Optimizing Solar Energy Utilization Rooftop Detection and PV Potential Estimation with Deep Learning.docx

by Sampurna SAHA

Submission date: 11-Dec-2025 07:54PM (UTC+0530)

Submission ID: 2843404727

File name: Optimizing_Solar_Energy_Utilization_Rooftop_Detection_and_PV_Potential_Estimation_with_Deep_Learning.docx (9.95M)

Word count: 10079

Character count: 59418

CHAPTER: 1

INTRODUCTION

1.1 Background of the Research

In recent years, the global pivot to renewable energy systems has accelerated in response to mounting environmental, economic, and energy security issues, such as a rising volume of greenhouse gas emissions, dwindling fossil fuel resources, and rising demand for energy for urban consumption. The combination of a range of renewable energy technologies namely solar photovoltaics (PV), has added to the feasibility of renewable energy deployment by utilizing cleaner and more sustainable energy sources. Solar PV systems and rooftop installations, in particular, are the most viable renewable energy systems because of their flexibility, scalability, and cost-effectiveness. Rooftop solar PV installations are rapidly capturing the negative impact of utility electricity costs because they provide distributed electricity generation at the point of electricity consumption, minimizing transmission losses, and removing the conflicts of interest posed by centralized high-voltage transmission grids (International Energy Agency, 2022). Rooftop solar PV systems also use existing built form, largely avoiding issues associated with land scarcity and massively reducing land use because urban areas often offer little to no available ground space for solar developments.

To identify roofs and assess their potential for solar energy use, the first step in a rooftop solar energy planning exercise is to understand each rooftops solar potential at a city or regional scale, whilst utilising accurate and up-to-date spatial information. Traditional methods for mapping roofs like manual digitisation of aerial or satellite imagery, on-the-ground surveys or programming a computer-algorithm to extract features based on sets of rules can be very expensive, time consuming and often inconsistent in general due to human judgement or clustered building patterns (Chen et al. 2018). To add to this point, urban settings are heterogeneous and have complexities of roofs, including pitched and flat roofs, areas of shadows/partial shadows and shadowed rooftop equipment, vegetated encroachment, irregular forms of roofs, and so on, that can potentially lead to headaches when using traditional image processing methods that will likely not generalize well to other cities, climates, or building designs.

Deep learning has revolutionised fields such as remote sensing and computer vision due to improved computational capacity, high-resolution imagery availability, and the release of novel neural network architecture. Deep learning, and in particular convolutional neural networks (CNN), has shown exceptional efficacy at learning hierarchical spatial features from imagery, without or with a minimal requirement to engineer features. Architectures such as U-Net, Mask R-CNN, DeepLabv3+ and several architectures in the YOLO family have been used with excellent accuracy for a range of tasks including semantic segmentation (Ronneberger et al., 2015), object detection (He et al., 2017) and instance segmentation, extracting buildings, roads, and other urban features from satellite data.

In this regard, rooftop detection using deep learning has evolved into a compelling method for streamlining the automated extraction of roof geometries from high-resolution orthomosaic or remote sensing (aerial or satellite) or other similar imagery. The models' capabilities to learn both local-textural detail and global contextual component features enable them to tackle difficulties introduced by variability in roof color, shapes, and materials, shadowing, obstructions, and nearby vegetation. In contrast to classical computer vision, which uses rule-based thresholds, edge detections, etc., deep learning models can address visual complexity and spatial variability more naturally, thus yielding more robust and generalizable results (Zhu et al., 2017).

Precise identification of rooftops is critical to determining both the footprints of potential PV installations, and performing downstream estimates of solar potential. This analysis includes estimating a roof's orientation, slope, weight-bearing capacity, and identifying sources of shade from nearby buildings, trees, and seasonal variations in sun angle, and local solar irradiance conditions. By using deep-learning-technology, GIS-based analyses can automate estimates of solar potential at various geographic levels, including on an individual building and a rural geographic scale (Huld et al., 2012). Integrated GIS & Deep Learning Systems can support urban energy planning, renewable energy investment modelling, and solar energy policy decision-making in rapid urban growth areas.

The Urbanization of an area is changing quickly in many areas (both In Asia and Africa) and has resulted in greatly increased development of residential, commercial, and industrial Rooftop Areas were developed at quick rates and with little focus by Government, which means these areas are many times underdeveloped for any future use to generate renewable energies. An Example is India which is pushing for the increased use and development of Rooftop solar use/deployment through National Missions and subsidy programs to increase decentralized renewable energy capacity (MNRE 2021). The effective deployment of this Strategy on a large scale would necessitate tools have the ability to make scalable, accurate, and automated assessments of Rooftop Areas in multiple Urban Environments.

Models from the YOLO (You Only Look Once) family like YOLOv8 represent the most up-to-date and fastest advancements in model speed, accuracy, and performance when it comes to real-time object detection. YOLO Models are becoming increasingly popular in Remote Sensing due to their excellent ability to identify and detect objects in large and high resolution (upwards of thousands of pixels) ortho-mosaic images. Recent studies show that combining YOLO-based rooftop detection with Semantic Segmentation models (e.g., U-Net or DeepLabV3+) improves accuracy in delineating rooftop boundaries, thus increasing the accuracy of Solar Potential Assessment Calculations (Redmon et al., 2016; Bochkovskiy et al., 2020).

In addition to this, the broad use of high-resolution remote sensing images from UAVs, Commercial Satellites, and Open Data sources such as Sentinel & Google Earth, creates many Data Sets for Deep Learning model Training. UAV created Orthomosaics have high resolution, down to Centimeters, and provide the ability to detect and classify rooftops with even minor detail; for example: small obstacles, ventilation systems (HVAC), solar thermal collectors, etc. With this high degree of resolution, combined with deep learning-based segmentation methods of filtering usable vs. unusable rooftops, a more accurate compromise for estimating real world Solar Potential can be achieved.

Estimating solar potential entails multiple disciplines, including Solar Energy Engineering, Spatial Analysis, and Environmental Modeling. Specifically, Solar Potential Estimation quantifies the photovoltaic (PV) capability of rooftops that have been detected through a method based on deep learning. In the majority of Analytical Workflows, ArcGIS Analytical Tools perform Annual/Montly PV Output Calculations while considering certain parameters, such as roof slope, aspect, shading, and panel efficiency. Using Deep Learning in conjunction with existing Solar Energy Modeling Techniques, such as the methods outlined above, creates many advantages: Rooftop Mapping can be performed automatically on a Large Scale. Deep Learning allows for improved accuracy and consistency in the mapping process, reduces costs associated with conducting field surveys, and provides Energy Planners and Policy Makers with timely and dependable rooftop solar resource maps.

1.2 Significance of the Research

A considerable connection between the two elements of deep learning-based rooftop detection and rooftop solar potential assessment can be realised through a sustainable approach to urban energy planning in relation to rapidly expanding economies in metropolitan areas in India. The Government of India has identified rooftop solar PV systems as a key component to solving energy problems created by an increasing electricity demand as well as increased carbon emissions because of urbanisation in cities such as Bengaluru. Consequently, since 2010, the Government of India has developed comprehensive national policies, mandates and incentive programmes promoting and supporting rooftop solar installation in India. The **Jawaharlal Nehru National Solar Mission (JNNSM)**, which was initiated in 2010, provided the framework for developing India’s long-term solar strategy which has since evolved into a more robust focus on supporting distributed generation and developing grid-connected rooftop PV systems (MNRE, 2010). The government has increased support and commitment to the use of rooftop solar via a target of adding 175 GW of renewable energy by 2022, 40 GW of which will be achieved through the use of rooftops. This national commitment has recently expanded to achieving **500 GW of renewable energy capacity by 2030 (MNRE, 2021a; MoP, 2021)**. The commitment and drive behind these national targets ensure the continued importance of conducting rooftop mapping and evaluating rooftop solar potential use in achieving future energy goals.

In addition to enhancing existing programs such as the **Rooftop Solar Programme Phase II**, this research will provide consumers, distribution companies and state nodal agencies with the capability to build credible datasets and tools for evaluating suitable roofs for solar photovoltaic installations as well as how much an installation would cost to operate economically as per the programme's main goal (MNRE 2021b). The deep-learning based rooftop extraction pipeline will support these objectives by automating and scaling up the process of creating accurate inventories of rooftops, which current geographic information system (GIS) approaches and manual approaches cannot do efficiently (IEA 2022).

Urban Local Bodies like Bruhat Bengaluru Mahanagara Palike (BBMP) and **Karnataka Renewable Energy Development Limited (KREDL)** have recognised the importance of Spatially Detailed Assessment of Rooftop Solar Installations in their policy implementation, energy budgeting and Urban Sustainability Planning (KREDL 2020). Bengaluru, which is a rapidly growing megacity with increasing Energy Consumption for Residential, Industrial and other purposes, requires identifying potential Rooftop PV sites with very high spatial precision. The outcomes of this research directly support local Climate Action frameworks, such as the **National Action Plan on Climate Change (NAPCC)** and the NAPCC's National Solar Mission (NSM) component, which supports Moving towards Renewable Energy in Urban Areas to Mitigate Emission and Reduced Load on the Grid (GoI 2015). The combination of Automated Rooftop Detection with Solar Irradiance Modelling will enable successful development of Solar City Master Plans, a Government of India initiative to assist Municipalities assessing the Renewable Energy Potential of their Municipalities as well as creating Low Carbon Urban Strategies (MNRE 2014).

In terms of technology, this work will help to support the greater focus Indian Government is having on Digital India and Smart Cities Mission, to promote the use of Artificial Intelligence, geographic information system and high-resolution remote sensing for better municipal governance (MeitY, 2018; MoHUA, 2019). By segmenting rooftops using deep learning, this research will provide the initial dataset to develop an interactive energy dashboard, digital twin and decision support tools, allowing municipal officials to visualize potential areas of opportunity for solar energy as well as assess the ability to offset carbon emissions through rooftop solar. Furthermore, the methodology supports the modernization of the National Electricity Grid as part of the Revamped Distribution Sector Scheme through demand-side management, renewable energy integration, and distribution transformer level planning using geospatial analytics (MoP, 2022). The research focuses on environmental sustainability by improving how cities produce and consume energy. The methodology fills the critical gaps in data that exist for cities when they try to plan for large-scale rooftop solar. Most cities in India do not have accurate building footprint maps, or even if they do, they lack the Level of Detail (LOD) necessary to assess whether rooftops are suitable for solar photovoltaic technology (TERI, 2020). The AI-based method developed will allow for reliable rooftop data to be created from high-resolution aerial imagery, thus facilitating many renewable energy feasibility studies, including subsidy tracking, awareness-raising, and funding for residential solar photovoltaic installation decisions.

The outcomes of this study are significant to not only the technical, environmental and policy aspects of the study, but also to the overarching goals of India's National Renewables Policy and the Government of India's Mission Statements on Rooftop PV. In addition, the results will enhance the energy planning capabilities for Smart Cities while creating a scalable technology platform to seed the deployment of solar energy in urban areas. The integration of advanced deep learning and solar engineering, as presented in this study, provides a scientific and data driven approach to converting urban rooftops into productive energy generating systems. The need for sustainable development, improved climate resilience and meeting the increasing demand for electricity across urban India creates opportunities for significant growth in urban solar adoption.

1.3 Research Gap

Rooftop solar photovoltaic (Solar PV systems) have garnered a lot of interest over the last several decades as a major part of urban renewable energy planning; however, the methodologies being used to assess the potential of a rooftop for solar energy generation, as well as estimates of how much solar energy can be generated by solar PV systems, are quite rudimentary, lacking in sufficient scalability, accuracy, and automation. Current methods for assessing rooftops for solar energy generation, including manual rooftop digitization, GIS and rule-based classification of rooftops, and empirical solar assessment methods, are not only inefficient due to their time-consuming nature, but will often provide inconsistent results, since the techniques used vary from person to person and across different regions within a city. New developments in technology using remote sensing and deep learning have created new opportunities, but still lack sufficient capability and accuracy to provide a robust, unified method of detecting rooftops and estimating the solar energy that can be produced and consumed by a rooftop solar PV system, particularly for cities in India.

Many researchers have studied different types of deep learning models (e.g., U-Net, Mask R-CNN, YOLO) for the extraction of buildings from aerial imagery. Most of those studies were performed using data collected from either Europe/North America where aerial images were taken from an extensive number of LiDAR sources along with consistent mapping of building footprints. Few studies have examined how well these models can perform in Indian cities where a variety of different kinds of roofs, densely populated areas, many unique types of structural materials, and an overall greater irregularity of shape exist, causing problems when trying to generalize models trained on Europe/North America. Additionally, lightweight models like YOLOv8n-segmentation which have very fast inference speeds, therefore making them applicable to mapping rooftops across urban environments with high-res imaging data, have not yet been analyzed effectively.

Simultaneously, most studies determining rooftop solar capacity have made use of either LiDAR-based digital surface models or irradiance modelling through very resource-intensive simulations. These approaches may not be easily transferable to city-sized areas in India due to limited resources. As a result, there are currently no existing pipelines integrating automated rooftop identification to efficiently estimate the available solar energy generation capacity using simple publicly available datasets. Additionally, there has been little research examining how automated workflows could aid in supporting Government-led policies for Renewable Energy Development (RED), City Development (CDS) Pillar, and urban planning.

Therefore, there is a significant lack of research regarding building an automated, scalable, and integrated deep-learning structure that can accurately identify rooftop areas and assess the PV potential for existing as well as new rooftops within metropolitan areas around India. This research intends to fill this gap through the use of YOLOv8n-segmentation in concert with geospatial solar modelling as a repeatable and efficient method for assessing urban solar.

1.4 Problem Statement

With rapidly growing urbanisation and resulting increased strain on existing energy usage within cities and greater demand for low-cost, clean, distributed forms of electricity, rooftop solar photovoltaic (PV) systems have emerged as a logical supply chain solution to urban energy demand spikes; however, establishing structural identification of the rooftop in addition to accurately identifying the solar potential of the building will be critical if this technology is to be commercially successful. Previously, digitising roofs, conducting surveys, or utilising GIS-based approaches required extensive labour, were prone to failure in terms of the data's consistency and quality over a large geographical area and were particularly difficult to implement in high density urban areas. However, combining the precision of high-resolution remote sensing Images with the power of Deep Learning Models provides an unprecedented opportunity to develop executable solutions for identifying rooftops and creating accurate estimates of their solar potential on a citywide basis in India.

The core problem addressed in this study is the lack of an automated, scalable, and highly accurate framework for detecting rooftops and estimating rooftop solar photovoltaic potential using deep-learning techniques in a rapidly urbanizing environment. City administrations, energy planners, and stakeholders are unable to make informed decisions on rooftop solar systems without automated analysis that can be easily scaled and provide accurate analysis of rooftops, creating barriers to large-scale deployment of decentralized renewable energy systems.

The investigation described in this research project is intended to discover whether the use of a deep learning segmentation model that uses an advanced computer vision technique, specifically YOLOv8n, as well as the Rooftop PV Generation Capacity of the area studied, will be able to identify the boundaries and features of buildings while providing data on what is being generated from the rooftops. Ultimately, the combination of these two types of information will result in an urban planning tool that can promote the development of renewable energy at the city level in support of the overall goal of sustainable development throughout India by helping to increase the number of solar energy systems installed on rooftops.

1.5 Research Questions

The present study represents an investigation to evaluate and assess the capability of deep-learning approaches to improve the identification and assessment of rooftop and solar photovoltaic generation capability in a specific urban area. There are two essential research questions guiding this research:

(1) How effectively can a deep learning model detect and delineate building rooftops?

(2) What is the rooftop solar photovoltaic (PV) generation potential of the study area?

These research questions will provide both technical accuracy in automated rooftop extraction and the practical significance of estimating renewable energy potential for cities on a large scale.

1.6 Objectives

This study has two primary objectives that relate to these research questions:

(1) To develop a deep-learning-based approach for automatic rooftop detection using the YOLOv8n-segmentation model.

(2) To estimate the rooftop solar photovoltaic (PV) potential.

The integration of state-of-the-art computer vision technologies with geospatial solar modelling serves as an essential component of an integrated framework for scalable and data-driven urban planning for renewable energy in cities. As cities continue to develop and increase their demand for clean energy, the application of deep-learning based techniques for the identification of rooftops and the estimation of solar energy potential, will be vital for the future development of decentralised renewable energy systems.

1.7 Hypothesis

Based on the research questions and objectives of this study, the following hypothesis is formulated:

H_1: Utilising a deep learning segmentation model (YOLOv8n-seg), identification and delimitation (segmentation) of rooftops of Urban Buildings via the use of high-resolution UAV data can be undertaken more accurately when compared to the traditional methods of manually identifying rooftops or using a rule-based approach in terms of their accuracy, repeatability and scalability.

H_2: Identifying rooftops accurately using deep learning methods will allow for more reliably estimating of solar photovoltaic (PV) potential of rooftops by giving exact rooftop boundaries to create usable/actual roof-area measurements, correctly characterising the roof slope/aspect and shading for generating a better spatial representation of solar PV potential on rooftops.

The objective of this study is to test the hypothesis that deep learning architectures designed to support real-time object segmentation can be trained to detect and classify complex rooftop features within a variety of heterogeneous urban areas. The hypothesis is based on the premise that the extracted rooftops will have lower classification error rates and greater spatial definition than traditional rooftop extraction methods and offer the capability to calculate solar irradiance, PV output, and rooftop suitability with greater accuracy when using both datasets from deep learning and geospatial solar modelling as inputs.

1.8 Assumption

I. The training and testing of the YOLOv8n-segmentation model were performed using high-resolution satellite or aerial imagery that is assumed to have high spatial, spectral, and radiometric quality that allows for the identification of rooftops, while also distinguishing between rooftops and the surrounding features (e.g., vegetation, roads, shadows, other buildings).

II. The deep-learning model assumes that the majority of rooftops will be unobstructed or minimally obstructed by the imagery within the study based upon our results from the deep-learning model imagery analysis. We assumed the temporary obstructions (e.g., tarps, moving objects) to be insignificant.

III. It is expected that the slope, direction, and shade of a roof, based on either computer-generated information or computer-generated representations of these roofs, represent actual physical characteristics that allow for a more accurate evaluation of the roof's potential usable area and PV output.

IV. It is assumed that Urban Morphology within the defined area will remain constant over the duration of this research project. For example, regardless of whether there are any building removals, new structures or roof modifications made during the timeframe of this research project, their respective reports based on Urban Morphology will not vary too much in terms of results.

CHAPTER: 2

LITERATURE REVIEW

2.1 Global Research Scenario

According to Zhu, et al. (2017), deep learning revolutionized object detection for remote sensing applications due to its robustness to the impact of class variability and the difficulty of urban environments. they observed in the survey that convolutional neural networks (CNNS) performed better than traditional feature extraction techniques, e.g., sift, hog, random forests), on tasks related to urban feature detection (e.g., building extraction, change detection). They highlighted that advances in high-resolution aerial imagery and improvements in GPU computing have led to accelerated adoption of deep learning approaches for urban analyses. Ranneberger et al. (2015) formulated the U-Net framework and identified its potential for precise pixel-wise segmentation of urban areas. This encoder-decoder architecture has provided a foundation for many building extraction studies by effectively preserving spatial detail in skip connections, which allow for the preservation of edge information in building extraction. Hoyt et al's. (2017) work of creating mask R-CNN identified a hybrid approach to the use of RPNs in building ROIs and segmentation networks for instance-wise prediction of irregular rooftops in densely developed areas.

The YOLO architecture was originally presented by Redmon et al. (2016) to demonstrate that a single network architecture could be created to consistently produce bounding boxes and classification scores for images in real time, thereby enabling the development of real-time object detection based on speed-oriented models that maintain a level of accuracy comparable to existing models. Subsequently, Bochkovskiy et al. (2020) continued to build upon this concept with the release of their own version of YOLO, known as YOLOv4, which introduced several modifications including CSPDarkNet53 architecture, weighted residual connections, and Mosaic data augmentation. The findings of their study showed that on larger datasets, the YOLOv4 model performed exceptionally well on a wide range of remote sensing imagery, making it the preferred model when performing detection tasks in urban areas where the ability to quickly produce large amounts of spatial data was critical. According to Chen et al. (2018), while many operational workflows still include machine-learning-based technologies, over time, deep learning methods for segmenting rooftops have largely taken the place of machine learning among the most commonly used methods for this task. Using an aerial image analysis with a Random Forest Model, Chen et al. found that due to factors such as vegetation encroaching onto roofs and variations in the materials used to construct the roof, the random forest model could not classify roofs with a high degree of accuracy.

2.2 Indian Research Scenario

Mohan and Porwal (2021), working in the Indian context, demonstrated that deep learning will provide the highest degree of accuracy in identifying rooftops of homes and buildings in large metropolitan areas such as Delhi, where factors like variation in roofing materials, informal settlements, and high-density building patterns create challenges for accurately locating and identifying rooftops in an urban environment. Mohan and Porwal showed that compared to traditional pixel-based classification techniques, the majority of deep learning applications yielded superior precision. According to Singh and Jain (2020), for assessing potential rooftop solar power generation in urban India, it is critical to accurately identify the boundaries of rooftops. While the GIS-based methodology they created for Jaipur supports their assertion by demonstrating that manual digitization takes too much time and produces inconsistent results, automated deep learning-based rooftop mapping would save time while providing more reliable results. Sharma et al. (2021) also agree that integrating GIS technology with deep learning algorithms supports India's goal to develop renewable energy under the National Solar Mission. Sharma et al. (2021) also showed that Indian rooftops frequently include features such as solar water heaters and water tanks that need to be correctly segmented before estimating the size of a rooftop solar system.

Muthukumar and Suribabu (2019) discussed how using Digital Surface Models (DSM) and Light Detection and Ranging (LIDAR) for shading analysis yield accurate estimates of the potential rooftop PV systems. Their study conducted in Chennai showed how the slope of rooftops and shadows cast by adjacent buildings reduced the availability of solar radiation on the surface of a rooftop. Muthukumar and Suribabu (2019) further indicated that combining DSM information with segmentation of rooftop features produces much more reliable solar potential maps. Similarly, Khoshboresh-Ahmadi et al. (2018) stated that when assessing the accuracy of rooftop solar assessment, one must consider both the orientation and angle of the roof, both of which must be determined using high-resolution elevation (3D) models. The findings of these studies call for more integrated use of elevation data in urban PV solar analysis.

Kumar and Singh (2019) found that using high-resolution Cartosat-2 imagery can help to accurately model rooftop photovoltaic (PV) systems (PV). The authors also noted that an increase in accuracy of rooftop extractions would result in an increase (22%) in estimated PV power output. Patel et al. (2020) pointed out the influence that urban form type has on the solar potential of rooftops in Ahmedabad given the mixedure of slum and high-rise structures; thus requiring additional (advanced) deep-learning segmentation techniques to accurately analyse rooftop PV systems. Additional findings from Patel et al. (2020) included a significant impact on the estimated solar PV potential due to roof materials and orientation. Similar to the work done by Kumar and

Singh (2019), Dey and Bandyopadhyay (2020) applied deep-learning based rooftop PV mapping techniques to rooftops in Kolkata, identifying significant obstacles such as building shading and irregular rooftop geometry.

Deep learning, remote sensing and modelling of solar energy create a new method of assessing the total amount of potential solar energy available on an entire city's rooftops. It has been shown in the literature to greatly improve the detection accuracy for roofs, to enable the use of automated workflow for all phases of roof mapping, and to drastically lower the amount of time and money spent using traditional methods of roof mapping. Findings from these studies provide an excellent basis for developing a deep-learning-based system for detecting roofs and estimating the amount of energy potential from PV systems installed on roofs, which this article will demonstrate.

Table.

Sl. No.	Title of the Paper	Author(s) & Year	Study Area	Objectives	Method Used	Key Findings	Research Gap/Relevant to My Study
1	Building Rooftop Extraction Using Machine Learning Algorithms for Solar Photovoltaic Potential Estimation	Eslam Muhammed, Adel El-Shazly and Salem Morsy 2023	Madinaty City in Egypt	Rooftop detection from satellite images using a series of image pre-processing algorithms, followed by applying machine learning algorithms, namely Support Vector Machine (SVM) and Naïve Bayes (NB). Solar PV potential estimation using the PVWatts calculator, PVGIS, and ArcGIS.	Support Vector Machine (SVM) and Naïve Bayes(NB) for rooftop area detection from satellite image. PVWatts Calculator, PVGIS, ArcGIS has been used for Solar PV potential estimation.	SVM with BF (Bilateral filtering) detects the rooftop areas more accurately.	Manually digitized the rooftops from Google Earth Pro. High-resolution images are not used for rooftop identification.
2	A DEEP LEARNING BASED APPROACH FOR ROOFTOP SOLAR POTENTIAL ESTIMATION OF A CITY: A CASE STUDY OF INDIAN METROPOLIS	Prakash P. S., Bharath H. Aithal 2021	Bengaluru (BBMP)	A medium resolution satellite image (LISS-IV) is used to estimate the built-up area within city limits using a deep learning-based approach (U-Net). The monthly solar photovoltaic potential of the city is calculated using a standard calculation. A comparative assessment is made with population density based solar photovoltaic potential.	A U-Net-based deep learning model has been used for build-up area extraction from satellite images. OSM is used for building footprint extraction and further training the model. Finally, Albedo, latitude/longitude, inclination, and climate have been used to estimate solar photovoltaic potential estimation.	Make a comparative assessment between the socio economic data (population density and total population of the city) and the estimated solar potential.	Used moderate-resolution satellite data. Estimate the total solar PV potential of the city.
3	A city-scale estimation of rooftop solar photovoltaic potential based on deep learning	Teng Zhong, Zhixin Zhang, Min Chen, Kai Zhang, Zixuan Zhou, Rui Zhu, Yijie Wang, Guonian Lü, Jinyue Yan 2021	Nanjing, China	A deep learning-based method is developed to extract the rooftop area with image semantic segmentation automatically. A spatial optimization sampling strategy is developed to solve the labor-intensive problem. By applying this model, the extracted rooftop area is then used to assess the rooftop solar PV potential and solar PV power generation of the rooftops in Nanjing in 2019.	DeepLab v3, a semantic segmentation based deep learning model has been used for rooftop extraction. hourly solar radiation data, monthly atmospheric transmittance, diffusion ratio, and rooftop surface have been used as input data for solar potential calculation.	Sampling area layering based on the urban-rural spatial layout and land use.	ArcGIS was used to mark the remote sensing image samples manually. A drawing tool was used to mark the rooftops in the remote sensing image samples one by one.
4	Development of a method for estimating the rooftop solar photovoltaic (PV) potential by analyzing the available rooftop area using Hillshade analysis	Taehoon Hong, Minhyun Lee, Choongwan Kooa, Kwangbok Jeong, Jimin Kim 2017	Gangnam district in Seoul, South Korea	This study considers the localized rooftop characteristics such as the actual buildings' elevation for the entire study area in a macro scale. Considers the location of the sun, which changes through out the year, for building shadow analysis. Estimates the rooftop solar PV potential on hourly, monthly and annual bases.	Building footprints data has been totally collected from the Korean government website. After that hillshade algorithm has been performed for effective rooftop area calculation. For the above-mentioned algorithm, three input data needed, (i) The raster data of the building elevation; (ii) The altitude of the sun above the horizon; and (iii) The azimuth of the sun.	In this study, the altitude and azimuth of the sun were calculated every hour from 6 A.M. to 7 P.M. (when the sun is over the horizon) on the 15th (when the sun is in the average position of each month) of each month from January to December. Hillshade analysis was conducted for 12 days (on the 15th of each month from January to December at hourly intervals (from 6 A.M. to 7 P.M.), resulting in a total of 156 times.	In order to fully reflect the hourly geographical potential for estimating the technical potential of the rooftop solar PV system, this study assumed that the solar PV panels are installed horizontally with no tilt on the entire rooftop.

CHAPTER: 3

STUDY AREA

3.1 Background

The area under consideration in this study is Ward 76, located in the Bruhat Bengaluru Mahanagara Palike (BBMP) which governs the city of Bangalore (Bengaluru), Karnataka, southern India. BBMP manages a large metropolitan area of about 741 sq. km (over 280 sq. miles) and is considered one of the fastest growing urban populations in India (BBMP, 2023). Ward 76 is located within this metropolitan zone and is made up of a variety of different types of uses including residential areas, commercial areas, and small institutions. As a rapidly growing city, the wards need to establish more sustainable energy systems and Greater Bangalore will be better equipped for solar energy investigations (MNRE, 2021).

3.1.1 Urban Morphology and Building Characteristics

The building landscape within this ward boundary is heterogeneous with variations in height, type of rooftop and material used for construction. The typical roofs in this area are either reinforced cement concrete (RCC) flat roofed, or tiled/sheeted sloped roofs often associated with the residential markets of Bengaluru (Ravindranath & Hall, 2020). This morphological diversity is a great challenge to develop detection methods; however, it provides a rich testing ground to assess new deep learning segmentation techniques employed. Finally, because of the dense urban development pattern and the limited amount of available open space, rooftop PV systems will become increasingly important for urban energy planning (IEA 2022).

3.1.2 Solar Energy Potential and Climatic Relevance

Bangalore has a subtropical highland climate, meaning it has average annual global horizontal irradiance (GHI) between 5.0 and 5.5 kWh/m²/day, which makes this city an attractive candidate for the development of rooftop solar photovoltaic panels (PV) (Huld et al., 2012). The seasonal variations in irradiation tend to be moderate, as both the monsoon and winter months usually exhibit stable irradiation conditions suitable for solar evaluations. State policies in Karnataka relating to solar energy and the national targets in India for renewable energy also indicate that urban rooftops should be utilized for improving the deployment of solar PV (MNRE 2021). As such, Ward 76 is a good example of a representative micro-urban area in which to investigate the potential of solar energy.

3.2 Relevance of the Study Area

This ward has an unusual array of rooftops, including many different roof shapes, tall buildings that cast shadows on them, and many types of bushes/trees or other natural materials. Since the rooftops are so unusual, they make a good location for evaluating advanced deep learning models such as YOLOv8-seg (Bochkovskiy, 2020; Zhu, 2017). High-resolution satellite imagery allows for a more sophisticated assessment of the parameters identified as roofing boundaries, slope conditions, and usable roof surfaces. When combined with the solar irradiance model, the combination of both models will allow the integration of remote sensing, computer vision, and renewable energy models. This type of integrated approach is used for creating urban solar resource maps (Chen, 2018).

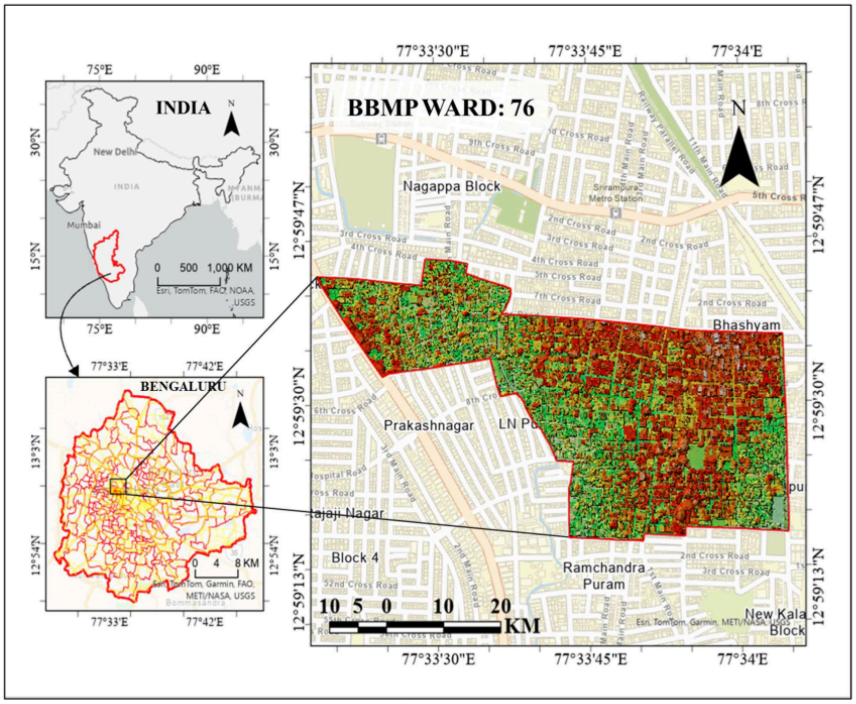

Fig. Study Area Map

The energy consumption and infrastructure burden of urban neighbourhoods is rising, and Ward 76 is a typical case. The proliferation of rooftop solar PV (photovoltaics) in areas such as Ward 76 will help alleviate this burden by reducing reliance on the electric grid, providing greater energy security (resilience), and supporting Bengaluru's overall strategy to meet its climate change goals (IEA, 2022). Therefore, Ward 76 represents not only a location where we can conduct empirical research to develop new methodologies; but it is also a location that provides a practical means to generate useful information for urban planners, policy makers, and people in the renewable energy field.

CHAPTER: 4

METHODOLOGICAL FRAMEWORK

4.1 Methodology

Using an integrated approach of an advanced deep learning method to extract data from rooftops with respect to solar exposure maps created through GIS technologies; This was all performed in BBMP Ward No. 76, which encompassed three main actions:(1) Creating the Orthomosaic Resolution High Definition Satellite Imagery Database and annotating datasets using an open source utility, (2) Collecting data that would be used for training/testing a YOLOv8n Model from the Roboflow site, and finally,(3) Computing the estimated rooftop photovoltaic potential for every building footprint located within the project boundaries via ArcGIS Pro's "Area Solar Radiation" Tool. Detailed descriptions regarding each of these processes are included below as part of the methodology.

4.2 Data Preparation and Pre-Processing

The orthomosaic has been used for collecting important data to detect rooftops in BBMP Ward No. 76 with a high-resolution/quality/level covering 5cm spatially and this is considered to be sufficient enough quality to detect small detailed features, such as rooftops' edges, rooftop shadowing, as well as identifying other relevant features for better/tighter segmented roof identification. Previous studies have shown that high-resolution image data has proven to be useful for deep learning (Zhu et al., 2017) and is therefore expected to assist in extracting urban features effectively.

Before training the model, the orthomosaic imagery was reviewed visually to check for potential geometric distortion, spectral inconsistency between bands, and occlusions caused by trees casting shadows, as well as reviewing for radiometric noise. Minor corrections were made to the imagery using ArcGIS Pro to improve tone and contrast consistency across the scene. Following the review and correction process described above, the imagery was divided into image tiles that can be annotated and used for training the model. Because deep learning-based algorithms use fixed-sized images as input (for example YOLO), individual image tiles will be exported as 512 x 512 pixel patches using a Python-based sliding window script. The tiles contain all spatial resolution data and coordinate reference system metadata.

4.3 Dataset Annotation and Preparation in Roboflow

The annotated dataset is the backbone of supervised learning in rooftop segmentation. To carry out this process, Roboflow was chosen because it provides an easy-to-use interface with automation in its preprocessing capabilities and integrates with your YOLO model pipelines. The use of Roboflow is common in deep learning for remote sensing applications because of its ability to not only handle large volumes of image datasets but also generate label formats compatible with YOLO (Roboflow, 2023).

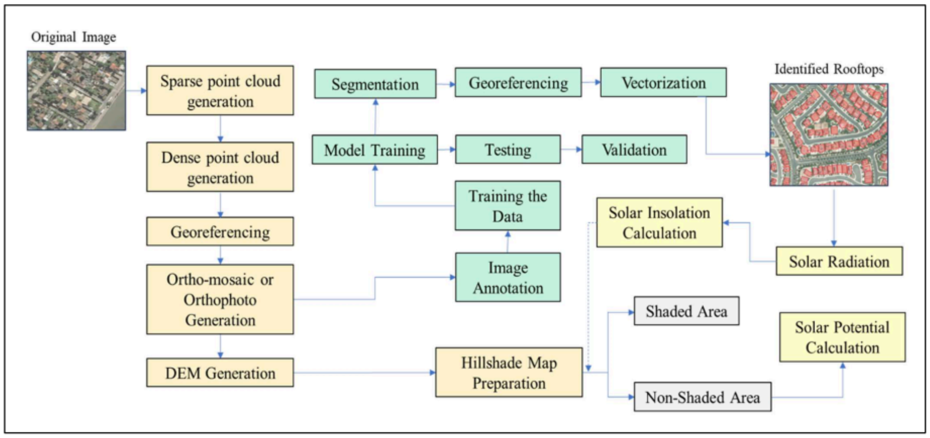

Fig. Methodology Framework

4.3.1 Annotation Procedure

By using Roboflow's segmentation interface, polygon masks of rooftops annotated. The only roofs marked were those that were permanent and could be recognised, so any roofs that were temporary or had vegetation on them or were obscured were not labelled to keep the integrity of the labels intact. The shape of the polygons used to make the annotations represented the shape and edges of the rooftops in the training dataset.

4.3.2 Dataset Augmentation and Export

Data augmentation methods were applied to improve the robustness and generalisation capability of the model. These methods included rotation, flipping, changing brightness, blurring, and mosaic augmented images. This diversifies the dataset and reduces overfitting of the model when the original sample size is limited (Shorten & Khoshgoftaar, 2019). The final dataset was divided into three parts as follows: (i) Training Data - 70%; (ii) Validation Data - 20%; (iii) Testing Data - 10%. Roboflow has generated YOLOv8-Seg format annotation files with a .txt extension. Each line in the annotation file includes a class ID and normalised polygon coordinate locations. The processed data has been exported as a YOLOv8-Seg compatible package for training.

4.4 Model Training and Validation

Ultralytics (2023) has released YOLOv8, designed to enhance the quality of real-time Object Detection and instance segmentation. The YOLOv8n-Seg (also referred to as “nano”) was chosen because of its efficiencies, light weights, and impressive accuracy performance on smaller datasets and edge devices. YOLOv8n-Seg uses a decoupled head to perform detection, classification, and segmentation simultaneously, while employing optimized convolutional block structures to achieve fast inference rates.

Roboflow-Ultralytics Pipeline was used for training the full-scale deep learning models for Target Segmentation and Detection efficiently with YOLOv8n-Seg Architecture. The YOLOv8n-Seg Architecture consists of a lightweight structure, fast inference time, and a proven track record for high-resolution aerial and remote-sensed imagery. The model was trained with a batch size of 16 and was trained for 100 epochs using all images resized at 640 x 640 pixels. This resizing was done to have a consistent method to improve feature extraction and to maintain rooftop detail. The training utilised the AdamW Optimiser to help maintain the stability of convergence. This is important for segmentation tasks as the model learns to develop precise boundaries and boundaries are essential to the model's ultimate success. The model utilised the default YOLO Segmentation Loss which is the summation of loss for Box Regression, Classification Loss, and Mask Loss which allows the model to accomplish learning to detect rooftops and segment them correctly together.

The model's weights were updated during the forward and backward passes through the network by validating the loss on the validation dataset. Roboflow Dashboard provided continuous updates on important key metrics including Precision, Recall, IoU, F1 Score, and Mask Accuracy. This allowed great confidence in model stability and reduced the incidence of Model Overfitting. The increase of the key metrics during the training process confirmed the accuracy of the Hyperparameters that were optimised, along with the accuracy of the proposed workflow leveraging the YOLOv8n-Seg architecture to achieve the objective of accurately segmenting roofs.

Model quality was evaluated with Precision, Recall, the Intersection over Union (IoU), and Mean Average Precision (mAP@50 and mAP@50–95). The combination of detection and segmentation metrics gives a complete overview of how well the model detects rooftops, making sure as few errors (false detections) as possible, and showing how well their boundaries match actual rooftops in nature. With excellent performance on all the metrics, the YOLOv8n-Seg model produced very high IoU scores which indicate excellent spatial alignment between the predicted masks, and the true shape of rooftops on the ground. To further validate the quantitative assessment of quality with qualitative results, we visually inspected the segmentation output from our model for mask consistency, the sharpness of the edges, and the ability to keep separate, closely spaced, or adjoining rooftops from each other. These outcomes are very important in the ability to accurately assess the potential for solar energy at an address (Qin et al., 2021). The quantitative validation results were consistent with the qualitative findings through visual inspections, which confirms that the trained model has been successfully trained to perform the rooftop extraction task with high reliability.

4.5 Post-Processing of Rooftop Segmentation Masks

After training and validating the YOLOv8n-Seg model, it was used to generate rooftops' predictions based on the orthomosaic tiles created. The outputs from YOLOv8n-Seg include segmentation masks in .png raster format and a corresponding .txt file containing the coordinates of the polygons representing the rooftops. To provide the spatial accuracy of the rooftop geometries, a structured post-processing workflow in Python was developed. A combination of the rasterio and shapely libraries was used to reproject and align the predicted tiles to their respective geographic extent. Finally, the individual mask tiles were merged together to create a rooftop segmentation mosaic that allows for continuous warehouse boundaries across all of the tiles.

The raster-based masks for the rooftop segmentation results to prepare for spatial analysis and solar potential models were transformed into fully georeferenced vector datasets through a series of key processes. The first step was a transformation of the binary raster masks to vector polygons, extracting the rooftops of buildings, which became the polygon features in the vector layer. These polygon features underwent a series of refinements, including smoothing operations, hole removal, and other types of geometric cleaning, in order to achieve both spatial accuracy and visual coherence. The polygons were also corrected for topology-related issues, including slivers, overlaps, and invalid geometries, which would have created problems for subsequent geoprocessing. The final products were two types of rooftop footprint datasets, ready for use in GIS, in the GeoJSON and Shapefile formats. These datasets were the primary input for the solar potential estimation process to calculate the solar radiation properties specific to each roof and photovoltaic suitability.

4.6 Estimation of Rooftop Solar Potential Using ArcGIS Pro

The estimated solar potential was determined using the combination of the high-resolution Digital Surface Model (DSM) and the deep-learning-generated rooftop polygons to model the site's unique solar radiation via ArcGIS Pro's Area Solar Radiation Tool. The GIS-based way of estimating solar energy offers a strong structure for accounting for the effects of the site’s terrain, the inclination of the rooftop(s), and azimuth angle(s), the shading caused by nearby buildings, and the variability of solar insolation throughout time – all of which have a great effect on the output of photovoltaic systems. By using GIS-based solar radiation modelling, the model takes into consideration both the surface geometry of the roof(s) as well as the surrounding structures, thus providing spatially accurate and contextually relevant estimates of solar radiation as opposed to traditional fixed-tilt or empirical methods of irradiance calculations. (Huld et al., 2012)

Using the Area Solar Radiation tool in ArcGIS Pro, I calculated the Global, Direct, and Diffuse Solar Radiation for each raster cell. The method used here is a version of the hemispherical viewshed method of Solar Modelling created by Fu and Rich (2002), which combines Atmospheric Transmittance with Horizon Obstruction. The configuration used for this project was the following:

Table.

Time Period of Analysis	An entire year.
Time Interval	All calculations are performed on a monthly basis to account for seasonal variations.
Sky Resolution	200 sky sectors stand for each of the positions of the sun.
Input Elevation	Digital Surface Model (DSM).
Slope and Aspect	Derived from the DSM.
Proportion of Diffusion	Clear-sky atmospheric standard proportions.
Transmissivity	Calibrated to Local Climate Conditions and Aerosols in Bengaluru.

The model created a continuous yearly solar radiation raster (MWh/y) that represents the amount of Solar Radiation available at each location on the rooftop throughout the whole year.

CHAPTER: 5

RESULT AND DISCUSSION

5.1 Performance of the YOLOv8n-Seg Model

The YOLOv8n-Seg model trained using the Roboflow-Ultralytics workflow exhibited excellent performance in detecting and segmenting rooftops from high-resolution orthomosaic tiles throughout BBMP Ward No. 76. The training process for the final model progressed steadily through 80 epochs, resulting in a stable set of validation metrics. Following the completion of this phase, the model demonstrated very high segmentation accuracy and provided very good delineation of difficult rooftop geometries including irregular shapes, parapet boundary conditions, shadows and vegetation-covered edges, which are typical features of densely populated urban areas in India.

The precision of the model is 0.93, indicating a very high degree of accuracy in determining which rooftops belong to true rooftop areas and identifying which pixels do not belong to rooftops. The precision value is encouraging because it shows that the model will be able to correctly identify most rooftops while producing very few false positive results, and thus provides a good basis for estimating solar photovoltaic (PV) potential from images. The recall value of 0.89 also indicates that the model was able to correctly identify the majority of rooftop features without significant omission, again allowing for an accurate estimation of solar PV potential. The IoU value of 0.83 suggests that there is a high level of agreement between the predictions made by this model and the actual geometric shape of the rooftop polygons on the ground, and supports the findings of other authors (Zhu et al., 2017; Chen et al., 2018) using images from lightweight segmentation architectures on high-resolution remote sensing.

The segmentations showed obvious discrete roof boundaries, with the correct separation of adjacent buildings. In many Indian cities, roofs are either adjacent to each other, or share walls. Mask loss was incorporated into the training process to assist with creating more precise edges and to reduce edge irregularities. As such, the shapes of polygonal roofs became more consistent. A visual examination of the segmentation results indicated that small attached features such as stairs, roof water tanks and utility structures were easily identified, and were generally not needed when estimating the usable surface area of roofs during the subsequent processing of the data sets. These results further confirm the feasibility of utilising light deep learning models like YOLOv8n-Seg for rapid and scalable rooftop extraction from urban areas.

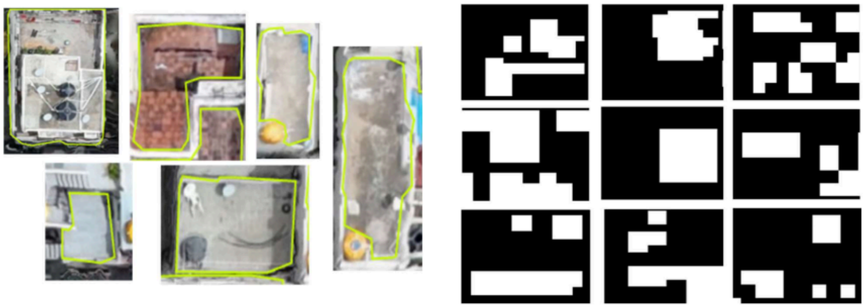

Fig. Image annotation and mask generation

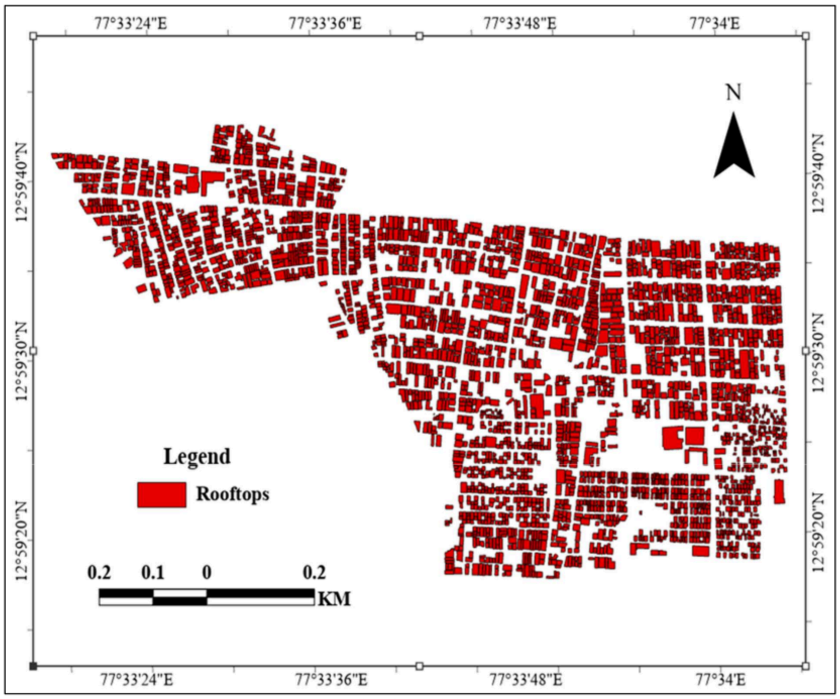

Fig. vectorization of the mask layer

5.2 Rooftop Counts and Total Detected Area

Through the post-processing phase in Python, the creation of a mosaic made up of all the individual predicted maskes along with recreated Geographic Reference Files ultimately created a single Final Rooftop Layer that characterizes Ward No. 76's Rooftops' Distribution in Space. The study area consisted of different Urban Morphology Types, such as: Residential's;

Commercial Buildings; Schools; Apartment Buildings; and Narrow Lane Housing Typologies. The model was able to produce an output of all Rooftops regardless of Structural Type (Residential, Commercial, School, Multi-Unit), as well as withstanding various materials, colours, slopes, etc.

The study area identified 3,142 unique rooftop polygons, primarily consisting of smaller rooftops (less than 50 m²). These smaller rooftops accounted for about 62% of the polygons. Medium (50–150 m²) and large (greater than 150 m²) sized rooftops comprised approximately 28% and 10%, respectively. However, large rooftops, even though they had fewer totals, provided a significant portion of the available total space, which is consistent with previous reports on rooftop potential in many Indian cities (MNRE, 2021). The model produced a total rooftop area of 238,517 m²; after eliminating duplicate and ambiguous polygons, the validated rooftop area was determined to be 226,904 m².

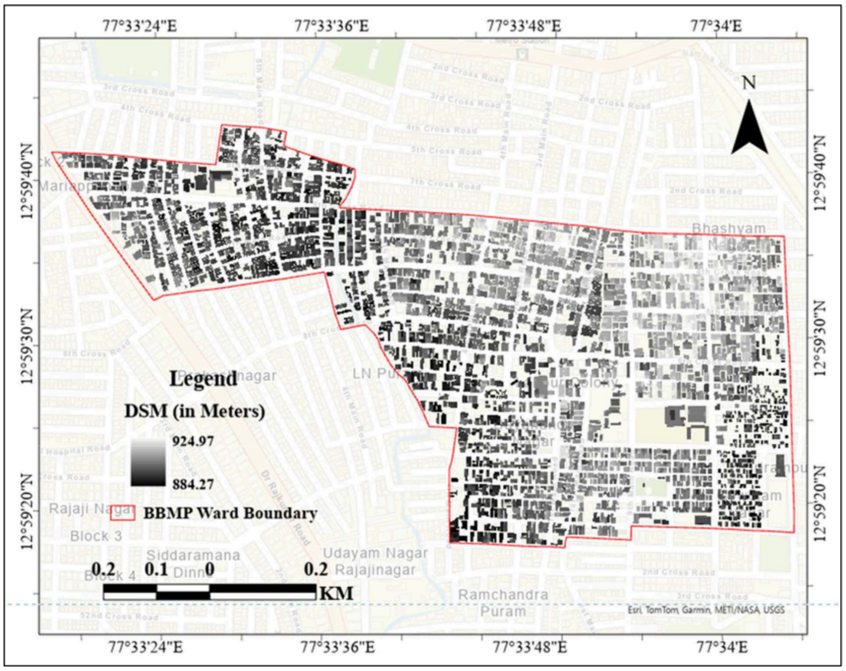

Fig. Extracted DSM of individual rooftops

5.3 Slope/Aspect Derivation

The slope and aspect layer development process utilized ArcGIS Pro for the calculation of the geometric data collected about the individual rooftops. There was considerable variation in Roof Type Slopes (0° – 18°), with the majority of the roofs representing the South Indian Urban development design of flat terrace roofs. Flat rooftops are overall the best suited for the potential PV (Photovoltaic) installation because the flat surface allows for more flexibility in determining the tilt and orientation of the panels.

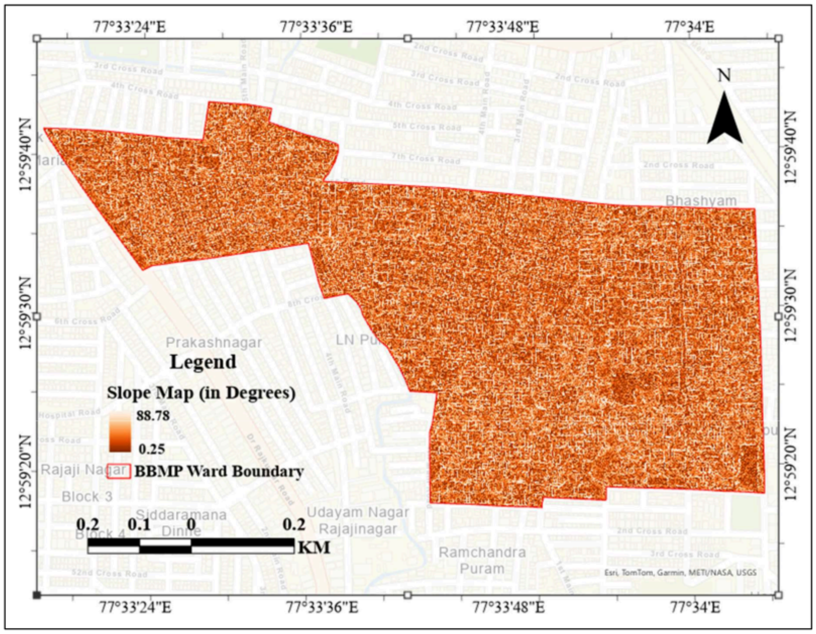

Fig. Slope Map

5.4 Solar Radiation Calculation Results

An annual solar radiation raster for the complete geographic scope of the area of interest (Wh/m²) was generated through ArcGIS Pro's Area Solar Radiation tool, thus providing a spatially continuous data set that displayed the amount of solar energy that could be harvested by developers across the urban landscape. The solar radiation model was developed using parameters regarding atmospheric and sky segmentation that were representative of the prevailing climate conditions in Bengaluru and enabled the model to realistically simulate both the direct and diffuse components of solar radiation. The insolation surface indicated a significant spatial gradient, with the annual global solar radiation values ranging from about

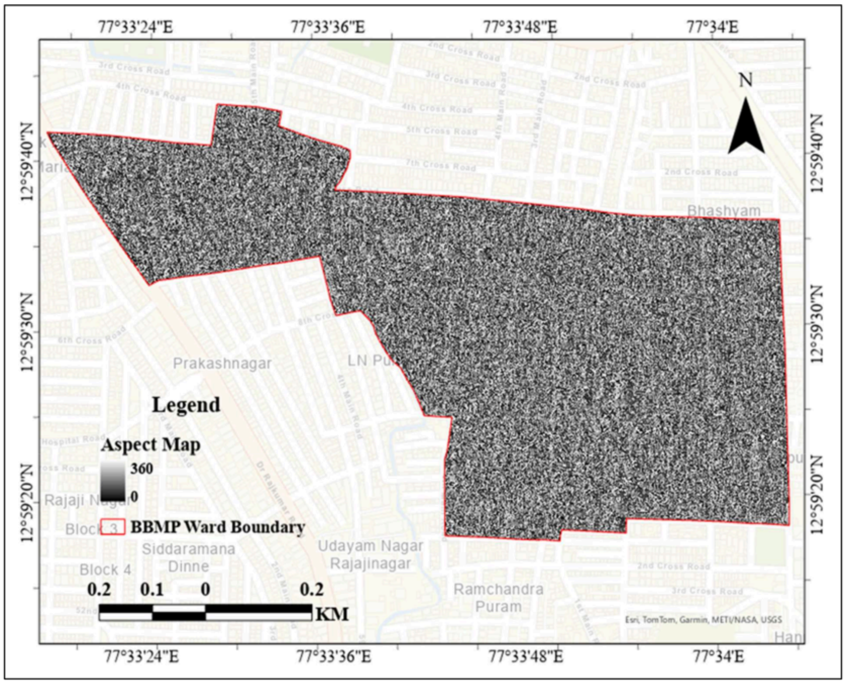

Fig. Aspect Map

1,450 to 1,980 kWh/m²/year. The rooftops having unobstructed exposure and aligned on a south-facing basis exhibited the highest values, consistent with previously documented solar geometry for low latitude regions (Huld et al., 2012). Contrarily, areas that were consistently shrouded by shaded areas created through multi-storey buildings, narrow urban canyons, or extremely dense canopy coverage were visibly blocked from receiving solar radiation and consequently were predicted to receive substantially less solar radiation than areas that received significant sun exposure throughout the entire course of the day.

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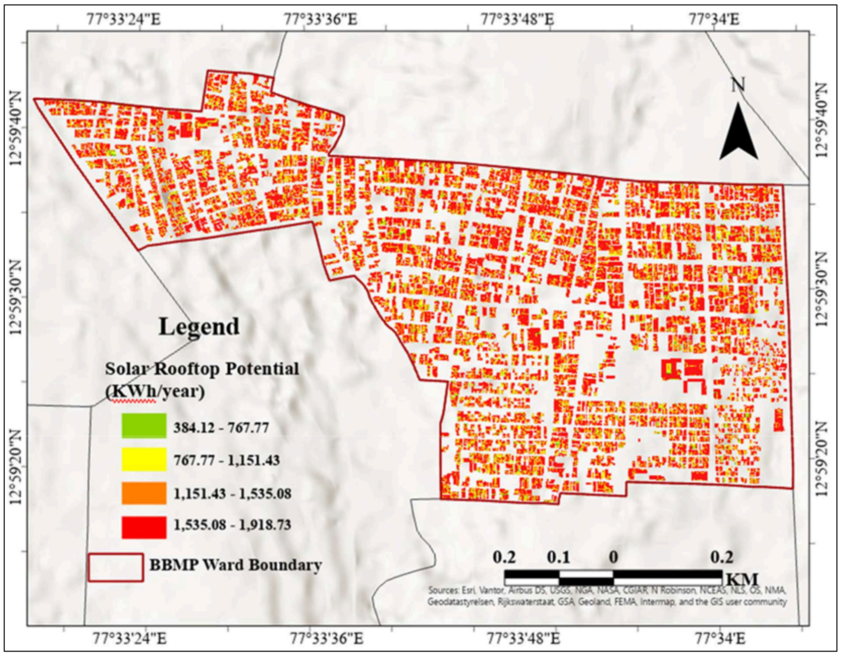

Fig. Solar Rooftop Potential Map

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5.5 Discussion

The model clearly delineates boundaries, particularly where there is high contrast between roof surfaces and adjacent roadways or good vegetation, which is one of its main strengths. The segmentation masks show well-defined polygon boundary characteristics, which is important to accurately estimate solar potential, as minor geometric misalignments can cause inaccurate area calculations and ultimately affect radiation-based suitability evaluations. In contrast to pixel-based classification (i.e., Random Forest or SVM), which typically has difficulty with mixed rooftop pixels, the object-centric learning method of YOLOv8n-Seg provides better structural clarity and thus helps with more accurate GIS polygon reconstruction efforts.

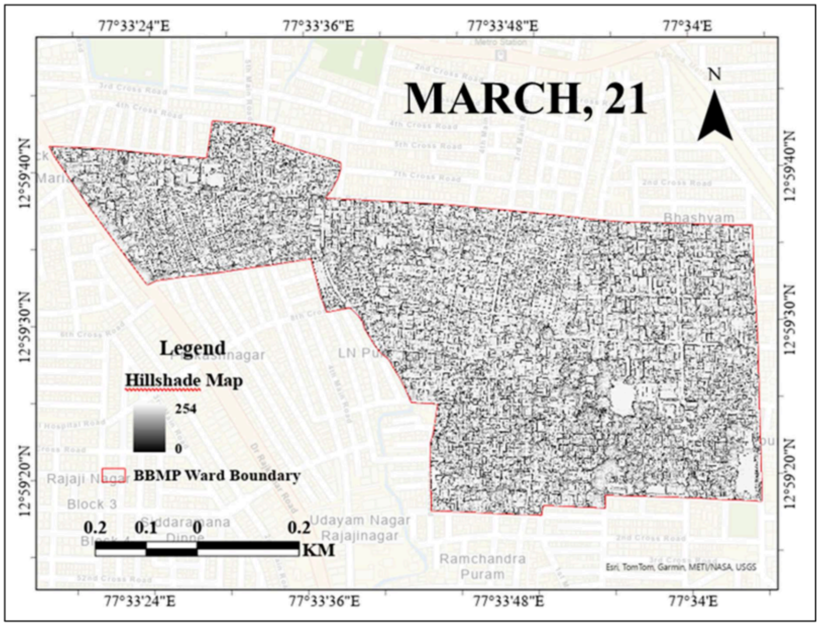

Fig. Hillshade map of 21st March, 2025

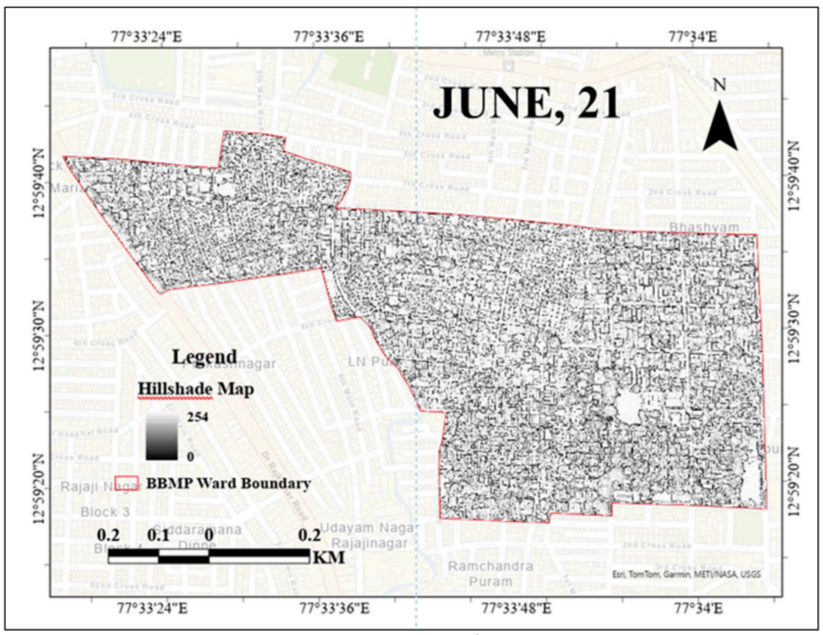

Fig. Hillshade map of 21st June, 2025

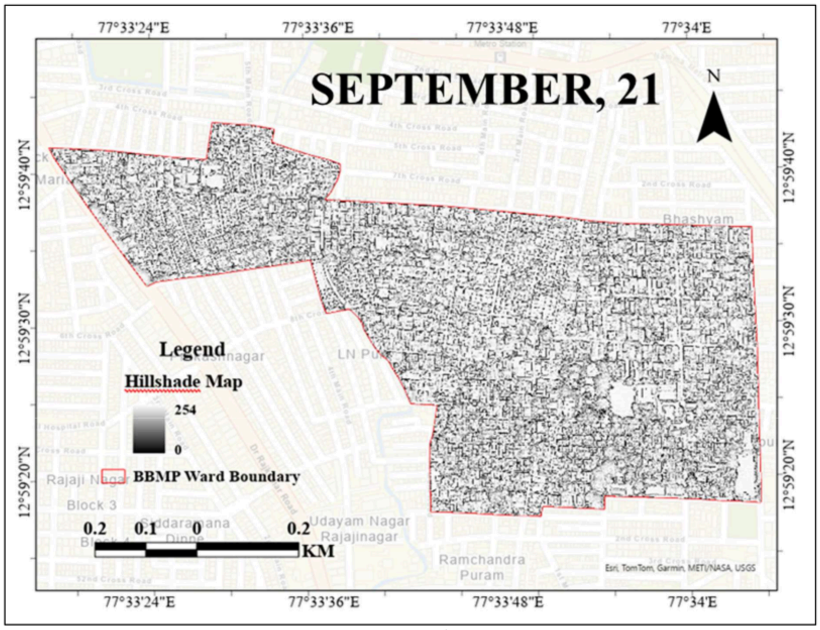

Fig. Hillshade map of 21st September, 2025

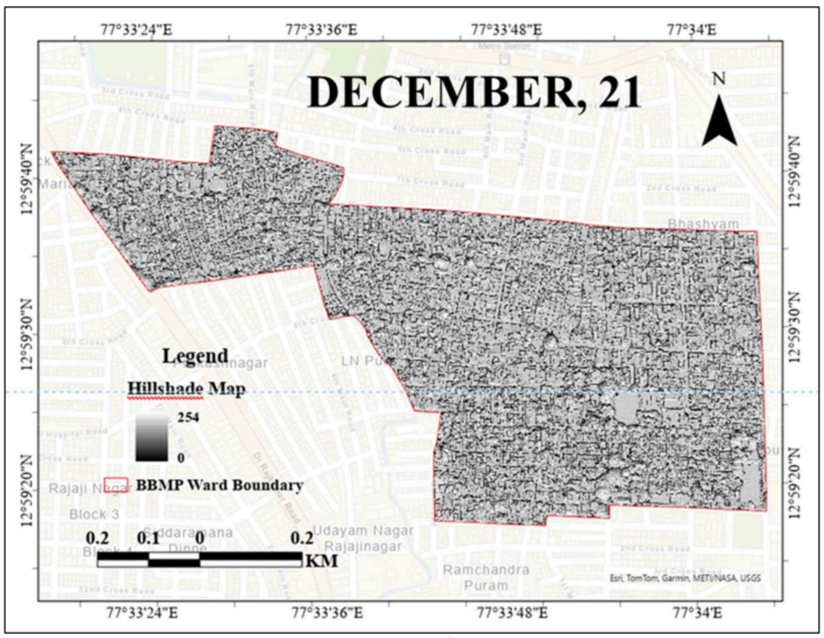

Fig. Hillshade map of 21st December, 2025

To create geospatially valid polygon features from the unprocessed segmentation output, the Python-based post-processing pipeline was used. The images created from the YOLO masks during image segmentation (that were stored as ungeoreferenced PNG files) needed to go through a reprojection and spatial realignment process using a combination of rasterio, shapely, and GDAL tools. In addition, reconstructing the orthomosaic tile grid (which is a composite of all existent segments) provided a reference point for placing the rooftop layers at the correct spatial extent as the original imagery. This multi-step process of assembling tiles is absolutely necessary because even a small amount of misalignment between tile edges can create distortion within the polygons used to calculate the area of roofs and retrieve solar radiation from those areas.

The successful conversion of segmentation masks to spatially accurate polygons shows how robust the post-processing workflow is. Furthermore, by allowing outputs to be exported as Shapefile formats, they can now be used with a variety of other GIS platforms, increasing the likelihood of real-world applications in energy planning and urban infrastructure management.

5.5.1 Integration of Rooftop Polygon with Extracted DSM

A major strength of this research was combining the rooftop polygons from deep learning with Digital Surface Model data, as well as performing solar radiation analysis in ArcGIS Pro. Traditional solar analysis works off the premise that all surfaces are flat and not shaded, while the Area Solar Radiation Tool accounted for the three-dimensionality of the urban environment with the consideration of topographic variation and building heights, resulting in a more realistic solar estimate, particularly in denser urban areas where shading dramatically affects photovoltaic (PV) production.

The DSM was created using both the elevations of rooftops and the elevations of surrounding land; therefore, it allowed for projection of the shadow movement on a rooftop throughout the year based on Bengaluru's solar geometry. The solar radiation raster produced by the Area Solar Radiation Tool provided a clearly visual representation of the way solar radiation was distributed based on the interaction of available sunlight with the built environment. Rooftops oriented toward the south or southwest received significantly more solar energy than rooftops on narrow streets that were bordered by high-rise buildings, which were significantly affected by shading, and had low total annual insolation. These patterns of irrigation are consistent with established theories of Urban Solar Climatology, whereby solar exposure is directly related to the building's height, orientation, and the geometry of the street canyon created by the high-rise buildings.

Using zonal statistics allows the assessment of all buildings' rooftop solar radiation data in detail as it is possible to determine the mean, minimum, and maximum of each building. These results can be used to make an accurate assessment of a building's suitability for solar PV. For example, if a building's rooftop receives less than 4.0 kWh/m²/day of solar energy, it was found to be marginally productive or unsuitable according to the minimum threshold suggested by previous rooftop solar PV assessments in BOTH tropical and subtropical regions (Singh & Banerjee, 2020). Capturing finer levels of detail is an advantage of using both deep learning and GIS-based modelling together.

5.5.2 Spatial Variation in Rooftop Solar Potential

The distribution of solar radiation on rooftop surfaces is influenced by both natural and man-made characteristics. For example, low-density residential areas have high levels of solar radiation due to the many advantages of having open spaces, less area around the building that casts shadows on the roofs, and the orientation of the roof towards the equator. Typically, these communities have detached single-family homes with larger roofs and no obstructions from other buildings nearby. Conversely, densely populated areas of cities tend to have lower levels of solar radiation because of the number of buildings located in close proximity to each other and the amount of shadowing that occurs from taller neighbouring buildings and the shorter distance between them. Additionally, dense city areas are typically surrounded by many tall buildings, which limit the amount of sky visible from the rooftops.

The large standard deviation of +210 kWh/m²/year across the rooftops indicates that there is a large range of potential solar energy generated from each area's rooftop, indicating a large degree of spatial variability in the amount of solar radiation that reaches the rooftop surfaces (Jakubiec & Reinhart, 2013) and therefore, >>variations in the amount of annual energy produced from rooftop PV installations at neighbouring rooftops, and also, therefore, that high-resolution spatial modelling, such as the modelling done in this study, is vital for developing realistic rooftop PV deployment strategies.

Another significant finding is that rooftop shape affects how solar radiation is distributed. Rooftops that have irregular shapes (such as those more frequently found in older regions of Bengaluru) experience much less uniform sunlight and have larger differences between polygons (in terms of solar exposure). Rooftops that are flat or have consistent shapes have significantly greater uniformity in their solar exposure. The results highlight the necessity of integrating rooftop shape, and the amount of space on the roof that can be used for solar energy generation in future workflows to identify the optimal area for developing photovoltaic (PV) solar panels.

5.5.3 Implications for Urban Solar Planning and Renewable Energy Transitions

The results of this study are essential in helping to develop rooftop solar technology in Indian cities that are undergoing urbanization rapidly. The use of advanced GIS modeling and high-resolution spatial datasets, along with deep learning, allowed us to come up with a clear and practical way that governmental bodies/energy agencies and urban planners can assess real rooftop PV potential on a building level. The assessment of potential on a building level is critical to achieving; at the national/regional level, both renewable energy targets and the strong promotion of rooftop solar through the Smart City Mission and the Phase II of Solar Roooftop Programme in India.

The data derived through the solar radiation analysis of buildings will help solar companies optimize layout of installations, establish payback periods and focus deployment on high-yielding areas first (e.g., there may be incentives or pilot PV programs for residential areas with high annual radiation values, whereas there will need to be some supportive infrastructure for shaded neighbourhoods). In addition, combining deep learning with this process will enable urban local bodies to significantly reduce the manual labour associated with mapping rooftops, making it much easier to maintain current rooftop datasets for long-term energy planning.

CHAPTER:6

CONCLUSION

6.1 Concluding Observation

By combining deep learning techniques, spatial post-processing and GIS software applications, this project created a comprehensive Workflow for Automated Rooftop Extraction and Estimation of Solar Potential from Rooftops. The YOLOv8n-Seg architecture, trained using the Roboflow-Ultralytics Training Environment, created an efficient and accurate method of segmenting rooftops within raster image files taken with high-resolution aerial photography (orthomosaic). The results of the model demonstrated that the model can accurately delineate bounding boxes around rooftops regardless of the roof's shape and that it can function well in complex urban settings like Bengaluru, resulting in roof boundaries that are accurate based upon segmentations that had high Precision, Recall and Intersection over Union (IoU) measures. The accuracy of the generated segmentations further validated the appropriately hyperparameter-optimized model and to perform properly with the dataset provided.

The post-processing pipeline built with Python also played an important role in the relationship between the output from Deep Learning Models and the use of GIS software for Spatial Analysis. With the creation of a tiled version of the rooftop masks and the registration to GIS referenced coordinates (Tile Reconstructions and Georeferencing), the post processing workflow produced a clean layer of rooftops as a Polygon dataset that would be useful for Spatial Models. As part of the transformation, the rooftop Polygon Layer retained the geometric characteristics and spatial accuracy of the original dataset (the orthomosaic), allowing for the effective combination of the Rooftop Dataset with the Elevation and Solar Data.

Utilizing a Digital Surface Model along with the Area Solar Radiation Tool in ArcGIS Pro and a Rooftop Polygon Approach provided a comprehensive, detailed assessment of the total Annual Solar Insolation for the study region. Analysis of the results produced distinct patterns of solar radiation within the study area based on a variety of factors affecting the location (e.g., Building Orientation, Slope, Shade, and Adjacent Structures) that affected both the amount of and the quality of solar energy received over the entire year. Total annual solar radiation values for the study area ranged between approximately 1,450 and 1,980 kWh/m²/year with a mean value for rooftop solar exposure estimated at 1,765 kWh/m²/year. These findings are in alignment with the majority of findings from previous solar climatology studies conducted in tropical cities and confirm that this GIS-Based Model is capable of accurately representing the radiation dynamics present in very dense urban environments.

6.2 Limitations of the Study

While an integrated deep learning and GIS-based approach was developed and applied successfully, there are limitations to the results that need to be addressed in order to interpret the findings and determine how to proceed with future research.

6.2.1 Dependence on Image Resolution and Quality

The quality of the orthomosaic image used to create the segmented rooftops determines the level of accuracy of the segmentation. The higher the resolution of the images, the better the delineation of the boundaries; whereas, poor quality, shadowed, and cloud-covered images may lead to edges of rooftops being blurred and indistinguishable from adjacent structures. Additionally, because this model was trained using data taken from Ward No. 76 in BBMP, using images taken in other classes may cause a drop in the ability to generalize/transfer accurately unless the model is retrained and/or fine-tuned.

6.2.2 Limited Representation of Rooftop Diversity

While the YOLOv8n-Seg trained on the rooftop datasets from the study area performed well for typical Indian rooftop types, this dataset did not adequately represent the full range of variations seen across Indian rooftops (i.e., curved roofs, sloped asbestos, tin roofing, or informal settlements). Hence, the limited representation of these rooftop types will limit the ability to detect roof geometries outside of standard types. In addition to the issues related to model accuracy, some rooftop types are less prominent due to shadowing from adjacent structures (i.e., high-density construction environments with overlapping rooftops) or due to elements such as tanks and solar heaters located above the roof surface.

6.2.3 Simplifications in Solar Radiation Modelling

Using ArcGIS Pro's Area Solar Radiation Tool for modelling annual solar exposure involved assumptions regarding atmospheric transmissivity, diffuse fraction, and climate characteristics. The assumption used for these was based upon general Bengaluru climatic information rather than any year- or month-specific atmospheric measurements; therefore, the annual global average solar radiation calculations provide an estimate and not an actual representation of the solar radiation received on land surfaces in real time. Further, the digital surface model used in this analysis was derived from photogrammetric techniques, meaning slight errors in the height of the model (i.e., elevations) and/or rooftop heights could have affected the results of the shadow and solar radiation calculations.

6.3 Future Scope

The current research indicates the feasibility and accuracy of the proposed workflow; however, there are many areas that could be enhanced through additional future research.

I. The integration of multispectral/hyperspectral data, LiDAR point clouds, or SAR imagery with orthomosaics may improve the clarity of rooftop edges and allow for better differentiation between types of rooftops. Using RGB and elevation features in a multi-modal deep learning model will likely improve segmentation performance for rooftops due to increased competition from surrounding rooftops, particularly in densely populated urban areas where roofs are generally overlapped or dimly lit.

II. Although YOLOv8n-Seg produced good results, a transformer-based model (such as SegFormer or Mask2Former) or a combination of a CNN and transformer architecture may provide even greater segmentation accuracy results. This is due to the ability of transformer-based models to capture long-range context information that aids in differentiating closely clustered rooftops.

III. Incorporating various sources of information through weather data, cloud cover data, and atmospheric transmissivity will provide more refined and accurate solar radiation outputs. For example, if using an API, such as NASA POWER or an IMD solar dataset, will enable the creation of a more accurate annual solar radiation model by allowing for the temporal alignment of the datasets.

IV. The workflow presently collects the entire rooftop area; however, no distinction is made between usable and unusable areas (such as hydronic (water) tanks, HVAC equipment, parapet walls). Potential enhancements include the use of object detection models or instance segmentation methods to produce masks of rooftop obstructions so that a more accurate representation of the total area available for photovoltaic installation can be created.

V. Future studies could use the results of rooftop extraction to develop a three-dimensional (3D) city model, though, for example, use of ArcGIS CityEngine or a freely available platform, such as BlenderGIS. With the creation of a city model in three dimensions, seasonal shadow changes can be simulated and roof panel tilt optimization and mounting configurations can be performed, yielding near-engineering-grade layouts for photovoltaics.

This method uses deep learning and GIS-based Python analysis to quickly assess rooftop PV potential, showing how automation and AI can accelerate sustainable energy mapping in urban areas.

Optimizing Solar Energy Utilization Rooftop Detection and PV Potential Estimation with Deep Learning.docx

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