Estimating Residental Solar Potential From Satellite Images

Abdullah Enes Yaman [1] **Hikmet Mete Çelik** [1]

Abstract

This paper presents a novel approach to estimating residential solar potential using satellite imagery, leveraging advanced machine learning techniques. With the growing urgency for sustainable energy solutions, our study focuses on utilizing high-resolution satellite images to analyze residential rooftops for solar panel installation viability. We employ the SegFormer model, fine-tuned on the DeepRoof dataset, to segment rooftops based on their orientation and suitability for solar energy generation. The methodology includes transforming directional data and creating segmentation masks. Our results demonstrate promising potential in identifying suitable rooftop areas for solar panels, although challenges like limited dataset diversity and image variability were encountered.

1. Introduction

In the era of growing environmental concerns and the urgent need for sustainable energy solutions, the potential of solar energy, particularly in residential areas, has become a focal point of research and innovation. Our project, "Estimating Residential Solar Potential From Satellite Images," embarks on an ambitious journey to harness the power of advanced machine learning techniques and satellite imagery to unlock the vast potential of solar energy for residential properties.

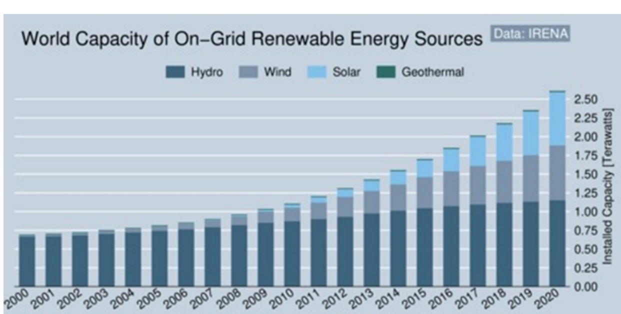

Figure 1. World Capacity On-Grid Renewable Energy Sources

The core objective of this research is to develop a robust and scalable model that can accurately estimate the solar energy potential of residential rooftops. By utilizing high-resolution satellite images, we aim to analyze and categorize rooftops based on their orientation and suitability for solar panel installation. This innovative approach not only promises to enhance the efficiency of solar energy utilization but also offers a user-friendly solution for homeowners and businesses to assess the solar potential of their properties.

In this context, our research is driven by two primary motivations: firstly, to contribute to the global effort of reducing carbon emissions by promoting the use of renewable energy sources; and secondly, to empower property owners with practical and accessible tools for evaluating the solar energy potential of their buildings. We envision a future where sustainable energy solutions are not just a choice but a convenient and economical standard for everyone.

As we proceed with this pioneering study, we are excited to explore the intersection of artificial intelligence, satellite imagery, and renewable energy, and are committed to advancing the field through our findings and innovations.

2. Related Work

The exploration of solar energy potential through satellite imagery is a burgeoning area of research, intersecting the fields of renewable energy, remote sensing, and machine learning. Our work builds upon a foundation laid by several key studies and methodologies that have significantly advanced our understanding and capabilities in these areas.

A pivotal study in our domain is the work by Lee et al. (2019), which presented a novel approach to estimating rooftop solar energy generation using satellite image segmentation. This study demonstrated the feasibility of using machine learning algorithms to analyze satellite imagery for identifying suitable rooftop areas for solar panel installation. The methodology adopted in this research serves as a benchmark for our project.

Further, the research conducted by Hong et al. (2017) on the development of methods for estimating the rooftop solar photovoltaic (PV) potential is particularly relevant. Their work involved analyzing the available rooftop area using Hillshade analysis, providing valuable insights into the spatial distribution of solar energy potential.

In our project, we aim to extend these methodologies by focusing on the segmentation of rooftops into different directional orientations, which is crucial for maximizing solar energy absorption. By integrating these advanced techniques with our novel approach, we seek to enhance the accuracy and usability of solar potential estimations for residential properties.

Our review of the related work underlines the importance of continuous innovation in this field and sets the stage for our contribution to the advancement of solar energy potential estimation using satellite imagery.

3. The Approach

3.1. Dataset

In our project, we utilize the DeepRoof dataset, which is integral to developing and validating our segmentation model for estimating residential solar potential from satellite images. This dataset is available at the following link: UMass Smart* Dataset Repository.

The DeepRoof dataset is a comprehensive collection of satellite images focusing on residential rooftops. What makes this dataset particularly valuable for our research is its detailed annotation of planar roof segments for each roof. These annotations are essential for training our model to recognize and differentiate various roof types and orientations, which is a critical factor in accurately assessing solar potential.

By employing the DeepRoof dataset, our approach is grounded in precise data source, allowing for the development of a more accurate and reliable model. This dataset's detailed annotations and high-quality images are pivotal in enabling our model to effectively learn and predict the solar potential of residential rooftops based on their characteristics and orientations.

In the next sections, we will delve deeper into our methodology, including data preprocessing, model development, and the specific machine learning techniques we employ to achieve our project goals.

3.2. Data Preprocessing

Data preprocessing is a critical phase in our project, where we refine and transform the raw satellite image data into a format conducive for efficient analysis and model training. This process involves three key steps: transforming directional data, creating segmentation masks, and cleaning unlabeled data, each crucial for the accuracy and effectiveness of our rooftop segmentation model.

3.2.1. Changing on Direction Data

Our dataset initially contains directional data for rooftops represented as angles. To simplify and streamline this data for our segmentation model, we have transformed these angular representations into four discrete labels corresponding to the cardinal directions: North, East, South, and West. This transformation is mathematically represented as:

$$\text{label} = \begin{cases} N, & \text{if } 0 \leq \theta < 45 \text{ or } 315 \leq \theta \leq 360 \\ E, & \text{if } 45 \leq \theta < 135 \\ S, & \text{if } 135 \leq \theta < 225 \\ W, & \text{if } 225 \leq \theta < 315 \end{cases} \tag{1}$$

where θ is the angle of the rooftop direction.

3.2.2. Mask Creation

In the next phase, we focus on creating segmentation masks from the VIA (VGG Image Annotator) format annotations. Each roof segment in the dataset is annotated with polygons that are converted into segmentation masks. Initially, the dataset included two additional labels: 'tree' and 'flat'. While we incorporated the 'flat' label as a distinct category in our analysis, representing flat rooftop surfaces, the 'tree' label was merged with the 'void' (background) category. This decision was made to simplify the segmentation task and focus on the key elements of rooftop orientation.

Consequently, our segmentation model works with a total of six labels: North, East, South, West, Flat and Void. These masks are colored uniquely based on the assigned directional label and the flat category, facilitating the model's ability to distinguish between different rooftop orientations and flat surfaces. This process is crucial for the accurate segmentation of rooftops in satellite images, ensuring that our model effectively differentiates between the targeted segments and the surrounding environment.

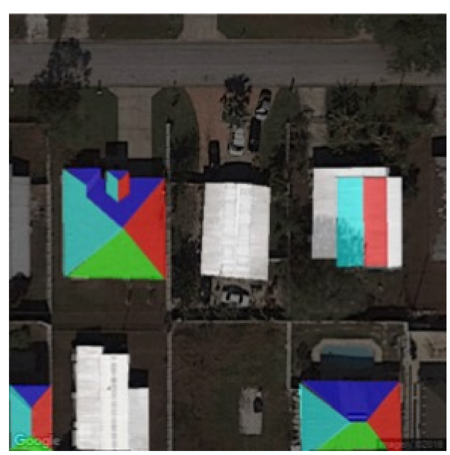

Figure 2. Sample Mask(Red means East, Cyan means West, Navy Blue means North, Green means South, White means Flat)

3.2.3. CLEANING UNLABELED DATA

To ensure the integrity and quality of our dataset, we have implemented a rigorous data-cleaning process. This involves the removal of images that lack proper annotations or are ambiguously labeled. By filtering out these images, we maintain a high standard of data quality, which is essential for the effective training and performance of our segmentation model.

3.3. Model Overview

In the model training phase of our project, we employed the SegFormer architecture, specifically the nvidia/segformer-b4-finetuned-ade-512-512 model, developed by NVIDIA and initially introduced by Xie et al. (2021). SegFormer is a cutting-edge, transformer-based neural network, optimized for high-resolution image processing and known for its exceptional efficiency and accuracy in semantic segmentation tasks. The segformer-b4 model, integral to the SegFormer series, has undergone extensive fine-tuning on the ADE20K dataset, a versatile and comprehensive dataset designed for semantic segmentation challenges. This rigorous pre-training regime equips the model with an enhanced ability to interpret and process complex image features, rendering it exceptionally suitable for our specific application of rooftop segmentation from satellite imagery.

3.3.1. THE PROPOSED SEGFORMER FRAMEWORK

The SegFormer is a novel neural network architecture specifically tailored for the task of semantic segmentation, as depicted in Figure 3. This framework is composed of two main components: an encoder and a decoder, each playing a vital role in the processing and interpretation of image data.

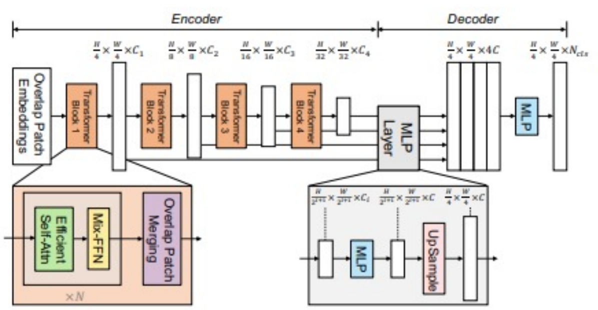

Figure 3. The architecture of the proposed SegFormer framework.

Encoder The encoder adopts a hierarchical transformer structure that processes the input image in stages. Starting with the original image, each subsequent stage in the encoder reduces the spatial resolution while increasing the channel depth, allowing the model to capture contextual information at multiple scales. The SegFormer encoder is unique in its omission of positional encodings, a common feature in transformer models, which contributes to the model's robustness during testing, even when the input resolution varies from the training phase.

Decoder On the other side, the decoder is designed to be lightweight. It aggregates the multiscale features from the encoder using a simple multi-layer perceptron (MLP). This design choice enhances the model's efficiency, enabling it to handle high-resolution images swiftly, which is essential for real-world applications where computational resources and response times are critical.

Multi-Scale Feature Fusion The encoder also features an innovative Multi-Scale Feature Fusion (MSFF) block that merges the features from various encoder stages. This fusion allows the model to maintain detailed spatial information, which is crucial for accurate segmentation.

In essence, SegFormer's architecture achieves a harmonious balance between deep representation and computational efficiency, which is instrumental for semantic segmentation tasks. Its strategic design choices, including the hierarchical transformer structure and a streamlined decoder, underpin its state-of-the-art performance across various benchmarks.

3.3.2. MODEL ADAPTATION FOR ROOFTOP SEGMENTATION

To tailor the SegFormer model for rooftop segmentation, we made specific adaptations to classify the four cardinal rooftop orientations – North, East, South, and West – in addition to flat and void categories. The model processes preprocessed satellite images, assigning each pixel to one of these six categories. Crucial to our methodology is the model's proficiency in handling high-resolution inputs, ensuring the retention of intricate rooftop details crucial for precise segmentation. This adaptation is pivotal in enabling the SegFormer to accurately identify and categorize rooftop features relevant to solar potential assessment.

3.3.3. TRAINING PROCESS

Our training process for the SegFormer model involved a meticulously designed regimen, with a specific focus on fine-tuning the model at a learning rate of 0.0001. This learning rate was carefully chosen to balance efficient learning speed with the need to minimize the risk of overshooting optimal weights during training. To optimize model efficiency and performance, we adjusted other training parameters, such as the batch size, set to 4.

A dual loss function approach was employed, integrating cross-entropy loss with IoU (Intersection over Unions). This strategy effectively hones the model's ability to balance between classification accuracy and the spatial accuracy of segmentation masks compared to the ground truth.

Moreover, we divided our dataset into three parts for training, validation, and testing, following a 60-20-20 split ratio. This partitioning ensured that 60% of the data was used for training the model, 20% for validation to fine-tune the parameters and avoid overfitting, and the remaining 20% for testing to assess the model's performance on unseen data. This approach of dividing the dataset is crucial for evaluating the model's effectiveness and ensuring its robustness and reliability.

Periodic validation checks were conducted to monitor for overfitting, further enhancing the model's robustness. This comprehensive training approach ensured the development of a reliable and accurate segmentation tool, tailored specifically for estimating solar potential from satellite imagery.

3.3.4. Evaluation Metrics

Our model's performance was evaluated using two main metrics: Accuracy and Intersection over Union (IoU).

Accuracy: This metric reflects the percentage of pixels correctly classified by the model in comparison to the total number of pixels. It indicates the overall effectiveness of the model in classifying each pixel.

Intersection Over Union (IoU): IoU measures the overlap between the model's predicted segmentation and the actual ground truth segmentation. It is calculated as the ratio of the intersection area to the union area of the predicted and true segmentation. A higher IoU signifies greater accuracy in segmenting distinct objects.

3.3.5. Estimating Solar Potential

The estimation of solar potential on residential rooftops is a critical component of our research, employing segmented satellite imagery to calculate the potential solar energy production. Our methodology integrates rooftop area segmentation, solar radiation data sourced from Koçer et al. (2016), and efficiency metrics for solar panels.

To accurately determine the area available for solar panels, we convert the pixel area from segmentation masks into actual square meters using the scale bar provided by Google Maps. This conversion is crucial for precise estimation, as it accounts for the real-world dimensions of the rooftop surfaces. It involves a pixel-to-meter conversion that considers the resolution of the imagery and the scaling factor indicated by the map's scale bar. The precise measurement of the area is vital to our methodology as it directly influences the calculation of the solar potential.

Our flexible approach allows for the estimation of solar potential both annually and for specific months by selecting appropriate solar radiation values for the given time period. The final estimations detail the potential solar energy production for each rooftop orientation—flat, north, south, east, and west—and the total potential across all orientations.

Integrating this method with the geographical radiation data from the comprehensive dataset cited in Koçer et al., we present a robust framework for assessing the solar installation viability in residential settings. The adaptability of our tool paves the way for its application in diverse geographical and urban settings, contributing to global efforts in sustainable energy planning and smart urban development.

4. Experimental Results

In this section, we present the outcomes of applying our trained model to a set of real-world images sourced from Google Maps and the test part of our dataset. The purpose of this exercise was to validate the model's effectiveness in a practical scenario, beyond the confines of the training dataset.

4.1. Test Images and Model Inference

The test images, carefully selected from Google Maps and the test part of our dataset, provided a diverse range of residential rooftops, each with unique characteristics and orientations. These images were subjected to inference using our trained SegFormer model, which was expected to identify and classify the various rooftop segments according to the labels defined during training.

4.2. Observations and Analysis

From the results of the model inference, we observed that the segmentation of flat surfaces (labeled as 'flat') was notably accurate. However, the performance on directional labels (North, East, South, West) was less satisfactory. The primary reasons for the model's suboptimal performance are as follows:

- **Limited Number of Images:** The original dataset lacked a sufficient number of images, which is critical for training a robust machine learning model. The scarcity of data points limited the model's exposure to various scenarios and conditions, affecting its ability to generalize well.

- **Lack of Roof Type Diversity:** The dataset did not encompass a wide variety of roof types. This lack of diversity in the training data led to challenges in accurately segmenting and labeling different rooftop orientations in the test images, which likely included roof types not represented in the training set.

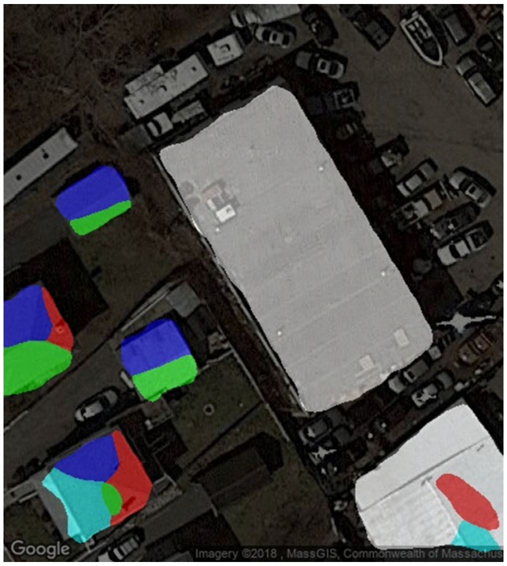

Figure 4. Sample Output (Red means East, Cyan means West, Navy Blue means North, Green means South, White means Flat)

4.3. Roof Segmentation

Our model achieved a Mean Accuracy of 0.65, showcasing a strong ability to correctly classify pixels. Notably, the accuracy for flat surfaces was exceptionally high at 0.91. The Mean IoU for our model was recorded at 0.47. For flat surfaces, the model performed remarkably well, achieving an IoU of 0.82.

Orientation	Accuracy	IoU
North	0.60	0.51
South	0.54	0.47
East	0.64	0.55
West	0.57	0.46
Flat	0.91	0.82
Mean Values	0.65	0.47

Table 1. Performance Across Different Labels

These results illustrate that while the model is highly effective in identifying flat surfaces, its performance varies across different rooftop orientations, with generally lower accuracy and IoU scores for non-flat orientations. This highlights areas for potential enhancement in future model iterations.

4.4. Solar Potential Energy Calculation

The fundamental formula used for estimating the energy output E from each rooftop segment is given by:

$$E = A \times r \times H \times PR \tag{2}$$

where:

- A is the total area of the rooftop segment (in m^2), derived from satellite image segmentation.
- r is the efficiency of the solar panels, assumed to be 17.5%.
- H is the average solar radiation on tilted panels (in kWh/m^2), obtained from the Ankara and districts location-based dataset and converted from MJ/m^2 to kWh/m^2.
- PR is the Performance Ratio, a coefficient for losses, typically ranging between 0.5 and 0.9. In our calculations, a default value of 0.75 is used.

Additionally, the tilt of the roof is factored into the calculations, especially for non-flat surfaces. For a roof with a tilt angle θ, the energy output is adjusted as follows:

$$H = H_{\text{location}} \times |\cos(\theta)| \tag{3}$$

This formula adjusts the energy output based on the cosine of the tilt angle, which affects the solar panel's exposure to sunlight. The default tilt angle is set at 27 degrees but can be modified as needed.

Figure 5. Segmented Rooftop

Rooftop Orientation	Area (m^2)	Energy (kWh)
North	30.62	5771.8
South	27.47	5177.82
West	46.20	8708.43
East	38.85	7322.2
Flat	21.26	4627.64
Total	164.4	31607.89

Table 2. Estimated Solar Energy Production by Rooftop Orientation for Figure 5

5. Conclusion

In conclusion, our research presents a significant advancement in the field of renewable energy, specifically in estimating residential solar potential using satellite imagery and advanced machine learning techniques. The successful application of the SegFormer architecture for rooftop segmentation and the innovative approach to calculating solar potential based on segmented rooftop areas demonstrate the feasibility and effectiveness of using AI and remote sensing for solar energy assessment.

Our model's ability to segment different rooftop orientations and calculate the solar potential with a notable degree of accuracy, especially for flat surfaces, highlights its practical utility in real-world scenarios. While the performance varies across different orientations, the results are promising and lay a strong foundation for further refinement and application.

The integration of comprehensive solar radiation data and consideration of factors such as rooftop orientation and tilt angles in our calculations underscore the model's sophistication and potential for customization based on specific user requirements. This flexibility, combined with the ability to estimate solar potential both annually and monthly, makes our methodology a valuable tool for homeowners, and urban planners in assessing and harnessing the solar energy potential of residential areas.

Future work will focus on enhancing the model's accuracy for various rooftop orientations, expanding the dataset to include more diverse roof types, and integrating more granular solar radiation data to refine the estimates further. Additionally, the potential for real-time solar potential assessment and integration with smart grid systems opens new avenues for research and application.

In summary, this study not only contributes to the academic understanding of AI-based solar potential assessment but also has significant implications for practical applications in the realm of sustainable energy solutions. By harnessing the power of satellite imagery and machine learning, we move closer to a future where renewable energy is not just a choice but an accessible and efficient standard for all.

References

Hong, T., Lee, M., Koo, C., Jeong, K., and Kim, J. Development of a method for estimating the rooftop solar photovoltaic (pv) potential by analyzing the available rooftop area using hillshade analysis. *Applied Energy*, 194:320–332, 2017. ISSN 0306-2619. doi: https://doi.org/10.1016/j.apenergy.2016.07.001. URL https://www.sciencedirect.com/science/article/pii/S0306261916309424.

Kocer, A., şevik, S., and Gungor, A. Ankara ve ilçeleri için güneş kolektörü optimum eğim açısının belirlenmesi. *Uludağ University Journal of The Faculty of Engineering*, 21:63–77, 06 2016. doi: 10.17482/uujfe.80088.

Lee, S., Iyengar, S., Feng, M., Shenoy, P., and Maji, S. Deeproof: A data-driven approach for solar potential estimation using rooftop imagery. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '19, pp. 2105–2113, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450362016. doi: 10.1145/3292500.3330741. URL https://doi.org/10.1145/3292500.3330741.

Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., and Luo, P. Segformer: Simple and efficient design for semantic segmentation with transformers, 2021.