Conventional global magnetic field maps, such as daily updated synoptic maps, have been constructed by merging together a series of observations from the Earth's viewing direction taken over a 27-day solar rotation period to represent the full surface of the Sun. It has limitations to predict real-time farside magnetic fields, especially for rapid changes in magnetic fields by flux emergence or disappearance. Here, we construct accurate synchronic magnetic field maps using frontside and AI-generated farside data. To generate the farside data, we train and evaluate our deep learning model with frontside SDO observations. We use an improved version of Pix2PixHD with a new objective function and a new configuration of the model input data. We compute correlation coefficients between real magnetograms and AI-generated ones for test data sets. Then we demonstrate that our model better generate magnetic field distributions than before. We compare AI-generated farside data with those predicted by the magnetic flux transport model. Finally, we assimilate our AI-generated farside magnetograms into the flux transport model and show several successive global magnetic field data from our new methodology.

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[구 SS-04] Visual Explanation of a Deep Learning Solar Flare Forecast Model and Its Relationship to Physical Parameters

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In this study, we present a visual explanation of a deep learning solar flare forecast model and its relationship to physical parameters of solar active regions (ARs). For this, we use full-disk magnetograms at 00:00 UT from the Solar and Heliospheric Observatory/Michelson Doppler Imager and the Solar Dynamics Observatory/ Helioseismic and Magnetic Imager, physical parameters from the Space-weather HMI Active Region Patch (SHARP), and Geostationary Operational Environmental Satellite X-ray flare data. Our deep learning flare forecast model based on the Convolutional Neural Network (CNN) predicts "Yes" or "No" for the daily occurrence of C-, M-, and X-class flares. We interpret the model using two CNN attribution methods (guided backpropagation and Gradient-weighted Class Activation Mapping [Grad-CAM]) that provide quantitative information on explaining the model. We find that our deep learning flare forecasting model is intimately related to AR physical properties that have also been distinguished in previous studies as holding significant predictive ability. Major results of this study are as follows. First, we successfully apply our deep learning models to the forecast of daily solar flare occurrence with TSS = 0.65, without any preprocessing to extract features from data. Second, using the attribution methods, we find that the polarity inversion line is an important feature for the deep learning flare forecasting model. Third, the ARs with high Grad-CAM values produce more flares than those with low Grad-CAM values. Fourth, nine SHARP parameters such as total unsigned vertical current, total unsigned current helicity, total unsigned flux, and total photospheric magnetic free energy density are well correlated with Grad-CAM values. This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIP) (2018-0-01422, study on analysis and prediction technique of solar flares).

[구 SS-05] Selection of Three (E)UV Channels for Solar Satellite Missions by Deep Learning

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We address a question of what are three main channels that can best translate other channels in ultraviolet (UV) and extreme UV (EUV) observations. For this, we compare the image translations among the nine channels of the Atmospheric Imaging Assembly on the Solar Dynamics Observatory using a deep learning model based on conditional generative adversarial networks. In this study, we develop 170 deep learning models: 72 models for single-channel input, 56 models for double-channel input, and 42 models for triple-channel input. All models have a single-channel output. Then we evaluate the model results by pixel-to-pixel correlation coefficients (CCs) within the solar disk. Major results from this study are as follows. First, the model with 131 Å shows the best performance (average CC = 0.84) among single-channel models. Second, the model with 131 and 1600 Å shows the best translation (average CC = 0.95) among double-channel models. Third, among the triple-channel models with the highest average CC (0.97), the model with 131, 1600, and 304 Å is suggested in that the minimum CC (0.96) is the highest. Interestingly they are