Advancing Solar Energy Potential Assessment Of Urban Landscapes: A Deep Learning And Computer Vision Based Architecture For High-Resolution Topographic Data Incorporating Temporal Shadowing

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Abstract

Accurately assessing solar energy potential is essential for effective urban planning and successful solar panel installations. While conventional methods consider factors like climate conditions, low-resolution topography, and mean solar radiation, there is a pressing need to incorporate high-resolution topographic data and account for the temporal shadowing effect caused by neighbouring structures and trees. This research aims to address these challenges and develop an algorithmic architecture specifically tailored for densely populated tropical areas like New Delhi in India.

By introducing computer vision techniques, this study pioneers a novel approach to analyzing temporal shadowing effects in urban environments. This integration significantly enhances the accuracy and efficiency of solar energy potential assessment while improving the methodology's scalability and generalizability. This study fills a critical gap by considering the temporal shadowing effect and utilizing high-resolution topographic data.

A key focus of this research is data-driven decision-making in renewable energy planning. This comprehensive approach enables more informed decisions in urban planning, paving the way for sustainable and resilient cities. The findings hold great promise for transforming urban energy planning and fostering the widespread adoption of solar energy systems.

Keywords: Solar Energy Potential, Urban Planning, Temporal Shadowing Effect, Rooftop PV mounting, PV installation, Renewable Energy Planning, Satellite Data, GIS, Computer Vision, Deep Learning, Solar Radiation, Google Earth Engine, Building footprint.

1. Introduction

In light of the intensifying global environmental crises and soaring energy demands, renewable energy sources, notably solar energy, have established a foothold as indispensable alternatives to conventional fossil fuels. Solar energy, with its abundant, pollution-free, and perpetually renewable nature, unfolds a spectrum of possibilities in paving the way towards a sustainable future, minimizing carbon emissions and mitigating climate change implications. Particularly, as metropolitan areas continue to increase, it becomes increasingly important to harvest solar energy efficiently inside these areas in order to fulfil the ever-increasing energy demands of modern cities.

India, according to NREAP (National Renewable Energy Action Plan) 2022, illuminated with an impressive average solar irradiation of 5.4 kWh/m2/day, positions itself as a potential powerhouse for solar energy generation. Despite this, the tangible adoption of solar energy within the nation is crippled by a myriad of barriers such as elevated costs associated with solar panels, a pervasive lack of awareness and knowledge about solar energy as discussed in his paper by Jain, 2020. However, recent advances in governmental backing and policy-driven support promises some social development and awareness to which demand is estimated to soar in near future. But these developmental paces need preparations years ahead. It is against this backdrop that the current research paper aims to carve out an innovative pathway to augment the solar energy potential in urban zones of India and similar landscapes.

In two separate studies by Kumar,2021 and Yuhu Zhang, 2020, it was already pointed out that one pivotal challenge throttling the development and optimization of solar energy in urban landscapes is the temporal shadowing effect, prominently witnessed in densely populated urban environments. This phenomenon refers to the obstruction or blocking of sunlight by neighbouring buildings, infrastructures, and vegetation, which inadvertently diminishes the

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volume of solar energy that can be proficiently harnessed. Temporal shadowing does not merely pose a physical barrier but also intricately influences the optimal solar energy yield by clouding photovoltaic systems at varying intervals throughout the day. Given the widespread and towering architecture that characterizes urban areas, particularly in India, the severity of these shadowing effects is notably amplified in such highly dense urban regions, demanding meticulous quantification and strategic circumvention to precisely gauge and enhance urban solar energy potential.

Historically, the assessment of solar energy potential has been rooted in simplified models and lengthy computational approaches, which have consistently fallen short of capturing the multifaceted interactions amongst shadows, terrains, and dynamic urban environments. Yet, as in a paper Siddharth Joshi, 2021 said, the dawn of technological advancements, encompassing remote sensing technology, high-resolution topographic data, deep learning algorithms, and computer vision techniques, heralds a promising horizon in or circumventing these constraints and giving more precise, reliable, and expansive evaluations of solar energy potential assessments.

In the field of Artificial Intelligence, computer vision Computer Vision is a field of AI that simulates Vision processing capabilities of human. Major Tasks are:

- Detection
- Recognition
- Segmentation
- Reconstruction
- Generation

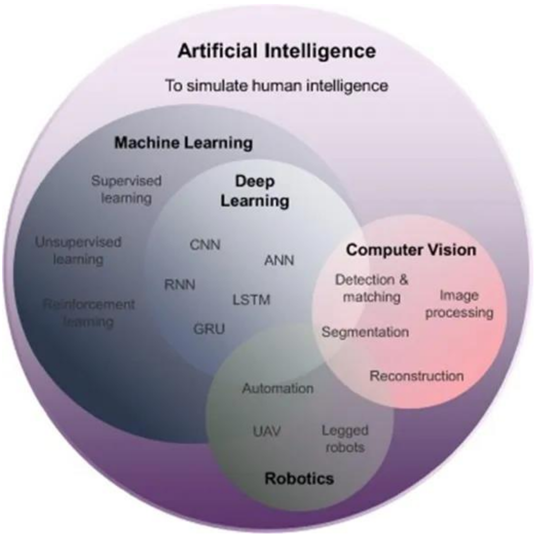

Fig. 1 Artificial Intelligence Venn Diagram (Shravani Upadhyay)

Some Deep Learning architectures are developed to perform these tasks very efficiently. Deep Learning encompasses the area of Artificial Intelligence study working on frameworks with complex neural networks that processes information with nodes and links exactly resembling neural networks in our brain. See Fig. 1 illustrated by Shravani Upadhyay et.al for structured Venn diagram to understand the hierarchical relationship between these terms.

This research paper aims to present a novel approach for assessing solar energy potential in Indian urban regions by incorporating high-resolution topographic data, deep learning algorithms, and computer vision techniques to account for temporal shadowing effects. The proposed methodology considers the specific challenges and characteristics of the Indian context, such as the high population density, diverse urban landscapes, and varying weather patterns, to ensure the accuracy and applicability of the results. The incorporation of technological innovations not only enhances the precision of measurements but also endeavors to surmount the previously insurmountable hurdles presented by temporal shadowing effects.

2. Data Source

In this study, primarily satellite imagery is used. The source for this type of data is combinational from different data collection instruments/missions, the Sentinel-2 MSI mission (Sentinel 2A and 2B) which has high-resolution multispectral data, Sentinel 3 OLCI, DEM/DSM. The images were finally chosen with a resolution is as good as 10 meters in the visible band which is best suitable for studying dense urban landscapes. Another markable dataset is High-Resolution Imagery data, Google Earth Images. In the Data aggregation step, developed by *Gorelick* and his team at Google, this data is collected from Google Earth Engine (Available on the web) and Google Earth Pro Software. The rest of the topographical and meteorological data is acquired from NASA's open GIS database for the last 10 years.

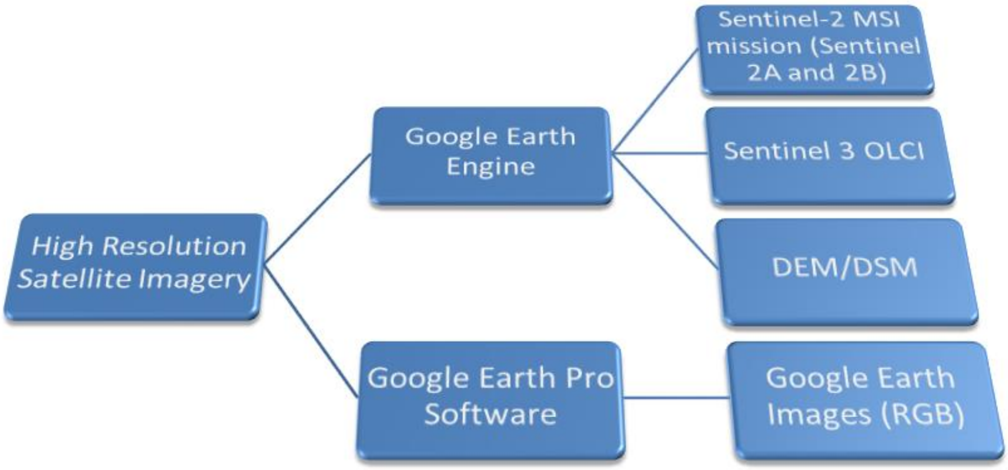

Fig. 2 Different Data sources used in this study

3. Methodology

The primary focus of this study is to recognize precise areas suitable for optimal electricity generation from solar panels, i.e., suitable rooftop area for PV installations, as evidently radiant with sunlight and predict the Solar Energy Potential of the area. To accomplish this, a multi-step methodology is employed, incorporating advanced computer vision techniques and deep learning architecture. An overview of working data flow is given in the Fig 3. The process begins by utilizing satellite data, which is fed into the system for data preprocessing following through the application of semantic segmentation, a powerful computer vision technique, the system extracts the suitable areas that will be subjected to further calculation and analysis. This segmentation process considers several crucial factors, including the Sun's position, seasonal effects like clouds, topological surface and shadowing effects caused by obstacles. Unlike traditional methods that involve tedious and time-consuming image analysis using masking techniques, the integration of deep learning streamlines the process, making it more efficient.

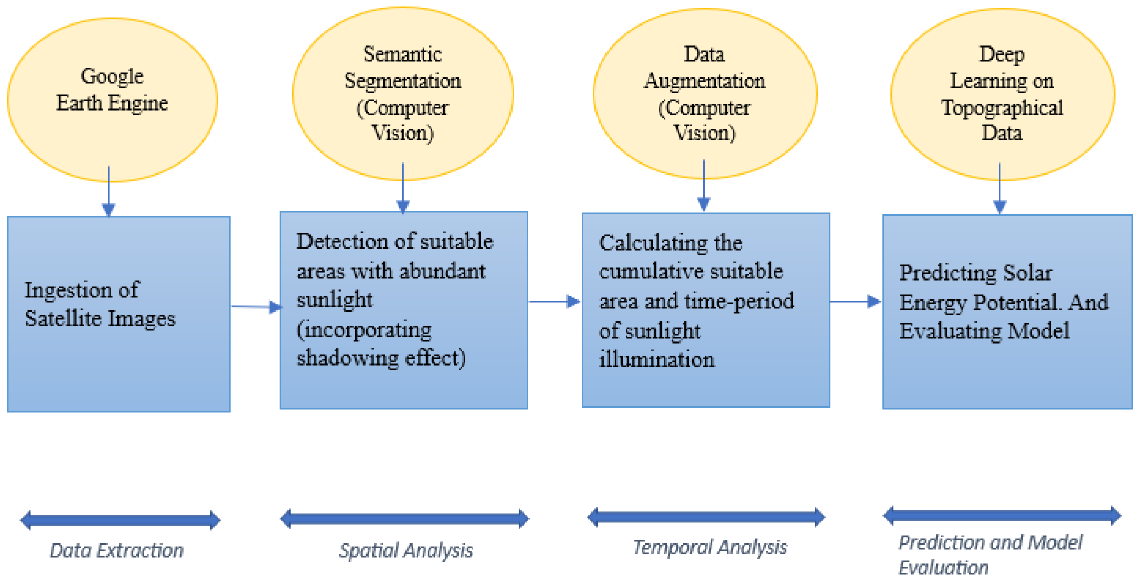

Fig. 3: High-Level Workflow of the proposed architecture for Solar Energy Potential Assessment

We have divide our workflow into two clear agenda. **One**, *detect and segment rooftops from satellite images*.and **second**, *analyze the variation in shadows on these rooftops over time*.

For this purpose we first acquired high-resolution satellite images from different random spots in New Delhi belonging to various types of Urban topography for spatial analysis, over different period of time for temporal analysis. For spatial analysis, the image samples can be more or less divided by the infrastructure style and density into: 1. High posh area, 2. Densely populated uniform high rise infrastructure, 3. Densely populated non-uniform infrastructure, 4. Less densely populated. We made sure that images were taken at roughly the same timestamps of the day across different dates to ensure consistent shadow analysis.

For a proper training dataset, we needed some annotated images which can be done manually by annotating a subset of images one by one, marking rooftops and shadows. And another method was taking some data as ground truth from certain opensource dataset like OpenBuilding (*W. Sirko* et.al), an open source dataset of building footprints which we have utilized as ground truth, which consists of outlines of buildings derived from high-resolution 50 cm satellite imagery. We chose the later approach. Then, split the dataset into training, validation, and test sets. Normalize and resize the images to a consistent size of 256x256. We used keras data augmentation techniques to enhance the dataset with time availability for satellite imagery. For our analysis we experimented with different deep learning frameworks starting from ANN (Artificial Neural Network), CNN (Convolutional Neural Network) to VGG-19 (Visual Geometry Group -19) and Resnet architectures. However, our interest peaked at UNet Architecture. UNet is primarily a CNN characterized by its U-shaped architecture. It consists of two main parts:

a. Contracting/Downsampling Path (Left side of the U):

   It consists of a series of convolutional layers followed by max-pooling layers. Each step involves two consecutive 3x3 convolutions (with ReLU activation), 2x2 max pooling operation with stride 2 for downsampling. At every step, the number of feature channels is doubled. This path aims to capture the context of the input image, reducing the spatial dimensions while increasing the depth (number of feature maps).

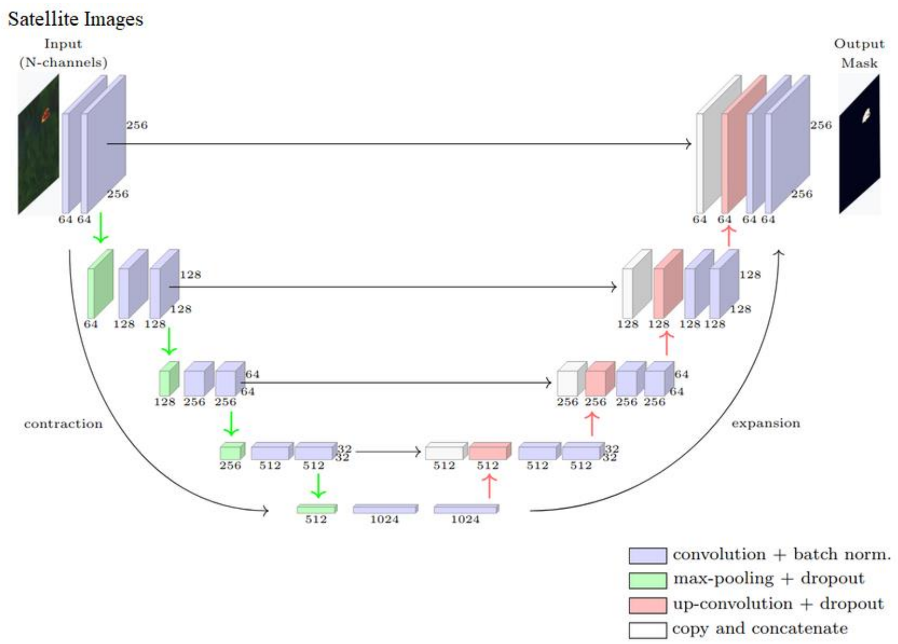

Fig.4. Modified UNet Architecture for Satellite Imagery

b. Expansive/Upsampling Path (Right side of the U):

This path upsamples the feature maps from the contracting path to recover the spatial dimensions. Each step in this path consists of an upsampling of the feature map, a 2x2 up-convolution that halves the number of feature channels, concatenation with the corresponding cropped feature map from the contracting path. This skip connection is crucial as it allows the network to use information from the downsampling phase, and two 3x3 convolutions (with ReLU activation). The expansive path allows the network to use the context captured in the contracting path to make precise localization, yielding a more accurate segmentation map.

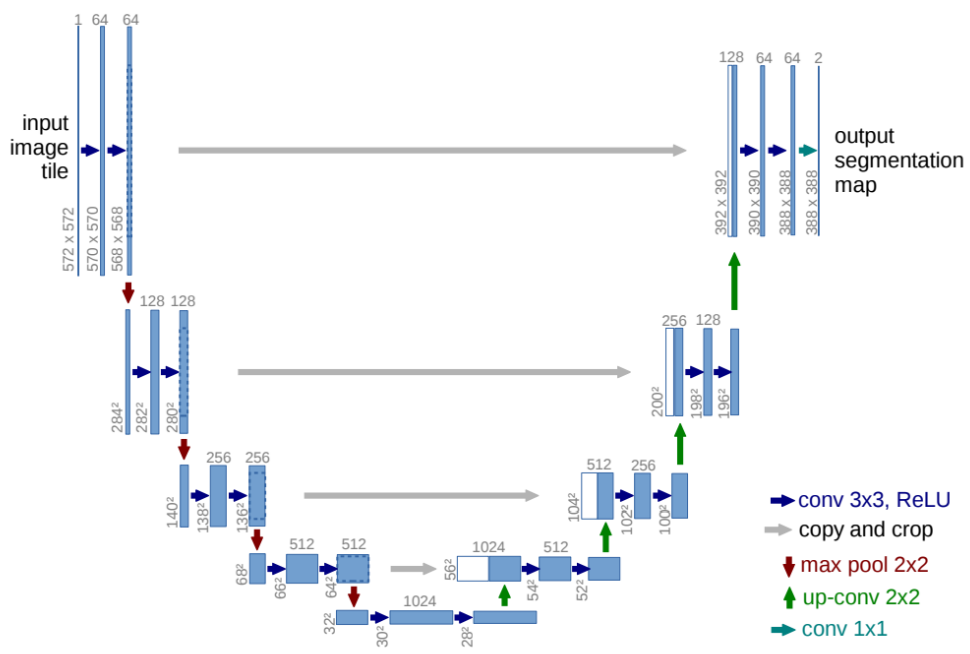

Fig.5. Basic UNet Architecture taken from its original source (Olaf Ronneberger, 2015)

The UNet architecture infamously used in biomedical image analysis, however its capability to understand the context of images and then localizing the features, is what needed for our use case. However, we posed many difficulties of resolution and image quality for this architecture to shine. In order to get the best results we targeted to implement the U-Net architecture tailored for satellite images.

As we moved to the second part of our objective to analyze the shadowing effect, we extracted the segmented rooftops from all temporal images and then analyzed the shadows and area under shadow versus irradiant areas on these extracted rooftops. We calculated total rooftop areas, effective area after removing the area under shadow for each rooftop in each image with each timestamps. We classified the rooftop based on average percentage under shadow using 2 thresholds.

a. The rooftops in green are more than 80% fully irradiant with direct sunlight,

b. The rooftops with yellow colour are the ones with 75-80% radiance, or 20-30% area of these rooftops is mostly in shadow.

c. The rooftops in red are the ones with 75% or less radiance, or more than 25% area of theses rooftops is mostly in shadows.

Further for validation we evaluated the model based on precision, recall and R-score, iteratively using fine-tuning and hyperparameter optimization between Precision and Recall, final model was decided. Precision tells what ratio of all classification was closer or exact match with the ground truth, while recall means what ratio of multiple calls the model is able to classify the same class. Both are considered evaluation metrics for machine learning or deep learning algorithms and models. Precision-Recall curves (Fig. 9 in Results and Discussion section) summarize the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.

The Fig. 6 summarizes the steps followed in the adopted methodology of this study.

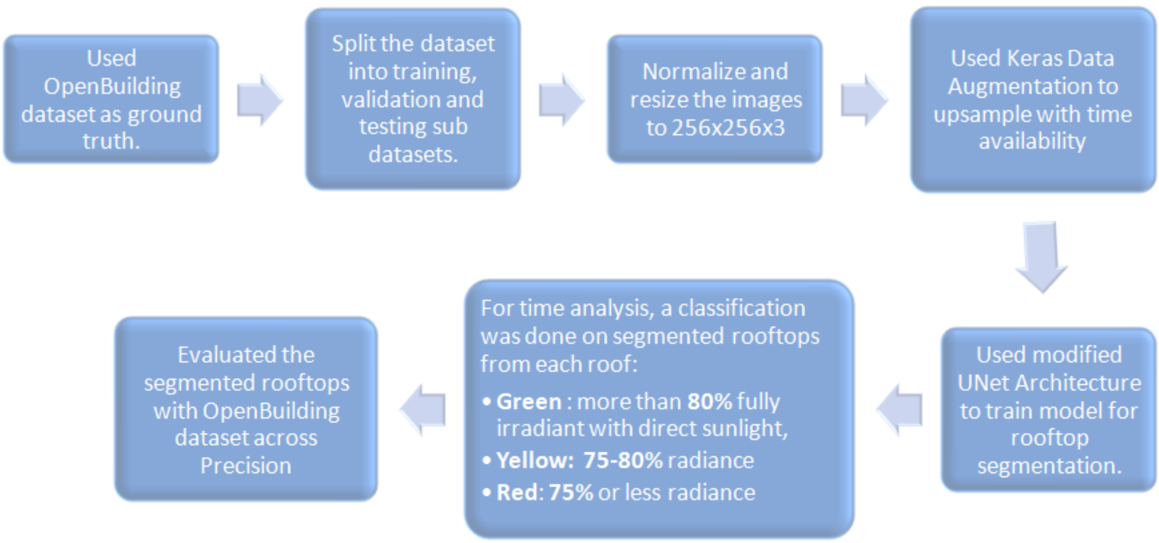

Fig. 6 Summary of steps followed in the adopted methodology

4. Results and Discussion

After data collection of high resolution satellite imagery, some sample images are attached from Fig.7.1-Fig.7.5 which were representative images collected from different data sources and regions in New Delhi with different infrastructure density and style. Fig.7.1 was collected from Posh or highly maintained area in New Delhi. Fig.7.2 was from less densely populated areas, Fig.7.4 belonged to densely populated areas with non-uniform infrastructure.

Fig. 7.1. Collected from Google Earth Image from Posh area in New Delhi

Fig.7.2 Collected from Google Earth Images from less dense urban region

Fig. 7.3 Collected from moderately dense urban region

Fig. 7.4 Satellite Images collected from densely populated areas with non-uniform infrastructure.

After Segmentation with enhanced visualisation, the building rooftops were segmented and were classified into Red, Yellow and Green color based on the percentage of the rooftop area being mostly in shadow. As described in Methodology section, the colors represent:

a. The rooftops in green are more than 80% fully irradiate with direct sunlight,

b. The rooftops with yellow color are the ones with 75-80% radiance, or 20-30% area of these rooftops is mostly in shadow.

c. The rooftops in red are the ones with 75% or less radiance, or more than 25% area of theses rooftops are mostly in shadows.

From the images, although most rooftops seem to be pigmented green, that is most part of the rooftops are usually directly illuminated by sun rays. Some rooftops that are marked red in Fig.8.1. and even fewer are marked as yellow, representing that posh areas have lineated rooftops without much difference in heights and so lesses regions with shadows on roof. While a similar trend is seen densely populated regions but with uniform infrastructure, Fig. 8.2. Fig. 8.4 and Fig 8.5 both are high populated regions with non-uniform infrastructure, but Fig 8.4 shows non-uniformity in heights of towers/buildings while Fig 8.5 shows non-uniformity in distribution of buildings on x-y-plane (or ground). But both have shown higher number of yellow and red coloured segments showing lesser best-suited rooftops for solar panels.

Fig. 8.1. Image segmentation result in High Posh Area

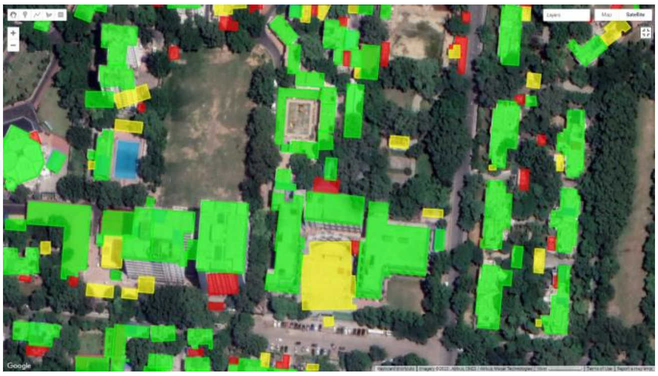

Fig. 8.2 Less densly populated area

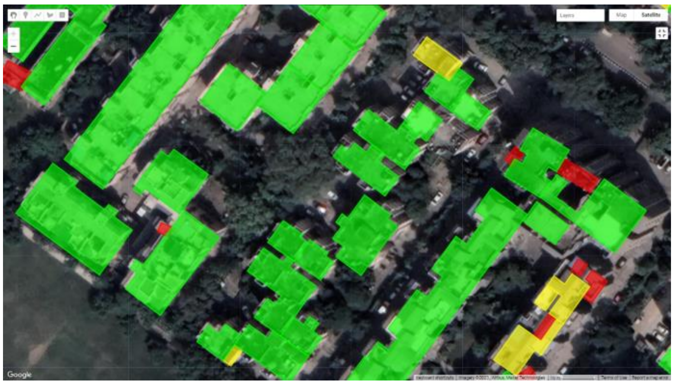

Fig. 8.3. Densely populated uniform high-rise infrastructure

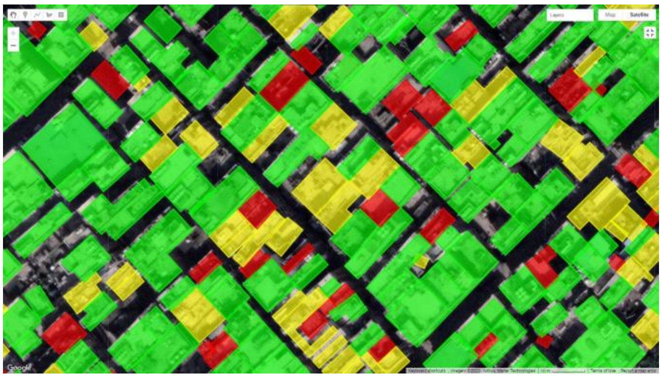

Fig. 8.4. Densely populated non-uniform infrastructure

Fig. 8.5. Densely populated non-uniform infrastructure

While performing model evaluation, we checked the trend of precision vs recall, Fig. 9, based on the ground truth, the building footprint data from OpenBuilding, it showed segmentation and classification confidence was higher in urban regions with high-density infrastructure, and our model also performed better in such regions this was not the case with any other reported algorithms, and it performed especially well in regions with uniform infrastructure which is anyway intuitive.

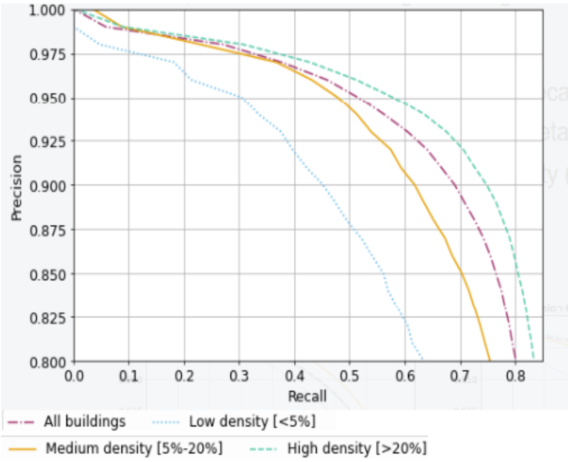

Fig. 9. Evaluation of Precision and Recall based on infrastructure density

5. Conclusion

The algorithm developed in this study leverages the potential of computer vision and deep learning architecture to optimize the best working weights for parameter aggregation from satellite imagery. This optimization process is crucial for accurately determining the suitable rooftop areas for planning the design and installation of photovoltaic (PV) panels. By incorporating deep learning, the algorithm reduces the complexity of the calculation, enabling users to easily assess the most suitable rooftop areas. Furthermore, the calculated areas are utilized to predict the most suitable roofs or buildings for PV installation and estimate the Solar Energy Potential for urban region planning. This prediction helps in making informed decisions about solar panel placement, ensuring maximum energy generation and utilization.

In addition to spatial analysis, this study also examines the temporal dimension of solar potential. By considering the variation of solar radiance available on roof over time, the research aims to incorporate time reference into the calculation by parameterizing shadows on roof. Utilizing the Data Augmentation technique of Computer Vision, the low quality or low data availability can be pushed further as well as the temporal effect can be easily parameterized and added to the analysis. The temporospatial analysis of solar radiation potential in the city is vital for understanding the dynamics of solar energy availability and optimizing its utilization. However, this is also one of the bottleneck for the algorithm as the quality of data is determined by augmentation limitations. In the era of data-driven decision-making, the whole challenge remains at the availability, accessibility and quality of data used in the study.

Further based on infrastructure density as well as style, the suitable rooftop area changes which is adequately exposed to sun rays, affecting precise assessment of solar potential. With proper spatio-temporal analysis can this be achieved to accurately assess solar potential and optimize PV designing for diverse Urban landscapes like India and New Delhi.

To validate the accuracy and effectiveness of the algorithm, the predicted results are compared with previous data labels and analysis results but for future work, we can utilize the ground truths obtained from ArcGIS rooftop detection algorithms, a widely used geographic information system. This comparison will provide a comprehensive assessment of the algorithm's performance, ensuring its reliability for practical applications.

The sustainable future of urban India hinges significantly on the efficient, unbridled harnessing of solar energy, necessitating a synergistic blend of technological advancements and context-specific methodologies. The proposed novel approach transcends traditional barriers and paves the way for accurate, reliable, and optimized solar energy potential assessments amidst the complexities and unique challenges witnessed within the Indian urban landscape. Consequently, this research not only stands to significantly augment the usage of solar energy in India but also charts a pragmatic course towards realizing a sustainable, energy-secure future, underscored by technological innovation and strategic planning.

6. Acknowledgments

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