Attention-based machine vision models and techniques for solar wind speed forecasting using solar EUV images

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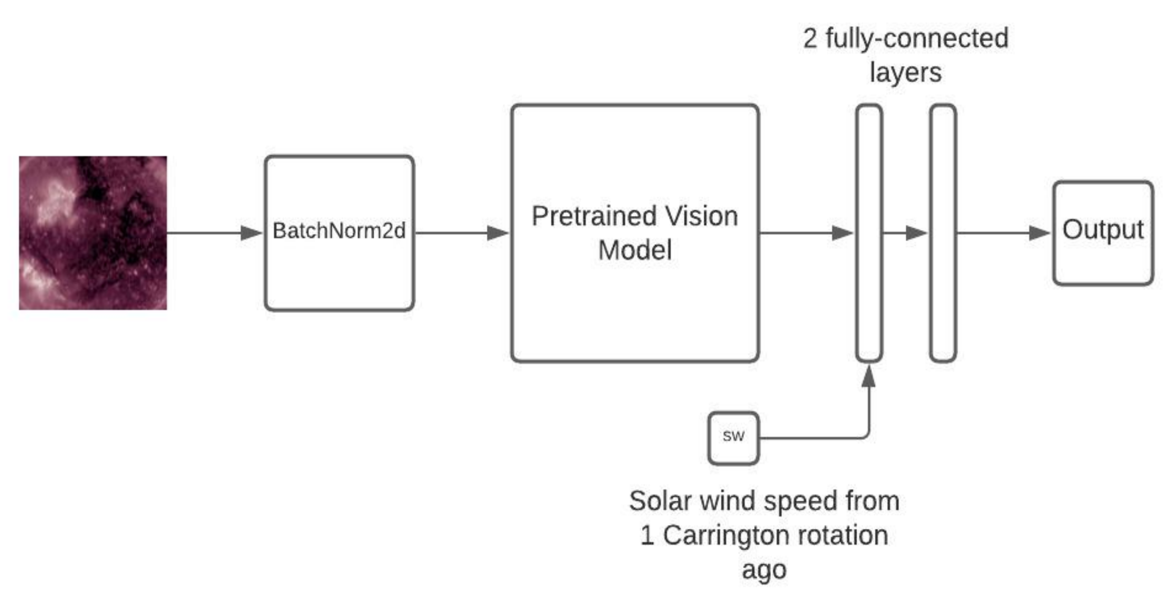
Introduction

Solar wind, a stream of charged particles, is emitted from the sun and arrives 2-7 days later at Earth. Earth itself is largely shielded from moderate solar winds by its magnetosphere, but these winds can cause geomagnetic disturbances - one of the main sources of uncertainty in orbital estimation. Extreme solar winds, can disrupt satellites, impact communication, and even damage power grids. Consequently, accurately forecasting the solar wind speed is very important for our modern society.

This study uses machine learning models to forecast the solar wind speed, as published by OmniWeb, using the Extreme UV images taken by the Solar Dynamics Observatory (SDO). Results for forecasting at a four-day lag from a single 211 Å image are presented.

Model Architecture

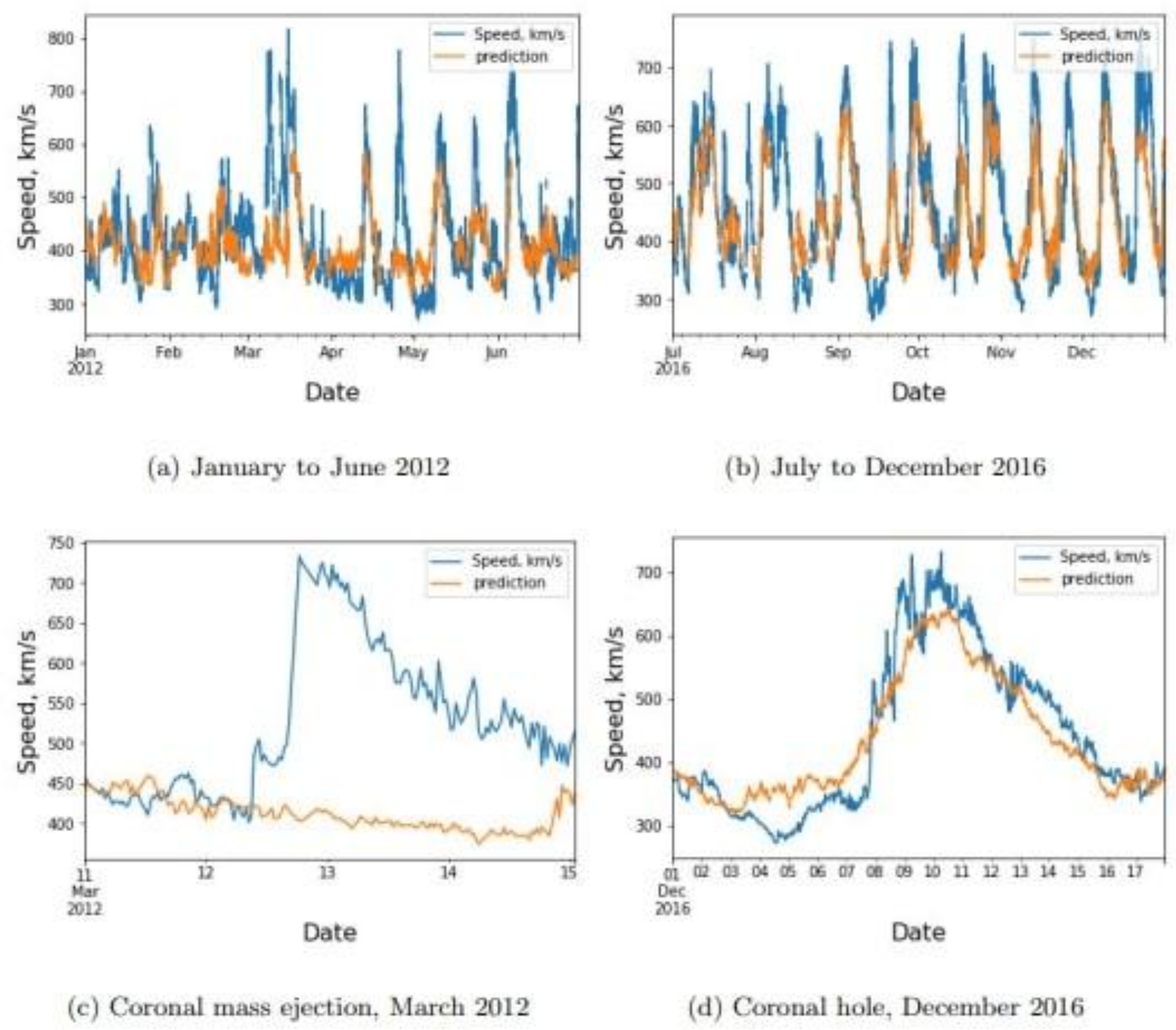


Model Performance

Our study finds attention-based models consistently outperform convolutional alternatives. Using the Swin Transformer as the pretrained model, the previous state-of-the-art is improved upon by 11.1% in RMSE and 17.4% in correlation for a test period over the 2010-2018 period. The model performance is highly dependence on the solar cycle, with the best performance occurring during the declining phase of the solar cycle when the solar activity is dominated by coronal holes.

Model Performance by solar feature

Figures a) and b) below show the model is much better at forecasting in the second half of 2016 than the start of 2012- the latter is driven by CMEs as opposed to 2016 which is driven by coronal holes.. The model is able to capture the speed profile of coronal holes much better than coronal mass ejection. EUV images at 30 minute cadence do not capture enough information about CMEs. Figure c) shows the model missing a CME in 2012. Figure d) shows the model capturing the profile of a CME in 2016.



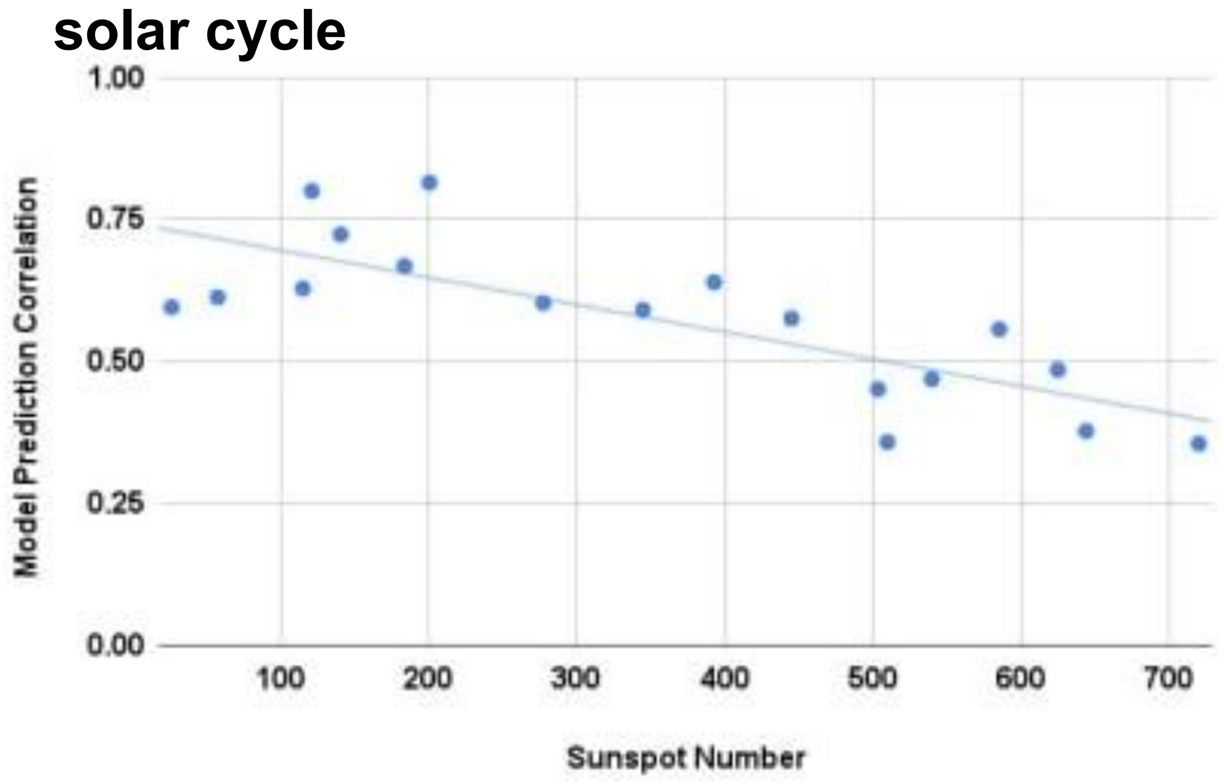
(a) January to June 2012

(b) July to December 2016

(c) Coronal mass ejection, March 2012

(d) Coronal hole, December 2016

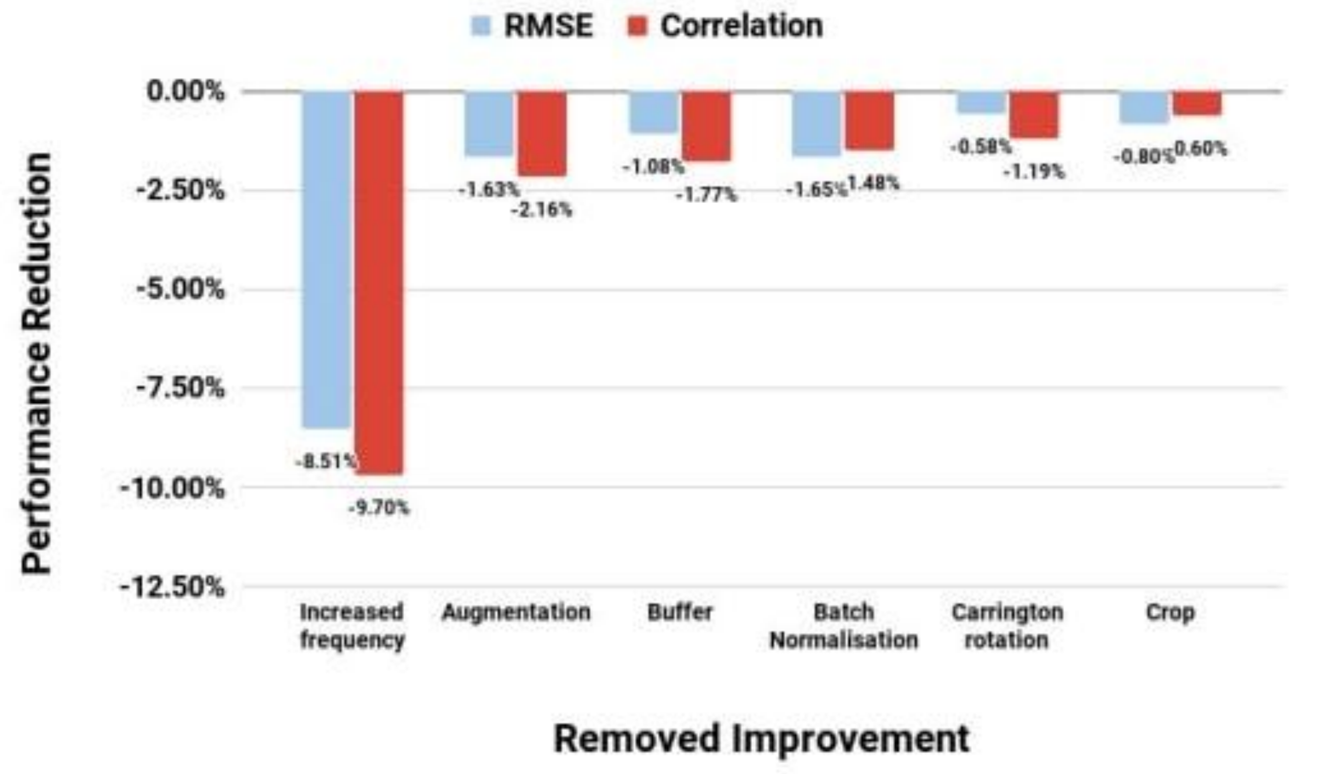
Model Performance over the solar cycle



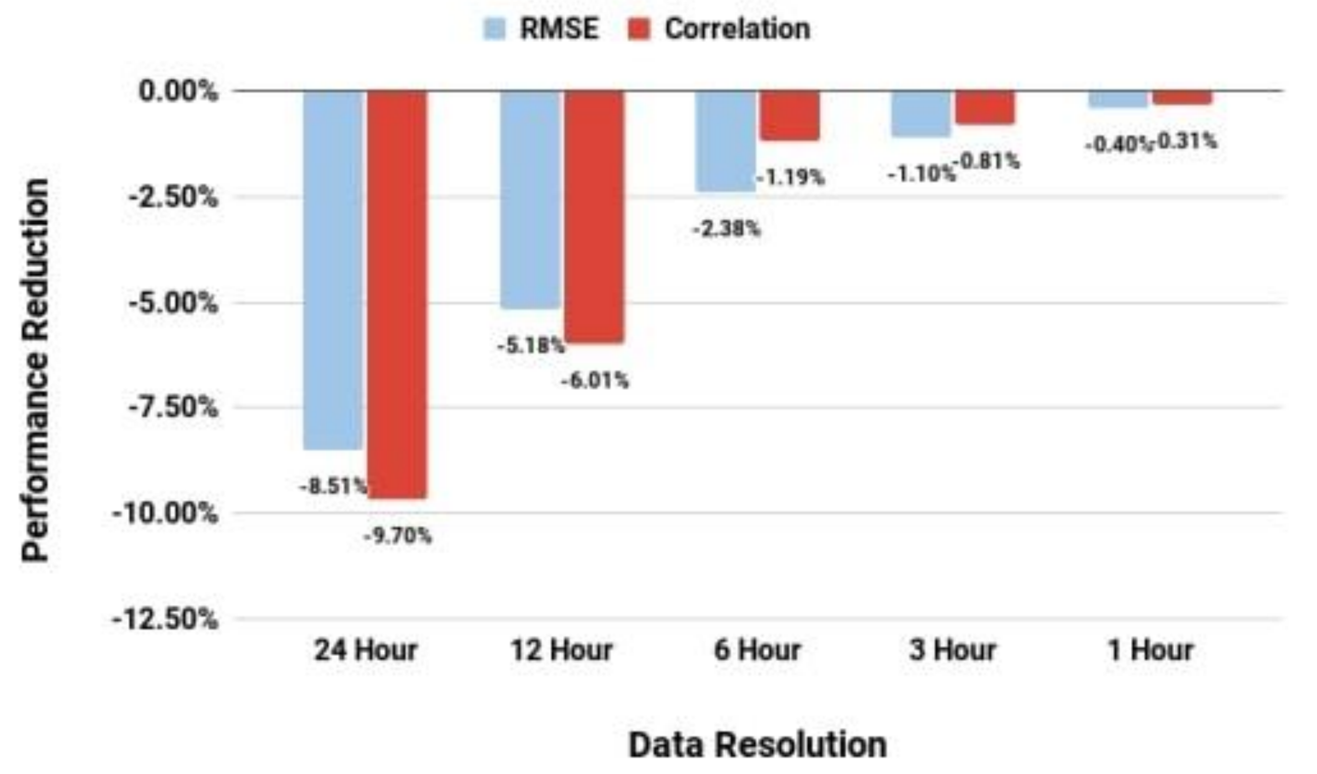
Ablation Study

To demonstrate the effect of our suggested techniques on the results, we conducted a study whereby each improvement is removed one at a time and the performance reduction reported.

The study finds that model performance can be improved by: 1) Increasing data resolution. 2) Augmenting the images by flipping north-to-south. 3) Adding a 4-day buffer between training and validation sets to keep them independent. 4) Normalising the image values before using a pre-trained model. 5) Adding the speed from one Carrington rotation ago (27 days). 6) Cropping the image to remove redundant information (at the poles and off-disk areas)



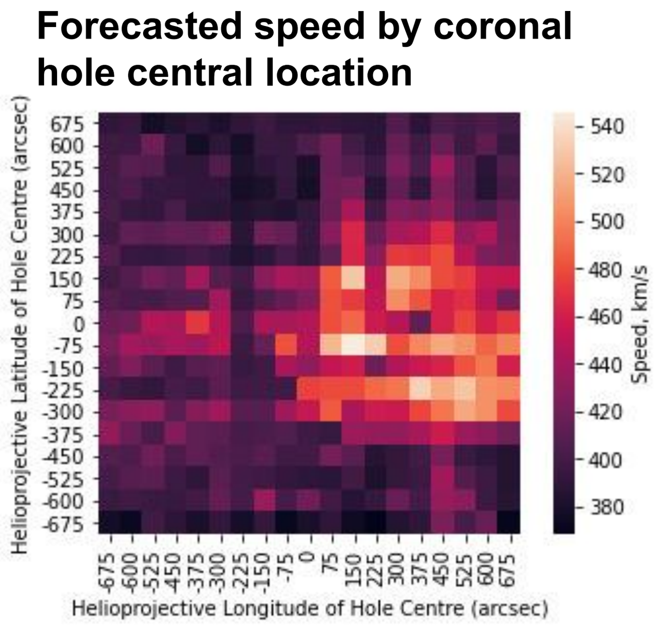
(a) Performance reduction resulting from removing one improvement at a time.

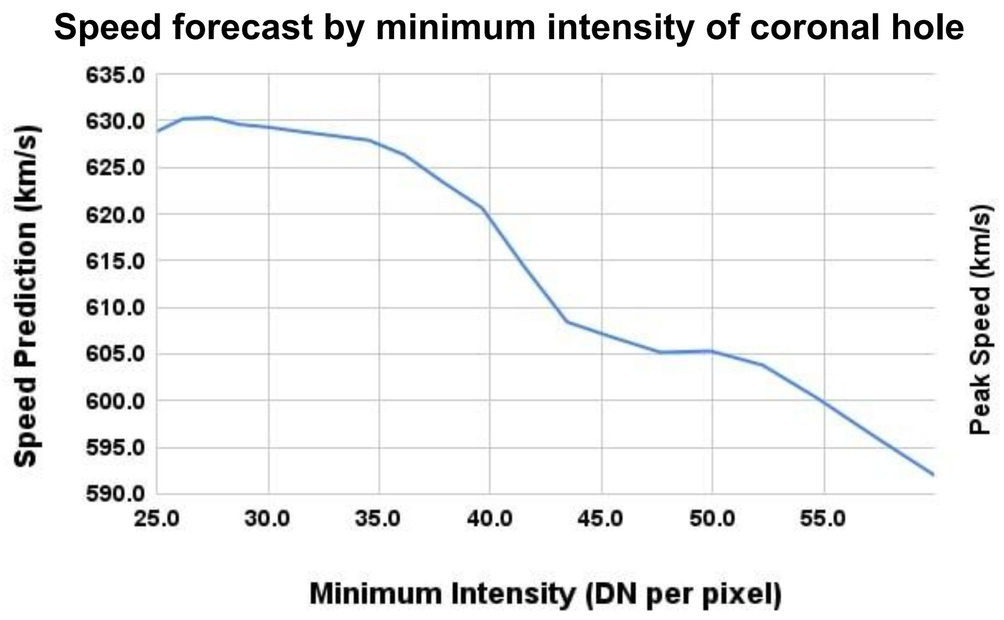


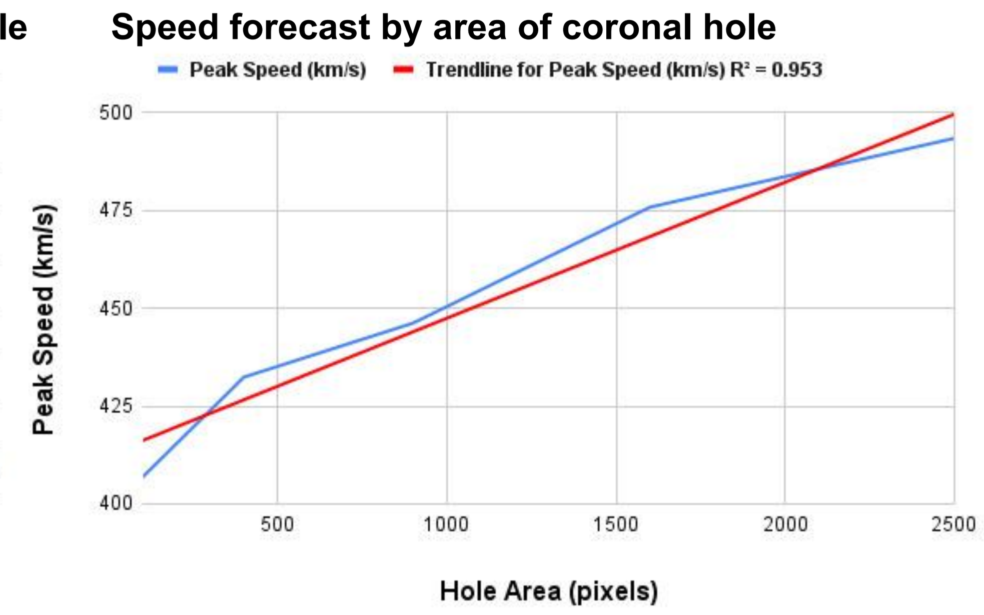
(b) Performance reduction compared to 30 minute resolution

Learned Coronal Hole Characteristics

The model has learnt empirically-verified relationships about coronal hole characteristics. Namely, the linear relationship between coronal hole area and solar wind speed at low latitudes, a negative correlation between coronal hole brightness and solar wind speed, coronal holes produce larger speeds the closer they are to the solar equator.







Model	RMSE	% Improvement	Correlation	% Improvement
Persistence(4 day)	127.59	-57.1%	0.080	-85.2%
Persistence(27 day)	100.86	-24.2%	0.426	-21.1%
Former state of the art [14]	81.21	-	0.54	-
Our models				
Solar InceptionNet v4	74.09	8.8%	0.609	12.7%
Solar DenseNet	73.92	9.0%	0.611	13.1%
Solar GoogleNet	73.71	9.2%	0.619	14.6%
Solar ResNet	73.52	9.5%	0.618	14.4%
Solar TNT	72.70	10.5%	0.629	16.5%
Solar Vision Transformer	72.66	10.5%	0.630	16.7%
Solar Swin Transformer	72.21	11.1%	0.634	17.4%

Key Point Summary

- Our study finds attention-based machine vision models outperform convolutional models at forecasting the solar wind speed at a 4 day time horizon.
- A set of techniques are developed to improve solar wind speed forecasting from solar EUV images.
- The model's performance is highly correlated with the solar cycle- with the best performance occurring in the declining phase when the solar activity is dominated by coronal holes