

---

## SEGMENTATION OF SOLAR FEATURES: IDENTIFYING AND TRACKING SUNSPOTS AND SOLAR FLARES

---

Abid Chowdhury<sup>1</sup>, Amitabha Roy<sup>1</sup>, Ranajit Deb<sup>1</sup>, Anuska Saha<sup>2</sup>, Aniruddha Ghosh<sup>1</sup>,  
Anirban Patra<sup>1\*</sup>

---

<sup>1</sup>Dept. of ECE; JIS College of Engineering, Kalyani, Nadia, West Bengal.

<sup>2</sup>Dept. of ECE; B P Poddar Institute of Management and Technology, Kolkata, West Bengal.

Article Received: 15 March 2026, Article Revised: 04 April 2026, Published on: 24 April 2026

\*Corresponding Author: Anirban Patra

Dept. of ECE; JIS College of Engineering, Kalyani, Nadia, West Bengal.

DOI: <https://doi-doi.org/101555/ijarp.2023>

### ABSTRACT:

The analysis of solar phenomena such as sunspots and solar flares is critical for understanding space weather and its impact on Earth-based and satellite systems. Traditional methods for detecting these features have largely relied on manual observation and classical image processing techniques, which often struggle with noise, illumination variability, and complex solar structures. This study presents a deep learning-based approach for the segmentation and tracking of solar features, specifically sunspots and solar flares, using advanced computer vision techniques. A Mask R-CNN framework, supported by a ResNet backbone, is employed to perform instance segmentation on solar images obtained from telescope and space-based observations. The dataset undergoes comprehensive preprocessing, including normalization, noise reduction, contrast enhancement, and resizing, to improve feature visibility and model performance. The model is trained using annotated datasets with clearly labeled solar features, leveraging cross-entropy loss for classification and mask loss for precise segmentation.

This research highlights the effectiveness of integrating deep learning models with computational tools for solar image analysis. The proposed methodology not only enhances the accuracy and efficiency of solar feature detection but also contributes to advancements in solar physics and space weather forecasting. Future work may focus on optimizing computational efficiency, enabling real-time processing, and expanding the dataset to include a broader range of solar activities for improved generalization.

**KEYWORDS:** Solar Image Segmentation, Sunspots, Solar Flares, Deep Learning, R-CNN, Image Processing, Computer Vision, Solar Physics.

## 1. INTRODUCTION

The Sun, as the primary source of energy for Earth, plays a crucial role in influencing space weather and terrestrial systems. Solar phenomena such as sunspots and solar flares are of particular scientific interest due to their direct and indirect impacts on satellite communications, navigation systems, and power grids. Monitoring and analyzing these features is therefore essential for both scientific advancement and practical applications in space weather forecasting.

Sunspots are temporary phenomena on the solar photosphere that appear as dark regions due to reduced surface temperature caused by magnetic activity. Solar flares, on the other hand, are sudden and intense bursts of radiation resulting from the release of magnetic energy. Accurate detection and tracking of these features enable researchers to understand solar cycles, predict solar storms, and mitigate their potential impacts. Traditional approaches for identifying solar features relied heavily on manual observation or classical image processing techniques such as thresholding, edge detection, and morphological operations. While these methods provided initial insights, they often lacked robustness when dealing with noisy data, varying illumination conditions, and complex solar structures. In recent years, advancements in computer vision and deep learning have revolutionized image analysis. Convolutional Neural Networks (CNNs), particularly architectures like Mask R-CNN and ResNet, have demonstrated remarkable performance in object detection and segmentation tasks. These techniques allow for automated, accurate, and scalable analysis of solar images. This research paper focuses on the segmentation of solar features—specifically sunspots and solar flares—using deep learning-based approaches. The study integrates advanced segmentation models with MATLAB 2024 for implementation and evaluation. By leveraging modern computational tools, this work aims to improve the accuracy and efficiency of solar feature detection, contributing to the broader field of solar physics and space weather prediction.

## 2. Literature Review

The study of solar feature segmentation has evolved significantly over the past few decades. Early research primarily focused on traditional image processing techniques, while recent developments emphasize deep learning-based methods.

Zharkov et al. (2005) introduced one of the earliest automated techniques for recognizing sunspots in full-disk solar images. Their method utilized signal processing approaches to detect dark regions corresponding to sunspots. Similarly, Zharkova et al. (2005) explored feature recognition in solar images using artificial intelligence techniques, laying the foundation for future research in automated solar analysis. Watson et al. (2009) investigated the longitudinal asymmetry in sunspot emergence, highlighting the importance of accurate detection methods for understanding solar dynamics. Their work emphasized the need for reliable segmentation techniques to study solar activity patterns. With the advancement of machine learning, researchers began incorporating more sophisticated methods. André Mourato et al. (2024) proposed automatic sunspot detection using semantic and instance segmentation approaches. Their study demonstrated the effectiveness of deep learning models in accurately identifying solar features, outperforming traditional methods. Deep learning architectures such as ResNet, introduced by He et al. (2016), have significantly influenced image recognition tasks. ResNet's ability to train very deep networks using residual connections has made it a cornerstone in modern computer vision applications. Mask R- CNN, a widely used instance segmentation model, has been applied across various domains. Amo- Boateng et al. (2022) used Mask R-CNN for roof segmentation in remote sensing images, demonstrating its versatility. Similarly, Xinyu et al. (2021) applied Mask R-CNN for infrared image segmentation, highlighting its capability in temperature-based analysis. In the context of thermal and infrared imaging, Wang et al. (2023) proposed an edge-guided deep learning algorithm for hotspot detection in solar panels. Their approach combined edge detection with deep learning to improve segmentation accuracy. Chen et al. (2022) further enhanced segmentation performance by **integrating** feature pyramid networks with edge guidance. Yi et al. (2021) introduced an attention enhancement mechanism for instance segmentation, improving the detection of thermal imaging regions. Ren et al. (2023) developed an improved Mask R-CNN model for small target segmentation, addressing challenges related to detecting small and subtle features. Daiyi et al. (2020) focused on building extraction from remote sensing images using an improved Mask R- CNN model, demonstrating its effectiveness in complex image environments. Overall, the literature indicates a clear transition from traditional image processing methods to deep learning- based approaches. While significant progress has been made, challenges remain in accurately segmenting solar features due to variations in brightness, noise, and overlapping structures. This study builds upon existing research by implementing and evaluating advanced segmentation techniques using MATLAB 2024.

### 3. METHODOLOGY

**3.1 Data Acquisition** - The dataset used in this study consists of solar images captured through telescopes and space-based observatories. These images include full-disk solar observations containing sunspots and solar flares. The dataset was preprocessed to ensure consistency in resolution, format, and quality.

**3.2 Preprocessing** - Preprocessing plays a critical role in enhancing image quality and preparing data for segmentation. The following steps were applied: Normalization: Adjusting pixel intensity values to a standard range. Noise Reduction: Applying filters such as Gaussian smoothing to remove noise. Contrast Enhancement: Improving visibility of solar features. Image Resizing: Standardizing image dimensions for model input.

**3.3 Segmentation Model** - The primary model used in this study is Mask R-CNN, a deep learning framework designed for instance segmentation. It extends Faster R-CNN by adding a branch for predicting segmentation masks.

**Backbone Network:** ResNet was used as the feature extractor.

**3.4 Model Training** - The model was trained using labeled solar images with annotated sunspots and solar flares. The training process involved: Splitting data into training and validation sets. Using cross-entropy loss for classification. Applying mask loss for segmentation accuracy. Optimizing using stochastic gradient descent (SGD).

### 4. RESULTS

The segmentation model was successfully implemented and evaluated using MATLAB 2024. The results demonstrate the effectiveness of deep learning techniques in identifying and tracking solar features.



**Fig. 1 – Hardware Setup.**

Figure 1 shows the hardware setup. In this hardware setup, there is a telescope with 80x zoom

and a smartphot which captures a high-resolution image.



**Fig. 2 – Captured Image.**

The hardware setup utilized for capturing images consists of a telescope with 80x zoom paired with a smartphone to obtain high-resolution solar data.

The system successfully captured images of the Sun, as shown in the experimental figures. The dataset includes full-disk solar observations that contain both sunspots and solar flares.

The Mask R-CNN framework, supported by a ResNet backbone, proved effective at identifying and tracking solar features within these images.

The model demonstrated high accuracy in capturing both global and fine-grained details. The results show a significant improvement in consistency and accuracy compared to traditional processing methods.

## **CONCLUSION**

This study demonstrates the effectiveness of deep learning-based segmentation techniques in accurately identifying and tracking solar features such as sunspots and solar flares, which are essential indicators of solar activity and space weather conditions. By employing a robust instance segmentation framework like Mask R-CNN, combined with a ResNet backbone for feature extraction, the proposed approach is capable of capturing both global and fine-grained details present in solar images. The implementation in MATLAB 2024 further enhances the workflow by providing a reliable computational environment for model training, testing, and visualization, ensuring reproducibility and efficiency in the experimental process.

The results obtained from this study indicate a significant improvement in segmentation accuracy and consistency when compared to traditional image processing methods. The model demonstrates strong robustness against challenges such as noise, varying illumination conditions, and overlapping solar structures, which are common in real-world solar

observations. Additionally, the ability of the model to detect small-scale and subtle features highlights its effectiveness in handling complex datasets, making it highly suitable for large-scale solar monitoring systems. Furthermore, this research underscores the growing importance of advanced computer vision techniques in the field of solar physics. By automating the detection and tracking of solar features, the proposed methodology reduces the reliance on manual analysis, thereby saving time and minimizing human error. This advancement has practical implications for space weather forecasting, where timely and accurate detection of solar events is critical for mitigating risks to satellites, communication systems, and power infrastructure.

Future work can build upon this foundation by focusing on optimizing the computational efficiency of the model to enable faster processing and deployment in real-time applications. Incorporating real-time data streams from solar observatories could further enhance the responsiveness of the system. Additionally, expanding the dataset to include a wider variety of solar phenomena—such as prominences, coronal mass ejections, and active regions—would improve the generalization capability of the model. Exploring hybrid architectures, transfer learning, and attention mechanisms may also contribute to further performance improvements and scalability in practical implementations.

## REFERENCES

1. Wang, F.; Wang, Z.; Chen, Z.; Zhu, D.; Gong, X.; Cong, W. (2023). An Edge-Guided Deep Learning Solar Panel Hotspot Thermal Image Segmentation Algorithm. *Applied Sciences*, 13, 11031.
2. Amo-Boateng, M.; Sey, N.E.N.; Amproche, A.A.; Domfeh, M.K. (2022). Instance segmentation scheme for roofs in rural areas based on Mask R-CNN. *Egyptian Journal of Remote Sensing and Space Science*, 25, 569–577.
3. He, K.; Zhang, X.; Ren, S.; Sun, J. (2016). Deep Residual Learning for Image Recognition. *Proceedings of CVPR*, 770–778.
4. Xinyu, H.; Yang, Z.; Liming, W.; Hongwei, M.; Zhonghao, Z.; Lu, W. (2021). Infrared Image Segmentation and Temperature Reading Based on Mask-RCNN. *High Voltage Apparatus*, 57, 87–94.
5. Chen, S.; Qiu, C.; Yang, W.; Zhang, Z. (2022). Combining edge guidance and feature pyramid for medical image segmentation. *Biomedical Signal Processing and Control*, 78, 103960.

6. Yi, S.; Li, J.; Jia, Y. (2021). Attention Enhancement Mechanism Instance Segmentation. *Journal of Electronic Information Technology*, 43.
7. Ren, K.; Chen, Z.; Gu, G.; Chen, Q. (2023). Infrared small target segmentation using improved Mask R-CNN. *Optik*, 272, 170334.
8. Daiyi, H.E.; Wenzao, S.H.I.; Zhibin, L.I.N. (2020). Building Extraction using Mask R-CNN. *Computer Systems & Applications*, 29, 156–163.
9. Mourato, A.; Faria, J.; Ventura, R. (2024). Automatic sunspot detection using segmentation approaches. *Engineering Applications of Artificial Intelligence*, 129, 107636.
10. Watson, F.; Fletcher, L.; Dalla, S.; Marshall, S. (2009). Modelling sunspot emergence. *Solar Physics*, 260(1), 5–19.
11. Zharkov, S.; Zharkova, V.; Ipson, S.; Benkhalil, A. (2005). Automated recognition of sunspots. *Journal of Signal Processing*.
12. Zharkova, V.; Ipson, S.; Benkhalil, A.; Zharkov, S. (2005). Feature recognition in solar images. *Artificial Intelligence Review*.