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Poster
In the evolving landscape of 21st-century space science, forecasting space weather events including solar flares and Coronal Mass Ejections (CMEs) is crucial but challenging. Solar flares are intense bursts of radiation originating from the release of magnetic fields. Flares occur in the active regions and are often accompanied by other solar events such as CMEs. These events could potentially affect the space atmosphere and various technologies near near-Earth leading to unexpected damage such as radio communication disturbance and power grid fluctuation. Nonetheless, monitoring the development of active regions over time and providing early warning of solar flares is essential to prevent disasters.

Nowadays, Deep learning approaches still play a crucial role in detecting and predicting events over time. By leveraging spatial data through convolution operations with temporal correlations, we propose 3D Convolution Temporal Networks (3DTCNs) to process and analyse active re- gion patches over time. In addition, separated predictor modules based on flare class are proposed to boost the performance of the EoFTCNets (EyeonFlareTemporalConvolutional- Networks) nowcasting system.

Our results show that our proposed architecture reaches and outperforms state-of-the-art approaches available in the literature with accuracy exceeding 96% for a time window of 24 hours. Moreover, the proposed architecture is lightweight and consumes fewer resources (?1.2 Watt on IntelMovidius MyriadX) enabling it to meet the requirements for onboard deployment and real-time space weather monitoring for early warnings. Recently, many researchers have focused on developing time series statistical models for solar flare forecasting using static active region parameters from a data product known as Space Weather Helioseismic and Magnetic Imager Active Region Patches (SHARPs). However, most of them require SHARPs parameters, which are hand-crafted features. This frequent use of SHARPs parameters, even with the deployment of Deep Neural Networks (DNNs) that effectively extract complex patterns, raises the question: is it possible to process and analyse HMI active regions without relying on any SHARPs parameters or handcrafted features? Can we achieve efficient and robust solar flare forecasting by extracting patterns directly from images? Some recent researchers have started replying to this question by introducing a three-dimensional CNN to develop separate models for forecasting C-class and M-class flares within the next 24 hours. Their results demonstrated the efficiency of lightweight DNNs in extracting complex and spatiotemporal patterns directly from active region magnetic fields. However, their work is limited by using regular convolution operations, which can access both past and future data points in the sequence, which is often undesirable for sequence modeling tasks where predictions should depend only on past information. In this work, we develop "EoFTCNets", a framework to accurately nowcast solar flares at early stages.

This work leveraging the performance Temporal Convolutional Network (TCN) builds upon and enhances our previous research, which used TCNs as baseline architecture for solar flare nowcasting. TCNs address the limitations of traditional CNNs by employing dilated causal convolutions, which exponentially expand the receptive field without increasing model depth. This approach efficiently captures long-range dependencies in sequence data while preserving temporal causality. However, our earlier study encountered several limitations, including challenges in accurately extracting relevant physical and geometric features from the images. Moreover, the limitations of the available data and the weak correlation between the features of active regions and solar flare labels present significant challenges. To address these issues, we propose expanding the TCN architecture to process images as input time series data, enabling effective analysis of data patterns over time by leveraging both spatial information and temporal correlations. Our proposed framework (EoFTCNets) is the stack of two separated blocks for multimodal fusion where the original active region patches and their corresponding masks are used for model training and inference. Inside each block, we implemented three separated prediction networks for a binary classification task for C-class flare, M-class flare, and X-class flare. The key to this work is eliminating the necessity of preprocessing data required when implementing statistical models using SHARPs parameters, instead building a lightweight time series architecture capable of direct process images, performing nowcasting in 24 hours, and reducing the computational resources onboard satellite.

The key contributions of this work are as follows:
• We eliminate the need for preprocessing data typically required for implementing statistical models using SHARP parameters, which are reliant on handcrafted features that can be inaccurate and time-consuming, instead constructing a sufficiently large time series dataset using HMI Magnetogram Active Region (AR) patches to effectively train the neural network for 24-window size forecasting.
• We propose the "EoFTCNets", an end-to-end framework for effectively forecasting solar flares, utilising two separate components, EoFPhyNet and EoFGeoNet, trained and inferred on the original AR patches and their masks, respectively. This approach en- ables the fusion of six decisions, ensuring robustness and accurate early warnings.
• We demonstrate state-of-the-art performance against existing approaches on the three ?-flare class.

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