Poster 58

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Developing Deep Learning for Solar Feature Recognition

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At a Glance

- Using a multi-channel solar dataset from SDO and labels using conventional image processing, we trained a neural net to segment solar features.
- We found using an LSTM-Unet hybrid created better convergence over a Unet.
- Including well known physics, like the PDF of sunspot locations, increased the accuracy of the model.
- The LSTM-Unet approach is only as good as the labels. We are currently working on a “fuzzy-labeling approach to introduce uncertainties to the training data.

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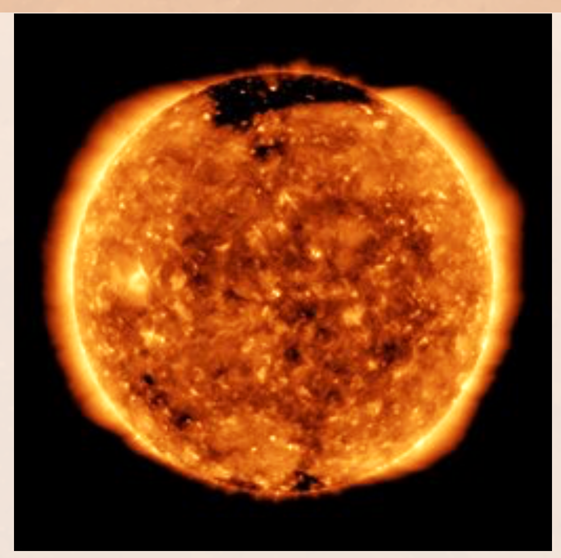
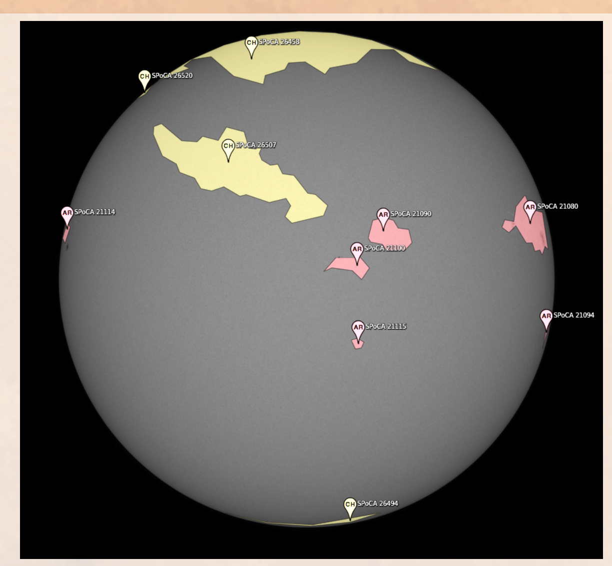
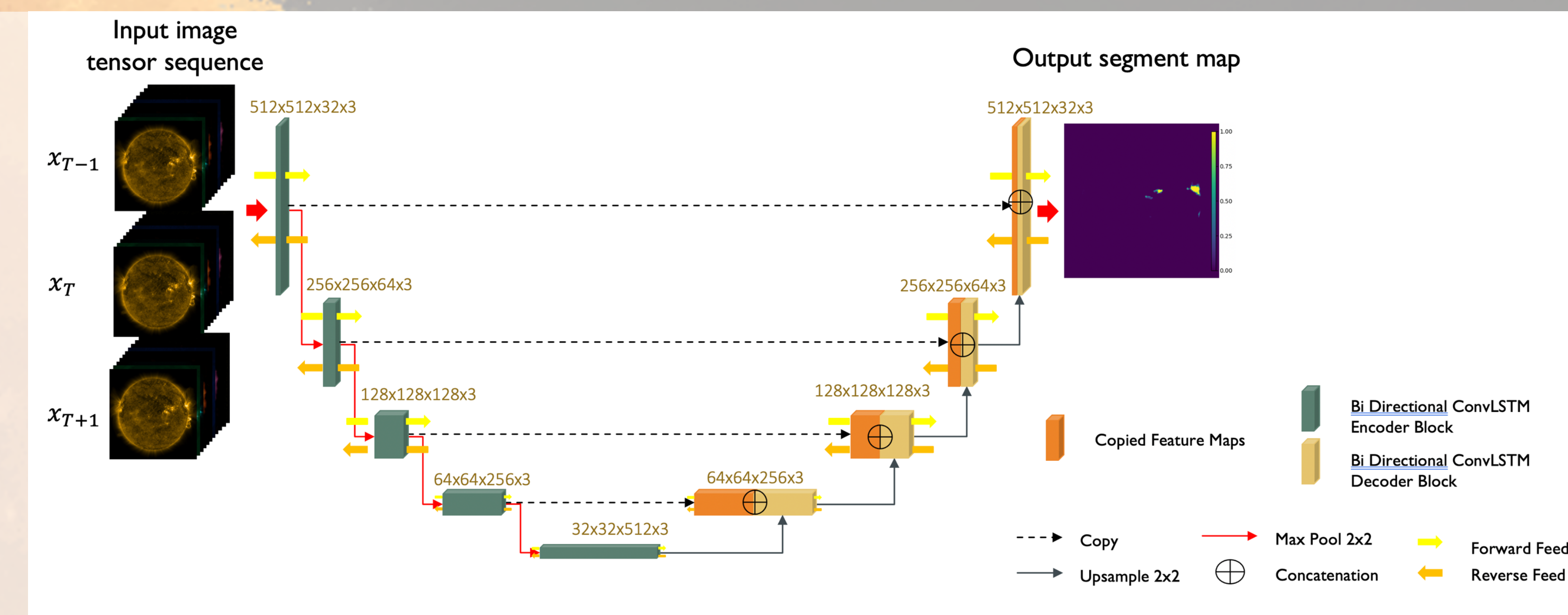




The Solar Dynamics Observatory (SDO) images the sun in extreme ultraviolet wavelengths (left) to reveal several features that evolve and influence the Earth: sunspots, coronal holes, and active regions (labels of these are shown in the image on the right). Our goal was to encode classical methods of feature labeling using ML to be able to run on the full 200 million image archive where conventional methods would not be able to perform.

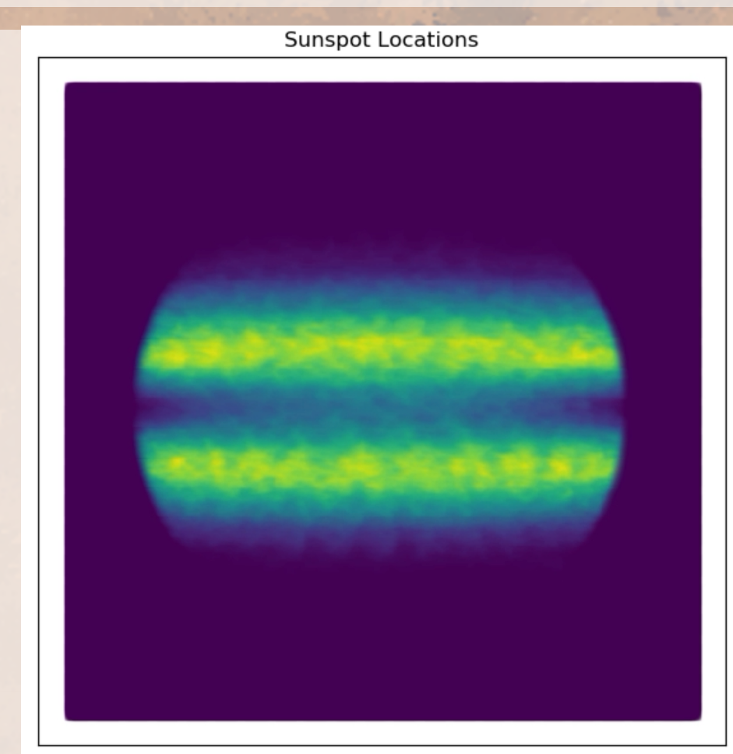
GRAY BOX MODEL

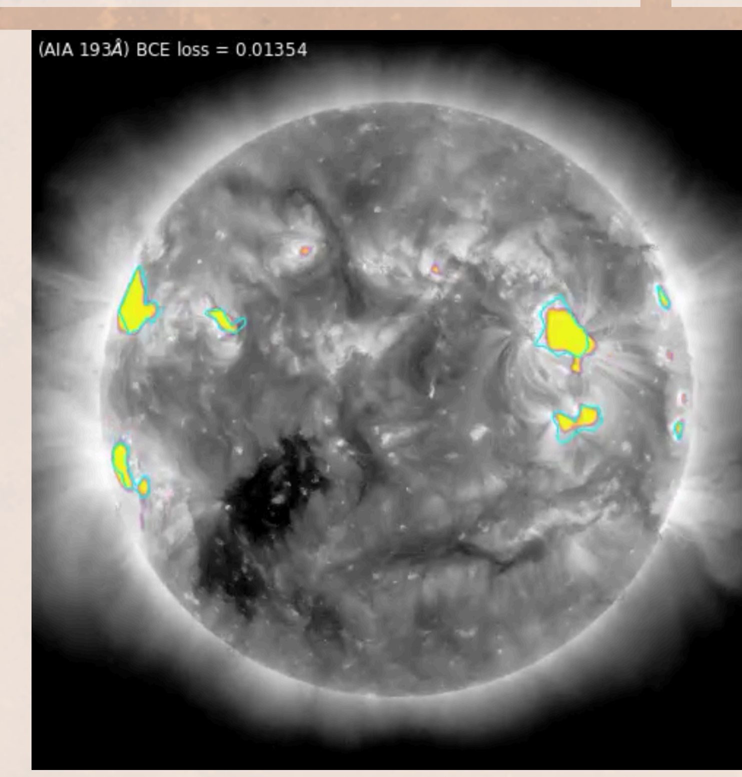
Encode existing scientific knowledge into a machine learning architecture.



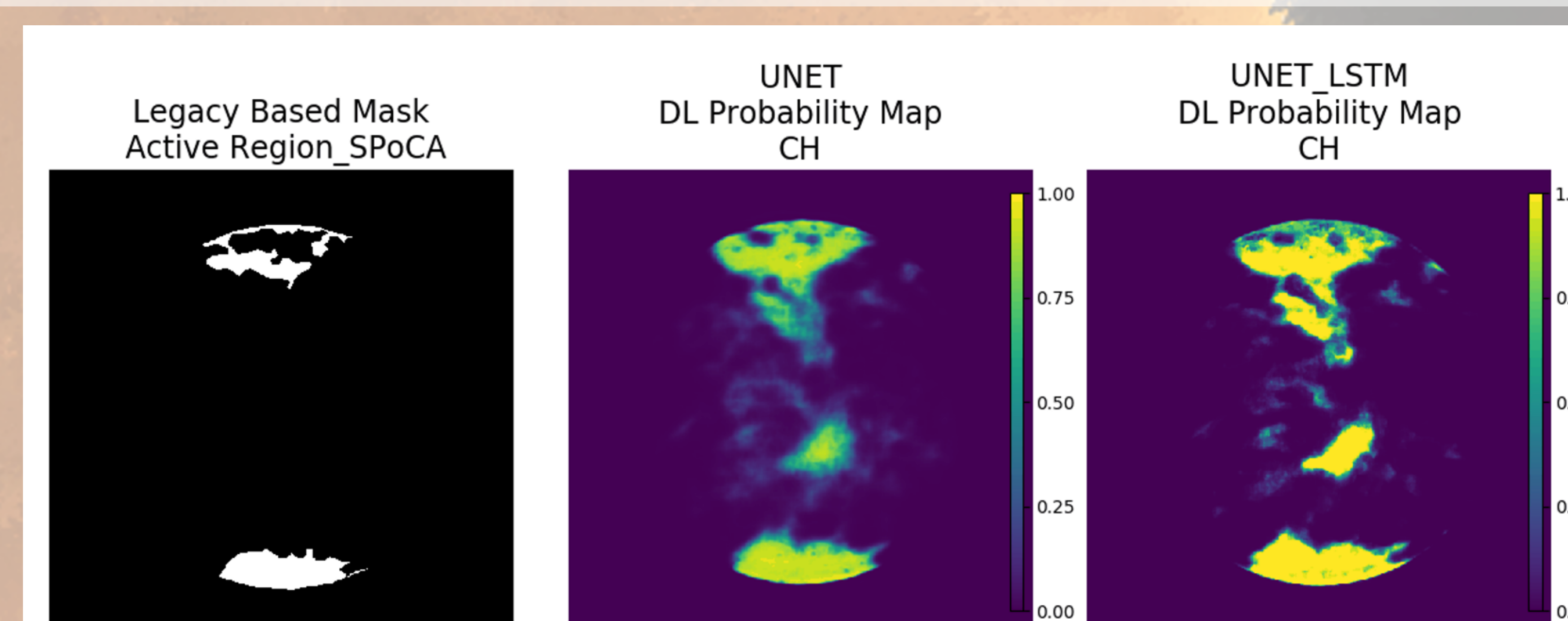
A Unet architecture is well suited to the high-resolution SDO images to detect solar features of various size. In training the Unet, we down-sampled the images by a factor of 4 to be able to include all 11 wavelength bands SDO produces. Not every solar feature is observed in each channel, but we wanted to make sure the Unet was judging the saliency of each channel correctly.

Because solar features evolve in time, we implemented a long short-term memory (LSTM) architecture on each layer of the Unet by passing a tensor of `[t-1, t, t+1]` through the pooling and up-sampling steps (shown above). This hybrid LSTM-Unet approach greatly improved the accuracy and convergence of the model (shown below). The drawback of the hybrid approach is that it requires 3-times the memory for training, which makes full resolution, 4k x 4k, images difficult to work with.





Adding in known systematics and physical phenomena greatly increased the accuracy of the model. We included a probability density function of sunspots (shown left), a function to model the degradation of the detectors, and six temporal signatures that are well known – both physical signals and systematic errors. The accuracy could be gauged by comparing predicted vs. measured labels of active regions (shown on the right).



Despite the robust models, there are still significant disagreements between the legacy labels and the DL probability maps (show above). Examining the input images raises the question if there is some error in the legacy labels. Currently we are working to create a probability map of training labels to better capture the uncertainty inherent in the solar features.

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ALTAMIRA NASA NVIDIA