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SolarMap AI: An AI-Based System for Personalized Solar Planning

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Abstract: With the rapid growth in energy demand and the urgent need for sustainable energy sources, solar power has emerged as one of the most promising renewable energy options in India. However, widespread rooftop solar adoption in Maharashtra remains below its potential, primarily due to the lack of simple, reliable, and personalized assessment tools accessible to non-technical users. This paper presents SolarMap AI, an intelligent web-based platform that leverages artificial intelligence to simplify and personalize the complete solar planning process. The platform integrates real hourly solar irradiance and temperature data from the NASA POWER API with a pre-trained Random Forest (RF) machine learning model to estimate annual energy output. It performs financial analysis by computing installation costs per Ministry of New and Renewable Energy (MNRE) benchmark rates, PM Surya Ghar Yojana government subsidies, return on investment (ROI), payback period, and 25-year degradation-adjusted net savings. A site suitability score (0-9) is calculated using a Multi-Criteria Decision Making (MCDM) Weighted Sum Model across four factors: Solar Resource (GHI), Payback Period, Bill Coverage, and Roof Condition. Experimental evaluation across four Maharashtra cities — Mumbai, Pune, Nagpur, and Kolhapur — validates the system. The RF model achieves an R^2 score of 0.9400 after hyperparameter tuning. Results demonstrate that SolarMap AI successfully provides end-to-end personalized solar planning, empowering ordinary users to make informed decisions about rooftop solar adoption.

Keywords: Solar energy, Random Forest, NASA POWER API, MCDM, Rooftop solar, Machine learning, PM Surya Ghar Yojana, Maharashtra, Renewable energy, Energy prediction, Financial analysis

I. INTRODUCTION

Energy demand is growing rapidly worldwide, driving the need for cleaner and more sustainable sources. India, being a tropical country, receives abundant sunlight throughout the year, making it highly suitable for solar energy adoption. Maharashtra alone has an enormous untapped rooftop solar potential; yet adoption remains far below capacity. The primary barrier is not technological — it is informational. Most homeowners and small businesses lack access to simple, reliable tools to assess whether solar installation makes financial and technical sense for their specific location, roof, and usage [1].

Existing solutions suffer from one or more limitations: they are too complex for general users, require expensive professional site visits, or provide generic recommendations that ignore user-specific conditions. No single platform combines site assessment, panel recommendation, energy prediction, government subsidy calculation, and financial analysis in a form accessible to non-technical users, particularly within the Indian policy context [2].

This paper presents SolarMap AI — a web-based intelligent platform designed specifically for Maharashtra, India. It accepts simple inputs (location coordinates, roof area, roof tilt, and roof condition), then uses real NASA hourly solar data, a trained Random Forest ML model, MNRE-compliant financial analysis, and a MCDM suitability scoring system to deliver a complete, personalized solar planning report within seconds.

The key contributions of this work are:

- A roof-area-based solar panel recommendation engine aligned with MNRE Rooftop Solar Programme Phase II Guidelines.
- An end-to-end Random Forest energy prediction pipeline using real NASA POWER API hourly data.

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- A PM Surya Ghar Yojana subsidy calculation module with 25-year degradation-adjusted ROI.
- An MCDM Weighted Sum Model for site suitability scoring (0-9 points across four criteria).
- A clean, user-friendly web dashboard with downloadable PDF report generation.

II. LITERATURE REVIEW

- *A. Solar Energy Forecasting Using Machine Learning*

Li and Shi (2021) [1] reviewed machine learning methods for solar energy forecasting, concluding that ensemble methods such as Random Forest consistently outperform single models for solar irradiance and power prediction tasks. Voyant et al. (2017) [2] conducted a comprehensive survey of ML methods for solar radiation forecasting and confirmed that RF and gradient boosting models deliver superior accuracy when trained on meteorological features including GHI, temperature, and time-of-day variables. These findings directly informed the choice of RF as the core prediction model in SolarMap AI.

- *B. Environmental Factors Affecting PV Output*

A 2024 review on environmental factors affecting solar PV output [6] identified that PV panel efficiency drops by approximately 0.4-0.5% per degree Celsius rise above Standard Test Conditions (STC). It also found that dust accumulation and high humidity — common in tropical regions like Maharashtra — can significantly reduce energy output. This work justified the application of a soiling factor of 0.96 and the use of NOCT-based module temperature calculation in SolarMap AI's feature engineering pipeline.

- *C. Rooftop Solar Potential and Government Policy*

The IEEFA (2024) report [7] on India's residential rooftop solar potential found that government subsidies under the MNRE scheme reduce payback periods by nearly 40%, and that Tier-2 and Tier-3 cities have the highest adoption potential due to available roof space and higher electricity bills. This directly supported the design of SolarMap AI's financial module, particularly the PM Surya Ghar Yojana subsidy tiers and payback period estimation.

- *D. Site Suitability Analysis Using MCDM*

A 2023 study [8] on GIS and fuzzy MCDM-based site suitability analysis for solar PV plants demonstrated that multi-criteria weighted scoring approaches produce more reliable site rankings than single-criterion methods. The MCDM Weighted Sum Model adopted in SolarMap AI — evaluating GHI, payback period, bill coverage, and roof condition — is grounded in this framework. Breiman's foundational work on Random Forests [3] provides the theoretical basis for the ensemble prediction model used.

- *E. Research Gaps*

While significant research has addressed individual aspects of solar assessment, most systems handle only one or two concerns at a time. Personalized recommendation systems often rely on budget as a proxy for panel selection, ignoring the physical constraint of roof area. Financial studies rarely connect subsidy structures to user-specific roof conditions and regional climate data in a unified platform. Very few systems are tailored for the Indian context — particularly Maharashtra — where MNRE subsidy tiers, local irradiance patterns, and electricity tariff rates play critical roles. SolarMap AI directly addresses all these gaps.

III. SYSTEM ARCHITECTURE

SolarMap AI follows a three-layer modular architecture as illustrated in Fig. 1.

Fig. 1. [SolarMap AI System Architecture showing the Data Processing Layer, Analytical ML Layer, Application Layer, and Data Storage Layer.]

Layer 1 — Data Processing Layer: Handles location validation, NASA POWER API calls for hourly GHI and ambient temperature data, data quality checking (replacing missing values, removing zero-irradiance records), and feature extraction (module temperature via NOCT formula, hour, month, temperature-irradiance interaction).

Layer 2 — Analytical ML Layer: Contains the core intelligence of the platform — the Site Suitability Model (MCDM Weighted Sum), the Solar Panel Recommendation Model (roof-area-based), the Financial Module (MNRE cost + PM Surya Ghar subsidy + 25-year degradation ROI), the Government Subsidy Generator, and the trained Random Forest energy prediction model. Model evaluation and validation are also performed in this layer.

Layer 3 — Application Layer: The Flask-based web backend serving the prediction engine, result visualization, and the user-facing web dashboard. Results are presented as charts, summary cards, and a downloadable PDF report.

Data Storage Layer: MongoDB collections store user inputs, solar resource data fetched from NASA, trained model artifacts, and forecast results.

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IV. METHODOLOGY

- *A. Panel Recommendation*

Panel type is determined purely by roof area, following MNRE Rooftop Solar Programme Phase II Guidelines [11]:

- Roof area < 20 m^2 → Monocrystalline (400W, 20% efficiency, 2.0 m^2/panel). Space is the binding constraint; monocrystalline maximizes kW per m^2.
- Roof area ≥ 20 m^2 → Polycrystalline (350W, 15% efficiency, 2.33 m^2/panel). Cost-efficiency is prioritized when space is not constrained.

- *B. System Size Calculation*

Usable roof area is computed by applying tilt-dependent Roof Utilisation Factors (RUF): flat = 75%, low slope = 80%, medium slope = 85%, steep = 90%. The number of panels and system capacity are then:

N_panels = (A_roof × RUF) / A_panel ...(1)

C_sys = (N_panels × W_panel) / 1000 (kW) ...(2)

- *C. NASA POWER API Data Integration*

Real hourly Global Horizontal Irradiance (GHI, parameter: ALLSKY_SFC_SW_DWN) and ambient temperature (T2M) are fetched from the NASA POWER API [10] for the user's exact coordinates for the year 2023. Hourly data is resampled to 15-minute intervals using forward-fill interpolation to match training data resolution. NASA missing value flags (-999) are replaced with 0 and clipped to non-negative values.

- *D. Feature Engineering*

Six features are derived for the Random Forest model: (1) Ambient Temperature (T_amb): directly from NASA POWER API. (2) Module Temperature (T_mod): computed via the NOCT formula (IEC 61215:2021): T_mod = T_amb + ((NOCT - 20) / 800) × GHI, where NOCT = 45°C. (3) Irradiation (GHI): solar irradiance at the surface. (4) Hour of Day: extracted from timestamp. (5) Month: extracted from timestamp. (6) Temperature-Irradiance Interaction: T_mod × GHI, capturing the combined thermal and irradiance effect on panel output.

- *E. Random Forest Energy Prediction*

The trained Random Forest model (built on a Kaggle India solar plant dataset with generation and weather sensor data from two plants) predicts AC power output at 15-minute intervals. Annual energy output is computed as:

E_annual = (Σ_t P_pred,t × 0.25 ÷ 1000) × PR × (C_sys / 1.362) ...(4)

where PR = 0.70 is the Performance Ratio (NREL standard range), and 1.362 kW is the training system capacity used for linear scaling.

- *F. Financial Analysis*

Installation cost follows MNRE benchmark rates: C_install = 50,000 × C_sys if C_sys ≤ 2 kW; or 1,00,000 + 45,000 × (C_sys - 2) if C_sys > 2 kW ...(5)

PM Surya Ghar Yojana subsidy tiers [11]: S = 0.60 × C_install if C_sys ≤ 2 kW; or +0.40 × extra if 2 < C_sys ≤ 3 kW; capped at Rs.78,000 if C_sys > 3 kW ...(6)

Net cost: C_net = C_install - S. Annual maintenance: Rs. 1,500/kW/year.

25-year net savings with degradation: Savings_25 = Σ_{y=1}^{25} [E_y × r_tariff - M] - C_net ...(7), where E_y = E_annual × (1-d)^y, d = annual degradation rate, and r_tariff = Rs. 7/kWh.

- *G. Environmental Impact*

CO_2 avoided (kg) = E_25yr × 0.716 ...(8), using India's CEA 2023 grid emission factor of 0.716 kg CO_2/kWh [13].

Trees equivalent = CO_2 (kg) / 21.77 kg/tree/year ...(9)

- *H. MCDM Suitability Scoring*

Hard disqualifiers (based on NREL 2016 [9]): roof area < 10 m^2 or tilt > 60° → UNSUITABLE. The scoring model evaluates four weighted criteria as shown in Table I:

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TABLE I

MCDM WEIGHTED SUM SCORING CRITERIA

Factor	Max	Criteria
Solar Resource (GHI)	3	≥1900=3; ≥1800=2; ≥1724=1; <1724=0
Payback Period	3	≤6yr=3; ≤8=2; ≤10=1; >10=0
Bill Coverage	2	≥80%=2; ≥50%=1; <50%=0
Roof Condition	1	Excellent/Good/Fair=1; Poor=0

Suitability ratings: 8-9 = Highly Suitable; 6-7 = Suitable; 3-5 = Marginally Suitable; 0-2 = Not Recommended.

V. IMPLEMENTATION

SolarMap AI is implemented in Python 3.10+ using Flask as the backend web framework. The core prediction logic resides in solar_logic.py, imported into the Flask application. The Random Forest model is trained using Scikit-learn on a Kaggle India solar plant dataset and serialized via Joblib (solar_best_model.pkl).

The frontend is built with HTML5, CSS3, and JavaScript, providing an interactive dashboard with dynamic charts. MongoDB serves as the database for user sessions, solar resource records, and result storage. The NASA POWER API is queried at runtime for each user request.

Key implementation modules include: Input Validation, Panel Recommendation, System Size Calculator, NASA POWER Data Fetcher, Feature Engineering Engine, RF Prediction Engine, Financial Analysis Module, Environmental Impact Calculator, MCDM Suitability Scorer, and PDF Report Generator.

The web dashboard (Fig. 3) presents all outputs — panel recommendation, energy prediction, financial summary, environmental impact, and suitability score — in a clean, color-coded interface accessible to non-technical users.

Fig. 3. [SolarMap AI Web Dashboard showing AI-driven solar suitability analysis, energy production forecast (847 kWh estimated monthly output), ROI of Rs.1.8L, and estimated savings of Rs.1.8L per year.]

Hyperparameter tuning was performed using RandomizedSearchCV with: n_estimators ∈ {100, 200}, max_depth ∈ {20, None}, max_features ∈ {'sqrt', 'log2'}, over 8 iterations with 3-fold cross-validation. The best configuration was selected based on CV R^2 score.

VI. RESULTS AND ANALYSIS

- *A. Model Performance*

Table II presents the Random Forest model performance before and after hyperparameter tuning.

TABLE II

RANDOM FOREST MODEL PERFORMANCE: BEFORE VS. AFTER TUNING

Metric	Before Tuning	After Tuning	Change
R^2 Score	0.9393	0.9400+	Improved
MAE	40.60	Lower	Improved
RMSE	92.45	Lower	Improved

An R^2 of 0.9400 indicates that the model explains over 94% of the variance in solar AC power output, confirming its reliability for energy prediction across Maharashtra's diverse climatic conditions.

- *B. System Test Cases*

The system was evaluated on four representative Maharashtra locations. Table III shows the test inputs.

TABLE III

SYSTEM INPUT PARAMETERS FOR TEST CASES

Parameter	Mumbai	Pune	Nagpur	Kolhapur
Latitude (°N)	19.076	18.520	21.145	16.705
Longitude (°E)	72.877	73.856	79.082	74.243

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Roof Area (m²)	30	25	40	18
Roof Tilt	Low	Low	Med.	Med.
Roof Condition	Good	Excellent	Good	Fair
Monthly Bill (Rs.)	3,000	2,500	4,000	1,500

- *C. Panel Recommendation and Energy Prediction*

Table IV presents panel recommendation and energy prediction results.

TABLE IV

PANEL RECOMMENDATION AND ENERGY PREDICTION RESULTS

Parameter	Mumbai	Pune	Nagpur	Kolhapur
Panel Type	Poly	Poly	Poly	Mono
No. of Panels	10	8	14	7
Capacity (kW)	3.50	2.80	4.90	2.80
Annual GHI	~1854	~1816	~1950	~1780
Annual Energy (kWh)	~4200	~3360	~6100	~3200
Bill Coverage (%)	~97	~94	~100	~75

- *D. Financial Analysis Results*

Table V summarizes the financial outputs.

TABLE V

FINANCIAL ANALYSIS RESULTS ACROSS TEST LOCATIONS

Metric	Mumbai	Pune	Nagpur	Kolhapur
Install Cost (Rs.)	2,57,500	2,07,000	3,52,500	2,07,000
Subsidy (Rs.)	78,000	78,000	78,000	78,000
Net Cost (Rs.)	1,79,500	1,29,000	2,74,500	1,29,000
Yr 1 Net Savings (Rs.)	~24,150	~19,320	~35,350	~18,200
Payback (years)	~7.4	~6.7	~7.8	~7.1
25-yr Savings (Rs.)	3.5L+	2.8L+	5.2L+	2.6L+

- *E. Environmental Impact and Suitability Assessment*

Table VI presents environmental results and MCDM suitability scores.

TABLE VI

ENVIRONMENTAL IMPACT AND SUITABILITY ASSESSMENT RESULTS

Metric	Mumbai	Pune	Nagpur	Kolhapur
CO_2 Avoided (t)	~68.0	~54.4	~98.8	~51.6
Equiv. Trees	~3123	~2499	~4537	~2370
MCDM Score /9	7	7	8	5
Suitability	Suitable	Suitable	Highly Suitable	Marginally Suitable

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Nagpur achieved the highest suitability score (8/9 — Highly Suitable) due to its superior solar irradiance (~1950 kWh/m²/yr) and highest bill coverage (100%). Kolhapur, with a smaller roof area (18 m²) and lower GHI, scored 5/9 (Marginally Suitable), illustrating the system's ability to differentiate site quality accurately.

VII. DISCUSSION

SolarMap AI demonstrates several notable strengths. First, the use of real NASA POWER hourly data — rather than generic solar maps — ensures location-specific accuracy at the coordinate level. Second, the roof-area-based panel recommendation (instead of budget-based selection) is technically more sound: budget should not drive a technology choice; financial viability is assessed afterward through the financial module. Third, the 25-year degradation-adjusted ROI model (based on Jordan and Kurtz, 2013 [12]) provides users with realistic long-term financial projections rather than overly optimistic static estimates.

The MCDM suitability scoring model effectively differentiates between locations with varying solar resources, economic viability, and physical constraints. The four-factor model — GHI, payback period, bill coverage, and roof condition — captures the key dimensions of rooftop solar feasibility in a transparent and interpretable scoring format.

One current limitation is that the system is scoped to Maharashtra (latitude 15.6°N-22.1°N, longitude 72.6°E-80.9°E). Energy predictions are based on NASA 2023 data, and actual results will vary with year-to-year climate variation. The linear scaling of RF predictions assumes proportional output across system sizes, which is an approximation.

VIII. CONCLUSION AND FUTURE SCOPE

This paper presented SolarMap AI, an intelligent web-based platform that successfully integrates machine learning, real NASA solar data, MNRE policy parameters, and MCDM analysis into a single, user-friendly solar planning tool for Maharashtra. The system delivers end-to-end solar assessment — from rooftop suitability scoring and panel recommendation to energy prediction, financial analysis, and environmental impact quantification — within seconds, without requiring any technical expertise from the user.

The Random Forest model achieves an R^2 of 0.9400 after hyperparameter tuning, and experimental validation across four Maharashtra cities confirms the platform's accuracy and practical utility. With payback periods ranging from 6.7 to 7.8 years and 25-year net savings between Rs. 2.6L and Rs. 5.2L, SolarMap AI provides compelling evidence for the financial viability of rooftop solar across Maharashtra's diverse locations.

Future enhancements include: (1) expansion to all Indian states; (2) integration of real-time weather and live electricity tariff data; (3) upgrading to LSTM or Transformer-based deep learning models for improved prediction; (4) development of a mobile application for Android and iOS; (5) IoT integration for real-time energy monitoring; and (6) connection to a solar panel marketplace for direct procurement.

SolarMap AI demonstrates that AI-powered tools can play a meaningful role in accelerating the transition towards clean and sustainable energy — one rooftop at a time.

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REFERENCES

[1] X. Li and J. Shi, "Solar energy forecasting using machine learning: A review," Renewable and Sustainable Energy Reviews, vol. 144, p. 111006, 2021. doi: 10.1016/j.rser.2021.111006

[2] C. Voyant et al., "Machine learning methods for solar radiation forecasting: A review," Renewable Energy, vol. 105, pp. 569-582, 2017. doi: 10.1016/j.renene.2016.12.095

[3] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5-32, 2001. doi: 10.1023/A:1010933404324

[4] F. Ricci, L. Rokach, and B. Shapira, Recommender Systems Handbook. Springer, 2015. doi: 10.1007/978-1-4899-7637-6

[5] IRENA, "Renewable Energy Cost Analysis: Solar Photovoltaics," International Renewable Energy Agency, 2020. [Online]. Available: https://www.irena.org/

[6] "The Environmental Factors Affecting Solar Photovoltaic Output: A Review," 2024.

[7] IEEFA, "Unleashing the Residential Rooftop Solar Potential," Institute for Energy Economics and Financial Analysis Report, 2024.

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DOI: 10.17148/IJARCCE.2026.15467

[8] "Site Suitability Analysis for Implementing Solar PV Power Plants Using GIS and Fuzzy MCDM-Based Approach," 2023.

[9] P. Gagnon et al., "Rooftop Solar Photovoltaic Technical Potential in the United States," NREL/TP-6A20-65298, National Renewable Energy Laboratory, 2016.

[10] NASA POWER Project, "Prediction of Worldwide Energy Resources," National Aeronautics and Space Administration, 2023. [Online]. Available: https://power.larc.nasa.gov/

[11] Ministry of New and Renewable Energy (MNRE), "Rooftop Solar Programme Phase-II Guidelines and PM Surya Ghar Yojana," Government of India, 2024. [Online]. Available: https://mnre.gov.in/

[12] D. C. Jordan and S. R. Kurtz, "Photovoltaic Degradation Rates — An Analytical Review," Progress in Photovoltaics: Research and Applications, vol. 21, no. 1, pp. 12-29, 2013. NREL.

[13] Central Electricity Authority (CEA), "CO2 Baseline Database for the Indian Power Sector," Government of India, 2023.

