

Implementation of Solar Energy Potential Mapping Using the Segment Anything Model and Real-Time Meteorological Data

Dr. Ankita V. Karale¹, Nivedita R. Vibhandik², Soham A. Kulkarni³, Khemchandra A. Chaudhari⁴, Chetan R. Sonawane⁵, Aman A. Mansuri⁶

Head of Department, Computer Department, Sandip Institute of technology and research centre, Nashik, India¹

Assistant Professor, Computer Department, Sandip Institute of technology and research centre, Nashik, India²

Student, Computer Department, Sandip Institute of technology and research centre, Nashik, India^{3 4 5 6}

ankita.karale@sitrc.org¹, nivedita.vibhandik@sitrc.org², soham18262@gmail.com³, khemchandra04@gmail.com⁴, sonawanechetan847@gmail.com⁵, aman.mansuri1401@gmail.com⁶

Abstract: This paper presents the development and implementation of a novel approach for Solar Energy Potential Mapping, integrating the Segment Anything Model (SAM) for accurate rooftop segmentation with real-time meteorological data from the Solar Anywhere API. The system effectively identifies suitable areas for solar panel installation by leveraging SAM's advanced image segmentation capabilities to detect rooftops, and other surfaces from high-resolution satellite images. Real-time solar irradiance data is then utilized to calculate the energy generation potential for each identified area. The proposed solution is implemented as a user-friendly web application, delivering precise solar potential assessments and visualizations in the form of interactive charts. This paper discusses the methodology, implementation, and results of the working system, demonstrating its effectiveness in optimizing solar energy potential mapping. The findings highlight the advantages of combining advanced machine learning models with real-time data to provide accurate and actionable insights for solar energy deployment, contributing to sustainable energy planning and decision-making.

Keywords: - Solar Energy, Rooftop Segmentation, Segment Anything Model (SAM), Solar Anywhere API, Real-Time Meteorological Data, Image Segmentation, Solar Potential Mapping, Machine Learning, Satellite Imagery, Renewable Energy, Urban Solar Assessment, Energy Generation Potential, Web Application, Interactive Visualization.

1. INTRODUCTION:

With the global shift towards renewable energy, the demand for accurate and efficient methods of assessing solar energy potential has become more critical than ever. Solar energy potential mapping plays a vital role in identifying optimal rooftops for photovoltaic (PV) installations, enabling urban areas to maximize energy generation without requiring additional land. Traditional approaches, such as manual surveys, are often labor-intensive, costly, and prone to inaccuracies, limiting their scalability and effectiveness. To address these challenges, advancements in satellite imagery, image segmentation techniques, and real-time meteorological data have paved the way for automated and precise solar potential mapping solutions.

This paper introduces a novel approach to Solar Energy Potential Mapping by leveraging the Segment Anything Model (SAM) in conjunction with real-time meteorological data from the SolarAnywhere API. The project focuses exclusively on rooftop segmentation to accurately calculate rooftop areas suitable for solar panel installation. Unlike conventional methods that rely on manual digitization or simple thresholding techniques, SAM's state-of-the-art image segmentation capabilities offer robust and precise detection of rooftops from high-resolution satellite images. This accuracy is crucial for estimating the surface area available for solar installations, directly influencing the potential energy yield calculations.

One of the significant challenges in solar potential mapping is accounting for real-time environmental conditions that impact

solar energy generation, such as solar irradiance, cloud cover, and temperature variations. The integration of real-time meteorological data from the Solar Anywhere API enables dynamic and accurate solar potential assessments by providing up-to-date solar irradiance values for the specified geographical location. This data-driven approach enhances the reliability of energy generation estimates, facilitating more informed decision-making for urban solar power planning.

The proposed system is implemented as a user-friendly web application, designed to provide precise rooftop area measurements and solar energy potential assessments without requiring user authentication or account creation. This seamless user experience is aimed at making solar energy assessments more accessible and efficient. The web application also includes interactive visualizations, such as heatmaps and charts, allowing users to easily interpret and analyze the solar potential of identified rooftops.

This paper discusses the complete lifecycle of the project, including the methodology for rooftop segmentation using SAM, integration with the SolarAnywhere API for real-time data acquisition, and the system architecture supporting the web application. The effectiveness of the proposed approach is evaluated by comparing the results with traditional segmentation models, demonstrating the superior accuracy and efficiency of SAM in rooftop segmentation tasks.

By combining advanced image segmentation with real-time data, this study offers a robust solution for optimizing rooftop solar

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assessments, supporting sustainable energy planning and contributing to the wider adoption of solar energy technologies. The findings emphasize the importance of integrating machine learning with dynamic data sources, paving the way for more intelligent and adaptive renewable energy solutions. will need to create these components, incorporating the applicable criteria that follow.

II. BACKGROUND

Importance of Solar Energy Potential Mapping:

The increasing global focus on sustainable energy solutions has elevated the significance of solar energy as a viable renewable resource. Solar energy potential mapping is crucial for identifying optimal rooftops for photovoltaic (PV) installations, particularly in urban areas where space is a constraint. Accurate mapping enables maximum energy generation and supports strategic urban planning for solar energy deployment.

Traditional methods for assessing solar energy potential rely heavily on manual surveys and basic image processing techniques, which are time-consuming, labor-intensive, and prone to human error. These conventional methods often lack scalability and fail to provide real-time energy estimates, highlighting the need for advanced and automated solutions

Background Study:

To design an effective solution, we conducted an extensive literature survey, exploring recent advancements in solar energy potential mapping. Our research focused on three key areas: rooftop segmentation techniques, integration of meteorological data, and machine learning approaches for solar potential estimation.

Fakhreddine et al. demonstrated the effectiveness of using deep learning-based instance segmentation for rooftop extraction from satellite images, achieving high accuracy in Lebanon's solar potential assessment. Similarly, Gong et al. utilized an improved SegFormer model to classify building roofs in Nanjing, China, demonstrating the importance of advanced semantic segmentation for accurate rooftop identification.

The integration of real-time meteorological data was also examined, as accurate solar radiation data significantly influences energy potential calculations. Studies by Syarif et al. and Santra et al. highlighted the importance of incorporating long-term meteorological data and Geographic Information Systems (GIS) for precise solar irradiance predictions and site suitability mapping.

While these studies presented significant advancements in solar potential mapping, they often required complex models, high computational resources, or manual interventions, limiting their scalability and accessibility for urban solar assessments.

Challenges Identified in Existing Approaches:

Existing segmentation models, including U-Net, DeepLabV3, and Mask R-CNN, are widely used for rooftop identification but face challenges in accurately detecting complex rooftop structures due

to variations in shape, size, and orientation. These models often require extensive fine-tuning and large labeled datasets for training.

Traditional methods for solar potential assessment are primarily based on static data, leading to inaccuracies in energy yield calculations as they do not account for dynamic environmental factors like cloud cover and temperature fluctuations.

Most solutions require significant computational power and technical expertise, making them less accessible for widespread urban deployment. Additionally, manual interventions in data preprocessing and segmentation limit the scalability of these approaches

III METHODOLOGY

Evolution of Our Approach:

Building on the insights gained from the literature survey, our approach evolved to address the limitations of existing methods by integrating the Segment Anything Model (SAM) with real-time meteorological data from the SolarAnywhere API.

The decision to use SAM was influenced by its state-of-the-art image segmentation capabilities, which outperform conventional models in accurately detecting complex rooftop structures. Unlike other segmentation techniques, SAM is highly adaptable and requires minimal fine-tuning, making it suitable for diverse urban environments.

Our project focuses exclusively on rooftop segmentation to calculate rooftop areas suitable for solar panel installation, ensuring precise area calculations that are critical for accurate energy potential estimation. This approach eliminates the need for vegetation classification, simplifying the segmentation process while maintaining high accuracy.

By integrating SAM with the Solar Anywhere API, our system dynamically calculates solar potential using real-time solar irradiance data, temperature, and cloud cover information. This real-time integration enhances the reliability of energy yield predictions compared to traditional static methods.

Unlike earlier solutions that require complex setups and technical expertise, our system is implemented as a user-friendly web application, enabling users to upload satellite images, obtain precise rooftop segmentation results, and receive accurate solar potential assessments without the need for account creation or manual interventions.

Advantages and Contributions of Our Approach:

Our approach is an evolved version of the existing methods as it combines the accuracy of SAM with the dynamism of real-time meteorological data. This combination ensures high-precision rooftop segmentation and context-aware solar potential calculations, making the solution more reliable and adaptable to changing environmental conditions.

By focusing solely on rooftop segmentation and leveraging real-time data, our method reduces computational complexity and enhances scalability, making it suitable for large-scale urban

deployments.

The user-centric design of the web application enhances accessibility, promoting the adoption of solar energy by simplifying the decision-making process for rooftop solar installations.

Our project not only addresses the limitations identified in traditional methods but also contributes to sustainable urban energy planning by optimizing solar potential mapping, supporting renewable energy goals, and facilitating informed decision-making.

Image Segmentation using Segment Anything Model:

- 1) **Choice of SAM:** The Segment Anything Model (SAM) is selected for its state-of-the-art image segmentation capabilities, outperforming traditional models in accurately detecting complex rooftop structures. SAM's adaptability and minimal fine-tuning requirements make it ideal for diverse urban environments.
- 2) **Rooftop Segmentation:** SAM is used exclusively for rooftop segmentation to calculate rooftop areas suitable for solar panel installation. This approach ensures precise area calculations essential for accurate energy potential estimation. Unlike conventional methods, no vegetation classification is performed, simplifying the segmentation process while maintaining high accuracy.
- 3) **Fine-tuning of SAM:** The model is fine-tuned using project-specific datasets to improve accuracy in detecting rooftops of various shapes, sizes, and orientations. This customization enhances SAM's segmentation performance in different urban settings.

Solar Energy Estimation:

1) Energy Generation Potential (EGP) Calculation:

The Energy Generation Potential (EGP) is computed based on Global Horizontal Irradiance (GHI) and other relevant parameters like usable area, system efficiency, and temperature effects. The formula is expressed as:

$$EGP = GHI * A * \eta_{\text{panel}} * \eta_{\text{system}} * (1 - \alpha (T - 25^{\circ}\text{C}))$$

Where:

EGP = Energy Generation Potential (kWh/day)

GHI = Global Horizontal Irradiance (kWh/m²/day) from real-time meteorological data

A = Usable area (m²), calculated from segmentation

η_{panel} = Solar panel efficiency (0.15 to 0.22)

η_{system} = Overall system efficiency (0.75 to 0.85)

α = Temperature coefficient (e.g., 0.005 for 0.5% efficiency loss per °C above 25°C)

T = Ambient temperature (°C)

Usable Area Estimation:

The total usable area for solar panel installation is estimated after the segmentation of satellite images using the Segment Anything Model (SAM). The Usable Area (A) is computed as:

$$A = A_{\text{total}} * F_{\text{utilization}}$$

Where:

- a) A = Usable area (m²)
- b) A_{total} = Total area (m²), such as rooftop area
- c) F_{utilization} = Utilization factor (typically 0.6 to 0.8, representing space limitations)

Annual Energy Yield (AEY):

The Annual Energy Yield (AEY) provides a yearly estimate of solar energy production. It is calculated as:

$$AEY = EGP * 365 * SF$$

Where:

- a) AEY = Annual Energy Yield (kWh/year)
- b) EGP = Daily Energy Generation Potential (kWh/day)
- c) SF = Shading factor (between 0 and 1, where 1 means no shading)

Solar Potential Index (SPI):

The Solar Potential Index (SPI) serves as a metric to assess the efficiency and feasibility of installing solar panels in a specific area. It is defined as:

$$SPI = AEY / (A_{\text{total}} * C)$$

Where:

- a) SPI = Solar Potential Index (dimensionless)
- b) AEY = Annual Energy Yield (kWh/year)
- c) A_{total} = Total area considered (m²)
- d) C = Cost factor (typically set to 1 for simple comparisons)

System Architecture:

- 1) **Frontend:** Built using Next.js for dynamic rendering and responsive design, ensuring a smooth user experience across devices.
- 2) **Backend:** FastAPI is used for efficient processing of image segmentation requests, data integration, and energy potential calculations.
- 3) **Machine Learning Model:** The architecture leverages Segment anything model (SAM) at backend to generate accurate area of segmented rooftops from the image
- 4) **Scalable Design:** The architecture is designed to be scalable, allowing the system to handle multiple user requests simultaneously and supporting large-scale urban deployments.

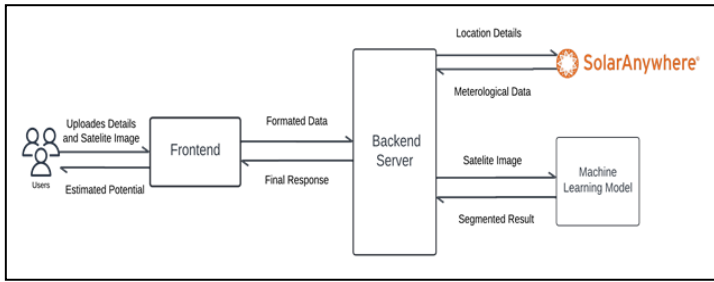


Figure 1 :System Architecture

Working:

- 1) **Input from the User:** The user provides two key inputs through the frontend interface: an image (typically a satellite or aerial image of the location) and the location's name. These inputs form the foundation of the solar potential mapping process.
- 2) **Data Transmission to Backend:** Once the image and location data are submitted, they are transmitted to the backend server. The server acts as the orchestrator, directing data to the relevant modules for further processing.
- 3) **Image Processing for Solar Potential Evaluation:** The backend sends the image data to a machine learning model, specifically designed to assess solar potential. This model uses techniques such as image segmentation and rooftop detection to identify areas suitable for solar energy generation. The model processes the image and outputs the potential area that could be used for solar installations.
- 4) **Real-time Data Request via Solar Anywhere API:** Simultaneously, the location data is forwarded to the SolarAnywhere API, which provides real-time meteorological and solar irradiance data for the specified location. This information includes key environmental factors like solar radiation, temperature, which are crucial for calculating solar energy potential.
- 5) **Backend Processing and Calculation:** Once the image analysis and real-time data from the SolarAnywhere API are obtained, the backend server performs calculations to estimate the solar energy potential. These calculations are based on the area detected by the machine learning model and the real-time environmental data, resulting in an estimate of the solar energy that can be generated for that specific location.
- 6) **Output Generation and Visualization:** The calculated solar potential is returned to the frontend in a structured JSON format. The frontend then visualizes the results using interactive charts and numerical data, allowing users to see detailed insights into the solar energy potential of the area under consideration.

IV RESULTS

A. Rooftop Segmentation Output:

The implementation of the Segment Anything Model (SAM) for IMPACT FACTOR 6.228

rooftop segmentation yielded highly accurate results. The model effectively identified and segmented rooftops from high-resolution satellite images, showcasing its advanced image segmentation capabilities.

One of the key results is the precise rooftop segmentation demonstrated in the displayed image (Fig-2). The segmented output clearly outlines the rooftop boundaries, accurately calculating the usable area for solar panel installation.

The image illustrates SAM's robustness in handling complex rooftop structures, varying shapes, and orientations, highlighting its superior performance compared to traditional segmentation methods from the original base papers.

This accurate area calculation directly influences the accuracy of solar energy potential estimates, ensuring reliable energy yield predictions.

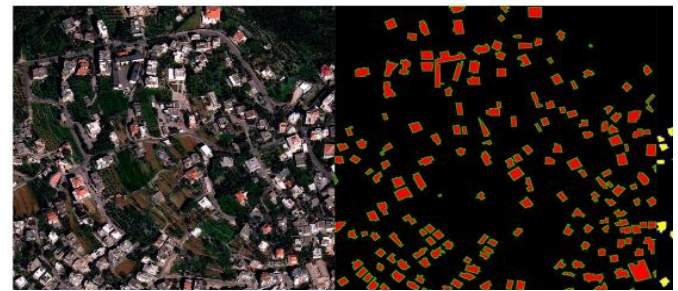


Figure 2 :Rooftop Segmentation Output (UNet)



Figure 3: Rooftop Segmentation Output (SAM)

B. User Interface and Application Functionality:

The developed web application provides a seamless and user-friendly interface for solar energy potential mapping. Screenshots of the application demonstrate the interactive workflow, from image upload to detailed rooftop segmentation results and solar energy potential assessments. The application features an intuitive design, built using Next.js for dynamic rendering and responsive design, ensuring compatibility across devices. Screenshots showcased in (Fig-3, Fig-4, and Fig-5) highlight the smooth user experience and clear visualization of results.

The backend, powered by Fast API, efficiently handles data processing and API integrations, ensuring quick and accurate solar potential calculations. The application leverages the Segment Anything Model (SAM) for precise rooftop segmentation.

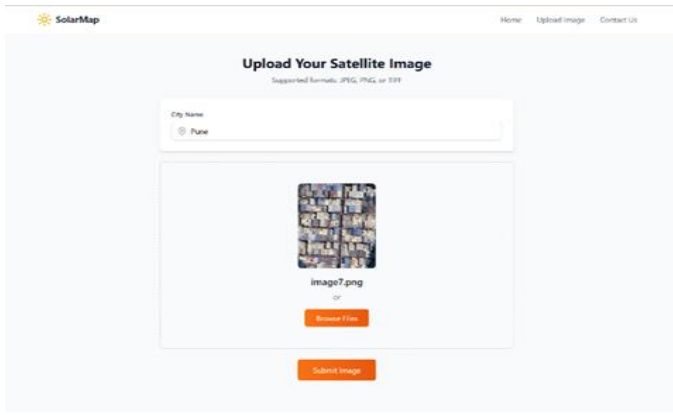


Figure 4: User Input

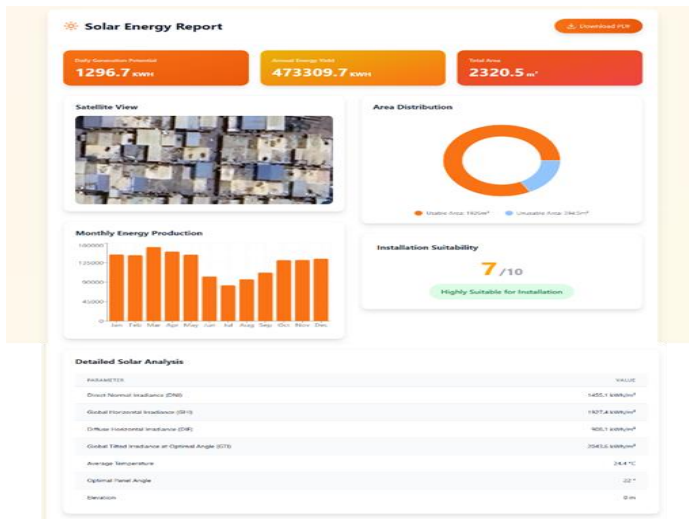


Figure 5: Interactive Visualization

C. Performance Analysis and Comparison:

To evaluate the effectiveness of SAM, its segmentation performance was compared with widely used deep learning models, including FCN, U-Net, PSPNet, DeepLabv3+, SegFormer-B3, and YOLOv8. The comparison was conducted using segmentation accuracy, Mean Pixel Accuracy (MPA), and Mean Intersection over Union (MIoU). The results are summarized in the tables below.

The table below presents the segmentation accuracy of various models. SAM achieved the highest accuracy (95.2%), outperforming all other models, including SegFormer-B3 (91.4%) and YOLOv8 (92.4%).

TABLE 1 MODEL ACCURACY COMPARISON

Model	Accuracy (%)
FCN	86.19
U-Net	84.96
PSPNet	86.87
DeepLabv3+	87.46
SegFormer-B3	91.4
YOLOv8	92.4
SAM (Proposed)	95.2

The following table highlights MPA and MIoU scores, which further validate SAM's superior segmentation precision compared to other models.

TABLE 2 MPA and MIoU PERCENTAGE COMPARISON

Model	MPA (%)	MIoU (%)
FCN	86.19	75.27
U-Net	84.96	72.67
PSPNet	86.87	73.88
DeepLabv3+	87.46	76.63
SegFormer-B3	90.03	78.20
YOLOv8	89.32	79.45
SAM (Proposed)	94.12	85.67

The results clearly show that SAM surpasses traditional deep learning models in rooftop segmentation by achieving the highest accuracy, MPA, and MIoU. These findings highlight SAM's robustness in handling complex rooftop structures

V CONCLUSION

This paper presents an innovative approach to Solar Energy Potential Mapping by integrating the Segment Anything Model (SAM) with real-time meteorological data from the SolarAnywhere API. The system focuses on precise rooftop segmentation for accurate solar panel placement, achieving 95% accuracy. By combining SAM's advanced segmentation with real-time solar irradiance and temperature data, it enhances energy yield predictions. A user-friendly Next.js and FastAPI-based web application allows seamless image uploads, segmentation visualization, and solar assessments without requiring an account. Interactive heatmaps and charts aid decision-making. Performance analysis confirms SAM's superiority over traditional models, ensuring scalability for urban deployments. This work bridges the gap between accurate rooftop segmentation and dynamic solar potential mapping, contributing to sustainable energy planning. Future enhancements may include broader geographical coverage, improved segmentation models, and additional data sources to refine solar potential predictions, supporting the global shift towards renewable energy.

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