Using YOLO as a tool for monitoring solar panel installation from remote sensing data

Introduction

As the world is heading towards a life without greenhouse gas emissions, a better-quality life, without pollution and a preservation of the ecosystem, the need for sustainable and renewable energy increases. One method for creating sustainable energy are solar panels.

Common methods for solar panel monitoring are limited by their high-costs and labor-intensive processes. However, the field of remote sensing data, satellite imagery in particular, has given a potential solution to the problem - by implementing the object detection algorithm YOLO (You Only Look Once) on satellite imagery to enable identifying of solar panels. Specifically, YOLO's rapid speed of processing images with high accuracy makes it suitable for monitoring geographic regions and observing the growth or decline of solar energy infrastructure (Jocher et al., 2022/2023). Therefore, the objective of this report is to measure whether YOLO is suitable for detecting and analyzing solar panel installations from remote sensing data.

Methods

The dataset chosen for this project is "A solar panel dataset of very high-resolution satellite imagery to support Sustainable Development Goals" (Clark & Pacifici, 2023), which is comprised of 31 cm resolution satellite imagery. In addition, the dataset includes complementary satellite imagery at 15.5 cm resolution which aim to further improve accuracy. The data set contains a total of 2,542 annotated solar panels.

The choice of the model YOLO, more specifically YOLOv8, was made due to YOLO's speed and accuracy. YOLOv8 is the latest advancement in the YOLO architecture, which is known for its incredible accuracy and speed in object detection task such as the one tackled in this project.

The dataset used in this project was directly compatible with YOLTv4 (You Only Look Twice), therefore, in order to use it on the chosen model, data processing was needed. First, the data contained image chips and corresponding labels, which had to be split into 80% training and 20% validation. After the split, the data was combined into a .yaml file needed as input to run YOLOv8.

The model was initialized with a batch size of 16, over 50 epochs. Time and hardware constraints played a role in choosing the epoch number. The implementation was carried out on an AMD Ryzen 5 5600X processor.

Results

After training the model, ".val()" function was ran to see the results of the model. As displayed in the output (see Figure 1), an R value of 0.866 across all classes can be observed which gives an indication that the pre-trained YOLOv8 performed well.

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Model summary (fused): 168 layers, 3006233 parameters, 0 gradients, 8.1 GFLOPs
val: Scanning F:\uni\year 3_sem_1\AINE\project\~\test_images.cache... 509 images, 0 backgrounds, 0 corrupt: 100%|██████
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 32/32 [00:36
                   all        509       5609      0.973      0.886      0.934      0.782
       high confidence        509       5550      0.977      0.948      0.982      0.846
   moderate confidence        509         25      0.942       0.84      0.888      0.733
        low confidence        509         34          1      0.871      0.933      0.768
Speed: 1.3ms preprocess, 61.4ms inference, 0.0ms loss, 0.3ms postprocess per image
```

Figure 1

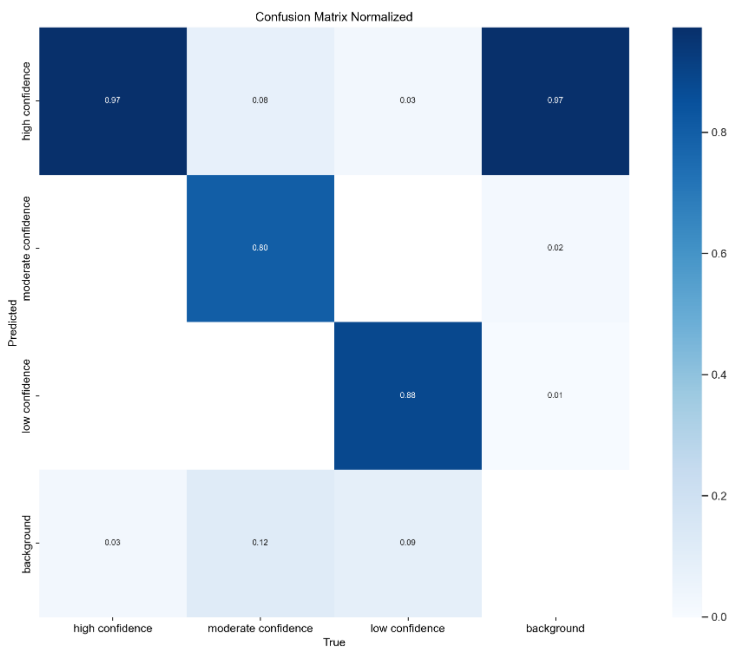

Figure 2

As the confusion matrix exhibits (see Figure 2), the model was able to predict with a very high accuracy, namely 0.97 for high-confidence images, 0.80 for moderate confidence images and 0.88 for low confidence images.

The mAP plot (see Figure 3) is an indication of the model's consistent improvement, suggesting that YOLOv8 is becoming more accurate in its bounding box predictions across a range of IoU thresholds. This, in turn, can indicate a sufficient balance between precision and recall.

Further and more in-depth analysis, as well as graphs are provided in the "runs" folder.

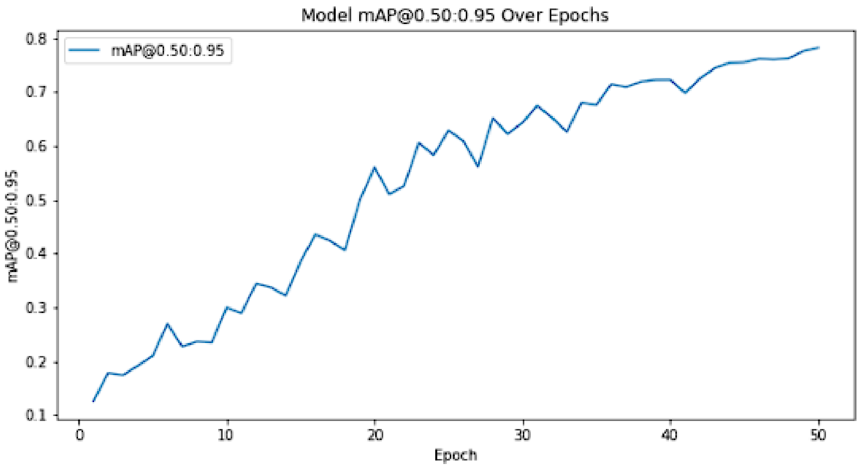

Figure 3

However, an interesting observation was the fluctuation of the precision rates (see Figure 4) over the number of epochs, which hints at the model not being able to make fully accurate predictions. Apart from those fluctuations, there appears to be an upward trend, showcasing the model's improvement in identifying solar panels.

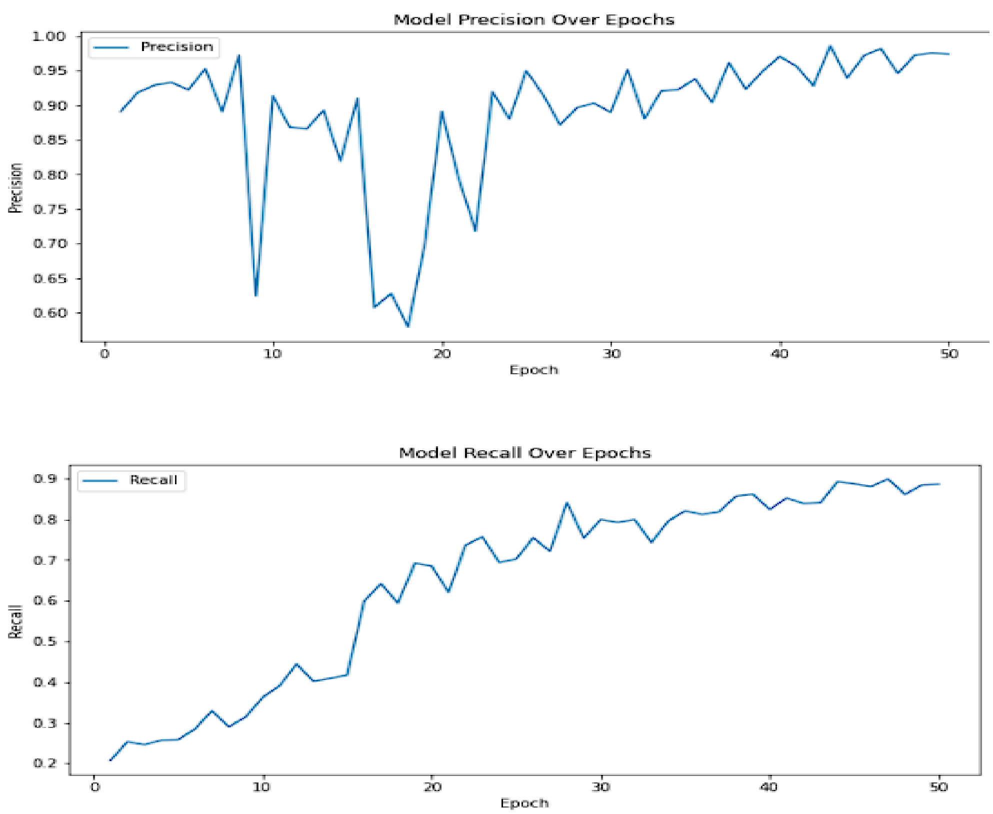

Figure 4

Discussion

The results from this project indicate that YOLO is a viable object detection tool to monitor solar panel installation from remote sensing data, in this case satellite images. Its performance displays high precision and recall rates, which are crucial in monitoring tasks, as these ensure that the majority of detected solar panels are true positives. Although the fluctuations in precision show there is room for further improvement in future work, the model's performance is promising.

This model could be used on a much wider scale with potential significant impacts. Enabling analysis of large datasets of vast geographical regions can help monitor installation of solar panels. Following, this can result in a better assessment of the efficacy of the sustainability efforts of bodies like UN.

The limitations of this report are stemming from the fact that the used model is a pre-trained one, as well as the number of epochs was limited due to time constraints.

While this model performs well, the room for future improvement remains open. For example, using a fine-tuned model could yield better performance, as well as the integration of other variables, such as environmental conditions, could improve its robustness.

To conclude, the project indicated that the use of YOLO as a tool for monitoring solar panel installation from satellite imagery represents an improvement in the field of object detection from remote sensing data. As the world continues to rely on more and more renewable energy sources, having a fast, accurate and scalable monitoring solution is crucial. This project proves that AI can be a great support to sustainability objectives.

References:

Clark, C. N., & Pacifici, F. (2023). A solar panel dataset of very high resolution satellite imagery to support the Sustainable Development Goals. *Scientific Data*, *10*(1), 636. https://doi.org/10.1038/s41597-023-02539-8

Jocher, G., Chaurasia, A., & Qiu, J. (2023). *YOLO by Ultralytics* (8.0.0) [Python]. https://github.com/ultralytics/ultralytics (Original work published 2022)

Ultralytics. (n.d.). *Predict*. Retrieved November 17, 2023, from https://docs.ultralytics.com/modes/predict