Solar Event Detection: YOLOv11 Implementation Documentation

Introduction:

This implementation is based on the research paper: *"Solar Event Detection Using Deep-Learning-Based Object Detection Methods"* by Baek et al. (2021), which investigates solar event localization involving three types of solar phenomena: **prominence**, **sunspot**, and **coronal hole**. The original study explores two object detection models-Single Shot Multiscale Detector (SSD) and Faster Region-based Convolutional Neural Network (Faster R-CNN),for detecting and localizing these solar events in solar imagery.

In this implementation, YOLOv11 has been chosen due to its significant architectural improvements over the classical YOLO family, particularly in handling multi-scale object detection tasks. While the original YOLO was limited to single-scale detections, YOLOv11 incorporates three innovative building blocks-**C3K2**, **SPPF**, and **C2PSA**-to enhance detection accuracy and granularity across different object sizes and features (Rao, 2023).

Why YOLOv11 Is Suitable for This Use Case

The architectural improvements in YOLOv11 are particularly well-suited for the detection of the three targeted solar events. Each of the functional blocks contributes uniquely:

- **C3K2 Block**: This module splits the input feature map and applies multiple 3×3 convolution filters in parallel. This not only optimizes the detection of smaller-scale features such as **sunspots**, but also enhances the resolution for detecting faint or ambiguous structures like **prominences** and **coronal holes**.

- **Spatial Pyramid Pooling Fast (SPPF) Block**: The SPPF module aggregates contextual information from different regions of the input at multiple scales. This enables the model to effectively capture spatial hierarchies and is especially beneficial for detecting **small-scale solar events**, such as sunspots, that vary in size across images.

- **Cross Stage Partial with Spatial Attention (C2PSA) Block**: The C2PSA block introduces spatial attention mechanisms that enhance the model's ability to focus on the most informative parts of an image. This becomes crucial when detecting **occluded or subtle features**, such as **prominences** partially hidden by solar structures or **coronal holes** that vary in intensity.

Incorporating these components allows YOLOv11 to better generalize to different spatial resolutions and feature complexities, making it a compelling choice for solar event detection tasks.

Implementation

This implementation has two versions, one in my local pc environment and another in Google Colaboratory, both of the versions have been discussed elaborately in this section. Since our local hardware resources and capabilities are limited, for the purpose of training, we have taken 400 images each for the three classes. For the purpose of validation, images were taken by the numbers- 27 for prominence, 48 for sunspot and 25 for coronal hole. 30 images were taken for testing purpose. The primary reason for this arrangement is (i) lack of resources and (ii) this is an initial implementation and experimentation with YOLOv11 to check its capabilities in terms of solar event detection. It can be inferred that the classical train:test ratio of 4:1 has not been maintained here and this arrangement has been constant in both local environment and Google Colaboratory

Local implementation

The main resources of the local pc is- CPU: AMD Ryzen 5 3400G with Radeon Vega Graphics, RAM: 8x2 GB DDR4. The graphics in the AMD APU could not be utilised, hence the entire execution was done on the CPU. YOLOv11m version was used and the number of epochs was kept to 3. 3 epochs were completed in 2.455 hours (Figure 1). The AP@50 for the events were, prominence = 0.143, sunspot = 0.477, coronal hole = 0.14 , hence mAP@50 was 0.253 (Figure 2).

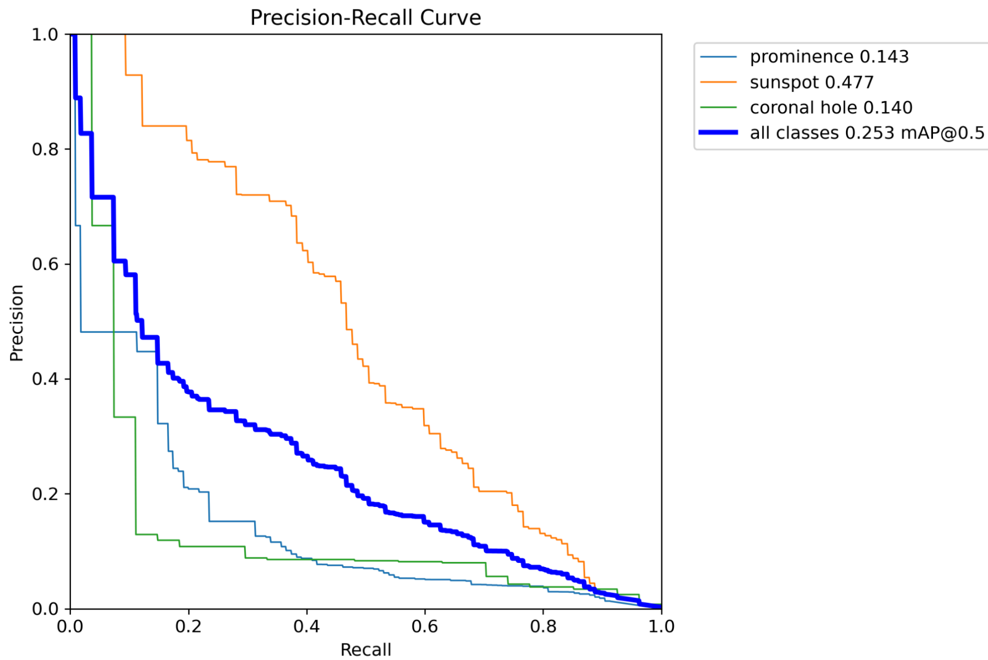
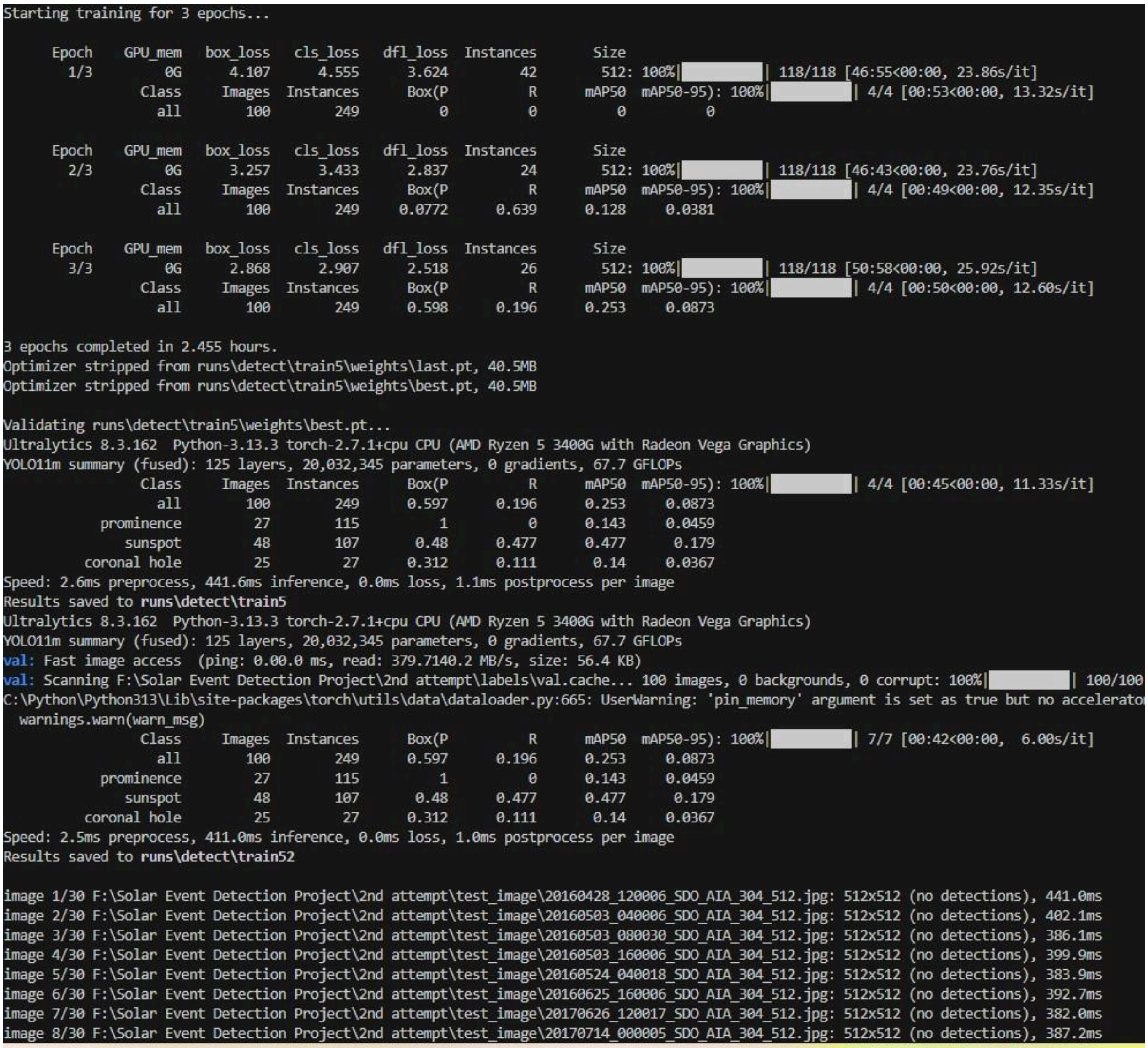


Figure 2: Precision-Recall Curve



```
Starting training for 3 epochs...

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
        1/3         0G      4.107      4.555      3.624         42        512: 100%|          | 118/118 [46:55<00:00, 23.86s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|          | 4/4 [00:53<00:00, 13.32s/it]
                   all        100        249          0          0          0          0

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
        2/3         0G      3.257      3.433      2.837         24        512: 100%|          | 118/118 [46:43<00:00, 23.76s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|          | 4/4 [00:49<00:00, 12.35s/it]
                   all        100        249     0.0772      0.639      0.128     0.0381

      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
        3/3         0G      2.868      2.907      2.518         26        512: 100%|          | 118/118 [50:58<00:00, 25.92s/it]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|          | 4/4 [00:50<00:00, 12.60s/it]
                   all        100        249      0.598      0.196      0.253     0.0873

3 epochs completed in 2.455 hours.
Optimizer stripped from runs\detect\train5\weights\last.pt, 40.5MB
Optimizer stripped from runs\detect\train5\weights\best.pt, 40.5MB

Validating runs\detect\train5\weights\best.pt...
Ultralytics 8.3.162  Python-3.13.3 torch-2.7.1+cpu CPU (AMD Ryzen 5 3400G with Radeon Vega Graphics)
YOLO11m summary (fused): 125 layers, 20,032,345 parameters, 0 gradients, 67.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|          | 4/4 [00:45<00:00, 11.33s/it]
                   all        100        249      0.597      0.196      0.253     0.0873
            prominence         27        115          1          0      0.143     0.0459
               sunspot         48        107       0.48      0.477      0.477      0.179
           coronal hole         25         27      0.312      0.111       0.14     0.0367
Speed: 2.6ms preprocess, 441.6ms inference, 0.0ms loss, 1.1ms postprocess per image
Results saved to runs\detect\train5
Ultralytics 8.3.162  Python-3.13.3 torch-2.7.1+cpu CPU (AMD Ryzen 5 3400G with Radeon Vega Graphics)
YOLO11m summary (fused): 125 layers, 20,032,345 parameters, 0 gradients, 67.7 GFLOPs
val: Fast image access  (ping: 0.0±0.0 ms, read: 379.7±140.2 MB/s, size: 56.4 KB)
val: Scanning F:\Solar Event Detection Project\2nd attempt\labels\val.cache... 100 images, 0 backgrounds, 0 corrupt: 100%|          | 100/100
C:\Python\Python313\Lib\site-packages\torch\utils\data\dataloader.py:665: UserWarning: 'pin_memory' argument is set as true but no accelerato
  warnings.warn(warn_msg)
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|          | 7/7 [00:42<00:00,  6.00s/it]
                   all        100        249      0.597      0.196      0.253     0.0873
            prominence         27        115          1          0      0.143     0.0459
               sunspot         48        107       0.48      0.477      0.477      0.179
           coronal hole         25         27      0.312      0.111       0.14     0.0367
Speed: 2.5ms preprocess, 411.0ms inference, 0.0ms loss, 1.0ms postprocess per image
Results saved to runs\detect\train52

image 1/30 F:\Solar Event Detection Project\2nd attempt\test_image\20160428_120006_SDO_AIA_304_512.jpg: 512x512 (no detections), 441.0ms
image 2/30 F:\Solar Event Detection Project\2nd attempt\test_image\20160503_040006_SDO_AIA_304_512.jpg: 512x512 (no detections), 402.1ms
image 3/30 F:\Solar Event Detection Project\2nd attempt\test_image\20160503_080030_SDO_AIA_304_512.jpg: 512x512 (no detections), 386.1ms
image 4/30 F:\Solar Event Detection Project\2nd attempt\test_image\20160503_160006_SDO_AIA_304_512.jpg: 512x512 (no detections), 399.9ms
image 5/30 F:\Solar Event Detection Project\2nd attempt\test_image\20160524_040018_SDO_AIA_304_512.jpg: 512x512 (no detections), 383.9ms
image 6/30 F:\Solar Event Detection Project\2nd attempt\test_image\20160625_160006_SDO_AIA_304_512.jpg: 512x512 (no detections), 392.7ms
image 7/30 F:\Solar Event Detection Project\2nd attempt\test_image\20170626_120017_SDO_AIA_304_512.jpg: 512x512 (no detections), 382.0ms
image 8/30 F:\Solar Event Detection Project\2nd attempt\test_image\20170714_000005_SDO_AIA_304_512.jpg: 512x512 (no detections), 387.2ms
```

Figure 1: Execution Summary

The confusion matrix created during the validation process is shown in Figure 3. As there were only 3 epochs and the version was YOLOv11m, which were not suitable for this kind of complex imagery, the model was amateurly trained. The matrix is incompleted as only 6 out of 107 instances of sunspot were correctly predicted (TP), 115 instances of prominence were incorrectly classified, and 27 instances of coronal holes. The other evaluation graphs can be found in the "Model_Evaluation directory".

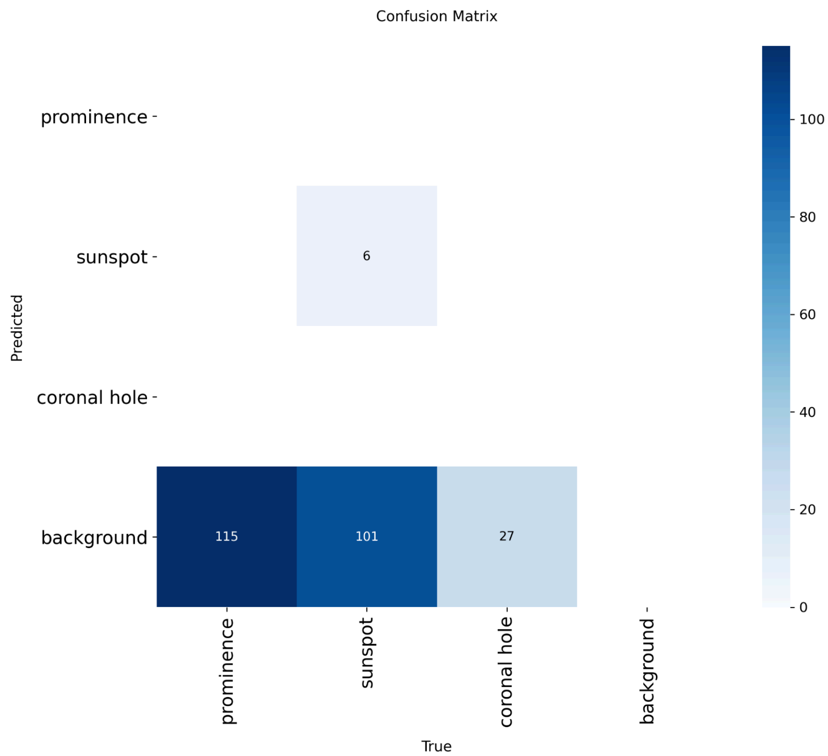


Figure 3: Confusion matrix created in validation process in Local PC

Results

Test images were used in the following order- Prominence:10, Sunspot: 10, Coronal Hole: 10. For the class prominence, no event was detected, as prominent has a vague filament like structure which is undetectable by such an amateur model. Four instances of sunspot was detected in 4 separate images, while 9 instances of sunspot was detected in a total of 5 images (Figure 4). All of the detection results can be seen in "Detection_Results" directory

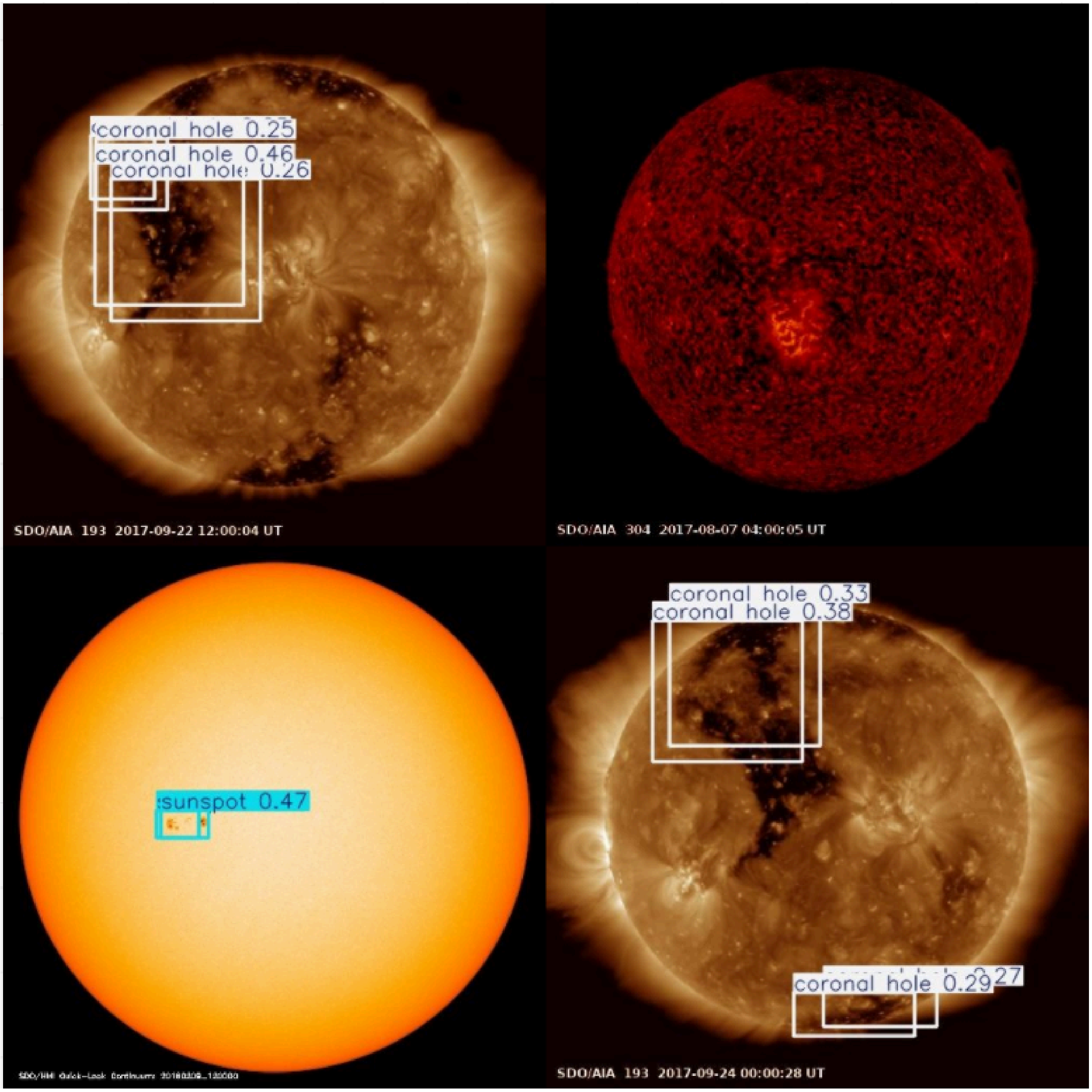


Figure 4: Detection Results from execution in Local environment

Google Colaboratory Implementation

The main resources of the google colab environment is- GPU: Tesla T4, RAM: 15095MiB.. YOLOv11x version was used and the number of epochs was kept to 50. 3 epochs were completed in 1.054 (Figure 1). The AP@50 for the events were, prominence = 0.85, sunspot = 0.958, coronal hole = 0.951 , hence mAP@50 was 0.92 (Figure 5). Evaluation graphs can be found in “runs/detect/train 32” directory.

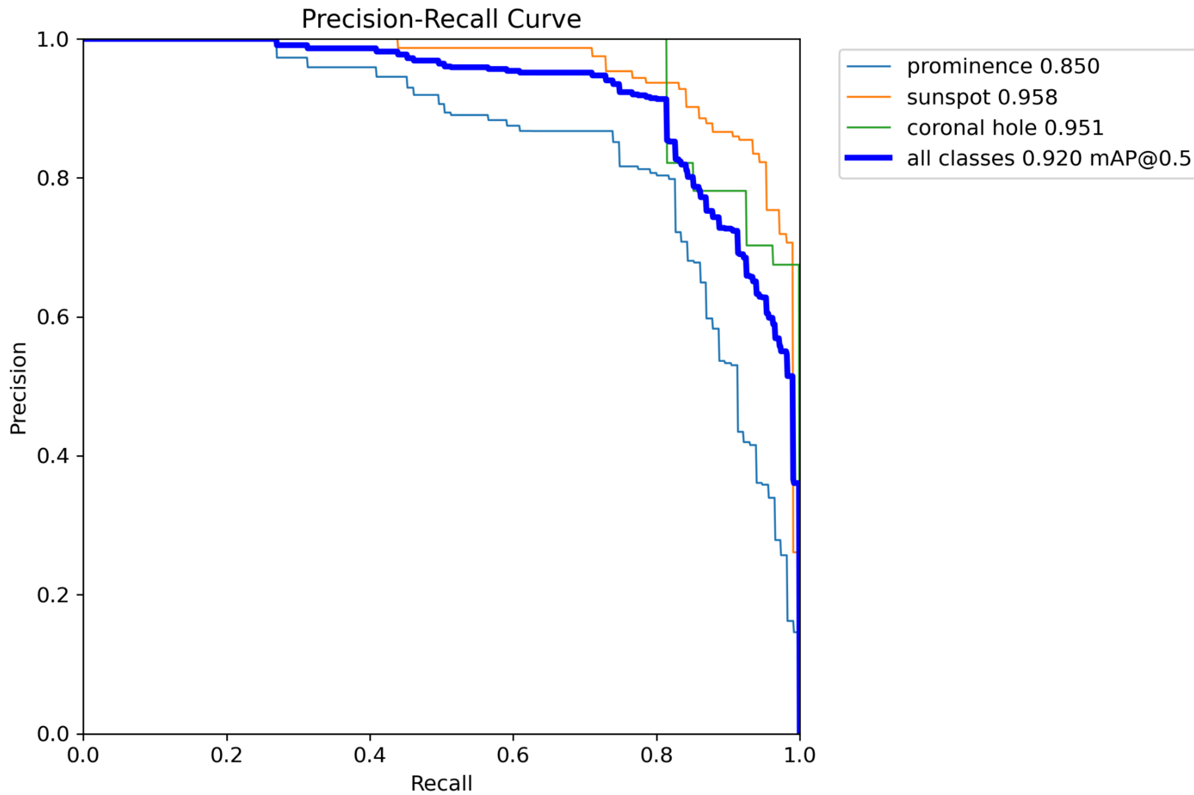


Figure 5: Precision recall curve for Google Colaboratory implementation

The confusion matrix created during the validation process is shown in Figure 6. As there were 50 epochs and the version was YOLOv11x, the results were much more accurate than the local implementation. For prominence, 97 instances out of 115 instances, for sunspot 94 out of 107 and for coronal hole 25 out of 27 were correctly recognised.

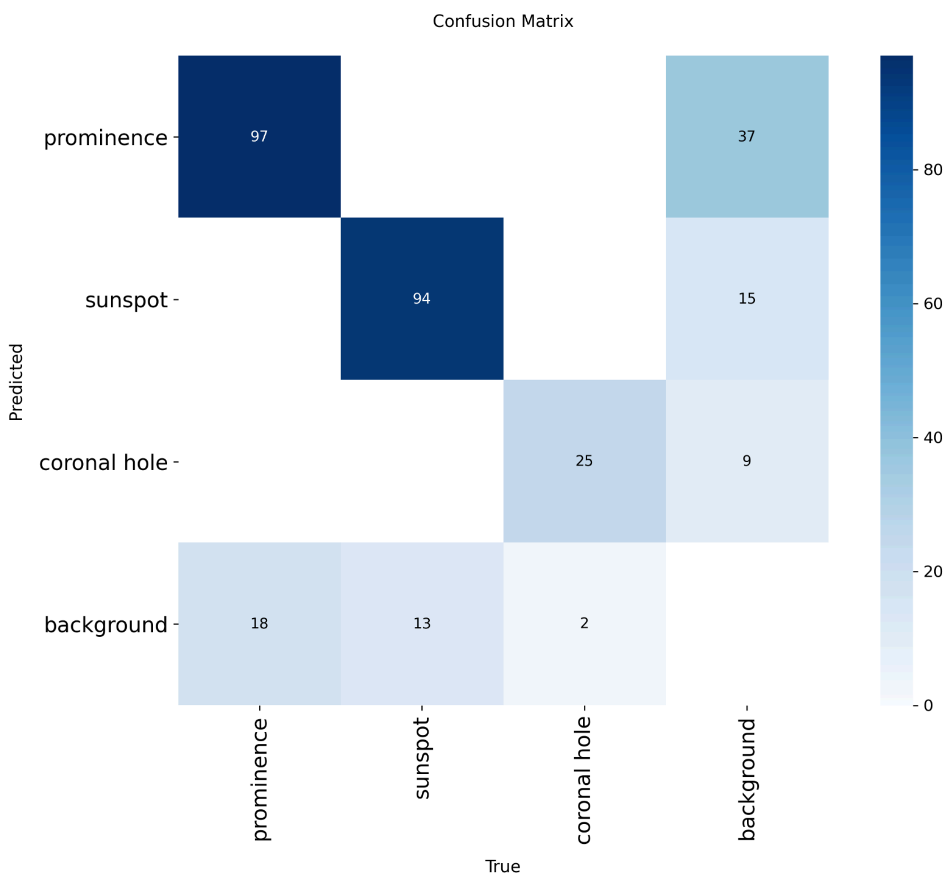


Figure 6: Confusion Matrix for Google Colaboratory model evaluation at validation stage

Results

Test images were used in the following order- Prominence:10, Sunspot: 10, Coronal Hole: 10. For the class prominence based images, the model is not very accurate in detecting the filament like structures, however not only prominence, but also coronal holes were detected most likely to the black patterns in the image. In terms of sunspots, the ones that are closely positioned are taken as a single event rather than discrete ones. Some of the results corresponding to three of the classes are shown in Figure 7. All of the detection results can be found in “runs/detect/train33”

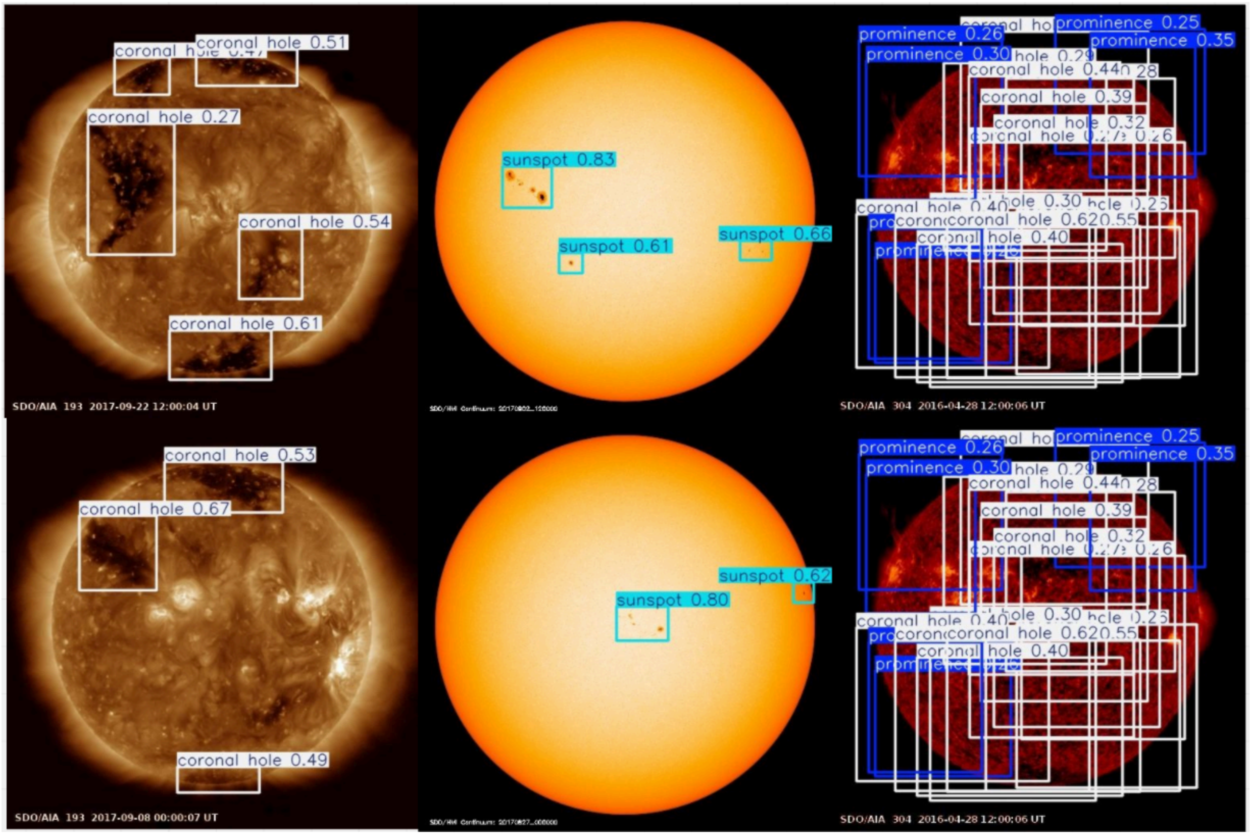


Figure 7: Detection results in Google Colaboratory

References

1. Baek, J. H., Kim, S., Choi, S., & et al. (2021). *Solar Event Detection Using Deep-Learning-Based Object Detection Methods*. *Solar Physics*, **296**, 160. https://doi.org/10.1007/s11207-021-01902-5

2. Rao, N. (2023). *YOLOv11 Explained: Next-Level Object Detection with Enhanced Speed and Accuracy*. *Medium*. Retrieved from: https://medium.com/@nikhil-rao-20/yolov11-explained-next-level-object-detection-with-enhanced-speed-and-accuracy-2dbe2d376f71
3. Ultralytics. (2024). *Ultralytics YOLO*. GitHub Repository. https://github.com/ultralytics/ultralytics