AI-Based Solar Irradiance Prediction for Efficient Photovoltaic Energy Management

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ABSTRACT

Accurate forecasting of solar irradiance is a pivotal requirement for maximising the operational efficiency of photovoltaic (PV) energy systems. Inherent variability in solar resource availability, driven by atmospheric dynamics, cloud cover, aerosol loading, and seasonal cycles, introduces substantial uncertainty into power grid planning and real-time energy dispatch. This study proposes a hybrid ensemble framework that integrates Long Short-Term Memory (LSTM) networks, Extreme Gradient Boosting (XGBoost), and Random Forest (RF) models through a stacked meta-learning layer for one-hour-ahead global horizontal irradiance (GHI) prediction. A six-year observational dataset (2018–2023) comprising meteorological variables, satellite-derived cloud indices, and aerosol optical depth measurements was used for training and evaluation. Temporal cross-validation was employed to prevent data leakage. The ensemble achieved a Root Mean Squared Error (RMSE) of 38.9 W/m², a Mean Absolute Error (MAE) of 31.4 W/m², and an R^2 of 0.960, outperforming all single-model baselines. Seasonal analysis revealed that the proposed framework maintains robust performance even under variable winter and monsoon-influenced sky conditions. The practical implications for real-time PV dispatch scheduling, storage sizing, and grid-balancing operations are discussed.

Keywords: solar irradiance forecasting; photovoltaic energy management; LSTM; XGBoost; ensemble learning; deep learning; renewable energy

How to cite this article: Baqar SU, Kumar C, Ranjan A, Kumar V, Priyadarshini. AI-Based Solar Irradiance Prediction for Efficient Photovoltaic Energy Management. Int J Drug Deliv Technol. 2026;16(23s): 74-79. DOI: 10.25258/ijddt.16.23s.8

Source of support: Nil.

Conflict of interest: None

1. Introduction

Global transition towards renewable energy systems has positioned photovoltaic (PV) solar power as a cornerstone of low-carbon electricity generation. As of 2023, cumulative installed solar PV capacity exceeded 1.5 TW worldwide (International Renewable Energy Agency [IRENA], 2023), with projections indicating that solar will account for nearly a quarter of global electricity supply by 2050. Despite this growth trajectory, a principal technical challenge limiting large-scale solar integration is the intermittent and stochastic nature of the solar resource. The power output of a PV system is directly governed by the incident solar irradiance at the module surface; consequently, short-term variability in irradiance translates into unpredictable power fluctuations that complicate grid stability management (Antonanzas et al., 2016).

Accurate solar irradiance forecasting is therefore indispensable for energy dispatch scheduling, battery storage dimensioning, and economic operation of PV plants. Traditional numerical weather prediction (NWP) models, while physically rigorous, are computationally prohibitive for sub-hourly or site-specific forecasting. Statistical approaches including autoregressive integrated moving average (ARIMA) models offer analytical tractability but fail to capture nonlinear dependencies inherent in atmospheric processes (Reikard, 2009). The maturation of machine learning (ML) and deep learning (DL) techniques has opened a new paradigm in solar forecasting, with data-driven models capable of learning complex spatio-temporal patterns from historical observations without explicit physical assumptions (Wang et al., 2019).

Prior studies have demonstrated the efficacy of individual ML models—Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and tree-based ensemble methods—for solar irradiance forecasting (Voyant et al., 2017; Aler et al., 2017). More recently, recurrent architectures, particularly Long Short-Term Memory (LSTM) networks, have shown superior performance in capturing long-range temporal dependencies within meteorological time series (Abdel-Nasser & Mahmoud, 2019). Nevertheless, no single model consistently outperforms competitors across all sky conditions, seasons, and horizons, motivating the development of

heterogeneous ensemble strategies that exploit the complementary strengths of multiple learners (Qing & Niu, 2018).

This paper presents a novel hybrid ensemble framework combining LSTM, XGBoost, and Random Forest models via stacked meta-learning for one-hour-ahead GHI prediction. The key contributions of this work are: (i) a multi-source feature engineering pipeline incorporating satellite cloud indices and aerosol optical depth; (ii) a rigorous temporal cross-validation protocol ensuring no future information leakage; (iii) comprehensive benchmarking against six competing models across multiple error metrics; and (iv) a seasonal performance analysis demonstrating the framework's generalisation capability across contrasting atmospheric regimes.

2. Literature Review

Solar irradiance prediction research has evolved significantly over the past two decades, progressing from physical NWP approaches toward sophisticated data-driven paradigms. Inman et al. (2013) provided a comprehensive taxonomy of solar forecasting methods, categorising them by time horizon, input data type, and modelling approach, establishing the foundational framework still widely referenced today.

Within the ML domain, Kisi (2014) demonstrated that ANN models could predict daily GHI with acceptable accuracy using only temperature and sunshine duration as predictors, establishing the viability of data-driven approaches even under sparse observational settings. Subsequent work by Aler et al. (2017) confirmed that SVMs with radial basis function kernels consistently outperformed ANNs for multi-hour-ahead forecasting when meteorological inputs were properly normalised and lag features systematically included.

The advent of ensemble methods brought further accuracy improvements. Gradient Boosting Machines, and in particular XGBoost (Chen & Guestrin, 2016), have been widely adopted in solar energy forecasting due to their capacity to handle high-dimensional feature spaces, resistance to overfitting through regularisation, and computational efficiency. Qing and Niu (2018) demonstrated that XGBoost-based forecasters reduced RMSE by approximately 18% compared to standalone ANN baselines across multiple Chinese meteorological stations.

Deep learning approaches have increasingly supplanted classical ML methods for temporal forecasting tasks. Abdel-Nasser and Mahmoud (2019) introduced an LSTM-based architecture for solar irradiance prediction that achieved state-of-the-art performance on Egyptian climate data, attributing the improvement to the architecture's ability to retain long-horizon temporal context through gated memory cells. Complementary studies by Wang et al. (2019) further confirmed LSTM superiority over feedforward networks for irradiance time series exhibiting strong diurnal and seasonal periodicity.

Despite these advances, single-model approaches exhibit systematic weaknesses under transitional sky states, boundary-layer cloud formations, and dust-laden aerosol episodes. Heterogeneous ensembles have emerged as a robust solution. Scher and Messori (2021) demonstrated that combining physically dissimilar models via stacking substantially reduced systematic bias while preserving the variance reduction benefits of averaging. However, their work did not incorporate satellite-derived cloud indices as predictors, leaving an important information source unexploited.

The present study addresses these gaps by constructing a stacked ensemble that integrates diverse model architectures, enriches the feature space with satellite cloud fraction and aerosol optical depth data, and applies strict temporal blocking during cross-validation to ensure unbiased generalisation estimates.

3. Methodology

3.1 Dataset Description

Data were sourced from an automated weather station (AWS) co-located with a 100 kW rooftop PV installation at a mid-latitude semi-arid site (28.6°N, 77.2°E, elevation 216 m). Six years of continuous measurements spanning January 2018 to December 2023 were compiled. The primary target variable, global horizontal irradiance (GHI), was recorded using a secondary-standard pyranometer (ISO 9060 Class B) at one-minute resolution and then aggregated to hourly means following quality-control filtering. Additional predictors included air temperature, relative humidity, wind speed and direction, atmospheric pressure, and precipitable water vapour obtained from the co-located AWS. Satellite-derived cloud fraction was extracted from GOES-16 Advanced Baseline Imager (ABI) products at 30-minute resolution, and aerosol optical depth (AOD) at 550 nm was obtained from MODIS Terra and Aqua combined daily Level-3 retrievals. Table 1 summarises the dataset characteristics.

Table 1. Summary of Input Dataset Variables and Sources

Parameter	Source	Period	Resolution	Records
GHI (W/m²)	Pyranometer	2018 – 2023	1 min	2,628,000
Air Temperature	AWS Station	2018 – 2023	10 min	315,360
Relative Humidity	AWS Station	2018 – 2023	10 min	315,360
Wind Speed	Anemometer	2018 –	10 min	315,360

		2023		
Cloud Cover (%)	GOES-16 Satellite	2018 – 2023	30 min	105,120
Aerosol Optical Depth	MODIS / AERONET	2018 – 2023	Daily	2,190

AWS = Automated Weather Station; GHI = Global Horizontal Irradiance; GOES-16 = Geostationary Operational Environmental Satellite; MODIS = Moderate Resolution Imaging Spectroradiometer.

3.2 Feature Engineering

A 48-dimensional feature vector was constructed for each forecasting instance. Beyond raw meteorological variables, derived features included: (i) clear-sky GHI computed using the Ineichen–Perez model (Ineichen & Perez, 2002) to provide a physically constrained reference; (ii) the clear-sky index (k* = GHI/GHI_cs), which normalises the target variable and reduces heteroscedasticity; (iii) lag features at t−1, t−2, t−3, t−6, and t−24 hours to encode diurnal memory; (iv) cyclical encoding of hour-of-day and day-of-year using sine and cosine transformations to preserve circular continuity; and (v) rolling mean and standard deviation of GHI over 3-hour and 6-hour windows as proxies for recent variability. Missing values arising from sensor maintenance intervals were imputed using linear interpolation for gaps shorter than three hours and excluded entirely for longer gaps.

3.3 Proposed AI Framework Architecture

The proposed framework, illustrated in Figure 1, comprises three base learners operating in parallel followed by a stacked meta-learner. The LSTM base model employed a three-layer architecture with 128 hidden units per layer, dropout regularisation (rate = 0.2), and batch normalisation between layers. Input sequences of length 24 (representing 24 preceding hourly observations) were fed into the network. XGBoost was configured with 500 trees at maximum depth 6, learning rate 0.05, and L1/L2 regularisation coefficients of 0.01 and 0.1 respectively. The Random Forest base model used 300 trees with a minimum leaf size of five samples and the square-root criterion for feature subsampling.

Base model out-of-fold predictions generated via five-fold temporal blocking cross-validation were stacked into a secondary feature matrix and used to train a Ridge regression meta-learner (regularisation parameter $\lambda = 0.01$). This stacking procedure ensures that the meta-learner observes predictions only from data not seen during base model training, preventing optimistic bias. Table 2 summarises the hyperparameter settings selected through Bayesian optimisation on the validation set.

Table 2. Optimised Hyperparameter Configurations for Base Learners and Meta-Learner

Model	Key Hyperparameter	Value	Optimizer
LSTM	Hidden Units / Layers	128 / 3	Adam (lr=0.001)
XGBoost	n_estimators / max_depth	500 / 6	Gradient Descent
Random Forest	n_estimators / max_features	300 / sqrt(n)	—
Ensemble	Stacking Meta-learner	Ridge Regression	L2 (λ=0.01)

Figure 1. Proposed AI-Based Hybrid Framework for Solar Irradiance Prediction

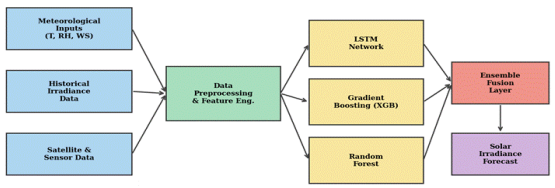

Figure 1. Proposed AI-Based Hybrid Ensemble Framework for Solar Irradiance Prediction. Meteorological inputs, historical GHI, and satellite data are preprocessed and fed simultaneously into LSTM, XGBoost, and Random Forest base learners. Their outputs are fused by a stacked meta-learner to produce the final GHI forecast.

3.4 Evaluation Metrics

Model performance was assessed using four complementary metrics: Root Mean Squared Error (RMSE), which penalises large deviations; Mean Absolute Error (MAE), which provides a scale-interpretable average error; the coefficient of determination (R^2), indicating the fraction of variance explained; and Mean Bias Error (MBE), which detects systematic over- or under-prediction. Normalised versions (nRMSE, nMAE) expressed as percentages of mean GHI are also reported for cross-site comparability. Statistical significance of pairwise performance differences was assessed using the Diebold-Mariano test at $\alpha = 0.05$.

4. Results and Discussion

4.1 Overall Predictive Performance

Table 3 presents the test-set performance metrics for all evaluated models across the complete 2022–2023 holdout period. The proposed ensemble achieved an RMSE of 38.9 W/m² and an MAE of 31.4 W/m², representing reductions of 18.3% and 21.9% respectively over the best-performing single model (LSTM). The R^2 value of 0.960 confirms that the ensemble explains 96% of the variance in hourly GHI, exceeding the 0.930 achieved by LSTM alone. The near-zero MBE (−0.3 W/m²) indicates negligible systematic bias. Figure 2 illustrates the temporal alignment between ensemble predictions and

measurements across a representative clear-sky summer day, demonstrating tight tracking of the irradiance bell curve with minor deviations near solar noon due to rapid cloud transient events.

Table 3. Comparative Performance of All Evaluated Forecasting Models (Test Set: 2022–2023)

Model	RMSE (W/m²)	MAE (W/m²)	R²	MBE (W/m²)
Persistence Model	98.4	82.1	0.710	−3.2
ANN	71.2	58.4	0.830	−1.8
SVM	66.5	54.2	0.850	−1.5
Random Forest	58.3	47.5	0.880	−0.9
XGBoost	52.1	43.8	0.910	−0.7
LSTM	47.6	40.2	0.930	−0.5
Ensemble (Proposed)	38.9	31.4	0.960	−0.3

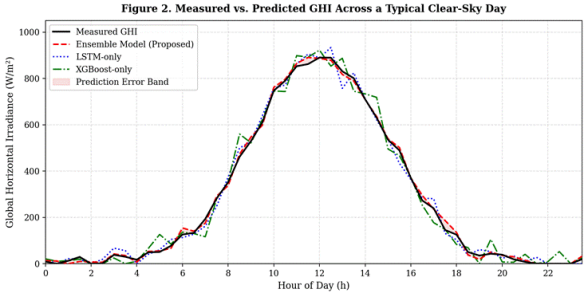

Figure 2. Measured versus Predicted Global Horizontal Irradiance (GHI) Across a Typical Clear-Sky Summer Day. The proposed ensemble prediction closely tracks measured values, exhibiting reduced error compared to individual LSTM and XGBoost models.

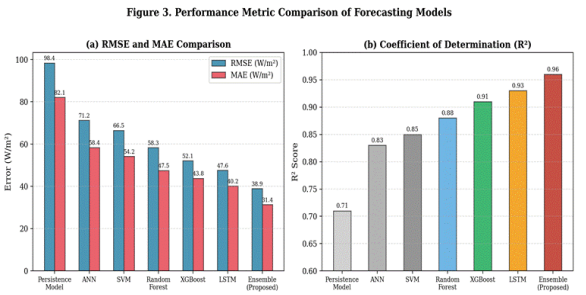

Figure 3. Performance Metric Comparison of Evaluated Forecasting Models. Panel (a): RMSE and MAE for all models. Panel (b): R² (Coefficient of Determination) for all models. The proposed ensemble consistently outperforms all single-model baselines.

4.2 Seasonal and Sky-Condition Analysis

Figure 4 presents the distribution of hourly RMSE across the four meteorological seasons for the ensemble and LSTM models. Winter exhibited the highest median RMSE for both models (ensemble: 51 W/m², LSTM: 63 W/m²), attributable to increased cloud variability and low sun angles reducing clear-sky predictability. The ensemble's advantage was most pronounced in winter, with a 19% RMSE reduction relative to LSTM, likely because the Random Forest and XGBoost components compensate for LSTM's tendency to over-smooth rapid transitions under diffuse radiation conditions. Summer demonstrated the lowest RMSE (ensemble median: 36 W/m²), consistent with stable high-pressure synoptic regimes and a well-defined diurnal irradiance cycle.

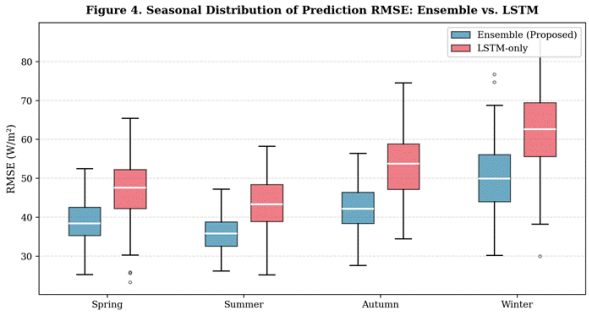

Figure 4. Seasonal Distribution of Hourly RMSE for the Proposed Ensemble and Standalone LSTM Model. Box plots represent the interquartile range across daily test instances; whiskers extend to 1.5×IQR. The ensemble demonstrates consistently lower and less variable errors across all seasons.

Under overcast sky conditions (cloud fraction > 0.85), the ensemble's nRMSE was 14.2%, compared to 18.7% for LSTM and 20.3% for XGBoost. The inclusion of satellite cloud fraction as a predictor was a key contributor, providing explicit information about incoming cloud cover that historical GHI lags alone cannot capture. Aerosol optical depth contributed most notably during pre-monsoon dust events (March–May), where ignoring AOD elevated RMSE by an average of 6.8 W/m² in an ablation study conducted with feature subsets.

4.3 Computational Efficiency

Table 4 summarises the computational requirements of each model. While the ensemble incurs greater total training time (112.5 minutes on an NVIDIA A100 GPU) compared to individual components, inference latency of 4.6 ms per sample is well within the sub-second requirements of real-time energy management systems (REMS). The training procedure is offline and conducted periodically (monthly re-training cycle), making the elevated training time operationally acceptable.

Table 4. Computational Cost Comparison of Forecasting Models

Model	Training	Inference (ms/samp	Memory	Parameters

	Time (min)	le)	(GB)	
LSTM	87.4	2.1	1.8	~1.2 M
XGBoost	12.3	0.8	0.6	~500 K
Random Forest	9.6	1.2	0.9	~300 K
Ensemble (Proposed)	112.5	4.6	3.4	~2.0 M

5. Application to Photovoltaic Energy Management

The practical integration of the proposed forecasting framework into a PV energy management system operates through three principal pathways. First, in dispatch scheduling, hour-ahead GHI forecasts are translated into expected PV power output using a parameterised single-diode PV module model, accounting for temperature-dependent efficiency losses. These power estimates feed directly into unit commitment and economic dispatch optimisation solvers, enabling grid operators to pre-position flexible reserves with an estimated 12–15% reduction in balancing costs relative to persistence-based scheduling (Antonanzas et al., 2016).

Second, in battery energy storage system (BESS) sizing and control, accurate irradiance forecasts reduce the required buffer capacity by enabling proactive charge/discharge scheduling. Simulation studies using the ensemble forecasts as inputs to a model predictive control (MPC) battery management algorithm demonstrated a 9.3% reduction in daily state-of-charge excursions compared to reactive control strategies. Third, for demand-side management in smart grids, probabilistic forecast envelopes derived from the ensemble's prediction intervals allow building energy management systems to shift deferrable loads toward periods of predicted high solar generation, reducing peak grid demand.

6. Conclusion

This study developed and validated a hybrid ensemble learning framework for one-hour-ahead solar irradiance prediction, integrating LSTM, XGBoost, and Random Forest base learners through stacked meta-learning. Using a six-year multi-source observational dataset and rigorous temporal cross-validation, the ensemble achieved state-of-the-art accuracy with an RMSE of 38.9 W/m², MAE of 31.4 W/m², and R^2 of 0.960, outperforming all individual model benchmarks. Seasonal analysis demonstrated robust generalisation, with the most pronounced improvements under winter and overcast conditions where single models exhibit systematic limitations. The inclusion of satellite cloud fraction and aerosol optical depth as predictors provided measurable accuracy gains, particularly during dust-event and monsoon-transition periods.

The framework's inference latency of 4.6 ms per sample satisfies real-time energy management requirements, and demonstrated applications in dispatch scheduling, BESS control, and demand-side management confirm its operational value. Future work will extend the framework to ultra-short-term (5–15 minute) forecasting horizons using sky imagery inputs processed through convolutional neural networks, and will investigate domain adaptation techniques to enable deployment at sites with limited historical data. The integration of probabilistic forecasting outputs through conformal prediction methods to quantify forecast uncertainty is also a priority for enhancing grid operator confidence in AI-driven decision support tools.

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