Machine Learning-Driven Solar Panel Site Selection and Rooftop Potential Estimation for Sustainable Development Goals

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Abstract: *Harnessing solar energy is a game-changer for sustainable development and alleviating poverty. Solar power not only combats climate change but also opens doors to economic opportunities and improves the quality of life in underserved areas. The installation of solar panels is essential for addressing global challenges such as poverty reduction and advancing Sustainable Development Goals. This work uses satellite and government data to map site suitability for solar panels, considering factors like Elevation, Wind speed, Surface temperature, Land use land cover, Normalized Differential Vegetation Index, Carbon Monoxide level, Solar irradiation, Population, Proximity to Residential areas, Water bodies, Power grids, and Roads. This study provides a comprehensive framework for evaluating solar panel site suitability, integrating environmental and infrastructural factors to optimize placement. Various machine learning models, like XGBoost, Random Forest Classifier, and Random Forest Regression, are trained and tested for the region of Rajasthan situated in India. The best model which is XGBoost resulted in an accuracy of 0.982, precision of 0.983, recall of 0.979, and F1 Score of 0.981 in training. Similarly, testing values were 0.934, 0.882, 0.985, and 0.931 for accuracy, precision, recall and F1 score respectively. The XGBoost model is selected to create a solar panel site suitability map. Using the pre-trained YOLOv8 model and Google Earth Pro images concrete roofs are detected. And then the rooftop images are clipped and processed to determine boundaries. Edge detection and contouring are used to calculate the rooftop area, estimating the number of solar panels and their potential power generation based on the available roof space. This study provides a clean and reliable energy solution that can reduce costs and improve life quality in underdeveloped and rural areas. By placing solar panels, the dependency on fossil fuels is decreased which helps in reducing greenhouse gas emissions and fostering environmental sustainability*

Keywords: Geospatial data, Image Processing, Machine learning, Solar Panel Site Suitability, Sustainable Development

Introduction

The installation of solar panels on the rooftops plays a pivotal role in tackling global challenges such as poverty reduction and advancing Sustainable Development Goal (SDG) of affordable and clean energy. As renewable energy sources gain prominence in mitigating climate change and promoting sustainable development, solar power stands out as a transformative solution with multifaceted benefits. Solar energy not only provides a clean and sustainable source of power but also contributes to energy security, economic development, and environmental conservation.

The objective of this study is to develop a comprehensive methodology for site suitability mapping of solar panels. This involves the integration of diverse data sources including satellite data and government datasets to assess various features such as elevation, wind speed, surface temperature, land cover, NDVI (Normalized Difference Vegetation Index), carbon monoxide levels, solar irradiation, population density, and proximity to residential areas, water bodies, power grids, and roads. By analyzing these factors, optimal locations for solar panel installations are identified that maximize efficiency and sustainability.

Machine learning techniques are employed to analyze the collected features and determine site suitability for solar panels. Regression models, such as the Random Forest Regressor, and classification models, including the XGBoost Classifier and Random Forest Classification, are trained to predict optimal locations. The best-performing model is then used to test a region and visualize a solar plant site suitability map. High-suitability areas are further analyzed for rooftop solar potential estimation.

The You Only Look Once (YOLO) family of models, known for real-time object detection, excels by predicting bounding boxes and class probabilities directly from full images in a single evaluation. YOLOv8, the latest in the series, incorporates cutting-edge features like advanced feature pyramids and self-attention mechanisms, further boosting precision and recall. These advancements make YOLOv8 highly effective for complex scenarios, including remote sensing and satellite imagery analysis. For rooftop solar potential, concrete roofs are detected using a pre-trained YOLOv8 model applied to Google Earth Pro images. Image processing techniques are then used to delineate rooftop boundaries and calculate the rooftop area through edge detection and contours. Based on the standard solar panel area, the number of panels that can be installed and the potential power generation are estimated.

Literature Review

This section highlights related works which use geospatial data for extracting various features for site suitability for placement of solar panels with the help of various techniques. It also talks about existing works related to estimation of rooftop solar potential.

Utilizing Geographic Information Systems (GIS) and the Multi-Influencing Factor (MIF) technique, site selection of solar photovoltaic power plants is done for Nashik, India (Rane et al., 2024). Key factors considered for this study include solar radiation, land use, topography, proximity to roads and power lines, and environmental impact. By assigning weights to these factors and performing a weighted overlay analysis, the study generates suitability maps that categorize the Nashik region into different levels of suitability for solar PV installation. The discovered solar PV farms were subjected to a Receiver Operating Characteristic (ROC) analysis to give a more comprehensive validation. The region Under Curve (AUC) value of 0.839 obtained from the projected site mapping indicates that the MIF technique used in the research region performed satisfactorily. This validation, along with ground truthing, comparison with existing installations, and sensitivity analysis, confirms the model's reliability.

The study (Kırcalı & Selim, 2021) evaluates the solar energy potential in Antalya Province, Turkey, with the aim of identifying suitable locations for solar farm establishment using a multi-criteria decision analysis (MCDA) framework, specifically the Analytical Hierarchy Process (AHP). The methodology involves a comprehensive literature review and expert consultations to establish three main criteria—solar parameters, logistical factors, and geographical considerations—along with ten sub criteria, including solar radiation, distance to substations, slope, and land use. Data sources include Landsat 8 satellite imagery, digital elevation models (DEM), and weather station records, which were processed in ArcGIS. The AHP was employed to assign weights to each criterion, allowing for a weighted linear combination of the sub criteria to produce a suitability index. The results reveal that approximately 484,795 hectares (24.02%) of the province are classified as suitable for solar farm development. This suitability map is intended as a critical resource for investors and decision-makers, guiding renewable energy initiatives and contributing to Turkey's energy independence and sustainability goals.

The spatial location choices of solar power plants in China are suggested with the help of machine learning techniques (Sun et al., 2023). A total of 21 factors like Land cover, slope, elevation, distance to water resources, surface annual mean air temperature, land cost, transportation convenience, distance to residential area and power grid, population density, electricity consumption, solarGHI, rooftop density is taken for analysis. Multi-Layer Perceptron (MLP), Random Forest (RF), and extreme gradient boosting (XGBoost) models were trained and validated. Subsequently, the suitability map was generated with five categories - very low, low, moderate, high, and very high. PV installation probability maps were generated with 1 km spatial resolution. RF model achieved higher AUC values (0.78) for the training and validation datasets among three ML models.

The work (Jiang et al., 2022) combines multi-resource satellite images and deep learning models to provide estimates of rooftop PV power generation. It applies a deep-learning based inversion model to estimate hourly solar radiation based on geostationary satellite images, and an automatic segmentation model to extract building footprint from high-resolution satellite images. Considering the data availability and practical requirements, Jiangsu Province, China is selected as the study area. Based on the deep network and hourly MTSAT-1R images, the spatial distribution, and temporal variations of GHI and DHI in 2018 are obtained. A five-class classification (extreme high, high, medium, low and extreme low) is done. And then based on the segmentation model and Gaofen-2/Beijing-2 satellite images, the building footprints, including locations and boundaries, are obtained at a spatial resolution of 1m. The available rooftop area is further reduced to the suitable area for solar panel installation. Furthermore, the net rooftop area for solar panel installation is estimated by counting installed solar panels in the cases where roof resources are fully utilized. Spatial overlay analysis, which multiplies the building density by the installation, correction, appropriateness, and capacity factors in that order, yields the rooftop PV technical potential.

Satellite imagery along with deep learning approaches have been used for object detection. Several Convolutional Neural Networks (CNN)-based architectures, including You Only Look Once (YOLO), Faster Region CNN (R-CNN), and Retina Net, have been proposed by researchers in recent years for object detection in satellite imagery (Li et al., 2022). The YOLO model can be used to detect roofs from Google Earth satellite images (Santos et al., 2023). The study extracted and annotated 500 ground truth images from different regions of the Philippines using the Computer Vision Annotation Tool (CVAT), resulting in a pre-processed and augmented dataset of 4,802 images. Using this custom dataset, the YOLOv4 model achieved superior performance in roof detection from Google Earth satellite images, with a mean average precision (mAP) of 92%. This outperformed other models like SSD MobileNet and Detectron 2 Faster R-CNN, which had mAP values of 83% and 79%, respectively. The results demonstrate YOLOv4's high accuracy and its potential for applications in urban planning. The performance of five popular deep learning object detection models - Detectron2, YOLOv5, YOLOv6, YOLOv7, and YOLOv8 has been studied (Adegun et al., 2023). Dataset of satellite images collected from the Google Earth Engine, containing diverse objects such as residences, roads, shorelines, swimming pools, and vegetation was augmented through techniques like flipping, rotating, and scaling to increase the diversity of the training data. The results show that YOLOv8 outperforms the other models, achieving the highest precision (68%), recall (60%), mAP50 (43%), and fastest detection speed (0.2 ms). Thus, YOLOv8 can be applied for object detection of roofs.

Methodology

The primary objective of this study is to identify suitable sites for installation of solar panels and perform roof-top solar potential estimation using a multi-faceted approach. The study is composed of 4 different modules - data collection and processing, model training, solar suitability mapping and roof-top solar potential estimation as shown in Figure 1.

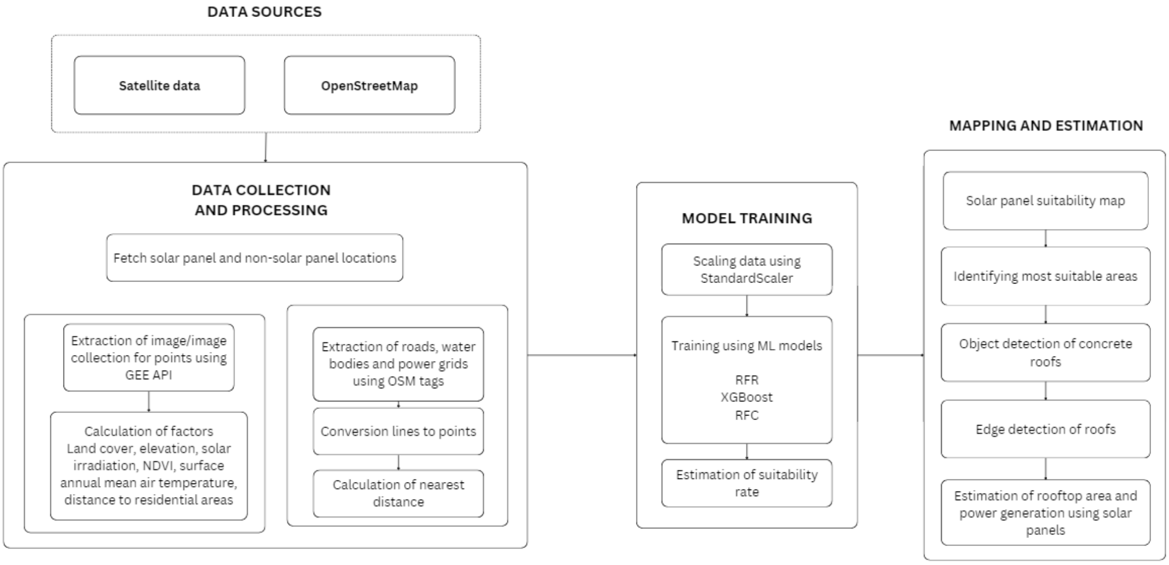


Figure 1: Architecture for site suitability for placement of solar panels and potential estimation

3.1. Data collection and processing:

To achieve the site suitability mapping of solar panels satellite data and OpenStreetMap data is used. Rajasthan, a state located in northwestern India, is chosen as the study area for solar potential due to its abundant sunshine, receiving an average solar insolation of 5.72 kWh/m² per day and approximately 325 sunny days annually. The state boasts vast arid and semi-arid regions, with over 200,000 square kilometers of land available for potential solar PV installations. This includes large tracts of unused and barren land, providing ample space for large-scale solar projects.

Using OpenStreetMap and QGIS, existing solar panel locations in Rajasthan, India are fetched. Non-solar panel locations are randomly sampled for the region. For each of these points, all the required features are collected. Google Earth Engine API is used to fetch the following features: elevation, wind speed, surface temperature, Land Cover Land Use, NDVI, CO, irradiation, population, and distance to residential areas. The image/image collections are fetched first after which band selection is performed to obtain the required feature. Table 1 shows the bands required to obtain the features from the satellite sources. For calculating NDVI, band composition is done with the help of equation given in Figure 2. QGIS and OpenStreetMap are used to fetch the distance from water bodies, power grids, and roads. Roads, water bodies and power grids are extracted for the Area Of Interest (AOI) and then these are converted to points which are used for distance calculation. For every point in the dataset, the nearest distance to each of these features is calculated. The dataset consists of 755 records out of which 355 are existing solar-panel locations and 400 are non-solar panel locations.

Table 1: Data Sources

Image/Image collection	**Bands**	**Feature**
FLDAS	Tair f tavg Wind f tavg	Surface temperature Wind Speed
Global Horizontal Irradiance	-	Irradiance
Sentinel 2	B4 (NIR), B8 (RED)	NDVI
NASA SRTM Digital Elevation 30m	elevation	Elevation
WorldPop Global Project Population Data	population	Population
Dynamic World V1	label	Land Use Land Cover (LULC)
GHSL: Global	built_characteristics	Distance to

settlement characteristics		residential areas
Sentinel 5P	CO_column_number_density	CO

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Figure 2: NDVI Equation

3.2. Model training

After all features are collected for both existing solar panel locations and random non-solar panel locations, scaling of data is done. Standard Scaler is used for this purpose. The dataset is split as 80-20 for training and testing, The model is now trained with the transformed dataset. Three different machine learning models are used. Random Forest Regressor, which is a versatile ensemble learning algorithm, XGBoost Classifier, which is an optimized distributed gradient boosting library designed for efficient and scalable training, and Random Forest Classification, which builds multiple decision trees and merges them to improve accuracy and avoid overfitting, are trained. To analyze the performance of regression models - RMSE and R2 score is calculated. Accuracy, precision, recall and F1 score is used to analyze performance of classification models. The best model is then chosen for testing a region and visualizing the solar plant site suitability map.

3.3. Solar suitability mapping

Among the trained models the best model is used to generate the solar plant site suitability map for the whole of Rajasthan, India. The first step involves loading the shape file of Rajasthan in QGIS. Now within the AOI points are sampled at 0.0003 degrees (~30m). The latitude and longitude are fetched for each of these points. Then, for every point all the required features are calculated which is fed to the trained model to estimate the suitability rate for every point. Finally, the estimated values are converted to a tiff file using mesh grid and interpolation. The suitability rates lie between 0 to 1, where 0 is least suitable and 1 is most suitable. Visualization is done for 5 ranges - not suitable, less suitable, moderately suitable, highly suitable, and most suitable. The parts of the region with greater suitability are then chosen for rooftop solar potential estimation.

3.4. Roof-top solar potential estimation

High-resolution satellite imagery from Google Earth Pro is used to build the dataset with top-view images of concrete roofs. After the dataset is built, image annotation is done with the help of LabelImg tool. The concrete roofs are annotated in the images. After annotation is done, the annotated dataset is used to customize the pre-trained YOLOv8 model. The model is trained for 100 epochs, and used for detecting the concrete roof tops. The results are filtered using a 0.5 confidence level. Then rooftop images of buildings are clipped and saved to a folder.

Image processing techniques are applied to fetch rooftop boundaries. Using edge detection and contours, the rooftop area is calculated. It begins by converting the input image to grayscale to simplify processing. Gaussian blur is then applied to reduce noise. Next, adaptive thresholding using OTSU thresholding is employed to segment the roof region effectively. Morphological operations further refine the segmentation to improve accuracy. Contours are then identified in the image, and the algorithm selects the contour with the largest area, representing the rooftop. The area is calculated and considered as the rooftop area. By dividing the rooftop area by the standard size of a 60-cell solar panel, the algorithm determines the number of solar panels that can be placed. Finally, the solar potential is computed in kwh/day by multiplying the power of a 60-cell solar panel by the number of panels to be placed, providing an estimation of the energy yield.

Results and Discussion

The findings for solar panel suitability mapping and rooftop potential estimation are detailed here. Features obtained are visualized for Rajasthan, India as shown in Figure 1. Figures 4(a), 4(b), 4(c), 4(d), 4(e), 4(f), 4(g), 4(h), and 4(i) visualize elevation, wind speed, surface temperature, CO, irradiation, NDVI, population, distance to water, and distance to residential areas, respectively. Other features include distance to roads and power grids.

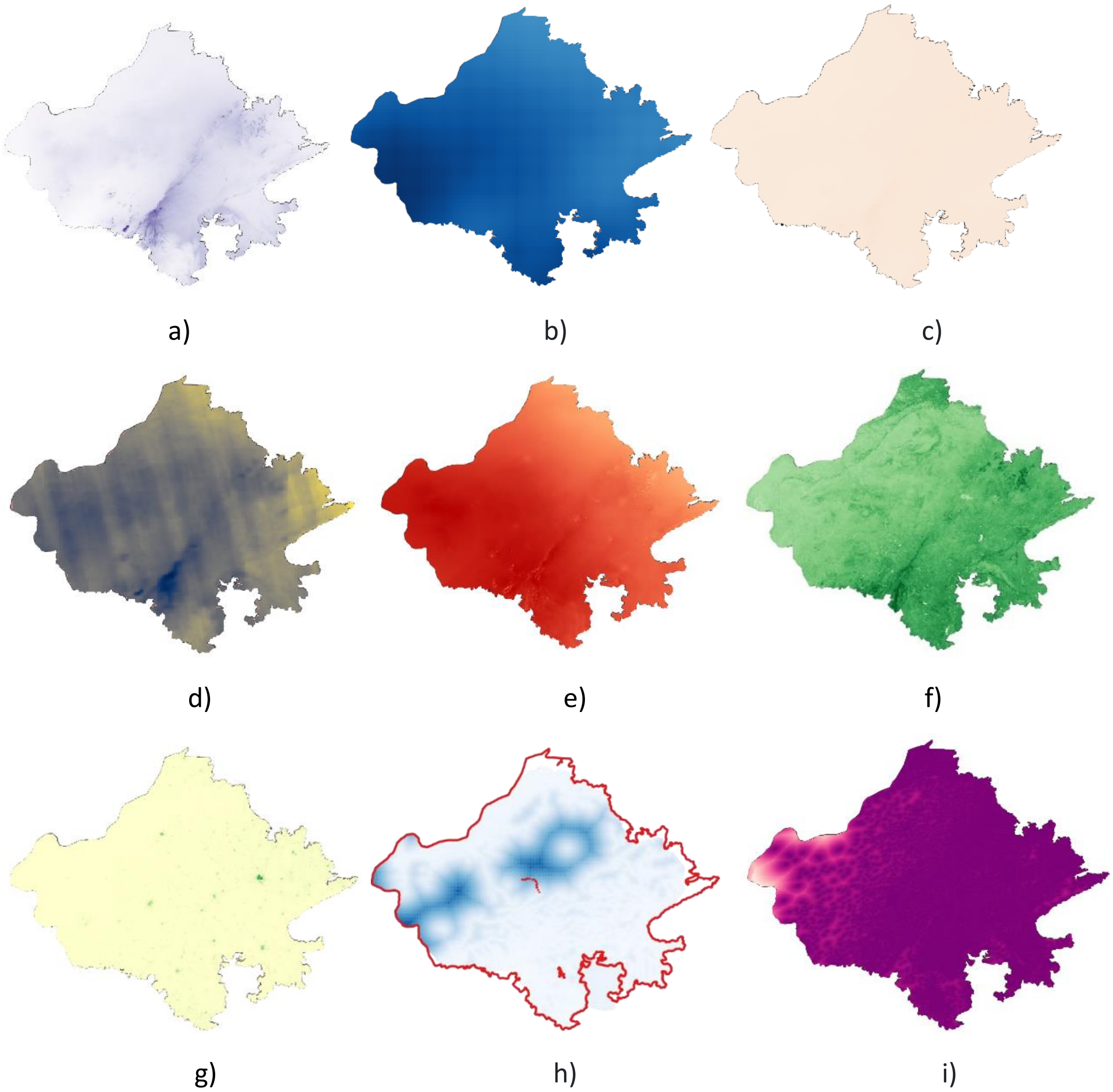


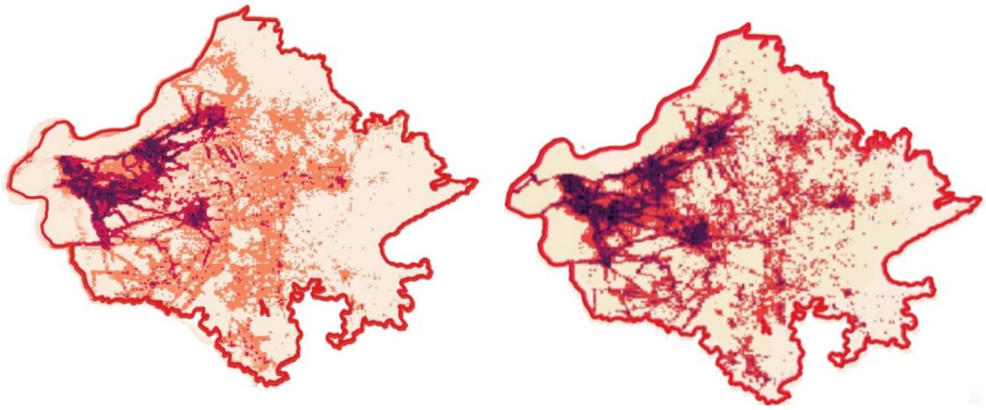
Figure 4: Rajasthan Features - Solar panel site suitability

The ML models - RFR (Figure 5(a)), XGBoost (Figure 5(b)), RFC (Figure 5(c)) are tested and the suitability map is generated as shown in Figure 5. The legend for these suitability maps is shown in Figure 5(d). The RMSE, R2 Score for RFR is tabulated in Table 2. These evaluation metrics are calculated as shown in Figure 6. The RMSE is calculated as shown in Figure 6(a) and the R2 score is calculated as given by the formula in the figure 6(b). The accuracy, precision, recall, and F1 scores for XGBoost and RFC models are tabulated in Table 3 using the formulas given in Figure 7. The best model which is XGBoost resulted in an accuracy of 0.982, precision of 0.983, recall of 0.979, and F1 score of 0.981 in training. Similarly testing values were 0.934, 0.882, 0.985, and 0.931 for accuracy, precision, recall and F1 score respectively.

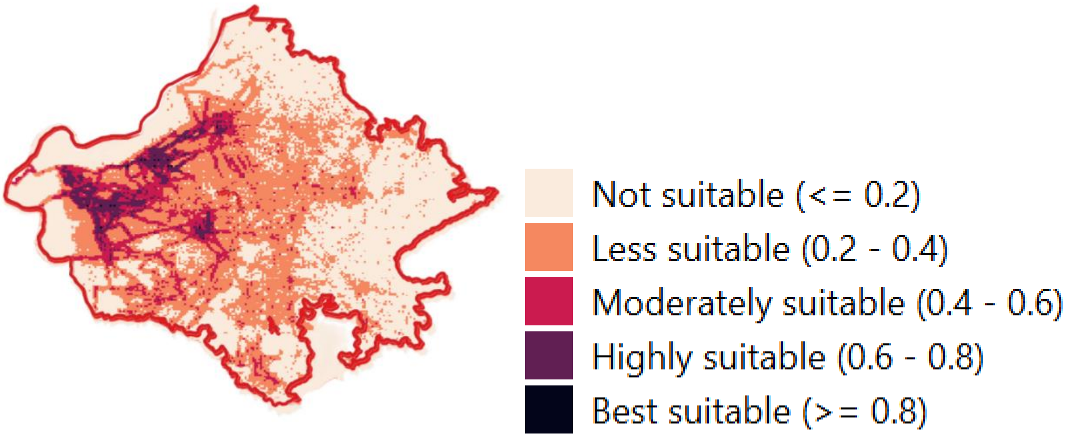
Various hyper-parameters were used for training the model. The ‘colsample bytree’ parameter value is 0.8 which gives the fraction of features(columns) to be randomly sampled for each tree. Other parameters used are- ’gamma,’ ’learning rate,’ ’max depth’, ’min child weight’, ’subsample’ and the values are 0, 0.1, 9, 3, 0.8 respectively.

These crucial hyperparameters are needed for tuning an XGBoost model's performance. Gamma controls how much new information each tree split contributes. Lower values lead to more conservative, complex trees, while higher values promote simpler models. Learning_rate hyperparameter shrinks the update to the model after each iteration, preventing overfitting. Smaller rates allow for more precise learning but require more training rounds. The hyperparameter max_depth restricts the maximum depth of each tree in the XGBoost ensemble. Shallower trees reduce overfitting but may miss complex patterns, while deeper trees can capture intricate details but risk overfitting. min_child_weight sets the minimum sum of weights required for a child node to be further split. Higher values prevent overfitting by avoiding overly specific branches based on few data points. subsample parameter regulates the portion of training data used to build each tree. Lower subsamples introduce randomness, reducing variance but potentially increasing bias. Higher values can lead to overfitting.

Fine-tuning these hyperparameters helps find the optimal balance between model complexity and generalizability. By adjusting them, an XGBoost model that captures the underlying patterns in the data effectively without memorizing specifics, leading to better performance on unseen data can be created.



a) b)



c) d)

Figure 5: Solar panel site suitability map for Rajasthan

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are predicted values
$y_1, y_2, \ldots, y_n$ are observed values
n is the number of observations

(a)

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2}$$

(b)

Figure 6: Regression Evaluvation Metrics-Formulas

Table 2: Regression Evaluvation Metrics-Solar panel site suitability

Model	Training RMSE	Training R2 score	Testing RMSE	Testing R2 Score
RFR	0.103	0.958	0.277	0.691

$$
\begin{aligned}
precision &= \frac{TP}{TP+FP} \\
recall &= \frac{TP}{TP+FN} \\
F1 &= \frac{2 \times precision \times recall}{precision + recall} \\
accuracy &= \frac{TP+TN}{TP+FN+TN+FP} \\
specificity &= \frac{TN}{TN+FP}
\end{aligned}
$$

Figure 7: Classification Evaluvation Metrics-Formulas

Table 3: Classification Evaluvation Metrics-Solar panel site suitability

Metric	XGBoost	RFC
Training Accuracy	0.982	0.952
Testing Accuracy	0.934	0.887
Training Precision	0.983	0.954
Testing Precision	0.882	0.859
Training Recall	0.881	0.944
Testing Recall	0.985	0.897
Training F1 Score	0.981	0.949
Testing F1 Score	0.931	0.869

$$
mAP = \frac{1}{k} \sum_{i}^{k} AP_i
$$

Figure 8: YOLOv8 Evaluvation Metrics-Formulas

Table 4: YOLOv8 Evaluvation Metrics-RoofType Classification

Metric	Precision	Recall	mAP50	mAP50-95
Concrete	0.972	0.82	0.972	0.668

The YOLOv8 model that captures the concrete roof from the aerial image gives a precision of 0.972, recall of 0.82, mAP50 of 0.972 and mAP50-95 of 0. 668.Precision and Recall are calculated using the Formulas given in Figure 7. Figure 8 gives the formula to calculate Mean Average Precision (MAP). mAP50 refers to the model's performance at an

Intersection Over Union (IoU) threshold of 0.5, whereas mAP50-95 averages the model's performance across IoU thresholds from 0.5 to 0.95 in steps of 0.05.

The best site for placing solar panels is taken from the top most suitable points predicted by the model. The aerial rooftop image is taken at 0.13 m/pixel from SAS Planet. This is the region Mawadiya Chowk, Pokaran in Rajasthan. The coordinates of the roof as shown in Figure 9(a) is 71.92144296729988, 26.912323715580104 and it receives 1596 (kWh/m^2/year) annual global insolation, and for solar panel of area 1 square meter it 239.4 kWh/m^2/year considering 15% efficiency and energy loss according to the Vedas Solar Calculator. The estimated rooftop area based on contour detection is 9269 pixels and 156.6461 square meters. Considering 1.66 square meters to be the area of 60-cell solar panels, 94 solar panels can be placed on this roof. If one solar panel can generate 1.5 kwh/day, the total solar potential of this roof is 141 kwh/day. On converting this to kwh/m^2/year the value obtained is 328.47 kWh/m²/year. After considering a 15% loss, the energy output would be 279.2 kWh/m²/year.it in a way that makes sense the first time around.

The roof shown in Figure 9(b) is another roof in the same area with coordinates 71.9221162231187, 26.912510280687034. This roof has an area of 8024 pixels and 135.6056 square meters. Eighty-two 60-cell solar panels can be placed and can generate 123 kwh/day which is 331.12 kWh/m²/year. After considering a 15% loss, the energy output would be 281.45 kWh/m²/year.

Area within the rooftop boundary in pixels: 9269.0

Area within the rooftop boundary in m2 approximately: 156.64610000000002

No.of Panels to be placed approximately: 94

Power generated(kwh/day) approximately: 141.0

a)

Area within the rooftop boundary in pixels: `8024.0`

Area within the rooftop boundary in m2 approximately: `135.6056`

No.of Panels to be placed approximately: `82`

Power generated(kwh/day) approximately: `123.0`

b)

Figure 9: Rooftop Area and Solar Power Potential Estimation

Conclusion and Recommendation

In conclusion, harnessing solar energy represents a transformative approach to achieving sustainable development goals and alleviating poverty. Solar power not only mitigates climate change but also unlocks economic opportunities and enhances quality of life, particularly in underserved regions. This study utilized satellite and government data to assess site suitability for solar panels, incorporating diverse factors such as elevation, wind speed, temperature, land use, vegetation index, carbon monoxide levels, solar irradiation, population density, and proximity to residential areas, water bodies, power grids, and roads.

Various machine learning models, including XGBoost and Random Forest, were trained and tested for suitability mapping in Rajasthan, India. The XGBoost model emerged as the optimal choice, achieving impressive training metrics with an accuracy of 0.982, precision of 0.983, recall of 0.979, and F1 score of 0.981. Testing results were also robust, with an accuracy of 0.934, precision of 0.882, recall of 0.985, and F1 score of 0.931.

Furthermore, the study employed the YOLOv8 model and Google Earth Pro images to detect concrete roofs, which were then analyzed to estimate rooftop areas suitable for solar panel installation. Edge detection and contouring techniques were applied to calculate potential power generation based on available roof space. This integrated approach offers a viable, clean energy solution that reduces costs and enhances quality of life in rural and underdeveloped areas.

By reducing reliance on fossil fuels, this initiative contributes significantly to greenhouse gas emissions reduction and fosters environmental sustainability. Thus, promoting solar energy deployment not only addresses global challenges but also paves the way for a more sustainable future. As a recommendation for the future work the calculation of rooftop area can be done using more advanced techniques to get the area more accurately. It is possible to make recommendations about where to put solar panels on the roof in relation to the tilt angle.

References

Adegun, A. A., Dombeu, J. V. F., Viriri, S., & Odindi, J. (2023). State-of-the-Art Deep Learning Methods for Objects Detection in Remote Sensing Satellite Images. Sensors, 23(13), 5849. https://doi.org/10.3390/s23135849

Jiang, H., Yao, L., Lu, N., Qin, J., Liu, T., Liu, Y., & Zhou, C. (2022). Geospatial assessment of rooftop solar photovoltaic potential using multi-source remote sensing data. Energy and AI, 10, 100185. https://doi.org/10.1016/j.egyai.2022.100185

Kırcalı, U., & Selim, S. (2021). Site suitability analysis for solar farms using the geographic information system and multi-criteria decision analysis: the case of Antalya, Turkey. Clean Technologies and Environmental Policy, 23(4), 1233–1250. https://doi.org/10.1007/s10098-020-02018-3

Li, Z., Wang, Y., Zhang, N., Zhang, Y., Zhao, Z., Xu, D., Ben, G., & Gao, Y. (2022). Deep Learning-Based Object Detection Techniques for Remote Sensing Images: A Survey. Remote Sensing, 14(10), 2385.https://doi.org/10.3390/rs14102385

Hassaan, M. A., Hassan, A., & Al-Dashti, H. (2021). GIS-based suitability analysis for siting solar power plants in Kuwait. The Egyptian Journal of Remote Sensing and Space Science, 24(3), 453-461. https://doi.org/10.1016/j.ejrs.2020.11.004

Rane, N. L., Günen, M. A., Mallick, S. K., Rane, J., Pande, C. B., Giduturi, M., Bhutto, J. K., Yadav, K. K., Tolche, A. D., & Alreshidi, M. A. (2024). GIS-based multi-influencing factor (MIF) application for optimal site selection of solar photovoltaic power plant in Nashik, India. Environmental Sciences Europe, 36(1). https://doi.org/10.1186/s12302-023-00832-2. https://doi.org/10.1186/s12302-023-00832-2

Santos, C. L. B., Medina, R. P., & Taylar, J. V. (2023). Computer Vision-Based Roof Detection using YOLOv4. https://doi.org/10.1109/icicyta60173.2023.10428714

Sun, Y., Zhu, D., Li, Y., Wang, R., & Ma, R. (2023). Spatial modelling the location choice of large-scale solar photovoltaic power plants: Application of interpretable machine learning techniques and the national inventory. Energy Conversion and Management, 289, 117198. https://doi.org/10.1016/j.enconman.2023.117198