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Reliability of AI-generated magnetograms from only EUV images

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Kim et al.[1] proposed an artificial intelligence (AI) model to predict the photospheric magnetograms of the Sun using extreme ultraviolet (EUV) observations as the only inputs, and concluded that their model is "reliable if the farside active regions conform to Hale's law, as long as the slight overestimation of their total flux and a possible slight difference in their tilt angle are considered". In this Matters Arising, we present a detailed sensitivity study of the AI algorithm used by Kim et al.[1]. Despite identifying issues in the data preparation process and the possibility of data leakage in their work[1], we also found the physics basis of this idea problematic. We detail our concerns and analysis below, as well as in the Supplementary Information.

Several new machine learning and/or AI techniques have been introduced recently and used for a variety of purposes in solar physics and space weather forecasting[2]. Using direct images or extracted features from the photospheric magnetic field only, or combined with solar EUV observations, a number of efforts have been made to predict the occurrence and/or onset time of solar flares employing statistical and/or machine learning methods[3–9]. In addition, using algorithms including the support vector machines and convolutional neural networks, the mean absolute error in predicting the arrival time of corona mass ejections has—remarkably—been reduced to as low as ~6 h (refs. [10,11]), providing further support for the use of machine learning/AI in space weather forecasting.

To study solar activity and predict space weather, Kim et al.[1] employed an AI technique (conditional generative adverserial networks) to predict solar photospheric magnetograms. They fed these conditional generative adversarial networks with full-disk EUV and photospheric magnetic field observations from the Atmospheric Imaging Assembly[12] (AIA) 304 Å passband and Helioseismic and Magnetic Imager[13] (HMI) onboard the Solar Dynamics Observatory (SDO). A model was then built with the SDO/AIA 304 Å images as the input to generate simultaneous SDO/HMI photospheric magnetograms. Kim et al.[1] then evaluated the model and found promising correlation coeffecients between the total unsigned magnetic flux (TUMF) of the generated and observed magnetograms. Kim et al.[1] concluded that using their method the photospheric magnetograms could be reliably forecasted to greatly improve our current knowledge of the farside active regions. However, there are several vital practical, as well as theoretical, issues in their study that to some extent mitigate the success of their model.

While preprocessing the SDO/HMI photospheric line-of-sight magnetograms (see the supplementary data and methods in ref. [1]), Kim et al. set the upper and lower saturation limits of the magnetic field strength at ±100 G. However, these limits are problematic, especially for active regions, considering one of the main purposes of their study was to predict the farside active regions of the Sun. The average absolute magnetic field strength of all 3,936 active regions detected from the original observations in the testing set of the data has been found to be 208 ± 54 G. Only 0.77% of all the active regions reveal an average absolute magnetic field strength of less than 100 G, among which only three active regions have an average absolute magnetic field strength less of than 90 G.

The slopes of black dots in Supplementary Fig. 1a suggest that the rescaled magnetograms with saturation limits of ±100 G give on average 0.45 and 0.67 of the original TUMF and net magnetic flux (NMF). In addition, the degree of the scattering of the dots yields the R^2 scores (Supplementary Equation (1)) of −0.07 and 0.77, respectively. The percentage of instances where the rescaled magnetograms yield the opposite sign of the NMF to the original observations is about 19.4%. The above evaluation suggests, again, that the generated magnetograms could still be notably different from the original observations—even if the model were perfect—if saturation limits of ±100 G are used when preparing the dataset. For a comparison, blue dots and lines in Supplementary Fig. 1b show the corresponding results for saturation limits of ±625 G. We note that setting inappropriate large saturation limits might also be problematic as that could introduce too much noise, which might then severely impact the ability of the generative models to capture the prior distribution. Thus we encourage researchers to evaluate carefully before choosing the saturation limits for normalization purposes. Moreover, Kim et al.[1] used observations in September and October in each year as the testing set and the rest as the training set, risking a possibility of a data leakage, considering that the Sun rotates at a period of ~27.3 days (see 'Potential data leakage' in the Supplementary Information).

In addition to the above practical issues, we do not expect the model to be successful based on the theoretical fact that EUV

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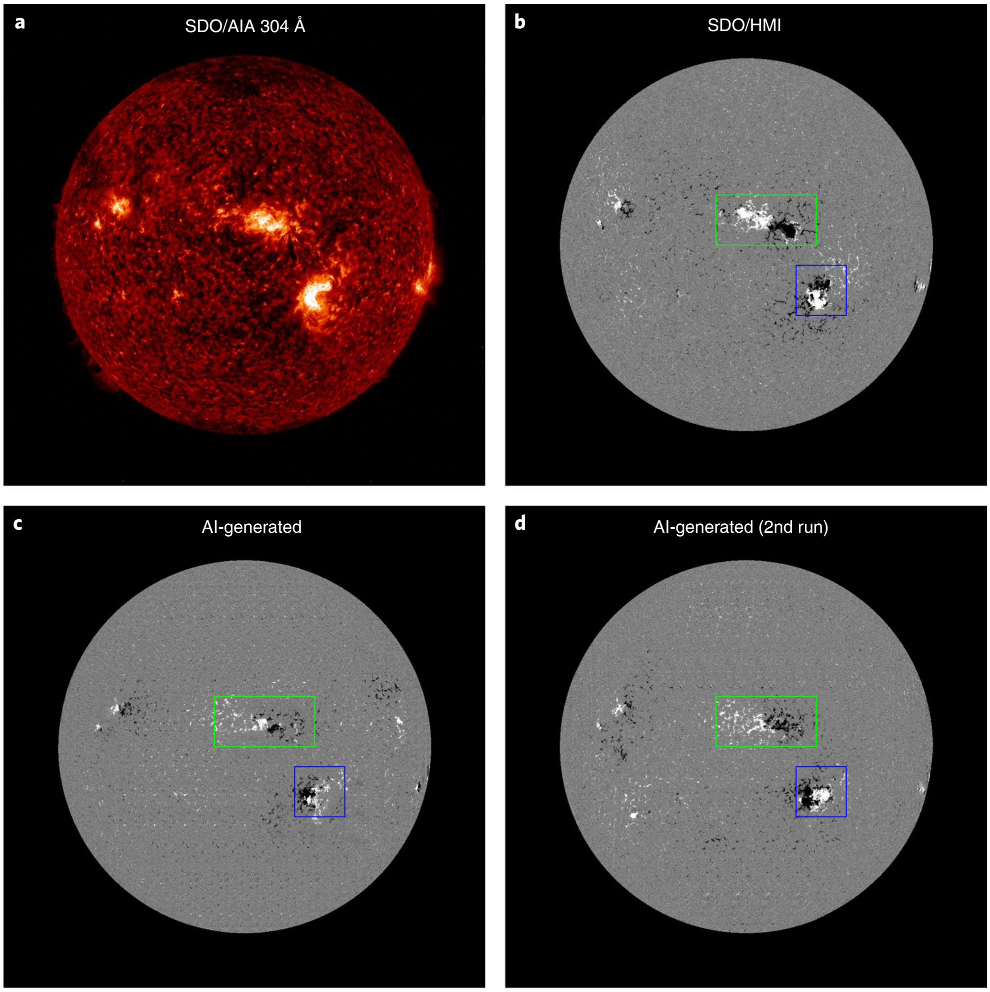

Fig. 1 | Example of the observations and the AI-generated magnetograms. a, SDO/AIA 304 Å observation. **b**, SDO/HMI photospheric magnetogram. Images were taken at 12:00 UT on 2017 September 5. **c**,**d**, AI-generated magnetograms of the Sun by two of our independent verification processes from the first (**c**) and second (**d**) runs, respectively. Green and blue boxes in **b**, **c** and **d** enclose two active regions.

observations of the chromosphere and corona do not provide any information about the magnetic field polarities of the photosphere. We trained the neural network to build an optimistic AI model using the code provided by Kim et al.[1], fed with the same dataset preprocessed with the same parameter settings (see 'Data and method' in the Supplementary Information). Figure 1 shows a comparison of the observations (Fig. 1b) and the magnetograms generated by the model we built (Fig.1c, first run), which could be directly compared with the one generated from the model built by Kim et al. (fig. 1 in ref. [1]). Overall, the AI models successfully identified the active regions presented in the original observation. However, the shapes of the active regions and the distributions of the positive and negative polarities are poorly reconstructed (see the two active regions enclosed in the green rectangle and blue square boxes in Fig. 1b,c). Furthermore, we ran the same procedure twice and built two new models (the best models built at 128 and 212 epochs for the second and third runs, respectively). The magnetogram generated by one of these two models (the second run) is shown in Fig. 1d. Obvious differences can be seen between the generated active regions in Fig. 1c,d, which should not happen with a robust and reliable model. We note that although we have used the same architecture, hyperparameters and training data in all of our three models, they are different models and are not exactly the same as that in Kim et al.[1]. The differences arose because the models all have different trained parameters due to factors including different weight initialization, the stochastic character of the optimizer and specificities of the loss hypersurface and so on. All further analysis shown below and in the Supplementary Information is based on the first model that we built. Detailed evaluations of the correlation between the generated (from the first run) and rescaled (with saturation limits of ±100 G) magnetograms (see 'Full-disk parameters' in the Supplementary Information) show that the proposed AI model is only successful in reproducing the TUMF of the global magnetic field, but fails to reconstruct the relative relations between the positive and negative polarities, as indicated by the low pixel-to-pixel cross-correlation and the low correlation between the NMFs. Integrating the TUMF information and area of the far-side active regions into dedicated models, together with the front-side magnetograms, could in some cases improve the performance in predicting the in situ solar wind speed[14].

We employ an automated detection system[15,16] to extract active regions and their parameters from the rescaled and the generated full-disk magnetograms. Supplementary Fig. 2 depicts a direct comparison between the active regions detected from the rescaled and generated magnetograms at 00:00 UT on 2011 September 28 as an example. One can clearly observe differences between the sizes, shapes and polarity inversion lines of the active regions in the northern hemisphere, especially in the two big active regions (one close to the disk centre and the other on the right). There are also missed active regions in the northern hemisphere and one extra active region in the southern hemisphere of the generated magnetogram compared with the rescaled one.

Statistical analysis (see 'Active region parameters' in the Supplementary Information and Supplementary Fig. 3) reveals that, on average, the model reproduces fewer than half of the active regions in each of the observations. The centres of the detected active regions in the AI-generated magnetograms are on average ~1.3° away in heliographic coordinates from the real ones. Detailed evaluations on a number of key parameters of the detected active regions (see 'Active region parameters' in the Supplementary Information and Supplementary Fig. 4) suggest that the AI model performs fairly well in predicting the areas of the active regions, but poorly in reproducing the NMF of the active regions and the total number, length and average magnetic gradient across polarity inversion lines. To conclude, our sensitivity study suggests that the AI model proposed by Kim et al.[1] may be far from providing scientifically reliable magnetograms.

Data availability

SDO/AIA and SDO/HMI data are publicly available from NASA's SDO website (https://sdo.gsfc.nasa.gov/data/). Details of the dataset we used are available at https://github.com/yiminking/pix2pix_EUV2HMI_datasets. Source data are provided with this paper.

Code availability

Codes for the AI models built in this paper are available at https://github.com/tykimos/SolarMagGAN. Codes used for the detection of active regions are available upon request from the corresponding author.

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Author contributions

J.L. led and conducted the data preparation and data analysis and drafted the manuscript. Yimin Wang led and performed the machine learning approach with Y.J. and M.B.K. contributing to the discussions. R.E., X.H. and J.L. recognized the core problems. R.E. suggested and led the overall research. Yuming Wang helped with the automated detection of active regions. All authors contributed to discussions and participated in the interpretation of the results. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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