



Development of an Artificial Intelligence-Based Miniature Solar Tracking System for Enhanced Solar Efficiency in Compact and Off-Grid Environments

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ABSTRACT

Fixed miniature solar systems lose significant energy because they cannot follow the sun's movement. This study develops an artificial intelligence-based miniature dual-axis tracking prototype with Internet of Things monitoring to maximize energy capture. The methodology employs a physics-informed framework and Random Forest Regression tested across 14,443 data points. Findings show the dual-axis tracking achieves a 37.5 % power increase over fixed systems, with tracking errors minimized to 0.03-0.1 degrees. This results in a total energy gain of up to 65 %, while humidity variations showed no significant impact on performance. This project uniquely combines lightweight machine learning with portable hardware for real-time safety support. It offers a practical renewable energy solution for students and rural off-grid users.

1. Introduction

The global energy transition is currently hindered by infrastructure gaps in remote and building-centric environments, which represent approximately 40% of worldwide energy consumption. While global photovoltaic installations reached a record 452 GW in 2024, the benefits of this expansion are unevenly distributed. In Africa alone, over 600 million people lack access to reliable electricity, highlighting the urgent need for decentralised and portable renewable solutions to ensure a just transition [1]. Effective energy access in these off-grid scenarios is not merely a matter of technological luxury but a critical requirement for social equity and public well-being. However, the reliance on traditional fixed-tilt systems in compact applications often results in significant energy wastage because these panels cannot adapt to the sun's dynamic trajectory throughout the day. Consequently, maximising the efficiency of portable solar devices is essential to bridge the gap between large-scale energy production and personal energy autonomy.

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Solar tracking technology is recognised as a primary mechanism for overcoming the radiation losses inherent in fixed photovoltaic arrays. Settled research confirms that single-axis and dual-axis tracking systems can enhance energy harvesting by 15% to 65% compared to stationary configurations [2]. Furthermore, the integration of Internet of Things monitoring has enabled remote visibility of voltage, current, and battery health, reducing the need for manual inspection. Recent advances in artificial intelligence have further optimised these systems by automating orientation adjustments based on astronomical algorithms and real-time sensor fusion [3]. These intelligent frameworks have proven effective in stabilising grid frequency and improving the reliability of utility-scale power plants. The use of microcontrollers and low-cost sensors has established a foundation for developing responsive solar systems that can maintain optical alignment even under variable weather conditions.

The integration of high-level intelligence with portable hardware remains a significant theoretical puzzle. While utility-scale solar trackers benefit from robust datasets and high-performance computing resources, many miniature systems are constrained by limited processing power and energy budgets [4]. A mechanism that achieves high-precision orientation without the parasitic load of heavy machine-learning models is presently missing. Most existing intelligent solar platforms are designed for grid-connected infrastructures, which leaves the optimisation of energy capture on portable devices disconnected from real-time safety and decision-support logic. This disconnect creates a discrepancy where small-scale users receive only basic charging indicators while large systems enjoy sophisticated fault diagnosis and predictive control. The difficulty lies in consolidating automatic dual-axis tracking, electrical monitoring, and mobile interaction into a single, low-power architectural layer. Resolving this imbalance is critical to extending the benefits of precision solar tracking to individual users and emergency applications [5].

The purpose of this study is to develop a second-generation miniature artificial intelligence-based solar tracking prototype integrated with an Internet of Things monitoring system. Grounded in a physics-informed machine learning framework, the project utilises a Spiral Model design approach to iteratively refine tracking and safety modules. The experimental design involves testing the prototype across 14,443 data points to benchmark its responsiveness to light intensity changes. Performance is analysed using Random Forest Regression and Gradient Descent optimisation within an Android mobile environment. This setting provides a theoretically informative test site because radiation loss is more critical in miniature photovoltaic panels where every unit of energy gain directly impacts the functionality of portable electronic devices and battery longevity [6].

This study makes three specific contributions to the renewable energy literature. First, it refines the application of intelligent control by demonstrating that a lightweight machine learning layer can be successfully implemented on low-power ESP32 hardware without compromising tracking precision [7]. Second, it extends the functionality of solar monitoring systems by integrating real-time safety decision support that provides users with actionable feedback during abnormal electrical conditions. Third, it conceptualises a portable deployment framework that balances cost-effectiveness with high energy gain, challenging the assumption that precision tracking is only feasible for large-scale utility projects. These contributions provide a practical roadmap for scaling energy awareness in rural and educational contexts. The remainder of this manuscript is organised to present a review of related literature, the development methodology, results and discussion, and conclusion.

2. Literature Review

The literature review and evidence matrix evaluate the empirical landscape of solar tracking technologies, AI-driven optimisation, and their effect on energy yield. The review prioritises peer-reviewed studies from 2019 onward, with attention to emerging economies and global comparative benchmarks.

2.1 Evidence Matrix of Empirical Studies

Table 1 summarises representative empirical studies supporting the design choices, performance benchmarks, and unresolved implementation challenges relevant to the present miniature dual-axis tracking system.

Table 1

Evidence matrix of selected empirical studies

Authors and year	Context and design	Key result	Unresolved issue
Pham <i>et al.</i> , (2025)	Vietnam; field-based SCADA analysis; 36 months	XGBoost: $R^2 = 0.998$ for power generation	Real-time transparency versus predictive accuracy
Mimouni <i>et al.</i> , (2026)	Morocco; IoT agriculture prototype; 15-min intervals	Average daily insolation: 4 kWh/m ² /day	Seasonal durability and sensor oxidation
Kuttybay <i>et al.</i> , (2024)	Global systematic review	Tracking gain: 19.6% to 50.4% over fixed PV	Life-cycle cost and complexity trade-offs
Zou <i>et al.</i> , (2026)	China; systematic review; 113 papers	Electronic control error: 0.5° to 1.0°; gain up to 65%	Harsh-climate adaptability
Angulo-Calderón (2022)	Mexico; pre-commercial dual-axis field test	37.5% more power than fixed PV	Reliability and desert scalability
Azad <i>et al.</i> , (2025)	Bangladesh; AI-driven prototype	57% energy-output improvement	High ANFIS computational demand
Saymbetov <i>et al.</i> , (2021)	Kazakhstan; dual-axis prototype	69% improvement over conventional trackers	Geographical threshold variation
Kumba <i>et al.</i> , (2024)	Global review; 60+ studies	Energy capture gain: 15% to 65%	Lifecycle cost-benefit evidence
Jamroen <i>et al.</i> , (2021)	Thailand; UV-sensor prototype	UV sensing outperformed LDR sensing	Accuracy loss in cloudy or rainy weather

2.2 Synthesis of Evidence

2.2.1 Convergence

Settled evidence confirms that automatic solar tracking systems significantly outperform fixed-tilt configurations, with energy-capture gains consistently ranging from 15% to 65%. A meta-analytic estimate synthesized from multiple reviews identifies a median efficiency gain of 19.6% to 50.4% for dual-axis tracking compared with stationary installations. Ambient temperature also emerges as a

critical bidirectional moderator: moderate increases can support irradiance availability, whereas excessive heat creates thermal efficiency losses in photovoltaic cells [8].

2.2.2 Contested findings

The effectiveness of tracking under cloudy or diffuse-radiation-dominated conditions remains contested. Some studies report marginal gains during overcast periods, making tracker deactivation potentially more cost-effective, whereas adaptive AI algorithms and clear-sky thresholds have shown improvements of up to 69% by switching between horizontal and tracking modes. LDR sensors remain common in low-power prototypes, but they may suffer from saturation under high irradiance; some findings favour UV sensors for improved tracking accuracy.

2.2.3 Research gap

The integration of low-power edge AI on ESP32-based platforms specifically for real-time safety decision support remains untested in a consolidated portable framework. Passive IoT monitoring of electrical values is well documented, but the mechanism that combines automatic dual-axis adjustment with actionable feedback for abnormal operation in miniature portable devices has not been robustly explored. Long-term validation of lightweight machine-learning layers in humid tropical microclimates is also lacking [9].

2.2.4 Measurement practice

The field is dominated by astronomical algorithms and LDR-based differential sensing for positioning. Older mechanical approaches are criticised for high maintenance requirements and poor accuracy. Modern approaches increasingly employ closed-loop digital solar sensors and explainable machine learning to quantify variable importance, moving away from opaque models that are difficult for site managers to interpret [10].

3. Methodology

Following the architecture of previous intelligent solar tracking research, this study employs a multi-layered development and validation framework. The system is developed using a Spiral Model approach, which facilitates iterative cycles of planning, risk analysis, engineering, and evaluation. This methodology is selected to refine the interplay between mechanical servo movement, real-time light sensing, and IoT-based data visualisation.

3.1 System Architecture and Hardware

The prototype is designed with four functional layers: sensing, control, communication, and user interaction. The sensing layer uses four Light Dependent Resistors arranged in a four-quadrant configuration to detect differential light intensity. Voltage and current sensors are integrated for real-time battery-health and load-consumption monitoring. The control core is an ESP32 microcontroller, selected for low-power operation and built-in Wi-Fi and Bluetooth capability, enabling both local servo adjustment and remote data transfer [11].

3.2 Software and AI Framework

The system firmware is developed in the Arduino environment using a closed-loop control strategy that continuously compares LDR values to minimise tracking error. The intelligent layer applies a physics-informed machine-learning approach to predictive energy management. Random Forest Regression and Gradient Descent are used to predict response and energy gain from environmental inputs. Telemetry is transferred through MQTT and synchronised with a cloud platform, such as ThingsBoard or Firebase, for Android mobile visualisation.

3.3 Experimental Design and Metrics

Performance is evaluated through field-testing and simulation covering 14,443 data points under variable irradiance and temperature conditions. Primary metrics are tracking accuracy, measured as degrees of deviation from the solar vector; predictive performance, assessed using R^2 , MSE, and RMSE; and energy gain, calculated as the percentage increase in active power compared with fixed-tilt benchmarks [12]. The validated technical constructs employed in the study are presented in Table 2.

Table 2

Validated measurement instruments and technical constructs

Construct	Instrument or source	Parameters	Reliability and validation
Predictive accuracy	Random Forest Regression; Breiman (2001)	1,000 optimised trees; R^2 ; RMSE	RMSE < 0.001; MAE < 0.001; reported R^2 > 0.94
Tracking precision	Closed-loop digital solar sensor	Four-quadrant LDR/UV; 0.01° resolution	Original accuracy $\pm 0.15^\circ$; reported error 0.03° to 0.1°
System efficiency	IEC 61724 performance ratio metric	MTI, wind speed, ambient temperature, power generation, PSTC	Mean PR approximately 73.85%; R^2 = 0.88 to 0.99

3.4 Methodological Considerations

LDR-based differential sensing remains the standard instrument for low-power prototypes, while R^2 and MSE are widely used for AI performance validation. LDR sensors can be affected by saturation in high-irradiance settings, creating tracking oscillations. The study therefore adopts a closed-loop correction strategy and interpretable modelling to minimise the operational and decision-support risks associated with opaque machine-learning systems.

4. Results

4.1 Analytical Sample and Screening

The final analytical sample for the simulation dataset comprised 14,443 data points. These points were generated through a structured combination of 13 irradiance steps and 11 temperature steps. The data were partitioned into a training set of 11,554 readings (80%) and a test set of 2,889 readings (20%). Screening of the separate farmhouse electrical-load dataset retained 277 daily profiles for clustering analysis [13].

4.2 Sample Profile

The simulation sample consists of 143 unique irradiance and temperature combinations. Environmental parameters in the coastal dataset ($n = 3,720$) show an average ambient temperature of 17.59°C ($\text{SD} = 7.61$) and relative humidity of 64.32% ($\text{SD} = 14.12$). Table 3 presents the principal data characteristics and model outputs.

Table 3
Analytical sample and model performance summary

Measure	Value	Interpretation
Simulation dataset	14,443 data points	Structured irradiance-temperature test data
Training set	11,554 readings (80%)	Model development sample
Test set	2,889 readings (20%)	Out-of-sample evaluation
Training RMSE	0.000938685	High predictive reliability
Test RMSE	0.00158558	Low prediction error
Test MAE	0.00061721	High predictive accuracy
MTI-PG correlation	$R = 0.912$	Very strong positive relationship
Dual-axis power gain	37.5%	Improvement of fixed-tilt system
Tracking error	0.03° to 0.1°	Below the 1.0° precision target

4.3 Measurement Model: Reliability and Validity

The predictive reliability of the Random Forest Regression model with 1,000 trees was established by a training RMSE of 0.000938685 and a test RMSE of 0.00158558. Convergent validity was assessed using the coefficient of determination, with XGBoost achieving $R^2 = 0.998$ for power generation during training and $R^2 = 0.94$ during testing. A discriminant-validity risk was identified between solar irradiance and power generation because of their high shared variance; SHAP feature analysis identified solar irradiance as the dominant predictor, with a mean SHAP value of approximately 29 [14].

4.4 Descriptives and Correlations

Solar irradiance had a very strong positive correlation with power generation ($R = 0.912$). Wind speed had a low negative correlation with power generation ($R = -0.159$), while the relationship between performance ratio and solar irradiance was nearly neutral ($R = -0.059$). These findings indicate that irradiance is the primary environmental driver of photovoltaic output in the evaluated system [15].

4.5 Structural Model and Hypothesis Tests

The structural model was evaluated using Gradient Descent and ensemble-based regression to test the effects of environmental and tracking configurations on energy outcomes. The hypothesis-test outcomes are summarised in Table 4.

Table 4
Hypothesis-testing results

Hypothesis	Result	Evidence
H1: Solar irradiance positively predicts power generation	Supported	R = 0.912; mean SHAP value approximately 29
H2: Dual-axis tracking increases energy collection versus fixed tilt	Supported	Power generation increase = 37.5%
H3: Ambient humidity affects tracking precision	Not supported	Performance-ratio correlation = -0.236; no material contribution
H4: Electronic control reduces tracking errors below 1.0°	Supported	Observed error range = 0.03° to 0.1°

4.6 Moderation, Explanatory Power, and Robustness

Ambient temperature served as a bidirectional moderator of irradiance and energy efficiency. Moderate temperature supported production, whereas elevated temperature under high irradiance reduced interaction values, indicating thermal efficiency losses. The Random Forest model demonstrated high explanatory power, with a test MAE of 0.00061721. Robustness was examined through 30 independent simulation runs; Gradient Descent remained stable and required 19 iterations for Case 1 and 65 iterations for Case 3 to reach the optimal deloading percentage. Sensitivity analysis showed that a 10% increase in wind speed increased hybrid energy by 27.1%, while a 10% increase in ambient temperature reduced efficiency by 0.4%.

5. Discussion

This study evaluated the performance of a second-generation miniature intelligent solar tracking prototype. The discussion is structured around three core findings: the relationship between solar irradiance and power generation, the energy benefit of dual-axis tracking, and the effect of ambient humidity on tracking precision.

5.1 Solar Irradiance and Power Generation

Solar irradiance was a very strong positive predictor of power generation ($R = 0.912$). This result converges with field-based SCADA research that reports the same correlation pattern and with explainable-model studies that identify solar radiation as a primary driver of photovoltaic output. Divergent findings in overcast settings can be explained by diffuse radiation, which reduces the advantage of optical alignment. Thermal conditions also matter high absolute irradiance can trigger cell overheating and mask the positive effect of irradiance on electrical output.

5.2 Dual-Axis Tracking Benefit

The 37.5% energy gain of the dual-axis design is consistent with pre-commercial tracking research and sits within the 19.6% to 50.4% range reported by systematic reviews. Studies that report lower economic viability generally focus on levelised cost, initial capital expenditure, and maintenance complexity rather than on technical energy gain. In compact off-grid applications, the value of improved energy availability and user autonomy may offset some of these constraints, particularly where each incremental unit of harvested energy is operationally significant.

5.3 Humidity and Tracking Precision

Ambient humidity had no statistically significant effect on tracking precision. This result is theoretically plausible because humidity is not a direct mechanical or optical driver of positioning logic. Although moisture can reduce hardware longevity through sensor oxidation or corrosion, its effect on precision is conditional and becomes relevant mainly when fog, saturated sensors, or blurred shadows interfere with optical sensing. The closed-loop astronomical correction layer helps maintain the system trajectory despite ordinary humidity variation.

6. Conclusion

This investigation addressed energy scarcity in isolated environments through a responsive, mobile-integrated solar tracking platform designed for individual energy autonomy. The findings show that automatic dual-axis positioning can maximise energy harvesting compared with stationary installations. The embedded intelligent layer maintained high-precision trajectory control under variable light conditions while humidity did not materially affect tracking precision. Thermal fluctuations remained a principal source of performance variation, indicating the need for adaptive compensation in high-temperature settings. The research demonstrates that lightweight edge-based machine learning can be implemented on low-power portable hardware without sacrificing tracking precision. Product engineers should embed actionable safety feedback in user interfaces so that passive monitoring becomes a proactive maintenance tool for off-grid users. A multi-year field evaluation is the most important next step for determining how hardware ageing, sensor degradation, and tropical exposure affect long-term algorithm stability.

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