channels from SDOML, but for the results presented here, we only used AIA 211 as input for the model. All images are normalized by their average count rate from the entire period. Various cadences of the image sequences are used, varying from 12min to 1 hour.



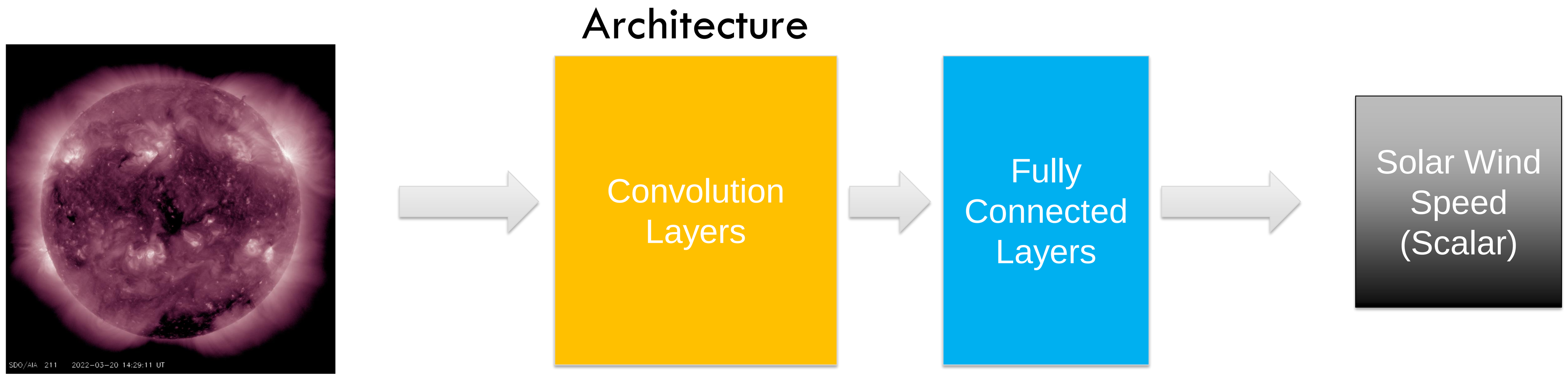
AIA 211 image, from March 20th, 2022. Credit: NASA.gov

Method

As a start point in this project a very simple Convolution Neural Networks (CNNs) model architecture, was used to try to predict solar wind speed at 1 AU using solar images.The model we present here only uses AIA 211 image as input and outputs the solar wind velocity with a fixed 4 days delay from the date of the image.

The model is trained and validated with images from 2010 to 2018 and tested on images from 2018. The split from train and validation is done training with data from January to August and validated with data from October to December.

Architecture



The cadence of the image sequences was varied to find the optimal combination of the results. For the sake of comparing results with similar projects already published we fixed the cadence at 30 minutes in the results presented here.

When comparing our preliminary results with results of similar projects, we have the following. The following results are root mean square error and Pearson correlation between the predicted output and ground truth output. The table shows the results metrics of different methods predicting solar wind speed. Therefore, is only used for illustration and not comparison.

	Persistent Model	Bailey et al. 2021	Upendran et al 2020	Brown et al 2022	Raju and Das, 2021	Our results
RMSE	85.16	79.2*	80.28**	71.65	78	79
Pearson Correlation	0.464	--	--	0.644	0.55	0.53

* Average value of RMSE for all years
** Best results for 211 A input.

As a start point, the results show a very good alignment with what was published before. The developed model has a better performance than the persistent model in both metrics and very similar results to Raju and Das, 2021. The results are also comparable with Brown et al 2022, which has many improvements done. These two last papers have similar approaches and therefore can be directly compared.

The main advantage of our method is its simplicity so far. We use very simple and small CNN architecture. We do not use attention-based, very deep architectures, nor transfer learning from ImageNet pre-trained models. These last are usually very heavy and costly architectures to (re)train. This is an early-stage work that shows promising results in the future.

Next Steps

We will keep working to optimize the performance. Several modifications can be such as, but not limited to, using more EUV channels as inputs, implementing a customized loss/cost function, pre-processing the input images, and other optimization we think may be interesting for the project.

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Acknowledgements

This project is supported by NASA under grant 80NSSC20K1580