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Poster
The Sun is an active star that drives energetic phenomena influencing planetary atmospheres, collectively known as Space Weather. Space Weather events, such as coronal mass ejections (CMEs)—large eruptions of plasma can significantly impact Earth's environment, spacecraft operations, and the safety of astronauts. The detection and analysis of CMEs rely heavily on data from the Large Angle Spectrometric Coronagraph (LASCO) instruments, specifically from the C2 and C3 coronagraphs, which provide visualisations with complementary fields of view. Despite the availability of large datasets sufficient for neural network training, reliance on extensive labelled data presents a challenge, as manual anno- tation requires specialised expertise and in-situ verification. In recent years, Deep Neural Networks (DNNs) have emerged as powerful tools for processing and analysing large-scale image datasets across various domains. Their success lies in their ability to automatically extract meaningful features from complex raw data, significantly reducing the need for hand-crafted features. Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) are common types of DNNs that can directly learn hierarchical features from images, such as edges, textures, and patterns, by training on labelled datasets. However, the reliance of these supervised DNNs on labelled datasets, where human-labelled data serves as the ground truth for training, poses significant challenges.

Obtaining accurate annotations is difficult and prone to human error, which can directly affect the performance of DNNs. In light of these challenges, there is a growing interest in developing restricted-label learning methods that reduce or eliminate the need for human-labelled data. Among them is self-supervised learning (SSL) which enables neural networks to learn representations that are robust and transferable to downstream tasks, such as event classification and detection.

In this work, propose CMEGNets (CME Guard Networks)—a novel framework for classifying LASCO images and detecting CMEs using self-supervised learning (SSL) techniques. This framework eliminates the need for human annotations, reducing the potential for human error while achieving high classification and detection accuracy. Our proposed framework exceeds 99% classification accuracy on LASCO C2, demonstrating significant improvements over traditional fully-supervised methods. Furthermore, despite the absence of labelled masks for CME segmentation, CMEGNets can qualitatively and quantitatively identify CME regions, producing coherent and interpretable segmentations that align with domain expert observations. These results highlight the potential of SSL to advance automated interpretation of LASCO data, making space weather monitoring more effective and efficient. The aim of this work is to explore the potential advantages of using SSL to address the labelling challenges in CME detection, removing the need for human annotation. To the best of our knowledge, our proposed "CMGNets" is the first framework that enables the classification of LASCO images and the detection of CMEs without human annotations.

The key contributions of our research are as follows:
• We present a novel framework, CMEGNets, for CME classification and detection that leverages self-supervised learning (SSL) without reliance on human annotations.
• An SSL method is employed to generate labelled datasets for LASCO image classification, enabling the training of a lightweight supervised Convolutional Neural Network (CNN) architecture that achieves over 99% accuracy while addressing hardware constraints, making it suitable for real-time space weather monitoring.
• We treat LASCO images containing CMEs as anomalies for segmentation purposes. We utilise a feature extraction block to compute the mean vector and covariance matrix for non-CME patches, modelling them as a multivariate Gaussian distribution. We then use the Mahalanobis distance to classify pixels, identifying

abnormal regions corresponding to CME areas. These contributions facilitate the automated interpretation of LASCO data and allow the monitoring of space weather while significantly reducing the need for extensive human labelling efforts.

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