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Full Text

Preamble

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Sunspot Group Detection and Classification by Dual Stream Convolutional Neural Network Method

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Abstract

The automatic detection and analysis of sunspots play a crucial role in understanding solar dynamics and predicting space weather events. This paper proposes a novel method for sunspot group detection and classification called the Dual-Stream Convolutional Neural Network with Attention Mechanism (DSCNN-AM). The network consists of two parallel streams that process different input data, enabling joint processing of spatial and temporal information during sunspot classification. It takes in white-light images as well as corresponding magnetic images that reveal both the optical and magnetic features of sunspots. The extracted features are then fused and processed by fully connected layers to perform detection and classification. An attention mechanism is further integrated to address the “edge dimming” problem, which improves the model’s ability to handle sunspots near the edge of the solar disk. The network is trained and tested on the SOLAR-STORM1 dataset. The results demonstrate that DSCNN-AM achieves superior performance compared to existing methods, with total accuracy exceeding 90%.

Key words: Sun: magnetic fields – Sun: flares – (Sun:) sunspots – DSCNN – Attention mechanism – Edge dimming

1. Introduction

Sunspots represent temporary dark regions on the solar photosphere that are cooler than surrounding areas. These features are closely linked to solar activity levels and can reflect space climate conditions. The detection and classification of sunspots is of great importance for space weather prediction [?, ?, ?, ?, ?] and for satellite operations and telecommunications [?, ?]. Despite advances in deep learning [?] and other machine learning approaches for sunspot group detection and classification, accurately identifying and classifying sunspots remains challenging, particularly when dealing with large datasets or images with complex backgrounds [?, ?].

Addressing these challenges is crucial, as highlighted by [?], who identified significant gaps in our understanding of solar active region (AR) statistics. One important factor affecting sunspot identification and classification accuracy is the edge dimming effect. This phenomenon occurs when a sunspot group ap-

proaches the edge of the solar disk, causing its white-light characteristics to become blurred and reducing the accuracy of magnetic field measurements due to projection effects.

The Mount Wilson classification scheme categorizes sunspot groups based on their magnetic polarity distribution and is highly valuable for revealing relationships between complex magnetic structures and solar storm formation. This scheme requires comprehensive analysis of multi-dimensional feature information to determine a sunspot group's magnetic type. The process begins with observing the sunspot group's structure using white-light images, followed by examining the polarity distribution on corresponding magnetograms. These observations are then combined to determine the magnetic classification.

To address the edge dimming problem in sunspot detection and classification, we propose a dual-stream convolutional neural network (DSCNN) method inspired by the Mount Wilson scheme. One branch extracts features from white-light images while the other extracts features from magnetograms. These distinct feature types are fused in the fully connected layer. The dual-stream architecture allows the model to capture both fine-grained details and broader contextual information, leading to better generalization across diverse sunspot appearances. Our model is also optimized for real-time processing, ensuring it can be deployed in operational settings where timely detection is critical.

The attention mechanism [?, ?] is a fine-tuning technique that adjusts weights, allowing the model to focus on the most relevant parts of the input data and ensuring that critical information such as sunspot edge details is adequately considered. In this paper, we adopt the attention mechanism to mitigate the edge dimming issue by ensuring that edges receive appropriate attention, thereby improving overall performance.

The remainder of this paper is organized as follows: Section 2 discusses related work, highlighting previous studies and their methodologies and explaining how our work builds upon and differs from them. Section 3 focuses on the SOLAR-STORM1 dataset, detailing its composition. Section 4 presents the architecture of the DSCNN, including the attention mechanism and its implementation. Section 5 delves into experiments and discussion, describing the experimental setup, results, comparisons with existing methods, and the impact of the attention mechanism on performance. Finally, Section 6 concludes the paper by summarizing key findings, contributions, and potential future research directions.

2. Related Work

In recent years, an increasing number of space missions have led to rapid accumulation of solar activity data. With the development of automatic sunspot recognition technology, numerous studies have focused on automatic sunspot classification. These methods can be broadly categorized into traditional approaches and deep learning methods.

Traditional methods include machine learning techniques and other statistics-based approaches. [?] proposed a system combining rough set theory and hybrid methods to preprocess and classify sunspots, leveraging domain knowledge to improve standalone methods. Though feasible, this approach suffers from complexity when faced with increased workloads. [?] introduced an automated method for classifying sunspot groups using Support Vector Machines (SVMs). Their technique involves several phases: extracting the solar disk from full-disk images, binarizing and smoothing the image, segmenting and grouping sunspots, extracting attributes from each group, and finally classifying sunspot groups using a one-against-all SVM approach. Similarly, [?] used decision trees and clustering methods which, despite their historical significance, require manual feature extraction, making them slower and more labor-intensive. This limitation was also encountered by [?], who developed a hybrid system integrating the McIntosh classification method with image processing and neural networks to detect and classify sunspots. Their approach enhanced both accuracy and efficiency by leveraging statistical techniques including fractional-order calculus, thresholding, and attribute extraction. Although it led to more accurate identification of sunspots, the method is complex and computationally intensive. [?] blended global and local thresholding to improve accuracy and robustness in sunspot detection and classification. While traditional approaches offer some advantages in detection precision, they face challenges related to parameter tuning and implementation and lack the ability to process complex solar images effectively.

Recent advancements in deep learning have significantly improved sunspot detection and classification performance. [?] utilized mathematical morphology for feature extraction in automated classification systems, combining traditional image processing with modern machine learning algorithms to handle the complex shapes of sunspots. [?] developed a deep learning algorithm that achieved high classification accuracy using white-light images. [?] further improved these methods by combining preprocessing, thresholding, and morphological operations for detection with comprehensive feature extraction for detailed analysis. Nevertheless, this approach remains sensitive to threshold settings and is computationally complex. [?] advanced these developments further by creating an ensemble model using multiple deep-learning algorithms, leveraging diverse perspectives from different models to uncover new insights. However, this approach still requires substantial computational resources. [?] created a unique model that provided insights into the various patterns of sunspots' magnetic dynamo that drives solar activity maxima and minima, applying machine learning algorithms to newly constructed annual sunspot time series from World Data Centers.

Additionally, [?] focused on utilizing deep convolutional neural networks (CNNs) for sunspot detection and classification in solar images. Despite offering significant advantages in accuracy and automation, this method presented challenges related to threshold sensitivity, noise sensitivity, computational complexity, and feature selection. [?] introduced a hybrid method that leveraged deep learning

techniques to identify and delineate sunspots. Although this method provides detailed, pixel-level classification of sunspots, the model requires substantial computational resources including high-performance GPUs for both training and inference.

Deep learning methods provide a promising approach for sunspot detection and classification. With massive solar datasets now available, deep learning methods have achieved far better performance than traditional methods. The main challenge for deep learning methods is to further improve classification accuracy. As mentioned earlier, the edge dimming phenomenon significantly impacts classification accuracy, and this paper aims to address it using a deep learning approach.

3. Dataset

The dataset used in this study is the SOLAR-STORM1 sunspot group dataset provided by the Space Environment Artificial Intelligence Early Warning Innovation Workshop, Observational Image Magnetic Classification Dataset [?]. This dataset is based on the Mount Wilson magnetic type classification scheme for sunspot groups and is divided into two parts: white-light images and magnetic images. Each component contains three classes: Alpha, Beta, and Betax. The dataset is publicly available from the Tianchi Experiment and consists of data from the Helioseismic and Magnetic Imager (HMI) labeled as Space-weather HMI Active Region Patches (SHARP), captured at 720-second intervals. Each file follows the naming convention: `hmi.sharp_{720s}.num.YYYYMMDD_{{hhmmss}}_{{TAI}}.magnetogram.Fits`, where “Fits” stands for Flexible Image Transport System, a digital file format used to store, transmit, and manipulate scientific images.

To ensure no object intersection occurs between the test set and training set after dataset division, the experimental data in this study are partitioned according to observation objects. The dataset consists of 14,469 total samples, each containing two images: a magnetogram and a white-light map. Specifically, it includes 4,709 magnetic field maps and white-light maps of Alpha sunspots (32.54% of the dataset), 7,353 magnetic field maps and white-light maps of Beta sunspots (50.82%), and 2,407 magnetic field maps and white-light maps of Betax sunspots (16.64%).

Due to the slow evolution of sunspot groups, they maintain the same magnetic type within certain time periods. Consequently, most sunspot groups exhibit high magnetic similarity when observed, posing challenges for classification accuracy. Figure 1 [Figure 1: see original paper] shows sample sunspots from our dataset.

4. Method

To address the edge dimming problem often encountered in sunspot images, we propose a DSCNN-AM architecture for sunspot group classification. This method integrates the ResNet50 model as the backbone and incorporates attention mechanisms. The model is built using a pre-trained Keras implementation that includes ten pre-trained models for image classification trained on ImageNet data. The construction process involves creating ResNet50 branches (loading ImageNet weights) for extracting features from white-light and magnetic images, named the white-light feature branch and magnetic image feature branch respectively. After extraction, the two feature sets are concatenated, flattened, and input into a fully connected layer with L2 regularization. The output then passes through another fully connected layer with Dropout before being classified using Softmax.

4.1. Network Architecture

The network structure is displayed in Figure 2 [Figure 2: see original paper], which illustrates the DSCNN architecture. We input the white-light image and magnetic image separately into the network, each entering different branches without sharing CNN weights. This produces two distinct feature vectors that are then concatenated and passed through a fully connected layer. The red arrows indicate shortcut connections that bypass certain layers, connecting earlier layers directly to later layers within the convolutional stages. These connections represent the residual units typical in ResNet architecture, which help improve gradient flow during training. Softmax is subsequently used for classification.

4.2. DSCNN-AM

To further enhance classification accuracy and mitigate the negative impact of edge dimming, we incorporate an attention mechanism into the model. This allows the network to assign greater weight to sunspot group areas when processing images, effectively filtering out edge dimming effects. In our modified model, shown in Figure 3 [Figure 3: see original paper], ResNet50 is integrated with attention mechanisms.

Specifically, ResNet50 is integrated with both Squeeze-and-Excitation Network (SE-Net) and Convolutional Block Attention Module (CBAM) attention mechanisms. SE-Net introduces channel-wise attention, while CBAM combines both channel-wise and spatial attention, ensuring the model can focus on the most relevant parts of input images. This integration enhances the model's ability to emphasize important features, leading to improved classification accuracy.

4.2.1. ResNet Unit Combined with Squeeze-and-Excitation Network (SE-Net) The Squeeze-and-Excitation Network, introduced by [?], applies channel-wise attention that recalibrates feature responses by explicitly modeling interdependencies between convolutional feature channels. The ResNet net-

work is composed of multiple residual units, and the process of images entering each residual module constitutes feature extraction. To employ the attention mechanism in each feature extraction process, it must be integrated into the residual module. The structure of the residual module combined with SE-Net is illustrated in Figure 4 [Figure 4: see original paper]. When feature map X enters the residual module, it is processed by SE-Net to form a refined feature map X . This refined feature map is then added to the initial feature map to produce the final feature map. This integration ensures the network focuses more on relevant areas, thereby improving sunspot classification accuracy.

4.2.2. ResNet Unit Combined with Convolutional Block Attention Module (CBAM) CBAM was introduced by [?] as a lightweight module that combines both spatial and channel-wise attention mechanisms to refine feature maps. Similar to the SE-Net integration, the CBAM module is incorporated into each residual unit. The structure of the residual module combined with CBAM is depicted in Figure 5 [Figure 5: see original paper].

As shown in the figure, when the feature map enters the module, it first passes through channel attention and then spatial attention. The process can be summarized as: $U = X \cdot Mc$; $F = U \cdot Ms$, where X is the feature map after convolution, Mc is the channel attention map, U is the feature map after channel attention processing, \cdot denotes element-wise multiplication, Ms is the spatial attention map, and F is the final feature map after spatial attention processing. The main modifications occur in the feature extraction section of the residual module, while the skip connection remains unchanged.

4.2.3. Model Construction During model construction, attention mechanisms are integrated into the residual units of ResNet50. The specific process involves first building separate branches: one incorporating SE-Net for channel-wise attention and another with CBAM for combined channel and spatial attention. Next, ResNet50 branches (SE-Net or CBAM) are created for extracting features from white-light and magnetic images, designated as branch 1 and branch 2 respectively. The outputs (out1 and out2) from these branches are then concatenated and processed with Flatten. The processed features are input into a fully connected layer with L2 regularization, followed by another fully connected layer with Dropout. Finally, features are fed into Softmax for classification. This construction is followed by training with ten-fold cross-validation to ensure robust evaluation.

4.2.4. Model Evaluation and Fusion Model evaluation and fusion employ ten-fold cross-validation to ensure objective performance assessment by mitigating the risk of improper data partitioning. This technique divides the dataset into ten parts, using nine parts for training and one part for testing in each iteration, ultimately providing a robust evaluation of model accuracy. After training, predictions from three dual-stream models—ResNet50, ResNet50 with SE-Net, and ResNet50 with CBAM—are evaluated. This process provides classification

performance and corresponding results for the fused models, demonstrating superior performance compared to non-fused approaches.

5. Experiment and Discussion

This section discusses the experimental setup and results. We present results from three main models: dual-stream ResNet50, dual-stream ResNet50 combined with SE-Net, and dual-stream ResNet50 combined with CBAM. The models were trained and evaluated using white-light and magnetic images separately and in combination.

5.1. Before Model Fusion

Here we evaluate the performance of different dual-stream ResNet50 models before applying fusion techniques. The aim is to establish a baseline for comparison and understand the impact of integrating attention mechanisms on model performance. The baseline dual-stream ResNet50 uses the standard ResNet50 architecture with dual input streams for white-light and magnetic maps, providing a reference point for evaluating the effectiveness of attention mechanisms. The dual-stream ResNet50 with SE-Net integrates SE-Net to improve feature recalibration by weighting the importance of different features, allowing us to investigate whether this addition improves performance metrics. The dual-stream ResNet50 with CBAM introduces both channel and spatial attention mechanisms to refine feature extraction, aiming to enhance the model's ability to focus on relevant features in the input data.

Table 1 summarizes experimental results for each model, providing accuracy, recall, and F1-score. The goal is to analyze how integration of SE-Net and CBAM affects performance compared to the baseline ResNet50 model. The baseline dual-stream ResNet50 model, using white-light and magnetic images as inputs, achieved 84.93% accuracy, 84.93% recall, and 84.87% F1-score. This serves as a reference point for evaluating performance improvements from integrating SE-Net and CBAM. The SE-Net model achieved 84.87% accuracy, 84.87% recall, and 84.41% F1-score, showing no significant improvement over the baseline. This may be due to equal contribution of feature maps in the classifier's view, indicating that SE-Net may not effectively enhance classification for this specific task. The CBAM model achieved 88.53% accuracy, 88.53% recall, and 88.22% F1-score, representing a significant improvement over the baseline with a 3.6% accuracy increase and 3.35% F1-score increase. The spatial attention mechanism in CBAM likely contributed to these improvements by allowing the model to better focus on relevant image features.

5.2. Model Fusion

For model fusion, we used outputs from the dual-stream ResNet50, dual-stream ResNet50 (SE-Net), and dual-stream ResNet50 (CBAM) models. We performed

10-fold cross-validation and fused results from ten small models, with results shown in Table 2 .

Comparing Tables 2 and 1 reveals improvement in all metrics post-fusion. The accuracy and weighted F1-scores for dual-stream ResNet50 improved by 5.68% and 5.7%, respectively. The dual-stream ResNet50 (SE-Net) displayed a 3.39% accuracy increase and 3.54% weighted F1-score increase. The dual-stream ResNet50 (CBAM) exhibited a 4.22% accuracy increase and 4.35% weighted F1-score increase. This indicates that model fusion enhances classification ability, likely due to better dataset utilization and integration of various sub-model capabilities. The improvements observed in the CBAM-integrated model and fusion results highlight the importance of attention mechanisms in enhancing classification performance. The spatial attention provided by CBAM allows the model to focus on the most relevant image regions, leading to better classification accuracy. Additionally, model fusion leverages the strengths of different sub-models, providing more robust and comprehensive classification capability.

5.3. Attention Mechanism Visualization

To provide intuitive understanding of the attention mechanism’s role, we include a heatmap visualization of its output. This visualization helps illustrate how the attention mechanism focuses on different image regions, thereby improving classification performance, as shown in Figure 6 [Figure 6: see original paper].

The figure displays four different input image indices. For each input image, corresponding heatmaps of the attention mechanism’s “Predict” and “Output” stages are shown, demonstrating how the attention mechanism emphasizes different areas within the input image to enhance classification accuracy.

We examine Betax class object 2048 as an example, featured in Figure 7 [Figure 7: see original paper]. The left image shows a white-light map of the sunspot group where features are blurred due to dimming effects and black background. The right image is a magnetogram that also shows decreased accuracy in magnetic field strength measurement because of these effects. As sunspots progress toward the solar limb, edge dimming further blurs white-light features and reduces magnetic field measurement accuracy. This image quality degradation can cause poor classification accuracy, and the transient appearance and evolution-related disappearance of sunspots are challenging to handle manually. However, our model’s attention mechanism can mitigate these effects, including edge dimming and background interference, improving classification accuracy.

We also examine Alpha class object 1360, depicted in Figure 8 [Figure 8: see original paper]. This object was consistently displayed as a unipolar sunspot group over three days (a–f), and the model classification was correct. However, if another sunspot had appeared near one of the sunspots in the group on any given day, the group’s features might have been classified differently, potentially as Beta or Betax. This demonstrates that brief appearances of additional sunspots

during the modeling process can lead to misclassification. The dual-stream CNN with attention mechanisms (SE-Net and CBAM) incorporated in our method helps mitigate this issue. The attention mechanisms allow the model to focus on the most relevant features and spatial regions, reducing the impact of edge dimming effects and background interference. As a result, the model achieves more accurate classifications even when sunspot features are blurred or evolve over time.

Additionally, we examine Beta class object 3120, shown in Figure 9 [Figure 9: see original paper]. The initial sunspot group is clearly bipolar, but during evolution the right sunspot gradually dissipates while the left sunspot remains. Consequently, when the image of this later-stage sunspot group is input into the model, it is likely to be incorrectly identified as Alpha. This blurred type feature formed due to sunspot group evolution may be a significant reason for poor classification accuracy. This example demonstrates the challenge of classifying evolving sunspot groups: the clear initial bipolar structure evolves into a less distinct single sunspot, leading to potential misclassification. Attention mechanisms can help by focusing on the most relevant features at different stages, and incorporating temporal information can further enhance the model's ability to correctly classify evolving sunspot groups.

Using the false positive rate as the horizontal axis and the true positive rate as the vertical axis, we plot the Receiver Operating Characteristic (ROC) curve shown in Figure 10 [Figure 10: see original paper]. Blue lines represent dual-stream ResNet50, red lines represent dual-stream ResNet50 (SE-Net), and black lines represent dual-stream ResNet50 (CBAM). Ideally, all categories would be correctly classified at the (0, 1) point, so each category's classification results should be as close as possible to (0, 1). The ROC curves plot the true positive rate against the false positive rate at various threshold settings. A larger Area Under Curve (AUC) indicates stronger classification performance. The dual-stream ResNet50 (CBAM) shows significant improvement in AUC values for Alpha and Betax classes compared to other models, although Beta class performance decreases, likely due to complex magnetic polarity distributions in some Beta images. This suggests that the attention mechanism might not fully cover magnetic polarity areas, leading to biased feature extraction.

Taking Betax class image 6975 from the dataset as an example, we input this image into the dual-stream ResNet50, dual-stream ResNet50 (SE-Net), and dual-stream ResNet50 (CBAM) fusion models, directly outputting the Softmax probability distribution. The results are shown in Table 3 .

Table 3 shows that object 6975 with edge dimming is classified as Beta by both dual-stream ResNet50 and dual-stream ResNet50 (SE-Net) with decision probabilities above 90%. This indicates that the SE-Net-enhanced network only provides channel weights to the feature map, which is insufficient for extracting effective classification features. In contrast, the dual-stream ResNet50 (CBAM) correctly classifies the image as Betax with 75.43% probability, significantly higher than the probabilities for Alpha and Beta. This suggests that when deal-

ing with images featuring edge dimming, spatial attention can better capture features conducive to accurate classification.

5.4. Comparative Analysis of Sunspot Detection and Classification Methods

The methods by [?], [?], and our proposed approach all aim to improve the accuracy and reliability of sunspot detection and classification. This study compares these methods based on classification accuracy, precision, recall, F1-score, and other relevant metrics. By evaluating these approaches, we identify the strengths and limitations of each method, providing valuable insights into the effectiveness of different techniques in sunspot detection and classification. This comparative analysis contributes to ongoing efforts to develop robust and reliable systems for solar activity monitoring and research.

Table 4 highlights the strengths and weaknesses of each method. Chola et al.'s AlexNet-based deep convolutional network approach achieves outstanding classification performance with near-perfect accuracy, precision, recall, and F1-score values. Veeramani et al.'s preprocessing and differencing method also demonstrates excellent performance with high accuracy, specificity, sensitivity, precision, and F1-score, as well as low Dice loss. Our proposed method, using dual-stream ResNet50 with SE-Net and CBAM attention mechanisms, shows robust performance in solving edge dimming cases, with the CBAM variant providing the best results in terms of accuracy and F1-score.

The Precision-Recall Curve in Figure 11 [Figure 11: see original paper] highlights the trade-offs between recall and F1-score for each method. The bar chart in Figure 12 [Figure 12: see original paper] shows the accuracy comparison for each method. By integrating these results into a comprehensive evaluation, we better understand the capabilities and limitations of each approach, facilitating the development of more effective and accurate models for solar activity monitoring.

6. Conclusion

We improve upon dual-stream ResNet50 by adding SE-Net and CBAM respectively to the residual network, forming two new models and comparing them with the baseline dual-stream ResNet50. The accuracy, F1-score, recall, and ROC curve are used to evaluate model performance. As noted, the added CBAM demonstrates better classification performance because it contains spatial attention. Experimental results also show that model fusion helps improve overall performance.

7. Future Work

In this paper, deep learning is applied to classify the magnetic types of sunspot groups. Despite progress, training time remains long, with each epoch taking 4 hours due to network complexity. Future work should focus on reducing network

complexity without compromising accuracy. Additionally, since only the circular area of the solar image is relevant while the rest is black, solutions are needed to mitigate the impact of this black background. For more accurate predictions, high-quality data are crucial, as magnetic type classification impacts solar storm prediction. Future research should involve creating a large, high-quality dataset of sunspot magnetic types.

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