Based on Vector Parameters from SDO/HMI

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We present the relationship between vector magnetic field parameters and solar major flare occurrence rate. Based on this, we are developing a forecast model of major flare (M and X-class) occurrence rate within a day using hourly vector magnetic field data of Space-weather HMI Active Region Patch (SHARP) from May 2010 to April 2017. In order to reduce the projection effect, we use SHARP data whose longitudes are within ±60 degrees. We consider six SHARP magnetic parameters (the total unsigned current helicity, the total photospheric magnetic free energy density, the total unsigned vertical

current, the absolute value of the net current helicity, the sum of the net current emanating from each polarity, and the total unsigned magnetic flux) with high F-scores as useful predictors of flaring activity from Bobra and Couvidat (2015). We have considered two cases. In case 1, we have divided the data into two sets separated in chronological order. 75% of the data before a given day are used for setting up a flare model and 25% of the data after that day are used for test. In case 2, the data are divided into two sets every year in order to reduce the solar cycle (SC) phase effect. All magnetic parameters are divided into 100 groups to estimate the corresponding flare occurrence rates. The flare identification is determined by using LMSAL flare locations, giving more numbers of flares than the NGDC flare list. Major results are as follows. First, major flare occurrence rates are well correlated with six magnetic parameters. Second, the occurrence rate ranges from 0.001 to 1 for M and X-class flares. Third, the logarithmic values of flaring rates are well approximated by two linear equations with different slopes: steeper one at lower values and lower one at higher values. Fourth, the sum of the net current emanating from each polarity gives the minimum RMS error between observed flare rates and predicted ones. Fifth, the RMS error for case 2, which is taken to reduce SC phase effect, are smaller than those for case 1.

[구 SS-03] Application of Convolution Neural Network to Flare Forecasting using solar full disk images

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In this study we apply Convolution Neural Network(CNN) to solar flare occurrence prediction with various parameter options using the 00:00 UT MDI images from 1996 to 2010 (total 4962 images). We assume that only X, M and C class flares correspond to “flare occurrence” and the others to “non-flare”. We have attempted to look for the best options for the models with two CNN pre-trained models (AlexNet and GoogLeNet), by modifying training images and changing hyper parameters. Our major results from this study are as follows. First, the flare occurrence predictions are relatively good with about 80 % accuracies. Second, both flare prediction models based on AlexNet and GoogLeNet have similar results but AlexNet is faster than GoogLeNet. Third, modifying the training images to reduce the projection effect is not effective. Fourth, skill scores of our flare occurrence model are mostly better than those of the previous models.

[구 SS-04] Application of Deep Learning to the Forecast of Flare Classification and Occurrence using SOHO MDI data

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A Convolutional Neural Network(CNN) is one of the well-known deep-learning methods in image processing and computer vision area. In this study, we apply CNN to two kinds of flare forecasting models: flare classification and occurrence. For this, we consider several pre-trained models (e.g., AlexNet, GoogLeNet, and ResNet) and customize them by changing several options such as the number of layers, activation function, and optimizer. Our inputs are the same number of SOHO)/MDI images for each flare class (None, C, M and X) at 00:00 UT from Jan 1996 to Dec 2010 (total 1600 images). Outputs are the results of daily flare forecasting for flare class and occurrence. We build, train, and test the models on TensorFlow, which is well-known machine learning software library developed by Google. Our major results from this study are as follows. First, most