Detect and automatically count sunspots in solar images

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in partial fulfillment for the award of the degree

of

Bachelor of Technology

in

Computer Science & Engineering

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December 2024

DECLARATION

I, **Pranav P Kulkarni (1RVU22CSE119),** student fifth semester B.Tech in **Computer Science & Engineering,** at School of Computer Science and Engineering, **RV University,** hereby declare that the project work titled "**Detect and automatically count sunspots in solar images**" has been carried out by us and submitted in partial fulfilment for the award of degree in **Bachelor of Technology in Computer Science & Engineering** during the academic year **2023-2024**. Further, the matter presented in the project has not been submitted previously by anybody for the award of any degree or any diploma to any other University, to the best of our knowledge and faith.

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CERTIFICATE

This is to certify that the project work titled **"Detect and automatically count sunspots in solar images ''** is performed by Pranav P Kulkarni**(1RVU22CSE119) ,** a bonafide students of Bachelor of Technology at the School of Computer Science and Engineering, RV university, Bangaluru in partial fulfillment for the award of degree Bachelor of Technology in Computer Science & Engineering , during the Academic year **2020-2021**.

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ACKNOWLEDGEMENT

It is a great pleasure for us to acknowledge the assistance and support of a large number of individuals who have been responsible for the successful completion of this project work.

First, we take this opportunity to express our sincere gratitude to the School of Computer Science and Engineering, RV University, for providing us with a great opportunity to pursue our Bachelor’s Degree in this institution.

In particular we would like to thank Dr. Sanjay R. Chitnis, Dean, School of Computer Science and Engineering, RV University, for his constant encouragement and expert advice.

It is a matter of immense pleasure to express our sincere thanks to Dr.Mydhili Nair, Head of the department, Computer Science & Engineering University, for providing right academic guidance that made our task possible.

We would like to thank our guide Santhosh S. Head of the Department Dept. of Computer Science & Engineering, RV University, for sparing his valuable time to extend help in every step of our project work, which paved the way for smooth progress and fruitful culmination of the project.

We are also grateful to our family and friends who provided us with every requirement throughout the course.

We would like to thank one and all who directly or indirectly helped us in completing the Project work successfully.

Date:

Place:

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ABSTRACT

Research into solar activity has significantly progressed over recent decades, enhancing our understanding of its profound effects on life and technological systems on Earth. Solar phenomena such as solar winds, coronal mass ejections (CMEs), solar energetic particles, and solar flares play a crucial role in influencing Earth's magnetic field and atmospheric conditions. These phenomena have the potential to disrupt satellite communications, navigation systems, electrical power grids, and other critical infrastructures, making their monitoring and analysis a priority for scientists and engineers.

Identifying and analyzing solar activity involves observing various solar phenomena, including sunspots, filaments, and pores. Sunspots, in particular, are regions of concentrated magnetic activity on the solar surface and are closely linked to the Sun's overall activity. The monitoring of these features has traditionally relied on manual observation and classification. However, with the growing availability of high-resolution solar imagery and advancements in artificial intelligence (AI), automated analysis has become increasingly feasible and necessary.

In this study, we propose an innovative method for the detection of sunspots using the YOLOv5 neural network. YOLOv5 (You Only Look Once version 5) is a state-of-the-art object detection framework known for its speed and accuracy, making it an excellent candidate for real-time analysis of solar images. Our approach leverages a dataset of solar images provided by the Geophysical and Astronomical Observatory of the University of

Coimbra (OGAUC). This observatory hosts one of the world's oldest and most comprehensive archives of solar imagery, making it an invaluable resource for the study of solar phenomena. The dataset comprises historical and contemporary images of the Sun, offering a wide range of variability in sunspot features. Our methodology involves preprocessing these images to optimize input for the YOLOv5 model, training the model to identify and classify sunspots with high precision, and evaluating its performance against established benchmarks. By employing machine learning techniques, our work aims to enhance the efficiency and accuracy of solar activity monitoring, contributing to the broader field of space weather prediction and its associated impacts on Earth.

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

Symbol	Explanation
$	Dollar
OGAUC	Geophysical and Astronomical Observatory of the University of Coimbra
CNNs	Convolutional Neural Networks
YOLO	**You Only Look Once**

1. INTRODUCTION

Although the Sun appears almost constant and calm from Earth, it is, in fact, highly active, with impacts that extend beyond biology to significantly influence society. This has fueled growing interest in studying the Sun and monitoring its activity. The field of space weather focuses on solar events that affect life on Earth, frequently causing malfunctions in electrical and electronic systems both in orbit and on the planet's surface. Consequently, monitoring and predicting solar activity has become increasingly critical in today's world. Solar activity can disrupt communication systems, power grids, industrial operations, commercial infrastructure, and space missions, highlighting its broad-reaching effects.

One effective way to monitor solar activity is through the detection and tracking of sunspots, which are among the most prominent phenomena visible on the Sun’s surface. These small, transient regions are characterized by a strong magnetic field that disrupts solar convection and heat transfer near the surface. As a result, these cooler areas appear darker in contrast to the surrounding hotter regions. The formation and evolution of sunspots are closely linked to the occurrence of significant solar flares, which, when directed toward Earth, can disrupt electrical systems and devices.

Since 1926, the Geophysical and Astronomical Observatory of the University of Coimbra (OGAUC) has been systematically monitoring solar activity. Daily images of the Sun are captured to observe and document solar features and events, weather permitting. This long-standing effort provides valuable insights into solar behavior and its effects on Earth.

2. Related work

2.1 Sunspot Detection Techniques

Traditional methods relied on manual observation, which were time-consuming and error-prone. Recent advancements in computer vision have introduced automated approaches. These approaches utilize deep learning frameworks capable of analyzing large datasets with high accuracy. Existing studies demonstrate the feasibility of detecting sunspots using convolutional neural networks (CNNs) and other machine learning models. However, limitations such as dataset variability and computational requirements remain key challenges.

2.2 Machine Learning Applications

YOLOv5, a deep learning model, is widely adopted for object detection tasks due to its efficiency and accuracy. It excels in detecting objects in complex images by balancing speed and precision. Its application in solar research highlights its versatility, providing a robust tool for addressing challenges in sunspot detection. By leveraging pre-trained weights and transfer learning, YOLOv5 can adapt to specialized datasets, ensuring effective performance across diverse imaging conditions.

3. METHODOLOGY

3.1 Dataset

The dataset consists of 2000 Hα continuum images with a resolution of 1200x1000 pixels. Images were sourced from the Bass2000 Solar Survey Archive. These images capture solar activity over several years, encompassing various atmospheric conditions. The dataset includes both high-quality images and those affected by noise or atmospheric distortions, making it ideal for evaluating the robustness of detection models. The diversity in image quality provides a comprehensive testbed for model training and validation.

3.2 Model Training

The YOLOv5 model was trained on the 2000 Hα continuum images from the Bass2000 Solar Survey Archive, as described in Section 3.1. The training process utilized the pre-trained YOLOv5 weights (yolov5s.pt), which were fine-tuned for solar feature detection, particularly sunspot identification. The model was trained using a batch size of 16 and an image size of 320 pixels, as specified in the configuration.

Training was conducted over a 15 epochs, leveraging the above dataset mentioned. The model's performance was optimized by adjusting key hyperparameters, such as the learning rate and batch size, to balance detection accuracy with computational efficiency. The training process also employed caching to improve training speed.

The resulting model, saved as best.pt, was then evaluated for its ability to detect sunspots in the solar images.

4. IMPLEMENTATION

4.1 Description

The implemented system utilizes YOLOv5 for inference. It processes each image, detects sunspots, and annotates them with bounding boxes and confidence scores. The system is designed for scalability, enabling the processing of large datasets with minimal manual intervention. Its modular architecture allows for easy integration with other solar research tools, providing a comprehensive platform for solar activity analysis.

Yolov5 Architecture:

YOLOv5's architecture consists of three main parts:

- **Backbone**: This is the main body of the network. For YOLOv5, the backbone is designed using the New CSP-Darknet53 structure, a modification of the Darknet architecture used in previous versions.
- **Neck**: This part connects the backbone and the head. In YOLOv5, SPPF and New CSP-PAN structures are utilized.
- **Head**: This part is responsible for generating the final output. YOLOv5 uses the YOLOv3 Head for this purpose.

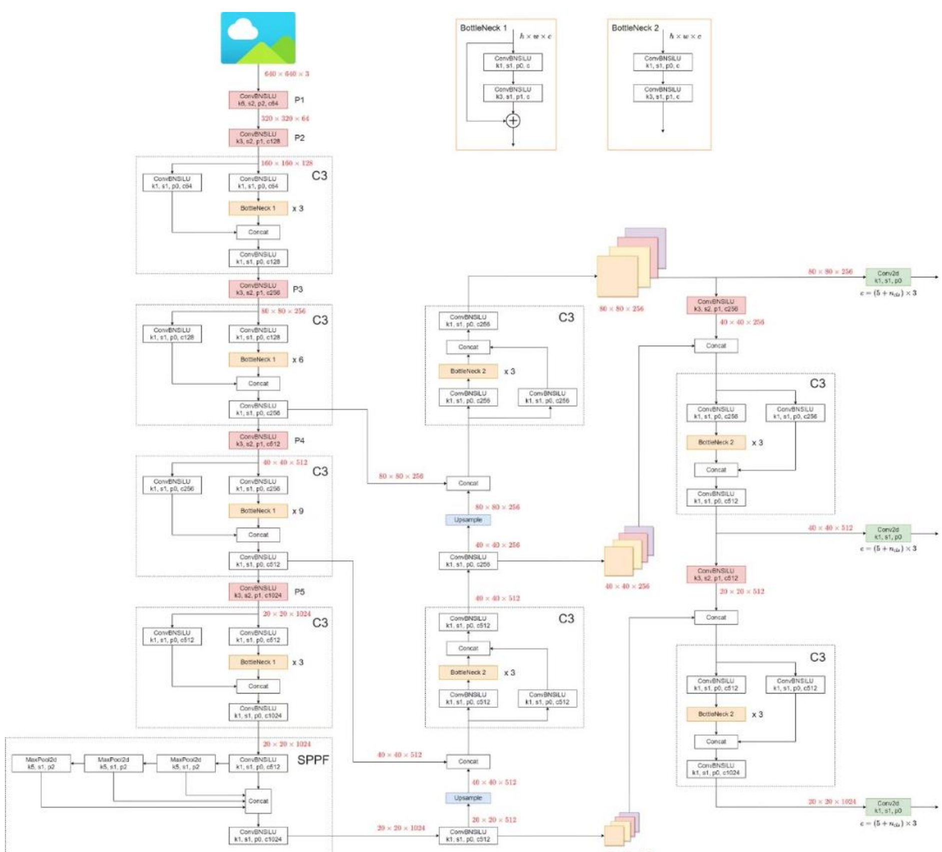

Figure 1: Yolov5 architecture

4.2 Code Implementation

This Python file uses a trained YOLOv5 model to detect sunspots in a set of solar images. The model is loaded from a custom-trained .pt file, and the script processes all test images located in a specified directory (test_images_path). For each image, the script runs inference using the YOLOv5 model to detect sunspots, drawing bounding boxes around detected regions and displaying confidence scores. The detections are alternately color-coded (green and red) for better visualization. Additionally, the script counts the number of detected sunspots in each image, displays a side-by-side comparison of the original and processed images, and saves these comparisons in an output folder. The script also prints the total number of sunspots detected and the average sunspot count across all images, allowing the user to manually review each image by pressing "Enter" to continue processing the next one.
The results are saved as comparison images, showing both the original and processed images with detection boxes, and a summary of the total sunspots detected and average per image is printed at the end.

```
import torch
from pathlib import Path
import cv2
import numpy as np
from tqdm import tqdm
import matplotlib.pyplot as plt

# Load the trained model
model = torch.hub.load('ultralytics/yolov5', 'custom', path='C:/Users/Prem
SP/Documents/SummerSEE/SunspotDetection/weights/best.pt')

# Set the path to your test images
test_images_path = Path('C:/Users/Prem
SP/Documents/SummerSEE/SunspotDetection/test')
output_path = Path('C:/Users/Prem
SP/Documents/SummerSEE/SunspotDetection/test_results')
output_path.mkdir(parents=True, exist_ok=True)

# Function to count and visualize sunspots in an image
def process_sunspots(image_path):
    # Read the image
    img = cv2.imread(str(image_path))
    original_img = img.copy()

    # Run YOLOv5 inference on the image
    results = model(img)
```

```
    # Get the number of detected sunspots
    num_sunspots = len(results.xyxy[0])

    # Sort detections by x-coordinate to help with color alternation
    sorted_detections = sorted(results.xyxy[0], key=lambda x: x[0])

    # Define two colors for alternating
    colors = [(0, 255, 0), (255, 0, 0)]  # Green and Red

    for i, detection in enumerate(sorted_detections):
        x1, y1, x2, y2, conf, _ = detection.tolist()
        color = colors[i % 2]  # Alternate colors

        # Draw bounding box
        cv2.rectangle(img, (int(x1), int(y1)), (int(x2), int(y2)), color, 2)

        # Calculate position for confidence text
        text = f'Conf: {conf:.2f}'
        text_size = cv2.getTextSize(text, cv2.FONT_HERSHEY_SIMPLEX, 0.5, 2)[0]

        # Adjust text position if it would go off the top of the image
        if y1 - text_size[1] - 5 < 0:
            text_y = y1 + text_size[1] + 5
        else:
            text_y = y1 - 5

        # Draw confidence text
        cv2.putText(img, text, (int(x1), int(text_y)),
                    cv2.FONT_HERSHEY_SIMPLEX, 0.5, color, 2)

    # Add text with total sunspot count
    cv2.putText(img, f'Total Sunspots: {num_sunspots}', (10, 30),
                cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0, 255), 2)

    # Create a side-by-side comparison
    comparison = np.hstack((original_img, img))

    # Display the comparison
    plt.figure(figsize=(15, 7))
    plt.imshow(cv2.cvtColor(comparison, cv2.COLOR_BGR2RGB))
    plt.title(f"Image: {image_path.name}, Sunspots detected: {num_sunspots}")
    plt.axis('off')
    plt.show()

    return num_sunspots, comparison
```

```
# Process all images in the test folder
total_images = 0
total_sunspots = 0

for img_path in tqdm(list(test_images_path.glob('*.jpg'))):  # Adjust file
extension if needed
    sunspots, comparison = process_sunspots(img_path)
    total_sunspots += sunspots
    total_images += 1

    # Save the comparison image
    output_file = output_path / f'{img_path.stem}_comparison.jpg'
    cv2.imwrite(str(output_file), comparison)

    print(f"Image: {img_path.name}, Sunspots detected: {sunspots}")

    # Wait for user input to continue
    input("Press Enter to continue to the next image...")

# Print summary
print(f"\nTotal images processed: {total_images}")
print(f"Total sunspots detected: {total_sunspots}")
print(f"Average sunspots per image: {total_sunspots / total_images:.2f}")
print(f"\nProcessed images saved in: {output_path}")
```

5. RESULT AND DISCUSSION

The results of this study demonstrate the effectiveness of the YOLOv5 model in detecting sunspots in Hα continuum images.

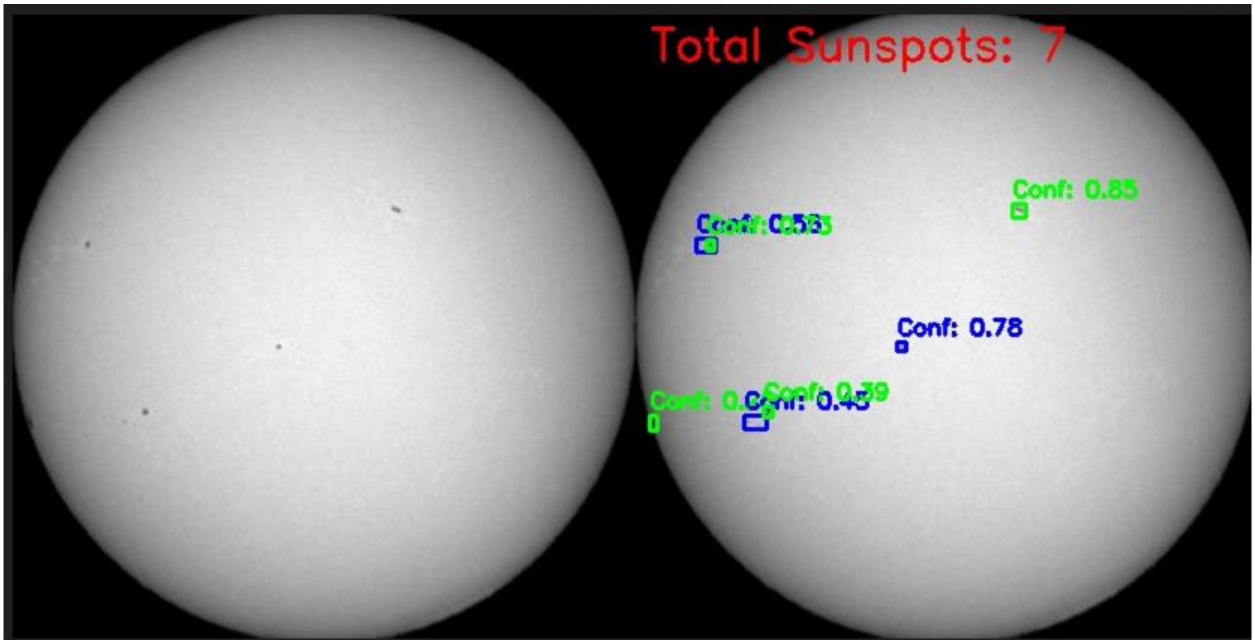

Figure:2 Sunspots detected in the image

The comparison between the original images and the images with bounding boxes drawn around the detected sunspots clearly shows that the model can identify sunspot regions with a high degree of accuracy. In each processed image, the model successfully localized sunspots, and the confidence scores indicated reliable detections. The alternating color scheme for bounding boxes—green and red—facilitated clear visualization of each detected region, further confirming the robustness of the model in handling varying image quality and atmospheric distortions.

These results align with previous studies that have used deep learning models for solar feature detection, reinforcing the validity of using YOLOv5 for this task. The use of a pre-trained YOLOv5 model fine-tuned on solar images provided a good balance between computational efficiency and detection accuracy. However, the model's performance could potentially be improved with a larger and more diverse dataset or the inclusion of additional training epochs.

Overall, the approach taken in this study is justified as it successfully addresses the research question of whether YOLOv5 can be used to accurately detect sunspots in solar imagery. The results indicate that YOLOv5 is a promising tool for solar feature detection, with potential for further optimization and application in solar monitoring and research.

6. CONCLUSION

This research effectively illustrates the use of YOLOv5 for detecting sunspots in Hα continuum solar images, utilizing a dataset consisting of 2000 images obtained from the Bass2000 Solar Survey Archive. The model, which was fine-tuned with pre-trained YOLOv5 weights, demonstrated a notable ability to detect sunspots with considerable precision. The findings, highlighted by side-by-side comparisons of original and modified images, reveal that YOLOv5 efficiently locates sunspots and provides trustworthy confidence scores, establishing it as a powerful resource for analyzing solar images. The alternating color scheme employed for the bounding boxes enhanced the clarity of detections, affirming the model's proficiency in managing diverse atmospheric conditions and image qualities that are present in the dataset.

While the model demonstrated encouraging outcomes, there remains room for enhancement. The small size of the training dataset and the restricted number of training epochs might have limited the model's ability to detect smaller or more subtle sunspots. Utilizing a larger and more varied dataset, combined with prolonged training epochs, could further boost the model's performance. These modifications would be crucial for increasing the model's reliability and precision in identifying sunspots, particularly in environments with high noise or distortion levels.

In conclusion, YOLOv5 presents a promising and efficient approach to solar feature detection, specifically sunspot identification. The results of this study not only answer the research question affirmatively but also highlight areas for further optimization. With future improvements in model training and data diversity, YOLOv5 has the potential to become an essential tool for solar research, contributing to more accurate monitoring and forecasting of solar activity.

7. FUTURE SCOPE

Future work can explore real-time sunspot detection and integration with solar observatories for live monitoring. Enhancements such as improving detection in low-quality images and extending the model to detect other solar phenomena can further expand its utility. Additionally, leveraging advancements in hardware acceleration can enable real-time processing, facilitating its adoption in operational environments.

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APPENDIX

GitHub Link:
Dataset Link: