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Satellite Image-Based Rooftop Solar Assessment Using CV and Geospatial Analysis

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Abstract: The Solar Roof Measurement and Energy Estimation System analyzes satellite photos of roofs. The premium version uses A.I. to determine if a roof is suitable for solar panels and calculates its area. The system has a FastAPI backend and a React frontend. This setup makes it easy to process information and interact with users. There are no expensive commercial applications in the algorithm pipeline for the Solar Roof Measurement and Energy Estimation System. Instead, it relies on free and openly available technology to create solar estimates. It uses Nominatim geocoding, Leaflet maps, OpenCV, and pvlib. The system measures the roof's size and pitch, and calculates its orientation and solar energy potential. With resources like Google Earth imagery and Google Maps, it provides a scalable and easily accessible way to plan renewable energy. It gives homeowners, businesses, and solar providers a fast, simple method to check if their roof is suitable for solar panels. The Solar Roof Measurement and Energy Estimation System includes image analysis, map, or direction search. The Solar Roof Measurement and Energy Estimation System is particularly helpful for users of energy that is efficient, sustainable, and environmentally friendly. This product quickly and affordably analyzes roofs, estimates energy, and aids in developing smart energy solutions.
Keyword: Solar PV, Rooftop Segmentation, YOLOv8, OpenCV, FastAPI, Energy Estimation, K-means Clustering, Roof Tilt.

I. INTRODUCTION

Solar energy has become one of the most important renewable energy sources due to the increasing demand for clean and sustainable power generation. Rapid urbanization, environmental pollution, and the depletion of non-renewable energy resources have encouraged researchers and industries to adopt solar photovoltaic systems for electricity production. Rooftop solar panel installation is widely preferred because it utilizes unused rooftop space and reduces dependency on conventional energy sources. This greatly reduces the amount of data needed, speeds up the training process, and still gives reliable results. Before installing solar panels, accurate rooftop analysis is essential to determine roof area, roof orientation, tilt angle, shadow effects, and solar energy generation capability. Traditional rooftop survey methods involve manual measurements, physical inspections, and expensive surveying equipment. These methods are time-consuming, costly, and difficult to implement on a large scale. Recent advancements in computer vision, image processing, and machine learning technologies have enabled automated rooftop analysis using satellite imagery. Open-source technologies such as OpenCV, FastAPI, ReactJS, and pvlib provide efficient tools for detecting rooftop boundaries, estimating rooftop dimensions, and calculating solar irradiance. These technologies reduce the need for expensive commercial APIs and manual surveys. The proposed Solar Roof Measurement and Energy Estimation System is designed to automate rooftop analysis using satellite images and computer vision techniques. The system captures rooftop images through map interfaces, processes them using OpenCV algorithms, and estimates roof dimensions, roof orientation, and yearly solar energy generation. A FastAPI backend and ReactJS frontend provide a scalable and user-friendly web platform for solar analysis. The main objective of this project is to develop a low-cost, open-source, and efficient rooftop solar estimation system that promotes renewable energy adoption and supports sustainable development.

A. Need for Personalized Rooftop Analysis Systems

The traditional method to estimate the capacity of rooftops for solar energy usage in buildings is based on the same solar energy calculation formula for all buildings, regardless of the variation in structure, orientation, shadow conditions, rooftop material and geographical location of individual houses. But, in the real world, every building roof will differ in size, roof slope, and shading, as well as nearby obstructions and energy needs. Due to this, the requirement of a personalized Solar roof analysis system is growing which can give each user and building a personalized answer. The use of rooftop specific parameters like usable area, shadow fraction, roof orientation, tilt angle and environmental conditions increases the accuracy of solar potential estimation in a personalized system. To identify the rooftop structure accurately from satellite images, the proposed system uses the advanced computer vision technique such as OCV-based analysis, contour extraction, GrabCut segmentation and K-means clustering. This allows the system to give recommendations specifically related to the building, including how many solar panels should be installed, how much energy the building can produce each year, how much the installation costs, how much the subsidy will cost, and the length of time it will take to pay for the installation with money saved.

Another significant personalizing argument is the different personal energy demand of the various users. The power used in residential, commercial and industrial buildings is used differently. An AI-based system can work out the size of the PV system needed in a bespoke fashion in relation to the energy demand and roof space of the user. This affects the proper and effective use of solar energy systems not to overutilize or overload systems. Additionally, the surrounding landscaping elements like trees, adjacent structures and roof-top obstructions tend to cast a shadow directly on the performance of solar panels. Generic estimation systems are unable to accurately handle these variations. Shadow analysis and orientation detection is performed on the spot through a personalized system to identify the effective rooftop area to be used. Thus, the proposed customized system can improve the accuracy, reliability and decision making of solar rooftop installation.

B. Personalized Solar Roof Analysis System

A key advantage of a custom solar roof analysis system is that it offers a personal solution to the problem of renewable energy and is accurate, efficient and user-specific. The current mode of estimation is mostly manual and generalizing approach which leads to inaccurate estimation of the solar capacity. Personalized systems are founded on artificial intelligence, computer vision and geospatial analysis and extend that to provide personalised solutions for each building. One of the primary benefits of personalization is better energy optimization. The system optimizes the placement of panels and energy generation depending on the roof's orientation and slope, so that they are best exposed to the sun to generate as much energy as possible. This results in an improvement of the overall performance ratio of PV systems and in an improvement of energy savings for the user.

Another important factor linked to personalized systems is the economic analysis. The proposed model calculates the installation cost, size of the subsidy, annual electricity savings and payback time for the project, depending on the dimensions of the roof and the size of the system. The tailored financial estimates help residents and enterprises decide on their solar energy choices. Scalability and automation are another interesting application that is valuable to customized systems. Manual rooftop surveys are time consuming, labour intensive and require a high degree of skill. The satellite images and machine learning algorithms streamline the rooftop detection and solar analysis, eliminating manual effort and saving processing time and costs. This makes large-scale testing of solar resources for smart city projects and government renewable energy projects sound investments.

C. Growing Demand for Intelligent Solar Assessment Systems

The demand for intelligent solar assessment systems has been further propelled by urbanization and increasing demand of electricity. There are many residential and commercial buildings that need a way to assess rooftop solar energy potential and the limitations of using the traditional manual method (slow, expensive and inaccurate) are becoming more of a concern. This has led to the use of automated, AI-driven rooftop analysis systems becoming a key component of the smart energy infrastructure today.

D. Need for an Integrated AI-Based System

The proposed integrated AI system integrates computer vision, machine learning, geospatial analysis, and financial modelling into a single platform. Rooftop segmentation and contour extraction is done using image processing techniques in OpenCV, and using K-means and Grabcut algorithms, the boundaries of the rooftop are estimated as accurately as possible. By combining these techniques, it is possible to determine areas of the roof surface suitable for use, directly from the satellite image.

II. LITERATURE SURVEY

A. Extracting Roof Polygons And Vectorized Data Roof Segmentation And Vectorization

The extraction of roof outlines from images using computer vision has been done for a long time, by following some conventional techniques like edge detection and GrabCut. Since then, deep learning has prevailed and convolutional networks such as U-Net have provided pixel-level accuracy for roof masking. Andrieux et al., for instance, used U-Net to distinguish roof slopes from ridges in aerial imagery. In addition, the advancement of object detection has also been significant in this area, with the introduction of real-time inference by YOLOv8 by Ultralytics for instance segmentation. When it comes to the accuracy of different roof shapes detection using YOLOv8, Ahmed et al. achieved 93.6%.

B. Shadow Analysis

The roof's area limited by shadows decreases the potential surface of solar panels. Some solutions to this are physics-based 3D simulation and image-based detection methods. Zeng et al., used morphological filtering and K-means clustering based on the intensity of the pixels to separate the shadowed pixels on rooftops. This approach is similar to clustering, but makes use of any available shade geometry with labels for generating shadow masks when no labels are available.

C. PV Modelling

The conversion of rooftop area to energy production is based on the common PV equations. A PVLib library, which is open-source software, and energy APIs such as OpenWeather are usually employed for these purposes. A pipeline has been created by Egbe et al to go from a roof mask to kilowatt-hour and capacity estimates. The same formulation is followed here, in the form $E = A \times I \times \eta \times PR$ the critical equations and assumptions that were applied in this work.

D. Deployment and APIs

Machine learning models are deployed using modern frameworks like FastAPI for scalability. Bautista et al. created a YOLO solar panel detector to serve via FastAPI. It is a similar approach that is also used here, with JWT authentication, which allows for both cloud and local deployments, providing built-in documentation. The React frontend uses Vite and Tailwind to communicate with these endpoints using Axis and to display the results as overlays on a static png, as well as in data tables.

III.METHODOLOGY

The proposed Solar Roof Measurement and Energy Estimation System is designed to automate rooftop analysis using Artificial Intelligence, Computer Vision, Machine Learning, and Photovoltaic (PV) energy modelling techniques. The system processes rooftop satellite images to identify rooftop boundaries, calculate rooftop area, estimate usable rooftop space, detect shadow regions, determine rooftop orientation and tilt angle, and estimate annual solar energy generation along with financial feasibility. The overall methodology integrates rooftop segmentation, geometric analysis, shadow analysis, energy estimation, and web-based deployment into a unified framework. The proposed methodology is divided into four major stages: dataset generation and rooftop parameter extraction, rooftop segmentation and polygon computation, shadow and orientation analysis, and photovoltaic energy and economic calculations. The complete system is deployed using a FastAPI backend and React frontend for scalable and interactive rooftop analysis.

The proposed methodology shown in Fig. 1 illustrates the complete workflow of the Solar Roof Measurement and Energy Estimation System. The system begins with rooftop image acquisition using satellite imagery and performs rooftop segmentation, shadow analysis, orientation estimation, photovoltaic energy calculation, and economic analysis to generate the final solar assessment results.

A. Dataset Description

The proposed system generates a CSV dataset containing rooftop analysis results for each building processed by the system. The dataset stores geometric, photovoltaic, environmental, and financial parameters related to rooftop solar analysis. These parameters are generated automatically using image processing and energy estimation algorithms. The geometric parameters include rooftop polygon coordinates, total rooftop area, and usable rooftop area. Rooftop polygon coordinates are extracted from rooftop boundaries detected in satellite images. The total rooftop area is calculated using the Shoelace Formula after converting image pixels into real-world dimensions through Ground Sample Distance (GSD) calculations.

The usable rooftop area is estimated using the following equation:

$$\text{usable\_area}_{m2} = \text{total\_area}_{m2} \times (1 - \text{shadow\_fraction})$$

where usable_area_{m2} represents the rooftop area available for solar panel installation, total_area_{m2} denotes the complete rooftop area, and shadow_fraction represents the percentage of rooftop area affected by shadows. This calculation helps determine the effective rooftop space suitable for photovoltaic panel placement.

The photovoltaic system parameters include the estimated number of solar panels and photovoltaic system capacity. The photovoltaic system capacity is estimated using:

$$\text{system\_capacitykWp} = \text{panels\_count} \times \text{Wp} / 1000$$

where system_capacitykWp represents the installed photovoltaic system capacity in kilowatt-peak, panels_count denotes the total number of solar panels, and Wp represents the watt-peak rating of each solar panel. This calculation estimates the total electricity generation capacity that can be installed on the rooftop surface. The rooftop orientation and tilt parameters are also included in the generated dataset. Roof orientation refers to the azimuth direction of the rooftop relative to geographic north, while roof tilt represents the inclination angle of the rooftop surface. These parameters are estimated using Principal Component Analysis (PCA) and Hough Transform-based geometric analysis techniques.

The annual solar energy generation is estimated using:

$$annual\_energy_{kWh} = system\_capacity_{kWp} \times H_{annual} \times PR$$

where $annual\_energy_{kWh}$ represents yearly photovoltaic energy generation, H_{annual} denotes annual solar irradiance, and PR represents the performance ratio of the photovoltaic system. The performance ratio accounts for practical energy losses caused by shading, inverter losses, temperature variation, and dust accumulation. The dataset also includes financial parameters such as gross installation cost, subsidy amount, net installation cost, annual electricity savings, and payback period. Environmental parameters such as carbon dioxide (CO_2) reduction and tree-equivalent environmental savings are also calculated using standard environmental conversion factors. The primary uncertainties in the proposed system arise from rooftop segmentation accuracy, Ground Sample Distance estimation, and meteorological data variation. Rooftop area uncertainty is mainly affected by segmentation accuracy and pixel-scale conversion errors, while energy estimation uncertainty is influenced by variations in weather conditions and irradiance data.

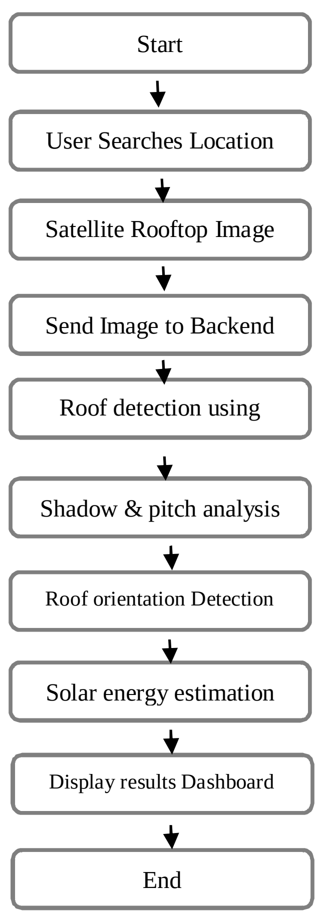

Fig. 1. Flowchart of Solar Roof Measurement for Energy Estimation

B. Rooftop Segmentation and Polygon Computation

Rooftop segmentation is one of the most important stages in the proposed system because accurate rooftop boundary extraction directly affects photovoltaic area estimation and energy calculations. The proposed methodology uses a hybrid segmentation approach based on YOLOv8 instance segmentation and OpenCV contour-based rooftop detection. YOLOv8 is a deep learning-based object detection and segmentation model capable of performing real-time rooftop segmentation with high accuracy. The preprocessing stage resizes and normalizes the rooftop image before passing it to the segmentation model. The YOLOv8 model generates a rooftop segmentation mask identifying rooftop regions in the satellite image. Morphological filtering and noise removal operations are then applied during postprocessing to improve segmentation quality and remove unwanted image artifacts.

The rooftop polygon is extracted using OpenCV contour detection functions such as cv2.findContours() and polygon approximation techniques such as approxPolyDP(). These methods convert rooftop masks into polygon coordinates suitable for rooftop area calculation. The rooftop polygon area is calculated using the Shoelace Formula and converted into square meters using the following equation:

$$Area_{m2}=Area_{pixels} \times (meters\_per\_pixel)^2$$

where $Area_{pixels}$ represents rooftop area measured in image pixels and *meters_per_pixel* represents the Ground Sample Distance conversion factor. The default Ground Sample Distance value used in the system is approximately 0.075 meters per pixel. If the YOLOv8 segmentation model is unavailable or produces low-confidence results, the system switches to an OpenCV-based fallback method. In this method, the rooftop image is converted into grayscale and processed using Gaussian blur filtering to reduce image noise. Thresholding and Canny edge detection are then applied to identify rooftop boundaries. Contour detection algorithms identify rooftop regions from the processed image. Geometric filtering is applied to remove invalid contours based on rooftop shape and area constraints. Finally, polygon smoothing techniques are used to generate rooftop polygon coordinates suitable for rooftop area estimation. The OpenCV-based segmentation method is computationally efficient and suitable for simple rooftop structures, although its accuracy is generally lower than deep learning-based segmentation for complex rooftops.

C. Shadow Analysis and Rooftop Orientation Estimation

Shadow analysis is an important component of rooftop solar assessment because shadows significantly reduce photovoltaic energy generation efficiency. Nearby buildings, trees, rooftop water tanks, and environmental obstructions can cast shadows on rooftop surfaces, reducing the usable area available for solar panel installation. The proposed system performs shadow detection using K-means clustering and image segmentation techniques. K-means clustering is an unsupervised machine learning algorithm used to group image pixels based on color similarity and intensity values. Rooftop image patches are converted into HSV color space for improved shadow separation. The rooftop image pixels are grouped into two clusters representing shadow and non-shadow regions. The ratio of shadow pixels to total rooftop pixels is calculated as the shadow fraction. Morphological filtering operations are applied to remove segmentation noise and improve shadow mask quality. The proposed system also estimates rooftop orientation and rooftop tilt angle using geometric analysis techniques. Principal Component Analysis (PCA) is applied to rooftop polygon vertices to determine the principal orientation axis of the rooftop. PCA is a statistical dimensionality reduction technique that identifies dominant directional patterns in rooftop geometry.

The rooftop azimuth angle is estimated using:

$$\gamma=\tan{-1}((y2-y1) / (x2-x1))$$

where γ represents the rooftop orientation angle relative to geographic north. Roof pitch estimation is performed using Hough Transform-based line detection techniques that identify rooftop edges and slope patterns from satellite images. Confidence scores for rooftop orientation and tilt estimation are calculated based on PCA variance ratios and consistency of Hough line detection results.

D. Photovoltaic Energy Estimation and System Architecture

The proposed system estimates photovoltaic energy generation using rooftop geometry, environmental conditions, and photovoltaic performance parameters. The usable rooftop area obtained after shadow analysis is used to estimate photovoltaic system capacity. The photovoltaic system capacity is calculated using:

$$system\_capacity_{kWp} = usable\_area_{m2} \times \eta_{mod}$$

where $usable\_area_{m2}$ represents the effective rooftop area available for solar panel installation and η_{mod} denotes photovoltaic module efficiency. Annual solar irradiance values are retrieved using location coordinates through weather APIs and environmental databases. For tilted rooftops, the effective solar irradiance is estimated using:

$$H_{tilted} = H_{horizontal} \times [\cos(\gamma - 180^\circ)\cos(\beta) + \sin(\gamma - 180^\circ)\sin(\beta)]$$

where H_{tilted} represents effective solar irradiance received by the rooftop, γ denotes rooftop azimuth angle, and β represents rooftop tilt angle.

The annual photovoltaic energy generation is calculated using:

$$E_{annual} = system\_capacity_{kWp} \times H_{tilted} \times PR$$

where PR represents the photovoltaic system performance ratio, typically assumed to be approximately 0.75. The proposed system also performs economic feasibility analysis by estimating installation cost, subsidy amount, annual electricity savings, and payback period. Annual savings are calculated using:

$$annual\_savings_{inr} = tariff \times E_{annual}$$

where tariff represents the local electricity tariff rate and E_{annual} represents yearly energy generation.

The entire system is implemented using a FastAPI backend and React-based frontend architecture. The backend modules perform rooftop segmentation, energy calculations, shadow analysis, database management, and report generation. The frontend provides image upload functionality, rooftop analysis visualization, interactive charts, and result presentation. The system uses JWT authentication for secure user access and API communication. Key API endpoints are responsible for image upload, rooftop segmentation, rooftop analysis, and photovoltaic energy calculations. The generated results are stored in CSV format and displayed through an interactive web-based dashboard for user-friendly rooftop solar assessment.

IV. MODELLING AND ANALYSIS

The modelling and analysis stage focuses on extracting meaningful rooftop parameters and analyzing rooftop solar suitability using machine learning techniques. After rooftop segmentation and energy estimation, multiple geometric, environmental, performance, and financial features are generated from the processed rooftop dataset. These features are further normalized and analyzed using clustering algorithms to identify rooftop categories with similar solar generation characteristics. The proposed modelling framework helps improve rooftop classification, solar suitability assessment, and infrastructure planning for large-scale renewable energy applications.

A. Feature Engineering

Feature engineering is one of the most important stages in machine learning and data analysis because the quality of extracted features directly affects the performance of predictive and clustering models. In the proposed system, multiple rooftop-related features are generated using geometric analysis, photovoltaic energy estimation, and financial modelling techniques. These features help represent rooftop characteristics numerically for further clustering and solar suitability analysis.

The generated features are categorized into geometric, performance, and financial parameters. Geometric parameters describe rooftop structure and environmental conditions, while performance features represent photovoltaic energy generation capability. Financial features estimate economic feasibility and investment recovery for rooftop solar installations.

Based on each roof top record several features are generated for the purpose of predictive analysis and clustering:

$$orientation\_factor = \cos(\theta)$$
$$tilt\_factor = \cos(\beta)$$

The orientation factor and tilt factor are used to estimate the effectiveness of rooftop alignment with respect to solar radiation. The parameter θ represents the deviation of rooftop orientation from the optimal south-facing direction, while β represents the rooftop tilt angle. Rooftops with favourable orientation and tilt angles receive higher solar irradiance and produce better photovoltaic energy output. The extracted dataset also contains photovoltaic performance parameters such as annual energy generation and installed system capacity. Financial parameters including net installation cost and payback period are generated to evaluate the economic feasibility of rooftop solar deployment.

Before clustering analysis, numerical features are normalized to ensure equal contribution of all parameters during machine learning analysis. Categorical rooftop parameters such as rooftop orientation labels are converted into numerical form using one-hot encoding techniques. Logarithmic transformation is applied to skewed variables such as rooftop area to improve data distribution consistency and clustering stability. Missing values in the dataset are replaced using median-based imputation techniques to improve robustness of the analysis process.

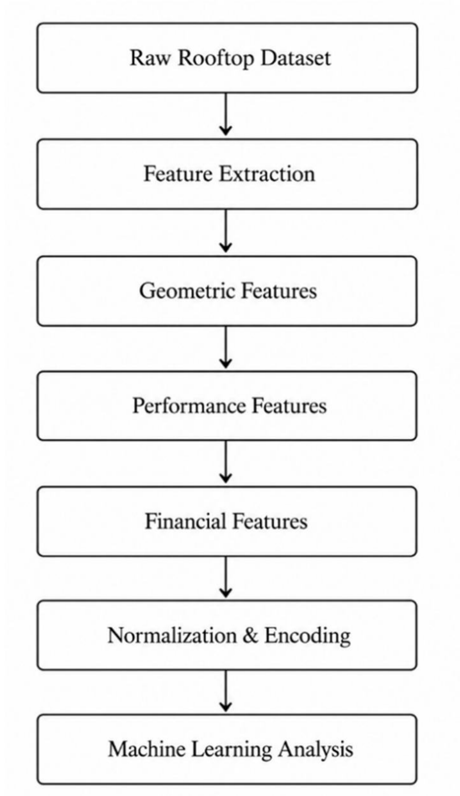

Fig. 2. Feature Engineering Pipeline for Rooftop Analysis

B. K-Means Clustering

K-Means clustering is an unsupervised machine learning algorithm used to group rooftops with similar solar generation characteristics into separate categories. Clustering helps identify rooftop patterns based on rooftop area, shadow conditions, photovoltaic energy generation, and economic feasibility. The proposed system uses K-Means clustering to classify rooftops into different solar suitability groups for infrastructure planning, renewable energy assessment, and decision-making.

Before clustering, all extracted rooftop features are normalized so that each parameter contributes equally during the clustering process. Feature normalization prevents parameters with large numerical ranges from dominating the clustering results and improves overall clustering stability. Categorical rooftop parameters are converted into numerical form using encoding techniques, while skewed numerical features are transformed using logarithmic scaling to improve data distribution consistency.

The K-Means clustering algorithm minimizes the within-cluster variance by reducing the distance between rooftop feature vectors and their corresponding cluster centroids. The optimization function used in the clustering process is given as:

$$J = \sum_{k=1}^{k} \sum_{i \in S_k} ||xi - \mu_k||^2$$

where xi represents the data points belonging to cluster iii, while μ_k denotes the centroid of the corresponding cluster. The optimization process groups rooftops with similar solar generation behaviour into the same cluster by minimizing the distance between rooftop feature vectors and cluster centroids.

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The optimal number of clusters is determined using the Elbow Method, which evaluates clustering inertia for different values of k, such as k=2,3,4,5 and 6. The Elbow Method identifies the point at which increasing the number of clusters no longer significantly reduces clustering variance. Experimental analysis indicated that k=3 provides the best balance between cluster compactness and cluster separation.

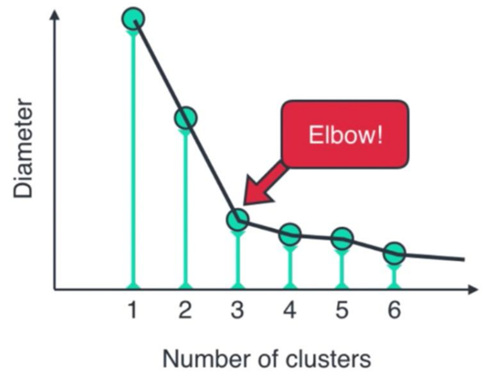

Fig. 3. Elbow Method for Optimal Cluster Selection

The quality of clustering is further evaluated using the Silhouette Coefficient, which measures the similarity of data points within the same cluster compared to neighbouring clusters. The Silhouette Coefficient is calculated as:

$$S = (b - a) / \max(a, b)$$

where a represents the mean intra-cluster distance and b represents the mean distance between a data point and the nearest neighbouring cluster. Higher silhouette coefficient values indicate better cluster separation and clustering compactness.

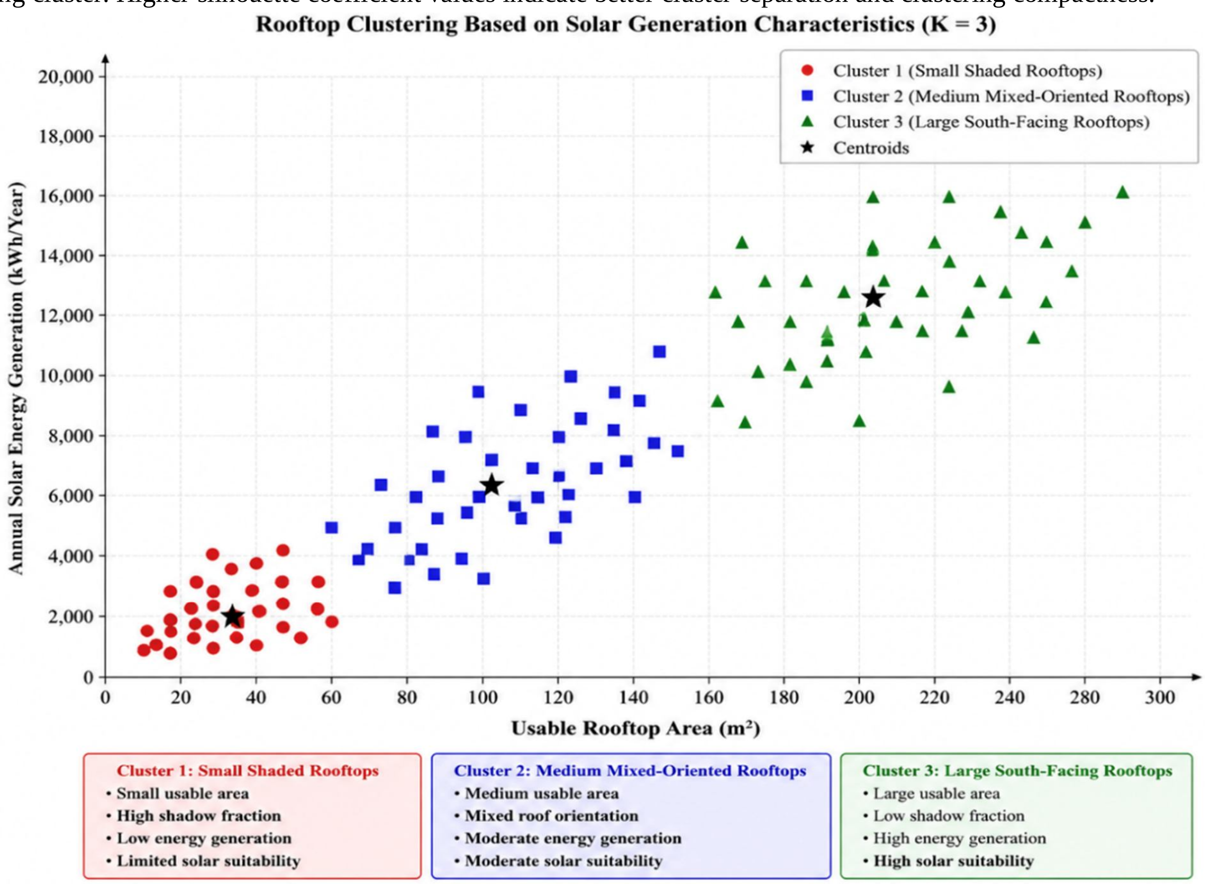

Fig. 4. Rooftop Clustering Based on Solar Generation Characteristics

Experimental results produced an approximate silhouette score of S≈0.52 indicating satisfactory clustering performance for rooftop categorization. Based on clustering analysis, three major rooftop categories were identified. The first cluster contains small shaded rooftops with lower photovoltaic energy generation capability. The second cluster consists of medium-capacity rooftops with mixed rooftop orientations and moderate solar performance. The third cluster represents large south-facing rooftops with high solar generation potential and improved economic feasibility. These rooftop categories are useful for smart city planning, renewable energy infrastructure management, and policy-level solar deployment strategies.

Additional clustering evaluation metrics such as the Davies–Bouldin Index and Calinski–Harabasz Score are also used to validate cluster separation quality and clustering compactness. These metrics further confirm the effectiveness of the proposed clustering model in identifying rooftop categories with similar solar generation characteristics.

V. RESULTS AND DISCUSSION

The proposed Solar Roof Measurement and Energy Estimation System was evaluated using rooftop satellite imagery and machine learning-based rooftop analysis techniques. The experiments focused on evaluating rooftop segmentation accuracy, shadow analysis performance, photovoltaic energy estimation, and clustering effectiveness. The proposed system integrates rooftop detection, solar energy prediction, and financial analysis into a unified AI-based framework for automated rooftop solar assessment. The experimental analysis demonstrates that the proposed methodology provides accurate rooftop segmentation, realistic photovoltaic energy estimation, and effective rooftop clustering for solar suitability analysis. The generated results also validate the effectiveness of integrating Computer Vision, Machine Learning, and photovoltaic modelling techniques for large-scale rooftop solar analysis.

A. Experimental Setup and Results

The available rooftop dataset containing approximately N≈500 rooftop samples was divided into training, validation, and testing subsets using a ratio of 60%, 20%, and 20%, respectively. Data augmentation techniques such as image rotation and horizontal flipping were applied to improve segmentation model generalization and reduce overfitting during training.

The YOLOv8 segmentation model was fine-tuned using rooftop satellite imagery for rooftop boundary detection and segmentation tasks. Training and inference experiments were performed on a GPU-based computing server equipped with an NVIDIA RTX 3090 graphics processing unit. The proposed system also used K-Means clustering with k=3 to classify rooftops according to solar generation characteristics and rooftop suitability.

Parameter	**Value**
YOLOv8 Input Size	640 × 640 px
Batch Size	8
Learning Rate	0.001
Epochs	50
K-Means Clusters (k)	3
Normalization Method	Min-Max Scaling
Performance Ratio (PR)	0.75

Table I. Experimental Parameters Used in the Proposed System

The segmentation experiments demonstrated satisfactory rooftop boundary detection accuracy for both deep learning-based and OpenCV-based rooftop extraction methods. The YOLOv8 segmentation model achieved improved rooftop segmentation performance for complex rooftop geometries, while OpenCV contour-based methods provided computationally efficient rooftop extraction for simple rooftop structures.

The rooftop clustering analysis successfully categorized rooftops into three major groups based on rooftop area, photovoltaic energy generation capability, shadow conditions, and rooftop orientation characteristics. The clustering results showed that large south-facing rooftops generated higher annual photovoltaic energy and exhibited better economic feasibility compared to smaller shadowed rooftops.

The photovoltaic energy estimation model produced realistic annual energy generation predictions based on rooftop geometry, solar irradiance, roof orientation, tilt angle, and shadow fraction. Financial analysis results indicated that the estimated payback period for most residential photovoltaic systems falls within the practical industrial range of approximately 5–10 years under standard tariff and subsidy conditions. The generated CSV output files contained rooftop geometry, photovoltaic system capacity, annual energy generation, carbon dioxide (CO_2) savings, installation cost, annual savings, and payback period for each rooftop analyzed by the proposed system.

B. Discussion

The proposed integrated AI-based system successfully automated the complete workflow from rooftop image acquisition to photovoltaic energy and economic estimation. The experimental results demonstrate that the integration of Computer Vision, Machine Learning, and photovoltaic energy modelling techniques provides accurate and scalable rooftop solar analysis. The relatively high rooftop segmentation accuracy confirms the effectiveness of both YOLOv8 segmentation and OpenCV-based contour extraction techniques in detecting rooftop boundaries from satellite images. Deep learning-based segmentation methods performed better for complex rooftop geometries, while OpenCV methods provided faster and computationally efficient rooftop extraction for simpler rooftop structures. The major sources of error in the proposed system arise from pixel quantization, rooftop orientation estimation, Ground Sample Distance calibration, and environmental variability. Pixel-scale inaccuracies directly affect rooftop area estimation and photovoltaic capacity calculation. Proper Ground Sample Distance calibration significantly reduced rooftop area estimation uncertainty.

Roof orientation and tilt estimation errors were minimized using geometric analysis techniques such as Principal Component Analysis (PCA) and Hough Transform-based rooftop edge detection. The estimated rooftop tilt error remained within approximately ±5°, which is acceptable for practical rooftop photovoltaic estimation applications. Shadow detection using K-Means clustering provided satisfactory rooftop shadow segmentation under normal illumination conditions. However, the clustering-based shadow analysis approach becomes less effective under extremely low-light or overexposed image conditions because of reduced color contrast between shadow and non-shadow regions. From an economic perspective, the estimated payback period results are consistent with practical residential rooftop photovoltaic systems currently used in the renewable energy industry. The analysis assumed fixed electricity tariffs and standard government subsidy schemes. In real-world scenarios, future variations in electricity pricing policies, subsidy programs, and energy market conditions may influence long-term photovoltaic system payback periods.

The current system assumes either flat rooftops or single-tilt rooftop structures for photovoltaic estimation. More complex rooftop geometries containing multiple rooftop facets may require advanced 3D rooftop reconstruction and multi-surface rooftop partitioning techniques for improved accuracy. Additionally, the current shadow analysis is performed using single-time image observations. Future improvements may include time-series solar shadow analysis across different seasons and daylight conditions for more accurate yearly solar irradiance estimation. The proposed system also assumes average irradiance values under standard atmospheric conditions. More accurate photovoltaic energy estimation could be achieved in future work by incorporating Typical Meteorological Year (TMY) datasets, dynamic weather forecasting, and long-term irradiance variability analysis.

Overall, the experimental analysis confirms that the proposed Solar Roof Measurement and Energy Estimation System provides an effective, scalable, and low-cost solution for automated rooftop solar assessment using Artificial Intelligence and Computer Vision techniques.

VI. CONCLUSION

The proposed Solar Roof Measurement and Energy Estimation System successfully integrates Computer Vision, Machine Learning, photovoltaic energy modelling, and financial analysis into a unified platform for automated rooftop solar assessment. The system performs rooftop detection, segmentation, shadow analysis, rooftop orientation estimation, photovoltaic energy prediction, and economic feasibility analysis using satellite imagery and Artificial Intelligence techniques. The proposed methodology combines YOLOv8 segmentation, OpenCV contour analysis, polygon-based rooftop area computation, irradiance estimation, and K-Means clustering to generate accurate solar suitability analysis for residential and commercial buildings. Experimental analysis demonstrated satisfactory rooftop segmentation accuracy and realistic photovoltaic energy estimation results. The clustering model successfully categorized rooftops into different solar suitability groups based on rooftop geometry, shadow conditions, and energy generation characteristics. The generated outputs include rooftop area, usable rooftop space, photovoltaic system capacity, annual energy generation, installation cost, annual savings, and payback period.

The proposed framework provides a scalable, low-cost, and reproducible solution for rooftop solar viability assessment using open-source technologies such as Python, FastAPI, OpenCV, PyTorch, PVLib, and ReactJS. Although the proposed system achieved satisfactory results, future improvements may include integration of 3D rooftop geometry reconstruction, seasonal shadow analysis, weather forecasting models, and battery storage optimization for more accurate photovoltaic energy prediction.

Overall, the proposed AI-based rooftop solar analysis system provides an efficient and intelligent solution for renewable energy planning, smart city development, and sustainable rooftop solar deployment.

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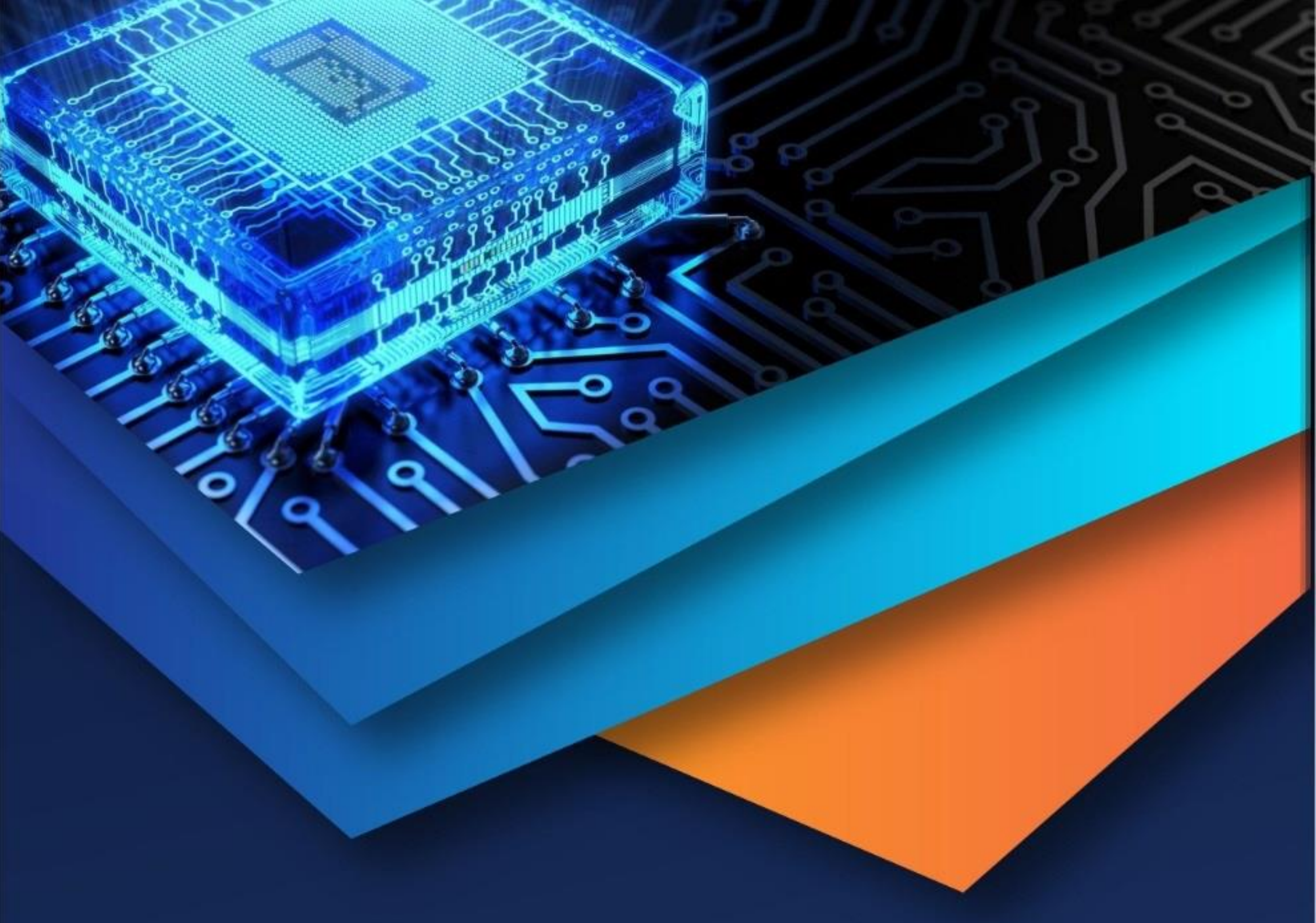

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