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Semantic Segmentation of Rooftop Photovoltaic Panel from Satellite and Aerial Images using Deep Learning

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Abstract— **This research paper investigates the application of Deep Learning, specifically employing the DeepLabV3 architecture, for Semantic Segmentation in identifying Rooftop Photovoltaic (PV) Panels from both Satellite and Aerial Images. The primary objective is to compute solar panel efficiency through precise identification and spatial analysis of PV panels. Leveraging DeepLabV3's pixel-level segmentation, this study provides detailed insights that enable a comprehensive assessment of solar panel performance. The proposed methodology involves the utilization of DeepLabV3 on satellite and aerial images, with a focus on classifying pixels corresponding to solar panels and deriving efficiency metrics. The research outcomes aim to enhance solar energy utilization and facilitate informed decision-making in the renewable energy sector. The experimental results indicate that the recognition using DeepLabV3 achieves an accuracy of 75%.**

Keywords— Deep Learning, DeepLabV3, Semantic Segmentation, Rooftop Photovoltaic Panels, Solar Panel Efficiency, Renewable Energy

I. INTRODUCTION

The increasing need for precise and efficient approaches to evaluate solar energy potential is closely linked to the expanding solar power industry. The application of semantic segmentation to identify rooftop photovoltaic (PV) panels emerges as a crucial solution to meet this demand. Semantic segmentation, a computer vision challenge, involves assigning a distinct label to each pixel in an image. However, the semantic segmentation of rooftop PV panels faces significant challenges. In the context of satellite and aerial imagery, PV panels often appear small, creating a substantial obstacle to their accurate identification amidst other elements. Adding to this complexity is the variability introduced by diverse materials, mounting systems, and environmental conditions, which impact the visual characteristics of PV panels. Furthermore, extraneous objects in images, such as vehicles, swimming pools, and roadways, can complicate accurate segmentation. Despite these challenges, semantic segmentation remains a robust methodology for precise estimation of solar energy. Deep learning has played a crucial role in overcoming these obstacles, demonstrating its effectiveness in semantic segmentation tasks. The continuous evolution of this field underscores its growing importance. The development of a tailored semantic segmentation model for rooftop PV panels holds significant potential to revolutionize the solar power sector, providing a transformative impact on accurate solar energy calculations.

II. LITERATURE SURVEY

The study of Peiran Li et al. [1] in the area of rooftop photovoltaic (PV) panel segmentation using satellite and aerial pictures responds to the industry's increasing need for accurate installed capacity data. They highlight segmentation issues including class imbalance and textural differences by utilizing affordable satellite and aerial photos. In addition to highlighting the value of varied, superior training material, this study suggests using convolutional neural networks (CNNs) equipped with transfer learning and attention mechanisms. The research does, however, note that there could be differences between its conclusions and actual situations, indicating that the suggested models might not always be applicable in all circumstances. A notable contribution to the investigation of photovoltaic (PV) panel segmentation using satellite and aerial data is made by Hou Jiang et al. [2]. In order to improve PV recognition, conversion efficiency modeling, and regional PV potential calculation, their research presents a multi-resolution dataset. The authors elucidated the efficacy of several segmentation models, such as U-Net, RefineNet, and DeepLab v3+, by conducting a thorough comparison. Their findings offer promising approaches for accurate PV segmentation that have potential uses in the solar energy industry. However, the constraints of the dataset provide a significant issue. It may not accurately depict every scenario that arises in real life, even if it includes a variety of solar panel types in a range of environments, including roofs and fields. This dataset gap may have an effect on how well the models perform in scenarios that aren't sufficiently covered. Sampath et al. [3] is a noteworthy source of information. Their well prepared dataset is a great resource for advancing studies in PV detection, modeling of conversion efficiency, and regional calculation of PV potential. The dataset is particularly strong since it includes a variety of backdrops and geographic resolutions, which makes it adaptable and useful for addressing a range of solar photovoltaics-related issues. The problem is dealing with real-world variances that might not be well reflected in the dataset. This disparity may have an impact on how well models perform in scenarios that aren't well represented by the dataset. Scholars who are interested in utilizing this dataset for their research can do so on Zenodo [4]. According to Yongqiang Luo et al. [5], significant Using satellite images, techniques for locating PV installations include semantic segmentation, object identification, and picture classification. With precision and recall rates ranging from 41% to 98.9% and 54.5% to 95.8% for rooftop PV segmentation, deep learning provides great accuracy. For increased accuracy, a graded segmentation process combines pixel-based, object-based, and deep learning techniques. Rooftop PV potential may be calculated by combining PV and roof segmentation approaches, with a roof availability coefficient of 0.25–0.46. To achieve global carbon neutrality and implement successful renewable energy policy, PV installations must be precisely identified and predicted. Using satellite image segmentation, Loi Lei et al. [6] presented a lightweight deep learning method that tackles a critical aspect of renewable energy estimation: solar panel identification. This important study provides a cost-effective and useful mechanism for locating solar arrays on rooftops and ground installations in a given area. The importance of solar panel detection is emphasized by the authors as a necessary first step in precisely measuring the amount of energy generated by distributed solar systems connected with traditional electricity grids. The paper's specific attention on tiny devices and computing efficiency is one of its notable contributions. The authors cleverly bring out the drawbacks of current cutting-edge deep learning segmentation models, highlighting how resource-intensive they are because of lengthy training cycles and many floating-point operations (FLOPS) and significant numbers of parameters. This problem is especially relevant when thinking about devices that have limited processing power [7].An effective strategy was put out by Yan, Jinyue, et al. [8] to solve a crucial need in the renewable energy industry. Finding the best places to install photovoltaic (PV) panels on rooftops is important for policymakers and a critical step in developing distributed energy networks. The study offers a viable way around the drawbacks of sparse datasets and conventional surveys by combining machine learning techniques with satellite and aerial photography. Large-scale mapping of possible locations for PV panel installation is made possible by this. In their excellent proposal, Gavoille et al. [9] addressed a significant obstacle in the planning of renewable energy. Predicting appropriate locations for photovoltaic (PV) The relevance of the study in promoting sustainable energy solutions is highlighted by installations that use aerial photos using deep learning algorithms. The paper's successful use of CNN-based deep learning techniques for precise PV installation area prediction is one of its strongest points. The authors use a state-of-the-art method that leverages CNN's ability to extract complex spatial characteristics from aerial photos. This approach works well for capturing the subtleties such as building orientation, shading, and structure that affect the viability of photovoltaic systems. In order to assess the amount of energy generated by dispersed solar arrays connected to traditional electric grids, Jianxun, Wang, et al. [10] provide a feasible method for identifying solar arrays in satellite photos at a reasonable price. This segmentation step is essential for the first stage of energy calculation based on images. In response to the demand for compact and lightweight segmentation models, the authors provide a novel deep learning architecture that integrates elements of the Unet and Mobilenet categorization architectures. In comparison to current state-of-the-art segmentation models, the suggested model seeks to be computationally efficient by needing fewer parameters, less training time, and fewer floating-point operations (FLOPS). It is important to conduct a comprehensive assessment of the limits and potential issues mentioned in the study. The suggested architectural design, although showing promise in terms of solar panel segmentation computational efficiency, it may encounter problems with dataset bias, generalization, trade-offs, complicated solar panel variability, real-world performance, and model sophistication. To gain a full knowledge of the practical applicability of the proposed model in various contexts, a detailed study of these elements is required [11]. In order to address the combined problem of reliably identifying solar arrays in satellite photos while maintaining computational efficiency, particularly for devices with limited resources, Krapf et al. [12] put forth a novel solution. The authors stress the need of identifying solar panels in satellite photos as a critical stage in calculating the amount of energy produced by dispersed solar arrays. The shortcomings of current deep learning segmentation models—namely, their computational complexity, which restricts their suitability for devices with constrained processing power—are effectively brought to light. Accurately segmenting solar panels in satellite photos while preserving computing efficiency is the major issue this work attempts to solve. The authors provide a unique segmentation architecture in recognition that conventional deep learning models could need an excessive amount of processing power. By maximizing computational efforts, this design seeks to achieve a balance that qualifies it for small-device deployment. In this way, the research advances the field by presenting a viable substitute that tackles the shortcomings of existing models and yields accurate but efficient solar panel segmentation outcomes. In their excellent proposal, Chris Deline et al. [13] noted that CNN-based methods have become effective instruments for segmenting solar panels automatically and extracting metadata from satellite images. An important development in solar energy research is the combination of unsupervised azimuth estimation and energy conversion prediction algorithms, which provide scalable methods for maximizing the efficiency and performance of solar arrays. There is a need for more research on CNN architectures and data-driven strategies to handle new problems and possibilities in the field of renewable energy technologies. CNN-based techniques, in particular the SegNet architecture put out by Joseph Camilo et al. [14], show promise for automating the identification and classification of small-scale photovoltaic arrays in high-resolution aerial photography. Precise approximation of PV array dimensions and forms enables thorough evaluation of energy resources behind-the-meter, facilitating well-informed choices in the design and administration of renewable energy sources. Further development of CNN-based segmentation algorithms through study will enhance the capabilities of PV identification algorithms and aid in the shift to environmentally friendly energy sources. SegNet's efficacy is limited, and comparing it to earlier CNNs mostly depends on the features and size of the assessment dataset. Restrictions on the variety or representativeness of the dataset may have an impact on how well the results translate to actual situations. The powerful automated recognition and mapping technique for PV panels in aerial photography presented by

Edoardo Arnaudo et al. [15] is an important field of study with implications for grid optimization and monitoring of renewable energy. Through the use of deep learning algorithms and high-resolution aerial data, researchers hope to create reliable detection models that can distinguish and identify PV panels with accuracy in a variety of settings. Ad hoc solutions and post-processing methods can be further tailored to improve automated detection algorithms' practical value and dependability in real-world scenarios. Further developments in algorithmic sophistication, assessment techniques, and data availability will propel automated PV panel identification forward and aid in the shift to sustainable energy systems. This system's limitation is the dataset's restricted coverage of PV panels, which makes it difficult to complete jobs later on, especially when using more sophisticated techniques like instance segmentation. While copy-paste augmentations and other basic dataset extension strategies help to enhance outcomes to some degree, the intrinsic limits of the dataset may restrict the effectiveness of more sophisticated techniques. CNN-based techniques, in particular the U-net architecture put out by Matthias Zech et al. [16], show promise for automatically identifying and mapping photovoltaic systems from aerial data. The Oldenburg, Germany study emphasizes how well FCNN-based methods work for precisely locating PV installations and calculating model uncertainty. These developments have an impact on planning and research projects related to renewable energy as they aid in the creation of transparent and trustworthy techniques for PV site detection. A significant breakthrough in solar panel recognition and energy estimate from dispersed solar arrays is presented by M. Arif Wani et al. [17] in their creation of effective deep learning segmentation architectures suited for tiny devices. In environments with limited resources, the suggested design provides a viable option to overcome the computational difficulties faced by the segmentation models now in use. This opens the door to the development of scalable and affordable solar energy monitoring systems. The highly helpful approach to identify PV panels was proposed by Pena Pereira et al. [18]. The study shows that U-Net architecture may achieve F1-scores of up to 91.75% in the classification of PV panels in high-resolution aerial pictures (10 cm). The findings also highlight how important it is to modify training data to match area-specific ground truth data, especially for urban and architectural characteristics, in order to improve detection precision. Deep learning-based methods for the identification and mapping of solar farms are presented by Rashmi Ravishankar et al. [19] and constitute a substantial development in remote sensing and renewable energy monitoring. When paired with semantic segmentation CNNs, the suggested deep learning architecture provides encouraging outcomes for precisely identifying solar farms from satellite data. Prolonged investigation in this domain, in conjunction with the dissemination of primary datasets and verification endeavors, advances dependable and effective techniques for monitoring solar photovoltaic capacity expansion and approximating energy production capacities. According to Olindo Isabella et al. [20], research shows how important it is to include 3D roof segments in quick-scan PV yield prediction techniques since doing so considerably increases yield estimations' accuracy when compared to utilizing only 2D land registration data of structures. These results add

Thus, the research advances the field by presenting a viable substitute that tackles the shortcomings of existing models and yields results for solar panel segmentation that are both accurate and efficient.

III. METHODOLOGY

This research proposes a Deep Learning-Based Semantic Segmentation of Rooftop Photovoltaic Panel from Aerial and Satellite Images. A detailed process for a project centered on the semantic segmentation and subsequent energy computation of solar panels based on input satellite pictures is summarized in the block diagram shown in Fig. 1 below. It is composed of the following blocks: calculate solar panel energy, preprocess image, use deep learning for semantic segmentation, input satellite images, and display result.

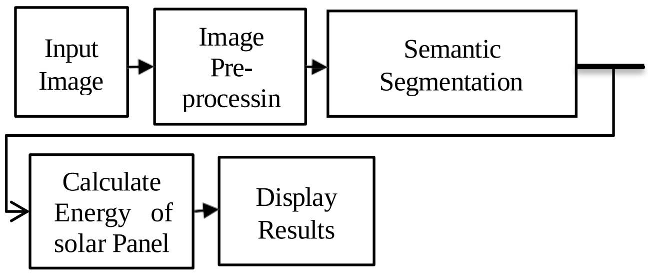

Fig.1. Block Diagram of proposed system

The PV panels have been identified using a machine learning technique, which is seen in Fig. 2.

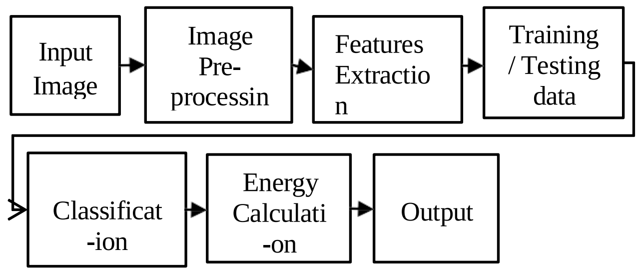

Fig.2. Machine Learning approach for proposed system

A. Dataset Collection and Pre-processing

A solar panel made up of 3,716 aerial image datasets is used to create the system. Eighty percent of the dataset 2,973 images are put aside for training, while forty-three percent are set aside for testing. The 256 by 256 pixel resolution photos come in three different formats: 0.8, 0.3, and 0.1.

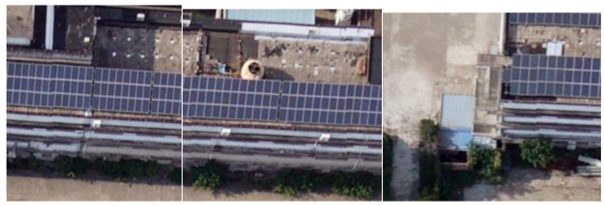

Fig.3. Sample images of the Rooftop PV panels

The photos were subjected to image editing operations like cropping, rotating, and flipping. Every image in the collection was scaled to 256 by 256 pixels before being turned into grayscale.

B. DeepLab V3+ Model

A cutting-edge semantic segmentation model called DeepLabv3+ is utilized to extract features from pictures. For pixel-level categorization, it makes use of a deep convolutional neural network (CNN) architecture. The feature extraction process shown in below.
The process begins with an input image including the items and scenarios that must be separated or understood.
1. Preprocessing: The input picture is preprocessed to ensure that it meets the model's criteria. Usually, this means reducing the image to a preset size and leveling the pixel values.

2.Backbone Network: ResNet, MobileNetv2, or Xception are examples of strong backbone networks that DeepLabv3+ employs to extract hierarchical properties from the input image. These backbone networks learn generic properties that are relevant to many different computer vision applications since they are pre-trained on large-scale picture categorization job.

3.Feature Pyramid Network: DeepLabv3+ incorporates a Feature Pyramid Network to gather multi-scale features. The model's ability to recognize objects of different sizes and scales is enhanced by FPN. 4. Atrous Convolution: DeepLabv3+ extends the receptive fields of convolutional filters by employing atrous convolutions, also called dilated convolutions, in place of conventional convolutional layers. With atrous convolutions, the model may incorporate contextual data over greater geographical extents without appreciably adding to its parameter count.
5. Spatial Pyramid Pooling (ASPP): DeepLabv3+ uses the Atrous Spatial Pyramid Pooling (ASPP) module, which makes use of parallel atrous convolutional layers with different dilation rates. This module helps the model to provide more accurate predictions at different spatial resolutions by gathering multi-scale contextual input.
6. Decoder Network: In DeepLabv3+, the decoder network smooths down the coarse segmentation maps produced by the preceding layers. High-resolution data is added to improve segmentation, and feature maps are upsampled using bilinear interpolation to the original image resolution.
7. Prediction: The final classification layer, which normally consists of a 1x1 convolution and a softmax activation function, receives the enhanced feature maps from the decoder network. DeepLabv3+ combines deep convolutional neural networks with complex architectural components including atrous convolutions, FPN, ASPP, and decoder networks to effectively extract rich and valuable information from images for accurate semantic segmentation.

C. Workflow

The workflow of the proposed system is depicted in Figure 5. Initially, image pre-processing is conducted on the input image, which includes tasks such as image cropping. Subsequently, the DeepLabV3+ model is employed to extract features from the pre-processed image. These extracted features are then classified into two categories: either rooftop or solar panel. If a solar panel is detected, energy is calculated using Formula (1). Finally, the energy calculation is displayed on the output.

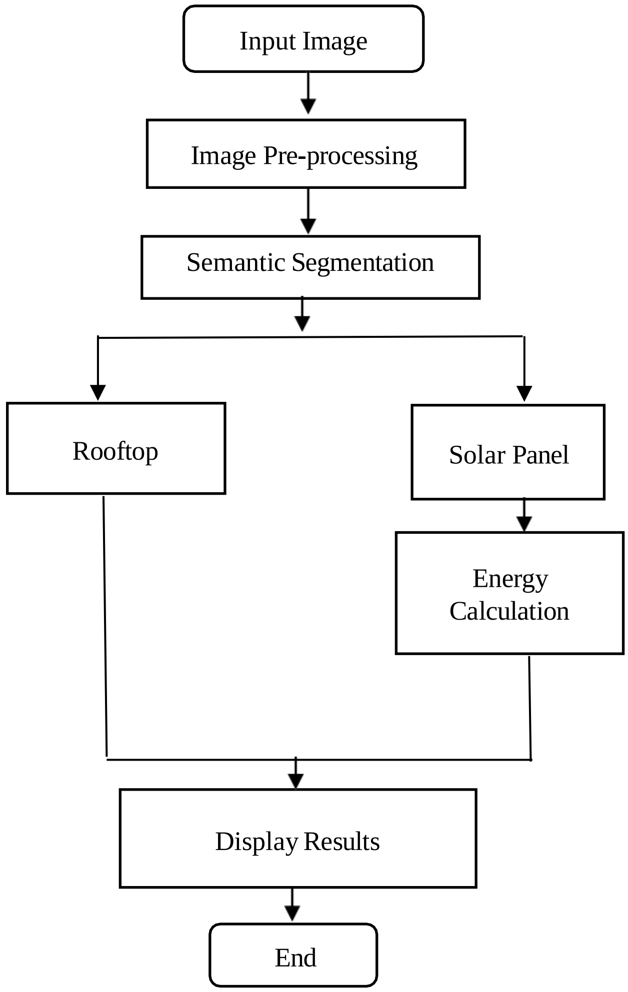

Fig.5. Flow diagram for dimensionality reduction

D. Calculations

We may utilize the segmented region to calculate solar energy after the tagged pictures are obtained at the output of the deep learning network. The area of the segmented solar zone must first be determined by squaring the predicted solar panel's pixel size.

After calculating the area, we can use the calculation below to determine how much power the PV system will produce..

$E=A*x*H*PR$ --------------------Formula (1)
Where, E = Energy (kWh)
A = Total area of solar panel calculated from segmented image
x = Efficiency of solar panel (in percent)
H = Average annual solar radiation
PR = Coefficient loss or Performance ratio (default value 0.75)

IV. RESULT

The proposed system recognizes the Solar panels and by using the formula the expected energy and predicted energy is calculated as shown in Fig.6.

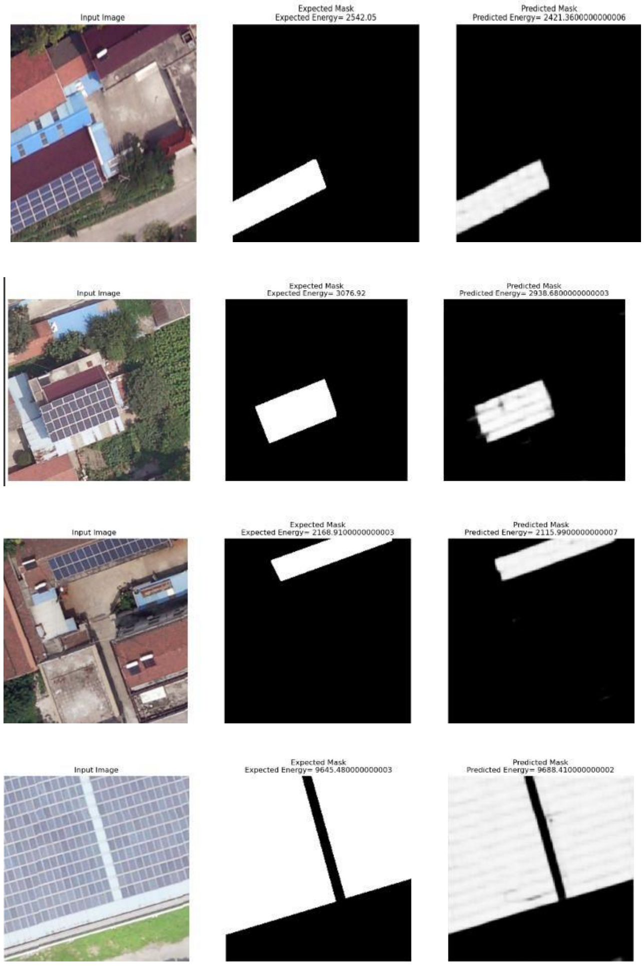

Fig.6. Final Outputs of proposed system

In this above predication the Expected Energy is 2542.05 and predicated Energy is 2421.3600000000006. Which means predication is 75% similar to the Expectation.

V. CONCLUSION

A major achievement in solar energy is the use of semantic segmentation, particularly with the DeepV3+ model, to detect rooftop photovoltaic (PV) panels in satellite and aerial photos. The accuracy of the DeepV3+ model is unmatched due to its ability to precisely manage issues with varied panel sizes and subtle environmental variations. dataset analysis and lowering human mistake rates, which improves efficiency both financially and in terms of time. The method increases the accuracy of solar energy potential estimates by minimizing false positives and differentiating across PV panels with different backgrounds. Decision-makers will benefit greatly from this advancement as it offers data-driven insights that are essential for infrastructure development, planning, and policy making. The accuracy of the DeepV3+ model bolsters the sustainability of solar systems by facilitating accurate solar energy computations and supporting environmental impact evaluations.

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