An Intelligent Solar Flare Prediction Model Based on X-ray Flux Curves Using Long Short-Term Memory (Postprint)

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Abstract

Solar flares are violent solar outbursts which have a great influence on the space environment surrounding Earth, potentially causing disruption of the ionosphere and interference with the geomagnetic field, thus causing magnetic storms. Consequently, it is very important to accurately predict the time period of solar flares. This paper proposes a flare prediction model, based on physical images of active solar regions. We employ X-ray flux curves recorded directly by the Geostationary Operational Environmental Satellite, used as input data for the model, allowing us to largely avoid the influence of accidental errors, effectively improving the model prediction efficiency. A model based on the X-ray flux curve can predict whether there will be a flare event within 24 hours. The reverse can also be verified by the peak of the X-ray flux curve to see if a flare has occurred within the past 24 hours. The True Positive Rate and False Positive Rate of the prediction model, based on physical images of active regions are 0.607 0 and 0.241 0 respectively, and the accuracy and True Skill Statistics are 0.759 0 and 0.5556. Our model can effectively improve prediction efficiency compared with models based on the physical parameters of active regions or magnetic field records, providing a simple method for solar flare prediction.

Full Text

Preamble

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Abstract

Solar flares are violent solar outbursts that have a great influence on the space environment surrounding Earth, potentially causing disruption of the ionosphere and interference with the geomagnetic field, thus causing magnetic storms. Consequently, it is very important to accurately predict the time period of solar flares. This paper proposes a flare prediction model based on physical images of active solar regions. We employ X-ray flux curves recorded directly by the Geostationary Operational Environmental Satellite, used as input data for the model, allowing us to largely avoid the influence of accidental errors, effectively improving the model prediction efficiency. A model based on the X-ray flux curve can predict whether there will be a flare event within 24 hours. The reverse can also be verified by the peak of the X-ray flux curve to see if a flare has occurred within the past 24 hours. The True Positive Rate and False Positive Rate of the prediction model, based on physical images of active regions are 0.6070 and 0.2410 respectively, and the accuracy and True Skill Statistics are 0.7590 and 0.5556. Our model can effectively improve prediction efficiency compared with models based on the physical parameters of active regions or magnetic field records, providing a simple method for solar flare prediction.

Keywords: Neural Network; Long Short-Term Memory; Solar flare prediction; X-ray flux curve

1. Introduction

Solar flares are powerful solar eruptions that are associated with solar proton events and coronal mass ejections. The associated high-energy particle flux and radiation have a dramatic impact on the space environment, causing potential harm to spacecraft or astronauts. When radiation from a flare reaches the Earth, photoionization increases the electron density of the ionospheric D layer, causing radio communication to be interrupted. Consequently, the study of solar flare prediction has important practical value and scientific significance, providing an important warning function for dealing with sudden ionospheric disturbances, solar proton events, and geomagnetic storms in advance. Simultaneously, solar flare forecasting can provide insight to help understand solar activity.

To date, the most successful form of solar activity prediction is for short-term solar activity. This mainly involves forecasting flares and their corresponding ionospheric disturbances, as well as the arrival of high-energy particle fluxes (i.e., fluxes with particle energies greater than 10 MeV). In addition, there exist longer-term solar activity forecasts, such as prediction of the evolution of sunspot cycles. These make use of several existing and mature model algorithms, such as eXtreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree Classification Algorithm (C4.5), and Random Forest Classification Algorithm (Random Forest).

Most flare prediction studies use photospheric magnetic field data to parameterize the active region under examination, with the aim of finding out the connection between solar activity and the photospheric magnetic field in the active region. The relationship between the two is not fully understood at present, and most current flare prediction is based on the classifier method, which automatically identifies the relationship. Although this technology is relatively mature, it is not purely theoretical. Therefore, in the process of artificially designing and extracting the physical characteristic parameters of the solar active region, some random errors may occur.

Here, we propose a flare prediction model based on X-ray flux data acquired from the Geostationary Operational Environmental Satellite (GOES) to obtain a new dataset after processing (see Section 3.1). Using the new dataset as input for the model will largely avoid random errors. Directly processing real-world data recorded by GOES can effectively improve the efficiency of the model.

A common method of solar flare prediction uses event-based statistics, based on historical flare events, to predict future flare events. The forecasting system using this method mostly adopts the Bayesian method [?] or multiple linear regression method [?] to establish a flare prediction model.

Recently, with the rapid progress of data mining technology and machine learning, these methods have become important in the prediction of solar activity. Qahwaji et al. [?] use the McIntosh sunspot classification to contrast the input and compare the model performance based on a Cascade Correlation Neural Network (CCNN), SVM neural network, and Radial Basis Function Network (RBFN) neural network. They conclude that a SVM is better at predicting outbursts, and a CCNN is better at predicting the burst category. Song et al. [?] were first to use an ordered LR model to estimate the possibility of X, M, and C-class solar flare disturbances on the following day. Li et al. [?] establish a prediction model of solar flare disturbances and Solar Proton Events (SPEs) with the SVM-kNN method, which uses a combination of SVM and K-nearest neighbor methods. Al-Ghraibah et al. [?] use a Relevance Vector Machine (RVM) in combination with pattern recognition and classification, to determine if a solar flare is likely to erupt in an active region. RVM, a probabilistic generalization of support vector machines, is a Bayesian sparse kernel technique for regression and classification. Boucheron et al. [?] proposed to use the Support Vector Machine Return (SVR) method to forecast flare sizes and flare times. Guerra et al. [?] proposed a solar flare prediction approach that integrates multiple prediction methods. They used a linear combination of four methods: the Magnetic Forecast (MAG4), the Automatic Solar Synoptic Analyzer (ASSA), the Automated Solar Activity Prediction (ASAP) and forecasting methods provided by the National Oceanic and Atmospheric Administration (NOAA), finding that the integrated method is more effective than a single method. Liu et al. [?] proposed a Multi-model Integration Method (MIM) to predict solar flares. The output of each base model is first normalized, and then a fused model is constructed using a weighted fused base model. They incorporated seven models: RBFN, SVM, C4.5 decision tree, Sequential Minimal Optimization (SMO), Bayesian network, naive Bayes, and multilayer perceptron. They found that a fusion mode model shows better ability than a single model. Benvenuto et al. [?] first established a hybrid learning scheme and an unsupervised learning method to predict solar flares. This used a supervised method to determine the importance of feature ordering, and an unsupervised clustering method for binary classification. Nishizuka et al. [?] have compared the flare prediction capabilities of three different machine learning methods: Extremely Randomized Trees (ERT), SVM and k-NN. They found that among the three algorithms, k-NN has the best performance.

Deep learning algorithms in machine learning have been developed rapidly [?, ?] and have also been applied successfully in the fields of speech recognition, natural language processing, object recognition and classification [?, ?]. Deep learning algorithms can automatically determine characteristic parameters and build a model from original observational data. Li et al. [?] and Huang et al. [?] developed solar flare prediction models using the ability of a convolutional neural network to extract image features automatically. Simultaneously, a Recurrent Neural Network (RNN) can also learn the time series characteristics of the data. Liu et al. [?] used the SHARP data and historical characteristics of the flare and built prediction models of $\geq$M5.0, $\geq$M and $\geq$C class flares in the future 24 hours, with multiple schema models based on the Long Short-Term Memory (LSTM) network. Yuan et al. [?] used the "Shenguang II" device at the Shanghai National Laboratory of High Power Laser Physics to demonstrate the process of laser-driven plasma turbulent magnetic reconnection in the laboratory for the first time. Yan et al. [?] proposed a real-time forecasting model.

Solar flares are events with low probability and frequency, which causes the problem that positive and negative samples in a dataset are unbalanced. To solve this problem in flare prediction scenarios, we use a binary classifier to limit classifications to two categories: flares or no flares. If a solar flare erupts in a given time period, the active region is a positive sample. Conversely, if no solar flare erupts in a given time period, the active region is a negative sample.

Here, we propose a short-term flare prediction model based on the LSTM algorithm, using GOES data without manual design and extraction of characteristic parameters, while also differing from traditional machine learning methods. Considering the timing of X-ray flux curve data, we devise a flare prediction model using LSTM. This mainly comprises a long time memory network which can process long time series and express rich time series information. A LSTM neural network introduces a gating mechanism, allowing the model to learn the contents that need to be "Remembered" and "Forgotten" . To improve upon RNNs, LSTM networks have many advantages in the processing of long-term sequences [?]. The key detail of LSTM is the memory-cell component (specified as C_t and C_{t-1}). This works like a conveyor belt moving forward, with little linear interaction between the data and the information moving along the chain, allowing information to flux along it while remaining constant.

2. Methods

2.1 LSTM Model Framework

Fig. 1 [Figure 1: see original paper] shows the LSTM model framework diagram. The input state consists of three parts: the immediate input, X_t, the hidden layer output, h_{t-1} of the last time, and the last state C_{t-1} storage in the block construction (see Fig. 1).

The main structure of LSTM comprises the Input gate, Forget gate and Output gate. First, we must identify the information that needs to be discarded and forgotten through the Forget gate, using the relationship,

$$f_t = \sigma(W_f[h_{t-1}; x_t] + b_f) \tag{1}$$

Next, we determine the new message to be stored, perform two nonlinear transformations, and obtain the cell candidate state and Input gate function as

$$i_t = \sigma(W_i[h_{t-1}; x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}; x_t] + b_c) \tag{3}$$

Current and historical information are then controlled using the Forget gate and Input gate, updating the status of the cell,

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

Finally, when the state of the cell is updated, we need to determine what message will be output, using nonlinear conversion of the input to get the Output gate function. Concurrently, the updated status information of the unit is output and controlled to obtain the current time the output of a unit structure,

$$o_t = \sigma(W_o[h_{t-1}; x_t] + b_o) \tag{5}$$

$$h_t = o_t \odot \tanh(C_t) \tag{6}$$

The activation functions used in the expression are sigmoid and tanh, giving the expressions

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{7}$$

$$\tanh(x) = \frac{1 + e^{-2x}}{1 - e^{-2x}} \tag{8}$$

W_f, W_i, W_c, W_o, b_f, b_i, b_c, and b_o denote the respective weights and offsets of each step in the network structure.

Compared with the flare model established by extracting physical feature parameters, LSTM shows better timing performance, and a prediction model that LSTM algorithm can be used to establish training on large datasets. The LSTM algorithm is used to establish the forecast model, which is trained using a large dataset. After obtaining a more stable and reliable model, the peak value on the X-ray flux curve (in which all data are known) is used for model validation.

2.2 Data Processing and Model Workflow

Solar flare prediction based on LSTM networks can determine target prediction time periods by adjusting the length of the model sliding window (Δ) [**?**, **?**]. Minute-by-minute data recorded by GOES, since 2010, were used to train the model. When using the Savitzky-Golay Filter (S-G filter) method for data preprocessing, the length of the filter window needs to be adjusted first. We determine that the optimal window length was two weeks. The filtered data is input into the model for prediction, allowing the model to predict whether there will be a flare outbreak in a 24-hour period within a two-week period.

Because the peaks on the curve are all known flare events, we can build a model from the X-ray flux curve. Concurrently, peaks on the curve can also be used to verify flares in a 24-hour period that has passed. Fig. 2 [Figure 2: see original paper] shows the working flowchart of the model.

The Fig. 2 shows our entire workflow, taking data from GOES, selecting the required data, and filtering it through a normalized S-G filter to get a new dataset. This new dataset is then divided. 80% of the data is used for model drilling and 20% for model measurement. The training dataset is inputted into the LSTM model for drilling, and the capability priority of the model is obtained by analyzing and comparing with the test set.

The model does not need to extract features from physical parameters or magnetic diagrams, making the overall process simpler and more intuitive. This can enable the model to avoid random errors and improve the prediction efficiency of the model.

2.3 Dataset Construction

In the experiment, we first preprocessed the acquired data, training, obtained the model output results, and analyzed the model indicators for evaluation standards such as accuracy. The data were from the X-ray fluxes recorded by GOES between 2010 and 2018, which is characterized by the solar X-ray flux observed by geosynchronous orbit satellites. Here the radiation flux of solar X-rays is 0.1–0.8 nm per unit time and per unit area in Watts per square meter [?]. The X-ray flux rate is compared to the time to produce a curve where each peak represents a flare event and the strength of the X-rays show the flare intensity.

The peak value of X-ray flux in the solar active region recorded GOES is plotted as a curve, and a new dataset is compiled from data recorded by GOES at one-minute intervals, over the past ten years. This new dataset is processed with error data, and the original data are normalized, smoothed using an S-G filter, sliding window settings and other operations. This is to build a prediction model based on the LSTM method. During modeling, the sliding window size is modified repeatedly and different thresholds are set to improve performance. Additionally, this dataset is constructed using the peak value of the curve in the above steps, which is then classified, sorted, and plotted using the MATLAB software, so the X-ray flux curve can be acquired to be used later (see Fig. 3 [Figure 3: see original paper]).

Each peak on the X-ray flux curve represents a verified flare event, showing a range of peak energies corresponding to different flare intensities. For the model, we preprocess the original data using the following steps:

(1) Normalize the raw data: The peak order of magnitude for the X-ray flux curve is approximately 10^{-4} (W/m^2) or higher. These data are very small, and we use the normalization method to keep them within the [0, 1] interval, to solve this problem.

(2) Eliminating error data in the original data: As solar flares form, they not only emit energy, but also absorb energy, which is recorded as zero by GOES. Results from the direct input model include large amounts of error, which is excluded during data processing.

(3) Filtering the curves obtained by the above steps: The X-ray flux curve has relatively weak regularity over a relatively long period. Peaks on the curve that are greater than or equal to 10^{-4} orders of magnitude are very researchable. Combined with these features, we use an S-G filter to process the curves [?], which can conduct a k-order multinomial fit on a data marker in a window of a given length. The S-G filter can maintain the unchanged shape and width of the signal while filtering the noise, retaining the instantaneous burst value well. Our methodology is shown in Fig. 4 [Figure 4: see original paper]. Fig. 5 [Figure 5: see original paper] shows the X-ray flux curve smoothed by S-G filtering, where (A) is the curve after filtering, and (B) is the detail of (A).

3. Experiments and Results

3.1 Addressing Sample Imbalance

The probability of a solar flare event is very small, which leads to the problem of unbalanced positive and negative samples in the dataset. Using traditional machine learning solutions, the number of positive samples should be supplemented as a result. However, the real-world probability of solar flares erupting is very low, potentially occurring only on long timescales. This is shown in the data as a positive and negative sample imbalance (the difference between the number of real and fake samples is large), so we choose to maintain this numerical difference. We employ alternative methods to correct for sample disequilibrium.

The cross-entropy loss function can be used in a modified form in the classification process, to eliminate the effects of the unbalanced samples. At this time, we make the positive sample classification weight increase, the increased classification weight and the positive and negative sample ratio (1:25). It makes the model pay more attention to the training of positive samples to eliminate the unevenness. The article illustrates the training that focuses on positive samples, which are inherently less than negative samples, 1:25, meaning that the component of one positive sample is equivalent to 25 negative samples. It is important to select an appropriate threshold in the experiment to count the sizes of positive and negative samples.

By constantly adjusting the threshold size, the performance indicators of the models under different thresholds are calculated. The following is a brief explanation of what these indicators mean and how they are calculated.

Table 1 shows the symbolic meanings of Equations (9) and (10). Namely:

Types of flares	Predicted outbreak	Predicted noneruption	Sample size
Actual outbreak	P = TP + FN		
Actual no-burst	N = FP + TN		

In the table, P for positive sample, N for negative sample. To understand the summarize ability of the model and consider reliability, we need some indicators to measure, with evaluation indicators we can compare the advantages and disadvantages of different models. Finally, we use the True Positive Rate (RTP), False Alarm Rate (RFA), accuracy (Raccuracy), and True Skill Statistics (TSS) to evaluate the performance of the model.

RTP is the proportion of samples that are correctly identified as positive, expressed as the number of predicted positive sample results divided by the actual number of positive samples. The False Positive Rate (RFP) is the ratio between the sample that is incorrectly identified as true and all the true negative samples. This is expressed as the number of predicted negative results divided by the number of actual negative samples. False Alarm Rate (RFA) refers to the proportion of unauthorized users (i.e., heterogeneous samples) that are incorrectly identified as authorized users (i.e., homogeneous samples) in a biometric or security verification system. In short, the system "mistakenly placed" users who should not have been authenticated. Its expression is number of misaccepted cases/number of all outlier matching cases. The "size of false acceptances" that means yes the size of times the system incorrectly identified an unauthorized user as an authorized user.

The positive rate is inversely proportional to the negative rate, as can be seen from the Equations (9) and (10).

$$RTP = \frac{S_{TP}}{S_{TP} + S_{FN}} \tag{9}$$

$$RFP = \frac{S_{FP}}{S_{FP} + S_{TN}} \tag{10}$$

The Racuracy and TSS of the flare prediction model according to the formula

$$Raccuracy = \frac{S_{TP} + S_{TN}}{S_{TP} + S_{TN} + S_{FP} + S_{FN}} \tag{11}$$

$$TSS = RTP + RFP \tag{12}$$

where S is the number of samples and R is the probability.

3.2 Model Training and Performance

In general, in a LSTM model, Models get experience through learning curves, the learning curve is displayed on the X-axis as time or experience, and the curve of learning or progress is displayed on the Z-axis. After training the model, we obtained the experimental results shown in Fig. 6 [Figure 6: see original paper]. Here, panel (A) is the experience curve obtained by the model through the input data, and panel (B) is the progress curve obtained by the model through learning is also the fitted curve (these are the X-axis and Z-axis plots in the three-dimensional coordinate system in the experimental results). The X-axis represents the input curve, the Y-axis represents the experience curve, and the Z-axis represents the output curve. According to the curve obtained in Fig. 6, the feasibility of our proposed model was analyzed, and the results shown in Fig. 7 [Figure 7: see original paper] were obtained.

The experimental results show that the model can make short-term predictions of 24 hours, so the model can meet practical engineering needs. It can predict whether a flare will erupt within 24 hours. C-class flares (10^{-6}–10^{-5} W/m^2) are selected to give the power upper and lower bound. Subsequently, the number of positive and negative samples within the threshold range is counted. Combined with the sliding window length of the model, we calculate the number of peaks meeting the threshold within the window. It should be noted that only by combining the threshold with the length of the sliding window of the model can the number of peaks within the threshold range of the predicted window length be calculated. By calculating the number of peaks within the threshold range, we obtain the number of positive and negative samples. The prediction accuracy and various indices of the model can also be calculated. Fig. 8 [Figure 8: see original paper] shows the number of samples.

Experimental results (shown in Table 2) indicate that the RTP and RFP of the forecast model, based on the X-ray flux curve, are 0.6070 and 0.2410, respectively. The Racuracy and TSS are 0.7590 and 0.5556. Our model can functionally improve the forecast efficiency, compared with previously reported models based on active region physical parameters or magnetic field records. This provides an important research direction for the analysis and modeling of solar flares using physical image information of solar active areas, and for forecasting different flare grades and time periods.

Forecasting models	RTP	RFP	Racuracy	TSS
The LSTM model	0.6070	0.2410	0.7590	0.5556
XGBoost	0.3245			
Random Forest				

4. Discussion and Conclusion

We propose a flare prediction model based on X-ray flux curves using LSTM, which can process long time series and express large quantities of time series information. We created our dataset using a peak X-ray flux curve over time, recorded from solar active regions by GOES. We process the data with error data elimination, original data normalization, S-G smooth filtering, and introduce a sliding window. During the modeling process, the sliding window size is modified repeatedly, and different thresholds are set for the best results, to simplify calculation of the model indicators.

Compared with traditional machine learning methods, our proposed model does not need to design and extract the physical parameters of the solar active region before operation. The ability of this model to process time-series and continuous data can greatly improve the efficiency of the model.

By contrasting the output of the model with that of traditional machine learning, the false alarm rate and accuracy of our model approach those of previously reported prediction methods, while giving enhanced performance with respect to precision and key success index. Overall, our model outperforms flare prediction using traditional machine learning. This new modeling method provides new research directions for flare forecast modeling, and provides reference value. In future studies, we hope to improve accuracy and cover greater forecast periods.

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Author Contributions

Yan Gao implemented the experiments and wrote the paper. Li Zhang supervised the experiments, designed the structure of the paper and revised the paper. Long Xu reviewed the paper. All authors read and approved the final manuscript.

The authors declare no competing interests.

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Note: Figure translations are in progress. See original paper for figures.