**Computer Vision Project:**

**Solar Panel Segmentation**

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# Introduction

In today's world, where sustainable energy sources are increasingly important, solar panels play a crucial role in reducing dependence on fossil fuels and decreasing greenhouse gas emissions. The solar panel segmentation project focuses on identifying and mapping solar panels on satellite images using machine learning and computer vision techniques. The goal of this project is to develop a reliable algorithm that can automatically detect and segment solar panels, enabling a better understanding of their distribution and efficiency. (1)

### Motivation

The motivation for this project stems from the need for more accurate data on installed solar panels globally. Precise mapping of solar panels allows for better estimation of solar energy production, infrastructure planning, and optimization of new solar panel placements. Additionally, the data obtained from this project can help governments and private sectors in monitoring progress towards sustainability goals and reducing carbon footprints.

### Objectives

1. **Develop a Machine Learning Model**: Create a machine learning model capable of accurately detecting and segmenting solar panels in diverse satellite imagery.
2. **Enhance Image Processing**: Implement advanced image processing techniques to improve detection accuracy under varying environmental conditions and terrains.
3. **Data Analysis and Mapping**: Analyze the segmented data to provide detailed insights on the geographic distribution and potential output of solar panels.
4. **Scalability and Optimization**: Ensure the solution is scalable and can be adapted to different geographical regions and satellite data sources.
5. **Contribute to Sustainable Energy Goals**: Provide actionable insights that could contribute to better planning and deployment of solar energy resources.

# Methodology

## Model Selection and Development

The project leverages a combination of two advanced pretrained models and a custom-developed model tailored to the specific needs of solar panel segmentation:

1. **DeepLabV3 ResNet-50**: This model is used for its superior contextual information integration, which is essential for accurate object segmentation at various scales. (2)
2. **FCN ResNet-50**: Employed for its fine detail in pixel-level prediction, which is crucial for precise delineation of solar panel edges. (3)
3. **Custom U-Net Architecture**: Specifically designed to address unique challenges such as overlapping panels and variable lighting conditions, this model features a series of convolutional and upscaling layers to capture detailed image features and improve localization accuracy.

## Data Preparation

The data preparation process is critical for training and involves several steps to ensure the models are trained on high-quality and relevant data:

1. **Directory and Dataset Setup**: Organizing the datasets into training, validation, and testing sets to ensure data is easily accessible and properly segmented.
2. **Data Splitting and Copying**: Images and masks are split into appropriate sets using sklearn's train\_test\_split, ensuring a balanced distribution for model training and validation.
3. **Image Processing**: Segmenting images into smaller tiles to enhance the model's ability to process and analyze finer details, which is crucial for high segmentation accuracy.

## Training and Validation

Training is conducted using a framework that includes:

1. **Training Setup**: Initialization of data loaders with image transformations to standardize input sizes and normalize pixel values.
2. **Model Training**: Iterative training of models using loss functions appropriate for segmentation tasks, with adjustments made based on real-time performance metrics.
3. **Optimization**: Employing Adam optimizer and learning rate schedulers to fine-tune model parameters for optimal performance.
4. **Validation**: Regular validation checks are performed using metrics like Intersection over Union (IoU) and F1 Score to evaluate model accuracy and adjust training parameters accordingly.

# Results and Analysis

## Training and Validation Performance

The performance of the models was tracked over 20 epochs, with training loss, validation loss, and validation metrics such as F1 scores and Intersection over Union (IoU) observed.

#### Training Loss

All models show a general downward trend in training loss, indicating effective learning over the epochs. However, different batch sizes and models converged at varying speeds. The Custom U-Net models consistently demonstrated the lowest training loss across both batch sizes, suggesting better optimization for this specific task. (*Figure 1.*)

Slika na kojoj se prikazuje tekst, crta, dijagram, radnja

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Figure 1. Training Loss

#### Validation Loss

The validation loss varied significantly across models, with some instances of sharp peaks indicating potential overfitting or instability in learning for certain configurations. The larger batch size generally resulted in a more stable decrease in validation loss, suggesting its role in smoothing out learning volatility. (*Figure 2.*)

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Figure 2. Validation Loss

#### F1 Scores

The F1 score, a measure of model accuracy, was relatively stable across models, with minor fluctuations. Custom U-Net models showed a trend of higher F1 scores, which aligns with their lower training and validation losses, indicating not only better learning but also superior generalization on the validation set.(*Figure 3*.)

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Figure 3. F1 Scores

#### IoU Scores

The IoU scores, which assess the overlap between predicted and actual solar panel areas, were consistent, with the Custom U-Net models typically performing better. This metric further confirms the suitability of the U-Net architecture for segmenting complex shapes like solar panels, which require precise pixel-level predictions. (*Figure 4.*)

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Figure 4. IoU Scores

## Qualitative Analysis of Segmentation Results

Visual inspection of the segmentation results reveals clear differences in model performance

#### DeepLabV3 and FCN Models

These models, particularly with lower batch sizes, sometimes struggled with edge consistency and small panel detection. The predicted masks occasionally missed thinner panels or fragmented larger panels into multiple sections. (*Figure 5., Figure 6*.)

Slika na kojoj se prikazuje paralelno, crta, sjena, crno-bijelo

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Figure 5. DeepLabV3 ResNet-50 - test results

# Slika na kojoj se prikazuje paralelno, crta, sjena, crno-bijelo Opis je automatski generiran

Figure 6. FCN ResNet-50 - test results

#### Custom U-Net Model

Demonstrated superior performance in capturing the complete structure of solar panels, even in challenging lighting conditions or when panels were partially obscured or overlapping. The masks generated by the U-Net models were closer to the actual configuration of the panels, displaying fewer segmentation errors and higher fidelity. (*Figure 7*.)

Slika na kojoj se prikazuje paralelno, crno-bijelo, sjena

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Figure 7. Custom U-Net - test results

### Application Example

All three models successfully marked the panels in the image, but with minor deviations. The first image is from the DeepLab3 model, the second is from the ResNet50 model where we can see that a small portion of the panel is missing from the prediction, and the third model is the custom U-Net model which also has minor deviations. (*Figure 8*)

# Slika na kojoj se prikazuje vanjski, snimka zaslona, kvadrat Opis je automatski generiranSlika na kojoj se prikazuje vanjski, snimka zaslona, kvadrat, ulica Opis je automatski generiran Slika na kojoj se prikazuje vanjski, snimka zaslona Opis je automatski generiran

Figure 8. Application examples for all three models

# Conclusion

Throughout this project, the performances of three distinct models—DeepLab3, ResNet50, and a custom U-Net—were analyzed for their effectiveness in segmenting solar panels from satellite imagery. It was shown that each model competently identified and delineated the panels, albeit with minor deviations. Despite individual operational strengths, all models were found to contribute similarly valuable capabilities to the task. This emphasizes the potential of utilizing multiple approaches concurrently to enhance overall accuracy and robustness in solar panel segmentation tasks. Future initiatives could focus on integrating the strengths of these models to optimize performance across a broader range of scenarios.

# References

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